

# Package: bnRep (via r-universe)

February 19, 2025

**Title** A Repository of Bayesian Networks from the Academic Literature

**Version** 0.0.1

**Description** A collection of Bayesian networks (discrete, Gaussian, and conditional linear Gaussian) collated from recent academic literature. The 'bnRep\_summary' object provides an overview of the Bayesian networks in the repository and the package documentation includes details about the variables in each network. A Shiny app to explore the repository can be launched with 'bnRep\_app()' and is available online at <https://manueleleonelli.shinyapps.io/bnRep>. For details see <https://github.com/manueleleonelli/bnRep>.

**License** MIT + file LICENSE

**Encoding** UTF-8

**Roxygen** list(markdown = TRUE)

**RoxygenNote** 7.3.2

**LazyData** true

**Imports** bnlearn, dplyr, DT, Rgraphviz, qgraph.shiny, shinyjs, shinythemes

**URL** <https://github.com/manueleleonelli/bnRep>

**BugReports** <https://github.com/manueleleonelli/bnRep/issues>

**Depends** R (>= 2.10)

**Suggests** knitr, rmarkdown, ggplot2, scales, stringr, RColorBrewer

**VignetteBuilder** knitr

**Config/pak/sysreqs** libglpk-dev make libicu-dev libjpeg-dev libpng-dev libxml2-dev zlib1g-dev

**Repository** <https://manueleleonelli.r-universe.dev>

**RemoteUrl** <https://github.com/manueleleonelli/bnrep>

**RemoteRef** HEAD

**RemoteSha** 19904c3b7acf6b98dd16848cf3808fc6c2348a39

## Contents

.onAttach . . . . .	6
accidents . . . . .	7
adhd . . . . .	8
adversarialbehavior . . . . .	9
aerialvehicles . . . . .	9
agropastoral1 . . . . .	11
agropastoral2 . . . . .	12
agropastoral3 . . . . .	13
agropastoral4 . . . . .	14
agropastoral5 . . . . .	15
aircrash . . . . .	16
algal1 . . . . .	16
algal2 . . . . .	17
algalactivity1 . . . . .	18
algalactivity2 . . . . .	19
algorithms1 . . . . .	19
algorithms2 . . . . .	20
algorithms3 . . . . .	21
algorithms4 . . . . .	21
algorithms5 . . . . .	22
algorithms6 . . . . .	23
APSystem . . . . .	23
arcticwaters . . . . .	24
argument . . . . .	26
asia . . . . .	27
aspergillus . . . . .	27
augmenting . . . . .	28
bank . . . . .	29
bankruptcy . . . . .	30
beam1 . . . . .	30
beam2 . . . . .	31
beatles . . . . .	32
blacksea . . . . .	32
blockchain . . . . .	34
bnRep . . . . .	35
bnRep_app . . . . .	36
bnRep_summary . . . . .	36
BOPfailure1 . . . . .	37
BOPfailure2 . . . . .	38
BOPfailure3 . . . . .	40
building . . . . .	41
bullet . . . . .	42
burglar . . . . .	43
cachexia1 . . . . .	44
cachexia2 . . . . .	44
cardiovascular . . . . .	45

case . . . . .	46
catchment . . . . .	47
charleston . . . . .	48
chds . . . . .	49
cng . . . . .	50
compaction . . . . .	53
conasense . . . . .	53
concrete1 . . . . .	54
concrete2 . . . . .	55
concrete3 . . . . .	55
concrete4 . . . . .	56
concrete5 . . . . .	57
concrete6 . . . . .	57
concrete7 . . . . .	58
consequenceCovid . . . . .	59
constructionproductivity . . . . .	60
coral1 . . . . .	61
coral2 . . . . .	62
coral3 . . . . .	62
coral4 . . . . .	63
coral5 . . . . .	64
corical . . . . .	65
corrosion . . . . .	66
corticosteroid . . . . .	67
covid1 . . . . .	67
covid2 . . . . .	68
covid3 . . . . .	69
covidfear . . . . .	70
covidrisk . . . . .	71
covidtech . . . . .	71
covidtest . . . . .	73
crimescene . . . . .	74
criminal1 . . . . .	75
criminal2 . . . . .	76
criminal3 . . . . .	77
criminal4 . . . . .	77
crypto . . . . .	78
curacao1 . . . . .	79
curacao2 . . . . .	80
curacao3 . . . . .	81
curacao4 . . . . .	82
curacao5 . . . . .	83
darktriad . . . . .	84
diabetes . . . . .	85
diagnosis . . . . .	85
dioxins . . . . .	86
disputed1 . . . . .	87
disputed2 . . . . .	88

disputed3 . . . . .	89
disputed4 . . . . .	90
dragline . . . . .	91
drainage . . . . .	93
dustexplosion . . . . .	94
earthquake . . . . .	95
ecosystem . . . . .	97
electricvehicle . . . . .	98
electrolysis . . . . .	99
emergency . . . . .	100
engines . . . . .	101
enrollment . . . . .	102
estuary . . . . .	102
expenditure . . . . .	104
fingermarks1 . . . . .	105
fingermarks2 . . . . .	106
fire . . . . .	107
firealarm . . . . .	108
firerisk . . . . .	108
flood . . . . .	109
fluids1 . . . . .	111
fluids2 . . . . .	111
fluids3 . . . . .	112
foodallergy1 . . . . .	113
foodallergy2 . . . . .	114
foodallergy3 . . . . .	114
foodsecurity . . . . .	115
fundraising . . . . .	116
gasexplosion . . . . .	117
gasifier . . . . .	118
GDIpathway1 . . . . .	119
GDIpathway2 . . . . .	121
get_network_list . . . . .	122
gonorrhoeae . . . . .	122
greencredit . . . . .	123
grounding . . . . .	124
healthinsurance . . . . .	125
humanitarian . . . . .	126
hydraulicssystem . . . . .	127
income . . . . .	128
intensification . . . . .	129
intentionalattacks . . . . .	130
inverters . . . . .	130
knowledge . . . . .	132
kosterhavet . . . . .	132
lawschool . . . . .	134
lexical . . . . .	135
lidar . . . . .	136

liquefaction . . . . .	137
liquidity . . . . .	138
lithium . . . . .	139
load_network . . . . .	140
macrophytes . . . . .	141
medicaltest . . . . .	142
megacities . . . . .	142
metal . . . . .	144
moodstate . . . . .	144
mountaingoat . . . . .	145
nanomaterials1 . . . . .	146
nanomaterials2 . . . . .	148
navigation . . . . .	150
nuclearwaste . . . . .	150
nuisancegrowth . . . . .	151
oildepot . . . . .	152
onlinerisk . . . . .	154
orbital . . . . .	156
oxygen . . . . .	157
parkinson . . . . .	159
perioperative . . . . .	160
permaBN . . . . .	161
phdarticles . . . . .	162
pilot . . . . .	162
pneumonia . . . . .	164
polymorphic . . . . .	167
poultry . . . . .	168
project . . . . .	170
projectmanagement . . . . .	171
propellant . . . . .	172
rainstorm . . . . .	174
rainwater . . . . .	176
redmeat . . . . .	176
resilience . . . . .	177
ricci . . . . .	179
rockburst . . . . .	180
rockquality . . . . .	180
ropesegment . . . . .	181
safespeeds . . . . .	182
sallyclark . . . . .	183
salmonella1 . . . . .	184
salmonella2 . . . . .	184
seismic . . . . .	185
shipping . . . . .	186
simulation . . . . .	188
softwarelogs1 . . . . .	188
softwarelogs2 . . . . .	189
softwarelogs3 . . . . .	190

softwarelogs4 . . . . .	191
soil . . . . .	192
soillead . . . . .	193
soilliquefaction1 . . . . .	193
soilliquefaction2 . . . . .	194
soilliquefaction3 . . . . .	195
soilliquefaction4 . . . . .	196
stocks . . . . .	196
student1 . . . . .	197
student2 . . . . .	199
suffocation . . . . .	200
tastingtea . . . . .	202
tbm . . . . .	203
theft1 . . . . .	203
theft2 . . . . .	204
titanic . . . . .	205
trajectories . . . . .	205
transport . . . . .	206
tuberculosis . . . . .	207
turbine1 . . . . .	207
turbine2 . . . . .	208
twinframework . . . . .	210
urinary . . . . .	210
vaccine . . . . .	212
vessel1 . . . . .	212
vessel2 . . . . .	213
waterlead . . . . .	214
wheat . . . . .	216
windturbine . . . . .	216
witness . . . . .	220
yangtze . . . . .	221

**Index****223**

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`.onAttach`*Message for the User*

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**Description**

Prints out a friendly reminder message to the user.

accidents

*accidents Bayesian Network***Description**

Analysis of maritime transport accidents using Bayesian networks.

**Format**

A discrete Bayesian network to provide transport authorities and ship owners with useful insights for maritime accident prevention. Probabilities were given within the referenced paper. The vertices are:

**AccidentType** (Collision, Grounding, Flooding, Fire/Explosion, Capsize, Contact/Crush, Sinking, Overboard, Others);

**EquipmentDevice** (Devices and equipment on board operate correctly, Devices and equipment not fully utilised or operated correctly);

**ErgonomicDesign** (Ergonomic friendly, Ergonomic impact of innovative bridge design);

**FairwayTraffic** (Good, Poor);

**GrossTonnage** (Less than 300, 300-1000, More than 1000, NA);

**HullType** (Steel, Wood, Aluminium, Others);

**Information** (Effective and updated information provided, Insufficient or lack of updated information);

**Length** (Less than 100, More than 100, NA);

**SeaCondition** (Good, Poor);

**ShipAge** (0,5, 6-10, 11-15, 16-20, More than 20, NA);

**ShipOperation** (Towing, Loading/Unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, Others);

**ShipSpeed** (Normal, Fast);

**ShipType** (Passenger vessel, Tug, Barge, Fishing vessel, Container ship, Bulk carrier, RORO, Tanker or chemical ship, Cargo ship, Others);

**TimeOfDay** (7am to 7pm, Other);

**VesselCondition** (Good, Poor);

**VoyageSegment** (In port, Departure, Arrival, Mid-water, Transit, Others);

**WeatherCondition** (Good, Poor);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Fan, S., Yang, Z., Blanco-Davis, E., Zhang, J., & Yan, X. (2020). Analysis of maritime transport accidents using Bayesian networks. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 234(3), 439-454.

adhd

*adhd Bayesian Network***Description**

Development of a computerized adaptive testing for ADHD using Bayesian networks: An attempt at classification.

**Format**

A discrete Bayesian network to classify ADHD symptom. Probabilities were given within the referenced paper. The vertices are:

**ADHD** ADHD symptom severity (No, Few, Moderate, Risk);

**Carelessness** Carelessness (Never, Sometimes, Often, Very Often);

**DifficultySustainingAttention** Difficulty sustaining attention in activities (Never, Sometimes, Often, Very Often);

**DoesntListen** Doesn't listen (Never, Sometimes, Often, Very Often);

**NoFollowThrough** No follow through (Never, Sometimes, Often, Very Often);

**CantOrganize** Can't organize (Never, Sometimes, Often, Very Often);

**AvoidsTasks** Avoids/dislikes tasks requiring sustained mental effort (Never, Sometimes, Often, Very Often);

**LosesItems** Loses important items (Never, Sometimes, Often, Very Often);

**EasilyDistractible** Easily distractible (Never, Sometimes, Often, Very Often);

**Forgetful** Forgetful in daily activities (Never, Sometimes, Often, Very Often);

**SquirmsAndFidgets** Squirms and fidgets (Never, Sometimes, Often, Very Often);

**CantStaySeated** Can't stay seated (Never, Sometimes, Often, Very Often);

**RunsExcessively** Runs/climbs excessively (Never, Sometimes, Often, Very Often);

**CantPlayQuietly** Can't play/work quietly (Never, Sometimes, Often, Very Often);

**OnTheGo** On the go, "driven by a motor" (Never, Sometimes, Often, Very Often);

**TalksExcessively** Talks excessively (Never, Sometimes, Often, Very Often);

**BlurtsOutAnswers** Blurts out answers (Never, Sometimes, Often, Very Often);

**CantWaitForTurn** Can't wait for turn (Never, Sometimes, Often, Very Often);

**IntrudesOthers** Intrudes/interrupts others (Never, Sometimes, Often, Very Often);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Jiang, Z., Ma, W., Flory, K., Zhang, D., Zhou, W., Shi, D., ... & Liu, R. (2023). Development of a computerized adaptive testing for ADHD using Bayesian networks: An attempt at classification. *Current Psychology*, 42(22), 19230-19240.



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adversarialbehavior     *adversarialbehavior Bayesian Network*

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**Description**

Inferring adversarial behaviour in cyber-physical power systems using a Bayesian attack graph approach.

**Format**

A discrete Bayesian network to define and solve the inference problem of adversarial movement in the grid infrastructure towards targets of physical impact. Probabilities were given within the referenced paper. The vertices are:

**RemoteAdversary** (TRUE, FALSE);

**RootAccessFTPServer** (TRUE, FALSE);

**FTPBasedBufferOverflow** (TRUE, FALSE);

**RemoteBufferOverflowOnSSHDaemon** (TRUE, FALSE);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Sahu, A., & Davis, K. (2023). Inferring adversarial behaviour in cyber-physical power systems using a Bayesian attack graph approach. *IET Cyber-Physical Systems: Theory & Applications*, 8(2), 91-108.

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aerialvehicles     *aerialvehicles Bayesian Network*

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**Description**

Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network.

**Format**

A discrete Bayesian network to analyze critical risks associated with unmanned aerial vehicles. Probabilities were given within the referenced paper. The vertices are:

**X1** Mechanical failures (yes, no);

**X2** Battery failures (yes, no);

**X3** Flight control system failures (yes, no);

- X4** Gust (yes, no);
- X5** Rain and snow (yes, no);
- X6** Thunderstorm (yes, no);
- X7** Visibility (yes, no);
- X8** Communication link failures (yes, no);
- X9** GPS failures (yes, no);
- X10** Ostacles (yes, no);
- X11** Route planning issues (yes, no);
- X12** Unclear airspace division (yes, no);
- X13** Unqualified knowledge and skills (yes, no);
- X14** Weak safety awareness (yes, no);
- X15** Lack of experience (yes, no);
- X16** Careless (yes, no);
- X17** Fatigue (yes, no);
- X18** Violations (yes, no);
- X19** Lack of legal awareness (yes, no);
- X20** Psychological problems (yes, no);
- X21** Undefined subject of supervision responsibility (yes, no);
- X22** Lack of unified industry standard (yes, no);
- X23** Unclear airworthiness certification procedures (yes, no);
- X24** Long flight approval cycle (yes, no);
- X25** Weak laws and regulations (yes, no);
- X26** Inadequate training system (yes, no);
- X27** Lack of supervision system (yes, no);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Xiao, Q., Li, Y., Luo, F., & Liu, H. (2023). Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network. *Technology in Society*, 73, 102229.

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agropastoral1

*agropastoral Bayesian Networks*

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### Description

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

### Format

A discrete Bayesian network to explore the influence of the environment on subsistence strategies (Fig. 5 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

**Agriculture** (None, <55, >=55);

**Animal\_Husbandry** (None, <25, >=25);

**Annual\_Temperature** (low, medium, high);

**CV\_Annual\_Precipitation** (low, medium, high);

**CV\_Annual\_Productivity** (low, medium, high);

**CV\_Annual\_Temperature** (low, medium, high);

**Distance\_Coast** (low, medium, high);

**Elevation** (low, medium, high);

**Fishing** (None, <25, >=25);

**Gathering** (None, <25, >=25);

**Hunting** (None, <25, >=25);

**Landscape** (Aquatic, Tundra, Desert, Forest, Grassland);

**Monthly\_Precipitation** (low, medium, high);

**Monthly\_Productivity** (low, medium, high);

**Slope** (low, medium, high);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, 17(10), e0276088.

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agropastoral2

*agropastoral Bayesian Networks*

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## Description

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

## Format

A discrete Bayesian network to explore the relationship between the environment and social organisation (Fig. 6 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

**Annual\_Temperature** (low, medium, high);

**Community\_Size** (<200, >=200)

**CV\_Annual\_Precipitation** (low, medium, high);

**CV\_Annual\_Productivity** (low, medium, high);

**CV\_Annual\_Temperature** (low, medium, high);

**Distance\_Coast** (low, medium, high);

**Elevation** (low, medium, high);

**Landscape** (Aquatic, Tundra, Desert, Forest, Grassland);

**Monthly\_Precipitation** (low, medium, high);

**Monthly\_Productivity** (low, medium, high);

**Slope** (low, medium, high);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, 17(10), e0276088.

**Description**

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

**Format**

A discrete Bayesian network to explore the relationship between the environment and social decisions (Fig. 7 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

**Annual\_Temperature** (low, medium, high);

**CV\_Annual\_Precipitation** (low, medium, high);

**CV\_Annual\_Productivity** (low, medium, high);

**CV\_Annual\_Temperature** (low, medium, high);

**Distance\_Coast** (low, medium, high);

**Elevation** (low, medium, high);

**Exchange\_InSettlement** (No, Yes);

**Landscape** (Aquatic, Tundra, Desert, Forest, Grassland);

**Monthly\_Precipitation** (low, medium, high);

**Monthly\_Productivity** (low, medium, high);

**Slope** (low, medium, high);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, 17(10), e0276088.

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 agropastoral4

 agropastoral Bayesian Networks
 

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### Description

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

### Format

A discrete Bayesian network to explore the relationship between the environment and social decisions (Fig. 8 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

**Annual\_Temperature** (low, medium, high);  
**Crop\_Specialisation** (No, Yes);  
**CV\_Annual\_Precipitation** (low, medium, high);  
**CV\_Annual\_Productivity** (low, medium, high);  
**CV\_Annual\_Temperature** (low, medium, high);  
**Distance\_Coast** (low, medium, high);  
**Elevation** (low, medium, high);  
**Exchange\_InSettlement** (No, Yes);  
**Exchange\_OutSettlement** (No, Yes);  
**Foraging\_Intensification** (No, Yes);  
**Landscape** (Aquatic, Tundra, Desert, Forest, Grassland);  
**Monthly\_Precipitation** (low, medium, high);  
**Monthly\_Productivity** (low, medium, high);  
**None** (No, Yes);  
**Permanent\_Migration** (No, Yes);  
**Reciprocity** (No, Yes);  
**Resource\_Diversification** (No, Yes);  
**Slope** (low, medium, high);  
**Storage** (No, Yes);  
**Temporal\_Migration** (No, Yes);  
**Transhumance** (No, Yes);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, 17(10), e0276088.

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agropastoral5

*agropastoral Bayesian Networks*

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## Description

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

## Format

A discrete Bayesian network to explore the relationship between social organisation and subsistence strategies. The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

**Community\_Organisation** (Clan communities, Missing, No exogamous clans);

**Community\_Size** (<200, >=200);

**Gathering** (None, <25, >=25);

**Household\_Organisation** (Small extended, Large extended, Nuclear);

**Settlement\_Types** (Camp, Hamlet, Homesteads, Village);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, 17(10), e0276088.

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 aircrash

*aircrash Bayesian Network*


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### Description

Application of a Bayesian network to aid the interpretation of blood alcohol (ethanol) concentrations in air crashes.

### Format

A discrete Bayesian network to model the relationships between analytical results, circumstantial evidence and the concentration of alcohol at the time of death in cases of air crash. Probabilities were given within the referenced paper. The vertices are:

**5HTOL5HIAARatio** (Above 20, Below 20);

**BACAtTimeOfDeath** (a101plus, a80-100, a50-80, a40-49, a30-39, a20-29, a10-19, Negative);

**EthanolConsumptionWithin8hrsOfDeath** (Yes, No);

**MeasuredBAC** (a101plus, a80-100, a50-80, a40-49, a30-39, a20-29, a10-19, Negative);

**PMAlcoholFormation** (PMF, No PMF);

**UACPositive** (UPositive, UNegative);

**VACPositive** (Positive, Negative);

**VOCDetected** (Detected, Not Detected);

**WitnessEvidenceOfETOHConsumption** (Positive, Negative);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Maskell, P. D., & Jackson, G. (2020). Application of a Bayesian network to aid the interpretation of blood alcohol (ethanol) concentrations in air crashes. *Forensic Science International*, 308, 110174.

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 algal1

*algal Bayesian Networks*


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### Description

Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian networks.



**Format**

A discrete Bayesian network to to forecast, in spring, mean total phosphorus and chlorophyll a concentration, mean water colour, and maximum cyanobacteria biovolume for the upcoming growing season (May–October) in Vansjø. Probabilities were given within the referenced paper. The vertices are:

**ChiA** Mean lake chl a concentration - Current (Low, High);

**ChiA\_PS** Mean lake chl a concentration - Previous (Low, High);

**Colour** Mean lake colour (Low, Medium, High);

**Cyanobacteria** Mean lake cyanobacterial biovolume (Low, High);

**RainSum** Precipitation sum (Low, High);

**TP** Mean lake TP concentration - Current (Low, High);

**TP\_PS** Mean lake TP concentration - Previous (Low, High);

**WindSpeed** Mean daily mean wind speed (Low, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Jackson-Blake, L. A., Clayer, F., Haande, S., Sample, J. E., & Moe, S. J. (2022). Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian network. *Hydrology and Earth System Sciences*, 26(12), 3103-3124.

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 algal2

*algal Bayesian Networks*


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**Description**

Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian networks.

**Format**

A Gaussian Bayesian network to to forecast, in spring, mean total phosphorus and chlorophyll a concentration, mean water colour, and maximum cyanobacteria biovolume for the upcoming growing season (May–October) in Vansjø. Probabilities were given within the referenced paper. The vertices are:

**ChiA** Mean lake chl a concentration - Current;

**ChiA\_PS** Mean lake chl a concentration - Previous;

**Colour** Mean lake colour;

**Cyanobacteria** Mean lake cyanobacterial biovolume;

**RainSum** Precipitation sum;  
**TP** Mean lake TP concentration - Current;  
**TP\_PS** Mean lake TP concentration - Previous;  
**WindSpeed** Mean daily mean wind speed;

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Jackson-Blake, L. A., Clayer, F., Haande, S., Sample, J. E., & Moe, S. J. (2022). Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian network. *Hydrology and Earth System Sciences*, 26(12), 3103-3124.

---

algalactivity1

*algalactivity Bayesian Networks*

---

### Description

Influence of resampling techniques on Bayesian network performance in predicting increased algal activity.

### Format

A discrete Bayesian network to to predict chlorophyll-a (chl-a) using a range of water quality parameters as predictors (Fig. 6 of the referenced paper). Probabilities were given within the referenced paper (a uniform was given to the vertex `Chl_a` since it was missing). The vertices are:

**C** (0, 1);  
**Chl\_a** (0, 1);  
**DO** (0, 1);  
**N** (0, 1);  
**P** (0, 1);  
**pH** (0, 1);  
**Te** (0, 1);  
**Tu** (0, 1);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Rezaabad, M. Z., Lacey, H., Marshall, L., & Johnson, F. (2023). Influence of resampling techniques on Bayesian network performance in predicting increased algal activity. *Water Research*, 244, 120558.

---

`algalactivity2`*algalactivity Bayesian Networks*

---

**Description**

Influence of resampling techniques on Bayesian network performance in predicting increased algal activity.

**Format**

A discrete Bayesian network to to predict chlorophyll-a (chl-a) using a range of water quality parameters as predictors (Fig. 7 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**C** (0, 1);

**Chl\_a** (0, 1);

**DO** (0, 1);

**N** (0, 1);

**P** (0, 1);

**pH** (0, 1);

**Te** (0, 1);

**Tu** (0, 1);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Rezaabad, M. Z., Lacey, H., Marshall, L., & Johnson, F. (2023). Influence of resampling techniques on Bayesian network performance in predicting increased algal activity. *Water Research*, 244, 120558.

---

`algorithms1`*algorithms Bayesian Networks*

---

**Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

**Format**

A Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 1, top). The probabilities were available from a repository. The vertices are:

**X1**

**X2**

**X3**

**X4**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. *Algorithms*, 17(1), 24.

---

algorithms2

*algorithms Bayesian Networks*

---

**Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

**Format**

A Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 1, bottom). The probabilities were available from a repository. The vertices are:

**X1**

**X2**

**X3**

**X4**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. *Algorithms*, 17(1), 24.

---

`algorithms3`*algorithms Bayesian Networks*

---

**Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

**Format**

A discrete Bayesian network to illustrate the algorithms developed in the associated paper (Figure 2, top). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4** (g, h);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. *Algorithms*, 17(1), 24.

---

`algorithms4`*algorithms Bayesian Networks*

---

**Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

**Format**

A discrete Bayesian network to illustrate the algorithms developed in the associated paper (Figure 2, bottom). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4** (g, h);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. *Algorithms*, 17(1), 24.

---

algorithms5

*algorithms Bayesian Networks*

---

**Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

**Format**

A conditional linear Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 3, top). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4**

**X5**

**X6**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. *Algorithms*, 17(1), 24.

---

algorithms6

*algorithms Bayesian Networks*

---

### Description

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

### Format

A conditional linear Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 3, bottom). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4**

**X5**

**X6**

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. *Algorithms*, 17(1), 24.

---

APSystem

*APSystem Bayesian Network*

---

### Description

An ERP data quality assessment framework for the implementation of an APS system using Bayesian networks.

**Format**

A discrete Bayesian network for data quality assessment. Probabilities were given within the referenced paper. The vertices are:

**QPlanDeliveryTime** (Complete, Incomplete);

**QSetupTime** (Complete, Incomplete);;

**PlanDeliveryTime** (Complete, Incomplete);

**SetupTime** (Complete, Incomplete);

**NNTransactionData** (Complete, Incomplete);

**NNMasterData** (Complete, Incomplete);

**NNValues** (High, Low);

**Completeness** (High, Low);

**Consistency** (High, Low);

**DataQuality** (High, Low);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Herrmann, J. P., Tackenberg, S., Padoano, E., Hartlief, J., Rautenstengel, J., Loeser, C., & Böhme, J. (2022). An ERP Data Quality Assessment Framework for the Implementation of an APS system using Bayesian Networks. *Procedia Computer Science*, 200, 194-204.

---

arcticwaters

*arcticwaters Bayesian Network*


---

**Description**

An object-oriented Bayesian network model for the quantitative risk assessment of navigational accidents in ice-covered Arctic waters.

**Format**

A discrete Bayesian network for the quantitative risk assessment of multiple navigational accidents in ice-covered Arctic waters. Probabilities were given within the referenced paper. The vertices are:

**AidNavigationFailure** (No, Yes);

**AirTemperature** (<0 degrees, >0 degrees);

**C\_BesettingInIce** (Significant, Severe, Catastrophic);

**C\_Collision** (Significant, Severe, Catastrophic);

**C\_Grounding** (Significant, Severe, Catastrophic);



**C\_ShipIceCollision** (Significant, Severe, Catastrophic);  
**ChannelDepth** (Inadequate, Adequate);  
**ChartUpdating** (No, Yes);  
**CommunicationEquipmentFailure** (No, Yes);  
**DriftIce** (No, Yes);  
**EnvironmentalObstacles** (No, Yes);  
**Fatigued** (No, Yes);  
**Fog** (No, Yes);  
**GrossTonnage** ((0,500], (500,3000], (3000,10000], >10000);  
**IceConcentration** (<3/10, 4/10-6/10, >7/10);  
**IceCondition** (Poor, Good);  
**IceStrength** (Low, Medium, High);  
**IceThickness** (<0.5m, >0.5m);  
**IceType** (Thin Ice, Medium Ice, Old Ice);  
**InadequateKnowledge** (No, Yes);  
**JudgmentFailure** (No, Yes);  
**LackCommunication** (No, Yes);  
**LackSafetyMeasures** (No, Yes);  
**LackSituationalAwareness** (No, Yes);  
**MechanicalEquipmentFailure** (No, Yes);  
**NavigatorFailure** (No, Yes);  
**Negligence** (No, Yes);  
**P\_BesettingInIce** (No, Yes);  
**P\_Collision** (No, Yes);  
**P\_Grounding** (No, Yes);  
**P\_ShipIceCollision** (No, Yes);  
**PowerFailure** (No, Yes);  
**PropellerFailure** (No, Yes);  
**RadarFailure** (No, Yes);  
**Rain** (No, Yes);  
**SeaCurrent** (No, Yes);  
**SeaTemperature** (<0 degrees, >0 degrees);  
**ShipType** (Oil Tanker, General Cargo Ship, Passenger Ship, Icebreaker, Others);  
**SteeringFailure** (No, Yes);  
**StrongWind** (No, Yes);  
**UnsafeAct** (No, Yes);  
**UnsafeCondition** (No, Yes);  
**UnsafeSpeed** (No, Yes);  
**Visibility** (Poor, Good);  
**WaterwayCondition** (Poor, Good);  
**WeatherCondition** (Poor, Good);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Fu, S., Zhang, Y., Zhang, M., Han, B., & Wu, Z. (2023). An object-oriented Bayesian network model for the quantitative risk assessment of navigational accidents in ice-covered Arctic waters. *Reliability Engineering & System Safety*, 238, 109459.

---

argument

*argument Bayesian Network*

---

**Description**

Towards an empirically informed normative Bayesian scheme-based account of argument from expert opinion.

**Format**

A discrete Bayesian network formalizing Walton's re-constructed set of critical questions. Probabilities were given within the referenced paper. The vertices are:

**DecisionProcess** (Not based on evidence, Integrative complexity, Absence of integrative complexity);

**DeliberativePractice** (FALSE, TRUE);

**ExpertAssertsHypothesis** (FALSE, TRUE);

**Feedback** (FALSE, TRUE);

**GenuineExpertise** (FALSE, TRUE);

**Hypothesis** (FALSE, TRUE);

**ObjectiveEvidence** (FALSE, TRUE);

**RegularPractice** (FALSE, TRUE);

**Validity** (High, Medium, High);

**WellInformedPractice** (FALSE, TRUE);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Pei, K. N., & Chin, C. S. A. (2023). Towards an empirically informed normative Bayesian scheme-based account of argument from expert opinion. *Thinking & Reasoning*, 29(4), 726-759.

---

asia

*asia Bayesian Network*

---

### Description

Local computation with probabilities on graphical structures and their application to expert systems.

### Format

A synthetic discrete Bayesian network to model the relationships between lung diseases and visits to Asia. Probabilities were given within the referenced paper. The vertices are:

**Bronchitis** (True, False);

**Dyspnea** (True, False);

**Lung\_Cancer** (True, False);

**Smoker** (True, False);

**Tuberculosis** (True, False);

**TuberculosisOrCancer** (True, False);

**Visit\_To\_Asia** (True, False);

**XRay\_Result** (True, False);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Lauritzen, S. L., & Spiegelhalter, D. J. (1988). Local computations with probabilities on graphical structures and their application to expert systems. *Journal of the Royal Statistical Society: Series B (Methodological)*, 50(2), 157-194.

---

aspergillus

*aspergillus Bayesian Network*

---

### Description

Using staged tree models for health data: Investigating invasive fungal infections by aspergillus and other filamentous fungi.

**Format**

A discrete Bayesian network modelling the relationship between risk factors and death by Aspergillus. The original dataset was used to learn the Bayesian network. The vertices are:

**CMV** CMV Infection (No, Si);

**DT** Diagnostic Time (<16 days, >=16 days);

**DTH** Death (No, Si);

**GR** Immunosuppression Groups (Neutropenia, IS-conventional, IS-non-conventional);

**ICU** Accessed the ICU (No, Si);

**IM** Immunotherapy (No, Si);

**MN** Malnutrition (No, Si);

**RP** Radiological Pattern (No, Si);

**SC** Systemic Corticoids (No, Si);

**SOT** Solid Organ Transplant (No, Si);

**VP** Viral Pneumonia (No, Si);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Filigheddu, M. T., Leonelli, M., Varando, G., Gómez-Bermejo, M. Á., Ventura-Díaz, S., Gorospe, L., & Fortún, J. (2024). Using staged tree models for health data: Investigating invasive fungal infections by aspergillus and other filamentous fungi. *Computational and Structural Biotechnology Journal*, 24, 12-22.

---

augmenting

*augmenting Bayesian Network*

---

**Description**

Augmenting learning components for safety in resource constrained autonomous robots.

**Format**

A discrete Bayesian network to estimate the probability that the car will remain on track, given its current state and control actions. Probabilities were given within the referenced paper. The vertices are:

**CmdSteeringOnTurn** (Leaf, Straight, Right);

**CurrentPosition** (Near, On, Far);

**CurrentSteering** (Straight, Left, Right);

**CurrentVelocity** (Slow, Medium, Fast);

**InTrack** (Yes, No);

**SafeTurnRegion** (Yes, No);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ramakrishna, S., Dubey, A., Burruss, M. P., Hartsell, C., Mahadevan, N., Nannapaneni, S., ... & Karsai, G. (2019, May). Augmenting learning components for safety in resource constrained autonomous robots. In 2019 IEEE 22nd International Symposium on Real-Time Distributed Computing (ISORC) (pp. 108-117). IEEE.

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 bank

*bank Bayesian Network*


---

**Description**

Structural learning of simple staged trees.

**Format**

A discrete Bayesian network to model whether customers subscribe to a product after being contacted by direct marketing campaigns of a Portuguese banking institution. The Bayesian network is learned via data as stated in the paper. The vertices are:

**marital** Marital status (divorced, married, single, unknown);

**education** Education (no\_uni, uni);

**contact** Type of direct marketing contact (cellular, telephone);

**subscription** (no, yes);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Leonelli, M., & Varando, G. (2024). Structural learning of simple staged trees. *Data Mining and Knowledge Discovery*, 38(3), 1520-1544.

---

bankruptcy

*bankruptcy Bayesian Network*

---

### Description

Using Bayesian networks for bankruptcy prediction: Some methodological issues.

### Format

A discrete Bayesian network for bankruptcy prediction. Probabilities were given within the referenced paper. The vertices are:

**BankruptcyStatus** (FALSE, TRUE);

**AuditorsOpinion** (FALSE, TRUE);

**StockReturn** (Low, Medium, High);

**NetIncomeRate** (Low, Medium, High);

**IndustryFailureRate** (Low, Medium, High);

**MarketableSecurities** (Low, Medium, High);

**FirmSize** (Low, Medium, High);

**NetIncomeNegative** (FALSE, TRUE);

**CashAssets** (Low, Medium, High);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Sun, L., & Shenoy, P. P. (2007). Using Bayesian networks for bankruptcy prediction: Some methodological issues. *European Journal of Operational Research*, 180(2), 738-753.

---

beam1

*beams Bayesian Network*

---

### Description

Bayesian networks and their application to the reliability of FRP strengthened beams.

**Format**

A discrete Bayesian network assess the structural reliability of bridge systems (Figure 2). Probabilities were given within the referenced paper. The vertices are:

**BeamShearSpan** (Low, High);

**FRPSheetsSpacing** (Low, High);

**ModelOfFailure** (Rupture, Debonding, Pass);

**ProbabilityOfFailure** (Fail, Pass);

**ShearGain** (Low, Medium, High);

**WrappingScheme** (Grooving, Side Bonding, Three Side Bonding, Three Side Bonding With Anchoring, Full Wrapping);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Obaid, O., & Leblouba, M. (2022, March). Bayesian Networks and Their Application to the Reliability of FRP Strengthened Beams. In International Civil Engineering and Architecture Conference (pp. 277-284). Singapore: Springer Nature Singapore.

---

 beam2

*beams Bayesian Network*


---

**Description**

Bayesian networks and their application to the reliability of FRP strengthened beams.

**Format**

A discrete Bayesian network assess the structural reliability of bridge systems (Figure 3). Probabilities were given within the referenced paper. The vertices are:

**BeamWidth** (Low, High);

**ConcreteStrength** (Low, High);

**ProbabilityOfFailure** (Fail, Pass);

**Reinforcement** (Low, High);

**TempAndHumidity** (Low, High);

**WaterCementRatio** (Low, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Obaid, O., & Leblouba, M. (2022, March). Bayesian Networks and Their Application to the Reliability of FRP Strengthened Beams. In International Civil Engineering and Architecture Conference (pp. 277-284). Singapore: Springer Nature Singapore.

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beatles	<i>beatles Bayesian Network</i>
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## Description

Measuring coherence with Bayesian networks.

## Format

A discrete Bayesian modelling a situation where a member of the Beatles band might be dead. Probabilities were given within the referenced paper. The vertices are:

**ExactlyOneBeatlesIsDead** (TRUE, FALSE);

**GeorgeIsAlive** (TRUE, FALSE);

**JohnIsAlive** (TRUE, FALSE);

**PaulIsAlive** (TRUE, FALSE);

**RingoIsAlive** (TRUE, FALSE);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Kowalewska, A., & Urbaniak, R. (2023). Measuring coherence with Bayesian networks. *Artificial Intelligence and Law*, 31(2), 369-395.

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blacksea	<i>blacksea Bayesian Network</i>
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---

## Description

Analyzing collision, grounding, and sinking accidents occurring in the Black Sea utilizing HFACS and Bayesian networks.



**Format**

A discrete Bayesian network to analyze the marine accidents. The probabilities were given within the referenced paper. The vertices are:

**AnchorageAreaSelection** (Appropriate, Inappropriate);  
**CargoShiftingOrInappropriateStability** (Yes, No);  
**CollisionAndContact** (Yes, No);  
**COLREG** (Not Violated, Violated);  
**CompanyManningStrategy** (Optimum Safe Manning, Minimum Safe Manning);  
**CrewAssignment** (Qualified Crew, Unqualified Crew);  
**DepartureFromPortInHeavyWeatherAndSeaCondition** (Yes, No);  
**ExternalInternalCommunication** (Adequate, Inadequate);  
**ExternalOperationalConditionsForCollisionAndContact** (Observed, Unobserved);  
**ExternalOperationalConditionsForGrounding** (Observed, Unobserved);  
**ExternalOperationalConditionsForSinking** (Observed, Unobserved);  
**Fatigue** (Yes, No);  
**Grounding** (Yes, No);  
**HeavyWeatherAndSeaConditions** (Yes, No);  
**InadequateManning** (Yes, No);  
**InlandVessel** (Yes, No);  
**InternalOperationalConditionsForCollisionAndContact** (Observed, Unobserved);  
**InternalOperationalConditionsForGrounding** (Observed, Unobserved);  
**InternalOperationalConditionsForSinking** (Observed, Unobserved);  
**Malfunction** (Observed, Unobserved);  
**ManoeuvreOfBridgeTeamMembers** (Appropriate, Inappropriate);  
**ManoeuvreOfCaptain** (Appropriate, Inappropriate);  
**ManoeuvreOfPilot** (Appropriate, Inappropriate);  
**ManoeuvreOfWatchkeepingOfficer** (Appropriate, Inappropriate);  
**NavigationArea** (Narrow Water, Port, Coastal Water, Open Sea, Anchorage);  
**NavigationOnStorm** (Yes, No);  
**ObservationDuringOperation** (Clear, Unclear);  
**OversightAndControl** (Adequate, Inadequate);  
**PilotOperationManagement** (Safe, Unsafe);  
**PlannedMaintenance** (Completed, Uncompleted);  
**PortCompanyPressure** (Yes, No);  
**PortOperationManagement** (Safe, Unsafe);  
**PortOperationPlanning** (Adequate, Inadequate);  
**Procedure** (Appropriate, Inappropriate);

**Sinking** (Yes, No);  
**SituationalAwareness** (Sufficient, Insufficient);  
**TrainingAndFamiliarization** (Sufficient, Insufficient);  
**TriggeringEventForCollisionAndContact** (Observed, Unobserved);  
**TriggeringEventForGrounding** (Observed, Unobserved);  
**TriggeringEventForSinking** (Observed, Unobserved);  
**TugboatOperation** (Operational, Faulty);  
**UseOfVesselInConditionOfExceedingDesignLimit** (Yes, No);  
**VesselAge** (Old, New);  
**VesselCargoOperationManagement** (Safe, Unsafe);  
**VesselCargoOperationPlanning** (Adequate, Inadequate);  
**VesselNavigationOperationManagement** (Safe, Unsafe);  
**VesselNavigationOperationPlanning** (Unsafe, Safe);  
**Visibility** (Poor, Good);

#### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

#### References

Ugurlu, O., Yildiz, S., Loughney, S., Wang, J., Kuntchulia, S., & Sharabidze, I. (2020). Analyzing collision, grounding, and sinking accidents occurring in the Black Sea utilizing HFACS and Bayesian networks. *Risk analysis*, 40(12), 2610-2638.

---

blockchain

*blockchain Bayesian Network*

---

#### Description

A machine learning based approach for predicting blockchain adoption in supply chain.

#### Format

A discrete Bayesian network to predict the probability of blockchain adoption in an organization. Probabilities were given within the referenced paper. The vertices are:

**BA** Blockchain adoption (Low, High);  
**COMPB** Compatibility (Low, High);  
**COMPX** Complexity (Low, High);  
**CP** Competitive pressure (Low, High);  
**PEOU** Perceived ease of use (Low, High);

**PFB** Perceived financial benefits (Low, High);

**PR** Partner readiness (Low, High);

**PU** Perceived usefulness (Low, High);

**RA** Relative advantage (Low, High);

**TE** Training and education (Low, High);

**TKH** Technical know-how (Low, High);

**TMS** Top management support (Low, High);

@return An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Kamble, S. S., Gunasekaran, A., Kumar, V., Belhadi, A., & Foropon, C. (2021). A machine learning based approach for predicting blockchain adoption in supply chain. *Technological Forecasting and Social Change*, 163, 120465.

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bnRep

*bnRep: A Repository of Bayesian Network Models*

---

## Description

A repository of discrete, Gaussian, and conditional linear Gaussian Bayesian networks from the recent academic literature.

## Details

The package includes over 200 Bayesian networks which appeared in recent academic papers. They can be accessed by their name, as provided in this documentation.

They are stored as `bn.fit` objects from the `bnlearn` package. Recall that in order to plot them, the function `bn.net` must be used to convert them into a graph object.

The package includes two handy functionalities:

- The `bnRep_summary` object: a dataframe including a lot of details about the Bayesian networks in the repository;
- The `bnRep_app` function, which launches a Shiny app to explore the Bayesian networks in the repository.

Thanks to the interface with `bnlearn`, functions from that package can be used to export the networks in other formats and use them in other platforms, such as Netica, Hugin, or Python.

---

bnRep_app	<i>Launch the Bayesian Network Viewer App</i>
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---

**Description**

This function launches the Shiny app that allows users to interactively view and filter the Bayesian networks repository.

**Usage**

```
bnRep_app()
```

**Value**

The function calls a Shiny app to plot networks in bnRep and explore the database of networks stored in bnRep\_summary.

---

bnRep_summary	<i>BnRep Summary</i>
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---

**Description**

Summary of the Bayesian networks in bnRep reporting various graph, definition and application details.

**Usage**

```
bnRep_summary
```

**Format**

A data frame with a row for each BN in bnRep and the following columns:

**Name** Name of the R object storing the BN;

**Type** Type of Bayesian network (Discrete, Gaussian, Hybrid);

**Structure** How the graph of the BN was defined (Data, Expert, Fixed, Knowledge, Mixed, Synthetic);

**Probabilities** How the probabilities of the BN were defined (Data, Expert, Knowledge, Mixed, Synthetic);

**Graph** Type of graph of the BN (Generic, K-Dep, Naive Bayes, Reverse Naive Bayes, Reverse Tree, TAN, Tree);

**Area** Subject area of the Bayesian network using the SJR classification (Agricultural Sciences, Business, Chemical Engineering, etc.);

**Nodes** Number of nodes in the BN;

**Arcs** Number of arcs in the BN;  
**Parameters** Number of free parameters in the BN;  
**Avg. Parents** Average number of parents;  
**Max Parents** Maximum number of parents;  
**Avg. Levels** Average number of discrete variables' levels;  
**Max Levels** Max number of discrete variables' levels;  
**Average Markov Blanket** Average size of a node's Markov blanket;  
**Year** Year of the publication where the BN appeared;  
**Journal** Journal where the BN appeared;  
**Reference** Reference of the paper where the BN appeared.

### Examples

```
summary(bnRep_summary)
```

---

BOPfailure1

*BOPfailure Bayesian Networks*

---

### Description

Providing a comprehensive approach to oil well blowout risk assessment.

### Format

A discrete Bayesian network for risk assessment of oil well blowout (Fig. 5 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**BOP\_System\_Failure** (F, S);  
**X1** BOP stack failure (F, S);  
**X2** Valve failure (F, S);  
**X3** BOP control system failure (F, S);  
**X4** Line failure (F, S);  
**X5** Choke manifold failure (F, S);  
**X6** Annular preventer (F, S);  
**X7** Ram preventer (F, S);  
**X8** Kill valve fail (F, S);  
**X9** Choke valve fail (F, S);  
**X10** Choke line fail (F, S);  
**X11** Kill line fail (F, S);  
**X12** Upper annular preventer fails (F, S);

- X13** Lower annular preventer fails (F, S);
- X14** Upper pipe ram fail (F, S);
- X15** Middle pipe ram fail (F, S);
- X16** Lower pipe ram failure (F, S);
- X17** Blind shear ram failure (F, S);
- X18** Power system failure (F, S);
- X19** 4Way valve failure (F, S);
- X20** Remote panel valve failure (F, S);
- X21** Signal line failure (F, S);
- X22** Accumulator line failure (F, S);
- X23** Air-driven pump failure (F, S);
- X24** Electric pump failure (F, S);
- X25** Choke valve failure (F, S);
- X26** Hydraulic choke valve failure (F, S);
- X27** Gate valve failure (F, S);
- X28** Choke remote panel failure (F, S);
- X29** Hydraulic choke valve failure (F, S);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Satiarvand, M., Orak, N., Varshosaz, K., Hassan, E. M., & Cheraghi, M. (2023). Providing a comprehensive approach to oil well blowout risk assessment. *Plos One*, 18(12), e0296086.

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BOPfailure2

*BOPfailure Bayesian Networks*

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### Description

Providing a comprehensive approach to oil well blowout risk assessment.

### Format

A discrete Bayesian network for risk assessment of oil well blowout (Fig. 3 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

- Kick** (F, S);
- X1** Efficient hydrocarbon formation (F, S);
- X2** Negative diffraction pressure (F, S);

- X3** Sufficient permeability (F, S);
- X4** Low hydrostatic pressure (F, S);
- X5** Low and lost Annular Pressure Loss (F, S);
- X6** Surface line failure (F, S);
- X7** Power failure (F, S);
- X8** Pump failure (F, S);
- X9** Operator failure to notice adjustment (F, S);
- X10** Pump control failure (F, S);
- X11** Leakage from the pump's fluid side (F, S);
- X12** Blowing (F, S);
- X13** Density reduction (F, S);
- X14** Volume reduction (F, S);
- X15** Inadequate holes fill up (F, S);
- X16** Mud loss (F, S);
- X17** Gas-cut mud (F, S);
- X18** Abnormal pressurize (F, S);
- X19** Swabbing while tripping (F, S);
- X20** Mud weight reduction (F, S);
- X21** Failure in Mud treatment equipment (F, S);
- X22** Formation (F, S);
- X23** Increasing mud weight (F, S);
- X24** Annular losses (F, S);
- X25** Bad cementing (F, S);
- X26** Casing failure (F, S);
- X27** Surging-piston effect (F, S);
- X28** Failure in centrifuge (F, S);
- X29** Failure in degasser (F, S);
- X30** Mud cleaner equipment in adjustment (F, S);
- X31** Power failure (F, S);
- X32** Agitator(mixer) failure (F, S);
- X33** Settlement of mud-weight substance (F, S);
- X34** Pulling the pipe too fast (F, S);
- X35** Using Mud with high viscosity and high gel strength (F, S);
- X36** Having balled up a bit (F, S);
- X37** Having thick wall cake (F, S);
- X38** Having a small clearance between the string and the hole (F, S);
- X39** Having and plugged drill string (F, S);

- X40** Directing the pipes at the speed inside the well (F, S);
- X41** Using mud of high viscosity & and high gel strength (F, S);
- X42** Having balled up (F, S);
- X43** Having Thick wall cake (F, S);
- X44** Having a small clearance between the string and the hole (F, S);
- X45** Using the float valve /nonreturn safety valve (F, S);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Satiarvand, M., Orak, N., Varshosaz, K., Hassan, E. M., & Cheraghi, M. (2023). Providing a comprehensive approach to oil well blowout risk assessment. *Plos One*, 18(12), e0296086.

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BOPfailure3

*BOPfailure Bayesian Networks*

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### Description

Providing a comprehensive approach to oil well blowout risk assessment.

### Format

A discrete Bayesian network for risk assessment of oil well blowout (Fig. 4 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

- Kick\_Detection\_Failure** (F, S);
- X1** Mud volume/ flow change (F, S);
- X2** Circulation pressure change (F, S);
- X3** Gas-cut (F, S);
- X4** Mud property change (F, S);
- X5** Rate of Penetration (ROP) change Failure (F, S);
- X6** Mud tank (F, S);
- X7** Flow Failure (F, S);
- X8** Pump Failure (F, S);
- X9** Pump Rate (Stroke Per Minute: SPM) (F, S);
- X10** Mud density (F, S);
- X11** Mud conductivity (F, S);
- X12** Failure of tank level indicator (float system) (F, S);
- X13** Failure of an operator to notice the tank level change (F, S);



- X14** Failure of flow meter (F, S);
- X15** Failure of an operator to notice the flow meter (F, S);
- X16** Failure of pressure gage (F, S);
- X17** Failure of an operator to notice a change in SPM (F, S);
- X18** Failure of stroke meter (F, S);
- X19** Failure of an operator to notice a change in P.R (F, S);
- X20** Failure of gas detector (F, S);
- X21** Failure of an operator to notice the gauge (F, S);
- X22** Failure of the density meter (F, S);
- X23** Failure of an operator to the density meter (F, S);
- X24** Failure of resistivity (F, S);
- X25** Failure of an operator to notice the conductivity change (F, S);
- X26** Failure of the ROP indicator (F, S);
- X27** Failure of the ROP change (F, S);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Satiarvand, M., Orak, N., Varshosaz, K., Hassan, E. M., & Cheraghi, M. (2023). Providing a comprehensive approach to oil well blowout risk assessment. *Plos One*, 18(12), e0296086.

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building

*building Bayesian Network*

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### Description

Sensitivity analysis in Gaussian Bayesian networks using a symbolic-numerical technique.

### Format

A Gaussian Bayesian network to assess the damage of reinforced concrete structures of buildings. Probabilities were given within the referenced paper. The vertices are:

- X1** Damage assessment;
- X2** Cracking state;
- X3** Cracking state in shear domain;
- X4** Steel corrosion;
- X5** Cracking state in flexure domain;
- X6** Shrinkage cracking;

- X7** Worst cracking in flexure domain;
- X8** Corrosion state;
- X9** Weakness of the beam;
- X10** Deflection of the beam;
- X11** Position of the worst shear crack;
- X12** Breadth of the worst shear crack;
- X13** Position of the worst flexure crack;
- X14** Breadth of the worst flexure crack;
- X15** Length of the worst flexure cracks;
- X16** Cover;
- X17** Structure age;
- X18** Humidity;
- X19** pH value in the air;
- X20** Content of chlorine in the air;
- X21** Number of shear cracks;
- X22** Number of flexure cracks;
- X23** Shrinkage;
- X24** Corrosion;

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Castillo, E., & Kjærulff, U. (2003). Sensitivity analysis in Gaussian Bayesian networks using a symbolic-numerical technique. *Reliability Engineering & System Safety*, 79(2), 139-148.

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bullet

*bullet Bayesian Network*

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### Description

Combined interpretation of objective firearm evidence comparison algorithms using Bayesian network.

### Usage

bullet

**Format**

A discrete Bayesian network to leverage the strengths of individual approaches to evaluate the similarity of features on two bullets. The network was available in a repository. The vertices are:

**Conclusion** (NotSource, Source);

**CCF** Cross-correlation function (CCF\_0\_1, CCF\_1\_2, CCF\_2\_3, CCF\_3\_4, CCF\_4\_5, CCF\_5\_6, CCF\_6\_7, CCF\_7\_8, CCF\_8\_9, CCF\_9\_10);

**CMPS** Congruent matching profile segments (CMPS\_0, CMPS\_1, CMPS\_2, CMPS\_3, ... , CMPS\_27);

**RF** Random forest (RF\_0\_1, RF\_1\_2, RF\_2\_3, RF\_3\_4, RF\_4\_5, RF\_5\_6, RF\_6\_7, RF\_7\_8, RF\_8\_9, RF\_9\_10);

**CMS** Consecutively matching striae (CMS\_0, CMS\_1, .... , CMS\_29);

**Details**

@usage NULL

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Spaulding, J. S., & LaCasse, L. S. (2024). Combined interpretation of objective firearm evidence comparison algorithms using Bayesian networks. *Journal of Forensic Sciences*.

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burglar

*burglar Bayesian Network*

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**Description**

Strategies for selecting and evaluating information.

**Format**

A discrete Bayesian network modeling a simple burglary scenario (Model 1, Table 2). The network was available from an associated repository. The vertices are:

**Burglar** (Suspect 1, Suspect 2, Suspect3);

**PrimaryItemStolen** (Jewellery, Electronics, Money);

**BurglaryTime** (Day, Night);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Liefgreen, A., Pilditch, T., & Lagnado, D. (2020). Strategies for selecting and evaluating information. *Cognitive Psychology*, 123, 101332.

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 cachexia1

*cachexia Bayesian Networks*


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**Description**

Model-preserving sensitivity analysis for families of Gaussian distributions.

**Format**

A Gaussian Bayesian networks comparing the dependence of metabolomics for people who suffer of Cachexia. The Bayesian network is learned as in the referenced paper. The vertices are:

**A** Adipate;

**B** Betaine;

**F** Fumarate;

**GC** Glucose;

**GM** Glutamine;

**V** Valine;

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Gorgen, C., & Leonelli, M. (2020). Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21(84), 1-32.

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 cachexia2

*cachexia Bayesian Networks*


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**Description**

Model-preserving sensitivity analysis for families of Gaussian distributions.

**Format**

A Gaussian Bayesian networks comparing the dependence of metabolomics for people who do not suffer of Cachexia. The Bayesian network is learned as in the referenced paper. The vertices are:

**A** Adipate;

**B** Betaine;

**F** Fumarate;

**GC** Glucose;

**GM** Glutamine;

**V** Valine;

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Gorgen, C., & Leonelli, M. (2020). Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21(84), 1-32.

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cardiovascular

*cardiovascular Bayesian Network*

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**Description**

A Bayesian network model for predicting cardiovascular risk.

**Format**

A discrete Bayesian network allowing for making inferences and predictions about cardiovascular risk factors. Probabilities were given within the referenced paper. The vertices are:

**Age** (18-24", 24-34, 34-44, 44-54, 54-64, 64-74);

**Anxiety** (No, Yes);

**BodyMassIndex** (Normal, Obese, Overweight, Underweight);

**Depression** (No, Yes);

**Diabetes** (No, Yes);

**EducationLevel** (1, 2, 3);

**Hypercholesterolemia** (No, Yes);

**Hypertension** (No, Yes);

**PhysicalActivity** (Insufficiently Active, Regularly Active);

**Sex** (Female, Male);

**SleepDuration** (6-9hours, <6hours, >9hours);

**SmokerProfile** (Ex\_Smoker, Non\_Smoker, Smoker);

**SocioeconomicStatus** (1, 2, 3);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ordovas, J. M., Rios-Insua, D., Santos-Lozano, A., Lucia, A., Torres, A., Kosgodagan, A., & Camacho, J. M. (2023). A Bayesian network model for predicting cardiovascular risk. *Computer Methods and Programs in Biomedicine*, 231, 107405.

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case

*case Bayesian Network*

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**Description**

Building a stronger case: Combining evidence and law in scenario-based Bayesian networks.

**Format**

A discrete Bayesian network for concrete legal fact idioms that qualify events in a narrative Bayesian network. The network was available from a public repository. The vertices are:

**Body** (f, t);  
**ComplicityMurder** (f, t);  
**DebtFightFK** (f, t);  
**FBarn** (f, t);  
**FightBarn** (f, t);  
**FStenGun** (f, t);  
**Help** (f, t);  
**Intent** (f, t);  
**KBarn** (f, t);  
**Killed** (f, t);  
**KKilled** (f, t);  
**Murder** (f, t);  
**Murdered** (f, t);  
**PlanBarnF** (f, t);  
**Premed** (f, t);  
**Prov** (f, t);  
**SBarn** (f, t);  
**ShootStenGun** (none, F, Not F);  
**TMathus** (f, t);  
**TSF1** (f, t);  
**TSF2** (f, t);  
**TSLocation** (f, t);  
**TStenGun** (f, t);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Van Leeuwen, L., Verbrugge, R., Verheij, B., & Renooij, S. (2024, June). Building a Stronger Case: Combining Evidence and Law in Scenario-Based Bayesian Networks. In 3rd International Conference on Hybrid Human-Artificial Intelligence, HHAI 2024 (pp. 291-299). IOS Press.

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 catchment

*catchment Bayesian Network*


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**Description**

A framework to diagnose the causes of river ecosystem deterioration using biological symptoms.

**Format**

A discrete Bayesian network to estimate the probability of individual stressors being causal for biological degradation at the scale of individual riverine ecosystems (Catchment BN). The network was available from an associated repository. The vertices are:

**Arable** (Low, Enhanced, Intermediate, High);

**N** (Low, Intermediate, High);

**Urban** (None, Enhanced, High);

**Fines** (Normal, Enhanced);

**Nitrate** (Low, Enhanced);

**Grazer** (Low, Medium, High);

**oPO4** (Low, High);

**BuffForest** (Low, High);

**BOD5** (Low, Enhanced, High);

**WaterQ** (Low, Fair, Good);

**OrgMatter** (Low, High);

**Stagnant** (No, Yes);

**HabitatQ** (Low, Fair, Good);

**Straight** (No, Yes);

**FlowQ** (Low, High);

**EPT** (Low, Medium, High);

**ASPT** (Low, Medium, High);

**SI** (Low, Medium, High);

**Shredder** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Feld, C. K., Saeedghalati, M., & Hering, D. (2020). A framework to diagnose the causes of river ecosystem deterioration using biological symptoms. *Journal of Applied Ecology*, 57(11), 2271-2284.

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charleston

*charleston Bayesian Network*


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**Description**

Parameterization framework and quantification approach for integrated risk and resilience assessments.

**Format**

A discrete Bayesian network for risk and resilience assessment of climate change impacts within the Charleston Harbor Watershed of South Carolina (Region 3). The probabilities were given within the referenced paper. The vertices are:

**AbilityToEvacuate** (Zero, Low, Medium, High);

**ActiveHurricane** (No, Yes);

**DrowningMortality** (Zero, Low, Medium, High);

**EvacuationRequired** (Zero, Low, Medium, High);

**ExtremePrecipitation** (Zero, Low, Medium, High);

**ExtremePrecipitationNonHurricane** (Zero, Low, Medium, High);

**FloodExposure** (Zero, Low, Medium, High);

**FloodHazard** (Zero, Low, Medium, High);

**FloodPreparedness** (No, Yes);

**HurricaneCategory** (Zero, Low, Medium, High);

**NuisanceFloodExposure** (Zero, Low, Medium, High);

**NuisanceFloodFrequency** (Zero, Low, Medium, High);

**NuisanceFloodHazard** (Zero, Low, Medium, High);

**PersonalVehicle** (No, Yes);

**PhysicalFloodProtection** (No, Yes);

**PopulationLocation** (Zero, Low, Medium, High);

**RegionWithCoastline** (No, Yes);

**RiskToHumanHealth** (Zero, Low, Medium, High);



**RoadwayAccessibility** (Zero, Low, Medium, High);  
**RoadwayLocation** (Zero, Low, Medium, High);  
**SeaLevelRise** (Zero, Low, Medium, High);  
**StormSurge** (Zero, Low, Medium, High);  
**StormSurgeProtection** (No, Yes);  
**TideLevelAboveHighTide** (Zero, Low, Medium, High);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Cains, M. G., & Henshel, D. (2021). Parameterization framework and quantification approach for integrated risk and resilience assessments. *Integrated Environmental Assessment and Management*, 17(1), 131-146.

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chds

*chds Bayesian Network*

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### Description

Refining a Bayesian network using a chain event graph.

### Format

A discrete Bayesian network looking at the effect the family's social background, the economic status and the number of family life events have on the child's health which is measured by rates of hospital admission. The Bayesian network is learned as in the referenced paper. The vertices are:

**Social** Social background (High, Low);  
**Economic** Economic status (High, Low);  
**Events** Number of life events (High, Average, Low);  
**Admission** Rate of hospital admissions (Yes, No);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Barclay, L. M., Hutton, J. L., & Smith, J. Q. (2013). Refining a Bayesian network using a chain event graph. *International Journal of Approximate Reasoning*, 54(9), 1300-1309.

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cng

*cng Bayesian Network*

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**Description**

Quantitative risk estimation of CNG station by using fuzzy bayesian networks and consequence modeling.

**Format**

A discrete Bayesian network for risk assessment in compressed natural gas (CNG) stations. The probabilities were given within the referenced paper. The vertices are:

- X1** Not up-to-date technology (T, F);
- X2** Lack of maintenance (T, F);
- X3** Unsafe equipment (T, F);
- X4** Type of ignition material (T, F);
- X5** The nature of the chemical substance (T, F);
- X6** Inspection defect in wear detection (T, F);
- X7** Improper use of the equipment (T, F);
- X8** Leakage (T, F);
- X9** High temperature (T, F);
- X10** Low temperature (T, F);
- X11** Horizontal wind speed (T, F);
- X12** Vertical wind speed (T, F);
- X13** Environmental stability and instability (T, F);
- X14** Sunny hours (T, F);
- X15** Relative humidity and evaporation rate (T, F);
- X16** Lighting (T, F);
- X17** Landslide (T, F);
- X18** Flood (T, F);
- X19** Earthquake (T, F);
- X20** Land settlement (T, F);
- X21** Deliberate vandalism (T, F);
- X22** Incidents related to the missile site (T, F);
- X23** Military attack (T, F);
- X24** Explosion of other equipment (T, F);
- X25** Deliberate error in the execution of the recipe (T, F);
- X26** Accidental collision valves (T, F);

- X27** Failure to issue a work permit (T, F);
- X28** Artificial lighting (T, F);
- X29** Natural lighting (T, F);
- X30** Lack of cost (T, F);
- X31** Requirements for conducting training classes by managers (T, F);
- X32** Fatigue (T, F);
- X33** Shift work (T, F);
- X34** Stress - internal causes) (T, F);
- X35** Stress - external causes (T, F);
- X36** Not having enough experience and skills (T, F);
- X37** Hearing loss - non-occupational causes (T, F);
- X38** Hearing loss - occupational causes (T, F);
- X39** Failure to notify the control room in time (T, F);
- X40** Fear of explosion and fire by operator (T, F);
- X41** Operator performance - temperature and humidity (T, F);
- X42** Chemical pollutants - particles (T, F);
- X43** Chemical pollutants - gas and steam (T, F);
- X44** Solid waste (T, F);
- X45** Liquid waste (T, F);
- X46** Adjacent commercial use (T, F);
- X47** Adjacent residential use (T, F);
- X48** Adjacent industrial use (T, F);
- X49** Land uses changes (T, F);
- X50** Room metering - measurement of changes (T, F);
- X51** Room metering - operator error (T, F);
- X52** Lack of standard dryer quality (T, F);
- X53** Disturbance in the electricity flow of the dryer (T, F);
- X54** Fire dryer heaters (T, F);
- X55** Leakage of tank (T, F);
- X56** Adjacent tanks (T, F);
- X57** Dispenser leakage and damage (T, F);
- X58** Disregarding dispenser safety signs (T, F);
- X59** Dispenser malfunction (T, F);
- X60** Improper management performance (T, F);
- AdjacentLandUses** (T, F);
- AnticipatedEvents** (T, F);
- ChemicalContaminants** (T, F);

**ClimateChanges** (T, F);  
**Dispenser** (T, F);  
**Dryer** (T, F);  
**EnvironmentChanges** (T, F);  
**Exhaustion** (T, F);  
**FailureToInspectAndOperateEquipment** (T, F);  
**FortuitousEvents** (T, F);  
**HearingLoss** (T, F);  
**HumanReasons** (T, F);  
**ImproperOperatorPerformance** (T, F);  
**InadequateTraining** (T, F);  
**LeakOfCNG** (T, F);  
**Lighting** (T, F);  
**MilitaryIncidents** (T, F);  
**NaturalDisasters** (T, F);  
**ProcessProblems** (T, F);  
**RoomMetering** (T, F);  
**Storage** (T, F);  
**Stress** (T, F);  
**TankStructure** (T, F);  
**Temperature** (T, F);  
**Wastes** (T, F);  
**WindSpeed** (T, F);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Abbasi Kharajou, B., Ahmadi, H., Rafiei, M., & Moradi Hanifi, S. (2024). Quantitative risk estimation of CNG station by using fuzzy bayesian networks and consequence modeling. *Scientific Reports*, 14(1), 4266.

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compaction	<i>compaction Bayesian Network</i>
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**Description**

A Bayesian approach toward the use of qualitative information to inform on-farm decision making: The example of soil compaction.

**Format**

A discrete Bayesian network to highlight the financial consequences of failing to adopt controlled traffic farming management for a particular agricultural enterprise. The probabilities were given within the referenced paper. The vertices are:

**ClayContent** (Very Low, Low, Medium, High, Very High);

**CompactionRisk** (Low, Medium, High);

**CompactionVulnerability** (Low, Medium, High);

**InherentSusceptibility** (Low, Medium, High);

**SoilWetness** (Dry, Moist, Wet);

**TotalExposure** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Roberton, S. D., Lobsey, C. R., & Bennett, J. M. (2021). A Bayesian approach toward the use of qualitative information to inform on-farm decision making: the example of soil compaction. *Geoderma*, 382, 114705.

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conasense	<i>conasense Bayesian Network</i>
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**Description**

Bayesian neural networks for 6G CONASENSE services.

**Format**

A discrete Bayesian network to support to optimization of the CONASENSE network. Probabilities were given within the referenced paper. The vertices are:

**Communication** (Bandwidth, CoverageArea, Latency, PacketLoss);

**Navigation** (Accuracy, Mobility, Speed);

**Sensing** (TransmissionRange, Angle, Uplink);

**Services** (Good, Moderate, Poor);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Henrique, P. S. R., & Prasad, R. (2022, October). Bayesian Neural Networks for 6G CONASENSE Services. In 2022 25th International Symposium on Wireless Personal Multimedia Communications (WPMC) (pp. 291-296). IEEE.

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concrete1

*concrete Bayesian Networks*

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**Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

**Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Model 1.1 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**Basement** (False, True);

**BlueConcrete** (False, True);

**BuildingClass** (Single Family House, MultiFamily House, School Building, Other Building);

**FloorArea** (0-150, 150-220, 220-360, 360-1500, >1500);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.

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 concrete2

*concrete Bayesian Networks*


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**Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

**Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Model 2.1 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**Basement** (False, True);

**BlueConcrete** (False, True);

**BuildingClass** (Single Family House, MultiFamily House, School Building, Other Building);

**ConstructionYear** (1930-1955, 1955-1960, 1960-1968, 1968-1975, 1975-1980);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.

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 concrete3

*concrete Bayesian Networks*


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**Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

**Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Model 3.1 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**AverageDistance** (0-150, 150-220, 220-360, 360-1500, >1500)

**BlueConcrete** (False, True);

**FloorArea** (0-150, 150-220, 220-360, 360-1500, >1500);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.

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`concrete4`*concrete Bayesian Networks*

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**Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

**Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - Single-Family Houses, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**AverageDistance** (0-300, 300-600, >600);

**Basement** (False, True);

**BlueConcrete** (False, True);

**ConstructionYear** (1930-1955, 1955-1960, 1960-1968, 1968-1975, 1975-1980);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.



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concrete5

*concrete Bayesian Networks*

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### Description

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

### Format

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - Multi-Family Houses, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**AverageDistance** (0-300, 300-600, >600);

**BlueConcrete** (False, True);

**FloorArea** (0-150, 150-220, 220-360, 360-1500, >1500);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.

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concrete6

*concrete Bayesian Networks*

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### Description

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

### Format

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - School Buildings, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**AverageDistance** (0-300, 300-600, >600);

**BlueConcrete** (False, True);

**FloorArea** (0-150, 150-220, 220-360, 360-1500, >1500);

**Value**

An object of class `bn.f.it`. Refer to the documentation of `bnlearn` for details.

**References**

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.

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concrete7

*concrete Bayesian Networks*

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**Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

**Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - Other Buildings, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**AverageDistance** (0-300, 300-600, >600);

**BlueConcrete** (False, True);

**ConstructionYear** (1930-1955, 1955-1960, 1960-1968, 1968-1975, 1975-1980);

**FloorArea** (0-150, 150-220, 220-360, 360-1500, >1500);

**NumberOfStairwells** (0, 1, 2, 3, 4);

**Value**

An object of class `bn.f.it`. Refer to the documentation of `bnlearn` for details.

**References**

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. *Expert Systems with Applications*, 222, 119812.

consequenceCovid

*consequenceCovid Bayesian Network***Description**

Global sensitivity analysis of uncertain parameters in Bayesian networks.

**Format**

A discrete Bayesian network including demographic information of the respondents of the Eurobarometer 93.1 together with their opinion about how the COVID-19 emergency was handled by local authorities and its consequences in the long term. The Bayesian network was learned as in the referenced paper. The vertices are:

**AGE** How old are you? (18-30, 30-50, 51-70, 70+);

**LIFESAT** On the whole, are you satisfied with the life you lead? (Yes, No);

**TRUST** Do you trust or not the people in your country? (Yes, No);

**SATMEAS** In general, are you satisfied with the measures taken to fight the Coronavirus outbreak by your government? (Yes, No);

**HEALTH** Thinking about the measures taken by the public authorities in your country to fight the Coronavirus and its effects, would you say that they... (Focus too much on health, Focus too much on economics, Are balanced);

**JUSTIFIED** Thinking about the measures taken by the public authorities in your country to fight the Coronavirus and its effects, would you say that they were justified? (Yes, No);

**PERSONALFIN** The Coronavirus outbreak will have serious economic consequences for you personally (Agree, Disagree, Don't know);

**COUNTRYFIN** The Coronavirus outbreak will have serious economic consequences for your country (Agree, Disagree, Don't know);

**INFO** Which of the following was your primary source of information during the Coronavirus outbreak? (Television, Written press, Radio, Websites, Social networks);

**COPING** Thinking about the measures taken to fight the Coronavirus outbreak, in particular the confinement measures, would you say that it was an experience...? (Easy to cope with, Both easy and difficult to cope with, Difficult to cope with);

**POLITICS** In political matters people talk of 'the left' and 'the right'. How would you place your views on this scale? (Left, Centre, Right, Don't know);

**OCCUPATION** Are you currently working? (Yes, No);

**GENDER** What is your sex? (Male, Female);

**COMMUNITY** Would you say you live in a... (Rural area or village, Small or middle sized town, Large town);

**CLASS** Do you see yourself and your household belonging to...? (Working class, Lower class, Middle class, Upper class);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ballester-Ripoll, R., & Leonelli, M. (2024). Global Sensitivity Analysis of Uncertain Parameters in Bayesian Networks. arXiv preprint arXiv:2406.05764.

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constructionproductivity

*constructionproductivity Bayesian Network*

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**Description**

Construction productivity prediction through Bayesian networks for building projects: case from Vietnam.

**Format**

A discrete Bayesian network to identify causal relationship and occurrence probability of critical factors affecting construction productivity. Probabilities were given within the referenced paper. The vertices are:

**Accidents** (Yes, No);

**AdverseWeather** (Yes, No);

**Age** (Yes, No);

**Attitude** (Yes, No);

**EngineerQualification** (Yes, No);

**Experience** (Yes, No);

**HealthStatus** (Yes, No);

**MaterialPresence** (Yes, No);

**OwnerFinance** (Yes, No);

**PlanningAndMethod** (Yes, No);

**Productivity** (Yes, No);

**Sex** (Yes, No);

**SkilledWorkers** (Yes, No);

**TaskComplexity** (Yes, No);

**TechnologyLevel** (Yes, No);

**WorkingFrequency** (Yes, No);

**WorkingTools** (Yes, No);

**Workmanship** (Yes, No);

@return An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Khanh, H. D., & Kim, S. Y. (2022). Construction productivity prediction through Bayesian networks for building projects: Case from Vietnam. *Engineering, Construction and Architectural Management*, 30(5), 2075-2100.

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coral1

*coral Bayesian Networks*

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## Description

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

## Format

A discrete Bayesian network for the evaluation of threats to reef condition globally (colony bleaching). The probabilities were given within the referenced paper. The vertices are:

**CoralColonyBleached** (Less than 0, 0-0.145, 0.145-0.374, 0.374-0.680, More than 0.680);

**AcidificationThreat** (Low, High);

**CoastalDevelopmentThreat** (Low, Medium, High);

**ManagementEffectiveness** (Ineffective, Partial, Effective);

**MarineBasedPollutionThreat** (Low, Medium, High);

**Overfishing** (Low, Medium, High);

**ThermalStress** (None, Severe);

**WatershedBasedPollutionThreat** (Low, Medium, High);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. *Integrated Environmental Assessment and Management*, 17(1), 165-187.

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 coral2

*coral Bayesian Networks*


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**Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

**Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (recently killed corals). The probabilities were given within the referenced paper. The vertices are:

**KilledCoralCover** (Less than 0, 0-0.075, 0.075-0.212, 0.212-0.450, More than 0.450);

**AcidificationThreat** (Low, High);

**CoastalDevelopmentThreat** (Low, Medium, High);

**ManagementEffectiveness** (Ineffective, Partial, Effective);

**MarineBasedPollutionThreat** (Low, Medium, High);

**Overfishing** (Low, Medium, High);

**ThermalStress** (None, Severe);

**WatershedBasedPollutionThreat** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. *Integrated Environmental Assessment and Management*, 17(1), 165-187.

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 coral3

*coral Bayesian Networks*


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**Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

**Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (live coral index). The probabilities were given within the referenced paper. The vertices are:

**ReefHealthIndex** (Less than 0, 0-0.118, 0.118-0.330, 0.330-0.683, More than 0.683);

**AcidificationThreat** (Low, High);

**CoastalDevelopmentThreat** (Low, Medium, High);

**ManagementEffectiveness** (Ineffective, Partial, Effective);

**MarineBasedPollutionThreat** (Low, Medium, High);

**Overfishing** (Low, Medium, High);

**ThermalStress** (None, Severe);

**WatershedBasedPollutionThreat** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. *Integrated Environmental Assessment and Management*, 17(1), 165-187.

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 coral4

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*coral Bayesian Networks*


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**Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

**Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (live coral cover). The probabilities were given within the referenced paper. The vertices are:

**LiveCoralCover** (Less than 0, 0-0.040, 0.040-0.122, 0.122-0.241, 0.241-0.417, More than 0.417);

**AcidificationThreat** (Low, High);

**CoastalDevelopmentThreat** (Low, Medium, High);

**ManagementEffectiveness** (Ineffective, Partial, Effective);

**MarineBasedPollutionThreat** (Low, Medium, High);

**Overfishing** (Low, Medium, High);

**ThermalStress** (None, Severe);

**WatershedBasedPollutionThreat** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. *Integrated Environmental Assessment and Management*, 17(1), 165-187.

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coral5

*coral Bayesian Networks*

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**Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

**Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (population bleaching). The probabilities were given within the referenced paper. The vertices are:

**CoralPopulationBleached** (Less than 0, 0-0.086, 0.086-0.265, 0.265-0.507, More than 0.507);

**AcidificationThreat** (Low, High);

**CoastalDevelopmentThreat** (Low, Medium, High);

**ManagementEffectiveness** (Ineffective, Partial, Effective);

**MarineBasedPollutionThreat** (Low, Medium, High);

**Overfishing** (Low, Medium, High);

**ThermalStress** (None, Severe);

**WatershedBasedPollutionThreat** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. *Integrated Environmental Assessment and Management*, 17(1), 165-187.



corical

*corical Bayesian Network***Description**

Risk-benefit analysis of the AstraZeneca COVID-19 vaccine in Australia using a Bayesian network modelling framework.

**Format**

A discrete Bayesian network to perform risk-benefit analysis of vaccination. The probabilities were given in the referenced paper. The vertices are:

**Age** (0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70+);

**AZVaccineDoses** (One, Two, Three, Four);

**BackgroundCSVTOver6Weeks** (Yes, No);

**BackgroundPVTOver6Weeks** (Yes, No);

**Covid19AssociatedCSVT** (Yes, No);

**Covid19AssociatedPVT** (Yes, No);

**DieFromBackgroundCSVT** (Yes, No);

**DieFromBackgroundPVT** (Yes, No);

**DieFromCovid19** (Yes, No);

**DieFromCovid19AssociatedCSVT** (Yes, No);

**DieFromCovid19AssociatedPVT** (Yes, No);

**DieFromVaccineAssociatedTTS** (Yes, No);

**IntensityOfCommunityTransmission** (None, ATAGI Low, ATAGI Med, ATAGI High, One Percent, Two Percent, NSW 200 Daily, NSW 1000 Daily, VIC 1000 Daily, QLD 1000 Daily);

**RiskOfSymptomaticInfection** (Yes, No);

**RiskOfSymptomaticInfectionUnderCurrentTransmissionAndVaccinationStatus** (Yes, No);

**SARSCoV2Variant** (Alpha Wild, Delta);

**Sex** (Male, Female);

**VaccineAssociatedTTS** (Yes, No);

**VaccineEffectivenessAgainstDeathIfInfected** (Effective, Not Effective);

**VaccineEffectivenessAgainstSymptomaticInfection** (Effective, Not Effective);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Lau, C. L., Mayfield, H. J., Sinclair, J. E., Brown, S. J., Waller, M., Enjeti, A. K., ... & Litt, J. (2021). Risk-benefit analysis of the AstraZeneca COVID-19 vaccine in Australia using a Bayesian network modelling framework. *Vaccine*, 39(51), 7429-7440.

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 corrosion

*corrosion Bayesian Network*


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### Description

Dynamic Bayesian network model to study under-deposit corrosion.

### Format

A discrete Bayesian network to understand different risk factors and their interdependencies in under-deposit corrosion and how the interaction of these risk factors leads to asset failure due to under-deposit corrosion. Probabilities were given within the referenced paper. The vertices are:

**BurstPressure** (High, Low);  
**Chloride** (High, Moderate, Low);  
**DefectDepth** (Yes, No);  
**DefectLength** (Yes, No);  
**FlowVelocity** (High, Moderate, Low);  
**InorganicDeposits** (Absent, Present);  
**MEG** (Absent, Present);  
**MixedDeposits** (Absent, Present);  
**OD** (High, Low);  
**OperatingPressure** (High, Moderate, Low);  
**OperatingTemperature** (High, Moderate, Low);  
**OrganicDeposits** (Absent, Present);  
**PartialPressureCO2** (High, Moderate, Low);  
**pH** (Acid, Neutral, Basic);  
**PipeFailure** (Yes, No);  
**ShearingForce** (High, Moderate, Low);  
**SolidDeposits** (High, Moderate, Low);  
**SteelGrade** (High, Low);  
**SuspendedDeposits** (High, Moderate, Low);  
**UDCCorrRate** (High, Moderate, Low);  
**UnderDepositGalvanicCell** (Poor, Fair, Good, Excellent);  
**WallThicknessLoss** (Yes, No).

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Dao, U., Sajid, Z., Khan, F., & Zhang, Y. (2023). Dynamic Bayesian network model to study under-deposit corrosion. *Reliability Engineering & System Safety*, 237, 109370.

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corticosteroid	<i>corticosteroid Bayesian Network</i>
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**Description**

Corticosteroid discontinuation, complete clinical response and remission in juvenile dermatomyositis.

**Format**

A discrete Bayesian network to compute the conditional probability of complete clinical response and remission. The probabilities were given within the referenced paper. The vertices are:

**FinalCSDCAchieved** (Achieved, Not Achieved);

**CCRAchieved** (Achieved, Not Achieved);

**RemissionAchieved** (Achieved, Not Achieved);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Kishi, T., Warren-Hicks, W., Bayat, N., Targoff, I. N., Huber, A. M., Ward, M. M., ... & with the Childhood Myositis Heterogeneity Study Group. (2021). Corticosteroid discontinuation, complete clinical response and remission in juvenile dermatomyositis. *Rheumatology*, 60(5), 2134-2145.

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covid1	<i>covid Bayesian Networks</i>
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**Description**

Uncovering hidden and complex relations of pandemic dynamics using an AI driven system.

**Format**

A discrete Bayesian network to classify the severity of covid-19 given different symptoms (Naive Bayes). The probabilities were available from a repository. The vertices are:

**CovidSeverity** (1. 1, 2. 2, 3. 3, 4. 4, 5. 5, 6. 6);

**Cough** (1. 0, 2. 1);

**Diarrhea** (1. 0, 2. 1);

**Fatigue** (1. 0, 2. 1);

**Fever** (1. 0, 2. 1);

**Headache** (1. 0, 2. 1);  
**LossOfSmell** (1. 0, 2. 1);  
**LossOfTaste** (1. 0, 2. 1);  
**MuscleSore** (1. 0, 2. 1);  
**RunnyNose** (1. 0, 2. 1);  
**Sob** (1. 0, 2. 1);  
**SoreThroat** (1. 0, 2. 1);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Demirbaga, U., Kaur, N., & Aujla, G. S. (2024). Uncovering hidden and complex relations of pandemic dynamics using an AI driven system. *Scientific Reports*, 14(1), 15433.

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covid2

*covid Bayesian Networks*

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### Description

Uncovering hidden and complex relations of pandemic dynamics using an AI driven system.

### Format

A discrete Bayesian network to classify the severity of covid-19 given different symptoms (TAN structure). The probabilities were available from a repository. The vertices are:

**CovidSeverity** (1. 1, 2. 2, 3. 3, 4. 4, 5. 5, 6. 6);  
**Cough** (1. 0, 2. 1);  
**Diarrhea** (1. 0, 2. 1);  
**Fatigue** (1. 0, 2. 1);  
**Fever** (1. 0, 2. 1);  
**Headache** (1. 0, 2. 1);  
**LossOfSmell** (1. 0, 2. 1);  
**LossOfTaste** (1. 0, 2. 1);  
**MuscleSore** (1. 0, 2. 1);  
**RunnyNose** (1. 0, 2. 1);  
**Sob** (1. 0, 2. 1);  
**SoreThroat** (1. 0, 2. 1);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Demirbaga, U., Kaur, N., & Aujla, G. S. (2024). Uncovering hidden and complex relations of pandemic dynamics using an AI driven system. *Scientific Reports*, 14(1), 15433.

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covid3

*covid Bayesian Networks*

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**Description**

Uncovering hidden and complex relations of pandemic dynamics using an AI driven system.

**Format**

A discrete Bayesian network to classify the severity of covid-19 given different symptoms (Generic BN). The probabilities were available from a repository. The vertices are:

**CovidSeverity** (1. 1, 2. 2, 3. 3, 4. 4, 5. 5, 6. 6);

**Cough** (1. 0, 2. 1);

**Diarrhea** (1. 0, 2. 1);

**Fatigue** (1. 0, 2. 1);

**Fever** (1. 0, 2. 1);

**Headache** (1. 0, 2. 1);

**LossOfSmell** (1. 0, 2. 1);

**LossOfTaste** (1. 0, 2. 1);

**MuscleSore** (1. 0, 2. 1);

**RunnyNose** (1. 0, 2. 1);

**Sob** (1. 0, 2. 1);

**SoreThroat** (1. 0, 2. 1);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Demirbaga, U., Kaur, N., & Aujla, G. S. (2024). Uncovering hidden and complex relations of pandemic dynamics using an AI driven system. *Scientific Reports*, 14(1), 15433.

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covidfear

*covidfear Bayesian Network*

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### **Description**

Learning and interpreting asymmetry-labeled DAGs: a case study on COVID-19 fear.

### **Format**

A discrete Bayesian network to understand the effect of demographic factors on the answers to the COVID-19 fear scale and the relationship between the scale items. The Bayesian network was learned as in the referenced paper. The vertices are:

**Age** (Young, Adult);

**Gender** (Female, Male);

**Fear** I am most afraid of COVID-19 (Disagree, Neither, Agree);

**Think** It makes me uncomfortable to think about COVID-19 (Disagree, Neither, Agree);

**Hands** My hands become clammy when I think about COVID-19 (Disagree, Neither, Agree);

**Life** I fear losing my life because of COVID-19 (Disagree, Neither, Agree);

**News** I become nervous or anxious when watching news and stories about COVID-19 on social media (Disagree, Neither, Agree);

**Sleep** I cannot sleep because I am worried about getting COVID-19 (Disagree, Neither, Agree);

**Hearth** My heart races or palpitates when I think about getting COVID-19 (Disagree, Neither, Agree);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Leonelli, M., & Varando, G. (2024). Learning and interpreting asymmetry-labeled DAGs: a case study on COVID-19 fear. *Applied Intelligence*, 54(2), 1734-1750.

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covidrisk

*covidrisk Bayesian Network*

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### Description

Highly efficient structural learning of sparse staged trees.

### Format

A discrete Bayesian network to investigate how various country risks and risks associated to the COVID-19 epidemics relate to each other. The Bayesian network is learned as in the referenced paper. The vertices are:

**HAZARD** (low, high);

**VULNERABILITY** (low, high);

**COPING** (low, high);

**RISK** (low, high);

**ECONOMIC** (low, high);

**BUSINESS** (low, high);

**POLITICAL** (low, high);

**COMMERCIAL** (low, high);

**FINANCING** (low, high);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Leonelli, M., & Varando, G. (2022, September). Highly efficient structural learning of sparse staged trees. In International Conference on Probabilistic Graphical Models (pp. 193-204). PMLR.

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covidtech

*covidtech Bayesian Network*

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### Description

The YODO algorithm: An efficient computational framework for sensitivity analysis in Bayesian networks.

**Format**

A discrete Bayesian network to model the relationship between the use of technology and the psychological effects of forced social isolation during the COVID-19 pandemic. The Bayesian network is learned as in the referenced paper. The vertices are:

**AGE** Age of respondent (<25, >=25);

**GENDER** Gender of respondent (Male, Female);

**BELONGINGNESS** How often the word we is used (Low, Medium, High);

**ANG\_IRR** Perceived level of anger/irritability (Low, Medium, High);

**SOCIAL** Perceived social support (Low, Medium, High);

**ANXIETY** Level of anxiety (Low, Medium, High);

**BOREDOM** Level of boredom (Low, Medium, High);

**LONELINESS** Perceived loneliness (Low, Medium, High);

**TECH\_FUN\_Q** Use of communication technology for fun in quarantine (Low, Medium, High);

**TECH\_FUN\_PQ** Use of communication technology for fun pre-quarantine (Low, Medium, High);

**TECH\_WORK\_Q** Use of communication technology for work in quarantine (Low, High);

**TECH\_WORK\_PQ** Use of communication technology for work pre-quarantine (Low, High);

**OUTSIDE** Times outside per week (0, 1, >=2);

**SQUARE\_METERS** Home square meters (<80, >=80);

**FAMILY\_SIZE** Number of individuals at home (1, 2, >=3);

**DAYS\_ISOLATION** Days since lockdown (0-10, 11-20, >20);

**REGION** Region of residence (Lombardy, Other);

**OCCUPATION** Occupation (Other, Smartworking, Student, Office work);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ballester-Ripoll, R., & Leonelli, M. (2023). The YODO algorithm: An efficient computational framework for sensitivity analysis in Bayesian networks. *International Journal of Approximate Reasoning*, 159, 108929.



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`covidtest`*covidtest Bayesian Network*

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**Description**

Discrete latent variables discovery and structure learning in mixed Bayesian networks.

**Format**

A conditional linear-Gaussian Bayesian network to predict the outcome of a covid test. The DAG structure was taken from the referenced paper and the probabilities learned from data (earliest version in the repository, missing data dropped). The vertices are:

**asthma** (FALSE, TRUE);  
**autoimmune\_dis** (FALSE, TRUE);  
**cancer** (FALSE, TRUE);  
**covid19\_test\_results** (Negative, Positive);  
**ctab** (FALSE, TRUE);  
**diabetes** (FALSE, TRUE);  
**diarrhea** (FALSE, TRUE);  
**fever** (FALSE, TRUE);  
**htn** (FALSE, TRUE);  
**labored\_respiration** (FALSE, TRUE);  
**loss\_of\_taste** (FALSE, TRUE);  
**pulse**  
**sob** (FALSE, TRUE);  
**sore\_throat** (FALSE, TRUE);  
**temperature**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Peled, A., & Fine, S. (2021). Discrete Latent Variables Discovery and Structure Learning in Mixed Bayesian Networks. In 20th IEEE International Conference on Machine Learning and Applications (pp. 248-255). IEEE.

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crimescene

*crimescene Bayesian Network*

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### Description

How did the DNA of a suspect get to the crime scene? A practical study in DNA transfer during lock-picking.

### Format

A discrete Bayesian network to study DNA transfer during lock-picking. Probabilities were given within the referenced paper. The vertices are:

**Hypothesis** (Prosecutor, Defense);

**SuspectCutTheFoil** (Yes, No);

**SuspectDNAOnFoilFromCutting** (Yes, No);

**SuspectDNAOnFoilFromPicking** (Yes, No);

**SuspectPickedLock** (Yes, No);

**UnknownPickedLock** (Yes, No);

**UnknownCutTheFoil** (Yes, No);

**UnknownDNAOnFoil** (Yes, No);

**DNAFoundOnFoil** (Suspect DNA On Foil, Suspect And Unknown DNA On Foil, Unknown DNA On Foil, No DNA On Foil);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Mayuoni-Kirshenbaum, L., Waiskopf, O., Finkelstein, N., & Pasternak, Z. (2022). How did the DNA of a suspect get to the crime scene? A practical study in DNA transfer during lock-picking. *Australian Journal of Forensic Sciences*, 54(1), 15-25.

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criminal1

*criminal Bayesian Networks*

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### Description

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

### Format

A discrete Bayesian network describing a criminal scenario (top-left of Figure 3). Probabilities were given within the referenced paper. The vertices are:

**Motive** (0,1);

**Sneak** (0,1);

**Stealing** (0,1);

**EPsychReport** (0,1);

**ObjectDroppedAccidentally** (0,1);

**ECameraSeenStealing** (0,1);

**EObjectGone** (0,1);

**ECamera** (0,1);

**Scenario1** (0,1);

**Scenario2** (0,1);

**Scenari3** (0,1);

**Constraint** (Scenario1, Scenario2, Scenario3, NA);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

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criminal2

*criminal Bayesian Networks*

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### Description

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

### Format

A discrete Bayesian network describing a criminal scenario (bottom-left of Figure 3). Probabilities were given within the referenced paper. The vertices are:

**Motive** (0,1);

**Sneak** (0,1);

**Stealing** (0,1);

**EPsychReport** (0,1);

**ObjectDroppedAccidentally** (0,1);

**ECameraSeenStealing** (0,1);

**EObjectGone** (0,1);

**ECamera** (0,1);

**Scenario1** (0,1);

**Scenario2** (0,1);

**Scenari3** (0,1);

**Constraint** (Scenario1, Scenario2, Scenario3, NA);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In *Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law* (pp. 323-332).

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criminal3

*criminal Bayesian Networks*

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### Description

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

### Format

A discrete Bayesian network describing a criminal scenario (top-right of Figure 3). Probabilities were given within the referenced paper. The vertices are:

**Motive** (0,1);

**Sneak** (0,1);

**Stealing** (0,1);

**EPsychReport** (0,1);

**ObjectDroppedAccidentally** (0,1);

**ECameraSeenStealing** (0,1);

**EObjectGone** (0,1);

**ECamera** (0,1);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

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criminal4

*criminal Bayesian Networks*

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### Description

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

**Format**

A discrete Bayesian network describing a criminal scenario (bottom-right of Figure 3). Probabilities were given within the referenced paper. The vertices are:

**Motive** (0,1);

**Sneak** (0,1);

**Stealing** (0,1);

**EPsychReport** (0,1);

**ObjectDroppedAccidentally** (0,1);

**ECameraSeenStealing** (0,1);

**EObjectGone** (0,1);

**ECamera** (0,1);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

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crypto

*crypto Bayesian Network*

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**Description**

Dynamic evolution of causal relationships among cryptocurrencies: an analysis via Bayesian networks.

**Format**

A discrete Bayesian modelling to examine the causal interrelationships among six major cryptocurrencies. Probabilities were given within the referenced paper. The vertices are:

**Bitcoin** (Down, Up);

**Binance\_Coin** (Down, Up);

**Ethereum** (Down, Up);

**Tether** (Down, Up);

**Litecoin** (Down, Up);

**Ripple** (Down, Up);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Amirzadeh, R., Thiruvady, D., Nazari, A., & Ee, M. S. (2024). Dynamic evolution of causal relationships among cryptocurrencies: an analysis via Bayesian networks. *Knowledge and Information Systems*, 1-16.

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 curacao1

*curacao Bayesian Networks*


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**Description**

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

**Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Conservation BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

**CulturalSiteProximity** (low, med, high);

**FloraRichness** (low, med, high);

**KeySpeciesPresence** (no, yes);

**NeighborhoodConservationValue** (low, high);

**NeighborhoodNaturalLandCover** (low, med, high);

**SpeciesRelatedConservationValue** (low, high);

**SuitabilityForConservation** (no, yes);

**VisitorDemand** (low, med, high);

**WatershedConservationValue** (low, high);

**WSAboveMarineProtectedArea** (no, yes);

**WSIncludesOtherKeyDesignations** (no, yes);

**WSIncludesRAMSARArea** (no, yes);

**WSLandscapeVariability** (low, med, high);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. *Environmental Science & Policy*, 156, 103733.

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curacao2

*curacao Bayesian Networks*

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### **Description**

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### **Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Tourism BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

**CoastalView** (no, yes);

**DistanceToTourismCore** (distant, nearby, inside);

**ImmediateBeachAccess** (no, yes);

**NaturalAmenities** (low, high);

**NeighborhoodSafetyScore** (low, medium, high);

**ProximityToPOIs** (far, near, immediate);

**ProximityToSouthernCoast** (far, near, immediate);

**RoadsWithin1KM** (no, yes);

**SiteInfrastructure** (low, high);

**SuitabilityForTourism** (no, yes);

**UtilityAccess** (no, yes);

**ViewExtent** (low, medium, high);

**ViewQuality** (low, high);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. *Environmental Science & Policy*, 156, 103733.



## Description

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

## Format

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Urban fabric BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

**AccessToPublicTransportation** (no, yes);  
**AirNuisance** (no, yes);  
**CoastalView** (no, yes);  
**LuxuryAmenities** (low, high);  
**NearbySupportingFunctions** (low, medium, high);  
**NeighborhoodFactors** (low, high);  
**NeighborhoodSafetyScore** (low, medium, high);  
**NoiseNuisance** (no, yes);  
**PollutedSoils** (no, yes);  
**PrimaryRoads** (no, yes);  
**ProximityToBeach** (no, yes);  
**ProximityToCoast** (far, near, immediate);  
**SiteFavorability** (low, high);  
**SlopeLimited** (no, yes);  
**SmallRoads** (no, yes);  
**SuitabilityForUrbanFabric** (no, yes);  
**TransportationAccess** (low, high);  
**ViewExtent** (low, medium, high);  
**ViewQuality** (low, high);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. *Environmental Science & Policy*, 156, 103733.

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curacao4

*curacao Bayesian Networks*

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### Description

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### Format

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Conventional agriculture BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

**AgriculturalDensity** (low, med, high);

**AllRoadAccess** (no, yes);

**BuiltUpDensity** (low, med, high);

**CoUserInteractionConstraints** (low, high);

**EnvironmentalConstraints** (yes, no);

**Geology** (colluvial clay, diabase or other, limestone bare rock);

**GroundwaterDepth** (less than 25m, between 25 and 60m, over 60m);

**InfrastructureConstraints** (low, high);

**ProductivityConstraints** (low, high);

**SiteConstraints** (low, high);

**Slope** (flat, moderate, steep);

**SuitabilityConventionalAgriculture** (no, yes);

**UtilitiesAccess** (no, planned, yes);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. *Environmental Science & Policy*, 156, 103733.

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 curacao5

 curacao Bayesian Networks
 

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### Description

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### Format

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Structural agriculture BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

**AgriculturalDensity** (low, med, high);

**AllRoadAccess** (no, yes);

**BuiltUpDensity** (low, med, high);

**CoUserInteractionConstraints** (low, high);

**EnvironmentalConstraints** (yes, no);

**Geology** (colluvial clay, diabase or other, limestone bare rock);

**GroundwaterDepth** (less than 25m, between 25 and 60m, over 60m);

**InfrastructureConstraints** (low, high);

**ProductivityConstraints** (low, high);

**SiteConstraints** (low, high);

**Slope** (flat, moderate, steep);

**SuitabilityStructuralAgriculture** (no, yes);

**UtilitiesAccess** (no, planned, yes);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. *Environmental Science & Policy*, 156, 103733.

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darktriad

*darktriad Bayesian Network*

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### **Description**

Bayesian Network modeling for Dark Triad, aggression, and empathy.

### **Format**

A conditional linear Gaussian Bayesian network to examine the validity of the constructed models as predictable. The probabilities were given within the referenced paper. The vertices are:

**Age**

**Gender** (Male, Female);

**Machiavellianism**

**Fantasy**

**EmotionalSusceptibility**

**Narcissism**

**Psychopathy**

**SelfOrientedEmotionalReactivity**

**VerbalAggression**

**PerspectiveTaking**

**OtherOrientedEmotional**

**PhysicalAggression**

**Hostility**

**Anger**

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Zaitsu, W. (2024). Bayesian Network modeling for Dark Triad, aggression, and empathy. *Personality and Individual Differences*, 230, 112805.

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diabetes

*diabetes Bayesian Network*

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**Description**

Sensitivity and robustness analysis in Bayesian networks with the bnmonitor R package.

**Format**

A discrete Bayesian network to predict whether or not a patient has diabetes, based on certain diagnostic measurements. The Bayesian network is learned as in the referenced paper. The vertices are:

**AGE** Age (Low, High);

**DIAB** Test for diabetes (Neg, Pos);

**GLUC** Plasma glucose concentration (Low, High);

**INS** 2-hour serum insulin (Low, High);

**MASS** Body mass index (Low, High);

**PED** Diabetes pedigree function (Low, High);

**PREG** Number of times pregnant (Low, High);

**PRES** Diastolic blood pressure (Low, High);

**TRIC** Triceps skin fold thickness (Low, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of bnlearn for details.

**References**

Leonelli, M., Ramanathan, R., & Wilkerson, R. L. (2023). Sensitivity and robustness analysis in Bayesian networks with the bnmonitor R package. *Knowledge-Based Systems*, 278, 110882.

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diagnosis

*diagnosis Bayesian Network*

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**Description**

An interpretable unsupervised Bayesian network model for fault detection and diagnosis.

**Format**

A discrete Bayesian network to support the process monitoring scheme. Probabilities were given within the referenced paper, although the variances were not clearly specified. The vertices are  $X_1, X_2, \dots, X_{16}$ .

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Yang, W. T., Reis, M. S., Borodin, V., Juge, M., & Roussy, A. (2022). An interpretable unsupervised Bayesian network model for fault detection and diagnosis. *Control Engineering Practice*, 127, 105304.

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dioxins

*dioxins Bayesian Network*

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**Description**

Designing optimal food safety monitoring schemes using Bayesian network and integer programming: The case of monitoring dioxins and DL-PCBs.

**Format**

A discrete Bayesian network to optimize the use of resources for food safety monitoring. The Bayesian network is learned as in the referenced paper. The vertices are:

**screeningResults** The results from the screening DR CALUX method (negative, suspect);

**year** The monitoring year (2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017);

**trimester** The quarter of the year (1, 2, 3, 4);

**animalSpecies** The animal species monitored (bovine animal, bovine animal for fattening, broiler, calf for fattening, cow, deer, duck, eel, fishm goat, goose, hen, horse, pig, poultry, rabbit, sheep, trout);

**product** The food product type (egg, liver, meat, milk);

**sampling place** The control points (aquaculture, farm, slaughterhouse);

**euMonitoring** The number of samples analyzed for EU monitoring to estimate background contamination in different products (0, 1, ..., 31);

**gcResults** The results from the GC/MS method (0, n, p);

**sampleSize** The number of samples collected during the monitoring period (196, 226, 254, 340, 352, 358, 365, 366, 379, 425).

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wang, Z., van der Fels-Klerx, H. J., & Oude Lansink, A. G. J. M. (2023). Designing optimal food safety monitoring schemes using Bayesian network and integer programming: The case of monitoring dioxins and DL-PCBs. *Risk Analysis*, 43(7), 1400-1413.

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disputed1

*disputed Bayesian Networks*

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### Description

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

### Format

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 2). The probabilities were given in the referenced paper. The vertices are:

**BGU** Background DNA U on sweater (false, true);

**DNAfind** DNA findings on sweater (false, true);

**DNAU** DNA U present on sweater (false, true);

**DNAX** DNA X present on sweater (false, true);

**Prop** Who strangled person Y? (H1, H2);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRUstrangledY** Transfer of DNA U from U to sweater via U strangling Y (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**UstrangledY** Unknown person strangled person Y (false, true);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. *Forensic Science International: Synergy*, 9, 100546.

disputed2

*disputed Bayesian Networks***Description**

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

**Format**

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 3). The probabilities were given in the referenced paper. The vertices are:

**BGFibers** Background on fibers matching Y top on sweater (false, true);

**BGU** Background DNA U on sweater (false, true);

**CaseFind** Case findings on sweater (false, true);

**DNAfind** DNA findings on sweater (DNA X, DNA U, DNA X + U, No DNA);

**DNAU** DNA U present on sweater (false, true);

**DNAX** DNA X present on sweater (false, true);

**FiberFind** Fiber findings on sweater (false, true);

**FibersSweater** Fibers matching Y garment on sweater (false, true);

**ItemProposition** Sweater worn by offender during incident (false, true);

**Prop** Who strangled person Y? (H1, H2);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRUstrangledY** Transfer of DNA U from U to sweater via U strangling Y (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**TPRYtoSweater** Transfer of fibers from Y top to sweater during incident (false, true);

**UstrangledY** Unknown person strangled person Y (false, true);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. *Forensic Science International: Synergy*, 9, 100546.



**Description**

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

**Format**

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 9). The probabilities were given in the referenced paper. The vertices are:

**BGFibers** Background fibers present on Y top (false, true);

**BGM** Background fibers matching sweater present on Y top (false, true);

**BGMnotM** Background fibers not matching sweater present on Y top (false, true);

**C52** Fibers matching Y top on sweater (false, true);

**C61** Background of fibers matching Y top on sweater (false, true);

**C7** Background DNA u on sweater (false, true);

**CaseFindSweater** Case findings on sweater (false, true);

**DNAfind** DNA findings on sweater (DNA X, DNA U, DNA X + U, No DNA);

**DNAU** DNA U present on sweater (false, true);

**DNAX** DNA X present on sweater (false, true);

**FiberfindSweater** Fiber findings on Sweater (false, true);

**FiberfindYtop** Fiber findings on Y top (matching, not matching, both matching and not matching, no fibers);

**FibersM** Fibers matching sweater on Y top (false, true);

**FibresnotM** Fibers not matching sweater on Y top (false, true);

**Prop** Who strangled person Y? (H1, H2);

**Sworn** Sweater worn by offender during incident (false, true);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRStoY** Transfer of fibers from sweater to Y top during incident (false, true);

**TPRUstrangledY** Transfer of DNA U from U to sweater via U strangling Y (false, true);

**TPRUtoY** Transfer of fibers from unknown garment to Y top during incdient (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**TPRYtoS** Transfer of fibers from Y top to sweater during incident (false, true);

**UstrangledY** Unknown person strangled person Y (false, true);

**Uworn** Unknown garment worn by offender during incident (false, true);

**WhichGarment** Which garment was worn by offender during incident? (sweater, unknown garment);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. *Forensic Science International: Synergy*, 9, 100546.

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disputed4

*disputed Bayesian Networks*

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### Description

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

### Format

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 10). The probabilities were given in the referenced paper. The vertices are:

**BGFibersYtop** Background fibers present on Y top (false, true);

**BGM** Background fibers matching sweater present on Y top (false, true);

**BGMnotM** Background fibers not matching sweater present on Y top (false, true);

**BGYonS** Background of fibers matching Y top on sweater (false, true);

**CaseFind** Case findings on sweater (false, true);

**DNAfind** DNA findings on sweater (DNA X, DNA U, DNA X + U, No DNA);

**DNAX** DNA X present on sweater (false, true);

**FiberfindSweater** Fiber findings on Sweater (false, true);

**FiberfindYtop** Fiber findings on Y top (matching, not matching, both matching and not matching, no fibers);

**FibersMSonY** Fibers matching sweater on Y top (false, true);

**FibersnotMSonY** Fibers not matching sweater on Y top (false, true);

**FibersYonS** Fibers matching Y top on Sweater (false, true);

**Prop** Who strangled person Y? (H1, H2);

- Sweater** Sweater worn by Mr. X during incident (false, true);
- TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);
- TPRStoYtop** Transfer of fibers from sweater to Y top during incident (false, true);
- TPRUtoYtop** Transfer of fibers from unknown garment to Y top during incident (false, true);
- TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);
- TPRYtoptoS** Transfer of fibers from Y top to sweater during incident (false, true);
- Unkown** Unknown garment worn by offender during incident (false, true);
- WhichGarment** Which garment was worn by offender during incident? (sweater, unknown garment);
- Xaltact** X wore sweater two weeks before incident (false, true);
- XstrangledY** Mr. X strangled person Y (false, true);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. *Forensic Science International: Synergy*, 9, 100546.

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dragline

*dragline Bayesian Network*

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### Description

Bayesian network approach for dragline reliability analysis: A case study.

### Format

A discrete Bayesian network for the evaluation of the reliability of a draglines system. Probabilities were given within the referenced paper. The vertices are:

- X1** Teeth Failure (True, False);
- X2** Adapter failure (True, False);
- X3** Equalizer pins (True, False);
- X4** Anchor pins (True, False);
- X5** Hitch shackle pins (True, False);
- X6** Drag motor failure (True, False);
- X7** Drag motor failure2 (True, False);
- X8** Control system failure (True, False);

- X9** Drag rope failure (True, False);
- X10** Gearbox failure (True, False);
- X11** Drag drum failure (True, False);
- X12** Drag chain failure (True, False);
- X13** Drag brake failure (True, False);
- X14** Drag socket failure (True, False);
- X15** Drag pulley failure (True, False);
- X16** Dump rope failure (True, False);
- X17** Dump socket failure (True, False);
- X18** Dump pulley failure (True, False);
- X19** Hoist motor 1 failure (True, False);
- X20** Hoist motor 2 failure (True, False);
- X21** Hoist rope failure (True, False);
- X22** Control system failure (True, False);
- X23** Hoist chain failure (True, False);
- X24** Hoist brake failure (True, False);
- X25** Rotate frame failure (True, False);
- X26** Roller failure (True, False);
- X27** Gearbox failure (True, False);
- X28** Control system failure (True, False);
- X29** Swing motor failure (True, False);
- X30** Swing motor failure (True, False);
- X31** Exciter failure (True, False);
- X32** M.G. set failure (True, False);
- X33** Synchronous motor failure (True, False);
- X34** DC problem failure (True, False);
- X35** Power failure (True, False);
- X36** Trailing cable failure (True, False);
- X37** Compressor failure (True, False);
- X38** Lubrication system failure (True, False);
- X39** Guide pulley failure (True, False);
- X40** Boom light failure (True, False);
- A1** (True, False);
- A2** (True, False);
- A3** (True, False);
- S1** Bucket and accessories (True, False);
- S2** Drag mechanism (True, False);

**S3** Rigging mechanism (True, False);  
**S4** Hoisting mechanism (True, False);  
**S5** Swing mechanism (True, False);  
**S6** Electrical auxiliary (True, False);  
**S7** Other subsystem (True, False);  
**Dragline** (True, False);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Kumar, D., Jana, D., Gupta, S., & Yadav, P. K. (2023). Bayesian network approach for dragline reliability analysis: A case study. *Mining, Metallurgy & Exploration*, 40(1), 347-365.

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drainage	<i>drainage Bayesian Network</i>
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### Description

Fuzzy Bayesian network fault diagnosis method based on fault tree for coal mine drainage system.

### Format

A discrete Bayesian network for fault diagnosis of a coal mine drainage system. The probabilities were available from a repository. The vertices are:

**AbnormalFlow** (T, F);  
**AirLeakageOfShaftSeal** (T, F);  
**GetValveFailure** (T, F);  
**ImpellerDamaged** (T, F);  
**LowSpeed** (T, F);  
**LowVoltage** (T, F);  
**MotorFault** (T, F);  
**PipelineFailure** (T, F);  
**PipelineRupture** (T, F);  
**Silting** (T, F);  
**WaterPumpFailure** (T, F);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Shi, X., Gu, H., & Yao, B. (2024). Fuzzy Bayesian Network Fault Diagnosis Method Based on Fault Tree for Coal Mine Drainage System. *IEEE Sensors Journal*.

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dustexplosion

*dustexplosion Bayesian Network*

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## Description

Scenario derivation and consequence evaluation of dust explosion accident based on dynamic Bayesian network.

## Format

A discrete Bayesian network for the accurate solution of scenario state probability. Probabilities were given within the referenced paper. The vertices are:

**AccidentDoNotOccur** (True, False);  
**AccidentUnderControl** (True, False);  
**BlastWavesThroughPipes** (True, False);  
**BuildingDamage** (I, II, III, IV);  
**Casualties** (I, II, III, IV);  
**CombustibleDustAccumulates** (True, False);  
**DirectEconomicLosses** (I, II, III, IV);  
**DustAccumulationUnderControl** (True, False);  
**DustCloudDisappearance** (True, False);  
**DustExplosionIntensityCoefficient** (I, II, III, IV, V);  
**EndOfRescue** (True, False);  
**EnvironmentalImpact** (I, II, III, IV);  
**EquipmentDamage** (I, II, III, IV);  
**ExplosionPreventionMeasures** (True, False);  
**ExtinctionOfSpark** (True, False);  
**IgnitingTheDustCloud** (True, False);  
**InitiateEmergencyResponse** (True, False);  
**Misoperation** (True, False);  
**NoExplosionControlMeasures** (True, False);  
**OpenFireExtinguished** (True, False);  
**PreventFurtherExpansion** (True, False);  
**RestrictedSpace** (True, False);  
**SparkDetectorExtinguishSparks** (True, False);  
**SparkOccurrence** (True, False);  
**StrengthenDustControl** (True, False);  
**TriggerSecondaryExplosion** (True, False);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Pang, L., Zhang, M., Yang, K., & Sun, S. (2023). Scenario derivation and consequence evaluation of dust explosion accident based on dynamic Bayesian network. *Journal of Loss Prevention in the Process Industries*, 83, 105055.

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 earthquake

*earthquake Bayesian Network*


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**Description**

A Bayesian Network risk model for estimating coastal maritime transportation delays following an earthquake in British Columbia.

**Format**

A discrete Bayesian network for estimating the delays in maritime transportation to island communities in British Columbia, resulting from a major earthquake in the region. Probabilities were given within the referenced paper. The vertices are:

**AD** Arrival-related delays (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**BSA** Bridge safety assessment required (Yes, No);

**BSD** Bathymetric survey required - destination (Yes, No);

**BSO** Bathymetric survey required - origin (Yes, No);

**BVOR** Bridge over navigation route (Yes, No);

**CIDD** Communication infrastructure damage - destination (Low, Medium, High);

**CIDO** Communication infrastructure damage - origin (Low, Medium, High);

**CN** Community needs (Low, Medium, High);

**CSR** Communication system restoration required (Yes, No);

**DAC** Delay due to arranging crew members (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**DD** Departure-related delays (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**DDG** Delay in dangerous goods reporting (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**DGR** Dangerous good reporting required (Yes, No);

**DL** Destination location (V\_Isl\_W, V\_Isl\_E, V\_Isl\_S);

**DTWD** Delay due to tsunami warning - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**DTWO** Delay due to tsunami warning - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**EEL** Earthquake epicentre location (V\_Isl\_W\_offshore, V\_Isl\_E\_offshore, V\_Isl\_Inland, BC\_ML);

**ESD** Earthquake severity - destination (VI\_or\_less, VII, VIII, IX, X\_or\_more);

**ESO** Earthquake severity - origin (VI\_or\_less, VII, VIII, IX, X\_or\_more);

**ESR** Earthquake severity - regional (VI\_or\_less, VII, VIII, IX, X\_or\_more);

**MMSC** Mandatory minimum ship crew required (Yes, No);

**OL** Origin location (V\_Isl\_W, V\_Isl\_E, V\_Isl\_S, BC\_ML);

**PAD** Personnel availability - destination (Low, Medium, High);

**PAO** Personnel availability - origin (Low, Medium, High);

**RD** Route delay (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TBS** Time required for bridge safety assessment (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TBSD** Time required for bathymetric survey - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TBSO** Time required for bathymetric survey - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TCSD** Time required for communication system restoration - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TCSO** Time required for communication system restoration - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TIDD** Terminal infrastructure damage - destination (Low, Medium, High);

**TIDO** Terminal infrastructure damage - origin (Low, Medium, High);

**TTRD** Time required for terminal recovery ops - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TTRO** Time required for terminal recovery ops - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TWD** Tsunami warning - destination (Yes, No);

**TWO** Tsunami warning - origin (Yes, No);

**VD** Voyage-related delays (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**VT** Vessel type (BC\_Ferries, Seaspn, Barge);

**WIDD** Waterway infrastructure damage - destination (Low, Medium, High);

**WIDO** Waterway infrastructure damage - origin (Low, Medium, High);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Goerlandt, F., & Islam, S. (2021). A Bayesian Network risk model for estimating coastal maritime transportation delays following an earthquake in British Columbia. *Reliability Engineering & System Safety*, 214, 107708.



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 ecosystem

 ecosystem Bayesian Network
 

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### Description

Evaluating the supply-demand balance of cultural ecosystem services with budget expectation in Shenzhen, China.

### Format

A discrete Bayesian network to infer the supply and demand match for cultural ecosystem services. Probabilities were given within the referenced paper. The vertices are:

**Bus** Density of bus and subway stations (Low, High);

**Road** Road density (Low, High);

**Lot** Density of public parking lots (Low, High);

**Traffic** Convenience for tourists to arrive (Low, Medium, High);

**Park** Convenience for visitors after arrival (Low, Medium, High);

**Green** Green space coverage rate (Low, Medium, High);

**Water** Whether there is a water body or not (No, Yes);

**Opportunity** Recreational convenience (Low, Medium, High);

**Potential** Aesthetic value of landscape (Low, Medium, High);

**People** Population density (Low, Medium, High);

**Supply** CES supply of communities (Low, Medium, High);

**Demand** CES demand of communities (Low, Medium, High);

**Budget** Balance of supply and demand (Deficit, Balance, Surplus).

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Wu, J., Jin, X., Wang, H., & Feng, Z. (2022). Evaluating the supply-demand balance of cultural ecosystem services with budget expectation in Shenzhen, China. *Ecological Indicators*, 142, 109165.

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electricvehicle      *electricvehicle Bayesian Network*

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### Description

Electric vehicle fire risk assessment based on WBS-RBS and fuzzy BN coupling.

### Format

A discrete Bayesian network to evaluate the risk of electric vehicle fire accidents. Probabilities were given within the referenced paper. The vertices are:

- ACF** Air conditioning equipment failure (yes, no);
- AM** Artificial modification (yes, no);
- AWE** Not aware of early fire (yes, no);
- BEP** Blocked exhaust pipe (yes, no);
- BF** Battery failure (yes, no);
- BO** Battery overcharge (yes, no);
- CBI** The car body is ignited (yes, no);
- CEF** Charging equipment fault (yes, no);
- CI** Collision ignition (yes, no);
- DTH** Defroster temperature too high (yes, no);
- EC** Electrical circuit failure (yes, no);
- ECF** Electronic component failure (yes, no);
- FFE** The vehicle is not equipped with fire-fighting equipment (yes, no);
- HF** Human factor (yes, no);
- IS** Ignition source (yes, no);
- ISC** Risk of internal spontaneous combustion of electric vehicles (yes, no);
- MMA** Man made arson (yes, no);
- OFE** The early open fire was not extinguished (yes, no);
- REI** Risk of external ignition (yes, no);
- SBB** (yes, no);
- SCB** Short circuit in battery (yes, no);
- TLD** Transmission line damage (yes, no);
- VFD** Electric vehicle fire disaster (yes, no);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Chen, J., Li, K., & Yang, S. (2022). Electric vehicle fire risk assessment based on WBS-RBS and fuzzy BN coupling. *Mathematics*, 10(20), 3799.

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electrolysis

*electrolysis Bayesian Network*

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**Description**

Safety analysis of proton exchange membrane water electrolysis system.

**Format**

A discrete Bayesian network to analyze evolving hazard scenarios, such as gas permeation/crossover during proton exchange membrane water electrolysis based on fluid dynamics and electrochemistry of electrolysis. Probabilities were given within the referenced paper. The vertices are:

**C** Operating current density (High, Low);

**F** Formation of hazardous H<sub>2</sub>/O<sub>2</sub> gas mixture (Yes, No);

**FPR** Formation of peroxide radicals which can cause membrane degradation (Yes, No);

**GP** Gas permeation (Yes, No);

**GRE** Gas recombiner employed (Yes, No);

**H** Relative humidity (High, Low);

**HCF** Hazardous condition formation (Yes, No);

**HOR** H<sub>2</sub> and O<sub>2</sub> recombination at catalyst/membrane surface (Yes, No);

**IOA** Inhibiting oxygen accumulation (Yes, No);

**IRF** Inhibiting reaching flammability range (Yes, No);

**P** Operating pressure (High, Low);

**RGP** Reduction in gas purity (Yes, No);

**SBT** Surface/bulk treatments of the polymeric membrane (Yes, No);

**SMT** Sufficient membrane thickness (Yes, No);

**T** Operating temperature (High, Low);

**V** Operating cell voltage (High, Low);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Liu, Y., Amin, M. T., Khan, F., & Pistikopoulos, E. N. (2023). Safety analysis of proton exchange membrane water electrolysis system. *Journal of Environmental Chemical Engineering*, 11(5), 110772.

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 emergency

*emergency Bayesian Network*


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### Description

A risk evaluation method for human-machine interaction in emergencies based on multiple mental models-driven situation assessment.

### Format

A discrete Bayesian network to evaluate risk in human-machine interaction in emergencies. The probabilities were given within the referenced paper. The vertices are:

- TS** Trim state (normal, abnormal);
- FP** Flap position (retracted, extended);
- CPMS** Cabin pressurization mode setting (automatic, manual);
- ECFS** Equipment cooling fan state (normal, failure);
- TC** Takeoff configuration (correct, wrong);
- CP** Cabine pressure (normal, low);
- ECA** Equipment cooling airflow (normal, low);
- OMD** Oxygen mask deployment (yes, no);
- TSI** Trim state indication (normal, abnormal);
- FPI** Flap position indication (retracted, extended);
- CPMSI** Cabin pressurization mode setting indication (automatic, manual);
- ECFCBI** Equipment cooling fan circuit break indication (on, off);
- CAW** Cabine altitud warning (yes, no);
- CLPL** Cabin low pressure light (illuminated, extinguished);
- OMDL** Oxygen mask deployment light (illuminated, extinguished);
- ECOL** Equipment cooling OFF light (illuminated, extinguished);
- ECFOL** Equipment cooling fan OFF light (illuminated, extinguished);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Guo, J., Ma, S., Zeng, S., Che, H., & Pan, X. (2024). A risk evaluation method for human-machine interaction in emergencies based on multiple mental models-driven situation assessment. *Reliability Engineering & System Safety*, 110444.

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engines

*engines Bayesian Network*

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### Description

A fuzzy Bayesian network risk assessment model for analyzing the causes of slow-down processes in two-stroke ship main engines.

### Format

A discrete Bayesian network to assess the factors contributing to the engine's slow-down processes. The probabilities were given in the referenced paper. The vertices are:

- H1** Oil mist high density (yes, no);
- H2** Scavenge air box fire (yes, no);
- H3** Piston cooling oil non flow (yes, no);
- H4** Cylinder lube oil non flow (yes, no);
- H5** Cylinder cooling fresh water low pressure (yes, no);
- H6** Cylinder cooling fresh water high temperature (yes, no);
- H7** Main lube oil low pressure (yes, no);
- H8** Thrust pad high temperature (yes, no);
- H9** Piston cooling oil high temperature (yes, no);
- H10** Exhaust gas high temperature (yes, no);
- H11** Stern tube bearing high temperature (yes, no);
- H** (yes, no);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Bashan, V., Yucesan, M., Gul, M., & Demirel, H. (2024). A fuzzy Bayesian network risk assessment model for analyzing the causes of slow-down processes in two-stroke ship main engines. *Ships and Offshore Structures*, 19(5), 670-686.

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 enrollment

*enrollment Bayesian Network*


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### Description

Research on evaluation methods for sustainable enrollment plan configurations in Chinese universities based on Bayesian networks.

### Format

A discrete Bayesian network for sustainable enrollment plan configurations aimed at enhancing the advanced education rate. The probabilities were given in the referenced paper. The vertices are:

**AdvancedEducationRate** (0, 1);

**AverageAdmissionScore** (0, 1, 2);

**CoursePassRate** (0, 1, 2);

**EmploymentRate** (0, 1, 2);

**FirstTimeGraduationRate** (0, 1, 2);

**StudentTeacherRatio** (0, 1, 2);

**TransferRate** (0, 1, 2);

**EnrollmentQuota** (-2, -1, 0, 1, 2);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Wang, K., Wang, T., Wang, T., & Cai, Z. (2024). Research on Evaluation Methods for Sustainable Enrollment Plan Configurations in Chinese Universities Based on Bayesian Networks. *Sustainability*, 16(7), 2998.

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 estuary

*estuary Bayesian Network*


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### Description

Predicting and scoring estuary ecological health using a Bayesian belief network.

**Format**

A discrete Bayesian network to calculate an Estuary Trophic Index (ETI) score ranging between 0 (no symptoms of eutrophication) to 1 (grossly eutrophic) for estuaries in Aotearoa New Zealand. The probabilities were given within the referenced paper. The vertices are:

**EstuaryType** (Coastal lake, Tidal lagoon, Tidal river);

**Intertidal** (0 to 5, 5 to 40, 40 to 100);

**Flushing** (0 to 3, 3 to 6, 6 to 10, More than 10);

**Salinity** (0 to 5, 5 to 30, More than 30);

**PotentialTNConcentration** (0 to 50, 50 to 100, 100 to 150, 150 to 200, 200 to 300, 300 to 400, 400 to 500, 500 to 600, 600 to 700, 700 to 1000, 1000 to 2000);

**Seasonality** (Less than 0.5, 0.5 to 0.65, More than 0.65);

**WaterColStratification** (Yes, No);

**ClosureDuration** (Open, Short close, Long close);

**SedimentLoad** (0 to 1, 1 to 5, 5 to 10, 10 to 20, 20 to 50, 50 to 100, More than 100);

**SedTrappingEfficiency** (0 to 0.1, 0.1 to 0.5, 0.5 to 0.85, 0.85 to 0.95, 0.95 to 1);

**SedDeposition** (0 to 0.1, 0.1 to 0.5, 0.5 to 1, 1 to 2, 2 to 5, 5 to 10, More than 10);

**SedMud** (0 to 12, 12 to 25, 25 to 34, 34 to 100);

**Macroalgae** (0.8 to 1, 0.6 to 0.8, 0.4 to 0.6, 0 to 0.4);

**Phytoplankton** (0 to 5, 5 to 10, 10 to 15, 15 to 25, 25 to 60, 60 to 100);

**MacroalgaeStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**PhytoplanktonStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**ETIPrimaryScore** (0 to 0.1, 0.1 to 0.2, 0.2 to 0.3, 0.3 to 0.4, 0.4 to 0.5, 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, 0.9 to 1.0);

**Oxygen** (7 to 8, 6 to 7, 5 to 6, 4 to 5);

**OxygenStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**SedToc** (0 to 0.5, 0.5 to 1.2, 1.2 to 2, 2 to 10);

**SedARPD** (More than 4, 2.5 to 4, 1 to 2.5, Less than 1);

**SedARPDStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**SedTocStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**SeagrassDecline** (Extreme, Severe, Moderate, Minor);

**SeagrassStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**Macrobenthos** (0 to 1.2, 1.2 to 3.3, 3.3 to 4.3, 4.3 to 7);

**MacrobenthosStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**ETISecondaryScore** (0 to 0.1, 0.1 to 0.2, 0.2 to 0.3, 0.3 to 0.4, 0.4 to 0.5, 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, 0.9 to 1.0);

**ETIScore** (0 to 0.1, 0.1 to 0.2, 0.2 to 0.3, 0.3 to 0.4, 0.4 to 0.5, 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, 0.9 to 1.0);

**ETIBand** (A, B, C, D);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Zeldis, J. R., & Plew, D. R. (2022). Predicting and scoring estuary ecological health using a Bayesian belief network. *Frontiers in Marine Science*, 9, 898992.

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expenditure

*expenditure Bayesian Network*

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**Description**

The FEDHC Bayesian network learning algorithm.

**Format**

A Gaussian Bayesian network modeling the monthly credit card expenditure of individuals. The code to learn the Bayesian network was given within the referenced paper (Figure 12.c). The vertices are:

**Card** Whether the application for a credit card was accepted or not;

**Reports** The number of major derogatory reports;

**Age** The age in years plus twelfths of a year;

**Income** The yearly income in \$10,000s;

**Share** The ratio of monthly credit card expenditure to yearly income;

**Expenditure** The average monthly credit card expenditure;

**Owner** Whether the person owns their home or they rent;

**Selfemp** Whether the person is self employed or not;

**Dependents** The number of dependents + 1;

**Months** The number of months living at current address;

**Majorcards** The number of major credit cards held;

**Active** The number of active credit accounts.

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Tsagris, M. (2022). The FEDHC Bayesian network learning algorithm. *Mathematics*, 10(15), 2604.



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fingermarks1

*fingermarks Bayesian Networks*

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### **Description**

Using case specific experiments to evaluate fingermarks on knives given activity level propositions.

### **Format**

A discrete Bayesian network for the evaluation of fingermarks given activity level propositions. The probabilities were given within the referenced paper. The vertices are:

- C1** Propositions (Hp, Hd);
- C2** Suspect stabbed the victim with the knife (True, False);
- C3** Suspect cut food with the knife (True, False);
- C4** Marks on handle - stabbing (FM S present, FM S absent);
- C5** Marks on back - stabbing (FM S present, FM S absent);
- C6** Marks on blade - stabbing (FM S present, FM S absent);
- C7** Marks on handle - cutting (FM S present, FM S absent);
- C8** Marks on back - cutting (FM S present, FM S absent);
- C9** Marks on blade - cutting (FM S present, FM S absent);
- C10** Findings - Marks on handle (FM S present, FM S absent);
- C11** Findings - Marks on blade (FM S present, FM S absent);
- C12** Findings - Marks on back (FM S present, FM S absent);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

de Ronde, A., Kokshoorn, B., de Puit, M., & de Poot, C. J. (2021). Using case specific experiments to evaluate fingermarks on knives given activity level propositions. *Forensic Science International*, 320, 110710.

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fingermarks2

*fingermarks Bayesian Networks*

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### Description

Using case specific experiments to evaluate fingermarks on knives given activity level propositions.

### Format

A discrete Bayesian network for the evaluation of fingermarks given activity level propositions. The probabilities were given within the referenced paper. The vertices are:

- C1** Propositions (Hp, Hd);
- C2** Suspect stabbed the victime with the knife (True, False);
- C3** Suspect cut food with the knife (True, False);
- C4** Marks on handle - stabbing (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C5** Marks on back - stabbing (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C6** Marks on blade - stabbing (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C7** Marks on handle - cutting (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C8** Marks on back - cutting (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C9** Marks on blade - cutting (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C10** Findings - Marks on handle (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C11** Findings - Marks on blade (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C12** Findings - Marks on back (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

de Ronde, A., Kokshoorn, B., de Puit, M., & de Poot, C. J. (2021). Using case specific experiments to evaluate fingermarks on knives given activity level propositions. *Forensic Science International*, 320, 110710.

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fire

*fire Bayesian Network*

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### Description

Psychological response in fire: A fuzzy Bayesian network approach using expert judgment.

### Format

A discrete Bayesian network to model causal relationship of psychological response at the initial stage of fire events. The probabilities were given within the referenced paper. The vertices are:

**AudioFireCues** (Yes, No);

**EmotionalStability** (Stable, Unstable);

**Escape** (True, False);

**FireCues** (Consistent, Not consistent);

**FireKnowledge** (Yes, No);

**LayoutFamiliarity** (Yes, No);

**PerceivedHazard** (Risky, Not risky);

**PsychologicalIncapacitation** (Mild, Severe);

**Stress** (Low, High);

**TimePressure** (Low, High);

**VisualFireCues** (Yes, No);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Ramli, N., Ghani, N. A., Ahmad, N., & Hashim, I. H. M. (2021). Psychological response in fire: a fuzzy Bayesian network approach using expert judgment. *Fire Technology*, 57, 2305-2338.

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 firealarm

*firealarm Bayesian Network*


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**Description**

When do numbers really matter?.

**Format**

A discrete Bayesian network to model a simple fire alarm system. Probabilities were given within the referenced paper. The vertices are:

**Fire** (true, false);

**Tampering** (true, false);

**Smoke** (true, false);

**Alarm** (true, false);

**Leaving** (true, false);

**Report** (true, false);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Hei Chan, Adnan Darwiche (2002). "When do numbers really matter?". *Journal of Artificial Intelligence Research* 17 (265-287).

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 firerisk

*firerisk Bayesian Network*


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**Description**

Predictive study of fire risk in building using Bayesian networks.

**Format**

A discrete Bayesian network to calculate the probability of fire ignition in buildings (root nodes were given a uniform distribution). The probabilities were available from a repository. The vertices are:

**A1** Deficient electrical installation (T, F);

**A2** Bad quality of electrical equipment (T, F);

**A3** Contact between incompatible products (T, F);

- B1** Mishandling of electrical devices (T, F);
- B2** Electrical overload (T, F);
- B3** Power cut (T, F);
- B4** Degradation of electrical wires (T, F);
- B5** Excessive heating in the conductors (T, F);
- B6** Insulation fault (T, F);
- B7** Short circuit (T, F);
- B8** Strong intensity electric (T, F);
- B9** Combustion of electrical equipment (T, F);
- B10** Appearance of electric arcs (T, F);
- B11** Appearance of sparks (T, F);
- B12** Chemical reactions (T, F);
- B13** Heat release (T, F);
- B14** Appearance of new products (T, F);
- C1** Electrical equipment malfunction (T, F);
- C2** Electrocution (T, F);
- C3** Fire ignition (T, F);
- C4** Poisoning (T, F);
- C5** Asphyxia (T, F);
- C6** Explosion (T, F);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Issa, S. K., Bakkali, H., Azmani, A., & Amami, B. (2024). Predictive study of fire risk in building using Bayesian networks. *Journal of Theoretical and Applied Information Technology*, 102(7).

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flood

*flood Bayesian Network*

---

### Description

A trade-off between farm production and flood alleviation using land use tillage preferences as a natural flood management (NFM) strategy.

**Format**

A discrete Bayesian network to analyse land use tillage practices for flood management, considering climate, soilscape, slope, and farming systems. Probabilities were given within the referenced paper. The vertices are:

**Bulk\_Density** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1, 1 to 1.25, 1.25 to 1.5);

**Daily\_Runoff** (0 to 18, 18 to 36, 36 to 54, 54 to 72);

**Erosion** (High, Low);

**Farm\_Yield** (Positive, Negative);

**Flood\_Alleviation** (Positive, Negative);

**Land\_Use** (Arable, Arable With Grass, Grassland, Woodland);

**Nutrients** (High, Low);

**Product\_Weight** (0 to 2550, 2550 to 5100, 5100 to 7650, 7650 to 10200);

**Rainfall** (0 to 0.4, 0.4 to 0.8, 0.8 to 1.2, 1.2 to 1.6, 1.6 to 2, 2 to 2.4, 2.4 to 2.8);

**Runoff** (0 to 7.7, 7.7 to 15.4);

**Senesced** (0 to 77.5, 77.5 to 155, 155 to 232.5, 232.5 to 310);

**Slope** (Flat, Sloped);

**SOMC** (0 to 1.833e5, 1.833e5 to 3.666e5, 3.666e5 to 5.499e5, 5.499e5 to 7.322e5, 7.322e5 to 9.165e5);

**Temperature** (7.5 to 8.54, 8.54 to 9.06, 9.06 to 9.58, 9.58 to 10.1, 10.1 to 10.62);

**Texture** (Loamy, Clay);

**Tillage** (Conservational, Conventional);

**VESS** (Fragile, Intact, Firm, Compact, Very Compact);

**Water** (0 to 159, 159 to 318, 318 to 477, 477 to 636);

**Water\_Stress** (0 to 3.66, 3.66 to 7.32, 7.32 to 10.98, 10.98 to 14.64);

**Weeds** (Present, Absent);

**Weight** (0 to 5000, 5000 to 10000, 10000 to 15000, 15000 to 20000, 20000 to 25000);

**Yield** (Decrease, Increase);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ali, Q. (2023). A trade-off between farm production and flood alleviation using land use tillage preferences as a natural flood management (NFM) strategy. *Smart Agricultural Technology*, 6, 100361.

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fluids1

*fluids Bayesian Networks*

---

**Description**

Use of Bayesian Networks for the investigation of the nature of biological material in casework.

**Format**

A discrete Bayesian network to assess the presence of blood in the recovered material and combine potentially contradictory observations. The network was available from an associated repository. The vertices are:

**OBTI** Blood test (Positive, Negative, Weak positive);

**Visual** (Red, Light red, Other);

**Concentration** Concentration of total DNA (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**Blood** (Yes, No);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Samie, L., Champod, C., Delemont, S., Basset, P., Hicks, T., & Castella, V. (2022). Use of Bayesian Networks for the investigation of the nature of biological material in casework. *Forensic Science International*, 331, 111174.

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fluids2

*fluids Bayesian Networks*

---

**Description**

Use of Bayesian Networks for the investigation of the nature of biological material in casework.

**Format**

A discrete Bayesian network to assess the presence of saliva in the recovered material and combine potentially contradictory observations. The network was available from an associated repository. The vertices are:

**Risk** Risk of false positive for saliva detection (High, Low);

**Saliva** (Yes, No);

**RSID** Saliva test (Positive, Negative, Weak positive);

**Concentration** Concentration of total DNA (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**Nature\_of\_stain** (Saliva, Fecal matter/vaginal secretion/sperm/breat milk/urine, Other);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Samie, L., Champod, C., Delemont, S., Basset, P., Hicks, T., & Castella, V. (2022). Use of Bayesian Networks for the investigation of the nature of biological material in casework. *Forensic Science International*, 331, 111174.

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fluids3

*fluids Bayesian Networks*

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### Description

Use of Bayesian Networks for the investigation of the nature of biological material in casework.

### Format

A discrete Bayesian network to assess the presence of sperm in the recovered material and combine potentially contradictory observations. The network was available from an associated repository. The vertices are:

**Concentration\_EPI** Total concentration of male DNA in non sperm fraction (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**Sperm** (Yes, No);

**Nature\_of\_stain** (At least Sperm, Lubricant/urine/vaginal secretion);

**Location** (Vaginal/condom/panties, Other);

**Concentration\_Total** Total concentration of male DNA (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**AZO** (Azoospermic, Non azoospermic);

**CT** Spermatozoa detection (Positive, Negative, 1 spz, Possible spz);

**PSA** Seminal fluid test (Positive, Negative, Weak positive);

**Concentration\_SP** Total concentration of male DNA in sperm fraction (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.



**References**

Samie, L., Champod, C., Delemont, S., Basset, P., Hicks, T., & Castella, V. (2022). Use of Bayesian Networks for the investigation of the nature of biological material in casework. *Forensic Science International*, 331, 111174.

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foodallergy1

*foodallergy Bayesian Networks*

---

**Description**

Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling.

**Format**

A discrete Bayesian network to estimate conditional probabilities of each food allergy when other food allergies are present (full population). Probabilities were given within the referenced paper. The vertices are:

**Cereals** (T, F);

**Eggs** (T, F);

**Fruits** (T, F);

**Milk** (T, F);

**Nuts** (T, F);

**Peanuts** (T, F);

**Seafood** (T, F);

**Veg\_Leg** (T, F);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Belmabrouk, S., Abdelhedi, R., Bougacha, F., Bouzid, F., Gargouri, H., Ayadi, I., ... & Rebai, A. (2023). Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling. *World Allergy Organization Journal*, 16(9), 100813.

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foodallergy2

*foodallergy Bayesian Networks*

---

**Description**

Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling.

**Format**

A discrete Bayesian network to estimate conditional probabilities of each food allergy when other food allergies are present (adults only). Probabilities were given within the referenced paper. The vertices are:

**Cereals** (T, F);

**Eggs** (T, F);

**Fruits** (T, F);

**Milk** (T, F);

**Nuts** (T, F);

**Peanuts** (T, F);

**Seafood** (T, F);

**Veg\_Leg** (T, F);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Belmabrouk, S., Abdelhedi, R., Bougacha, F., Bouzid, F., Gargouri, H., Ayadi, I., ... & Rebai, A. (2023). Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling. *World Allergy Organization Journal*, 16(9), 100813.

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foodallergy3

*foodallergy Bayesian Networks*

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**Description**

Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling.

**Format**

A discrete Bayesian network to estimate conditional probabilities of each food allergy when other food allergies are present (children only). Probabilities were given within the referenced paper. The vertices are:

**Cereals** (T, F);  
**Eggs** (T, F);  
**Fruits** (T, F);  
**Milk** (T, F);  
**Nuts** (T, F);  
**Peanuts** (T, F);  
**Seafood** (T, F);  
**Veg\_Leg** (T, F);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Belmabrouk, S., Abdelhedi, R., Bougacha, F., Bouzid, F., Gargouri, H., Ayadi, I., ... & Rebai, A. (2023). Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling. *World Allergy Organization Journal*, 16(9), 100813.

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foodsecurity

*foodsecurity Bayesian Network*

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**Description**

Coherent combination of probabilistic outputs for group decision making: an algebraic approach.

**Format**

A discrete Bayesian network modelling a food security scenario. Probabilities were given within the referenced paper. The vertices are:

**Cost**  
**EducationalAttainment**  
**Health**  
**SocialCohesion**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Leonelli, M., Riccomagno, E., & Smith, J. Q. (2020). Coherent combination of probabilistic outputs for group decision making: an algebraic approach. *OR Spectrum*, 42(2), 499-528.

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fundraising

*fundraising Bayesian Network*

---

## Description

A coupled mathematical model of the dissemination route of short-term fund-raising fraud.

## Format

A discrete Bayesian network to analyze the dissemination, identification, and causation of fund-raising fraud. Probabilities were given within the referenced paper. The vertices are:

**FailureInvest** (Yes, No);

**FinancialFraud** (Yes, No);

**LackAwareness** (Yes, No);

**LackKnowledge** (Yes, No);

**LackRegulation** (Yes, No);

**OverTrust** (Yes, No);

**PatsyInvestment** (Yes, No);

**PromotionalMessages** (Yes, No);

@return An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Yang, S., Su, K., Wang, B., & Xu, Z. (2022). A coupled mathematical model of the dissemination route of short-term fund-raising fraud. *Mathematics*, 10(10), 1709.

gasexplosion

*gasexplosion Bayesian Network***Description**

Risk assessment of unsafe acts in coal mine gas explosion accidents based on HFACS-GE and Bayesian networks.

**Format**

A discrete Bayesian network to analyze unsafe human acts in coal mine gas explosion accidents. Probabilities were given within the referenced paper. The vertices are:

**AccidentalViolations** (Non-occurrence, Occurrence);

**CreateAFalseImpressionToDeceiveTheRegulators** (Non-occurrence, Occurrence);

**DecisionErrors** (Non-occurrence, Occurrence);

**DepartmentsAndInstitutionsAreNotComplete** (Non-occurrence, Occurrence);

**HabitualViolations** (Non-occurrence, Occurrence);

**IllegalCommand** (Non-occurrence, Occurrence);

**InadequateEmergencyPlan** (Non-occurrence, Occurrence);

**InsufficientCrackdownOnIllegalActivities** (Non-occurrence, Occurrence);

**InsufficientSupervisionOfWorkSafety** (Non-occurrence, Occurrence);

**MentalStates** (Non-occurrence, Occurrence);

**OrganizeProductionInViolationOfLawsAndRegulations** (Non-occurrence, Occurrence);

**PerceptualErrors** (Non-occurrence, Occurrence);

**PhysicalIntellectualDisability** (Non-occurrence, Occurrence);

**SafetyEducationAndTraning** (Non-occurrence, Occurrence);

**SafetySupervisionIsInadequate** (Non-occurrence, Occurrence);

**SecurityManagementConfusion** (Non-occurrence, Occurrence);

**SafetySupervisionIsInadequate** (Non-occurrence, Occurrence);

**SecurityManagementConfusion** (Non-occurrence, Occurrence);

**SkillBasedErrors** (Non-occurrence, Occurrence);

**TechnicalEnvironment** (Non-occurrence, Occurrence);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Niu, L., Zhao, J., & Yang, J. (2023). Risk assessment of unsafe acts in coal mine gas explosion accidents based on HFACS-GE and Bayesian networks. *Processes*, 11(2), 554.

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 gasifier

*gasifier Bayesian Network*


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### Description

Failure risk assessment of coal gasifier based on the integration of bayesian network and trapezoidal intuitionistic fuzzy number-based similarity aggregation method (TpIFN-SAM).

### Format

A discrete Bayesian network for the failure-risk assessment of process system. Probabilities were given within the referenced paper. The vertices are:

**AbnormalCoalWater** Abnormal flow rate of coal water (Occurred, NotOccurred);

**AbnormalLiquidLevel** Abnormal liquid level (Occurred, NotOccurred);

**AbnormalQuenchWater** Abnormal flow rate of quench water (Occurred, NotOccurred);

**AbnormalTemperature** Abnormal temperature (Occurred, NotOccurred);

**AntiCorrosion** Anti-corrosion layer damaged (Occurred, NotOccurred);

**BurnerDamaged** Burner damaged (Occurred, NotOccurred);

**CorrosionFailure** Corrosion failure (Occurred, NotOccurred);

**Cracking** Cracking in the quench ring or vertical pipe (Occurred, NotOccurred);

**DeliberateDestruction** Deliberate destruction (Occurred, NotOccurred);

**ExternalCorrosion** External corrosion (Occurred, NotOccurred);

**FurnaceBricks** Slag opening blocked by molten furnace bricks (Occurred, NotOccurred);

**GasifierAbnormality** Gasifier abnormality (Occurred, NotOccurred);

**GasifierFailure** Gasifier failure (Occurred, NotOccurred);

**GaugeDamaged** Liquid-level gauge damaged by blockage (Occurred, NotOccurred);

**HighCO2** High CO<sub>2</sub> content (Occurred, NotOccurred);

**HighConcentration** High concentration of coal slurry (Occurred, NotOccurred);

**HighFlow** High flow rate (Occurred, NotOccurred);

**HighFlowRate** High flow rate of coal slurry (Occurred, NotOccurred);

**HighH2O** High H<sub>2</sub>O content (Occurred, NotOccurred);

**HighH2S** High H<sub>2</sub>S content (Occurred, NotOccurred);

**HighOxygen** High oxygen-flow rate (Occurred, NotOccurred);

**HumanOrganization** Human organization factors (Occurred, NotOccurred);

**ImproperOperation** Improper operation (Occurred, NotOccurred);

**Insulation** Insulation layer damaged (Occurred, NotOccurred);

**InternalCorrosion** Internal corrosion (Occurred, NotOccurred);

**Leakage** Leakage of drain valve of quench water (Occurred, NotOccurred);

**LowConcentration** Low concentration of coal slurry (Occurred, NotOccurred);  
**LowFlowRate** Low flow rate of coal slurry (Occurred, NotOccurred);  
**LowLiquidLevel** Low liquid rate in quench chamber (Occurred, NotOccurred);  
**LowOxygen** Low oxygen-flow rate (Occurred, NotOccurred);  
**MediumContent** Medium content (Occurred, NotOccurred);  
**PiecesOfSlag** Slag opening blocked by large pieces of slag (Occurred, NotOccurred);  
**PreJobTraining** Pre-job training is not up to standard (Occurred, NotOccurred);  
**PressureFluctuation** Pressure fluctuation (Occurred, NotOccurred);  
**SensorDamaged1** Temperature sensor damaged (Occurred, NotOccurred);  
**TemperatureSensor** Temperature sensor damaged (Occurred, NotOccurred);  
**TooHighTemperature** Too-high temperature (Occurred, NotOccurred);  
**TooLowTemperature** Too-low temperature (Occurred, NotOccurred);  
**Unattended** Unattended/unsafe supervision (Occurred, NotOccurred);  
**UnintentionalDestruction** Unintentional destruction (Occurred, NotOccurred);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Liu, Y., Wang, S., Liu, Q., Liu, D., Yang, Y., Dan, Y., & Wu, W. (2022). Failure risk assessment of coal gasifier based on the integration of bayesian network and trapezoidal intuitionistic fuzzy number-based similarity aggregation method (TpIFN-SAM). *Processes*, 10(9), 1863.

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GDIpathway1

*GDIpathway Bayesian Networks*

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### Description

Integrative network modeling highlights the crucial roles of Rho-GDI signaling pathway in the progression of non-small cell lung cancer.

### Format

A discrete Bayesian network to pinpoint key cellular factors and pathways likely to be involved with the onset and progression of non-small cell lung cancer (healthy patients). The network was available from an associated repository. The vertices are:

**ARHGAP6** (Above, Below);

**ARHGEF19** (Above, Below);

**CD44** (Above, Below);

**CDC42-IT1** (Above, Below);

**CDH1** (Above, Below);  
**CFL2** (Above, Below);  
**DAGLB** (Above, Below);  
**DGKZ** (Above, Below);  
**DLC1** (Above, Below);  
**ECM1** (Above, Below);  
**ERMAP** (Above, Below);  
**ERMP1** (Above, Below);  
**GNA11** (Above, Below);  
**GNG11** (Above, Below);  
**GPRC5A** (Above, Below);  
**ITGB2** (Above, Below);  
**LACTB** (Above, Below);  
**LIMK2** (Above, Below);  
**PAAF1** (Above, Below);  
**PAK1** (Above, Below);  
**PAK1** (Above, Below);  
**PIP** (Above, Below);  
**PIP4K2A** (Above, Below);  
**PIP5K1B** (Above, Below);  
**RAC2** (Above, Below);  
**RHOJ** (Above, Below);  
**ROCK2** (Above, Below);  
**RTKN** (Above, Below);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Gupta, S., Vundavilli, H., Osorio, R. S. A., Itoh, M. N., Mohsen, A., Datta, A., ... & Tripathi, L. P. (2022). Integrative network modeling highlights the crucial roles of rho-GDI signaling pathway in the progression of non-small cell lung cancer. *IEEE Journal of Biomedical and Health Informatics*, 26(9), 4785-4793.



**Description**

Integrative network modeling highlights the crucial roles of Rho-GDI signaling pathway in the progression of non-small cell lung cancer.

**Format**

A discrete Bayesian network to pinpoint key cellular factors and pathways likely to be involved with the onset and progression of non-small cell lung cancer (unhealthy patients). The network was available from an associated repository. The vertices are:

**ARHGAP6** (Above, Below);

**ARHGEF19** (Above, Below);

**CD44** (Above, Below);

**CDC42-IT1** (Above, Below);

**CDH1** (Above, Below);

**CFL2** (Above, Below);

**DAGLB** (Above, Below);

**DGKZ** (Above, Below);

**DLC1** (Above, Below);

**ECM1** (Above, Below);

**ERMAP** (Above, Below);

**ERMP1** (Above, Below);

**GNA11** (Above, Below);

**GNG11** (Above, Below);

**GPRC5A** (Above, Below);

**ITGB2** (Above, Below);

**LACTB** (Above, Below);

**LIMK2** (Above, Below);

**PAAF1** (Above, Below);

**PAK1** (Above, Below);

**PAK1** (Above, Below);

**PIP** (Above, Below);

**PIP4K2A** (Above, Below);

**PIP5K1B** (Above, Below);

**RAC2** (Above, Below);

**RHOJ** (Above, Below);

**ROCK2** (Above, Below);

**RTKN** (Above, Below);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Gupta, S., Vundavilli, H., Osorio, R. S. A., Itoh, M. N., Mohsen, A., Datta, A., ... & Tripathi, L. P. (2022). Integrative network modeling highlights the crucial roles of rho-GDI signaling pathway in the progression of non-small cell lung cancer. *IEEE Journal of Biomedical and Health Informatics*, 26(9), 4785-4793.

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<code>get_network_list</code>	<i>Get the list of available Bayesian network files</i>
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**Description**

This function lists all the `.rda` files in the data directory.

**Usage**

```
get_network_list()
```

**Value**

A character vector of network file names.

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<code>gonorrhoeae</code>	<i>gonorrhoeae Bayesian Network</i>
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**Description**

Policy, practice, and prediction: model-based approaches to evaluating N. gonorrhoeae antibiotic susceptibility test uptake in Australia.

**Format**

A discrete Bayesian network to simulate the clinician-patient dynamics influencing antibiotic susceptibility test initiation. The probabilities were given within the referenced paper. The vertices are:

**ASTTest** (Initiated, Not initiated);

**ClinicianExperience** (Experienced, Unexperienced);

**EpidemiologicalFactors** (High risk group, Low risk group);

**InitialTreatmentFailure** (Treatment success, Treatment failure);

**MedicationAdherence** (Proper Adherence, Improper Adherence);

**NumberPartners** (One, Two to five, More than six);  
**PastDiagnoses** (One, Two to four, five to nine, More than ten);  
**PersistingSymptoms** (Symptoms persist, Symptoms resolve);  
**SexualOrientation** (Heterosexual, Homosexual);  
**UnpromptedTest** (Initiated, Not initiated);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Do, P. C., Assefa, Y. A., Batikawai, S. M., Abate, M. A., & Reid, S. A. (2024). Policy, practice, and prediction: model-based approaches to evaluating N. gonorrhoeae antibiotic susceptibility test uptake in Australia. *BMC Infectious Diseases*, 24(1), 498.

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greencredit

*greencredit Bayesian Network*

---

### Description

The coupling relationships and influence mechanisms of green credit and energy-environment-economy under China's goal of carbon neutrality.

### Format

A discrete Bayesian network investigate the coupling relationships and influence mechanisms of green credit and 3E system. Probabilities were given within the referenced paper (missing distributions were set as uniform). The vertices are:

**ECS** Energy consumption structure (High, Medium, Low);

**EI** Energy intensity (High, Medium, Low);

**EPI** Environment (High, Medium, Low);

**GCI** Interest expense proportion (High, Medium, Low);

**GDP** Economy sharing (High, Medium, Low);

**IS** Green economy (High, Medium, Low);

**OU** Economy opening up (High, Medium, Low);

**PEC** Per capita energy consumption (High, Medium, Low);

**TP** Economy innovation (High, Medium, Low);

**UR** Economy coordination (High, Medium, Low);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Chai, J., Wang, Y., Hu, Y., Zhang, X., & Zhang, X. (2023). The Coupling Relationships and Influence Mechanisms of Green Credit and Energy-Environment-Economy Under China's Goal of Carbon Neutrality. *Journal of Systems Science and Complexity*, 36(1), 360-374.

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grounding

*grounding Bayesian Network*

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## Description

A framework for quantitative analysis of the causation of grounding accidents in arctic shipping.

## Format

A discrete Bayesian network to for quantitative analysis of the causation of grounding accidents in Arctic shipping. Probabilities were given within the referenced paper (some information appeared incorrect). The vertices are:

**BW** Bad Weather (No, Yes);

**DAM** Damage (No, Yes);

**DE** Dependent equipment (No, Yes);

**GRO** Grounding (No, Yes);

**ICC** Insufficient communication and collaboration (No, Yes);

**IER** Imperfect emergency (No, Yes);

**ILC** Improper labeling of the chart (No, Yes);

**INE** Inefficient use of navigation equipment (No, Yes);

**IO** Improper operation (No, Yes);

**IPS** Insufficient preparation for sailing (No, Yes);

**IRP** Improper route planning (No, Yes);

**IRR** Irregularities (No, Yes);

**IS** Insufficient supervision (No, Yes);

**ISL** Inconsistent standardization and language (No, Yes);

**ISS** Insufficient supervision system, rules and regulations (No, Yes);

**IWP** Insufficient work plan (No, Yes);

**LID** Limited information dissemination channels (No, Yes);

**LNE** Lack of navigation equipment (No, Yes);

**LSM** Lack of safety management system (No, Yes);

**LT** Lack of training (No, Yes);

**MIJ** Misjudgment (No, Yes);

**OD** Outdated data (No, Yes);

**PC** Poor communication at high latitudes (No, Yes);  
**PEC** Poor external communication (No, Yes);  
**PF** Psychological factors (No, Yes);  
**PFC** Poor traffic conditions (No, Yes);  
**PSA** Poor situational awareness (No, Yes);  
**PSM** Poor safety management (No, Yes);  
**PSQ** Poor service quality (No, Yes);  
**SMS** Ship SMS conflict (No, Yes);  
**UCD** Unupdated chart data (No, Yes);  
**UDL** Unclear division of labour (No, Yes);  
**UPA** Unreasonable planning and arrangement (No, Yes);  
**UR** Underestimate the risk (No, Yes);  
**US** Unsafe speed (No, Yes);  
**WD** Wrong decision (No, Yes);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Fu, S., Yu, Y., Chen, J., Xi, Y., & Zhang, M. (2022). A framework for quantitative analysis of the causation of grounding accidents in arctic shipping. *Reliability Engineering & System Safety*, 226, 108706.

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healthinsurance      *healthinsurance Bayesian Network*

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### Description

Discrete latent variables discovery and structure learning in mixed Bayesian networks.

### Format

A conditional linear-Gaussian Bayesian network to predict health insurance charges. The DAG structure was taken from the referenced paper and the probabilities learned from data. The vertices are:

**age**  
**bmi**  
**charges**  
**children** (0, 1, 2, 3, 4, 5)  
**region** (northeast, northwest, southeast, southwest);  
**sex** (female, male);  
**smoker** (no, yes);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Peled, A., & Fine, S. (2021). Discrete Latent Variables Discovery and Structure Learning in Mixed Bayesian Networks. In 20th IEEE International Conference on Machine Learning and Applications (pp. 248-255). IEEE.

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humanitarian

*humanitarian Bayesian Network*

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**Description**

You only derive once (YODO): Automatic differentiation for efficient sensitivity analysis in Bayesian networks.

**Format**

A discrete Bayesian network to assess the country-level risk associated with humanitarian crises and disasters. The Bayesian network is learned as in the referenced paper. The vertices are:

**RISK** (low, medium, high);

**EARTHQUAKE** (low, medium, high);

**FLOOD** (low, medium, high);

**TSUNAMI** (low, medium, high);

**TROPICAL\_CYCLONE** (low, medium, high);

**DROUGHT** (low, medium, high);

**EPIDEMIC** (low, medium, high);

**PCR** Projected conflict risk (low, medium, high);

**CHVCI** Current highly violent conflict intensity (low, medium, high);

**D\_AND\_D** Development and deprivation (low, medium, high);

**ECON\_DEP** Economic dependency (low, medium, high);

**UNP\_PEOPLE** Unprotected people (low, medium, high);

**HEALTH\_COND** Health conditions (low, medium, high);

**CHILDREN\_U5** (low, medium, high);

**RECENT\_SHOCKS** (low, medium, high);

**FOOD\_SECURITY** (low, medium, high);

**OTHER\_VULN\_GROUPS** Other vulnerable groups (low, medium, high);

**GOVERNANCE** (low, medium, high);

**COMMUNICATION** (low, medium, high);

**PHYS\_INFRA** Physical infrastructure (low, medium, high);

**ACCESS\_TO\_HEALTH** (low, medium, high);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ballester-Ripoll, R., & Leonelli, M. (2022, September). You only derive once (YODO): automatic differentiation for efficient sensitivity analysis in Bayesian networks. In International Conference on Probabilistic Graphical Models (pp. 169-180). PMLR.

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 hydraulicsystem

*hydraulicsystem Bayesian Network*


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**Description**

Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network.

**Format**

A discrete Bayesian network to to analyze time series hydraulic system operation reliability. Probabilities were given within the referenced paper. The vertices are:

**YellowHydraulicSystem** (True, False);

**GreenHydraulicSystem** (True, False);

**BlueHydraulicSystem** (True, False);

**HydraulicSystem** (True, False);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Pan, W. H., Feng, Y. W., Liu, J., & Lu, C. (2023). Operation reliability monitoring towards fault diagnosis of airplane hydraulic system using quick access recorder flight data. *Measurement Science and Technology*, 34(5), 055111.

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 income

*income Bayesian Network*


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### Description

The FEDHC Bayesian network learning algorithm.

### Format

A discrete Bayesian network modeling the factors affecting the income of individuals. The code to learn the Bayesian network was given within the referenced paper (Figure 13.c) The vertices are:

**Income** (0-40'000, 40'000+);

**Sex** (male, female);

**Marriage** (married, cohabitation, divorced, widowed, single);

**Age** (14-34, 35+);

**Education** (college graduate, no college graduate);

**Occupation** (professional/managerial, sales, laborer, clerical/service, homemaker, student, military, retired, unemployed);

**Bay** Number of years in bay area (1-9, 10+);

**No of people** Number of people living in the house (1, 2+);

**Children** (0, 1+);

**Rent** (own, rent, live with parents/family);

**Type** (house, condominium, apartment, mobile home, other);

**Ethnicity** (American Indian, Asian, black, east Indian, hispanic, white, pacific islander, other);

**Language** (english, spanish, other);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Tsagris, M. (2022). The FEDHC Bayesian network learning algorithm. *Mathematics*, 10(15), 2604.



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intensification	<i>intensification Bayesian Network</i>
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### Description

Modeling intensification decisions in the Kilombero Valley floodplain: A Bayesian belief network approach.

### Format

A discrete Bayesian network to or identifying determinants of intensification and their interrelationships. The Bayesian network is learned as in the referenced paper. The vertices are:

**AccessToCredi** (No, Yes);

**AgeofHHHead** (25-35, 35-45, 45-55, >55);

**Choice\_Of\_Intensification\_Strategy** (ApplyFertilizer, ApplyImprovedSeed, CropMultipleTimes, None, UseIrrigation, UseIrrigationAndFertilizerApplication);

**CommercializationIndex** (<30%, 30-60%, >60%);

**CropChoice** (Maize, Rice, RiceAndMaize, RiceMaizeAndVegit, Vegetables, VegitAndMaize, VegitAndRice);

**DistanceToBigMarket** (<15km, 15-30km, >30km);

**ExpectedPriceOfMaize** (0, 0-800, 800-861.111, 861.111-1111.11);

**ExpectedPriceOfRice** (0 to 1000, 1000 to 1200, 1200 to 1500, 1500 to 1900);

**FarmerType** (AgroPastoralist, Diversifier, Subsistence);

**Income** (0-160, 160-280, 280-600, 600-15800);

**LabourInManDays** (<120, 120-220, 220-400, >400);

**PercentOfNonFarmIncome** (None, <30%, >30%);

**ShareOfHiredLabour** (<10%, 10-60%, >60%);

**SizeOfCropLand** (<3Ha, 3-6Ha, 6-9Ha, >9Ha);

**SizeOfHousehold** (<4, 4-7, >7);

**TopographicWetnessIndex** (14-18, 18-23, 23-32);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Gebrekidan, B. H., Heckeleei, T., & Rasch, S. (2023). Modeling intensification decisions in the Kilombero Valley floodplain: A Bayesian belief network approach. *Agricultural Economics*, 54(1), 23-43.

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intentionalattacks      *intentionalattacks Bayesian Network*

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### Description

Probability elicitation for Bayesian networks to distinguish between intentional attacks and accidental technical failures.

### Format

A discrete Bayesian network modeling a floodgate in the Netherlands. Probabilities were given within the referenced paper. The vertices are:

- X1** Weak physical access-control (True, False);
- X2** Sensor data integrity verification (True, False);
- U1** Lack of physical maintenance (True, False);
- U2** Well-written maintenance procedure (True, False);
- Y** Major cause for sensor sends incorrect water level measurements (Intentional Attack, Accidental Technical Failure);
- Z1** Abnormalities in the other locations (True, False);
- Z2** Sensor sends correct water level measurements after cleaning the sensor (True, False)
- Z3** Sensor sends correct water level measurements after recalibrating the sensor (True, False);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Chockalingam, S., Pieters, W., Teixeira, A. M., & van Gelder, P. (2023). Probability elicitation for Bayesian networks to distinguish between intentional attacks and accidental technical failures. *Journal of Information Security and Applications*, 75, 103497.

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inverters      *inverters Bayesian Network*

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### Description

Intelligent fault inference of inverters based on a three-layer Bayesian network.

**Format**

A discrete Bayesian network to infer the probable uncertain faults. Probabilities were given within the referenced paper. The vertices are:

**AbnormalPulseVoltageWaveform** (TRUE, FALSE);  
**APhaseFailure** (TRUE, FALSE);  
**APhaseNegativeWaveFormDistortion** (TRUE, FALSE);  
**APhasePositiveWaveFormDistortion** (TRUE, FALSE);  
**BPhaseFailure** (TRUE, FALSE);  
**BPhaseNegativeWaveFormDistortion** (TRUE, FALSE);  
**BPhasePositiveWaveFormDistortion** (TRUE, FALSE);  
**C1Failure** (TRUE, FALSE);  
**C1VoltageAnomaly** (TRUE, FALSE);  
**C2Failure** (TRUE, FALSE);  
**C2VoltageAnomaly** (TRUE, FALSE);  
**CapacitanceParameterWeakening** (TRUE, FALSE);  
**CPhaseFailure** (TRUE, FALSE);  
**CPhaseNegativeWaveFormDistortion** (TRUE, FALSE);  
**CPhasePositiveWaveFormDistortion** (TRUE, FALSE);  
**DCLinkFailure** (TRUE, FALSE);  
**G1PulseMissing** (TRUE, FALSE);  
**G2PulseMissing** (TRUE, FALSE);  
**G3PulseMissing** (TRUE, FALSE);  
**G4PulseMissing** (TRUE, FALSE);  
**G5PulseMissing** (TRUE, FALSE);  
**G6PulseMissing** (TRUE, FALSE);  
**T1OC** (TRUE, FALSE);  
**T2OC** (TRUE, FALSE);  
**T3OC** (TRUE, FALSE);  
**T4OC** (TRUE, FALSE);  
**T5OC** (TRUE, FALSE);  
**T6OC** (TRUE, FALSE);  
**VoltageWaveFormAsymmetry** (TRUE, FALSE);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Han, S., He, Y., Zheng, S., & Wang, F. (2019). Intelligent Fault Inference of Inverters Based on a Three-Layer Bayesian Network. *Mathematical Problems in Engineering*, 2019(1), 3653746.

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 knowledge

*knowledge Bayesian Network*


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**Description**

Dynamic knowledge inference based on Bayesian network learning.

**Format**

A discrete Bayesian network to predict whether students would pass specific courses. Probabilities were given within the referenced paper. The vertices are:

**Math** (Pass, Fail);

**C** (Pass, Fail);

**Java** (Pass, Fail);

**Database** (Pass, Fail);

**Android** (Pass, Fail);

**Web** (Pass, Fail);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wang, D., AmrilJaharadak, A., & Xiao, Y. (2020). Dynamic knowledge inference based on Bayesian network learning. *Mathematical Problems in Engineering*, 2020(1), 6613896.

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 kosterhavet

*kosterhavet Bayesian Network*


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**Description**

A Bayesian network to inform the management of key species in Kosterhavet National Park under contrasting storylines of environmental change.

**Format**

A discrete Bayesian network to predict the consequences of human activities for coastal ecosystems and identify areas for directed abatement measures. Probabilities were given within the referenced paper (missing probabilities were given a uniform distribution). The vertices are:

**LeisureBoating** Boats per year in marinas and natural harbors (for natural harbors only high season from Jul. 01 to Aug. 07 considered) within Kosterhavet National Park (Low, Medium, High);

- TrawlingFrequency** Number of trawling events per area and year within Kosterhavet National Park (Low, High);
- MusselCultivation** Extent of oysters and blue mussels farms within Kosterhavet National Park (Low, Medium, High, Very high);
- DevelopedLand** Proportion of developed land in the catchments of marine water bodies (Low, High);
- AgriculturalLand** Proportion of agricultural land in the catchments of marine water bodies (Low, Medium, High);
- TNExchange** Annual net total nitrogen exchange between marine water bodies (Low, Medium, High);
- TPEXchange** Annual net phosphorus exchange between marine water bodies (Low, Medium, High);
- RadiativeForcing** Scenarios of radiative forcing till the end of 2100 (Current, RF45, RF85);
- Precipitation** Annual mean precipitation on land within the catchments of marine water bodies (Low, High);
- Discharge** Sum of discharges from rivers and runoff from land into marine water bodies (Low, Medium, High);
- Wind** Maximum summer (Jun.-Aug.) offshore wind speed (Low, Medium, High);
- DIN** Mean winter (Dec.-Feb.) dissolved inorganic nitrogen concentration in surface waters (Low, Medium, High);
- DIP** Mean winter (Dec.-Feb.) dissolved inorganic phosphorus concentration in surface waters (Low, Medium, High);
- POM** Annual mean concentration POM (POC - chl-a) (Low, High);
- NutrientEnrichmentRisk** Dependent on combination of states of DIN, DIP and POM (Low, Medium, High);
- Noise** Noise from leisure boats (Low, Medium, High);
- AnchorDamageRisk** Risk of seafloor in shallow bays being impacted by anchor damage of leisure boats (Low, High);
- WaterTemperatureShallow** Mean summer (Jun.- Aug.) sea surface temperature - depth < 10m (Low, Medium, High);
- Transparency** Mean summer (Jun-Aug) Secchi depth (Low, Medium, High);
- OxygenShallow** Lowest percentile of summer (Jun.-Aug.) oxygen concentration of surface water - depth < 10m (Low, Medium, High);
- OxygenDeep** Lowest percentile of summer (Jun.-Aug.) oxygen concentration of surface water - depth < 60m (Low, Medium, High);
- Turbidity** Amount of dry weight (Low, Medium, High);
- BottomSubstrate** Type of bottom substrate (Soft, Hard);
- SeafloorDisturbance** Benthic quality index (Low, High);
- WaterTemperatureDeep** Mean summer (Jun.- Aug.) sea surface temperature - depth < 60m (Low, High);
- TNLoad** Annual load of total nitrogen to marine water bodies (Low, Medium, High);
- TPLoad** Annual load of total phosphorus to marine water bodies (Low, Medium, High);

- SedimentLoad** Annual sediment load to marine water bodies (Low, Medium, High);
- HabitatQuality** Dependent on combination of states of oxygen (deep), turbidity (deep), seafloor disturbance (Low, Medium, High);
- Cod** Catch per unit effort (Low, Medium, High);
- IntermediateFishPredators** Abundance of intermediate fish predators (e.g. Gobiidae, three-spined stickleback) (Low, Medium, High);
- Mesograzers** Abundance of mesograzers (e.g. amphipods, isopods)(Low, Medium, High);
- FilamentousAlgae** Maximum summer (May-Aug.) cover of filamentous algae in eelgrass meadows (Low, Medium, High);
- Phytoplankton** Mean summer (Jun.-Aug.) chl-a concentration (Low, Medium, High);
- Zooplankton** Strongly responds to phytoplankton with weaker links to temperature and oxygen concentration (Low, Medium, High);
- Prey** Dependent on combination of states of zooplankton and seafloor disturbance (Low, Medium, High);
- Eelgrass** Extent of eelgrass meadows within Kosterhavet National Park (Decrease, No change, Increase);
- NorthernShrimp** Catch per unit effort (Decrease, No change, Increase);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Rettig, K., Hansen, A. S., Obst, M., Hering, D., & Feld, C. K. (2023). A Bayesian network to inform the management of key species in Kosterhavet National Park under contrasting storylines of environmental change. *Estuarine, Coastal and Shelf Science*, 280, 108158.

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lawschool

*lawschool Bayesian Network*

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### Description

A survey on datasets for fairness-aware machine learning.

### Format

A discrete Bayesian network modeling law school admission records. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset. The vertices are:

**fam\_inc** The student's family income bracket (1, 2, 3, 4, 5);

**fulltime** Whether the student will work full-time or part-time (1, 2);

**lsat** The student's LSAT score ( $\leq 37$ , 37);

**male** Whether the student is male or female (female, male);

- pass\_bar** Whether the student passed the bar exam on the first try (negative, positive);
- racetxt** Race (non-white, white);
- tier** Tier (1, 2, 3, 4, 5, 6);
- ugpa** The student's undergraduate GPA ( $<3$ ,  $>=3.3$ );
- zfygpa** The first year law school GPA ( $<=0$ ,  $>0$ );
- zgpa** The cumulative law school GPA ( $<=0$ ,  $>0$ );

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 12(3), e1452.

lexical

*lexical Bayesian Network***Description**

Accounting for the relationship between lexical prevalence and acquisition with Bayesian networks and population dynamics.

**Format**

A Gaussian Bayesian network to analyze various measures of lexical dispersion and assess the extent to which they are linked to age of acquisition. Probabilities were given within the referenced paper. The vertices are:

- aoa** Age of acquisition;
- area** Area in which the word is known;
- genre\_disp** Dispersion across genres;
- log\_freq** Logarithm of word frequency;
- log\_range** Logarithm of dispersion across texts;
- prev\_heard** Fraction of speakers that have already heard a word;
- prev\_used** Fraction of speakers that have already used a word;
- social\_disp** Entropy of educational status per word;

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Baumann, A., & Sekanina, K. (2022). Accounting for the relationship between lexical prevalence and acquisition with Bayesian networks and population dynamics. *Linguistics Vanguard*, 8(1), 209-224.

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 lidar

*lidar Bayesian Network*


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## Description

Decision support using SAR and LiDAR machine learning target classification and Bayesian belief networks.

## Format

A discrete Bayesian network to compute posterior event probabilities for sample analyst scenarios. Probabilities were given within the referenced paper. The vertices are:

**ActivityIndustrialArea** (Routine, Unusual);

**ActivitySiteA** (Routine, Unusual);

**ActivitySiteB** (Routine, Unusual);

**ThunderstormsA** (High, Low);

**ThunderstormsB** (High, Low);

**TrafficUnusualEvent** (True, False);

**UsualRushHourTraffic** (True, False);

**VehicleDensityA** (High, Low);

**VehicleDensityB** (High, Low);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Bogart, C., Solorzano, L., & Lam, S. (2022, May). Decision support using SAR and LiDAR machine learning target classification and Bayesian belief networks. In *Geospatial Informatics XII* (Vol. 12099, pp. 28-36). SPIE.



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liquefaction	<i>liquefaction Bayesian Network</i>
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**Description**

A continuous Bayesian network regression model for estimating seismic liquefaction-induced settlement of the free-field ground.

**Format**

A Gaussian Bayesian network to predict seismic liquefaction-induced settlement. The Bayesian network is learned using the data available from the referenced paper. The vertices are:

**Ds**

**GWT**

**Inamax**

**InR**

**Int**

**Mw**

**N160**

**S**

**Sigmav**

**Ts**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Hu, J., Xiong, B., Zhang, Z., & Wang, J. (2023). A continuous Bayesian network regression model for estimating seismic liquefaction-induced settlement of the free-field ground. *Earthquake Engineering & Structural Dynamics*, 52(11), 3216-3237.

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liquidity

*liquidity Bayesian Network*

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### **Description**

An artificial neural network and Bayesian network model for liquidity risk assessment in banking.

### **Format**

A discrete Bayesian network demonstrate applicability and exhibit the efficiency, accuracy and flexibility of data mining methods when modeling ambiguous occurrences related to bank liquidity risk measurement. Probabilities were given within the referenced paper. The vertices are:

**X1** (FALSE, TRUE);

**X2** (FALSE, TRUE);

**X3** (FALSE, TRUE);

**X4** (FALSE, TRUE);

**X5** (FALSE, TRUE);

**X6** (FALSE, TRUE);

**X7** (FALSE, TRUE);

**X8** (FALSE, TRUE);

**X9** (FALSE, TRUE);

**X10** (FALSE, TRUE);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Tavana, M., Abtahi, A. R., Di Caprio, D., & Poortarigh, M. (2018). An Artificial Neural Network and Bayesian Network model for liquidity risk assessment in banking. *Neurocomputing*, 275, 2525-2554.

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lithium

*lithium Bayesian Network*

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### **Description**

Fire accident risk analysis of lithium battery energy storage systems during maritime transportation.

### **Format**

A discrete Bayesian network to evaluate the fire accident risk of lithium battery energy storage system in the process of maritime transportation. Probabilities were given within the referenced paper. The vertices are:

- X1** Bad weather condition (True, False);
- X2** Improper storage (True, False);
- X3** Improper ballast (True, False);
- X4** High ship speed (True, False);
- X5** Defect of binding equipment (True, False);
- X6** Improper maintenance of binding equipment (True, False);
- X7** Improper binding (True, False);
- X8** Contact accident (True, False);
- X9** Collision accident (True, False);
- X10** Direct sunlight (True, False);
- X11** Stowage adjacent to engine room (True, False);
- X12** Stowage adjacent to oil tank (True, False);
- X13** High ambient temperature (True, False);
- X14** Cargo hold flooding (True, False);
- X15** No installation of short-circuit prevention device (True, False);
- X16** High humidity (True, False);
- X17** Lack of insulation (True, False);
- X18** Overcharge (True, False);
- X19** Over discharge (True, False);
- X20** Defect of separate (True, False);
- X21** Burrs on the electrode surface (True, False);
- X22** No installation of monitoring devices (True, False);
- X23** Monitoring equipment cannot cover all goods (True, False);
- X24** Damage of monitoring equipment (True, False);
- X25** The monitoring equipment does not have real-time alarm function (True, False);
- X26** The crew does not patrol according to regulations (True, False);

**X27** Insufficient firefighting equipment (True, False);  
**X28** Failure of firefighting equipment (True, False);  
**X29** Firefighting equipment is not suitable for putting out lithium battery fires (True, False);  
**X30** Crew members are not trained in lithium battery firefighting (True, False);  
**X31** (True, False);  
**X1** The crew did not know the correct way to put out the lithium battery fire (True, False);  
**BindingFailure** (True, False);  
**ExternalShortCircuit** (True, False);  
**HighTemperature** (True, False);  
**Impact** (True, False);  
**ImproperOperation** (True, False);  
**InsufficientFirefightingCapacity** (True, False);  
**InsufficientFireMonitoring** (True, False);  
**InternalShortCircuit** (True, False);  
**LBESSCatchFire** (True, False);  
**LBESSFireAccident** (True, False);  
**PoorShipStability** (True, False);  
**ShortCircuit** (True, False);  
**UnableToPutOutFire** (True, False);  
**ViolentRolling** (True, False);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Zhang, C., Sun, H., Zhang, Y., Li, G., Li, S., Chang, J., & Shi, G. (2023). Fire accident risk analysis of lithium battery energy storage systems during maritime transportation. *Sustainability*, 15(19), 14198.

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load\_network

*Load a Bayesian network*

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### Description

This function loads a selected Bayesian network file.

### Usage

```
load_network(network_name)
```

**Arguments**

network\_name    The name of the network file to load.

**Value**

A bn.fit object representing the Bayesian network.

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macrophytes	<i>macrophytes Bayesian Network</i>
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**Description**

Mechanical removal of macrophytes in freshwater ecosystems: Implications for ecosystem structure and function.

**Format**

A discrete Bayesian network to assess the implications of macrophyte removal on interrelated ecosystem properties across a wide range of environmental conditions. The probabilities were given within the referenced paper (missing probabilities were given a uniform distribution). The vertices are:

**BenthicFishForaging** (Low, Moderate, High);

**Disturbance** (Low, Moderate, High);

**Ecosystem** (Standing floating, Standing submerged, Flowing submerged);

**EcosystemServices** (Flooding, Birds, Nutrient retention, Angling, Swimming, Boating, Hydropower, Irrigation, Invasive species);

**EpiphyticInvertebrates** (Low, Moderate, High);

**Flow** (Low, Moderate, High);

**Light** (Low, High);

**NutrientLoading** (Low, Moderate, High);

**Phytoplankton** (Low, Moderate, High);

**PiscivorousFish** (Present, Absent);

**PiscivorousFishPredation** (Low, High)

**PlanktivorousFish** (Low, High);

**PlantRemoval** (None, Partial, Full);

**Resources** (Low, Moderate, High);

**Zooplankton** (Low, Moderate, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Thiemer, K., Schneider, S. C., & Demars, B. O. (2021). Mechanical removal of macrophytes in freshwater ecosystems: Implications for ecosystem structure and function. *Science of the Total Environment*, 782, 146671.

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 medicaltest

*medicaltest Bayesian Network*


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**Description**

Global sensitivity analysis of uncertain parameters in Bayesian networks.

**Format**

A discrete Bayesian network representing a synthetic example of two medical tests. Probabilities were given within the referenced paper. The vertices are:

**Test1** (no, yes);

**Test2** (no, yes);

**Disease** (no, yes);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ballester-Ripoll, R., & Leonelli, M. (2024). Global Sensitivity Analysis of Uncertain Parameters in Bayesian Networks. arXiv preprint arXiv:2406.05764.

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 megacities

*megacities Bayesian Network*


---

**Description**

Air pollution risk assessment related to fossil fuel-driven vehicles in megacities in China by employing the Bayesian network coupled with the fault tree method.

**Format**

A discrete Bayesian network to quantitatively assess the risk factors of excess vehicle emissions and their impact on air quality for China's typical megacities. Probabilities were given within the referenced paper (the model refers to Beijing in 2014). The vertices are:

- X1** Lack of supervision and policy guide (True, False);
- X2** Excess vehicles (True, False);
- X3** Severe traffic jam (True, False);
- X4** Aging of catalytic unit and combustor (True, False);
- X5** Vehicle desing defect (True, False);
- X6** Examination defect (True, False);
- X7** Non-strict supervision (True, False);
- X8** Oil refinery capability defect (True, False);
- X9** Market demand (True, False);
- X10** Excess heavy trucks (True, False);
- X11** Excess yellow label cars (True, False);
- M1** Consumption of unqualified oil (True, False);
- M2** Bad traffic situation (True, False);
- M3** Emission by vehicles with defects (True, False);
- M4** Severe emission of high pollution vehicles (True, False);
- M5** Production of inferior oil (True, False);
- M6** Excess high pollution vehicles using (True, False);
- ExcessVehicleEmission** (True, False);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Li, H., Huang, W., Qian, Y., & Klemes, J. J. (2023). Air pollution risk assessment related to fossil fuel-driven vehicles in megacities in China by employing the Bayesian network coupled with the Fault Tree method. *Journal of Cleaner Production*, 383, 135458.

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 metal

*metal Bayesian Network*


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### Description

Bayesian belief network modeling of accident occurrence in metal lathe machining operations.

### Format

A discrete Bayesian network to model the uncertainty surrounding the occurrence of a fly-out accident during metal lathe machining operations and its corresponding consequences. Probabilities were given within the referenced paper. The vertices are:

**CAF** Chuck association fault (Okay, Faulty);

**WHF** Workpiece holding failure (N-Fail, FLRE);

**TPF** Tool-post fault (Okay, Faulty);

**CF** Coolant fault (Okay, Faulty);

**OS** Operating speed (Proper, Improper);

**SGF** Safety guards fault (Okay, Faulty);

**IFR** Wrong feed rate (HR, HE);

**FlyOutAccident** (Fatal, Major, Minor).

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Akinyemi, O. O., Adeyemi, H. O., Olatunde, O. B., Folorunsho, O., & Musa, M. B. (2022). Bayesian belief network modeling of accident occurrence in metal lathe machining operations. *Mindanao Journal of Science and Technology*, 20(2).

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 moodstate

*moodstate Bayesian Network*


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### Description

Inference of mood state indices by using a multimodal high-level information fusion technique.



**Format**

A discrete Bayesian network to perform high-level information fusion. Probabilities were given within the referenced paper (one node is not included). The vertices are:

**Anxiety** (0-2, 3-5);

**DepressiveState** (TRUE, FALSE);

**EEG** (>0, <0);

**Energy** (0-2, 3-5);

**Irritability** (0-3, 4-5);

**MoodState** (+3, +2, +1, 0, -1, -2, -3);

**Sleep** (<6 Hours, >6 Hours);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Tai, C. H., Chung, K. H., Teng, Y. W., Shu, F. M., & Chang, Y. S. (2021). Inference of mood state indices by using a multimodal high-level information fusion technique. *IEEE Access*, 9, 61256-61268.

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 mountaingoat

*mountaingoat Bayesian Network*


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**Description**

Using Bayesian networks to map winter habitat for mountain goats in coastal British Columbia, Canada.

**Format**

A discrete Bayesian network to predict the suitability of habitats for mountain goats. Probabilities were given within the referenced paper. The vertices are:

**Distance\_Escape\_Terrain** (On Escape Terrain, <=150m away, <=300m away, >300m away);

**Elevation** (<=500m, <=900m, <=1300m, <=1700m, >1700m);

**Forest\_Age\_Class** (Early, Mid, Mature, Old, Non-Forested);

**Location** (Observations, Random));

**Slope** (Shallow, Moderate, Steep);

**Snow\_Zone** (Shallow, Moderate, Deep, Very Deep);

**Solar\_Insolation** (Very Low, Low, Moderate, High, Very High));

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Wilson, S. F., Nietvelt, C., Taylor, S., & Guertin, D. A. (2022). Using Bayesian networks to map winter habitat for mountain goats in coastal British Columbia, Canada. *Frontiers in Environmental Science*, 10, 958596.

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nanomaterials1

*nanomaterial Bayesian Networks*

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**Description**

Probabilistic model for assessing occupational risk during the handling of nanomaterials.

**Format**

A discrete Bayesian network for the assessment of the occupational risk associated with the handling of nanomaterials in research laboratories (before expert opinion). Probabilities were given within the referenced paper. The vertices are:

**Risk** (High, Medium, Low);

**Hazard** (High, Medium, Low);

**ClassificationGHS** (1, 2, 3, 4, 5);

**VariablesPhysicoChemical** (High, Medium, Low);

**RiskControl** (High, Medium, Low);

**Exposure** (High, Medium, Low);

**PersonalProtectiveEquipment** (High, Medium, Low);

**AdministrativeMeasures** (High, Medium, Low);

**ProtectionByUsingCollectiveProtectiveEquipment** (Full containment/isolation, Enclosed ventilation, Local ventilation, General mechanical ventilation);

**BodyProtection** (No use, Cotton lab coats, Synthetic material lab coats, Chemical protection coveralls);

**HandProtection** (No use, Rubber gloves, Nitrile gloves - 1 pair, Nitrile gloves - 2 pairs);

**EyesProtection** (No use, Safety glasses, Safety goggles, Face shields);

**RespiratoryProtection** (No use, Safety mask without selection criteria, Respiratory mask according to the respiratory protection program);

**FootProtection** (Open shoes, Work shoes, Safety shoes for chemical agents);

**OccupationalEnvironmentRiskProgram** (No, Yes, Yes - consider NMs);

**MedicalSurveillance** (No, Yes, Yes - consider NMs);

**RespiratoryProtectionProgram** (No, Yes, Yes - consider NMs);

**PeriodicMaintenanceOfCPE** (No, Yes - less than 12 months, Yes - more than 12 months);  
**StandardOperatingProcedureOfTask** (No, Yes);  
**RiskTrainingInvolvingNMs** (No, Yes);  
**Frequency** (Daily, Weekly, Monthly, Semiannual, Yearly);  
**DustFormation** (With, Without);  
**AerosolFormation** (With, Without);  
**Amount** (<10mg, 10-100mg, >100mg);  
**Duration** (<30min, 30-240min, >240min);  
**SurfaceArea** (< 10 m<sup>2</sup>, 10-49 m<sup>2</sup>, >50 m<sup>2</sup>);  
**Agglomeration** (With, Without);  
**Morphology** (Spherical, Plates, Rods);  
**CrystallineStructure** (With, Without);  
**SolubilityInWater** (Dissolution pH 5 to 9, Insoluble);  
**SizeOfAtLeastOneDimension** (Less than 100, More than 100);  
**SuspensionStability** (Less than 30, More than 30);  
**SurfaceChargeInSolution** (Charged, Neutral);  
**SurfaceModificationWithHydrophilicGroups** (Without, With);  
**AcuteToxicityDermalExposure** (Less than 50, 50-200, 200-1000, 1000-2000, 2000-5000, No effect);  
**ChronicToxicityExposureByDustInhalation** (Less than 0.02, 0.02-0.2, No effect);  
**AcuteToxicityExposureByGasInhalation** (Less than 100, 100-500, 500-2500, 2500-20000, No effect);  
**ChronicToxicityByTheExposureRouteInhalationGas** (Less than 50, 50-200, No effect);  
**PotentiallyCarcinogenic** (Confirmed for humans, Possibly toxic to humans, No effect);  
**AcuteToxicityExposureByDustInhalation** (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);  
**ChronicToxicityByTheExposureRouteInhalationDust** (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);  
**RespiratorySensitization** (There is evidence for humans, There are positive tests for animal testing, No effect);  
**ChronicToxicityInTheAquaticEnvironment** (Less than 0.01, 0.01-0.1, 0.1-1, No effect);  
**SkinIrritation** (Skin corrosion, Skin irritation, ILskin irritation, No effect);  
**ChronicToxicityDermalExposure** (Less than 20, 20-200, No effect);  
**EyeIrritation** (No effect, Reversible irritation, Irreversible damage);  
**AcuteToxicityInTheAquaticEnvironment** (Less than 1, 1-10, 10-100, No effect);  
**AcuteToxicityByTheExposureRouteOral** (Less than 5, 5-50, 50-300, 300-2000, 2000-5000, No effect);  
**ChronicToxicityExposureOral** (Less than 10, 10-100, No effect);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Schmidt, J. R. A., Nogueira, D. J., Nassar, S. M., Vaz, V. P., da Silva, M. L. N., Vicentini, D. S., & Matias, W. G. (2020). Probabilistic model for assessing occupational risk during the handling of nanomaterials. *Nanotoxicology*, 14(9), 1258-1270.

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nanomaterials2

*nanomaterial Bayesian Networks*

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**Description**

Probabilistic model for assessing occupational risk during the handling of nanomaterials.

**Format**

A discrete Bayesian network for the assessment of the occupational risk associated with the handling of nanomaterials in research laboratories (after expert opinion). Probabilities were given within the referenced paper. The vertices are:

**Risk** (High, Medium, Low);

**Hazard** (High, Medium, Low);

**ClassificationGHS** (1, 2, 3, 4, 5);

**VariablesPhysicoChemical** (High, Medium, Low);

**RiskControl** (High, Medium, Low);

**Exposure** (High, Medium, Low);

**PersonalProtectiveEquipment** (High, Medium, Low);

**AdministrativeMeasures** (High, Medium, Low);

**ProtectionByUsingCollectiveProtectiveEquipment** (Full containment/isolation, Enclosed ventilation, Local ventilation, General mechanical ventilation);

**BodyProtection** (No use, Cotton lab coats, Synthetic material lab coats, Chemical protection coveralls);

**HandProtection** (No use, Rubber gloves, Nitrile gloves - 1 pair, Nitrile gloves - 2 pairs);

**EyesProtection** (No use, Safety glasses, Safety goggles, Face shields);

**RespiratoryProtection** (No use, Safety mask without selection criteria, Respiratory mask according to the respiratory protection program);

**FootProtection** (Open shoes, Work shoes, Safety shoes for chemical agents);

**OccupationalEnvironmentRiskProgram** (No, Yes, Yes - consider NMs);

**MedicalSurveillance** (No, Yes, Yes - consider NMs);

**RespiratoryProtectionProgram** (No, Yes, Yes - consider NMs);

**PeriodicMaintenanceOfCPE** (No, Yes - less than 12 months, Yes - more than 12 months);  
**StandardOperatingProcedureOfTask** (No, Yes);  
**RiskTrainingInvolvingNMs** (No, Yes);  
**Frequency** (Daily, Weekly, Monthly, Semiannual, Yearly);  
**DustFormation** (With, Without);  
**AerosolFormation** (With, Without);  
**Amount** (<10mg, 10-100mg, >100mg);  
**Duration** (<30min, 30-240min, >240min);  
**SurfaceArea** (< 10 m<sup>2</sup>g, 10-49 m<sup>2</sup>g, >50 m<sup>2</sup>g);  
**Agglomeration** (With, Without);  
**Morphology** (Spherical, Plates, Rods);  
**CrystallineStructure** (With, Without);  
**SolubilityInWater** (Dissolution pH 5 to 9, Insoluble);  
**SizeOfAtLeastOneDimension** (Less than 100, More than 100);  
**SuspensionStability** (Less than 30, More than 30);  
**SurfaceChargeInSolution** (Charged, Neutral);  
**SurfaceModificationWithHydrophilicGroups** (Without, With);  
**AcuteToxicityDermalExposure** (Less than 50, 50-200, 200-1000, 1000-2000, 2000-5000, No effect);  
**ChronicToxicityExposureByDustInhalation** (Less than 0.02, 0.02-0.2, No effect);  
**AcuteToxicityExposureByGasInhalation** (Less than 100, 100-500, 500-2500, 2500-20000, No effect);  
**ChronicToxicityByTheExposureRouteInhalationGas** (Less than 50, 50-200, No effect);  
**PotentiallyCarcinogenic** (Confirmed for humans, Possibly toxic to humans, No effect);  
**AcuteToxicityExposureByDustInhalation** (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);  
**ChronicToxicityByTheExposureRouteInhalationDust** (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);  
**RespiratorySensitization** (There is evidence for humans, There are positive tests for animal testing, No effect);  
**ChronicToxicityInTheAquaticEnvironment** (Less than 0.01, 0.01-0.1, 0.1-1, No effect);  
**SkinIrritation** (Skin corrosion, Skin irritation, ILskin irritation, No effect);  
**ChronicToxicityDermalExposure** (Less than 20, 20-200, No effect);  
**EyeIrritation** (No effect, Reversible irritation, Irreversible damage);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Schmidt, J. R. A., Nogueira, D. J., Nassar, S. M., Vaz, V. P., da Silva, M. L. N., Vicentini, D. S., & Matias, W. G. (2020). Probabilistic model for assessing occupational risk during the handling of nanomaterials. *Nanotoxicology*, 14(9), 1258-1270.

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 navigation

*navigation Bayesian Network*


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**Description**

Safety analysis of RNP approach procedure using fusion of FRAM model and Bayesian belief network.

**Format**

A discrete Bayesian network to demonstrate the existing variability in functions that are part of the complex navigation system. Probabilities were given within the referenced paper. The vertices are:

**ToAcquireGPSSignal** (Accurate, Acceptable, Inaccurate);

**ToCheckAircraftPositionExecutingRNPPProcedure** (Accurate, Acceptable, Inaccurate);

**ToKeepAircraftOnProgrammedRoute** (Accurate, Acceptable, Inaccurate);

**ToShowAircraftPositionBasedOnGPSSignal** (Accurate, Acceptable, Inaccurate);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Oliveira, D., Moraes, A., Junior, M. C., & Marini-Pereira, L. (2023). Safety analysis of RNP approach procedure using fusion of FRAM model and Bayesian belief network. *The Journal of Navigation*, 76(2-3), 286-315.

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 nuclearwaste

*nuclearwaste Bayesian Network*


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**Description**

Comprehensiveness of scenarios in the safety assessment of nuclear waste repositories.

**Format**

A discrete Bayesian network to obtain bounds on the probability that the reference safety threshold is violated. Probabilities were given within the referenced paper. The vertices are:

**BarrierDegradation** (Fast, Slow);

**ChemicalDegradation** (Fast, Slow);

**CrackAperture** (Micro, Macro);

**DiffusionCoefficient** (Low, High);

**DistributionCoefficient** (Low, High);  
**Earthquake** (BDBE, Major);  
**HydraulicConductivity** (Low, Medium, High);  
**MonolithDegradation** (Very Fast, Fast, Slow);  
**WaterFlux** (Low, High);  
**DoseRate** (Violated, Not Violated);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Tosoni, E., Salo, A., Govaerts, J., & Zio, E. (2019). Comprehensiveness of scenarios in the safety assessment of nuclear waste repositories. *Reliability Engineering & System Safety*, 188, 561-573.

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nuisancegrowth

*nuisancegrowth Bayesian Network*

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### Description

Drivers of perceived nuisance growth by aquatic plants.

### Format

A discrete Bayesian network approach to integrate the perception of nuisance with the consequences of plant removal. Probabilities were given within the referenced paper (missing entries were given uniform probabilities). The vertices are:

**Activity** (Swimming, Boating, Angling, Biodiversity, Aesthetics, Bird-watching);  
**BenthicFishForaging** (Low, Moderate, High);  
**Disturbance** (Low, Moderate, High);  
**Ecosystem** (Standing floating, Standing submerged, Flowing submerged);  
**EpiphyticInvertebrates** (Low, Medium, High);  
**Flow** (Low, Medium, High);  
**Light** (Low, High);  
**MacrophyteGrowth** (Very low, Low, Medium, High, Very high);  
**MacrophyteRemoval** (None, Partial Full);  
**MacrophyteSpecies** (*Elodea nuttallii*, *Pontederia crassipes*, *Ludwigia*, *Juncus bulbosus*, *Sagittaria sagittifolia*);  
**NutrientLoading** (Low, Moderate, High);  
**Perception** (Nuisance, No nuisance);

**Phytoplankton** (Low, Moderate, High);  
**PiscivorousFish** (Absent, Present);  
**PiscivorousFishPredation** (Low, High);  
**PlanktivorousFish** (Low, High);  
**Resources** (Low, Moderate, High);  
**RespondentType** (Resident, Visitor);  
**Zooplankton** (Low, Moderate, High);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Thiemer, K., Immerzeel, B., Schneider, S., Sebola, K., Coetzee, J., Baldo, M., ... & Vermaat, J. E. (2023). Drivers of perceived nuisance growth by aquatic plants. *Environmental Management*, 71(5), 1024-1036.

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oildepot

*oildepot Bayesian Network*

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### Description

Dynamic risk analysis of oil depot storage tank failure using a fuzzy Bayesian network model.

### Format

A discrete Bayesian network for failure risk analysis of oil storage tank leakage. Probabilities were given within the referenced paper. The vertices are:

**X1** (True, False);  
**X2** (True, False);  
**X3** (True, False);  
**X4** (True, False);  
**X5** (True, False);  
**X6** (True, False);  
**X7** (True, False);  
**X8** (True, False);  
**X9** (True, False);  
**X10** (True, False);  
**X11** (True, False);  
**X12** (True, False);



**X13** (True, False);  
**X14** (True, False);  
**X15** (True, False);  
**X16** (True, False);  
**X17** (True, False);  
**X18** (True, False);  
**X19** (True, False);  
**X20** (True, False);  
**X21** (True, False);  
**X22** (True, False);  
**X23** (True, False);  
**X24** (True, False);  
**X25** (True, False);  
**M1** Internal corrosion (True, False);  
**M2** External corrosion (True, False);  
**M3** Liquid level exceeded safe level (True, False);  
**M4** Equipment failure (True, False);  
**M5** Personnel issue (True, False);  
**M6** Not found in time (True, False);  
**M7** Corrosion (True, False);  
**M8** Overfill (True, False);  
**M9** Environment (True, False);  
**M10** Design defect (True, False);  
**M11** Equipment ageing (True, False);  
**M12** Tank hazard (True, False);  
**M13** Lax supervision (True, False);  
**M14** Rules and regulation (True, False);  
**M15** Inadequate management (True, False);  
**TankLeakage** (True, False);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Zhou, Q. Y., Li, B., Lu, Y., Chen, J., Shu, C. M., & Bi, M. S. (2023). Dynamic risk analysis of oil depot storage tank failure using a fuzzy Bayesian network model. *Process Safety and Environmental Protection*, 173, 800-811.

**Description**

Online risk modeling of autonomous marine systems: Case study of autonomous operations under sea ice.

**Format**

A discrete Bayesian network to develop online risk models for an autonomous marine system. Probabilities were given in an associated GitHub repository. The vertices are:

**Acoustic\_Link\_Quality** (Acceptable, Unacceptable);  
**Acoustic\_Link\_Quality\_buoy** (Acceptable, Unacceptable);  
**Altitude\_of\_AUV** (High, Medium, Low);  
**Control\_algorith\_is\_flawed** (Acceptable, Unacceptable);  
**Copy\_2\_of\_Control\_algorith\_is\_flawed** (Acceptable, Unacceptable);  
**Copy\_2\_SoftwareFailure** (Yes, No);  
**Copy\_of\_Air\_temperature** (Yes, No);  
**Copy\_of\_Control\_algorith\_is\_flawed** (Acceptable, Unacceptable);  
**Copy\_of\_Environmental\_constraint** (High, Medium, Low);  
**Copy\_of\_Flawed\_algorithm** (Acceptable, Unacceptable);  
**Copy\_of\_Operator\_effectiveness** (High, Medium, Low);  
**Copy\_of\_Research\_vessel\_effectiveness** (High, Medium, Low);  
**Copy\_of\_RIF2Waypoint** (Yes, No);  
**Copy\_of\_Salvage** (Yes, No);  
**Copy\_of\_SoftwareFailure** (Yes, No);  
**Copy\_of\_Strong\_wind** (Yes, No);  
**Copy\_of\_Training\_level** (High, Medium, Low);  
**Copy\_of\_Weather\_condition** (Good, Poor);  
**Copy\_RIF5** (Yes, No);  
**Current\_speed** (High, Medium, Low);  
**Depth\_of\_AUV** (High, Medium, Low);  
**Difficulty\_of\_AUV\_salvage** (High, Medium, Low);  
**Difficulty\_of\_salvage\_operation** (High, Medium, Low);  
**Difficulty\_to\_pinpoint\_the\_vehicle** (High, Medium, Low);  
**Dist\_to\_home** (High, Medium, Low);  
**Environmental\_complexity** (High, Medium, Low);

**Failure\_of\_ADCP\_DVL** (Acceptable, Unacceptable);  
**Failure\_of\_CTD\_sensor** (Acceptable, Unacceptable);  
**Failure\_of\_IMU\_module** (Acceptable, Unacceptable);  
**Failure\_of\_temperature\_sensor** (Acceptable, Unacceptable);  
**Fins** (Reliable, Failure);  
**Flawed\_algorithm\_of\_waypoint\_generation** (Acceptable, Unacceptable);  
**GNSS\_accuracy** (Acceptable, Unacceptable);  
**H1** (Yes, No);  
**H2** (Yes, No);  
**H5** (Yes, No);  
**H6** (Yes, No);  
**H7** (Yes, No);  
**Ice\_concentration** (High, Medium, Low);  
**Ice\_Environment** (Good, Poor);  
**Ice\_Ruggnes** (High, Medium, Low);  
**Ice\_thickness** (High, Medium, Low);  
**Improper\_handling\_of\_navigation\_errors** (Yes, No);  
**InaccurateWaypoint** (Yes, No);  
**Loss\_of\_AUV** (Loss, Damage, No);  
**Loss\_of\_mission** (Yes, No);  
**Multipath\_From\_Ice** (Good, Medium, Poor);  
**Position\_Measurement\_Quality** (Yes, No);  
**Power\_capacity** (High, Medium, Low);  
**Power\_system** (Yes, No);  
**Propulsion\_system\_fails\_to\_provide\_necessary\_motion** (Yes, No);  
**Range\_to\_buoy** (Long, Medium, Close);  
**Reliability\_GPS\_Module** (Reliable, Failure);  
**Reliability\_of\_acoustic\_module\_in\_AUV** (Reliable, Failure);  
**Reliability\_of\_the\_propulsion\_system** (Reliable, Failure);  
**ReliabilityAcousticNavigation** (Reliable, Failure);  
**RIF\_Range\_Quality** (Yes, No);  
**RIF2Propulsion** (Yes, No);  
**RIF2Waypoint** (Yes, No);  
**RIF3** (Yes, No);  
**RIF3Collision** (Yes, No);  
**RIF3Inaccurate** (Yes, No);  
**RIF4** (Yes, No);

**RIF5** (Yes, No);  
**RSSI\_commu** (Acceptable, Unacceptable);  
**RSSI\_ranging** (Acceptable, Unacceptable);  
**SIL\_commu** (Acceptable, Unacceptable);  
**SIL\_ranging** (Acceptable, Unacceptable);  
**SoftwareFailure** (Yes, No);  
**Speed\_of\_AUV** (High, Medium, Low);  
**Steering\_system\_fails\_to\_provide\_necessary\_motion** (Yes, No);  
**Time\_left\_to\_salvage\_the\_vehicle\_if\_it\_losts** (Plenty, Enough, Not Enough);  
**Tool\_effectiveness** (High, Medium, Low);  
**UCA17\_N\_1** (Yes, No);  
**UCA17\_P\_1** (Yes, No);  
**UCA18\_N\_1** (Yes, No);  
**UCA18\_P\_1** (Yes, No);  
**UCA5\_P\_1** (Yes, No);  
**UCA6\_N\_1** (Yes, No);  
**UCA6\_N\_2** (Yes, No);  
**UCA6\_N\_3** (Yes, No);  
**Vessel\_constraint** (High, Medium, Low);  
**Visibility** (High, Medium, Low);  
**Water\_Environment** (Good, Poor);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Yang, R., Bremnes, J. E., & Utne, I. B. (2023). Online risk modeling of autonomous marine systems: case study of autonomous operations under sea ice. *Ocean Engineering*, 281, 114765.

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orbital

*orbital Bayesian Network*

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### Description

Approaching intention prediction of orbital maneuver based on dynamic Bayesian network.

**Format**

A (dynamic) discrete Bayesian network to help operators recognize the approaching intention quickly and systemically. Probabilities were given within the referenced paper. Ten time slices of the dynamic network are constructed. The vertices in the first time slice are:

**ApproachingIntentionT1** (Hover, Attach, Capture, Approach);

**LocationT1** (Within the threat range, Outside the threat range);

**ManeuverT1** (Maneuver, Non-maneuver);

**RelativeVelocityT1** (Fast, Slow);

**HeadingT1** (0-110 degrees, 110 degrees);

**RelativeDistanceT1** (Far, Near);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Shibo, C. H. E. N., Jun, L. I., Yaen, X. I. E., Xiande, W. U., Shuhang, L. E. N. G., & Ruochu, Y. A. N. G. (2023). Approaching Intention Prediction of Orbital Maneuver Based on Dynamic Bayesian Network. *Transactions of Nanjing University of Aeronautics & Astronautics*, 40(4).

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oxygen

*oxygen Bayesian Network*


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**Description**

Providing an approach to analyze the risk of central oxygen tanks in hospitals during the COVID-19 pandemic.

**Format**

A discrete Bayesian network to calculate failure rates of oxygen tanks in hospitals during the COVID-19 pandemic. Probabilities were given within the referenced paper. The vertices are:

**CorrosionCausedByTheEnvironment** (True, False);

**CorrosiveEnvironment** (True, False);

**DefectInTheTankDryer** (True, False);

**DefectInTheTankPressureGauge** (True, False);

**DefectInTheTankReliabilityGauge** (True, False);

**DefectsInConnectingTankFastenersF1** (True, False);

**DefectsInConnectingTankFastenersF2** (True, False);

**DefectsInConnectionsAndGauges** (True, False);

**DefectsInInletAndOutletValvesV1** (True, False);

**DefectsInInletAndOutletValvesV2** (True, False);  
**DefectsInTankEquipmentRepairs** (True, False);  
**DefectsInTheExternalCoatingSystemOfTheTank** (True, False);  
**DefectsInTheInspectionAndTestingProgramOfTankDevices** (True, False);  
**DefectsInTheTankCoating** (True, False);  
**ExternalCorrosionOfTheTank** (True, False);  
**FailureInProtectiveMeasures** (True, False);  
**FailureInRepairsAndMaintenance** (True, False);  
**FailureOfConnectionsAndFasteners** (True, False);  
**FailureOfGauges** (True, False);  
**FailureToUseStandardAndUpdatedInstructions** (True, False);  
**HumanError** (True, False);  
**InadequacyOfPeopleSkills** (True, False);  
**InternalCorrosionOfTheTank** (True, False);  
**OperationalError** (True, False);  
**OrganizationalWeakness** (True, False);  
**OxygenLeakage** (True, False);  
**TankCorrosion** (True, False);  
**ValveLeakage** (True, False);  
**WeakEducationSystem** (True, False);  
**WeaknessInPurchasingTankEquipment** (True, False);  
**WeaknessInTheInstallationOfTankEquipment** (True, False);

### **Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### **References**

Laal, F., Hanifi, S. M., Madvari, R. F., Khoshakhlagh, A. H., & Arefi, M. F. (2023). Providing an approach to analyze the risk of central oxygen tanks in hospitals during the COVID-19 pandemic. *Heliyon*, 9(8).

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parkinson

*parkinson Bayesian Network*

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**Description**

AI reveals insights into link between CD33 and cognitive impairment in Alzheimer's disease.

**Format**

A Gaussian Bayesian network to simulate a down-expression of the putative drug target CD33, including potential impact on cognitive impairment and brain pathophysiology. Probabilities were given within the referenced paper. The vertices are:

**Cluster\_1**

**Cluster\_2**

**Cluster\_3**

**Cluster\_4**

**Cluster\_6**

**Cluster\_7**

**Cluster\_8**

**Cluster\_9**

**Cluster\_11**

**Cluster\_14**

**Cluster\_15**

**Cluster\_16**

**Cluster\_17**

**Cluster\_18**

**Cluster\_19**

**Cluster\_20**

**Cluster\_21**

**Cluster\_25**

**Cluster\_26**

**Cluster\_27**

**cognition**

**PatDemo\_educ**

**PatDemo\_sex**

**PatDemo\_apoe**

**PatDemo\_age**

**PatDemo\_brainregion**

**REL**  
**PPARG**  
**TRAF1**  
**GRIN1**  
**CASP7**  
**NAV3**  
**DLG4**  
**CD33**

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Raschka, T., Sood, M., Schultz, B., Altay, A., Ebeling, C., & Frohlich, H. (2023). AI reveals insights into link between CD33 and cognitive impairment in Alzheimer's Disease. *PLOS Computational Biology*, 19(2), e1009894.

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perioperative	<i>perioperative Bayesian Network</i>
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### Description

Development of a perioperative medication suspension decision algorithm based on Bayesian networks.

### Format

A discrete Bayesian network for the estimation of the drug suspension period even in the presence of competing risks. The probabilities were available from a repository. The vertices are:

**DrugSuspension** (0 days, 5 days, 7 days);

**ThromboticRisk** (High, Medium, Low);

**BleedingRisk** (High, Null);

**PlateletCount** (High, Medium, Low);

**AbnormalAPTT** (High, Medium, Low);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.



## References

Kawaguchi, S., Fukuda, O., Kimura, S., Yeoh, W. L., Yamaguchi, N., & Okumura, H. (2024, January). Development of a Perioperative Medication Suspension Decision Algorithm Based on Bayesian Networks. In 2024 IEEE/SICE International Symposium on System Integration (SII) (pp. 7-12). IEEE.

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permaBN

*permaBN Bayesian Network*

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## Description

PermaBN: A Bayesian Network framework to help predict permafrost thaw in the Arctic.

## Format

A discrete Bayesian network to simulate permafrost thaw in the continuous permafrost region of the Arctic. The probabilities were given within the referenced paper. The vertices are:

**ActiveLayerIceContent** (Low, Medium, High);

**AirTemperature** (Low, Medium, High);

**Aspect** (North, East, South, West);

**Insulation** (Low, Medium, High);

**Rain** (Low, Medium, High);

**Season** (Snow free, Snow);

**Snow** (Low, Medium, High);

**SnowDepth** (None, Low, Medium, High);

**SoilDensity** (Low, Medium, High);

**SoilMoisture** (Low, Medium, High);

**SoilTemperature** (Low, Medium, High);

**SoilWaterInput** (Low, Medium, High);

**ThawDepth** (Low, Medium, High);

**VegetationHeight** (Low, Medium, High);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Beall, K., Loisel, J., & Medina-Cetina, Z. (2022). PermaBN: A Bayesian Network framework to help predict permafrost thaw in the Arctic. *Ecological Informatics*, 69, 101601.

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phdarticles

*phdarticles Bayesian Network*

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### Description

The R package stagedtrees for structural learning of stratified staged trees.

### Format

A discrete Bayesian network modeling factors affecting the number of publications of PhD students. The Bayesian network is learned as in the referenced paper. The vertices are:

**Articles** Number of articles during the last three years of PhD (0, 1-2, >2);

**Gender** (male, female);

**Kids** If the student has at least one kid 5 or younger (yes, no);

**Married** (yes, no));

**Mentor** Number of publications of the student's mentor (low, medium, high);

**Prestige** Prestige of the university (high, low);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Carli, F., Leonelli, M., Riccomagno, E., & Varando, G. (2022). The R Package stagedtrees for Structural Learning of Stratified Staged Trees. *Journal of Statistical Software*, 102, 1-30.

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pilot

*pilot Bayesian Network*

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### Description

Dynamic analysis of pilot transfer accidents.

### Format

A discrete Bayesian network to classify ADHD symptom. Probabilities were given within the referenced paper. The vertices are:

**AdverseSeaSwell** (Yes, No);

**AdverseWind** (Yes, No);

**CommercialPressure** (Yes, No);

**ExcessiveEnvironmentFactors** (Yes, No);

**ExcessiveMotionVessel** (Yes, No);  
**ExcessiveShipSpeed** (Yes, No);  
**FailureHandholds** (Yes, No);  
**HeavyRain** (Yes, No);  
**HumanFailures** (Yes, No);  
**ImproperShipHandling** (Yes, No);  
**InappropriateAngle** (Yes, No);  
**IncorrectHeigth** (Yes, No);  
**IncorrectRigging** (Yes, No);  
**IndividualFailure** (Yes, No);  
**LackOfSafetyCulture** (Yes, No);  
**LackOfSupervision** (Yes, No);  
**ManeuveringFailures** (Yes, No);  
**NonCertifiedPilotLadder** (Yes, No);  
**NonComplyTrapdoor** (Yes, No);  
**OperationalFailures** (Yes, No);  
**OrganizationalFailure** (Yes, No);  
**PilotLadder** (Yes, No);  
**PilotTransferAccident** (Yes, No);  
**PoorCombinationLadder** (Yes, No);  
**PoorCommunicationWithPilotBoat** (Yes, No);  
**PoorConditionPTA** (Yes, No);  
**PoorIllumination** (Yes, No);  
**PoorISMSystem** (Yes, No);  
**PoorPilotLadder** (Yes, No);  
**PTAEquipmentFailure** (Yes, No);  
**PTAFailure** (Yes, No);  
**PTAPreparedWindward** (Yes, No);  
**RestrictedVisibility** (Yes, No);  
**RetrievalLine** (Yes, No);  
**RiggingFailure** (Yes, No);  
**SecuringFailure** (Yes, No);  
**SecuringFailurePilot** (Yes, No);  
**SecuringFailurePTA** (Yes, No);  
**ShipSideObstructed** (Yes, No);  
**StructuralFailure** (Yes, No);  
**SubstandardActs** (Yes, No);  
**SubstandardConditions** (Yes, No);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Sakar, C., & Sokukcu, M. (2023). Dynamic analysis of pilot transfer accidents. *Ocean Engineering*, 287, 115823.

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pneumonia

*pneumonia Bayesian Network*

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**Description**

Predicting the causative pathogen among children with pneumonia using a causal Bayesian network.

**Format**

A discrete Bayesian network to predict causative pathogens for childhood pneumonia. Probabilities were given within the referenced paper. The vertices are:

**Age Group** Age group of study participant. In the model, we define each group as follow: Infant ( $\leq 2$ yo), PreSchool (2-5yo), School (5-18yo);

**Ethnicity** Australian Indigenous status of participant, including Aboriginal, Pacific Islander, and Maori (Indigenous, NonIndigenous);

**SmokerInHousehold** (Yes, No);

**Prematurity** Born  $<37$  weeks gestation (Yes, No);

**ChildcareDays** Childcare or school attendance, day/s per week (Five or more, Two to four, One or less);

**ImpairedImmunity** Primary immunodeficiencies, immunocompromising, or use of immunosuppressive drug (Reported, Unknown);

**ChronicRespiratoryDisease** (Reported, Unknown);

**PreviousSignificantInfection** Previous episode of confirmed significant infection e.g. bacteraemia, meningitis, osteomyelitis, urinary infection, and etc (Reported, Unknown);

**InfluenzaSeason** Participant was enrolled (present to hospital) during the influenza season in Australia, which is defined as June to September (No, Yes);

**PneumococcalVaccine** The number of pneumococcal vaccine received, according to Australian Childhood Immunisation Register (ACIR); a child is defined as fully vaccinated if three or more doses were recorded, and under vaccinated if less than three doses (UnderVax, Fully-Vax);

**InfluenzaVaccine** Influenza vaccine received within one year prior to this presentation/ enrolment, according to ACIR (No, Yes);

**LevelOfExposure** This refers to the child's exposure to pathogens with more transient and transmissible characteristics (High, Low);

- SusceptibilityToColonisation** This summarises the level of a child's susceptibility to nasopharyngeal colonisation by typical bacterial pathogens that can be responsible for the presenting case of pneumonia (High, Low);
- SusceptibilityToProgression** This describes the extent of the child to progress to more severe manifestation of pneumonia if infected (High, Low);
- RSVInNasopharynx** Any detection of RSV from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- HMPVInNasopharynx** Any detection of HMPV from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- InfluenzaInNasopharynx** Any detection of influenza from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- ParainfluenzaInNasopharynx** Any detection of parainfluenza from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- MycoplasmaInNasopharynx** Any detection of mycoplasma from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- TypicalBacteriaInNasopharynx** Any detection of typical bacteria is present in nasopharynx via either the prospective study or routine clinical investigation (Yes, No);
- ViralNasopharyngealInfection** Replication of viral-like pathogens is occurring in the nasopharyngeal tissues (Present, Absent);
- ThroatInfection** Replication of viral-like pathogens is occurring in the laryngeal tissues (Present, Absent);
- ViralLikePneumonia** Replication of viral-like pathogens is occurring in the terminal air spaces of the respiratory tract (Present, Absent);
- TypicalBacterialPneumonia** Typical bacteria is invading the terminal air spaces of the respiratory tract (Present, Absent);
- CausativePathogenForPneumonia** The cause of presenting pneumonia (TypicalBac, ViralLike, NoPneumonia);
- UpperAirwayInvolvement** Involvement of other site/s of respiratory tract concurrent with the presenting pneumonia episode (NP, Throat, NPAndThroat, No);
- SubjectGroup** X-ray confirmed pneumonia (Case, Control);
- DiagnosisBacterialPneumonia** In this study, bacterial pneumonia is clinically diagnosed based on clinical diagnosis of pleural effusion or positive blood culture result (Yes, No);
- Cough** (Recorded, Unknown);
- Headache** (Recorded, Unknown);
- Rhinorrhoea** (Recorded, Unknown);
- SoreThroat** (Recorded, Unknown);
- Earache** (Recorded, Unknown);
- Fever** (Recorded, Unknown);
- Irritability** (Recorded, Unknown);
- OtherPain** (Recorded, Unknown);
- HighestTemperature** (Above 39, Between 38 and 39, Below 38);

- ChillSweat** (Recorded, Unknown);
- Vomiting** (Recorded, Unknown);
- Diarrhoea** (Recorded, Unknown);
- ReducedOralIntake** (Recorded, Unknown);
- EnergyLoss** (Recorded, Unknown);
- Wheezing** (Recorded, Unknown);
- Crackles** (Recorded, Unknown);
- DurationOfSymptomsOnset** (More than one week, Three to seven days, One or two days);
- PleuralEffusion** The build-up of excess fluid between the layers of the pleura outside the lungs. The true status of pleural effusion can not be directly observed, therefore is latent. Clinical diagnosis of pleural effusion is used as a surrogate for the true status (thus classified as signs and is observable) (Yes, No);
- AbdominalPain** (Recorded, Unknown);
- ChestPain** (Recorded, Unknown);
- BreathingDifficulty** (Recorded, Unknown);
- RespiratoryRate** (Above 50, Between 30 and 50, Below 30);
- Rash** (Recorded, Unknown);
- CurrentPhenotype** This was introduced as a summary node of patient presentation phenotypes based on signs and symptoms relevant to pneumonia (Type1, Type2);
- BloodCultureResult** Detection of any (non-contaminant) bacteria from blood culture via routine clinical investigation (Positive, Negative, NotDone);
- PleuralFluidResult** Detection of any bacteria from pleural fluid via either PCR or culture (Positive, Negative, NotDone);
- CRActiveProtein** (Above 70, Between 30 and 70, Below 30);
- WhiteCellCount** (Above 18, Between 10 and 18, Below 10);
- NeutrophilProportion** (Above 80, Between 50 and 80, Below 50);
- OxygenSaturation** (Below 92, Between 92 and 95, Above 95);
- HospitalTransfer** Transferred from another hospital/facility (Yes, No);
- AntibioticExposure** Any antibiotic use in the 7 days or 24 hours prior to this presentation/admission (LastDay, LastWeek, No);
- BloodCulturePerformed** (Yes, No);
- O2Type** If the child has been put on supplementary oxygen when measuring oxygen saturation (SuppO2, RoomAir);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Wu, Y., Mascaro, S., Bhuiyan, M., Fathima, P., Mace, A. O., Nicol, M. P., ... & Blyth, C. C. (2023). Predicting the causative pathogen among children with pneumonia using a causal Bayesian network. *PLoS Computational Biology*, 19(3), e1010967.

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 polymorphic

*polymorphic Bayesian Network*


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**Description**

Reliability analysis of high-voltage drive motor systems in terms of the polymorphic Bayesian network.

**Format**

A discrete Bayesian network to depict the high-voltage drive motor system's miscellaneous fault states. Probabilities were given within the referenced paper. The vertices are:

**PresenceAbrasiveParticles** (Normal, Degradation, Failed);  
**ExcessiveSpeed** (Normal, Degradation, Failed);  
**PoorLubrication** (Normal, Degradation, Failed);  
**InappropriateClearance** (Normal, Degradation, Failed);  
**HighTemperatureGluing** (Normal, Degradation, Failed);  
**ScratchVibration** (Normal, Degradation, Failed);  
**Indentation** (Normal, Degradation, Failed);  
**ImproperLubrication** (Normal, Degradation, Failed);  
**ImproperAssembly** (Normal, Degradation, Failed);  
**Moisture** (Normal, Degradation, Failed);  
**ExcessiveInterShaftCurrent** (Normal, Degradation, Failed);  
**ChemicalCorrosion** (Normal, Degradation, Failed);  
**HighFrequencyPulse Voltage** (Normal, Degradation, Failed);  
**LocalizedHighTemperatures** (Normal, Degradation, Failed);  
**PoorCooling** (Normal, Degradation, Failed);  
**SeverePartialDischarges** (Normal, Degradation, Failed);  
**SurfaceCorrosion** (Normal, Degradation, Failed);  
**PlasticDeformation** (Normal, Degradation, Failed);  
**CorrosionFailure** (Normal, Degradation, Failed);  
**InsulationDeterioration** (Normal, Degradation, Failed);  
**WearFault** (Normal, Degradation, Failed);  
**SystemDegradation** (Normal, Degradation, Failed);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Zheng, W., Jiang, H., Li, S., & Ma, Q. (2023). Reliability Analysis of High-Voltage Drive Motor Systems in Terms of the Polymorphic Bayesian Network. *Mathematics*, 11(10), 2378.

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poultry

*poultry Bayesian Network*

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**Description**

Practical application of a Bayesian network approach to poultry epigenetics and stress.

**Format**

A discrete Bayesian network to provide further insights into the relationships among epigenetic features and a stressful condition in chickens. The Bayesian network is learned as in the referenced paper. The vertices are:

**ARHGAP26** (0,1);

**BOP1** (0,1);

**CANX** (0,1);

**CWC25** (0,1);

**DGKD** (0,1);

**DMR1** (0,1);

**DMR2** (0,1);

**DMR5** (0,1);

**DMR6** (0,1);

**DMR7** (0,1);

**DOCK5** (0,1);

**EEPD1** (0,1);

**EFR3B** (0,1);

**ENS10218** (0,1);

**ENS27231** (0,1);

**ENS46425** (0,1);

**ENS47746** (0,1);

**ENS50012** (0,1);

**ENS50641** (0,1);

**ENS51236** (0,1);

**ENS53725** (0,1);

**FBN1** (0,1);

**GNAO1** (0,1);

**GRP141** (0,1);

**LOC101750642** (0,1);

**LOC770074** (0,1);



**LRP5** (0,1);  
**MFSD4A** (0,1);  
**MIP** (0,1);  
**OCLN** (0,1);  
**PAPK2** (0,1);  
**PLXNA2** (0,1);  
**POP5** (0,1);  
**RP1\_2705\_3** (0,1);  
**SCHIP1** (0,1);  
**SELENOI** (0,1);  
**SHISA2** (0,1);  
**SKOR2** (0,1);  
**STAT3** (0,1);  
**Stress** (0,1);  
**TPST2** (0,1);  
**TRMT10A** (0,1);  
**TLL9** (0,1);  
**VGLL4** (0,1);  
**XRCC4** (0,1);  
**ZBTB48** (0,1);  
**ZDHHC18** (0,1);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Videla Rodriguez, E. A., Pertille, F., Guerrero-Bosagna, C., Mitchell, J. B., Jensen, P., & Smith, V. A. (2022). Practical application of a Bayesian network approach to poultry epigenetics and stress. *BMC Bioinformatics*, 23(1), 261.

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project

*project Bayesian Network*

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**Description**

A collective efficacy-based approach for bi-objective sustainable project portfolio selection using interdependency network model between projects.

**Format**

A discrete Bayesian network to analyze the criticality and possible impact of a project's failure on each other and on the entire portfolio. Probabilities were given within the referenced paper. The vertices are:

**P1** (F, T);

**P2** (F, T);

**P3** (F, T);

**P4** (F, T);

**P5** (F, T);

**P6** (F, T);

**P7** (F, T);

**P8** (F, T);

**P9** (F, T);

**P10** (F, T);

**P11** (F, T);

**P12** (F, T);

**P13** (F, T);

**P14** (F, T);

**P15** (F, T);

**P16** (F, T);

**P17** (F, T);

**P18** (F, T);

**P19** (F, T);

**P20** (F, T);

**P21** (F, T);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Ebnerasoul, M., Ghannadpour, S. F., & Haeri, A. (2023). A collective efficacy-based approach for bi-objective sustainable project portfolio selection using interdependency network model between projects. *Environment, Development and Sustainability*, 25(12), 13981-14001.

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projectmanagement

*projectmanagement Bayesian Network*

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## Description

Project Complexity and Risk Management (ProCRiM): Towards modelling project complexity driven risk paths in construction projects.

## Format

A discrete Bayesian network to identify critical risks and selecting optimal risk mitigation strategies at the commencement stage of a project. Probabilities were given within the referenced paper (uniform priors were given to root nodes). The vertices are:

- C1** Lack of experience with the involved team (YES, NO);
- C2** Use of innovative technology (YES, NO);
- C3** Lack of experience with technology (YES, NO);
- C4** Strict quality requirements (YES, NO);
- C5** Multiple contracts (YES, NO);
- C6** Multiple stakeholders and variety of perspectives (YES, NO);
- C7** Political instability (YES, NO);
- C8** Susceptibility to natural disasters (YES, NO);
- R1** Contactor's lack of experience (YES, NO);
- R2** Suppliers' default (YES, NO);
- R3** Delays in design and regulatory approvals (YES, NO);
- R4** Contract related problems (YES, NO);
- R5** Economic issues in country (YES, NO);
- R6** Major design changes (YES, NO);
- R7** Delays in obtaining raw material (YES, NO);
- R8** Non-availability of local resources (YES, NO);
- R9** Unexpected events (YES, NO);
- R10** Increase in raw material price (YES, NO);
- R11** Changes in project specifications (YES, NO);
- R12** Conflicts with project stakeholders (YES, NO);
- R13** Decrease in productivity (YES, NO);

- R14** Delays/interruptions (YES, NO);
- O1** Decrease in quality of work (YES, NO);
- O2** Low market share/reputational issues (YES, NO);
- O3** Time overruns (YES, NO);
- O4** Cost overruns (YES, NO);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Qazi, A., Quigley, J., Dickson, A., & Kirytopoulos, K. (2016). Project Complexity and Risk Management (ProCRiM): Towards modelling project complexity driven risk paths in construction projects. *International Journal of Project Management*, 34(7), 1183-1198.

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propellant	<i>propellant Bayesian Network</i>
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### Description

A Bayesian network-based safety assessment method for solid propellant granule-casting molding process.

### Format

A discrete Bayesian network to assess the safety of the solid propellant granule-casting molding process. Probabilities were given within the referenced paper. The vertices are:

- AbsorptionAnomaly** (True, False);
- CalenderingRepellentWaterTimesAnomaly** (True, False);
- CalenderingRepellingWaterTemperatureAnomaly** (True, False);
- CalenderingRollDistanceAnomaly** (True, False);
- CastingAnomaly** (True, False);
- CastingDifferentialPressureAnomaly** (True, False);
- CastingTimeAnomaly** (True, False);
- CatalystGrindingAnomaly** (True, False);
- CentrifugalRunningTimeAnomaly** (True, False);
- CirculatingWaterTemperatureAnomaly** (True, False);
- CirculationWaterTemperatureAnomaly** (True, False);
- CuringAnomaly** (True, False);
- CuringTemperatureAnomaly** (True, False);

**CuringTimeAnomaly** (True, False);  
**CuttingAnomaly** (True, False);  
**DryingOfMedicineGranulesAnomaly** (True, False);  
**DryingRepellentWaterAnomaly** (True, False);  
**DryingRepellingWaterTemperatureAnomaly** (True, False);  
**DryingRepellingWaterTimeAnomaly** (True, False);  
**DryingSolventRemovingAnomaly** (True, False);  
**DryingTemperatureAnomaly** (True, False);  
**DryingTimeAnomaly** (True, False);  
**ExtrusionAnomaly** (True, False);  
**ExtrusionStrengthAnomaly** (True, False);  
**FloodingTimeAnomaly** (True, False);  
**FrequencyOfWaterChangeAnomaly** (True, False);  
**GranuleCastingMoldingAnomaly** (True, False);  
**GrindingTimeAnomaly** (True, False);  
**HoldingPressureAnomaly** (True, False);  
**HoldingTimeAnomaly** (True, False);  
**JacketTemperatureAnomaly** (True, False);  
**KneadingAnomaly** (True, False);  
**KneadingTimeAnomaly** (True, False);  
**LengthSettingValueAnomaly** (True, False);  
**LiquidPreparationAnomaly** (True, False);  
**MedicineGranulesDryingTemperatureAnomaly** (True, False);  
**MedicineGranulesDryingTimeAnomaly** (True, False);  
**PolishAnomaly** (True, False);  
**PolishTimeAnomaly** (True, False);  
**RepellentWaterAnomaly** (True, False);  
**ShineAnomaly** (True, False);  
**ShineTimeAnomaly** (True, False);  
**SolventRemovingAnomaly** (True, False);  
**TemperatureAnomaly** (True, False);  
**VacuumDegreeAnomaly1** (True, False);  
**VacuumDegreeAnomaly2** (True, False);  
**VacuumTimeAnomaly1** (True, False);  
**VacuumTimeAnomaly2** (True, False);  
**WaterAdditionAnomaly** (True, False);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Bi, Y., Wang, S., Zhang, C., Cong, H., Gao, W., Qu, B., & Li, J. (2023). A bayesian network-based safety assessment method for solid propellant granule-casting molding process. *Journal of Loss Prevention in the Process Industries*, 83, 105089.

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rainstorm

*rainstorm Bayesian Network*

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**Description**

Deduction of sudden rainstorm scenarios: integrating decision makers' emotions, dynamic Bayesian network and DS evidence theory.

**Format**

A discrete Bayesian network to simulate the dynamic change process of scenario deduction. Probabilities were given within the referenced paper. The vertices are:

**EmAct1** Activate the flood prevention emergency plan; organize emergency rescue teams to garrison key safety points and increase the intensity of inspections; each site is equipped with sufficient special flood prevention materials and equipment (Effective, Void);

**EmAct2** Improve the level of flood prevention emergency response; organize the maintenance of houses; restrict people's travel; clean up the water outlet in time; and do a good job in popularizing flood prevention emergency measures (Effective, Void);

**EmAct3** Vigorous dredging of drainage channels, all personnel involved in flood control (Effective, Void);

**EmAct4** Strengthen inspections and inspections of rivers, reservoirs, geological disasters, urban infrastructure, etc.; force all factories with hidden dangers (enterprises that may have water inlets and hot furnaces, etc.) to stop work and production (Effective, Void);

**EmAct5** Enterprises continue to close down and add infrastructure (Effective, Void);

**EmAct6** Arrange professional personnel to guide the dangerous situation of the reservoir on the spot; excavate the drainage trough as soon as possible to reduce the water level, add hydrological stations, and strengthen supervision and early warning (Effective, Void);

**EmAct7** Extensive excavation of emergency drainage channels; transfer of personnel in hazardous areas; and increase of emergency equipment and medical teams (Effective, Void);

**EmAct8** Accelerate the transfer of personnel from disaster areas, add high-tech rescue equipment (Effective,Void);

**Scenario1** Rainstorm (True, False);

**Scenario2** Precipitation continues to increase (True, False);

**Scenario3** The ground area is reduced by water (True, False);

- Scenario4** The weather continued to deteriorate and heavy rainstorms occurred (True, False);
- Scenario5** Secondary disasters occur (True, False);
- Scenario6** Heavy rains trigger small floods (True, False);
- Scenario7** Heavy rains triggered large flooding (True, False);
- Scenario8** Floods trigger landslides (True, False);
- Scenario9** All stagnant water is discharged (True, False);
- Scenario10** The flood disappeared (True, False);
- Scenario11** The danger was completely controlled and the rainstorm disappeared (True, False);
- Sent1** Optimistic/pessimistic (Optimism, Gloomy);
- Sent2** Optimistic/pessimistic (Optimism, Gloomy);
- Sent3** Optimistic/pessimistic (Optimism, Gloomy);
- Sent4** Optimistic/pessimistic (Optimism, Gloomy);
- Sent5** Optimistic/pessimistic (Optimism, Gloomy);
- Sent6** Optimistic/pessimistic (Optimism, Gloomy);
- Sent7** Optimistic/pessimistic (Optimism, Gloomy);
- Sent8** Optimistic/pessimistic (Optimism, Gloomy);
- Target1** The normal living order of the people, and make all the preparations for the deterioration of heavy rains (Attain, Miss);
- Target2** Ensure that all the water outlets are unblocked, and all the rest are protected at home except for the necessary travel personnel (Attain, Miss);
- Target3** Water in the ground area is accelerating and decreasing (Attain, Miss);
- Target4** Ensure that all hidden factories are shut down, avoid other accidents such as explosions, and ensure that all infrastructure is operating normally (Attain, Miss);
- Target5** The whole society is subordinate to the unified organization of the state (Attain, Miss);
- Target6** Ensures reservoir danger is under control and casualties continue to decrease (Attain, Miss);
- Target7** Ensure that the water level is controlled, all personnel in the danger area are evacuated, and there is no increase in the number of casualties (Attain, Miss);
- Target8** The supply of medical supplies is timely, the efficiency of search and rescue is guaranteed, and the number of casualties is no longer increasing (Attain, Miss);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Xie, X., Tian, Y., & Wei, G. (2023). Deduction of sudden rainstorm scenarios: integrating decision makers' emotions, dynamic Bayesian network and DS evidence theory. *Natural Hazards*, 116(3), 2935-2955.

rainwater

*rainwater Bayesian Network***Description**

Short-term instead of long-term rainfall time series in rainwater harvesting simulation in houses: An assessment using Bayesian Network.

**Format**

A discrete Bayesian network to predict if a given short-term time series leads to results similar to those obtained using a long-term time series. Probabilities were given within the referenced paper. The vertices are:

**Representativeness** (Yes, No);

**SeriesLength** (One Year, Two Year, Three Year, Four Year, Five Year, Six Year, Seven Year, Eighth Year, Nine Year, Ten Year, Fifteen Year, Twenty Year);

**SeasonalityIndex** (High, Medium, Low);

**RainwaterDemand** (Demand 20, Demand 30, Demand 40, Demand 50);

**AverageAnnualRainfall** (High, Medium, Low);

**AverageNumberOfDryDaysPerYear** (High, Medium, Low);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Geraldi, M. S., & Ghisi, E. (2019). Short-term instead of long-term rainfall time series in rainwater harvesting simulation in houses: An assessment using Bayesian Network. *Resources, Conservation and Recycling*, 144, 1-12.

redmeat

*redmeat Bayesian Network***Description**

Framing and tailoring prefactual messages to reduce red meat consumption: Predicting effects through a psychology-based graphical causal model.



**Format**

A discrete Bayesian network to predict the potential effects of message delivery from the observation of the psychosocial antecedents. Probabilities were given within the referenced paper. The vertices are:

**Baseline\_Intention** (high, medium, low);

**Desensitization** (high, medium, low);

**Diffused\_Responsibility** (high, medium, low);

**Food\_Involvement** (high, medium, low);

**Future\_Intention** (high\_positive, low\_positive, neutral, low\_negative, high\_negative);

**Message** (gain, nonloss, nongain, loss);

**Perceived\_Control** (high, medium, low);

**Perceived\_Severity** (high, medium, low);

**Prevention\_Focus** (high, medium, low);

**Promotion\_Focus** (high, medium, low);

**Systematic\_Processing** (high, medium, low);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Catellani, P., Carfora, V., & Piastra, M. (2022). Framing and tailoring prefactual messages to reduce red meat consumption: Predicting effects through a psychology-based graphical causal model. *Frontiers in Psychology*, 13, 825602.

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 resilience

*resilience Bayesian Network*


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**Description**

Quantifying resilience of socio-ecological systems through dynamic Bayesian networks.

**Format**

A discrete Bayesian network for the evaluation and modeling of socio-ecological systems structure. Probabilities were given within the referenced paper. The vertices are:

**Absorption** 1920-1960 (false, true);

**Absorption1** 1960-1980 (false, true);

**Absorption2** 1980-2019 (false, true);

**Adaptation** 1920-1960 (false, true);

- Adaptation1** 1960-1980 (false, true);
- Adaptation2** 1980-2019 (false, true);
- Autonomy** Development of subsistence means and a market economy in which inhabitants own the means of production and influence the dynamics of production processes: 1920-1960 (deficient, low);
- Autonomy1** As Autonomy: 1960-1980 (deficient, low);
- Autonomy1** As Autonomy: 1989-2019 (low, moderate);
- Connectivity** The concept refers to a device's availability to be connected to another or a network. The connectivity emphasizes communicational, social and infrastructural dimensions: 1920-1960 (deficient, low);;
- Connectivity1** As Connectivity: 1960-1980 (low, moderate);
- Connectivity2** As Connectivity: 1980-2019 (high, moderate);
- Density** Average number of inhabitants of a country, region, urban or rural area in relation to a given unit area of the territory where that country, region or area is located: 1920-1960 (low, moderate);
- Density1** As Density: 1960-1980 (low, moderate);
- Density2** As Density: 1980-2019 (high, moderate);
- Diversity** Palynological diversity calculated using the palynological richness from the Monquentiva pollen record. This variable indicates the diversity of vegetation represented in the pollen record: 1920-1960 (low, moderate)
- Diversity1** As Diversity: 1960-1980 (high, low, moderate);
- Diversity2** As Diversity: 1980-2019 (high, moderate);
- FCover** Percentage of tree taxa calculated from the Monquentiva pollen record: 1920-1960 (low, moderate);
- FCover1** As FCover: 1960-1980 (low, moderate);
- FCover2** As FCover: 1980-2019 (high, low, moderate);
- Fires** Fire activity at local and regional levels from the Monquentiva charcoal record. The fire record is obtained from the analysis of charcoal in the Monquentiva sediments: 1920-1960 (high, moderate);
- Fires1** As Fires: 1960-1980 (high, low, moderate);
- Fires2** As Fires: 1980-2019 (low, moderate);
- Function** 1920-1960 (false, true);
- Function1** 1960-1980 (false, true);
- Function2** 1980-2019 (false, true);
- Organization** : 1920-1960 (deficient, low);
- Organization1** As Organization: 1960-1980 (low, moderate);
- Organization2** As Organization: 1980-2019 (high, moderate);
- Precipitation** Annual precipitation recorded at the meteorological station No3506029, Embalse Tominé, Guatavita, Colombia: 1920-1960 (high, low, moderate);
- Precipitation1** As Precipitation: 1960-1980 (low, moderate);

**Precipitation2** As Precipitation: 1980-2019 (high, low, moderate);

**Transformation** 1920-1960 (true, false);

**Transformation1** 1960-1980 (true, false);

**Transformation2** 1980-2019 (true, false);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Franco-Gaviria, F., Amador-Jimenez, M., Millner, N., Durden, C., & Urrego, D. H. (2022). Quantifying resilience of socio-ecological systems through dynamic Bayesian networks. *Frontiers in Forests and Global Change*, 5, 889274.

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ricci

*ricci Bayesian Network*

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### Description

A survey on datasets for fairness-aware machine learning.

### Format

A discrete Bayesian network modeling the results of a promotion exam within a fire department. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset (the variable Promoted was constructed manually). The vertices are:

**Combine** The combined score ( $<70$ ,  $\geq 70$ );

**Oral** The oral exam score ( $<70$ ,  $\geq 70$ );

**Position** The desired promotion (Lieutenant, Captain);

**Promoted** Whether an individual obtains a promotion (FALSE, TRUE);

**Race** (White, Non-White);

**Written** The written exam score ( $<70$ ,  $\geq 70$ );

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 12(3), e1452.

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rockburst	<i>rockburst Bayesian Network</i>
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**Description**

Dynamic early warning of rockburst using microseismic multi-parameters based on Bayesian network.

**Format**

A Gaussian Bayesian network to give early-warning of rockbursts. The probabilities were given within the referenced paper. The vertices are:

**Rockburst** (No, Yes);

**MMAV** (Sligth, Medium, Strong);

**SRAV** (Small, Medium, Big);

**ASAV** (Small, Medium, Big);

**DSDAV** (Small, Medium, Big);

**SEAV** (Low, Medium, High);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Li, X., Mao, H., Li, B., & Xu, N. (2021). Dynamic early warning of rockburst using microseismic multi-parameters based on Bayesian network. *Engineering Science and Technology, an International Journal*, 24(3), 715-727.

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rockquality	<i>rockquality Bayesian Network</i>
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**Description**

A probability prediction method for the classification of surrounding rock quality of tunnels with incomplete data using Bayesian networks.

**Format**

A discrete Bayesian network to predict the probability for the classification of surrounding rock quality of tunnel with incomplete data. Probabilities were given within the referenced paper. The vertices are:

**BQ** Basic quality of rock mass (Num1, Num2, Num3, Num4, Num5);

**Groundwater** (DryWet, MoistDripping, RainlikeDripping, TubularGushing);

**InSituStress** (Low, Medium, High, ExtremelyHigh);

**RockHardness** (Hard, SlightlyHard, SlightlySoft, Soft, ExtremelySoft);

**RockMassIntegrity** (Complete, SlightlyComplete, SlightlyBroken, Broken, ExtremelyBroken);

**RockMassStructure** (State1, State2, State3, State4, State5);

**RockQuality** (I, II, III, IV, V);

**StructuralPlaneIntegrity** (Good, Ordinary, Bad, VeryBad);

**WeatheringDegree** (Fresh, Slight, Medium, Severe, Extreme).

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ma, J., Li, T., Li, X., Zhou, S., Ma, C., Wei, D., & Dai, K. (2022). A probability prediction method for the classification of surrounding rock quality of tunnels with incomplete data using Bayesian networks. *Scientific Reports*, 12(1), 19846.

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 ropesegment

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*ropesegment Bayesian Network*


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**Description**

Availability optimization of a dragline subsystem using Bayesian network.

**Format**

A discrete Bayesian network to analyze the availability of the rope segment. Probabilities were given within the referenced paper. The vertices are:

**DragRopeFault** (TRUE, FALSE);

**DragChainLinkBroken** (TRUE, FALSE);

**DragHitchShacklePinOut** (TRUE, FALSE);

**DumpRopeFault** (TRUE, FALSE);

**DumpSocketPinOut** (TRUE, FALSE);

**HoistRopeSystem** (TRUE, FALSE);

**HoistChainPinOut** (TRUE, FALSE);  
**DragSubsystem** (TRUE, FALSE);  
**DumpSubsystem** (TRUE, FALSE);  
**HoistSubsystem** (TRUE, FALSE);  
**RopeSegment** (TRUE, FALSE);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Jana, D., Kumar, D., Gupta, S., & Gupta, K. K. (2024). Availability optimization of a dragline subsystem using Bayesian network. *Journal of The Institution of Engineers (India): Series D*, 105(1), 77-88.

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safespeeds

*safespeeds Bayesian Network*

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### Description

Modelling driver expectations for safe speeds on freeway curves using Bayesian belief networks.

### Format

A discrete Bayesian network to model driver expectations using measured speeds in 153 curves and data on the characteristics of the curve approaches. The probabilities were given in the referenced paper. The vertices are:

**Angle** (A010-100, A100-200, A200-310);

**CurveSign** (Present, Not Present);

**Direction** (Left, Right);

**ExpectedSafeSpeed** (S060-069, S070-079, S080-089, S090-099, S100-109, S110-119, S120-129, S130-140);

**NumberOfLanes** (One, Two, Three, Four);

**PrecedingCurveSpeed** (S060-080, S080-100, S100-120, S120-140, Tangent);

**PrecedingRoadwayType** (Connector Road, Deceleration Lane, Fork, Main Carriageway, Merge, Weaving Section);

**SpeedSign** (AdvSpeed50, AdvSpeed60, AdvSpeed70, AdvSpeed80, AdvSpeed90, SpeedLimit50, SpeedLimit60, SpeedLimit70, SpeedLimit80, SpeedLimit90, NoSpeedLimit);

**WarningSign** (Present, Not Present);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Vos, J., Farah, H., & Hagenzieker, M. (2024). Modelling driver expectations for safe speeds on freeway curves using Bayesian belief networks. *Transportation Research Interdisciplinary Perspectives*, 27, 101178.

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sallyclark

*sallyclark Bayesian Network*

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**Description**

Measuring coherence with Bayesian networks.

**Format**

A discrete Bayesian modelling the evidence from the Sally Clark trial. Probabilities were given within the referenced paper. The vertices are:

**ABrusing** (TRUE, FALSE);

**ADisease** (TRUE, FALSE);

**AMurder** (TRUE, FALSE);

**BBruising** (TRUE, FALSE);

**BDisease** (TRUE, FALSE);

**BMurder** (TRUE, FALSE);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Kowalewska, A., & Urbaniak, R. (2023). Measuring coherence with Bayesian networks. *Artificial Intelligence and Law*, 31(2), 369-395.

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salmonella1

*salmonella Bayesian Networks*

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### Description

Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain.

### Format

A discrete Bayesian network to show the existence of dependencies between resistance to antimicrobials. Probabilities were given within the referenced paper. The vertices are (s stands for susceptible, r for resistant):

**CHL** Chloramphenicol (s, r);

**CIP** Ciprofloxacin (s, r);

**CTX** Cefotaxime (s, r);

**FFC** Florfenicol (s, r);

**GEN** Gentamicin (s, r);

**NAL** Nalidixic acid (s, r);

**TET** Tetracycline (s, r);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Teng, K. T. Y., Aerts, M., Jaspers, S., Ugarte-Ruiz, M., Moreno, M. A., Saez, J. L., ... & Alvarez, J. (2022). Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain. *BMC Veterinary Research*, 18(1), 333.

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salmonella2

*salmonella Bayesian Networks*

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### Description

Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain.



**Format**

A discrete Bayesian network to show the existence of dependencies between resistance to antimicrobials. Probabilities were given within the referenced paper. The vertices are (s stands for susceptible, r for resistant):

**AMP** Ampicillin (s, r);  
**CAZ** Cefotaxime (s, r);  
**CHL** Chloramphenicol (s, r);  
**CIP** Ciprofloxacin (s, r);  
**CTX** Cefotaxime (s, r);  
**GEN** Gentamicin (s, r);  
**NAL** Nalidixic acid (s, r);  
**SMX** Sulfamethoxazole (s, r);  
**TET** Tetracycline (s, r);  
**TMP** Trimethoprim (s, r);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Teng, K. T. Y., Aerts, M., Jaspers, S., Ugarte-Ruiz, M., Moreno, M. A., Saez, J. L., ... & Alvarez, J. (2022). Patterns of antimicrobial resistance in *Salmonella* isolates from fattening pigs in Spain. *BMC Veterinary Research*, 18(1), 333.

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 seismic

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*seismic Bayesian Network*


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**Description**

Probabilistic seismic risk assessment of a reinforced concrete building considering hazard level and the resulting vulnerability using Bayesian Belief Network.

**Format**

A discrete Bayesian network for the identification of the seismic risk associated with a particular building which can be utilised to guide stakeholders, policymakers and designers in the efficient planning of emergency response, rescue operations and recovery activities. The probabilities were given in the referenced paper. The vertices are:

**ConstructionQuality** (Low, Medium, High);  
**Distance** (Short, Medium, Long);  
**Fragility** (Low, Medium, High);

**LiveLoad** (Low, Medium, High);  
**Magnitude** (Low, Medium, High);  
**SeismicHazard** (Low, Medium, High);  
**SeismicRisk** (Low, Medium, High);  
**ShakingIntensity** (Low, Medium, High);  
**StrengthDegradation** (Low, Medium, High);  
**Vulnerability** (Low, Medium, High);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Roy, G., Sen, M. K., Singh, A., Dutta, S., & Choudhury, S. (2024). Probabilistic seismic risk assessment of a reinforced concrete building considering hazard level and the resulting vulnerability using Bayesian Belief Network. *Asian Journal of Civil Engineering*, 25(3), 2993-3009.

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shipping

*shipping Bayesian Network*

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### Description

Leverage Bayesian Network and Fault Tree Method on Risk Assessment of LNG Maritime Transport Shipping Routes: Application to the China–Australia Route.

### Format

A discrete Bayesian network to evaluate the occurrence likelihood of risk of transporting liquefied natural gas on the China–Australia Route. Probabilities were given within the referenced paper. The vertices are:

**AirlineInherentRisks** (Yes, No);  
**CoastalPortsRisk** (Yes, No);  
**DeepChannel** (Yes, No);  
**DifficultHandlingLNG** (Yes, No);  
**FewerPorts** (Yes, No);  
**FireRiskLNG** (Yes, No);  
**HeavyFog** (Yes, No);  
**HeavyTraffic** (Yes, No);  
**HighCurrent** (Yes, No);  
**HighWaves** (Yes, No);  
**ImpactEpidemic** (Yes, No);

**InfluencePoliticalGame** (Yes, No);  
**InfluenceWeather** (Yes, No);  
**LNGLoadingRisk** (Yes, No);  
**LNGTransportRisk** (Yes, No);  
**LongDistance** (Yes, No);  
**LowVisibility** (Yes, No);  
**MaritimeSecurity** (Yes, No);  
**MilitaryConflict** (Yes, No);  
**NonTraditionalThreat** (Yes, No);  
**ObjectiveFactors** (Yes, No);  
**PiracyAttack** (Yes, No);  
**PoorDraftLevel** (Yes, No);  
**PoorOrganization** (Yes, No);  
**SafetyPerformanceLNG** (Yes, No);  
**SafetyRoutes** (Yes, No);  
**SeaBreezeEffect** (Yes, No);  
**SovereigntyDispute** (Yes, No);  
**StrongSeaBreeze** (Yes, No);  
**StrongWinds** (Yes, No);  
**SubjectiveFactors** (Yes, No);  
**Thunderstorms** (Yes, No);  
**TransportLNGRisk** (Yes, No);  
**UncertainNavigablePeriod** (Yes, No);  
**UnsafePersonnel** (Yes, No);  
**VesselRisk** (Yes, No);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Chang, Z., He, X., Fan, H., Guan, W., & He, L. (2023). Leverage Bayesian network and fault tree method on risk assessment of LNG maritime transport shipping routes: Application to the China-Australia route. *Journal of Marine Science and Engineering*, 11(9), 1722.

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simulation	<i>simulation Bayesian Network</i>
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**Description**

Integration of fuzzy reliability analysis and consequence simulation to conduct risk assessment.

**Format**

A discrete Bayesian network to assist asset managers in evaluating the risk arising from the operations. Probabilities were given within the referenced paper. The vertices are:

**JointFailure** (True, False);

**PressureRegulatorLeakage** (True, False);

**SealFailure** (True, False);

**ValveActivation** (True, False);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Leoni, L., & De Carlo, F. (2023). Integration of fuzzy reliability analysis and consequence simulation to conduct risk assessment. *Journal of Loss Prevention in the Process Industries*, 83, 105081.

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softwarelogs1	<i>softwarelogs Bayesian Networks</i>
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**Description**

Bayesian Network analysis of software logs for data-driven software maintenance.

**Format**

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

**error** Error that has occurred (`com.mysql`, etc.);

**class** Class that throws the error (`chessleague.db`, etc.);

**severity** Severity of the entry (SEVERE, WARNING, INFO);

**method** Method where the error has occurred (`deleteAccount`, etc.);

**thread\_name** Name of the thread (`AutoDeployer`, etc.);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. *IET Software*, 17(3), 268-286.

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 softwarelogs2

*softwarelogs Bayesian Networks*


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**Description**

Bayesian Network analysis of software logs for data-driven software maintenance.

**Format**

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

**page\_t\_0** (A128GCM, dir, HS512, SunJSSE version 1.8, AdminCron, AdminLeagues, AdminMarket, AdminNotices, AdminSuggestion, AdminSuggestions, AdminUser, AdminUsers, AllLeagues, Bid, Calendar, Classification, Cron, DirectorOfChess, ErrorPage, Finance, Help, Index, Invite, LastMovements, League, Lineup, Market, MarketOperations, NewAccount, NewPassword, NewSuggestion, OfferPlayer, OldSeasons, Play, Player, Privacy, Results, SearchPlayer, Start, Team, Trainer, Transactions, UserConfiguration, ViewOffers);

**user\_type\_t\_0** (active, occasional, regular, very active);

**load\_time\_t\_0** (high, low, medium, optimal);

**time\_on\_page\_t\_0** (high, low, medium, very low).

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. *IET Software*, 17(3), 268-286.

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softwarelogs3

*softwarelogs Bayesian Networks*

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## Description

Bayesian Network analysis of software logs for data-driven software maintenance.

## Format

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

**load\_time** (high, low, medium, optimal);

**language** (bg, ca, cw, de, en, es, eu, fr, gl, it, jwe content encryption algorithms, jwe key management algorithms, jws signature algorithms, nl, pl, pt, ru, sr, unknown, zh);

**user** (high, low, medium, optimal);

**page** (high, low, medium, very low);

**action** (A128KW, A192GCM, ES256, SunJCE version 1.8, bad captcha, bad email, bad recaptcha, bonus, bonus introduced is not a number, cancelBid, contract-sponsor, correctBPIOL, create, create division, create offer, createLeague, createLeagues, cronDiariom cronDiarioAuto, cronEVO, cronJornada, cronJornadaAuto, cronSemanaAuto, cronTemporada, deleteAccount, deleteMessage, edit, fire player, fire trainer, hire trainer, load market page, load page, load round, logout, pay bonus, prepare team, publish a suggestion, redirect, search player, search top players, sendNotice, set new password, successful-search-players, successful bid, successfully send invitation, successfully create account, tried to create an offer, unsuccessful-search-players, unsuccessful bid-already invested, unsuccessful bid-amount too low, unsuccessful bid-less than initial price, unsuccessful bid-negative amount, unsuccessful bid-not enough available money, unsuccessful bid-wrong number format, update account, updateRatingList, username in use, wrongcaptcha send invitation);

**day** (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday);

**action\_duration** (high, low, medium, optimal);

**time\_on\_page** (high, medium, low, very low);

**num\_petitions** (1-3, 3-6, 6-59);

**country** (Argentina, Austria, Belgium, Canada, China, Czechia, France, Germany, Italy, Mexico, Peru, Portugal, Russia, Saudi Arabia, Slovakia, Spain, Turkey, Uganda, Ukraine, United Arab Emirates, United States, unknown, Venezuela);

**browser** (Mozilla, not set, Android Webview, Chrome, Edge, Firefox, Opera, Safari, Safari in-app, Samsung Internet, UC Browser, unknown);

**device** (desktop, mobile, tablet, unknown);

**num\_errors** (high, low, medium, none);

**user\_type** (ocasional, regular, very active);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. *IET Software*, 17(3), 268-286.

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 softwarelogs4

*softwarelogs Bayesian Networks*


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**Description**

Bayesian Network analysis of software logs for data-driven software maintenance.

**Format**

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

**load\_time** (high, low, medium, optimal);

**language** (bg, ca, cw, de, en, es, eu, fr, gl, it, jwe content encryption algorithms, jwe key management algorithms, jws signature algorithms, nl, pl, pt, ru, sr, unknown, zh);

**user** (high, low, medium, optimal);

**page** (high, low, medium, very low);

**action** (A128KW, A192GCM, ES256, SunJCE version 1.8, bad captcha, bad email, bad recaptcha, bonus, bonus introduced is not a number, cancelBid, contract-sponsor, correctBPIOL, create, create division, create offer, createLeague, createLeagues, cronDiariom cronDiarioAuto, cronEVO, cronJornada, cronJornadaAuto, cronSemanaAuto, cronTemporada, deleteAccount, deleteMessage, edit, fire player, fire trainer, hire trainer, load market page, load page, load round, logout, pay bonus, prepare team, publish a suggestion, redirect, search player, search top players, sendNotice, set new password, successful-search-players, successful bid, successfully send invitation, successfully create account, tried to create an offer, unsuccessful-search-players, unsuccessful bid-already invested, unsuccessful bid-amount too low, unsuccessful bid-less than initial price, unsuccessful bid-negative amount, unsuccessful bid-not enough available money, unsuccessful bid-wrong number format, update account, updateRatingList, username in use, wrongcaptcha send invitation);

**day** (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday);

**action\_duration** (high, low, medium, optimal);

**time\_on\_page** (high, medium, low, very low);

**num\_petitions** (1-3, 3-6, 6-59);

**country** (Argentina, Austria, Belgium, Canada, China, Czechia, France, Germany, Italy, Mexico, Peru, Portugal, Russia, Saudi Arabia, Slovakia, Spain, Turkey, Uganda, Ukraine, United Arab Emirates, United States, unknown, Venezuela);

**browser** (Mozilla, not set, Android Webview, Chrome, Edge, Firefox, Opera, Safari, Safari in-app, Samsung Internet, UC Browser, unknown);  
**device** (desktop, mobile, tablet, unknown);  
**num\_errors** (high, low, medium, none);  
**user\_type** (ocasional, regular, very active);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. *IET Software*, 17(3), 268-286.

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soil

*soil Bayesian Network*

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### Description

Characteristic study of some parameters of soil irrigated by magnetized waters.

### Format

A discrete Bayesian network to display the water treatment impact on soil characteristics. Probabilities were given within the referenced paper. The vertices are:

**Depth** (0-20, 20-40);  
**EC** (Less than 1.4, More than 1.4);  
**Intensity** (Less than 0.3, More than 0.3);  
**Length** (Less than 20, More than 20);  
**pH** (Less than 7.7, More than 7.7);  
**W** (Less than 10, More than 10);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Ben Amor, H., Elaoud, A., Ben Hassen, H., Ben Salah, N., Masmoudi, A., & Elmoueddeb, K. (2020). Characteristic study of some parameters of soil irrigated by magnetized waters. *Arabian Journal of Geosciences*, 13, 1-11.



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soillead

*soillead Bayesian Network*

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### Description

Lead distribution in urban soil in a medium-sized city: household-scale analysis.

### Format

A discrete Bayesian network to classify residential parcels by risk of exceeding residential gardening standards. The probabilities were given within the referenced paper. The vertices are:

**SoilPbAbove100ppm** (0,1);

**BlackPercentage** (Below 0.355, 0.355-0.727, Above 0.727);

**DistanceToMajorRoad** (Below 500, 500-1000, Above 1000);

**HouseAge** (Below 4.2, 4.2-7.9, Above 7.9);

**HouseValue** (Below 1.292, 1.292-2.859, Above 2.859);

**MedianHouseholdIncome** (Below 0.255, 0.255-0.470, Above 0.470);

**SoilClay** (Below 26.14, 26.14-33.125, Above 33.125);

**SoilPH** (Below 5.316, 5.316-5.974, Above 5.974);

**SoilSamplingLocation** (Dripline, Streetside, Yard);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Obeng-Gyasi, E., Roostaei, J., & Gibson, J. M. (2021). Lead distribution in urban soil in a medium-sized city: household-scale analysis. *Environmental Science & Technology*, 55(6), 3696-3705.

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soilliquefaction1

*soilliquefaction Bayesian Networks*

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### Description

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

**Format**

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.a). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

**ConePenetrationResistance** (small, medium, big, super);

**EartquakeMagnitude** (medium, strong, big, super);

**LiquefactionPotential** (no, yes);

**MeanGrainSize** (medium, strong, big, super);

**PeakGroundAcceleration** (low, medium, high, super);

**TotalVerticalStress** (small, medium, big, super);

**VerticalEffectiveStress** (small, medium, big, super);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. *Frontiers of Structural and Civil Engineering*, 15, 490-505.

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 soilliquefaction2

*soilliquefaction Bayesian Networks*


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**Description**

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

**Format**

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.b). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

**ConePenetrationResistance** (small, medium, big, super);

**EartquakeMagnitude** (medium, strong, big, super);

**LiquefactionPotential** (no, yes);

**MeanGrainSize** (medium, strong, big, super);

**PeakGroundAcceleration** (low, medium, high, super);

**TotalVerticalStress** (small, medium, big, super);

**VerticalEffectiveStress** (small, medium, big, super);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. *Frontiers of Structural and Civil Engineering*, 15, 490-505.

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 soilliquefaction3

*soilliquefaction Bayesian Networks*


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**Description**

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

**Format**

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.c). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

**ConePenetrationResistance** (small, medium, big, super);

**EartquakeMagnitude** (medium, strong, big, super);

**LiquefactionPotential** (no, yes);

**MeanGrainSize** (medium, strong, big, super);

**PeakGroundAcceleration** (low, medium, high, super);

**TotalVerticalStress** (small, medium, big, super);

**VerticalEffectiveStress** (small, medium, big, super);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. *Frontiers of Structural and Civil Engineering*, 15, 490-505.

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 soilliquefaction4

*soilliquefaction Bayesian Networks*


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### Description

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

### Format

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.d). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

**ConePenetrationResistance** (small, medium, big, super);

**EartquakeMagnitude** (medium, strong, big, super);

**LiquefactionPotential** (no, yes);

**MeanGrainSize** (medium, strong, big, super);

**PeakGroundAcceleration** (low, medium, high, super);

**TotalVerticalStress** (small, medium, big, super);

**VerticalEffectiveStress** (small, medium, big, super);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. *Frontiers of Structural and Civil Engineering*, 15, 490-505.

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 stocks

*stocks Bayesian Network*


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### Description

Gaussian Bayesian network model of healthcare, food and energy sectors in the pandemic: Turkiye case.

**Format**

A Gaussian Bayesian network to explore the causal relations between the healthcare, food, and energy sectors. The probabilities were given in the paper. The vertices are:

**AEFES**  
**AKSEN**  
**CCOLA**  
**ENJSA**  
**KERVT**  
**LKMNH**  
**MPARK**  
**ODAS**  
**PENGD**  
**TUKAS**  
**ULKER**  
**ULUUN**  
**ZOREN**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Sener, E., & Demir, I. (2024). Gaussian Bayesian network model of healthcare, food and energy sectors in the pandemic: Turkiye case. *Heliyon*, 10(1).

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student1

*student Bayesian Networks*

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**Description**

A survey on datasets for fairness-aware machine learning.

**Format**

A discrete Bayesian network modeling students' achievement in the secondary education of two Portuguese schools in 2005–2006 in the Portuguese subject. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset. The vertices are:

**activities** Extra-curricular activities (yes, no);  
**address** Student's home address type (Rural, Urban);  
**age** Student's age (15, 16, 17, ..., 22);

**class** Final grade (< 10, >= 10);

**failures** Number of past class failures (0, 1, 2, 3);

**famsize** Race (non-white, white);

**famsup** Family size (Less or equal to 3, Greater than 3);

**Fedu** Father's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher Education);

**Fjob** Father's job (At Home, Healthcare Related, Other, Civil Services, Teacher);

**G1** First period grade (< 10, >= 10);

**G2** Second period grade (< 10, >= 10);

**goout** Going out with friends (Very Low, Low, Medium, High, Very High);

**guardian** Student's guardian (Mother, Father, Other);

**higher** Wants to take higher education (yes, no);

**internet** Internet access at home (yes, no);

**Medu** Mother's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher Education);

**Mjob** Mother's job (At Home, Healthcare Related, Other, Civil Services, Teacher);

**nursery** Attended nursery school (yes, no);

**paid** Extra paid classes within the course subject (yes, no);

**Pstatus** Parent's cohabitation status (Living together, Apart);

**reason** Reason to choose this school (Close to Home, School Reputation, Course Preference, Other);

**romantic** With a romantic relationship (yes, no);

**school** Student's school (Gabriel Pereira, Mousinho da Silveira);

**schoolsup** Extra educational support (yes, no);

**sex** Student's sex (Female, Male);

**traveltime** Home to school travel time (Less than 15min, 15 to 30 mins, 30 mins to 1 hour, More than 1 hour);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 12(3), e1452.

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 student2

*student Bayesian Networks*


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**Description**

A survey on datasets for fairness-aware machine learning.

**Format**

A discrete Bayesian network modeling students' achievement in the secondary education of two Portuguese schools in 2005–2006 in the Mathematics subject. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset. The vertices are:

- activities** Extra-curricular activities (yes, no);
- address** Student's home address type (Rural, Urban);
- age** Student's age (15, 16, 17, ..., 22);
- class** Final grade (< 10, >= 10);
- failures** Number of past class failures (0, 1, 2, 3);
- famsize** Race (non-white, white);
- famsup** Family size (Less or equal to 3, Greater than 3);
- Fedu** Father's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher Education);
- Fjob** Father's job (At Home, Healthcare Related, Other, Civil Services, Teacher);
- G1** First period grade (< 10, >= 10);
- G2** Second period grade (< 10, >= 10);
- goout** Going out with friends (Very Low, Low, Medium, High, Very High);
- guardian** Student's guardian (Mother, Father, Other);
- higher** Wants to take higher education (yes, no);
- internet** Internet access at home (yes, no);
- Medu** Mother's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher Education);
- Mjob** Mother's job (At Home, Healthcare Related, Other, Civil Services, Teacher);
- nursery** Attended nursery school (yes, no);
- paid** Extra paid classes within the course subject (yes, no);
- Pstatus** Parent's cohabitation status (Living together, Apart);
- reason** Reason to choose this school (Close to Home, School Reputation, Course Preference, Other);
- romantic** With a romantic relationship (yes, no);
- school** Student's school (Gabriel Pereira, Mousinho da Silveira);
- schoolsup** Extra educational support (yes, no);
- sex** Student's sex (Female, Male);
- traveltime** Home to school travel time (Less than 15min, 15 to 30 mins, 30 mins to 1 hour, More than 1 hour);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsis, E. (2022). A survey on datasets for fairness-aware machine learning. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 12(3), e1452.

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suffocation

*suffocation Bayesian Network*

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**Description**

Human-related hazardous events assessment for suffocation on ships by integrating Bayesian network and complex network.

**Format**

A Gaussian Bayesian network to investigate the human-related factors associated with suffocation on ships during docking repair. The probabilities were given within the referenced paper. The vertices are:

- N4** The safety supervisor on board the ship did not perceive the unsafe actions of the operators and failed to correct the inappropriate operations;
- N5** The representative of the ship owner was absent during the operation;
- N8** Nitrogen leakage
- N10** The safety management department of the shipyard failed to strictly implement all safety measures during the holiday season;
- N11** The safety management department of the shipyard did not attach great importance to the safety of the operation on site, and the safety issues were not paid much attention;
- N12** The quality management system in the safety management department was found be defective in the aspect of the required process guidance documents;
- N13** The shipyard failed to effectively supervise the operators on site to strictly implement the safety management system and the operation instruction;
- N14** The safety management department of the shipyard did not strictly implement the safety management regulations - there was no confirmation of the key operation;
- N16** The superintendent of the civil marine project failed to effectively supervise the issues in risk prevention;
- N17** The managers and officers in the civil marine project failed to pay much attention to the preventive measures in the field of safety when formulating the operation plan;
- N18** The superintendent of the civil marine project did not eliminate the potential dangers for the common operation in time;
- N20** The nitrogen accumulated in the enclosed space on site;



- N22** The person in charge of the operation on site did not implement safety-related regulations, such as confirmation, lighting, and supervision;
- N23** The person in charge of the operation on site failed to give input on the operation environment and provide caution to the operators;
- N24** The person in charge of the on-site operation did not confirm the ventilation;
- N25** The operators on site did not implement the required risk-prevention measures for the operation in the limited space;
- N26** The operator on site did not apply for a permit for the operation procedures;
- N27** The person in charge of the operation on site failed to check the operation permit in the limited space before the operation;
- N28** The person in charge of the operation on site did not confirm the implementation of gas detection;
- N29** The person in charge of the operation on site did not effectively perform their designated responsibility during the operation;
- N30** The work associated with risk identification before the operation was not performed by the person in charge of the operation;
- N32** The removing of the U pipe containing nitrogen in the enclosed space is usually characterized by high risk, which was not did not receive due attention from the operators on site;
- N33** The risk-prevention measures applicable for the enclosed space were not in place before the operation, and various potential risks were not effectively identified;
- N34** The process guidance documents for the officers in the general assembly department were absent;
- N35** The officers in the general assembly department failed to identify all the risks associated with the temporary operation;
- N36** The officers in the general assembly department failed to implement the safety-related measures designed for the holiday season;
- N37** The person on duty in the general assembly department did not perform their responsibilities effectively;
- N38** The officers in the general assembly department failed to implement the safety training for the temporary operators in relation to operative environments and the potential risks;
- N39** The officers in the general assembly department did not effectively perform their supervision and risk monitoring responsibilities;
- N40** Most of the people involved in the accident were found to have low awareness of the safety-related issues during the May 1st Labor Day;
- UA** Unsafe acts;
- UP** Precondition for unsafe acts;
- US** Unsafe supervision;
- OI** Organizational influence;
- PersonnelSuffocation**

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Qiao, W., Guo, H., Huang, E., Deng, W., Lian, C., & Chen, H. (2022). Human-Related Hazardous Events Assessment for Suffocation on Ships by Integrating Bayesian Network and Complex Network. *Applied Sciences*, 12(14), 6905.

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tastingtea

*tastingtea Bayesian Network*

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## Description

A Bayesian network for modelling the Lady tasting tea experiment.

## Format

A discrete Bayesian network for modelling the Lady Tasting Tea experiment. The probabilities were given in the referenced paper. The vertices are:

**AbilityToTaste** (0.5, 0.75, 1);

**Cup1** (tea, milk);

**Cup2** (tea, milk);

**Cup3** (tea, milk);

**Cup4** (tea, milk);

**Cup5** (tea, milk);

**Cup6** (tea, milk);

**Cup7** (tea, milk);

**Cup8** (tea, milk);

**TestOutcome1** (tea, milk);

**TestOutcome2** (tea, milk);

**TestOutcome3** (tea, milk);

**TestOutcome4** (tea, milk);

**TestOutcome5** (tea, milk);

**TestOutcome6** (tea, milk);

**TestOutcome7** (tea, milk);

**TestOutcome8** (tea, milk);

## Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

## References

Xie, G. (2024). A Bayesian network for modelling the Lady tasting tea experiment. *PloS one*, 19(7), e0307866.

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 tbn

*tbn Bayesian Network*


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### Description

Risk assessment of TBM jamming based on Bayesian networks.

### Format

A discrete Bayesian network to assess the risk of tunnel boring machine jamming. The Bayesian network was learned as in the referenced paper. The vertices are:

**Expansive\_Surrounding\_Rock** (High, Low, Medium, None);

**Fault\_Zone** (High, Low, Medium, None);

**In.Situ\_Stress** (High, Low, Medium, None);

**Large\_Deformation\_Surrounding\_Rock** (Serious, Slight);

**Rock\_Mass\_Classes** (High, Low, Medium, None);

**Soft.Hard\_Interbedded\_Rock** (High, Low, Medium, None);

**TBM\_Jamming** (No, Yes);

**Tunnell\_Collapse** (Serious, Slight);

**Underground\_Water** (High, Low, Medium, None);

**Water.And.Mud\_Inrush** (Serious, Slight);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Lin, P., Xiong, Y., Xu, Z., Wang, W., & Shao, R. (2022). Risk assessment of TBM jamming based on Bayesian networks. *Bulletin of Engineering Geology and the Environment*, 81, 1-15.

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 theft1

*theft Bayesian Networks*


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### Description

Evaluating methods for setting a prior probability of guilt.

**Format**

A discrete Bayesian network representing a legal scenario. Probabilities were given within the referenced paper. The vertices are:

**EredHanded** (F, T);

**EseenCS** (F, T);

**EWallet** (F, T);

**Guilty** (F, T);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023). Evaluating Methods for Setting a Prior Probability of Guilt. In *Legal Knowledge and Information Systems* (pp. 63-72). IOS Press.

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theft2

*theft Bayesian Networks*

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**Description**

Evaluating methods for setting a prior probability of guilt.

**Format**

A discrete Bayesian network representing a legal scenario. Probabilities were given within the referenced paper. The vertices are:

**AtCrimeScene** (F, T);

**EredHanded** (F, T);

**EseenCS** (F, T);

**EWallet** (F, T);

**Guilty** (F, T);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023). Evaluating Methods for Setting a Prior Probability of Guilt. In *Legal Knowledge and Information Systems* (pp. 63-72). IOS Press.

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titanic	<i>titanic Bayesian Network</i>
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**Description**

The R Package stagedtrees for Structural Learning of Stratified Staged Trees.

**Format**

A discrete Bayesian network modeling the survival of the Titanic passengers. The Bayesian network was learned as in the referenced paper. The vertices are:

**Class** (1st, 2nd, 3rd, Crew);

**Sex** (Male, Female);

**Age** (Child, Adult);

**Survived** (No, Yes).

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Carli, F., Leonelli, M., Riccomagno, E., & Varando, G. (2022). The R Package stagedtrees for Structural Learning of Stratified Staged Trees. *Journal of Statistical Software*, 102, 1-30.

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trajectories	<i>trajectories Bayesian Network</i>
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**Description**

Context-specific causal discovery for categorical data using staged trees.

**Format**

A discrete Bayesian network modeling the trajectory of patients hospitalized due to COVID. The Bayesian network is learned as in the referenced paper. The vertices are:

**SEX** (male, female);

**ICU** (0, 1);

**OUT** (death, survived);

**AGE** (child, adult, elder);

**RSP** (intub, mask, no);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Leonelli, M., & Varando, G. (2023, April). Context-specific causal discovery for categorical data using staged trees. In International Conference on Artificial Intelligence and Statistics (pp. 8871-8888). PMLR.

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transport

*transport Bayesian Network*

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**Description**

Bayesian networks: with examples in R.

**Format**

A discrete Bayesian network modeling transport choices of a population. Probabilities were given within the referenced paper. The vertices are:

- A** Age (young, adult, old);
- S** Sex (M, F);
- E** Education (high uni);
- O** Occupation (emp, self);
- R** Residence (small, big);
- T** Transport (car, train, other);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Scutari, M., & Denis, J. B. (2014). Bayesian networks: with examples in R. Chapman and Hall/CRC.

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tuberculosis

*tuberculosis Bayesian Network*

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### Description

A decision support system for tuberculosis prevalence in South Africa.

### Format

A discrete Bayesian network to educate, inform, and prescribe measures to take when visiting a high prevalence location. The probabilities were given within the referenced paper. The vertices are:

**Location** (Nkangala, Gert Sibande, Ehlanzeni);

**Gender** (Male, Female);

**AgeGroup** (0 to 35, 35 to 65, More than 65);

**Tuberculosis** (Pulmonary, ExtraPulmonary);

**TreatmentOutcome** (Alive, Died);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Razwiedani, M., & Kogeda, O. P. (2021). A Decision Support System for Tuberculosis Prevalence in South Africa. In *Computational Science and Its Applications*. Springer International Publishing.

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turbine1

*turbine Bayesian Networks*

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### Description

Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions.

### Format

A Gaussian Bayesian network for the estimation of technical relationships among structural dynamic responses of the tower of a floating spar-type offshore wind turbine. Probabilities were given within the referenced paper. The vertices are:

**PtfmPitch** Platform pitch tilt angular (rotational) displacement;

**PtfmRoll** Platform roll tilt angular (rotational) displacement;

- PtfmSurge** Platform horizontal surge (translational) displacement;
- PtfmSway** Platform horizontal sway (translational) displacement;
- TTDspFA** Tower-top/yaw bearing fore-aft (translational) deflection (relative to the undeflected position);
- TTDspPtch** Tower-top/yaw bearing angular (rotational) pitch deflection (relative to the undeflected position);
- TTDspRoll** Tower-top/yaw bearing angular (rotational) roll deflection (relative to the undeflected position);
- TTDspSS** Tower-top/yaw bearing side-to-side (translation) deflection (relative to the undeflected position);
- TwrBsFxt** Tower base fore-aft shear force;
- TwrBsFyt** Tower base side-to-side shear force;
- TwrBsMxt** Nonrotating tower-top/yaw bearing roll moment;
- TwrBsMyt** Nonrotating tower-top/yaw bearing pitch moment;
- YawBrFxp** Tower-top/yaw bearing fore-aft (nonrotating) shear force;
- YawBrFyp** Tower-top/yaw bearing side-to-side (nonrotating) shear force;
- YawBrMxp** Nonrotating tower-top/yaw bearing roll moment;
- YawBrMyp** Nonrotating tower-top/yaw bearing pitch moment;

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Rostam-Alilou, A. A., Zhang, C., Salboukh, F., & Gunes, O. (2022). Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions. *Ocean Engineering*, 244, 110230.

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turbine2

*turbine Bayesian Networks*

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### Description

Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions.



**Format**

A Gaussian Bayesian network for the estimation of technical relationships among structural dynamic responses of the tower of a floating spar-type offshore wind turbine. Probabilities were given within the referenced paper. The vertices are:

**PtfmPitch** Platform pitch tilt angular (rotational) displacement;

**PtfmRoll** Platform roll tilt angular (rotational) displacement;

**PtfmSurge** Platform horizontal surge (translational) displacement;

**PtfmSway** Platform horizontal sway (translational) displacement;

**TTDspFA** Tower-top/yaw bearing fore-aft (translational) deflection (relative to the undeflected position);

**TTDspPch** Tower-top/yaw bearing angular (rotational) pitch deflection (relative to the undeflected position);

**TTDspRoll** Tower-top/yaw bearing angular (rotational) roll deflection (relative to the undeflected position);

**TTDspSS** Tower-top/yaw bearing side-to-side (translation) deflection (relative to the undeflected position);

**TwrBsFxt** Tower base fore-aft shear force;

**TwrBsFyt** Tower base side-to-side shear force;

**TwrBsMxt** Nonrotating tower-top/yaw bearing roll moment;

**TwrBsMyt** Nonrotating tower-top/yaw bearing pitch moment;

**YawBrFxp** Tower-top/yaw bearing fore-aft (nonrotating) shear force;

**YawBrFyp** Tower-top/yaw bearing side-to-side (nonrotating) shear force;

**YawBrMxp** Nonrotating tower-top/yaw bearing roll moment;

**YawBrMyp** Nonrotating tower-top/yaw bearing pitch moment;

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Rostam-Alilou, A. A., Zhang, C., Salboukh, F., & Gunes, O. (2022). Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions. *Ocean Engineering*, 244, 110230.

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 twinframework

*twinframework Bayesian Network*


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### Description

Sustainable operation and maintenance modeling and application of building infrastructures combined with digital twin framework.

### Format

A discrete Bayesian network to identify critical factors during the in-service phase and achieve sustainable operation and maintenance for building infrastructures. Probabilities were given within the referenced paper. The vertices are:

**Weather** (Fine weather, Bad weather);

**SocialActivities** (Active, No activity);

**Time** (Non-working hours, Working hours);

**CampusActivities** (Campus activities, No campus activities);

**PersonnelType** (Student, Social personnel);

**EquipmentStatus** (Good equipment, Equipment abnormality)

**UsingPlayground** (Use, Not in use);

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Jiao, Z., Du, X., Liu, Z., Liu, L., Sun, Z., & Shi, G. (2023). Sustainable Operation and Maintenance Modeling and Application of Building Infrastructures Combined with Digital Twin Framework. *Sensors*, 23(9), 4182.

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 urinary

*urinary Bayesian Network*


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### Description

Urinary tract infections in children: building a causal model-based decision support tool for diagnosis with domain knowledge and prospective data.

**Format**

A discrete Bayesian network to describe the causal relationships among variables relevant to paediatric urinary tract infections. Probabilities were given within the referenced paper. The vertices are:

**AbdoPain** (Yes, Unknown);  
**AgeGroup** (LessThan6Mon, Btw6MonAnd2Yr, Btw2And5Yr, Above5Yr);  
**CauseUTI** (EColi, OtherGramNeg, GramPos, None);  
**CollMethod** (CleanCatch, Catheter, SupraAsp);  
**ContaminationRisk** (High, Low);  
**CRPLLevel** (Above70, Btw15And70, Below50, NotDone);  
**CurrPhenotype** (Type1, Type2, Type3);  
**Diarrhea** (Yes, No);  
**EColi** (Positive, Negative);  
**EColiPresence** (High, Low);  
**EmpricAbxGroup3** (Narrow, Broader);  
**Epithelials** (Low, Moderate);  
**FeverPR** (Yes, No);  
**GramPos** (Positive, Negative);  
**GramPosPresence** (High, Low);  
**Irritable** (Yes, No);  
**Lethargy** (Yes, No);  
**Microscopy\_bacts** (Many, Moderate, Few, NotSeen);  
**NauseaOrVomit** (Yes, No);  
**NeutLevel** (Above15, Btw8And15, Below8, NotDone);  
**OnAbxEDGroup3** (No, Narrow, Broader);  
**OtherGramNeg** (Positive, Negative);  
**OtherGramNegPresence** (High, Low);  
**PoorIntake** (Yes, No);  
**PrevUriKidProbs** (Reported, Unknown);  
**RespSymp** (Yes, No);  
**Sex** (Female, Male);  
**TemperatureLvl2** (Abv385, Btw375and385, Btw365and375, Below365);  
**UltraSound** (Abnormal, Unknown, NotDone);  
**Urin\_Leuc** (High, Moderate, Low);  
**Urin\_LeucEst** (High, Moderate, Low, NotDetected);  
**Urin\_Nitrite** (Detected, NotDetected);  
**UrinSym\_haematuria** (Yes, Unknown);  
**UrinSym\_PainOrDiscomf** (Yes, Unknown);  
**UrinSym\_smelly** (Yes, Unknown);  
**WCCLevel** (Above18, Btw10And18, Below10, NotDone);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ramsay, J. A., Mascaro, S., Campbell, A. J., Foley, D. A., Mace, A. O., Ingram, P., ... & Wu, Y. (2022). Urinary tract infections in children: building a causal model-based decision support tool for diagnosis with domain knowledge and prospective data. *BMC Medical Research Methodology*, 22(1), 218.

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vaccine	<i>vaccine Bayesian Network</i>
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**Description**

Sensitivity analysis in multilinear probabilistic models.

**Format**

A (synthetic) discrete Bayesian network modeling a vaccine scenario. Probabilities were given within the referenced paper. The vertices are:

**Screening\_Test** (Negative, Positive);

**Disease** (Healthy, Mildly, Severly);

**Vaccine** (No, Yes);

@return An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Leonelli, M., Gorgen, C., & Smith, J. Q. (2017). Sensitivity analysis in multilinear probabilistic models. *Information Sciences*, 411, 84-97.

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vessel1	<i>vessel Bayesian Networks</i>
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**Description**

Analysis of fishing vessel accidents with Bayesian network and Chi-square methods.

**Format**

A discrete Bayesian network to understand the occurrence of accidents in fishing vessels and to estimate the occurrence of accidents in variable conditions (Sinking, Fig. 1). Probabilities were given within the referenced paper. The vertices are:

**CarryingLoadAboveTransportLimits** (Yes, No);

**DesignDefect** (Yes, No);

**HuntingEquipmentOverload** (Yes, No);

**LossOfBuoyancy** (Yes, No);

**LossOfStability** (Yes, No);

**LossOfWaterTightness** (Present, Absent);

**Overload** (Yes, No);

**PlannedMaintenance** (Completed, Uncompleted);

**Sinking** (Yes, No);

**UnstableLoading** (Yes, No);

**UsedHuntingEquipment** (Proper, Improper);

**VesselAge** (Old, New);

**VesselPipelines** (Corroded, Normal);

**VesselStructure** (Worn, Normal);

**WaterIntake** (Yes, No);

**WeatherAndSeaConditions** (Bad, Good);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ugurlu, F., Yildiz, S., Boran, M., Ugurlu, O., & Wang, J. (2020). Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. *Ocean Engineering*, 198, 106956.

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 vessel2

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*vessel Bayesian Networks*


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**Description**

Analysis of fishing vessel accidents with Bayesian network and Chi-square methods.

**Format**

A discrete Bayesian network to understand the occurrence of accidents in fishing vessels and to estimate the occurrence of accidents in variable conditions (Collision, Fig. 2). Probabilities were given within the referenced paper. The vertices are:

**AlcoholDrugUse** (Yes, No);

**BridgeWithoutAWatchkeeper** (Yes, No);

**Collision** (Yes, No);

**Fatigue** (Yes, No);

**IntentionOfTargetVessel** (Understood, Not understood);

**InterShipCommunication** (Proper, Improper);

**Lookout** (Proper, Improper);

**Manning** (Minimum num, Optimum num);

**OccupationWithOtherTasks** (Yes, No);

**PresenceOfTargetVessel** (Not Detected, Detected);

**RestrictedVisibility** (No, Yes);

**TypeOfNavigation** (Coastal Waters, Off Shore, Port);

**UseOfNavigationEquipment** (Adequate, Inadequate);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Ugurlu, F., Yildiz, S., Boran, M., Ugurlu, O., & Wang, J. (2020). Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. *Ocean Engineering*, 198, 106956.

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waterlead

*waterlead Bayesian Network*

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**Description**

Improved decision making for water lead testing in U.S. child care facilities using machine-learned Bayesian networks.

**Format**

A discrete Bayesian network to predict building-wide water lead risk in over 4,000 child care facilities in North Carolina according to maximum and 90th percentile lead levels from water lead concentrations at 22,943 taps. The Bayesian network was learned using the code in the referenced paper. The vertices are:

**Target** (0, 1);

**PER\_FREE** ((-Inf, 0.505], (0.505,0.956],(0.956, Inf]);

**PER\_NON\_WHITE** ((-Inf, 0.0996], (0.0996,0.958], (0.958, Inf]);

**TOTAL\_ENROLL** ((-Inf, 2.69], (2.69, 22.8], (22.8, Inf]);

**nsamples** ((-Inf, 4.1], (4.1, 23], (23, Inf]);

**perc\_filtered** ((-Inf, 0.169], (0.169, 0.725], (0.725, Inf]);

**head\_start** (0, 1);

**school** (0, 1);

**home\_based** (0, 1);

**Y\_N\_FIXTURE\_CHG** (dk, no, yes);

**fixture\_year\_cat** (1988to2014, after2014, pre1988);

**year\_began\_operating\_cat** (1988to2014, after2014, pre1988);

**type\_binary** (GW, SW);

**ph\_binary** (0, 1);

**chloramines** (0, 1);

**connections\_cat** ((1e+04,Inf], (3.3e+03, 1e+04], (1, 3.3e+03]);

**ruca\_cat** (Metropolitan, Micropolitan, Rural, Small town);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Mulhern, R. E., Kondash, A. J., Norman, E., Johnson, J., Levine, K., McWilliams, A., ... & Hoponick Redmon, J. (2023). Improved decision making for water lead testing in US child care facilities using machine-learned Bayesian networks. *Environmental Science & Technology*, 57(46), 17959-17970.

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wheat	<i>wheat Bayesian Network</i>
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### Description

Embedding expert opinion in a Bayesian network model to predict wheat yield from spring-summer weather.

### Format

A discrete Bayesian network to predict wheat yield. Probabilities were given within the referenced paper. The vertices are:

**MaximumTemperature** (Low, Medium, High);

**MeanTemperature** (Moderate, Other);

**NDVIinMarch** (Low, Medium, High, Very High);

**Rainfall** (Dry, Average, Very Wet, Drought and Very Wet);

**Yield** (Very Low, Low, Average, High, Very High).

### Value

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

### References

Mahmood, S. A., Karampoiki, M., Hammond, J. P., Paraforos, D. S., Murdoch, A. J., & Todman, L. (2023). Embedding expert opinion in a Bayesian network model to predict wheat yield from spring-summer weather. *Smart Agricultural Technology*, 4, 100224.

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windturbine	<i>windturbine Bayesian Network</i>
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### Description

Reliability analysis of a floating offshore wind turbine using Bayesian Networks.

### Format

A discrete Bayesian network to model and analyze the reliability of a floating offshore wind turbine. The probabilities were given within the referenced paper. The vertices are:

**B01** Human error (Yes, No);

**B02** Resonance (Yes, No);

**B03** Faulty welding (Yes, No);



- B04** Material fatigue (Yes, No);
- B05** Pillar damage (Yes, No);
- B06** Capsize (Yes, No);
- B07** Anchor failure (Yes, No);
- B08** Poor operation environment (Yes, No);
- B09** Insufficient emergency measurement (Yes, No);
- B10** Strong wave (Yes, No);
- B11** Lightning strike (Yes, No);
- B12** Storm (Yes, No);
- B13** Typhoon (Yes, No);
- B14** Planes crash (Yes, No);
- B15** Biological collision (Yes, No);
- B16** Inefficient detection (Yes, No);
- B17** Pipe joint corrosion (Yes, No);
- B18** Pipe joint weld defect (Yes, No);
- B19** Pipe joint fatigue (Yes, No);
- B20** Fairlead corrosion (Yes, No);
- B21** Fairlead fatigue (Yes, No);
- B22** Transitional chain wear (Yes, No);
- B23** Friction chain wear (Yes, No);
- B24** Mooring winch failure (Yes, No);
- B25** Buoys friction chain wear (Yes, No);
- B26** Anchor pickup device damage (Yes, No);
- B27** Abnormal stress (Yes, No);
- B28** Invalid maintenance (Yes, No);
- B29** Mooring lines wear (Yes, No);
- B30** Mooring lines fatigue (Yes, No);
- B31** Mooring lines corrosion (Yes, No);
- B32** Hydraulic motor failure (Yes, No);
- B33** Over pressure (Yes, No);
- B34** Accumulation failure (Yes, No);
- B35** Lighting protection failure (Yes, No);
- B36** Limit switch fails (Yes, No);
- B37** Abnormal vibration (Yes, No);
- B38** Oil leakage (Yes, No);
- B39** Filters failure (Yes, No);
- B40** Power 1 failure (Yes, No);

- B41** Power 2 failure (Yes, No);
- B42** Vane damage (Yes, No);
- B43** Anemometer damage (Yes, No);
- B44** Abnormal filter (Yes, No);
- B45** Poor quality lubrication oil (Yes, No);
- B46** Dirt lubrication oil (Yes, No);
- B47** Abnormal vibration (Yes, No);
- B48** Glued (Yes, No);
- B49** Pitting (Yes, No);
- B50** Corrosion of pins (Yes, No);
- B51** Abrasive wear (Yes, No);
- B52** Pitting - gear bearing (Yes, No);
- B53** Gear tooth deterioration (Yes, No);
- B54** Excessive pressure (Yes, No);
- B55** Excess temperature (Yes, No);
- B56** Fatigue - gear (Yes, No);
- B57** Poor design of teeth gears (Yes, No);
- B58** Tooth surface defects (Yes, No);
- B59** Measurement facilities failure (Yes, No);
- B60** Wire fault (Yes, No);
- B61** Leak (Yes, No);
- B62** Asymmetry (Yes, No);
- B63** Structural deficiency (Yes, No);
- B64** Abnormal vibration (Yes, No);
- B65** Abnormal instrument reading (Yes, No);
- B66** Fail to synchronize (Yes, No);
- B67** Broken bars (Yes, No);
- B68** Fail to start on demands (Yes, No);
- B69** Sensor failure (Yes, No);
- B70** Temperature above limitation (Yes, No);
- B71** Yaw subsystem failure (Yes, No);
- B72** Drive train failure (Yes, No);
- B73** Brake failure (Yes, No);
- B74** Controller failure (Yes, No);
- B75** Transformer failure (Yes, No);
- B76** Sensors failure (Yes, No);
- B77** Converter failure (Yes, No);

- B78** Blades structure failure (Yes, No);
- B79** Hub failure (Yes, No);
- B80** Bearings failure (Yes, No);
- A01** Mooring subsystem failure (Yes, No);
- A02** Tower failure (Yes, No);
- A03** Floating foundation failure (Yes, No);
- A04** Devices failure (Yes, No);
- A05** Extreme sea condition (Yes, No);
- A06** Collapse due to environment (Yes, No);
- A07** Hit by dropped objects (Yes, No);
- A08** Watertight fault (Yes, No);
- A09** Other devise failure (Yes, No);
- A10** Pipe joint failure (Yes, No);
- A11** Fairlead failure (Yes, No);
- A12** Mooring lines broken (Yes, No);
- A13** Mooring line breakage (Yes, No);
- A14** Mooring lines wear (Yes, No);
- A15** Accumulating wear (Yes, No);
- A16** Hydraulic system failure (Yes, No);
- A17** Alarm facilities failure (Yes, No);
- A18** Wrong pitch angle (Yes, No);
- A19** Hydraulic oil failure (Yes, No);
- A20** Power failure (Yes, No);
- A21** Meteorological unit failure (Yes, No);
- A22** Lubrication failure (Yes, No);
- A23** Abnormal gear (Yes, No);
- A24** Bearings fault (Yes, No);
- A25** Tooth wear - gears (Yes, No);
- A26** Cracks in gears (Yes, No);
- A27** Offset of teeth gears (Yes, No);
- A28** Rotor and stator failure (Yes, No);
- A29** Bearing failure (Yes, No);
- A30** Abnormal signals (Yes, No);
- A31** No centricity generation (Yes, No);
- A32** Overheating (Yes, No);
- A33** Speed train failure (Yes, No);
- A34** Electric component failure (Yes, No);

**A35** Blades failure (Yes, No);  
**A36** Rotor failure (Yes, No);  
**S1** Support structure failure (Yes, No);  
**S2** Pitch system failure (Yes, No);  
**S3** Gearbox failure (Yes, No);  
**S4** Generator failure (Yes, No);  
**S5** Auxiliary system failure (Yes, No);  
**FOWTMalffunctions** Flowing offshore wind turbine malfunctions (Yes, No);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Li, H., Soares, C. G., & Huang, H. Z. (2020). Reliability analysis of a floating offshore wind turbine using Bayesian Networks. *Ocean Engineering*, 217, 107827.

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witness

*witness Bayesian Network*

---

**Description**

Measuring coherence with Bayesian networks.

**Format**

A discrete Bayesian modelling a situation where equally reliable witnesses try to identify a criminal. Probabilities were given within the referenced paper. The vertices are:

**W1SteveDidIt** Witness 1 report: Steve did it (True, False);  
**W2SteveDidIt** Witness 2 report: Steve did it (True, False);  
**W3SteveMartinOrDavidDidIt** Witness 3 report: Steve, Martin, or David did it (True, False);  
**W4SteveJohnOrJamesDidIt** Witness 4 report: Steve, John, or James did it (True, False);  
**W5SteveJohnOrPeterDidIt** Witness 5 report: Steve, John, or Peter did it (True, False);  
**WhoCommittedTheDeed** Who is the criminal (Steve, Martin, David, John, James, Peter);

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Kowalewska, A., & Urbaniak, R. (2023). Measuring coherence with Bayesian networks. *Artificial Intelligence and Law*, 31(2), 369-395.

**Description**

Towards system-theoretic risk management for maritime transportation systems: A case study of the yangtze river estuary.

**Format**

A discrete Bayesian network to determine the probabilities and consequences of accident scenarios in maritime transportation systems. Probabilities were given within the referenced paper (some inconsistencies in the numbers provided). The vertices are:

**AssessmentFailure** Assessment failure (Yes, No);

**AvoidanceRules** Strengthen the study of international maritime ship collision avoidance rules (Adopted, Unadopted);

**CautiousDriving** Cautious driving to keep lookout in the cautionary area of YRE (Adopted, Unadopted);

**Collision** Collision probability (Yes, No);

**CompetentCrew** Failure to have a competent crew (Yes, No);

**ConsequenceCollision** Collision consequence (Serious, Moderate, Minor);

**ConsequenceContact** Contact consequence (Serious, Moderate, Minor);

**ConsequenceSinking** Sinking consequence (Serious, Moderate, Minor);

**Contact** Contact probability (Yes, No);

**CrewTraining** Strengthen crew training on operation in narrow and crowded waters (Adopted, Unadopted);

**EarlyMeasures** Failure to take early measures (Yes, No);

**EquipmentFailure** Operation equipment failure (Yes, No);

**GrossTonnage** Gross tonnage (< 3000 tons, 3000-10000 tons, > 10000 tons);

**HardwareMaintenance** Strengthen ship hardware maintenance and management (Adopted, Unadopted);

**ImproperStowage** Improper stowage (Yes, No);

**InadequateCommunication** Inadequate communication (Yes, No);

**NegligentLookout** Negligent lookout (Yes, No);

**NoGiveWay** No give way (Yes, No);

**QualifiedCrew** Strengthen the supervision of competent crew according to law (Adopted, Unadopted);

**ResourceManagement** Enhance teamwork resource management training on the bridge (Adopted, Unadopted);

**SafetyTraining** Strengthening crew safety awareness training (general) (Adopted, Unadopted);

- ShipAge** Ship age (<10 years, 10-20 years, > 20 years);
- ShipTracking** Strengthen ship tracking management (Adopted, Unadopted);
- ShipType** Ship type (Carrier/Container, Tanker, Other ship);
- Sinking** Sinking probability (Yes, No);
- SupervisingCompanies** Strengthen the inspection of the effectiveness of safety management of supervising shipping companies (Adopted, Unadopted);
- SupervisionVessel** Strengthen the supervision of inland river vessel companies by the YRE port and navigation department (Adopted, Unadopted);
- TrafficFlow** Traffic flow (Heavy, NormalOrLow);
- UnsafeSpeed** Unsafe speed (Yes, No);
- Visibility** Visibility (Poor, Good);
- Wind** Wind ( $\geq$  Category 5, < Category 5).

**Value**

An object of class `bn.fit`. Refer to the documentation of `bnlearn` for details.

**References**

Fu, S., Gu, S., Zhang, Y., Zhang, M., & Weng, J. (2023). Towards system-theoretic risk management for maritime transportation systems: A case study of the yangtze river estuary. *Ocean Engineering*, 286, 115637.

# Index

- \* **CLGBN**
  - algorithms5, 22
  - algorithms6, 23
  - covidtest, 73
  - darktriad, 84
  - healthinsurance, 125
- \* **Datasets**
  - bnRep\_summary, 36
- \* **GBN**
  - algal2, 17
  - algorithms1, 19
  - algorithms2, 20
  - building, 41
  - cachexia1, 44
  - cachexia2, 44
  - diagnosis, 85
  - expenditure, 104
  - foodsecurity, 115
  - lexical, 135
  - liquefaction, 137
  - parkinson, 159
  - stocks, 196
  - suffocation, 200
  - turbine1, 207
  - turbine2, 208
- \* **KDep**
  - mountaingoat, 145
- \* **NaiveBayes**
  - accidents, 7
  - adhd, 8
  - agropastoral5, 15
  - bankruptcy, 30
  - burglar, 43
  - concrete6, 57
  - covid1, 67
  - enrollment, 102
  - moodstate, 144
  - perioperative, 160
  - softwarelogs3, 190
  - theft1, 203
  - witness, 220
- \* **ReverseNaiveBayes**
  - beatles, 32
  - hydraulicsystem, 127
  - medicaltest, 142
  - metal, 144
  - simulation, 188
  - soilliquefaction1, 193
  - wheat, 216
- \* **ReverseTree**
  - beam1, 30
  - beam2, 31
  - BOPfailure1, 37
  - BOPfailure2, 38
  - BOPfailure3, 40
  - cng, 50
  - compaction, 53
  - curacao1, 79
  - curacao2, 80
  - curacao3, 81
  - curacao4, 82
  - curacao5, 83
  - dragline, 91
  - drainage, 93
  - ecosystem, 97
  - electricvehicle, 98
  - fluids2, 111
  - gasifier, 118
  - gonorrhoeae, 122
  - lithium, 139
  - megacities, 142
  - navigation, 150
  - oildepot, 152
  - pilot, 162
  - polymorphic, 167
  - propellant, 172
  - rockquality, 180
  - ropesegment, 181

- shipping, 186
- soilliquefaction2, 194
- soilliquefaction4, 196
- suffocation, 200
- tuberculosis, 207
- \* **TAN**
  - bullet, 42
  - coral1, 61
  - coral2, 62
  - coral3, 62
  - coral4, 63
  - coral5, 64
  - covid2, 68
  - dioxins, 86
  - rainwater, 176
  - rockburst, 180
  - safespeeds, 182
  - waterlead, 214
- \* **Tree**
  - chds, 49
  - concrete3, 55
  - concrete4, 56
  - concrete5, 57
  - concrete7, 58
  - nanomaterials1, 146
  - nanomaterials2, 148
  - orbital, 156
  - sallyclark, 183
  - theft2, 204
- .onAttach, 6
- accidents, 7
- adhd, 8
- adversarialbehavior, 9
- aerialvehicles, 9
- agropastoral1, 11
- agropastoral2, 12
- agropastoral3, 13
- agropastoral4, 14
- agropastoral5, 15
- aircrash, 16
- algal1, 16
- algal2, 17
- algalactivity1, 18
- algalactivity2, 19
- algorithms1, 19
- algorithms2, 20
- algorithms3, 21
- algorithms4, 21
- algorithms5, 22
- algorithms6, 23
- APSystem, 23
- arcticwaters, 24
- argument, 26
- asia, 27
- aspergillus, 27
- augmenting, 28
- bank, 29
- bankruptcy, 30
- beam1, 30
- beam2, 31
- beatles, 32
- blacksea, 32
- blockchain, 34
- bnRep, 35
- bnRep\_app, 36
- bnRep\_summary, 36
- BOPfailure1, 37
- BOPfailure2, 38
- BOPfailure3, 40
- building, 41
- bullet, 42
- burglar, 43
- cachexia1, 44
- cachexia2, 44
- cardiovascular, 45
- case, 46
- catchment, 47
- charleston, 48
- chds, 49
- cng, 50
- compaction, 53
- conasense, 53
- concrete1, 54
- concrete2, 55
- concrete3, 55
- concrete4, 56
- concrete5, 57
- concrete6, 57
- concrete7, 58
- consequenceCovid, 59
- constructionproductivity, 60
- coral1, 61
- coral2, 62
- coral3, 62
- coral4, 63



- coral5, 64
- corical, 65
- corrosion, 66
- corticosteroid, 67
- covid1, 67
- covid2, 68
- covid3, 69
- covidfear, 70
- covidrisk, 71
- covidtech, 71
- covidtest, 73
- crimescene, 74
- criminal1, 75
- criminal2, 76
- criminal3, 77
- criminal4, 77
- crypto, 78
- curacao1, 79
- curacao2, 80
- curacao3, 81
- curacao4, 82
- curacao5, 83
  
- darktriad, 84
- diabetes, 85
- diagnosis, 85
- dioxins, 86
- disputed1, 87
- disputed2, 88
- disputed3, 89
- disputed4, 90
- dragline, 91
- drainage, 93
- dustexplosion, 94
  
- earthquake, 95
- ecosystem, 97
- electricvehicle, 98
- electrolysis, 99
- emergency, 100
- engines, 101
- enrollment, 102
- estuary, 102
- expenditure, 104
  
- fingermarks1, 105
- fingermarks2, 106
- fire, 107
- firealarm, 108
  
- firerisk, 108
- flood, 109
- fluids1, 111
- fluids2, 111
- fluids3, 112
- foodallergy1, 113
- foodallergy2, 114
- foodallergy3, 114
- foodsecurity, 115
- fundraising, 116
  
- gasexplosion, 117
- gasifier, 118
- GDIpathway1, 119
- GDIpathway2, 121
- get\_network\_list, 122
- gonorrhoeae, 122
- greencredit, 123
- grounding, 124
  
- healthinsurance, 125
- humanitarian, 126
- hydraulicsystem, 127
  
- income, 128
- intensification, 129
- intentionalattacks, 130
- inverters, 130
  
- knowledge, 132
- kosterhavet, 132
  
- lawschool, 134
- lexical, 135
- lidar, 136
- liquefaction, 137
- liquidity, 138
- lithium, 139
- load\_network, 140
  
- macrophytes, 141
- medicaltest, 142
- megacities, 142
- metal, 144
- moodstate, 144
- mountaingoat, 145
  
- nanomaterials1, 146
- nanomaterials2, 148
- navigation, 150

nuclearwaste, 150  
nuisancegrowth, 151

oildepot, 152  
onlinerisk, 154  
orbital, 156  
oxygen, 157

parkinson, 159  
perioperative, 160  
permaBN, 161  
phdarticles, 162  
pilot, 162  
pneumonia, 164  
polymorphic, 167  
poultry, 168  
project, 170  
projectmanagement, 171  
propellant, 172

rainstorm, 174  
rainwater, 176  
redmeat, 176  
resilience, 177  
ricci, 179  
rockburst, 180  
rockquality, 180  
ropesegment, 181

safespeeds, 182  
sallyclark, 183  
salmonella1, 184  
salmonella2, 184  
seismic, 185  
shipping, 186  
simulation, 188  
softwarelogs1, 188  
softwarelogs2, 189  
softwarelogs3, 190  
softwarelogs4, 191  
soil, 192  
soillead, 193  
soilliquefaction1, 193  
soilliquefaction2, 194  
soilliquefaction3, 195  
soilliquefaction4, 196  
stocks, 196  
student1, 197  
student2, 199

suffocation, 200

tastingtea, 202  
tbn, 203  
theft1, 203  
theft2, 204  
titanic, 205  
trajectories, 205  
transport, 206  
tuberculosis, 207  
turbine1, 207  
turbine2, 208  
twinframework, 210

urinary, 210

vaccine, 212  
vessel1, 212  
vessel2, 213

waterlead, 214  
wheat, 216  
windturbine, 216  
witness, 220

yangtze, 221