Explanation Capabilities of Bayesian Networks in Dynamic Industrial Domains

Concha Bielza, Pedro Larrañaga

Computational Intelligence Group
Departamento de Inteligencia Artificial
Universidad Politécnica de Madrid

ECAI-2023 Workshop “XAI for Industry 4.0 & 5.0”
Krakóv - October 1, 2023

Outline

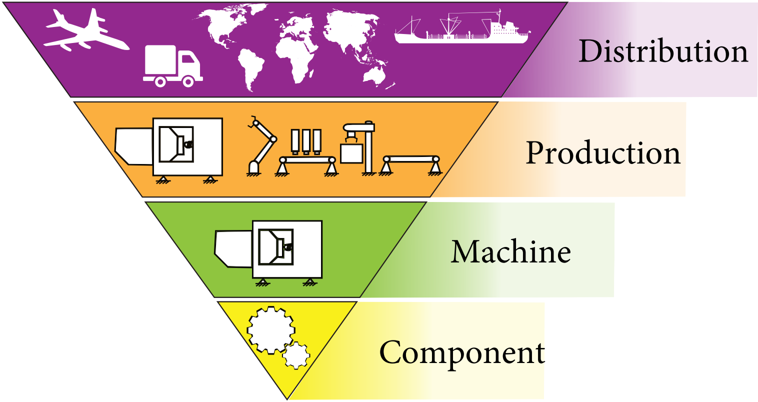
Outline

Industrial ecosystems according to the EC

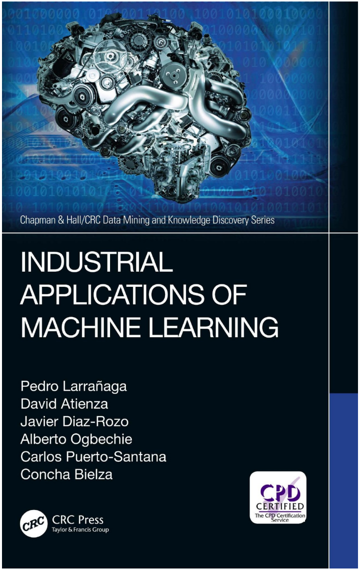
Types of industries

Industry	Define	Examples
Primary	Exploit natural resources and produce raw materials.	Mining, farming
Secondary	Process raw materials and manufacture and finished goods	Production of cars, food, and clothes
Tertiary	Distribute goods and provide services	Supermarkets, hairdressing, travel agents
Quaternary	Information-based services	Teaching, journalism, banking
Quinary	Decision making, Household services	Carpet cleaning, child care, restaurants

Levels

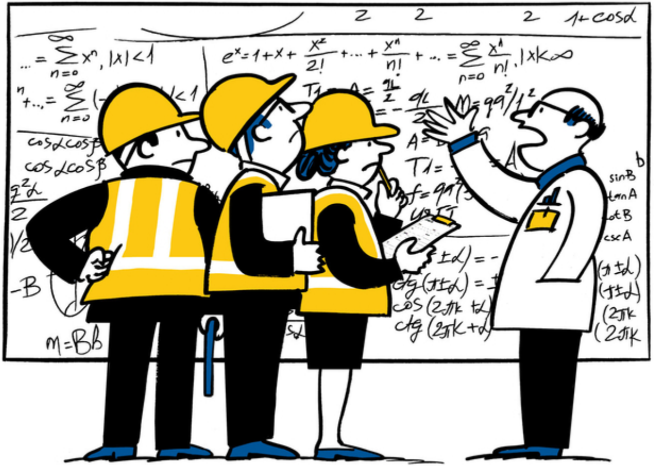


Book: CRC Press. 2019

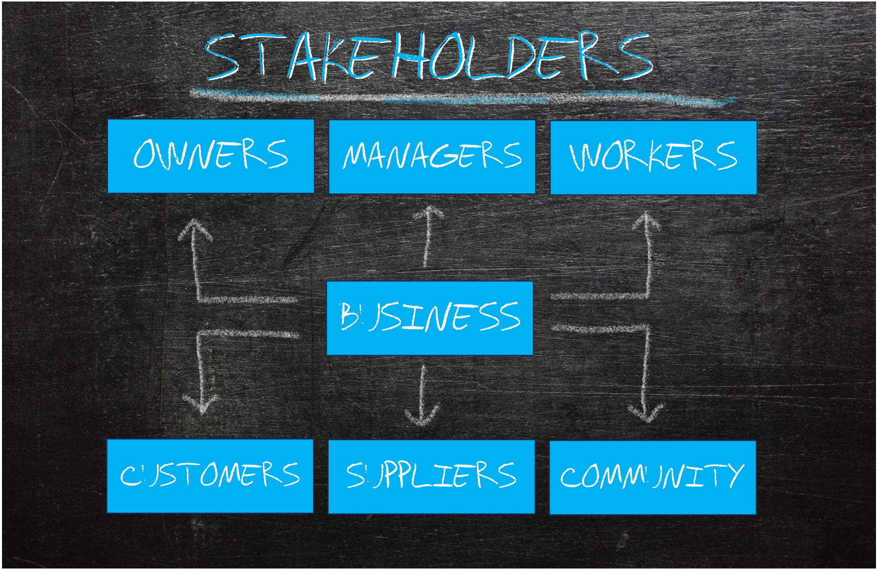


Explanations to...

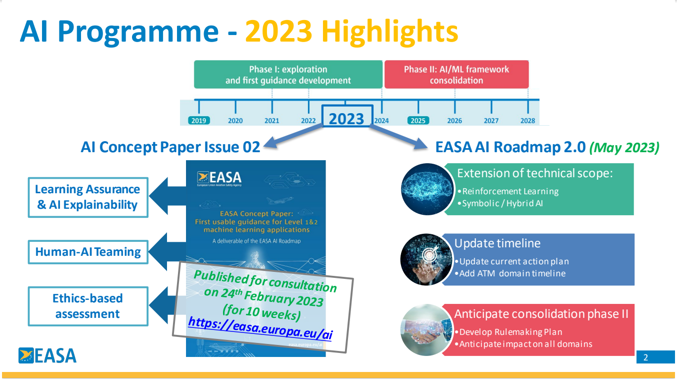
justify, understand, discover, robustness, bias, improvement, transferability, human comprehensibility

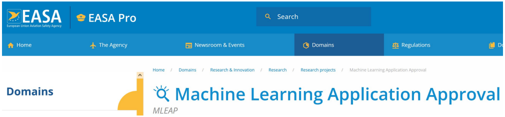


Stakeholders

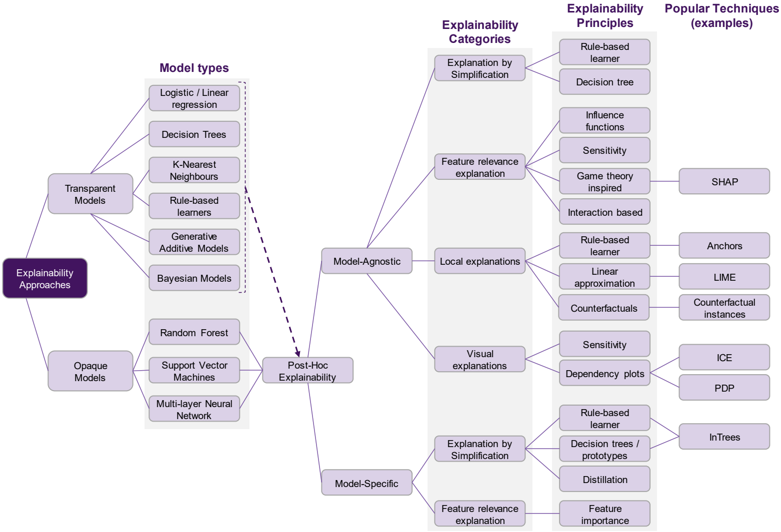


Regulation of AI devices in industry





Taxonomy of XAI approaches (Belle and Papantonis, 2021)

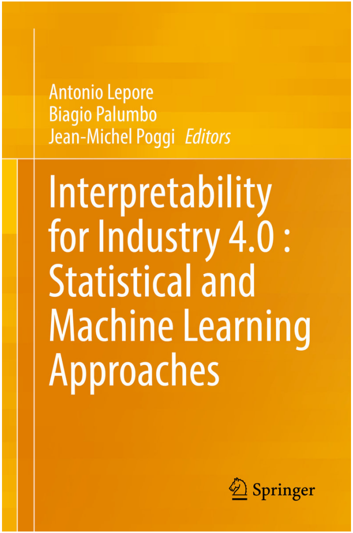


Interpretability (Lipton, 2016)

Human in the loop

- Interpretability stands for a human-level understanding of the inner working of the model
  - Simulatability: model ability to be simulated by a human. Simplicity alone is not enough (e.g., very large amount of simple rules). At the level of the entire model
  - Decomposability: ability to break down a model into parts and then interpret them. At the level of individual components
  - Algorithmic transparency: ability to understand the procedure the model goes through to generate its output. At the level of the training algorithm

Literature



2022

Literature

Journal of Intelligent Manufacturing (2023) 34:57–83
https://doi.org/10.1007/s10845-021-01903-y

Data-driven dynamic causality analysis of industrial systems using interpretable machine learning and process mining

Karim Nadim[1,2] · Ahmed Ragab[1,2,3] · Mohamed-Salah Ouali[1]

Computers and Chemical Engineering 152 (2021) 107381

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

ELSEVIER

Adding interpretability to predictive maintenance by machine learning on sensor data

Bram Steurtewagen, Dirk Van den Poel*

Process Safety and Environmental Protection 170 (2023) 647–659

Contents lists available at ScienceDirect

Process Safety and Environmental Protection

journal homepage: www.journals.elsevier.com/process-safety-and-environmental-protection

ELSEVIER

Review of interpretable machine learning for process industries

A. Carter[a], S. Imtiaz[a,*], G.F. Naterer[b]

Human Factors in Model Interpretability: Industry Practices, Challenges, and Needs

SUNGSOO RAY HONG, New York University, USA
JESSICA HULLMAN, Northwestern University, USA
ENRICO BERTINI, New York University, USA

Proc. ACM Hum.-Comput. Interact., Vol. 4, No. CSCW1, Article 68. Publication date: May 2020.

Technological Forecasting & Social Change 183 (2022) 121940

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

ELSEVIER

Towards expert–machine collaborations for technology valuation: An interpretable machine learning approach

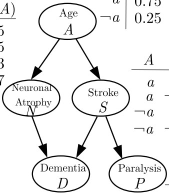
Juram Kim[a], Gyumin Lee[b], Seungbin Lee[c], Changyong Lee[d,*]

Outline

Bayesian networks

Probabilistic graphical models

- Directed acyclic graph
- $p(X_1, \ldots, X_n) = \prod_{i=1}^{n} p(X_i \mid \mathbf{Pa}(X_i))$
- Conditional independence: **W** and **T** are conditionally independent given **Z** $\Leftrightarrow p(\mathbf{W}|\mathbf{T},\mathbf{Z}) = p(\mathbf{W}|\mathbf{Z})$



A	$p(A)$
a	0.75
$\neg a$	0.25

A	N	$p(N\|A)$
a	n	0.15
a	$\neg n$	0.85
$\neg a$	n	0.03
$\neg a$	$\neg n$	0.97

A	S	$p(S\|A)$
a	s	0.10
a	$\neg s$	0.90
$\neg a$	s	0.02
$\neg a$	$\neg s$	0.98

N	S	D	$p(D\|N,S)$
n	s	d	0.96
n	s	$\neg d$	0.04
n	$\neg s$	d	0.40
n	$\neg s$	$\neg d$	0.60
$\neg n$	s	d	0.45
$\neg n$	s	$\neg d$	0.55
$\neg n$	$\neg s$	d	0.10
$\neg n$	$\neg s$	$\neg d$	0.90

S	P	$p(P\|S)$
s	p	0.75
s	$\neg p$	0.25
$\neg s$	p	0.05
$\neg s$	$\neg p$	0.95

$p(A, N, S, D, P) = p(A)p(N|A)p(S|A)p(D|N,S)p(P|S)$

Bayesian networks

Probabilistic graphical models

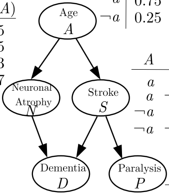
- Directed acyclic graph
- $p(X_1, \ldots, X_n) = \prod_{i=1}^{n} p(X_i \mid \mathbf{Pa}(X_i))$
- Conditional independence: **W** and **T** are conditionally independent given **Z** $\Leftrightarrow p(\mathbf{W}|\mathbf{T},\mathbf{Z}) = p(\mathbf{W}|\mathbf{Z})$

Inference

- Exact: variable elimination, message passing
- Approximate: sequential simulation and MCMC

A	$p(A)$
a	0.75
$\neg a$	0.25

A	N	$p(N\|A)$
a	n	0.15
a	$\neg n$	0.85
$\neg a$	n	0.03
$\neg a$	$\neg n$	0.97

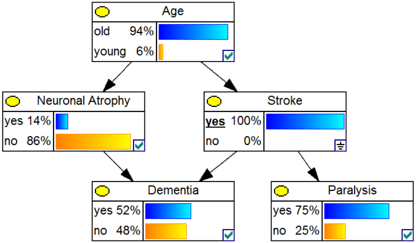


A	S	$p(S\|A)$
a	s	0.10
a	$\neg s$	0.90
$\neg a$	s	0.02
$\neg a$	$\neg s$	0.98

N	S	D	$p(D\|N,S)$
n	s	d	0.96
n	s	$\neg d$	0.04
n	$\neg s$	d	0.40
n	$\neg s$	$\neg d$	0.60
$\neg n$	s	d	0.45
$\neg n$	s	$\neg d$	0.55
$\neg n$	$\neg s$	d	0.10
$\neg n$	$\neg s$	$\neg d$	0.90

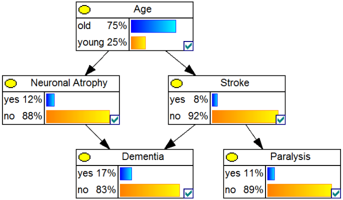
S	P	$p(P\|S)$
s	p	0.75
s	$\neg p$	0.25
$\neg s$	p	0.05
$\neg s$	$\neg p$	0.95

$$p(A, N, S, D, P) = p(A)p(N|A)p(S|A)p(D|N, S)p(P|S)$$

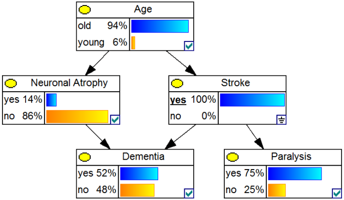


$p(X_i|\texttt{Stroke=yes})$

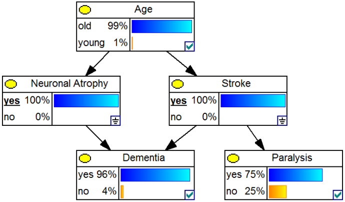
Conditional independence



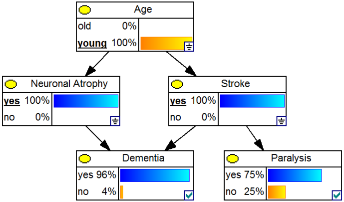
$p(X_i)$



$p(X_i|\texttt{Stroke=yes})$



$p(X_i|\texttt{Stroke=yes, Neural Atrophy=yes})$

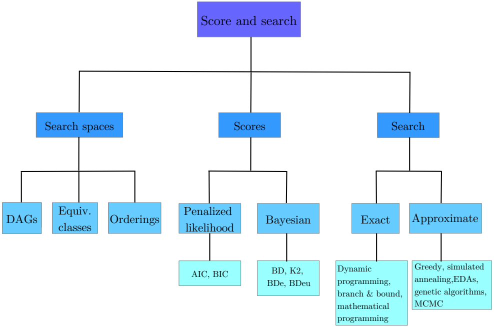


$p(X_i|\texttt{Stroke=yes, Neural Atrophy=yes, Age=young})$

Learning BNs from data

STRUCTURE LEARNING

1. Detecting conditional independencies between triples of variables by hypothesis tests
2. Score and search methods



PARAMETER LEARNING: $p(X_i = x_i \mid \mathbf{Pa}(X_i) = \mathbf{pa}_i^j)$

1. Maximum likelihood estimation
2. Bayesian estimation

Machine learning and Bayesian networks

MACHINE LEARNING

Multi-output regression

- Problem transformation methods
  - Single-target method
  - Multi-target regressor stacking
  - Regressor chains
- Algorithm adaptation methods
  - Multi-output suppor vector regression
  - Kernel methods
  - Multi-target regression trees
  - Rule method
  - Gaussian Bayesian networks

Clustering

- Non-probabilistic
  - Hierarchical
    - Agglomerative
    - Divisive
  - Partitional
    - K-means
    - K-medians
    - K-modes
    - Fuzzy C-means
    - Self-organizing map
    - Spectral clustering
    - K-medoids
    - Affinity propagation
    - K-plane clustering
    - Fuzzy C-shell
    - DBSCAN
- Probabilistic
  - Finite-mixture models
  - Bayesian networks

Multiview-clustering

- Agglomerative clustering
- Density-based
- Principal component analysis
  - Canonical correlation analysis
- Spectral clustering
- Co-regularization
- Ensemble clustering
- Bayesian networks

Feature subset selection

- Filter approaches
  - Univariate filters
  - Multivariate filters
- Wrapper methods
  - Bayesian networks-based EDAs
- Embedded methods
- Hybrid methods

Supervised classification

- Non-probabilistic
  - Nearest neighbors
  - Classification trees
  - Rule induction
  - Artificial neural networks
  - Support vector machines
- Probabilistic
  - Discriminant analysis
  - Logistic regression
  - Bayesian network classifiers
- Metaclassifiers
  - Fusion of outputs
  - Stacked generalization
  - Cascading
  - Bagging
  - Random forest
  - Boosting
  - Hybrid classifiers

Discovery associations

- Association rules
- Bayesian networks

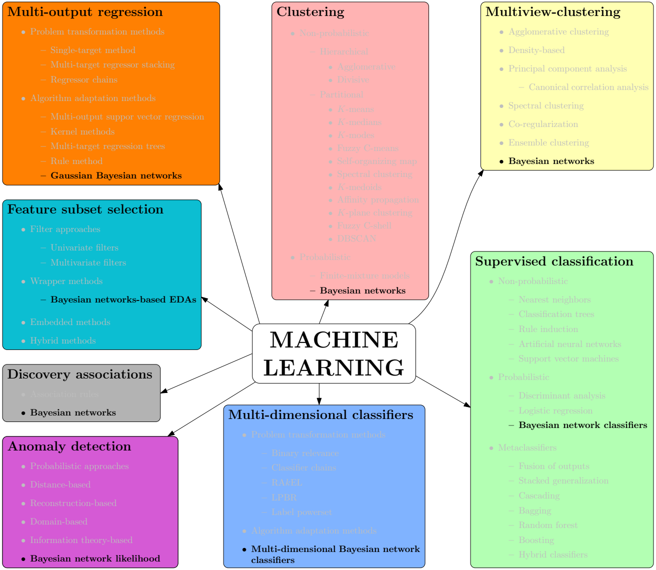
Anomaly detection

- Probabilistic approaches
- Distance-based
- Reconstruction-based
- Domain-based
- Information theory-based
- Bayesian network likelihood

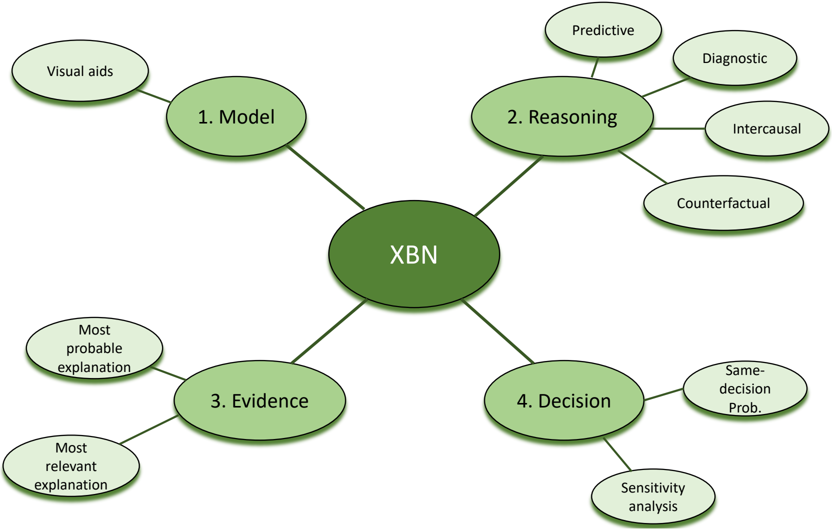
Multi-dimensional classifiers

- Problem transformation methods
  - Binary relevance
  - Classifier chains
  - RAkEL
  - LPBR
  - Label powerset
- Algorithm adaptation methods
- Multi-dimensional Bayesian network classifiers

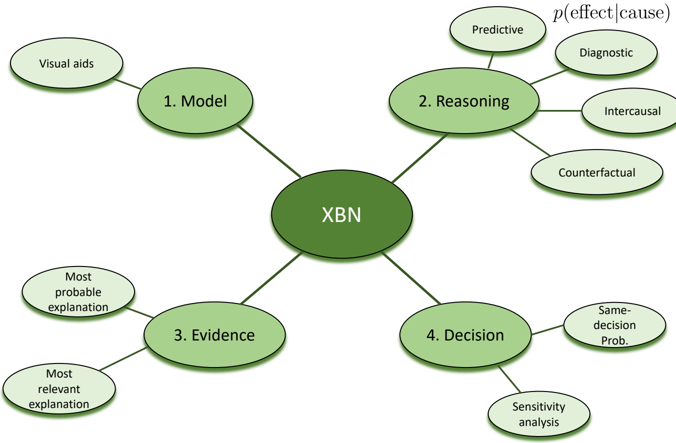
Machine learning and Bayesian networks



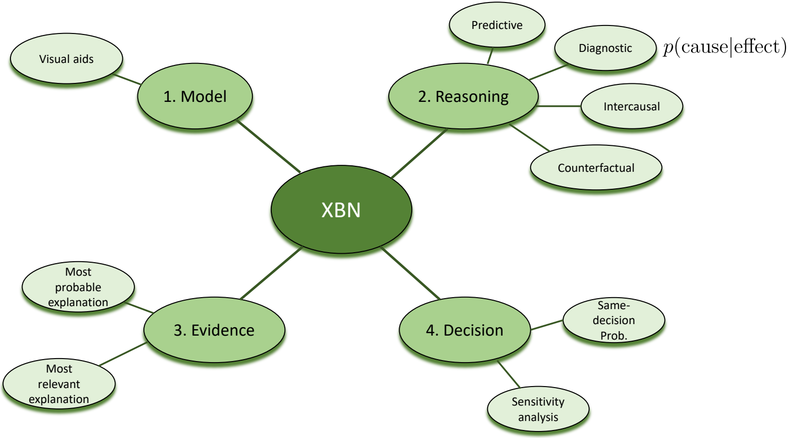
Explainability with Bayesian networks (XBN)



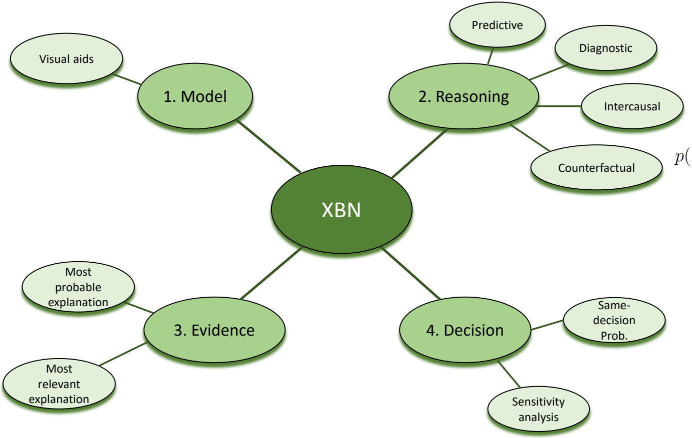
Explainability with Bayesian networks (XBN)

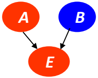


Explainability with Bayesian networks (XBN)



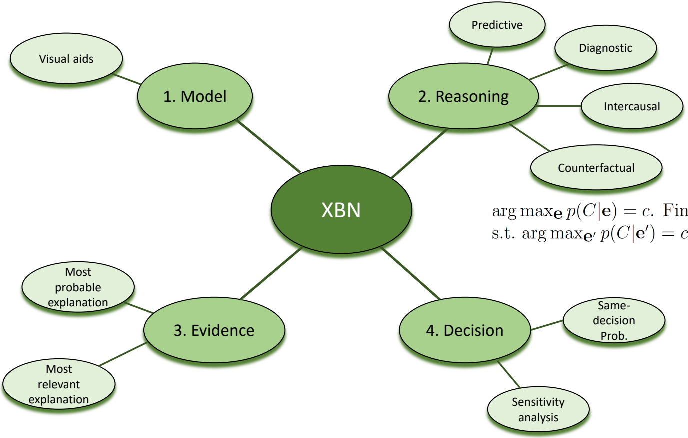
Explainability with Bayesian networks (XBN)





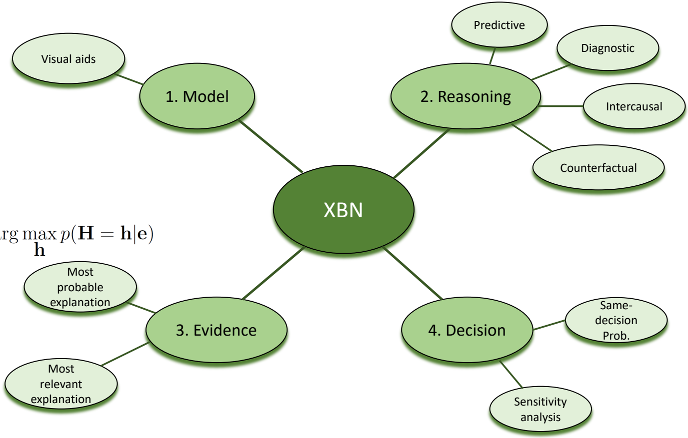
$p(B|A = a, E = e)$

Explainability with Bayesian networks (XBN)



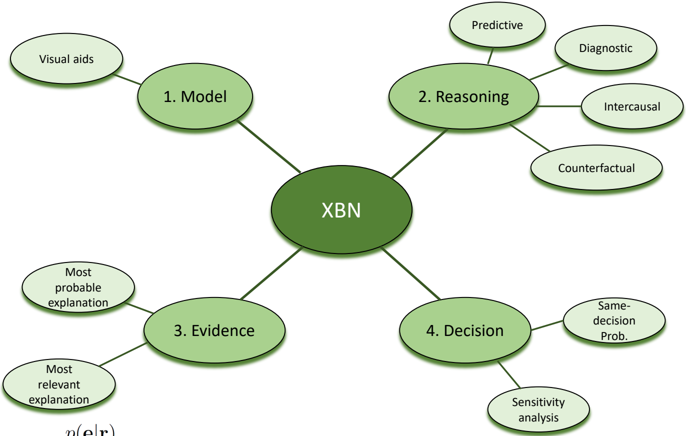
$\arg\max_{\mathbf{e}} p(C|\mathbf{e}) = c$. Find $\mathbf{e}' \approx \mathbf{e}$
s.t. $\arg\max_{\mathbf{e}'} p(C|\mathbf{e}') = c' \neq c$

Explainability with Bayesian networks (XBN)



$$\mathbf{h}^* = \arg\max_{\mathbf{h}} p(\mathbf{H} = \mathbf{h}|\mathbf{e})$$

Explainability with Bayesian networks (XBN)

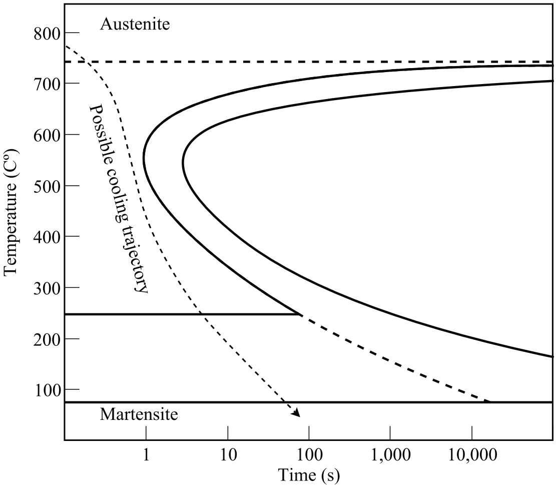


$$\mathbf{r}^* = \arg\max_{\mathbf{r}} \frac{p(\mathbf{e}|\mathbf{r})}{p(\mathbf{e}|\neg\mathbf{r})}, \quad \mathbf{R} \subset \mathbf{H}$$

Outline

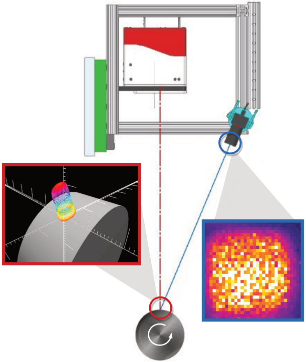
Quenching with laser

Larrañaga,..., Bielza (2019)

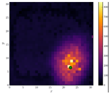


TTT curve with a possible cooling trajectory of a hardening process

Quenching with laser



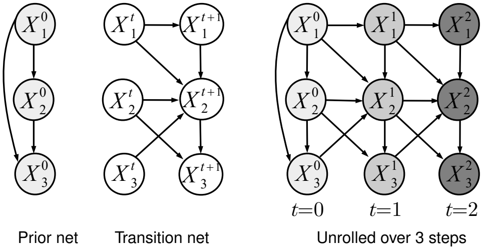
- Laser beams are able to heating small and localized areas
- High-speed thermal cameras
- One full rotation of the surface of each crankshaft took 21.5 seconds (sequences of 21,500 frames)



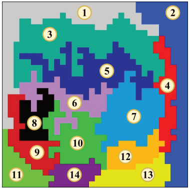
Quenching with laser: dynamic Bayesian networks

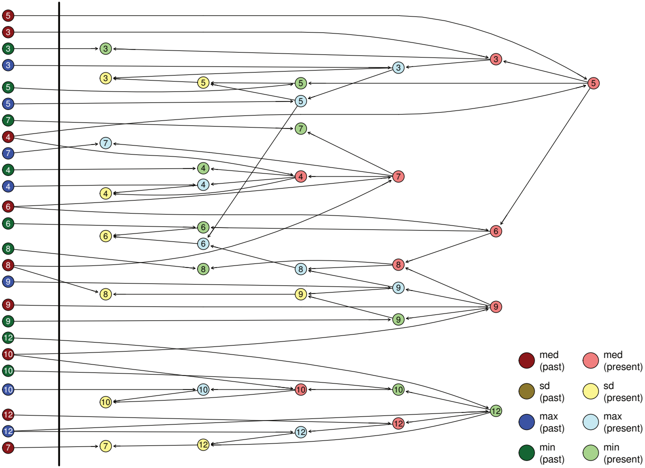
Factorization

- Discretize timeline into a set of time slices, regularly spaced (predetermined granularity)
- Value of each variable at time $t_0 = 0, t_0 + \Delta, t_0 + 2\Delta, ..., T$
- Transition arcs forward in time, arcs within a slice
- $p(\mathbf{X}^0, ..., \mathbf{X}^T) = \underbrace{p(\mathbf{X}^0)}_{\text{initial distribution}} \prod_{t=1}^{T} \underbrace{p(\mathbf{X}^t \mid \mathbf{X}^{0:t-1})}_{\text{transition net}} = p(\mathbf{X}^0) \prod_{t=1}^{T} \underbrace{p(\mathbf{X}^t \mid \mathbf{X}^{t-1})}_{\text{Markovian order 1}}$ unrolled BN
- Stationary



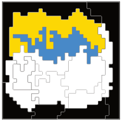
Quenching with laser: transition network



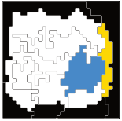


Vertical line separates the past and the present frames

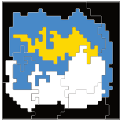
Quenching with laser: Markov blanket of each region



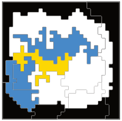
Region 3



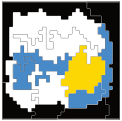
Region 4



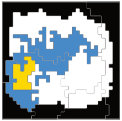
Region 5



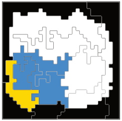
Region 6



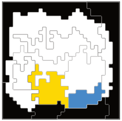
Region 7



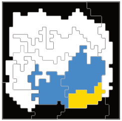
Region 8



Region 9

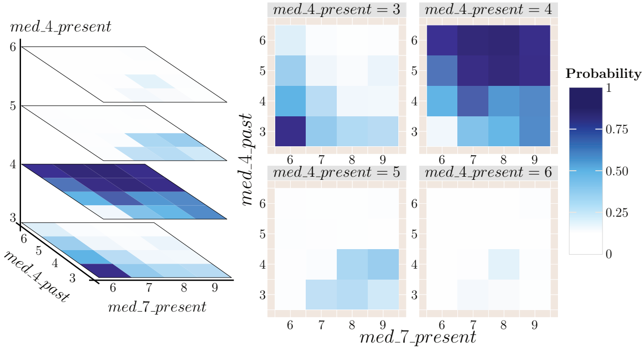


Region 10



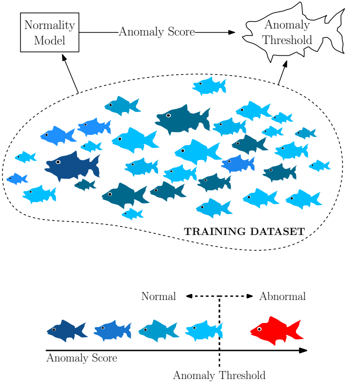
Region 12

Quenching with laser: conditional probability tables



Values of $p(\text{Reg4}^t|\text{Reg7}^t, \text{Reg4}^{t-1})$

Quenching with laser: anomaly detection by likelihood



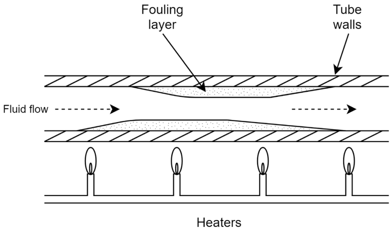
1. Estimate a probabilistic model (based on dynamic Bayesian networks) from the normal instances
2. Establish a threshold in this joint probability distribution
3. Compare the likelihood of the new instance with the likelihood threshold

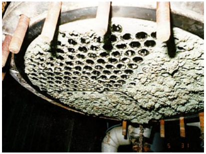
- Why this anomaly? $\Rightarrow$ Likelihood decomposition
- Can we generate synthetic anomalies? Defect in the laser power supply unit, camera sensor wear...

Outline

Fouling in industrial furnaces

Quesada, Valverde, Larrañaga, Bielza (2021)

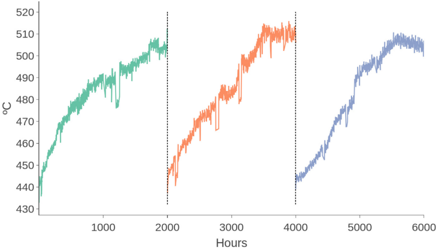




Impurities deposited

Clean tubes periodically

In the tubes, preheat the oil before entering the furnace

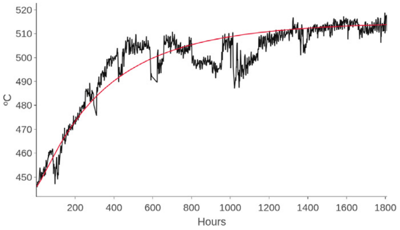


iid trayectories (cycles) to learn (different lengths)

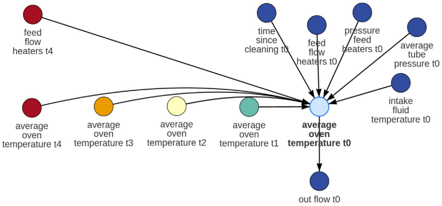
Predict temperature to be provided to the walls as the fouling evolves, specially in the long term ($T = 2000$h)

- And so help operators when the next cleaning
- 5 years ($\sim$2.7 months), 20 cycles ($\sim$2000h), hourly data (43,415h)
- 35 variables: physical properties (pressure, temperatures, feed flow heaters...) from sensors

Fouling in industrial furnaces



Predictions of a test cycle (red)
$p(X^{t+h}|\mathbf{e}^{0:t})$



DGBN (order 4)

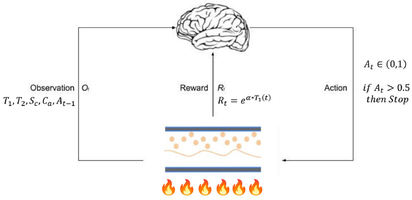
- D(Gaussian)BNs, different Markovian orders
- Simulate scenarios (effect of some X_i on the target)
- dbnR package, with visualization tool

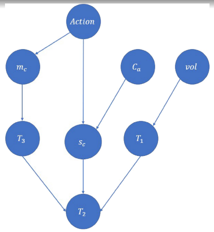
Other inferences

- $p(X^t|\mathbf{e}^{0:t})$ (filtering)
- $p(X^{t-h}|\mathbf{e}^{0:t})$ (smoothing)

Fouling: with actions

Valverde, Quesada, Larrañaga, Bielza (2023)





Reinforcement learning

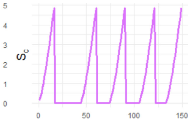
- Policy based on a Bayesian network

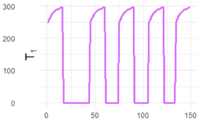
Two options of Bayesian networks

1. Ordinary differential equations + Action node
2. Partial expert knowledge + rest learned from data

- In 1 and 2, BN parameter adaptation based on the reward function and likelihood

Validation: Set different scenarios by varying some inputs of the ordinary differential equations

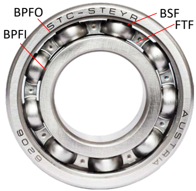




Outline

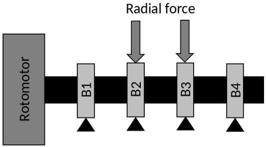
Ball-bearing degradation

Puerto-Santana, Larrañaga, Bielza (2022a)



Real bearing

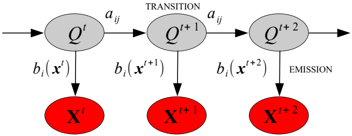
https://www.electricmotorengineering.com/



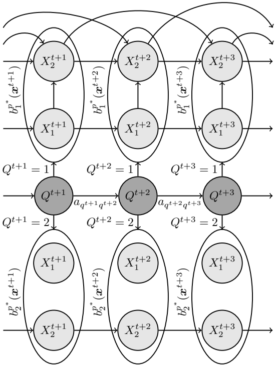
Setup; until one fails (Qian et al., 2017)

- Vibrational sensors → signals → filtered signals → Fourier transform → 4 fundamental frequencies related to typical bearing defects in its components (inner/outer rings, rollers and cage). 20 kHz
- Observed variables: ball pass frequency outer (BPFO), inner (BPFI), ball spin frequency (BSF), fundamental train frequency (FTF)

Ball-bearing degradation: hidden Markov models



Hidden Markov model



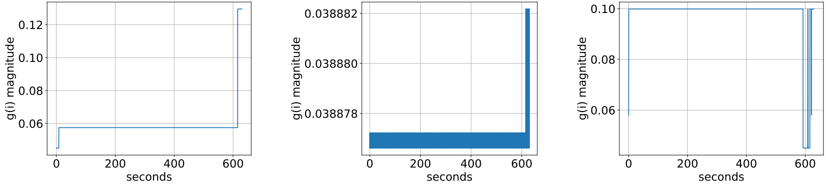
Autoregressive asymmetric linear Gaussian HMM

Puerto-Santana et al (2022b, 2022c, 2023)

- Hidden state = bearing health state

Ball-bearing degradation: results

- At B3: “Viterbi path” $\{Q^t\}$ for explaining the evidence. Interpretable?
- Rather, map $g(i) : Q \to \mathbb{R}$ depending on the model parameters (automatic numerical labeling). In this case, g adds the mean magnitudes of all variables

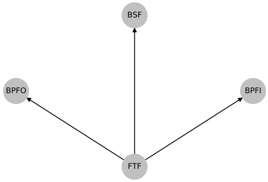


Our model (✓) LMSAR (✓) Naive-HMM (inconsistent)

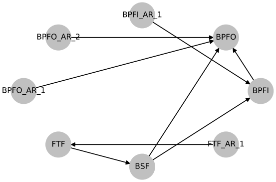
- ✓ = expected behavior; but LMSAR has insignificant differences in g values

Ball-bearing degradation: results

- Interpret the state-specific Gaussian BNs:



(a) BN given healthy bearings



(b) BN given a bad health

(a) cage frequencies (FTF) determine the remaining variables;

(b) more complex, with other relationships and AR (impact of the past)

Outline

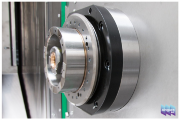
Machine-tool condition monitoring

Diaz-Rozo, Bielza, Larrañaga (2020)

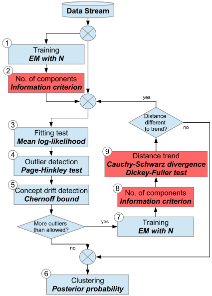
- A machine-tool that produces engine crankshafts at high speed
- 31 machining cycles (crankshafts). 30 s and 3000 instances each
- Variables: angular speed, temperature, power, and torque, taken from each of the two spindle heads of the machine

(a) Crankshaft machine-tool

(b) Crankshaft (credit: Abilene Machine (CC BY 2.0))

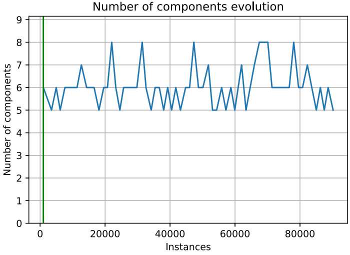


(c) Spindle head

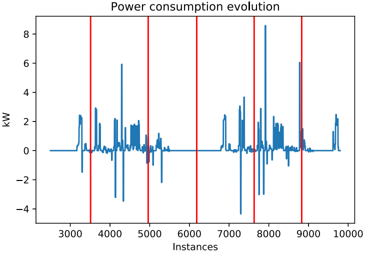


- Multivariate Gaussian mixture model: $f(\mathbf{x}, \boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k f_k(\mathbf{x}; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$, with f_k a Gaussian
- K can change

Machine-tool condition monitoring: results



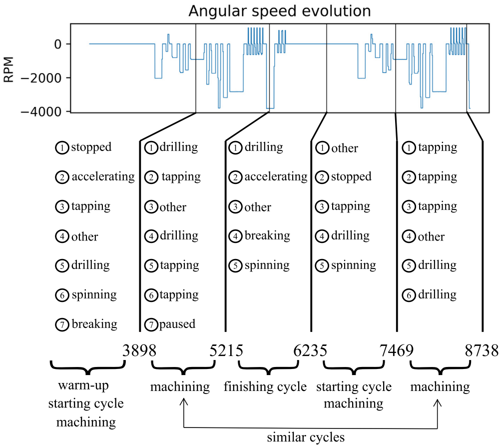
(a) $N = 1000$



(b) Concept drifts location ($N = 1000$)

- N is the window length used for training

Machine-tool condition monitoring: interpretation



First:

Component	Rule	Number of instances
1	Power $\neq 0$ W Temperature $\in [34.12, 34.16]$ °C ** Torque ≈ 0 N m ** Angular speed ≈ 0 RPM	359
2	--> Temperature ≈ 34.2 °C Torque > 0 N m Angular speed $\geqslant 85.6$ RPM	339
3	Power $\neq 0$ W --> Temperature $\in [34.12, 34.16]$ °C Torque $\in [0.23, 0.31]$ N m and $[-0.12, -1.03]$ N m	374
4	Other	1717
5	Power $\geqslant 0$ --> Temperature $\in [34.14 - 34.25]$ °C Torque $\geqslant 0.26$ N m	42
6	--> Temperature ≈ 34.2 °C Torque ≈ 0 N m	305
7	--> Temperature ≈ 34.2 °C Torque $\geqslant -0.20$ N m $\wedge$ Angular speed $\leqslant -57.12$ RPM	745

Third:

1	Angular speed $\neq 3820$ RPM	10
2	Power $\leqslant 0.16$ W Angular speed $\leqslant -3820$ RPM	20
3	Other	936
4	Temperature $\leqslant 36.0$ °C Angular speed $\leqslant -3819$ RPM	32
5	Angular speed ≈ -3819 RPM	18

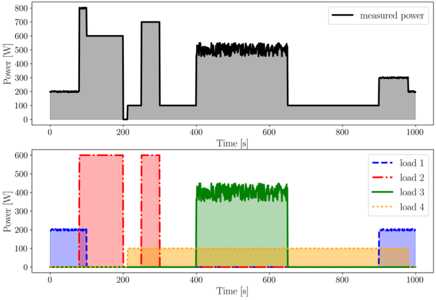
- Interpret clusters: for insights into machining process and evolution
- Cluster number as the class variable to induce a set of rules (RIPPER)

Outline

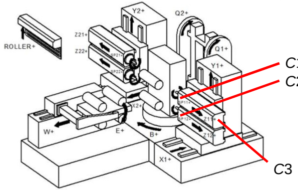
Energy disaggregation

Villa-Blanco, Larrañaga, Bielza (2021)

▶ Identify the operation of individual motors by using the aggregate power consumption



Brucke et al. (2020)

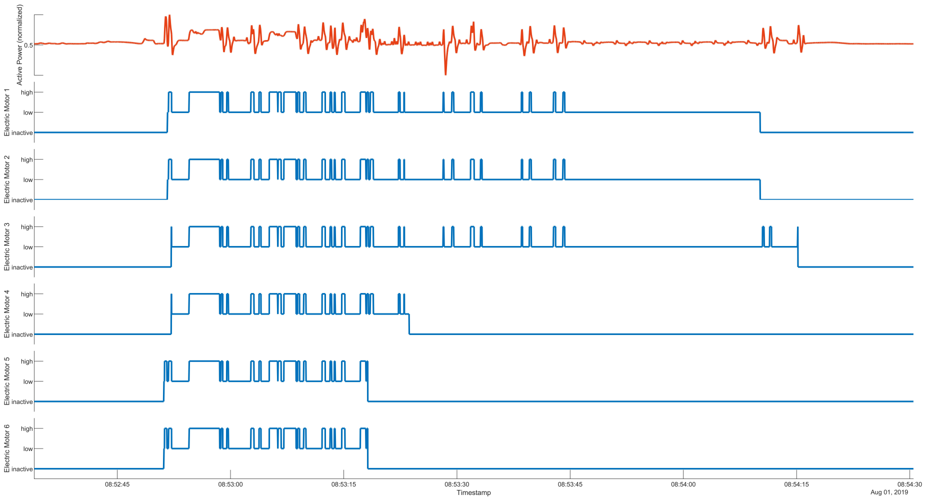


video

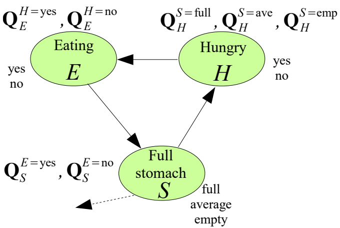
- Electrical measurements from an industrial machine working in a real environment (high power consumers)
- Variables: intensity (I), voltage (V), active power (P), reactive power (Q), and apparent power (S), observed at 500Hz and discretized into 30 states (equal width) $\times 3$ (3-phase motors, A, B, C) $\rightarrow$ 15 variables
- Classify the power consumption state (high/low/inactive) of each motor $C1$-$C6$ (6 classes), by using the energy consumption of the machine as a whole
- Physical relations: $C1$-$C2$, $C5$-$C6$ work together on similar tasks. $C3$ and $C4$ work synchronously with the motor pairs $C1/C2$ and $C5/C6$, respectively

Energy disaggregation: datasets

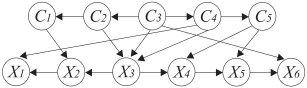
- 15 datasets. Training sequences all last 0.3 s (needs of the company); 150 obs/seq



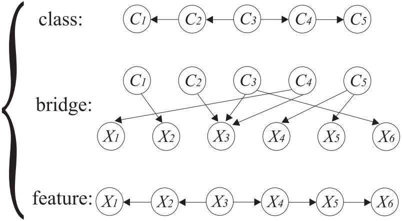
Energy disaggregation: Multi-CTBNCs



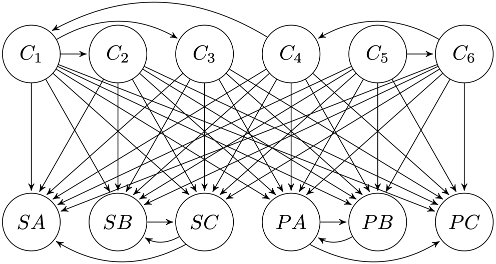
Energy disaggregation: Multi-**CT**BN**C**s



Bielza, Li, Larrañaga (2011)

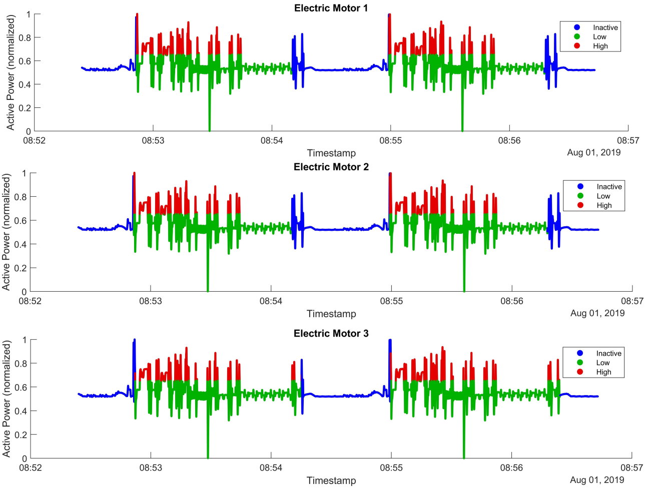


Energy disaggregation: Multi-CTBNCs



- Significant differences wrt 6 independent CTBNC (global Acc 0.74 vs 0.68; F1 0.81 vs 0.8)
- Expected relationships: *C*'s match the setup, same children for all *C*'s in the bridge subgraph (similar motors), feature subgraph with 3-phase connections of *S* and *P*

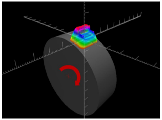
Energy disaggregation: predictions

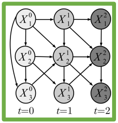


Outline

Conclusions

Quenching with laser



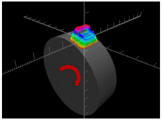


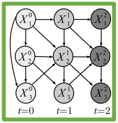
Dynamic Bayesian network

Fouling in furnaces

Conclusions

Quenching with laser

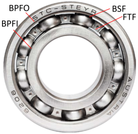


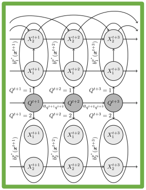


Dynamic Bayesian network

Fouling in furnaces

Ball-bearing degradation

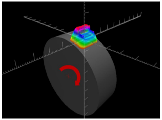


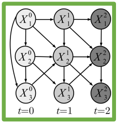


Hidden Markov model

Conclusions

Quenching with laser

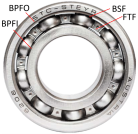


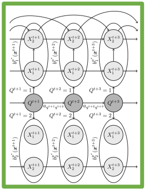


Dynamic Bayesian network

Fouling in furnaces

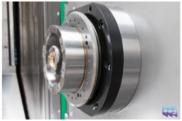
Ball-bearing degradation

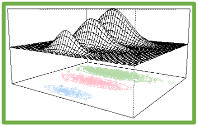




Hidden Markov model

Machine-tool condition monitoring

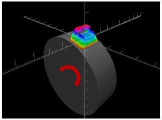


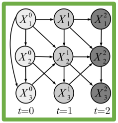


Gaussian mixture model

Conclusions

Quenching with laser

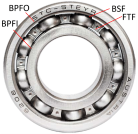


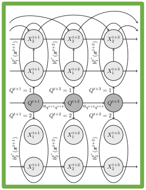


Dynamic Bayesian network

Fouling in furnaces

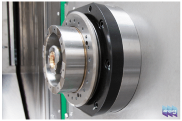
Ball-bearing degradation

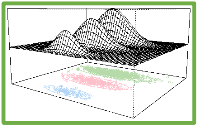




Hidden Markov model

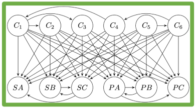
Machine-tool condition monitoring



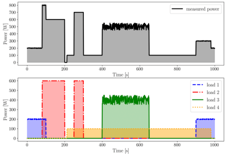


Gaussian mixture model

Multi-CTBNC

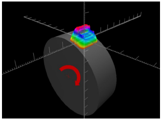


Energy disaggregation

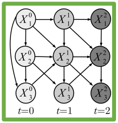


Conclusions

Quenching with laser



Condition monitoring

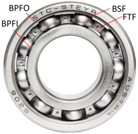


Dynamic Bayesian network

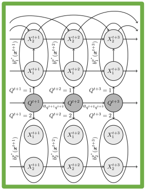
Fouling in furnaces

Prescriptive maintenance

Ball-bearing degradation

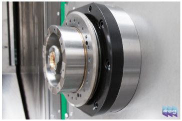


Condition monitoring

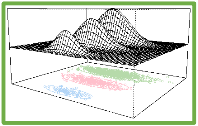


Hidden Markov model

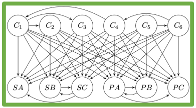
Machine-tool condition monitoring



Condition monitoring

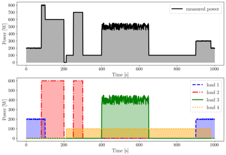


Gaussian mixture model



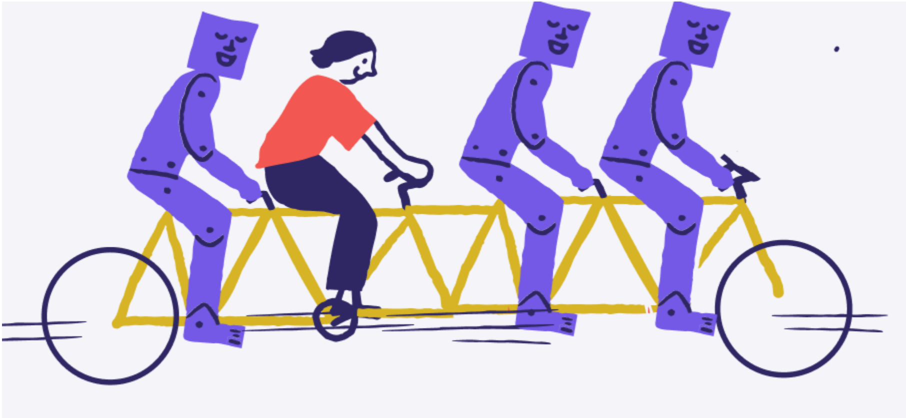
Multi-CTBNC

Energy disaggregation



Consumption efficiency

Human-machine tandem



References

- Bielza C, Li G, Larrañaga P (2011) Multi-dimensional classification with Bayesian networks, *International Journal of Approximate Reasoning*, 52, 705-727
- Diaz-Rozo J, Bielza C, Larrañaga P (2020) Machine-tool condition monitoring with Gaussian mixture models-based dynamic probabilistic clustering, *Engineering Applications of Artificial Intelligence*, 89, 103434
- Quesada D, Valverde G, Larrañaga P, Bielza C (2021) Long-term forecasting of multivariate time series in industrial furnaces with dynamic Gaussian Bayesian networks, *Engineering Applications of Artificial Intelligence*, 103, 104301
- Puerto-Santana C, Larrañaga P, Bielza C (2022a) Autoregressive asymmetric linear Gaussian hidden Markov models, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(9), 4642-4658
- Puerto-Santana C, Bielza C, Diaz-Rozo J, Ramirez-Gargallo G, Mantovani F, Virumbrales G, Labarta J, Larrañaga P (2022b) Asymmetric HMMs for online ball-bearing health assessments, *IEEE Internet of Things Journal*, 9(20), 20160-20177
- Puerto-Santana C, Larrañaga P, Bielza C (2022c) Feature saliencies in asymmetric hidden Markov models, *IEEE Transactions on Neural Networks and Learning Systems*, in press
- Puerto-Santana C, Larrañaga P, Bielza C (2023) Feature subset selection in data-stream environments using asymmetric hidden Markov models and novelty detection, *Neurocomputing*, 554, 126641
- Valverde G, Quesada D, Larrañaga P, Bielza C (2023) Causal reinforcement learning based on Bayesian networks applied to industrial settings, *Engineering Applications of Artificial Intelligence*, 125, 106657
- Villa-Blanco C, Larrañaga P, Bielza C (2021) Multi-dimensional continuous time Bayesian network classifiers, *International Journal of Intelligent Systems*, 36(12), 7839-7866

Thanks to...

aingura IIoT | ETXE-TAR | REPSOL | GOBIERNO DE ESPAÑA – MINISTERIO DE CIENCIA, INNOVACIÓN Y UNIVERSIDADES | Comunidad de Madrid

EXPLANATION CAPABILITIES OF BAYESIAN NETWORKS IN DYNAMIC INDUSTRIAL DOMAINS

Concha Bielza, Pedro Larrañaga

Computational Intelligence Group
Departamento de Inteligencia Artificial
Universidad Politécnica de Madrid

ECAI-2023 Workshop “XAI for Industry 4.0 & 5.0”
Kraków - October 1, 2023