Aalto University
School of Science

Applications of Bayesian Networks

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Presentation *4*
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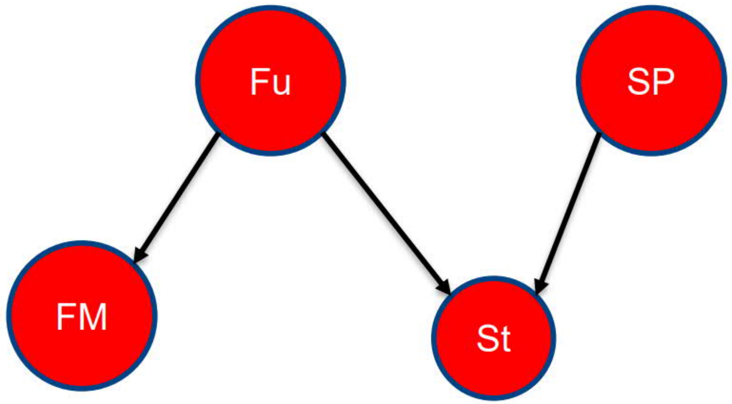
Recap of BNs: car example

- **Nodes and states**
  - Fuel: Fu {yes, no}
  - Fuel meter standing: FM {full, ½, empty}
  - Clean spark plugs: SP {yes, no}
  - Start: St {yes, no}



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Fire alarm system

Jing, C. and Jingqi F., 2012. Fire Alarm System Based on Multi-Sensor Bayes Network. Procedia Engineering 29, pp. 2551 – 2555.

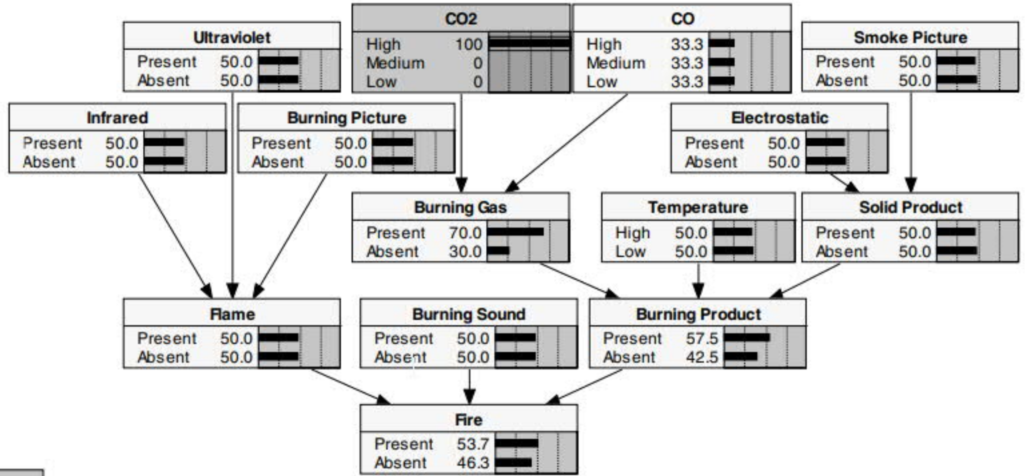
Rationale

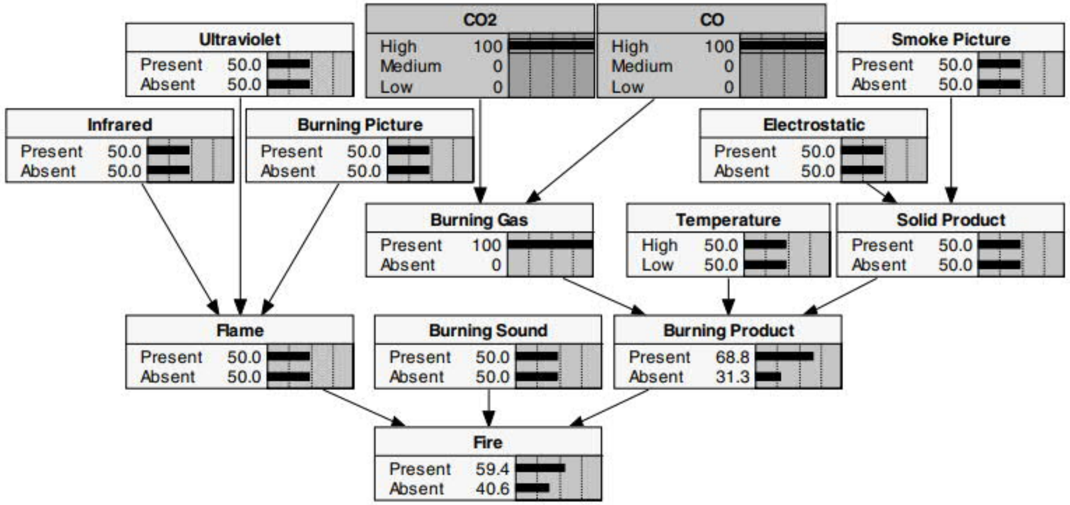
- **Goal: prevent false positives and false negatives**
- **Combine data from multiple sensors**
- **BN is effective tool to handle uncertain knowledge**

Building BN model

- **Identify nodes**
  - Expert knowledge
  - Discretize continuous states
- **Identify network structure**
  - Expert knowledge
  - Algorithms
- **Fill Conditional Probability Table (CPT) for each node**
  - Expert knowledge
  - Algorithms

Examples


Ultraviolet
Present 50.0
Absent 50.0
CO2
High 100
Medium 0
Low 0
CO
High 33.3
Medium 33.3
Low 33.3
Smoke Picture
Present 50.0
Absent 50.0
Infrared
Present 50.0
Absent 50.0
Burning Picture
Present 50.0
Absent 50.0
Electrostatic
Present 50.0
Absent 50.0
Burning Gas
Present 70.0
Absent 30.0
Temperature
High 50.0
Low 50.0
Solid Product
Present 50.0
Absent 50.0
Flame
Present 50.0
Absent 50.0
Burning Sound
Present 50.0
Absent 50.0
Burning Product
Present 57.5
Absent 42.5
Fire
Present 53.7
Absent 46.3

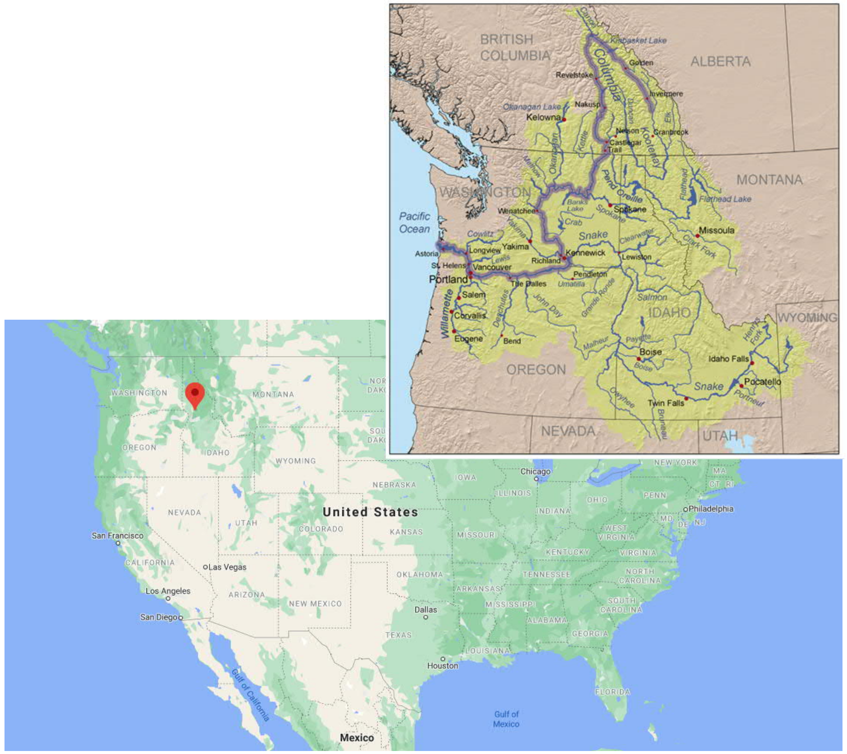

Ultraviolet
Present 50.0
Absent 50.0
CO2
High 100
Medium 0
Low 0
CO
High 100
Medium 0
Low 0
Smoke Picture
Present 50.0
Absent 50.0
Infrared
Present 50.0
Absent 50.0
Burning Picture
Present 50.0
Absent 50.0
Electrostatic
Present 50.0
Absent 50.0
Burning Gas
Present 100
Absent 0
Temperature
High 50.0
Low 50.0
Solid Product
Present 50.0
Absent 50.0
Flame
Present 50.0
Absent 50.0
Burning Sound
Present 50.0
Absent 50.0
Burning Product
Present 68.8
Absent 31.3
Fire
Present 59.4
Absent 40.6

Fish and wildlife population

Marcot et al., 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. Forest Ecology and Management 153, pp. 29-42.

Modelling populations in Columbia river basin

- **BN on three levels of geographical resolution for wildlife**
  - Site
  - Subwatershed
  - Basin
- **Two level BN for fishes**
  - Habitat, biotic and migratory conditions
  - Landscape characteristics, management activities

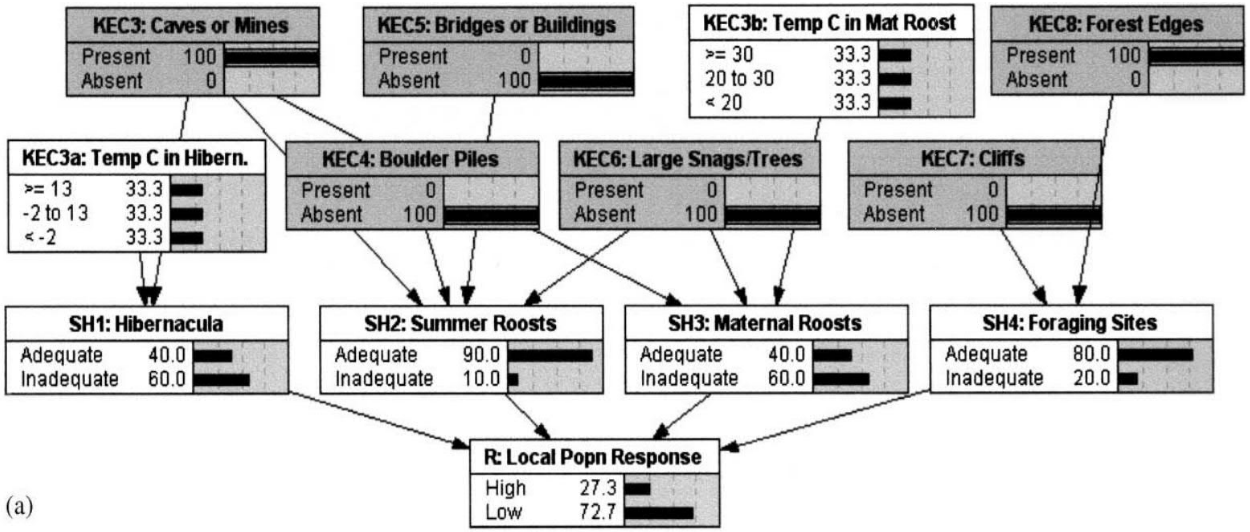


General structure of BNs

- **Input nodes are key environmental correlates (KEC) taken from species-environment relations (SER) database**
- **Proxy variables derived from geographic information systems (GIS) database are used to represent KECs**
- **Conditional probabilities mostly based on expert judgment, or from empirical data if available**

Site level network

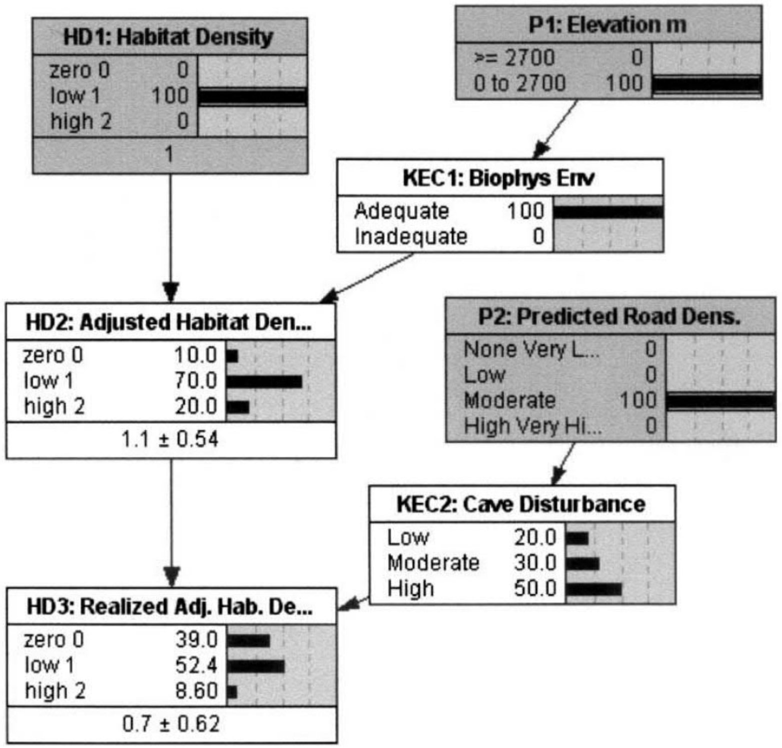
- **Inputs are properties that can be determined on the ground e.g. presence of forest edges, temperature of hibernacula**
- **Output is populatio response**



(a)

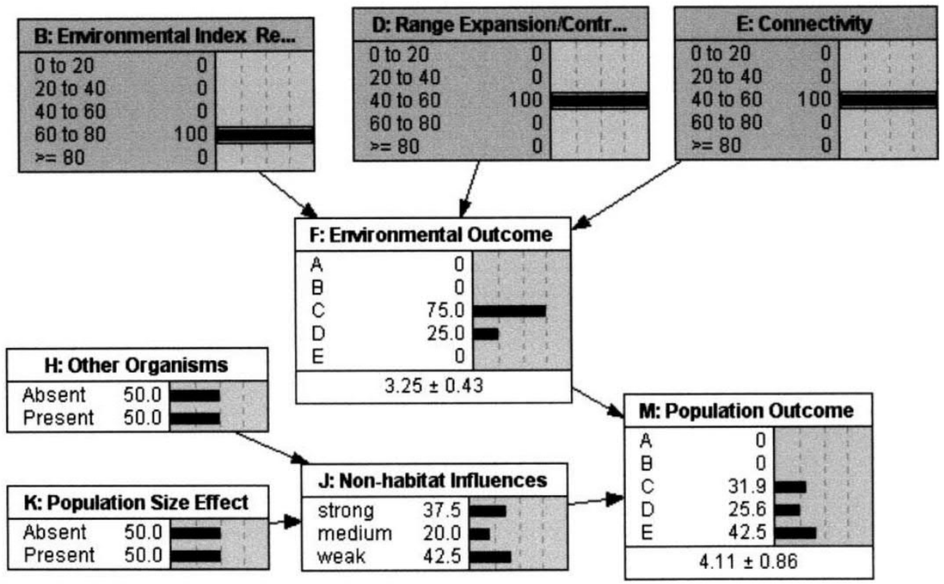
Subwatershed level network

- Inputs are KECs on less fine grain level e.g. cave disturbance and externally calculated habitat density
- Output is habitat density



Basin level network

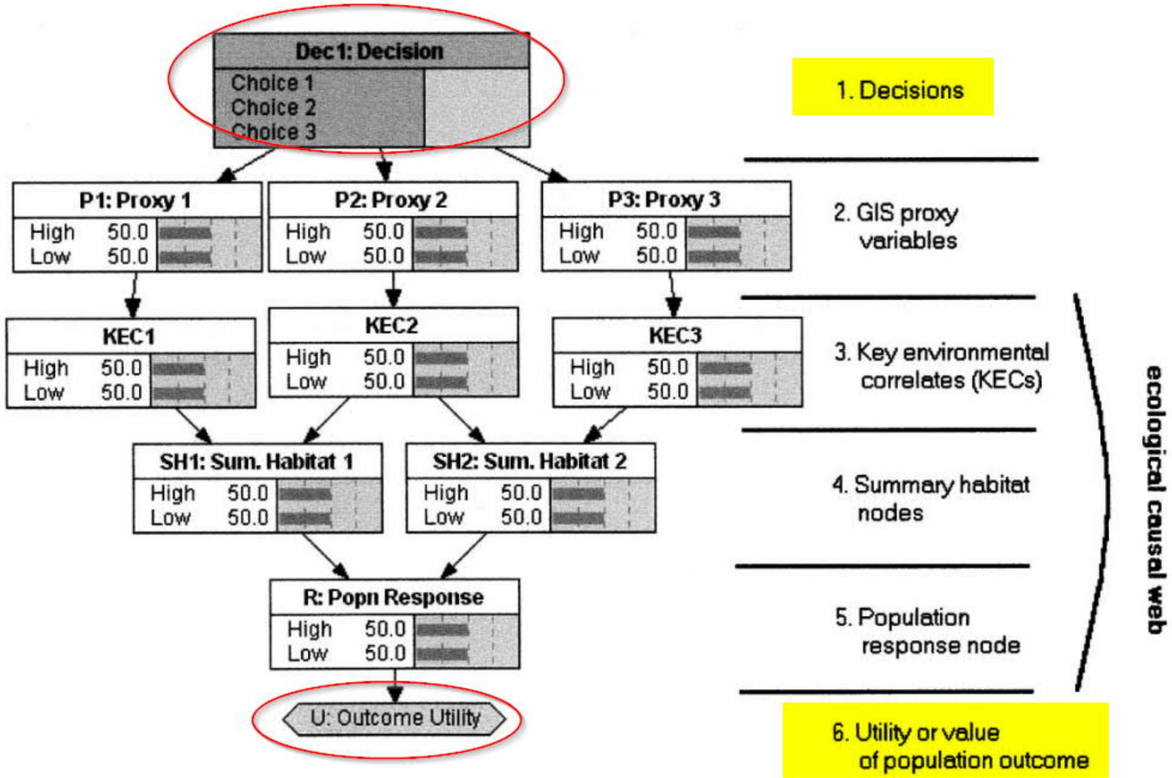
- Same for all species
- Subwatershed level BN outputs are aggregated back to GIS and resulting summary is given as input to basin level BN
- Other inputs: population size and other organisms



(c)

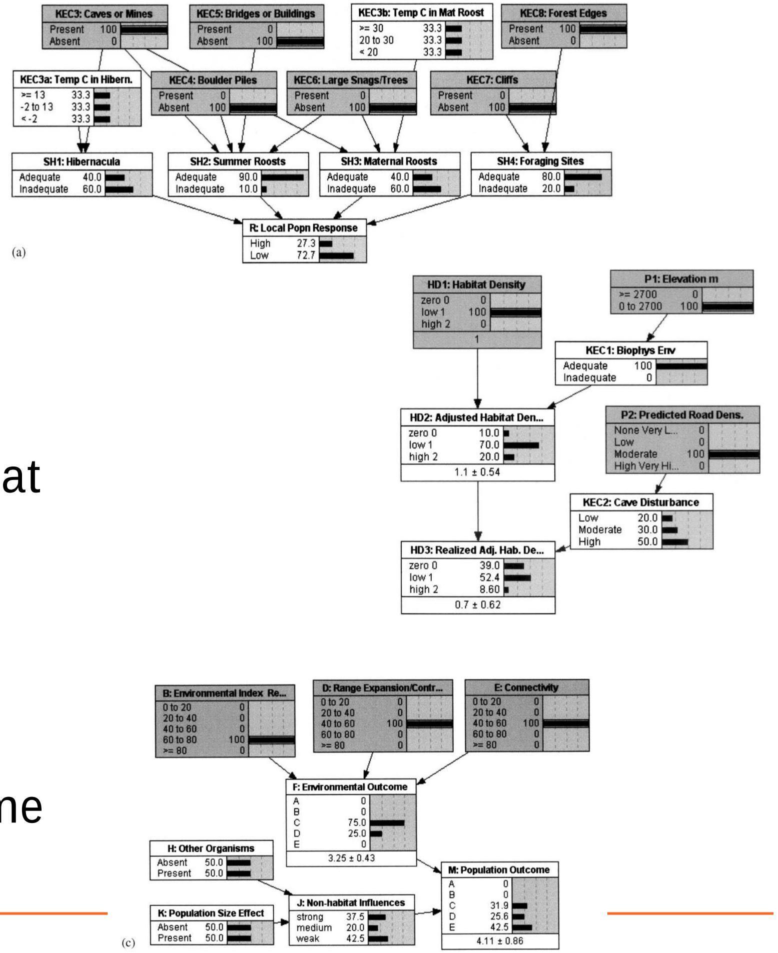
Usage in decision making

Add decision nodes that affect proxy variables and utility node to outcome to help decision making.



Summary

- **Site**
  - KECs => local population response
  - Decision nodes, utility
- **Subwatershed**
  - KECs, habitat density => realized habitat density
  - Decision nodes, utility
- **Basin**
  - Aggregated figures from Subwatershed level calculations => population outcome



Usage of the model

- **Organizing knowledge**
- **Sensitivity analysis**
  - What nodes/decision have biggest impact?
- **Using as part of evolving and adaptive framework to assess outcomes of decision**

Benefits

- Display visually influencing factors and their interactions
- Combine categorical and continuous variables
- Uses both empirical data and expert judgment
- Gives quantitative predictions

Limitations

- **Subwatershed BNs were very similar due to lack of suitable GIS variables**
- **There can be many possible structures for site level network**
- **No feedback loops or other temporal or spatial dynamics**
    - Differential equation systems better for feedback loops
- **Relies heavily on (possibly biased) expert assessment**

Thank you :)

References

- **Slide 2 image:** Leppinen, J., 2020. Decision trees and Bayesian networks. Seminar presentation, Aalto University. Viewed 22.9.2020. Available (requires Aalto credentials) from https://mycourses.aalto.fi/pluginfile.php/1271793/course/section/163539/0918_leppinen.pdf
- **Slide 9 image of USA:** Google Maps, 2020. Viewed 22.9.2020. Available from https://www.google.com/maps/place/46%C2%B000'00.0%22N+116%C2%B000'00.0%22W/@39.3135751,-110.4124876,4z/data=!4m5!3m4!1s0x0:0x0!8m2!3d46!4d-116?hl=en
- **Slide 9 map of Columbia river basin:** Wikipedia, 2020. Columbia River drainage basin. Viewed 22.9.2020. Available from https://en.wikipedia.org/wiki/Columbia_River_drainage_basin#/media/File:Columbiarivermap.png
- **Slide 10 image of bat**: Cover image from Gruver, J., Keinath, D., 2006. Townsend's Big-eared Bat (Corynorhinus townsendii): A Technical Conservation Assessment. US forest service. Viewed 22.9.2020. Available from https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb5181908.pdf

Other images are from related articles.

Homework 1/2

Pekka has a habit to be late from the first lecture of the day. Two factors especially affect whether he is late or not: does he remember to set an alarm on previous night and whether lecturer has changed classroom from what was previously announced. He remembers to set alarm clock on previous night with probability 0.8 and lecturer changes classroom from previously announced with probability 0.1. Conditional probabilities for him being late / not late are given in the table below.

		Alarm clock	
		On	Off
Is classroom different?	Yes	(0.40, 0.60)	(0.95, 0.05)
	no	(0.01, 0.99)	(0.50, 0.50)

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Homework 2/2

1. Draw Bayesian network that models the situation.
2. Calculate probability for Pekka being late from the first lecture.
3. Assume (unrealistically) that if Pekka has multiple alarm clocks whether he remembers to set alarm on one clock is independent from setting alarm on other clocks. How many alarm clocks Pekka needs that his probability for being late from the first lecture is less than 5%?

DL 2.10.

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