



Aalto University  
School of Science



# Improving Construction of Conditional Probability Tables for Ranked Nodes in Bayesian Networks

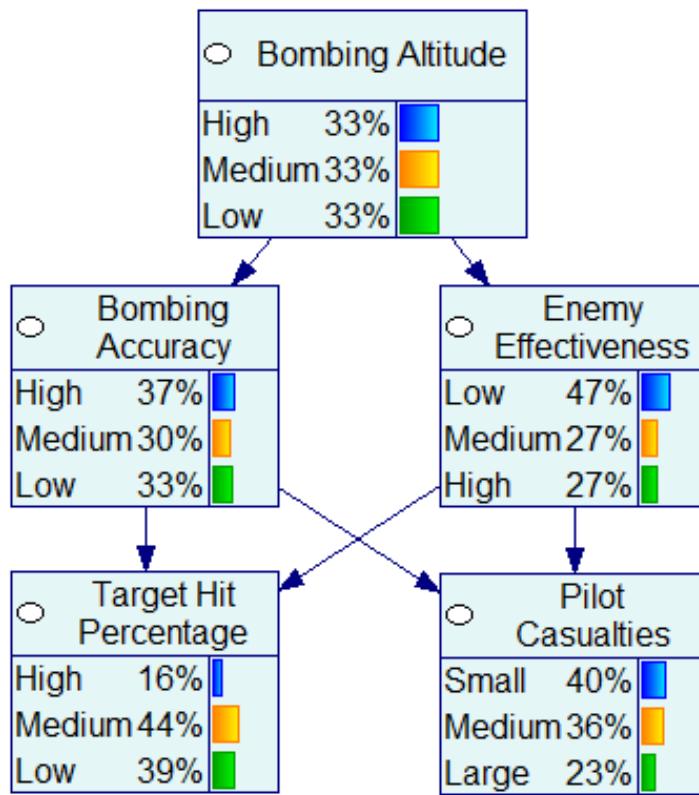
Pekka Laitila, Kai Virtanen

[pekka.laitila@aalto.fi](mailto:pekka.laitila@aalto.fi), [kai.virtanen@aalto.fi](mailto:kai.virtanen@aalto.fi)

Systems Analysis Laboratory, Department of Mathematics and Systems  
Analysis

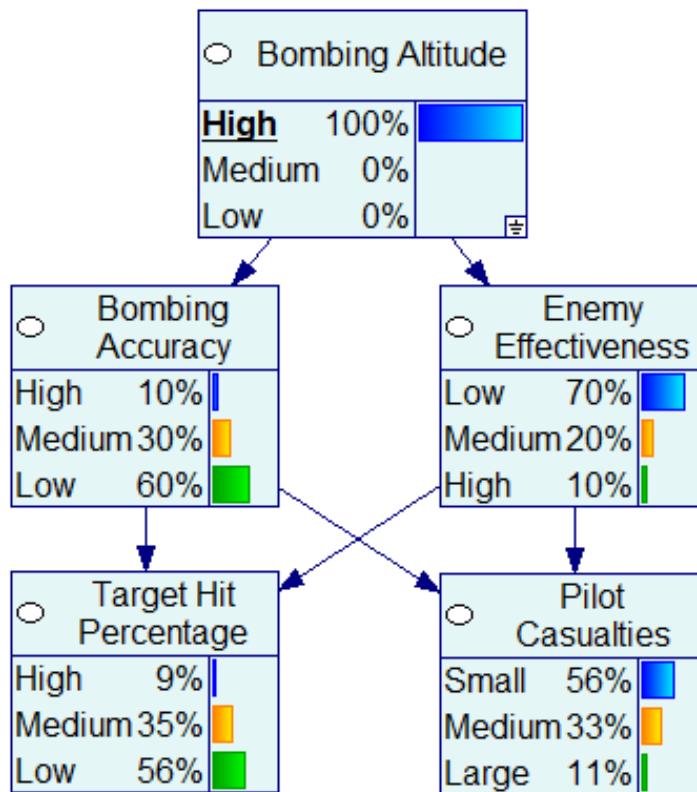
# Bayesian networks (BNs)

- Represent uncertain knowledge
  - Reasoning under uncertainty



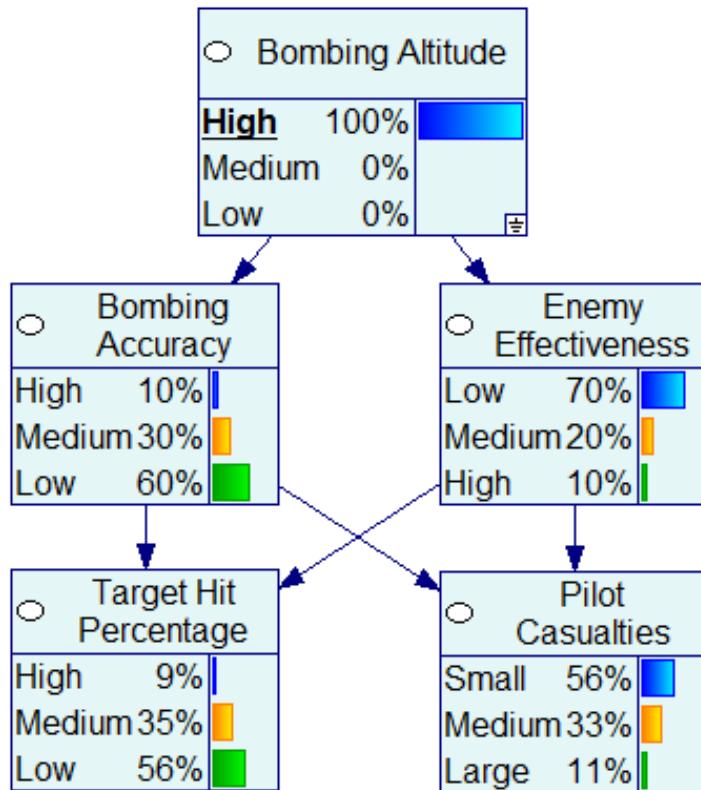
# Bayesian networks (BNs)

- Represent uncertain knowledge
  - Reasoning under uncertainty



# Bayesian networks (BNs)

- Represent uncertain knowledge
- Reasoning under uncertainty



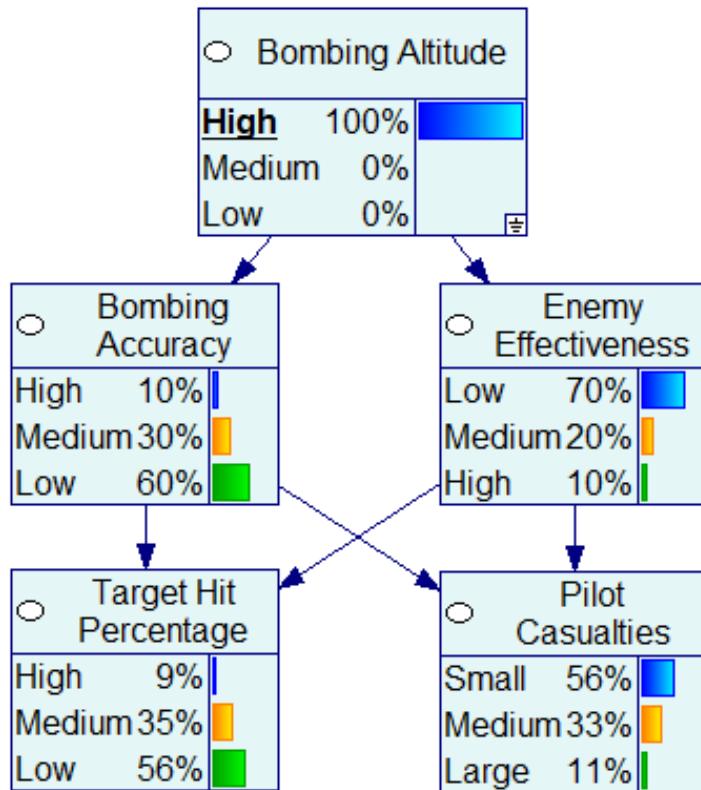
## Conditional probability tables (CPTs)

- Quantify dependence between linked nodes

	Bombing Altitude	High	Medium	Low
Bombing Accuracy	High	0.1	0.3	0.7
	Medium	0.3	0.4	0.2
	Low	0.6	0.3	0.1

# Bayesian networks (BNs)

- Represent uncertain knowledge
- Reasoning under uncertainty



## Conditional probability tables (CPTs)

- Quantify dependence between linked nodes

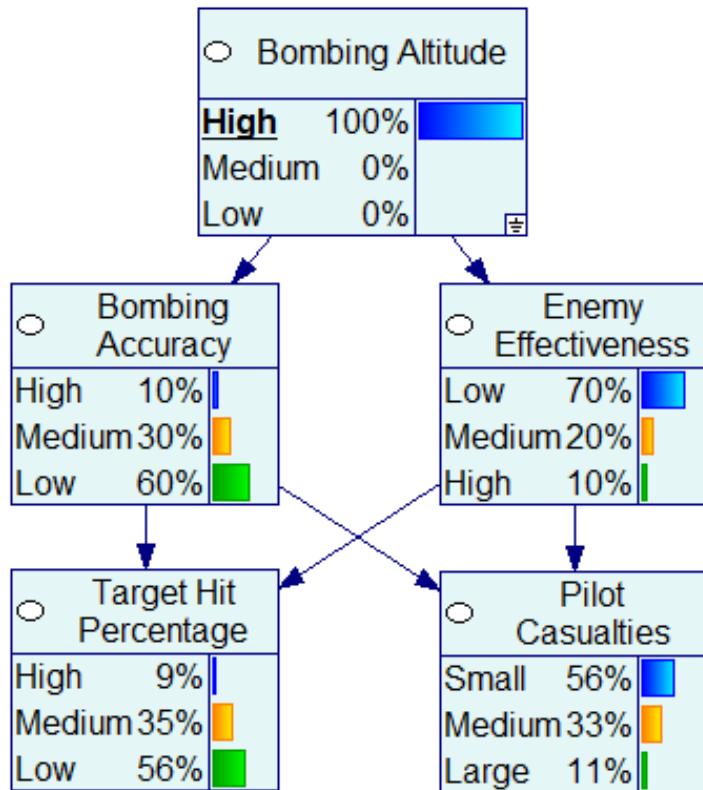
	Bombing Altitude	High	Medium	Low
Bombing Accuracy	High	0.1	0.3	0.7
	Medium	0.3	0.4	0.2
	Low	0.6	0.3	0.1

## Challenge of expert elicitation

Construction of CPTs based on expert elicitation is time consuming and prone to biases

# Bayesian networks (BNs)

- Represent uncertain knowledge
- Reasoning under uncertainty



## Conditional probability tables (CPTs)

- Quantify dependence between linked nodes

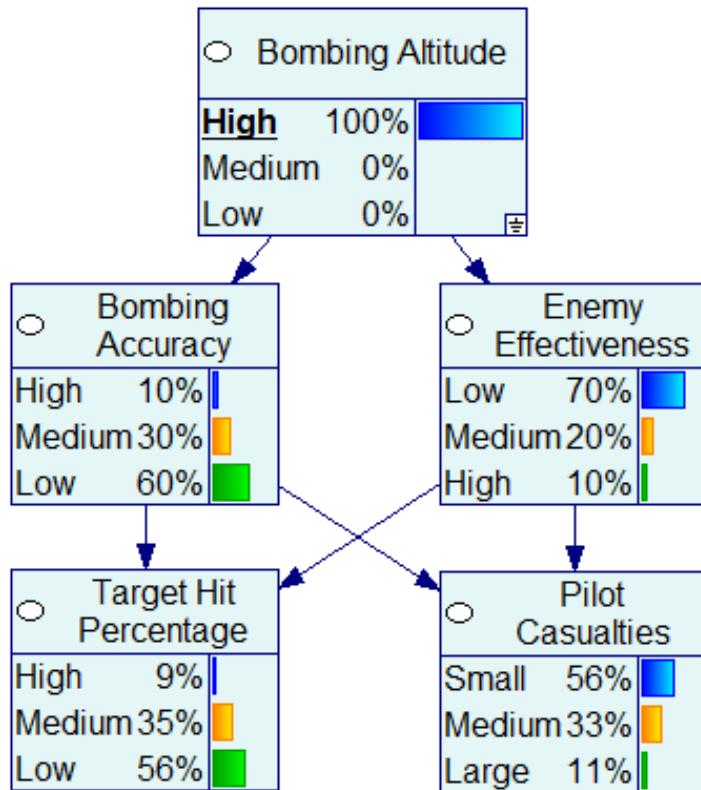
	Bombing Altitude	High	Medium	Low
Bombing Accuracy	High	0.1	0.3	0.7
	Medium	0.3	0.4	0.2
	Low	0.6	0.3	0.1

## Challenge of expert elicitation

- Direct estimation
- Probability scale methods
- Gamble-like methods
- Probability wheel
- etc.

# Bayesian networks (BNs)

- Represent uncertain knowledge
  - Reasoning under uncertainty



## Conditional probability tables (CPTs)

- Quantify dependence between linked nodes

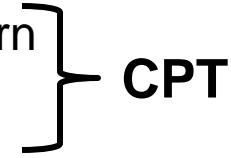
	Bombing Altitude	High	Medium	Low
Bombing Accuracy	High	0.1	0.3	0.7
	Medium	0.3	0.4	0.2
	Low	0.6	0.3	0.1

## Challenge of expert elicitation

- Direct estimation
  - Probability scale methods
  - Gamble-like methods
  - Probability wheel
  - etc

## - Inadequate!

# Construction of CPTs with parametric methods

- **Idea:**
    1. Probabilistic relationship between nodes fits a standard pattern
    2. Expert assigns parameters characterizing the pattern
  - **Benefit:**
    - Number of parameters << Number of CPT entries → Expert saves time!
- 

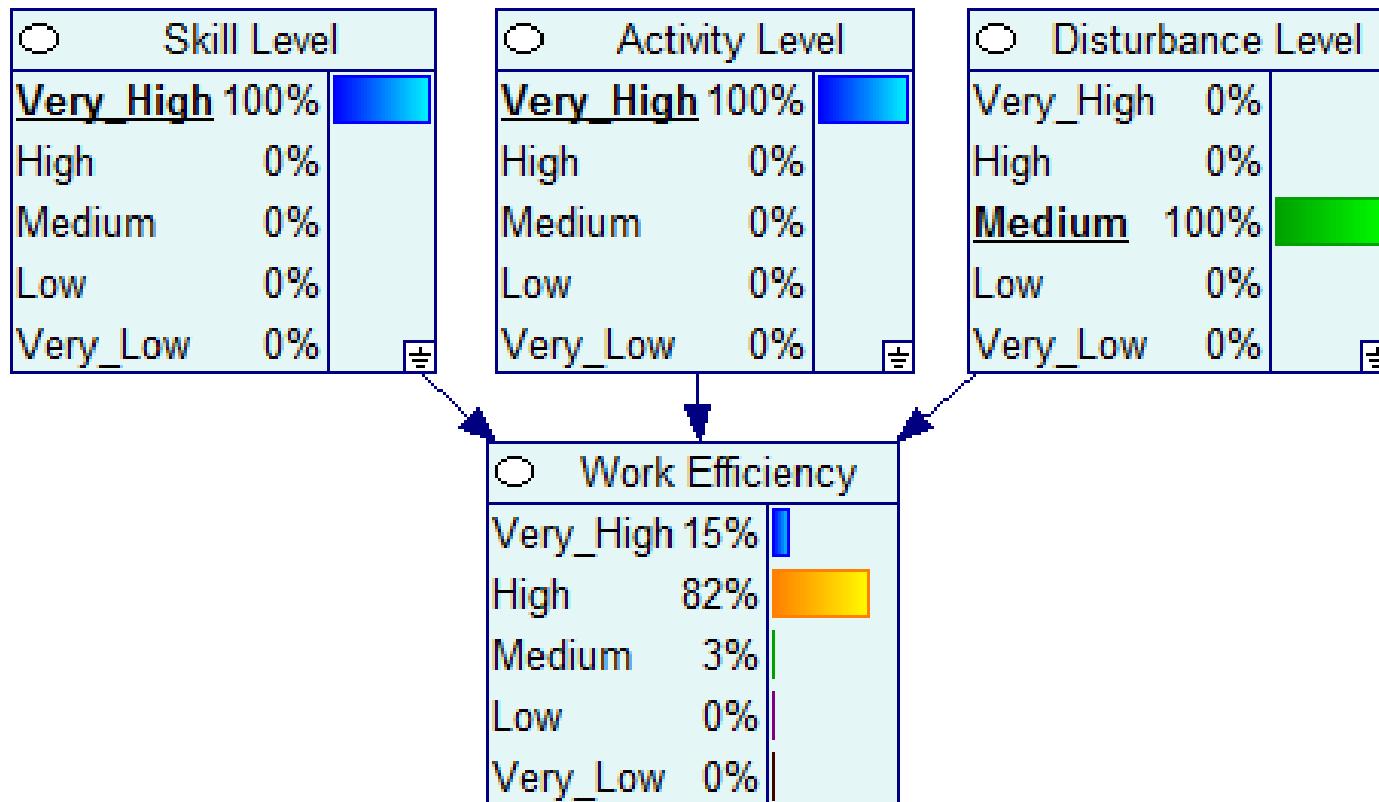
# Construction of CPTs with parametric methods

- **Idea:**
    1. Probabilistic relationship between nodes fits a standard pattern
    2. Expert assigns parameters characterizing the pattern
  - **Benefit:**
    - Number of parameters << Number of CPT entries → Expert saves time!
- } CPT

- **Challenges we have recognized in "Ranked Nodes Method" (RNM)**
  - Parameters lack clear interpretations → Hampers assignment
  - Application requires technical insight → Use inefficient
- **Our contribution for alleviating efforts of the expert**
  - Interpretations that facilitate determination of parameters
  - Guidelines for efficient use of RNM

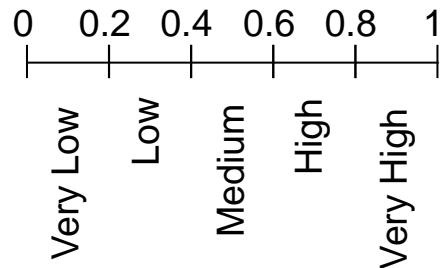
# Ranked Nodes (Fenton, Neil, and Caballero, 2007)

Represent by ordinal scales continuous quantities that lack a well-established interval scale

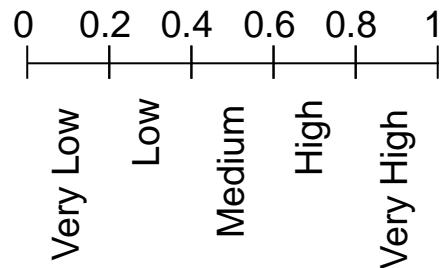


# Ranked Nodes Method (RNM) (Fenton, Neil, and Caballero, 2007)

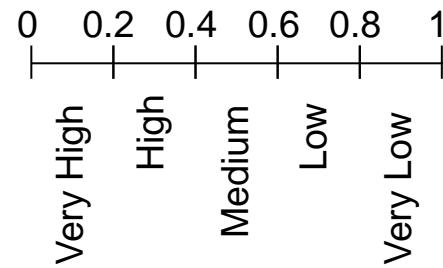
**X1: Skill Level**



**X2: Activity Level**



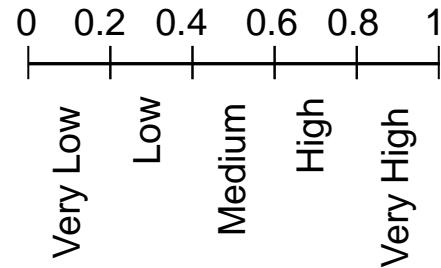
**X3: Disturbance Level**



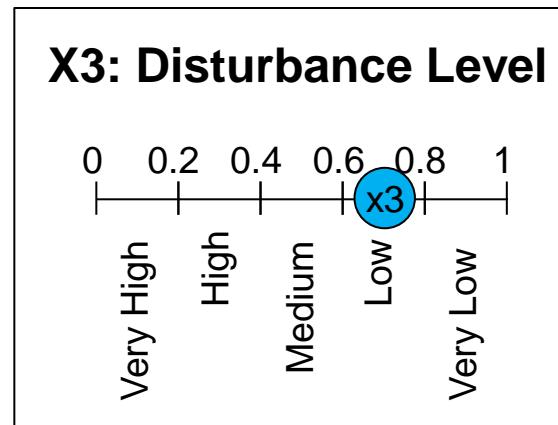
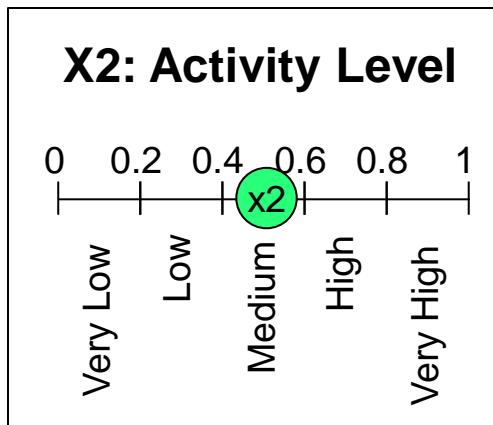
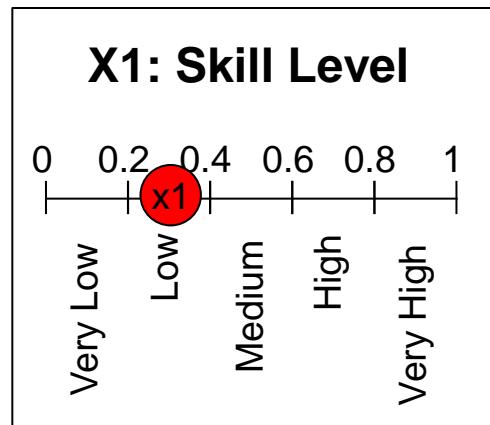
Parameters to be elicited

- Aggregation function  $F$
- Weights of parent nodes  $w_1$   $w_2$   $w_3$
- Uncertainty parameter  $\sigma$

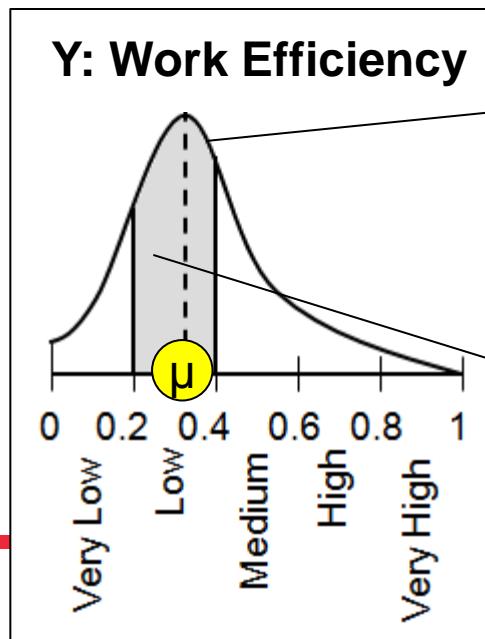
**Y: Work Efficiency**



# Ranked Nodes Method (RNM) (Fenton, Neil, and Caballero, 2007)



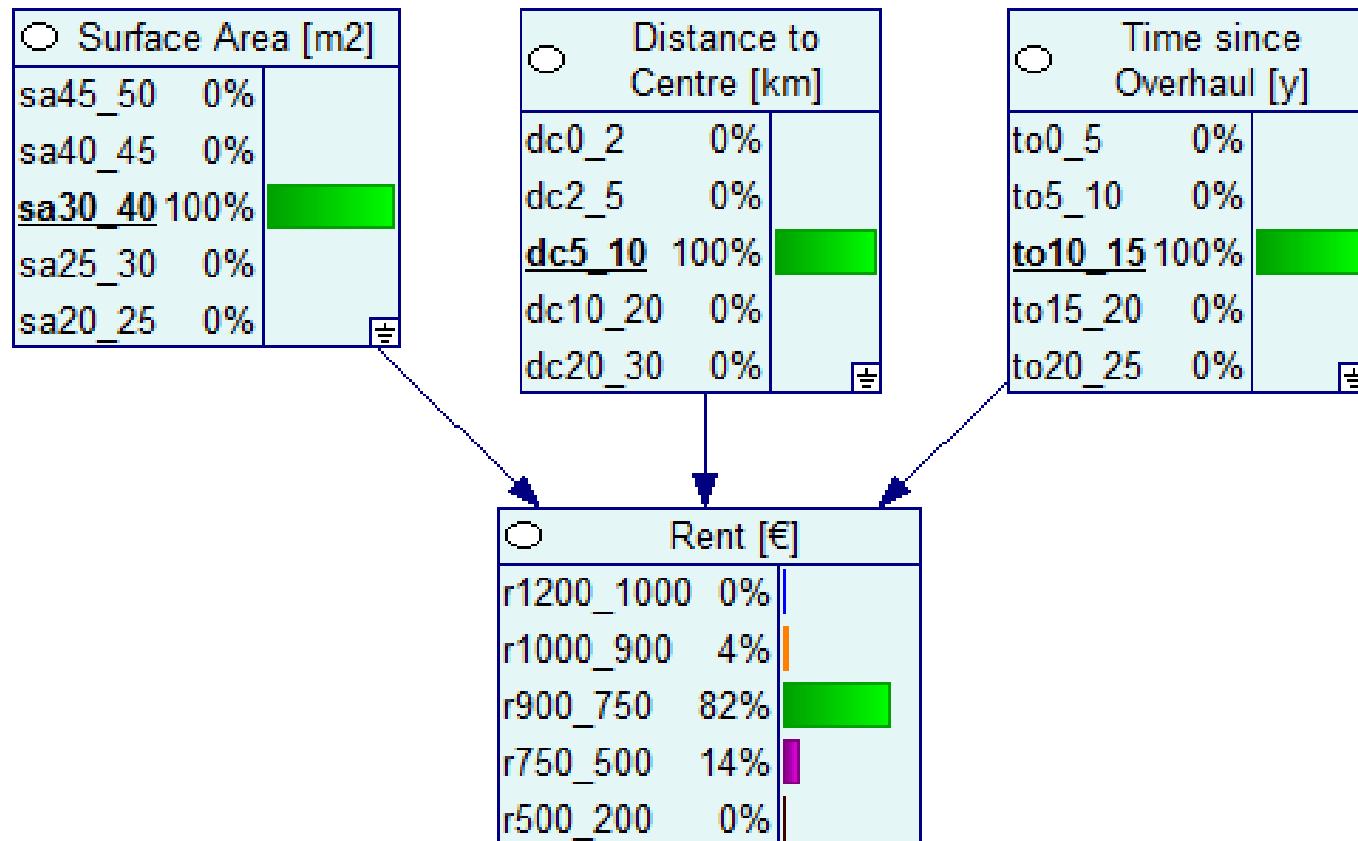
- Parameters to be elicited
- Aggregation function  $F$
  - Weights of parent nodes  $w_1$   $w_2$   $w_3$
  - Uncertainty parameter  $\sigma$



$$\text{TNormal}(\mu, \sigma, 0, 1),$$
$$\mu = F(x_1, x_2, x_3, w_1, w_2, w_3)$$
$$P(Y=\text{Low} | X_1=\text{Low}, X_2=\text{Medium}, X_3=\text{Low})$$

# Challenges recognized with RNM

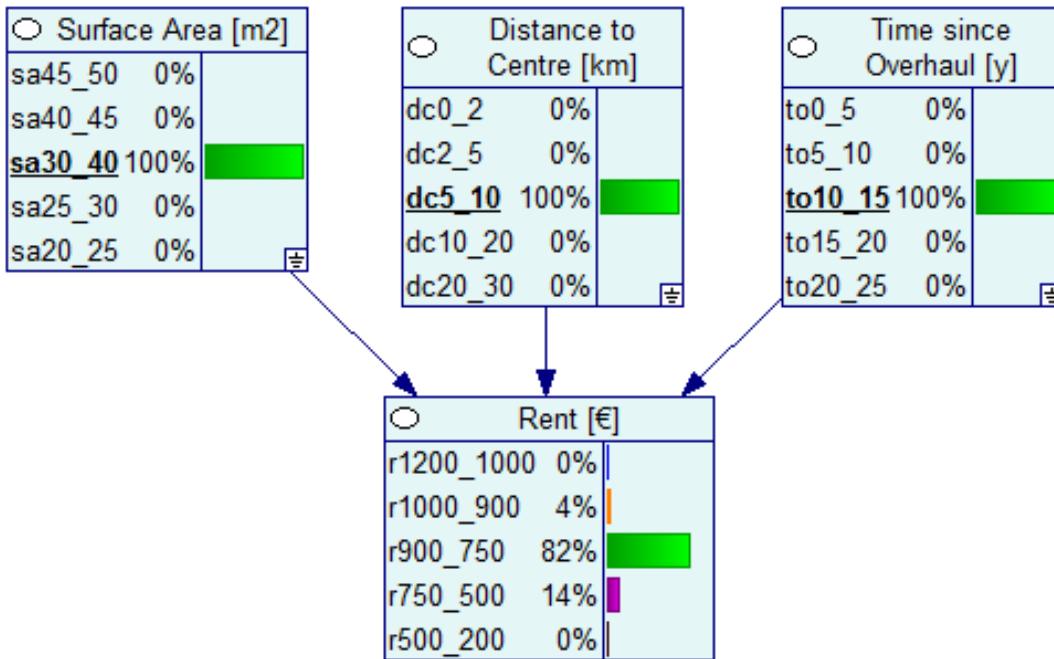
1. Parameters lack interpretations → Expert must determine values by trial and error → Slow and difficult!
2. Application to nodes with interval scales: Ignorant user may form ordinal scales that prevent construction of sensible CPTs



# RNM and nodes with interval scales: New approach (Laitila and Virtanen, 2016)

## Formation of suitable ordinal scales

- Divide interval scales freely into equal amount of subintervals
- Ask the expert about the mode of child node in scenarios corresponding to equal ordinal states of parent nodes  
→ Update discretizations accordingly

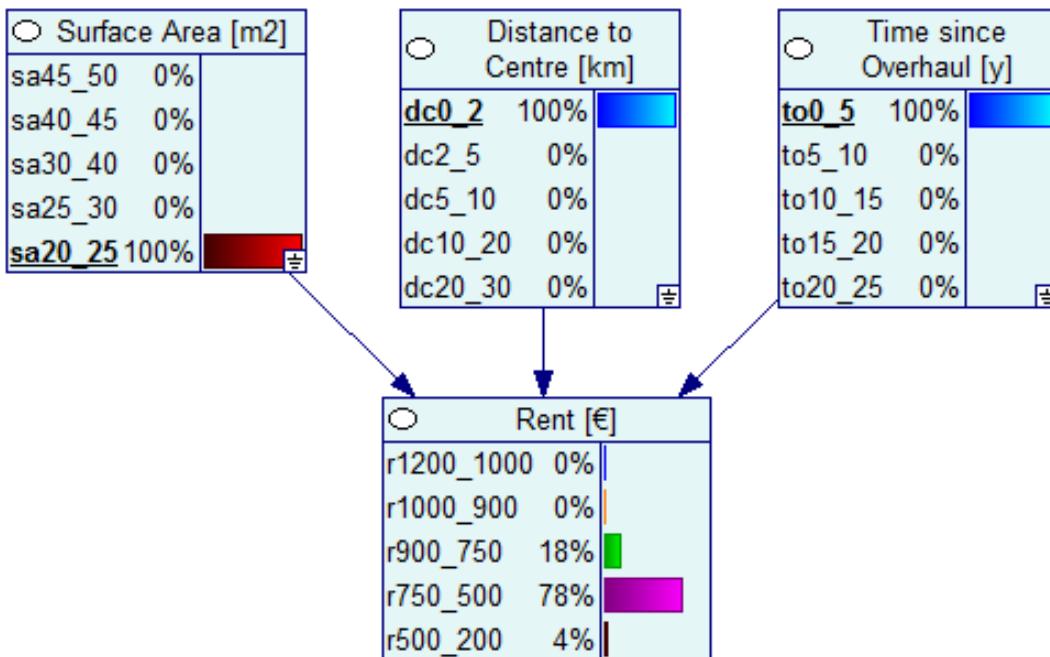


"What is the most likely rent for a 40 m<sup>2</sup> apartment that is 5 km from the centre and has 10 years since overhaul?"  
"I'd say its 900 €."

# RNM and nodes with interval scales: New approach (Laitila and Virtanen, 2016)

## Determination of aggregation function F and weights w1,...,wn

- Ask the expert about the mode of child node in scenarios corresponding to extreme ordinal states of parent nodes
  - F and w1,...,wn determined based on interpretations derived for weights



"What is the most likely rent for a 20 m<sup>2</sup> apartment that is right in the centre and has just been renovated?"

"I'd say its 600 €."

# Conclusion

- Parametric methods ease up construction of CPTs for BNs by expert elicitation
- New approach facilitates use of RNM
  - Further relief to expert elicitation
    - Currently applied in a case study concerning performance of air surveillance network
    - Applicable to BNs and Influence Diagrams
      - Supports decision making under uncertainty
- Future research
  - Human experiment: new approach vs. direct parameter estimation
  - Generalisation of the approach to nodes without interval scales

# References

- P. Laitila and K. Virtanen, “Improving Construction of Conditional Probability Tables for Ranked Nodes in Bayesian Networks,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 7, pp. 1691–1705, 2016
- N. Fenton, M. Neil, and J. Caballero, “Using Ranked Nodes to Model Qualitative Judgments in Bayesian Networks,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 19, no. 10, pp. 1420–1432, 2007
- S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Prentice Hall, 2003