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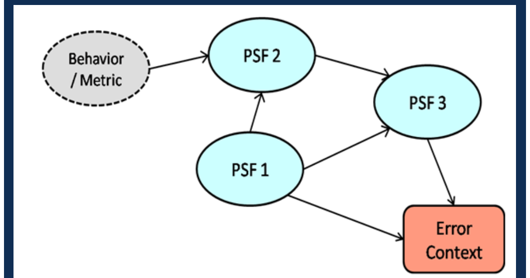

$P(EC \cap PSF1 \cap PSF2 \cap PSF3 \cap BM)$

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Bayesian Networks: Decision support under uncertainty

Katrina M. Groth, 6231

6230 Uncertainty Quantification and Sensitivity Analysis Training

April 22, 2014

U.S. DEPARTMENT OF ENERGY   NNSA National Nuclear Security Administration

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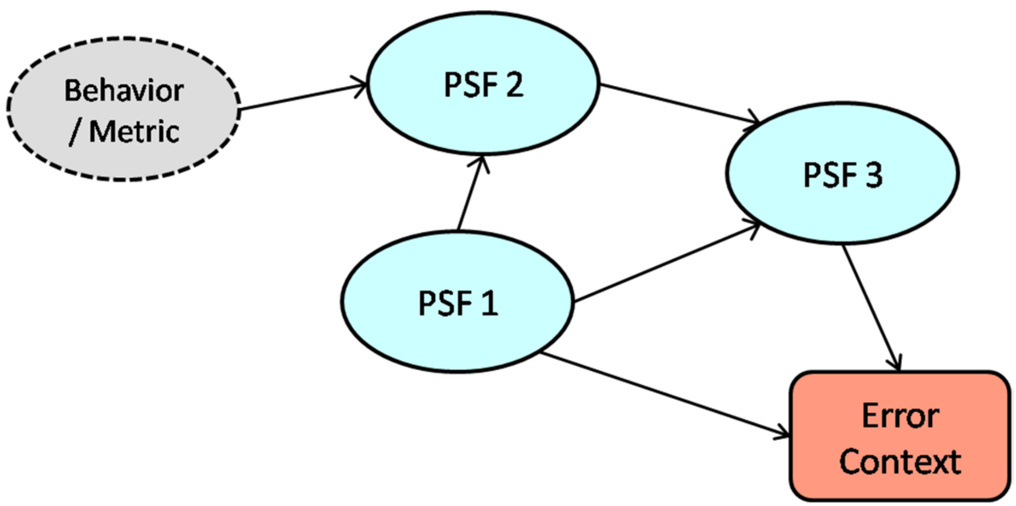
Switching gears

- Much of this course focuses on using data to reason **about** our uncertainty
- In this segment, we use probability to help us reason **with (or despite)** that uncertainty
  - Especially: Limited data, distributed expertise, complex problems
- …With a tool called a Bayesian Network (BN)



	Parent	$Pr(a)$	$Pr(\bar{a})$
Child	$Pr(b)$	$Pr(b\|a)$	$Pr(b\|\bar{a})$
	$Pr(\bar{b})$	$Pr(\bar{b}\|a)$	$Pr(\bar{b}\|\bar{a})$

Does this matter for you?

- You can ignore me if you have gobs of relevant data, about your exact systems, in all of the possible use cases, and that experience uniquely constrains the future…

- You might want to listen if you've ever said...
  - "..But we don't have enough data to make a decision"
  - "We can't quantify that, so it can't be part of the analysis"
  - "Let's just ask the experts"
  - "We can't quantify a probability that low"

- And in case you're thinking "But I'm not a Bayesian"
  - It doesn't matter, this is about *causality*, not statistics

Terminology, abbreviations, notation

- Joint distribution: $P(A \cap B) = P(A, B)$
- Marginal (unconditional) distribution: $P(A)$
- Conditional distribution: $P(A|B)$

- BN = Bayesian (Belief) Network
- HCL = Hybrid Causal Logic
- HRA = Human Reliability Analysis
- PRA = Probabilistic Risk Assessment
- PSF = Performance Shaping Factor

Outline

- What is a BN?
- Building a BN
- Inference with BNs
- HRA Example
- A few BNs for PRA and safety
- Wrap-up

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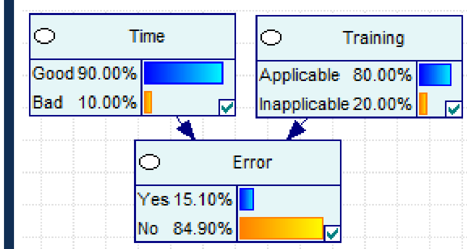
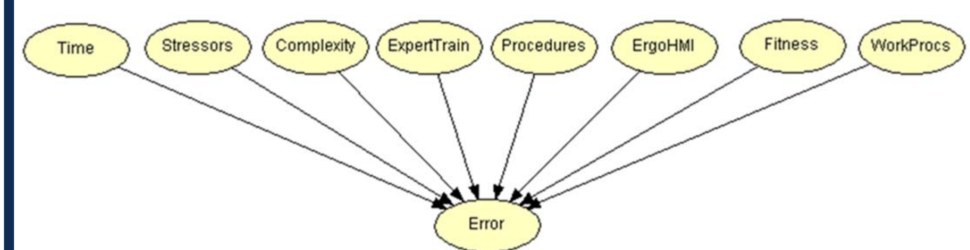


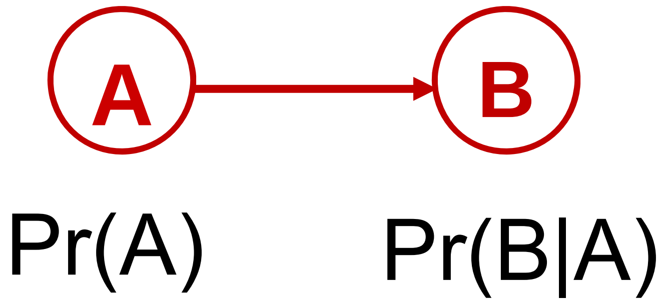


Bayesian Network: A tool & a model

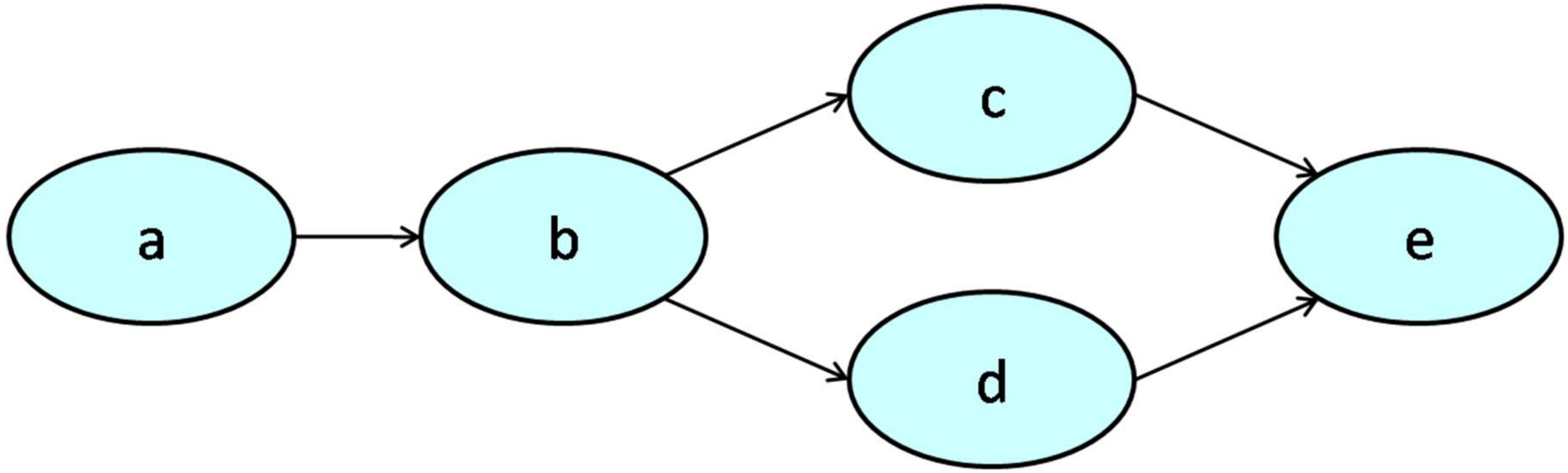
- A model which…
  - Explicitly encodes relevant variables & dependencies
  - …In terms of a simplified probability distribution
  - Permits multiple types of data/information to be used in a single reasoning framework.
- A tool for **reasoning under uncertainty**
  - Conducting inference (reasoning from cause to effect) and diagnosis (reasoning from effect to cause)
  - About uncertain states, with limited information, under changing conditions

BN basic structure

- A BN is a directed acyclic graph (DAG) with nodes representing random variables
- An arrow from one node to another represents probabilistic influence
- Each node has an associated probability distribution (usually discrete)



BNs by another name…



- A type of Probabilistic Graphical Model (PGM)
  - A marriage of probability theory and graph theory
  - Markov models (un-directed), BNs (directed, acyclic)
- Also called: Bayesian belief network, belief network, causal graph, causal network, probabilistic network, influence diagram, expert system

Some BN application areas

- Medicine
  - CHILDE: Congenital heart disease diagnosis
  - MUNIN: Preliminary Diagnosis of neuromuscular diseases
  - SWAN: System for insulin adjustment for diabetics
  - PATHFINDER: Diagnosis of breast cancer
- Business and Management
  - Market forecasting in oil industry
  - Finance-Fraud/Uncollectible debt collection
  - Modeling impact of organizational change
- Engineering & Science
  - Diagnosis of faults in waste water treatment process
  - Failure mode and effect analysis with BBN’s
  - BOBLO: Expert system based for cattle blood group determination

How could they be used in PRA?

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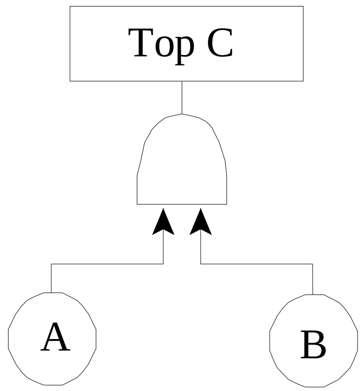
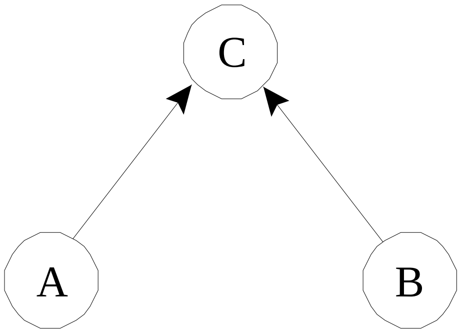
- To build a defensible probability distribution for hard-to-quantify problems (e.g., HRA, aging, software)
  - To break problems down into quantifiable (or elicitable) chunks
  - To add additional levels of detail and traceability
  - To address dependency
- To enable use of *some data* for problems where the alternative is *no data* (e.g., HRA)
- To enable *appropriate* use of experts (appropriate experts, appropriate probability elicitation)
- To provide causal understanding, not just statistics.

How to implement in PRA– Option 1: Replace Fault / Event Trees with BNs



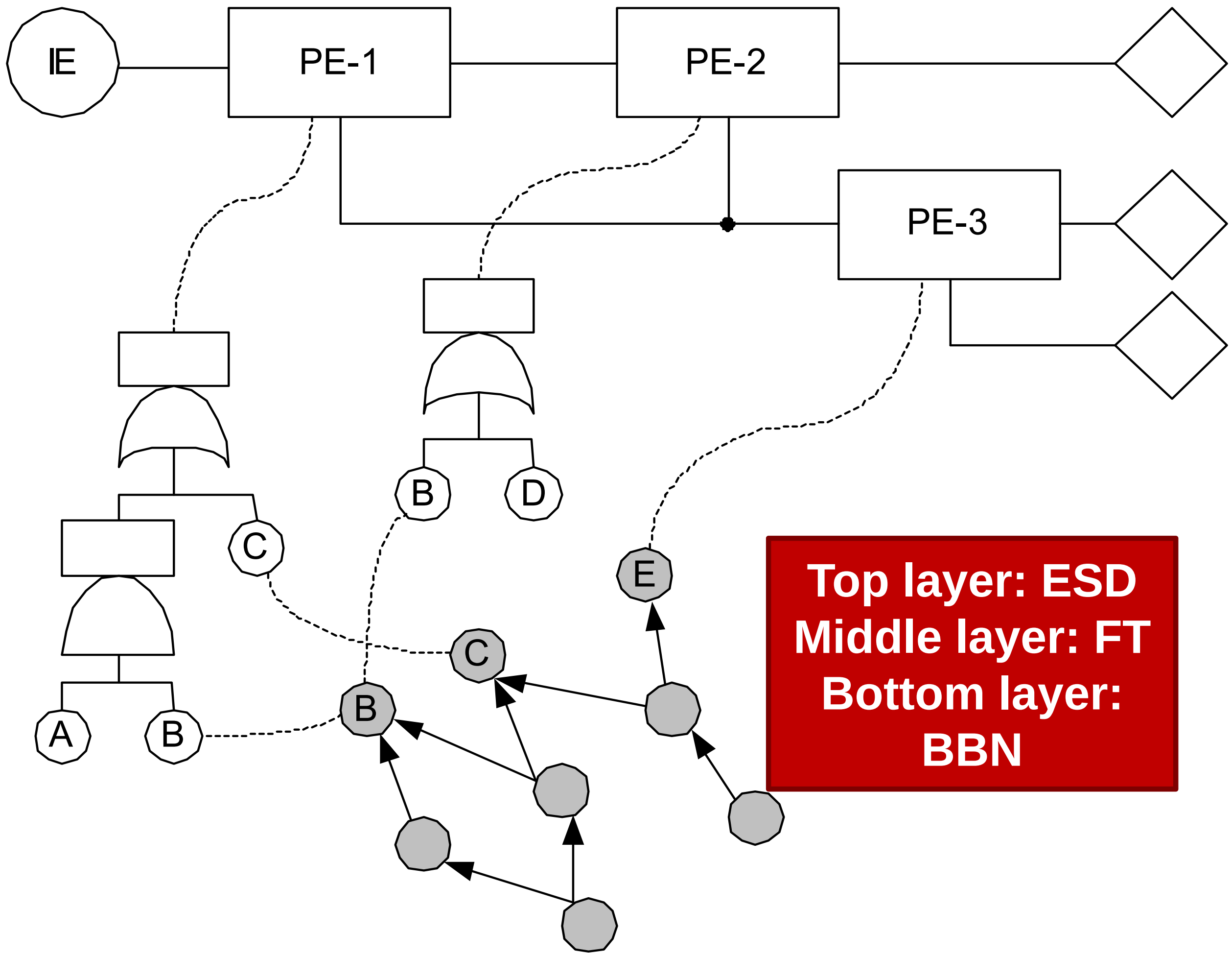
$$\Pr(c) = \Pr(A)\Pr(B)$$



$$\Pr\left(C=1 \middle| A=0, B=0\right)=0$$
$$\Pr\left(C=1 \middle| A=0, B=1\right)=0$$
$$\Pr\left(C=1 \middle| A=1, B=0\right)=0$$
$$\Pr\left(C=1 \middle| A=1, B=1\right)=1$$

$$\begin{aligned}\Pr(C) &= \Pr\left(C \middle| A,B\right)\Pr(A,B) + \Pr\left(C \middle| \overline{A},B\right)\Pr\left(\overline{A},B\right)\\ &\quad + \Pr\left(C \middle| A,\overline{B}\right)\Pr\left(A,\overline{B}\right) + \Pr\left(C \middle| \overline{A},\overline{B}\right)\Pr\left(\overline{A},\overline{B}\right)\\ &= \Pr(A,B)\end{aligned}$$

How to implement in PRA -the better option: HCL/Trilith: Adds BNs to the PRA Framework



Groth, Katrina; Wang, Chengdong & Mosleh, Ali. Hybrid causal methodology and software platform for probabilistic risk assessment and safety monitoring of socio-technical systems. *Reliability Engineering and System Safety,* **2010**, *95*, 1276-1285

So why are these Bayesian?

Judea Pearl says:

"Bayes means:
(1) using knowledge we possess prior to obtaining data,
(2) encoding such knowledge in the language of probabilities
(3) combining those probabilities with data and
(4) accepting the combined results as a basis for decision making and performance evaluation."

Judea Pearl, "Bayesianism and causality, or, why I am only a half-Bayesian"
Foundations of Bayesianism, **2001**, *24*, 19-34

BNs: Two aspects

- Building the model (Learning/Elicitation)
  - Identify the nodes
  - Structuring the graph
  - Assigning Conditional Probability Distributions (CPDs)
- Using the model (Inference)
  - Evidence propagation/belief updating – the process of computing the probability distribution, given the evidence
  - Occurs via inference algorithms, e.g., exact inference, sampling

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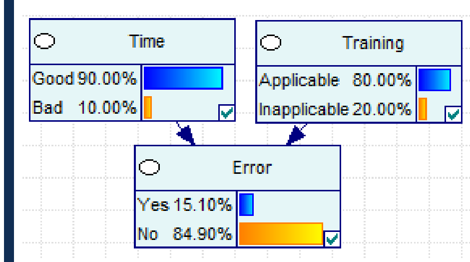
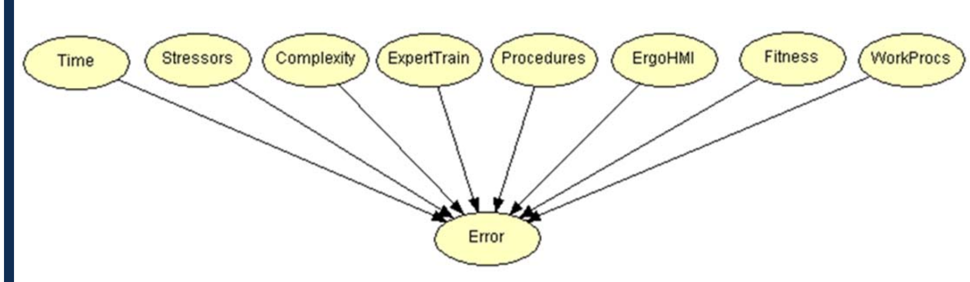
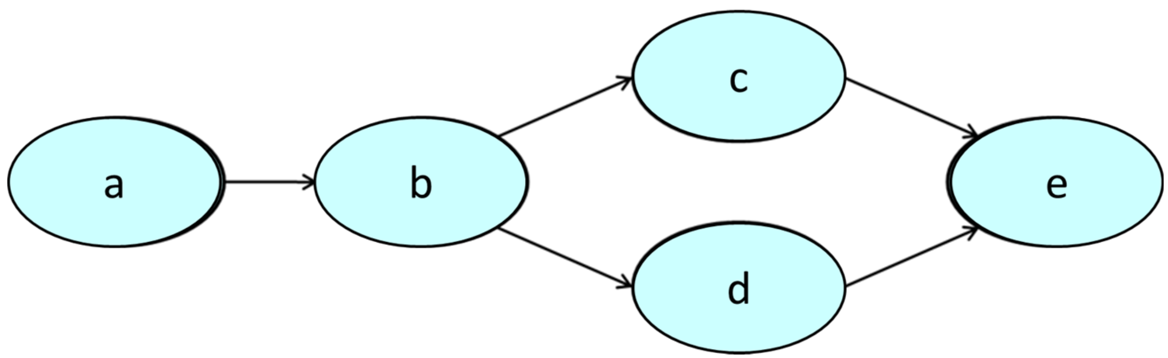




BN pieces

- BN encodes
  - Relevant variables and their states
  - (In)dependency among variables
  - The simplified joint probability distribution of the system

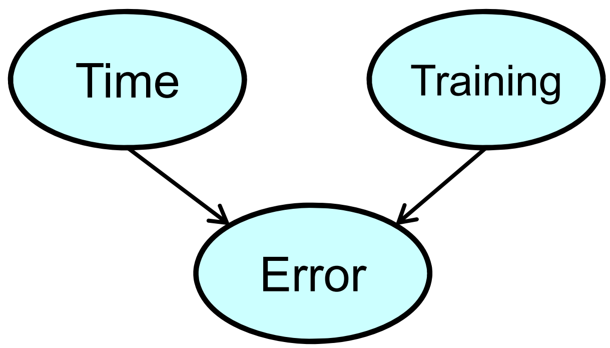


$$\boldsymbol{P(a,b,c,d,e) = P(e|a,b,c,d,) * P(d|a,b,c,) * P(c|a,b) * P(b|a) * P(a)}$$

$$\boldsymbol{= P(e|c,d) * P(d|b) * P(c|b) * P(b|a) * P(a)}$$

BN language

- Consider the following simple net



- Nodes *Time* and *Training* are **parent nodes** for node *Error; Error* is their **child node.**
- *Time* and *training* are also (they have no parents)
- *Time* and *training* are <u>conditionally</u> independent

Underlying formulas

Remember… $0 \le P \le 1$ and $\sum P(\text{universe}) = 1$

Law of Total Probability	$P(a_i) = \sum_j P(a_i \cap b_j)$ **Marginalizes** out variables
Chain Rule (of Probability)	$P(X_n \cap X_{n-1} \cap \ldots \cap X_2 \cap X_1) =$ $P(X_n \mid X_{n-1}, \ldots X_2, X_1) * P(X_{n-1} \mid \ldots X_2, X_1) * P(X_2 \mid X_1) * P(X_1)$ **Factorizes** a joint probability into conditional probabilities
Chain Rule (of BNs) *(The above, with conditional independence)*	If A and B are independent… P(A|B) = P(A) and thus P(A ∩ B) = P(A) · P(B) $P(X_1, X_2, \ldots X_n) = \prod_i P(X_i \mid Par_G(X_i))$
Bayes' Theorem	$P(X \mid E) = \frac{\Pr(E \mid X)\Pr(X)}{\Pr(E)}$ Allows forward and backward **propagation of evidence**

Mathematical Formalism

- Assume binary states for all nodes (for now)
  - Time

Good	0.9
Bad	0.1

  - Training

Applicable	0.8
Inapplicable	0.2

  - Error

Time	Good		Bad	
Training	Applicable	Inapplicable	Applicable	Inapplicable
Yes	0.1	0.25	0.3	0.5
No	0.9	0.75	0.7	0.5

To find the probability of Error="yes"

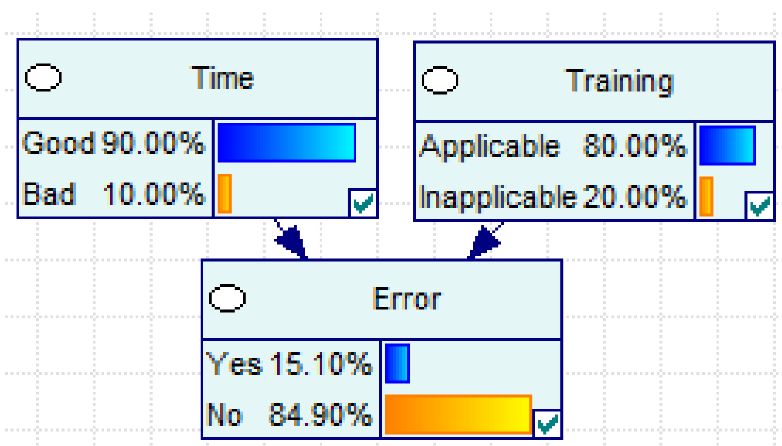
Computational Steps:

1. List all the combinations of the states of its parents,
2. Calculate the probabilities of these combinations
3. For each combination of states calculate the conditional probability* of the states of error given the states of its parents
4. Compute the marginal probability of error

* The conditional probabilities are interpreted as the degree of influence of various states of the parents on the states of error

To find the probability of Error=“yes”

Time	Training	Probability of Combination	Conditional Probability of Error = YES	Unconditional Probability of Z = z
Good	Applic.	=.9*.8	0.1	p_1 = .9*.8*.1=0.72
Good	Inapplic.	=.9*.2	0.25	p_2= .9*.2*.25=0.45
Bad	Applic.	=.1*.8	0.3	p_3= .1*.8*.3=0.024
Bad	Inapplic.	=.1*.2	0.5	p_4= .1*.2*.5=0.010
				$P = \Sigma p_i$ = **.151**



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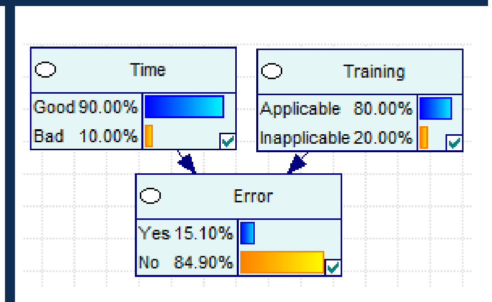
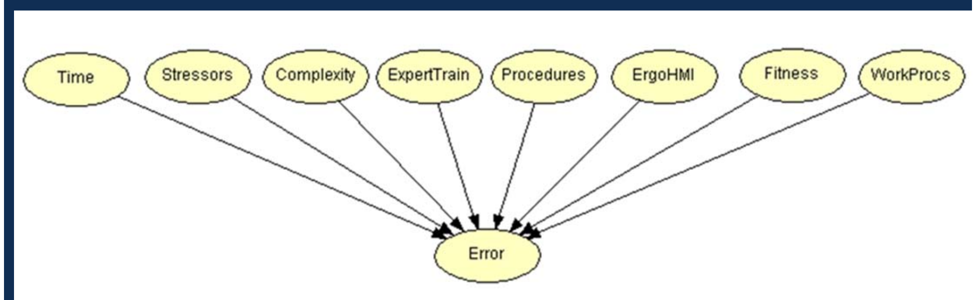
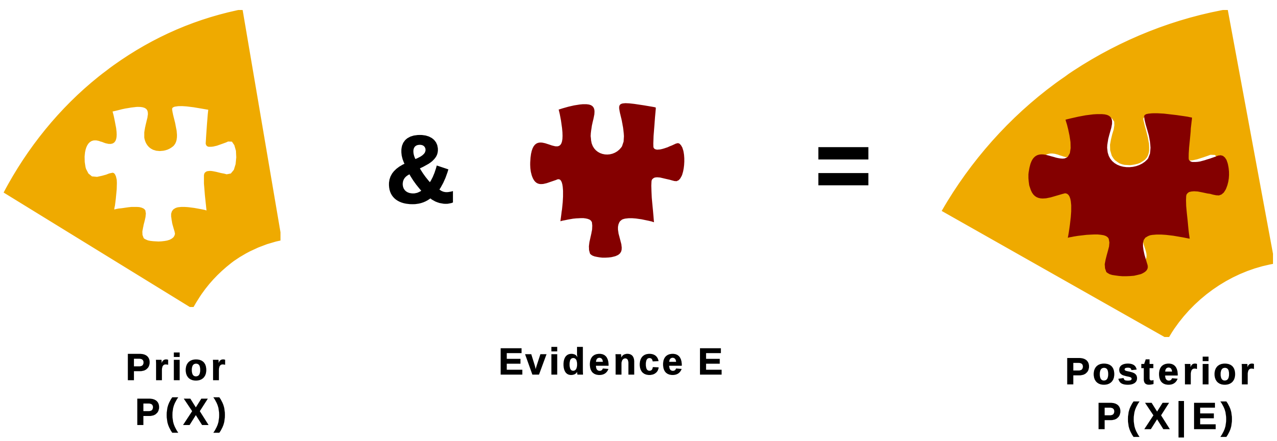




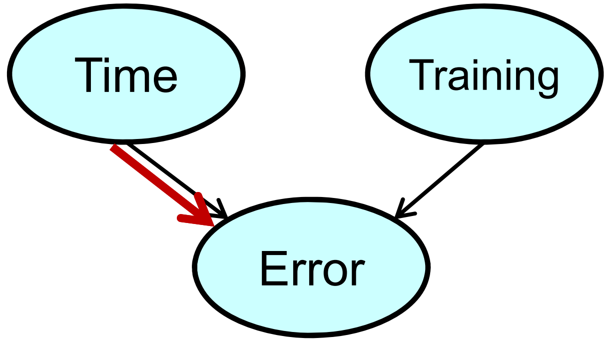
Inference in a BN

- The fully quantified model represents the entirety of the prior information available to the analyst
- The analyst makes an observation about the state of one or more variables.
- We calculate the posterior probability of the rest of the network.

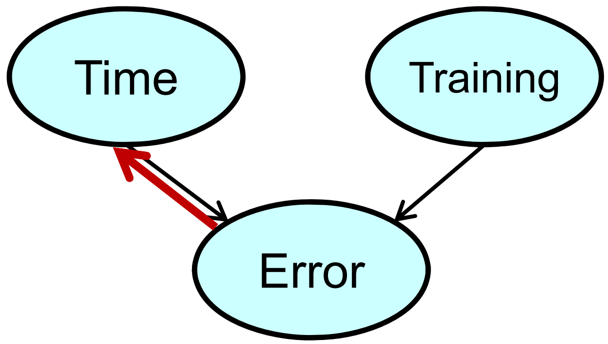


Types of reasoning/inference

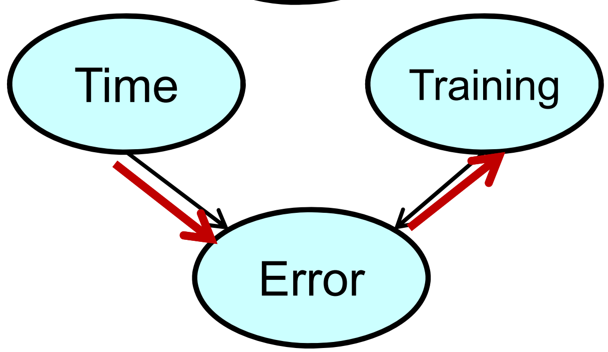
Causal:
(Forward propagation; Induction)



Evidential:
(Backward propagation; Diagnosis)



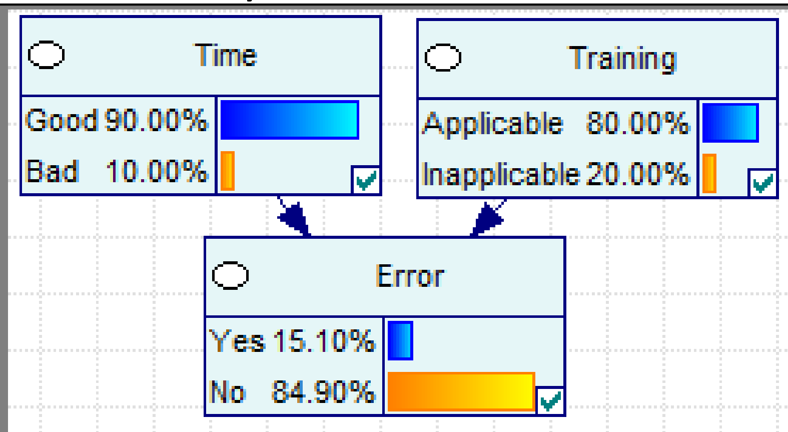
Intercausal:



Forward reasoning

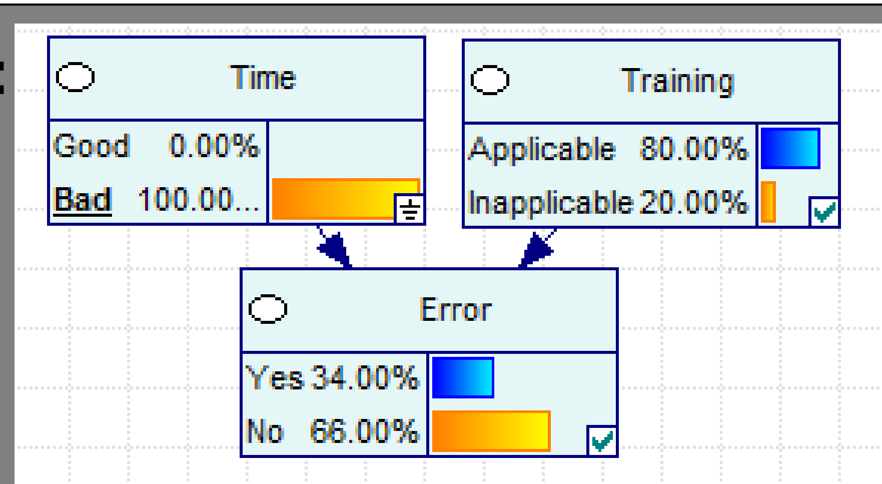
- Observing *Time=Bad* changes belief about error (P(Yes) goes from .151 to .34)

Prior: (Before)



Observation: Time = Bad

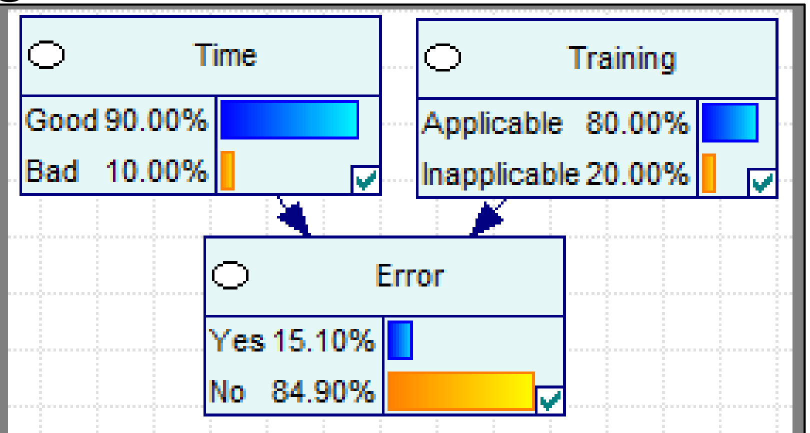
Posterior: (After)



Backward reasoning

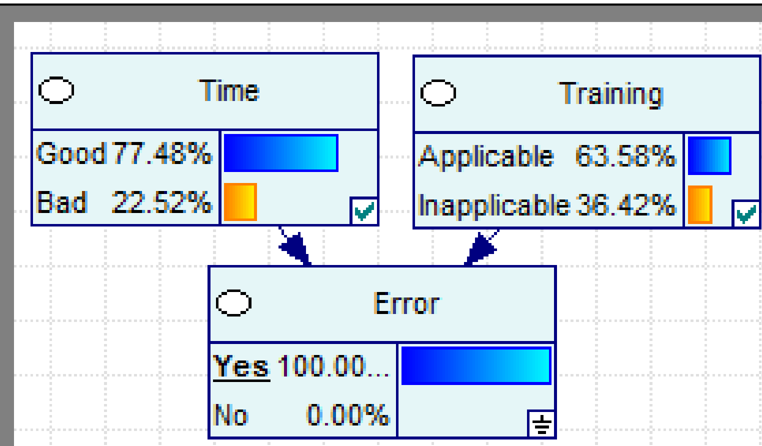
- Observing *Error=yes* changes belief about both time and training

Prior: (Before)



Observation: Error = yes

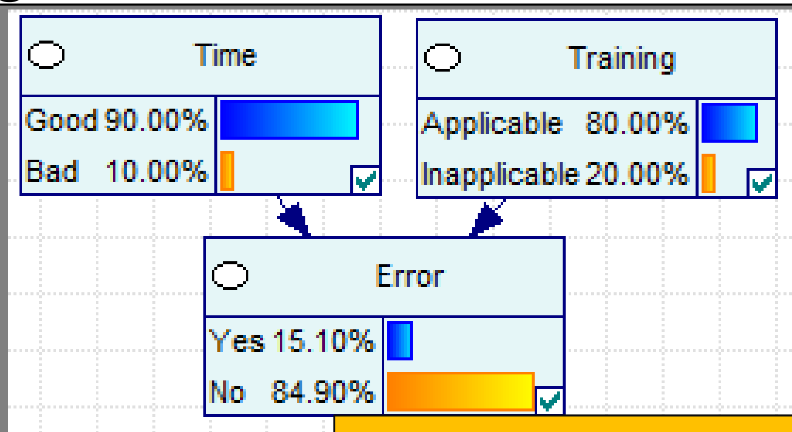
Posterior: (After)



Intercausal reasoning (both)

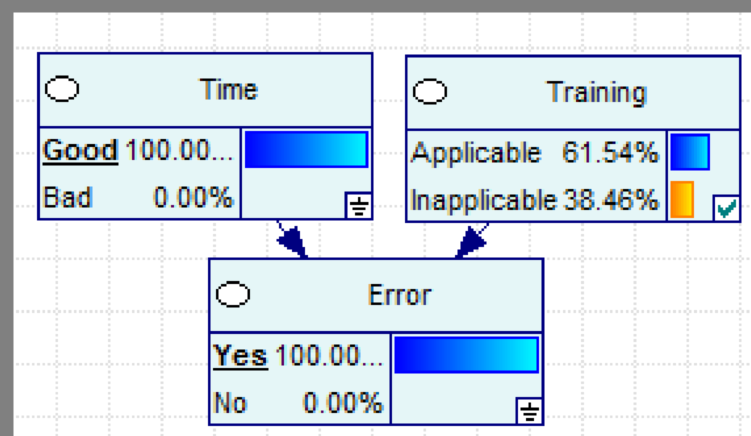
- Observing *Error=yes and Time = Good* changes belief about training

Prior: (Before)



Observations: Error = yes; Time = Good

Posterior: (After)



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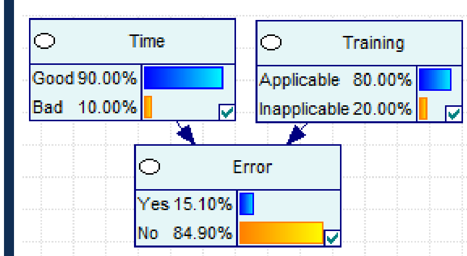
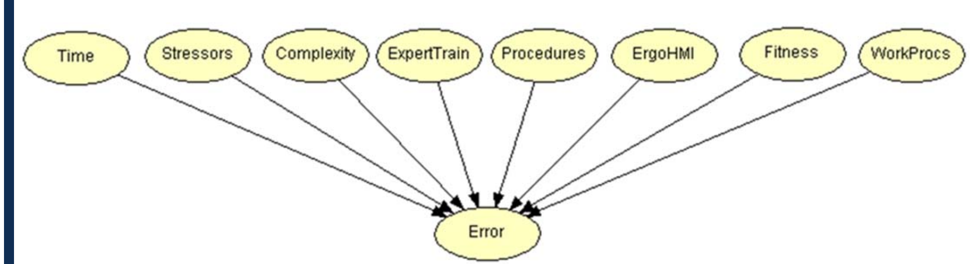




Example HRA method: SPAR-H

1. Assess context in terms of PSFs (Performance Shaping Factors)

- Available time
- Stress/stressors
- Complexity
- Experience/training
- Procedures
- Ergonomics/HMI
- Fitness for duty
- Work processes

2. Calculate HEP (Human Error Probability)

$$HEP = NHEP \cdot \prod_{i=1}^{8} PSF_i$$

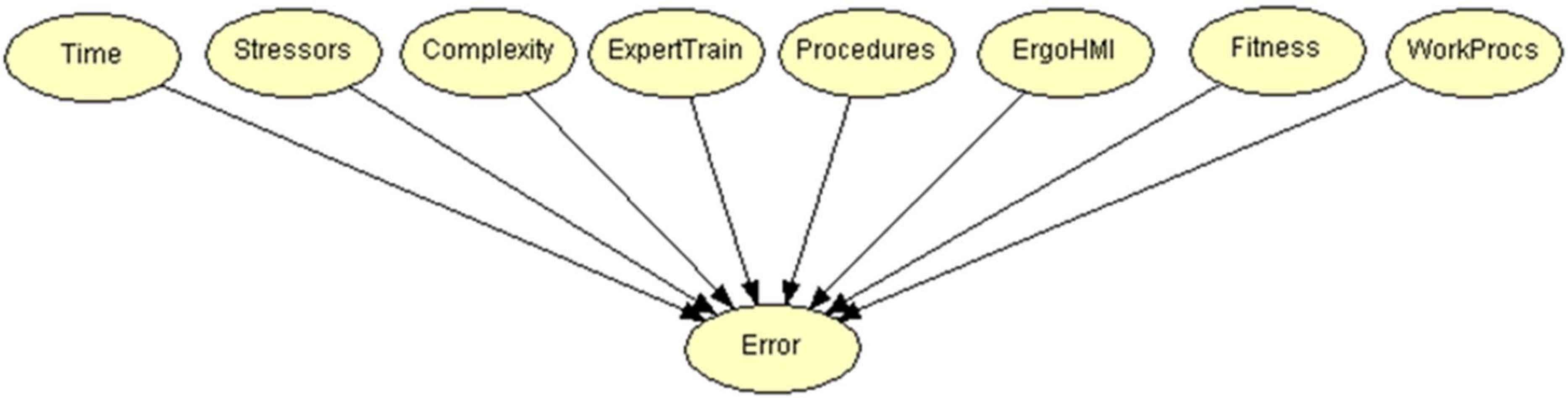
Where NHEP = 0.01 for diagnosis tasks and 0.001 for action tasks

PSFs	PSF Levels	Multiplier for Action	
Available Time	Inadequate time	P(failure) = 1.0	☐
	Time available is ≈ the time required	10	☐
	Nominal time	1	☐
	Time available is ≥ 5x the time required	0.1	✓
	Time available is ≥ 50x the time required	0.01	☐
	Insufficient Information	1	☐
Stress/ Stressors	Extreme	5	☐
	High	2	☐
	Nominal	1	☐
	Insufficient Information	1	✓
Complexity	Highly complex	5	☐
	Moderately complex	2	✓
	Nominal	1	☐
	Insufficient Information	1	☐
Experience/ Training	Low	3	☐
	Nominal	1	✓
	High	0.5	☐
	Insufficient Information	1	☐
Procedures	Not available	50	☐
	Incomplete	20	☐
	Available, but poor	5	☐
	Nominal	1	✓
	Insufficient Information	1	☐
Ergonomics/ HMI	Missing/Misleading	50	☐
	Poor	10	☐
	Nominal	1	☐
	Good	0.5	☐
	Insufficient Information	1	✓
Fitness for Duty	Unfit	P(failure) = 1.0	☐
	Degraded Fitness	5	☐
	Nominal	1	☐
	Insufficient Information	1	✓
Work Processes	Poor	5	☐
	Nominal	1	☐
	Good	0.5	✓
	Insufficient Information	1	☐

Challenges for SPAR-H

- Poor handling of uncertainty
  - Is “unknown” really equivalent to “nominal”?
- Poor credibility (HRA in general, not just SPAR-H)
  - In PRA, data is used to build credibility/confidence;
  - Very few HRA methods use data, and those that do use very little data
  - Use of expert-elicited probabilities
    - System expert != probability expert.
- Traceability
  - Tenuous link between inputs and outputs
    - Subjective – your “high stress” might be my “low stress” situation

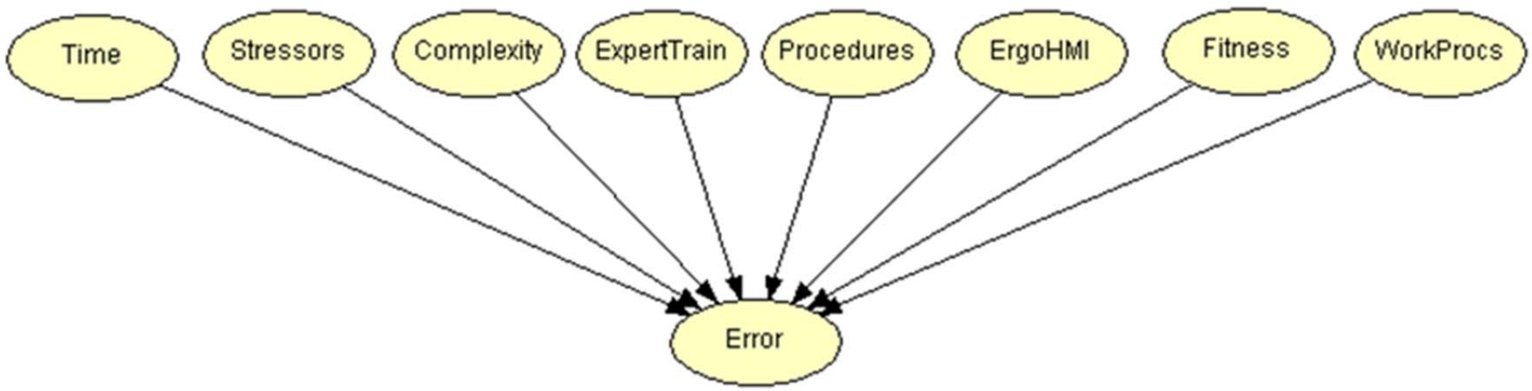
SPAR-H BN: Structure



- SPAR-H method:
  - 8 PSFs affect error probability
  - PSFs act independently on error (margin independence)
  - Interdependency among PSFs is acknowledged, but not modeled

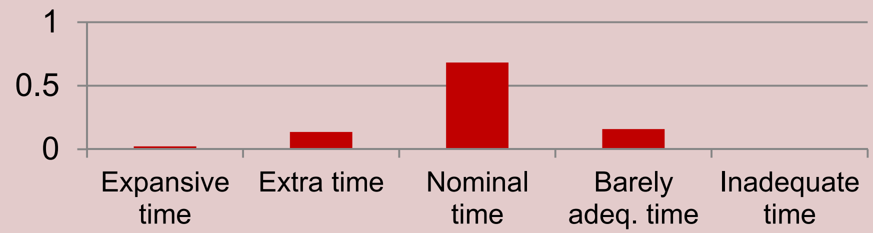
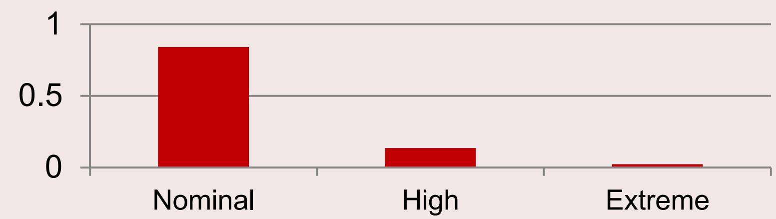
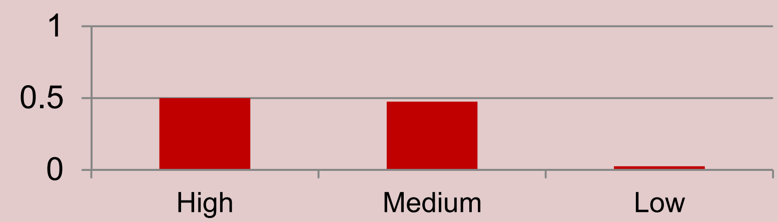
Quantification

Factorizing the joint distribution allows us to specify different parts of the model using different sources of information (including data)



$$P(Error) = \sum_{PSFs} [P(Error|Time, Stress, Complexity, ExpertTrain, Procedures, ErgoHMI, Fitness, WorkProcs) * P(Time) * P(Stress) * P(Complexity) * P(ExpertTrain) * P(Procedures) * P(ErgoHMI) * P(Fitness) * P(WorkProcs)]$$

Quantification: P(PSFs)

<table>
<tr><th>PSF</th><th>Source</th><th>Probability distribution</th></tr>
<tr><td>P(Time)
5 states</td><td>NUREG/CR-6949</td><td>
</td></tr>
<tr><td>P(Stress)
3 states</td><td>NUREG/CR-6949</td><td>
</td></tr>
<tr><td>P(ExpertTrain)
3 states</td><td>Curve fit
(Available from plant data)</td><td>
</td></tr>
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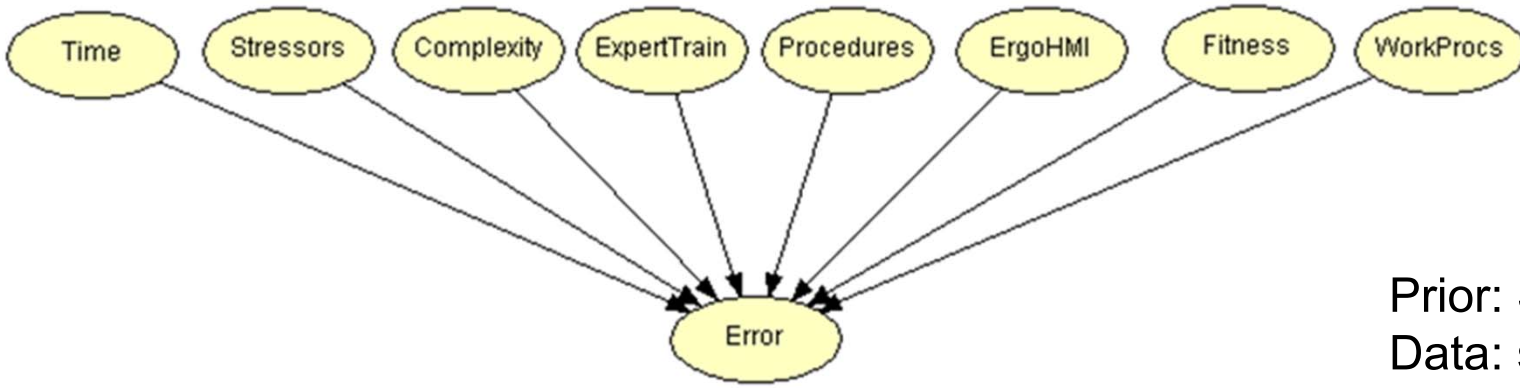
Similar NUREG/CR-6949 values for: P(Complexity), P(Procedures), P(ErgoHMI), P(Fitness), P(WorkProcs)

Next steps: Adding simulator data to this model (ask me after class)

HRA: BN version of SPAR-H



Prior: SPAR-H
Data: simulator

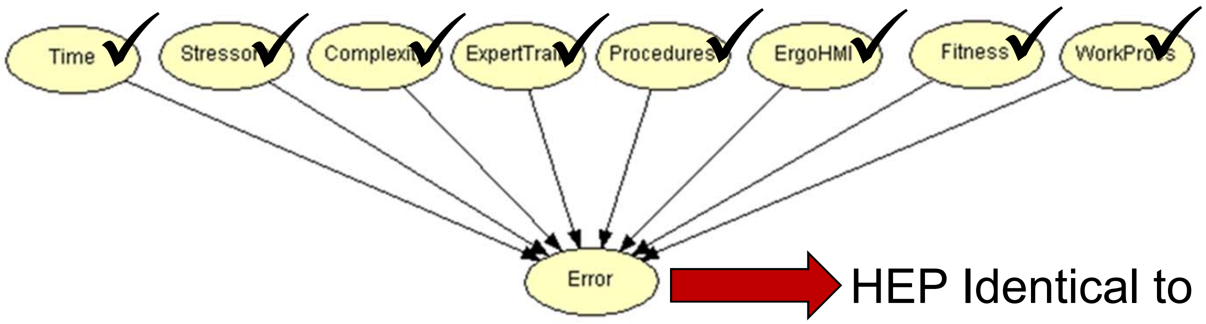
$$P(Error) = \sum_{PSFs} P(Error|Time, Str, Compl, Expert, Procs, HMI, Fit, WPs) *$$

$$\ldots \underbrace{P(Time) * P(Stress) * P(Complexity) * P(Expert) * P(Procs) * P(HMI) * P(Fit) * P(WPs)}_{\text{Priors: Experts; Industry data}}$$

Groth, Katrina M. & Swiler, Laura P. Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H. Reliability Engineering and System Safety, ***2013****, 115, 33-42.*

BN benefits: addresses uncertainty

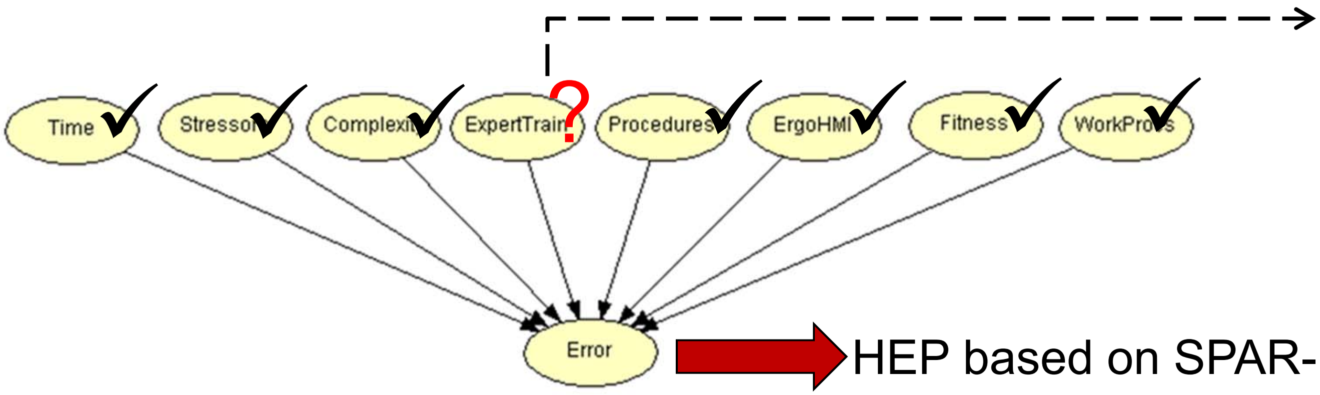
- Certainty cases:

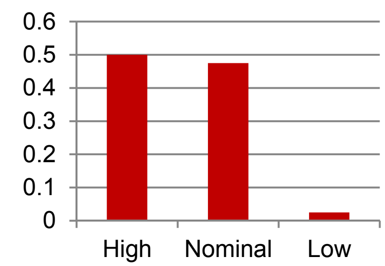


HEP Identical to SPAR-H model

- “Insufficient Information” cases:

Uses prior distribution rather than assuming nominal

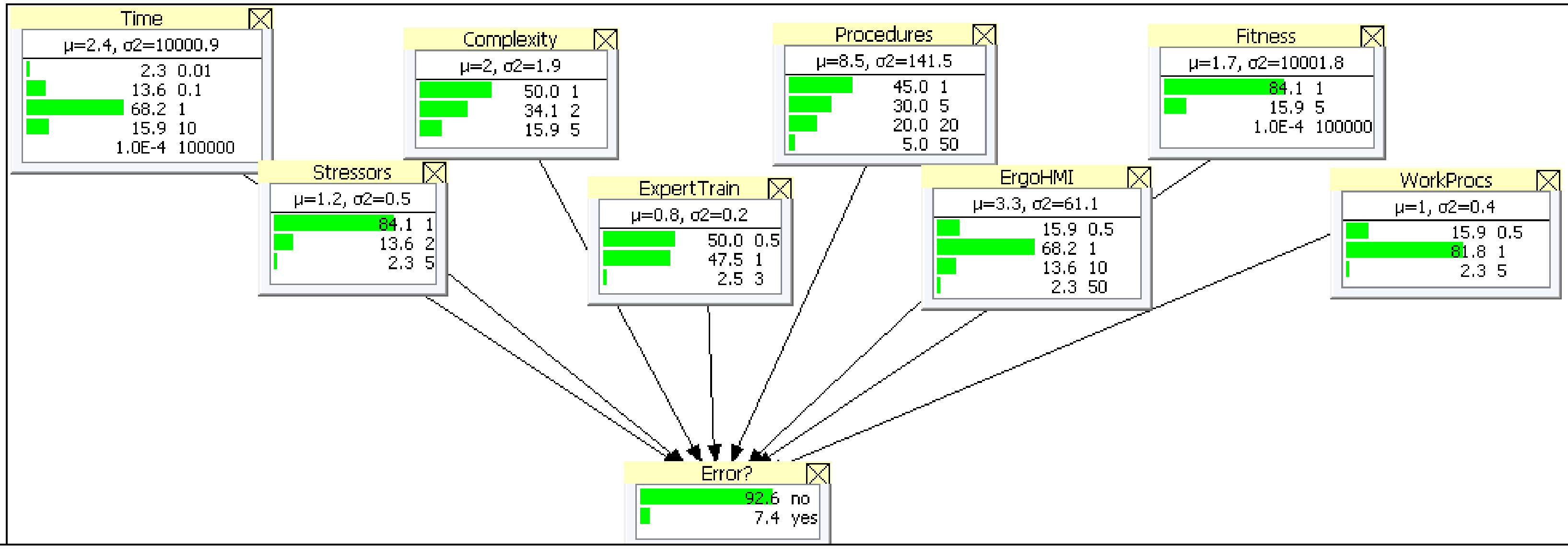




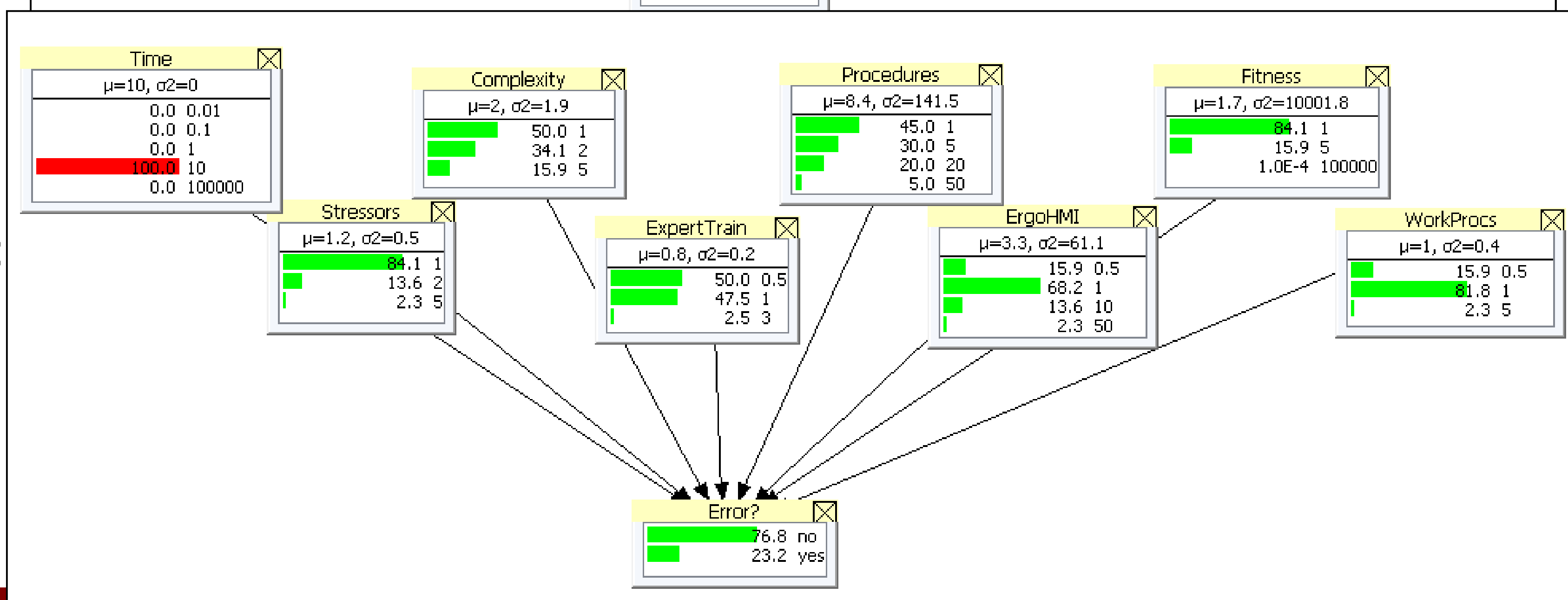
HEP based on SPAR-H model AND prior distribution of unknowns

Causal reasoning (Just like SPAR-H)

Prior:

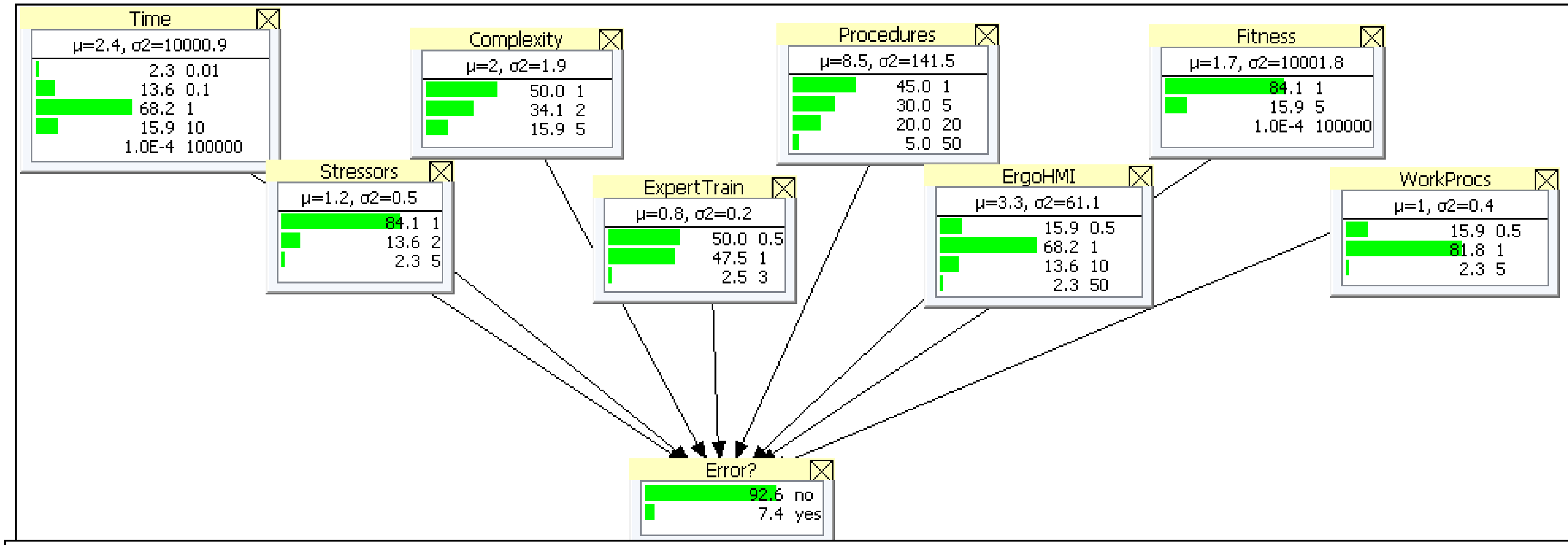


Posterior:

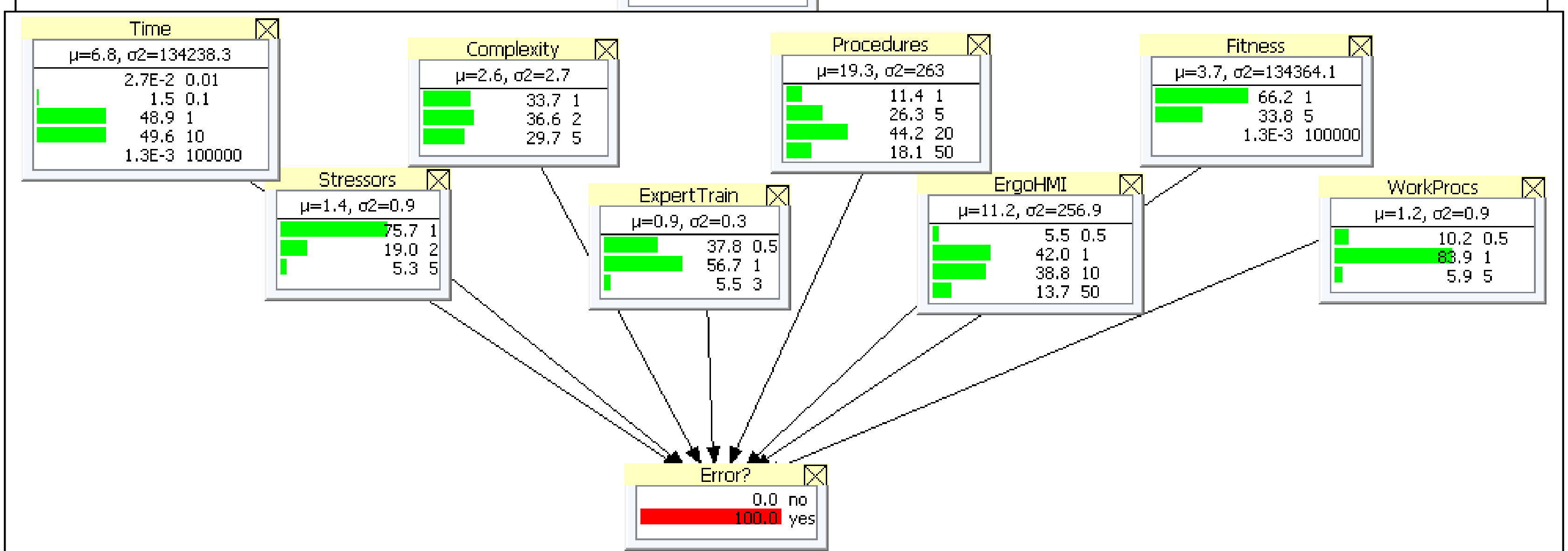


Evidential reasoning (New, powerful!)

Prior:

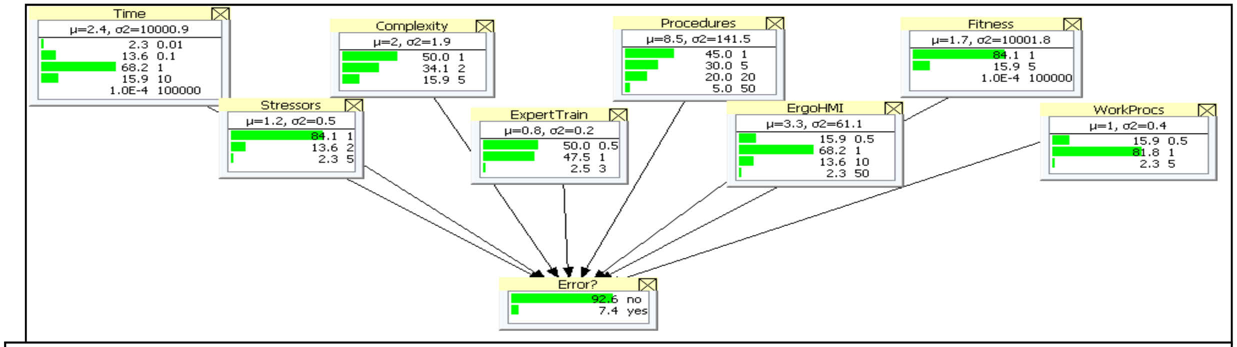


Posterior:

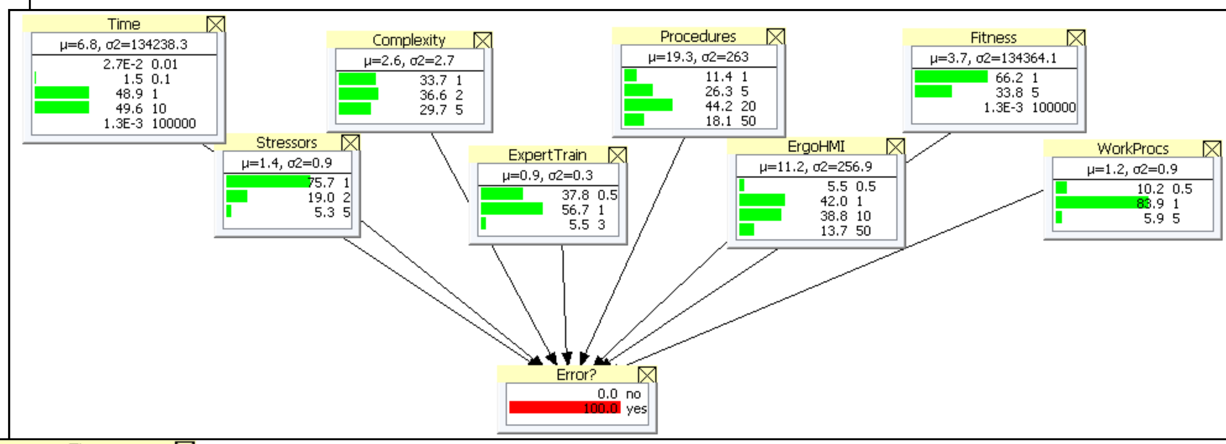


Intercausal reasoning (Explaining away)

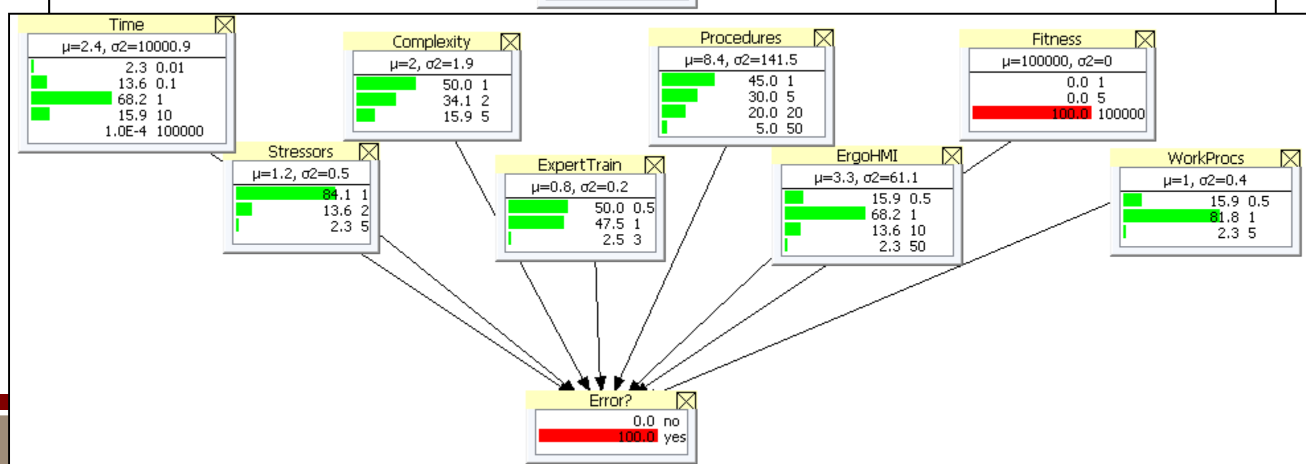
Prior:



Posterior (1):

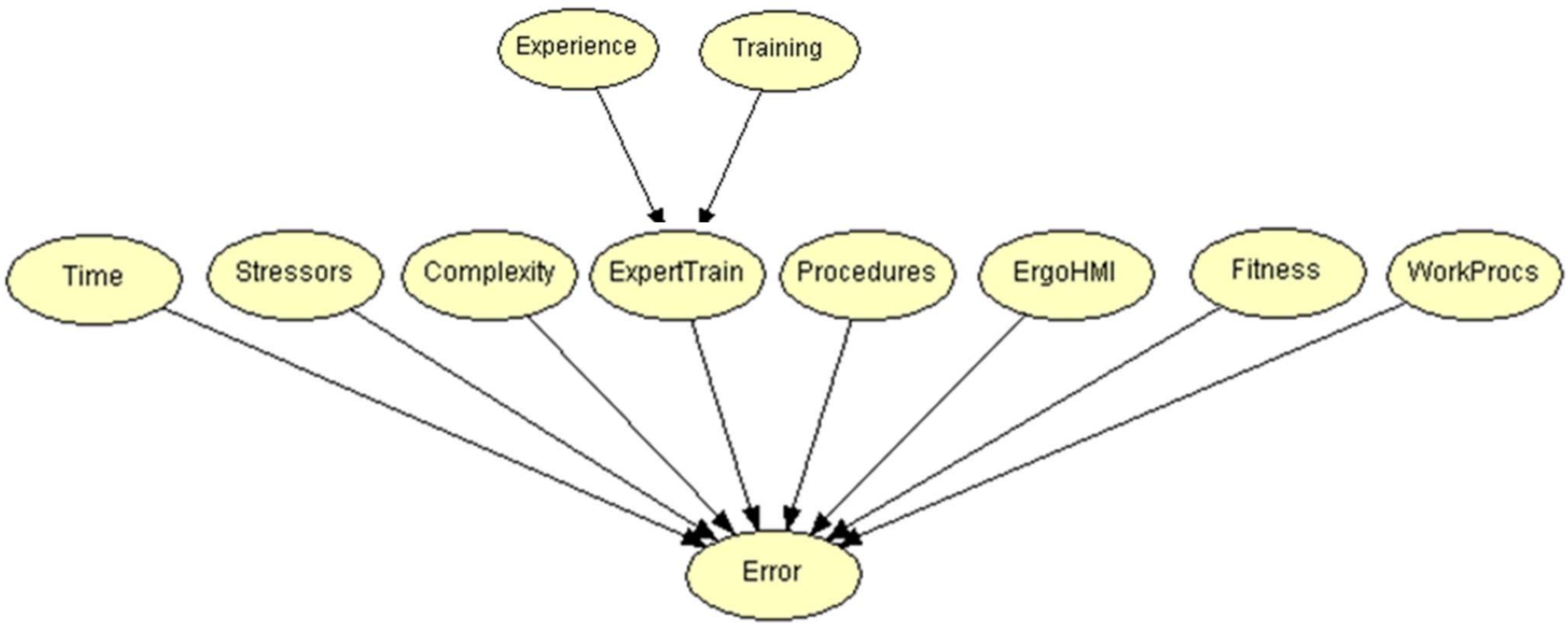


Posterior (2):



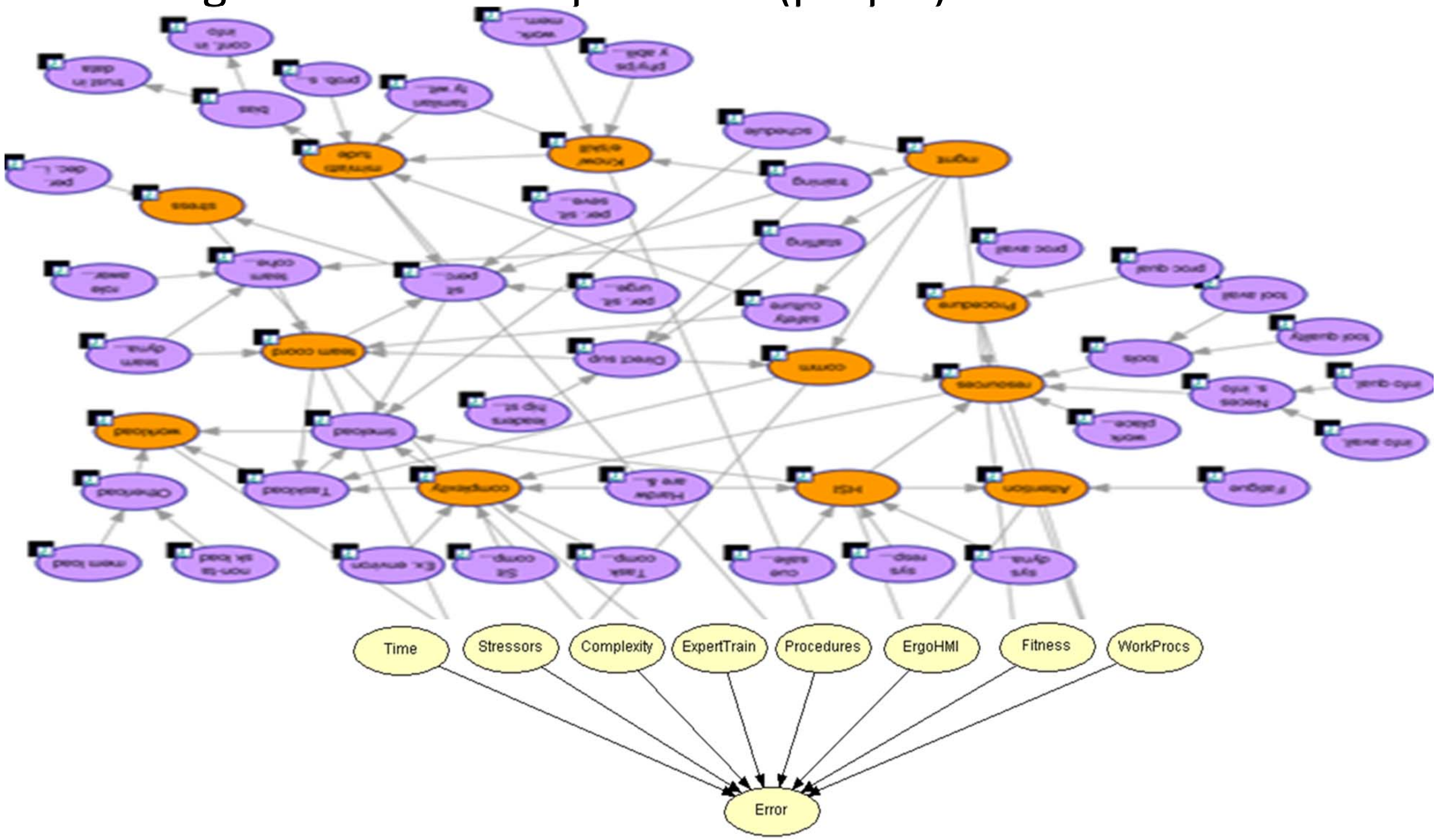
Next steps: Extending the model

- Expanded model using additional Performance Influencing Factors (PIFs)



Even deeper: Internal algorithm

- Linking more detailed questions (purple) to the PSFs



Top portion from: N. Ekanem, A model-based Human Reliability Analysis Methodology (PHOENIX method). Ph. D. Thesis. *University of Maryland,* **2013.**

Implications for HRA

1. **Using HRA data adds credibility**
    1. It's possible to use HRA data to update existing HRA methods.
    2. It is inconsistent with PRA practice to NOT update HRA methods.
    3. You don't need perfect HRA data to do the updating, if you separate out the probabilities of the PSFs from the probabilities of error, given PSFs.

2. **Expanding causal details adds traceability**
    1. Adding plant-specific details makes it easier to assign PSF states (reduces subjectivity of PSF assignments)
    2. Also adds value to users – more detailed identification of ways to prevent human errors

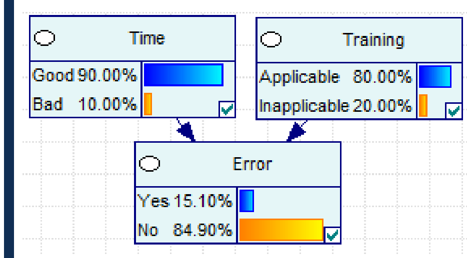
Outline

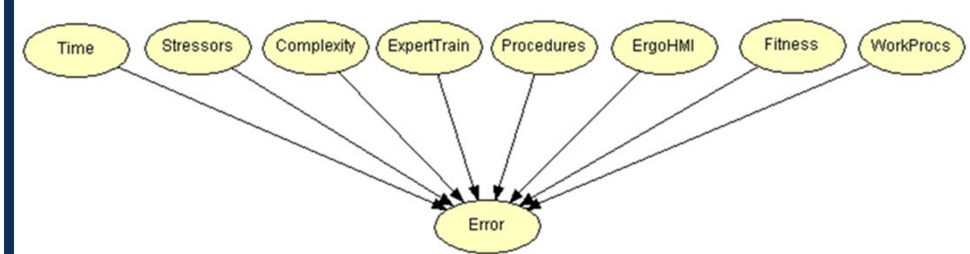
- What is a BN?
- Building a BN
- Inference with BNs
- HRA Example
- A few BNs for PRA and safety
- Wrap-up

Exceptional service in the national interest

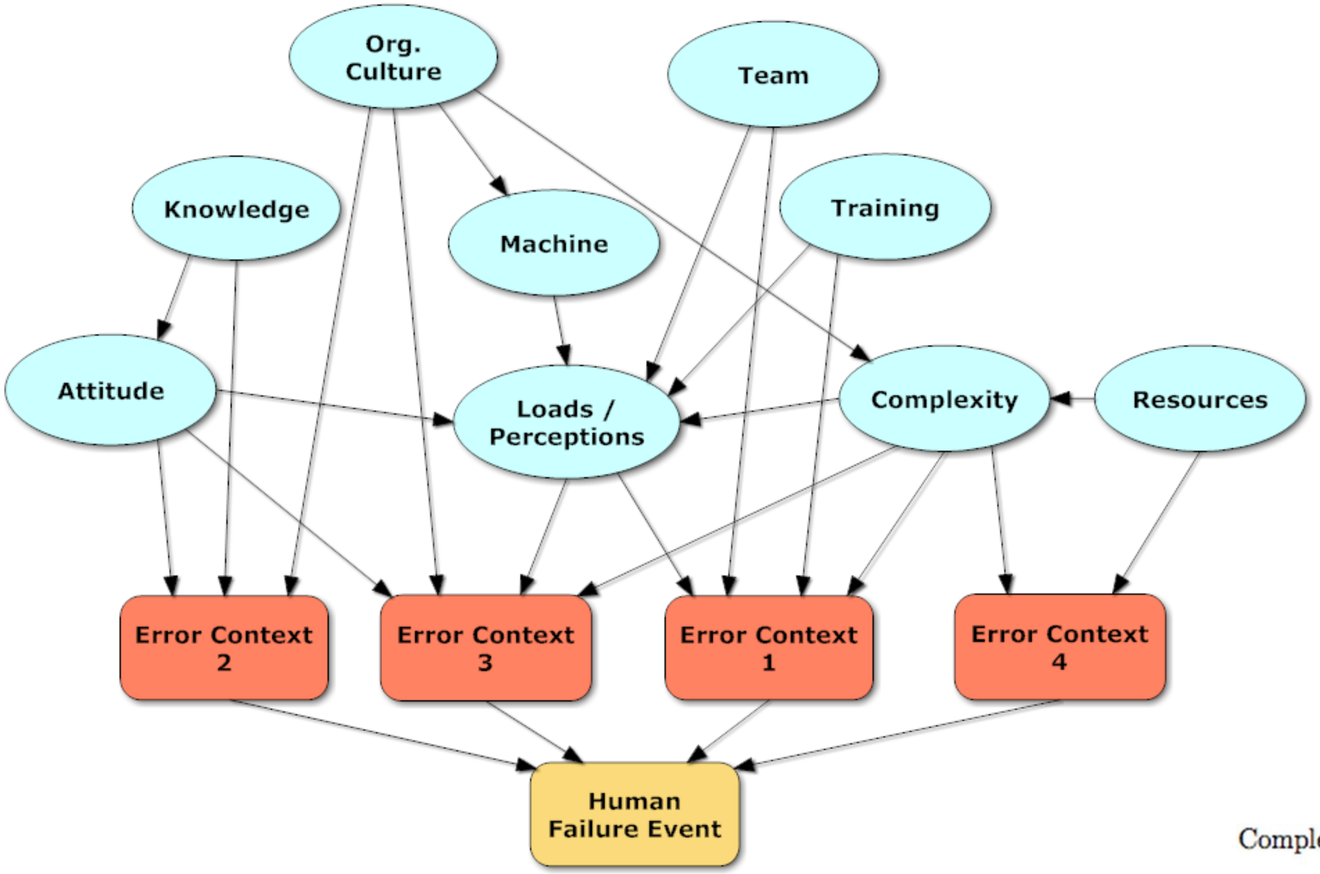
Sandia National Laboratories

Parent	$Pr(a)$	$Pr(\overline{a})$
$Pr(b)$	$Pr(b\|a)$	$Pr(b\|\overline{a})$
$Pr(\overline{b})$	$Pr(\overline{b}\|a)$	$Pr(\overline{b}\|\overline{a})$





Nuclear HRA: Data-informed quantification model



Training		
	LTA	0.37
	Adequate	0.63

Org. Culture		
	LTA	0.48
	Adequate	0.52

Resources		
	LTA	0.40
	Adequate	0.60

Team		
	LTA	0.46
	Adequate	0.54

Knowledge		
	LTA	0.53
	Adequate	0.47

		Org. Culture	
		LTA	Adeq.
Machine	LTA	0.36	0.62
	Adequate	0.64	0.38

		Knowledge	
		LTA	Adeq.
Attitude	LTA	0.47	0.87

	Org. Culture	LTA		Adeq.	
	Resources	LTA	Adeq.	LTA	Adeq.
Complexity	LTA	0.62	0.50	0.57	0.52
	Adequate	0.38	0.50	0.43	0.48

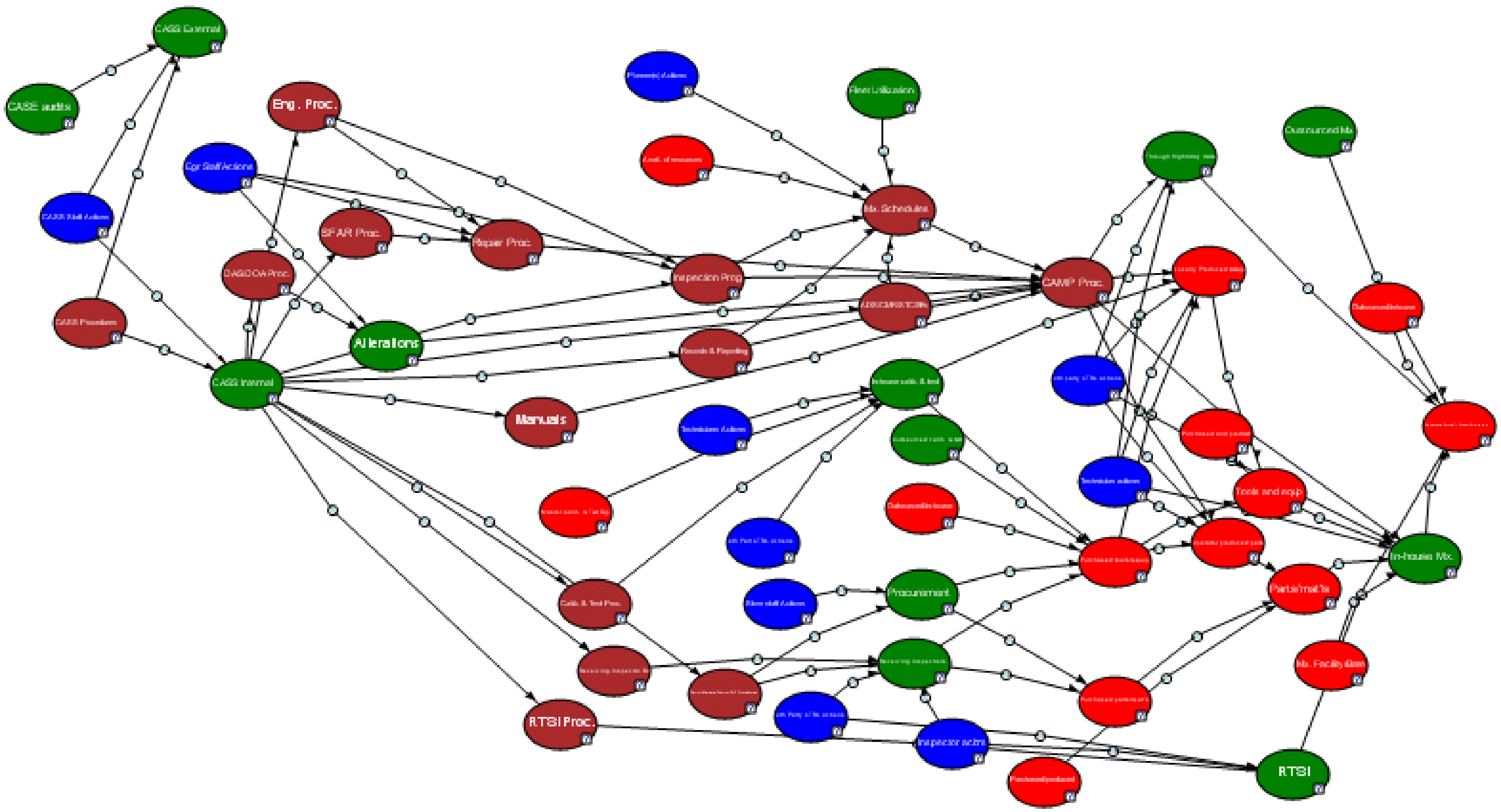
$$P(HFE) = \sum_{PSFs} P(HFE|EC1, EC2, EC3, EC4) * P(EC1|PSFs) * P(EC2|PSFs) * P(EC3|PSFs) * P(EC4|PSFs) * P(PSFs)$$

Baseline: P(Err)

1.88E-03

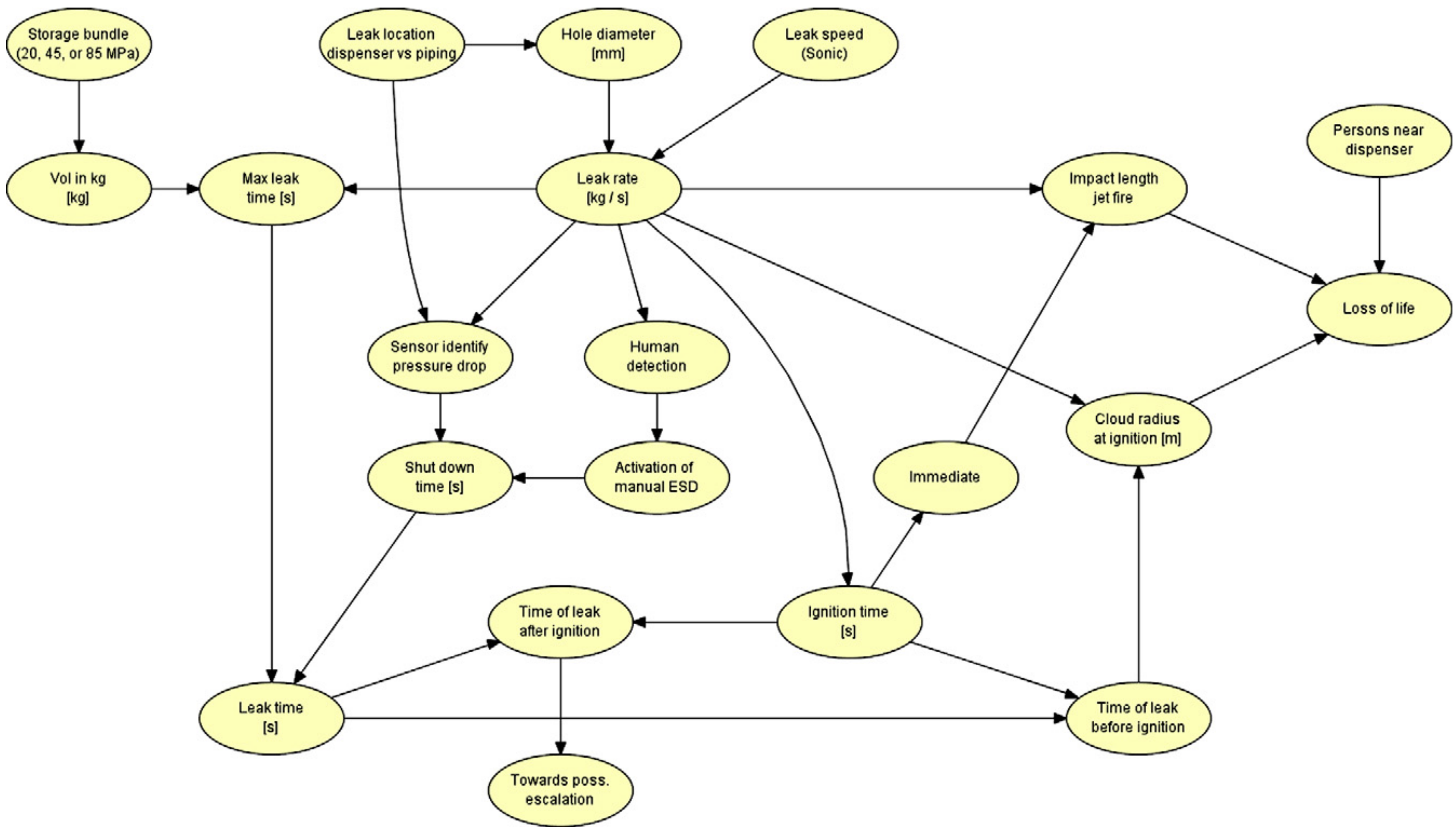
*Groth, Katrina M. & Mosleh, Ali. Deriving causal Bayesian networks from human reliability analysis data: A methodology and example model. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, **2012**, 226, 361-379.*

Aircraft Maintenance Model



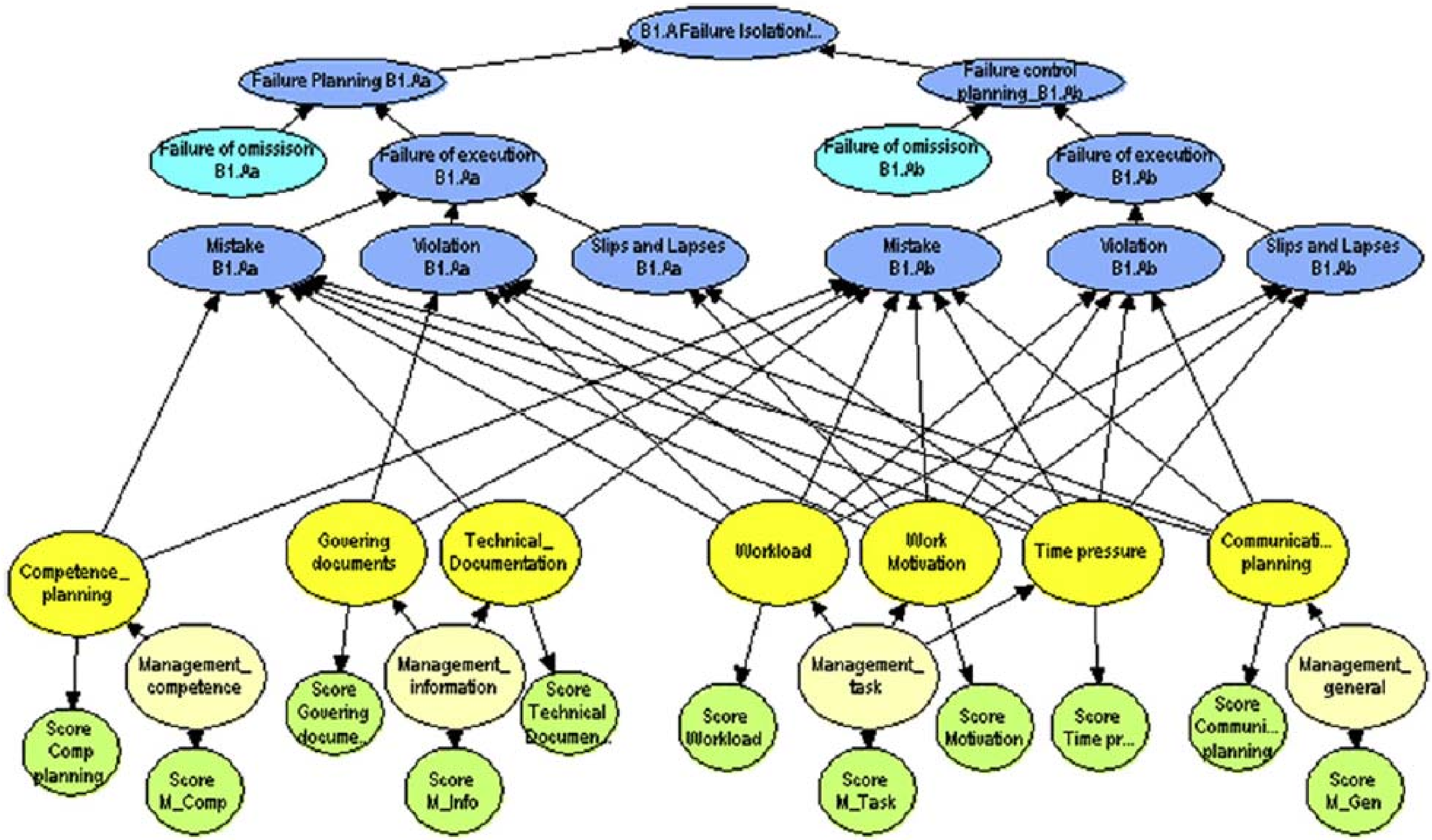
Eghbali GH. *Causal model for air carrier maintenance*. Report prepared for Federal Aviation Administration. Atlantic City, NJ: Hi-Tec Systems; 2006.

PRA: Hydrogen dispensing



Haugom, G. P. & Friis-Hansen, P. Risk modelling of a hydrogen refuelling station using Bayesian network. *International Journal of Hydrogen Energy,* **2011**, *36*, 2389-2397.

PRA: Offshore oil maintenance errors



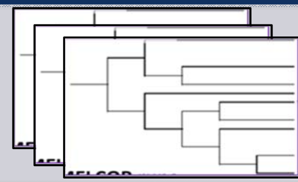
Vinnem, J. E.; Bye, R.; Gran, B. A.; Kongsvik, T.; Nyheim, O. M.; Okstad, E. H.; Seljelid, J. & Vatn, J. Risk modelling of maintenance work on major process equipment on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries,* **2012**, *25*, 274-292

BN-Based "Smart SAMGs"

Generate spectrum of accident scenarios

Goal: Identify potential accident scenarios

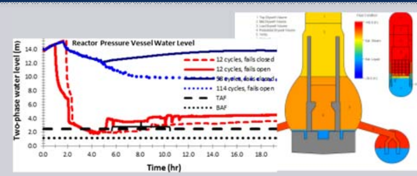
Tool: DDET/ADAPT simulation scheduler



Simulate reactor physics for each scenario

Goal: Predict range of plant parameters for known system faults

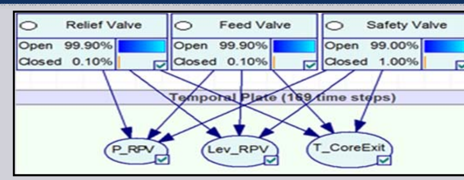
Tool: MELCOR



Encode results in a generic knowledge base

Goal: Build a map between known parameters and known faults

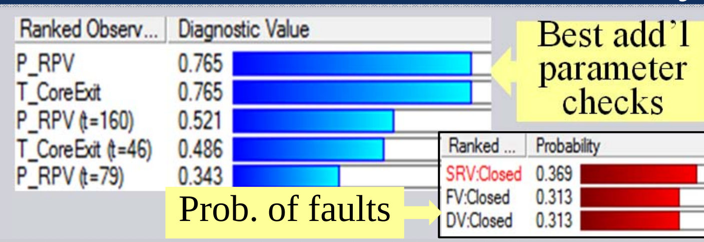
Tool: Bayesian Networks



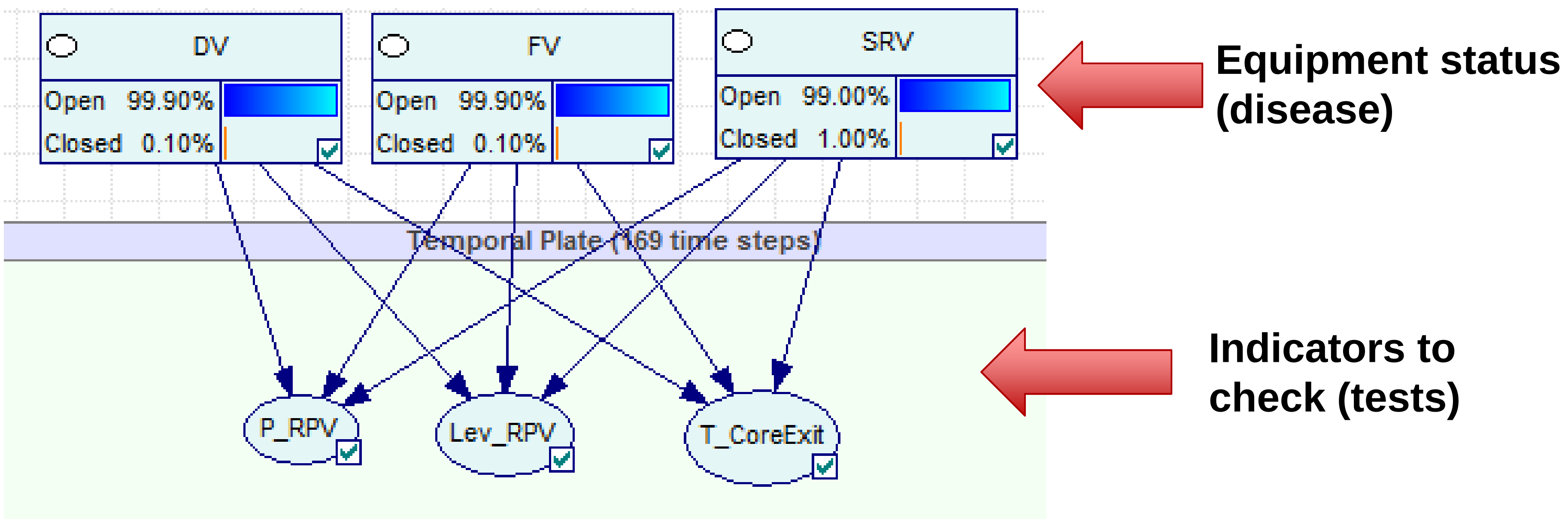
Enable queries for specific parameters, faults, under uncertainty

Goal: Enable users to diagnose specific faults, identify key indicators, ask "what-if"

Tool: Probabilistic queries, differential diagnosis, value of information



"Smart SAMGS: Building a probabilistic map between plant conditions and plant parameters



Groth, K. M.; Denman, M. R.; Cardoni, J. N. & Wheeler, T. A. Proof of Principle Framework for Developing Dynamic Risk-Informed Severe Accident Management Guidelines. SAND2013-8324. *Sandia National Laboratories*, **2013**

Smart SAMG diagnosis

Prior (Unknown accident)

Ranked ...	Probability
SRV:Closed	0.010
DV:Closed	0.001
FV:Closed	0.001

1.0% chance of SRV failure
0.1% chance of DV failure
0.1% chance of FV failure

Ranked Observ...	Diagnostic Value
Lev_RPV	0.896
P_RPV	0.856
T_CoreExit	0.856
T_CoreExit (t=46)	0.651
P_RPV (t=160)	0.650
T_CoreExit (t=146)	0.615
P_RPV (t=79)	0.485
P_RPV (t=25)	0.464
T_CoreExit (t=72)	0.443
T_CoreExit (t=63)	0.439

Suggests checking RPV level (t0), RPV pressure (t0), Core Exit temp (t0)

Observation: RPV Level (time 0) = low

Posterior (Condition-specific)

Ranked ...	Probability
SRV:Closed	1.000
FV:Closed	< 0.001
DV:Closed	< 0.001

~100% chance of SRV failure
<0.1% chance of DV failure
<0.1% chance of FV failure

Ranked Observ...	Diagnostic Value
Lev_RPV (t=110)	0.072
Lev_RPV (t=157)	0.072
Lev_RPV (t=93)	0.071
Lev_RPV (t=62)	0.070
Lev_RPV (t=35)	0.070
Lev_RPV (t=83)	0.070
Lev_RPV (t=37)	0.070
Lev_RPV (t=153)	0.070
Lev_RPV (t=165)	0.069
Lev_RPV (t=65)	0.069

Suggests checking RPV level (110, t157, t93)

A single key observation dramatically changes belief about ECCS status and value of additional tests

Implemented in GeNIe: http://genie.sis.pitt.edu/

Diagnostic value of tests

For FV failure

Ranked Observ...	Diagnostic Value
T_CoreExit (t=46)	0.319
Lev_RPV	0.316
T_CoreExit (t=146)	0.232
P_RPV (t=160)	0.224
P_RPV (t=128)	0.217
T_CoreExit (t=108)	0.202
Lev_RPV (t=157)	0.200
P_RPV (t=58)	0.197
Lev_RPV (t=68)	0.195
T_CoreExit	0.191
P_RPV	0.191
Lev_RPV (t=159)	0.188
Lev_RPV (t=151)	0.187
T_CoreExit (t=44)	0.184
P_RPV (t=79)	0.184
Lev_RPV (t=46)	0.182
T_CoreExit (t=123)	0.176
P_RPV (t=101)	0.175
T_CoreExit (t=72)	0.174
T_CoreExit (t=63)	0.171
Lev_RPV (t=106)	0.167

Suggested checks: Core exit temp (t46), RPV level(t0)

For SRV failure

Ranked Observ...	Diagnostic Value
Lev_RPV	0.896
P_RPV	0.856
T_CoreExit	0.856
T_CoreExit (t=46)	0.651
P_RPV (t=160)	0.650
T_CoreExit (t=146)	0.615
P_RPV (t=79)	0.485
P_RPV (t=25)	0.464
T_CoreExit (t=72)	0.443
T_CoreExit (t=63)	0.439
Lev_RPV (t=160)	0.433
Lev_RPV (t=61)	0.421
T_CoreExit (t=44)	0.414
P_RPV (t=58)	0.406
Lev_RPV (t=156)	0.406
T_CoreExit (t=123)	0.382
T_CoreExit (t=108)	0.372
Lev_RPV (t=161)	0.364
T_CoreExit (t=98)	0.361
P_RPV (t=128)	0.359
T_CoreExit (t=70)	0.358

Suggested checks: RPV Press(t0), RPV level(t_0)

Different tests provide greater diagnostic power for different diseases (and some provide little value for either disease)

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Parent	$Pr(a)$	$Pr(\overline{a})$
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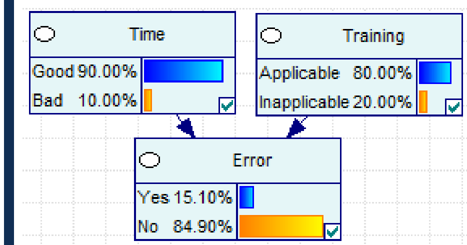
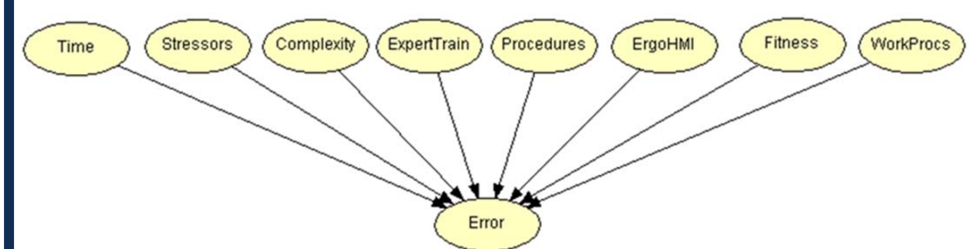




If you want to get more complicated

- Continuous BNs
- Dynamic BNs
- Inference algorithms
- Value of information
- Bayesian updating the probabilities in the BN

Software packages

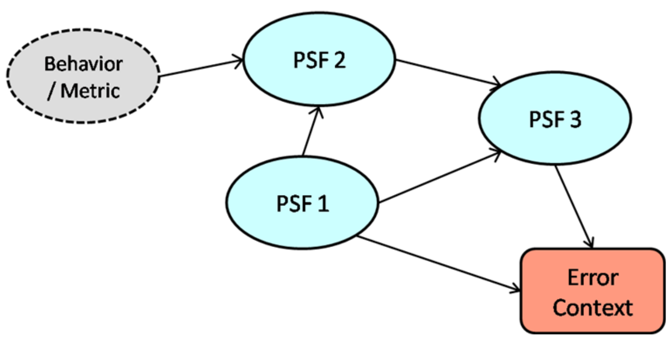
- Tools with graphical user interfaces
  - GeNIe (http://genie.sis.pitt.edu/)
  - Hugin (http://www.hugin.com)
  - Netica (http://www.norsys.com/)
  - MSBNx (http://research.microsoft.com/en-us/um/redmond/groups/adapt/msbnx/)
- Other flexible tools
  - Bayes Net Toolbox for Matlab (https://code.google.com/p/bnt/)
- Designed for Risk Analysts:
  - Trilith (University of Maryland, contact Ali Mosleh or Katrina Groth)
    - Integration of BNs with ET/FT
  - AgenaRisk (Commercial package)
    - (BNs only)

Key benefits

- **Completeness**: Includes all relevant variables, not just easily observable variables or variables where data is plentiful. Allows variables to be interdependent.
- **Documentation**: Explicitly represents all variables and relationships deemed relevant to the problem space.
- **Simplification**: Decomposes problem into manageable pieces; simplifies acquisition of probability distribution.
  - It's easier to gather data about p(d|b) than about p(d|a,b,c…)
- **Credibility**: The BN allows analyst to assemble information from multiple sources into a single model.
  - Populating the model with the most credible information (or expert)
- **Modifiability**: Analysts can update conditionally independent sections of the model without changing the entire model. Model is expandable in scope and depth.
- **Insight**: Enables analysts to make predictions without perfect information; enables understanding of cause-and-effect behavior, performing "what-if" analyses.

Summary

- BNs are tool for:
  - Encoding a knowledge base (via a series of conditional probabilities)
  - Performing probabilistic reasoning (induction, deduction) with the knowledge base
- Benefits:
  - <u>Completeness & Insight</u>: Includes all variables, not just those with data
  - <u>Simplicity</u>: Decomposes a large problem into manageable pieces
  - <u>Credibility</u>: Models built with info. & data from multiple sources



$$P(EC \cap PSF1 \cap PSF2 \cap PSF3 \cap BM)$$

$$= P(EC|PSF1, PSF3) * P(PSF3|PSF1, PSF2) * P(PSF2|PSF1, BM) * P(PSF1) * P(BM)$$

Parting thought

Probability is not really about numbers;

it is about the structure of reasoning.

Glenn Shafer

Rutgers University

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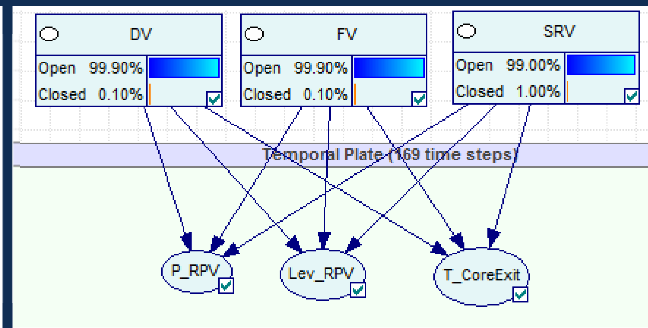
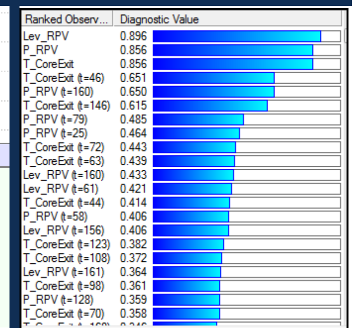
$$P(X_1, X_2, \ldots X_n) = \prod_i P(X_i | Par_G(X_i))$$

$$P(X|E) = \frac{\Pr(E|X)\Pr(X)}{\Pr(E)}$$





Thank you!

Katrina Groth

6231 – Risk and Reliability Analysis

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U.S. DEPARTMENT OF ENERGY

NNSA National Nuclear Security Administration

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References (1)

- Introductory:
  - Norman Fenton and Martin Neil (2013) *Risk Assessment and Decision Analysis with Bayesian Networks.* CRC Press.
  - Finn V. Jensen and Thomas D. Nielsen (2007) *Bayesian Networks and Decision Graphs.* Springer.
  - Langseth, H. & Portinale, L. Bayesian networks in reliability. *Reliability Engineering and System Safety,* **2007**, *92*, 92-108.
  - M. Druzdzel and L. Van der Gaag, Building probabilistic networks: Where do the numbers come from," *IEEE Transactions on Knowledge and Data Engineering*, vol. 12, no. 4, pp. 481-486, 2000
- Theoretical
  - Judea Pearl (1998) *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.* Morgan Kaufman
  - Judea Pearl, "Bayesianism and causality, or, why I am only a half-Bayesian" *Foundations of Bayesianism*, 2001, 24, 19-34 .

References (2)

- Example models in this presentation

  - Ekanem, N. A model-based Human Reliability Analysis Methodology (PHOENIX method). Ph. D. Thesis. *University of Maryland,* **2013**
  - Eghbali GH. Causal model for air carrier maintenance. Report prepared for Federal Aviation Administration. Atlantic City, NJ: Hi-Tec Systems; 2006.
  - Groth, Katrina M. & Swiler, Laura P. Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H. *Reliability Engineering and System Safety,* **2013***, 115*, 33-42.
  - Groth, Katrina M. & Mosleh, Ali. Deriving causal Bayesian networks from human reliability analysis data: A methodology and example model. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, **2012**, 226, 361-379.
  - Groth, Katrina; Wang, Chengdong & Mosleh, Ali. Hybrid causal methodology and software platform for probabilistic risk assessment and safety monitoring of socio-technical systems. *Reliability Engineering and System Safety,* **2010***, 95*, 1276-1285
  - Groth, K. M.; Denman, M. R.; Cardoni, J. N. & Wheeler, T. A. Proof of Principle Framework for Developing Dynamic Risk-Informed Severe Accident Management Guidelines. SAND2013-8324. Sandia National Laboratories, 2013
  - Haugom, G. P. & Friis-Hansen, P. Risk modelling of a hydrogen refuelling station using Bayesian network. *International Journal of Hydrogen Energy,* **2011***, 36*, 2389-2397.
  - Vinnem, J. E.; Bye, R.; Gran, B. A.; Kongsvik, T.; Nyheim, O. M.; Okstad, E. H.; Seljelid, J. & Vatn, J. Risk modelling of maintenance work on major process equipment on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries,* **2012***, 25*, 274-292