Belief Networks

Artificial Intelligence: A Modern Approach
by Russell & Norvig
Chapter 15, 19

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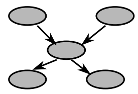
Belief Network (Bayesian Network)

A graph which represents the dependence between variables



Bayes' rule:

P(B/A) = P(A/B) P(B) / P(A)

P(B/A) = (0.5 * 1/50000) / (1/20) = 0.0002

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Properties of Belief Nets

1) A set of random variables make up the nodes of the network

2) A set of direct links or arrows connect pairs of nodes. An arrow from node X to node Y means that X has a direct influence on Y

3) Each node has a conditional probability table that quantifies the effects that the parents have on the node

4) The graph has no directed cycles

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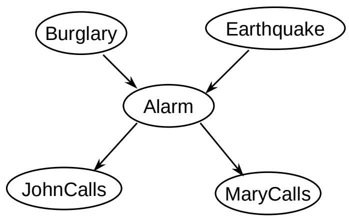
Example



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Example

Burglary	Quake	P(Alarm| Burglary, Quake)	
		True	False
True	True	0.950	0.050
True	False	0.940	0.060
False	True	0.290	0.710
False	False	0.001	0.999

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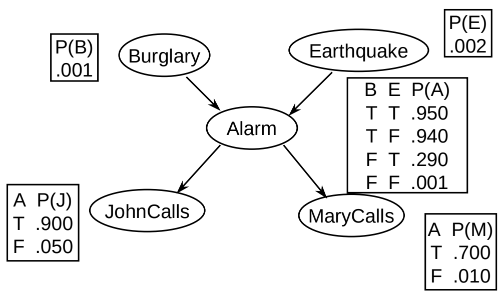
Example



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Derivative-Free Optimization

Example - using the network

$P(x_1, \ldots, x_n)$ = sum $P(x_i$ | Parents$(x_i))$ for all I

Probability that alarm sounded, but neither a burglary nor an earthquake has occurred, and both John and Mary call.

P(J ^ M ^ A ^ not B ^ not E)
= P(J|A) P(M|A) P(A|notB^notE) P(notB) P(notE)
= 0.90 * 0.70 * 0.001 * 0.999 * 0.998
= 0.00062

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Derivative-Free Optimization

Creating a belief net

Each node must be conditionally independent from its predecessors

$P(X_i | x_{i-1}, \ldots, x_1) = P(X_i|\text{Parents}(x_i))$

The parents of node x_i should only be the nodes that directly influence it

P(M|J, A, B, E) = P(M|A)

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Derivative-Free Optimization

Network Construction

1) Choose the set of relevant variables, X_i
2) Choose an ordering for the variables
3) While there are variables left:
   a) Pick a variable X_i and add a node to the network for it.
   b) Set Parents(X_i) to some minimal set of nodes already in the net such that it is conditionally independent from all nodes not in Parents(X_i)
   c) Define the conditional probability table for X_i

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Derivative-Free Optimization

Applications of BBN

GE Power Systems - Diagnosing Power Generators
GE Transportation - DiagnosingTrains
Kana - E-mail handling
Micorsoft - Office Assistant

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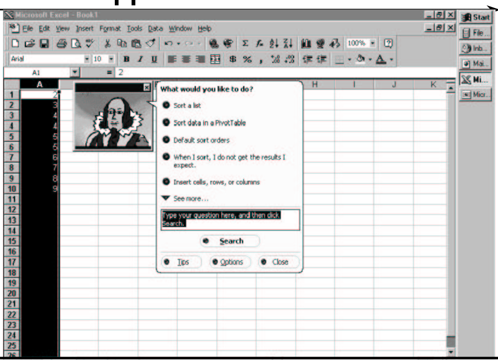
Derivative-Free Optimization

BBN Applications - Lumiere



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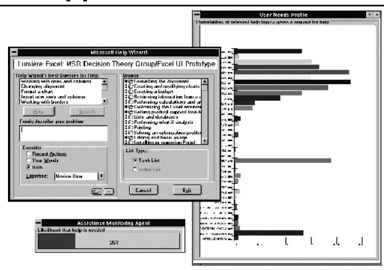
Derivative-Free Optimization

BBN Applications - Lumiere



The bargraph is a probability distribution about the needs of the user. The large, red bar indicates the system's computation of the likelihood that the user would like being notified with some assistance.

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BBN Tools

GeNIe - Graphical Network Interface (Pittsburg CMU)
http://www2.sis.pitt.edu/~genie/about_genie.html

Netica - Norsys Software Corporation
http://www.norsys.com/

Microsoft Belief Network - Microsoft
http://www.research.microsoft.com/research/dtg/msbn/default.htm

matlab - University of California
http://www.cs.berkeley.edu/~murphyk/Bayes/bnt.html

Locomotive Cooling System Belief Network

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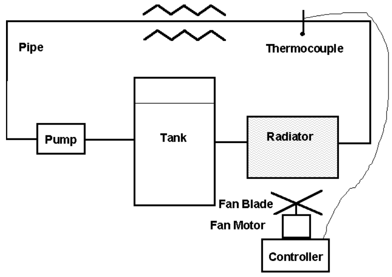
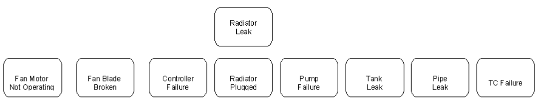
http://snook.crd.ge.com/coe/conclusi.htm

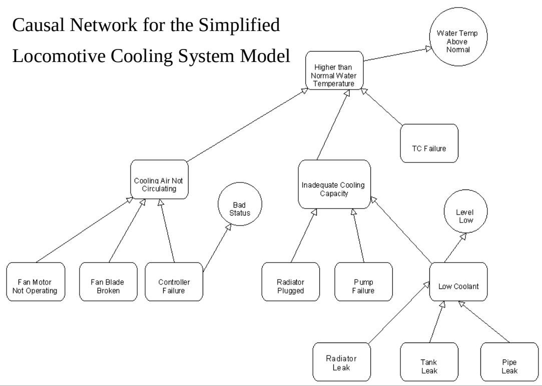
Simplified Model of a Locomotive Cooling System



Locomotive Cooling System Model Failure Modes

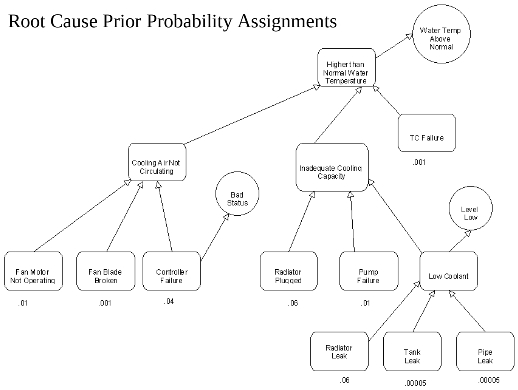


Causal Network for the Simplified Locomotive Cooling System Model



Derivative-Free Optimization

Root Cause Prior Probability Assignments



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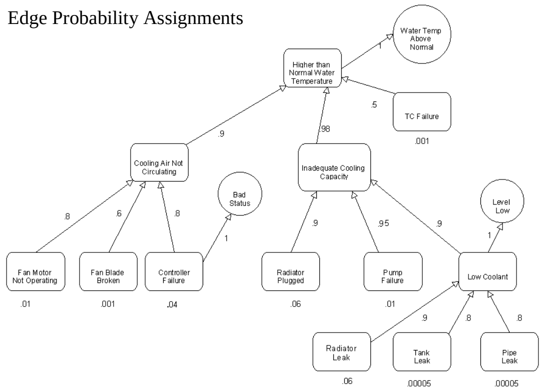
Derivative-Free Optimization

Edge Probability Assignments



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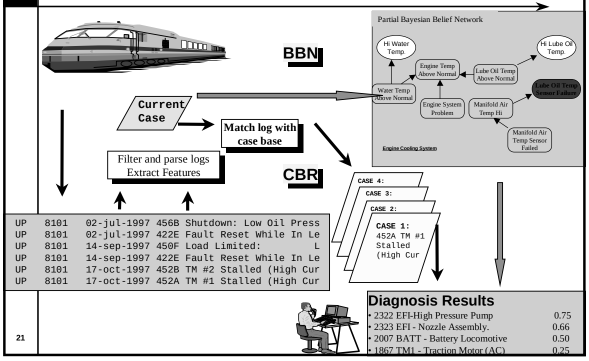
Derivative-Free Optimization

Bayesian Belief Network and Case-Based Reasoning



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