Bayesian Network Tutorial
Introduction

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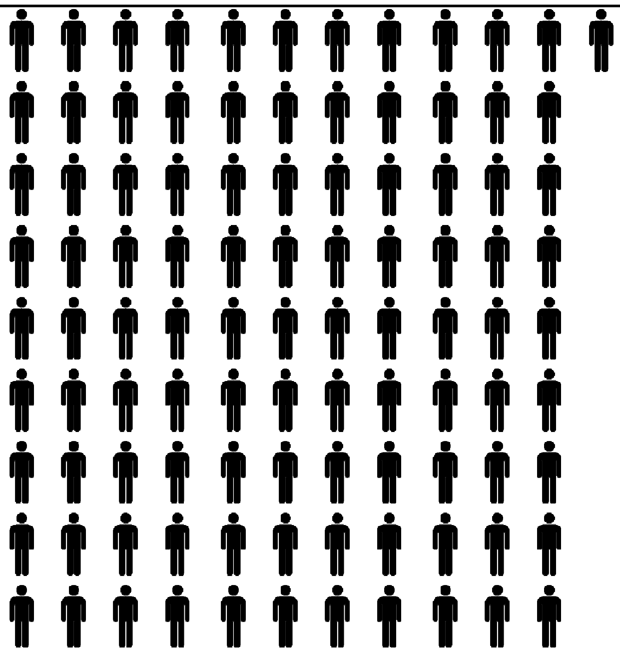
Overview

- Cancer Treatment
- Bayesian Networks
- Independence
- Types of Inference
- Types of Evidence
- Extensions

Cancer Test

Suppose there is a 8% chance that a person has cancer. If they do have cancer there is a 90% the cancer test will be positive. While if they do not have cancer there is 91% chance the test will be negative.

Now suppose someone is told the test for cancer is positive. What is the chance they have cancer?

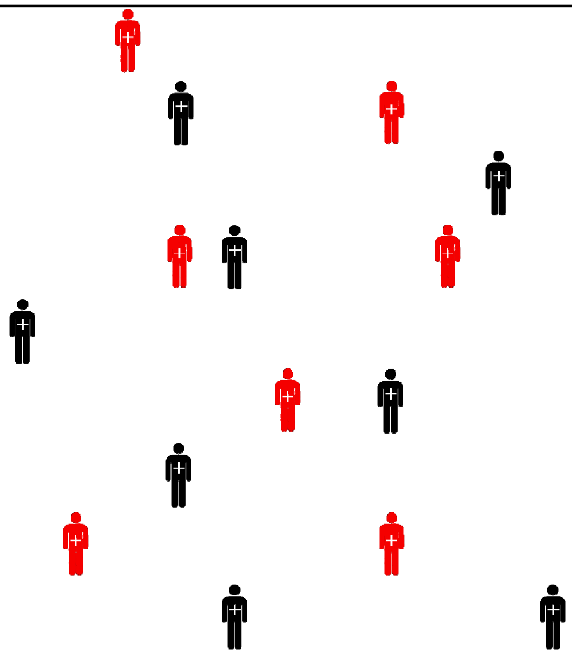


Take 100 random people

8% have cancer

90% of those with cancer have a positive test

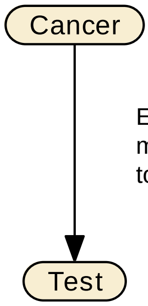
9% of those without cancer have a positive test



If test is positive then chance of cancer is

$$\frac{7}{7+8} \approx 0.47 \quad 47\%$$

Cancer Test Network

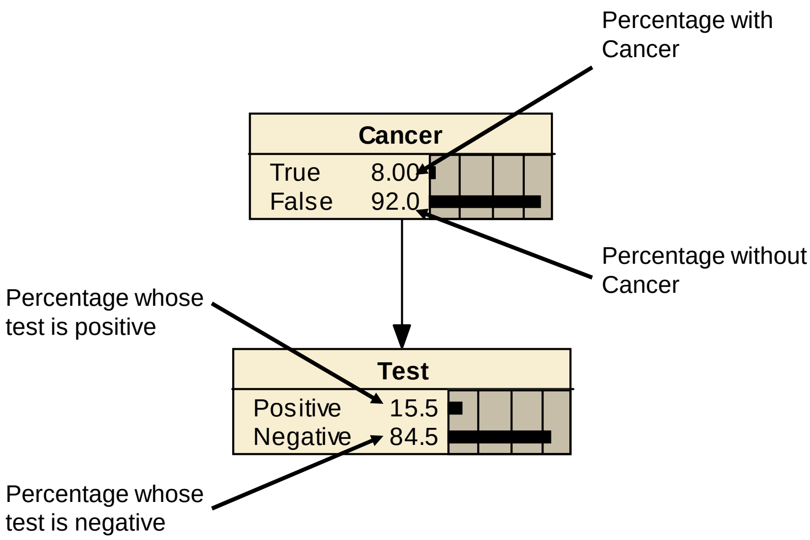


True	False
8%	92%

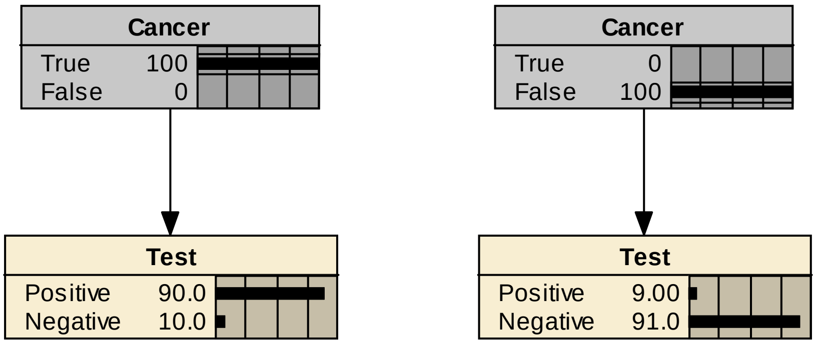
Each row must sum to 100%

Cancer	Positive	Negative
True	90%	10%
False	9%	91%

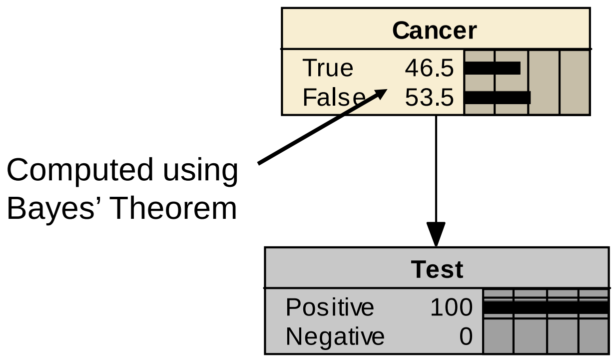
Belief Bars



Adding Evidence



Inference



Rev. Thomas Bayes

(1702-1761)

Bayes' Theorem

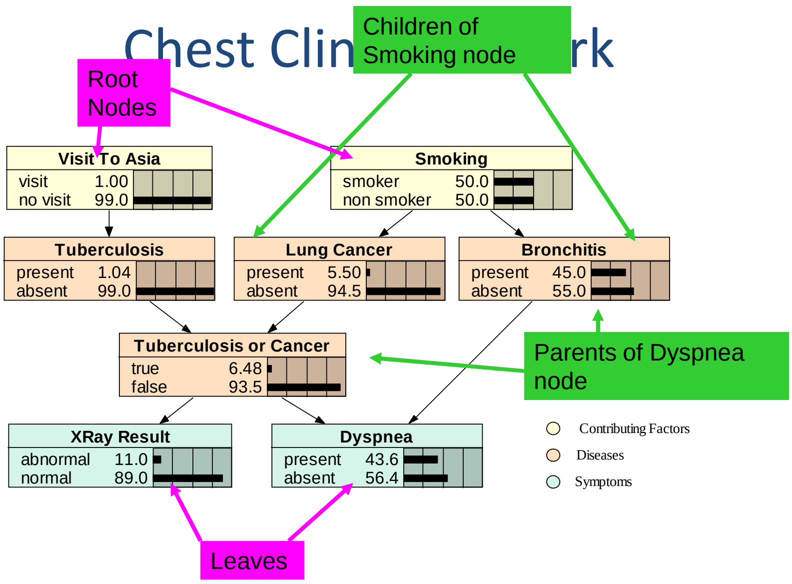
Pierre-Simon,
Marquis de Laplace

(1749-1827)

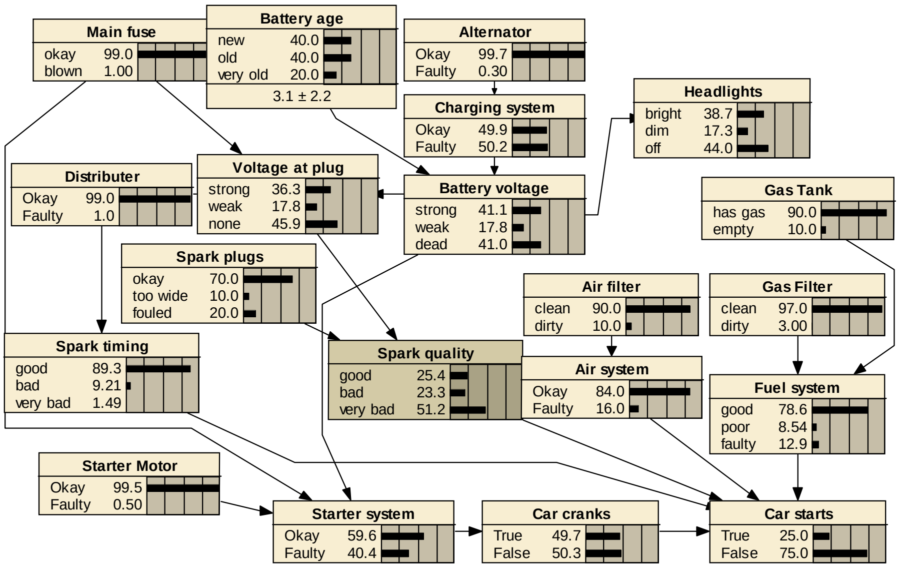
$$p(Cancer \mid Test+) = \frac{\#\,People\ with\ Cancer\ \&\ Test+}{\#\,People\ with\ Test+}$$

$$\#\,People\ with\ Cancer = \#\,People \times p(Cancer)$$
$$\#\,People\ without\ Cancer = \#\,People \times p(\neg Cancer)$$
$$\#\,People\ with\ Cancer\ \&\ Test+ = \#\,People\ with\ Cancer \times p(Test+ \mid Cancer)$$
$$\#\,People\ without\ Cancer\ \&\ Test+ = \#\,People\ without\ Cancer \times p(Test+ \mid \neg Cancer)$$

$$p(Cancer \mid Test+) = \frac{\#\,People \times p(Cancer) \times p(Test+ \mid Cancer)}{\#\,People \times p(Cancer) \times p(Test+ \mid Cancer) + \#\,People \times p(\neg Cancer) \times p(Test+ \mid \neg Cancer)}$$
$$= \frac{p(Cancer) \times p(Test+ \mid Cancer)}{p(Cancer) \times p(Test+ \mid Cancer) + p(\neg Cancer) \times p(Test+ \mid \neg Cancer)}$$



Car Diagnosis 2



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Bayesian Networks


Judea Pearl

- Has nodes and directed edges between nodes.
- Nodes represent features.
- Each feature can have multiple values
  - Discrete or continuous
- Each node has a table that represent the chance of the value of the feature occurring, given the values of the parent nodes.
- No cycles are allowed.

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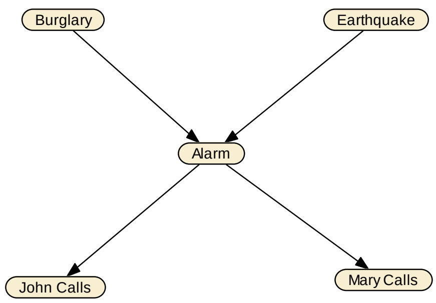
Multiple paths ok but not cycles

Judea Pearl's Alarm Network



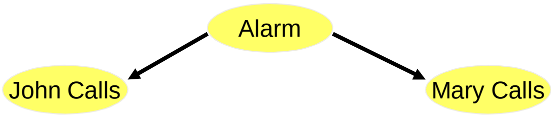
Causal Chains

- If your belief in a **Burglary** occurring changes, then your belief in **Alarm** going off and consequently your belief that **John will Call** will change.
- If your belief that **John will Call** changes, then so does your belief in the **Alarm** going off and your belief that a **Burglary** has occurred.

Conditional Independence

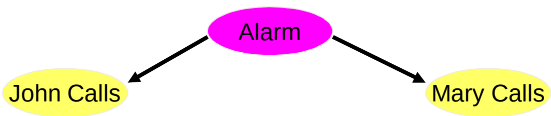
- If you know that the **Alarm** has gone off, then changes in belief of a **Burglary** occuring does not effect your belief in **John Calls**, and visa-versa.
- **Burglary** is independent of **John Calls** given you know whether **Alarm** has gone off.

Common Causes



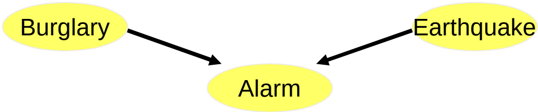
- If your belief in a **John Calls** changes then your belief in **Alarm** going off, and consequently your belief that **Mary Calls** changes.
- Also visa-versa.

Conditional Independence



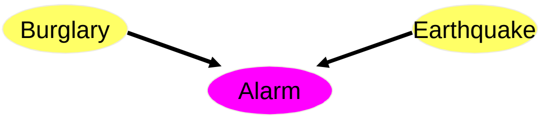
- If you know whether **Alarm** has gone off, then your beliefs in **John Calls** and **Mary Calls** are independent, i.e., changing one does not change the other.

Common Effects



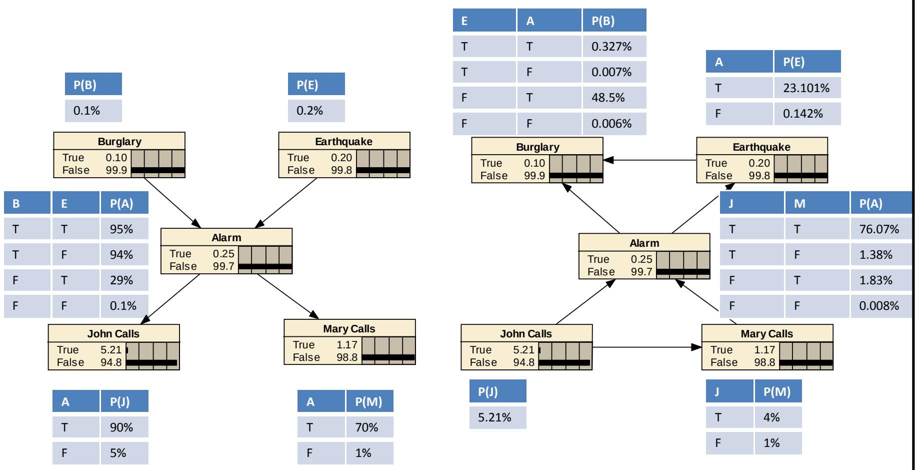
- If you don't know whether **Alarm** has gone off or not, then your beliefs in **Burglary** and **Earthquake** are independent, i.e., changing one does not change the other.

Conditional Dependence



- If you do know whether **Alarm** has occurred, then your beliefs of **Burglary** and **Earthquake** are dependent, i.e., changing one does change the other.
- Known as explaining away.

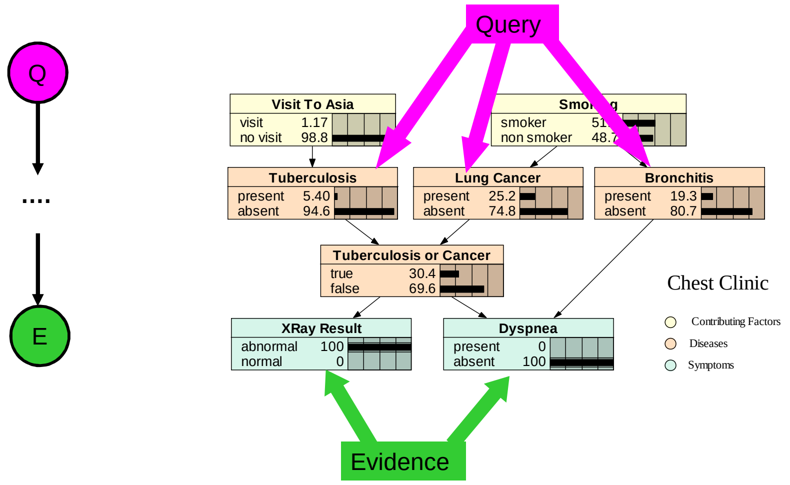
Equivalent Networks



Types of Inference

- Diagnostic
- Casual
- Intercasual
- Mixed

Diagnostic



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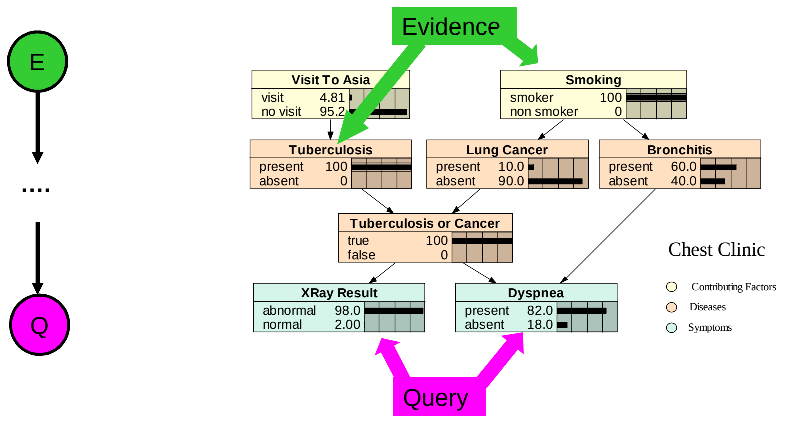
Casual



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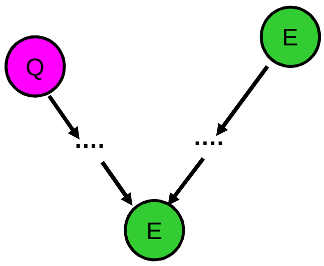
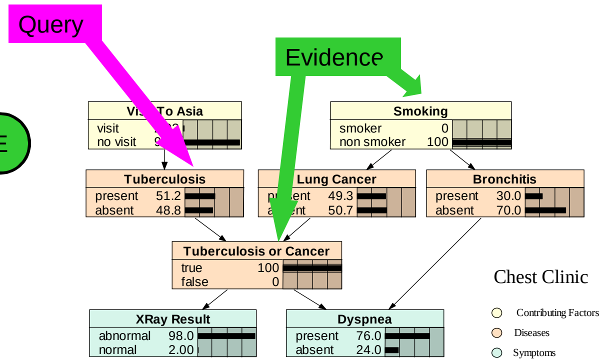
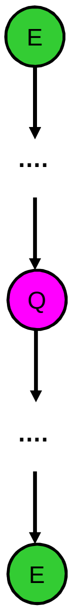
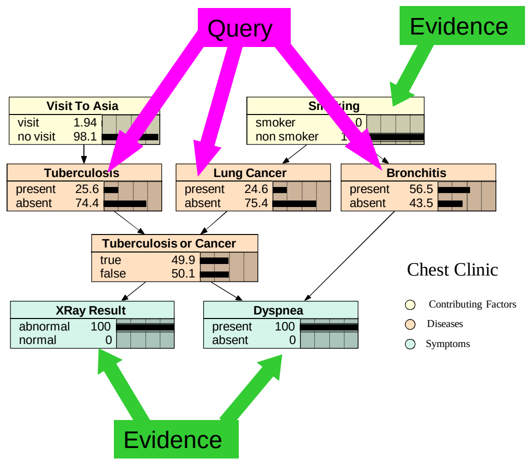
Intercasual





Mixed





Types of Evidence

- Specific evidence
  - A definite finding that a node has a particular value.
- Negative evidence
  - A definite finding that a node has **not** got a particular value.
- Likelihood (virtual evidence)
  - Uncertain information about the values of a node.

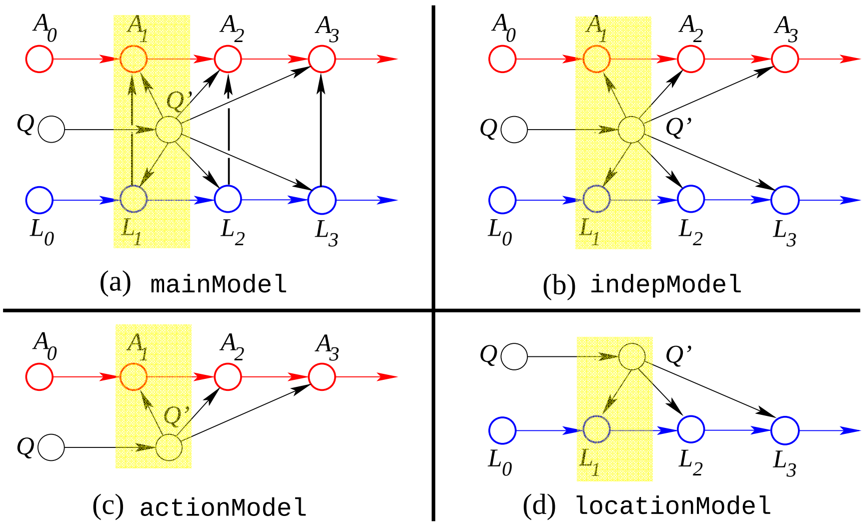
Benefits of Bayesian Networks

- A visual representation of the relationships between attributes.
- Compact Representation of the joint probability distribution.
- Allows efficient belief updating.
- Correct probabilistic reasoning.

Extensions

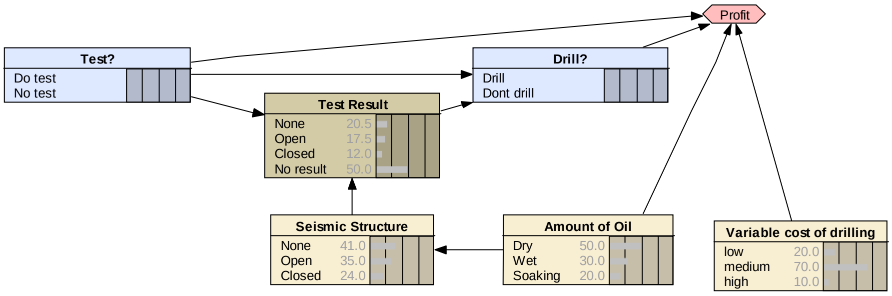
- Dynamic Networks
  - Used to model beliefs changing over time
  - Hidden Markov Models and Kalman Filters are special cases.
- Decision Networks (Influence Diagrams)
  - Used for decision making
- Object-oriented Bayesian networks
  - Used to model large, complex hierarchical systems

Dynamic Bayesian Networks



(a) mainModel (b) indepModel (c) actionModel (d) locationModel

Decision Networks



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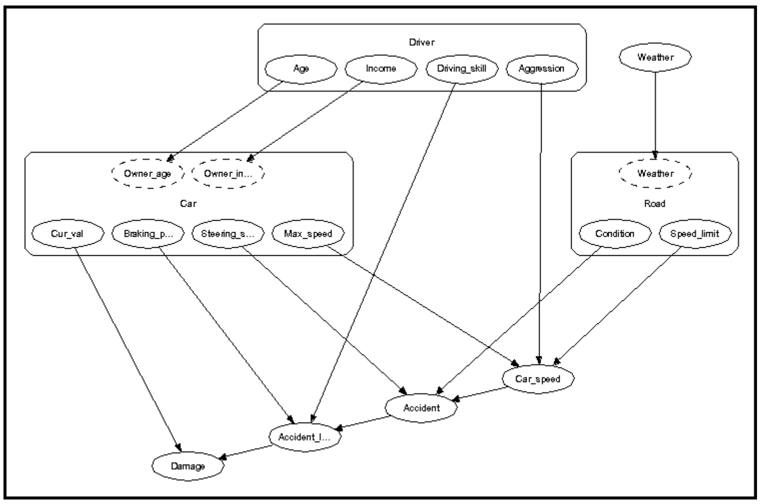
Object Oriented Bayesian Network



http://www.hugin.com/

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Further Reading

- R.E. Neapolitan, "*Learning Bayesian Networks*", Pearson Education, Inc., 2004
- F.V. Jensen, "*Bayesian Networks and Decision Graphs*", Springer-Verlag, Inc., 2001
- K.B. Korb and A.E. Nicholson, "*Bayesian Artificial Intelligence*", Chapman & Hall/CRC, Second Edition, 2011
- J. Pearl, "*Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*", Morgan Kaufmann Publishers, 1988
- D. Koller and N. Friedman, "*Probabilistic Graphical Models: Principles and Techniques*", MIT Press, 2009