

Bayesian Networks for Risk Assessment

**Society of Information Risk Analysts
14 November 2014**

**Norman Fenton
Queen Mary University of London
and
Agena Ltd**

Outline

**Overview of Bayes and
Bayesian networks**

**Why Bayesian networks are
needed for risk assessment**

The challenges

Applications

www.BayesianRisk.com

RISK ASSESSMENT AND DECISION ANALYSIS WITH BAYESIAN NETWORKS

NORMAN FENTON
MARTIN NEIL

CRC Press
A CHAPMAN & HALL BOOK

"... although there have been several excellent books dedicated to Bayesian Networks and related methods, these books tend to be aimed at readers who already have a high-level of mathematical sophistication As such they are not really accessible to readers who are not already proficient in those subjects. This book is an exciting development because it addresses this problem".

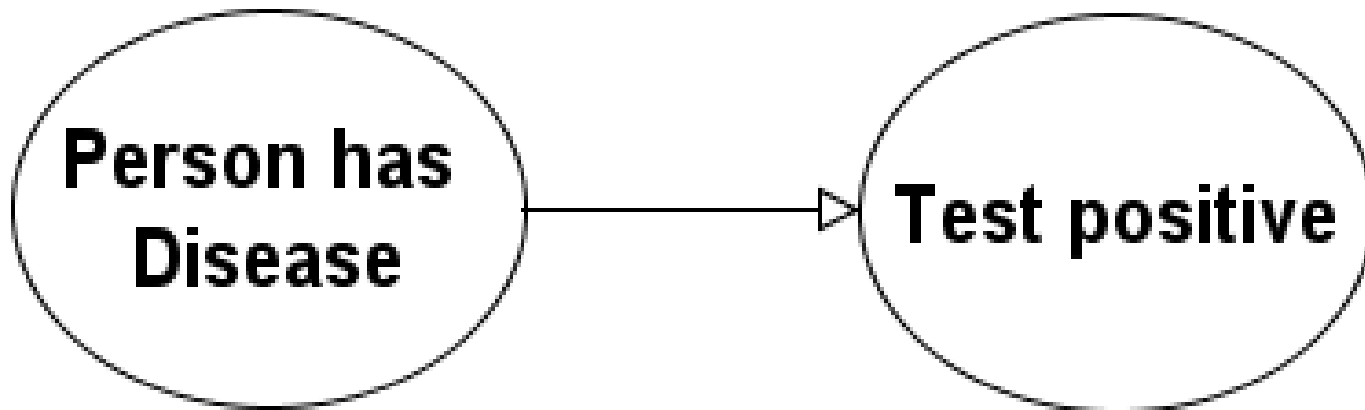
Judea Pearl, winner 2011 Turing Award for work on AI reasoning

www.AgenaRisk.com

A typical probability problem

Hypothesis

Evidence



1 in a 1000

False	0.999
True	0.0010

100% accurate for those with disease; 95% accurate for those without

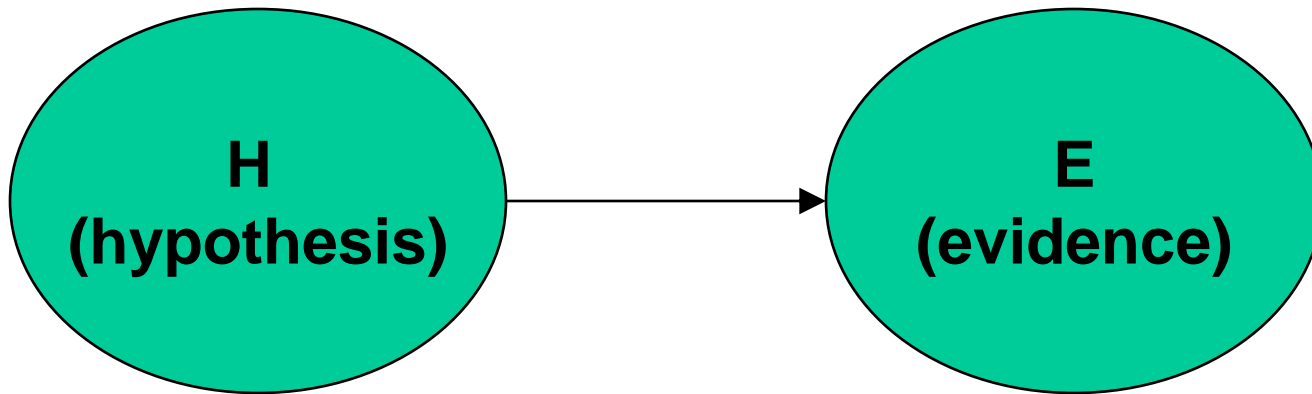
Person has Disease	False	True
False	0.95	0.0
True	0.05	1.0

What is the probability a person has the disease if they test positive?

Bayes Theorem

Have a prior $P(H)$ (“person has disease”)

Now get some evidence E (“test result positive”)

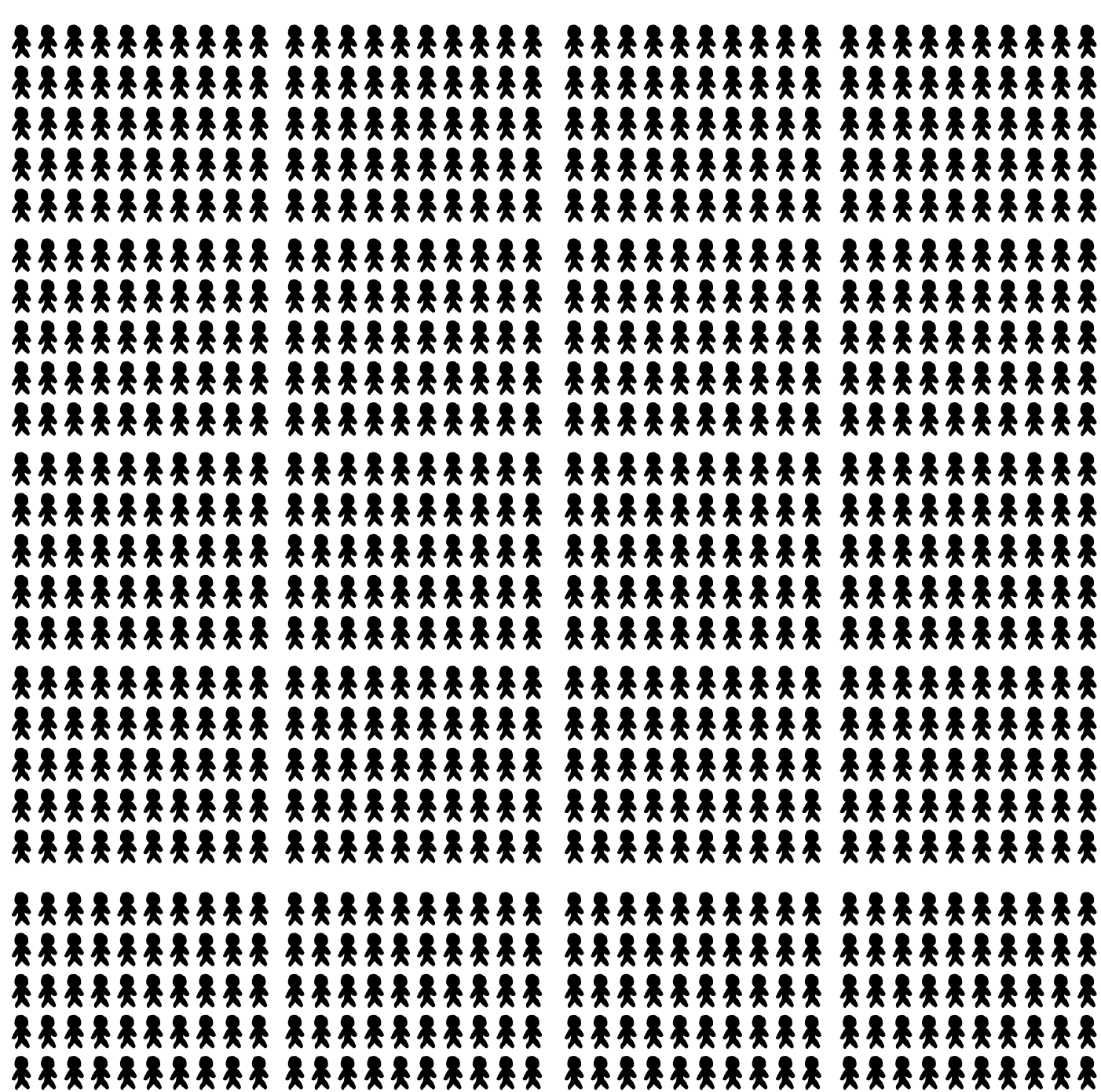


We know $P(E|H)$

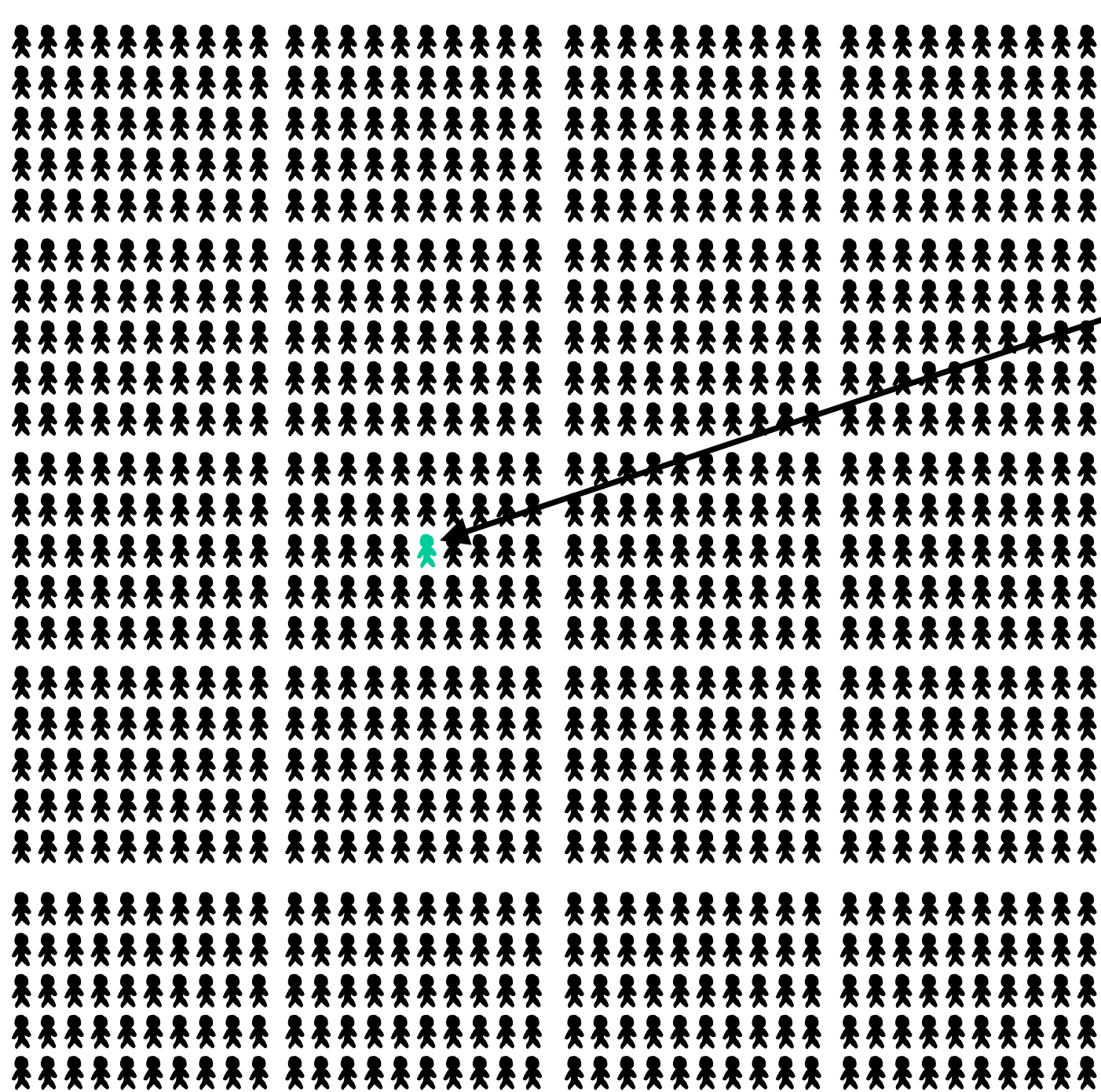
But we want the posterior $P(H|E)$

$$P(H|E) = \frac{P(E|H) * P(H)}{P(E)} = \frac{P(E|H) * P(H)}{P(E|H) * P(H) + P(E|\text{not } H) * P(\text{not } H)}$$

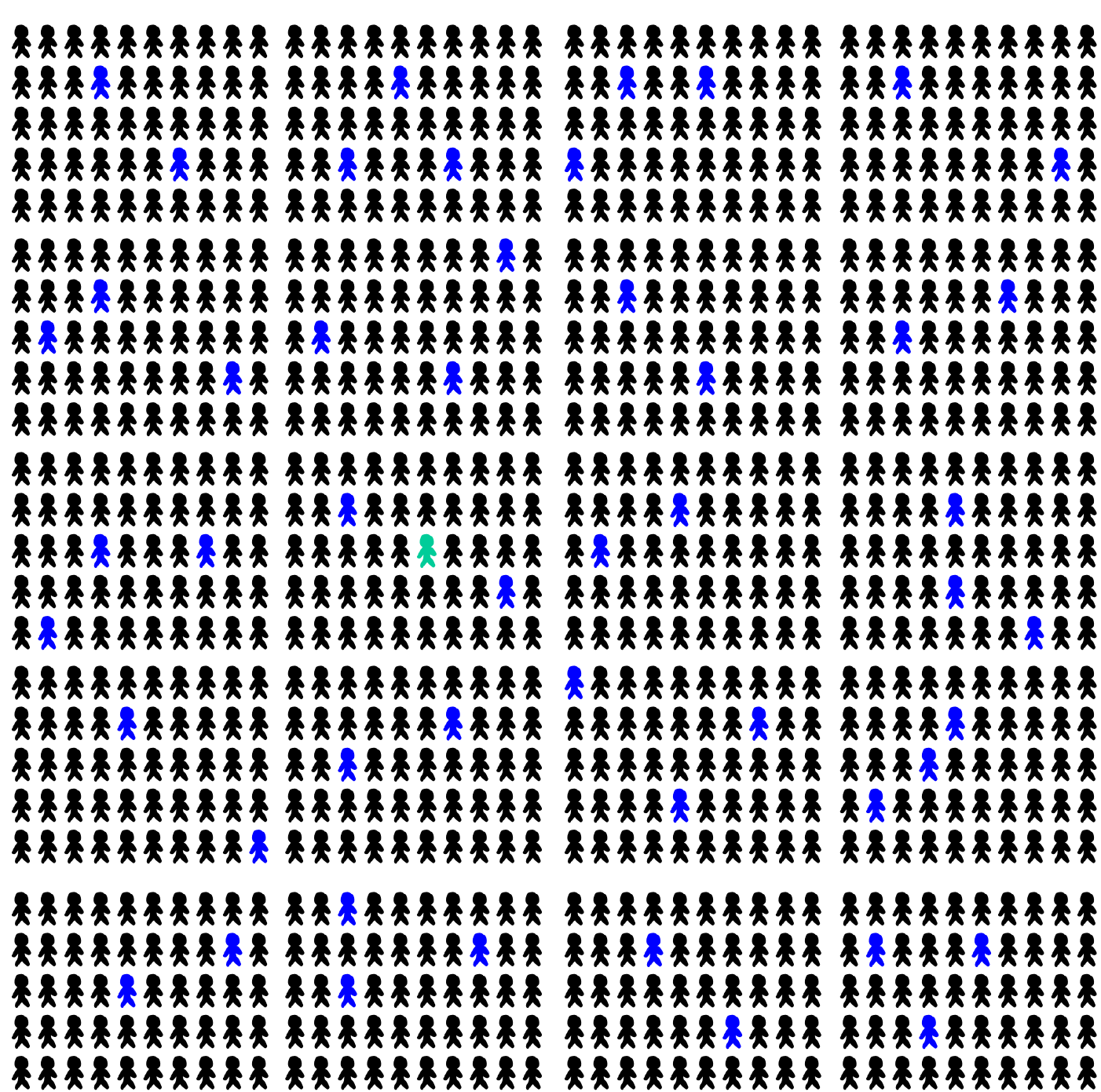
$$P(H|E) = \frac{1 * 0.001}{1 * 0.001 + 0.05 * 0.999} = \frac{0.001}{0.5005} \approx 0.02$$



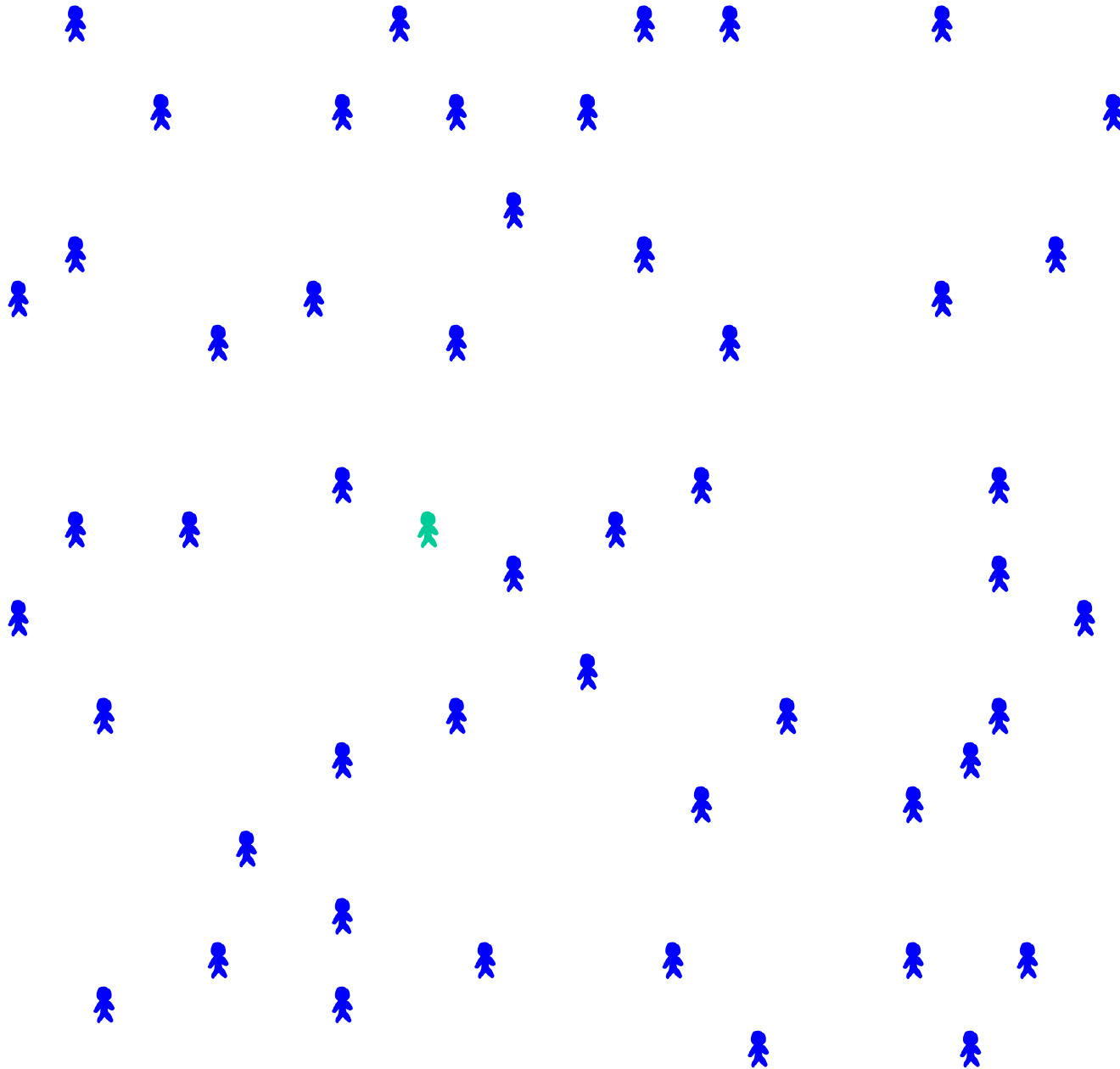
Imagine 100,000
people



Out of whom
10 has the
disease



But about 500
of the
Remaining
9990 people
without the
disease test
positive

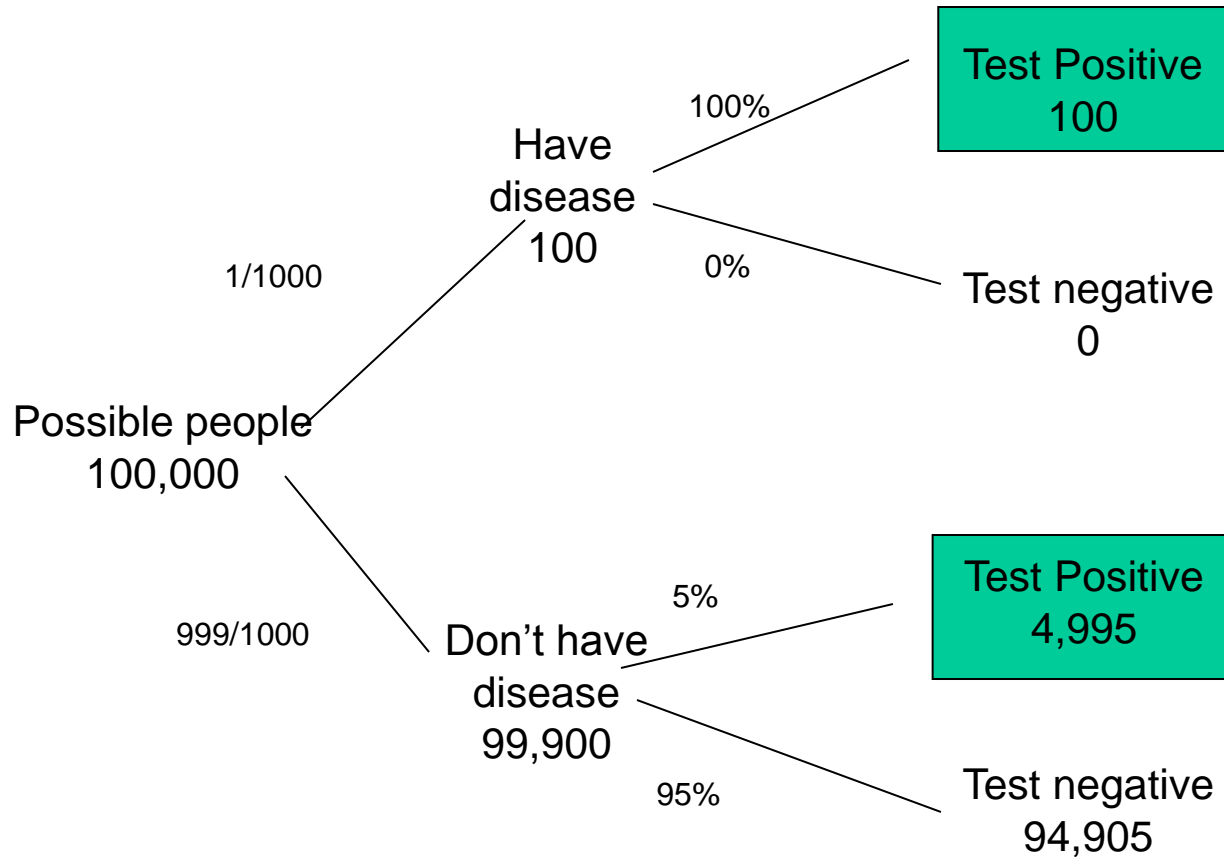


**So 10 out of
510 who test
positive
actually have
the disease**

**That's just
under 2%**

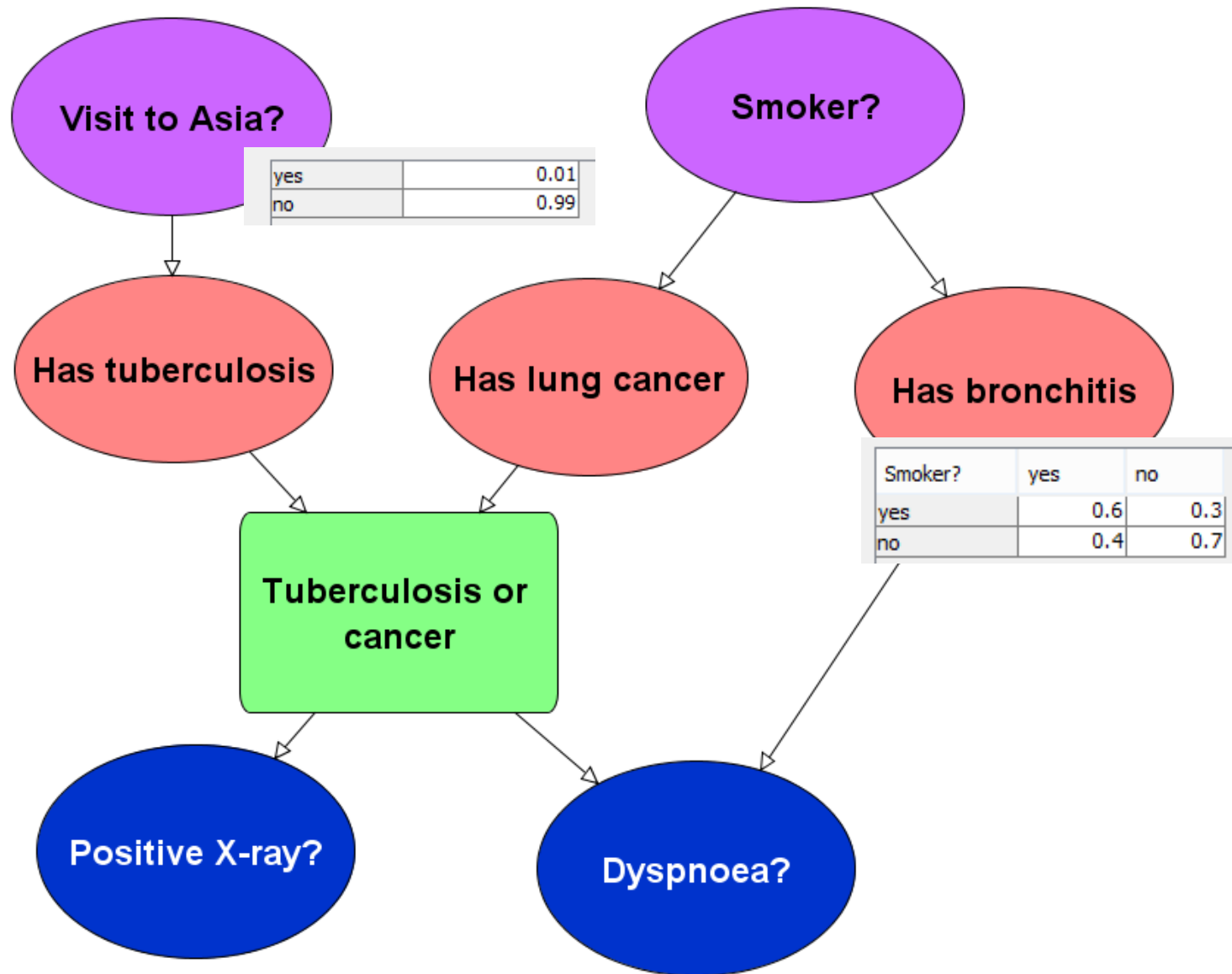
**That's very
different from
the 95%
assumed by
most medics**

An alternative visual explanation



So 100 out of 5,095 who test positive match actually have the disease, i.e. Under 2%

A Classic BN



Bayesian Propagation

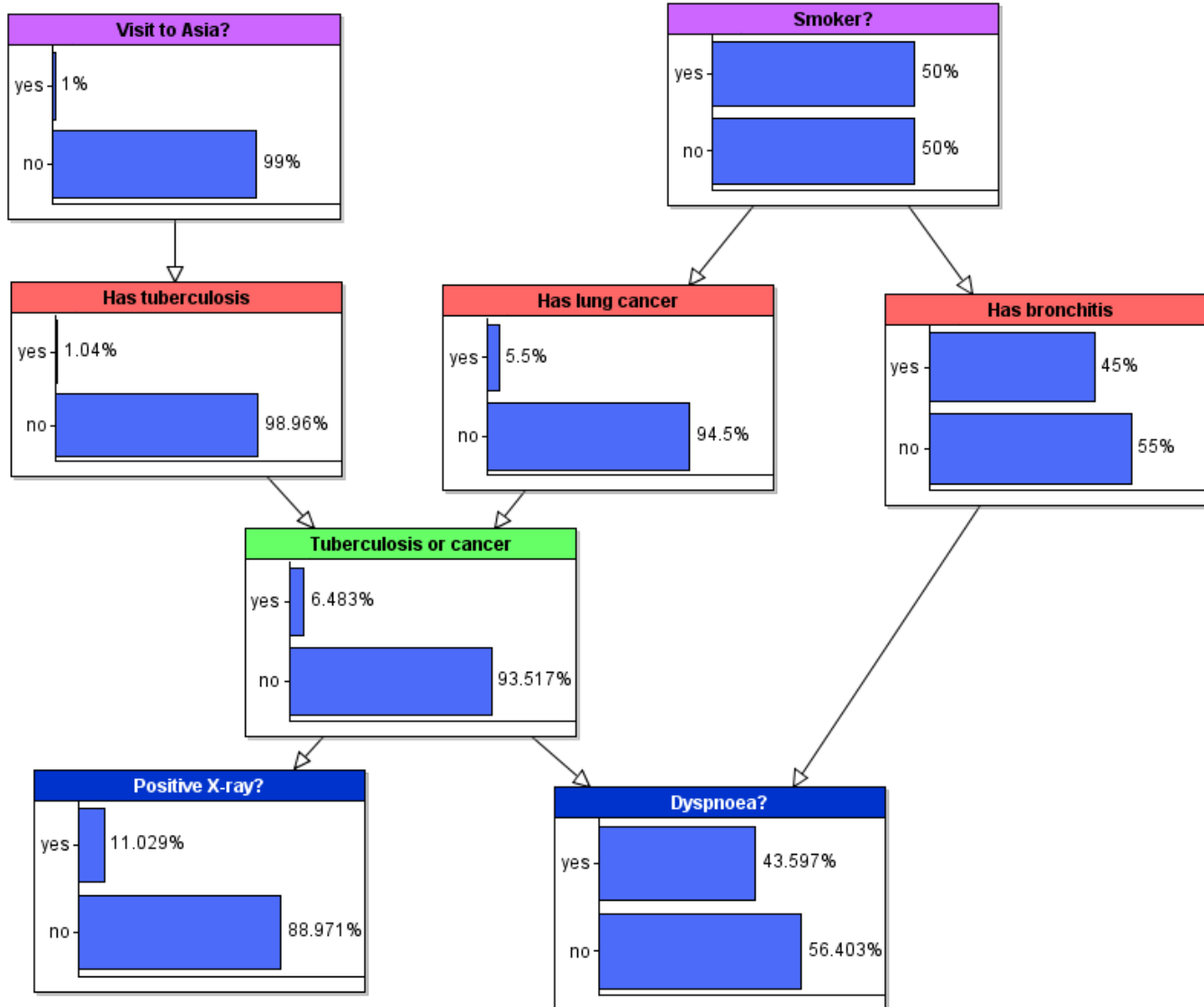
Applying Bayes theorem to update all probabilities when new evidence is entered

Intractable even for small BNs

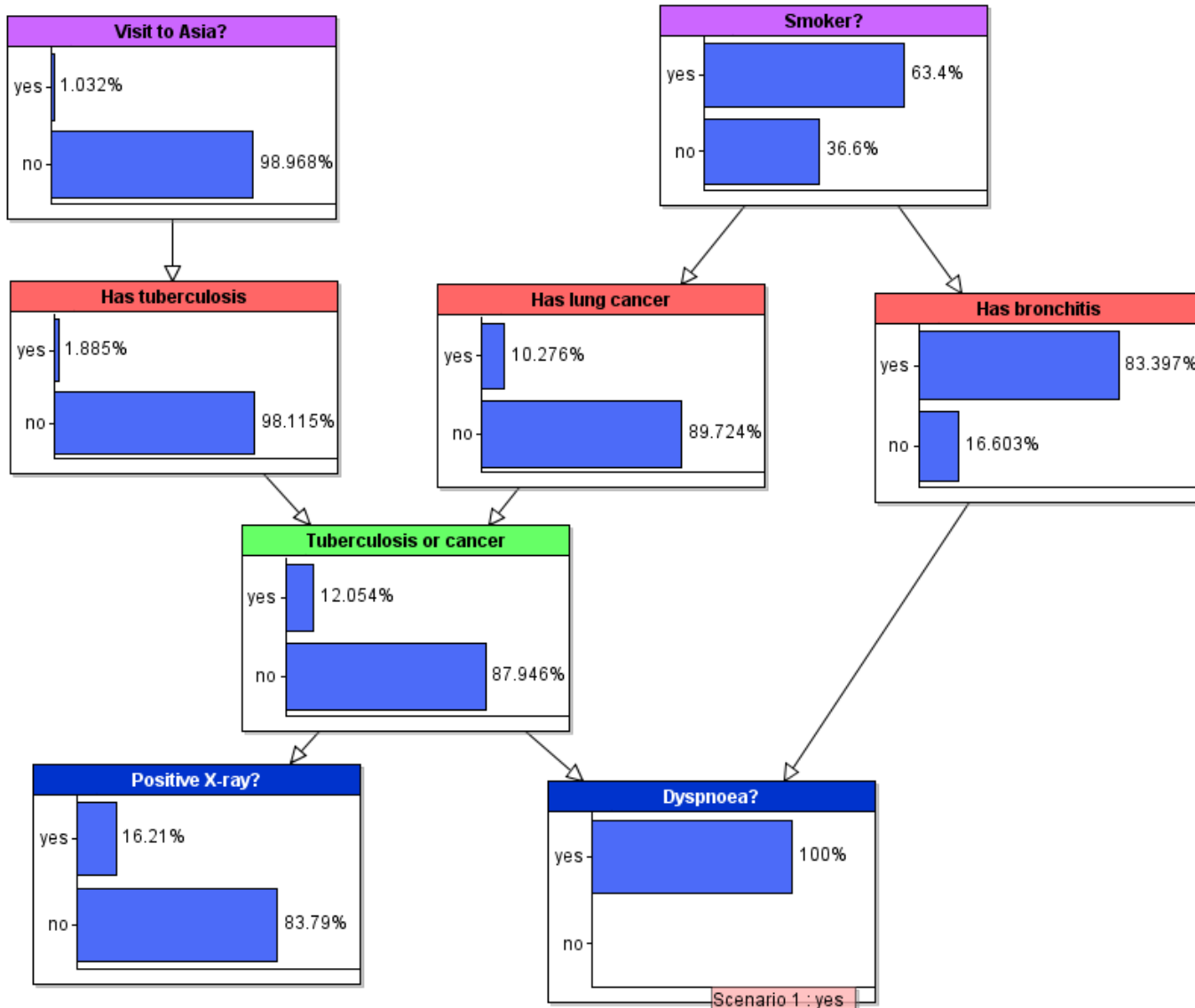
Breakthrough in late 1980s - fast algorithms

Tools implement efficient propagation

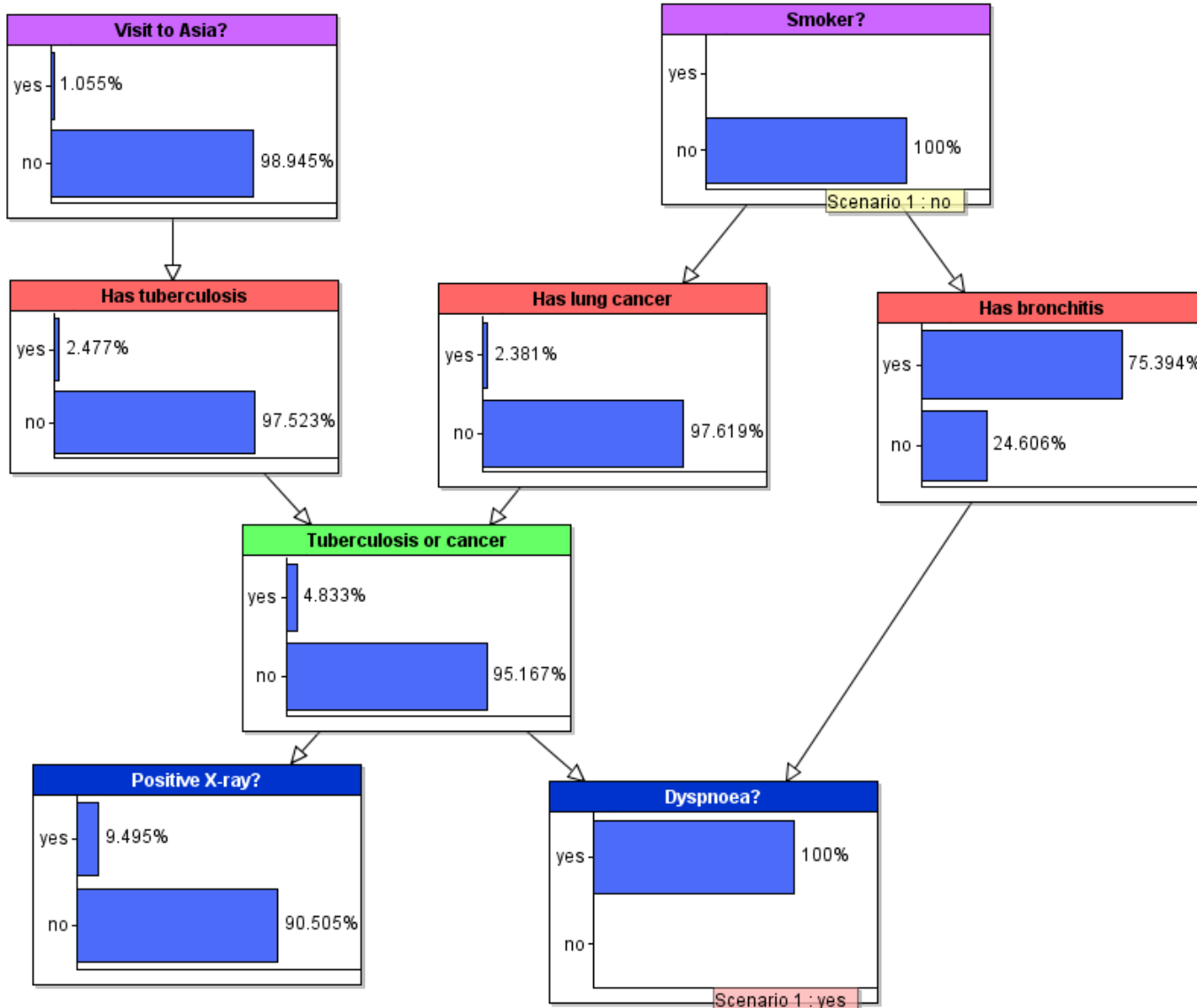
A Classic BN: Marginals



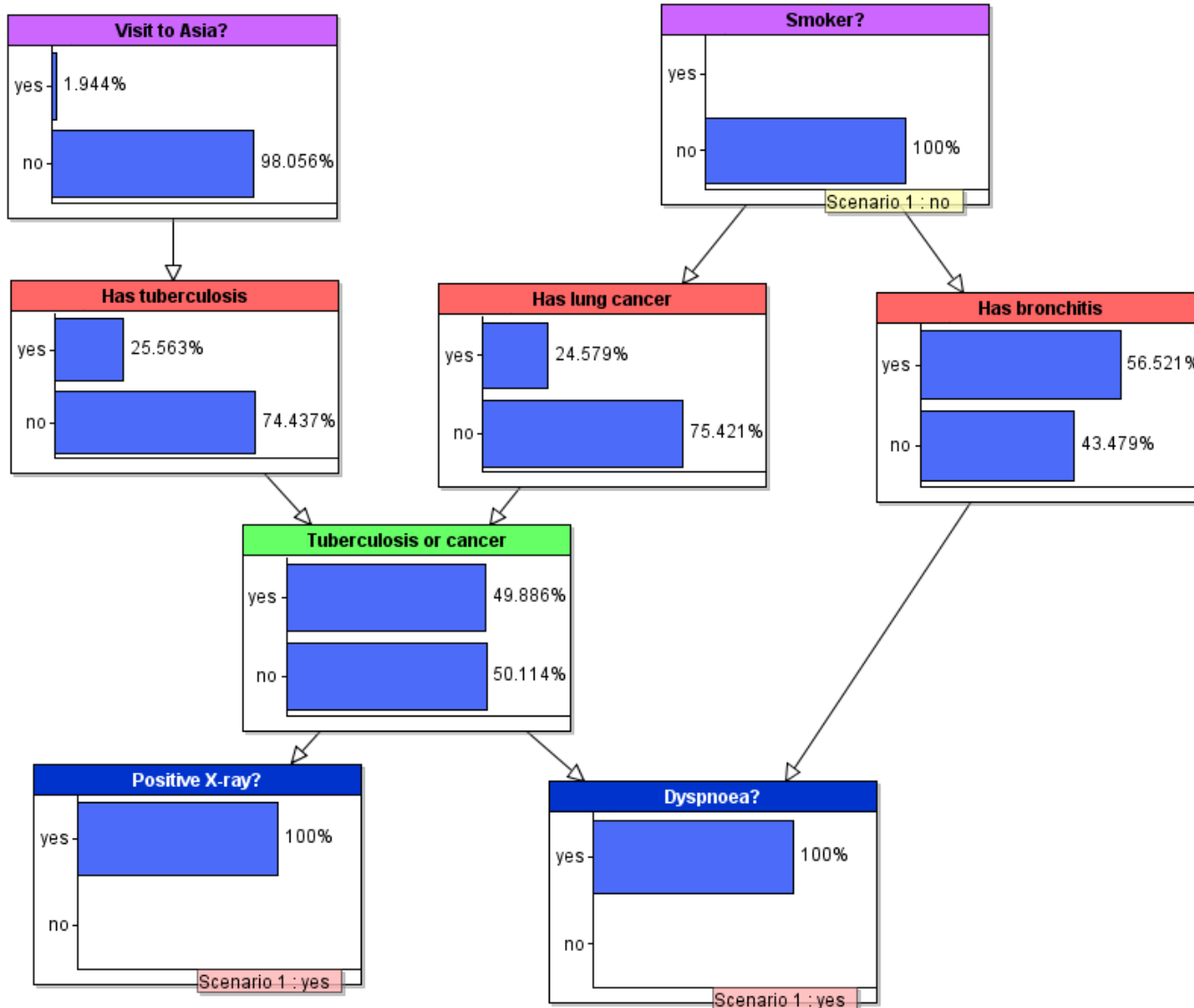
Dyspnoea observed



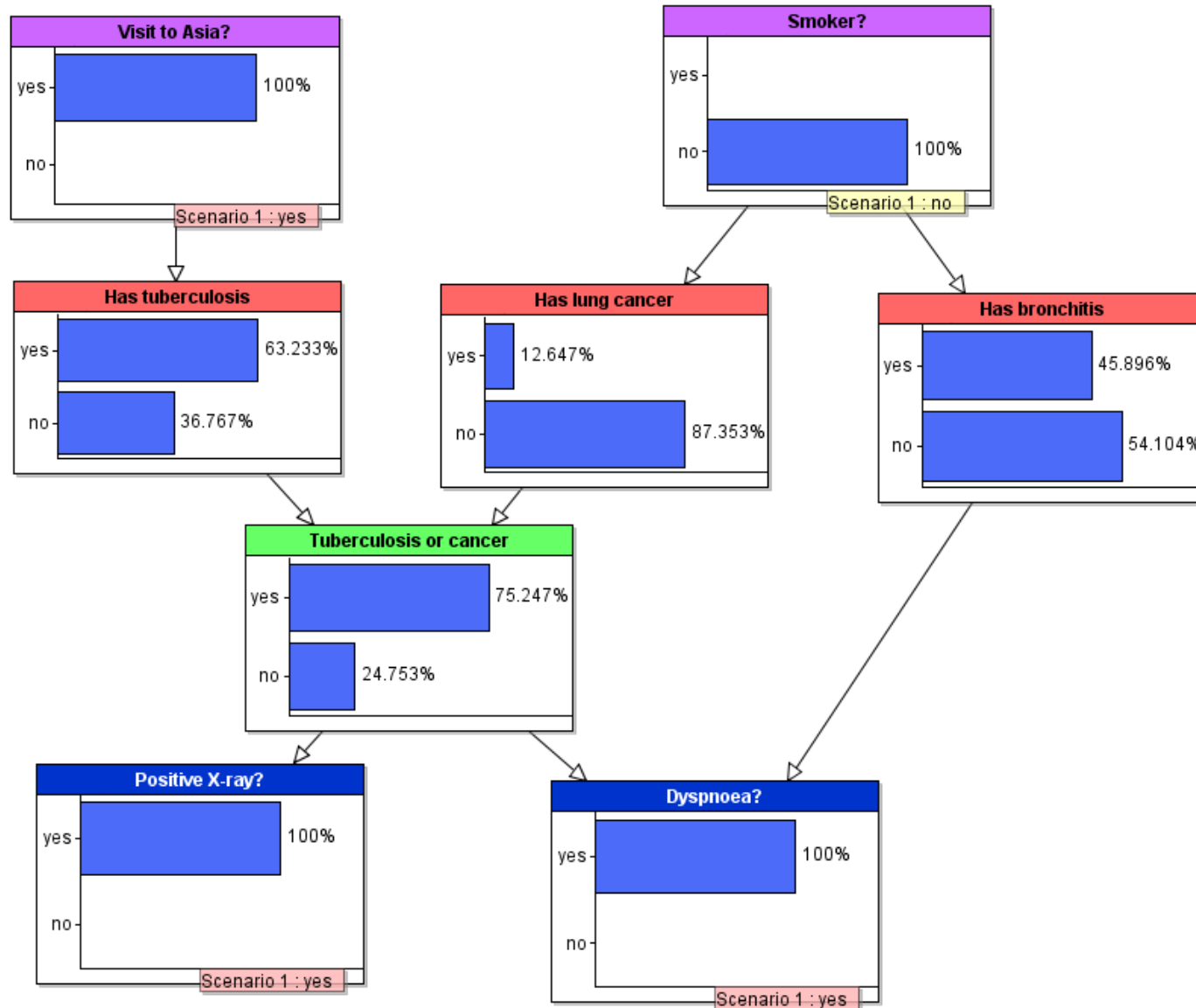
Also non-smoker



Positive x-ray



..but recent visit to Asia



The power of BNs

Explicitly model causal factors

Reason from effect to cause and vice versa

‘Explaining away’

Overturn previous beliefs

Make predictions with incomplete data

Combine diverse types of evidence

Visible auditable reasoning

Why Bayesian networks are needed for risk assessment

Assessing Risk of Road Fatalities: Classic Statistical Approach

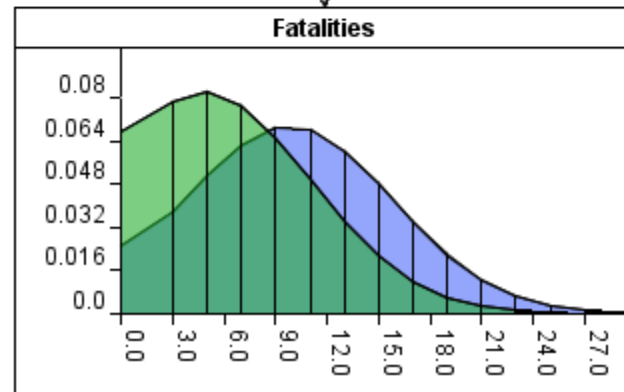
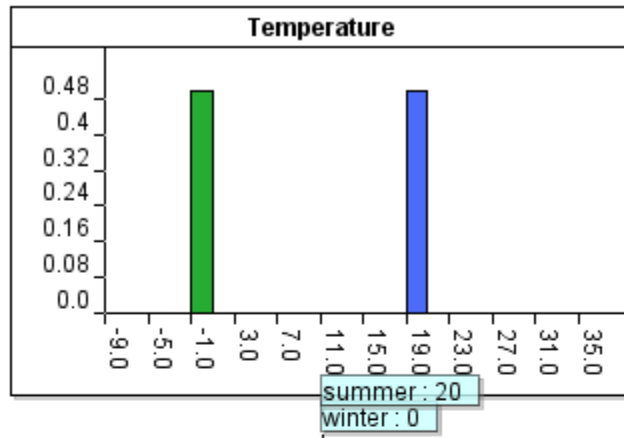
Temperature

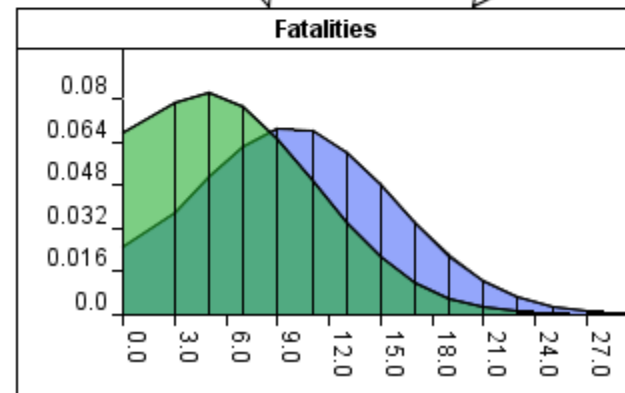
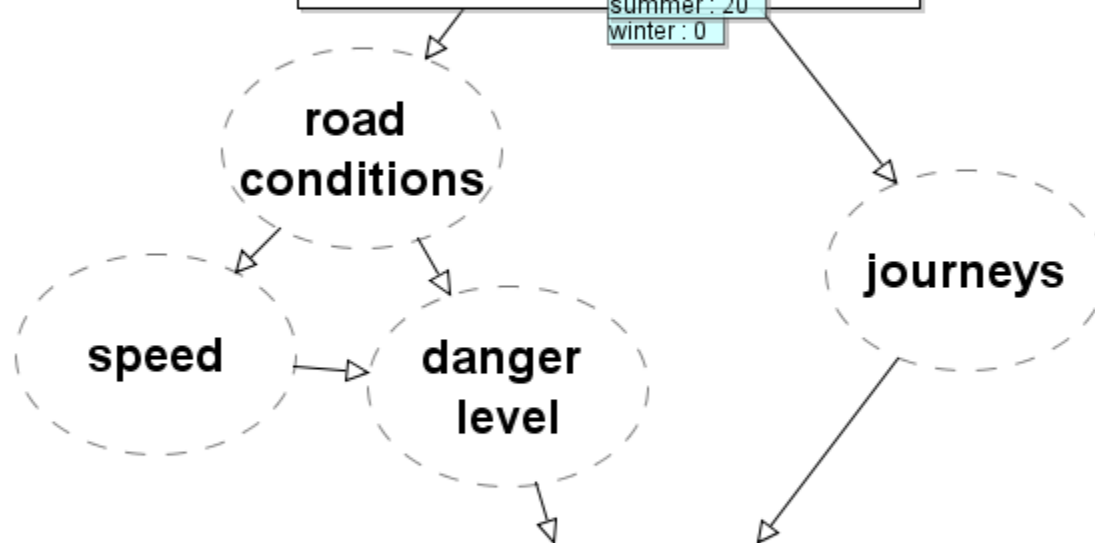
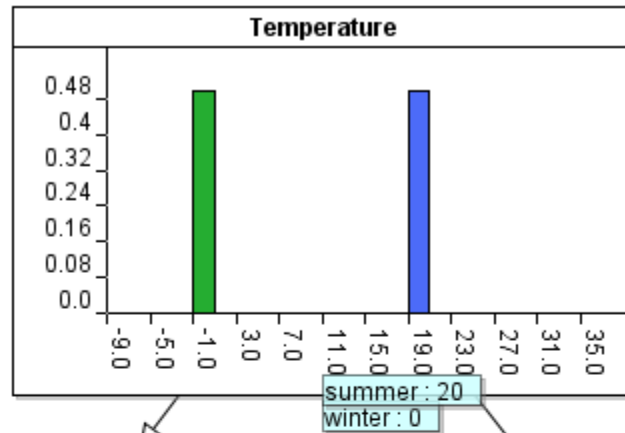
Colder months

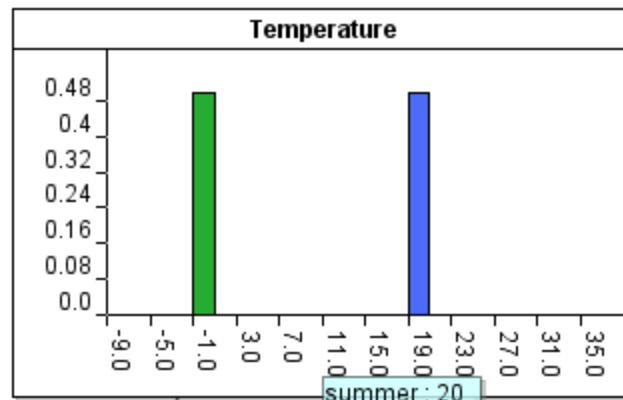
Number of
Fatalities

Fewer fatalities

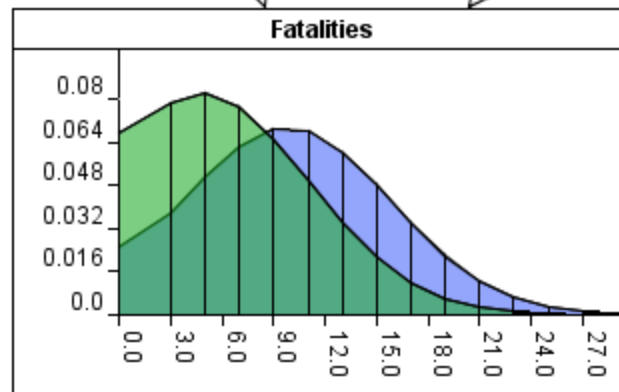
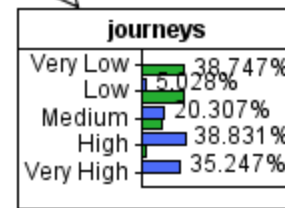
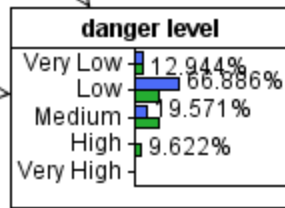
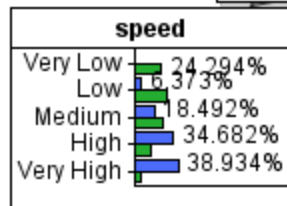
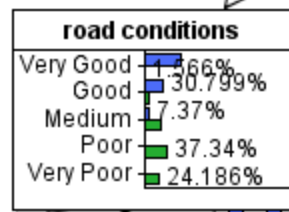


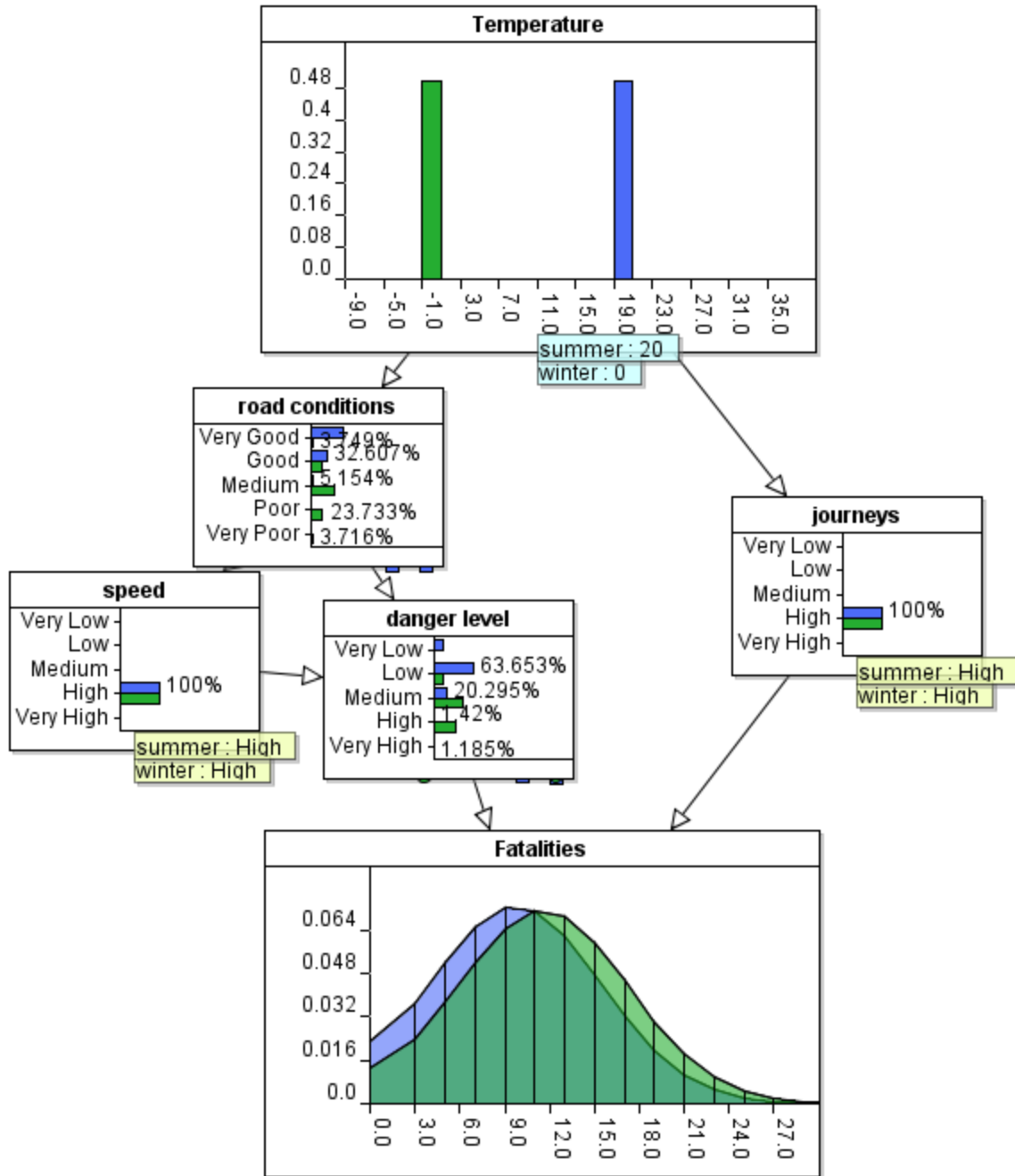






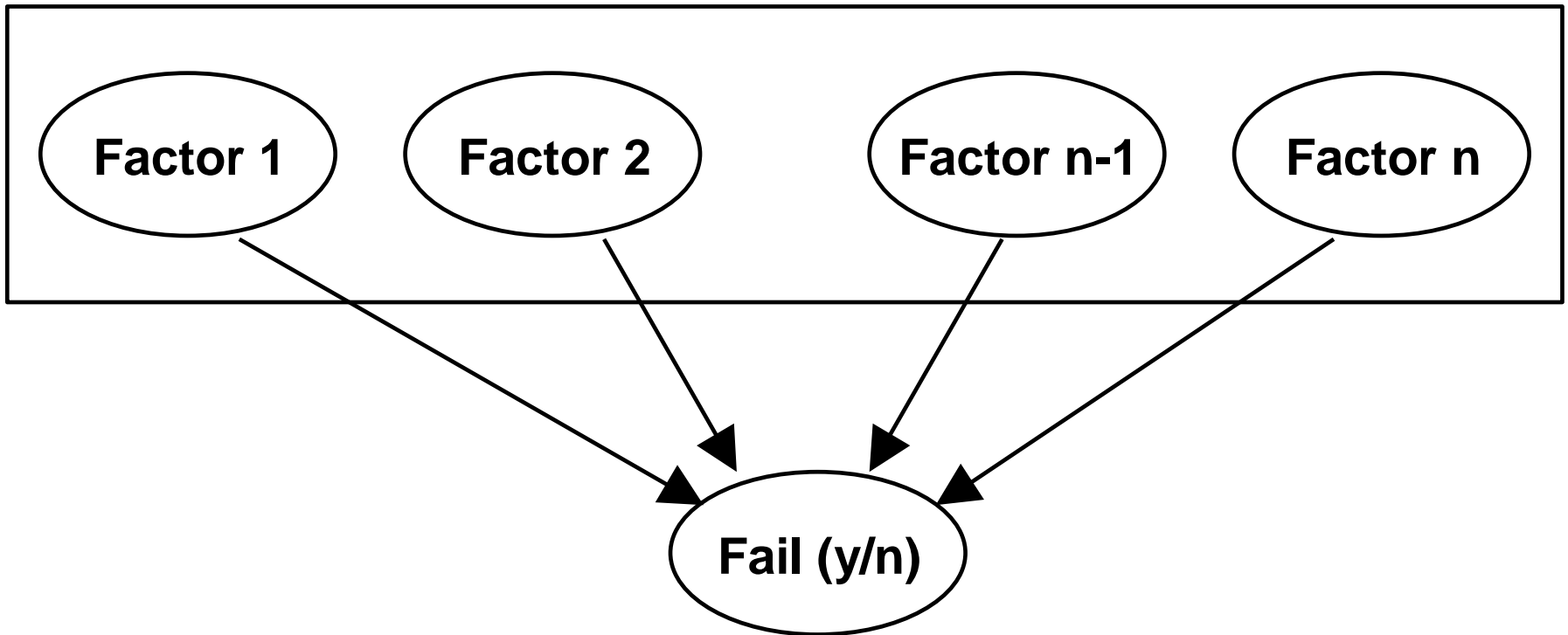
summer : 20
winter : 0





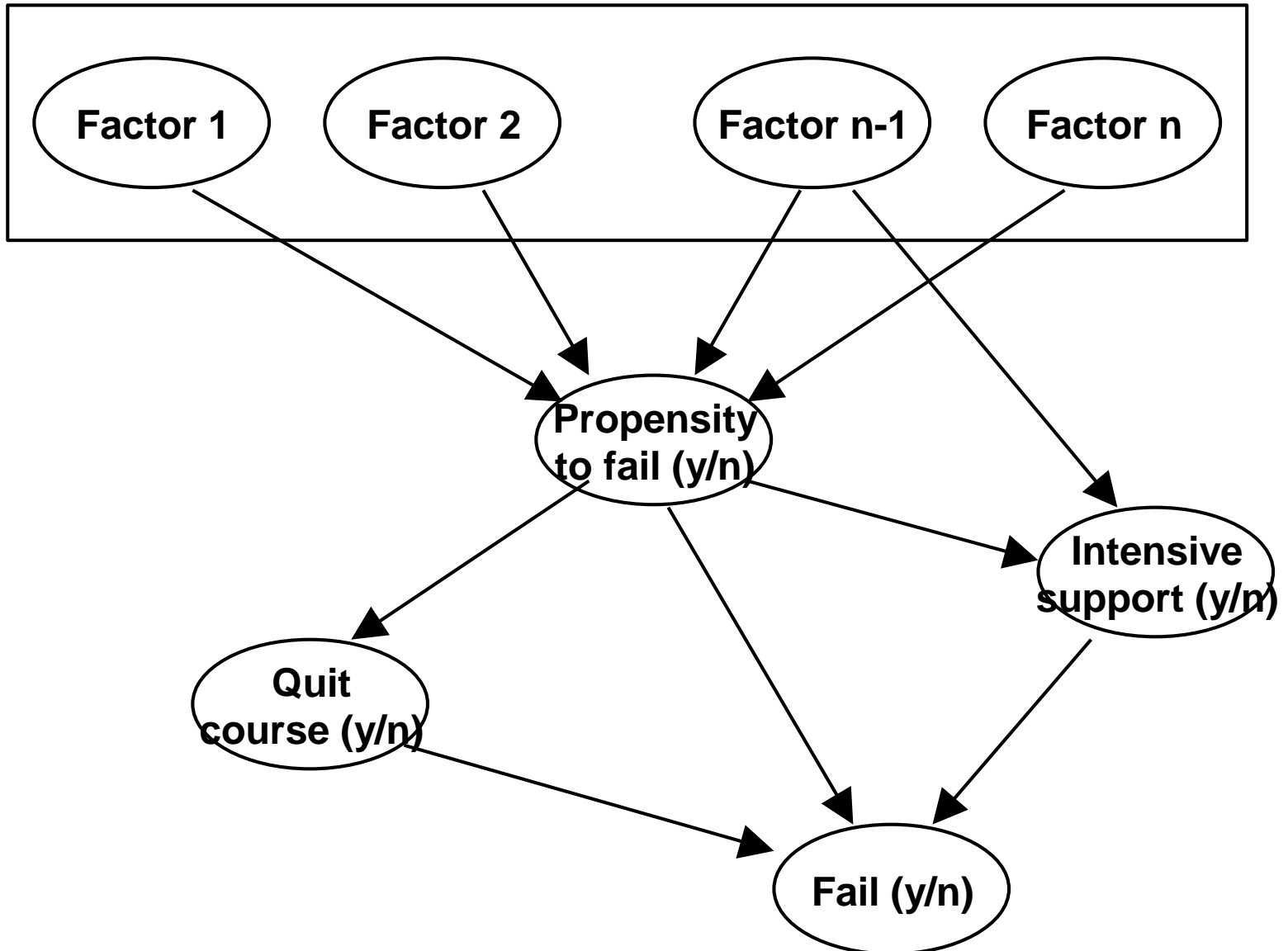
Classic (but wrong) approach to risk

Static factors



What we really need

Static factors

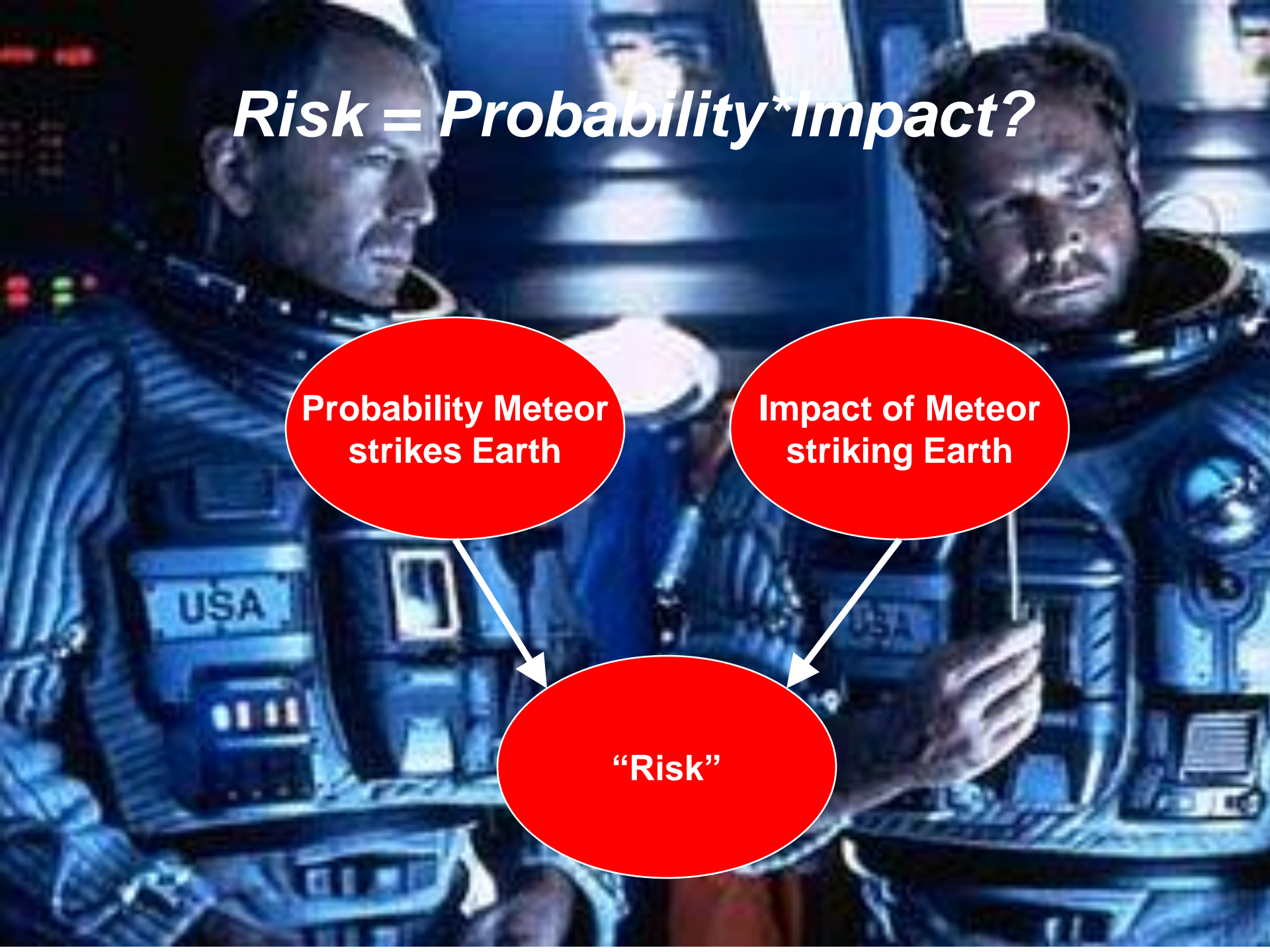


Risk = Probability*Impact?

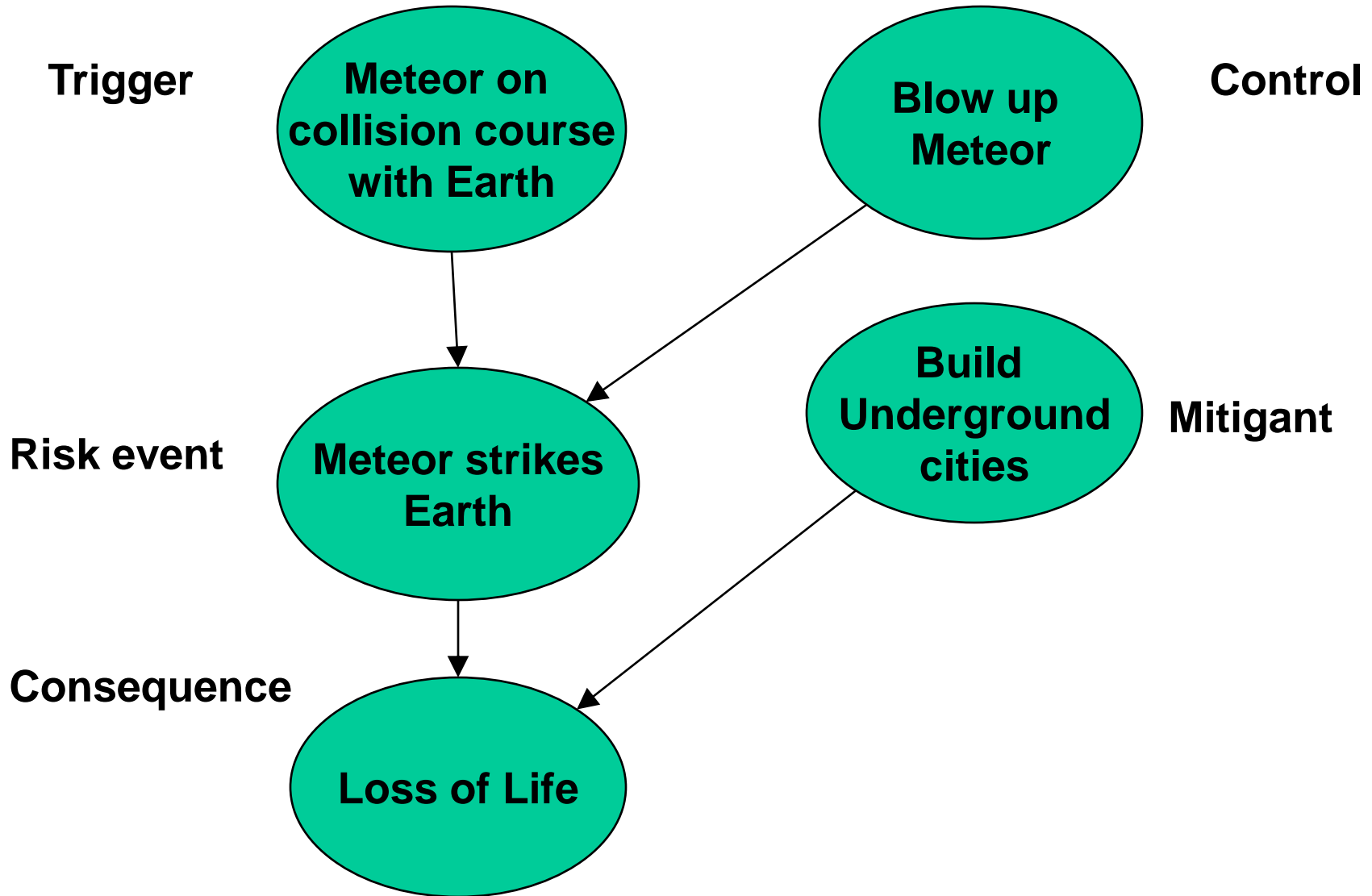
**Probability Meteor
strikes Earth**

**Impact of Meteor
striking Earth**

“Risk”



Bayesian Net with causal view of risk



The challenges

Bayesian Networks: Barriers and Challenges

Resistance to subjective probabilities

Building realistic models

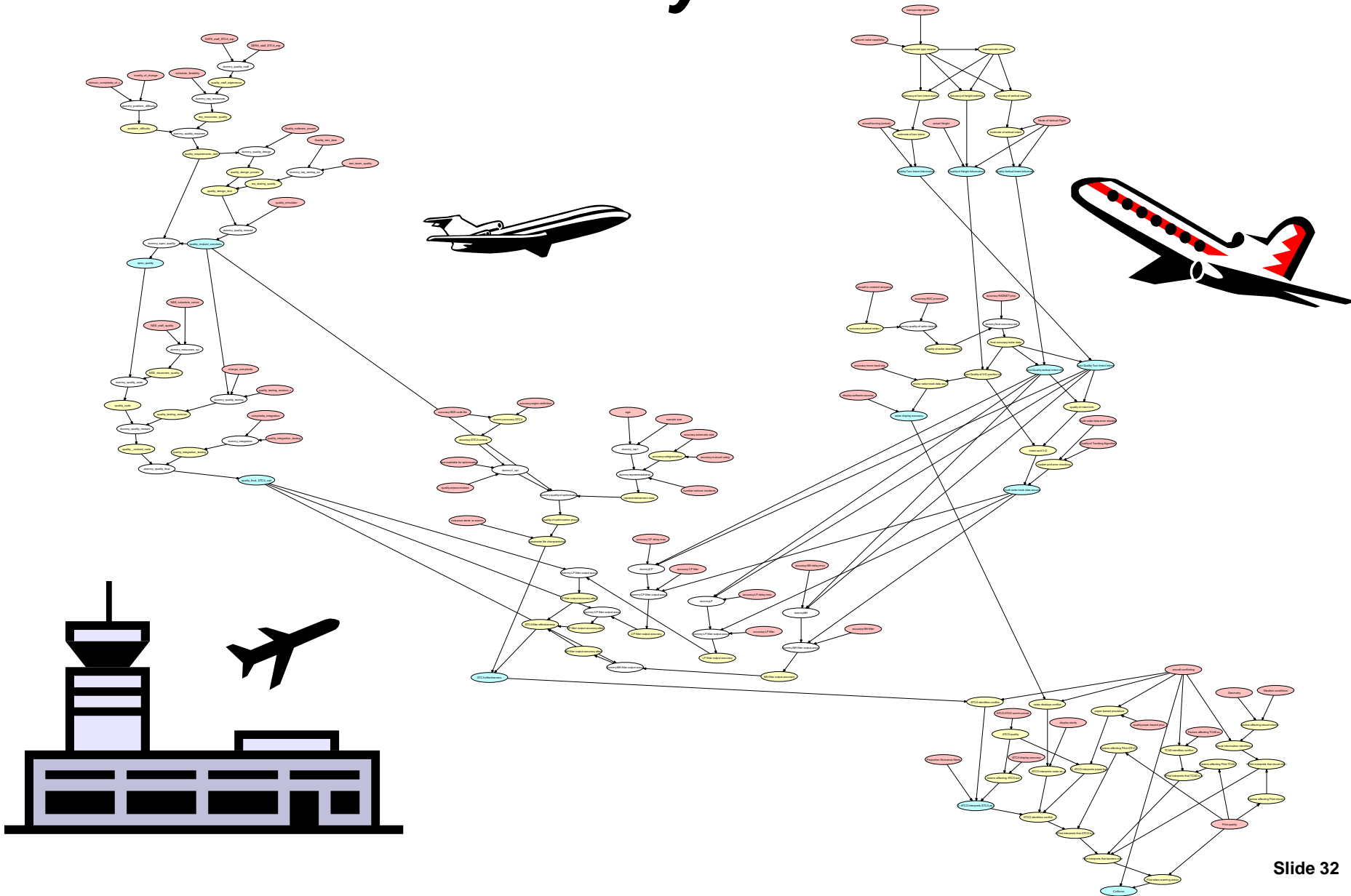
Handling continuous variables properly

Resistance to Bayes

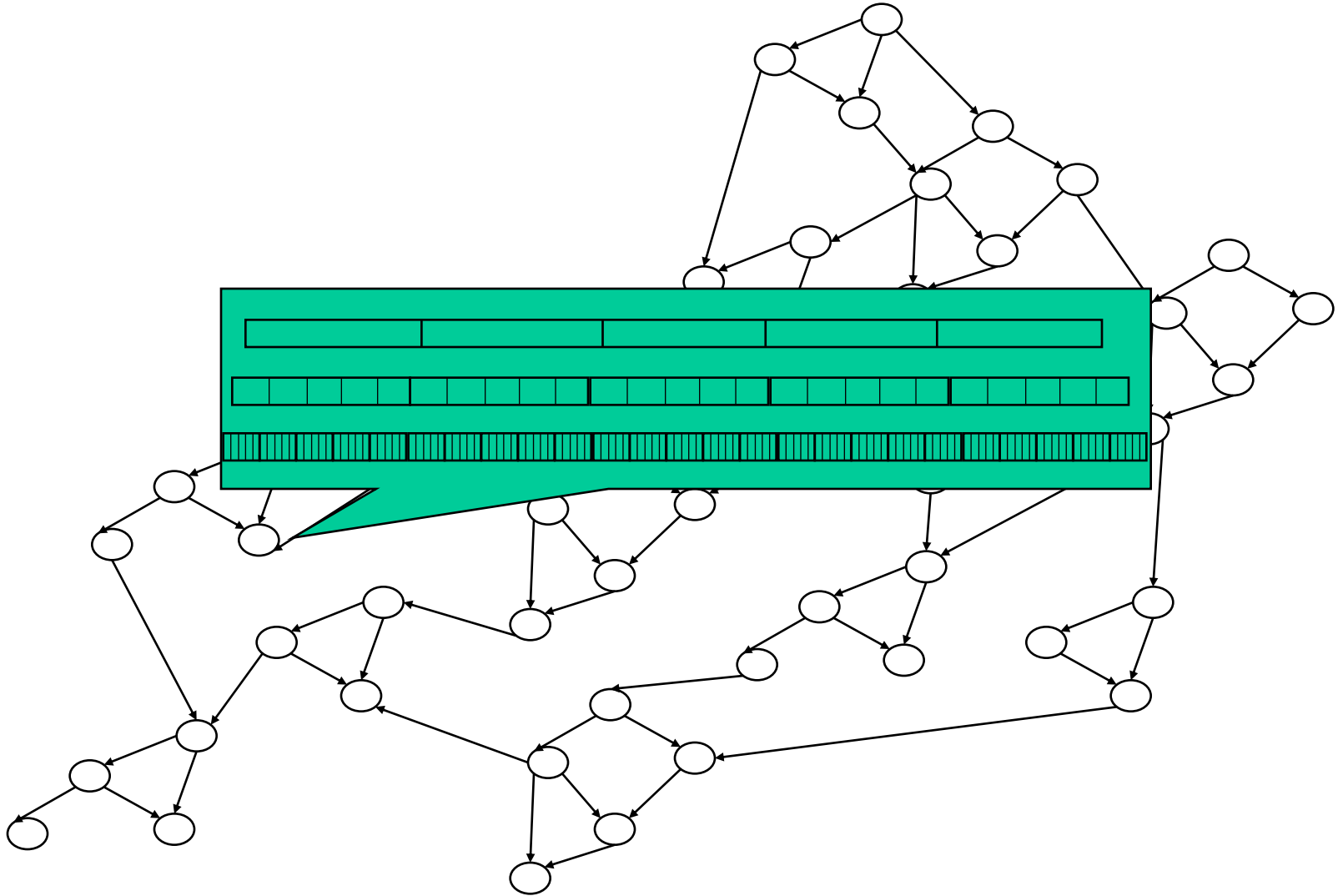
- **OK – but even if I accept the calculations are ‘correct’ I don’t accept subjective priors**

There is no such thing as a truly objective frequentist approach

A Real World Bayesian Network



How to build big BNs?



Options for Building BNs

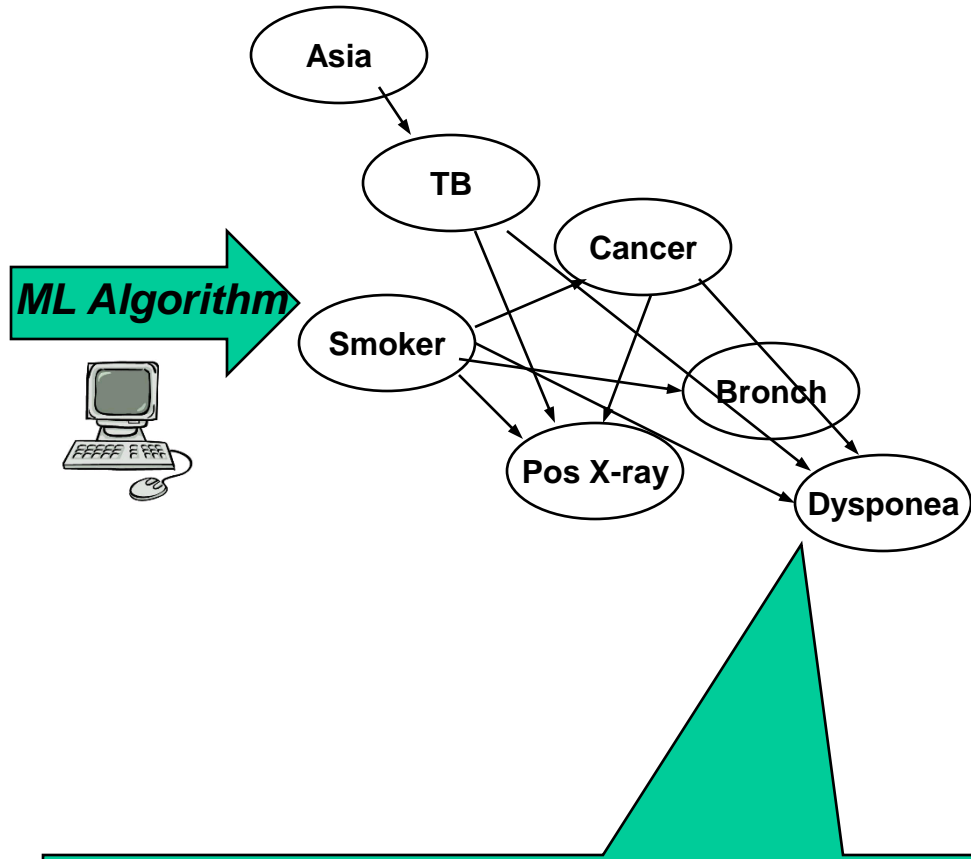
Structure and probability tables all learnt from data only ('machine learning')

Structure informed by experts, probability tables learnt from data

Structure and tables built by experts

Machine Learning Option

VisitAsia	Tuberculosis	Smoking	Cancer	TbOrCa	XRay	Bronchitis	Dyspnea
No_Visit	Absent	Smoker	Absent	False	Normal	Present	Present
No_Visit	Absent	Smoker	Absent	False	Normal	Absent	Absent
No_Visit	Absent	Smoker	Absent	False	Normal	Absent	Absent
No_Visit	Absent	NonSmoker	Absent	False	Normal	Absent	Present
No_Visit	Absent	Smoker	Absent	False	Normal	Absent	Absent
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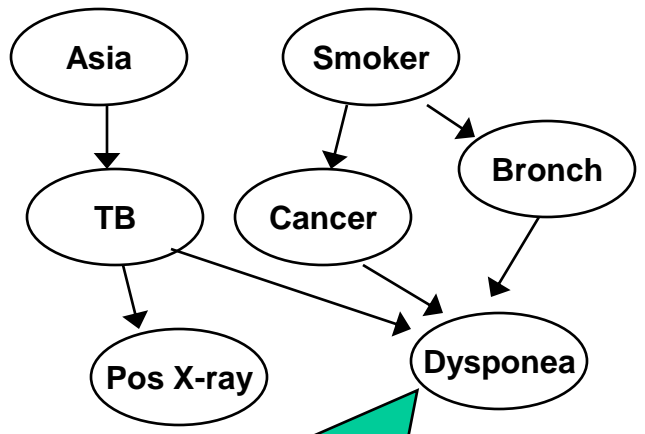
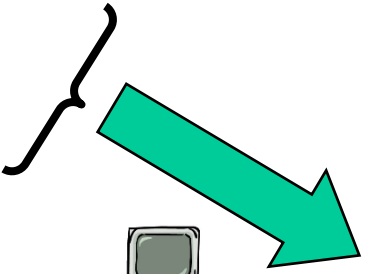
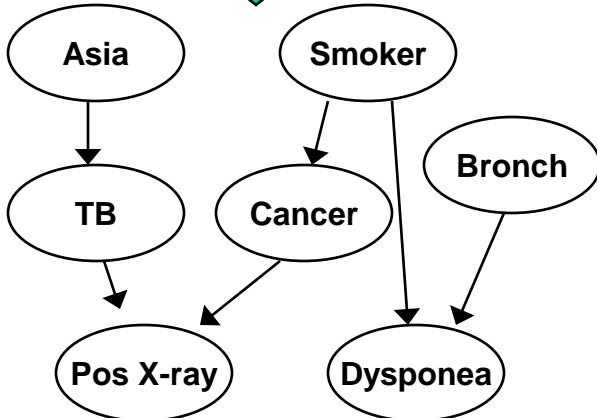


Has bronchitis	yes				no			
Has lung cancer	yes		no		yes		no	
Has tuberculosis	yes	no	yes	no	yes	no	yes	no
yes	0.25373134	0.56179774	0.5235602	0.73964494	0.45833334	0.6666667	0.7518797	0.6430868
no	0.74626863	0.43820223	0.4764398	0.26035503	0.5416667	0.33333334	0.24812031	0.35691318

Structure informed by experts

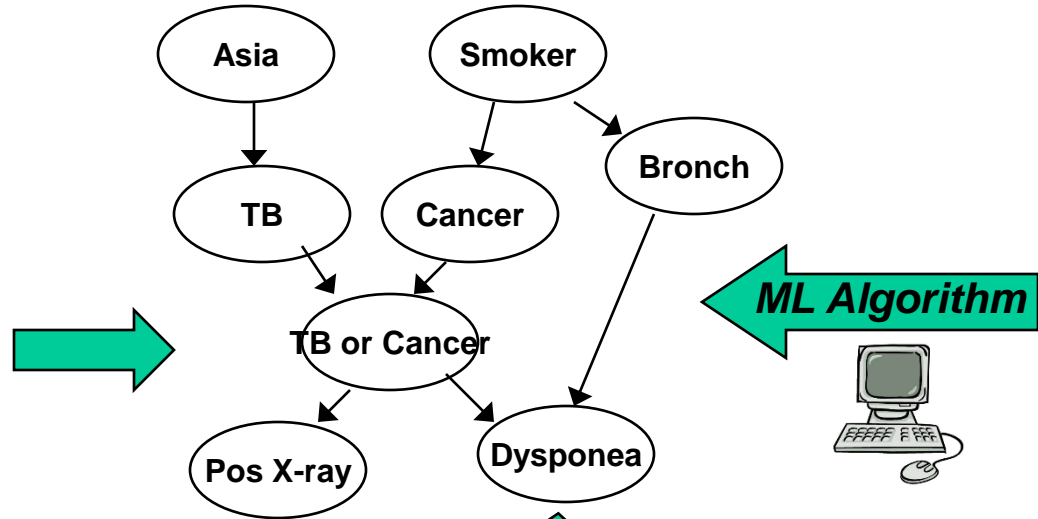


Visit/Asia	Tuberculosis	Smoking	Cancer	TbOrCa	XRay	Bronchitis	Dyspnea
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Has tuberculosis	yes				no			
	yes		no		yes		no	
	yes	no	yes	no	yes	no	yes	no
yes	0.25373134	0.56179774	0.5235602	0.73964494	0.45833334	0.6666667	0.7518797	0.6430868
no	0.74626863	0.43820223	0.4764398	0.26035503	0.5416667	0.33333334	0.24812031	0.35691318

Structure and tables by experts



Visit	Tuberculosis	Smoking	Cancer	TbOrCa	XRay	Bronchitis	Dyspnea
No_Visit	Absent	Smoker	Absent	False	Normal	Present	Present
No_Visit	Absent	Smoker	Absent	False	Normal	Absent	Absent
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No_Visit	Absent	Smoker	Absent	False	Normal	Present	Present
No_Visit	Absent	NonSmoker	Absent	False	Normal	Present	Present
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No_Visit	Absent	Smoker	Absent	False	Abnormal	Absent	Absent
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No_Visit	Absent	NonSmoker	Absent	False	Normal	Present	Present

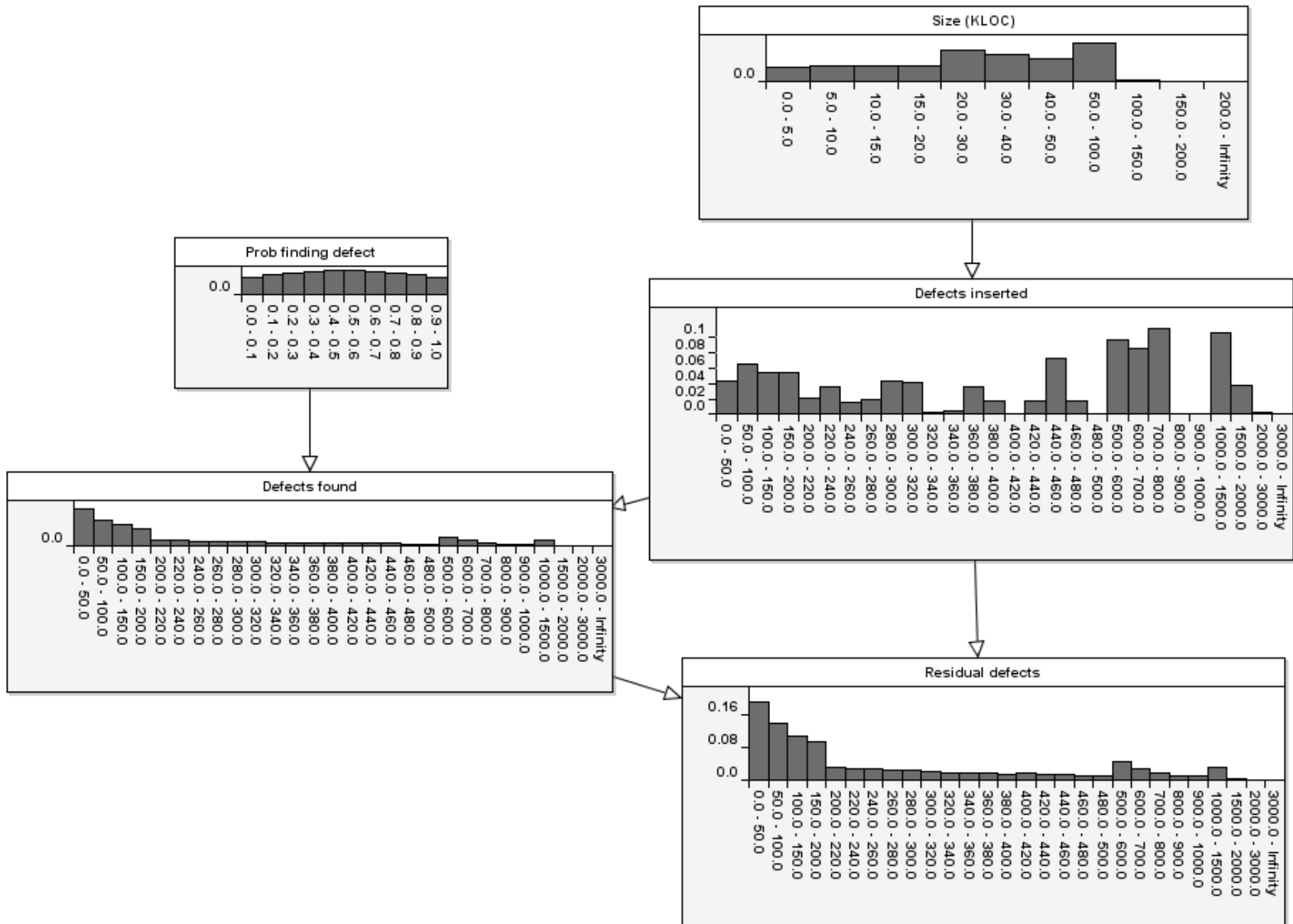
Has bronchitis	yes		no	
	yes	no	yes	no
Tuberculosis...				
yes	0.875	0.7619048	0.68085104	0.1122449
no	0.125	0.23809524	0.31914896	0.8877551

Handling continuous nodes

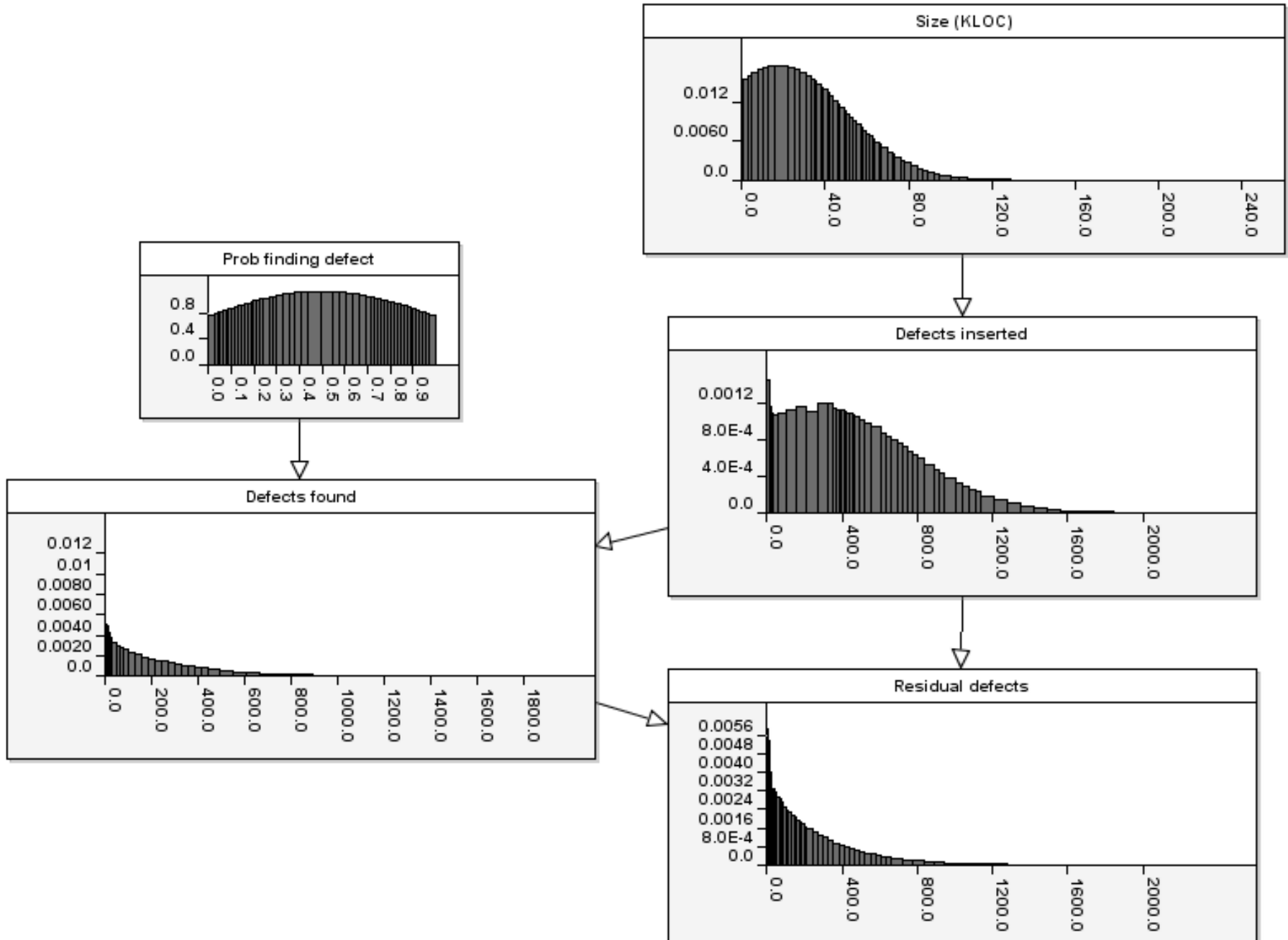
**Static discretisation: inefficient
and devastatingly inaccurate**

**Developments in dynamic
discretisation will have
revolutionary effect**

Static discretization



Dynamic discretization



Typical Applications

Predicting reliability of critical systems

QinetiQ



Military Truck Simulation

Typical Applications

Software defect prediction



Typical Applications

Aircraft accident traffic risk



Typical Applications



MOTOROLA

**Warranty return rates of
electronic parts**



Typical Applications



**Operational risk in
financial institutions**



Typical Applications



**Hazards in
petrochemical industry**



Typical Applications



R vs Levi Bellfield

**Probabilistic and risk
based legal arguments**

Conclusions

Genuine risk assessment requires causal Bayesian networks

Bayesian networks have been used effectively in a range of real world problems.

Major remaining barrier to widespread use is conceptual/presentational

www.BayesianRisk.com

RISK ASSESSMENT AND DECISION ANALYSIS WITH BAYESIAN NETWORKS

NORMAN FENTON
MARTIN NEIL

CRC Press
A CHAPMAN & HALL BOOK

"... although there have been several excellent books dedicated to Bayesian Networks and related methods, these books tend to be aimed at readers who already have a high-level of mathematical sophistication As such they are not really accessible to readers who are not already proficient in those subjects. This book is an exciting development because it addresses this problem".

Judea Pearl, winner 2011 Turing Award for work on AI reasoning

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