Bayesian Networks & BayesiaLab

Artificial Intelligence for Research, Analytics, and Reasoning

BAYESIALAB

Hello

my name is

Stefan Conrady



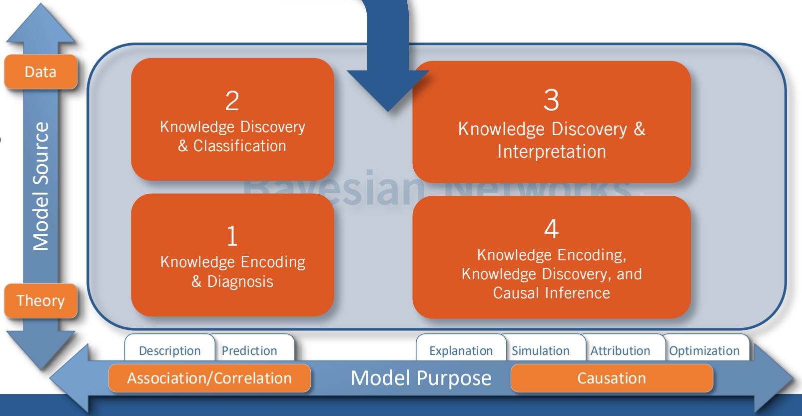




Today's Agenda

90 min.

- Introduction — You are here
- Frequently Asked Questions
- Motivation: Artificial Intelligence—the Promise and the Peril
- Objective: Artificial Intelligence for Research, Analytics, and Reasoning
- Map of Analytic Modeling: Source & Purpose of Models
- Introducing Bayesian Networks
- Example: Differential Diagnosis of Diseases
- The BayesiaLab Software Platform
- Examples

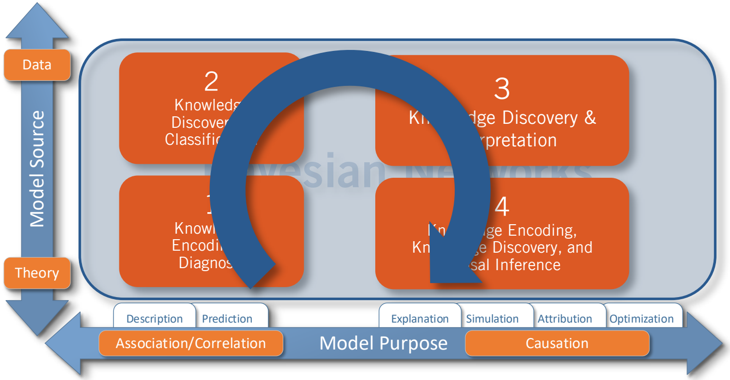


Today's Agenda (cont'd)

Examples

150 min.

- Knowledge Encoding & Diagnosis
- Knowledge Discovery & Classification
- Knowledge Discovery & Interpretation
- Causal Inference



Introduction

Our Company

Our Product

The Paradigm

BAYESIAN NETWORKS*

Judea Pearl
Cognitive Systems Laboratory
Computer Science Department
University of California, Los Angeles, CA 90024
judea@cs.ucla.edu

Bayesian networks were developed in the late 1970's to model distributed processing in reading comprehension, where both semantical expectations and perceptual evidence must be combined to form a coherent interpretation. The ability to coordinate bi-directional inferences filled a void in expert systems technology of the early 1980's, and Bayesian networks have emerged as a general representation scheme for uncertain knowledge [Pearl, 1988, Heckerman *et al.*, 1995, Jensen, 1996, Castillo *et al.*, 1997].

Bayesian networks are directed acyclic graphs (DAGs) in which the nodes represent vari-

Co-founded in 2001

by Dr. Lionel Jouffe &

Dr. Paul Munteanu

BAYESIALAB

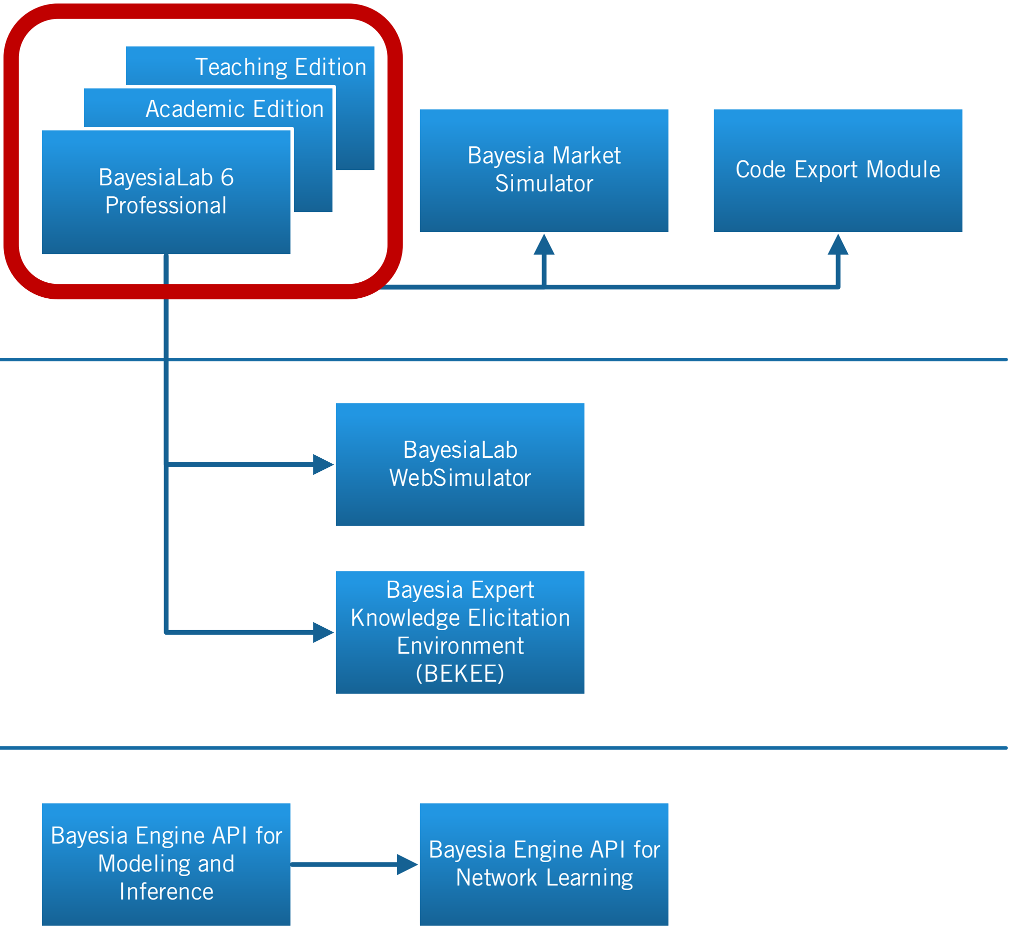

BayesiaLab
Professional
API
Code Export
Education
Academic

BAYESIALAB

Desktop Software

Web Application

API



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EADS
Holiday Inn
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IHG
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Unilever
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SOCIETE GENERALE
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BBDO
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GfK
Nestlé
Fractal
NTT
MAi
National Analysts
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Firmenich
SAMSUNG
france telecom
Cargill
eDF
Ipsos
McGill
P&G
CDC
eni
Hilton
HOTELS & RESORTS
LANCASTER UNIVERSITY
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tns
SMUCKER'S
IMRB
international
RUSH UNIVERSITY
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Microsoft
Team Detroit
sanofi pasteur
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Deloitte.
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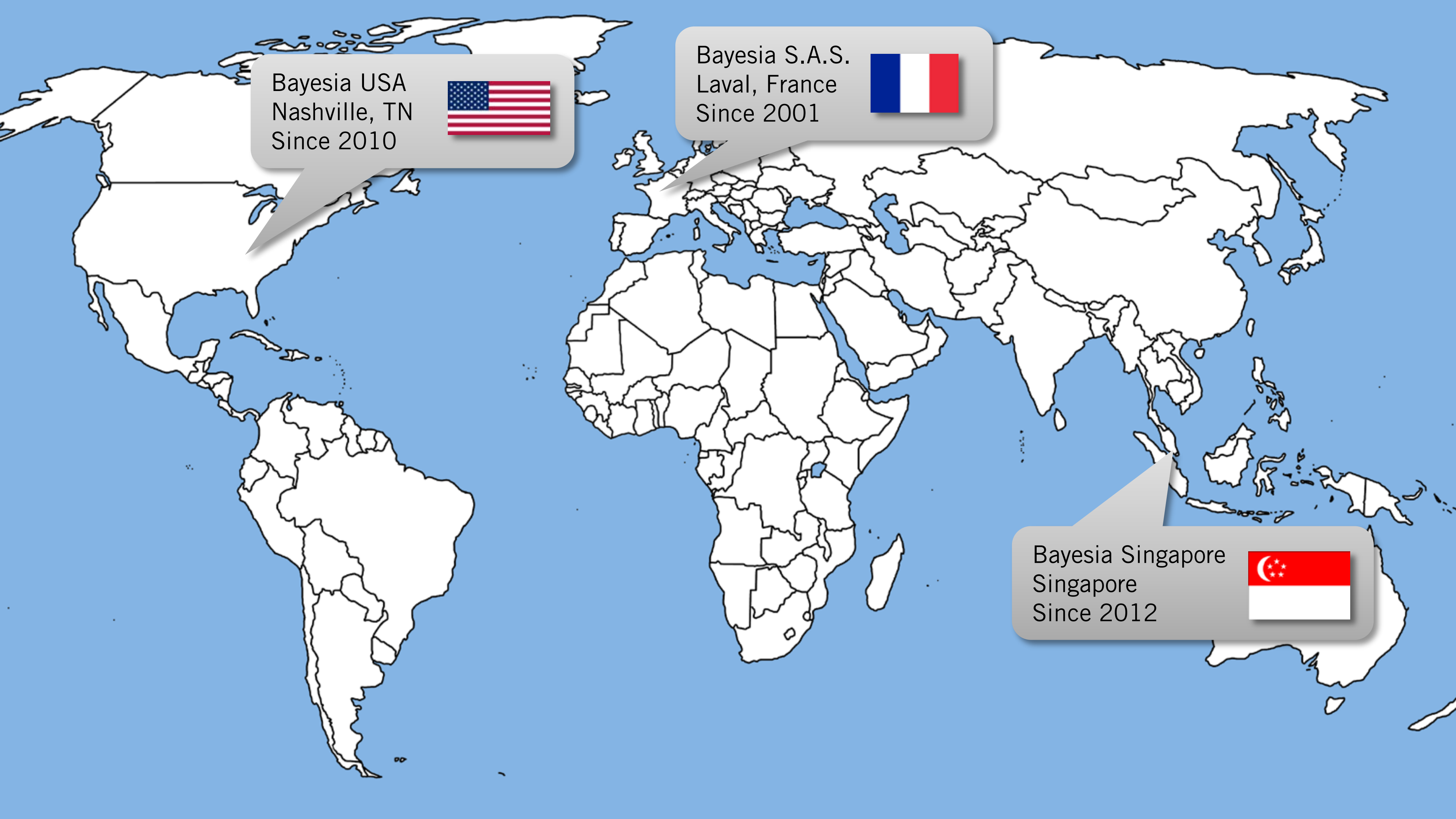
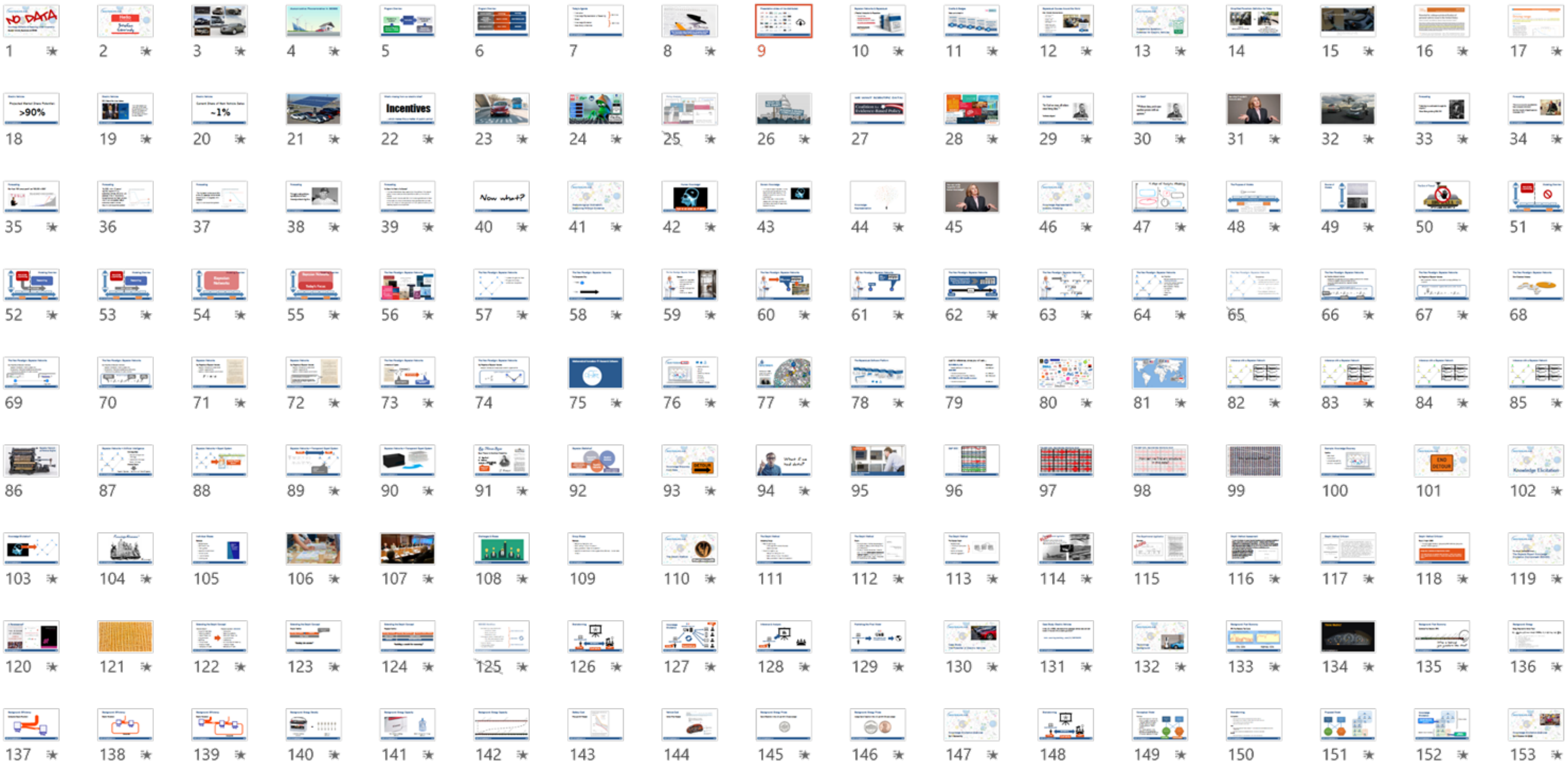

Bayesia USA
Nashville, TN
Since 2010
Bayesia S.A.S.
Laval, France
Since 2001
Bayesia Singapore
Singapore
Since 2012

Frequently Asked Questions

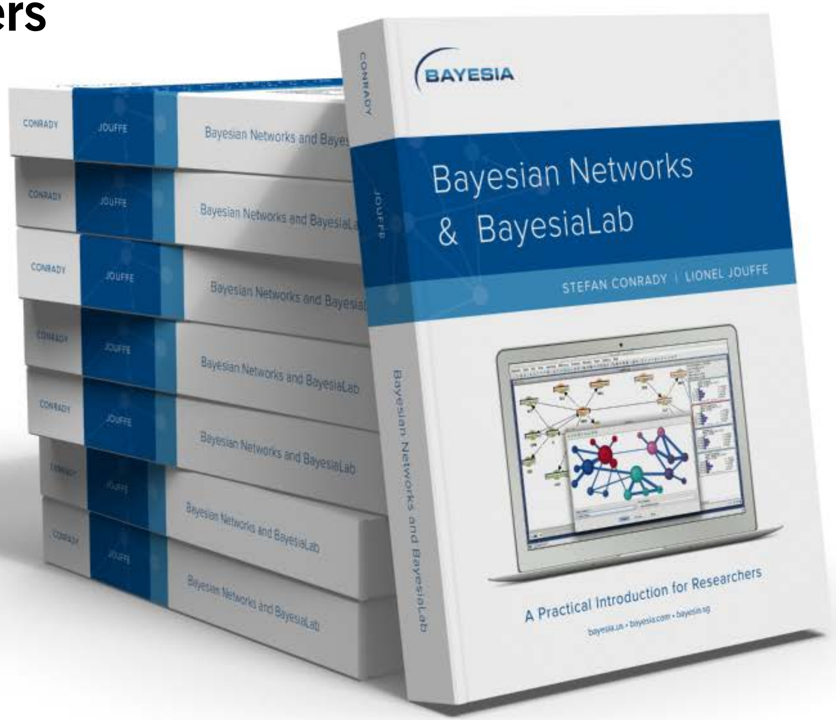
Presentation slides will be available



Bayesian Networks & BayesiaLab

A Practical Introduction for Researchers

- Free download:
  www.bayesia.com/book
- Hardcopy available on Amazon:
  http://amzn.com/0996533303



BayesiaLab Courses Around the World

3-Day Introductory BayesiaLab Courses: bayesia.com/events

- September 25–27, 2017
  Paris, France
- October 24–26, 2017
  New York City
- November 20–22, 2017
  Singapore (SOLD OUT)
- November 27–29, 2017
  Sydney, Australia

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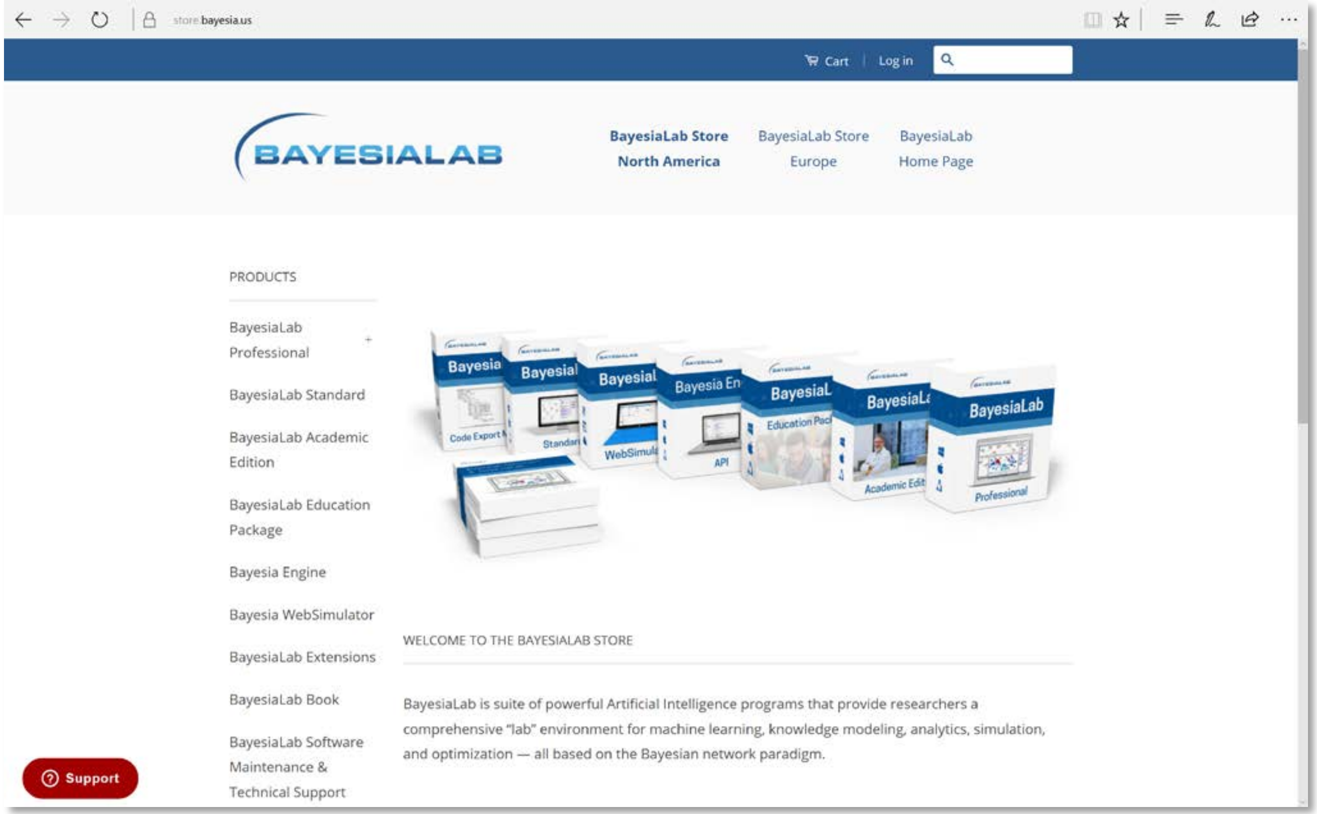

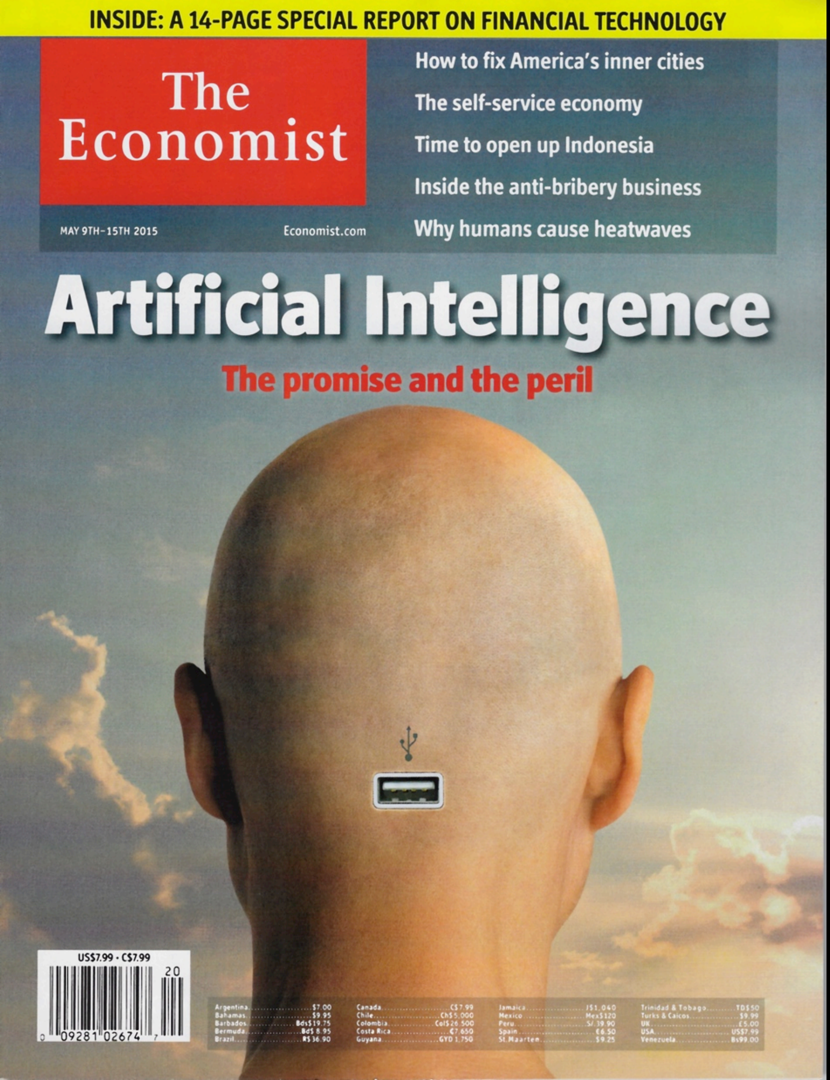
INSIDE: A 14-PAGE SPECIAL REPORT ON FINANCIAL TECHNOLOGY
The Economist
How to fix America's inner cities
The self-service economy
Time to open up Indonesia
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Why humans cause heatwaves
MAY 9TH–15TH 2015
Economist.com
Artificial Intelligence
The promise and the peril
US$7.99 · C$7.99


DOMHNALL GLEESON ALICIA VIKANDER AND OSCAR ISAAC
EX MACHINA
WHAT HAPPENS TO ME IF I FAIL YOUR TEST?

“The development of full artificial intelligence could spell the end of the human race.”—Stephen Hawking, December 2014

Artificial Intelligence a Threat?

Elon Musk
@elonmusk

Follow

If you're not concerned about AI safety, you should be. Vastly more risk than North Korea.

8:29 PM - Aug 11, 2017

2,429 13,681 37,782


NO HYPE ZONE
NEXT 200 SLIDES
Big Data Is the New Oil
We need to find it,
Extract it, Refine it, Distribute it and
use it to drive Economic Prosperity
Dr Andrew Seit
THE FUTURE OF
DATA-DRIVEN
INNOVATION
Harvard Business Review
GETTING CONTROL OF BIG DATA
Data Models
AI
Processing Power
Big
DataDriven Business
Cognitive
Predictive/ Prescriptive analytics
Descriptive analytics
Discover, report, analyze
Predict, decide, act
Reason, understand, learn
What happened?
What will happen? What should I do?
What can we discover?
Stage-1
Machine Consciousness
Stage-2
Machine Intelligence
Currently Technology is here
Stage-3
Siri
Alexa
Cortana
Machine Learning
Stages of Artificial Intelligence
BIG DATA & ANALYTICS
ALTHOUGH AI IS AL
IN THOUSANDS OF CO
AROUND THE WORLD, M
AND THE END
OF THE HUMAN
BIG DAT
VOLUME
VELOCITY
SPEED OF CHANGE
VARIETY
TIM PHILLIPS
DATA-DRIVEN BUSINESS
USE REAL-LIFE NUMBERS TO IMPROVE YOUR BUSINESS BY 352%
Gartner Analytic Ascendancy Model
How can we make it happen?
Prescriptive Analytics
What will happen?
Predictive Analytics
Why did it happen?
Diagnostic Analytics
What happened?
Descriptive Analytics
VALUE
DIFFICULTY
Information
Hindsight
Insight
Foresight
Optimization
Gartner
Big Data And Artificial
Intelligence For A Better Future
OodlesTechnologies
www.oodlestechnologies.com

WIRED

DAVID WEINBERGER BACKCHANNEL 04.18.17 08:22 PM

OUR MACHINES NOW HAVE KNOWLEDGE WE'LL NEVER UNDERSTAND

WIRED

ALIEN KNOWLEDGE

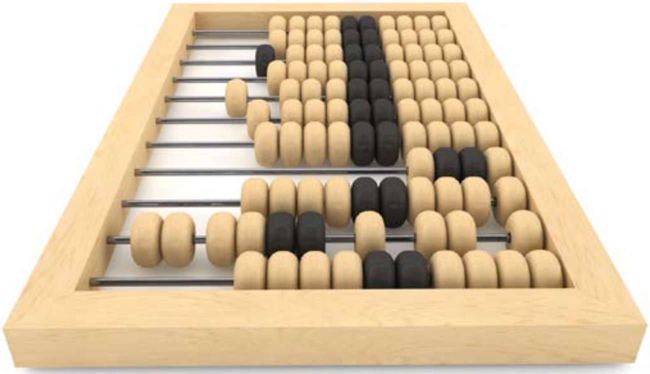
WHEN MACHINES JUSTIFY KNOWLEDGE

Alien Knowledge?

We used to only not know how our brains work.

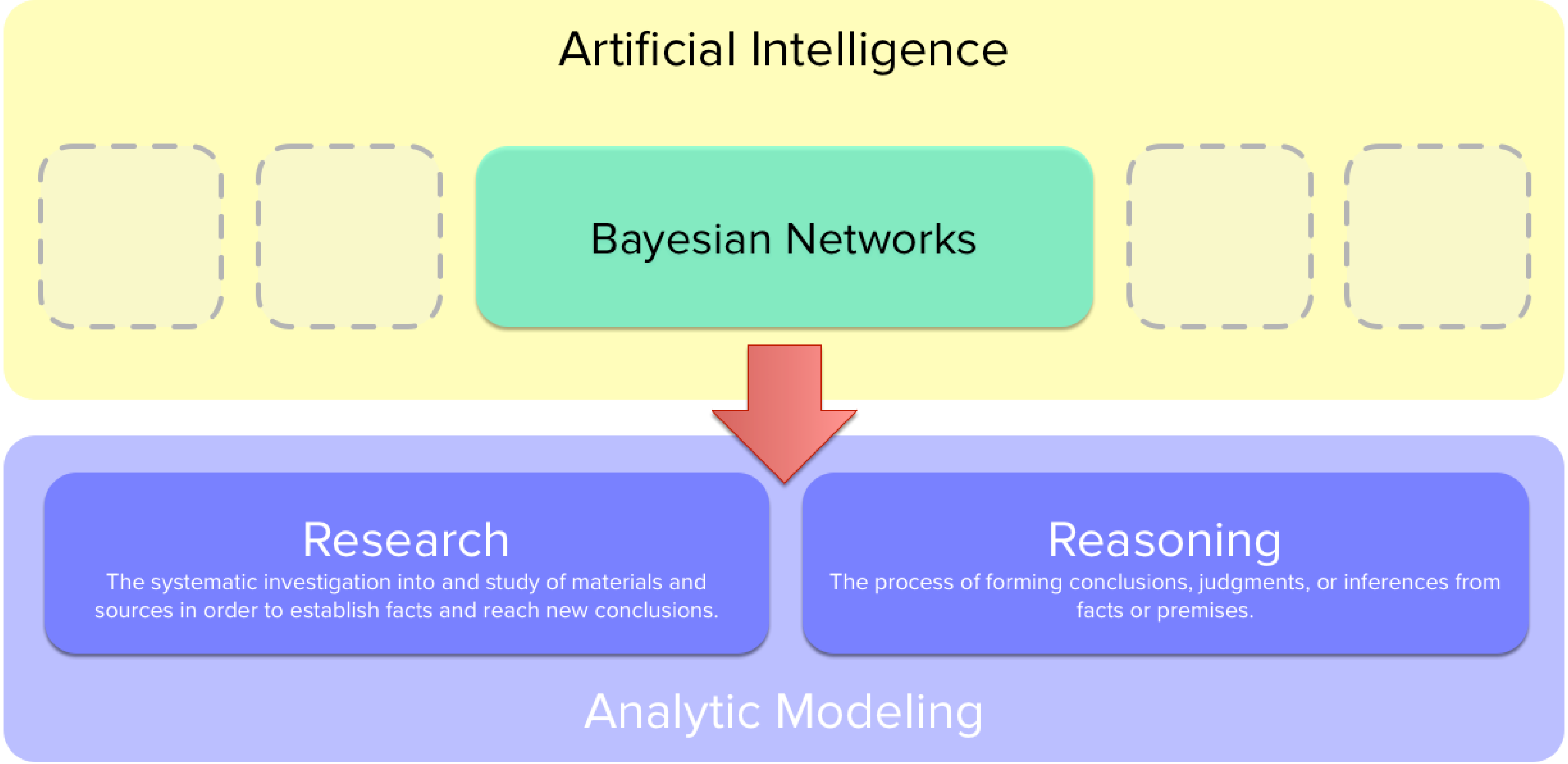
Now we also don't know how our machines work.

Today's Objective

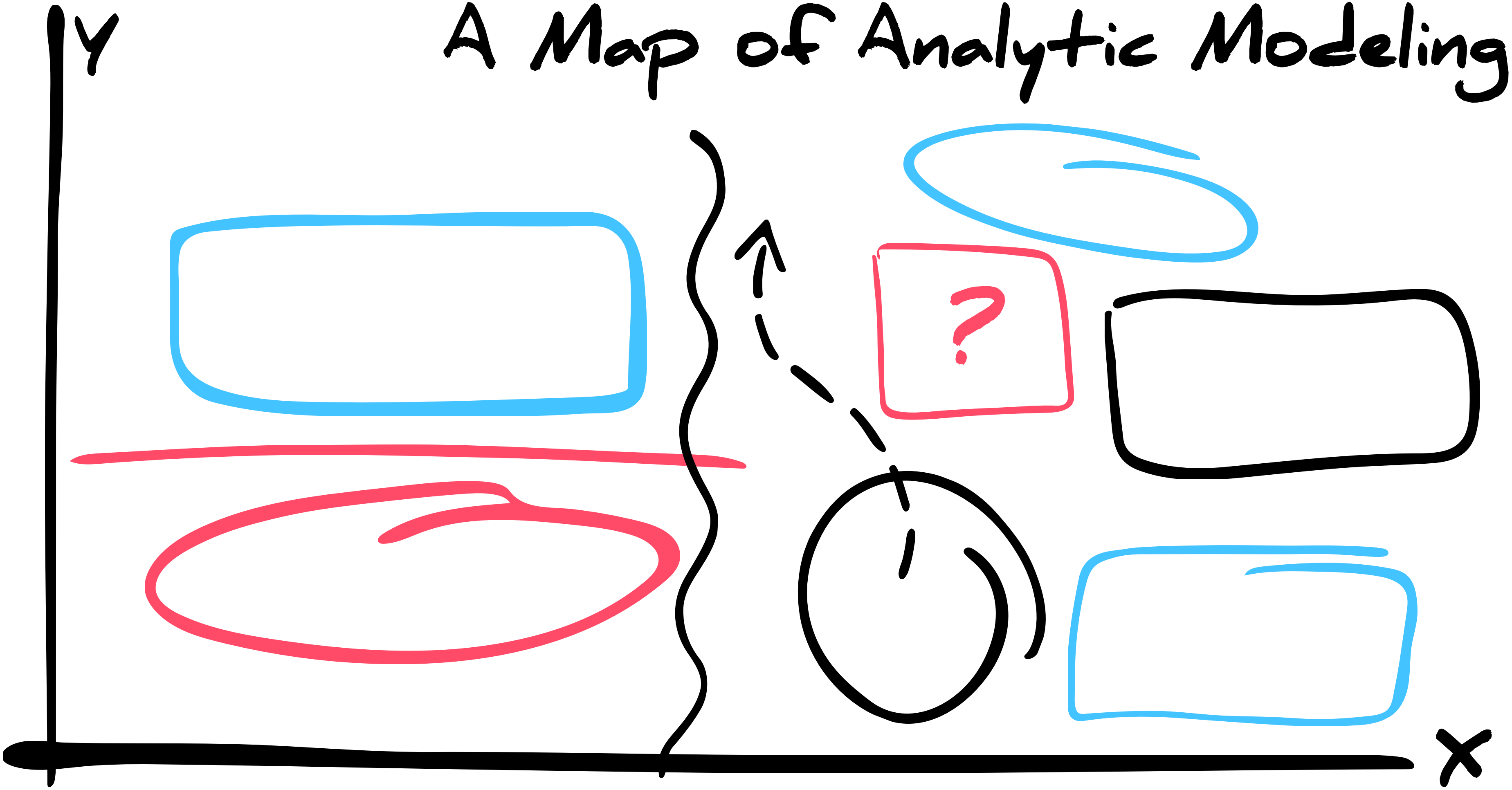


Artificial Intelligence solving a problem for you, as a "black box."

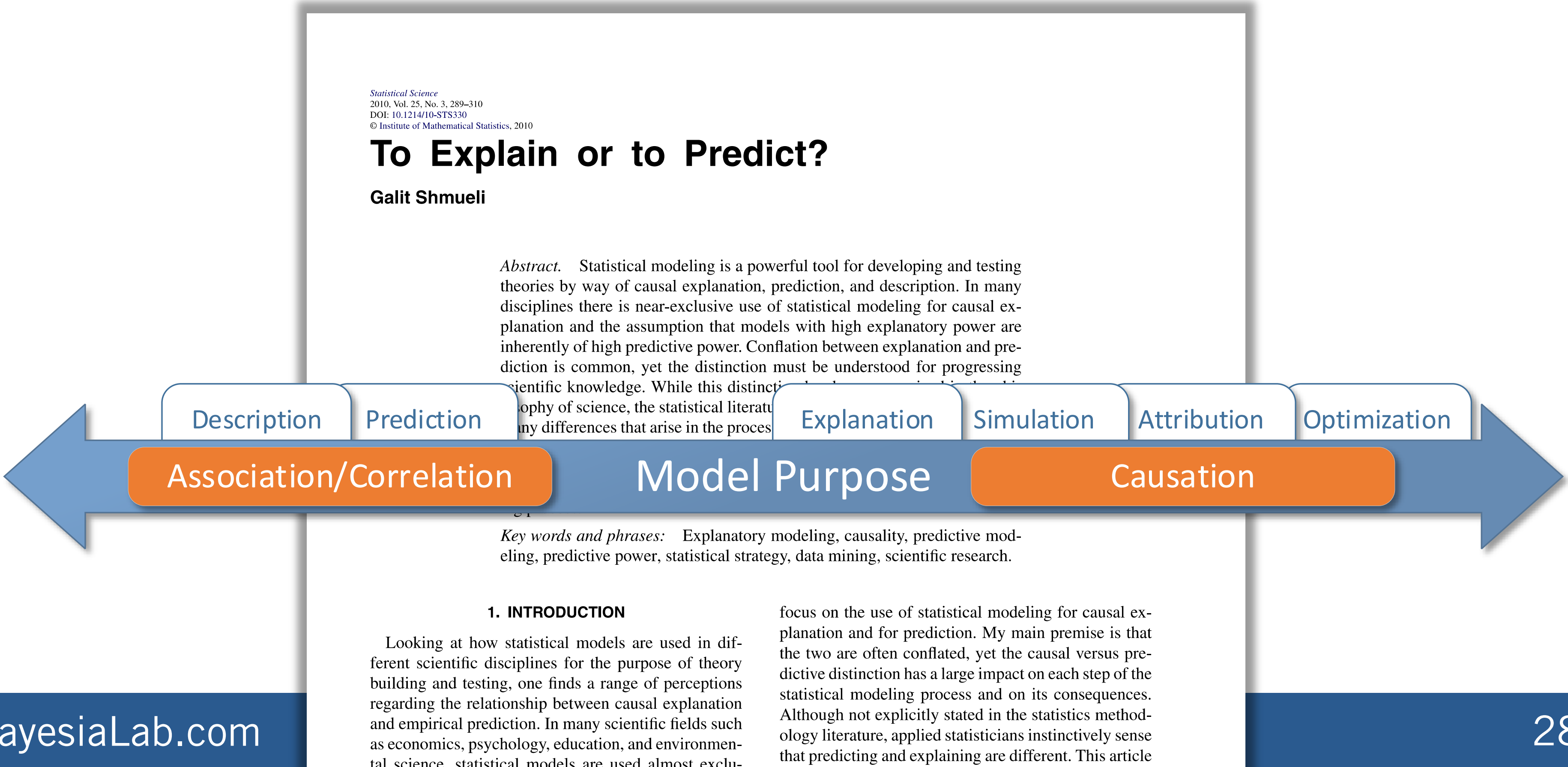
Artificial Intelligence as a practical support for research and reasoning.


Artificial Intelligence
Bayesian Networks
Research
The systematic investigation into and study of materials and sources in order to establish facts and reach new conclusions.
Reasoning
The process of forming conclusions, judgments, or inferences from facts or premises.
Analytic Modeling

A Map of Analytic Modeling



The Purpose of Models



Statistical Science
2010, Vol. 25, No. 3, 289–310
DOI: 10.1214/10-STS330

To Explain or to Predict?

Galit Shmueli

Abstract. Statistical modeling is a powerful tool for developing and testing theories by way of causal explanation, prediction, and description. In many disciplines there is near-exclusive use of statistical modeling for causal explanation and the assumption that models with high explanatory power are inherently of high predictive power. Conflation between explanation and prediction is common, yet the distinction must be understood for progressing scientific knowledge. While this distincti... ...ophy of science, the statistical literatu... ...ny differences that arise in the proces...

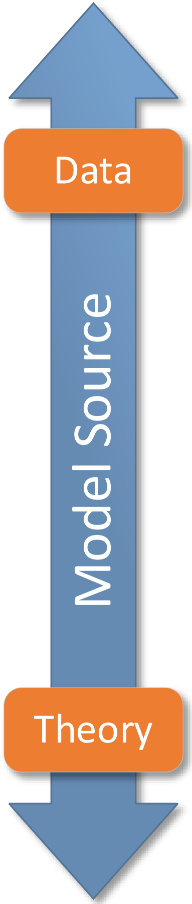
Key words and phrases: Explanatory modeling, causality, predictive modeling, predictive power, statistical strategy, data mining, scientific research.

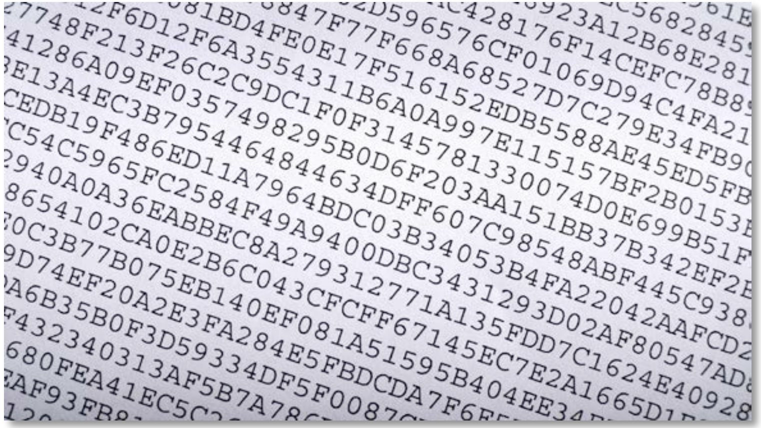
1. INTRODUCTION

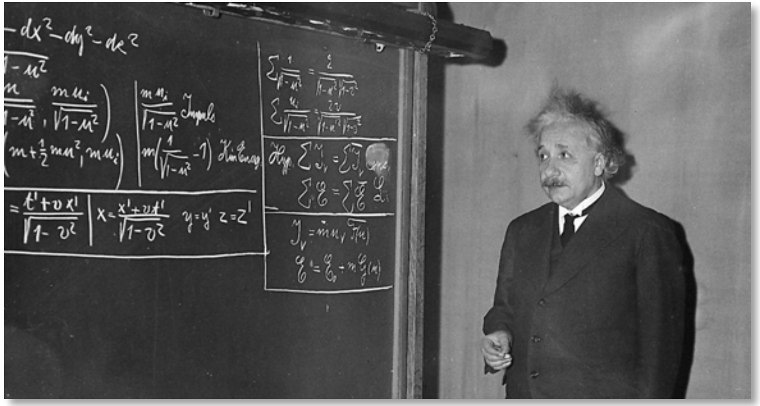
Looking at how statistical models are used in different scientific disciplines for the purpose of theory building and testing, one finds a range of perceptions regarding the relationship between causal explanation and empirical prediction. In many scientific fields such as economics, psychology, education, and environmental science, statistical models are used almost exclu-

focus on the use of statistical modeling for causal explanation and for prediction. My main premise is that the two are often conflated, yet the causal versus predictive distinction has a large impact on each step of the statistical modeling process and on its consequences. Although not explicitly stated in the statistics methodology literature, applied statisticians instinctively sense that predicting and explaining are different. This article

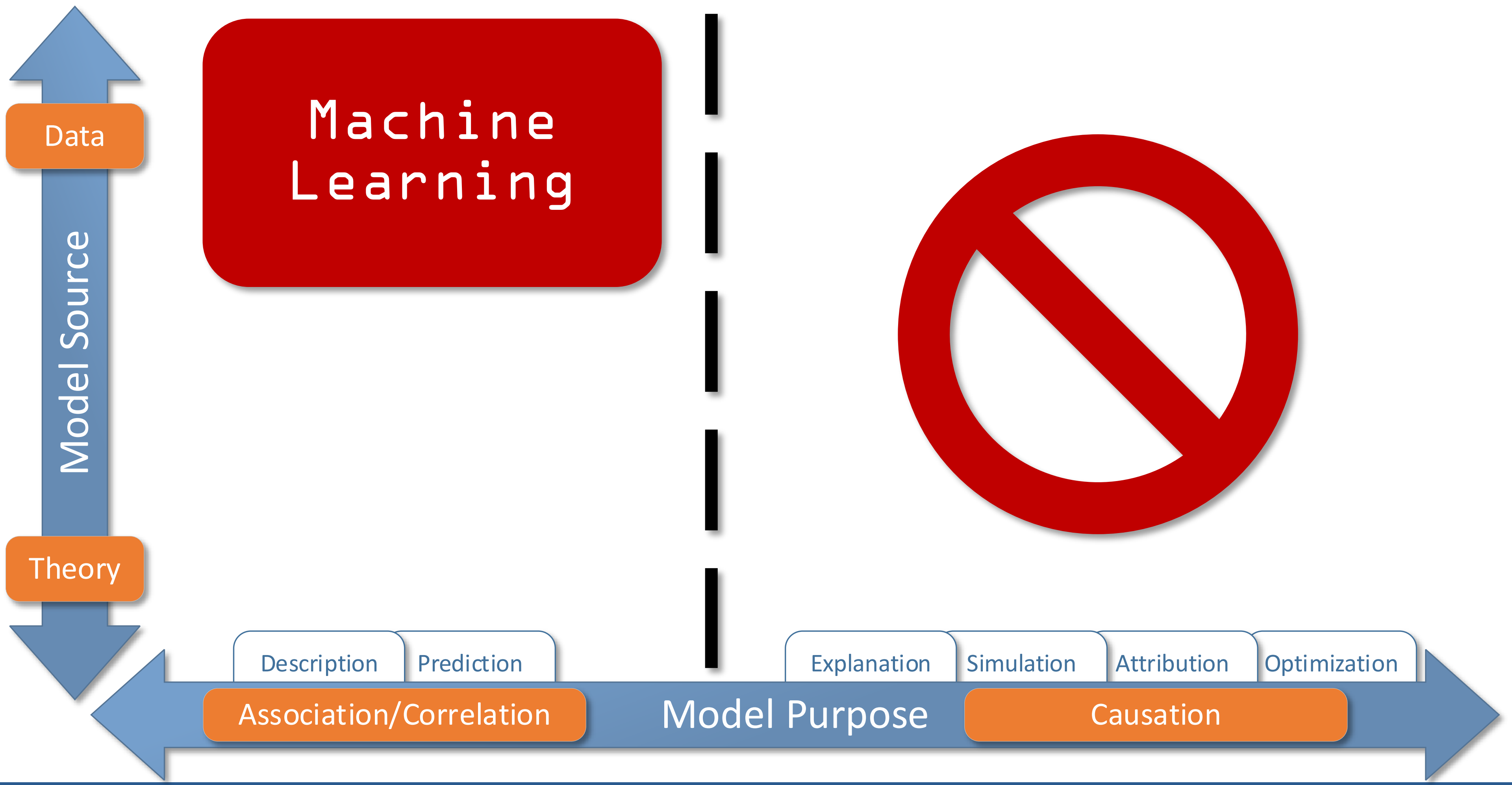
Source of Models



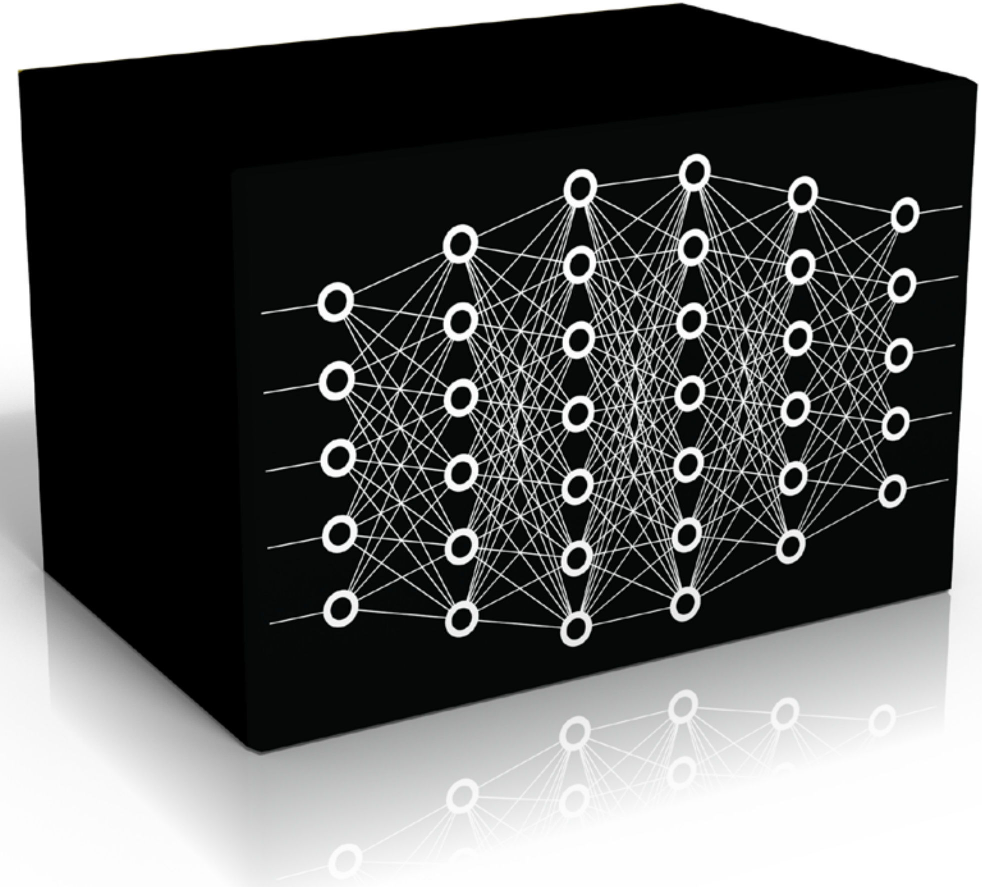




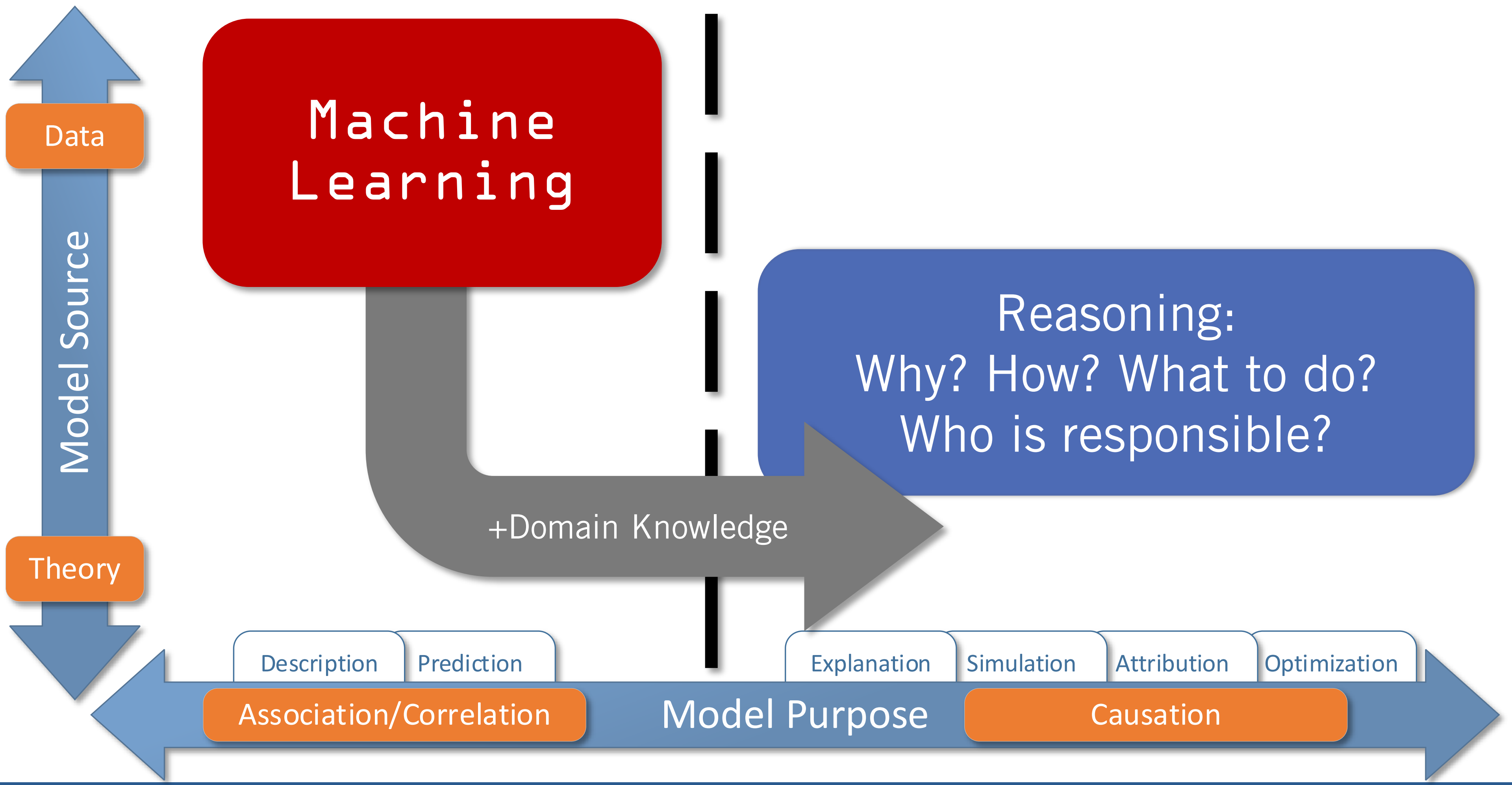
The End of Theory?

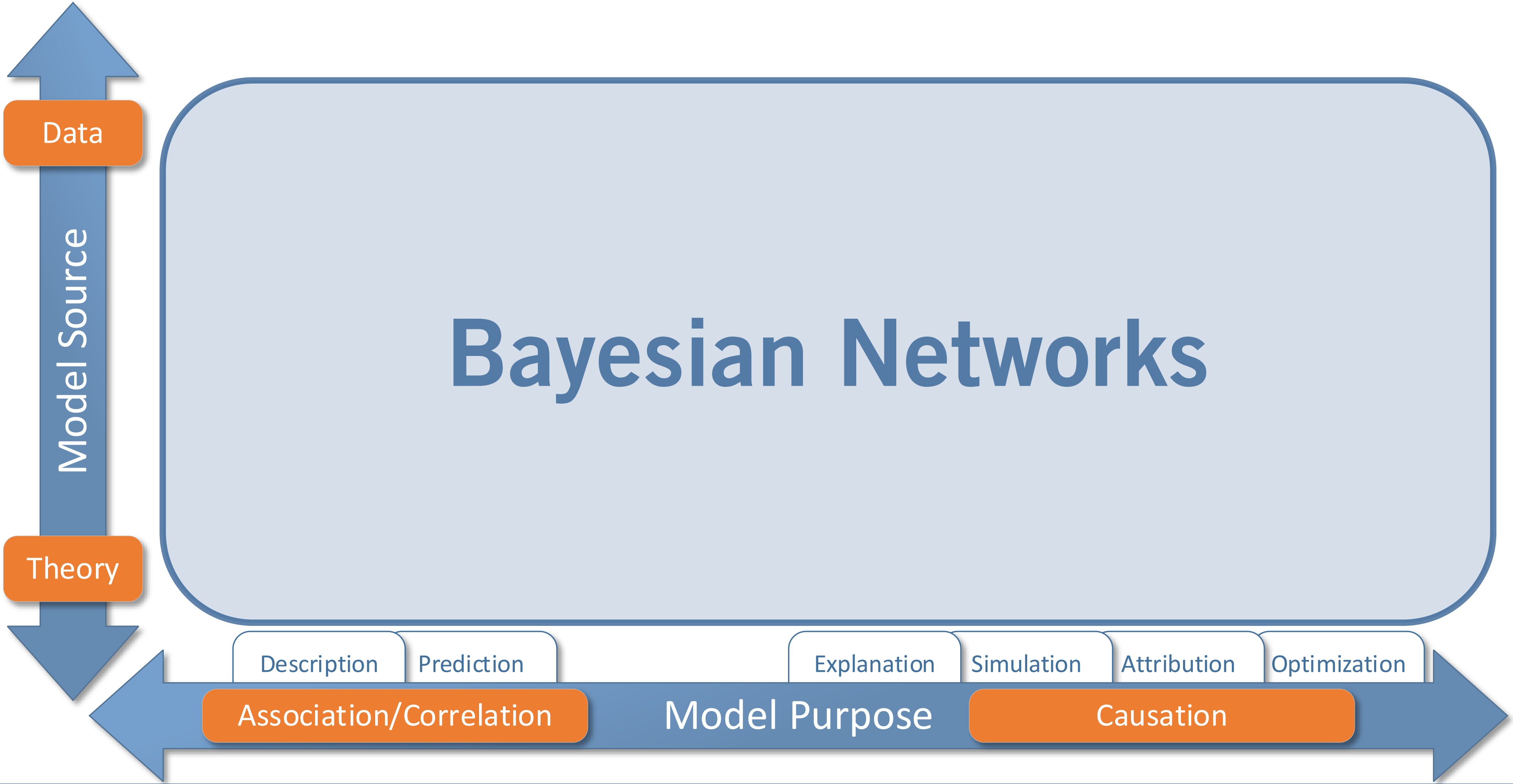

Machine Learning
Data
Model Source
Theory
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Why?

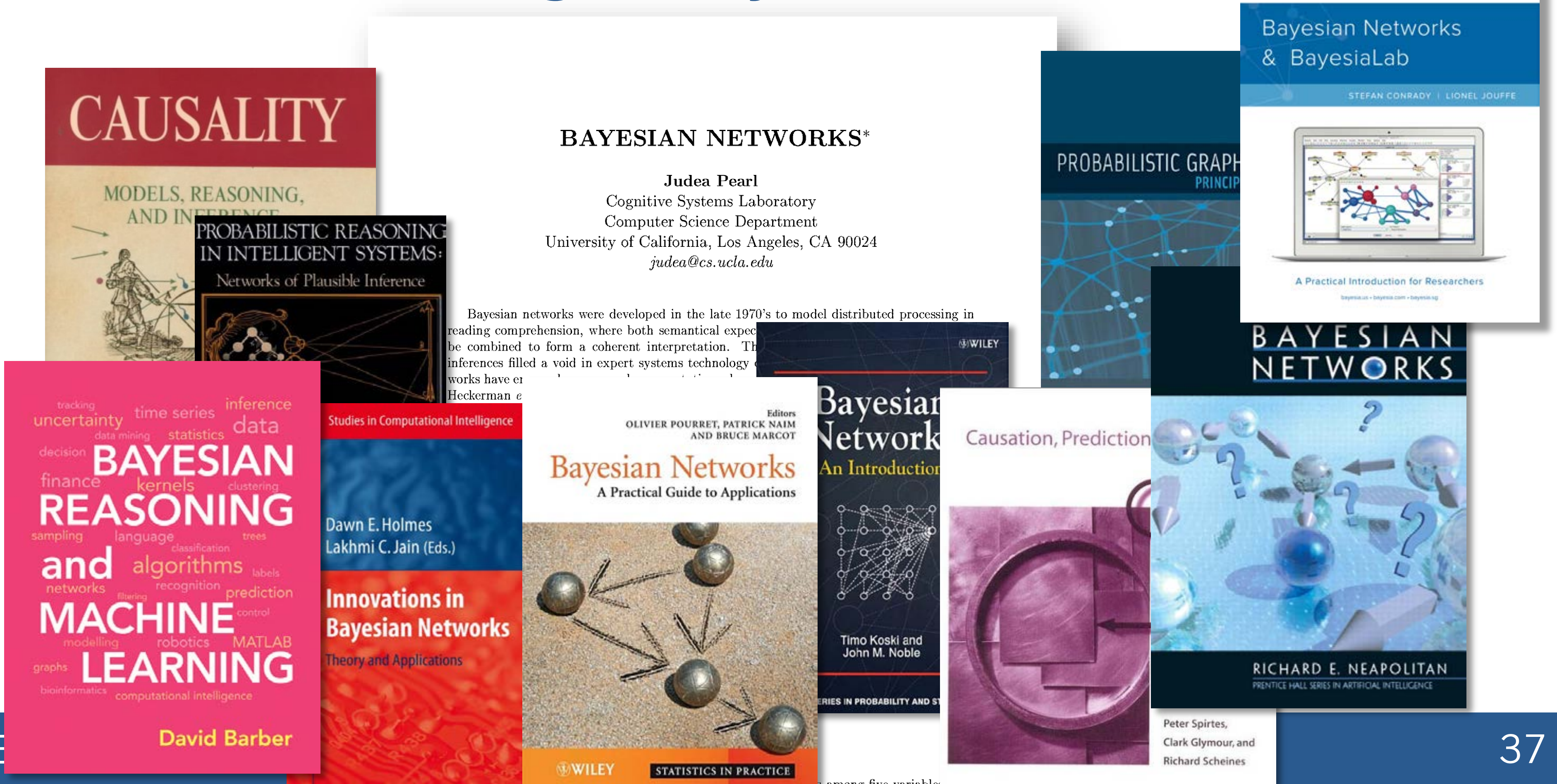


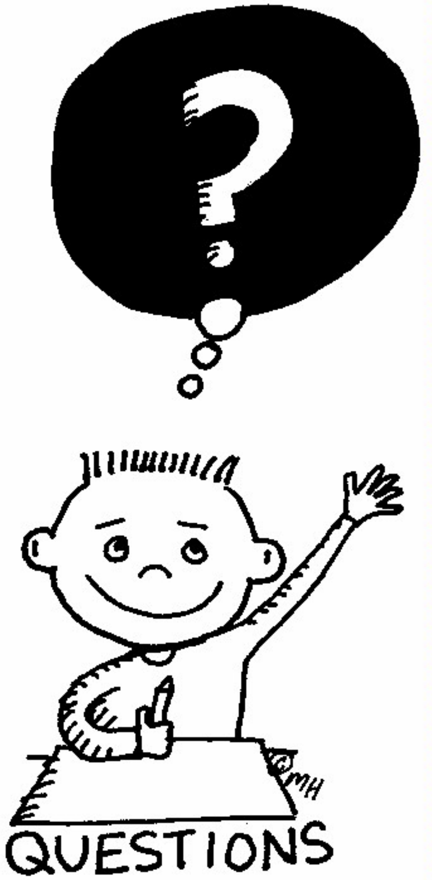
Why does this matter?


Machine Learning
Reasoning:
Why? How? What to do?
Who is responsible?
+Domain Knowledge
Data
Model Source
Theory
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation


Data
Model Source
Theory
Bayesian Networks
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

The New Paradigm: Bayesian Networks

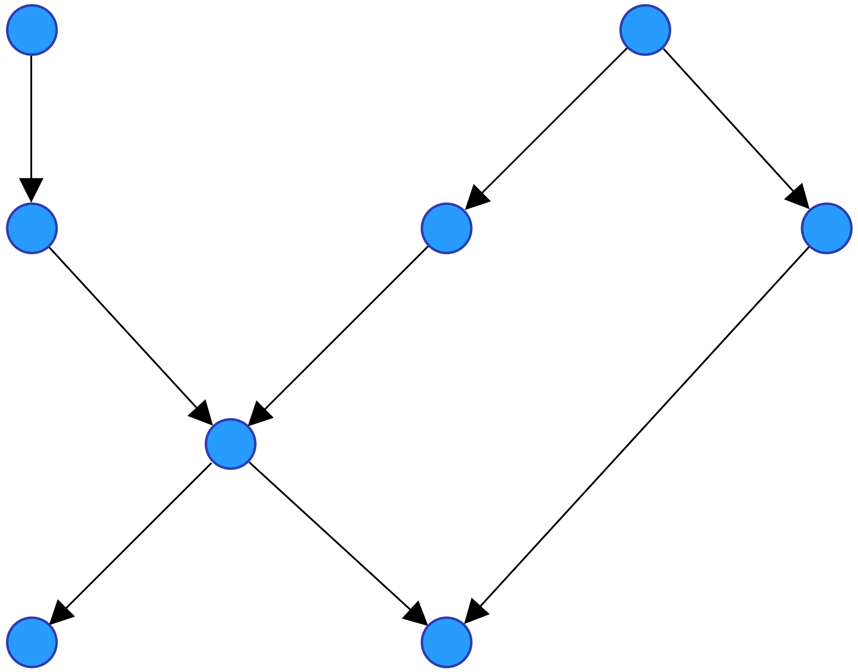



?
©MH
QUESTIONS

Introducing Bayesian Networks

Example: Differential Diagnosis of Diseases

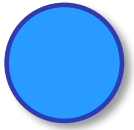
The New Paradigm: Bayesian Networks



- A probabilistic graphical model.
- The graph is the model.
- No formulas, no equations!

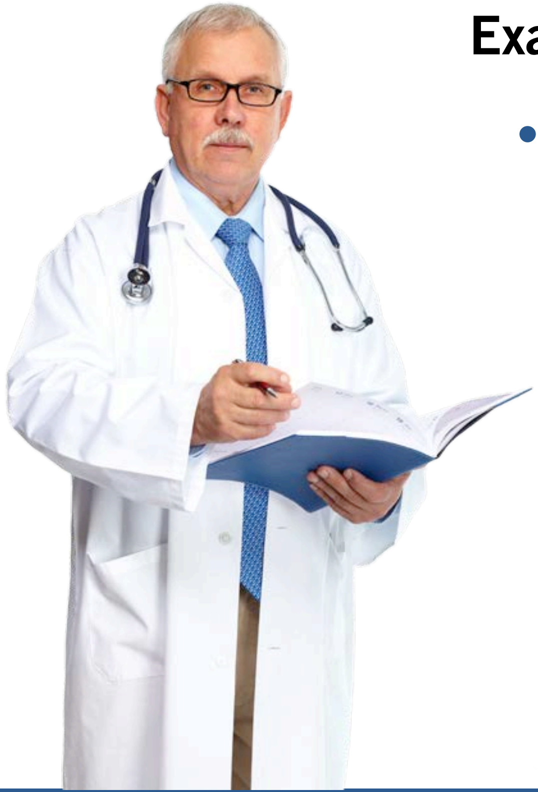
The New Paradigm: Bayesian Networks

Two Components Only:

- Node 

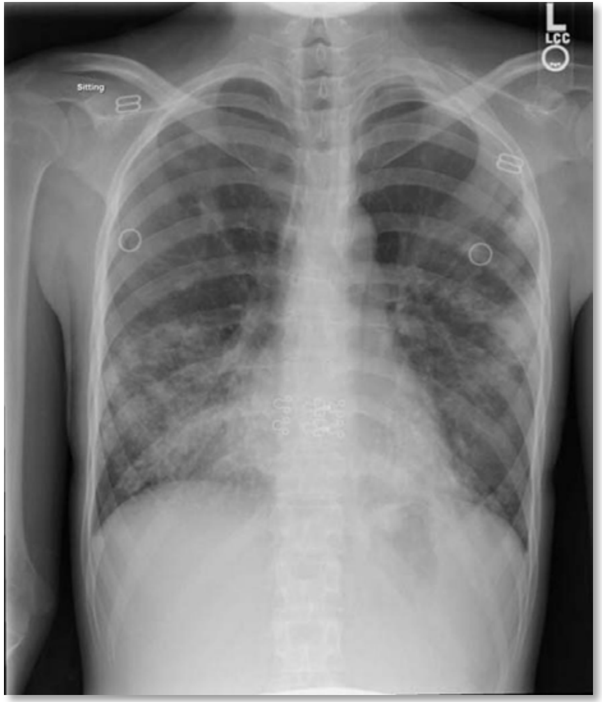
- Arc 

The New Paradigm: Bayesian Networks



Example

- Decision support for the differential diagnosis of lung diseases that have common symptoms:
    - Bronchitis
    - Pneumonia
    - Tuberculosis
    - Lung Cancer



Case courtesy of Radswiki, Radiopaedia.org, rID: 12040

All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks

This is an inference task!

- P(Bronchitis | Symptom_1,…, Symptom_n, Risk Factor_1,…, Risk Factor_n)=?
- P(Pneumonia | Symptom_1,…, Symptom_n, Risk Factor_1,…, Risk Factor_n)=?

Probability of

- s | Symptom_1,…, Symptom_n, Risk Factor_1,…, Risk Factor_n)=?
- P(Lung Cancer | Symptom_1,…, Symptom_n, Risk Factor_1,…, Risk Factor_n)=?

given


MUTE
PFL
POST
PRE

The New Paradigm: Bayesian Networks

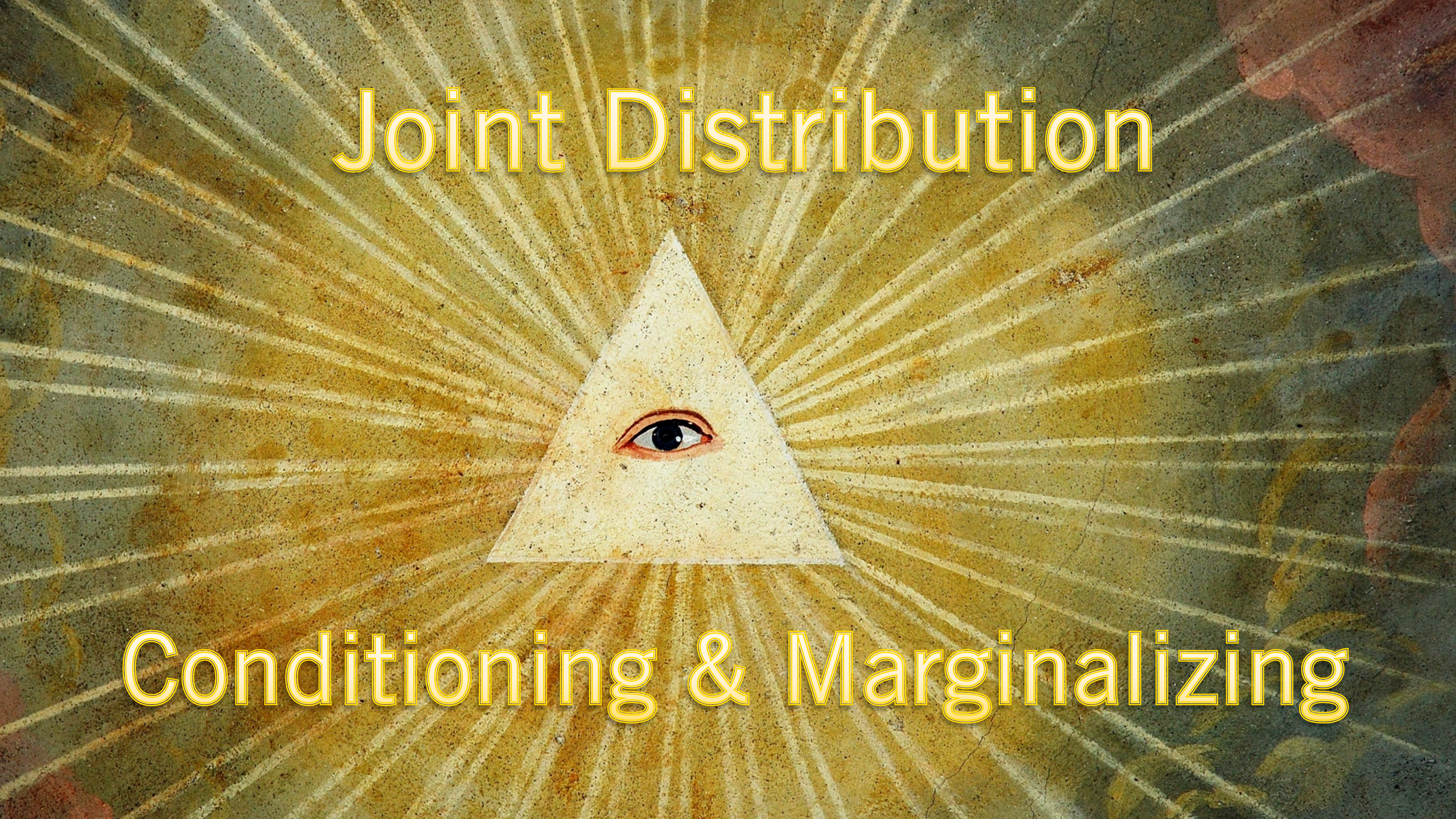
How would such a "inference engine" work?

How do we "perform inference" in this problem domain?

We…

- marginalize
- condition

on the basis of the joint probability distribution of all risk factors, conditions, symptoms, etc.


Joint Distribution
Conditioning & Marginalizing

The New Paradigm: Bayesian Networks

Joint Probability Table for Two Variables: $\mathrm{P(Fever,\ Pneumonia)}$

Fever	Pneumonia	Joint Probability
None	FALSE	77.5%
None	TRUE	0.9%
Low	FALSE	15.5%
Low	TRUE	0.1%
High	FALSE	4.9%
High	TRUE	1.1%
		100.0%

6 rows

Describes the co-occurrence of conditions $\mathrm{P(Fever\ and\ Pneumonia)}$

All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks

Marginalizing over Fever

Fever	Pneumonia	Joint Probability
~~None~~	FALSE	77.5%
~~None~~	TRUE	0.9%
~~Low~~	FALSE	15.5%
~~Low~~	TRUE	0.1%
~~High~~	FALSE	4.9%
~~High~~	TRUE	1.1%

Pneumonia	Probability (Pneumonia)
FALSE	97.9%
TRUE	2.1%

Marginalizing over or “discarding” Fever

Marginal distribution of Pneumonia

All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks

Conditioning on Fever=High

Fever	Pneumonia	Joint Probability
~~None~~	~~FALSE~~	~~77.5%~~
~~None~~	~~TRUE~~	~~0.9%~~
~~Low~~	~~FALSE~~	~~15.5%~~
~~Low~~	~~TRUE~~	~~0.1%~~
High	FALSE	4.9%
High	TRUE	1.1%

Pneumonia	Joint Probability	P(Pneumonia|Fever=High)
FALSE	4.9%	82.4%
TRUE	1.1%	17.6%
	6.0%	

Conditioning on Fever=High

Probability of Pneumonia given Fever=High

All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks

Joint Probability: $\mathrm{P}(\text{Fever, Pneumonia, Tuberculosis, Age, High-Risk})$

Variables:	**Possible States:**
Age	3
High-Risk Area (for Tuberculosis)	2
Pneumonia	2
Tuberculosis	2
Fever	3

This would require a table with 72 rows

General Multiplication Rule

Product Rule:

$$P(A,B) = P(A|B) \times P(B)$$

$$P(B,A) = P(B|A) \times P(A)$$

We can extend this for three variables:

$$P(A,B,C) = P(A|B,C) \times P(B,C) = P(A|B,C) \times P(B|C) \times P(C)$$

and in general to n variables, which gives us the Chain Rule:

$$P(A_1, A_2, \ldots, A_n) = P(A_1|A_2, \ldots, A_n) \times P(A_2|A_3, \ldots, A_n) \times P(A_{n-1}|A_n) \times P(A_n)$$

The New Paradigm: Bayesian Networks

Joint Probability:

P(Fever, Pneumonia, Tuberculosis, Age, High-Risk)

Applying the Chain Rule:

P(Fever, Pneumonia, Tuberculosis, Age, High-Risk)=

P(Fever|Pneumonia, Tuberculosis, Age, High-Risk)P(Pneumonia, Tuberculosis, Age, High-Risk)=

P(Fever|Pneumonia, Tuberculosis, Age, High-Risk)P(Pneumonia|Tuberculosis, Age, High-Risk)P(Tuberculosis, Age, High-Risk)=

P(Fever|Pneumonia, Tuberculosis, Age, High-Risk)P(Pneumonia|Tuberculosis, Age, High-Risk)P(Tuberculosis|Age, High-Risk)P(Age, High-Risk)=

P(Fever|Pneumonia, Tuberculosis, Age, High-Risk)P(Pneumonia|Tuberculosis, Age, High-Risk)P(Tuberculosis|Age, High-Risk)P(Age|High-Risk)P(High-Risk)

The New Paradigm: Bayesian Networks

Joint Probability:

Probability Calculus

Domain Knowledge

$$P(\text{Fever}, \text{Pneumonia}, \text{Tuberculosis}, \text{Age}, \text{High-Risk}) =$$

$$P(\text{Fever}|\text{Pneumonia}, \text{Tuberculosis}, \text{Age}, \text{High-Risk})P(\text{Pneumonia}|\text{Tuberculosis}, \text{Age}, \text{High-Risk})P(\text{Tuberculosis}|\text{Age}, \text{High-Risk})P(\text{Age}|\text{High-Risk})P(\text{High-Risk}) =$$

$$P(\text{Fever}|\text{Pneumonia}, \text{Tuberculosis}, \cancel{\text{Age}, \text{High-Risk}})P(\text{Pneumonia}|\cancel{\text{Tuberculosis}}, \text{Age}, \cancel{\text{High-Risk}})P(\text{Tuberculosis}|\text{Age}, \text{High-Risk})P(\text{Age}\cancel{|\text{High-Risk}})P(\text{High-Risk})$$

Domain knowledge: encoding of independence assumptions

The New Paradigm: Bayesian Networks

Joint Probability:

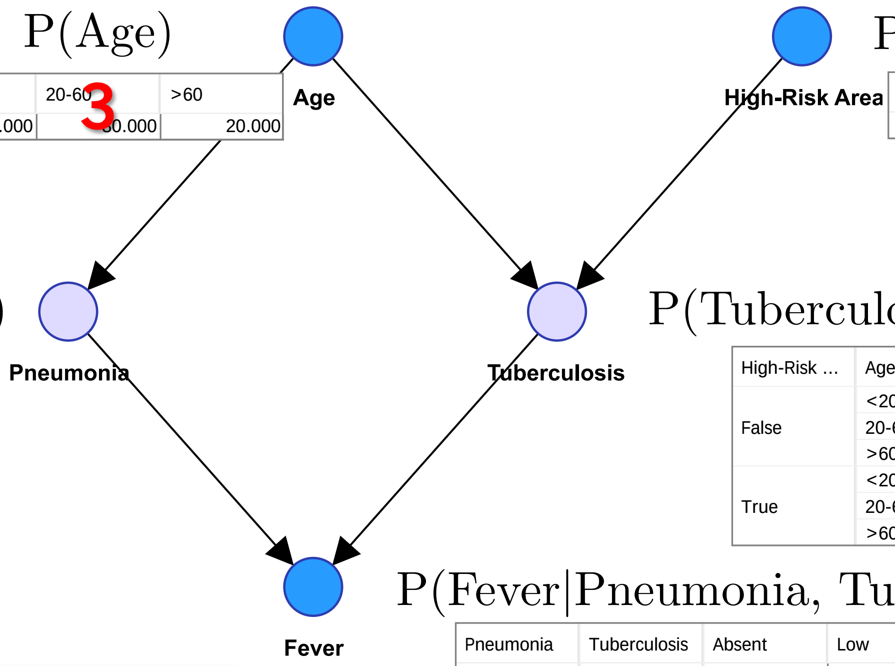
P(Fever, Pneumonia, Tuberculosis, Age, High-Risk)=

P(Fever|Pneumonia, Tuberculosis, ~~Age, High-Risk~~)P(Pneumonia|~~Tuberculosis~~, Age, ~~High-Risk~~)P(Tuberculosis|Age, High-Risk)P(Age~~|High-Risk~~)P(High-Risk)

$$\prod \left.\begin{array}{l} \mathrm{P(Fever|Pneumonia,\ Tuberculosis)} \\ \mathrm{P(Pneumonia|Age)} \\ \mathrm{P(Tuberculosis|Age,\ High\text{-}Risk)} \\ \mathrm{P(Age)} \\ \mathrm{P(High\text{-}Risk)} \end{array}\right\} \text{How can we interpret this?}$$

The New Paradigm: Bayesian Networks

Representing the Joint Probability as a Bayesian Network



$P(\text{Age})$ **3**

<20	20-60	>60
50.000	30.000	20.000

$P(\text{High-Risk})$ **2**

False	True
50.000	50.000

$P(\text{Pneumonia} \mid \text{Age})$ **6**

Age	False	True
<20	99.000	1.000
20-60	98.000	2.000
>60	95.000	5.000

$P(\text{Tuberculosis} \mid \text{Age, High-Risk})$ **8**

High-Risk ...	Age	False	True
False	<20	99.000	1.000
	20-60	99.500	0.500
	>60	99.500	0.500
True	<20	95.000	5.000
	20-60	97.500	2.500
	>60	97.500	2.500

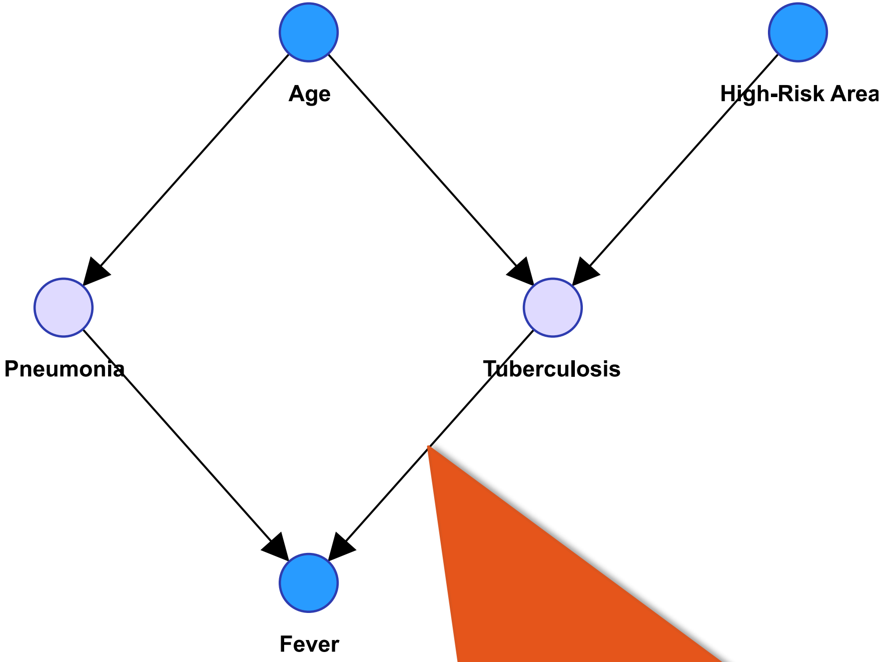
$P(\text{Fever} \mid \text{Pneumonia, Tuberculosis})$ **12**

Pneumonia	Tuberculosis	Absent	Low	High
False	False	80.000	15.000	5.000
	True	45.000	50.000	5.000
True	False	45.000	5.000	50.000
	True	0.000	50.000	50.000

3+2+6+12+8=31 vs. 72

The New Paradigm: Bayesian Networks

Representing the Joint Probability as a Bayesian Network



- The global semantics of Bayesian networks specifies that the full joint distribution is given by the product:

$$P(x_i, \ldots, x_n) = \prod_i P(x_i \mid pa_i)$$

Parent Nodes

- Thus, a Bayesian network is a compact representation of the JPD.

We can marginalize and condition on the basis of the network.

The New Paradigm: Bayesian Networks

Factorization

- The only way to deal with large distributions is to constrain the nature of the variable interactions in some manner, both to render specification and ultimately inference in such systems tractable.
- The key idea is to specify which variables are independent of others, leading to a structured factorization of the joint probability distribution.
- Bayesian networks are a way to depict the independence assumptions made in a distribution.

$$P(x_i, \ldots, x_n) = \prod_i P(x_i \mid pa_i)$$

Is this worth the effort?

The New Paradigm: Bayesian Networks

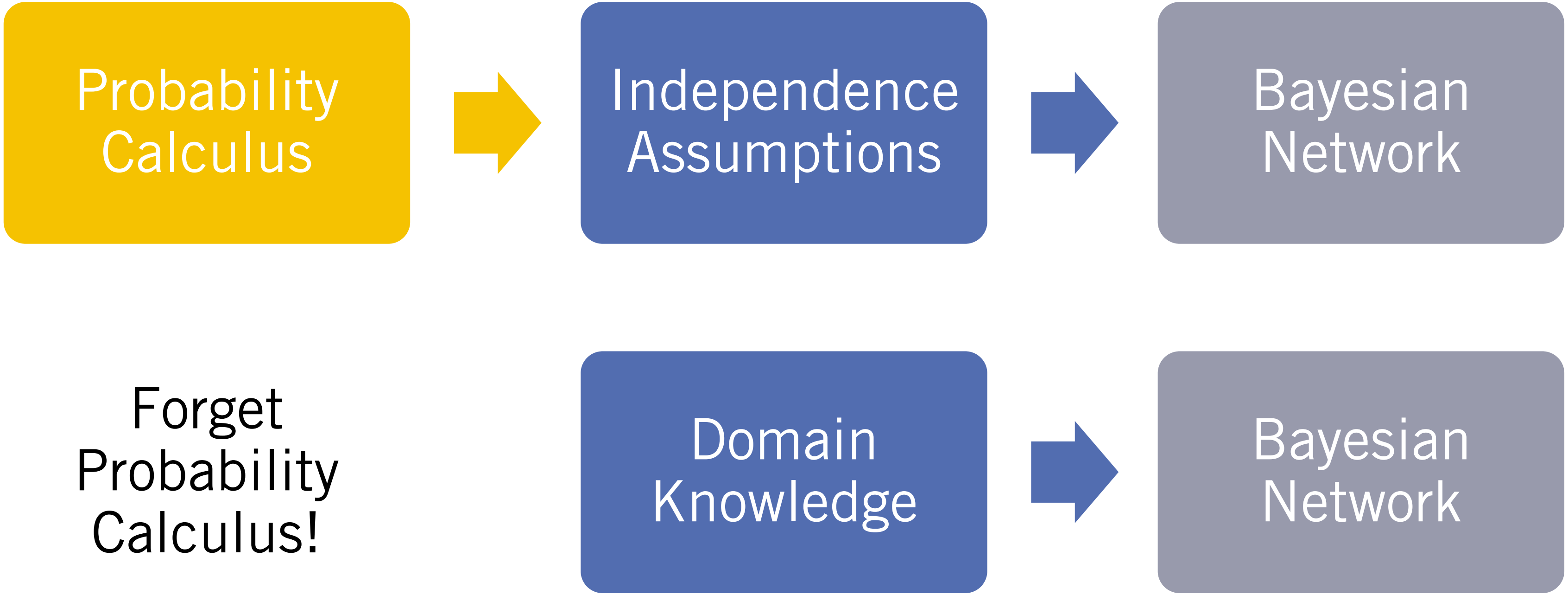
Joint Probability:

$$\mathrm{P}(\text{Season, Smoker, Age, High-Risk, Bronchitis, Lung Cancer, Pneumonia, Tuberculosis, Airway Obstruction/Constriction, Lung Lesions, Dyspnea, Fever, X-Ray Abnormalities})$$

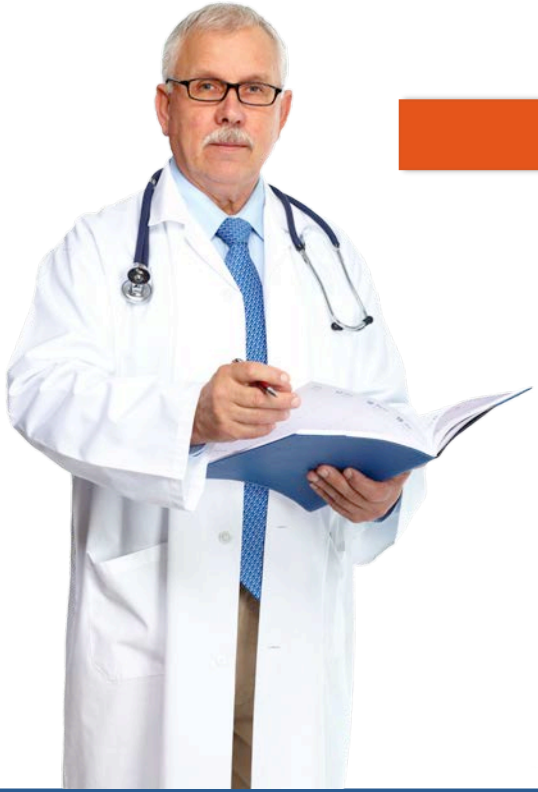
$$4 \times 2 \times 3 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 3 \times 2$$

- This would require a Joint Probability Table with **36,684** rows, i.e. we would need to specify **36,684** probabilities.
- Instead, we can represent the same Joint Probability Distribution using a Bayesian network and specify only **63** probabilities.

The New Paradigm: Bayesian Networks

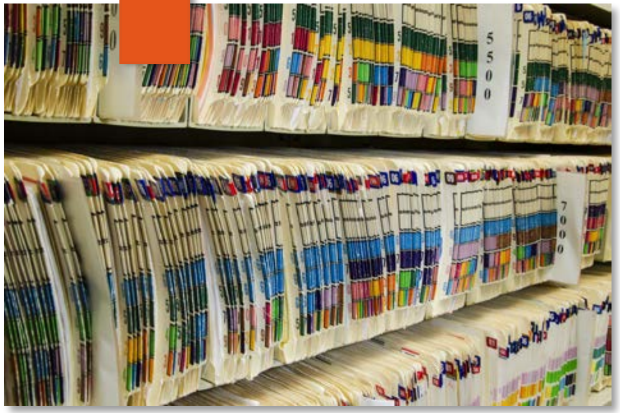


The New Paradigm: Bayesian Networks



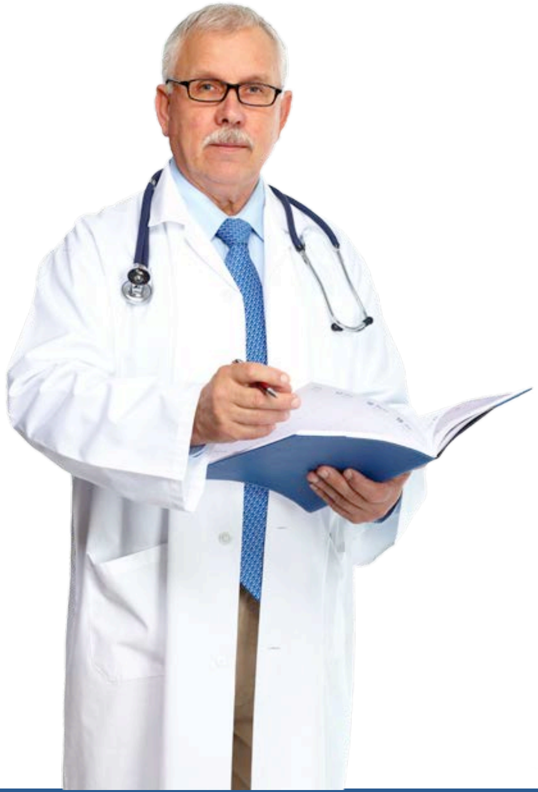
Node:
Variable of Interest

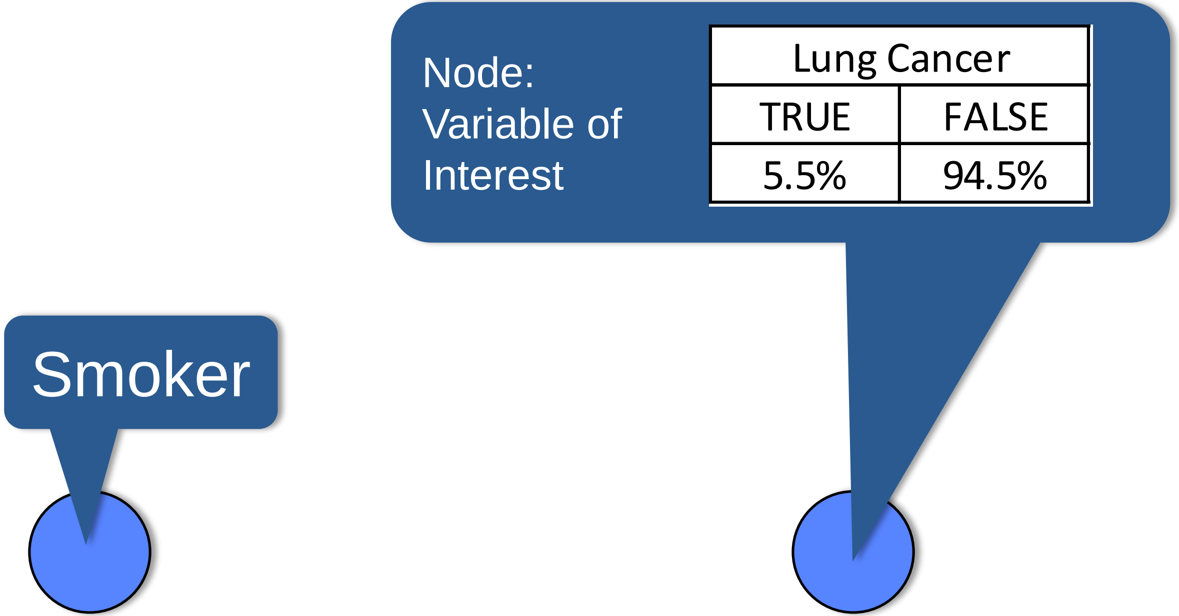
Smoker	
TRUE	FALSE
50%	50%



All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks





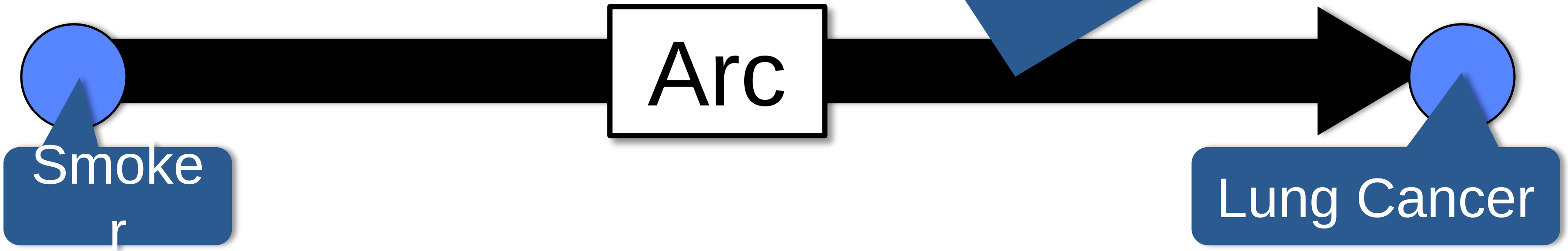
Lung Cancer	
TRUE	FALSE
5.5%	94.5%

All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks

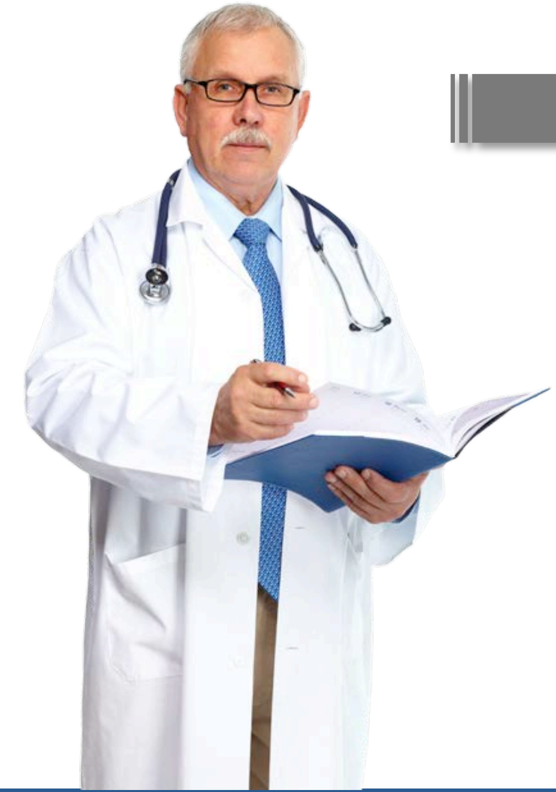
Discrete & Nonparametric
Probabilistic Relationship
P(Lung Cancer|Smoker)

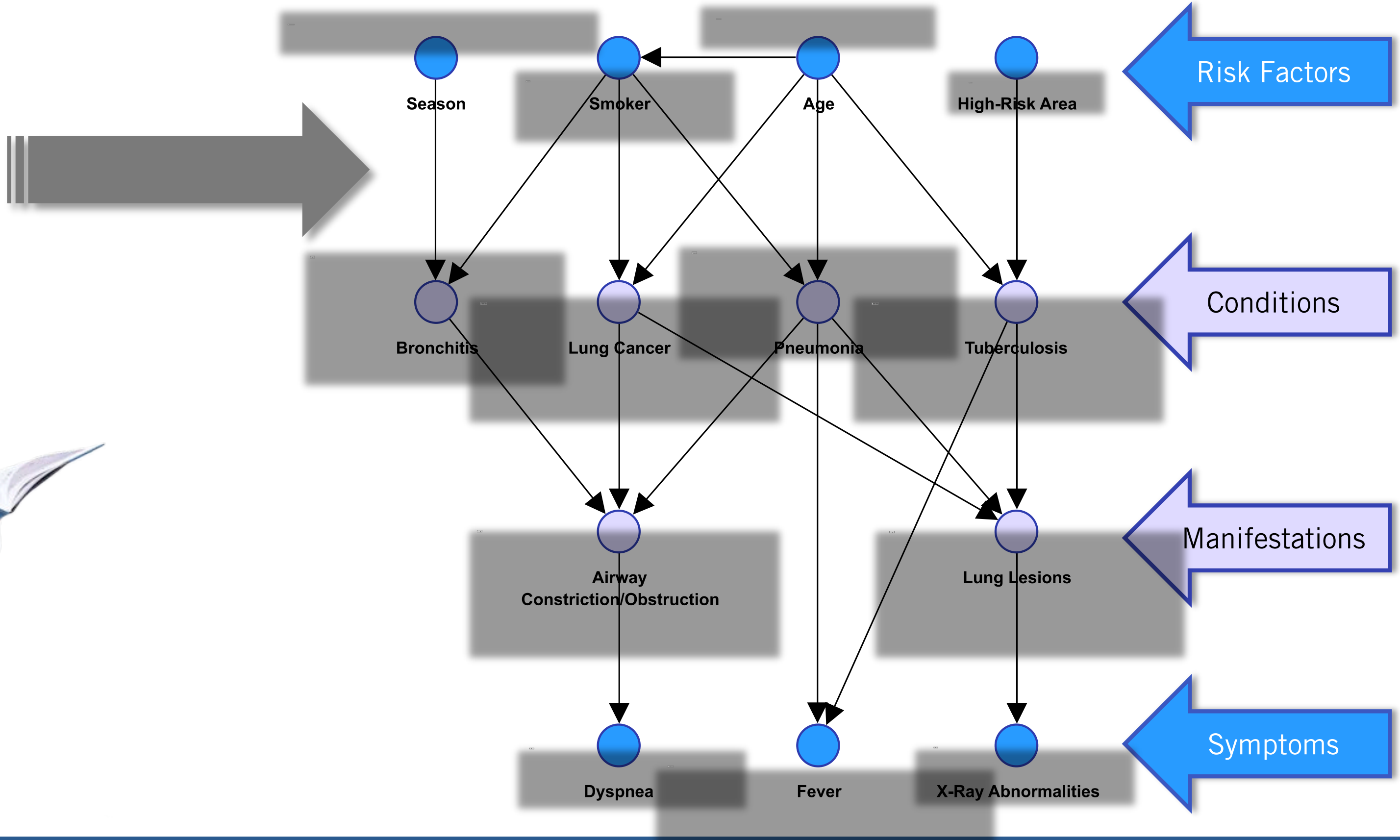
	Lung Cancer	
Smoker	FALSE	TRUE
FALSE	99%	1%
TRUE	90%	10%



All numerical values provided in this example are fictional.

The New Paradigm: Bayesian Networks





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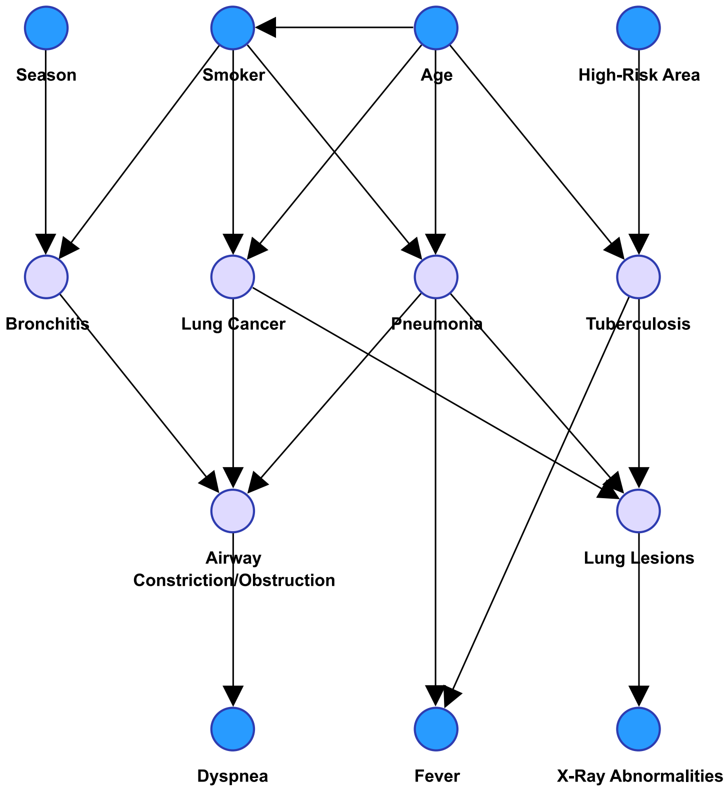
The New Paradigm: Bayesian Networks



Key Properties

- Compact representation of the **Joint Probability Distribution**
- No distinction between dependent and independent variables
- Bayesian Inference
- Omni-directional Inference
- Nonparametric
- Nonlinear
- Probabilistic
- Causal

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

- Representation (or approximation) of the joint probability distribution of all variables.
- No distinction between dependent and independent variables.
- Numerical and categorical variables are treated identically.
- Nonparametric.

Compare to algebraic formula:
Representation of **one** variable of the joint probability distribution, i.e. y=f(x)

Dependent

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

Independen
t

Independen
t

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

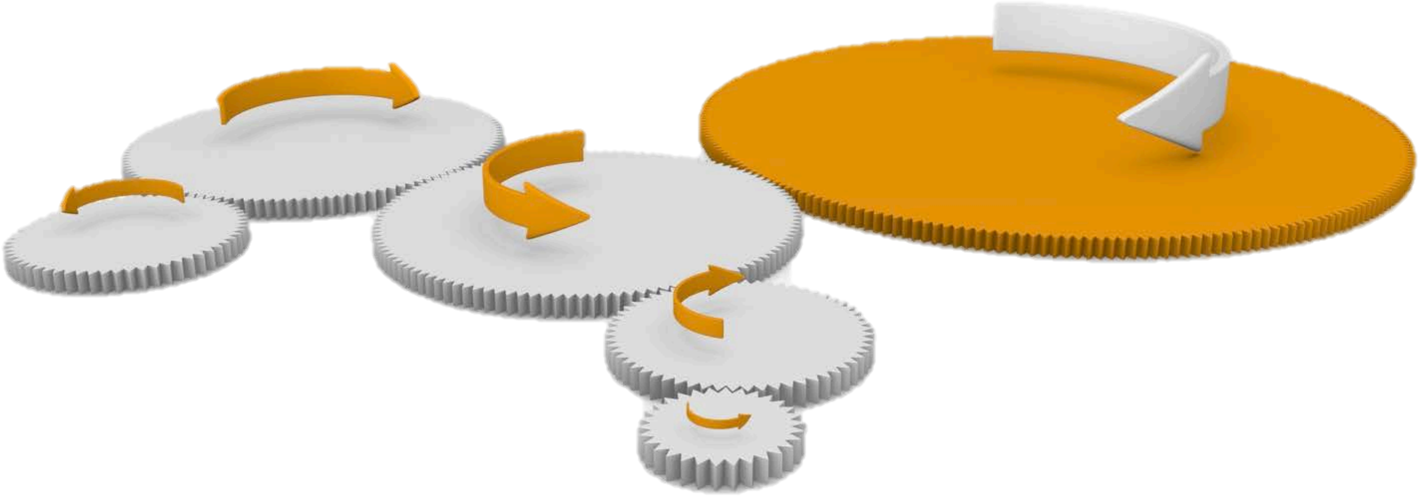
- Omni-directional Inference, i.e. evaluation is always performed in all directions.

Compare to “uni-directional” algebraic formula and human intuition

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

The New Paradigm: Bayesian Networks

Omni-Directional Inference



Rev. Thomas Bayes

Bayes' Theorem for Conditional Probabilities

H: *Hypothesis*

E: *Evidence*

$$P(H \mid E) = \frac{P(E \mid H)\,P(H)}{P(E)}$$

"Probability of H given E"

T. Bayes.

1763
PHILOSOPHICAL TRANSACTIONS

[370]

quodque ſolum, certa nitri ſigna præbere, ſed plura concurrere debere, ut de vero nitro producto dubium non relinquatur.

LII. *An Eſſay towards ſolving a Problem in the Doctrine of Chances. By the late Rev. Mr.* Bayes, *F. R. S. communicated by Mr.* Price, *in a Letter to* John Canton, *A. M. F. R. S.*

Dear Sir,

Read Dec. 23, 1763. I Now ſend you an eſſay which I have found among the papers of our deceaſed friend Mr. Bayes, and which, in my opinion, has great merit, and well deſerves to be preſerved. Experimental philoſophy, you will find, is nearly intereſted in the ſubject of it; and on this account there ſeems to be particular reaſon for thinking that a communication of it to the Royal Society cannot be improper.

He had, you know, the honour of being a member of that illuſtrious Society, and was much eſteemed by many in it as a very able mathematician. In an introduction which he has writ to this Eſſay, he ſays, that his deſign at firſt in thinking on the ſubject of it was, to find out a method by which we might judge concerning the probability that an event has to happen, in given circumſtances, upon ſuppoſition that we know nothing concerning it but that, under the ſame circum-

Bayesian Networks

Key Properties

- Bayesian networks are inherently probabilistic.
- Evidence and inference are represented as distributions.
- Inference can be performed with partial evidence.

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

- Bayesian networks are inherently probabilistic.
- Evidence and inference are represented by distributions.
- Inference can be performed with partial evidence.

Compare to algebra

Deterministic Point Estimate

Single Value Input

Single Value Input

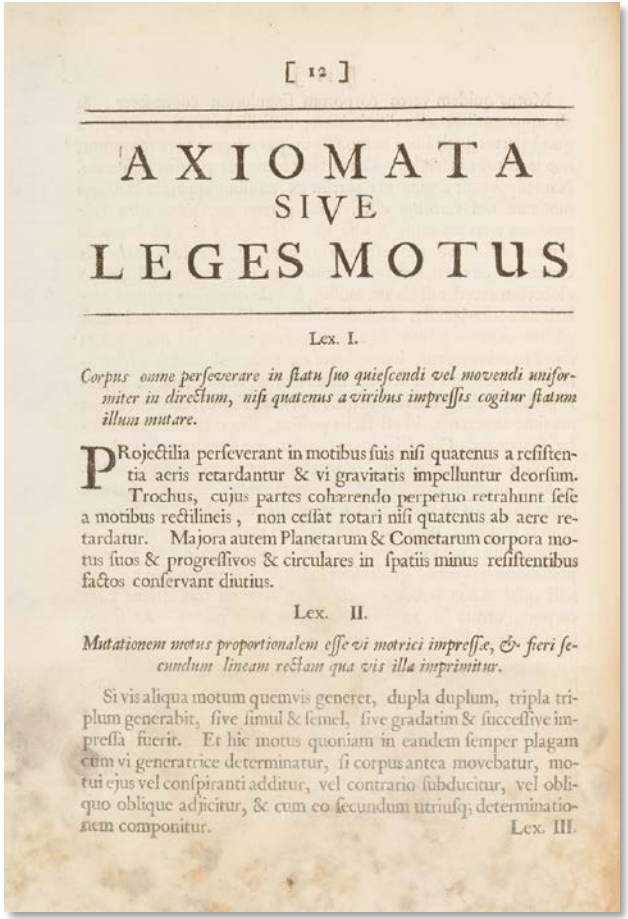
$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

Bayesian Networks

Key Properties of Bayesian Networks

- Bayesian networks can encode causal direction, algebra cannot.
- Example: Newton's Second Law of Motion

$$F = m \cdot a$$


[12]

AXIOMATA
SIVE
LEGES MOTUS

Lex. I.

Corpus omne perſeverare in ſtatu ſuo quieſcendi vel movendi uniformiter in directum, niſi quatenus a viribus impreſſis cogitur ſtatum illum mutare.

Projectilia perſeverant in motibus ſuis niſi quatenus a reſiſtentia aeris retardantur & vi gravitatis impelluntur deorſum. Trochus, cujus partes cohærendo perpetuo retrahunt ſeſe a motibus rectilineis, non ceſſat rotari niſi quatenus ab aere retardatur. Majora autem Planetarum & Cometarum corpora motus ſuos & progreſſivos & circulares in ſpatiis minus reſiſtentibus factos conſervant diutius.

Lex. II.

Mutationem motus proportionalem eſſe vi motrici impreſſæ, & fieri ſecundum lineam rectam qua vis illa imprimitur.

Si vis aliqua motum quemvis generet, dupla duplum, tripla triplum generabit, ſive ſimul & ſemel, ſive gradatim & ſucceſſive impreſſa fuerit. Et hic motus quoniam in eandem ſemper plagam cum vi generatrice determinatur, ſi corpus antea movebatur, motui ejus vel conſpiranti additur, vel contrario ſubducitur, vel oblique adjicitur, & cum eo ſecundum utriuſq; determinationem componitur.

Lex. III.

The New Paradigm: Bayesian Networks

Limitations of Algebra: Newton's Second Law of Motion


[12]

AXIOMATA

LEGES

Lex. I.

Corpus omne perseverare in statu suo quiescendi vel movendi uniformiter in directum, nisi quatenus a viribus impressis cogitur statum illum mutare.

Projectilia perseverant in motibus suis nisi quatenus a resistentia aeris retardantur & vi gravitatis impelluntur deorsum. Trochus, cujus partes cohaerendo perpetuo retrahunt sese a motibus rectilineis, non cessat rotari nisi quatenus ab aere retardatur. Majora autem Planetarum & Cometarum corpora motus suos & progressivos & circulares in spatiis minus resistentibus factos conservant diutius.

Lex. II.

Mutationem motus proportionalem esse vi motrici impressae, & fieri secundum lineam rectam qua vis illa imprimitur.

Si vis aliqua motum quemvis generet, dupla duplum, tripla triplum generabit, sive simul & semel, sive gradatim & successive impressa fuerit. Et hic motus quoniam in eandem semper plagam cum vi generatrice determinatur, si corpus antea movebatur, motui ejus vel conspiranti additur, vel contrario subducitur, vel oblique oblique adjicitur, & cum eo secundum utriusq; determinationem componitur.

Lex. III.

"Mutationem motus"

"vi motrici impressæ"

$$a = \frac{F}{m}$$

solving for *mass*

$$m = \frac{F}{a}$$

Causal Assignment

Causal Interpretation
Not Possible

The New Paradigm: Bayesian Networks

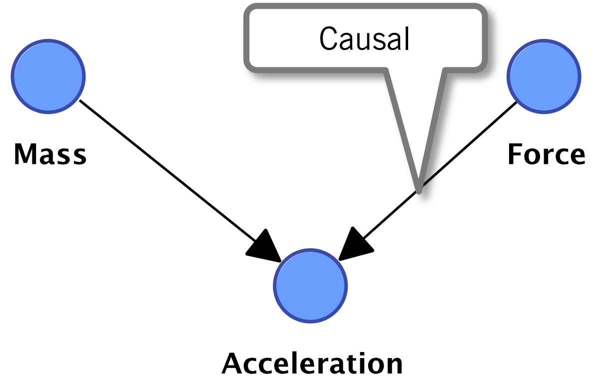
Key Properties of Bayesian Networks

- Bayesian networks can encode causal direction, algebra cannot.

Algebra vs. Bayesian Network

Causal or non-causal?

$$a = \frac{F}{m}$$



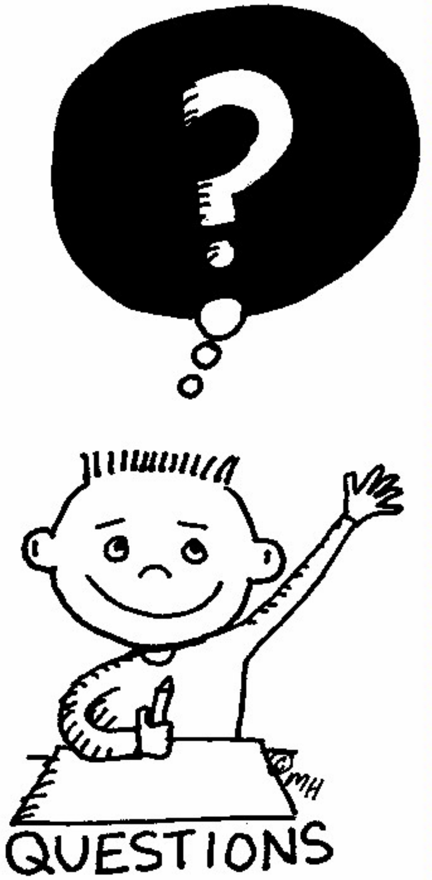
Why is this so important?

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

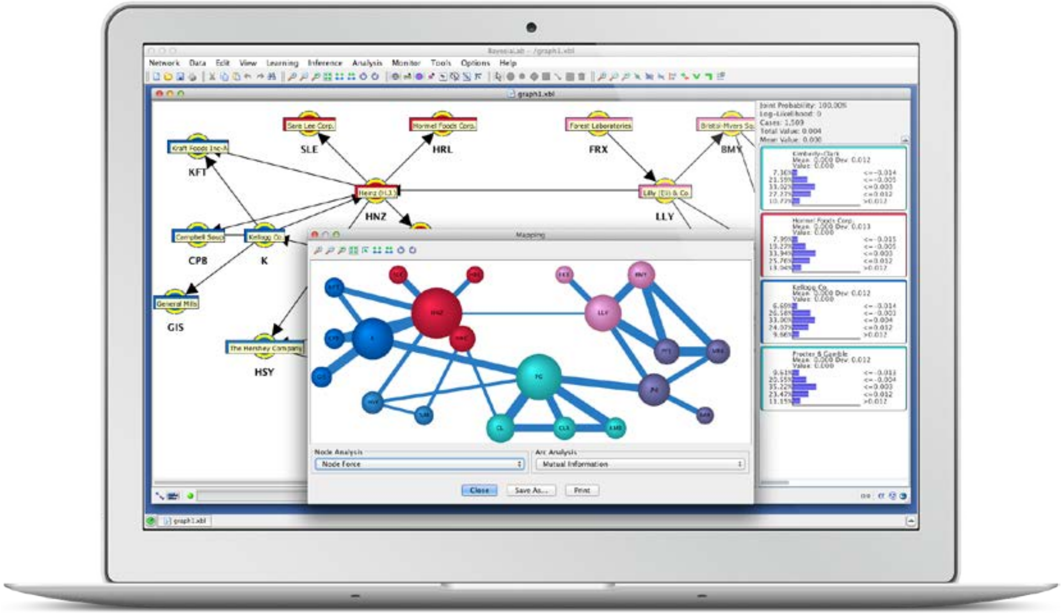
- With a causal Bayesian network we can formally perform causal inference, i.e. we can simulate interventions through the manipulation of a model.
- This is what is required for formal policy analysis.

See Example 4


QUESTIONS

Sounds great, but how can I use a Bayesian network in practice?

BAYESIALAB



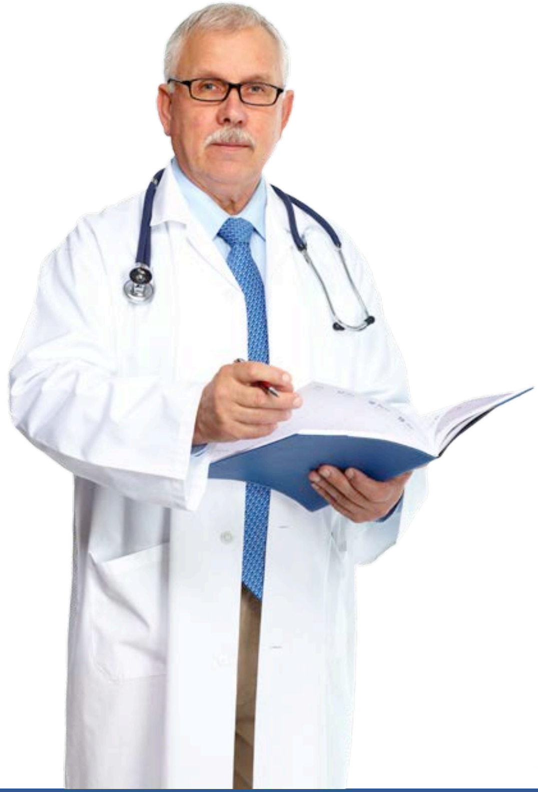
A desktop software for:

- learning
- editing
- performing inference
- analyzing
- simulating
- optimizing

with Bayesian networks.

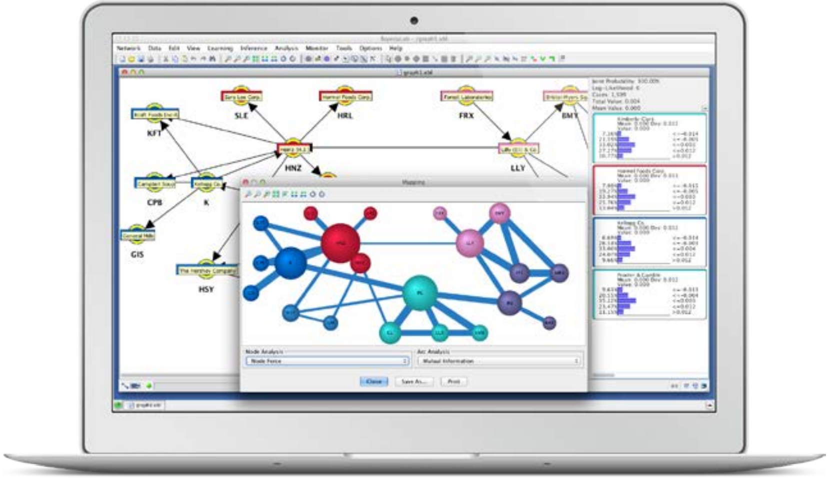
Mathematical Formalism → Research Software

Inference with a Bayesian Network & BayesiaLab

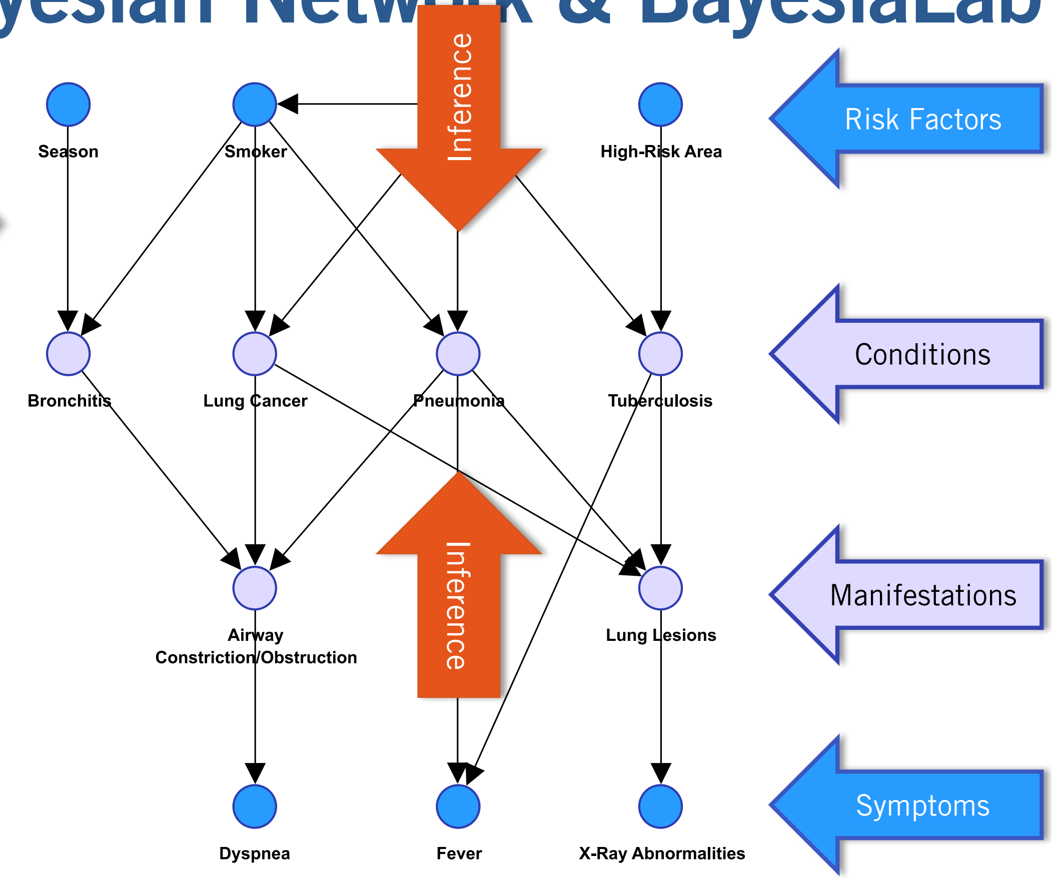


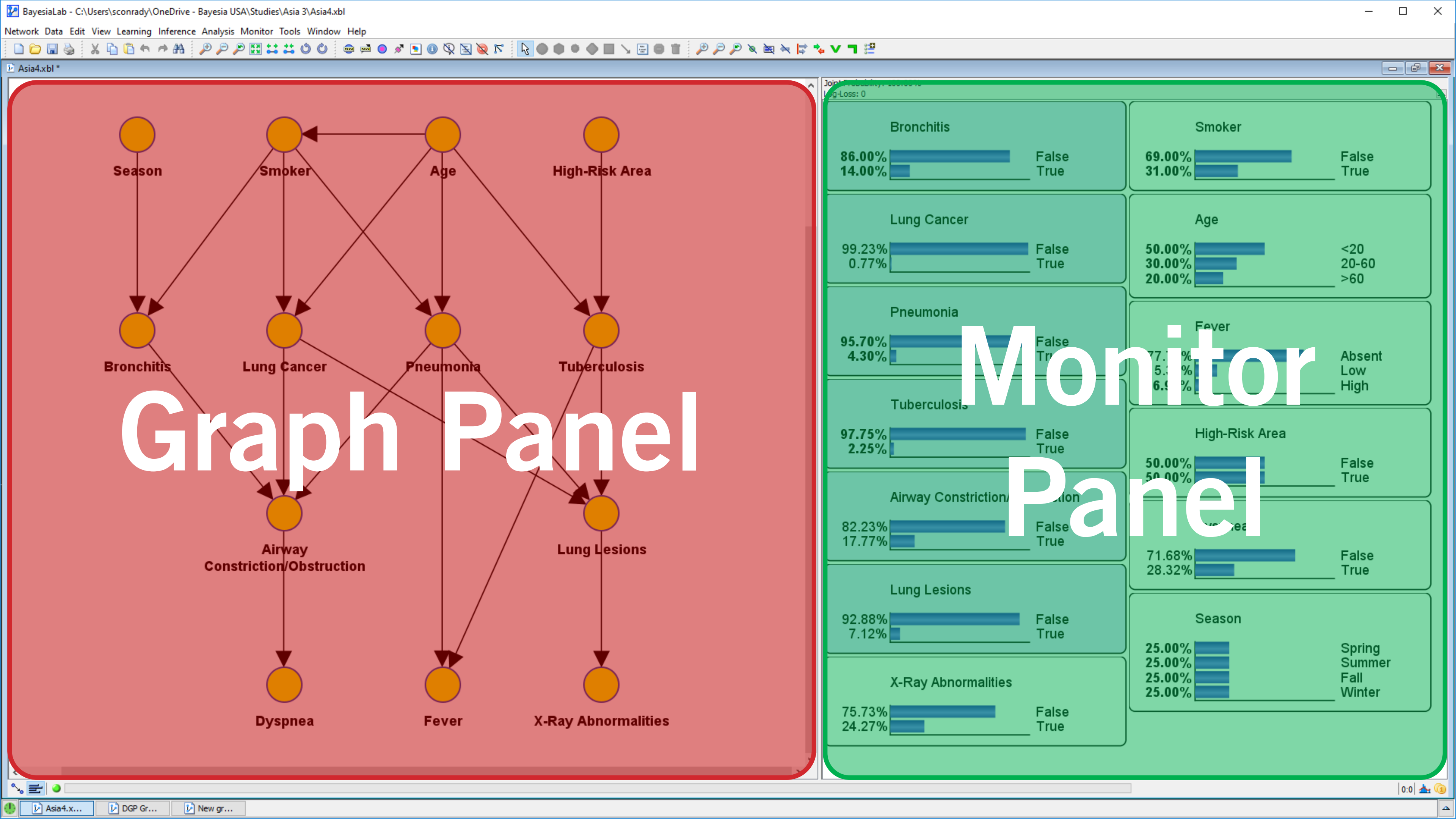
Introductory Example:

Differential Diagnosis



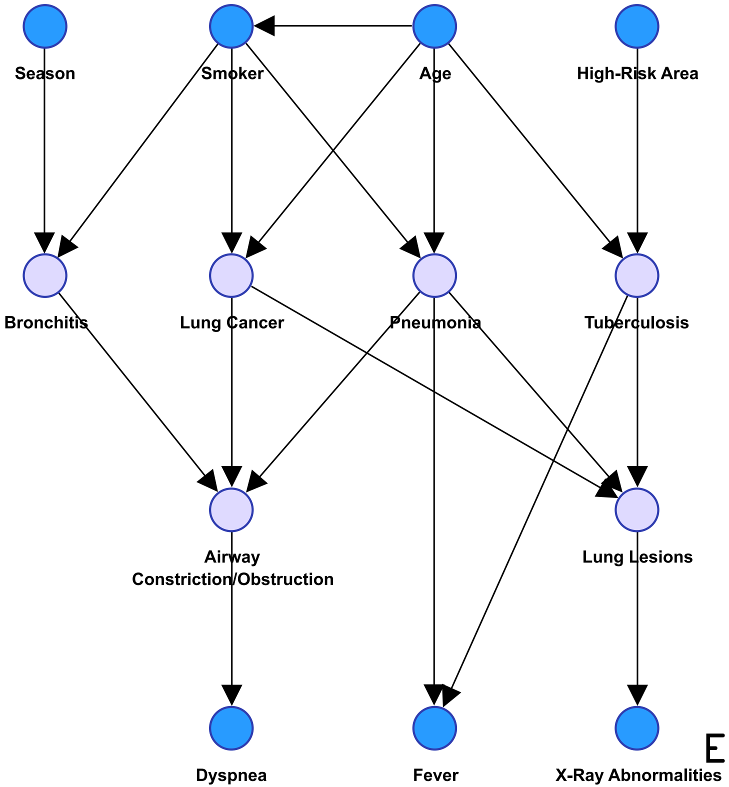
Inference with a Bayesian Network & BayesiaLab





BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Asia 3\Asia4.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Asia4.xbl *
Season
Smoker
Age
High-Risk Area
Bronchitis
Lung Cancer
Pneumonia
Tuberculosis
Airway Constriction/Obstruction
Lung Lesions
Dyspnea
Fever
X-Ray Abnormalities
Graph Panel
Log-Loss: 0
Bronchitis
86.00% False
14.00% True
Smoker
69.00% False
31.00% True
Lung Cancer
99.23% False
0.77% True
Age
50.00% <20
30.00% 20-60
20.00% >60
Pneumonia
95.70% False
4.30% True
Fever
Absent
Low
High
Tuberculosis
97.75% False
2.25% True
High-Risk Area
50.00% False
True
Airway Constriction/Obstruction
82.23% False
17.77% True
71.68% False
28.32% True
Lung Lesions
92.88% False
7.12% True
Season
25.00% Spring
25.00% Summer
25.00% Fall
25.00% Winter
X-Ray Abnormalities
75.73% False
24.27% True
Monitor Panel
Asia4.x...
DGP Gr...
New gr...

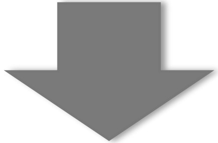
Bayesian Networks = Artificial Intelligence



Knowledge Base

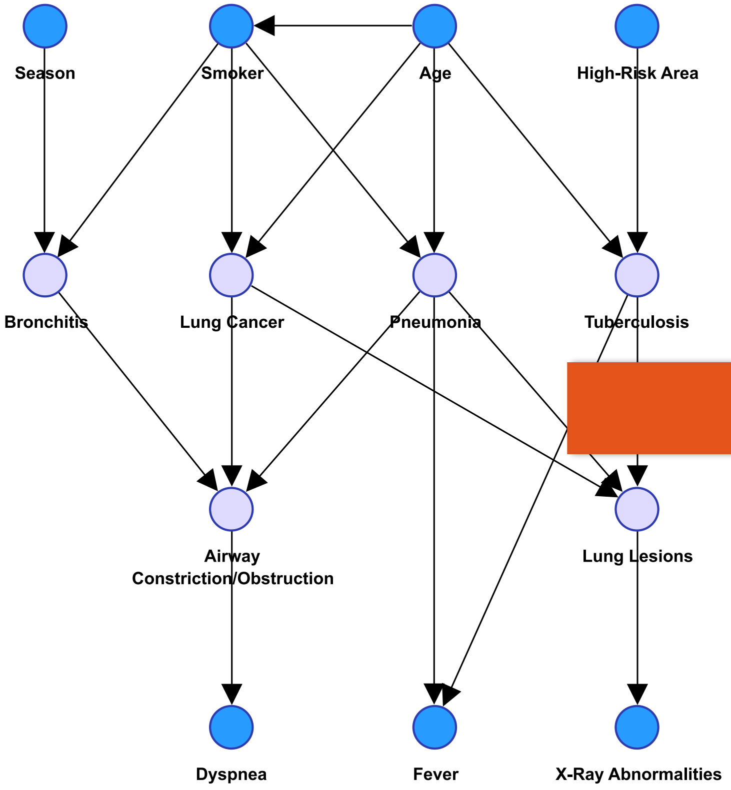
- Declarative/Propositional Knowledge
- Associational Knowledge
- Causal Knowledge

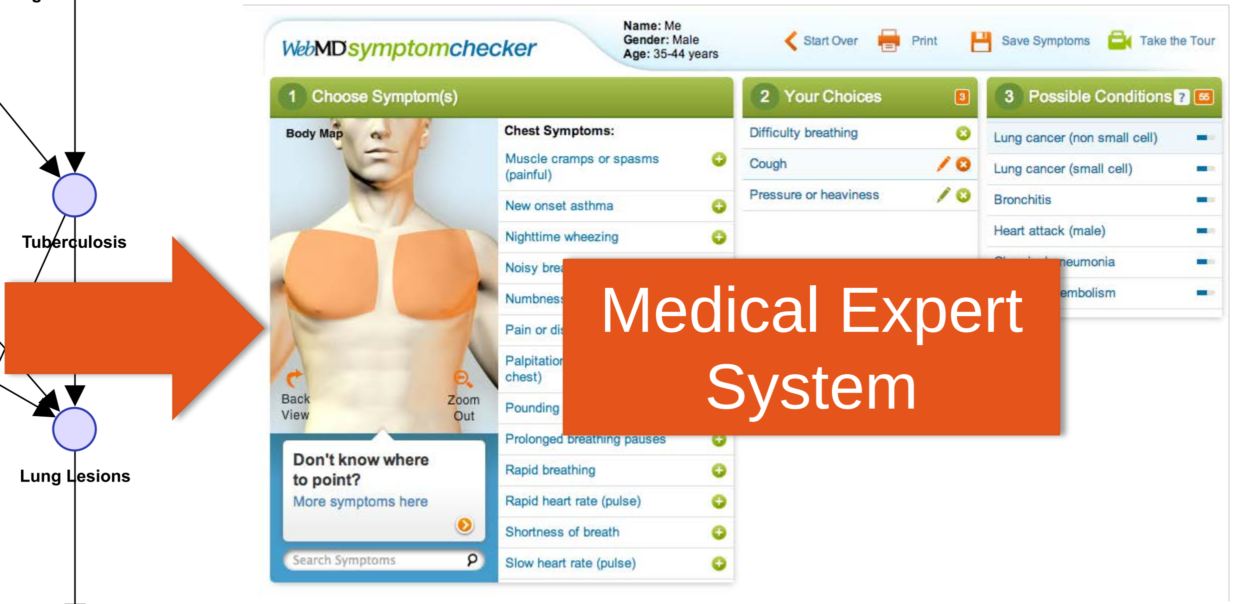
Inference Engine



Expert System ➔ Artificial Intelligence

Bayesian Networks = Expert System



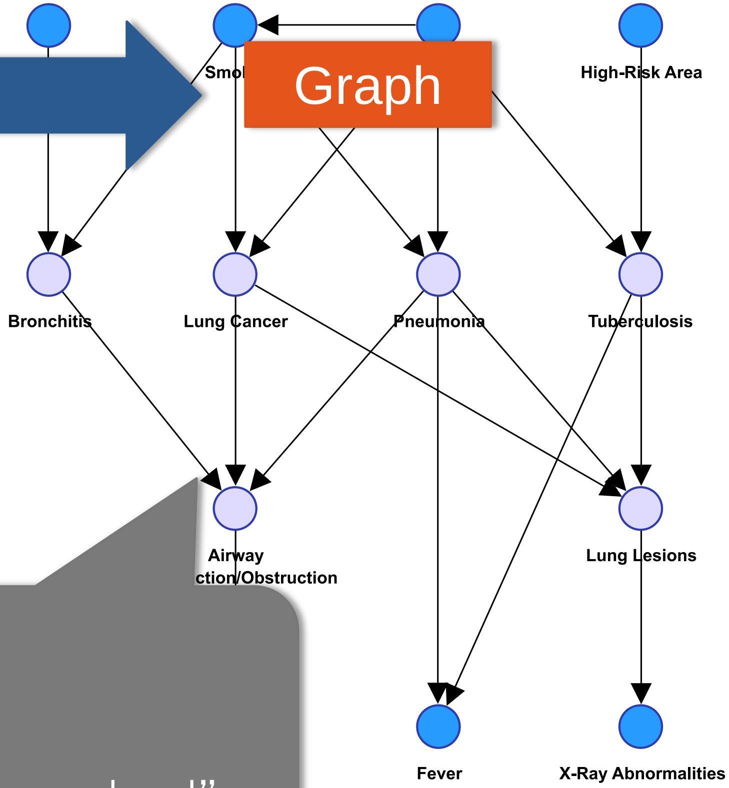


Bayesian Networks = Transparent Expert System

Formula

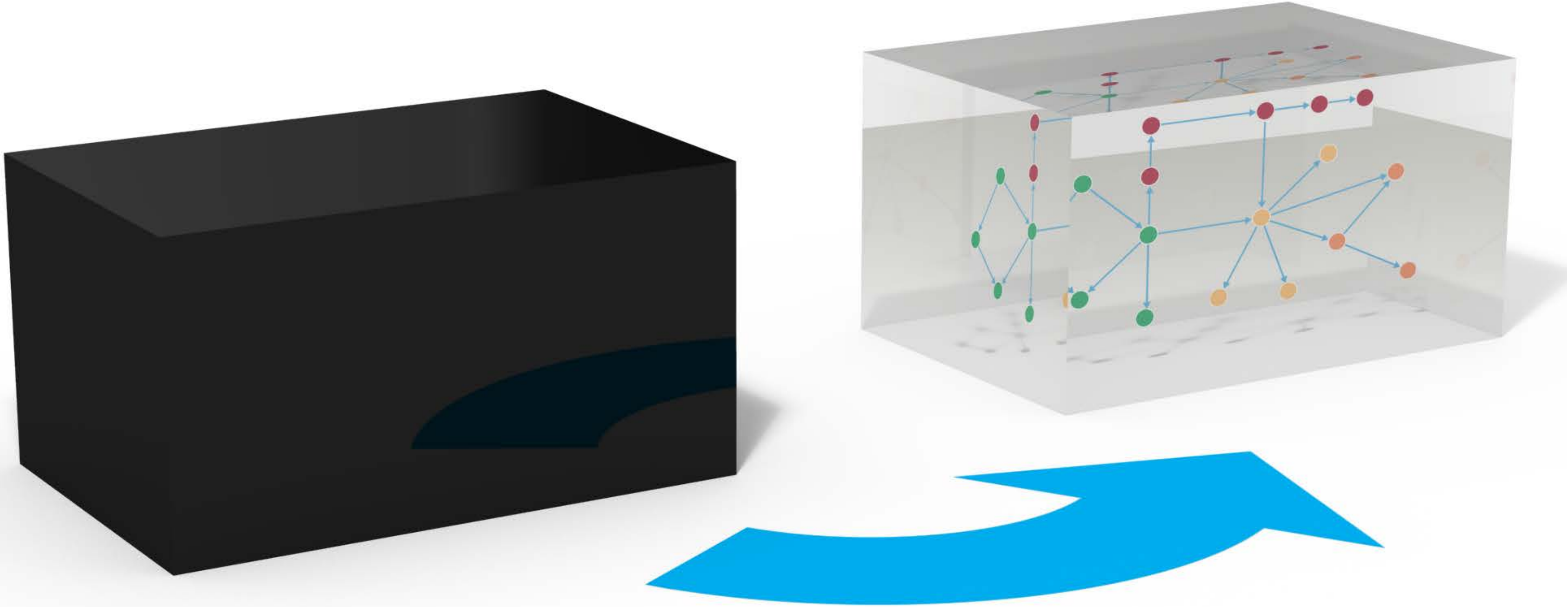
Graph

$$\overbrace{\frac{dI^{MT}_{F3}}{dt}}^{\text{Change in F3 infecteds on treatment}} = \overbrace{\tau^{MT}_{F2} I^{MT}_{F2}}^{\text{Progress from F2 during treatment}} + \overbrace{\eta_{F3} I^{M}_{F3}}^{\text{Commenced treatment (F3)}} - \left(\overbrace{\mu}^{\text{Background death}} + \overbrace{\mu_D}^{\text{Drug-related death}} + \overbrace{\xi}^{\text{Exit rate}} + \overbrace{\lambda_{HIV}}^{\text{Force of HIV infection}} + \overbrace{(1-\gamma^{M}_{F3})\nu^{M}_{F}}^{\text{Cease treatment (F3)}} + \overbrace{\gamma^{M}_{F3}\nu^{M}_{F}}^{\text{Viral clearance on treatment (F3)}} + \overbrace{\tau^{MT}_{F3}}^{\text{Progress to F4 during treatment}} \right) I^{MT}_{F3}$$

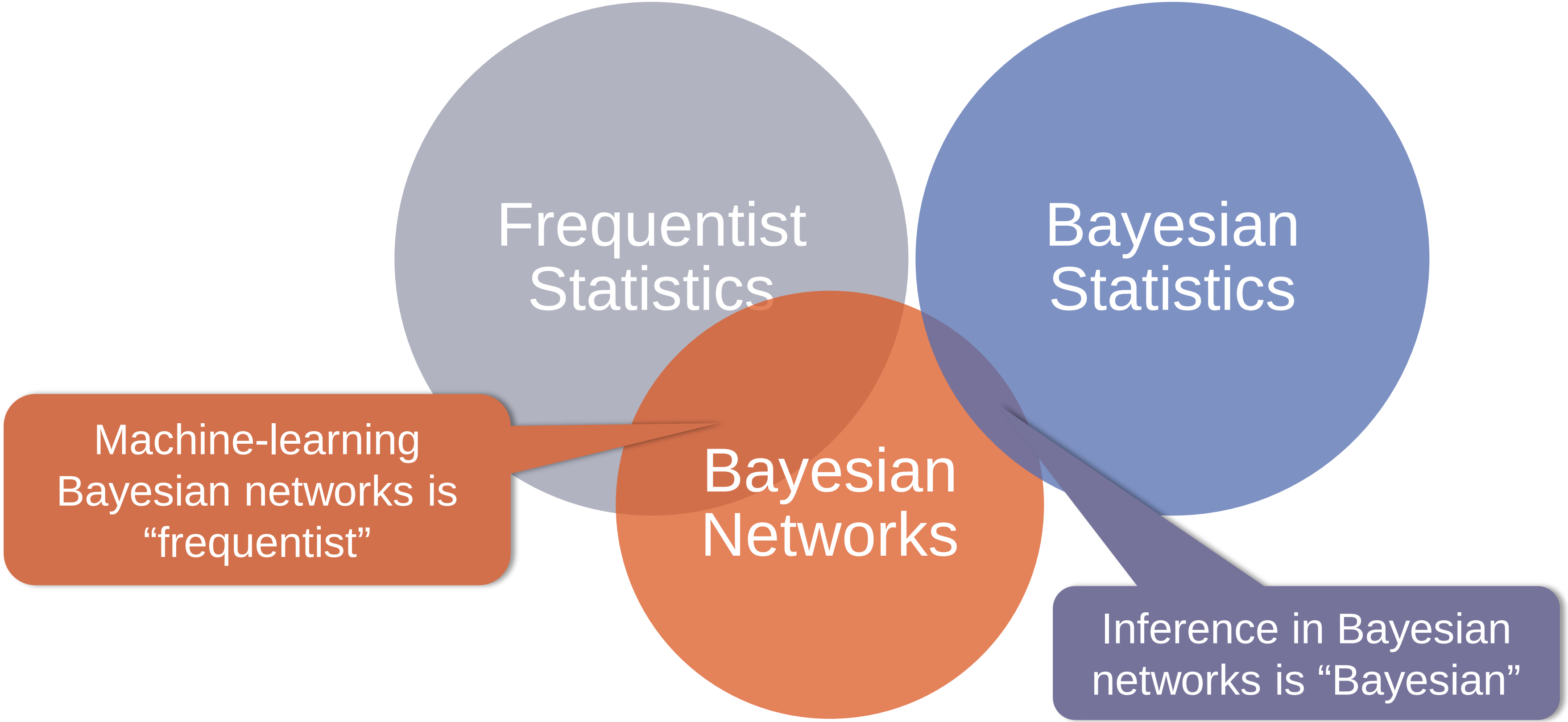


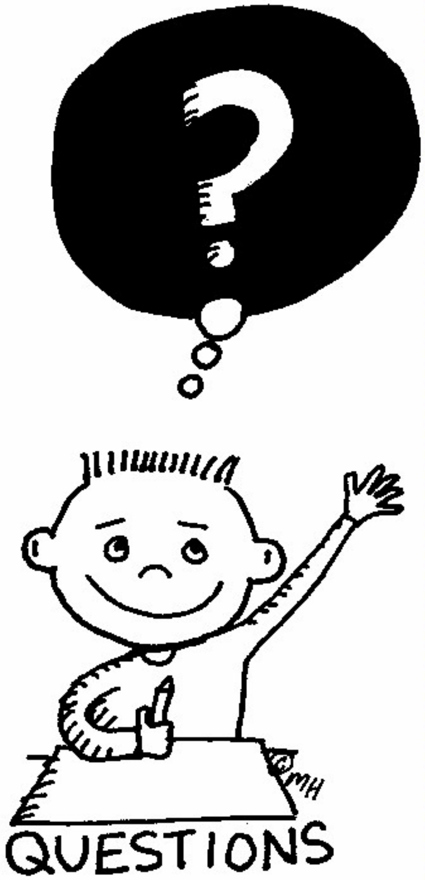
- Interpretable
- Transparent
- Intuitive
- Less “cognitive overhead”

Bayesian Networks = Transparent Expert System



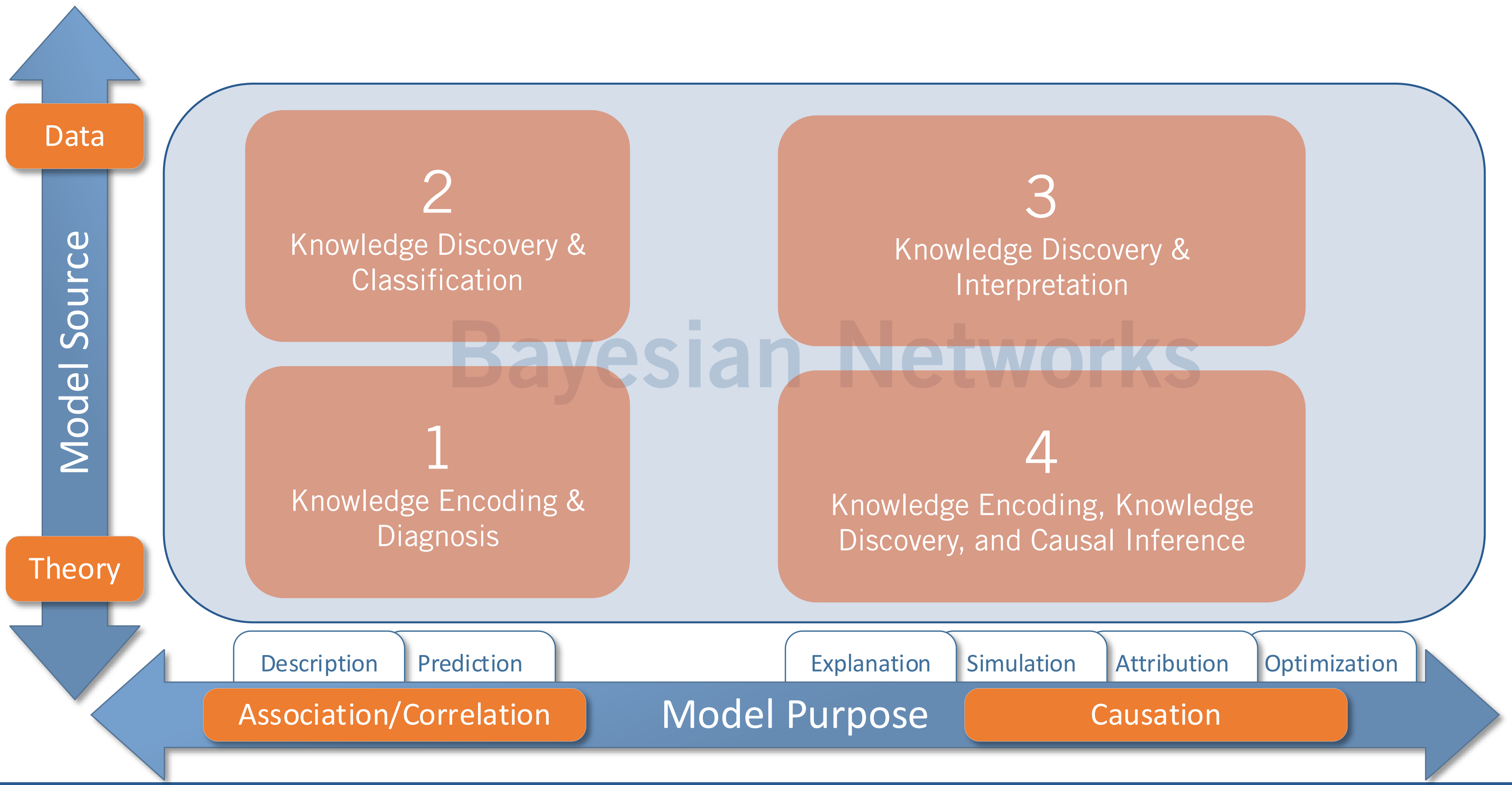
Bayesian Statistics?

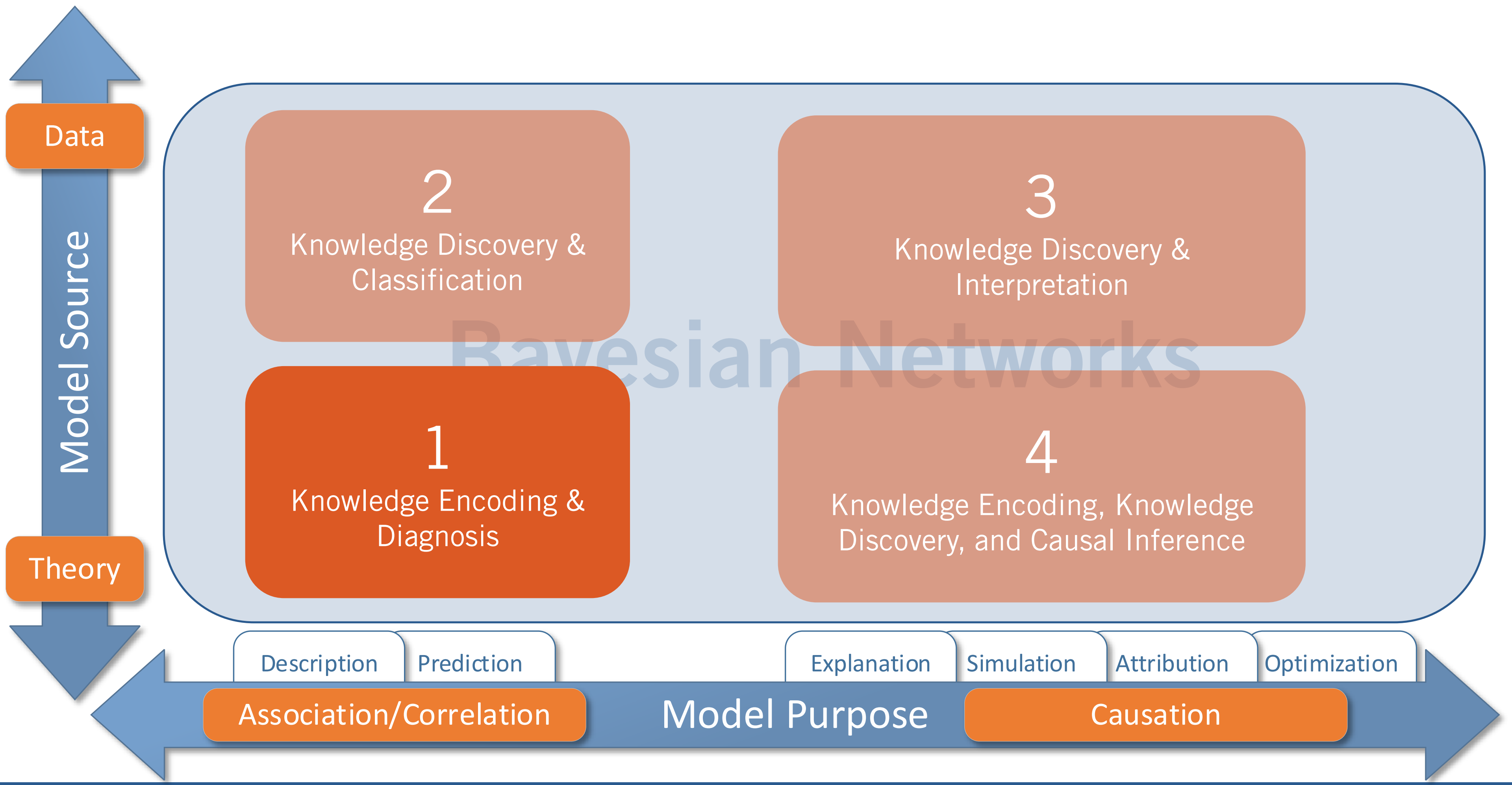



?
©MH
QUESTIONS

BAYESIALAB

Coffee Break


Data
Model Source
Theory
2
Knowledge Discovery & Classification
3
Knowledge Discovery & Interpretation
Bayesian Networks
1
Knowledge Encoding & Diagnosis
4
Knowledge Encoding, Knowledge Discovery, and Causal Inference
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation



Data
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Optimization
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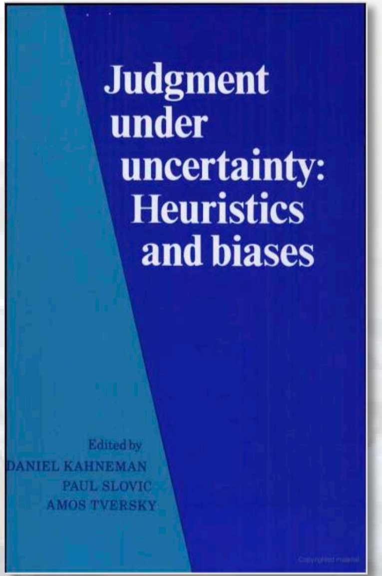
Model Purpose
Causation

Example 1a: Probabilistic Inference

Probabilistic Inference

Human Reasoning Experiment
(adapted from Kahneman & Tversky, 1980)

- A cab was involved in a hit-and-run accident at night.
- Two taxicab companies are operating in the city, one with yellow and one with white taxis:
  - 85% are yellow
  - 15% are white



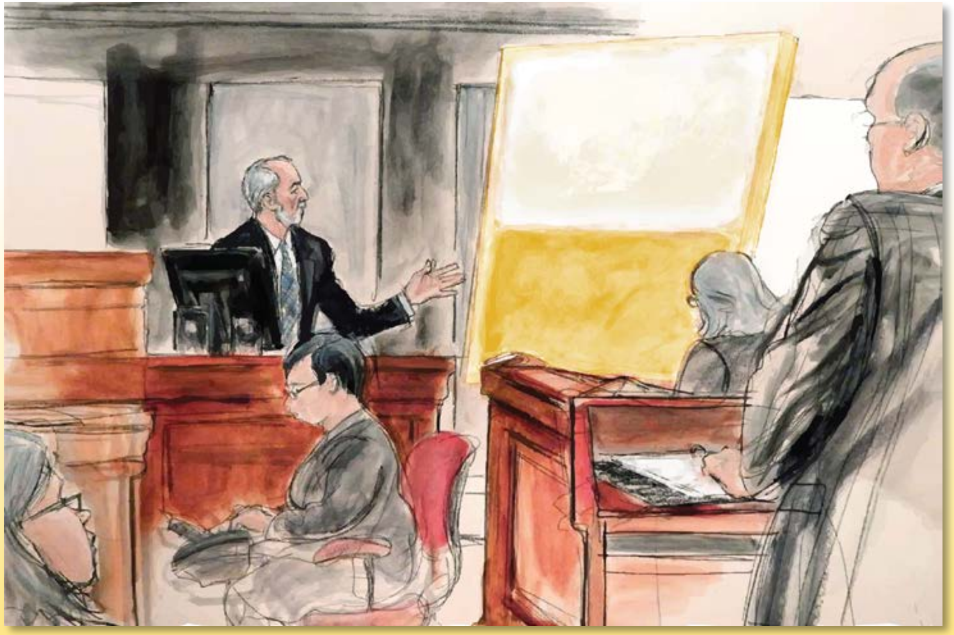
Probabilistic Inference

- A witness identified the taxi involved in the accident as white…

Probabilistic Inference

At the Trial

- A witness testifies that taxi involved in the accident was white.
- Furthermore, an expert witness explains that human vision has an 80% sensitivity in terms of distinguishing between white and yellow given light conditions at the time of the accident.



Probabilistic Inference

You are the jury!

- What is the probability that the taxi was actually white?

Probabilistic Inference

Your Answer:

$$P(Taxi{=}white \mid Witness{=}white){=}55\%$$

Typical Answer:

$$P(Taxi{=}white \mid Witness{=}white){=}80\%$$

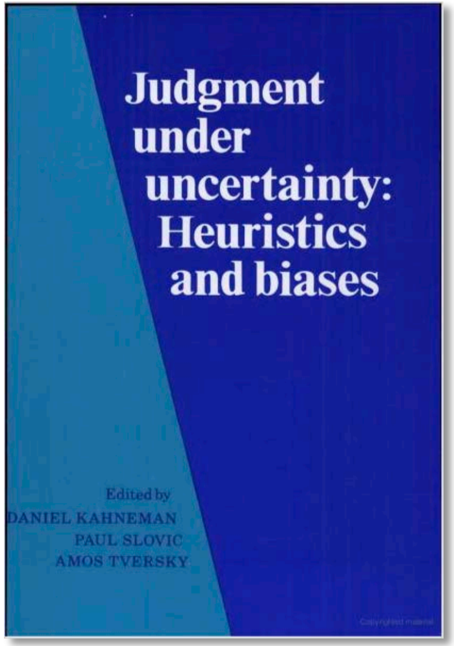
Correct Answer:

$$P(Taxi{=}white \mid Witness{=}white){=}?$$

Probabilistic Inference

See Chapter 4

Abductive Reasoning & Cognitive Bias



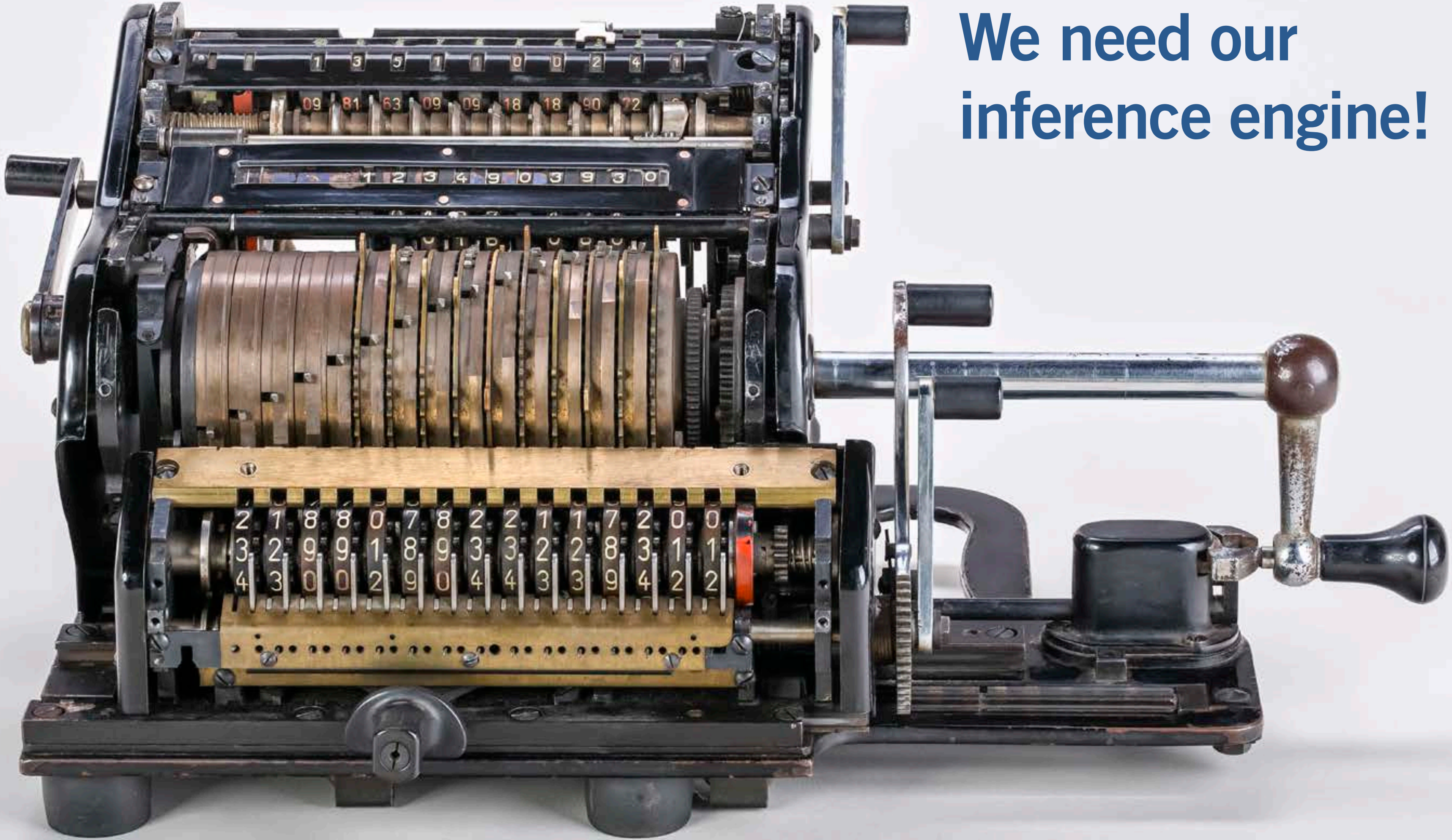
Probabilistic Inference

- We need to perform ***diagnostic*** probabilistic inference, i.e. from effect to cause, to answer this question.
- Bayes' Rule allows us to compute the probability $P(Taxi{=}white \mid Witness{=}white)$:

$$P(H \mid E) = \frac{P(E \mid H)\,P(H)}{P(E)}$$

$$P(Taxi = white \mid Witness = white) = \frac{P(Witness = white \mid Taxi = white)P(Taxi = white)}{P(Witness = white)} =$$

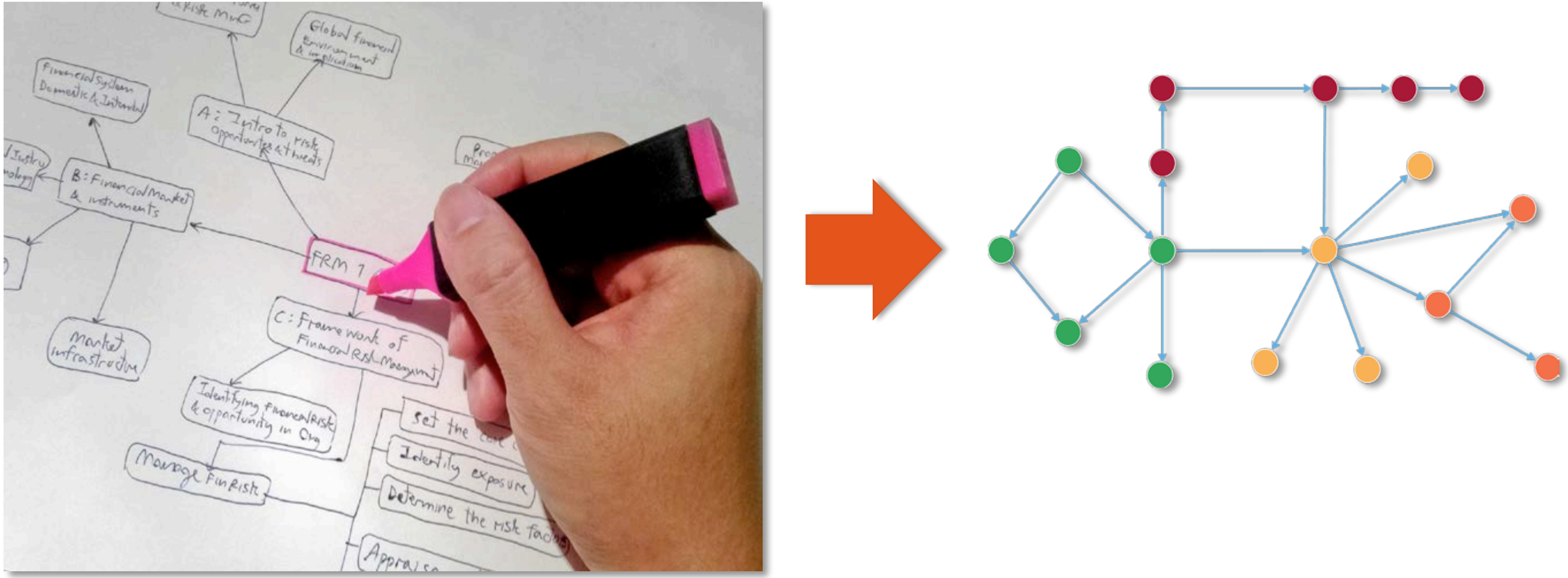
$$\frac{P(Witness = white \mid Taxi = white)P(Taxi = white)}{P(Witness = white \mid Taxi = white)P(Taxi = white) + P(Witness = white \mid Taxi = yellow)P(Taxi = yellow)}$$



We need our inference engine!

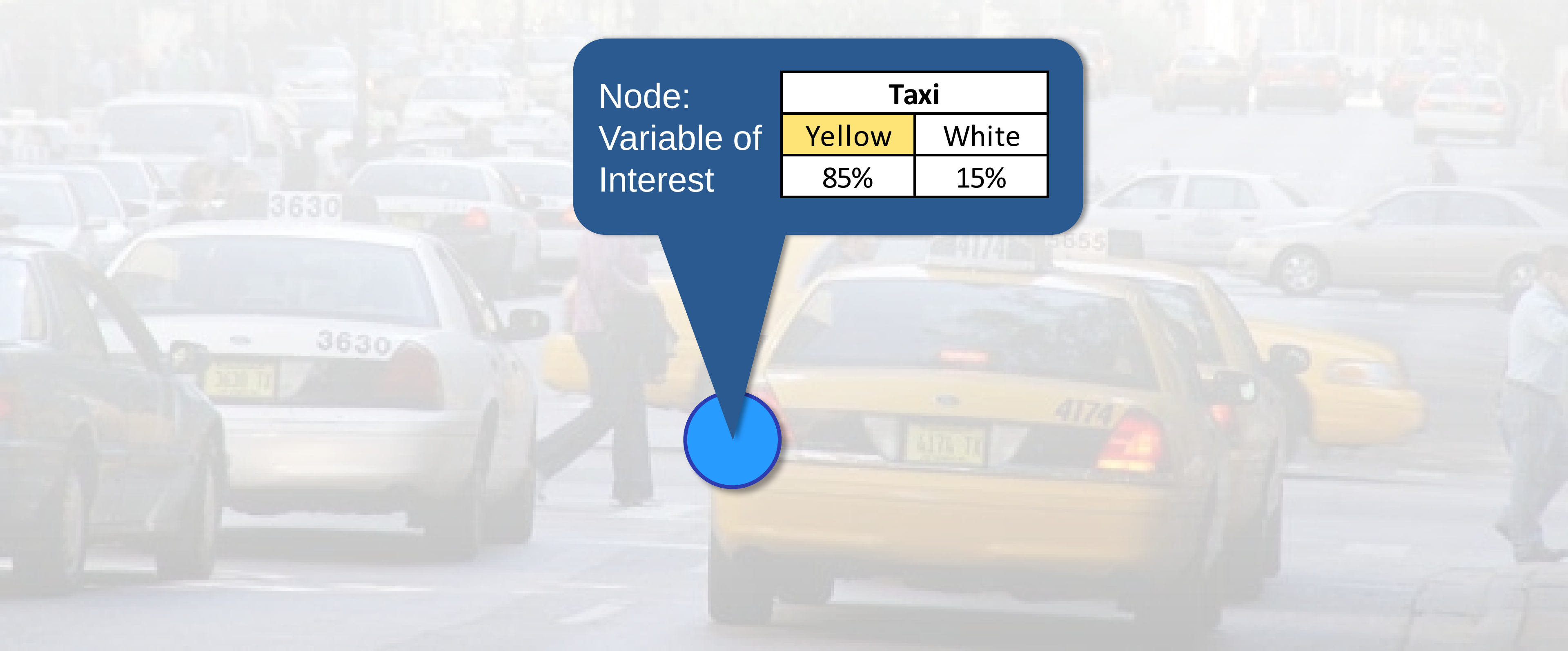
Knowledge Modeling

Encoding Expert Knowledge



Probabilistic Inference

We encode our domain knowledge regarding the taxi cab example:



Node:
Variable of Interest

Taxi	
Yellow	White
85%	15%

Probabilistic Inference

We encode our domain knowledge regarding the taxi cab example:

Node:
Variable of Interest

Taxi	
Yellow	White
85%	15%

Node:
Variable of Interest

Witness	
Yellow	White
?	?

Probabilistic Inference

We encode our domain kno

Node:
Variable of
Interest

Taxi	
Yellow	White
85%	15%

Arc:
Discrete & Nonparametric
Probabilistic Relationship

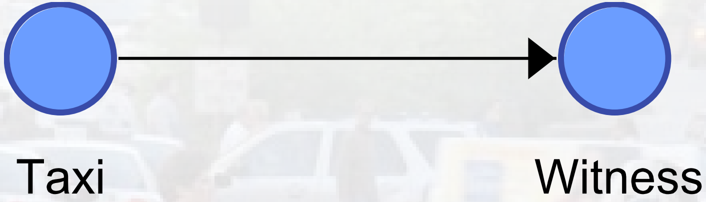
		Witness	
		Yellow	White
Taxi	Yellow	80%	20%
	White	20%	80%

Node:
Variable of
Interest

Witness	
Yellow	White
?	?

Probabilistic Inference

We encode our domain knowledge regarding the taxi cab example:



Yellow	White
85.000	15.000

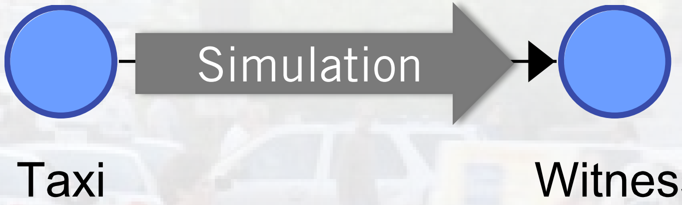
Marginal Distribution

Taxi	Yellow	White
Yellow	80.000	20.000
White	20.000	80.000

Conditional Probability Table

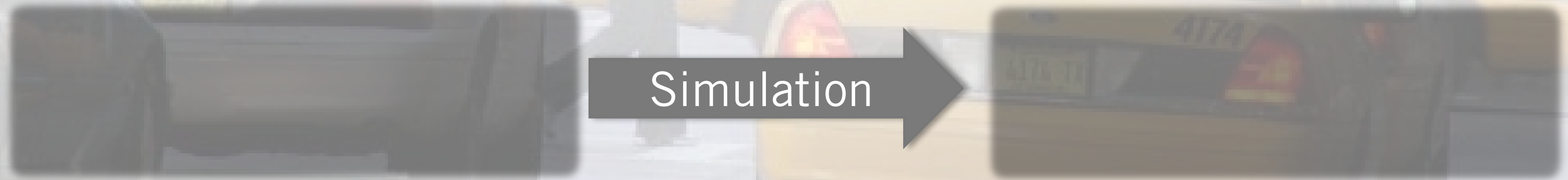
Probabilistic Inference

Inference based on evidence:



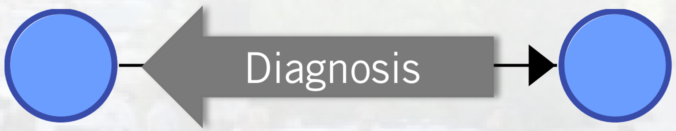
Yellow	White
85.000	15.000

Taxi	Yellow	White
Yellow	80.000	20.000
White	20.000	80.000



Probabilistic Inference

Performing inference based on observing evidence:



Taxi

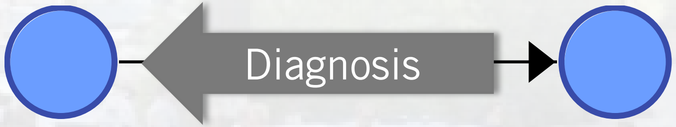
Yellow	White
85.000	15.000

Witness

Taxi	Yellow	White
Yellow	80.000	20.000
White	20.000	80.000

Probabilistic Inference

Performing inference based on observing evidence:

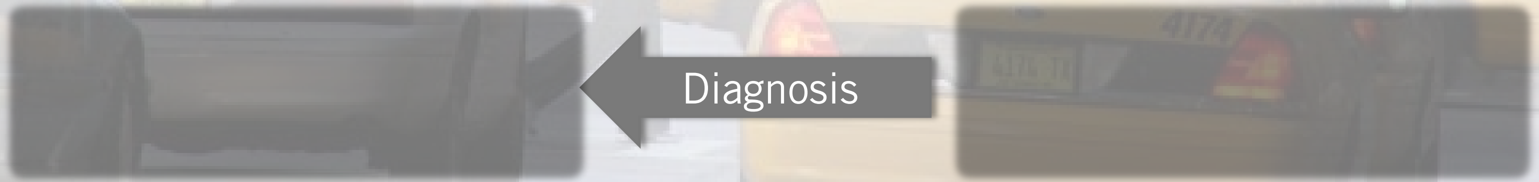


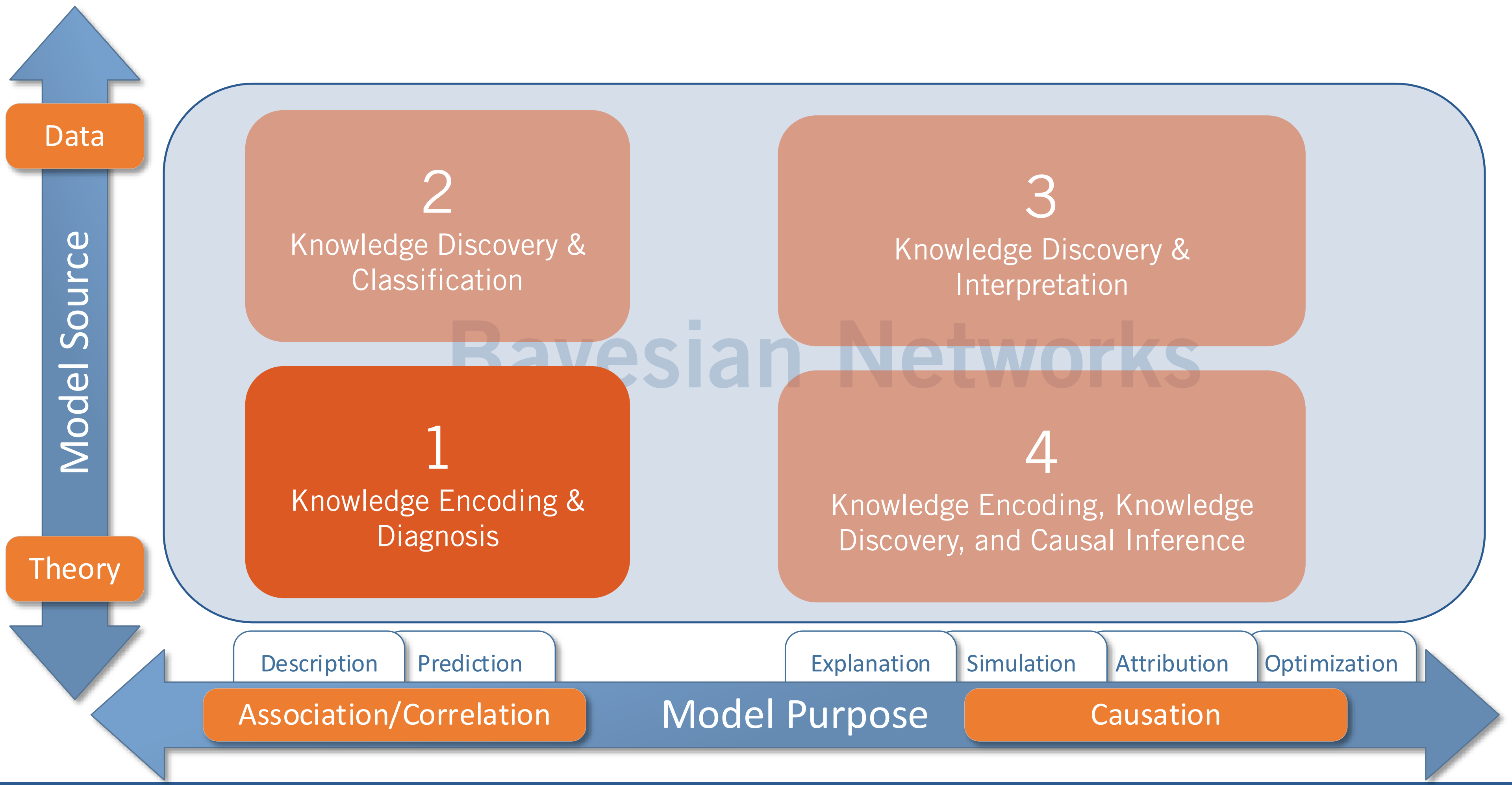
Taxi

Yellow	White
85.000	15.000

Witness

Taxi	Yellow	White
Yellow	80.000	20.000
White	20.000	80.000




Data
Model Source
Theory
2
Knowledge Discovery &
Classification
3
Knowledge Discovery &
Interpretation
Bayesian Networks
1
Knowledge Encoding &
Diagnosis
4
Knowledge Encoding, Knowledge
Discovery, and Causal Inference
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

See Chapter 4

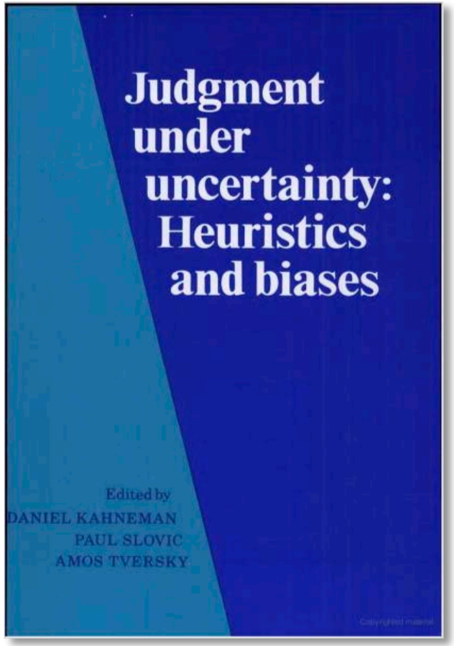
Example 1b: Where is my bag?

Knowledge Modeling & Reasoning Under Uncertainty

Probabilistic Inference

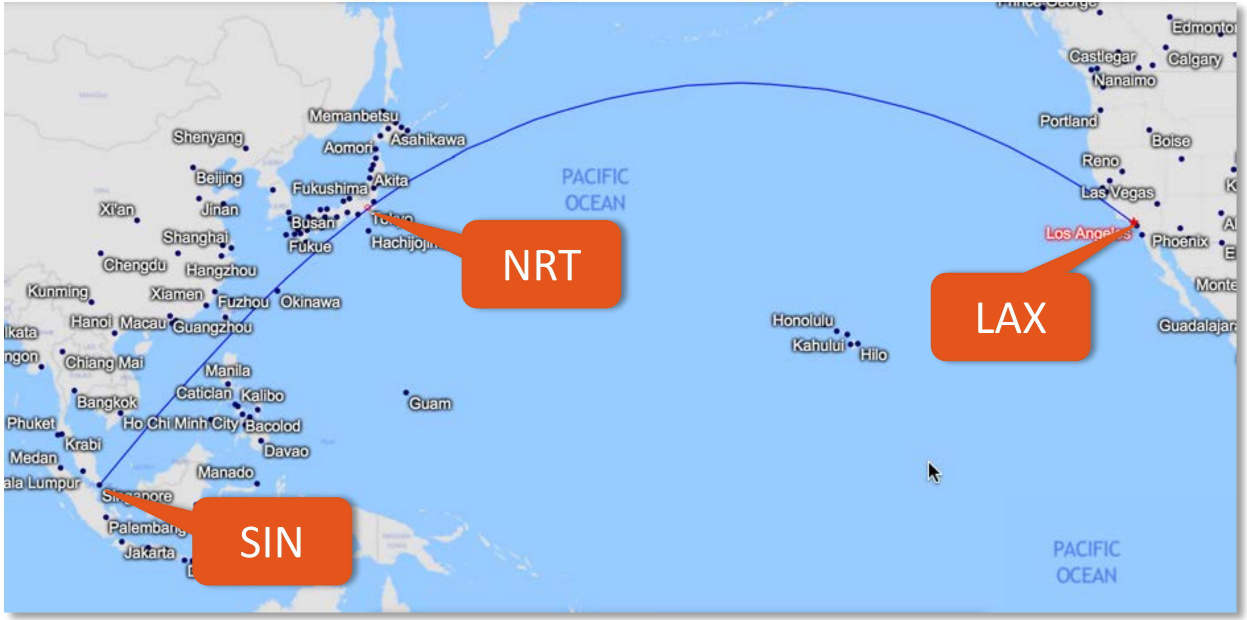
See Chapter 4

Abductive Reasoning & Cognitive Bias



Example 1b: Where is my bag?

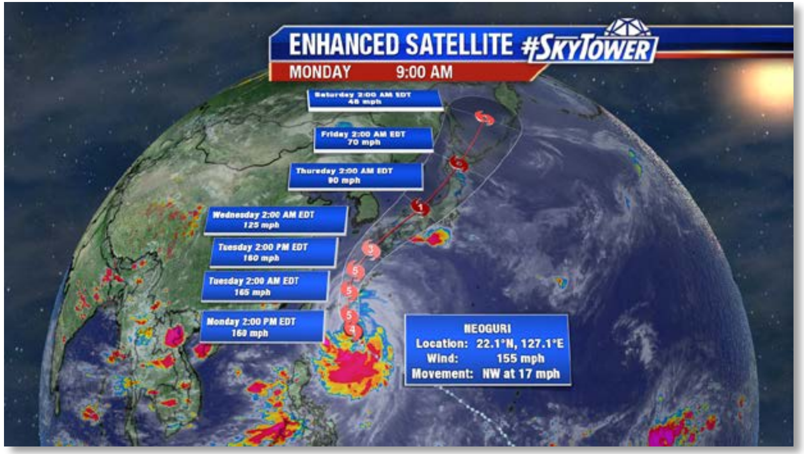
Travel Route: Singapore (SIN) → Tokyo (NRT) → Los Angeles (LAX)



Where is my bag?

My travel progress:

- I check in one piece of luggage in Singapore.
- However, my flight from Singapore to Tokyo departs with a delay due to a Typhoon in the South China Sea.
- As a result, I arrive very late in Narita and only have a short time to get to my departure gate for LAX.



3F After Passport Control

International Departure Lobby (Boarding Gate)
Duty Free & Shopping Area

SSID : FreeWiFi-NARITA

Information Counter	Elevator
Restroom	Escalator
Multi-function Restroom	Nursery
Multi-function Restroom (Ostomates' Toilet)	Smoking Area
Transfer Counter	Massage Chairs
Prayer Room	AED
International Departure	

These stores and facilities are available only for passengers who have completed departure procedures. Not available for use by those on tours and those picking up or dropping off passengers.

Restaurants & Cafes

Cafes & Light Meals	
S31	FaSoLa Cafe coffee & beer No.4 Satellite
S51	FaSoLa Cafe coffee & beer No.5 Satellite
S34	CAFE & BAR AVION
N22	Snack & Café AVION No.2 Satellite
N31	DOUTOR COFFEE SHOP
N34	Snack & Café AVION No.1 Satellite
Fast Food	
C6	McDonald's
Japanese Cuisine	
S36	Sushi Kyotatsu
C3	My Favorite Japanese Foods TATSU
Food Court	
S10	Tokyo Food Bar

Shops

Books & Magazines	
S52	Fa-So-La BOOKS
C5	KAIZOSHA Bookstore
Travel Goods & Pharmaceuticals	
S57	Fa-So-La DRUGSTORE No. 5 Satellite
N21	Fa-So-La DRUGSTORE No. 2 Satellite
Electrical Appliances/Foods/Folk Craft	
S21	Fa-So-La TAX FREE AKIHABARA
S32	ANA DUTY & TAX FREE SHOP
S38	Fa-So-La SOUVENIR No. 3 Satellite
S55	Fa-So-La DIGITAL CUBE
N4	Fa-So-La TAX FREE ASAKUSA
N12	Fa-So-La SOUVENIR KOTOBUKI
Souvenirs & Misc. Goods	
S8	Fa-So-La TAX FREE KAGURA
S37	TENSHODO
S54	Fa-So-La ITOEN
S56	Fa-So-La FUJI-DOLL
N32	GATE WAY No.1 Satellite
Fashion & Misc. Goods	
S9	Fa-So-La LADIES' Bags & Accessories
Kabuki Gallery Shop	
C12	Kabuki Gate
Duty Free Shops	
S11	ANA DUTY FREE SHOP
S12	Fa-So-La DUTY FREE South Wing Store
S17	Fa-So-La WATCHES
S18	Fa-So-La DUTY FREE Cosmetics & Perfumery
S19	Fa-So-La DUTY FREE Liquor & Tobacco
S32	ANA DUTY & TAX FREE SHOP
S35	Fa-So-La DUTY FREE No. 3 Satellite
N5	JAPAN DUTY FREE NORTH 2
N11	JAPAN DUTY FREE NORTH 1
Brand Boutiques	
S1	ANA DUTY FREE SHOP MEN (MONTBLANC/TUMI/ Other men's clothing accessories/ Fashion accessories)
S2	Fashion & Luxury (SWAROVSKI/LACOSTE/ FURLA/Folli Follie)
S3	LOEWE
S4	BURBERRY
S5	COACH
S6	BVLGARI
S7	Cartier
S14	HERMÈS
S15	Salvatore Ferragamo
S16	TIFFANY & CO.
S58	PLEATS PLEASE ISSEY MIYAKE/ BAO BAO ISSEY MIYAKE
N1	HERMÈS
N2	BVLGARI
N3	Salvatore Ferragamo
N7	CHANEL FRAGRANCE & BEAUTY NORTH
N8	Chloé
N9	MONTBLANC
Duty Free Pick-up Counter	
C13	Japan Duty Free GINZA
C13	LOTTE DUTY FREE
C13	TAKASHIMAYA DUTY FREE SHILLA & ANA

※For business hours and the phone number of all the stores and facilities, please refer to P30 onward.

Service Facilities

Currency Exchange	
S20·S53	GPA
C11	Mizuho Bank
ATM	
S13·N6	Seven Bank
Traveler's Insurance	
S40·S59 N23·N33	Automatic Policy Sales Terminal
Relaxation Facilities	
C2	Dayrooms & Showers
C7	Raffine
C14	Narita TraveLounge
Children's Facilities	
S33·S60 C1	Kids Park ※Because this is not a daycare center, it is necessary for children to be accompanied by an adult.
Japanese Culture Introduction Corner	
S61	Japanese Culture Introduction/Experience Corner
Airline Lounges	
S30·S50	ANA SUITE LOUNGE
S30·S50	ANA LOUNGE
S39	United Club
S39	United Global First Lounge
C10	KAL LOUNGE (Korean Air)
N20·N30	DELTA Sky Club

Please enjoy the use of the showers and nap rooms when connecting to international flights or before boarding.

Where is my bag?

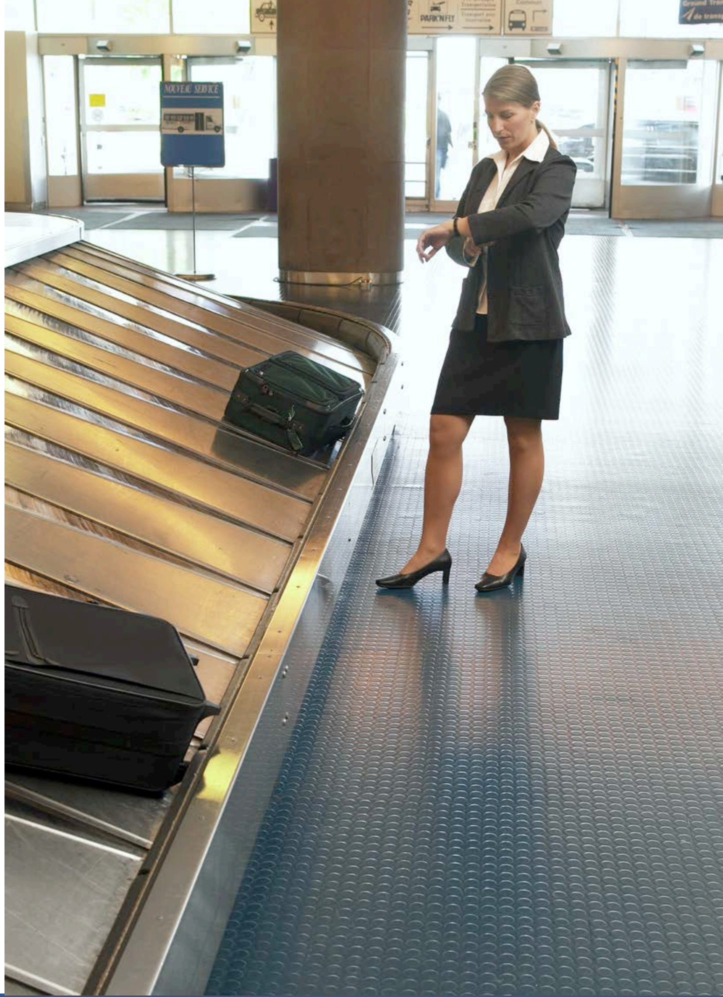
- I manage to get to the gate just in time and get my boarding pass for the flight to LAX.
- However, the gate agent in Narita tells me that my checked luggage may not make it onto the flight.

SINGAPORE AIRLINES
152
154
156
D-ABYJ
Sky Chefs


Bag Claim
Ground Transport

Where is my bag?

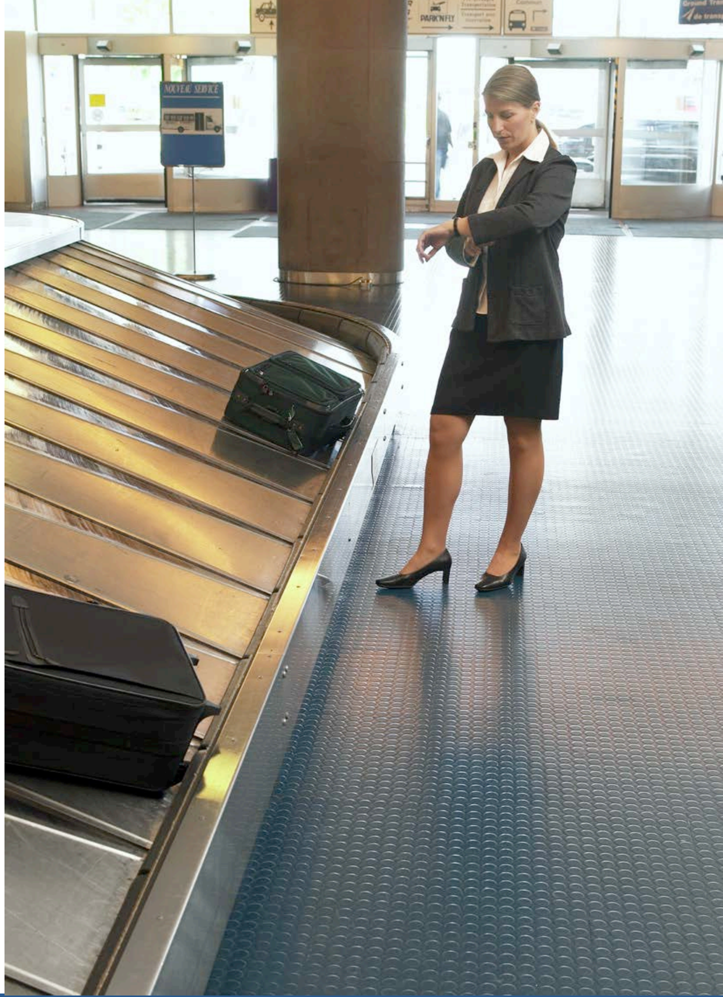
- After immigration at LAX, I proceed to the baggage claim area.
- Luggage is delivered on the carousel, but, **after 5 minutes**, I still do not see my bag.
- What is the probability that I will still get my bag?



Where is my bag?

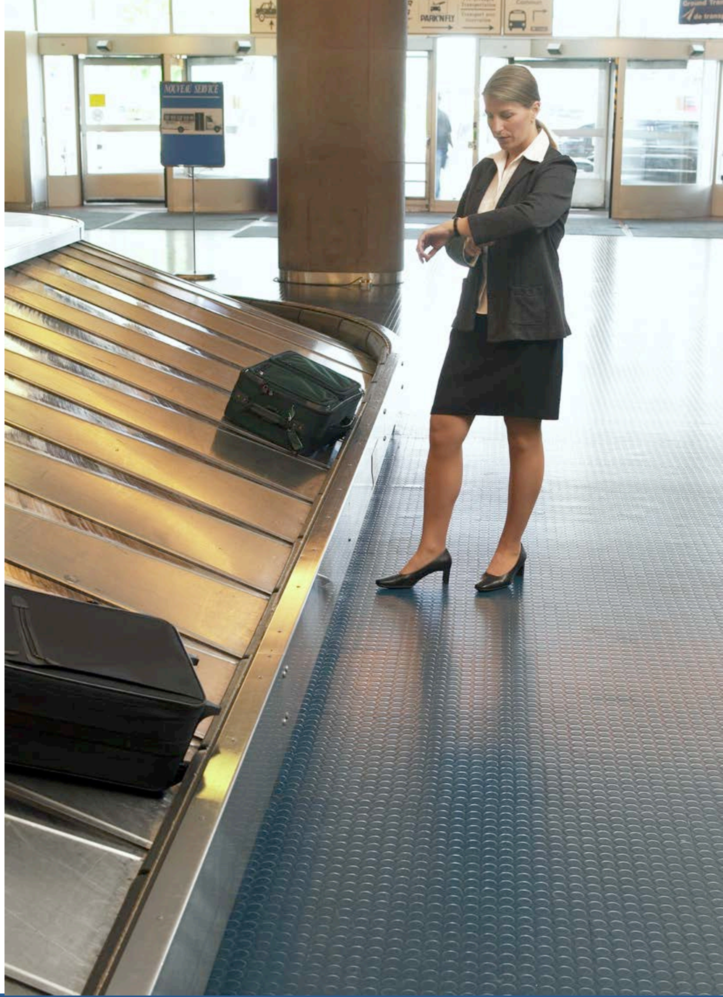
Task

- Encode available knowledge into a Bayesian network.
- Perform probabilistic inference given observations, i.e. reason from effect to cause (diagnosis).

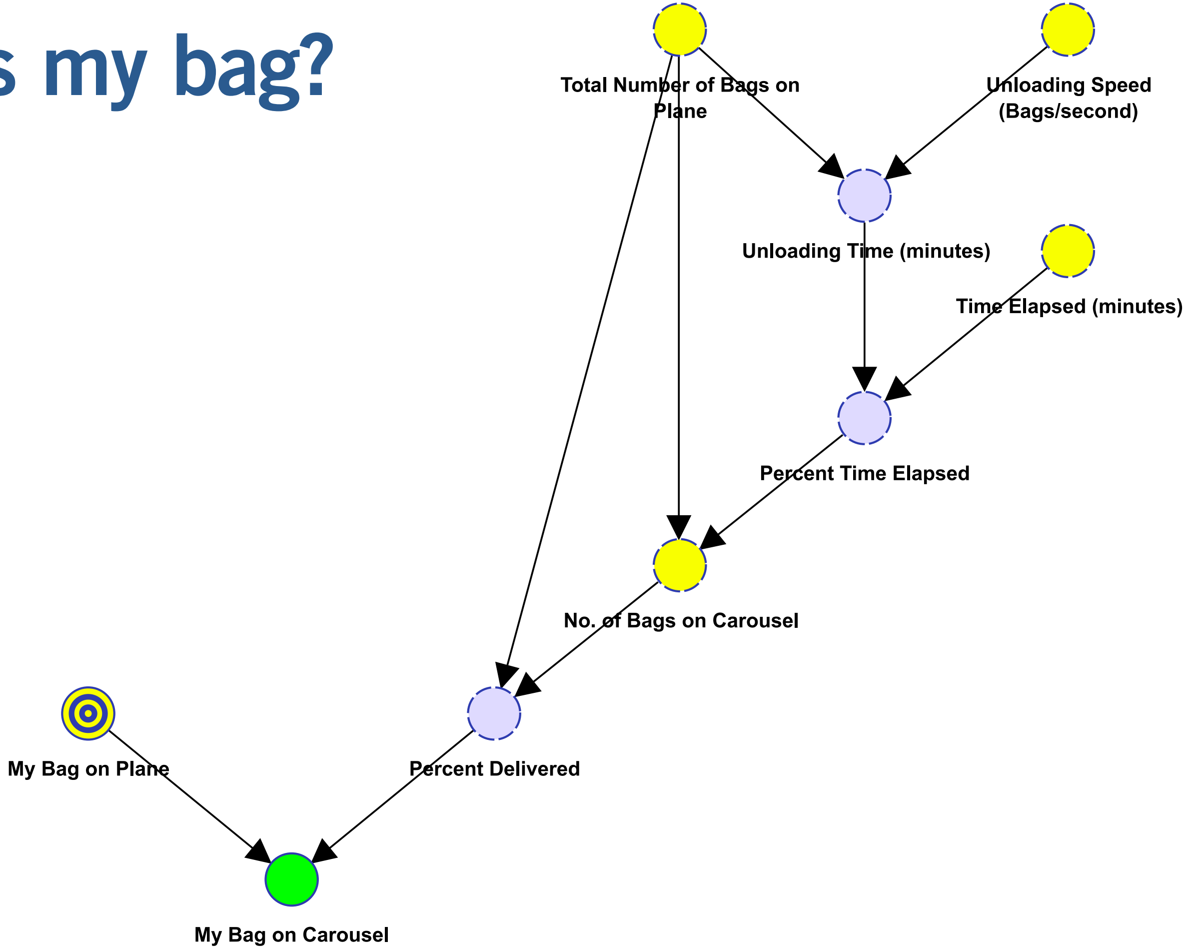


Where is my bag?

- After immigration at LAX, I proceed to the baggage claim area.
- Luggage is delivered on the carousel, **a total of 50 bags in the first 5 minutes**, yet I still do not see my bag.
- What is the probability that I will still get my bag?



Where is my bag?



Where is my bag?

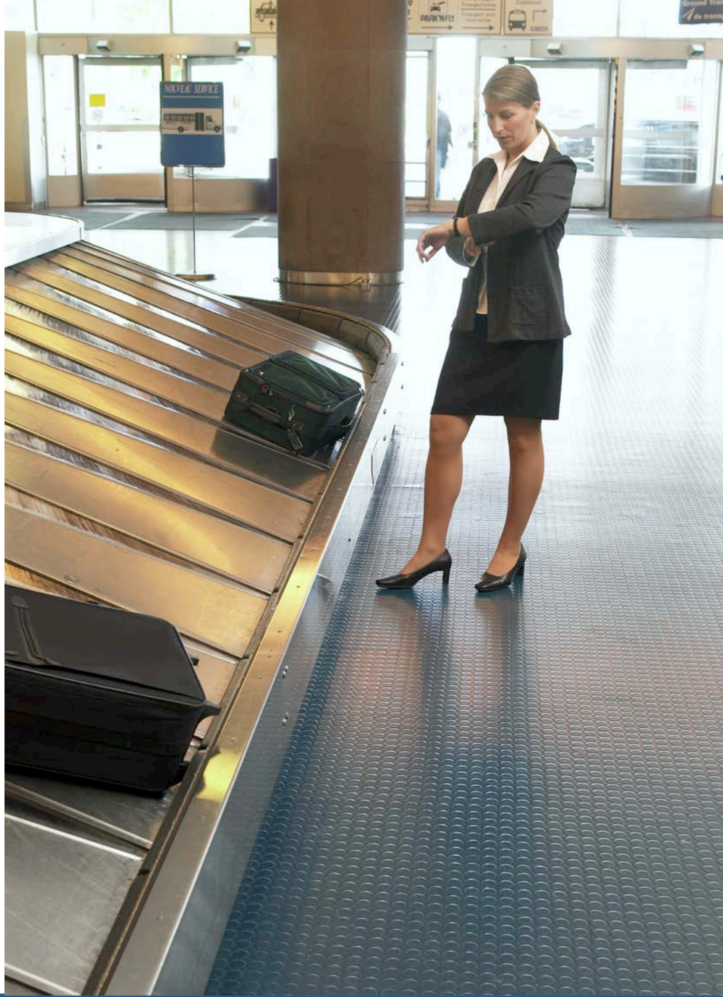
More important questions:

- Will the patient ultimately respond to the current treatment?
- Should we continue a search and rescue effort?
- Should we still follow the original business strategy, i.e. “hold the course”?

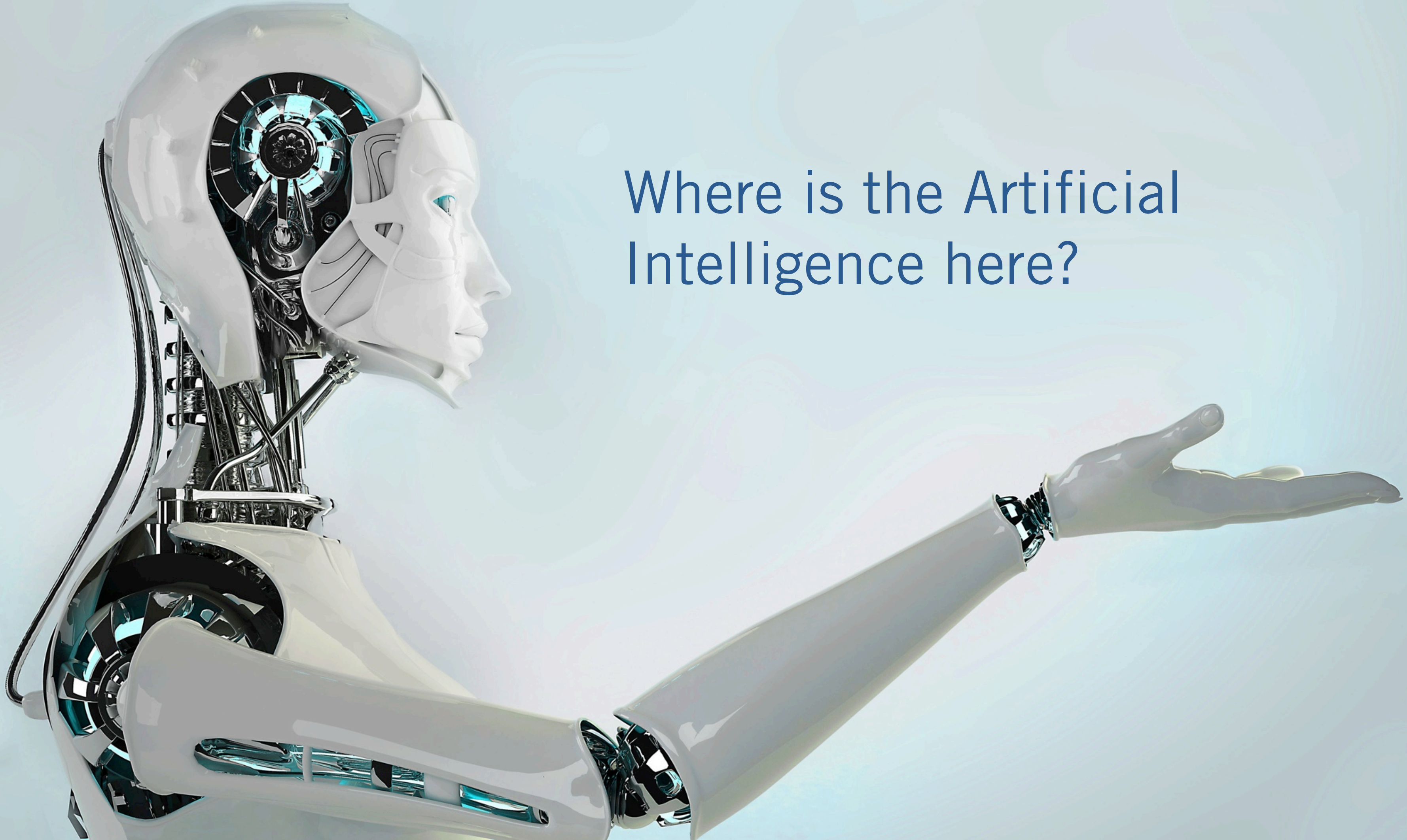
Where is my bag?

Key Points

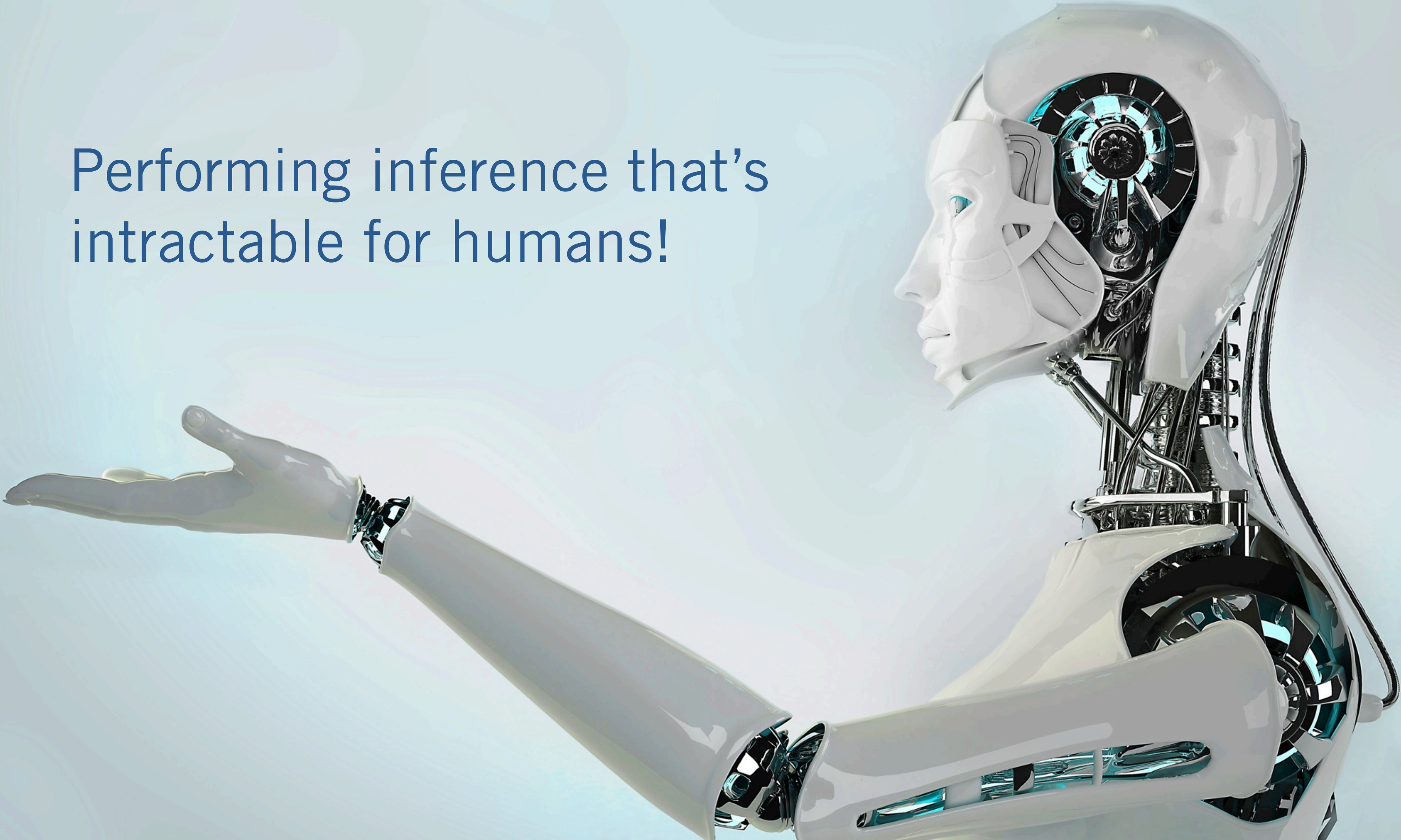
- Encoding of knowledge
- Reasoning under uncertainty
- Reasoning
    - from cause to effect (simulation)
    - from effect to cause (diagnosis)
- Inter-causal reasoning

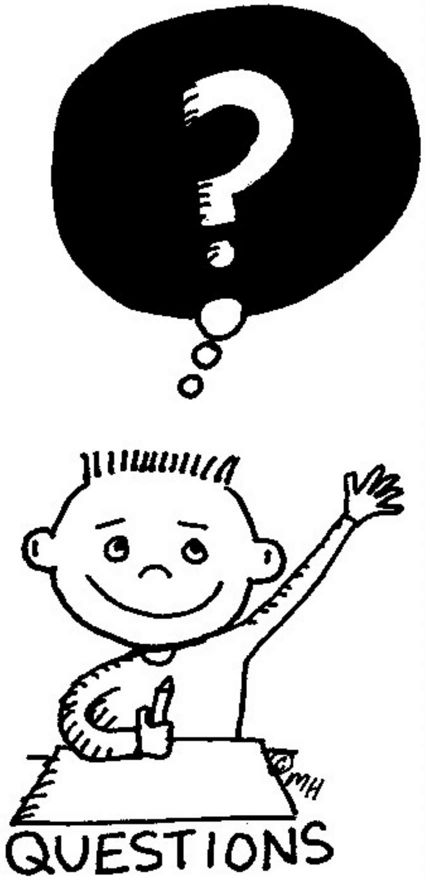


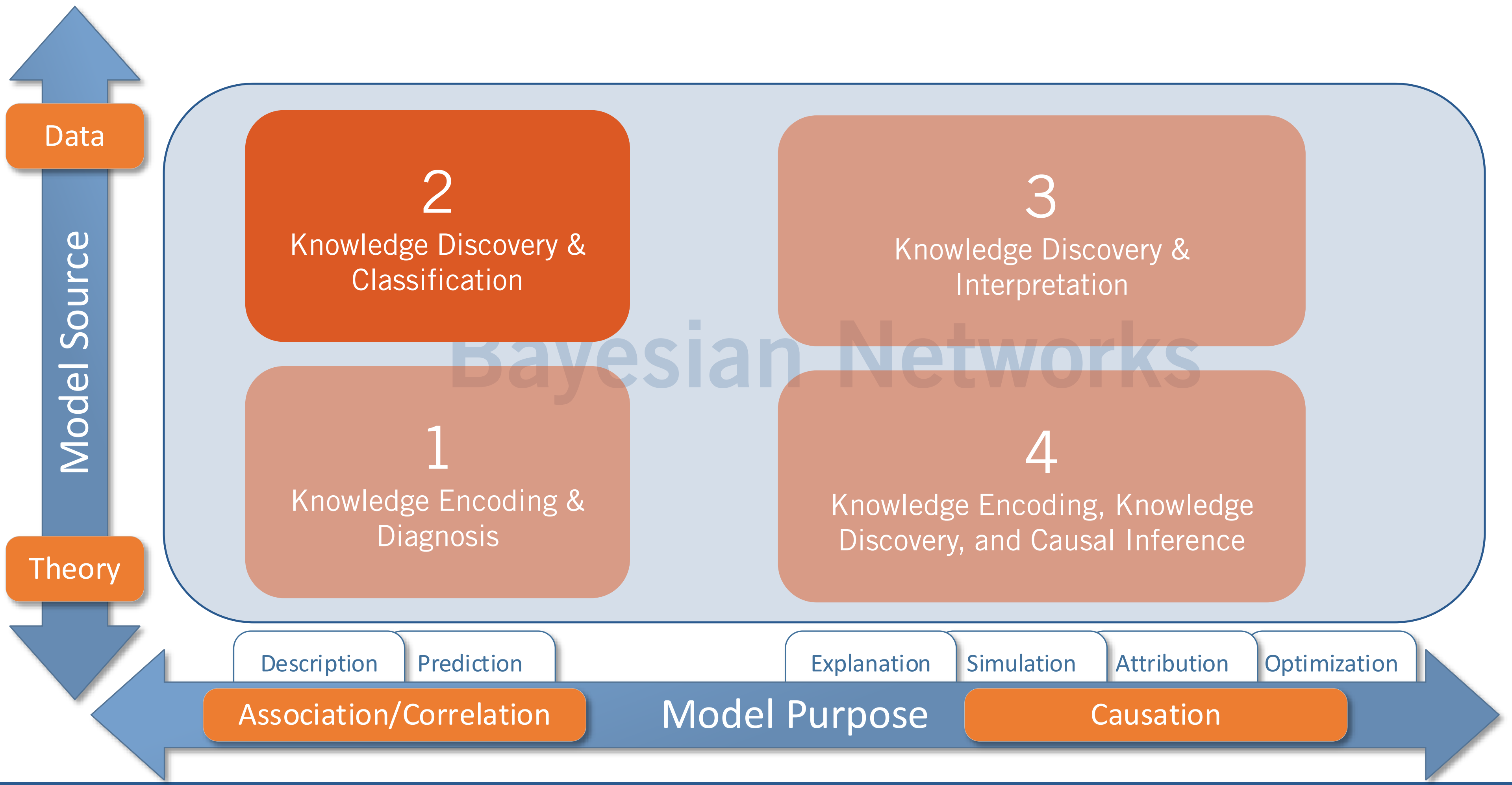
Where is the Artificial Intelligence here?



Performing inference that’s intractable for humans!




QUESTIONS


Data
Model Source
Theory
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Knowledge Discovery & Interpretation
Bayesian Networks
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4
Knowledge Encoding, Knowledge Discovery, and Causal Inference
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Example 2: Breast Cancer Diagnostics

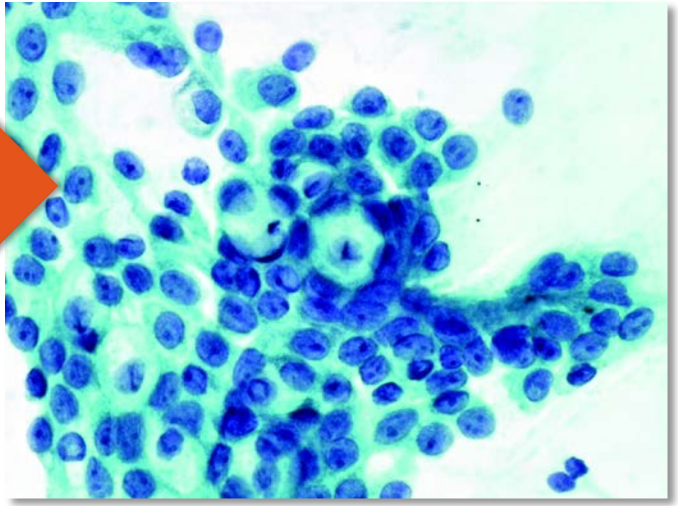
Knowledge Discovery & Classification

See Chapter 6

Breast Cancer Diagnostics

Image Analysis of Fine Needle Aspirates

- Sensitivity of Fine Needle Aspiration with visual interpretation varies widely (65% to 98%)



Breast Cancer Diagnostics

Image Analysis of Fine Needle Aspirates

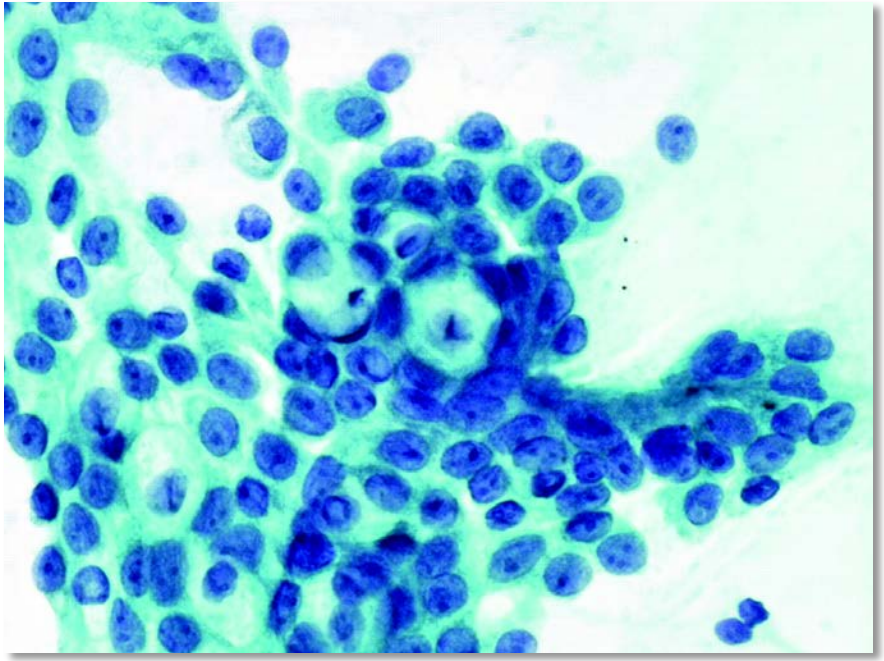
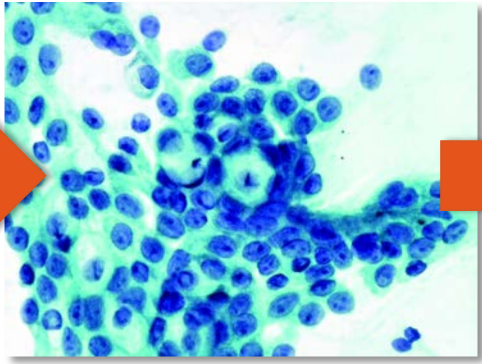
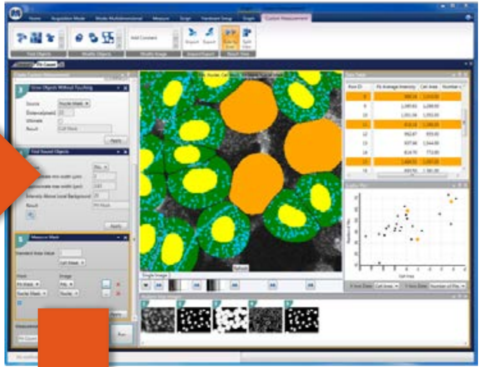


Image Attributes

- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape
- Marginal Adhesion
- Single Epithelial Cell Size
- Bare Nuclei
- Bland Chromatin
- Normal Nucleoli
- Mitoses

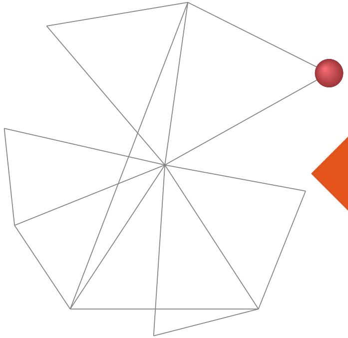
Workflow



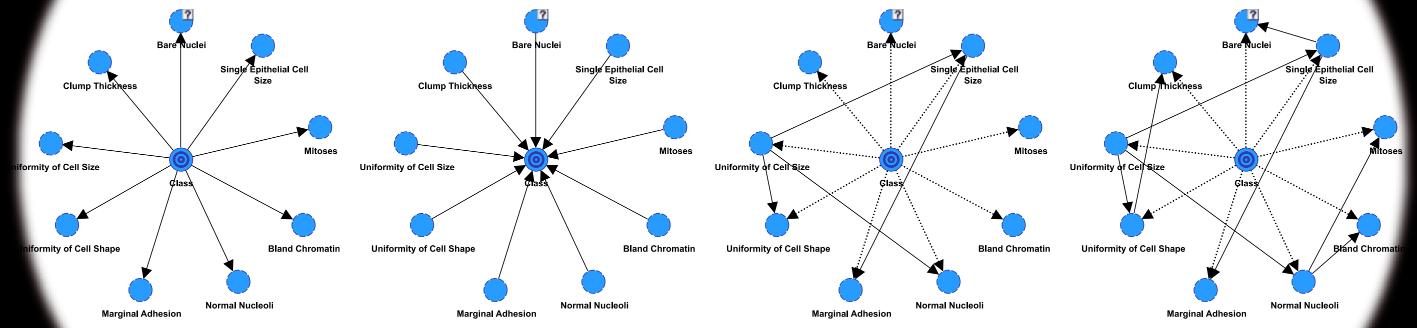


Wisconsin Breast Cancer Database

Sample Code number	Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses	Class
1000025	5	1	1	1	2	1	3	1	1	2
1002945	5	4	4	5	7	10	3	2	1	2
1015425	3	1	1	1	2	2	3	1	1	2
1016277	6	8	8	1	3	4	3	7	1	2
1017023	4	1	1	3	2	1	3	1	1	2
1017122	8	10	10	8	7	10	9	7	1	4
1018099	1	1	1	1	2	10	3	1	1	2
1018561	2	1	2	1	2	1	3	1	1	2
1033078	2	1	1	1	2	1	1	1	5	2



Learning=Searching



Learning=Searching

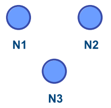
Number of Possible Networks

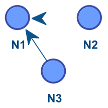
- 2 Nodes: 3

Learning=Searching

Number of Possible Networks

- 2 Nodes: 3
- 3 Nodes: 25

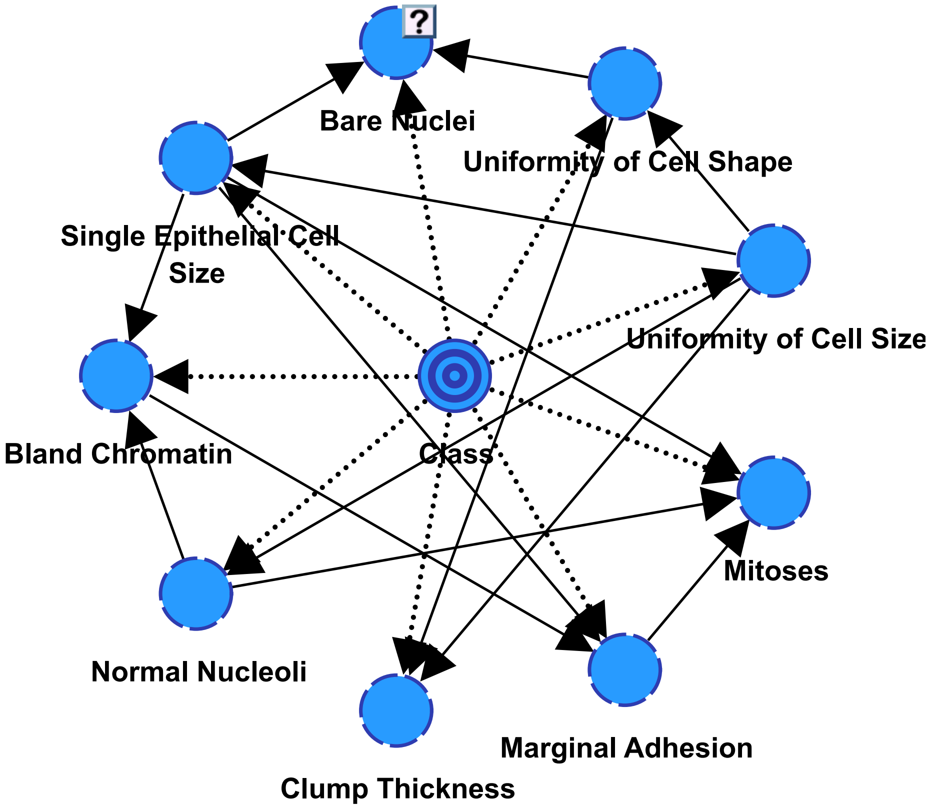




Learning=Searching

Number of Possible Networks

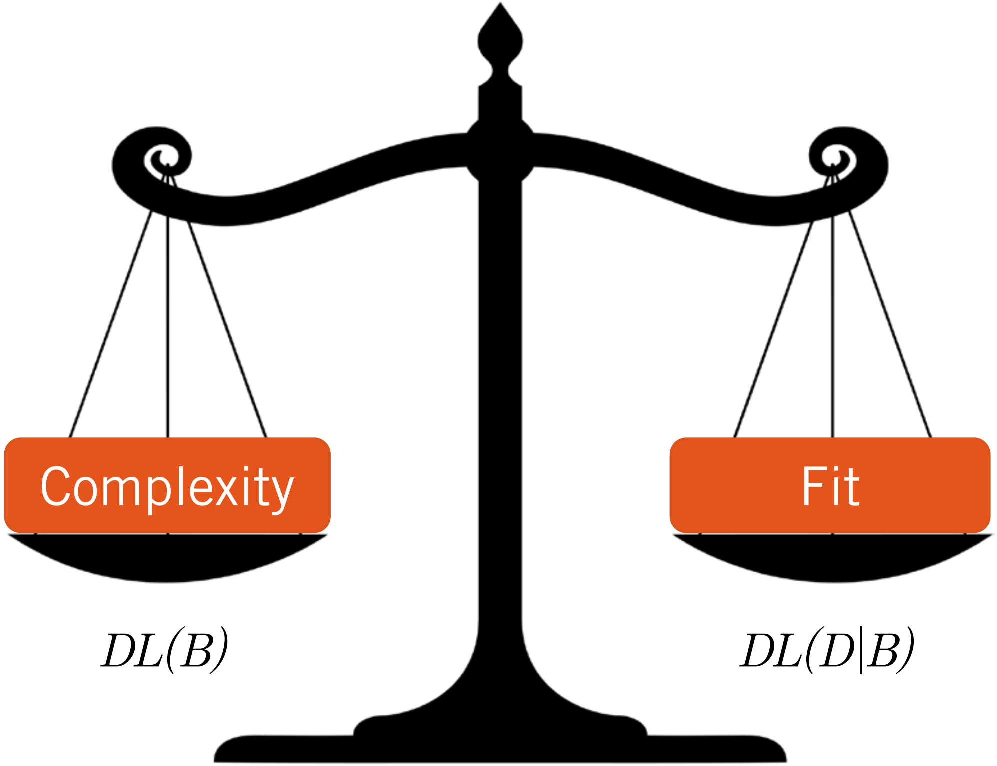
- 2 Nodes: 3
- 3 Nodes: 25
- 4 Nodes: 543
- 5 Nodes: 29,281
- 6 Nodes: 3.8×10^{6}
- 7 Nodes: 1.1×10^{9}
- 8 Nodes: 7.8×10^{11}
- 9 Nodes: 1.2×10^{15}
- 10 Nodes: 4.2×10^{18}



Learning=Searching

Minimum Description Length

- $DL(B)$ is the number of bits to represent the Bayesian network B (graph and probabilities), and
- $DL(D|B)$ is the number of bits to represent the dataset D given the Bayesian network B (likelihood of the data given the Bayesian network).



$$MDL(B,D)=\alpha \cdot DL(B)+DL(D|B)$$

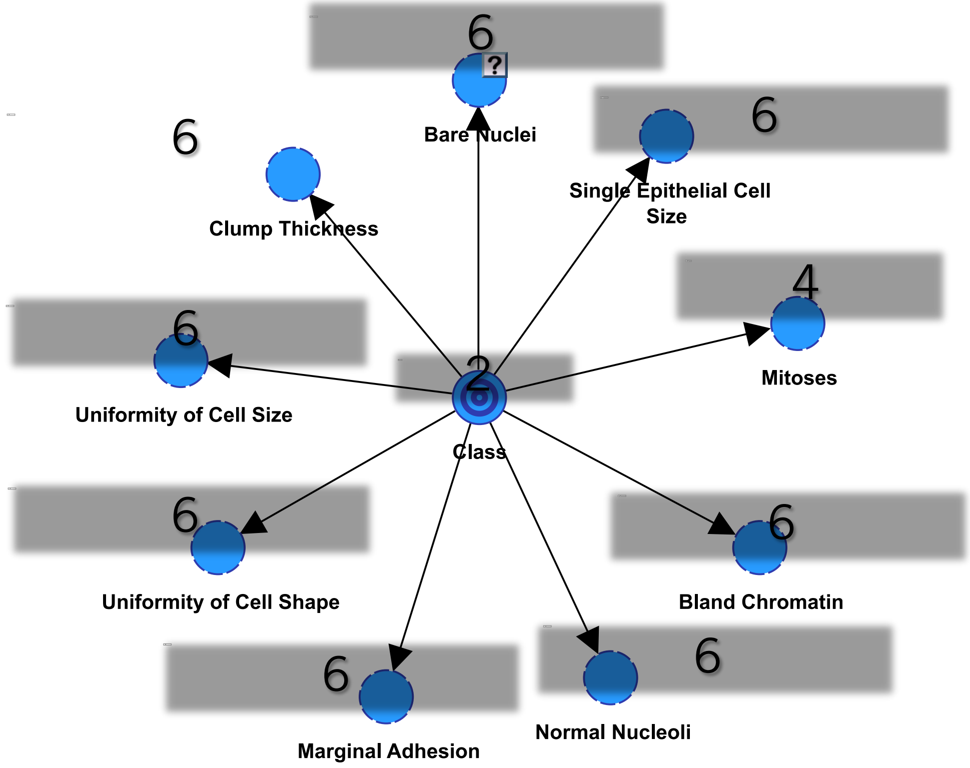
Structural Coefficient α

Breast Cancer Diagnostics

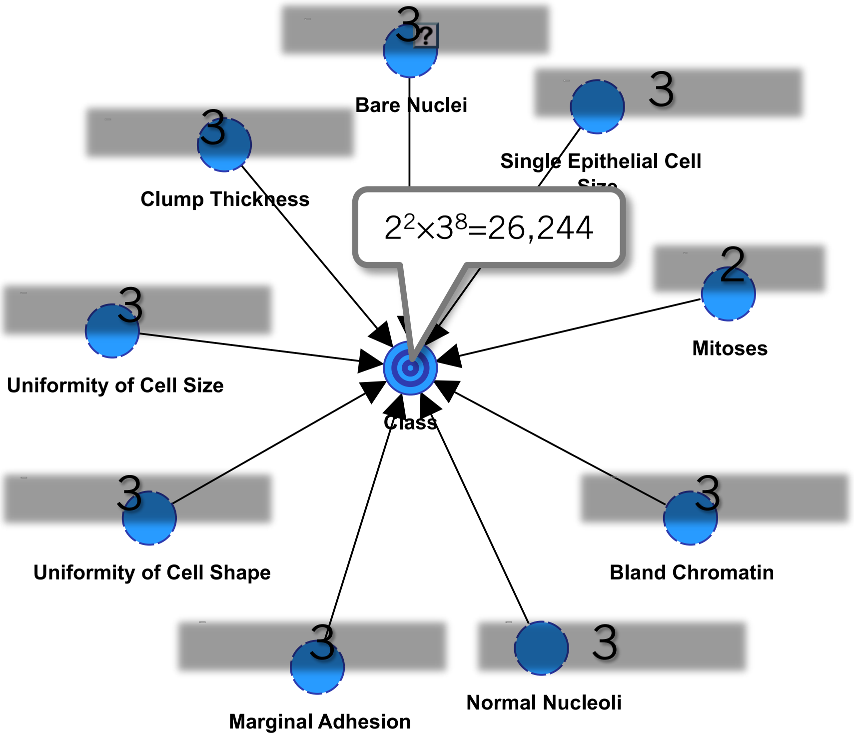
Workflow

- Data Import
- Tree Discretization
- Supervised Learning – Augmented Markov Blanket
- Network Analysis
    - Performance Analysis and Cross-Validation
    - Mapping
    - Adaptive Questionnaire
    - Target Interpretation Tree

Objective: A Parsimonious Model

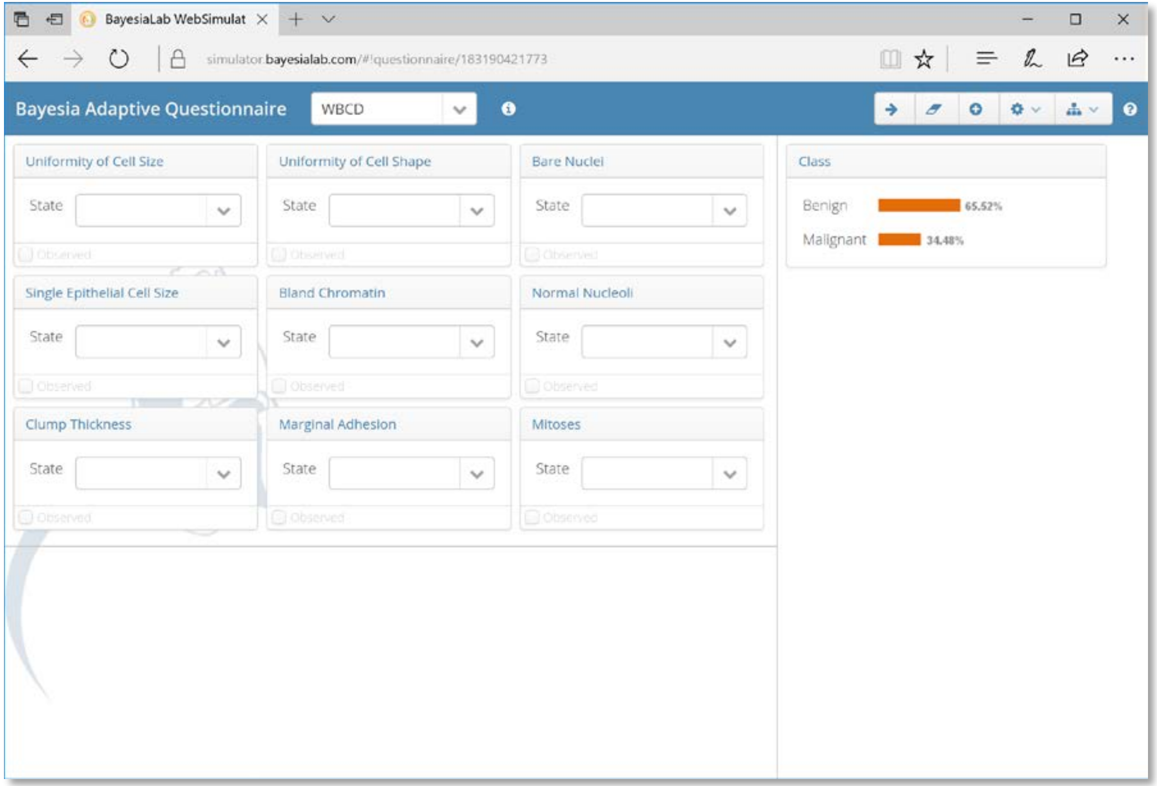


$2+6+6+6+6+6+6+6+6+4=54$ cells

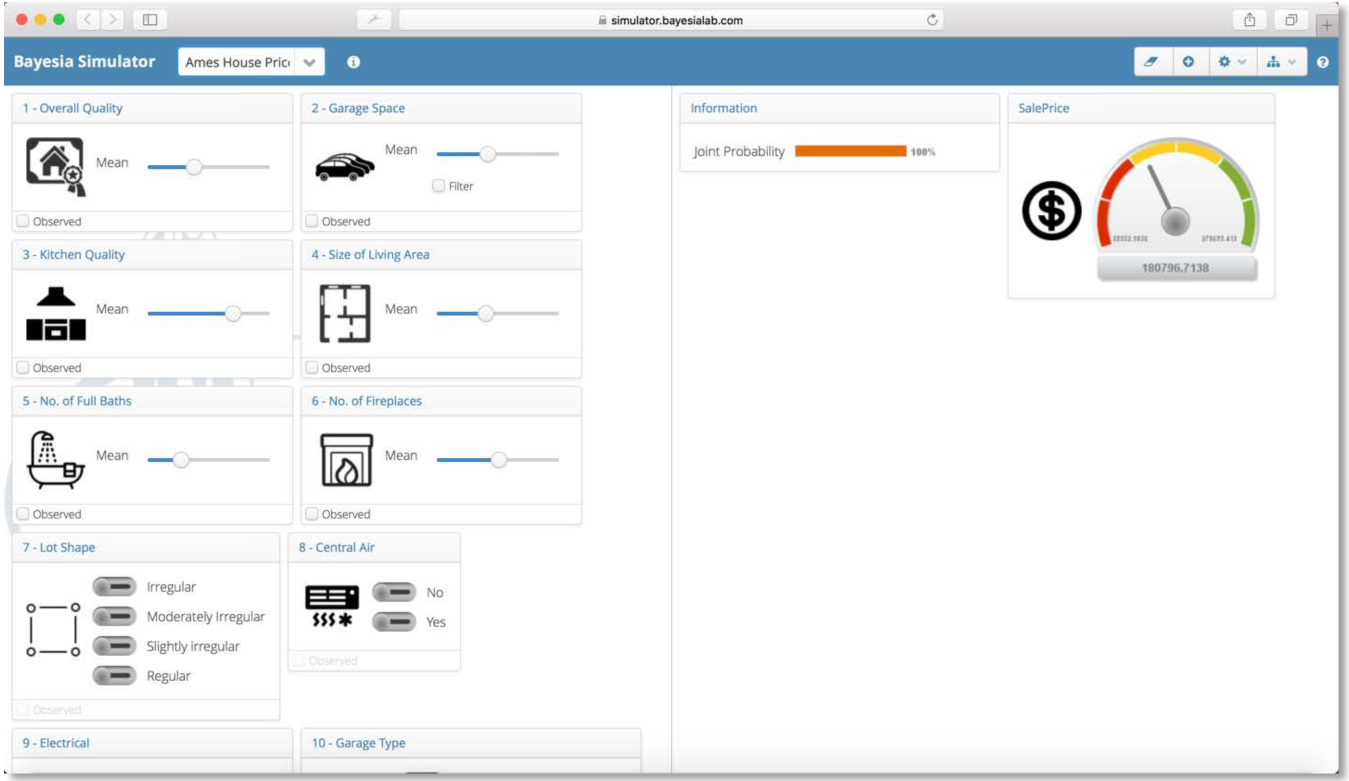


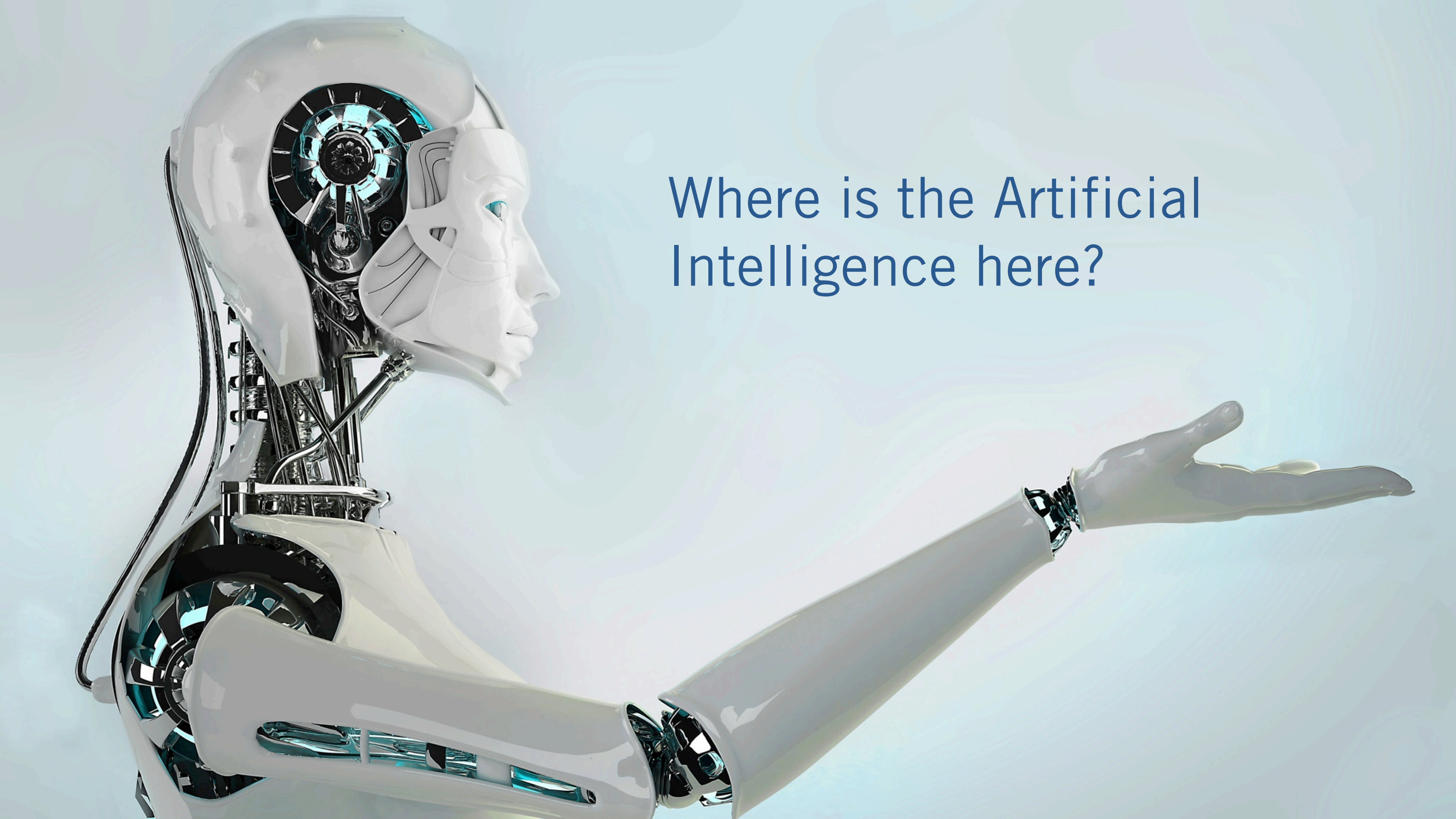
$2^2 \times 3^8 + (8 \times 3) + 2 = 26{,}270$ cells

BayesiaLab WebSimulator

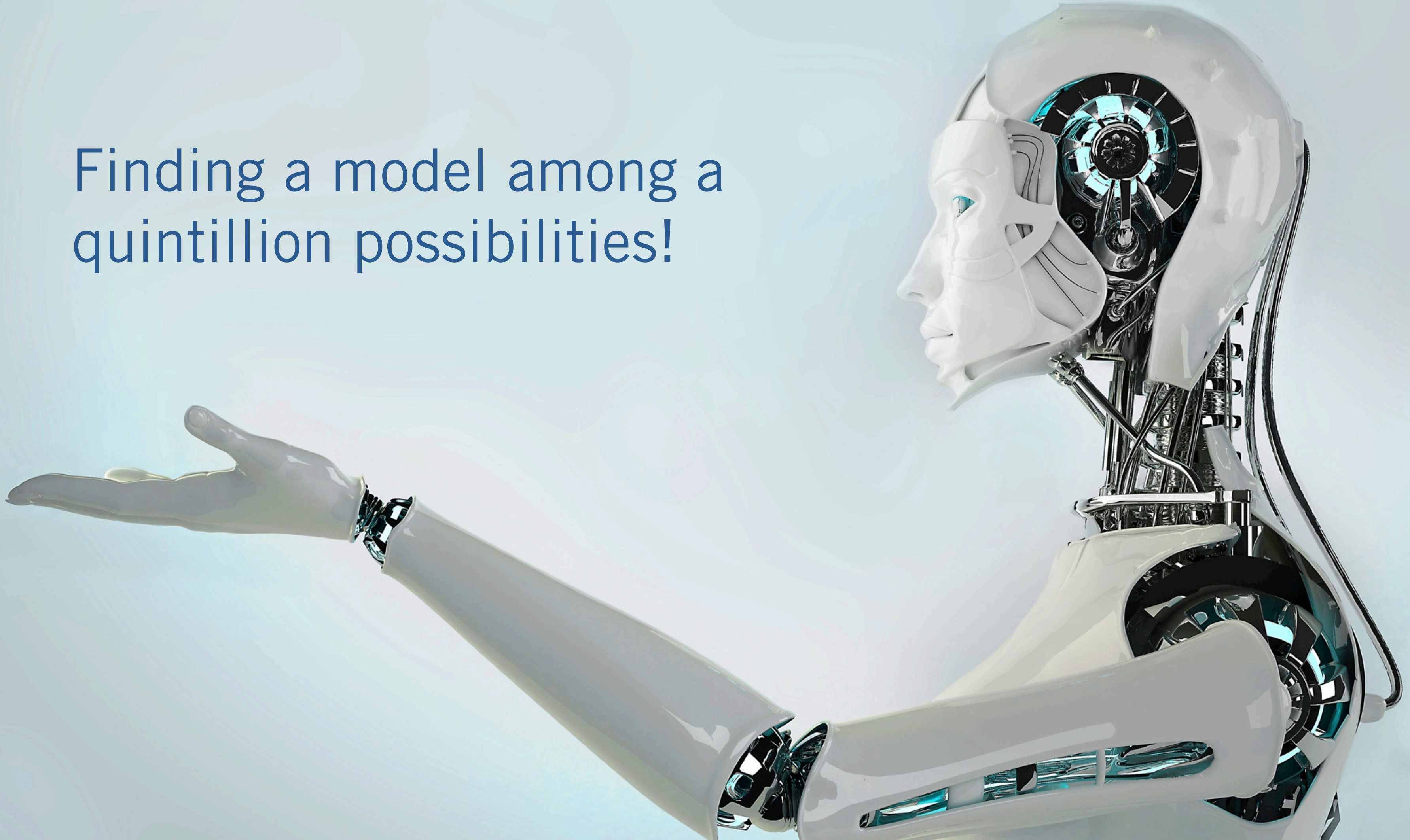


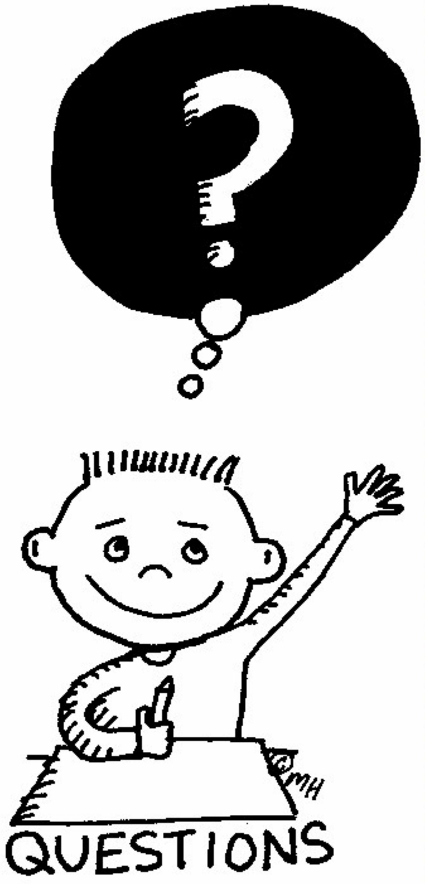
BayesiaLab WebSimulator

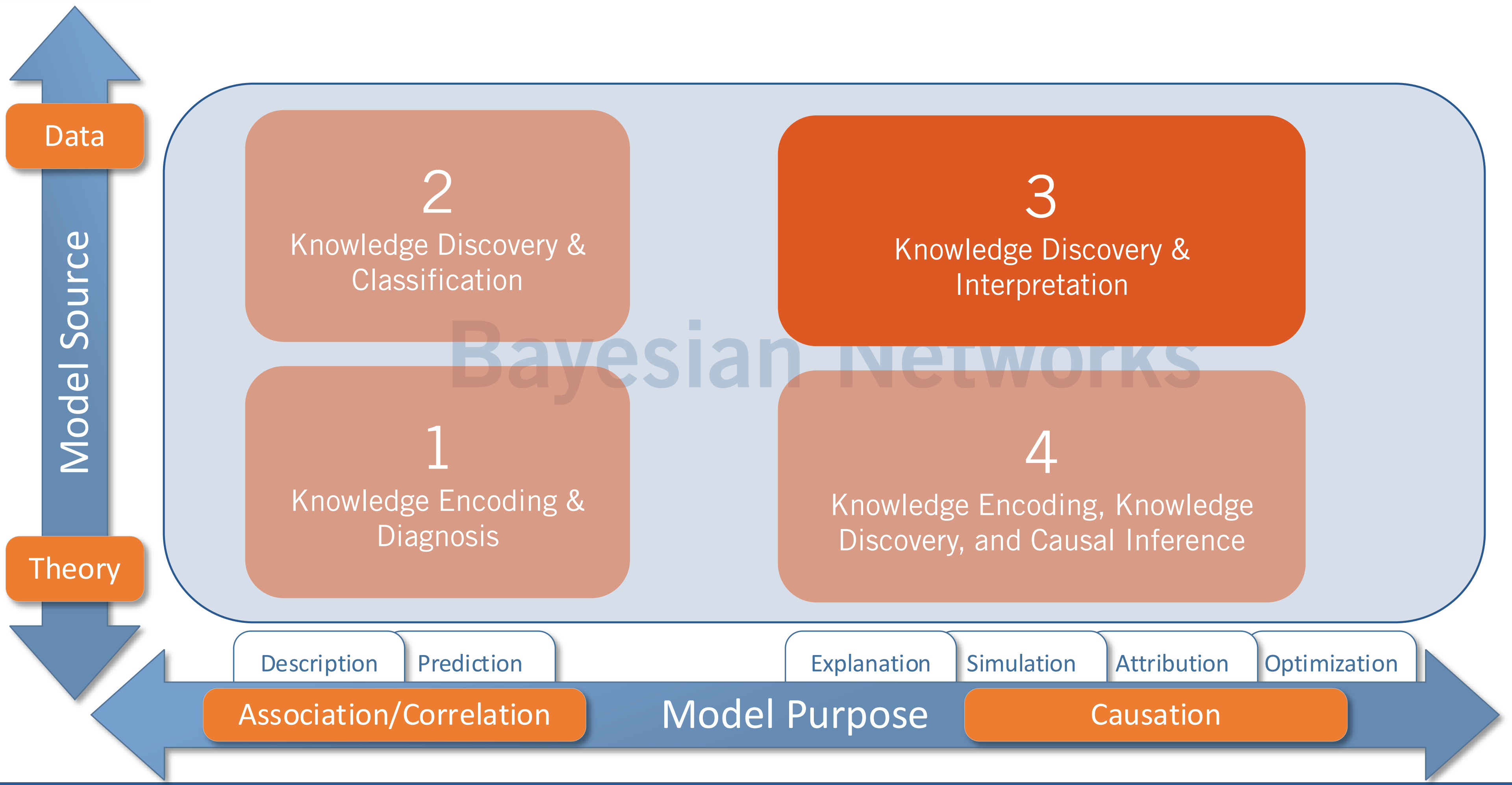



Where is the Artificial
Intelligence here?

Finding a model among a quintillion possibilities!




QUESTIONS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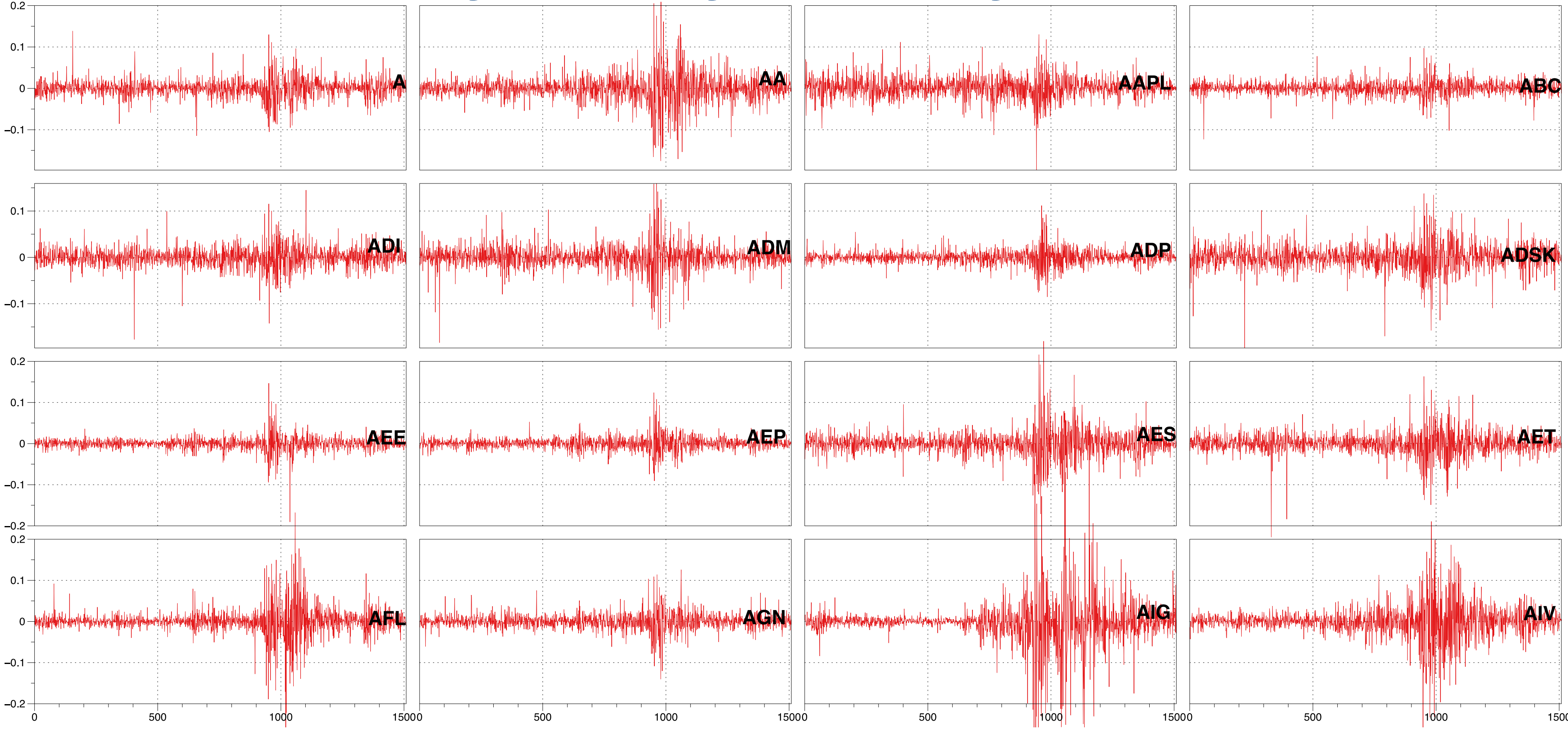
Causation

See Chapter 7

Knowledge Discovery & Anomaly Detection

The S&P 500, day-over-day returns by stock



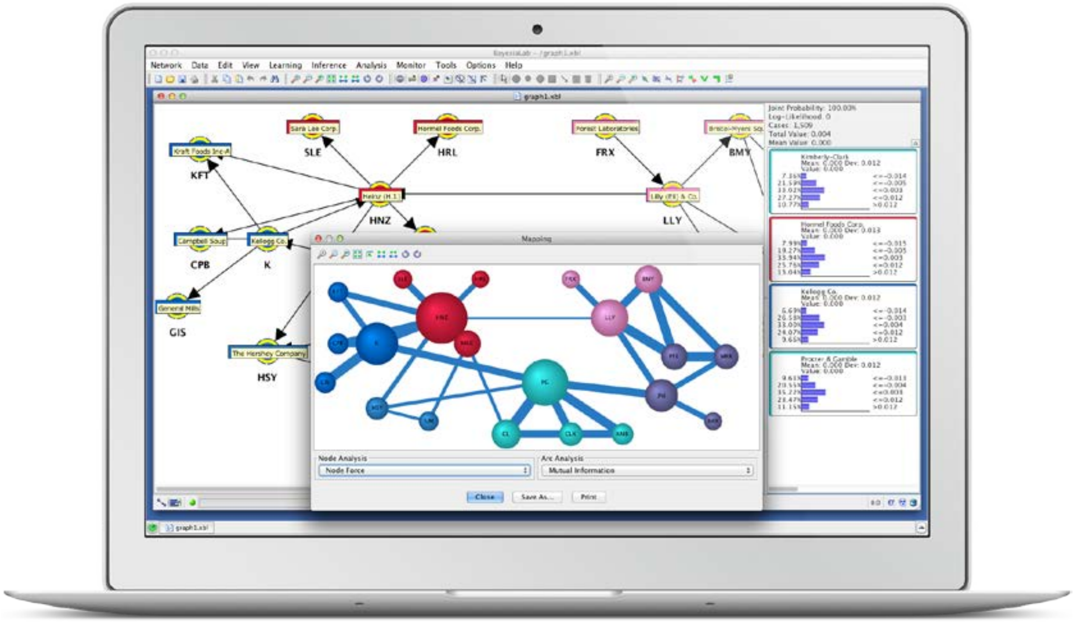
Why is this so difficult?

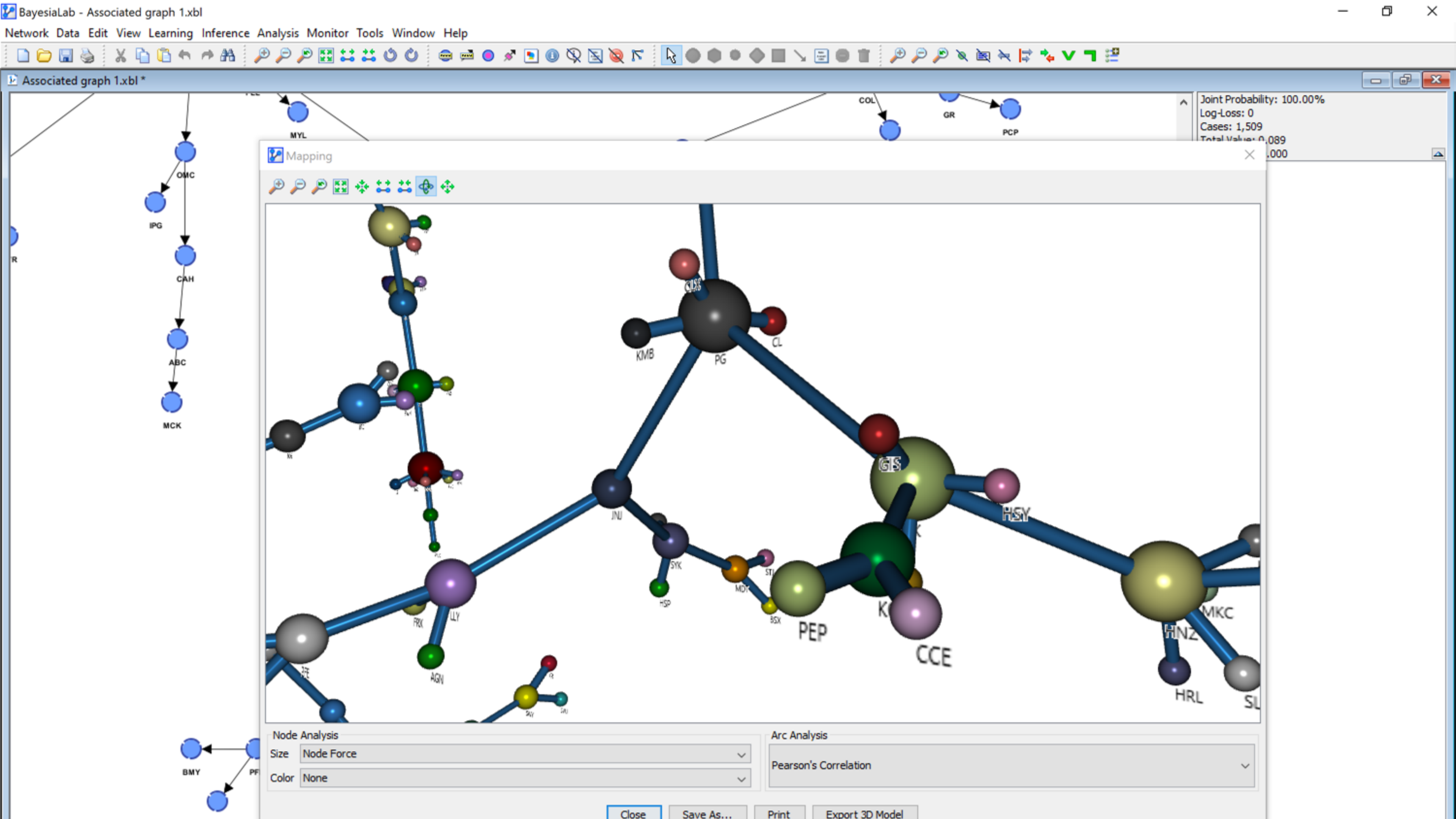
	A	AA	AAPL	ABC	ADI	ADM	ADP	ADSK	AEE	AEP	AES	AET	AFL	AGN	AIV	AIZ	AKAM	AKS	ALL	ALTR	AMAT	AMD	AMGN	AMT
A		0.570668	0.46678	0.408163	0.533252	0.425324	0.535525	0.495613	0.531351	0.486749	0.490094	0.384297	0.476417	0.465186	0.506165	0.450875	0.4315	0.533276	0.490529	0.521889	0.541416	0.454983	0.388191	0.526454
AA	0.570668		0.412423	0.363121	0.432512	0.49727	0.513374	0.453742	0.540668	0.487494	0.555778	0.386198	0.505749	0.417878	0.533665	0.525495	0.433653	0.691676	0.558741	0.443481	0.502896	0.406542	0.357239	0.532022
AAPL	0.46678	0.412423		0.236667	0.43525	0.323588	0.403402	0.417302	0.340484	0.322327	0.319482	0.289725	0.334087	0.328982	0.402068	0.340316	0.38855	0.432112	0.351426	0.444068	0.463454	0.395558	0.330339	0.437053
ABC	0.408163	0.363121	0.236667		0.329262	0.298421	0.416881	0.31158	0.440094	0.417974	0.347976	0.408529	0.294418	0.391646	0.33699	0.360633	0.288028	0.340885	0.39043	0.318401	0.309671	0.244243	0.36276	0.347773
ADI	0.533252	0.432512	0.43525	0.329262		0.321593	0.483858	0.482746	0.425898	0.371848	0.343594	0.314271	0.389693	0.366576	0.462091	0.371839	0.426141	0.460124	0.423266	0.691107	0.638214	0.495377	0.330517	0.467126
ADM	0.425324	0.49727	0.323588	0.298421	0.321593		0.378516	0.322902	0.452433	0.403492	0.417093	0.305003	0.366817	0.304062	0.366267	0.358504	0.389176	0.452943	0.392224	0.352995	0.339473	0.274791	0.266671	0.414046
ADP	0.535525	0.513374	0.403402	0.416881	0.483858	0.378516		0.452686	0.542809	0.527541	0.456298	0.372908	0.50101	0.486193	0.526986	0.507023	0.406286	0.476395	0.514611	0.513513	0.515278	0.394056	0.406387	0.48288
ADSK	0.495613	0.453742	0.417302	0.31158	0.482746	0.322902	0.452686		0.421398	0.402325	0.442238	0.349215	0.417223	0.389226	0.447525	0.405751	0.392804	0.43849	0.41419	0.46149	0.497755	0.396007	0.333145	0.45594
AEE	0.531351	0.540668	0.340484	0.440094	0.425898	0.452433	0.542809	0.421398		0.756735	0.590583	0.424766	0.513378	0.475327	0.474898	0.473565	0.321768	0.452686	0.537636	0.447271	0.436028	0.31983	0.390525	0.465076
AEP	0.486749	0.487494	0.322327	0.417974	0.371848	0.403492	0.527541	0.402325	0.756735		0.565275	0.403458	0.42596	0.440173	0.419188	0.458727	0.318872	0.422276	0.459285	0.396228	0.417472	0.292099	0.398822	0.446867
AES	0.490094	0.555778	0.319482	0.347976	0.343594	0.417093	0.456298	0.442238	0.590583	0.565275		0.378383	0.476892	0.40224	0.420327	0.453099	0.34483	0.492532	0.476188	0.349014	0.398017	0.315139	0.308978	0.438492
AET	0.384297	0.386198	0.289725	0.408529	0.314271	0.305003	0.372908	0.349215	0.424766	0.403458	0.378383		0.370713	0.421565	0.364347	0.420521	0.249157	0.360531	0.427641	0.290668	0.279035	0.275143	0.321026	0.401321
AFL	0.476417	0.505749	0.334087	0.294418	0.389693	0.366817	0.50101	0.417223	0.513378	0.42596	0.476892	0.370713		0.418877	0.588516	0.588617	0.351403	0.446767	0.634718	0.390395	0.459462	0.364762	0.285856	0.50493
AGN	0.465186	0.417878	0.328982	0.391646	0.366576	0.304062	0.486193	0.389226	0.475327	0.440173	0.40224	0.421565	0.418877		0.422619	0.396071	0.323589	0.388559	0.443402	0.332295	0.393542	0.347243	0.345897	0.461649
AIV	0.506165	0.533665	0.402068	0.33699	0.462091	0.366267	0.526986	0.447525	0.474898	0.419188	0.420327	0.364347	0.588516	0.422619		0.558192	0.408232	0.49093	0.644666	0.485371	0.541239	0.390922	0.30768	0.512831
AIZ	0.450875	0.525495	0.340316	0.360633	0.371839	0.358504	0.507023	0.405751	0.473565	0.458727	0.453099	0.420521	0.588617	0.396071	0.558192		0.353718	0.45162	0.616235	0.378966	0.430116	0.315676	0.343417	0.513195
AKAM	0.4315	0.433653	0.38855	0.288028	0.426141	0.389176	0.406286	0.392804	0.321768	0.318872	0.34483	0.249157	0.351403	0.323589	0.408232	0.353718		0.438362	0.364883	0.435992	0.428331	0.368554	0.245363	0.419715
AKS	0.533276	0.691676	0.432112	0.340885	0.460124	0.452943	0.476395	0.43849	0.452686	0.422276	0.492532	0.360531	0.446767	0.388559	0.49093	0.45162	0.438362		0.478014	0.420897	0.475609	0.423204	0.337167	0.508704
ALL	0.490529	0.558741	0.351426	0.39043	0.423266	0.392224	0.514611	0.41419	0.537636	0.459285	0.476188	0.427641	0.634718	0.443402	0.644666	0.616235	0.364883	0.478014		0.436321	0.503192	0.387605	0.312268	0.525026
ALTR	0.521889	0.443481	0.444068	0.318401	0.691107	0.352995	0.513513	0.46149	0.447271	0.396228	0.349014	0.290668	0.390395	0.332295	0.485371	0.378966	0.435992	0.420897	0.436321		0.645041	0.490712	0.332572	0.480285
AMAT	0.541416	0.502896	0.463454	0.309671	0.638214	0.339473	0.515278	0.497755	0.436028	0.417472	0.398017	0.279035	0.459462	0.393542	0.541239	0.430116	0.428331	0.475609	0.503192	0.645041		0.481282	0.354883	0.482778
AMD	0.454983	0.406542	0.395558	0.244243	0.495377	0.274791	0.394056	0.396007	0.31983	0.292099	0.315139	0.275143	0.364762	0.347243	0.390922	0.315676	0.368554	0.423204	0.387605	0.490712	0.481282		0.230527	0.390012
AMGN	0.388191	0.357239	0.330339	0.36276	0.330517	0.266671	0.406387	0.333145	0.390525	0.398822	0.308978	0.321026	0.285856	0.345897	0.30768	0.343417	0.245363	0.337167	0.312268	0.332572	0.354883	0.230527		0.327344
AMT	0.526454	0.532022	0.437053	0.347773	0.467126	0.414046	0.48288	0.45594	0.465076	0.446867	0.438492	0.401321	0.50493	0.461649	0.512831	0.513195	0.419715	0.508704	0.525026	0.480285	0.482778	0.390012	0.327344	
AMZN	0.447969	0.369067	0.450858	0.269919	0.420969	0.313261	0.41627	0.383973	0.32218	0.314108	0.28071	0.280863	0.359955	0.336944	0.397449	0.347806	0.385661	0.390437	0.351342	0.443469	0.435212	0.318144	0.330847	0.412541
AN	0.434231	0.421882	0.356532	0.32279	0.396946	0.3356	0.48281	0.398276	0.418626	0.403467	0.396463	0.31938	0.398142	0.405956	0.527987	0.379416	0.325586	0.385994	0.468298	0.407543	0.442268	0.38444	0.24893	0.454988
AON	0.355157	0.302349	0.313291	0.285397	[illegible]	[illegible]	0.415268	0.316525	0.34569	[illegible]	0.263416	0.288455	0.375479	0.357269	[illegible]	[illegible]	0.274928	[illegible]	[illegible]	0.333994	0.335388	0.251346	0.277415	0.371444
APA	0.526604	0.650504	0.418089	0.336526	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.391492	0.432124	0.354574	0.370017	0.505615
APC	0.511121	0.615743	0.400957	0.331357	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.379509	0.420906	0.355932	0.348863	0.498139
APD	0.599624	0.660684	0.474523	0.393305	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.387473	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.48682	0.535256	0.432996	0.381744	0.549406
APH	0.609062	0.595131	0.440578	0.379512	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.555311	0.569614	0.457246	0.353911	0.543522
APOL	0.259251	0.198149	0.238565	0.197063	0.263308	0.188051	[illegible]	0.19829	0.224831	0.225768	0.196726	0.14888	0.187304	0.273628	0.249256	0.207321	0.226805	0.189848	0.209487	0.265137	0.280968	0.199441	0.242931	0.251218
ARG	0.463581	0.545822	0.365495	0.312003	0.394891	0.396253	0.454898	0.397411	0.426527	0.394095	0.422672	0.326101	0.41313	0.439539	0.468224	0.469585	0.393391	0.517099	0.45627	0.399145	0.450687	0.382813	0.327768	0.464636
ATI	0.551702	0.671155	0.468605	0.32646	0.469434	0.46153	0.481823	0.474792	0.426529	0.404646	0.501507	0.367617	0.485348	0.427184	0.535394	0.46796	0.483708	0.70012	0.469976	0.432982	0.516144	0.429832	0.317248	0.561005
AVB	0.506355	0.522914	0.40051	0.35525	0.461656	0.387026	0.563926	0.469986	0.492949	0.458627	0.44052	0.39079	0.592147	0.46746	0.835156	0.542785	0.426172	0.490971	0.627993	0.480013	0.527593	0.389846	0.341269	0.547976
AVP	0.425979	0.475688	0.281466	0.373409	0.361129	0.321322	0.441828	0.364843	0.444585	0.404014	0.415096	0.329632	0.41179	0.360338	0.418638	0.458887	0.301925	0.397706	0.483325	0.344494	0.386897	0.263946	0.30347	0.410762
AVY	0.571726	0.59043	0.442901	0.414121	0.477182	0.405785	0.587385	0.491581	0.544327	0.506429	0.519419	0.388443	0.537959	0.473899	0.566537	0.524823	0.454944	0.541885	0.537097	0.479813	0.53628	0.408182	0.364864	0.51576
AXP	0.550383	0.556598	0.451681	0.348597	0.491924	0.383629	0.552367	0.503484	0.529938	0.463986	0.498597	0.418844	0.627479	0.482441	0.66095	0.565521	0.433048	0.530309	0.6349	0.490164	0.533405	0.445452	0.354874	0.523076
AZO	0.389197	0.36613	0.359618	0.323528	0.37567	0.315157	0.430439	0.350516	0.36747	0.368242	0.28232	0.316557	0.314598	0.363471	0.440819	0.349817	0.339267	0.383425	0.421363	0.395659	0.390238	0.30307	0.306064	0.409042
BA	0.536792	0.553126	0.389873	0.376812	0.417567	0.406261	0.530019	0.478263	0.499183	0.480277	0.491165	0.382159	0.438039	0.431316	0.495379	0.463915	0.395861	0.478367	0.463653	0.422577	0.463405	0.373107	0.373122	0.472803
BAC	0.433308	0.493382	0.366495	0.270889	0.377217	0.352033	0.44551	0.425861	0.405937	0.350801	0.392386	0.382054	0.616912	0.38116	0.634658	0.51943	0.343526	0.458582	0.616693	0.379977	0.452684	0.351244	0.267629	0.443082
BAX	0.364164	0.337779	0.241404	0.40777	0.302511	0.28644	0.415321	0.300811	0.435701	0.433536	0.347148	0.374889	0.322228	0.384565	0.327158	0.348232	0.265074	0.284101	0.380461	0.310075	0.313548	0.196071	0.38861	0.348706
BBBY	0.468221	0.423139	0.413509	0.328158	0.473787	0.297855	0.510004	0.456691	0.4146	0.426185	0.369653	0.342143	0.423561	0.429473	0.547763	0.43304	0.376829	0.408935	0.506375	0.481281	0.504136	0.378435	0.3283	0.499238
BBT	0.433809	0.463028	0.368087	0.279989	0.411282	0.342422	0.476331	0.425786	0.411694	0.350015	0.383004	0.35486	0.598343	0.401062	0.666529	0.515845	0.358925	0.414523	0.61633	0.449899	0.485143	0.360988	0.29298	0.479336
BBY	0.495356	0.449696	0.399563	0.347432	0.45022	0.291525	0.490867	0.44886	0.43886	0.382908	0.385523	0.401162	0.45557	0.424426	0.541647	0.431485	0.4222	0.433192	0.518191	0.455636	0.495246	0.401394	0.302345	0.502447
BCR	0.391906	0.310775	0.230796	0.370898	0.3114	0.303303	0.423118	0.302315	0.375128	0.395765	0.281414	0.309679	0.250455	0.368434	0.28138	0.25144	0.259484	0.293674	0.283488	0.338499	0.30658	0.19321	0.327033	0.324939
BDX	0.381317	0.358334	0.28627	0.432165	0.342131	0.326909	0.416168	0.361338	0.428896	0.431607	0.339695	0.380397	0.29795	0.38625	0.315431	0.341334	0.31698	0.294382	0.364802	0.349085	0.346809	0.242783	0.355392	0.375279
BEN	0.585555	0.595731	0.483591	0.393013	0.528481	0.426946	0.601154	0.539768	0.527287	0.491285	0.51718	0.462026	0.611032	0.518374	0.687858	0.559709	0.458693	0.542917	0.66387	0.545534	0.59278	0.439221	0.384992	0.584196
BHI	0.496655	0.607791	0.365382	0.301868	0.410752	0.429127	0.483844	0.413269	0.516468	0.457134	0.521625	0.308698	0.475569	0.427503	0.450773	0.488756	0.376165	0.584975	0.462373	0.39785	0.440008	0.36379	0.351432	0.489411
BIG	0.417729	0.370997	0.34669	0.300351	0.414284	0.296822	0.424466	0.345094	0.337216	0.340012	0.298675	0.246715	0.324984	0.319566	0.464709	0.348216	0.325918	0.389046	0.392591	0.414227	0.458111	0.331507	0.265201	0.394915
BIIB	0.309555	0.285352	0.238974	0.251218	0.283607	0.222656	0.301568	0.279752	0.289901	0.282314	0.266317	0.25128	0.232275	0.299019	0.285074	0.268744	0.242028	0.27073	0.285807	0.291492	0.287344	0.229893	0.327606	0.300888
BK	0.489067	0.468321	0.464737	0.313512	0.436839	0.421527	0.531194	0.447572	0.468614	0.430723	0.410842	0.4326	0.590017	0.425655	0.643937	0.555759	0.398695	0.473072	0.602925	0.462608	0.501537	0.364609	0.384531	0.534049
BLL	0.532978	0.569608	0.438978	0.381642	0.452186	0.415632	0.527822	0.467046	0.503021	0.491044	0.47442	0.429851	0.457009	0.449432	0.515473	0.450148	0.402386	0.540175	0.503263	0.451672	0.470438	0.393521	0.37076	0.515988
BMC	0.484901	0.426124	0.39192	0.337104	0.44692	0.35346	0.483539	0.436898	0.39745	0.391245	0.394793	0.306678	0.384154	0.383363	0.415601	0.405406	0.434695	0.384378	0.385776	0.458195	0.469597	0.357352	0.319991	0.442105
BMS	0.557018	0.546	0.445594	0.40427	0.474782	0.419983	0.585078	0.465557	0.512328	0.478471	0.48273	0.385279	0.520274	0.456144	0.594567	0.491022	0.395979	0.504484	0.537416	0.491115	0.530614	0.372977	0.381359	0.538431
BMY	0.411691	0.412368	0.3273	0.41428	0.363813	0.314146	0.428291	0.37372	0.470029	0.455511	0.363957	0.407842	0.353649	0.431329	0.380266	0.352307	0.301861	0.330497	0.390222	0.370411	0.345948	0.269758	0.376972	0.396006
BRCM	0.490844	0.385385	0.485508	0.255478	0.625875	0.299905	0.441099	0.442124	0.319002	0.309001	0.290782	0.250998	0.346102	0.342665	0.398453	0.305771	0.424602	0.421353	0.338205	0.644431	0.580699	0.452178	0.308477	0.434288
BSX	0.436815	0.416474	0.28357	0.344597	0.350234	0.272351	0.405498	0.336515	0.439737	0.412979	0.383164	0.365185	0.363128	0.431504	0.365194	0.356593	0.298881	0.374756	0.431941	0.351716	0.352277	0.310221	0.351996	0.369692
BTU	0.510592	0.670683	0.411981	0.296738	0.417331	0.484134	0.417278	0.409263	0.453023	0.393542	0.503184	0.316202	0.429952	0.387467	0.466927	0.436209	0.447905	0.664027	0.430931	0.399014	0.427335	0.389681	0.33163	0.50623
BXP	0.505837	0.523994	0.421196	0.347926	0.503783	0.393692	0.56129	0.483873	0.484937	0.440005	0.463325	0.384944	0.608646	0.441914	0.825278	0.540962	0.433873	0.508949	0.619793	0.497654	0.544885	0.396281	0.329636	0.553332
C	0.417005	0.419585	0.343292	0.249441	0.377965	0.328598	0.415691	0.433343	0.400565	0.345319	0.39913	0.393014	0.551257	0.365664	0.524075	0.48817	0.32679	0.409656	0.552036	0.354703	0.418927	0.348903	0.232241	0.428006
CA	0.549523	0.504771	0.450596	0.334365	0.507735	0.407018	0.543418	0.464942	0.496246	0.44533	0.468206	0.344968	0.456771	0.450045	0.504631	0.44069	0.410707	0.453196	0.459919	0.545819	0.519701	0.413429	0.377604	0.494334
CAG	-0.003684	0.02276	-0.025557	0.022018	0.010912	0.024514	-0.034525	-0.026237	0.028289	0.023338	-0.019872	-0.027597	-0.07364	-0.007176	-0.017301	0.013334	-0.004646	0.011745	0.023311	0.014633	0.015303	-0.018471	-0.019379	0.022957
CAH	0.324064	0.340098	0.220634	0.475718	0.298567	0.249979	0.373953	0.287879	0.362118	0.332586	0.309738	0.351571	0.309586	0.334583	0.316234	0.329159	0.236831	0.306169	0.349887	0.295712	0.311517	0.254185	0.288913	0.322284
CAM	[illegible]	0.624778	0.429512	0.310122	0.43619	0.48486	0.463858	0.413028	0.492698	0.447058	0.544783	0.317838	0.452579	0.429352	0.461615	0.434438	0.410534	0.624599	0.441948	0.422347	0.454833	0.393625	0.330634	0.498737
CAT	0.592166	0.657227	0.442608	0.358513	0.494344	0.44908	0.544992	0.500966	0.507931	0.453722	0.507983	0.356756	0.527594	0.46727	0.5627	0.474372	0.446984	0.606228	0.533464	0.487701	0.538366	0.454934	0.32592	0.506686
CB	0.480213	0.457227	0.418036	0.38095	0.426432	0.386522	0.567561	0.458827	0.52091	0.502698	0.455697	0.44888	0.585353	0.437052	0.583735	0.599227	0.365528	0.433759	0.677012	0.445354	0.468949	0.364804	0.413702	0.532896

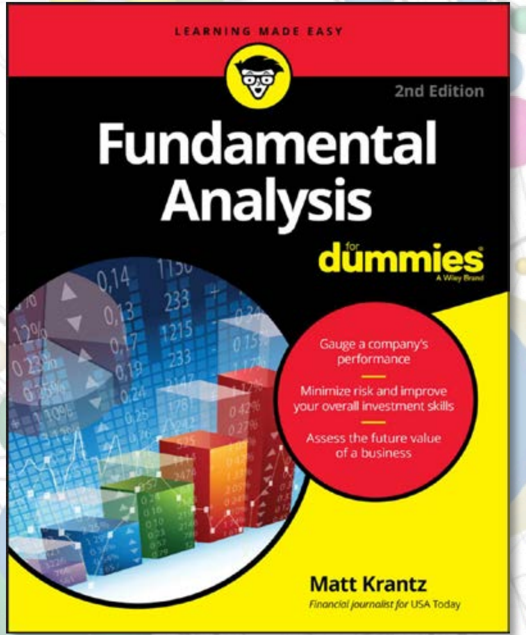
Example: Knowledge Discovery

Workflow

- Data Import
- Discretization
- Unsupervised Learning
- Structural Interpretation



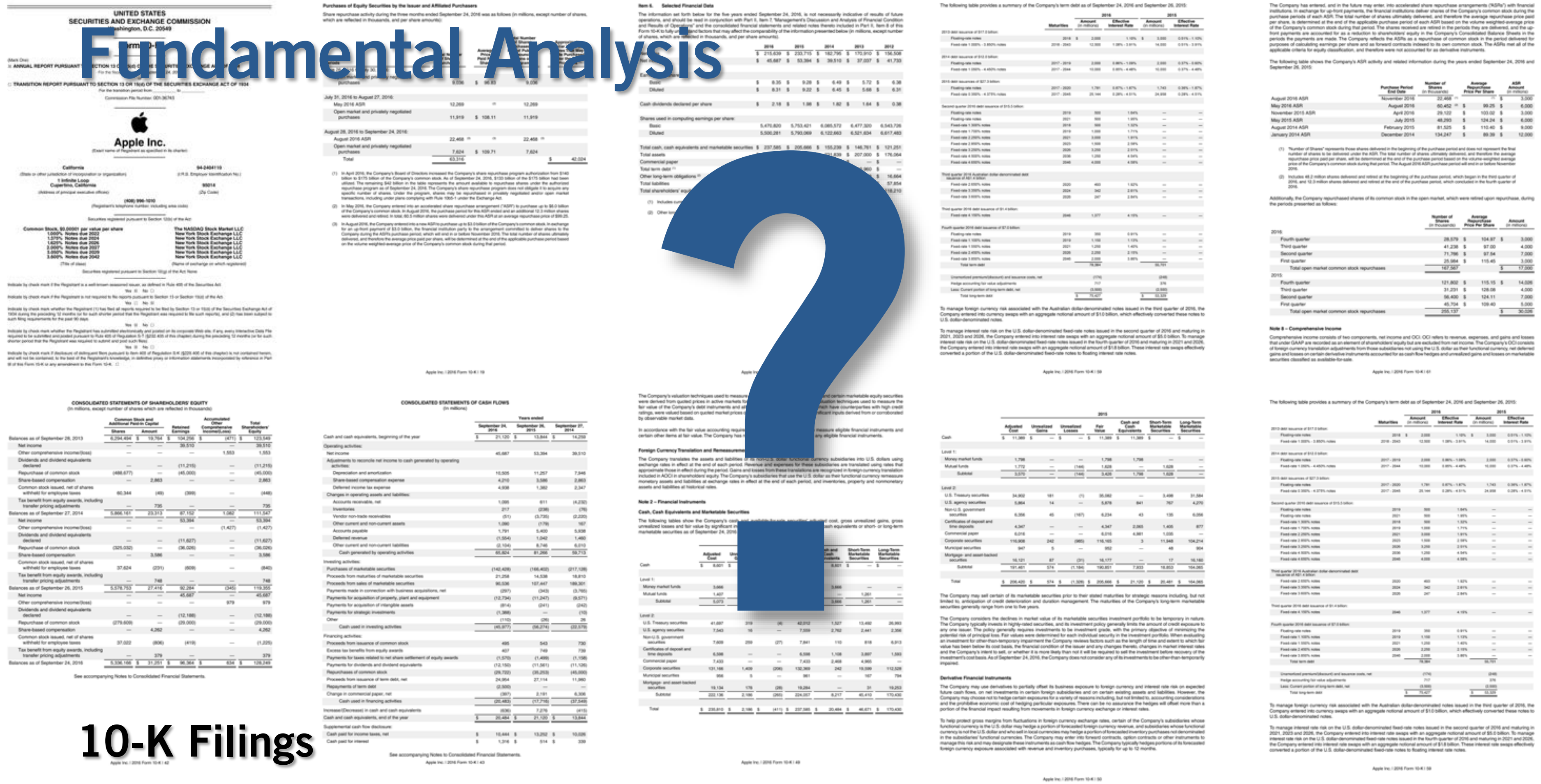

BayesiaLab - Associated graph 1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 1.xbl *
Joint Probability: 100.00%
Log-Loss: 0
Cases: 1,509
Mapping
Node Analysis
Size Node Force
Color None
Arc Analysis
Pearson's Correlation
Close
Save As...
Print
Export 3D Model
MYL
COL
GR
PCP
OMC
IPG
CAH
ABC
MCK
BMY
KMB
PG
CL
GIS
HSY
JNJ
SYK
HSP
PEP
CCE
MKC
HNZ
HRL
LLY
AGN



Example 3b: Fundamental Stock Analysis

Knowledge Discovery from Financial Statements

Fundamental Analysis



10-K Filings

Fundamental Analysis

- Shares
- Shares split adjusted
- Split factor
- Current Assets
- Assets
- Current Liabilities
- Liabilities
- Shareholders equity
- Non-controlling interest
- Preferred equity
- Goodwill & intangibles
- Long-term debt
- Revenue
- Earnings
- Earnings available for common stockholders
- EPS basic
- EPS diluted
- Dividend per share
- Cash from operating activities
- Cash from investing activities
- Cash from financing activities
- Cash change during period
- Cash at end of period
- Capital expenditures
- Price
- Price high
- Price low
- ROE
- ROA
- Book value of equity per share
- P/B ratio
- P/E ratio
- Cumulative dividends per share
- Dividend payout ratio
- Long-term debt to equity ratio
- Equity to assets ratio
- Current ratio
- Net margin
- Asset turnover
- Free cash flow per share

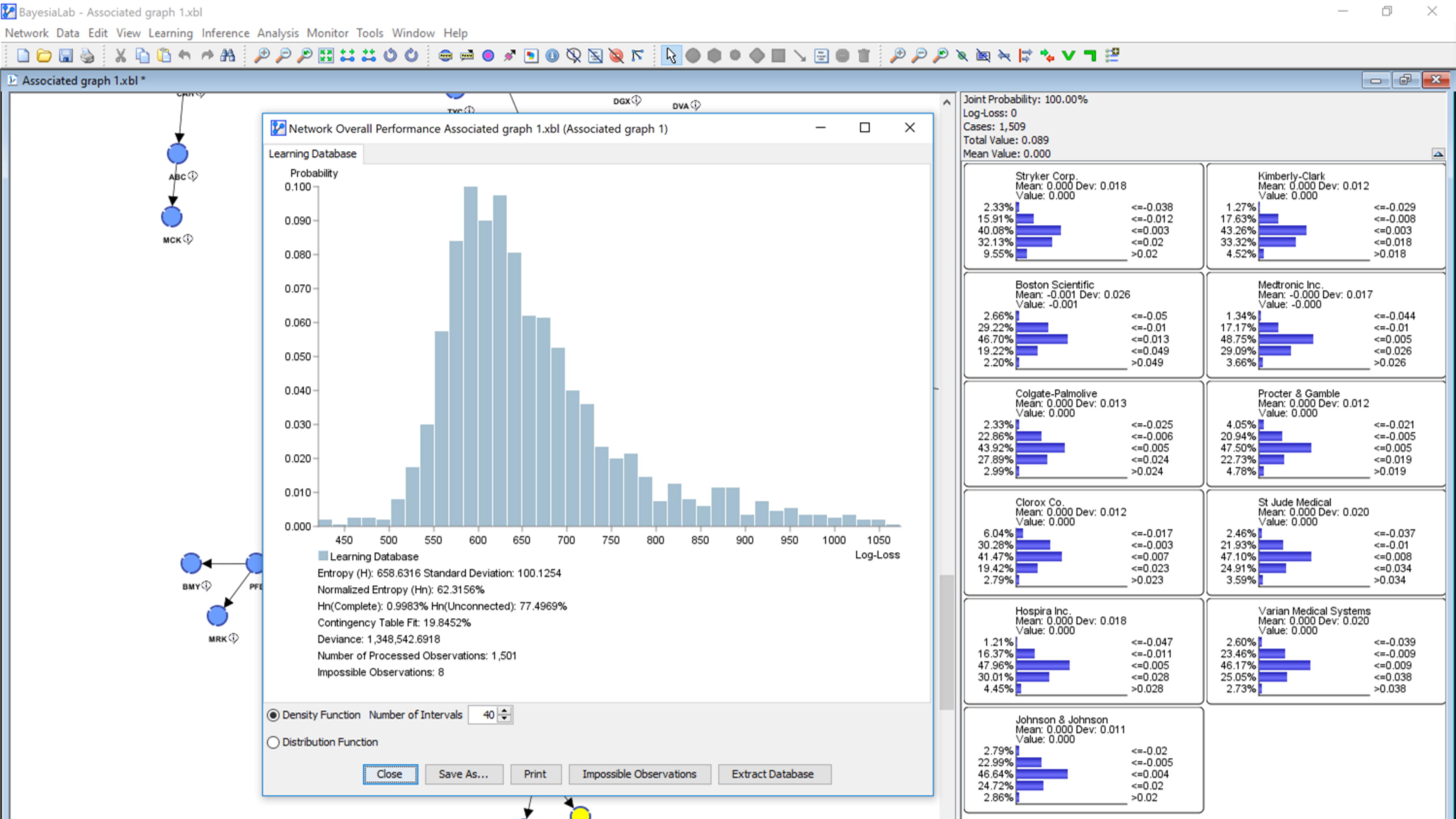
Example 3c: Anomaly Detection

The Curse of Dimensionality

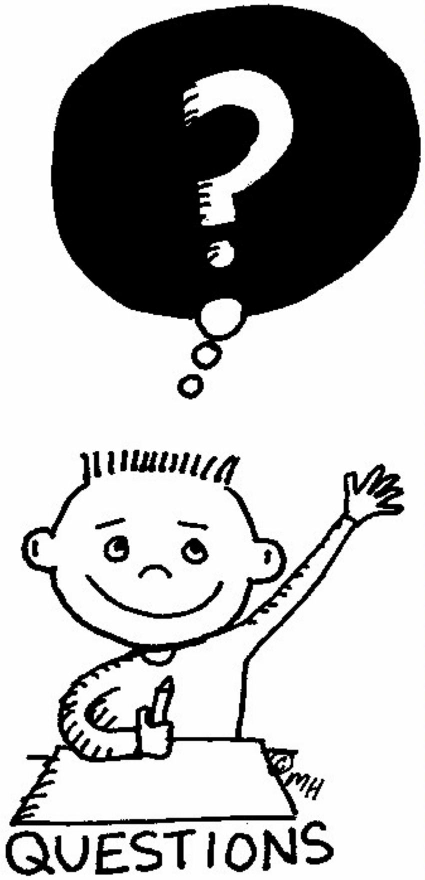
- "...as dimensionality increases, the distance to the nearest data point approaches the distance to the farthest data point."
- In other words, the contrast in distances of different data points becomes nonexistent. For high dimensional data sets, this means using outlier detection methods that are based on nearest neighbor will lead to outlier scores that are indistinguishable.

Anomaly Detection with Bayesian Networks

- With a Bayesian network, we can avoid the problem of the nearest/farthest distance measure, which becomes unreliable in higher dimensions.
- For any new observation, we can compute its likelihood given the network. This tells us how probable or improbable an observation is.



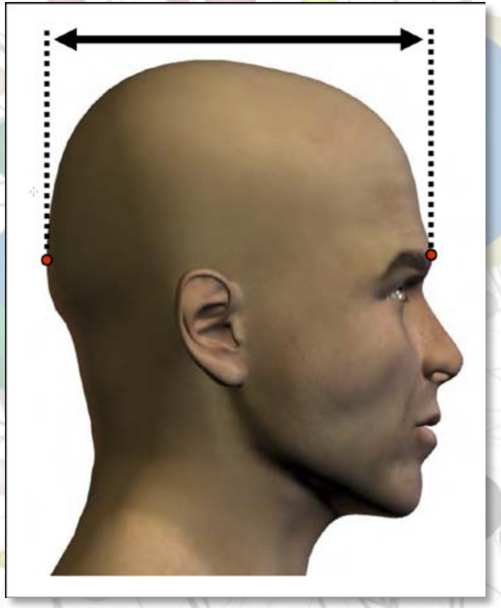
BayesiaLab - Associated graph 1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 1.xbl *
ABC
MCK
DGX
DVA
BMY
MRK
Network Overall Performance Associated graph 1.xbl (Associated graph 1)
Learning Database
Probability
0.100
0.090
0.080
0.070
0.060
0.050
0.040
0.030
0.020
0.010
0.000
450 500 550 600 650 700 750 800 850 900 950 1000 1050
Log-Loss
Learning Database
Entropy (H): 658.6316 Standard Deviation: 100.1254
Normalized Entropy (Hn): 62.3156%
Hn(Complete): 0.9983% Hn(Unconnected): 77.4969%
Contingency Table Fit: 19.8452%
Deviance: 1,348,542.6918
Number of Processed Observations: 1,501
Impossible Observations: 8
Density Function Number of Intervals 40
Distribution Function
Close
Save As...
Print
Impossible Observations
Extract Database
Joint Probability: 100.00%
Log-Loss: 0
Cases: 1,509
Total Value: 0.089
Mean Value: 0.000
Stryker Corp.
Mean: 0.000 Dev: 0.018
Value: 0.000
2.33% <=-0.038
15.91% <=-0.012
40.08% <=0.003
32.13% <=0.02
9.55% >0.02
Kimberly-Clark
Mean: 0.000 Dev: 0.012
Value: 0.000
1.27% <=-0.029
17.63% <=-0.008
43.26% <=0.003
33.32% <=0.018
4.52% >0.018
Boston Scientific
Mean: -0.001 Dev: 0.026
Value: -0.001
2.66% <=-0.05
29.22% <=-0.01
46.70% <=0.013
19.22% <=0.049
2.20% >0.049
Medtronic Inc.
Mean: -0.000 Dev: 0.017
Value: -0.000
1.34% <=-0.044
17.17% <=-0.01
48.75% <=0.005
29.09% <=0.026
3.66% >0.026
Colgate-Palmolive
Mean: 0.000 Dev: 0.013
Value: 0.000
2.33% <=-0.025
22.86% <=-0.006
43.92% <=0.005
27.89% <=0.024
2.99% >0.024
Procter & Gamble
Mean: 0.000 Dev: 0.012
Value: 0.000
4.05% <=-0.021
20.94% <=-0.005
47.50% <=0.005
22.73% <=0.019
4.78% >0.019
Clorox Co.
Mean: 0.000 Dev: 0.012
Value: 0.000
6.04% <=-0.017
30.28% <=-0.003
41.47% <=0.007
19.42% <=0.023
2.79% >0.023
St Jude Medical
Mean: 0.000 Dev: 0.020
Value: 0.000
2.46% <=-0.037
21.93% <=-0.01
47.10% <=0.008
24.91% <=0.034
3.59% >0.034
Hospira Inc.
Mean: 0.000 Dev: 0.018
Value: 0.000
1.21% <=-0.047
16.37% <=-0.011
47.96% <=0.005
30.01% <=0.028
4.45% >0.028
Varian Medical Systems
Mean: 0.000 Dev: 0.020
Value: 0.000
2.60% <=-0.039
23.46% <=-0.009
46.17% <=0.009
25.05% <=0.038
2.73% >0.038
Johnson & Johnson
Mean: 0.000 Dev: 0.011
Value: 0.000
2.79% <=-0.02
22.99% <=-0.005
46.64% <=0.004
24.72% <=0.02
2.86% >0.02


QUESTIONS

BAYESIALAB

Example 3d

ANSUR II Database

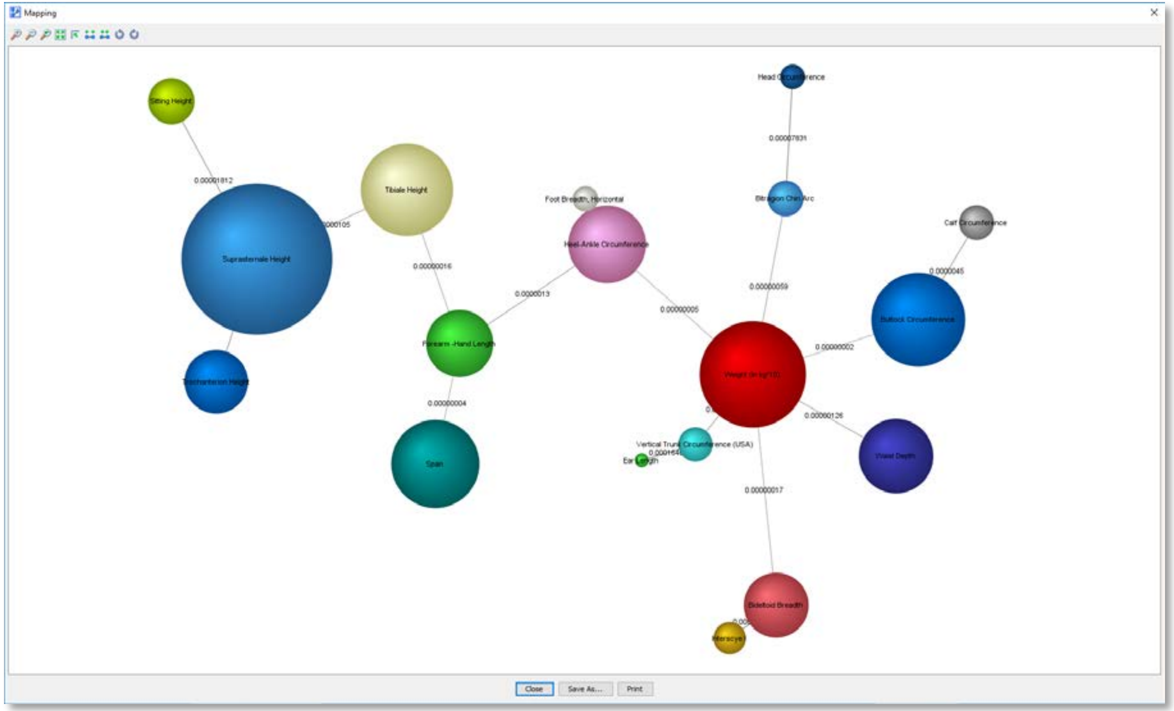


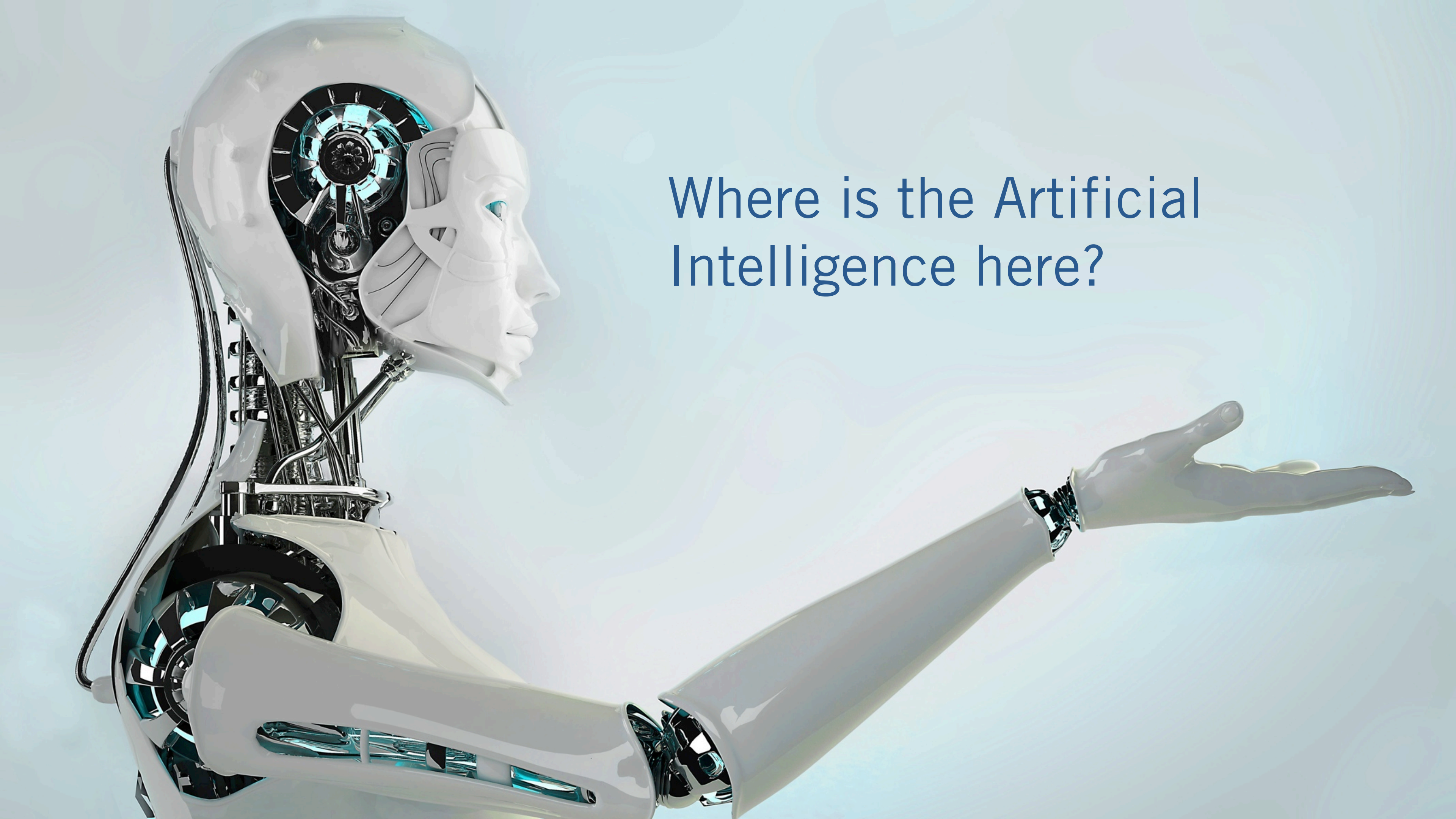
ANSUR II Database

Dendrogram

ANSUR II Database

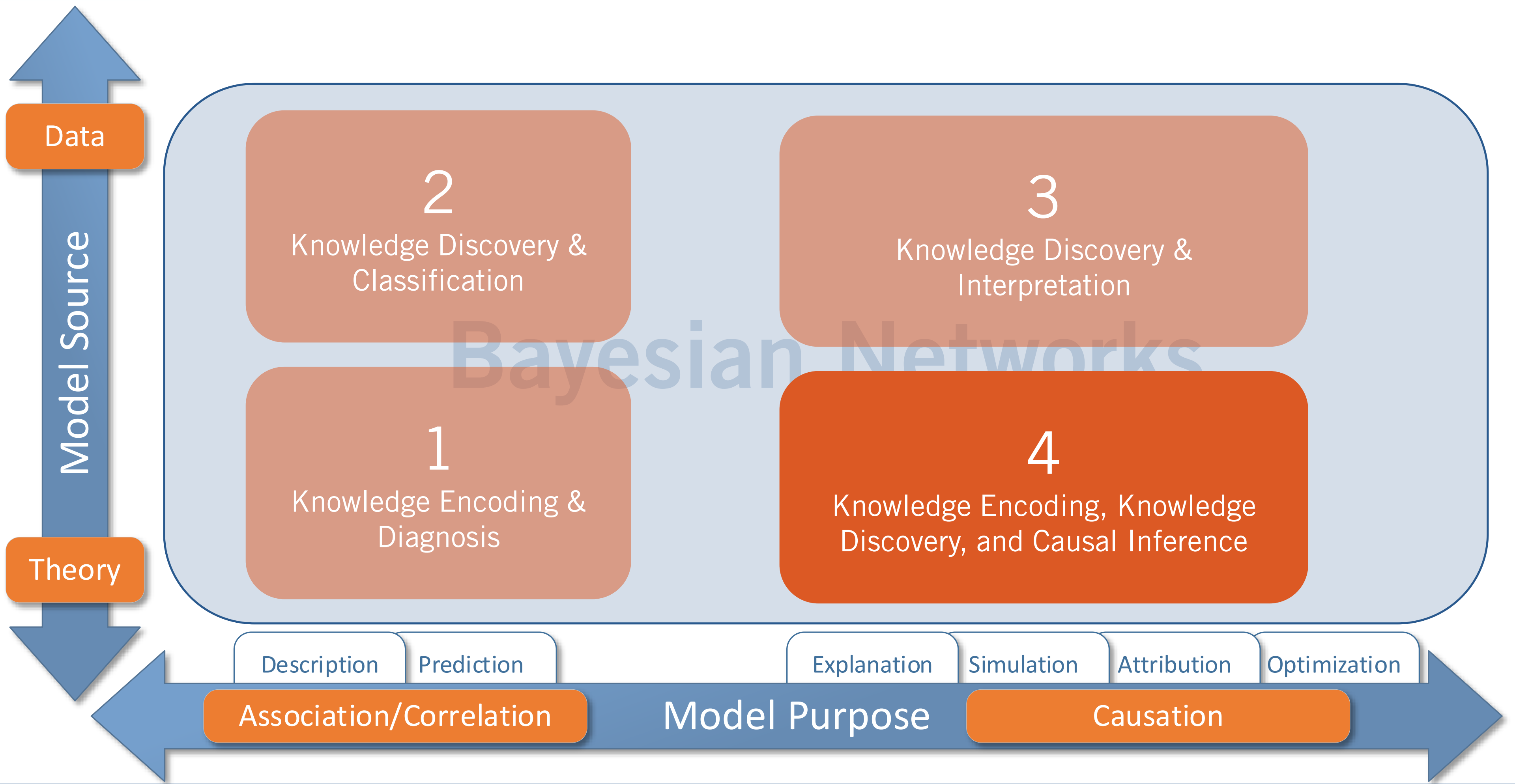
Mapping




Where is the Artificial
Intelligence here?

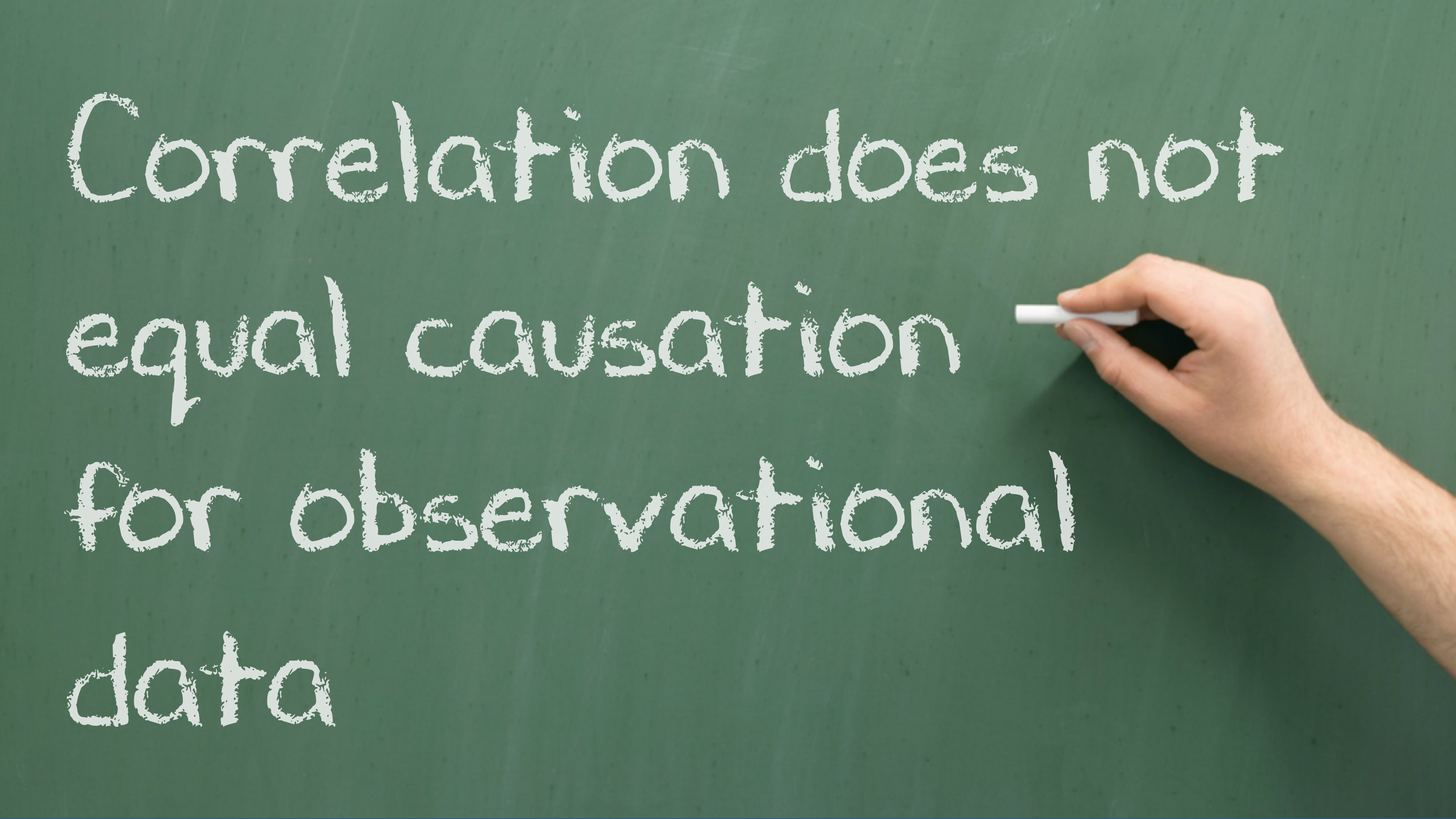
Finding a single model for hundreds of variables!

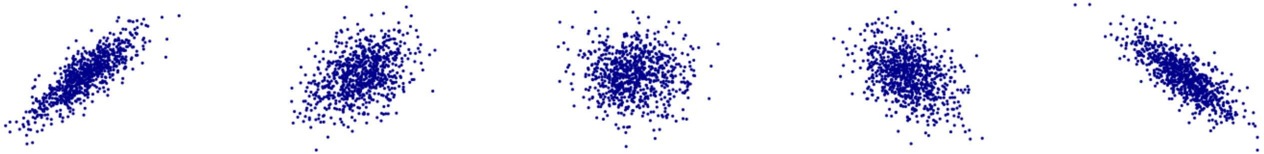
Coffee Break


Data
Model Source
Theory
2
Knowledge Discovery & Classification
3
Knowledge Discovery & Interpretation
Bayesian Networks
1
Knowledge Encoding & Diagnosis
4
Knowledge Encoding, Knowledge Discovery, and Causal Inference
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Example 4a

House Price Analysis


Correlation does not
equal causation
for observational
data

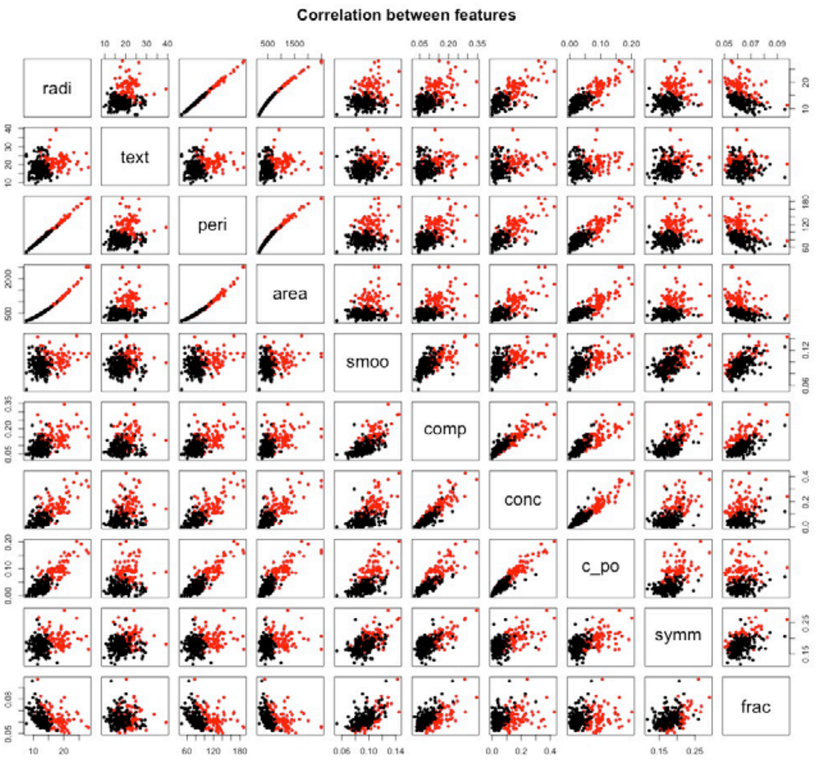


Observational Data → Association/Correlation

Observational vs. Causal Inference

Why?

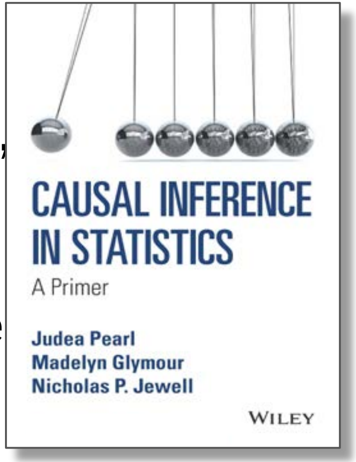
- Observational data only provides associations/correlations.
- A statistical model can approximate the joint probability distribution of the data produced by the domain under study.
- However, with such a statistical model we can only perform **observational inference**, i.e. produce **predictions**.



Observational vs. Causal Inference

Observational Inference (Prediction)

"given that I see"



Causal Inference (Inte

"given that I do"

ambiguous


21
14
BUST
APRIL
900
EMILY
100
RYAN
0


A

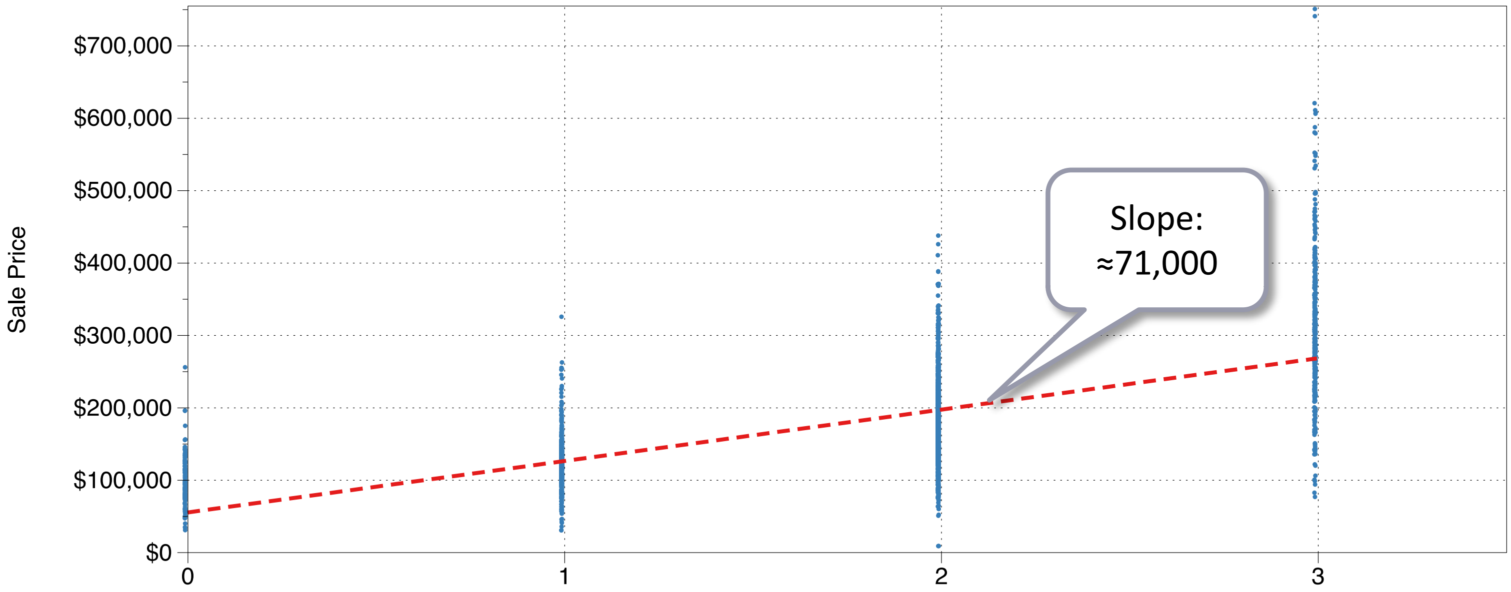

B


C

Observational vs. Causal Inference

See Chapter 5

Ames Dataset: Sale Prices of Single-Family Homes



Observational Data → Observational Inference/Prediction

Observational vs. Causal Inference

Clever Homeowner:

- “I’ll add two garages to my house and increase its value by $142,000”

Observational vs. Causal Inference

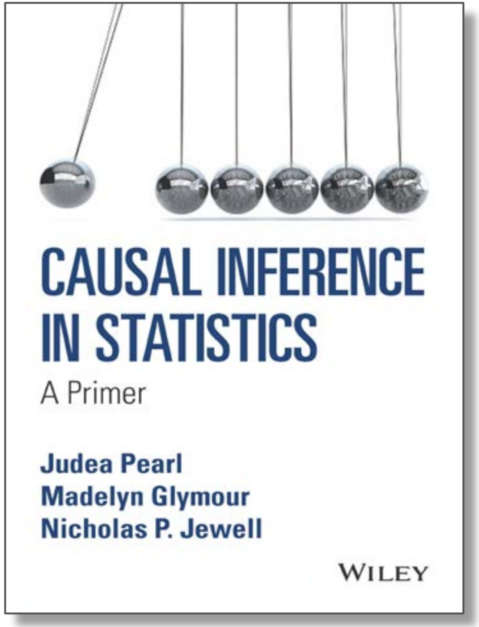
Observational vs. Causal Inference

Intervention

Observational vs. Causal Inference

Observational Inference (Conditioning)

- “When we condition on a variable, we change nothing; we merely narrow our focus to the subset of cases in which the variable takes the value we are interested in. What changes, then, is our perception about of the world, not the world itself.”











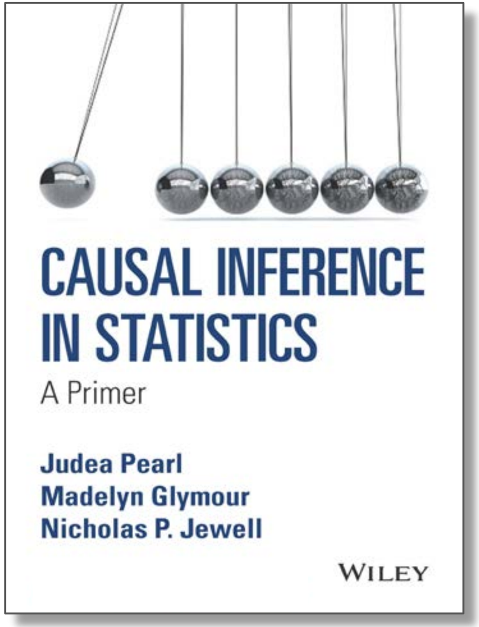





Observational vs. Causal Inference

Causal Inference (Intervention)

- "When we intervene on a variable in a system, we fix its value. We change the system, and the values of other variables often change as a result."



Observational vs. Causal Inference

Statistical Model → Observational Inference/Prediction

-

Regression

Causal Model → Causal Inference/Intervention

???

Observational vs. Causal Inference

Predictive Model:
Observational Inference

Causal Model:
Causal Inference


Questions?

Example 4b

The Effect of Advertising

Causal Inference?

- Lexus ran a commercial at the 2015 Super Bowl.
- Then, the company conducted a survey* among auto shoppers to understand the effect of the Super Bowl commercial on purchase behavior.

*fictional example

Causal Inference?

Dataset: 1,000 Observations, i.e. Survey Responses

Ad Exposure	Purchase	Gender	Test Drive
1	0	1	0
0	1	1	1
1	0	1	1
1	1	1	1
0			1
0			0
1	0	0	0
0	1	0	0
1	0	1	0
1	1	0	0

Non-Experimental,
Observational Data

Causal Inference?

Analysis by Cross-Tab

Ad Exposure	Purchase
No	60%
Yes	45%

-15%

Regression Analysis

$$Purchase = -0.15 \times Ad\ Exposure + 0.6$$

Causal Inference?

However, analyzing the data by Gender reveals:

Gender	Ad Exposure	Purchase
Male	No	30%
	Yes	35%
Female	No	70%
	Yes	75%

Regression Analysis

$$Purchase = 0.05 \times Ad\ Exposure + 0.4 \times Gender + 0.3$$

Causal Inference?

Analyzing the data by Test Drive reveals:

Test Drive	Ad Exposure	Purchase
No	No	60%
	Yes	50%
Yes	No	60%
	Yes	30%

-10%

-40%

Regression Analysis

$$Purchase = -0.2 \times Ad\ Exposure - 0.09 \times Test\ Drive + 0.67$$

Causal Inference?

However, analyzing the data by Gender and Test Drive shows:

Test Drive	Gender	Ad Exposure	Purchase
No	Male	No	30%
		Yes	40%
	Female	No	70%
		Yes	80%
Yes	Male	No	30%
		Yes	20%
	Female	No	70%
		Yes	60%

$$Purchase = 0.004 \times Ad\ Exposure + 0.4 \times Gender - 0.1 \times Test\ Drive + 0.37$$

So, what's the a ffect?

“given that I see”

Test Drive	Gender	Ad Exposure	chase
No	Male	No	30%
		Yes	40%
	≈ 0	No	70%
		Yes	80%
Yes	Male	No	30%
		Yes	20%
	Female	No	70%
		Yes	60%

“given that I see”

Gender	Ad Exp e	Purchase
Male	No	30%
	$+0.05$	35%
Female		70%
	Yes	75%

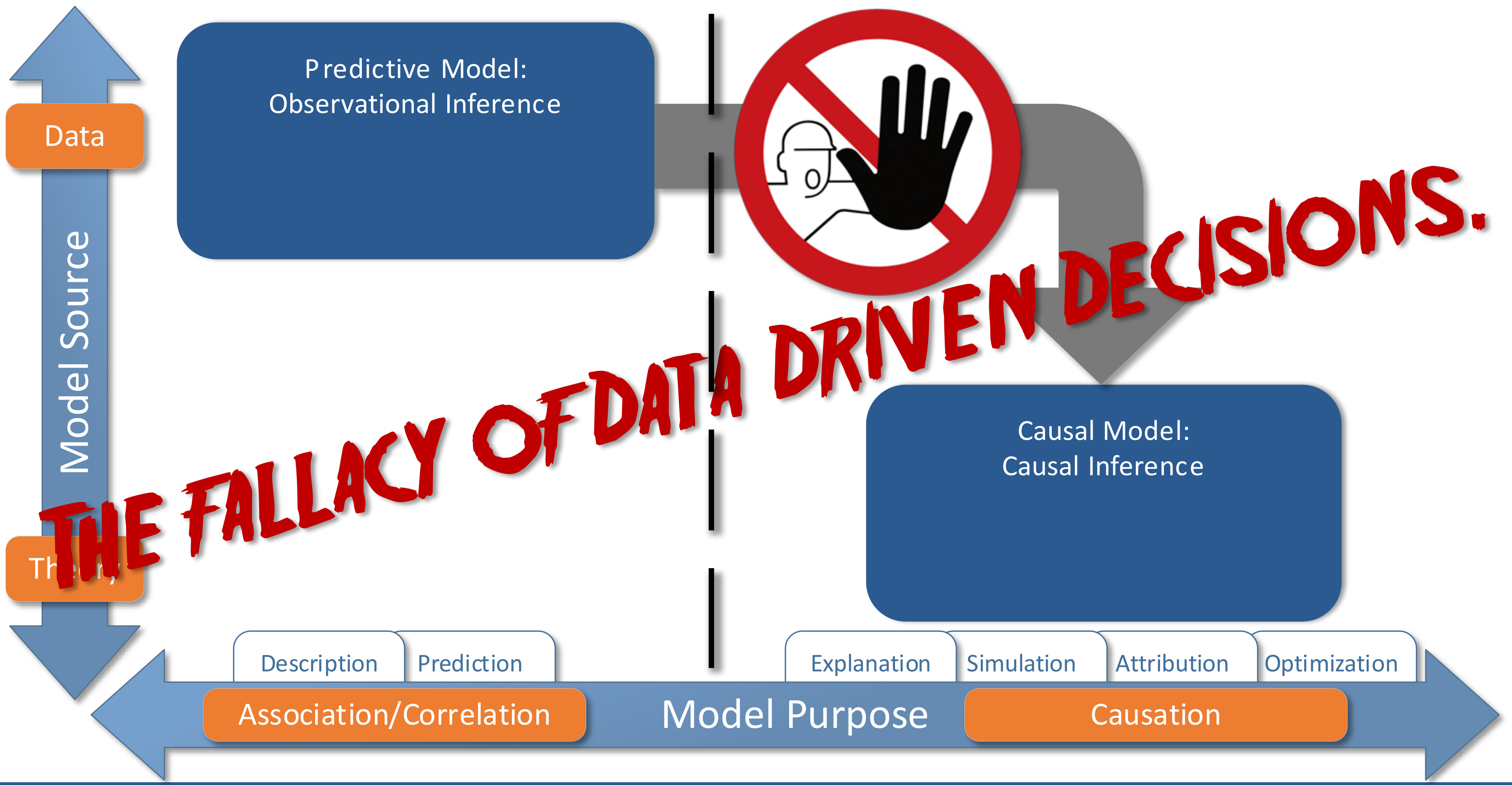
Ad Exposure	Purchase
No -0.15	60%
Yes	45%

“given that I see”

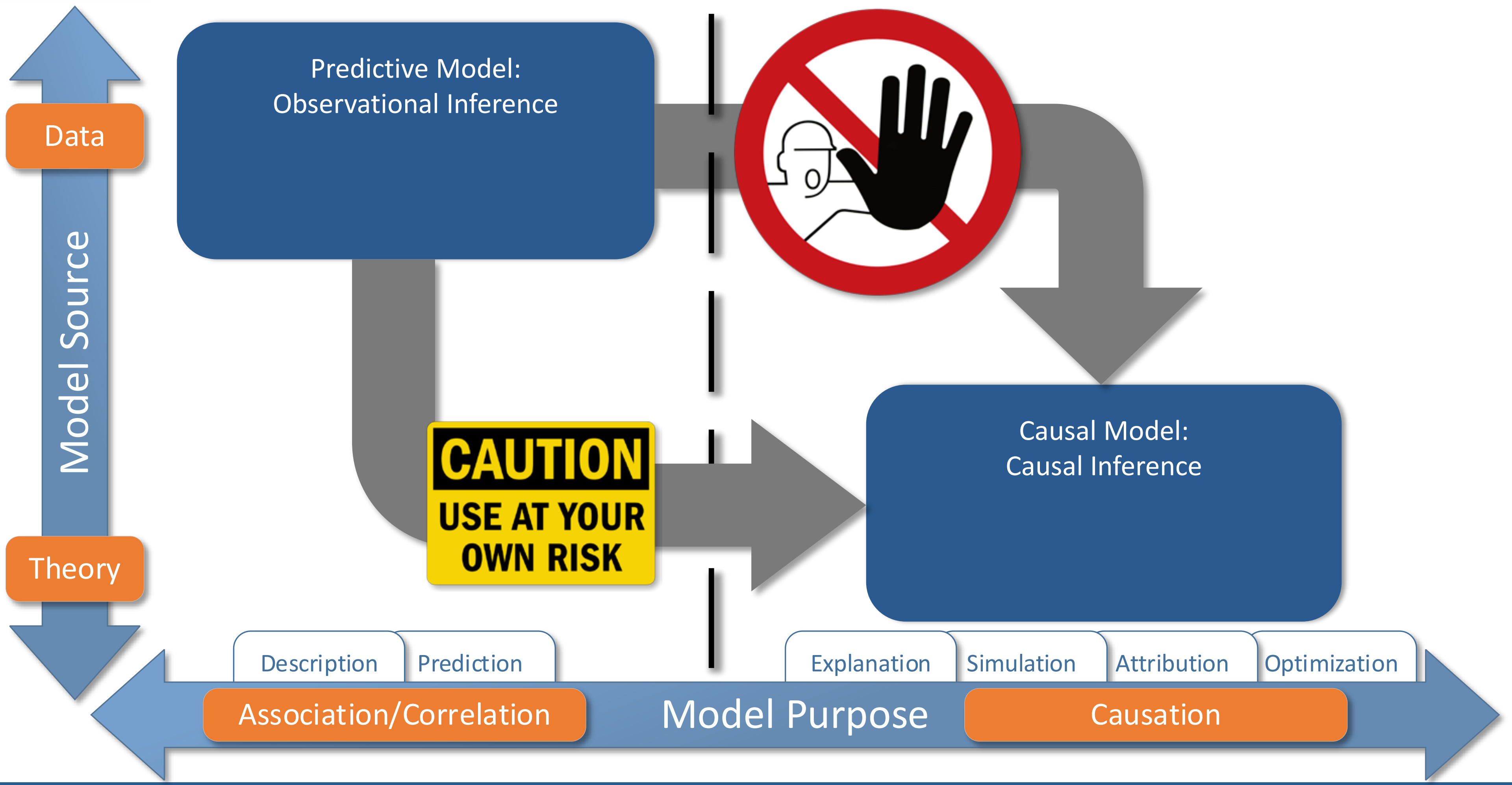
“given that I see”

Test Drive	Ad Exposure	Purchase
No	No	60%
	-0.2	50%
Yes		60%
	Yes	30%


RUSSELL GLASS · SEAN CALLAHAN
THE
BIG DATA
DRIVEN
BUSINESS
DATA
DRIVEN
Data-Driven
Decision-Making
O'REILL
Data
Driven
Creating a Data C
5 Steps To Powering
Data Driven Decision Makin
increasing sales with
DATA - DRIVEN
MARKETING
$
$
$
$
$
loginradius
Data
driven
decisions
DATA-DRIVEN decisions in a
FORTUNE 500
MAKING
DATA-DRIVEN
DECISIONS
with
+ableau
+
THE DATA-DRIVEN
FUTURE
GET #DATADRIVEN
Data-Driven
Marketing
DataDriven
Business


Predictive Model:
Observational Inference
Causal Model:
Causal Inference
Data
Model Source
Theory
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation
THE FALLACY OF DATA DRIVEN DECISIONS.

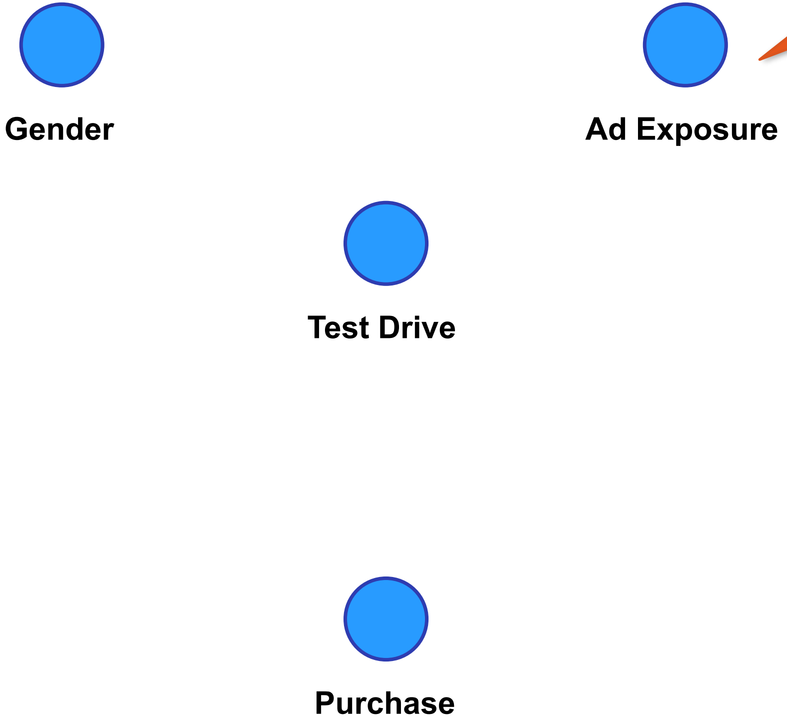
Instead of Data:


Predictive Model:
Observational Inference
Causal Model:
Causal Inference
CAUTION
USE AT YOUR OWN RISK
Data
Model Source
Theory
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Causal Inference?

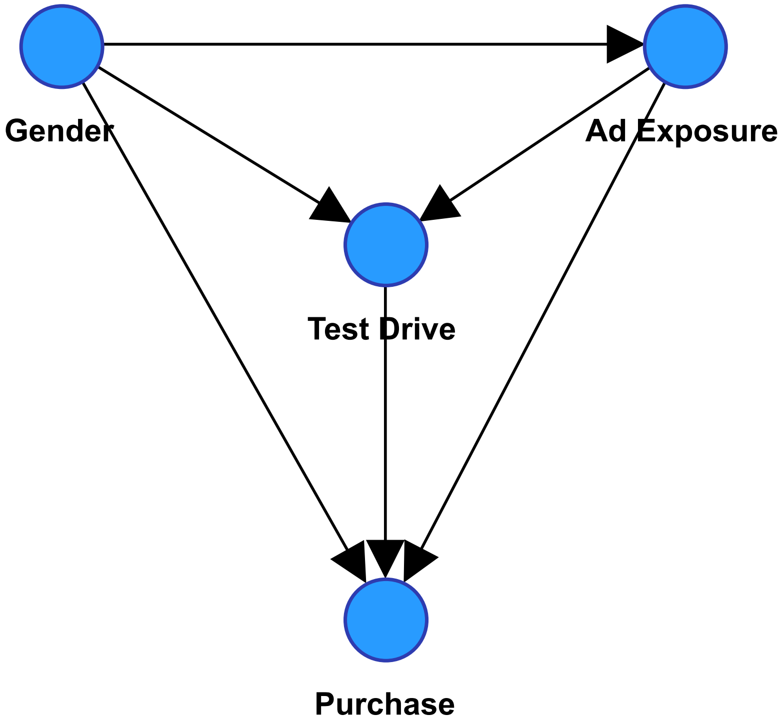
What's the story here?

Develop Theory



Causal Inference?

Our Theory!



Controlling for Confounders

More frequently, however, multivariate analysis is required for evaluating determination, i.e. the effect of a postulated risk factor on an outcome. One needs to know what this effect is after controlling for confounding factors. One may also wish to assess whether such

ing and OA was modified by other potential risk factors, we performed multiple logistic regression analysis, simulta neously controlling for multiple potential confounders. Fo this analysis, age and weight (as MRW) were analyzed a continuous variables unless otherwise specified.

Smokers and nonsmokers were compared using *t* tests for continuous variables and chi-square for categorica using th

Controlling variables

To assess the relationship between food insecurity and nutritional and health consequences, it is crucial to control for potential confounding variables. Sociodemographic, economic, psychological, physical functioning, health and behavioral, and adverse health conditions have been known to influence nutrient intakes, anthropometry, self-reported health status and nutritional risk (Betts and Vivian

Hip Fractures

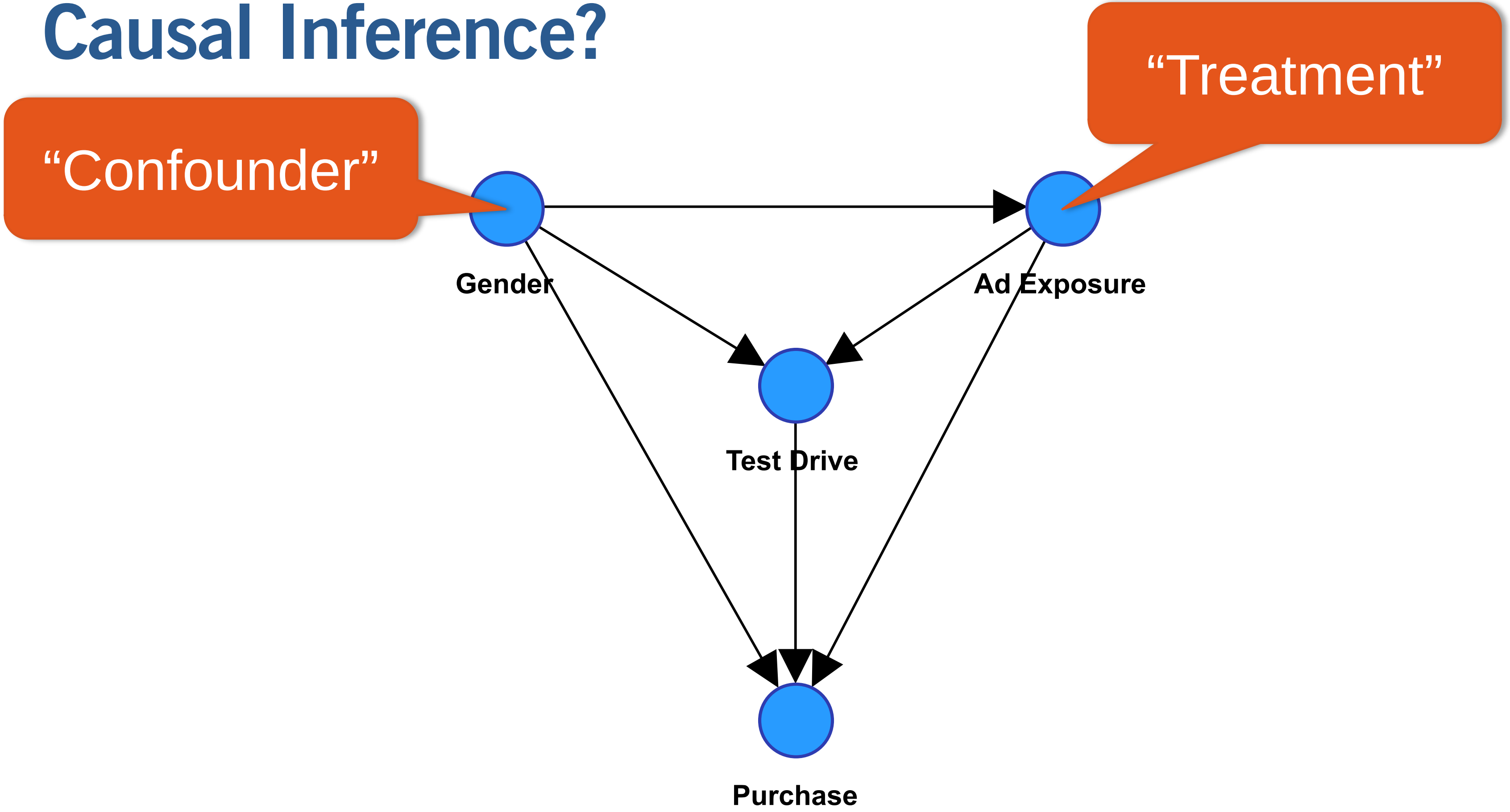
In bivariate models, baseline hypnotic use predicted a 46% greater risk of future hip fracture, and baseline insomnia predicted a 45% greater risk (Table 2). After adjustment for age, sex, and all other potential confounders listed in Table 1, baseline hypnotic use, insomnia, and combinations of the

a strong inverse relationship between the prevalence rate of *H pylori* infection and childhood socioeconomic class, which persisted after controlling for confounding variables. A high prevalence rate of *H pylori* infection was observed in those who had low socioeconomic

plored.[49 50] As much of the literature on neighbourhood social factors and health outcomes is exploratory in nature, a variety of approaches towards adjusting for confounding factors hav been taken, and the causal pathways tha underlie hypotheses about the effects of neigh bourhood social factors are often not explici

This approach should ensure an unbiased estimate of the relationship between insomnia, depression, and anxiety, while adequately controlling for confounding variables. Table 2 shows those variables that were found to be confounders in each analysis using the above procedures.

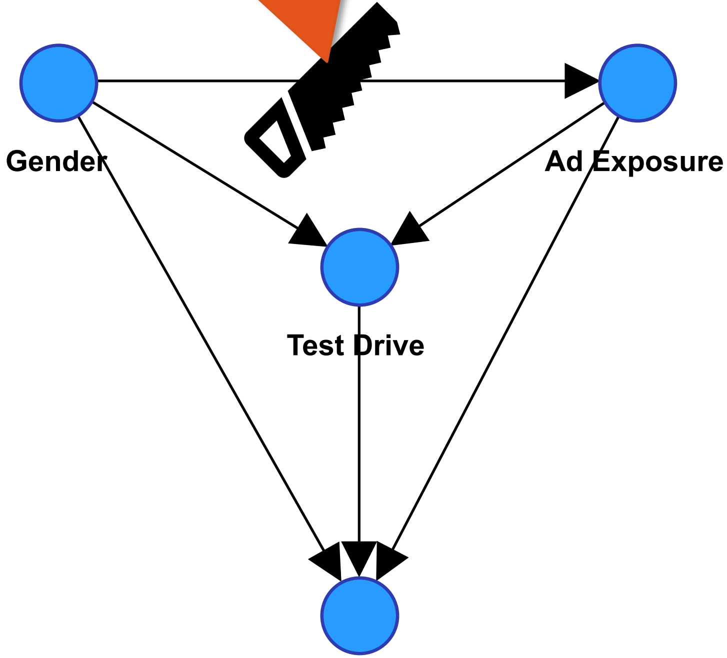
Causal Inference?

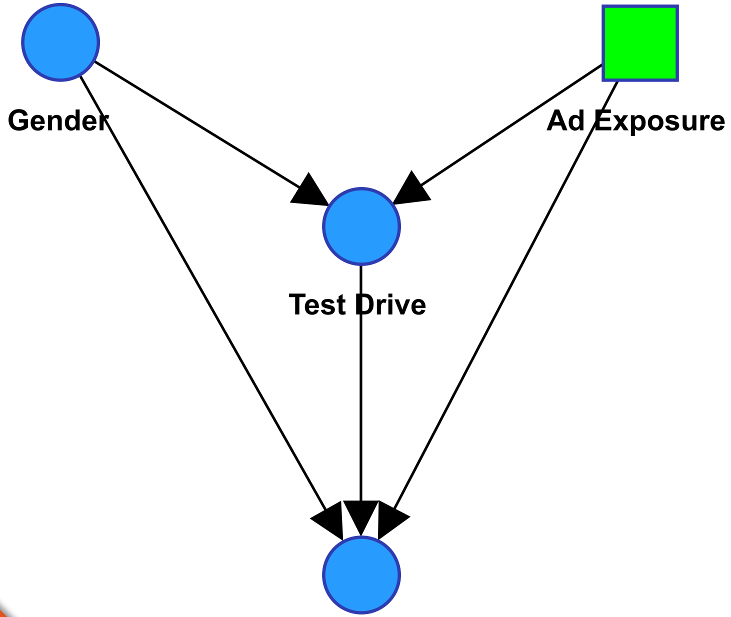


Causal Inference?

“Graph Surgery”

Caus… g an Intervention





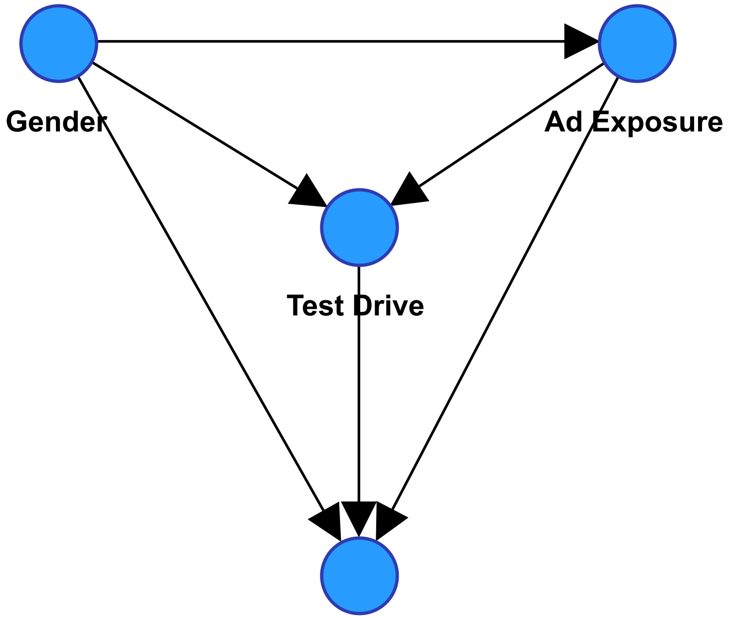
Causal Model

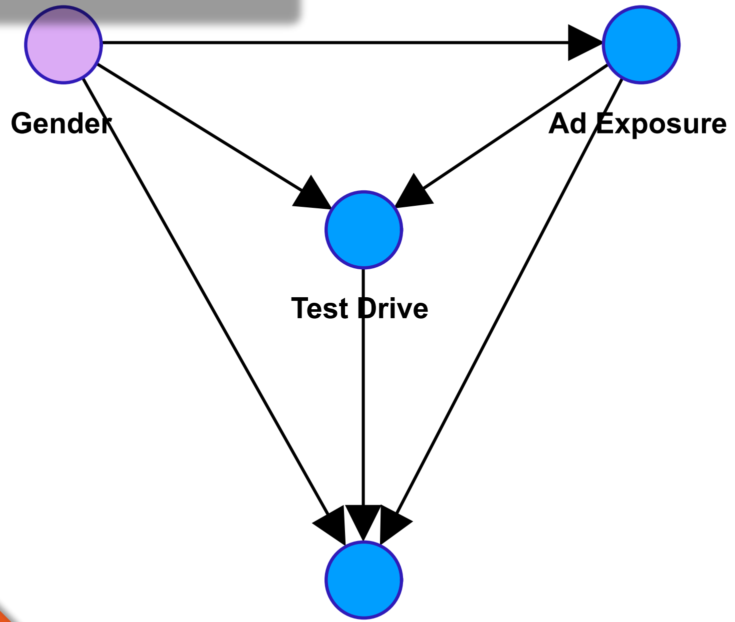
Intervention Model

Causal Inference?

“Fix Probabilities”

Causal Inference: Simulating an Intervention





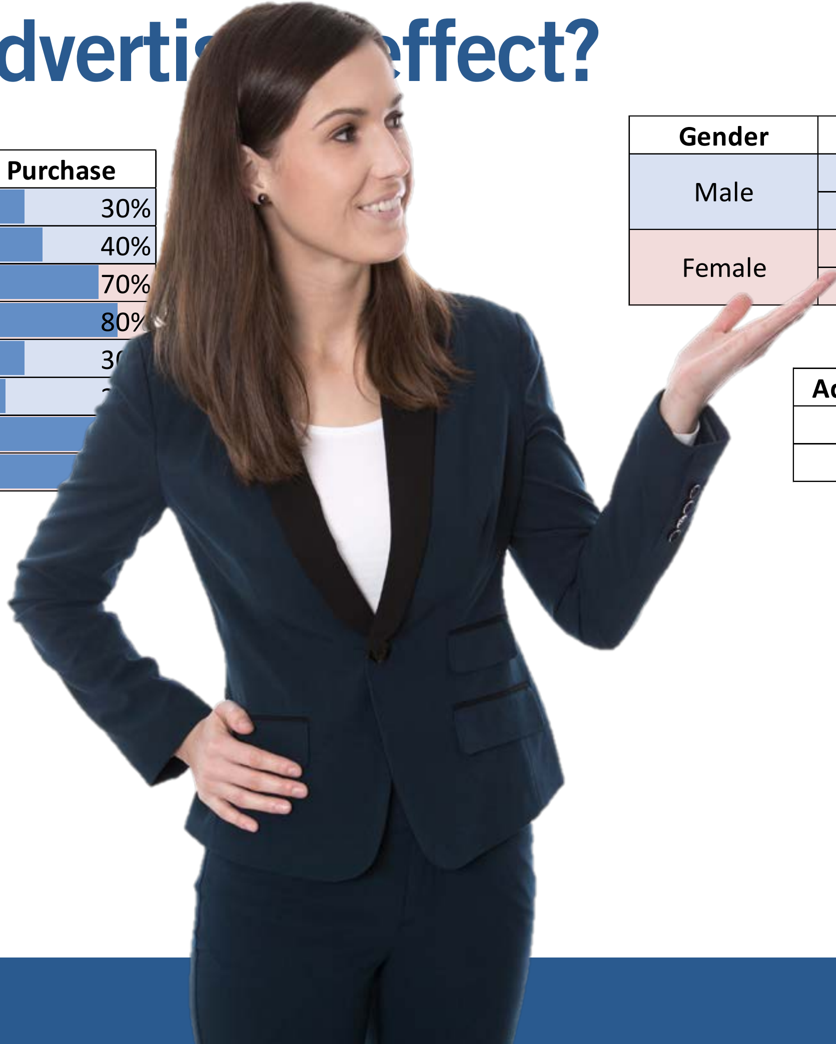
Causal Model

Intervention Model

So, what’s the adverti effect?

Test Drive	Gender	Ad Exposure	Purchase
No	Male	No	30%
		Yes	40%
	[illegible]	No	70%
		Yes	80%
Yes	Male	No	[illegible]
		Yes	[illegible]
	Female	No	[illegible]
		Yes	[illegible]

≈ 0



Gender	Ad Exposure	Purchase
Male	No	30%
	[illegible]	35%
Female	[illegible]	70%
	Yes	75%

$+0.05$

Ad Exposure	Purchase
No	60%
Yes	45%

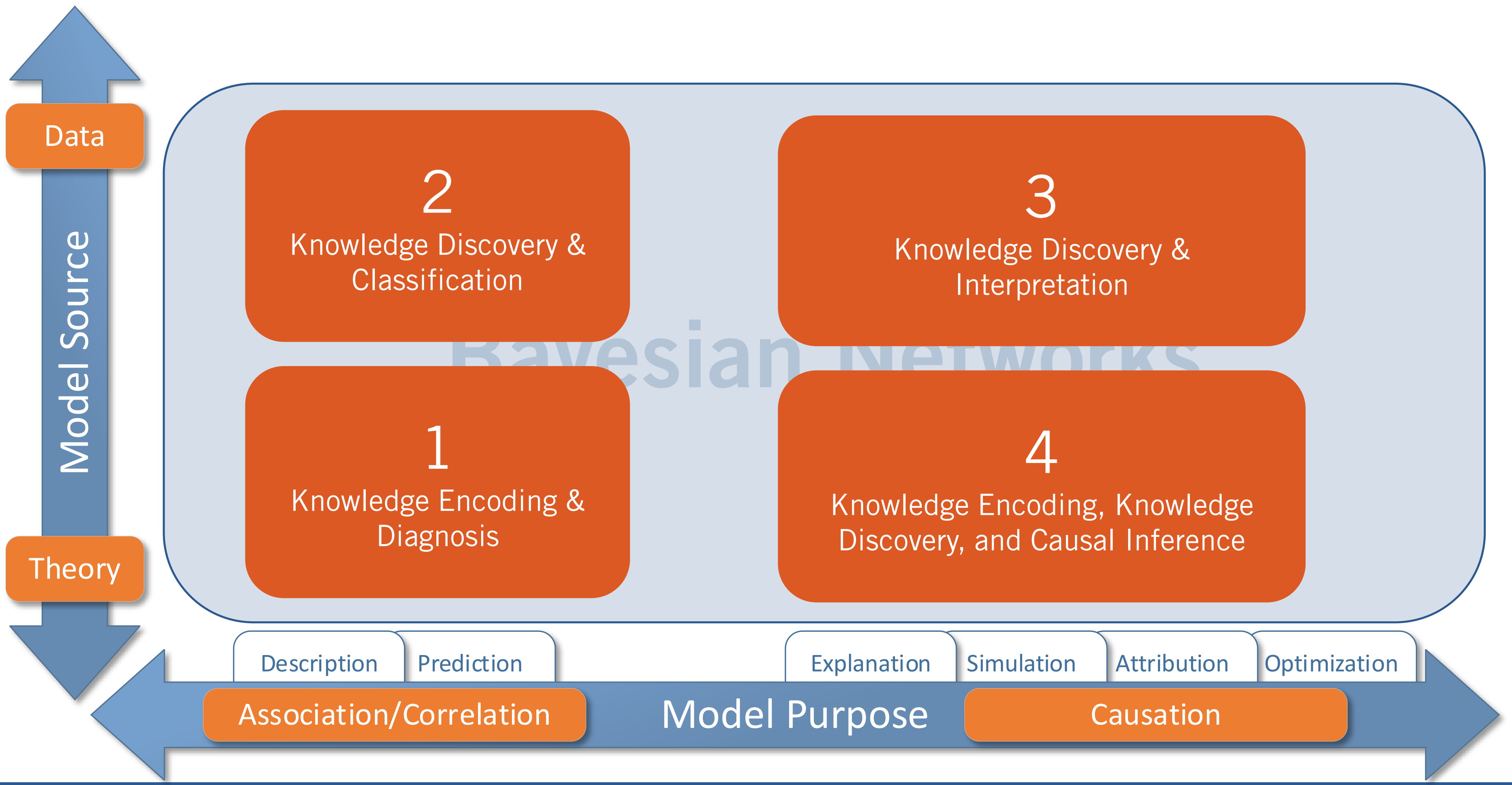
-0.15

Test Drive	Ad Exposure	Purchase
No	No	60%
	[illegible]	50%
Yes	[illegible]	60%
	Yes	30%

-0.2

Where is the Artificial Intelligence here?


No Artificial Intelligence. Here
we need Human Intelligence!


Data
Model Source
Theory
2
Knowledge Discovery & Classification
3
Knowledge Discovery & Interpretation
1
Knowledge Encoding & Diagnosis
4
Knowledge Encoding, Knowledge Discovery, and Causal Inference
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

BayesiaLab Evaluation

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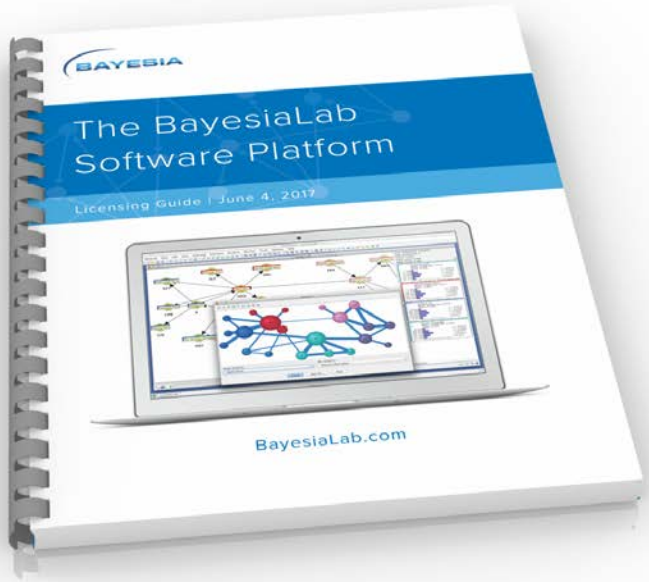

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Thank You!

stefan.conrady@bayesia.us

BayesianNetwork

linkedin.com/in/stefanconrady

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Information Theory

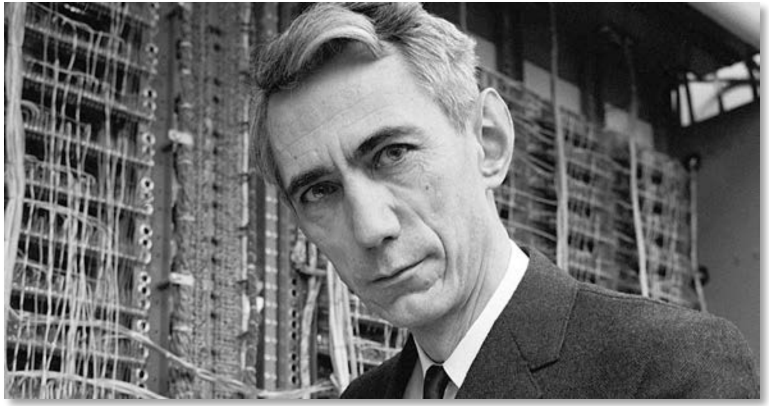
Appendix 1

Information Theory

Information-Theoretic Measures

- Entropy
- Mutual Information
- Arc Force (Kullback-Leibler Divergence)

See Chapter 5



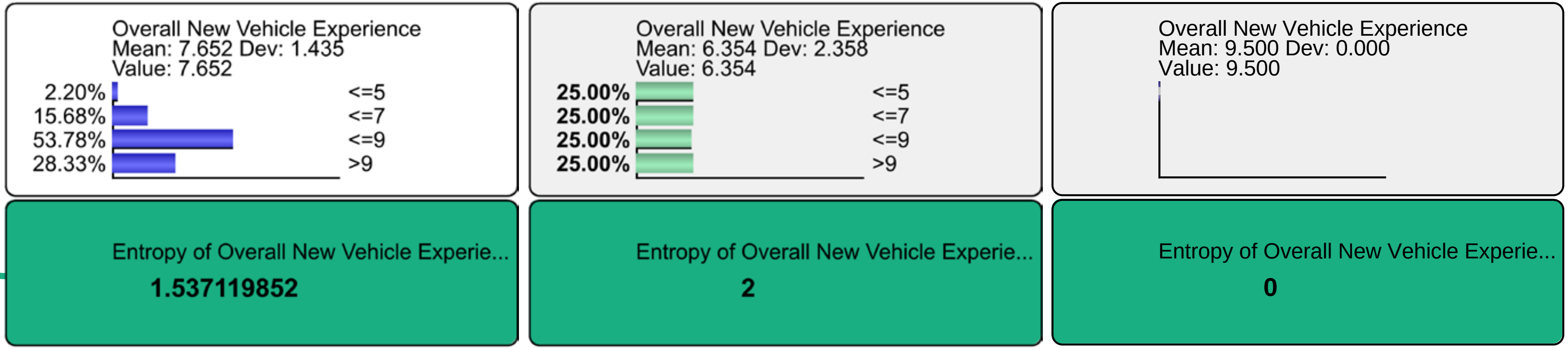
Claude Shannon (1916-2001)

Information Theory

Entropy: a measure of "uncertainty"

$$H(X) = -\sum_{x \in X} P(x)\log_2 P(x)$$

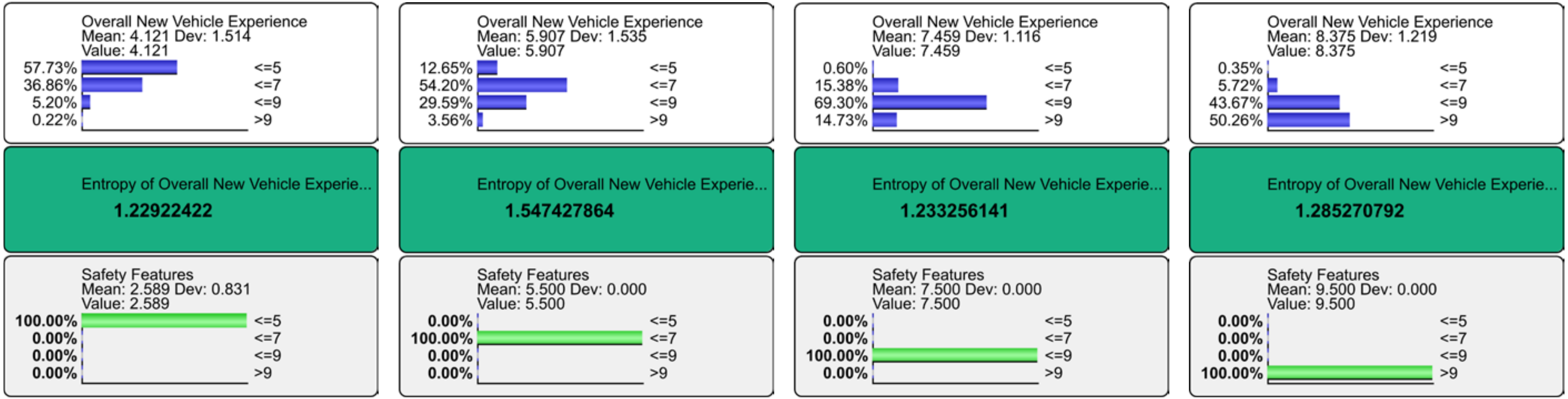
$$H(Overall\ NVE) = 1.54$$



Marginal Entropy | Maximal Entropy | Minimal Entropy

Information Theory

Conditional Entropy



Information Theory

Mutual Information

Mutual Information

Marginal Entropy

Conditional Entropy