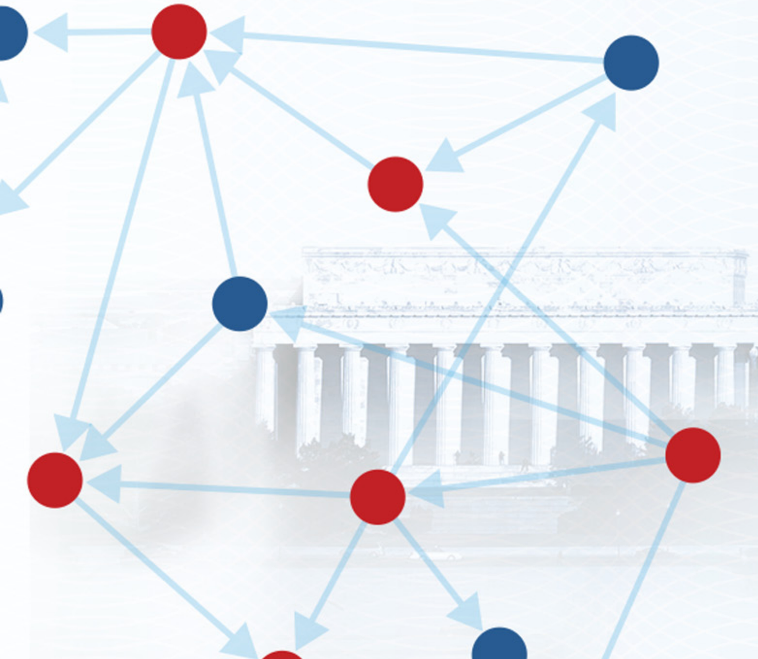
BAYESIALAB



Intelligence Analysis with Artificial Intelligence and Bayesian Networks

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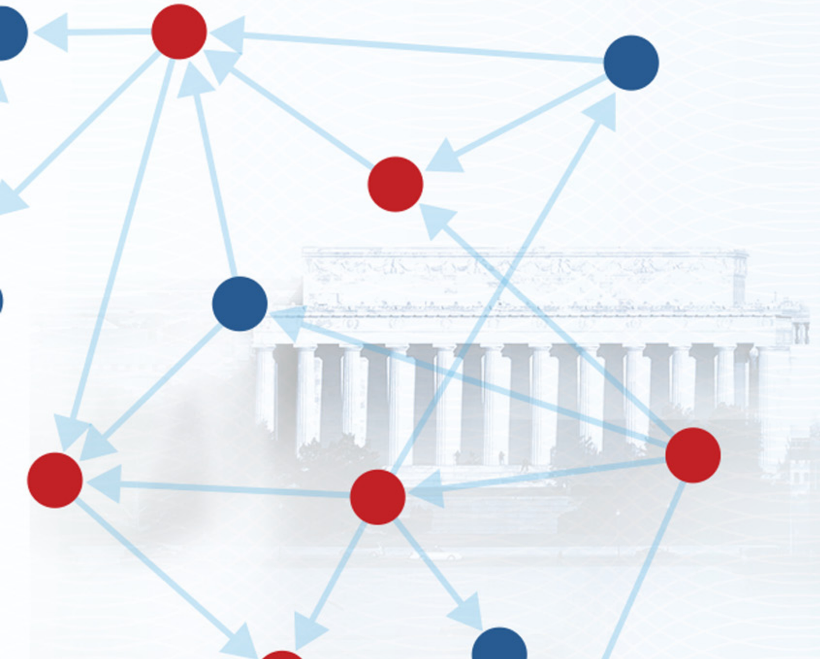


Hello

my name is

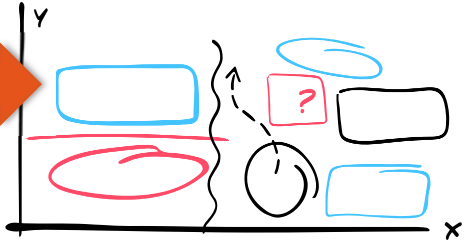
David Aebischer


BAYESIALAB
Hello
my name is
Stefan Conrady

Part I: Introduction

60 min.

- Introduction: Our Company and Technology
- Motivations:
    - The Promise, the Peril, and the Limitations of Artificial Intelligence
    - Human Cognitive Limitations & Biases in Reasoning
- Objective:
    - Human-Machine Teaming
    - Practical Artificial Intelligence for Here & Now
- Dimensions of Reasoning
- Introducing Bayesian Networks as a Reasoning Framework

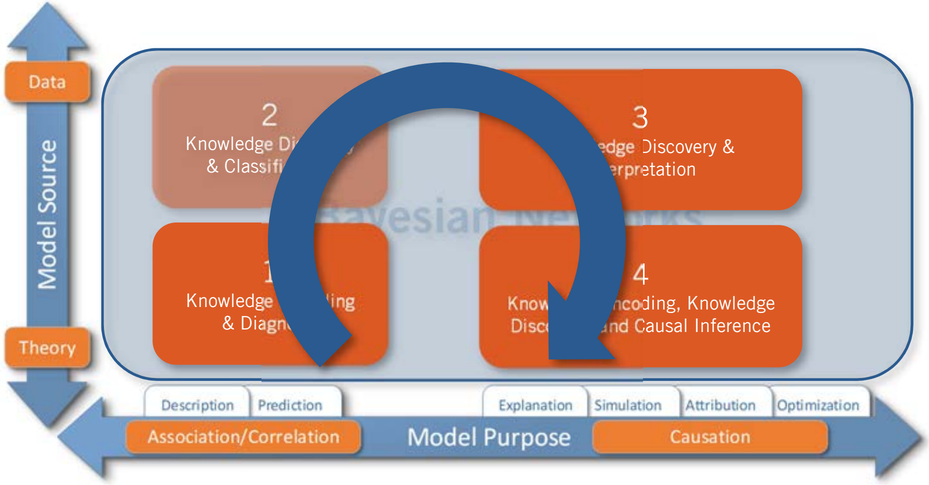


Part II: Examples

120 min.

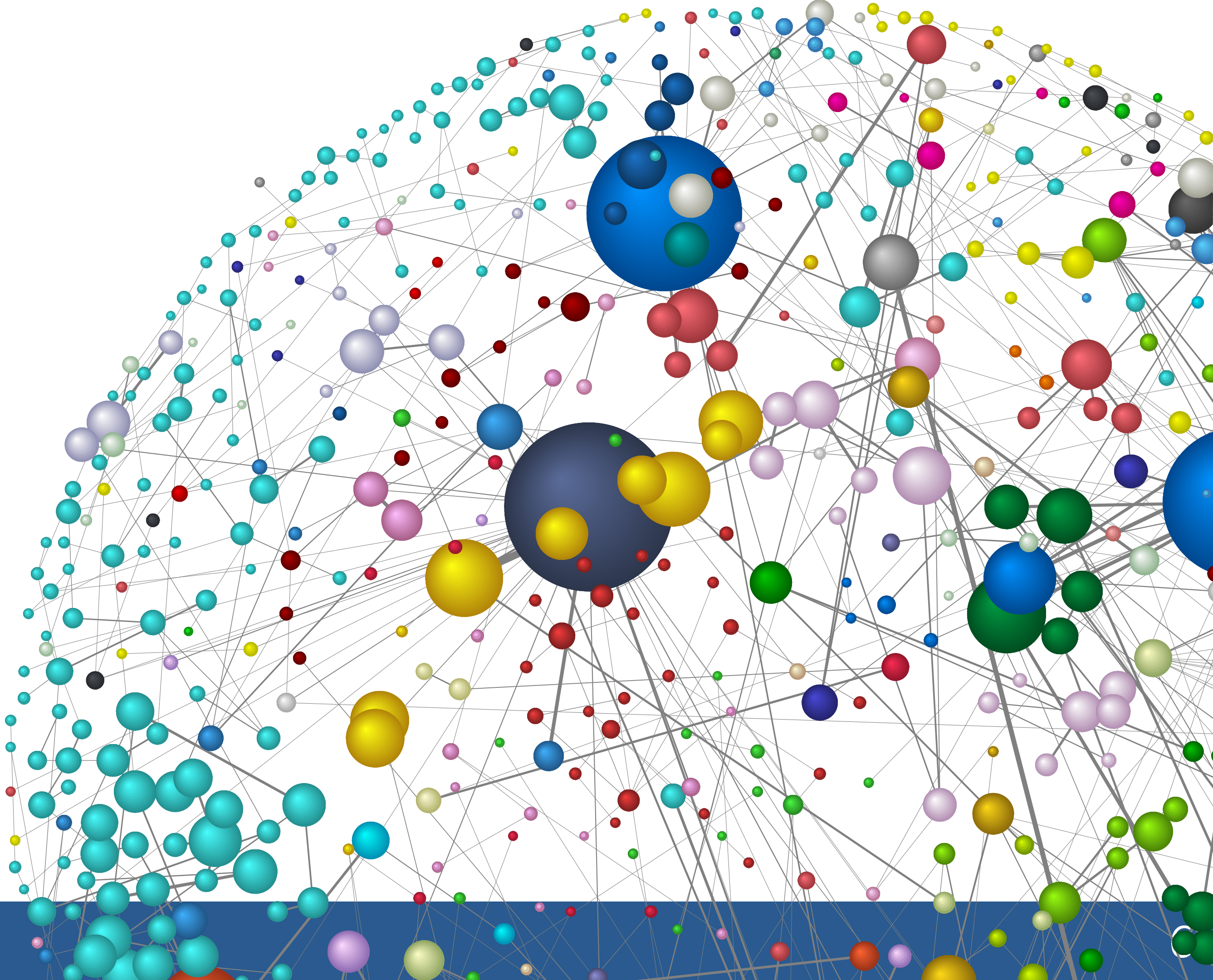
Examples

- Knowledge Encoding & Reasoning
    - Friend or Foe?
    - Where is my Bag?
    - Monty Hall or
      Choose Your Battles Wisely!
    - Formal Knowledge Elicitation
- Knowledge Discovery
    - Interpretation
    - Anomaly Detection
- Causal Inference
    - Simpson’s Paradox



BAYESIA
Your Decision Partner

Co-founded in 2001
by Dr. Lionel Jouffe &
Dr. Paul Munteanu



Disambiguation

BAYESIA
Your Decision Partner

Our Company

BAYESIALAB

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-

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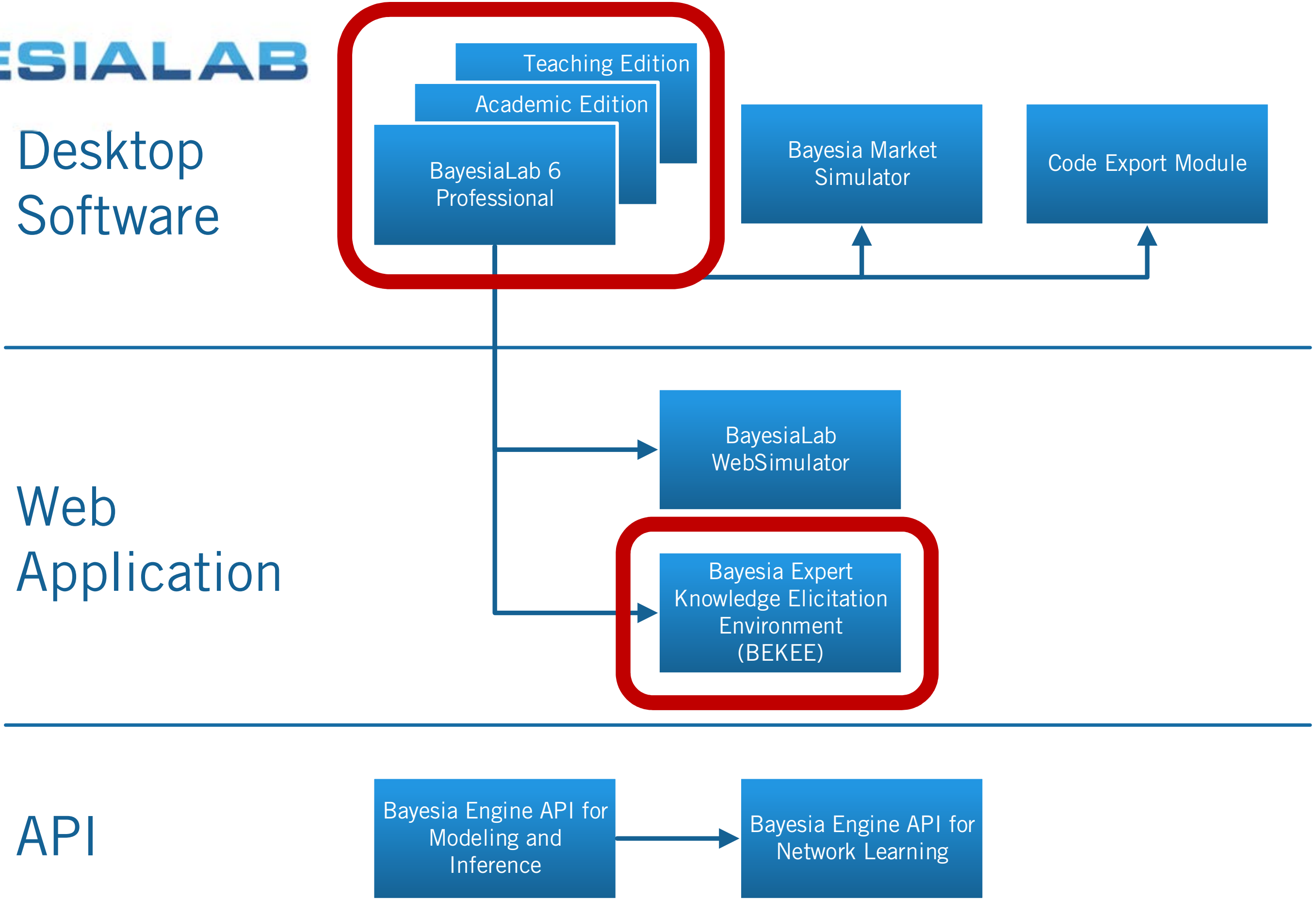
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Teaching Edition
Academic Edition
BayesiaLab 6 Professional
Bayesia Market Simulator
Code Export Module
Web Application
BayesiaLab WebSimulator
Bayesia Expert Knowledge Elicitation Environment (BEKEE)
API
Bayesia Engine API for Modeling and Inference
Bayesia Engine API for Network Learning

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NASA
Booz | Allen | Hamilton
THE WORLD BANK
GEORGETOWN UNIVERSITY
DASSAULT AVIATION
LOCKHEED MARTIN
bp
charles SCHWAB
groupm
WPP
ArcelorMittal
the pert group
UNIVERSITY of VIRGINIA
RENAULT
gsk GlaxoSmithKline
sodexo
USGS science for a changing world
NYU
DELL
Lilly
Mu Sigma DO THE MATH
EADS
Holiday Inn
SONY
IHG InterContinental Hotels Group
Unilever
synovate Research reinvented
SOCIETE GENERALE
STANFORD UNIVERSITY
BBDO
HYATT
NYU Langone MEDICAL CENTER
GfK
Nestlé
Fractal
NTT
MAi
National Analysts WORLDWIDE RESEARCH CONSULTING
Firmenich
SAMSUNG
GP Georgia-Pacific
FDA
Cargill
EDF
Ipsos
P&G
CDC
eni
Hilton HOTELS & RESORTS
LANCASTER UNIVERSITY
VirginiaTech
McGill
SNCF
Polk
IMRB international
CATERPILLAR
orange
Burke SINCE 1931
DGA
SAINT-GOBAIN
AIRBUS
tns
SMUCKER'S
MillwardBrown
Microsoft
Team Detroit
sanofi pasteur
PENNSTATE
American Diabetes Association
ACXIOM
MARS
Deloitte.
Rotman UNIVERSITY OF TORONTO
cancer care ontario | action cancer ontario
UCLA
L'ORÉAL
SAFRAN
intel
AIRFRANCE
TOTAL
Northwestern Mutual
LSU LOUISIANA STATE UNIVERSITY
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Bayesian Networks & BayesiaLab

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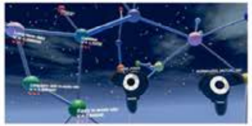
Event

Free Seminar in Boston: Knowledge Discovery with Bayesian Networks and Virtual Reality



Date+Time

Friday, January 19, 2018 from 1:00 PM to 4:00 PM (EST)

Location

CIC Boston—Lighthouse West
50 Milk Street
20th Floor
Boston, MA 02109

Payment Status

Free Order

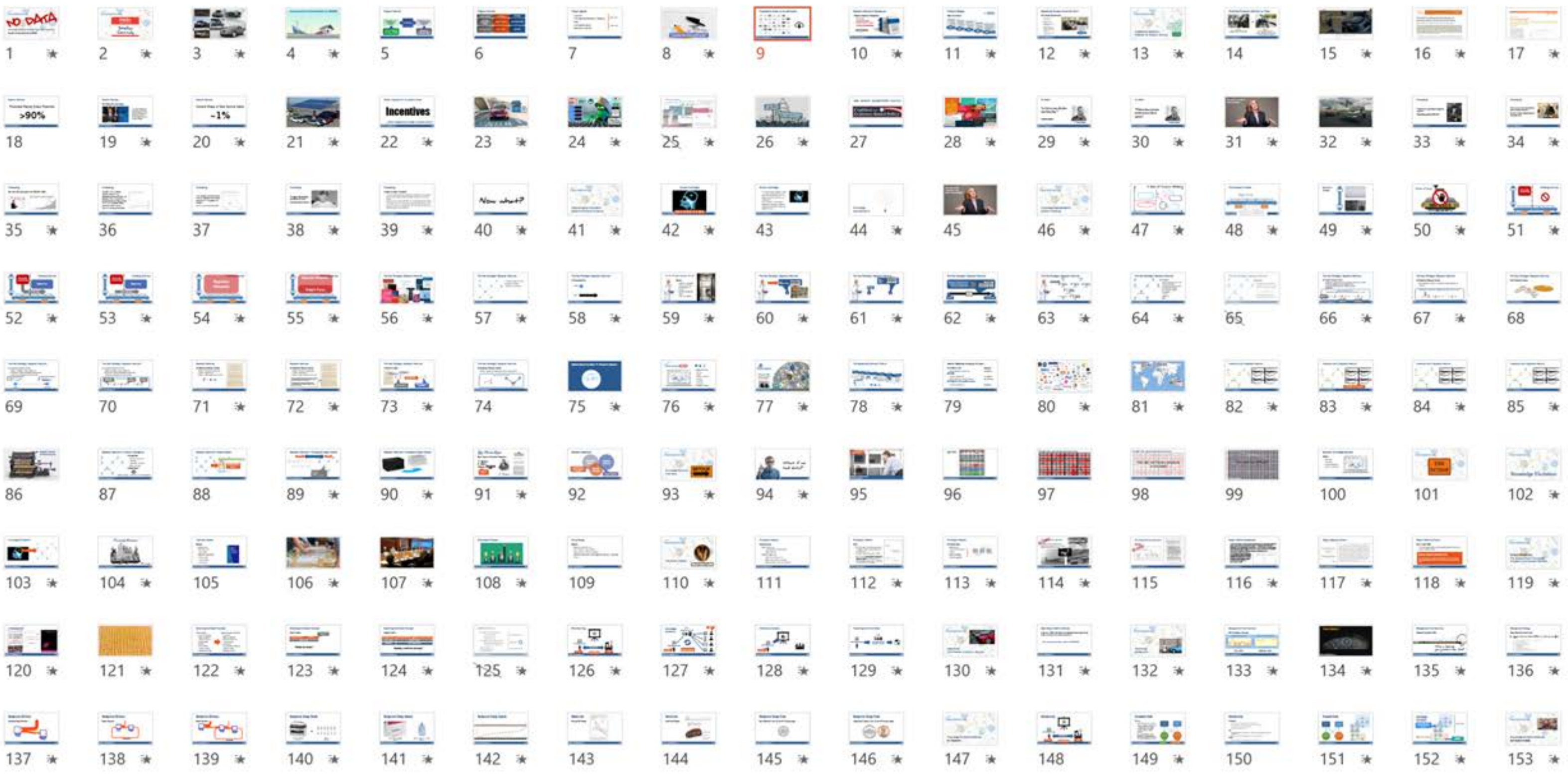
Order Info

[illegible]

Type

Seminar: Knowledge Discovery with Bayesian Networks and Virtual Reality

Presentation slides will be available

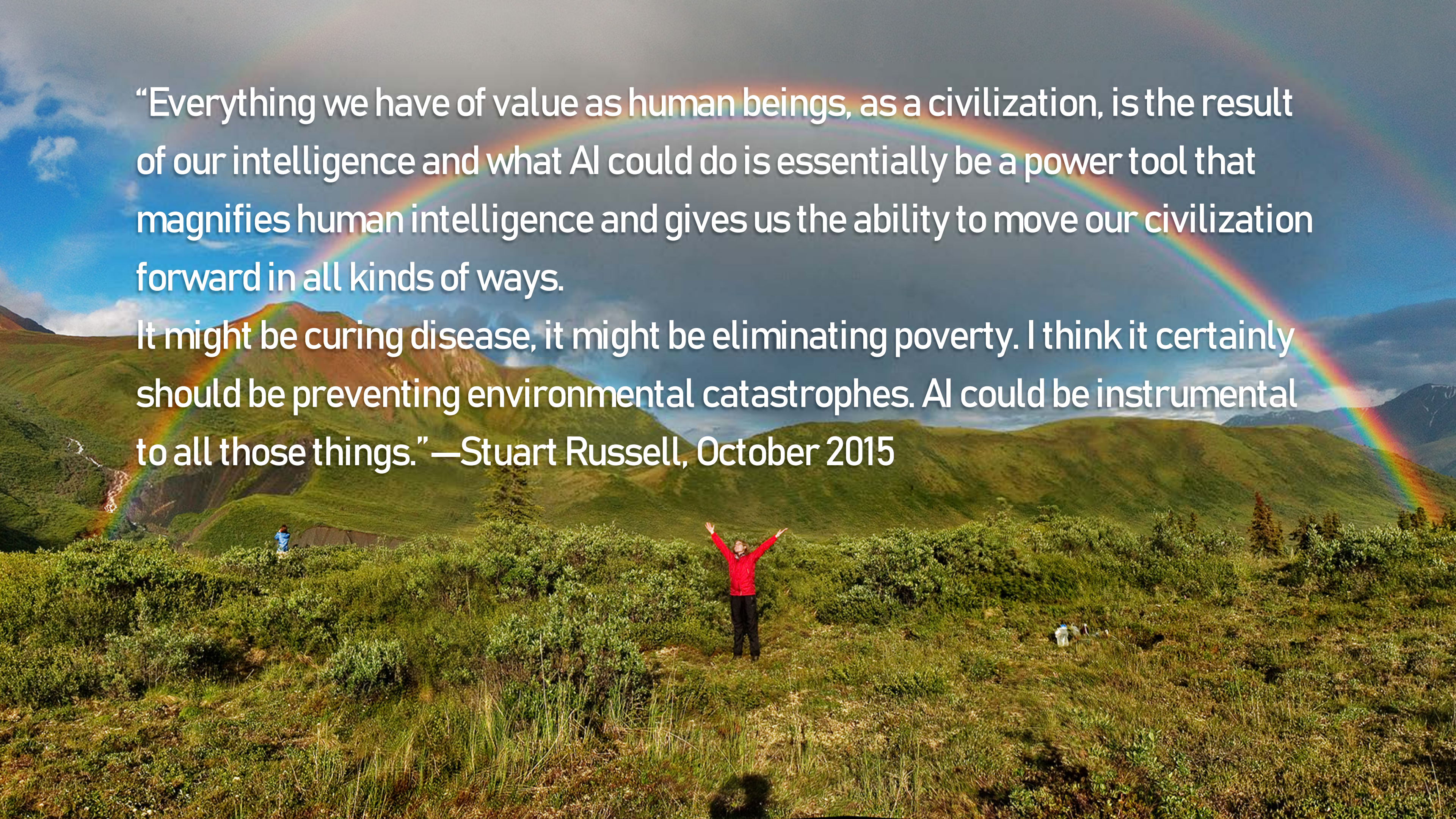


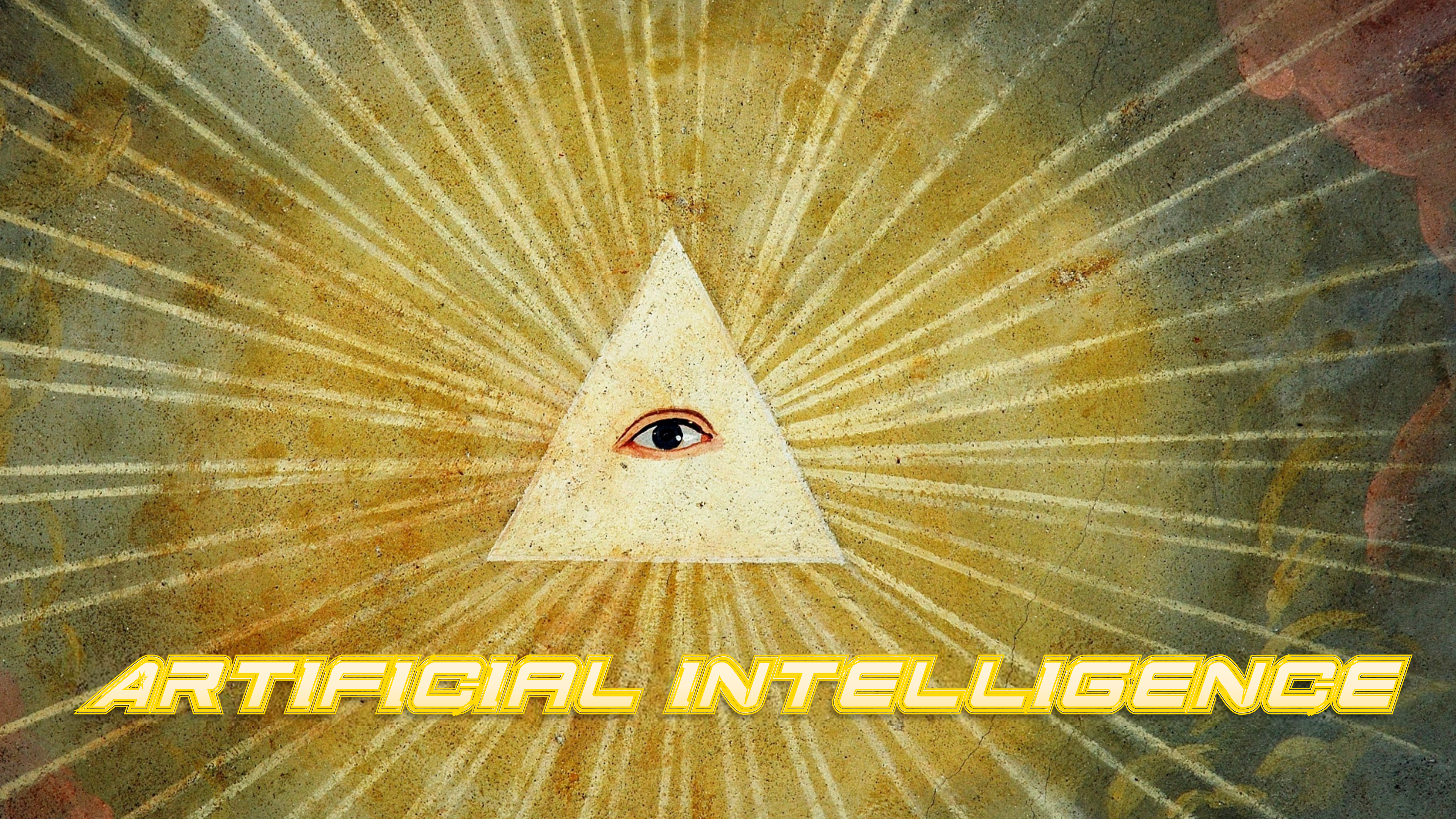
Motivation

The Promise, the Peril, and the Limits of Artificial Intelligence

I WANT TO SAY TWO WORDS TO YOU:

ARTIFICIAL INTELLIGENCE


"Everything we have of value as human beings, as a civilization, is the result of our intelligence and what AI could do is essentially be a power tool that magnifies human intelligence and gives us the ability to move our civilization forward in all kinds of ways.
It might be curing disease, it might be eliminating poverty. I think it certainly should be preventing environmental catastrophes. AI could be instrumental to all those things."—Stuart Russell, October 2015


ARTIFICIAL INTELLIGENCE


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

Artificial Intelligence is greater concern than climate change or terrorism, says new head of British Science Association

MORE STORIES

1 Anything could now happen on Brexit as Barnier bluff goes wrong

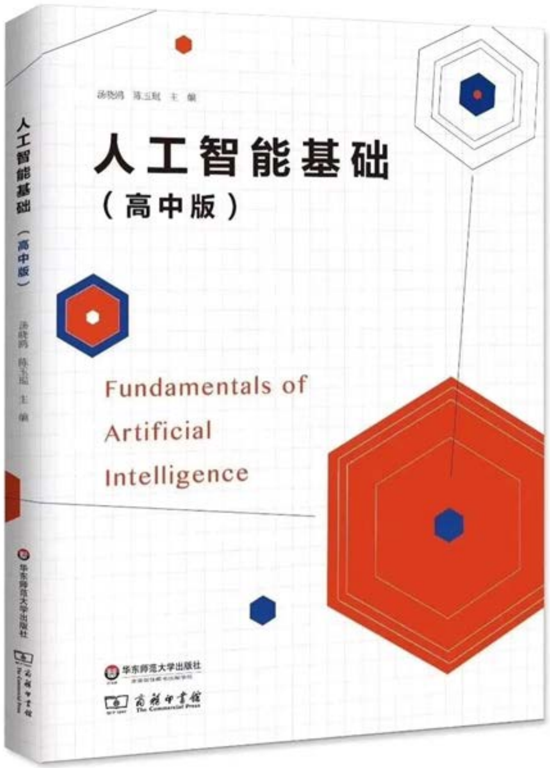
2 Almost $40bn wiped off cryptocurrency market as Bitcoin rout intensifies

3 My daughter was seen by the NHS 47 times but no one realised her condition was fatal

4 Sixty Conservative MPs to launch plan to take down Theresa May's Chequers deal this weekend

5 Royal Navy warship 'confronted by Chinese military' in South China Sea

Artificial Intelligence an Adversarial Threat?



中国人工智能

The Washington Post

The Pentagon. (Photo/Charles Dharapak/AP file photo)

By Drew Harwell
September 7 at 10:39 AM

The military's research arm said Friday it will invest up to $2 billion over the next five years toward new programs advancing artificial intelligence, stepping up both a technological arms race with China and an ideological clash with Silicon Valley over the future of powerful machines.

The Switch

Defense Department pledges billions toward artificial intelligence research

NO HYPE ZONE
NEXT 200 SLIDES
Big Data Is the New Oil
We need to find it, Extract it, Refine it, Distr
use it to drive Economic
Forbes
AI: The Killer App for Your Business
FUTURE OF
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ARTIFICIAL INTELLIGENCE
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Inside the anti-bribery business
Why humans cause heatwaves
Artificial Intelligence
The promise and the peril
ALTHOUGH AI IS ALREA
IN THOUSANDS OF CO
AROUND THE WORLD,
OPPORTUNITIES HAVE NOT YET
BEEN TAPPED.
ARTIFICIAL INTELLIGENCE AND THE END OF THE HUMAN ERA
OUR FINAL INVENTION
JAMES BARRAT
TIM PHILLIPS
DATA-DRIVEN BUSINESS
USE REAL-LIFE NUMBERS TO IMPROVE YOUR BUSINESS BY 352%
VARIETY
Stage-1
Machine Consciousness
Stage-2
Machine Intelligence
Currently Technology is here
Stage-3
Siri
Alexa
Cortana
Machine Learning
Stages of Artificial Intelligence
Gartner Analytic Ascendancy
Descriptive Analytics
Diagnostic Analytics
Predictive Analytics
Prescriptive Analytics
What happened?
Why did it happen?
What will happen?
How can we make it happen?
Information
Hindsight
Insight
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VALUE
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For A Better Future
BIG DATA
OodlesTechnologies
www.oodlestechnologies.com
BayesiaLab.com

WIRED

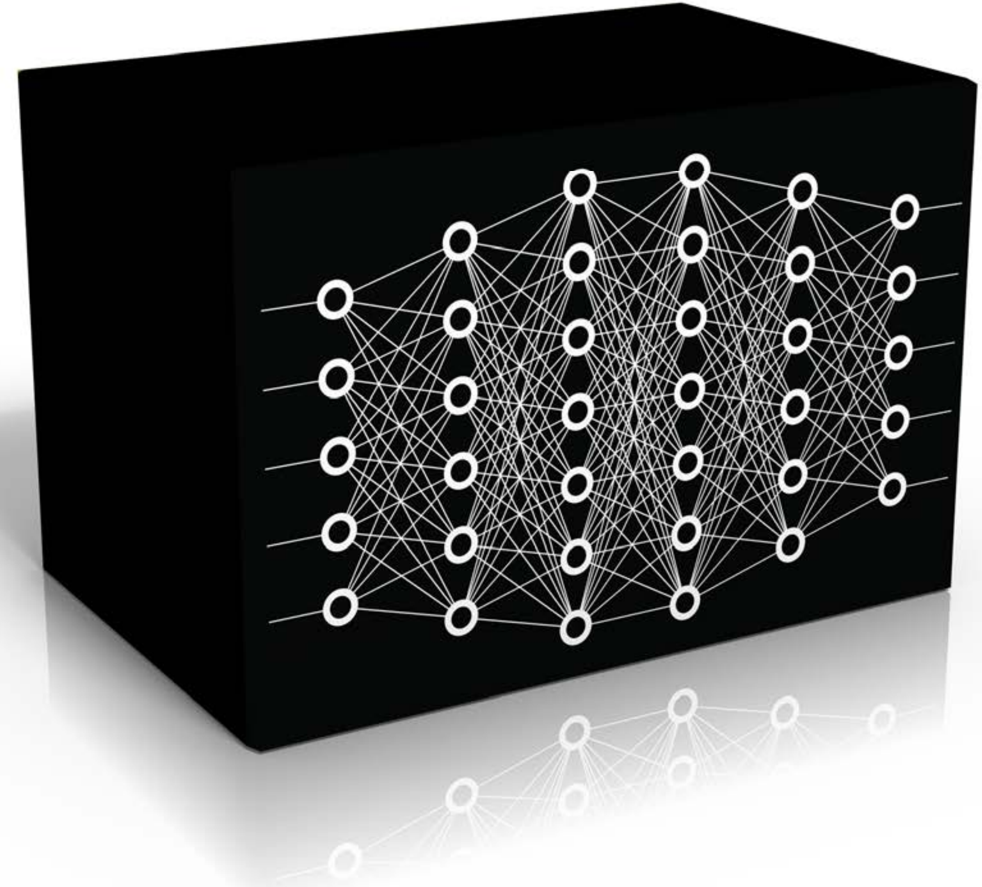
DAVID WEINBERGER BACKCHANNEL 04.18.17 08:22 PM

OUR MACHINES NOW HAVE KNOWLEDGE WE'LL NEVER UNDERSTAND

WIRED

ALIEN KNOWLEDGE

WHEN MACHINES JUSTIFY KNOWLEDGE



Motivation

Small Brain

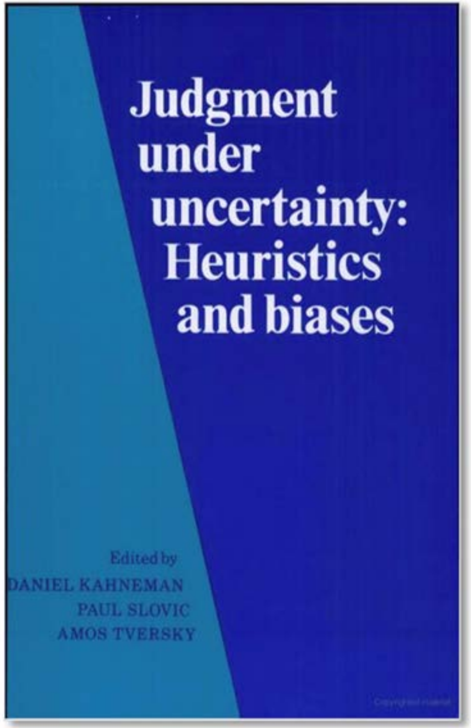

COGNITIVE
LIMIT
3
DIMENSIONS
HUMANS ONLY

Motivation

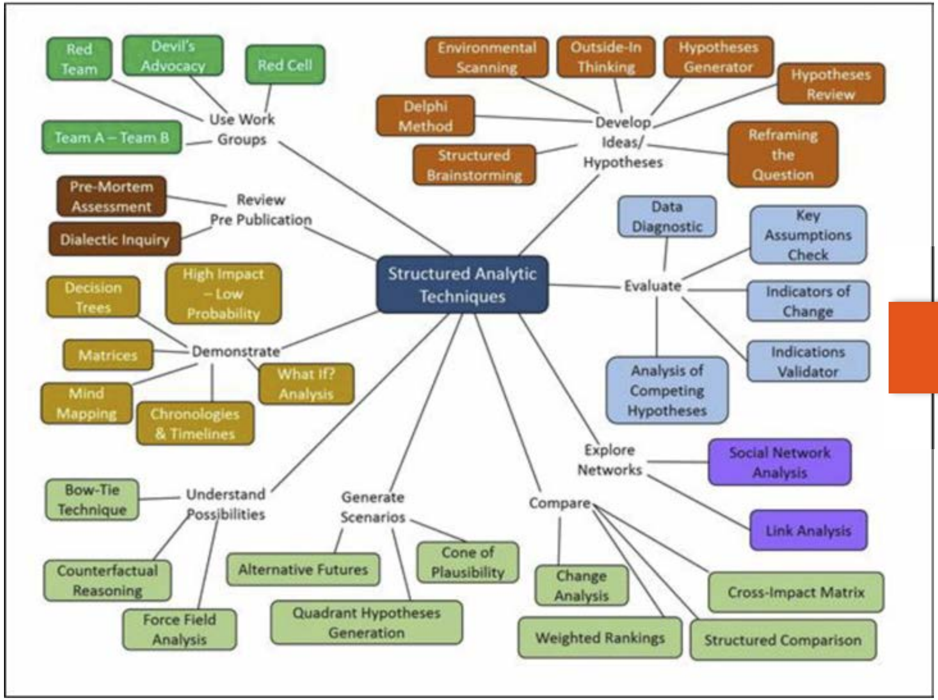
Fundamental Challenges in Human Reasoning

- Cognitive Biases
- Comprehending High-Dimensional Domains
- Dealing with Uncertainty
- Combining Data and Theory
- Distinguishing Observation and Causation

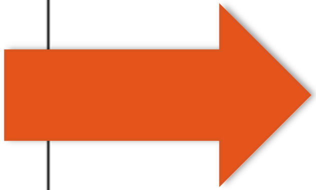
Human reasoning is flawed!



Motivation

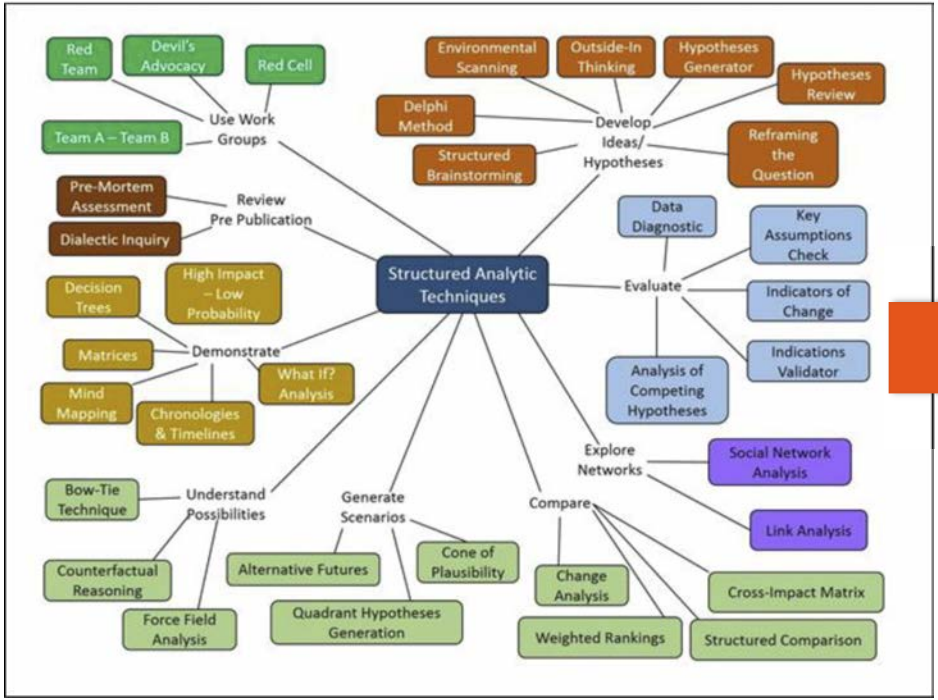


Structured Analytics Techniques
Source: AFH14-133 27 SEPTEMBER 2017 31



Inference must still happen in the human brain

Motivation



Structured Analytics Techniques
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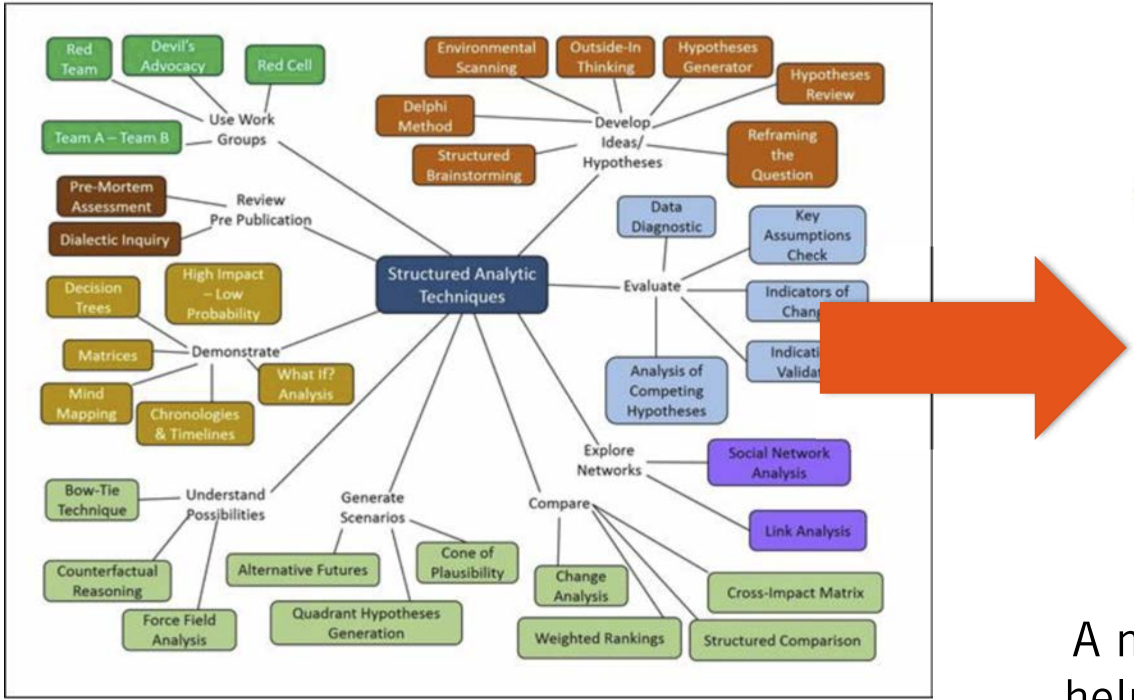
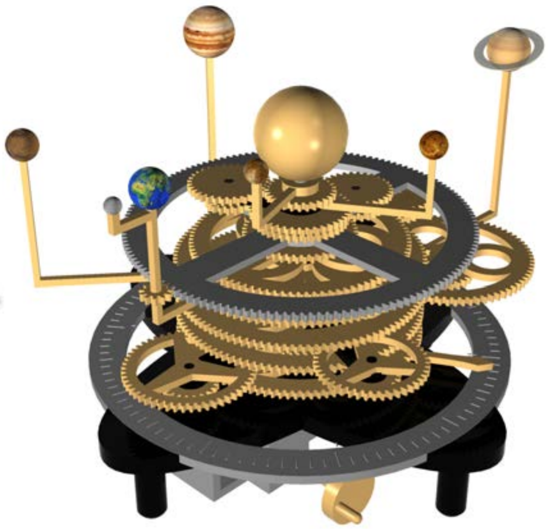
Decision Maker

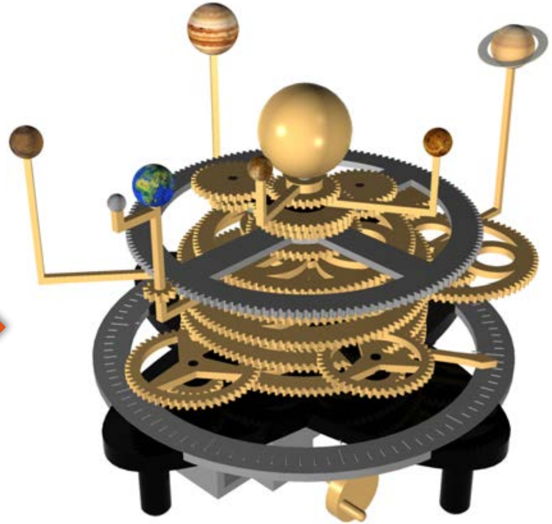
Objective: Explicit Inference & Reasoning





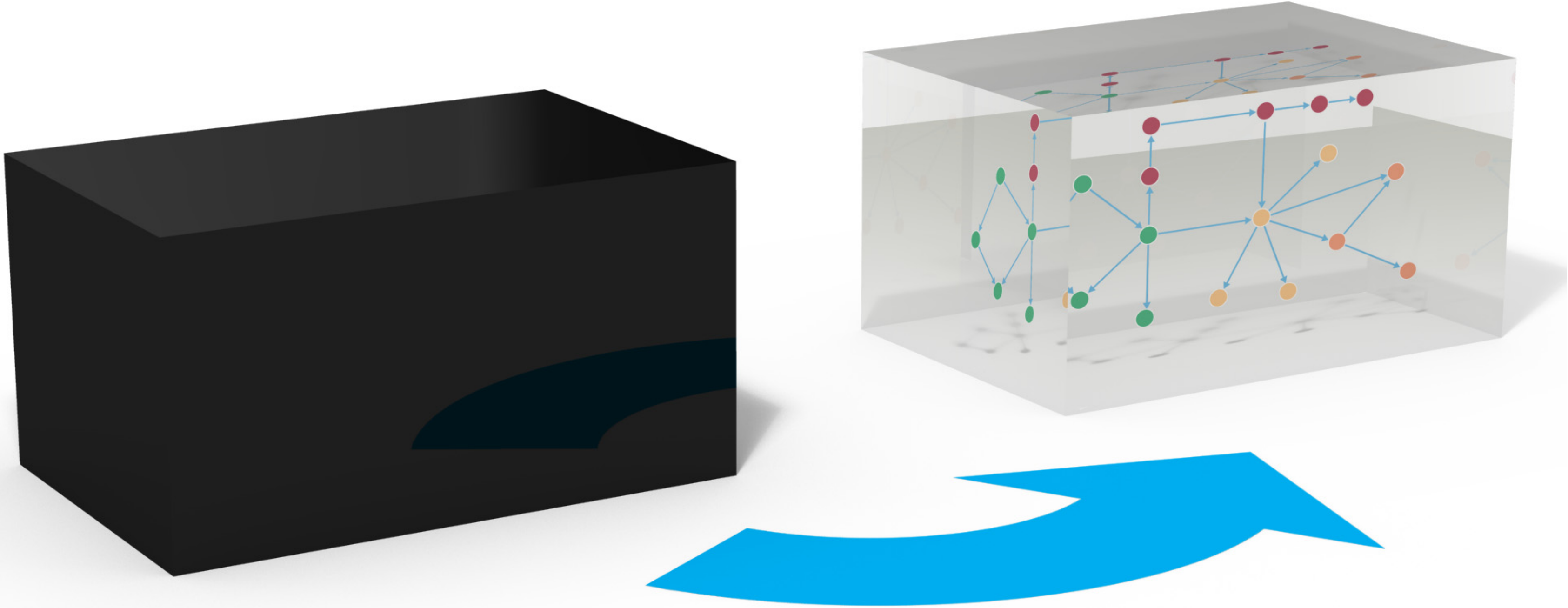
A modeling framework that can help you understand, think, and reason explicitly.

Objective: Explicit Inference & Reasoning



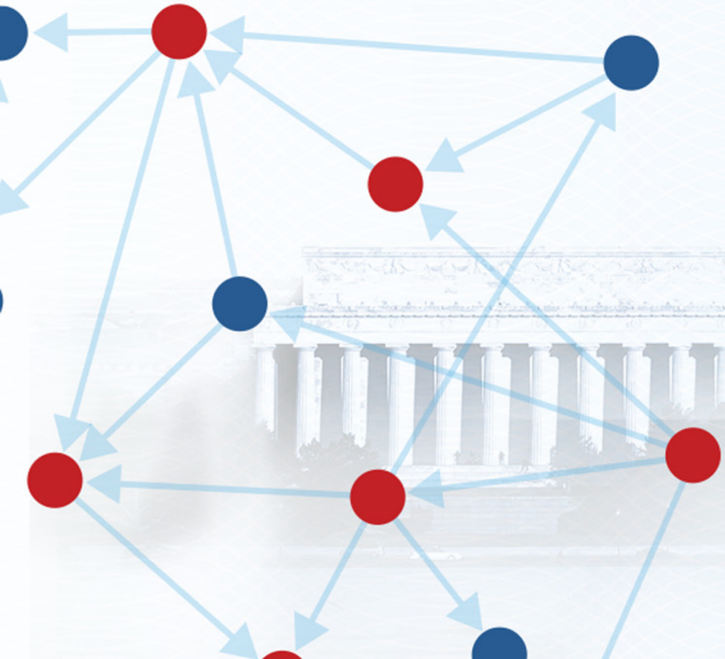
A modeling framework that can help you understand, think, and reason explicitly.

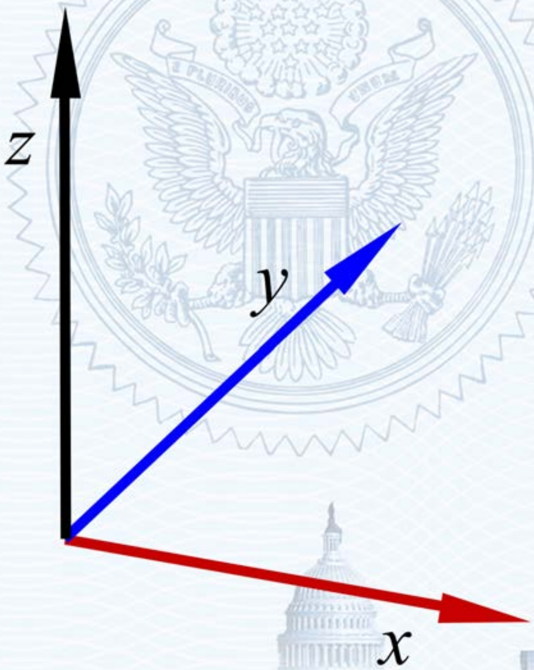
Objective: Explicit Inference & Reasoning



Objective: Human-Machine Teaming for Reasoning

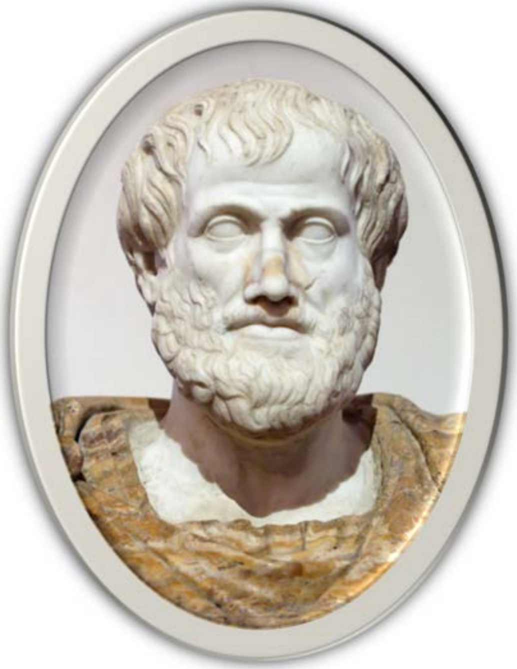
Dimensions of Reasoning

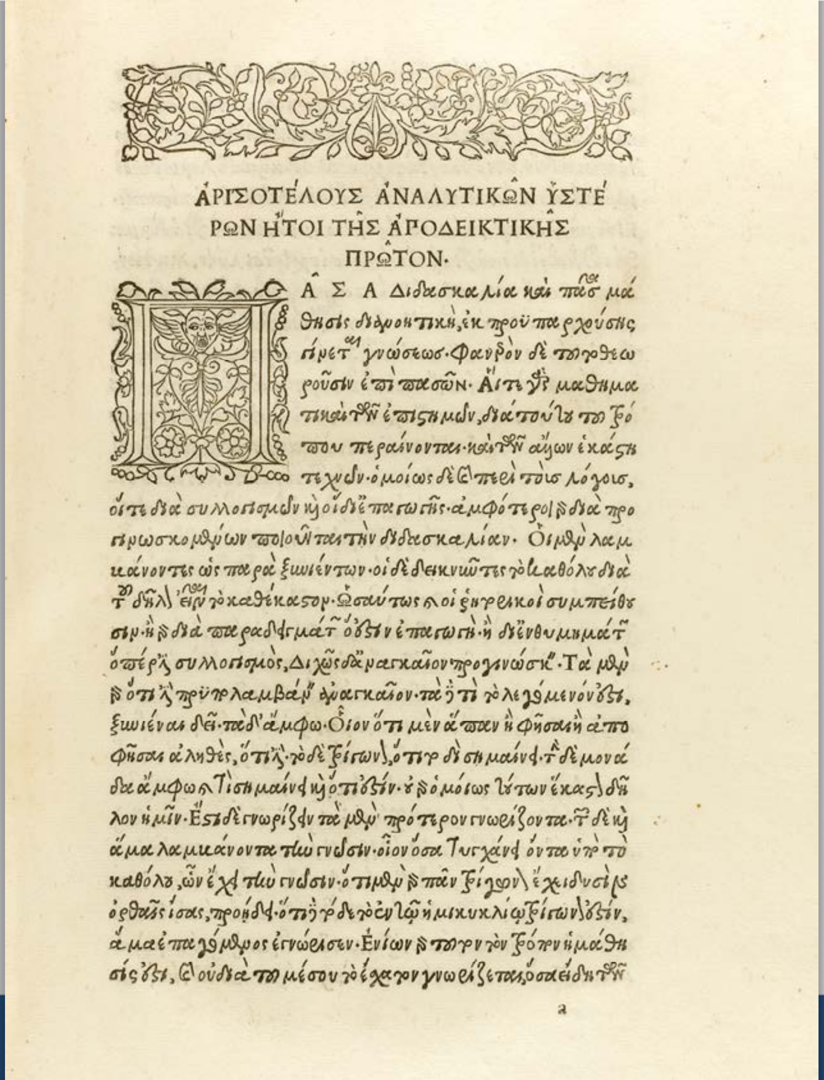




Deductive Logic

Aristotle (384-322 BC)





ΑΡΙΣΤΟΤΕΛΟΥΣ ΑΝΑΛΥΤΙΚΩΝ ΥΣΤΕΡΩΝ ΗΤΟΙ ΤΗΣ ΑΡΟΔΕΙΚΤΙΚΗΣ ΠΡΩΤΟΝ.

ΑΣΑ διδασκαλία καὶ πᾶσα μάθησις διανοητική, ἐκ προϋπαρχούσης γίνεται γνώσεως.

Deductive Logic

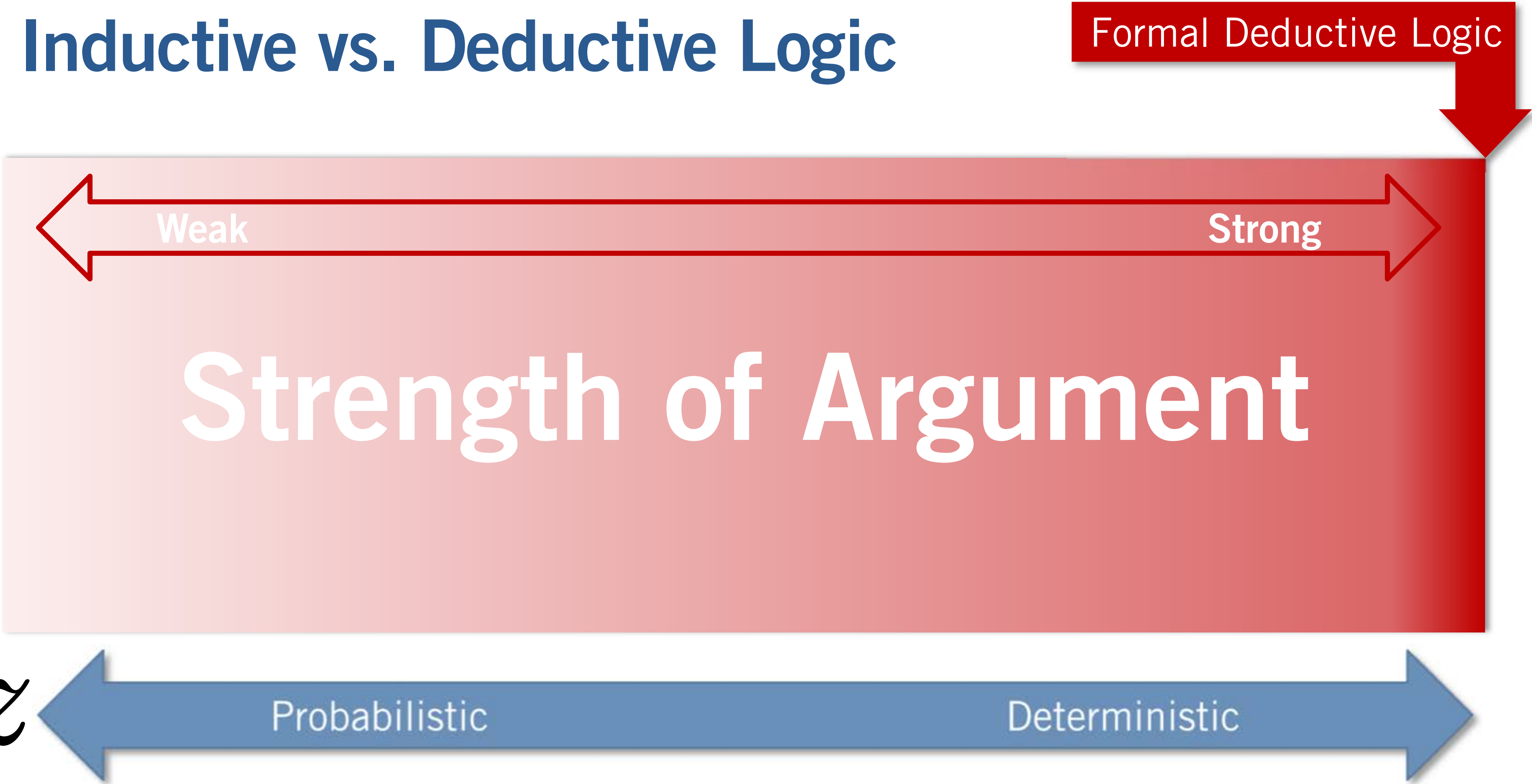
Limitations of Logic

"Classical logic has no explicit mechanism for representing the degree of certainty of premises in an argument, nor the degree of certainty in a conclusion, given those premises."

J. Williamson, Handbook of the Logic of Argument and Inference: The Turn Toward the Practical

Logic is not enough!

Inductive vs. Deductive Logic



2000 Years Later…

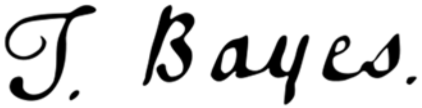
Bayes' Theorem for Conditional Probabilities

H: *Hypothesis*

E: *Evidence*

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

"Probability of H given E"



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-

Probabilistic Reasoning

Mathematical Formulation of Probabilistic Reasoning

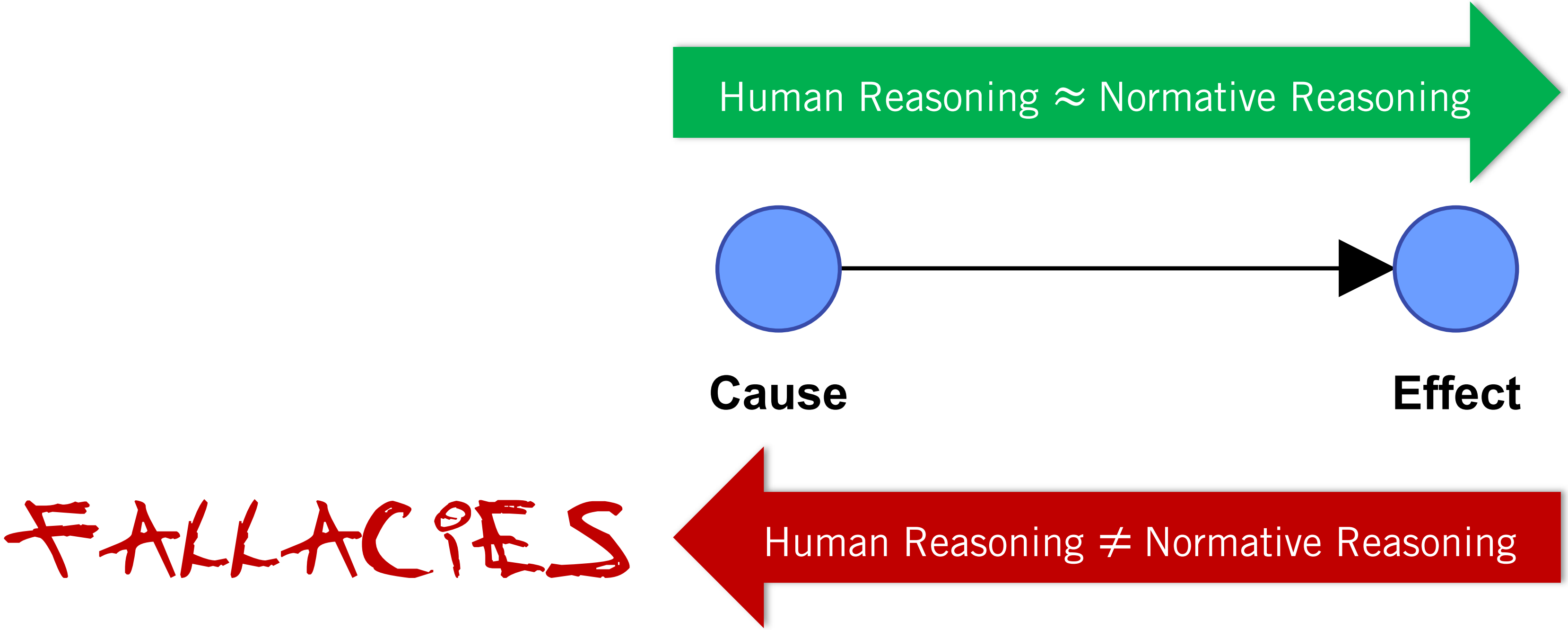
"Bayesian inference is important because it provides a normative and general-purpose procedure for reasoning under uncertainty."

Inductive Reasoning: Experimental, Developmental, and Computational Approaches, edited by Aidan Feeney and Evan Heit

This is it!

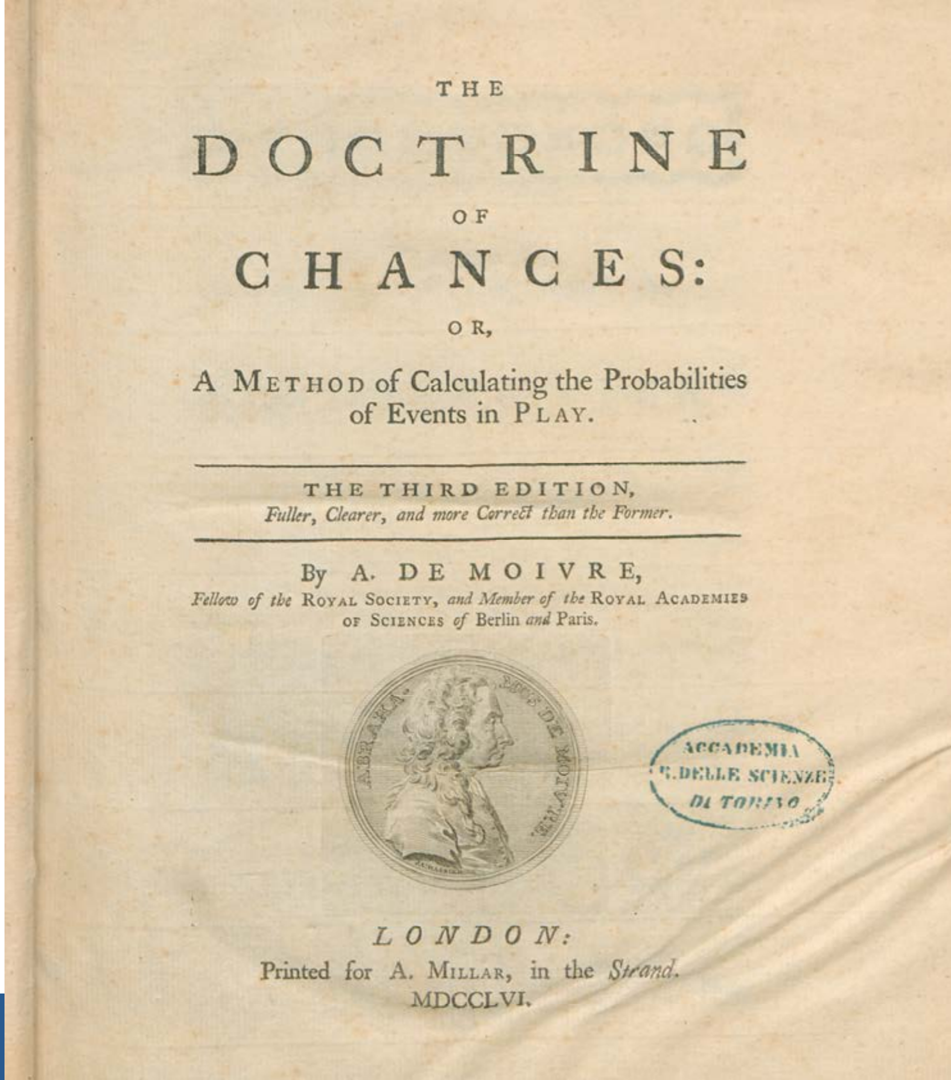
Why is this so important?

Human Cognitive Limitations and Biases Under Uncertainty



250 Years Later…

- "…despite the mathematization of probability in the Enlightenment, mathematical probability theory remains, to this very day, **entirely unused** in criminal courtrooms, when evaluating the 'probability' of the guilt of a suspected criminal."
  James Franklin, The Science of Conjecture: Evidence and Probability before Pascal, 2001 The Johns Hopkins Press


THE

DOCTRINE

OF

CHANCES:

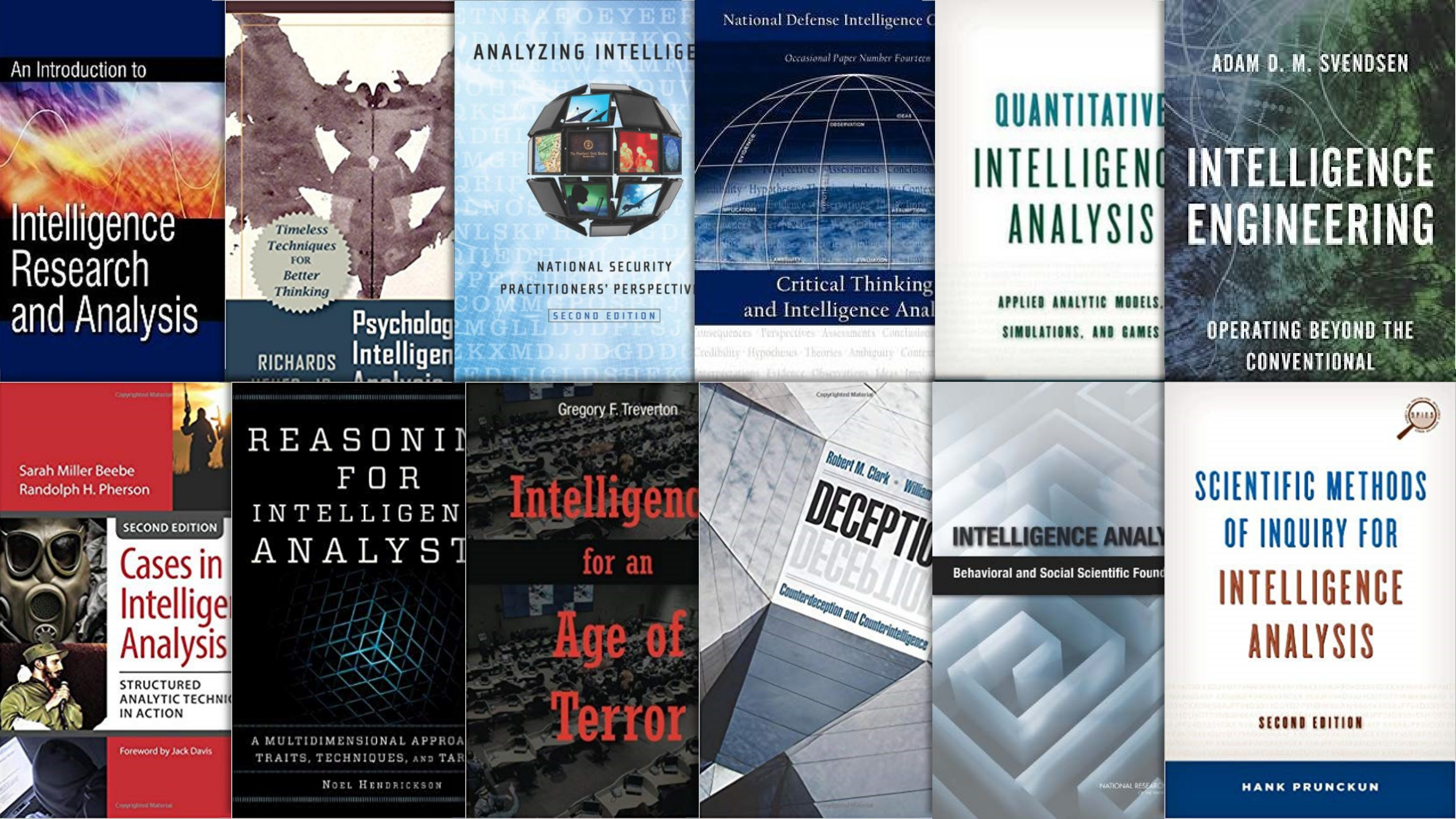
OR,

A METHOD of Calculating the Probabilities of Events in PLAY.

THE THIRD EDITION,
Fuller, Clearer, and more Correct than the Former.

By A. DE MOIVRE,
Fellow of the ROYAL SOCIETY, *and Member of the* ROYAL ACADEMIES OF SCIENCES *of* Berlin *and* Paris.

LONDON:
Printed for A. MILLAR, in the *Strand.*
MDCCLVI.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Timeless Techniques FOR Better Thinking
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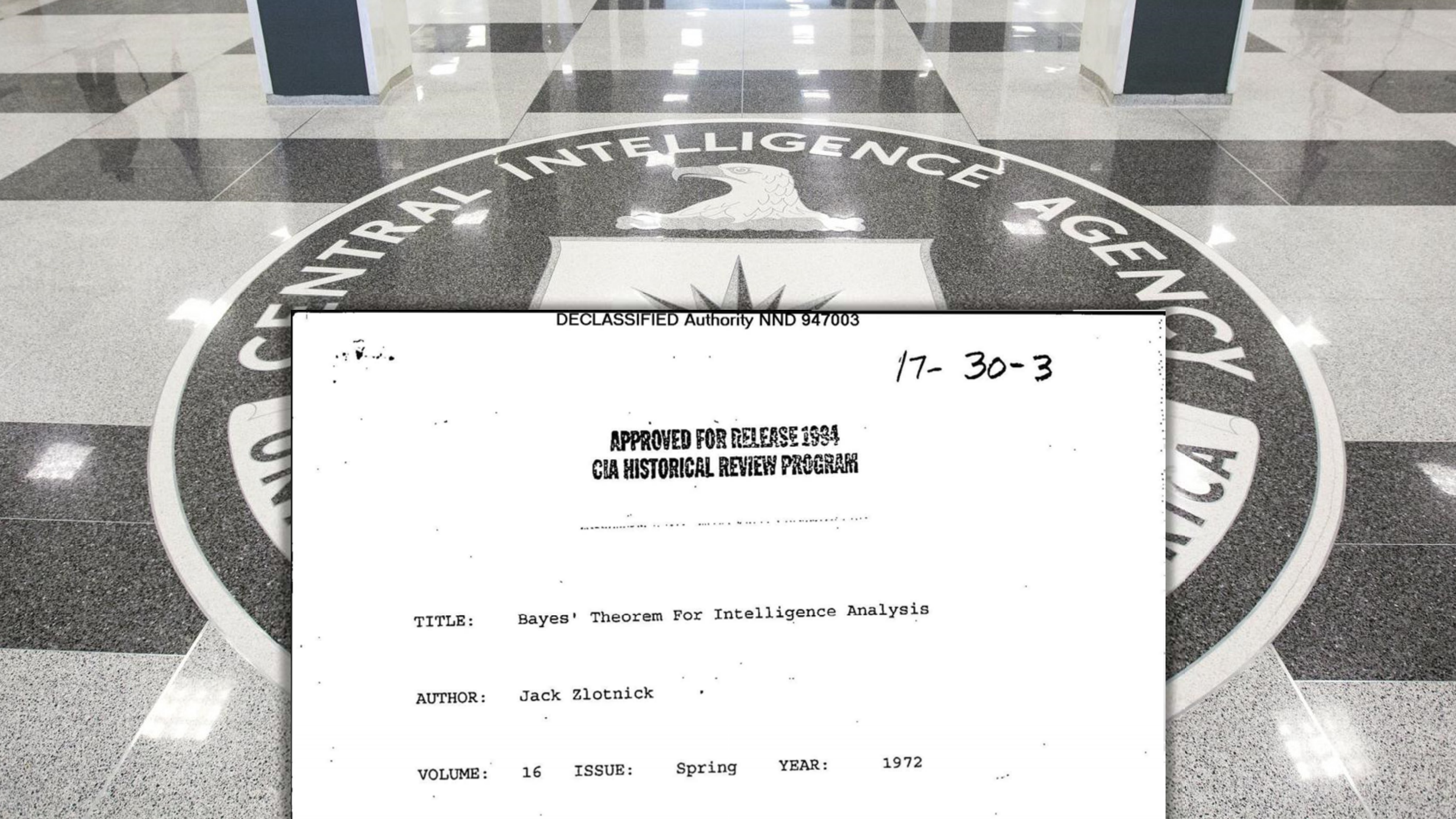

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17- 30-3

APPROVED FOR RELEASE 1994
CIA HISTORICAL REVIEW PROGRAM

TITLE: Bayes' Theorem For Intelligence Analysis

AUTHOR: Jack Zlotnick

VOLUME: 16 ISSUE: Spring YEAR: 1972

Bayesian Inference in the Intelligence Community

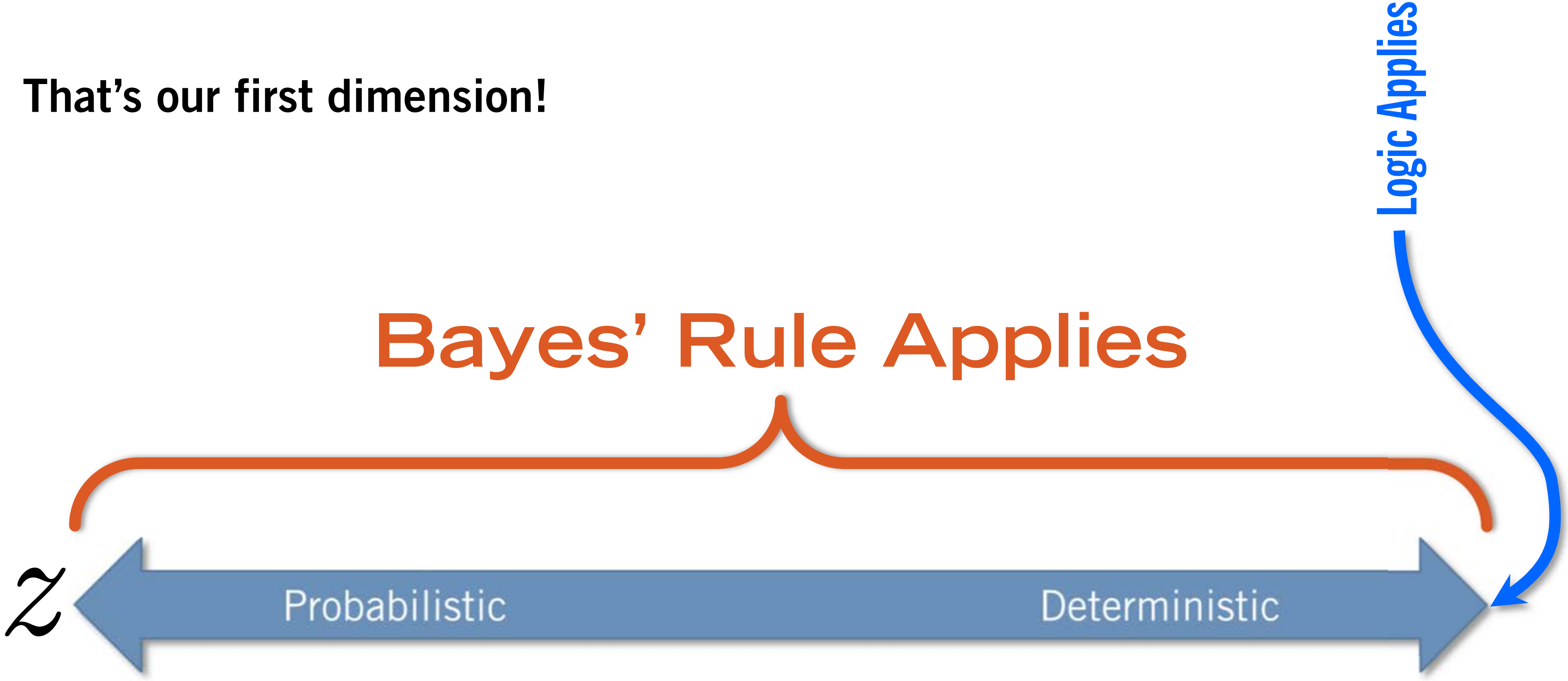
"Due to the highly mathematical nature of Bayesian Decision Analysis, many users will feel uneasy trusting the resulting assessments."

Captain David Lawrence Graves, USAF, Bayesian Analysis Methods for Threat Prediction MSSI Thesis (Washington: Defense Intelligence College, July 1993)

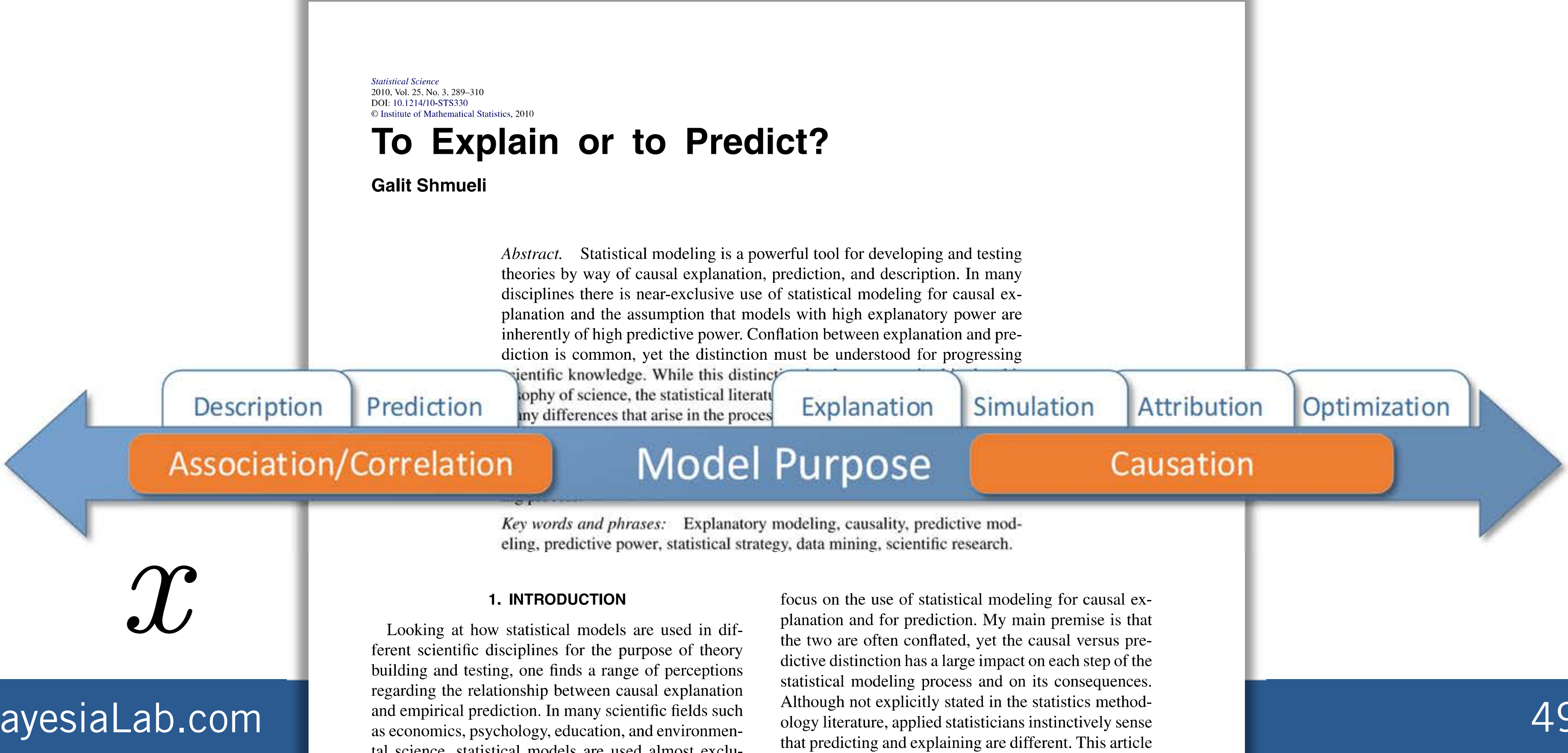
Seriously?

Dimensions of Reasoning

That's our first dimension!



Dimensions of Reasoning



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 ...ientific knowledge. While this distinct... ...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

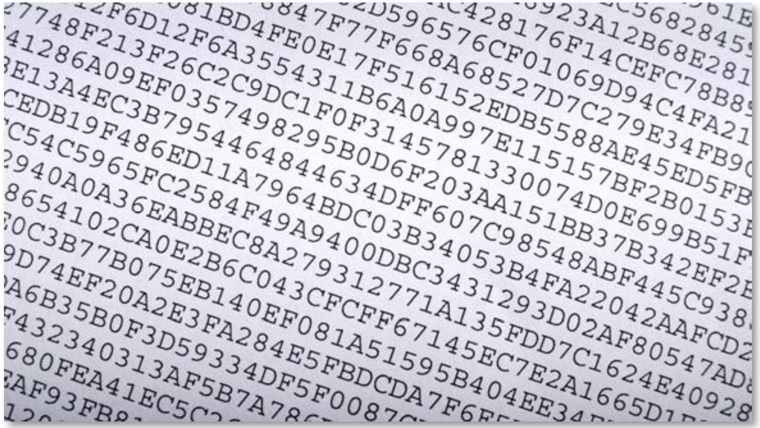
Looking at how statistical models are used in different scientific disciplines for the purpose of theory building and testing, one finds a range of perceptions regarding the relationship between causal explanation and empirical prediction. In many scientific fields such as economics, psychology, education,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

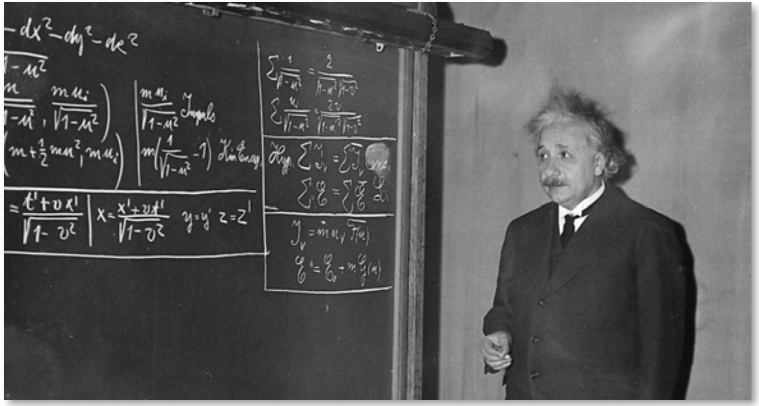
focus on the use of statistical modeling for causal explanation and for prediction. My main premise is that the two are often conflated, yet the causal versus predictive distinction has a large impact on each step of the statistical modeling process and on its consequences. Although not explicitly stated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

x

Dimensions of Reasoning

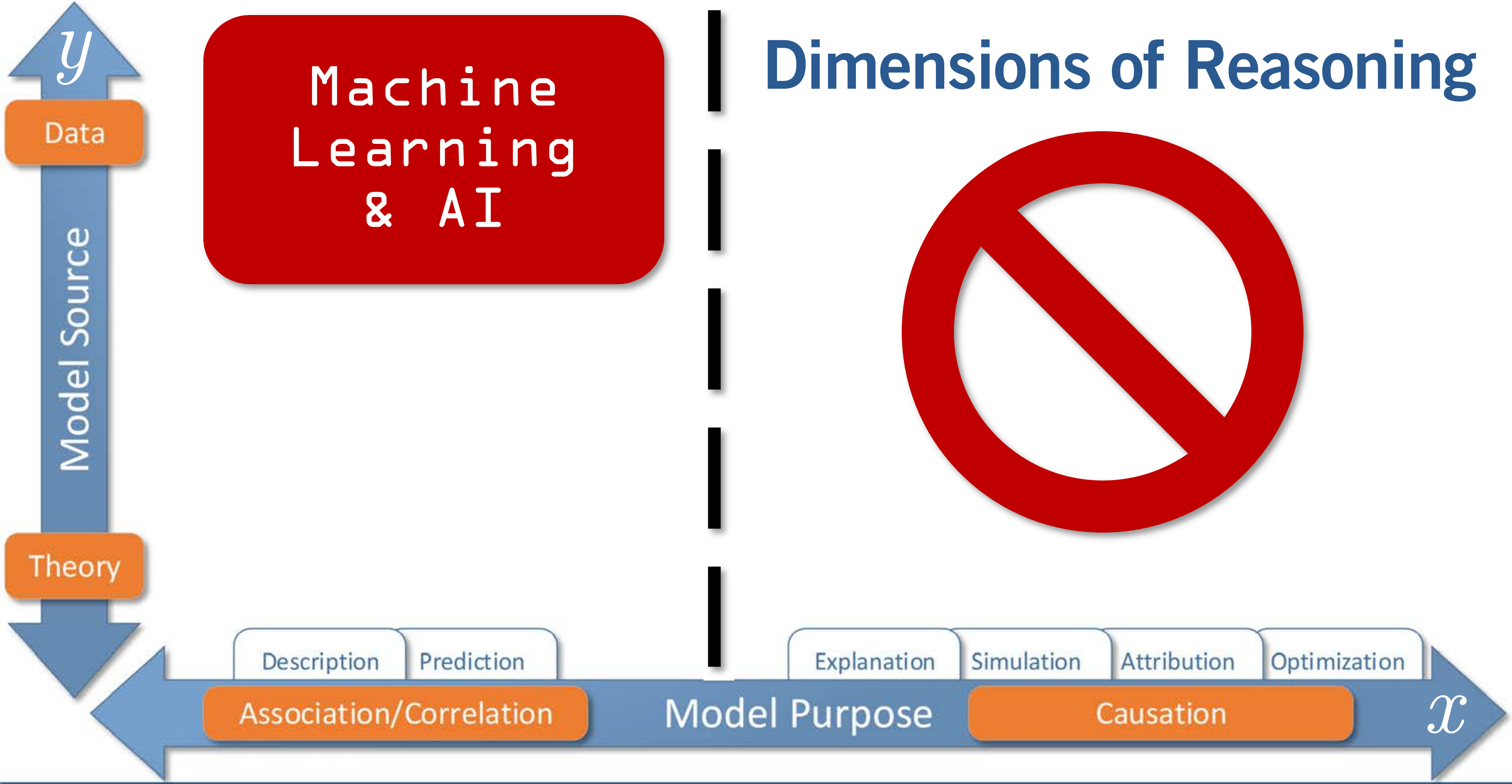
y



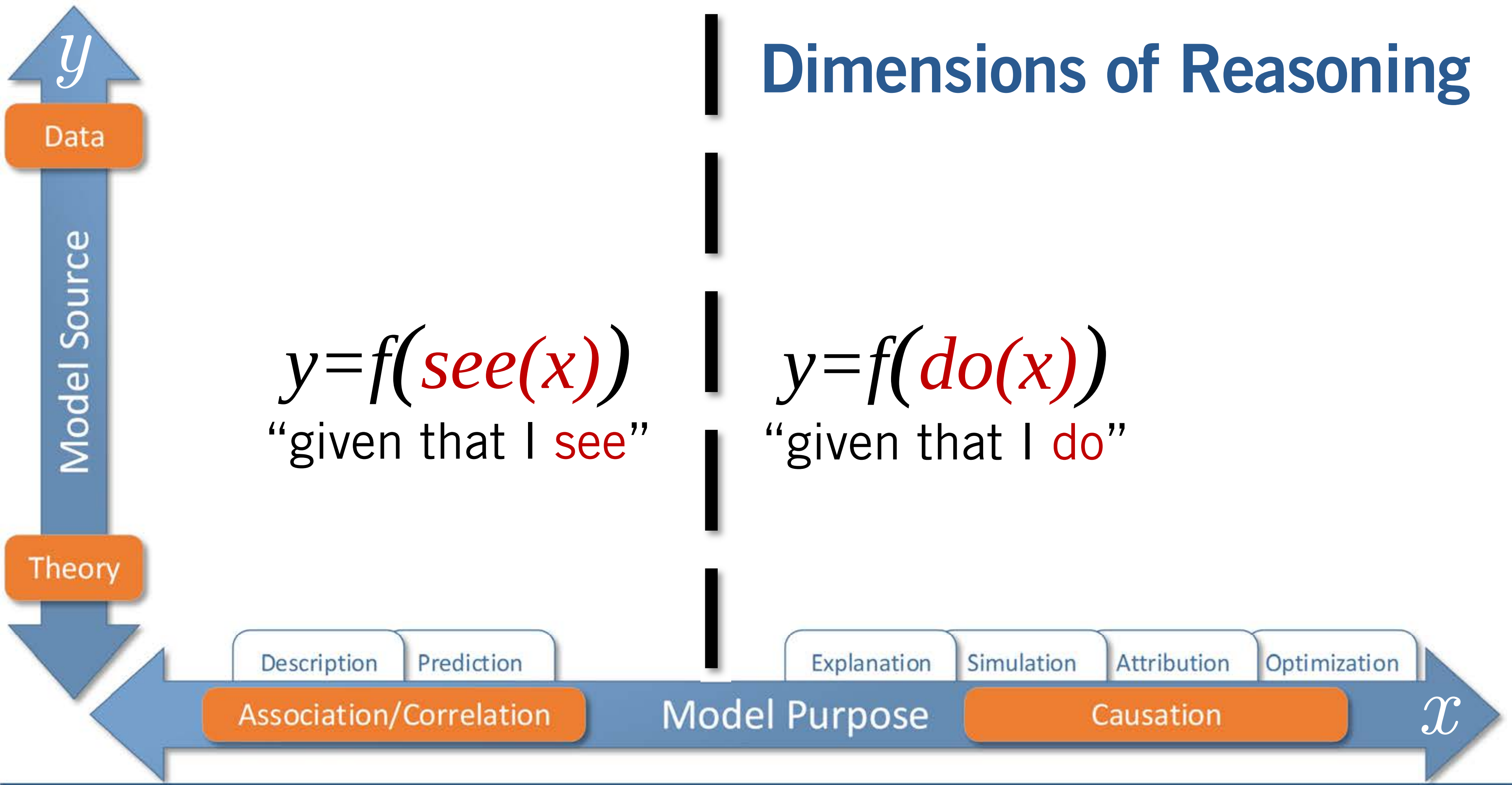


The End of Theory?

Dimensions of Reasoning



Dimensions of Reasoning



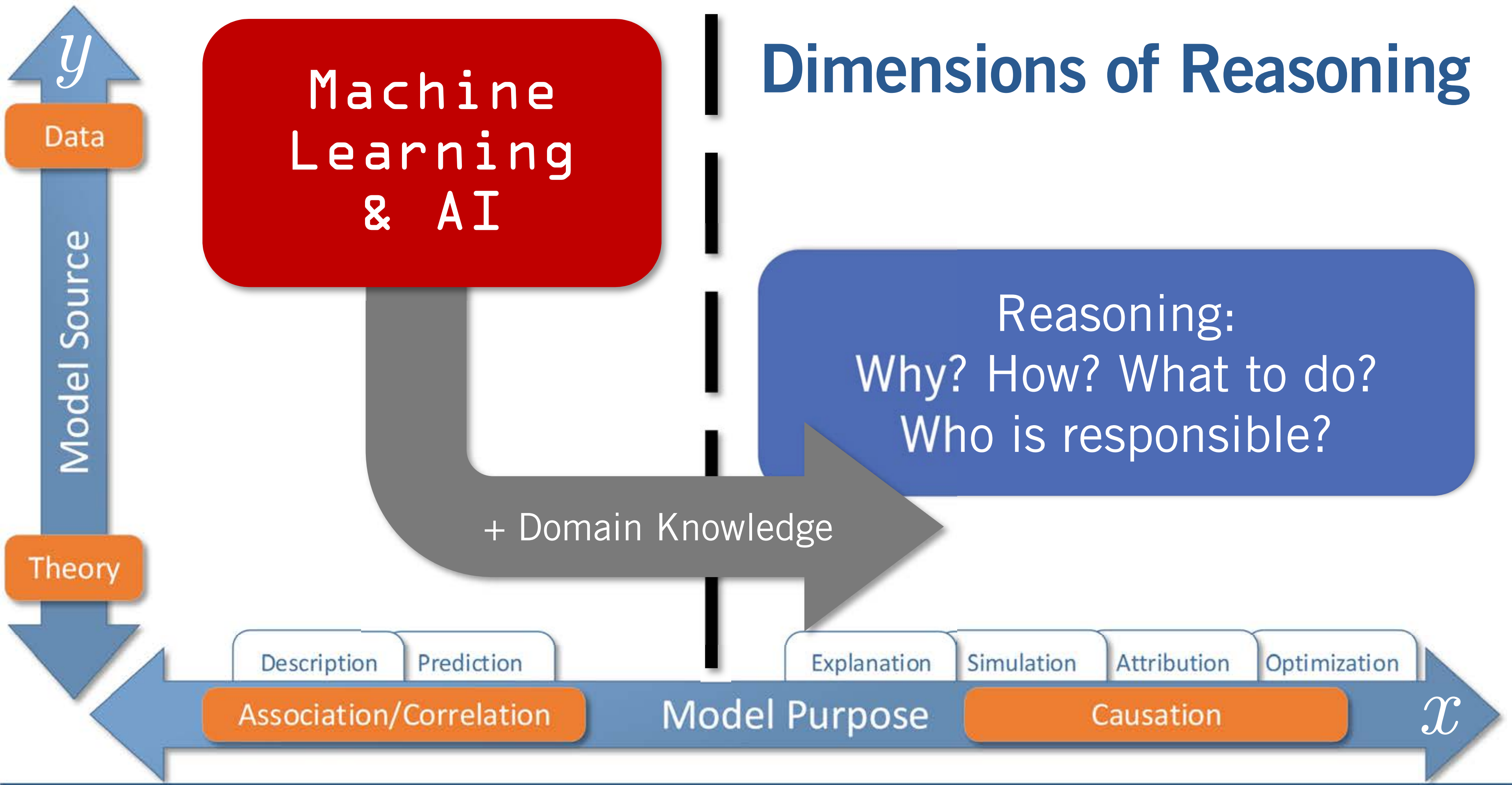
$$y=f(see(x))$$

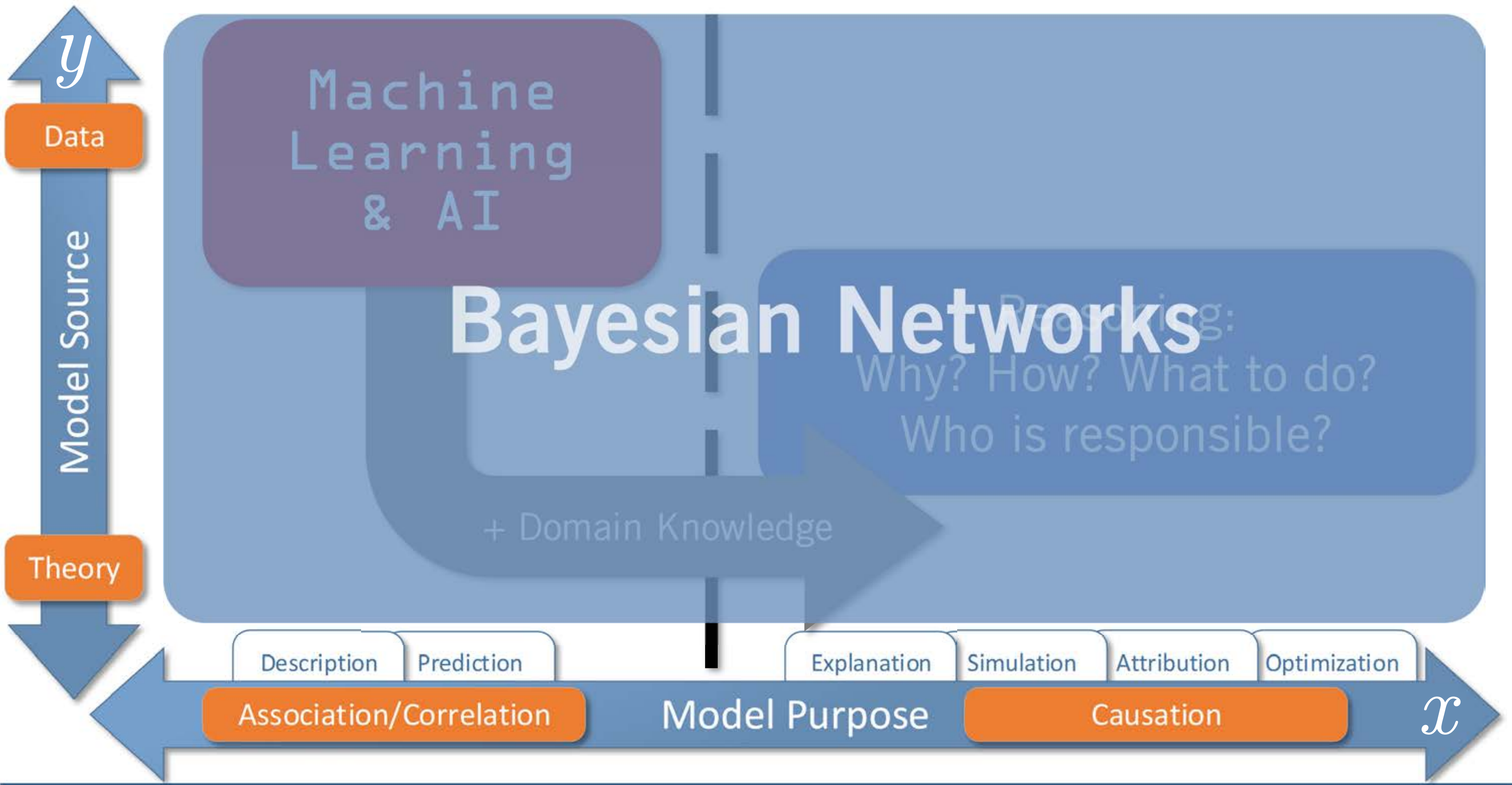
"given that I see"

$$y=f(do(x))$$

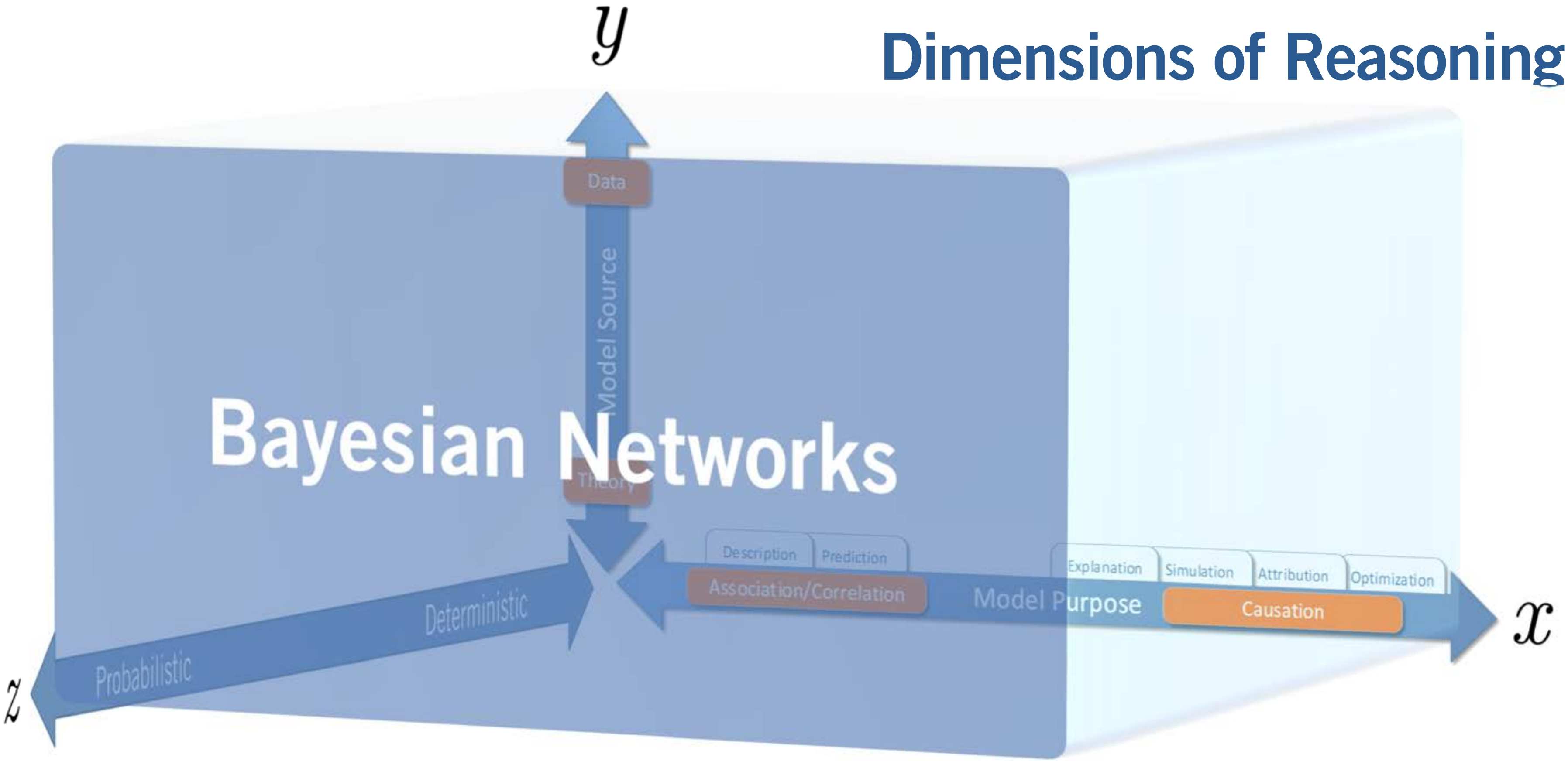
"given that I do"

Dimensions of Reasoning

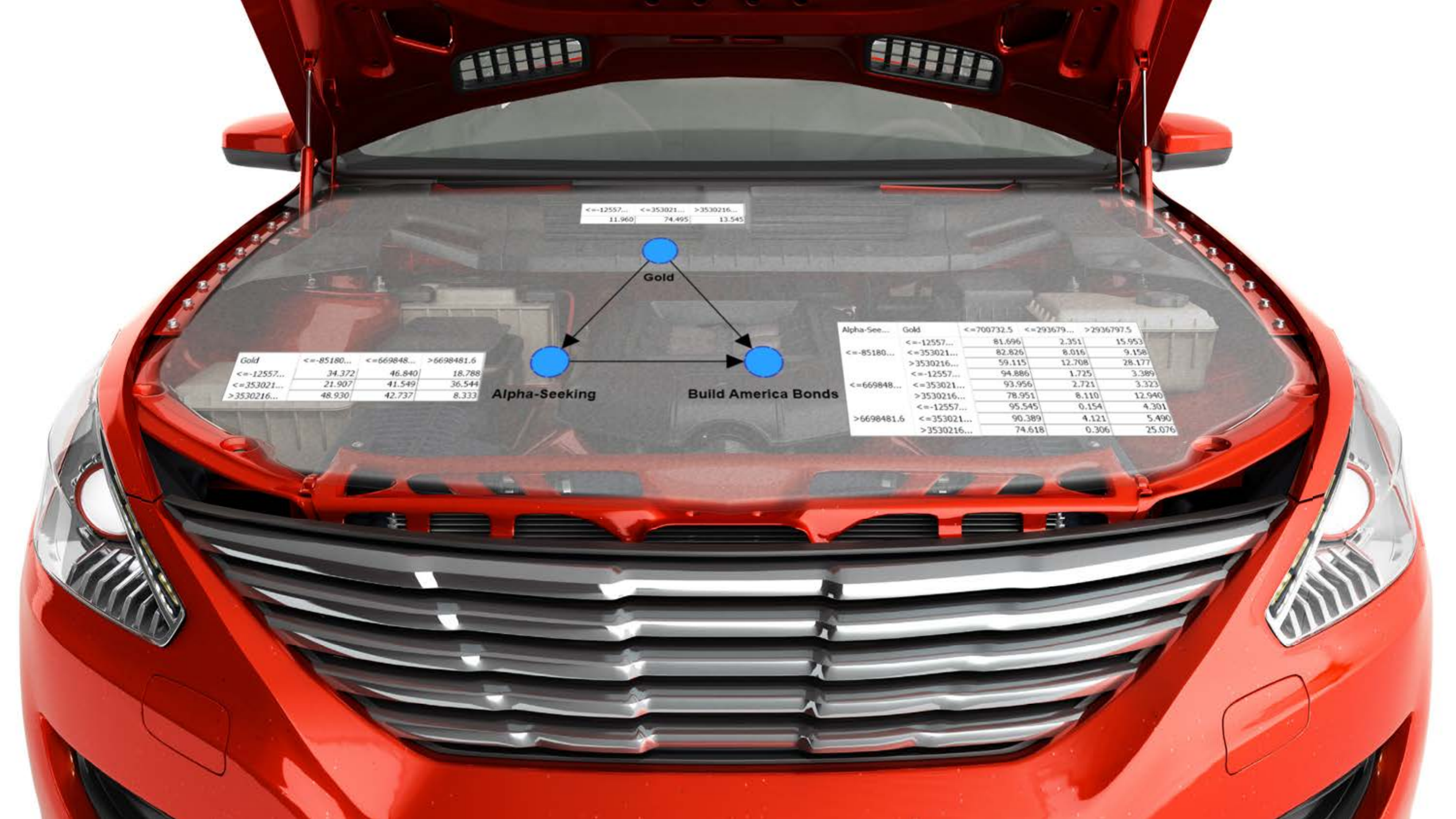



y
Data
Model Source
Theory
Machine Learning & AI
Bayesian Networks
Why? How? What to do?
Who is responsible?
+ Domain Knowledge
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation
x

Dimensions of Reasoning



The New Paradigm: Bayesian Networks



<=-12557...	<=353021...	>3530216...
11.960	74.495	13.545

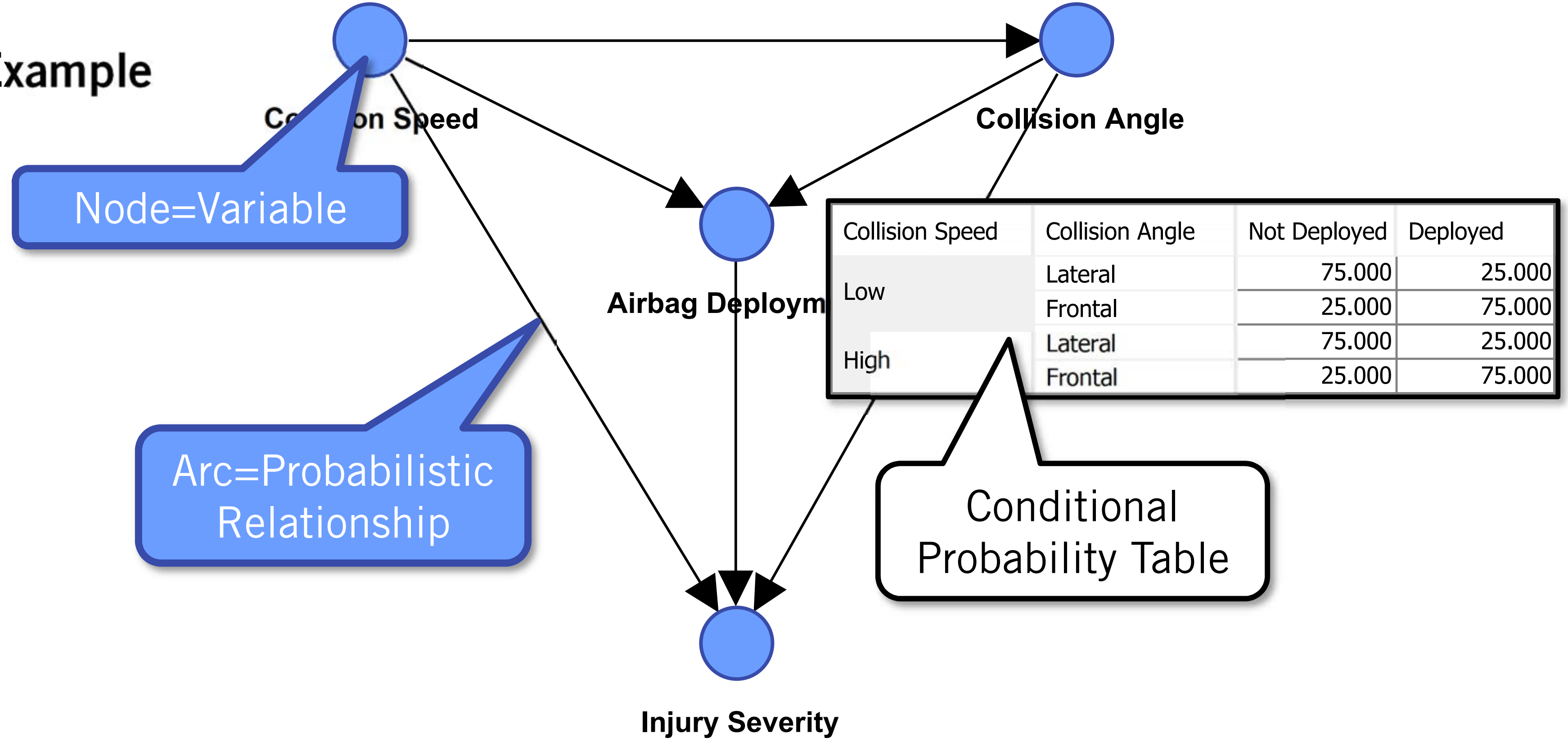
Gold
Alpha-Seeking
Build America Bonds

Gold	<=-85180...	<=669848...	>6698481.6
<=-12557...	34.372	46.840	18.788
<=353021...	21.907	41.549	36.544
>3530216...	48.930	42.737	8.333

Alpha-See...	Gold	<=700732.5	<=293679...	>2936797.5
	<=-12557...	81.696	2.351	15.953
<=-85180...	<=353021...	82.826	8.016	9.158
	>3530216...	59.115	12.708	28.177
	<=-12557...	94.886	1.725	3.389
<=669848...	<=353021...	93.956	2.721	3.323
	>3530216...	78.951	8.110	12.940
	<=-12557...	95.545	0.154	4.301
>6698481.6	<=353021...	90.389	4.121	5.490
	>3530216...	74.618	0.306	25.076

The New Paradigm: Bayesian Networks

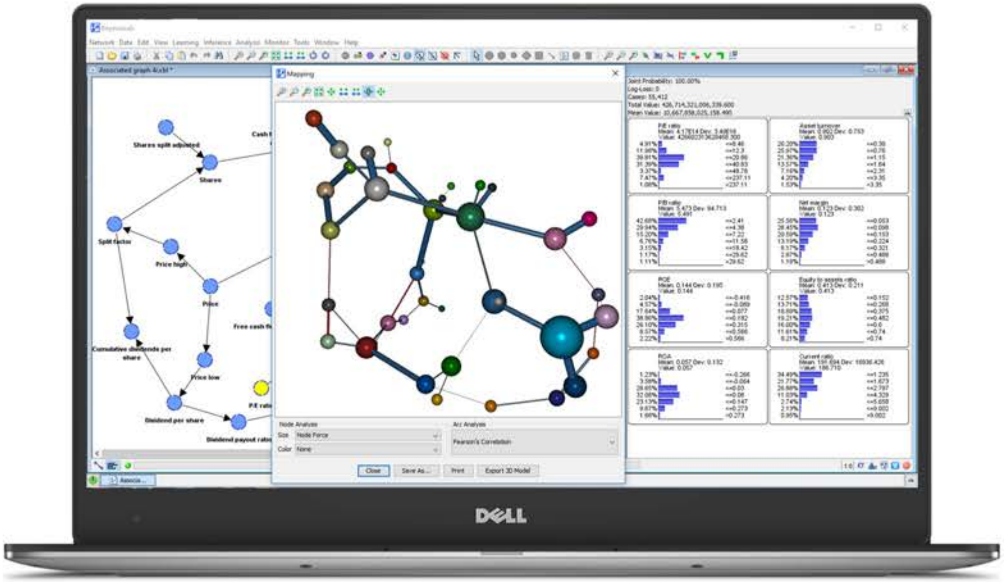
Example



Collision Speed	Collision Angle	Not Deployed	Deployed
Low	Lateral	75.000	25.000
	Frontal	25.000	75.000
High	Lateral	75.000	25.000
	Frontal	25.000	75.000

Mathematical Formalism ➔ Research Software

BAYESIALAB



A desktop software for:

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

with Bayesian networks.

Artificial Intelligence?

Implementation Example

informs.
http://pubsonline.informs.org/journal/inte/

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THE FRANZ EDELMAN AWARD
Achievement in Operations Research

Bayesian Networks for Combat Equipment Diagnostics

David Aebischer,[a] John Vatterott, Jr.,[a] Michael Grimes,[a] Andrew Vatterott,[a] Roderick Jordan,[a] Carlo Reinoso,[a] Bradford Alex Baker,[a] William D. Aldrich,[a] Luis Reinoso,[a] Rodolfo Villalba,[a] Michael Johnson,[a] Christopher Myers,[a] Stefan Conrady,[a] Joseph A. Tatman,[a] Suzanne M. Mahoney,[a] Darrin L. Whaley,[a] Amanda B. Hepler[a]

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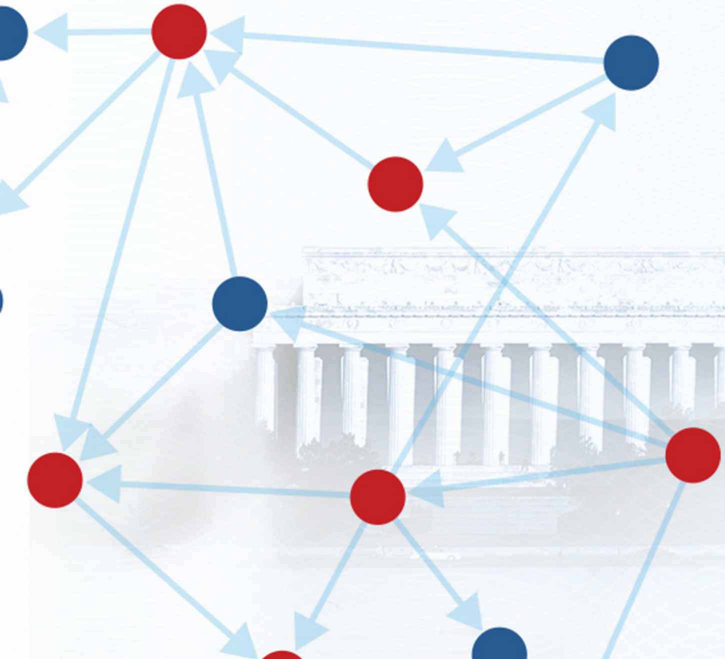
https://doi.org/10.1287/inte.2016.0883

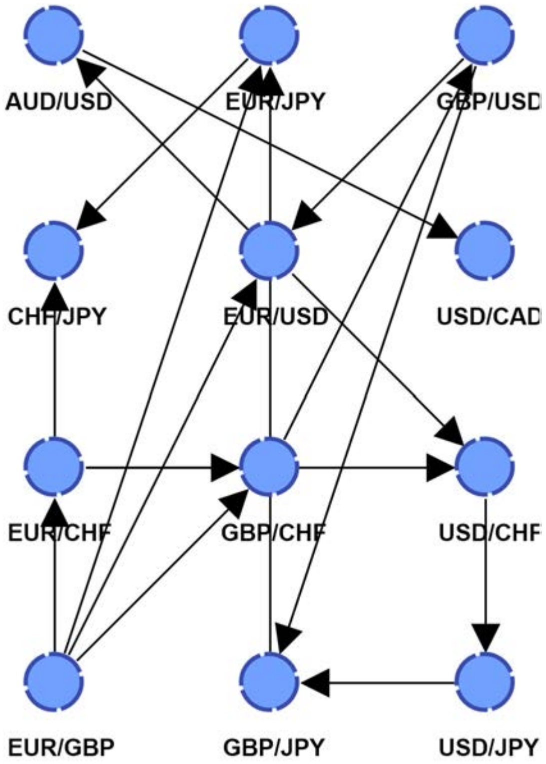
Abstract. The lives of U.S. soldiers in combat depend on complex weapon systems and advanced technologies. In combat conditions, the resources available to support the operation and maintenance of these systems are minimal. Following the failure of a critical system, technical support personnel may take days to arrive via helicopter or ground

BAYESIALAB



Conceptual Advantages of Bayesian Networks for Reasoning

The New Paradigm: Bayesian Networks



Key Properties

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

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

- 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

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

Independent

Independent

The New Paradigm: Bayesian Networks

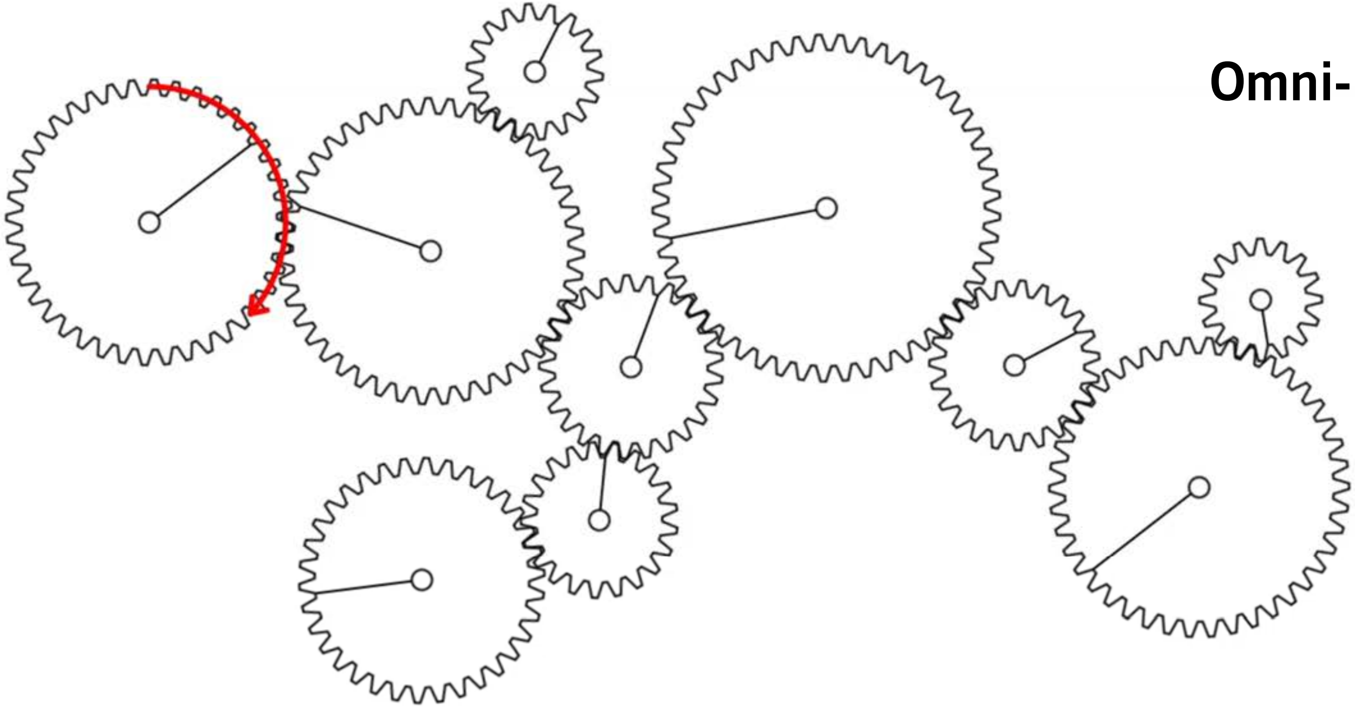
Key Properties of Bayesian Networks

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

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

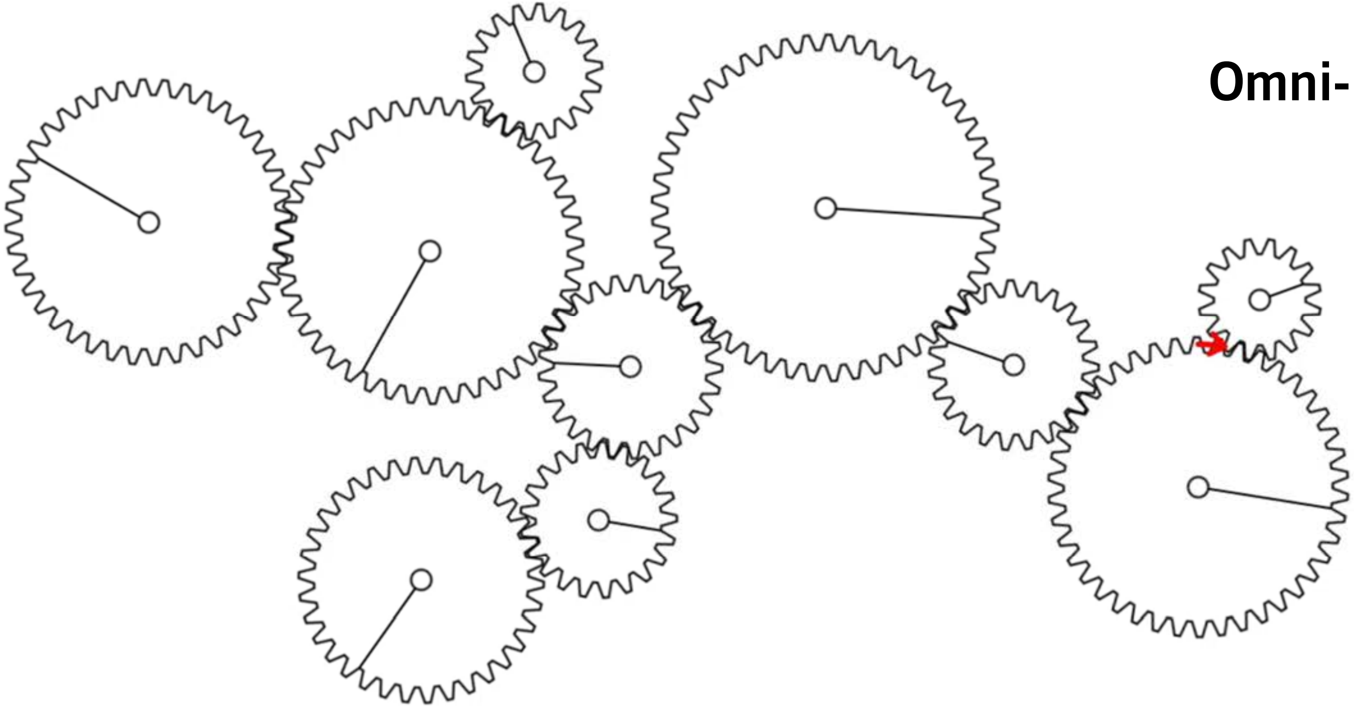
$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

The New Paradigm: Bayesian Networks



Omni-Directional Inference

The New Paradigm: Bayesian Networks

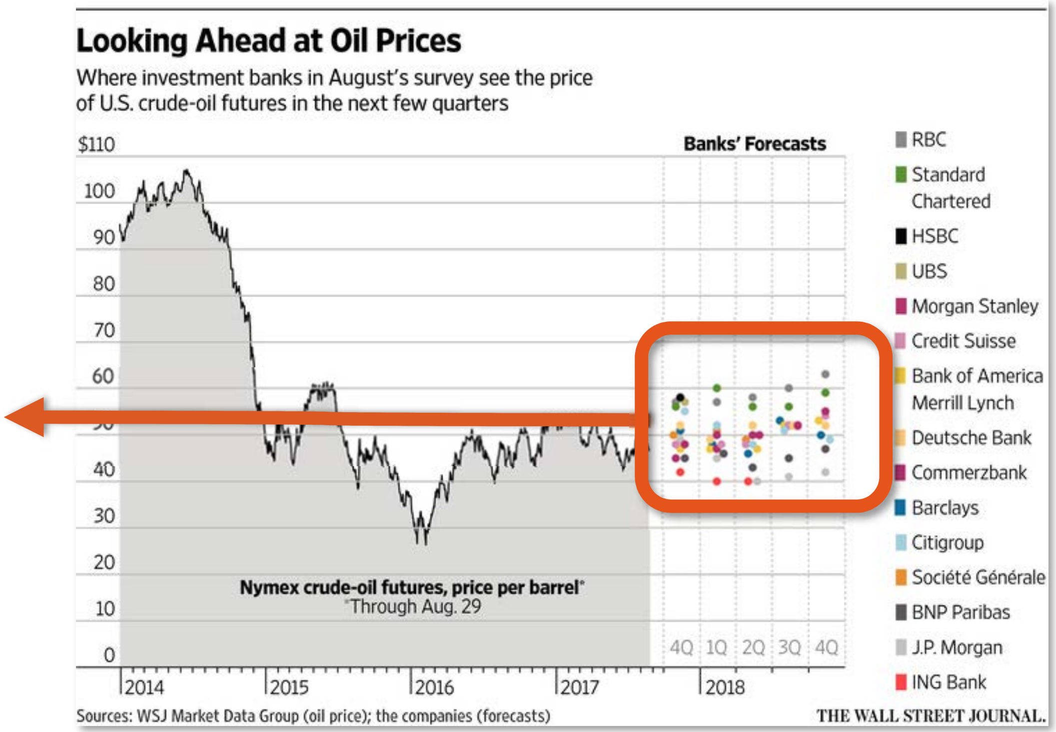


Omni-Directional Inference

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

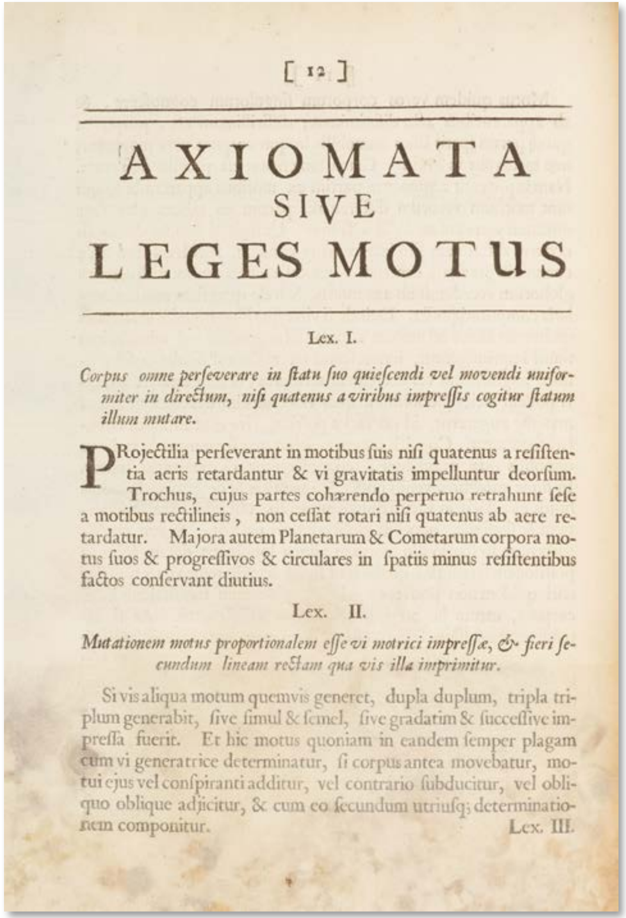
$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

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


LEGES MOTU

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.

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Lex. III.

"Mutationem motus"

"vi motrici impressæ"

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

Causal Assignment

solving for *mass*

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

Causal Interpretation Not Possible

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

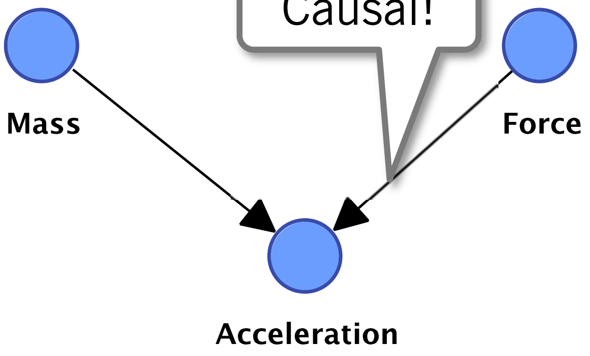
- Bayesian networks can formally encode a causal direction*, algebra cannot.

Algebra vs. Bayesian Network

Causal or non-causal?

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

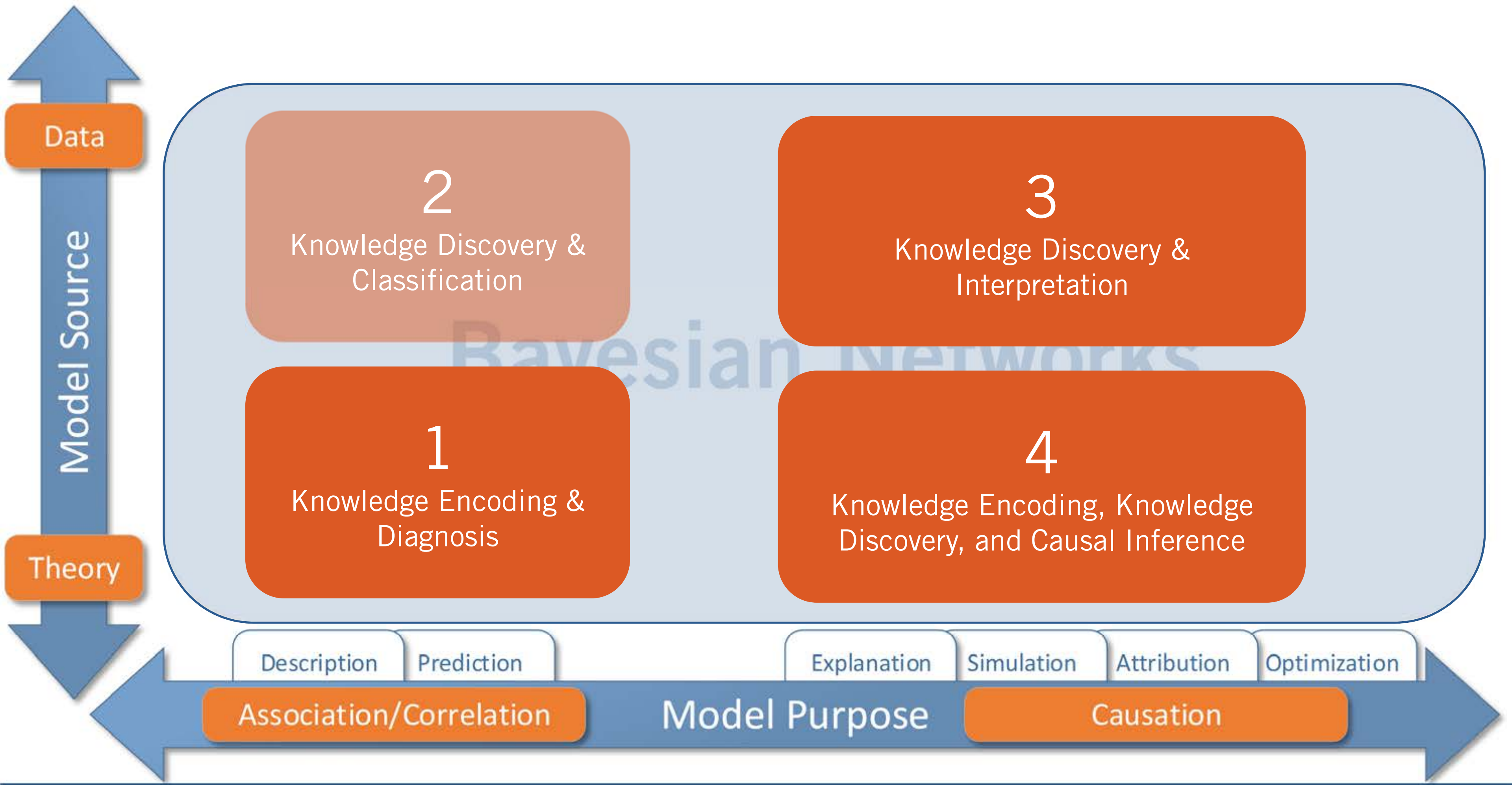
Causal!

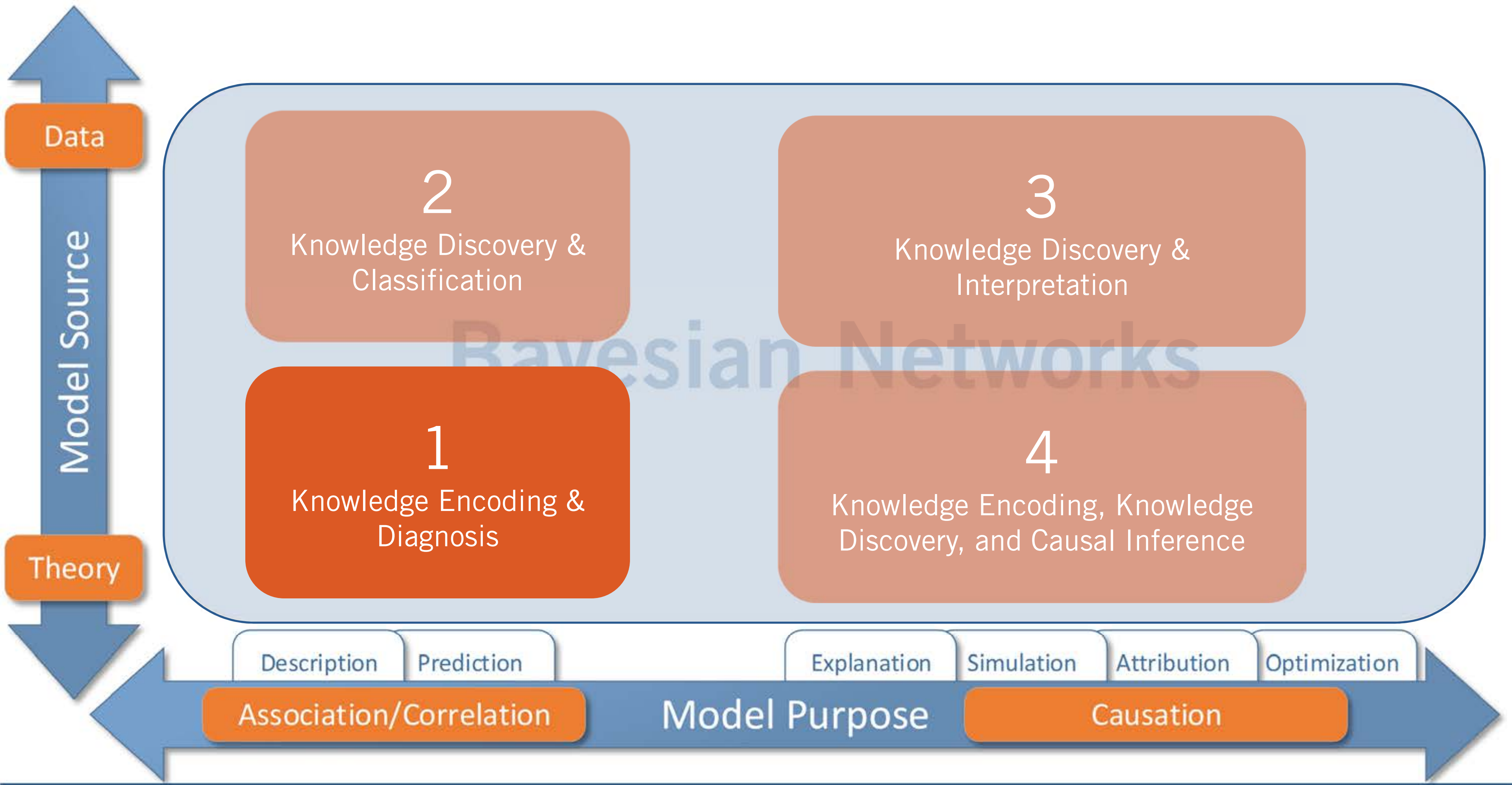


*Applies to manually encoded networks

Examples

Bayesian Networks in Practice


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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Knowledge Encoding, Knowledge Discovery, and Causal Inference
Description
Prediction
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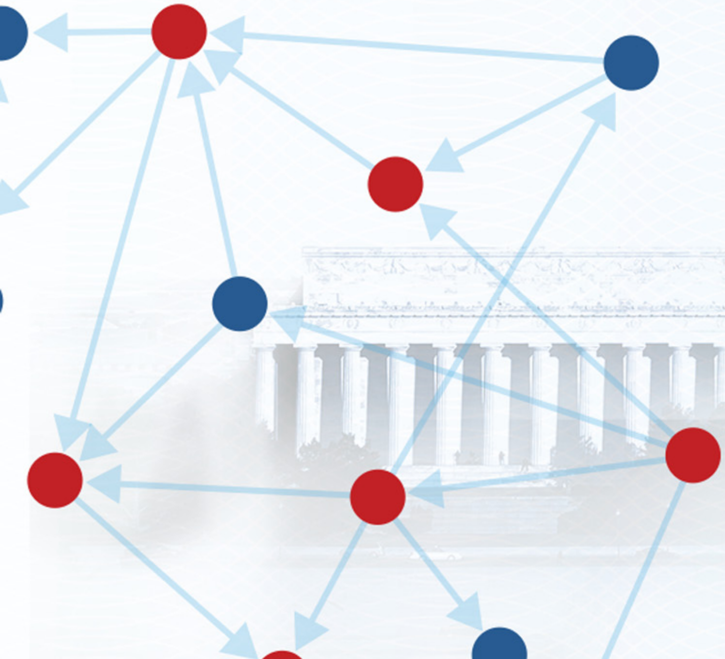
BAYESIALAB



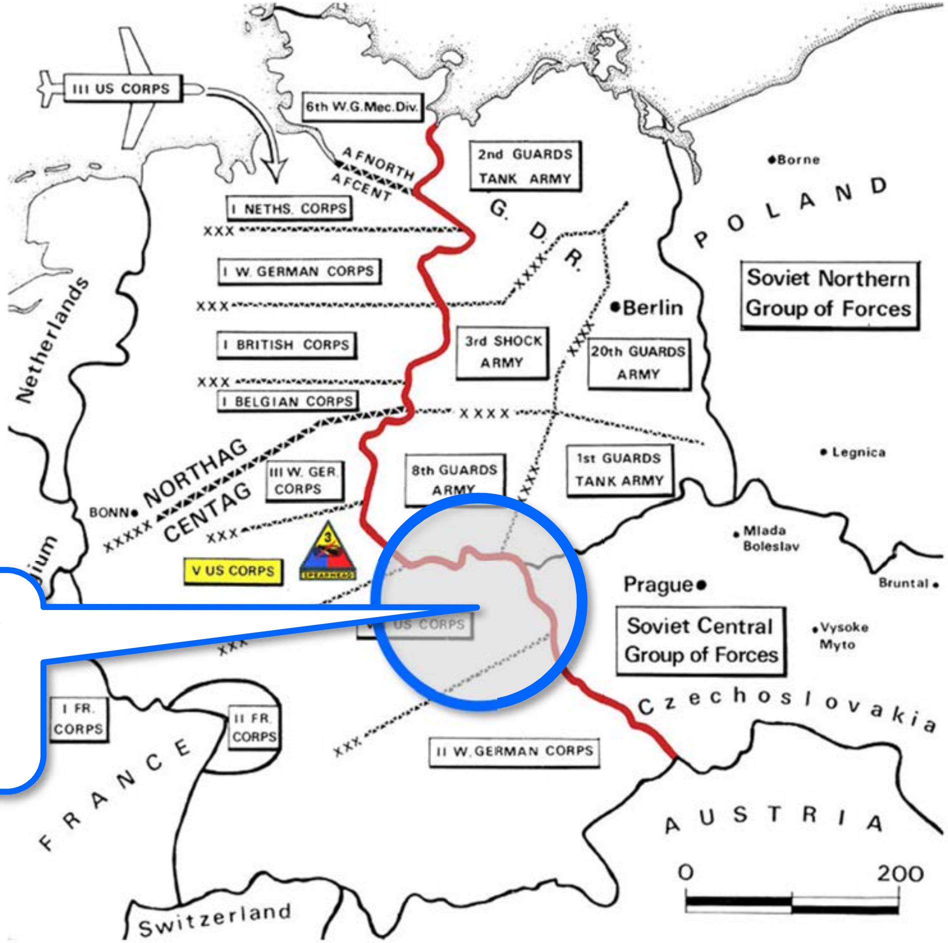
Friend or Foe?

Diagnostic Decision Support Under Extreme Uncertainty

Friend or Foe?

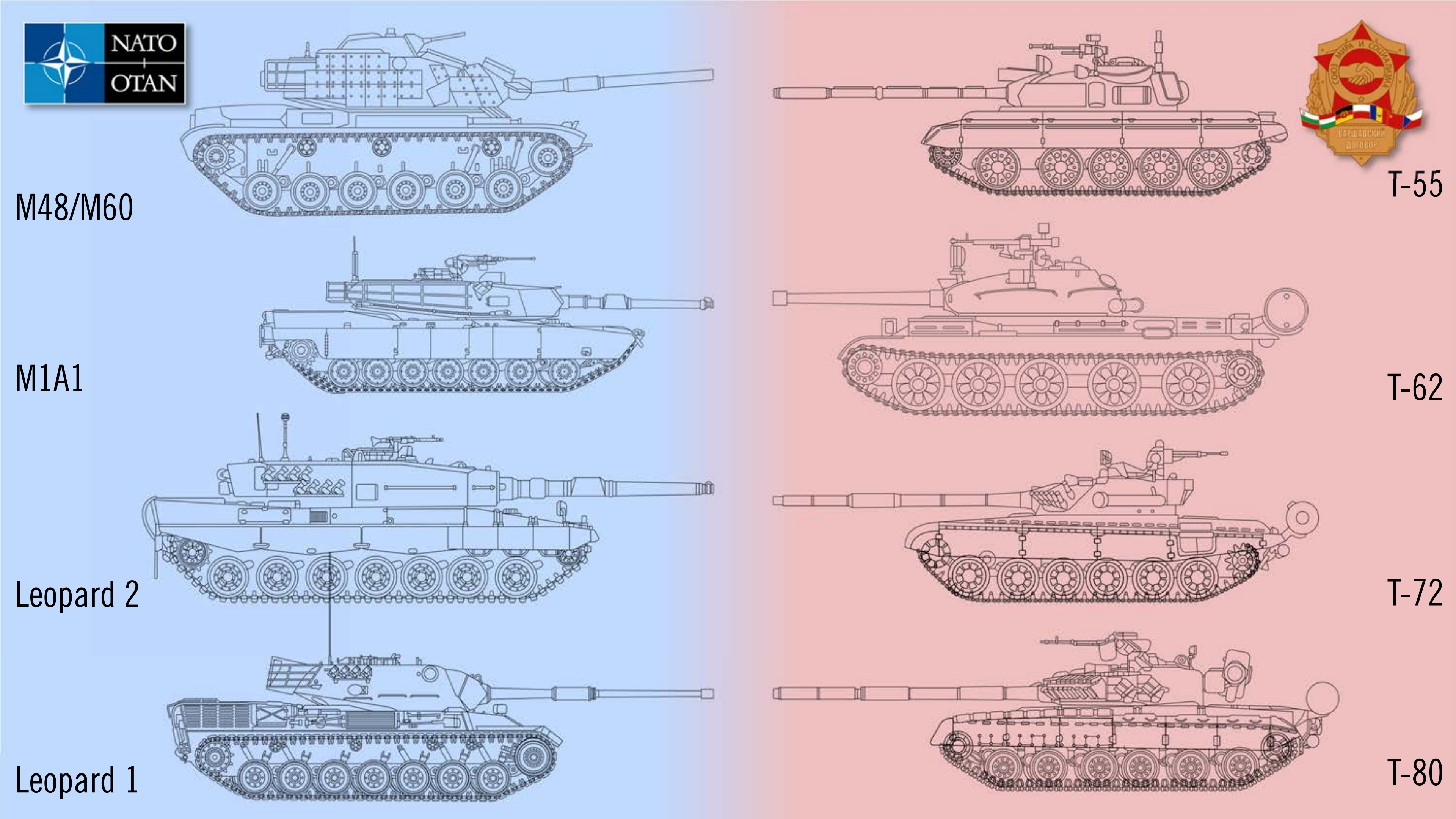
A Counterfactual Scenario:

- Central Europe, Summer of 1989
- Warsaw Pact forces invade West Germany



Nations in Combat within a 60-mile Radius: West Germany, East Germany, France, Canada, USA, Czechoslovakia, Soviet Union, etc.

Map: Strategic Geography: NATO, the Warsaw Pact, and the Superpowers; by Hugh Faringdon; 1989.


NATO
OTAN
M48/M60
M1A1
Leopard 2
Leopard 1
T-55
T-62
T-72
T-80

Friend or Foe?

Tank Identification Handbook, 1982

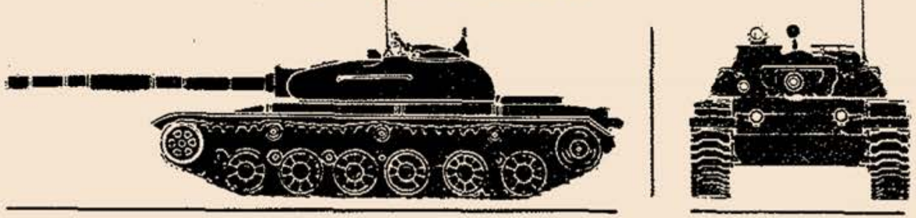
ST 7-193 F

UNITED STATES

TANK IDENTIFICATION HANDBOOK

UNITED STATES ARMY INFANTRY SCHOOL
FORT BENNING, GEORGIA

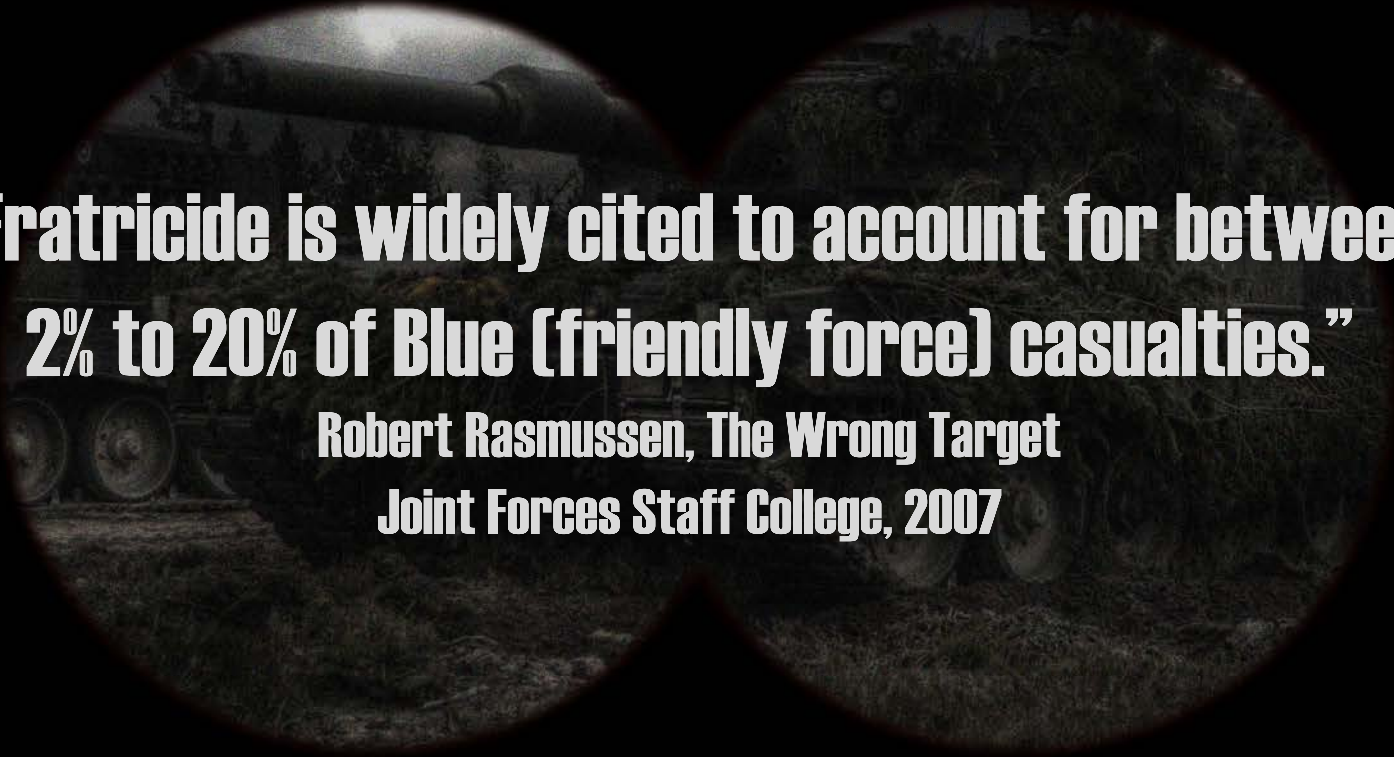
T—72 TANK



SUCCESSOR TO THE T-62 BATTLE TANK

1. TURRET CENTRALLY MOUNTED ON CHASSIS
2. TANK COMMANDER'S IR SEARCHLIGHT IS LOCATED ON RIGHT OF TURRET HATCH
3. VEHICLE ID NIGHT LIGHT
4. GUN SIMILAR TO T-62
5. THREE TRACK SUPPORT ROLLERS
6. SIX EVENLY SPACED ROAD WHEELS

1. WADING CAPABILITY SIMILAR TO T-55
2. GUN 115MM TO 122MM
3. COAX 7.62MM MG
4. CBR PROTECTIVE LINER
5. CREW: 4



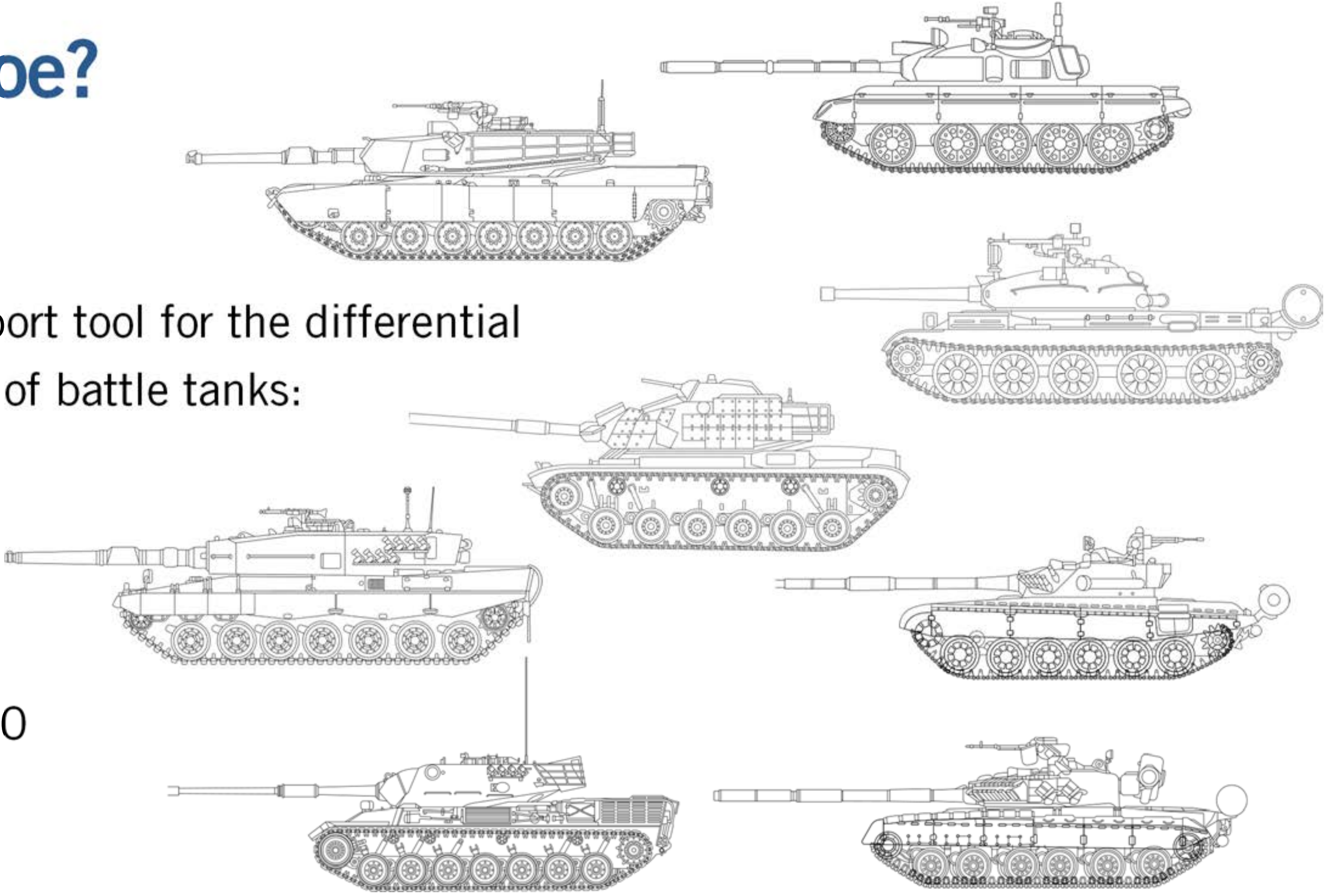
"Fratricide is widely cited to account for between 2% to 20% of Blue (friendly force) casualties."

Robert Rasmussen, The Wrong Target
Joint Forces Staff College, 2007

Friend or Foe?

Objective

- Decision support tool for the differential identification of battle tanks:
- M1A1
- M48/60
- Leopard 1/2
- T-55/62/72/80



All numerical values provided in this example are fictional.

Friend or Foe?

This is an inference task!

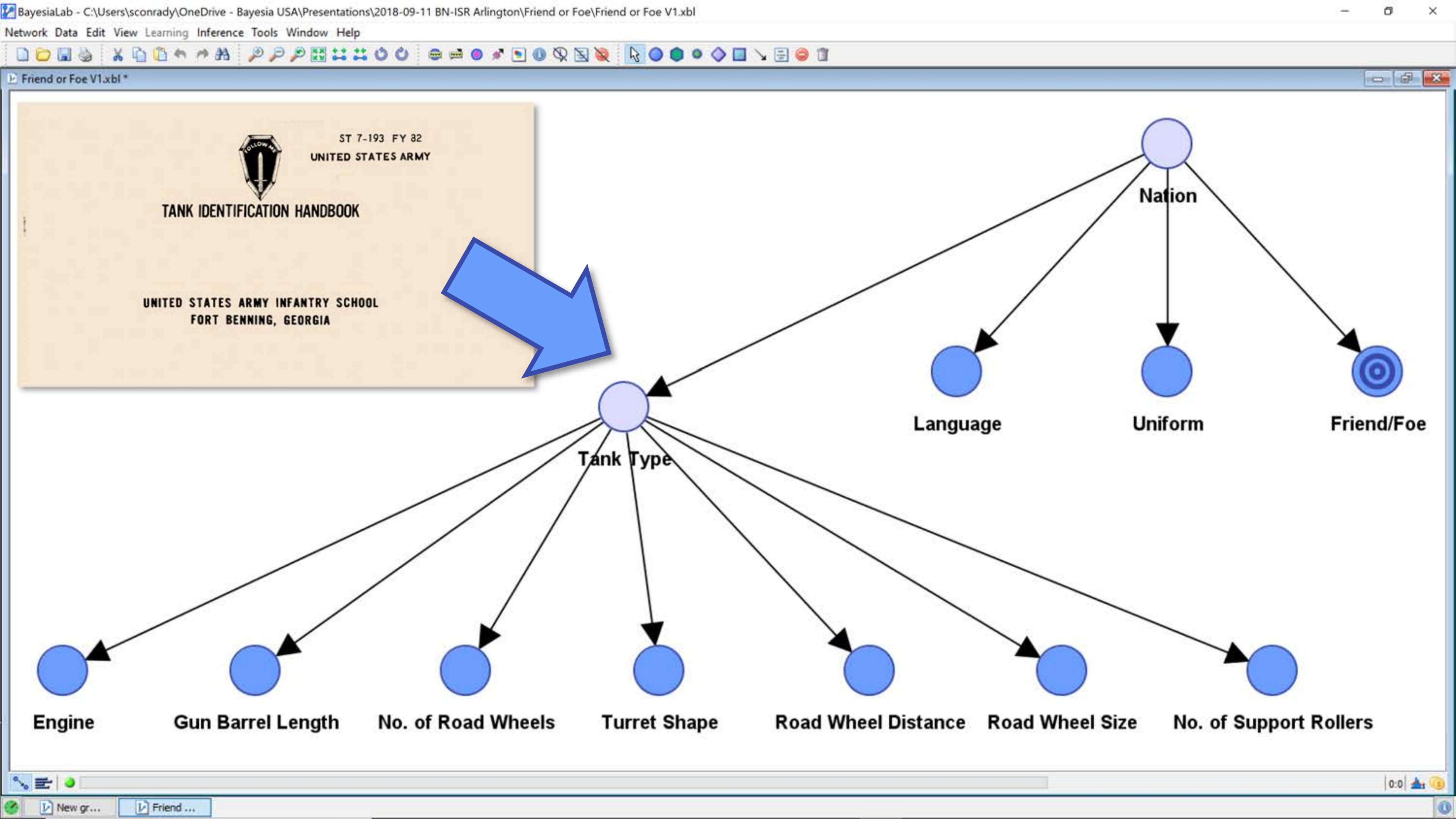
- P(M1A1 | Turret Shape, Barrel Length, Wheels, Wheel Distance, etc.)=?
- P(T-80 | Turret Shape, Barrel Length, Wheels, Wheel Distance, etc.)=?

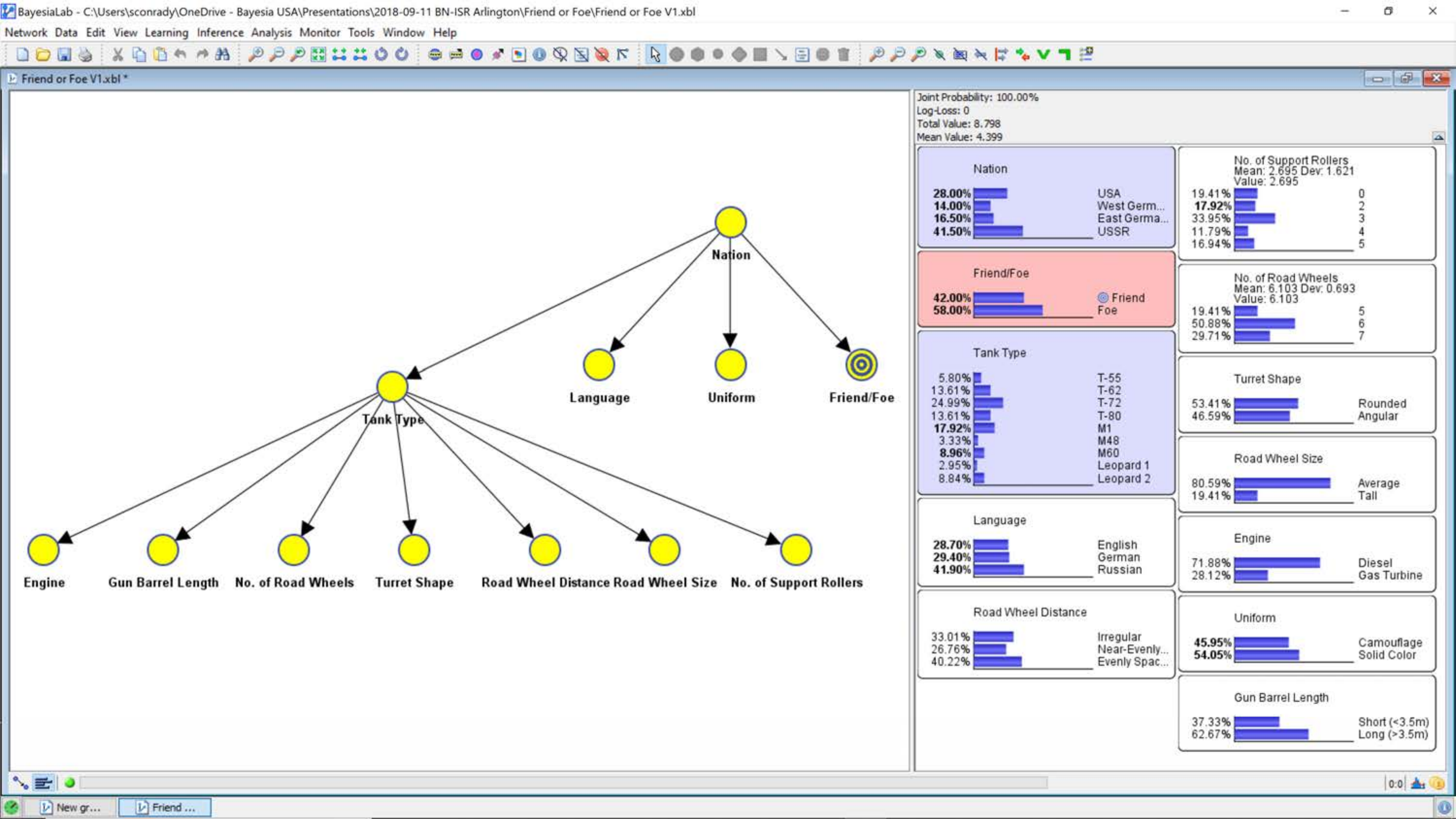
Probability of

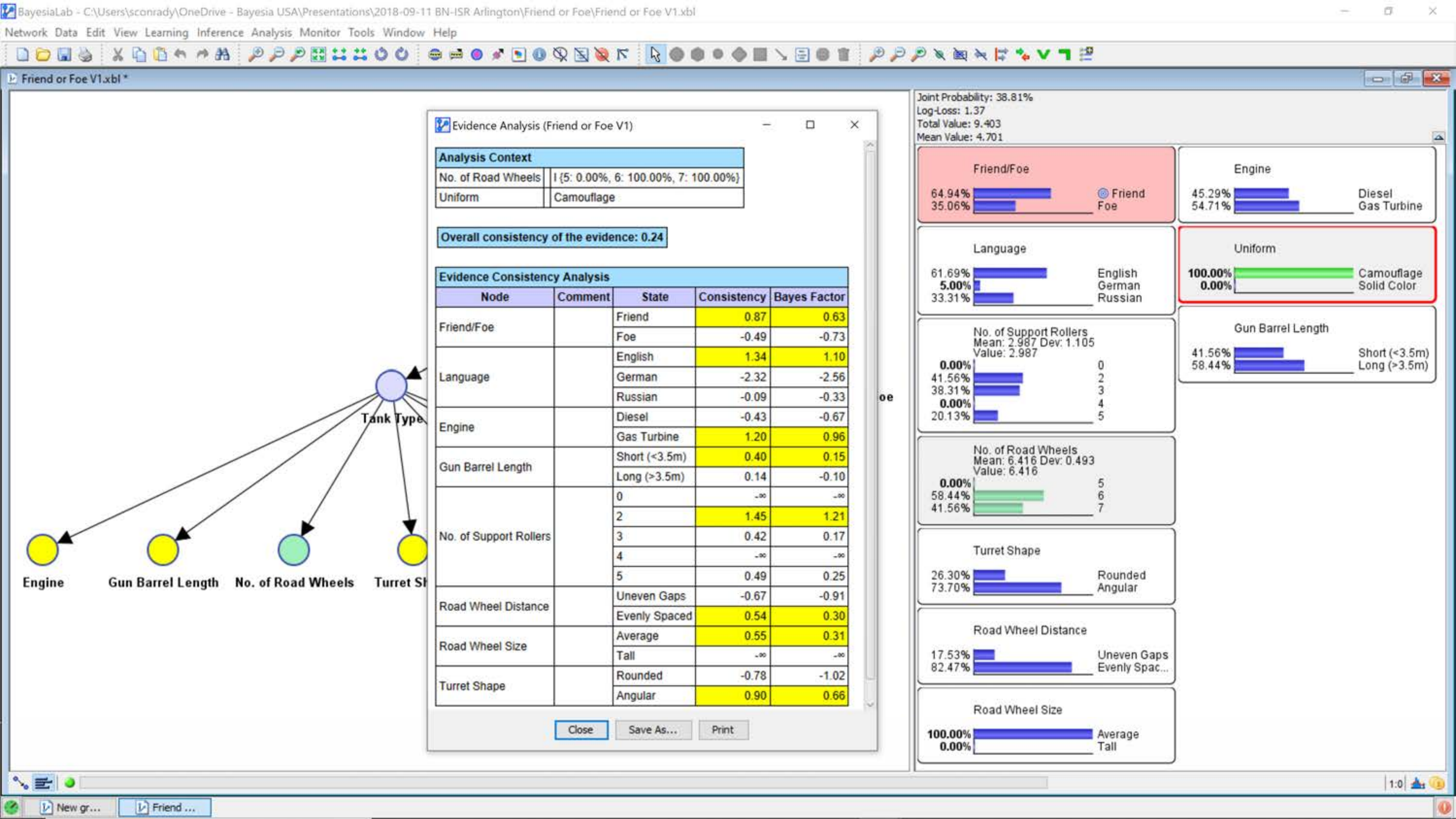
- Shape, Barrel Length, Wheels, Wheel Distance, etc.)=?
- P(M60 | Turret Shape, Barrel Length, Wheels, Wheel Distance, etc.)=?

given

We need a knowledge base & inference engine!


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Friend or Foe\Friend or Foe V1.xbl
Network Data Edit View Learning Inference Tools Window Help
Friend or Foe V1.xbl *
ST 7-193 FY 82
UNITED STATES ARMY
TANK IDENTIFICATION HANDBOOK
UNITED STATES ARMY INFANTRY SCHOOL
FORT BENNING, GEORGIA
Nation
Tank Type
Language
Uniform
Friend/Foe
Engine
Gun Barrel Length
No. of Road Wheels
Turret Shape
Road Wheel Distance
Road Wheel Size
No. of Support Rollers
New gr...
Friend ...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Friend or Foe\Friend or Foe V1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Friend or Foe V1.xbl *
Nation
Language
Uniform
Friend/Foe
Tank Type
Engine
Gun Barrel Length
No. of Road Wheels
Turret Shape
Road Wheel Distance
Road Wheel Size
No. of Support Rollers
Joint Probability: 100.00%
Log-Loss: 0
Total Value: 8.798
Mean Value: 4.399
Nation
28.00% USA
14.00% West Germ...
16.50% East Germa...
41.50% USSR
Friend/Foe
42.00% Friend
58.00% Foe
Tank Type
5.80% T-55
13.61% T-62
24.99% T-72
13.61% T-80
17.92% M1
3.33% M48
8.96% M60
2.95% Leopard 1
8.84% Leopard 2
Language
28.70% English
29.40% German
41.90% Russian
Road Wheel Distance
33.01% Irregular
26.76% Near-Evenly...
40.22% Evenly Spac...
No. of Support Rollers
Mean: 2.695 Dev: 1.621
Value: 2.695
19.41% 0
17.92% 2
33.95% 3
11.79% 4
16.94% 5
No. of Road Wheels
Mean: 6.103 Dev: 0.693
Value: 6.103
19.41% 5
50.88% 6
29.71% 7
Turret Shape
53.41% Rounded
46.59% Angular
Road Wheel Size
80.59% Average
19.41% Tall
Engine
71.88% Diesel
28.12% Gas Turbine
Uniform
45.95% Camouflage
54.05% Solid Color
Gun Barrel Length
37.33% Short (<3.5m)
62.67% Long (>3.5m)
New gr...
Friend ...



BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Friend or Foe\Friend or Foe V1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Friend or Foe V1.xbl *
Evidence Analysis (Friend or Foe V1)

Analysis Context	
No. of Road Wheels	I {5: 0.00%, 6: 100.00%, 7: 100.00%}
Uniform	Camouflage

Overall consistency of the evidence: 0.24

Evidence Consistency Analysis

Node	Comment	State	Consistency	Bayes Factor
Friend/Foe		Friend	0.87	0.63
		Foe	-0.49	-0.73
Language		English	1.34	1.10
		German	-2.32	-2.56
		Russian	-0.09	-0.33
Engine		Diesel	-0.43	-0.67
		Gas Turbine	1.20	0.96
Gun Barrel Length		Short (<3.5m)	0.40	0.15
		Long (>3.5m)	0.14	-0.10
No. of Support Rollers		0	-∞	-∞
		2	1.45	1.21
		3	0.42	0.17
		4	-∞	-∞
		5	0.49	0.25
Road Wheel Distance		Uneven Gaps	-0.67	-0.91
		Evenly Spaced	0.54	0.30
Road Wheel Size		Average	0.55	0.31
		Tall	-∞	-∞
Turret Shape		Rounded	-0.78	-1.02
		Angular	0.90	0.66

Close
Save As...
Print
Tank Type
Engine
Gun Barrel Length
No. of Road Wheels
Turret Sh
oe
Joint Probability: 38.81%
Log-Loss: 1.37
Total Value: 9.403
Mean Value: 4.701
Friend/Foe
64.94% Friend
35.06% Foe
Engine
45.29% Diesel
54.71% Gas Turbine
Language
61.69% English
5.00% German
33.31% Russian
Uniform
100.00% Camouflage
0.00% Solid Color
Gun Barrel Length
41.56% Short (<3.5m)
58.44% Long (>3.5m)
No. of Support Rollers
Mean: 2.987 Dev: 1.105
Value: 2.987
0.00% 0
41.56% 2
38.31% 3
0.00% 4
20.13% 5
No. of Road Wheels
Mean: 6.416 Dev: 0.493
Value: 6.416
0.00% 5
58.44% 6
41.56% 7
Turret Shape
26.30% Rounded
73.70% Angular
Road Wheel Distance
17.53% Uneven Gaps
82.47% Evenly Spac...
Road Wheel Size
100.00% Average
0.00% Tall
New gr...
Friend ...

Knowledge Base & Inference Engine

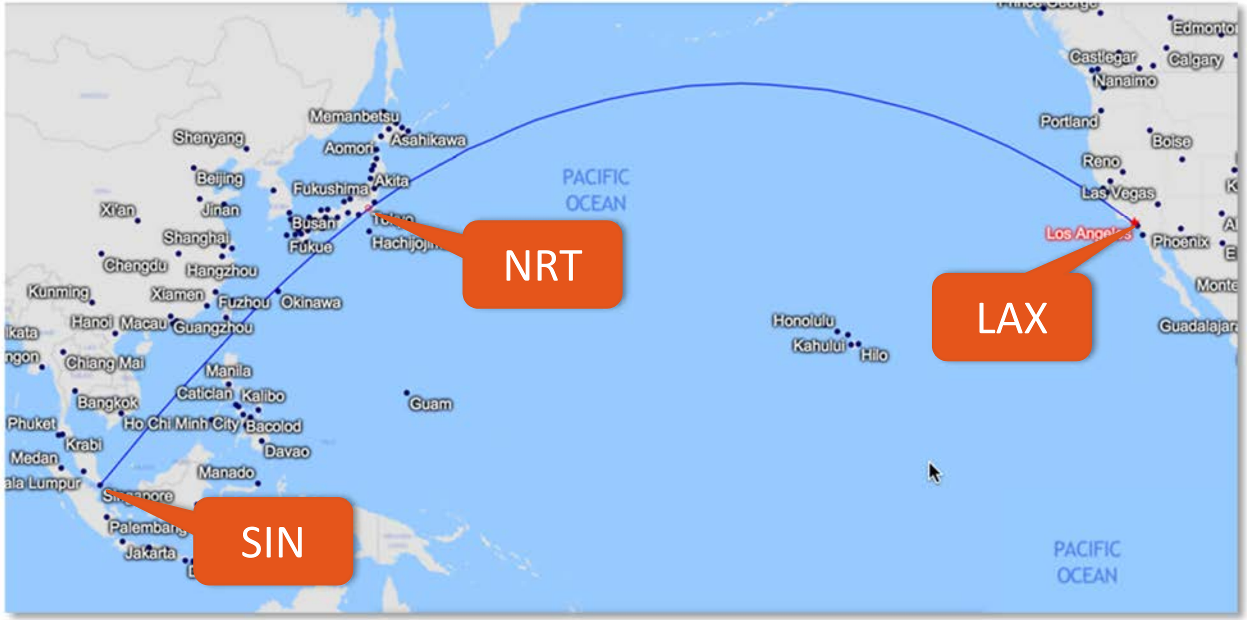
See Chapter 4

Where is my bag?

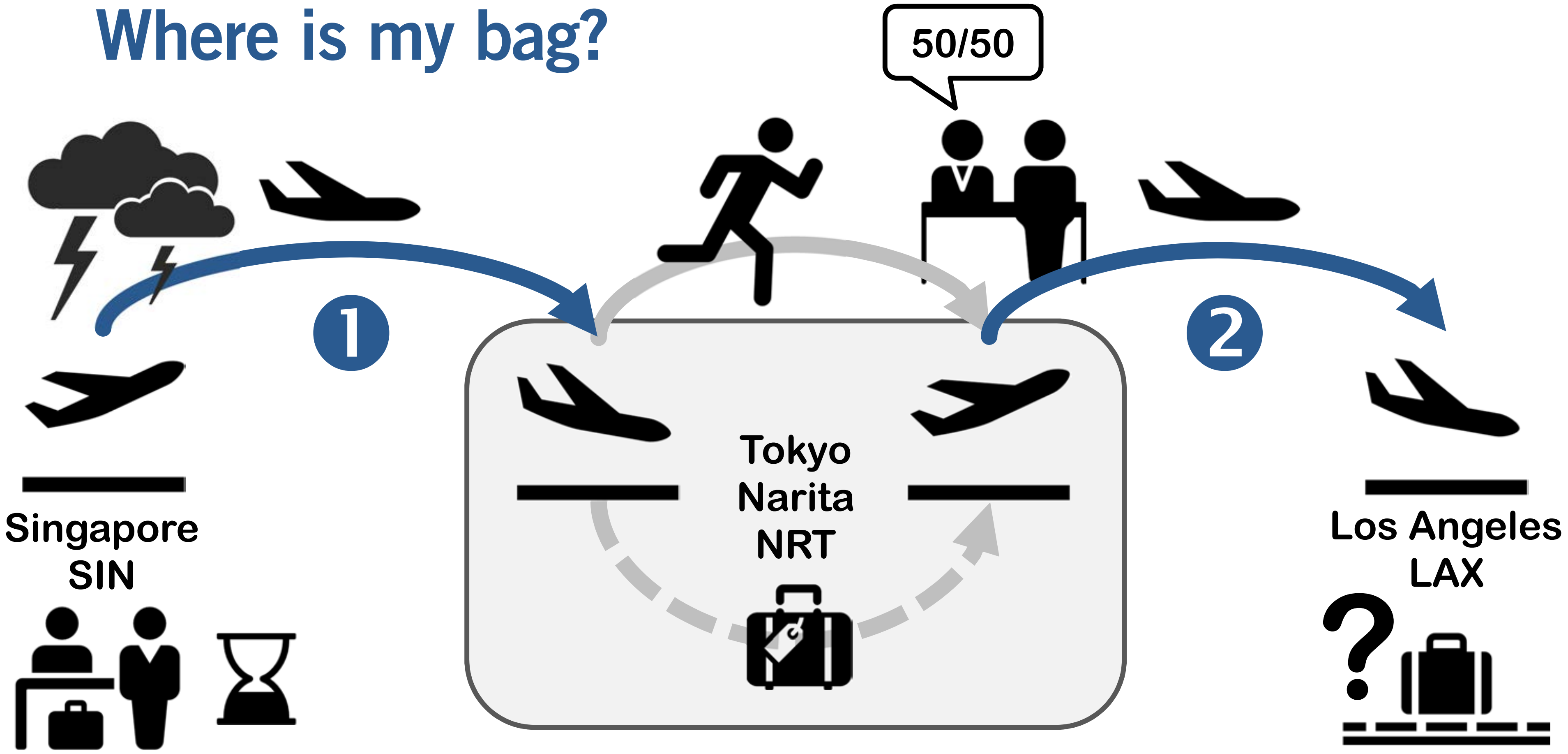
Knowledge Modeling & Reasoning Under Uncertainty

Example: Where is my bag?

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



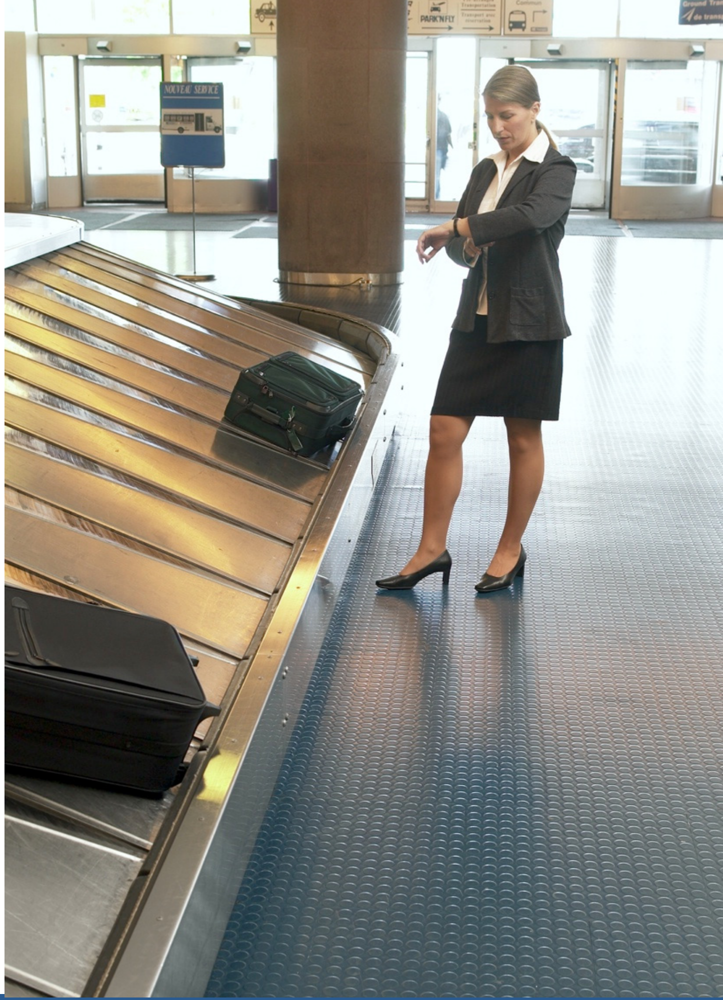
Where is my bag?



Where is my bag?

Scenario 1

- Luggage delivery starts onto the carousel.
- **After 5 minutes**, I still do not see my bag.
- What is the probability that I will still get my bag?

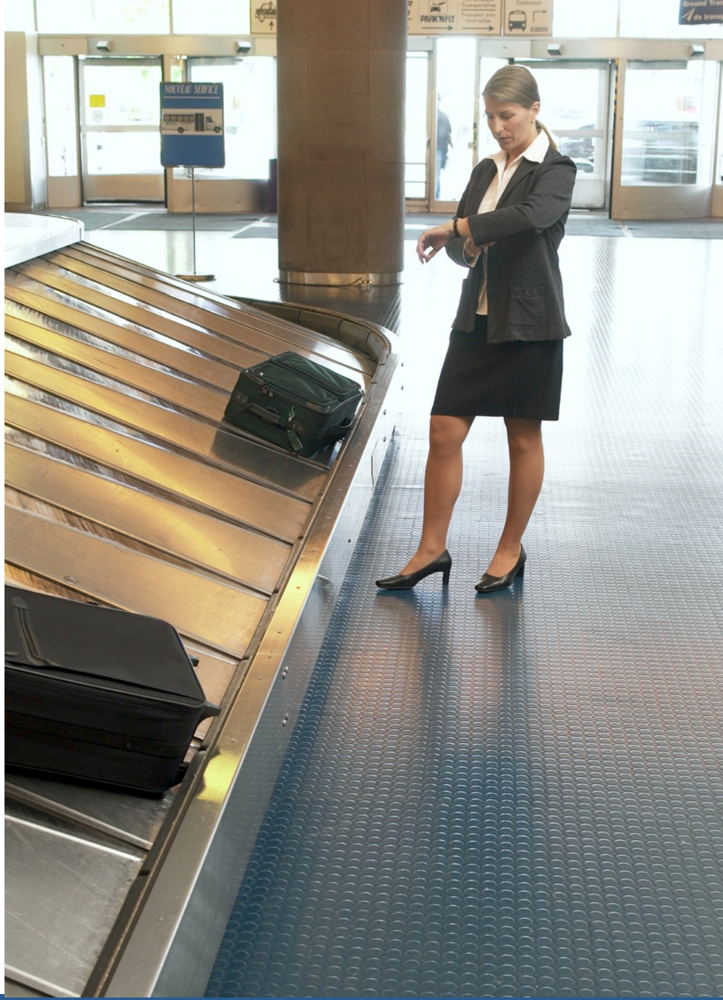


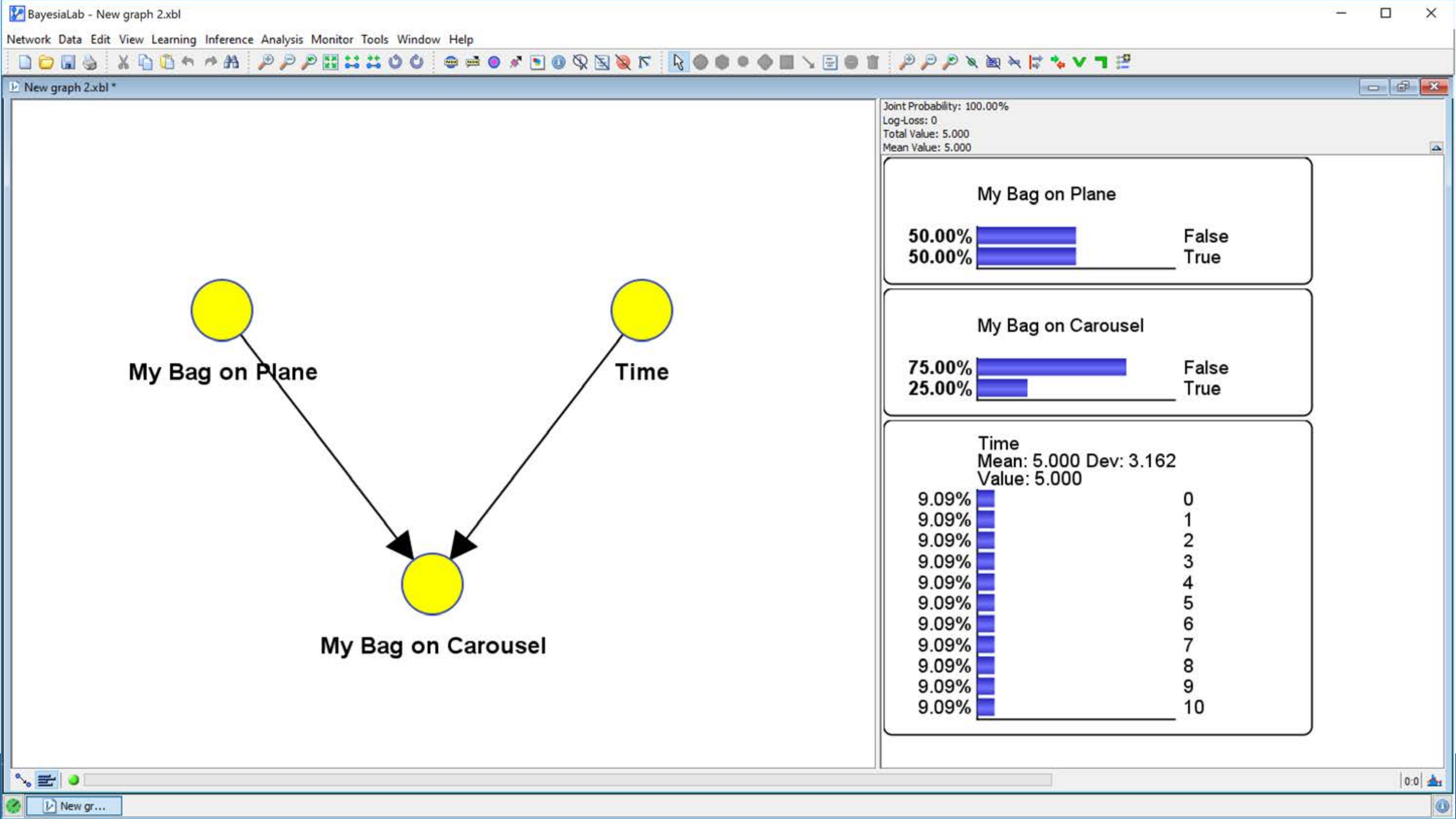

SINGAPORE AIRLINES
152
154
156
D-ABYJ
Sky Chefs
IS MY BAG IN THERE?

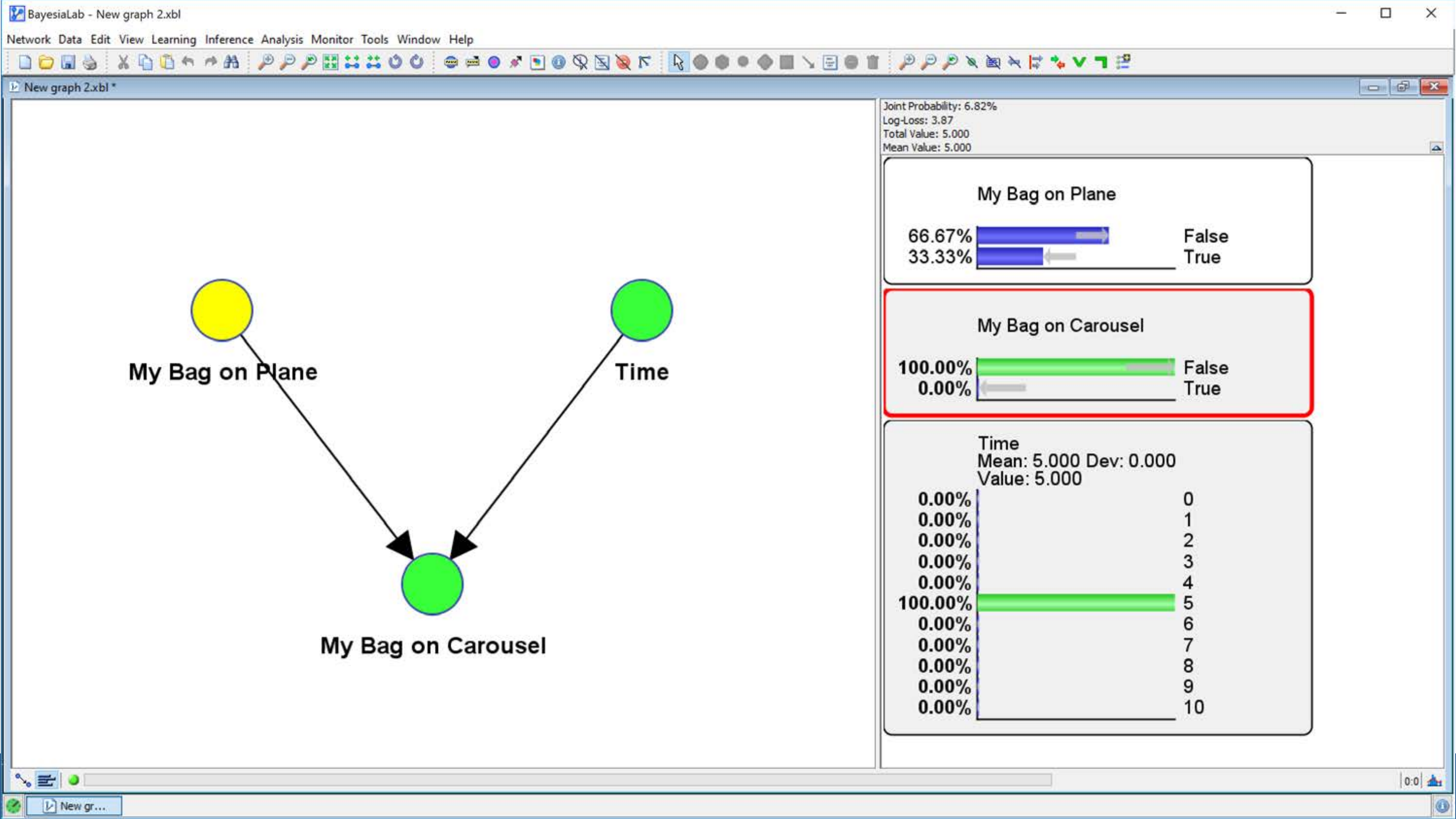
Where is my bag?

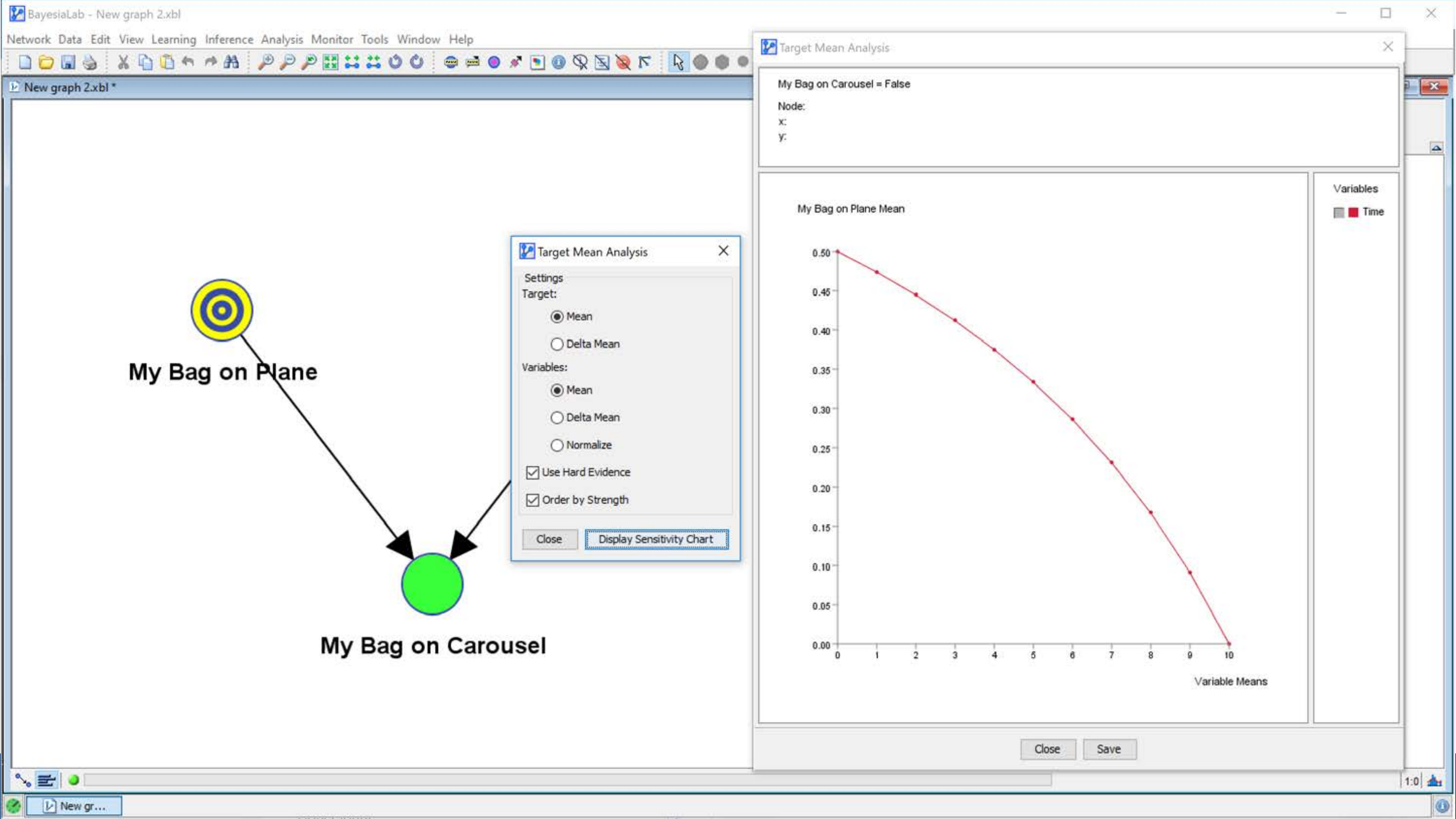
Proposed Workflow

- Encode the available — albeit very limited — knowledge into a Bayesian network.
- Use BayesiaLab to perform probabilistic inference given our observations.




BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
My Bag on Plane
Time
My Bag on Carousel
Joint Probability: 100.00%
Log-Loss: 0
Total Value: 5.000
Mean Value: 5.000
My Bag on Plane
50.00% False
50.00% True
My Bag on Carousel
75.00% False
25.00% True
Time
Mean: 5.000 Dev: 3.162
Value: 5.000
9.09% 0
9.09% 1
9.09% 2
9.09% 3
9.09% 4
9.09% 5
9.09% 6
9.09% 7
9.09% 8
9.09% 9
9.09% 10
New gr...

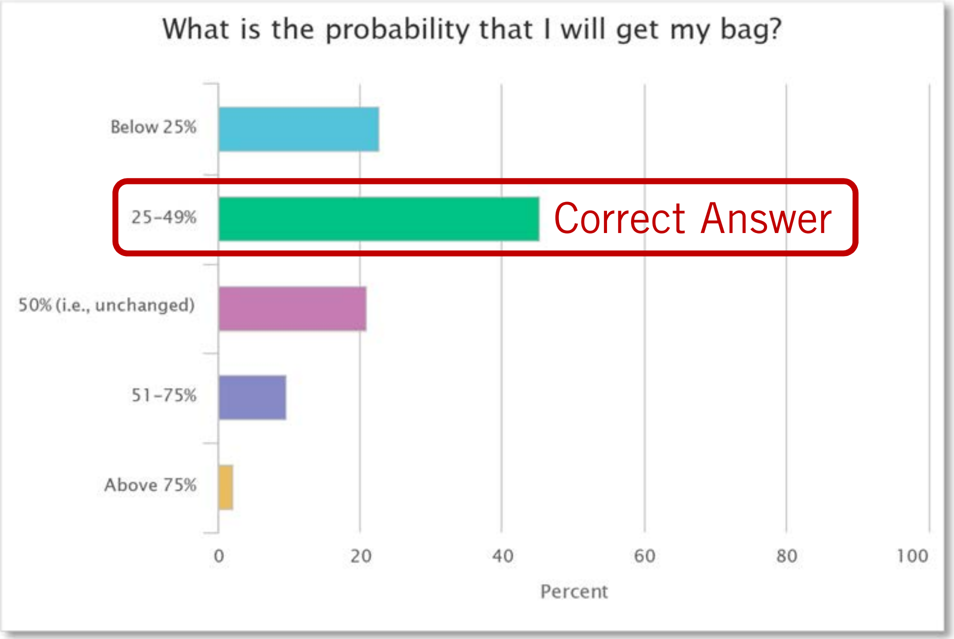

BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
My Bag on Plane
Time
My Bag on Carousel
Joint Probability: 6.82%
Log-Loss: 3.87
Total Value: 5.000
Mean Value: 5.000
My Bag on Plane
66.67% False
33.33% True
My Bag on Carousel
100.00% False
0.00% True
Time
Mean: 5.000 Dev: 0.000
Value: 5.000
0.00% 0
0.00% 1
0.00% 2
0.00% 3
0.00% 4
100.00% 5
0.00% 6
0.00% 7
0.00% 8
0.00% 9
0.00% 10
New gr...


BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
My Bag on Plane
My Bag on Carousel
Target Mean Analysis
Settings
Target:
Mean
Delta Mean
Variables:
Mean
Delta Mean
Normalize
Use Hard Evidence
Order by Strength
Close
Display Sensitivity Chart
Target Mean Analysis
My Bag on Carousel = False
Node:
x:
y:
My Bag on Plane Mean
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0 1 2 3 4 5 6 7 8 9 10
Variable Means
Variables
Time
Close
Save
New gr...

Where is my bag?

Results from Webinar Poll

- Only 45% of the participants arrived at the correct answer.



Where is my bag?

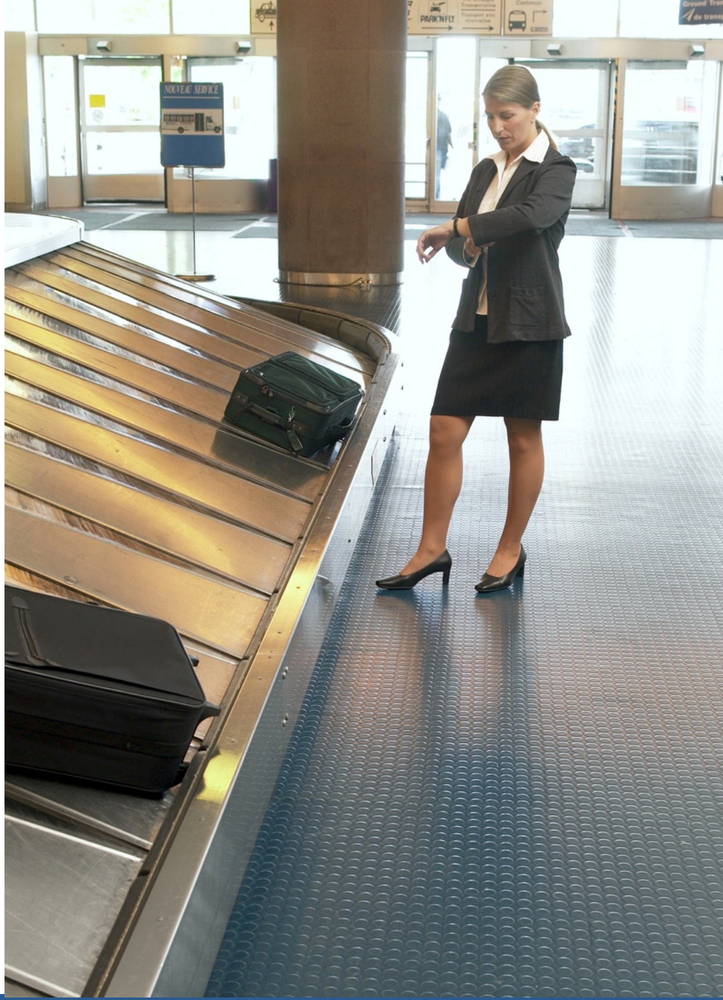
More important questions:

- 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

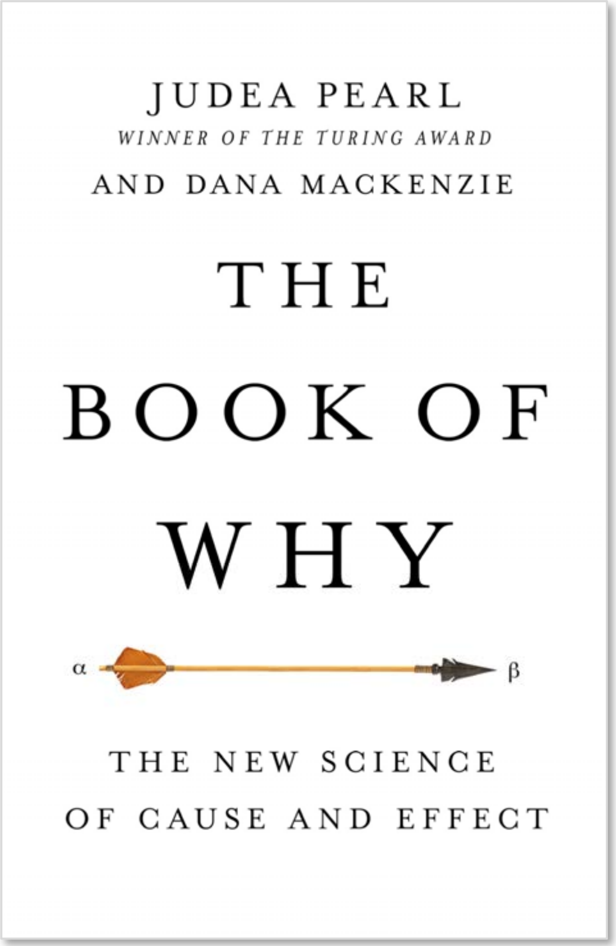
- Encoding of knowledge
- Reasoning under uncertainty
- Reasoning
    - from cause to effect (simulation)
    - from effect to cause (diagnosis)
- Inter-causal reasoning



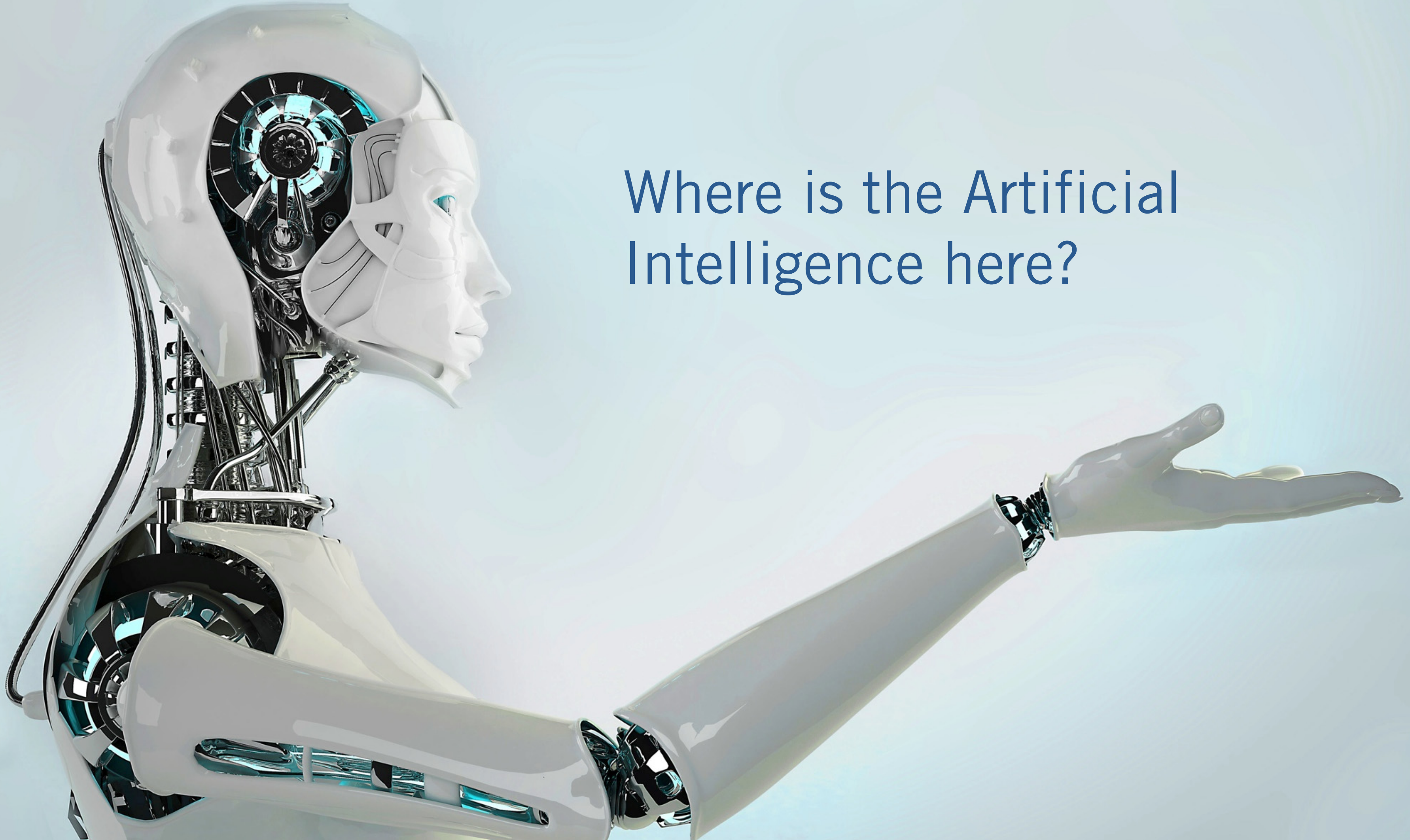
Where is my bag?

Learn more about this example…

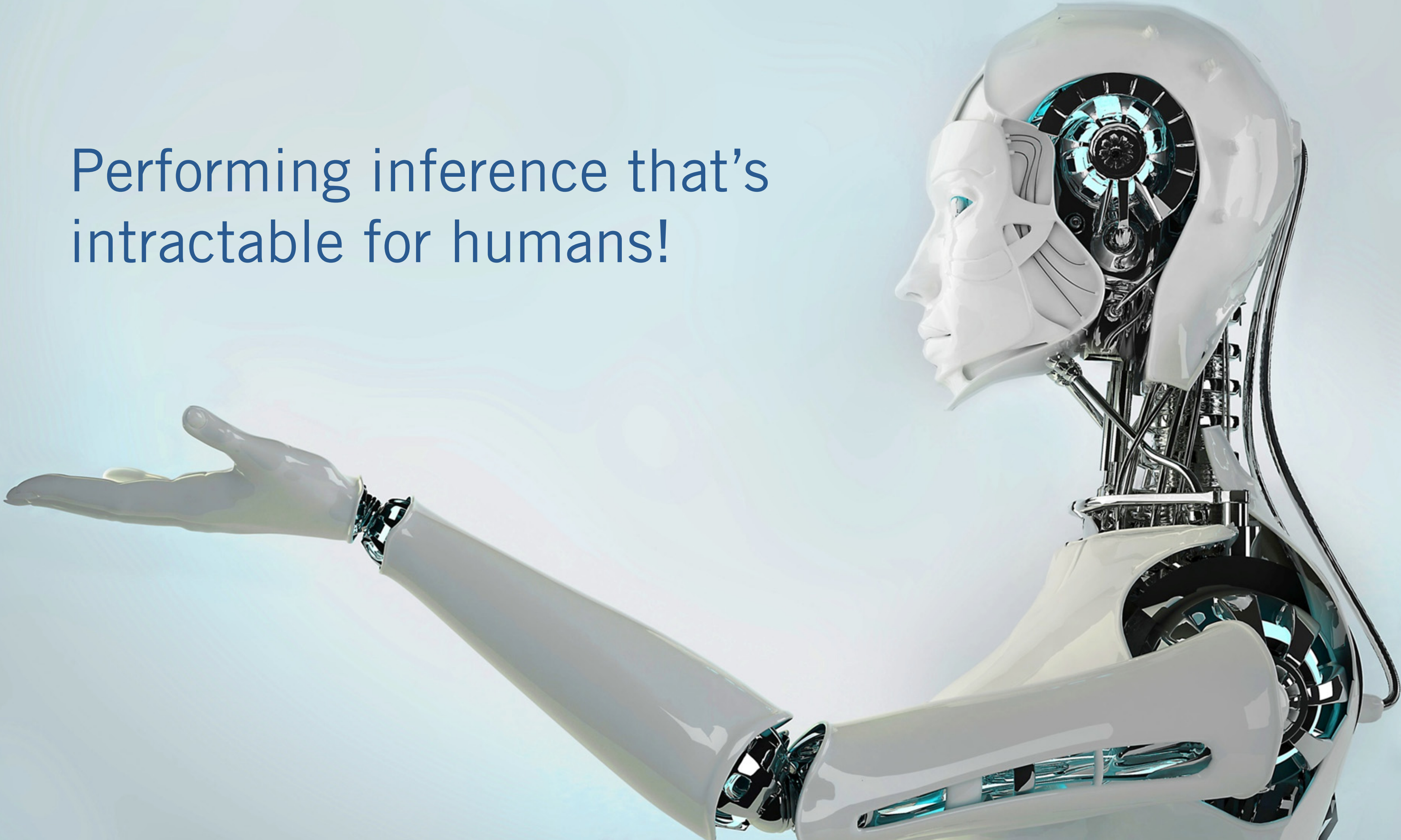
- pp. 118-119



Where is the Artificial Intelligence here?



Performing inference that's intractable for humans!



Coffee Break

The Monty Hall Puzzle

Mission

Hypothetical Mission Assignment

- You are tasked with to conduct a raid to destroy a secret aircraft prototype on enemy territory.
- This aircraft has been traced to a remote military air base and is presumed to be located in one of three separate underground hangars inside a mountain on this facility.
- As a result, you have a one-in-three chance of hitting your target with your first strike.

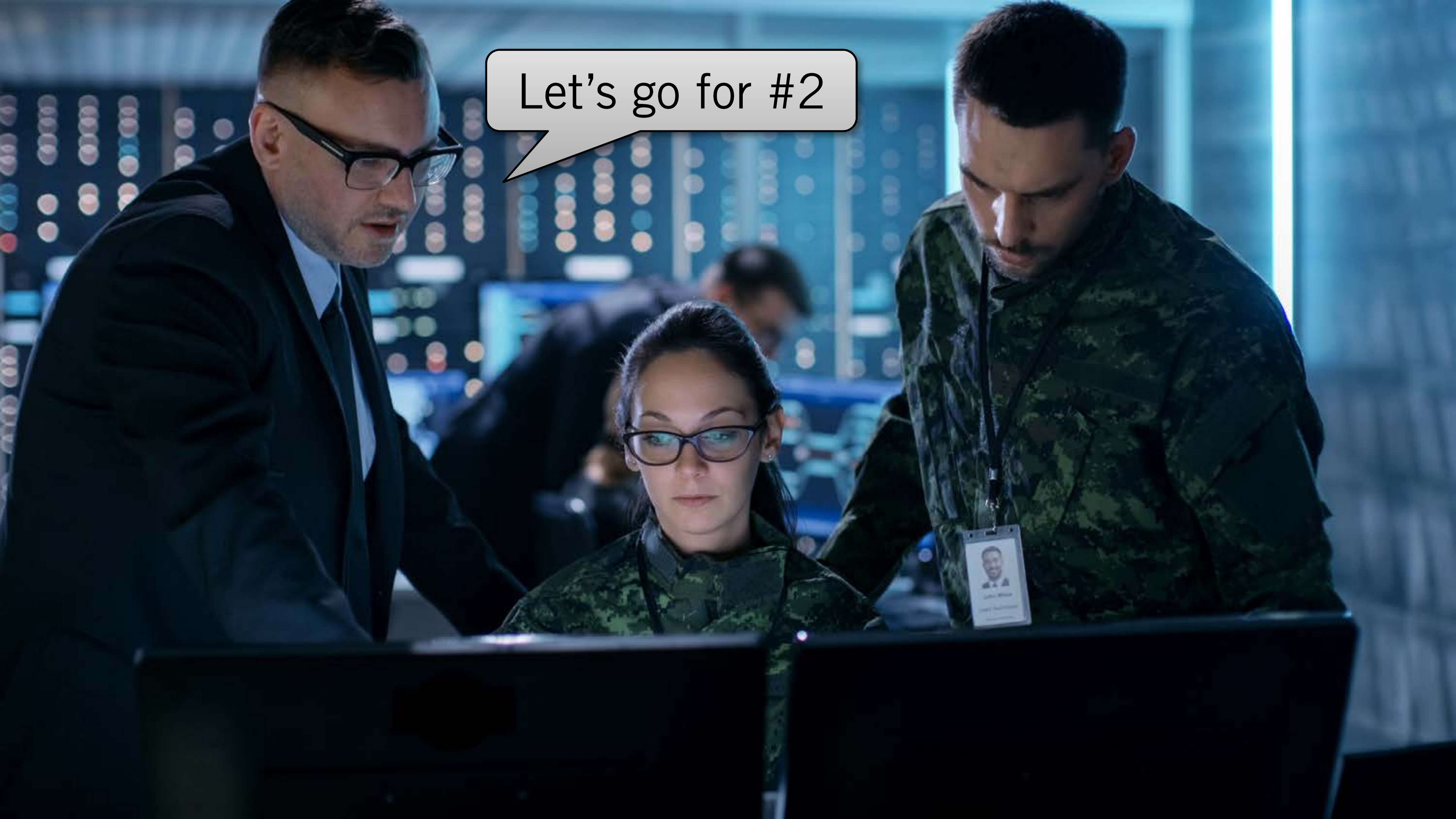

Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image Landsat / Copernicus
Image IBCAO
Image U.S. Geological Survey
Google Earth


Underground Hangars
1
2
3
Google Earth
Image © 2018 CNES / Airbus

Mission

Expected Conditions

- Each hangar entrance is guarded by infantry soldiers.
- Furthermore, the base has two infantry fighting vehicles, which can be dispatched to the hangars within minutes.

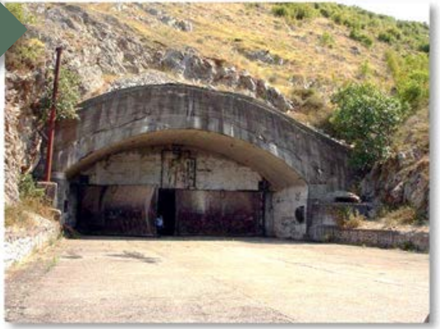

Let’s go for #2

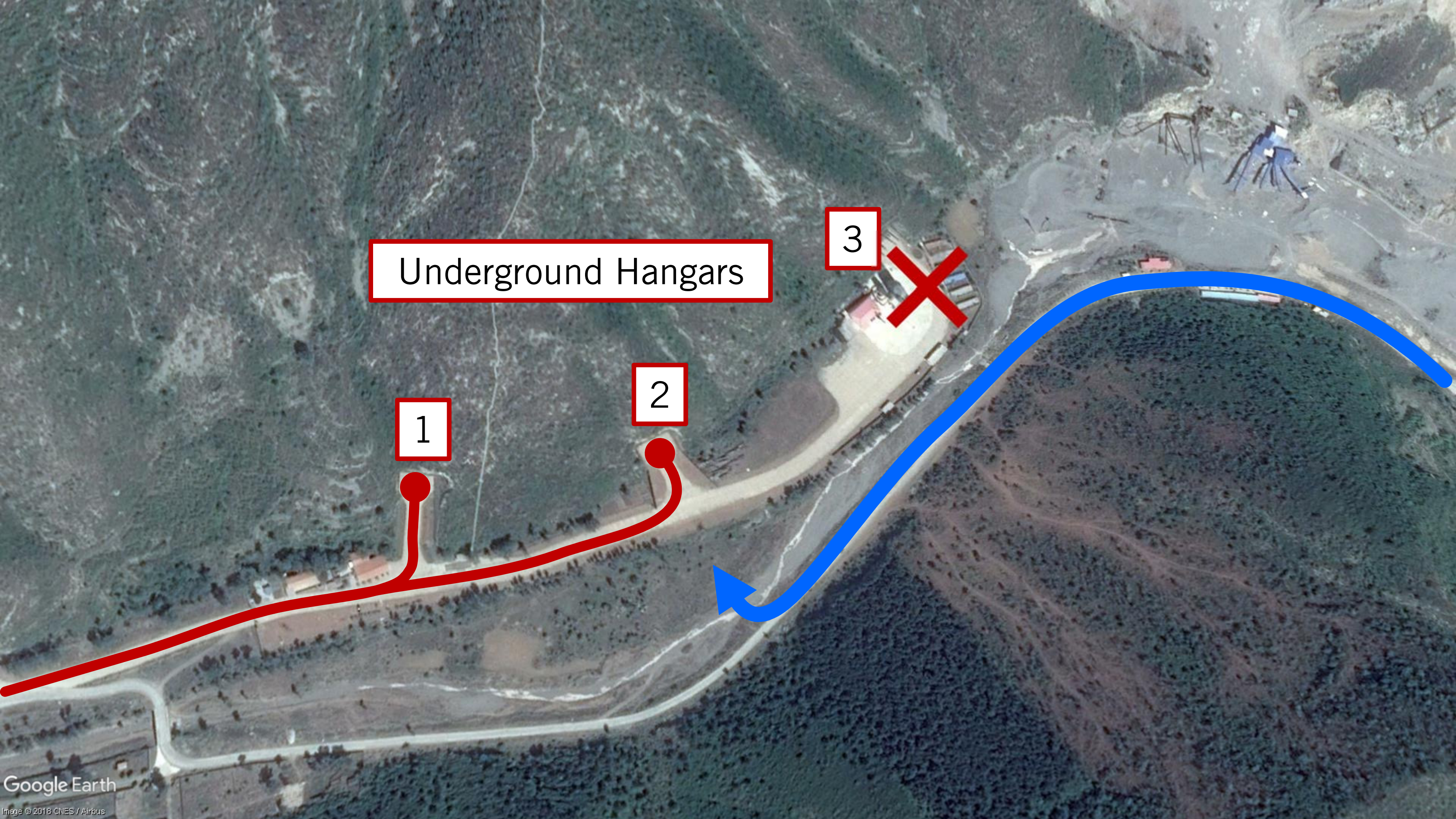

Underground Hangars
1
2
3
Google Earth
Image © 2018 CNES / Airbus

Mission

Mission Progress

- Your raid — and your approach to hangar #2 — is detected, and two infantry fighting vehicles are immediately positioned as a defense in front of hangars #1 and #2.
- Hangar #3 remains unprotected, thus revealing that this hangar does not contain the target.
- Since the target can only be in hanger #1 or #2, one of the hangars is the true target while the other one is merely a decoy.





Underground Hangars
1
2
3
Google Earth
Image © 2018 CNES / Airbus

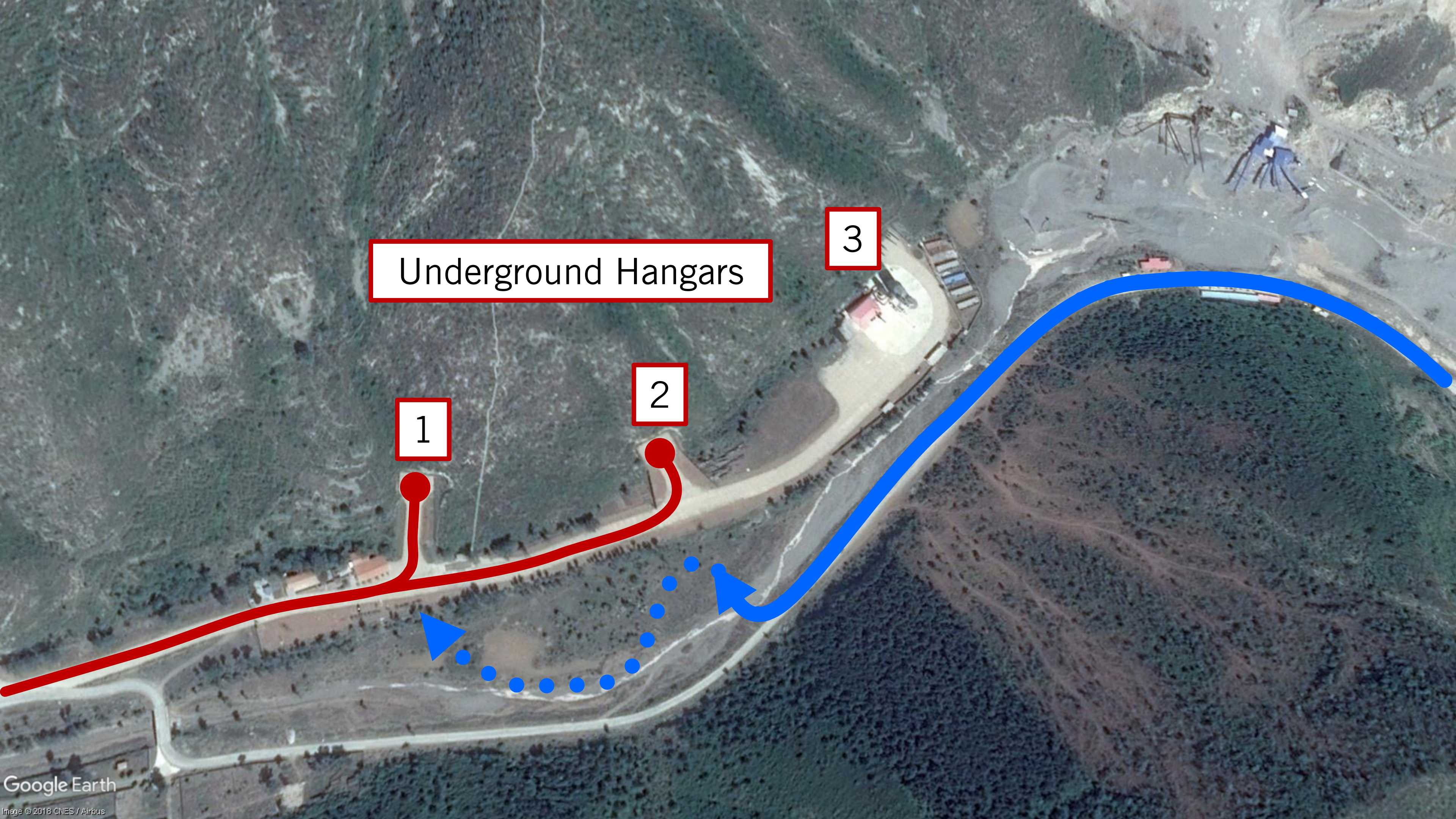
Choose Your Battle Wisely!

Mission Status

- You have enough time and firepower to overpower the enemy forces and carry out your mission at either one of the two hangars, but not at both.
- So, you have only one shot at completing your task!

Decision Point

- Do you proceed with your original objective of attacking hangar #2?
- Or, do you change your original plan to go after hangar #1?


Underground Hangars
1
2
3
Google Earth
Image © 2018 CNES / Airbus

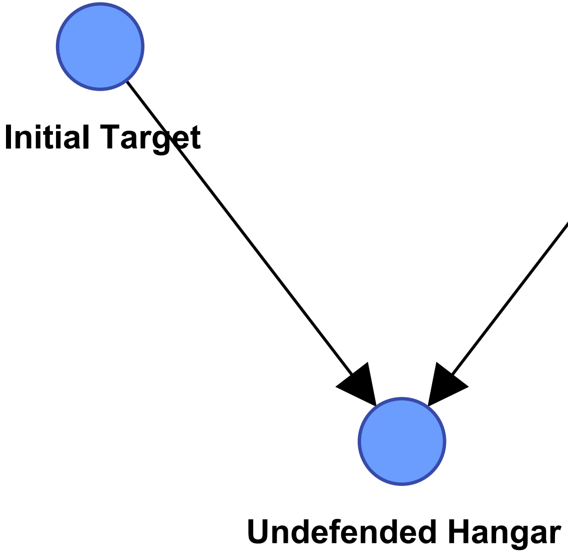
Choose Your Battle Wisely!

Let's take a vote…

Encoding our Intelligence

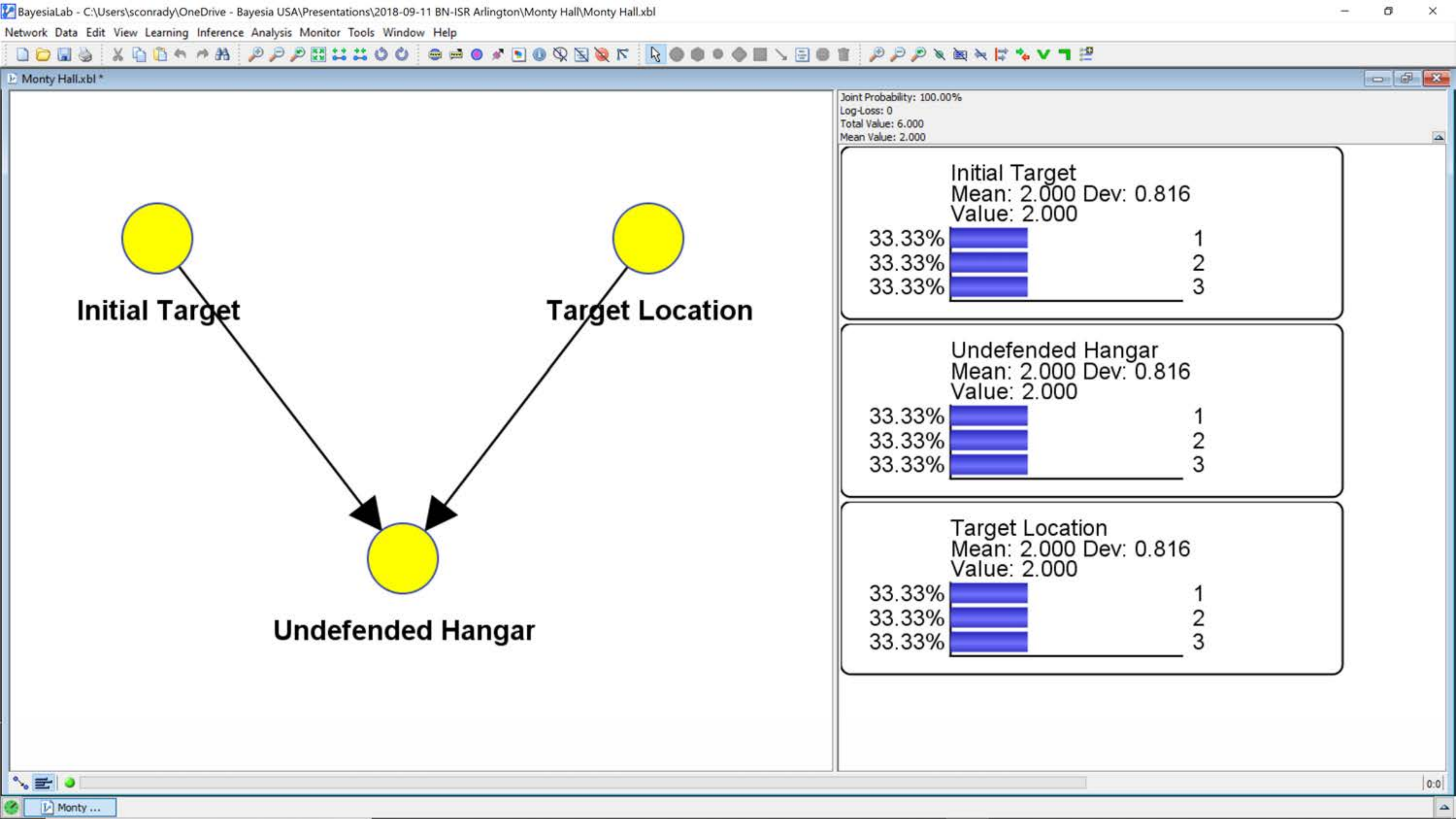
1	2	3
33.333	33.333	33.333

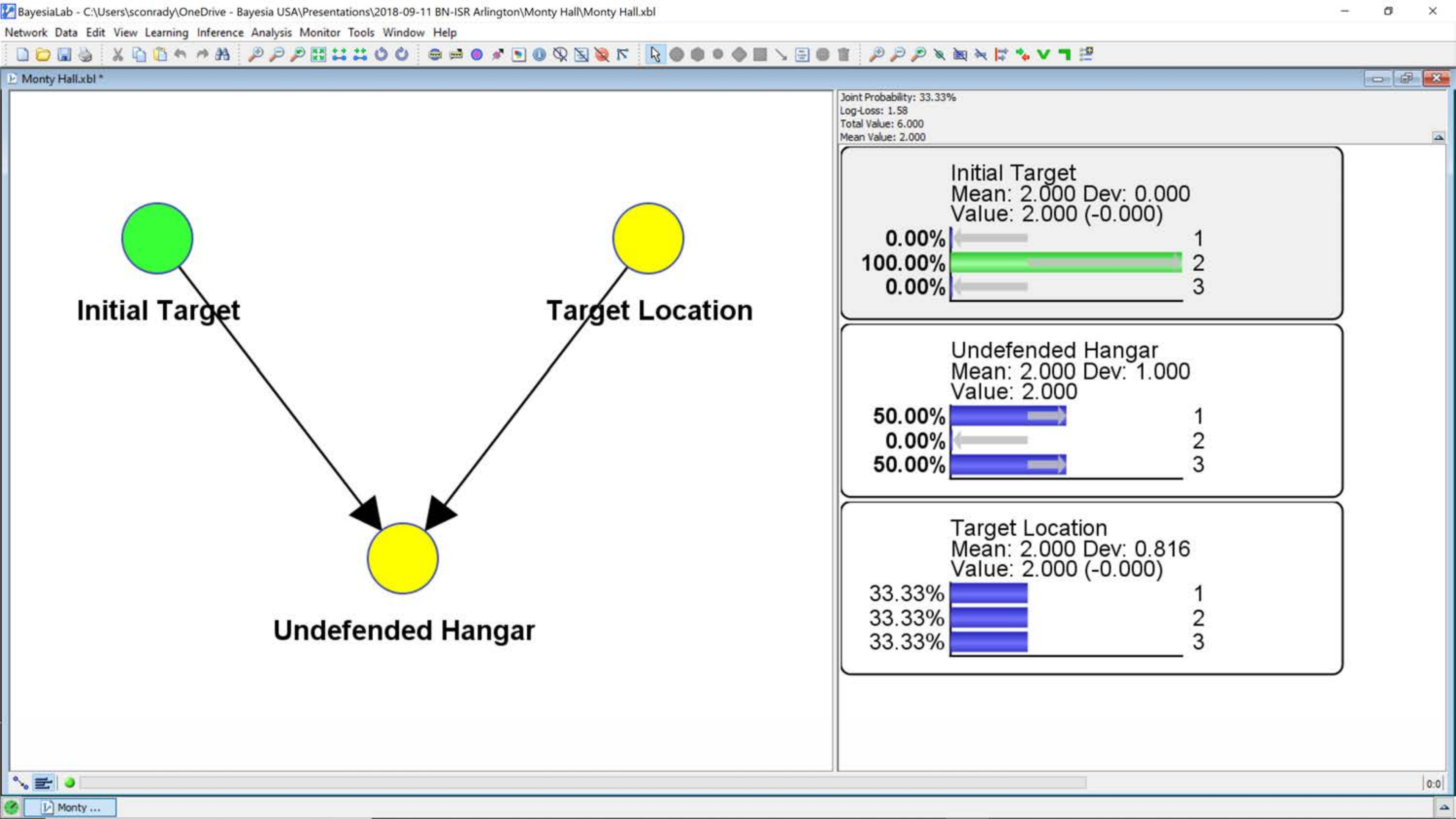
1	2	3
33.333	33.333	33.333

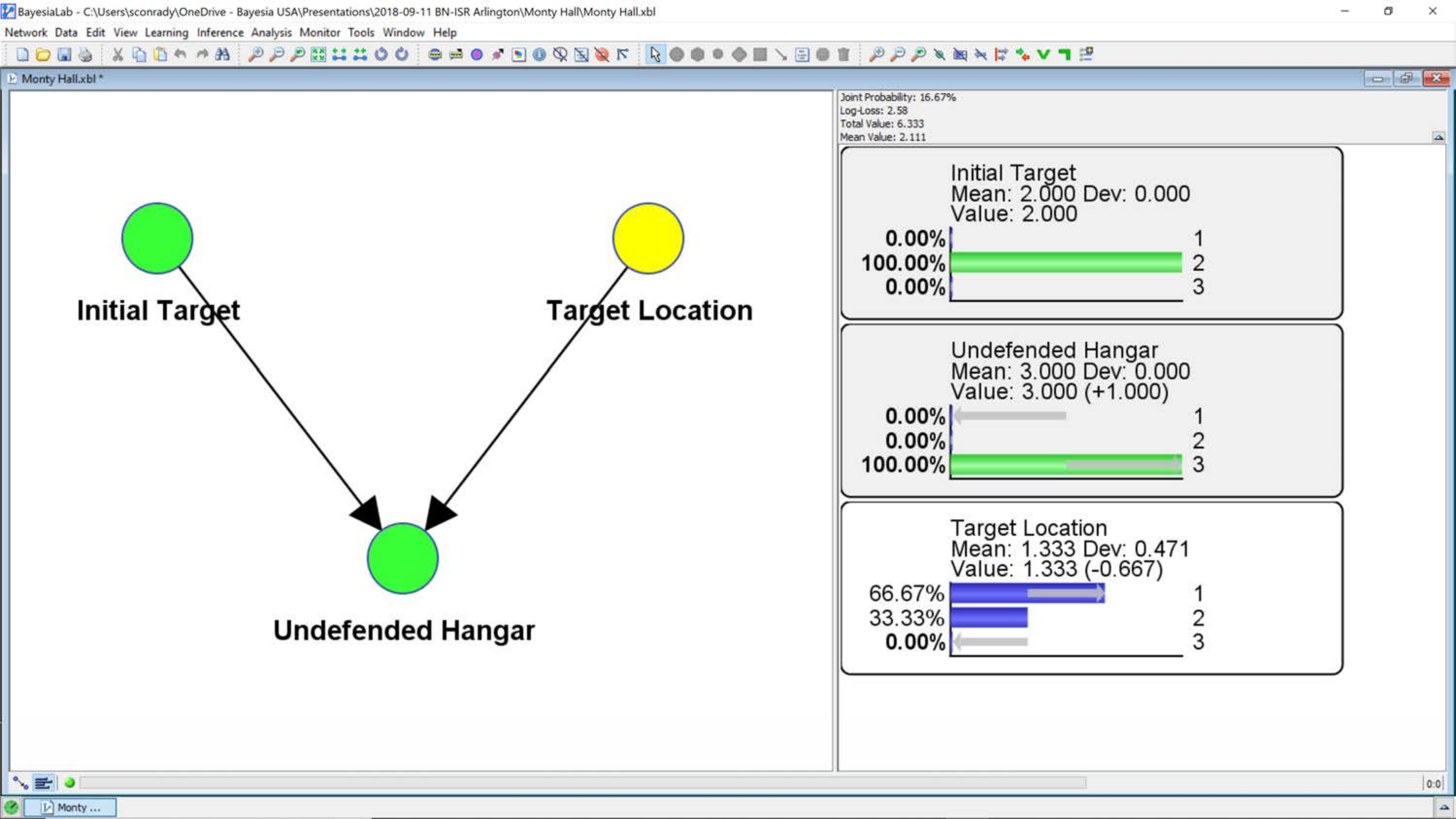


Our beliefs about the enemy's behavior.

Initial Target	Target Location	1	2	3
1	1	0.000	50.000	50.000
	2	0.000	0.000	100.000
	3	0.000	100.000	0.000
2	1	0.000	0.000	100.000
	2	50.000	0.000	50.000
	3	100.000	0.000	0.000
3	1	0.000	100.000	0.000
	2	100.000	0.000	0.000
	3	50.000	50.000	0.000

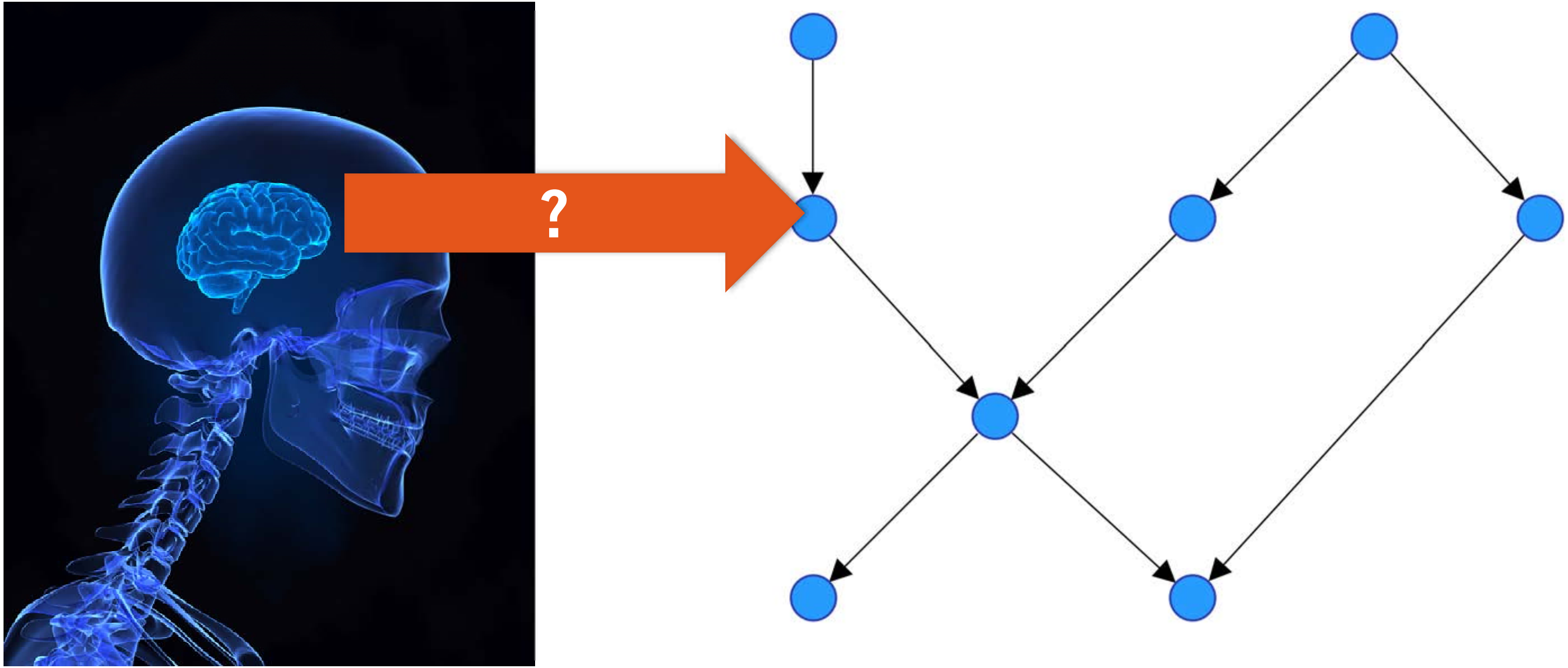

BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Monty Hall\Monty Hall.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Monty Hall.xbl *
Initial Target
Target Location
Undefended Hangar
Joint Probability: 100.00%
Log-Loss: 0
Total Value: 6.000
Mean Value: 2.000
Initial Target
Mean: 2.000 Dev: 0.816
Value: 2.000
33.33% 1
33.33% 2
33.33% 3
Undefended Hangar
Mean: 2.000 Dev: 0.816
Value: 2.000
33.33% 1
33.33% 2
33.33% 3
Target Location
Mean: 2.000 Dev: 0.816
Value: 2.000
33.33% 1
33.33% 2
33.33% 3
Monty ...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Monty Hall\Monty Hall.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Monty Hall.xbl *
Initial Target
Target Location
Undefended Hangar
Joint Probability: 33.33%
Log-Loss: 1.58
Total Value: 6.000
Mean Value: 2.000
Initial Target
Mean: 2.000 Dev: 0.000
Value: 2.000 (-0.000)
0.00% 1
100.00% 2
0.00% 3
Undefended Hangar
Mean: 2.000 Dev: 1.000
Value: 2.000
50.00% 1
0.00% 2
50.00% 3
Target Location
Mean: 2.000 Dev: 0.816
Value: 2.000 (-0.000)
33.33% 1
33.33% 2
33.33% 3
0:0
Monty ...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Monty Hall\Monty Hall.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Monty Hall.xbl *
Initial Target
Target Location
Undefended Hangar
Joint Probability: 16.67%
Log-Loss: 2.58
Total Value: 6.333
Mean Value: 2.111
Initial Target
Mean: 2.000 Dev: 0.000
Value: 2.000
0.00% 1
100.00% 2
0.00% 3
Undefended Hangar
Mean: 3.000 Dev: 0.000
Value: 3.000 (+1.000)
0.00% 1
0.00% 2
100.00% 3
Target Location
Mean: 1.333 Dev: 0.471
Value: 1.333 (-0.667)
66.67% 1
33.33% 2
0.00% 3
Monty ...

The Bayesia Expert Knowledge Elicitation Environment

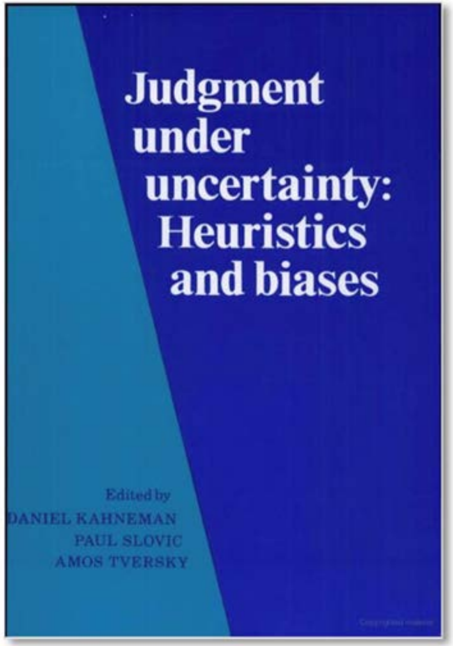
Knowledge Elicitation?



Individual Biases

Examples

- Overconfidence
- Confirmation bias
- Framing effect
- Escalation of commitment
- Availability bias
- Illusion of control
- Anchoring bias



Group Biases

Examples

- Groupthink (“toeing the line”)
- Social loafing (“hiding in the crowd”)
- Group polarization (“taken to the extreme”)
- Escalation of commitment (“throwing good money after bad”, “sunken costs fallacy”)

BAYESIALAB

The Delphi Method

A Consultation of the Delphic Oracle:
Themis on the Tripod with King Aegeus, c. 440 BC

The Delphi Method

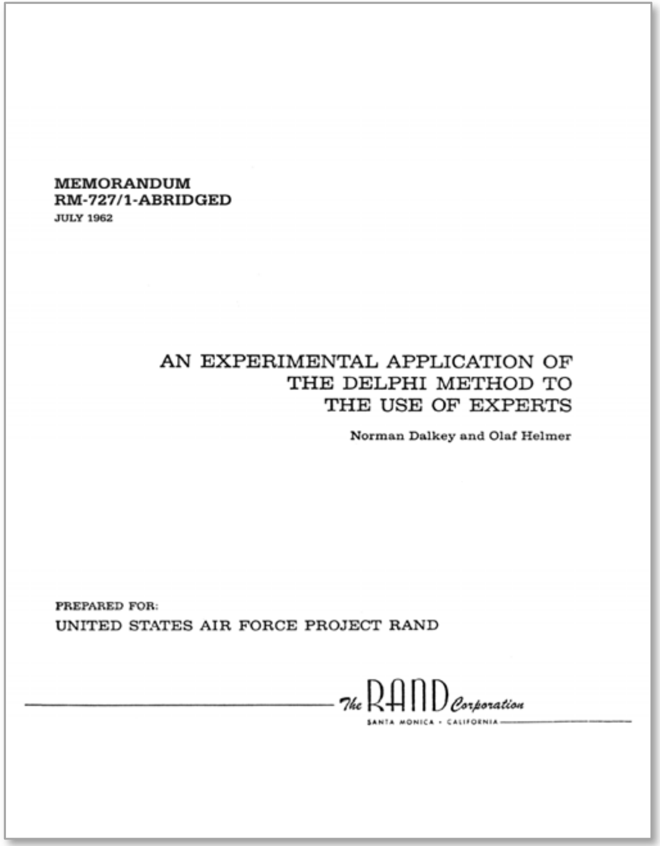
Interacting Groups

- Take the positive, e.g.
    - Knowledge from a variety of sources
    - Creative synthesis
- Prevent the negative, e.g.
    - Groupthink (“toeing the line”)
    - Social loafing (“hiding in the crowd”)
    - Group polarization (“taken to the extreme”)

The Delphi Method

Origins

- The original Delphi method was developed in the 1940s and 50s by Norman Dalkey of the RAND Corporation.
- The Delphi method was devised in order to obtain the most **reliable opinion consensus of a group of experts** by subjecting them to a series of questionnaires in depth interspersed with controlled opinion feedback.



MEMORANDUM
RM-727/1-ABRIDGED
JULY 1962

AN EXPERIMENTAL APPLICATION OF
THE DELPHI METHOD TO
THE USE OF EXPERTS

Norman Dalkey and Olaf Helmer

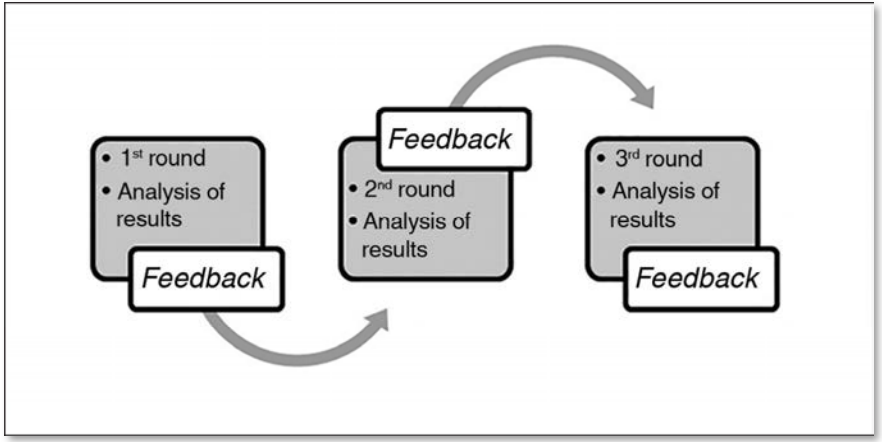
PREPARED FOR:
UNITED STATES AIR FORCE PROJECT RAND

The RAND Corporation
SANTA MONICA • CALIFORNIA

The Delphi Method

The Classical Delphi

- Interviews via questionnaires
- Anonymity of participants
- Iteration
- Controlled feedback
- Statistical aggregation



First Experimental Application

"to solicit expert opinion to the selection, from the point of view of a Soviet strategic planner, of an optimal U.S. industrial target system…"

Delphi Method Assessment

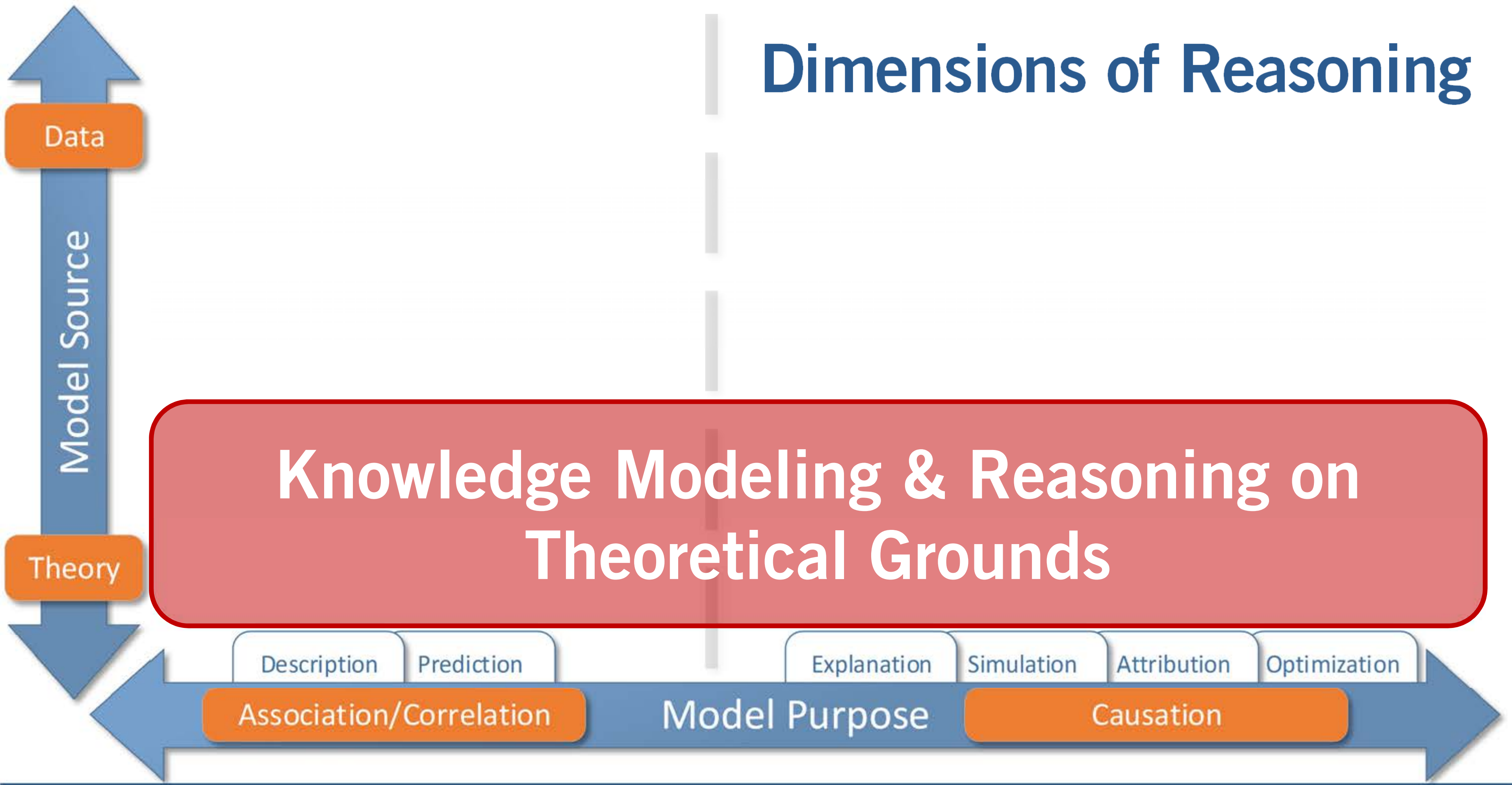
"In view of the absence of a proper theoretical foundation and the consequent inevitability of having, to some extent, to rely on intuitive expertise—a situation which is still further compounded by its multidisciplinary characteristics—we are faced with two options: **we can either throw up our hands in despair** and wait until we have an adequate theory enabling us to deal with socioeconomic and political problems as confidently as we do with problems in physics and chemistry, **or we can make the most of an admittedly unsatisfactory situation and try to obtain the relevant intuitive insights of experts** and then use their judgments as systematically as possible."

ANALYSIS OF THE FUTURE: THE DELPHI METHOD

Olaf Helmer

March 1967

Dimensions of Reasoning



Knowledge Modeling & Reasoning on Theoretical Grounds

20 15
161

Conceptual Overview

Source	Objective	Methodology	Technology
Data	Knowledge Discovery & Inference	Bayesian Networks	BAYESIALAB
Theory	Knowledge Elicitation	Delphi Method	BEKEE

Policy Development?

Proposed Policy Development Approach

- Domain Knowledge Encoding

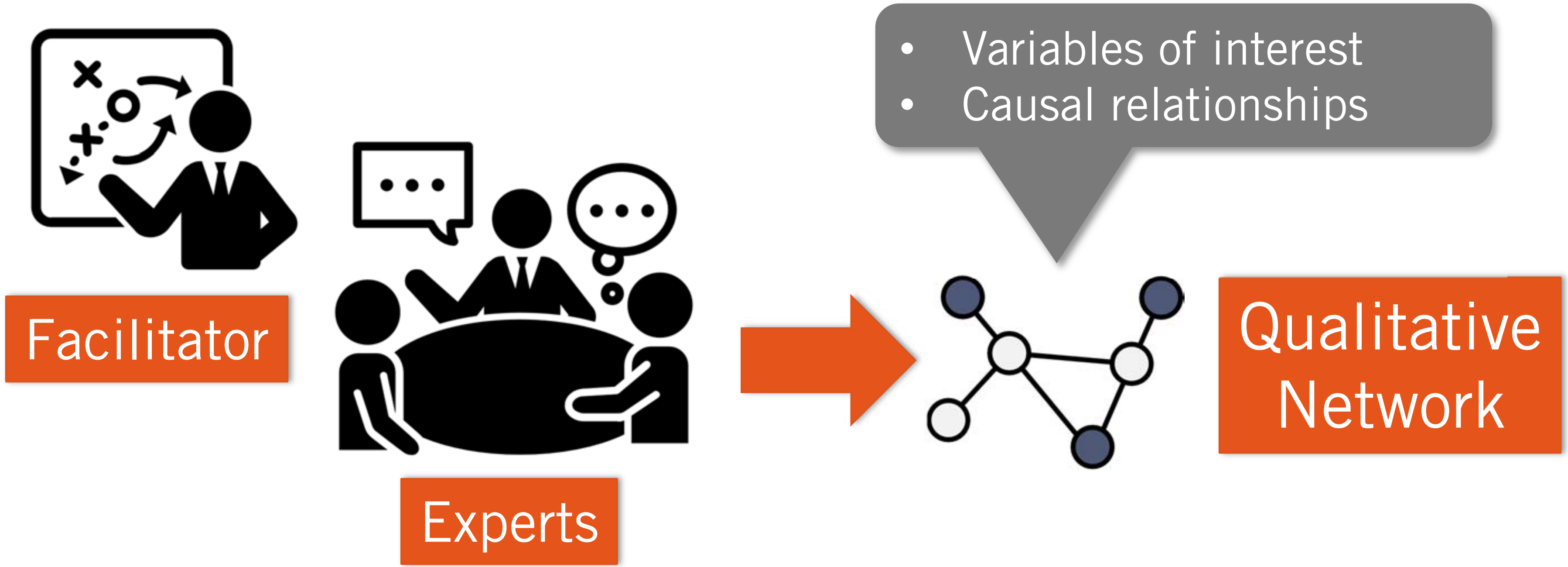
- Probability Elicitation

Plasmodium spp	False	True
False	80.000	20.000
True	20.000	80.000

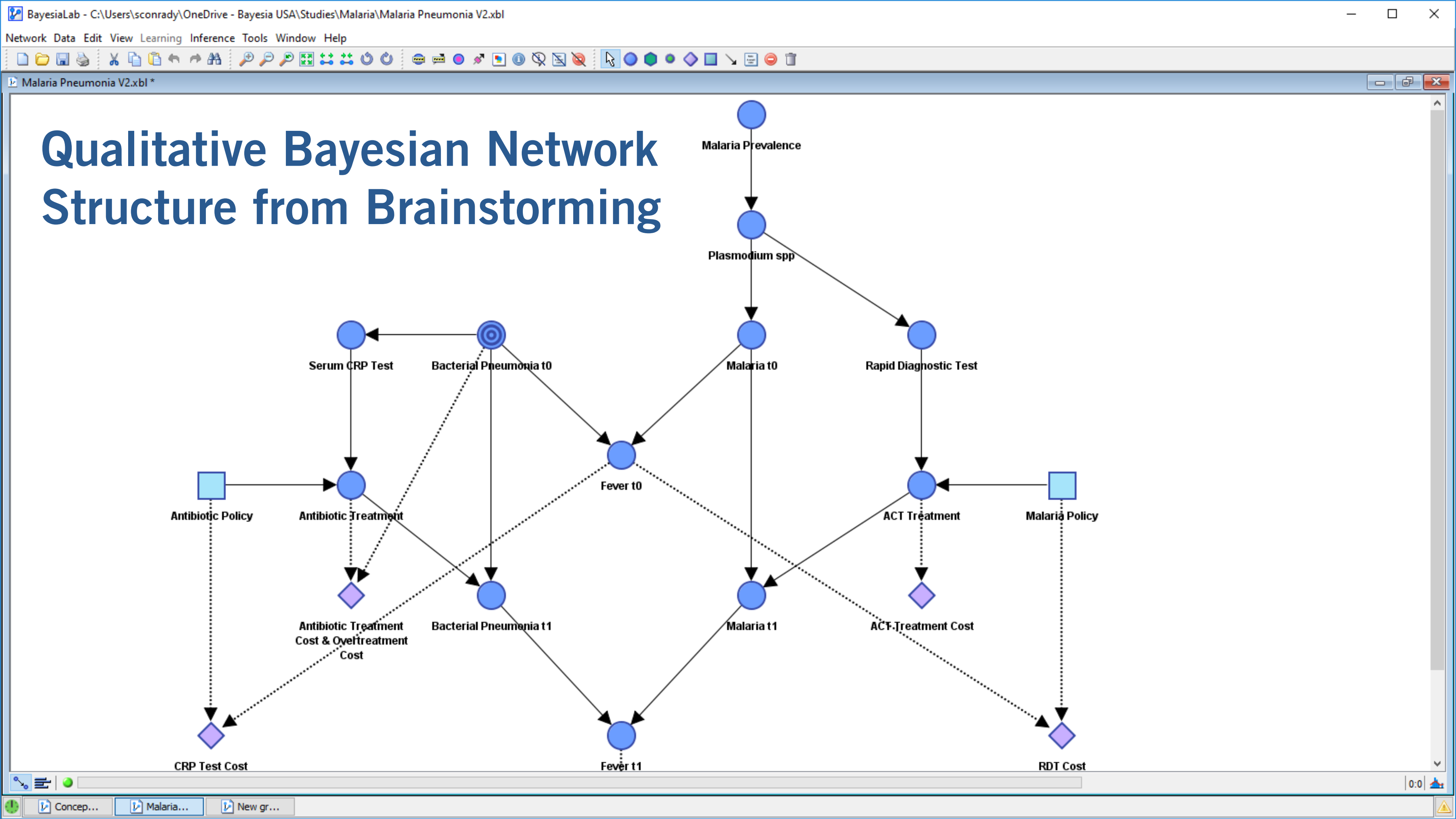
- Cost/Utility Assessment

- Optimization

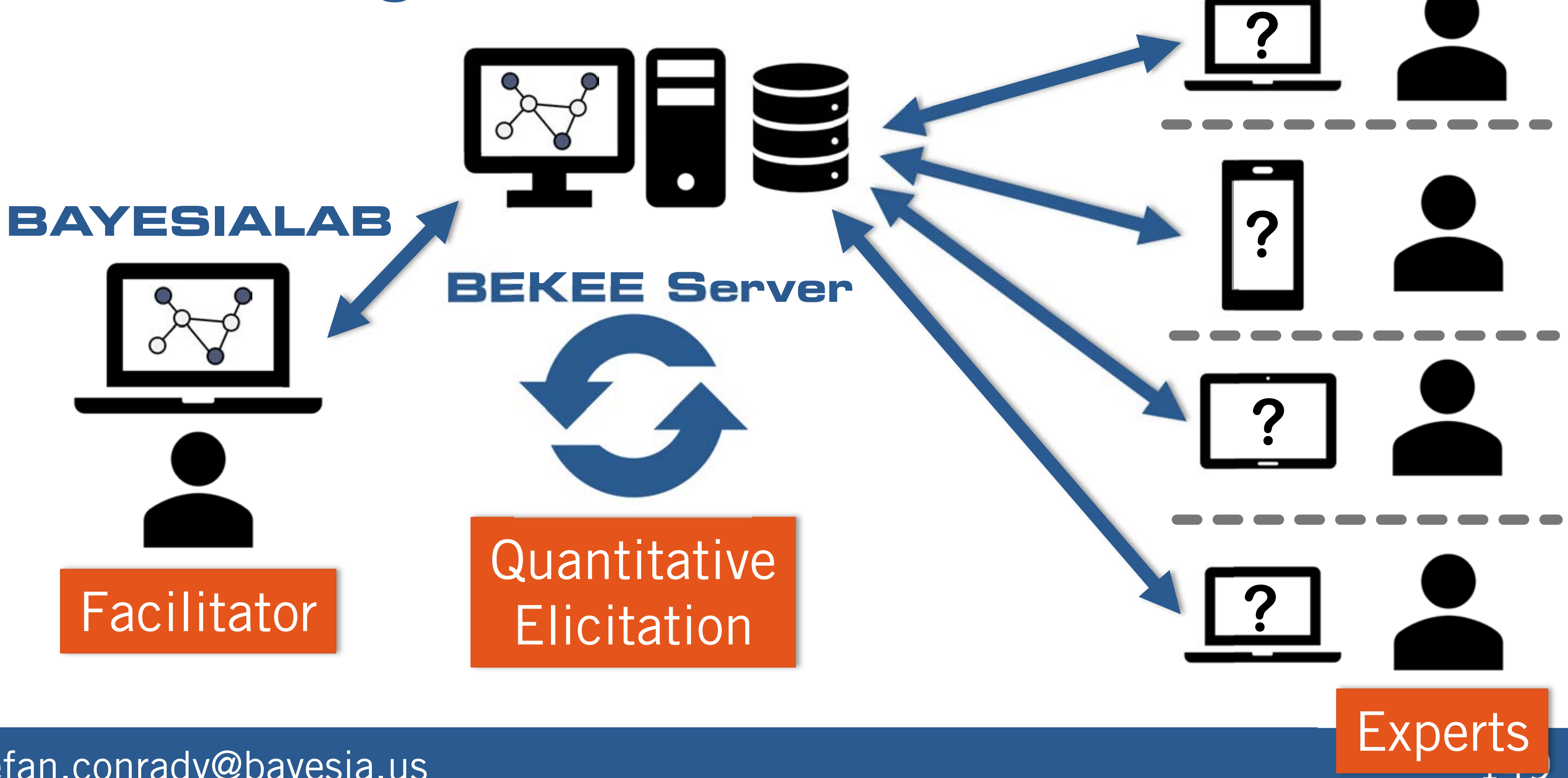
1. Brainstorming & Model Construction



Qualitative Bayesian Network Structure from Brainstorming

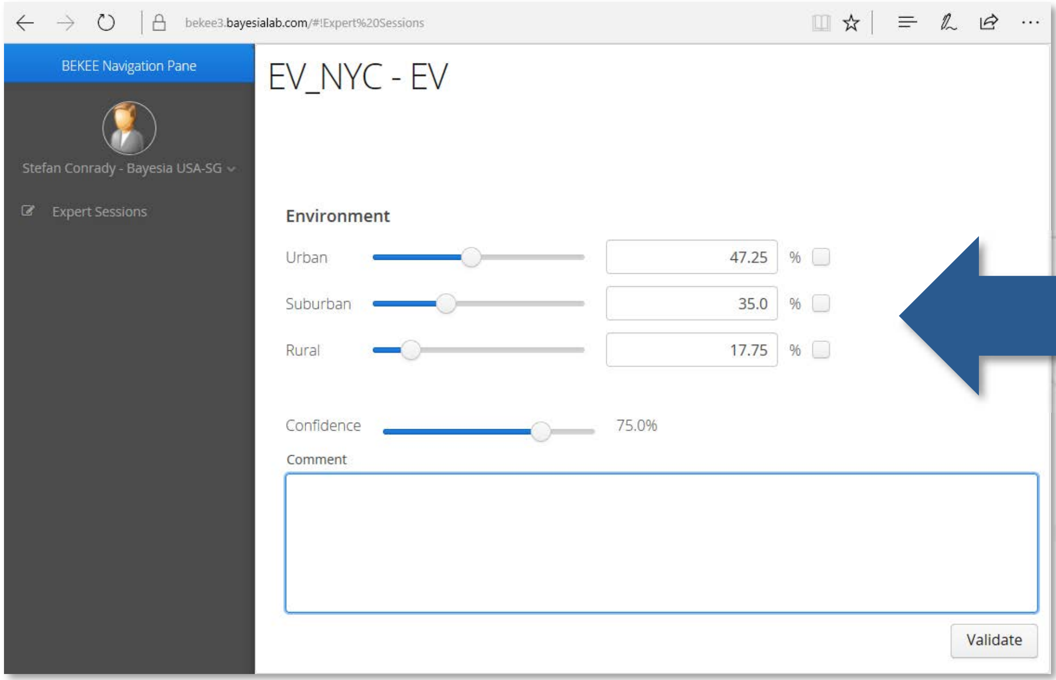


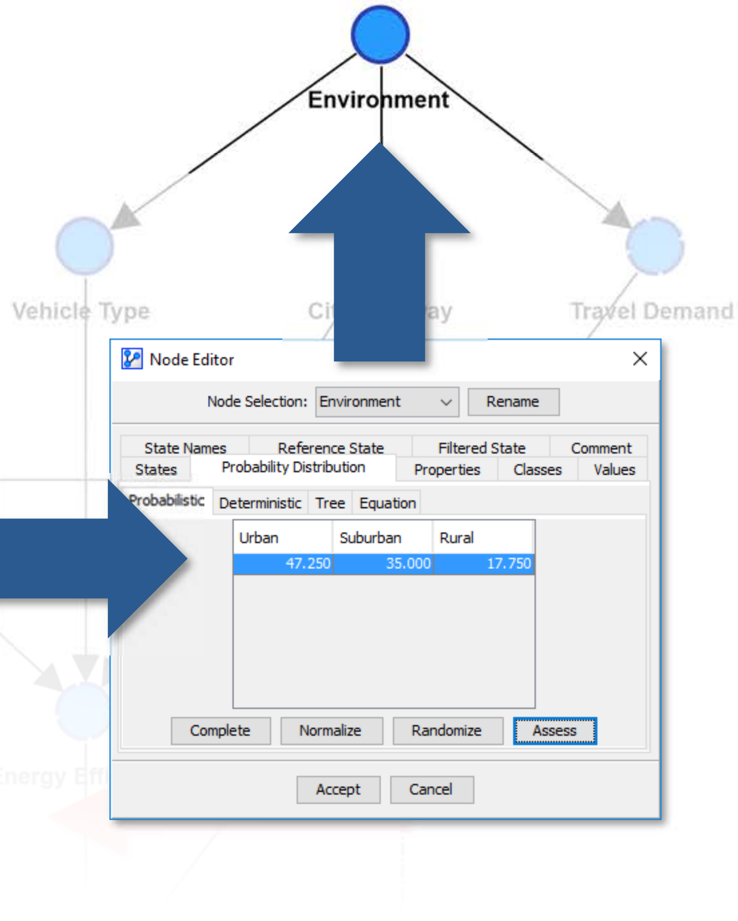
2. Knowledge Elicitation



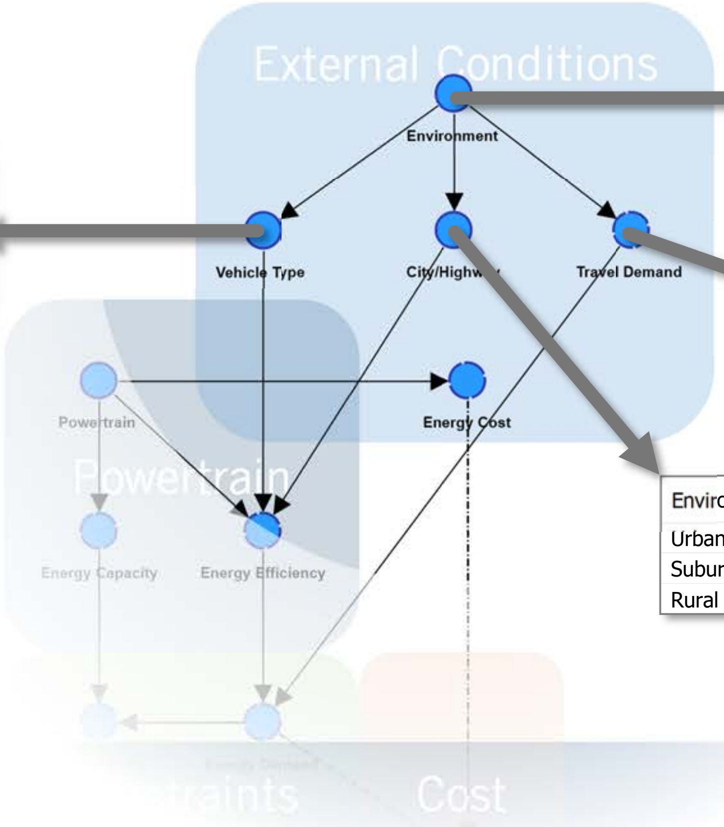
Knowledge Elicitation

Your Assessment Task





Knowledge Elicitation



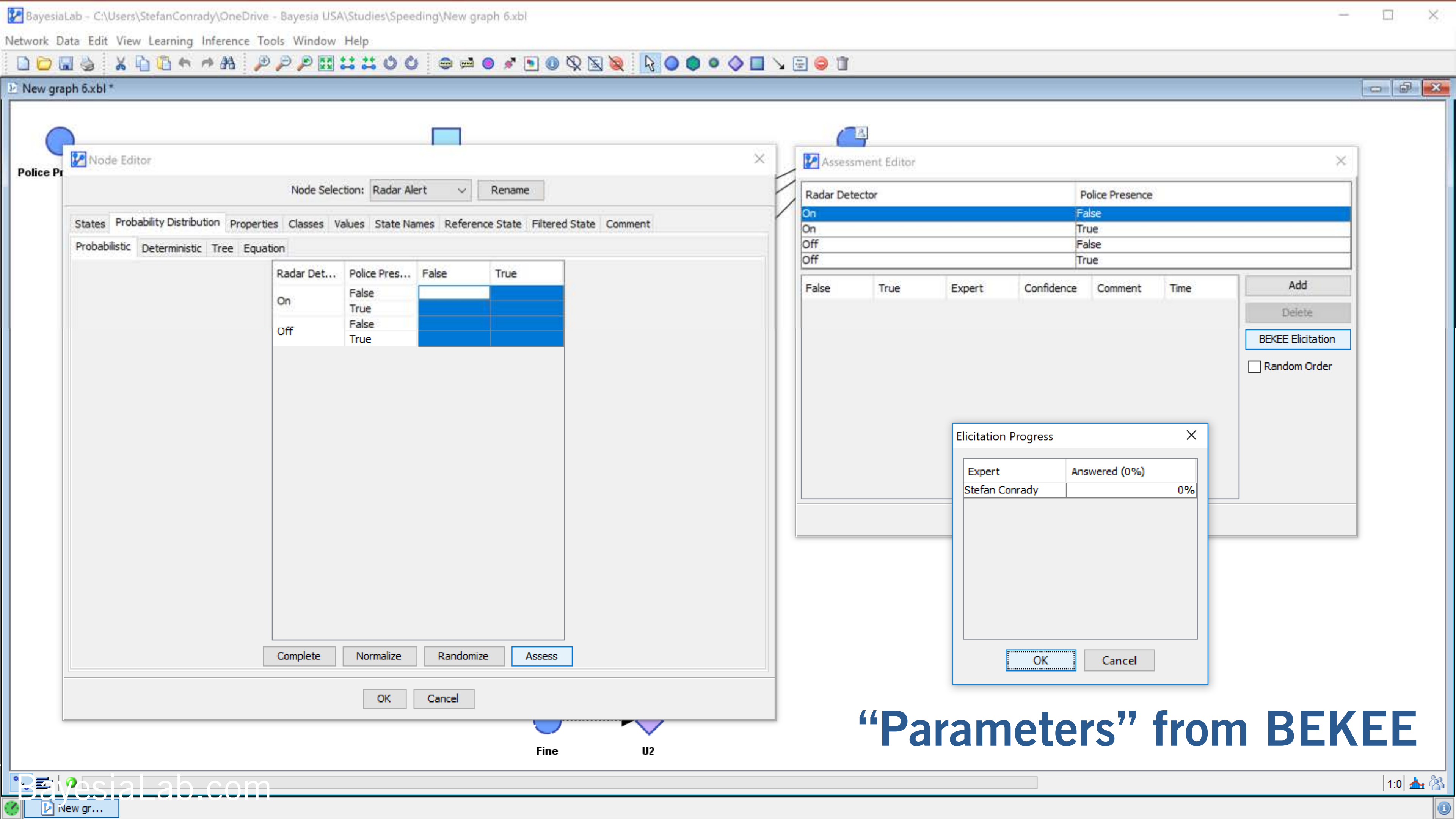
Urban	Suburban	Rural
33.333	33.333	33.333

Environment	Car	Truck
Urban	75.000	25.000
Suburban	50.000	50.000
Rural	25.000	75.000

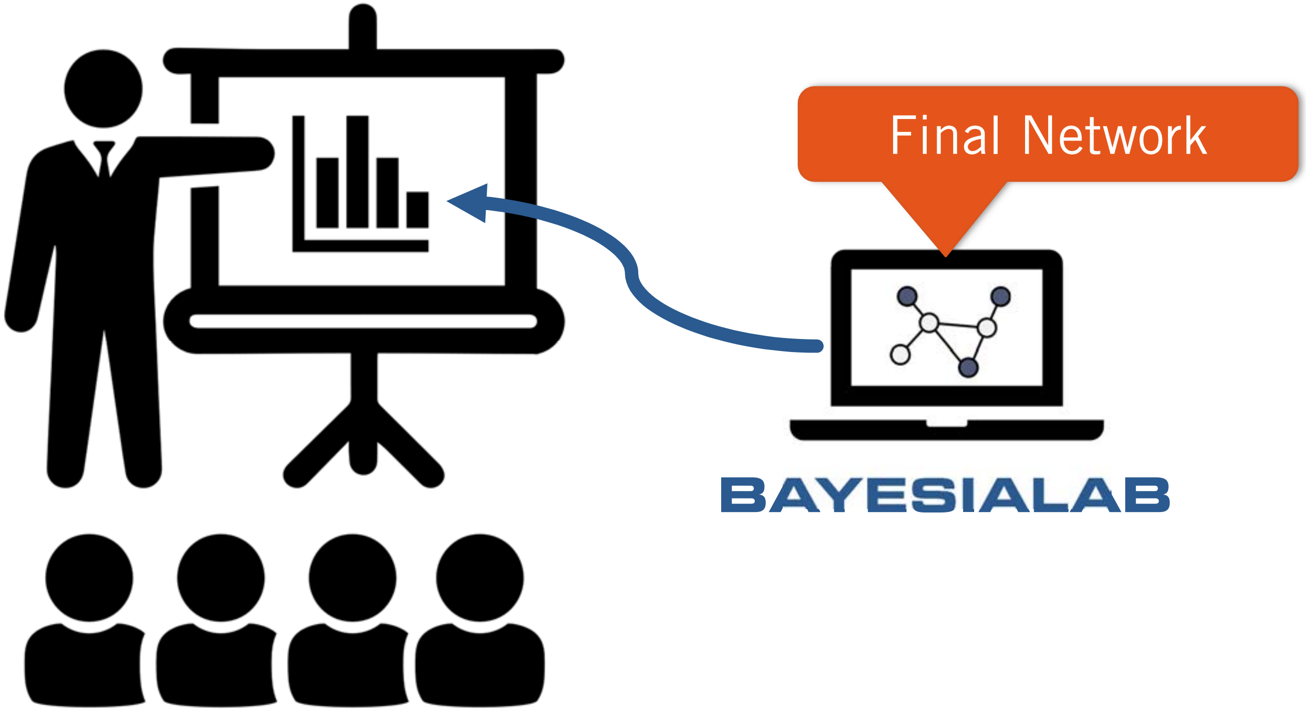
Environment	<=5	<=10	<=15
Urban	18.000	18.000	18.000
Suburban	16.000	16.000	16.000
Rural	12.000	12.000	12.000

Environment	City	Highway
Urban	80.000	20.000
Suburban	50.000	50.000
Rural	20.000	80.000

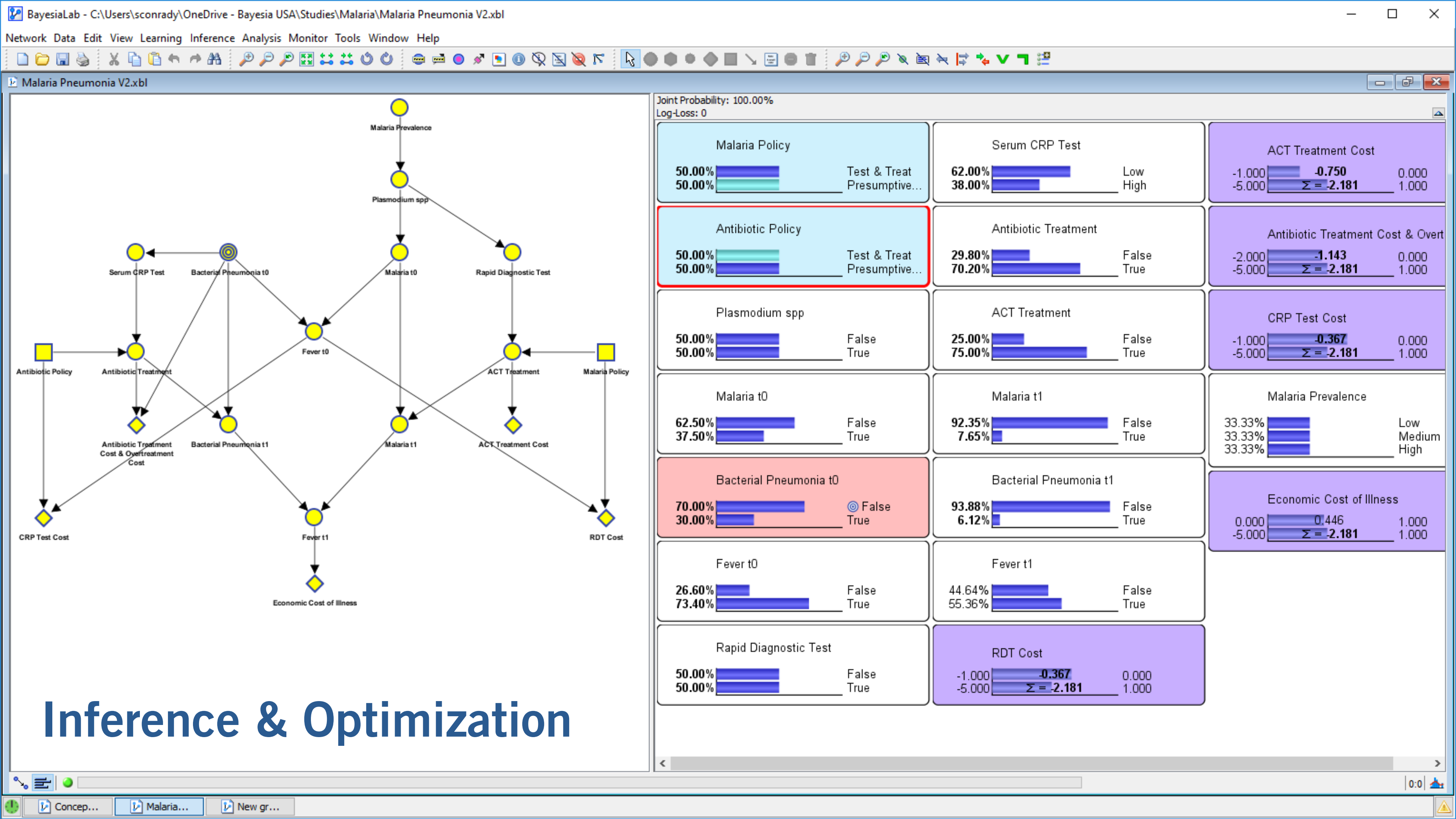
“Parameters” from BEKEE

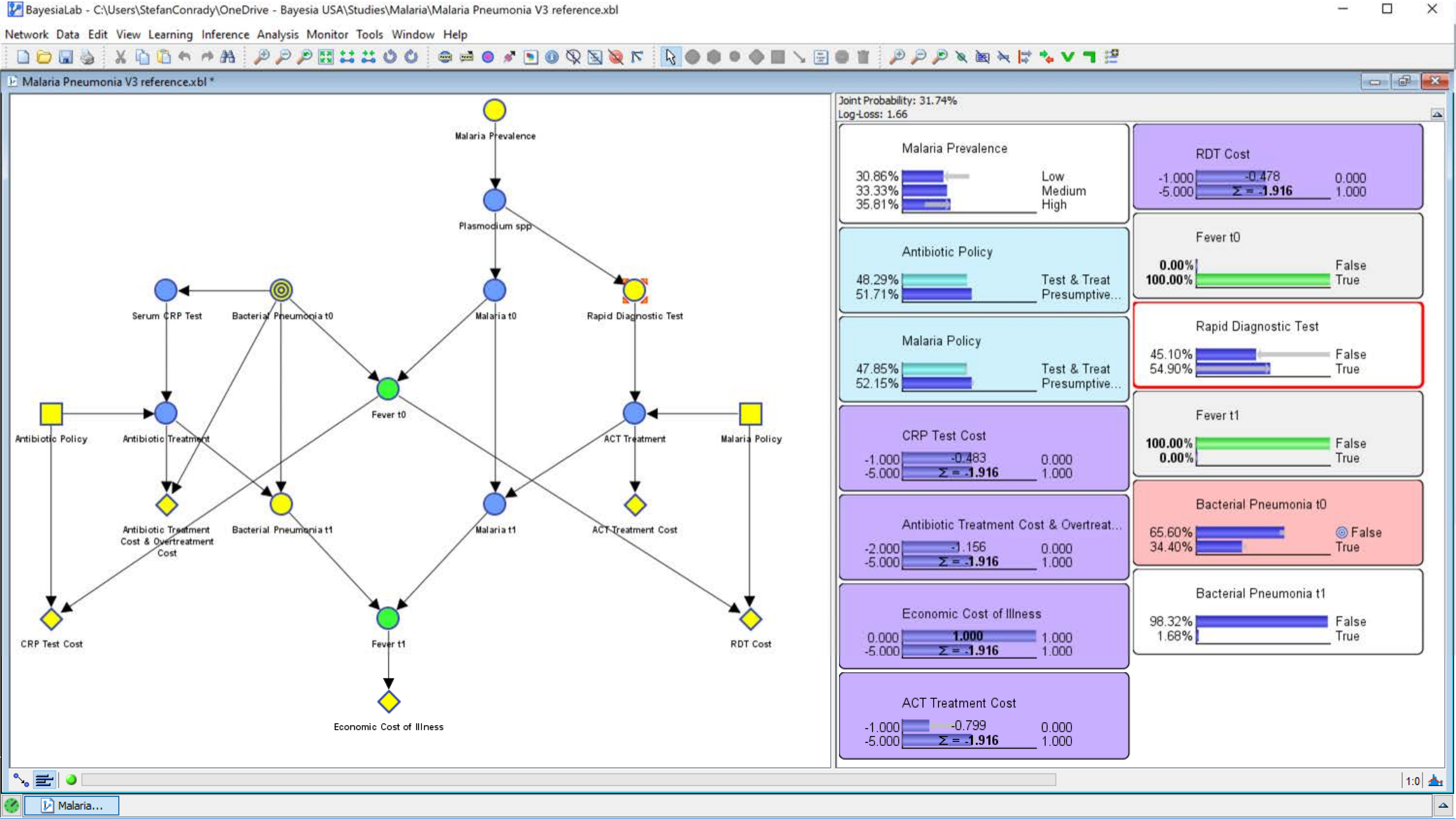


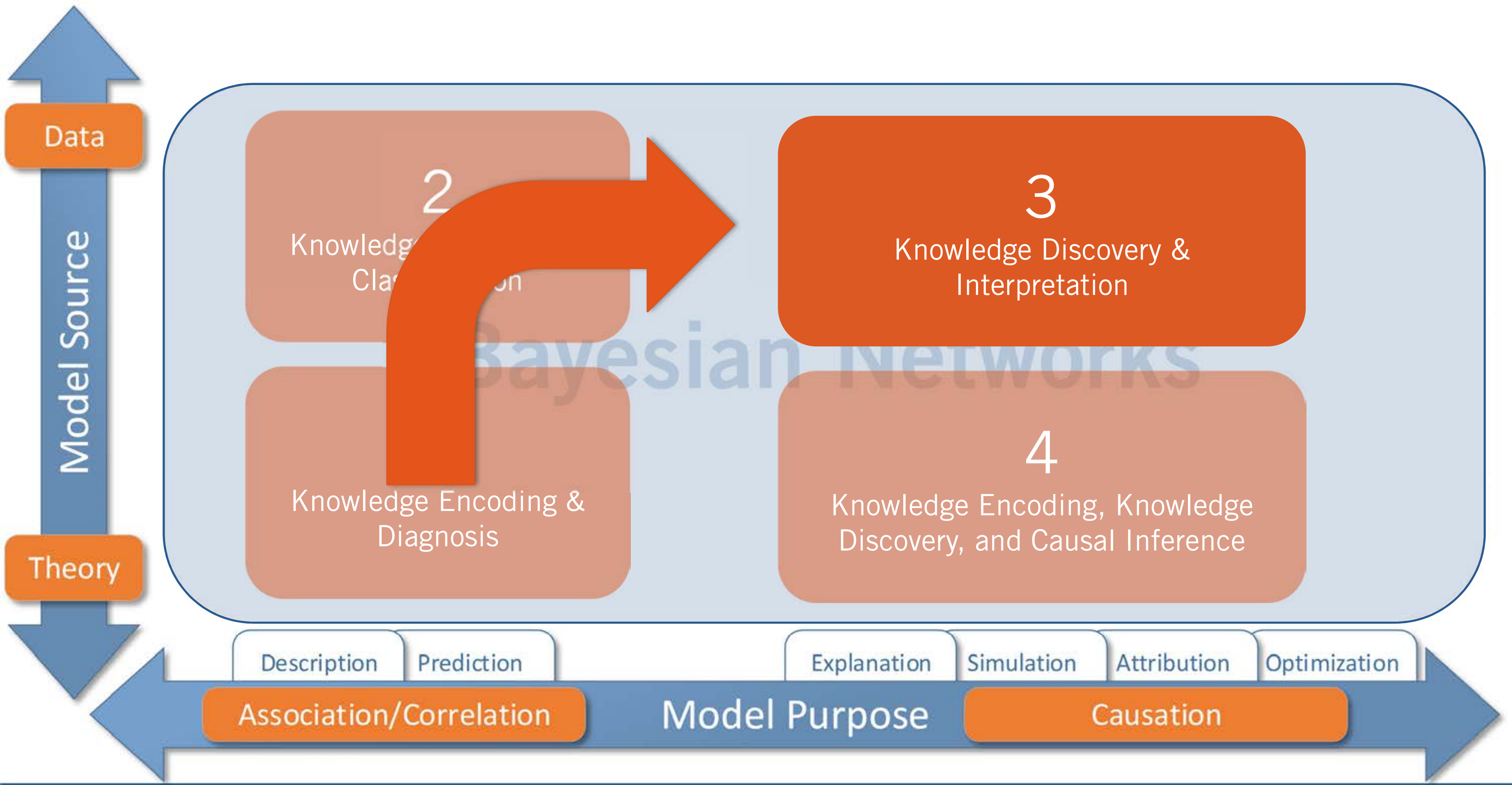
3. Inference, Analysis, and Optimization



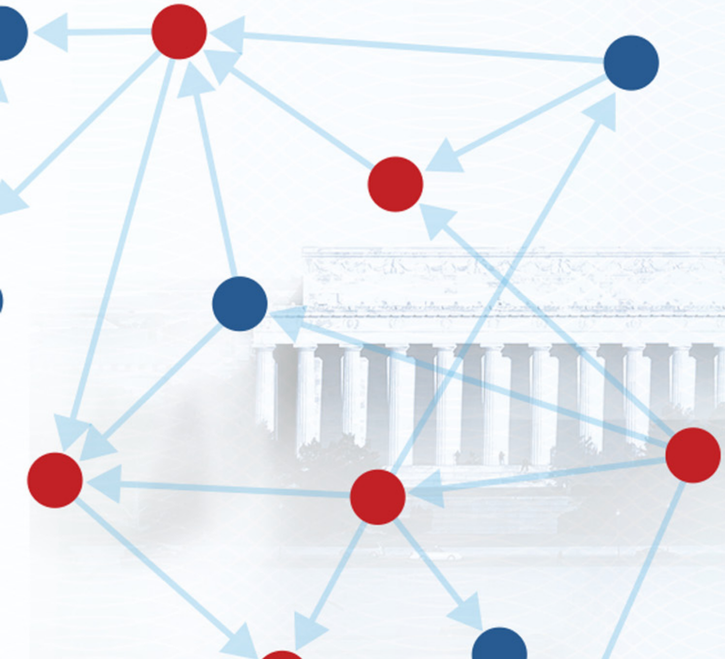
Inference & Optimization




BayesiaLab - C:\Users\StefanConrady\OneDrive - Bayesia USA\Studies\Malaria\Malaria Pneumonia V3 reference.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Malaria Pneumonia V3 reference.xbl *
Malaria Prevalence
Plasmodium spp
Serum CRP Test
Bacterial Pneumonia t0
Malaria t0
Rapid Diagnostic Test
Fever t0
Antibiotic Policy
Antibiotic Treatment
ACT Treatment
Malaria Policy
Antibiotic Treatment Cost & Overtreatment Cost
Bacterial Pneumonia t1
Malaria t1
ACT Treatment Cost
CRP Test Cost
Fever t1
RDT Cost
Economic Cost of Illness
Joint Probability: 31.74%
Log-Loss: 1.66
Malaria Prevalence
30.86% Low
33.33% Medium
35.81% High
RDT Cost
-1.000 -0.478 0.000
-5.000 Σ = -1.916 1.000
Antibiotic Policy
48.29% Test & Treat
51.71% Presumptive...
Fever t0
0.00% False
100.00% True
Malaria Policy
47.85% Test & Treat
52.15% Presumptive...
Rapid Diagnostic Test
45.10% False
54.90% True
CRP Test Cost
-1.000 -0.483 0.000
-5.000 Σ = -1.916 1.000
Fever t1
100.00% False
0.00% True
Antibiotic Treatment Cost & Overtreat...
-2.000 -1.156 0.000
-5.000 Σ = -1.916 1.000
Bacterial Pneumonia t0
65.60% False
34.40% True
Economic Cost of Illness
0.000 1.000 1.000
-5.000 Σ = -1.916 1.000
Bacterial Pneumonia t1
98.32% False
1.68% True
ACT Treatment Cost
-1.000 -0.799 0.000
-5.000 Σ = -1.916 1.000
1:0
Malaria...


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

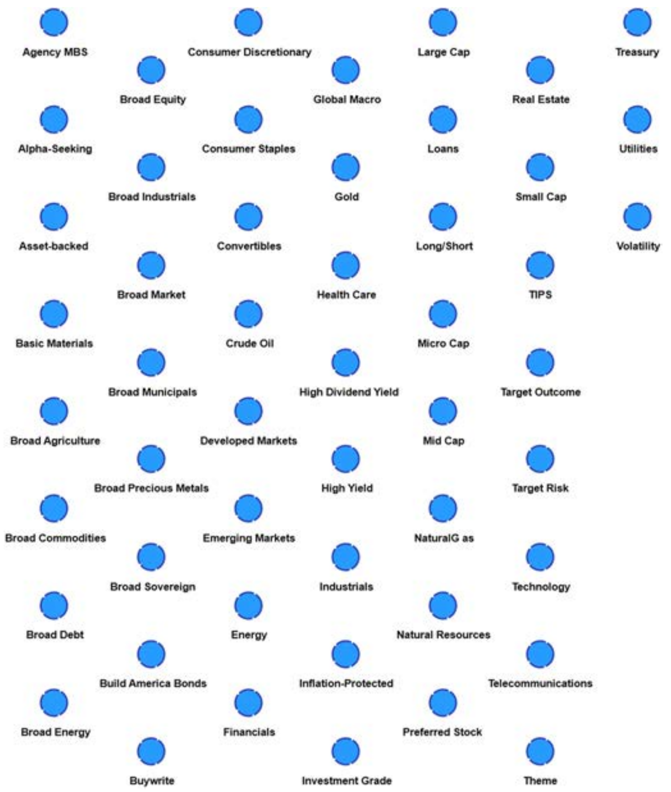
BAYESIALAB



Exchange-Traded Funds

Knowledge Discovery, Interpretation, and Anomaly Detection

Problem Domain: Money Flows

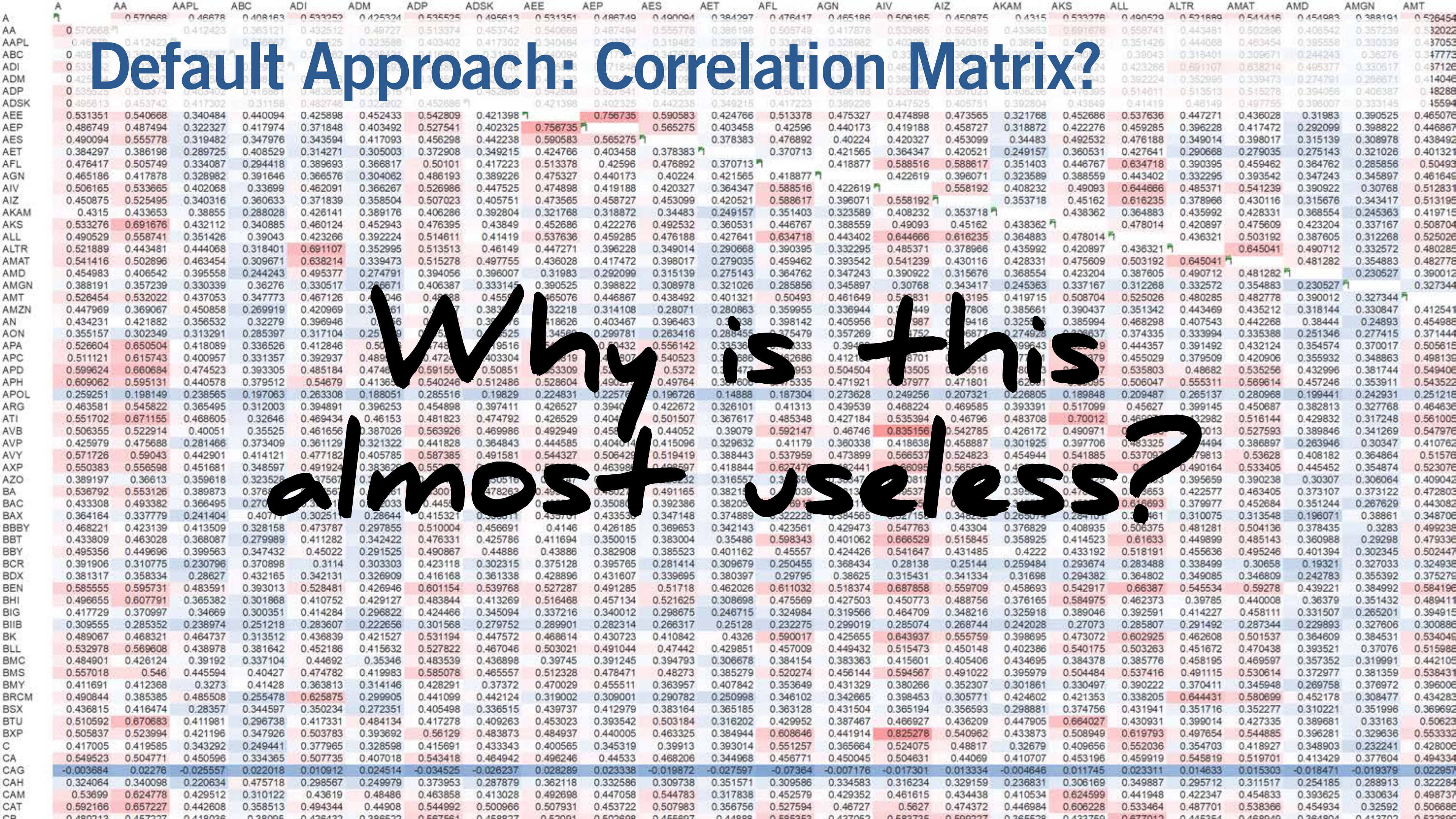


Daily ETF Flows
By Investment Focus

Main Objective

Deep Understanding

Default Approach: Correlation Matrix?

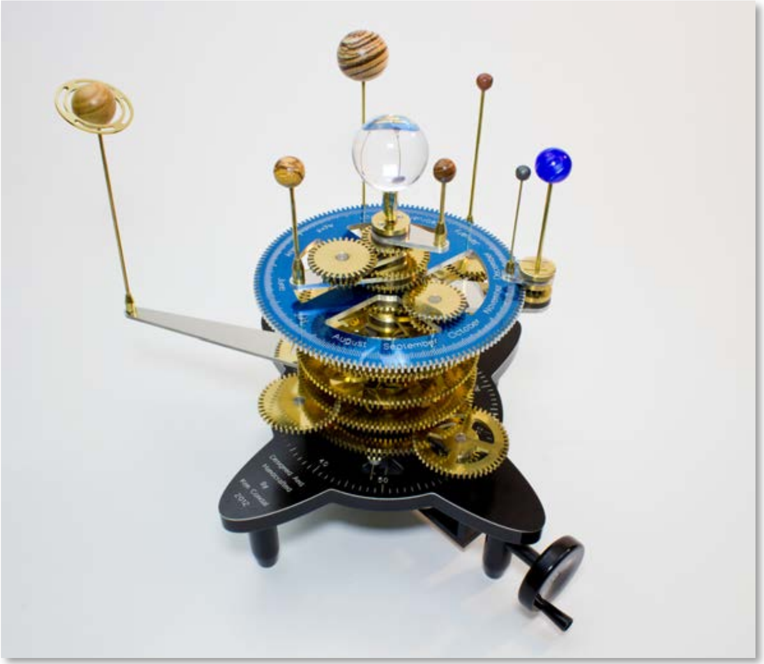


Why is this almost useless?

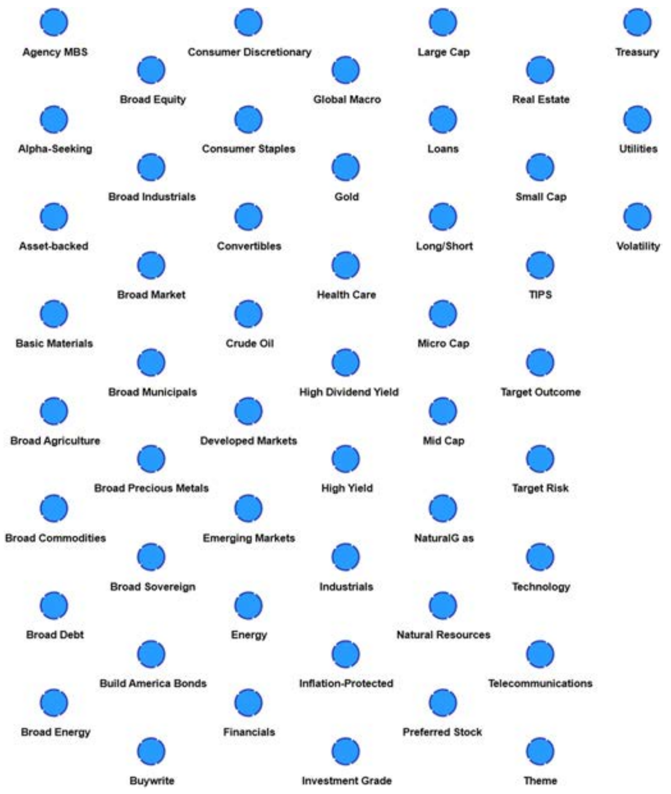
Objective: Deep Understanding

"Deep understanding means knowing, not merely how things behaved yesterday, but also how things will behave under new hypothetical circumstances..."

Judea Pearl, Causality (2009), Cambridge University Press

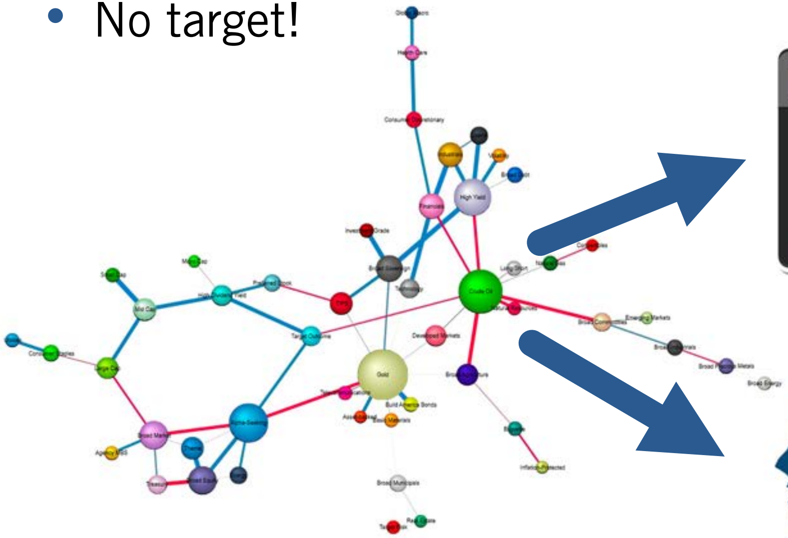


Bayesian Network Learning



Objective

- Learn single model for all 51 variables.
- No target!



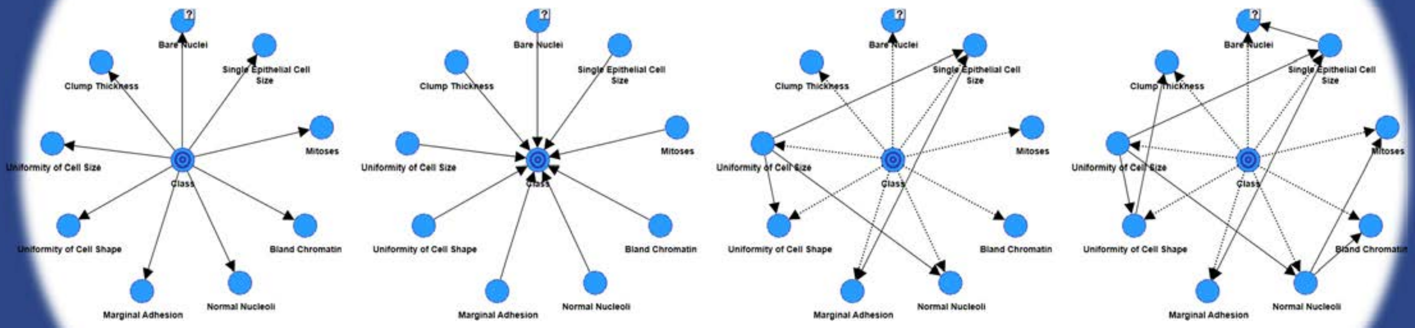
Example 4: Exchange-Traded Funds

BayesiaLab Workflow

- Data Source:
  - 1,147 Exchange-Traded Funds
  - Timeframe: 2014 – 2018
  - Daily Flow grouped by 51 investment themes
- Data Import
- Unsupervised Learning
  - SopLEQ (SC=0.35)

- Alpha-Seeking
- Basic Materials
- Broad Equity
- Consumer Discretionary
- Energy
- Financials
- High Dividend Yield
- Industrials
- Mid Cap
- Natural Resources
- Preferred Stock
- Technology
- Agency MBS
- Asset-backed
- Broad Agriculture
- Broad Commodities
- Broad Debt
- Broad Energy
- Broad Industrials
- Broad Market
- Broad Municipals
- Broad Sovereign
- Build America Bonds
- Buywrite
- Consumer Staples
- Convertibles
- Crude Oil
- Developed Markets
- Emerging Markets
- Global Macro
- Gold
- Health Care
- High Yield
- Inflation-Protected
- Investment Grade
- Large Cap
- Loans
- Long/Short
- Micro Cap
- Natural Gas
- Real Estate
- Small Cap
- TIPS
- Target Outcome
- Target Risk
- Telecommunications
- Theme
- Treasury
- Utilities
- Volatility
- Broad Precious Metals

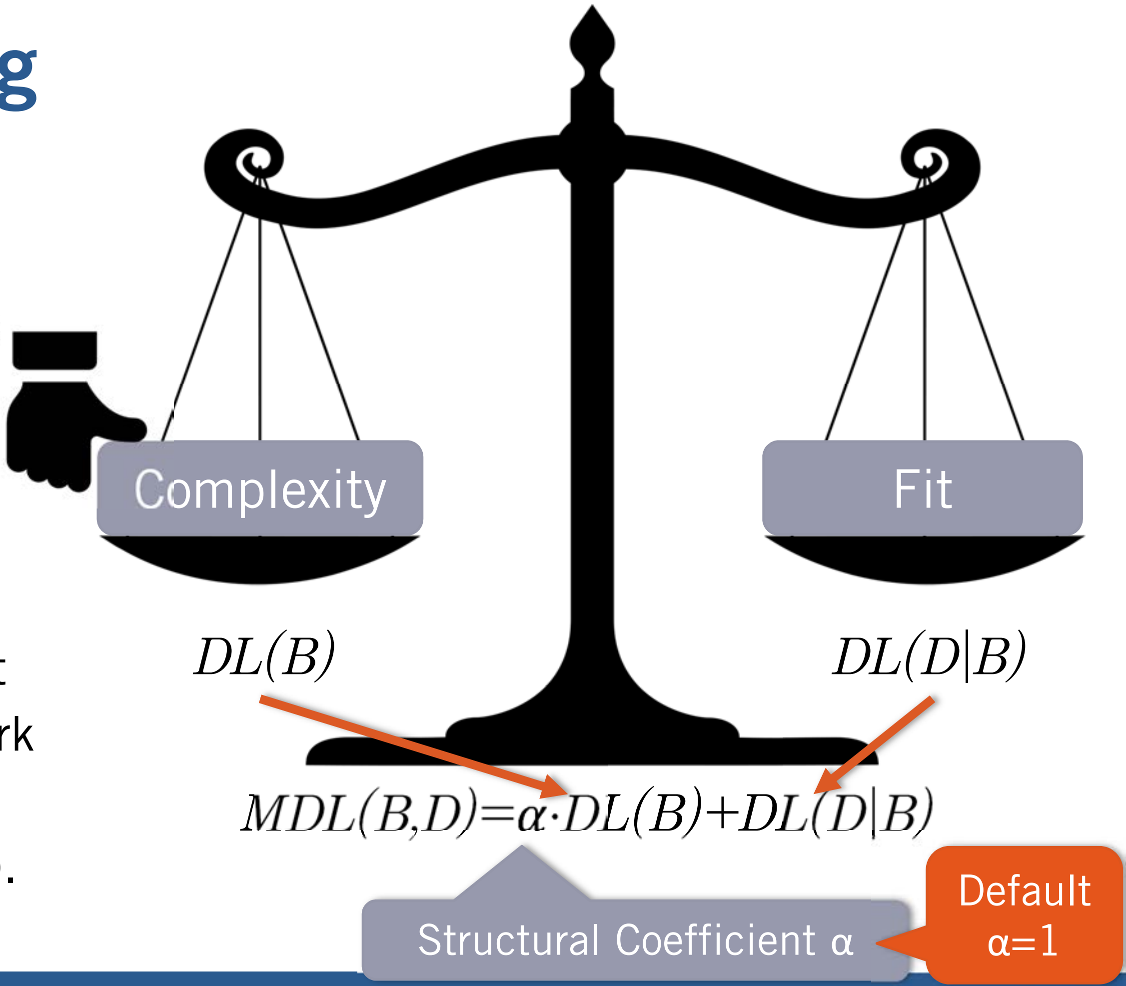
Learning=Searching



Learning=Searching

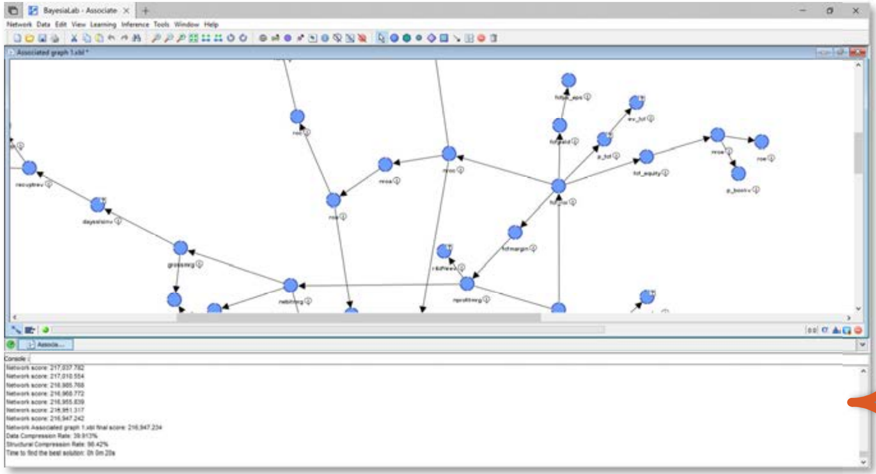
Minimum Description Length

- $DL(B)$ 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).

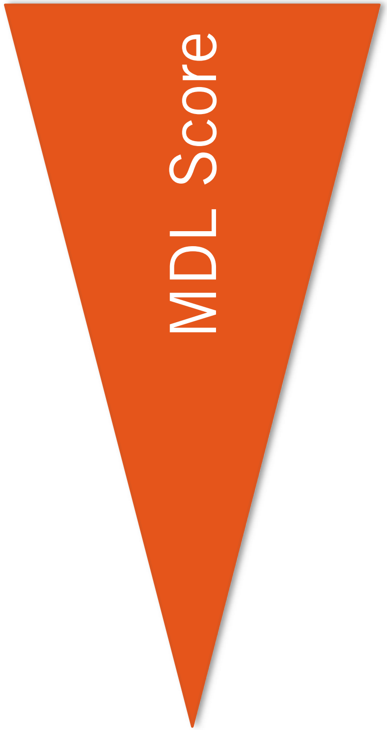


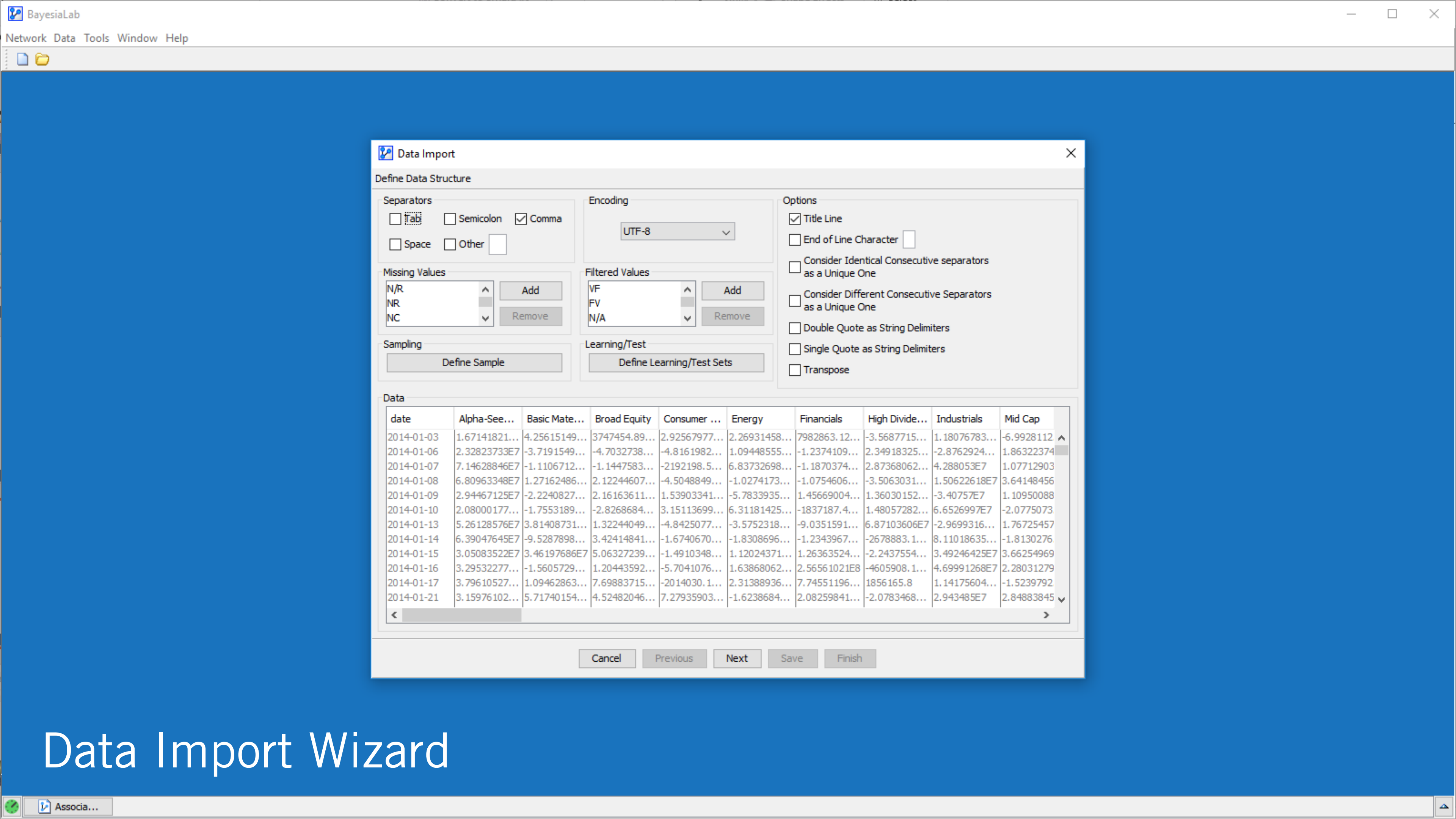
Learning=Searching

Minimum Description Length

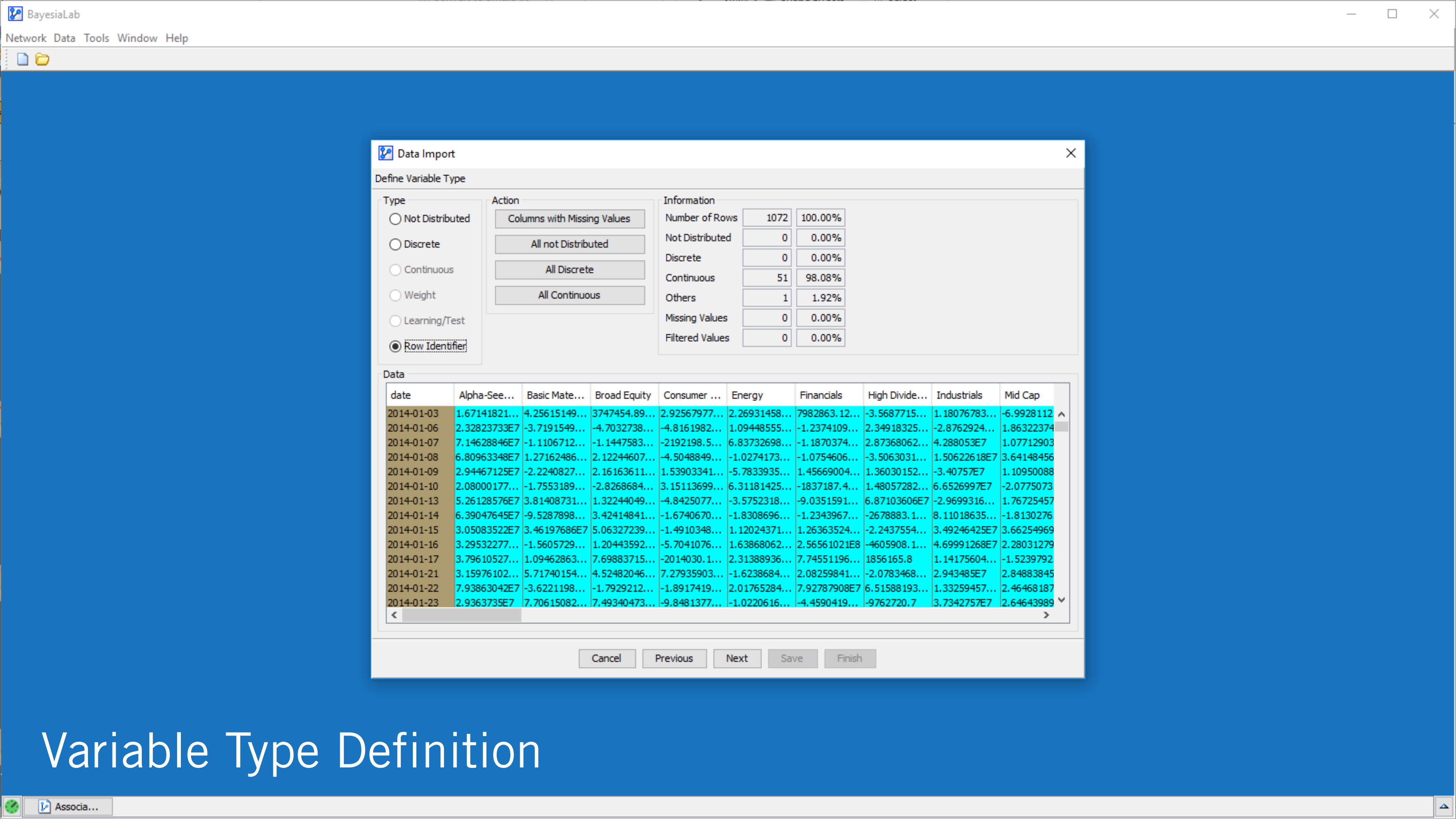


Network score: 217,884.553
Network score: 217,743.338
Network score: 217,610.856
Network score: 217,483.237
Network score: 217,359.875
Network score: 217,241.952
Network score: 217,195.628
Network score: 217,152.903
Network score: 217,113.827
Network score: 217,075.16
Network score: 217,037.782
Network score: 217,010.554
Network score: 216,985.768
Network score: 216,968.772
Network score: 216,955.839
Network score: 216,951.317
Network score: 216,947.242
Network Associated graph 1.xbl final score: 216,947.234
Data Compression Rate: 39.913%
Structural Compression Rate: 98.42%
Time to find the best solution: 0h 0m 20s

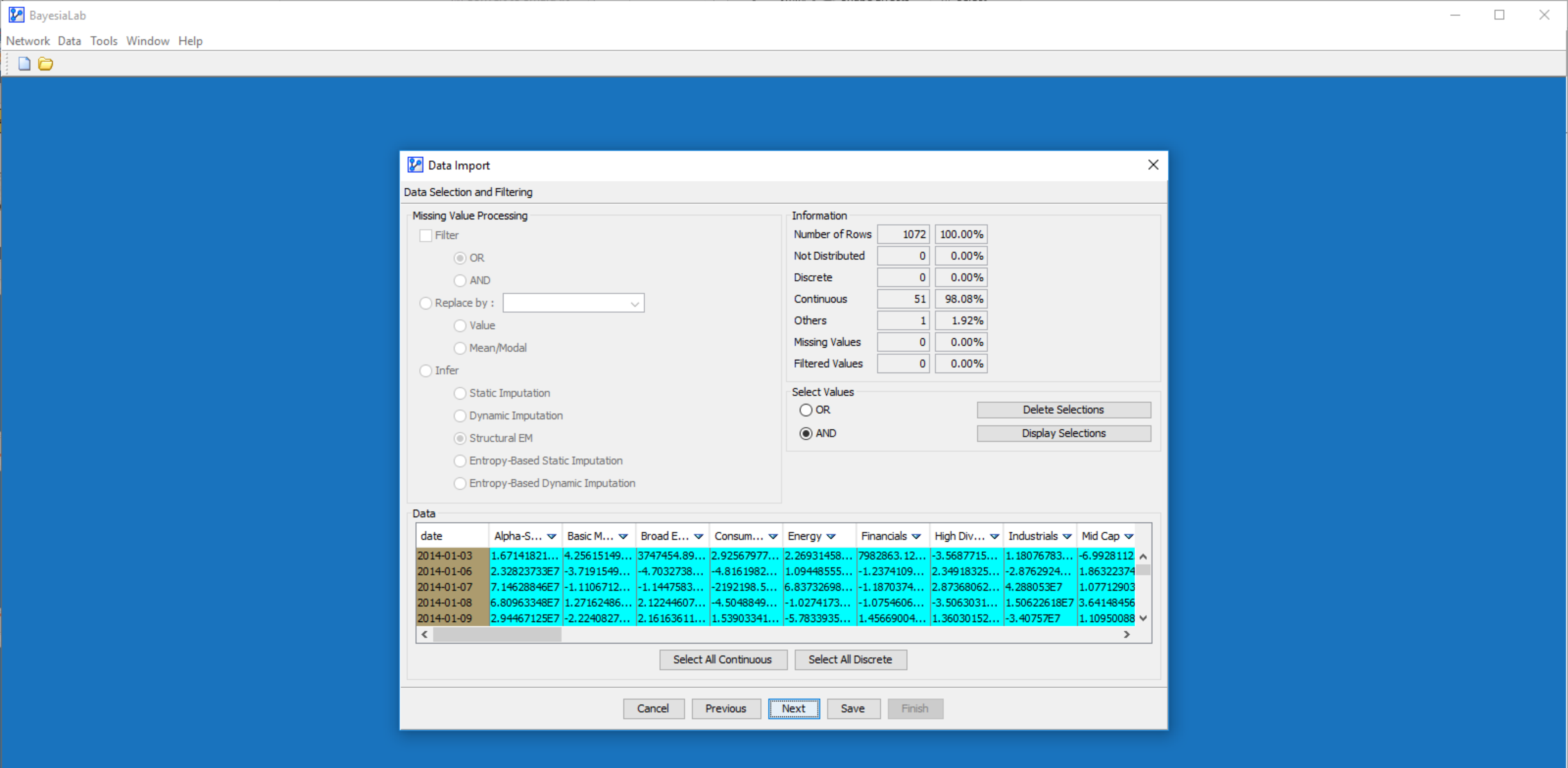




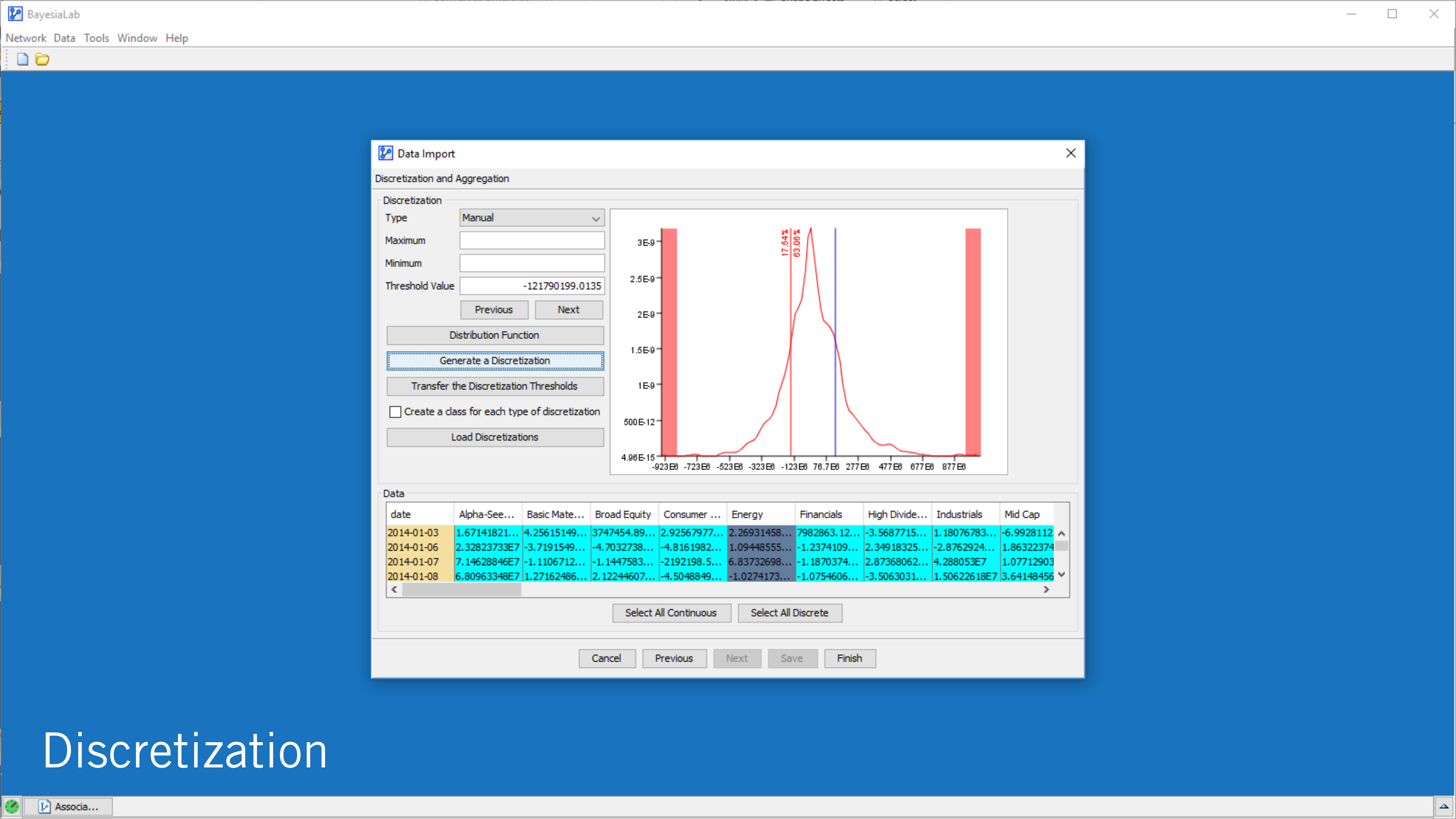
Data Import Wizard



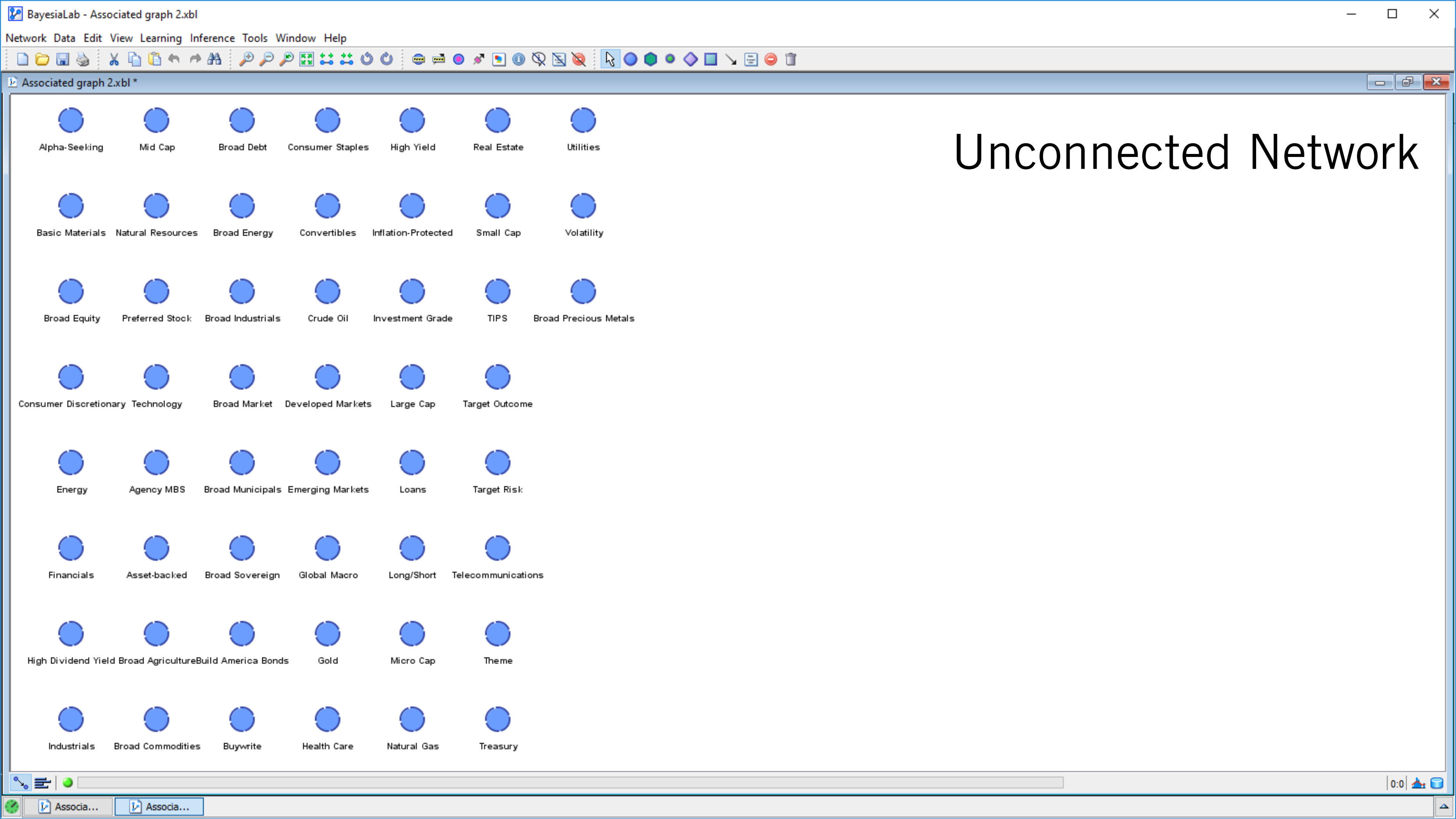
Variable Type Definition



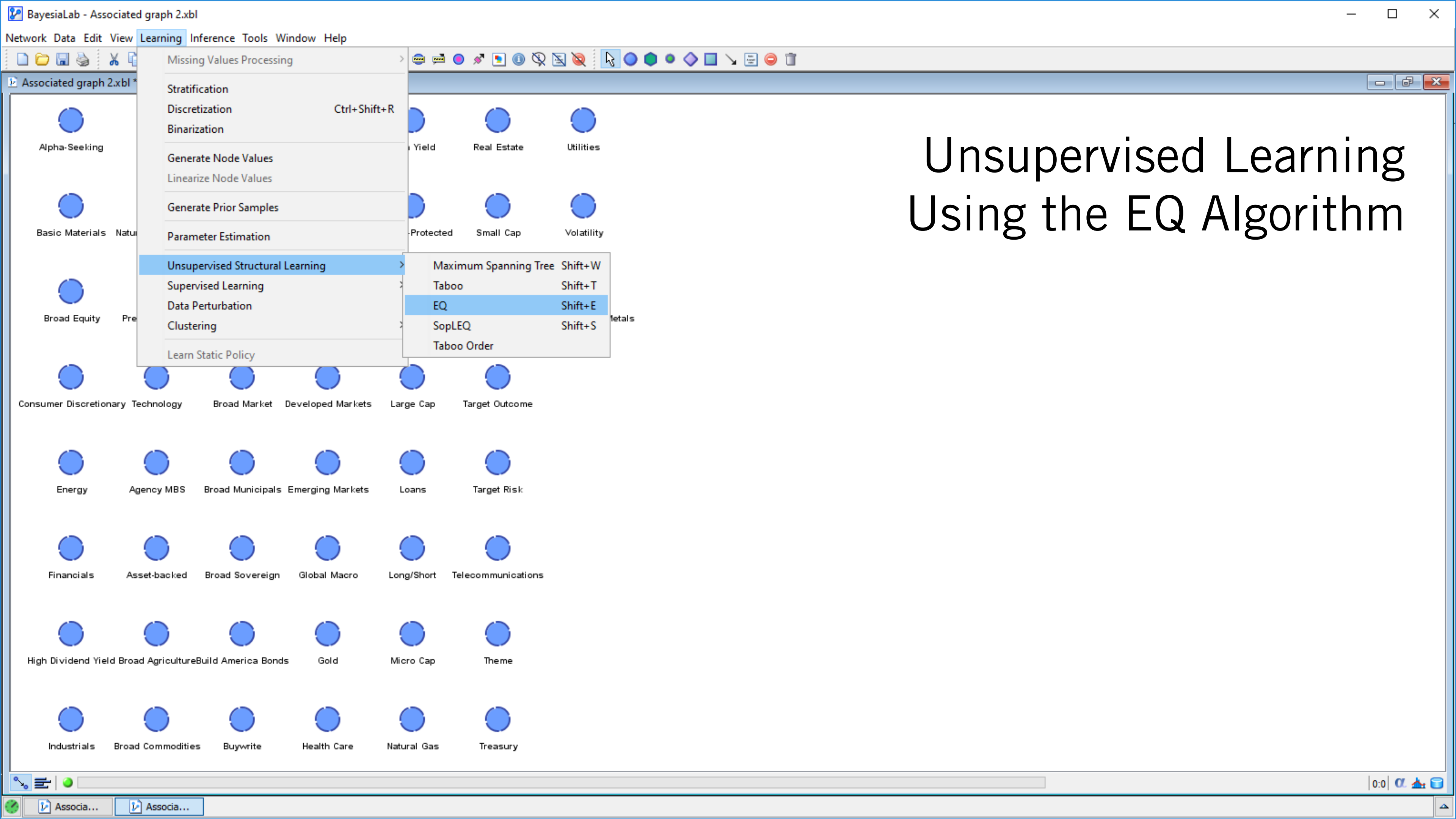
Missing Values Processing

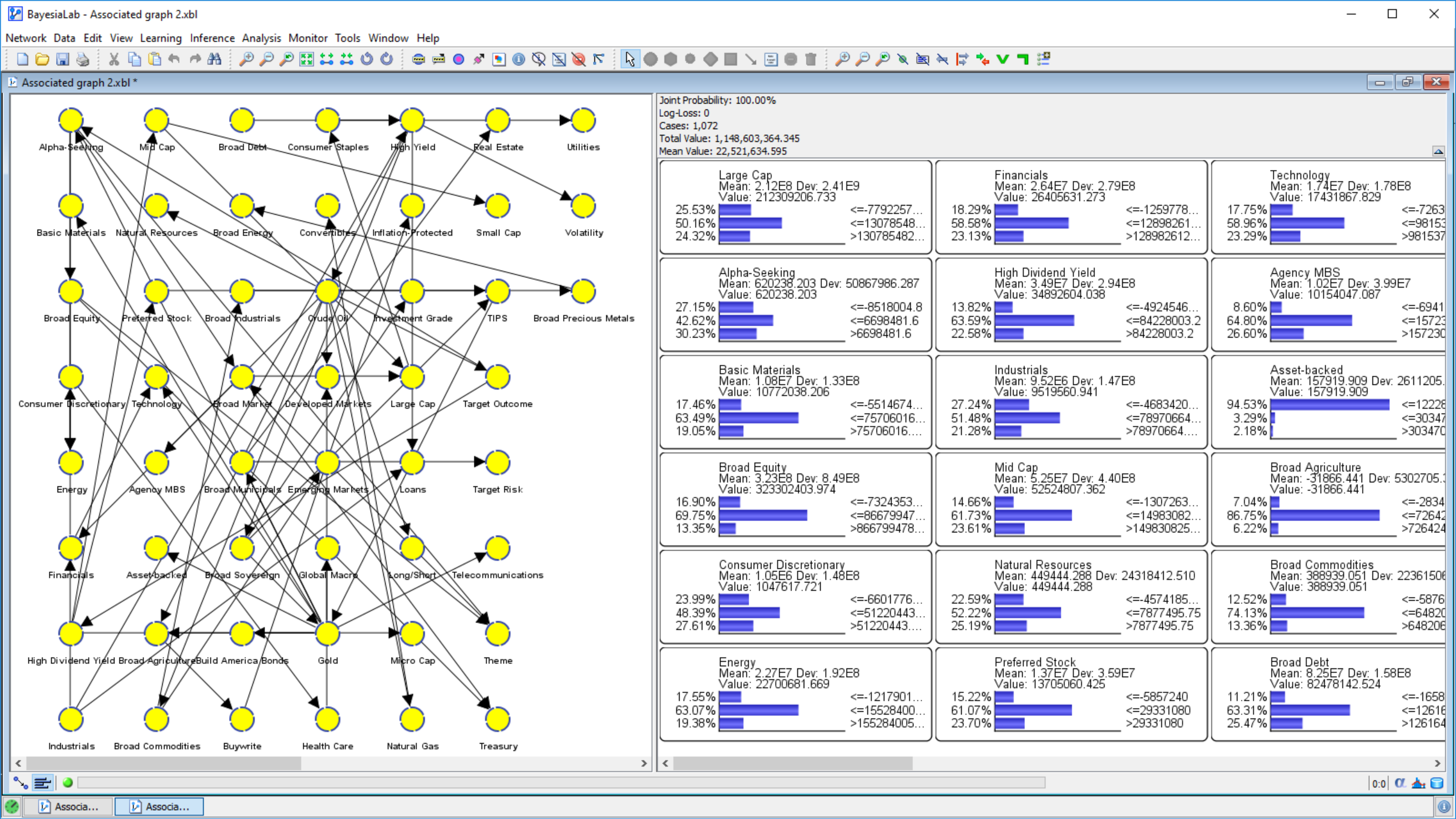


Discretization


BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 2.xbl *
Unconnected Network
Alpha-Seeking
Mid Cap
Broad Debt
Consumer Staples
High Yield
Real Estate
Utilities
Basic Materials
Natural Resources
Broad Energy
Convertibles
Inflation-Protected
Small Cap
Volatility
Broad Equity
Preferred Stock
Broad Industrials
Crude Oil
Investment Grade
TIPS
Broad Precious Metals
Consumer Discretionary
Technology
Broad Market
Developed Markets
Large Cap
Target Outcome
Energy
Agency MBS
Broad Municipals
Emerging Markets
Loans
Target Risk
Financials
Asset-backed
Broad Sovereign
Global Macro
Long/Short
Telecommunications
High Dividend Yield
Broad Agriculture
Build America Bonds
Gold
Micro Cap
Theme
Industrials
Broad Commodities
Buywrite
Health Care
Natural Gas
Treasury
Associa...
Associa...

Unsupervised Learning Using the EQ Algorithm





BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
Alpha-Seeking
Mid Cap
Broad Debt
Consumer Staples
High Yield
Real Estate
Utilities
Basic Materials
Natural Resources
Broad Energy
Convertibles
Inflation-Protected
Small Cap
Volatility
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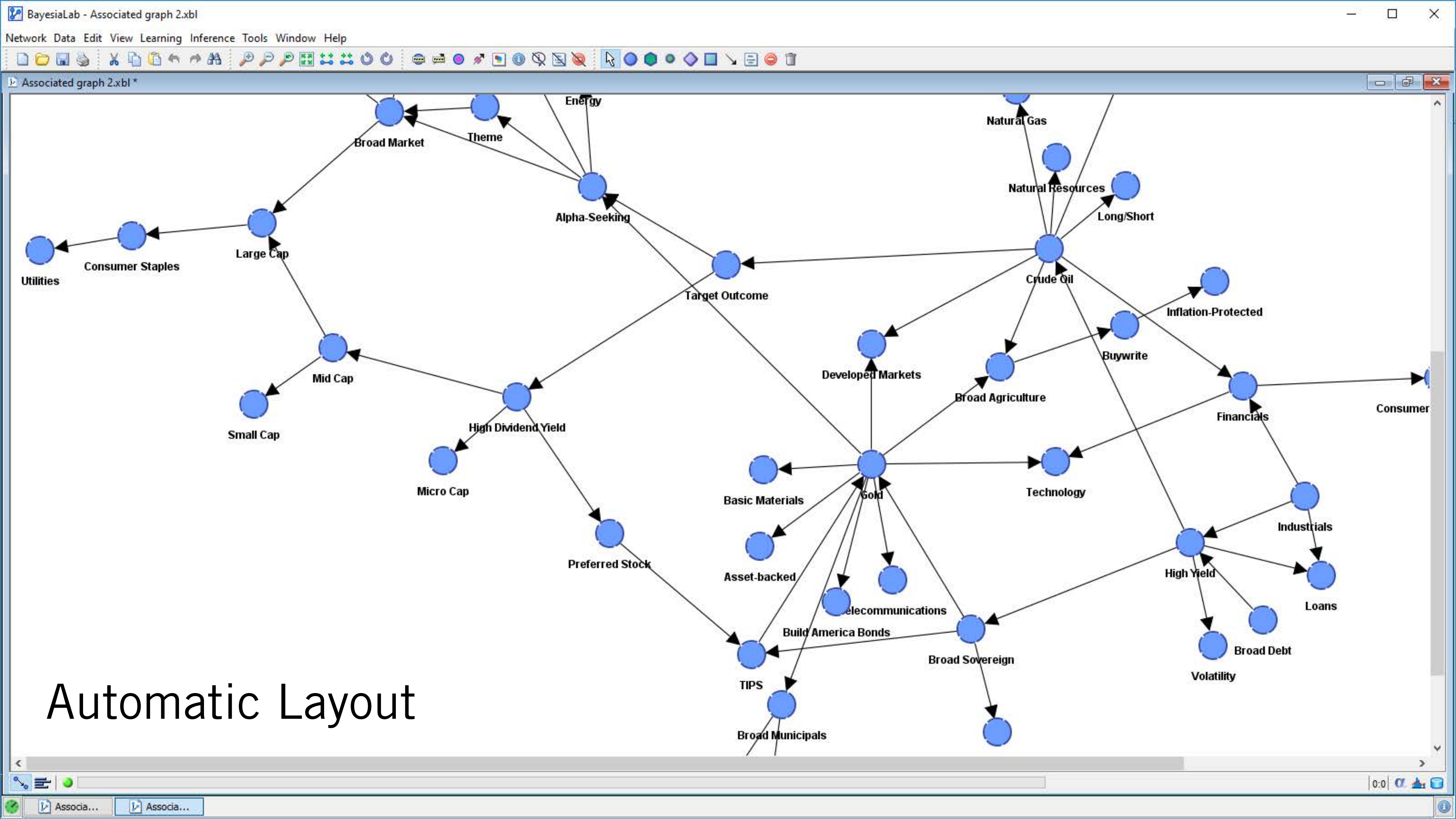
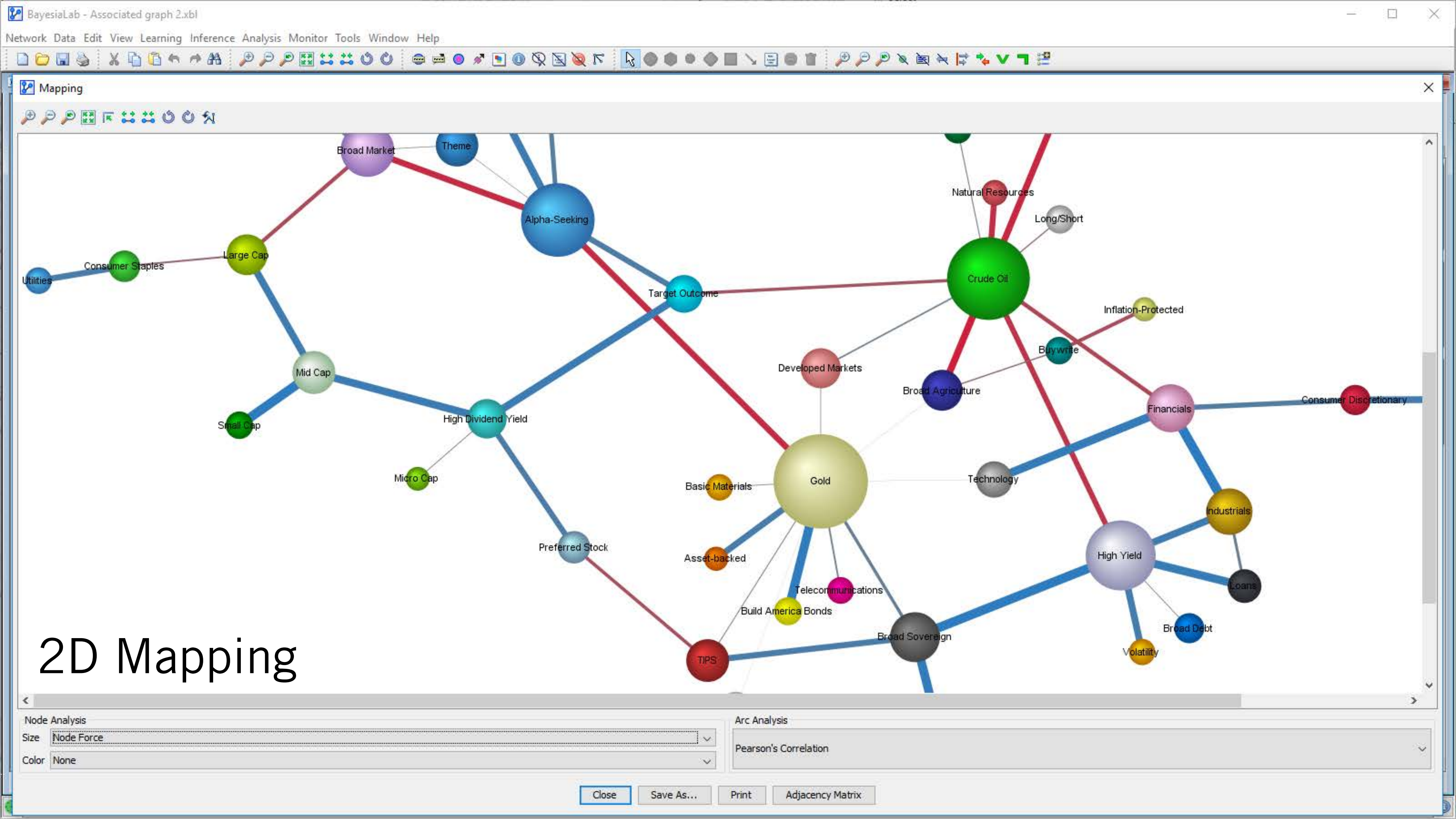
Target Risk
Financials
Asset-backed
Broad Sovereign
Global Macro
Long/Short
Telecommunications
High Dividend Yield
Broad Agriculture
Build America Bonds
Gold
Micro Cap
Theme
Industrials
Broad Commodities
Buywrite
Health Care
Natural Gas
Treasury
Joint Probability: 100.00%
Log-Loss: 0
Cases: 1,072
Total Value: 1,148,603,364.345
Mean Value: 22,521,634.595
Large Cap
Mean: 2.12E8 Dev: 2.41E9
Value: 212309206.733
25.53% <=-7792257...
50.16% <=13078548...
24.32% >130785482...
Financials
Mean: 2.64E7 Dev: 2.79E8
Value: 26405631.273
18.29% <=-1259778...
58.58% <=12898261...
23.13% >128982612...
Technology
Mean: 1.74E7 Dev: 1.78E8
Value: 17431867.829
17.75% <=-7263
58.96% <=98153
23.29% >981537
Alpha-Seeking
Mean: 620238.203 Dev: 50867986.287
Value: 620238.203
27.15% <=-8518004.8
42.62% <=6698481.6
30.23% >6698481.6
High Dividend Yield
Mean: 3.49E7 Dev: 2.94E8
Value: 34892604.038
13.82% <=-4924546...
63.59% <=84228003.2
22.58% >84228003.2
Agency MBS
Mean: 1.02E7 Dev: 3.99E7
Value: 10154047.087
8.60% <=-6941
64.80% <=15723
26.60% >157230
Basic Materials
Mean: 1.08E7 Dev: 1.33E8
Value: 10772038.206
17.46% <=-5514674...
63.49% <=75706016...
19.05% >75706016....
Industrials
Mean: 9.52E6 Dev: 1.47E8
Value: 9519560.941
27.24% <=-4683420...
51.48% <=78970664...
21.28% >78970664....
Asset-backed
Mean: 157919.909 Dev: 2611205.
Value: 157919.909
94.53% <=12228
3.29% <=30347
2.18% >303470
Broad Equity
Mean: 3.23E8 Dev: 8.49E8
Value: 323302403.974
16.90% <=-7324353...
69.75% <=86679947...
13.35% >866799478...
Mid Cap
Mean: 5.25E7 Dev: 4.40E8
Value: 52524807.362
14.66% <=-1307263...
61.73% <=14983082...
23.61% >149830825...
Broad Agriculture
Mean: -31866.441 Dev: 5302705.
Value: -31866.441
7.04% <=-2834
86.75% <=72642
6.22% >726424
Consumer Discretionary
Mean: 1.05E6 Dev: 1.48E8
Value: 1047617.721
23.99% <=-6601776...
48.39% <=51220443...
27.61% >51220443....
Natural Resources
Mean: 449444.288 Dev: 24318412.510
Value: 449444.288
22.59% <=-4574185...
52.22% <=7877495.75
25.19% >7877495.75
Broad Commodities
Mean: 388939.051 Dev: 22361506
Value: 388939.051
12.52% <=-5876
74.13% <=64820
13.36% >648206
Energy
Mean: 2.27E7 Dev: 1.92E8
Value: 22700681.669
17.55% <=-1217901...
63.07% <=15528400...
19.38% >155284005...
Preferred Stock
Mean: 1.37E7 Dev: 3.59E7
Value: 13705060.425
15.22% <=-5857240
61.07% <=29331080
23.70% >29331080
Broad Debt
Mean: 8.25E7 Dev: 1.58E8
Value: 82478142.524
11.21% <=-1658
63.31% <=12616
25.47% >126164
0:0
Associa...
Associa...

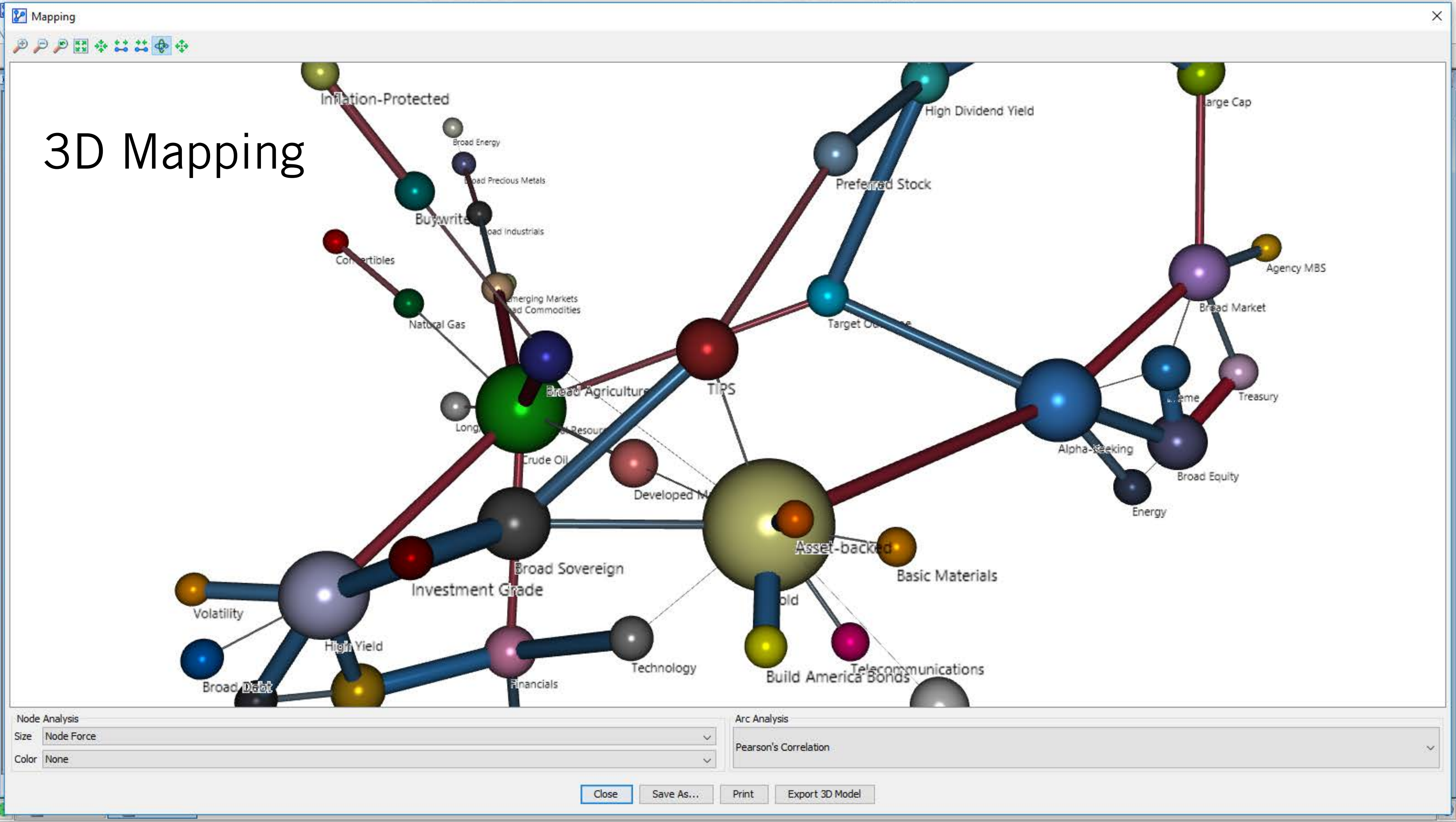


Automatic Layout

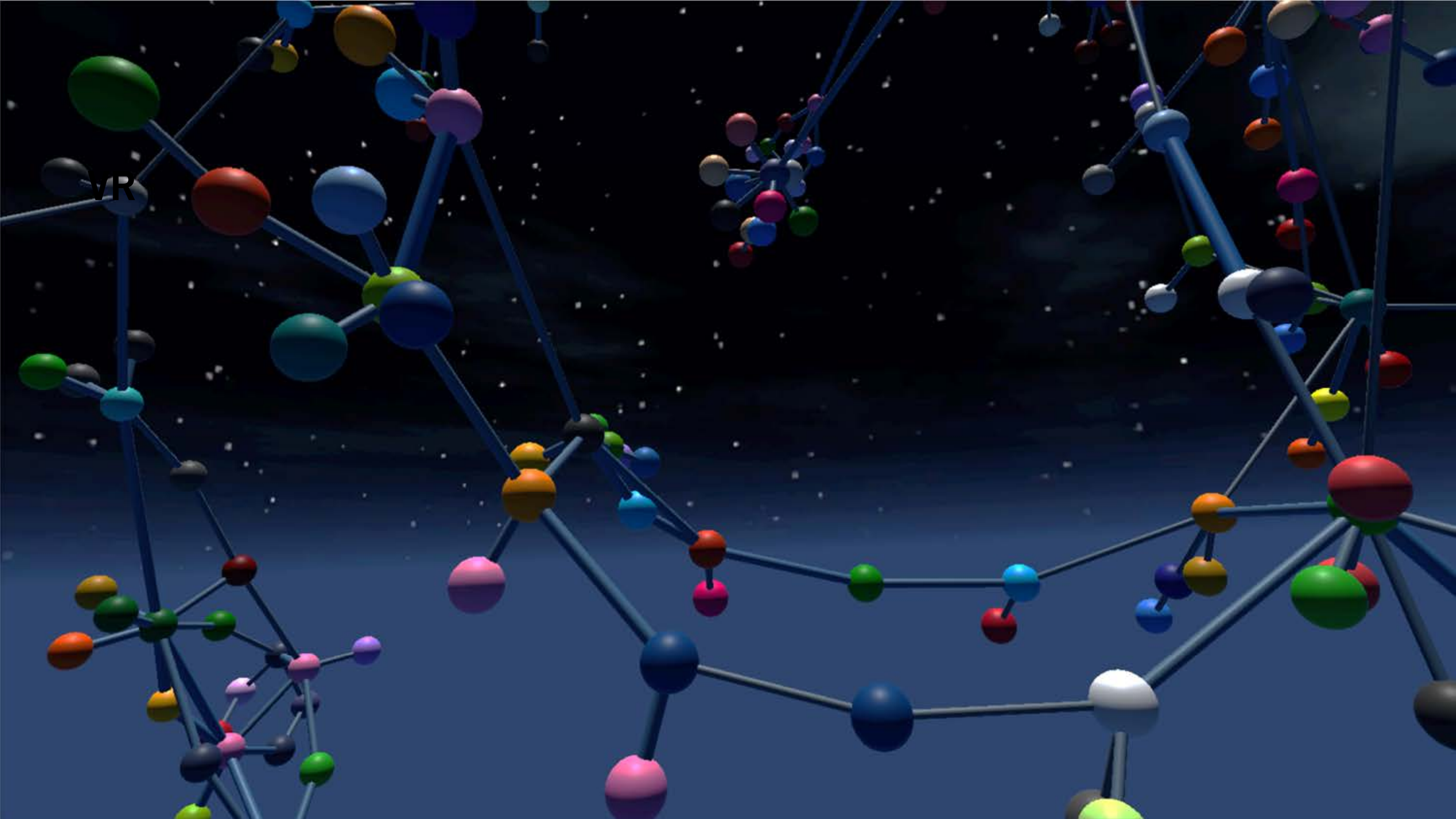
2D Mapping

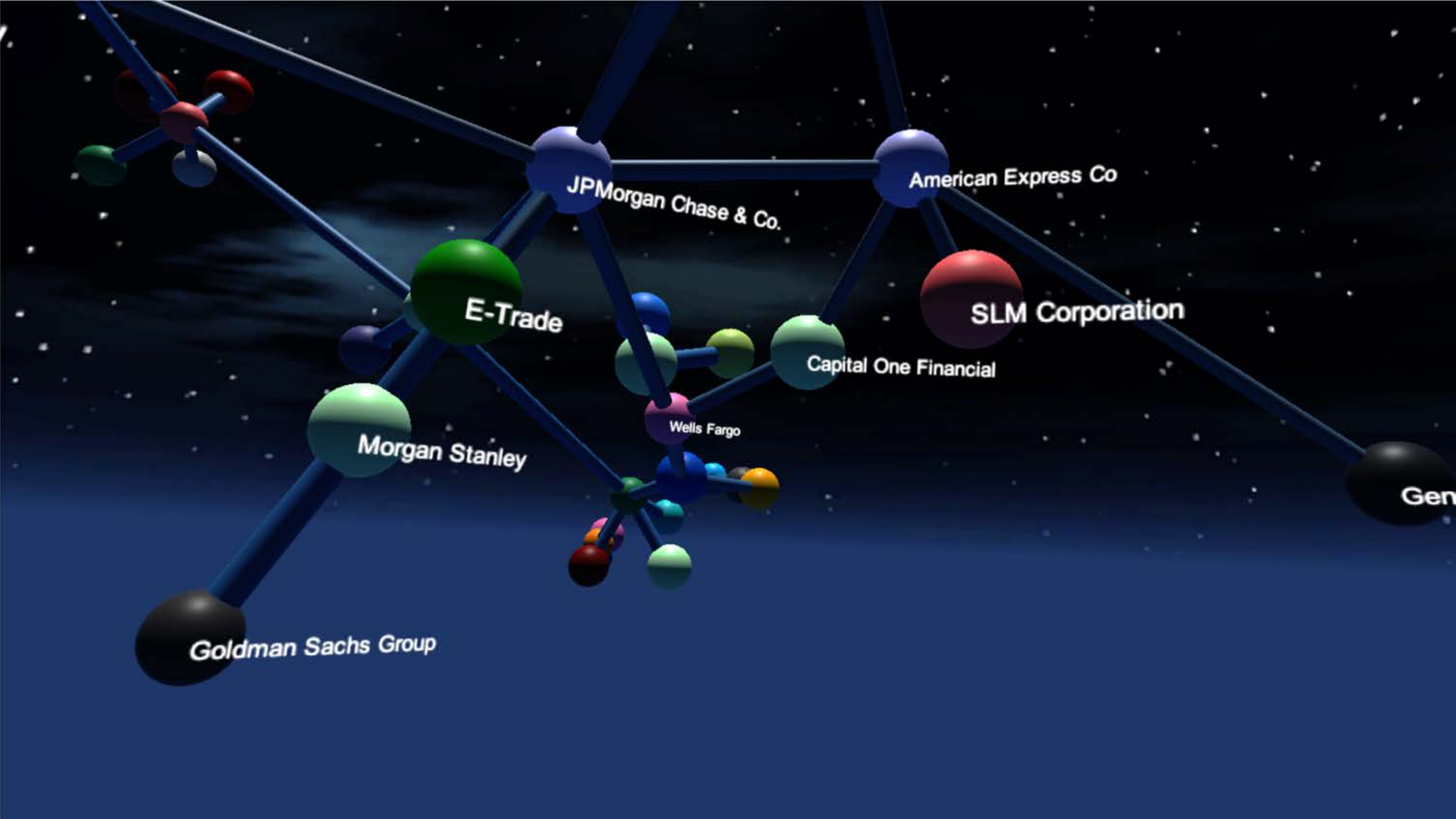

BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Mapping
Broad Market
Theme
Alpha-Seeking
Natural Resources
Long/Short
Crude Oil
Consumer Staples
Utilities
Large Cap
Target Outcome
Inflation-Protected
Buywrite
Developed Markets
Broad Agriculture
Financials
Consumer Discretionary
Mid Cap
Small Cap
High Dividend Yield
Micro Cap
Gold
Basic Materials
Technology
Industrials
Preferred Stock
Asset-backed
High Yield
Loans
Telecommunications
Build America Bonds
Broad Debt
Broad Sovereign
Volatility
TIPS
Node Analysis
Size
Node Force
Color
None
Arc Analysis
Pearson's Correlation
Close
Save As...
Print
Adjacency Matrix

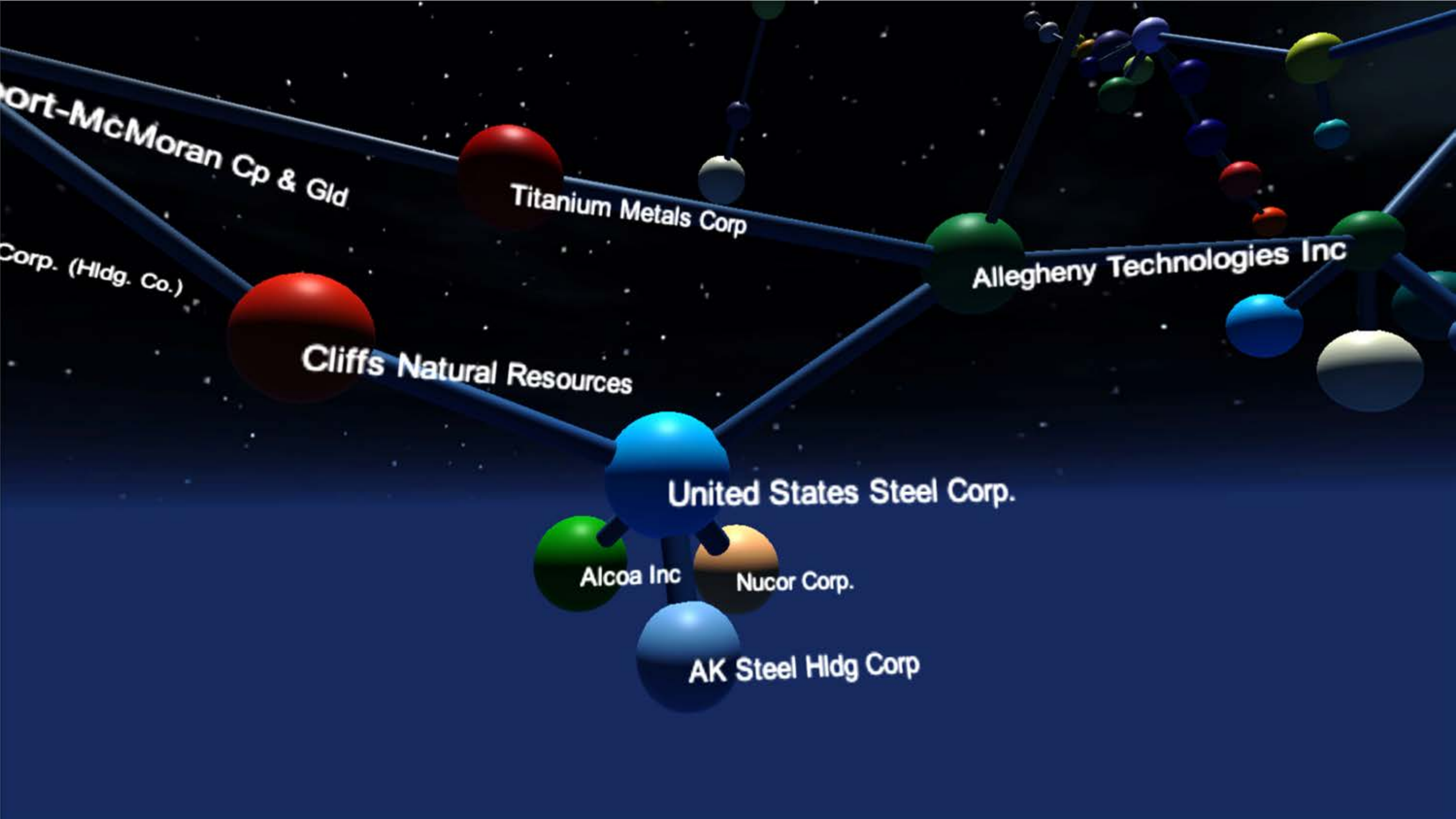
3D Mapping



Mapping
Inflation-Protected
Broad Energy
Buywrite
Convertibles
Natural Gas
High Dividend Yield
Large Cap
Preferred Stock
Agency MBS
Broad Market
Target
Broad Agriculture
TIPS
Treasury
Alpha-Seeking
Broad Equity
Energy
Crude Oil
Developed
Asset-backed
Basic Materials
Broad Sovereign
Investment Grade
Volatility
High Yield
Broad Debt
Financials
Technology
Build America Bonds
Telecommunications
Node Analysis
Size
Node Force
Color
None
Arc Analysis
Pearson's Correlation
Close
Save As...
Print
Export 3D Model

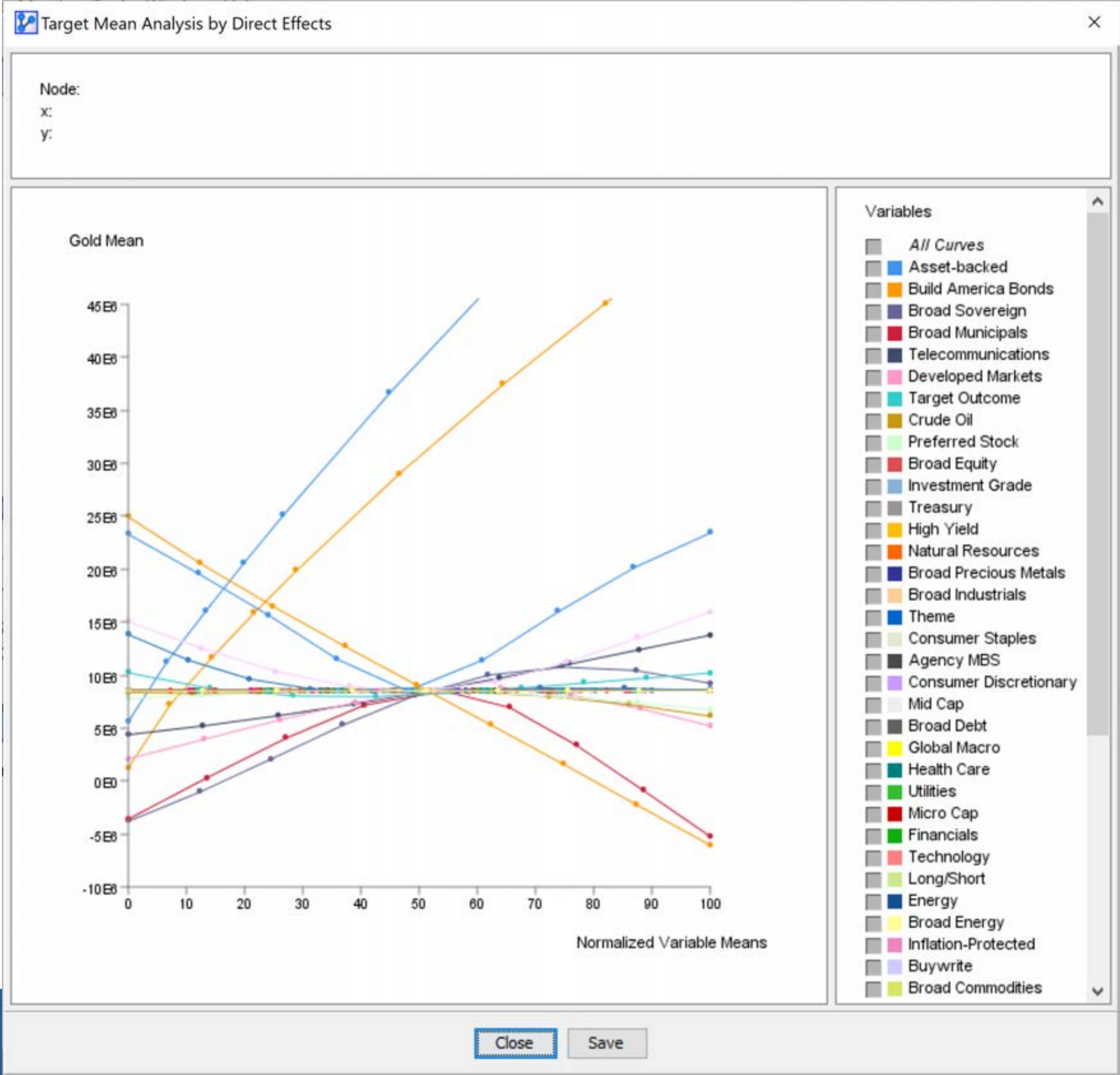

VR


JPMorgan Chase & Co.
American Express Co
E-Trade
SLM Corporation
Capital One Financial
Wells Fargo
Morgan Stanley
Goldman Sachs Group
Gen


ort-McMoran Cp & Gld
Titanium Metals Corp
Corp. (Hldg. Co.)
Cliffs Natural Resources
Allegheny Technologies Inc
United States Steel Corp.
Alcoa Inc
Nucor Corp.
AK Steel Hldg Corp

ETF

Target Mean Analysis (Direct Effect)



Anomaly Detection

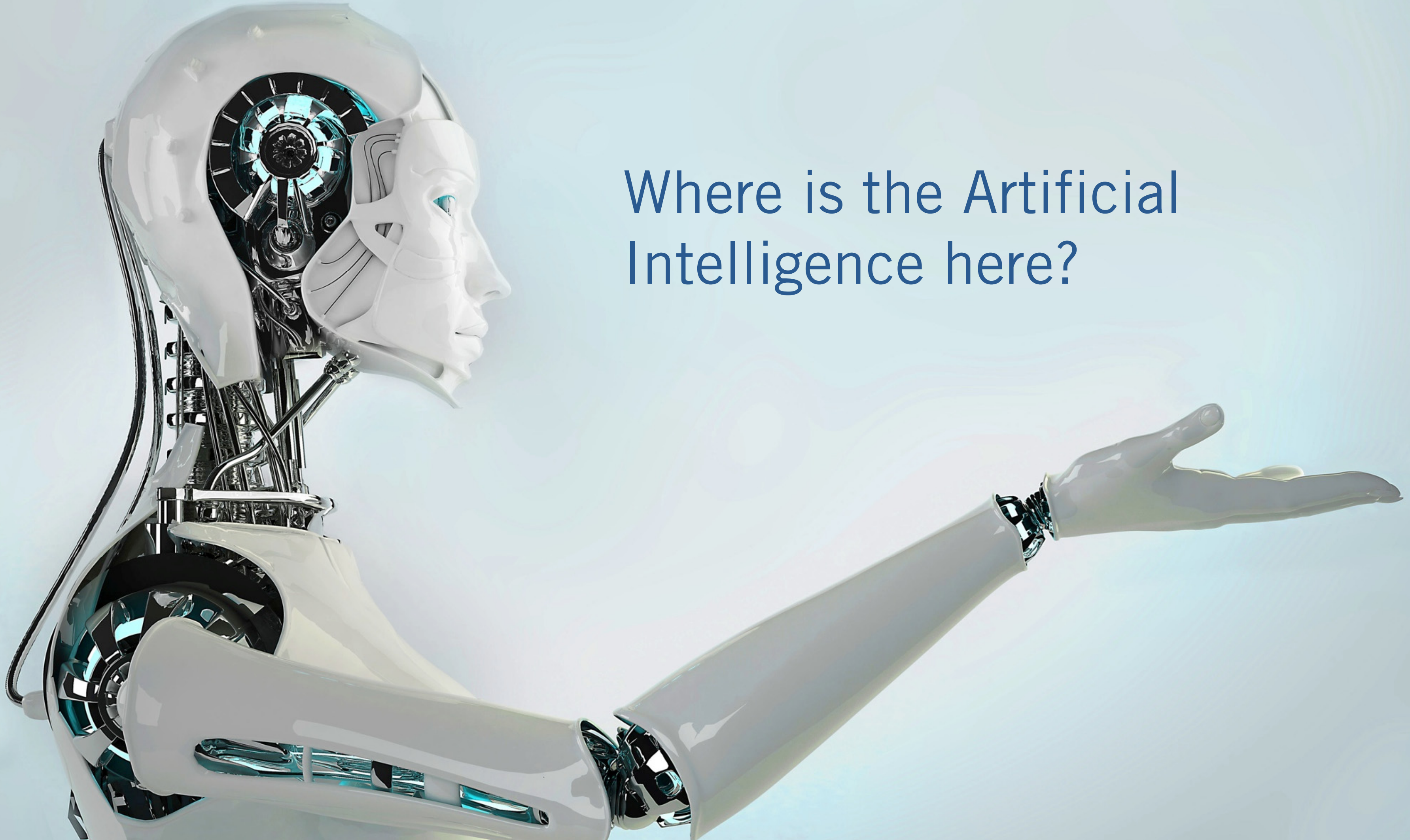
The Curse of Dimensionality

- "...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

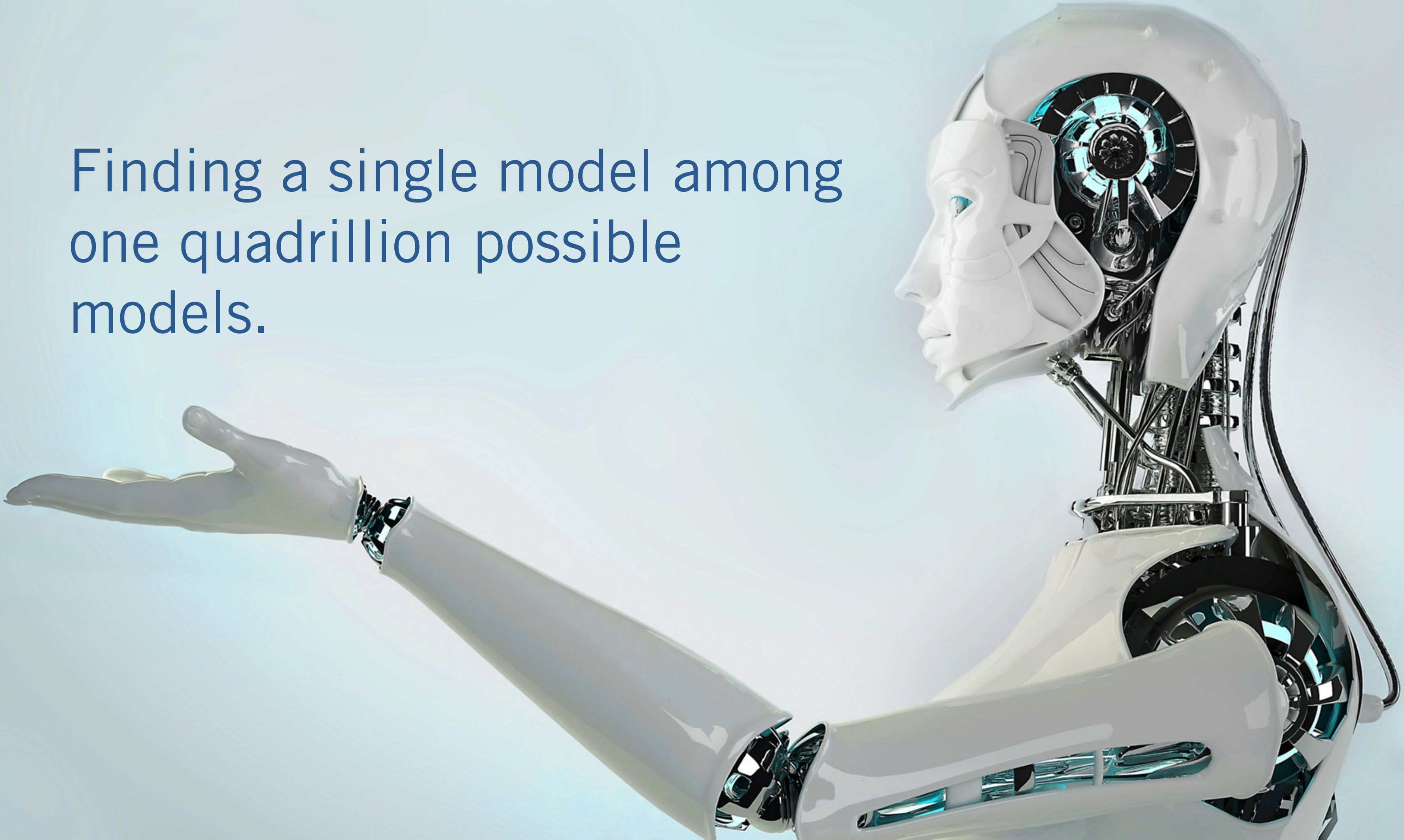
Anomaly Detection with Bayesian Networks

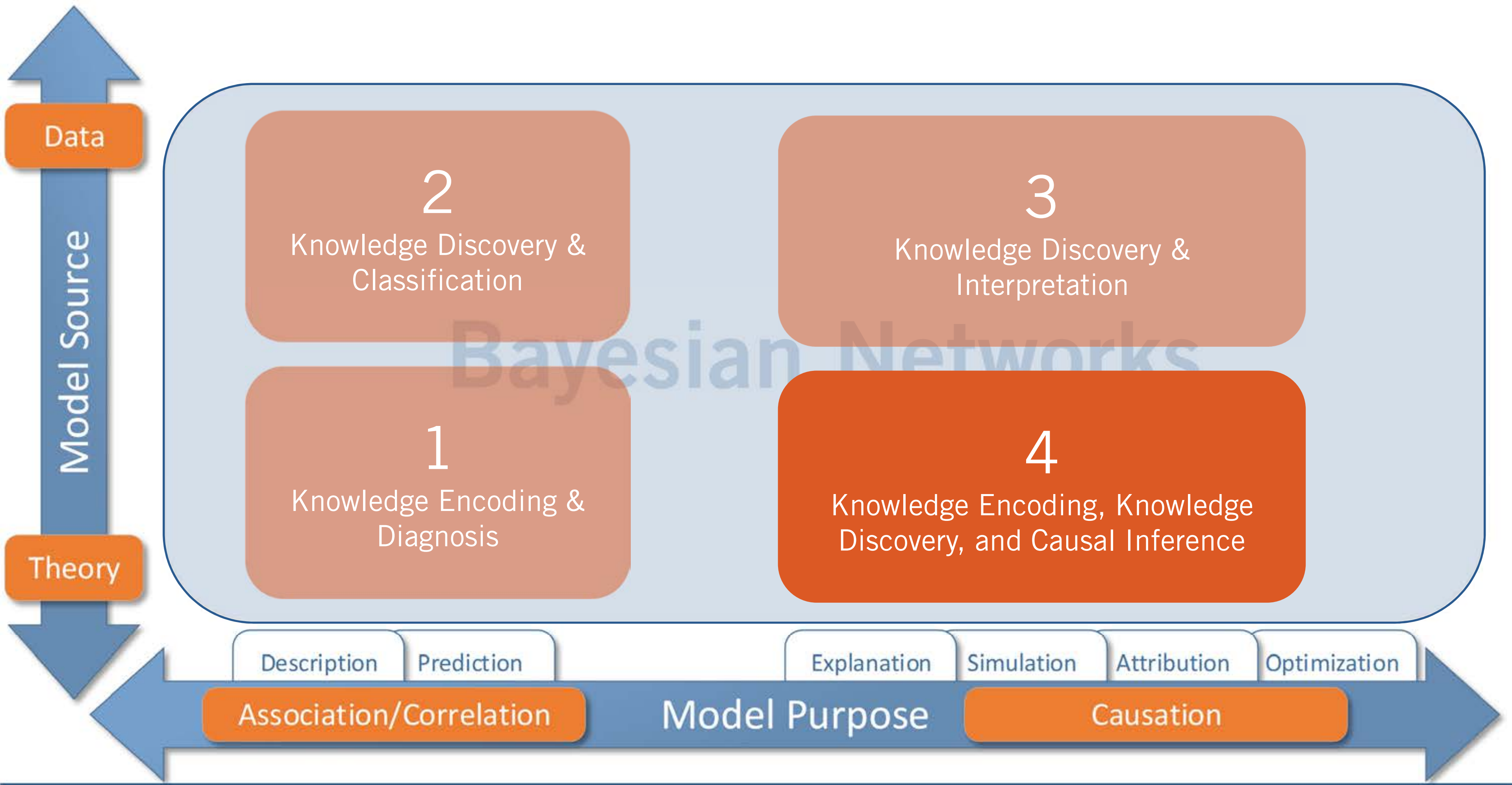
- With a Bayesian network, we can avoid the problem of the nearest/farthest distance measure, which becomes unreliable in higher dimensions.
- For any new observation, we can compute its likelihood given the network. This tells us how probable or improbable an observation is.



Where is the Artificial Intelligence here?

Finding a single model among one quadrillion possible models.

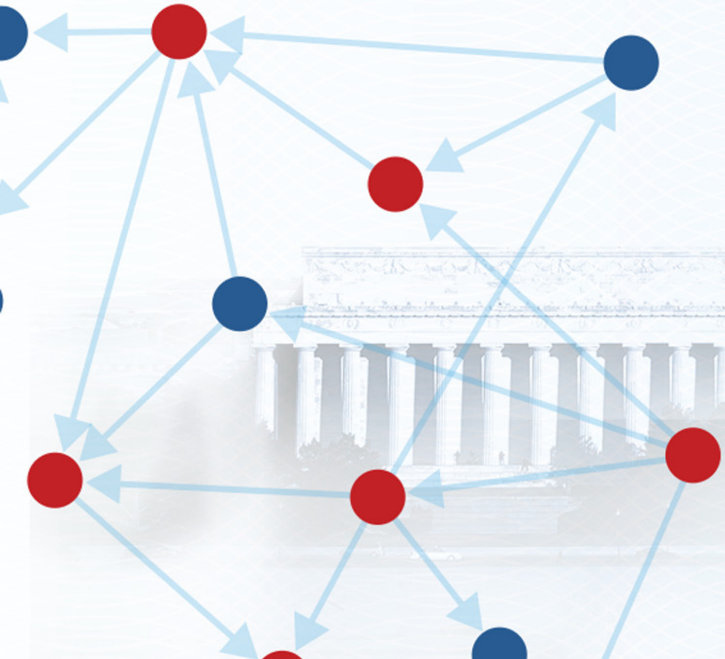



Data
Model Source
Theory
2
Knowledge Discovery & Classification
3
Knowledge Discovery & Interpretation
Bayesian Networks
1
Knowledge Encoding & Diagnosis
4
Knowledge Encoding, Knowledge Discovery, and Causal Inference
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation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

BAYESIALAB

Causal Inference

Evaluating the Effectiveness of Information Campaigns



Countering Anti-American Attitudes in Germany


1001 LIVROS
1001 MARAVILHAS NATURAIS
1001 FILMES

Introductory Example

Telephone Survey

- Afterwards, a market research firm conducts a telephone survey of 1,000 adults to understand the effect of the promotion on attitudes.

Ad Exposure	Nationality	Website Visit	Attitude
0	1	0	0
0	0	1	1
0	1	0	0
0	0	0	0
1	1	0	1
[illegible]	[illegible]	0	0
[illegible]	[illegible]	1	1
[illegible]	[illegible]	1	0
[illegible]	[illegible]	⋮	⋮
[illegible]	[illegible]	1	0

Observational Data

Introductory Example

Analyzing the survey with a cross-tab…

Ad Exposure	Nationality	Website Visit	Attitude
0	1	0	0
0	0	1	1
0	1	0	0
0	0	0	0
1	1	0	1
1	1	0	0
1	0	1	1
0	1	1	0
⋮	⋮	⋮	⋮
0	1	1	0

Ad Exposure	Attitude
No	60%
Yes	45%

-15%

Introductory Example

However, grouping the survey data by Gender reveals:

Ad Exposure	Nationality	Website Visit	Attitude
0	1	0	0
0	0	1	1
0	1	0	0
0	0	0	0
1	1	0	1
1	1	0	0
1	0	1	1
0	1	1	0
⋮	⋮	⋮	⋮
0	1	1	0

Nationality	Ad Exposure	Attitude
German	No	30%
	Yes	35%
Other	No	70%
	Yes	75%

+5%

Introductory Example

How is this possible?

Ad Exposure	Attitude
No	60%
Yes	45%

Nationality	Ad Exposure	Attitude
German	No	30%
	Yes	35%
Other	No	70%
	Yes	75%

-15%

Simpson's Paradox

+5%

Simpson's paradox is a phenomenon in probability and statistics, in which an effect appears in subgroups of data but disappears or reverses when these groups are combined.

Introductory Example

Grouping the data by Website Visit shows:

Ad Exposure	Nationality	Website Visit	Attitude
0	1	0	0
0	0	1	1
0	1	0	0
0	0	0	0
1	1	0	1
1	1	0	0
1	0	1	1
0	1	1	0
⋮	⋮	⋮	⋮
0	1	1	0

Website Visit	Ad Exposure	Attitude
No	No	60%
	Yes	50%
Yes	No	60%
	Yes	30%

-10%

-30%

Introductory Example

Finally, grouping the data by Gender and Test Drive reveals:

Ad Exposure	Nationality	Website Visit	Attitude
0	1	0	0
0	0	1	1
0	1	0	0
0	0	0	0
1	1	0	1
1	1	0	0
1	0	1	1
0	1	1	0
⋮	⋮	⋮	⋮
0	1	1	0

Website Visit	Nationality	Ad Exposure	Attitude
No	German	No	30%
		Yes	40%
	Other	No	70%
		Yes	80%
Yes	German	No	30%
		Yes	20%
	Other	No	70%
		Yes	60%

+10%

-10%

So, what’s the advertising effect?

Website Visit	Nationality	Ad Exposure	Attitude
No	German	No	30%
		Yes	40%
	Other	No	70%
		Yes	80%
Yes	German	No	30%
		Yes	20%
	Other	No	70%
		Yes	60%

≈ 0

Nationality	Ad Exposure	Attitude
German	No	30%
	[illegible]	35%
Other	No	70%
	Yes	75%

+0.05

Ad Exposure	Attitude
No	60%
Yes	45%

−0.15

Website Visit	Ad Exposure	[illegible]
No	No	60%
	[illegible]	50%
Yes	No	60%
	Yes	30%

−0.2


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
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$
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loginradius
Data
driven
decisions
DATA-DRIVEN decisions in a
FORTUNE 500
MAKING
DATA-DRIVEN
DECISIONS
with
tableau
+
THE DATA-DRIVEN
FUTURE
GET #DATADRIVEN
Data-Driven
Marketing
Data Driven
Business

Observational vs. Causal Inference

$$y=f(x)$$

ambiguous

Observational Inference (Prediction)

$$y=f(\mathit{see}(x))$$

"given that I see"

Causal Inference (Intervention)

$$y=f(\mathit{do}(x))$$

"given that I do"

Map of Analytic Modeling & Reasoning

Data

Model Source

Theory

Was it good to "do" this promotion?

$$y=f(see(x))$$

"given that I see"

$$y=f(do(x))$$

"given that I do"

Description | Prediction

Explanation | Simulation | Attribution | Optimization

Association/Correlation

Model Purpose

Causation

So, what's the a… …ffect?

"given that I see"

Website Visit	Nationality	Ad Exposure	Atti…
No	German	No	30%
		Yes	40%
	Other	No	70%
		Yes	80%
Yes	German	No	30%
		Yes	20%
	Other	No	70%
		Yes	60%

≈ 0

"given that I see"

Nationality	Ad Expo…e	Attitude
German	No	30%
		35%
Other		70%
	Yes	75%

$+0.05$

Ad Exposure	Attitude
No	60%
Yes	45%

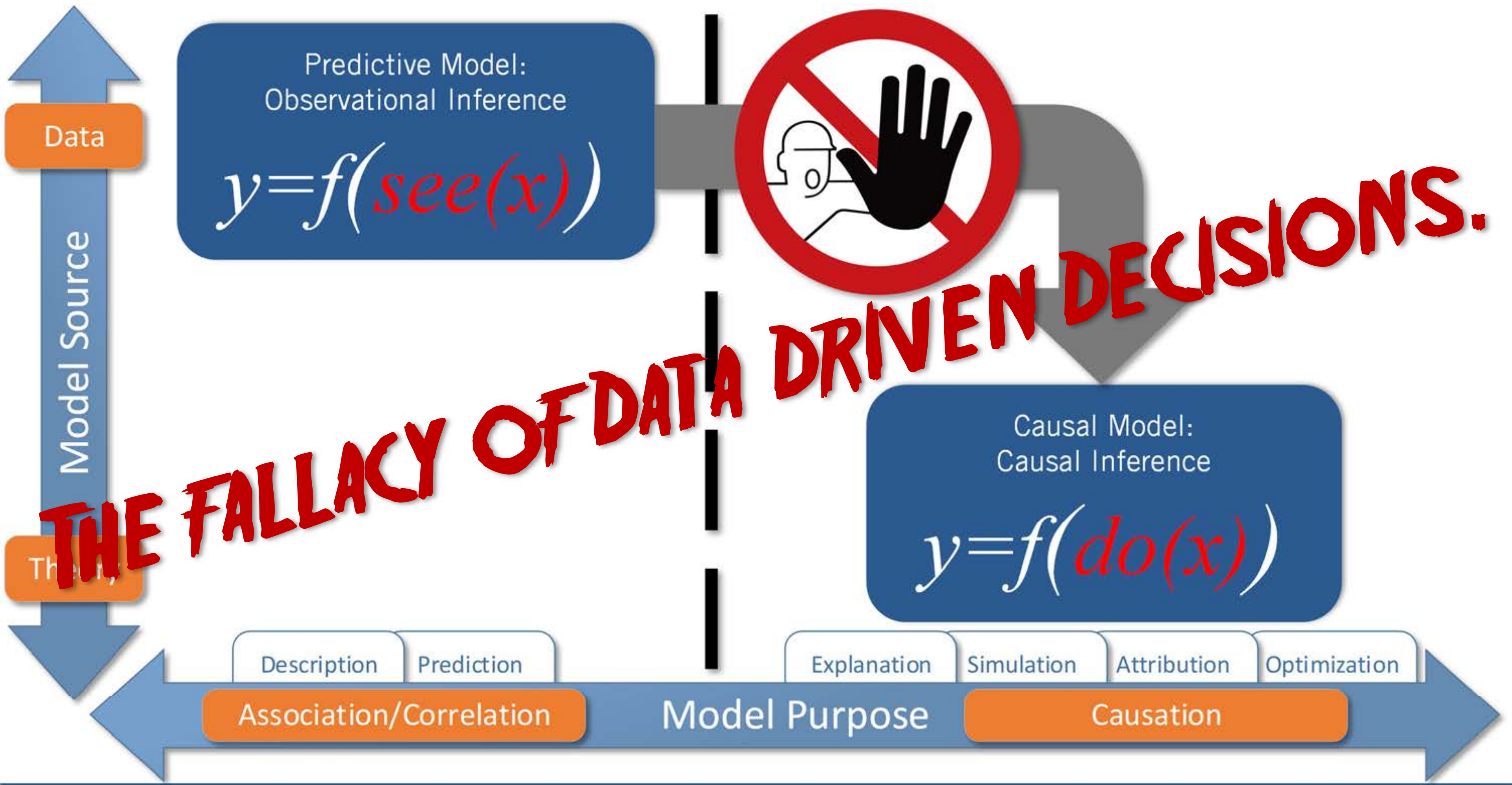
-0.15

"given that I see"

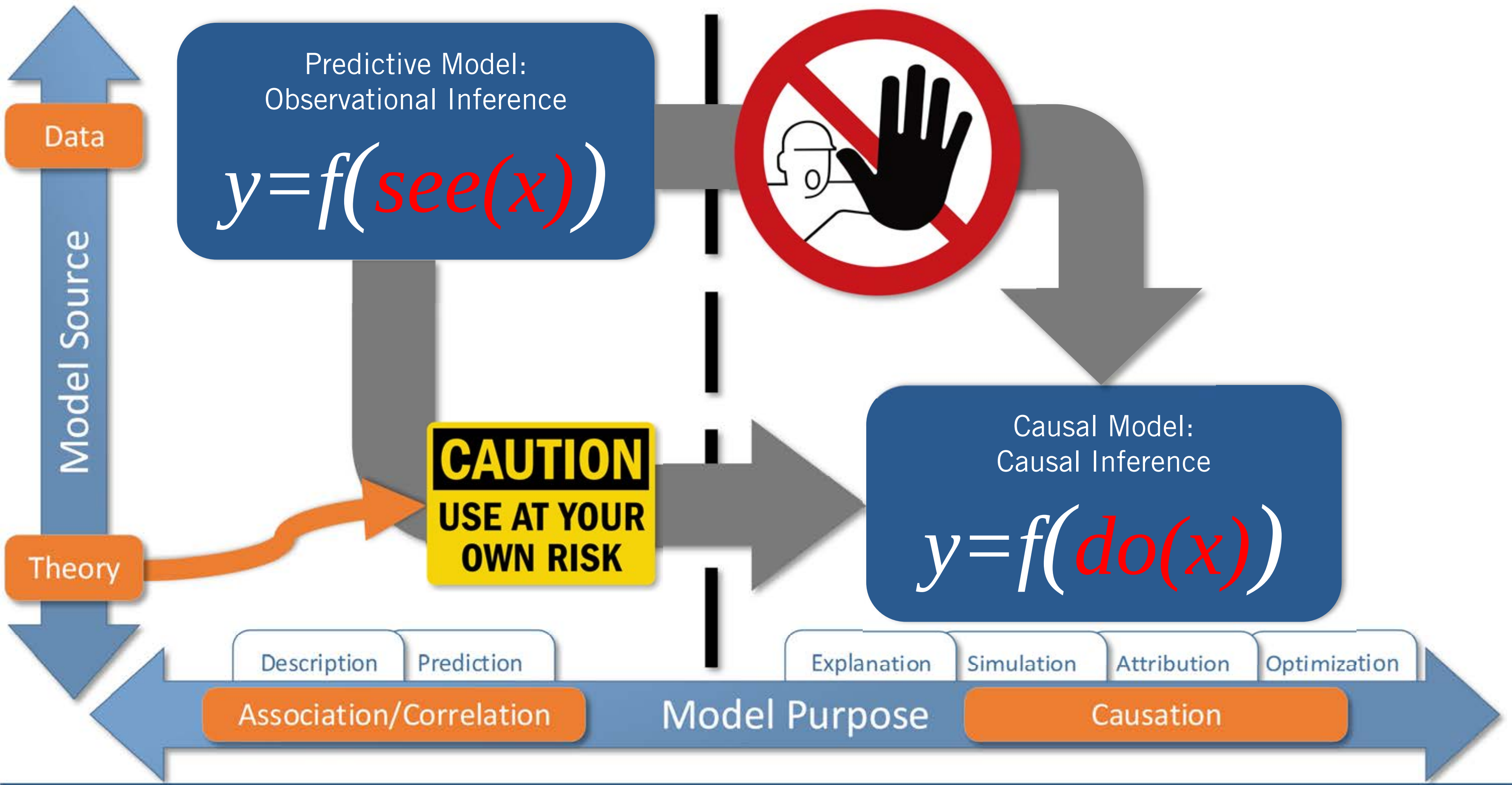
"given that I see"

Website Vi…	Ad Exposure	Att…
No	No	60%
		50%
Yes		60%
	Yes	30%

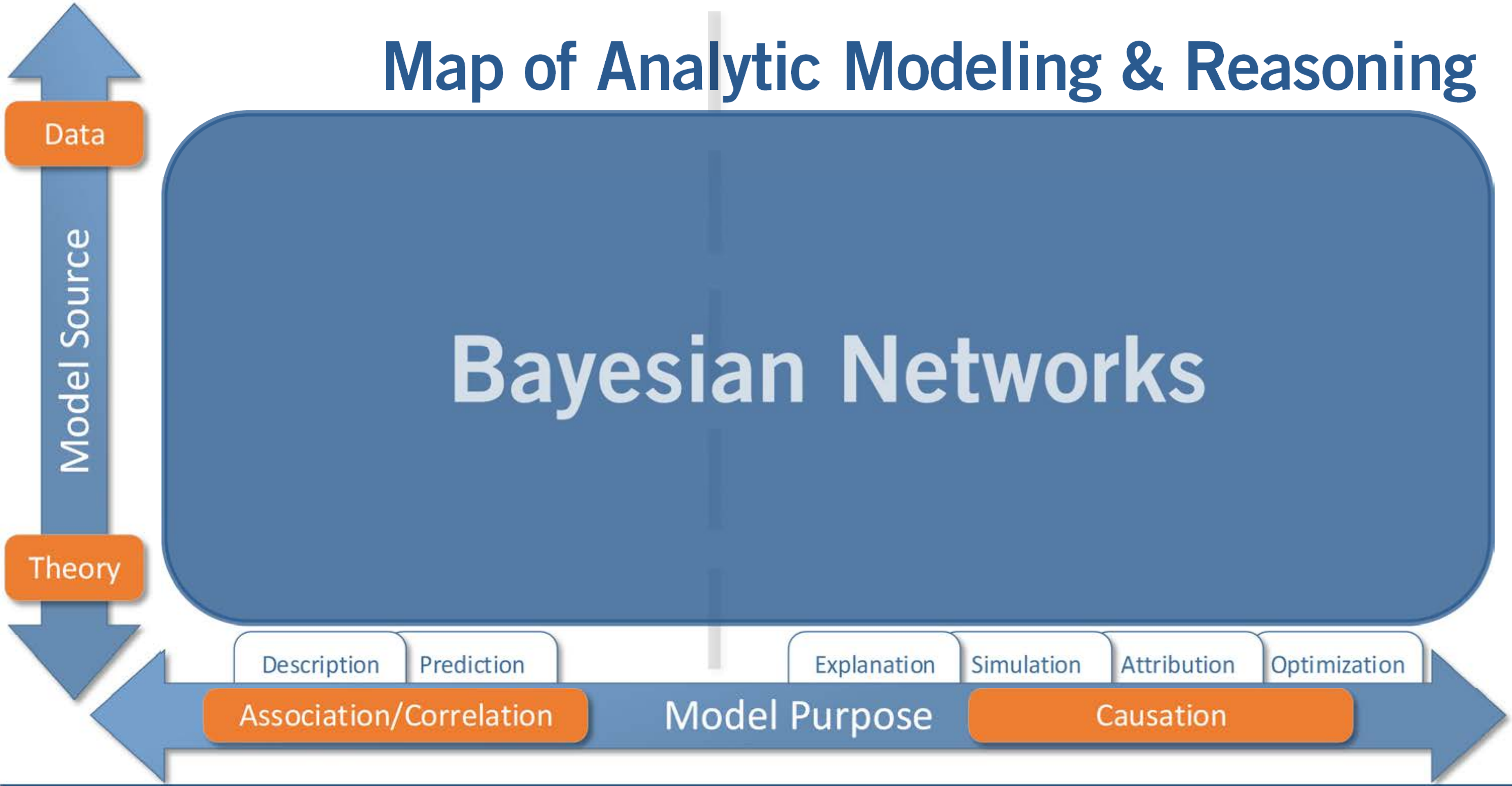
-0.2


THE FALLACY OF DATA DRIVEN DECISIONS.
Predictive Model:
Observational Inference
$y = f(see(x))$
Causal Model:
Causal Inference
$y = f(do(x))$
Data
Model Source
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Once upon a time. . .


Predictive Model:
Observational Inference
$y=f(see(x))$
Data
Model Source
Theory
CAUTION
USE AT YOUR OWN RISK
Causal Model:
Causal Inference
$y=f(do(x))$
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Map of Analytic Modeling & Reasoning



Introductory Example

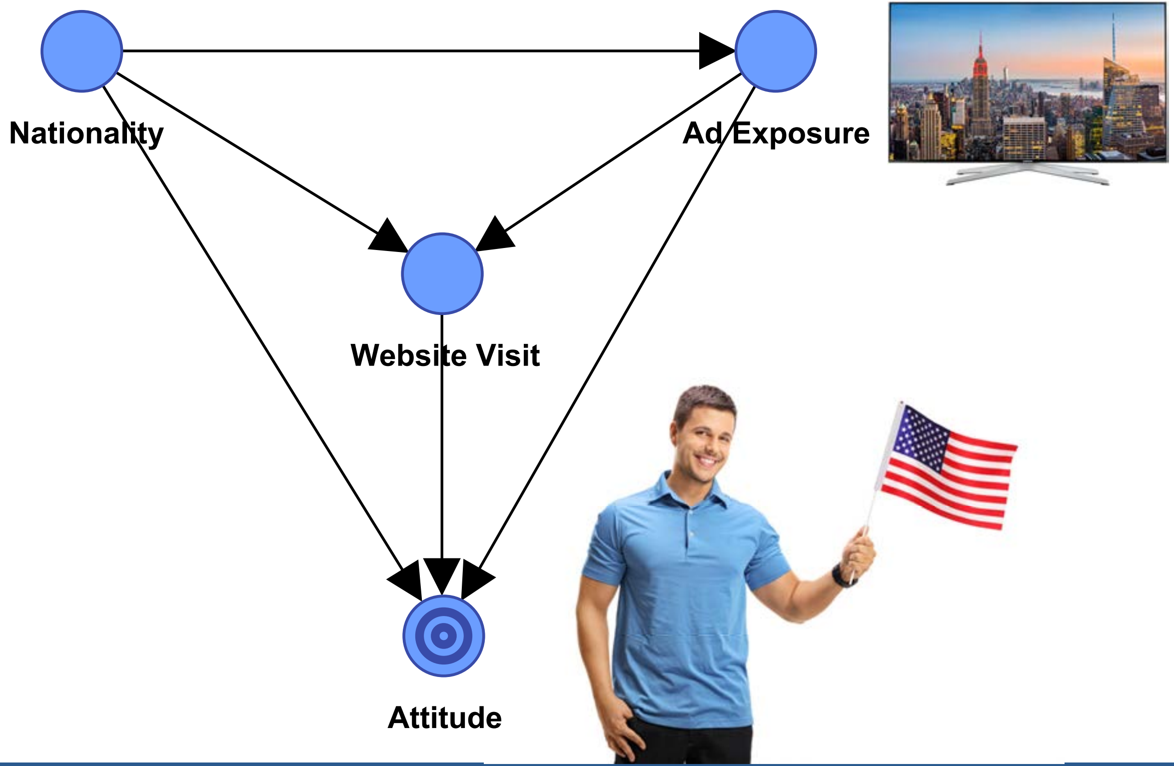
Develop Theory

What's the story here?

Introductory Example

Our Theory!

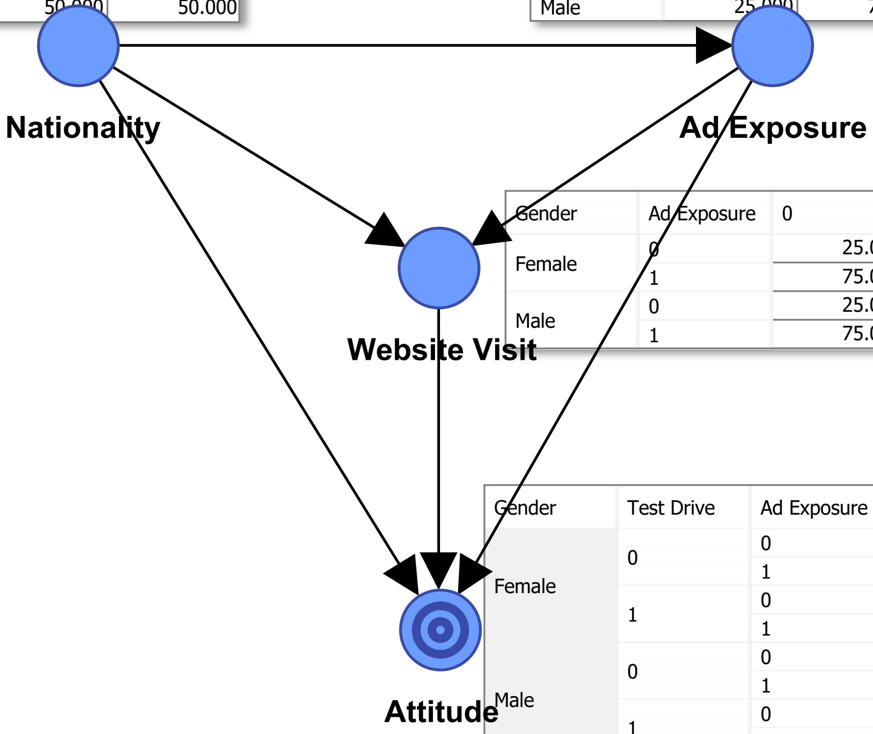
That’s the story! Now we have the qualitative part of a causal Bayesian network.



Introductory Example

"Parameters"

- We can estimate the quantitative part of the network from the survey data.
- As a result, we have a Bayesian network, which we can use for inference.



Female	Male
50.000	50.000

Gender	0	1
Female	75.000	25.000
Male	25.000	75.000

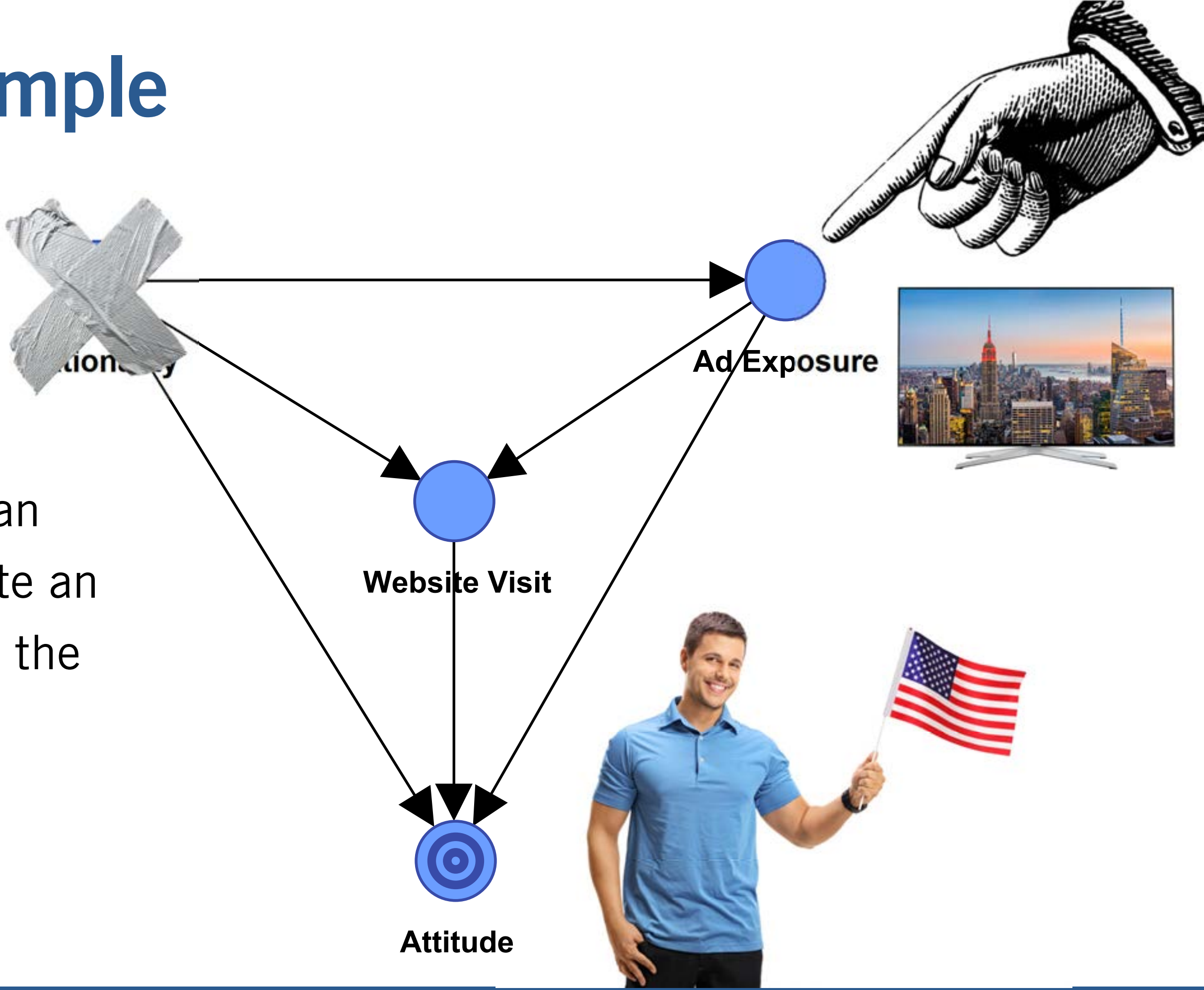
Gender	Ad Exposure	0	1
Female	0	25.000	75.000
	1	75.000	25.000
Male	0	25.000	75.000
	1	75.000	25.000

Gender	Test Drive	Ad Exposure	0	1
Female	0	0	30.000	70.000
		1	20.000	80.000
	1	0	30.000	70.000
		1	40.000	60.000
Male	0	0	70.000	30.000
		1	60.000	40.000
	1	0	70.000	30.000
		1	80.000	20.000

Introductory Example

Our "Model of the World"

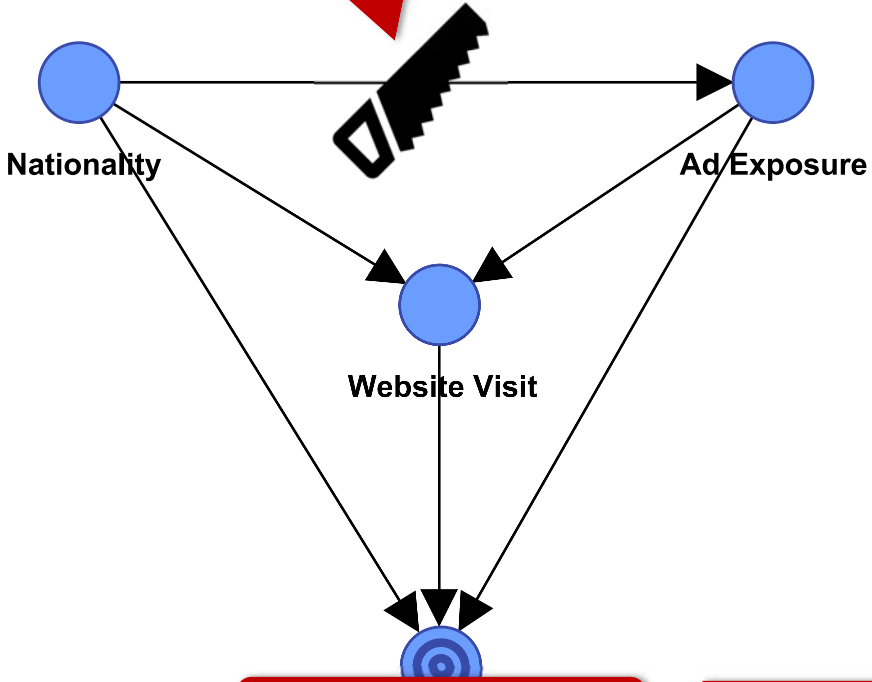
- How can we obtain the effect of Ad Exposure?
- With this causal Bayesian network, we can simulate an intervention to estimate the causal effect.



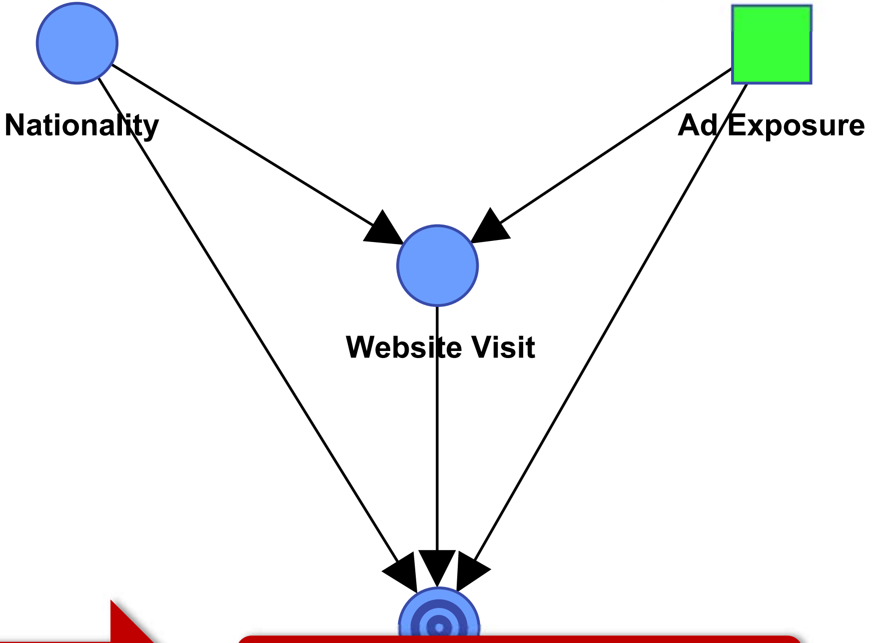
Introductory Example

“Graph Surgery”

Caus … **ing an Intervention**



Causal Model

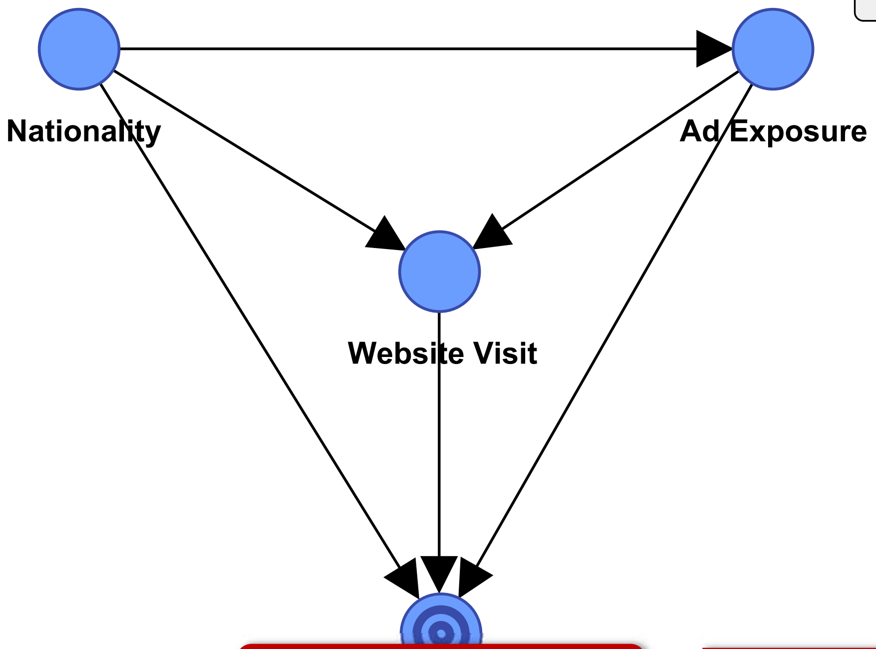


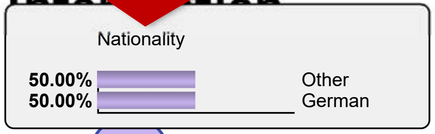
Intervention Model

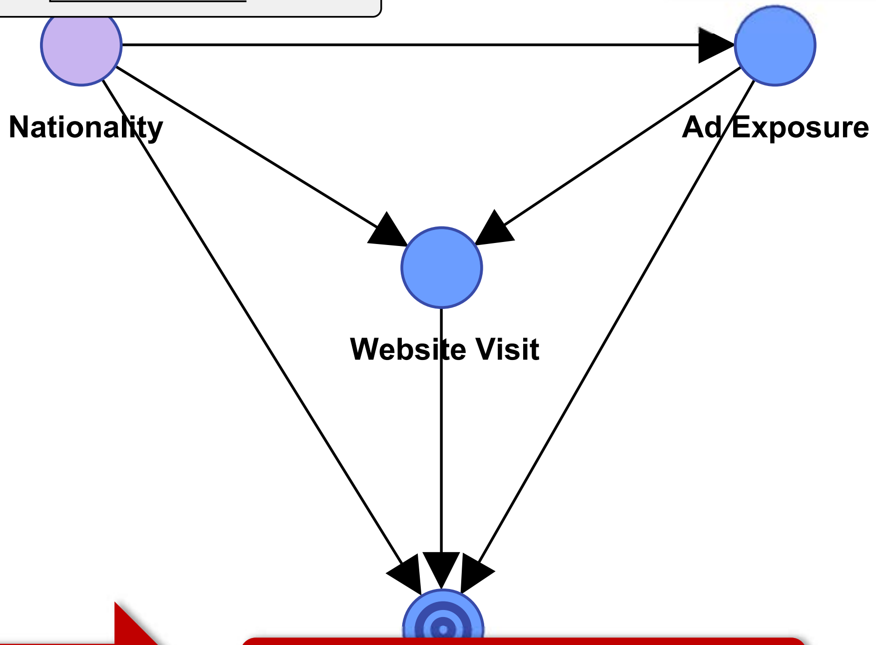
Introductory Exampl

Fix Probabilities with Likelihood Matching

Causal Inference: Simulating an

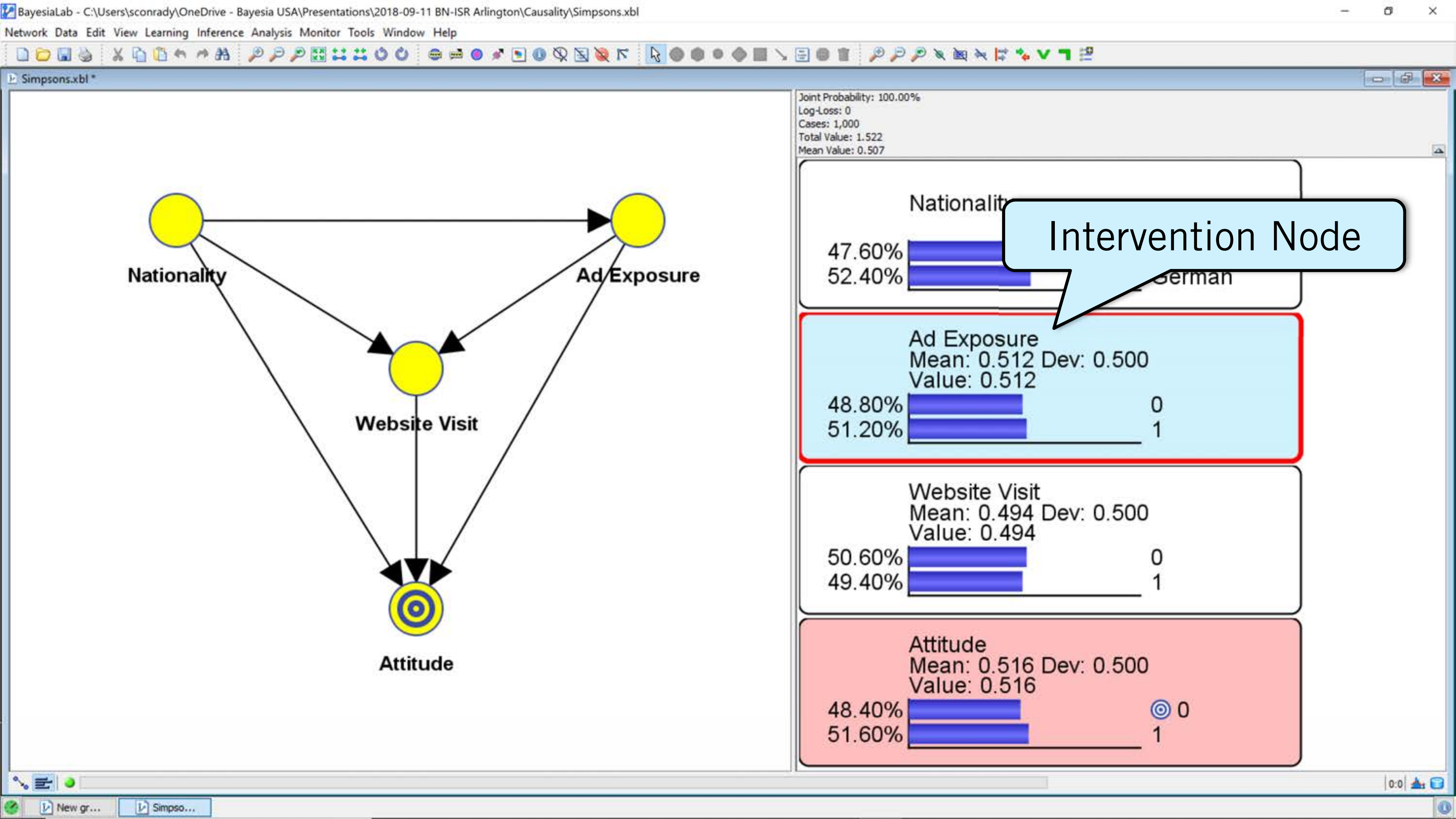


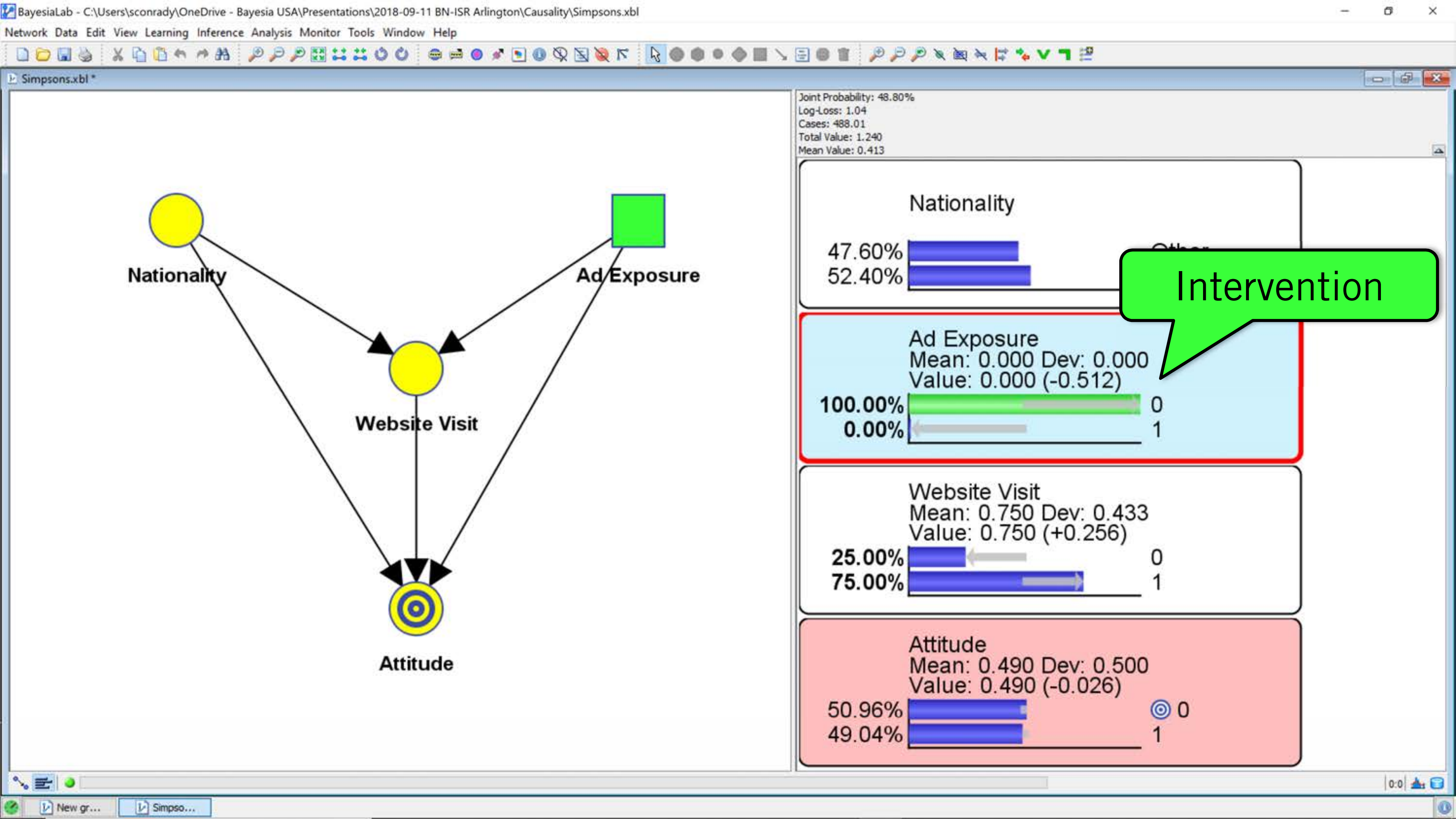


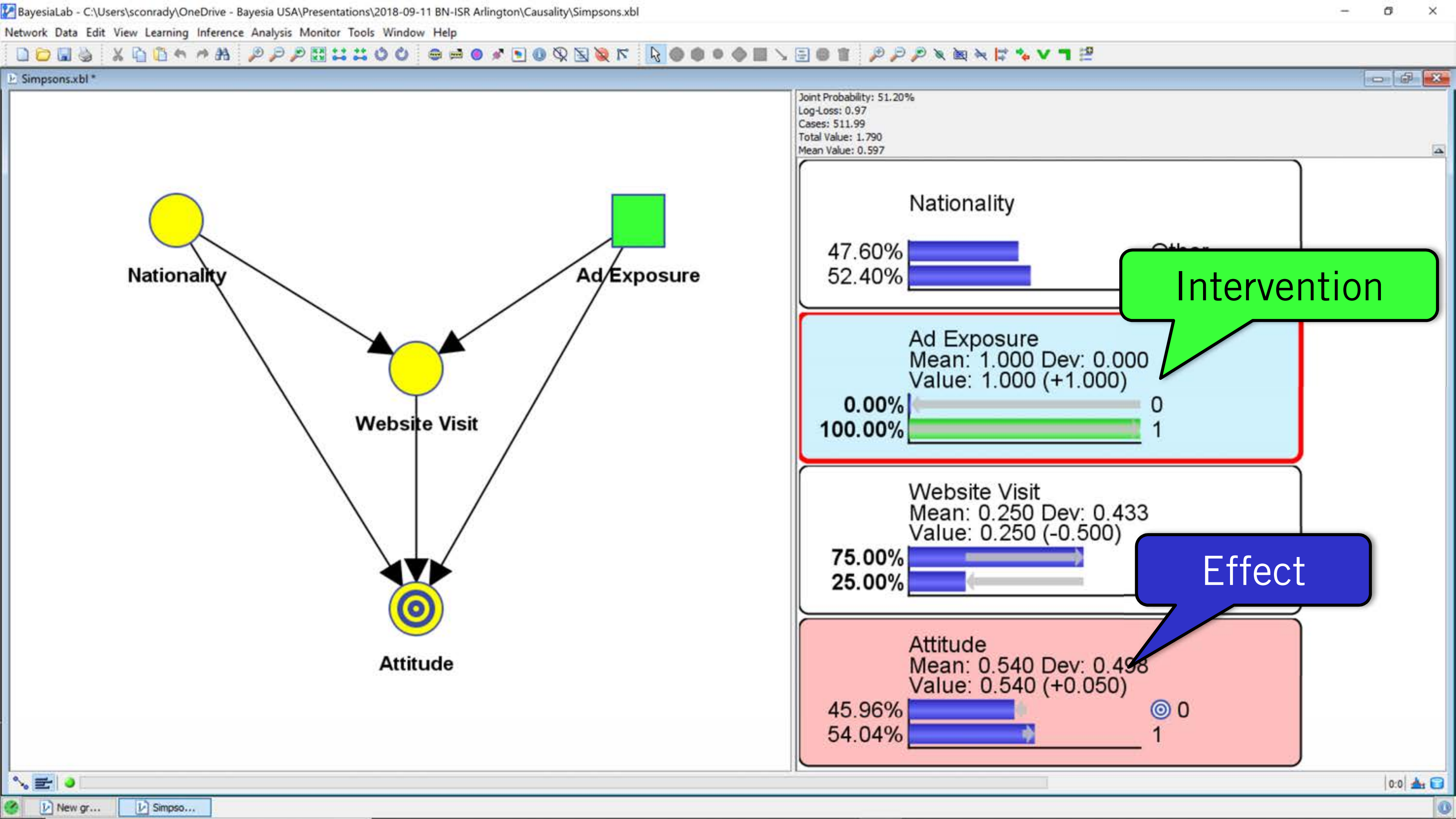


Causal Model

Intervention Model


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Causality\Simpsons.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Simpsons.xbl *
Nationality
Ad Exposure
Website Visit
Attitude
Joint Probability: 100.00%
Log-Loss: 0
Cases: 1,000
Total Value: 1.522
Mean Value: 0.507
Nationalit
47.60%
52.40%
German
Intervention Node
Ad Exposure
Mean: 0.512 Dev: 0.500
Value: 0.512
48.80% 0
51.20% 1
Website Visit
Mean: 0.494 Dev: 0.500
Value: 0.494
50.60% 0
49.40% 1
Attitude
Mean: 0.516 Dev: 0.500
Value: 0.516
48.40% 0
51.60% 1
New gr...
Simpso...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Causality\Simpsons.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Simpsons.xbl *
Nationality
Ad Exposure
Website Visit
Attitude
Joint Probability: 48.80%
Log-Loss: 1.04
Cases: 488.01
Total Value: 1.240
Mean Value: 0.413
Nationality
47.60%
52.40%
Intervention
Ad Exposure
Mean: 0.000 Dev: 0.000
Value: 0.000 (-0.512)
100.00% 0
0.00% 1
Website Visit
Mean: 0.750 Dev: 0.433
Value: 0.750 (+0.256)
25.00% 0
75.00% 1
Attitude
Mean: 0.490 Dev: 0.500
Value: 0.490 (-0.026)
50.96% 0
49.04% 1
New gr...
Simpso...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Presentations\2018-09-11 BN-ISR Arlington\Causality\Simpsons.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Simpsons.xbl *
Nationality
Ad Exposure
Website Visit
Attitude
Joint Probability: 51.20%
Log-Loss: 0.97
Cases: 511.99
Total Value: 1.790
Mean Value: 0.597
Nationality
47.60%
52.40%
Ad Exposure
Mean: 1.000 Dev: 0.000
Value: 1.000 (+1.000)
0.00% 0
100.00% 1
Website Visit
Mean: 0.250 Dev: 0.433
Value: 0.250 (-0.500)
75.00%
25.00%
Attitude
Mean: 0.540 Dev: 0.498
Value: 0.540 (+0.050)
45.96% 0
54.04% 1
Intervention
Effect
New gr...
Simpso...

So, what's the adverti[illegible] effect?

Website Visit	Nationality	Ad Exposure	Attitude
No	German	No	30%
		Yes	40%
	Other	No	70%
		Yes	80%
Yes	German	No	30%
		Yes	20%
	Other	No	[illegible]
		Yes	[illegible]

≈ 0

Nationality	Ad Exposure	Attitude
German	No	30%
	[illegible]	35%
Other	No	70%
	Yes	75%

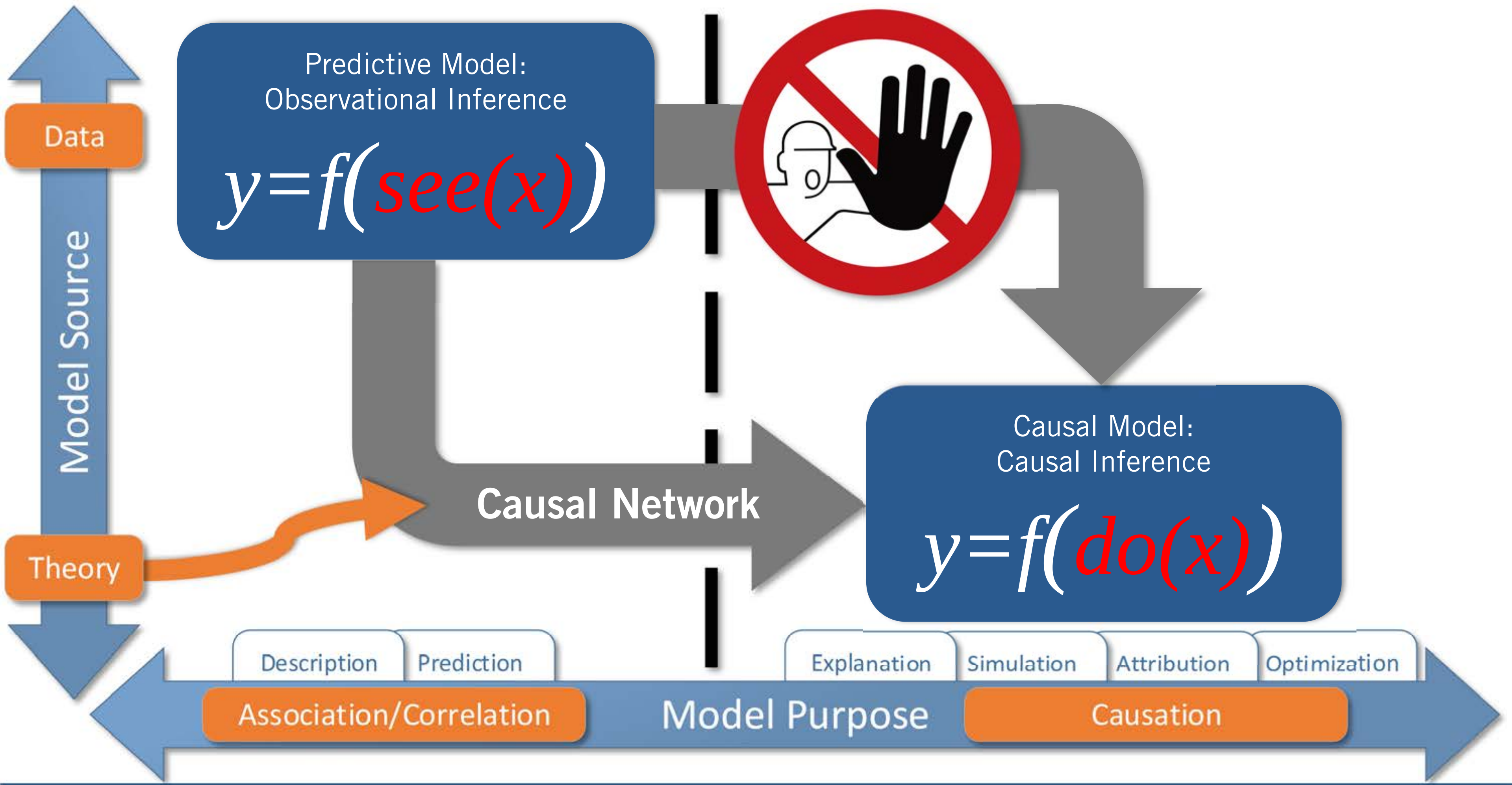
+0.05

Ad Exposure	Attitude
No	60%
Yes	45%

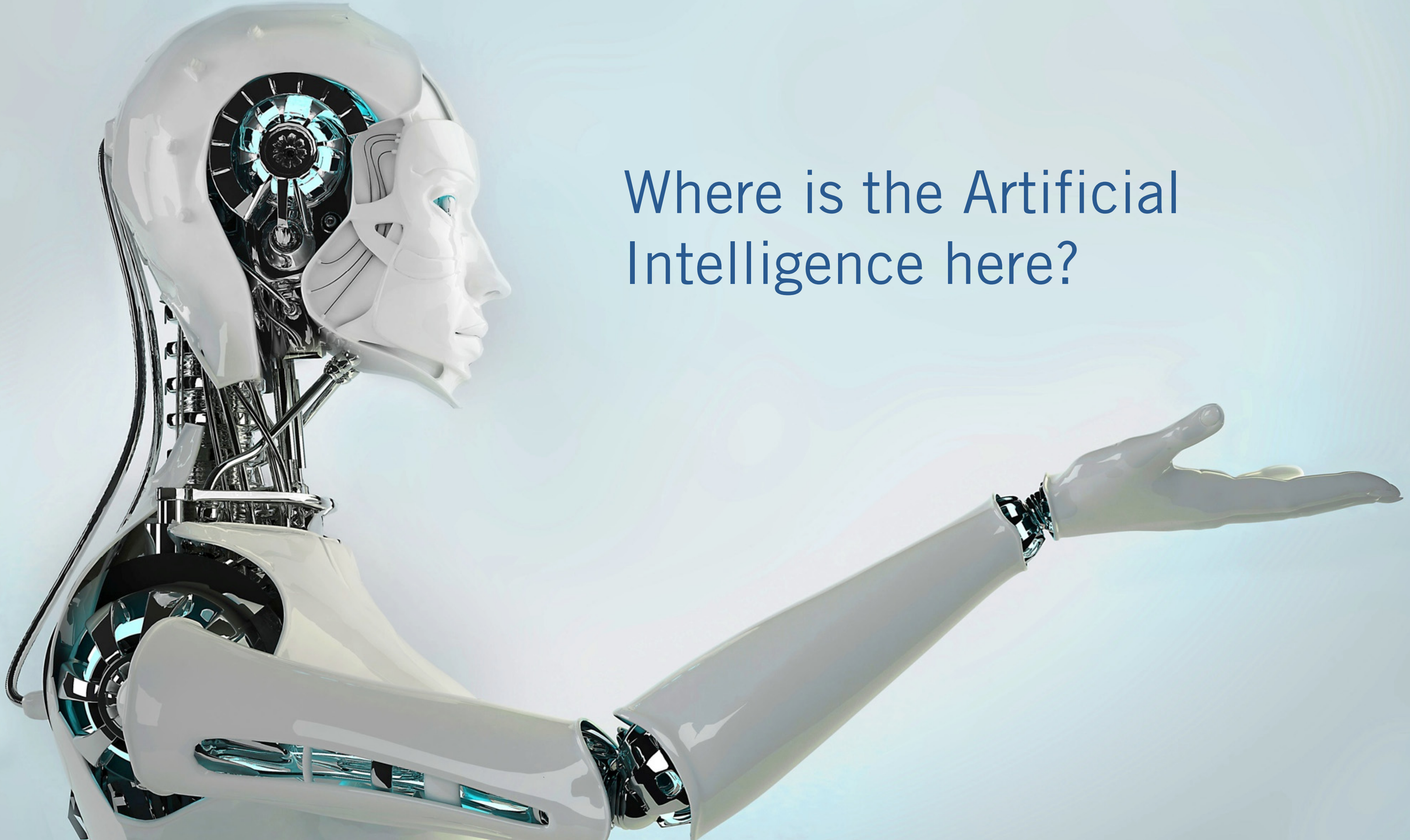
−0.15

Website Visit	Ad Exposure	Attitude
No	No	60%
	[illegible]	50%
Yes	No	60%
	Yes	30%

−0.2


Predictive Model:
Observational Inference
$y=f(see(x))$
Data
Model Source
Theory
Causal Network
Causal Model:
Causal Inference
$y=f(do(x))$
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Where is the Artificial Intelligence here?

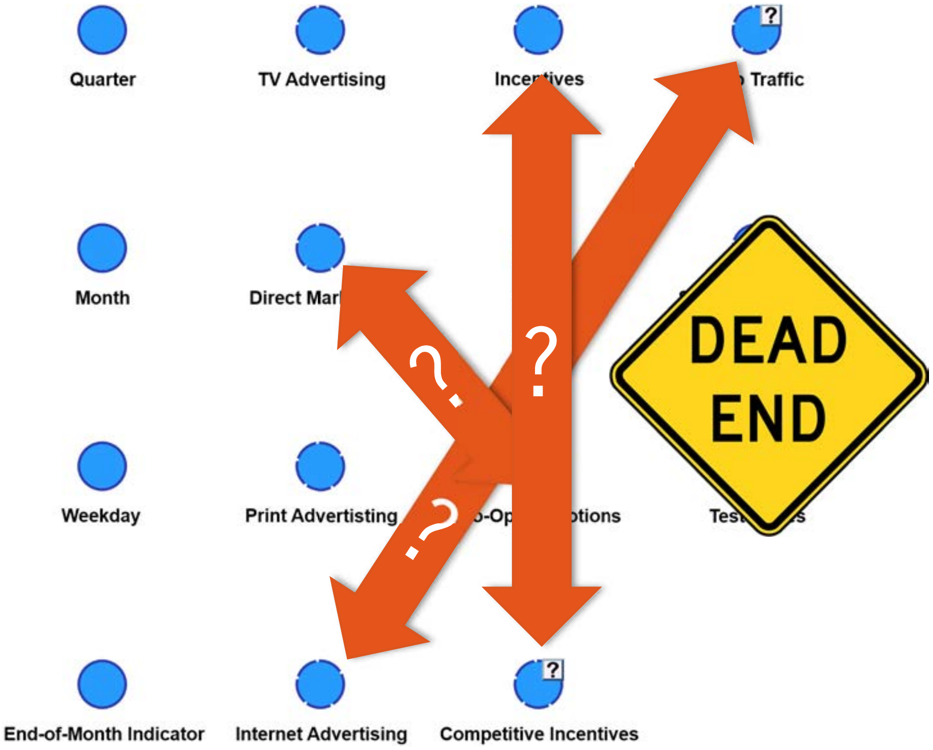


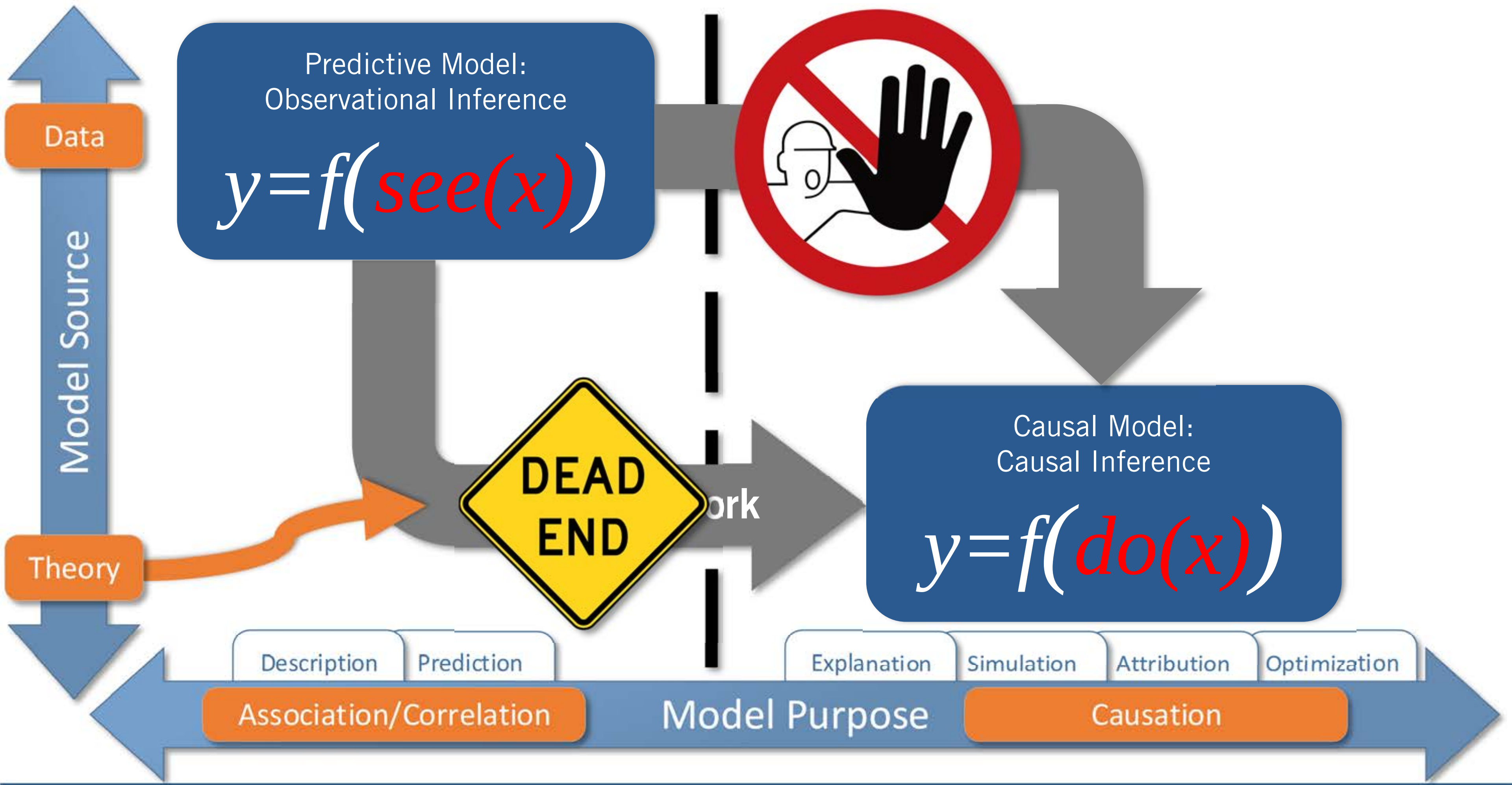

No Artificial Intelligence. Here,
we need human intelligence!

Resource Allocation Optimization

Causal Assumptions?

- Recall: Causal inference requires causal assumptions, e.g., a causal networks!
- But, given the number of variables, there are 2.38×10^{41} possible causal network graphs!
- Causal directions are not always obvious.





Predictive Model:
Observational Inference
$y=f(see(x))$
Causal Model:
Causal Inference
$y=f(do(x))$
DEAD END
ork
Model Source
Data
Theory
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Now What?

We need a different kind of theory

Disjunctive Cause Criterion

NIH Public Access
Author Manuscript
Biometrics. Author manuscript; available in PMC 2012 December 1.

Published in final edited form as:
Biometrics. 2011 December ; 67(4): 1406–1413. doi:10.1111/j.1541-0420.2011.01619.x.

A new criterion for confounder selection

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Abstract

We propose a new criterion for confounder selection when the underlying causal structure is unknown and only limited knowledge is available. We assume all covariates being considered are pretreatment variables and that for each covariate it is known (i) whether the covariate is a cause of treatment, and (ii) whether the covariate is a cause of the outcome. The causal relationships the covariates have with one another is assumed unknown. We propose that control be made for any covariate that is either a cause of treatment or of the outcome or both. We show that irrespective of the actual underlying causal structure, if any subset of the observed covariates suffices to control

Disjunctive Cause Criterion

VanderWeele and Shpitser (2011)

- "We propose that control be made for any [pre-treatment] **covariate** that is either a cause of **treatment** or of the **outcome** or both."

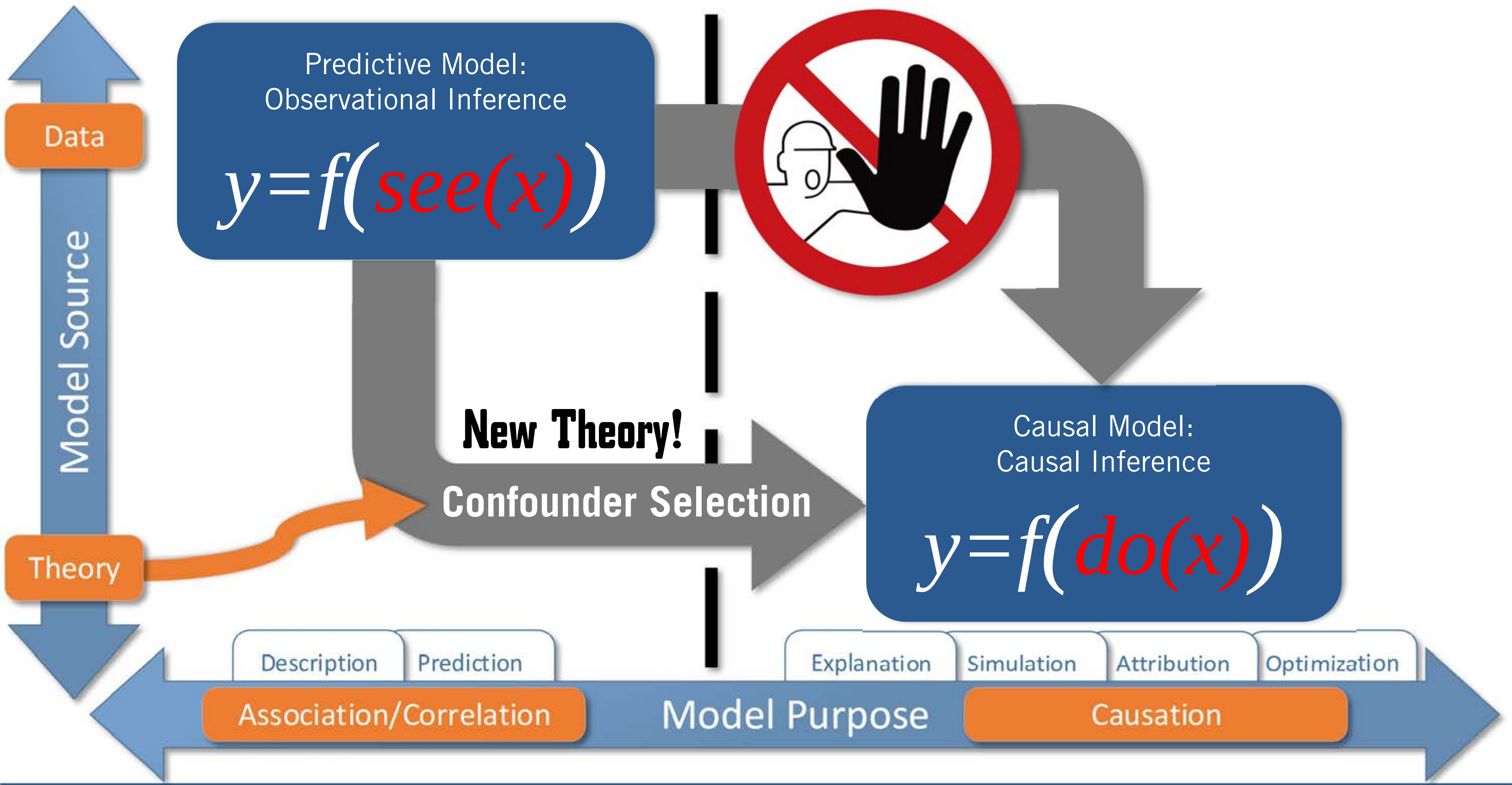
Sales

Confounder

Advertisement

Implementation in BayesiaLab:
Likelihood Matching on Confounders in
Direct Effects Analysis
➔ Causal Effect, i.e., the Advertising Effect

IMPORTANT ASSUMPTION:
NO UNOBSERVED CONFOUNDERS

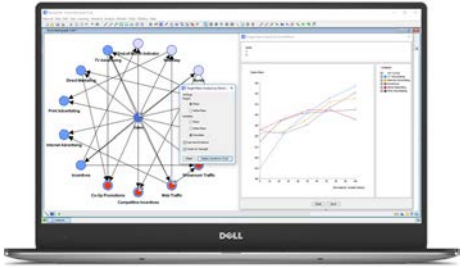

Predictive Model:
Observational Inference
$y=f(see(x))$
Data
Model Source
Theory
New Theory!
Confounder Selection
Causal Model:
Causal Inference
$y=f(do(x))$
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

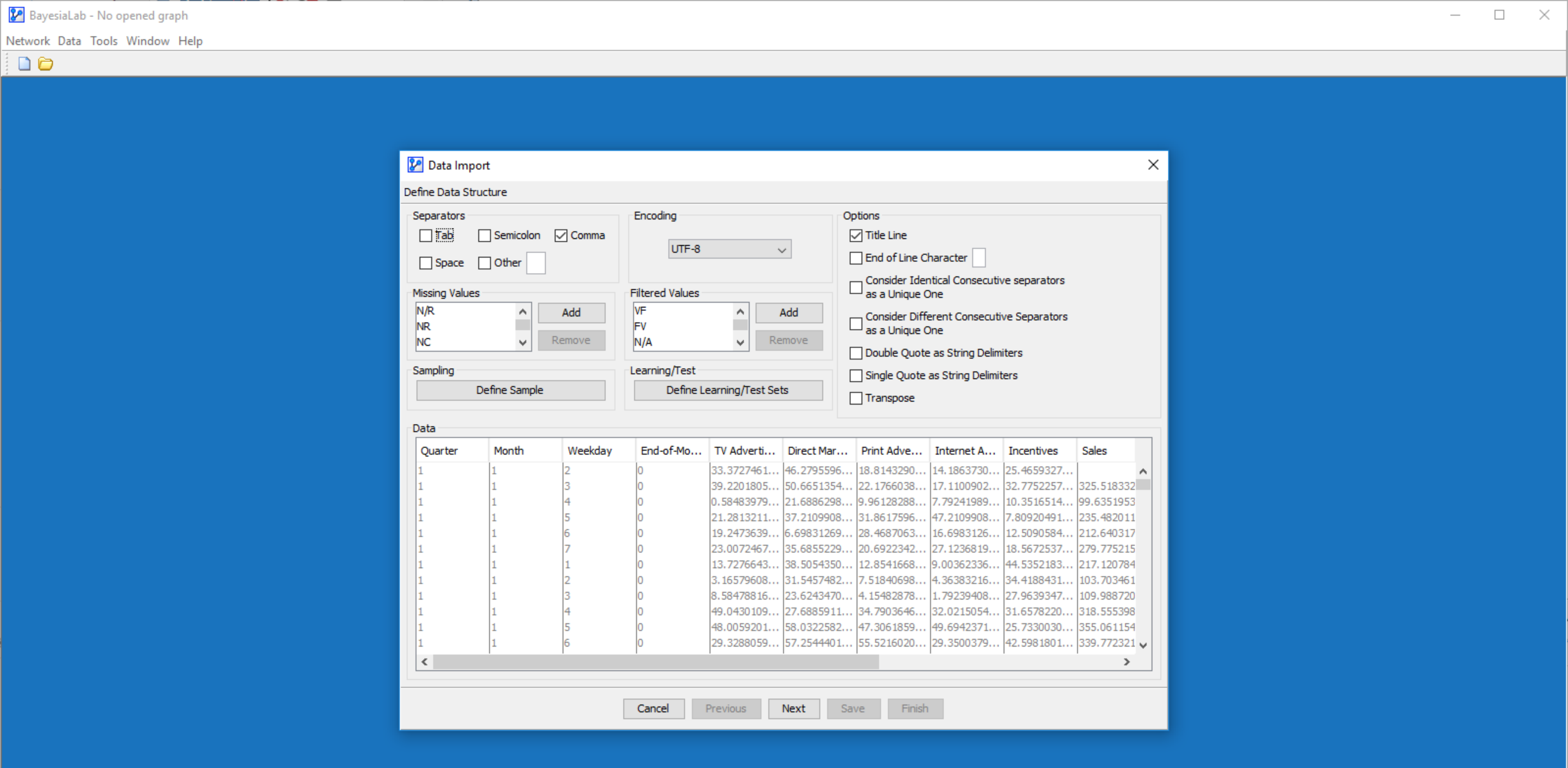
Resource Allocation Optimizati

All Data is Synthetic

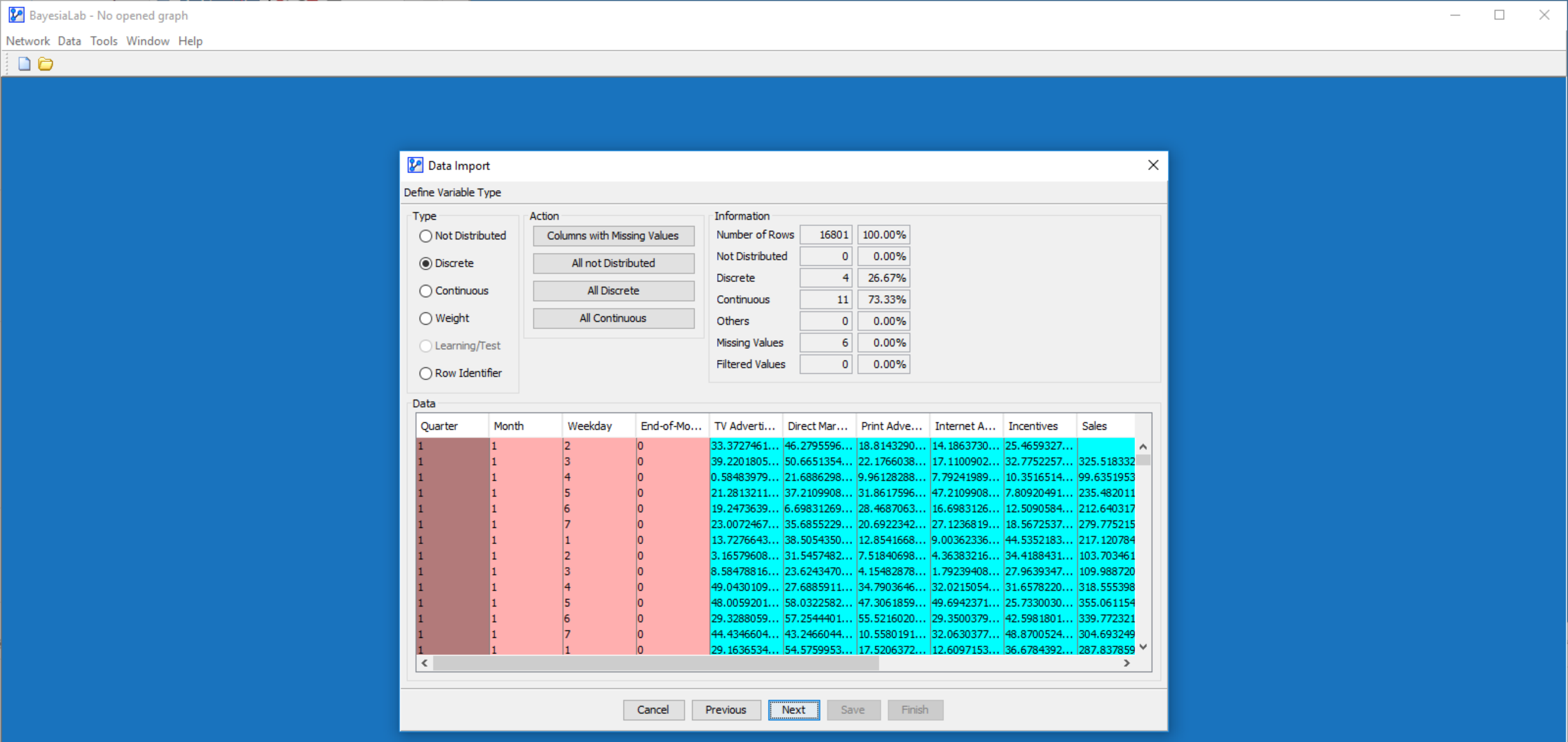
Proposed Workflow

- Import historical sales and marketing data.
- Machine-learn a predictive model with BayesiaLab.
- Determine **Confounders** vs. **Non-Confounders**, using the **Disjunctive Cause Criterion**.
- Estimate and evaluate **Direct Effects** response curves.
- Introduce **Function Node** and assign media costs.
- Perform **Genetic Target Optimization**.
- Apply **Network Temporalization**.
- Add **Constraint Nodes** between t and t-1 marketing variables.
- Perform **Genetic Target Optimization** on dynamic network.

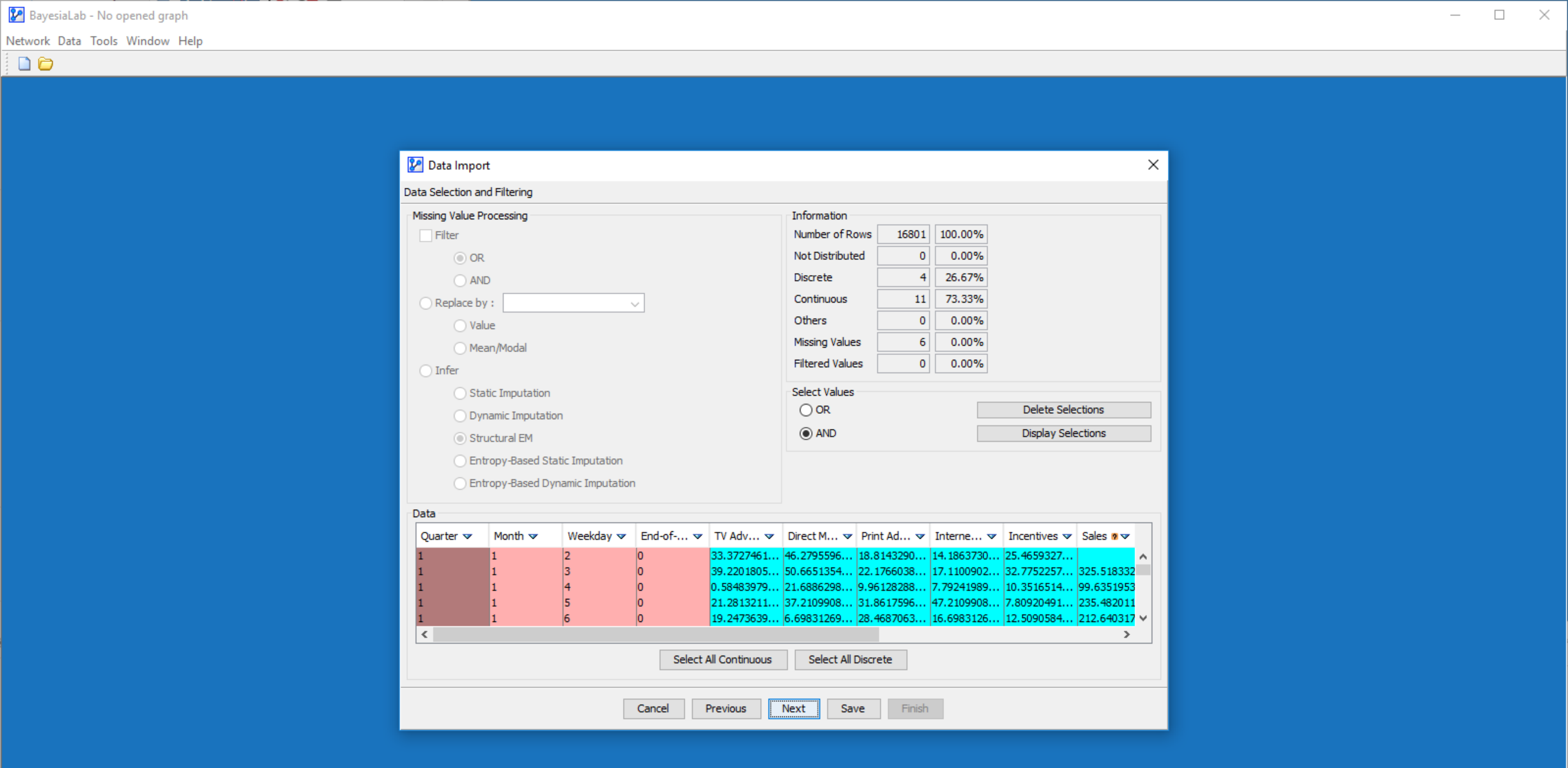




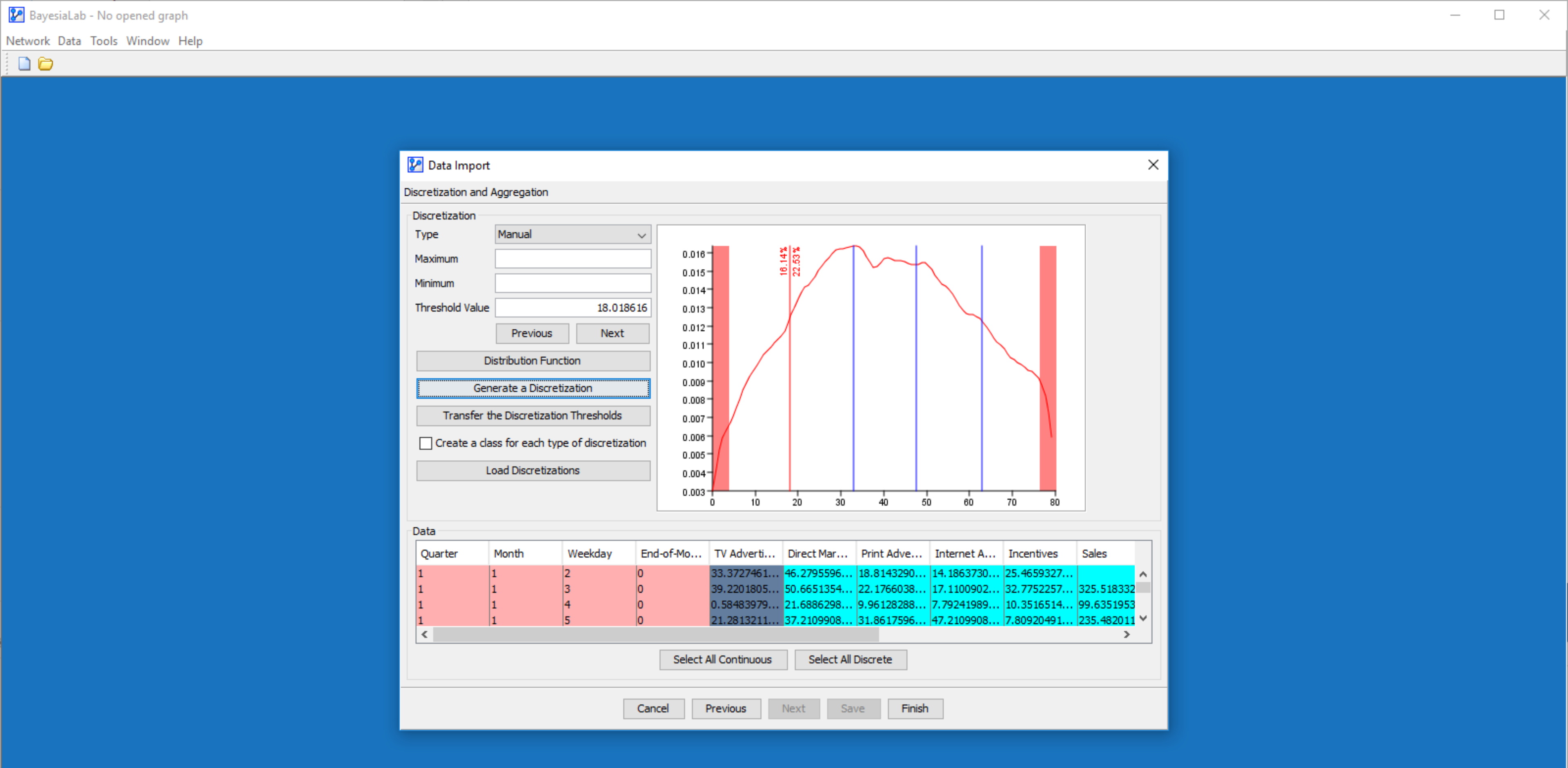
Data Import Wizard



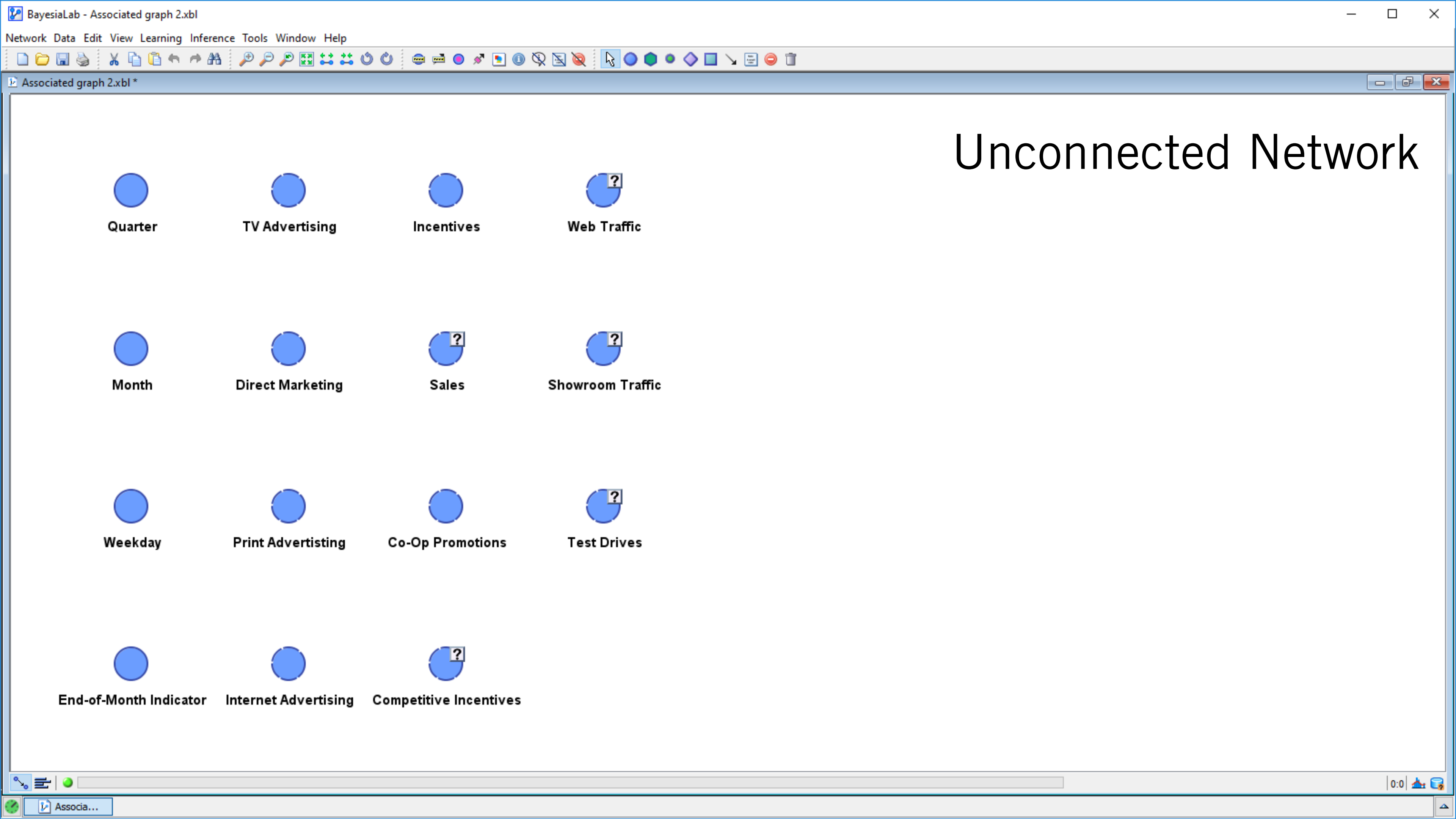
Variable Type Definition



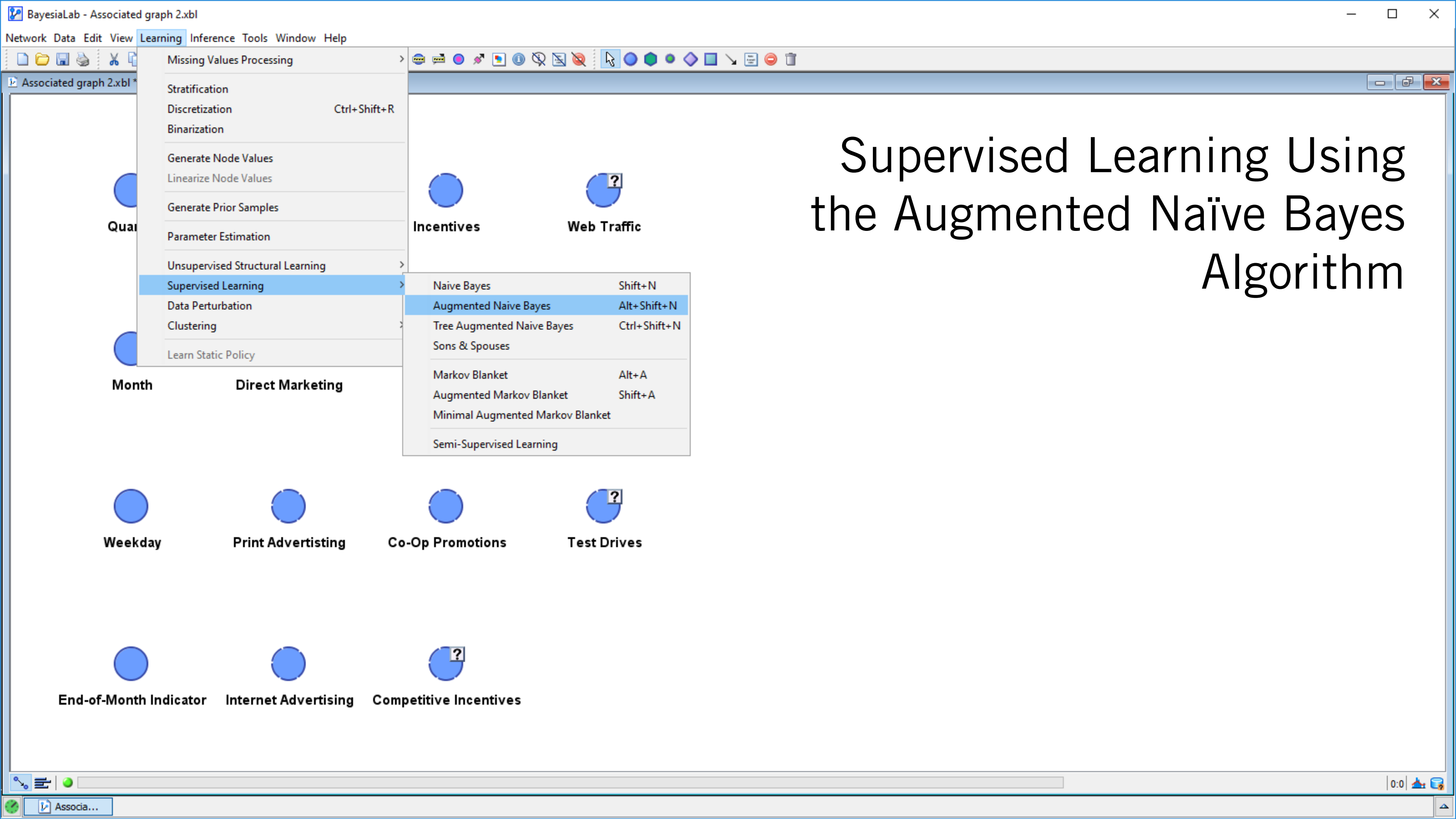
Missing Values Processing

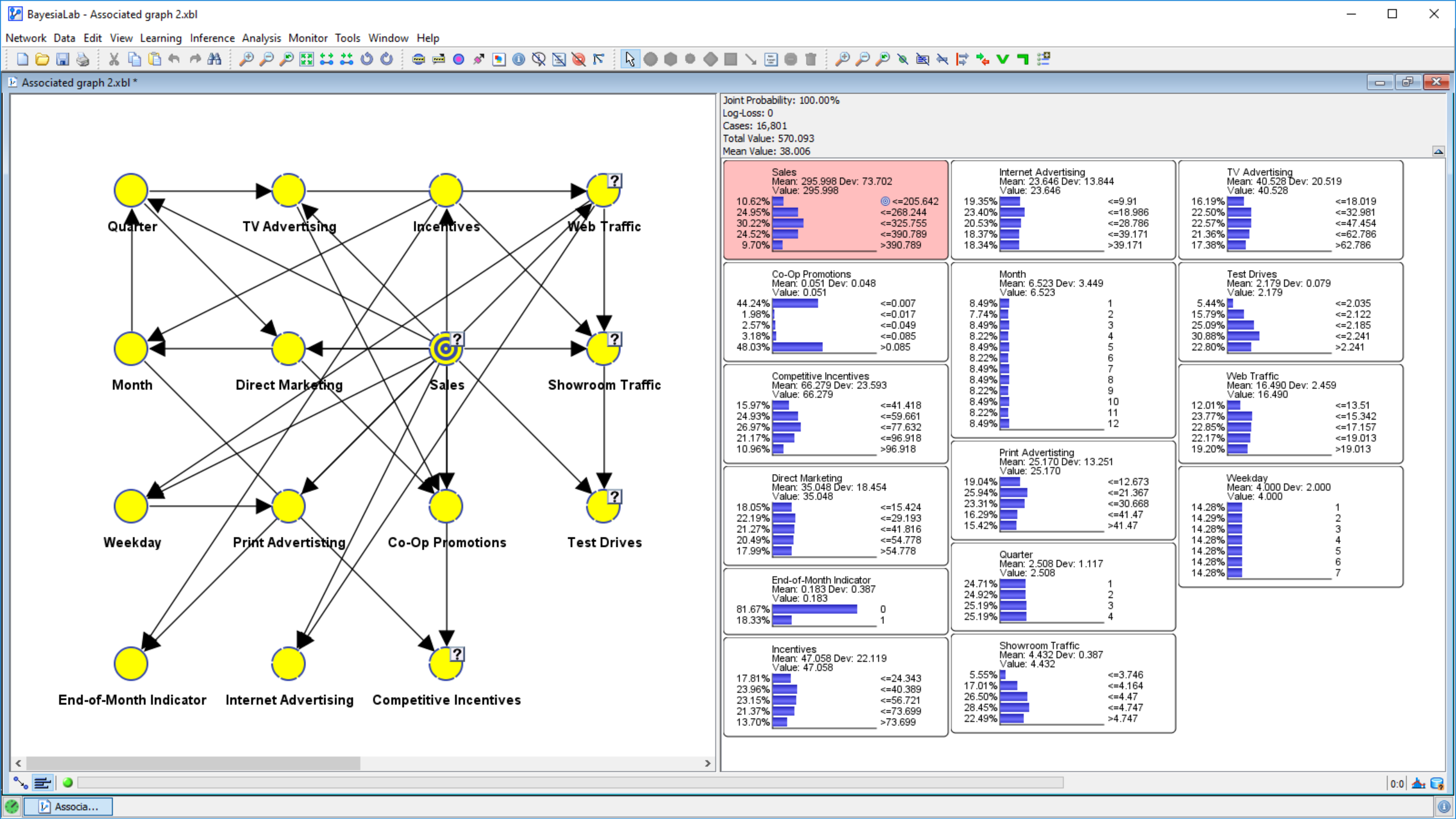


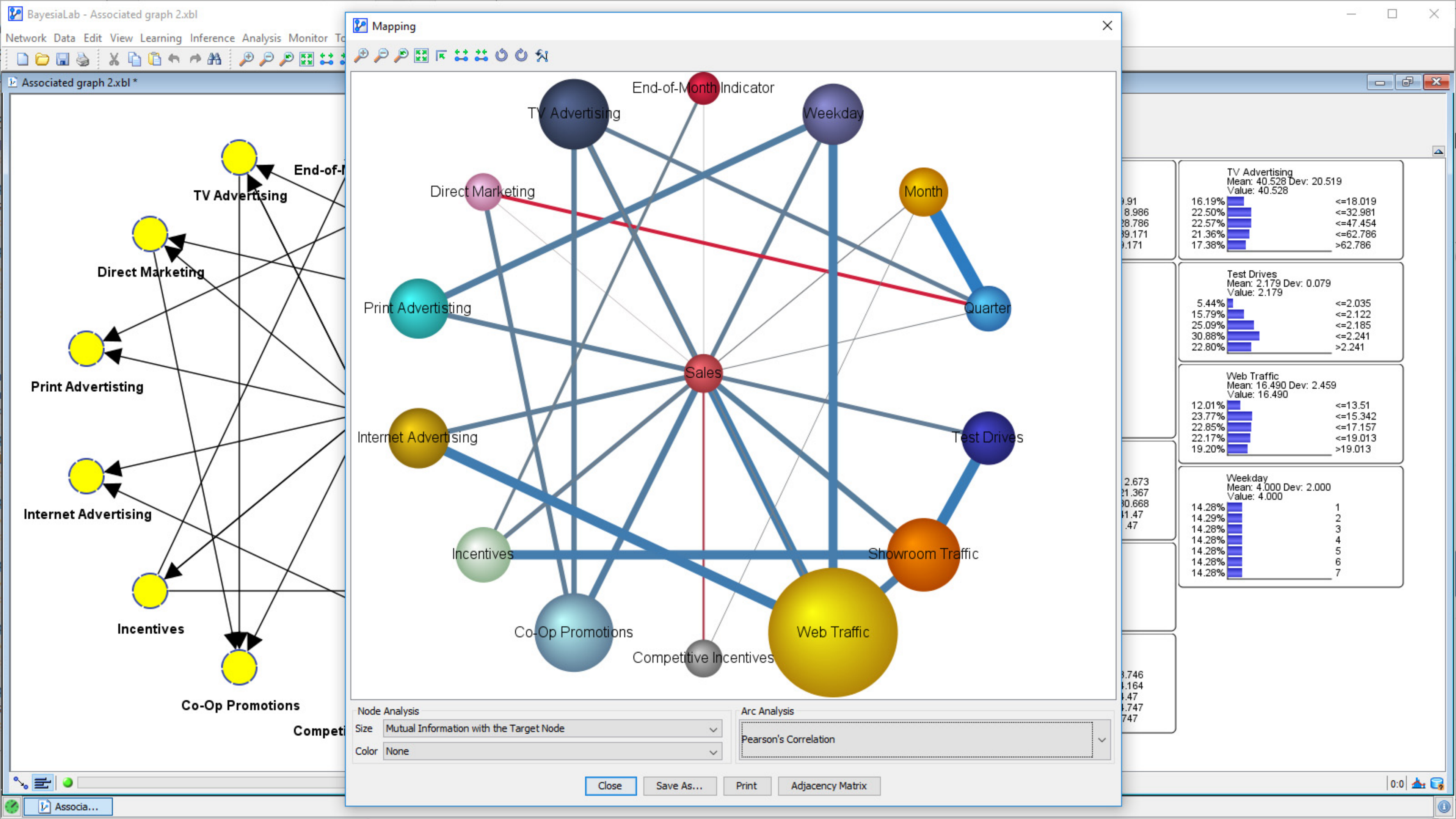
Discretization


BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 2.xbl *
Unconnected Network
Quarter
TV Advertising
Incentives
Web Traffic
Month
Direct Marketing
Sales
Showroom Traffic
Weekday
Print Advertising
Co-Op Promotions
Test Drives
End-of-Month Indicator
Internet Advertising
Competitive Incentives
Associa...

Supervised Learning Using the Augmented Naïve Bayes Algorithm




BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
Quarter
TV Advertising
Incentives
Web Traffic
Month
Direct Marketing
Sales
Showroom Traffic
Weekday
Print Advertising
Co-Op Promotions
Test Drives
End-of-Month Indicator
Internet Advertising
Competitive Incentives
Joint Probability: 100.00%
Log-Loss: 0
Cases: 16,801
Total Value: 570.093
Mean Value: 38.006
Sales
Mean: 295.998 Dev: 73.702
Value: 295.998
10.62% <=205.642
24.95% <=268.244
30.22% <=325.755
24.52% <=390.789
9.70% >390.789
Internet Advertising
Mean: 23.646 Dev: 13.844
Value: 23.646
19.35% <=9.91
23.40% <=18.986
20.53% <=28.786
18.37% <=39.171
18.34% >39.171
TV Advertising
Mean: 40.528 Dev: 20.519
Value: 40.528
16.19% <=18.019
22.50% <=32.981
22.57% <=47.454
21.36% <=62.786
17.38% >62.786
Co-Op Promotions
Mean: 0.051 Dev: 0.048
Value: 0.051
44.24% <=0.007
1.98% <=0.017
2.57% <=0.049
3.18% <=0.085
48.03% >0.085
Month
Mean: 6.523 Dev: 3.449
Value: 6.523
8.49% 1
7.74% 2
8.49% 3
8.22% 4
8.49% 5
8.22% 6
8.49% 7
8.49% 8
8.22% 9
8.49% 10
8.22% 11
8.49% 12
Test Drives
Mean: 2.179 Dev: 0.079
Value: 2.179
5.44% <=2.035
15.79% <=2.122
25.09% <=2.185
30.88% <=2.241
22.80% >2.241
Competitive Incentives
Mean: 66.279 Dev: 23.593
Value: 66.279
15.97% <=41.418
24.93% <=59.661
26.97% <=77.632
21.17% <=96.918
10.96% >96.918
Web Traffic
Mean: 16.490 Dev: 2.459
Value: 16.490
12.01% <=13.51
23.77% <=15.342
22.85% <=17.157
22.17% <=19.013
19.20% >19.013
Print Advertising
Mean: 25.170 Dev: 13.251
Value: 25.170
19.04% <=12.673
25.94% <=21.367
23.31% <=30.668
16.29% <=41.47
15.42% >41.47
Direct Marketing
Mean: 35.048 Dev: 18.454
Value: 35.048
18.05% <=15.424
22.19% <=29.193
21.27% <=41.816
20.49% <=54.778
17.99% >54.778
Weekday
Mean: 4.000 Dev: 2.000
Value: 4.000
14.28% 1
14.29% 2
14.28% 3
14.28% 4
14.28% 5
14.28% 6
14.28% 7
Quarter
Mean: 2.508 Dev: 1.117
Value: 2.508
24.71% 1
24.92% 2
25.19% 3
25.19% 4
End-of-Month Indicator
Mean: 0.183 Dev: 0.387
Value: 0.183
81.67% 0
18.33% 1
Showroom Traffic
Mean: 4.432 Dev: 0.387
Value: 4.432
5.55% <=3.746
17.01% <=4.164
26.50% <=4.47
28.45% <=4.747
22.49% >4.747
Incentives
Mean: 47.058 Dev: 22.119
Value: 47.058
17.81% <=24.343
23.96% <=40.389
23.15% <=56.721
21.37% <=73.699
13.70% >73.699
0:0
Associa...



BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor
Associated graph 2.xbl *
TV Advertising
Direct Marketing
Print Advertising
Internet Advertising
Incentives
Co-Op Promotions
Mapping
End-of-Month Indicator
TV Advertising
Weekday
Direct Marketing
Month
Print Advertising
Quarter
Sales
Internet Advertising
Test Drives
Incentives
Showroom Traffic
Co-Op Promotions
Competitive Incentives
Web Traffic
Node Analysis
Size
Mutual Information with the Target Node
Color
None
Arc Analysis
Pearson's Correlation
Close
Save As...
Print
Adjacency Matrix
TV Advertising
Mean: 40.528 Dev: 20.519
Value: 40.528
16.19% <=18.019
22.50% <=32.981
22.57% <=47.454
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17.38% >62.786
Test Drives
Mean: 2.179 Dev: 0.079
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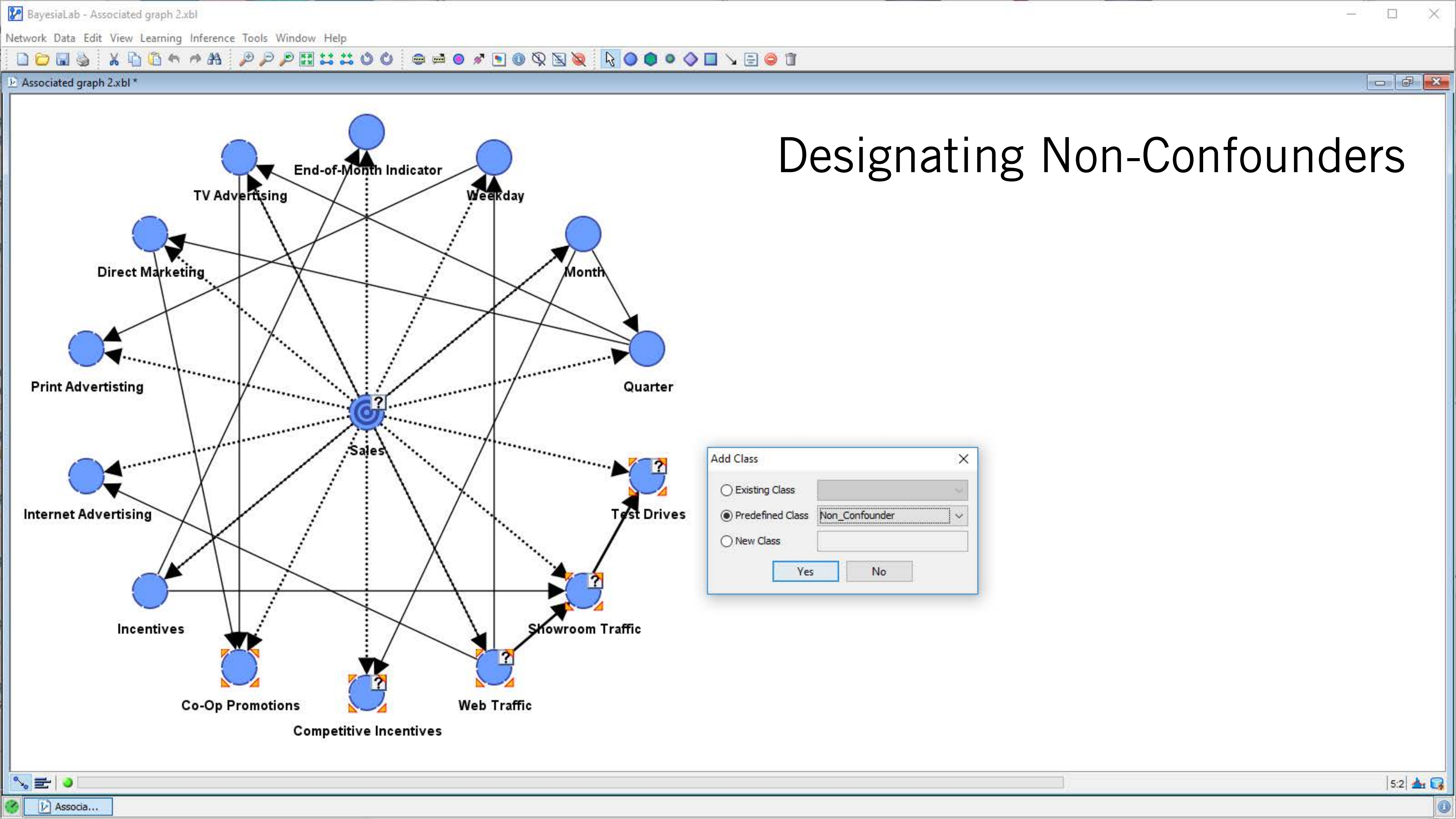
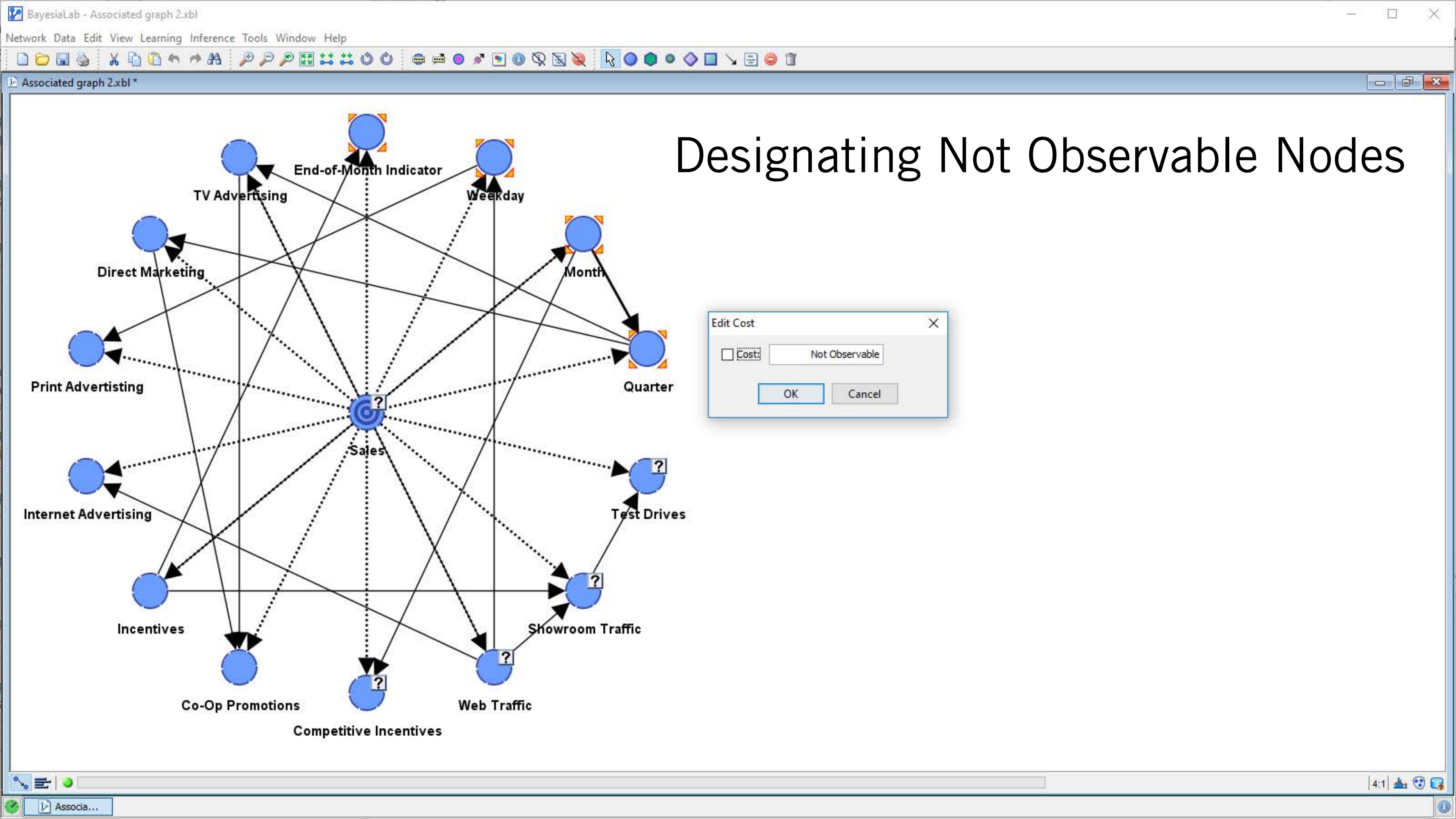
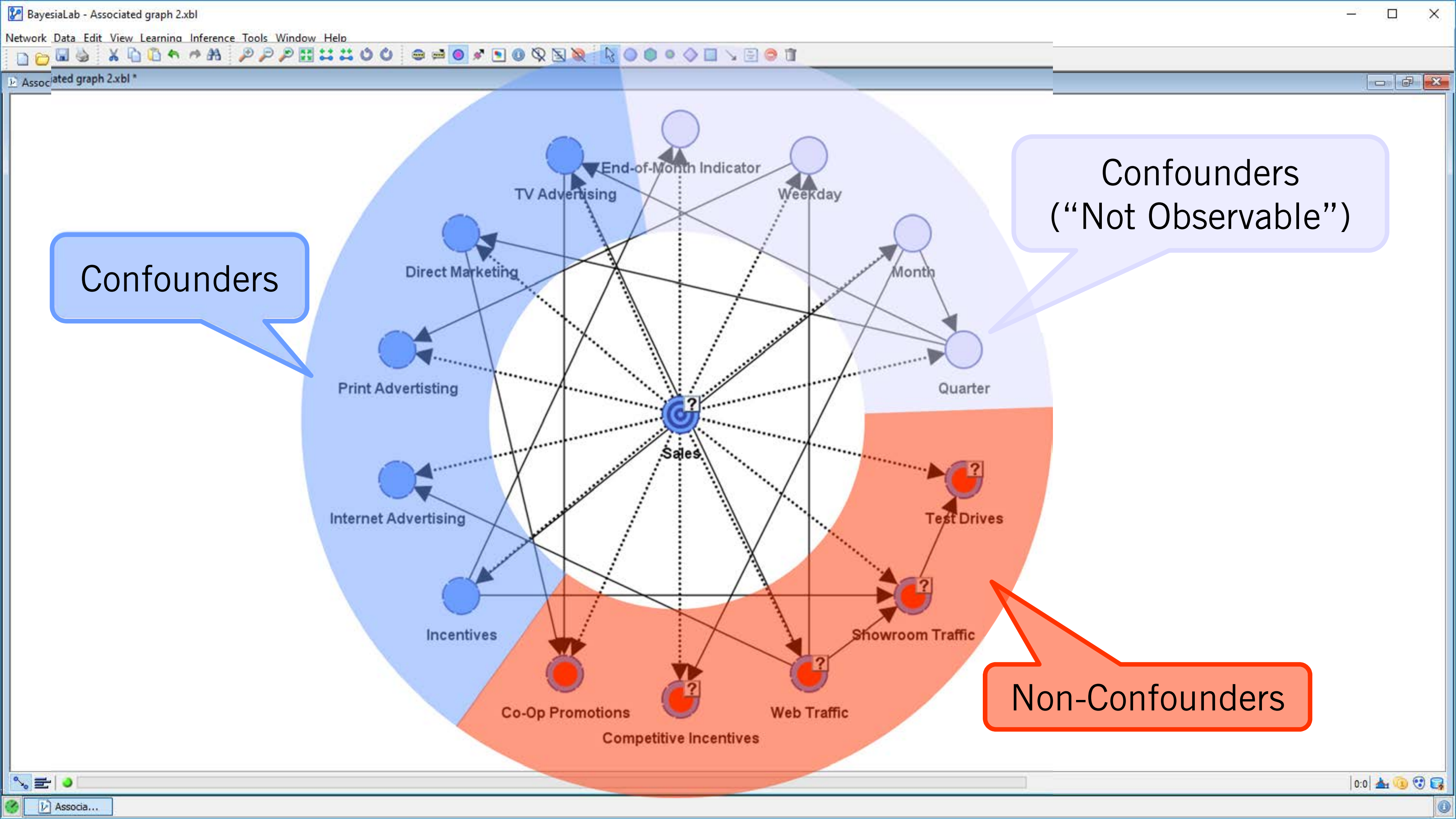
Mean: 16.490 Dev: 2.459
Value: 16.490
12.01% <=13.51
23.77% <=15.342
22.85% <=17.157
22.17% <=19.013
19.20% >19.013
Weekday
Mean: 4.000 Dev: 2.000
Value: 4.000
14.28% 1
14.29% 2
14.28% 3
14.28% 4
14.28% 5
14.28% 6
14.28% 7
Associa...

Designating Non-Confounders

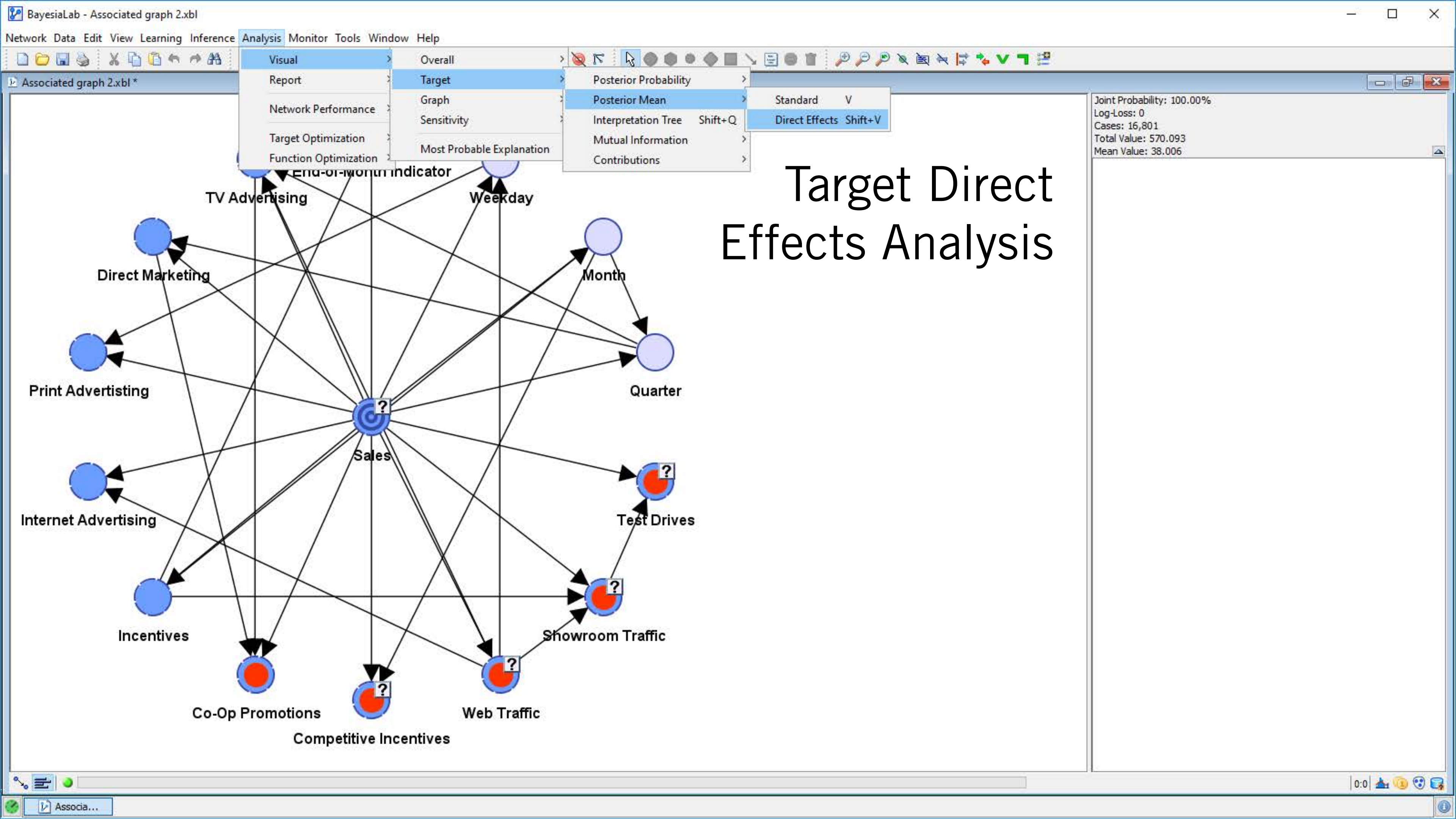


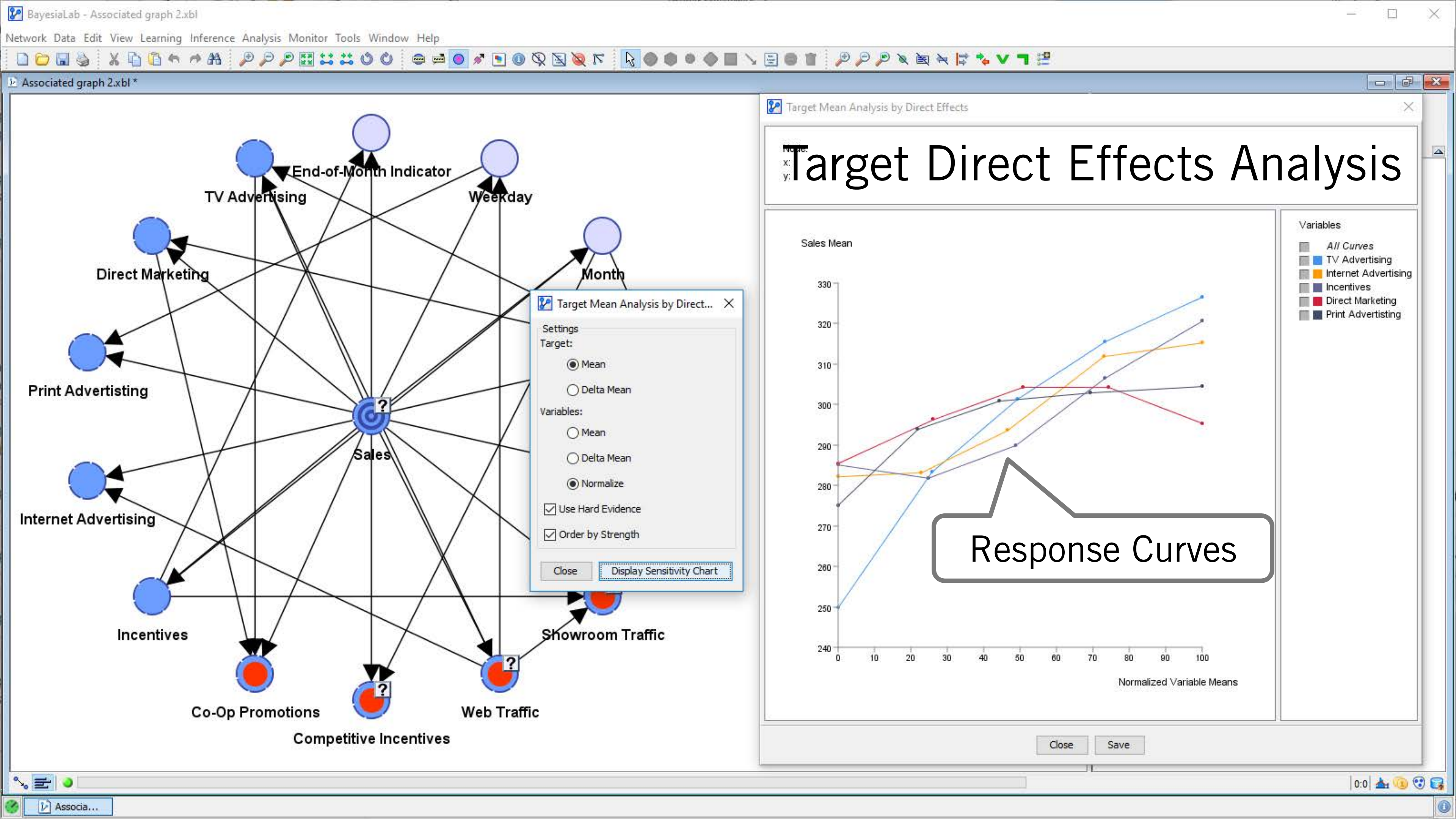
Designating Not Observable Nodes



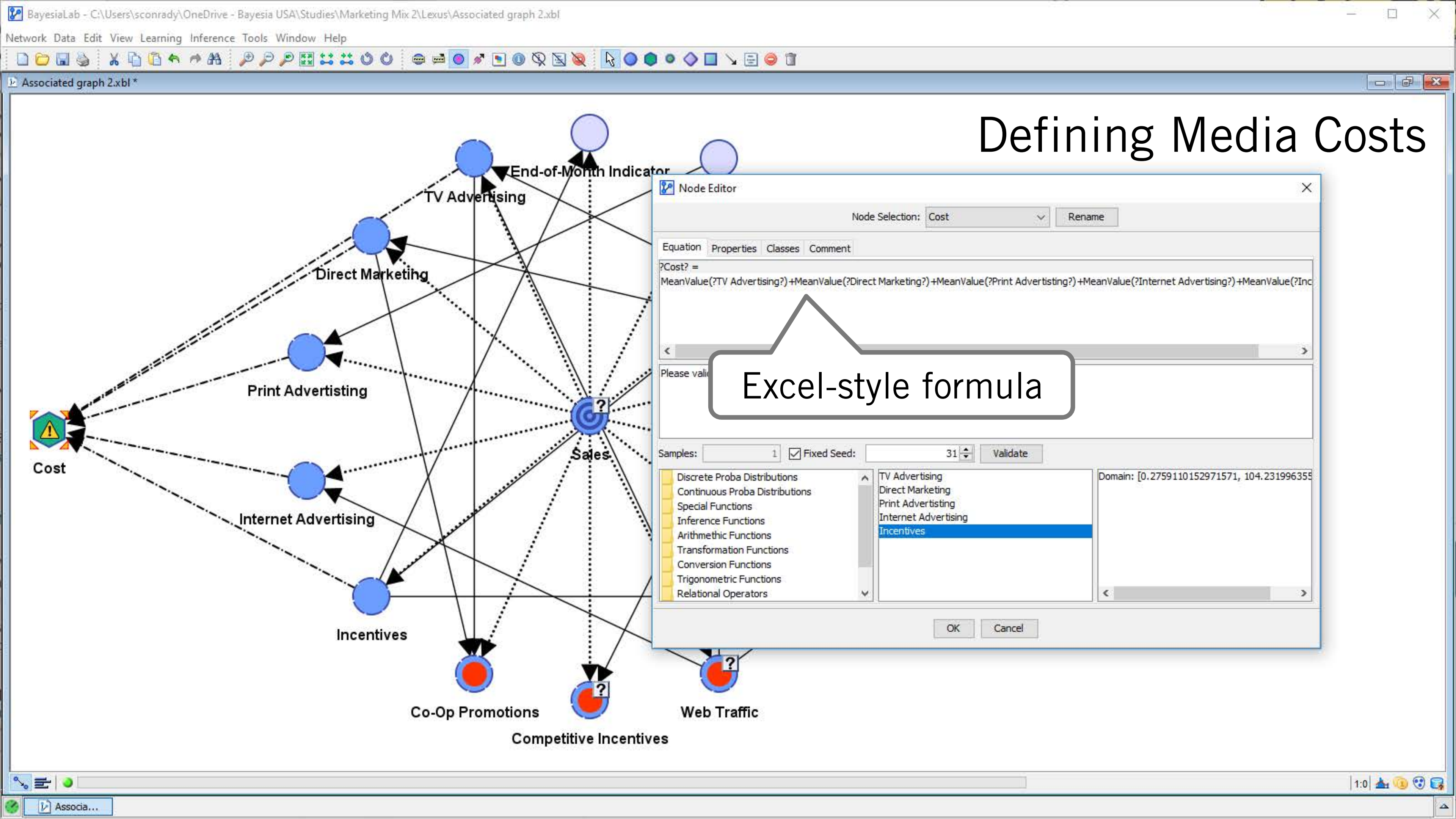


BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 2.xbl *
Confounders
Confounders
("Not Observable")
Non-Confounders
End-of-Month Indicator
TV Advertising
Weekday
Direct Marketing
Month
Print Advertising
Quarter
Sales
Internet Advertising
Test Drives
Incentives
Showroom Traffic
Co-Op Promotions
Web Traffic
Competitive Incentives

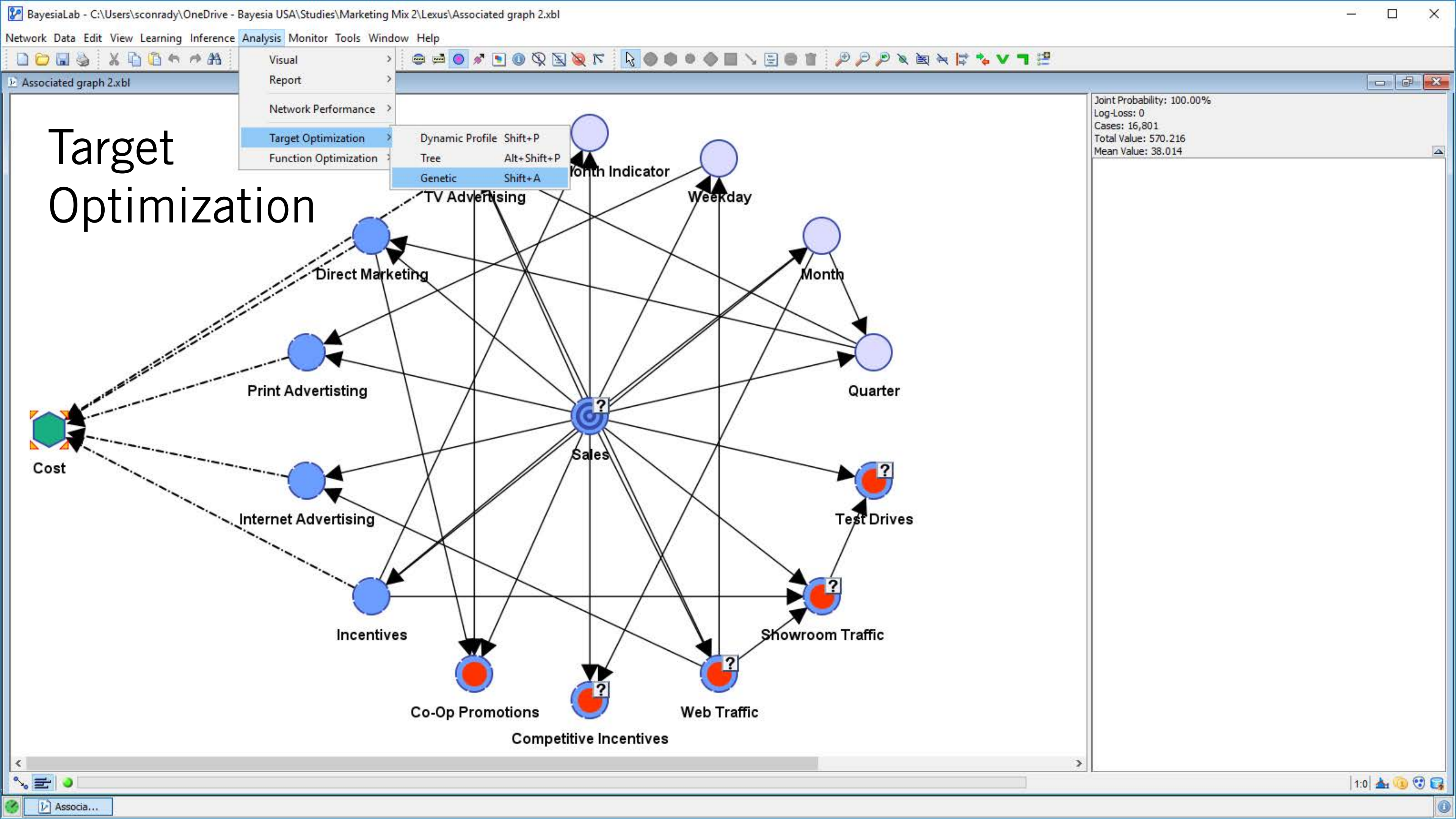

Target Direct Effects Analysis
BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
Visual
Report
Network Performance
Target Optimization
Function Optimization
Overall
Target
Graph
Sensitivity
Most Probable Explanation
Posterior Probability
Posterior Mean
Interpretation Tree Shift+Q
Mutual Information
Contributions
Standard V
Direct Effects Shift+V
Joint Probability: 100.00%
Log-Loss: 0
Cases: 16,801
Total Value: 570.093
Mean Value: 38.006
End-of-Month Indicator
TV Advertising
Weekday
Direct Marketing
Month
Print Advertising
Quarter
Sales
Internet Advertising
Test Drives
Incentives
Showroom Traffic
Co-Op Promotions
Web Traffic
Competitive Incentives
Associa...

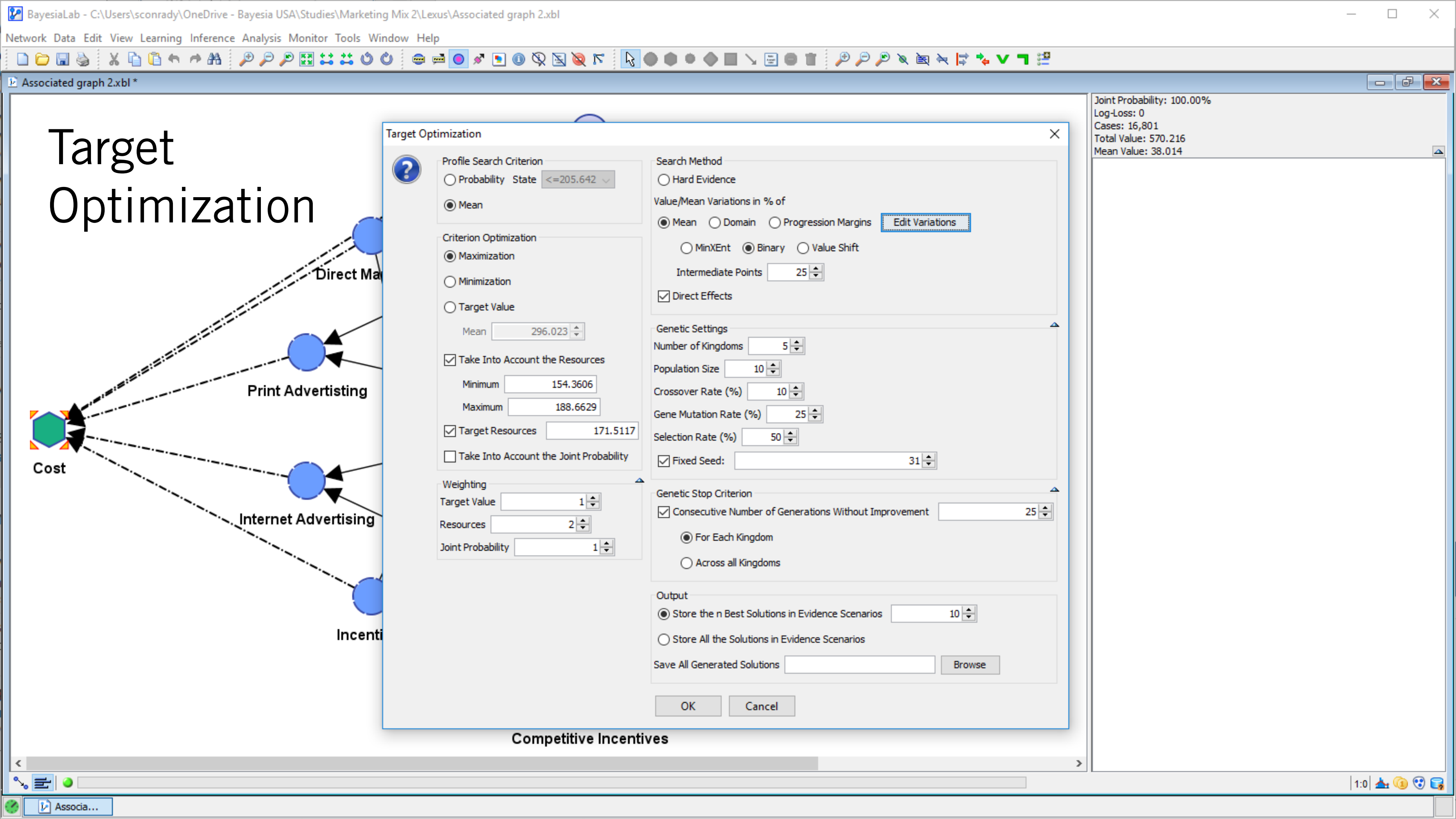

BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
End-of-Month Indicator
TV Advertising
Weekday
Direct Marketing
Month
Print Advertising
Sales
Internet Advertising
Incentives
Showroom Traffic
Co-Op Promotions
Web Traffic
Competitive Incentives
Target Mean Analysis by Direct...
Settings
Target:
Mean
Delta Mean
Variables:
Mean
Delta Mean
Normalize
Use Hard Evidence
Order by Strength
Close
Display Sensitivity Chart
Target Mean Analysis by Direct Effects
Target Direct Effects Analysis
Sales Mean
330
320
310
300
290
280
270
260
250
240
0 10 20 30 40 50 60 70 80 90 100
Normalized Variable Means
Variables
All Curves
TV Advertising
Internet Advertising
Incentives
Direct Marketing
Print Advertising
Response Curves
Close
Save
Associa...

Defining Media Costs



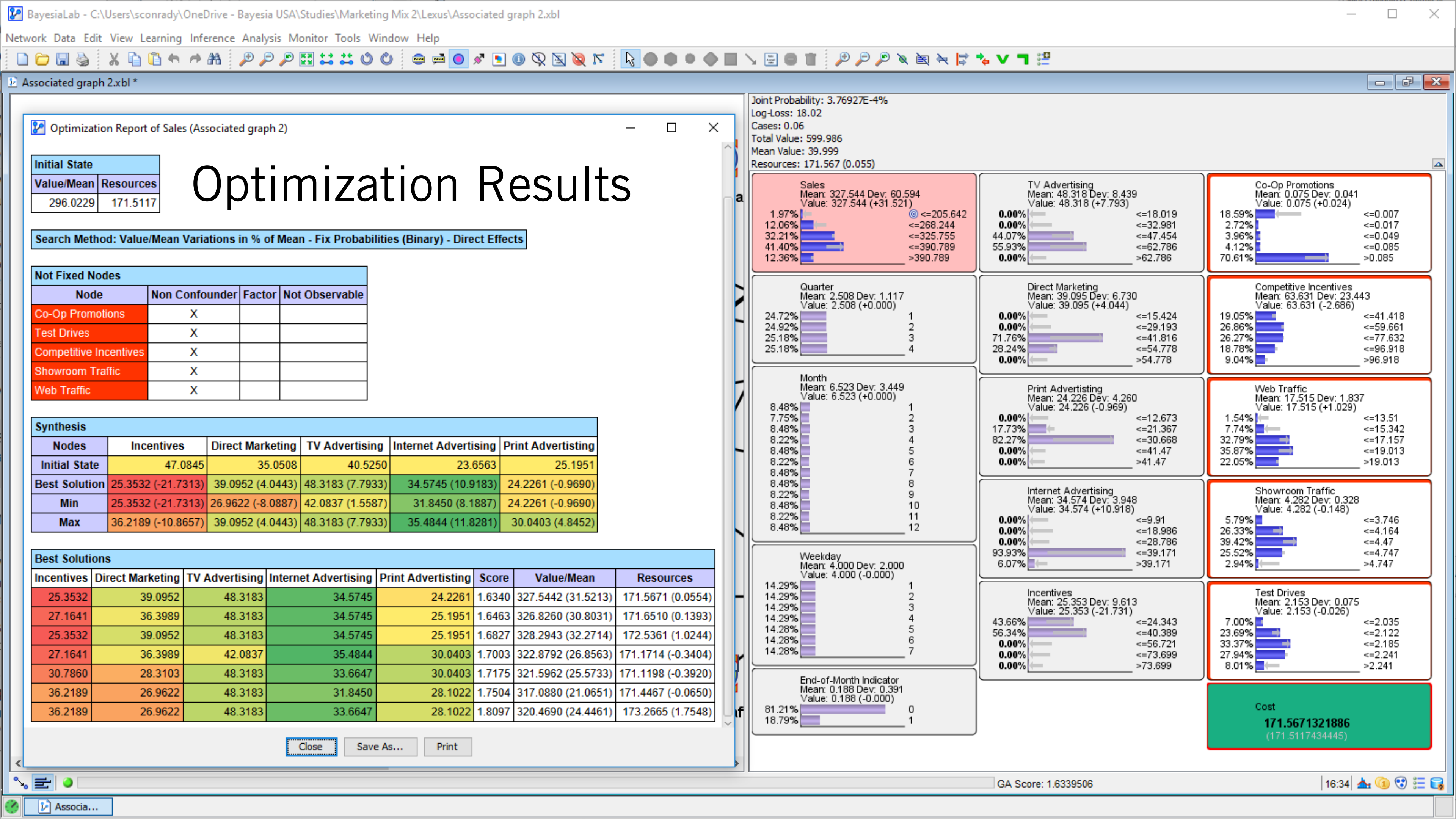
Target Optimization





BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Marketing Mix 2\Lexus\Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
Target Optimization
Direct Ma
Print Advertising
Cost
Internet Advertising
Incenti
Competitive Incentives
Target Optimization
Profile Search Criterion
Probability State <=205.642
Mean
Criterion Optimization
Maximization
Minimization
Target Value
Mean 296.023
Take Into Account the Resources
Minimum 154.3606
Maximum 188.6629
Target Resources 171.5117
Take Into Account the Joint Probability
Weighting
Target Value 1
Resources 2
Joint Probability 1
Search Method
Hard Evidence
Value/Mean Variations in % of
Mean Domain Progression Margins Edit Variations
MinXEnt Binary Value Shift
Intermediate Points 25
Direct Effects
Genetic Settings
Number of Kingdoms 5
Population Size 10
Crossover Rate (%) 10
Gene Mutation Rate (%) 25
Selection Rate (%) 50
Fixed Seed: 31
Genetic Stop Criterion
Consecutive Number of Generations Without Improvement 25
For Each Kingdom
Across all Kingdoms
Output
Store the n Best Solutions in Evidence Scenarios 10
Store All the Solutions in Evidence Scenarios
Save All Generated Solutions Browse
OK Cancel
Joint Probability: 100.00%
Log-Loss: 0
Cases: 16,801
Total Value: 570.216
Mean Value: 38.014
1:0
Associa...

Optimization Results



Optimization Report of Sales (Associated graph 2)

Initial State	
Value/Mean	Resources
296.0229	171.5117

Search Method: Value/Mean Variations in % of Mean - Fix Probabilities (Binary) - Direct Effects

Not Fixed Nodes			
Node	Non Confounder	Factor	Not Observable
Co-Op Promotions	X		
Test Drives	X		
Competitive Incentives	X		
Showroom Traffic	X		
Web Traffic	X		

Synthesis					
Nodes	Incentives	Direct Marketing	TV Advertising	Internet Advertising	Print Advertising
Initial State	47.0845	35.0508	40.5250	23.6563	25.1951
Best Solution	25.3532 (-21.7313)	39.0952 (4.0443)	48.3183 (7.7933)	34.5745 (10.9183)	24.2261 (-0.9690)
Min	25.3532 (-21.7313)	26.9622 (-8.0887)	42.0837 (1.5587)	31.8450 (8.1887)	24.2261 (-0.9690)
Max	36.2189 (-10.8657)	39.0952 (4.0443)	48.3183 (7.7933)	35.4844 (11.8281)	30.0403 (4.8452)

Best Solutions							
Incentives	Direct Marketing	TV Advertising	Internet Advertising	Print Advertising	Score	Value/Mean	Resources
25.3532	39.0952	48.3183	34.5745	24.2261	1.6340	327.5442 (31.5213)	171.5671 (0.0554)
27.1641	36.3989	48.3183	34.5745	25.1951	1.6463	326.8260 (30.8031)	171.6510 (0.1393)
25.3532	39.0952	48.3183	34.5745	25.1951	1.6827	328.2943 (32.2714)	172.5361 (1.0244)
27.1641	36.3989	42.0837	35.4844	30.0403	1.7003	322.8792 (26.8563)	171.1714 (-0.3404)
30.7860	28.3103	48.3183	33.6647	30.0403	1.7175	321.5962 (25.5733)	171.1198 (-0.3920)
36.2189	26.9622	48.3183	31.8450	28.1022	1.7504	317.0880 (21.0651)	171.4467 (-0.0650)
36.2189	26.9622	48.3183	33.6647	28.1022	1.8097	320.4690 (24.4461)	173.2665 (1.7548)

Close Save As... Print

Concluding Remarks

BayesiaLab Trial

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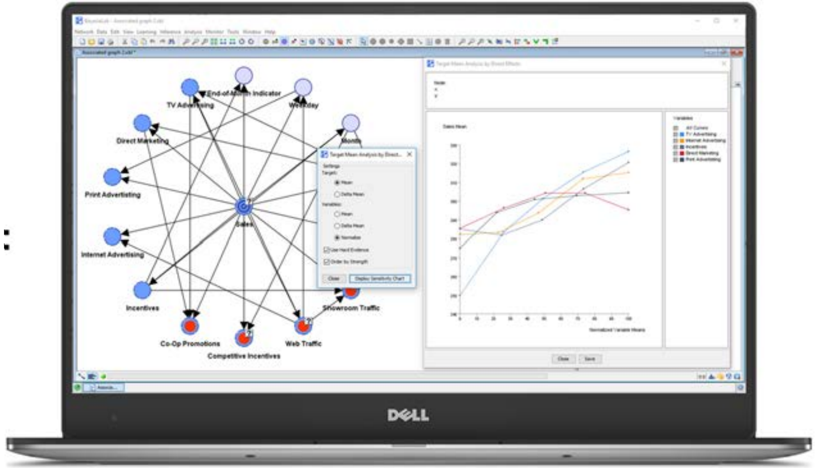
  www.bayesialab.com/evaluation



Upcoming Events

Webinars & Seminars:

• September 21	Webinar: Adversarial Reasoning
• November 13	Seminar in Arlington, VA Artificial Intelligence for Intelligence Analysis
• November 15	Seminar in New York City: Health Economics with Bayesian Networks

Register here: bayesia.com/events

BayesiaLab Courses Around the World in 2018

- October 29–31
  Introductory Course
  Chicago, IL
- November 13–15
  Introductory Course
  McLean, VA (internal)
- November 16–20
  Advanced Course
  McLean, VA (internal)
- December 10–12
  Introductory Course
  Sydney, Australia

Learn More & Register: bayesia.com/events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Thank You!

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