Contribution Analysis with Counterfactuals

Stefan Conrady | stefan.conrady@bayesia.us | +1 888-386-8383

Webinar on June 26, 2019

Today's Agenda

Motivation

- How do causes contribute to observed outcomes?
- A century-old question familiar to John Wannamaker, Henry Ford, J.C. Penney, and Michael Dell.

Objective

- We wish to estimate the proportional contributions of causes towards outcomes from observational data.

Central Ideas

- We need to calculate contributions with counterfactuals.
- But first, we have to infer counterfactuals with a causal model.

Today's Agenda (cont'd)

Contribution Analysis Workflow

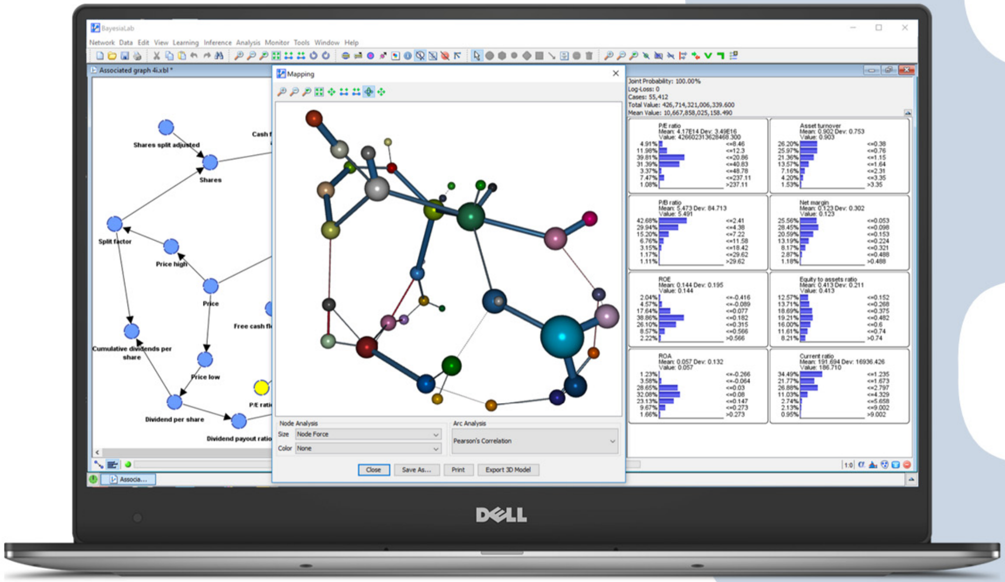
- We produce synthetic data from an arbitrarily-defined data-generating process.
- We machine learn a non-causal Bayesian Network from that data to approximate the joint probability distribution of the underlying data.
- By making causal assumptions, we can infer outcomes based on counterfactuals conditions.

Today's Agenda (cont'd)

Contribution Analysis Workflow (cont'd)

- Contribution Calculations
  - Type 1 vs. Type 2 Contributions
  - Model-Based vs. Data-Based Contributions
  - Baseline Contributions
  - Synergies
  - Temporal Decomposition

BAYESIALAB



A desktop software for:

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

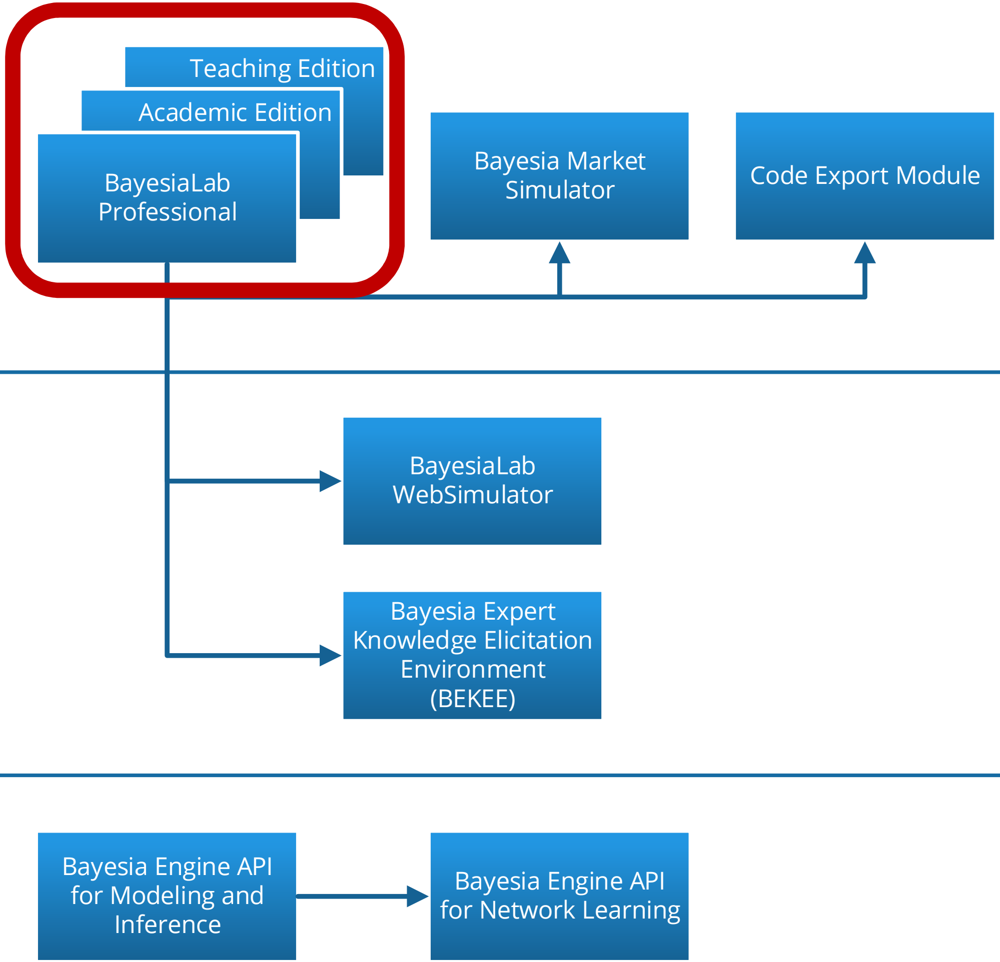
with Bayesian networks.

BAYESIALAB

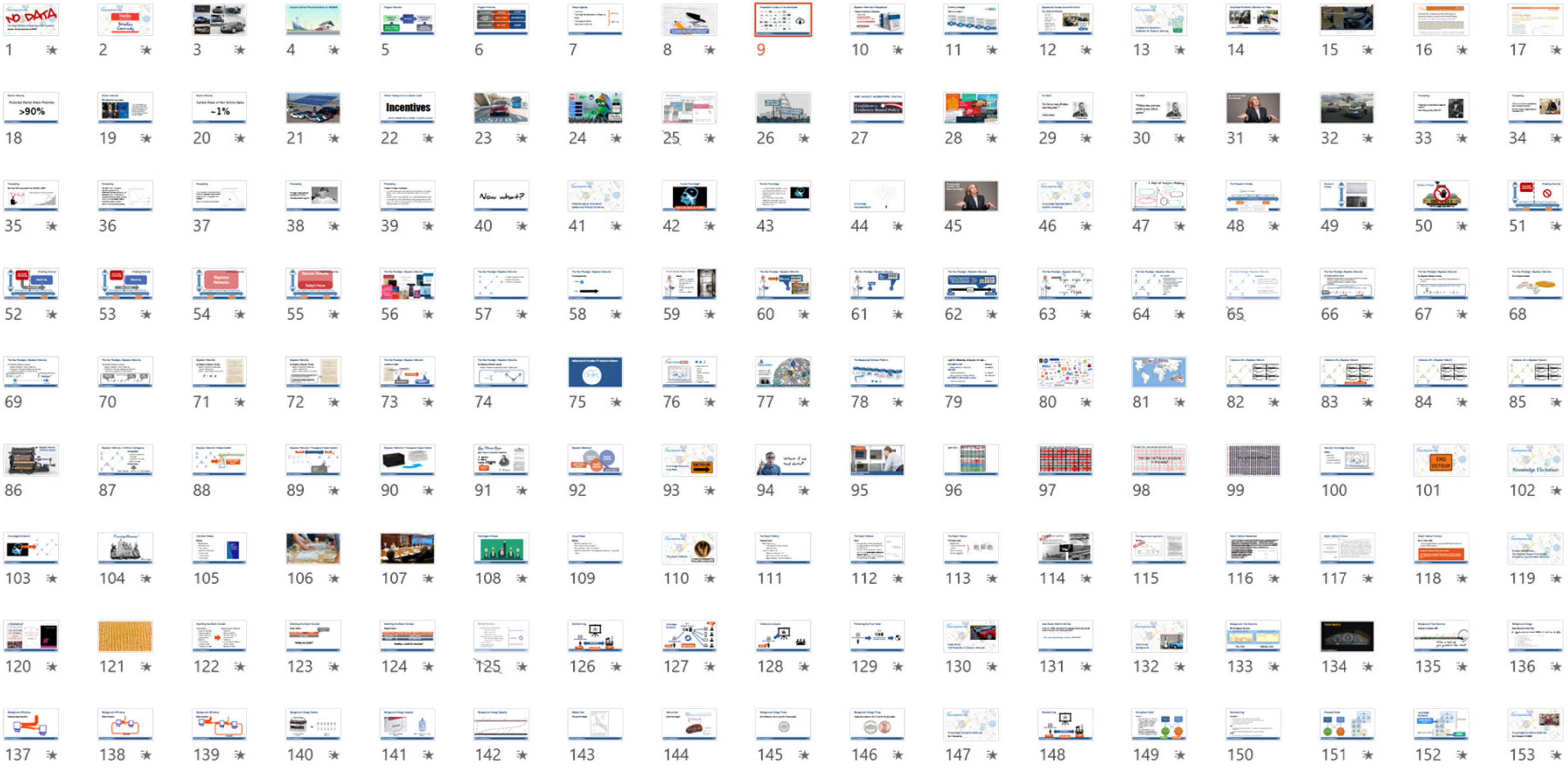
Desktop Software

Web Application

API



Slides, networks, and video will be available



Motivation

Calculating Contributions

John Wannamaker

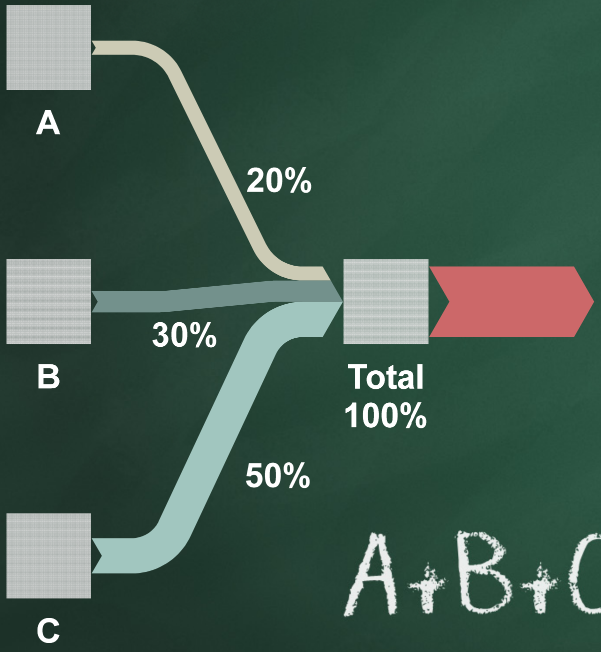
Henry Ford

J.C. Penney

I know I waste half of my advertising dollars; I just wish I knew which half.

Motivation

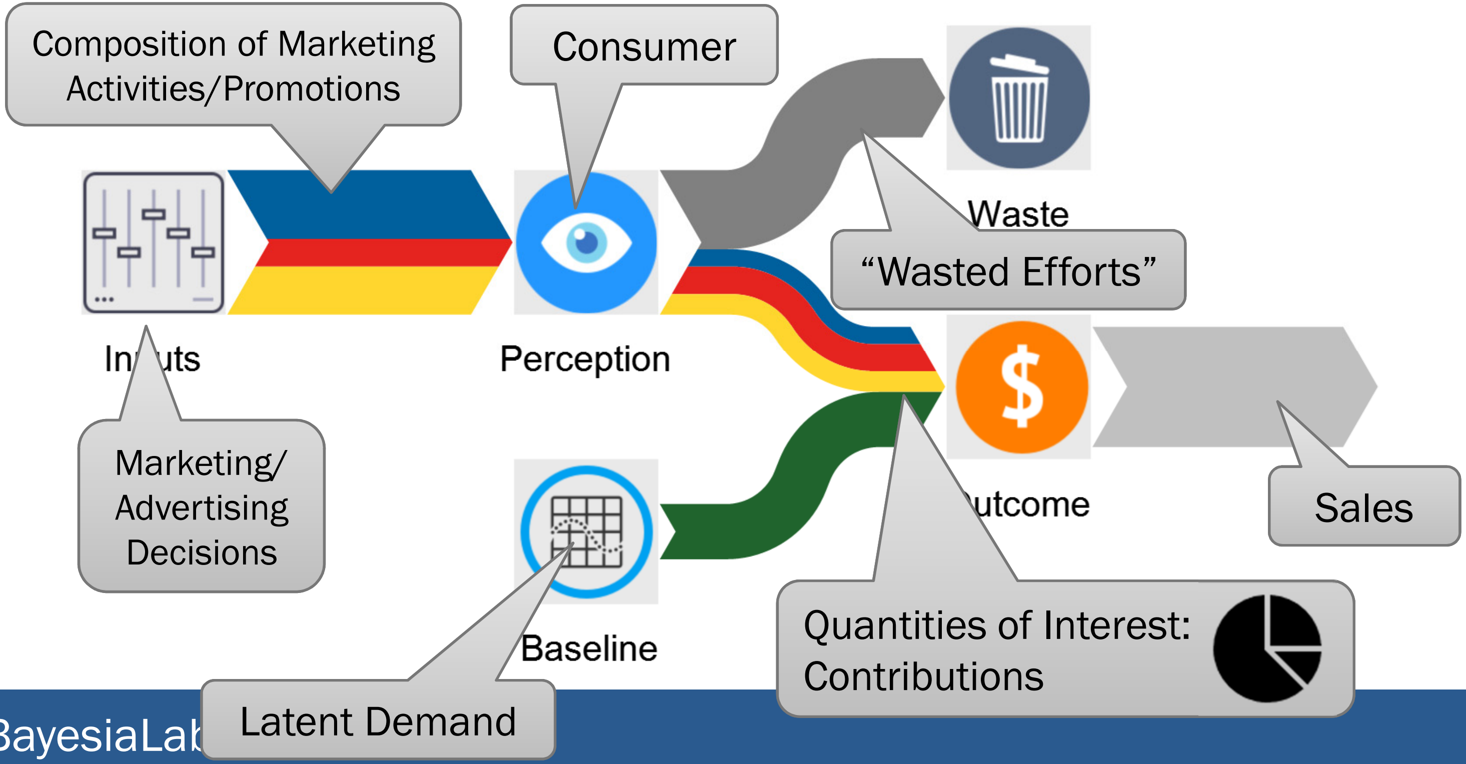
Contribution — Colloquial Interpretation



A+B+C=Total

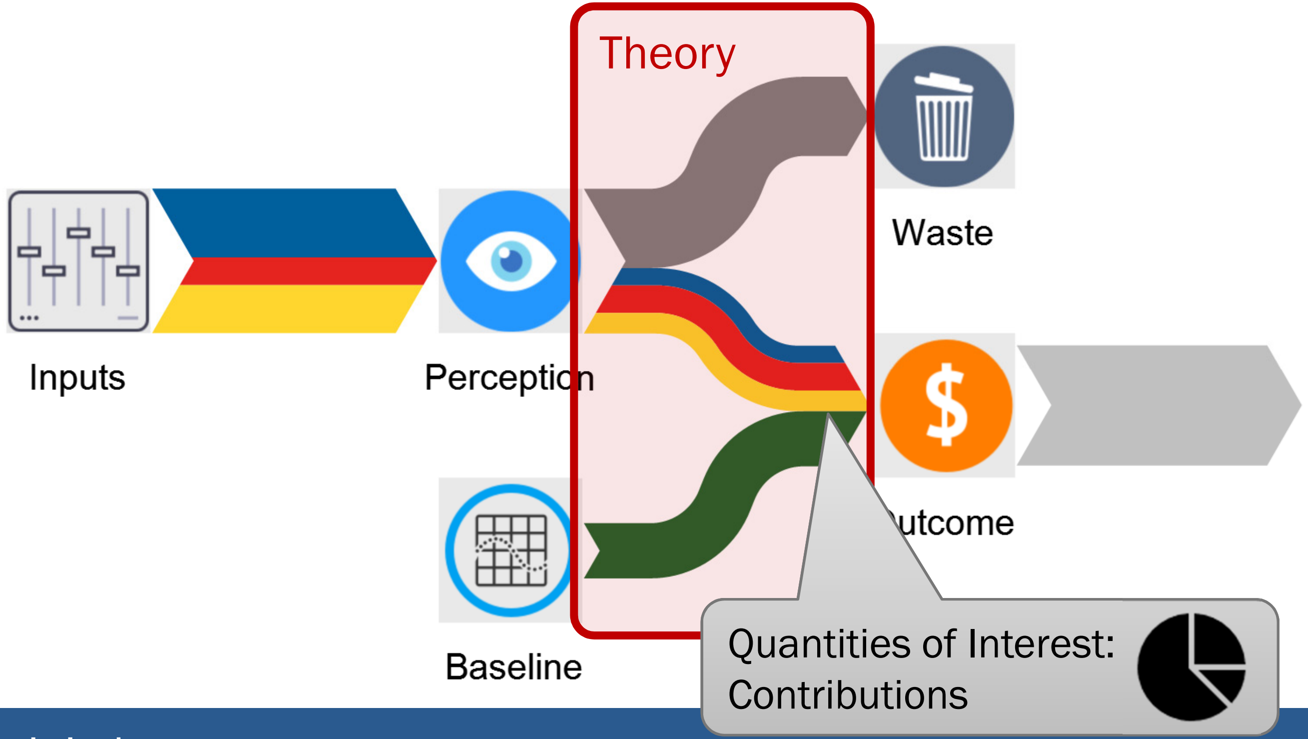
Motivation

What is Contribution in the Marketing Context?



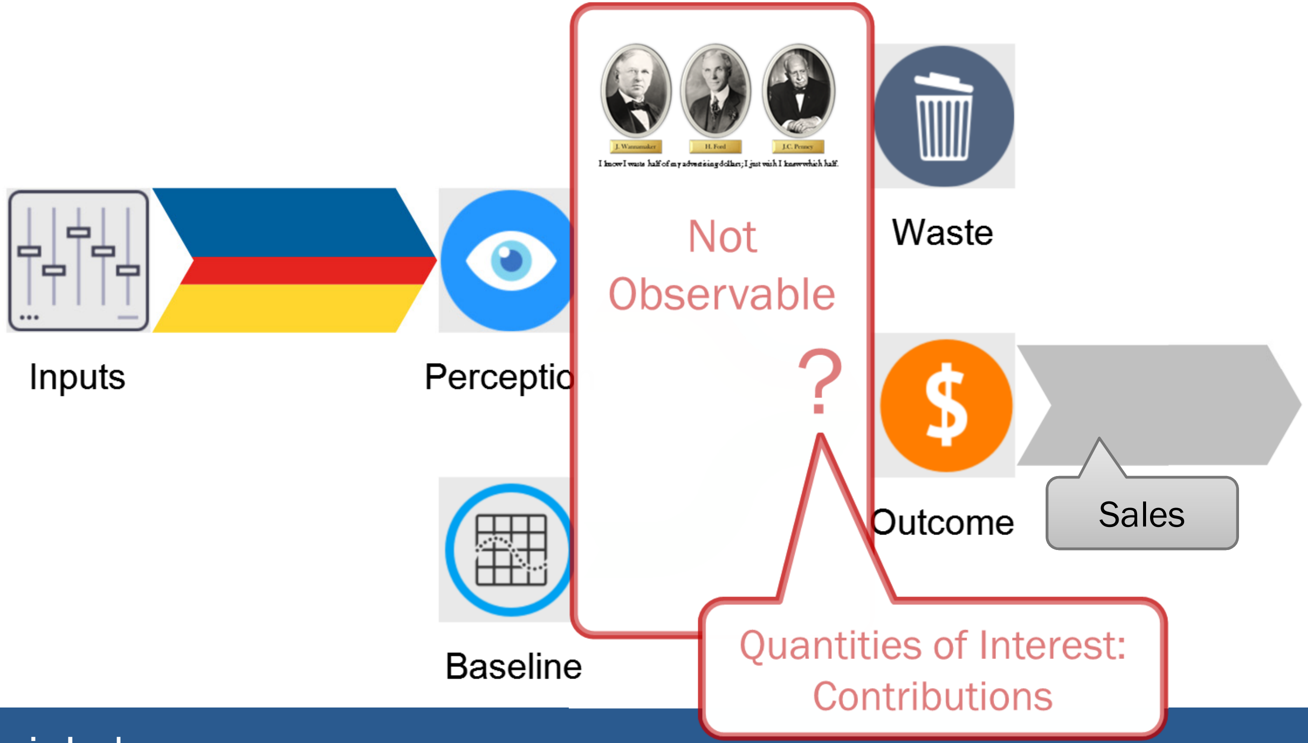
Motivation

What is Contribution in the Marketing Context?



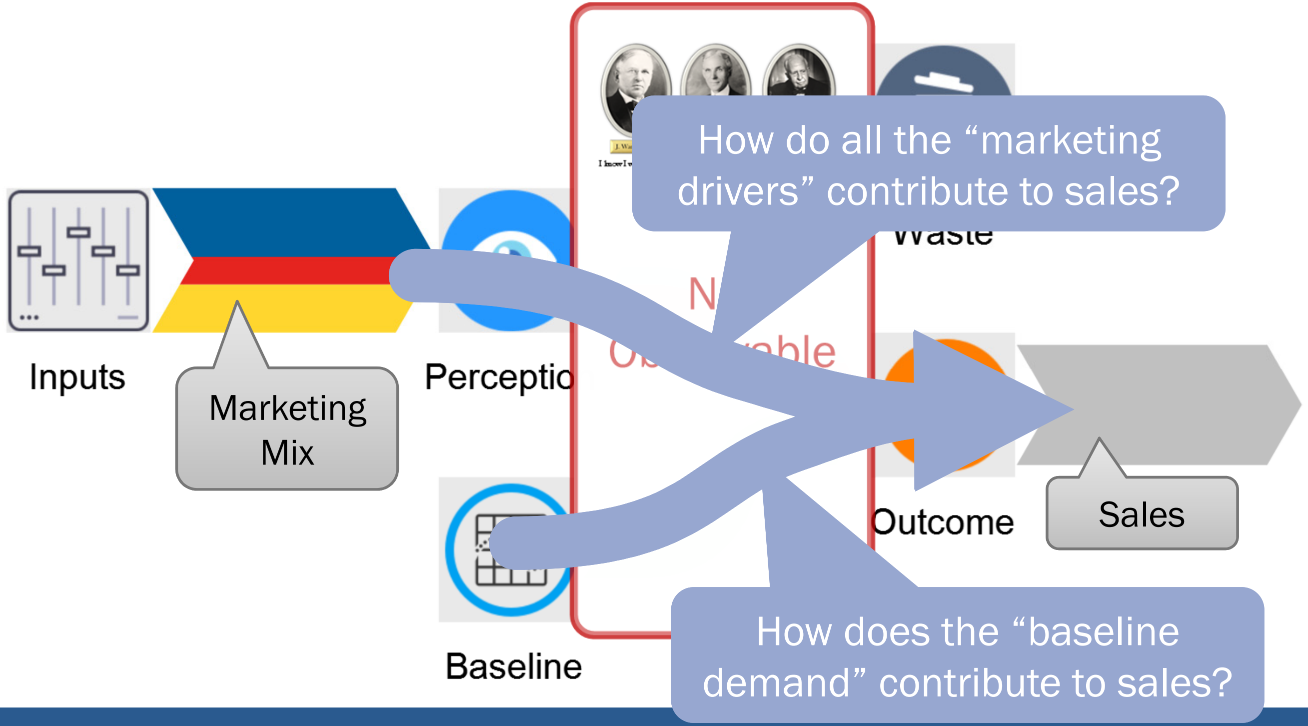
Motivation

What is Contribution in the Marketing Context?



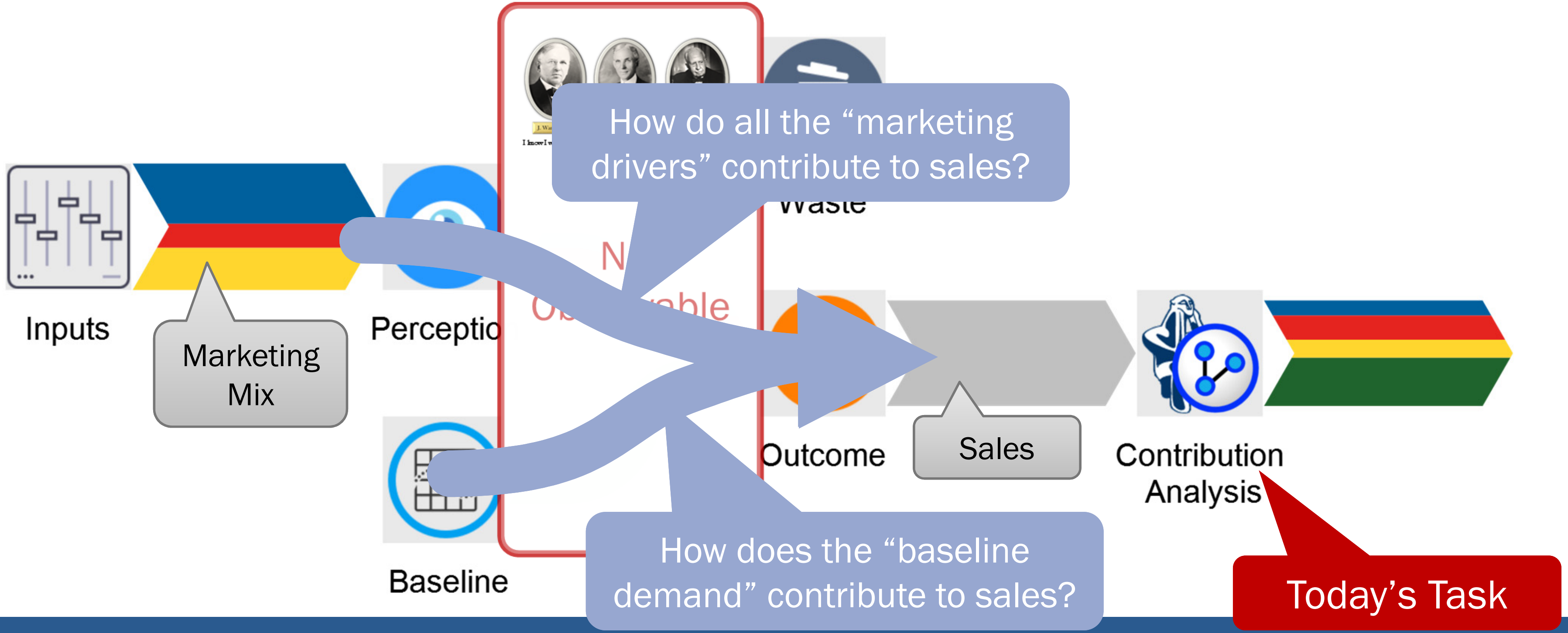
Objective: Contribution Analysis

Decomposing Sales & Recovering the Unobservable Contributions



Objective: Contribution Analysis

Decomposing Sales & Recovering the Unobservable Contributions



Objective: Contribution Analysis

Decomposing Sales & Recovering the Unobservable Contributions

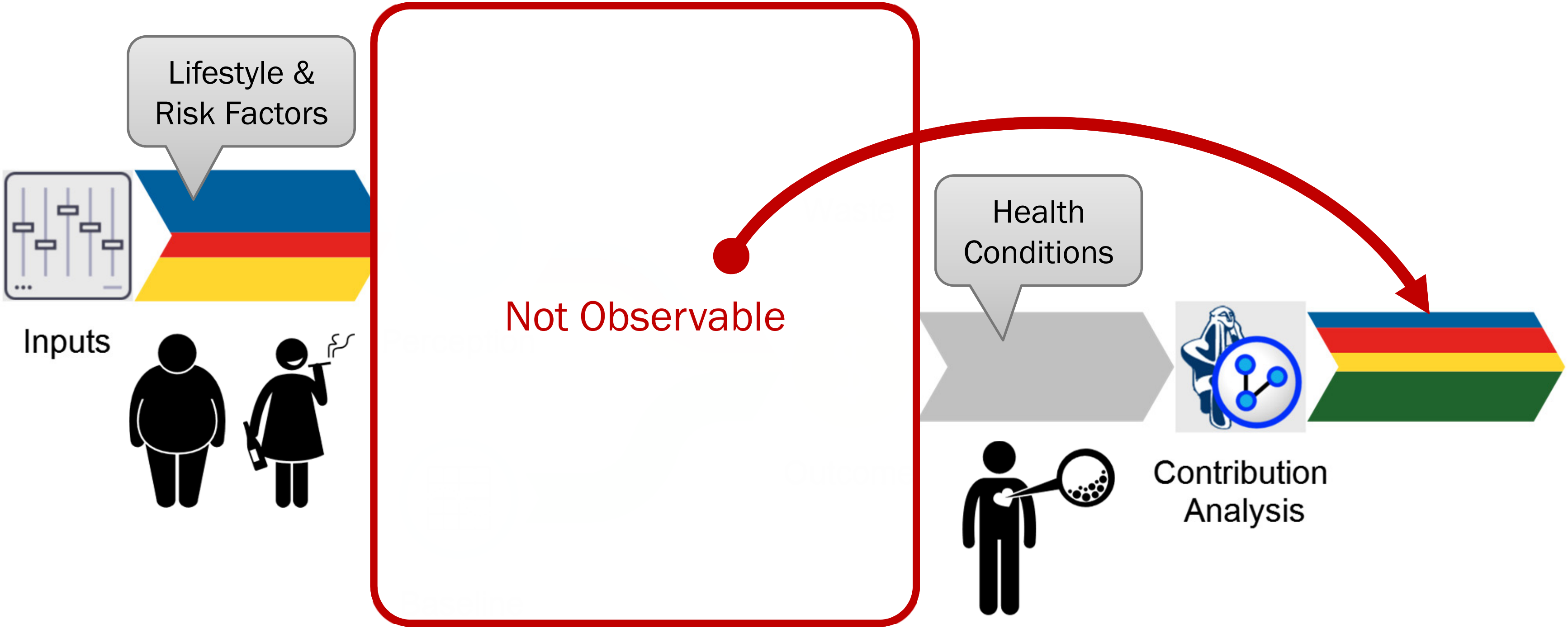
Caveat

Effects vs. Contributions

- **Effect sizes** are "forward-looking" quantities, representing the capability of a cause, when invoked, to bring about an outcome.
    - At a speed of 2,000 rpm, my car's engine will produce 700Nm of torque.
- **Contributions** are backward-looking, i.e., decomposing an outcome and attributing it proportionally to multiple causes.
    - Success is 80% attitude and 20% aptitude.
    - Technical malfunction and human negligence were equal contributors to the accident.

Objective: Contribution Analysis

Decomposing the Outcome & Recovering its Unobservable Contributions



“What sales did we generate with the money we spent on the advertising campaign?”

“Counterfactual”

Common Synonyms

- false
- incorrect
- made up
- truthless
- untrue
- untruthful
- wrong

Counterfactuals

Had we instead chosen...

Had it not been for...

What if...

Counterfactuals

Rephrasing Michael Dell's Question

- What is the difference between:
  - Sales given that we ran the advertising campaign spending x dollars.
  - Sales if we had not run the advertising campaign, i.e., spending 0 dollars.

Factual

Counterfactual

NOT OBSERVABLE

Counterfactuals

Defining (Type 1) Contributions with Counterfactuals

$$\text{Decomposition}(X) = \text{Sales}(X = x_{\text{factual}}) - \text{Sales}(do(X = x_{\text{counterfactual}} = 0))$$

What we actually did

Had we **done** $X=0$ instead

$$\text{Contribution}(X) = \frac{\text{Decomposition}(X)}{\text{Sales}(X = x_{\text{factual}})}$$

Counterfactuals

Defining Contributions with Counterfactuals

$$\mathrm{Decomposition}(X) = \mathrm{Sales}(X = x_{\mathrm{factual}}) - \mathrm{Sales}(\mathrm{do}(X = x_{\mathrm{counterfactual}} = 0))$$

- What would have been the sales volume had we not run the advertising campaign?
- Can we somehow calculate this counterfactual sales volume?

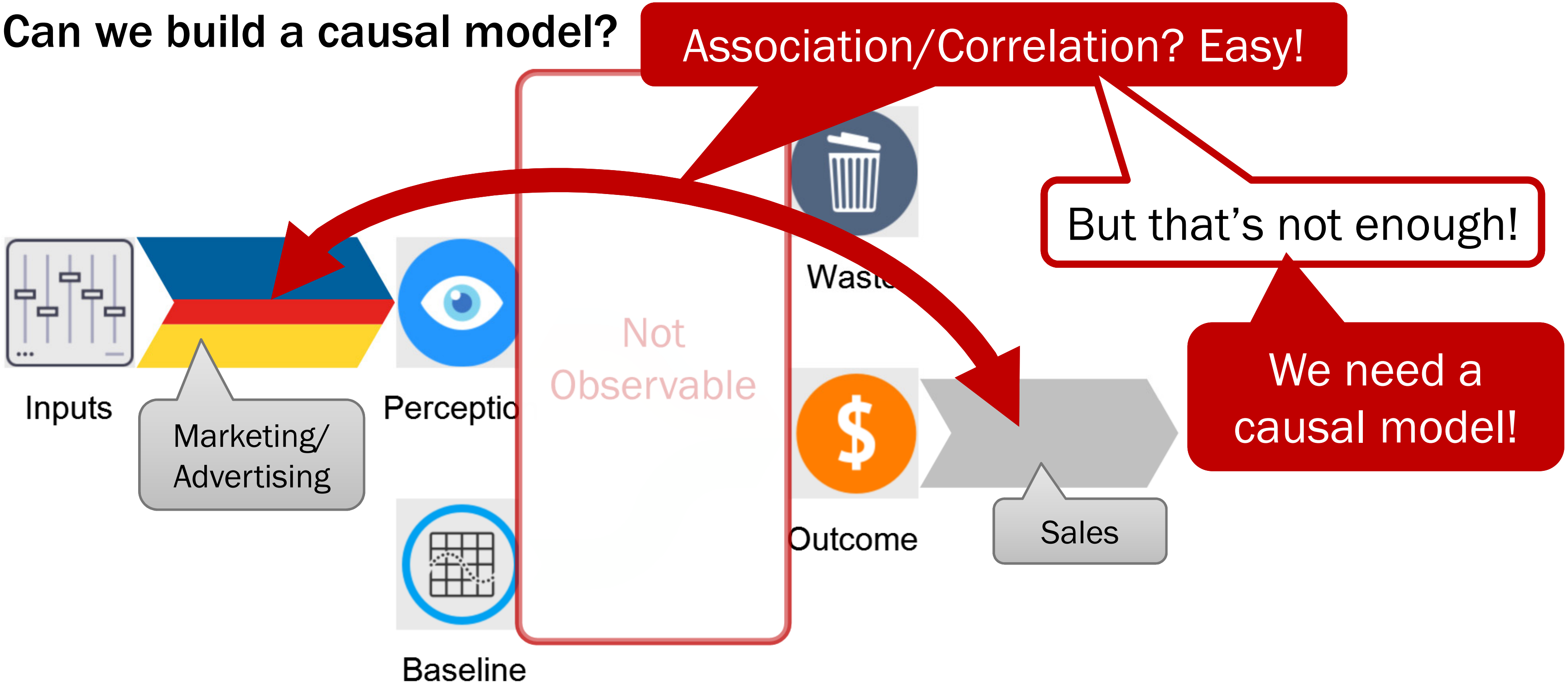
Had we **done** $X=0$ instead

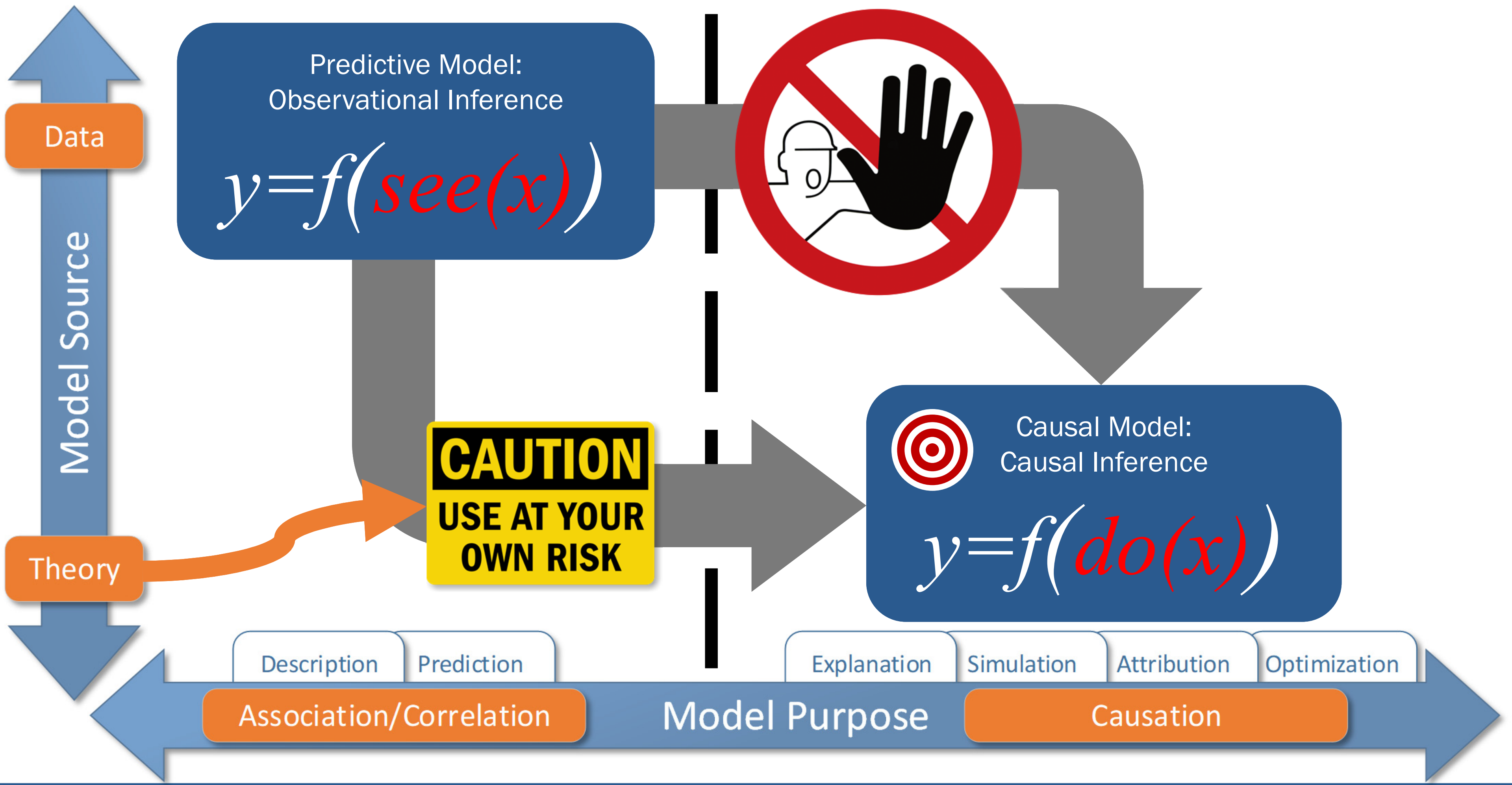
This is a causal question!

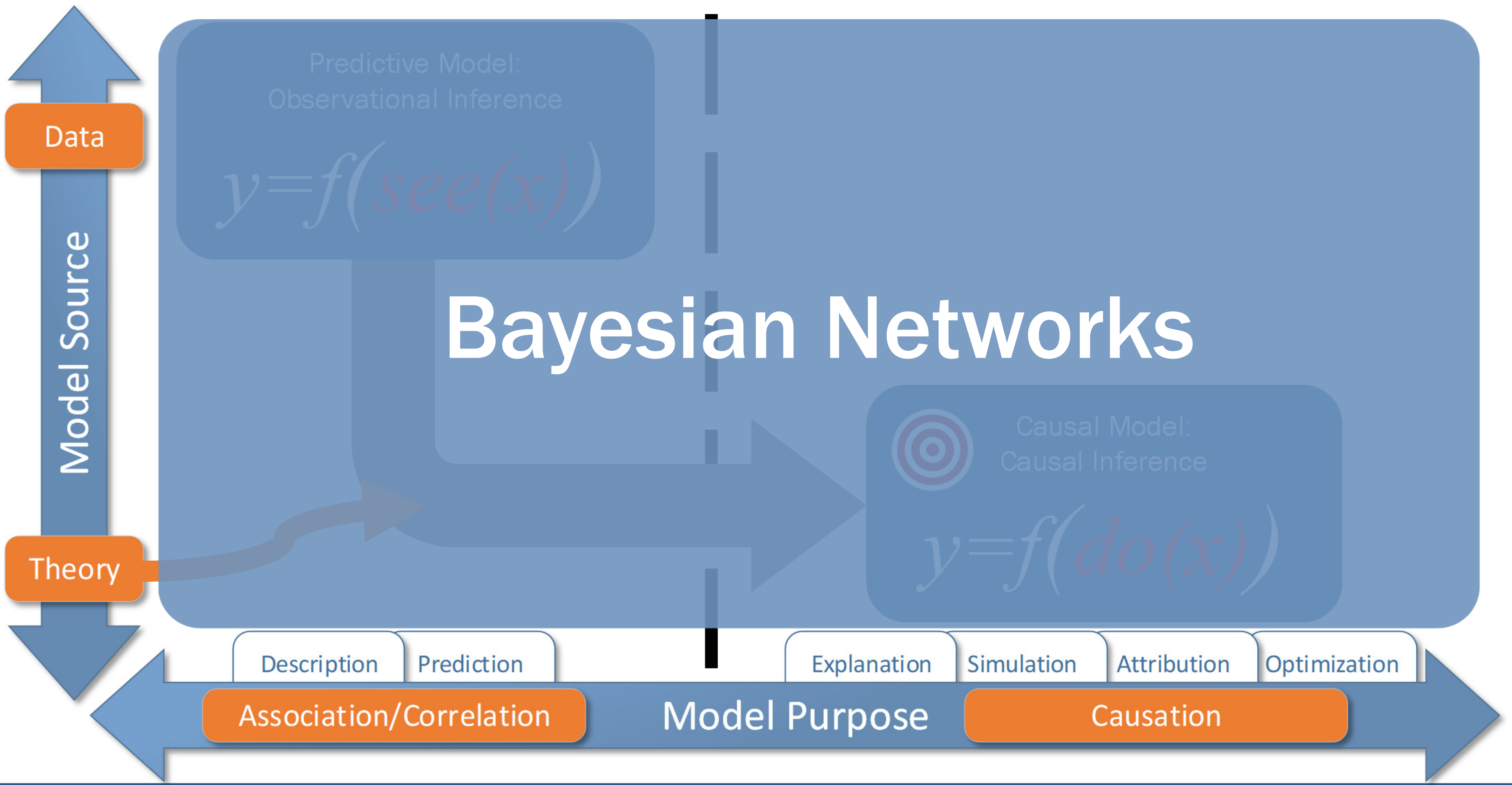
We could answer this causal question if we had a causal model and were able to simulate a counterfactual condition, i.e., $\mathrm{do}(X=0)$.

Causality

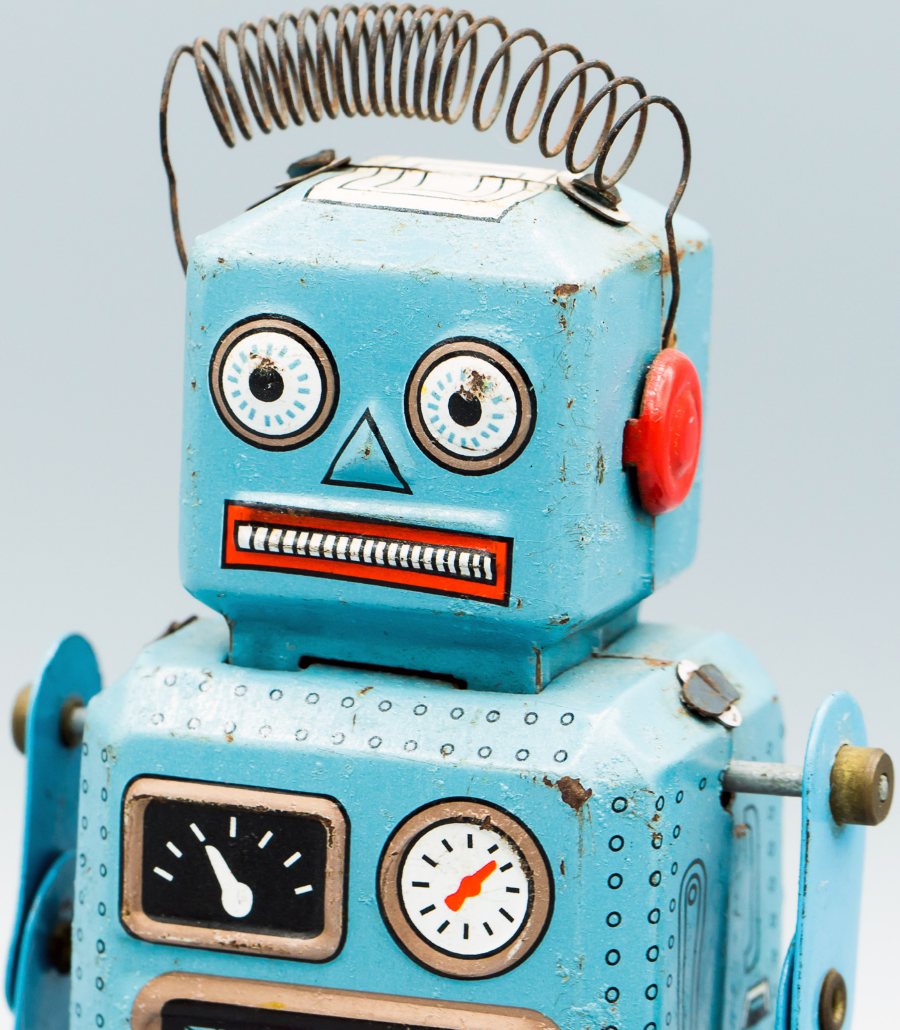
Can we build a causal model?




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


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

BAYESIALAB



Contribution Analysis

WITH A TOY EXAMPLE

Contribution Analysis

We have a fictional domain with this known data-generating process:

$$Y \leftarrow X_1 \times X_2 + X_3$$

We know exactly how the variables X contribute to the outcome Y.

- $X_1 \sim \mathcal{N}(5,3)$
- $X_2 \sim \mathcal{N}(5,3)$
- $X_3 \sim \mathcal{N}(25,5)$
- Note the causal assignment ($\leftarrow$)
- 5,000 Observations

Contribution Analysis

Y: "Outcome"

X_1, X_2, X_3: "Causes", "Drivers", etc.

We have a fictional domain with this known data-generating process:

$$Y \leftarrow X_1 \times X_2 + X_3$$

- $X_1 \sim \mathcal{N}(5,3)$
- $X_2 \sim \mathcal{N}(5,3)$
- $X_3 \sim \mathcal{N}(25,5)$
- Note the causal assignment ($\leftarrow$)
- 5,000 Observations

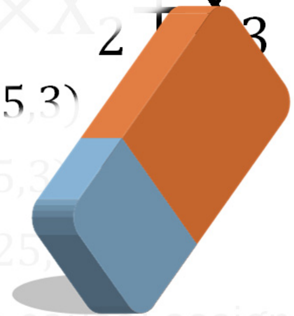
Y	X1	X2	X3
51.01	5.71	4.26	26.66
44.47	4.25	5.36	21.66
21.54	3.61	0.00	21.54
23.79	4.16	0.38	22.21
28.72	0.00	0.00	28.72
17.85	0.20	4.08	17.04
76.77	9.24	5.75	23.67
43.36	[illegible]	[illegible]	22.60
29.24	[illegible]	[illegible]	22.64
57.38	3.79	10.51	17.55

Synthetic Data

Contribution Analysis

We have a fictional domain with this known data-generating process:

$$Y \leftarrow X_1 \times X_2 + X_3$$



- $X_1 \sim \mathcal{N}(5,3)$
- $X_2 \sim \mathcal{N}(5,3$
- $X_3 \sim \mathcal{N}(25,$
- Note the causal assignment ($\leftarrow$)
- 5,000 Observations

Y: “Outcome”

X_1, X_2, X_3: “Causes”, “Drivers”, etc.

Y	X1	X2	X3
51.01	5.71	4.26	26.66
44.47	4.25	5.36	21.66
21.54	3.61	0.00	21.54
23.79	4.16	0.38	22.21
28.72	0.00	0.00	28.72
17.85	0.20	4.08	17.04
76.77	9.24	5.75	23.67
43.36	4.07	5.10	22.60
29.24	1.23	5.38	22.64
57.38	3.79	10.51	17.55

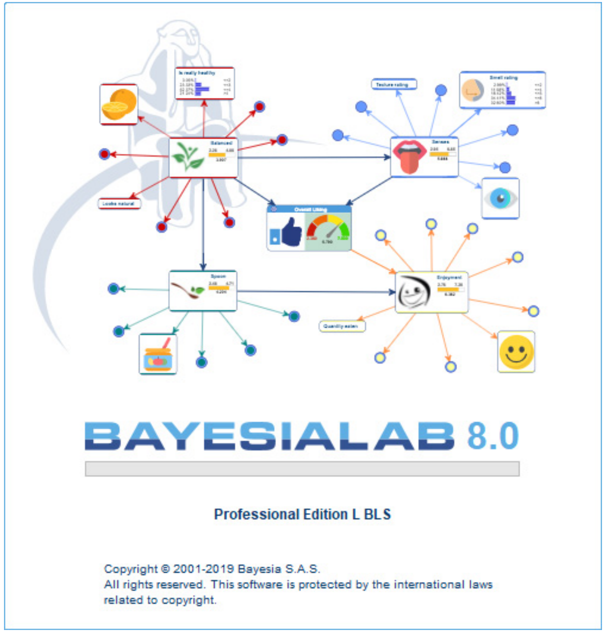
Contribution Analysis

Y	X1	X2	X3
51.01	5.71	4.26	26.66
44.47	4.25	5.36	21.66
21[illegible]	[illegible]	[illegible]	[illegible]54
23[illegible]	[illegible]	[illegible]	[illegible]21
28.72	[illegible]	[illegible]	[illegible].72
17.85	[illegible]	[illegible]	17.04
76.77	[illegible]	[illegible]	23.67
43.36	[illegible]	[illegible]	22.60
29.24	1.23	5.38	22.64
57.38	3.79	10.51	17.55

That's the typical starting point: Plenty of data, but little knowledge of the DGP.

Objective: Estimate contributions of drivers X_1, X_2, X_3

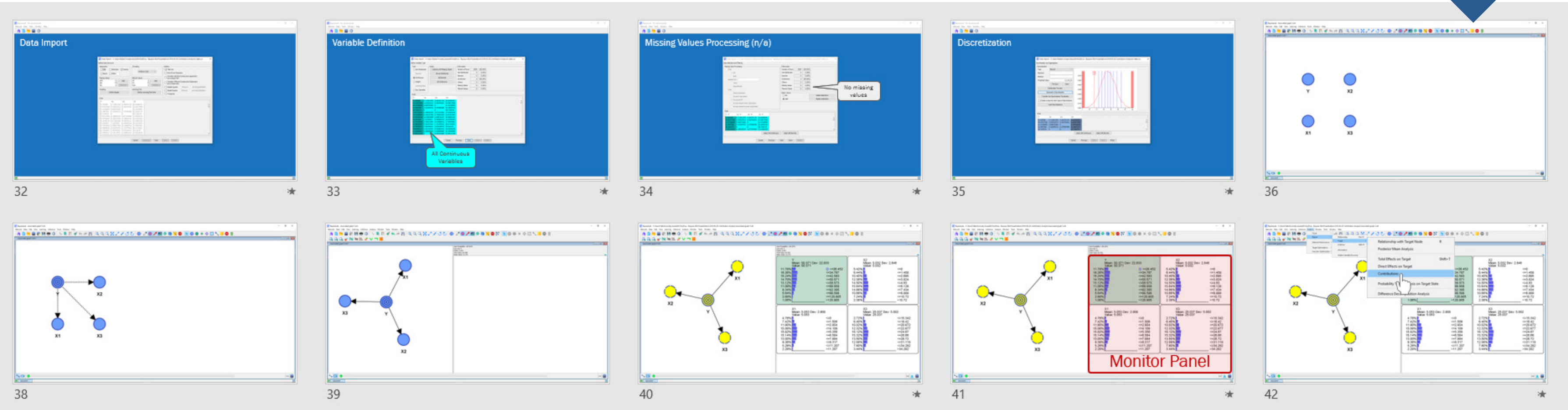
Workflow: Contribution Analysis with Bayesian Networks and BayesiaLab



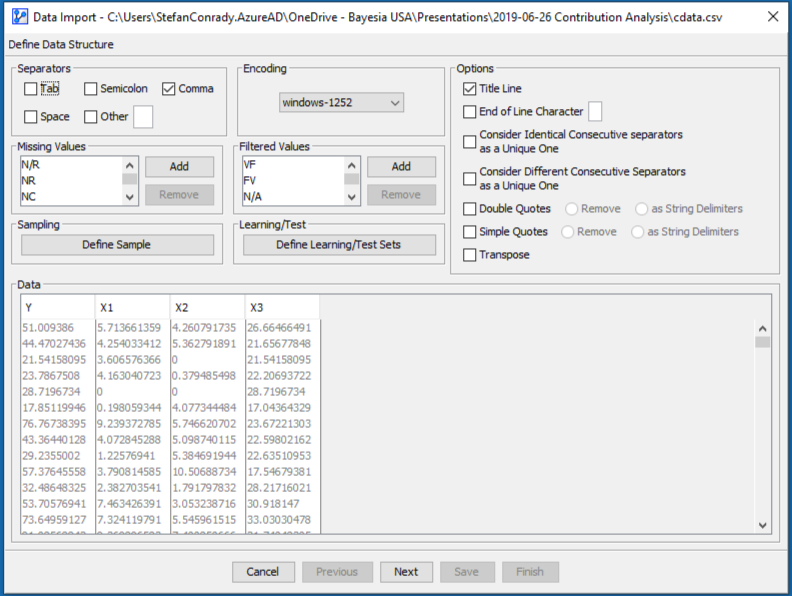
Contribution Analysis

Note on Workflow Presentation

1. Quick preview of BayesiaLab's contribution analysis implementation.
2. Step-by-step review of all individual steps involved in the calculations.



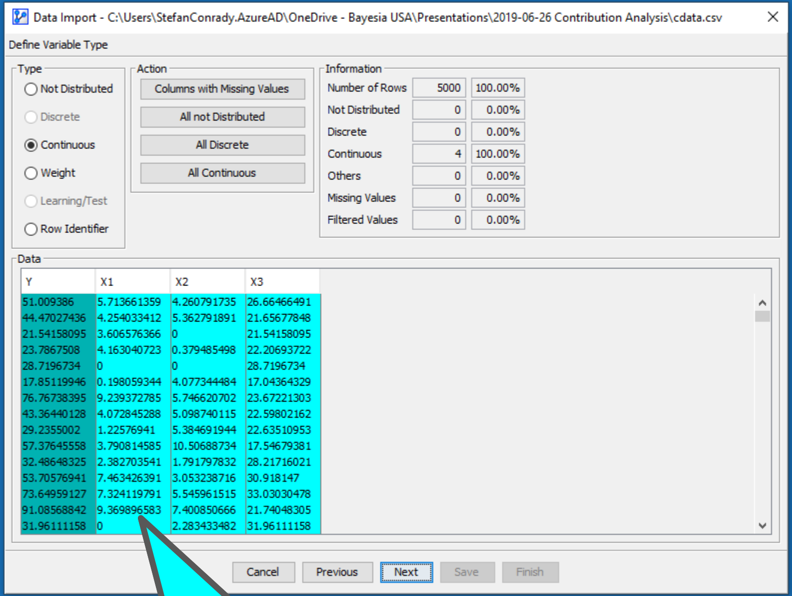
Data Import


Data Import - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\cdata.csv
Define Data Structure
Separators
Tab
Semicolon
Comma
Space
Other
Encoding
windows-1252
Options
Title Line
End of Line Character
Consider Identical Consecutive separators as a Unique One
Consider Different Consecutive Separators as a Unique One
Double Quotes
Remove
as String Delimiters
Simple Quotes
Remove
as String Delimiters
Transpose
Missing Values
N/R
NR
NC
Add
Remove
Filtered Values
VF
FV
N/A
Add
Remove
Sampling
Define Sample
Learning/Test
Define Learning/Test Sets
Data
Y
X1
X2
X3
51.009386 5.713661359 4.260791735 26.66466491
44.47027436 4.254033412 5.362791891 21.65677848
21.54158095 3.606576366 0 21.54158095
23.7867508 4.163040723 0.379485498 22.20693722
28.7196734 0 0 28.7196734
17.85119946 0.198059344 4.077344484 17.04364329
76.76738395 9.239372785 5.746620702 23.67221303
43.36440128 4.072845288 5.098740115 22.59802162
29.2355002 1.22576941 5.384691944 22.63510953
57.37645558 3.790814585 10.50688734 17.54679381
32.48648325 2.382703541 1.791797832 28.21716021
53.70576941 7.463426391 3.053238716 30.918147
73.64959127 7.324119791 5.545961515 33.03030478
Cancel
Previous
Next
Save
Finish

BayesiaLab - No opened graph

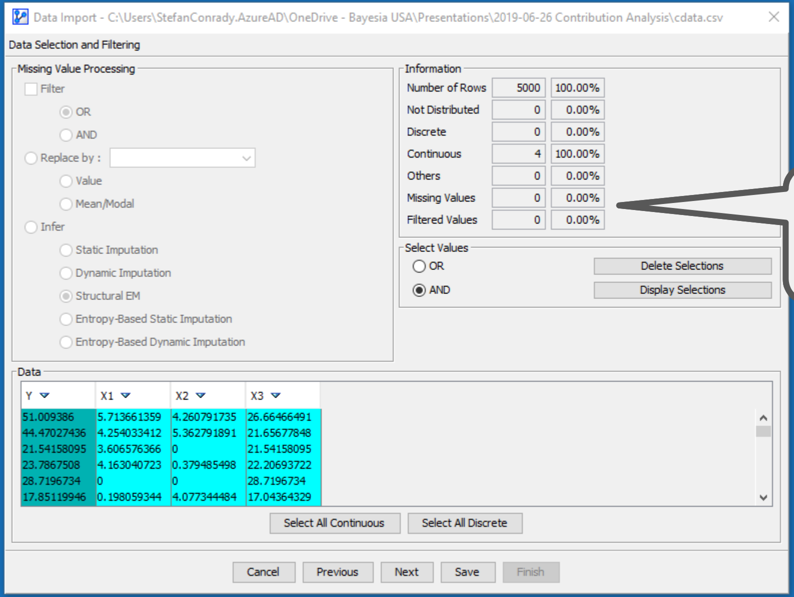
Network Data Tools Window Help

Variable Definition



All Continuous Variables

Missing Values Processing (n/a)

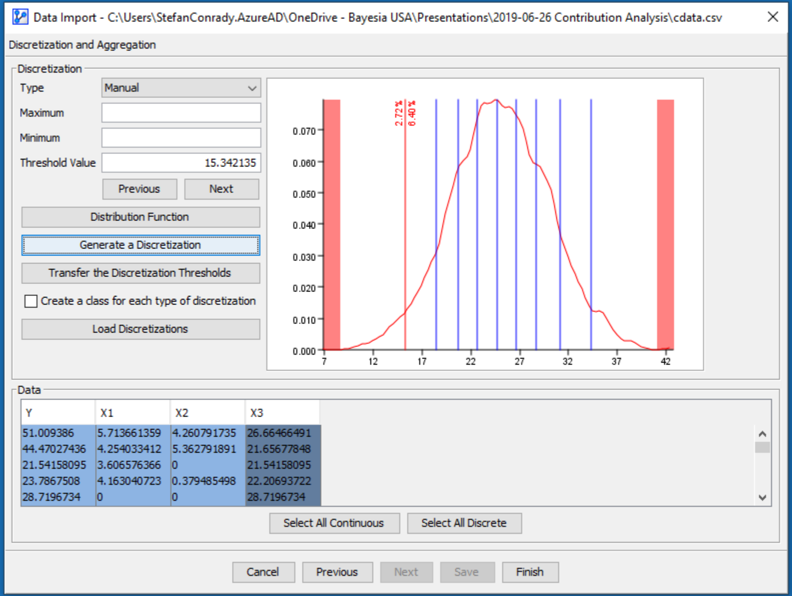


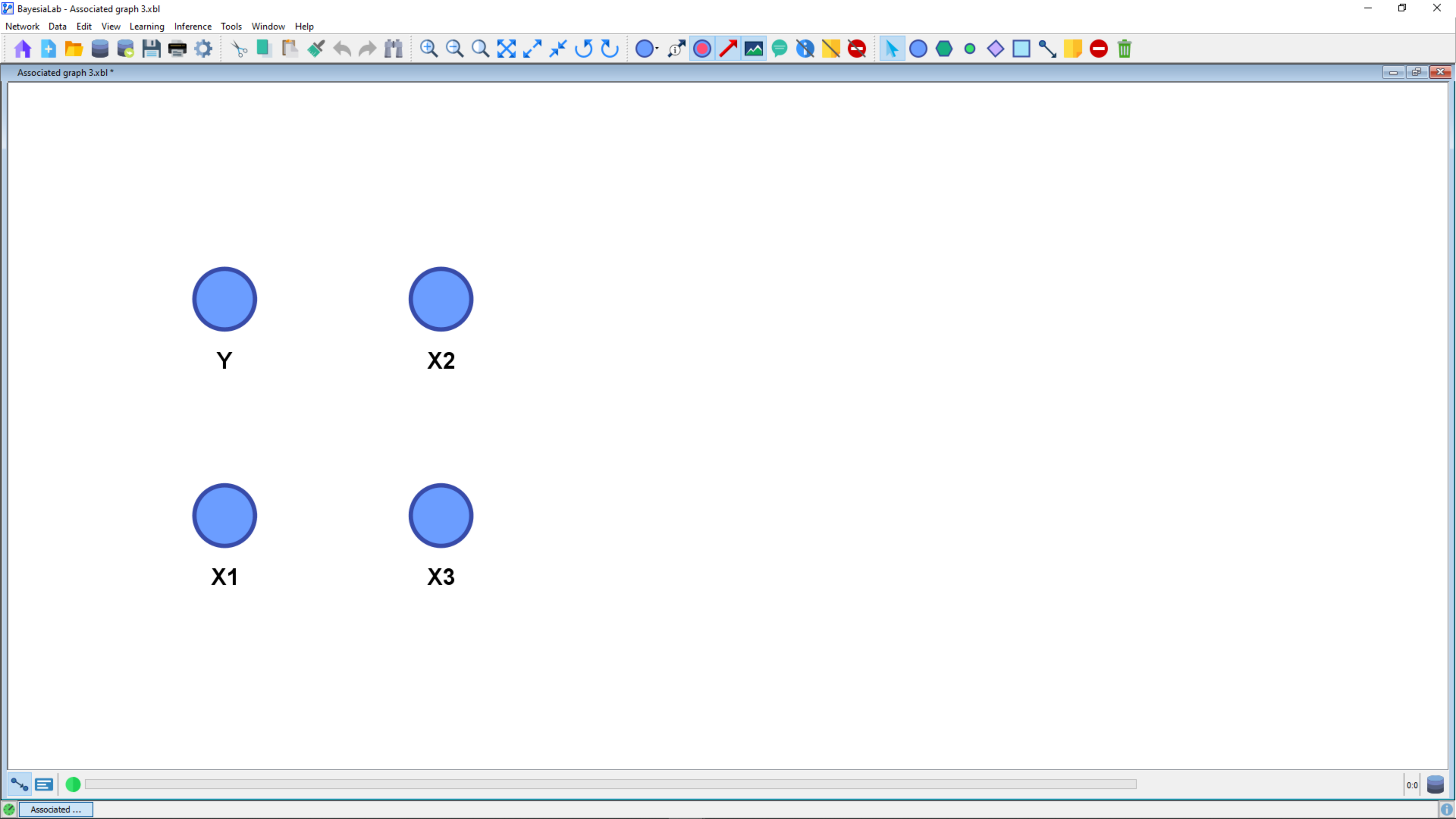
No missing values

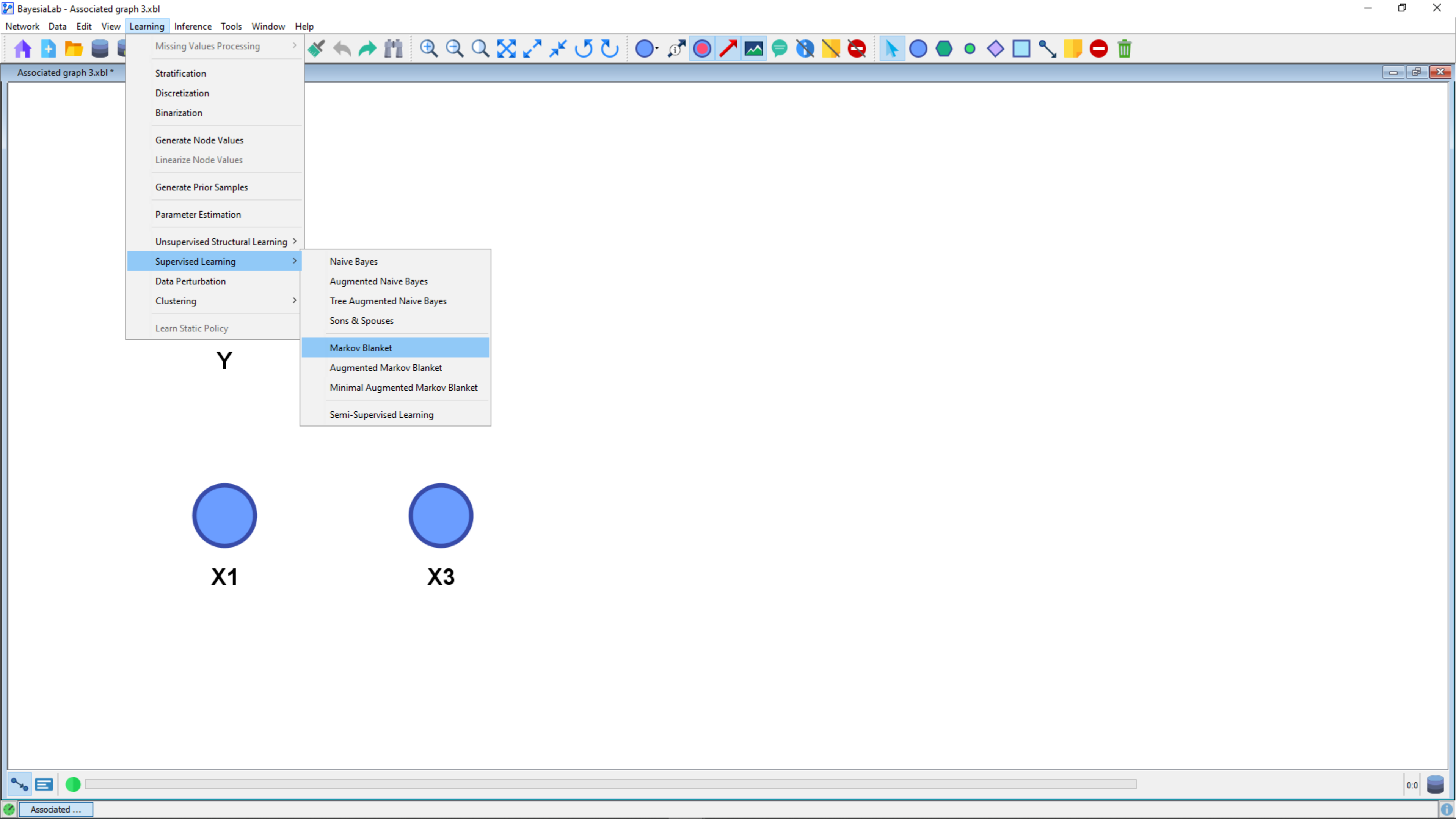
BayesiaLab - No opened graph

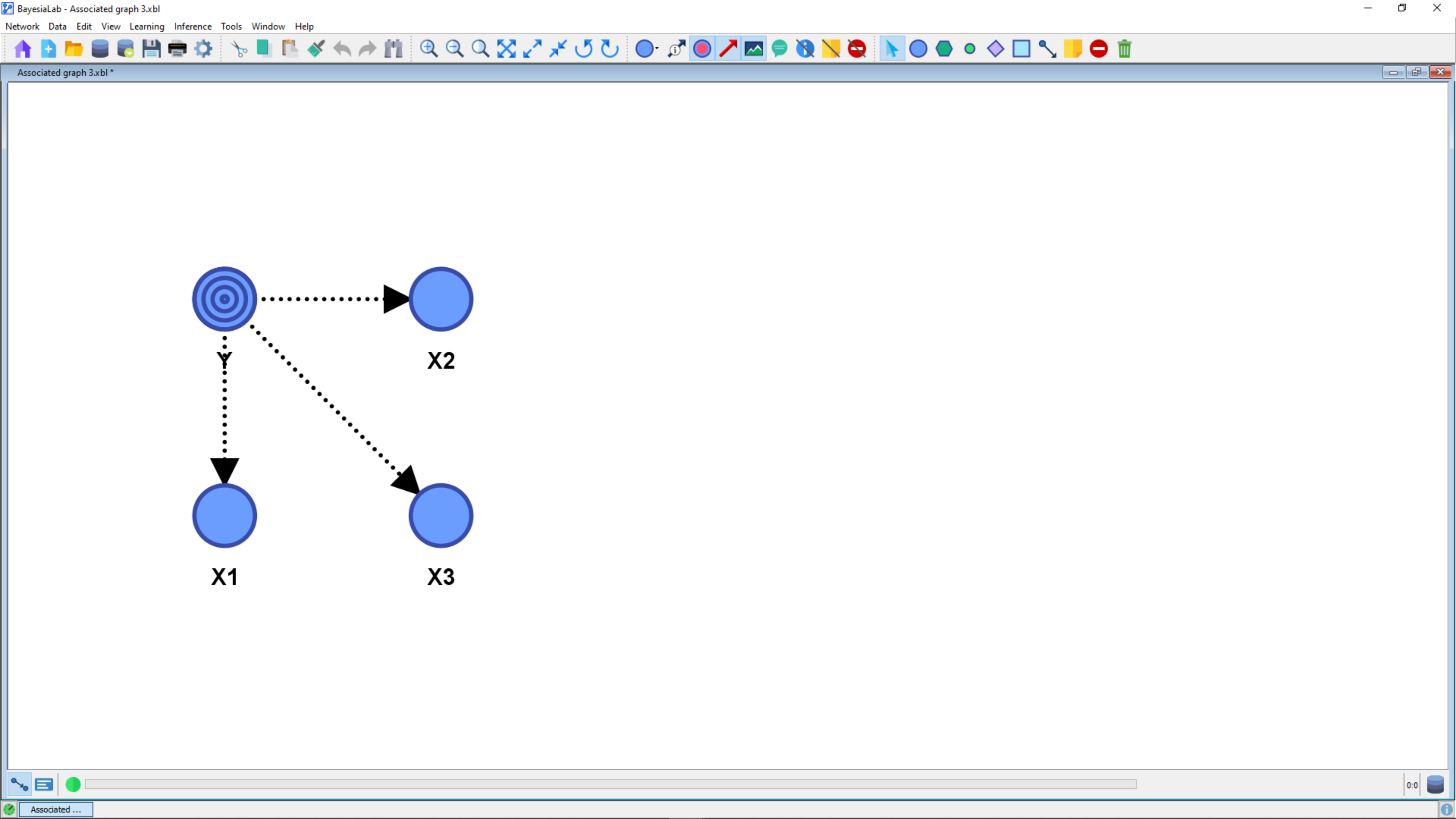
Network Data Tools Window Help

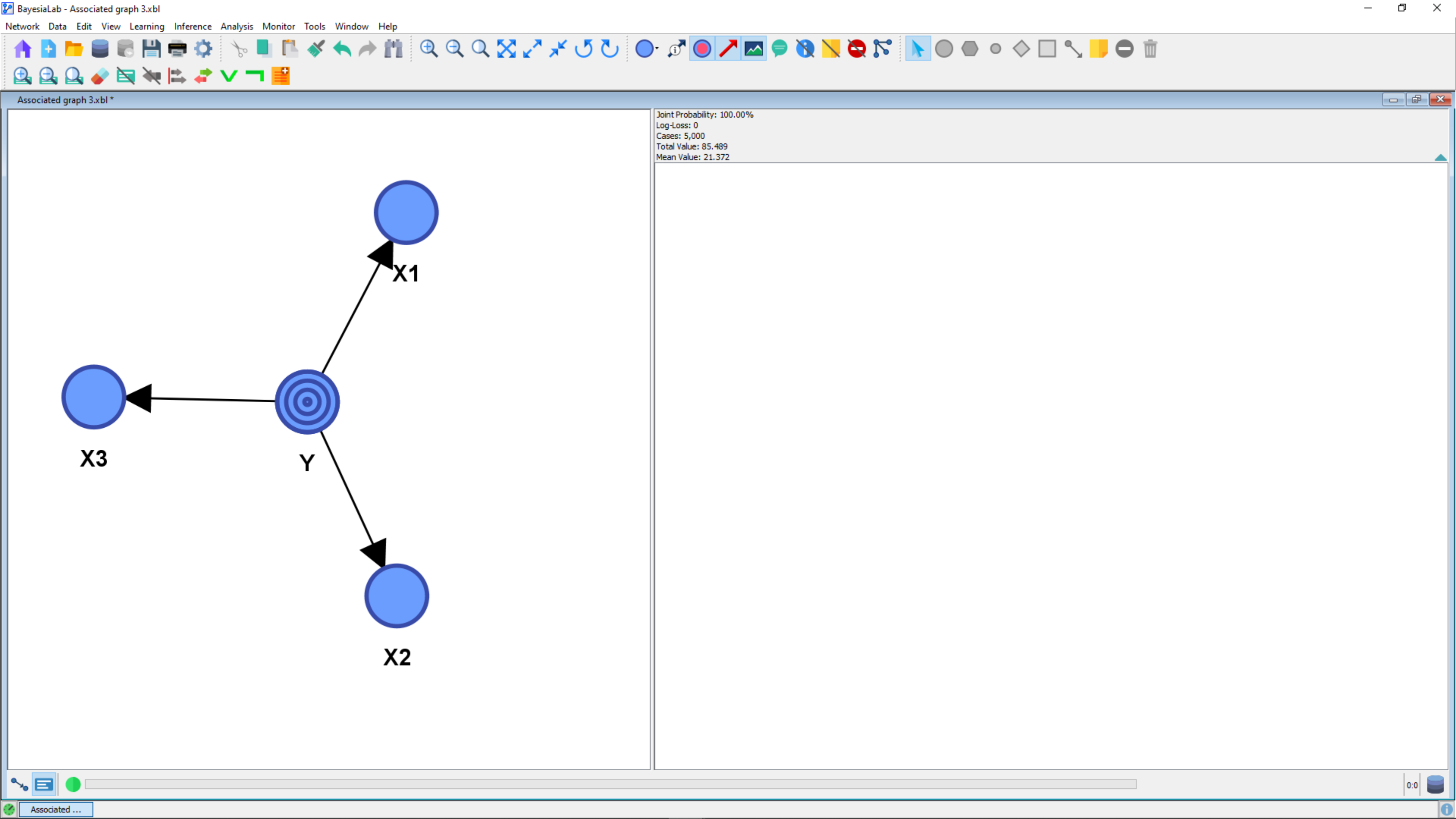
Discretization

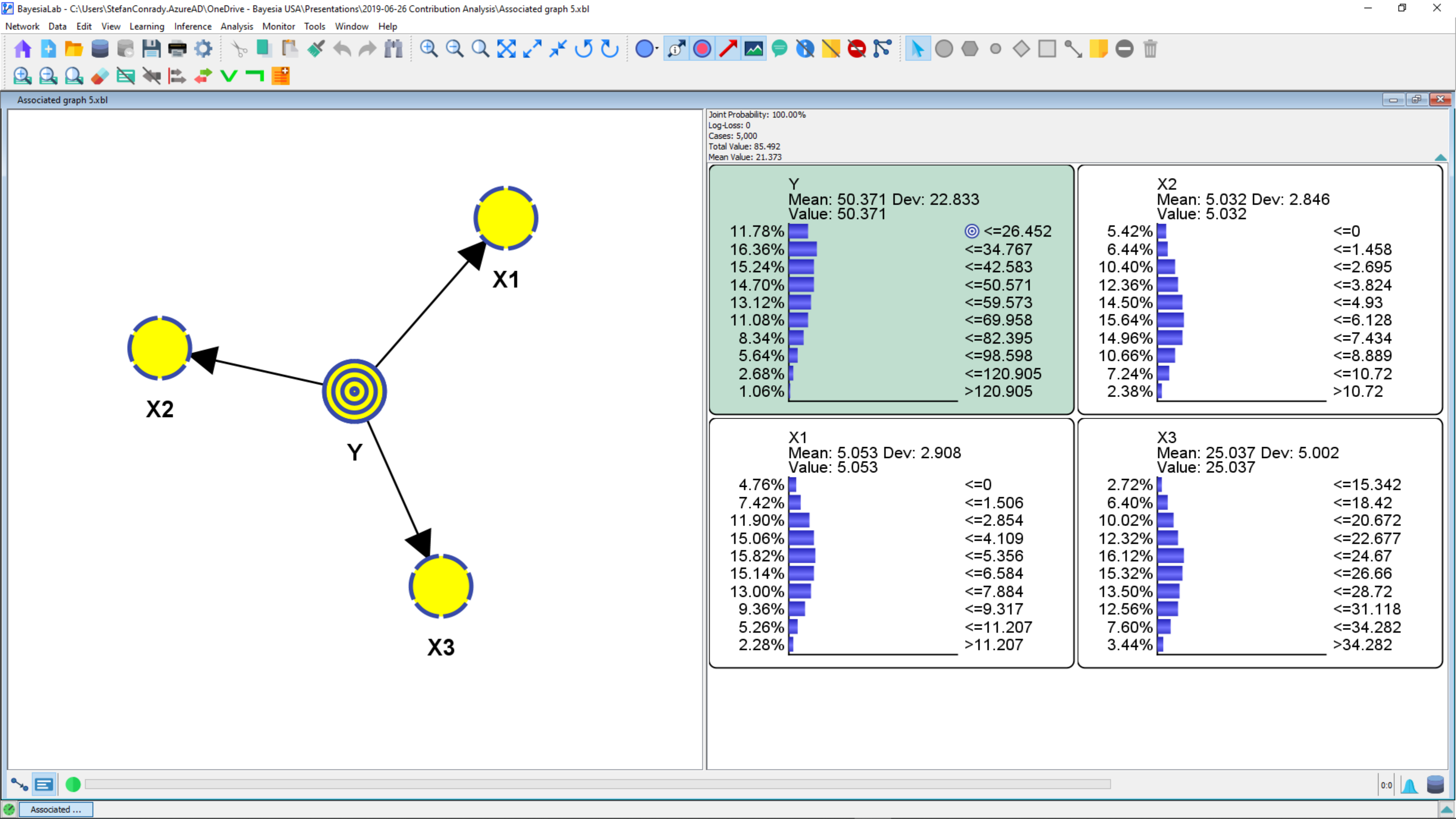


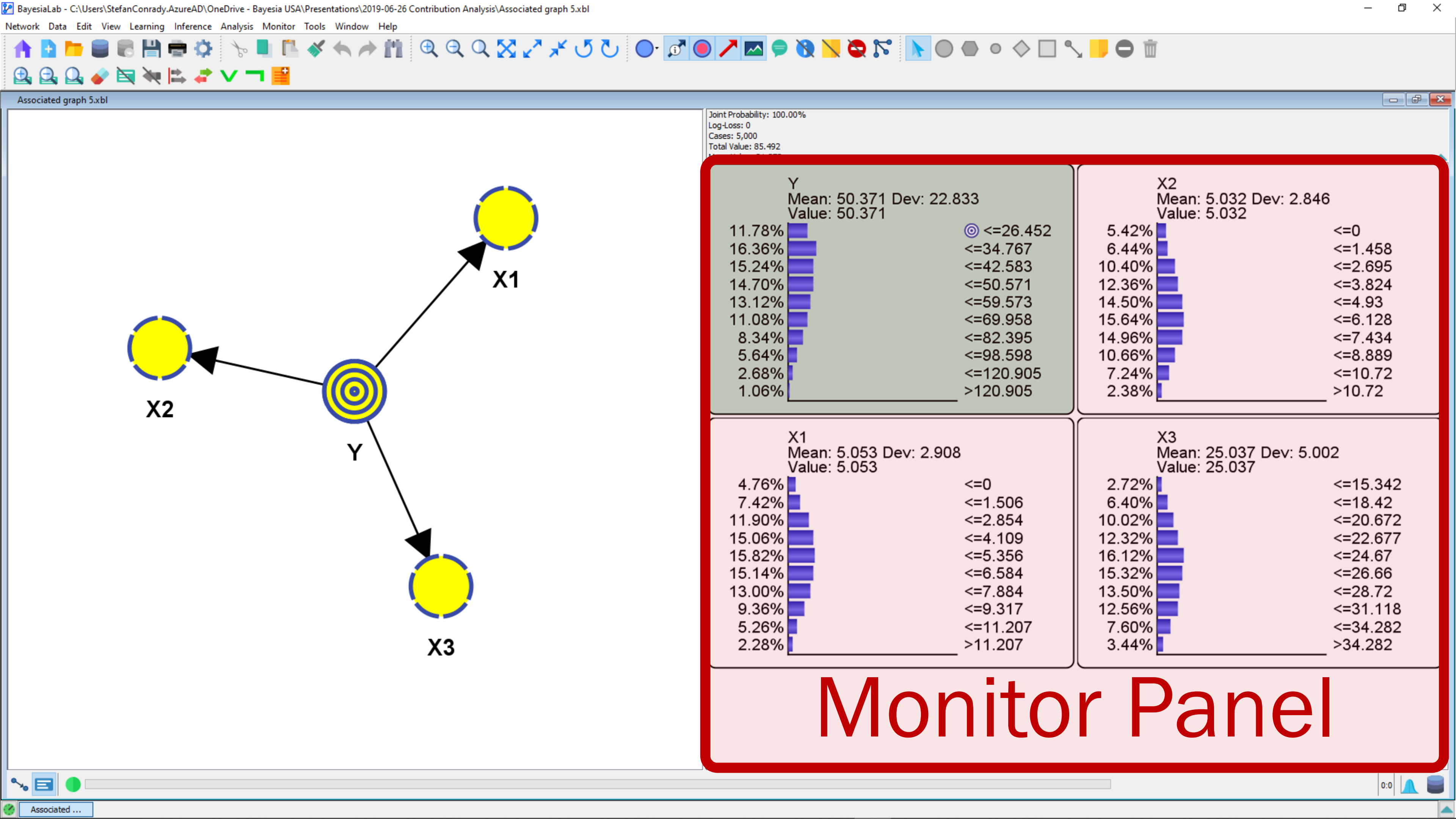

BayesiaLab - Associated graph 3.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 3.xbl *
Y
X2
X1
X3
0:0
Associated ...


BayesiaLab - Associated graph 3.xbl
Network
Data
Edit
View
Learning
Inference
Tools
Window
Help
Associated graph 3.xbl *
Missing Values Processing
Stratification
Discretization
Binarization
Generate Node Values
Linearize Node Values
Generate Prior Samples
Parameter Estimation
Unsupervised Structural Learning
Supervised Learning
Data Perturbation
Clustering
Learn Static Policy
Naive Bayes
Augmented Naive Bayes
Tree Augmented Naive Bayes
Sons & Spouses
Markov Blanket
Augmented Markov Blanket
Minimal Augmented Markov Blanket
Semi-Supervised Learning
Y
X1
X3
Associated ...

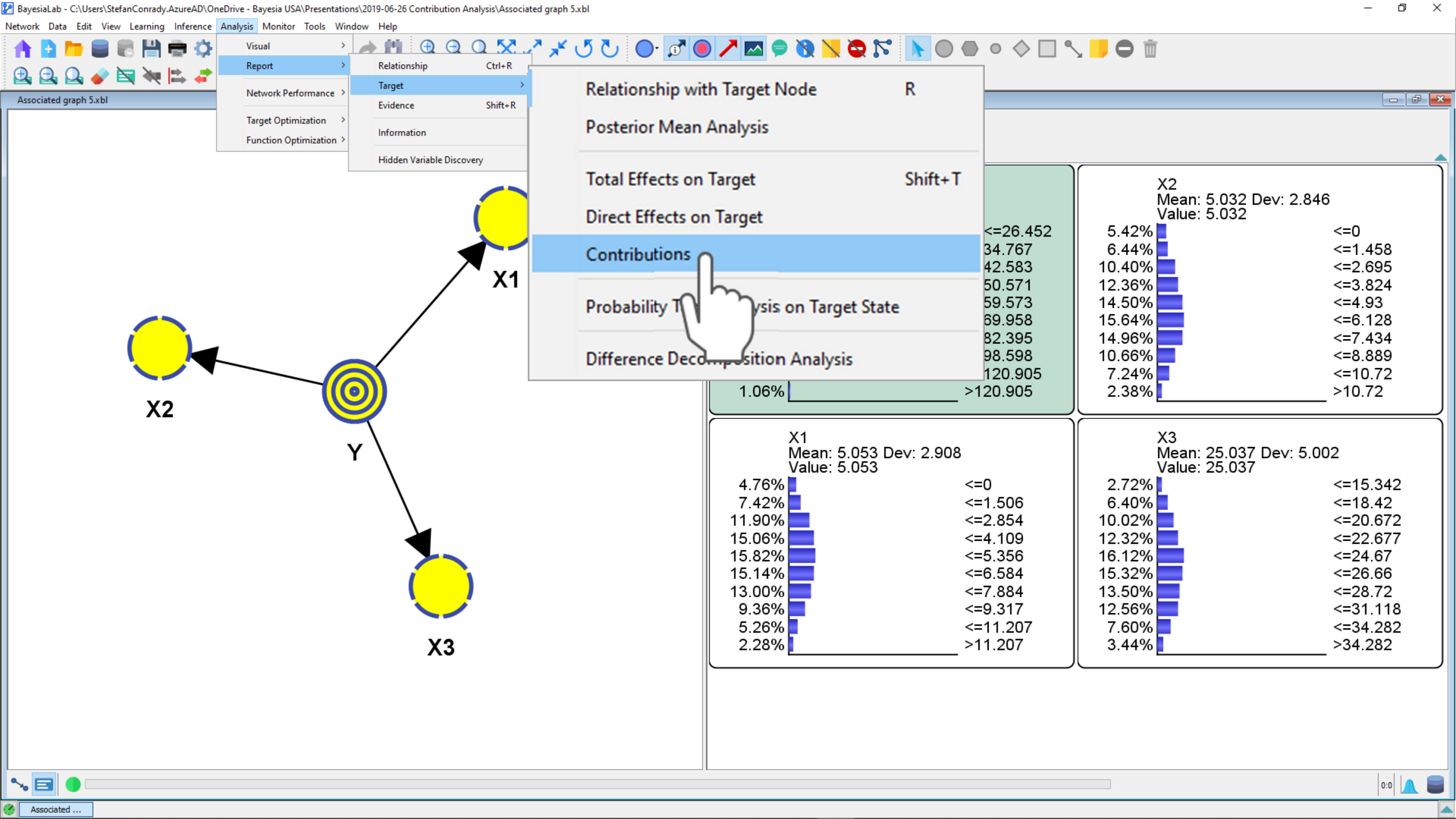

BayesiaLab - Associated graph 3.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 3.xbl *
Y
X2
X1
X3
Associated ...
0:0


BayesiaLab - Associated graph 3.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 3.xbl *
Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,000
Total Value: 85.489
Mean Value: 21.372
X1
X3
Y
X2
Associated ...

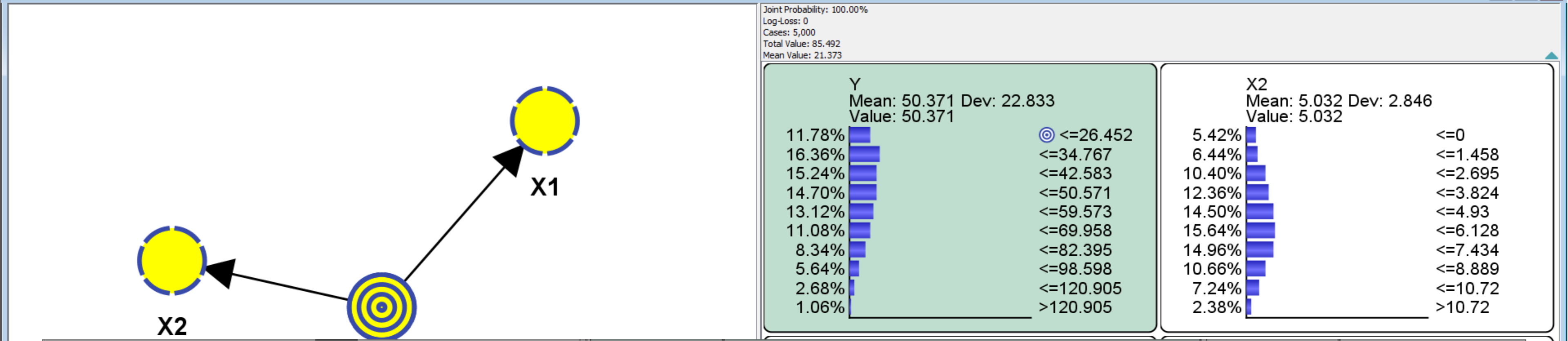

BayesiaLab - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\Associated graph 5.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 5.xbl
X1
X2
Y
X3
Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,000
Total Value: 85.492
Mean Value: 21.373
Y
Mean: 50.371 Dev: 22.833
Value: 50.371
11.78% <=26.452
16.36% <=34.767
15.24% <=42.583
14.70% <=50.571
13.12% <=59.573
11.08% <=69.958
8.34% <=82.395
5.64% <=98.598
2.68% <=120.905
1.06% >120.905
X2
Mean: 5.032 Dev: 2.846
Value: 5.032
5.42% <=0
6.44% <=1.458
10.40% <=2.695
12.36% <=3.824
14.50% <=4.93
15.64% <=6.128
14.96% <=7.434
10.66% <=8.889
7.24% <=10.72
2.38% >10.72
X1
Mean: 5.053 Dev: 2.908
Value: 5.053
4.76% <=0
7.42% <=1.506
11.90% <=2.854
15.06% <=4.109
15.82% <=5.356
15.14% <=6.584
13.00% <=7.884
9.36% <=9.317
5.26% <=11.207
2.28% >11.207
X3
Mean: 25.037 Dev: 5.002
Value: 25.037
2.72% <=15.342
6.40% <=18.42
10.02% <=20.672
12.32% <=22.677
16.12% <=24.67
15.32% <=26.66
13.50% <=28.72
12.56% <=31.118
7.60% <=34.282
3.44% >34.282
Associated ...



BayesiaLab - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\Associated graph 5.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 5.xbl
X1
X2
Y
X3
Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,000
Total Value: 85.492
Y
Mean: 50.371 Dev: 22.833
Value: 50.371
11.78% <=26.452
16.36% <=34.767
15.24% <=42.583
14.70% <=50.571
13.12% <=59.573
11.08% <=69.958
8.34% <=82.395
5.64% <=98.598
2.68% <=120.905
1.06% >120.905
X2
Mean: 5.032 Dev: 2.846
Value: 5.032
5.42% <=0
6.44% <=1.458
10.40% <=2.695
12.36% <=3.824
14.50% <=4.93
15.64% <=6.128
14.96% <=7.434
10.66% <=8.889
7.24% <=10.72
2.38% >10.72
X1
Mean: 5.053 Dev: 2.908
Value: 5.053
4.76% <=0
7.42% <=1.506
11.90% <=2.854
15.06% <=4.109
15.82% <=5.356
15.14% <=6.584
13.00% <=7.884
9.36% <=9.317
5.26% <=11.207
2.28% >11.207
X3
Mean: 25.037 Dev: 5.002
Value: 25.037
2.72% <=15.342
6.40% <=18.42
10.02% <=20.672
12.32% <=22.677
16.12% <=24.67
15.32% <=26.66
13.50% <=28.72
12.56% <=31.118
7.60% <=34.282
3.44% >34.282
Monitor Panel
Associated ...


BayesiaLab - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\Associated graph 5.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Visual
Report
Network Performance
Target Optimization
Function Optimization
Relationship Ctrl+R
Target
Evidence Shift+R
Information
Hidden Variable Discovery
Relationship with Target Node R
Posterior Mean Analysis
Total Effects on Target Shift+T
Direct Effects on Target
Contributions
ysis on Target State
Difference Dec
sition Analysis
Associated graph 5.xbl
X1
X2
Y
X3
<=26.452
34.767
42.583
50.571
59.573
69.958
82.395
98.598
120.905
1.06% >120.905
X2
Mean: 5.032 Dev: 2.846
Value: 5.032
5.42% <=0
6.44% <=1.458
10.40% <=2.695
12.36% <=3.824
14.50% <=4.93
15.64% <=6.128
14.96% <=7.434
10.66% <=8.889
7.24% <=10.72
2.38% >10.72
X1
Mean: 5.053 Dev: 2.908
Value: 5.053
4.76% <=0
7.42% <=1.506
11.90% <=2.854
15.06% <=4.109
15.82% <=5.356
15.14% <=6.584
13.00% <=7.884
9.36% <=9.317
5.26% <=11.207
2.28% >11.207
X3
Mean: 25.037 Dev: 5.002
Value: 25.037
2.72% <=15.342
6.40% <=18.42
10.02% <=20.672
12.32% <=22.677
16.12% <=24.67
15.32% <=26.66
13.50% <=28.72
12.56% <=31.118
7.60% <=34.282
3.44% >34.282
Associated ...

Contribution Analysis Report



Contributions (Associated graph 5) [2]

Contributions on Y (Base: 48.8998%)

Node	Mean Contribution	Decomposition 1 (Model)	Contribution 1 (Model)	Decomposition 2 (Model)	Contribution 2 (Model)	Decomposition 1 (Data)	Contribution 1 (Data)	Decomposition 2 (Data)	Contribution 2 (Data)
X1	21.3815%	22.8142	45.0989%	0.9638	1.9052%	99,458.2723	36.3607%	4,819.0001	2.1613%
X2	21.3292%	22.8088	45.0883%	0.8455	1.6714%	99,624.8467	36.5256%	4,227.7506	2.0315%
X3	8.3895%	4.8512	9.5899%	3.4264	6.7733%	21,580.0313	9.4535%	17,131.9246	7.7414%

Synergies

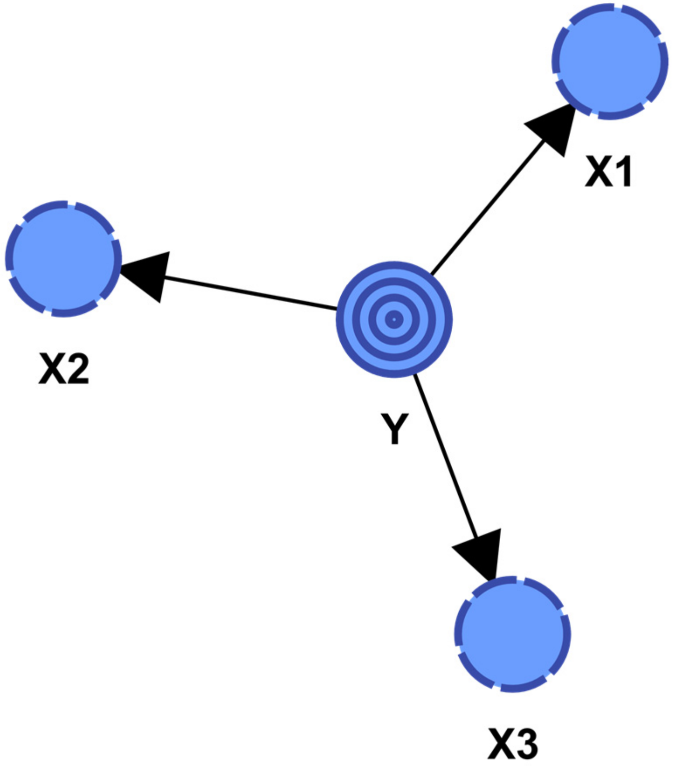
Node	Node	Mean Synergy	Decomposition (Model)	Contribution (Model)	Decomposition (Data)	Contribution (Data)
X1	X2	75.6832%	21.0754	75.9858%	93,774.5458	75.3807%
X2	X3	2.6116%	0.6498	2.3427%	3,583.3804	2.8805%
X1	X3	2.1035%	0.5369	1.9358%	2,825.5564	2.2713%

Close Save As... Print Curves

Contribution Analysis

Was that a proper causal model?

Contribution Analysis

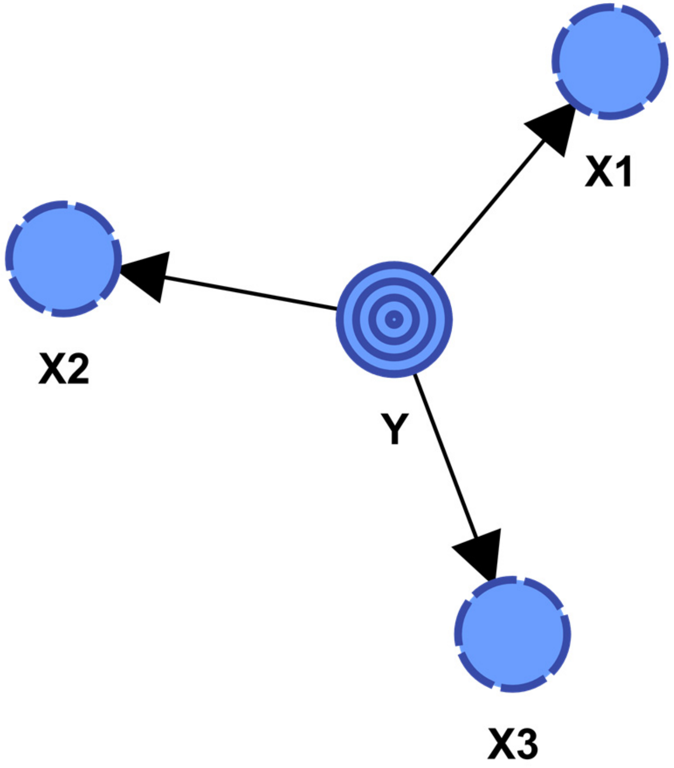


- Is this this Bayesian network a proper causal model for the given domain?

NO!

$$\neq \quad Y \leftarrow X_1 \times X_2 + X_3$$

Contribution Analysis



- However, this Bayesian network serves as an approximation of the joint probability distribution of the underlying data.
- As it turns out, we can still use this machine-learned, non-causal Bayesian network for causal inference!
- How? We need to condition on the confounders!
- What are the confounders?
- The **Disjunctive Cause Criterion** helps us identify them!

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.

NIH-PA Author Manuscript

A new criterion for confounder selection

Tyler J. VanderWeele and
Departments of Epidemiology and Biostatistics, Harvard School of Public Health 677 Huntington Avenue, Boston, MA 02115, Phone: 617-432-7855; Fax: 617-4321884

Ilya Shpitser
Department of Epidemiology, Harvard School of Public Health 677 Huntington Avenue, Boston, MA 02115

Tyler J. VanderWeele: tvanderw@hsph.harvard.edu

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

NIH-PA Auth

Disjunctive Cause Criterion

VanderWeele and Shpitser (2011)

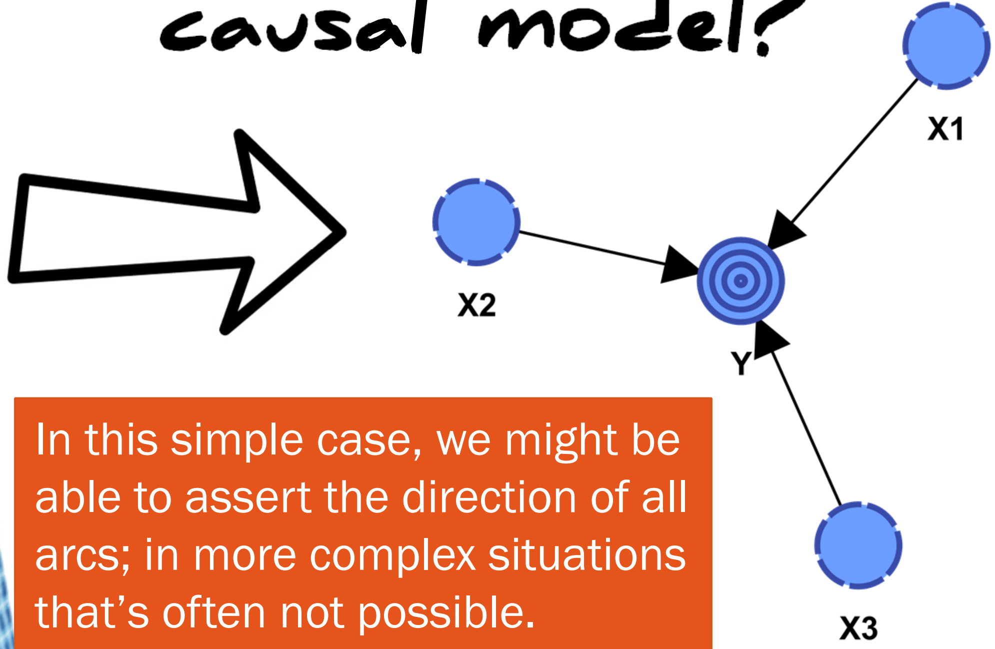
- "We propose that control be made for any [pre-treatment] **covariate** that is either a cause of **treatment** or of the **outcome** or both."

Implementation in BayesiaLab:
Likelihood Matching on Confounders in
Direct Effects Analysis → Causal Effect

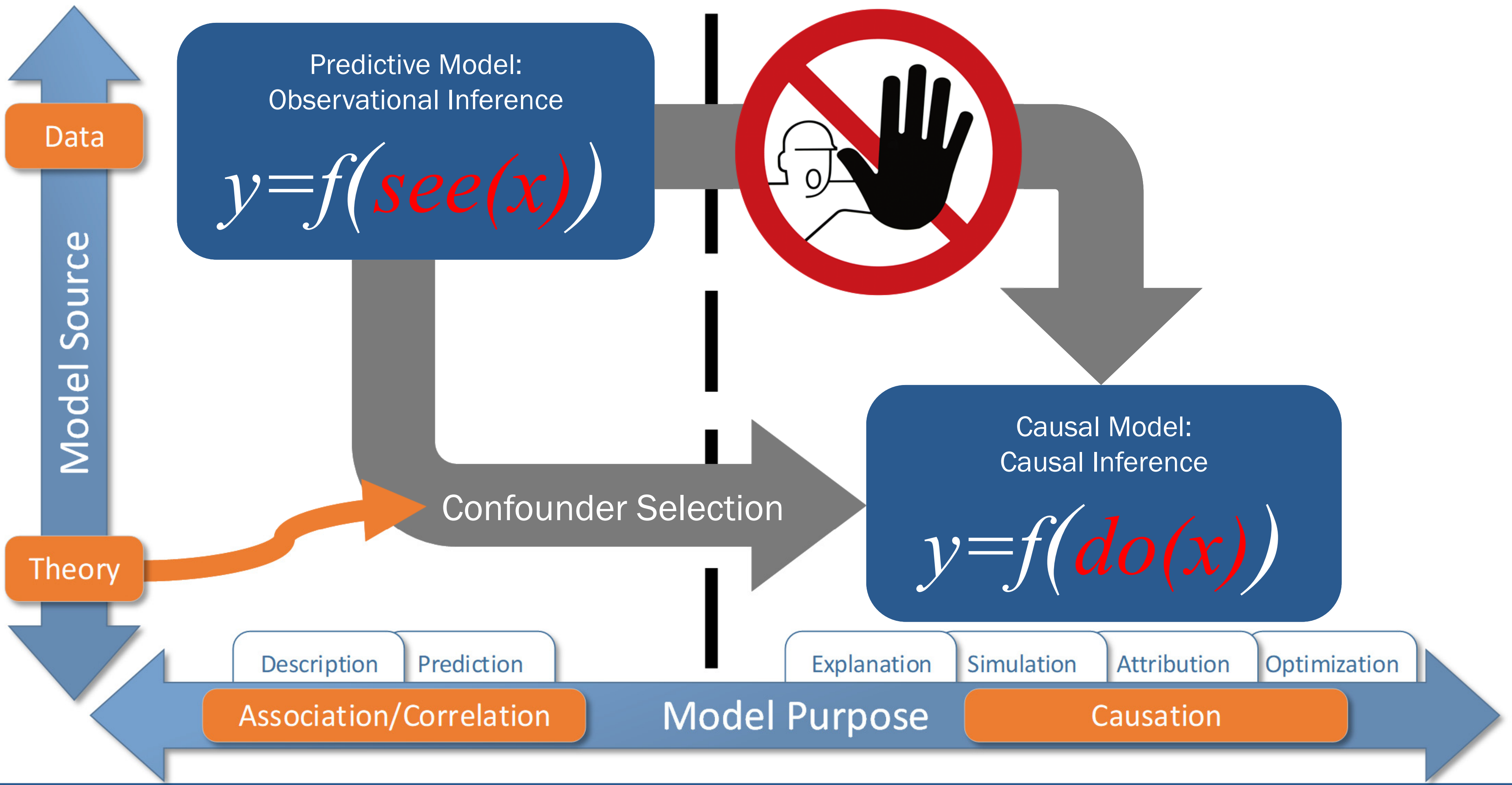
IMPORTANT ASSUMPTION:
NO UNOBSERVED CONFOUNDERS

Contribution Analysis

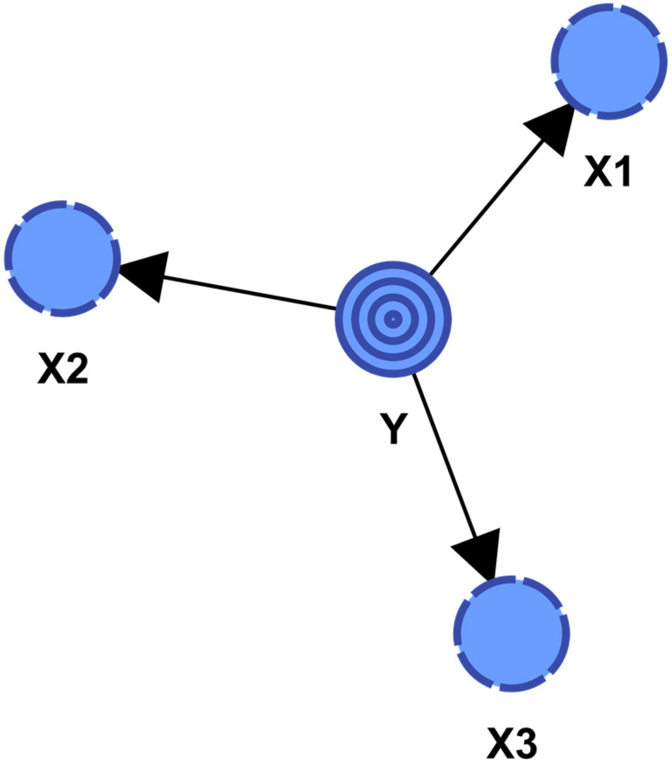
Why are we not creating a "real" causal model?



In this simple case, we might be able to assert the direction of all arcs; in more complex situations that's often not possible.

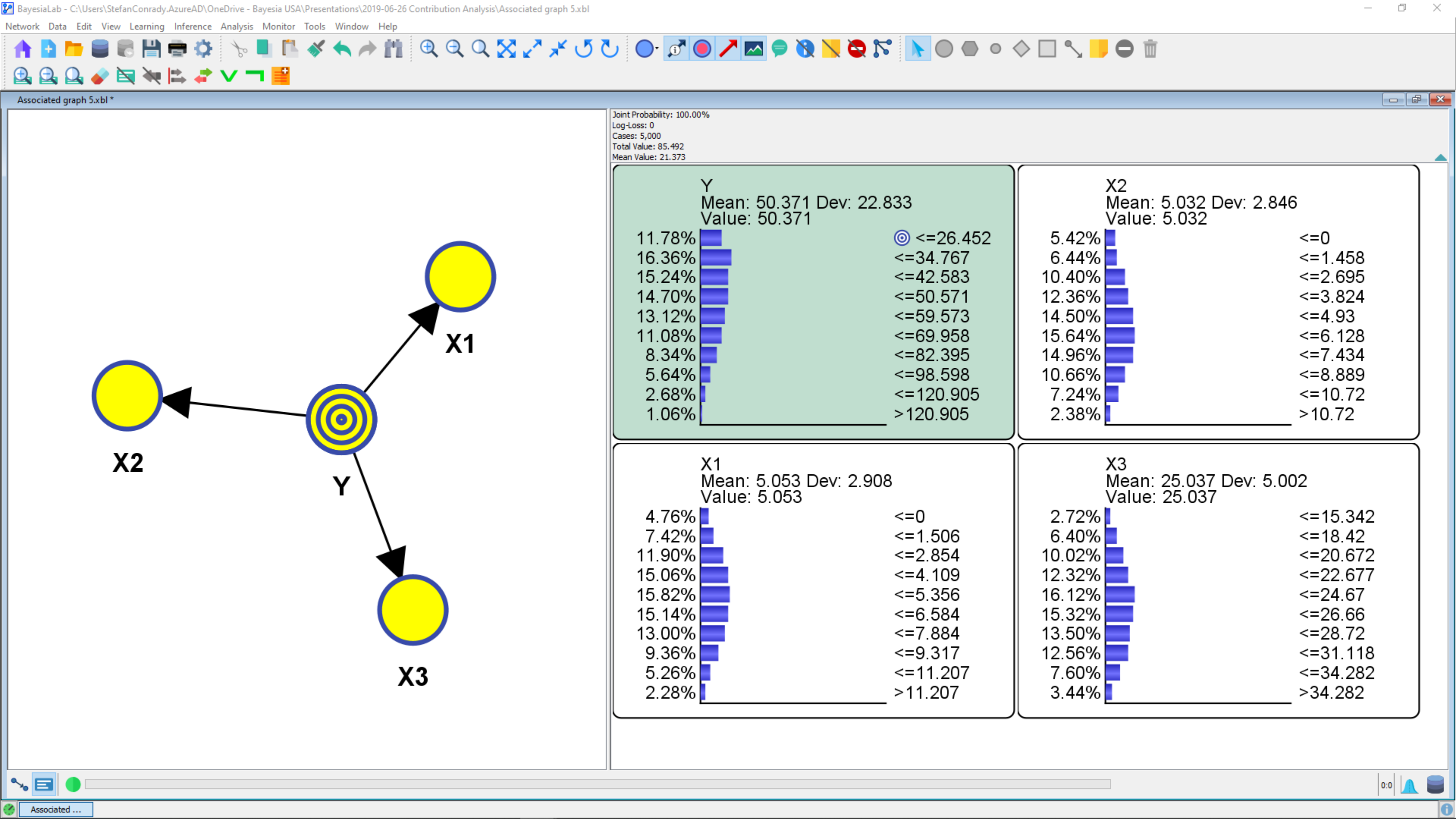

Predictive Model:
Observational Inference
$y=f(see(x))$
Data
Model Source
Theory
Confounder Selection
Causal Model:
Causal Inference
$y=f(do(x))$
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Contribution Analysis

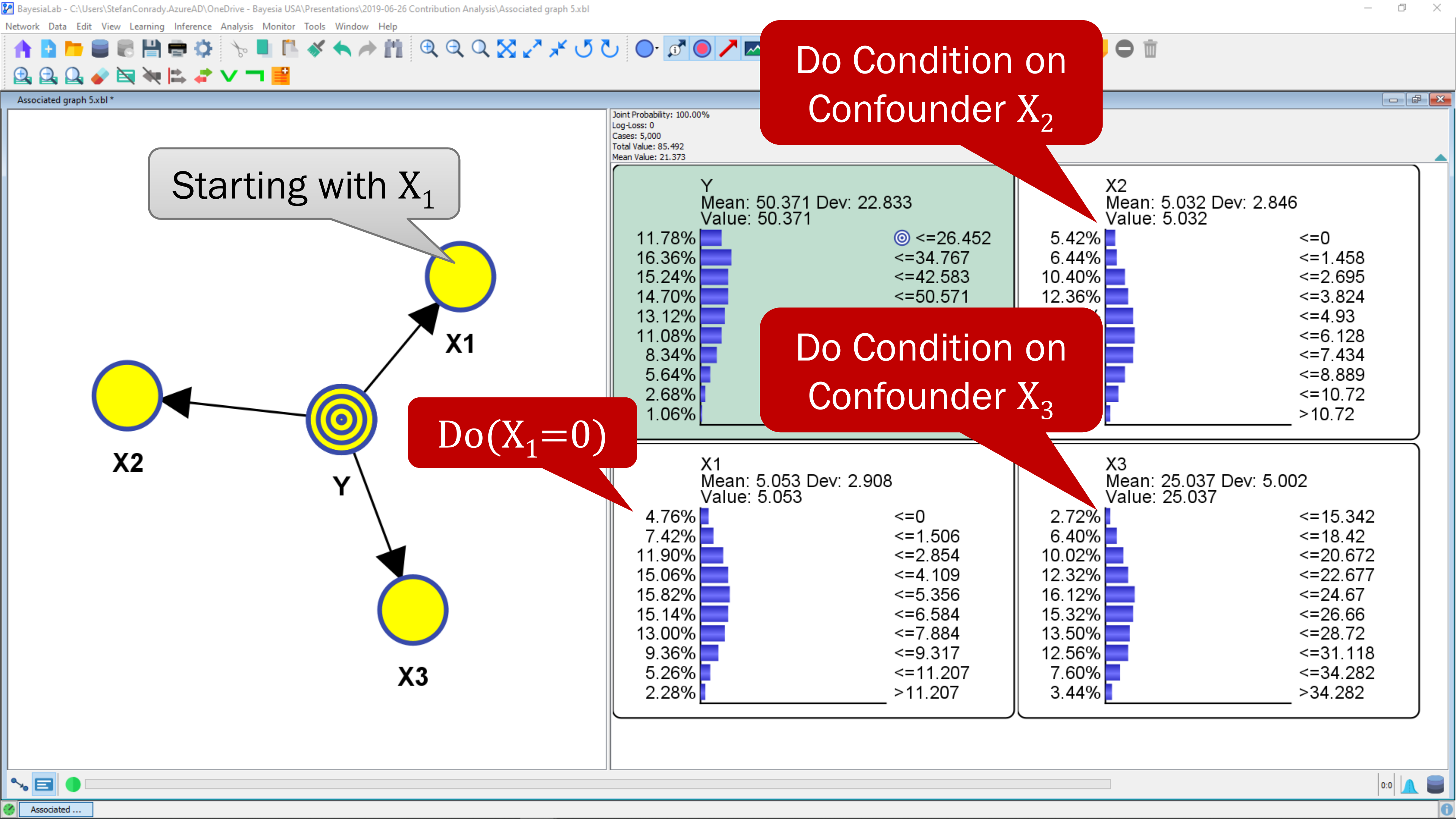


Simulating Counterfactual Interventions

- We can now use this Bayesian network model to simulate counterfactual interventions on any of the X variables to infer their individual causals effect on Y.
- As a result, we can answer questions, such as:
    - What would have been the value of Y, had X_1 not been at the factual level but had we set it to a counterfactual level of $X_1=0$?



BayesiaLab - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\Associated graph 5.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 5.xbl *
X1
X2
Y
X3
Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,000
Total Value: 85.492
Mean Value: 21.373
Y
Mean: 50.371 Dev: 22.833
Value: 50.371
11.78% <=26.452
16.36% <=34.767
15.24% <=42.583
14.70% <=50.571
13.12% <=59.573
11.08% <=69.958
8.34% <=82.395
5.64% <=98.598
2.68% <=120.905
1.06% >120.905
X2
Mean: 5.032 Dev: 2.846
Value: 5.032
5.42% <=0
6.44% <=1.458
10.40% <=2.695
12.36% <=3.824
14.50% <=4.93
15.64% <=6.128
14.96% <=7.434
10.66% <=8.889
7.24% <=10.72
2.38% >10.72
X1
Mean: 5.053 Dev: 2.908
Value: 5.053
4.76% <=0
7.42% <=1.506
11.90% <=2.854
15.06% <=4.109
15.82% <=5.356
15.14% <=6.584
13.00% <=7.884
9.36% <=9.317
5.26% <=11.207
2.28% >11.207
X3
Mean: 25.037 Dev: 5.002
Value: 25.037
2.72% <=15.342
6.40% <=18.42
10.02% <=20.672
12.32% <=22.677
16.12% <=24.67
15.32% <=26.66
13.50% <=28.72
12.56% <=31.118
7.60% <=34.282
3.44% >34.282
Associated ...

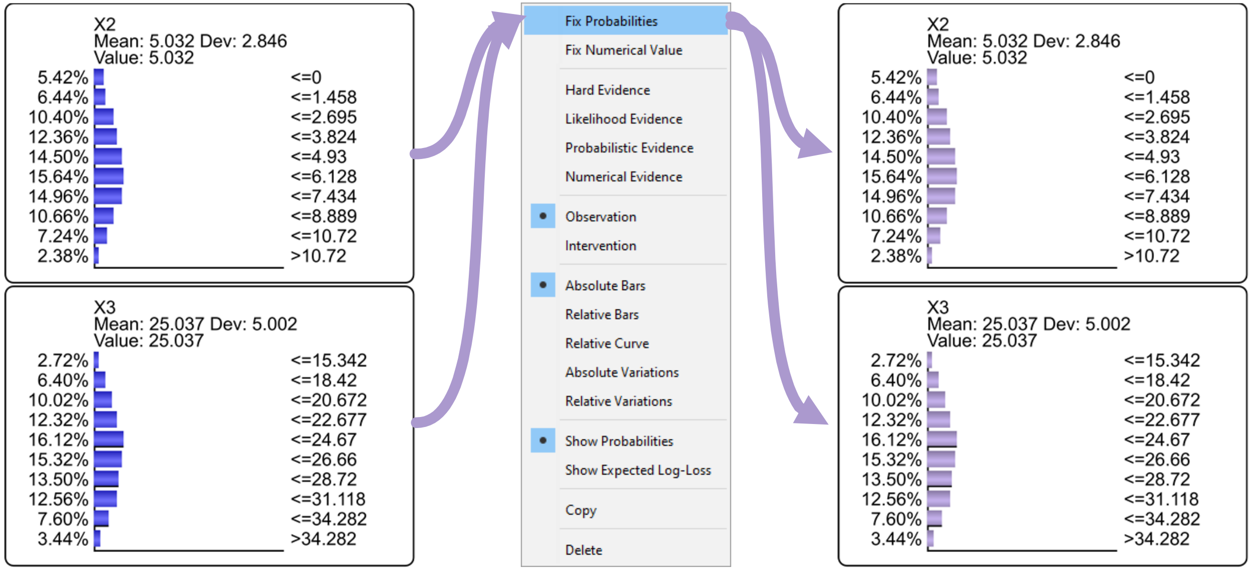


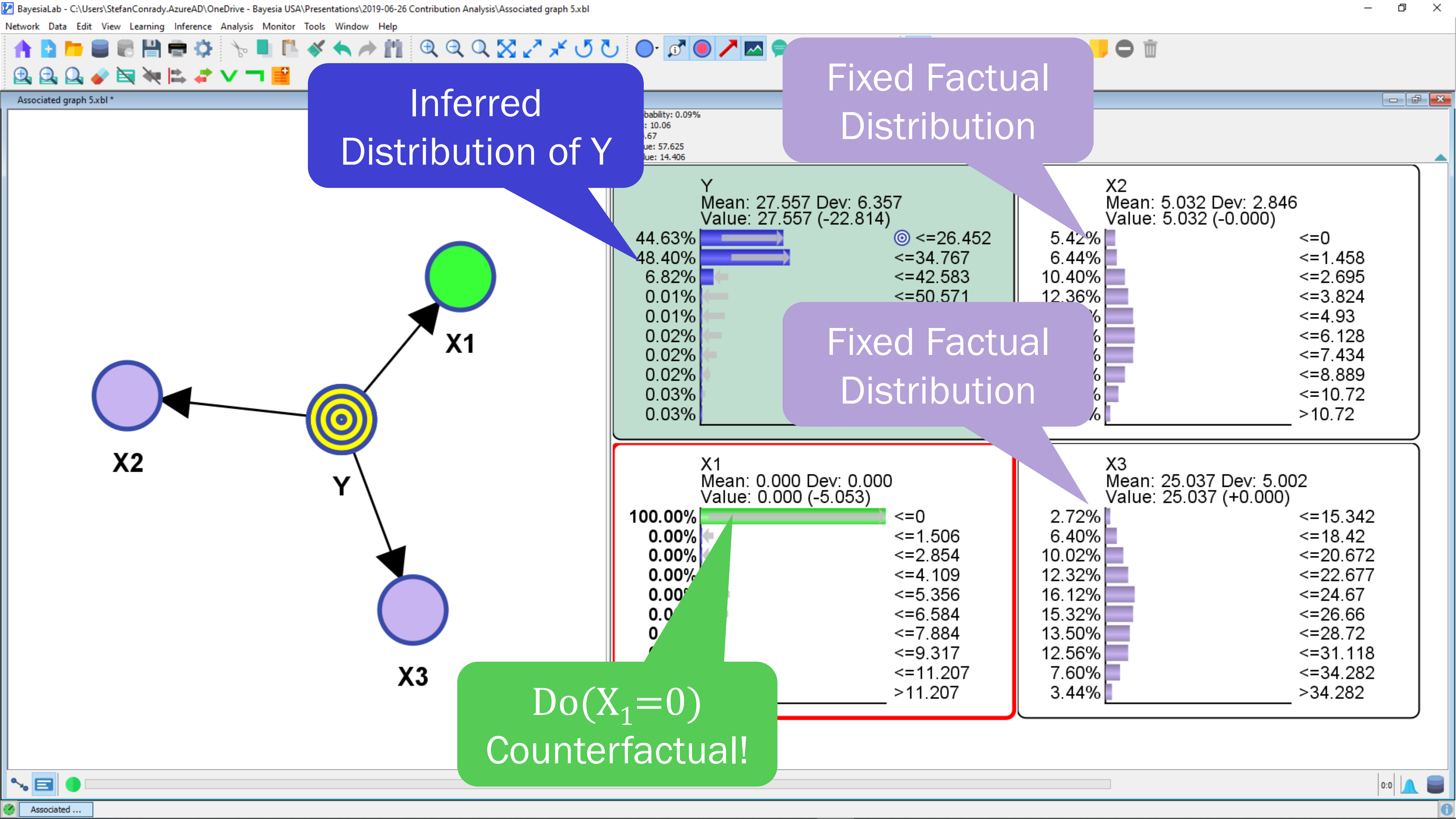
BayesiaLab - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\Associated graph 5.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 5.xbl *
Starting with X_1
X1
X2
Y
X3
Do Condition on Confounder X_2
Do Condition on Confounder X_3
Do(X_1=0)
Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,000
Total Value: 85.492
Mean Value: 21.373
Y
Mean: 50.371 Dev: 22.833
Value: 50.371
11.78% <=26.452
16.36% <=34.767
15.24% <=42.583
14.70% <=50.571
13.12%
11.08%
8.34%
5.64%
2.68%
1.06%
X2
Mean: 5.032 Dev: 2.846
Value: 5.032
5.42% <=0
6.44% <=1.458
10.40% <=2.695
12.36% <=3.824
<=4.93
<=6.128
<=7.434
<=8.889
<=10.72
>10.72
X1
Mean: 5.053 Dev: 2.908
Value: 5.053
4.76% <=0
7.42% <=1.506
11.90% <=2.854
15.06% <=4.109
15.82% <=5.356
15.14% <=6.584
13.00% <=7.884
9.36% <=9.317
5.26% <=11.207
2.28% >11.207
X3
Mean: 25.037 Dev: 5.002
Value: 25.037
2.72% <=15.342
6.40% <=18.42
10.02% <=20.672
12.32% <=22.677
16.12% <=24.67
15.32% <=26.66
13.50% <=28.72
12.56% <=31.118
7.60% <=34.282
3.44% >34.282
Associated ...

Contribution Analysis

How can we condition on the confounders in this Bayesian network?

- We use BayesiaLab's **Likelihood Matching** algorithm and fix the probabilities of the confounders.

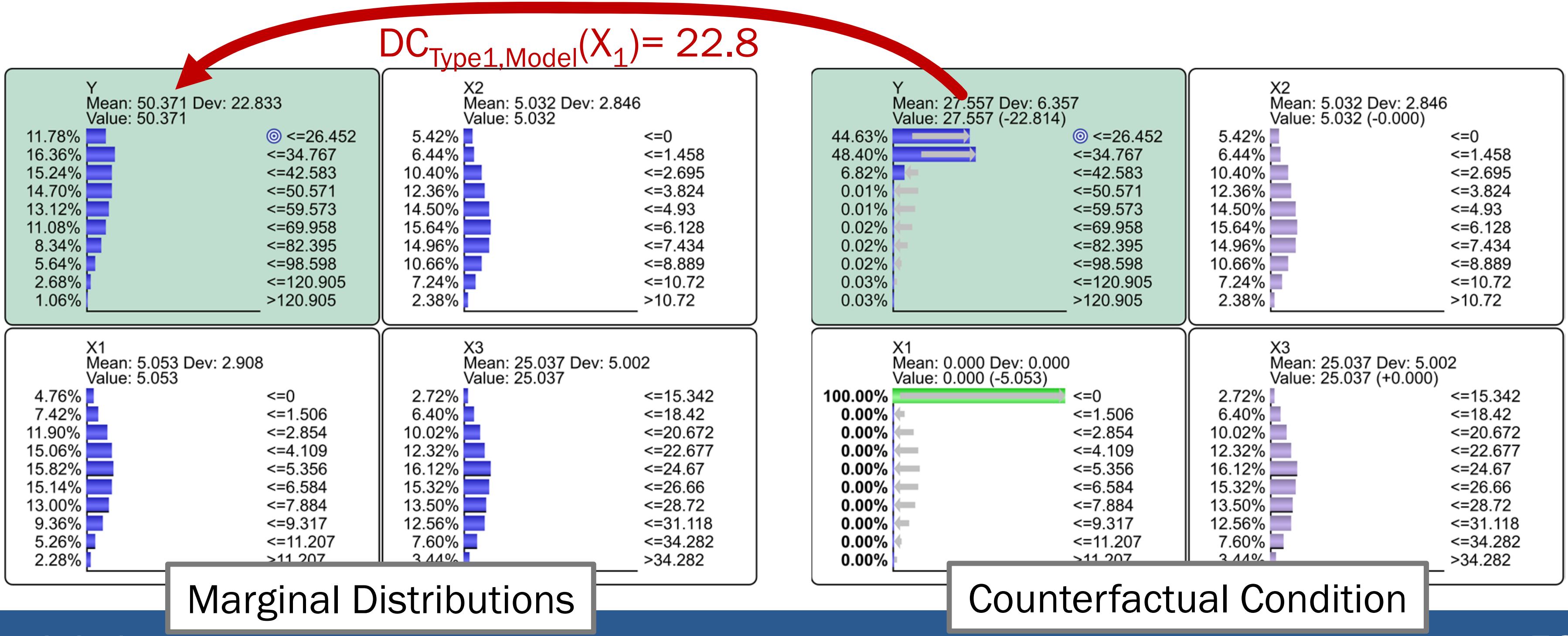




BayesiaLab - C:\Users\StefanConrady.AzureAD\OneDrive - Bayesia USA\Presentations\2019-06-26 Contribution Analysis\Associated graph 5.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 5.xbl *
Inferred Distribution of Y
Fixed Factual Distribution
Fixed Factual Distribution
Do(X_1=0) Counterfactual!
X1
X2
Y
X3
Y
Mean: 27.557 Dev: 6.357
Value: 27.557 (-22.814)
44.63% <=26.452
48.40% <=34.767
6.82% <=42.583
0.01% <=50.571
0.01%
0.02%
0.02%
0.02%
0.03%
0.03%
X2
Mean: 5.032 Dev: 2.846
Value: 5.032 (-0.000)
5.42% <=0
6.44% <=1.458
10.40% <=2.695
12.36% <=3.824
<=4.93
<=6.128
<=7.434
<=8.889
<=10.72
>10.72
X1
Mean: 0.000 Dev: 0.000
Value: 0.000 (-5.053)
100.00% <=0
0.00% <=1.506
0.00% <=2.854
0.00% <=4.109
<=5.356
<=6.584
<=7.884
<=9.317
<=11.207
>11.207
X3
Mean: 25.037 Dev: 5.002
Value: 25.037 (+0.000)
2.72% <=15.342
6.40% <=18.42
10.02% <=20.672
12.32% <=22.677
16.12% <=24.67
15.32% <=26.66
13.50% <=28.72
12.56% <=31.118
7.60% <=34.282
3.44% >34.282
Associated ...

Contribution Analysis

Decomposition (X_1), Type 1, Based on Model



Contribution Analysis

Contribution (X_1), Type 1, Based on Model

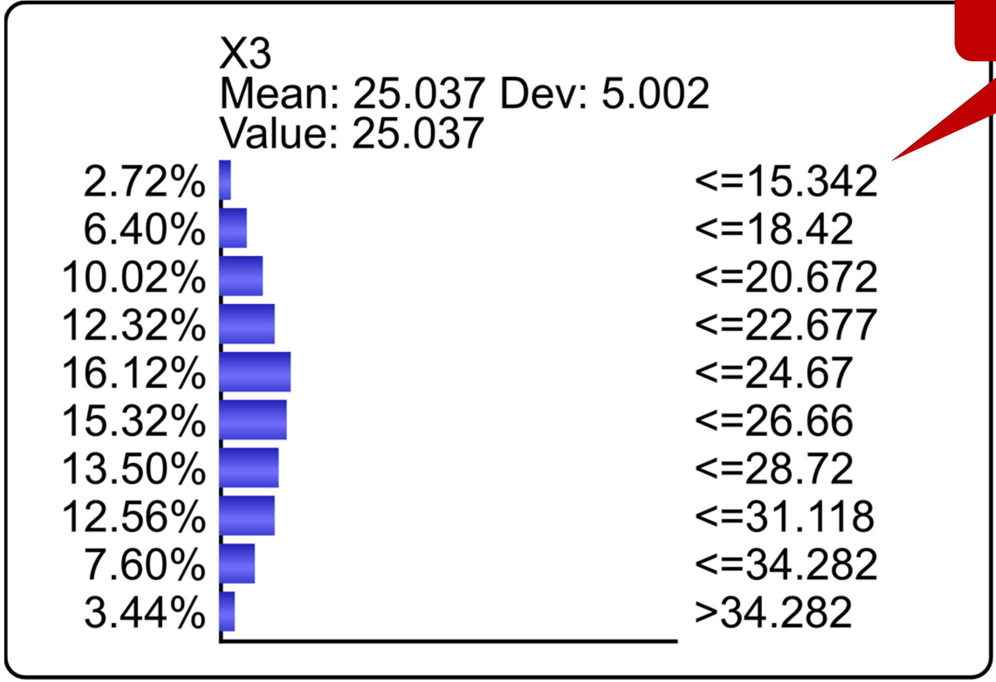
$$C_{Type1,Model}(X_1) = \frac{DC_{Type1,Model}\,(X_1)}{E(Y)} = \frac{22.8}{50.4} = 0.45 = 45\%$$

- As per this model, 45% of the observed value of Y is due to X_1 being at its factual level as opposed to being at a counterfactual level of $X_1=0$.
- Is this the true contribution of X_1?
- Perhaps there is another way of looking at it.
- One could argue that we should look at X_1 being the only “contributor”, i.e., setting X_1 to its *factual* level and X_2 and X_3 to their *counterfactual* levels.

A Toy Example

What's the counterfactual state of X_3 ?

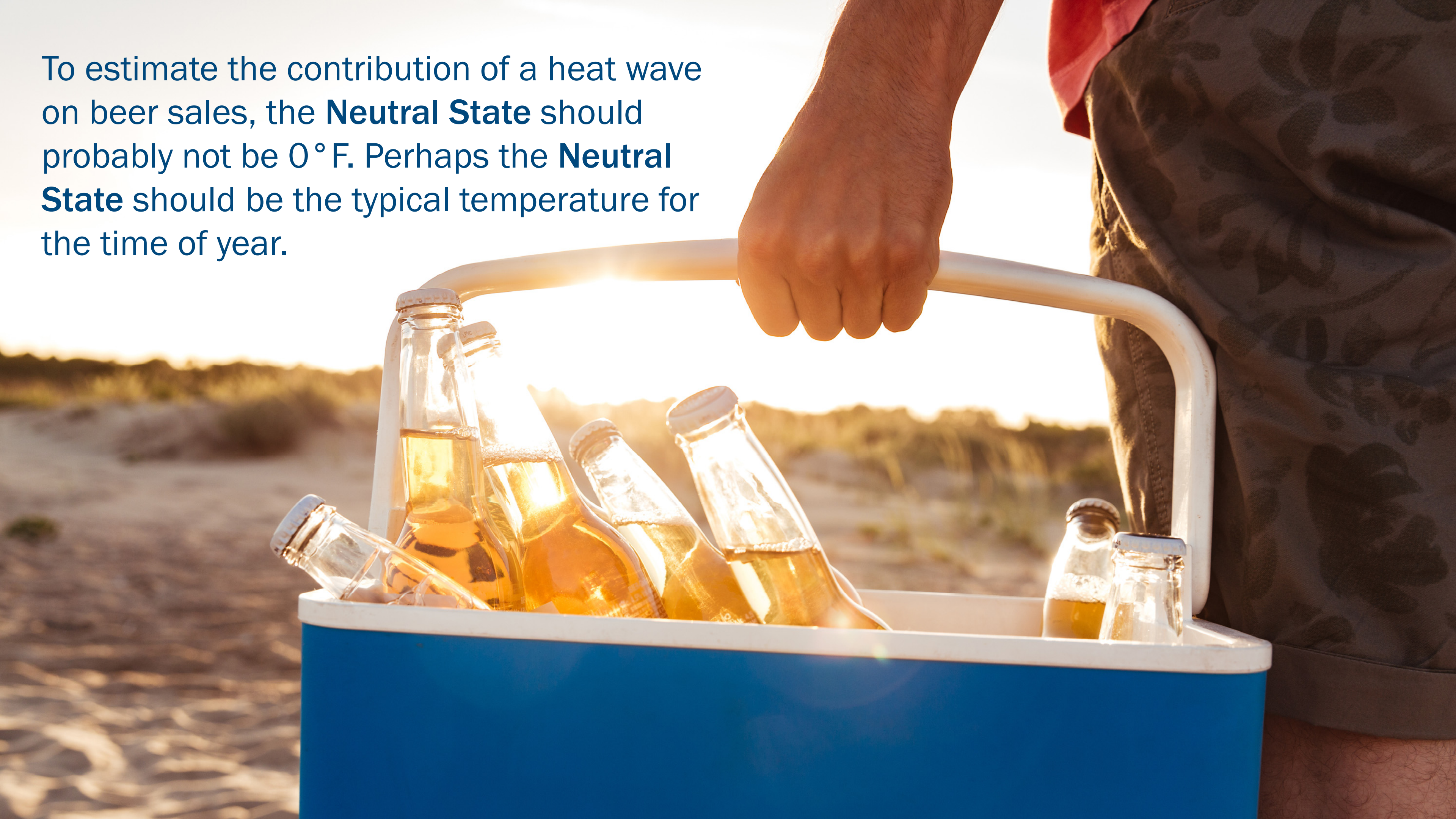
No $X_3=0$?



Contribution Analysis

"Neutral State"

- So far, we've simply used 0 as the default counterfactual state.
- However, there could be many other possible counterfactual states, i.e., anything other than what actually occurred.
- Which state is suitable as the **Neutral State** entirely depends on the context and must be determined from domain knowledge.
- The **Neutral State** typically represent concepts, such as: zero, absence, average, default, false, minimum, standard, least possible, basic, nothing, nil, void, normal, natural, etc.

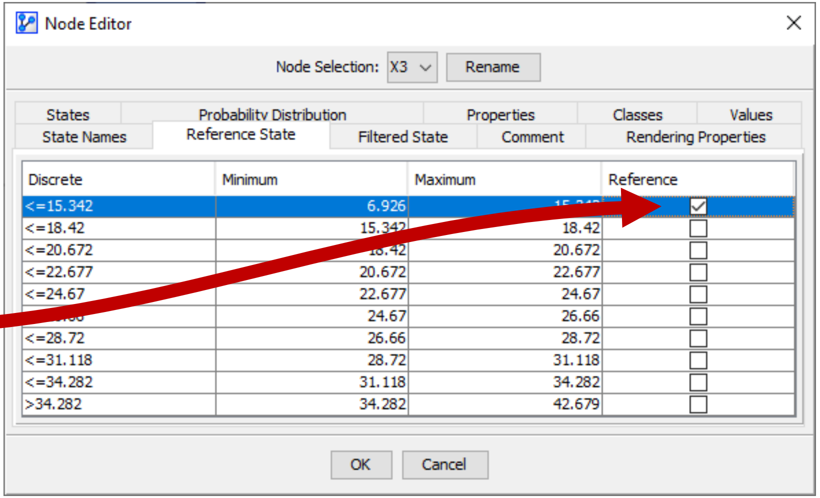


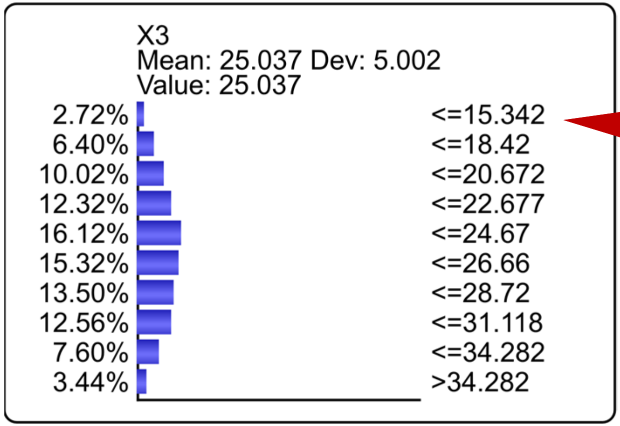
To estimate the contribution of a heat wave on beer sales, the **Neutral State** should probably not be 0°F. Perhaps the **Neutral State** should be the typical temperature for the time of year.

Contribution Analysis

What's the counterfactual state of X_3 ?

- Unless specified with the **Reference State**, BayesiaLab selects the smallest numerical value as the **Neutral State.**



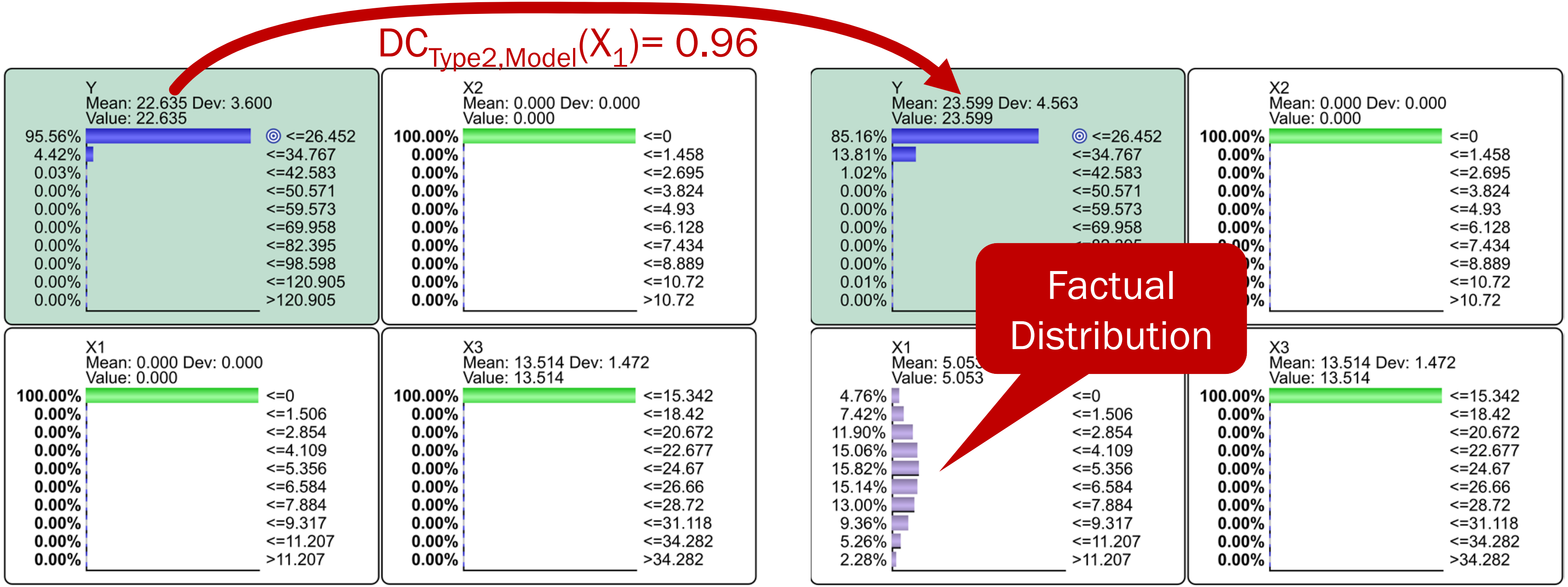


Neutral State:
X3<=15.342

Contribution Analysis

"...look at X_1 being the only "contributor", i.e., setting X_1 to its *factual* level and X_2 and X_3 to their *counterfactual* levels."

Decomposition (X_1), Type 2, Based on Model



Contribution Analysis

Contribution (X_1), Type 2, Based on Model

$$C_{Type2,Model}(X_1) = \frac{DC_{Type2,Model}\,(X_1)}{E(Y)} = \frac{0.96}{50.4} = 0.019 = 1.9\%$$

- If X_1 were the only active variable, 1.9% of the observed value of Y is due to X_1 being at its factual distribution as opposed to being at a counterfactual level of $X_1=0$.
- So, what is the true contribution of X_1 on Y?
  - $C_{Type1,Model}(X_1) = 45\%$
  - $C_{Type2,Model}(X_1) = 1.9\%$

But wait, there is more...

Contribution Analysis

Decomposition (X_1), Type 1, Based on Data

Observation	Inferred	Factual	Factual	Factual
i	Y	X1	X2	X3
1	53.27	5.71	4.26	26.66
2	46.86	4.25	5.36	21.66
3	25.48	0.20	4.08	17.04
4	30.42	4.16	0.38	22.21
…	…	…	…	…
5000	42.77	3.78	4.60	18.49
Sum	237,746.49			

Observation	Inferred	Counterfactual Neutral State	Factual	Factual
i	Y	X1	X2	X3
1	29.98	0.00	4.26	26.66
2	24.63	0.00	5.36	21.66
3	23.52	0.00	4.08	17.04
4	24.76	0.00	0.38	22.21
…	…	…	…	…
5000	23.52	0.00	4.60	18.49
Sum	138,682.43			

$$DC_{Type1,Data}(X_1) = 237{,}746.40 - 138{,}682.43 = 99{,}064.46$$

$$C_{Type1,Data}(X_1) = \frac{99{,}064.46}{237{,}746.40} = 0.417 = 41.7\%$$

Contribution Analysis

Decomposition (X_1), Type 2, Based on Data

Observation	Inferred	Counterfactual Neutral State	Counterfactual Neutral State	Counterfactual Neutral State
i	Y	X1	X2	X3
1	21.79	0.00	0.00	13.69
2	21.79	0.00	0.00	13.69
3	21.79	0.00	0.00	13.69
4	21.79	0.00	0.00	13.69
…	…	…	…	…
5000	21.79	0.00	0	13.69
	108,946.72			

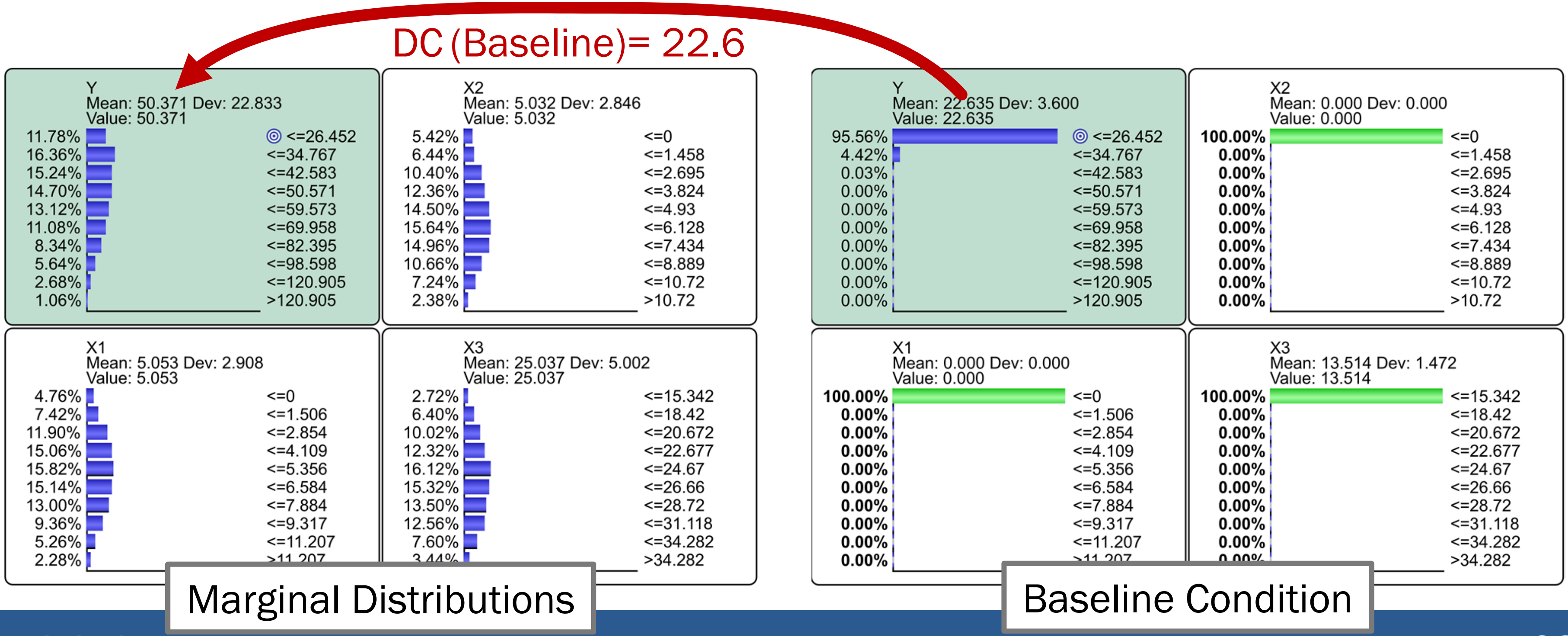
Observation	Inferred	Factual	Counterfactual Neutral State	Counterfactual Neutral State
i	Y	X1	X2	X3
1	23.56	5.71	0.00	13.69
2	23.07	4.25	0.00	13.69
3	22.40	0.20	0.00	13.69
4	23.07	4.16	0.00	13.69
…			…	…
5000	23.07	3.78	0	13.69
	114,786.33			

$$DC_{Type2,Data}(X_1) = 114{,}786.33 - 108{,}946.72 = 5{,}839.61$$

$$C_{Type2,Data}(X_1) = \frac{5{,}839.61}{108{,}946.72} = 0.0536 = 5.36\%$$

Contribution Analysis

Decomposition (Baseline), Type 1, Based on Model



Contribution Analysis

Contribution (Baseline), Based on Model

$$C_{Model}(Baseline) = \frac{DC_{Model}\,(Baseline)}{E(Y)} = \frac{22.6}{50.4} = 0.45 = 45\%$$

Contribution Analysis

Decomposition (Baseline), Based on Data

Observation	Inferred	Factual	Factual	Factual
i	Y	X1	X2	X3
1	53.27	5.71	4.26	26.66
2	46.86	4.25	5.36	21.66
3	25.48	0.20	4.08	17.04
4	30.42	4.16	0.38	22.21
…	…	…	…	…
5000	42.77	3.78	4.60	18.49
Sum	237,746.49			

Observation	Inferred	Counterfactual Neutral State	Counterfactual Neutral State	Counterfactual Neutral State
i	Y	X1	X2	X3
1	21.79	0.00	0.00	13.69
2	21.79	0.00	0.00	13.69
3	21.79	0.00	0.00	13.69
4	21.79	0.00	0.00	13.69
…	…	…	…	…
5000	21.79	0.00	0	13.69
	108,946.72			

$$DC_{Data}(Baseline) = 108{,}946.72$$

$$C_{Data}(Baseline) = \frac{108{,}946.72}{237{,}746.49} = 0.46 = 46\%$$

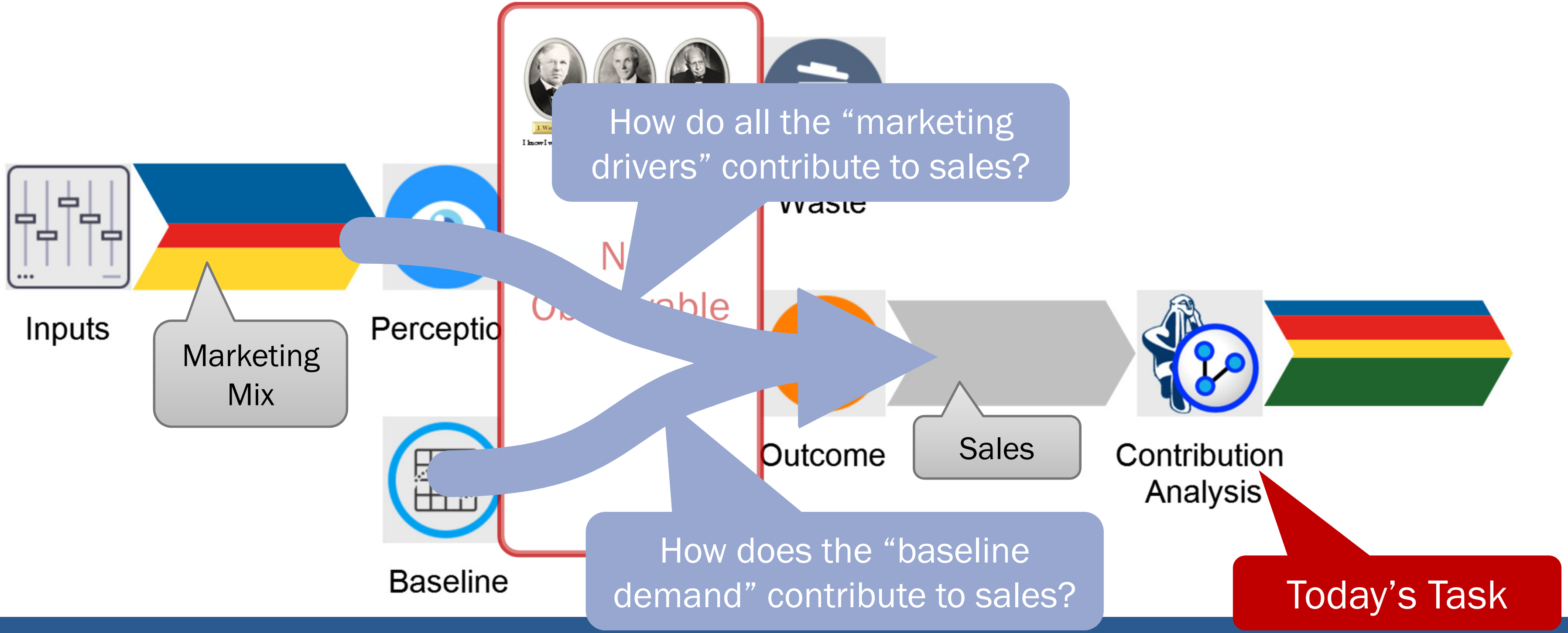
Contribution Analysis

BayesiaLab’s Contribution Analysis Report

Contributions on Y (Base: 48.8998%)									
Node	Mean Contribution	Decomposition 1 (Model)	Contribution 1 (Model)	Decomposition 2 (Model)	Contribution 2 (Model)	Decomposition 1 (Data)	Contribution 1 (Data)	Decomposition 2 (Data)	Contribution 2 (Data)
X1	21.38%	22.8142	45.10%	0.9638	1.91%	99,458.27	36.36%	4,819.00	2.16%
X2	21.33%	22.8088	45.09%	0.8455	1.67%	99,624.85	36.53%	4,227.75	2.03%
X3	8.39%	4.8512	9.59%	3.4264	6.77%	21,580.03	9.45%	17,131.92	7.74%

Objective: Contribution Analysis

Decomposing Sales & Recovering the Unobservable Contributions



Contribution Analysis

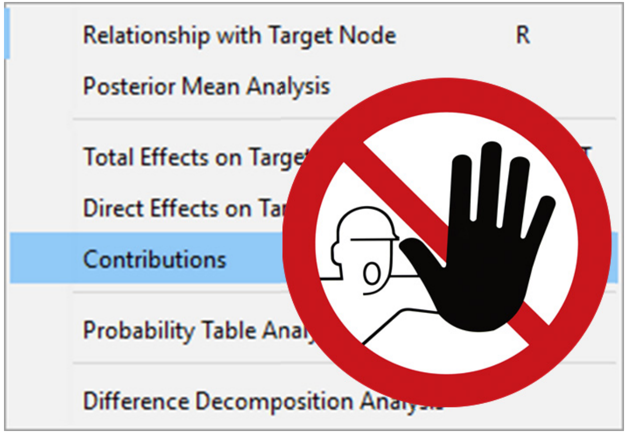
BayesiaLab's Contribution Analysis Report

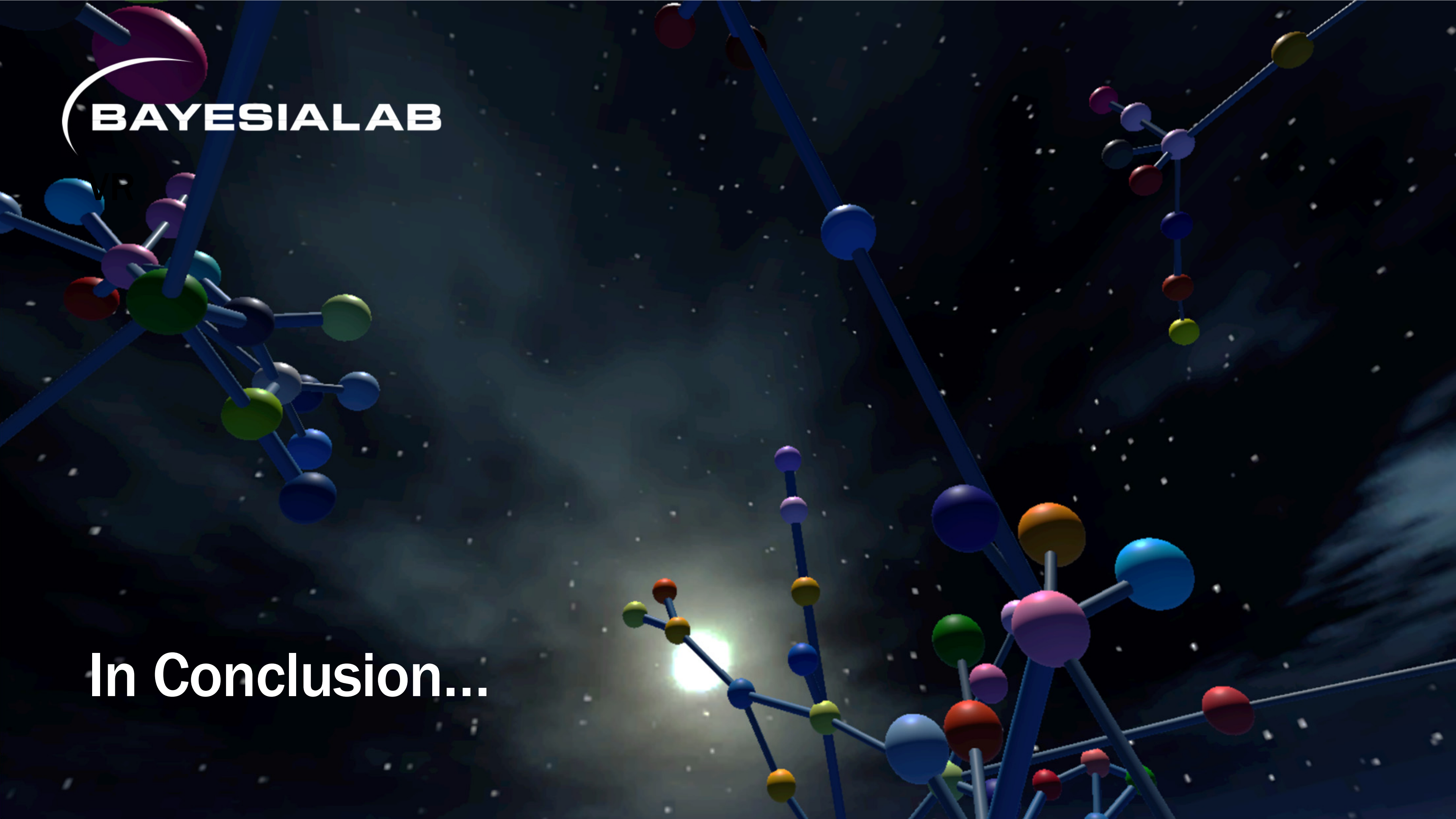
Contributions on Y (Base: 48.8998%)		
Node	Mean Contribution	Decomposit (Model)
X1	21.38%	22.
X2	21.33%	22.
X3	8.39%	4.

Contribution Analysis

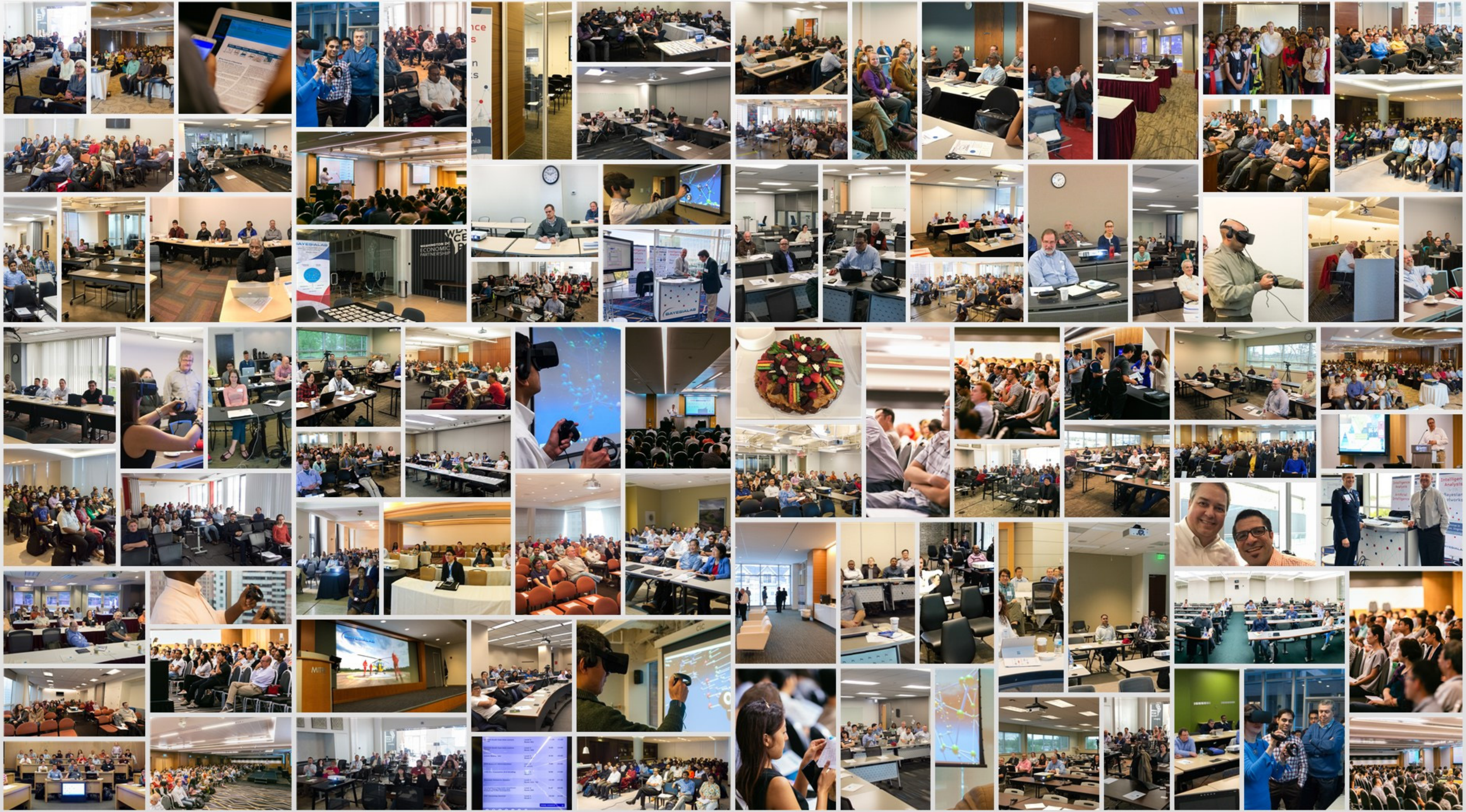
Important Caveats

- Before you click "Contributions"
    - Validate your model.
    - Review causal assumptions and confounders.
    - Consider unobserved confounders.
    - Review causal effects for plausibility with domain experts.
    - Understand the calculation before reporting results.



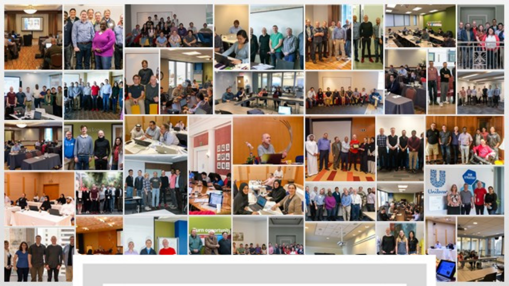


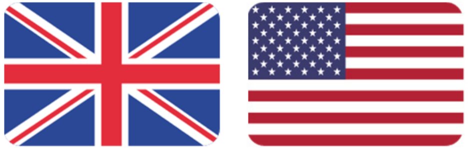
In Conclusion...



BayesiaLab Courses Around the World in 2019

- Introductory Course
  September 18–20
  Paris, France
- Advanced Course
  September 23–25
  Paris, France
- Introductory Course
  October 7–9
  Durham, North Carolina
- Advanced Course
  October 14–16
  Durham, North Carolina





Note that these courses will be conducted in English!

Learn More & Register: bayesia.com/events

BAYESIALAB

7TH ANNUAL

BayesiaLab Conference

DURHAM

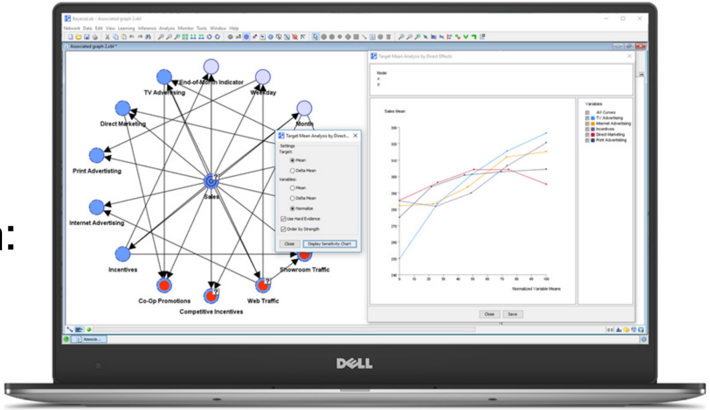
2019

NORTH CAROLINA
BIOTECHNOLOGY CENTER

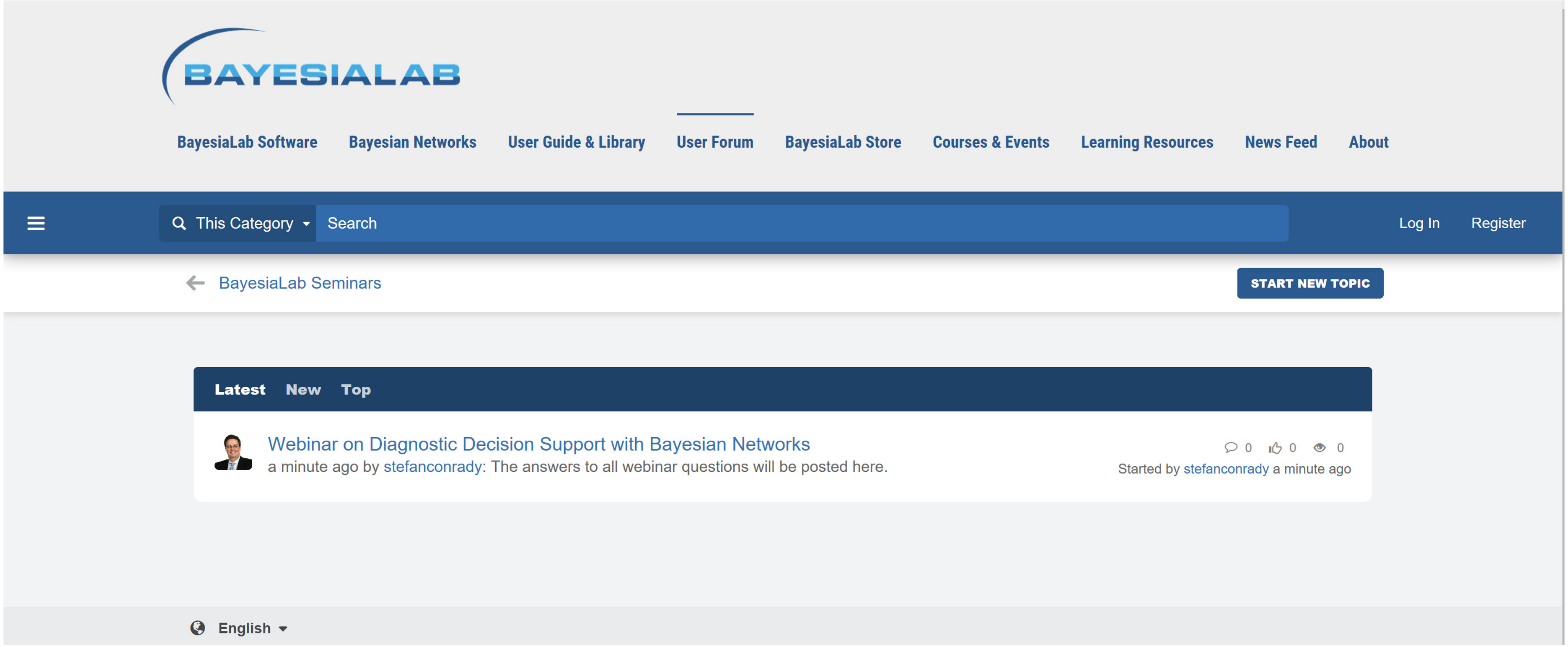
BayesiaLab Trial

Try BayesiaLab Today!

- Download Demo Version (10-Node Limit):
  www.bayesialab.com/trial-download
- Apply for Unrestricted 30-Day Evaluation Version:
  www.bayesialab.com/evaluation



User Forum: bayesia.com/community



Thank You!

stefan.conrady@bayesia.us

BayesianNetwork

linkedin.com/in/stefanconrady

facebook.com/bayesia