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The webinar will start at:

13:00:00

The current time is:

13:00:49

Central Daylight Time
UTC-5

Product Cannibalization

A Prototypical Marketing Science Problem

Introduction

Your Hosts Today

- Stefan Conrady
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- Stacey Blodgett
  stacey.blodgett@bayesia.us

Today’s Program

Motivation & Background

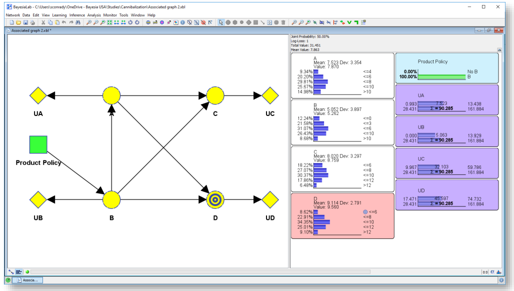
- Definitions
- Introductory Example

Representation

- Conceptual Framework: Bayesian Networks
- Probabilistic Reasoning

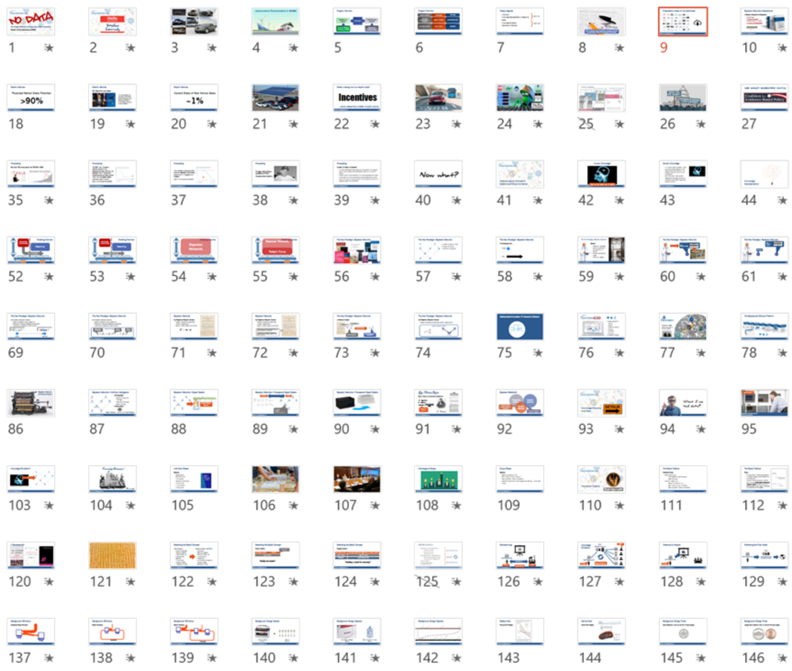
Learning, Estimation, and Inference

- Causal Reasoning?
- Unsupervised Learning
- Disjunctive Cause Criterion
- Assign Utilities
- Evaluate Policies



All Fictional Numbers

Webinar Slides & Recording Available



Motivation & Background

Definitions

- Typically, a new product adversely affects the sales of existing products:
  - If it affects your competitor's products, it's

    CONQUEST

  - If it affects your own products, it's

    CANNIBALIZATION



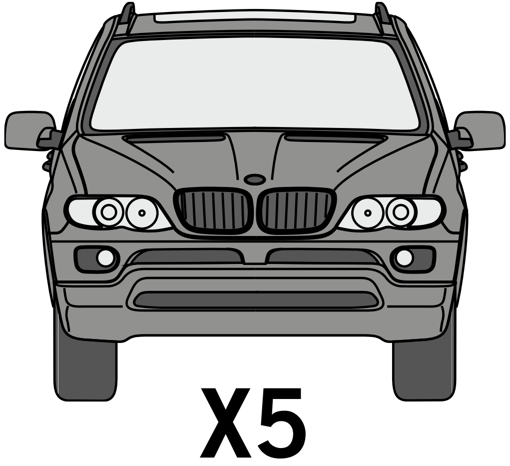




Motivation & Background

Introductory Example: 2000 BMW X5

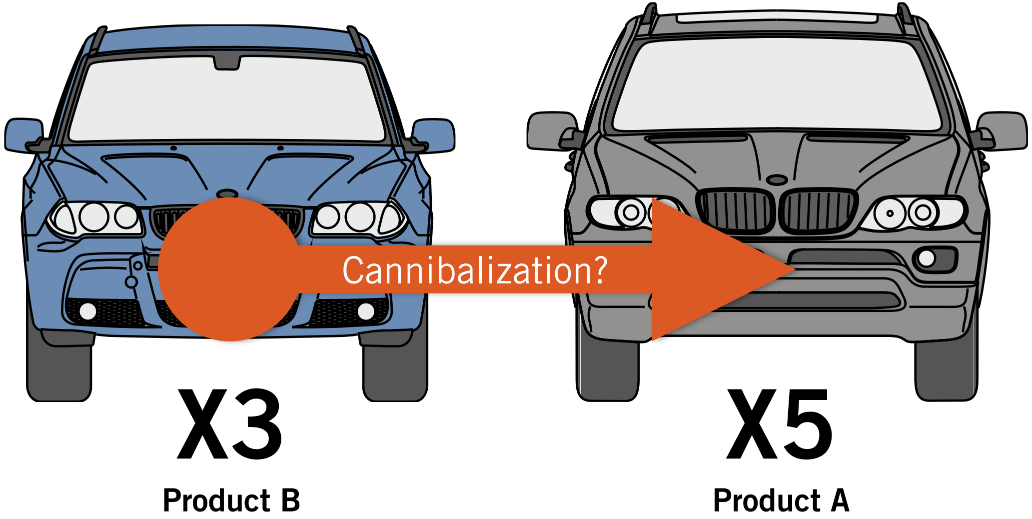
- First SUV in the BMW product portfolio.



Motivation & Background

Introductory Example: New BMW X3 vs. Existing BMW X5

- New, smaller X3 launched in 2004



Bayesian Network Representation

Bayesian Network Representation

Conceptual Network

$P(Sales_B)$

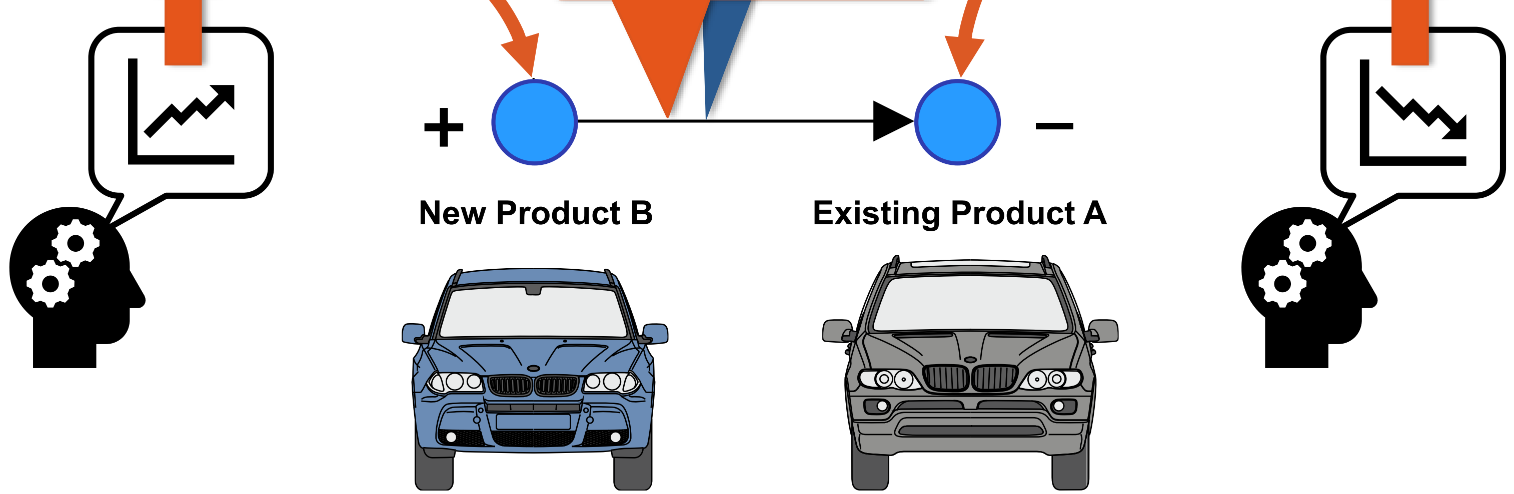
0	1	2
20.000	40.000	40.000

Product B *causes* lower sales of Product A

"Cannibalization"

$P(Sales_A|Sales_B)$

New Produ...	0	1	2
0	20.000	40.000	40.000
1	40.000	30.000	30.000
2	60.000	[illegible]	20.000

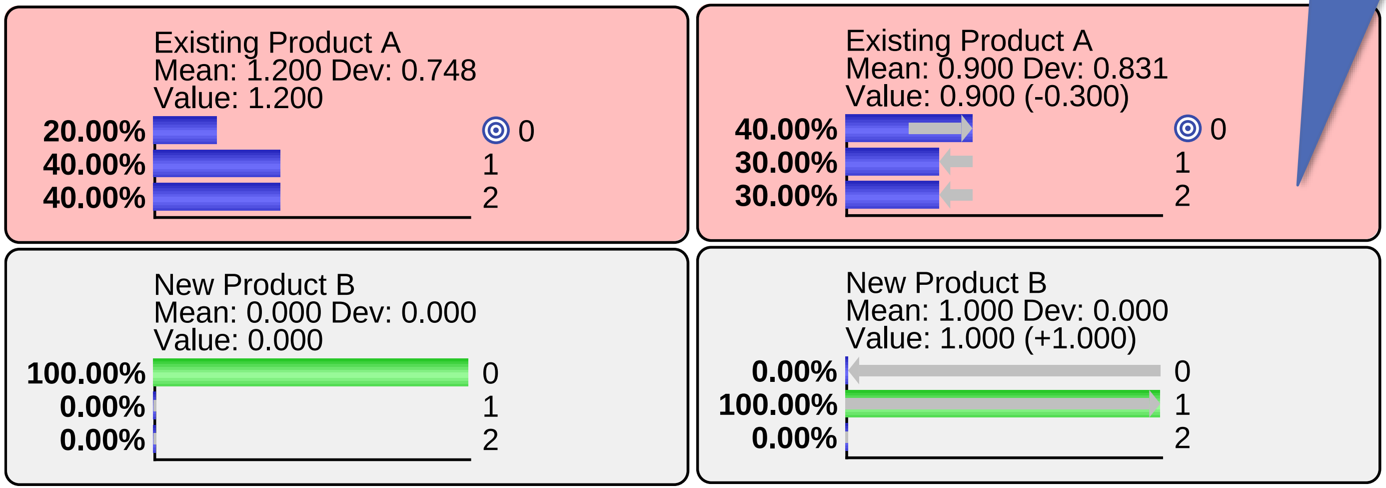


Bayesian Network Representation

Obvious, as we encoded that as our domain knowledge into the network.

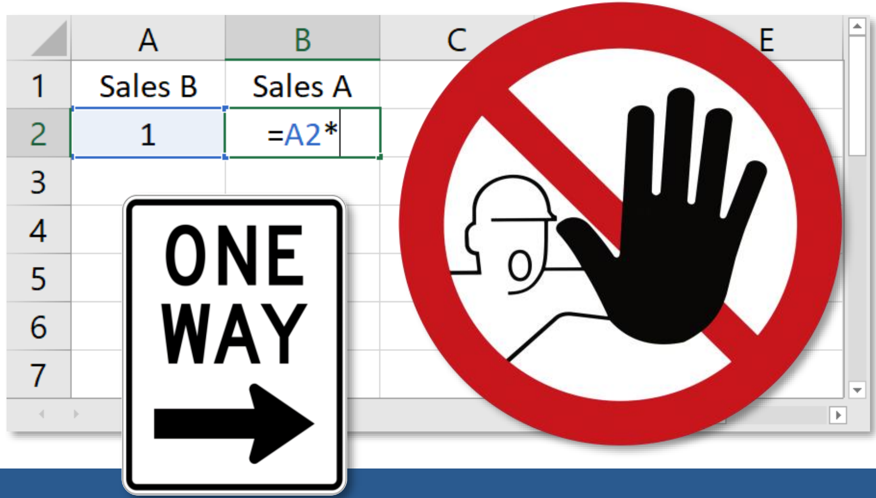
Inference

- Computing the cannibalization effect C of Product B on Product A:
  - C(B→A) = -0.3 (unit effect)



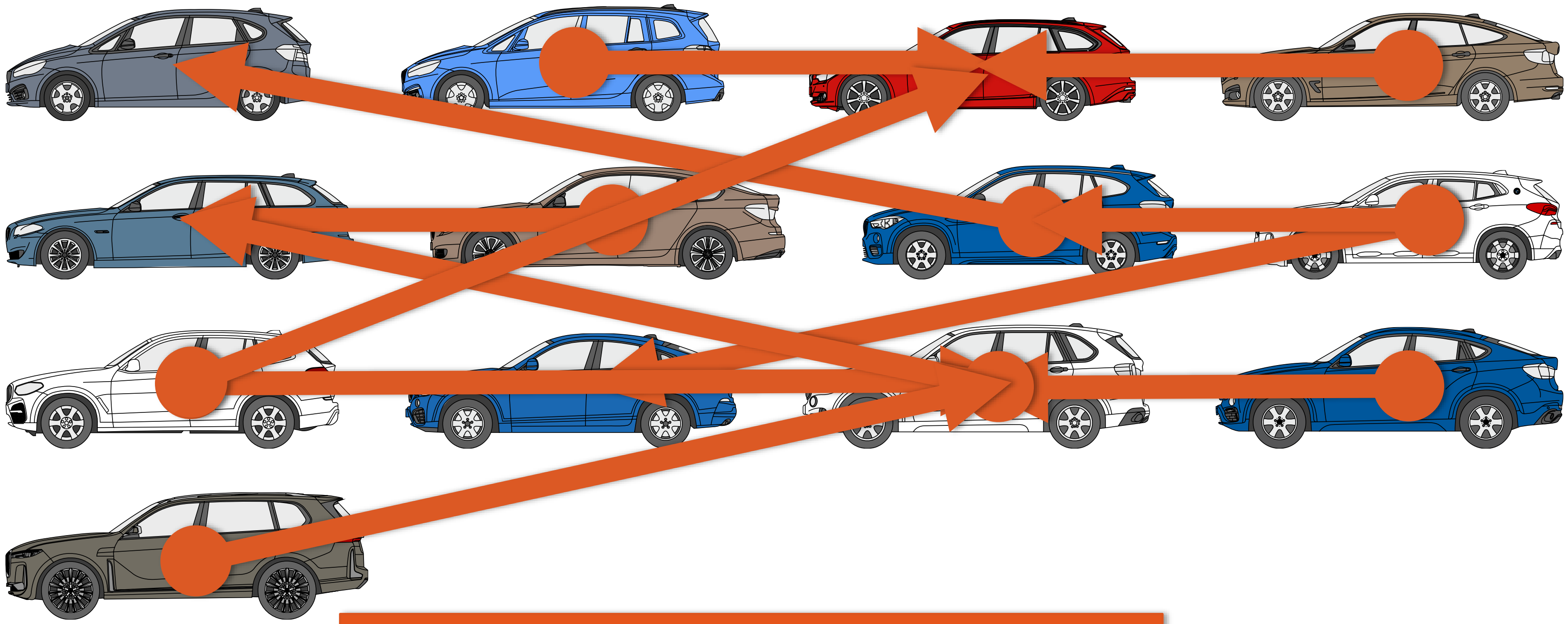
Bayesian Network Representation

Can't we do this in Excel?



Motivation & Background

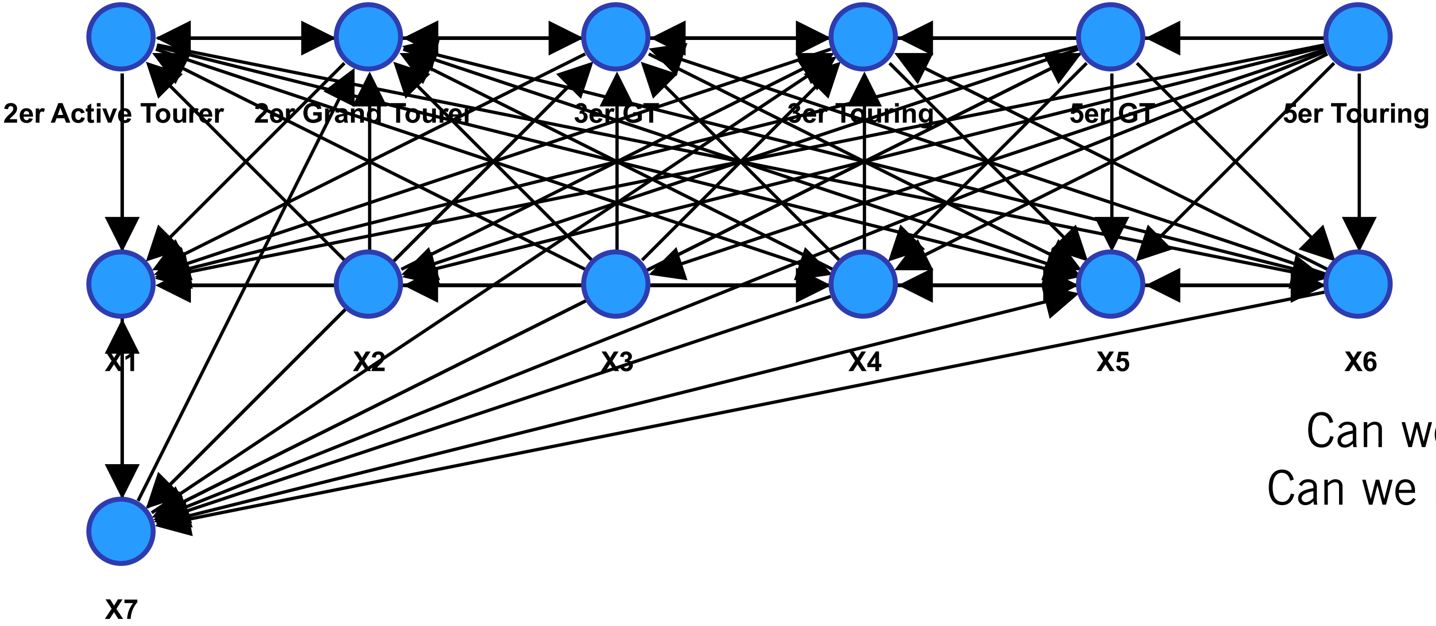
Example: BMW Portfolio of “Utility-Type” Vehicles in 2018

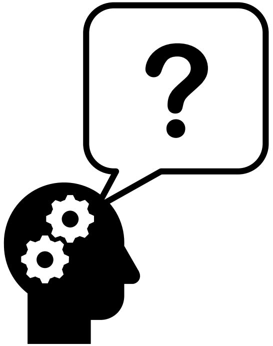


All products are cannibalizing each other!

Bayesian Network Representation

A Fully Connected Network?





Can we specify it? No.
Can we machine-learn it?
Perhaps.

Learning & Estimating Cannibalization

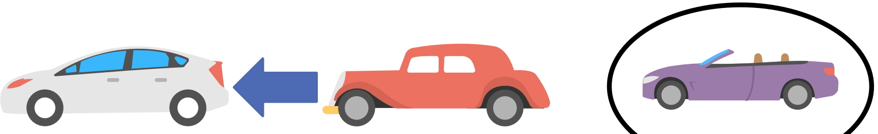
Learning & Estimating Cannibalization

Couldn't we just ask auto buyers?

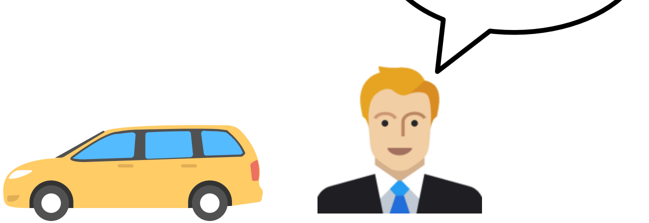
Learning & Estimating Cannibalization

Understanding Cannibalization by Other Means?

- Trade-Ins
    - New and old product not comparable



- Auto Buyer Surveys (2nd Choice)
    - Respondents tend to exaggerate their counterfactual choice (“I would have bought the convertible, but we need the third row.”)



- Choice Experiments
    - Hypothetical choices are noncommittal
    - Expensive to conduct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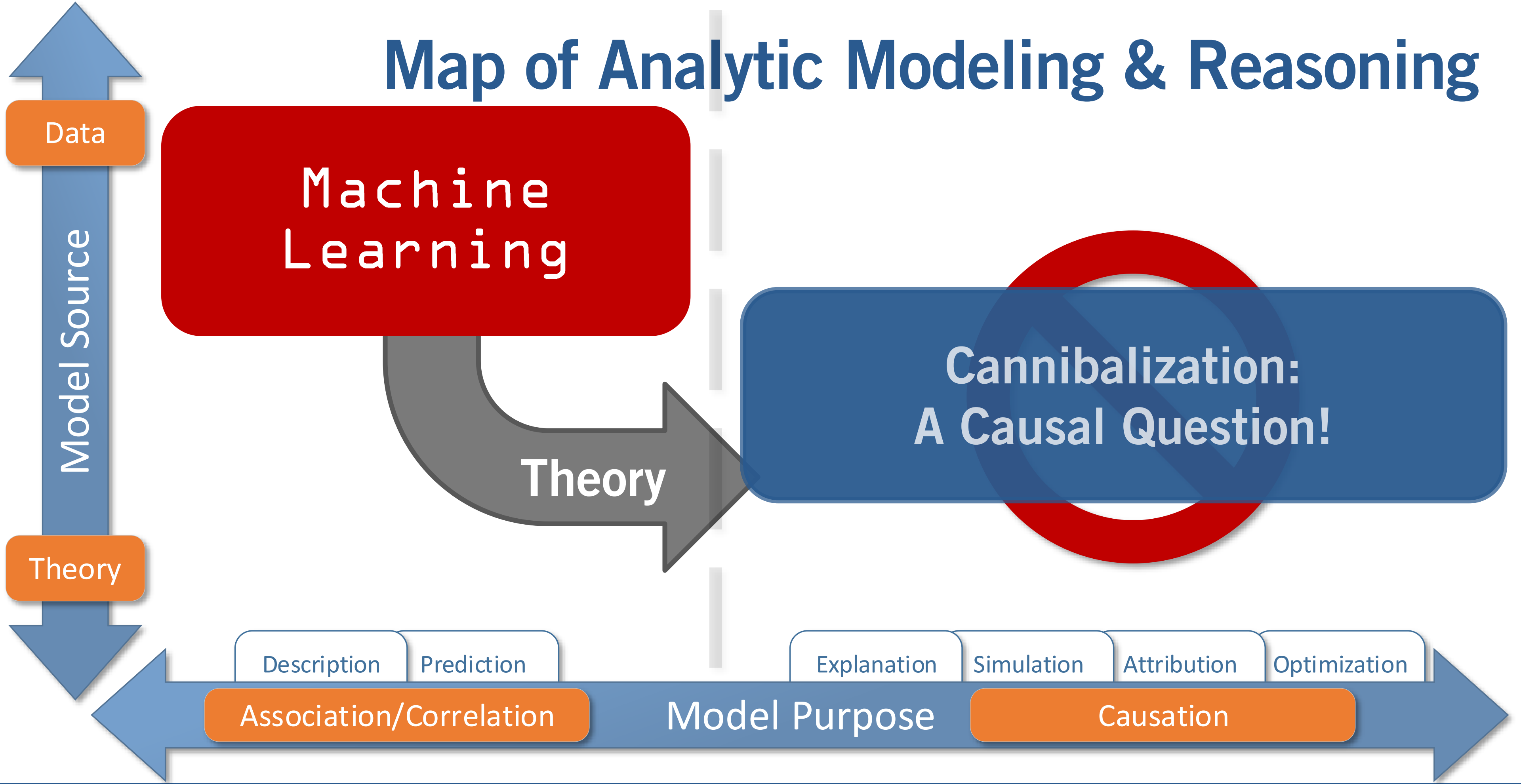
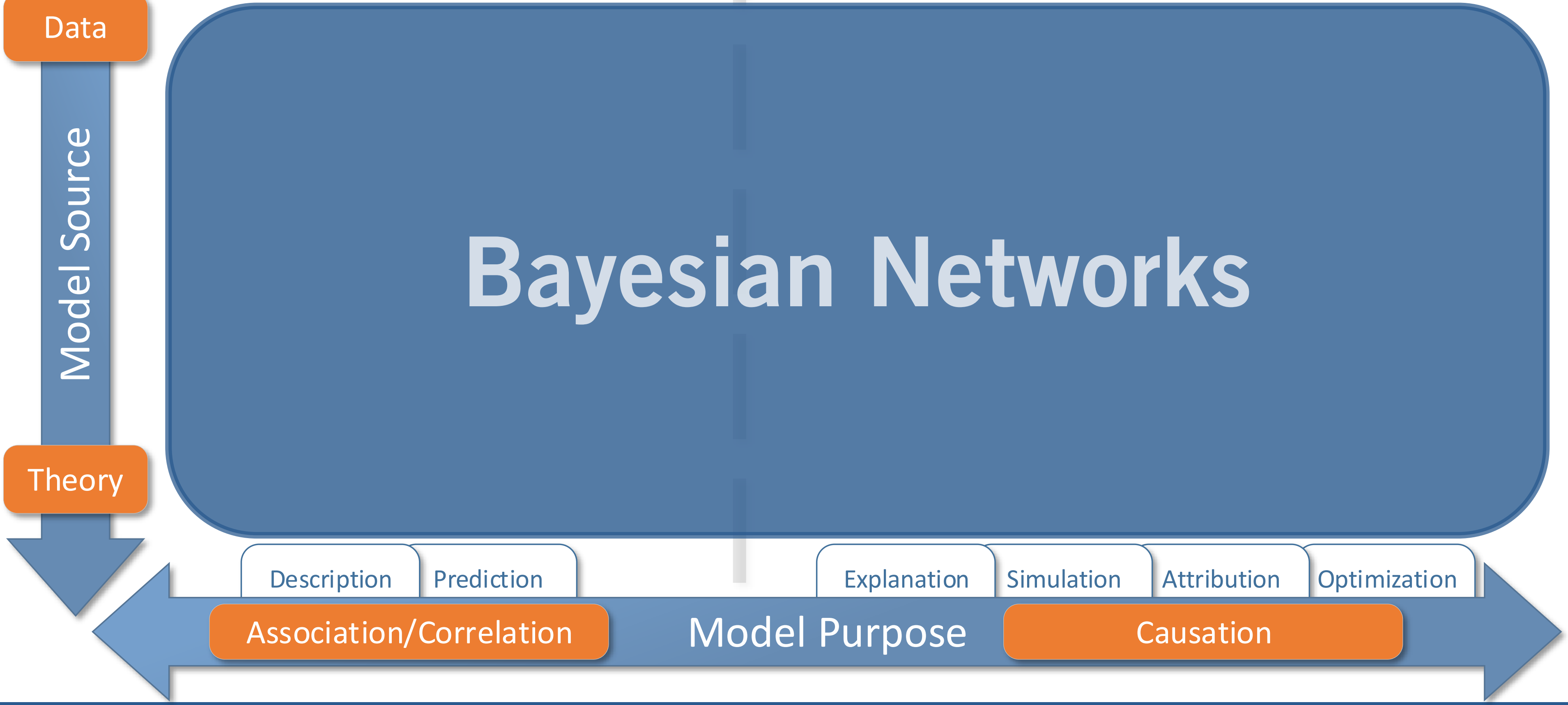
THE BIG DATA DRIVEN BUSINESS
DATA DRIVEN
Data-Driven Decision-Making
increasing sales with
DATA - DRIVEN MARKETING
loginradius
O'REILL
Data Driven
Creating a Data C
5 Steps To Powering
ata Driven Decision Makin
DATA-DRIVEN decisions in a FORTUNE 500
MAKING DATA-DRIVEN DECISIONS
with
tableau
+
THE DATA-DRIVEN
FUTURE
GET #DATADRIVEN
Data-Driven Marketing
DataDriven Business
stefan.conrady@bay

Map of Analytic Modeling & Reasoning



Map of Analytic Modeling & Reasoning



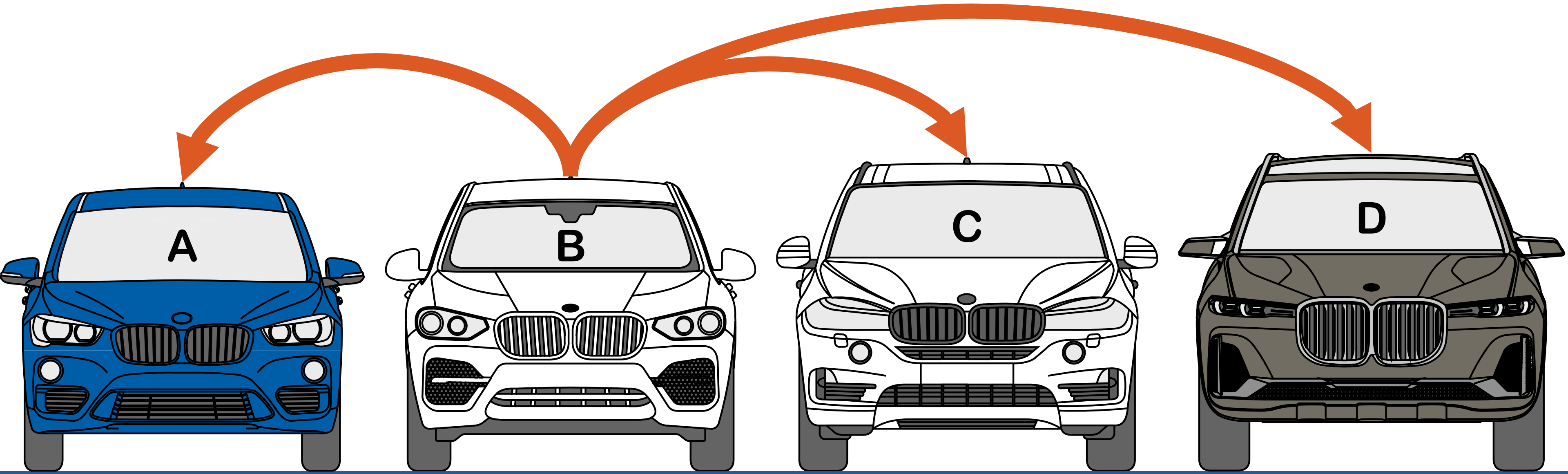
Learning & Estimating Cannibalization

A Fictional Case Study

Learning & Estimating Cannibalization

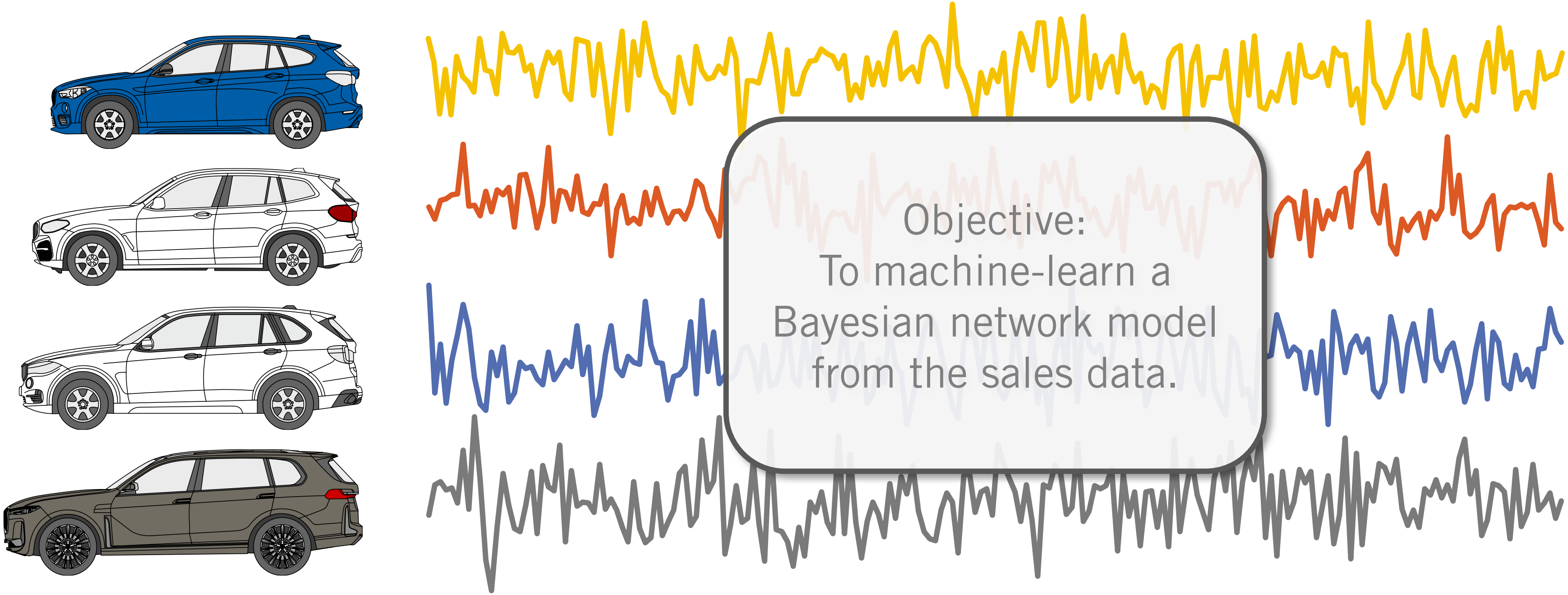
Case Study Question:

- What is the cannibalization effect of B on A, C, and D?



Learning & Estimating Cannibalization

Daily Sales Data



Objective:
To machine-learn a Bayesian network model from the sales data.

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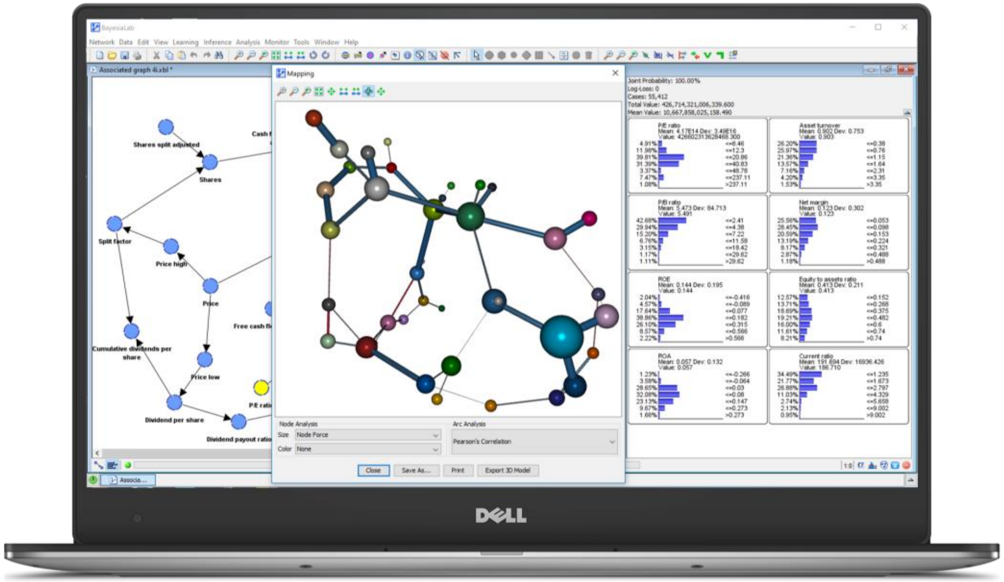
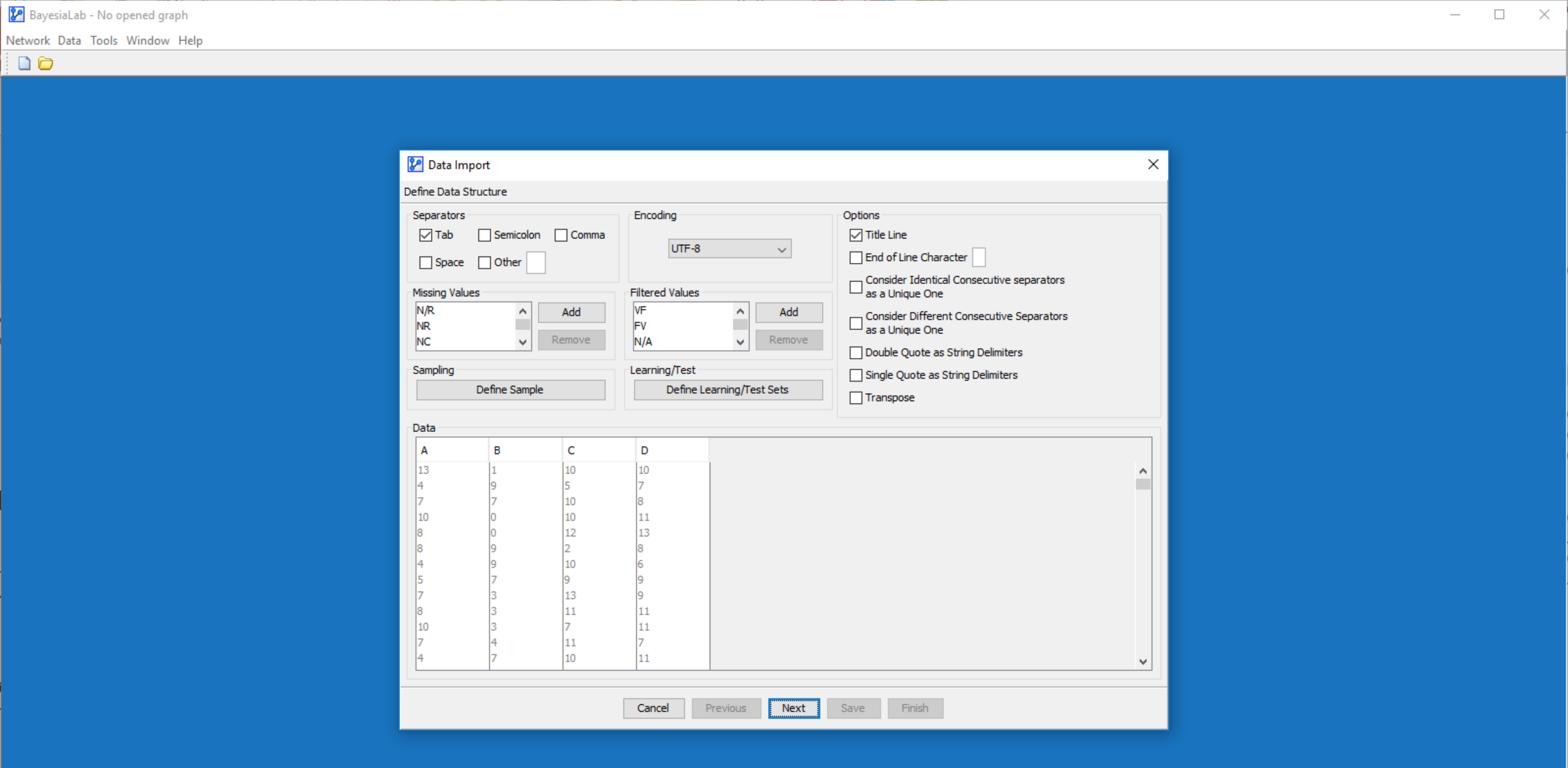


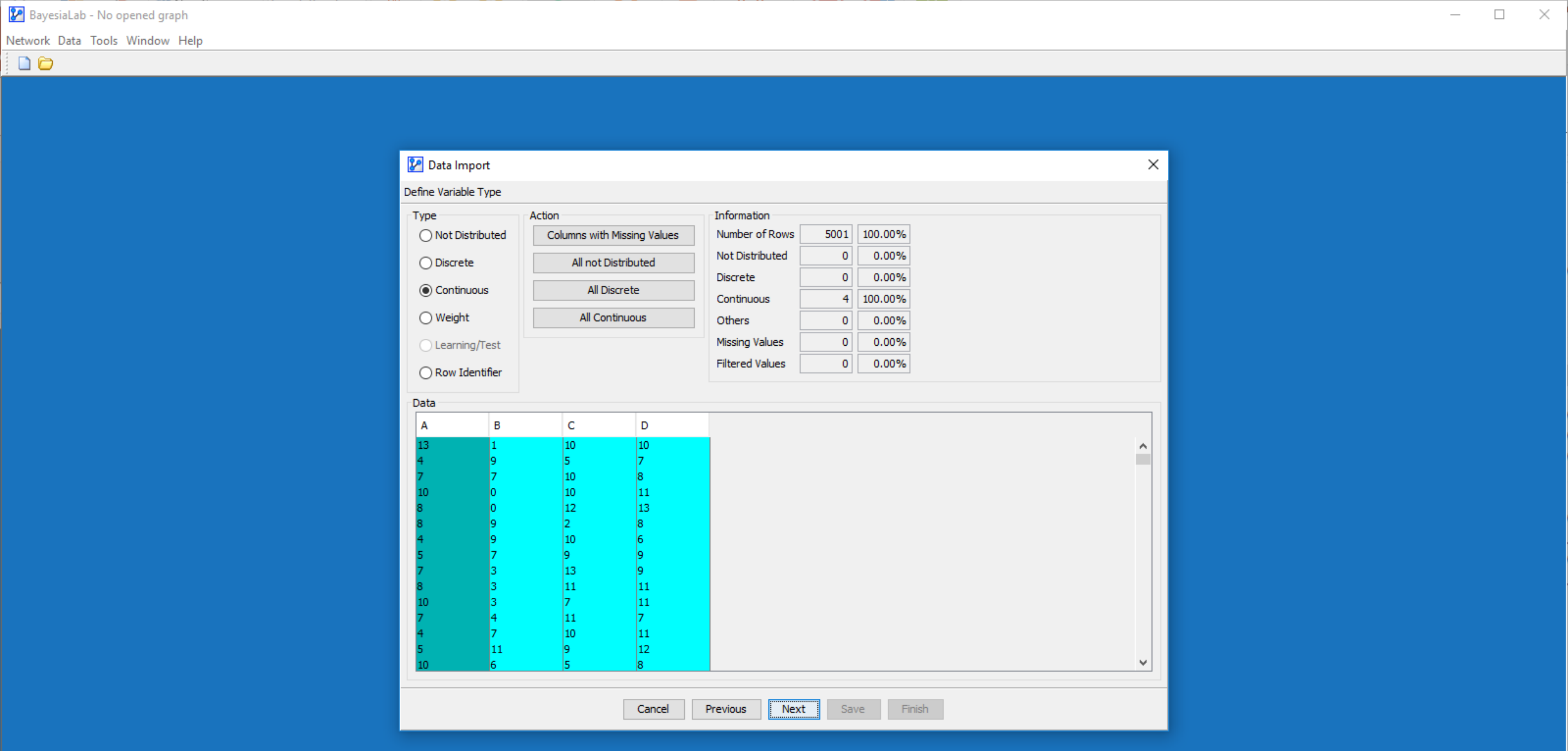
A desktop software for:

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

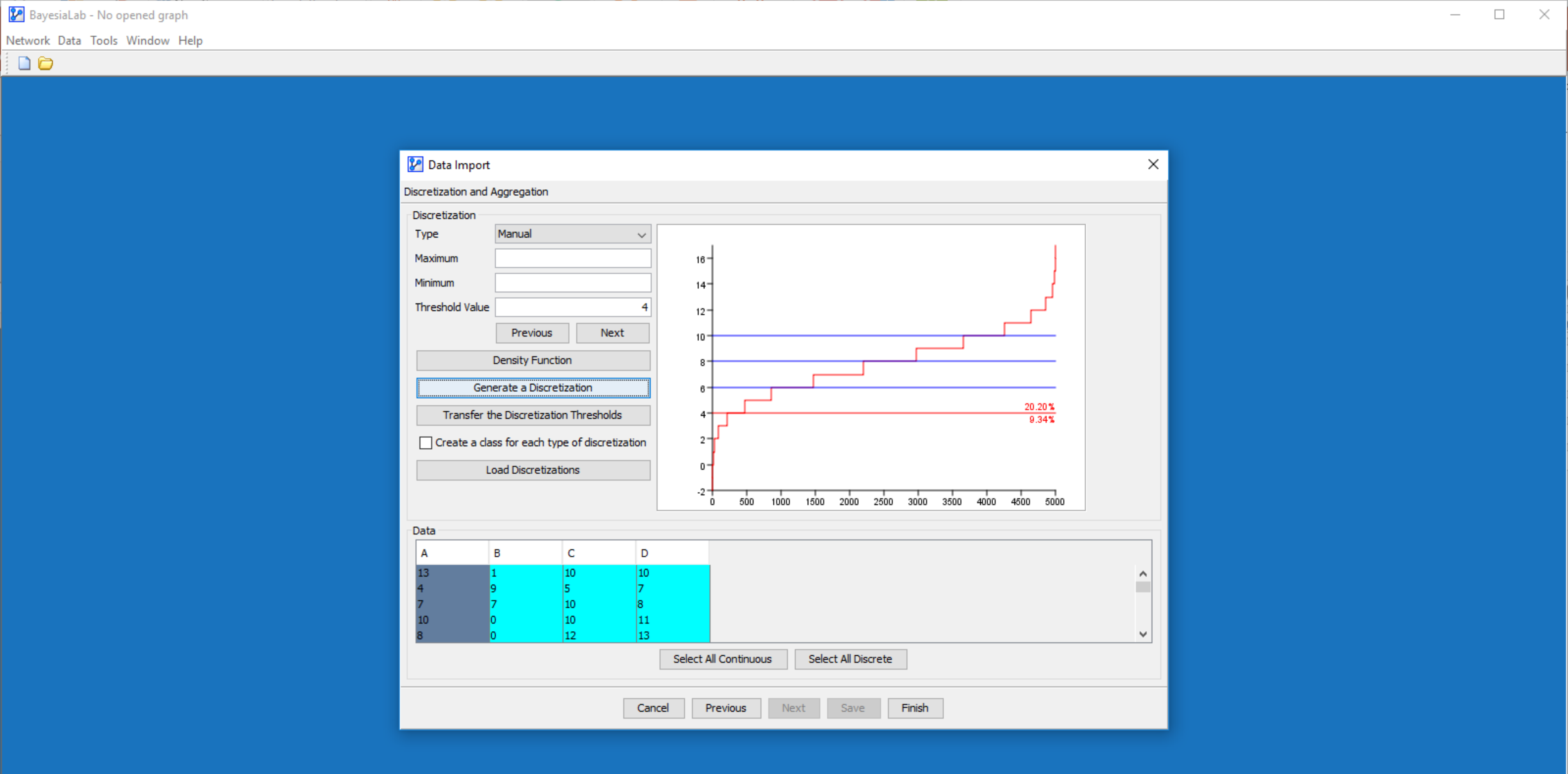
with Bayesian networks.



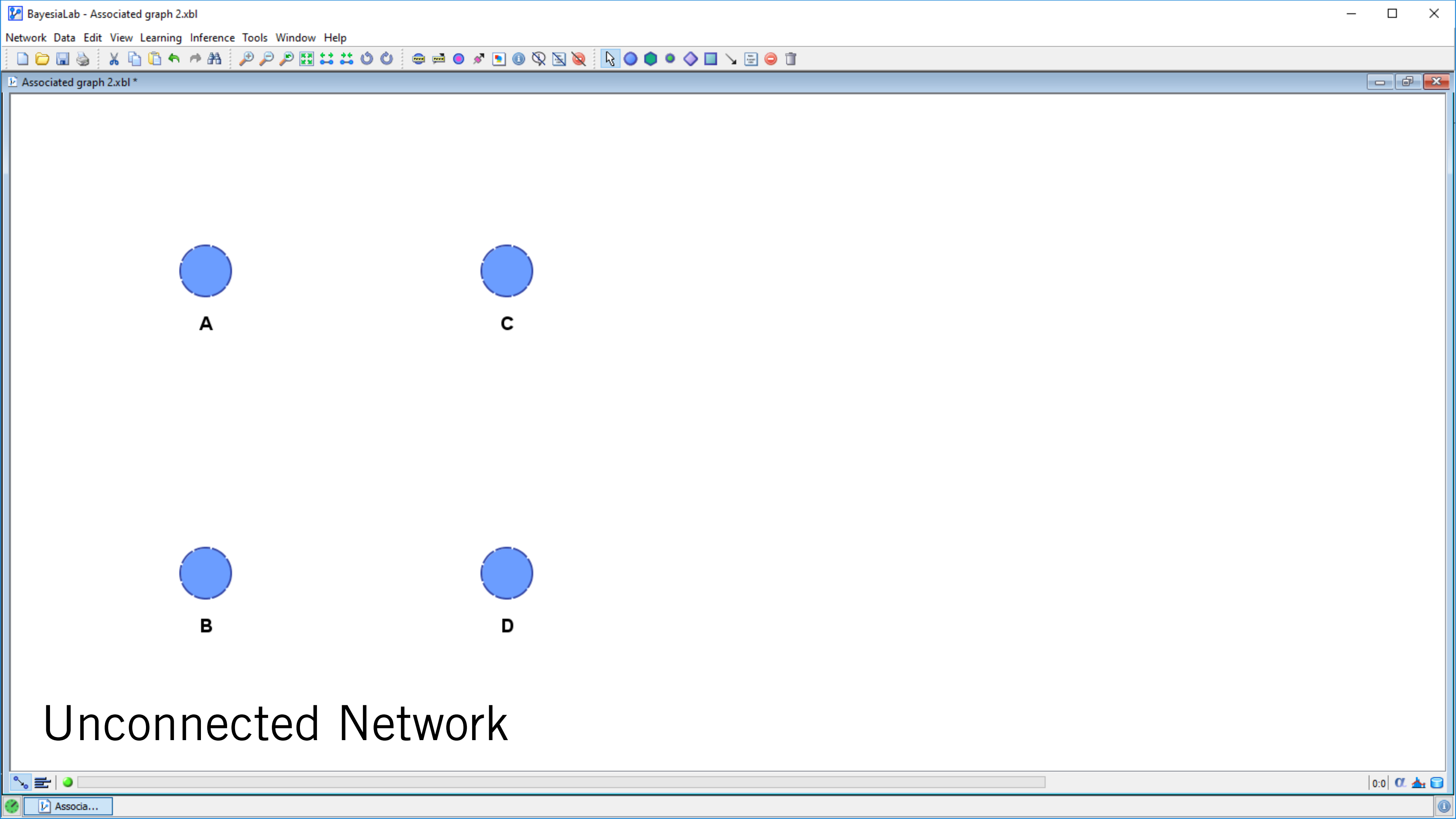
Data Import Wizard

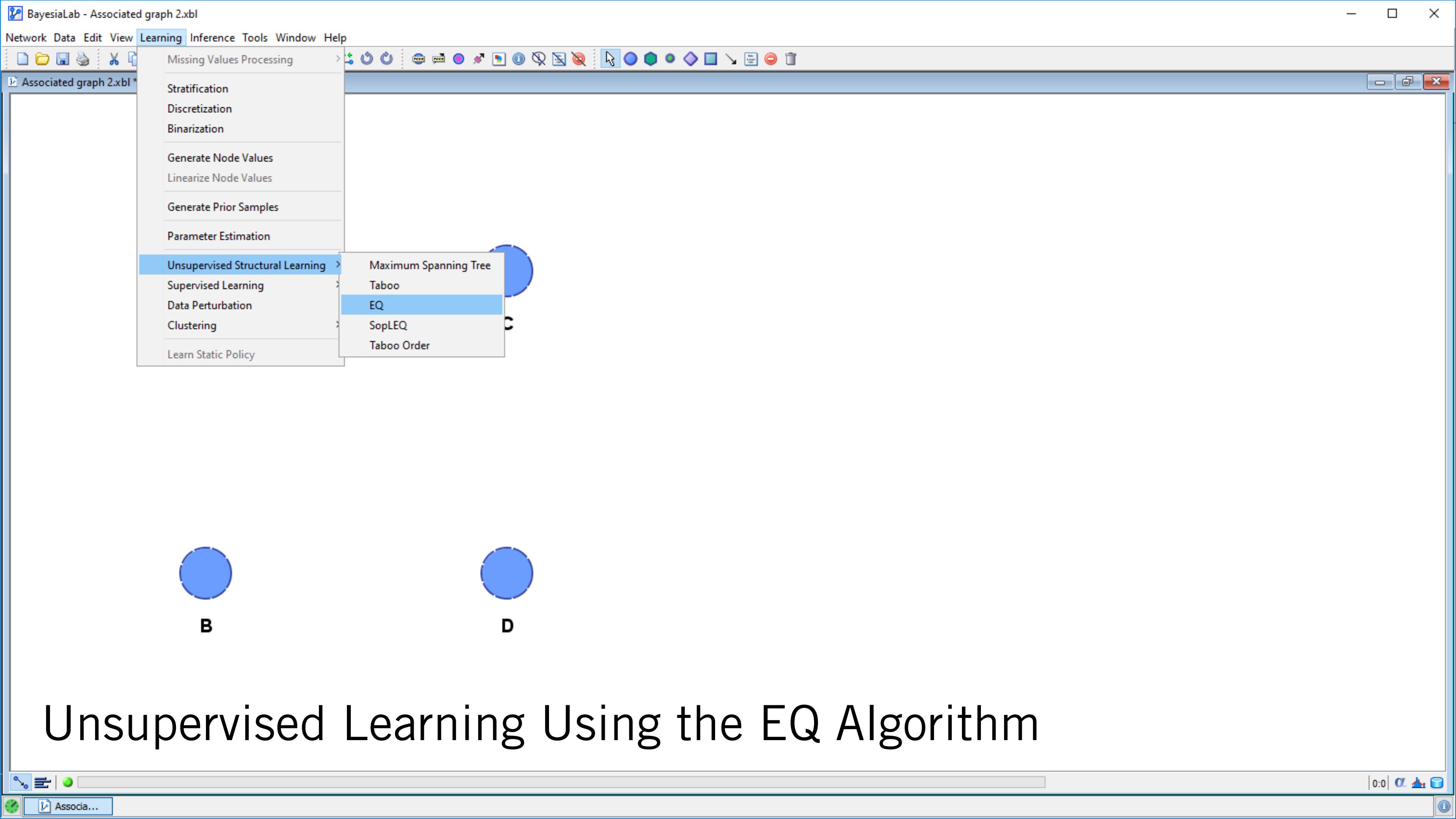


Variable Type Definition

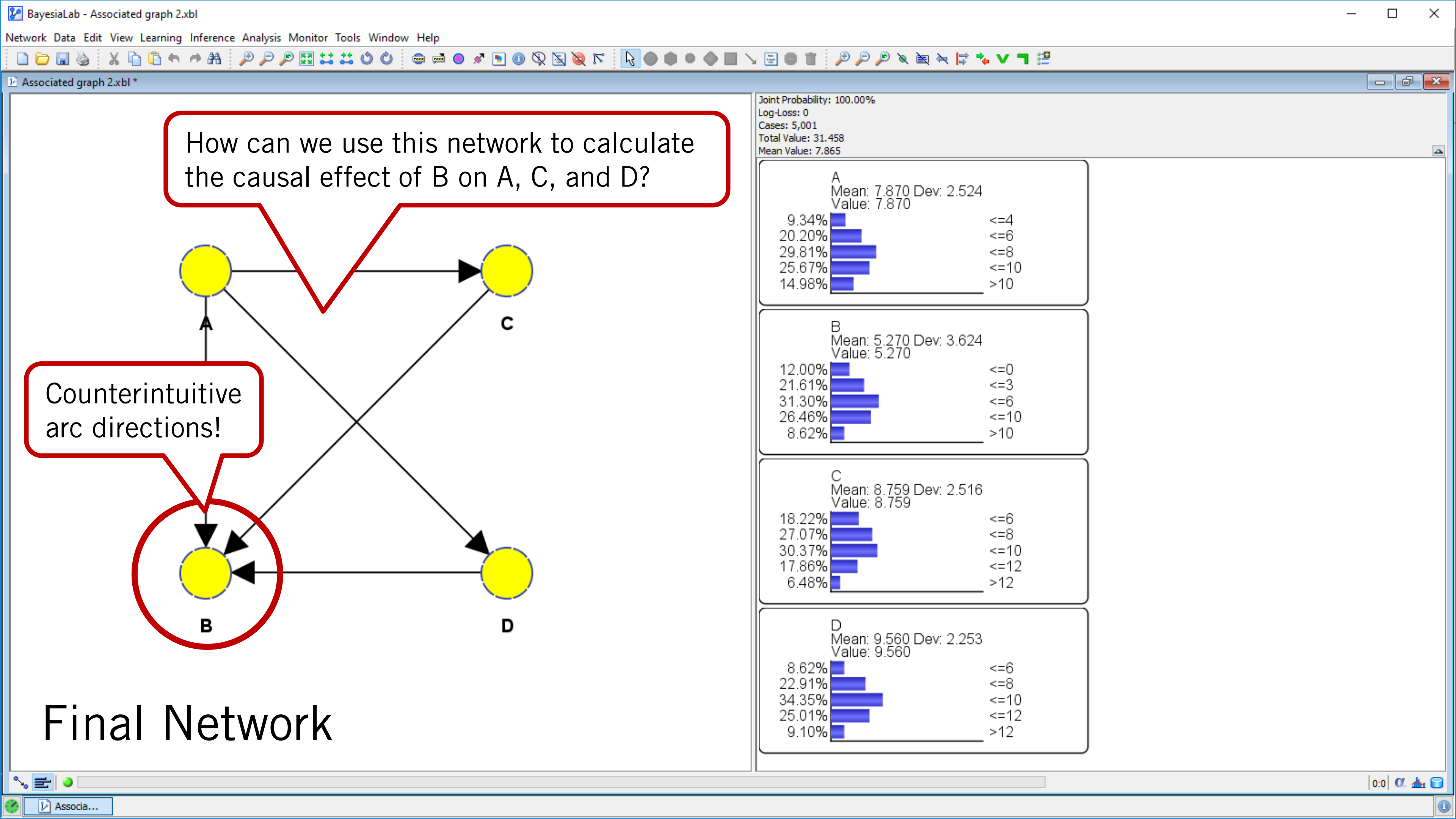


Discretization


BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 2.xbl *
A
C
B
D
Unconnected Network
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 *
How can we use this network to calculate the causal effect of B on A, C, and D?
Counterintuitive arc directions!
A
C
B
D
Final Network
Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,001
Total Value: 31.458
Mean Value: 7.865
A
Mean: 7.870 Dev: 2.524
Value: 7.870
9.34% <=4
20.20% <=6
29.81% <=8
25.67% <=10
14.98% >10
B
Mean: 5.270 Dev: 3.624
Value: 5.270
12.00% <=0
21.61% <=3
31.30% <=6
26.46% <=10
8.62% >10
C
Mean: 8.759 Dev: 2.516
Value: 8.759
18.22% <=6
27.07% <=8
30.37% <=10
17.86% <=12
6.48% >12
D
Mean: 9.560 Dev: 2.253
Value: 9.560
8.62% <=6
22.91% <=8
34.35% <=10
25.01% <=12
9.10% >12
Associa...

Disjunctive Cause Criterion

NIH-PA Author Manuscript

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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

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."

Cannibalized Product

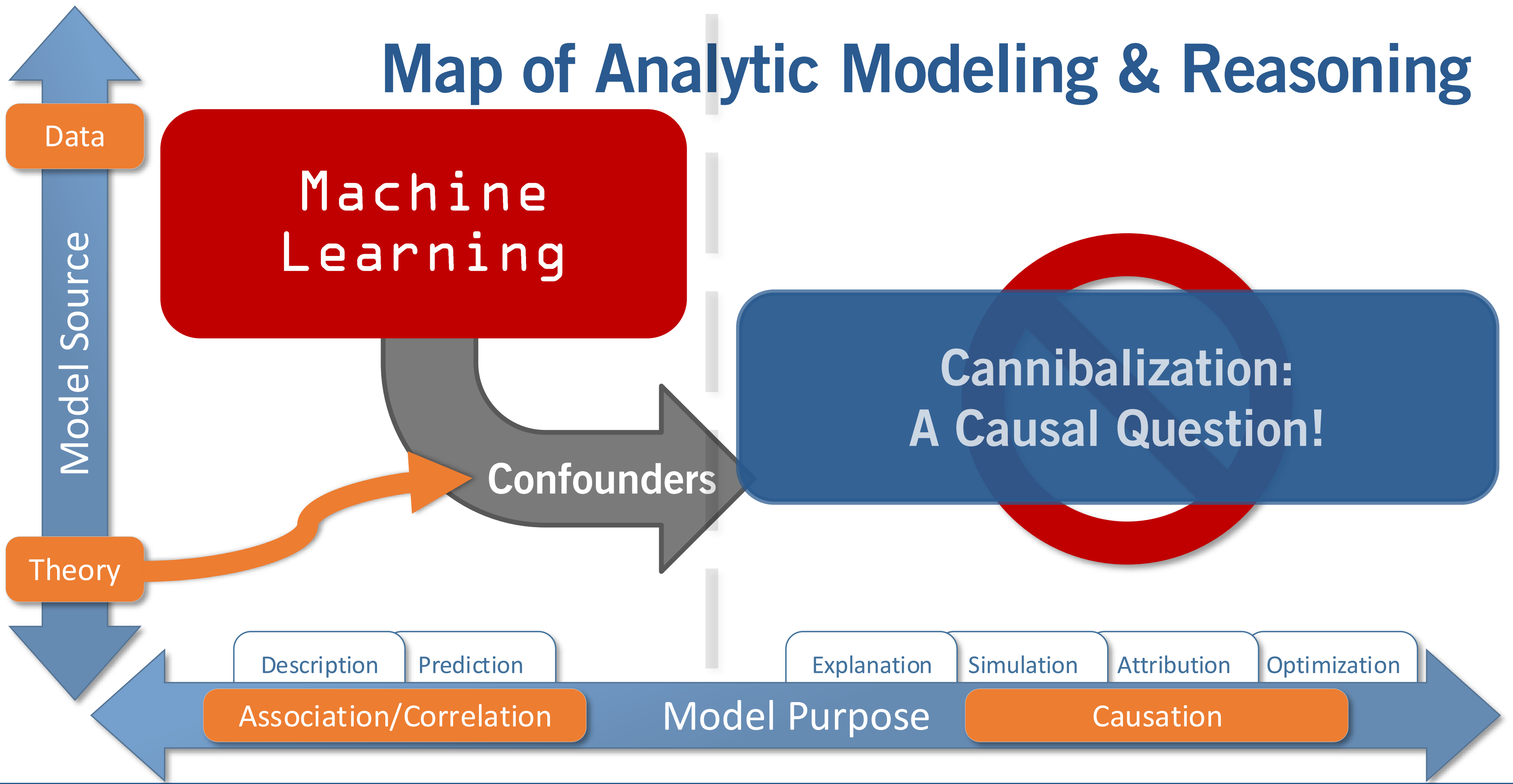
Confounder

Cannibalizing Product

Implementation in BayesiaLab:
Likelihood Matching on Confounders in
Direct Effects Analysis
→ Causal Effect, i.e., the Cannibalization Rate

IMPORTANT ASSUMPTION:
NO UNOBSERVED CONFOUNDERS

Map of Analytic Modeling & Reasoning

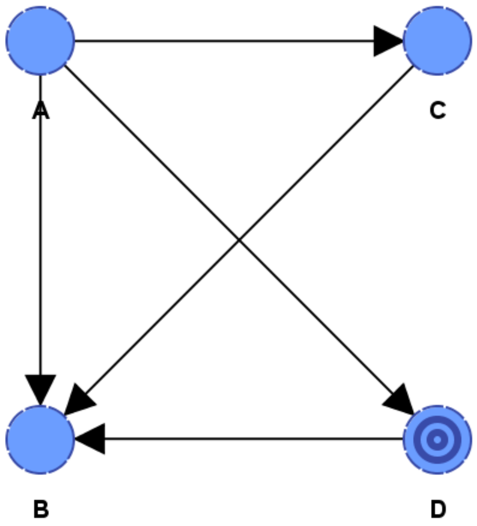


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Cannibalization\Associated graph 2.xbl

Network Data Edit View Learning Inference Analysis Monitor Tools Window Help

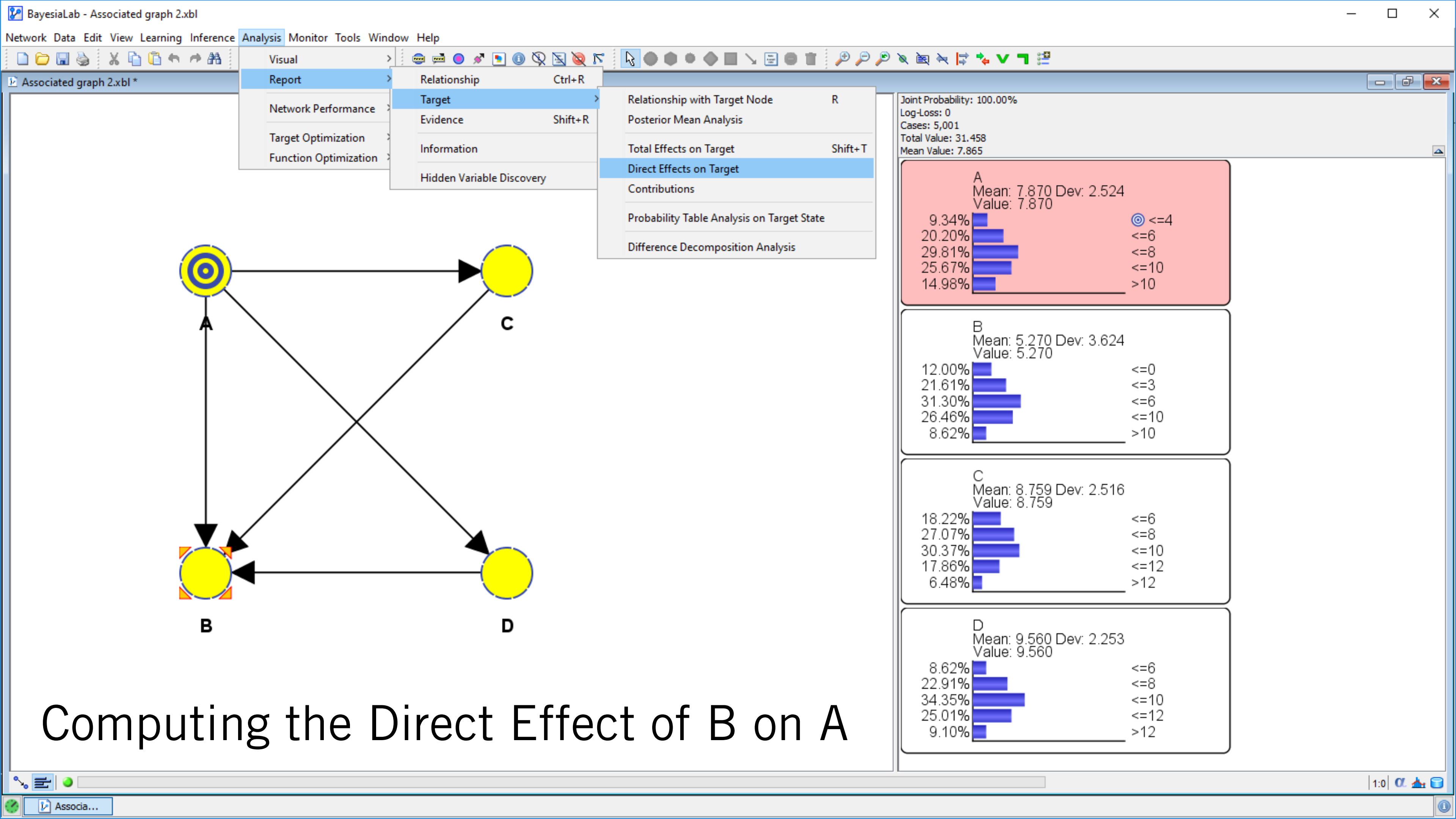
Associated graph 2.xbl

Joint Probability: 100.00%
Log-Loss: 0
Cases: 5,001
Total Value: 31.458
Mean Value: 7.865

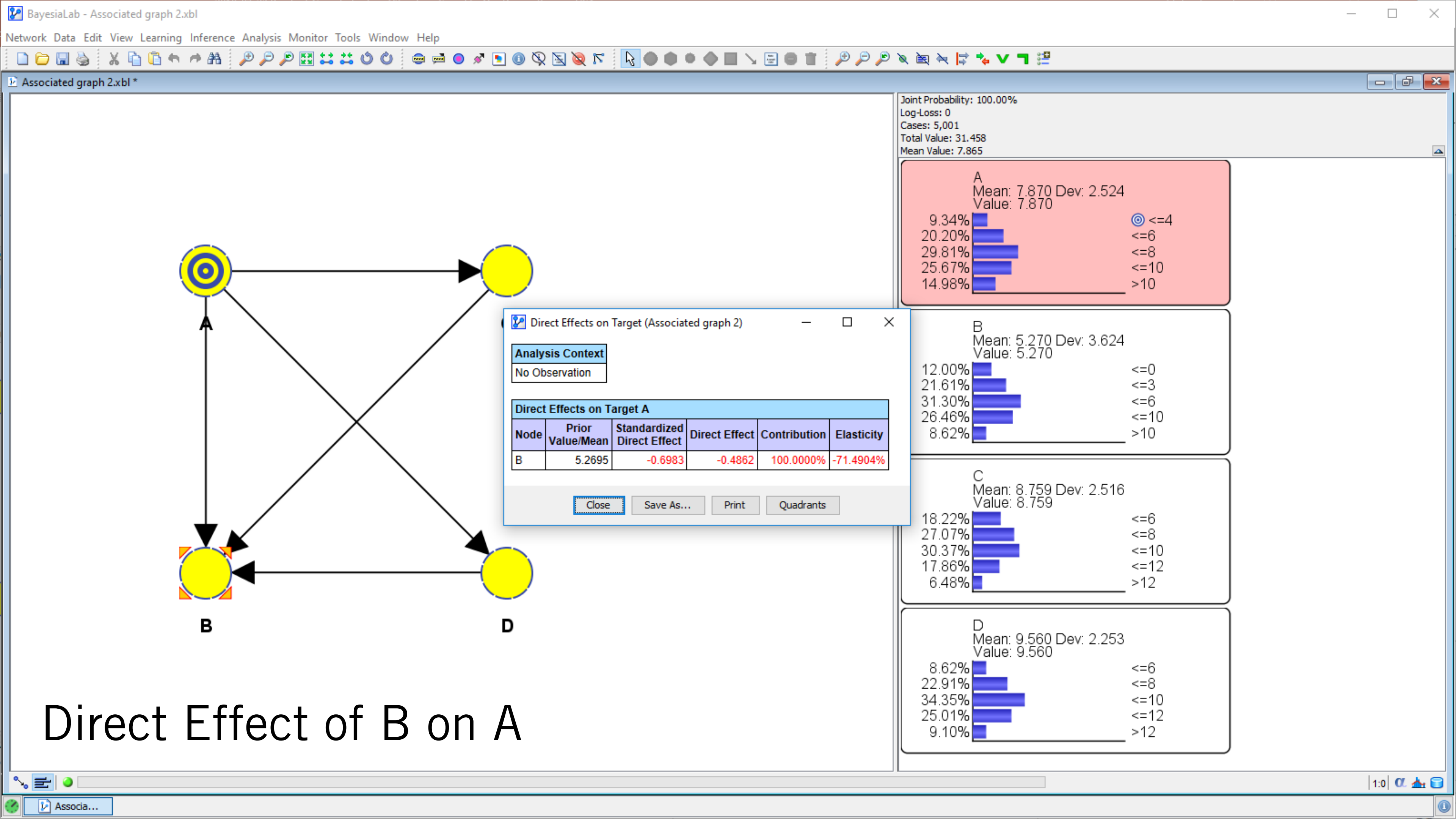


We need to define *confounders* and *non-confounders*. By default, all nodes are *confounders*.

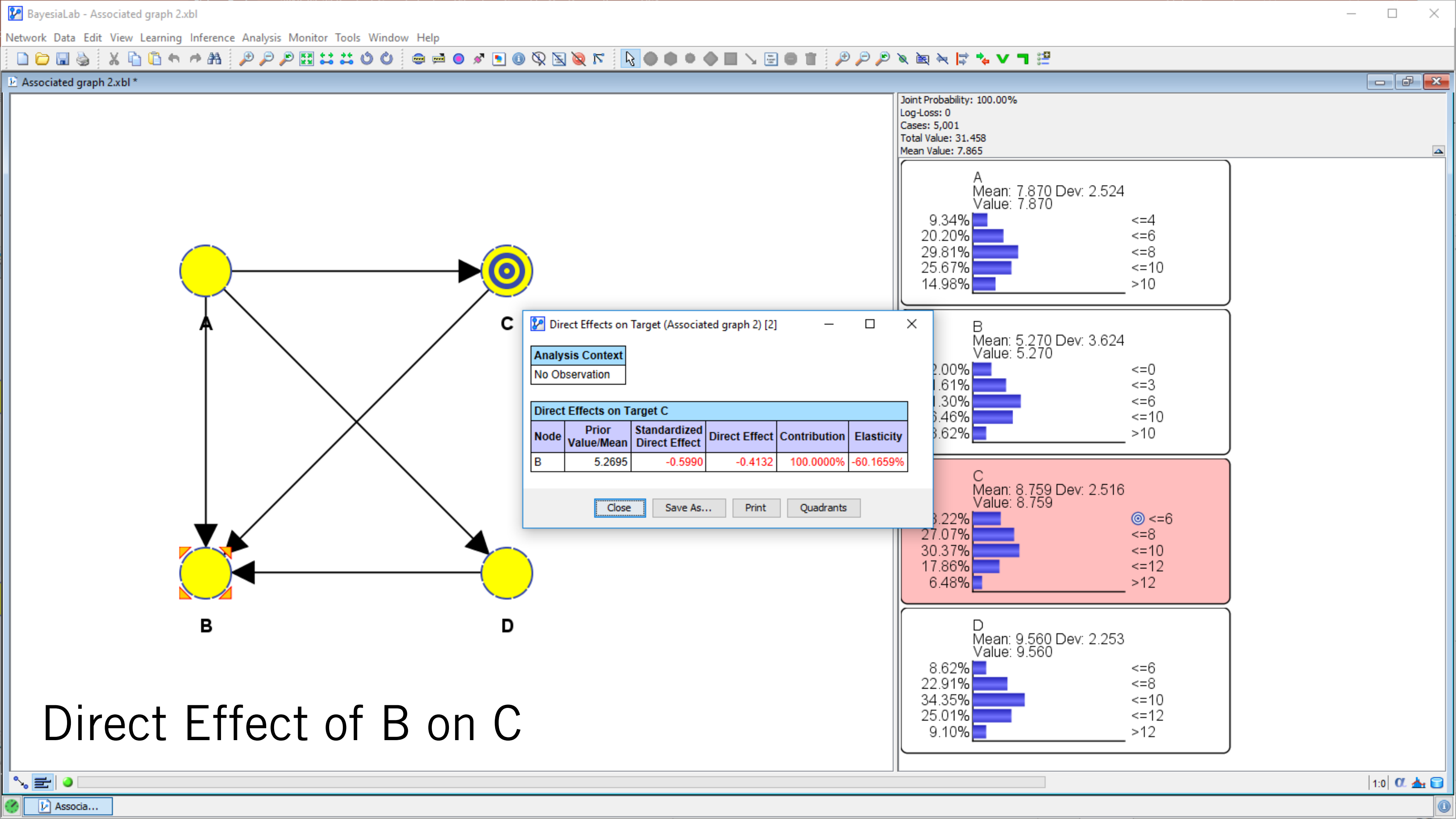
Final Network



Computing the Direct Effect of B on A



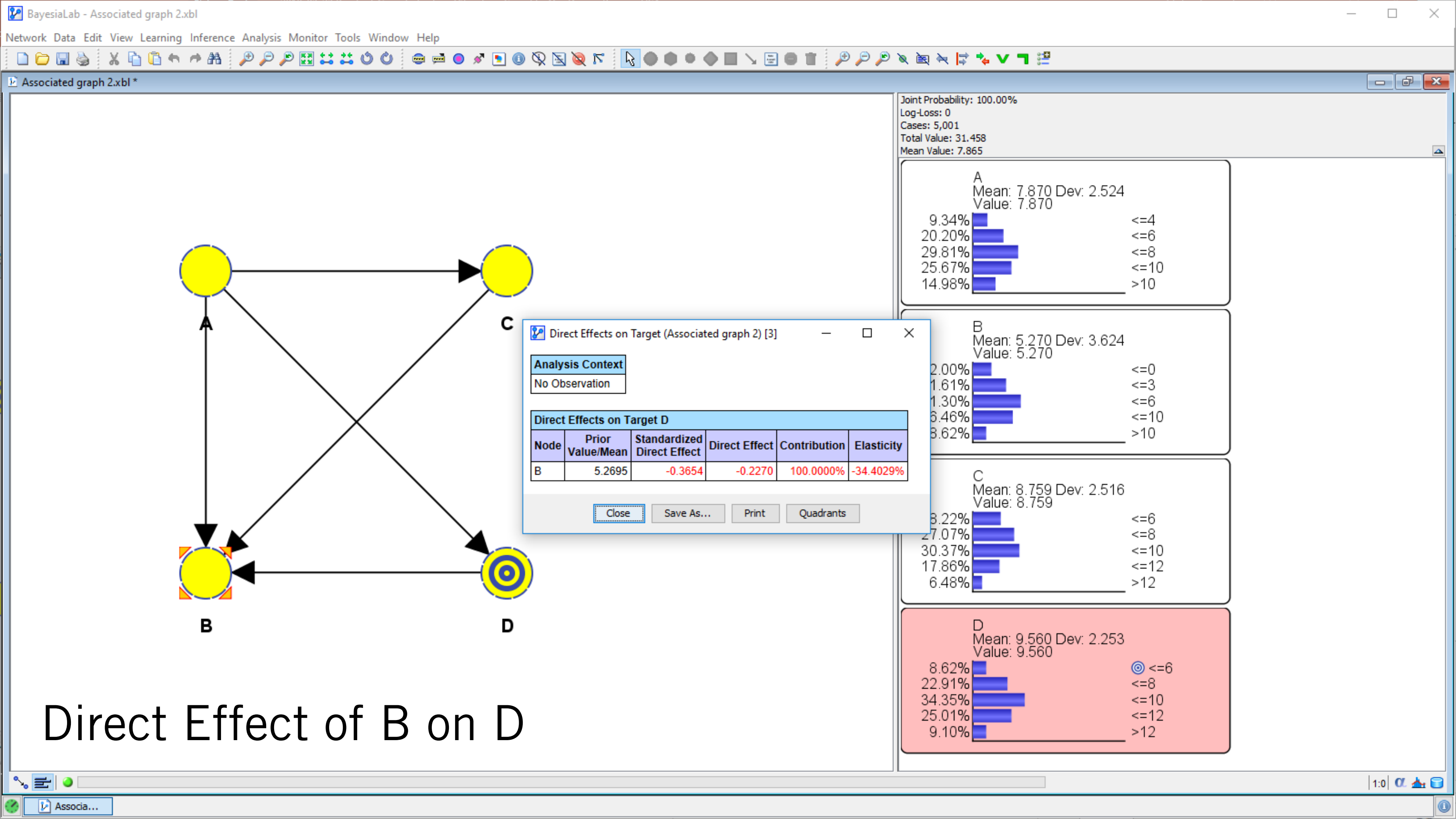
Direct Effect of B on A



Analysis Context
No Observation

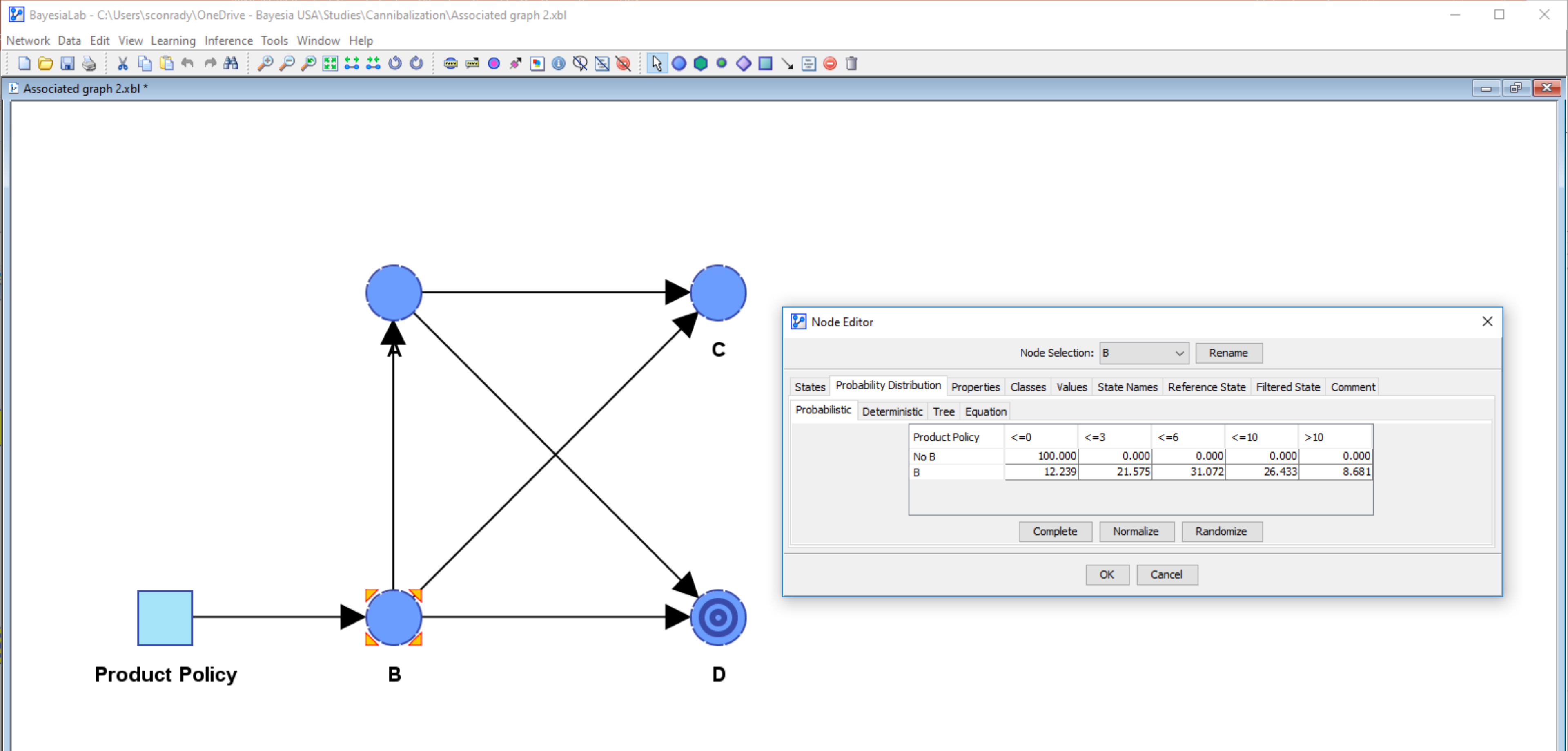
Direct Effects on Target C					
Node	Prior Value/Mean	Standardized Direct Effect	Direct Effect	Contribution	Elasticity
B	5.2695	-0.5990	-0.4132	100.0000%	-60.1659%

Direct Effect of B on C

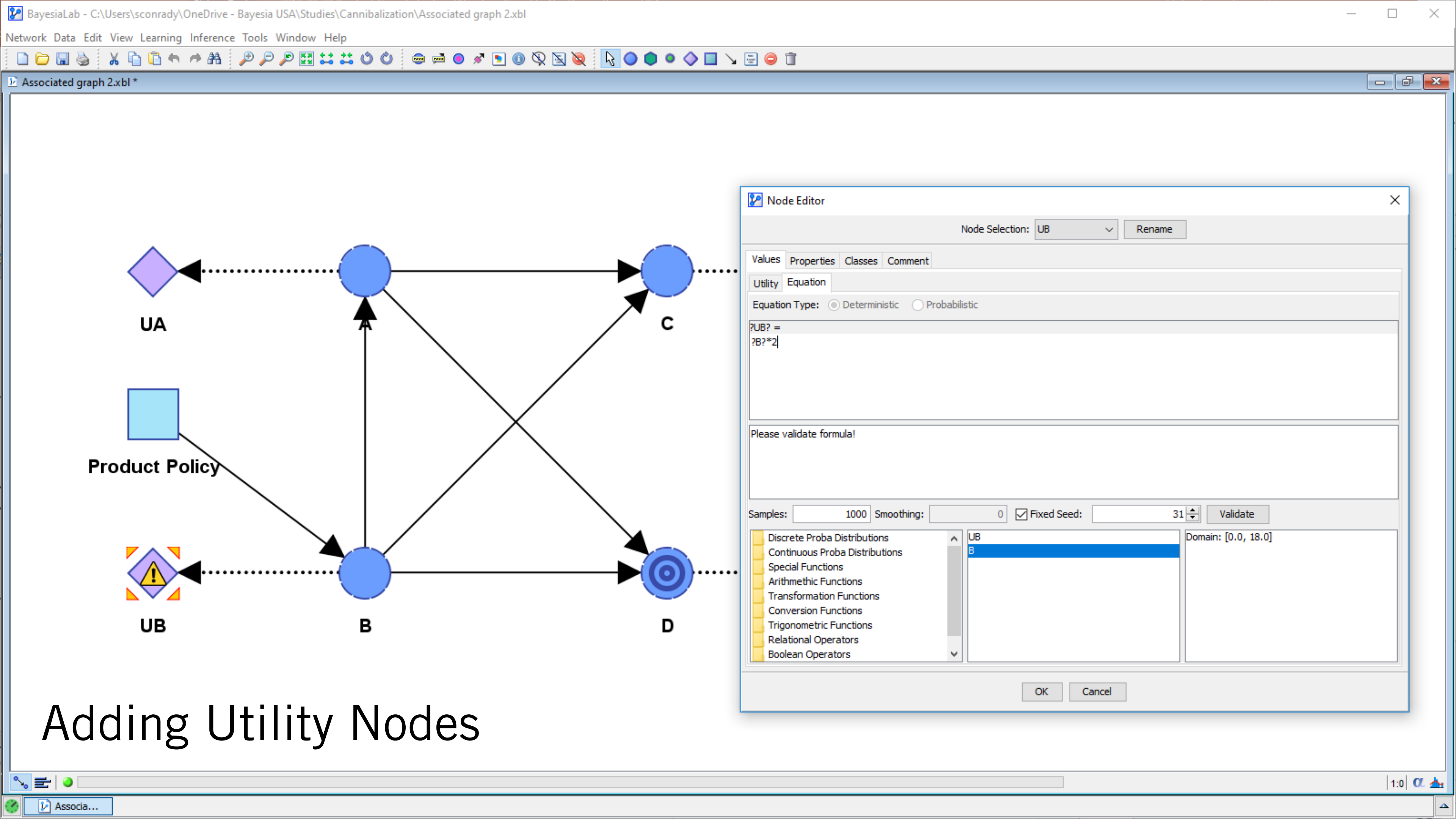


Direct Effects on Target D					
Node	Prior Value/Mean	Standardized Direct Effect	Direct Effect	Contribution	Elasticity
B	5.2695	-0.3654	-0.2270	100.0000%	-34.4029%

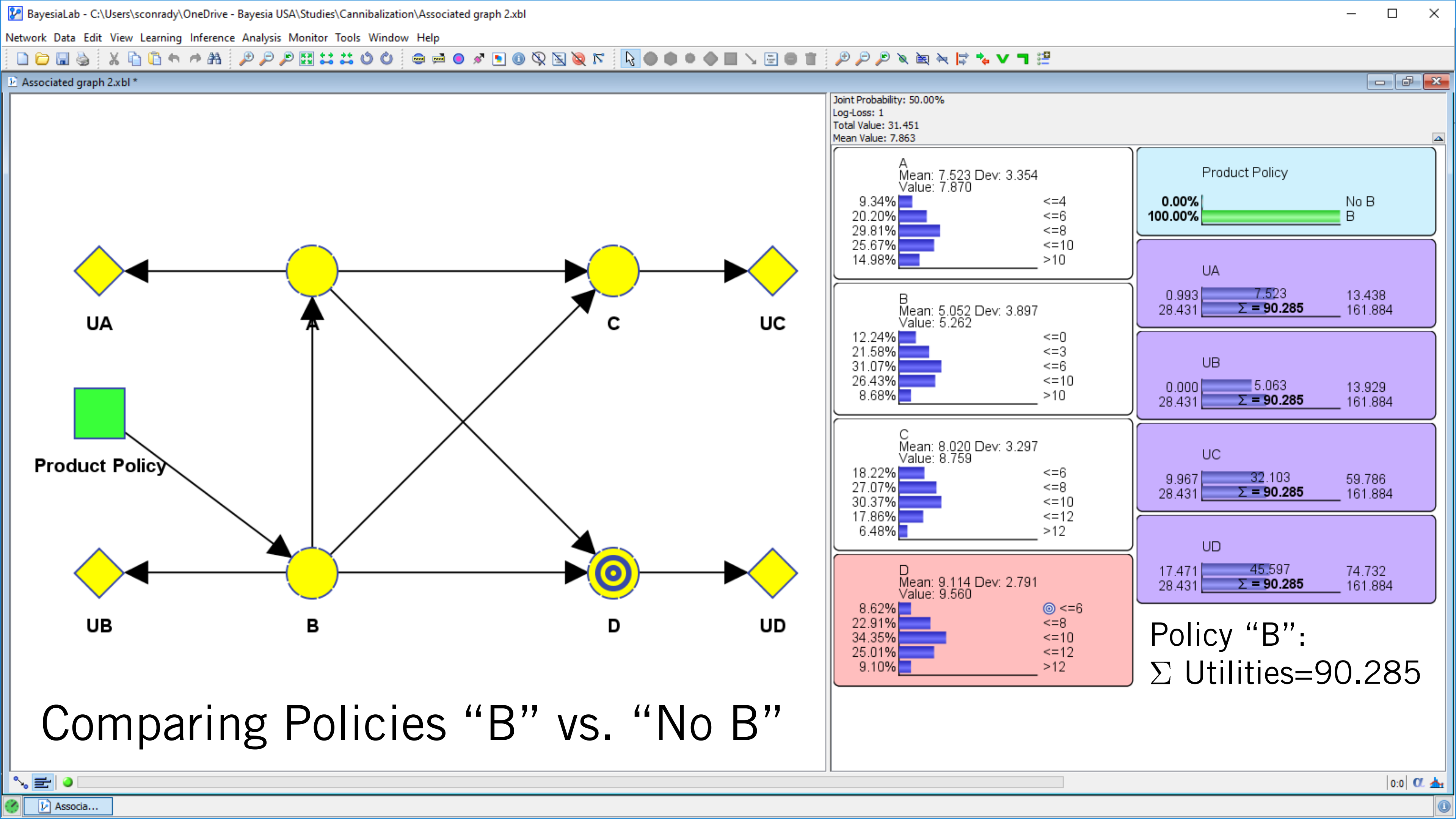
Direct Effect of B on D



Adding a Decision Node

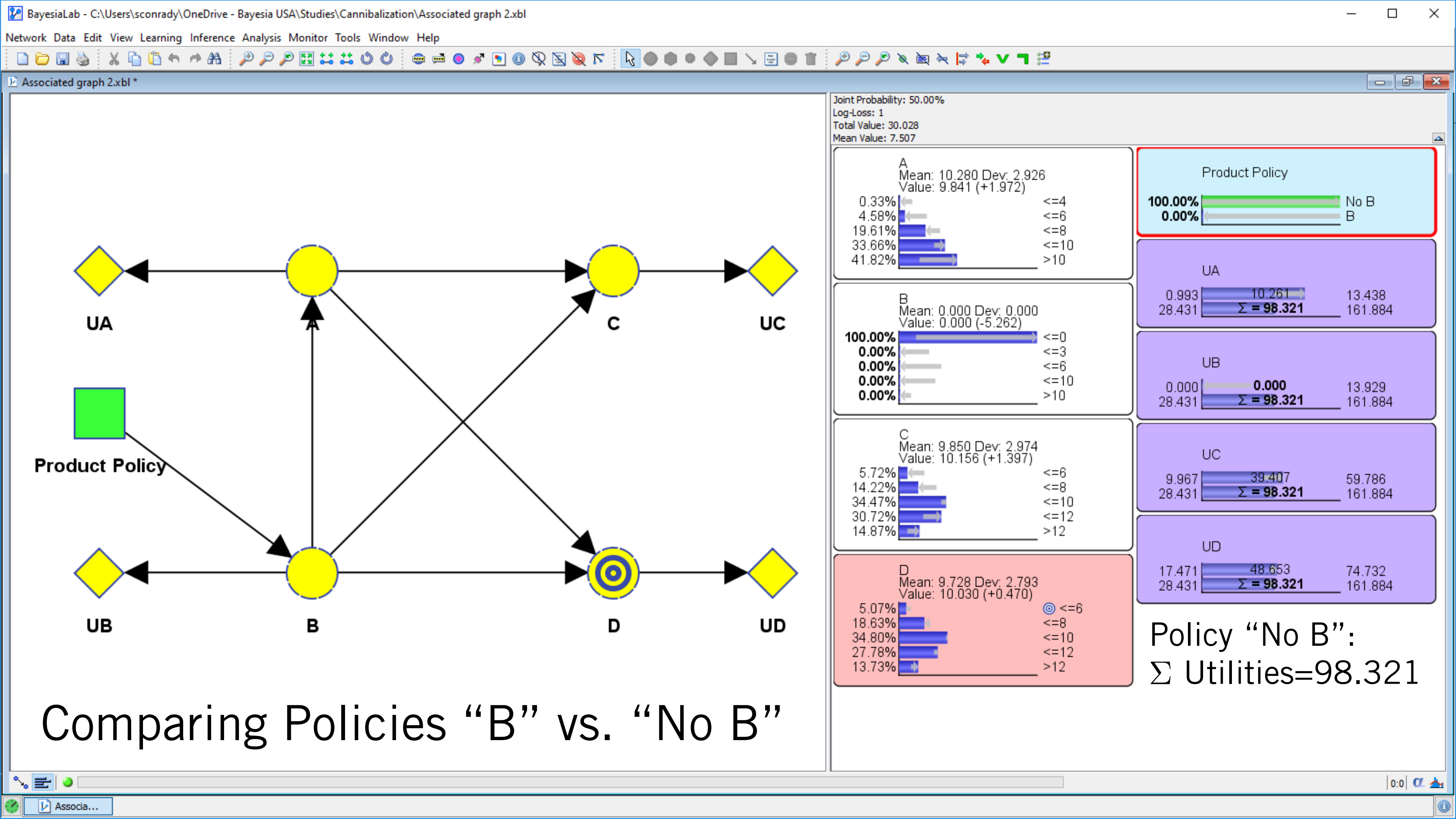


Adding Utility Nodes



Policy "B":
Σ Utilities=90.285

Comparing Policies "B" vs. "No B"



Policy “No B”:
Σ Utilities=98.321

Comparing Policies “B” vs. “No B”

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In Conclusion…

Webinar Series: Friday at 1 p.m. (Central)

Upcoming Webinars:

- March 30 Good Friday — No Webinar
- April 6 t.b.d.
- April 13 t.b.d.

Register here: bayesia.com/events

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  - May 16–18, 2018: Seattle Introductory BayesiaLab Course
  - May 21–23, 2018: Seattle Advanced BayesiaLab Course
  - June 5–7, 2018: Paris, France Introductory BayesiaLab Course
  - June 26–28, 2018: Boston Introductory BayesiaLab Course
  - July 23–25, 2018: San Francisco Introductory BayesiaLab Course
  - September 26–28, 2018: New Delhi Introductory BayesiaLab Course
  - October 29–31, 2018: Chicago Introductory BayesiaLab Course
  - November 5–7, 2018: Chicago Advanced BayesiaLab Course
- 6th Annual BayesiaLab Conference in Chicago >

BayesiaLab 7

Artificial Intelligence for Research, Analytics, and Reasoning

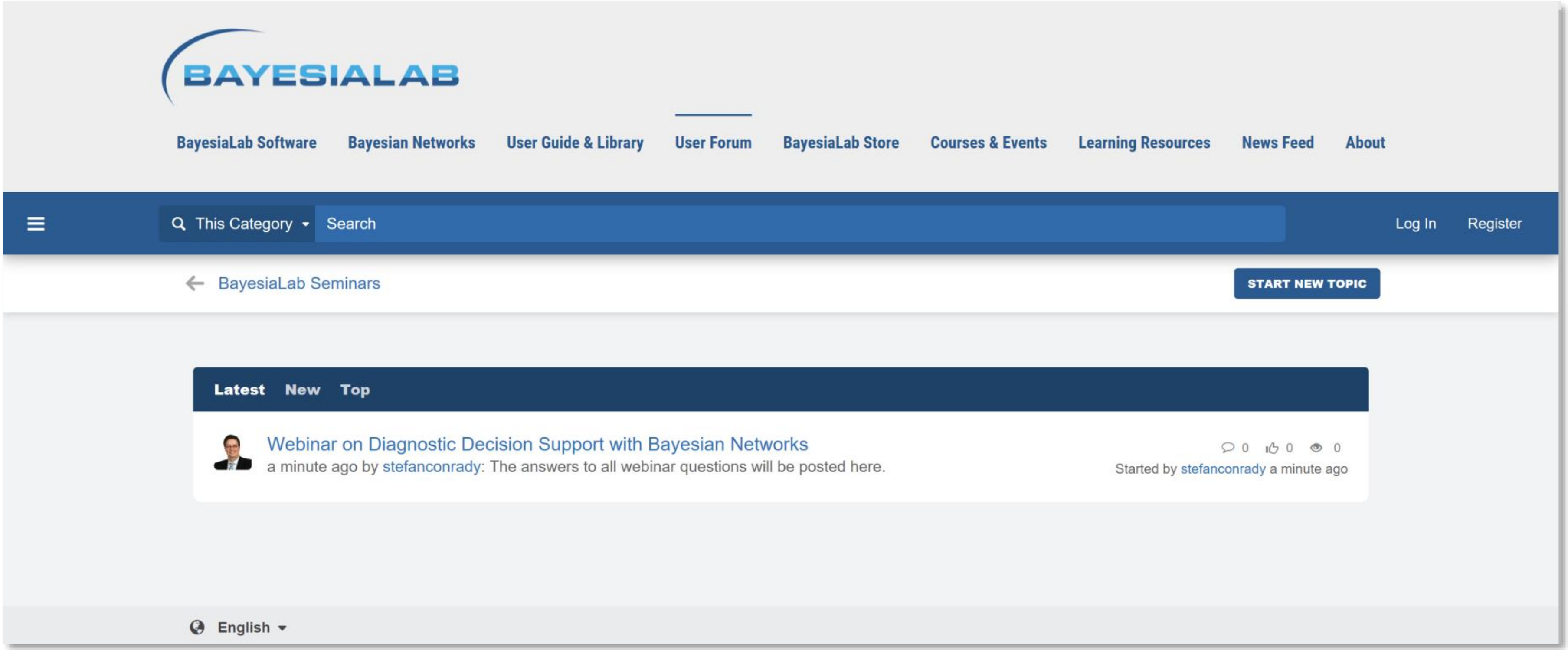
What is BayesiaLab?

Support

Schedule Demo

www.bayesia.com/2018-04-11-intro-course-sydney-nsw?__hstc=221168007.5bc10468db2061b448b8c96d64fc37dd.1503008180141.1521497802489.1521820559889.128&__hssc=221168007.2.1521820559889&__hsfp=3344690374

User Forum: bayesia.com/community



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- Apply for Unrestricted Evaluation Version:
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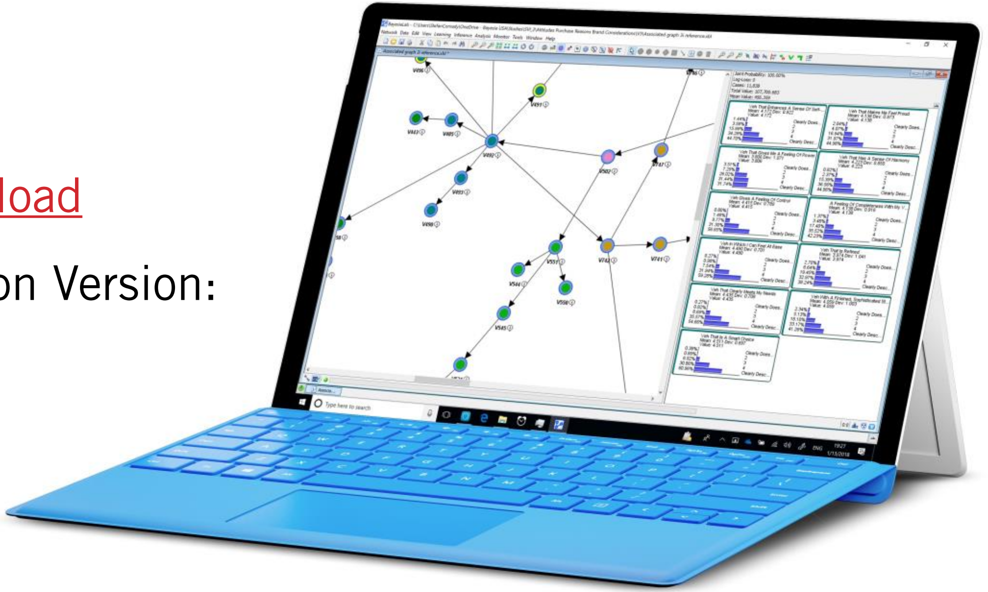

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- April 11–13
  Sydney, Australia
- May 16–18
  Seattle, WA
- June 26–28
  Boston, MA
- July 23–25
  San Francisco, CA
- August 29–31
  London, UK
- September 26–28
  New Delhi, India
- October 29–31
  Chicago, IL
- December 4–6
  New York, NY

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Introductory BayesiaLab Course
in San Francisco, California
July 23–25, 2018

6th Annual BayesiaLab Conference in Chicago
November 1–2, 2018

Thank You!

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