Marketing Mix Optimization

Causal Inference in Marketing Science

The webinar will start at:

13:00:00

The current time is:

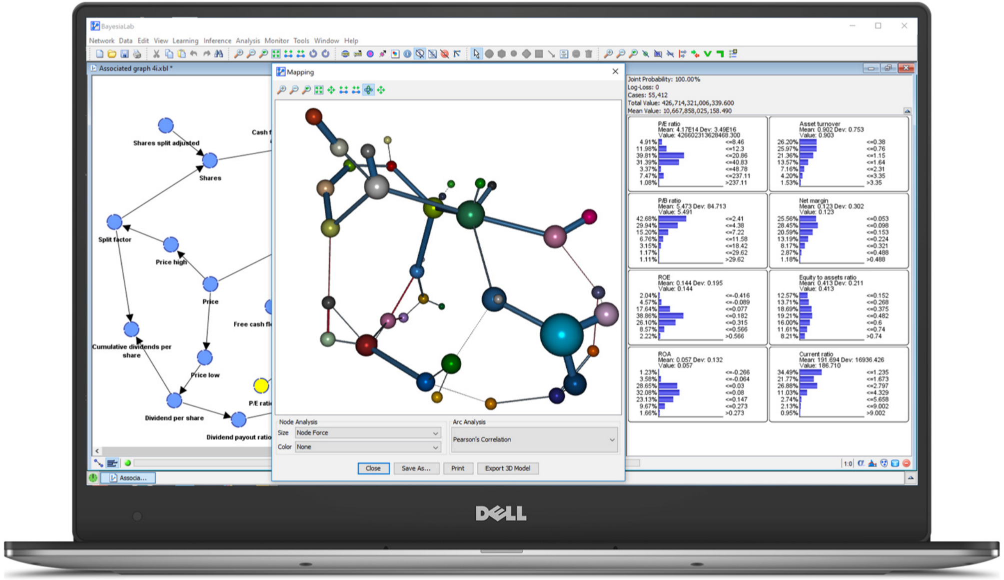
12:47:30

Central Daylight Time, UTC-5

Stefan Conrady

stefan.conrady@bayesia.us

BAYESIALAB



A desktop software for:

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

with Bayesian networks.

Today's Program

1. Motivation & Background

- Introductory Example:
  The Generic 2000 Commercial
- Simpson's Paradox & Causality

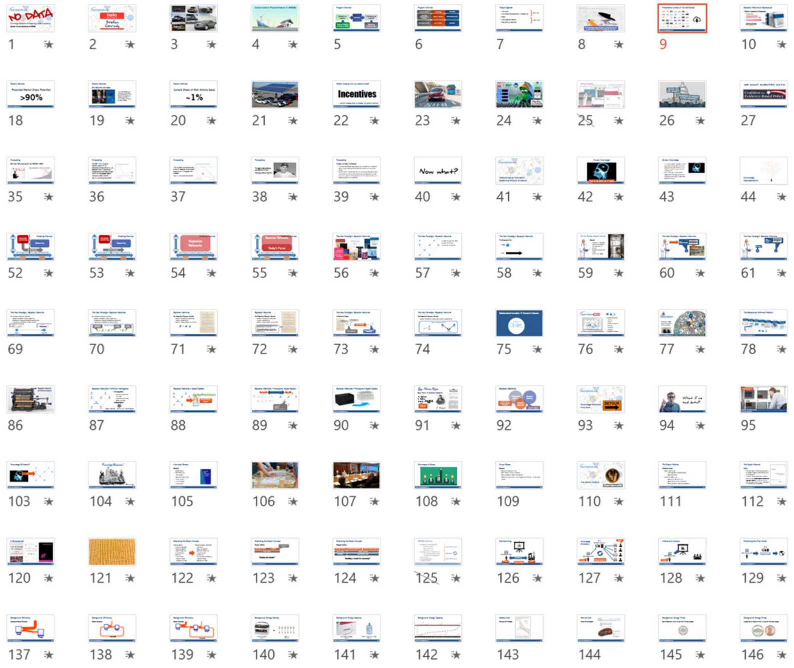
20 min.

2. Marketing Mix Modeling Workflow

- Causal Assumptions?
- Disjunctive Cause Criterion
- Machine-Learning with BayesiaLab
- Causal Inference & Optimization

40 min.

Webinar Slides, Data, and Recording Available



Bayesian Networks & BayesiaLab

A Practical Introduction for Researchers

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

amazon

Introductory Example

GENERIC
2000

- The Generic Car Company runs a commercial at the Super Bowl for its new model, the Generic 2000.

- The Generic Car Company runs a commercial at the Super Bowl for its new model, the Generic 2000.

Introductory Example

Telephone Survey

- Afterwards, Generic conducts a telephone survey of 1,000 car shoppers to understand the effect of the Super Bowl commercial on shopping and purchase behavior.

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

Observational Data

Introductory Example

Analyzing the survey with a cross-tab...

Ad Exposure	Gender	Test Drive	Purchase
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	Purchase
No	60%
Yes	45%

-15%

Introductory Example

However, grouping the survey data by Gender reveals:

Ad Exposure	Gender	Test Drive	Purchase
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

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

+5%

Introductory Example

How is this possible?

Ad Exposure	Purchase
No	60%
Yes	45%

-15%

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

+5%

Simpson's Paradox

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 Test Drive shows:

Ad Exposure	Gender	Test Drive	Purchase
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

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

-10%

-40%

Introductory Example

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

Ad Exposure	Gender	Test Drive	Purchase
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

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

+10%

-10%

So, what's the advertising effect?

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

≈ 0

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

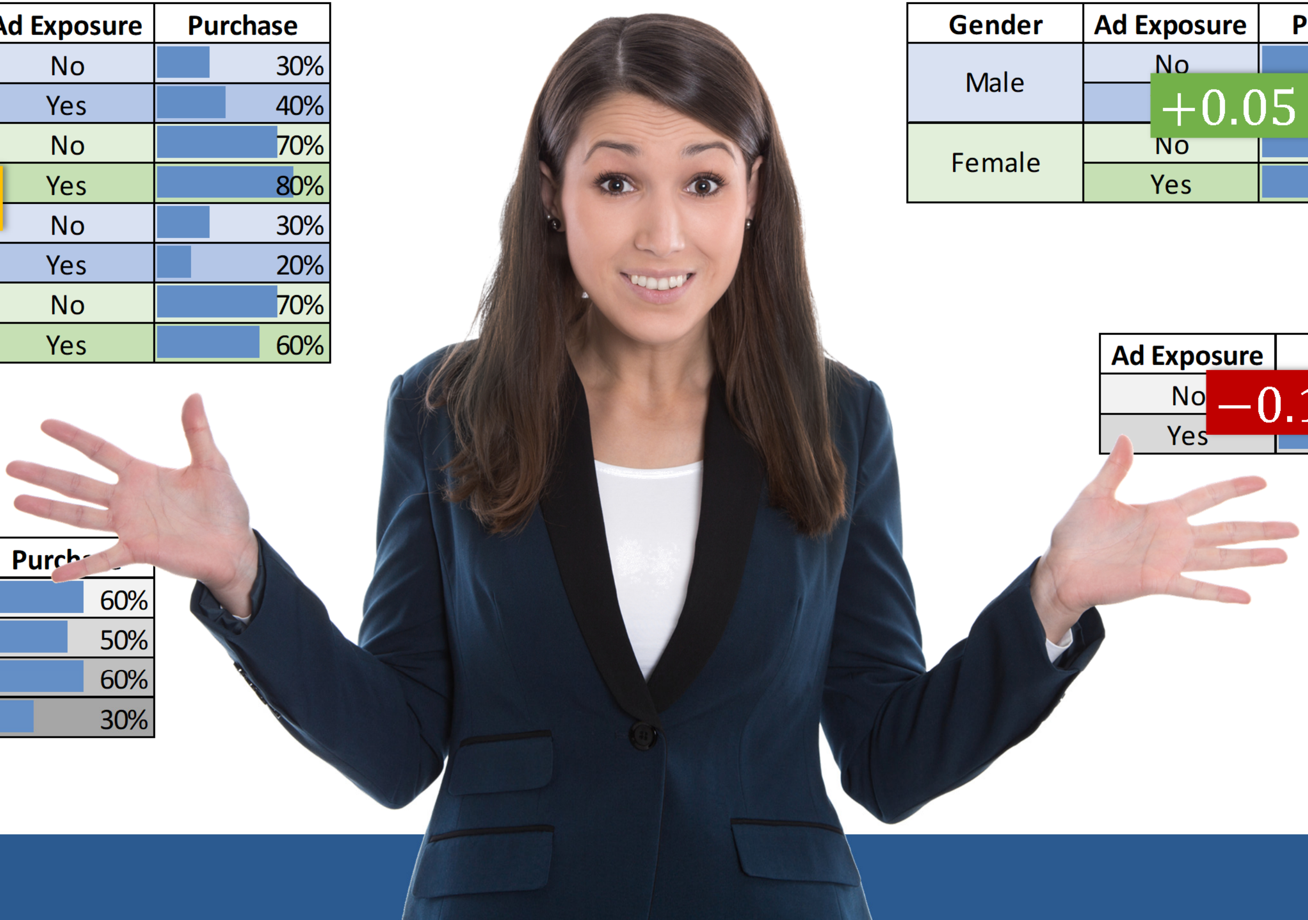
$+0.05$

Ad Exposure	Purchase
No	60%
Yes	45%

-0.15

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

-0.2



Your Opinion?

Did this commercial have a positive or negative effect on purchase?


RUSSELL GLASS · SEAN CALLAHAN
THE
BUSINESS
DATA
DRIVEN
O'REILL
Data
Driven
Creating a Data C
Data-Driven
Decision-Making
increasing sales with
DATA - DRIVEN
MARKETING
$
$
$
$
$
loginradius
5 Steps To Powering
Data Driven Decision Makin
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
DataDriven
Business

Introductory Example

$$Purchase = \boxed{-0.15 \cdot Ad\ Exposure} + 0.6\ (R^2 = 0.02)$$

-0.15

$$Purchase = 0.05 \cdot Ad\ Exposure + 0.4 \cdot Gender + 0.3\ (R^2 = 0.14)$$

$+0.05$

$$Purchase = -0.2 \cdot Ad\ Exposure - 0.1 \cdot Test\ Drive + 0.67\ (R^2 = 0.03)$$

-0.2

$$Purchase = 0.001 \cdot Ad\ Exposure + 0.4 \cdot Gender - 0.1 \cdot Test\ Drive + 0.37\ (R^2 = 0.15)$$

≈ 0

$$y=f(x)$$

Observational vs. Causal Inference

$$y=f(x)$$

ambiguous

Observational Inference (Prediction)

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

"given that I see"

Causal Inference (Intervention)

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

"given that I do"

Map of Analytic Modeling & Reasoning

Data

Model Source

Theory

Was it good to "do" this commercial?

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

"given that I see"

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

"given that I do"

Description | Prediction

Association/Correlation

Model Purpose

Explanation | Simulation | Attribution | Optimization

Causation

So, what's the a … ffect?

“given that I see”

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

≈ 0

“given that I see”

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

+0.05

“given that I see”

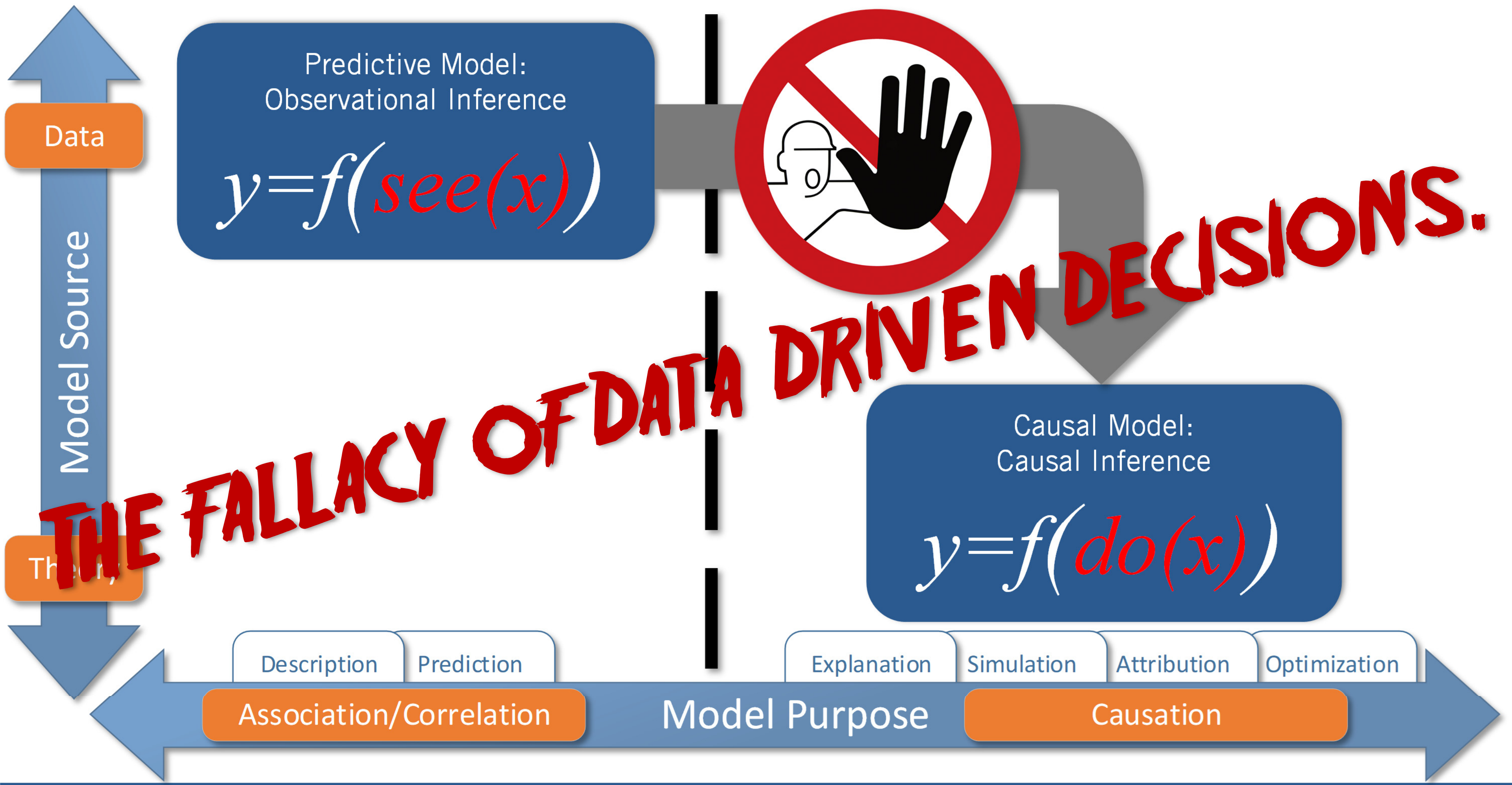
Test Drive	Ad Exposure	Purchase
No	No	60%
	Yes	50%
Yes	No	60%
	Yes	30%

−0.2

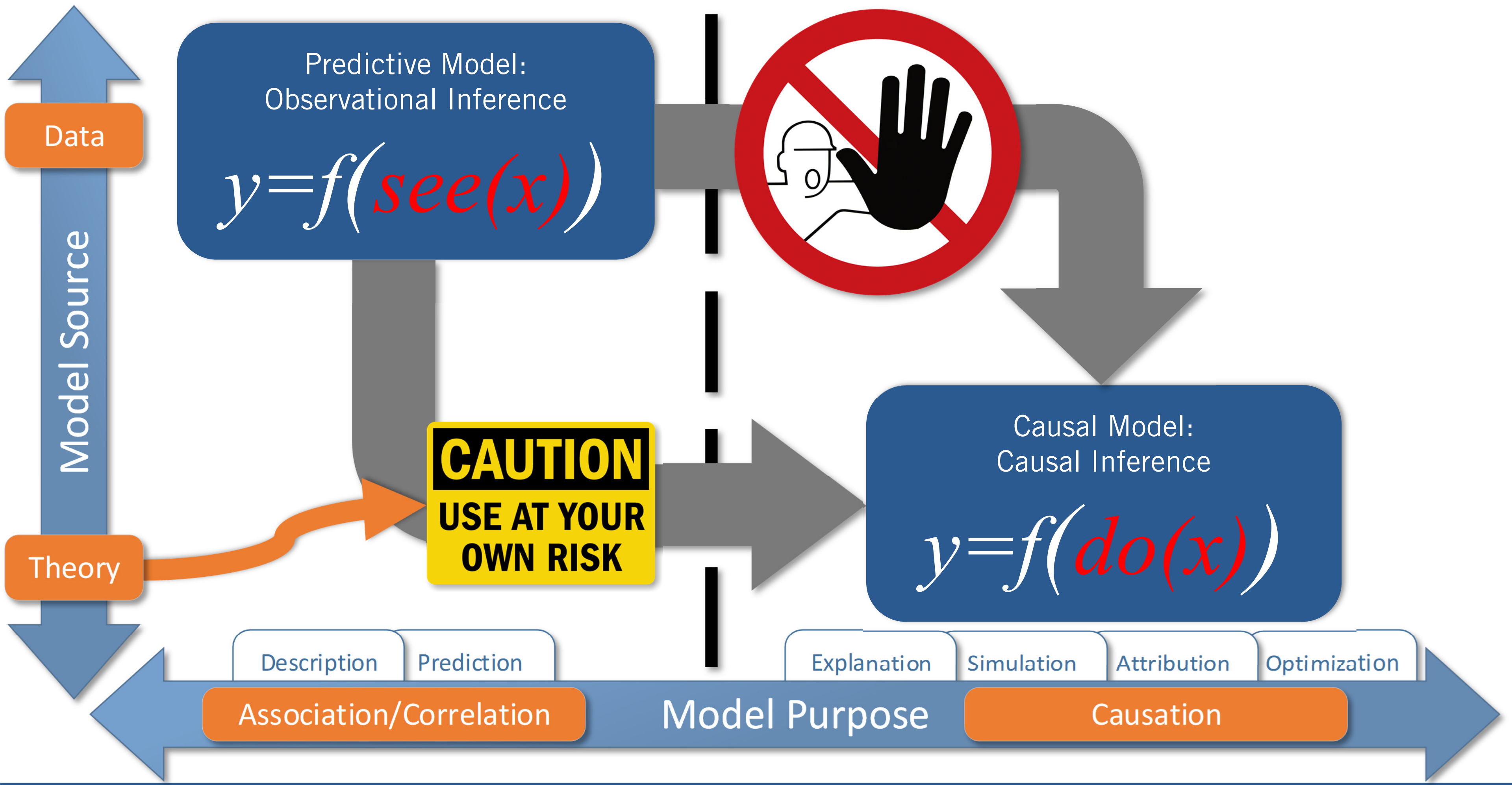
Ad Exposure	Purchase
No	60%
Yes	45%

−0.15

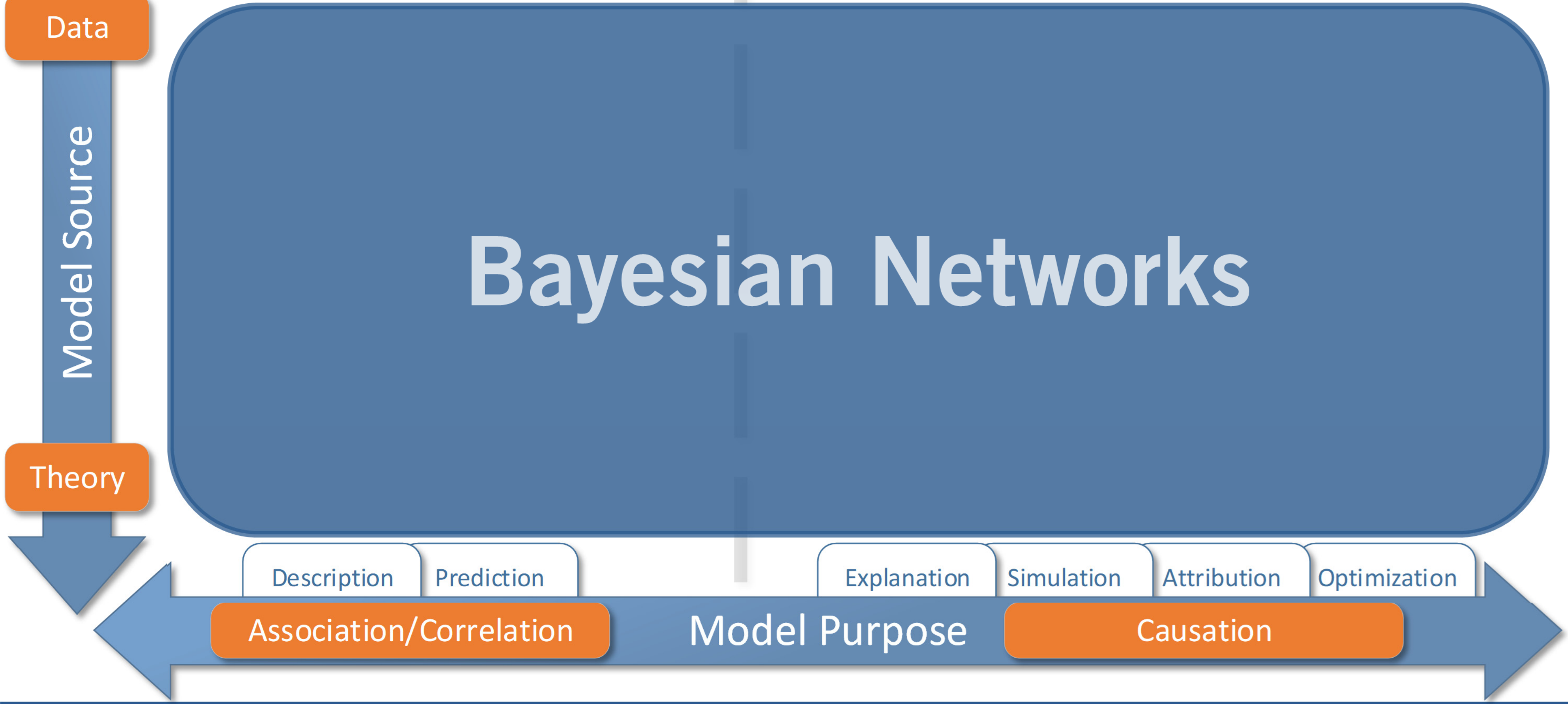
“given that I see”


THE FALLACY OF DATA DRIVEN DECISIONS.
Data
Model Source
Predictive Model:
Observational Inference
y=f(see(x))
Causal Model:
Causal Inference
y=f(do(x))
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

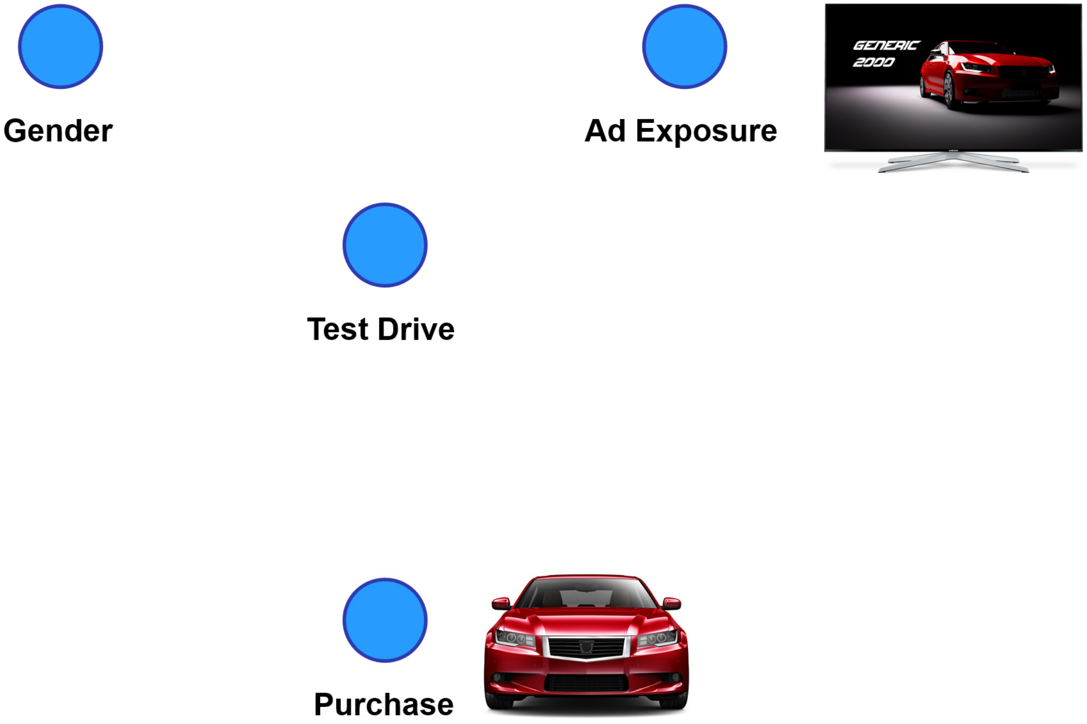
Map of Analytic Modeling & Reasoning



Introductory Example

Develop Theory

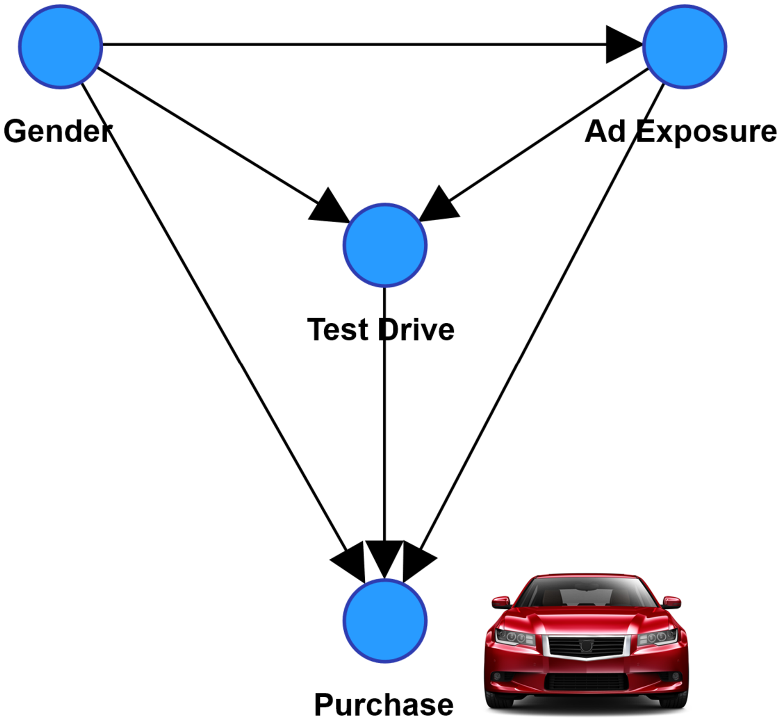
What's the story here?



Introductory Example

Our Theory!

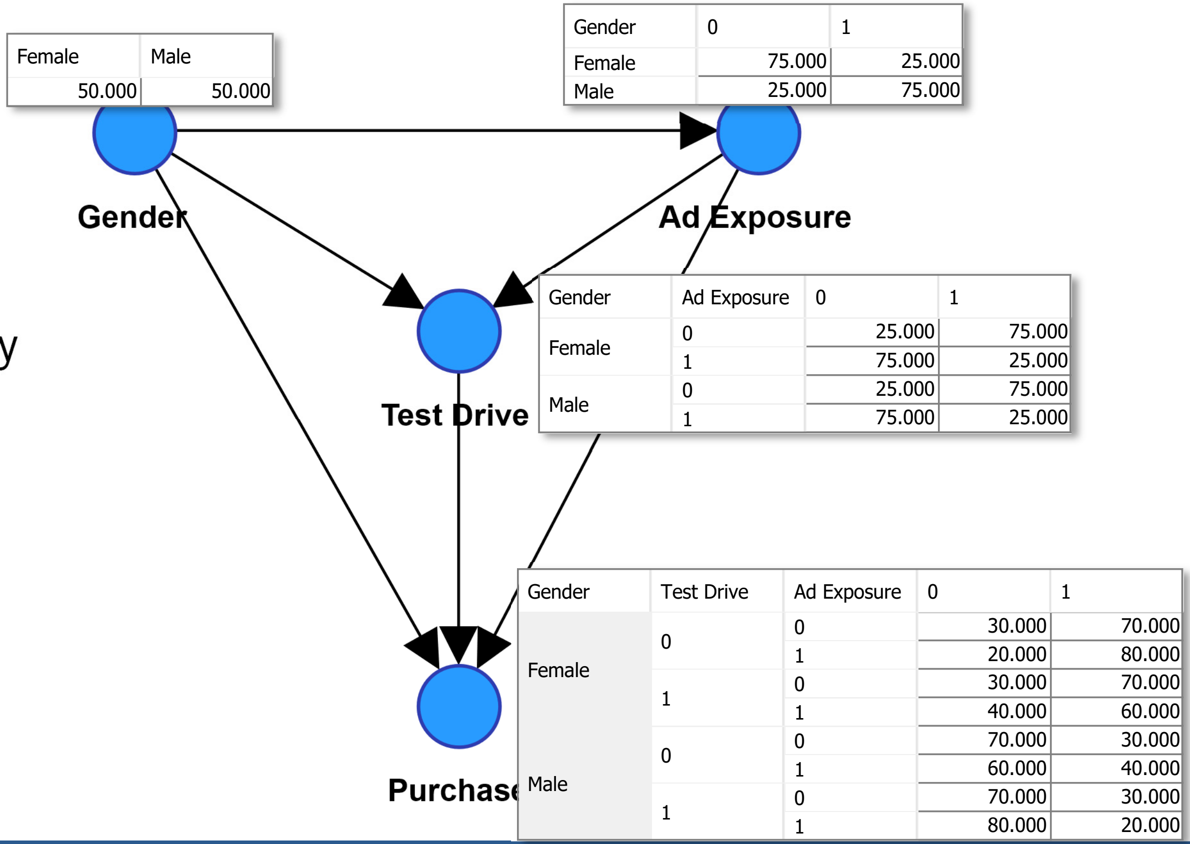
That’s the story! Now we have the qualitative part of a causal Bayesian network.



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

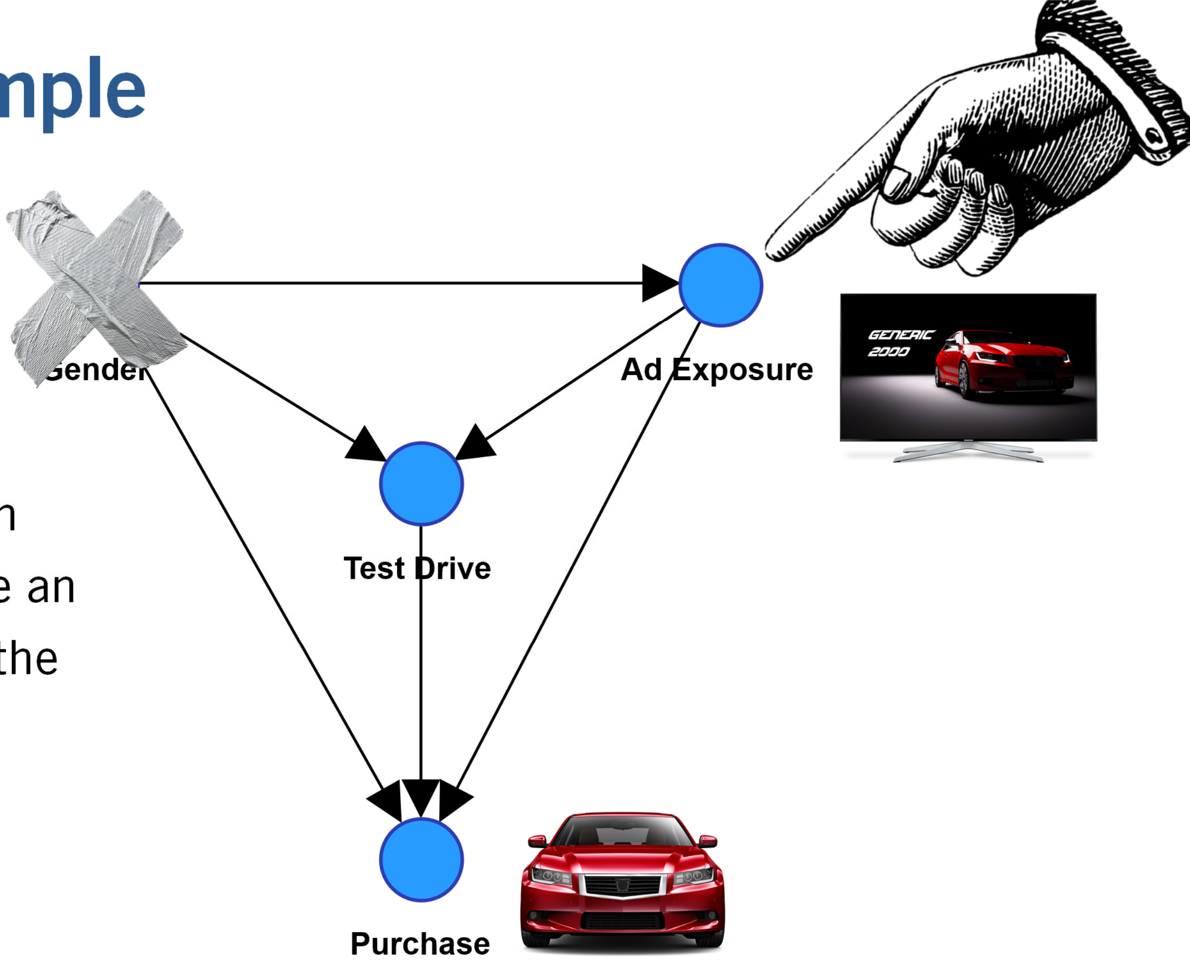
Gender	Ad Exposure	0	1
Female	0	25.000	75.000
	1	75.000	25.000
Male	0	25.000	75.000
	1	75.000	25.000

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"

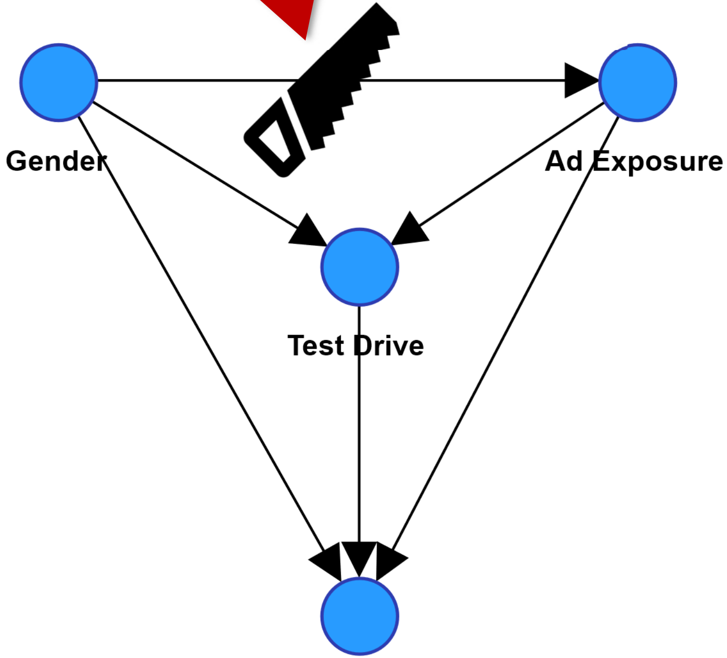
- How can we obtain the effect of Ad Exposure?
- With this causal Bayesian network, we can simulate an intervention to estimate the causal effect.

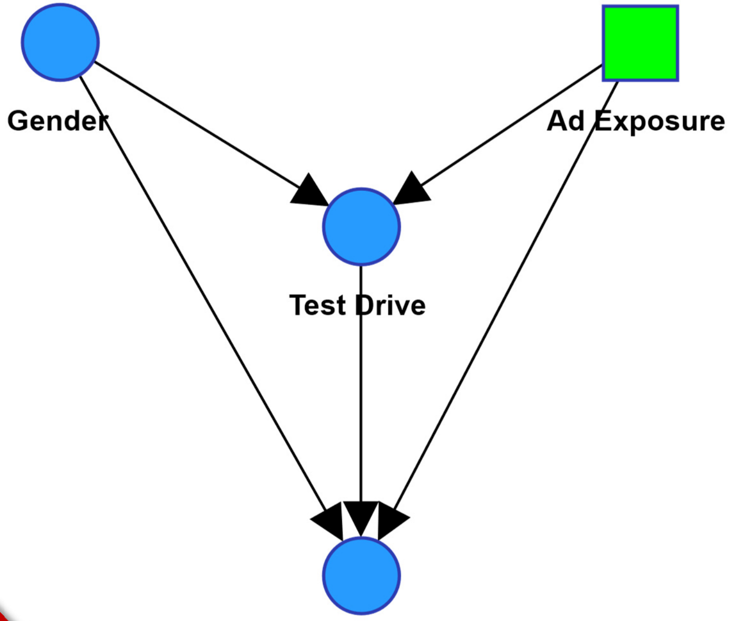


Introductory Example

“Graph Surgery”

Caus ing an Intervention





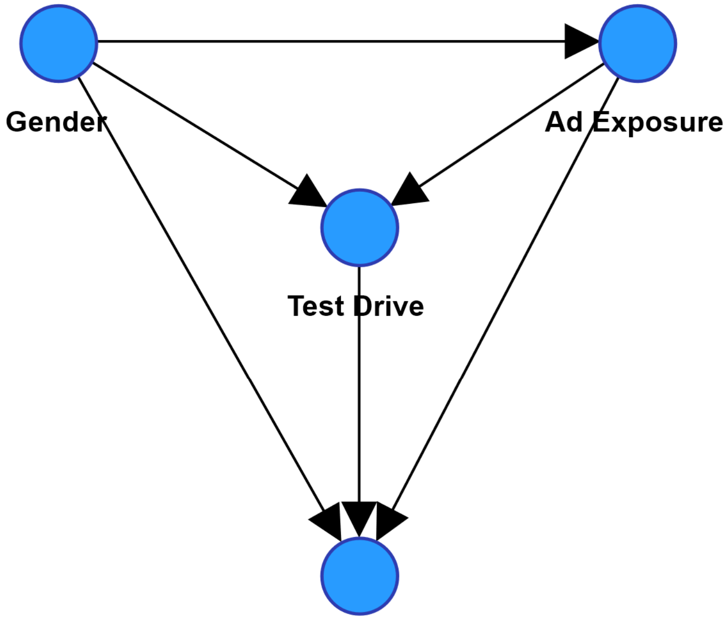
Causal Model

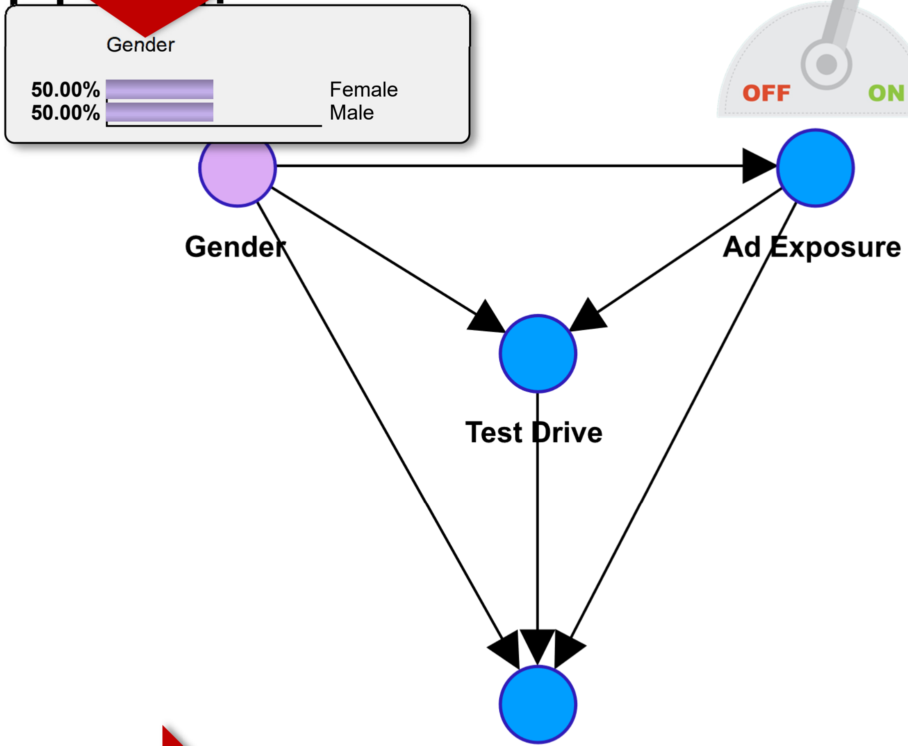
Intervention Model

Introductory Exampl

Causal Inference: Simulating an

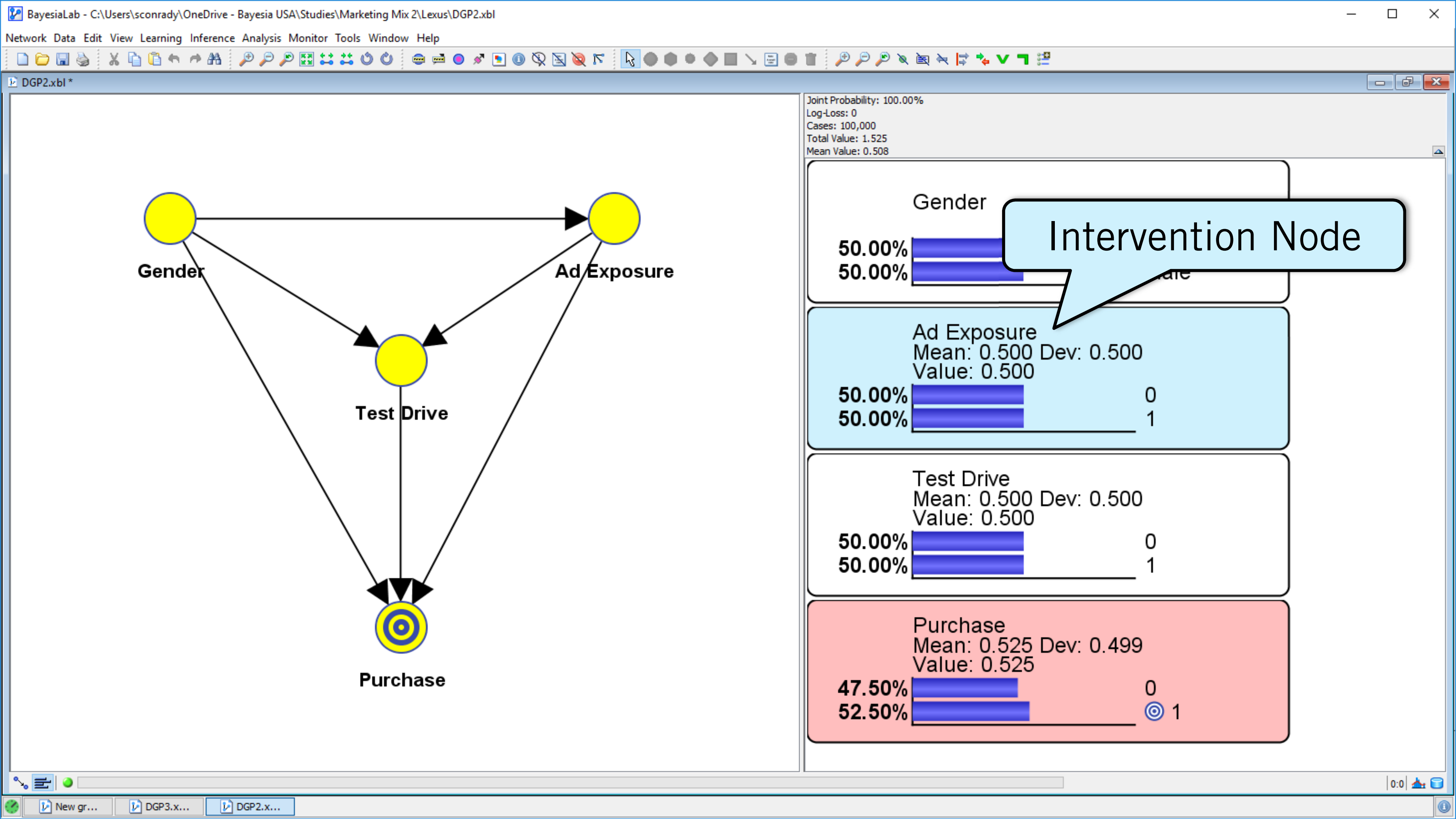
Fix Probabilities with Likelihood Matching

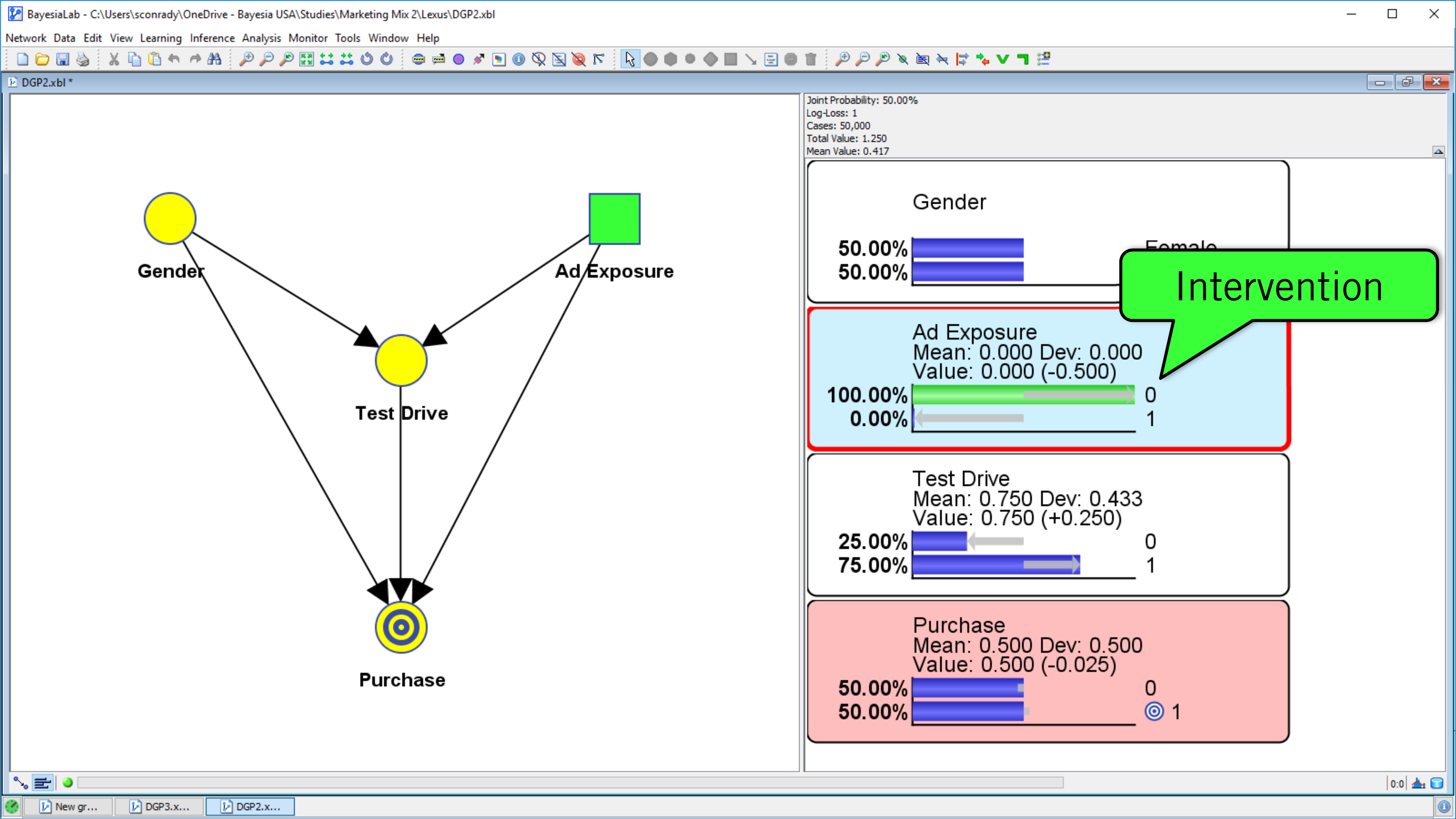


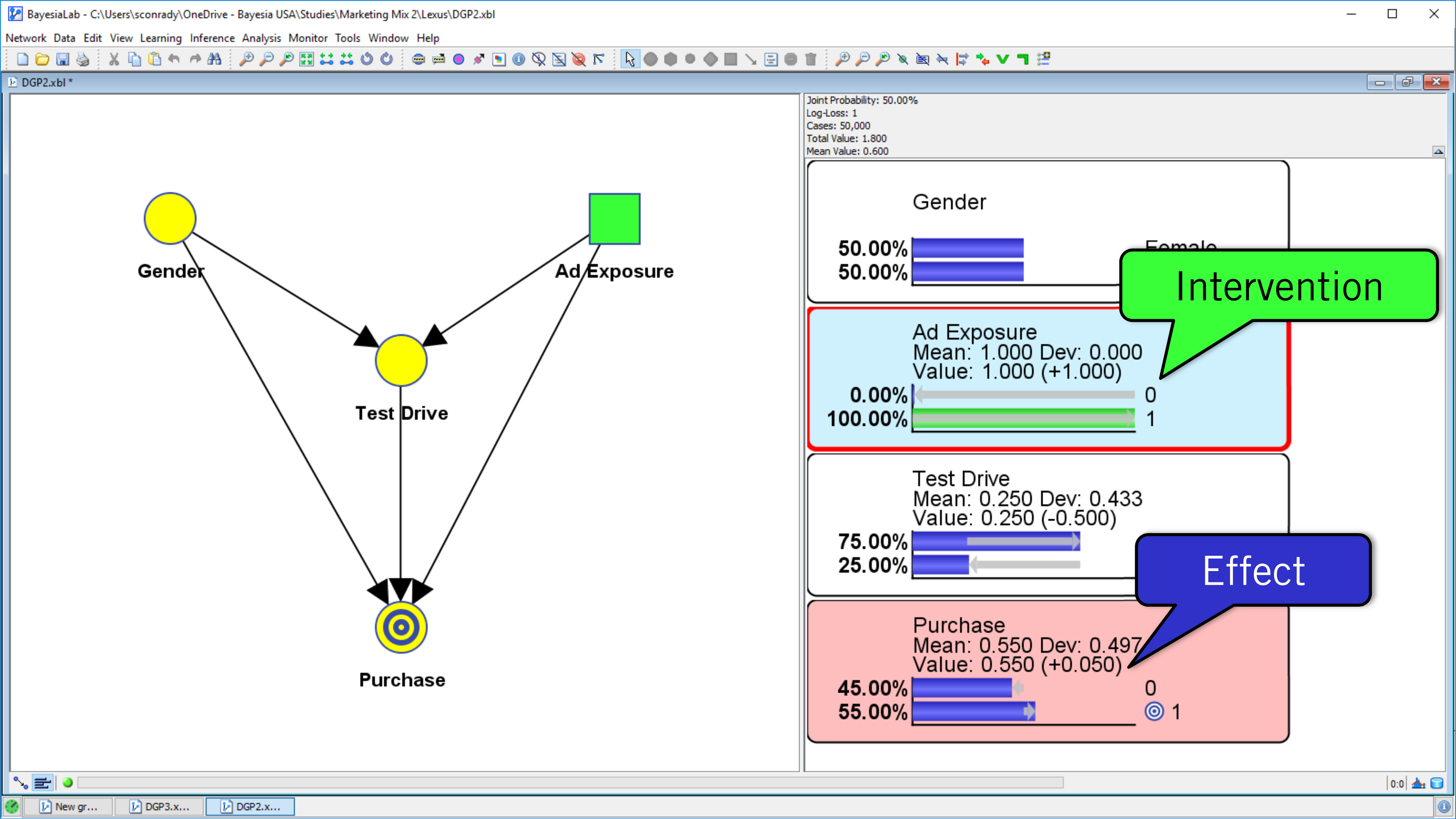


Causal Model

Intervention Model


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Marketing Mix 2\Lexus\DGP2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
DGP2.xbl *
Gender
Ad Exposure
Test Drive
Purchase
Joint Probability: 100.00%
Log-Loss: 0
Cases: 100,000
Total Value: 1.525
Mean Value: 0.508
Gender
50.00%
50.00%
Intervention Node
Ad Exposure
Mean: 0.500 Dev: 0.500
Value: 0.500
50.00% 0
50.00% 1
Test Drive
Mean: 0.500 Dev: 0.500
Value: 0.500
50.00% 0
50.00% 1
Purchase
Mean: 0.525 Dev: 0.499
Value: 0.525
47.50% 0
52.50% 1
New gr...
DGP3.x...
DGP2.x...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Marketing Mix 2\Lexus\DGP2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
DGP2.xbl *
Gender
Ad Exposure
Test Drive
Purchase
Joint Probability: 50.00%
Log-Loss: 1
Cases: 50,000
Total Value: 1.250
Mean Value: 0.417
Gender
50.00%
50.00%
Intervention
Ad Exposure
Mean: 0.000 Dev: 0.000
Value: 0.000 (-0.500)
100.00% 0
0.00% 1
Test Drive
Mean: 0.750 Dev: 0.433
Value: 0.750 (+0.250)
25.00% 0
75.00% 1
Purchase
Mean: 0.500 Dev: 0.500
Value: 0.500 (-0.025)
50.00% 0
50.00% 1
New gr...
DGP3.x...
DGP2.x...


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Marketing Mix 2\Lexus\DGP2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
DGP2.xbl *
Gender
Ad Exposure
Test Drive
Purchase
Joint Probability: 50.00%
Log-Loss: 1
Cases: 50,000
Total Value: 1.800
Mean Value: 0.600
Gender
50.00%
50.00%
Intervention
Ad Exposure
Mean: 1.000 Dev: 0.000
Value: 1.000 (+1.000)
0.00% 0
100.00% 1
Test Drive
Mean: 0.250 Dev: 0.433
Value: 0.250 (-0.500)
75.00%
25.00%
Effect
Purchase
Mean: 0.550 Dev: 0.497
Value: 0.550 (+0.050)
45.00% 0
55.00% 1
New gr...
DGP3.x...
DGP2.x...

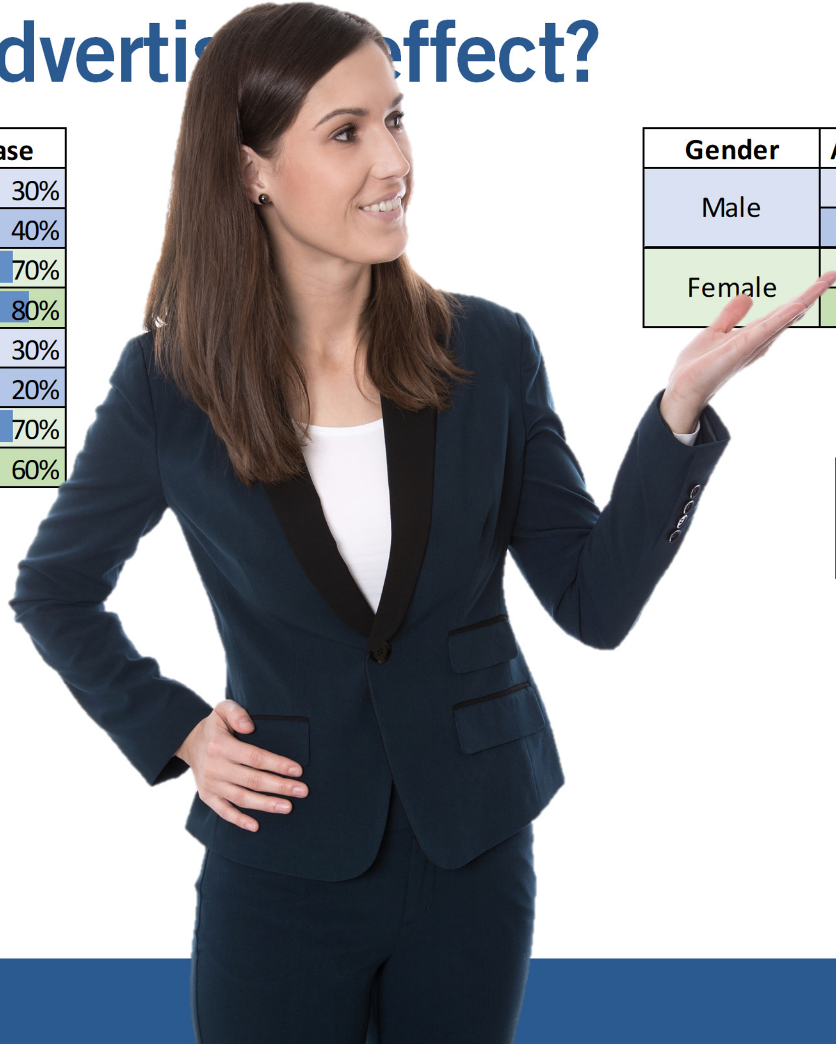
So, what's the adverti ffect?

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

≈ 0

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

+0.05



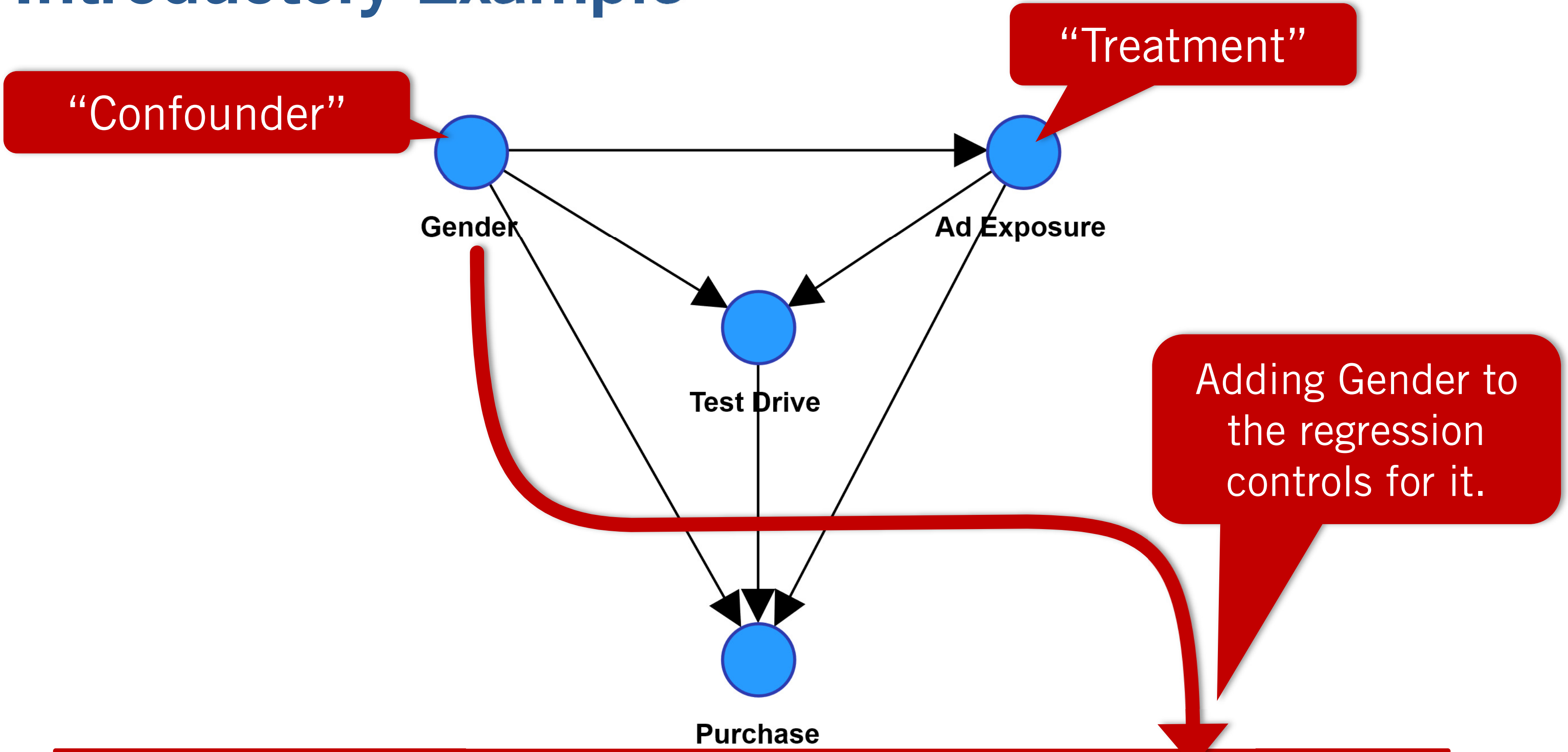
Ad Exposure	Purchase
No	60%
Yes	45%

−0.15

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

−0.2

Introductory Example



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


ACME GENERIC
AUTO CENTER


100%
0
100%
0
100%
NEWSPAPER
RADIO
100%
0
100%
TELEVISION
INTERNET
0%
25
50
75
100%
SUCCESS
METRICS

J. Wannamaker

H. Ford

J.C. Penney

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

Marketing Mix Optimization

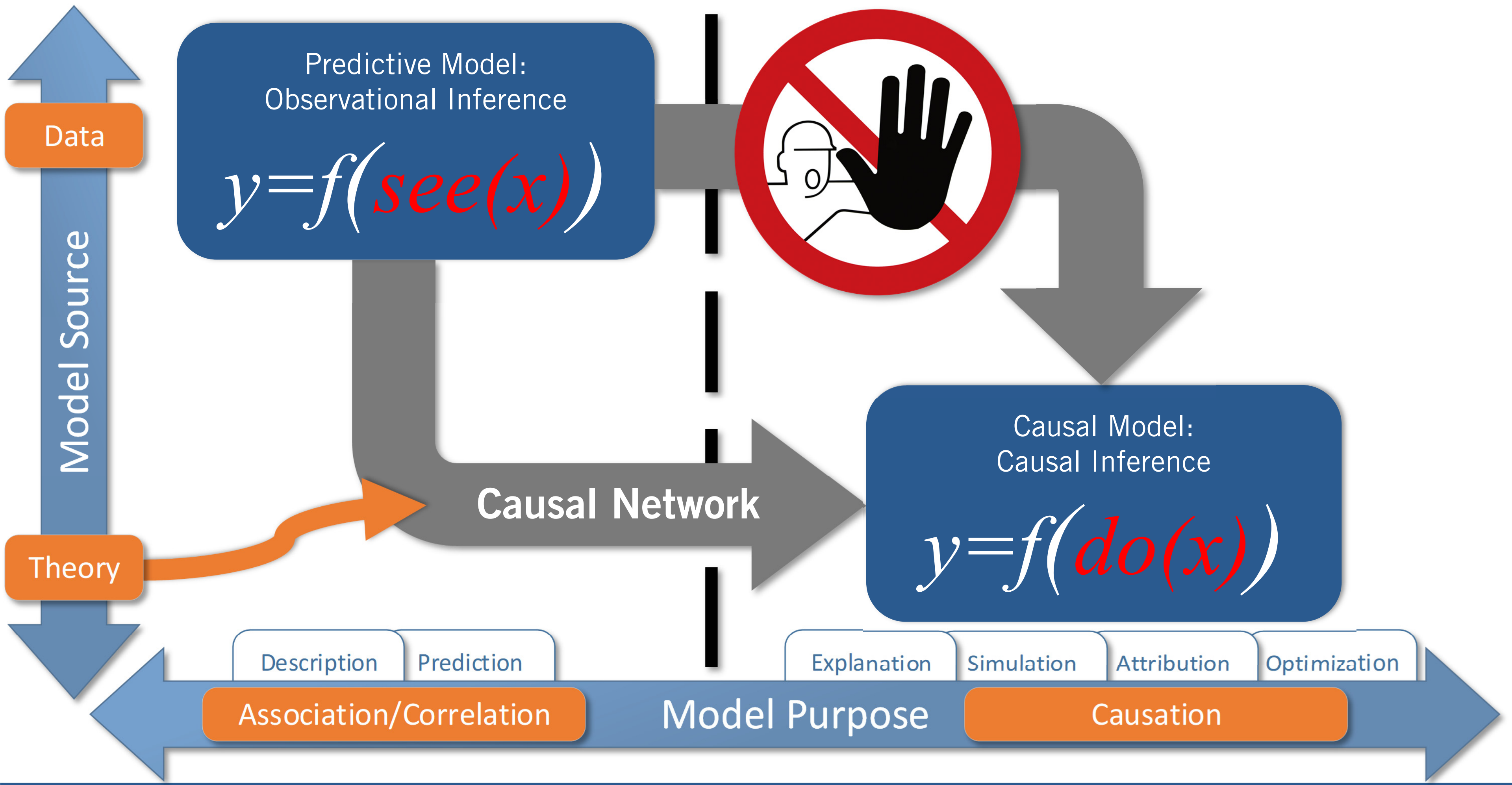
ACME GENERIC AUTO CENTER

Objective

- Maximize sales within a given marketing budget.

Historical Sales & Media Data

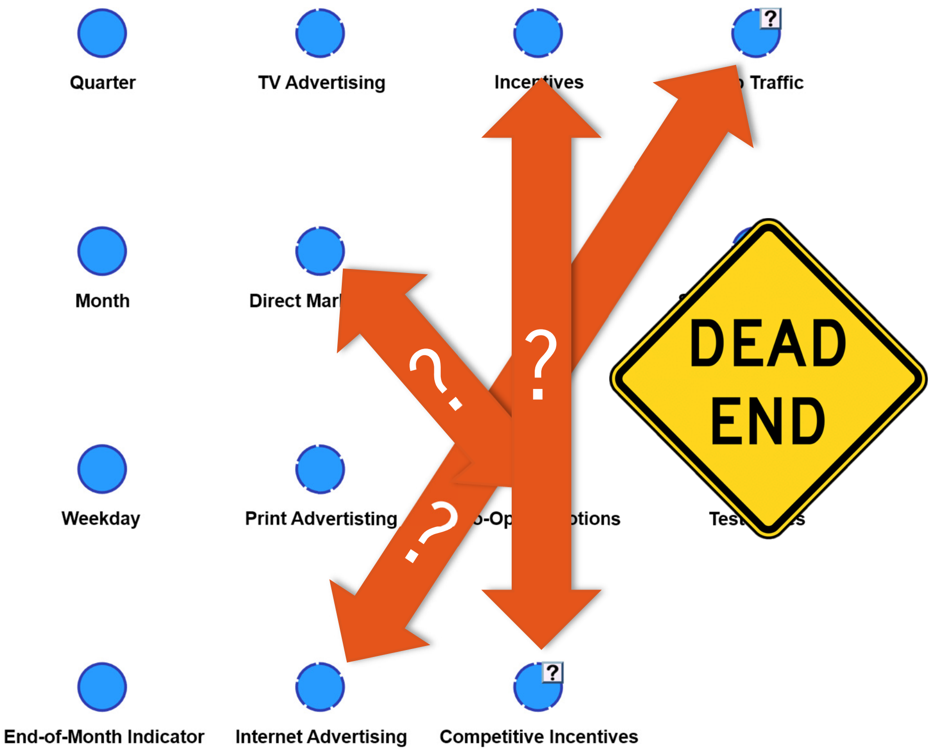
- Quarter
- Month
- Weekday
- End-of-Month Indicator
- TV Advertising
- Direct Marketing
- Print Advertising
- Internet Advertising
- Incentives
- Sales
- Co-Op Promotions
- Competitive Incentives
- Web Traffic
- Showroom Traffic
- Test Drives

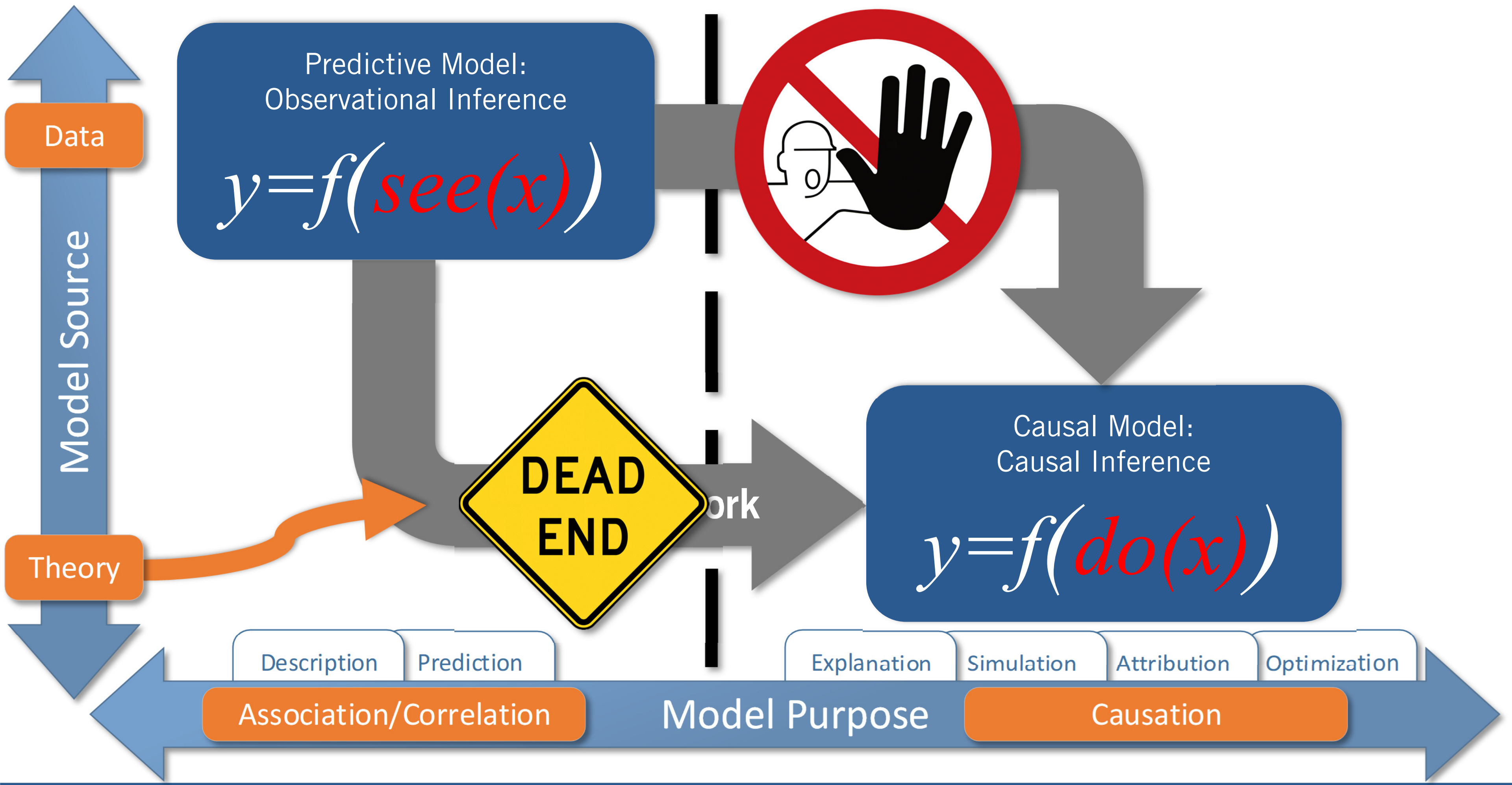

Predictive Model:
Observational Inference
$y=f(see(x))$
Causal Model:
Causal Inference
$y=f(do(x))$
Causal Network
Data
Theory
Model Source
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

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

Now What?

We need a different kind of theory

Disjunctive Cause Criterion

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

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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."

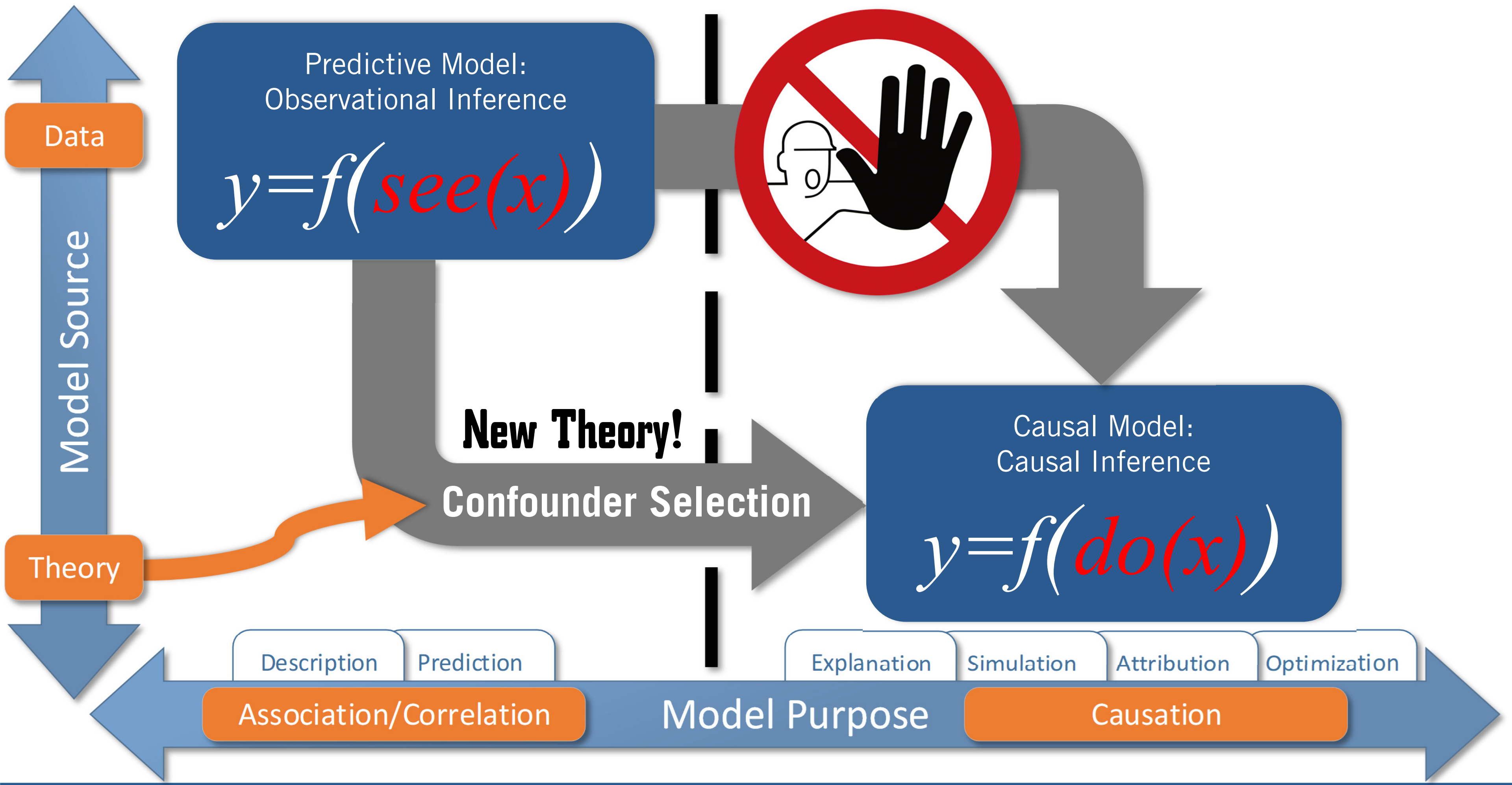
Sales

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

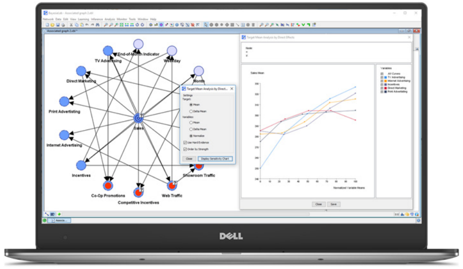

Predictive Model:
Observational Inference
y=f(see(x))
Data
Model Source
Theory
New Theory!
Confounder Selection
Causal Model:
Causal Inference
y=f(do(x))
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

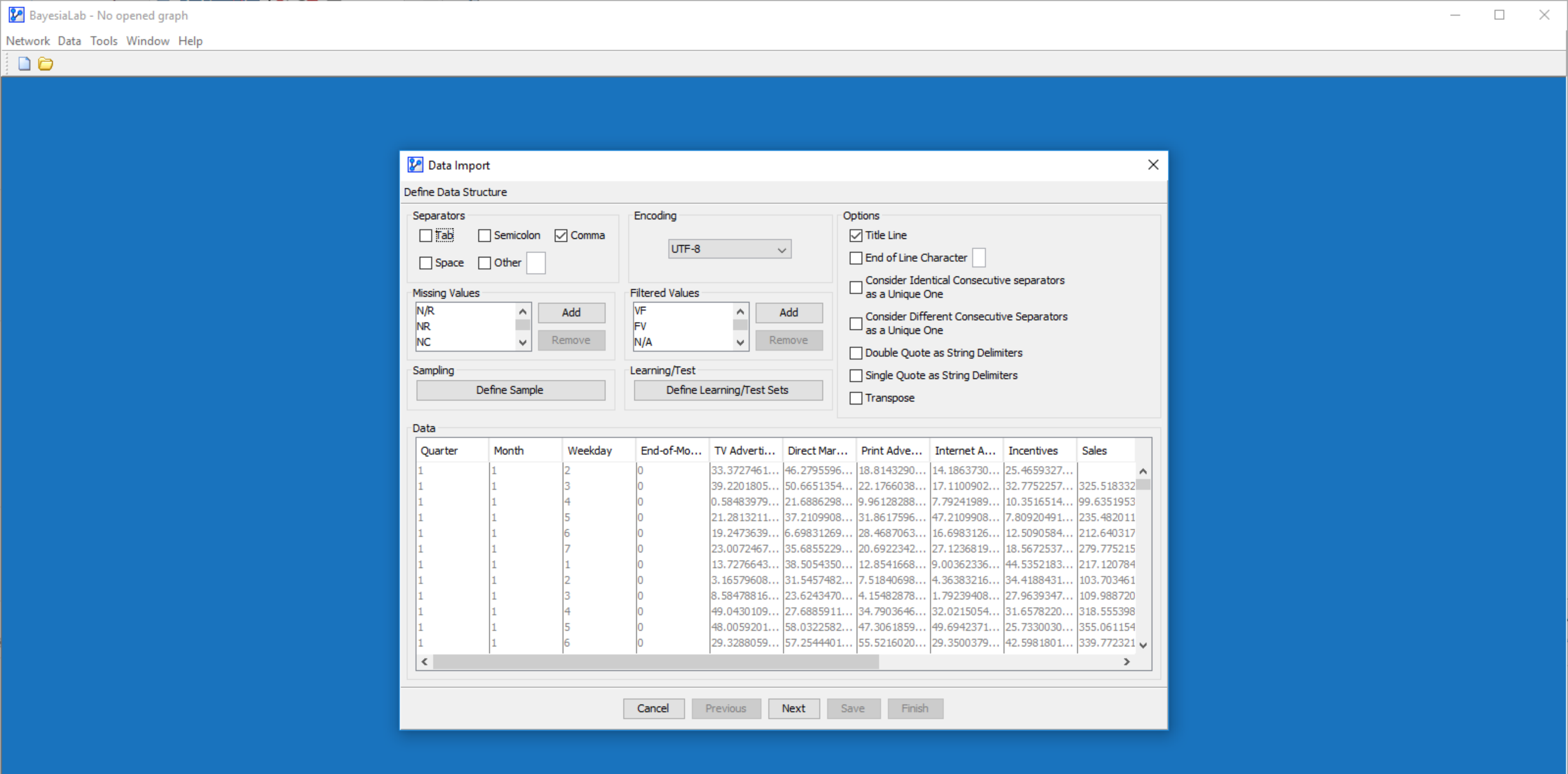
Marketing Mix Optimization

All Data is Synthetic

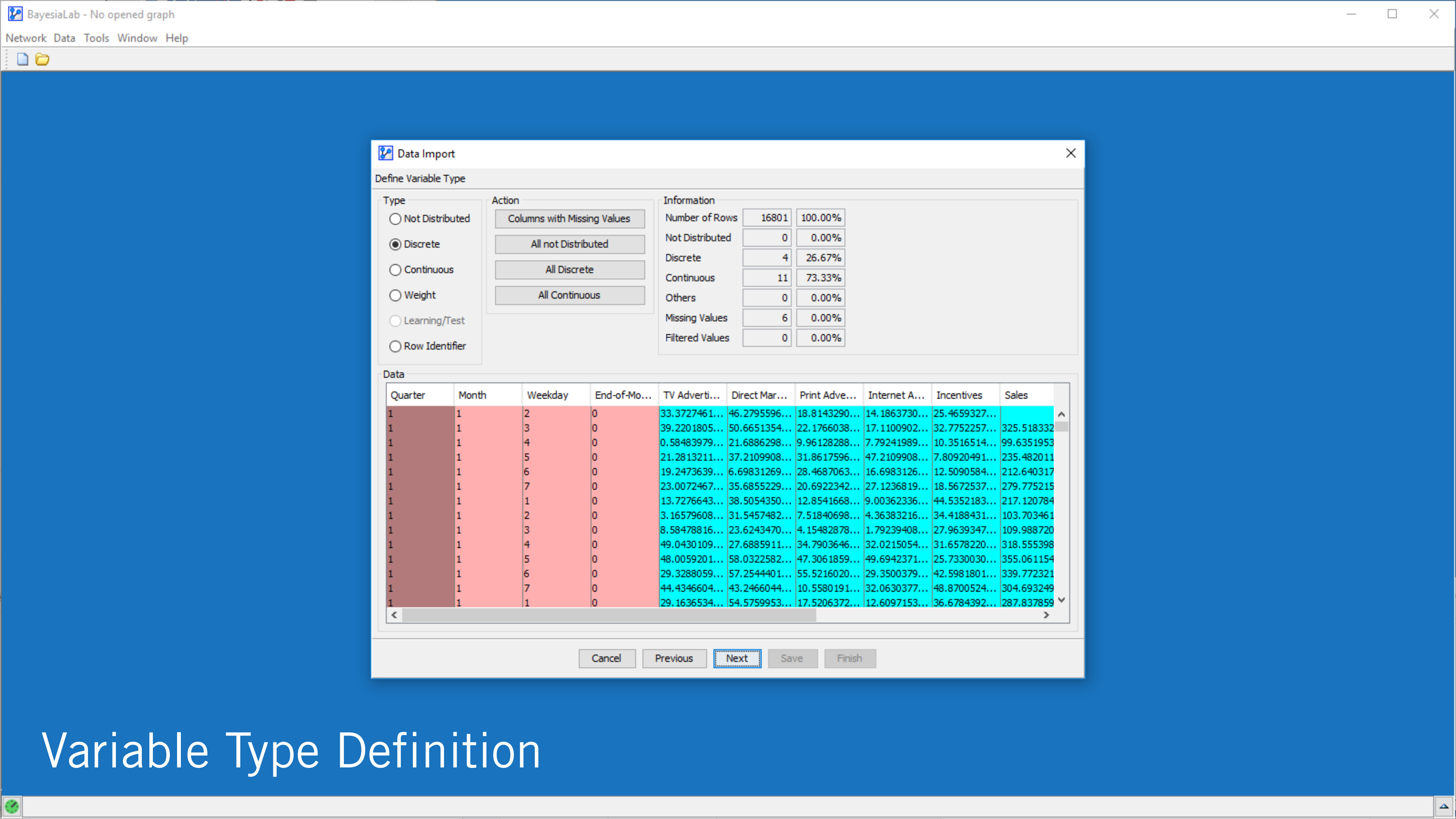
Proposed Workflow

- 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.

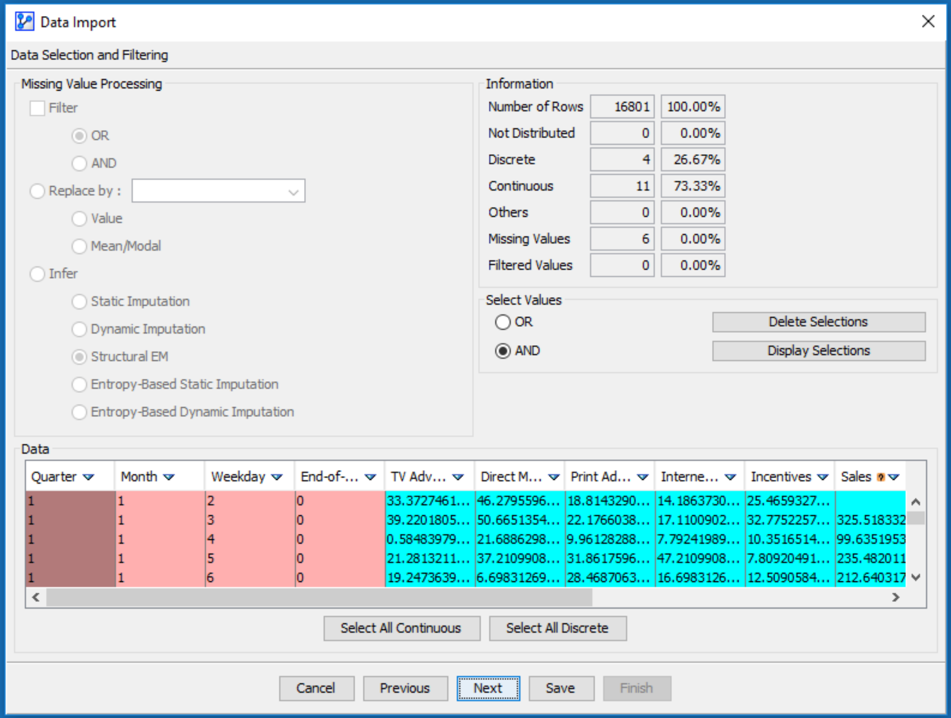




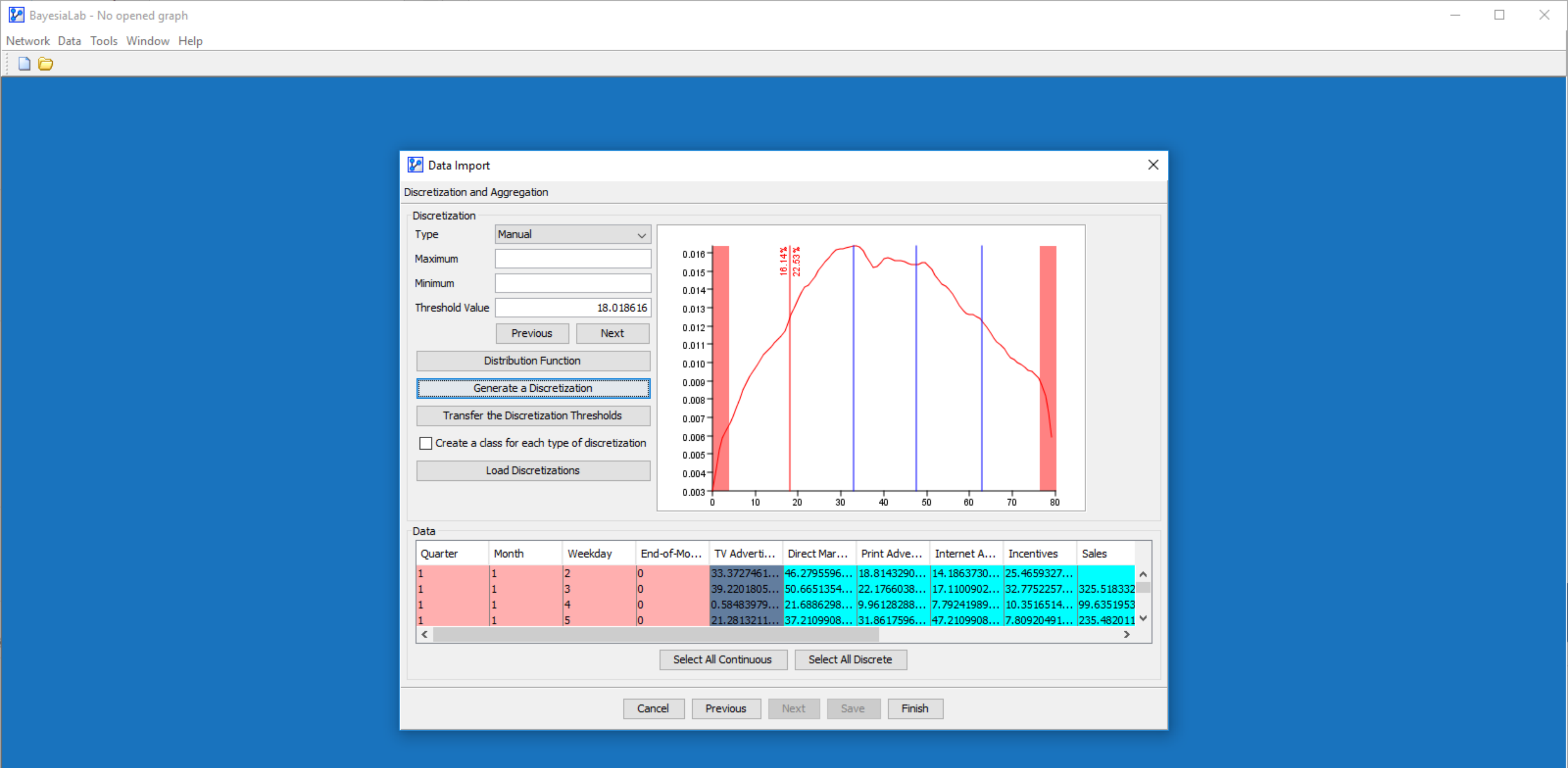
Data Import Wizard



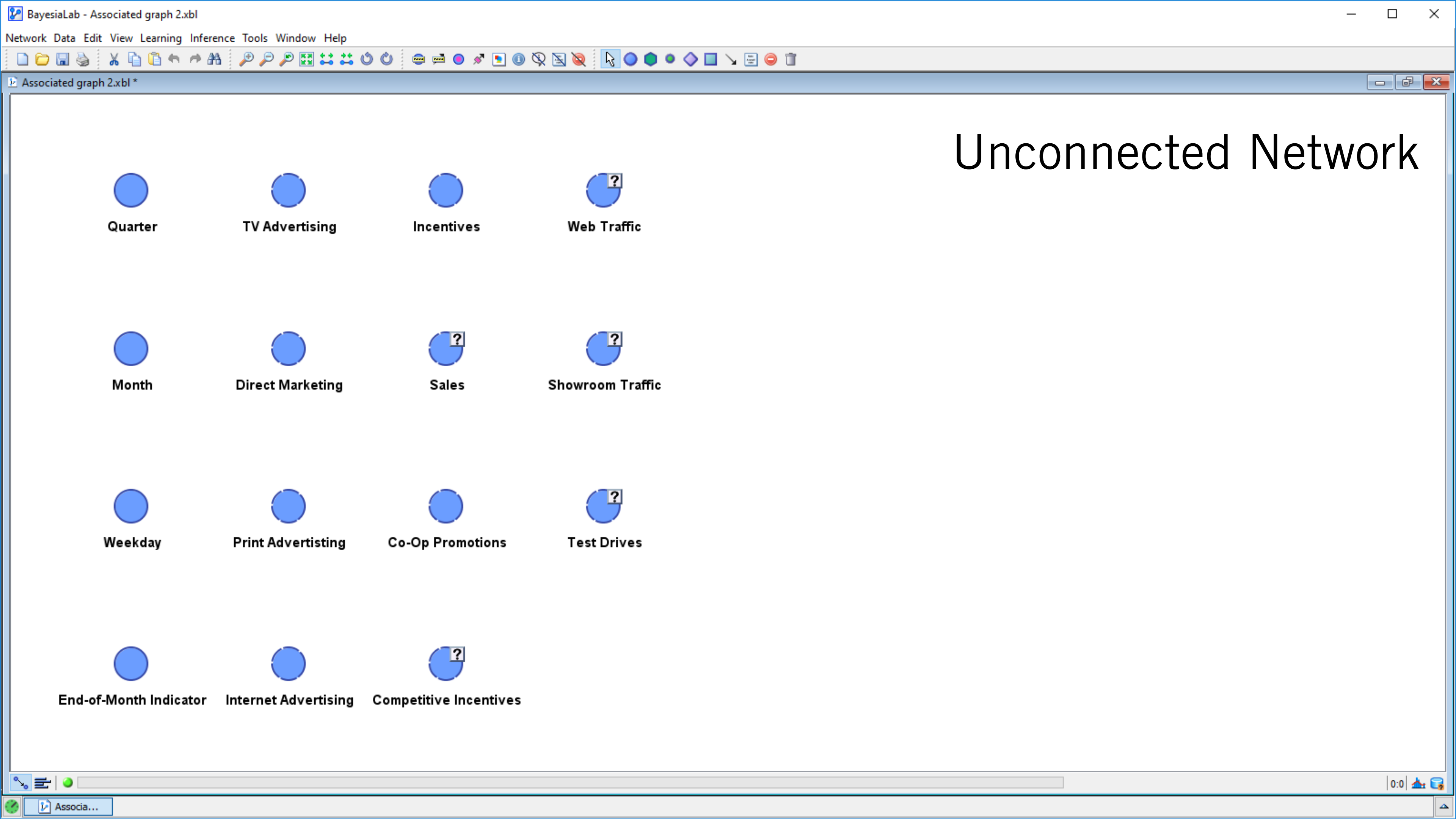
Variable Type Definition



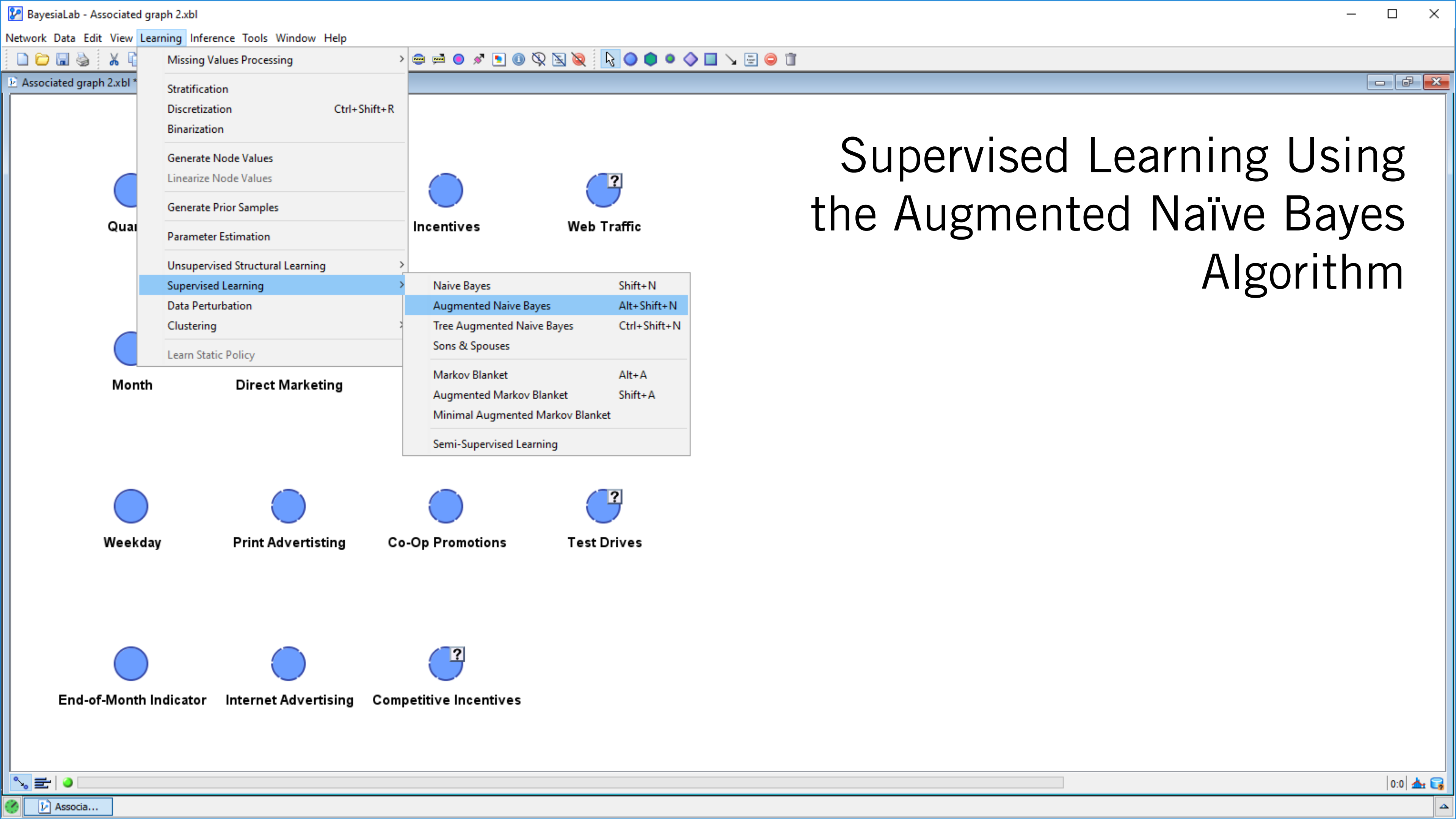
Missing Values Processing

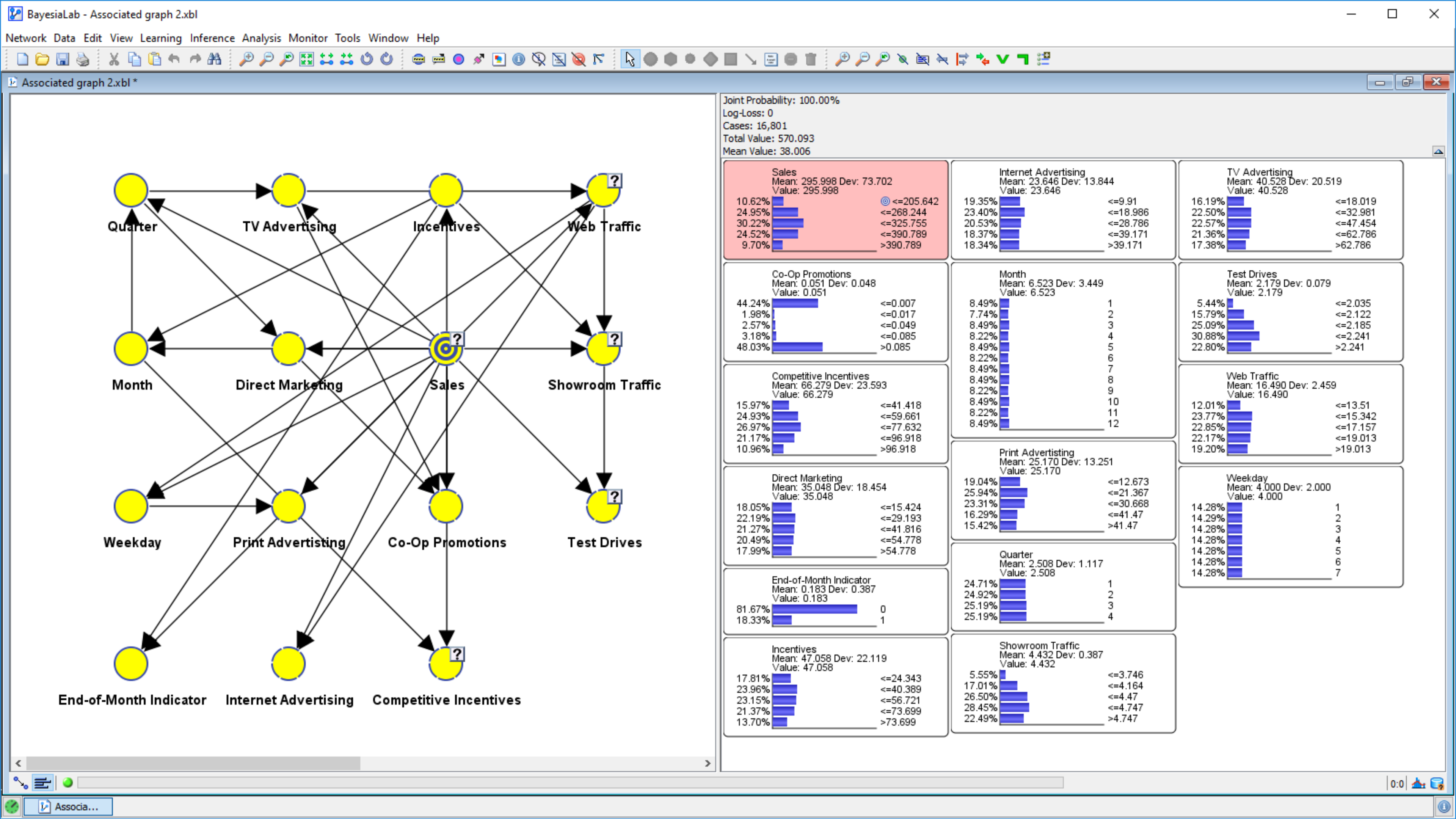


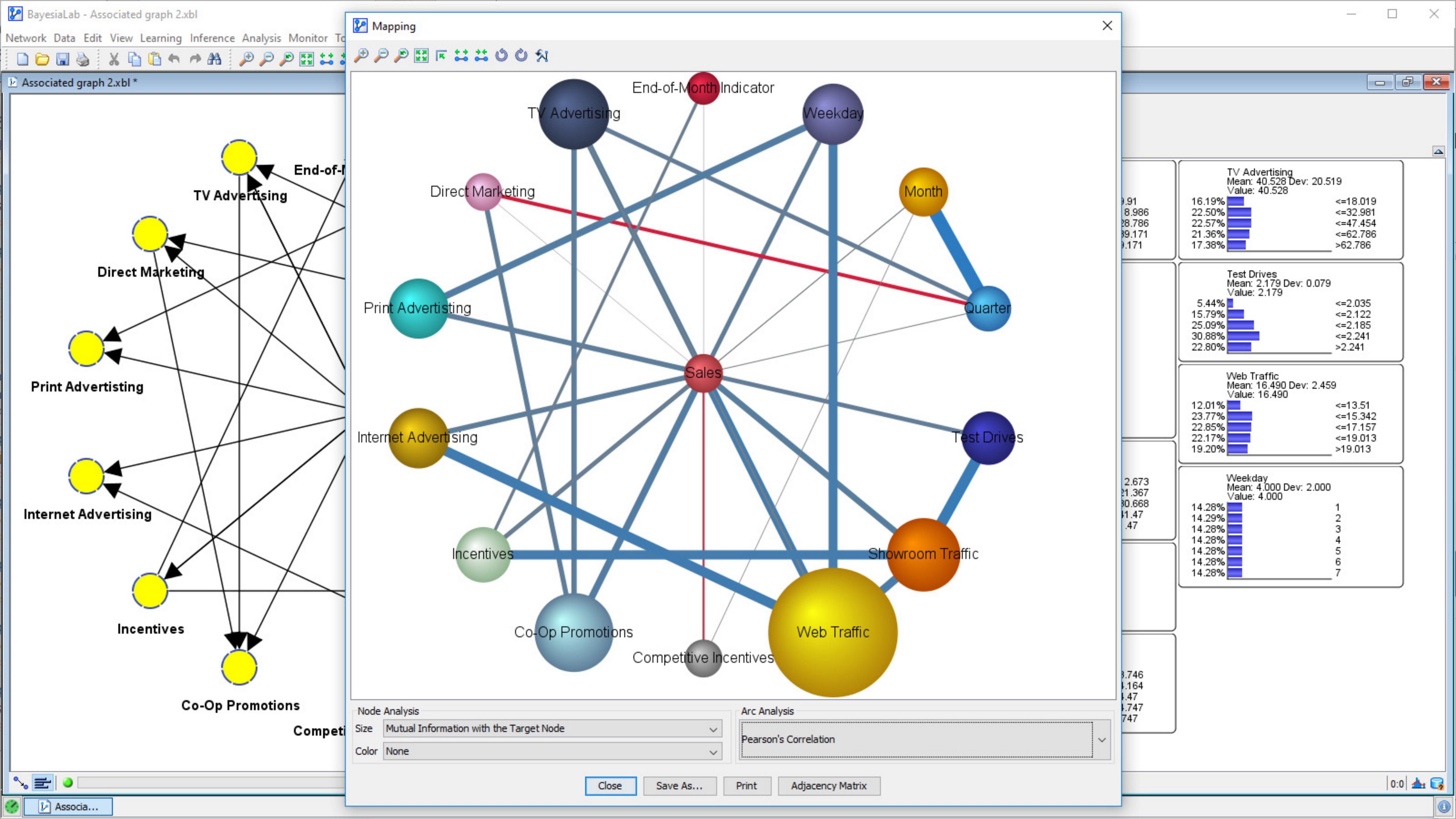
Discretization


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

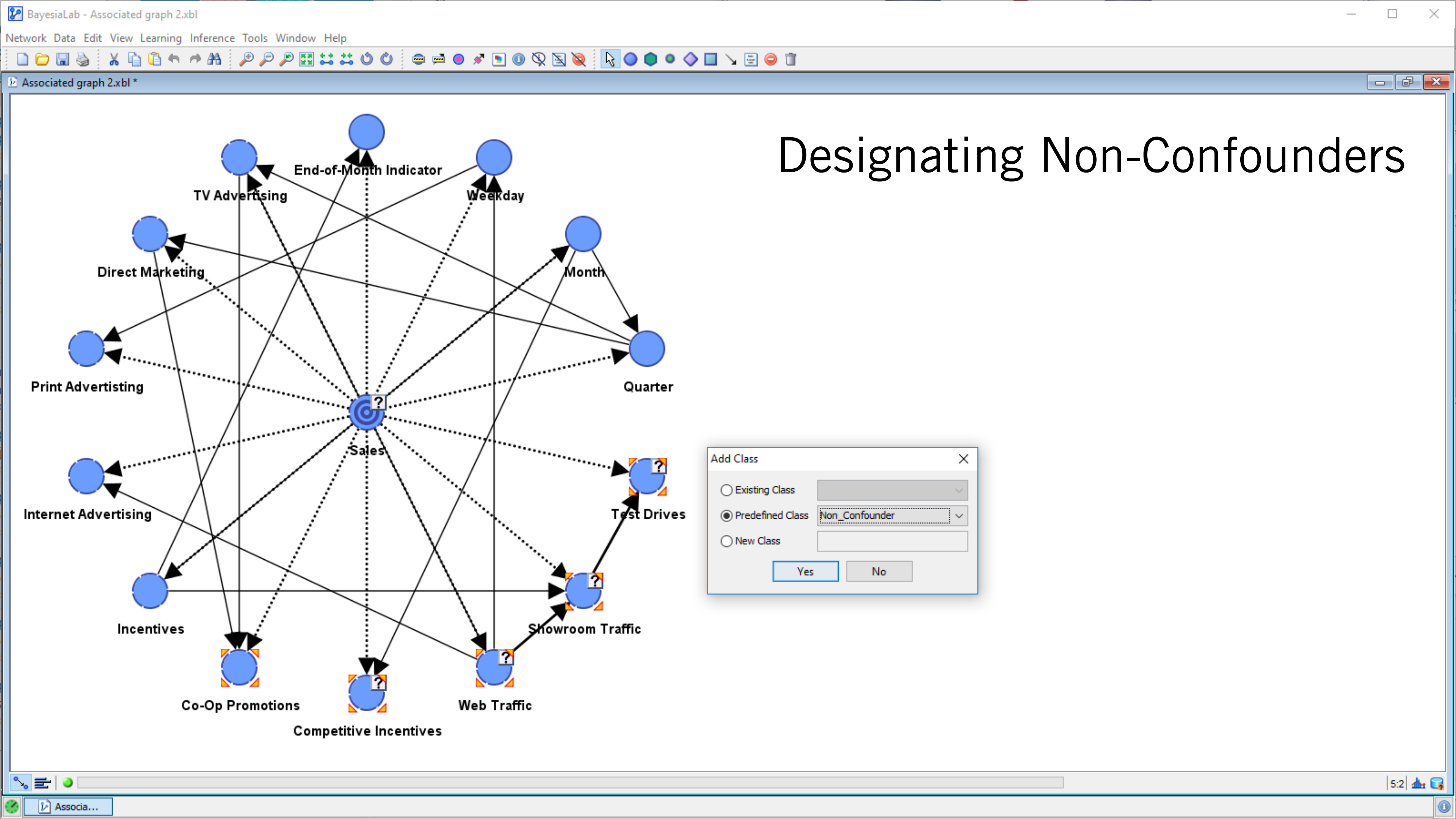



BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
Quarter
TV Advertising
Incentives
Web Traffic
Month
Direct Marketing
Sales
Showroom Traffic
Weekday
Print Advertising
Co-Op Promotions
Test Drives
End-of-Month Indicator
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
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
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
0:0
Associa...

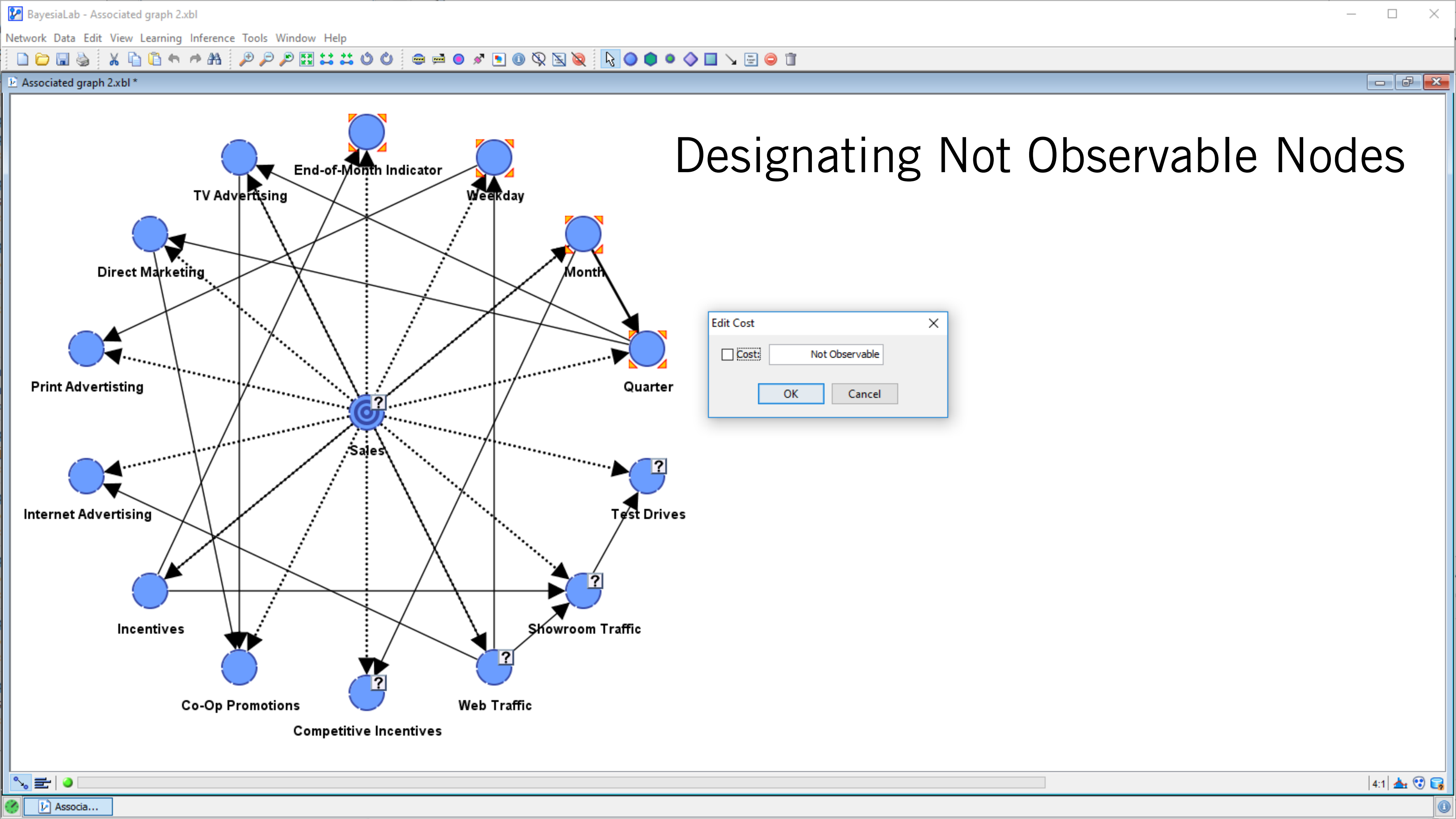


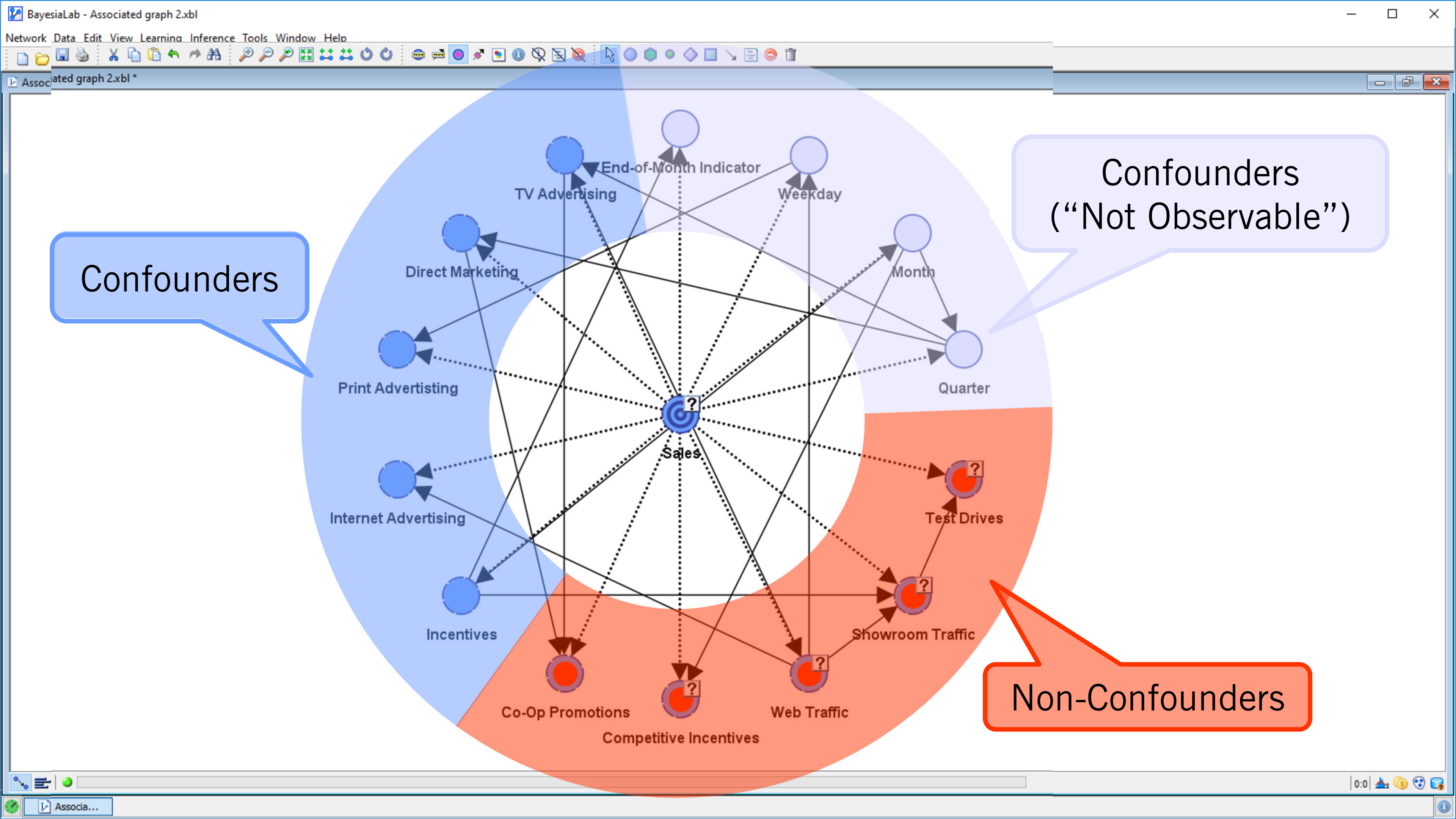
BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor
Associated graph 2.xbl *
TV Advertising
Direct Marketing
Print Advertising
Internet Advertising
Incentives
Co-Op Promotions
Mapping
End-of-Month Indicator
TV Advertising
Weekday
Direct Marketing
Month
Print 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
21.36% <=62.786
17.38% >62.786
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
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
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



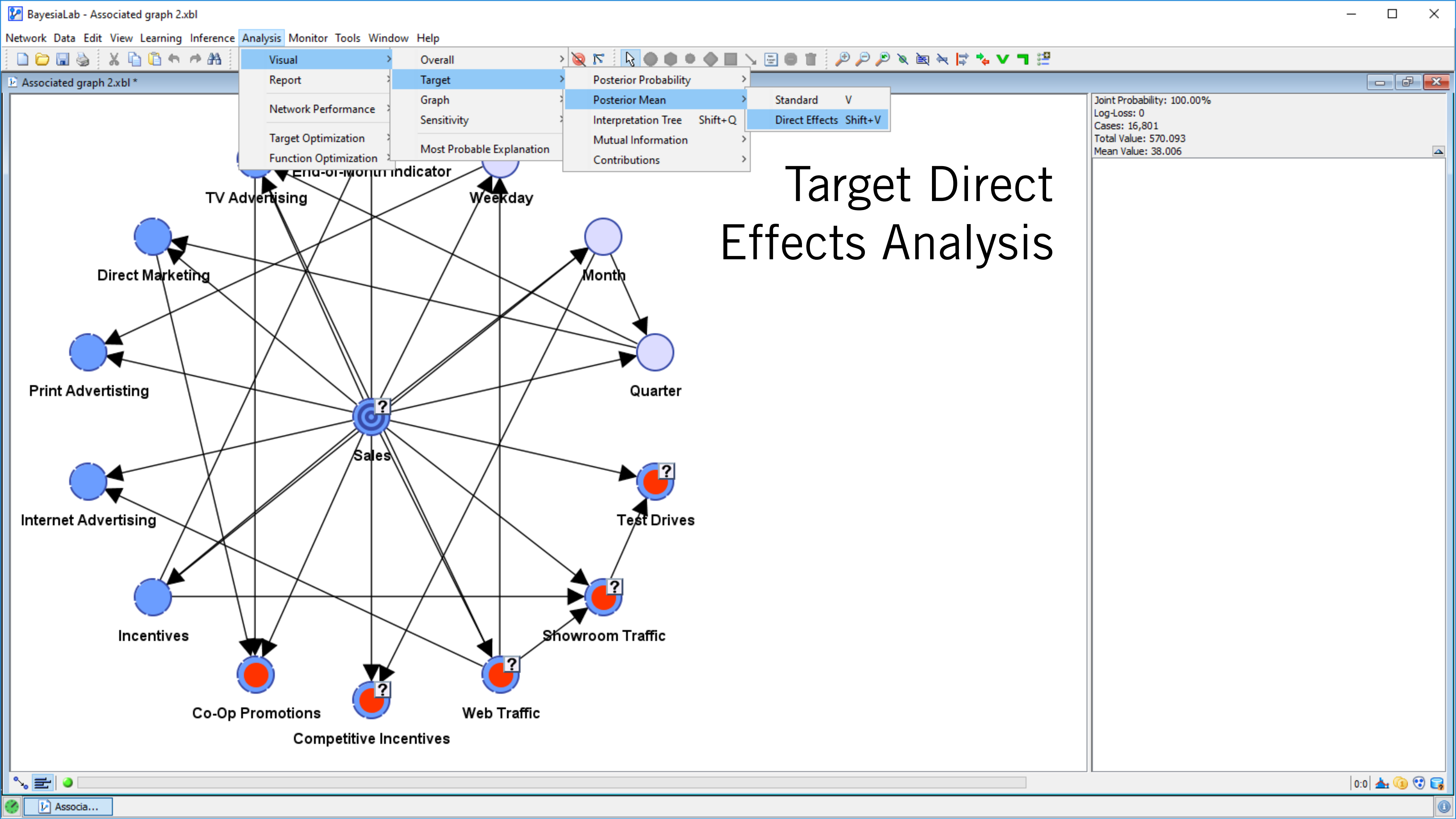
Designating Not Observable Nodes

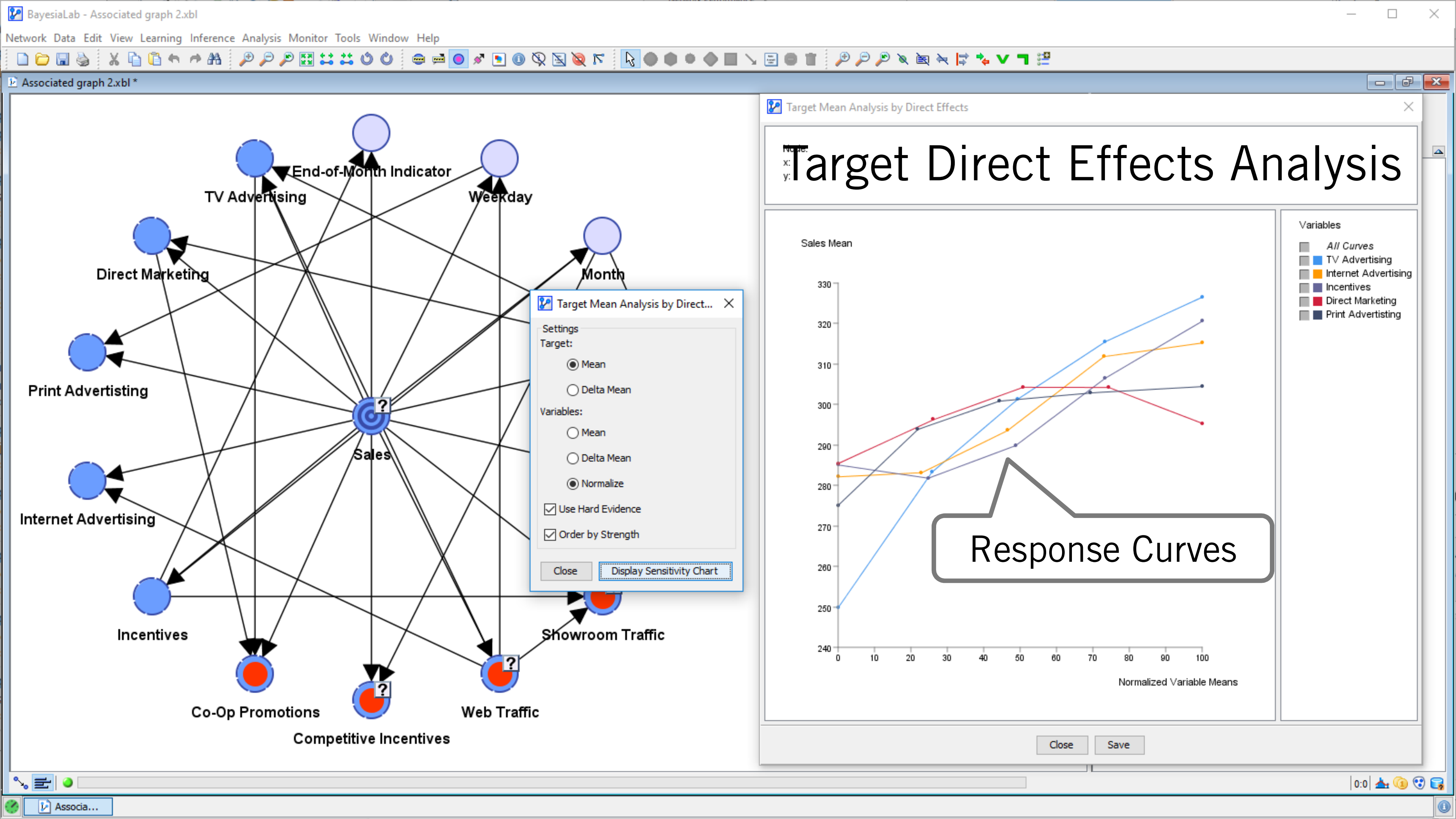


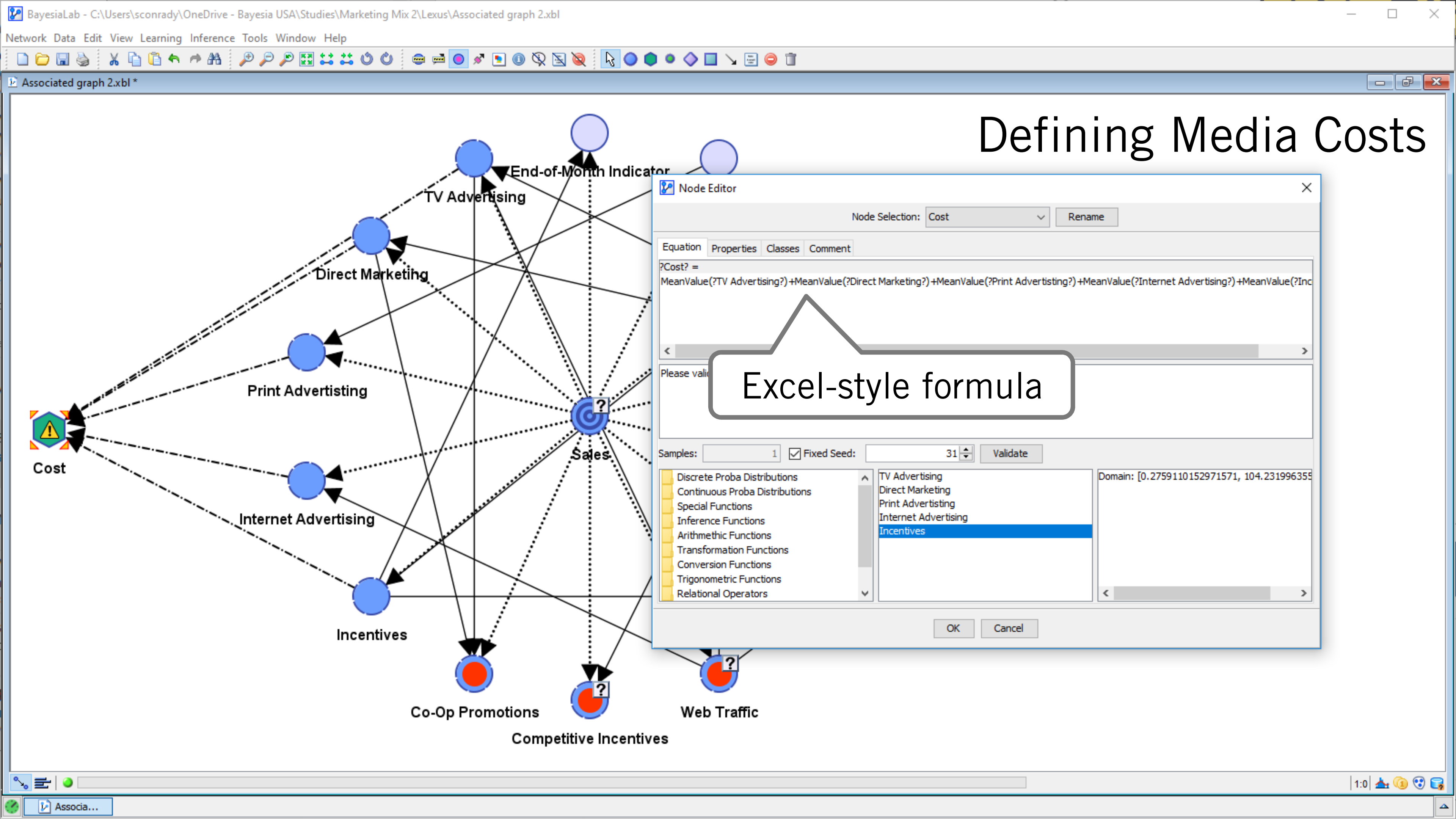


BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 2.xbl *
Confounders
Confounders
("Not Observable")
Non-Confounders
TV Advertising
End-of-Month Indicator
Weekday
Direct Marketing
Month
Print Advertising
Quarter
Sales
Internet Advertising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

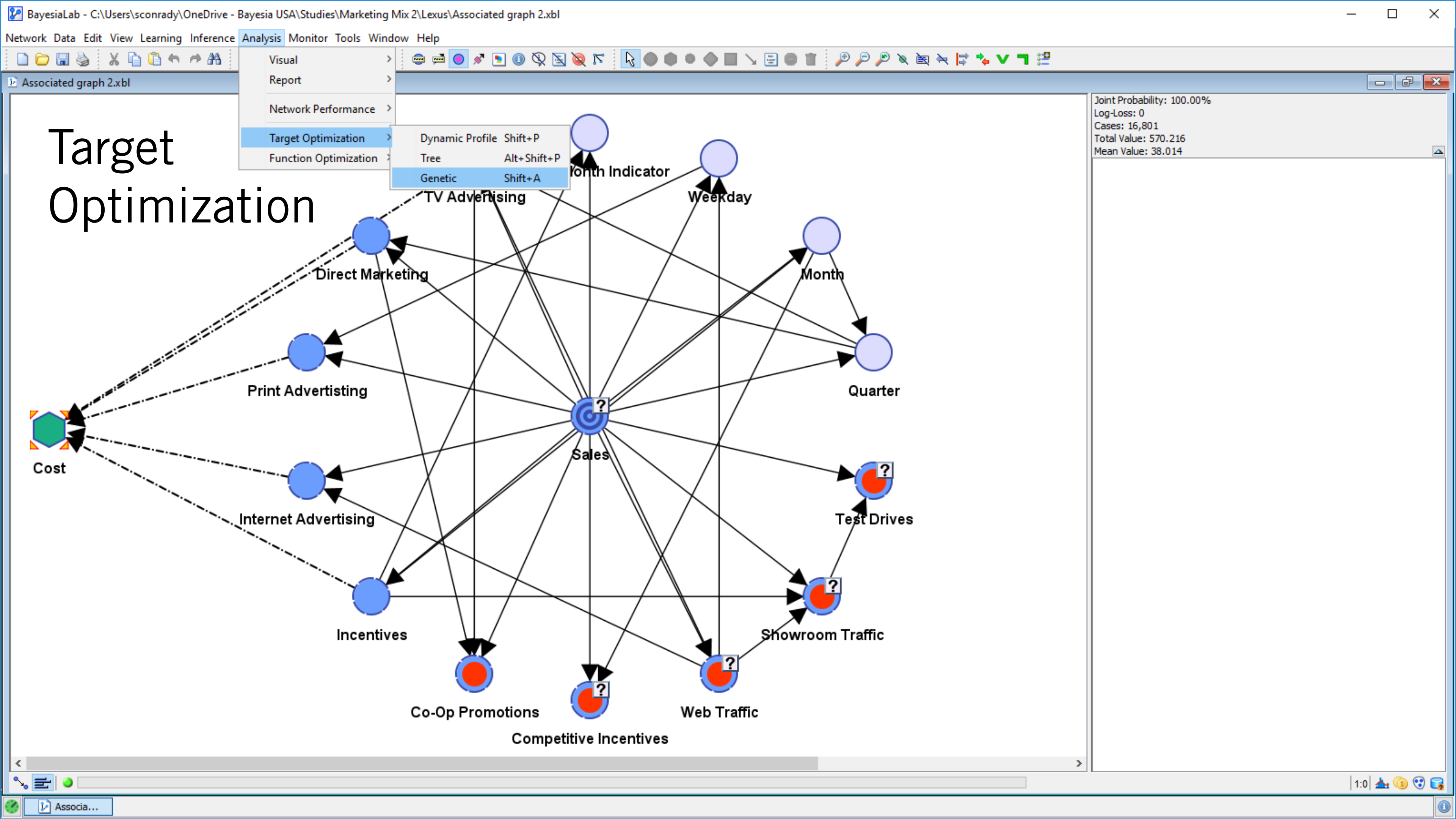
Target Direct Effects Analysis

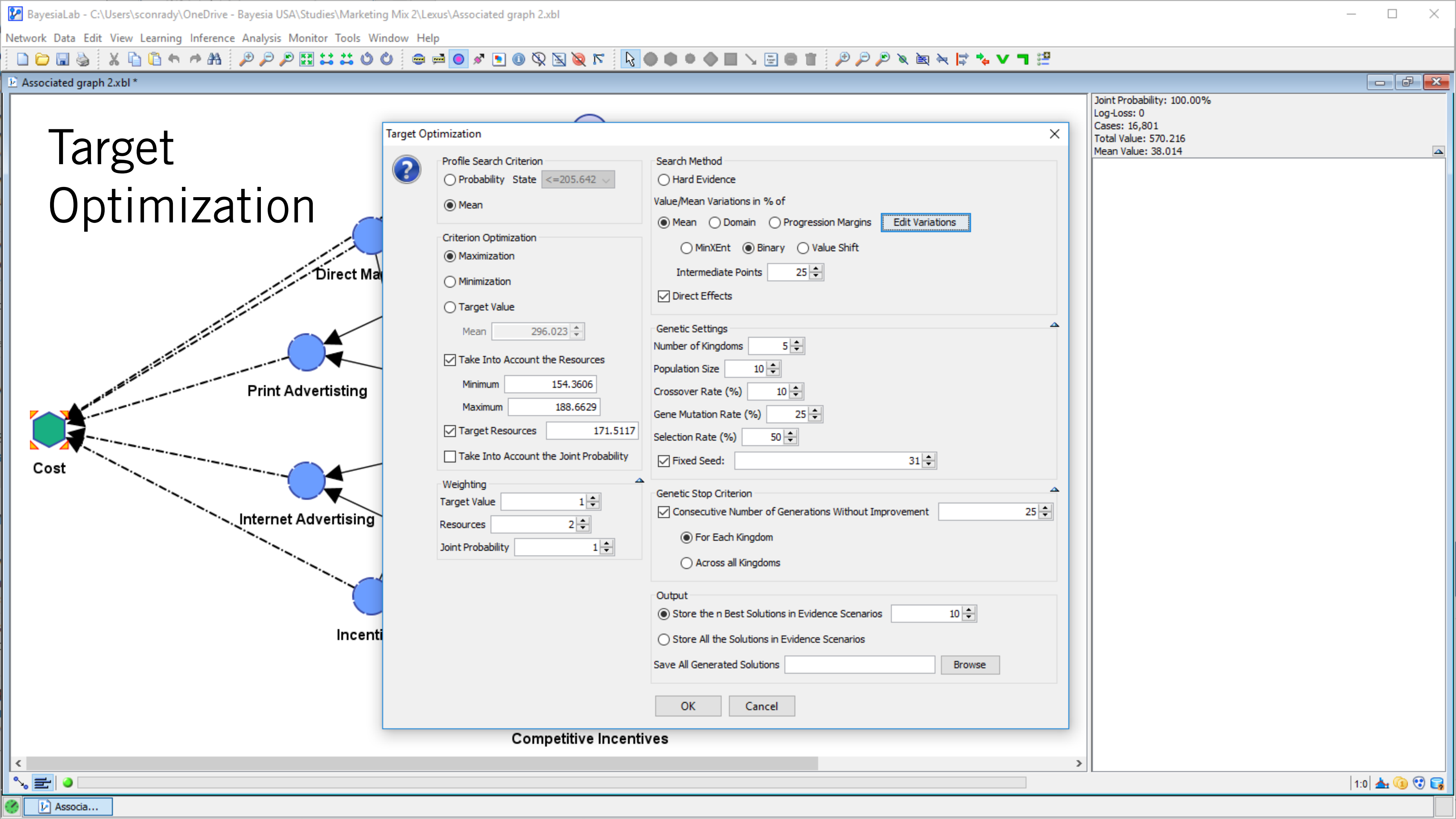



BayesiaLab - Associated graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Associated graph 2.xbl *
End-of-Month Indicator
TV Advertising
Weekday
Direct Marketing
Month
Print Advertising
Sales
Internet Advertising
Incentives
Showroom Traffic
Co-Op Promotions
Web 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
Response Curves
Variables
All Curves
TV Advertising
Internet Advertising
Incentives
Direct Marketing
Print Advertising
Close
Save
Associa...


Defining Media Costs
BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Marketing Mix 2\Lexus\Associated graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
Associated graph 2.xbl *
TV Advertising
End-of-Month Indicator
Direct Marketing
Print Advertising
Cost
Sales
Internet Advertising
Incentives
Co-Op Promotions
Competitive Incentives
Web Traffic
Node Editor
Node Selection: Cost
Rename
Equation
Properties
Classes
Comment
?Cost? =
MeanValue(?TV Advertising?)+MeanValue(?Direct Marketing?)+MeanValue(?Print Advertising?)+MeanValue(?Internet Advertising?)+MeanValue(?Inc
Excel-style formula
Please vali
Samples: 1
Fixed Seed: 31
Validate
Discrete Proba Distributions
Continuous Proba Distributions
Special Functions
Inference Functions
Arithmethic Functions
Transformation Functions
Conversion Functions
Trigonometric Functions
Relational Operators
TV Advertising
Direct Marketing
Print Advertising
Internet Advertising
Incentives
Domain: [0.2759110152971571, 104.231996355
OK
Cancel
Associa...

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
Joint Probability: 100.00%
Log-Loss: 0
Cases: 16,801
Total Value: 570.216
Mean Value: 38.014
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
Associa...

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

Optimization Report of Sales (Associated graph 2)

Optimization Results

Initial State	
Value/Mean	Resources
296.0229	171.5117

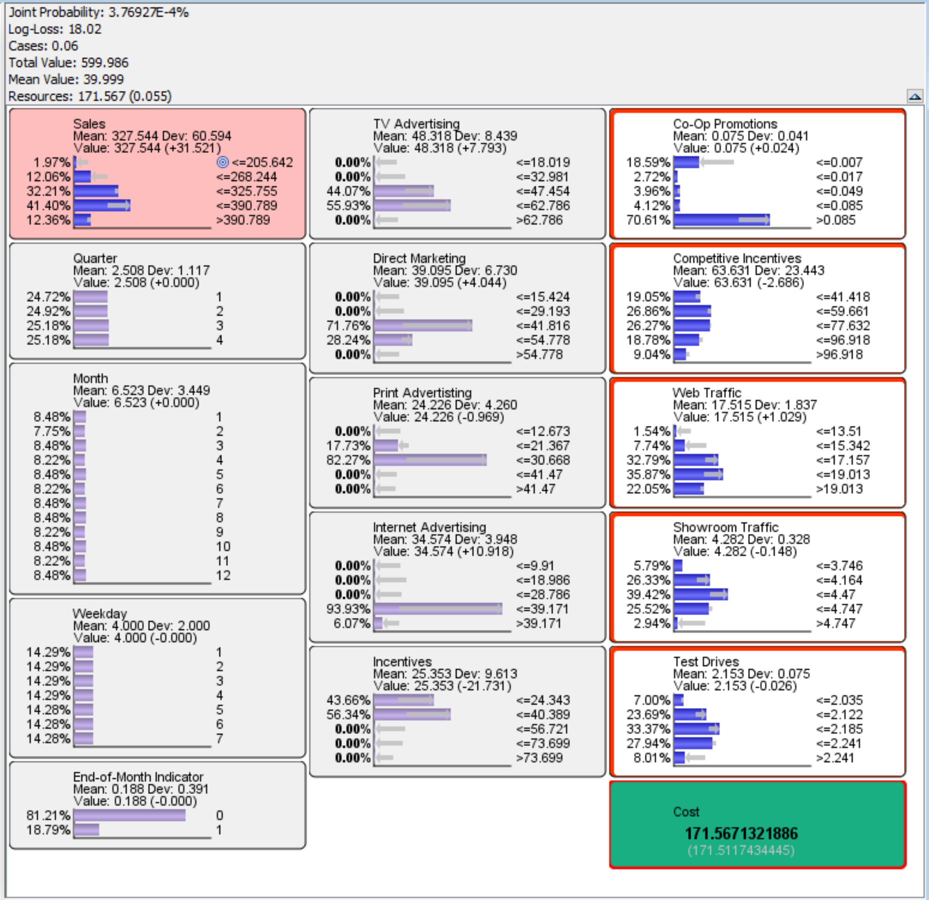
Search Method: Value/Mean Variations in % of Mean - Fix Probabilities (Binary) - Direct Effects

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)

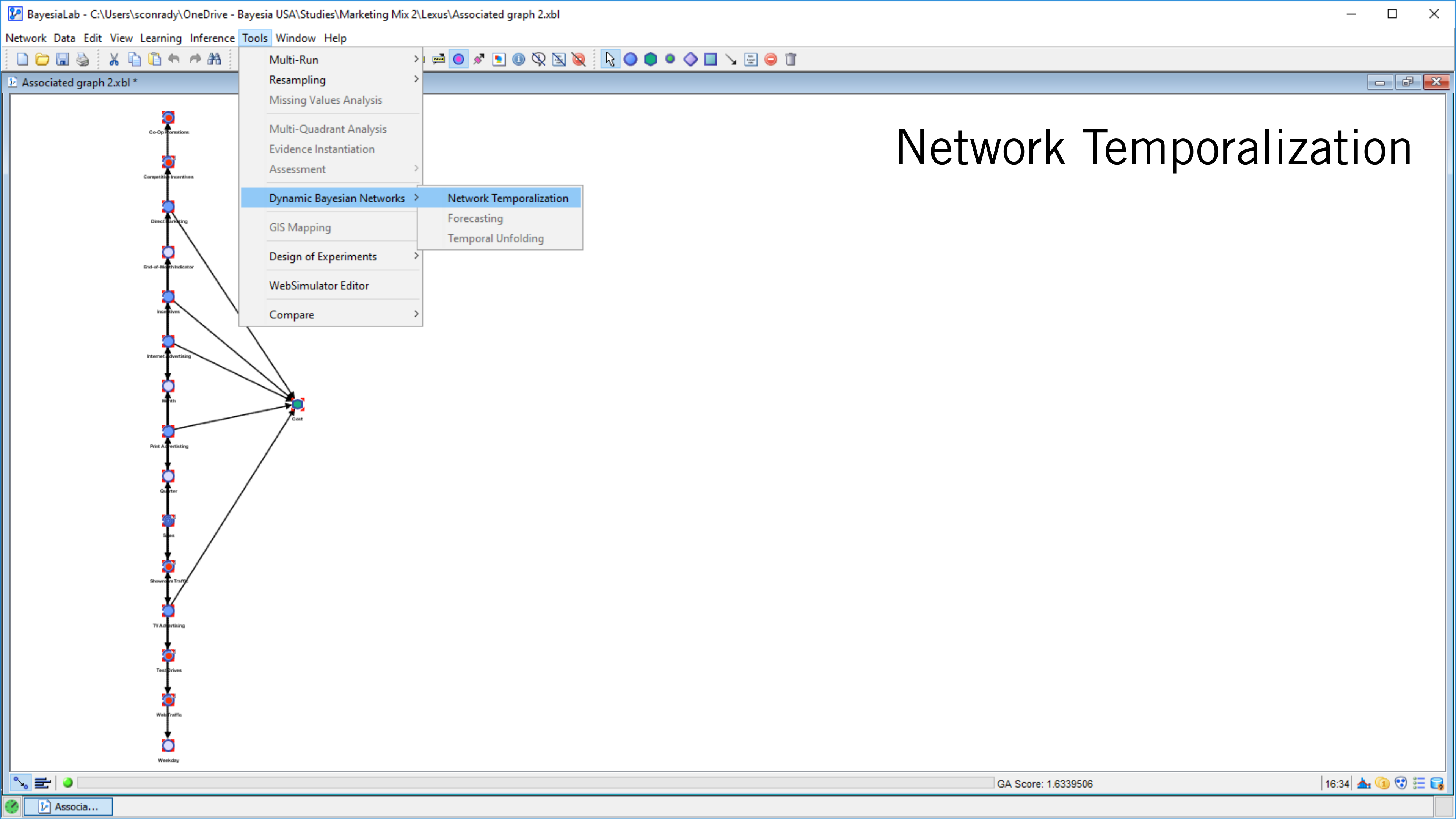
Best Solutions							
Incentives	Direct Marketing	TV Advertising	Internet Advertising	Print Advertising	Score	Value/Mean	Resources
25.3532	39.0952	48.3183	34.5745	24.2261	1.6340	327.5442 (31.5213)	171.5671 (0.0554)
27.1641	36.3989	48.3183	34.5745	25.1951	1.6463	326.8260 (30.8031)	171.6510 (0.1393)
25.3532	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

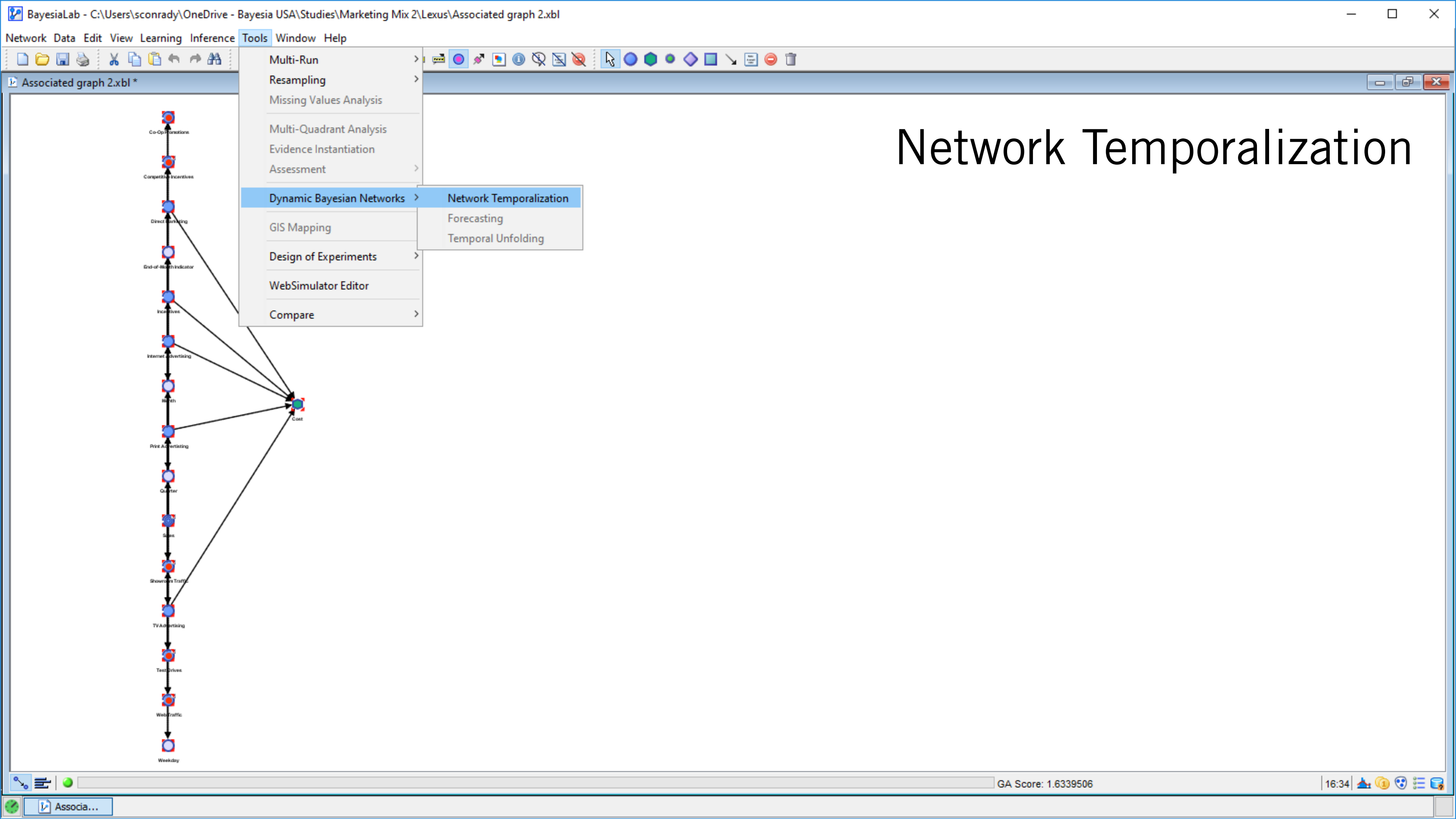


GA Score: 1.6339506

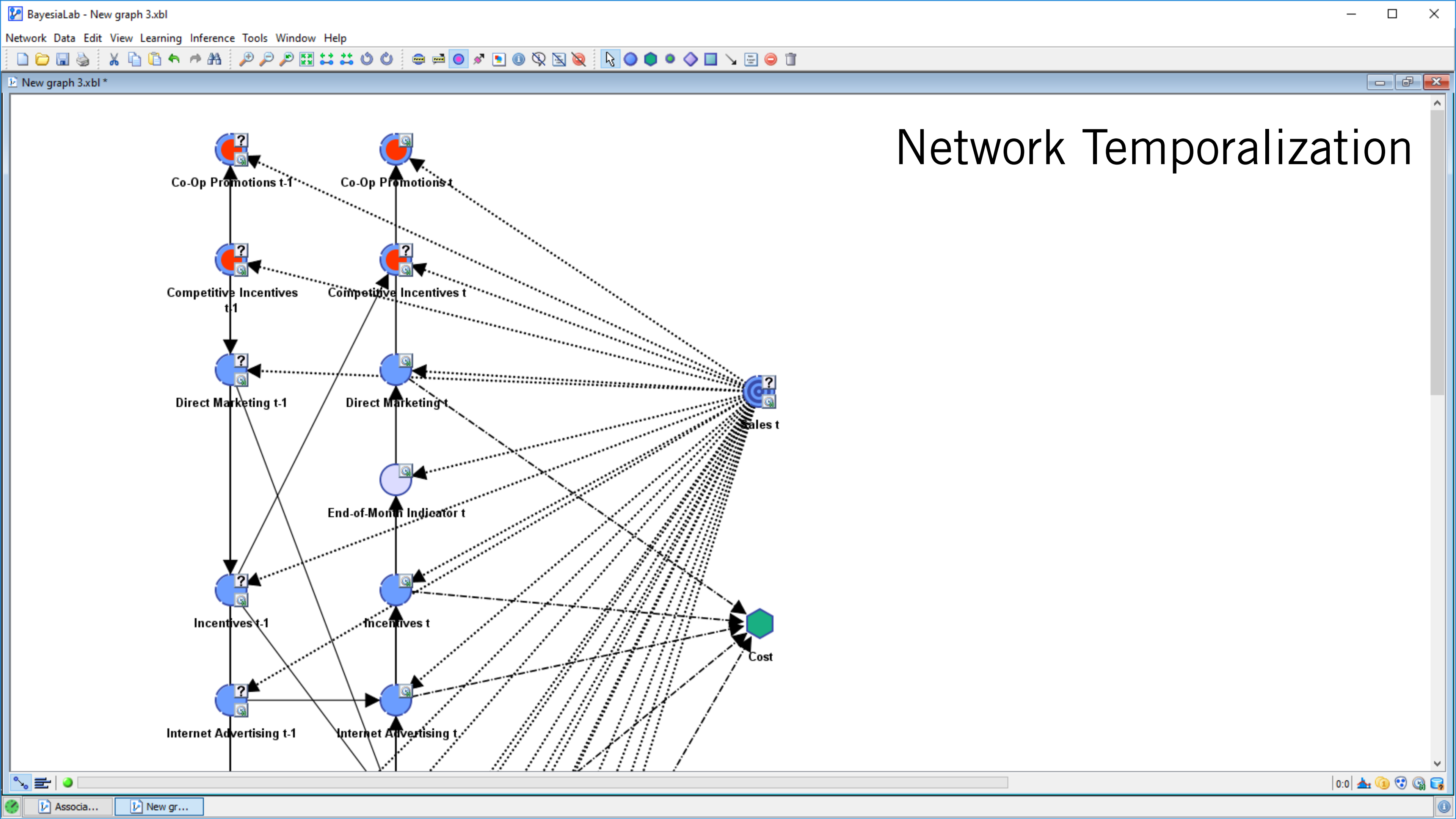
Network Temporalization

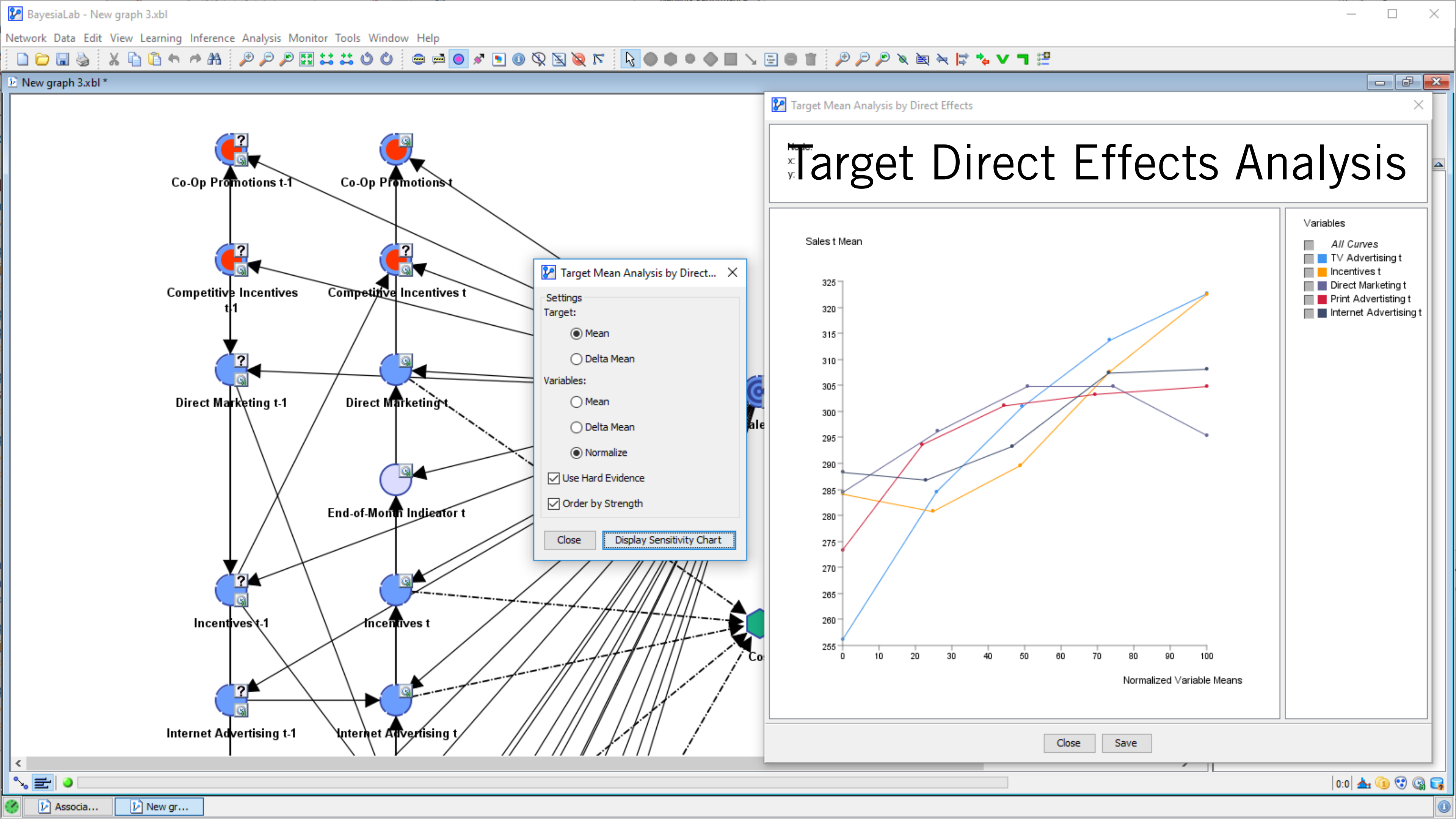


Network Temporalization



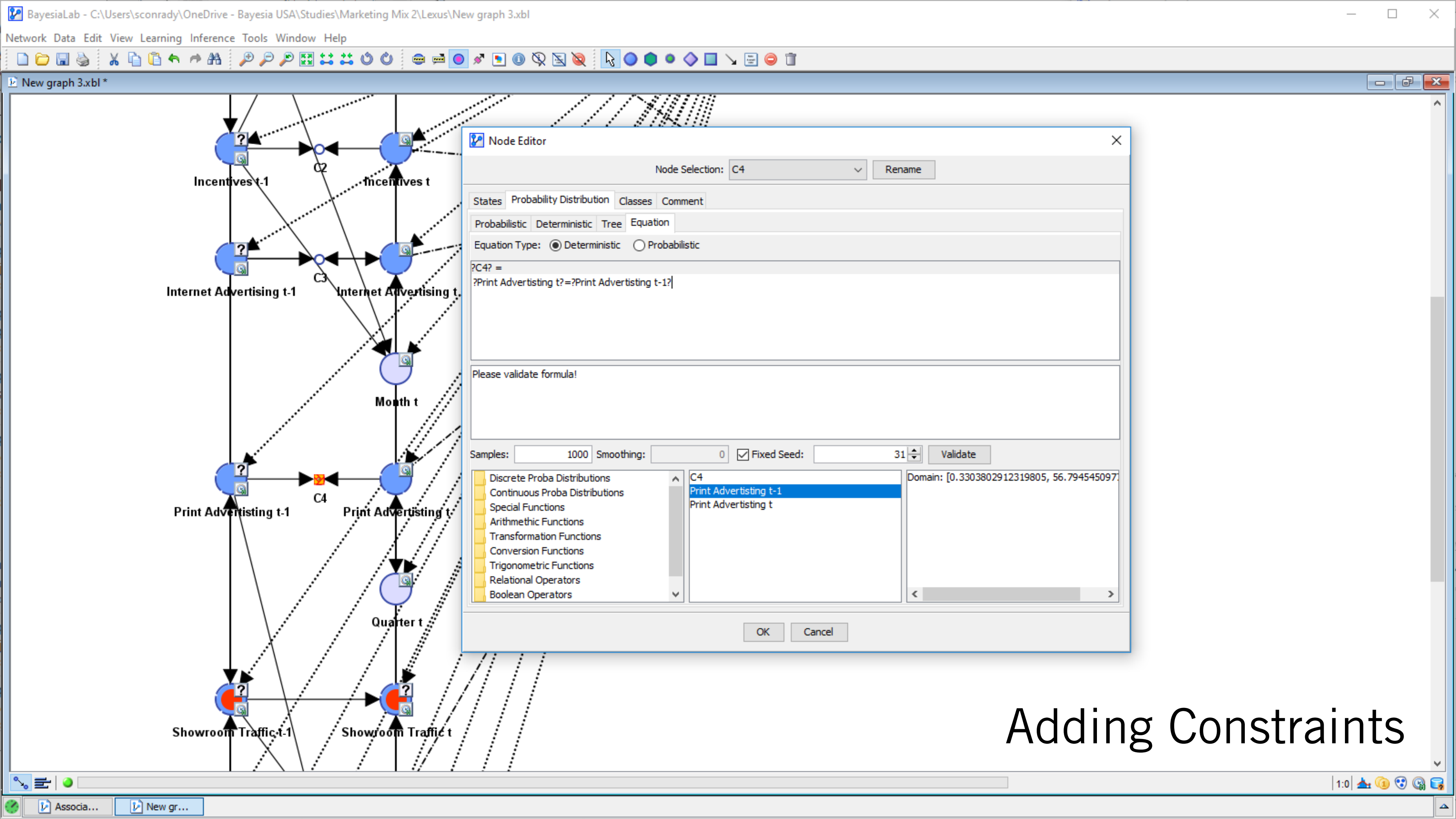
Network Temporalization

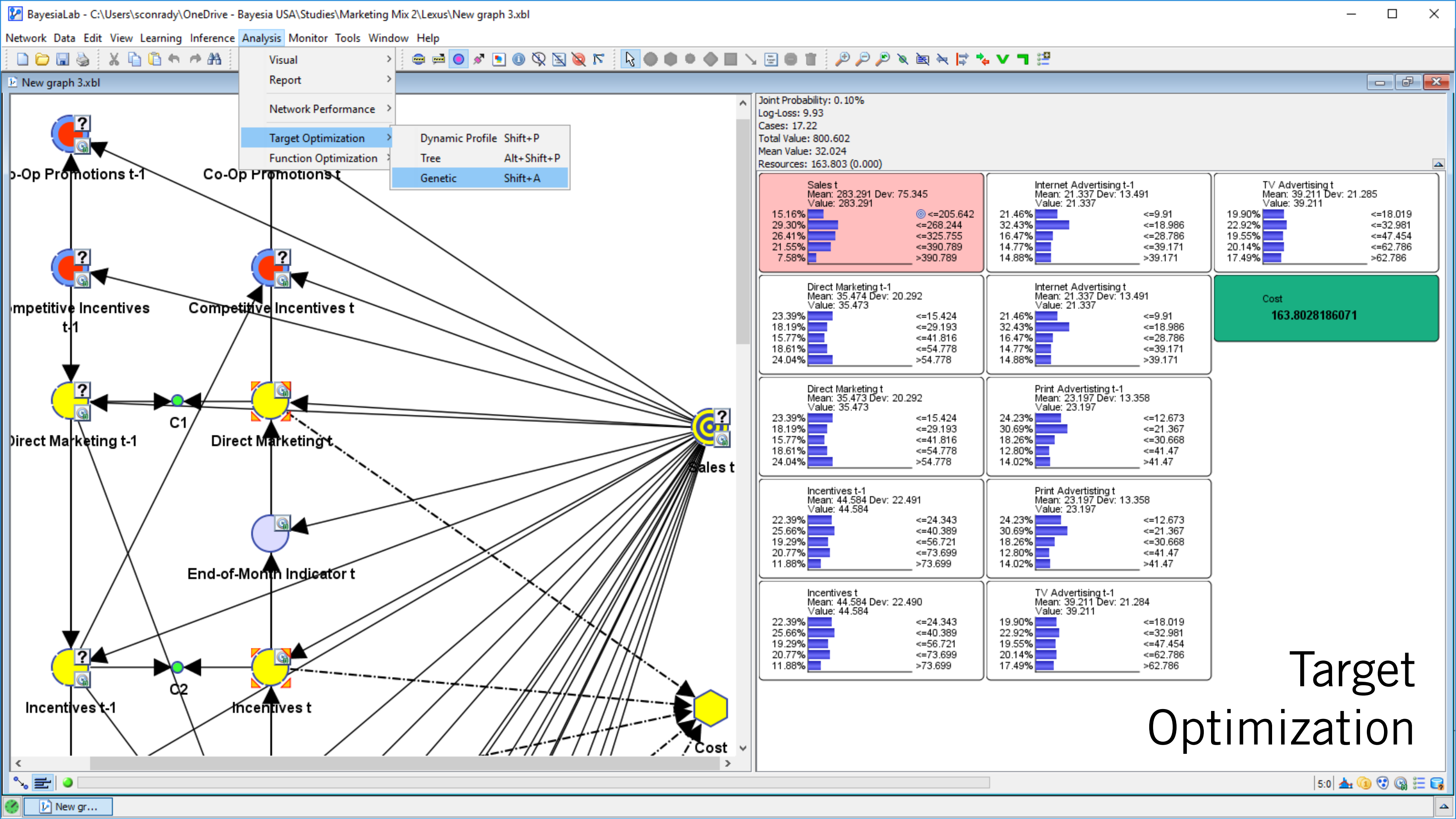




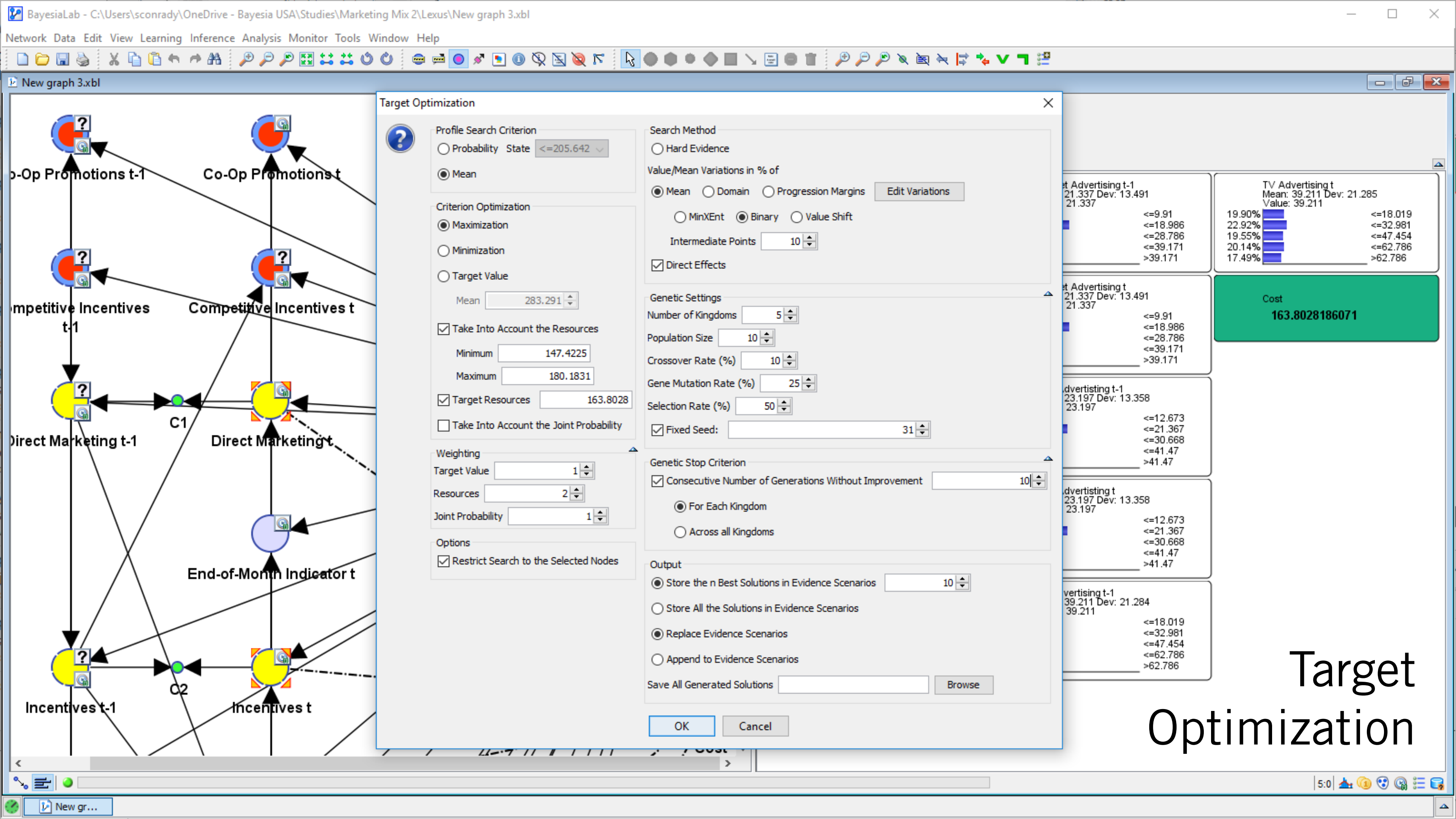
BayesiaLab - New graph 3.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 3.xbl *
Co-Op Promotions t-1
Co-Op Promotions t
Competitive Incentives t-1
Competitive Incentives t
Direct Marketing t-1
Direct Marketing t
End-of-Month Indicator t
Incentives t-1
Incentives t
Internet Advertising t-1
Internet Advertising t
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 t Mean
Normalized Variable Means
Variables
All Curves
TV Advertising t
Incentives t
Direct Marketing t
Print Advertisting t
Internet Advertising t
Close
Save
Associa...
New gr...

Adding Constraints





Target Optimization



Target Optimization

Optimization Report of Sales t (New graph 3) [7]

Initial State	
Value/Mean	Resources
283.2911	163.8028

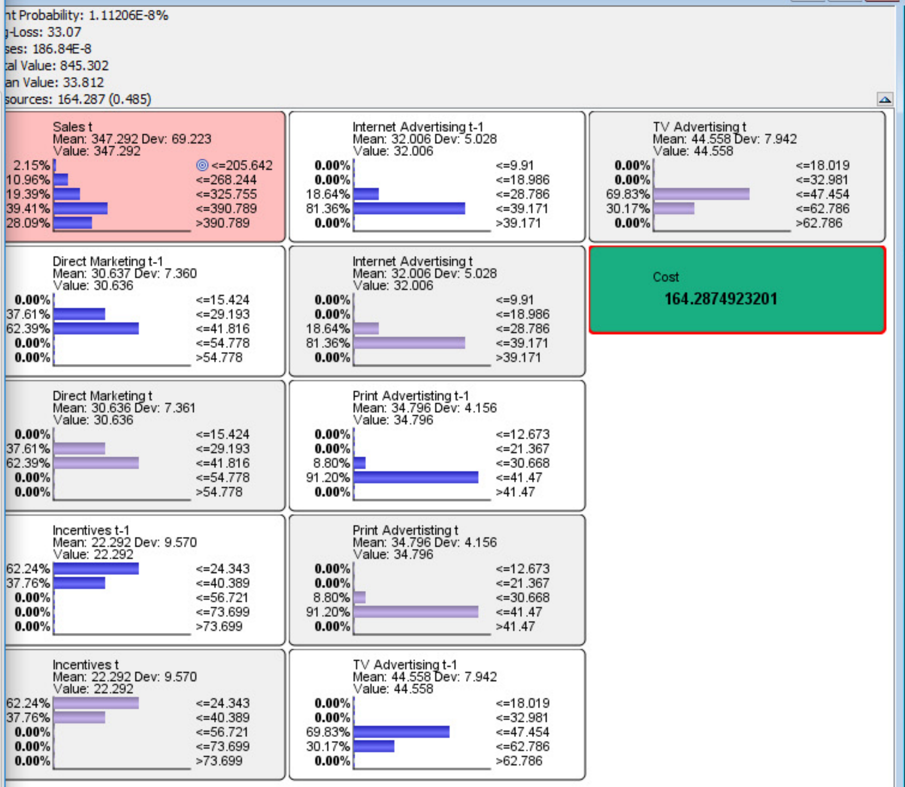
Search Method: Value/Mean Variations in % of Mean - Fix Probabilities (Binary) - Direct Effects

Not Fixed Nodes			
Node	Non Confounder	Factor	Not Observable
Co-Op Promotions t-1	X		
Co-Op Promotions t	X		
Test Drives t-1	X		
Print Advertisting t-1	X		
Web Traffic t-1	X		
Test Drives t	X		
Competitive Incentives t-1	X		
Showroom Traffic t-1	X		
Competitive Incentives t	X		
Direct Marketing t-1	X		
Internet Advertising t-1	X		
Showroom Traffic t	X		
Web Traffic t	X		
Incentives t-1	X		
TV Advertising t-1	X		

Synthesis					
Nodes	Print Advertisting t	Internet Advertising t	Incentives t	Direct Marketing t	TV Advertising t
Initial State	23.1973	21.3372	44.5840	35.4735	39.2108
Best Solution	34.7960 (11.5987)	32.0058 (10.6686)	22.2920 (-22.2920)	30.6362 (-4.8373)	44.5577 (5.3469)
Min	22.1429 (-1.0544)	22.3071 (0.9699)	22.2920 (-22.2920)	20.9616 (-14.5119)	40.9931 (1.7823)
Max	34.7960 (11.5987)	32.0058 (10.6686)	46.6105 (2.0265)	33.8610 (-1.6124)	55.2516 (16.0408)

Best Solutions							
Print Advertisting t	Internet Advertising t	Incentives t	Direct Marketing t	TV Advertising t	Score	Value/Mean	Resources
34.7960	32.0058	22.2920	30.6362	44.5577	1.4787	347.2922 (64.0012)	164.2875 (0.4847)
34.7960	30.0661	22.2920	30.6362	44.5577	1.5911	341.0152 (57.7242)	162.3477 (-1.4551)
30.5783	22.3071	22.2920	33.8610	55.2516	1.6423	329.3229 (46.0319)	164.2898 (0.4870)
22.1429	32.0058	46.6105	20.9616	40.9931	1.7613	321.5851 (38.2941)	162.7138 (-1.0890)

Close Save As... Print



Optimization Results

GA Score: 1.4787359


BAYESIALAB
VR
In Conclusion...

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

Upcoming Webinars:

- April 13 Analyzing Capital Flows of Exchange-Traded Funds
- April 20 GIS Mapping with BayesiaLab

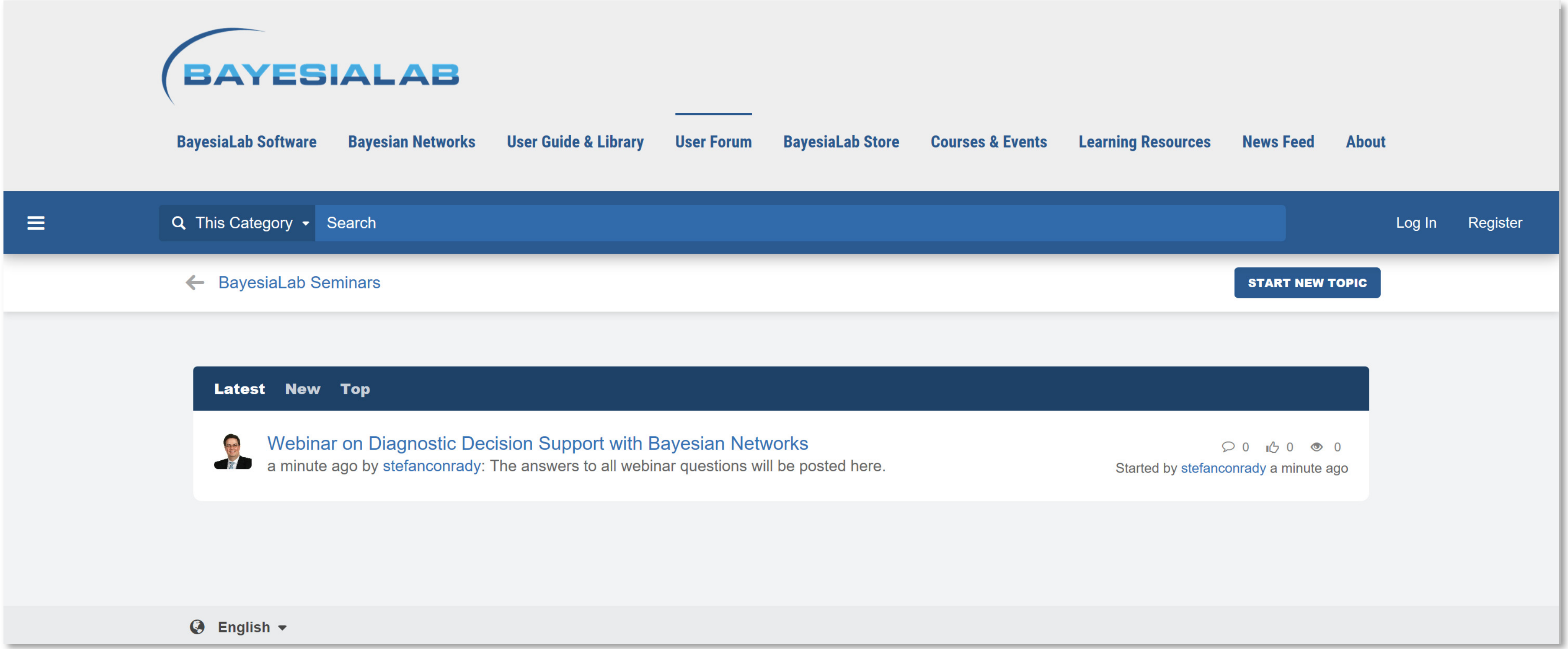
Register here: bayesia.com/events

BayesiaLab 7

Artificial Intelligence for Research, Analytics, and Reasoning

What is BayesiaLab?

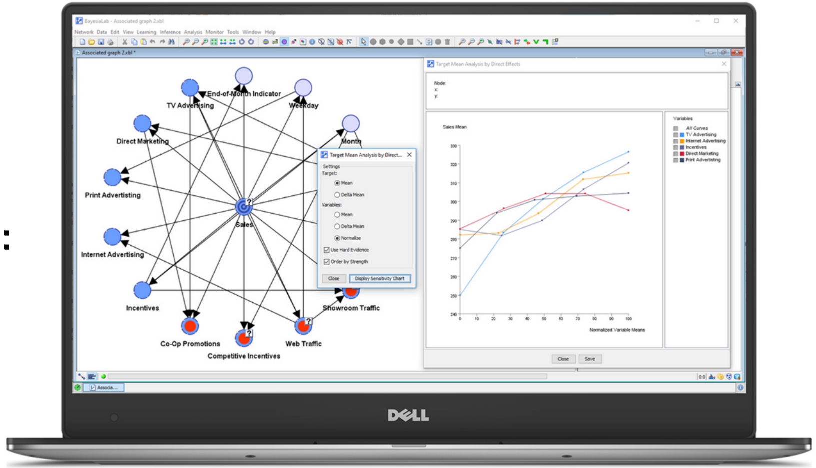
User Forum: bayesia.com/community



BayesiaLab Trial

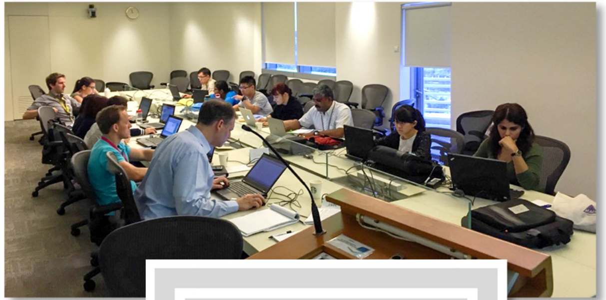
Try BayesiaLab Today!

- Download Demo Version:
  www.bayesialab.com/trial-download
- Apply for Unrestricted Evaluation Version:
  www.bayesialab.com/evaluation



BayesiaLab Courses Around the World in 2018

- 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 Course

Learn More & Register: bayesia.com/events


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

Thank You!

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