

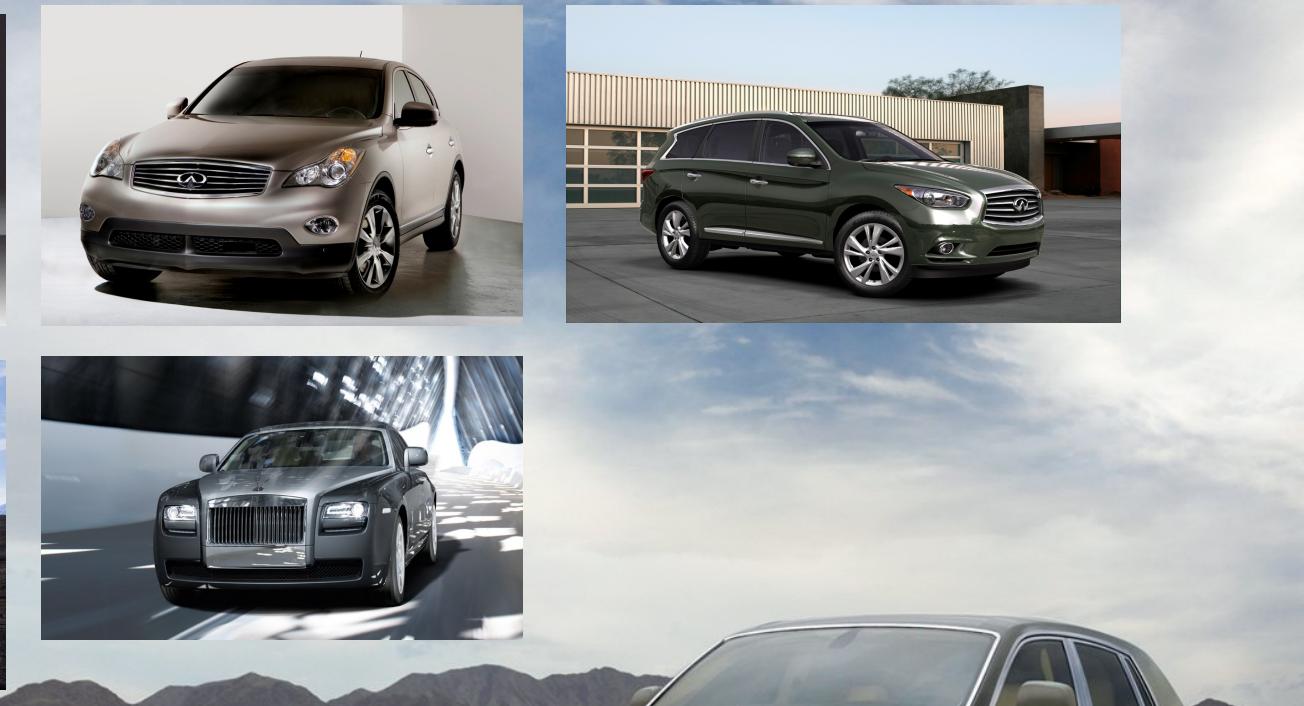


Key Drivers Analysis & Optimization Based on Consumer Survey Data



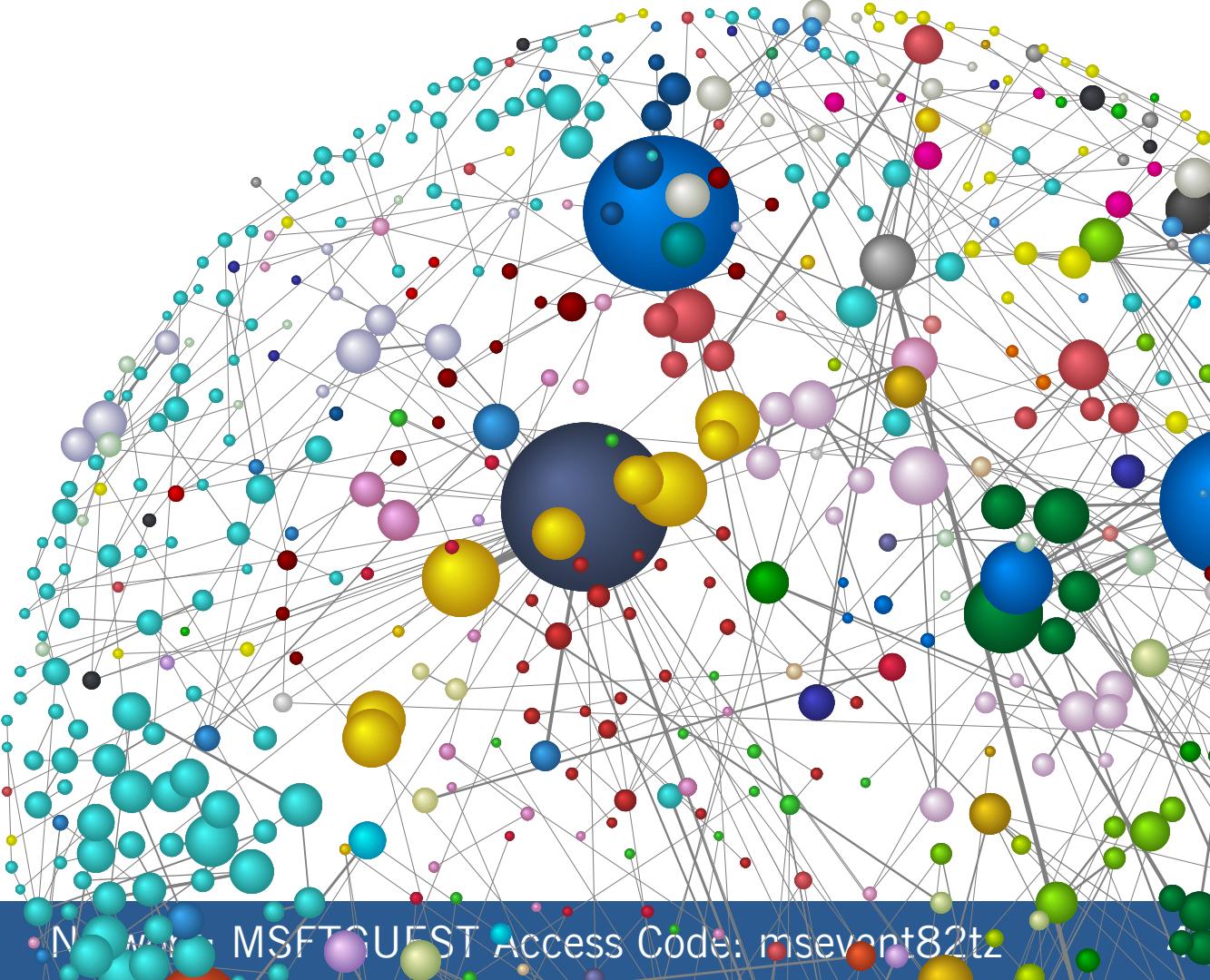
Hello
my name is

*Stefan
Conrady*





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



stefan.conrady@bayesia.us

NEXT MSFTQUEST Access Code: msevent82tz

The BayesiaLab Software Platform





Bayesia USA
Nashville, TN
Since 2010



Bayesia S.A.S.
Laval, France
Since 2001



Bayesia Singapore
Singapore
Since 2012

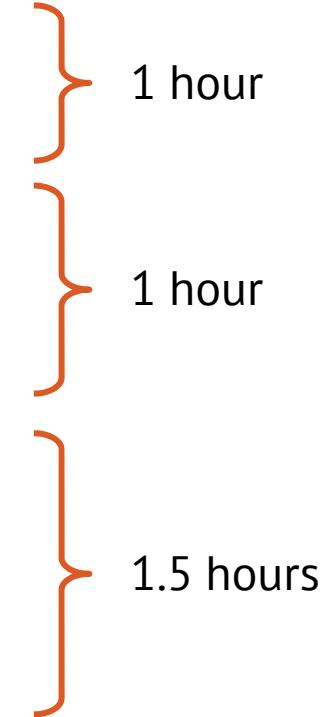


Seminar Series

2016/17 BayesiaLab Lecture Program

- Marketing Mix Modeling and Optimization
- **Key Drivers Analysis and Optimization**
- Knowledge Elicitation and Reasoning
- Bayesian Networks—Artificial Intelligence for Research, Analytics, and Reasoning

Today's Agenda

- An Overview of Analytic Modeling
 - The Bayesian Network Paradigm
 - Key Drivers Analysis
 - Conceptual Challenges
 - Statistical Challenges
 - Case Study: Auto Buyer Satisfaction Survey
 - Building a Probabilistic Structural Equation Model for Key Driver Analysis with BayesiaLab
 - Optimization of Key Drivers
- 

Presentation slides will be available

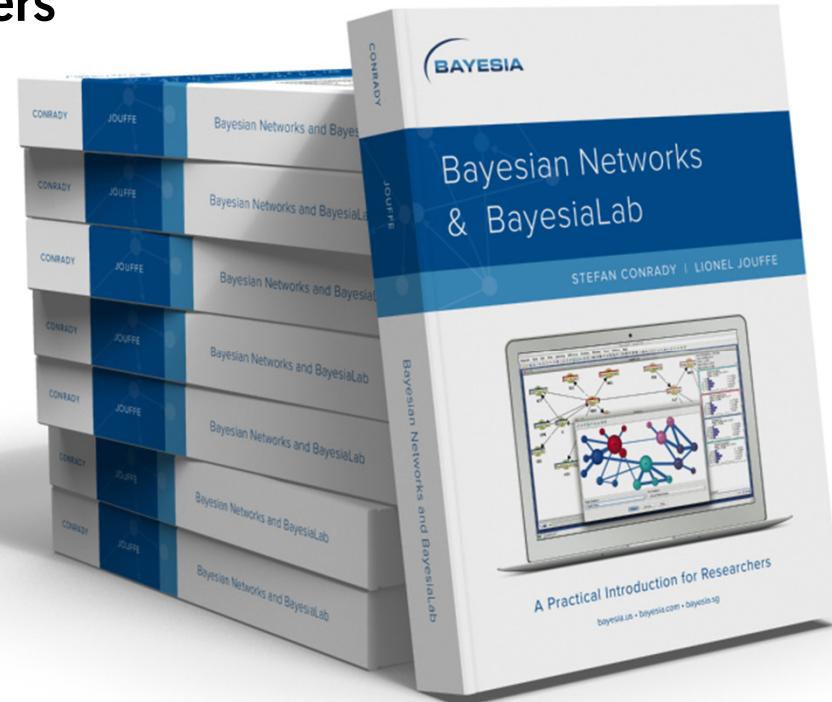


1 ★	2 ★	3 ★	4 ★	5	6	7	8 ★	9	10 ★	11 ★	12 ★	13 ★	14	15 ★	16 ★	17 ★
18	19 ★	20 ★	21 ★	22 ★	23 ★	24 ★	25 ★	26 ★	27	28 ★	29 ★	30 ★	31 ★	32 ★	33 ★	34 ★
35 ★	36	37	38 ★	39 ★	40 ★	41 ★	42 ★	43	44 ★	45	46 ★	47 ★	48 ★	49 ★	50 ★	51 ★
52 ★	53 ★	54 ★	55 ★	56 ★	57 ★	58 ★	59 ★	60 ★	61 ★	62 ★	63 ★	64 ★	65	66 ★	67 ★	68
69	70	71 ★	72 ★	73 ★	74	75 ★	76 ★	77 ★	78 ★	79	80 ★	81 ★	82 ★	83 ★	84 ★	85 ★
86	87	88	89 ★	90 ★	91 ★	92	93 ★	94 ★	95	96	97	98	99	100	101	102 ★
103 ★	104 ★	105	106 ★	107 ★	108 ★	109	110 ★	111	112 ★	113 ★	114 ★	115	116 ★	117 ★	118 ★	119 ★
120 ★	121 ★	122 ★	123 ★	124 ★	125 ★	126 ★	127 ★	128 ★	129 ★	130 ★	131 ★	132 ★	133 ★	134 ★	135 ★	136 ★
137 ★	138 ★	139 ★	140 ★	141 ★	142 ★	143	144	145 ★	146 ★	147 ★	148	149 ★	150	151 ★	152 ★	153 ★

Bayesian Networks & BayesiaLab

A Practical Introduction for Researchers

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



Credits & Badges



Make sure to check in!



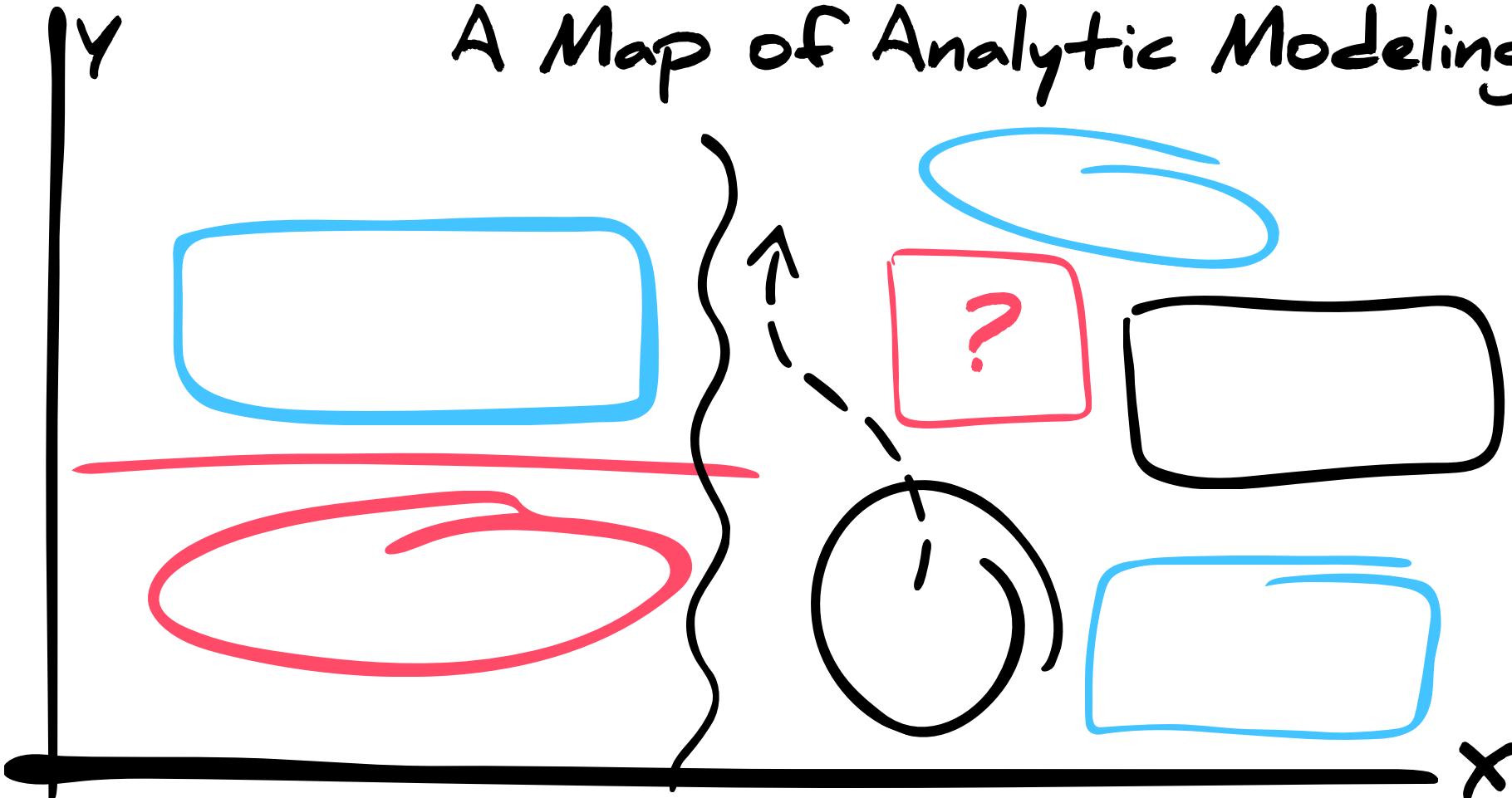
BayesiaLab Courses Around the World

3-Day Introductory BayesiaLab Courses

- June 13-15, 2017
Paris, France
- June 27-29, 2017
Chicago, Illinois
- September 6-8, 2017
Redmond, Washington
- September 25-27, 2017
Paris, France
- October 24-26, 2017
Durham, North Carolina
- November 20–22, 2017
Singapore
- November 27–29, 2017
Sydney, Australia



A Map of Analytic Modeling



The Purpose of Models

Statistical Science
2010, Vol. 25, No. 3, 289–310
DOI: 10.1214/10-STS330
© Institute of Mathematical Statistics, 2010

To Explain or to Predict?

Galit Shmueli

Description

Prediction

Explanation

Simulation

Optimization

Model Purpose

Association/
Correlation

Causation

sus a predictive goal. The purpose of this article is to clarify the distinction between explanatory and predictive modeling, to discuss its sources, and to reveal the practical implications of the distinction to each step in the modeling process.

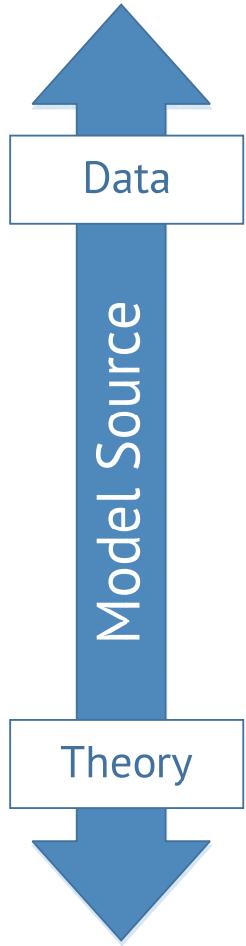
Key words and phrases: Explanatory modeling, causality, predictive modeling, predictive power, statistical strategy, data mining, scientific research.

1. INTRODUCTION

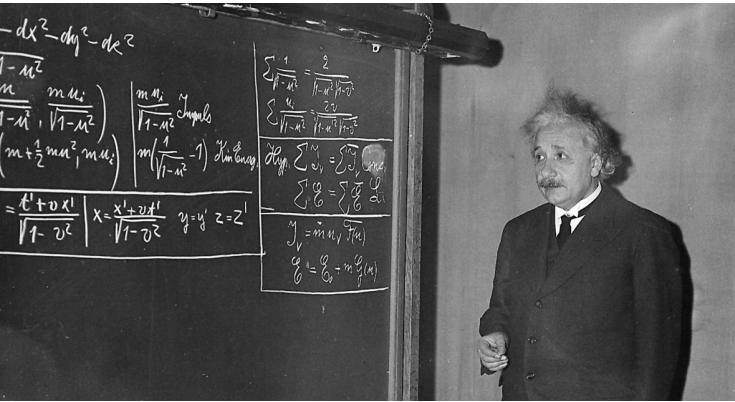
Looking at how statistical models are used in different scientific disciplines for the purpose of theory building and testing, one finds a range of perceptions regarding the relationship between causal explanation and empirical prediction. In many scientific fields such as economics, psychology, education,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

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

Source of Models



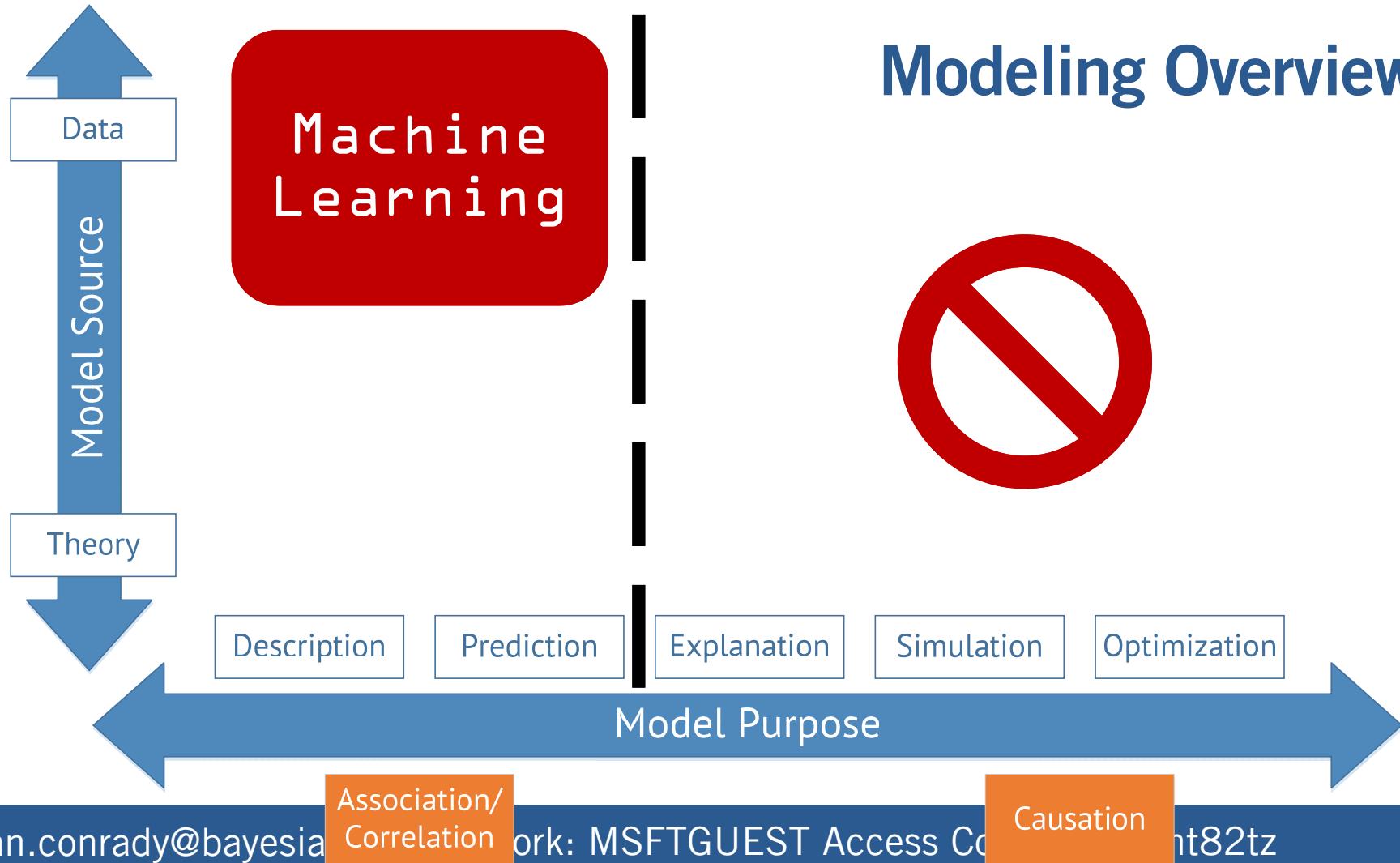
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A6B35B0F3D59334DF5F0087C
F432340313AF5B7A78C
680FEA41EC5C2
EA93FB8
120



The End of Theory?



Modeling Overview



Why does this
matter?

Key Drivers Analysis & Optimization Based on Consumer Opinion Survey Data

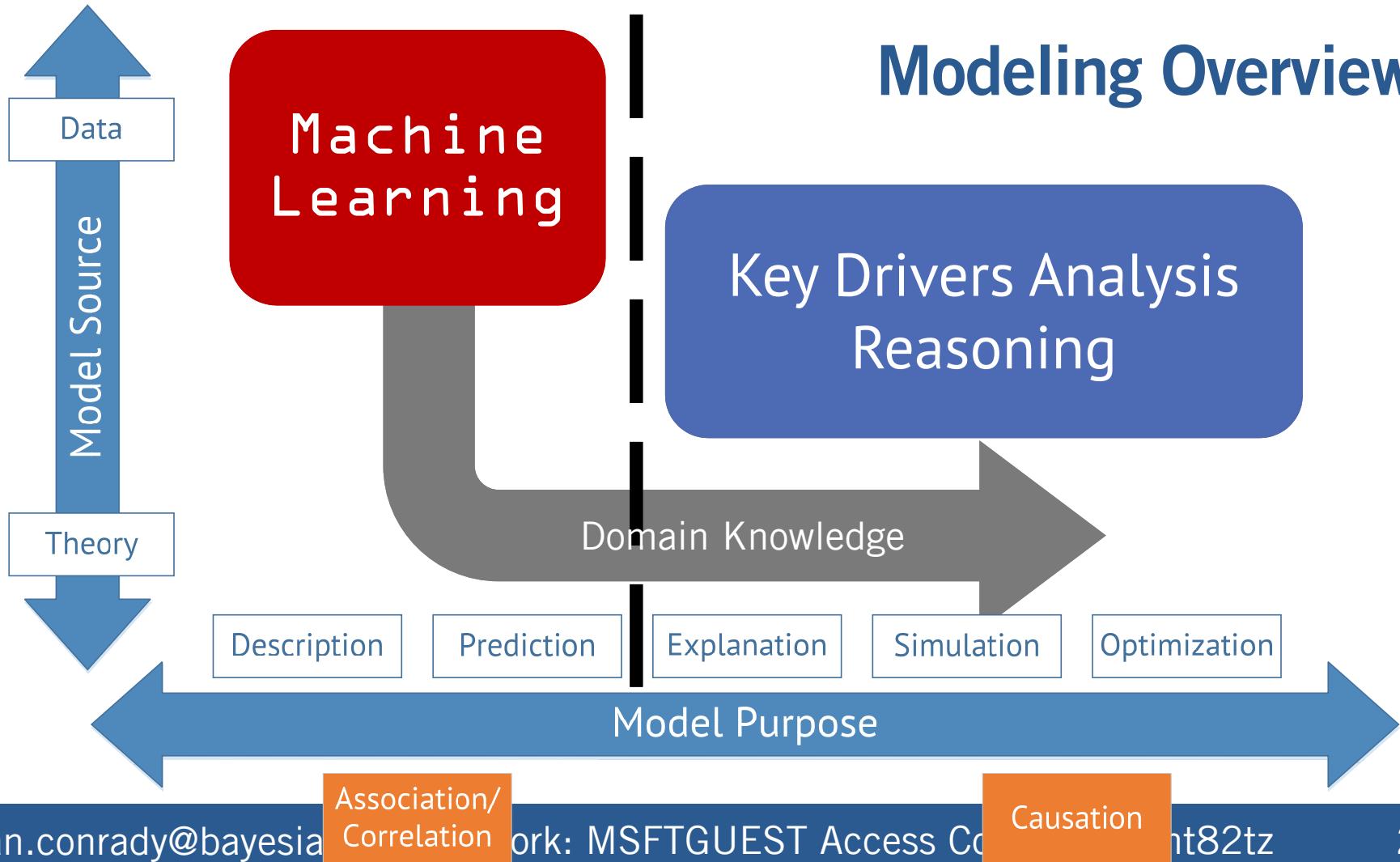
A Definition:

“A key driver analysis **investigates the relationships** between potential drivers and customer behavior such as the likelihood of a positive recommendation, overall satisfaction, or propensity to buy a product.”

Source: <https://select-statistics.co.uk/blog/key-driver-analysis/>

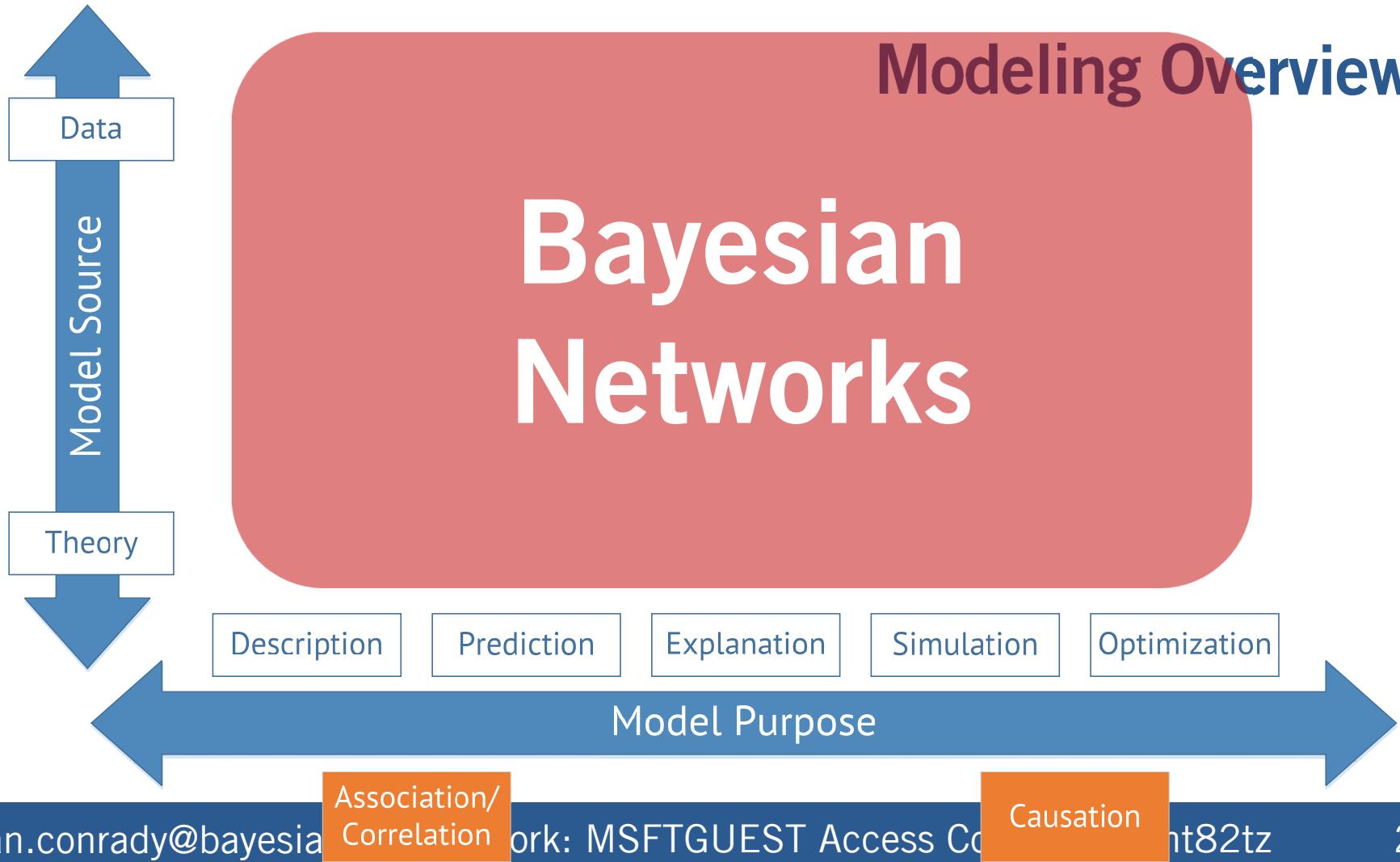


Modeling Overview

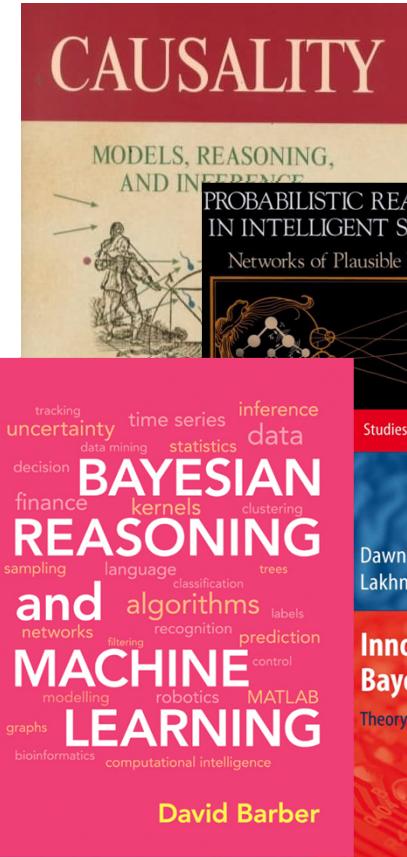


Modeling Overview

Bayesian Networks



The New Paradigm: Bayesian Networks

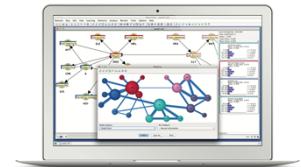
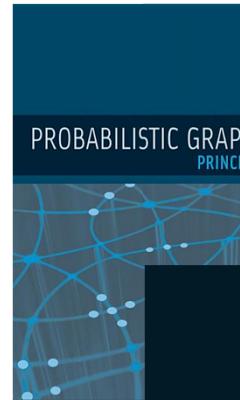
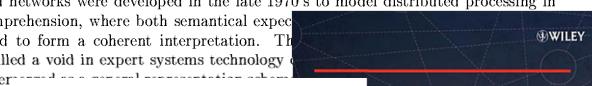


Judea Pearl

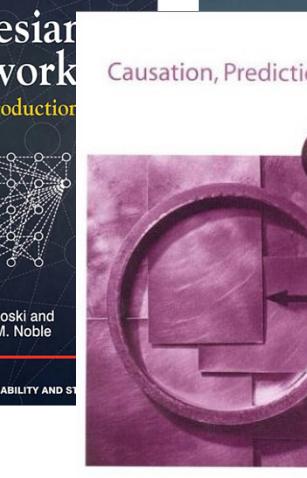
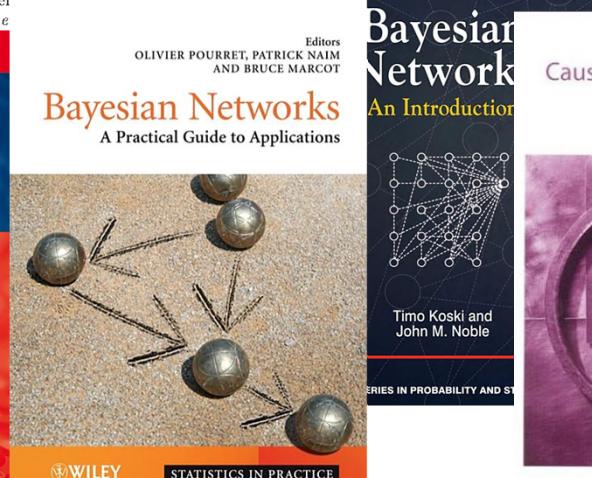
Cognitive Systems Laboratory Computer Science Department

University of California, Los Angeles, CA 90024
judea@cs.ucla.edu

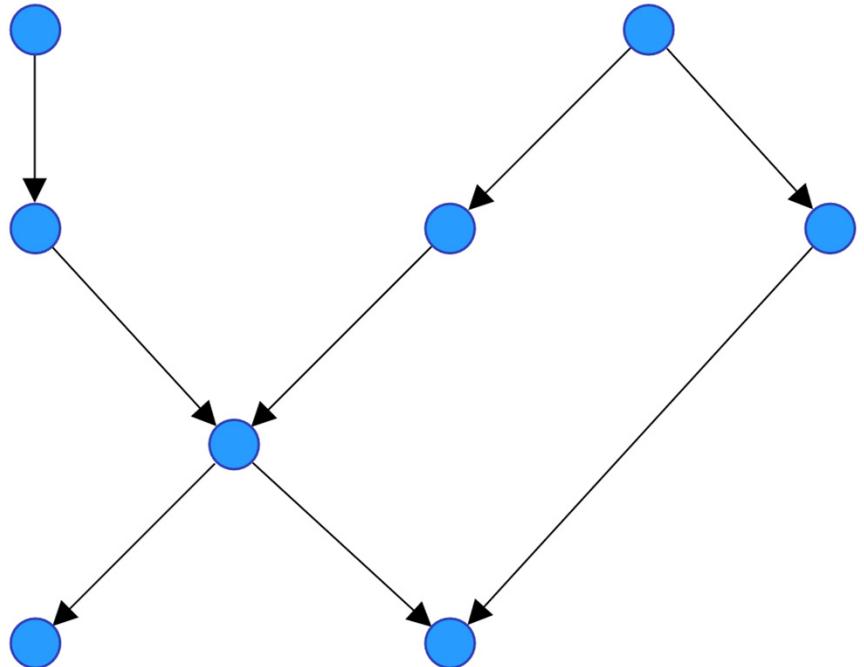
Bayesian networks were developed in the late 1970's to model distributed processing in reading comprehension, where both semantical expectation and inference can be combined to form a coherent interpretation. The inferences filled a void in expert systems technology which have ever since been represented as a general representation scheme.



[bayesia.us](#) • [bayesia.com](#) • [bayesia.sg](#)



The New Paradigm: Bayesian Networks



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

The New Paradigm: Bayesian Networks

Two Components Only:

- Node



- Arc



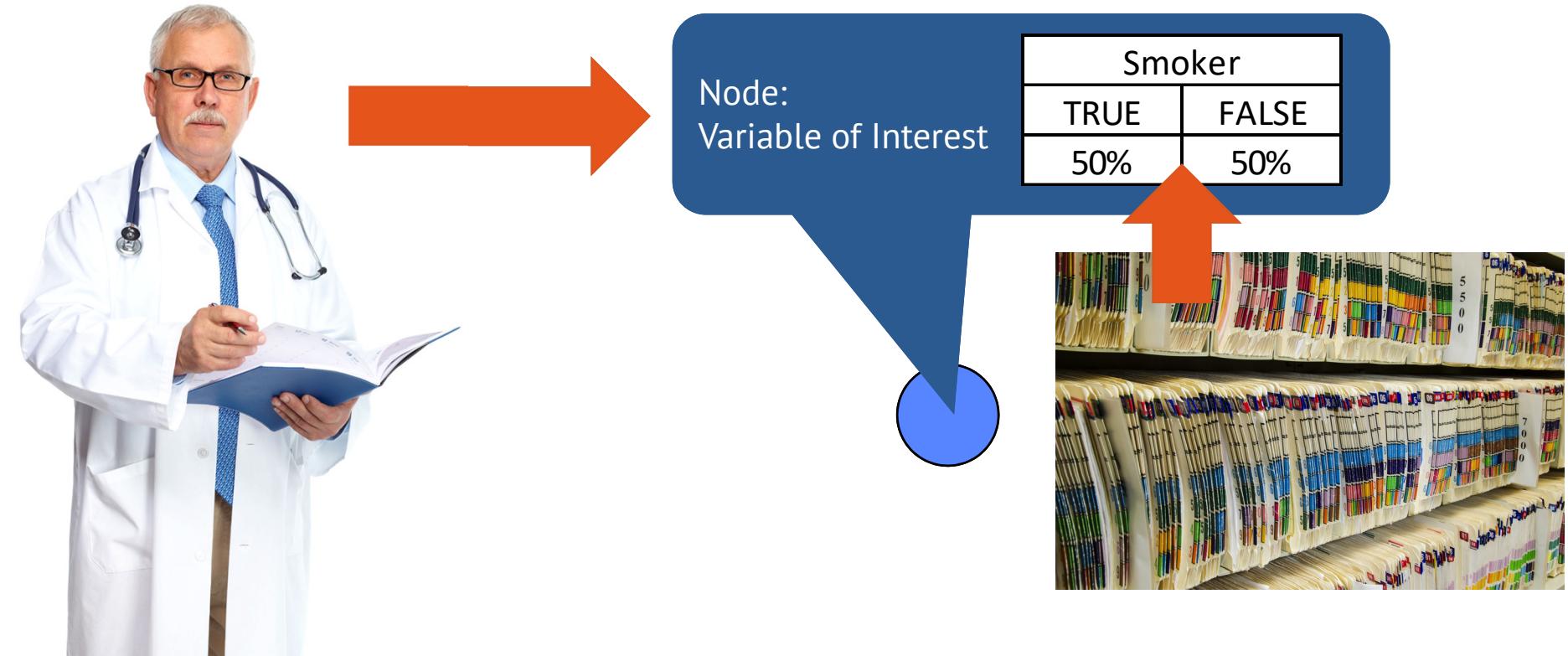
The New Paradigm: Bayesian Networks

Example

- A specialist in respiratory medicine summarizes his knowledge about his patients.
- Lauritzen & Spiegelhalter (1988)
- Fenton & Neil (2013)



The New Paradigm: Bayesian Networks



The New Paradigm: Bayesian Networks



Smoker

Node:
Variable of
Interest

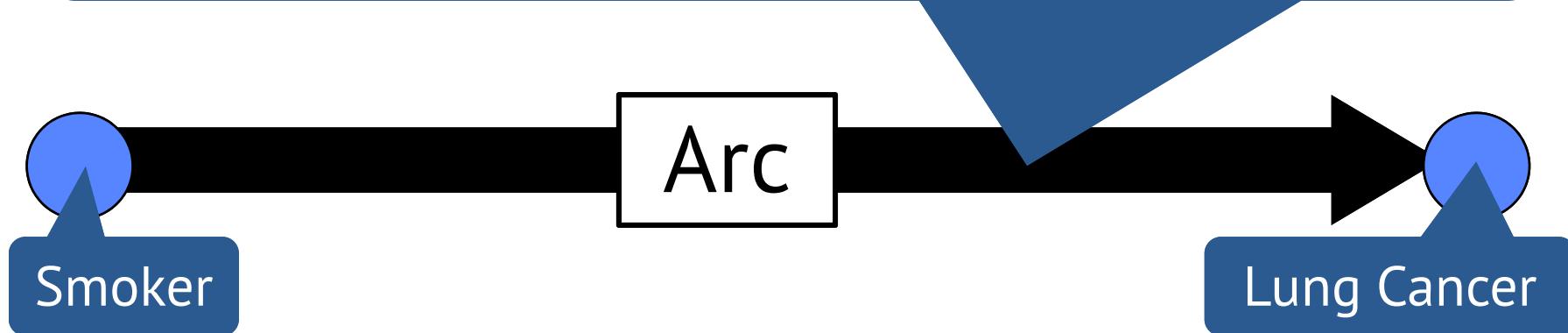
Lung Cancer	
TRUE	FALSE
5.5%	94.5%



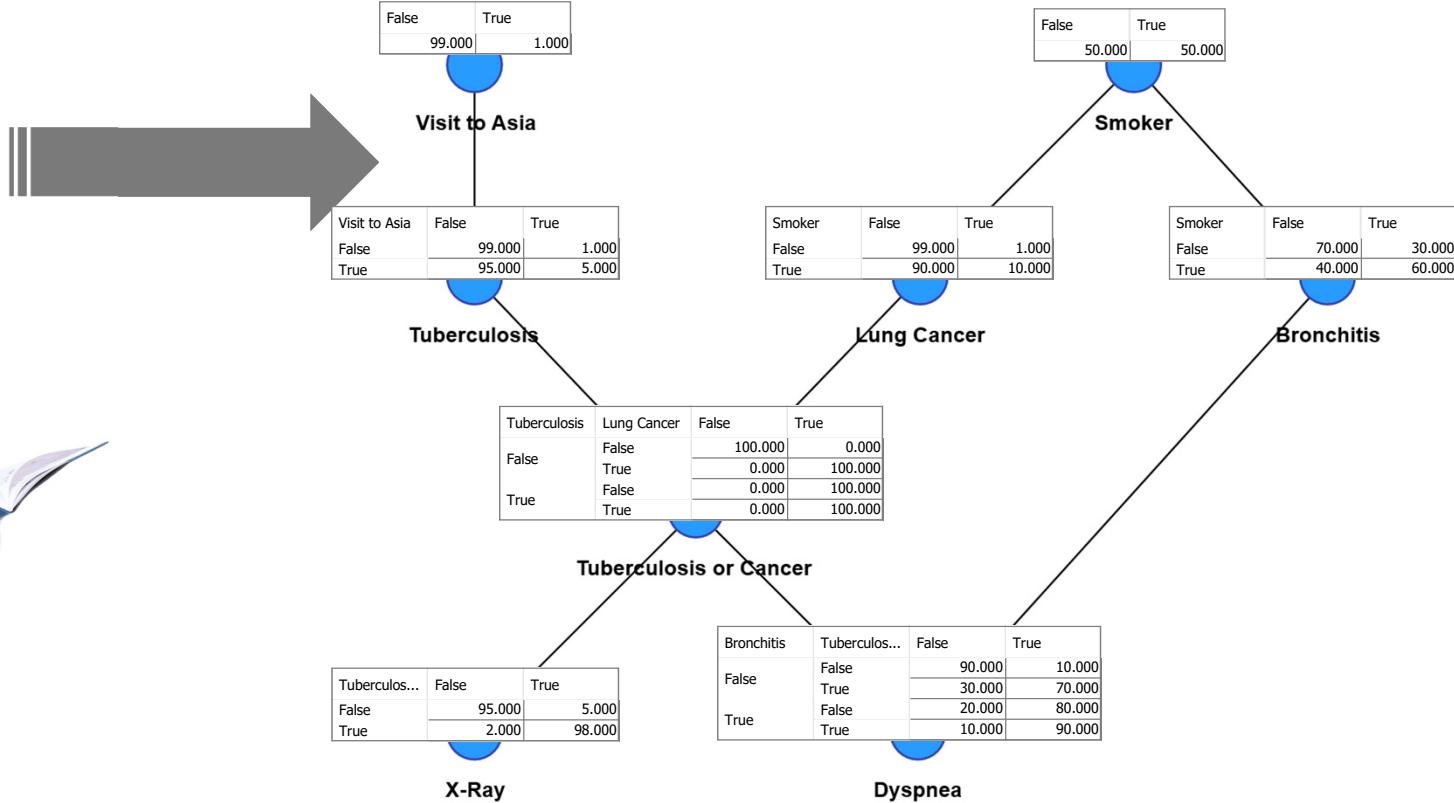
The New Paradigm: Bayesian Networks

Discrete & Nonparametric
Probabilistic Relationship
 $P(\text{Lung Cancer}|\text{Smoker})$

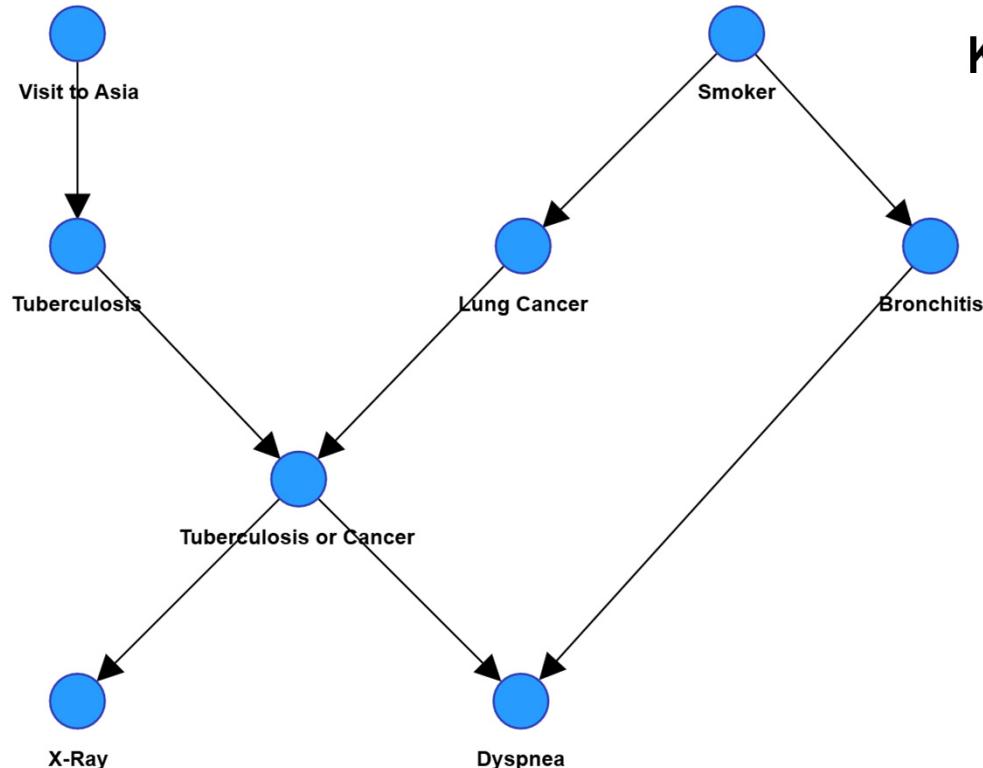
		Lung Cancer	
		Smoker	TRUE
Smoker	FALSE	99%	1%
	TRUE	90%	10%



The New Paradigm: Bayesian Networks



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
- Nonlinear
- Probabilistic
- Causal

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

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

Compare to algebraic formula:

Representation of one variable of the joint probability distribution, i.e. $y=f(x)$

Dependent

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

Independent

Independent

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

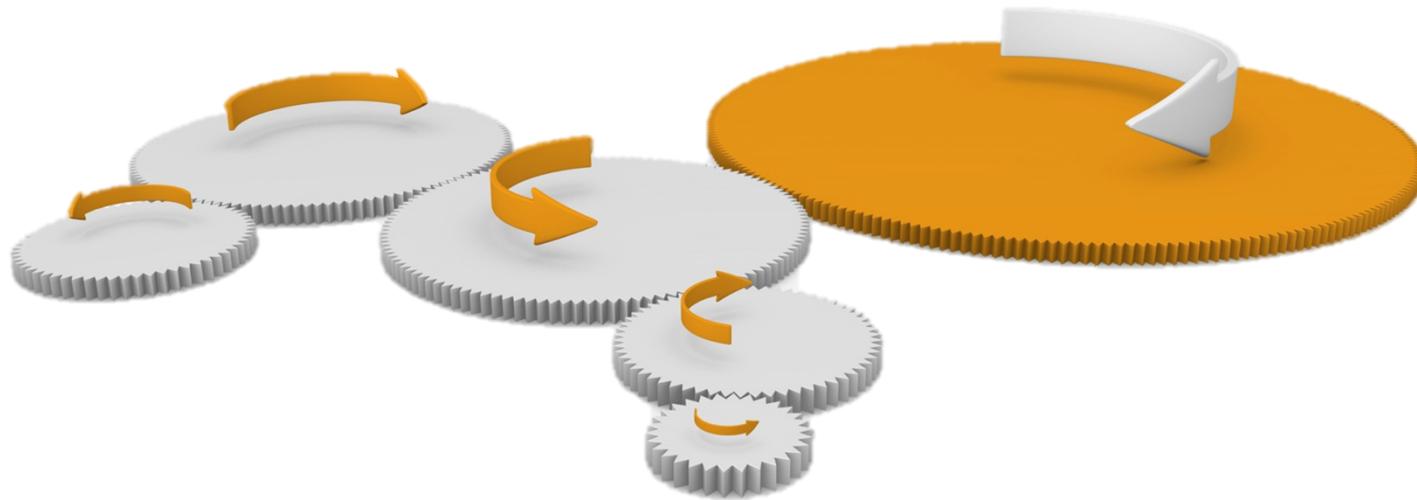
- Omni-directional Inference, i.e. evaluation is always performed in all directions.

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


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

The New Paradigm: Bayesian Networks

Omni-Directional Inference



The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

- 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.

Deterministic
Point Estimate

Compare to algebra

Single
Value Input

Single
Value Input

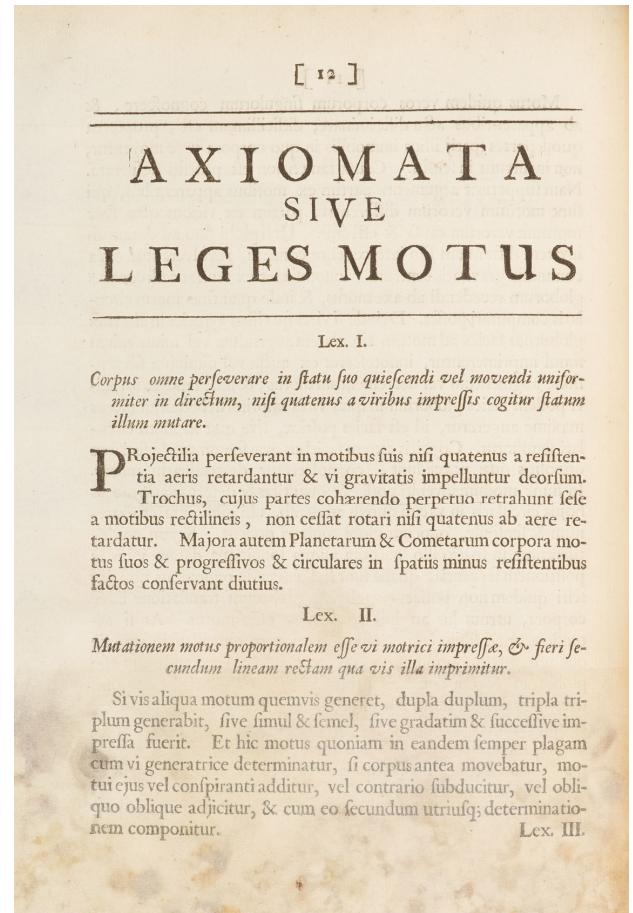
$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n$$

Bayesian Networks

Key Properties of Bayesian Networks

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

$$F = m \cdot a$$



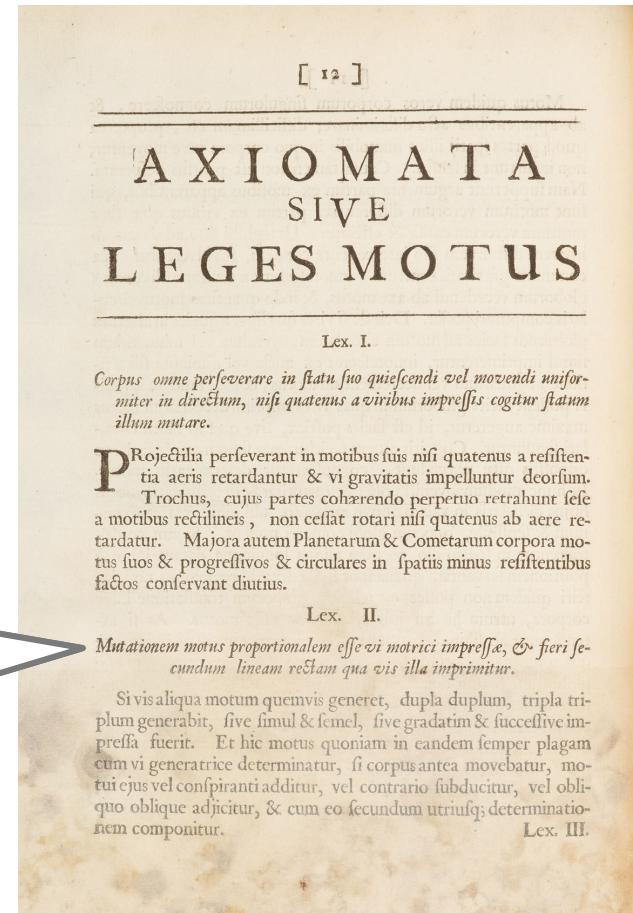
Bayesian Networks

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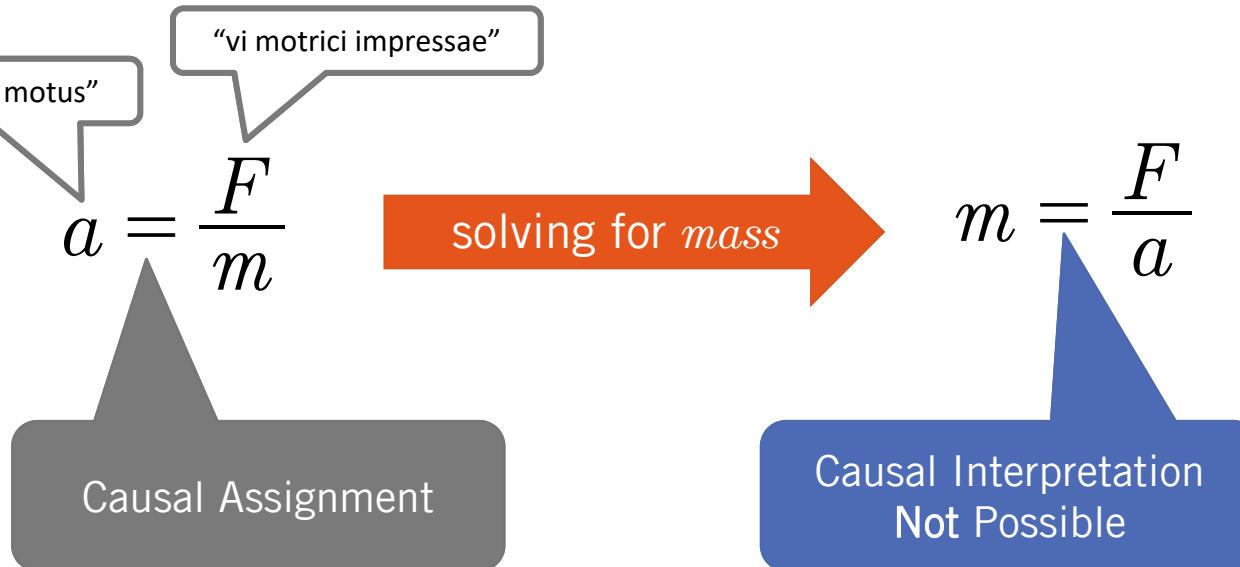
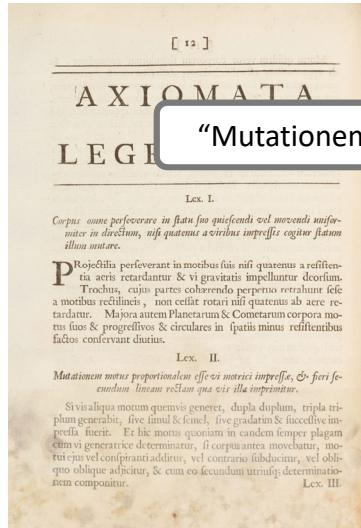
“Mutationem motus proportionalem esse vi motrici impressæ, & fieri secundum lineam rectam qua vis illa imprimitur.”

“A change in motion is proportional to the motive force impressed and takes place along the straight line in which that force is impressed.”



The New Paradigm: Bayesian Networks

Limitations of Algebra



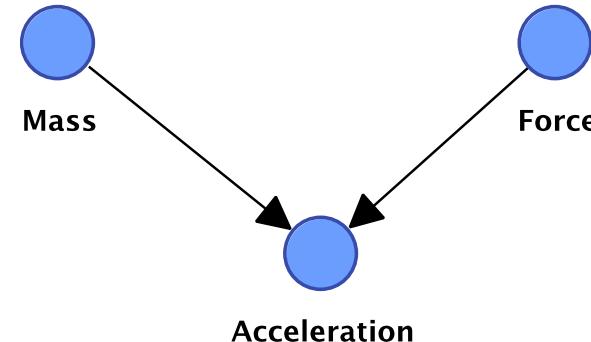
The New Paradigm: Bayesian Networks

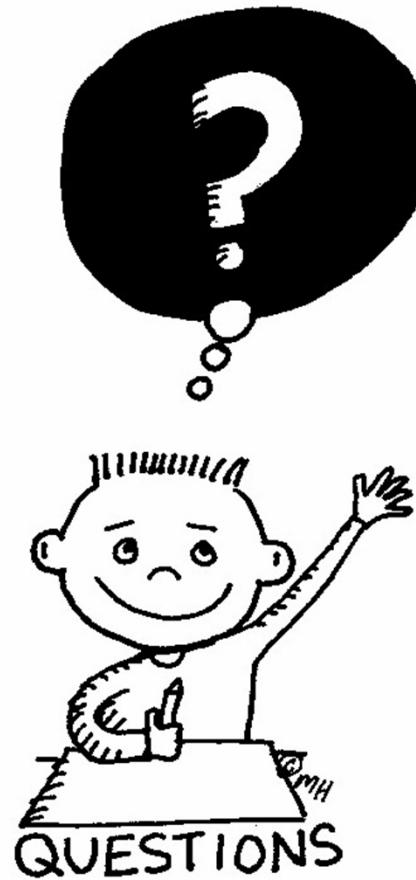
Key Properties of Bayesian Networks

- Bayesian networks can encode causal direction, algebra cannot.

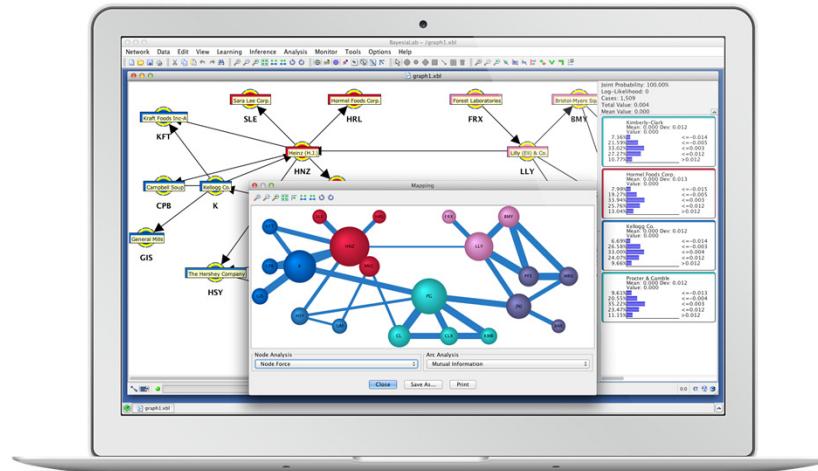
Algebra vs. Bayesian Network

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

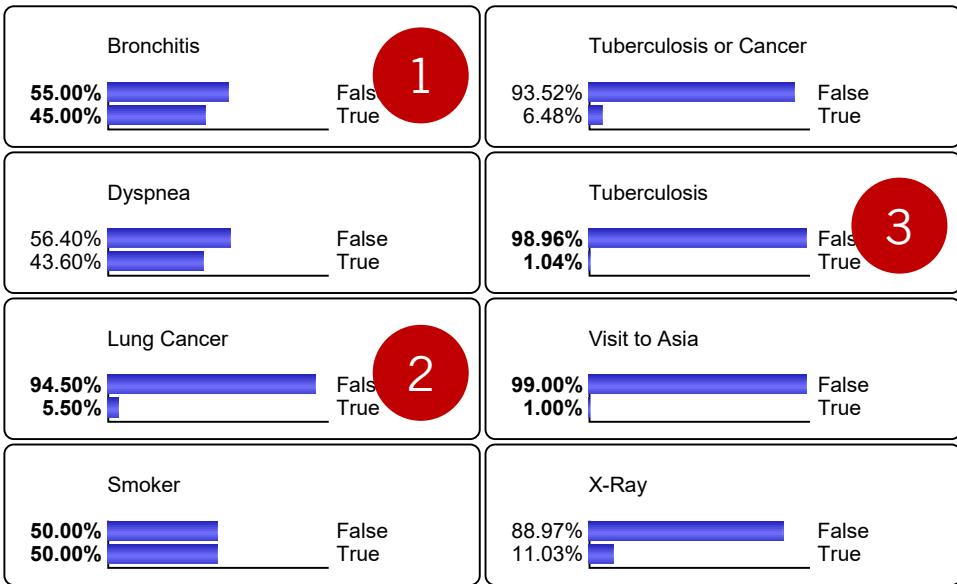
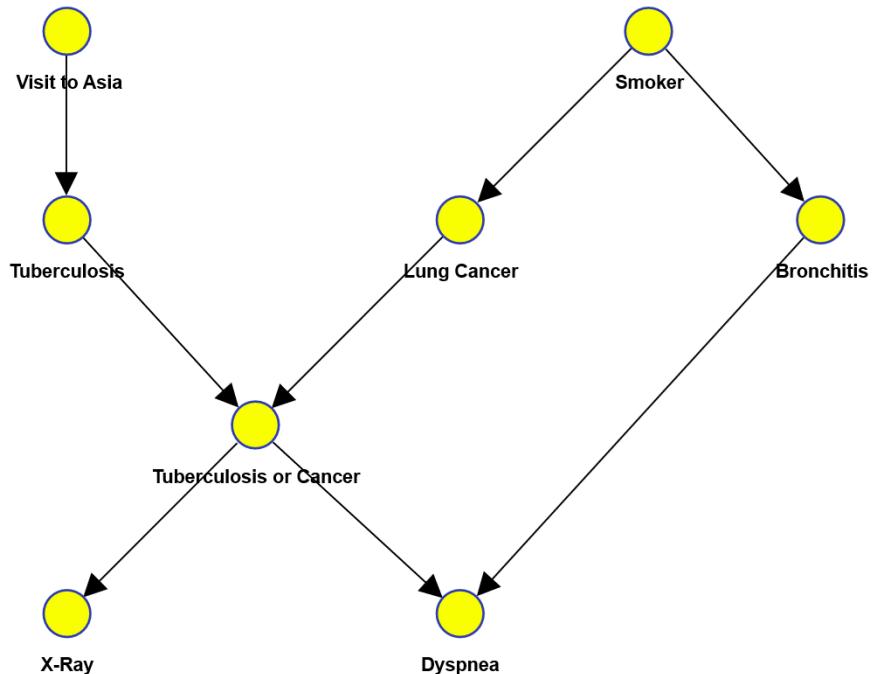




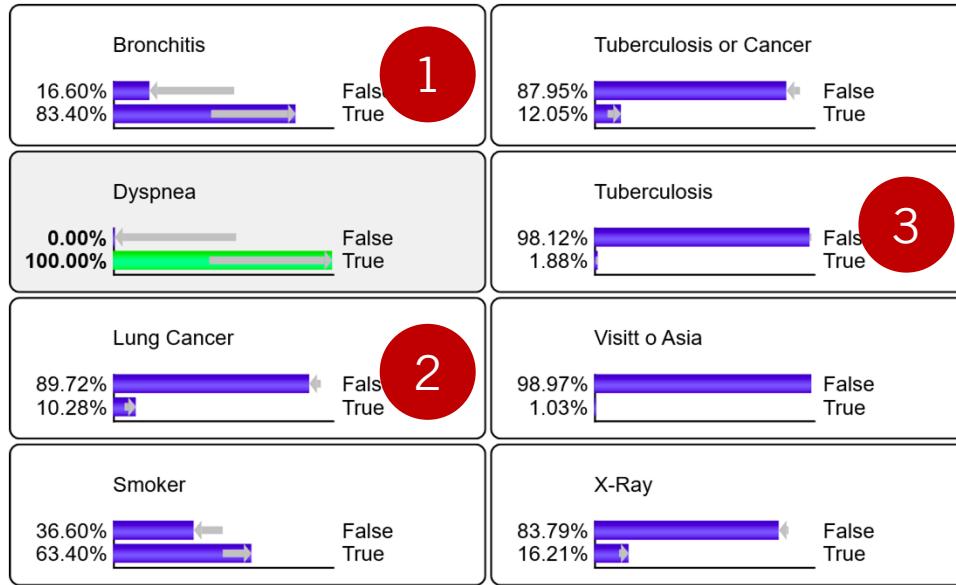
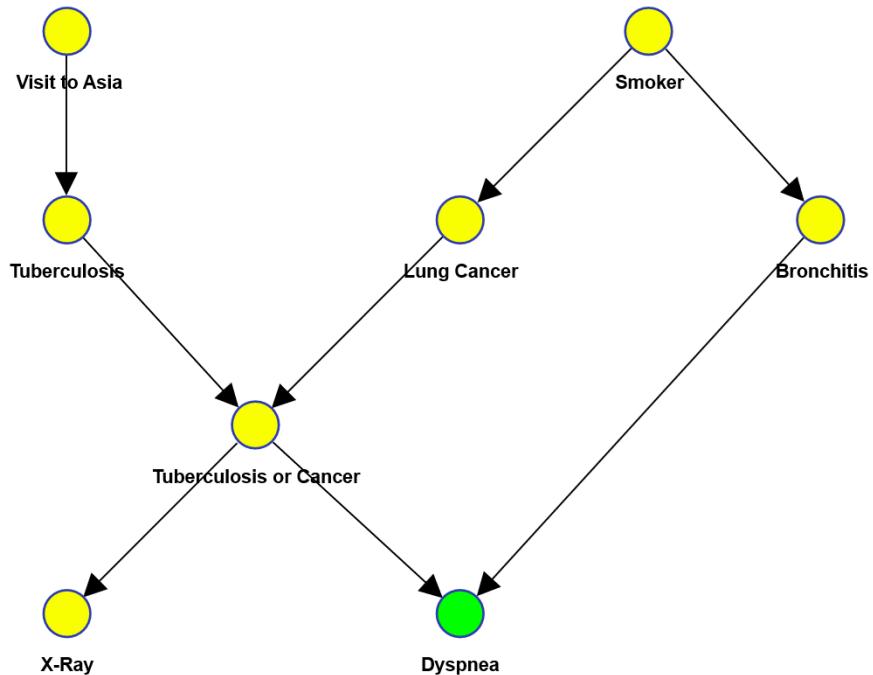
Inference with a Bayesian Network & BayesiaLab



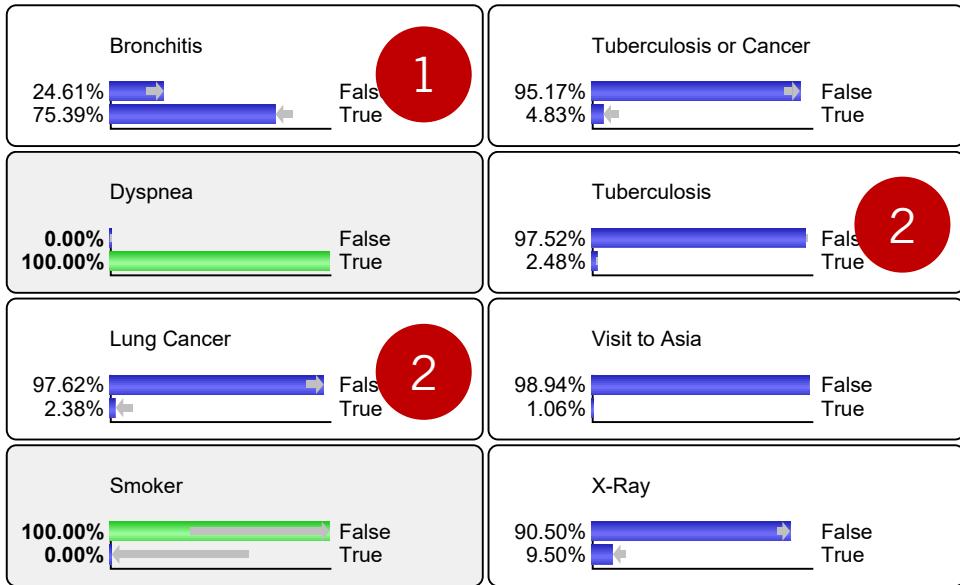
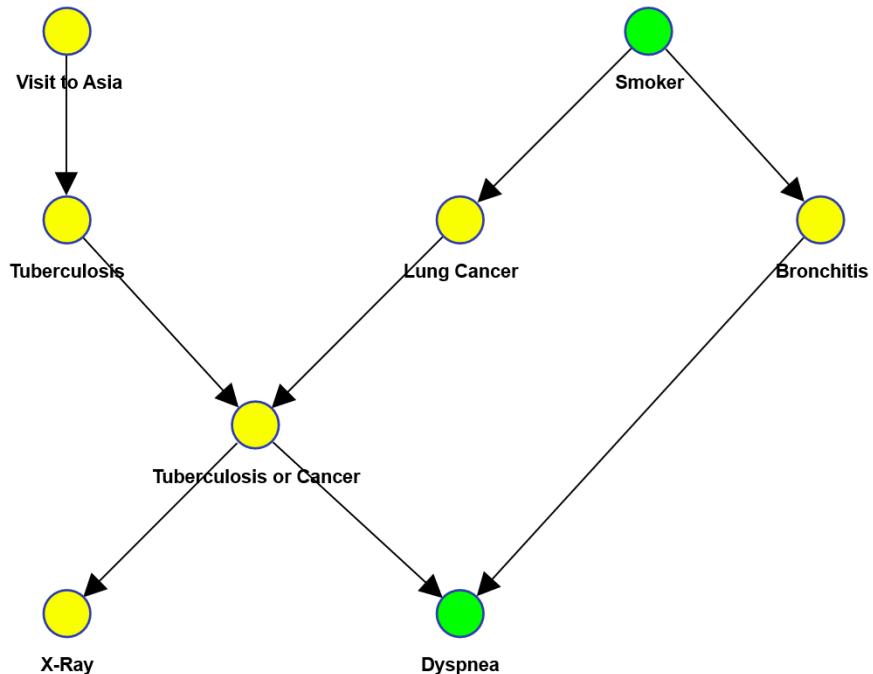
Inference with a Bayesian Network



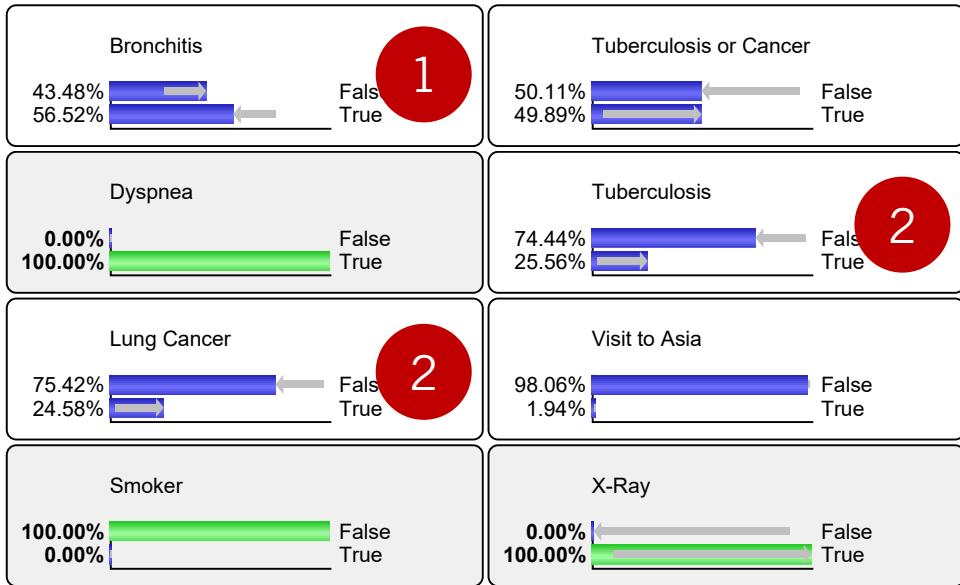
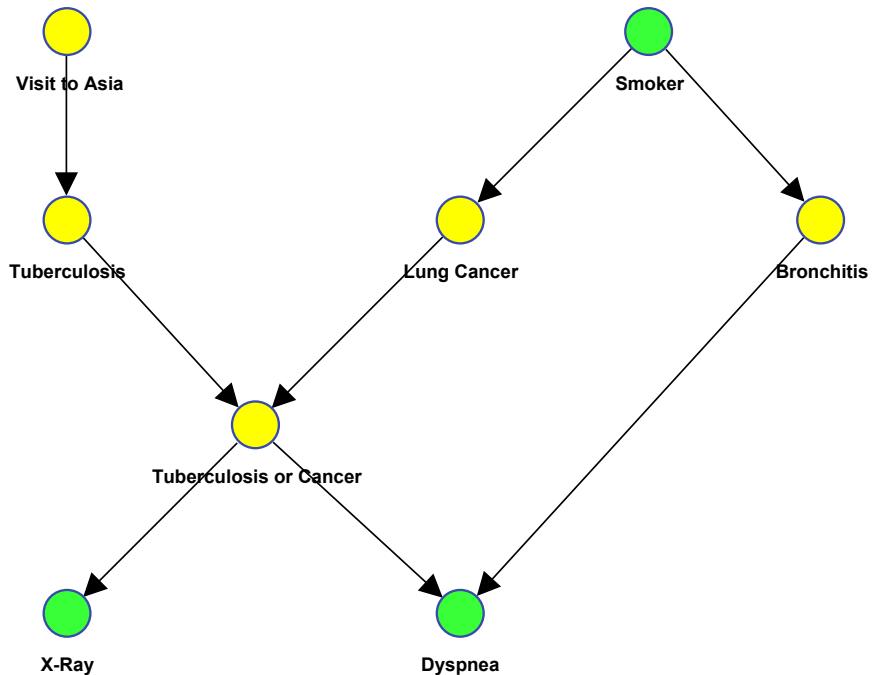
Inference with a Bayesian Network



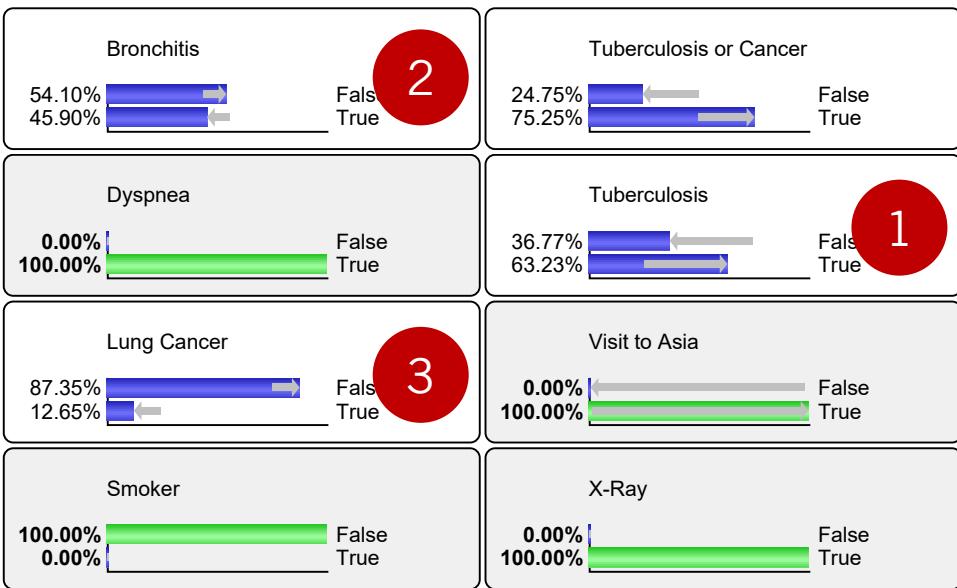
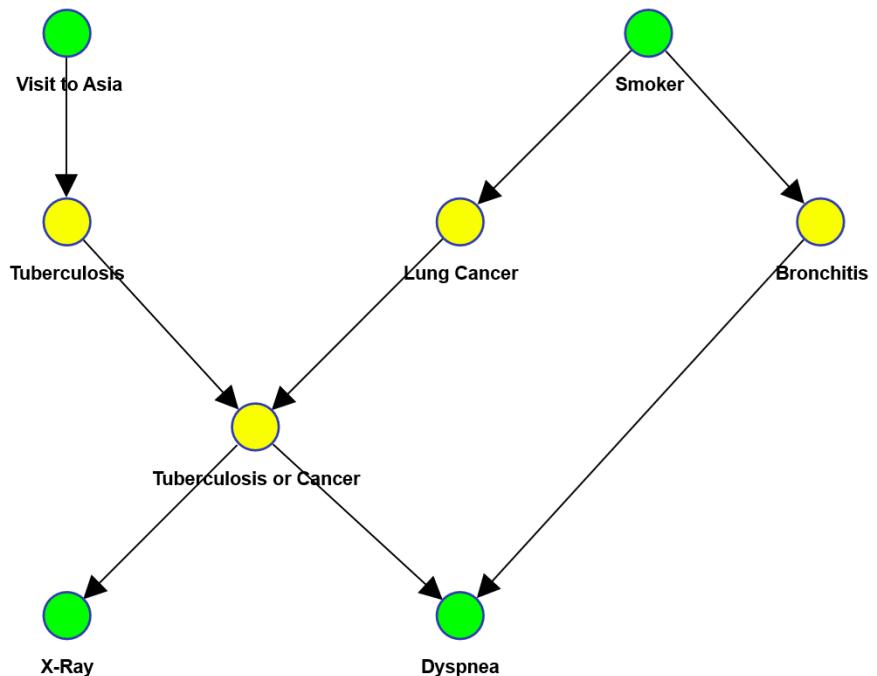
Inference with a Bayesian Network



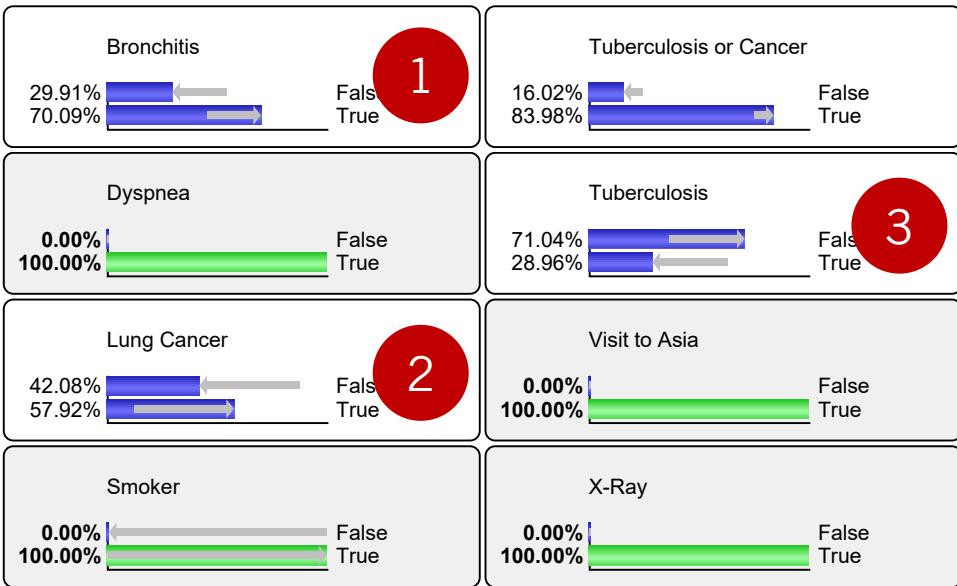
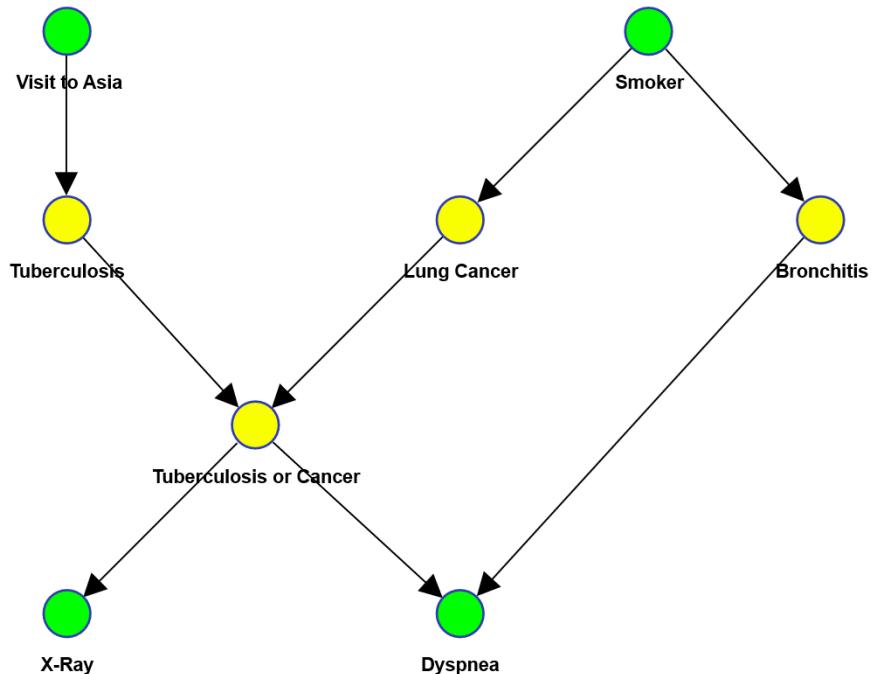
Inference with a Bayesian Network



Inference with a Bayesian Network



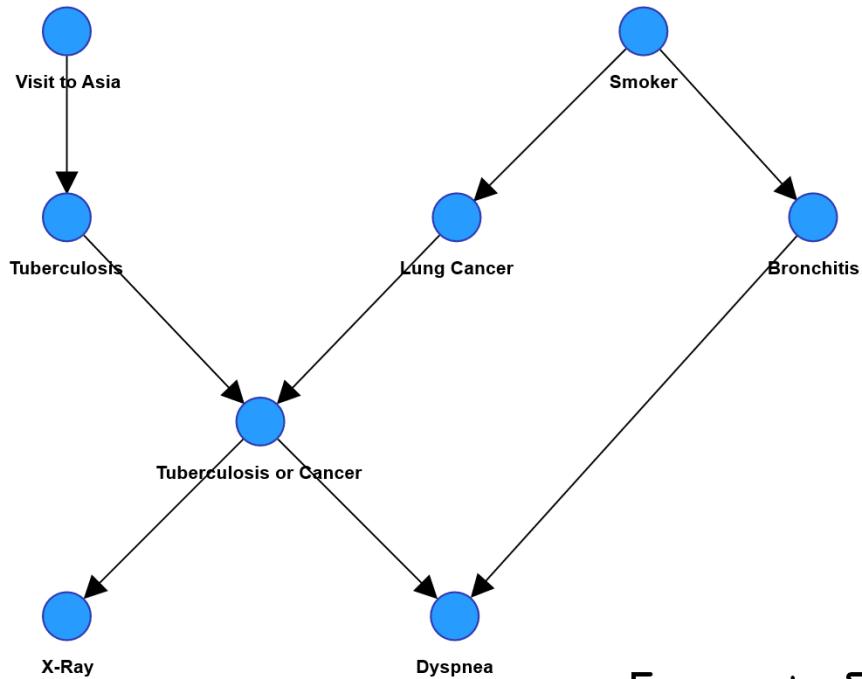
Inference with a Bayesian Network



Bayesian Network
=Inference Engine



Bayesian Networks = Artificial Intelligence



Knowledge Base

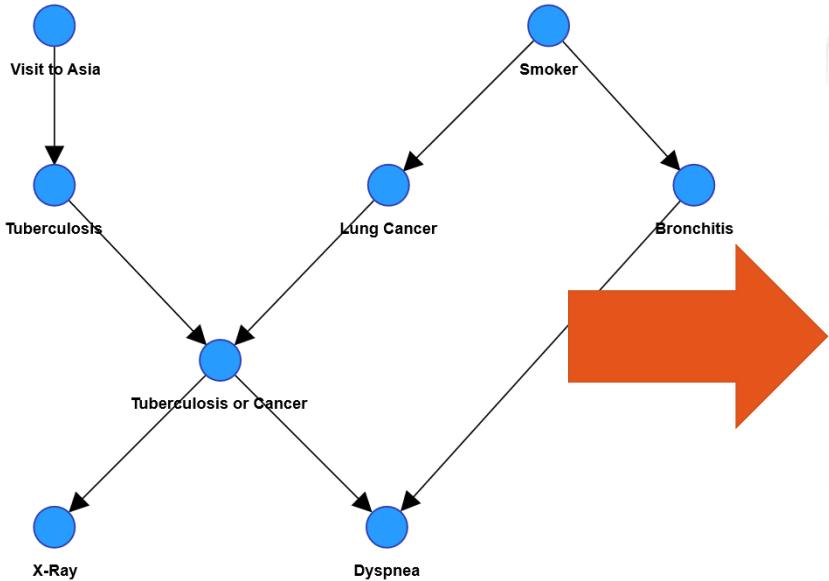
- Declarative/Propositional Knowledge
- Associational Knowledge
- Causal Knowledge

Inference Engine



Expert System - Artificial Intelligence

Bayesian Networks = Expert System



WebMDsymptomchecker

Name: Me
Gender: Male
Age: 35-44 years

1 Choose Symptom(s)

Body Map

Chest Symptoms:

- Muscle cramps or spasms (painful)
- New onset asthma
- Nighttime wheezing
- Noisy breathing
- Numbness
- Pain or discomfort
- Palpitation (chest)
- Pounding
- Prolonged breathing pauses
- Rapid breathing
- Rapid heart rate (pulse)
- Shortness of breath
- Slow heart rate (pulse)

Back View Zoom Out

Don't know where to point?
More symptoms here

Search Symptoms

2 Your Choices

- Difficulty breathing
- Cough
- Pressure or heaviness

3 Possible Conditions

- Lung cancer (non small cell)
- Lung cancer (small cell)
- Bronchitis
- Heart attack (male)
- Chronic pneumonia
- Stroke
- Embolism

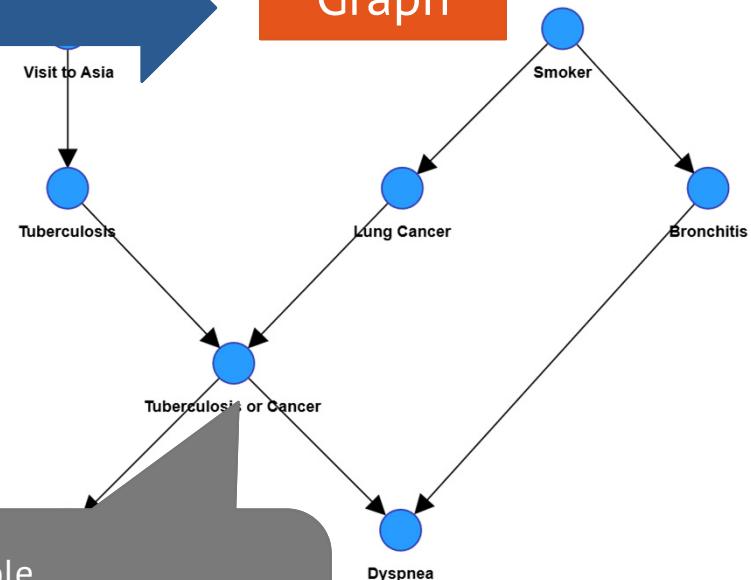
Medical Expert System

Bayesian Networks = Transparent Expert System

Formula

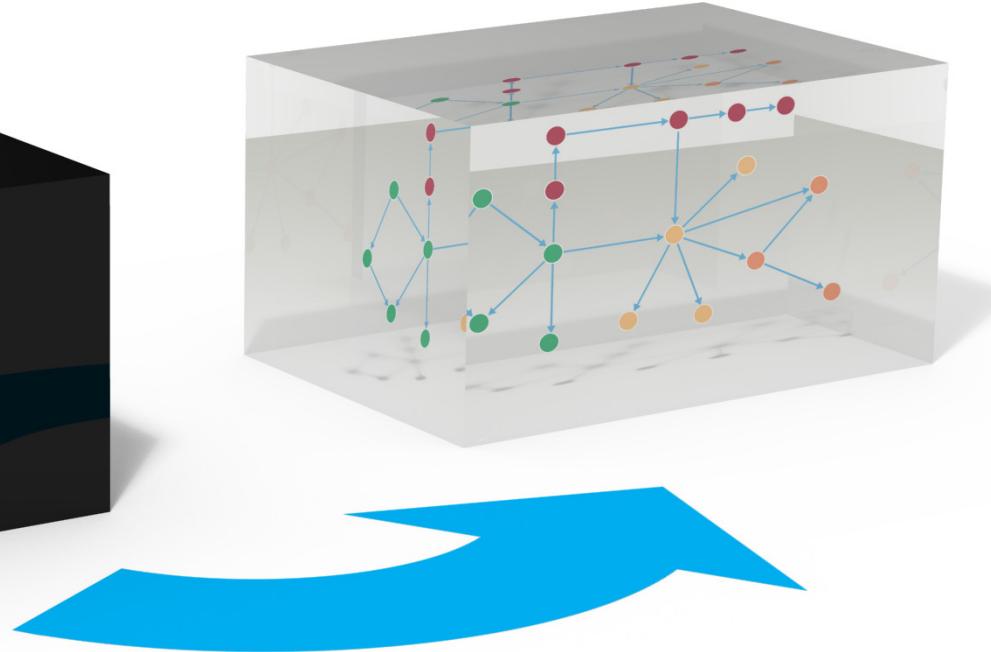
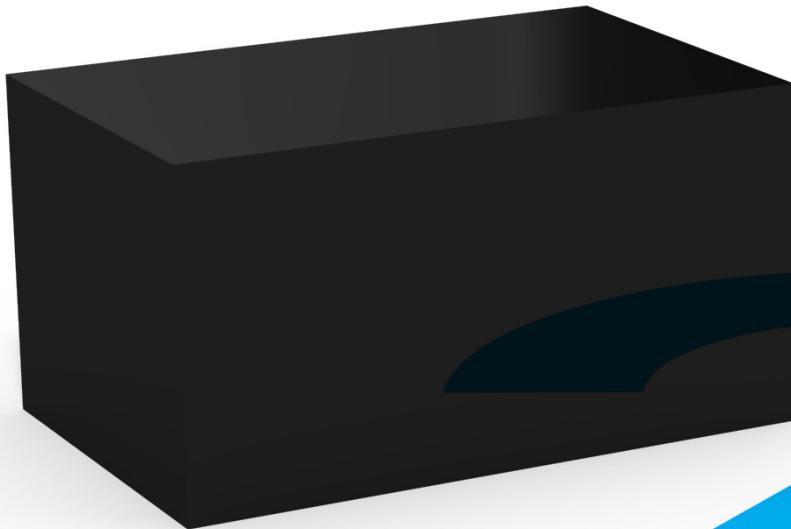
$$\frac{dI_{F3}^{MT}}{dt} = \underbrace{\tau_{F2}^{MT} I_{F2}^{MT}}_{\text{Progress from } F2 \text{ during treatment}} + \underbrace{\eta_{F3} I_{F3}^M}_{\text{Commenced treatment (F3)}} - \left(\underbrace{\mu}_{\text{Background death}} + \underbrace{\mu_D}_{\text{Drug-related death}} + \underbrace{\xi}_{\text{Exit rate}} \right) I_{F3}^{MT} \\ + \underbrace{\lambda_{HIV}}_{\text{Force of HIV infection}} + \underbrace{(1 - \gamma_{F3}^M) V_F^M}_{\text{Cease treatment (F3)}} + \underbrace{\gamma_{F3}^M V_F^M}_{\text{Viral clearance on treatment (F3)}} + \underbrace{\tau_{F3}^{MT}}_{\text{Progress to F4 during treatment}} \right) I_{F3}^{MT}$$

Graph



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

Bayesian Networks = Transparent Expert System



Rev. Thomas Bayes

Bayes' Theorem for Conditional Probabilities

H : Hypothesis

E : Evidence

$$P(H | E) = \frac{P(E | H)P(H)}{P(E)}$$

“Probability of
 H given E ”



T. Bayes.

1763

PHILOSOPHICAL
TRANSACTIONS

[370]

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

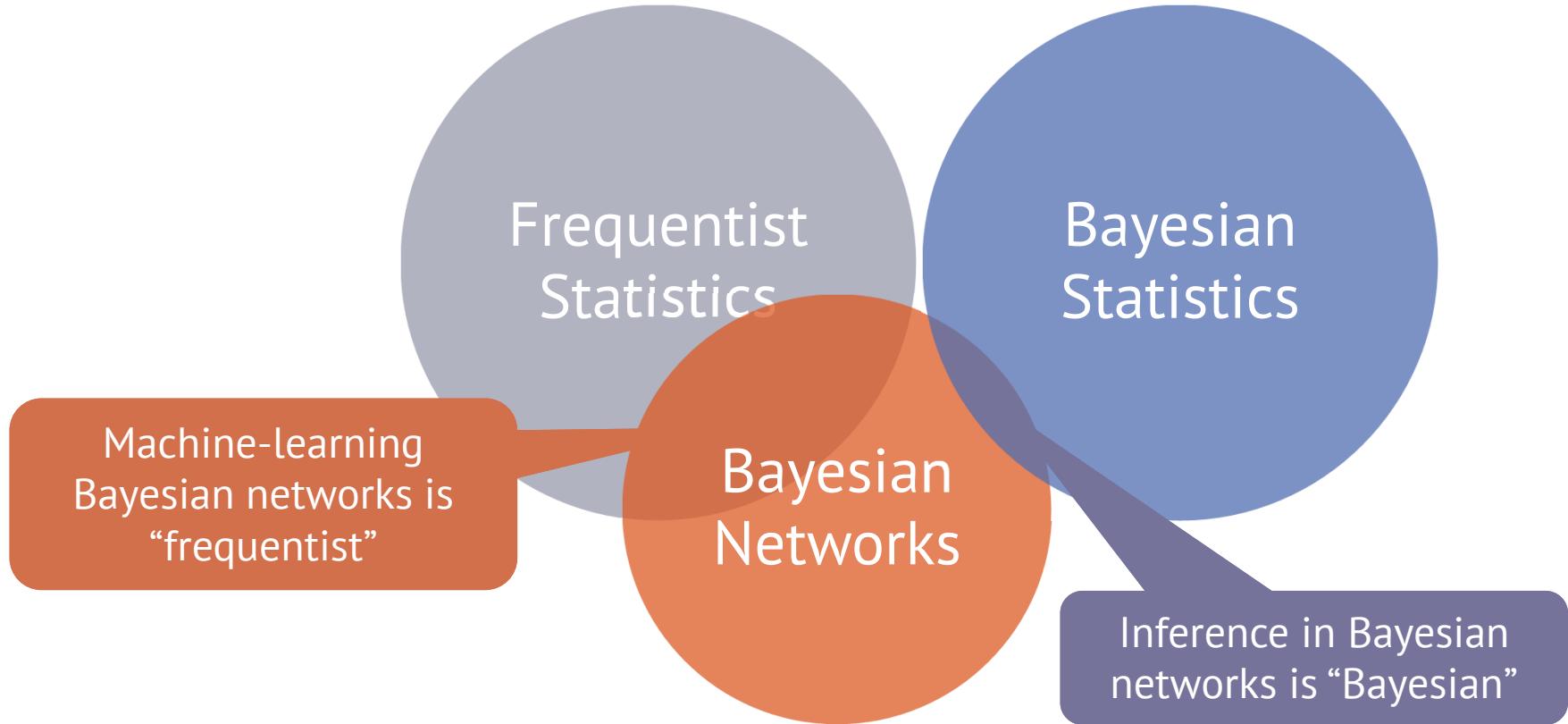
LII. *An Essay towards solving a Problem in the Doctrine of Chances. By the late Rev. Mr. Bayes, F. R. S. communicated by Mr. Price, in a Letter to John Canton, A. M. F. R. S.*

Dear Sir,

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

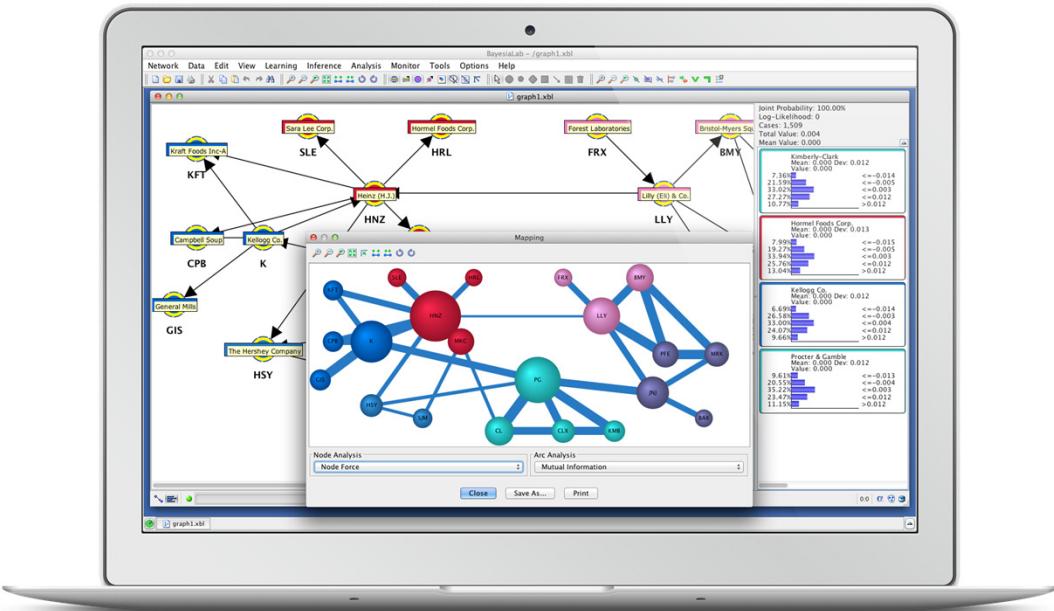
He had, you know, the honour of being a member of that illustrious Society, and was much esteemed by many in it as a very able mathematician. In an introduction which he has writ to this Essay, he says, that his design at first in thinking on the subject of it was, to find out a method by which we might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

Bayesian Statistics?



A white humanoid robot with glowing blue internal components, looking thoughtful.

Sounds great, but how can I
get a Bayesian Network?



A desktop software for:

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

with Bayesian networks.

Mathematical Formalism → Research Software







BAYESIALAB

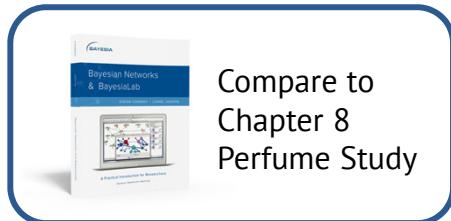
**Key Drivers Analysis & Optimization
Based on Consumer Survey Data**

Example: Auto Buyer Satisfaction Study

Strategic Vision

New Vehicle Experience Study™

- 200,000+ records
- 1,000+ variables



2009 NEW VEHICLE
EXPERIENCE STUDY™
5A

(Mailing date / Recipient ID / Vehicle description)

STRATEGIC VISION
PO Box 1270 • Maumee, OH 43537

Please have the person who drives this vehicle **the most** fill out this questionnaire.

Check ONE box in the list below to designate your selected national charity:

<input type="checkbox"/> Alzheimer's Association	<input type="checkbox"/> The Breast Cancer Fund	<input type="checkbox"/> Mothers Against Drunk Driving (MADD)
<input type="checkbox"/> American Cancer Society	<input type="checkbox"/> Epilepsy Foundation	<input type="checkbox"/> Other (specify national charity)
<input type="checkbox"/> American Heart Association	<input type="checkbox"/> March of Dimes Birth Defects Foundation	

NOTE: Please use a pencil or any dark color ball point pen to register your answers, keeping your marks INSIDE the boxes.

Correct marks: Correct numbers: **25**

About your new vehicle . . .

1. How would you rate YOUR OVERALL SATISFACTION with your new vehicle? ("X" one box)

<input type="checkbox"/> Completely satisfied	<input type="checkbox"/> Very satisfied	<input type="checkbox"/> Fairly well satisfied	<input type="checkbox"/> Somewhat dissatisfied	<input type="checkbox"/> Very dissatisfied
---	---	--	--	--

2. Overall, how would you judge the initial quality of your new vehicle?

<input type="checkbox"/> Excellent	<input type="checkbox"/> Very good	<input type="checkbox"/> Good	<input type="checkbox"/> Fair	<input type="checkbox"/> Poor
------------------------------------	------------------------------------	-------------------------------	-------------------------------	-------------------------------

3. Would you recommend your new vehicle to a friend or relative? Definitely Probably No, I would not

4. How do you feel about I feel a definite emotional connection to my new vehicle I feel some emotional connection to my new vehicle I feel no emotional connection to my new vehicle

5. Overall, how would you judge your experience with your new vehicle? ("X" one box)

<input type="checkbox"/> Delightful	<input type="checkbox"/> Excellent	<input type="checkbox"/> Satisfactory	<input type="checkbox"/> Unsatisfactory	<input type="checkbox"/> A failure
-------------------------------------	------------------------------------	---------------------------------------	---	------------------------------------

6. Everything considered, how likely are you in the future to purchase or lease another new vehicle made by the same manufacturer? Definitely will Probably will Don't know Probably won't Definitely will not

7. How would you describe the percentage of your involvement in the decision to purchase or lease your new vehicle? More than half About half Less than half

8. What type of transmission does this vehicle have? Automatic Manual

9. What series (trim level) is this vehicle (examples: Base, GT, GS, Limited, LS, LT, SE, XL, etc.)?

10. Which of the following features do you have on this new vehicle? ("X" as many as apply)

<input type="checkbox"/> Anti-lock brakes	<input type="checkbox"/> Heated/cooled seats	<input type="checkbox"/> Multiple-disc CD player	<input type="checkbox"/> Power driver seat	<input type="checkbox"/> Reverse object sensing
<input type="checkbox"/> Automatic temperature control	<input type="checkbox"/> High-wattage premium audio	<input type="checkbox"/> Navigation system	<input type="checkbox"/> Power moonroof	<input type="checkbox"/> Satellite radio
<input type="checkbox"/> Collision avoidance cruise control	<input type="checkbox"/> Keyless access/start	<input type="checkbox"/> Optional air bags (side impact, side curtains, etc.)	<input type="checkbox"/> Power passenger seat	<input type="checkbox"/> Separate passenger/driver climate control
<input type="checkbox"/> DVD entertainment system	<input type="checkbox"/> Leather seats	<input type="checkbox"/> Power adjustable pedals	<input type="checkbox"/> Premium wheels/tires	<input type="checkbox"/> Stability control
	<input type="checkbox"/> MP3/other digital audio	<input type="checkbox"/> Power adjustable pedals	<input type="checkbox"/> Rear seat - split folding	<input type="checkbox"/> Traction control
			<input type="checkbox"/> Remote start	

* IF your new vehicle is an SUV, a MINIVAN, or a FULL SIZE VAN:

10 a. Which of the following features do you have on your new SUV/van? ("X" as many as apply)

<input type="checkbox"/> Air suspension	<input type="checkbox"/> Power liftgate	<input type="checkbox"/> Power sliding doors	<input type="checkbox"/> Running boards	<input type="checkbox"/> Third row seating	<input type="checkbox"/> Trailer hitch receiver
---	---	--	---	--	---

10 b. Is your van a 'conversion' van (e.g., Bivouac, Starcraft, etc.)? Yes No

* IF your new vehicle is a PICKUP TRUCK:

10 c. Which of the following features do you have on your new pickup truck? ("X" as many as apply)

<input type="checkbox"/> Long bed (over 7 feet)	<input type="checkbox"/> Bed extender	<input type="checkbox"/> Long wheelbase	<input type="checkbox"/> Limited slip rear axle
<input type="checkbox"/> Bedliner	<input type="checkbox"/> Cab steps	<input type="checkbox"/> 4-wheel anti-lock brakes	<input type="checkbox"/> Trailer hitch receiver

11. What feature(s) **NOT** on this vehicle would you like to have on your **next** new vehicle? (e.g. heated seats, run-flat tires, etc.)

Feature 1 _____ Feature 2 _____

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PLEASE OPEN TO PAGE 2 ➔

Thanks!



Strategic Vision Inc.

- Strategic Vision is a research-based consultancy with more than 35 years of experience in understanding the consumers' and constituents' decision-making systems for a variety of Fortune 100 clients, 10 Downing Street, Coca-Cola, American Airlines, Procter & Gamble, the White House and including most automotive manufacturers and many advertising agencies. The company specializes in identifying consumers' complete, motivational hierarchies, including the product attributes, personal benefits, value/emotions and images that drive perceptions and behaviors. Strategic Vision has at its core a large-scale syndicated automotive experience and "Pulse of the Customer" (POC) study that collects more than 350,000 responses annually, using over 1,500 comprehensive data points. Since its foundation in 1972 and incorporation in 1989, Strategic Vision—led by company founders Darrel Edwards, Ph.D., J. Susan Johnson, Sharon Shedroff, with Alexander Edwards—has used in-depth Discovery Interviews and Value Centered Survey instruments that provide comprehensive, integrated and actionable outcomes, linking behavior to attributes to consequences to values and emotions to images.

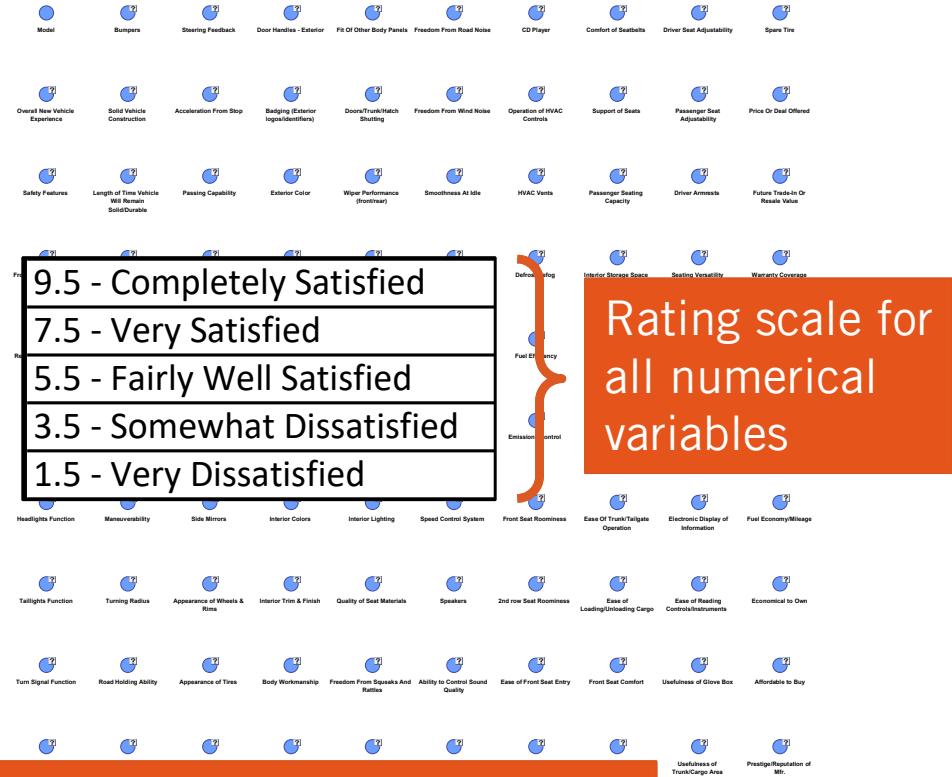
Subset Under Study: MY2009 Midsize Sedans



Chrysler Sebring
Dodge Avenger
Ford Fusion
Chevrolet Malibu
Kia Optima
Honda Accord
Nissan Altima
Toyota Camry
Mazda6
Hyundai Sonata

Subset from New Vehicle Experience Survey

- 98 questions about satisfaction of features and vehicle attributes.
- 1 question about overall satisfaction (“Overall New Vehicle Experience NVES”).
- 1 categorical variable representing the vehicle model.
- 4,214 survey responses.



Note: This dataset is not publicly available and cannot be downloaded. For a training dataset, please see the Perfume Study in Chapter 8



**Key Drivers Analysis & Optimization
Based on Consumer Survey**

Oxymoron



Key Drivers Analysis & Optimization Based on Consumer Opinion Survey Data

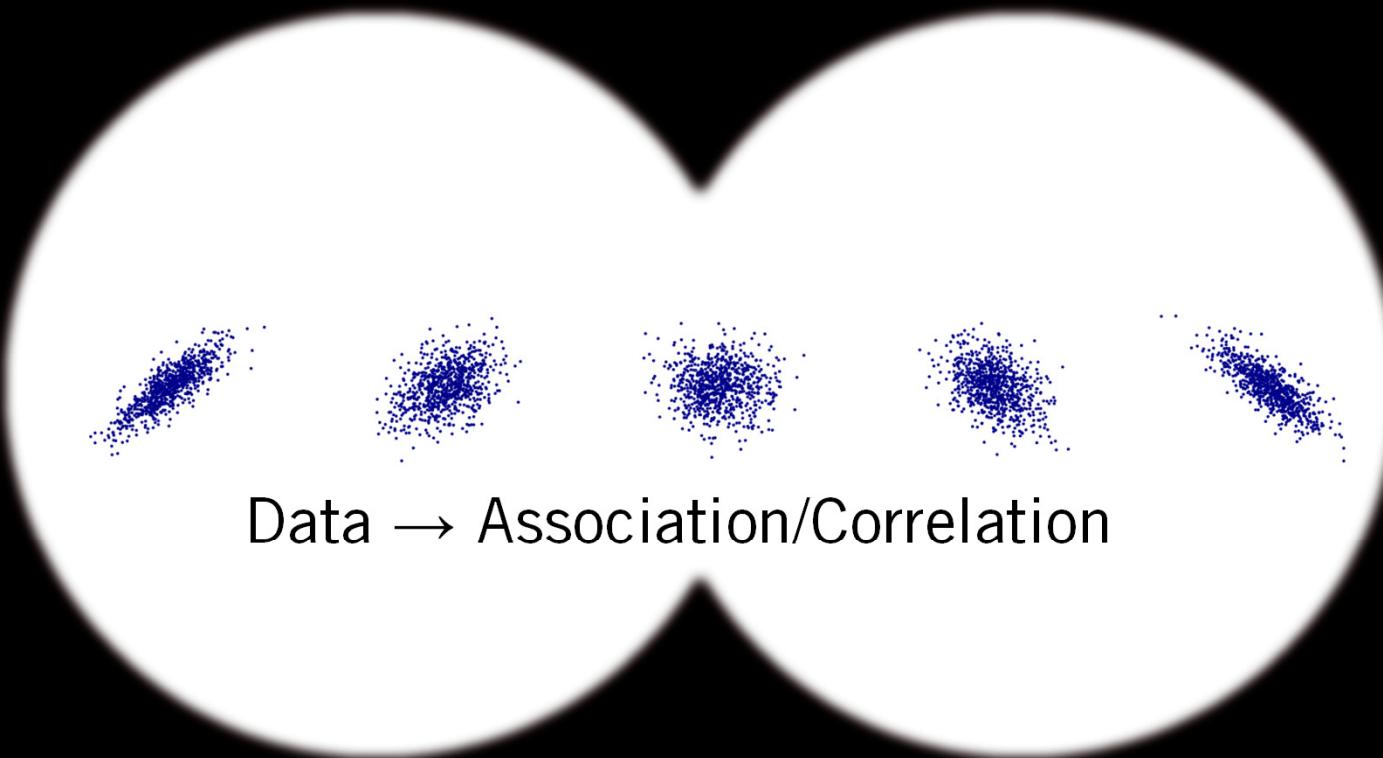
“Driver”

- A fundamentally causal concept.
- Implies knowledge of the causal direction.



“Opinion Survey Data”

- Non-experimental data, i.e. observational data.

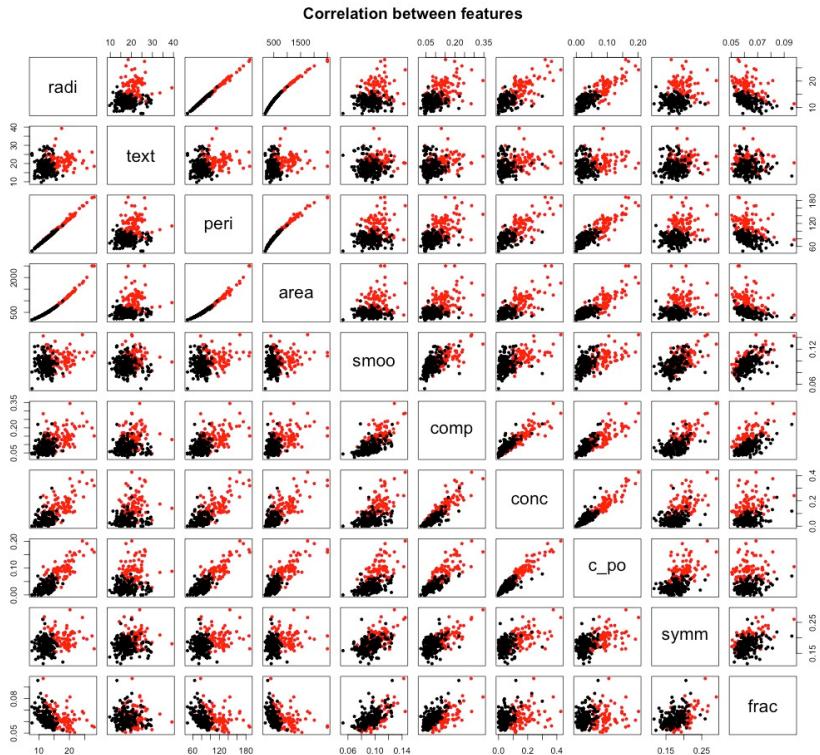


Data → Association/Correlation

Key Drivers Analysis

Why?

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



Correlation does not
equal causation!



Key Drivers Analysis & Optimization Based on Consumer Opinion Survey Data

$$y=f(x)$$

ambiguous



Observational Inference (Prediction)

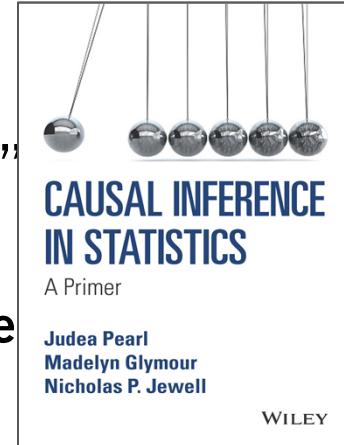
$$y=f(\text{see}(x))$$

“given that I see”

Causal Inference (Intervention)

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

“given that I do”



21



APRIL

900

EMILY

100

RYAN

0

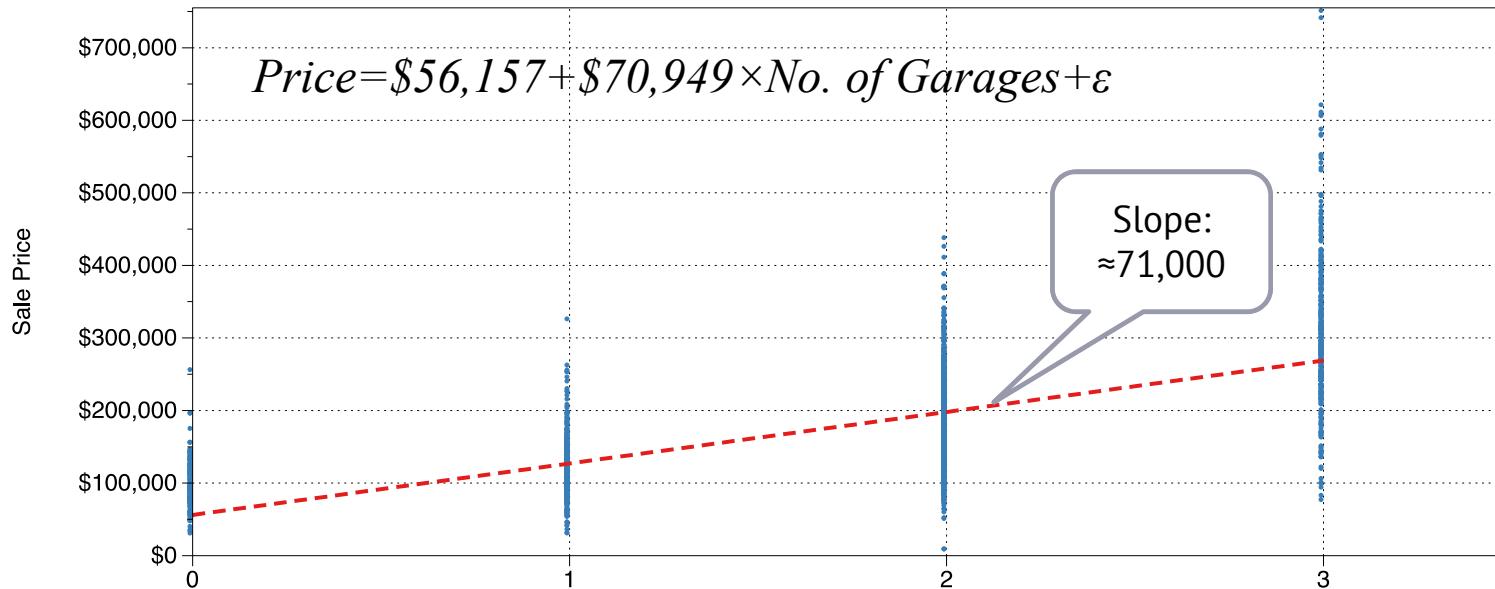
CATCH



Observational vs. Causal Inference

See Chapter 5

Ames Dataset: Sale Prices of Single-Family Homes



Observational Data → Observational Inference/Prediction

Observational vs. Causal Inference

Clever Homeowner:

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



Observational vs. Causal Inference



Observational vs. Causal Inference

Intervention

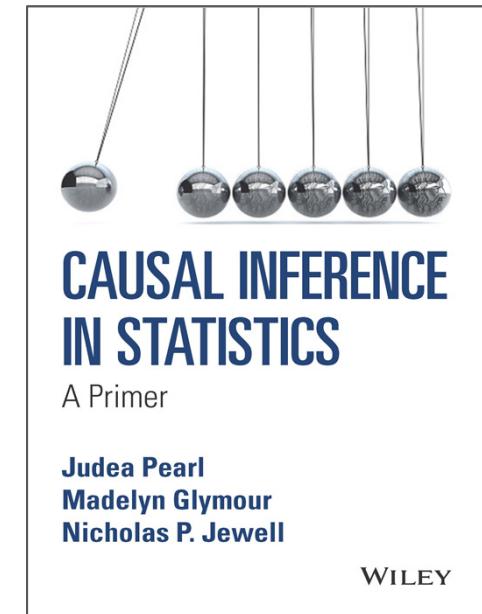


Observational vs. Causal Inference

Observational Inference (Conditioning)

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

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

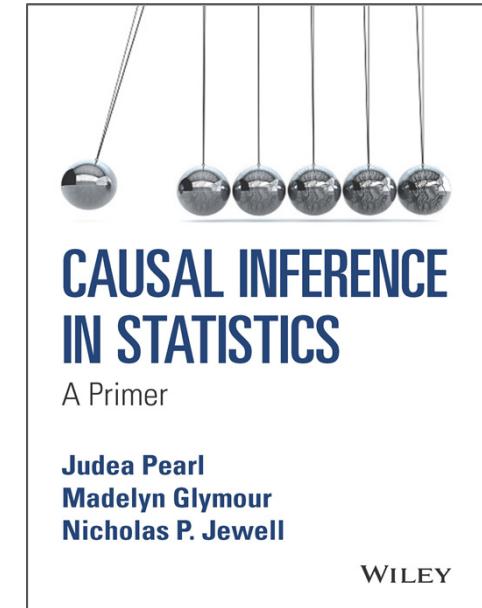


Observational vs. Causal Inference

Causal Inference (Intervention)

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

$$y=f(\textcolor{red}{do}(x))$$



Observational vs. Causal Inference

Statistical Model → Observational Inference/Prediction

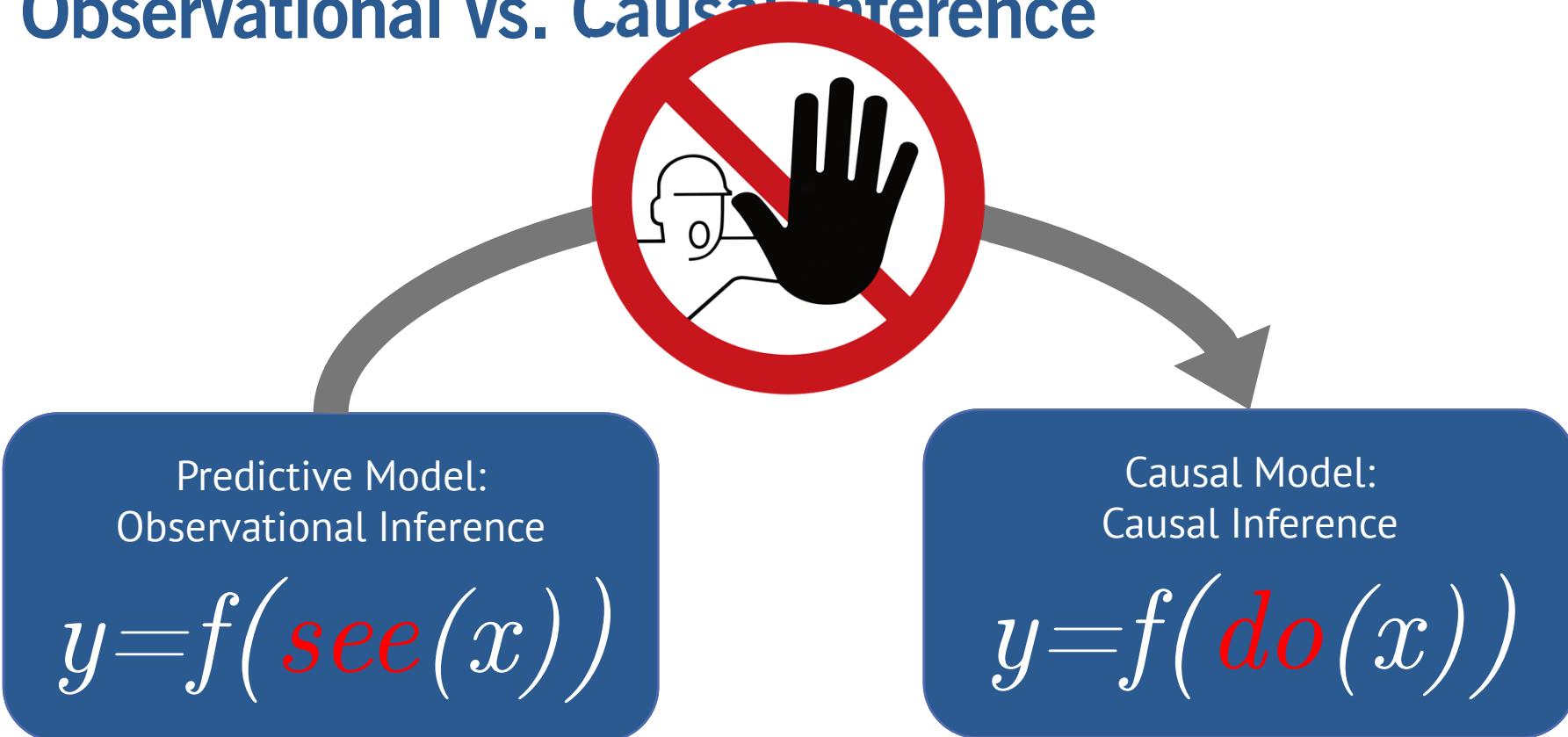
- $Price = \$56,157 + \$70,949 \times No. \text{ of Garages} + \varepsilon$

Regression

Causal Model → Causal Inference/Intervention

???

Observational vs. Causal Inference



Key Drivers Analysis & Optimization Based on Consumer Opinion Survey Data

“Driver”

- A fundamentally causal concept.
- Implies knowledge of the causal direction.



“Opinion Survey Data”

- Non-experimental data, i.e. observational data.

Key Drivers Analysis & Optimization

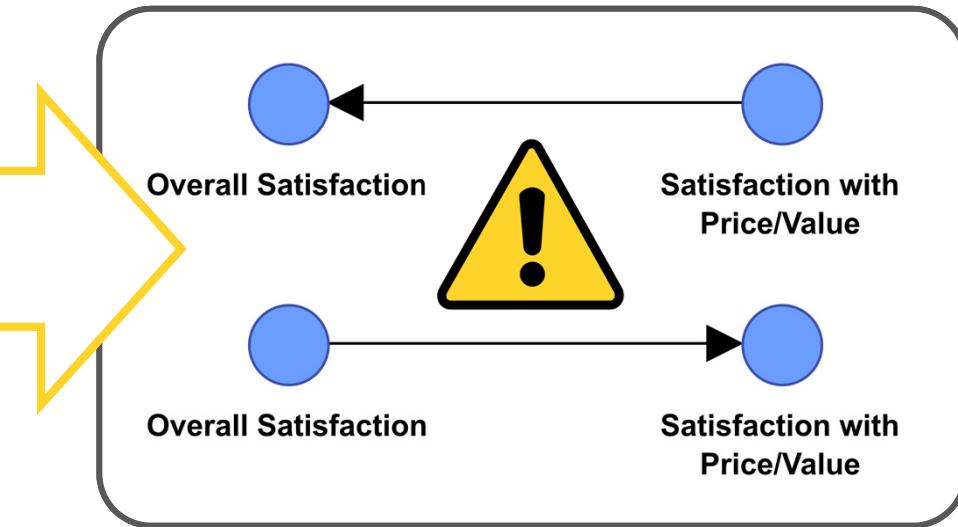
Based on Consumer Opinion Survey Data

“Driver”

- A fundamentally causal concept.
- Implies knowledge of the causal direction.

“Opinion Survey Data”

- Non-experimental data, i.e. observational data.



Key Drivers Analysis & Optimization

Based on Consumer Opinion Survey Data

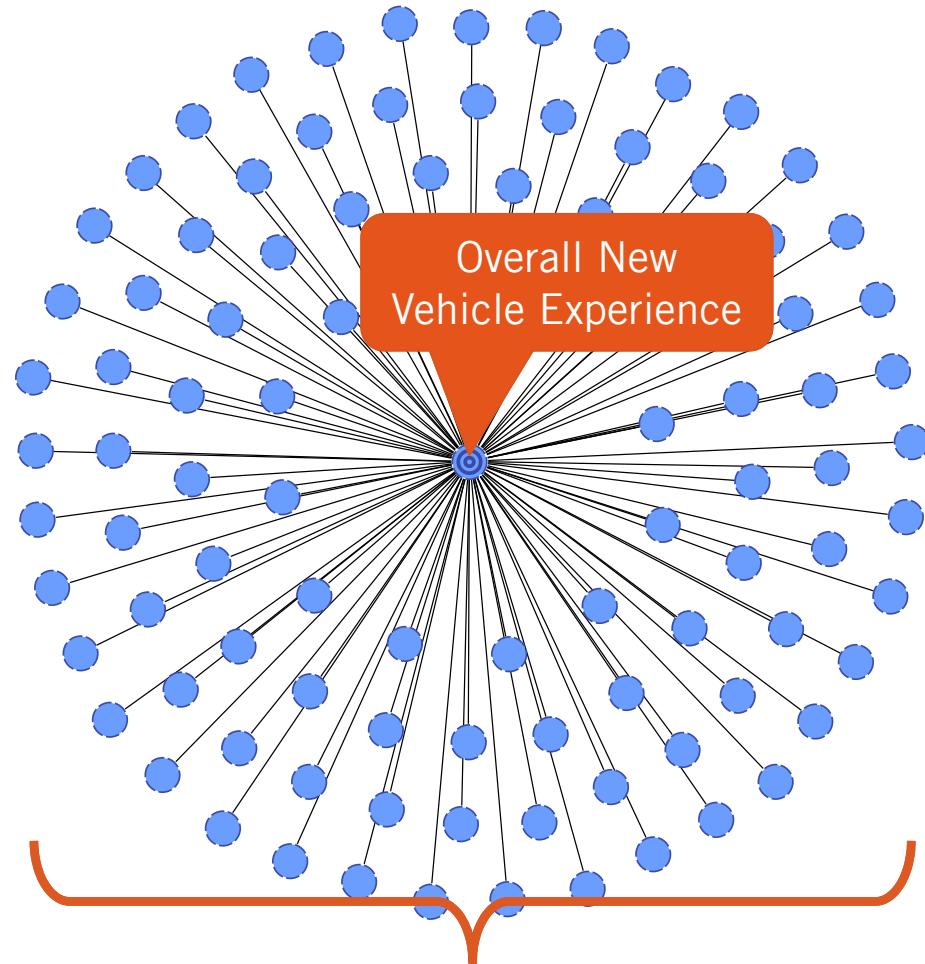


Can we make some
causal assumptions?

Causal Assumptions?

Can we make a causal assumption?

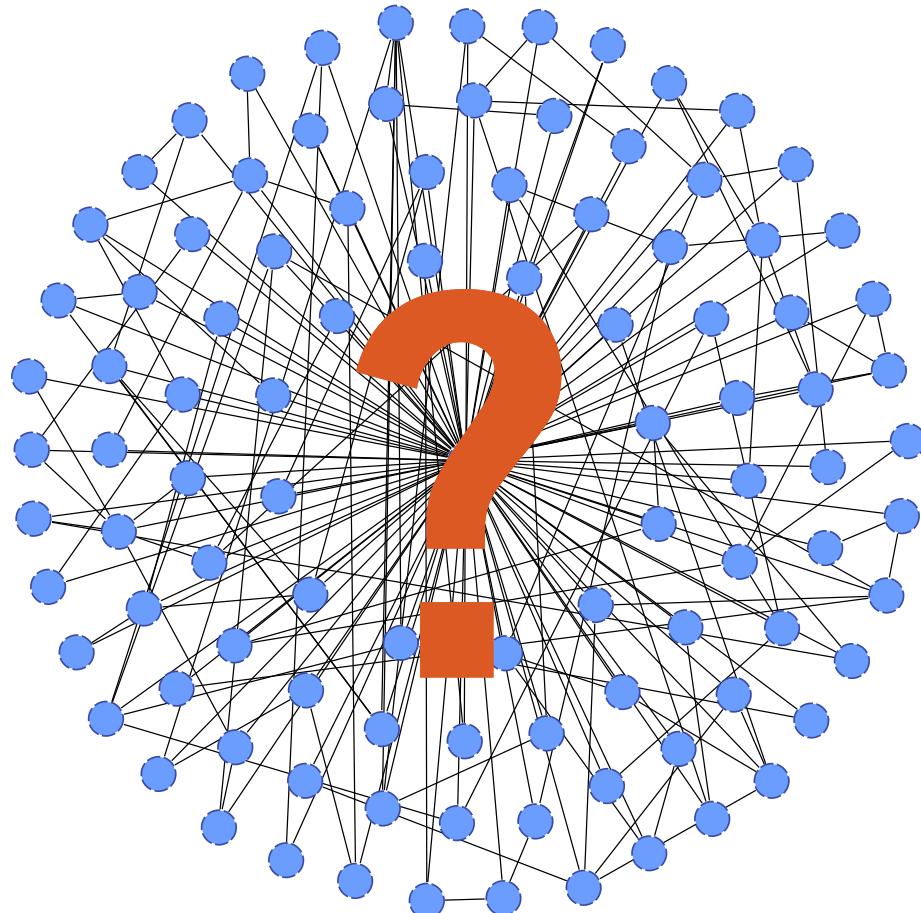
- E.g., all individual ratings (“drivers”) are a cause of the overall rating?
- Yes, but what would be the causal relationships between the drivers, as they are probably not independent?



Causal Assumptions?

Can we make a causal assumption?

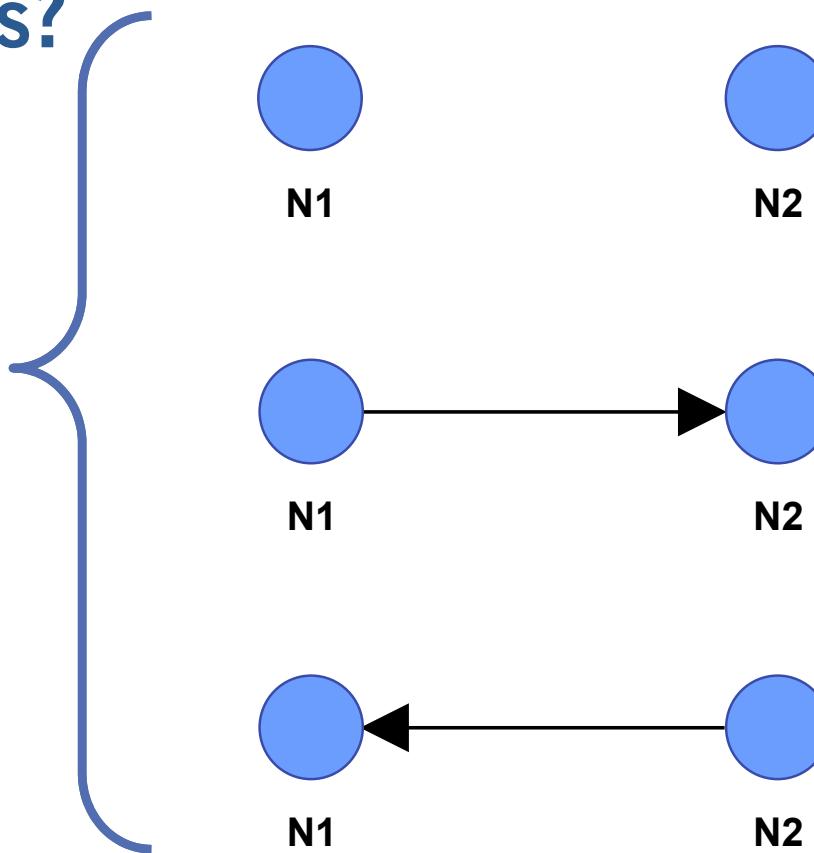
- E.g., all individual ratings (“drivers”) are a cause of the overall rating?
- Yes, but what would be the causal relationships between the drivers, as they are probably not independent?



Causal Assumptions?

**Number of Possible
Causal Structures**

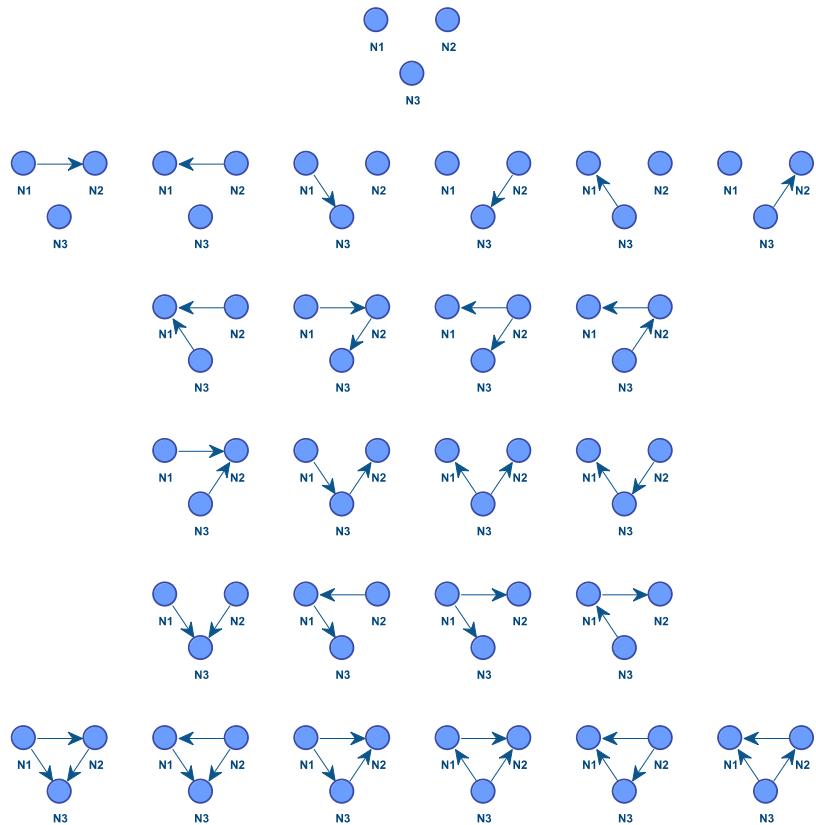
- 2 Nodes: 3



Causal Assumptions?

Number of Possible Causal Structures

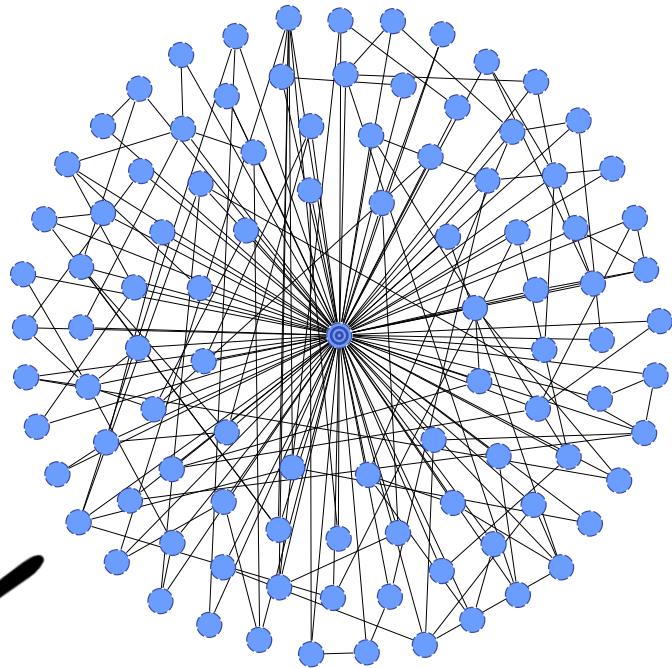
- 2 Nodes: 3
- 3 Nodes: 25



Causal Assumptions?

Number of Possible Causal Structures

- 2 Nodes: 3
- 3 Nodes: 25
- 4 Nodes: 543
- 5 Nodes: 29,281
- 6 Nodes: 3.8×10^6
- 7 Nodes: 1.1×10^9
- 8 Nodes: 7.8×10^{11}
- 9 Nodes: 1.2×10^{15}
- 10 Nodes: 4.2×10^{18}
- 11 Nodes: 3.2×10^{22}
- \vdots
- 100 Nodes: 1.1×10^{1631}



Good luck!

Causal Assumptions?

Observational Inference Only!

- We need to give up on formal causal inference because...
 - We cannot possibly know the true causal structure.
 - And, we can't "cause" anyway, i.e. we cannot directly manipulate consumer opinion.



Key Drivers Analysis & Optimization Based on Consumer Opinion Survey Data

“Driver”

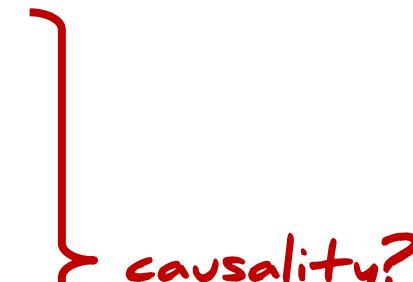
- A fundamentally causal concept.
- Implies knowledge of the causal direction.

“Opinion Survey Data”

- Non-experimental data, i.e. observational data.

“Optimization”

- Measured variables cannot be directly manipulated.
- Multitude of subjects.
- No natural constraints.



causality?



optimization?

Key Drivers Analysis & Optimization Based on Consumer Opinion Survey Data

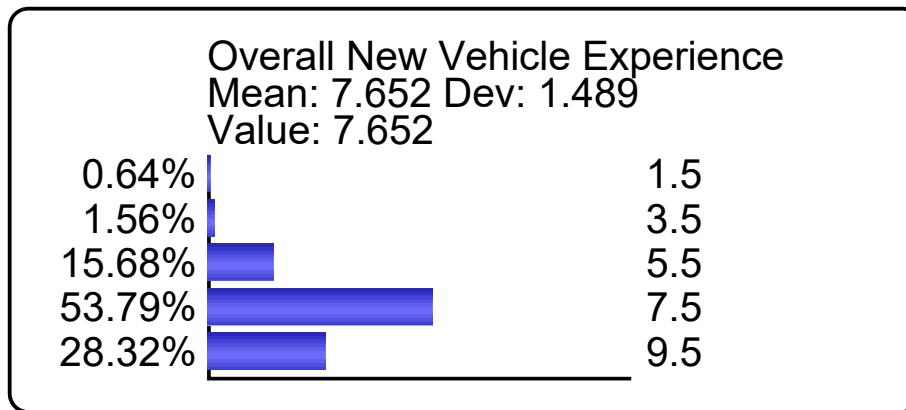


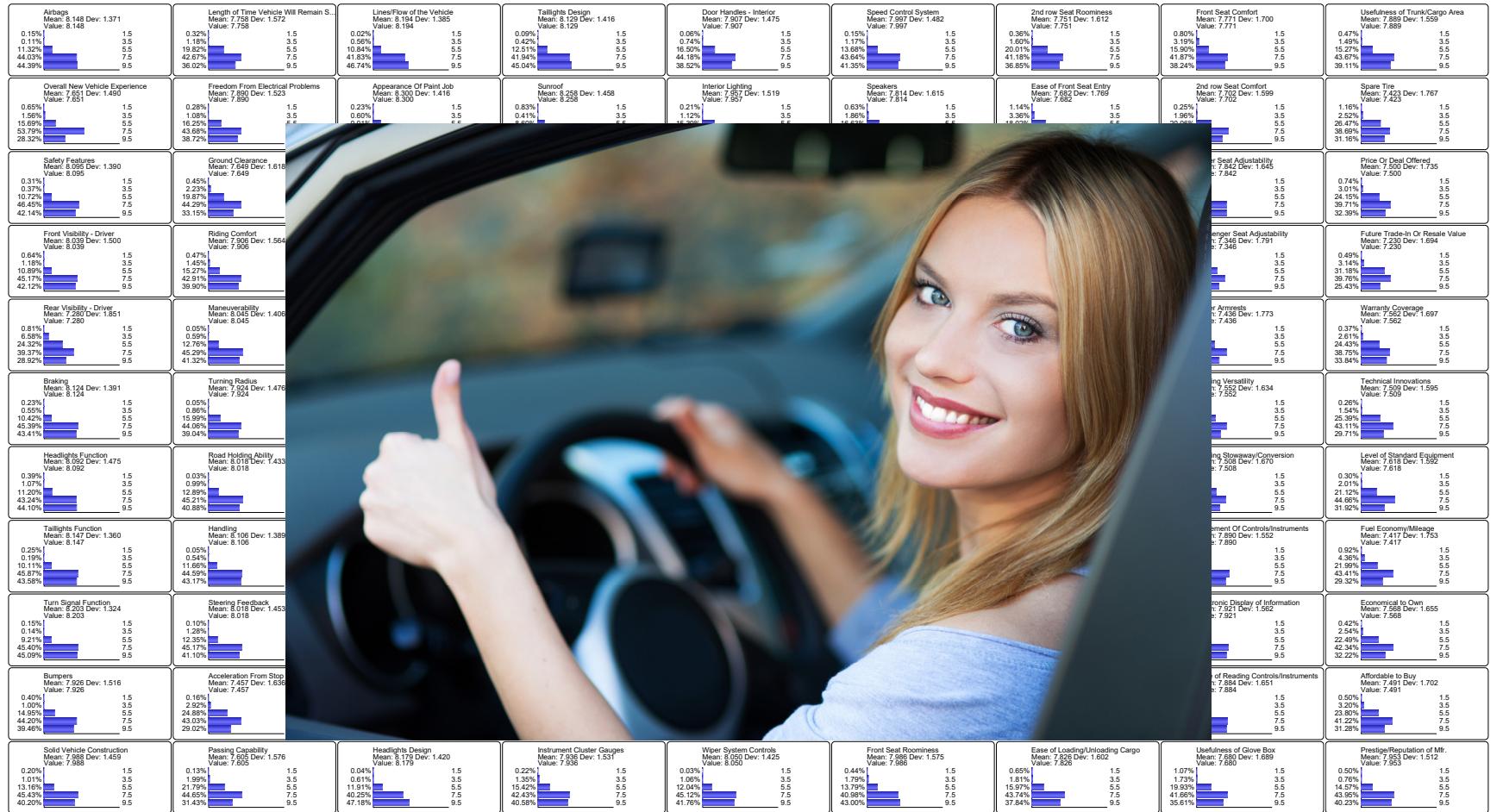
Statistical Problems

Statistical Challenges in Key Drivers Analysis

Estimation Challenges

- Small Variance
 - Only ~2% of all ratings are below “Fairly Well Satisfied”





Statistical Challenges in Key Drivers Analysis

Estimation Challenges (cont'd)

- High-dimensional Multi-Collinearity

Statistical Challenges in Key Drivers Analysis

Estimation Challenges (cont'd)

- Multi-Collinearity
- Slopes of curves are nearly identical.



Key Drivers Analysis

How about a regression?



Key Drivers Analysis

How about...

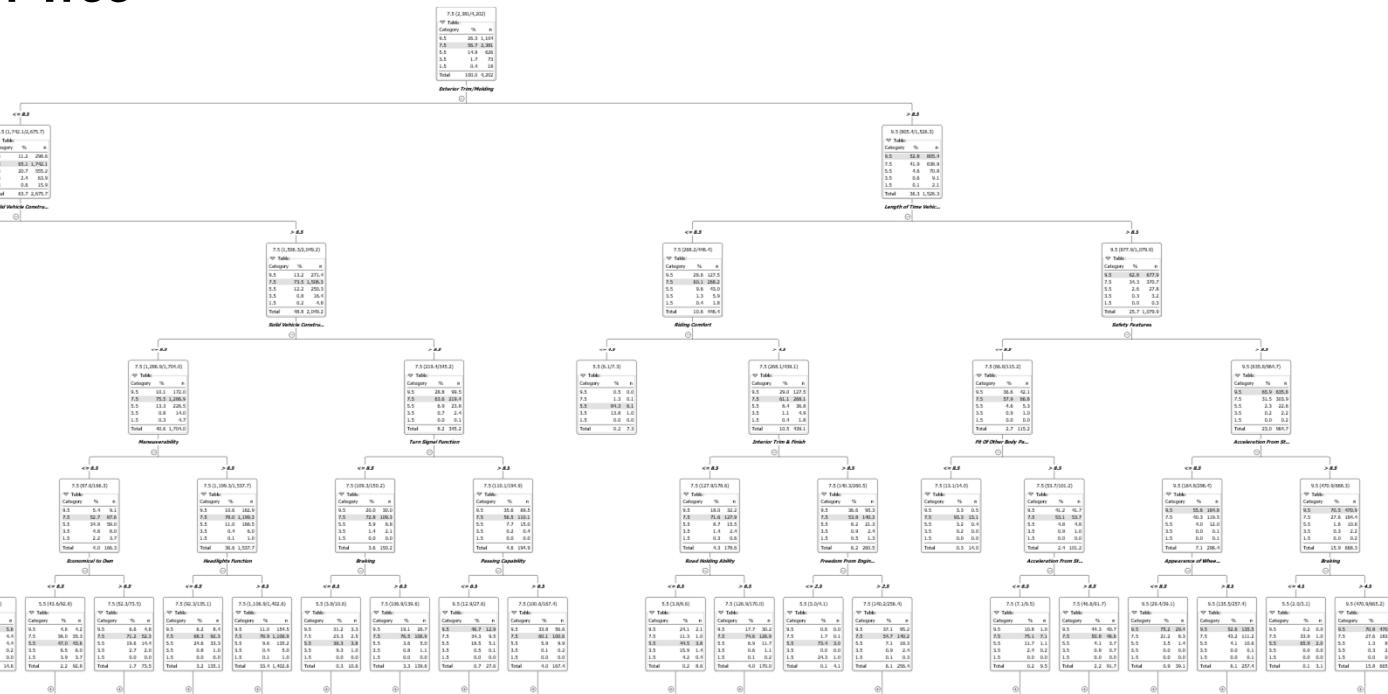
- Neural Networks
- Decision Trees
- Random Forests
- Ensemble Models
- Etc.



Great predictive performance,
but difficult interpretability

Key Drivers Analysis

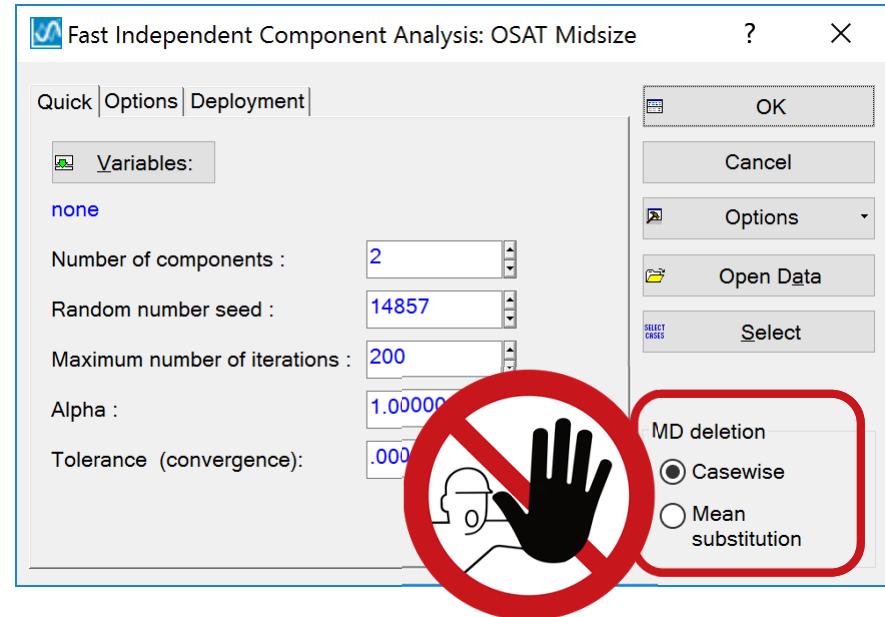
Example: Decision Tree



Statistical Challenges in Key Drivers Analysis

Estimation Challenges (cont'd)

- Missing Values
 - 5% of all data points are missing (21,110).
 - 77% of survey response contain at least one missing value.



Summary of Challenges

Conceptual Challenges

- “Driver”
 - A fundamentally causal concept.
- “Opinion Survey Data”
 - Non-experimental data.
- “Optimization”

Derive Constraints

Multitude of subjects.

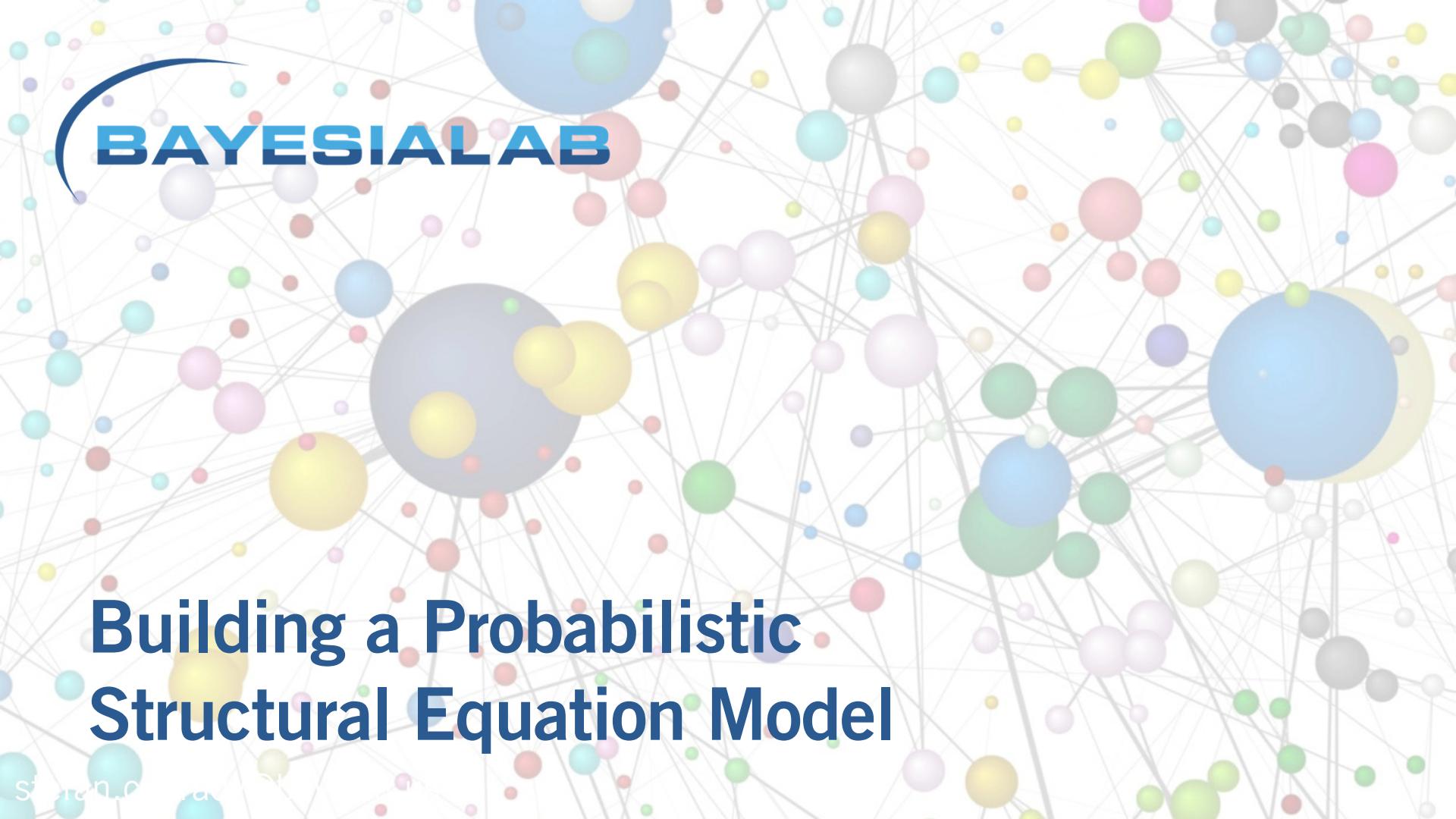
Simulate Scenarios

Statistical Challenges

- Leverage Information Theory
- Find Factors
- Machine-Learn a Bayesian Network



Building a Probabilistic Structural Equation Model



Key Drivers Analysis

Proposed Workflow

- Perform Factor Analysis
 - A machine-learned Bayesian network structure produces intuitive clusters for factor induction.
- Build a Non-Causal Probabilistic Structural Equation Model
 - A Probabilistic Structural Equation Model with a Bayesian network does not require causal assumptions, which we don't have.
- Perform Optimization
 - The explicit representation of the joint probability in a Bayesian network provides natural constraints for optimization.

Key Drivers Analysis

Practical Advantages of Using Bayesian Networks

- We can utilize information-theoretic measures for learning structure and quantifying relationships.
- We can “embrace” collinearity instead of suppressing it as a nuisance.
- Without parametric constraints, we have no problems with potential nonlinearity.
- We can easily handle missing values.

Key Drivers Analysis

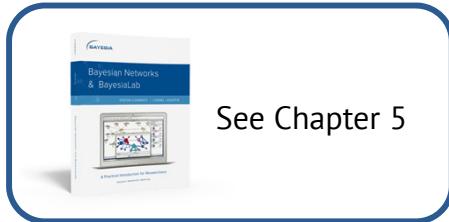
Nomenclature

- We are trying to induce **factors** that can summarize multiple **manifest variables**.
- A **factor** is often referred to as a **latent variable**, as opposed to an observed, **manifest variable**.
- As such, **factors** do not exist, they are merely theoretical constructs.
- Creating **factors** is a variable reduction technique (compare to Factor Analysis, Principal Components Analysis, etc.)

Information Theory

Information-Theoretic Measures

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



See Chapter 5



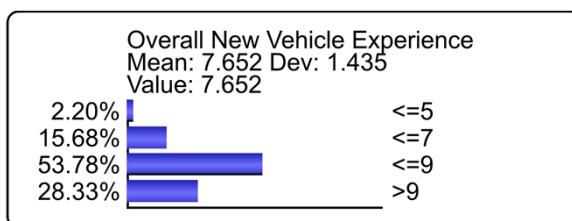
Claude Shannon (1916-2001)

Information Theory

Entropy: a measure of “uncertainty”

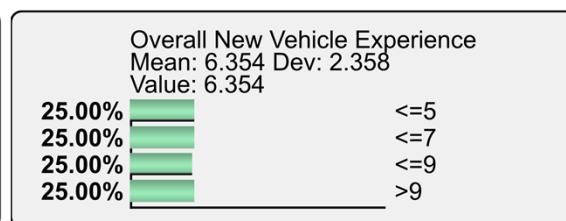
$$H(X) = - \sum_{x \in X} P(x) \log_2 P(x)$$

$H(\text{Overall NVE}) = 1.54$



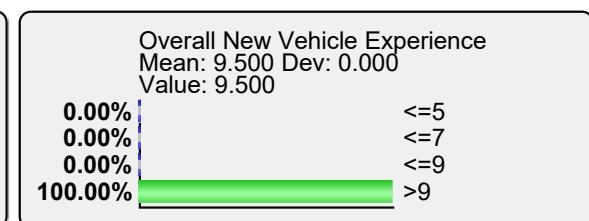
Entropy of Overall New Vehicle Experie...
1.537119852

Marginal Entropy



Entropy of Overall New Vehicle Experie...
2

Maximal Entropy



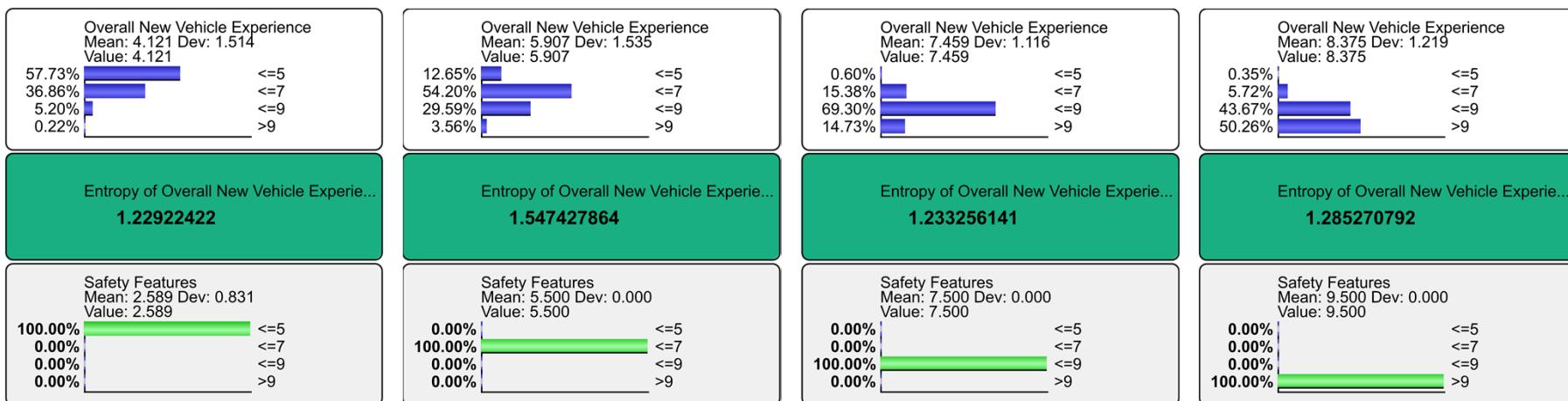
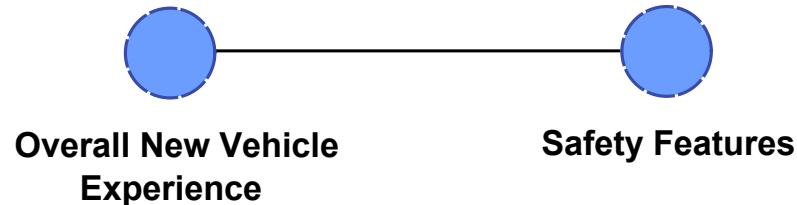
Entropy of Overall New Vehicle Experie...
0

Minimal Entropy

Information Theory

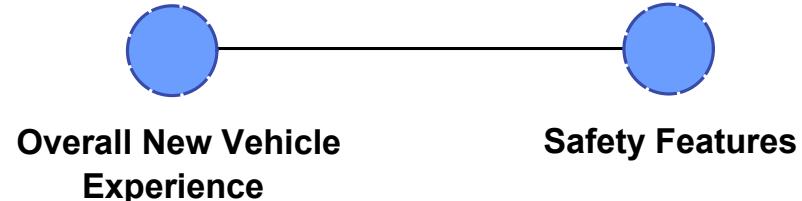
Conditional Entropy

$$H(\text{Overall NVE} \mid \text{Safety Features})$$



Information Theory

Mutual Information



$$I(\text{Overall NVE}, \text{Safety Features}) = H(\text{Overall NVE}) - H(\text{Overall NVE} | \text{Safety Features})$$

The equation for Mutual Information is shown, with three components highlighted by orange brackets and arrows:

- Mutual Information:** The first term $H(\text{Overall NVE})$.
- Marginal Entropy:** The second term $H(\text{Overall NVE} | \text{Safety Features})$.
- Conditional Entropy:** The third term $H(\text{Overall NVE} | \text{Safety Features})$.



Displayed Points: 98

x: 8.39931

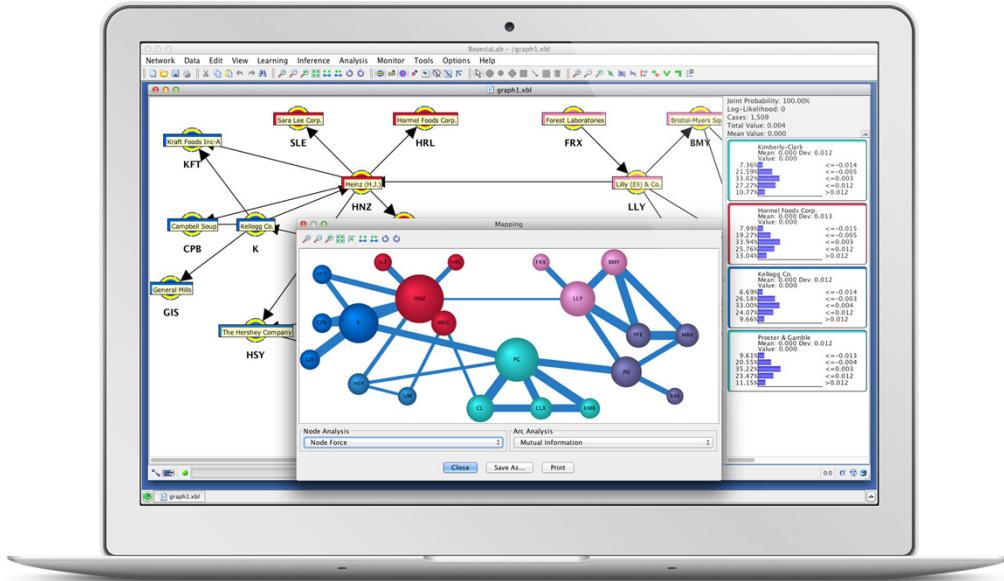
Mutual Information with Overall New Vehicle Experience



Workflow with BayesiaLab

Proposed Workflow

- Machine-learn a Bayesian network
- Validate network
- Perform clustering
- Induce factors
- Construct PSEM
- Perform Multi-Quadrant Analysis
- Optimize with Target Dynamic Profile



Network Learning

Number of Possible Bayesian Networks

- 2 Nodes: 3
- 3 Nodes: 25
- 4 Nodes: 543
- 5 Nodes: 29,281
- 6 Nodes: 3.8×10^6
- 7 Nodes: 1.1×10^9
- 8 Nodes: 7.8×10^{11}
- 9 Nodes: 1.2×10^{15}
- 10 Nodes: 4.2×10^{18}
- 11 Nodes: 3.2×10^{22}
- ⋮
- 100 Nodes: 1.1×10^{1637}

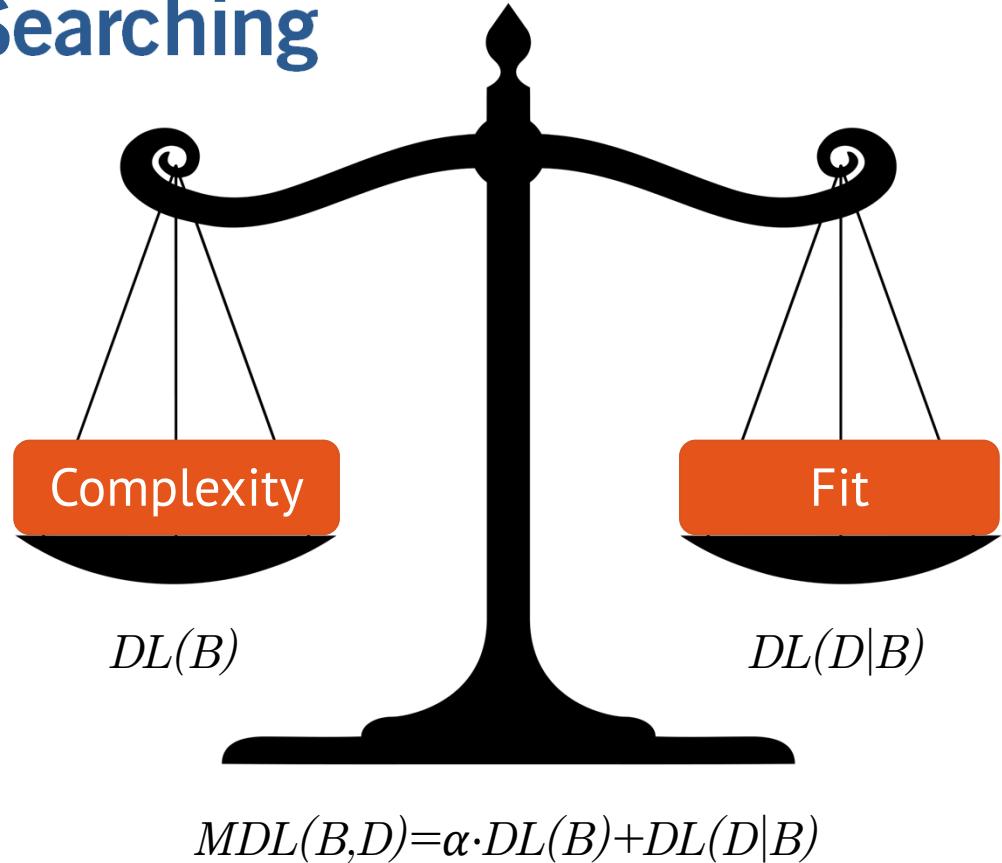
Search Space



Network Learning=Searching

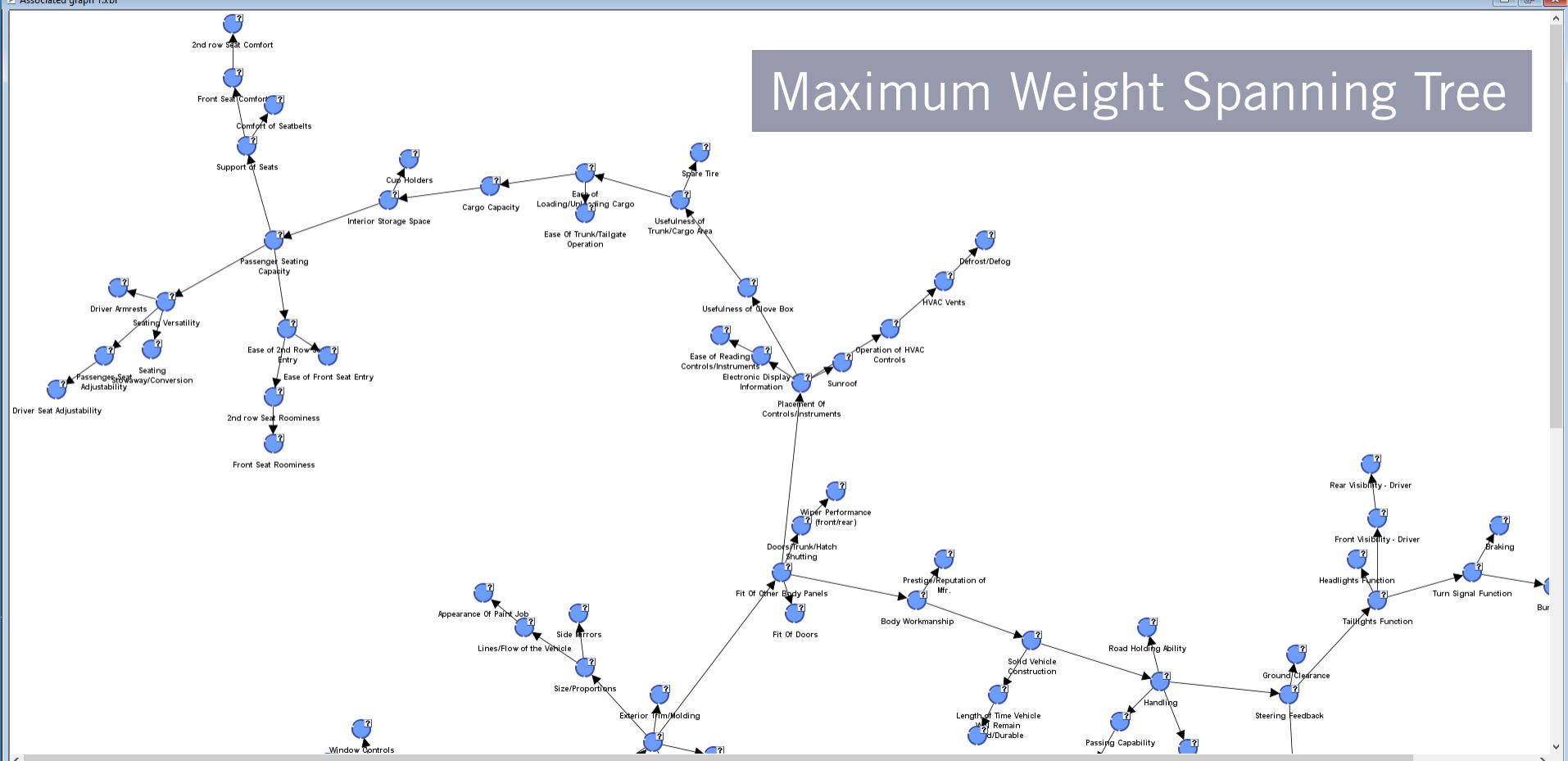
Minimum Description Length

- $DL(B)$ 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).



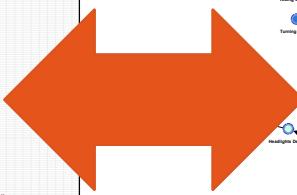
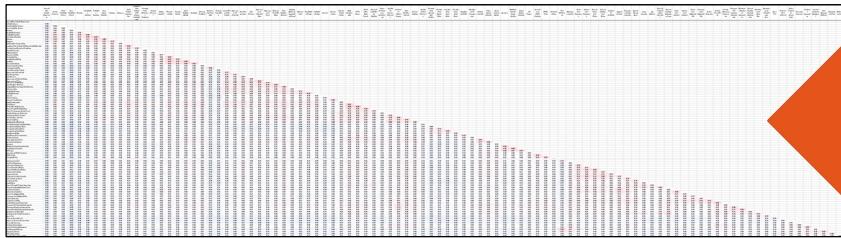
Structural Coefficient α

Maximum Weight Spanning Tree

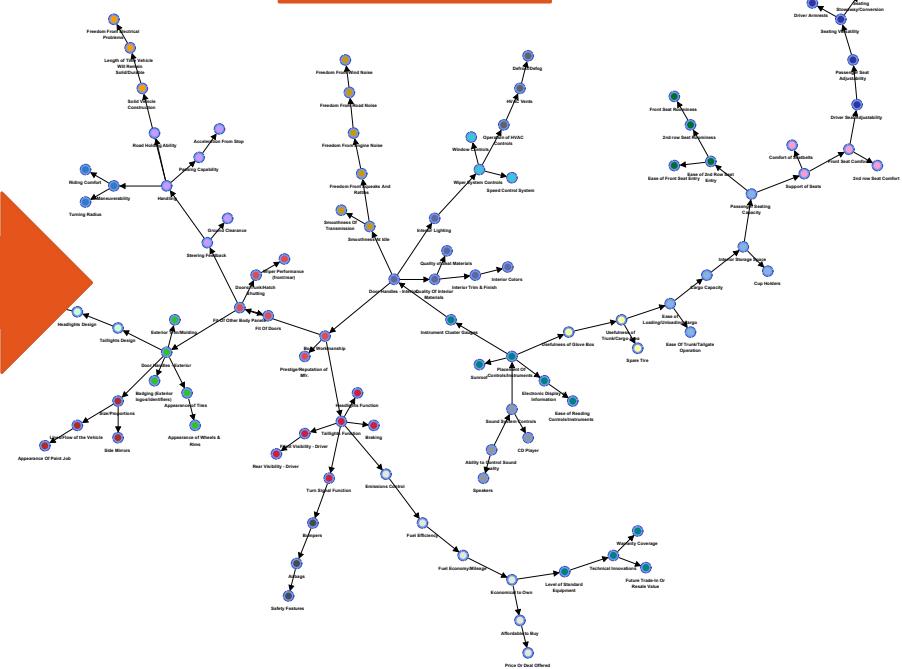


Knowledge Discovery

Correlation Matrix



Network



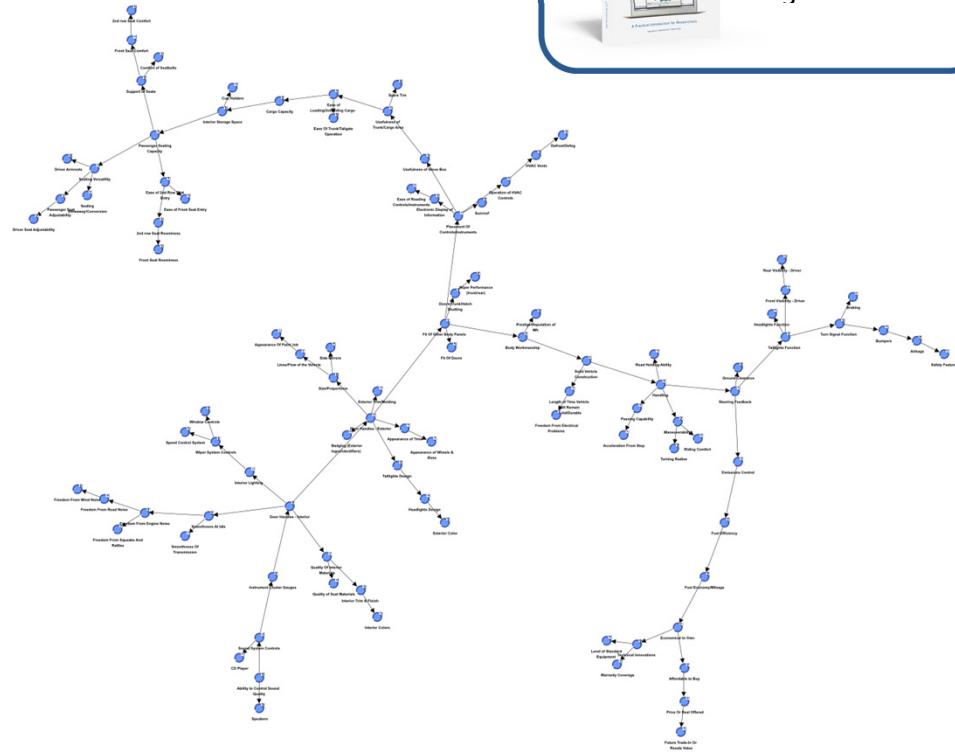
Clustering

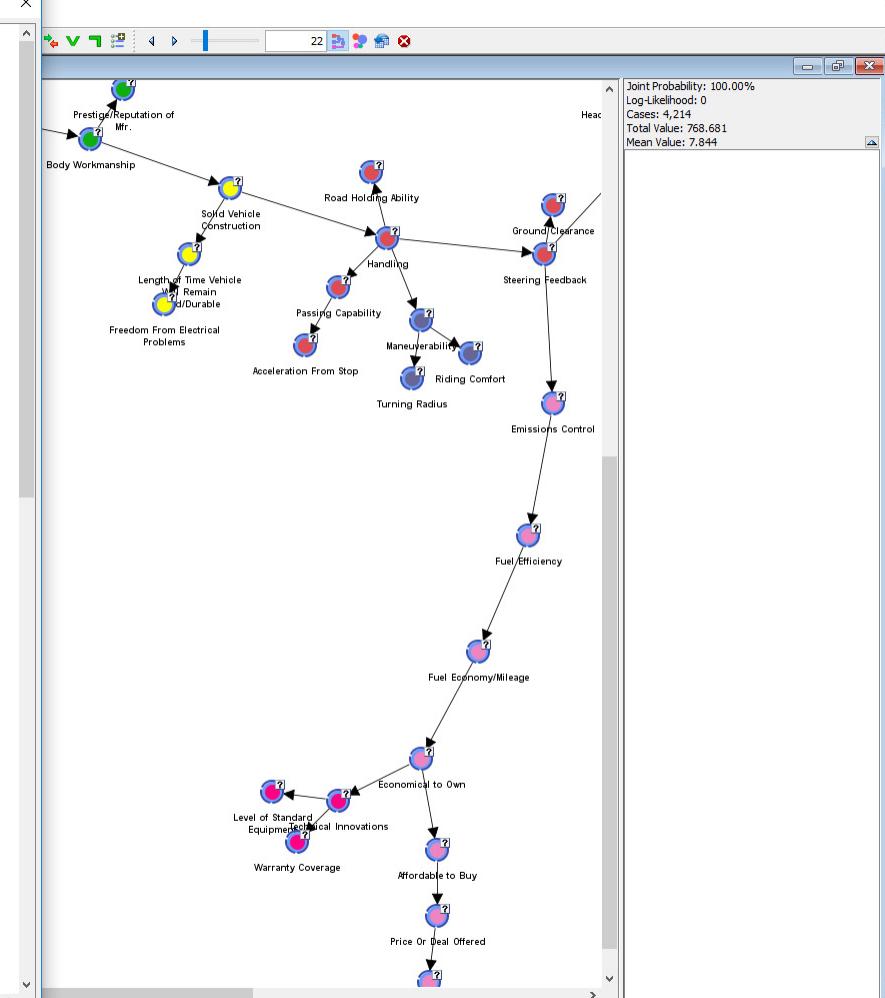
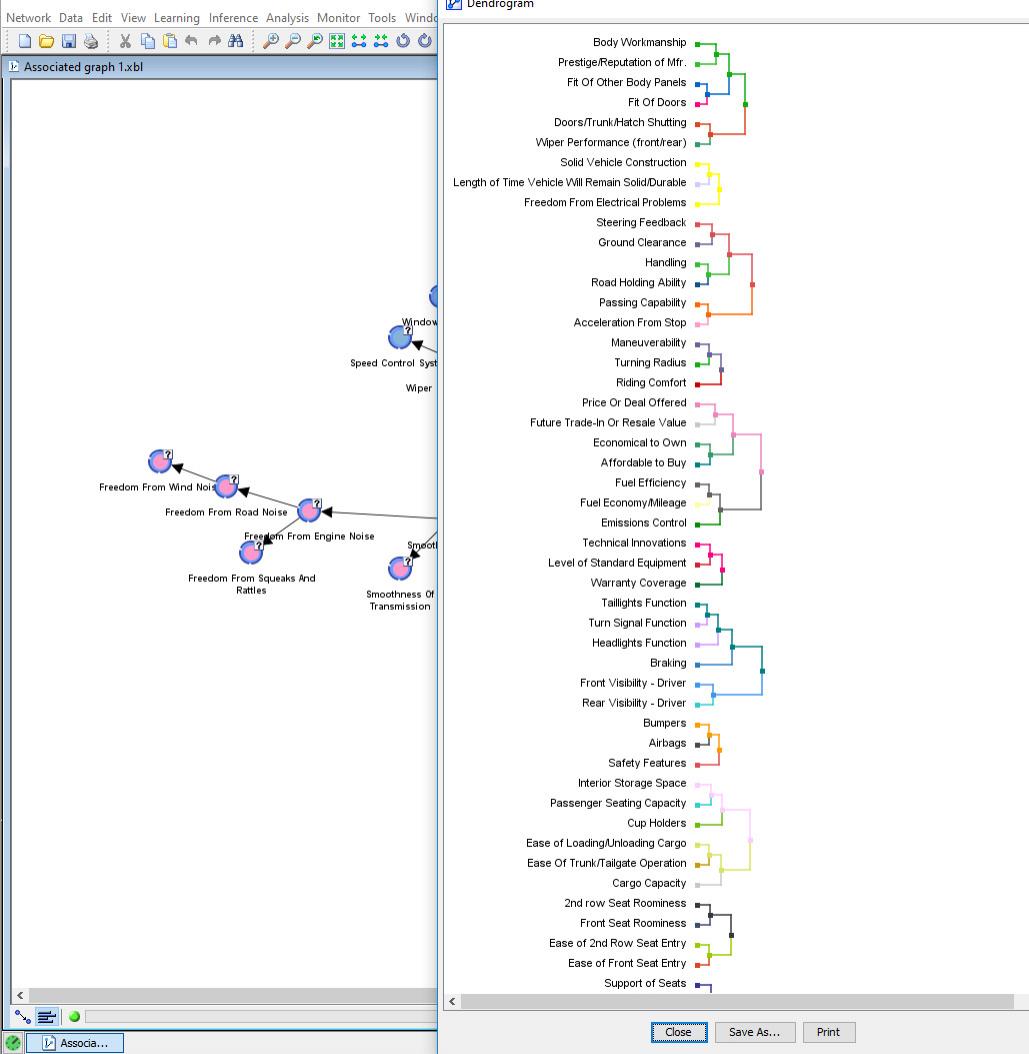


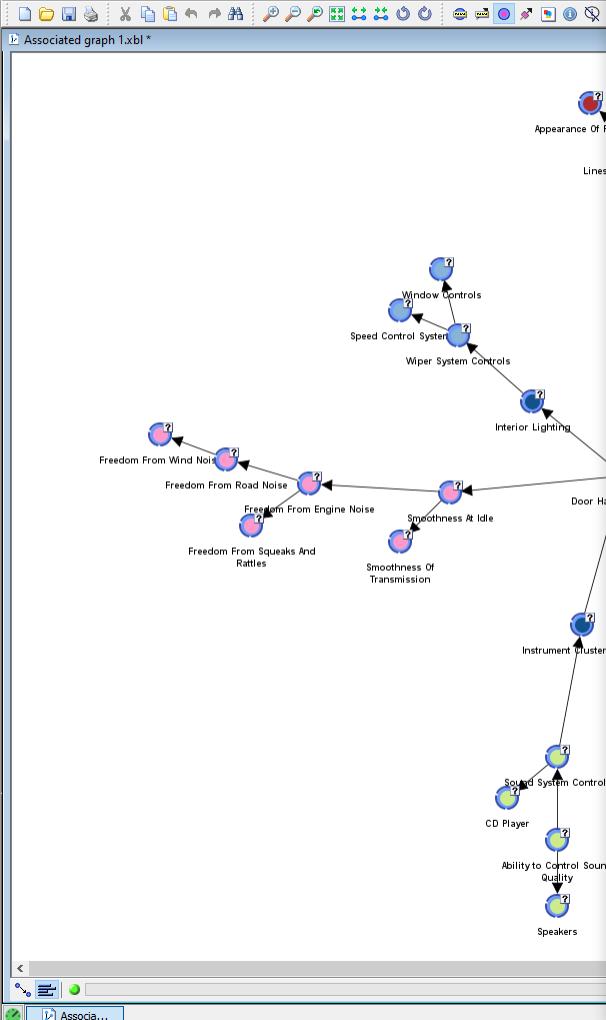
See Chapter 8
Page 216

Variable Clustering

- Hierarchical agglomerative process using Arc Force (Kullback-Leibler Divergence).
 - Why not a traditional factor analysis?
 - Limited number of factors and difficult interpretability.

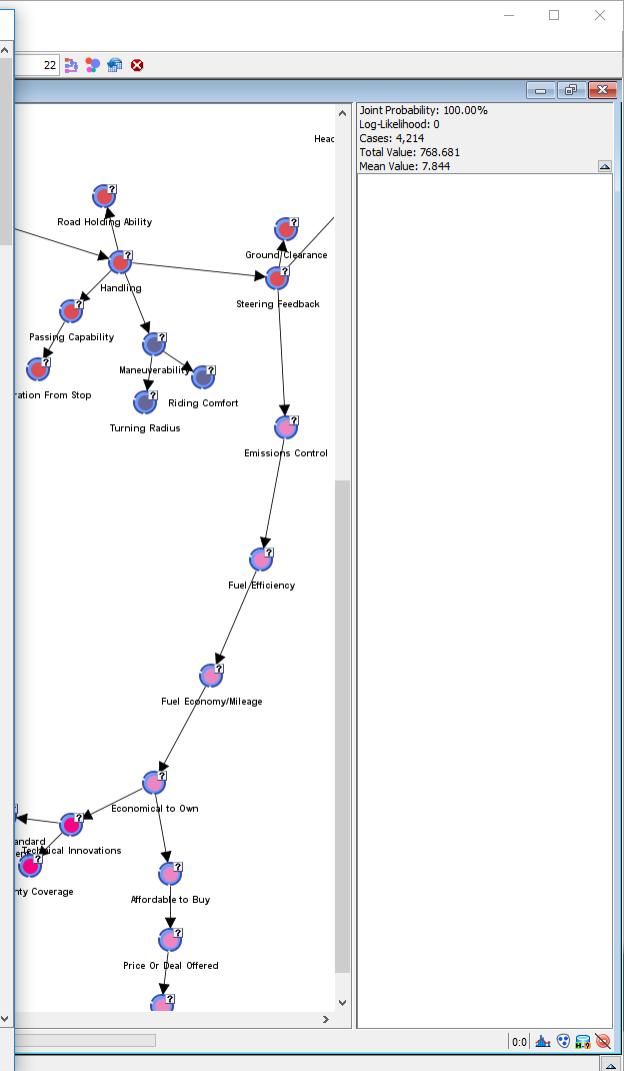


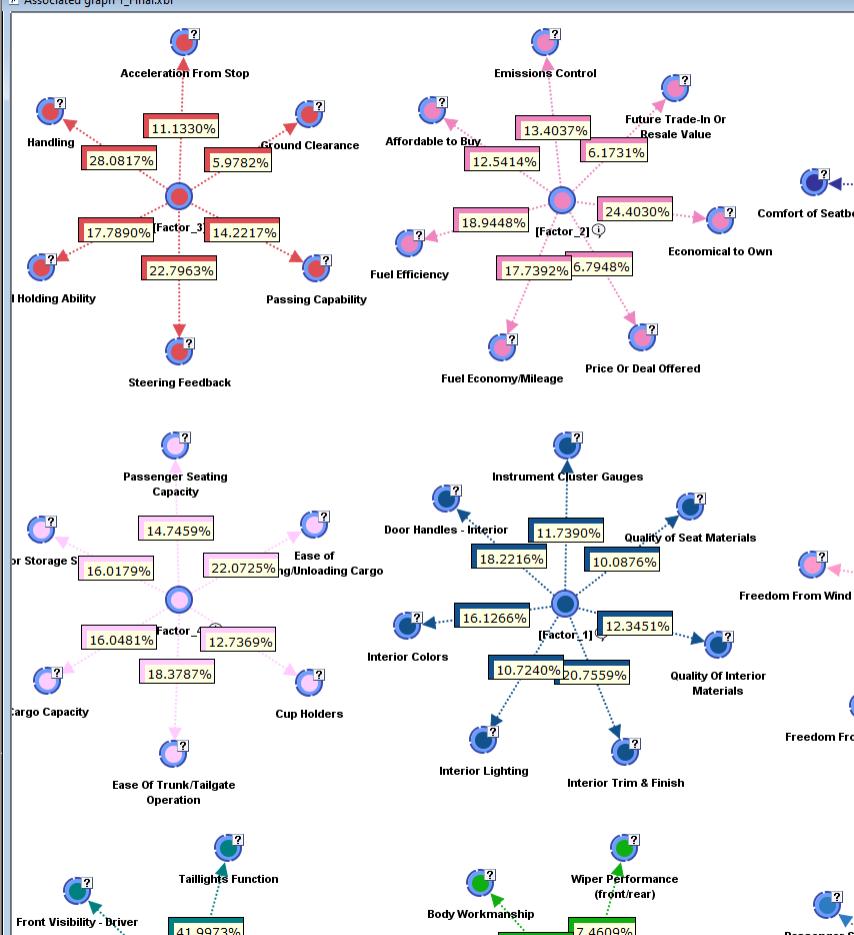




Variable Clustering Report (Associated graph 1)

Classes	Nodes
	Tailights Function
	Turn Signal Function
	Front Visibility - Driver
	Headlights Function
	Braking
	Rear Visibility - Driver
[Factor_0]	Window controls
[Factor_0]	Speed Control System
[Factor_0]	Wiper System Controls
[Factor_0]	Interior Lighting
[Factor_1]	Freedom From Wind Noise
[Factor_1]	Freedom From Road Noise
[Factor_1]	Freedom From Engine Noise
[Factor_1]	Freedom From Squeaks And Rattles
[Factor_1]	Smoothness At Idle
[Factor_1]	Smoothness Of Transmission
[Factor_1]	Door Handles - Interior
[Factor_1]	Quality Of Interior Materials
[Factor_1]	Interior Trim & Finish
[Factor_1]	Interior Colors
[Factor_1]	Interior Lighting
[Factor_1]	Instrument Cluster Gauges
[Factor_1]	Quality of Seat Materials
[Factor_2]	Fuel Economy/Mileage
[Factor_2]	Economical to Own
[Factor_2]	Fuel Efficiency
[Factor_2]	Affordable to Buy
[Factor_2]	Price Or Deal Offered
[Factor_2]	Emissions Control
[Factor_2]	Future Trade-In Or Resale Value
[Factor_3]	Handling
[Factor_3]	Steering Feedback
[Factor_3]	Passing Capability
[Factor_3]	Road Holding Ability
[Factor_3]	Acceleration From Stop
[Factor_3]	Ground Clearance
[Factor_4]	Interior Storage Space
[Factor_4]	Ease of Loading/Unloading Cargo
[Factor_4]	Cargo Capacity
[Factor_4]	Ease Of Trunk/Tailgate Operation
[Factor_4]	Passenger Seating Capacity
[Factor_4]	Cup Holders
[Factor_5]	Freedom From Engine Noise
[Factor_5]	Freedom From Road Noise
[Factor_5]	Smoothness At Idle
[Factor_5]	Freedom From Wind Noise
[Factor_5]	Smoothness Of Transmission
[Factor_5]	Freedom From Squeaks And Rattles





Node significance with respect to the information gain brought by the node to the knowledge of [Factor]

Node	Mutual information	Normalized Mutual Information (%)	Relative significance	Mean Value	G-test	Degrees of Freedom	p-value	G-test (Data)	Degrees of Freedom (Data)	p-value (Data)
Taillights Function	1.1652	85.1852%	1.0000	8.1396	6,807.1043	6	0.0000%	6,836.5957	6	0.0000%
Turn Signal Function	1.0980	80.2720%	0.9423	8.1993	6,414.4936	6	0.0000%	6,441.4170	6	0.0000%
Headlights Function	0.9682	70.7824%	0.8309	8.0867	5,656.1828	6	0.0000%	5,696.9640	6	0.0000%
Braking	0.7935	58.0088%	0.6810	8.1188	4,635.4362	6	0.0000%	4,527.8086	6	0.0000%
Front Visibility - Driver	0.6588	48.1498%	0.5652	8.0314	3,847.6288	6	0.0000%	3,873.6572	6	0.0000%
Rear Visibility - Driver	0.4695	34.3237%	0.4029	7.2762	2,742.7915	6	0.0000%	2,753.5657	6	0.0000%

Fig. 4. Globalization Table 2.5

100

Page 49

Continued

Deviance 5.858 0661

Node significance with respect to the information gain brought by the node to the knowledge of [Factor]

Node	Mutual information	Normalized Mutual Information (%)	Relative significance	Mean Value	G-test	Degrees of Freedom	p-value	G-test (Data)	Degrees of Freedom (Data)	p-value (Data)
Door Handles - Interior	1.0783	60.9865%	1.0000	7.9098	6,299.3515	9	0.0000%	6,362.0244	9	0.0000%
Interior Trim & Finish	0.9510	53.7844%	0.8819	7.8337	5,555.4427	9	0.0000%	5,608.4858	9	0.0000%
Quality Of Interior Materials	0.9237	52.2409%	0.8566	7.7704	5,396.0175	9	0.0000%	5,348.2388	9	0.0000%
Instrument Cluster Gauges	0.8949	50.6140%	0.8299	7.9358	5,227.9697	9	0.0000%	5,221.6064	9	0.0000%
Quality of Seat Materials	0.8839	49.9908%	0.8197	7.6854	5,163.5953	9	0.0000%	5,216.8110	9	0.0000%
Interior Lighting	0.8629	48.8045%	0.8003	7.9583	5,041.0623	9	0.0000%	5,026.9395	9	0.0000%
Interior Colors	0.8517	48.1700%	0.7898	7.8195	4,975.5280	9	0.0000%	4,998.5947	9	0.0000%

[Factor 2] - Economic

Performance Test

Mean_Purity: 02.4875%

Continued

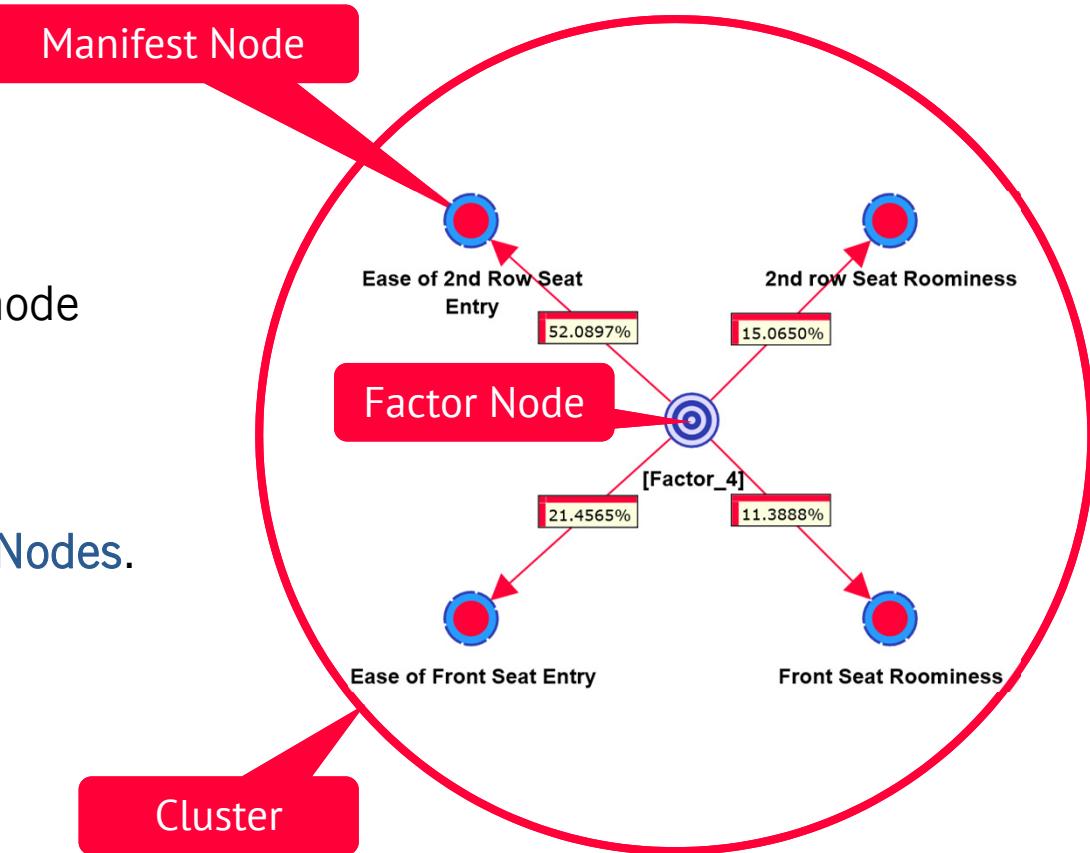
Deviance 6,458.5305

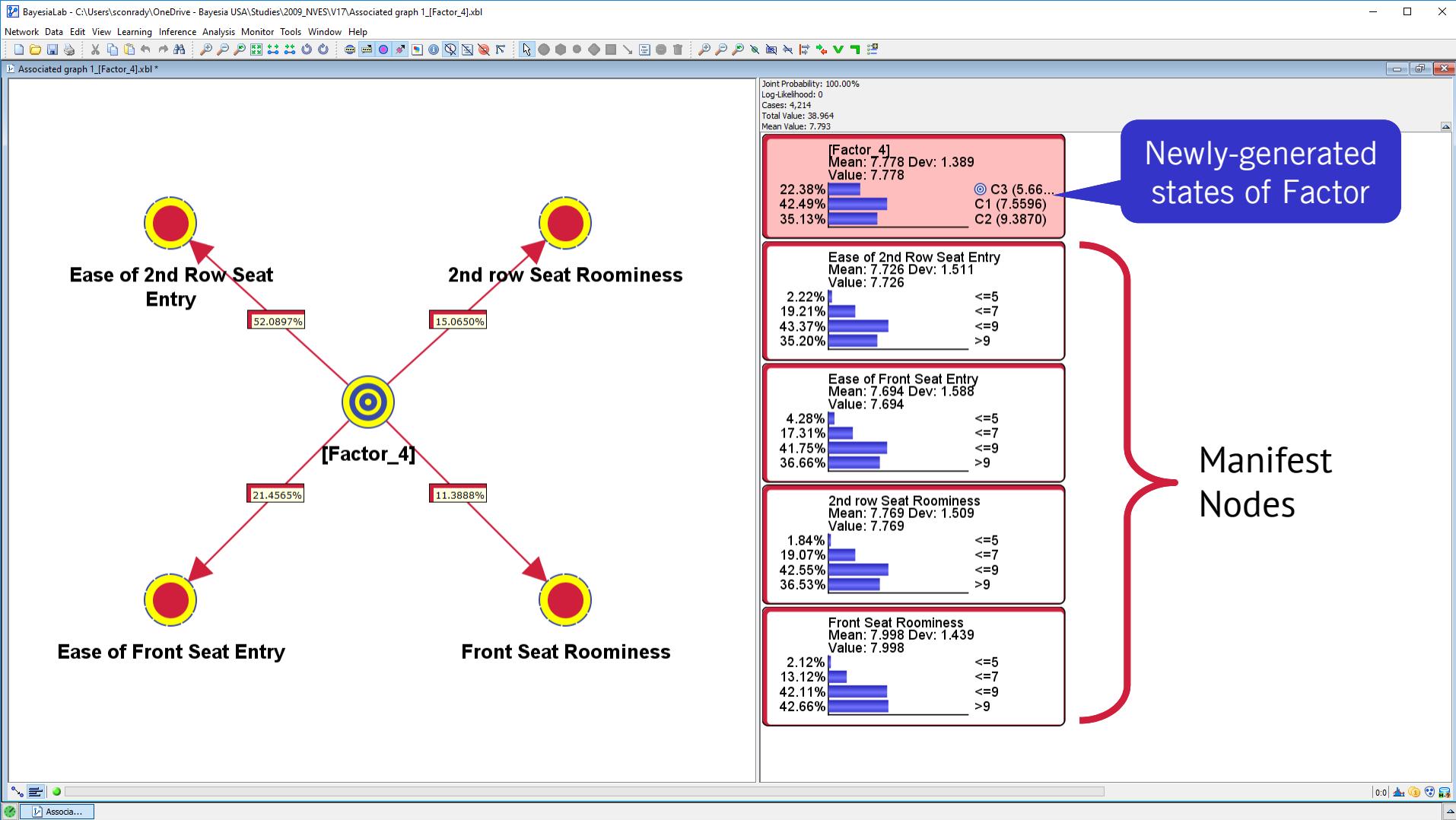
Node significance with respect to the information gain brought by the node to the knowledge of [Factor_2]										
Node	Mutual Information	Normalized Mutual Information (%)	Relative significance	Mean Value	G-test	Degrees of Freedom	p-value	G-test (Data)	Degrees of Freedom (Data)	p-value (Data)
Economical to Own	1.1189	55.9232%	1.0000	7.5662	6,536.4631	12	0.0000	6,534.9297	12	0.0000
Fuel Economy/mileage	0.9774	48.8515%	0.8735	7.4136	5,709.9052	12	0.0000	5,682.6992	12	0.0000

Factors

Nomenclature

- Manifest node = observed node
- Factor = latent variable
- In BayesiaLab, a cluster is implemented as a **Class of Nodes**.

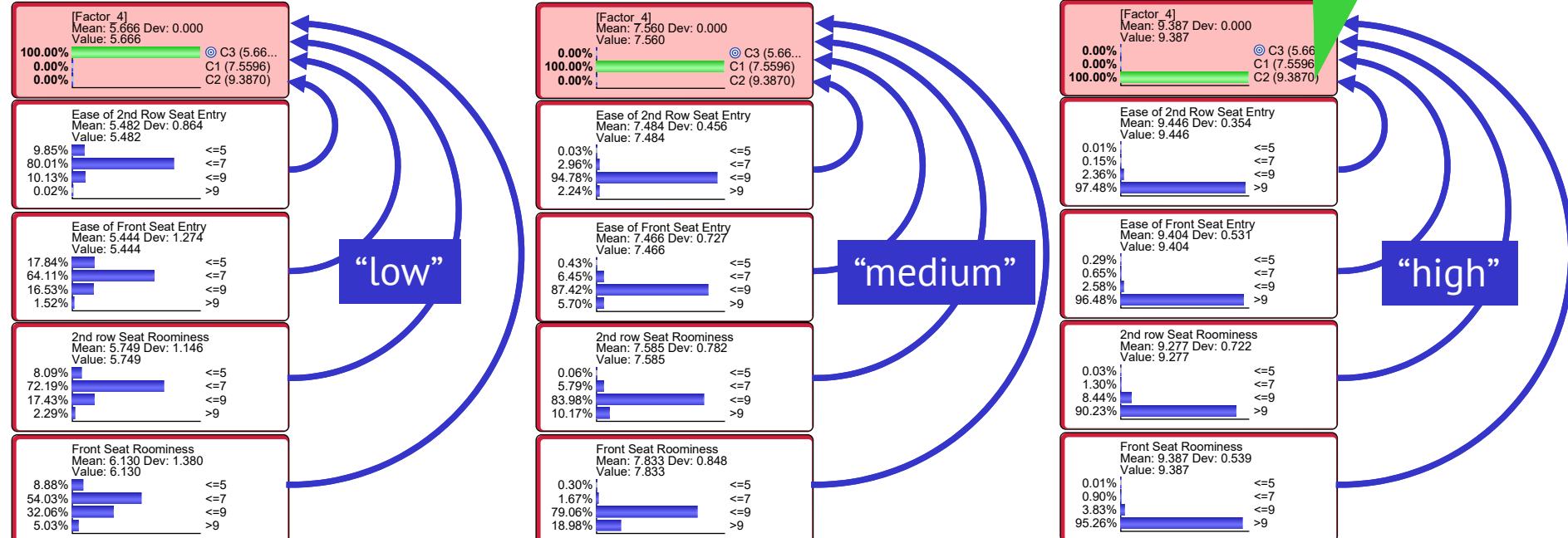


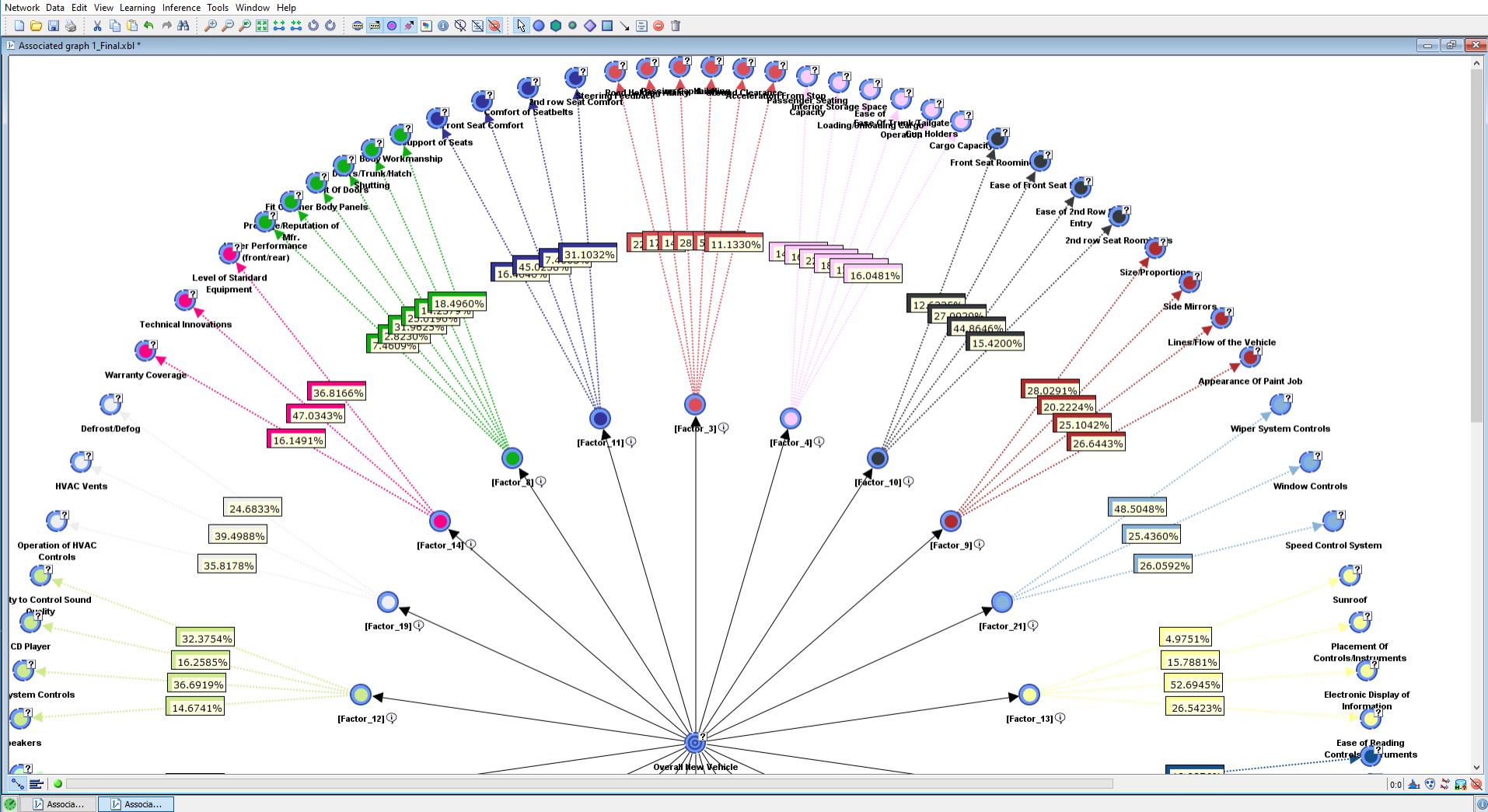


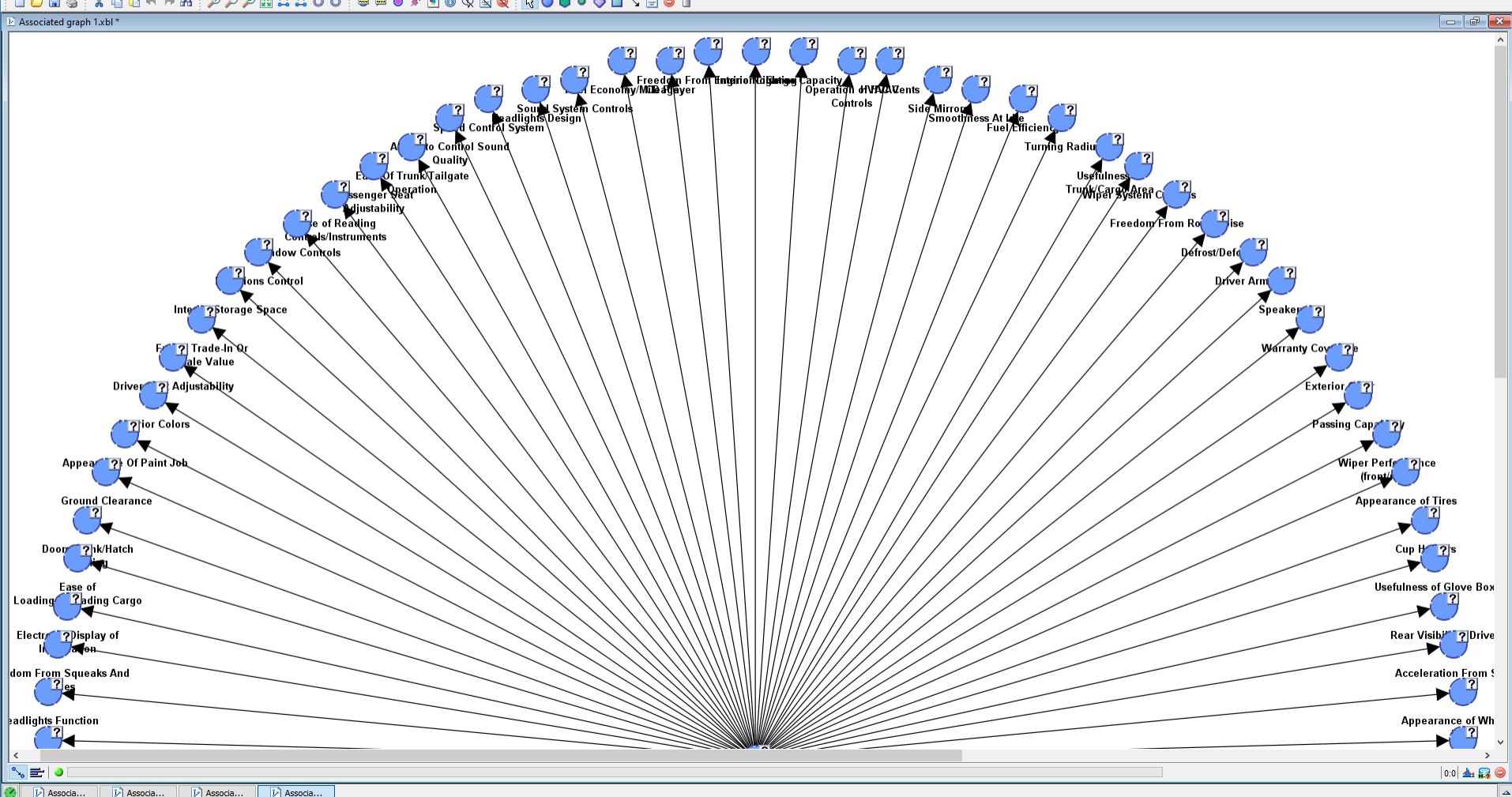
Factors

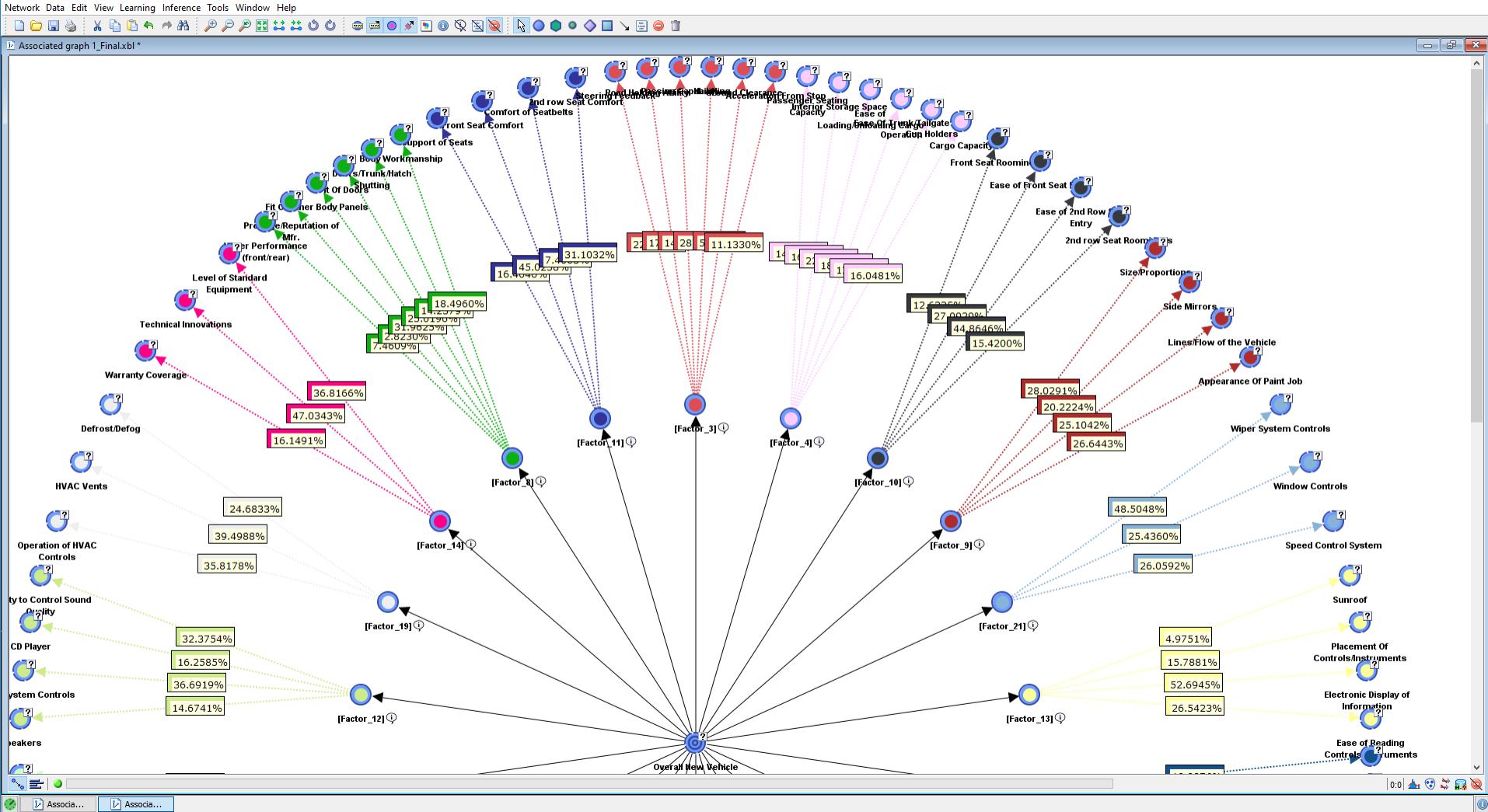
Factor States Summarize the States of the Manifest Nodes

Numerical values of the factor states are the weighted averages of the values of the manifest states



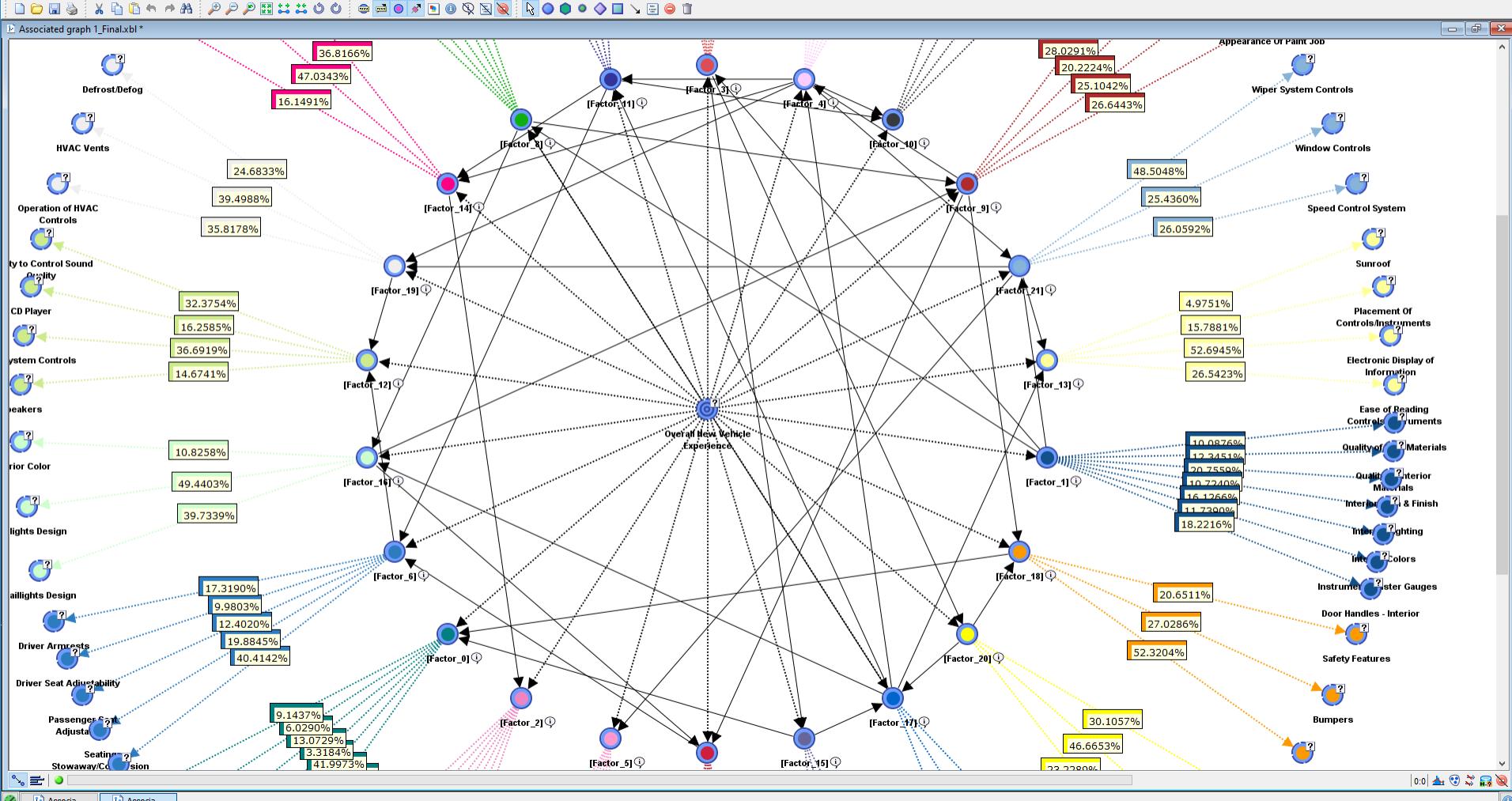


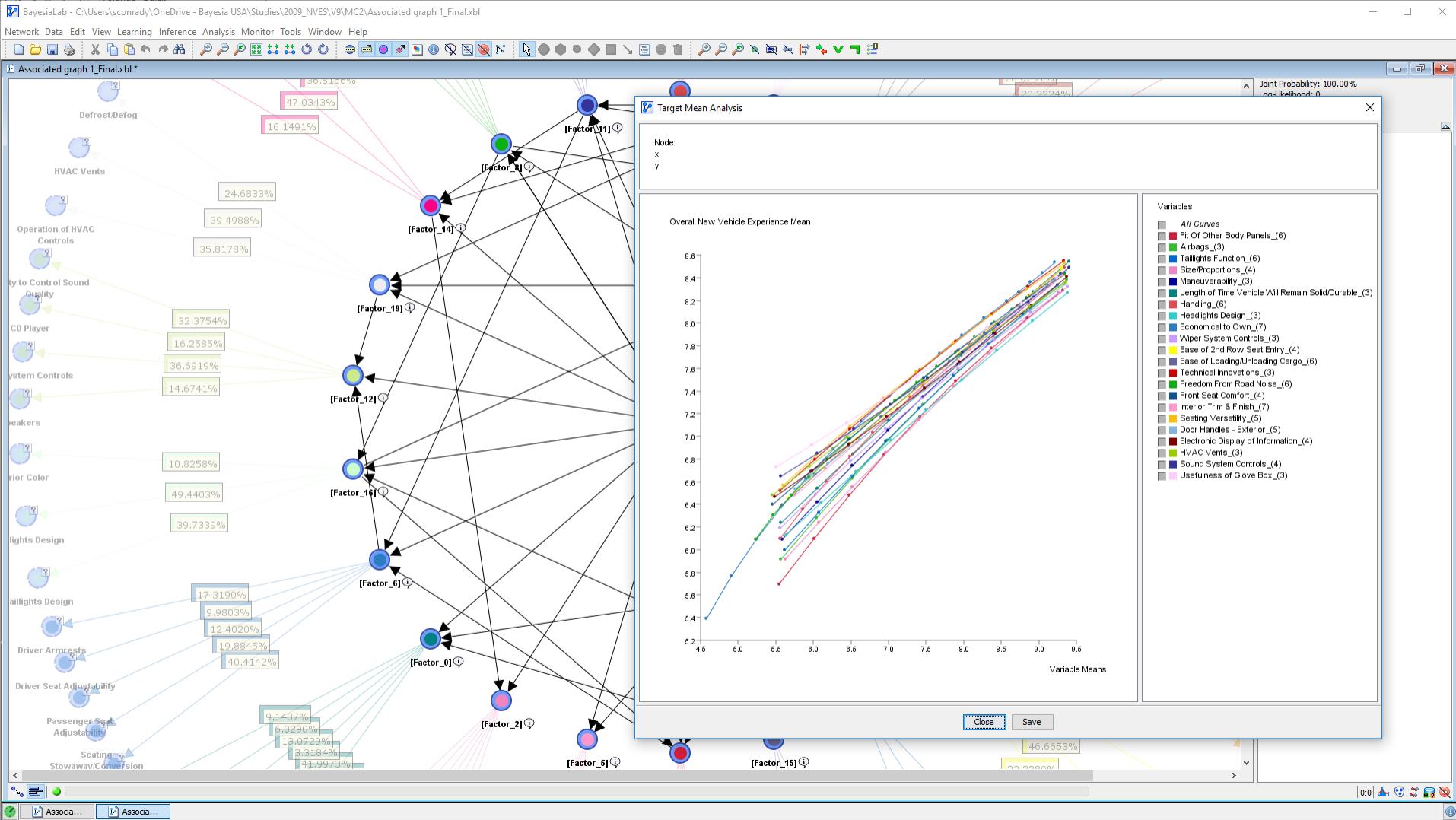




Completing the PSEM

- There is no reason to assume that the newly-generated factors are orthogonal.
- We use Taboo Learning to discover the relationships between the Factors

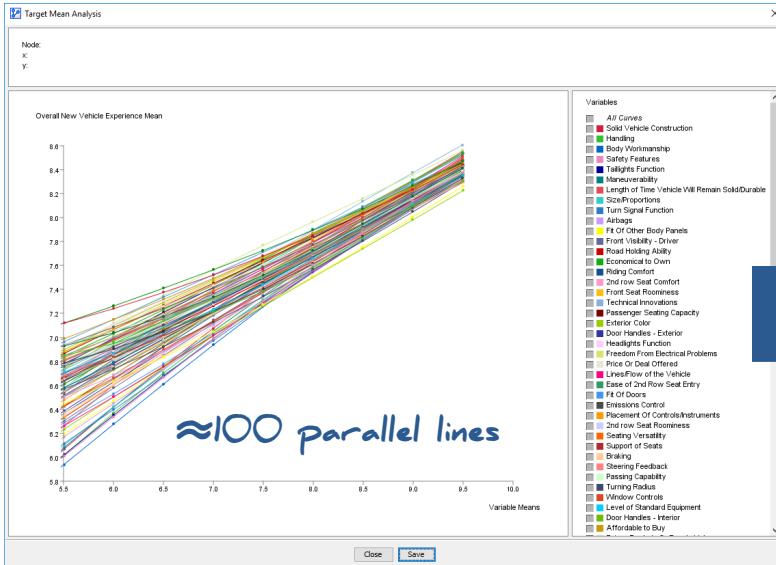




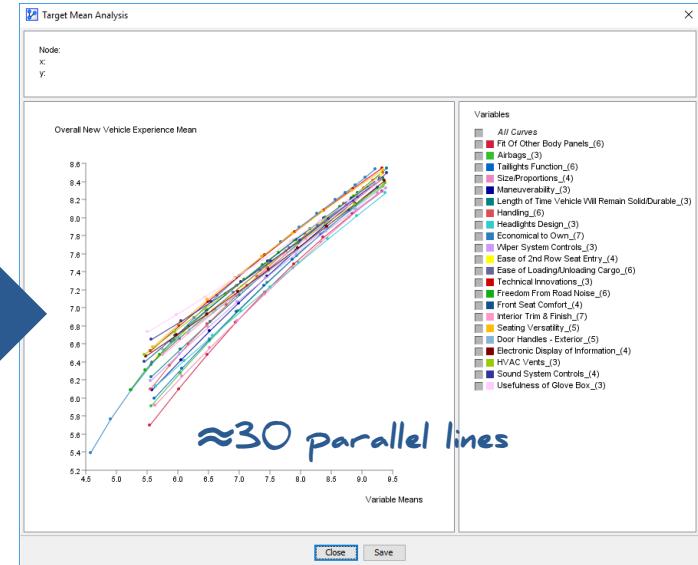
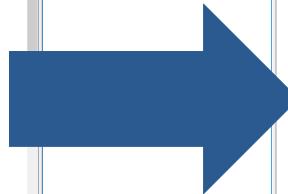
Key Drivers Analysis

Key Drivers Analysis

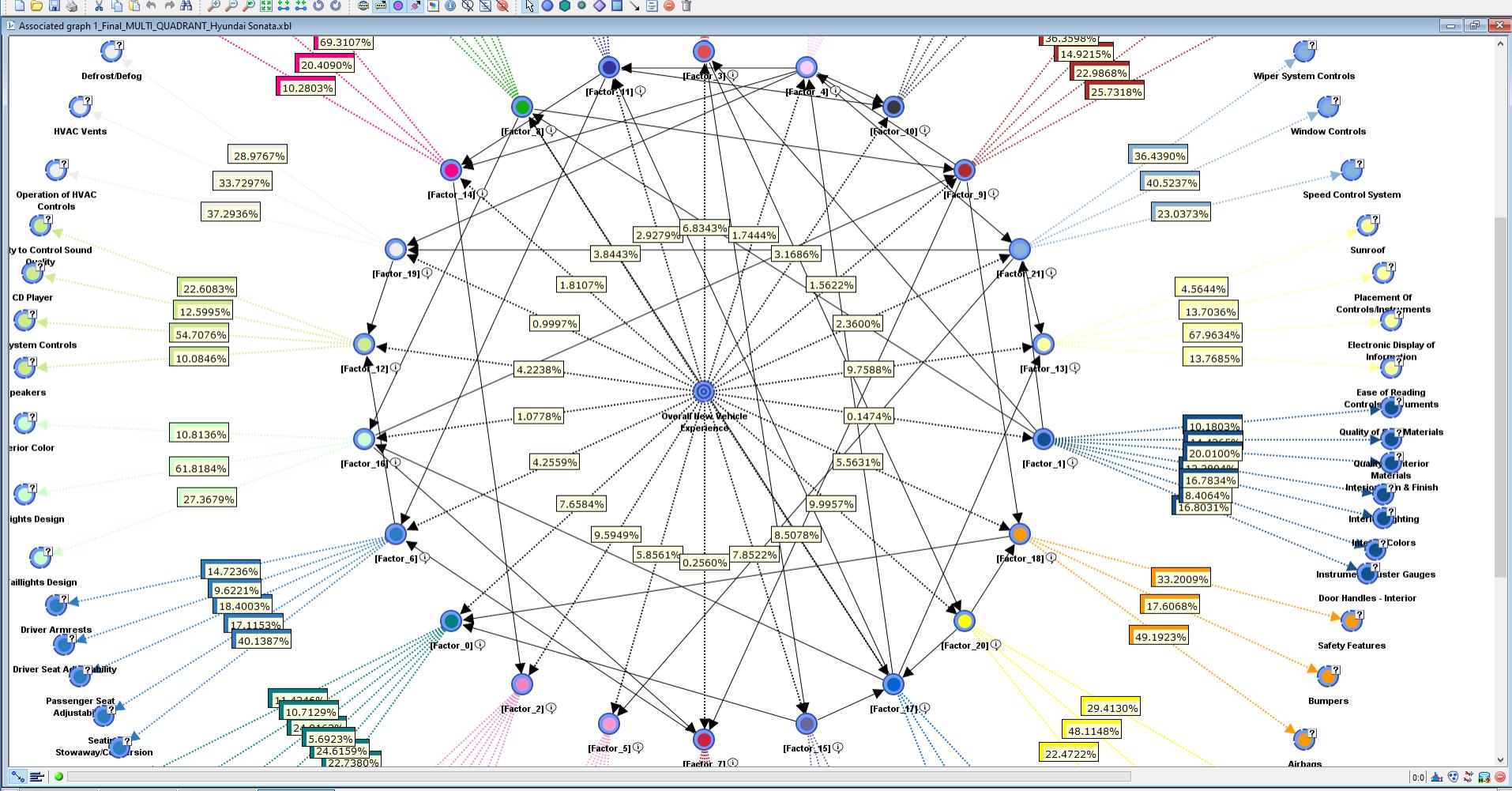
What did we gain?



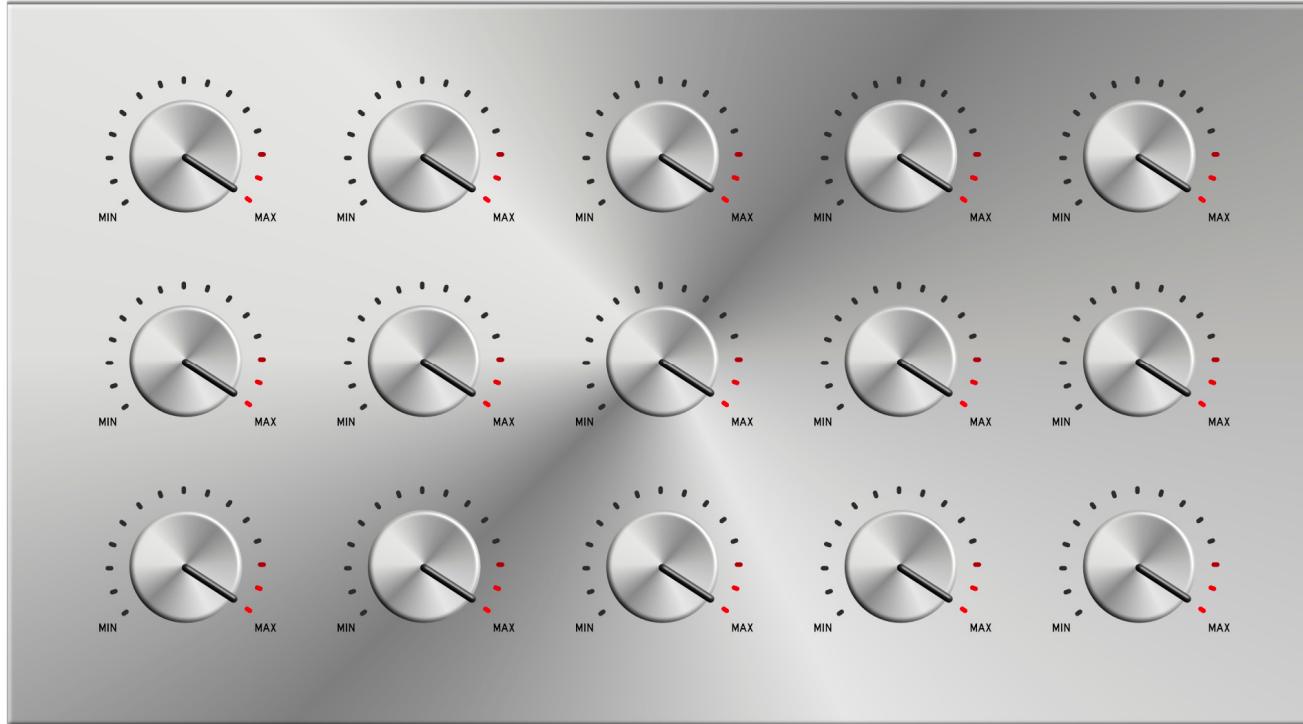
Overall New Vehicle Experience vs. Manifest Ratings



Overall New Vehicle Experience vs. Factor Ratings



Optimization



We have no constraints, so why not set all “drivers” to their maximum levels?

Optimization

Optimization Constraint #1

- “Gain” × Joint Probability ÷ Cost

Optimization Constraint # 2

- Automatic calculation of “gap to best level” via Multi-Quadrant Analysis
- Expert-defined constraints

Simulation of Values

- Minimum Cross-Entropy

Optimization Objective

- Establish Priorities

Optimization

Optimization Constraint #1

- “Gain” × Joint Probability ÷ Cost

Optimization Constraint # 2

- Expert-defined constraints
- Automatic calculation of “gap to best level” via Multi-Quadrant Analysis

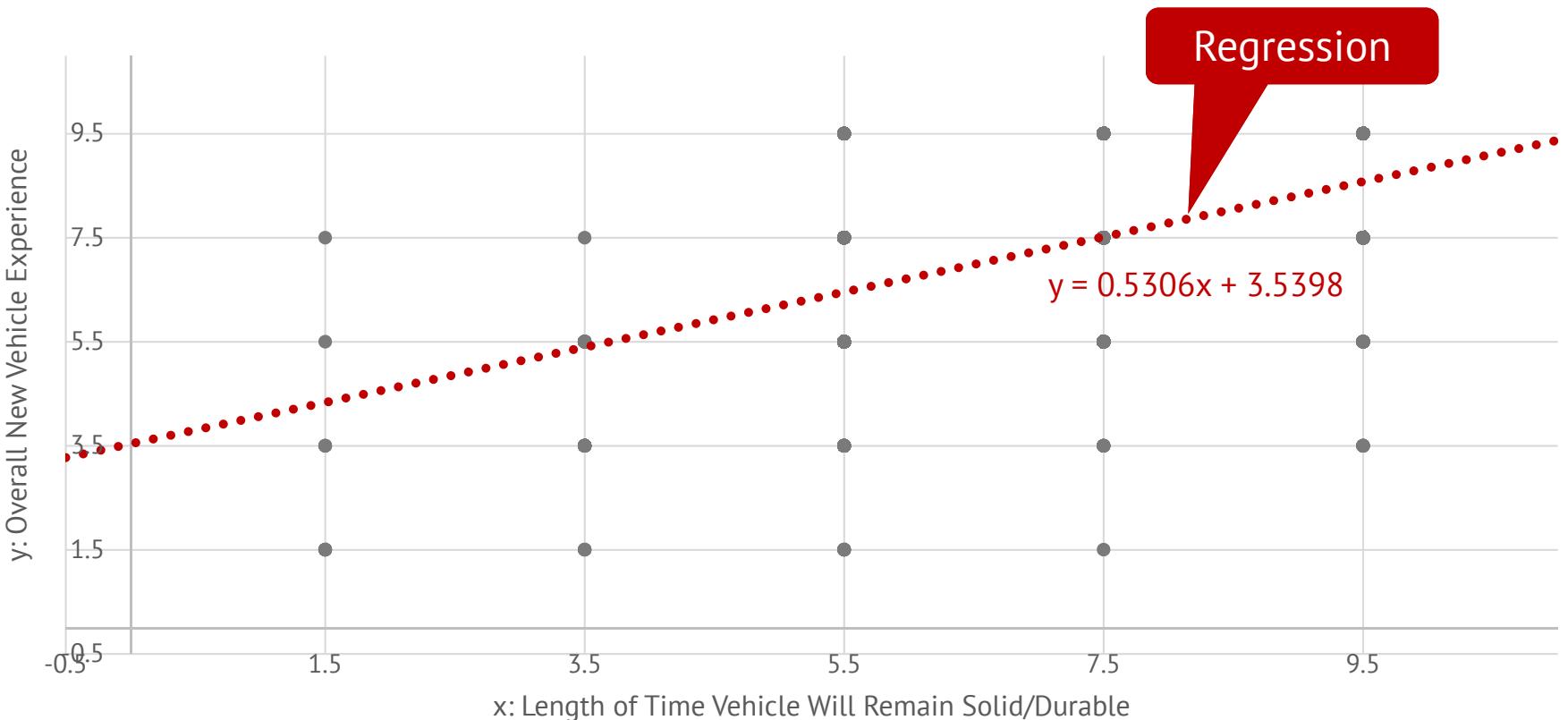
Simulation of Values

- Minimum Cross-Entropy

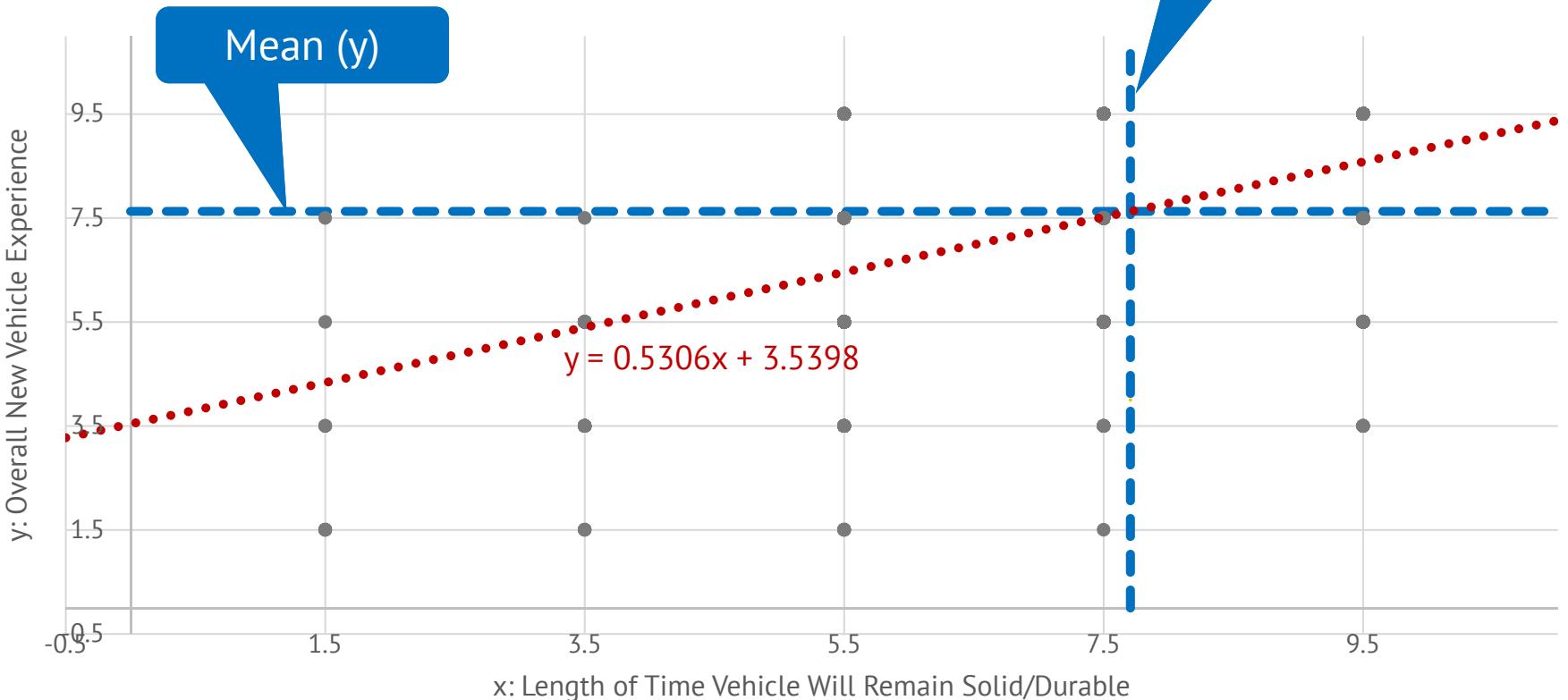
Optimization Objective

- Establish Priorities

Compare to Regression

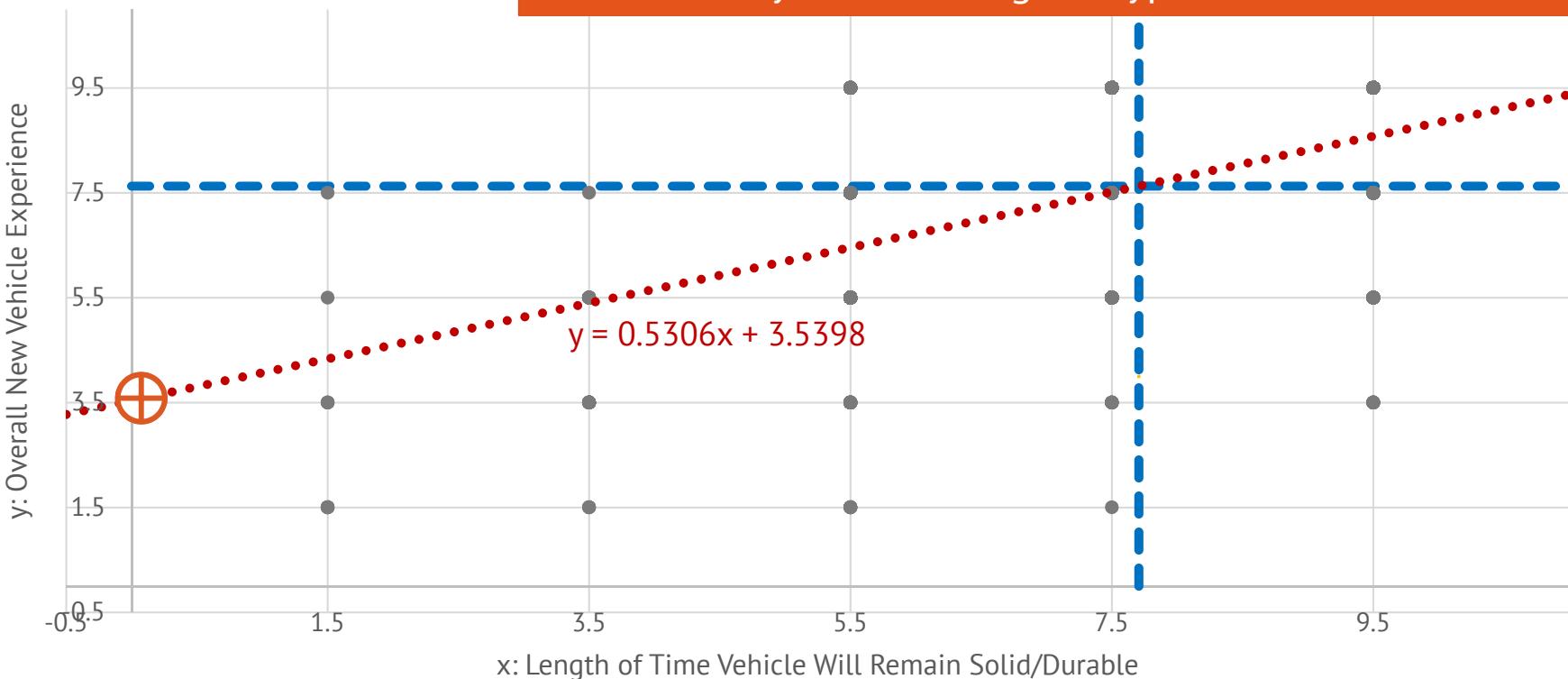


Compare to Regression

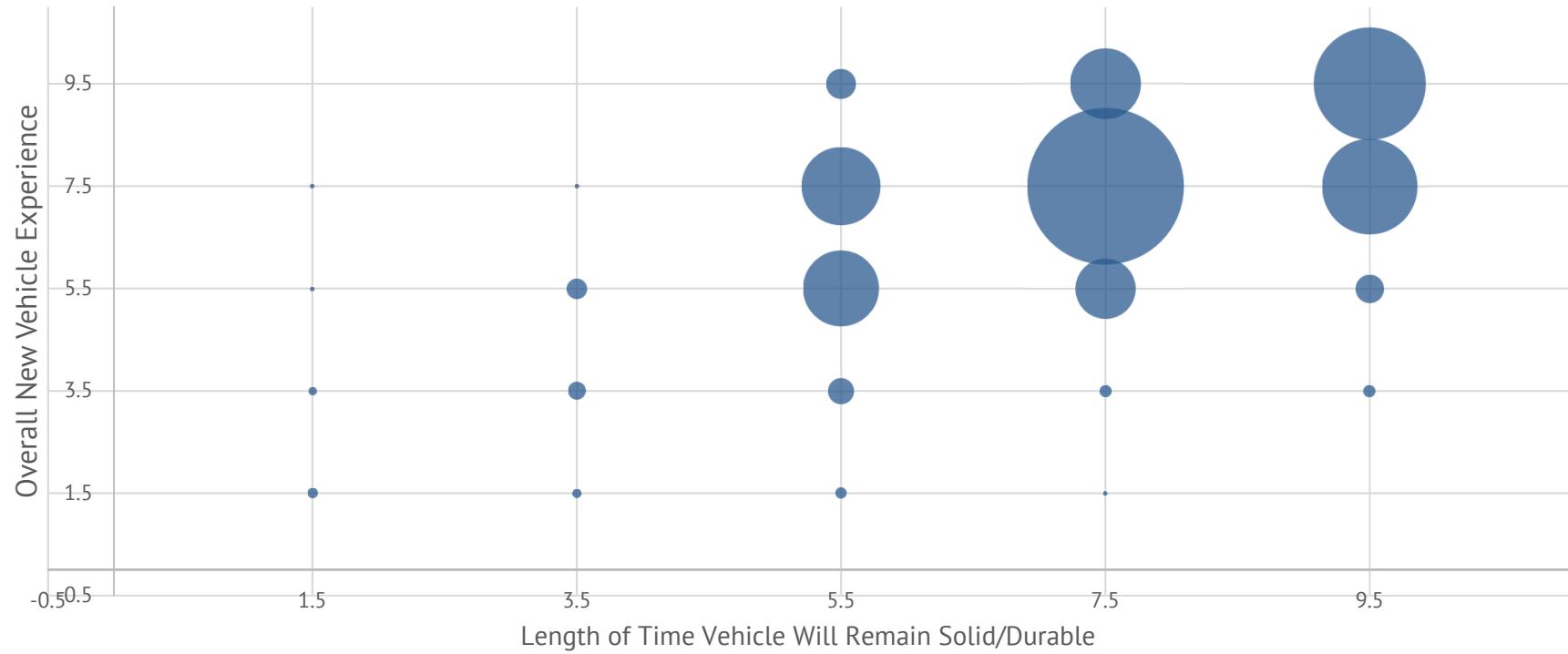


Compare to Regression

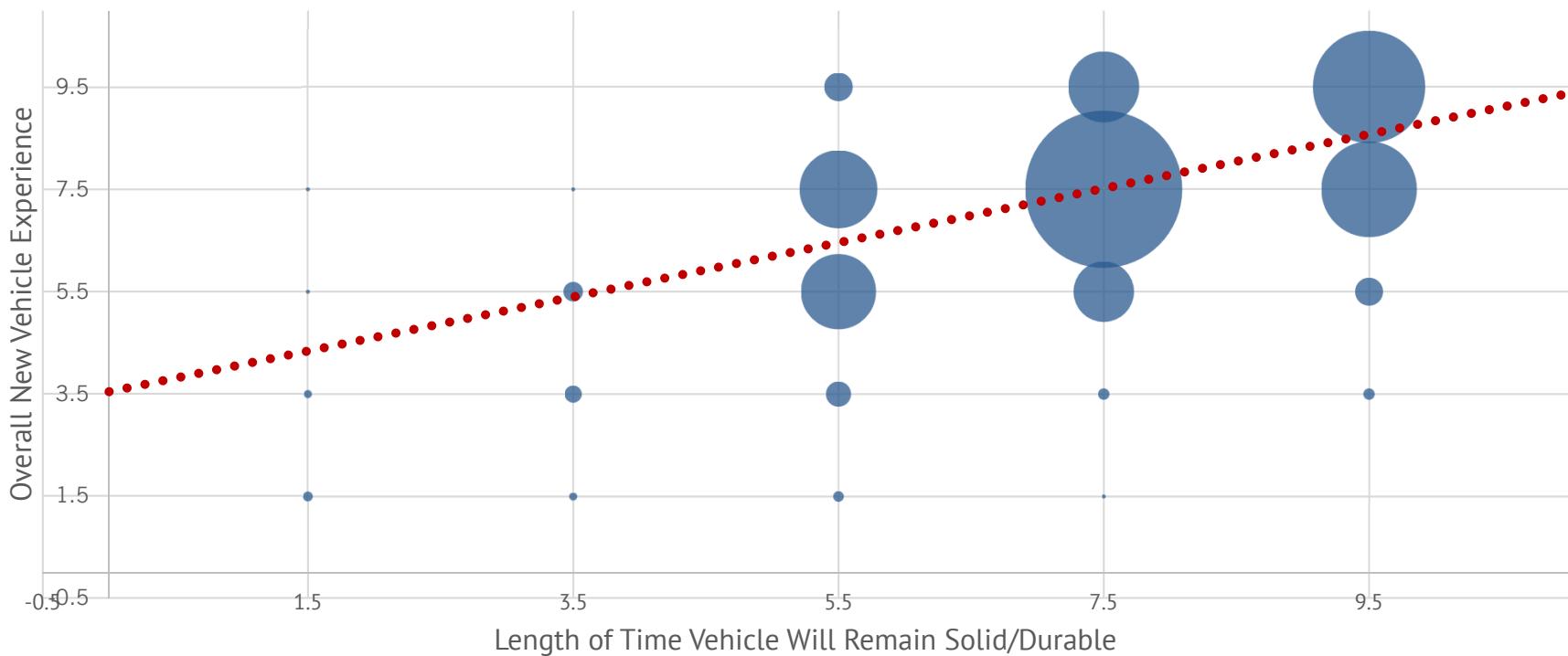
Simulation by conditioning on hypothetical values of x



Joint Distribution



Joint Distribution



Joint Distribution

Marginal Distribution

Overall New Vehicle Experience	9.5	0	8	47	547	755
	7.5	1	8	219	1475	301
	5.5	7	38	338	363	49
	3.5	4	18	23	1	0
	1.5	6	4	1	1	0
	100%	1.5	3.5	5.5	7.5	9.5
Length of Time Vehicle Will Remain Solid/Durable						

Joint Distribution

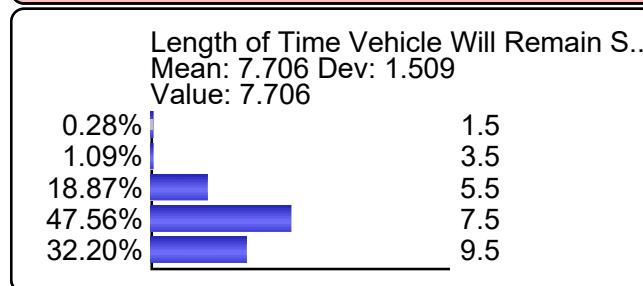
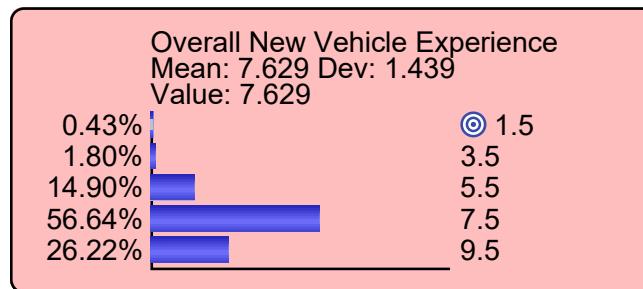
Is this realistic?

Distribution of y conditional on x=9.5 → Mean(y)=8.78

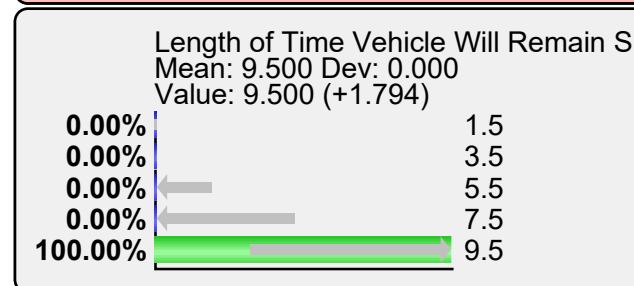
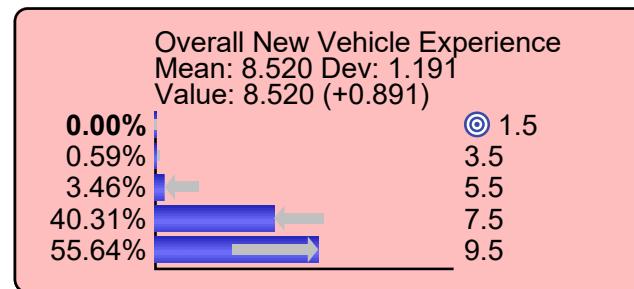
Overall New Vehicle Experience	9.5	0	0	0	0	755
	7.5	0	0	0	0	301
	5.5	0	0	0	0	49
	3.5	0	0	0	0	0
	1.5	0	0	0	0	0
	1.5	3.5	5.5	7.5	9.5	
Length of Time Vehicle Will Remain Solid/Durable						

Joint Distribution

Simulation of Values



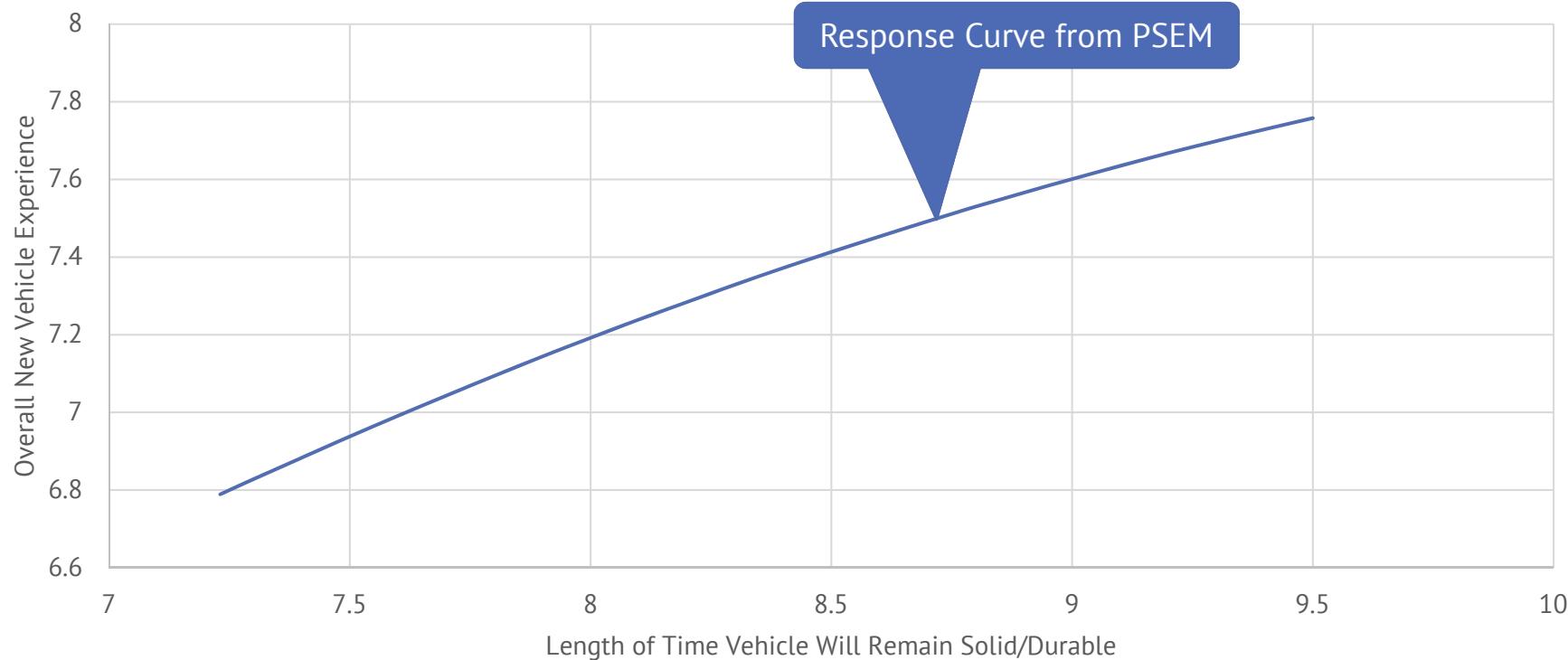
Joint Probability: 100%



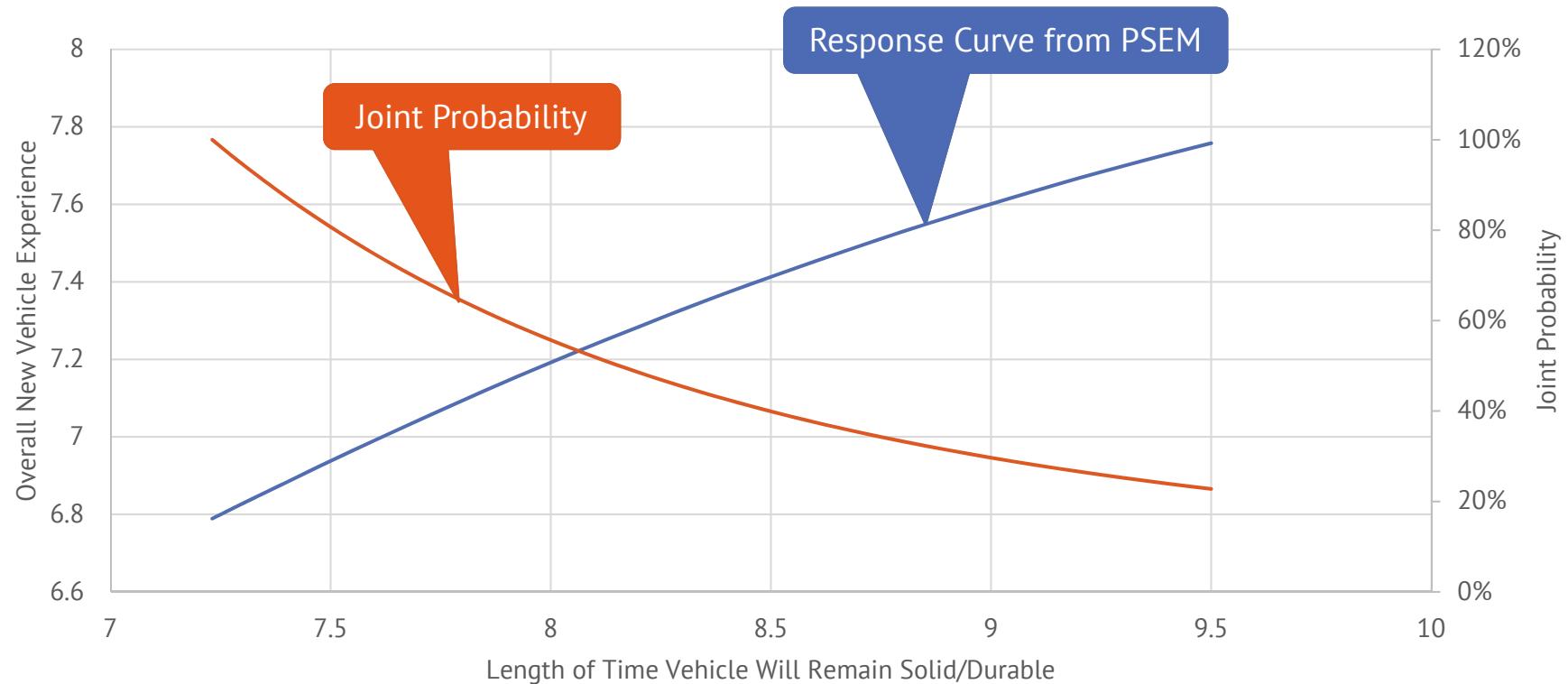
Joint Probability: 26%

Why not go
to the max?

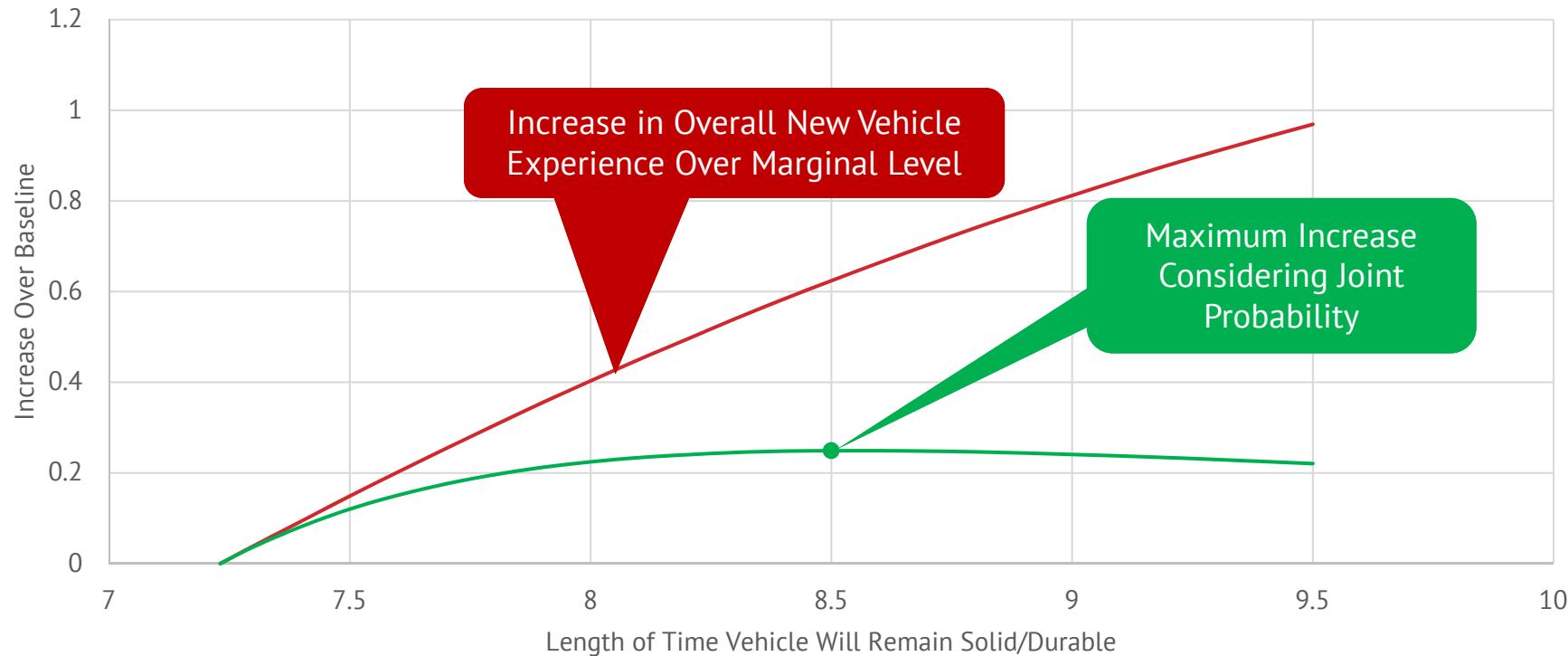
Optimization Constraint #1



Optimization Constraint #1



Optimization Constraint #1



Optimization

Optimization Constraint #1

- “Gain” × Joint Probability ÷ Cost

Optimization Constraint # 2

- Expert-defined constraints
- Automatic calculation of “gap to best level” via Multi-Quadrant Analysis

Simulation of Values

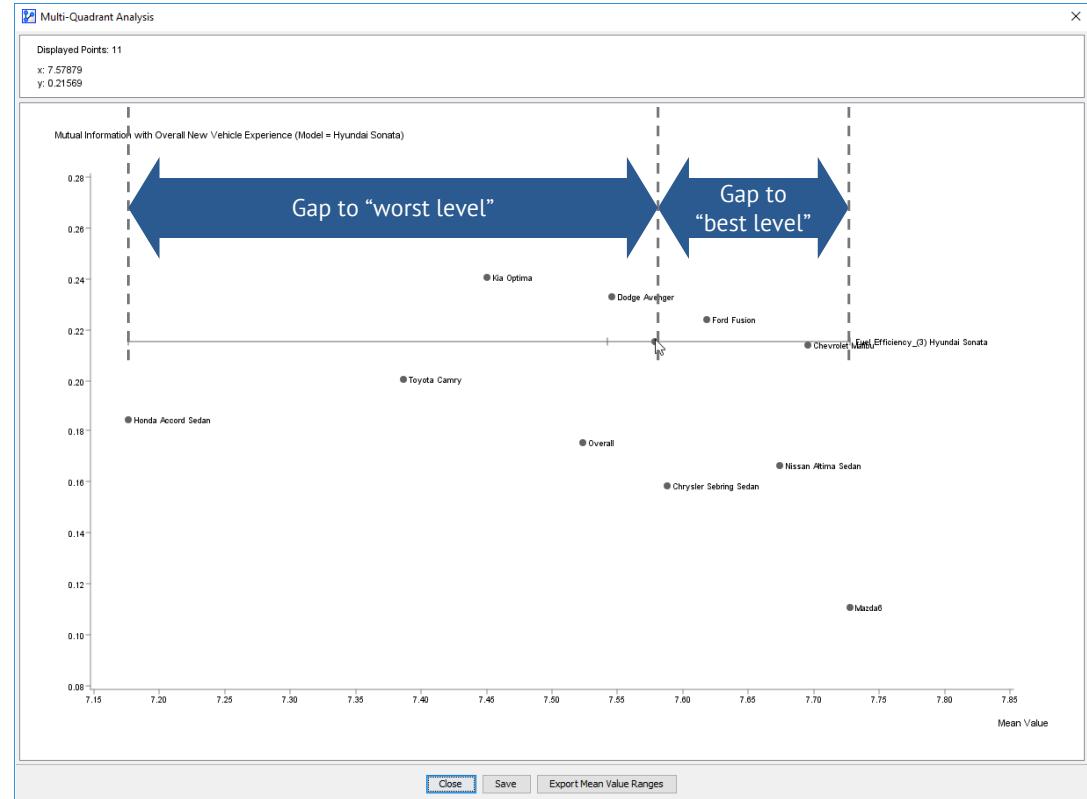
- Minimum Cross-Entropy

Optimization Objective

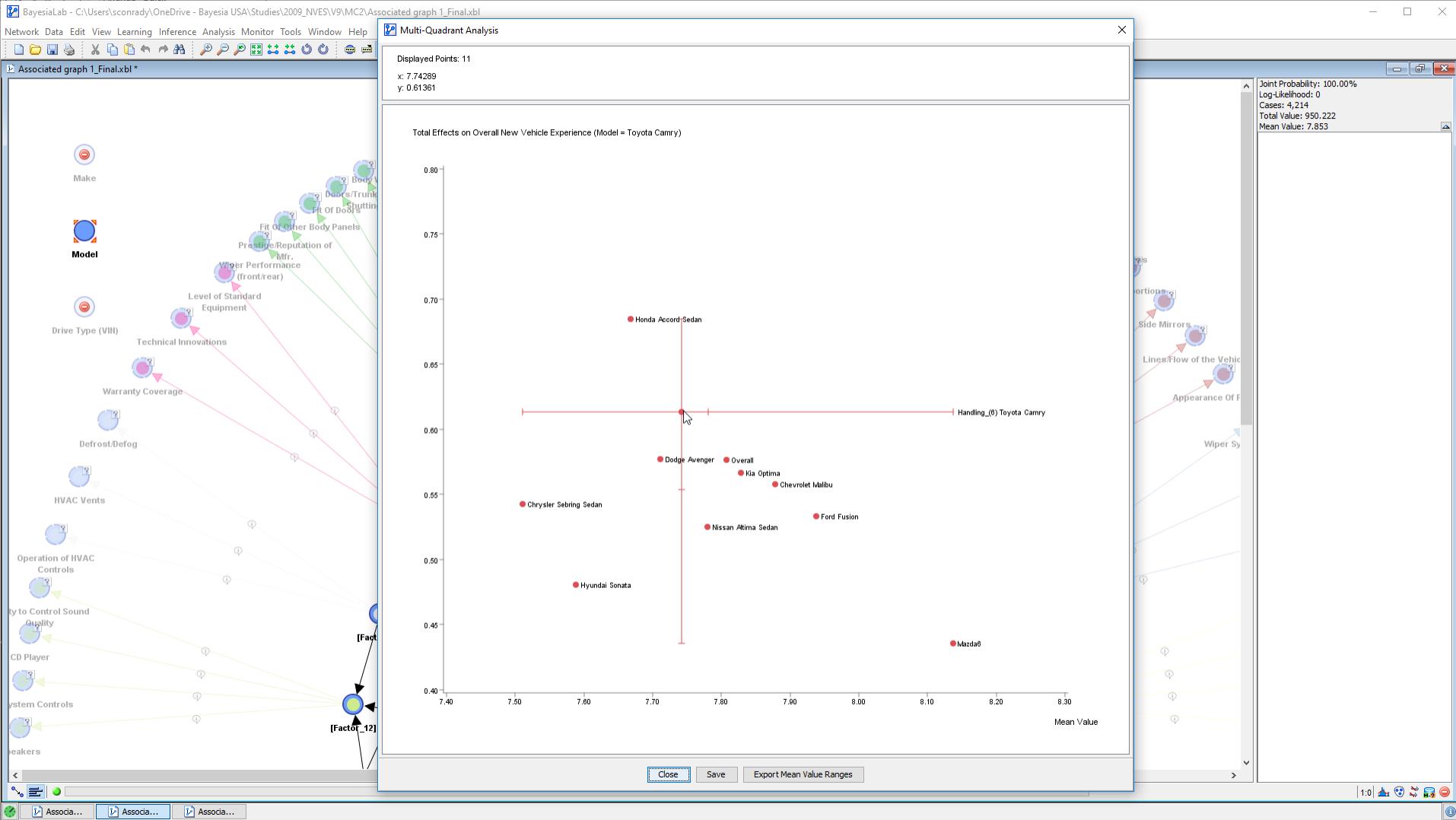
- Establish Priorities

Constraint #2

Multi-Quadrant Analysis as Source of Constraints







Optimization

Optimization Constraint #1

- “Gain” × Joint Probability ÷ Cost

Optimization Constraint # 2

- Expert-defined constraints
- Automatic calculation of “gap to best level” via Multi-Quadrant Analysis

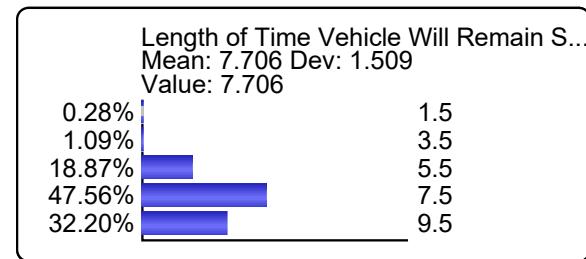
Simulation of Values

- Minimum Cross-Entropy

Optimization Objective

- Establish Priorities

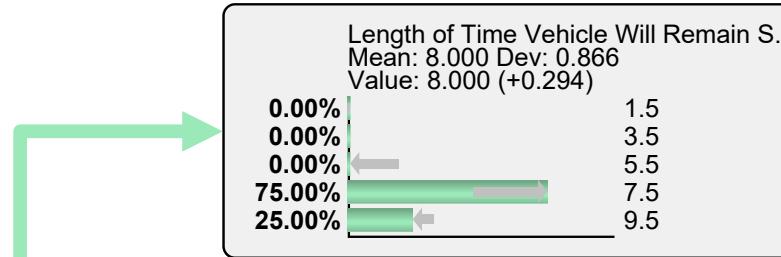
Simulation



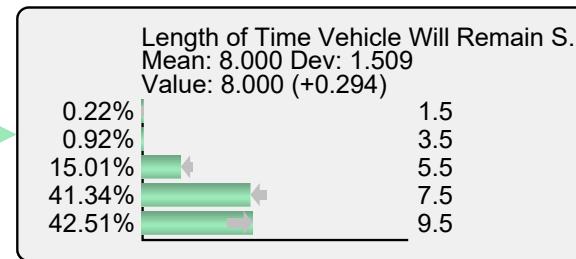
Marginal Distribution

Mean: 7.706

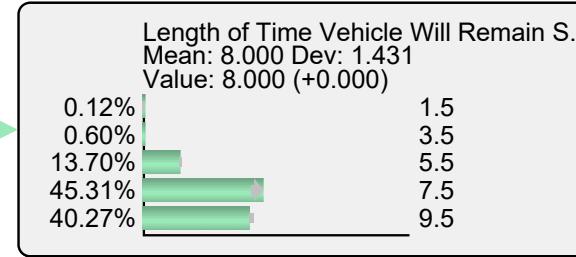
Now simulate a mean value of 8



Binary



Value Shift



MinXEnt



Optimization

Optimization Constraint #1

- “Gain” × Joint Probability ÷ Cost

Optimization Constraint # 2

- Expert-defined constraints
- Automatic calculation of “gap to best level” via Multi-Quadrant Analysis

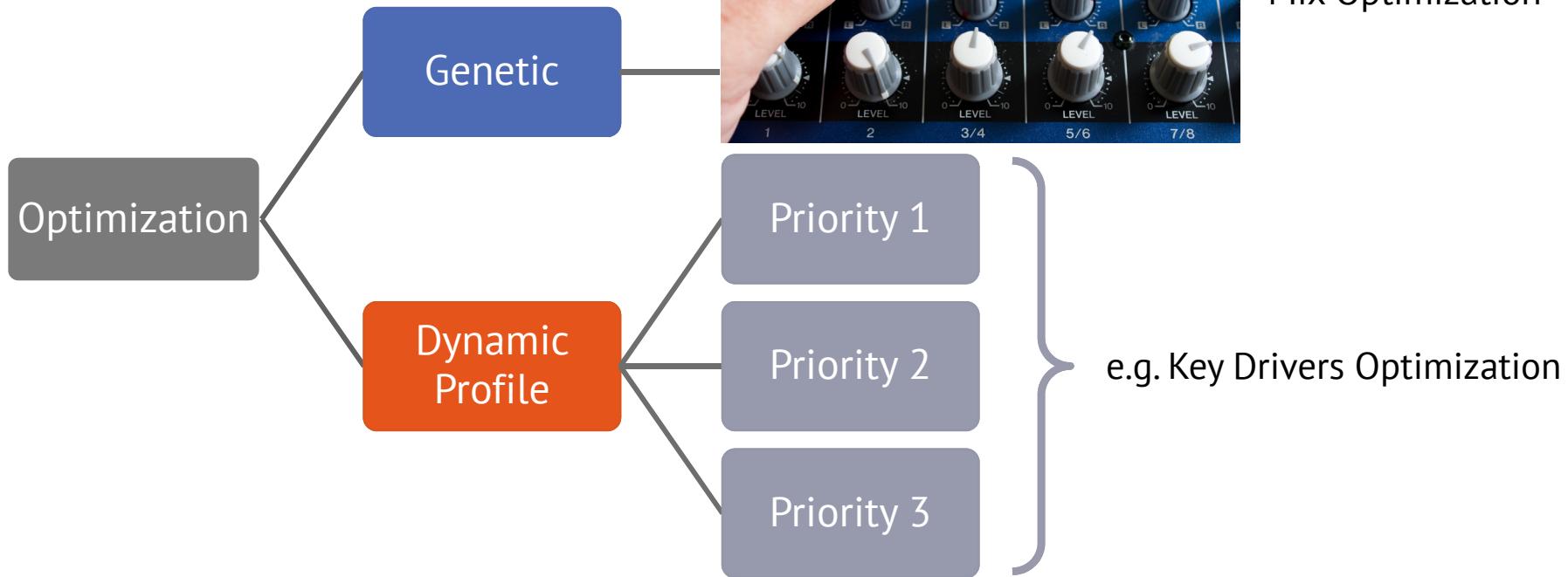
Simulation of Values

- Minimum Cross-Entropy

Optimization Objective

- Establish Priorities

Optimization



Optimization

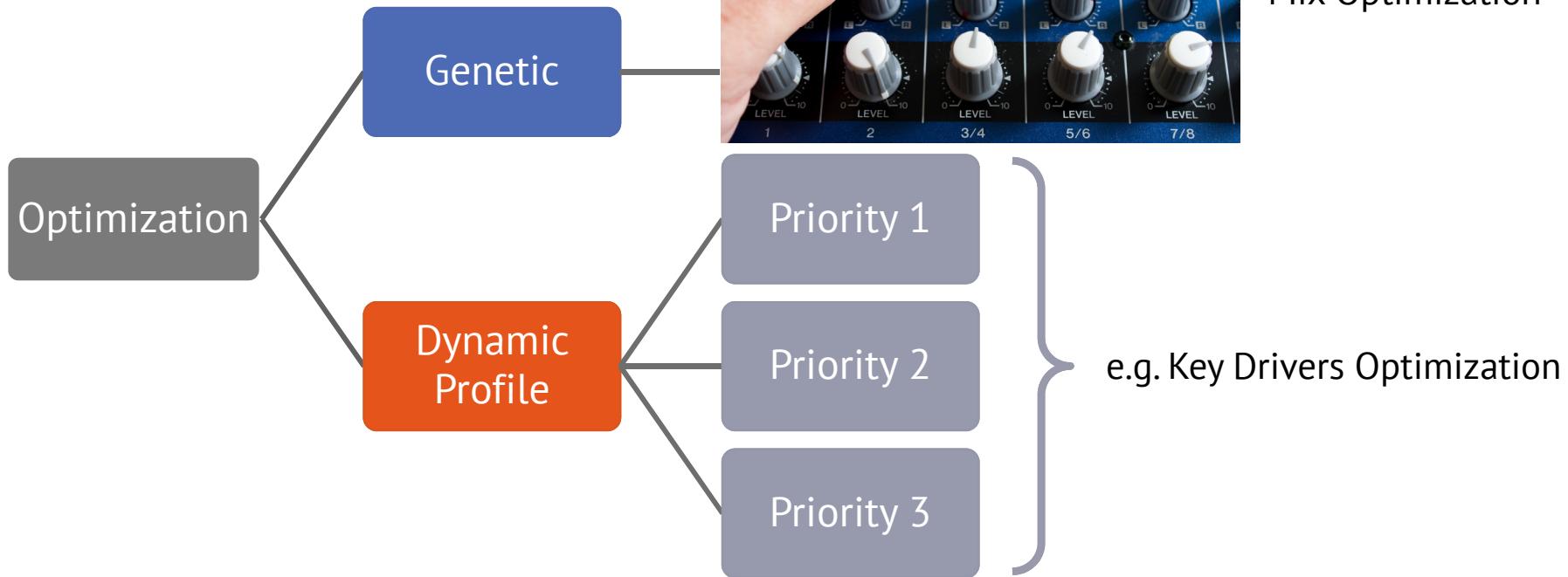
Genetic Optimization

Factor 15	Factor 1	Factor 2	Factor 5	Factor 7	Factor 25	Factor 27	Factor 3	Factor 10	Factor 23	Factor 21	Factor 6	Factor 12	Factor 20	Factor 24	Factor 14	Factor 22	Factor 26	Factor 17	Factor 18	Factor 13	Factor 0	Factor 4	Factor 8	Factor 11	Factor 9	Factor 16	Factor 19
7.98	7.6428	7.9837	7.9843	7.6736	7.7203	7.5317	7.6944	7.3772	7.902	7.6704	7.9897	7.7471	7.9541	7.7341	7.8653	7.6782	7.2518	7.5818	7.8011	7.6539	7.3971	7.6046	7.7374	7.7305	7.6038	7.8068	7.5773
7.8751	7.6428	8.4286	7.9096	8.1286	7.5816	8.1922	8.2986	7.2026	8.4386	8.1330	8.3600	8.3615	8.2713	7.7502	8.2785	8.1439	7.9747	7.9716	8.2469	8.0311	7.3551	7.7844	7.4880	8.1497	7.5302	7.8068	7.6538
(-0.1049)	(0.0000)	(0.4450)	(-0.0747)	(0.4549)	(-0.1387)	(0.6605)	(0.6042)	(-0.1746)	(0.5366)	(0.4627)	(0.3703)	(0.6144)	(0.3172)	(0.0161)	(0.4132)	(0.4657)	(0.7229)	(0.3898)	(0.4458)	(0.3771)	(-0.0420)	(0.1798)	(-0.2494)	(0.4191)	(-0.0735)	(0.0000)	(0.0765)



Is this
“actionable”?

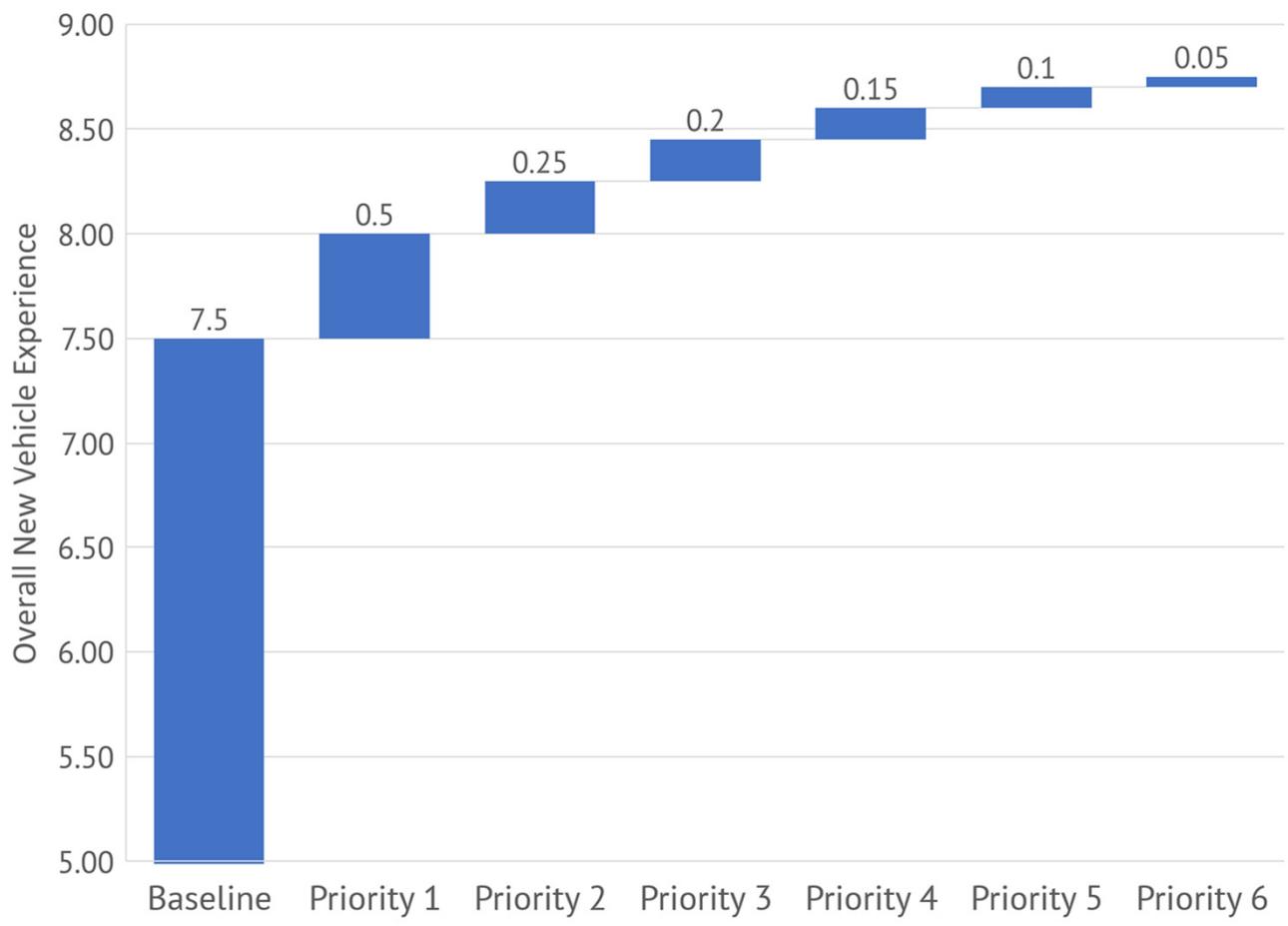
Optimization

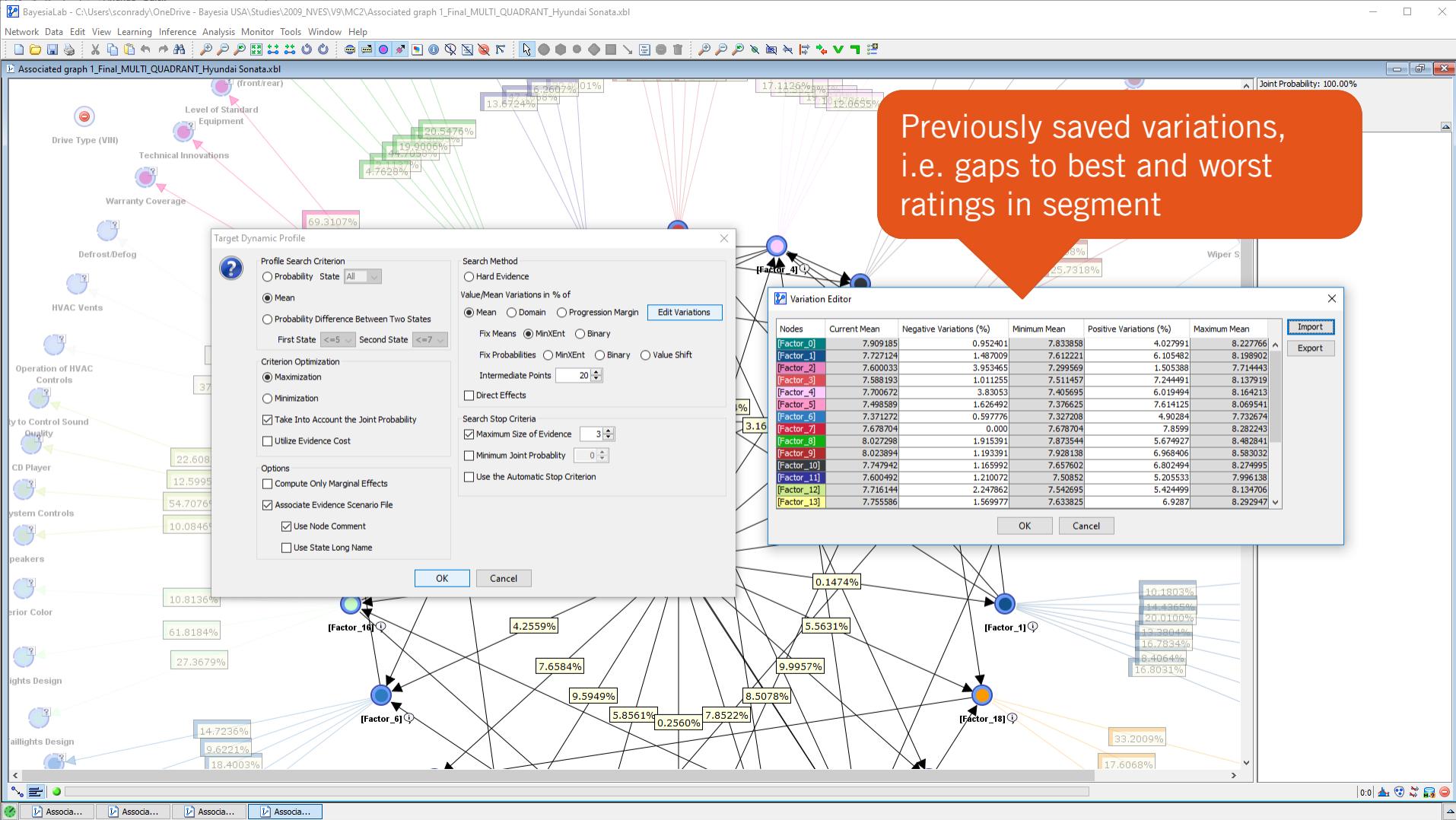


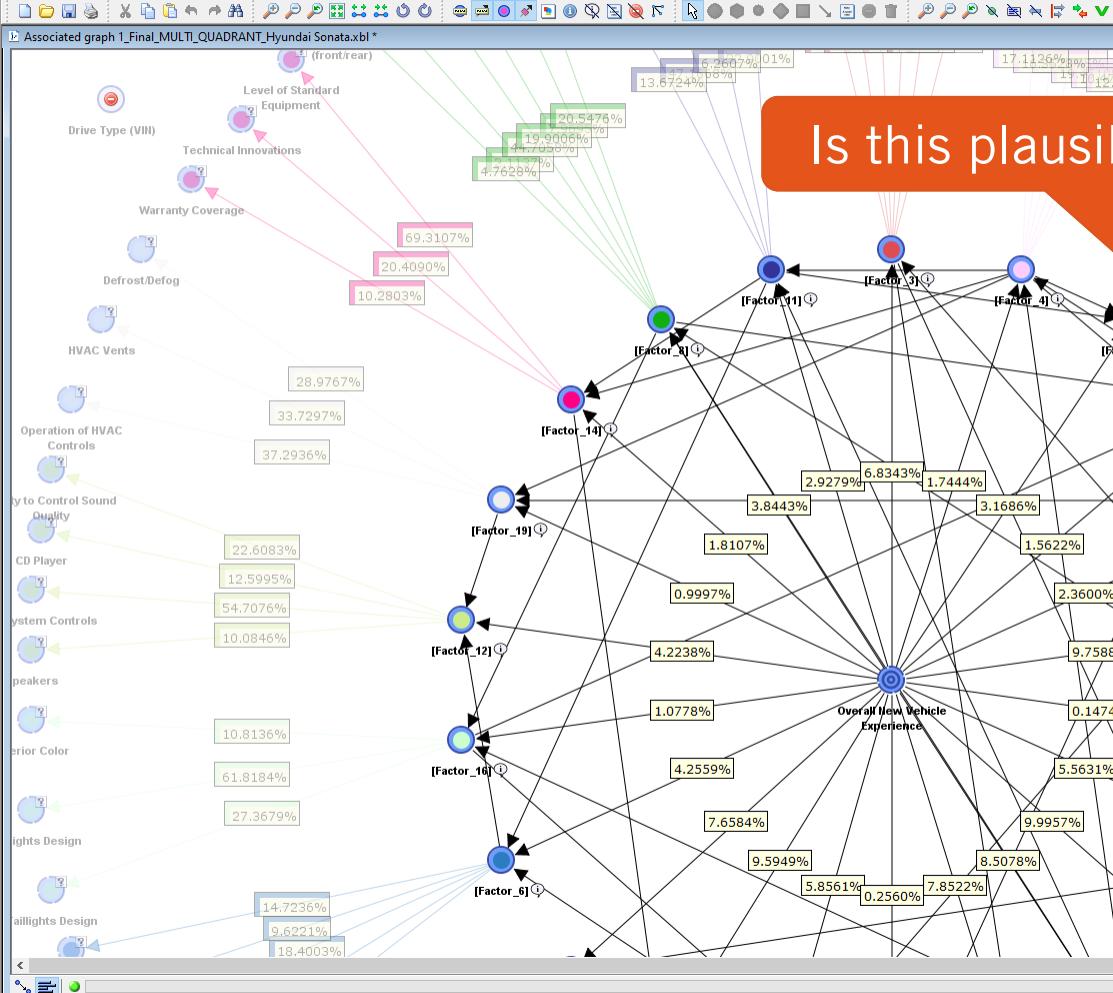


Optimization

Target Dynamic Profile







Target Dynamic Profile Associated graph 1_Final_MULTI_QUADRANT_Hyundai Sonata...

Analysis Context

Search method: Value/Mean Variations in % of Mean - Fix Mean (MinEnt)

Overall New Vehicle Experience							
Node	Initial Value/Mean	Value/Mean at T	Final Value/Mean	Value/Mean	95% Credible Interval	Joint Probability	
A priori					7.7035	0.2017	100.0000%
[Factor_13]	7.7556	7.7556	8.2929	8.0093	0.1940	64.5194%	
[Factor_9]	8.0239	8.2747	8.5830	8.0817	0.1964	56.196%	
[Factor_5]	7.4986	7.8567	8.0695	8.1297	0.1947	49.7302%	
[Factor_10]	7.7479	8.1453	8.2750	8.1465	0.1970	46.7377%	
[Factor_3]	7.5882	8.0384	8.1379	8.1579	0.1956	44.4684%	
[Factor_17]	7.6191	8.1351	7.8730	8.1823	0.1935	13.0344%	
[Factor_7]	7.6787	8.1506	8.2822	8.1858	0.1930	11.0292%	
[Factor_21]	7.8604	8.4219	8.4602	8.1868	0.1931	11.4884%	

Other Nodes		
Node	Initial Value/Mean	Final Value/Mean
[Factor_6]	7.3713	7.8833
[Factor_11]	7.6905	8.0438
[Factor_15]	7.8546	8.3574
[Factor_1]	7.7271	8.3058
[Factor_8]	8.0273	8.5528
[Factor_16]	8.0174	8.5457
[Factor_4]	7.7007	8.1974
[Factor_14]	7.7194	8.0644
[Factor_2]	7.6000	7.9218
[Factor_19]	7.6479	8.1150
[Factor_12]	7.7161	8.1560
[Factor_18]	8.0067	8.3638
[Factor_20]	7.6885	8.1348
[Factor_0]	7.9092	8.2847

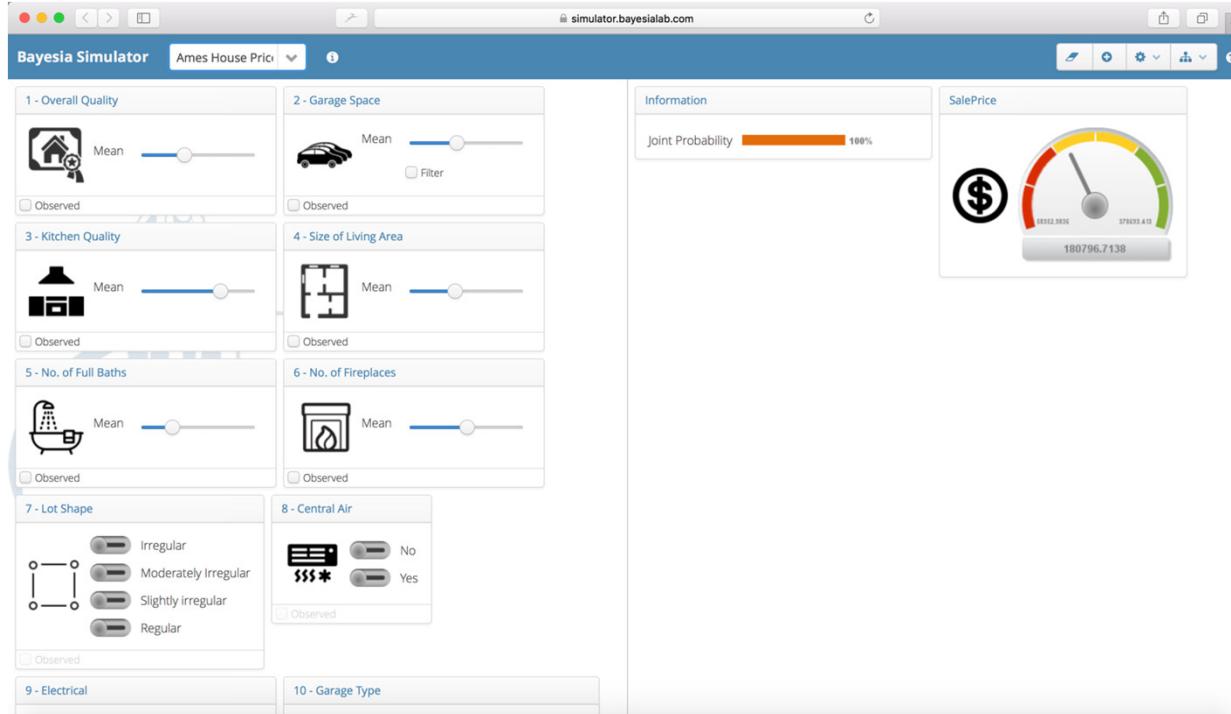
Close Save As... Print Save Scenario

2009 Hyundai Sonata



Definitely!

BayesiaLab WebSimulator



Just for reference, since you will ask...

BAYESIALAB

Starting at

- Desktop Software (Win/Mac/Linux) \$10,900/year

BEKEE

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BAYESIALAB WebSimulator

- Web Service Subscription \$3,600/year

BayesiaLab

We want you to try BayesiaLab:

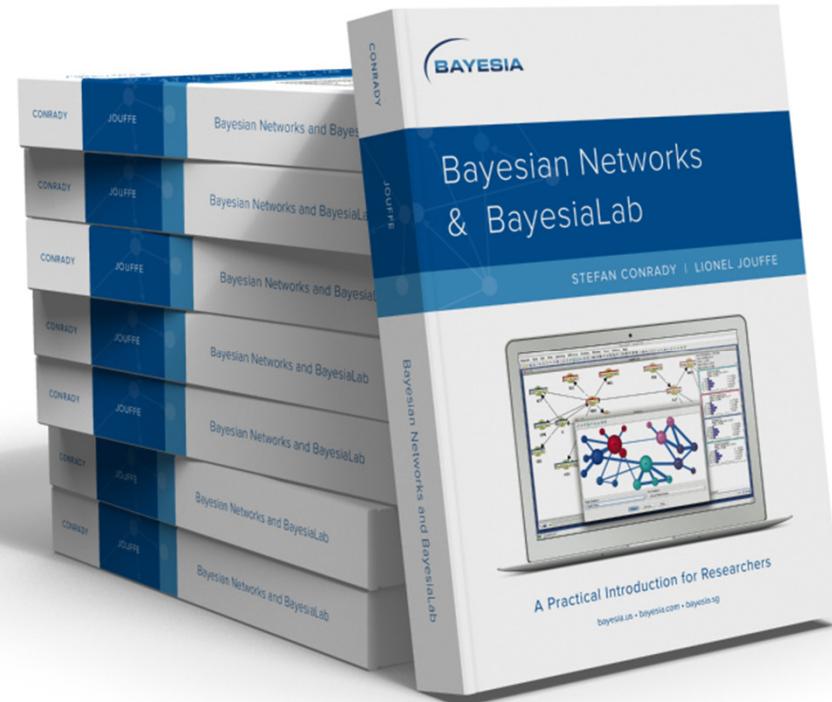
- Restricted trial version:
www.bayesia.com/trial-download
- An unrestricted evaluation version is available upon request.



Bayesian Networks & BayesiaLab

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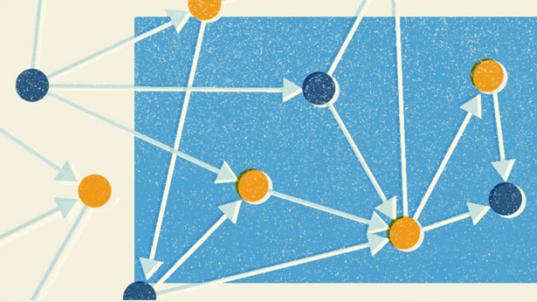


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- October 24-26, 2017
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- November 20–22, 2017
Singapore
- November 27–29, 2017
Sydney, Australia





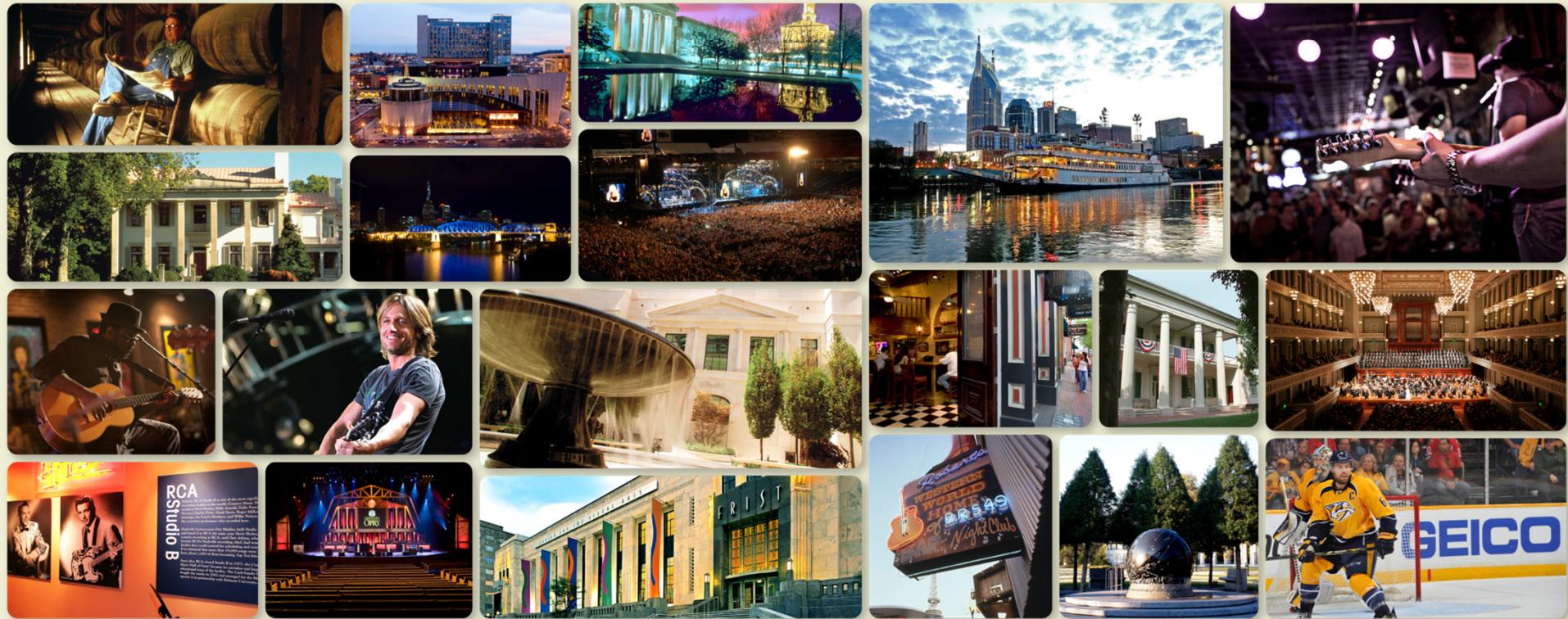
4TH ANNUAL

BAYESIALAB CONFERENCE



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5th Annual BayesiaLab Conference

September 28-29, 2017

PARIS



Final Questions?



Thank You!



stefan.conrady@bayesia.us



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