



**BAYESIALAB**

# Spatial Optimization With Bayesian Networks & BayesiaLab

The webinar will start at:

**13:00:00**

The current time is:

**13:00:54**

Central Daylight Time, UTC-5

# Today's Program

## Introduction

- Our Team
- Our Company
- Our Technology

## Introductory Software Demo

- Mapping with BayesiaLab and the Google Maps API

## Spatial Computation & Optimization

- Example 1: Drive Time Bands
- Example 2: Hub Location Optimization



20 min.



40 min.

# Your BayesiaLab Team Today



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# Disambiguation



Our Company



Our Product

## The Paradigm

### BAYESIAN NETWORKS\*

**Judea Pearl**

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Computer Science Department

University of California, Los Angeles, CA 90024

*judea@cs.ucla.edu*

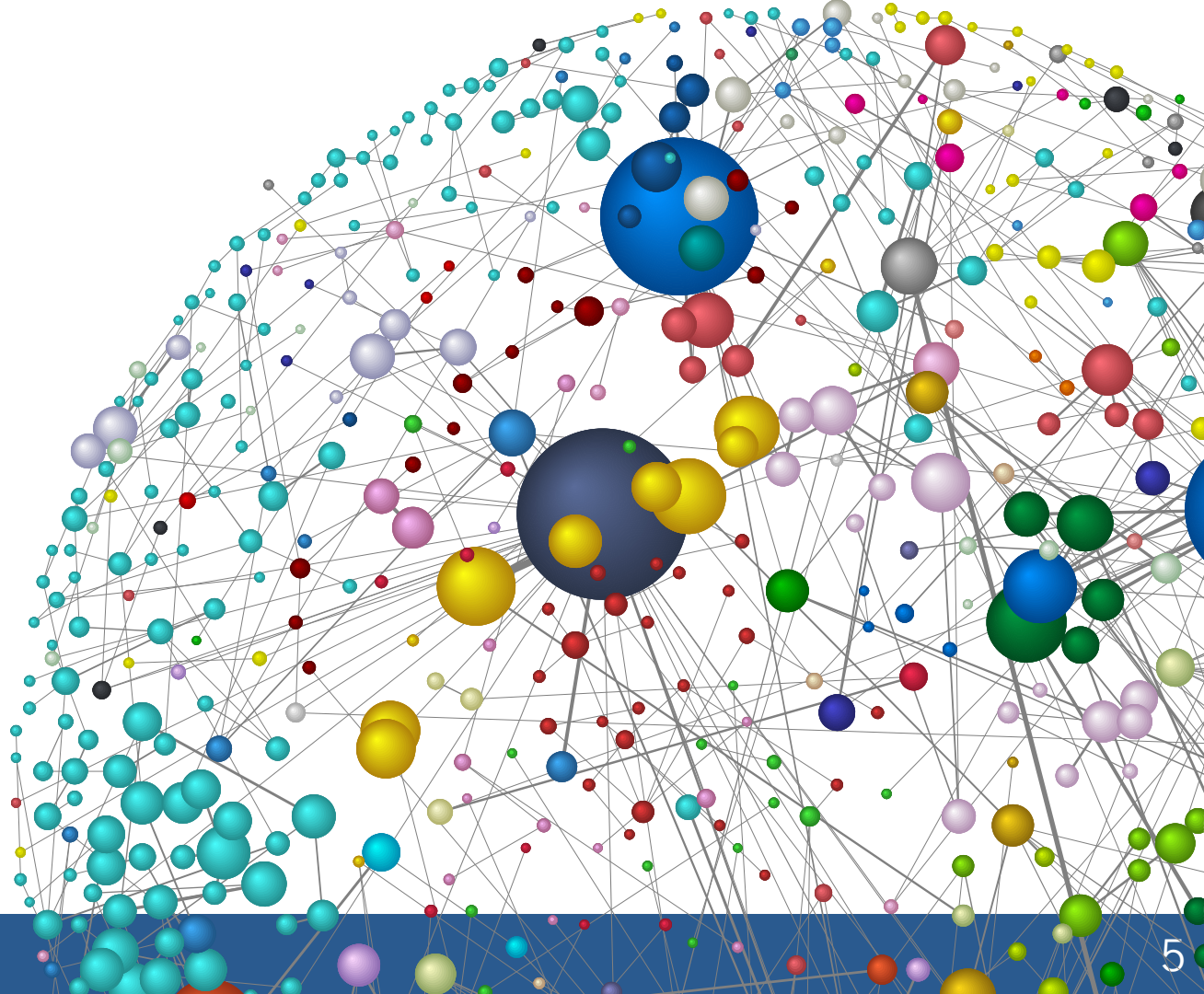
Bayesian networks were developed in the late 1970's to model distributed processing in reading comprehension, where both semantical expectations and perceptual evidence must be combined to form a coherent interpretation. The ability to coordinate bi-directional inferences filled a void in expert systems technology of the early 1980's, and Bayesian networks have emerged as a general representation scheme for uncertain knowledge [Pearl, 1988, Heckerman *et al.*, 1995, Jensen, 1996, Castillo *et al.*, 1997].

Bayesian networks are directed acyclic graphs (DAGs) in which the nodes represent vari-





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



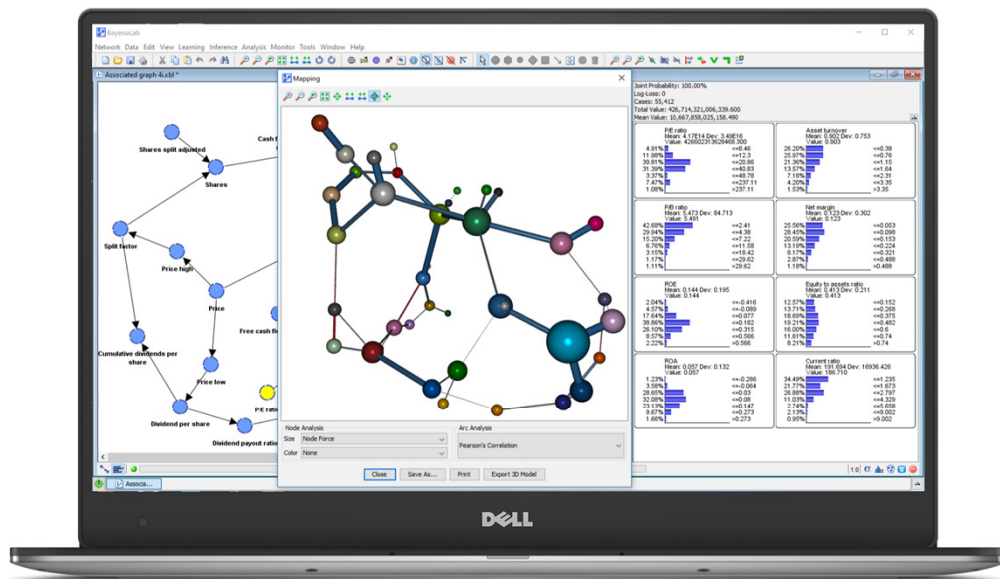


# Bayesian Networks & BayesiaLab

## A Practical Introduction for Researchers

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





A desktop software for:

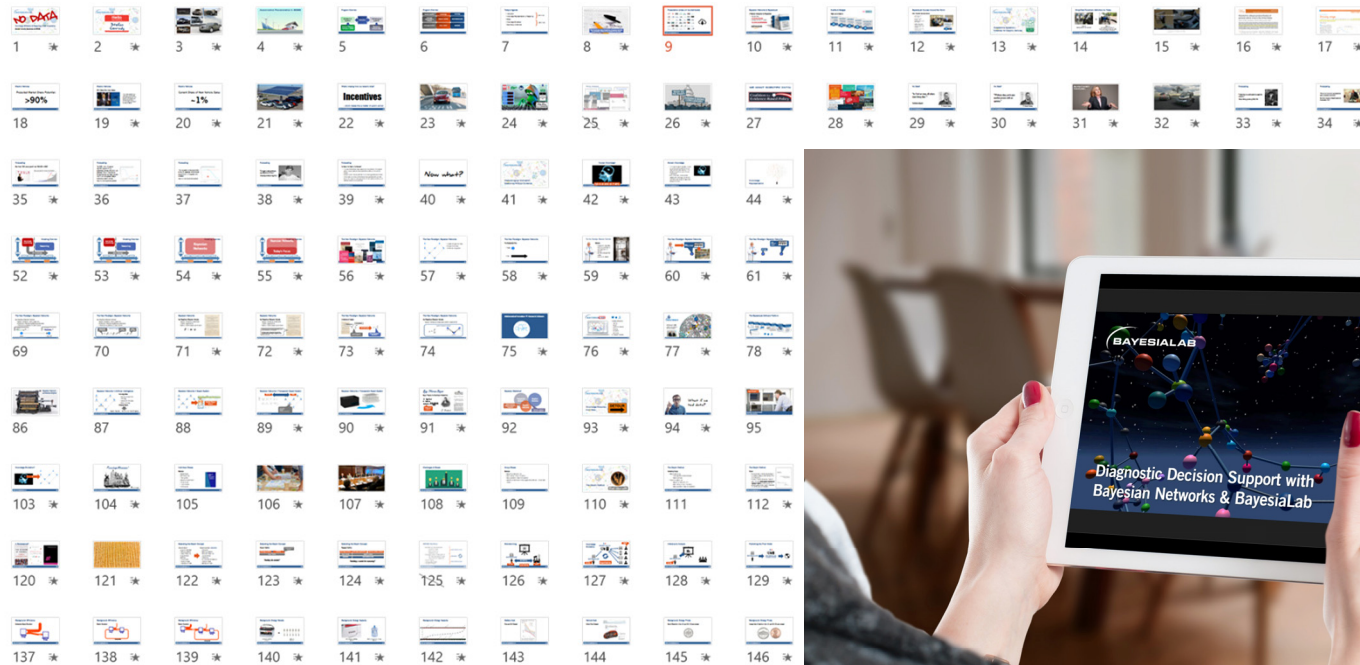
- encoding
- learning
- editing
- performing inference
- analyzing
- simulating
- optimizing

**& GIS  
Mapping**

with Bayesian networks.



# Webinar Slides, Data, and Recording Available

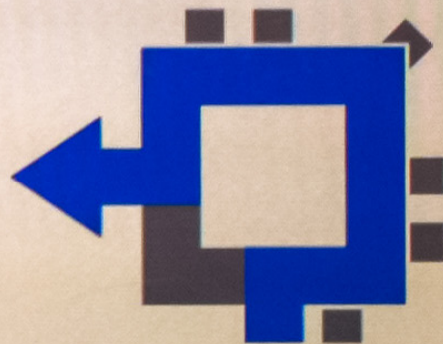
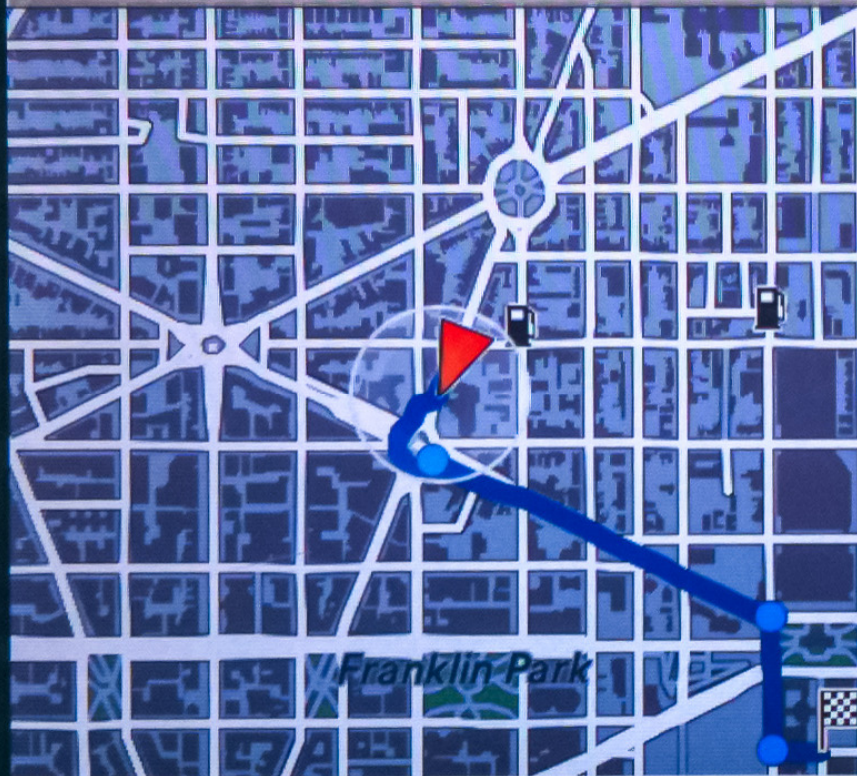


# Motivation





MASSACHUSETTS AVE NW

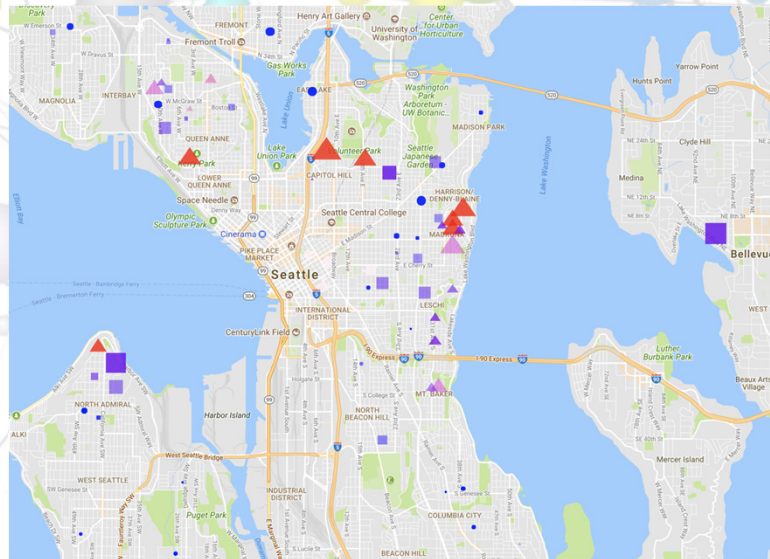


50 ft

0.20 mi

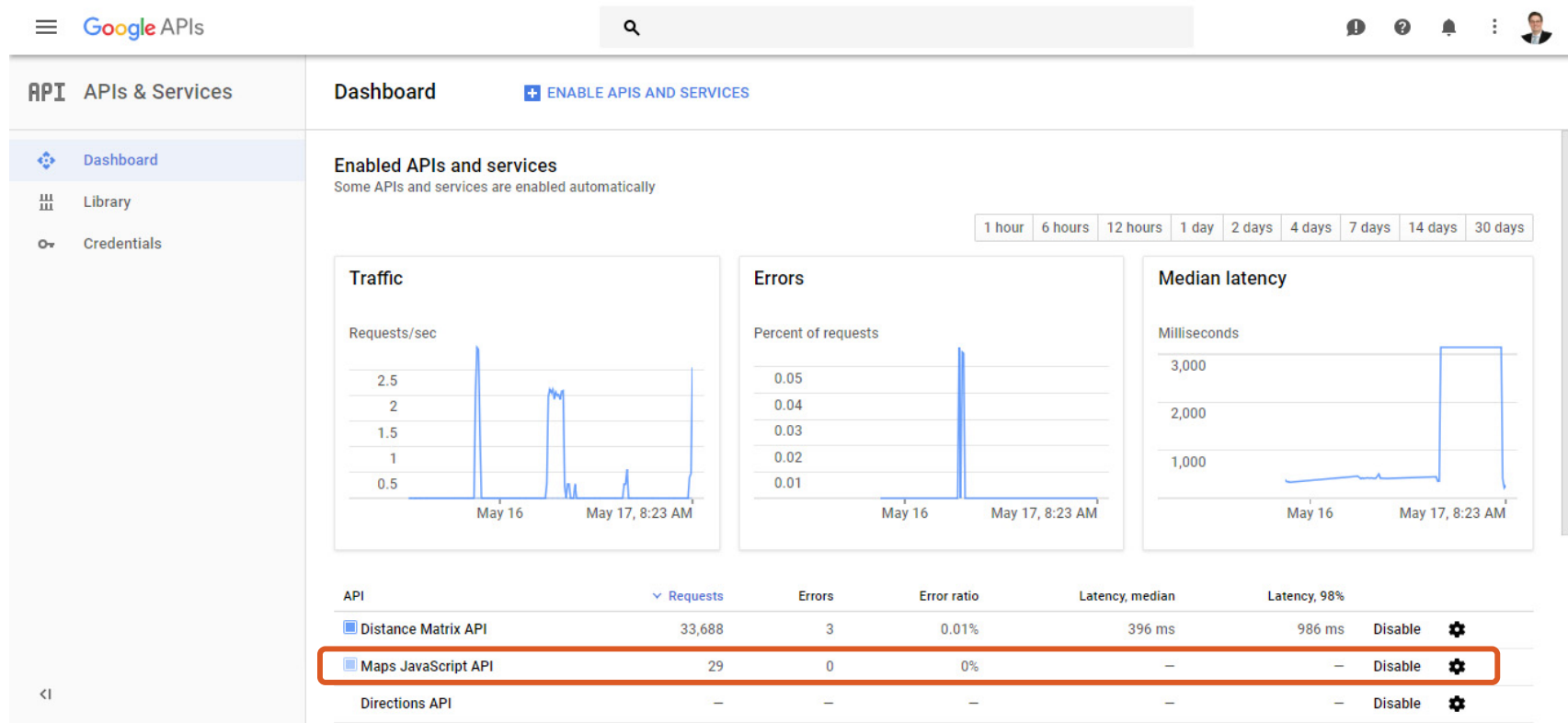




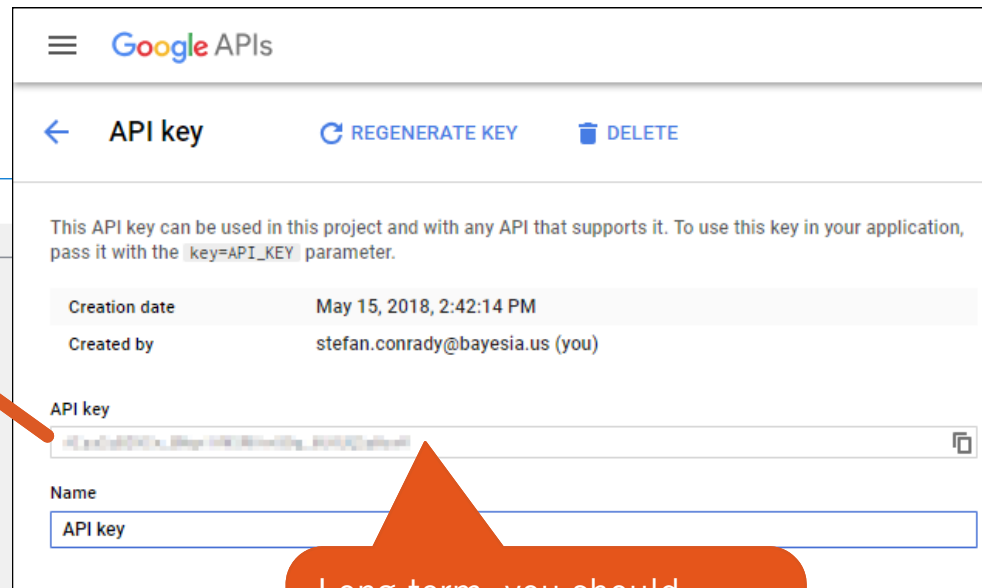
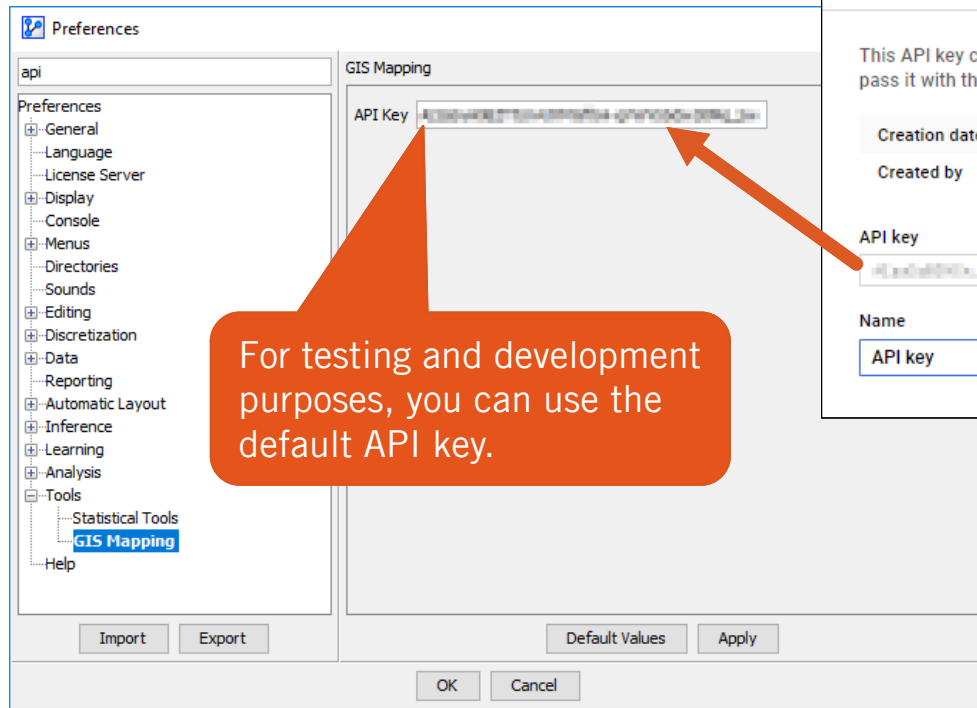


# GIS Mapping with BayesiaLab and the Google API

# Google Maps JavaScript API



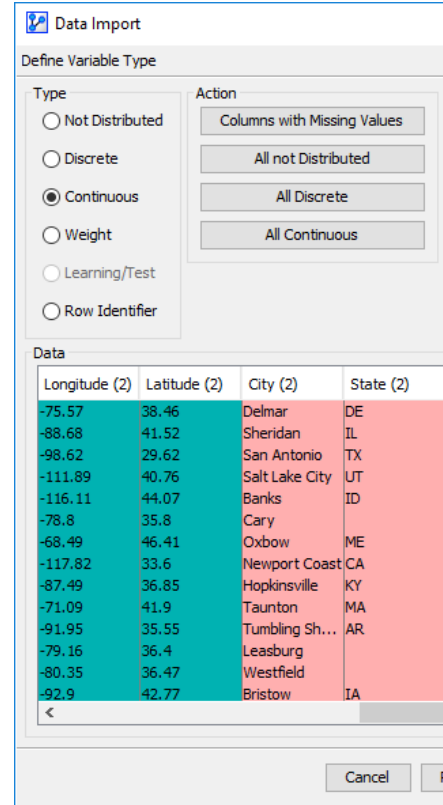
# BayesiaLab Setup



# GIS Mapping with BayesiaLab and the Google API

## The Basics

- BayesiaLab can display observed or inferred values with coordinates on a Google map.
- Longitude and latitude are used as coordinates.
- Longitude and latitude must be defined as continuous variables and **discretized** during import, even though they will be used as **undiscretized** values for map display.



Data Import

Define Variable Type

Type

- ☐ Not Distributed
- ☐ Discrete
- ☒ Continuous
- ☐ Weight
- ☐ Learning/Test
- ☐ Row Identifier

Action

- Columns with Missing Values
- All not Distributed
- All Discrete
- All Continuous

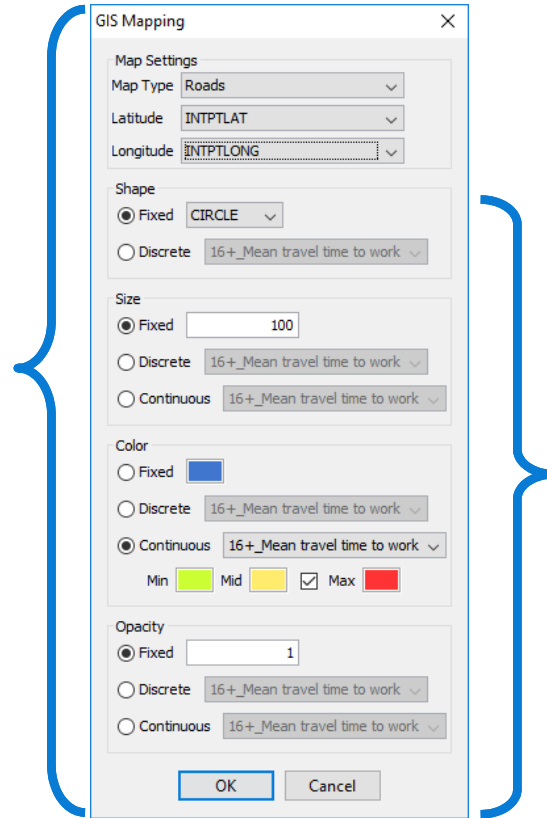
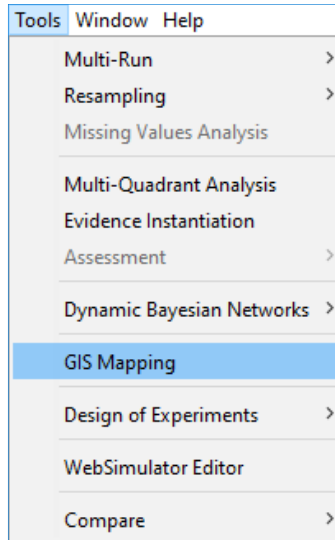
Data

Longitude (2)	Latitude (2)	City (2)	State (2)
-75.57	38.46	Delmar	DE
-88.68	41.52	Sheridan	IL
-98.62	29.62	San Antonio	TX
-111.89	40.76	Salt Lake City	UT
-116.11	44.07	Banks	ID
-78.8	35.8	Cary	NC
-68.49	46.41	Oxbow	ME
-117.82	33.6	Newport Coast	CA
-87.49	36.85	Hopkinsville	KY
-71.09	41.9	Taunton	MA
-91.95	35.55	Tumbling Sh...	AR
-79.16	36.4	Leasburg	TX
-80.35	36.47	Westfield	MA
-92.9	42.77	Bristow	IA

<

Cancel

# GIS Mapping with BayesiaLab and the Google API

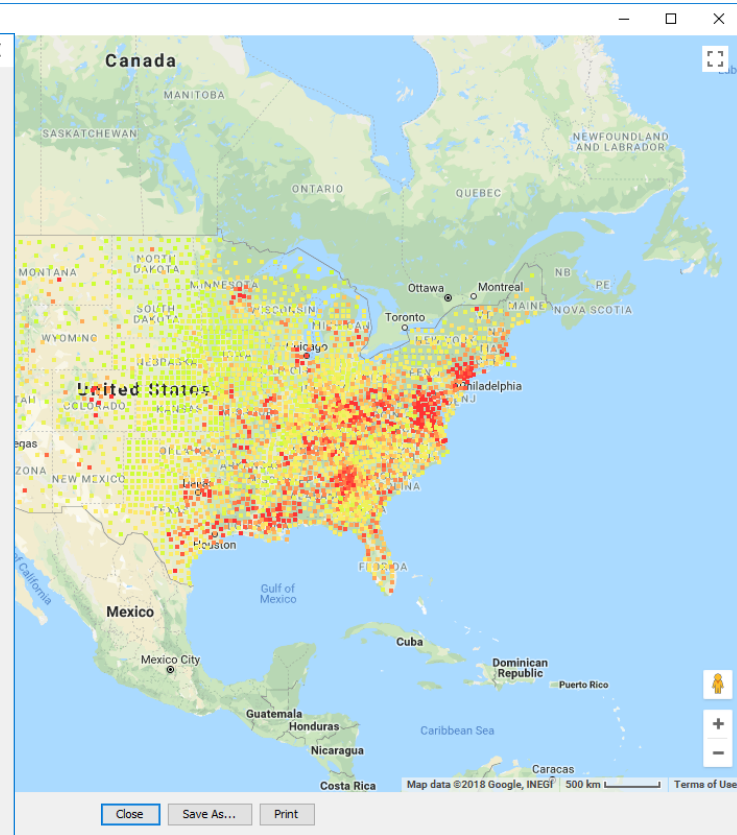
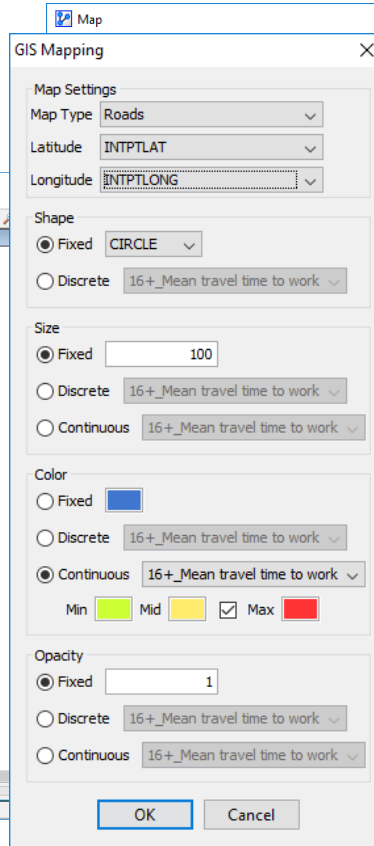
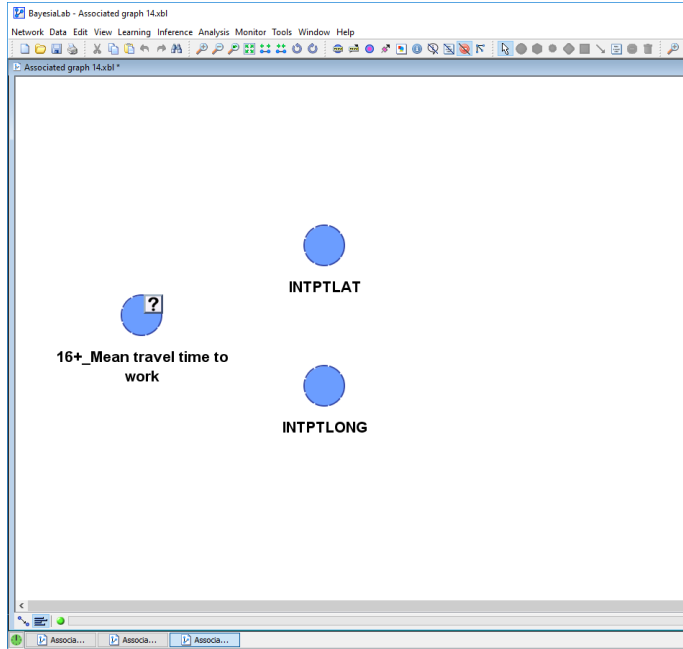


Four attributes can be displayed per observations:

- Shape
- Size
- Color
- Opacity

# Introductory Example: Mapping Commuting Time

## Commuting Time by County







# Spatial Learning and Optimization

Bayesian Networks & BayesiaLab




# Spatial Learning and Optimization

## Optimization Problems Under Consideration

1. One origin, one destination


➔ Shortest Path Problem

 2. One origin, many destinations

➔ Drive Time Bands

3. Many origins, one destination

➔ Store Location Problem

 4. Many origins, one hub, many destinations

➔ Hub Location Problem

5. Many origins, multiple hubs, many destinations

➔ Multi-Hub Location Problem

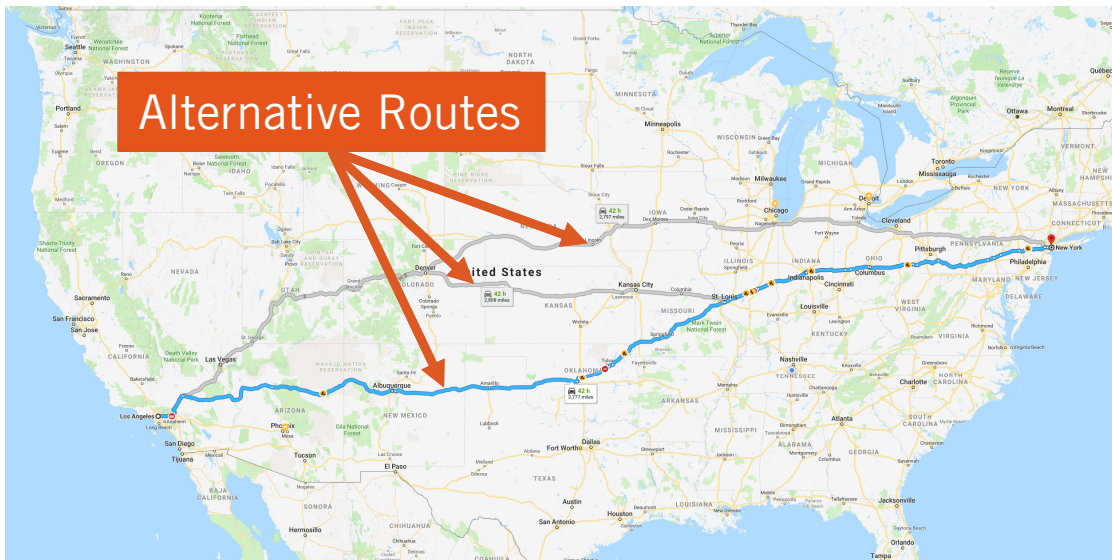
## Common Objective

- Minimize “cost function,” e.g., travel time, distance, fuel consumption, number of turns, etc.
- Further assumption: all “participants” have same objective.

# Drive Time Bands

## Computing the “Cost” for One Origin and One Destination

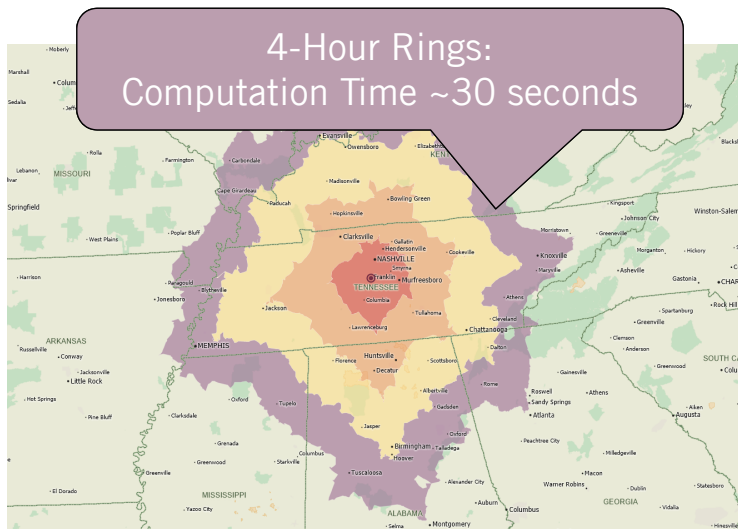
- “Search the Map” → slow, but accurate



# Drive Time Bands

## Computing the Cost for One Origin and Many Destinations

- “Search the Map” → slow, but accurate



# Drive Time Bands

## Computing the Cost

- “Search the Map” → slow, but accurate

- Great-Circle Distance Computation

$$\begin{aligned}d &= 2r \arcsin\left(\sqrt{\text{hav}(\varphi_2 - \varphi_1) + \cos(\varphi_1) \cos(\varphi_2) \text{hav}(\lambda_2 - \lambda_1)}\right) \\&= 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1) \cos(\varphi_2) \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)\end{aligned}$$

- Easy and fast to calculate.
- “As the crow flies” may be an unrealistic assumption.
- Travel time may be more relevant than distance.

# Drive Time Bands

## Idea: “Create a Look-Up Table for All Origin-Destination Pairs”

- 29,788 ZIP Codes in the U.S.
- A complete distance matrix would contain 887,324,944 cells.
- Current computation speed with Google Distance Matrix API: 2 requests/sec.
- Estimated computation time: ~14 years.

APPROXIMATE!

# Drive Time Bands

## Idea

- Approximation through machine learning.

## Proposed Approach

- Utilize database of actual point-to-point travel data.
- Learn a Bayesian network from this dataset.
- Now we can infer the “cost” as a function of origin and destination.





# Drive Time Bands



## Workflow in Detail



- Take a random sample (~100,000) of origin-destination ZIP code pairs and calculate routes with the Google Distance Matrix API.
- Perform Augmented Naïve Learning.
- Evaluate Target Performance.
- Associate new data set with points to be evaluated.
- Generate map.







  Associa...

  Associa...

  Associa...

  Associa...



**Data Import**

Discretization and Aggregation

Multiple Discretization

Type: Tree

Intervals: 25

Target: Time (h)

☐ Create a class for each type of discretization

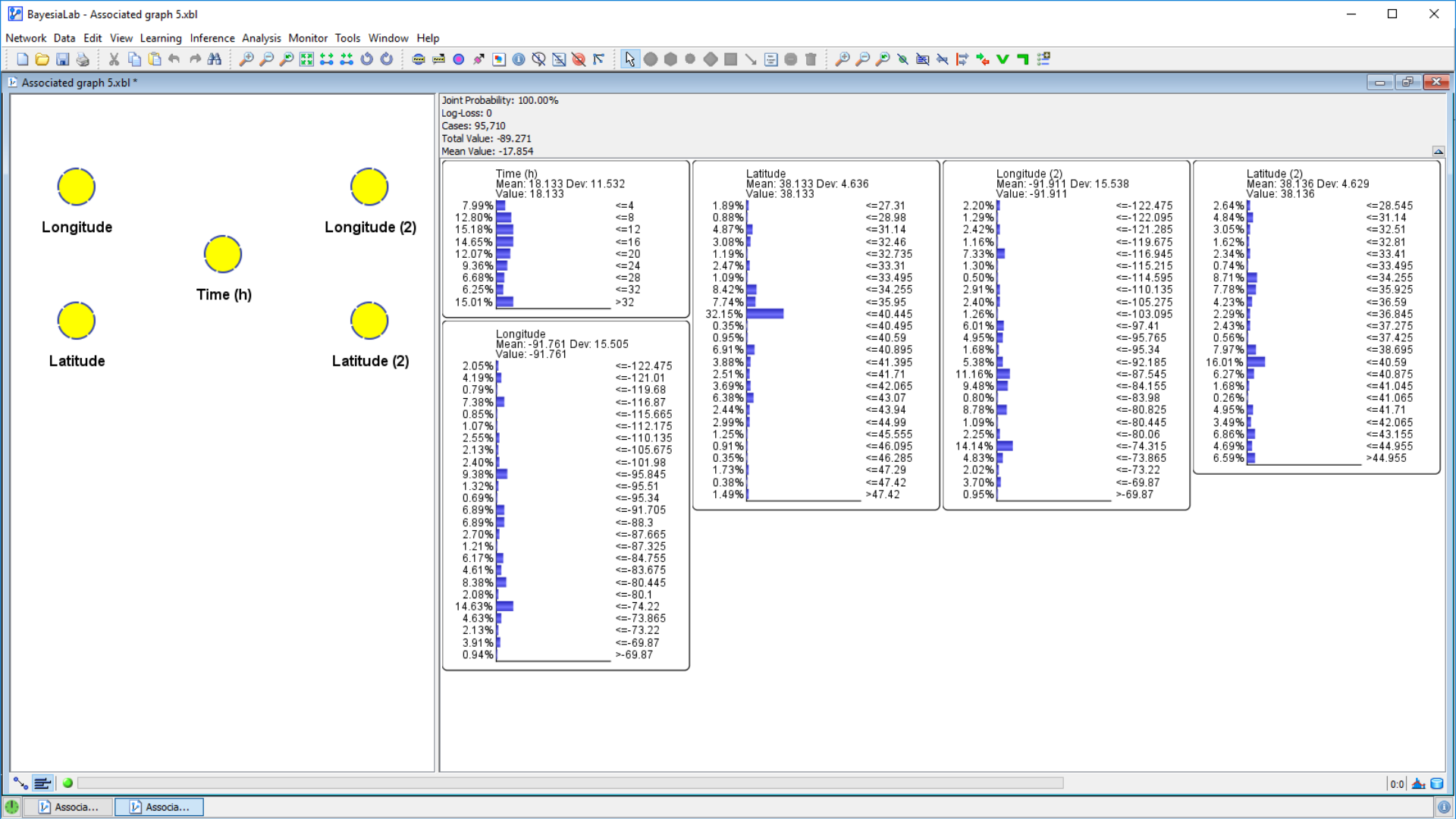
Load Discretizations

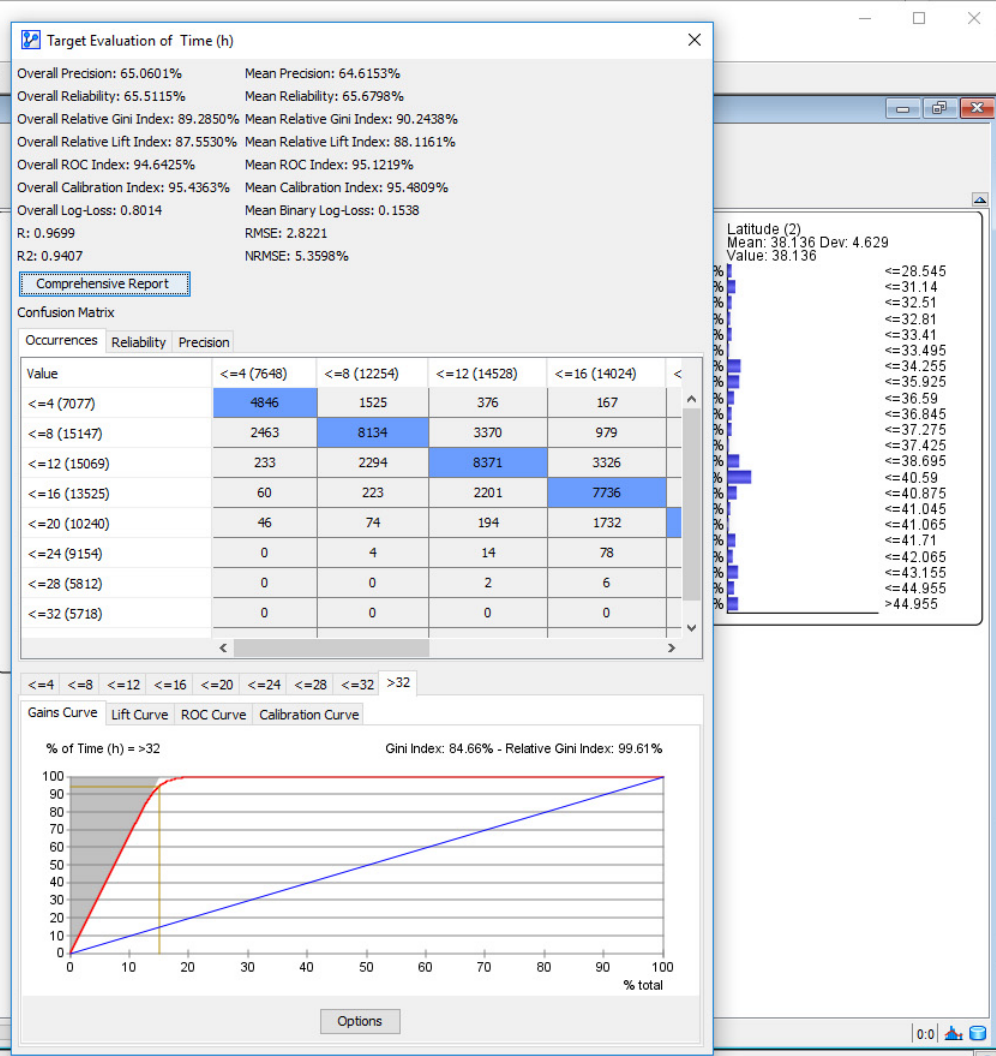
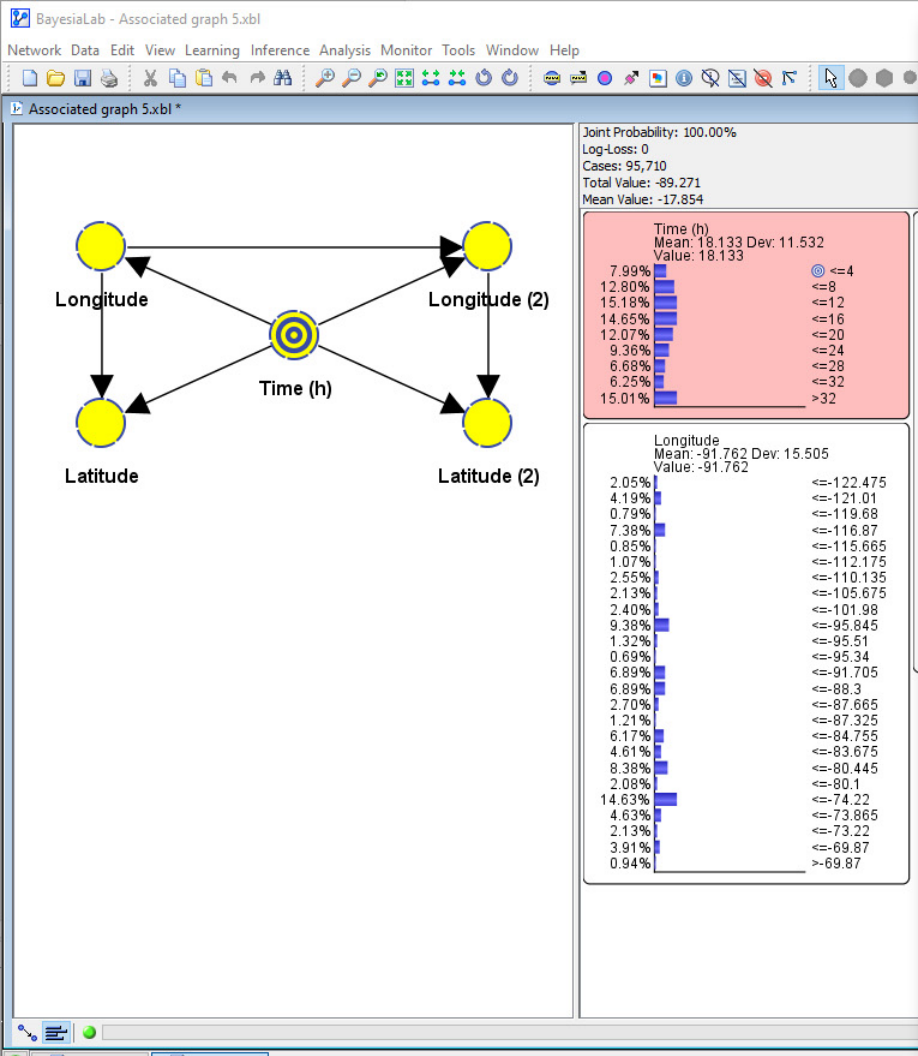
Data

Longitude	Latitude	City	State	Zipcode	Longitude (2)	Latitude (2)	City (2)	State (2)	Zipcode (2)	Time (h)
-89.8	37.44				-75.57	38.46				15.24694444
-89.8	37.44				-88.68	41.52				5.313611111
-89.8	37.44				-98.62	29.62				13.18111111
-89.8	37.44				-111.89	40.76				20.87638889
-89.8	37.44				-116.11	44.07				25.88611111
-89.8	37.44				-78.8	35.8				11.67916667
-89.8	37.44				-68.49	46.41				24.59388889
-89.8	37.44				-117.82	33.6				27.59416667
-89.8	37.44				-87.49	36.85				2.9425
-89.8	37.44				-71.09	41.9				19.25972222
-89.8	37.44				-91.95	35.55				4.341944444
-89.8	37.44				-79.16	36.4				11.54527778
-89.8	37.44				-80.35	36.47				10.07194444

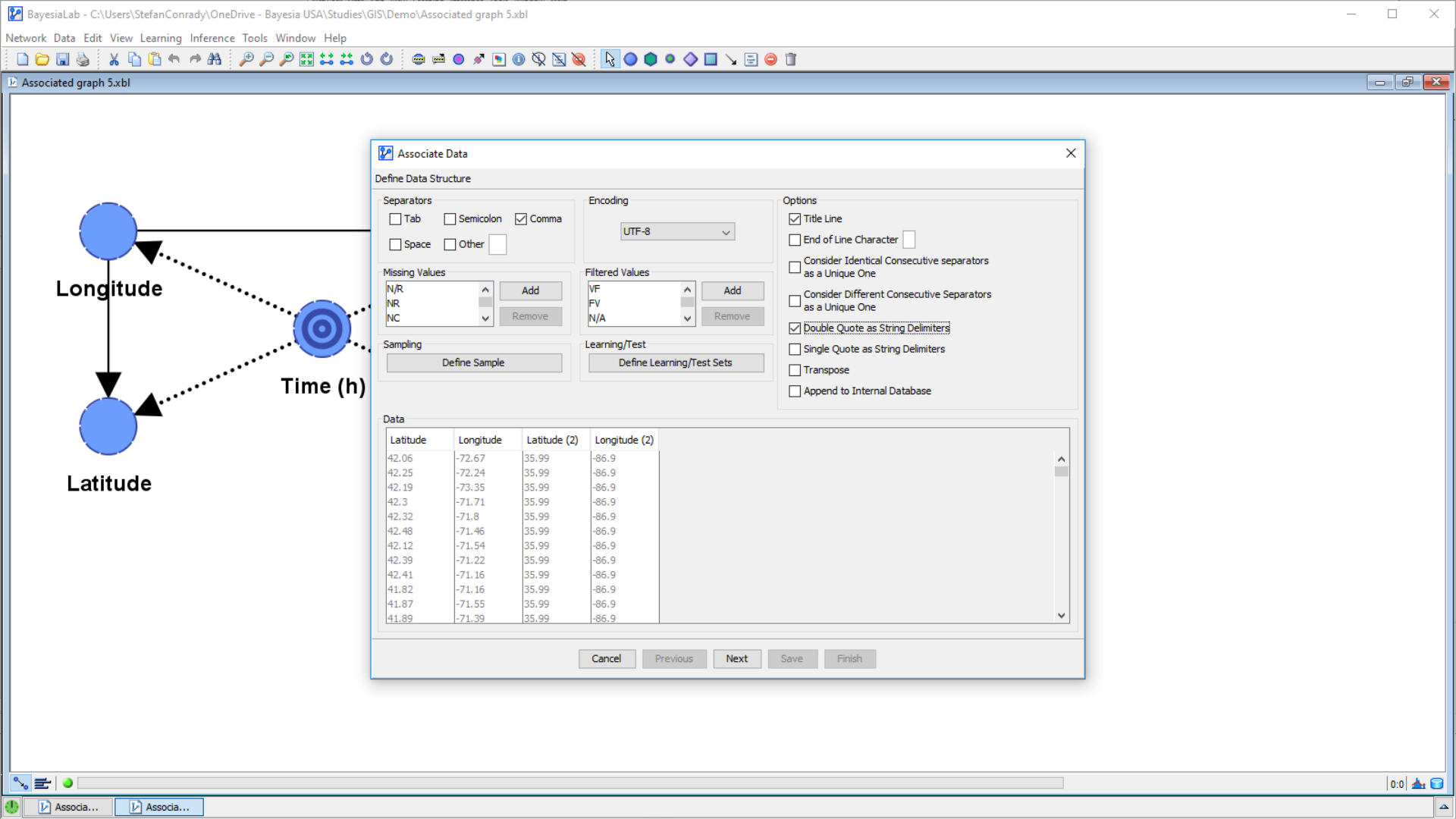
Select All Continuous Select All Discrete

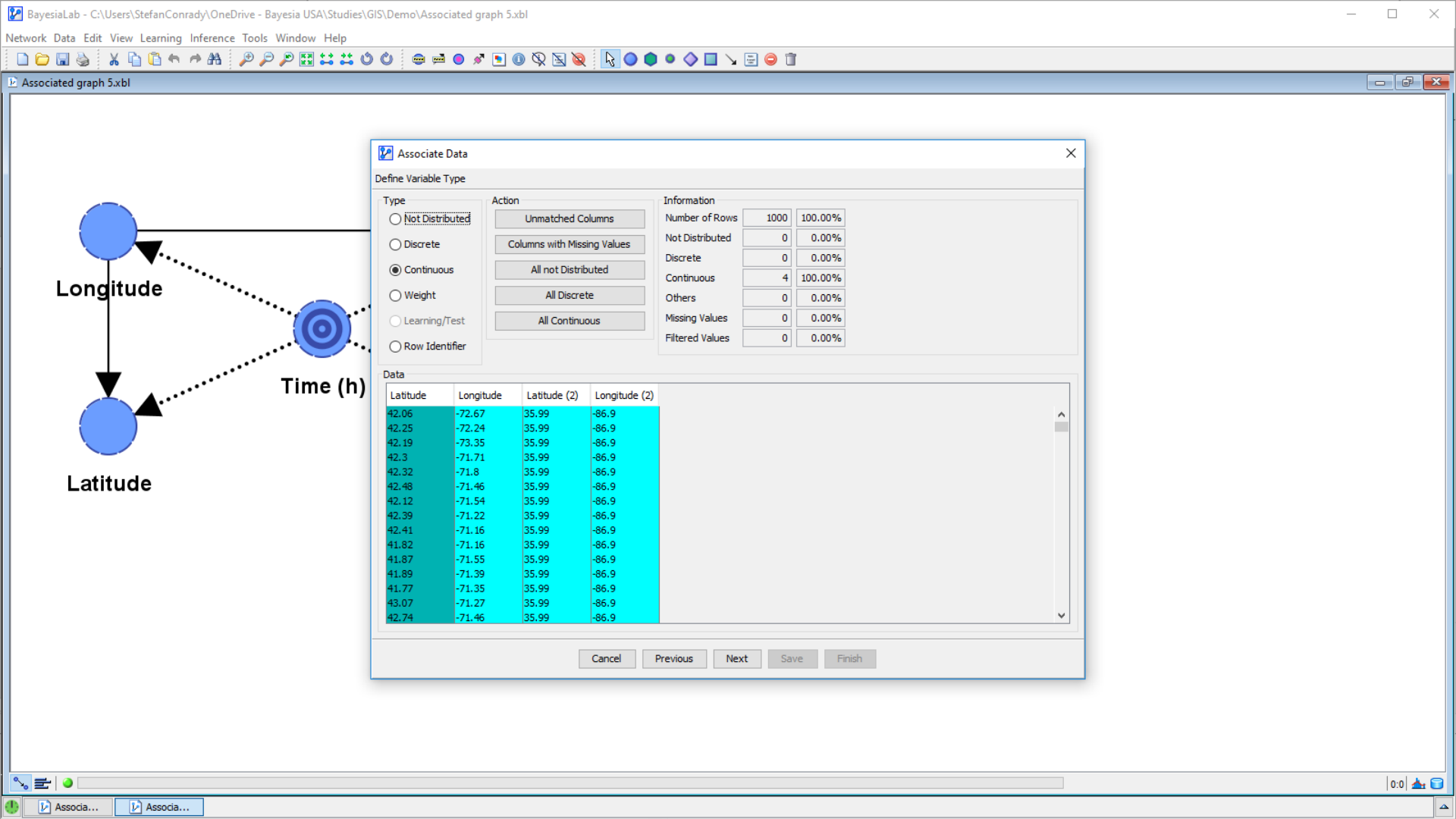
Cancel Previous Next Save Finish

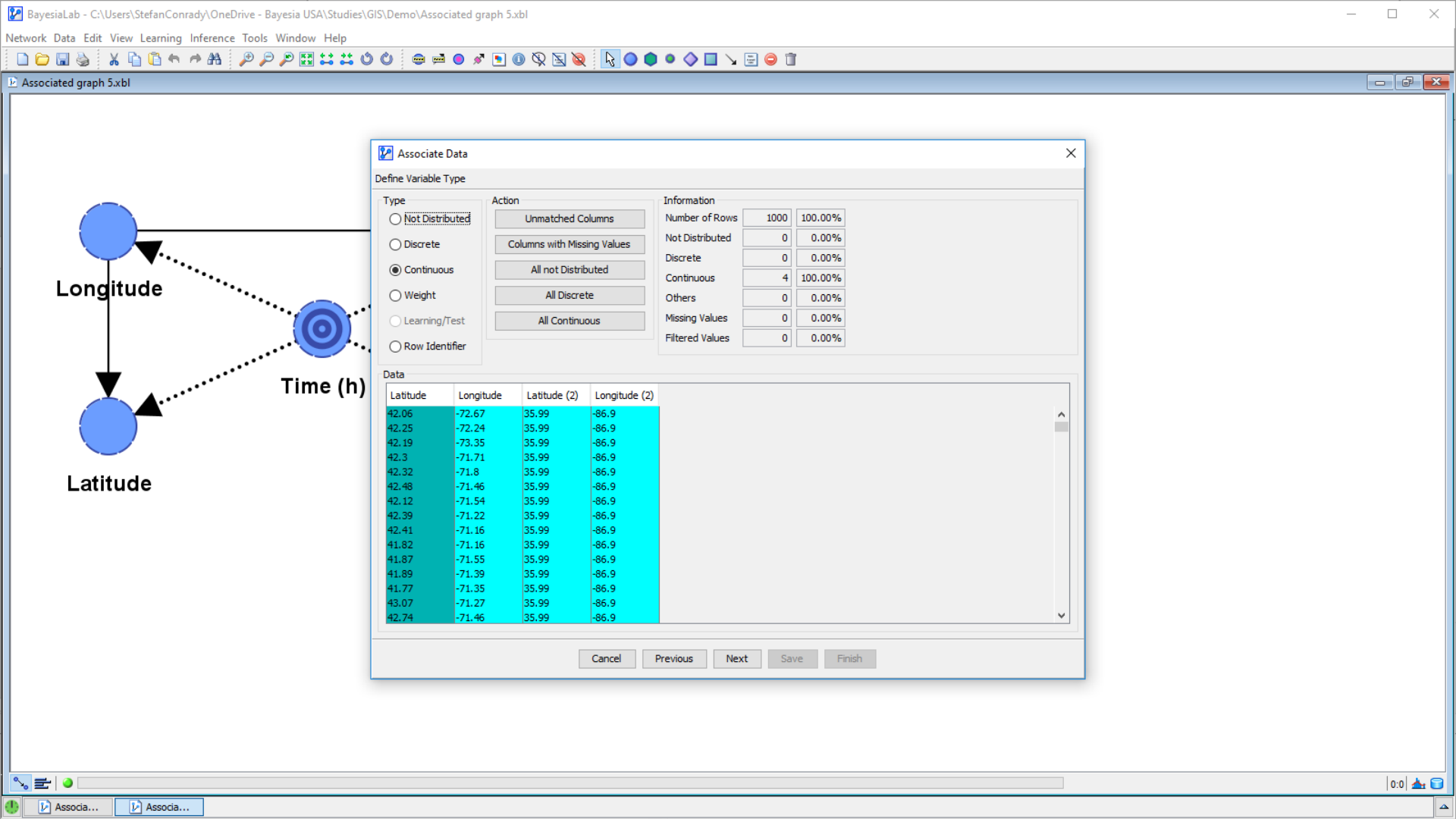


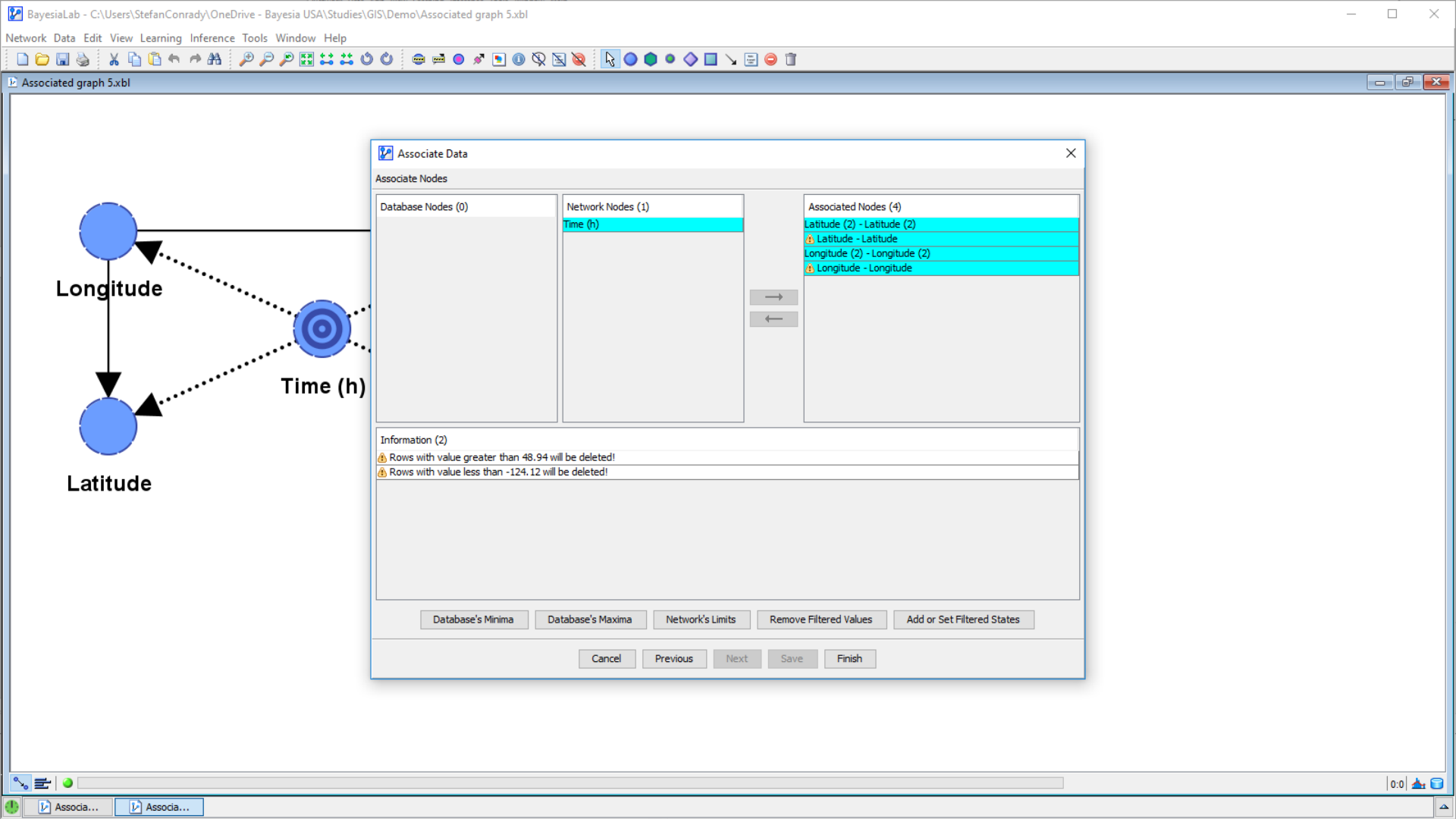


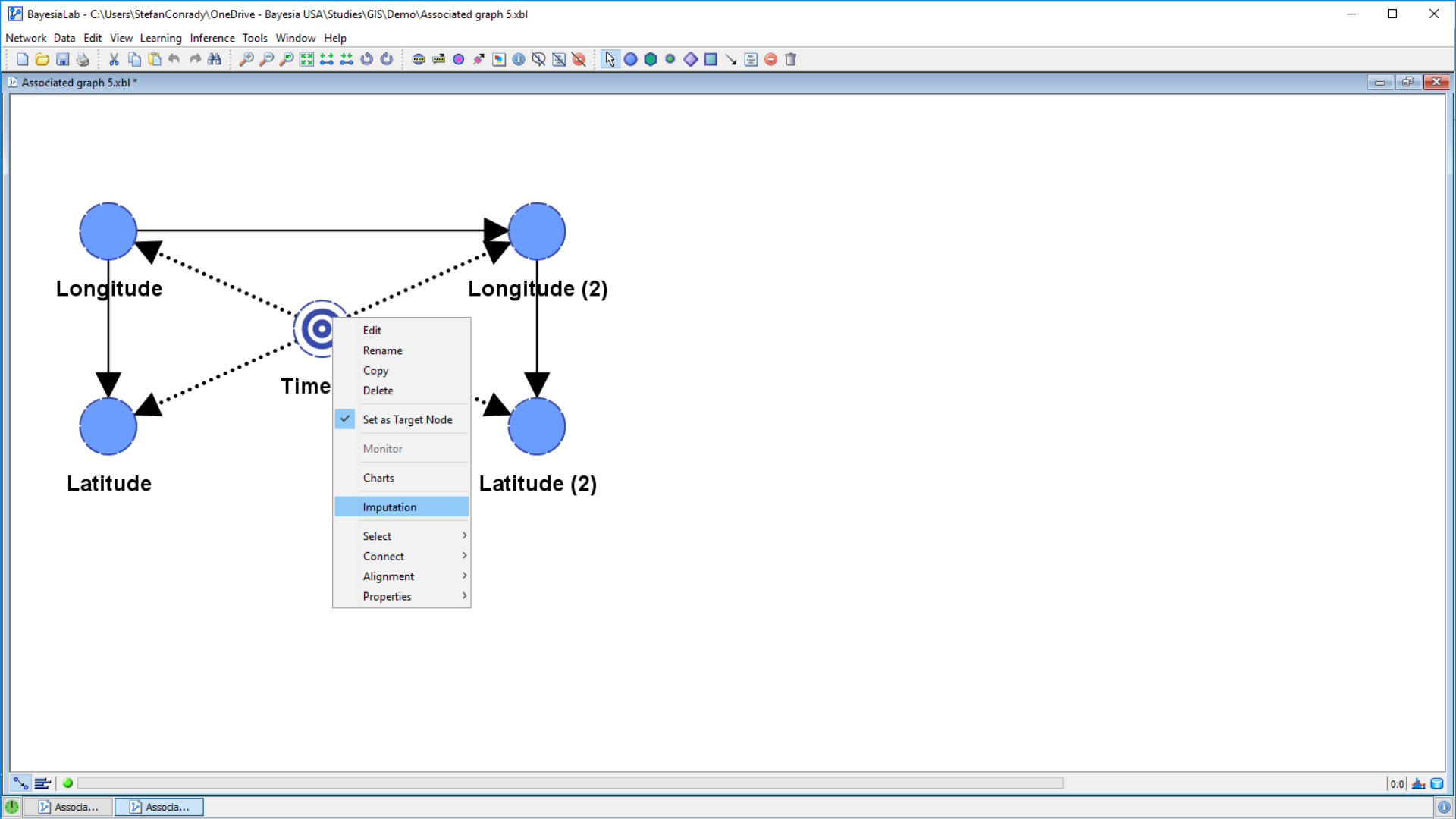


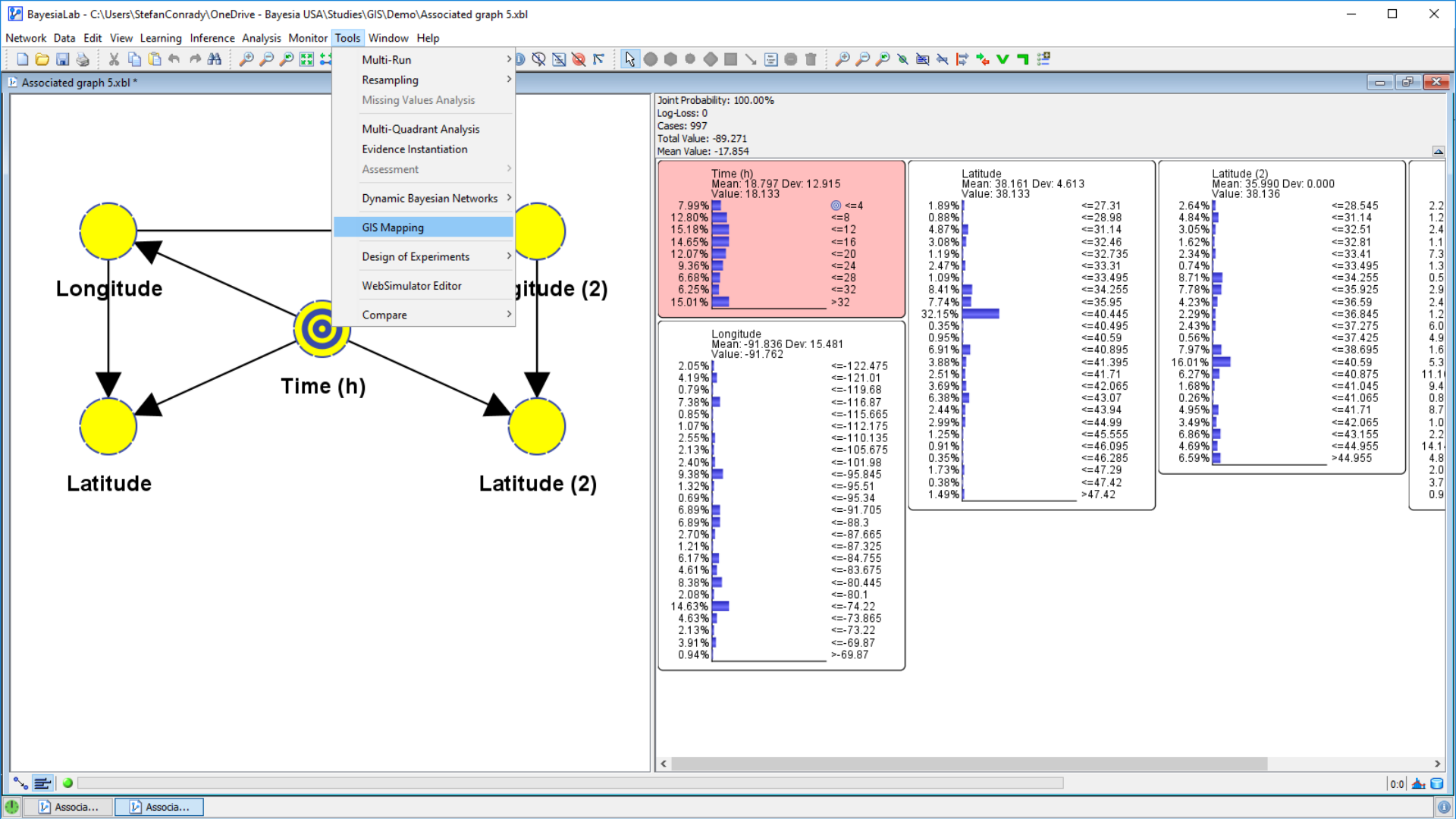


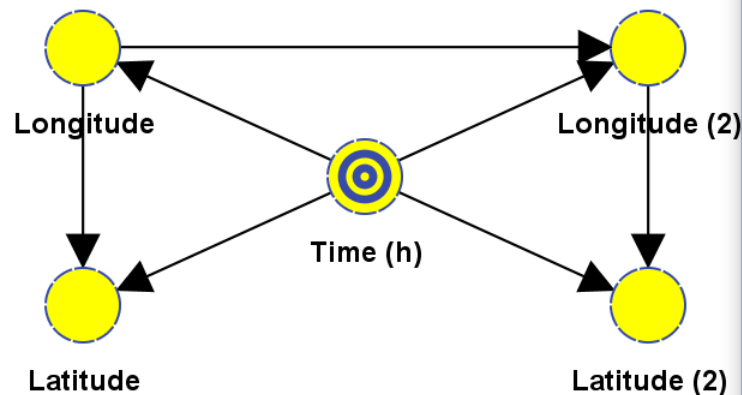












Joint Probability: 100.00%  
Log-Loss: 0  
Cases: 997  
Total Value: -89.271

### GIS Mapping

Map Settings

Map Type: Roads

Latitude: Latitude

Longitude: Longitude

Shape

☒ Fixed: CIRCLE

☐ Discrete: Latitude (2)

Size

☒ Fixed: 100

☐ Discrete: Latitude (2)

☐ Continuous: Latitude (2)

Color

☐ Fixed: [Blue]

☐ Discrete: Latitude (2)

☒ Continuous: Time (h)

Min: [Green] Mid: [Yellow] Max: [Red]

Opacity

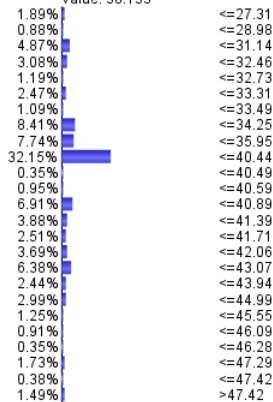
☒ Fixed: 1

☐ Discrete: Latitude (2)

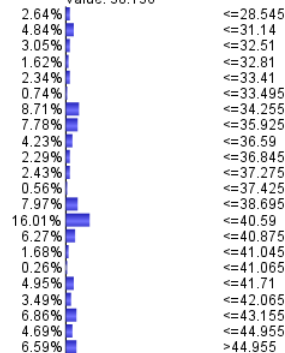
☐ Continuous: Latitude (2)

OK Cancel

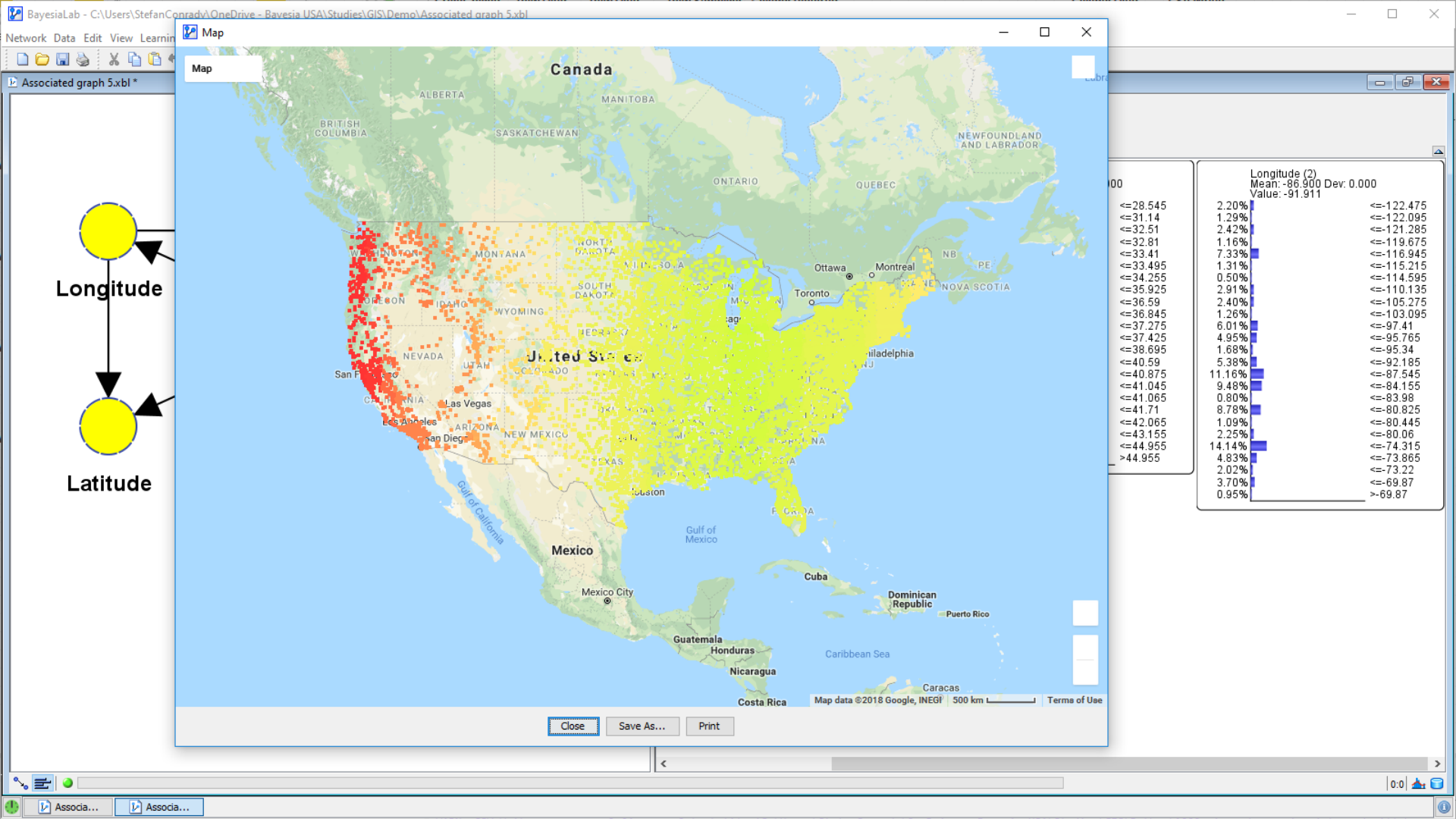
Latitude  
Mean: 38.161 Dev: 4.613  
Value: 38.133



Latitude (2)  
Mean: 35.990 Dev: 0.000  
Value: 38.136



2.2  
1.2  
2.4  
1.1  
7.3  
1.3  
0.5  
2.9  
2.4  
1.2  
6.0  
4.9  
1.6  
5.3  
11.1  
9.4  
0.8  
8.7  
1.0  
2.2  
14.1  
4.8  
2.0  
3.7  
0.9





# Drive Time Bands

## Computing the Cost

- “Search the Map”  
→ slow, but accurate
- Great-Circle Distance Computation  
→ fast, but inaccurate
- Learn & Infer  
→ fast and good approximation




# Spatial Learning and Optimization

Example 2: Hub Location

# Spatial Learning and Optimization

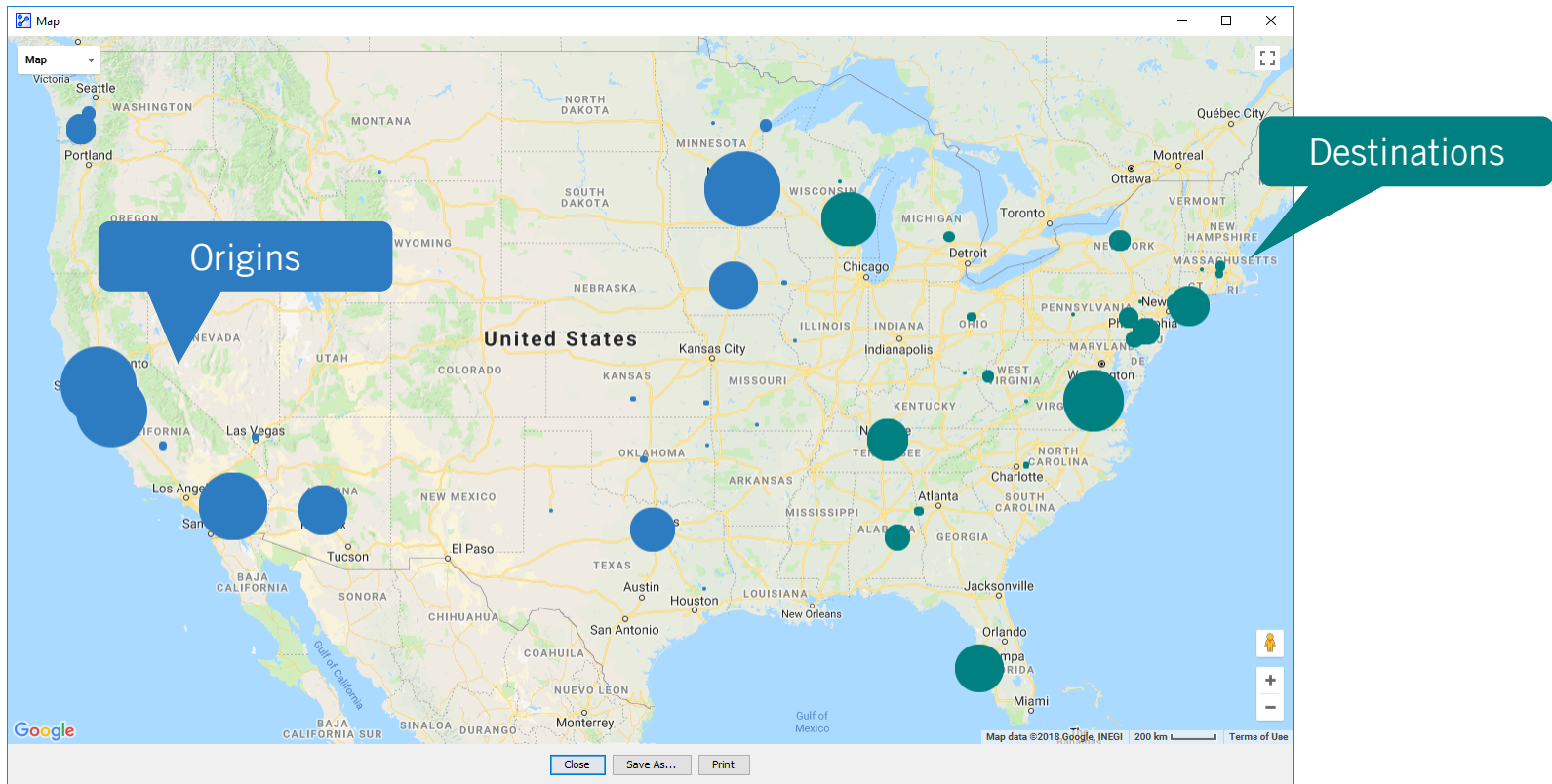
## Optimization Problems Under Consideration

- |  |                              |
|--|------------------------------|
| 1. One origin, one destination   | ➔ Shortest Path Problem      |
| 2. One origin, many destinations   | ➔ Drive Time Bands           |
| 3. Many origins, one destination   | ➔ Store Location Problem     |
|  4. Many origins, one hub, many destinations | ➔ Hub Location Problem       |
| 5. Many origins, multiple hubs, many destinations  | ➔ Multi-Hub Location Problem |

## General Objective

- Minimize “cost function,” e.g., travel time, distance, fuel consumption, number of turns, etc.
- Further assumption: all “participants” have same objective.

# Hub Location Problem

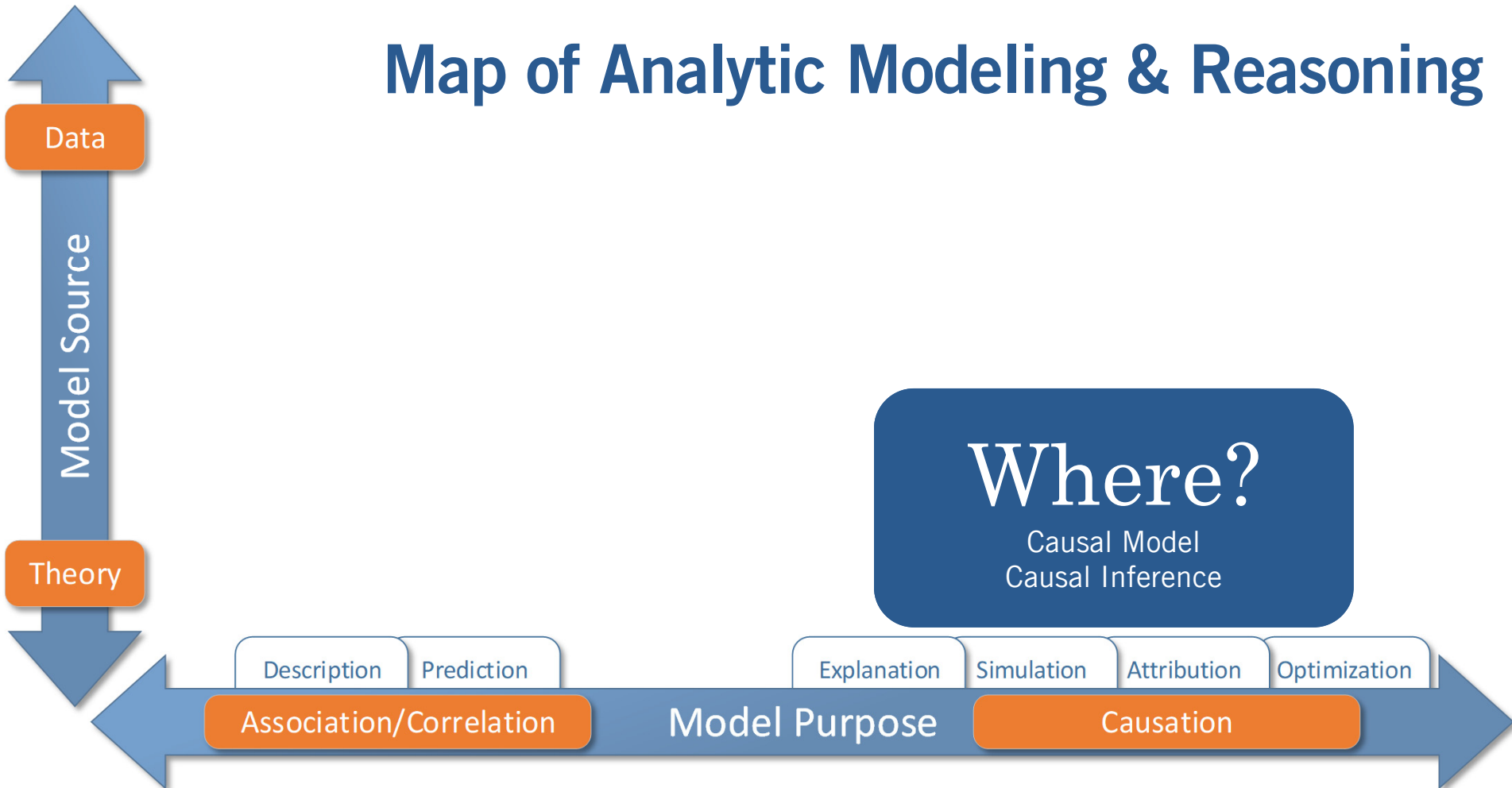


# Hub Location Problem

## Workflow

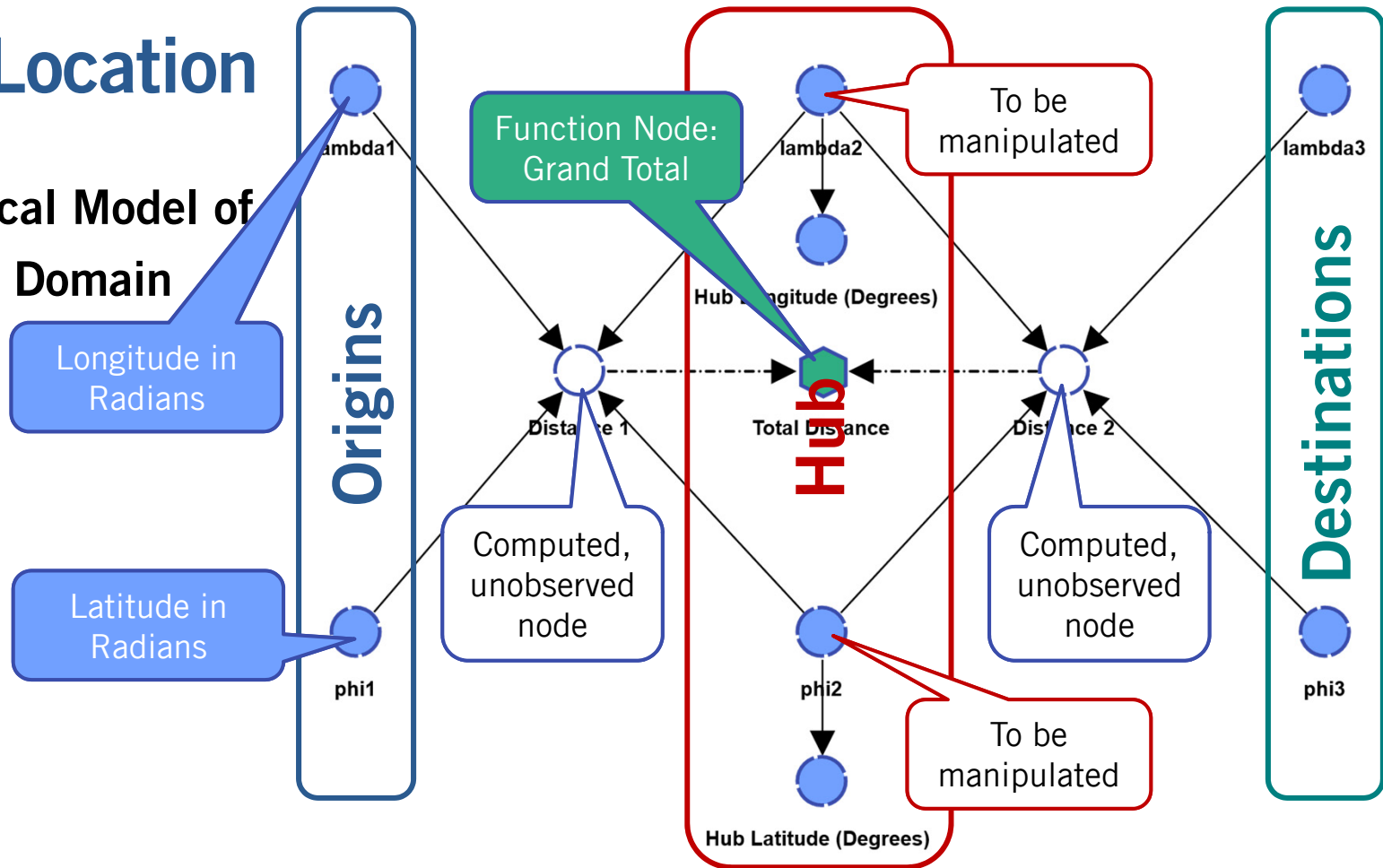
- Encode theoretical model of problem domain.
- Define Nodes
  - Observed
  - Unobserved
  - Functions
- Load data for origins and destinations.
- Perform Function Optimization.

# Map of Analytic Modeling & Reasoning



# Hub Location

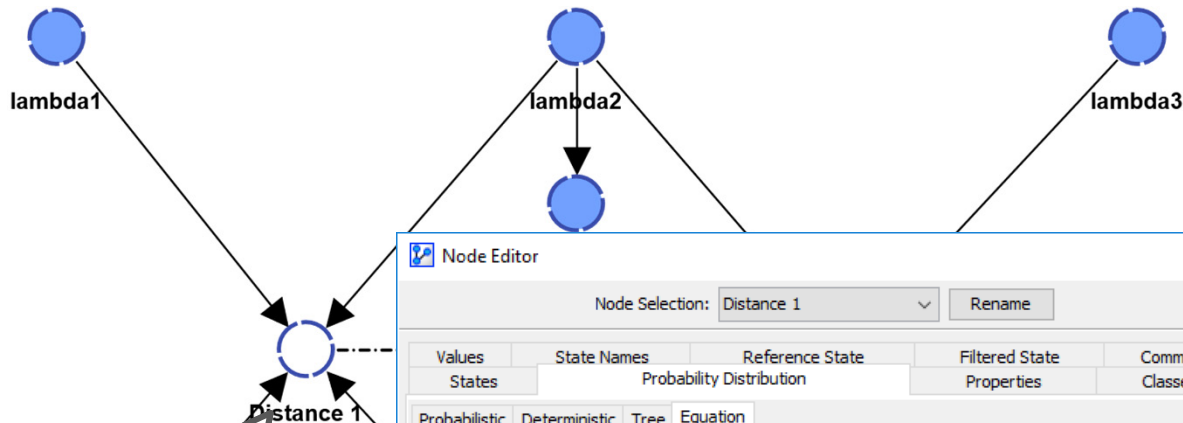
## Theoretical Model of Problem Domain



# Hub Location

## Theoretical Model of Problem Domain

$$d = 2r \arcsin \left( \sqrt{\text{hav}(\varphi_2 - \varphi_1) + \cos(\varphi_1) \cos(\varphi_2) \text{hav}(\lambda_2 - \lambda_1)} \right)$$
$$= 2r \arcsin \left( \sqrt{\sin^2 \left( \frac{\varphi_2 - \varphi_1}{2} \right) + \cos(\varphi_1) \cos(\varphi_2) \sin^2 \left( \frac{\lambda_2 - \lambda_1}{2} \right)} \right)$$



Node Editor

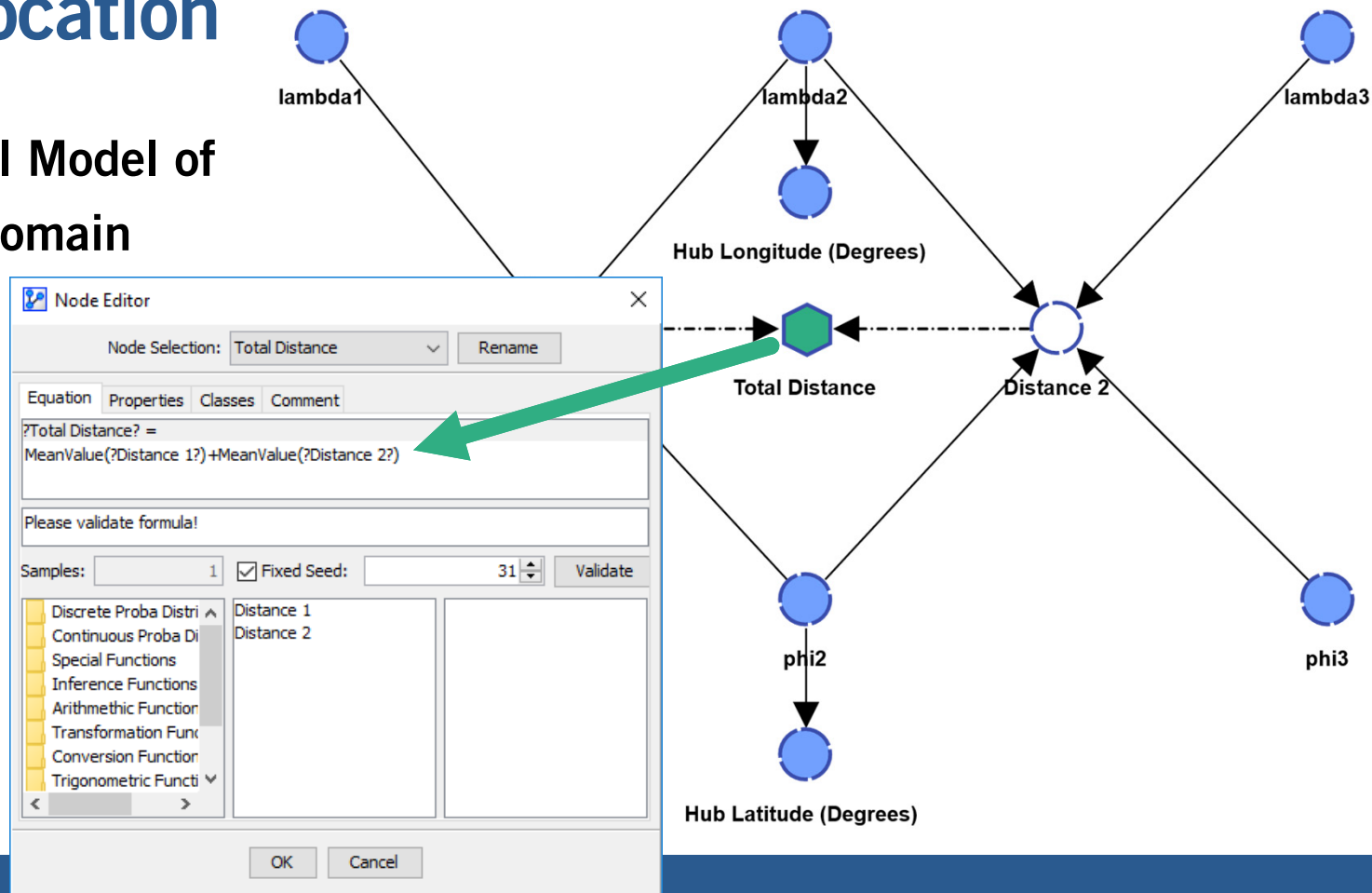
Node Selection: Distance 1 Rename

Values	State Names	Reference State	Filtered State	Comment
States	Probability Distribution		Properties	Classes
<p>Probabilistic <input type="radio"/> Deterministic <input checked="" type="radio"/> Tree <input type="radio"/> Equation <input type="radio"/></p> <p>Equation Type: <input checked="" type="radio"/> Deterministic <input type="radio"/> Probabilistic</p> <p>?Distance 1? =</p> $2*3959*Asin(sqrt((Sin((?phi1?-?phi1?)/2))^2+Cos(?phi1?)*Cos(?phi2?)*(Sin((?lambda2?-?lambda1?)/2))^2))$ <p>Table successfully generated!</p> <p>Sample: 1000 Smoothing: 0 <input checked="" type="checkbox"/> Fixed Seed: 31 <span>Valid:</span></p> <div><div><div>Discrete Proba Distributions</div><div>Continuous Proba Distribution</div><div>Special Functions</div><div>Arithmetic Functions</div><div>Transformation Functions</div><div>Conversion Functions</div><div>Trigonometric Functions</div><div>Relational Operators</div></div><div><div>Distance 1</div><div>lambda1</div><div>phi1</div><div>lambda2</div><div>phi2</div></div></div> <p><span>OK</span> <span>Cancel</span></p>				



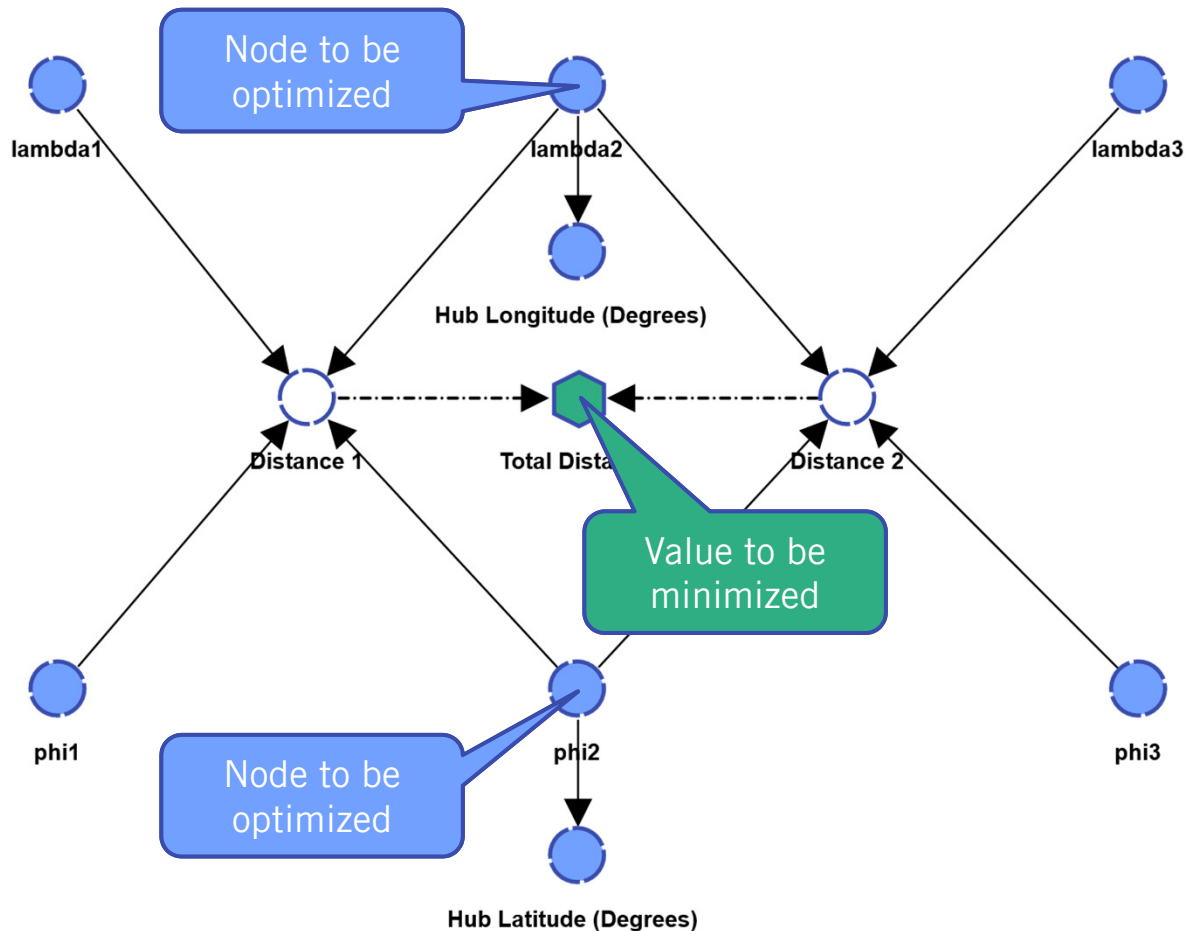
# Hub Location

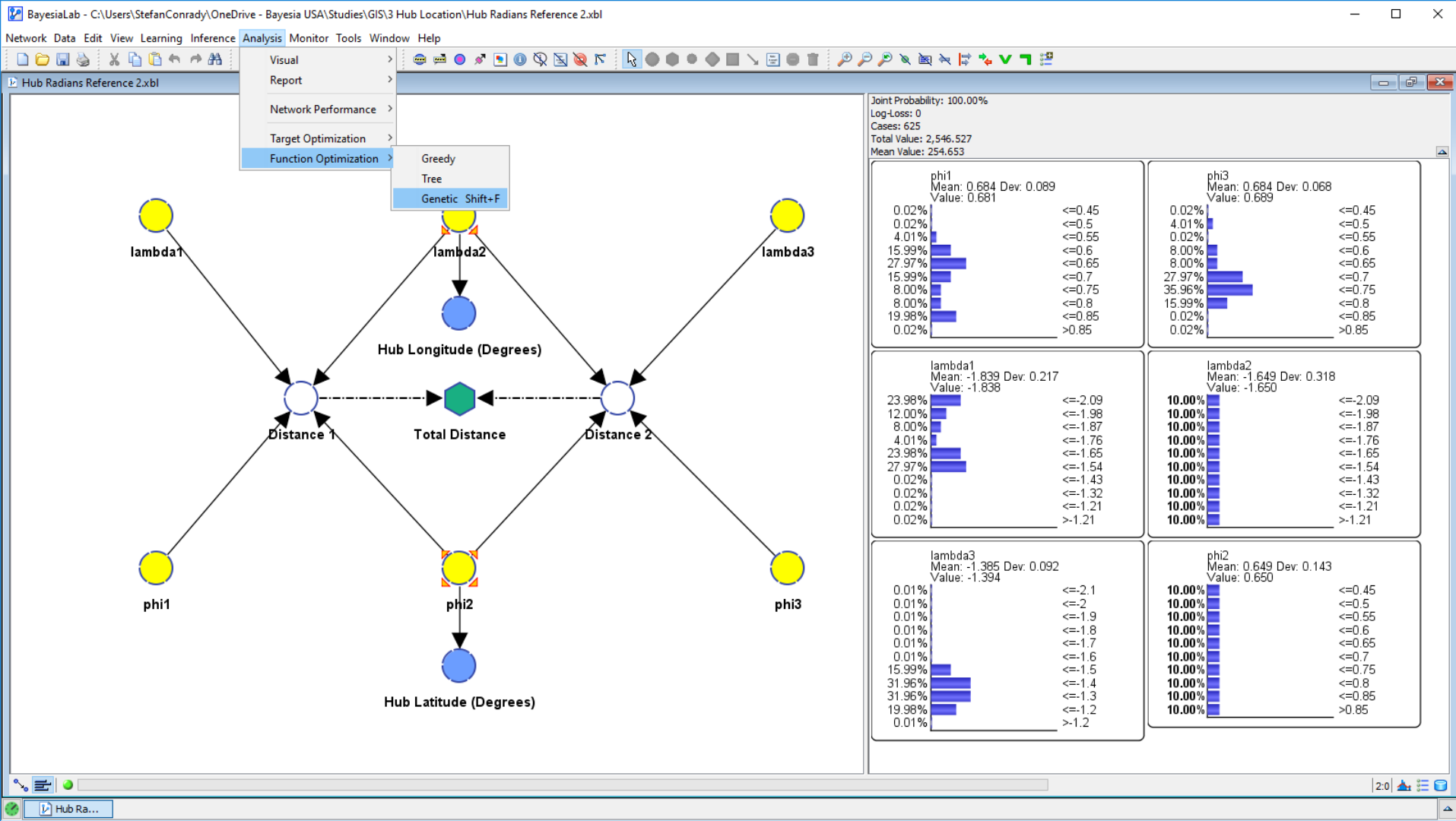
## Theoretical Model of Problem Domain

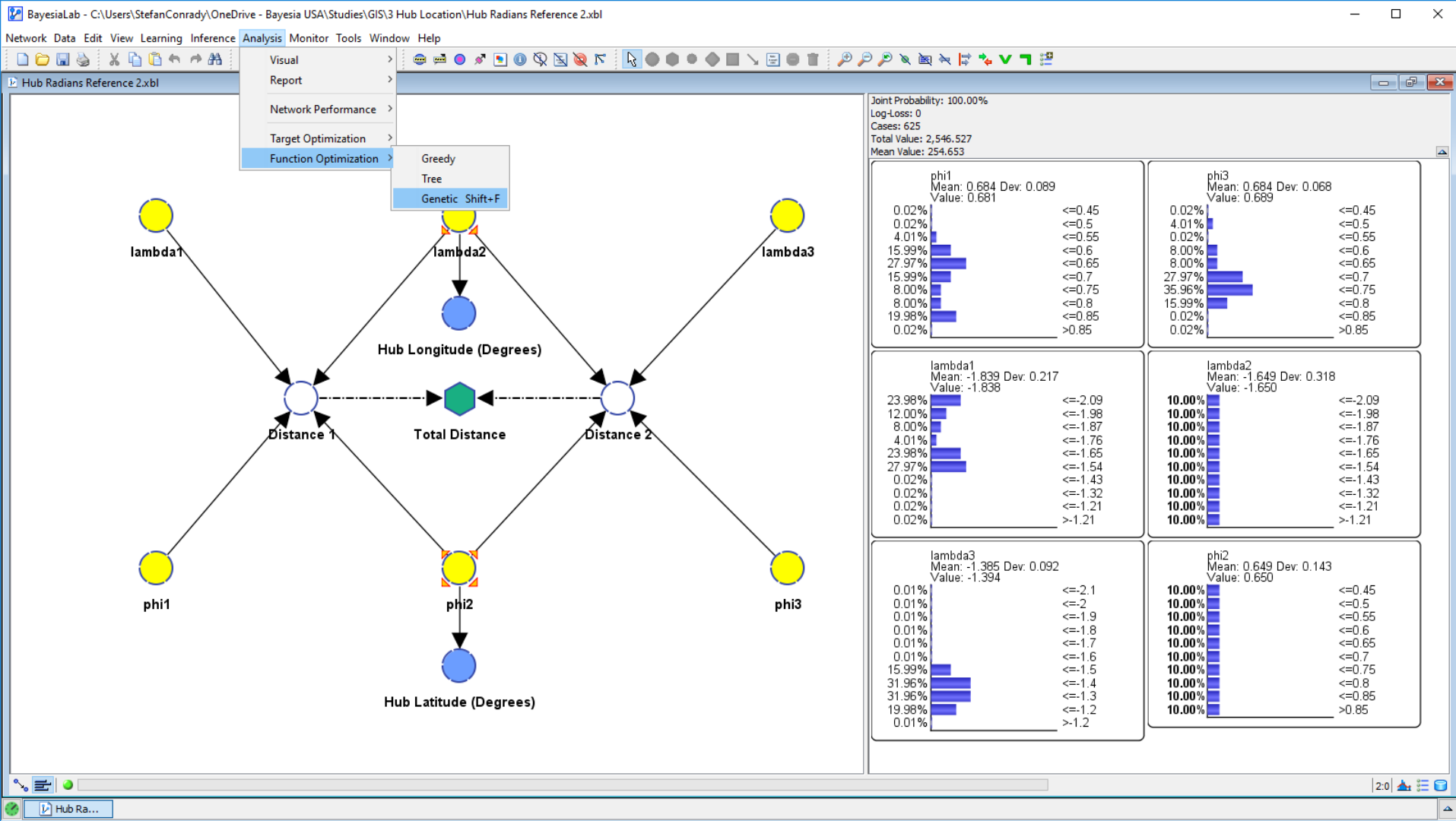


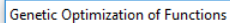
# Hub Location

## Theoretical Model of Problem Domain

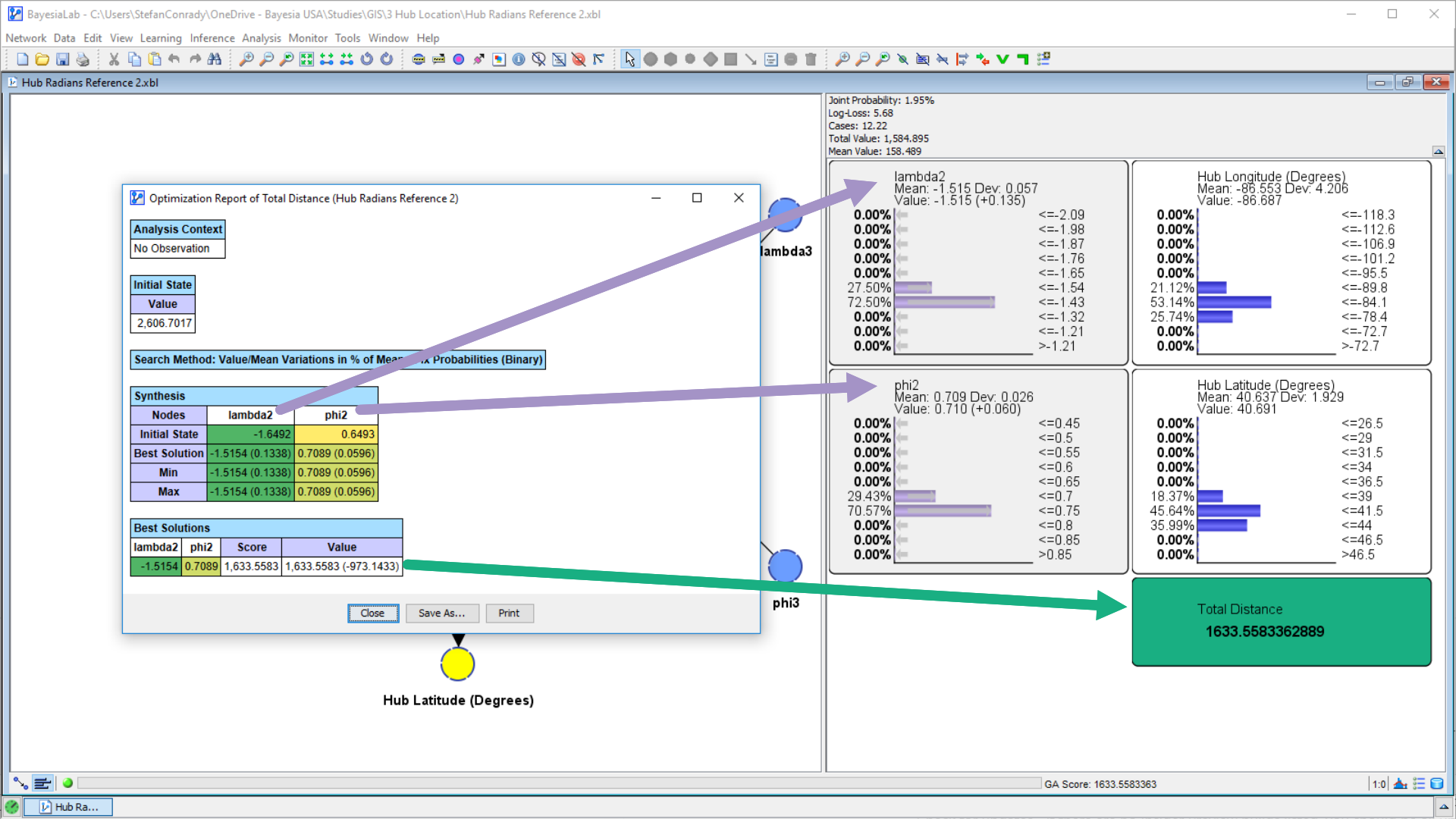




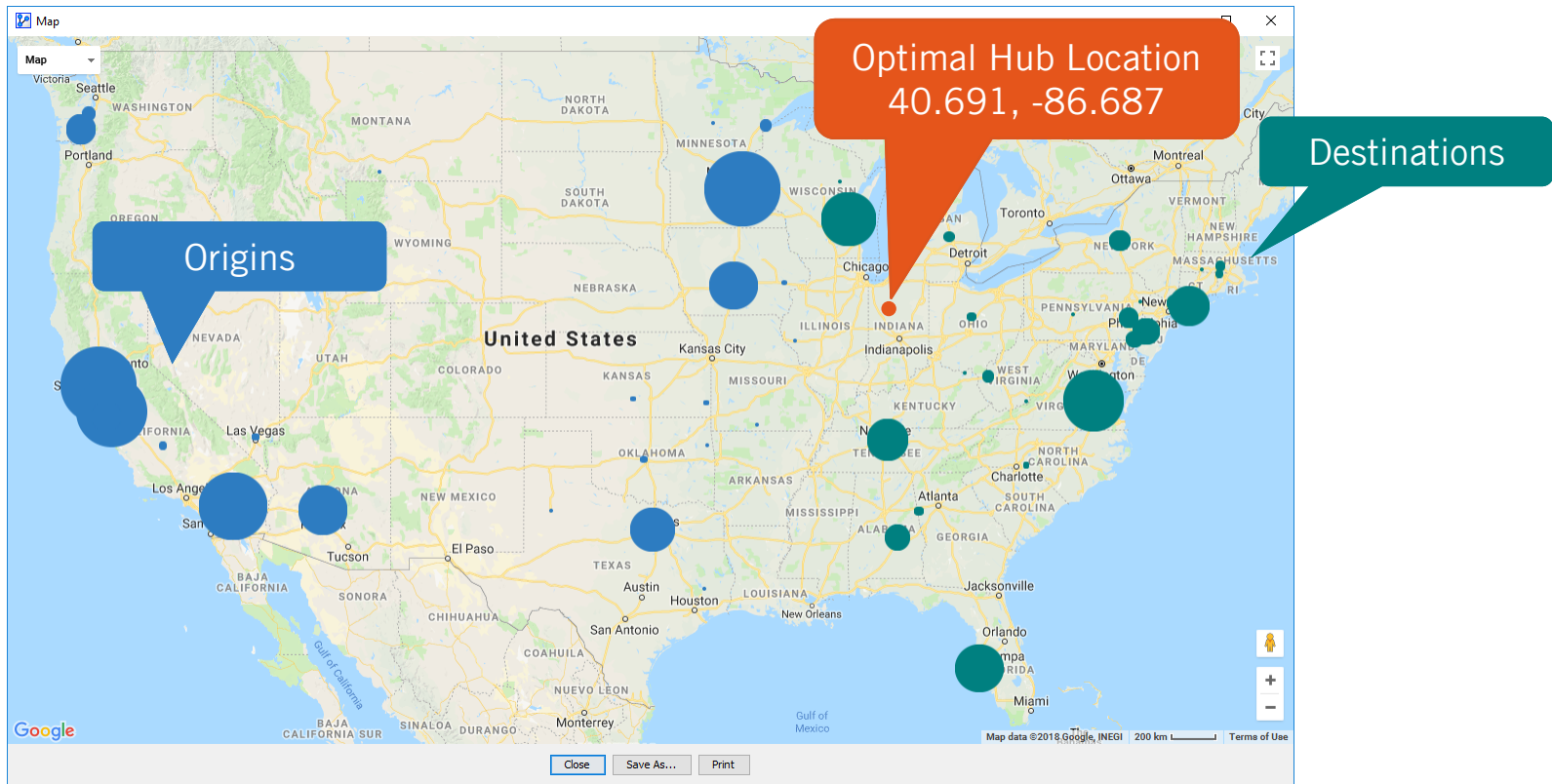




n: 0.684 Dev: 0.068 re: 0.689	$\leq 0.45$ $\leq 0.5$ $\leq 0.55$ $\leq 0.6$ $\leq 0.65$ $\leq 0.7$ $\leq 0.75$ $\leq 0.8$ $\leq 0.85$ $> 0.85$
oda2 n: -1.649 Dev: 0.318 re: -1.650	$\leq -2.09$ $\leq -1.98$ $\leq -1.87$ $\leq -1.76$ $\leq -1.65$ $\leq -1.54$ $\leq -1.43$ $\leq -1.32$ $\leq -1.21$ $> -1.21$
n: 0.649 Dev: 0.143 re: 0.650	$\leq 0.45$ $\leq 0.5$ $\leq 0.55$ $\leq 0.6$ $\leq 0.65$ $\leq 0.7$ $\leq 0.75$ $\leq 0.8$ $\leq 0.85$ $> 0.85$



# Hub Location Problem





**In Conclusion...**



# Upcoming Events

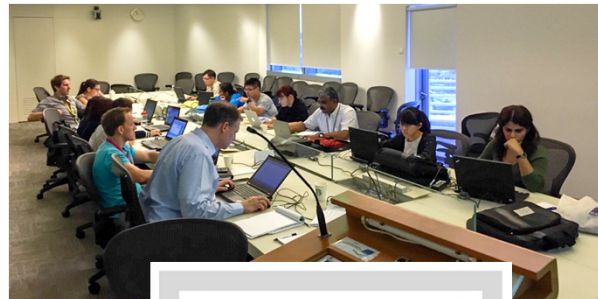
## Webinars & Seminars:

- June 1            Webinar: Health Outcomes Research
- June 19          Seminar in Chicago: Knowledge Discovery in Financial Data

**Register here: [bayesia.com/events](https://bayesia.com/events)**

# BayesiaLab Courses Around the World in 2018

- 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

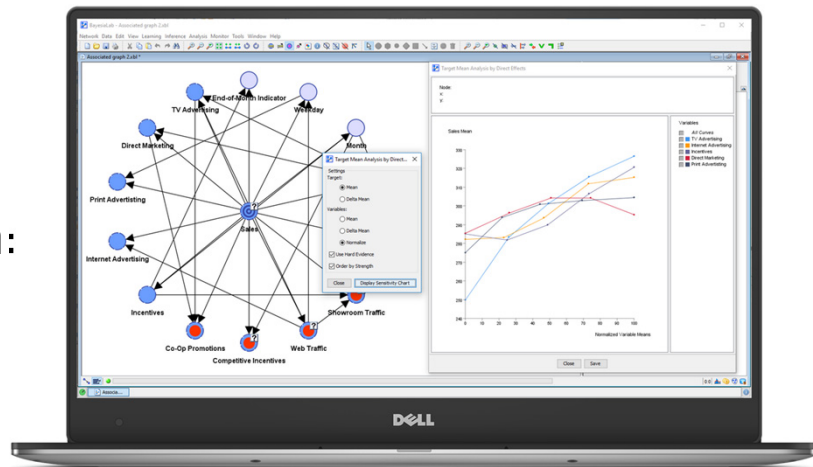


Learn More & Register: [bayesia.com/events](https://bayesia.com/events)


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[www.bayesia.com/evaluation](http://www.bayesia.com/evaluation)



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 [Webinar on Diagnostic Decision Support with Bayesian Networks](#)  
a minute ago by [stefanconrady](#): The answers to all webinar questions will be posted here.

 0  0  0

Started by [stefanconrady](#) a minute ago

 English ▾



# 6<sup>th</sup> Annual BayesiaLab Conference in Chicago

## November 1–2, 2018



# Thank You!



[stefan.conrady@bayesia.us](mailto:stefan.conrady@bayesia.us)



[BayesianNetwork](#)



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[facebook.com/bayesia](https://www.facebook.com/bayesia)