

Today's Program

Introduction

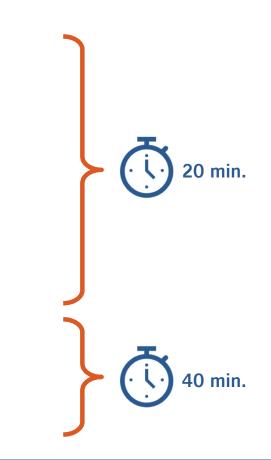
- Our Team
- Our Company
- Our Technology

Introductory Software Demo

Mapping with BayesiaLab and the Google Maps API

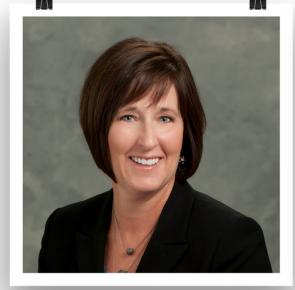
Spatial Computation & Optimization

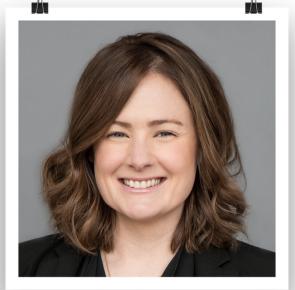
- Example 1: Drive Time Bands
- Example 2: Hub Location Optimization



Your BayesiaLab Team Today







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Disambiguation





Our Product

The 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 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 (DACs) in which the nodes represent vari-



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





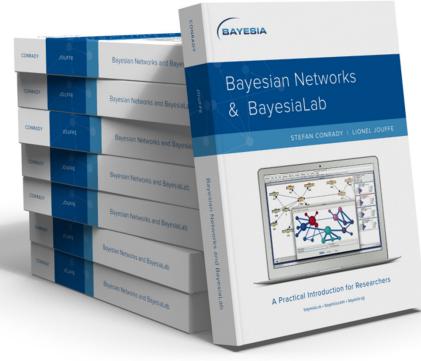


Bayesian Networks & BayesiaLab

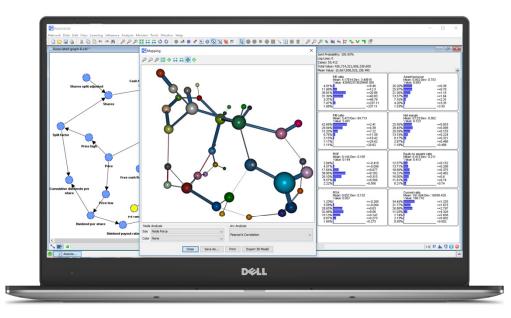
A Practical Introduction for Researchers

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







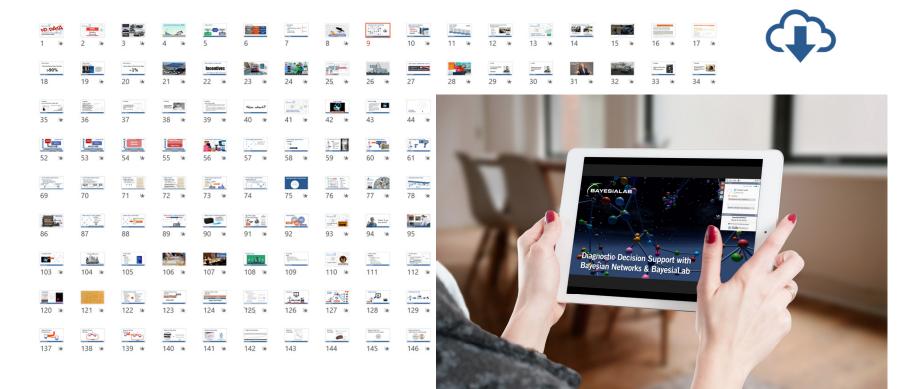


A desktop software for:

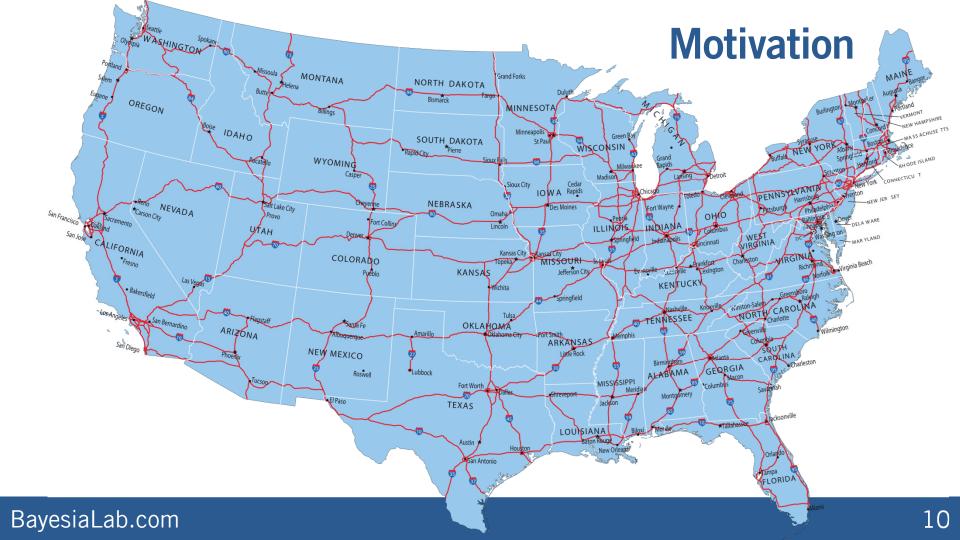
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with Bayesian networks.

Webinar Slides, Data, and Recording Available

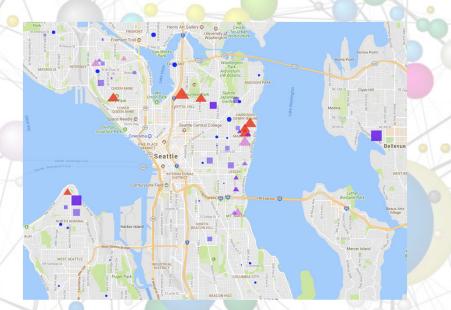


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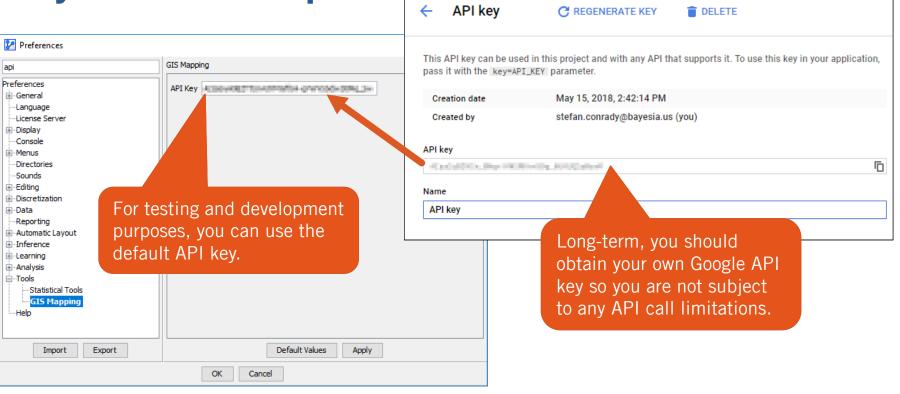


GIS Mapping with BayesiaLab and the Google API

Google Maps JavaScript API

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BayesiaLab Setup



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Google APIs

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.

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GIS Mapping with BayesiaLab and the Google API

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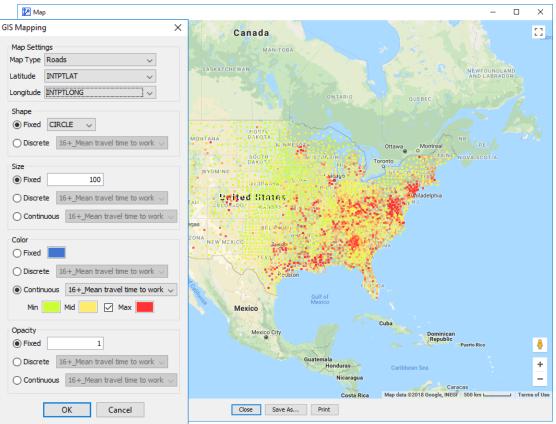
BayesiaLab.com

Tools

Introductory Example: Mapping Commuting Time

Commuting Time by County

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Spatial Learning and Optimization

Bayesian Networks & BayesiaLab

Spatial Learning and Optimization

Optimization Problems Under Consideration

- 1. One origin, one destination
- 2. One origin, many destinations
- 3. Many origins, one destination
- 4. Many origins, one hub, many destinations
- 5. Many origins, multiple hubs, many destinations

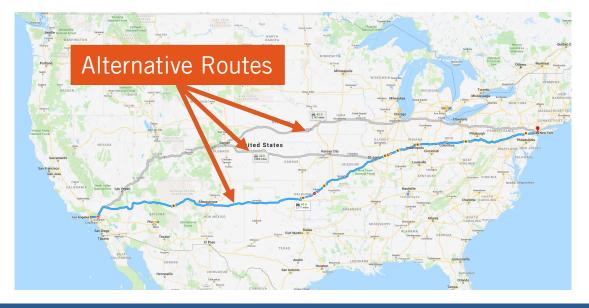
Common Objective

- → Shortest Path Problem
- ➔ Drive Time Bands
- ➔ Store Location Problem
- → Hub Location Problem
- ➔ Multi-Hub Location Problem

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

Computing the "Cost" for One Origin and One Destination

• "Search the Map" → slow, but accurate



Computing the Cost for One Origin and Many Destinations

• "Search the Map" → slow, but accurate



Computing the Cost

- "Search the Map" \rightarrow slow, but accurate
- Great-Circle Distance Computation

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- Easy and fast to
- calculate. "As the crow flies" may be an unrealistic ٠ assumption.
- Travel time may be more relevant that • distance.

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

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.



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Drive Time Bands

Workflow in Detail

- Take a random sample (~100,000) of origindestination 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.



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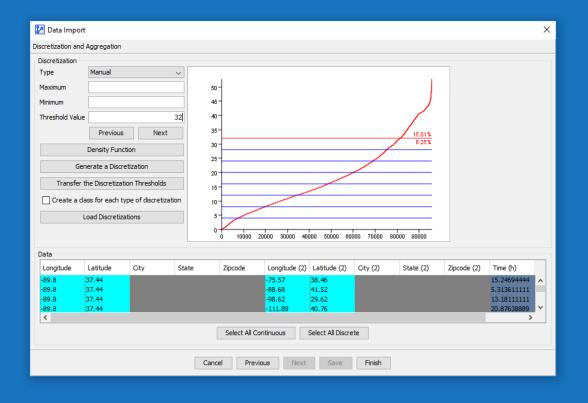
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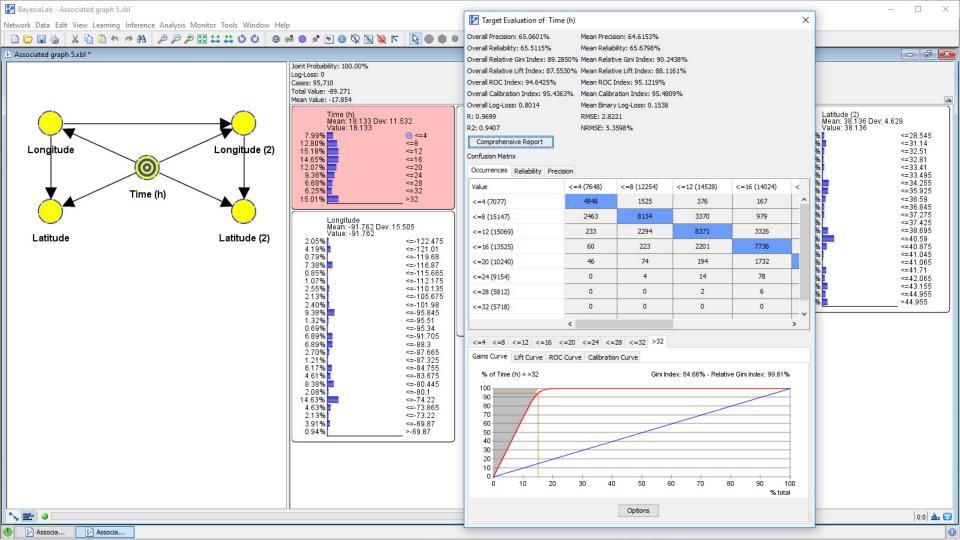
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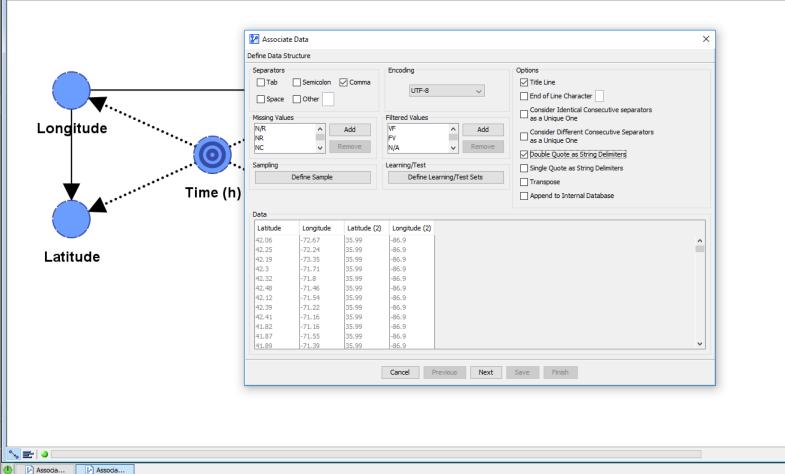


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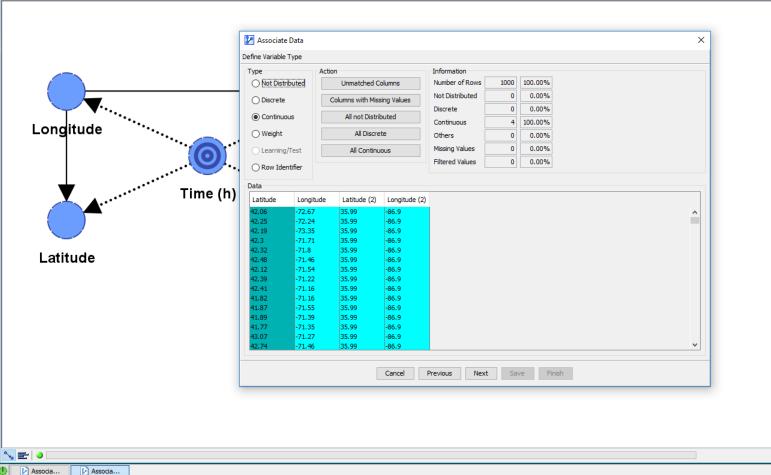
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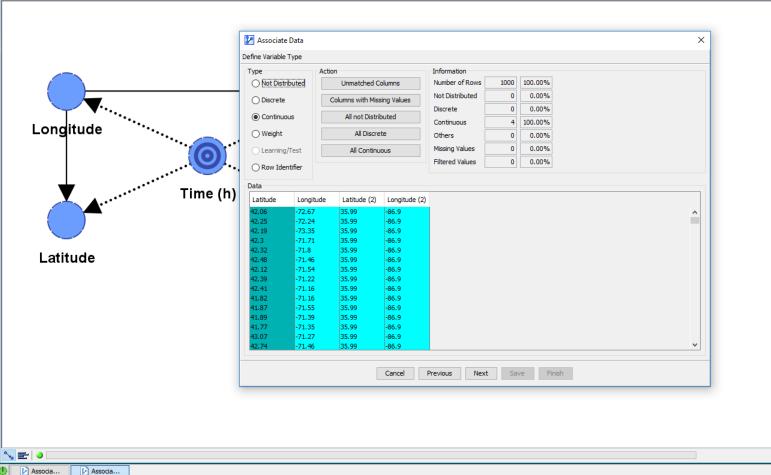
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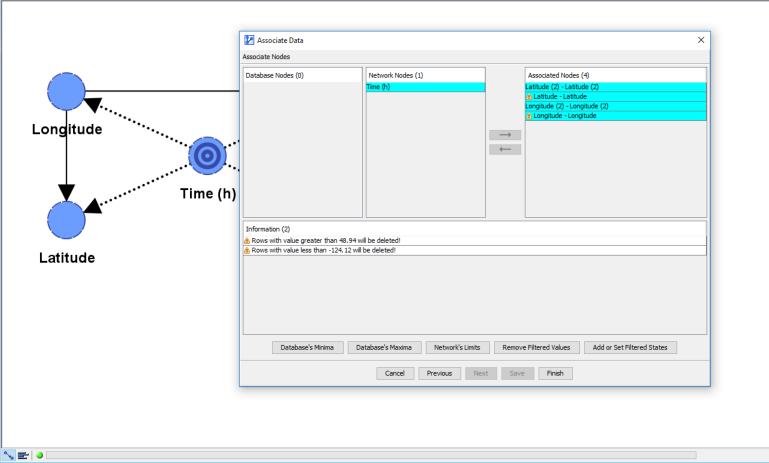
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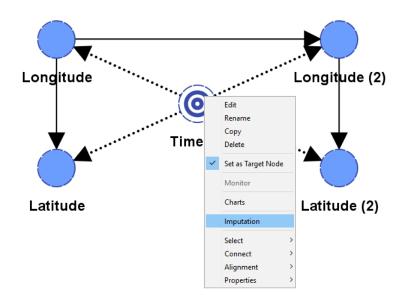
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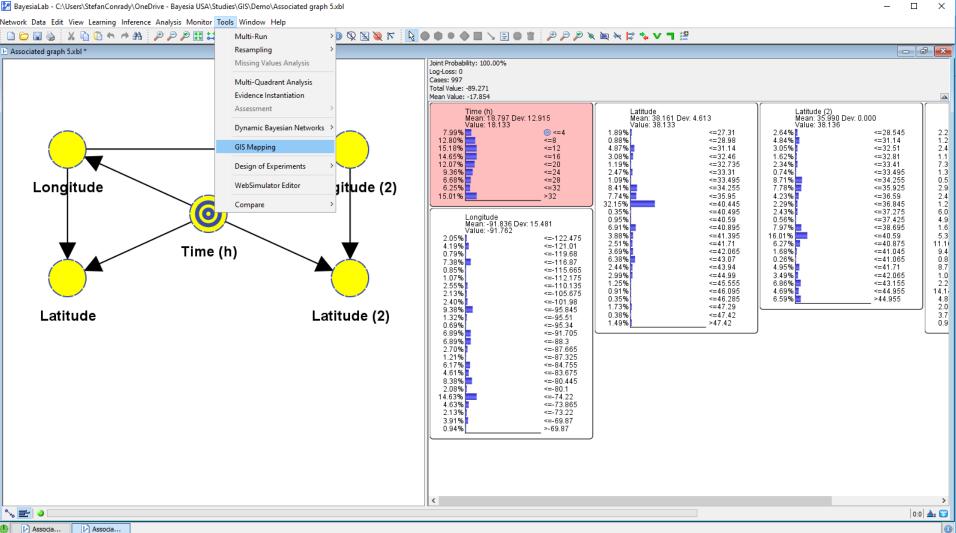
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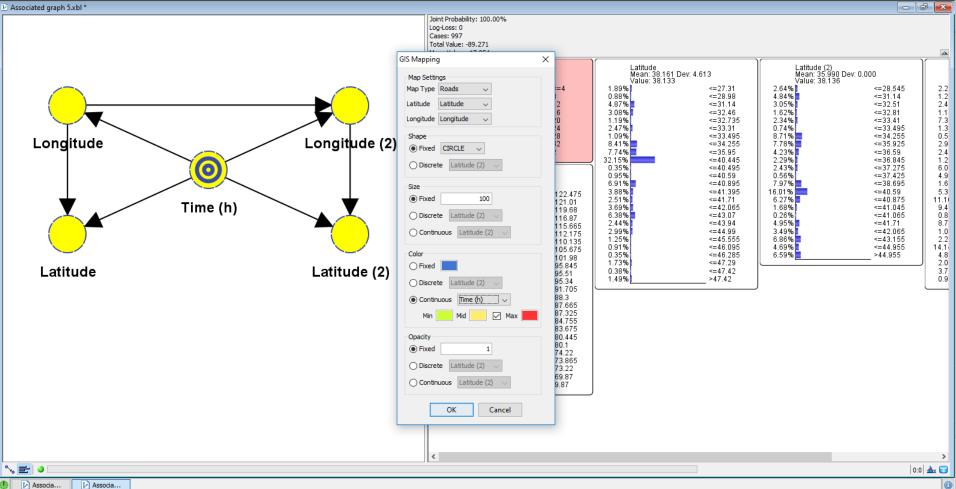
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help

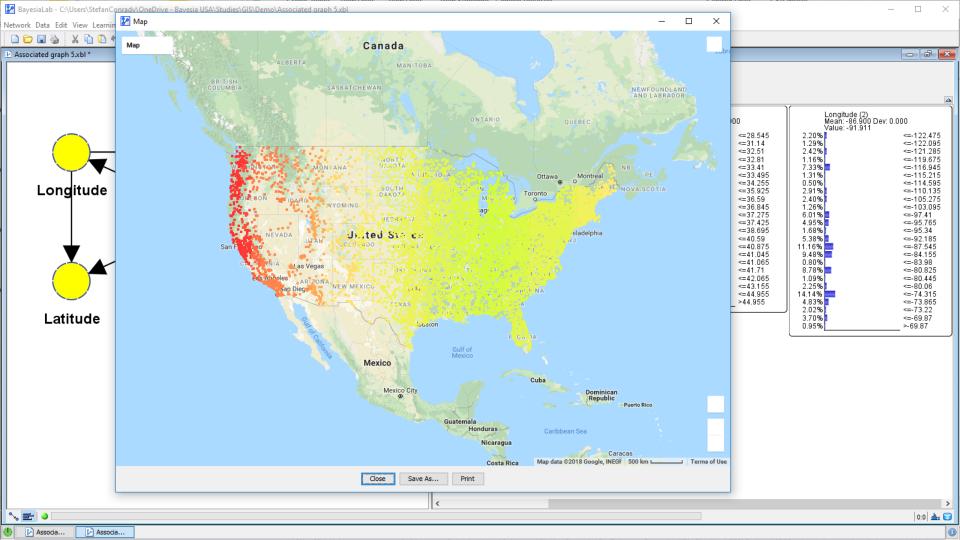


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Drive Time Bands

Computing the Cost

- "Search the Map"
- Great-Circle Distance Computation
- Learn & Infer

- \rightarrow slow, but accurate
- ➔ fast, but inaccurate
- → fast and good approximation

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Spatial Learning and Optimization

Example 2: Hub Location

Spatial Learning and Optimization

Optimization Problems Under Consideration

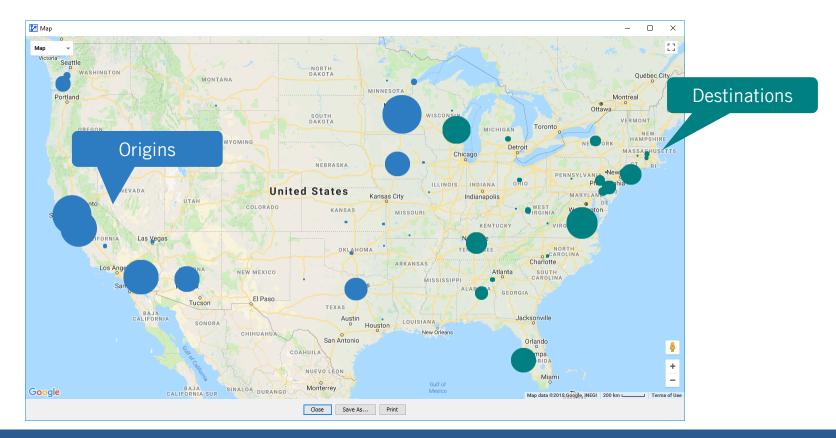
- 1. One origin, one destination
- 2. One origin, many destinations
- 3. Many origins, one destination
- 4. Many origins, one hub, many destinations
- 5. Many origins, multiple hubs, many destinations

General Objective

- ➔ Shortest Path Problem
- ➔ Drive Time Bands
- ➔ Store Location Problem
- → Hub Location Problem
- ➔ Multi-Hub Location Problem

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

Hub Location Problem

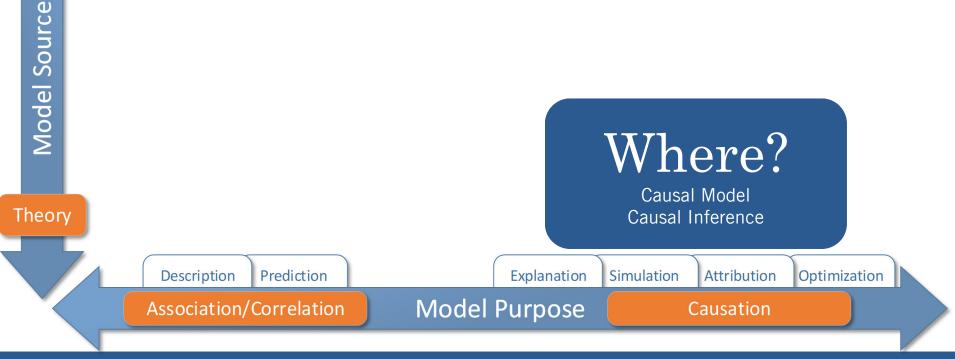


Hub Location Problem

Workflow

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

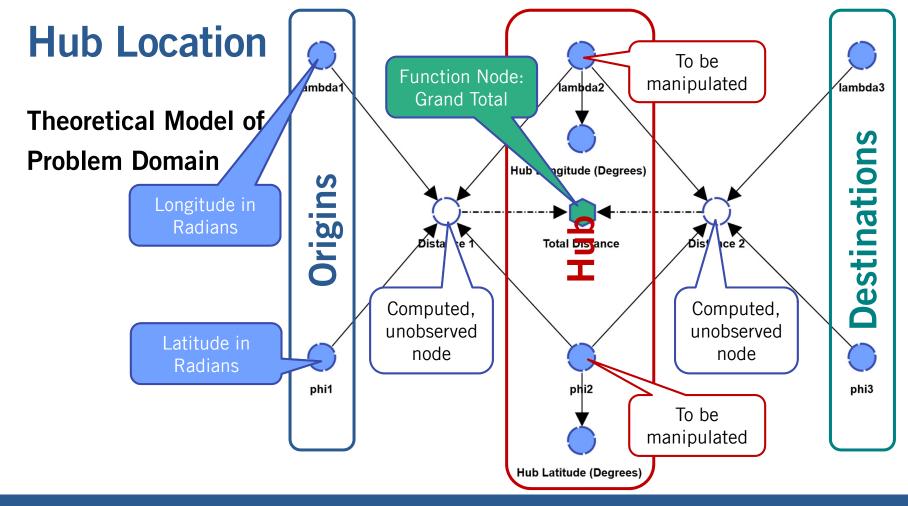
Map of Analytic Modeling & Reasoning

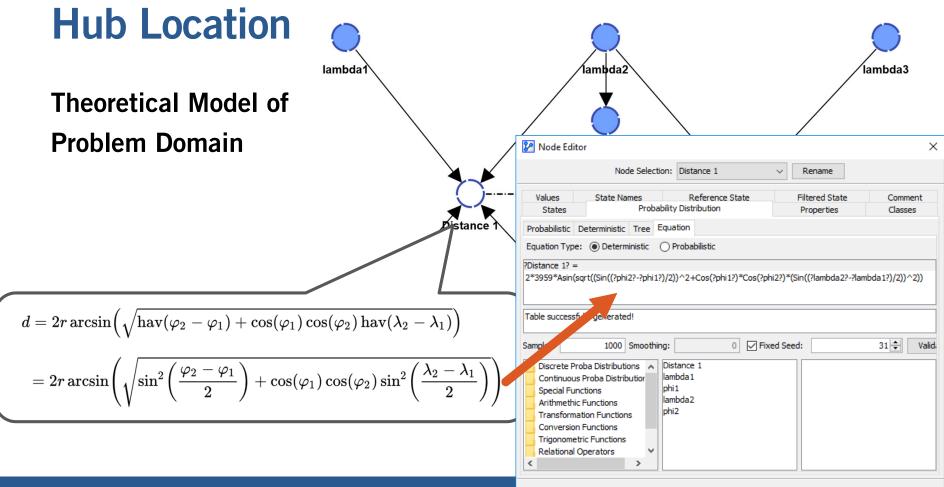


Data

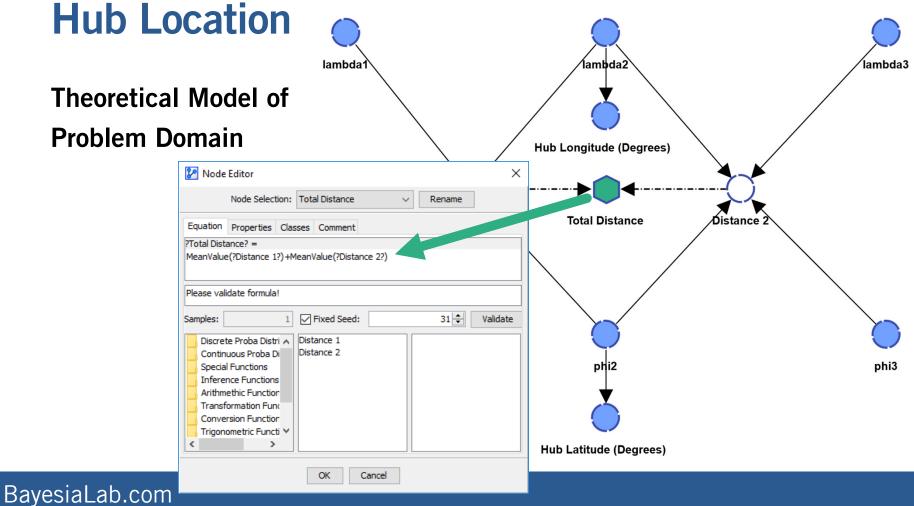
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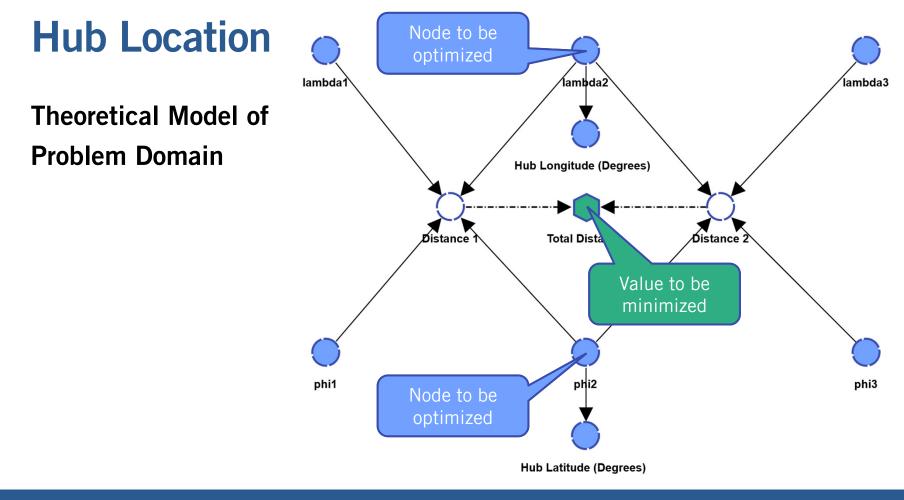
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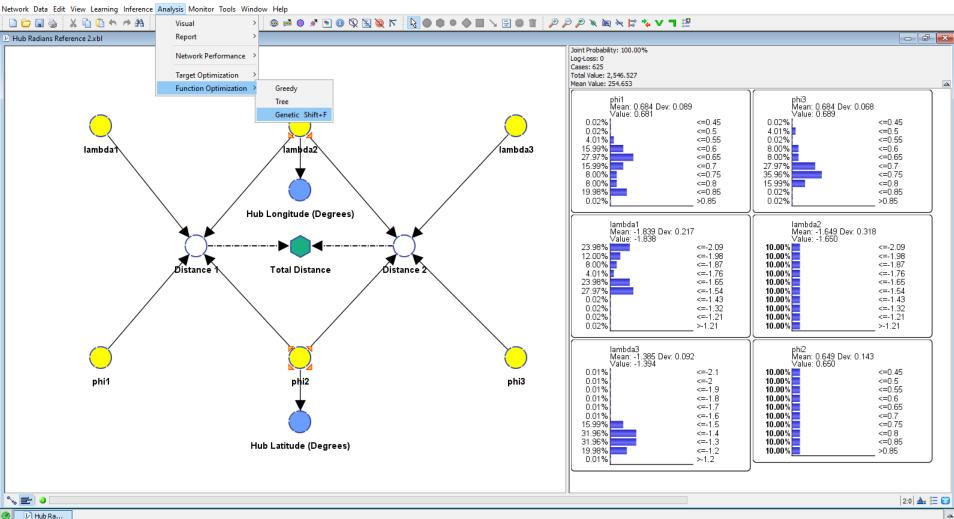








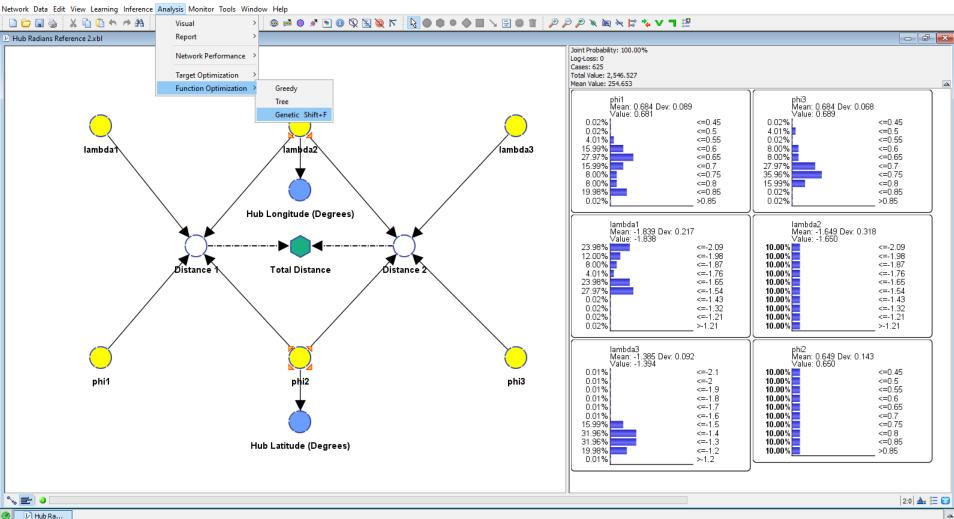




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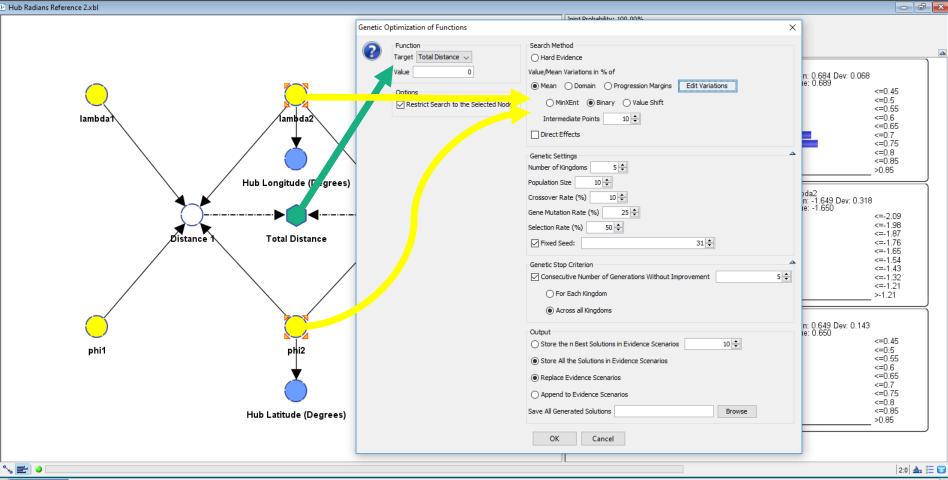
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Hub Radians Reference 2.xbl

😥 Hub Ra...

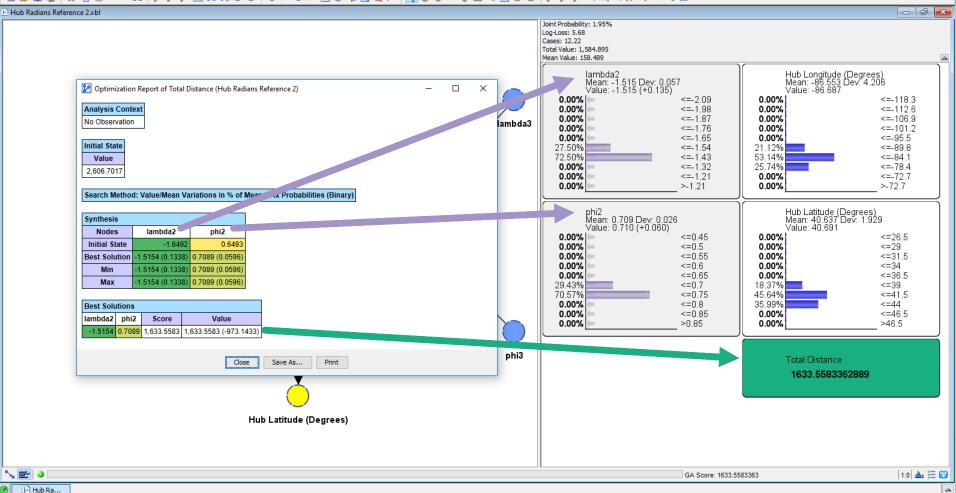


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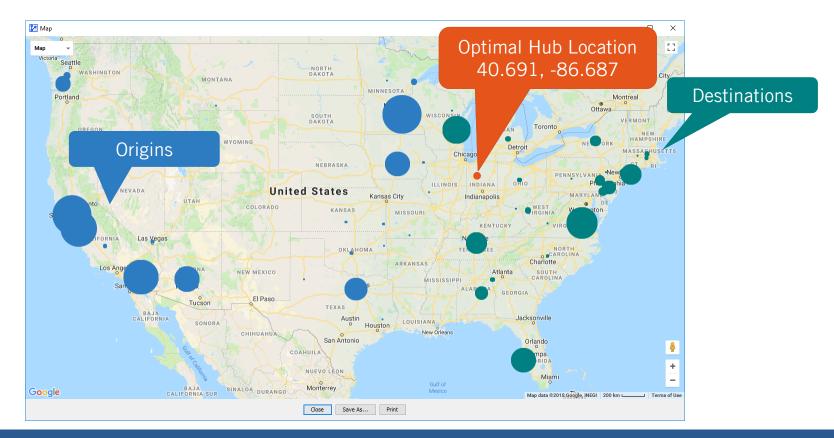
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Hub Location Problem



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In Conclusion...

Upcoming Events

Webinars & Seminars:

- June1 Webinar: Health Outcomes Research
- June 19 Seminar in Chicago: Knowledge Discovery in Financial Data

Register here: bayesia.com/events

BayesiaLab Courses Around the World in 2018

- June 26–28
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 Chicago, IL
- December 4–6 New York, NY





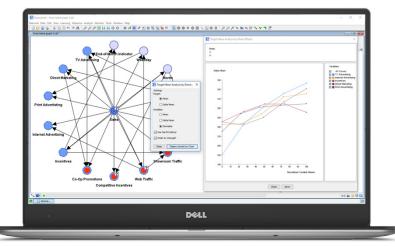
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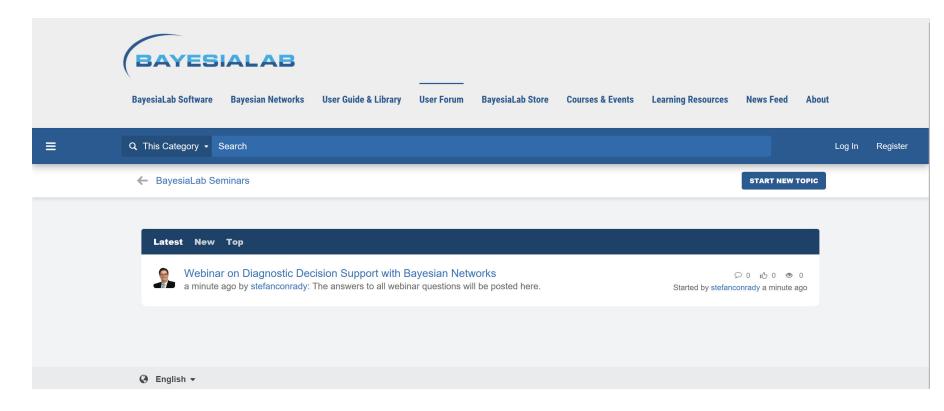
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Thank You!



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