The presentation will start at:

13:00:00

The current time is:

13:00:42

Central Standard Time, UTC-6

Probabilistic Reasoning with Bayesian Networks and BayesiaLab

Introduction

Your Hosts Today

- Stefan Conrady
  stefan.conrady@bayesia.us

- Stacey Blodgett
  stacey.blodgett@bayesia.us

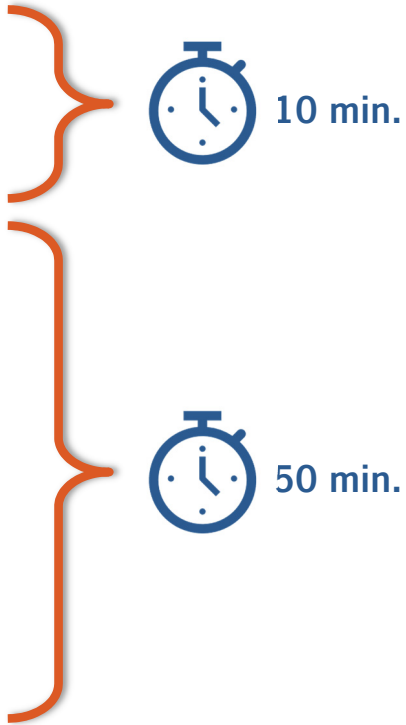
Today's Agenda

Motivation & Background

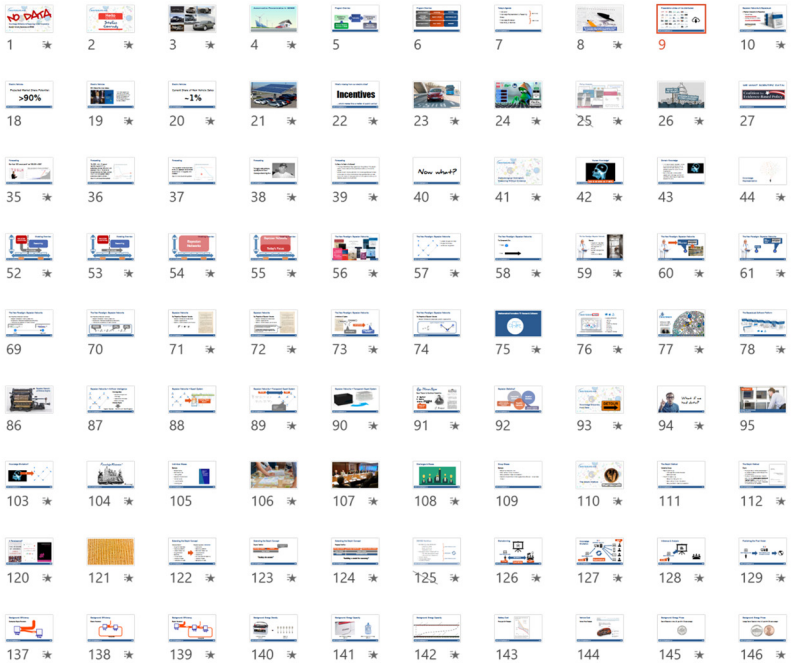
- Logic vs. Probabilistic Reasoning

Examples of Probabilistic Reasoning

- Example 1: What color is the taxi?
- Bayesian Networks to the Rescue!
- Knowledge Encoding & Inference with Bayesian Networks & BayesiaLab
- Example 2: Where is my bag?



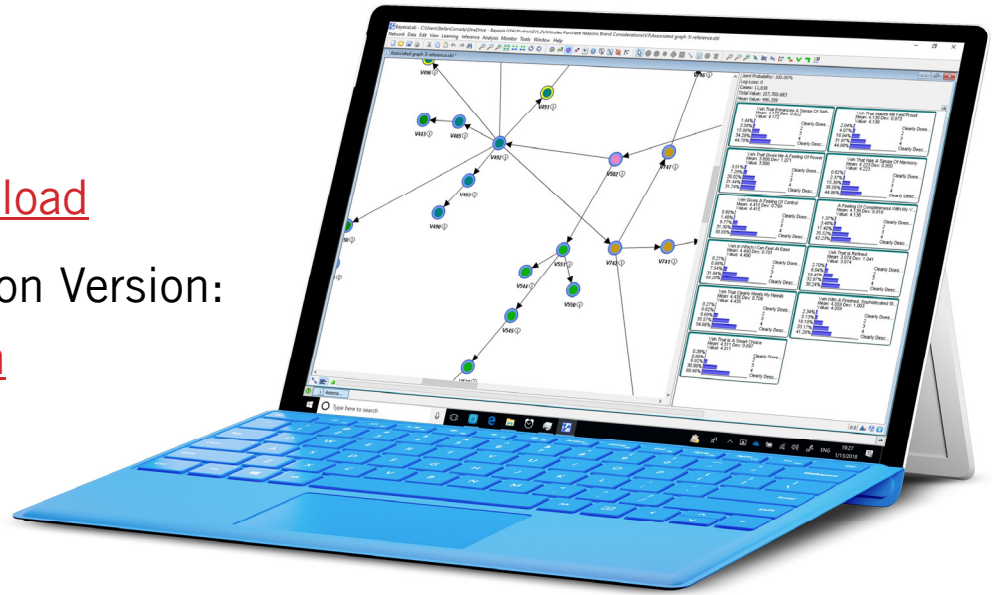
Webinar Slides & Recording Available



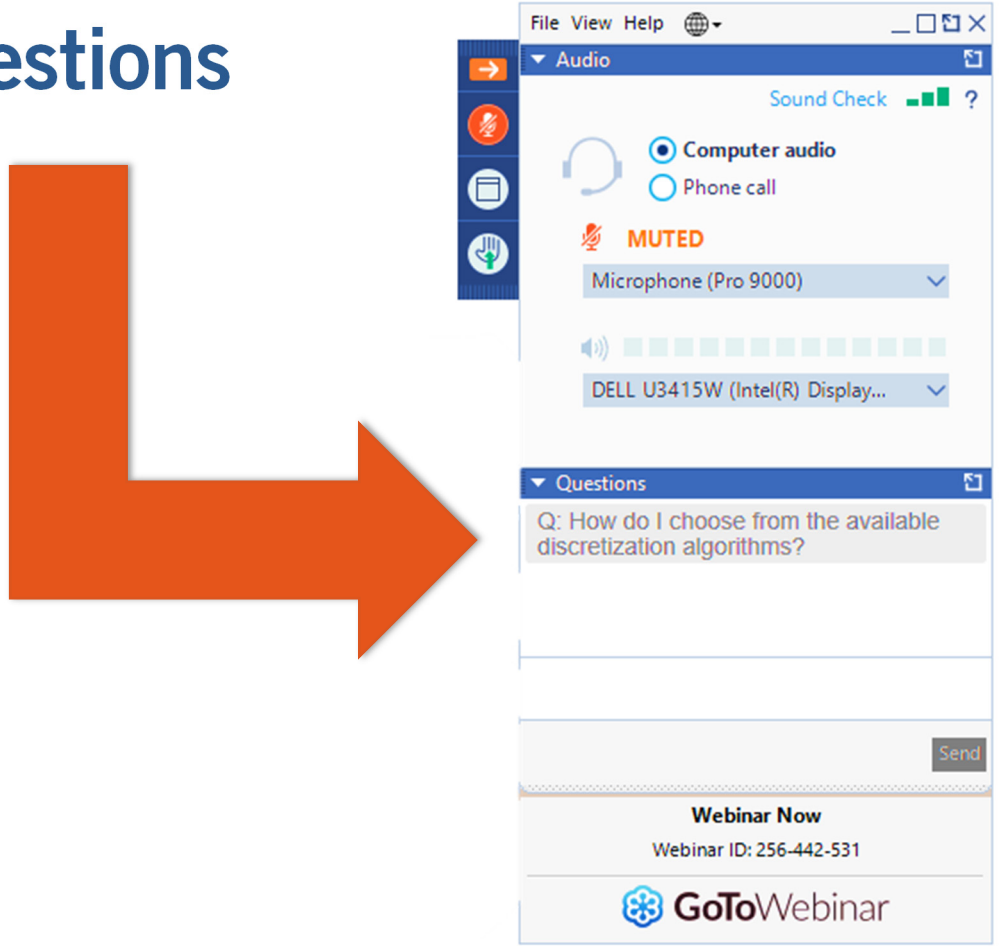
BayesiaLab Trial

Try BayesiaLab Today!

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



Questions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Audio
Sound Check
Computer audio
Phone call
MUTED
Microphone (Pro 9000)
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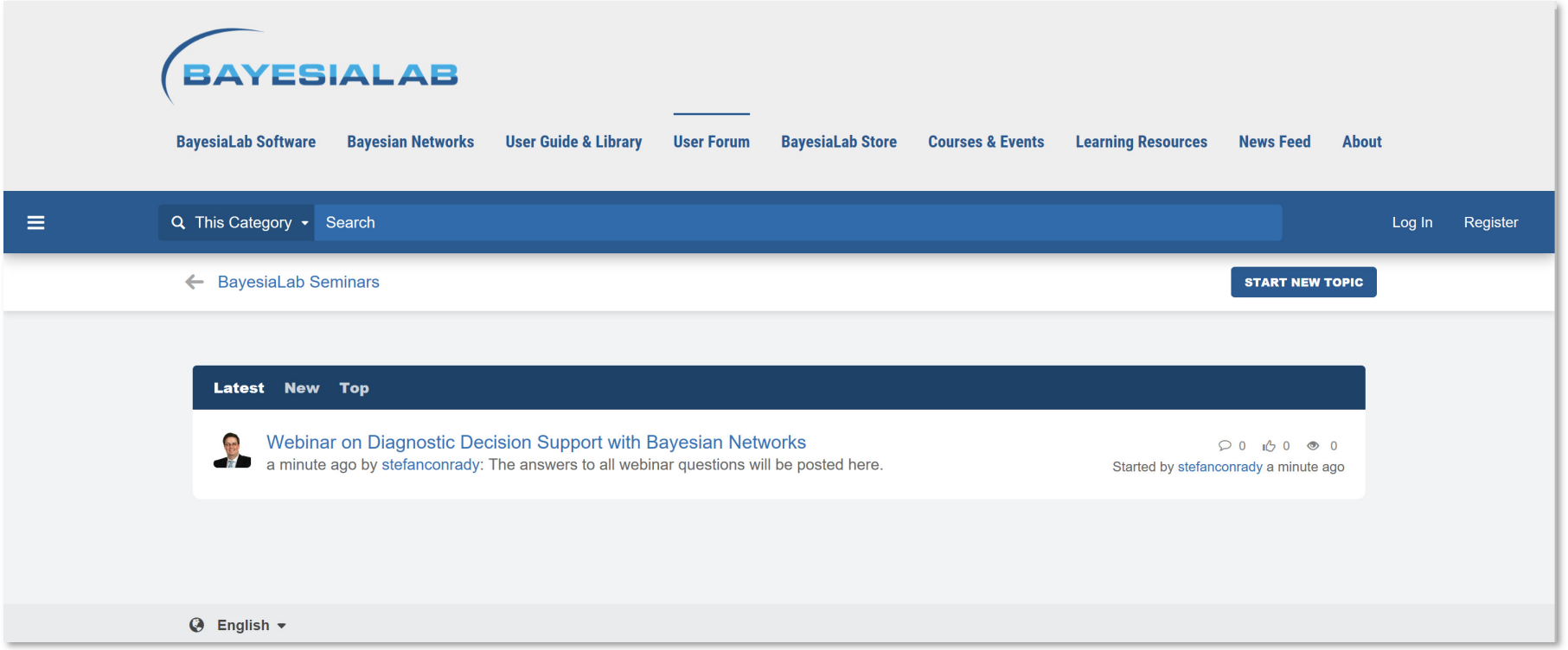
Questions
Q: How do I choose from the available discretization algorithms?
Send
Webinar Now
Webinar ID: 256-442-531
GoToWebinar

User Forum: bayesia.com/community

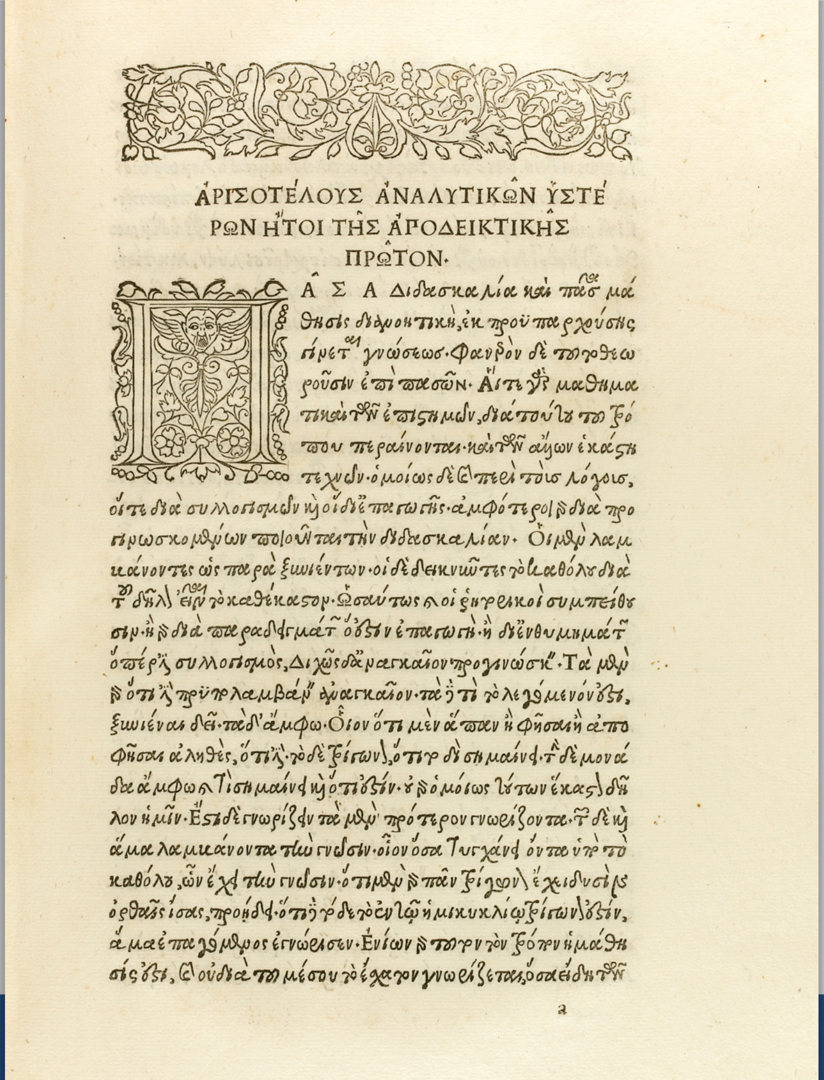


BAYESIALAB

Motivation & Background: Reasoning

Deductive Logic

Aristotle (384-322 BC)


ΑΡΙΣΤΟΤΕΛΟΥΣ ΑΝΑΛΥΤΙΚΩΝ ΥΣΤΕΡΩΝ ΗΤΟΙ ΤΗΣ ΑΠΟΔΕΙΚΤΙΚΗΣ ΠΡΩΤΟΝ.

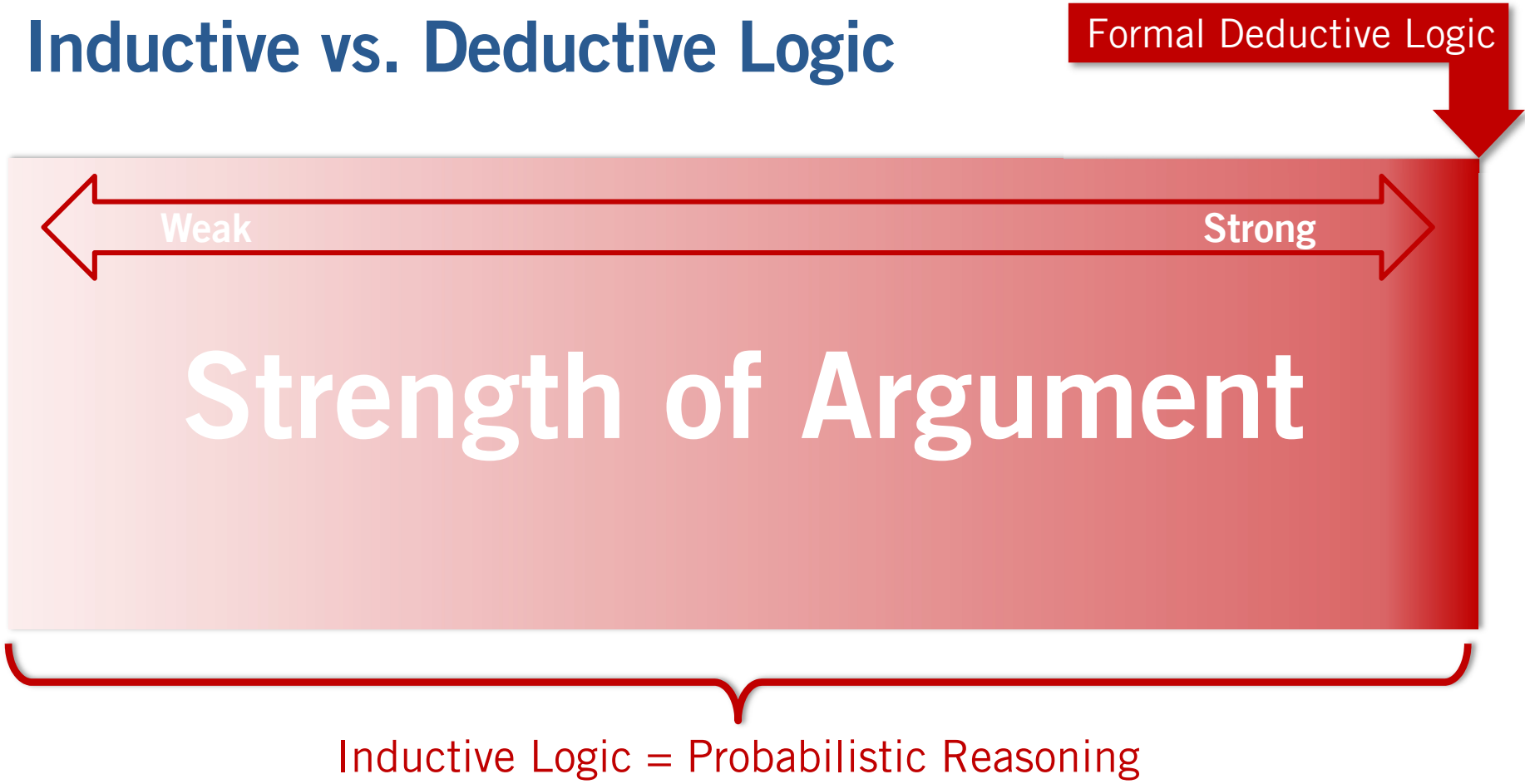
Deductive Logic

Limitations of Logic

- "Classical logic has no explicit mechanism for representing the degree of certainty of premises in an argument, nor the degree of certainty in a conclusion, given those premises."
  Source: J. Williamson, Handbook of the Logic of Argument and Inference: The Turn Toward the Practical

LOGIC IS NOT ENOUGH!

Inductive vs. Deductive Logic



2000 Years Later…

Bayes' Theorem for Conditional Probabilities

H: *Hypothesis*

E: *Evidence*

$$P(H \mid E) = \frac{P(E \mid H)\,P(H)}{P(E)}$$

"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 preſerved. 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-

Probabilistic Reasoning

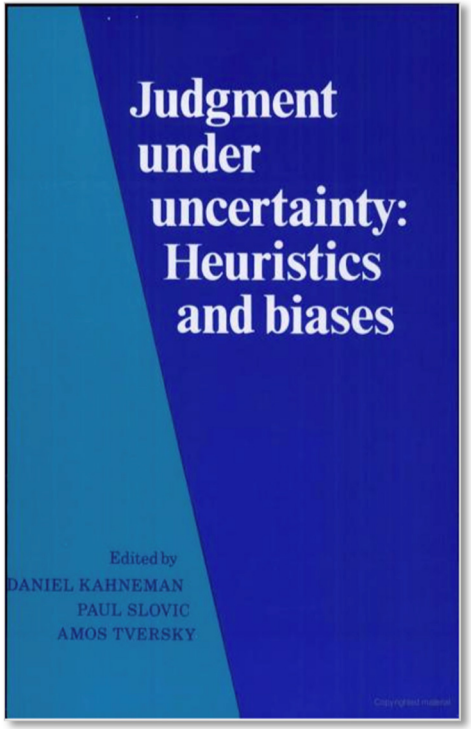
Mathematical Formulation of Inductive Reasoning

- "Bayesian inference is important because it provides a **normative and general-purpose procedure for reasoning under uncertainty**."
  Source: Inductive Reasoning: Experimental, Developmental, and Computational Approaches, edited by Aidan Feeney and Evan Heit

Probabilistic Reasoning

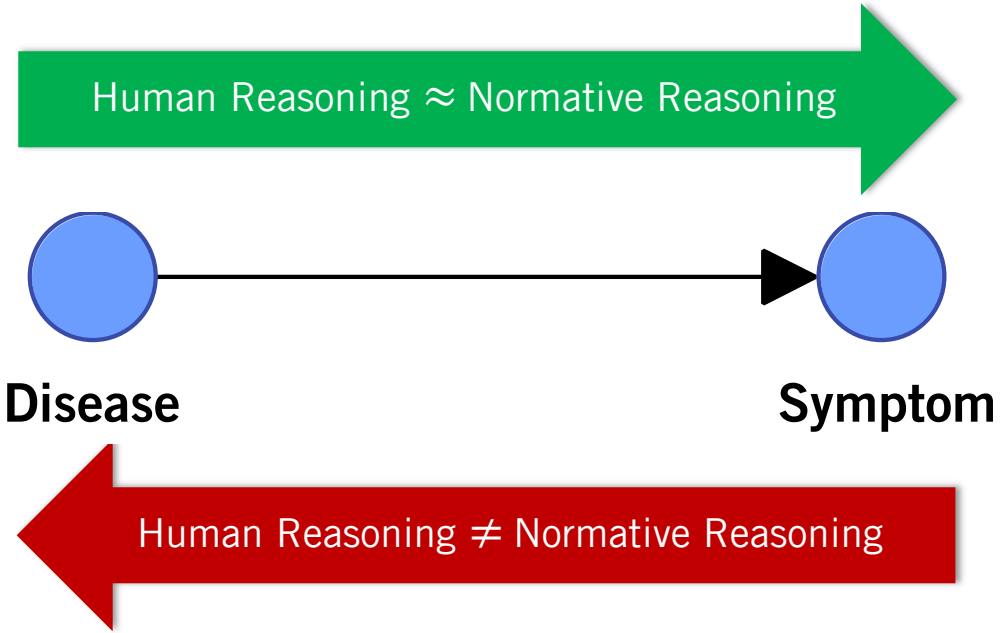
Human reasoning

is flawed!



Why is this so important?

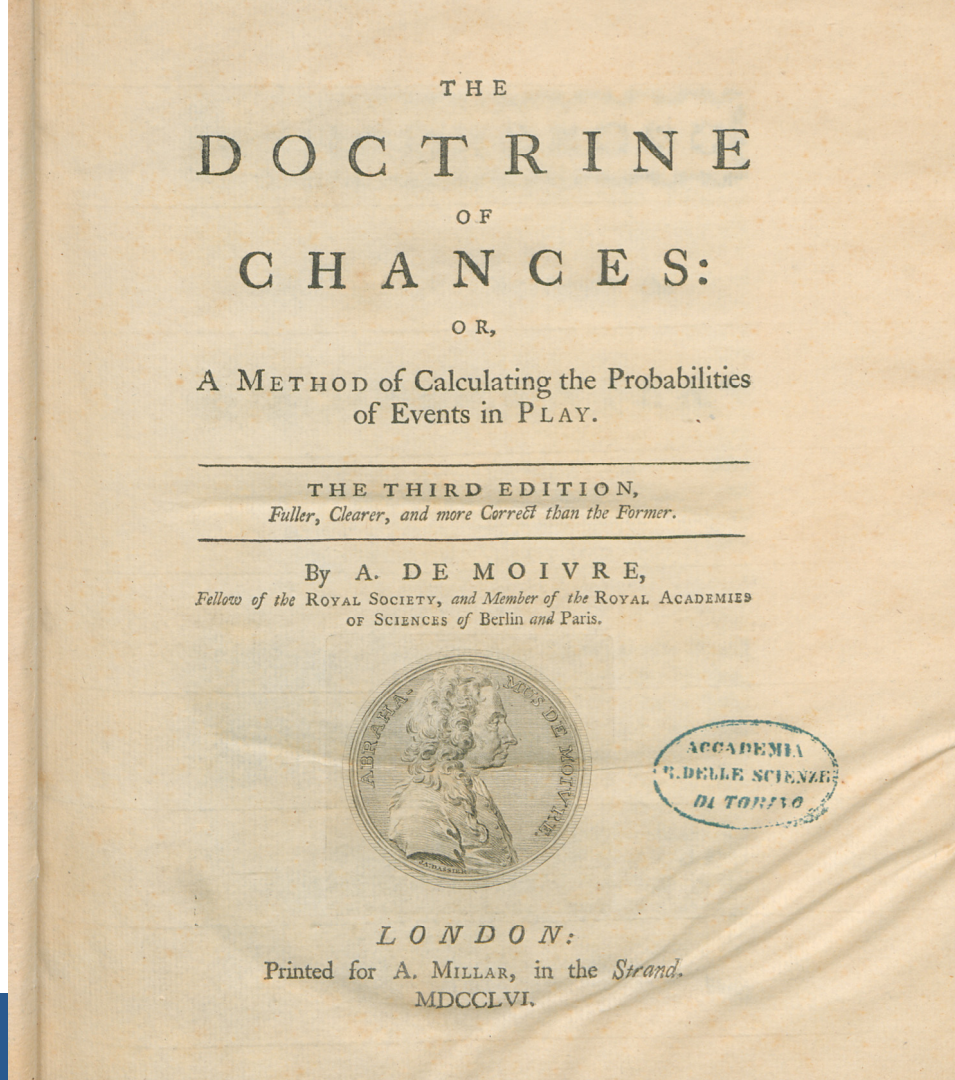
Human Cognitive Limitations and Biases Under Uncertainty



FALLACIES

250 Years Later…

- "…despite the mathematization of probability in the Enlightenment, mathematical probability theory remains, to this very day, entirely unused in criminal courtrooms, when evaluating the 'probability' of the guilt of a suspected criminal."
  James Franklin, The Science of Conjecture: Evidence and Probability before Pascal, 2001 The Johns Hopkins Press


THE

DOCTRINE

OF

CHANCES:

OR,

A METHOD of Calculating the Probabilities of Events in PLAY.

THE THIRD EDITION,
Fuller, Clearer, and more Correct than the Former.

By A. DE MOIVRE,
Fellow of the ROYAL SOCIETY, *and Member of the* ROYAL ACADEMIES OF SCIENCES *of* Berlin *and* Paris.

ABRAHA. MOIVRE.

ACCADEMIA R. DELLE SCIENZE DI TORINO

LONDON:
Printed for A. MILLAR, in the *Strand*.
MDCCLVI.

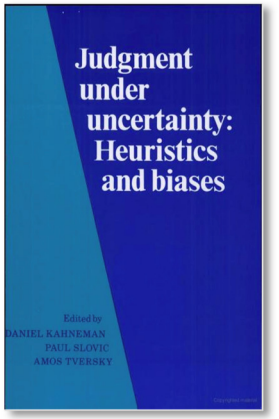
BAYESIALAB

Example 1: What Color is the Taxi?

Knowledge Modeling & Reasoning Under Uncertainty

What Color is the Taxi?

*adapted from Kahneman & Tversky, 1980

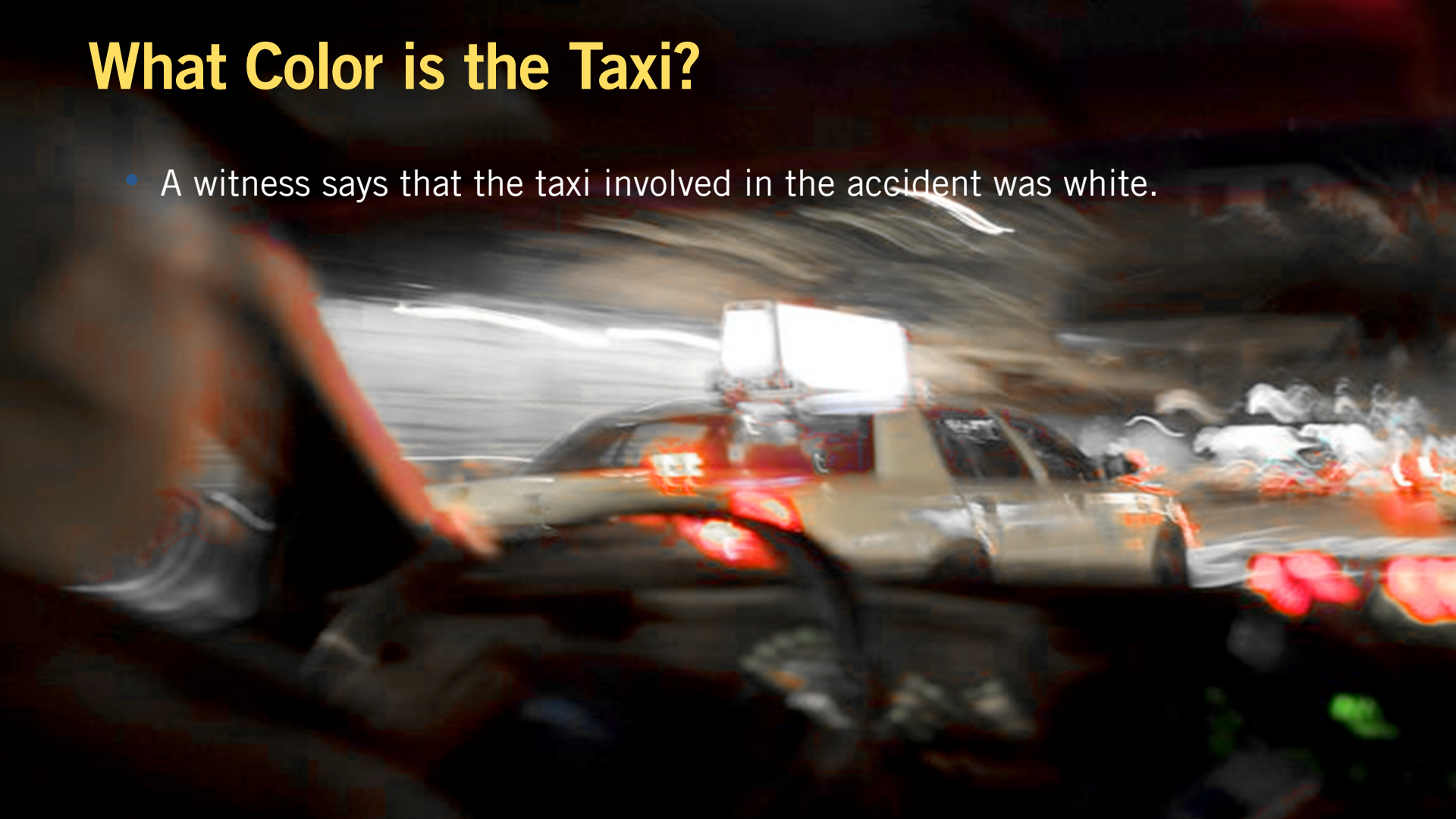


Human Reasoning Experiment*

- A taxi was involved in a hit-and-run accident at night.
- Only two taxi companies operate in this city, the Yellow Cab Co. and the White Cab Co.
  - 85% of taxis belong to the Yellow Cab Co.
  - 15% of taxis belong to the White Cab Co.

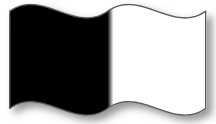
What Color is the Taxi?

- A witness says that the taxi involved in the accident was white.



What Color is the Taxi?

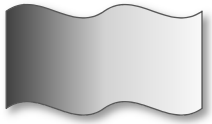
At the trial in "Logiland," where formal deductive logic rules…



- Premise 1
    - Taxi caused accident ✓
- Premise 2
    - Two taxi companies in town, yellow and white ✓
- Premise 3
    - Accident witness: Taxi was white ✓
- Conclusion
    - White Taxi Co. is responsible for accident

What Color is the Taxi?

At the Trial in "Likeliland"



- An expert witness explains that human vision has an 80% accuracy in terms of distinguishing between white and yellow given light conditions at the time of the accident.
  - $P(\text{Witness}=\text{white} \mid \text{Color}=\text{white})=80\%$
  - $P(\text{Witness}=\text{yellow} \mid \text{Color}=\text{white})=20\%$
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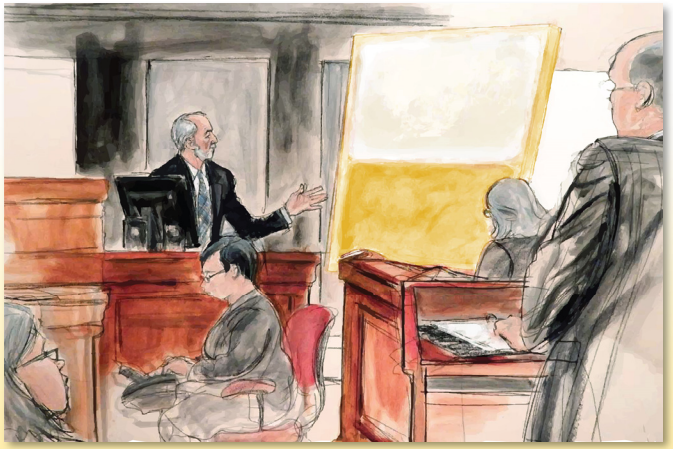
  - $P(\text{Witness}=\text{white} \mid \text{Color}=\text{yellow})=20\%$



What Color is the Taxi?

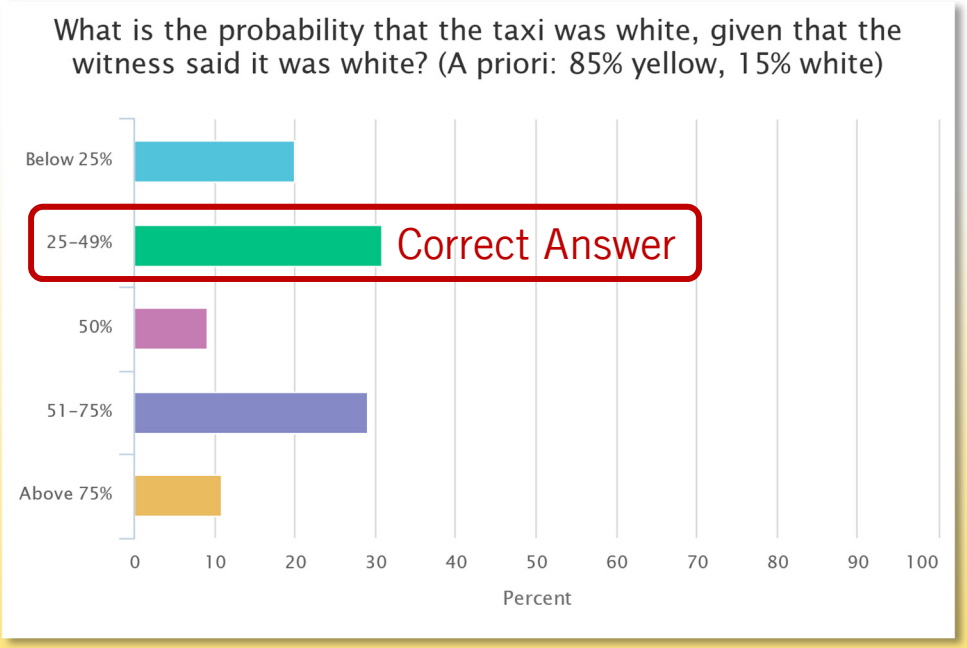
You are the jury in “Likeliland”!

- Given the three premises and the expert witness statement, what is the probability that the taxi was white?

What Color is the Taxi?

Results from Webinar Poll

- Correct Answer: 41.38%



What Color is the Taxi?

- We need to perform probabilistic inference to answer this question.
- Bayes' Rule allows us to compute the probability $P(Taxi{=}white \mid Witness{=}white)$:

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

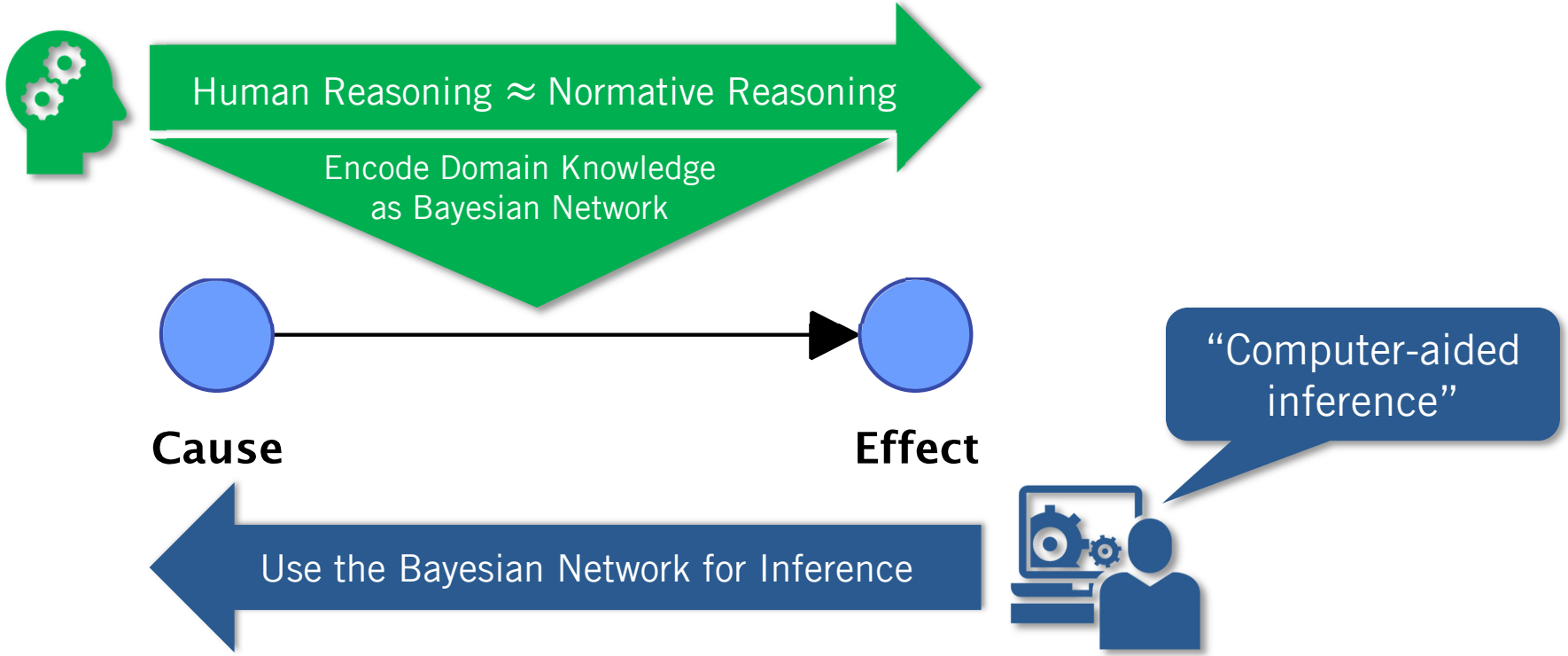
$$P(Taxi = white \mid Witness = white) = \frac{P(Witness = white \mid Taxi = white)P(Taxi = white)}{P(Witness = white)} =$$

$$\frac{P(Witness = white \mid Taxi = white)P(Taxi = white)}{P(Witness = white \mid Taxi = white)P(Taxi = white) + P(Witness = white \mid Taxi = yellow)P(Taxi = yellow)}$$

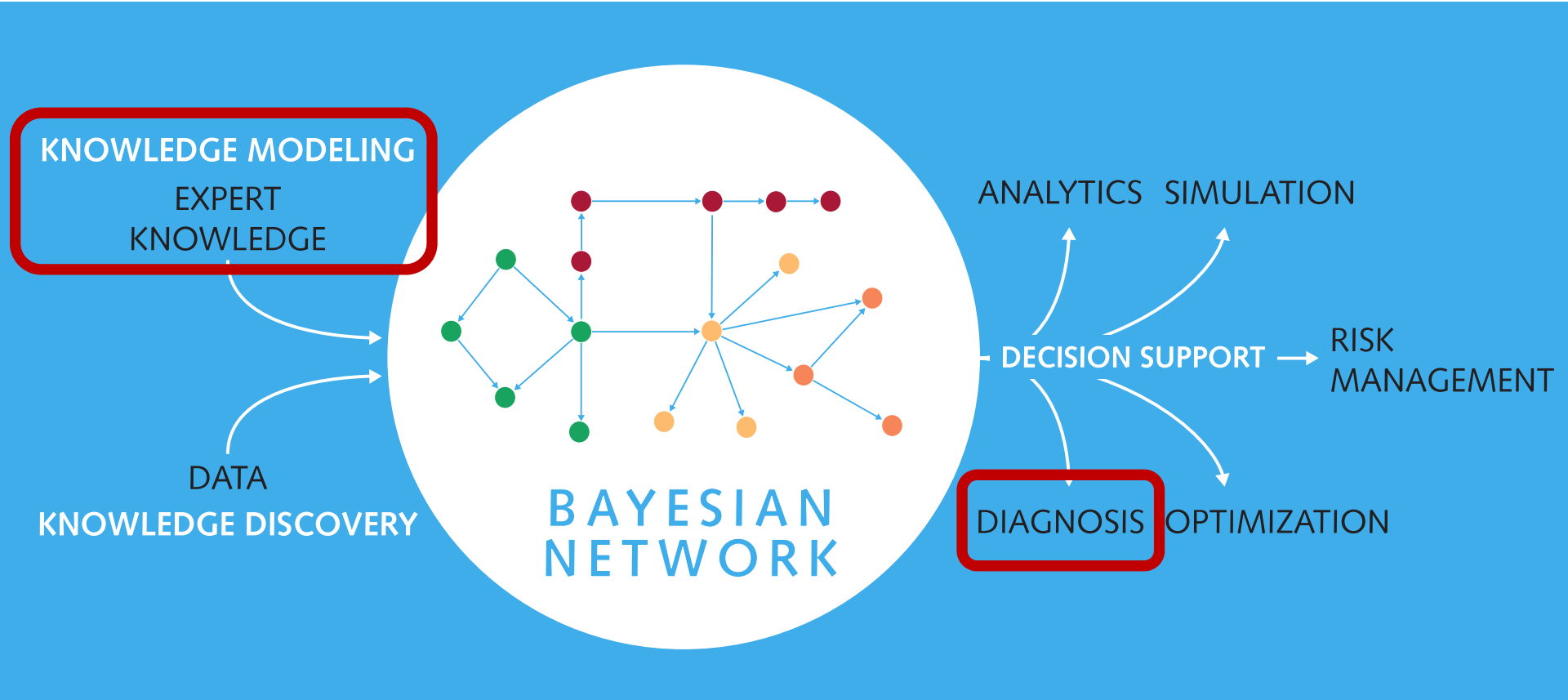
Correct, but impractical

Bayesian Networks to the Rescue!

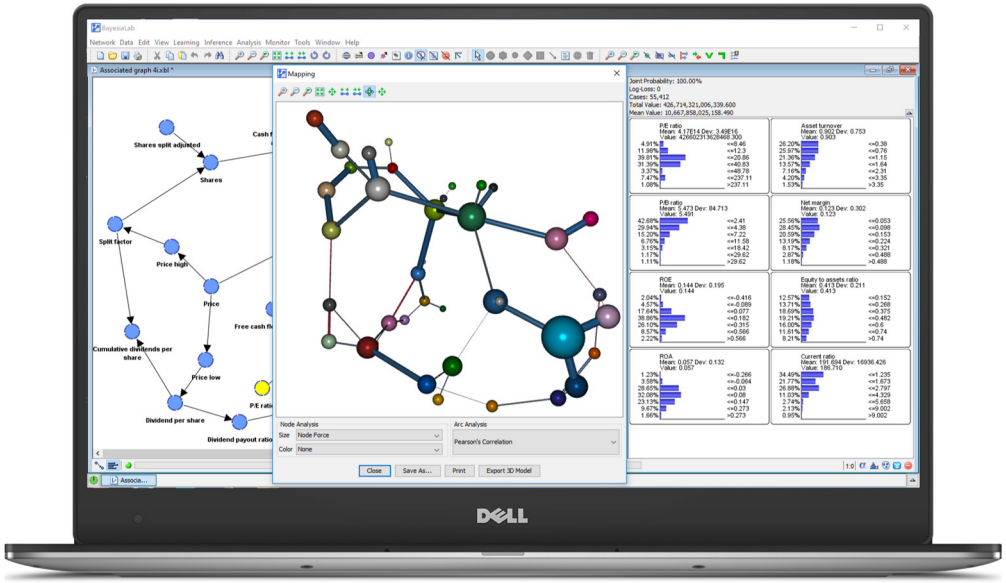
Overcoming our Limitations



The BayesiaLab Workflow



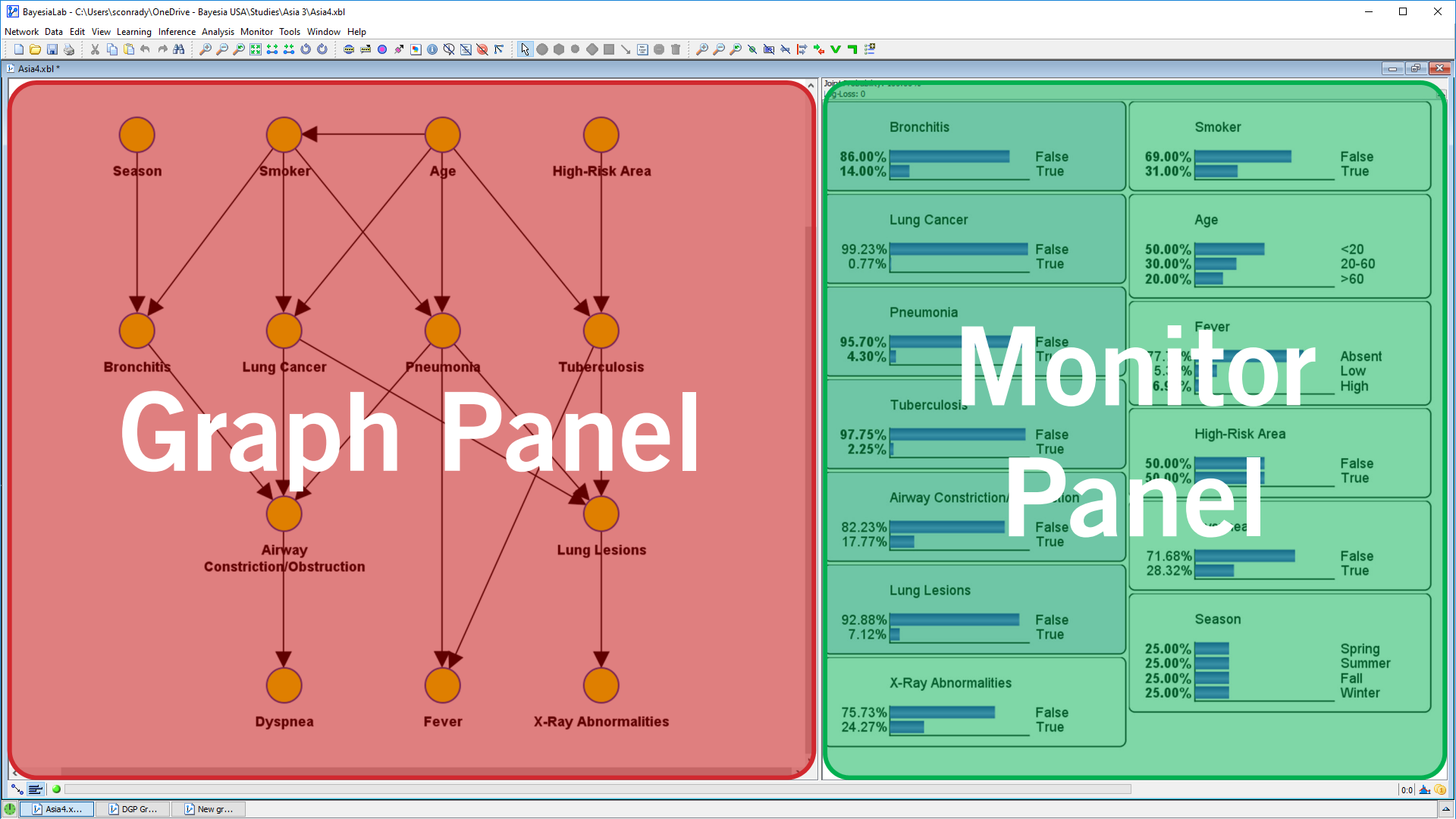
BAYESIALAB



A desktop software for:

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

with Bayesian networks.


BayesiaLab - C:\Users\sconrady\OneDrive - Bayesia USA\Studies\Asia 3\Asia4.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
Asia4.xbl *
Season
Smoker
Age
High-Risk Area
Bronchitis
Lung Cancer
Pneumonia
Tuberculosis
Airway Constriction/Obstruction
Lung Lesions
Dyspnea
Fever
X-Ray Abnormalities
Graph Panel
Bronchitis
86.00% False
14.00% True
Smoker
69.00% False
31.00% True
Lung Cancer
99.23% False
0.77% True
Age
50.00% <20
30.00% 20-60
20.00% >60
Pneumonia
95.70% False
4.30%
Fever
Absent
Low
High
Tuberculosis
97.75% False
2.25% True
High-Risk Area
50.00% False
50.00% True
Airway Constriction/
82.23% False
17.77% True
71.68% False
28.32% True
Lung Lesions
92.88% False
7.12% True
Season
25.00% Spring
25.00% Summer
25.00% Fall
25.00% Winter
X-Ray Abnormalities
75.73% False
24.27% True
Monitor Panel
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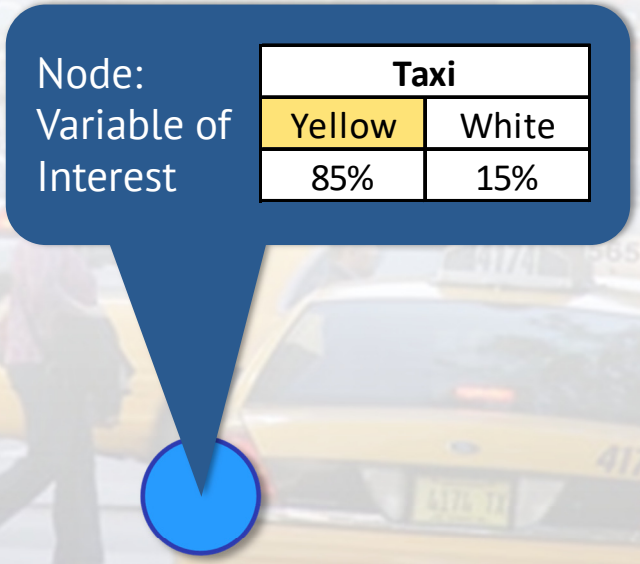
What Color is the Taxi?

We encode our domain knowledge regarding the taxi cab example:



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What Color is the Taxi?

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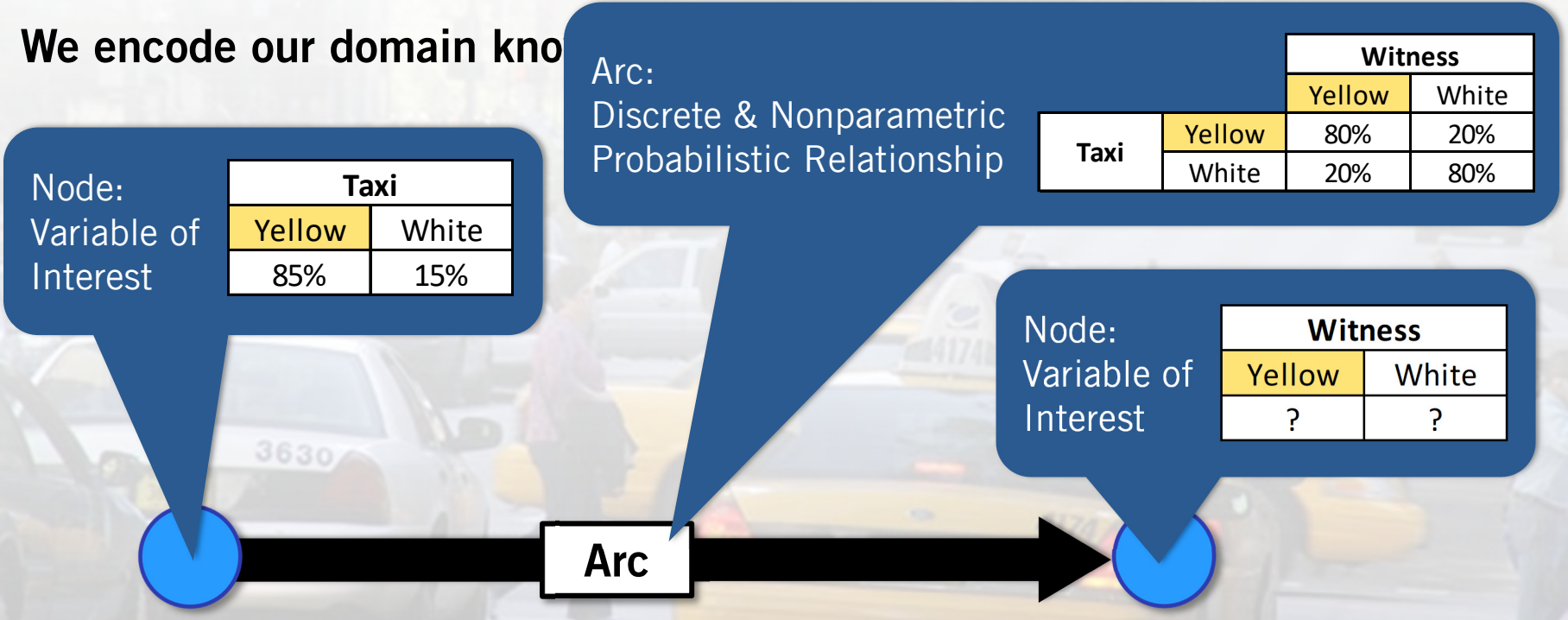

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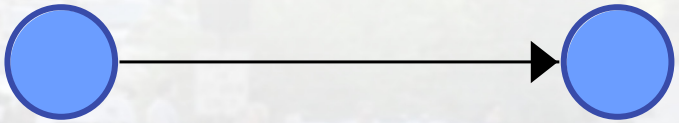


Taxi

Yellow	White
85.000	15.000

Marginal Distribution

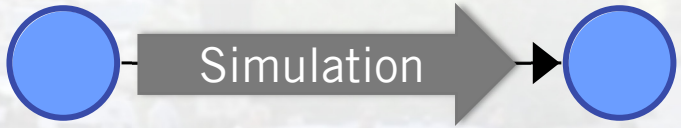
Witness

Taxi	Yellow	White
Yellow	80.000	20.000
White	20.000	80.000

Conditional Probability Table

What Color is the Taxi?

Inference based on evidence:



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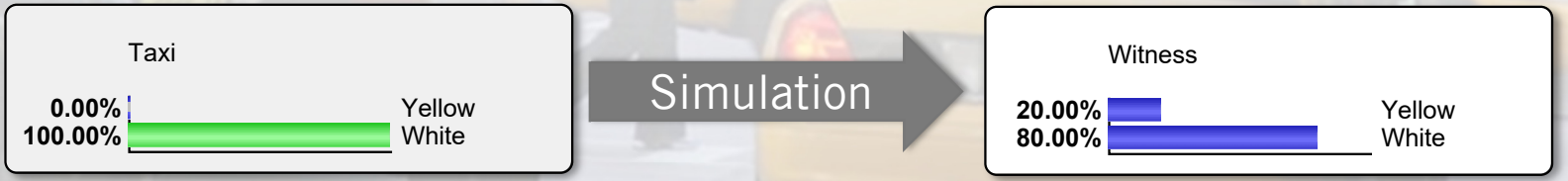
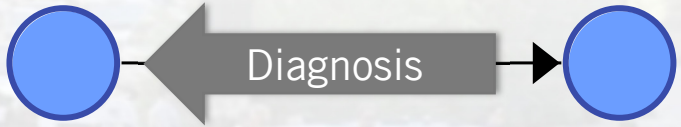


What Color is the Taxi?

Performing inference based on observing evidence:



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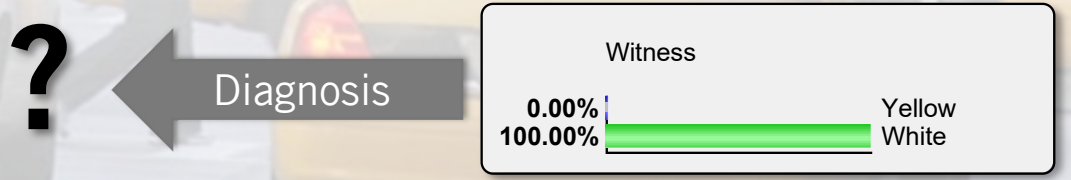

What Color is the Taxi?

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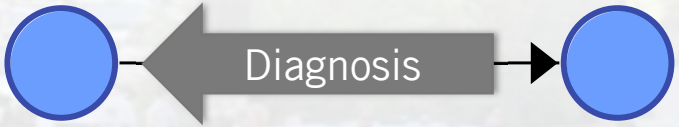
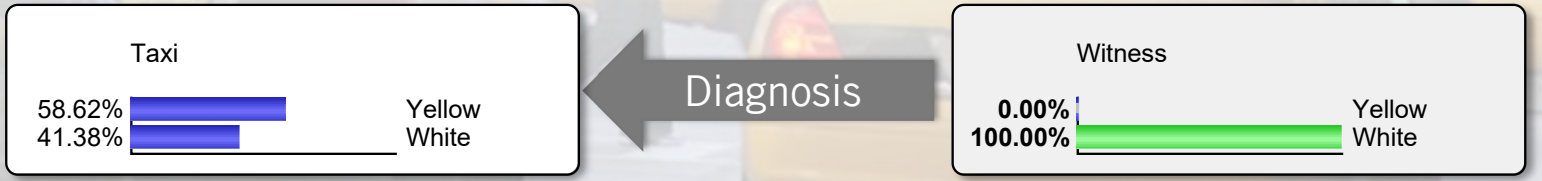


Taxi

Yellow	White
85.000	15.000

Witness

Taxi	Yellow	White
Yellow	80.000	20.000
White	20.000	80.000



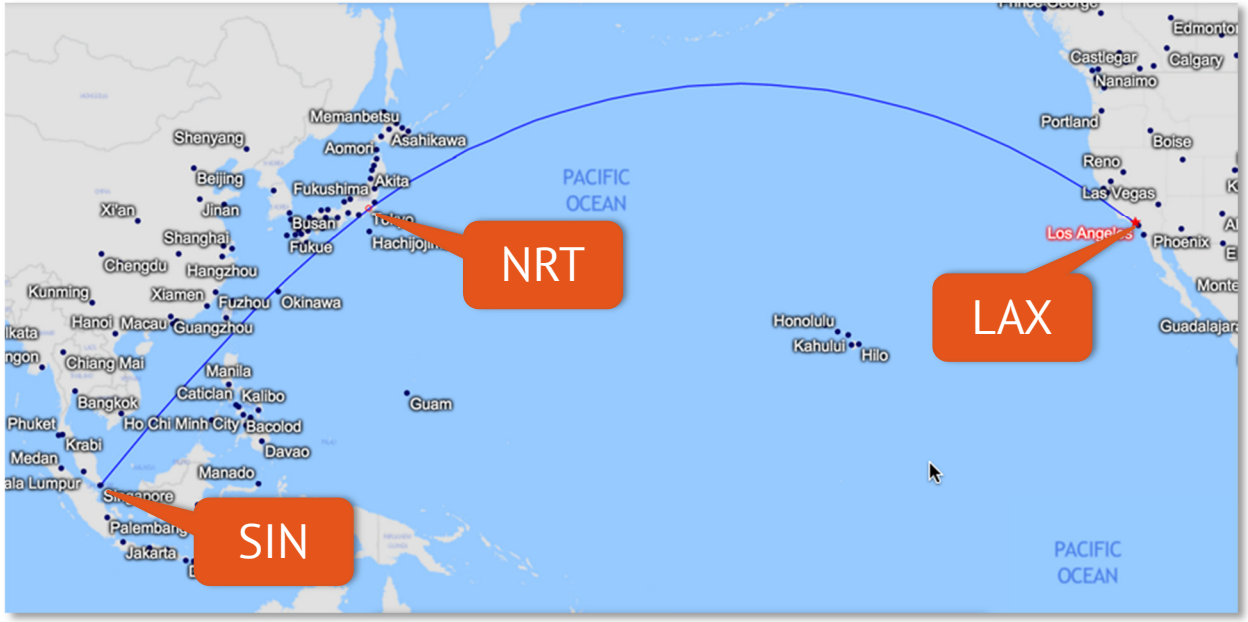
See Chapter 4

Example 2: Where is my bag?

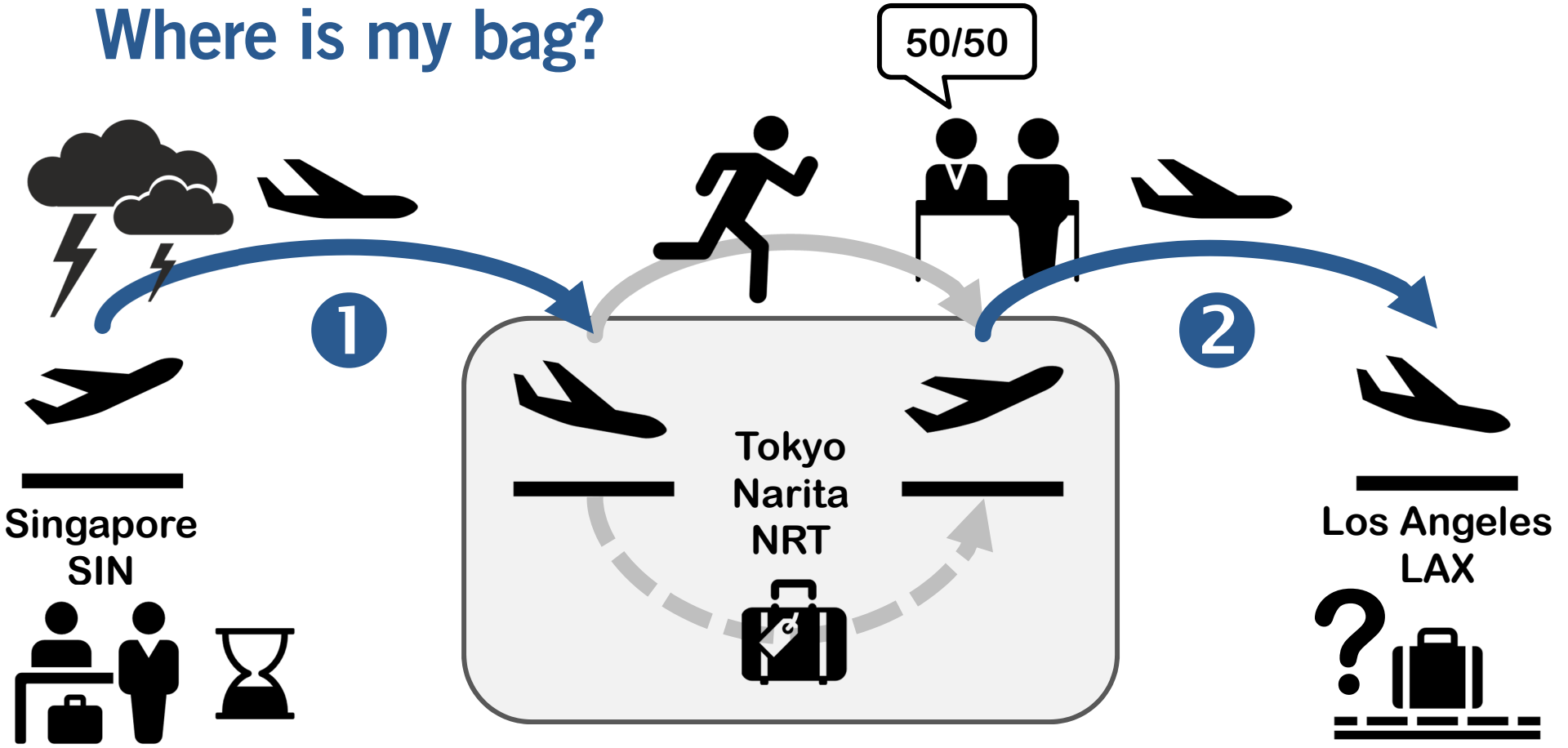
Knowledge Modeling & Reasoning Under Uncertainty

Example 2: Where is my bag?

Travel Route: Singapore (SIN) ➔ Tokyo/Narita (NRT) ➔ Los Angeles (LAX)



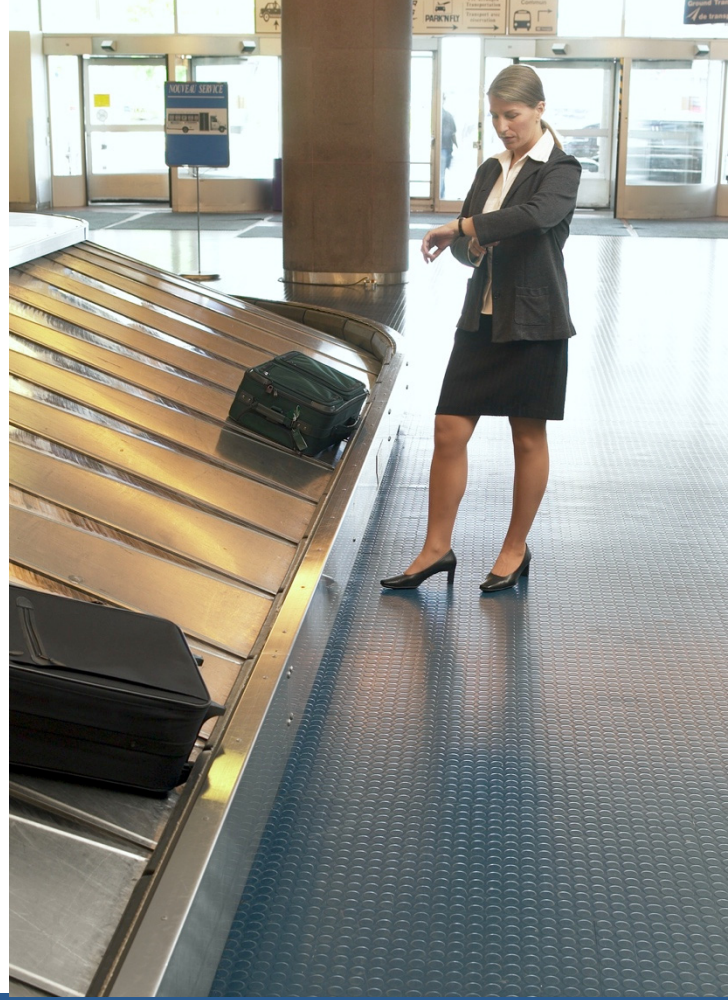
Where is my bag?



Where is my bag?

Scenario 1

- Luggage delivery starts onto the carousel.
- **After 5 minutes**, I still do not see my bag.
- What is the probability that I will still get my bag?

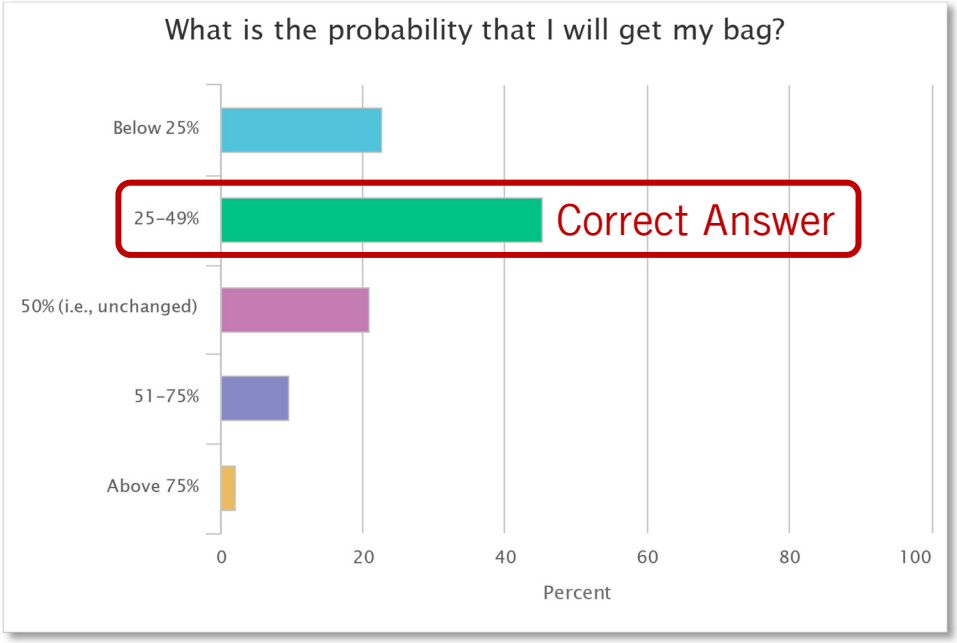



SINGAPORE AIRLINES
D-ABYJ
9V-SKH
Sky Chefs
152
154
156
IS MY BAG IN THERE?

Where is my bag?

Results from Webinar Poll

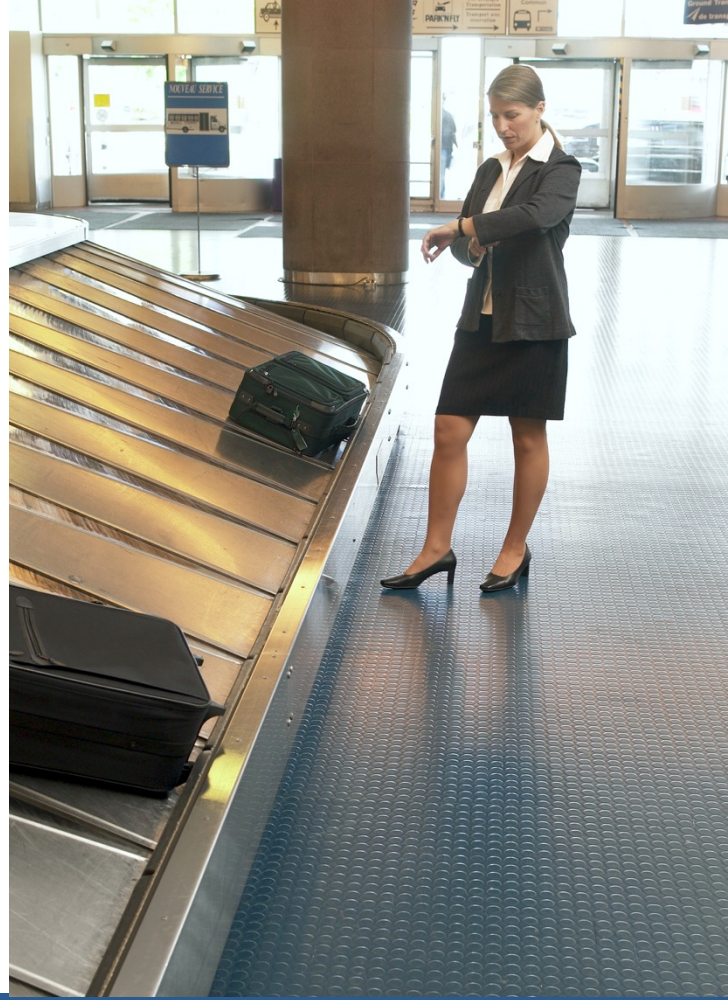
- Correct Answer: 33%

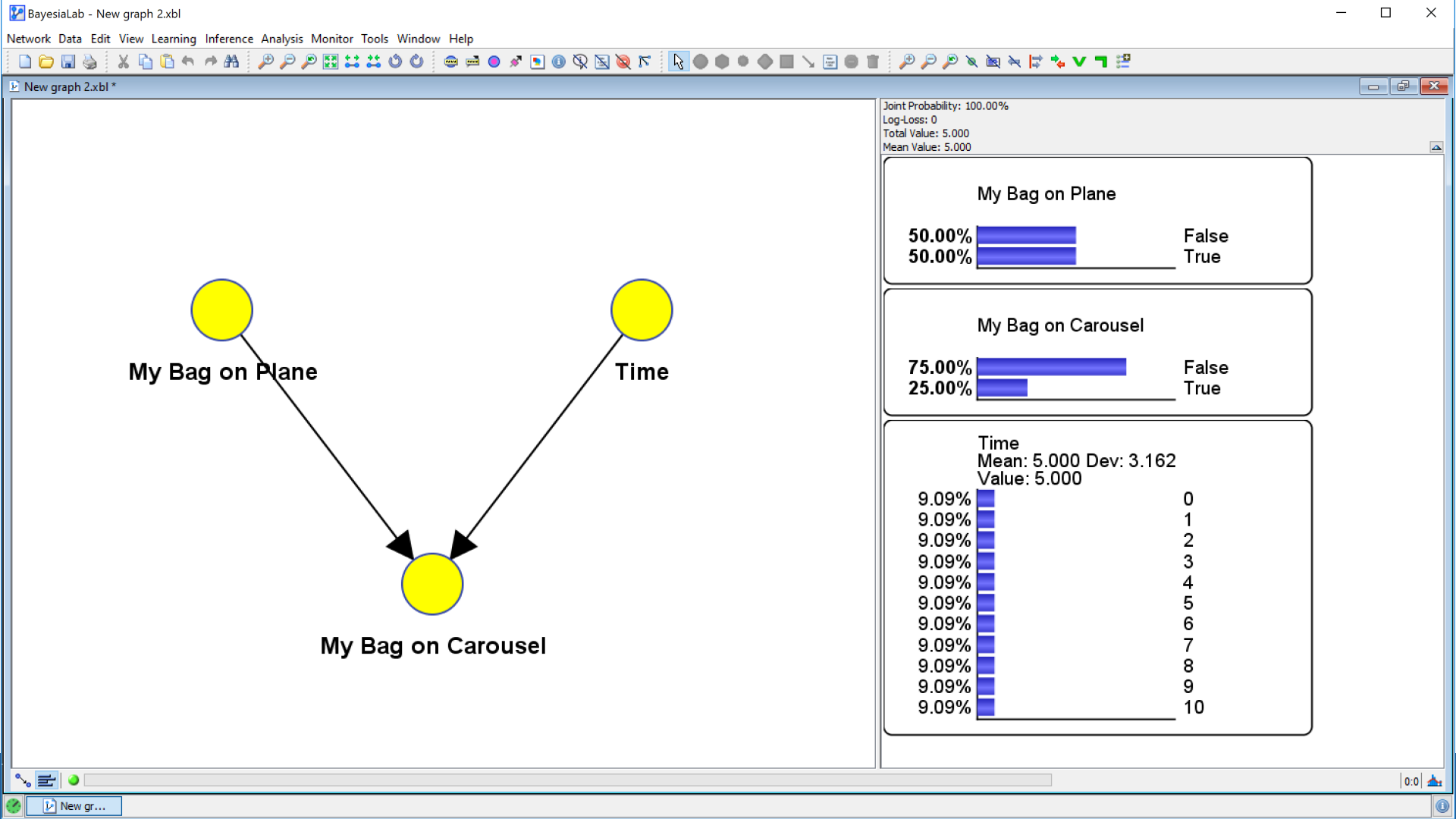


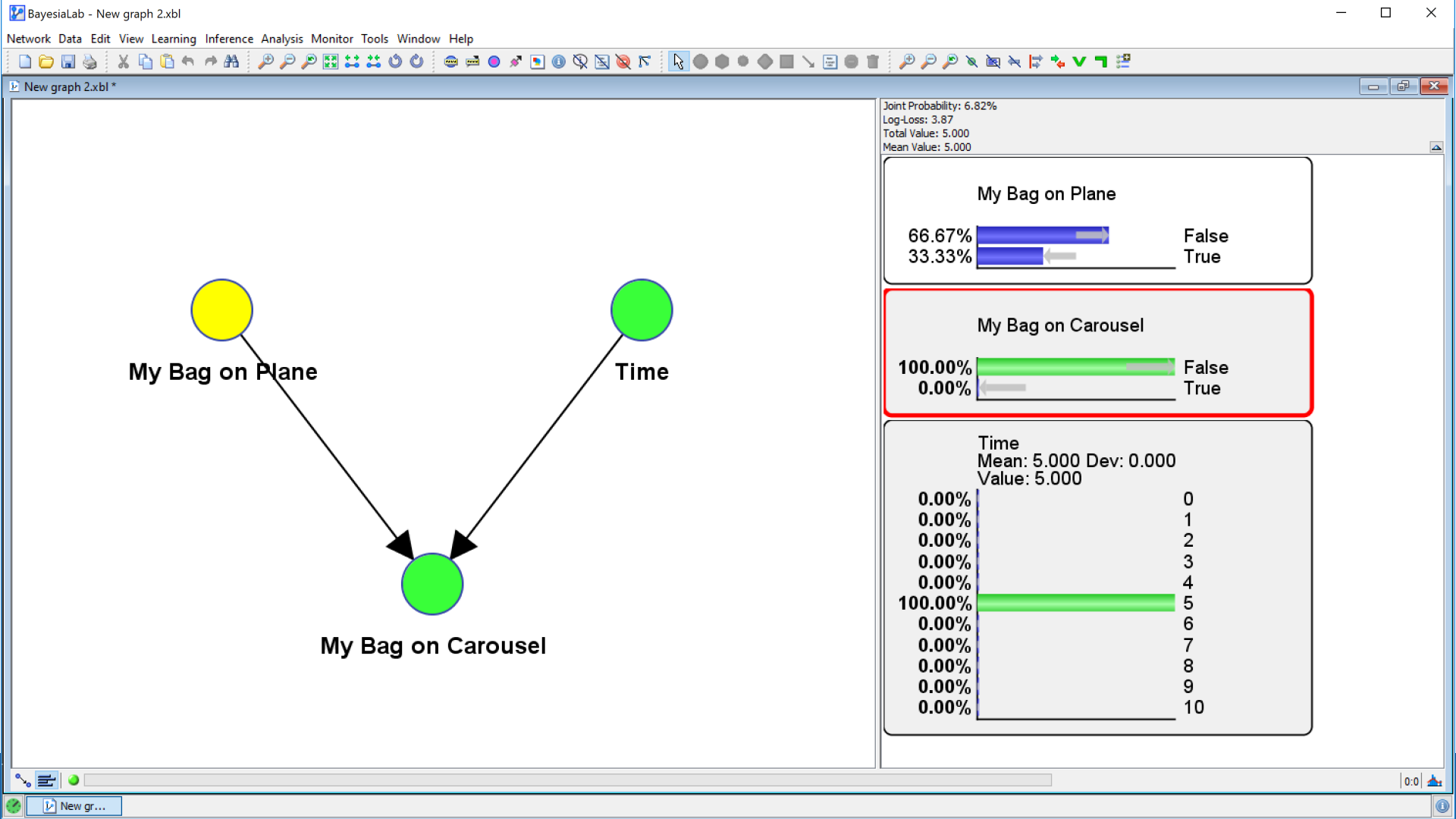
Where is my bag?

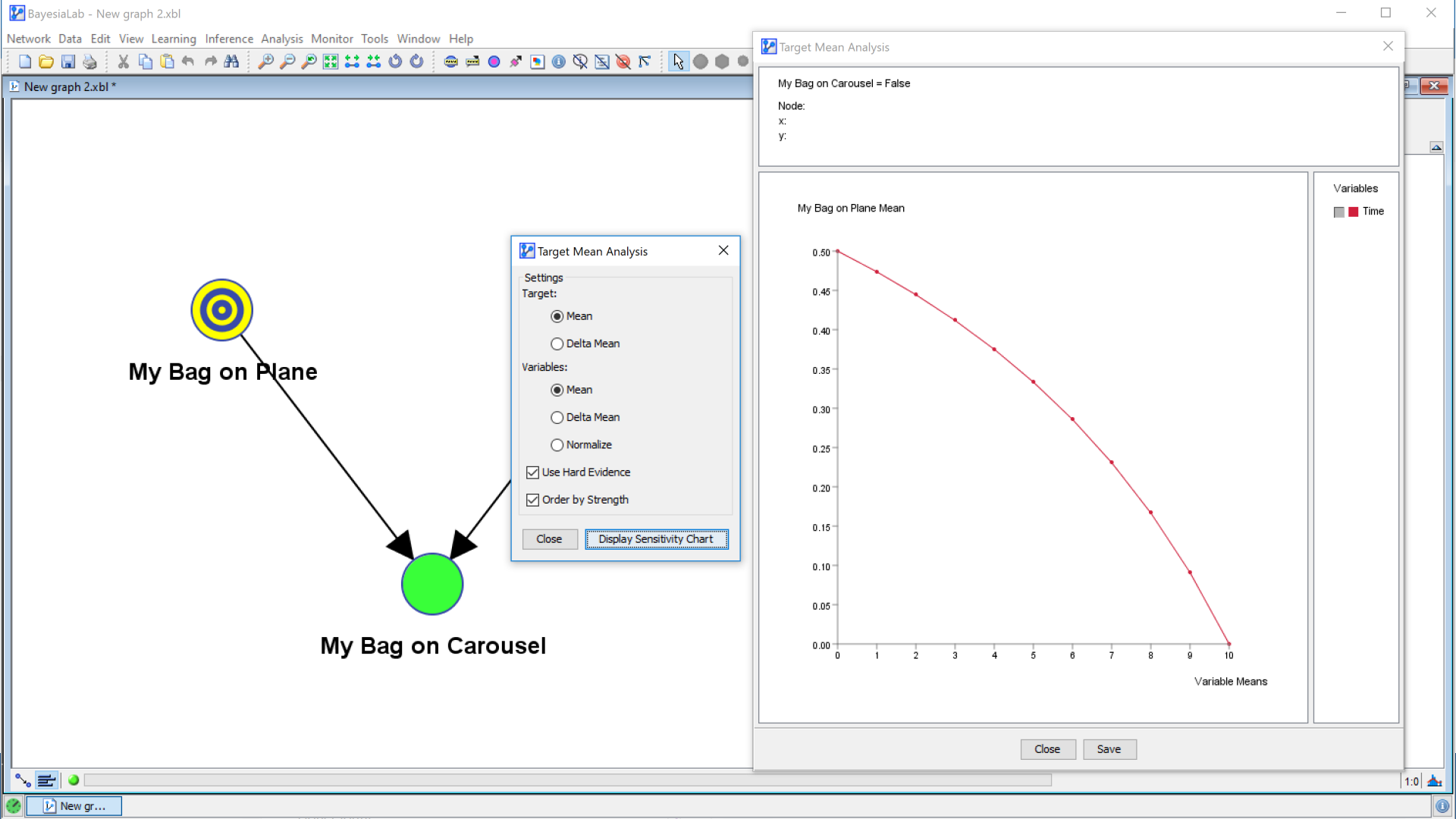
Proposed Workflow

- Encode the available — albeit very limited — knowledge into a Bayesian network.
- Use BayesiaLab to perform probabilistic inference given our observations.




BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
My Bag on Plane
Time
My Bag on Carousel
Joint Probability: 100.00%
Log-Loss: 0
Total Value: 5.000
Mean Value: 5.000
My Bag on Plane
50.00% False
50.00% True
My Bag on Carousel
75.00% False
25.00% True
Time
Mean: 5.000 Dev: 3.162
Value: 5.000
9.09% 0
9.09% 1
9.09% 2
9.09% 3
9.09% 4
9.09% 5
9.09% 6
9.09% 7
9.09% 8
9.09% 9
9.09% 10

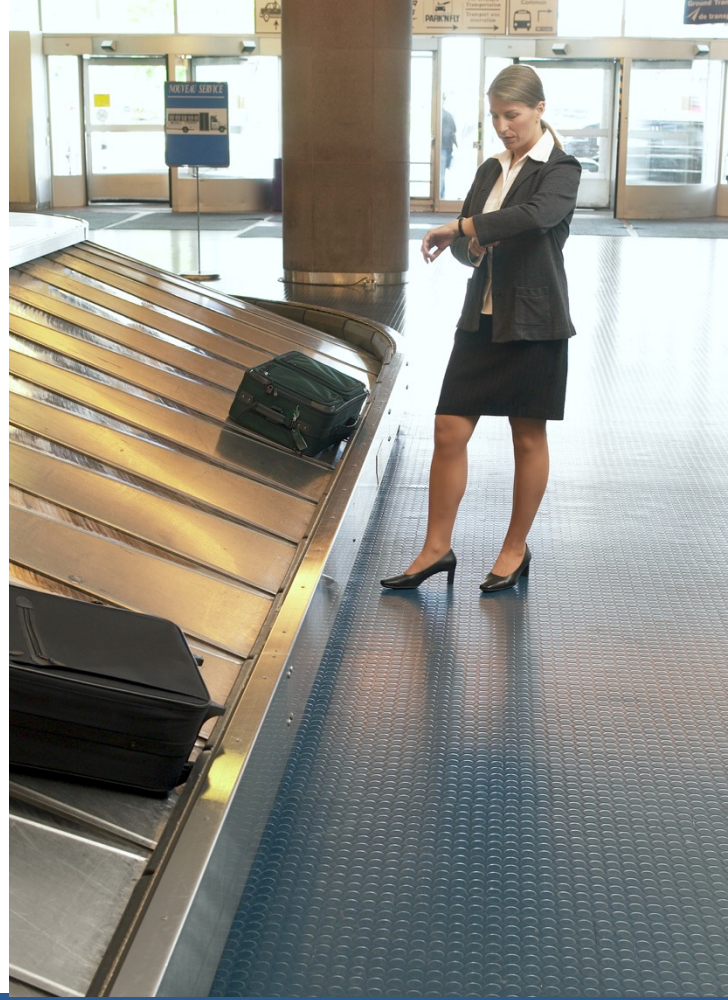

BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
My Bag on Plane
Time
My Bag on Carousel
Joint Probability: 6.82%
Log-Loss: 3.87
Total Value: 5.000
Mean Value: 5.000
My Bag on Plane
66.67% False
33.33% True
My Bag on Carousel
100.00% False
0.00% True
Time
Mean: 5.000 Dev: 0.000
Value: 5.000
0.00% 0
0.00% 1
0.00% 2
0.00% 3
0.00% 4
100.00% 5
0.00% 6
0.00% 7
0.00% 8
0.00% 9
0.00% 10

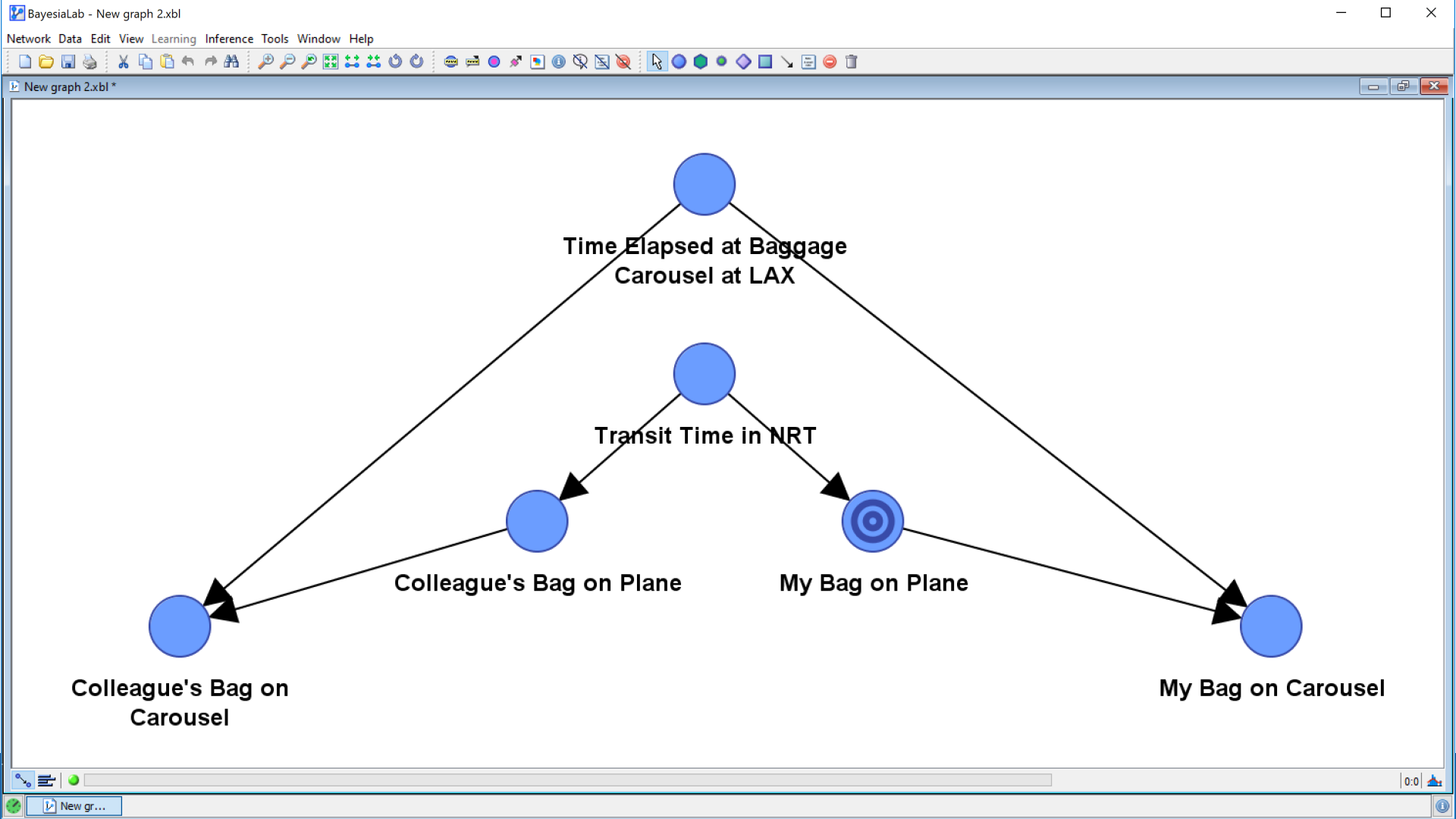

BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
My Bag on Plane
My Bag on Carousel
Target Mean Analysis
Settings
Target:
Mean
Delta Mean
Variables:
Mean
Delta Mean
Normalize
Use Hard Evidence
Order by Strength
Close
Display Sensitivity Chart
Target Mean Analysis
My Bag on Carousel = False
Node:
x:
y:
My Bag on Plane Mean
Variables
Time
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0 1 2 3 4 5 6 7 8 9 10
Variable Means
Close
Save

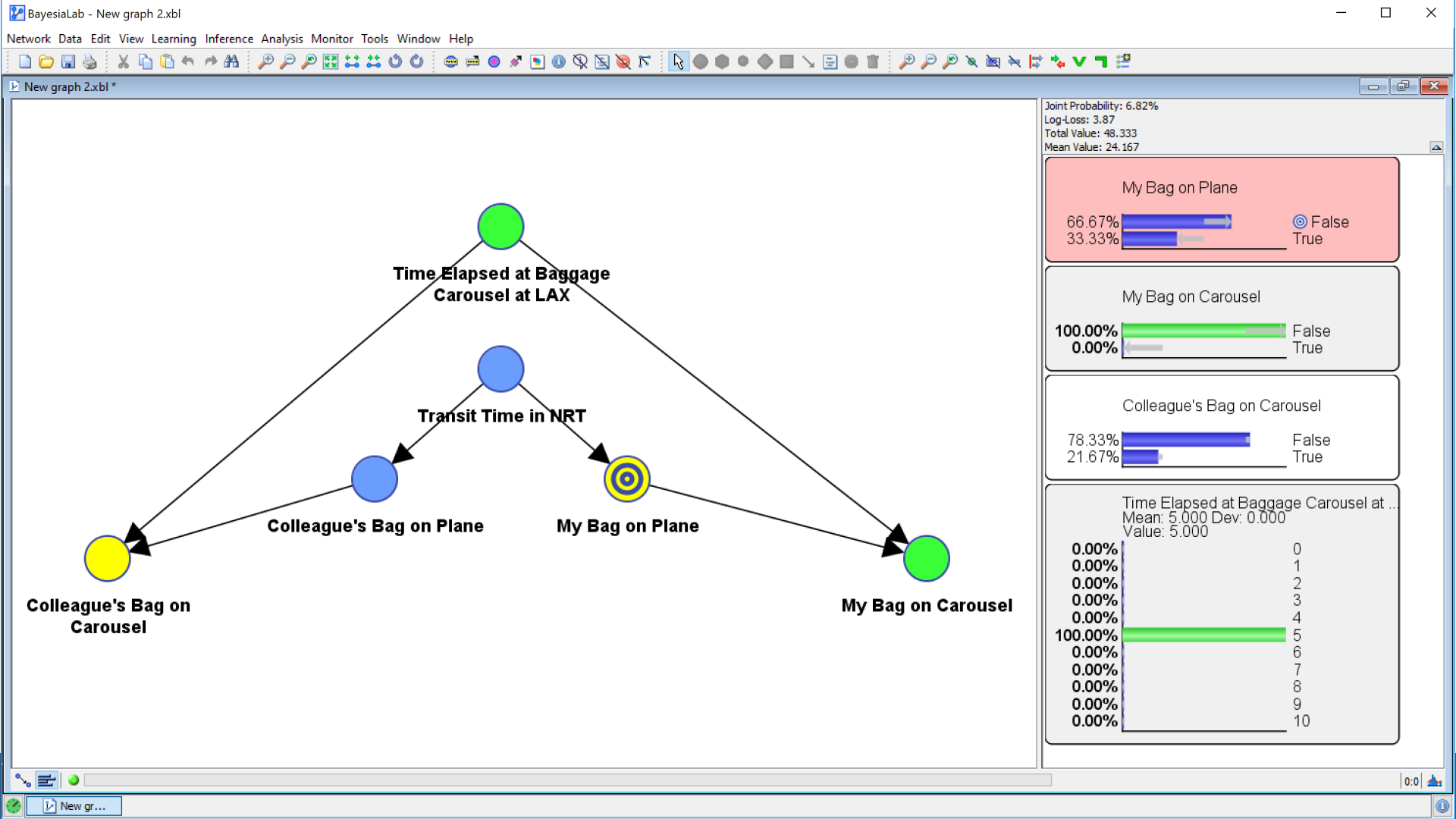
Where is my bag?

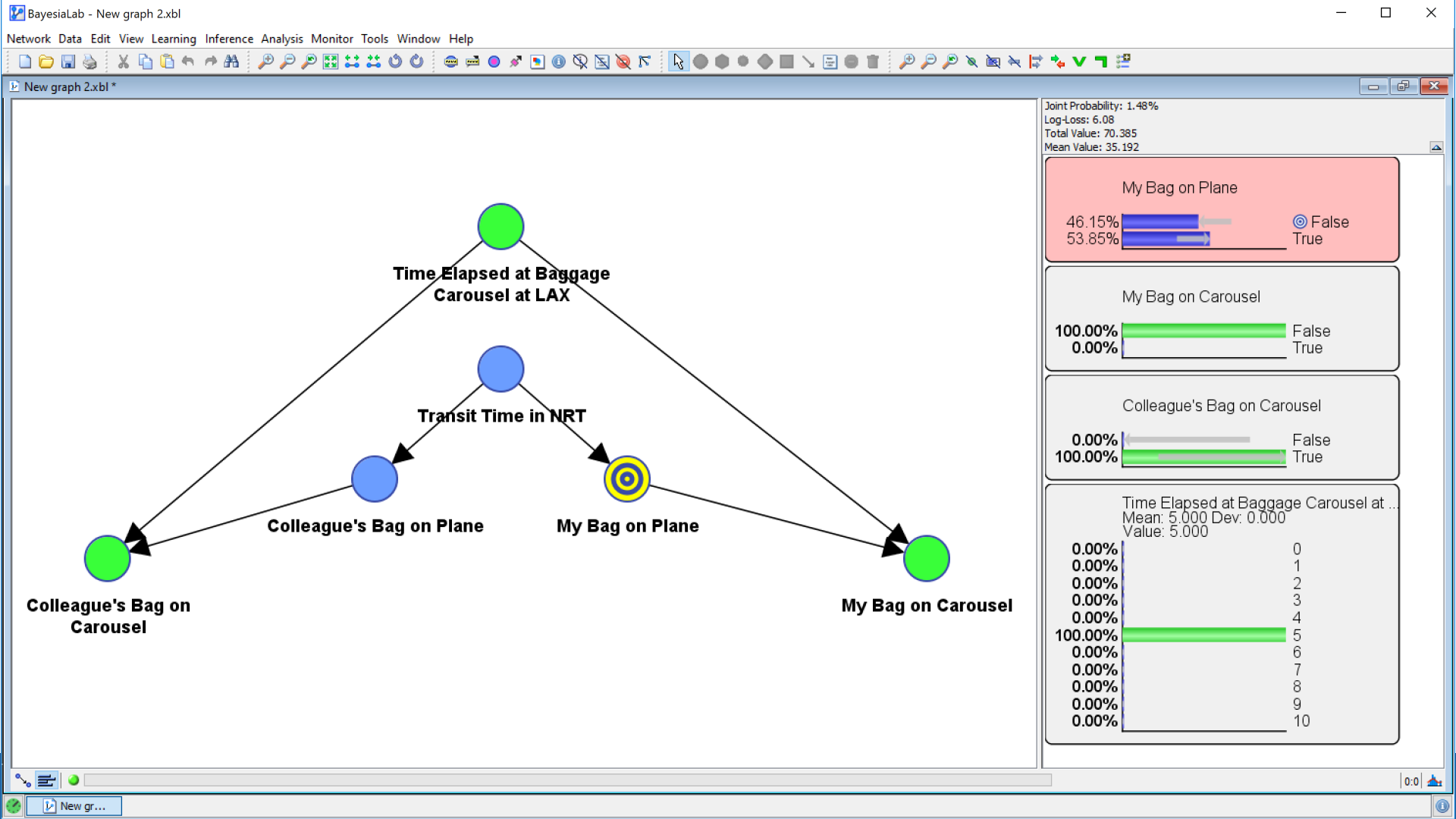
Scenario 2

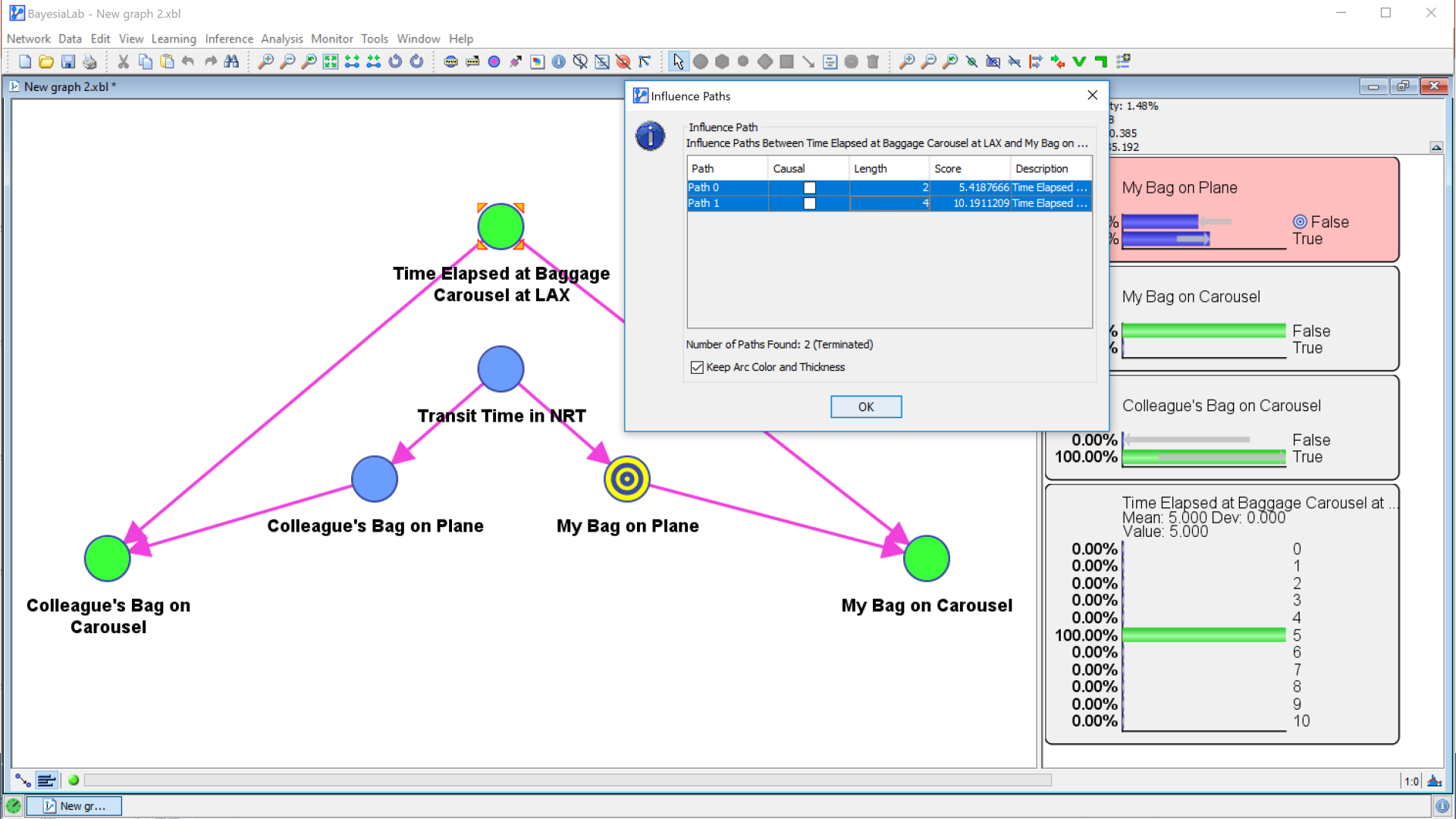
- Luggage delivery starts onto the carousel.
- After 5 minutes, I still do not see my bag.
- **However, now I see a colleague, who traveled on the same itinerary, pick up his bag.**
- What is now the probability that I will still get my bag?




BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Tools Window Help
New graph 2.xbl *
Time Elapsed at Baggage Carousel at LAX
Transit Time in NRT
Colleague's Bag on Plane
My Bag on Plane
Colleague's Bag on Carousel
My Bag on Carousel


BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
Time Elapsed at Baggage Carousel at LAX
Transit Time in NRT
Colleague's Bag on Plane
My Bag on Plane
Colleague's Bag on Carousel
My Bag on Carousel
Joint Probability: 6.82%
Log-Loss: 3.87
Total Value: 48.333
Mean Value: 24.167
My Bag on Plane
66.67% False
33.33% True
My Bag on Carousel
100.00% False
0.00% True
Colleague's Bag on Carousel
78.33% False
21.67% True
Time Elapsed at Baggage Carousel at ...
Mean: 5.000 Dev: 0.000
Value: 5.000
0.00% 0
0.00% 1
0.00% 2
0.00% 3
0.00% 4
100.00% 5
0.00% 6
0.00% 7
0.00% 8
0.00% 9
0.00% 10

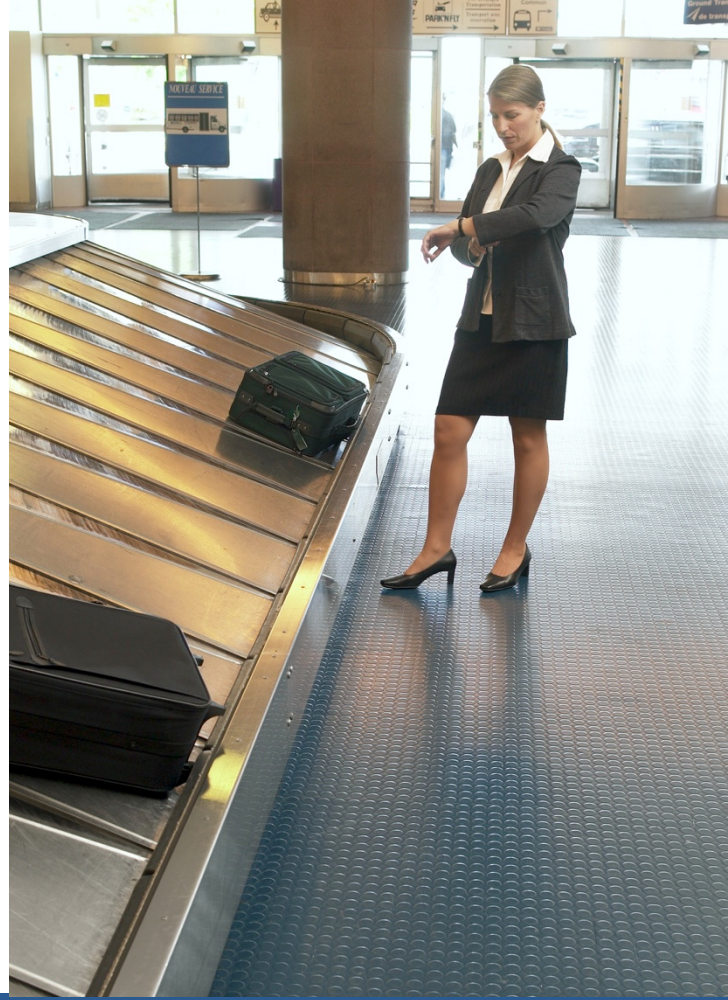

BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
Time Elapsed at Baggage Carousel at LAX
Transit Time in NRT
Colleague's Bag on Plane
My Bag on Plane
Colleague's Bag on Carousel
My Bag on Carousel
Joint Probability: 1.48%
Log-Loss: 6.08
Total Value: 70.385
Mean Value: 35.192
My Bag on Plane
46.15% False
53.85% True
My Bag on Carousel
100.00% False
0.00% True
Colleague's Bag on Carousel
0.00% False
100.00% True
Time Elapsed at Baggage Carousel at ...
Mean: 5.000 Dev: 0.000
Value: 5.000
0.00% 0
0.00% 1
0.00% 2
0.00% 3
0.00% 4
100.00% 5
0.00% 6
0.00% 7
0.00% 8
0.00% 9
0.00% 10


BayesiaLab - New graph 2.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 2.xbl *
Influence Paths
Influence Path
Influence Paths Between Time Elapsed at Baggage Carousel at LAX and My Bag on ...
Path Causal Length Score Description
Path 0 2 5.4187666 Time Elapsed ...
Path 1 4 10.1911209 Time Elapsed ...
Number of Paths Found: 2 (Terminated)
Keep Arc Color and Thickness
OK
Time Elapsed at Baggage Carousel at LAX
Transit Time in NRT
Colleague's Bag on Plane
My Bag on Plane
Colleague's Bag on Carousel
My Bag on Carousel
My Bag on Plane
False
True
My Bag on Carousel
False
True
Colleague's Bag on Carousel
0.00%
False
100.00%
True
Time Elapsed at Baggage Carousel at ...
Mean: 5.000 Dev: 0.000
Value: 5.000
0.00% 0
0.00% 1
0.00% 2
0.00% 3
0.00% 4
100.00% 5
0.00% 6
0.00% 7
0.00% 8
0.00% 9
0.00% 10

Where is my bag?

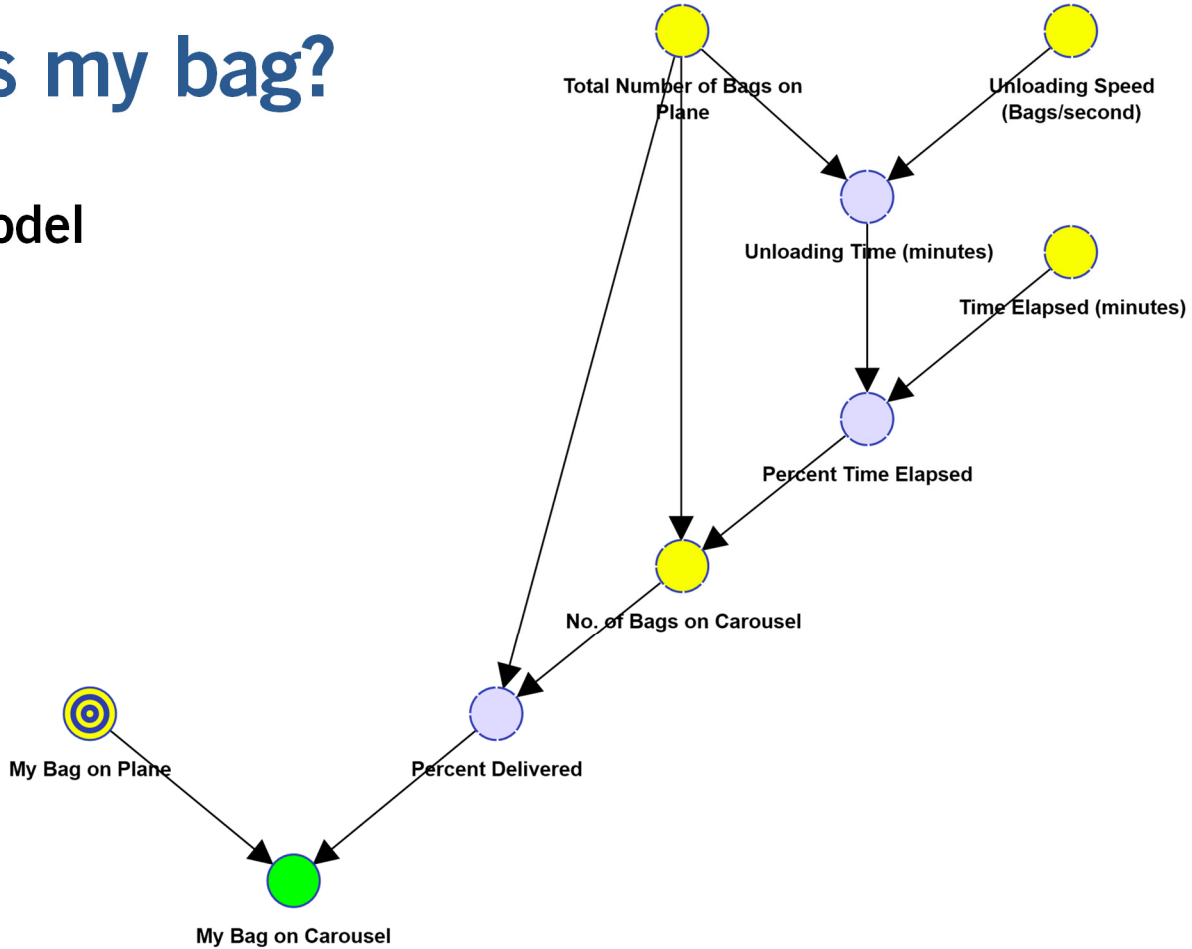
Scenario 3

- Luggage is delivered on the carousel, **a total of 50 bags in the first 5 minutes**, yet I still do not see my bag.
- What is the probability that I will still get my bag?



Where is my bag?

Extended Model



Where is my bag?

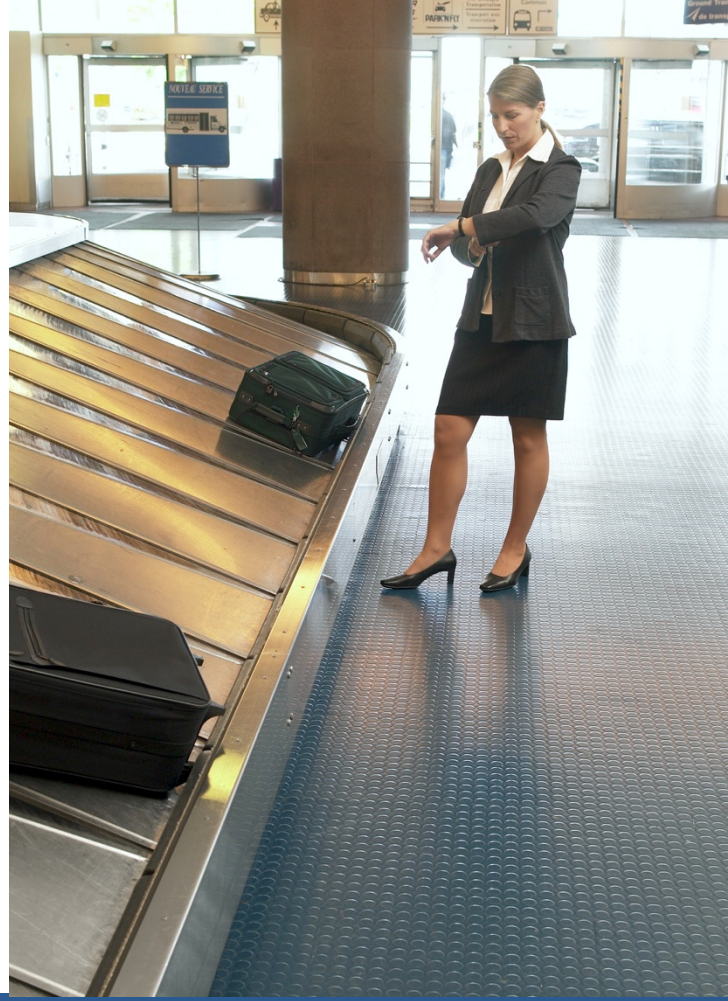
More important questions:

- Will the patient ultimately respond to the current treatment?
- Should we continue a search and rescue effort?
- Should we still follow the original business strategy, i.e. “hold the course”?

Where is my bag?

Key Points

- Encoding of knowledge
- Reasoning under uncertainty
- Reasoning
    - from cause to effect (simulation)
    - from effect to cause (diagnosis)
- Inter-causal reasoning



In Conclusion…

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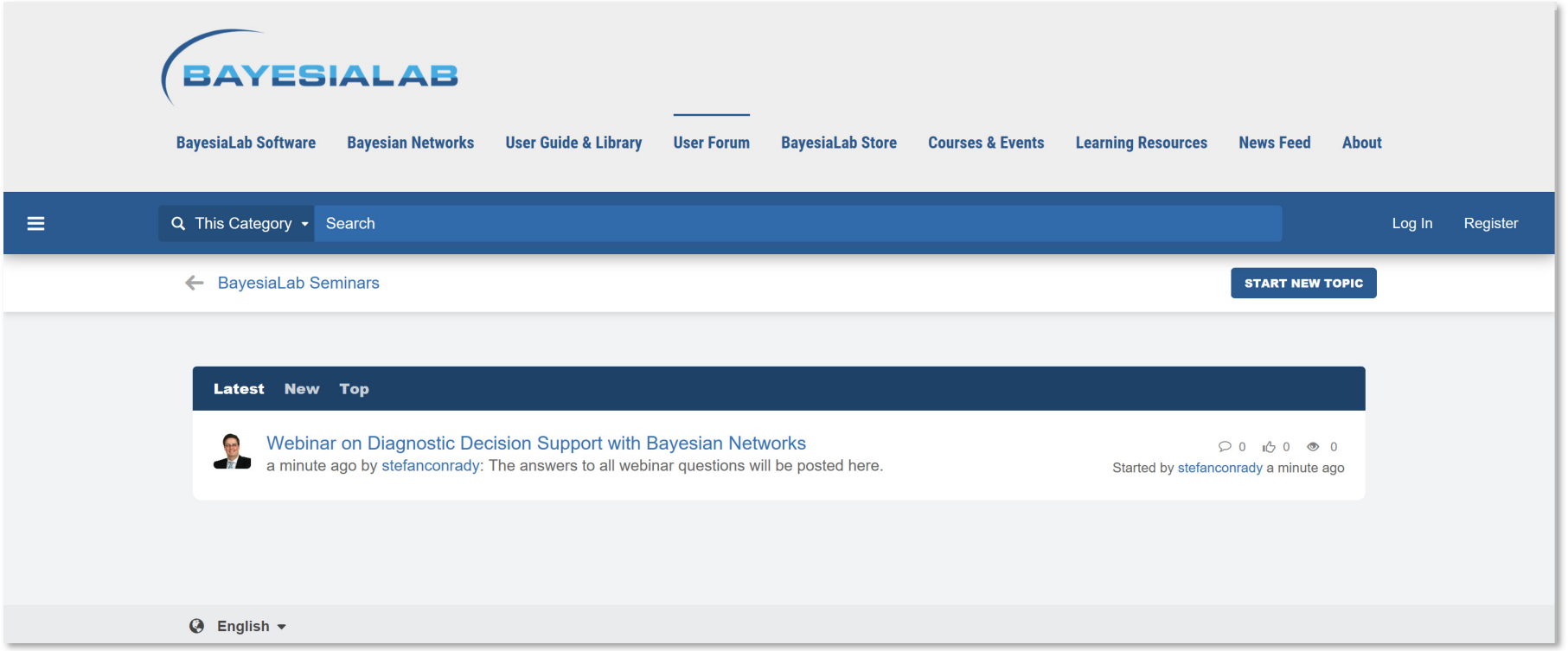

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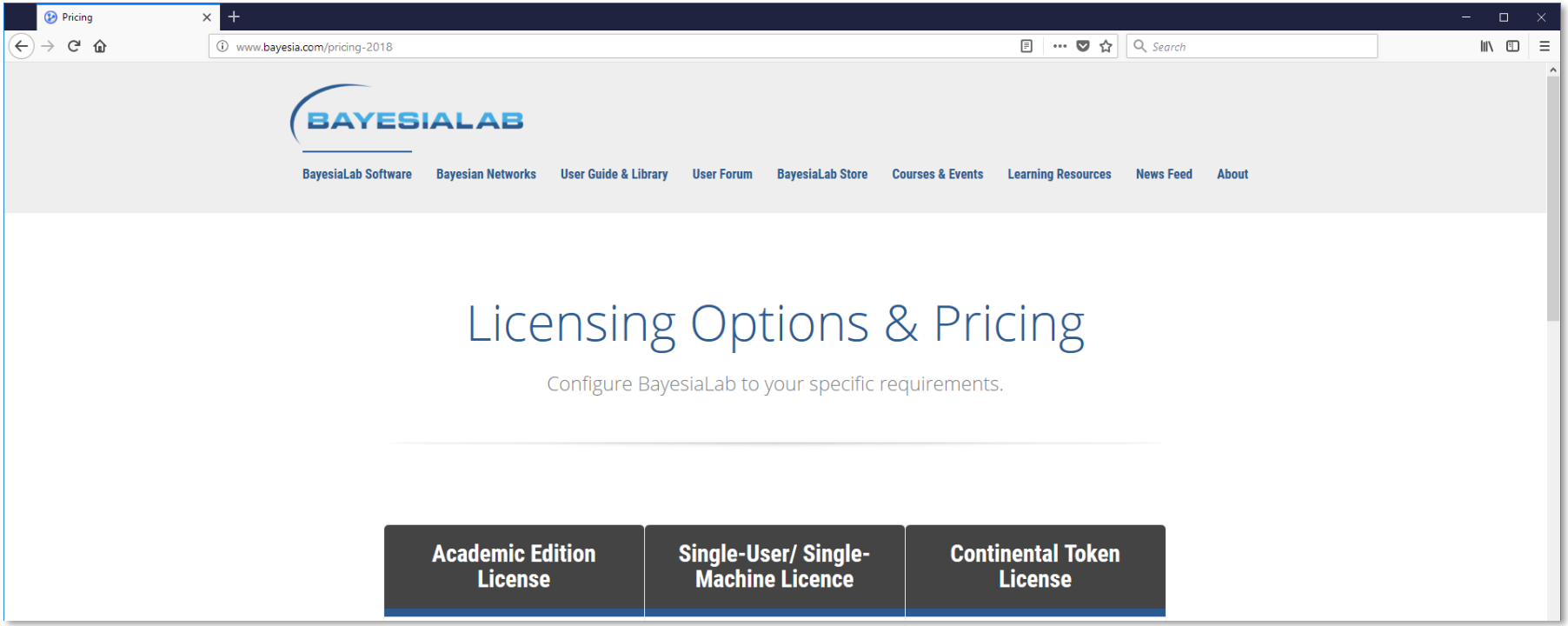

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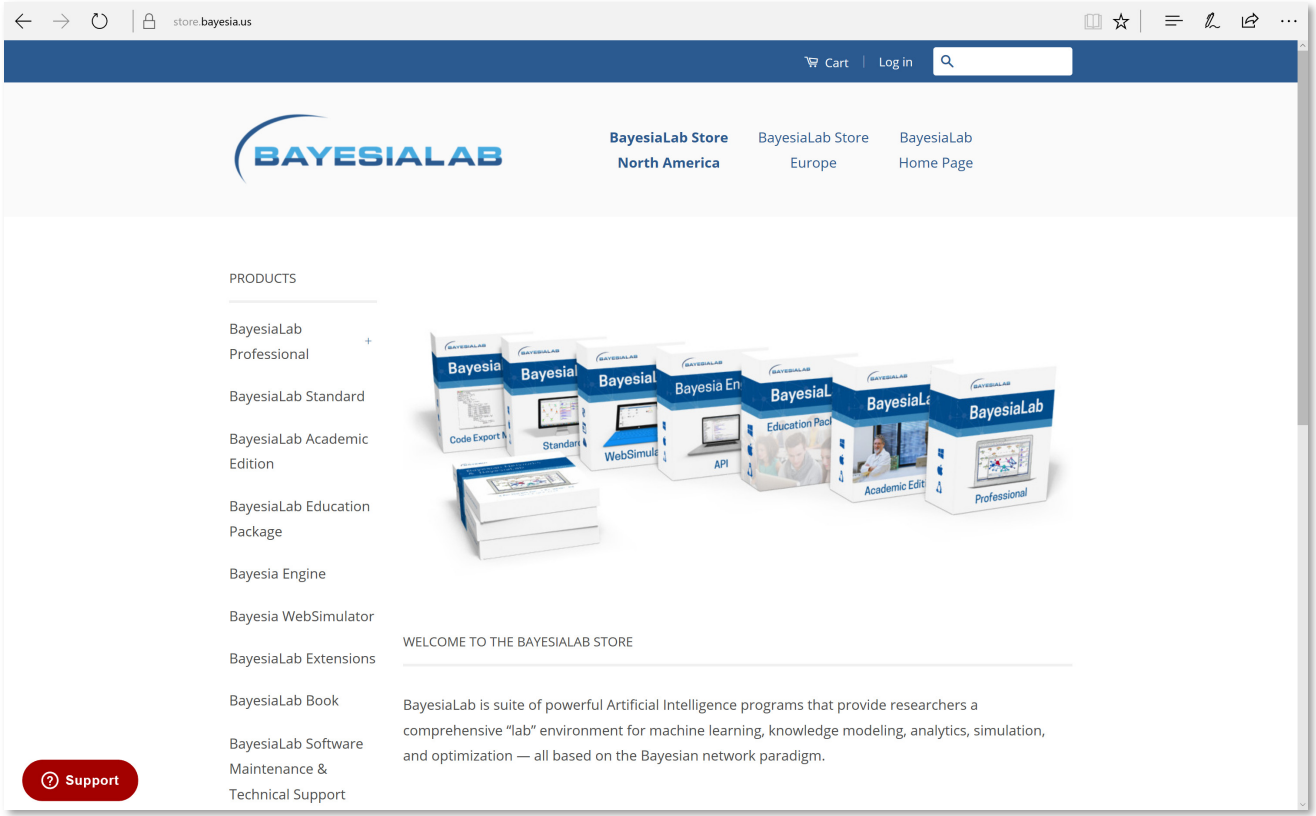

Webinar Series: Friday at 1 p.m. (Central)

Upcoming Webinars:

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- March 16 Optimizing Health Policies with Bayesian Networks
- March 23 t.b.d.

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- September 26–28
  New Delhi, India
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  Chicago, IL
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  New York, NY

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November 1–2, 2018

Thank You!

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