



Causality & Certainty in Criminal Sentencing

Bayesian Networks & BayesiaLab

The webinar will start at:
13:00:00

Today's Program

Introduction

- Our Team & Our Company

Motivation & Background

- Disparity in Criminal Sentencing
- Federal Sentencing Guidelines
- Legislation & Supreme Court Rulings



20 min.

Analyzing Federal Sentencing Data

- Certainty: Information Theory & Entropy
- Fairness: Causality



40 min.

Your BayesiaLab Team Today



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Disambiguation



Our Company



Our Product

The Paradigm

BAYESIAN NETWORKS*

Judea Pearl

Cognitive Systems Laboratory

Computer Science Department

University of California, Los Angeles, CA 90024

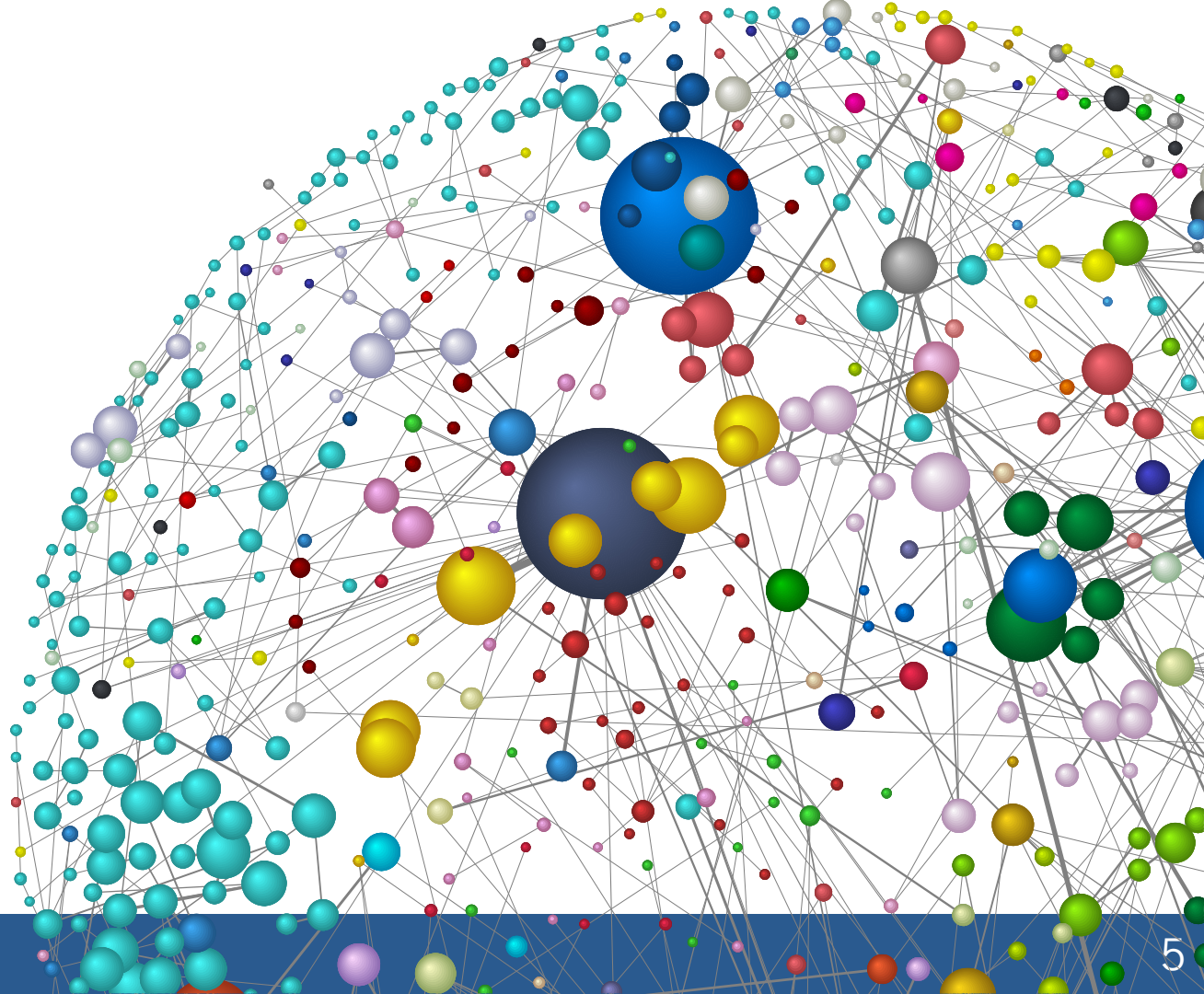
judea@cs.ucla.edu

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 (DAGs) in which the nodes represent vari-



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



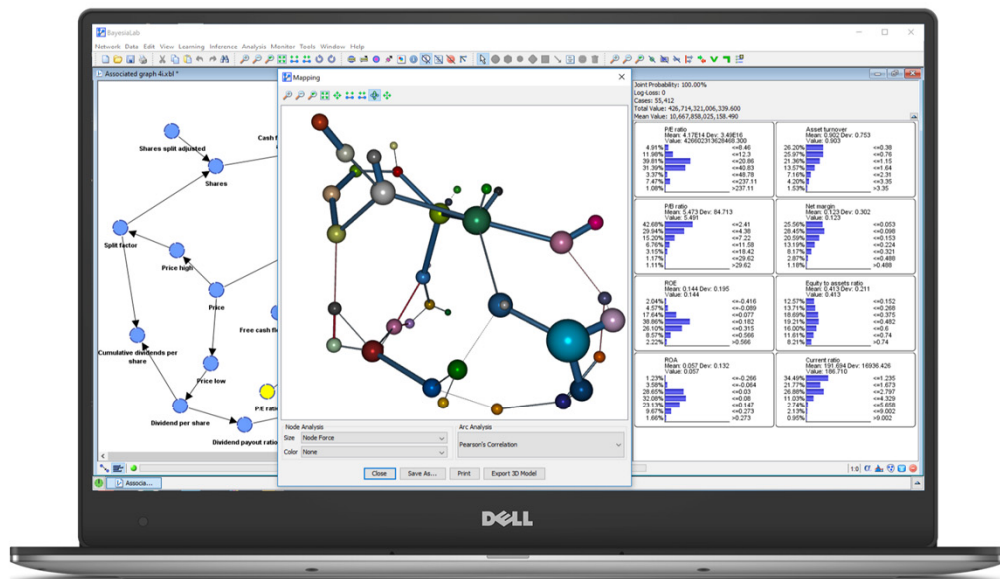


Bayesian Networks & BayesiaLab

A Practical Introduction for Researchers

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



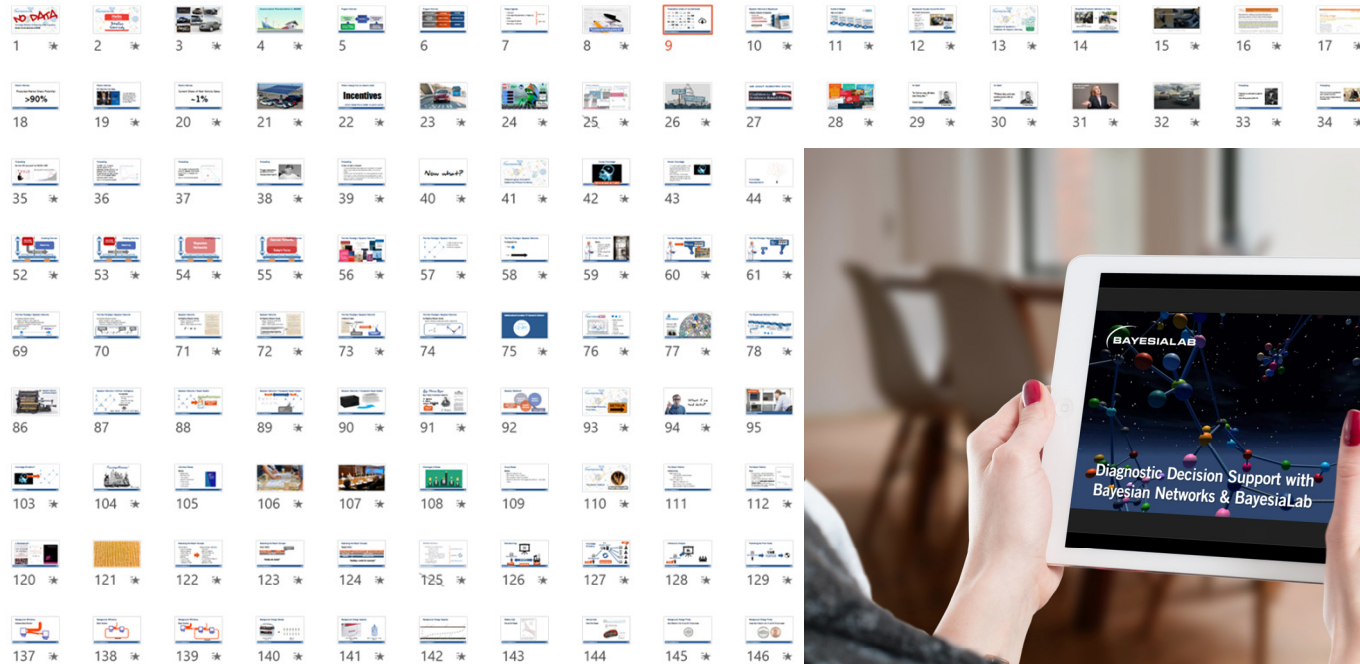


A desktop software for:

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

with **Bayesian networks**.

Webinar Slides, Data, and Recording Available



Caveat

- In this webinar, we focus exclusively on methodological questions and do not endeavor to arrive at substantive findings.
- While we work with real data, any effect size estimates are for illustration purposes only and should be considered fictional.





Background & Motivation

1 In 3 Black Males Will Go To Prison In Their Lifetime, Report Warns



By Saki Knafo

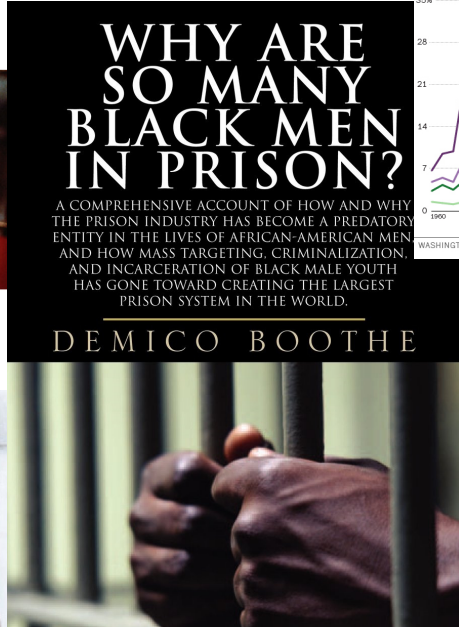


AP/WIDEWORLD



"THE MASS INCARCERATION AND ROUTINE CRIMINALIZATION OF YOUNG BLACK MEN IN THE US IS NOT A STATISTICAL ABERRATION BUT A SYSTEMIC ABOMINATION."
- GARY YOUNG
THE GUARDIAN

IT'S TIME TO THINK **BEYOND BARS.** fb.com/beyondbars



Racial and ethnic gaps shrink in U.S. prison population

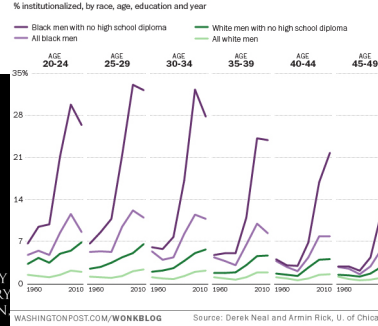
Sentenced federal and state prisoners by race and Hispanic origin, 2009–2016



Note: Whites and blacks include only those who are single-race, not Hispanic. Hispanics are of any race. Prison population is defined as inmates sentenced to more than a year in federal or state prison.
Source: Bureau of Justice Statistics.

2009 '10 '11 '12 '13 '14 '15 '16

Incarceration rates skyrocket in recent decades



1.5 Million Missing Black Men

By JUSTIN WOLFERS, DAVID LEONHARDT and KEVIN QUINCY APRIL 20, 2015

For every 100 black women not in jail, there are only 83 black men. The remaining men – 1.5 million of them – are, in a sense, **missing**.



Among cities with sizable black populations, the largest single gap is in **Ferguson, Mo.**



North Charleston, S.C., has a gap larger than 75 percent of cities.

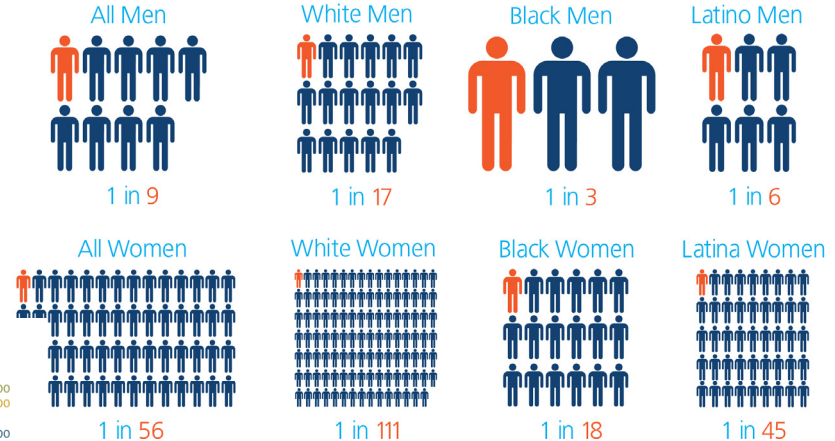


This gap – driven mostly by incarceration and early deaths – **barely exists among whites.**



Figures are for non-incarcerated adults who are 25 to 54.

Lifetime Likelihood of Imprisonment



e: Bonczar, T. (2003). *Prevalence of Imprisonment in the U.S. ation, 1974–2001*. Washington, D.C.: Bureau of Justice Statistics



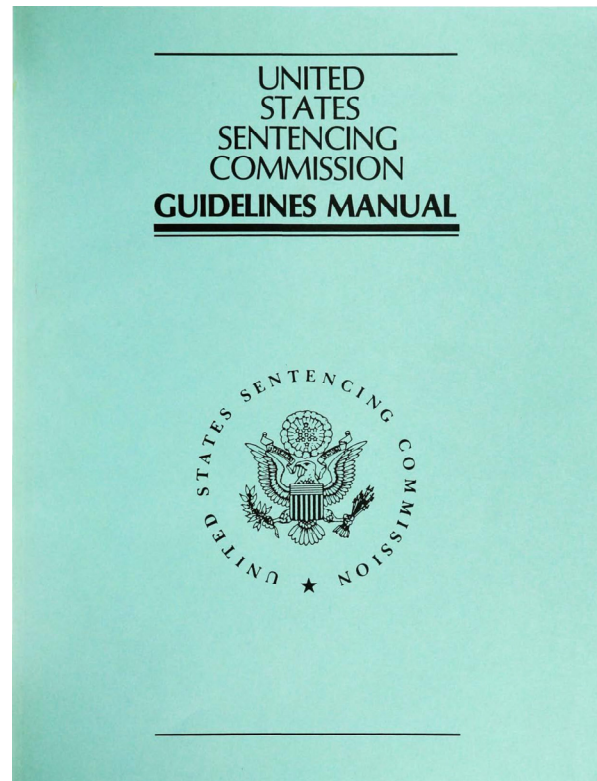
Too much discretion?



Background

Federal Sentencing Guidelines

- The Guidelines are the product of the United States Sentencing Commission, which was created by the Sentencing Reform Act of 1984. The Guidelines' primary goal was to alleviate sentencing disparities that research had indicated were prevalent in the existing sentencing system, and the guidelines reform was specifically intended to provide for **determinate sentencing**.



Background

Federal Sentencing Guidelines

Offense Seriousness

➔ Base Level Offense

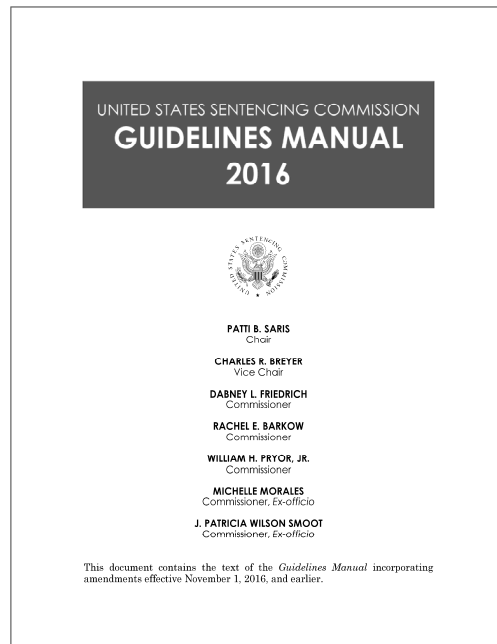
± Specific Offense Characteristics

± Adjustments

+ Criminal History

= Final Offense Level

→ Sentence Range





PART D — OFFENSES INVOLVING DRUGS AND NARCO-TERRORISM

<i>Historical Note</i>	Effective November 1, 1987. Amended effective November 1, 2007 (amendment 711).
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1. UNLAWFUL MANUFACTURING, IMPORTING, EXPORTING, TRAFFICKING, OR POSSESSION; CONTINUING CRIMINAL ENTERPRISE

§2D1.1. Unlawful Manufacturing, Importing, Exporting, or Trafficking (Including Possession with Intent to Commit These Offenses); Attempt or Conspiracy

(a) Base Offense Level (Apply the greatest):

- (1) **43**, if the defendant is convicted under 21 U.S.C. § 841(b)(1)(A), (b)(1)(B), or (b)(1)(C), or 21 U.S.C. § 960(b)(1), (b)(2), or (b)(3), and the offense of conviction establishes that death or serious bodily injury resulted from the use of the substance and that the defendant committed the offense after one or more prior convictions for a similar offense; or
- (2) **38**, if the defendant is convicted under 21 U.S.C. § 841(b)(1)(A), (b)(1)(B), or (b)(1)(C), or 21 U.S.C. § 960(b)(1), (b)(2), or (b)(3), and the offense of conviction establishes that death or serious bodily injury resulted from the use of the substance; or
- (3) **30**, if the defendant is convicted under 21 U.S.C. § 841(b)(1)(E) or 21 U.S.C. § 960(b)(5), and the offense of conviction establishes that death or serious bodily injury resulted from the use of the substance and that the defendant committed the offense after one or more prior convictions for a similar offense; or
- (4) **26**, if the defendant is convicted under 21 U.S.C. § 841(b)(1)(E) or 21 U.S.C. § 960(b)(5), and the offense of conviction establishes that death or serious bodily injury resulted from the use of the substance; or
- (5) the offense level specified in the Drug Quantity Table set forth in subsection (c), except that if (A) the defendant receives an adjustment under §3B1.2 (Mitigating Role); and (B) the base offense level under subsection (c) is (i) level **32**, decrease by 2 levels; (ii) level **34** or level **36**, decrease by 3 levels; or (iii) level **38**, decrease by 4 levels. If the resulting offense level

SENTENCING TABLE (in months of imprisonment)

Offense Level	Criminal History Category (Criminal History Points)					
	I (0 or 1)	II (2 or 3)	III (4, 5, 6)	IV (7, 8, 9)	V (10, 11, 12)	VI (13 or more)
1	0–6	0–6	0–6	0–6	0–6	0–6
2	0–6	0–6	0–6	0–6	0–6	1–7
3	0–6	0–6	0–6	0–6	2–8	3–9
4	0–6	0–6	0–6	2–8	4–10	6–12
5	0–6	0–6	1–7	4–10	6–12	9–15
6	0–6	1–7	2–8	6–12	9–15	12–18
7	0–6	2–8	4–10	8–14	12–18	15–21
8	0–6	4–10	6–12	10–16	15–21	18–24
9	4–10	6–12	8–14	12–18	18–24	21–27
10	6–12	8–14	10–16	15–21	21–27	24–30
11	8–14	10–16	12–18	18–24	24–30	27–33
12	10–16	12–18	15–21	21–27	27–33	30–37
13	12–18	15–21	18–24	24–30	30–37	33–41
14	15–21	18–24	21–27	27–33	33–41	37–46
15	18–24	21–27	24–30	30–37	37–46	41–51
16	21–27	24–30	27–33	33–41	41–51	46–57
17	24–30	27–33	30–37	37–46	46–57	51–63
18	27–33	30–37	33–41	41–51	51–63	57–71
19	30–37	33–41	37–46	46–57	57–71	63–78
20	33–41	37–46	41–51	51–63	63–78	70–87
21	37–46	41–51	46–57	57–71	70–87	77–96
22	41–51	46–57	51–63	63–78	77–96	84–105
23	46–57	51–63	57–71	70–87	84–105	92–115
24	51–63	57–71	63–78	77–96	92–115	100–125
25	57–71	63–78	70–87	84–105	100–125	110–137
26	63–78	70–87	78–97	92–115	110–137	120–150
27	70–87	78–97	87–108	100–125	120–150	130–162
28	78–97	87–108	97–121	110–137	130–162	140–175
29	87–108	97–121	108–135	121–151	140–175	151–188
30	97–121	108–135	121–151	135–168	151–188	168–210
31	108–135	121–151	135–168	151–188	168–210	188–235
32	121–151	135–168	151–188	168–210	188–235	210–262
33	135–168	151–188	168–210	188–235	210–262	235–293
34	151–188	168–210	188–235	210–262	235–293	262–327
35	168–210	188–235	210–262	235–293	262–327	292–365
36	188–235	210–262	235–293	262–327	292–365	324–405
37	210–262	235–293	262–327	292–365	324–405	360–life
38	235–293	262–327	292–365	324–405	360–life	360–life
39	262–327	292–365	324–405	360–life	360–life	360–life
40	292–365	324–405	360–life	360–life	360–life	360–life
41	324–405	360–life	360–life	360–life	360–life	360–life
42	360–life	360–life	360–life	360–life	360–life	360–life
43	life	life	life	life	life	life

Background

(Bench Opinion)

OCTOBER TERM, 2004

1

Syllabus

NOTE: Where it is feasible, a syllabus (headnote) will be released, as is being done in connection with this case, at the time the opinion is issued. The syllabus constitutes no part of the opinion of the Court but has been prepared by the Reporter of Decisions for the convenience of the reader. See *United States v. Detroit Timber & Lumber Co.*, 200 U. S. 321, 337.

SUPREME COURT OF THE UNITED STATES

Syllabus

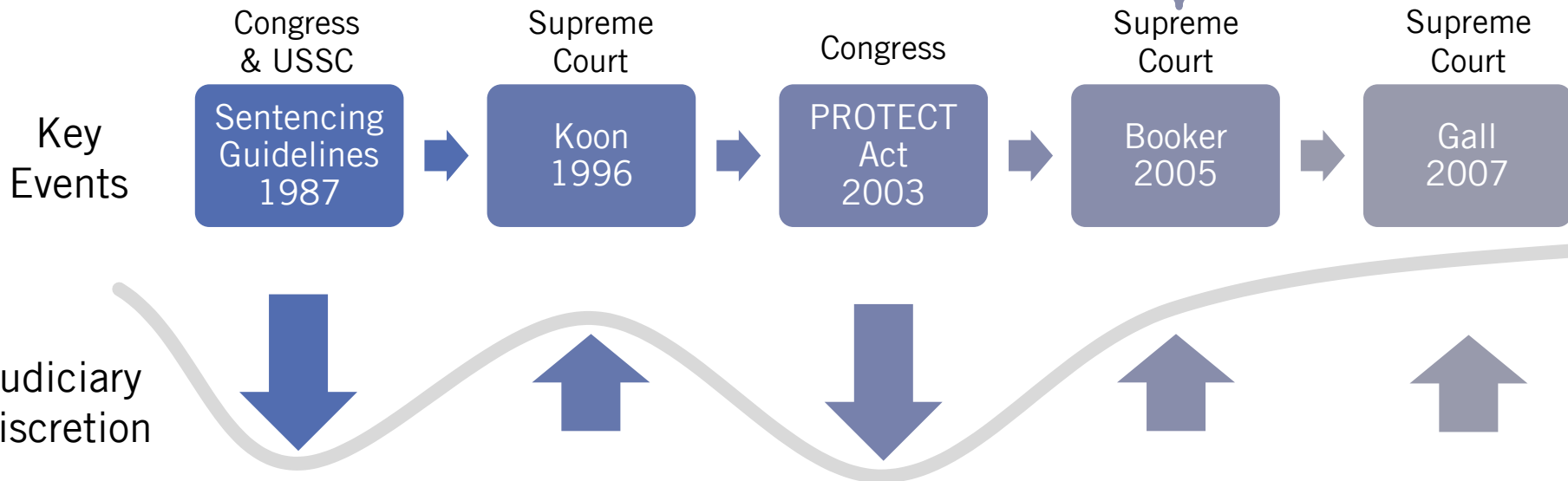
UNITED STATES *v.* BOOKER

CERTIORARI TO THE UNITED STATES COURT OF APPEALS FOR
THE SEVENTH CIRCUIT

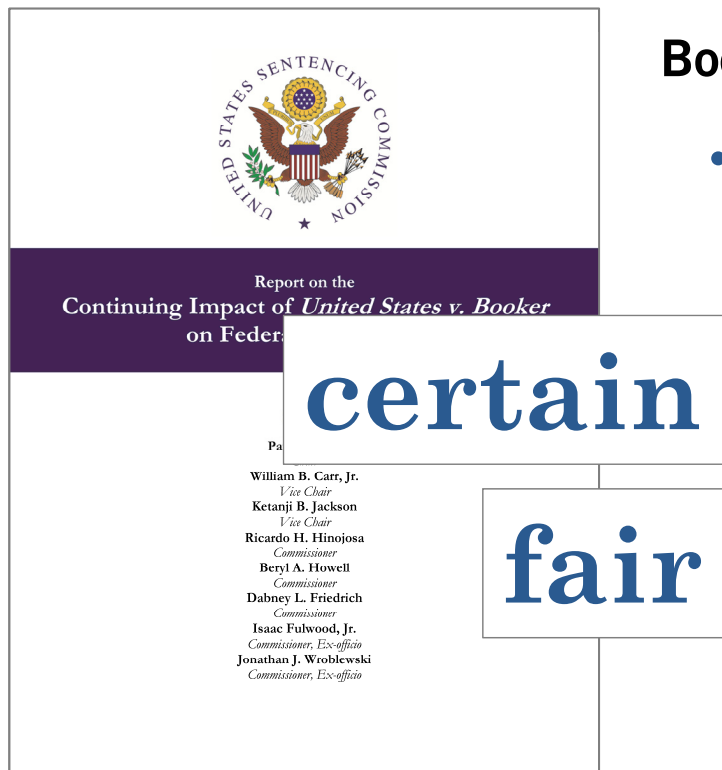
No. 04–104. Argued October 4, 2004—Decided January 12, 2005*

Under the Federal Sentencing Guidelines, the sentence authorized by the jury verdict in respondent Booker's drug case was 210-to-262

Guidelines are
“advisory”
not mandatory



Research Questions



Booker Report

- The United States Sentencing Commission (“the Commission”) submits this report to Congress¹ on the impact of *United States v. Booker*² on federal sentencing in order to assist Congress in its efforts to ensure **certain and fair sentencing** that avoids unwarranted sentencing disparities while maintaining sufficient flexibility,³ as envisioned in the Sentencing Reform Act of 1984 (“SRA”).

Research Questions

- How can we translate “certain” and “fair” into measurable quantities that can be estimated from data?

“Certain”

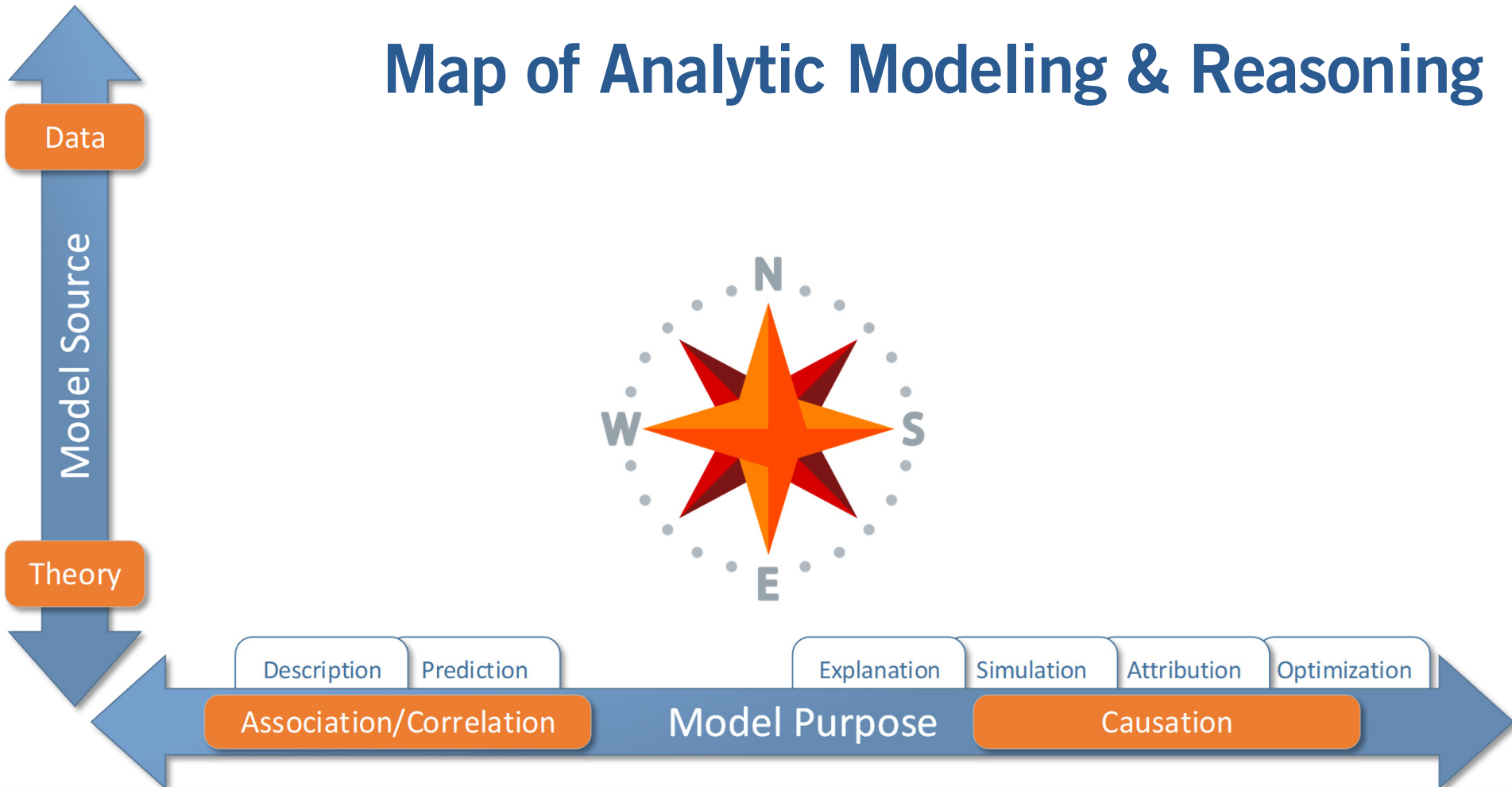
- We quantify uncertainty by calculating the entropy of the distributions of sentences.

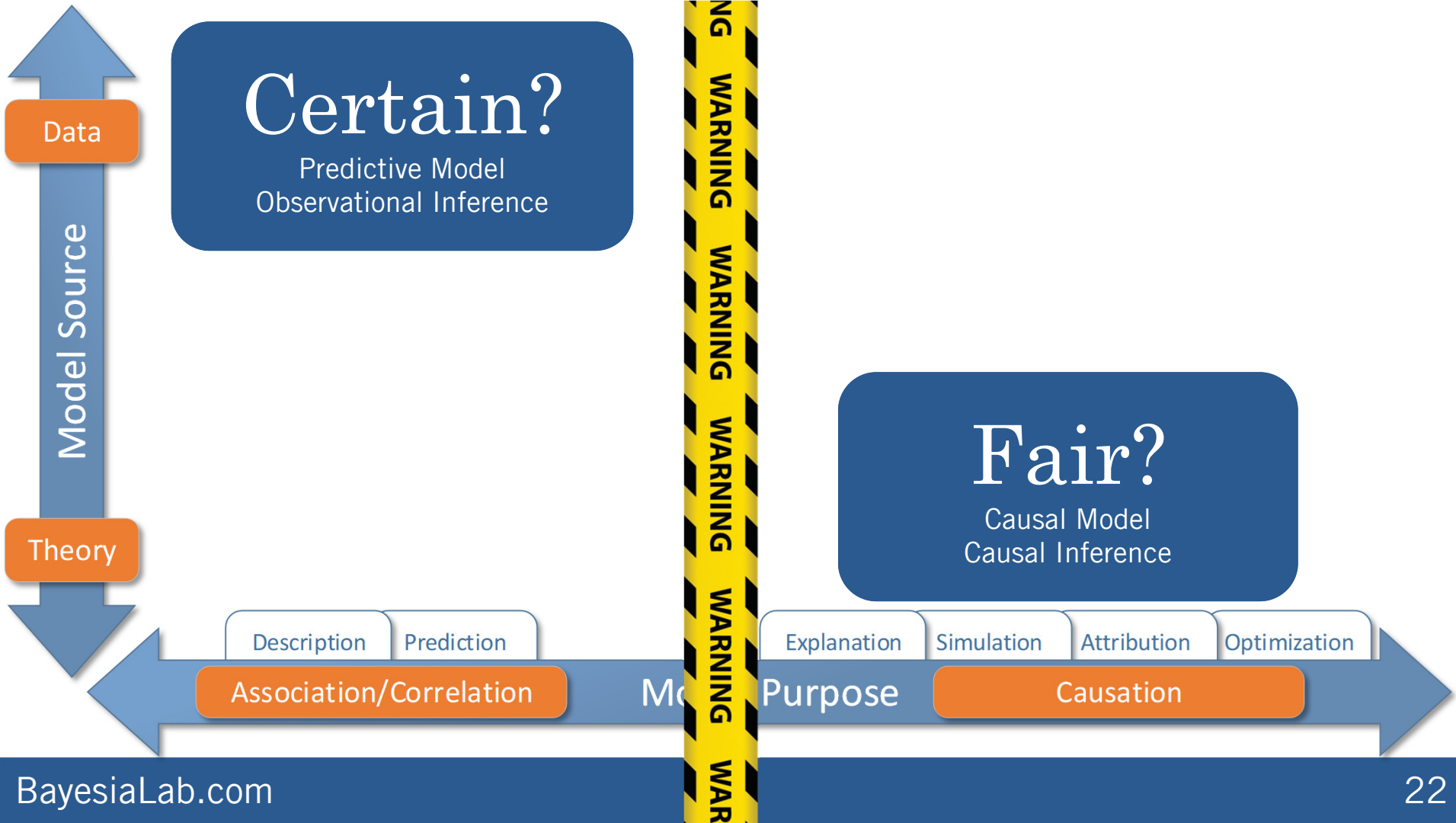
“Fair”

- We consider “fair” as the absence of extra-legal causes in sentencing. Thus, we need to estimate the potential effects of extra-legal causes.

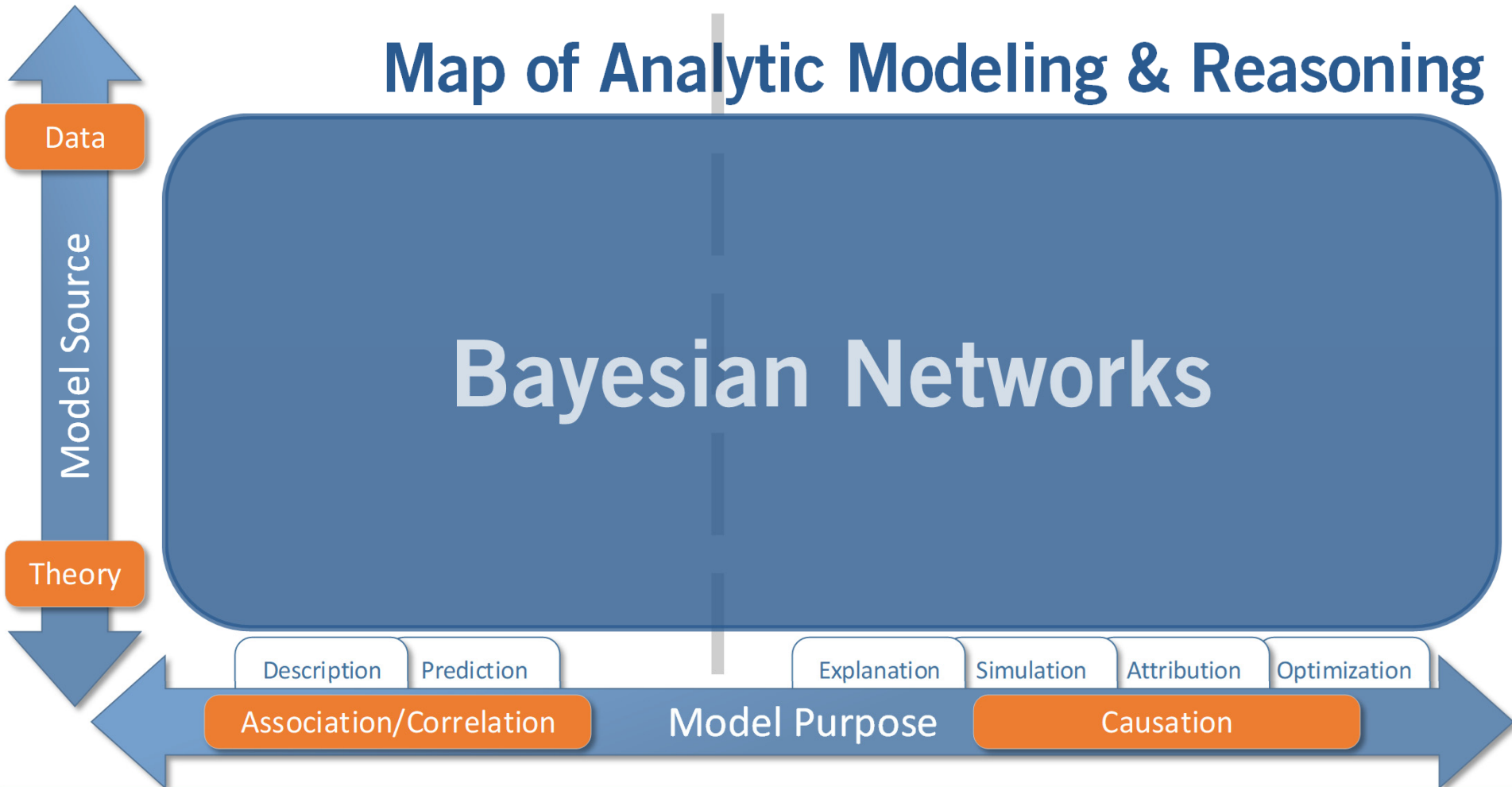


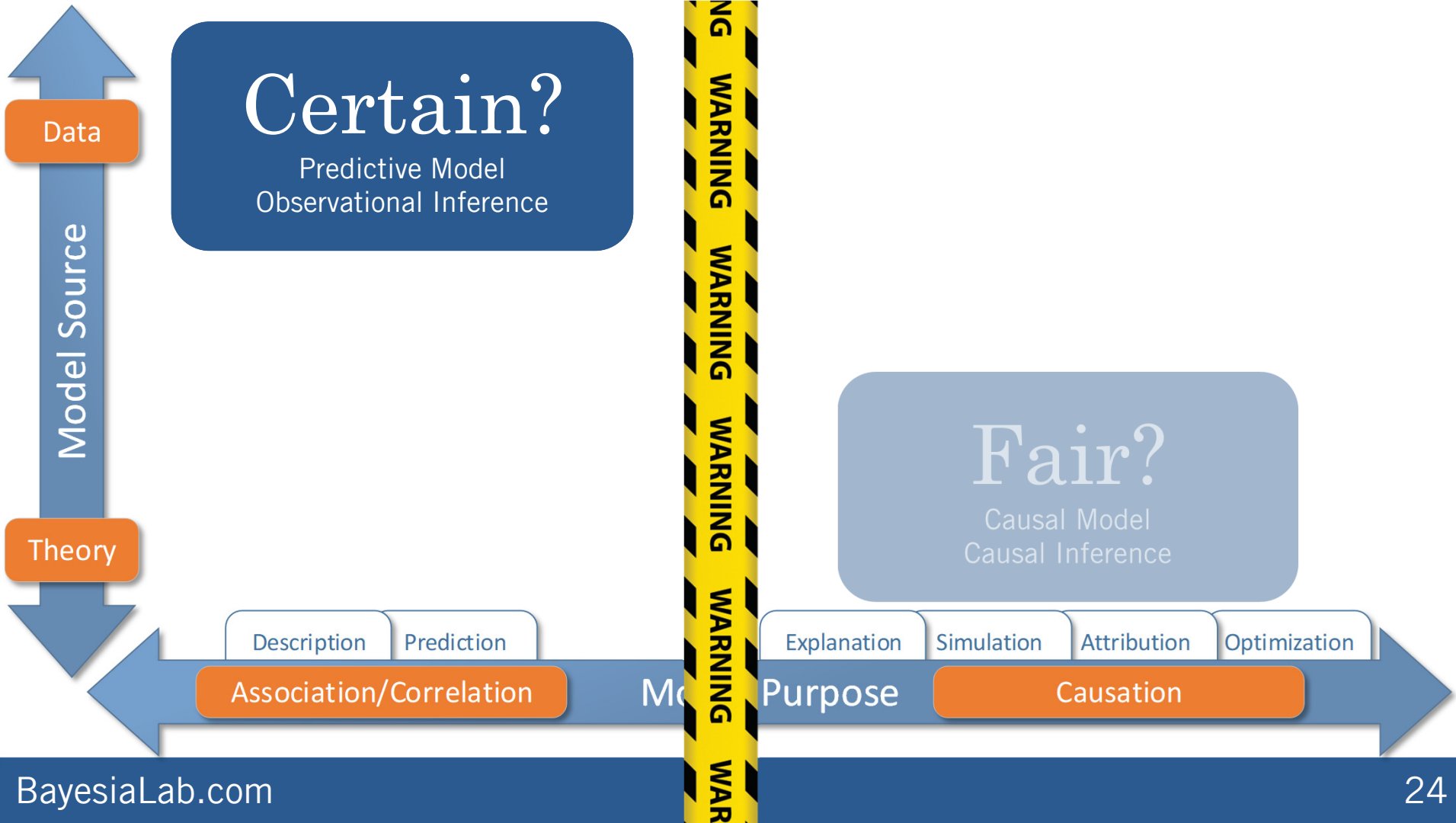
Map of Analytic Modeling & Reasoning





Map of Analytic Modeling & Reasoning







Individual Offender Datafiles

The Commission's individual datafiles provide information on the sentences imposed in cases involving individuals. In these datafiles the individual is the unit of analysis. These datafiles do not contain information from the Commission's Organizational, Resentencing, or Appeals Databases.

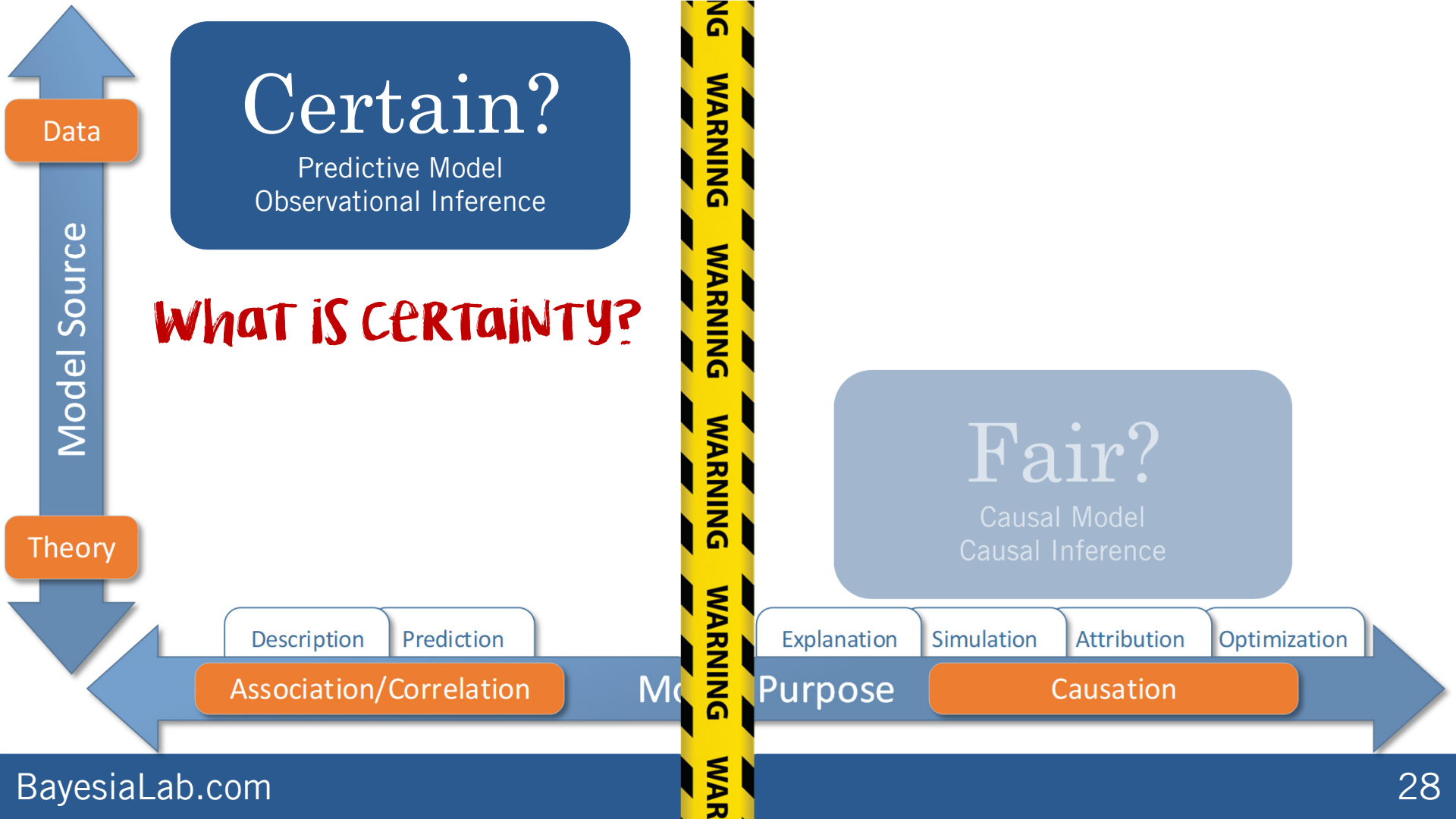
Datafiles (downloads are SAS and SPSS compatible)

- [Fiscal Year 2017](#)
- [Fiscal Year 2016](#)
- [Fiscal Year 2015](#)
- [Fiscal Year 2014](#)
- [Fiscal Year 2013](#)
- [Fiscal Year 2012](#)
- [Fiscal Year 2011](#)
- [Fiscal Year 2010](#)
- [Fiscal Year 2009](#)
- [Fiscal Year 2008](#)
- [Fiscal Year 2007](#)
- [Fiscal Year 2006](#)
- [Fiscal Year 2005](#)
- [Fiscal Year 2004](#)
- [Fiscal Year 2003](#)
- [Fiscal Year 2002](#)

Study Dataset: USSC Booker Report

Federal
Criminal
Sentences
319,172
Observations
1996-2011

- accap: Armed Career Criminal Status
- age: Age
- aggdum: Aggravated Role Adjustment
- booker2: Sentence vs. Guideline Range
- career: Career Offender Impact on Final Offense Level
- caroffap: Career Offender Status Applied
- circdist: Circuit District
- mitdum: Mitigating Role Application
- moncirc: Judicial Circuit
- monsex: Gender
- newcit: Citizenship
- newcnvtn: Plea or Trial
- neweduc: Education
- newrace: Race
- offtype2: Primary Offense Type (**Drug Trafficking Only**)
- period: Time Period (**Koon/PROTECT/Booker/Gall Only**)
- primary: Primary Drug Type
- quarter: Fiscal Year Quarter
- sa: Sentence vs. Guideline Range (Expanded)
- safevalve: Safety Valve Provision
- sentimp: Sentence Type
- totchpts: Criminal History Points Applied
- weapon: SOC Weapon Enhancement
- xcrhissr: Defendant's Final Criminal History Category (I-VI)
- glmin: Trumped Guideline Minimum
- fy: Fiscal Year
- usscidn: USSC ID
- sensplt0: Trumped Total Prison Sentence
- loss_2b: Dollar Amount of Loss
- gdl: Chapter Two Guideline

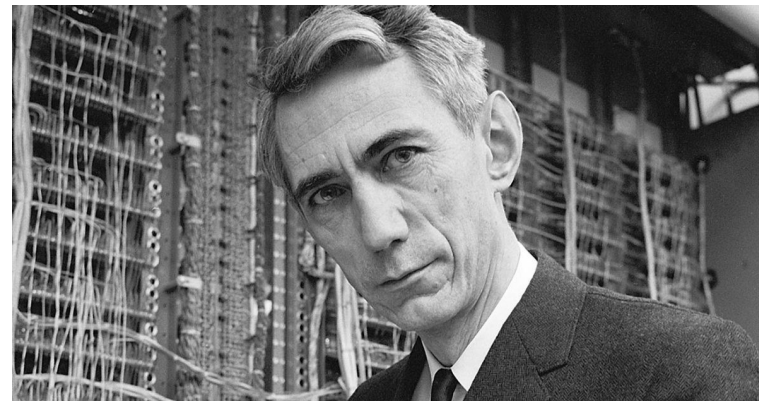


Information Theory



“Information is the
resolution of uncertainty.”

Claude Shannon, 1948

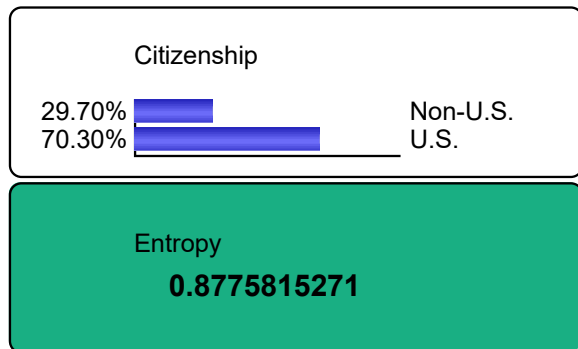


Claude Shannon (1916-2001)

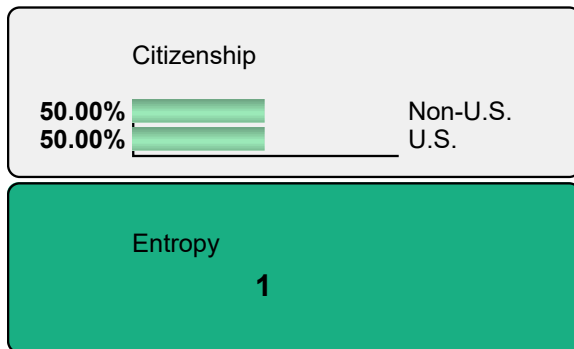
Information Theory

Entropy, a measure of “uncertainty”

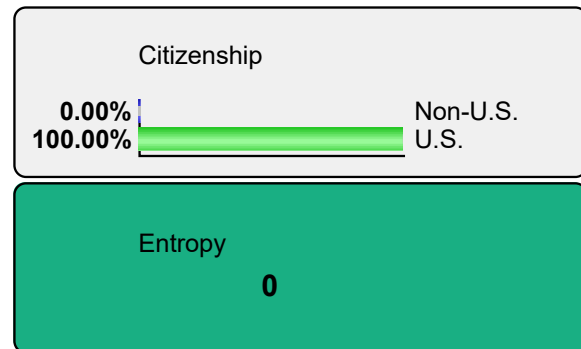
$$H(X) = - \sum_{x \in X} p(x) \times \log_2 p(x)$$



Marginal Entropy



Maximum Entropy

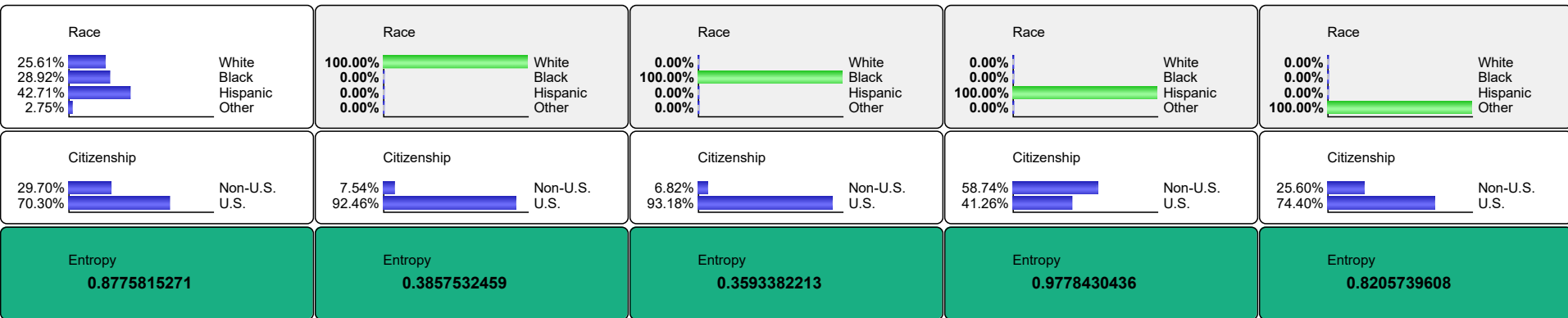
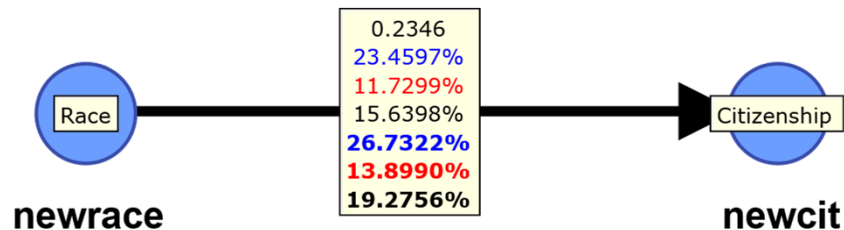


Minimum Entropy

Information Theory

Conditional Entropy

$$H(\text{Citizenship}|\text{Race})$$



$$H(\text{Citizenship})=0.8776$$

$$H(\text{Citizenship}|\text{Race})=0.6429$$

Information Theory

Mutual Information

$$I(\text{Citizenship}, \text{Race}) = H(\text{Citizenship}) - H(\text{Citizenship}|\text{Race})$$

0.2346

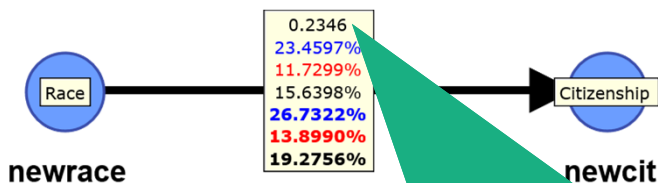
Mutual Information

0.8776

Marginal Entropy

0.6429

Conditional Entropy



This is the amount of information
Citizenship and Race have in common.

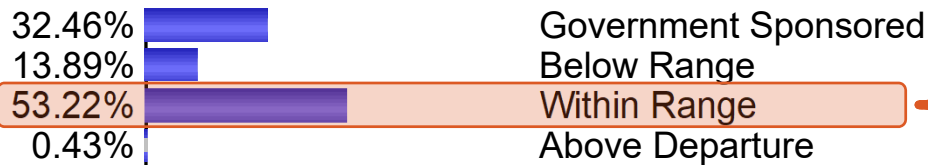
Mutual Information is a
symmetrical metric.

Certain?

Departures from Guideline (booker2)

- What is the entropy over time?

Sentence vs. Guideline Range



UNITED STATES SENTENCING COMMISSION
GUIDELINES MANUAL
2016



PATTI B. SARIS
Chair

CHARLES R. BREYER
Vice Chair

DABNEY L. FRIEDRICH
Commissioner

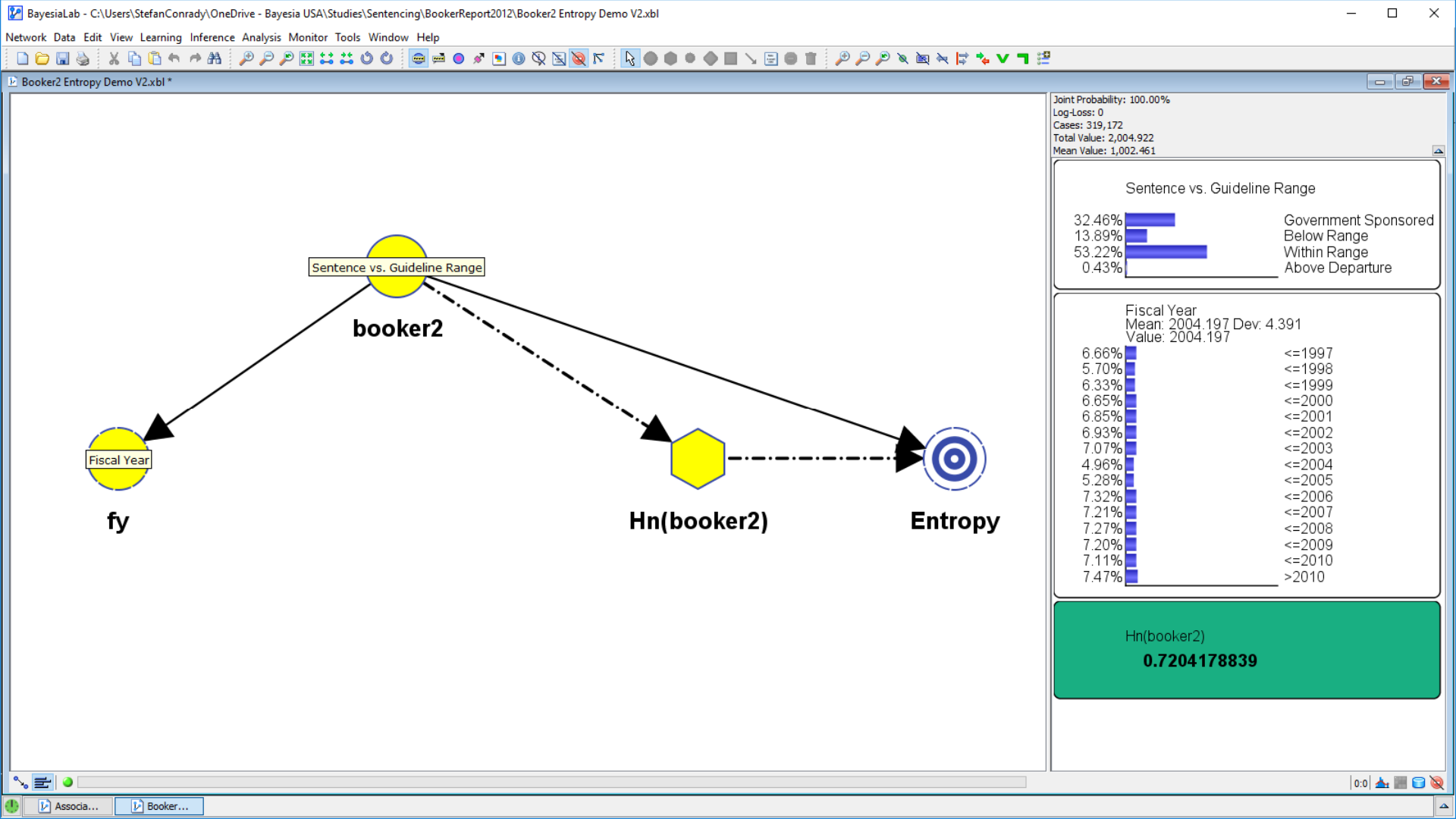
RACHEL E. BARKOW
Commissioner

WILLIAM H. PRYOR, JR.
Commissioner

MICHELLE MORALES
Commissioner, Ex-officio

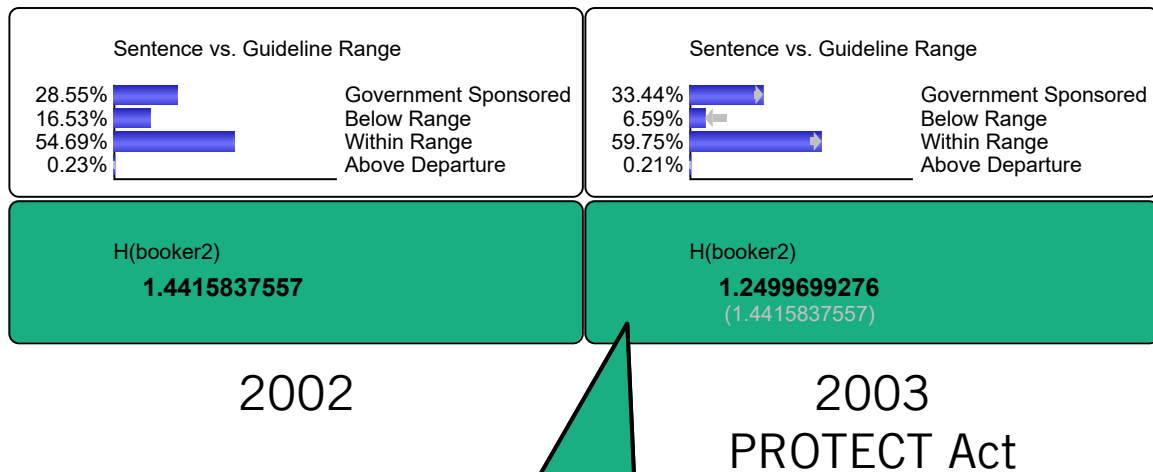
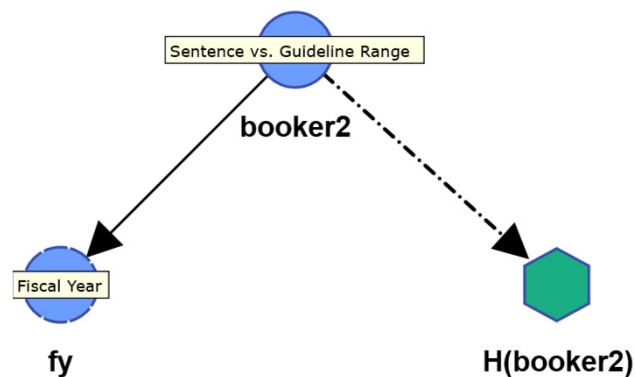
J. PATRICIA WILSON SMOOT
Commissioner, Ex-officio

This document contains the text of the *Guidelines Manual* incorporating amendments effective November 1, 2016, and earlier.



Certain?

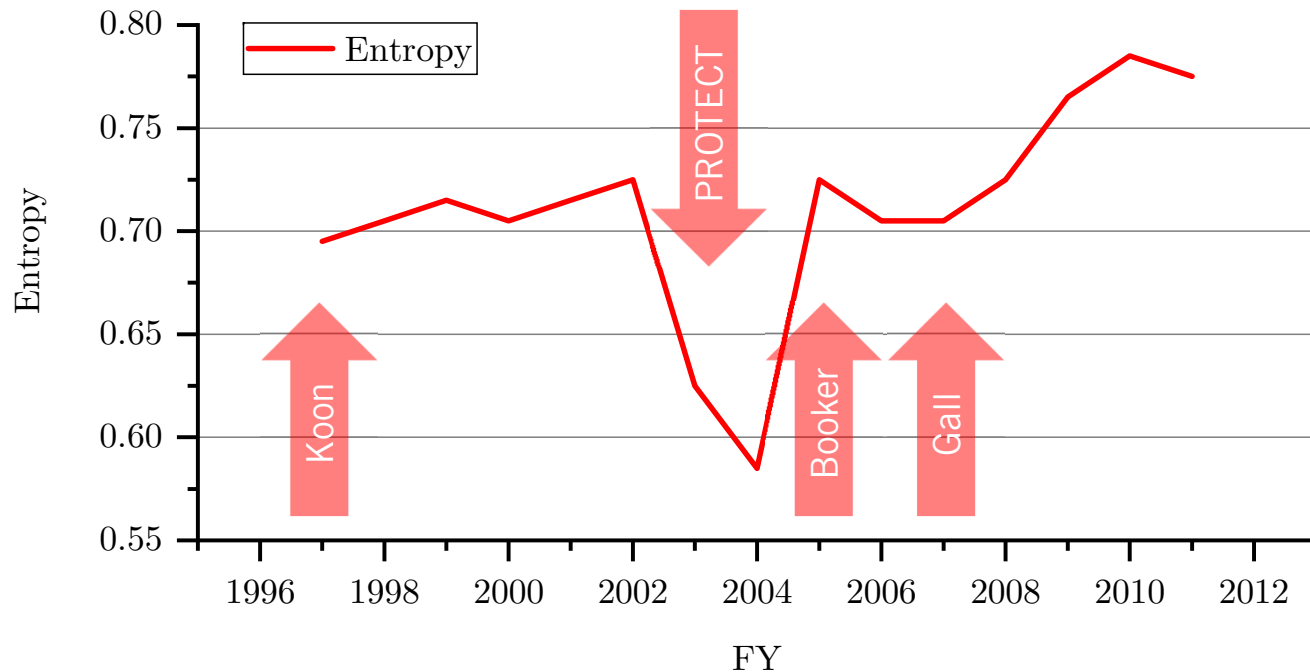
Measuring Uncertainty as a Function of Time Period



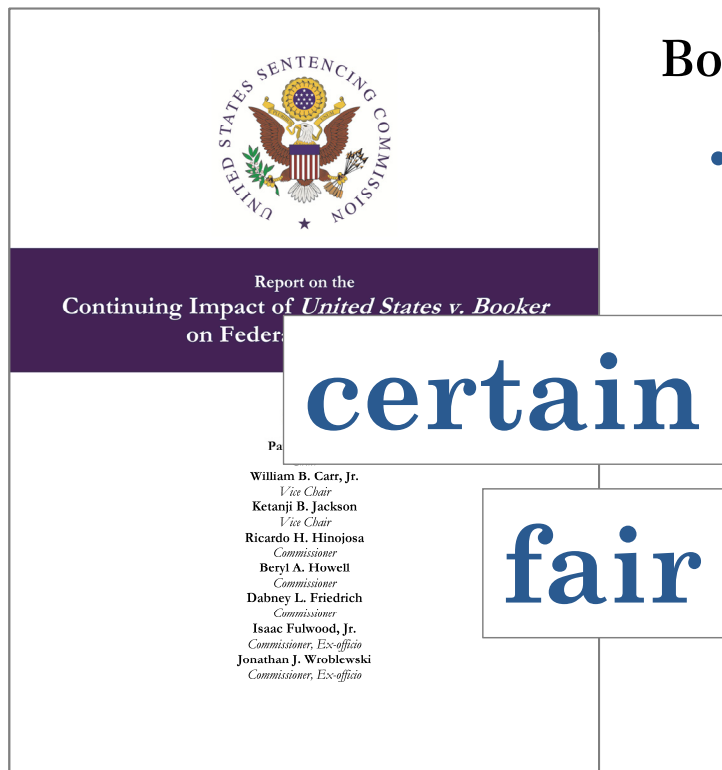
Lower Entropy
→ Less Uncertainty

Conditional Entropy

Normalized Entropy of Sentence vs. Guideline Range over Time

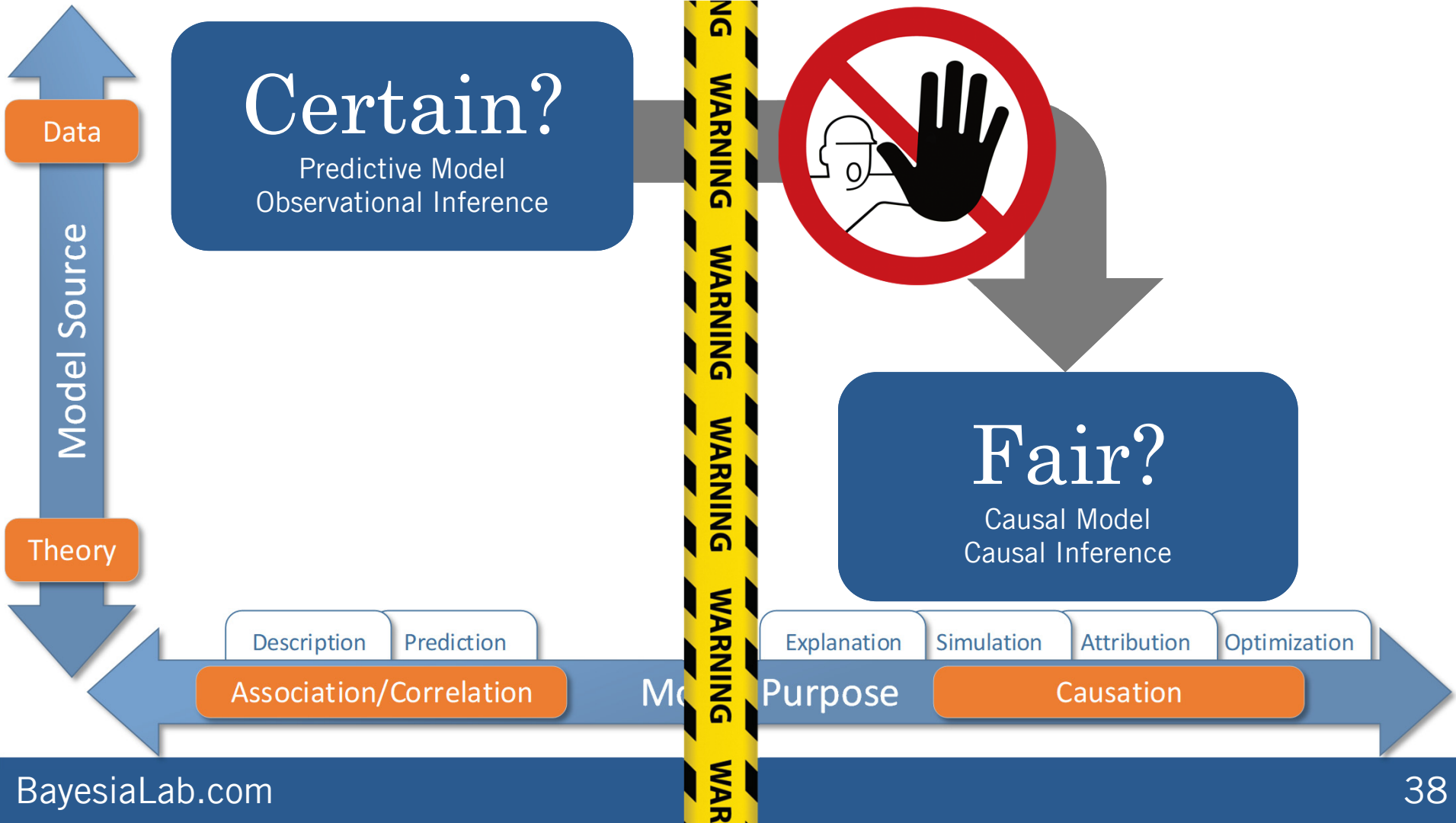


Research Questions



Booker Report

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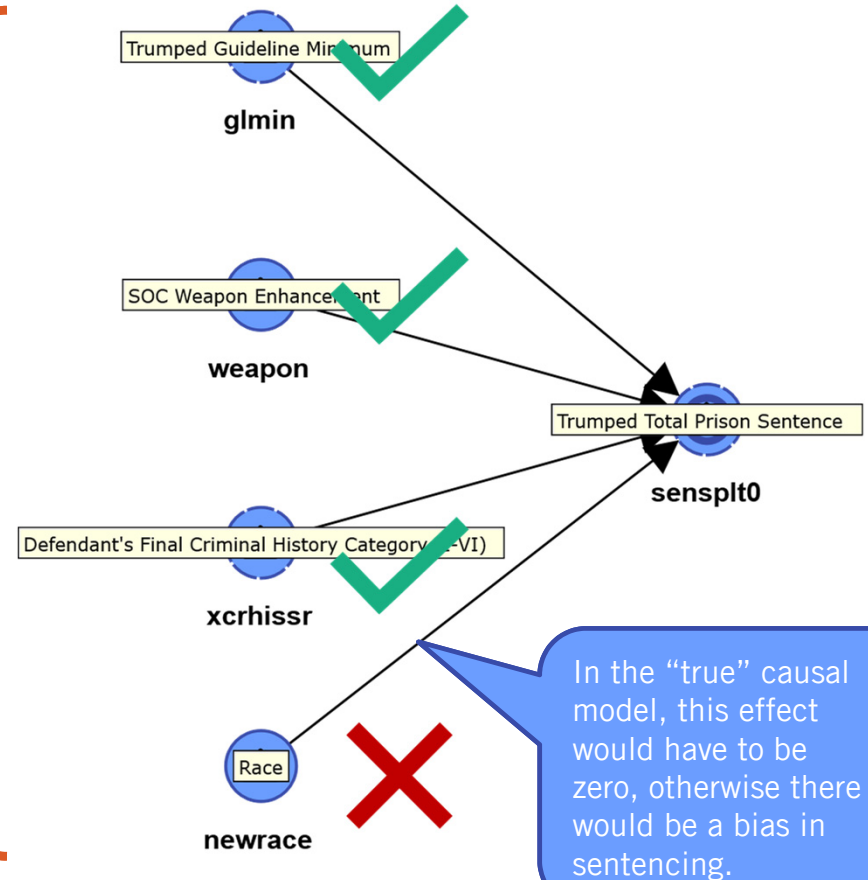


Causality?

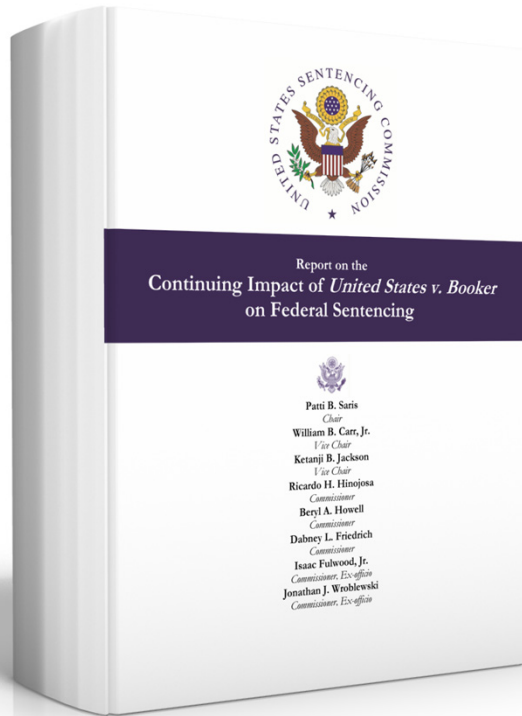
Why is this a causal question?

A possible
causal model

Race must not “cause” sentence!



Causality?



Booker Report:

- 1430 pages
- 1 footnote on “causality”

¹⁹ Correlation and causation are different concepts. A variable that is correlated with another may not be caused by it.

[I]n interpreting the results of a multiple regression analysis, it is important to distinguish between correlation and causality. Two variables are correlated when the events associated with the variables occur more frequently together than one would expect by chance. . . . A correlation between two variables does not imply that one event causes the second. Therefore, in making causal inferences, it is important to avoid spurious correlation. Spurious correlation arises when two variables are closely related but bear no causal relationship because both are caused by a third, unexamined variable. . . . Causality cannot be inferred by data analysis alone; rather, one must infer that a causal relationship exists on the basis of an underlying causal theory that explains the relationship between the two variables. Even when an appropriate theory has been identified, causality can never be inferred directly. One must look for empirical evidence that there is a causal relationship. Conversely, the fact that two variables are correlated does not guarantee the existence of a relationship; it could be that the model – a characterization of the underlying theory – does not reflect the correct interplay among the explanatory variables.

Booker Report

- “The principal benefit of multivariate regression analysis is that it **controls** for the effect of each factor in the analysis by comparing offenders who are similar to one another in relevant ways. For example, **controlling** for the presumptive sentence (guideline minimum) and offense type means that Black male offenders convicted of firearms offenses and who faced a guideline minimum of 46 months of imprisonment are compared to White male offenders convicted of firearms offenses who faced a guideline minimum of 46 months of imprisonment. By **controlling** for such factors and comparing similarly situated offenders to each other, multivariate regression analysis seeks to answer the question: if two offenders are similar in certain ways, what other factors might be associated with those two offenders receiving different sentences? In addition, multivariate regression analysis measures the extent of the difference in outcomes.”



Report on the Continuing Impact of *United States v. Booker* on Federal Sentencing



Multivariate Analysis - Zero Confinement Excluded Booker

The RRS Procedure
Model: MODEL1
Dependent Variable: logsplit1

Number of Observations Read 14186
Number of Observations Used 14186

Analyze

Source DF
Model 23
Error 16604
Corrected Total 16627

Root MSE
Dependent Mean
Coeff Var

Variable	DF	Parameter Estimate
Intercept	1	1.67061
logsplit1	1	0.49375
logsplit1	1	0.43786
sexmale2	1	0.01841
port	1	0.12373
immigration	1	-0.20252
corrupt	1	-0.11417
whitecoll	1	-0.11772
ignores	1	-0.06692
substant	1	-0.01773
newcrim	1	-0.04209
corrupt	1	-0.09448
whitefemale	1	-0.19946
blackmale	1	-0.19396
blackfemale	1	-0.14956
blackmale	1	-0.16015
blackfemale	1	-0.01225
blackmale	1	-0.24663
blackfemale	1	-0.01041
othermale	1	-0.16017
agejunior	1	-0.16601
educ	1	-0.01374
citizen	1	0.02884

Multivariate Analysis - Zero Confinement Excluded BOOKER

The RRS Procedure
Model: MODEL1
Dependent Variable: logsplit1

Number of Observations Read 14186
Number of Observations Used 14186

Analyze

Source DF
Model 23
Error 19162
Corrected Total 19185

Root MSE
Dependent Mean
Coeff Var

Variable	DF	Parameter Estimate
Intercept	1	1.76679
logsplit1	1	0.44482
logsplit1	1	0.0081385
sexmale2	1	0.12373
port	1	0.08086
immigration	1	-0.15079
corrupt	1	-0.10114
whitecoll	1	-0.07359
ignores	1	-0.01176
substant	1	-0.02853
newcrim	1	-0.10000
corrupt	1	0.48190
whitefemale	1	-0.16602
blackmale	1	-0.36294
blackfemale	1	-0.16609
blackmale	1	-0.05194
blackfemale	1	-0.01041
othermale	1	-0.04524
otherfemale	1	-0.20198
agejunior	1	-0.04574
educ	1	-0.16607
agejunior	1	0.08089
educ	1	-0.01197
citizen	1	0.04249

Analyze

Source DF
Model 23
Error 19048
Corrected Total 19071

Root MSE
Dependent Mean
Coeff Var

Variable	Label	Parameter Estimate
Intercept	Intercept	1.76679
logsplit1	logsplit1	0.44482
logsplit1	logsplit1	0.0081385
sexmale2	sexmale2	0.12373
port	port	0.08086
immigration	immigration	-0.15079
corrupt	corrupt	-0.10114
whitecoll	whitecoll	-0.07359
ignores	ignores	-0.01176
substant	substant	-0.02853
newcrim	newcrim	-0.10000
corrupt	corrupt	0.48190
whitefemale	whitefemale	-0.16602
blackmale	blackmale	-0.36294
blackfemale	blackfemale	-0.16609
blackmale	blackmale	-0.05194
blackfemale	blackfemale	-0.01041
othermale	othermale	-0.04524
otherfemale	otherfemale	-0.20198
agejunior	agejunior	-0.04574
educ	educ	-0.16607
agejunior	agejunior	0.08089
educ	educ	-0.01197
citizen	citizen	0.04249

Analyze

Source DF
Model 23
Error 19048
Corrected Total 19071

Root MSE
Dependent Mean
Coeff Var

Variable	Label	Parameter Estimate
Intercept	Intercept	1.76679
logsplit1	logsplit1	0.44482
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newcrim	newcrim	-0.10000
corrupt	corrupt	0.48190
whitefemale	whitefemale	-0.16602
blackmale	blackmale	-0.36294
blackfemale	blackfemale	-0.16609
blackmale	blackmale	-0.05194
blackfemale	blackfemale	-0.01041
othermale	othermale	-0.04524
otherfemale	otherfemale	-0.20198
agejunior	agejunior	-0.04574
educ	educ	-0.16607
agejunior	agejunior	0.08089
educ	educ	-0.01197
citizen	citizen	0.04249

MULTIVARIATE ANALYSIS RESULTS

Multivariate Analysis - All Cases
Gall

The RRS Procedure
Model: MODEL1
Dependent Variable: logsplit1

Number of Observations Read 261407
Number of Observations Used 261407

Analysis of Variance

Source DF
Model 23
Error 859974
Corrected Total 860000

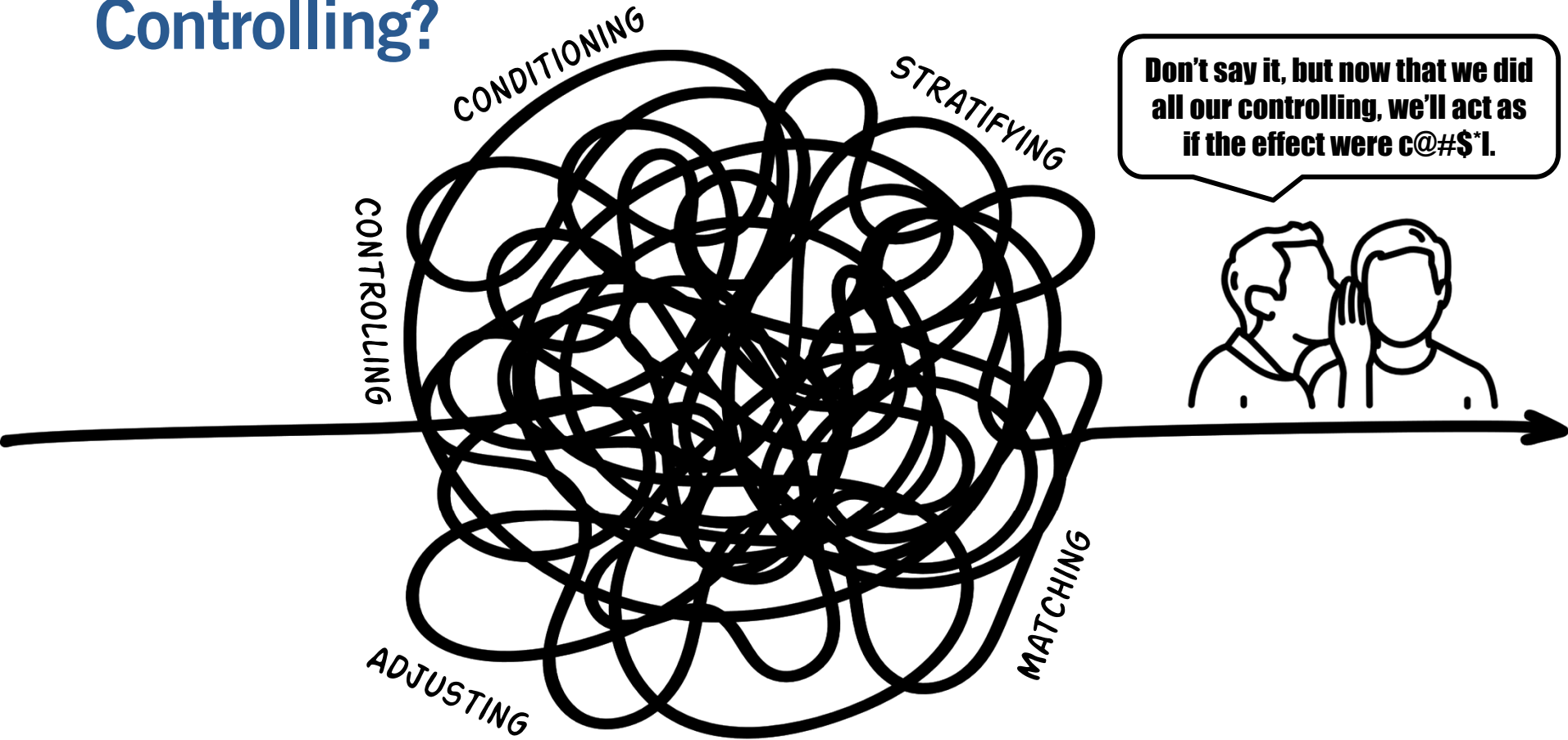
Root MSE
Dependent Mean
Coeff Var

Variable	DF	Sum of Squares	Mean Square	F Value	Pr > F
Intercept	1	1.47183	1.47183	0.003	0.959
logsplit1	1	2.78224	2.78224	0.003	0.959
logsplit1	1	0.00000	0.00000	0.000	1.000
sexmale2	1	0.00000	0.00000	0.000	1.000
port	1	0.00000	0.00000	0.000	1.000
immigration	1	0.00000	0.00000	0.000	1.000
corrupt	1	0.00000	0.00000	0.000	1.000
whitecoll	1	0.00000	0.00000	0.000	1.000
ignores	1	0.00000	0.00000	0.000	1.000
substant	1	0.00000	0.00000	0.000	1.000
newcrim	1	0.00000	0.00000	0.000	1.000
corrupt	1	0.00000	0.00000	0.000	1.000
whitefemale	1	0.00000	0.00000	0.000	1.000
blackmale	1	0.00000	0.00000	0.000	1.000
blackfemale	1	0.00000	0.00000	0.000	1.000
blackmale	1	0.00000	0.00000	0.000	1.000
blackfemale	1	0.00000	0.00000	0.000	1.000
othermale	1	0.00000	0.00000	0.000	1.000
otherfemale	1	0.00000	0.00000	0.000	1.000
agejunior	1	0.00000	0.00000	0.000	1.000
educ	1	0.00000	0.00000	0.000	1.000
agejunior	1	0.00000	0.00000	0.000	1.000
educ	1	0.00000	0.00000	0.000	1.000
citizen	1	0.00000	0.00000	0.000	1.000

Parameter Estimates

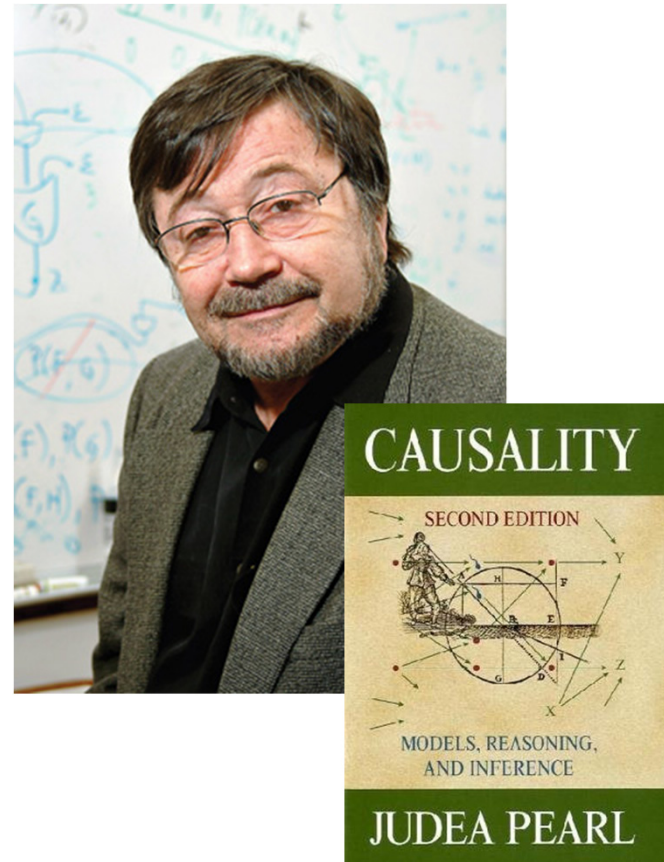
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	1.47183	0.00000	0.000	1.000	0.000
logsplit1	1	0.00000	0.00000	0.000	1.000	0.000
sexmale2	1	0.00000	0.00000	0.000	1.000	0.000
port	1	0.00000	0.00000	0.000	1.000	0.000
immigration	1	0.00000	0.00000	0.000	1.000	0.000
corrupt	1	0.00000	0.00000	0.000	1.000	0.000
whitecoll	1	0.00000	0.00000	0.000	1.000	0.000
ignores	1	0.00000	0.00000	0.000	1.000	0.000
substant	1	0.00000	0.00000	0.000	1.000	0.000
newcrim	1	0.00000	0.00000	0.000	1.000	0.000
corrupt	1	0.00000	0.00000	0.000	1.000	0.000
whitefemale	1	0.00000	0.00000	0.000	1.000	0.000
blackmale	1	0.00000	0.00000	0.000	1.000	0.000
blackfemale	1	0.00000	0.00000	0.000	1.000	0.000
blackmale	1	0.00000	0.00000	0.000	1.000	0.000
blackfemale	1	0.00000	0.00000	0.000	1.000	0.000
othermale	1	0.00000	0.00000	0.000	1.000	0.000
otherfemale	1	0.00000	0.00000	0.000	1.000	0.000
agejunior	1	0.00000	0.00000	0.000	1.000	0.000
educ	1	0.00000	0.00000	0.000	1.000	0.000
agejunior	1	0.00000	0.00000	0.000	1.000	0.000
educ	1	0.00000	0.00000	0.000	1.000	0.000
citizen	1	0.00000	0.00000	0.000	1.000	0.000

Controlling?



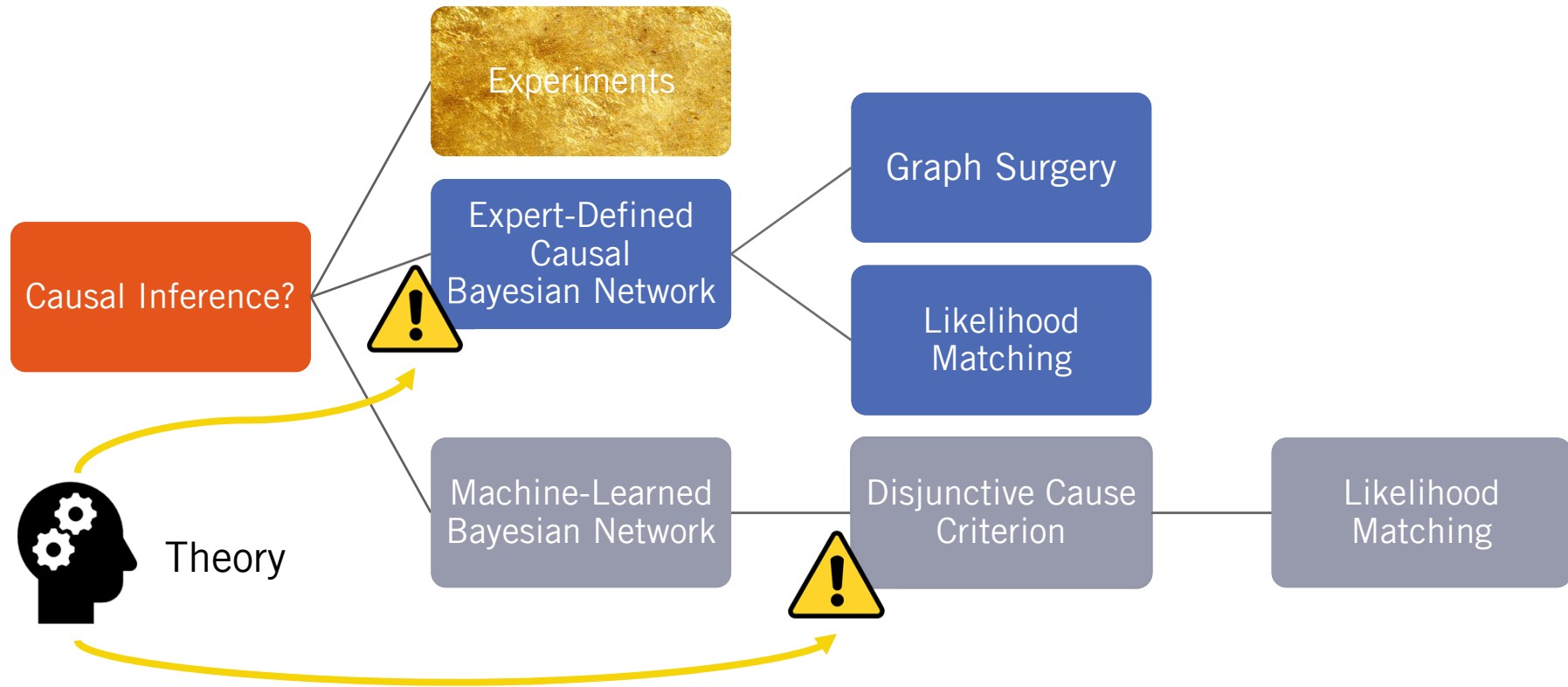
Controlling?

“The prevailing attitude is that adding more covariates can cause no harm and can absolve one from thinking about causal relationships...”
Judea Pearl in Causality (2009)





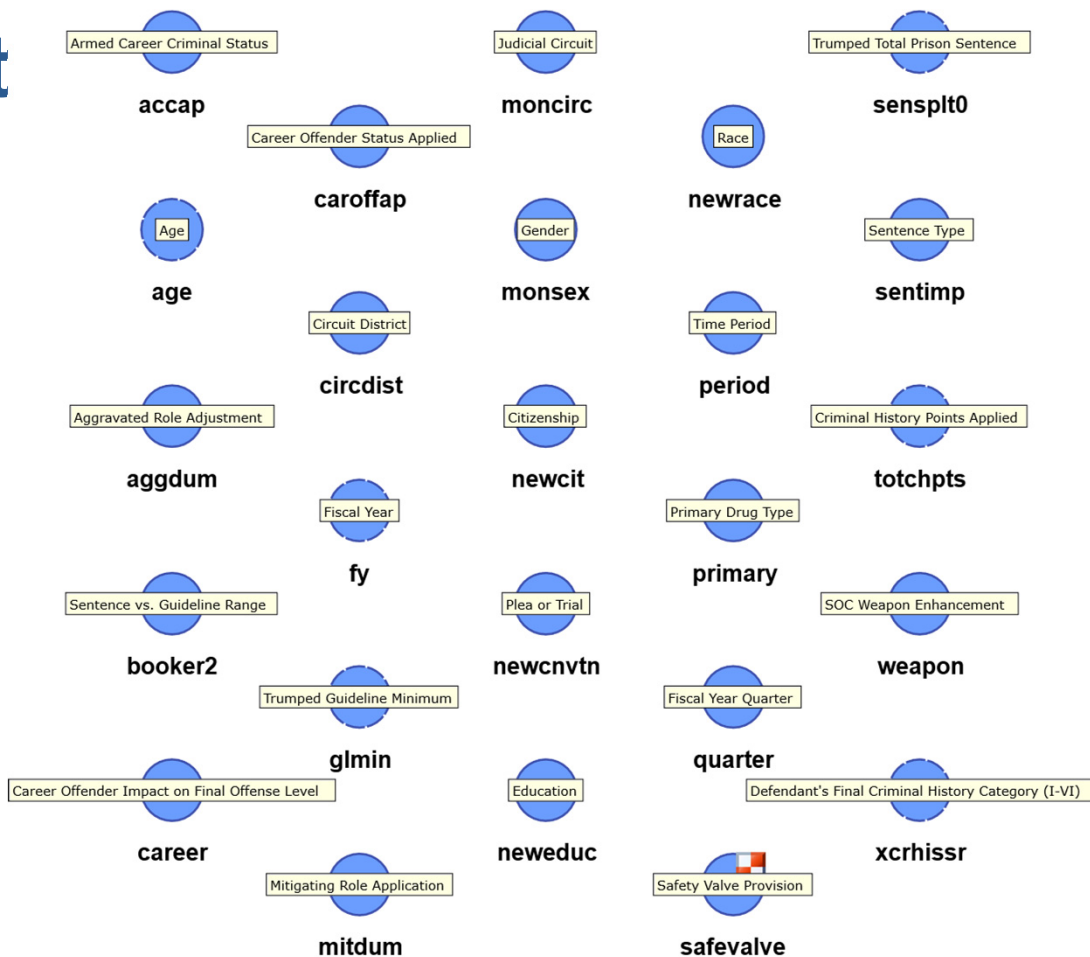
Causality?



Model Development

Encoding a Causal Model

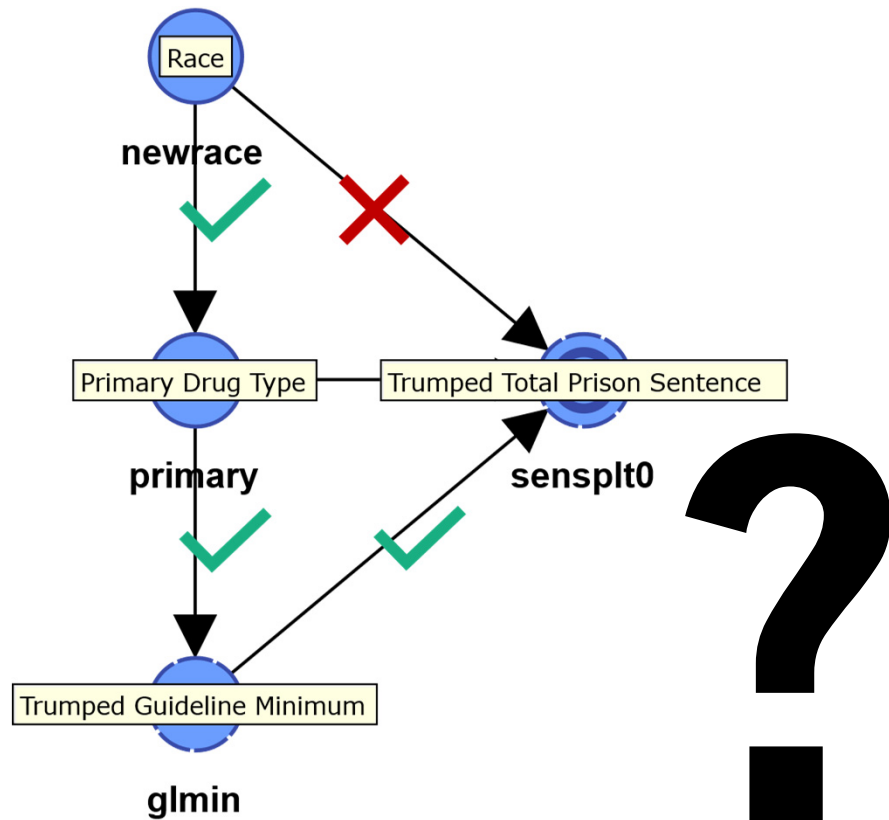
- What causes the *Total Prison Sentence*?
- Everything?



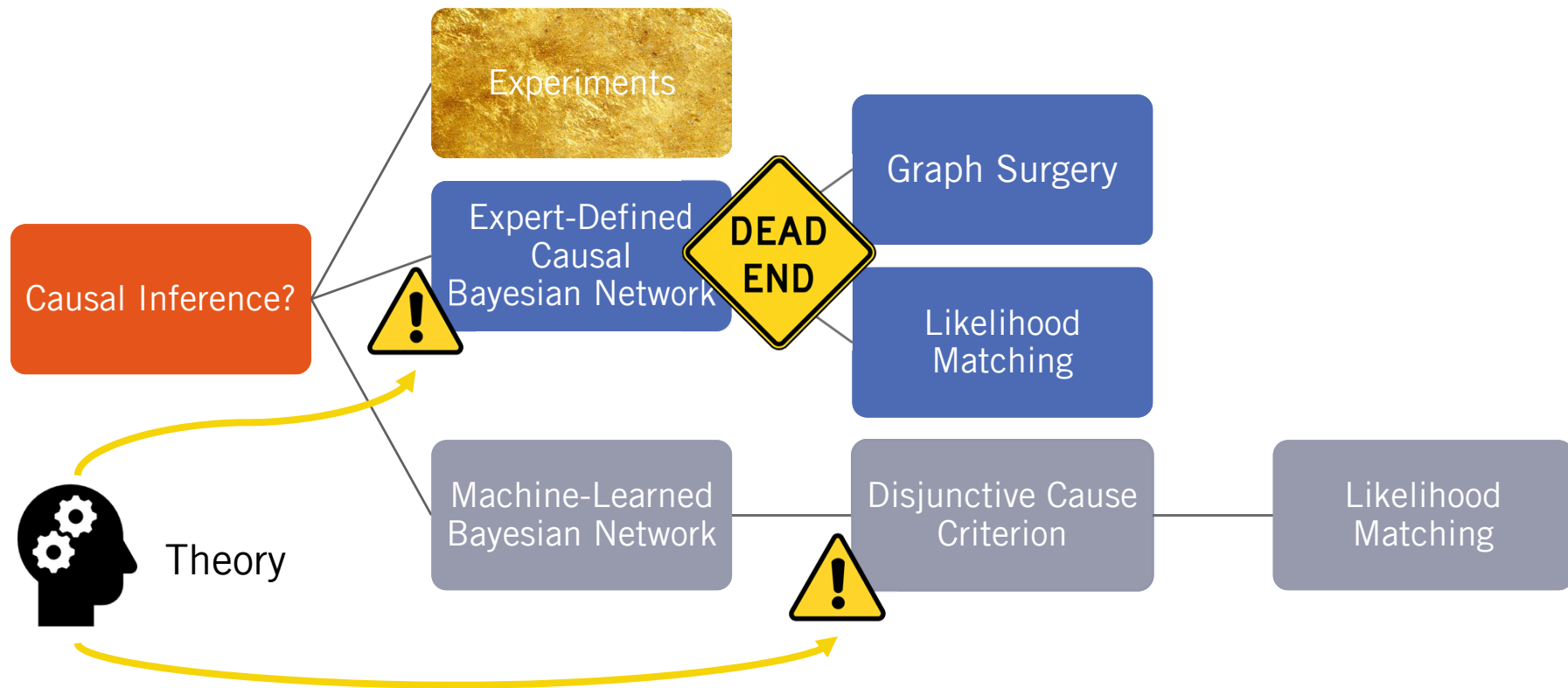
Model Development

Encoding a Causal Model

- How do the variables cause each other?
- There are way too many assumption we would have to make!



Causality?



Disjunctive Cause Criterion



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Biometrics. Author manuscript; available in PMC 2012 December 1.

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Biometrics. 2011 December ; 67(4): 1406–1413. doi:10.1111/j.1541-0420.2011.01619.x.

A new criterion for confounder selection

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Abstract

We propose a new criterion for confounder selection when the underlying causal structure is unknown and only limited knowledge is available. We assume all covariates being considered are pretreatment variables and that for each covariate it is known (i) whether the covariate is a cause of treatment, and (ii) whether the covariate is a cause of the outcome. The causal relationships the covariates have with one another is assumed unknown. We propose that control be made for any covariate that is either a cause of treatment or of the outcome or both. We show that irrespective of the actual underlying causal structure, if any subset of the observed covariates suffices to control

Disjunctive Cause Criterion

VanderWeele and Shpitser (2011)

- “We propose that control be made for any [pre-treatment] covariate that is either a cause of **treatment** or of the **outcome** or both.”

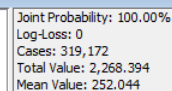
Race

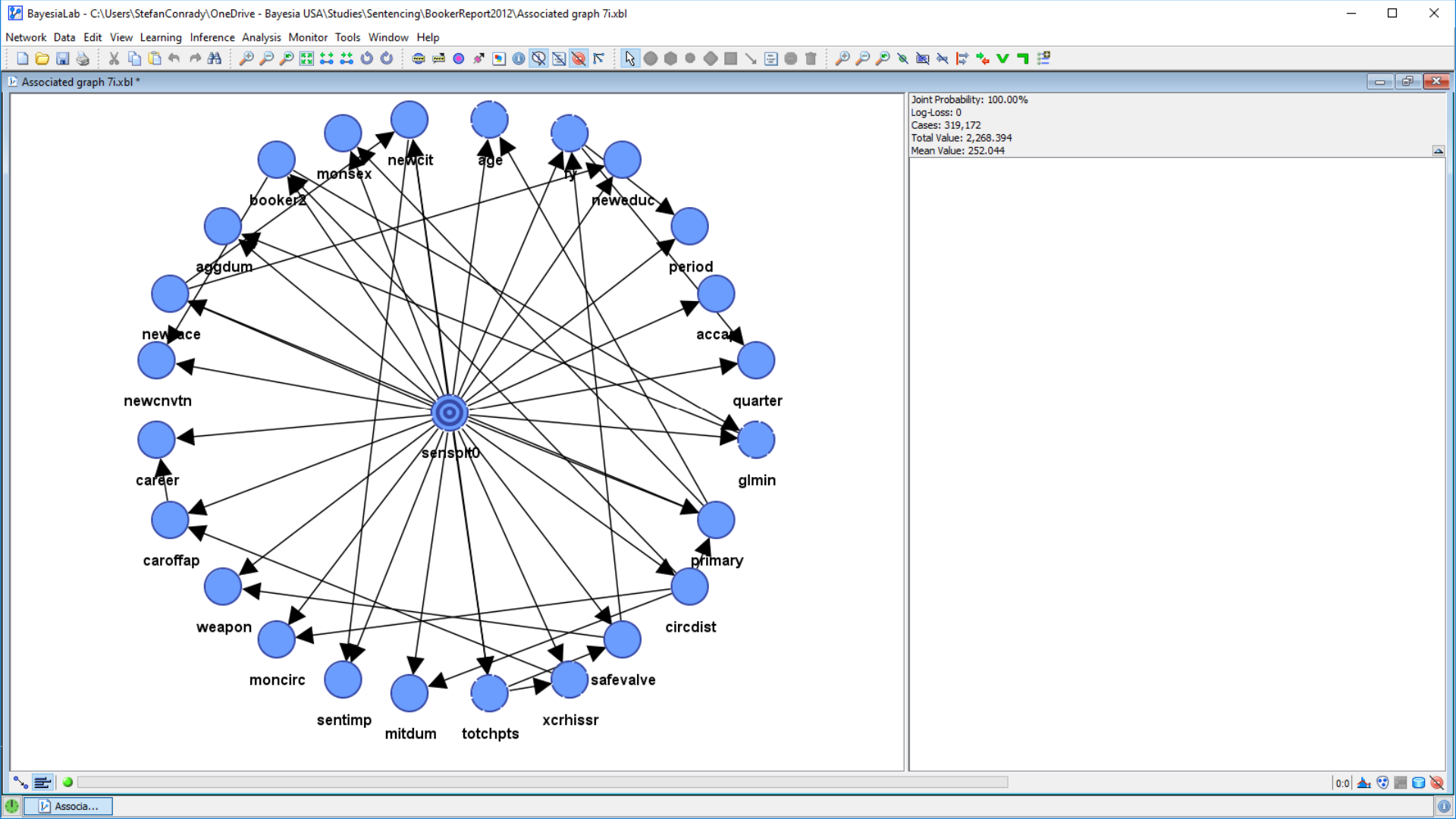
Sentence

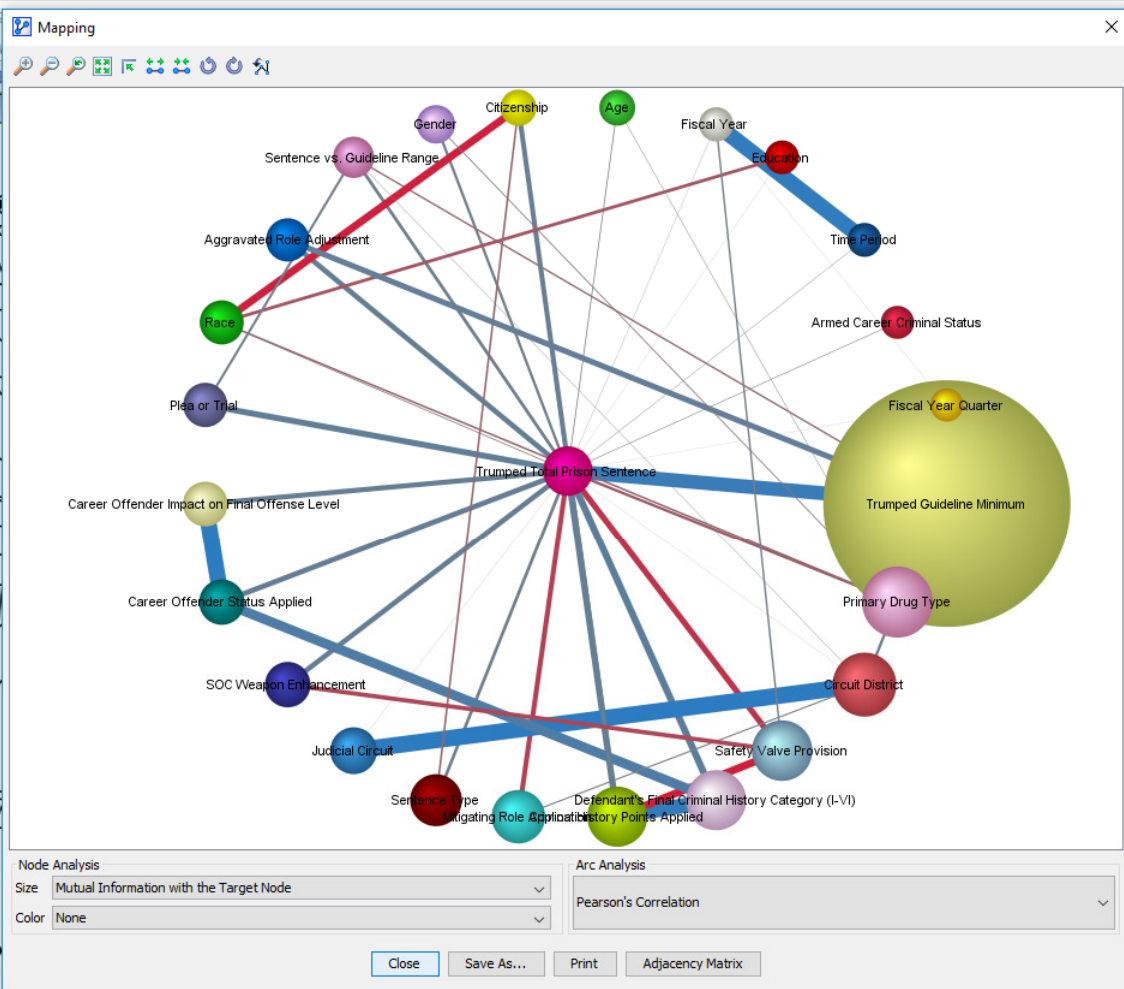
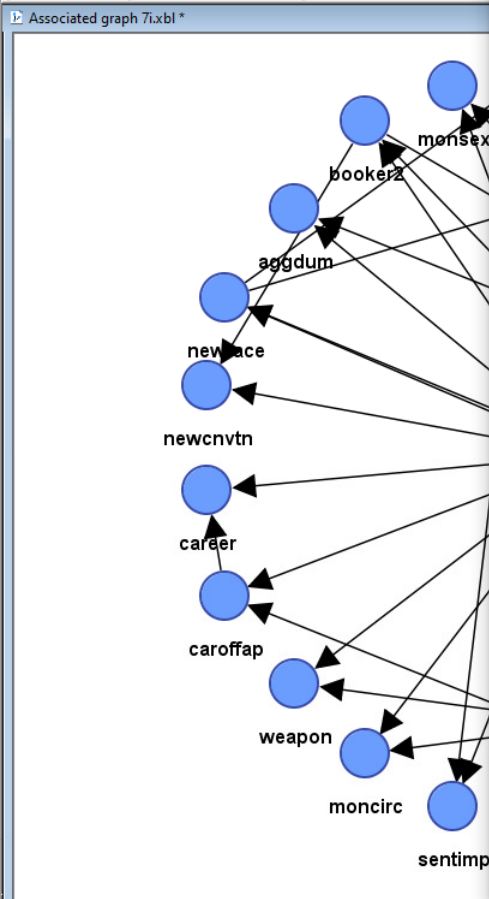
Implementation in BayesiaLab:
Likelihood Matching on Confounders in
Direct Effects Analysis → Causal Effect

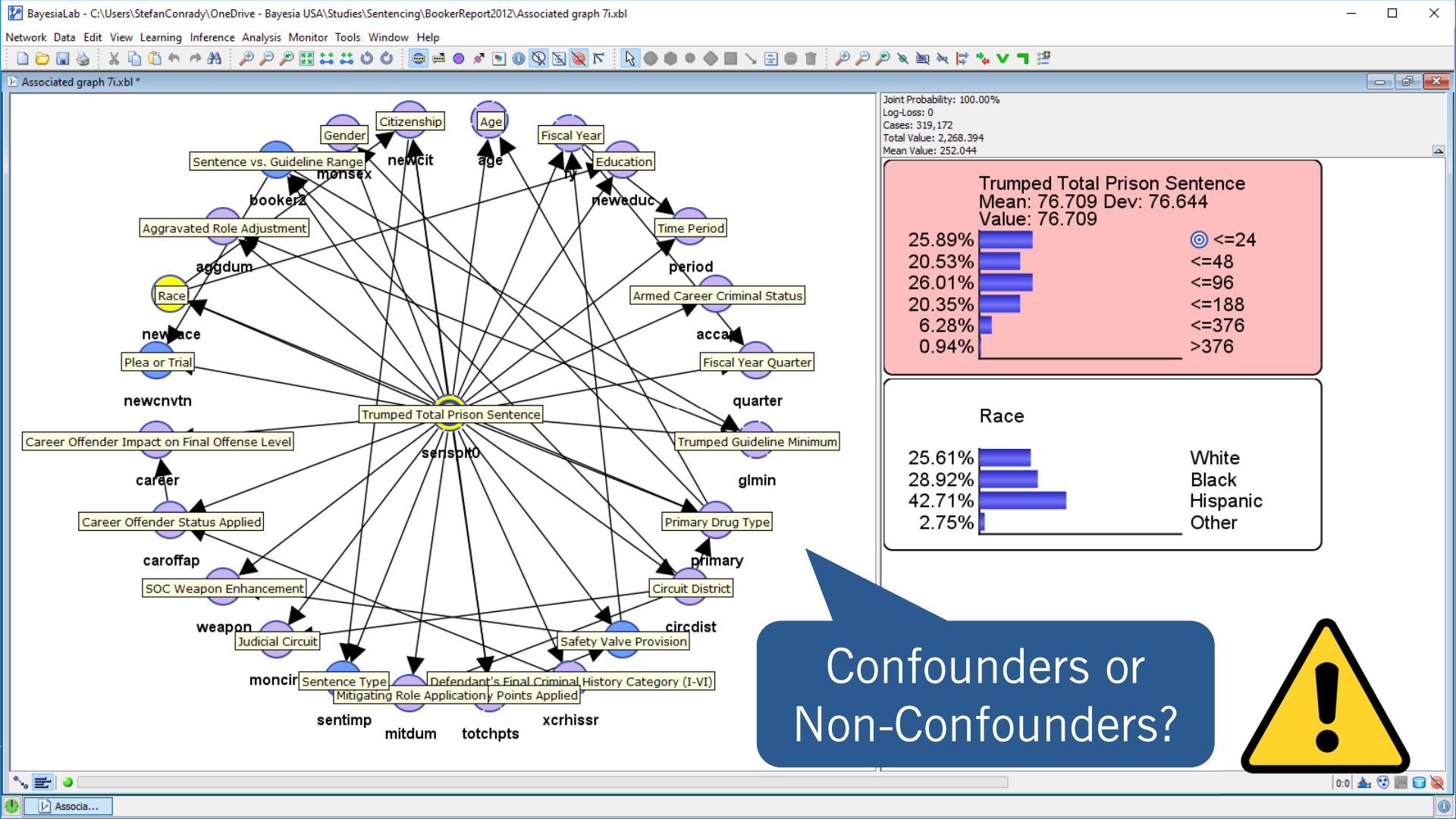
“Confounder” in BayesiaLab

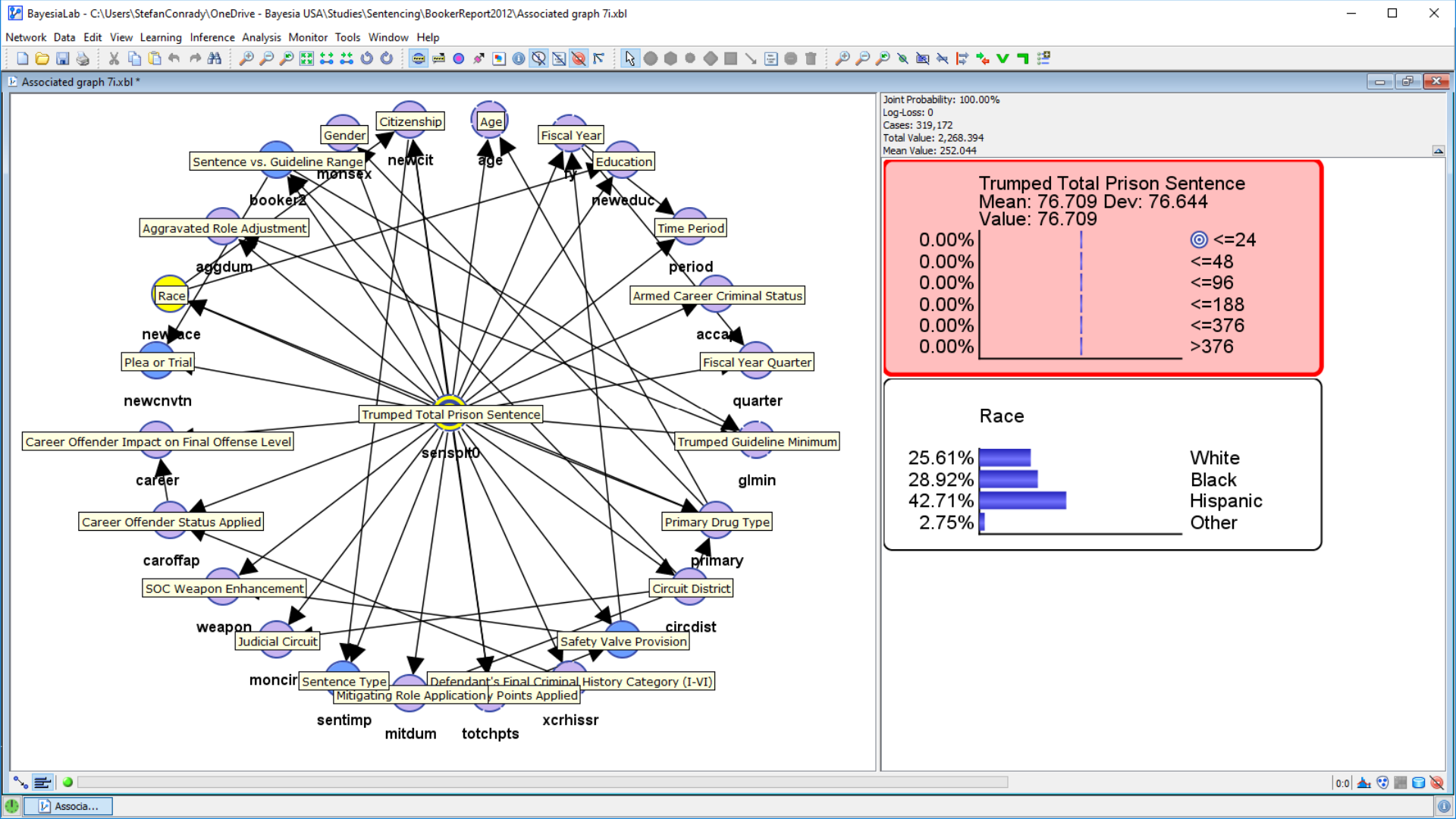
**IMPORTANT ASSUMPTION:
NO UNOBSERVED CONFOUNDERS**

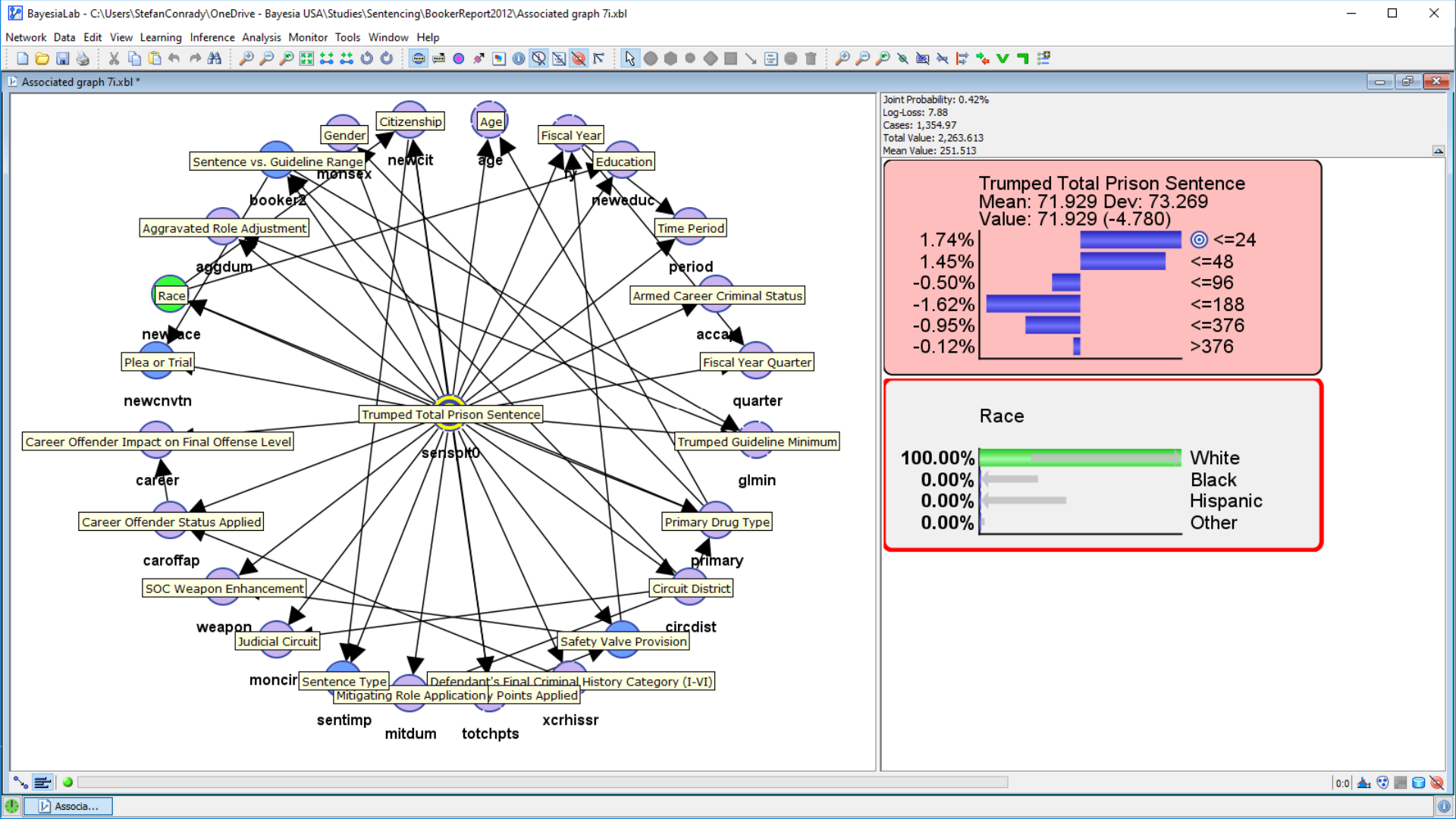


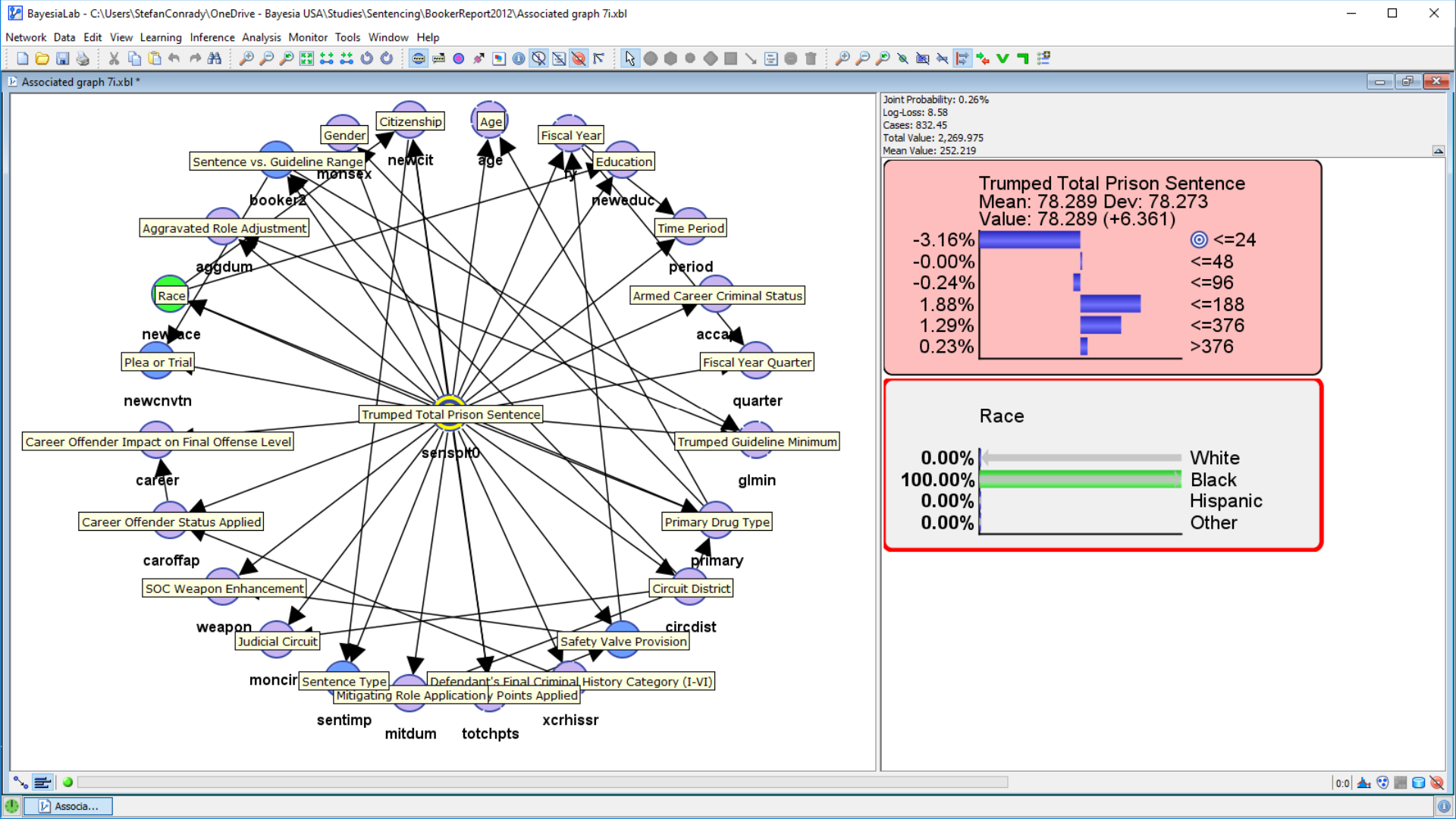


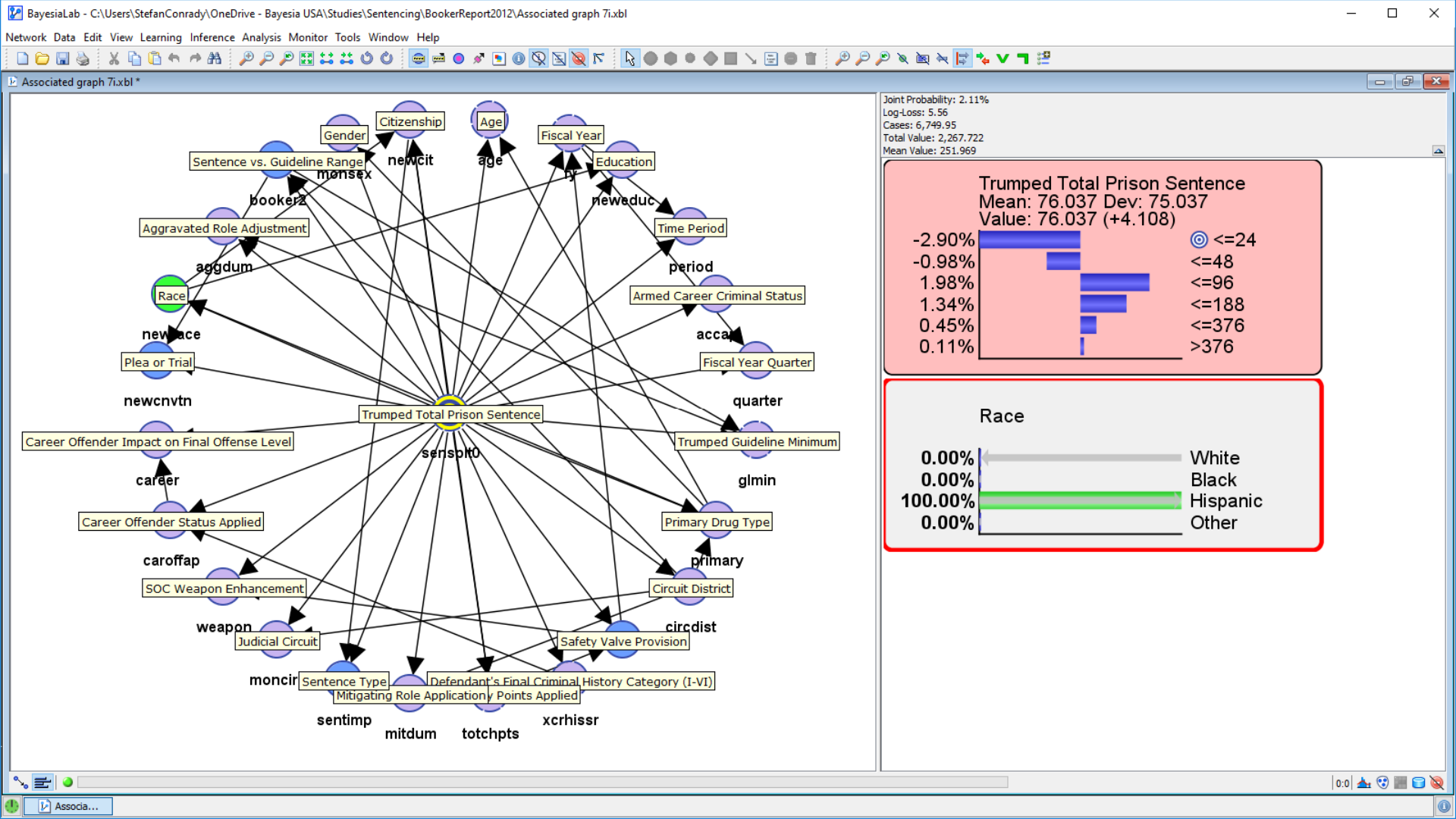


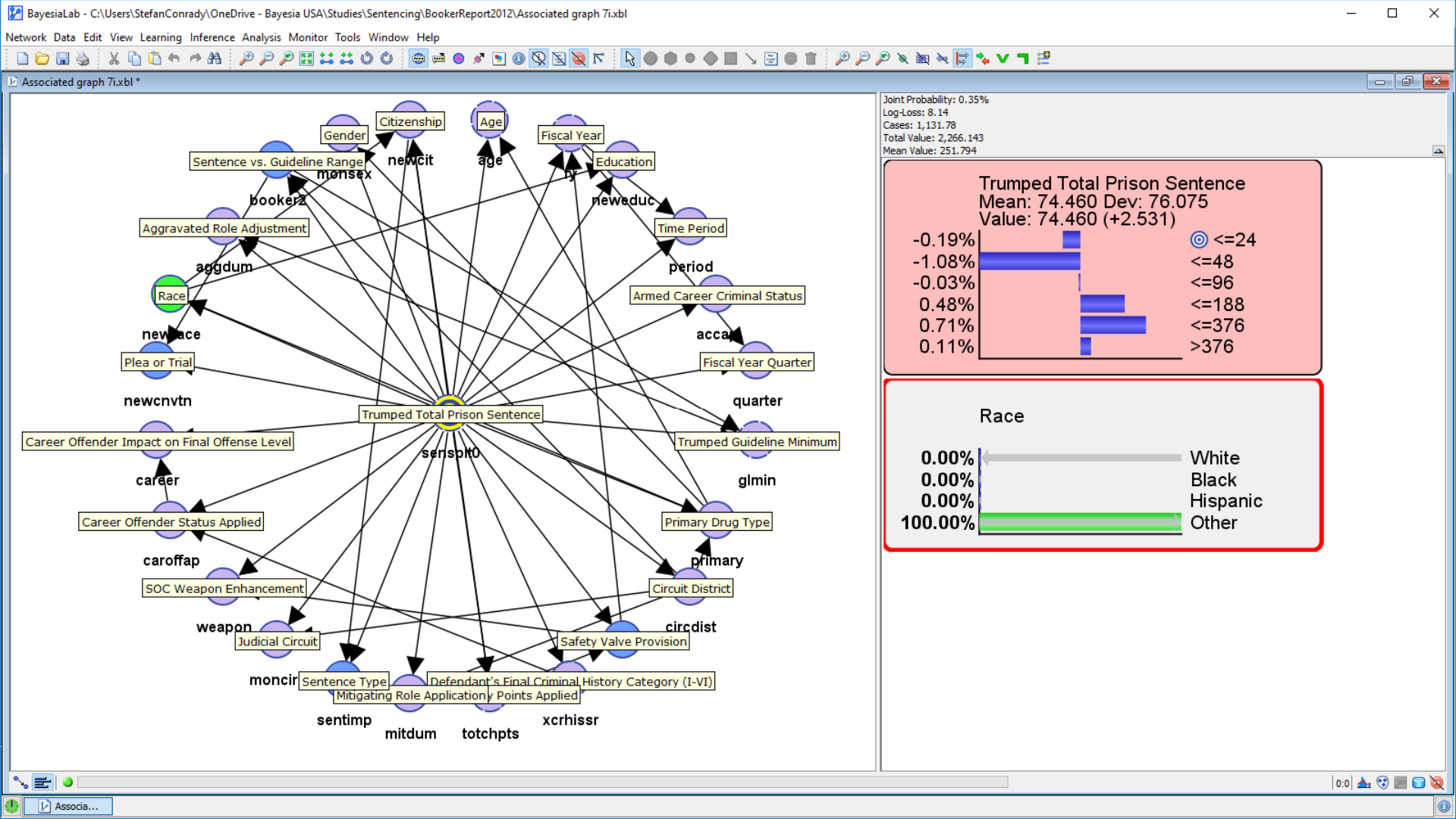








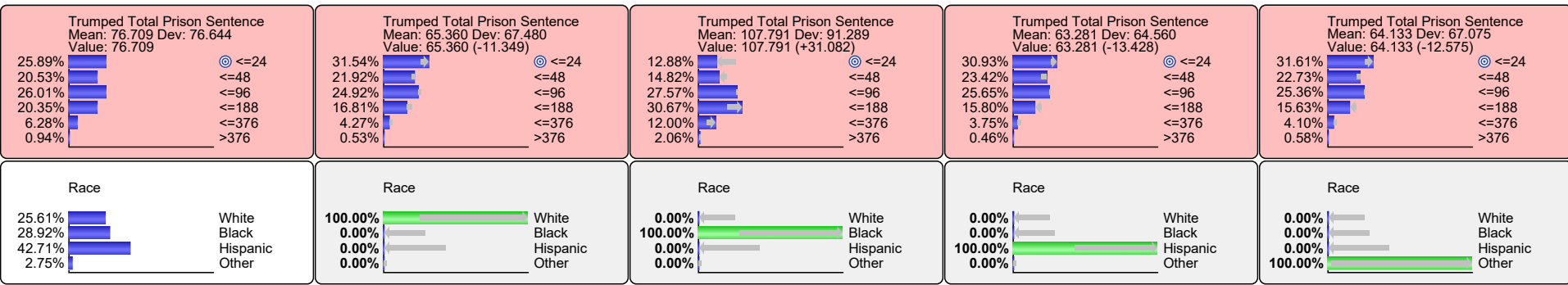




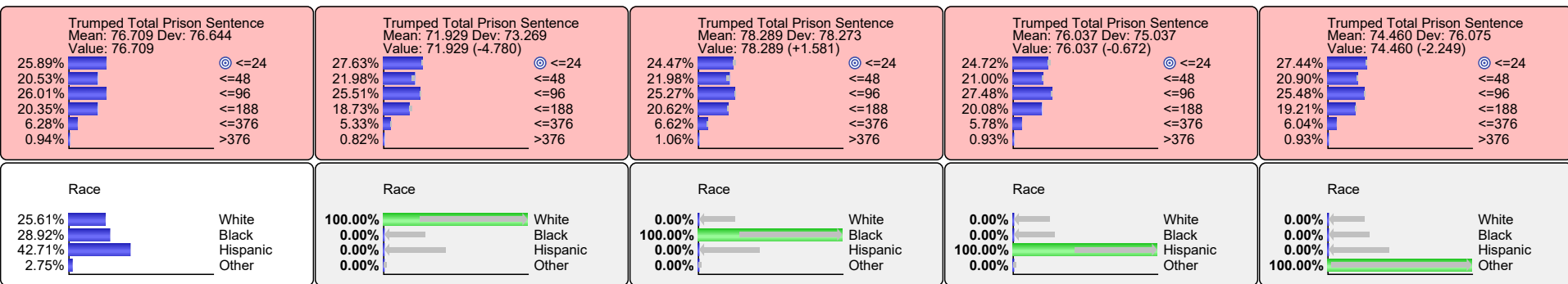
Effects Analysis

**IMPORTANT ASSUMPTION:
NO UNOBSERVED CONFOUNDERS**

Observational Inference



Causal Inference





In Conclusion...

Upcoming Events

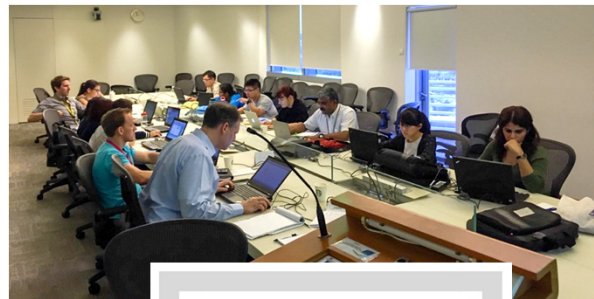
Webinars & Seminars:

- May 18 Webinar: Geographic Optimization Mapping with BayesiaLab
- June 1 Webinar: Topic t.b.d.
- June 19 Seminar in Chicago: Knowledge Discovery in Financial Data

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- July 23–25
San Francisco, CA
- August 29–31
London, UK
- September 26–28
New Delhi, India
- October 29–31
Chicago, IL
- December 4–6
New York, NY

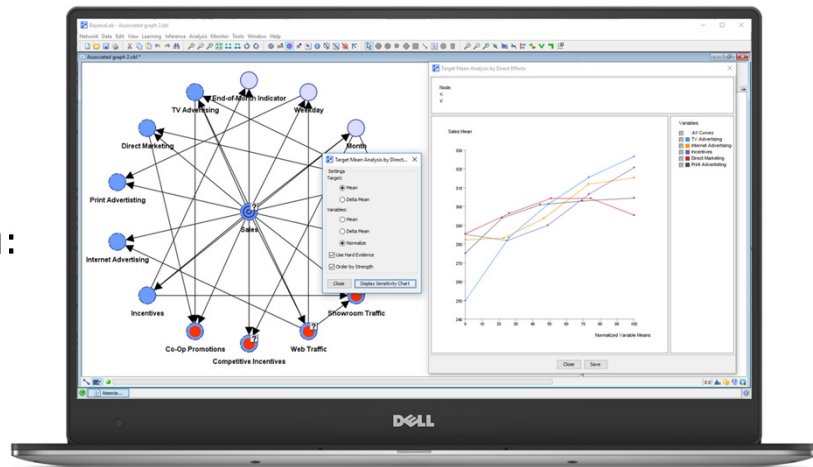


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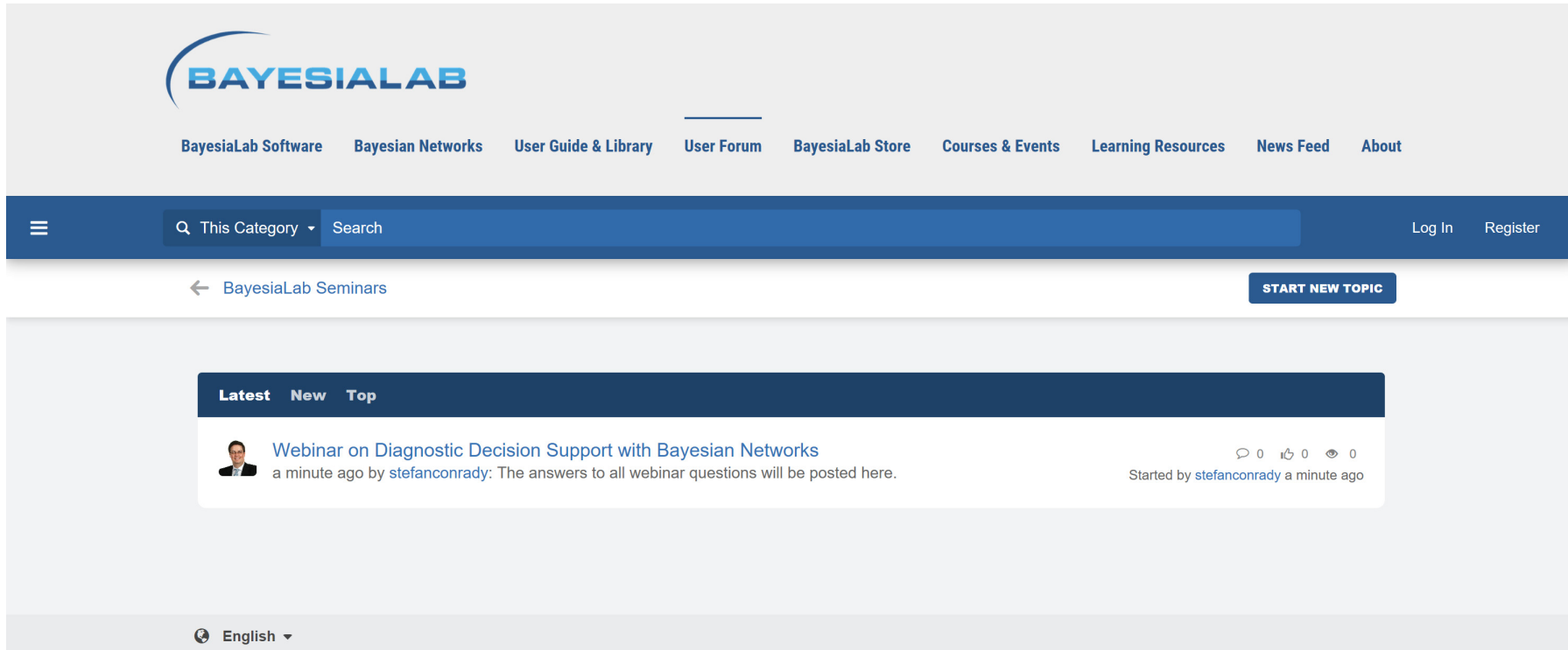
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The screenshot shows the BayesiaLab User Forum interface. At the top is the BayesiaLab logo. Below it is a navigation bar with links: BayesiaLab Software, Bayesian Networks, User Guide & Library, User Forum (which is underlined), BayesiaLab Store, Courses & Events, Learning Resources, News Feed, and About. A dark blue search bar spans the width of the page, containing a hamburger menu icon, a search icon, the text 'This Category', a search input field, and 'Log In' and 'Register' links. Below the search bar, a breadcrumb trail shows 'BayesiaLab Seminars' with a back arrow. A 'START NEW TOPIC' button is in the top right. The main content area has a tabbed interface with 'Latest', 'New', and 'Top' tabs. The 'Latest' tab is active, showing a post by 'stefanconrady' titled 'Webinar on Diagnostic Decision Support with Bayesian Networks'. The post text says 'The answers to all webinar questions will be posted here.' and it was started 'a minute ago'. To the right of the post are icons for replies (0), likes (0), and views (0). At the bottom left, there is a language selector set to 'English'.


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Started by [stefanconrady](#) a minute ago

🌐 English ▼

6th Annual BayesiaLab Conference in Chicago

November 1–2, 2018



Thank You!



stefan.conrady@bayesia.us



[BayesianNetwork](#)



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