

TECHNISCHE  
UNIVERSITÄT  
DARMSTADT



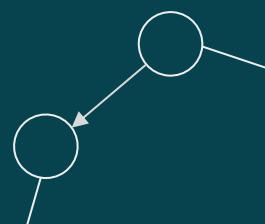
# Code Tutorial on Different Causality Topics

Matej Zečević

27<sup>th</sup> July 2023



Machines Climbing Pearl's Ladder of Causation



# What we've seen\* so far

- Lecture 1: Motivation and Conceptual Introduction to Causality
- Lecture 2: Formal Basics and Causal Discovery
- Lecture 3: Causal Identification and Estimation
- **Lecture 4: Code Tutorial (Previous and Related Topics)**

\* and hopefully learned

# 5 Exercises

## Core Topics: Identification, Estimation, Discovery

1. Simpson's Paradox
2. Parent Adjustment
3. Backdoor Adjustment
4. Estimation with Machine Learning
5. Causal Discovery

# 5 Exercises

## Core Topics: Identification, Estimation, Discovery

- |                                     |        |
|-------------------------------------|--------|
| 1. Simpson's Paradox                | 10 min |
| 2. Parent Adjustment                | 15 min |
| 3. Backdoor Adjustment              | 15 min |
| 4. Estimation with Machine Learning | 10 min |
| 5. Causal Discovery                 | 5 min  |
- 

of **supervised** trial-and-error

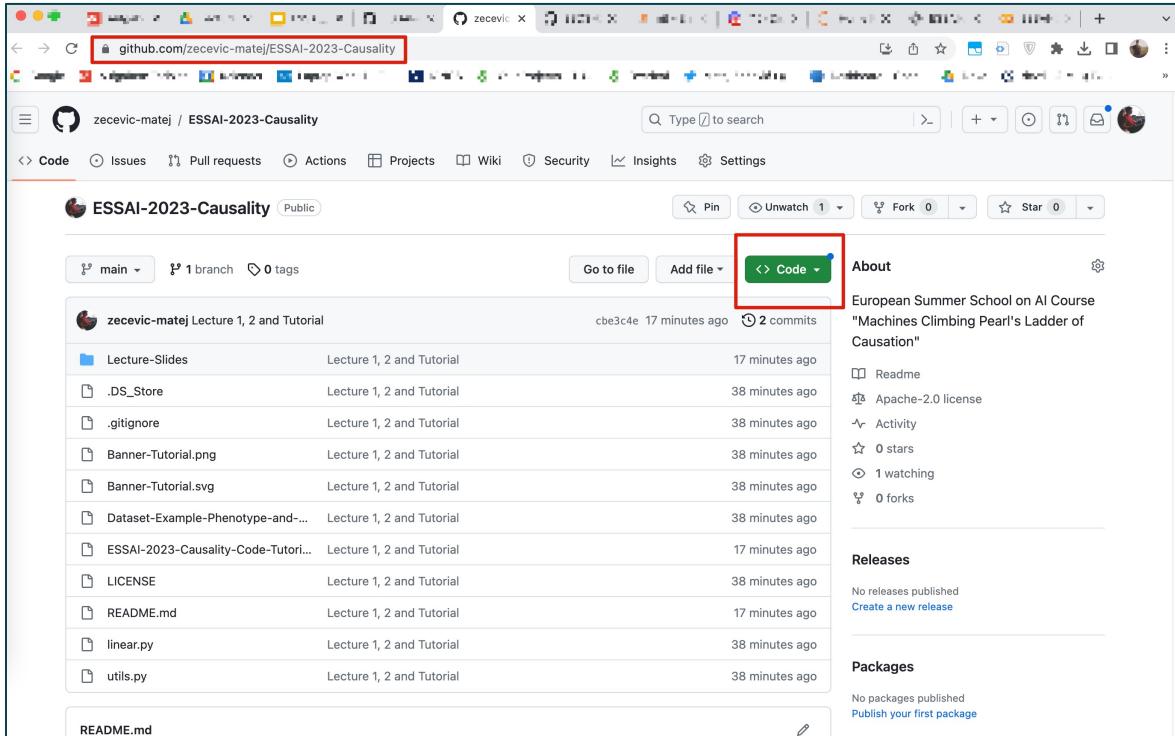
with 5 min **solution** after each exercise = **80 min in total**



**ESSAI & ACAI 2023**  
LJUBLJANA, SLOVENIA

Machines Climbing Pearl's Ladder of Causation

Go to the  
GitHub  
Repository and  
download it to  
your local drive  
as ZIP folder



Open the  
Jupyter  
Notebook  
(.ipynb)

The screenshot shows a GitHub repository page for 'zecevic-matej / ESSAI-2023-Causality'. A red arrow points to the repository name at the top. Another red arrow points to the file 'ESSAI-2023-Causality-Code-Tutorial.ipynb' in the file list on the left.

**ESSAI-2023-Causality / ESSAI-2023-Causality-Code-Tutorial.ipynb**

zecevic-matej Lecture 1, 2 and Tutorial cbe3c4e · 7 minutes ago History

Preview Code Blame 2405 lines (2405 loc) · 91.8 KB

Raw ⌂ ⌄ ⌅ ⌆

### Machines Climbing Pearl's Ladder of Causation

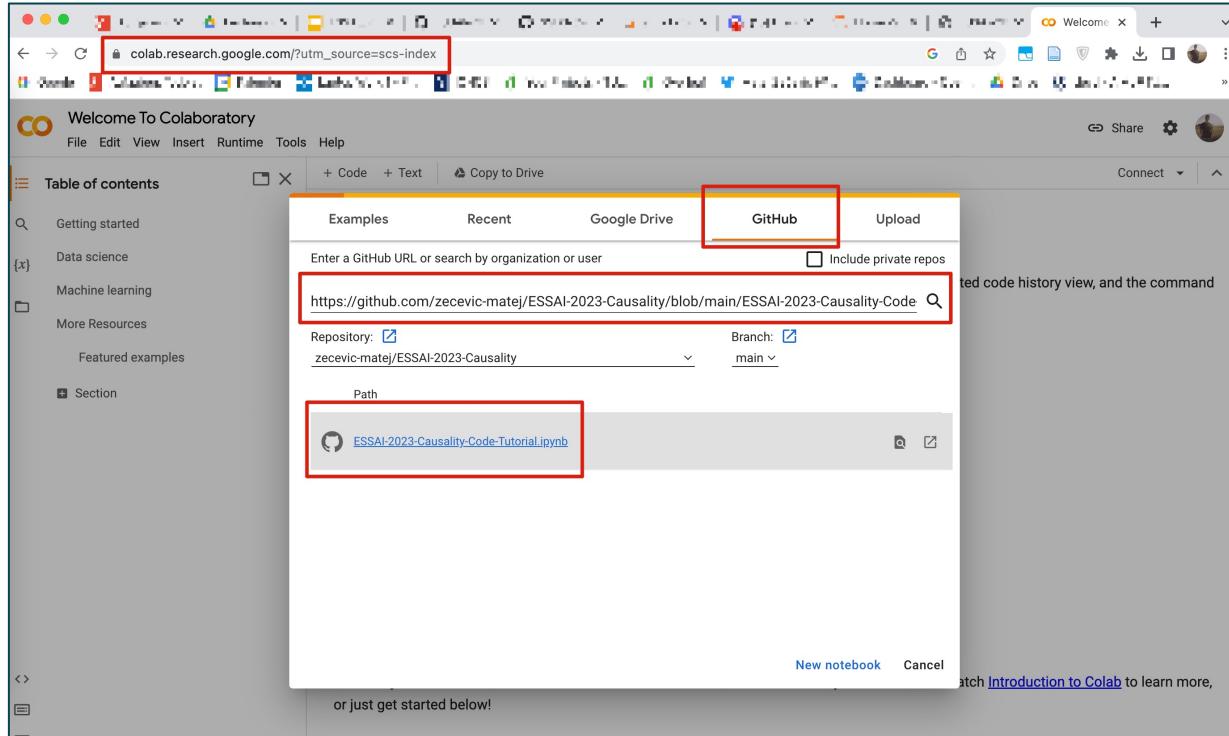
ESSAI & ACAI 2023  
LJUBLJANA, SLOVENIA  
 $X \rightarrow Y$

### Code Tutorial on Different Causality Topics

This tutorial combines elements from two previously existing tutorials. One of them first authored by Alexandre Drouin with

<https://github.com>

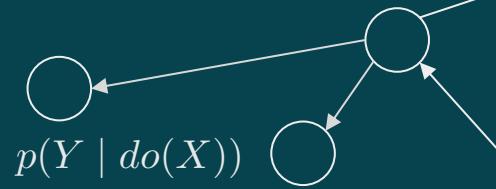
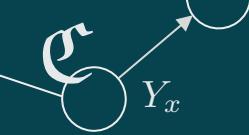
Copy the File's  
URL, open  
Google's Colab  
Online Coding  
Tool and open  
the Notebook



Upload the 3  
remaining files  
.py, .csv) from  
your unzipped,  
local repo copy

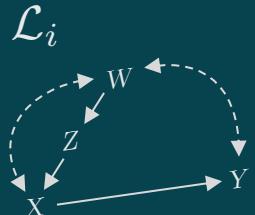
The screenshot shows a Jupyter Notebook interface with the following details:

- Title Bar:** ESSAI-2023-Causality-Code-Tutorial.ipynb
- File Tree (Left Sidebar):** Shows a directory structure with files: sample\_data, Dataset-Example-Phenotype-and-G..., linear.py, and utils.py. The upload icon () is highlighted with a red box.
- Main Content Area:**
  - Section Header:** Machines Climbing Pearl's Ladder of Causation
  - Image:** Logo for ESSAI & ACAI 2023 LJUBLJANA, SLOVENIA featuring a green dragon-like creature.
  - Text:** X → ? Y
  - Section Header:** Code Tutorial on Different Causality Topics
  - Text:** This tutorial combines elements from two previously existing tutorials. One of them first authored by [Alexandre Drouin](#) with contributions from [Philippe Brouillard](#) and [Thibaud Godon](#). We are grateful for the amazing scientists involved in making this tutorial a reality, thank you!
  - Text:** **Abstract:** This tutorial will consist of 5 exercises. We will cover the famous Simpson's paradox and accordingly follow up with a practical introduction to the estimation of causal effects. We will experiment with the concepts of average treatment effect, randomization, covariate adjustment, and inverse probability weighting to derive common estimators from the literature. We will also see where machine learning models fit into such estimators. Formal derivations will be presented and supported by extensive visualizations. Finally, we will give some examples of causal discovery for learning any of the causal structures that we assume/model in the first place.
  - Section Header:** Outline
  - List:**
    - Exercise 1: Simpson's paradox (15 min)
    - Exercise 2: Identification and estimation via parent adjustment (20 min)
- Bottom Status Bar:** Disk 53.90 GB available



# Let's Code!

See you in Google Colab



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Machines Climbing Pearl's Ladder of Causation

# Exercise I: Simpson's paradox (10 min)

## Complete it now!

**Done, discussing solution (5 min)**

Exercise I: Simpson's paradox (10 min)

## Exercise 2: Parent Adjustment (15 min)

Complete it now!

**Done, discussing solution (5 min)**

Exercise 2: Parent Adjustment (15 min)

# Exercise 3: Backdoor Adjustment (15 min)

Complete it now!

**Done, discussing solution (5 min)**

Exercise 3: Backdoor Adjustment (15 min)

# Exercise 4: Estimation via ML (10 min)

## Complete it now!

**Done, discussing solution (5 min)**

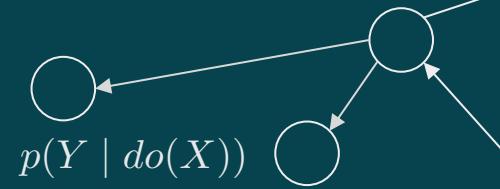
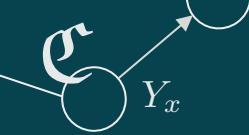
Exercise 4: Estimation via ML (10 min)

# Exercise 5: Causal Discovery (5 min)

## Complete it now!

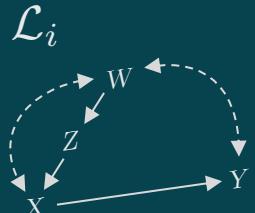
**Done, discussing solution (5 min)**

Exercise 5: Causal Discovery (5 min)



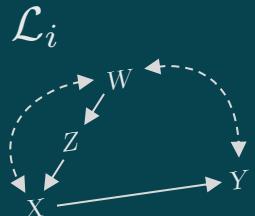
# That's a wrap!

Feel free to reach out:  
[matej.zecevic@tu-darmstadt.de](mailto:matej.zecevic@tu-darmstadt.de)





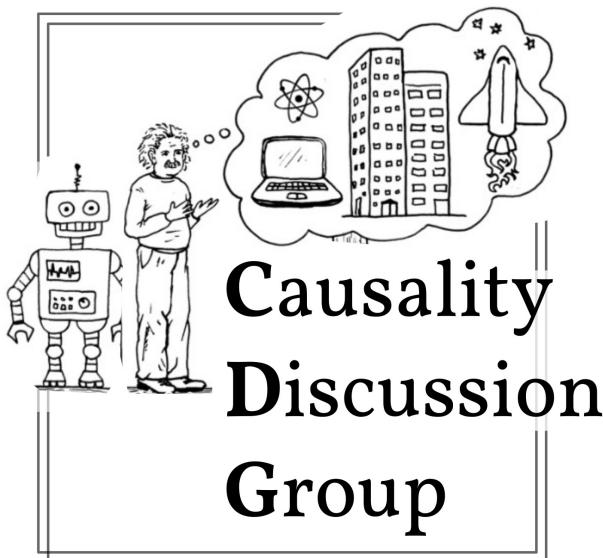
# Z | Announcements



Want to discuss more  
*following* this talk?

# Every Week with Paper Authors

→ **Discuss LIVE**



**530** members  
on Slack

Join the community  
via  
[discuss.causality.link](https://discuss.causality.link)

Past Sessions: [Password: Causality, Direct Access Link]

- ▷ Session 01.03.2023 | **Deep Counterfactual Estimation with Categorical Background Variables** | Discussant: Edward De Brouwer
- ▷ Session 22.02.2023 | **Information-Theoretic Causal Discovery and Intervention Detection over Multiple Environments** | Discussant: Osman Ali Mian
- ▷ Session 08.02.2023 | **CLEAR: Generative Counterfactual Explanations on Graphs** | Discussants: Jing Ma, Ruocheng Guo
- ▷ Session 01.02.2023 | **Causal Transformer for Estimating Counterfactual Outcomes** | Discussant: Valentyn Melnychuk
- ▷ Session 25.01.2023 | **Abstracting Causal Models** | Discussant: Sander Beckers
- ▷ Session 18.01.2023 | **Desiderata for Representation Learning: A Causal Perspective** | Discussant: Yixin Wang
- ▷ Session 11.01.2023 | **Causal Feature Selection via Orthogonal Search** | Discussant: Ashkan Soleymani
- ▷ Session 14.11.2022 | **Rewind 2022** | Final session of 2022 to simply rewind on what we experienced throughout the year
- ▷ Session 07.12.2022 | **Causal Inference Through the Structural Causal Marginal Problem** | Discussant: Luigi Gresele
- ▷ Session 30.11.2022 | **Selecting Data Augmentation for Simulating Interventions** | Discussant: Maximilian Ilse
- ▷ Session 23.11.2022 | **On Disentangled Representations Learned from Correlated Data** | Discussant: Frederik Träuble
- ▷ Session 16.11.2022 | **Causal Curiosity: RL Agents Discovering Self-supervised Experiments for Causal Repr. Learning** | Discussant: Sumedh Sontakke
- ▷ Session 09.11.2022 | **Causal Machine Learning: A Survey and Open Problems** | Discussants: Jean Kaddour, Aengus Lynch
- ▷ Session 02.11.2022 | **A Critical Look at the Consistency of Causal Estimation with Deep Latent Variable Models** | Discussant: Severi Rissanen
- ▷ Session 26.10.2022 | **Nonlinear Invariant Risk Minimization: A Causal Approach** | Discussant: Chaochao Lu
- ▷ Session 19.10.2022 | **CausalVAE: Disentangled Representation Learning via Neural Structural Causal Models** | Discussant: Mengyue Yang
- ▷ Session 12.10.2022 | **Weakly Supervised Causal Representation Learning** | Discussant: Johann Brehmer
- ▷ Session 05.10.2022 | **Towards Causal Representation Learning** | Discussant: Anirudh Goyal
- ▷ Session 21.09.2022 | **Selection Collider Bias in Large Language Models** | Discussant: Emily McMillin
- ▷ Session 14.09.2022 | **The Causal-Neural Connection: Expressiveness, Learnability, and Inference** | Discussants: Kai-Zhan Lee, Kevin Xia
- ▷ Session 07.09.2022 | **Self-Supervised Learning with Data Augmentations Provably Isolates Content from Style** | Discussant: Julius von Kügelgen

35+ Sessions  
Completed  
and  
All Recorded



Want to learn more  
*about the genealogy*  
of causality research?

# Genealogy of Causality

Access via [genealogy.causality.link](http://genealogy.causality.link)



Name	Institution	Supervisor	Location	Previous Positions
<b>UCLA</b>				
Judea Pearl	UCLA	?	US	Rutgers, Technion, New
Wesley Salmon	UCLA	Hans Reichenbach	US	?
Hans Reichenbach	UCLA	Paul Hensel, Max Noeth	US	Berlin, Istanbul, Erlange
<b>John Hopkins</b>				
Ilya Shpitser	John Hopkins		US	UCLA, Judea Pearl
<b>Oregon State University</b>				
Karthika Mohan	Oregon State University	Judea Pearl	US	
<b>CMU</b>				
Kun Zhang	CMU		Pittsburgh, US	MPI Tübingen
Clark Glymour	CMU	Wesley Salmon	Pittsburgh, US	
Peter Spirtes	CMU		Pittsburgh, US	
<b>ETH Zürich</b>				
Peter Bühlmann	ETH		Zürich	?
Marloes Maathuis	ETH		Zürich	?
Nicolai Meinshausen	ETH			
<b>LMU Munich</b>				
Stephan Hartmann	LMU		Munich, Germany	
<b>MPI Tübingen</b>				
Bernhard Schölkopf	MPI Tübingen	Vladimir Vapnik	Tübingen, Germ	TU Berlin
Ulrike von Luxburg	MPI Tübingen		Tübingen, Germany	
Michel Besserve				

# Genealogy of Causality

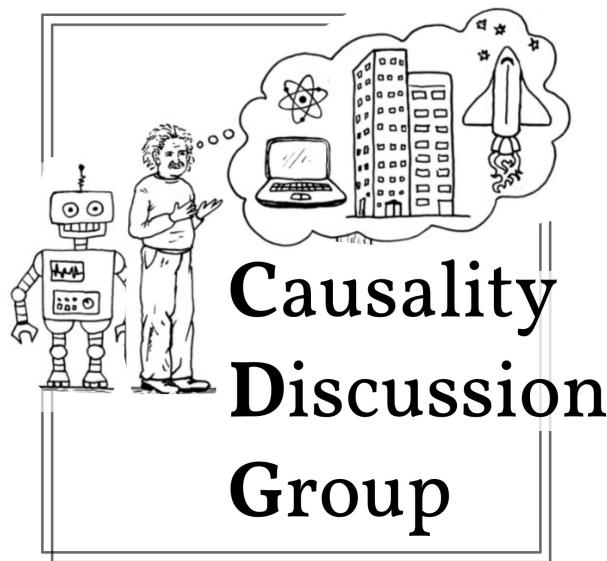
Access via [genealogy.causality.link](http://genealogy.causality.link)



The image is a composite of two main visual elements. On the left, a classic World War II recruitment poster for 'Rosie the Riveter' is displayed. It features a woman in a blue work shirt and a red polka-dot bandana flexing her right bicep. A speech bubble above her contains the text 'We Want You! To Extend This!' in yellow. On the right, a screenshot of a genealogy software application is shown. The interface includes a navigation bar at the top with tabs for 'Name', 'Institution', 'Superior', 'Location', and 'Previous Positions'. Below the navigation bar, there is a list of names and institutions, each represented by a small green rectangular card. The cards contain the name, institution, and a brief description of their role or position. The cards are arranged vertically, with some overlapping. The overall aesthetic is a blend of historical recruitment imagery and modern digital data visualization.

Name	Institution	Superior	Location	Previous Positions
UCLA	University of California, Los Angeles	John Doe	Los Angeles, CA	Professor, Researcher
Stanford	Stanford University	Jane Doe	Palo Alto, CA	Professor, Researcher
Harvard	Harvard University	John Smith	Boston, MA	Professor, Researcher
MIT	Massachusetts Institute of Technology	Jane Smith	Cambridge, MA	Professor, Researcher
Cornell	Cornell University	John Johnson	Ithaca, NY	Professor, Researcher
UC Berkeley	University of California, Berkeley	Jane Johnson	Berkeley, CA	Professor, Researcher
ETH Zurich	ETH Zurich	John Doe	Zürich, Switzerland	Professor, Researcher
University College London	University College London	Jane Doe	London, UK	Professor, Researcher
LAEU	LAEU	John Doe	Leipzig, Germany	Professor, Researcher
MPRI	MPRI	Jane Doe	Paris, France	Professor, Researcher
UNI	UNI	John Doe	Vienna, Austria	Professor, Researcher

Join the community  
via [discuss.causality.link](https://discuss.causality.link)



Access the genealogy  
via [genealogy.causality.link](https://genealogy.causality.link)

Genealogy of Causality				
Name	University	Advisors	Current Position	Previous Positions
<b>UCLA</b>				
Judea Pearl				Rutgers, Technion, New
Wesley Salmon	UCLA	Hans Reichenbach	US	?
Hans Reichenbach	UCLA	Paul Hensel, Max Noeth	US	Berlin, Istanbul, Erlange
<b>John Hopkins</b>				
Ilya Shpitser	John Hopkins		US	UCLA, Judea Pearl
<b>Oregon State University</b>				
Karthika Mohan	Oregon State University	Judea Pearl	US	
<b>CMU</b>				
Kun Zhang	CMU		Pittsburgh, US	MPI Tübingen
Clark Glymour	CMU	Wesley Salmon	Pittsburgh, US	
Peter Spirtes	CMU		Pittsburgh, US	
<b>ETH Zürich</b>				
Peter Bühlmann	ETH		Zürich	?
Marloes Maathuis	ETH		Zürich	?
Nicolai Meinshausen	ETH			
<b>LMU Munich</b>				
Stephan Hartmann	LMU		Munich, Germany	
<b>MPI Tübingen</b>				
Bernhard Schölkopf	MPI Tübingen	Vladimir Vapnik	Tübingen, Germ	TU Berlin
Ulrike von Luxburg	MPI Tübingen		Tübingen,	Germany
Michel Besserve				