

A close-up photograph of a hand in a dark suit jacket and white shirt cuff, striking a matchstick. The matchstick is lit, with a bright yellow flame and a trail of sparks. To the left of the lit matchstick, there are seven other unlit matchsticks standing upright in a row on a dark, textured wooden surface. The background is blurred, showing more of the wooden surface.

# Causal Inference Theory and Applications in Enterprise Computing

Dr. Matthias Uflacker, Johannes Huegle, Christopher Schmidt

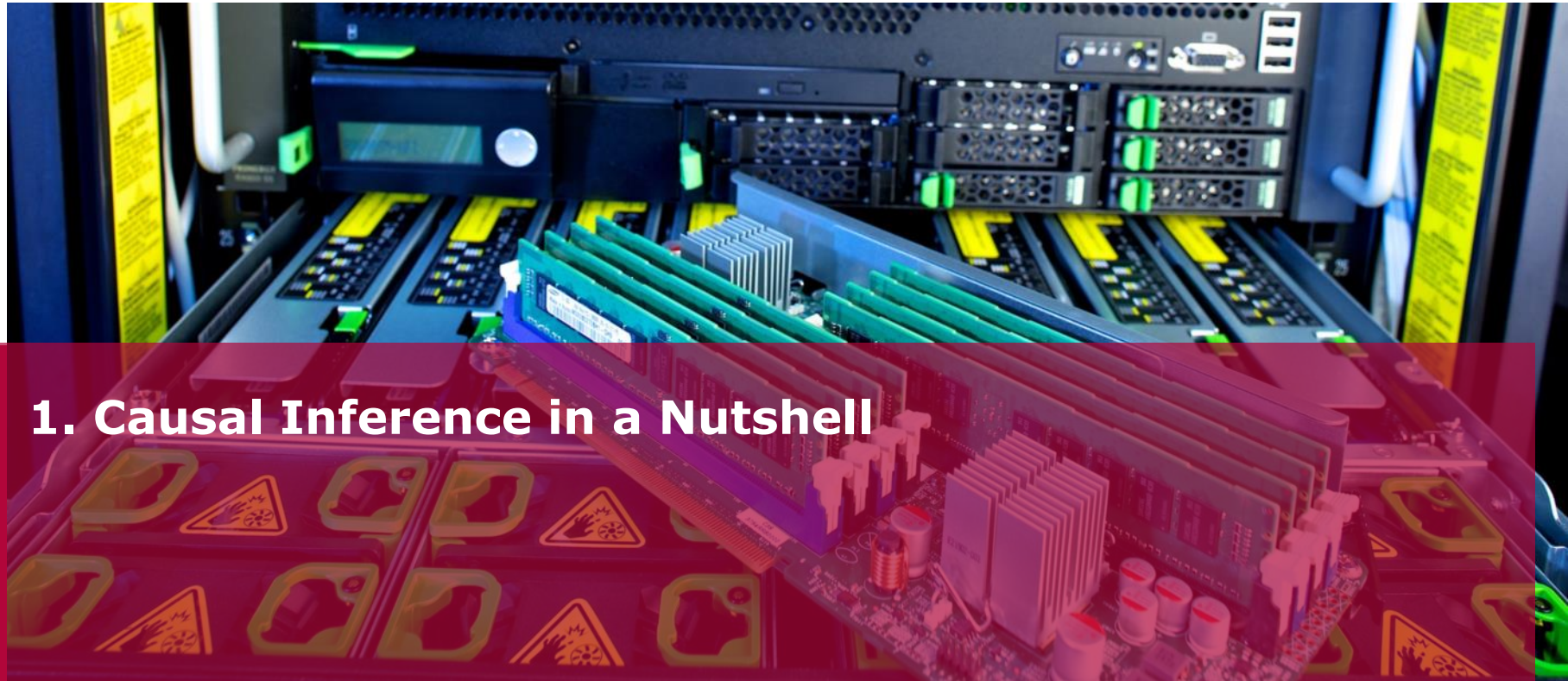
April 10, 2019

# Agenda

April 10, 2019

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- 1. Causal Inference in a Nutshell**
- 2. Causal Inference in Application**
- 3. Introduction to Research Topics**
- 4. Further Reading**



# 1. Causal Inference in a Nutshell

# 1. Causal Inference in a Nutshell

## Recap: Summary

---

### **Traditional statistics, machine learning, etc.**

- About **associations**
- Model the **distribution** of the data
- Predict given **observations**

### **Causal Inference**

- About **causation**
- Model the **mechanism** that generates the data
- Predict results of **interventions**

**Causal Inference**  
Theory and Applications  
in Enterprise Computing

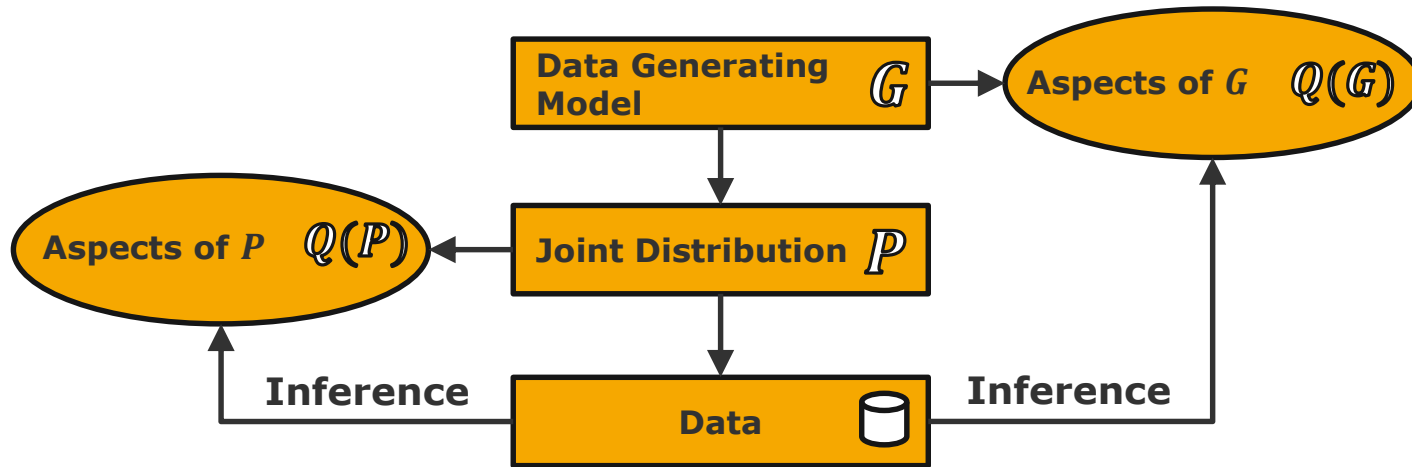
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# 1. Causal Inference in a Nutshell

## Recap: Concept

### Traditional Statistical Inference Paradigm

### Paradigm of Structural Causal Models



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E.g., what is the sailors' probability of recovery when **we see** a treatment with lemons?

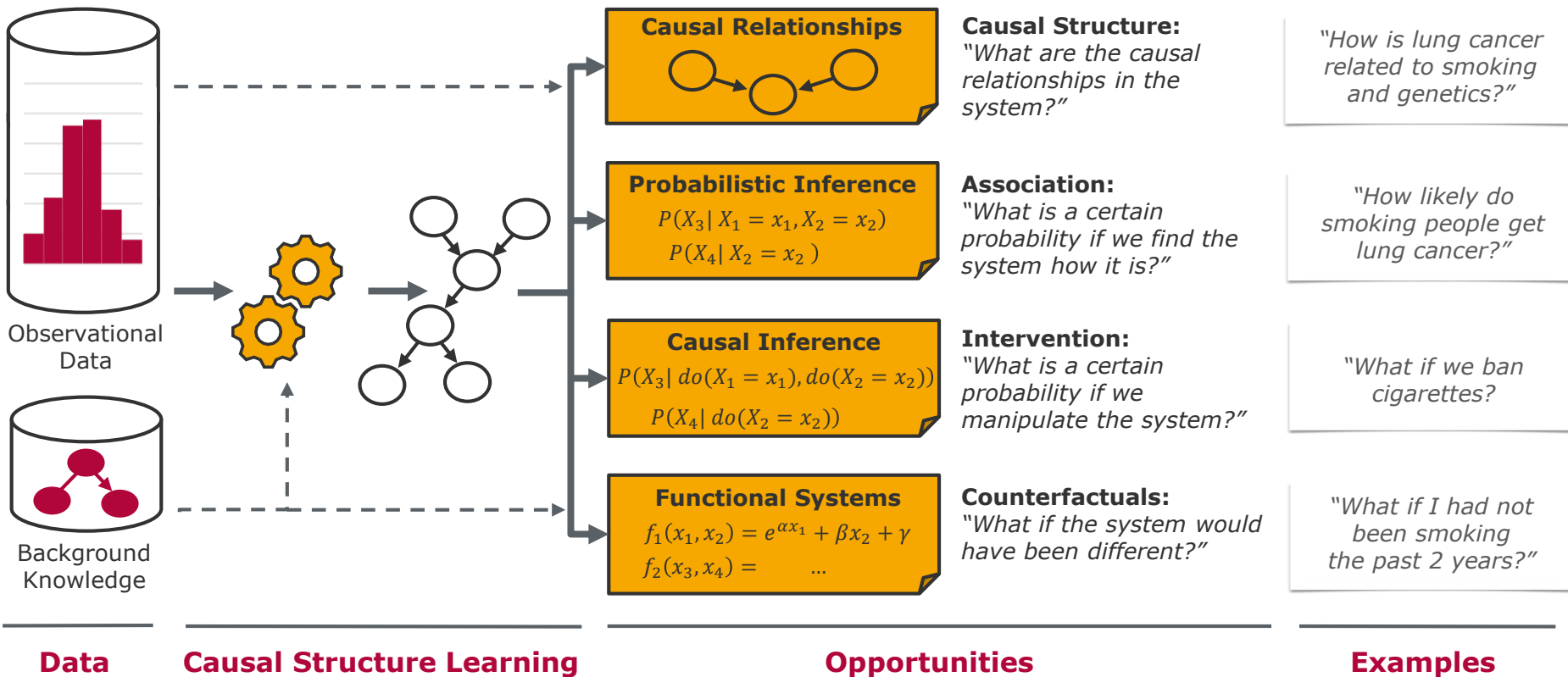
$$Q(P) = P(\text{recovery}|\text{lemons})$$

E.g., what is the sailors' probability of recovery if **we do** treat them with lemons?

$$Q(G) = P(\text{recovery}|\text{do}(\text{lemons}))$$

# 1. Causal Inference in a Nutshell

## Recap: Inference Procedure





## 2. Causal Inference in Application

# 2. Causal Inference in Application

## Causal Relationships (I/II)

*"What are the principal structural properties of genetic control programs of the cell's biological processes?"*



**Probabilistic Inference**

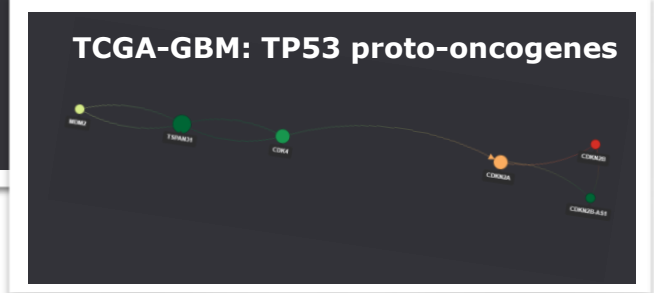
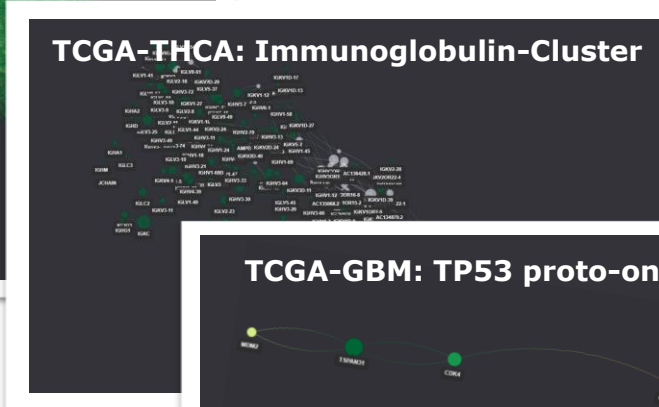
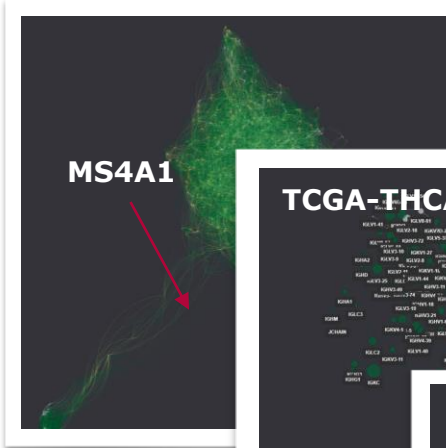
$$P(X_3 | X_1 = x_1, X_2 = x_2)$$
$$P(X_4 | X_2 = x_2)$$

**Causal Inference**

$$P(X_3 | do(X_1 = x_1), do(X_2 = x_2))$$
$$P(X_4 | do(X_2 = x_2))$$

**Functional Systems**

$$f_1(x_1, x_2) = e^{\alpha x_1} + \beta x_2 + \gamma$$
$$f_2(x_3, x_4) = \dots$$



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# 2. Causal Inference in Application

## Causal Relationships (II/II)

*"What are causes or effects of errors in a complex automotive production process?"*

**Causal Relationships**



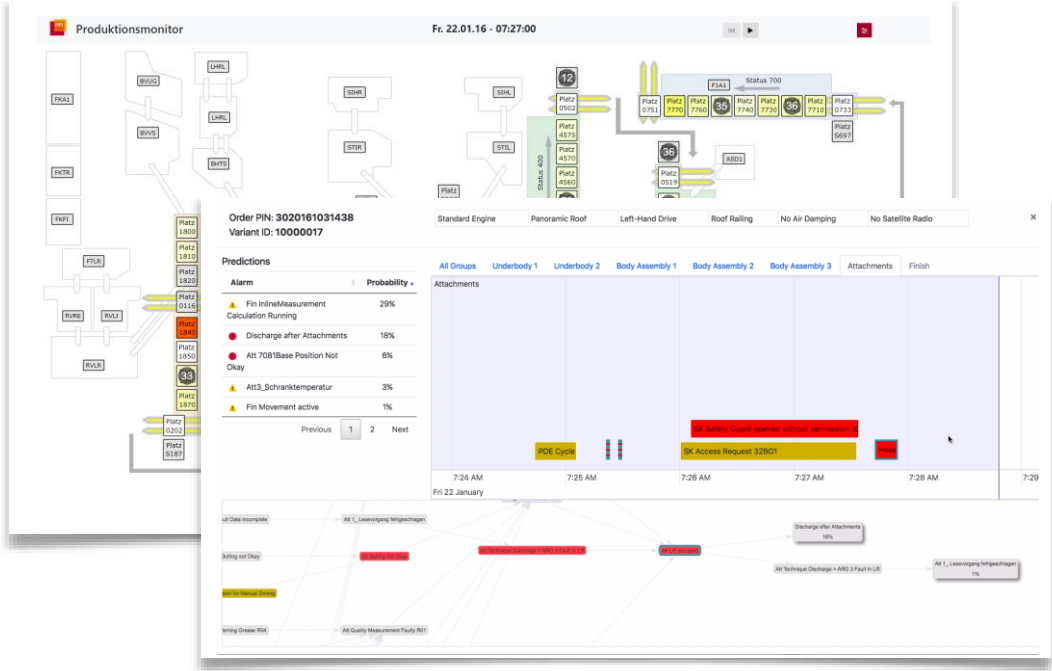
**Probabilistic Inference**

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# 2. Causal Inference in Application

## Probabilistic Inference (I/II)

**"Given current error occurring in an automotive production process, what effect is likely?"**

**Causal Relationships**

**Probabilistic Inference**

$$P(X_3 | X_1 = x_1, X_2 = x_2)$$

$$P(X_4 | X_2 = x_2)$$

**Causal Inference**

$$P(X_3 | do(X_1 = x_1), do(X_2 = x_2))$$

$$P(X_4 | do(X_2 = x_2))$$

**Functional Systems**

$$f_1(x_1, x_2) = e^{\alpha x_1} + \beta x_2 + \gamma$$

$$f_2(x_3, x_4) = \dots$$

Produktionsmonitor | Fr. 22.01.16 - 07:27:00

Order PIN: 3020161031438  
Variant ID: 10000017

**Predictions**

Alarm	Probability
Fin InlineMeasurement Calculation Running	29%
Discharge after Attachments	18%
Att 7081Base Position Not Okay	6%
Att3_Schranktemperatur	3%
Fin Movement active	1%

**Alarm**

Alarm	Probability
Fin InlineMeasurement Calculation Running	29%
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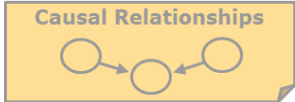
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# 2. Causal Inference in Application

## Probabilistic Inference (II/II)

*“How to leverage knowledge about likely effects given errors in the current production situation ?”*



**Probabilistic Inference**

$$P(X_3 | X_1 = x_1, X_2 = x_2)$$

$$P(X_4 | X_2 = x_2)$$

**Causal Inference**

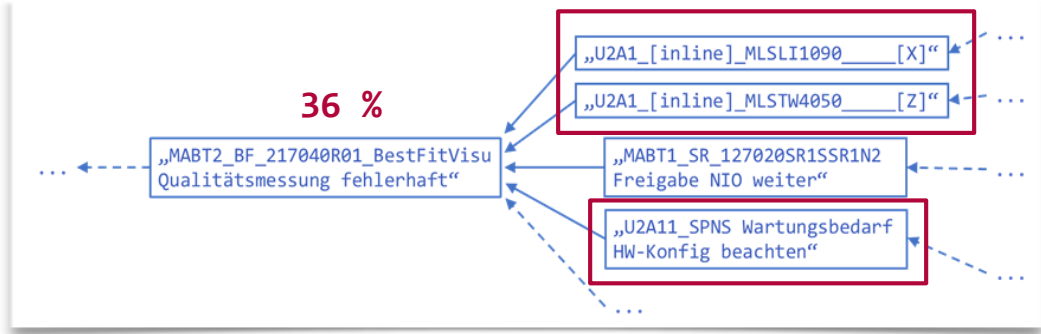
$$P(X_3 | do(X_1 = x_1), do(X_2 = x_2))$$

$$P(X_4 | do(X_2 = x_2))$$

**Functional Systems**

$$f_1(x_1, x_2) = e^{\alpha x_1} + \beta x_2 + \gamma$$

$$f_2(x_3, x_4) = \dots$$



```

if („U2A1_[inline]_MLSLI1090__[X]“ < LRL) and („U2A1_[inline]_MLSLI1090__[X]“ < LRL)
    then „MABT2_BF_217040R01_BestFitVisu Qualitätsmessung fehlerhaft“

if „MABT1_SR_127020SR1SSR1N2 Freigabe NIO weiter“
    then „MABT2_BF_217040R01_BestFitVisu Qualitätsmessung fehlerhaft“

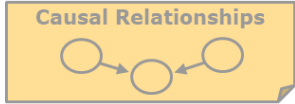
if „U2A11_SPNS Wartungsbedarf HW-Konfig beachten“
    then „MABT2_BF_217040R01_BestFitVisu Qualitätsmessung fehlerhaft“
    
```

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 Slide 11

# 2. Causal Inference in Application

## Causal Inference

**"What is the causal effect behind the complex causal structures in a production process?"**



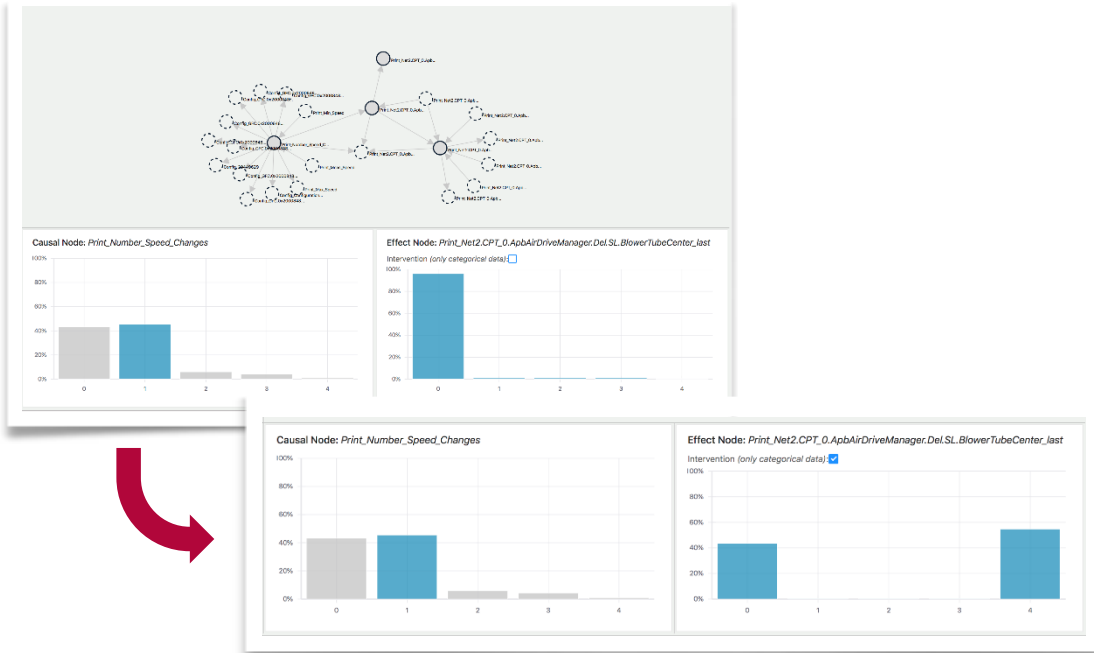
**Probabilistic Inference**

$$P(X_3 | X_1 = x_1, X_2 = x_2)$$
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**Causal Inference**

$$P(X_3 | do(X_1 = x_1), do(X_2 = x_2))$$
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**Functional Systems**

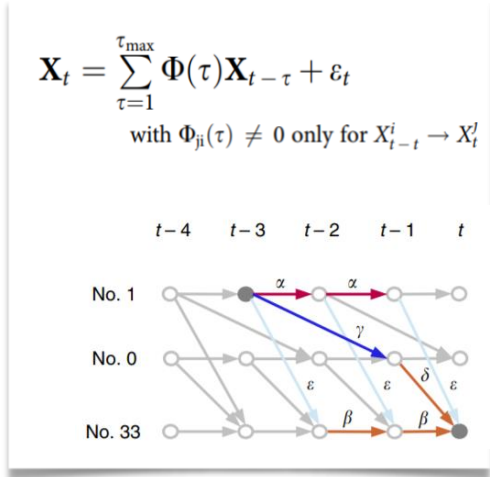
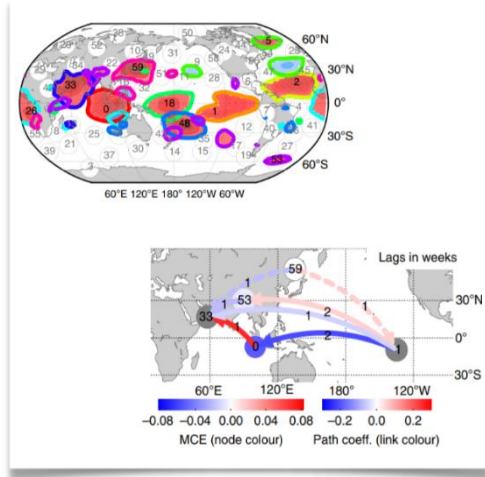
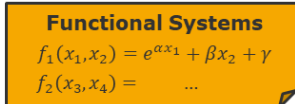
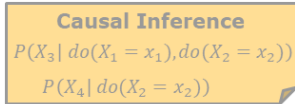
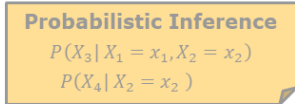
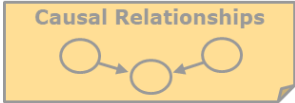
$$f_1(x_1, x_2) = e^{\alpha x_1} + \beta x_2 + \gamma$$
$$f_2(x_3, x_4) = \dots$$


**Causal Inference Theory and Applications in Enterprise Computing**

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# 2. Causal Inference in Application Functional Systems

**"What are the time lags within climate processes that generate local air pressures ?"**



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# 2. Causal Inference in Application

## Lecture Example

### Scope

- Mathematical concepts determine a conceptual causal inference procedure
- A simple example accompanies our lecture
  - will be extended when needed
  - you are invited to work in a personal notebook

Scenario: The causal relationships in a cooling house

### Content

1. Introduction to R
2. Use Case
3. Causal Graphical Models
4. Conditional Independence Testing
5. Constraint-based Causal Structure Learning
6. Causal Inference on Causal Graphs
7. Further Opportunities of Causal Structures

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in Enterprise Computing

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Schmidt

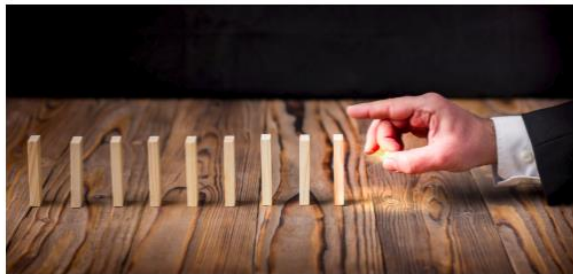
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# 2. Causal Inference in Application

## Jupyter Notebook

### Causal Inference - Theory and Applications

In our lecture [Causal Inference - Theory and Applications](#), we look at the mathematical concepts that build the basis of causal inference.



### Causal Inference in Application

We now look how these concepts are applied on observational data to derive causal relationships and how to use the do-operator to receive an estimation of the causal effect. In order to give you an overview on the related procedure, this notebook gives a step by step approach in the context of a simple cooling house example.

#### Table of Contents

1. [Introduction to R](#)
  - A. [Getting Started](#)
  - B. [Some Examples](#)
2. [Use Case](#)
  - A. [Description](#)

### Causal Inference Theory and Applications in Enterprise Computing

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## 2. Causal Inference in Application

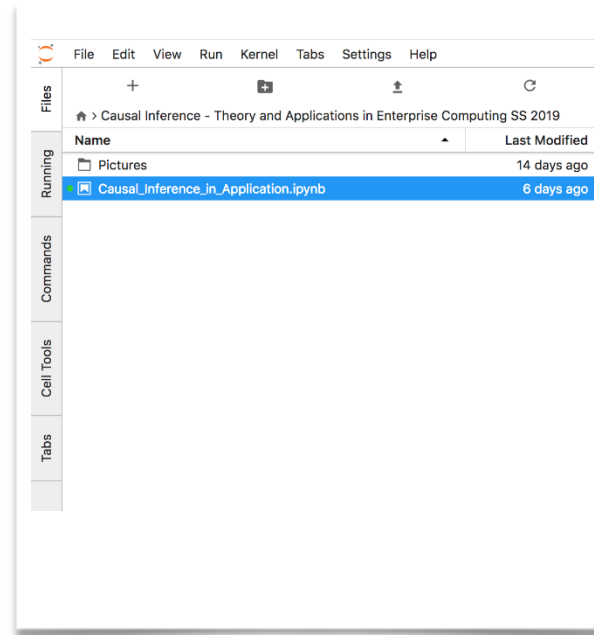
### Access Information

### System

<http://vm-k8s-ctrl.eaalab.hpi.uni-potsdam.de:31157/>

### Procedure

1. Login via LDAP (standard HPI credentials)
2. Send email to [christopher.schmidt@hpi.de](mailto:christopher.schmidt@hpi.de)
3. We copy you the Master Notebook into your user space for you to work with
4. Adapt and work in your own notebooks
5. Let us know if you require new packages or if anything does not work, as intended



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**3. Introduction to Research Topics**

Processor	RAM	Cores
Rx600 S5	1 TB	32
Rx600 S6	512 GB	40

**Cloud Computing:**

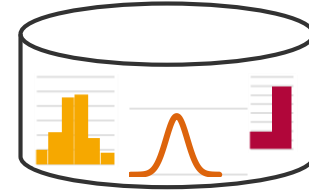
Endpoints	RAM
2	512 GB

# 3. Introduction to Research Topics

## Overview on Topics

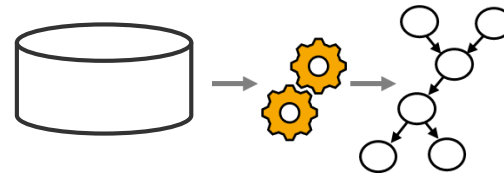
### ■ **Data, Distributions, Independence**

Work on topics in the application of learnt techniques beyond the examples given in this lecture (e.g., heterogeneous data distributions)



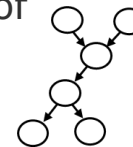
### ■ **Causal Structure-Learning**

Work on topics in the context of performance improvements of causal structure learning algorithms (e.g., hardware acceleration)



### ■ **Applications Scenarios**

Work on challenges and opportunities in the application of causal inference techniques on real-world data (e.g., industrial manufacturing)



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# 3. Introduction to Research Topics

## Topic Application

---

### ■ ***How to work on a topic?***

1. Understand theoretic basis and your selected topic
2. Work on implementation
3. Present results
4. Write scientific report in a review process

### ■ ***How to apply for a topic?***

- Build groups of around three students
- Send prioritized list of top 3 topics to [Johannes Huegle](#) until: *Fri April 26, 11.59 PM*
- Topic Assignments: *Tue April 30, 9:00 AM*

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The screenshot shows the RStudio interface with the following components:

- Source Editor:** Contains R code for loading data and creating a plot.

```
1 library(ggplot2)
2 source("plots/formatPlot.R")
3
4 view(diamonds)
5 summary(diamonds)
6
7 summary(diamonds$price)
8 aveSize <- round(mean(diamonds$carat), 4)
9 clarity <- level(diamonds$clarity)
10
11 p <- qplot(carat, price,
12           data=diamonds, color=clarity,
13           xlab="Carat", ylab="Price",
14           main="Diamond Pricing")
15
```
- Workspace:** Shows the loaded data frame: diamonds (53940 obs. of 10 variables).
- Values:** Lists variables and their types: aveSize (0.7979), clarity (character [8]), p (ggplot [8]).
- Functions:** Lists functions used: format.plot(plot, size).
- Console:** Shows the output of the plot creation, with the title "Diamond Pricing" visible at the bottom.

## 4. Further Reading

# 3. Further Reading

## Programming

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### R

- Torfs et. al. (2014), [A \(very\) short introduction to R.](#)
- Venables et. al. (2018), [An Introduction to R- Notes on R: A Programming Environment for Data Analysis and Graphics.](#)
- Kalisch et. al. (2017), [Package 'pcalg'](#).
- Kalisch et. al. (2017), [Causal Inference using Graphical Models with the Package pcalg](#), Journal of Statistical Software.
- Scutari (2007), [Learning Bayesian Networks with the bnlearn R Package.](#)

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Thank you  
for your attention!