Universität Stuttgart
IPVS – Institute for Parallel and Distributed Systems
Analytic Computing

Advanced Topics in Machine Learning
1 Introduction Part 1



Prof. Dr. Steffen Staab
Dr. Rafika Boutalbi
Zihao Wang
https://www.ipvs.uni-stuttgart.de/departments/ac/

Today‘s objectives (Monday, Oct 18, 2020)

Completing this slide deck you should

- Know what the course is about
- Know whether you are right here
- Know key terminology

Who is this course for?

- Students who
  - successfully completed the course on Machine Learning
    - SS2021 or earlier

This semester

- All lectures will be given offline
- Recorded online videos from last year will be available, however:
  - I did the course the first time last year and hope to improve it this year
  - Semester is a bit longer
  - What counts is eventually the material presented **this semester**

How to successfully pass the course?

- Master lecture material

Magazin » Ingenieurwissenschaften » Informatik » Lehrveranstaltungen » Winter 2020/21 » Advanced Topics in Machine Learning [Vorlesung]

- Submit excercises
  - Join the exercises
    - Universität 38 - V 38.03 (UN38/EG/V 38.03)
    - Thursdays, first time 21.10.21 08:00 - 09:30
  - Acquire admission to exam by meeting criteria specified for the excercises
- Pass exam (see next slide)

Exam

- date and time will be organized decentrally
  - if there would be fewer than 10 candidates we would give it as oral examinations

Literature (we will only look at selections)

Focus

Probabilistic Graphical Models will mostly be based on:
Daphne Koller, Nir Friedman. Probabilistic Graphical Models. MIT Press, 2009. Download from: https://djsaunde.github.io/read/books/pdfs/probabilistic%20graphical%20models.pdf

Addendum

Part 2 Causal Inference will mostly be based on:
Jonas Peters, Dominik Janzing, Bernhard Schölkopf. Elements of Causal Inference. Foundations and Learning Algorithms. MIT Press 2018. Download from: https://library.oapen.org/bitstream/handle/20.500.12657/26040/11283.pdf

Koller et al. also covers Causality to some extent!

Maybe check out:

M. Deisenroth, A. A. Faisal, C. Soon Ong. Mathematics for Machine Learning. Cambridge University Press, 2020.

Why this course?


Why?
How?
What?

Machine Learning

What?

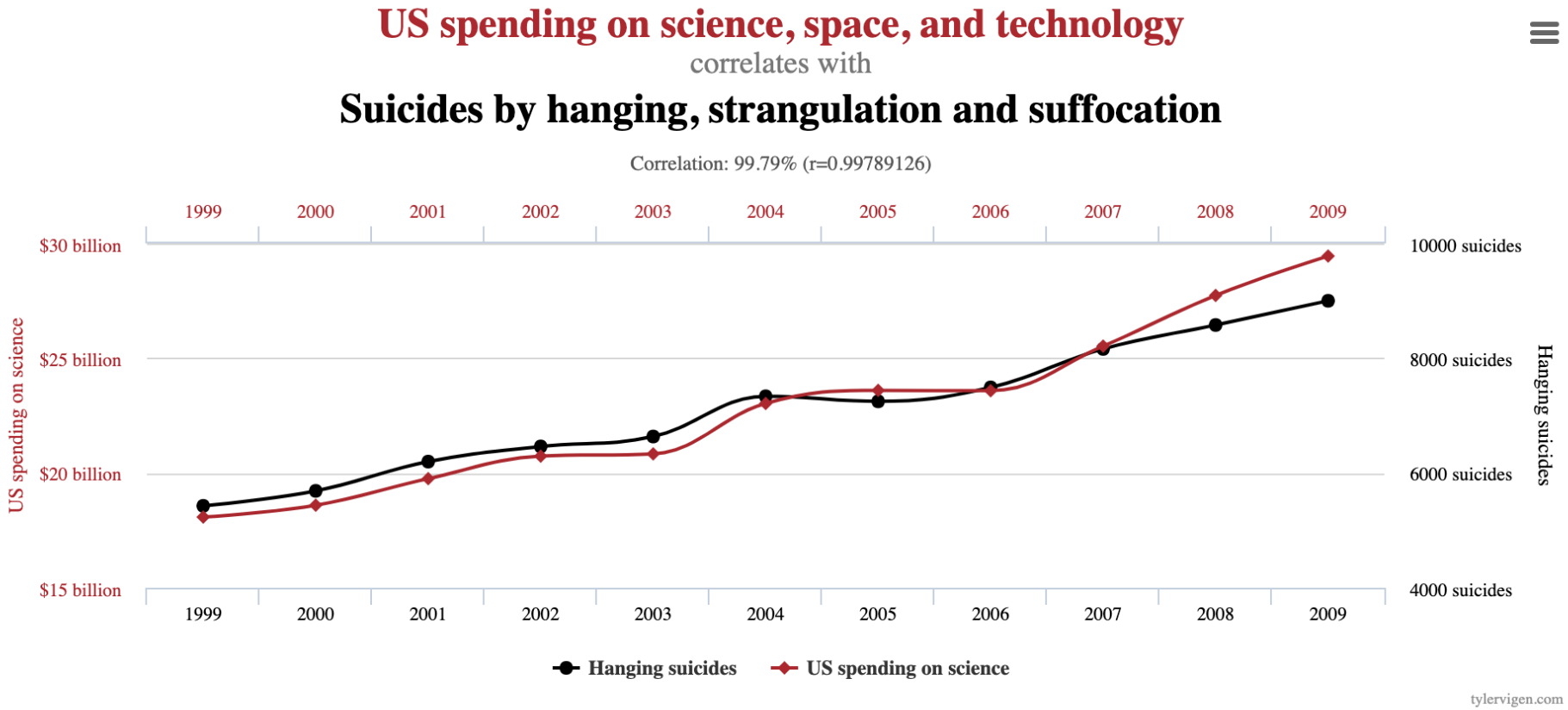
- Supervised Learning
  - Classification
  - Regression
  - Reinforcement learning
- Unsupervised Learning
  - Representation learning
  - Clustering

How? / Why?

- Causality
- Explainable Machine Learning

Issue 1: Spurious correlations

this does not explain that

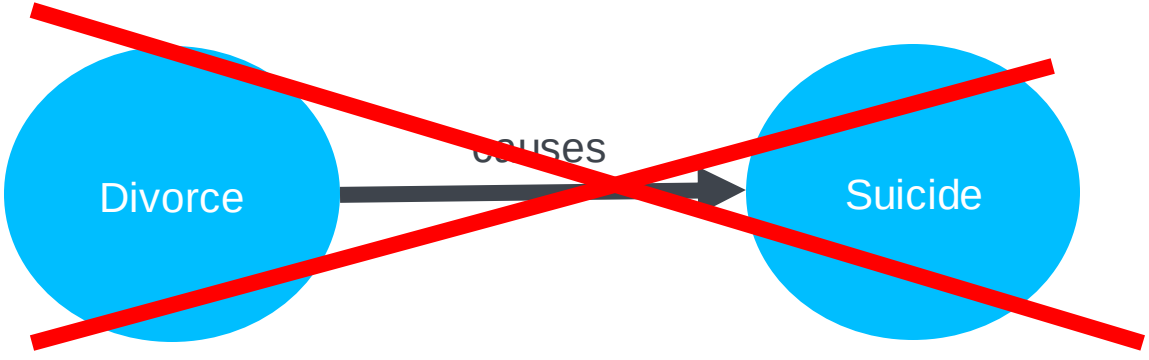


Data sources: U.S. Office of Management and Budget and Centers for Disease Control & Prevention

check out: https://tylervigen.com/spurious-correlations

Issue 2: Even correlations need not be an explanation

- „ Divorce Is a Risk Factor for Suicide, Especially for Men“
  https://www.psychologytoday.com/us/blog/acquainted-the-night/201906/divorce-is-risk-factor-suicide-especially-men



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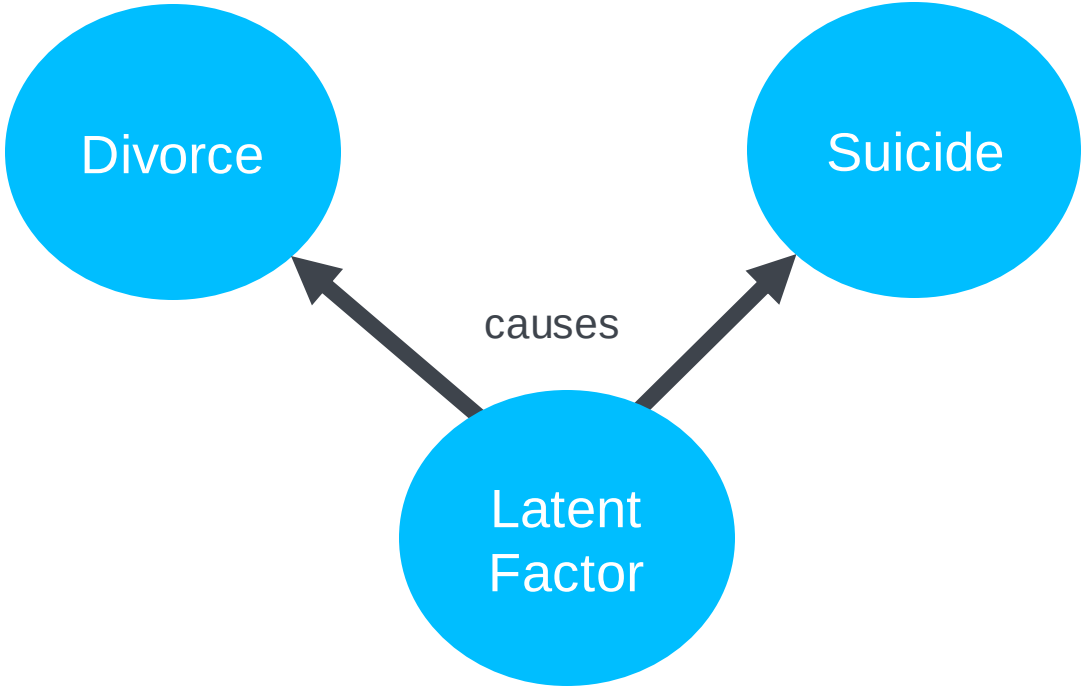
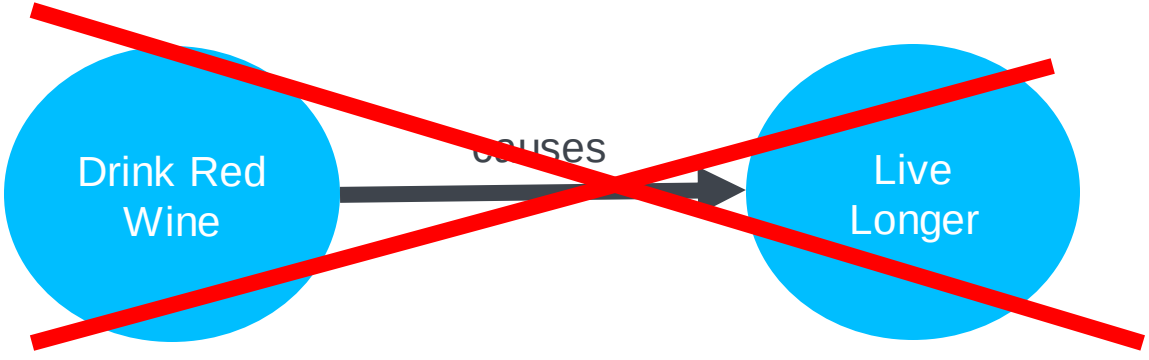


Issue 2: Even correlations need not be an explanation

„Does Red Wine Help You Live Longer?“

https://time.com/5552041/does-red-wine-help-you-live-longer/



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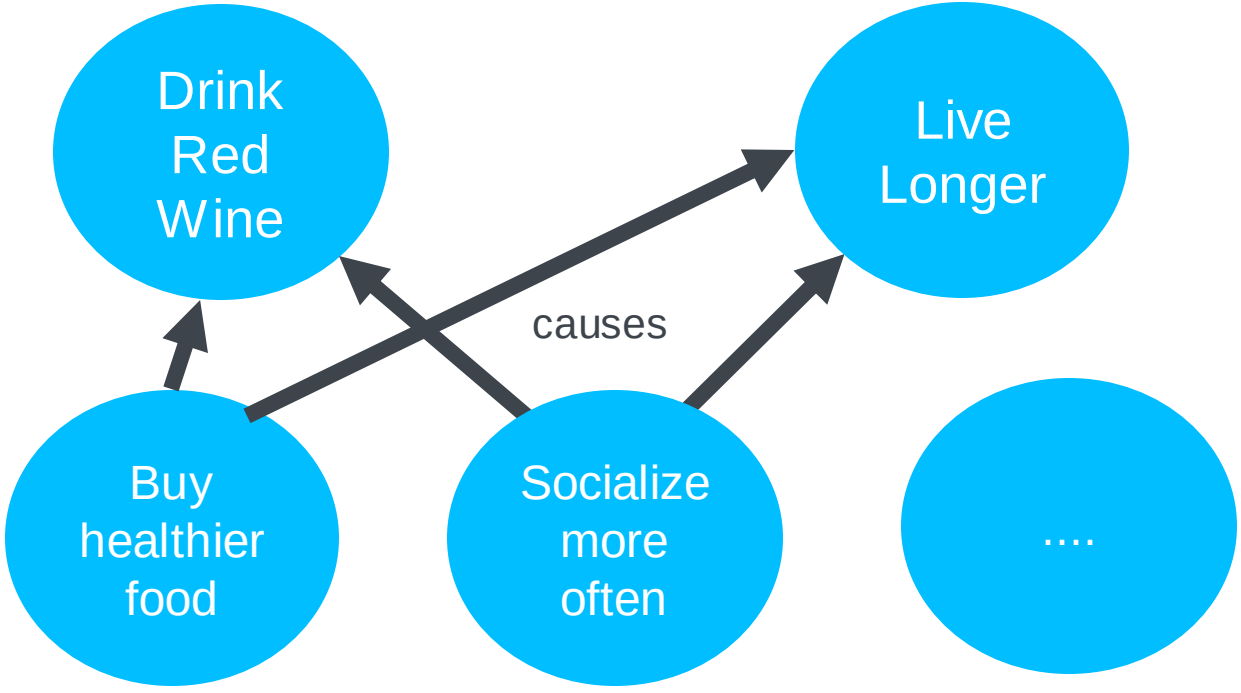

Summarize

- We want to learn:
  - what correlates with what?
  - what causes what?
- Then
  - we can explain
  - we can interfere

Approach

- Focus on probabilistic graphical models
  - Foundation for work on explainability and causality
  - Foundation for work on deep learning
  - Foundation for work on working with (knowledge) graphs
- If you have ideas for master theses in these areas, we love to hear about them

Rough Roadmap

Koller et al.: Page 1

- „The key property of **a declarative representation** is the **separation of knowledge and reasoning**. The representation has its **own clear semantics**, **separate from the algorithms** that one can apply to it.
- Thus, we can develop a general suite of algorithms that apply any model within a broad class, whether in the domain of medical diagnosis or speech recognition. Conversely, we can improve our model for a specific application domain without having to modify our reasoning algorithms constantly.“

What kind of representation?

- Logical Representations
  - Databases
  - Knowledge Graphs
    - RDF
    - Hyper-relational
    - Amazon, Google, Microsoft,..
    - ...

summer

term

What kind of representation?

- Logical Representations
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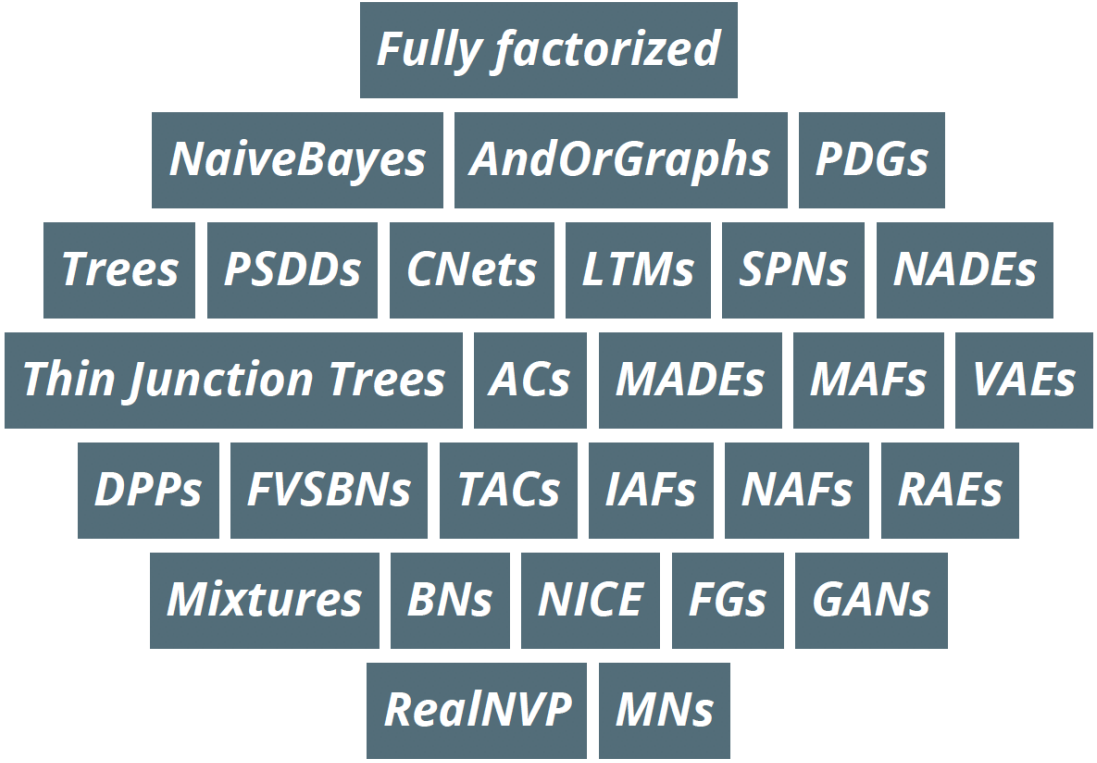
summer term

- Probabilistic Representations
  - Probabilistic Databases
  - Probabilistic Graphical Models
    - Bayes Networks
    - Markov Networks
    - HMM, CRF,...
  - Probabilistic Circuits

this course

There exist all kind of mixtures:
fuzzy logics, logics with probabilities, etc. etc.

From: Vergari et al. „Probabilistic Circuits“ Tutorial at ECML-PKDD2020



The Alphabet Soup of probabilistic models

- Probabilistic Knowledge
  - Representation
  - Inference (query)
  - Learning
- Causality
  - Representation
  - Inference (query)
  - Learning

Focus

Part 1 Probabilistic Graphical Models will mostly be based on:
Daphne Koller, Nir Friedman. Probabilistic Graphical Models. MIT Press, 2009.

Lesser extent

Part 2 Causal Inference will mostly be based on:
Jonas Peters, Dominik Janzing, Bernhard Schölkopf. Elements of Causal Inference. Foundations and Learning Algorithms. MIT Press 2018. Koller et al. also covers Causality!

Universität Stuttgart
IPVS

Thank you!

Steffen Staab

E-Mail Steffen.staab@ipvs.uni-stuttgart.de
Telefon +49 (0) 711 685-To be defined
www. ipvs.uni-stuttgart.de/departments/ac/

Universität Stuttgart
Analytic Computing, IPVS
Universitätsstraße 32, 50569 Stuttgart