# Advanced Machine Learning

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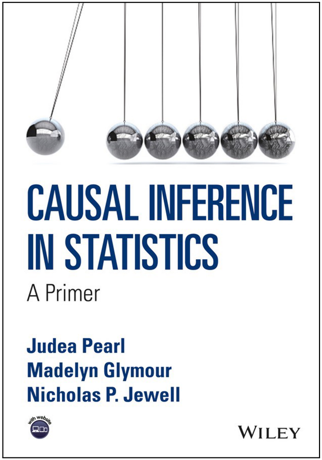
# Practical matters

- Lectures: Thijs van Ommen
- Teaching assistant: Samira Shirzadeh
- Every week:
  - a four-hour slot, usually half lecture, half tutorial session
  - a two-hour slot: lecture

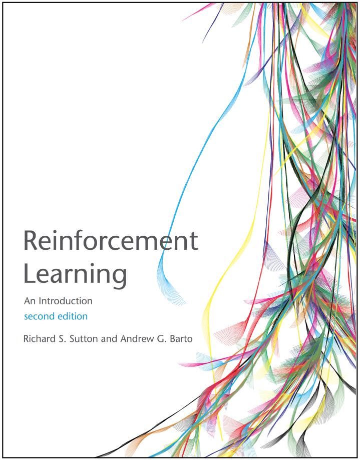
  Four-hour slot is initially on Tuesdays, but switches to Thursdays after three weeks (see Osiris)
- Tutorial session: either theoretical or programming
  - Theoretical questions: not handed in or graded, but provided as practice for exam. Your own responsibility!
  - Programming assignments (3 or 4): coding in Python, plus a small written report. In groups of three. Make up 20% of the final grade.

  Use these sessions to ask your questions about the assignments!
- Exam: 80% of final grade; you will be able to bring some of your own notes (precise rules TBA)

# Two books




Causal inference



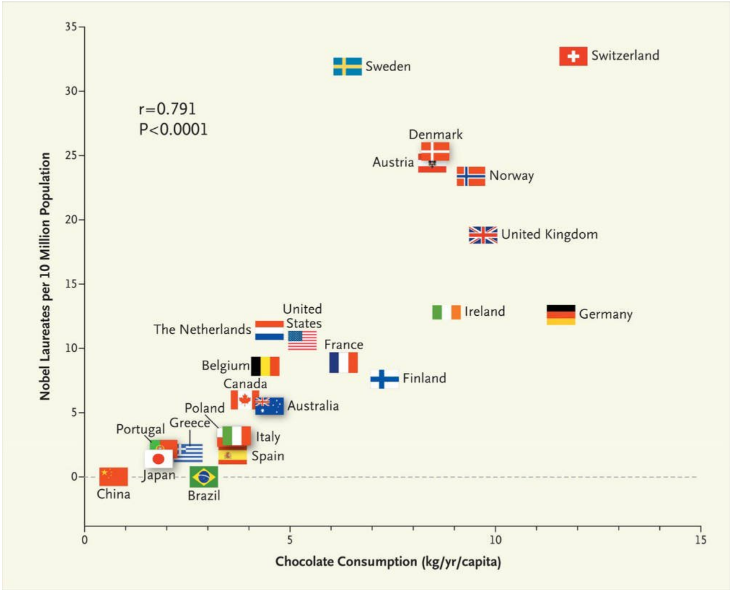

Reinforcement learning

# Causal inference: overview

Causal inference is the subfield of machine learning (/ statistics) that deals with cause-effect (= causal) relations

Most of machine learning (/statistics) is concerned with finding associations in the data. These may become invalid when something changes about the process generating the data. Example:

# Chocolate consumption and Nobel prize winners



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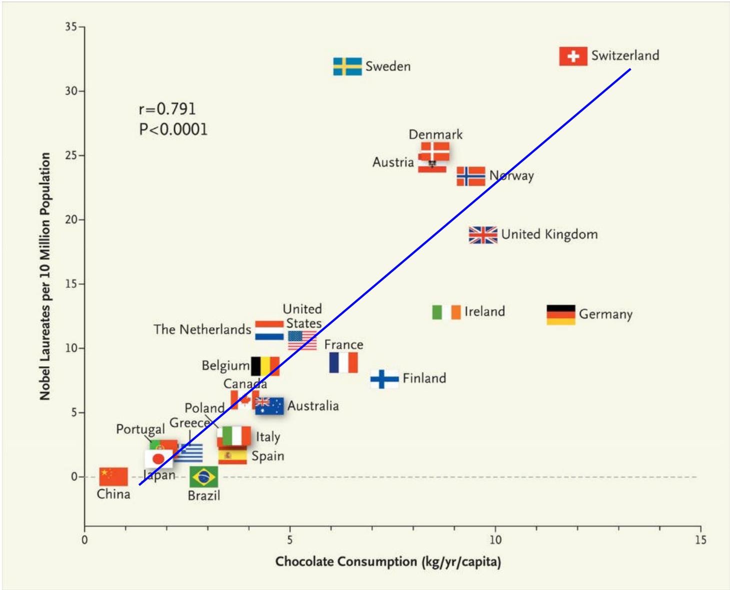

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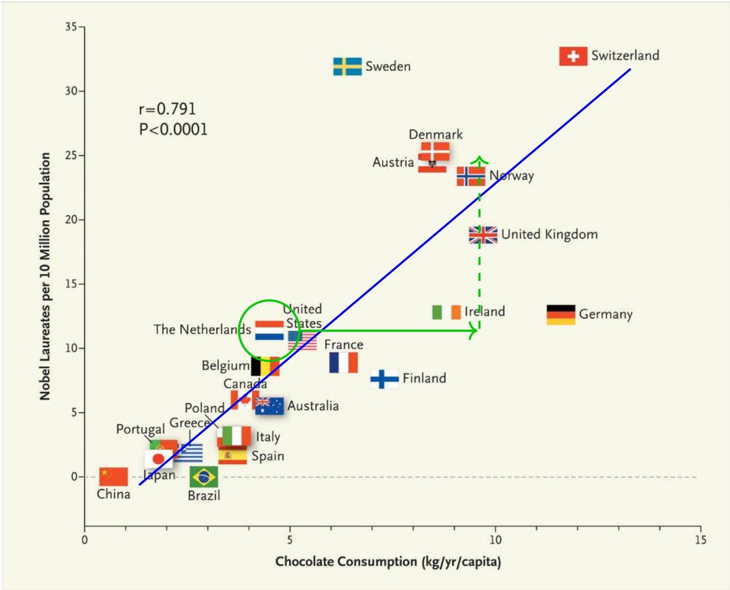
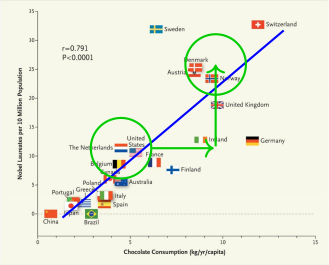


# Different causal models explaining the data

($C$ = *Chocolate consumption*; $N$ = *Nobel prize winners*)

**If** $C$ **causes** $N$**:**



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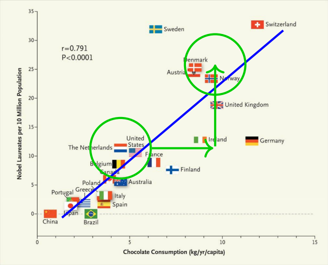
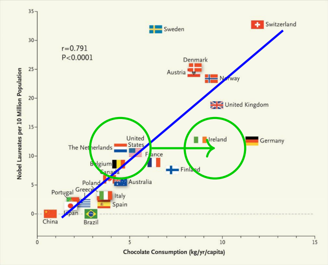
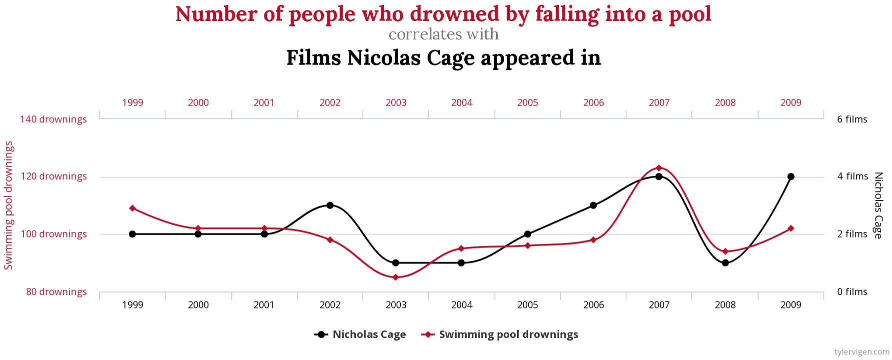



**Otherwise:**

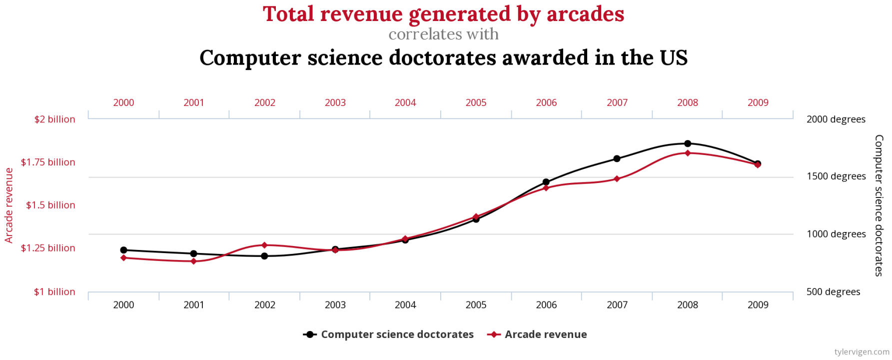


# Correlation vs. Causation (1)




Source: `http://tylervigen.com/spurious-correlations`

# Correlation vs. Causation (2)

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# Causal inference: overview of topics

- Definition of *structural causal models* (SCMs)
- Reasoning about interventions
- Reasoning about counterfactuals
- Topics not in the book, e.g.: causal discovery; latent confounders; other applications in machine learning

# Reinforcement learning: overview

Reinforcement learning is the subfield of machine learning that deals with learning from interaction with an unknown environment

Ingredients (Markov Decision Process):

- agent moves from *state* to state
- based on *action* (but with a random component)
- gets some *reward* in each time step

# Challenges of reinforcement learning

Unlike supervised learning:

- the agent only gets feedback on the *chosen* action;
- the feedback is delayed: it applies to sequences of actions;
- by choosing actions, the agent is in control of what data is seen.

# Recent successes of deep reinforcement learning

Atari games *(Deepmind, 2013)*

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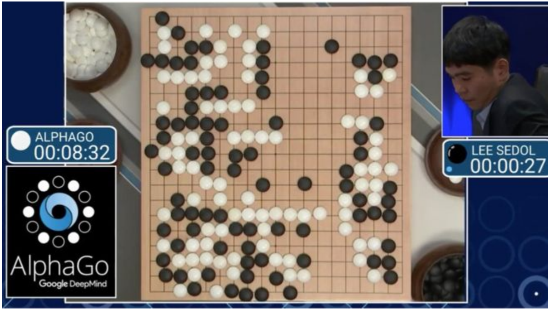



Google's AlphaGo beats world champion Lee Sedol at Go (2016)

# Reinforcement learning: topics

Part I of the book:

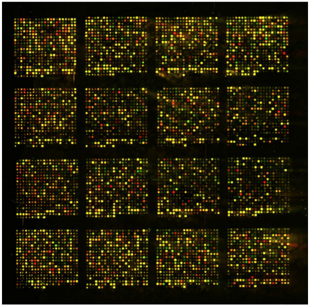
- Bandit problems, Markov decision processes, temporal-difference learning

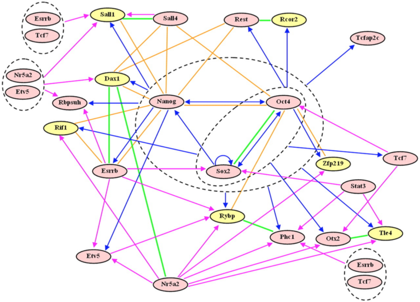
Part II of the book:

- 'Approximate' case: incorporating supervised learning methods into RL
- Off-policy methods
- Policy gradient methods

# Causal inference

**Genetics**:
how to infer gene regulatory networks from micro-array data?

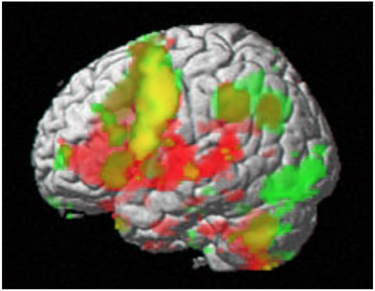


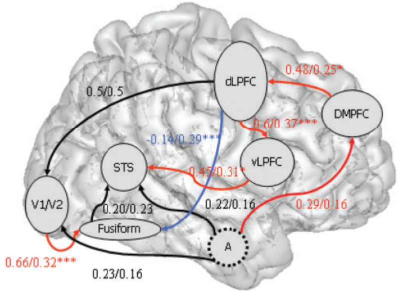


# Causality: ubiquitous in the sciences

**Social sciences**:
does playing violent computer games cause aggressive behavior?


**Neuroscience**:
how to infer functional connectivity networks from fMRI data?





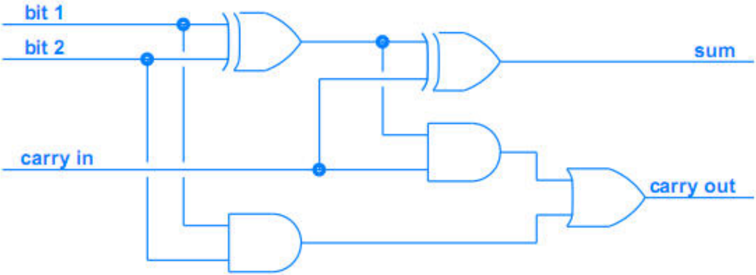
# Causality: ubiquitous in the sciences

**Economy:**
Does austerity reduce national debt?

# Causality: ubiquitous in daily life

We use causality every day to understand the world around us

# Causality in engineering




Causality is a very useful concept in engineering.

Using causal reasoning, engineers can not only predict what happens when a system operates normally, but also when an external *intervention* changes part of the system.

Being able to predict what happens under interventions allows to exert *control*.

# A formal theory of causality?

*Causality* is a central notion in science, decision-making and daily life.

**Question**

Can we formalize causal reasoning?

Important step forward: the work of Judea Pearl

*ACM Turing Award 2011: "For fundamental contributions to artificial intelligence through the development of a calculus for probabilistic and causal reasoning."*

# Pearl's approach to causality

Builds on probability theory. Advantages:

- Allows us to represent the strength of causal relations.
  E.g. 'reckless driving causes accidents' — but not in every instance of reckless driving
- We want to learn from data, but the data won't tell us anything with certainty

So the causal relations we talk about will exist between *random variables*

# Problems in formalizing causal reasoning: probabilities

**Example (Simpson's paradox)**

We collect electronic patient records to investigate the effectiveness of a new drug against a certain disease.

| Random variable | Meaning | Possible values |
|---|---|---|
| $T$ | treatment taken? | drug, no drug |
| $R$ | patient recovered? | recovery, no recovery |
| $G$ | gender | male, female |

# Problems in formalizing causal reasoning: probabilities

**Example (Simpson's paradox, continued)**

It can happen that:

1. The probability of recovery is lower for patients that took the drug:
$$P(\text{recovery} \mid \text{drug}) < P(\text{recovery} \mid \text{no drug})$$
2. For **both male and female** patients, the relation is **opposite**:
$$P(\text{recovery} \mid \text{drug}, \text{male}) > P(\text{recovery} \mid \text{no drug}, \text{male})$$
$$P(\text{recovery} \mid \text{drug}, \text{female}) > P(\text{recovery} \mid \text{no drug}, \text{female})$$

Would you use this drug for treatment?

# Should we recommend this drug? (1/2)

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So: the drug aids recovery, but the above story explains why in the aggregated data, the drug appears to be harmful

# Should we recommend this drug? (2/2)

Now replace ‘gender’ by ‘blood pressure’ (after treatment).

Possible story: the drug is toxic, but it also lowers blood pressure, which in turn aids recovery.

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Now replace 'gender' by 'blood pressure' (after treatment).

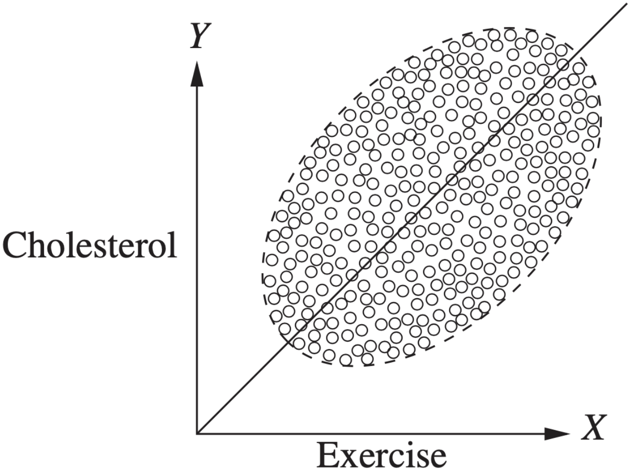
Possible story: the drug is toxic, but it also lowers blood pressure, which in turn aids recovery.

Now we should look at the *aggregate* data to get the answer!

The answer (to 'Should we recommend this drug?') can't be found in the data alone. Fancy classifiers, deep learning and big data do not really help us here!

# Simpson's paradox with continuous data

Another example, for continuous data:



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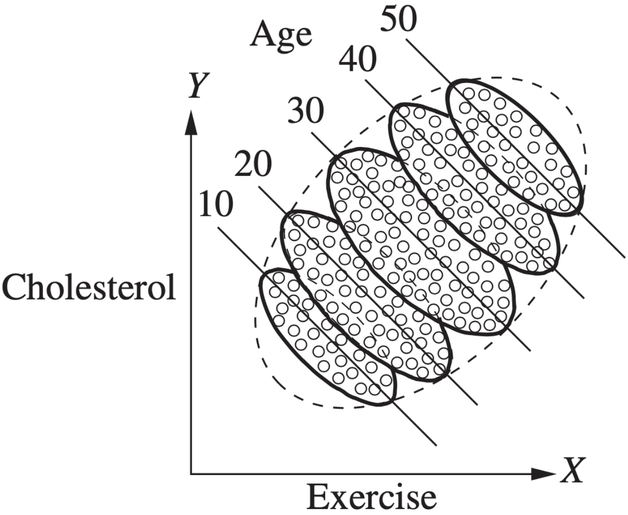

# Paradox?

- It is perfectly possible for correlations to flip around when we condition on another variable (the data table and the figures prove this!)
- It is *not* possible for a causal relation to flip around like that: if a drug causes recovery for both men and women, it causes recovery for the combined group

So Simpson's paradox is only paradoxical if we misinterpret *correlation* (between *drug* and *recovery*) as causation (from *drug* to *recovery*)