Algorithmic Fairness
A Major Challenge Area for Ethics of Data-Based Business

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The data science pipeline and ethics

Ethical issues

Data Privacy
Data Protection

Impact on our world?
Threat of societal values, e.g.
- Freedom
- Justice and fairness
- ...

The COMPAS Case

- 2016: ProPublica investigates a risk assessment tool for criminal recidivism (COMPAS)
  - developed by a private company (Northpointe)
  - used in many US states over years (>1 Mio criminals assessed)

- ProPublica showed that the tool was racially biased
  - black people more likely to be wrongly predicted to re-offend than white people

- Northpointe had to change its name (now equivant) as a consequence of the public debate

Amazon’s sexist hiring algorithm

- 2014: Amazon starts building algorithms to review job applicants
- 2015: Amazon detects gender bias for software developer jobs
  › Reason: male-specific expressions
- Attempts to remove gender bias failed (!)
- 2017: Amazon announces the stop of the program, trying to limit image problems

The Austrian AMS

- 2018: The Austrian Public Employment Service Austria (Arbeitsmarktservice AMS) announces the introduction of a software sorting unemployed people according to their chances on the job market.
- Prediction model developed by private company Synthesis GmbH
- Prediction uses a regression model
  - Factor “female” has a negative coefficient (Der Standard, 20.10.2018)
- Public debate about efficiency vs. fairness – still ongoing

Context: Data-based decisions in business

Individualized decision making on humans, based on their data
Typical ML case: decision based on prediction

- Goal: maximize business goal by taking individualized decisions, based on prediction
  - E.g. credit risk, risk of recidivism, risk of failing, …
- Driver: Huge business potential to be harvested
Algorithmic bias in data-based decisions?


- Algorithm: sets of instructions within computer programs that determine how these programs read, collect, process, and analyze data to generate some readable form of analysis or output.

- The term *algorithmic bias* describes *systematic and repeatable errors that create unfair outcomes*, such as privileging one arbitrary group of users over others.

**Problem 1:** Data-based decision algorithms are typically biased
  - Business goal optimization does not care about bias!

**Problem 2:** Developers do not care
  - Many are not even aware of the problem of bias

**Problem 3:** Unfair algorithms are actually implemented
  - Reputation risk, negative societal impact
Algorithmic bias in research

- Issue is on the research agenda since about 2015
- Many publications in the Machine Learning community
  - Reasons for bias (inappropriate data, suboptimal learning procedures, algorithmic issues, ….)
  - Important result: just ignoring sensitive variables („Fairness Through Unawareness») does not do the job
  - Countermeasures for different prediction algorithms developed
  - Etc.
- Conceptual learnings
  - Fairness can be measured by statistical properties of prediction or decision algorithm
  - Fairness can be defined in different ways
COMPAS revisited

For binary prediction problems: Confusion matrix

COMPAS: 1 = re-offend, 0 = not re-offend

Result: FP rate higher for black people → „unfair“
Fairness criteria

Simplest problem statement:
› Consider two groups (A and B)
› Consider a prediction of binary variable Y: prediction = \( \hat{y} \), true value = y
› Decision = prediction: \( D = \hat{y} \)

Some fairness criteria:
› Demographic parity: \( P[D = 1 | A] = P[D = 1 | B] \)
› Equal FPR: \( P[D = 1 | y = 0, A] = P[D = 1 | y = 0, B] \)
› Equal odds = Equal FPR and Equal TNR
› Equal Positive Predictive Value: \( P[y = 1 | \hat{y} = 1, A] = P[y = 1 | \hat{y} = 1, B] \)
What is fair? - Fairness definitions

- Fairness can be defined differently
  - E.g. Arvind Narayanan (FAT* 2018): Tutorial: 21 fairness definitions and their politics

- Typically, different fairness criteria are mutually exclusive: They cannot be met simultaneously! (Kleinberg et al 2016)

- A choice has to be made!

<table>
<thead>
<tr>
<th>Definition</th>
<th>Paper</th>
<th>Citation #</th>
<th>Result</th>
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<tbody>
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<td>3.2.1 Predictive parity</td>
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<td>3.2.3 False negative error rate balance</td>
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<td>3.2.5 Conditional use accuracy equality</td>
<td>[8]</td>
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<td>3.3.4 Balance for negative class</td>
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<td>4.1 Causal discrimination</td>
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<td>4.2 Fairness through unawareness</td>
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<td>4.3 Fairness through awareness</td>
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<td>5.2 No unresolved discrimination</td>
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<td>5.3 No proxy discrimination</td>
<td>[15]</td>
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<td>5.4 Fair inference</td>
<td>[19]</td>
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Table 1: Considered Definitions of Fairness

COMPAS revisited (II)

- COMPAS actually fulfills an important fairness criterion: positive predictive value (PPV) is well met (Kleinberg et al 2016, Chouldechova 2017)

- But: FPR and FNR are different for blacks and whites → this was what ProPublica brought up

- It can be shown for arbitrary prediction algorithms (Chouldechova 2017):

\[
FPR = \frac{p}{1-p} \frac{1-PPV}{PPV} (1-FNR)
\]

No prediction algorithm can meet both fairness criteria simultaneously!
What is fair?

- Fairness and justice has a long history in moral and political philosophy
- Equal rules for all (procedural fairness)
  - Business potential lies exactly in discrimination!
- So we have to analyse the consequences
  - Consequentialist ethics
- Different philosophical concepts of fairness and justice, e.g.
  - Welfare economics and utilitarianism
  - different theories to explain what makes discrimination wrong
The problem of algorithmic fairness

For developing a „fair algorithm“, two problems have to be solved

☐ An ethical choice problem (decision): What is fair?
   › may depend on the concrete situation
   › is an ethical question, not a technical one
   › choice must be justified and defended (towards customers and society)
   › Result: fairness criterion expressed in statistical terms (measurable)

☐ A technical problem: Create a decision algorithm that meets the specified fairness criterion
   › ML literature shows some solutions for some fairness criteria, but not a general solution procedure
   › Issues: Input data for learning procedures? How to train models? How to assess decision models? …

Necessary: Integration of ethics and engineering!
Integrated solution approach

- Based on solid philosophical concepts
- Structured approach (discourse)
- Do-able for non-philosophers (managers and Data Scientists!)
- Maximization of business goal with fairness constraints, or
  Multicriteria optimization
  „Fairness by design“
- Assessment possible
Conclusion

- Algorithmic fairness is an important issue for all companies doing data-based business
  - Second big issue after data privacy and protection
  - Ethical responsibility AND economic risk
- Fairness is an ethical issue, not primarily a technical one
  - Different fairness definitions possible
  - What is considered fair depends on situation and stakeholders
- Creating fair algorithms needs the combination of an ethical decision making process (which fairness do we want to produce?) with a technical solution method (how to produce this fairness?)
  - Ethical discourse needs integration of all stakeholders - engineering can't do it alone!
  - Specific expertise is needed for the model builders – often a problem today
- Field is new, up to now no integrated methodology is available to make sure that decision algorithms are fair in a well-defined, understood and explainable way
  - There is some work to do!
Thank you for your attention!