

Algorithmic Fairness

A Major Challenge Area for Ethics of Data-Based Business

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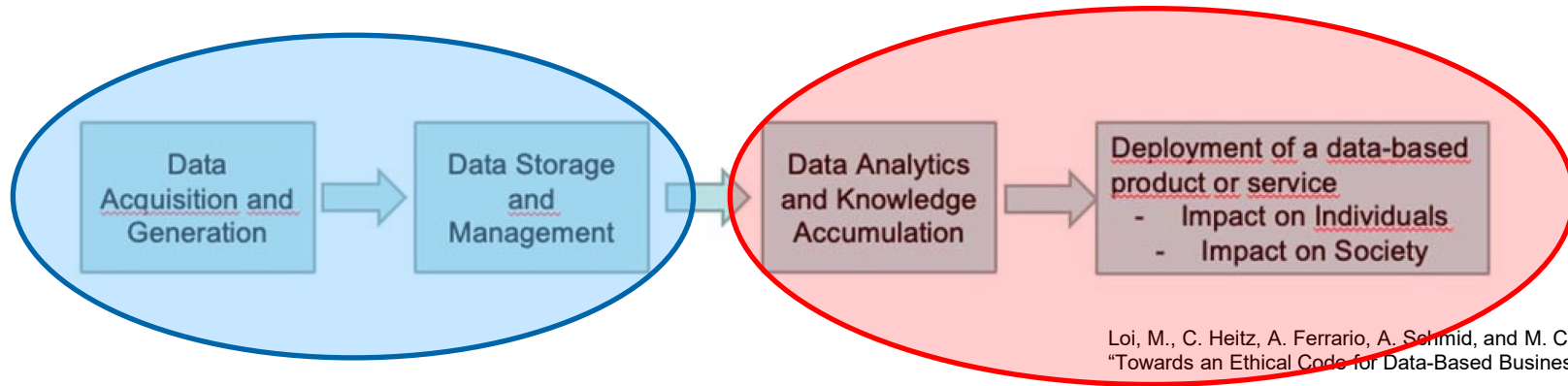


Universität
Zürich^{UZH}
Digital Society Initiative



Swiss Alliance for
Data-Intensive Services

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



Julia Angwin, Jeff Larson. 2016. "Machine Bias." Text/html. ProPublica. May 23, 2016.
<https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>.

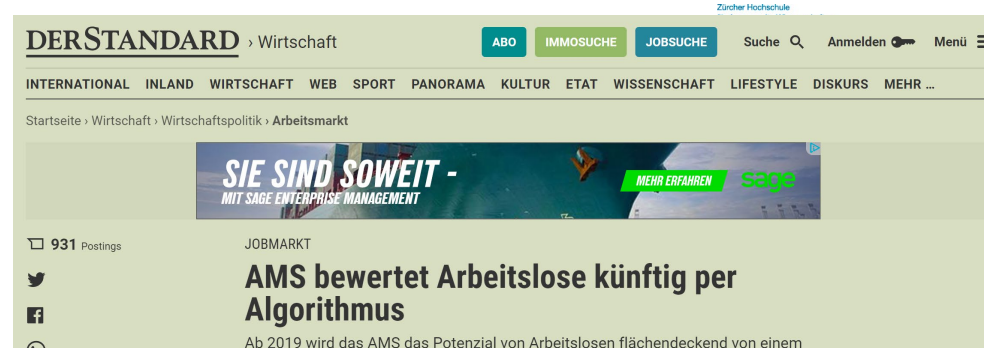
Amazon's sexist hiring algorithm



- 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

Reuters. 2018. "Amazon Scraps Secret AI Recruiting Tool That Showed Bias against Women," October 10, 2018. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>.

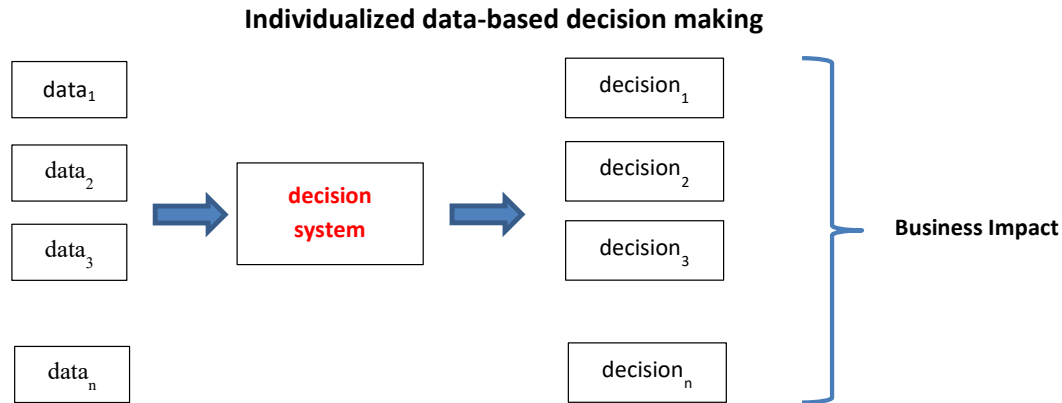
The Austrian AMS



- 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

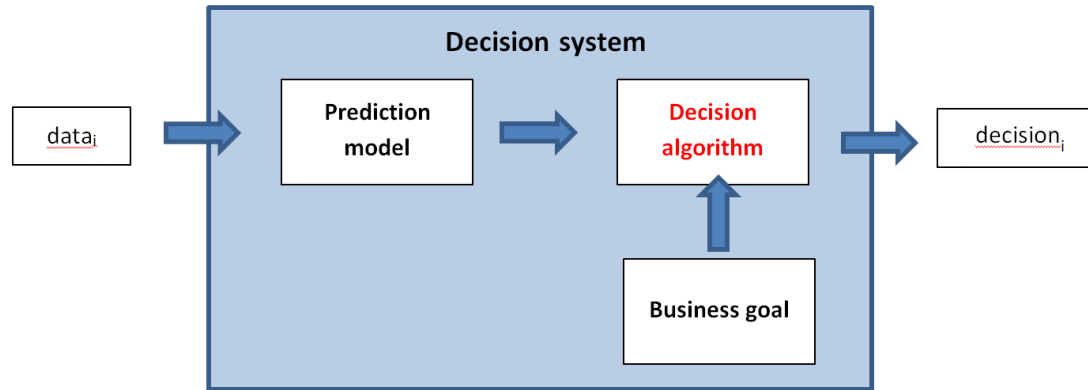
Holl, Jürgen, Günter Kernbeiß, and Michael Wagner-Pinter. 2018. “Das AMS-Arbeitsmarktchancen-Modell,”

Context: Data-based decisions in business



- Individualized decision making on humans, based on their data

Typical ML case: decision based on prediction



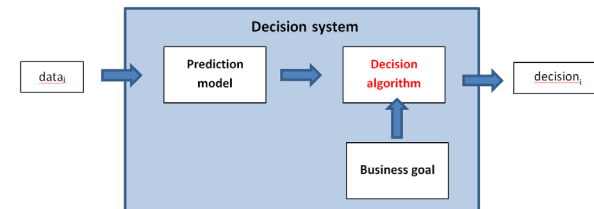
- Goal: maximize business goal by taking individualized decisions, based on prediction
 - › E.g. credit risk, risk of recidivism, risk of failing, ...
- Driver: Huge business potential to be harvested

Algorithmic bias in data-based decisions?

Definition «algorithmic bias» (https://en.wikipedia.org/wiki/Algorithmic_bias):

- 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

Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

- For binary prediction problems: Confusion matrix
- COMPAS: 1 = re-offend, 0 = not re-offend
- Result: FP rate higher for black people → „unfair“

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

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

	Definition	Paper	Citation #	Result
3.1.1	Group fairness or statistical parity	[12]	208	×
3.1.2	Conditional statistical parity	[11]	29	✓
3.2.1	Predictive parity	[10]	57	✓
3.2.2	False positive error rate balance	[10]	57	×
3.2.3	False negative error rate balance	[10]	57	✓
3.2.4	Equalised odds	[14]	106	×
3.2.5	Conditional use accuracy equality	[8]	18	×
3.2.6	Overall accuracy equality	[8]	18	✓
3.2.7	Treatment equality	[8]	18	×
3.3.1	Test-fairness or calibration	[10]	57	✓
3.3.2	Well calibration	[16]	81	✓
3.3.3	Balance for positive class	[16]	81	✓
3.3.4	Balance for negative class	[16]	81	×
4.1	Causal discrimination	[13]	1	×
4.2	Fairness through unawareness	[17]	14	✓
4.3	Fairness through awareness	[12]	208	×
5.1	Counterfactual fairness	[17]	14	-
5.2	No unresolved discrimination	[15]	14	-
5.3	No proxy discrimination	[15]	14	-
5.4	Fair inference	[19]	6	-

Table 1: Considered Definitions of Fairness

Verma, Sahil, and Julia Rubin. 2018. "Fairness Definitions Explained." In Proceedings of the International Workshop on Software Fairness - FairWare '18, 1–7. Gothenburg, Sweden: ACM Press. <https://doi.org/10.1145/3194770.3194776>

- 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!**

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):

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

↑
prevalence

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

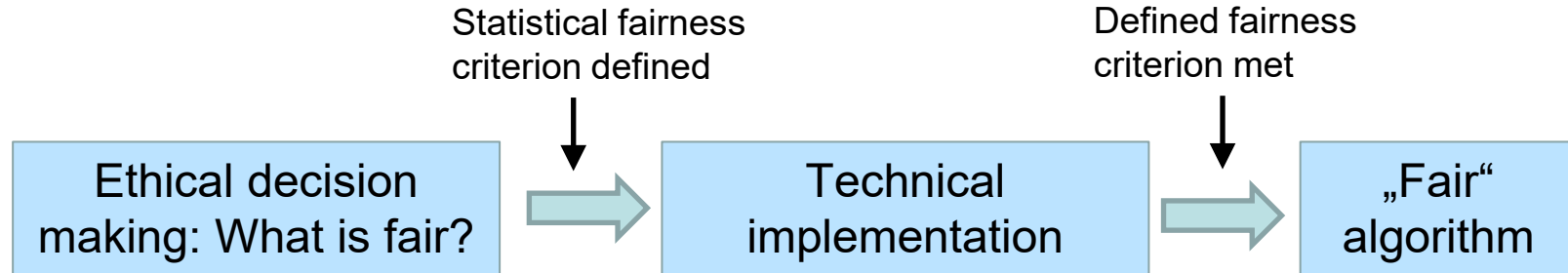
The problem of algorithmic fairness

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!