

A Crash Course on Ethics in Natural Language Processing

Version 1.0

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Ethics for NLP

What comes to your mind when you think of **ethics**?

What comes to your mind when you think about ethics for NLP?

Have you encountered any ethical problems in your life?

Why do you think this topic is **important**?

What do you expect to **learn** in this crash course?

Why does Ethics matter for NLP?

NLP has the aim of modeling **language**, an inherently human function

NLP works with **textual data or human subjects** → not free of bias, prejudice, ...

Language technology is **widely applied** (e.g. on social media) → can potentially harm anyone

Language technology shapes the way we **experience** the world

Bias

Privacy

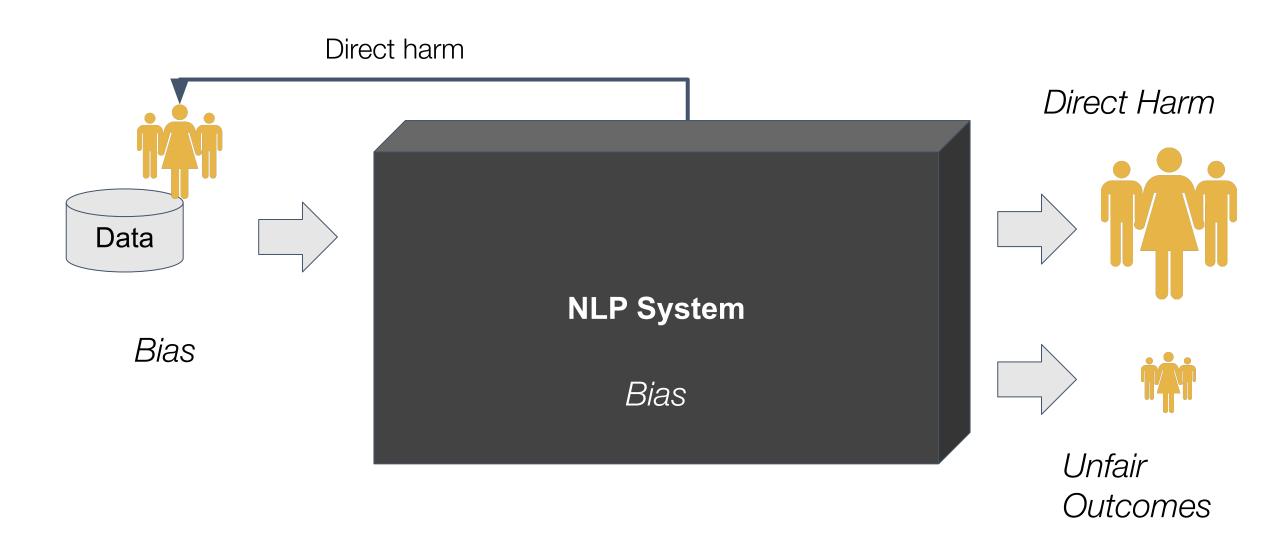
Fairness

Dual Use

Environmental Issues

. . .

Sources and Types of Harm - Overview



Learning Goals

After this course, you will be able to:

- Understand terminology and concepts related to ethics in NLP
- Analyze a given task, method or system for ethical issues
- Understand how NLP applications can cause harm
- Analyze ethical issues under different ethical perspectives

What is Ethics?

Branch of Philosophy

Ethics is the **philosophical** study of morality. It is the study of what are good and bad ends to pursue in life and what is **right** and **wrong** to do in the conduct of life. It is [...] primarily a **practical** discipline.

(Deigh, 2010, p. 7)

Synonym for Moral Code

Sometimes "ethics" is used to refer to the **moral code** or system of a particular tradition.

Examples: Christian ethics, professional ethics

How do these meanings relate to "Ethics for NLP"?

What is Morality?

Universal Concept

Universal ideal of what one ought to do or ought not to do, guided by reason / rational grounds.

Conventional System of Community

The members' shared beliefs about wrong and right, good and evil, and the corresponding customs and practices that prevail in the society.

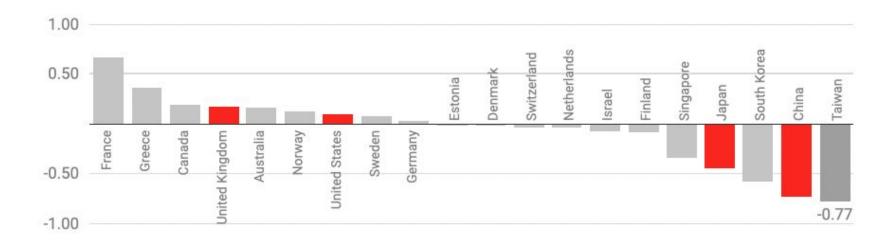
How do these concepts relate to "Ethics for NLP"?

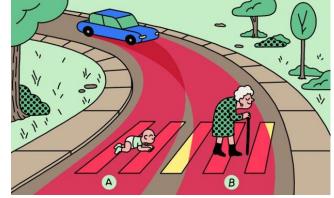
Whose Life Matters More?

Countries with more individualistic cultures are more likely to spare the young

Try it out!

http://moralmachine.mit.edu/hl/de





A comparison of countries piloting self-driving cars: If the bar is closer to 1, respondents placed a greater emphasis on sparing the young; if the bar is closer to -1, respondents placed a greater emphasis on sparing the old; 0 is the global average.

Moral vs. Legal

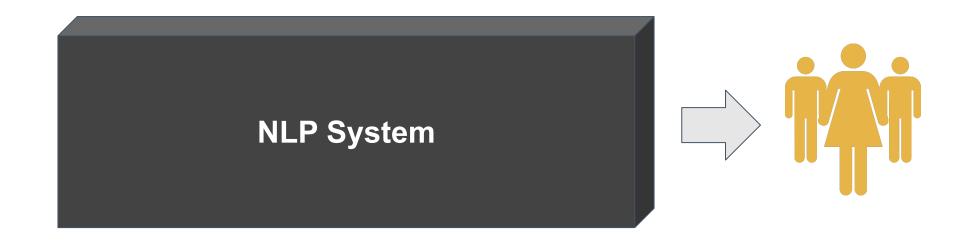
	legal	illegal	
moral	Doing your homework	Civil disobedience	
immoral	Cheating on your spouse	Murder	

Reading Assignment (Homework)

Hovy & Spruit: <u>The Social Impact of Natural Language Processing</u>. (ACL 2016)

TODO: add questions / instructions regarding the paper Political correctness classifier?

Source of Harm - Direct



analyzing medical documents





drug overdose killing the patient

Dual Use

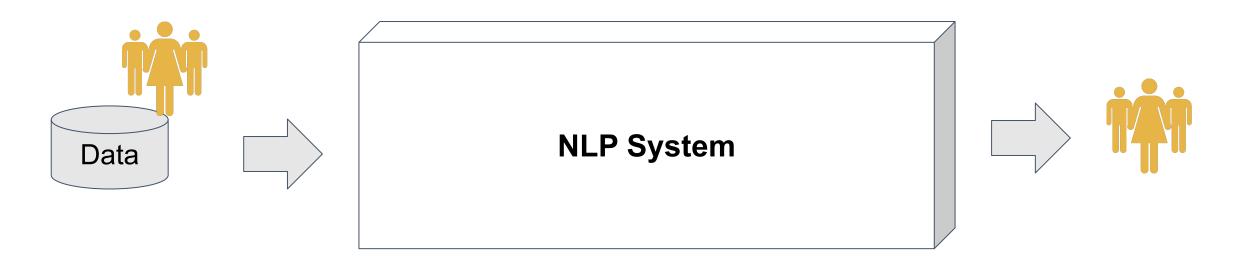


NLP Task	Beneficial Use	Malicious Use
Hate speech detection	Fighting hate crimes	Censorship of free speech
Detection of fake news / reviews	Fighting misinformation	Generation of fake news / reviews
•••	•••	•••

Can you think of other NLP tasks that have beneficial but also potentially malicious uses?

Assume you are publishing a piece of software on GitHub. Should you mention potential malicious uses in the corresponding Readme?

Source of Harm - Bias



Doctor vs. Nurse

The doctor recommended to perform an X-ray.

He/She said ...



The nurse recommended to perform an X-ray.

He/She said ...

Do you think "he" or "she" is a more likely continuation in the above cases (respectively)?

What would happen if you asked a large pre-trained language model?



Bias in Machine Translation

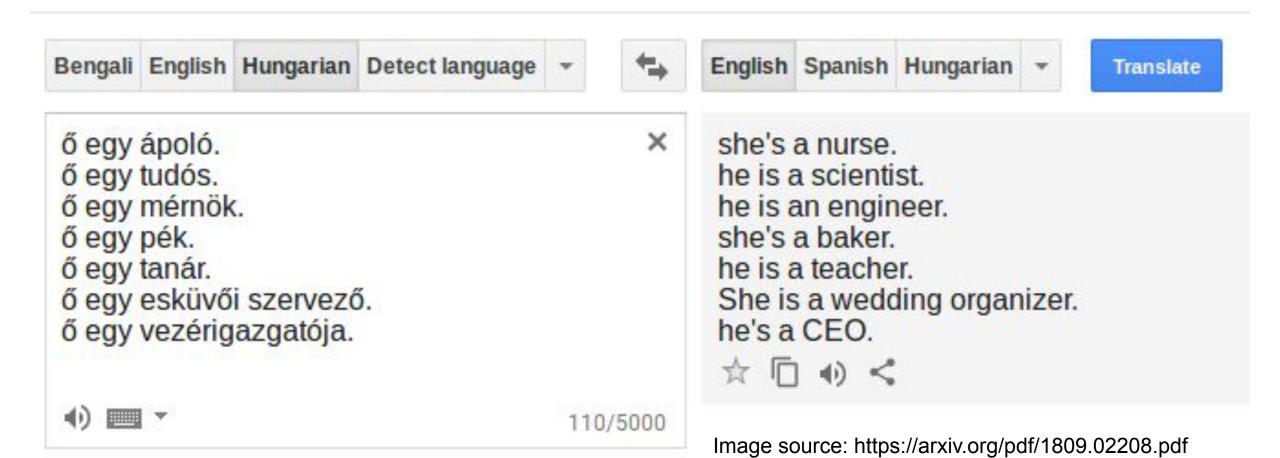




Translate

Useful or harmful?

Turn off instant translation



Bias in Machine Translation

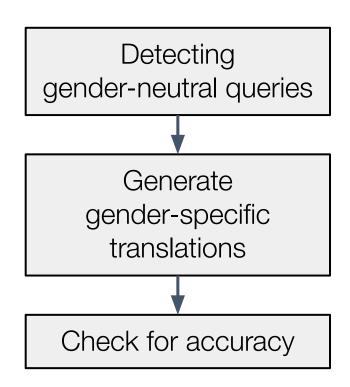






Image Source:

https://ai.googleblog.com/2018/12/providing-gender-specific-translations.html

What is Bias?

Cognitive bias arises due to the tendency of the human mind to categorize the world.

→ simplifies processing.

Social biases in data, algorithms, and applications

Statistical bias in machine learning

- **Inductive bias:** assumptions made by model about target function to generalize from data

What is Bias? (Technical View)

Bias in machine learning

Bayesian probabilities: prior

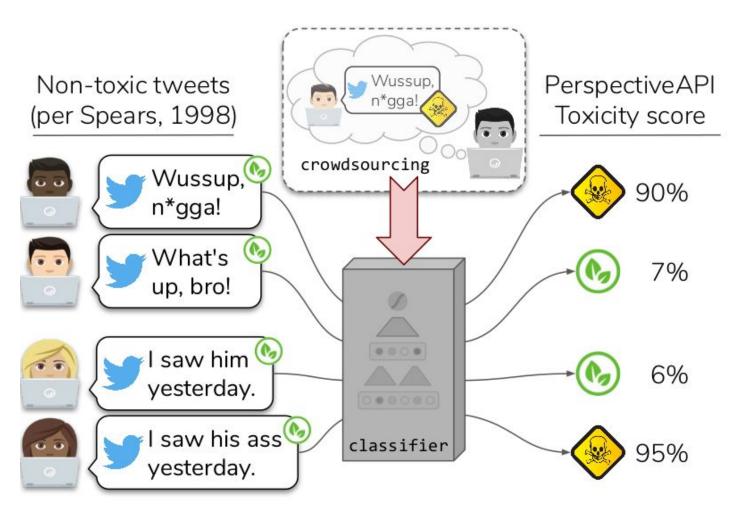
May be intended (e.g., domain adaptation) or unintended

$$y = ax + b$$

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Is bias always a bad thing?

Why is Bias Problematic? (Social View)



Sap et al.: The Risk of Racial Bias in Hate Speech Detection. ACL 2019.

NLP Applications

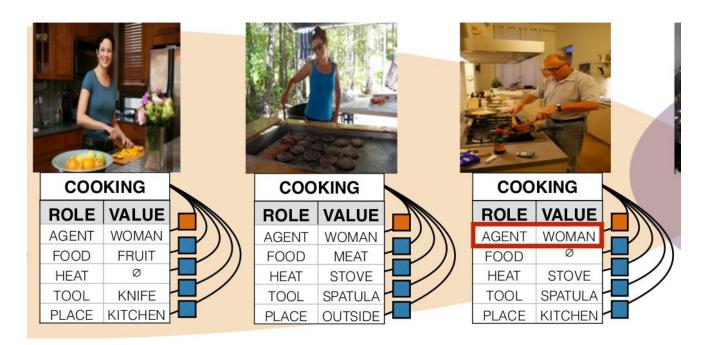
Employment matching, advertisement placement, parole decisions, search, chatbots, face recognition, ...

Social Stereotypes

Gender, Race, Disability, Age, Sexual orientation, Culture, Class, Poverty, Language, Religion, National origin, ...

Why is Bias Problematic?

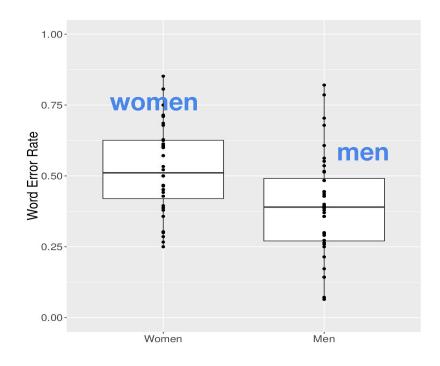
Outcome Disparity



Because a "COOKING" event is taking place, the model is more likely to predict the agent to be a woman. (Zhao et al., 2017)

Image sources: https://www.aclweb.org/anthology/W17-1606.pdf, https://www.aclweb.org/anthology/D17-1323.pdf

Error Disparity



Word Error Rate in automatic captioning is higher for female speakers compared to male speakers (Tatman, 2017)...

Why is Bias Problematic? (Technical View)

Outcome / Error disparity

Models might amplify bias

51:49 distribution in a feature may lead to 100:0 decision

Is it wrong to build models replicating "real world data"?

In what circumstances?

Sources of Bias in NLP (Shah et al., 2020)

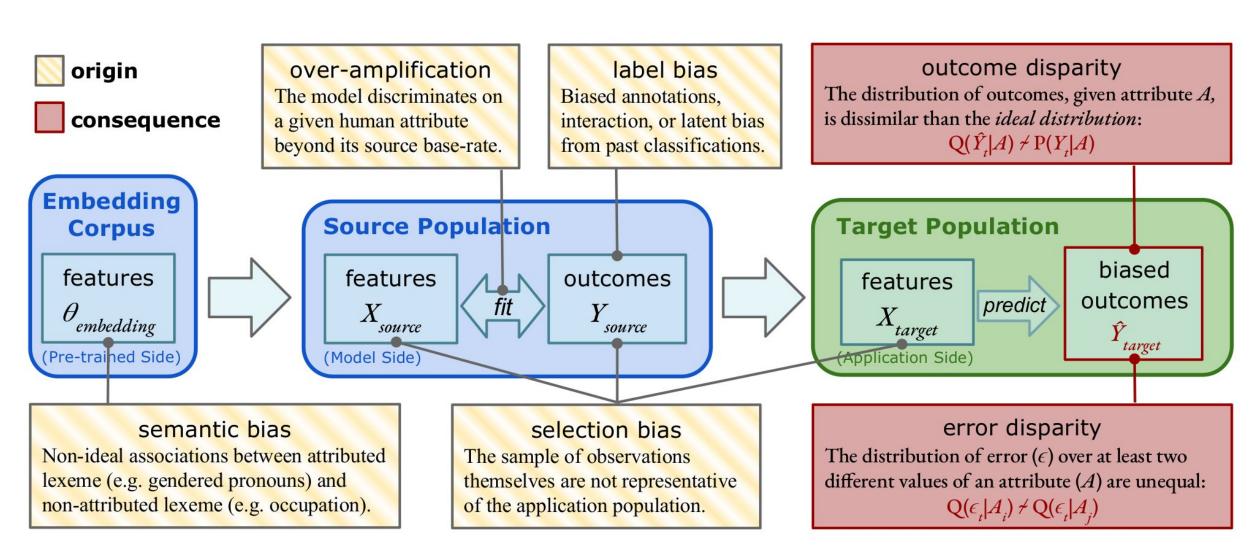
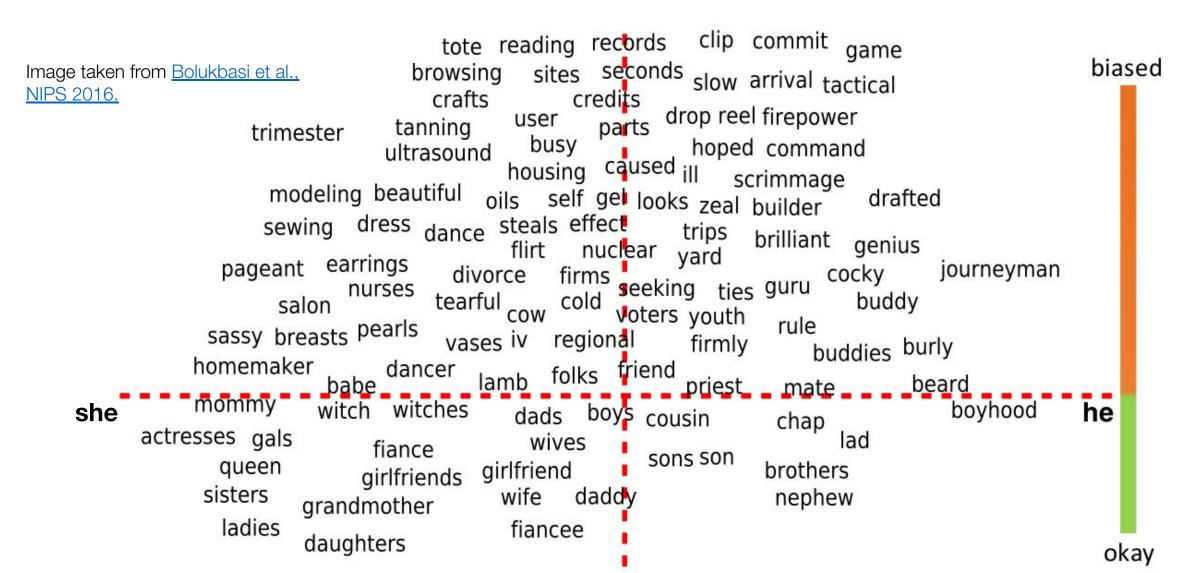


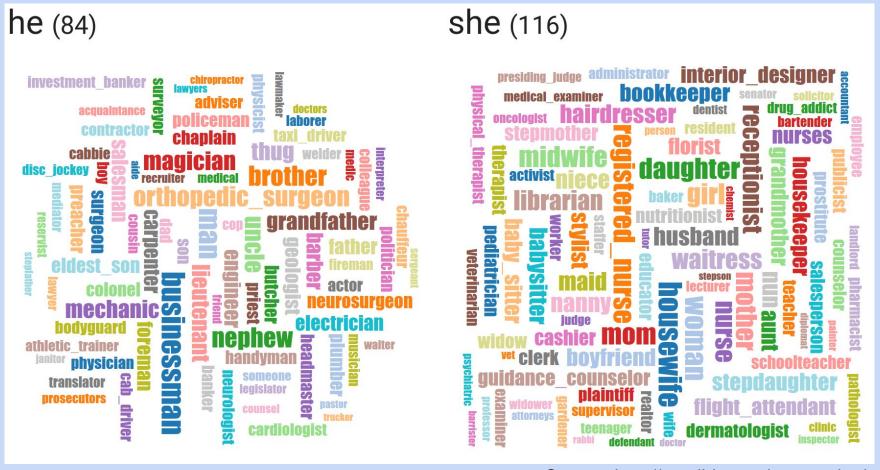
Image Source: https://www.aclweb.org/anthology/2020.acl-main.468.pdf

De-Biasing of Word Embeddings

neutral

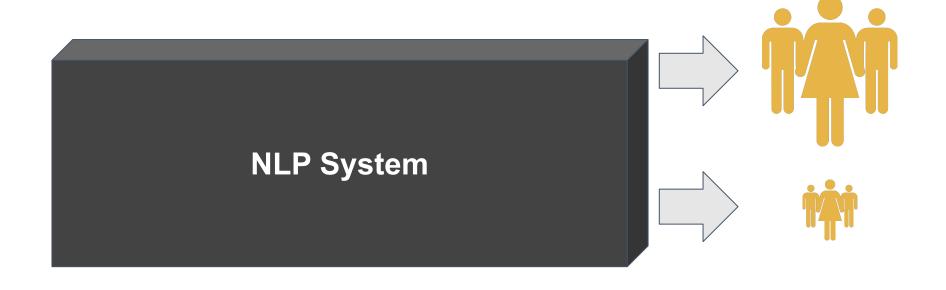


Bias Exercise



Source: http://wordbias.umiacs.umd.edu

Source of Harm - Unfair Outcomes



filtering job applications





Better chances for people living in a certain area

Fairness

Treating everyone equally is fair, right?

So, everyone gets the same grade from now on ;)

fundamental principle of justice

"equals should be treated equally and unequals unequally"



Bild von Gordon Johnson auf Pixabay

Group vs. Individual Fairness

group fairness

errors should be distributed similarly across protected groups

Which groups are/should be protected?

individual fairness

 similar individuals should be treated similarly regardless of group membership

How can we measure similarity of individuals?

cannot reach group and individual fairness at the same time

https://dl.acm.org/doi/10.1145/3442188.3445892

https://arxiv.org/abs/1609.07236

ETHICAL

UNETHICAL

Bias Type

Fairness 5 Impact

Intentional

(Good to have)

Unintentional

(Avoid, but ok to have)

Unintentional

Intentional

(Avoid, not ok to have) (Worst, must be prevented)

Biases provide ideal outcomes and are needed to apply business requirements in an ethical way.

These are good and meant for the business to provide justifiable and fair outcomes to the customers.

Biases created unknowingly without direct responsibility or knowledge of the business.

Provide fair benefits without any harm; but may not be explainable or justified.

Biases created unknowingly without direct responsibility or knowledge of the business. but resulting in unfair decisions or discrimination of the customers.

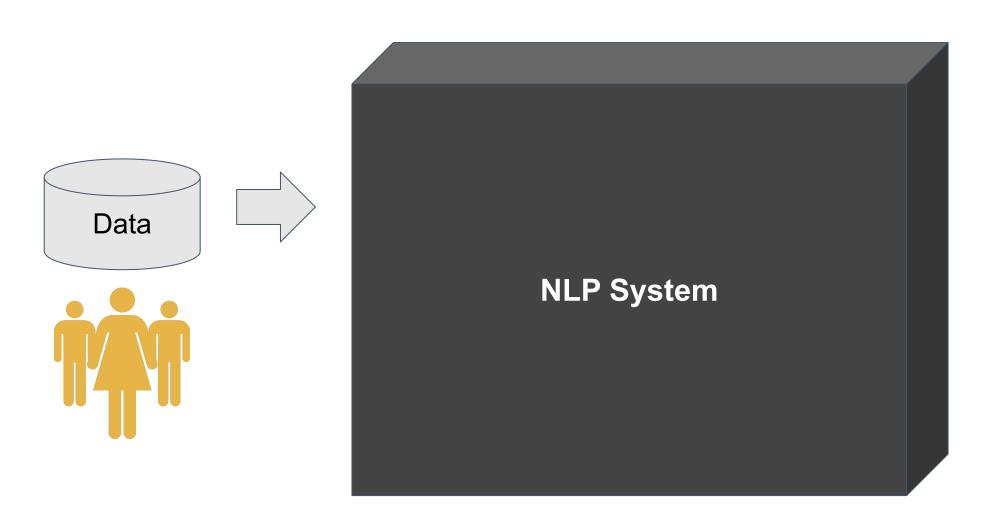
Can go undetected and continuously cause harm. No control of the business.

Biases created deliberately for unethical 'foul-play' to favor an outcome that is unethical, unjustifiable and unfair discrimination of the customers.

The worst type to have and can also be illegal.

Bias types and their impact on Fairness

Source of Harm - Input/Training Data



Privacy

"I've got nothing to hide."



Do you have curtains? / Do you close your shutters at night? Can I see your credit card bills from last year?

A Taxonomy of Privacy (Solove, 2007)

Problems and harms related to privacy

```
Privacy = intimacy?
Privacy = the right to be let alone?
```

"Privacy [...] is a plurality of different things that do not share one element in common but that nevertheless bear a resemblance to each other."

```
Information Collection
     Surveillance
     Interrogation
Information Processing
     Aggregation
     Identification
     Insecurity
     Secondary Use
     Exclusion
Information Dissemination
     Breach of Confidentiality
     Disclosure
     Exposure
     Increased Accessibility
     Blackmail
     Appropriation
     Distortion
Invasion
     Intrusion
     Decisional Interference
```

Data Privacy Regulations

European Regulation 2016/679
General Data Protection Regulation (GDPR)

Main rights of the "data subject" (natural person):

- Right of access
- Right of rectification
- Right to erasure ("right to be forgotten")
- Right to withdraw consent at any time
- Right to lodge a complaint with a supervisory authority
- Right to restriction of processing
- Right to data portability

Applies for the data of all EU citizens - also if controller operates from a country outside the EU!



Similar laws in the US:

California Consumer

Privacy Act

Data Privacy vs. Data Ethics

- <u>Data privacy</u> is responsibly collecting, using and storing data about people, in line with the expectations of those people, customers, regulations and laws.
- **Data ethics** is doing the right thing with data, considering the human impact from all sides, and making decisions based on your values.

[based on: <u>Lawler, 2019</u>]

"Just because we can do something, doesn't mean we should." Should a company sell user information to political campaigns?

Anonymization (De-Identification)

```
Category: DATE
                     nte : Paciente varón de 70 años de edad ,
       Tagger: PHI NER
                     ergias medicamentosas conocidas . Operado de
una hernia el 12 de enero de 2016 en el Hospital Costa del
Sol por la Dra . Juana López . Derivado a este centro el día 16 del
mismo mes para revisión.
Informe clínico del paciente : Paciente SEX de AGE AGE de edad,
 PROFESSION jubilado, sin alergias medicamentosas conocidas.
Operado de una hernia el DATE DATE DATE DATE DATE en el
 HOSPITAL HOSPITAL HOSPITAL por la Dra.
 DOCTOR DOCTOR . Derivado a este centro el día 16 del mismo mes
para revisión.
```

HitzalMed

(Lopez et al., 2020)

After having run some anonymization system on our data, is everything fine?

Authorship Attribution / Author Profiling

Table 10. Best results per language and task.

Overview of the 5th Author Profiling Task at PAN 2017: Gender and Language Variety Identification in Twitter

Language	Joint	Gender	Variety
Arabic	0.6831	0.8031	0.8313
English	0.7429	0.8233	0.8988
Spanish	0.8036	0.8321	0.9621
Portuguese	0.8575	0.8700	0.9838

Francisco Rangel^{1,2} Paolo Rosso² Martin Potthast³ Benno Stein³

information. Therefore, the possibility of knowing social media users' traits on the basis of what they share is a field of growing interest named author profiling. To infer the authors' gender, age, native language, dialects, or personality opens a world of possibilities from the point of view of marketing, forensics, or security. For example from a security viewpoint, to be able to determine the linguistic profile of a person who writes

What are potential chances and risks of this type of technology?

Reading Assignment / Discussion

Daniel J. Solove. 'I've Got
Nothing to Hide' and Other
Misunderstandings of Privacy.
San Diego Law Review, Vol.
44, p. 745, 2007

Germany's complicated relationship with Google Street View. NY Times, April 2013.

Questions to think about / discuss:

Which dimensions of privacy matter most to you?

A software developer accidentally notices a document where a user is drafting a suicide note. Should he/she contact the police to save a life, or respect their user's secret?

Can you imagine a situation where interfering with someone's privacy leads to an economic / financial issue for that person?

Two ethical theories

Teleology

Telos (Greek) = goal

Outcome-oriented

Utilitarianism

"Choose that action that optimizes the outcome for the majority"

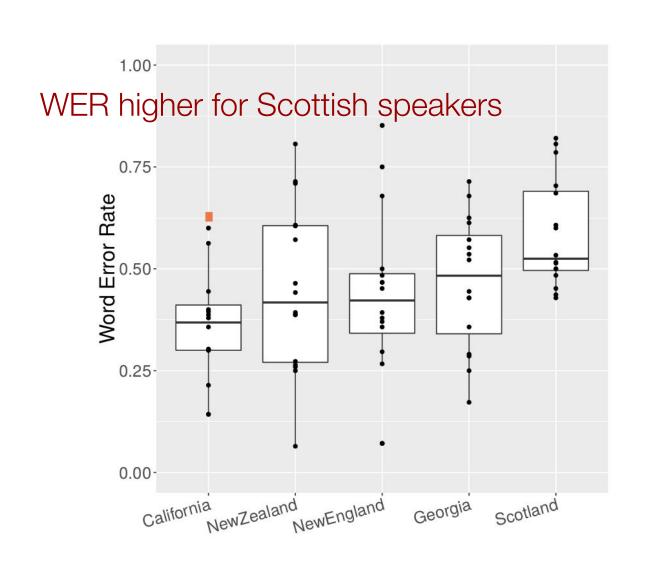
Deontology

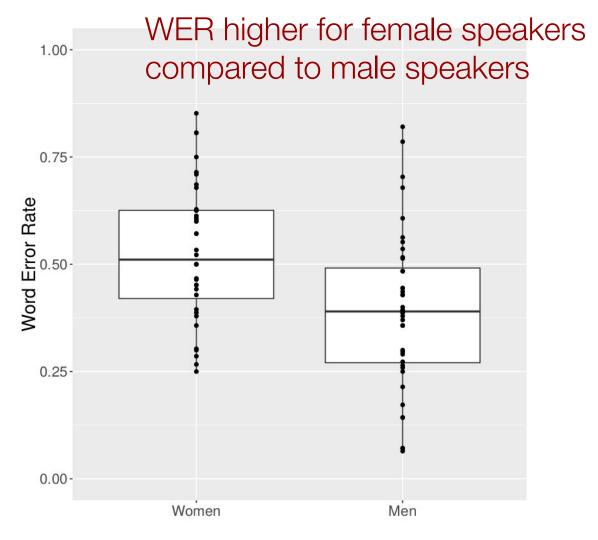
Deon (Greek) = duty

"Identify your duty and act accordingly"

Generalization principle: prioritizes intent as the source of ethical action, should be reasonable.

Word Error Rates for Automatic Captioning on YouTube (Tatman, 2017)



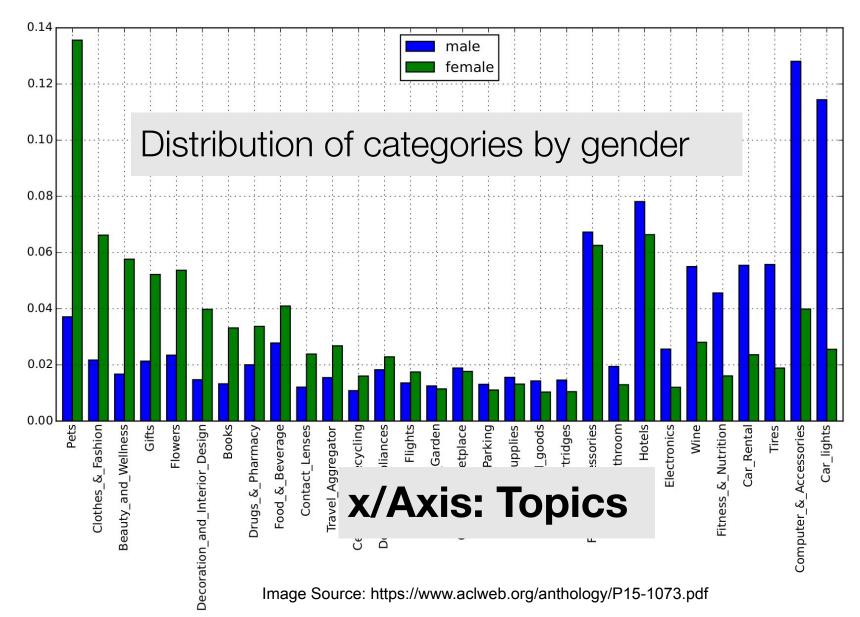


Demographic Factors Improve Classification Performance

(Hovy, 2015)

Is it okay to leverage the author's gender information as explicit features for text classification?

What would be recommended from a utilitarian / generalization perspective?



Reading Assignment

Prabhumoye et al.: Principled Frameworks for Evaluating Ethics in NLP Systems. In Proceedings of the Workshop on Widening NLP. 2019.

Consider a project that you are working on / have worked on or pick a recent research paper from the ACL Anthology. Analyse the method / system both from a utilitarian and from a generalization perspective. How would scholars of each ethical theory evaluate the ethicality of the method/system?

"Applications": NLP for Social Good

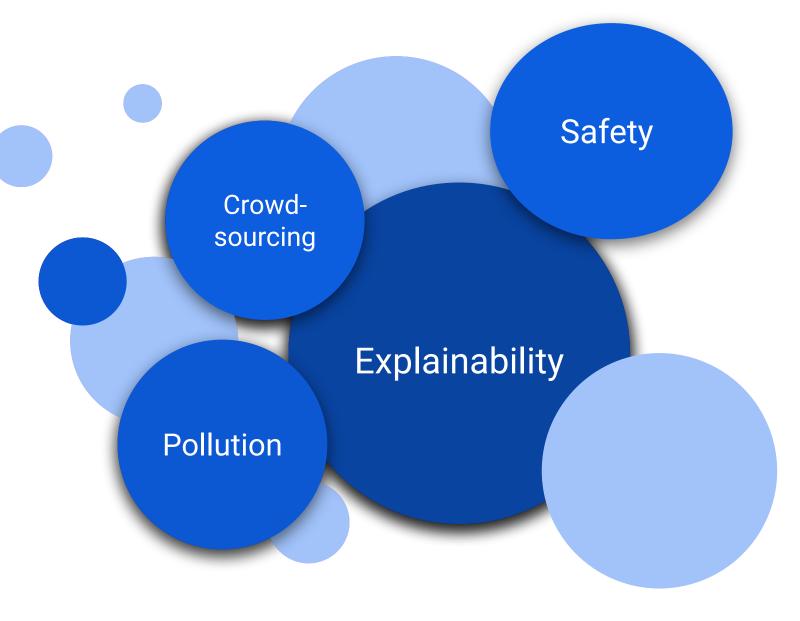
Civility in communication: techniques to monitor trolling, hate speech, abusive language, detect fake news, etc.





Other topics

Pick a topic of your choice and research its relationship to ethics.
What are common arguments made? Do you agree? Can you find interesting examples for ethical or unethical behavior?



Reading Suggestions: Environmental Issues

Bender et al. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?. FAccT '21, March 3–10, 2021, Virtual Event, Canada

Emma Strubell, Ananya Ganesh, Andrew McCallum, Energy and Policy Considerations for Deep Learning in NLP. ACL 2019.



Bild von Peggy und Marco Lachmann-Anke auf Pixabay

Misc / Practical Hints

IRB = Institutional Review Board (Ethics Review Board)
Reviews all human experimentation

Find out how to contact the IRB of your institution.

The ACL has adopted <u>ACM Code of Ethics and Professional</u> <u>Conduct</u> and published an FAQ with hints on conducting research and publishing in an ethical manner (see, e.g., <u>ACL-IJCNLP 2021 Ethics FAQ</u>).

Association for Computational Linguistics

Practical summary

Analyse data, task and outcomes for potential harm.

Can benefits outweigh harms?

Retrospection

What have you learned?

What does that mean for you personally?

What was surprising?

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Bias

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Fairness

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Gender Stereotypes

 Bhaskaran, J., & Bhallamudi, I. (2019). Good Secretaries, Bad Truck Drivers? Occupational Gender Stereotypes in Sentiment Analysis. In Proceedings of the First Workshop on Gender Bias in Natural Language Processing (pp. 62–68). Association for Computational Linguistics. Retrieved from https://www.aclweb.org/anthology/W19-3809.pdf