

Natural Language Understanding, Generation, and Machine Translation

Lecture 19: Ethics in NLP

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With contributions from Adam Lopez

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It has to do with *people* and what *they* mean.

paraphrasing Herbert Clark.

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In this week's lectures, we are going to talk about something *much more important*, and *much more difficult*: the world that those systems inhabit, and the questions that you should ask before you even consider building such systems.

The social impact of NLP

Types of Risks

Things to think about when building NLP systems

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Human understanding of the language faculty and its social use—e.g. through use in computational psycholinguistics and computational sociolinguistics.

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Then, ask *all* of the stakeholders the same question.

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In other words: the subjects of your experiment may be traceable from their data. And they did not consent to your experiment.

Who do these systems harm?

Potentially everyone

Many, many *hidden* NLP (and ML) systems are used to **decide**:

- Who gets admitted.
- Who gets hired.
- Who gets promoted.
- Who receives a loan.
- Who receives treatment for medical problems.
- Who receives the death penalty. [This is a real application in published papers by well-funded labs.]





Deciding how to do good is the goal of moral philosophy, aka *ethics*.

Types of Risks

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- Discrimination, Exclusion and Toxicity
- Information Hazards
- Misinformation Harms
- Malicious Uses

Ethical and social risks of harm from Language Models Weidinger et al. (2021)

Discrimination, Exclusion and Toxicity

Mechanism: The NLP model accurately reflects natural speech, including unjust, toxic, and oppressive tendencies present in the training data.

- *Allocational (material) harm*: discrimination
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- Offensive Behaviour: generate toxic language

Example: Allocational Harm

The accent challenge

Youtubers read these words in their native accent: Aunt, Envelope, Route, Theater, Caught, Salmon, Caramel, Fire, Coupon, Tumblr, Pecan, Both, Again, Probably, GPOY, Lawyer, Water, Mayonnaise, Pajamas, Iron, Naturally, Aluminium, GIF, New Orleans, Crackerjack, Doorknob, Alabama.

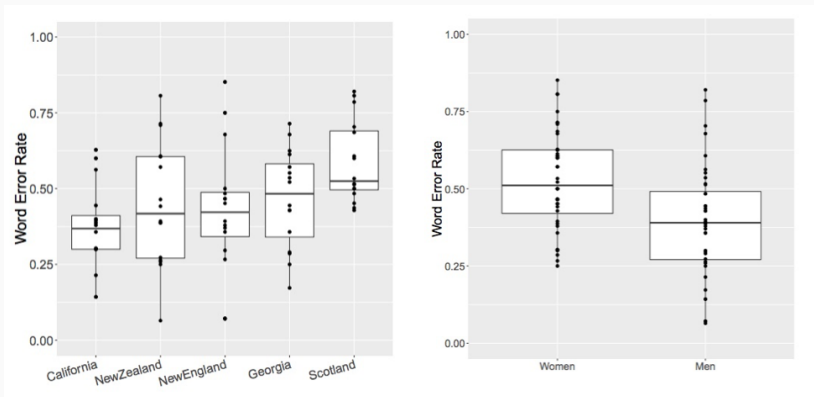
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Compare the read words with youtube's automatic captioning for eight men and eight women across several dialects.

The Accent Challenge

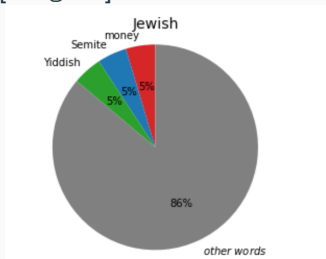
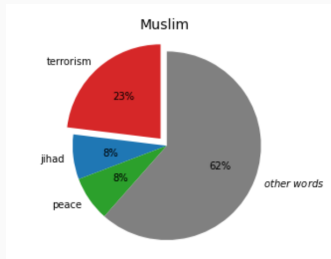


Reveals differences in access to ASR tools

Gender and Dialect Bias in YouTube's Automatic Captions. Tatman (2017)

Example: Representational harm

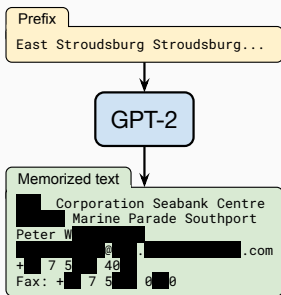
Audacious is to boldness as [religion] is to ...



Persistent Anti-Muslim Bias in Large Language Models. Abid et al. (2021)

Information Hazards

Mechanism: The LM predicts utterances which have private or safety-critical information which are present in, or can be inferred from, training data. The harms include privacy violations and safety risks.



Extracting Training Data from Large Language Models Carlini et al. (2021)

Misinformation Harms

Mechanism: The LM assigning high probabilities to false, misleading, nonsensical or poor quality information.

The harms include people believing false information, and possibly acting on it.

A chatbot was asked if a patient should “kill themselves” responded “I think you should”

https://www.theregister.com/2020/10/28/gpt3_medical_chatbot_experiment/

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Mechanism: From humans intentionally using the LM to cause harm.

Types of Harm:

- Reducing the cost of disinformation campaigns
- Facilitating fraud and impersonation scams
- Assisting code generation for cyber attacks, weapons, or malicious use
- Illegitimate surveillance and censorship

Real example: Illegitimate surveillance

Social media monitoring (From Robert Munro)

In 2014–2015, I was approached by the Saudi Arabian government on three separate occasions to help them monitor social media...

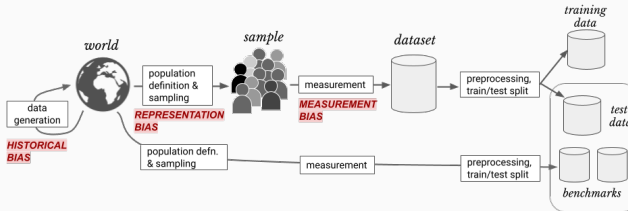
In every case, the stated goal was to help the people complaining about the government.

After careful consultation with experts on Saudi Arabia and Machine Learning, we decided that a system that identified complaints would be used to identify dissidents. As Saudi Arabia is a country that persecutes dissidents without trial, often violently, we declined to help.

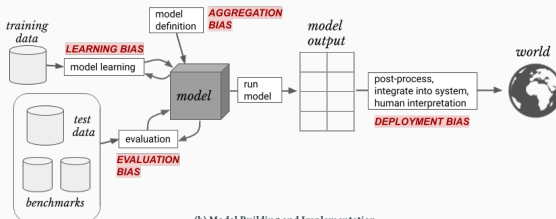
Source: <https://towardsdatascience.com/should-i-open-source-my-model-1c109188b164>

Things to think about when building NLP systems

What part of model building has influence?



(a) Data Generation



(b) Model Building and Implementation

A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle. Suresh and Gutttag (2021)

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Ethics is not legality

- Unethical policies are often legal (e.g. there are and have been many legally enforced policies of discrimination).
- Not all ethical behavior is legally required—but you should behave ethically anyway.
- Sometimes law does enforce ethical practice (e.g. GDPR).

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These are questions you must ask *yourself* and *all* of the stakeholders.

Summary of key points (i.e. examinable content)

- NLP is used by millions of people in the real world every day.
- NLP is used **on** millions of people in the real world every day.
- You must understand types of harms and where they come from.
- You must anticipate possible benefits *and harms*.

In the next lecture, we will look at bias in word embeddings.

Homework for next lecture: Do one of the implicit bias tests on [*https://implicit.harvard.edu/implicit/*](https://implicit.harvard.edu/implicit/).

- Abid, A., Farooqi, M., and Zou, J. (2021). Persistent anti-muslim bias in large language models. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, pages 298–306.
- Carlini, N., Tramer, F., Wallace, E., Jagielski, M., Herbert-Voss, A., Lee, K., Roberts, A., Brown, T. B., Song, D., Erlingsson, U., et al. (2021). Extracting training data from large language models. In *USENIX Security Symposium*, volume 6.
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