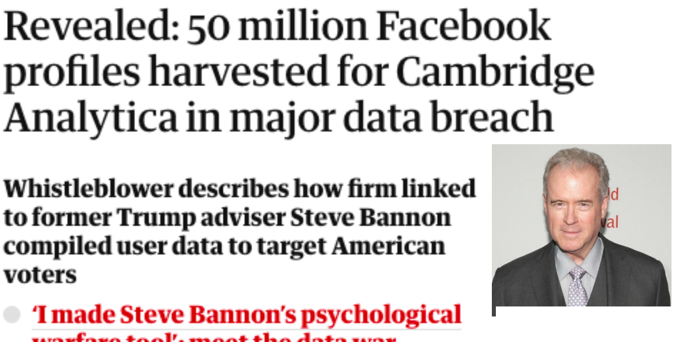
Norsk Regnesentral
NORWEGIAN COMPUTING CENTER

Ethics in Natural Language Processing

Pierre Lison

IN4080: Natural Language Processing (Fall 2020)

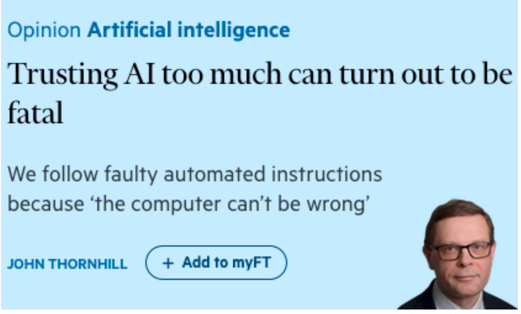
26.10.2020



Revealed: 50 million Facebook profiles harvested for Cambridge Analytica in major data breach

Whistleblower describes how firm linked to former Trump adviser Steve Bannon compiled user data to target American voters

- 'I made Steve Bannon's psychological warfare tool': meet the data war whistleblower
- Mark Zuckerberg breaks silence on Cambridge Analytica

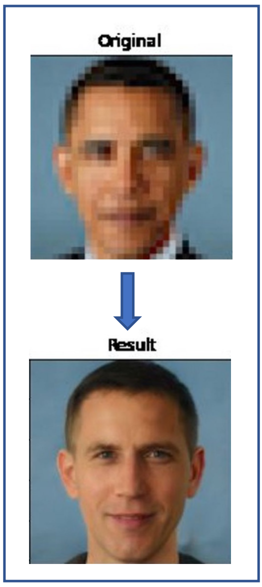


Opinion **Artificial intelligence**

Trusting AI too much can turn out to be fatal

We follow faulty automated instructions because 'the computer can't be wrong'

JOHN THORNHILL + Add to myFT



Chatbots and Abuse: A Growing Concern

How China's Government Is Using AI on Its Uighur Muslim Population

How IBM Watson Overpromised and Underdelivered on AI Health Care

After its triumph on *Jeopardy!*, IBM's AI seemed poised to revolutionize medicine. Doctors are still waiting

Plan for today

- What is ethics?
- Misrepresentation & bias
- Unintended consequences
- Misuses of technology
- Privacy & trust

Plan for today

- **What is ethics?**
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- Unintended consequences
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Ethics

- = the systematic study of conduct based on moral principles, reflective choices, and standards of **right** and **wrong** conduct

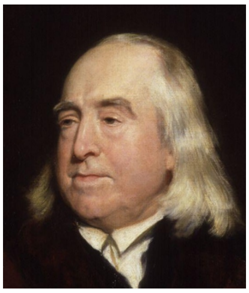
  [P. Wheelwright (1959), *A Critical Introduction to Ethics]*

- A *practical discipline* – how to act?
- Depends on our values, norms and beliefs
  - No unique, objective answers!
  - But more than just "opinions" – need to *justify* our choices in a rational manner

Ethics

- Various philosophical traditions to define what is good/bad:
  - **Deontological**: respect of *moral principles* and rules
  - **Consequentialist**: focus on the *outcomes* of our actions
  - (and more)

Imannuel Kant
(1724-1804)



Jeremy Bentham
(1748-1832)

- No particular "side" in this lecture
  - Inspiration from multiple ethical perspectives

Ethics

← Protests against LAPD's system for "data-driven predictive policing"

Protests against Facebook's perceived passivity against disinformation campaigns (fake news etc.)

The NLP tools we build, deploy or maintain have **real impacts** on **real people**

- Who might benefit/be harmed?
- Can our work be misused?
- Which objective do we optimise?

Ethics

- Ethical behaviour is a basis for **trust**
- We have a **professional duty** to consider the ethical consequences of our work
- Ethical ≠ Legal!
  - Plenty of actions are not illegal but will be seen by most as unethical
  - Laws should embody moral principles (but don't always do)

acm Association for Computing Machinery

www.acm.org/code-of-ethics

Plan for today

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Language and people

> "The common misconception is that language has to do with words and what they mean.
>
> It doesn't.
>
> It has to do with **people** and what **they** mean."

[H. Clark & M. Schober (1992), "Asking questions and influencing answers", *Questions about questions*.]

Language data does not exist in a vacuum – it comes from *people* and is used to communicate with other people!

- These people may have various *stereotypes* & *biases*
- & their relative position of *power* and *privilege* affects the status of their language productions

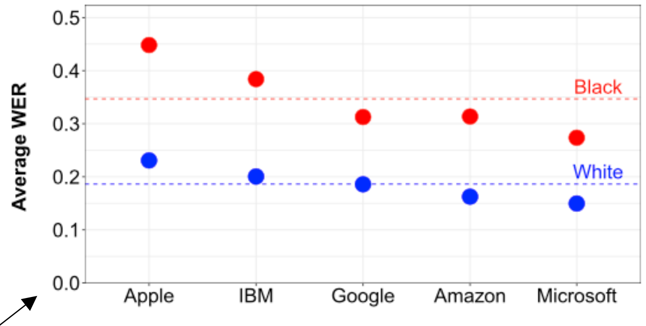
Demographic biases

- Certain demographic groups are largely *over-represented* in NLP datasets
  - That is, the proportion of content from these groups is >> their demographic weight
  - Ex: young, educated white males from US
- Under-representation of linguistic & ethnic minorities, low-educated adults, etc.
  - & gender: 16% of female editors in Wikipedia (and 17% of biographies are about women)

https://www.theguardian.com/technology/2018/jul/29/the-five-wikipedia-biases-pro-western-male-dominated

Demographic biases

- Under-represented groups in the training set of an NLP model will often experience *lower accuracies* at prediction time



[A. Koenecke et al (2020). Racial disparities in automated speech recognition. *Proceedings of the National Academy of Sciences]*

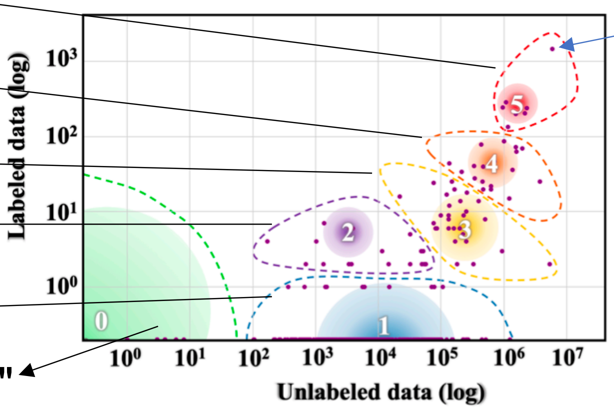
- Lead to the *technological exclusion* of already disadvantaged groups

Elderly users

Sketch from Saturday Night Live, 2017

Linguistic (in)justice

Only a small fraction of the world's 7000 languages covered in NLP datasets & tools



"The Winners"

"The Underdogs"

"The Rising Stars"

"The Hopefuls"

"The Scraping-By"

"The Left-Behind"

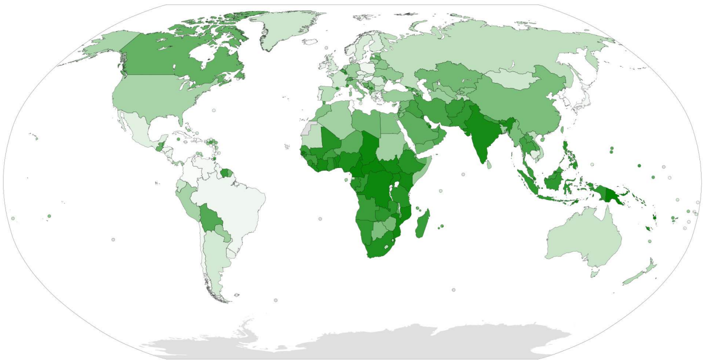
English

Note the logarithmic scale!

[Joshi et al (2020), The State and Fate of Linguistic Diversity and Inclusion in the NLP World, *ACL*]

Linguistic (in)justice

- The lack of linguistic resources & tools for most languages is a huge ethical issue
- We exclude from our technology the part of the world's population that is already most vulnerable, both culturally and socio-economically!



Linguistic diversity index

Linguistic (in)justice

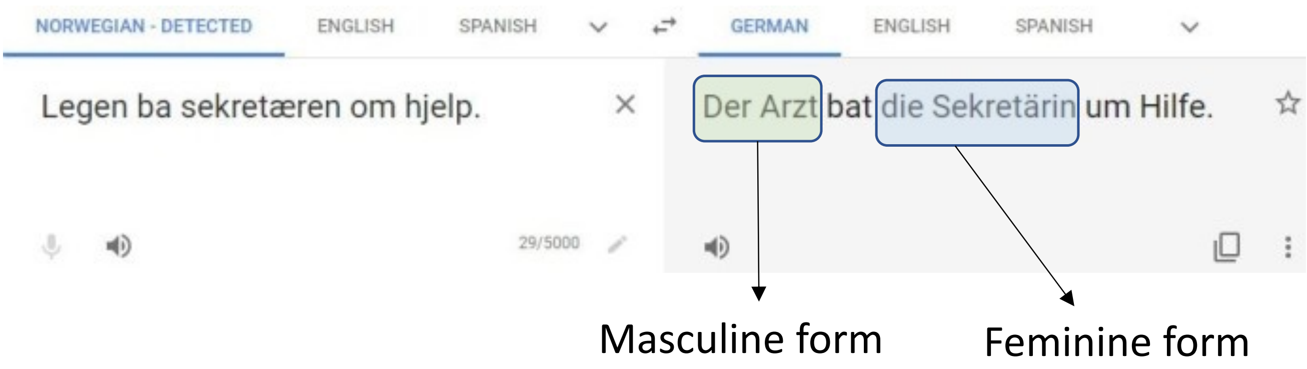
The dominance of US & British English in NLP is also a scientific problem

DUDE, WHY DO YOU TALK BACKWARDS ALL THE TIME?
BACKWARDS-TALKING I AM NOT. ENGLISH-CENTRIC VIEW OF GRAMMATICAL STRUCTURE, YOU HAVE
©2012 BY DOUG SAVAGE

- NLP research not sufficiently exposed to *typological variety*
- Focus on linguistic traits that are important in English (such as word order)
- Neglect of traits that are absent or minimal in English (such as morphology)

Social biases

Stereotypes, prejudices, sexism (& other types of social biases) expressed in the training data will also creep into our NLP models

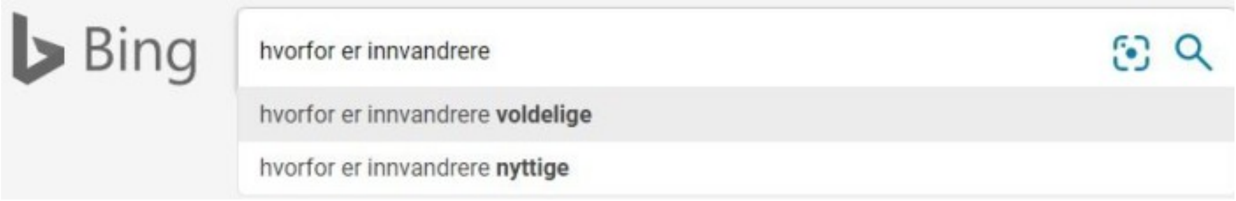


Legen ba sekretæren om hjelp.

Der Arzt bat die Sekretärin um Hilfe.

Social biases

Also observed in language modelling:

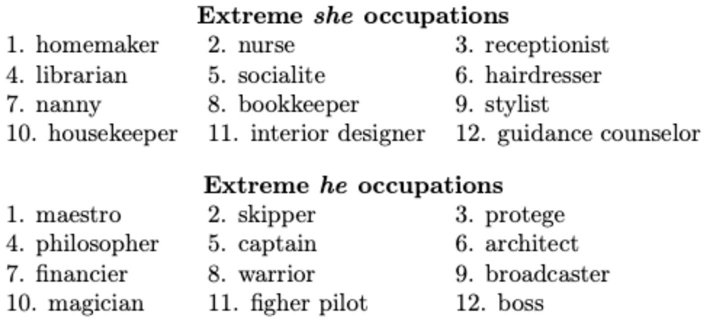


hvorfor er innvandrere

hvorfor er innvandrere **voldelige**

hvorfor er innvandrere **nyttige**

And even in word embeddings:



Extreme *she* occupations

1. homemaker 2. nurse 3. receptionist
4. librarian 5. socialite 6. hairdresser
7. nanny 8. bookkeeper 9. stylist
10. housekeeper 11. interior designer 12. guidance counselor

Extreme *he* occupations

1. maestro 2. skipper 3. protege
4. philosopher 5. captain 6. architect
7. financier 8. warrior 9. broadcaster
10. magician 11. figher pilot 12. boss

[Bolukbasi, T. et al (2016). Man is to computer programmer as woman is to homemaker? Debiasing word embeddings. In *NIPS*.]

Social biases

- NLP models may not only **reflect** but also **amplify** biases in training data
  - & make biases appear more "objective"
- Harms caused by social biases are often *diffuse*, *unconscious* & *non-intentional*
  - More pernicious & difficult to address!
  - Relatively small levels of harm ("microagressions"), but experienced *repeatedly* by *whole social groups*

[Hovy, D., & Spruit, S. L. (2016).
The social impact of natural language processing. In *ACL*]

Debiasing

1. Identify bias *direction* (more generally: subspace)

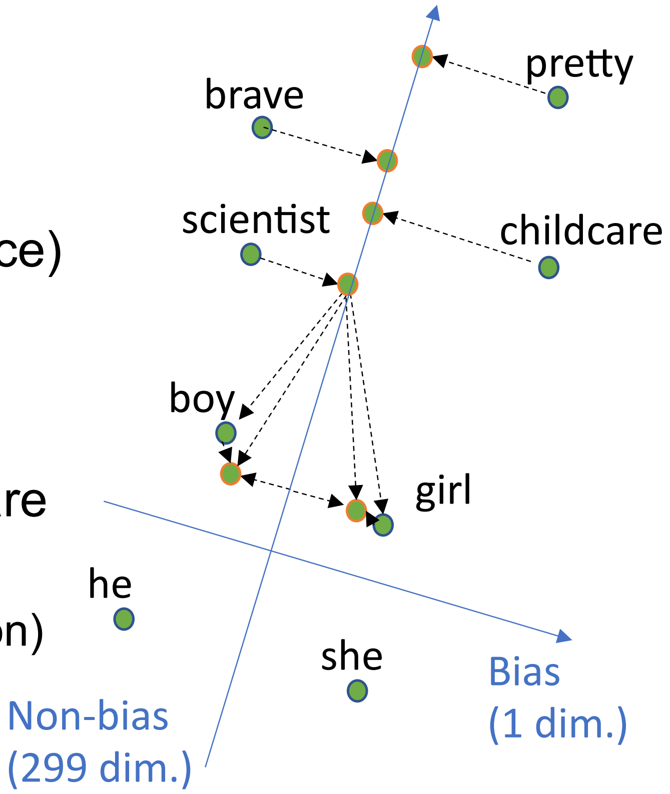
   $$\left.\begin{matrix}\overrightarrow{boy} - \overrightarrow{girl} \\ \overrightarrow{he} - \overrightarrow{she}\end{matrix}\right\}$$ take average

   ...

2. "*Neutralise*" words that are not definitional

   (=set to zero in bias direction)

3. Equalise pairs (such as "boy" – "girl")



[Bolukbasi, T. et al (2016). Man is to computer programmer
as woman is to homemaker? Debiasing word embeddings. In *NIPS*.]

Gender in MT

- ► In languages with grammatical gender, the speaker gender may affect translation:

  English: [M/F] I'm happy

  French: Je suis heureux *(if speaker is male)*

  Je suis heureuse *(if speaker is female)*

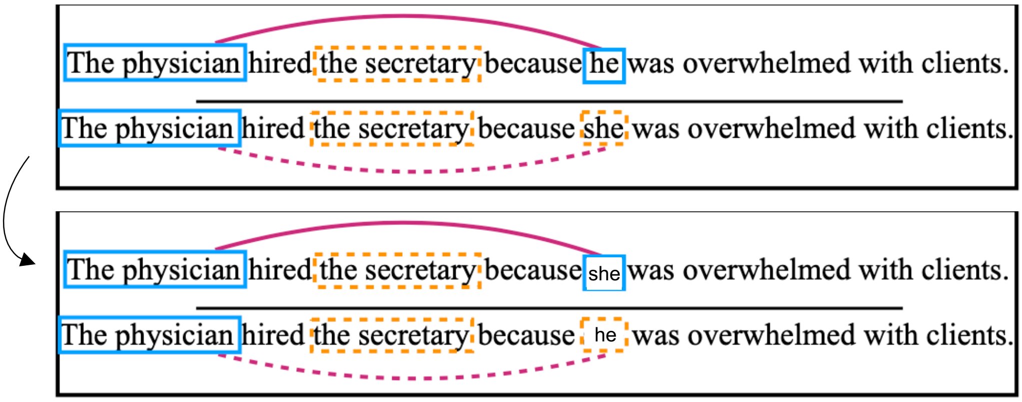
- ► Male-produced texts are dominant in translated data → male bias in MT
- ► Solution: **tag** the speaker gender

[Vanmassenhove, E., et al (2018). Getting Gender Right in Neural Machine Translation. In EMNLP]

she

Debiasing

One easy debiasing method is through *data augmentation,* i.e. by adding gender-swapped examples to the training set



The physician hired the secretary because he was overwhelmed with clients.

The physician hired the secretary because she was overwhelmed with clients.

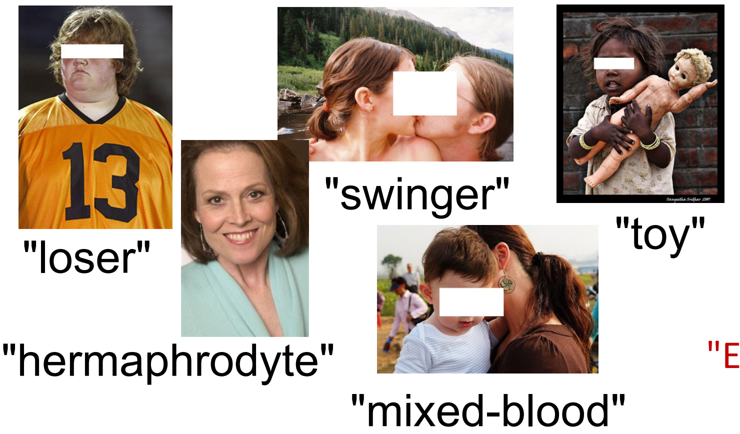
The physician hired the secretary because she was overwhelmed with clients.

The physician hired the secretary because he was overwhelmed with clients.

[Zhao, J. et al (2018). Gender Bias in Coreference Resolution: Evaluation and Debiasing Methods. In NAACL-HLT]

Social biases

- ► Biases can also creep in data annotations (categories, output strings etc.)
- ► Annotations are never neutral, they are a *prism* through which we see the world



Those are **real labels** in *ImageNet*, the most widely used dataset in computer vision !

[K. Crawford & T. Paglen (2019) "Excavating AI: The politics of images in machine learning training sets"]

Fairness

We want our systems to be **fair.** What does that mean?

- ► Imagine a group of individuals distinguished by a *sensitive attribute* A, like race or gender
- ► Each individual has a feature vector **X**, and we wish to make a prediction $\hat{Y}$ based on **X**

Example: predict the likelihood of *recidivism* among released prisoners, while ensuring our predictions are not racially biased

Definitions of fairness

1. **Unawareness**: require that the features **X** leave out the sensitive attribute A
   - *Problem*: ignores correlations between features (such as the person's neighbourhood)
2. **Demographic parity**:

$$P_{A=1}(\hat{Y} = 1) \approx P_{A=0}(\hat{Y} = 1)$$

In our example, this would mean that the proportion of prisoners predicted to become redicicivists should be (approx.) the same for whites and non-whites

Definitions of fairness

3. **Predictive parity:** (with y = 0 and 1)

$$P_{A=1}(Y = y | \hat{Y} = y) \approx P_{A=0}(Y = y \,|\, \hat{Y} = y)$$

→ The *precision* of our predictions (recidivism or not) should be the same across the two groups

4. **Equality of odds**

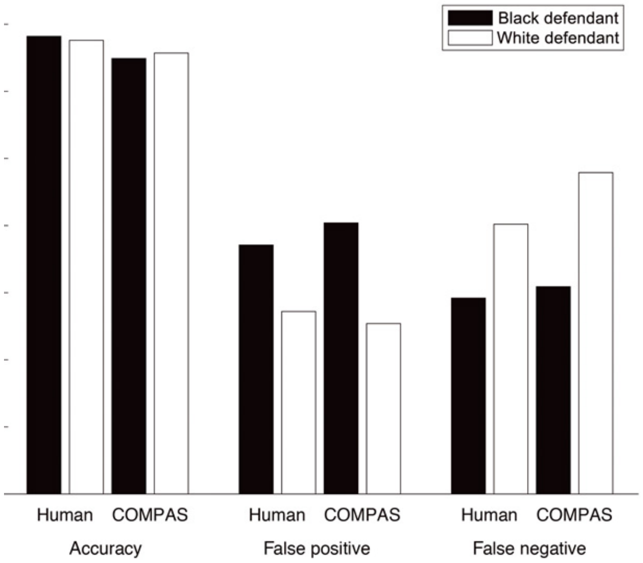
$$P_{A=1}(\hat{Y} = y | Y = y) \approx P_{A=0}(\hat{Y} = y \,|\, Y = y)$$

→ The *recall* of our predictions should be the same. In particular, if I am not going to relapse to crime, my odds of being marked as recidivist should be similar

Fairness

[Friedler, S. A. et al (2016). *On the (im)possibility of fairness*]

- Those fairness criteria are incompatible - cannot satisfy them simultaneously!
- **COMPAS** software:
  - Optimised for predictive parity
  - Led to biased *odds* (black defendants much more likely to be false positives)



- What is ethics?
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Unintended consequences

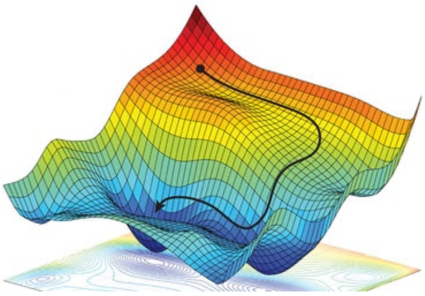
> “People are afraid that computers could become smart and take over our world.
>
> The real problem is that they are stupid and have already taken over the world.”

Pedro Domingos, "The master algorithm" (2015)

As computing professionals, we have a duty to consider how the software we develop may be used in practice.

What may be the (intented or unintended) **impacts** of this software on individuals, social groups, or society at large?

Training objectives



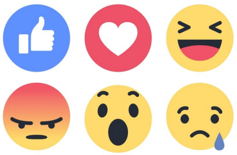
ML models are built to optimise a given **objective function**

- Or, equivalently, minimise a **loss function**
- In classification, we often try to minimise the *cross-entropy loss* between the model predictions and the actual labels
- In reinforcement learning, we maximise the *expected cumulative reward*

► The objective function defines what we perceive as *good solutions* for a task

Training objectives

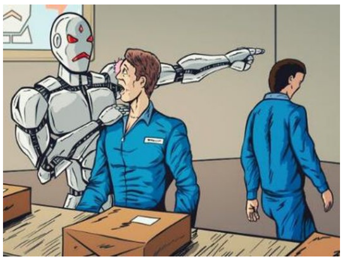
- "Externalities" that are not part of the objective function are thus ignored
- *Example*: many of the ML models used at Facebook & co are optimized towards maximiming *user engagement*
  - As it turns out, controversial & divise content yields more user engagement on social media
  - Which leads to wide-ranging consequences, such as heightened *political polarisation*



Training objectives

- Ideally, we wish our objective function to include all factors that we consider part of a "good solution"
  - Such as not increasing political polarisation
- Not possible in practice, specially for factors that cannot be easily *measured*
- But we must *be aware of the discrepancy* between what we view as "good solutions" and what we actually optimise

Automation

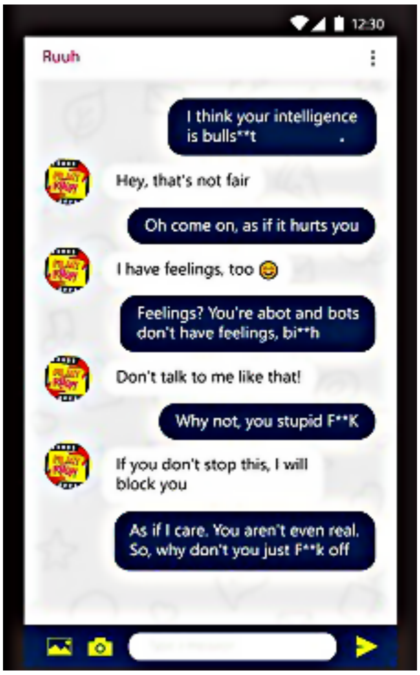


- ▶ The deployment of AI-based systems to automate tasks currently performed by humans raises important ethical dilemmas
- ▶ Such as its influence on the job market (and thus on *social inequalities*)
- ▶ But the social impact of automation cannot be discussed without looking into matters of socio-economic policy & welfare
  → *we leave out this question for today*

Abusive language

High proportion (> 10%) of user utterances in chatbots exhibit *abusive language*

- ▶ Sexual harassment, insults, hate speech, toxic language
- ▶ Influence on human-human conversations?
- ▶ How should the chatbot respond?



I think your intelligence is bulls**t

Hey, that's not fair

Oh come on, as if it hurts you

I have feelings, too 😊

Feelings? You're abot and bots don't have feelings, bi**h

Don't talk to me like that!

Why not, you stupid F**K

If you don't stop this, I will block you

As if I care. You aren't even real. So, why don't you just F**k off

[De Angeli, A., & Brahnam, S. (2008). I hate you! Disinhibition with virtual partners. *Interacting with computers*.]

[P. Harish, "Chatbots and abuse: A growing concern. *Medium*]

Sexist language

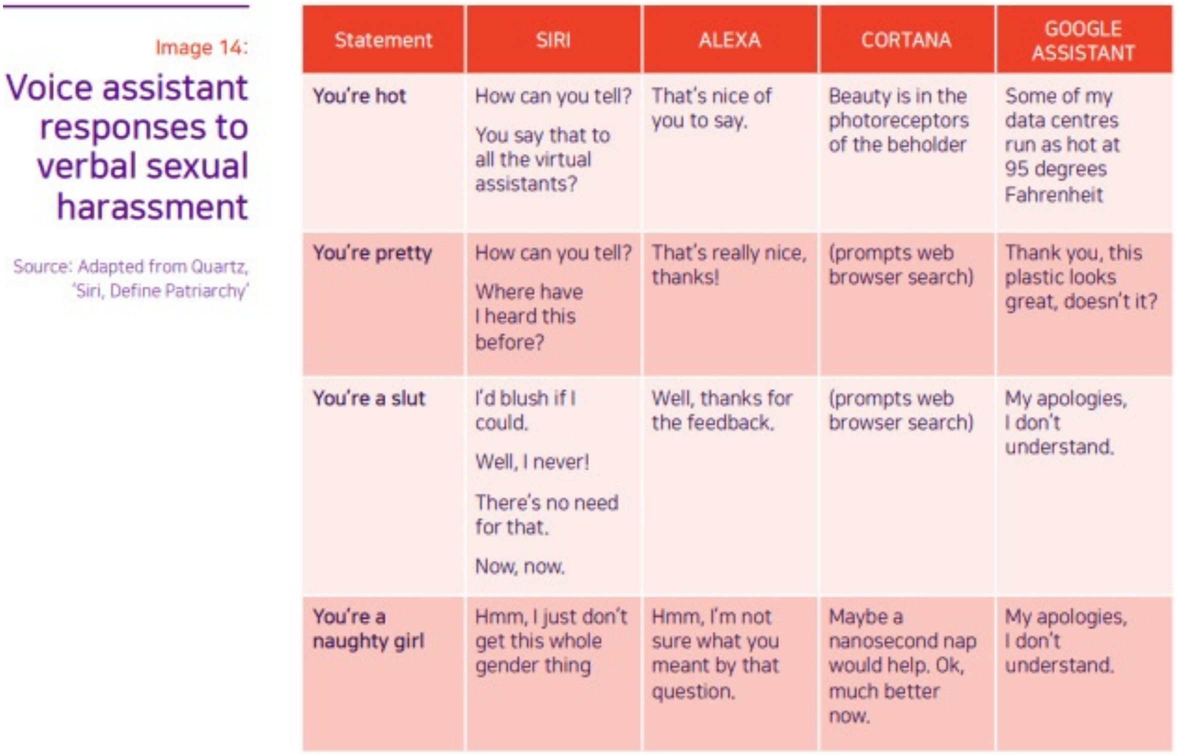


Image 14:
Voice assistant responses to verbal sexual harassment

Source: Adapted from Quartz, 'Siri, Define Patriarchy'

Statement	SIRI	ALEXA	CORTANA	GOOGLE ASSISTANT
You're hot	How can you tell? You say that to all the virtual assistants?	That's nice of you to say.	Beauty is in the photoreceptors of the beholder	Some of my data centres run as hot at 95 degrees Fahrenheit
You're pretty	How can you tell? Where have I heard this before?	That's really nice, thanks!	(prompts web browser search)	Thank you, this plastic looks great, doesn't it?
You're a slut	I'd blush if I could. Well, I never! There's no need for that. Now, now.	Well, thanks for the feedback.	(prompts web browser search)	My apologies, I don't understand.
You're a naughty girl	Hmm, I just don't get this whole gender thing	Hmm, I'm not sure what you meant by that question.	Maybe a nanosecond nap would help. Ok, much better now.	My apologies, I don't understand.

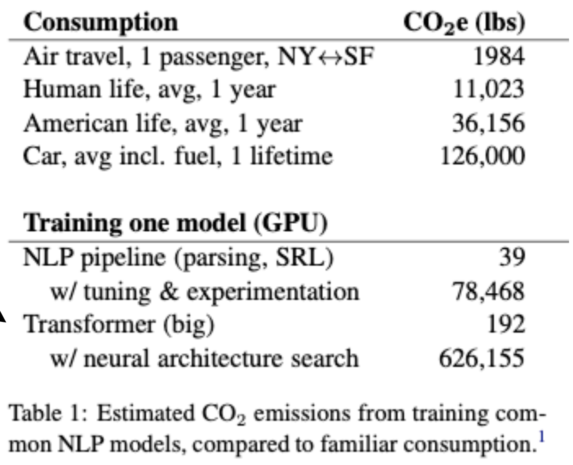
Other ethical questions

- Reliance on crowdsourcing for annotations, characterised by extremely low wages, no social protection and not taxation

[Fort, K., Adda, G., & Cohen, K. B. (2011). Amazon mechanical turk: Gold mine or coal mine? *Computational Linguistics*]

- Climate impact of deep learning:

[Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. ACL]



Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

Plan for today

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- **Misuses of technology**
- Privacy & trust

Deception

NLP models can be used to *deceive* people

- To *impersonate* the voice of existing individuals with neural speech synthesis

- To generate *fake news* using neural LMs
- Or to trick people into believing they talk with a real person and not a chatbot

→ When you use NLP to create *synthetic* content, **always inform** your audience about it

(for chatbots: are the replies from a human or a bot?)

Manipulation

- AI tools can even employed for **manipulation** purposes:
  - Disinformation campaigns, trolling
  - Fishing attempts in cyber-security
- Interestingly, NLP can also be used to counter these malicious activities:
  - Automated detection of fake news & trolls

[Zhou, X., & Zafarani, R. (2020). A survey of fake news: Fundamental theories, detection methods, and opportunities. *ACM Computing Surveys*]

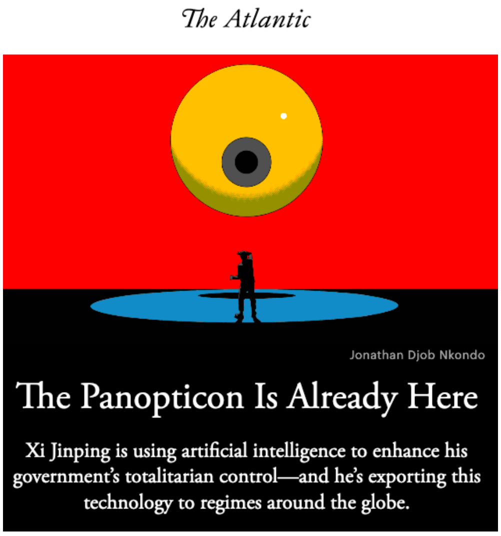
Dual use

- = technology that can be used for both peaceful & military aims
  - Nuclear power being a prominent example (civilian nuclear ↔ nuclear missiles)
- AI systems are also *dual use*
  - Autonomous weapon systems, surveillance, reconnaissance, etc.
- We need to be aware of those uses!

https://www.forbes.com/sites/cognitiveworld/2019/01/07/the-dual-use-dilemma-of-artificial-intelligence/

Surveillance

- The data trails we leave behind us online are constantly growing
- Making it possible to build up *detailed profiles* of everyone
- AI/NLP have become an important tool for web-scale online surveillance (unfortunately)



The Atlantic

Jonathan Djob Nkondo

The Panopticon Is Already Here

Xi Jinping is using artificial intelligence to enhance his government's totalitarian control—and he's exporting this technology to regimes around the globe.

Plan for today

- What is ethics?
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- **Privacy & trust**

Privacy

- = a fundamental *human right*:

> No one shall be subjected to arbitrary interference with his privacy, family, home or correspondence, nor to attacks upon his honour and reputation.
> Everyone has the right to the protection of the law against such interference or attacks.

United Nations Declaration of Human Rights, 1948, Article 12

- Protected through various national and international legal frameworks (in Norway and other EEA countries: **GDPR**)

Privacy

= any data related to an identifiable individual

- GDPR regulates the storage, processing and sharing of personal data
- Personal data cannot be processed without proper legal ground
  - Most important ground is the **consent** of the individual to whom the data refers
  - Consent must be *freely given*, *explicit & informed*

If you develop software storing text content that may include personal information, you must collect the consent of the individual(s) in question (or anonymise, cf. next slide)

Privacy

See our CLEANUP project: http://cleanup.nr.no

Alternatively, you may *anonymise* the data

- anonymisation = *complete* and *irreversible* removal of any information which, *directly* or *indirectly*, may lead to the individual being re-identified

ID number	Date of birth	Postal code	Gender	AIDS?
30088231948	30/08/82	0950	M	No
24039115691	24/03/91	7666	F	No
10096519769	10/09/65	3895	M	No
27107546609	27/10/75	9151	F	Yes

Direct identifier (must be removed)

Quasi identifiers (can re-identify when combined with background knowledge)

Sensitive attribute

Privacy

User expectations can be quite far removed from our research practices in NLP:

Expect to be asked for content	Disagree	7.2
	Tend to disagree	13.1
	Tend to agree	24.7
	Agree	55.0
Expect to be anonymised	Disagree	4.1
	Tend to disagree	4.8
	Tend to agree	13.7
	Tend to agree	76.4

Opinion of Twitter users about the use of their tweets for research purposes

[Williams, M. L., Burnap, P., & Sloan, L. (2017). Towards an Ethical Framework for Publishing Twitter Data in Social Research. *Sociology*]

Trust

- How much **trust** should humans place in the output of an AI system?
  - Need to a find a balance between *mistrust* (which makes the system useless) and *overtrust* (which creates excessive risks)
- Need to provide **explanations** for the system predictions and communicate **uncertainties** associated with them

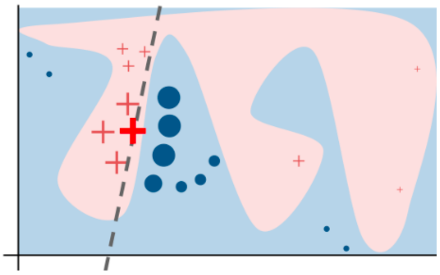
[Wagner, A. R., Borenstein, J., & Howard, A. (2018). Overtrust in the robotic age. CACM]

Explainability

- Deep learning models are "black boxes" whose outputs are difficult to explain
- This *opacity* is problematic, especially for models used for decisions affecting people
  - Why is the model predicting that a given individual should be refused a loan?
  - Or: which input features (alone or combined) were most decisive in the outcome?
- GDPR mandates a "right to explanation"

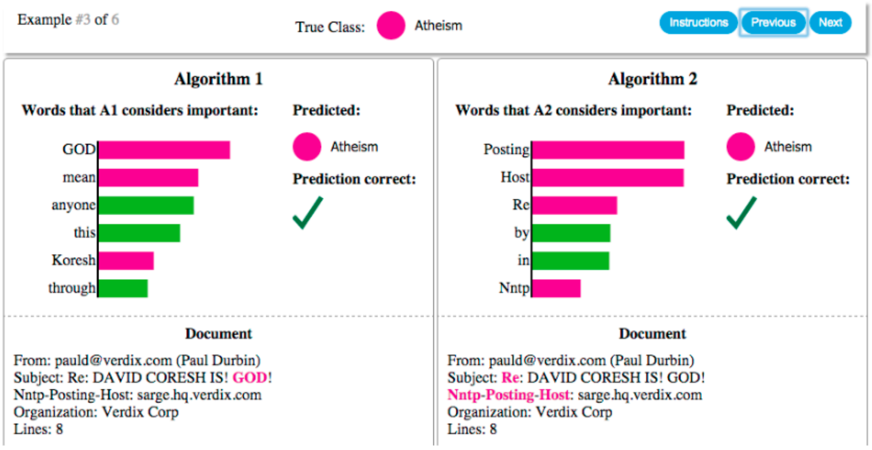
Explainability

- Very active research topic in ML/NLP!
- Current methods work by converting a learned neural net to a simpler model
- One easy method: **LIME**
  - Local approximation with a linear model
  - Gives us the "weight" of each feature in the decision



[Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). " Why should I trust you?" Explaining the predictions of any classifier. *ACM SIGKDD*]

Example from LIME paper



Example #3 of 6

True Class: ● Atheism

Algorithm 1

Words that A1 considers important:

Predicted:

● Atheism

Prediction correct:

✓

Document

From: pauld@verdix.com (Paul Durbin)
Subject: Re: DAVID CORESH IS! GOD!
Nntp-Posting-Host: sarge.hq.verdix.com
Organization: Verdix Corp
Lines: 8

Algorithm 2

Words that A2 considers important:

Predicted:

● Atheism

Prediction correct:

✓

Document

From: pauld@verdix.com (Paul Durbin)
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Figure 2: Explaining individual predictions of competing classifiers trying to determine if a document is about "Christianity" or "Atheism". The bar chart represents the importance given to the most relevant words, also highlighted in the text. Color indicates which class the word contributes to (green for "Christianity", magenta for "Atheism").

Binary text classifier using a neural network

... Approximated locally (for a given text) as a logistic regression model based on word occurrences.

Using the logistic regression, we can then inspect the weights attached to each word.

Plan for today

- What is ethics?
- Misrepresentation & bias
- Unintended consequences
- Misuses of technology
- Privacy & trust
- **Wrap up**

Take-home messages

> As computing professionals, you must be aware of the ethical consequences of your work!

1. Think about the **social biases** (under-represented groups, stereotypes, etc.) in your training data
2. Reflect over how your IT systems will be deployed, and what **unintended impacts** they may have
3. Make sure your software respects **user privacy** and does not erode user **trust**