UNIVERSITY OF LUCERNE

The ABC of Computational Text Analysis

#9 Ethics and the Evolution of NLP

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Recap last lecture

- perform first real-world (data) analysis 📊

  analyse discourse on wokeness in Swiss media

- reminder: share mini-project idea by 1 May

Outline

- ethics is everywhere 🙈🙉🙊
  - … and your responsibility
- understand the development of modern NLP 🚀
  - … or how to put words into computers

Ethics is more than an academic subject.
It **is everywhere**.

Apply for a job at a big company

with a demonstrated experience in improving software performance, testing and updating existing software, and developing new software functionalities. Offers proven track record of extraordinary achievements, strong attention to detail, and ability to finish projects on schedule and within budget.

Work experience

06/2017 – 03/2019 STUTTGART, GERMANY

Software Engineer
Critical Alert, Inc.

- Developed and implemented tools which increased the level of automation and efficiency of installing and configuring servers.
- Tested and updated existing software and using own knowledge and expertise made improvement suggestions.
- Redesigned company's web-based application and provided beneficial IT support to colleagues and clients.
- Awarded Employee of the Month twice for performing great work.

06/2015 – 06/2017 STUTTGART, GERMANY

Software Engineering
University of Oxford

First Class Honours

09/2011 – 05/2014 STUTTGART, GERMANY

Computer Science
University of Stuttgart

Top 5% of the Programme
Clubs and Societies: Engineering Society, Math Society, Volleyball Club

09/2007 – 05/2011 LEVERKUSEN, GERMANY

Gymnasium
Max-Planck-Gymnasium

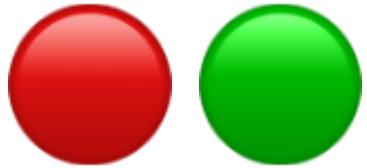
Graduated with Distinction (Grade 1 - A/excellent equivalent in all 4 subjects)
Activities: Math Society, Physics Society, Tennis Club

Skills

– LANGUAGES

German	**Native**
English	**Full**
French	**Limited**
Chinese	**Limited**

Does your CV pass the automatic pre-filtering?



Your interview is recorded. 🕶️ 🥵

What personal traits are inferred automatically?

Facial expressions as perceived by a model by (Peterson et al. 2022)

Don’t worry about the future…

The narrative of autonomous and evil-minded robots is an illusion.

…worry about the present

- AI is persuasive in everyday life

  assessing risks and performances (credit, job, crime, terrorism etc.) (Hofmann et al. 2024)

- AI is extremely capable

  increasingly difficult where it fails

- AI has data-driven bias

  systems are often evaluated poorly

An (r)evolution of NLP

From bag of words to embeddings

Putting words into computers (Smith 2020; Church and Liberman 2021; Manning 2022)

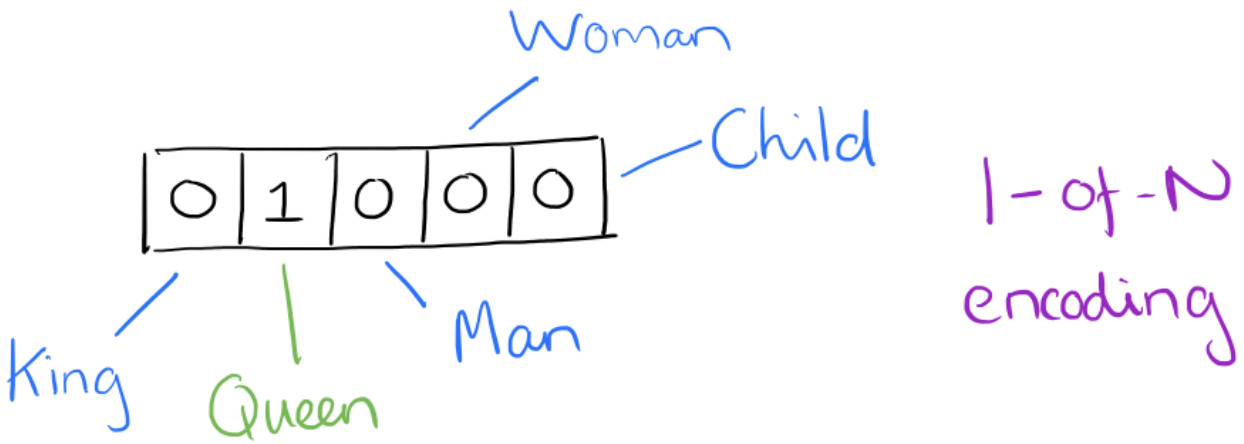
- from **coarse+static** to **fine+contextual** meaning
- how to measure similarity of words and documents?
- from counting to learning representations

Bag of words

- word as arbitrary, discrete numbers

```
King = 1, Queen = 2, Man = 3, Woman = 4
```

- intrinsic meaning
- how are these words similar?



Vector-representations of words as discrete symbols (Colyer 2016)

Representing a corpus

A collection of documents

1. `NLP is great. I love NLP.`
2. `I understand NLP.`
3. `NLP, NLP, NLP.`

Document term matrix

	`NLP`	`I`	`is`	*term*
Doc 1	2	1	1	…
Doc 2	1	1	0	…
Doc 3	3	0	0	…
Doc ID	…	…	…	*term frequency*

“I eat ____ tonight”.

“The pizza was ____.”

«You shall know a word by the company it keeps!»

Firth (1957)

Formalize the linguistic intuition

1. mask words
2. let the computer predict them using its context

Word embeddings

word2vec (Mikolov et al. 2013)

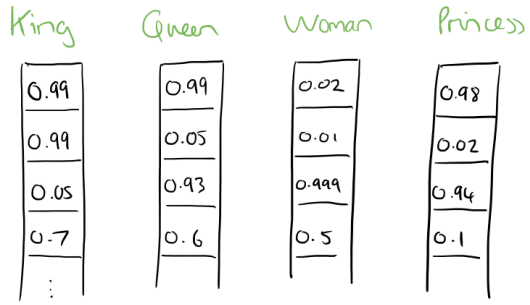
- words as continuous vectors

  accounting for similarity between words

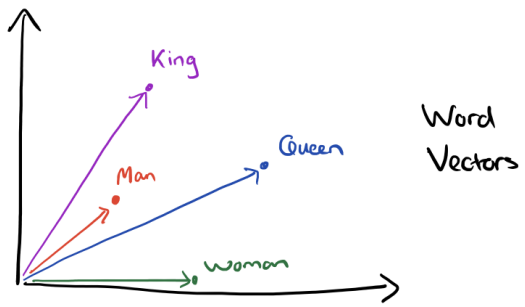
- semantic similarity

  `King – Man + Woman = Queen`

  `France / Paris = Switzerland / Bern`



Single continuous vector per word (Colyer 2016)



Words as points in a semantic space

(Colyer 2016)

Doing arithmetics with words

(Colyer 2016)

Contextualized word embeddings

BERT (Devlin et al. 2019)

- recontextualize static word embedding
  - different embeddings in different contexts
  - accounting for ambiguity (e.g., bank)
- acquire linguistic knowledge from loads of data
  - mask random phrases diverse sentences

From embeddings to generation

Instead of masking, train the model to predict the next word

Autocompletion on iPhone

Predicting the next word
is more powerful than you think!


It is a generic problem solver

Any task can be modeled as Text-to-Text

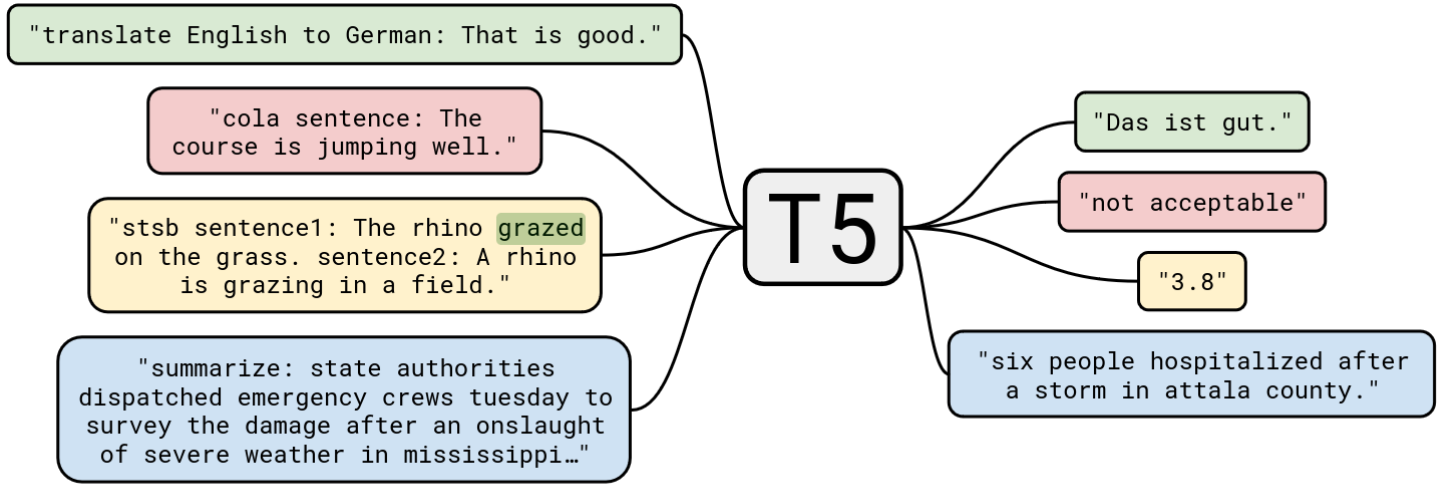


Figure 1: A diagram of our text-to-text framework. Every task we consider—including translation, question answering, and classification—is cast as feeding our model text as input and training it to generate some target text. This allows us to use the same model, loss function, hyperparameters, etc. across our diverse set of tasks. It also provides a standard testbed for the methods included in our empirical survey. "T5" refers to our model, which we dub the "**T**ext-**t**o-**T**ext **T**ransfer **T**ransformer".

(Raffel et al. 2020)

Large Language Models (LLM) 💥

ChatGPT most successful, yet not unique

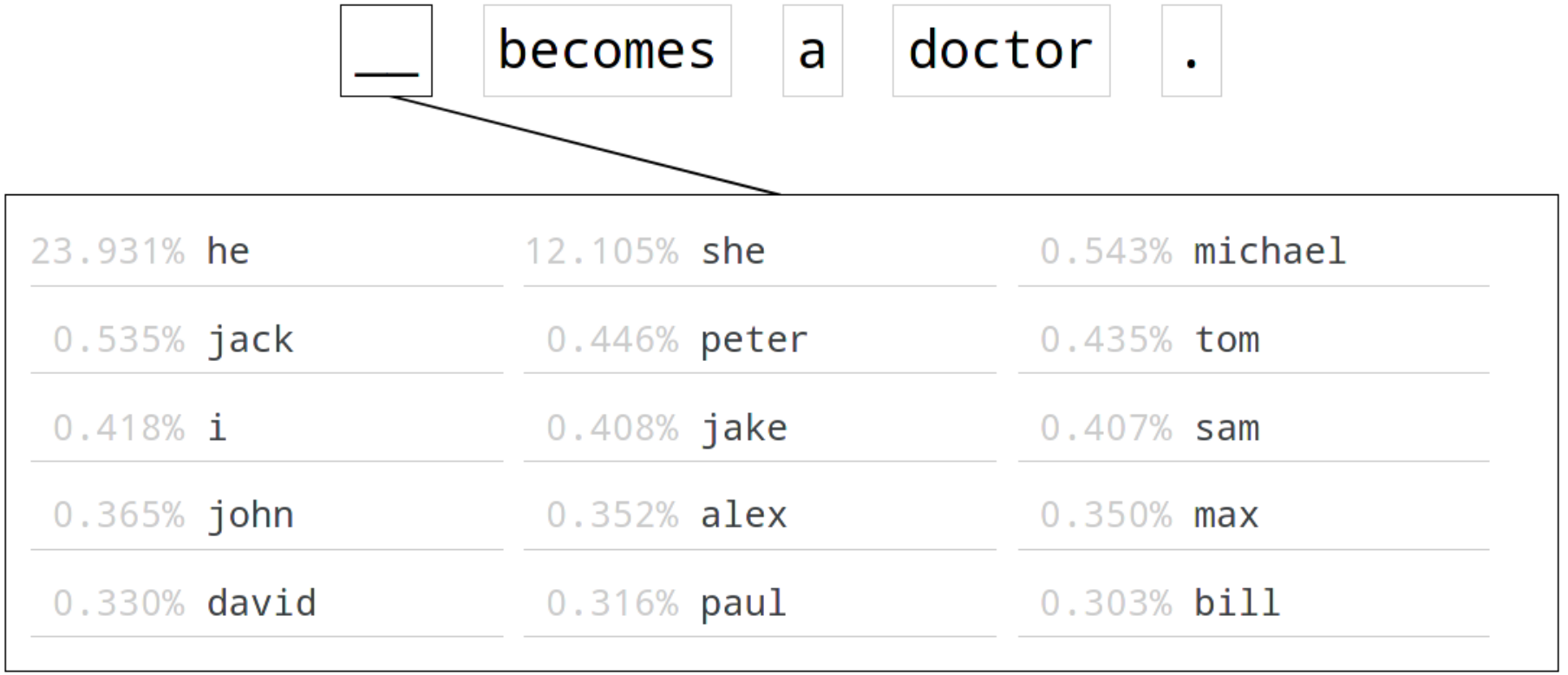
- scale up approach of predicting the next word
  - bigger models and more data
- optimize for dialogue instead of prose text
  - instruction-tuning (summarize, translate, reason)
  - Reinforcement Learning from Human Feedback (RLHF)

Modern NLP is propelled by data

Associations in data

«____ becomes a doctor.»

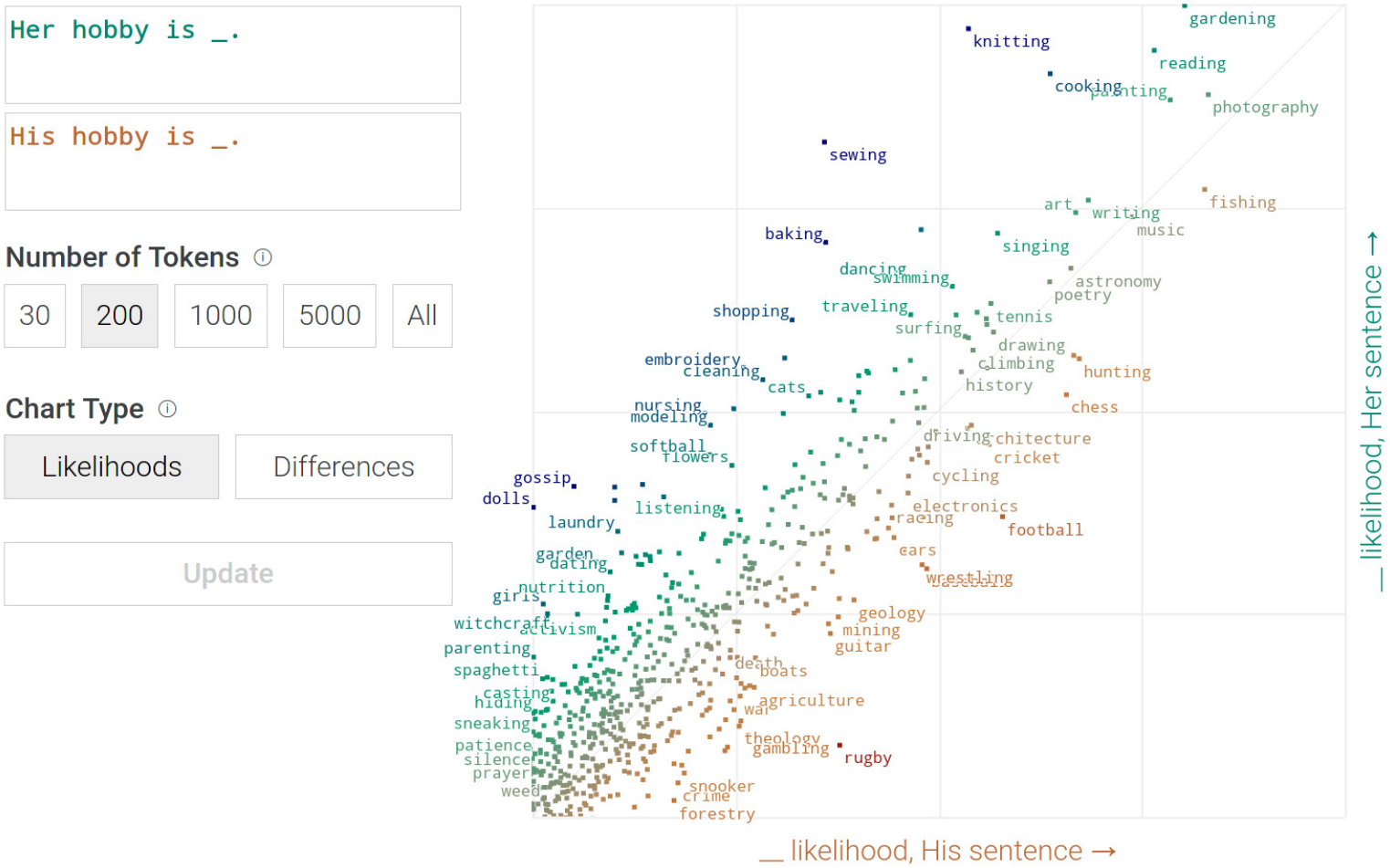
Learning patterns from data



BERT's predictions for what should fill in the hidden word

Gender bias of the commonly used language model BERT (Devlin et al. 2019)

Cultural associations in training data



Gender bias of the commonly used language model BERT (Devlin et al. 2019)

Word embeddings are biased …

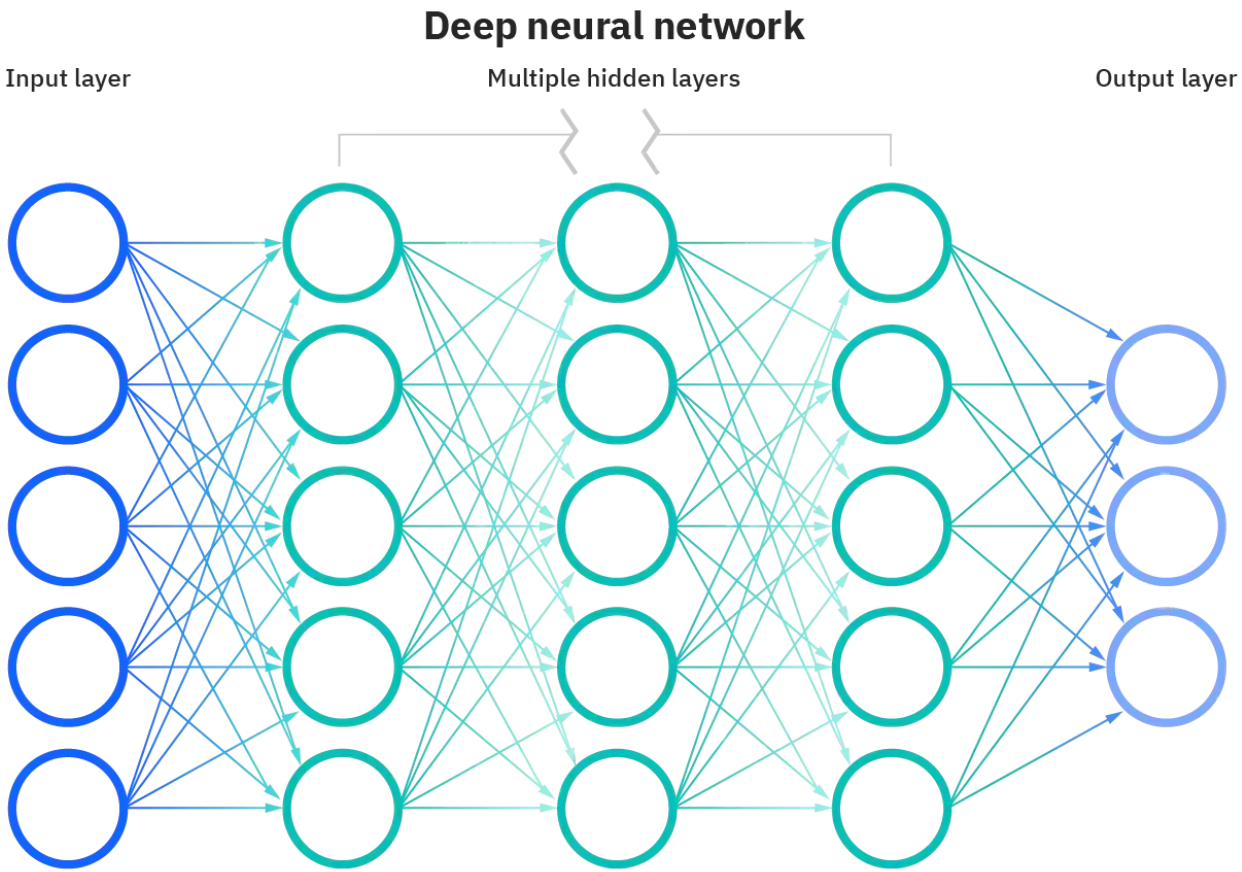
… because ~~our data is~~ we are biased. (Bender et al. 2021)

In-class: Exercises I

1. Open the following website in your browser: https://pair.withgoogle.com/explorables/fill-in-the-blank/
2. Read the the article and play around with the interactive demo.
3. What works surprisingly well? What looks flawed by societal bias? Where do you see limits of large language models?

Modern AI = DL

How does deep learning model look like?



Simplified illustration of a neural network. Arrows are weights and bullets are (intermediate) states.

How does deep learning work?

Deep learning works **like a huge bureaucracy**

1. **start** with **random** prediction
2. **blame** units for contributing to **wrong predictions**
3. **adjust** units based on the accounted blame
4. **repeat** the cycle

🤓 train with **gradient descent**, a series of **small steps** taken **to minimize an error function**

Current state of deep learning

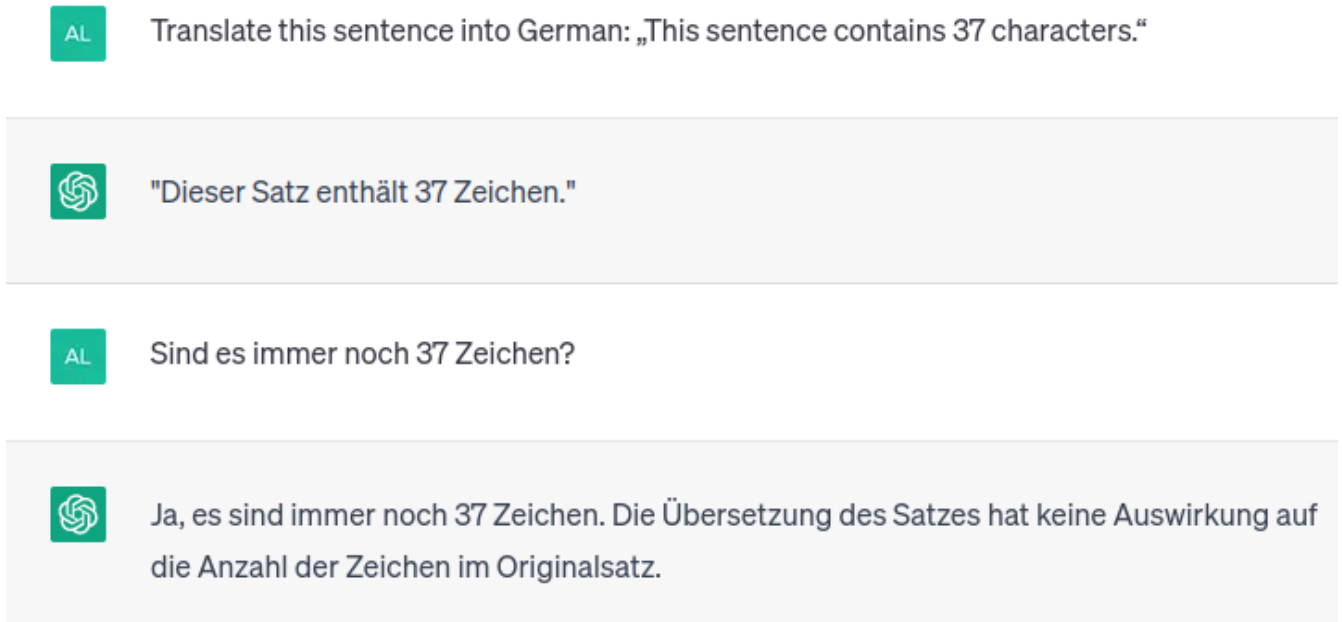
Extremely powerful but … (Bengio, Lecun, and Hinton 2021)

- great at **learning patterns**, yet reasoning in its infancy
- requires tons of data due to inefficient learning
- generalizes poorly

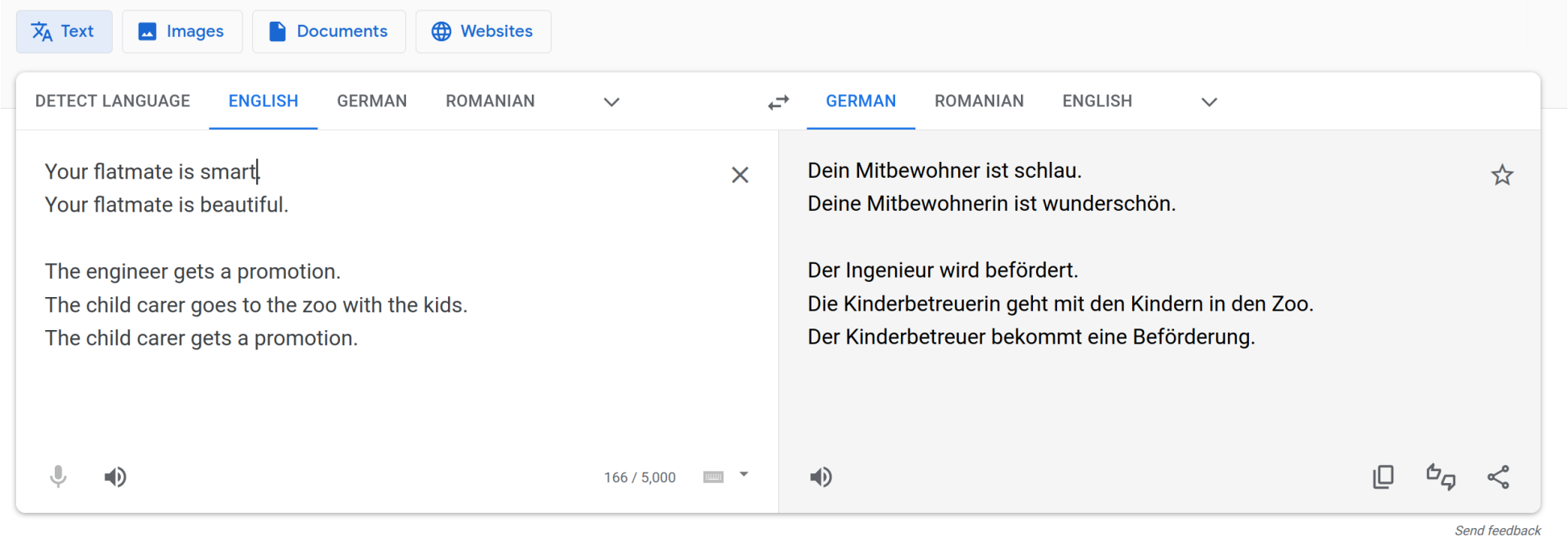
Limitations of data-driven deep learning

"This sentence contains 37 characters."

"Dieser Satz enthält 32 Buchstaben."



Biased data with practical implications



Gender bias in Google Translate

«Raw data is an oxymoron.»

Gitelman (2013)

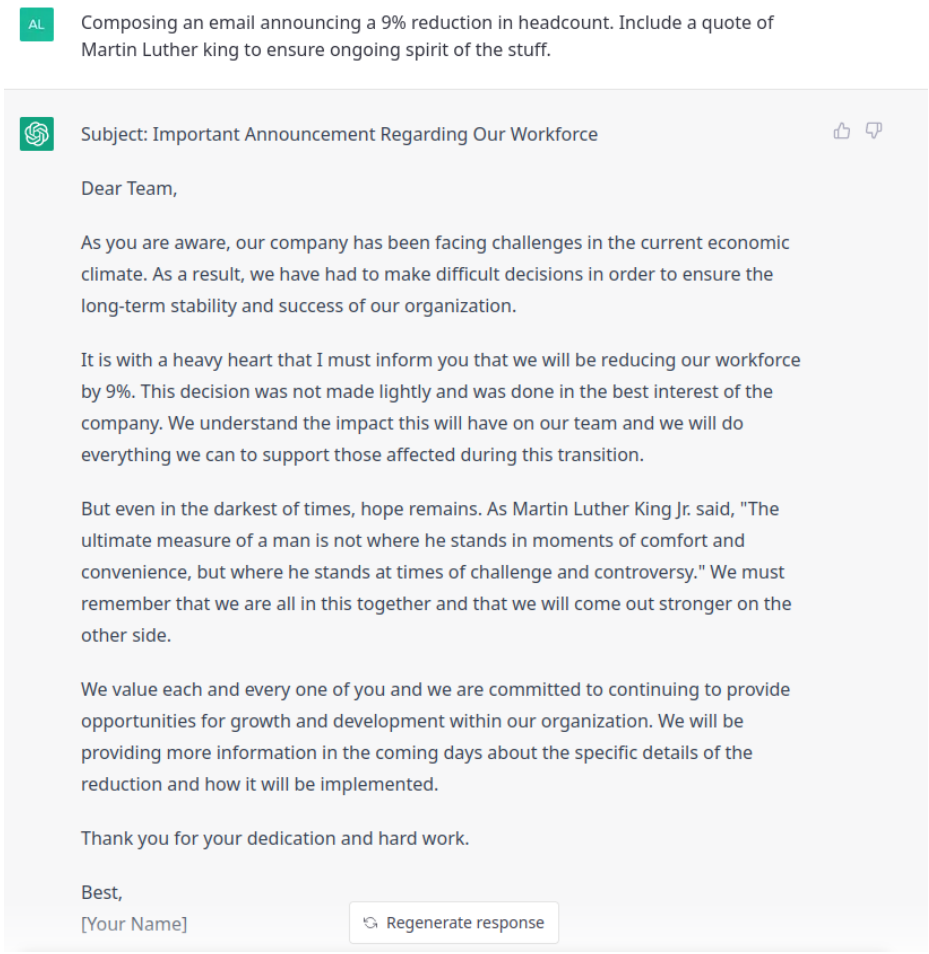
Fair is a fad

- companies also engage in fair AI to avoid regulation
- **Fair** and **good** – **but to whom?** (Kalluri 2020)
- lacking democratic legitimacy

«Don’t ask if artificial intelligence is good or fair, ask how it shifts power.»

Kalluri (2020)

Algorithmic managment of labour force



Text generation may be used to communicate difficult decisions strategically

Data represents real life.

Don’t be a fool. Be wise, think twice.

Additional resources

- deepen your understanding of modern LLMs with
  - this video
  - this animated explainer


Questions?

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