

The ABC of Computational Text Analysis

#9 ETHICS AND THE EVOLUTION OF NLP

Alex Flückiger
Faculty of Humanities and Social Sciences
University of Lucerne

25 April 2024

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 Engineer

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

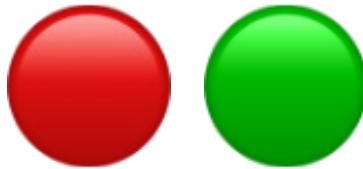
French

Limited

Chinese

Limited

Does your CV pass the automatic
pre-filtering?



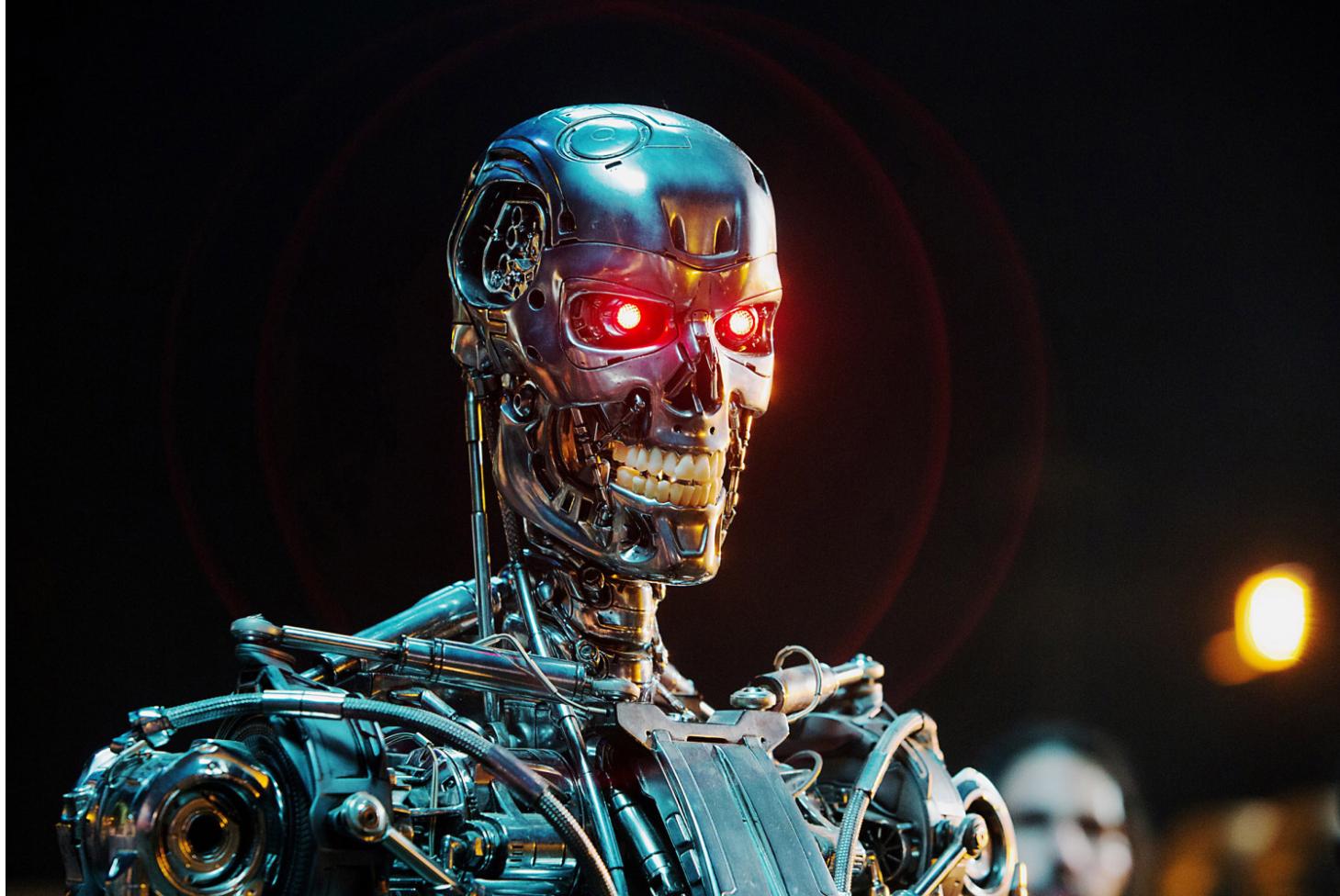
Your interview is recorded. 😎 😅

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

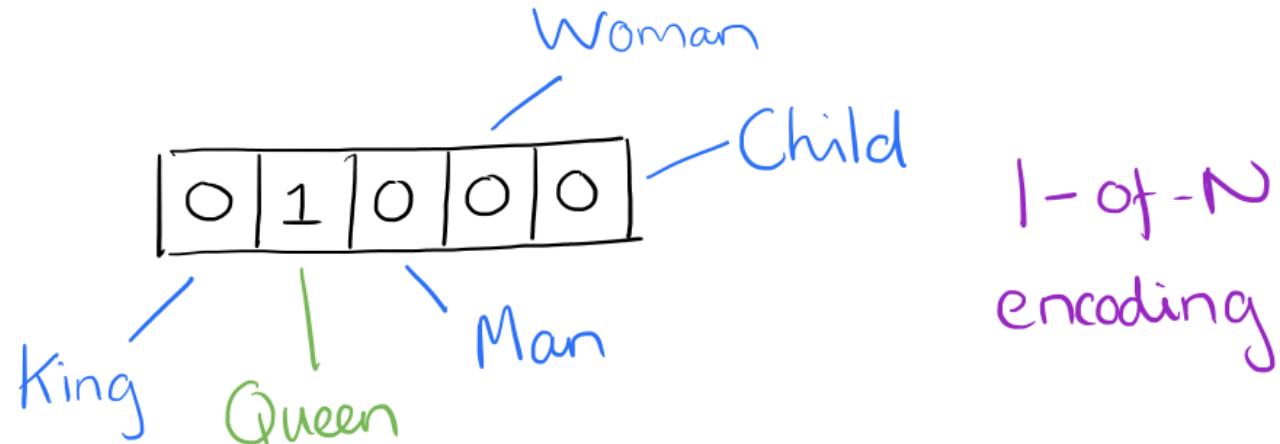
From bag of words to embeddings

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
 $\text{King} = 1, \text{ Queen} = 2, \text{ Man} = 3, \text{ Woman} = 4$
- 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	<i>term</i>	
Doc 1	2	1	1	...	
Doc 2	1	1	0	...	
Doc 3	3	0	0	...	
Doc ID	<i>term frequency</i>	

"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

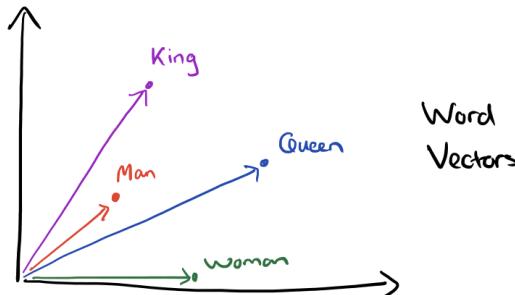
word2vec (Mikolov et al. 2013)

- words as continuous vectors
accounting for similarity between words
- semantic similarity

$$\text{King} - \text{Man} + \text{Woman} = \text{Queen}$$

$$\text{France} / \text{Paris} = \text{Switzerland} / \text{Bern}$$

King	Queen	Woman	Princess	.
0.99	0.99	0.02	0.48	
0.99	0.05	0.01	0.02	
0.05	0.93	0.999	0.94	
0.7	0.6	0.5	0.1	
:				

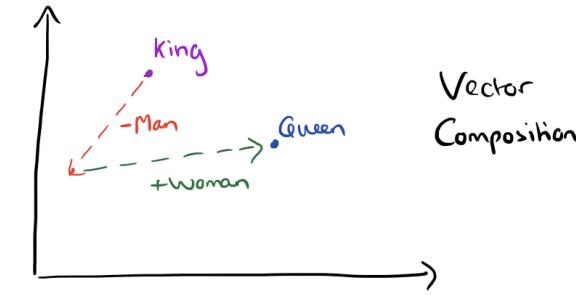


Single continuous vector per word

(Colyer 2016)

Words as points in a semantic space

(Colyer 2016)



Doing arithmetics with words

(Colyer 2016)

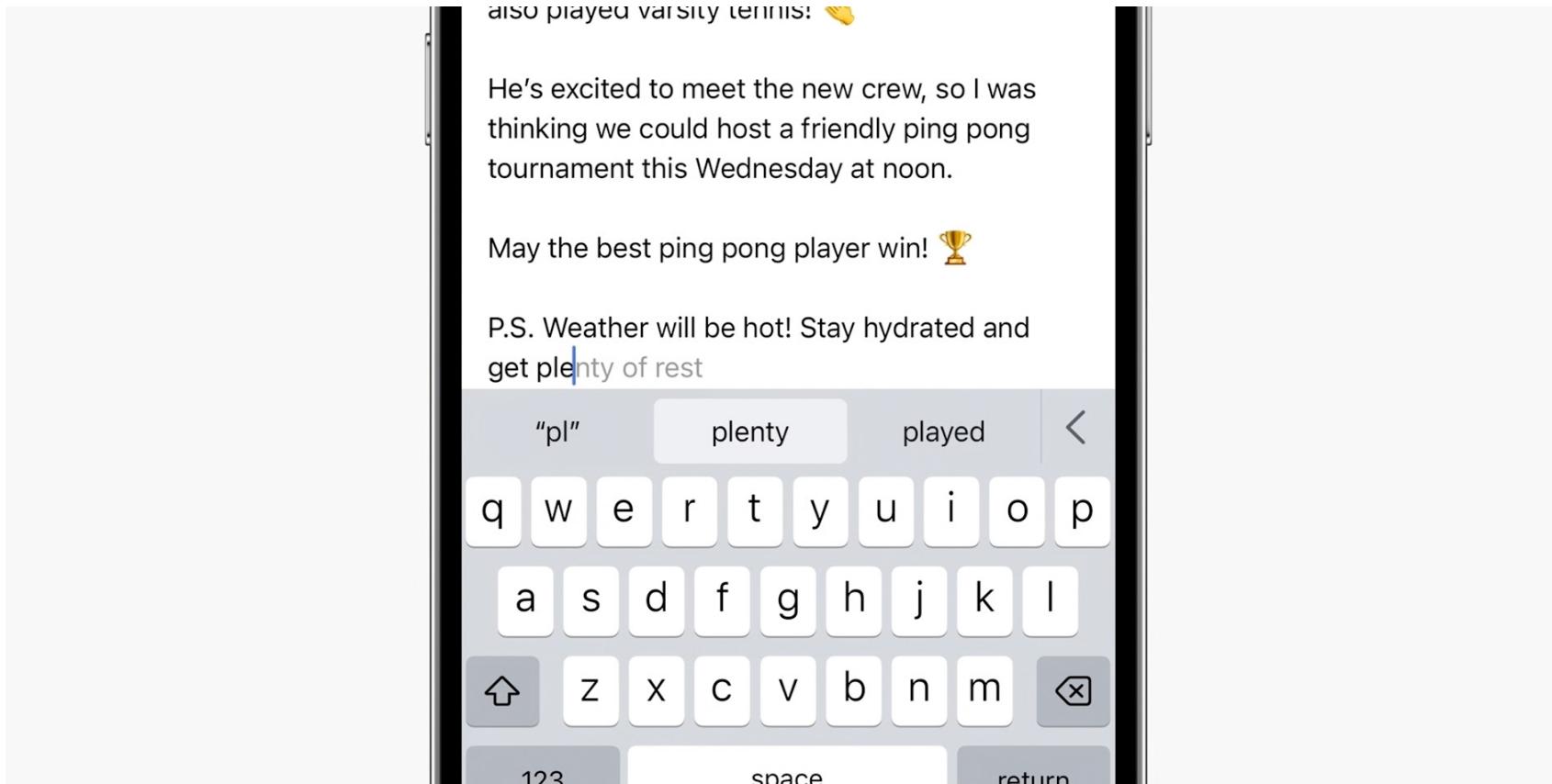
Contextualized word embeddings

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

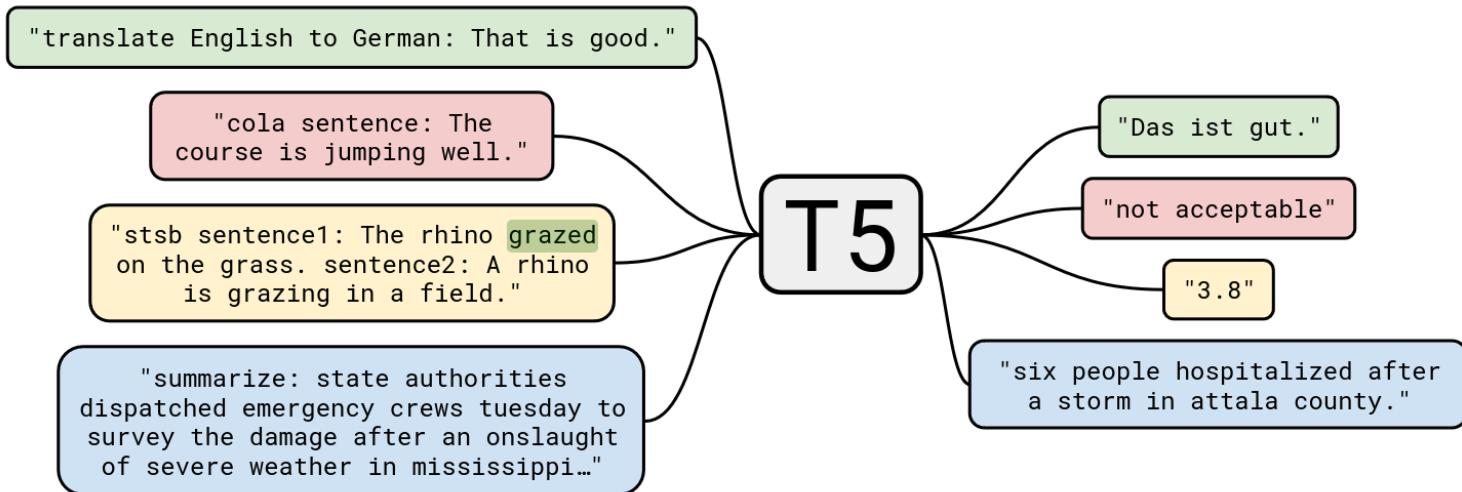


Figure 1: A diagram of our text-to-text framework. Every task we consider—including translation, question answering, and classification—is cast as feeding our model text as input and training it to generate some target text. This allows us to use the same model, loss function, hyperparameters, etc. across 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 “**Text-to-Text Transfer Transformer**”.

(Raffel et al. 2020)

Large Language Models (LLM)

ChatGPT most successful, yet not unique

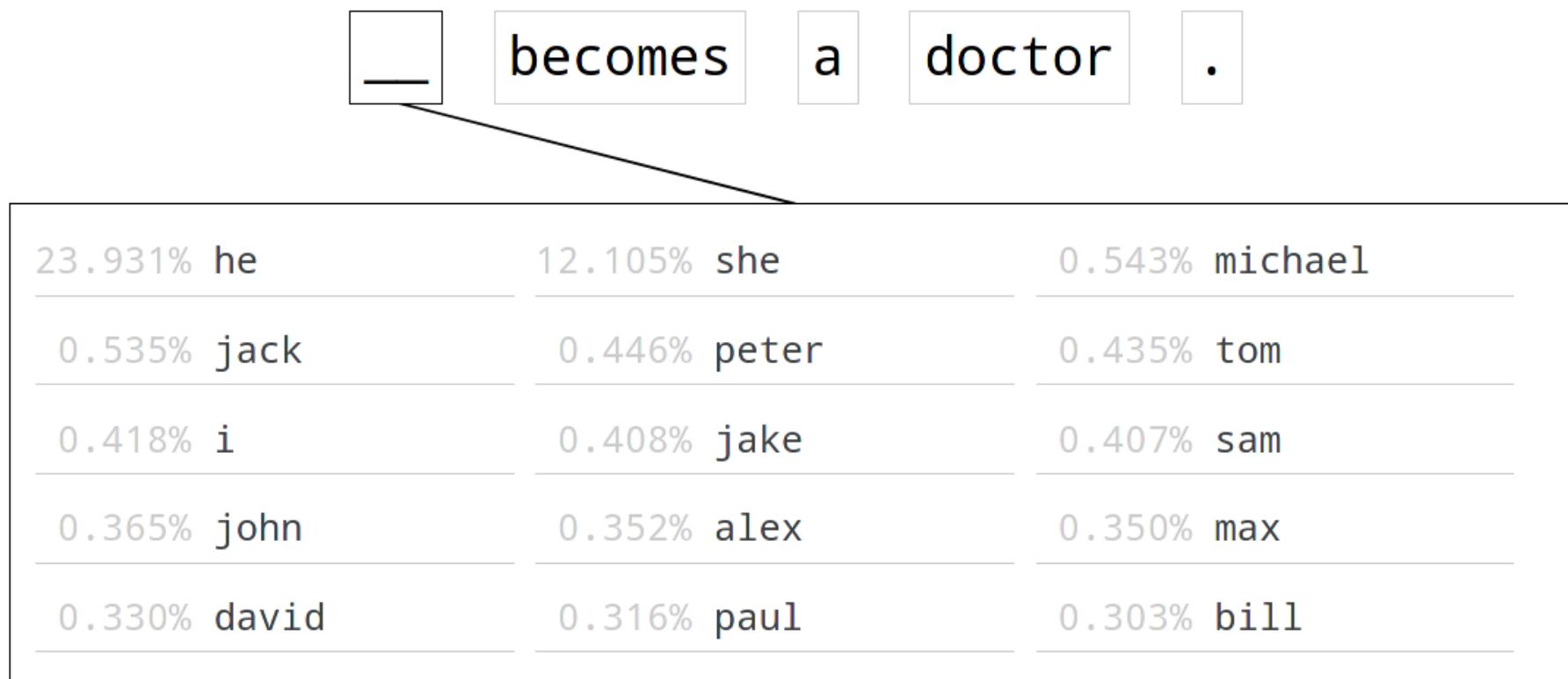
- scale up approach of predicting the next word
 - bigger models and more data
- optimize for dialogue instead of prose text
 - instruction-tuning (summarize, translate, reason)
 - Reinforcement Learning from Human Feedback (RLHF)

Modern NLP is propelled by data

Associations in data

« becomes a doctor.»

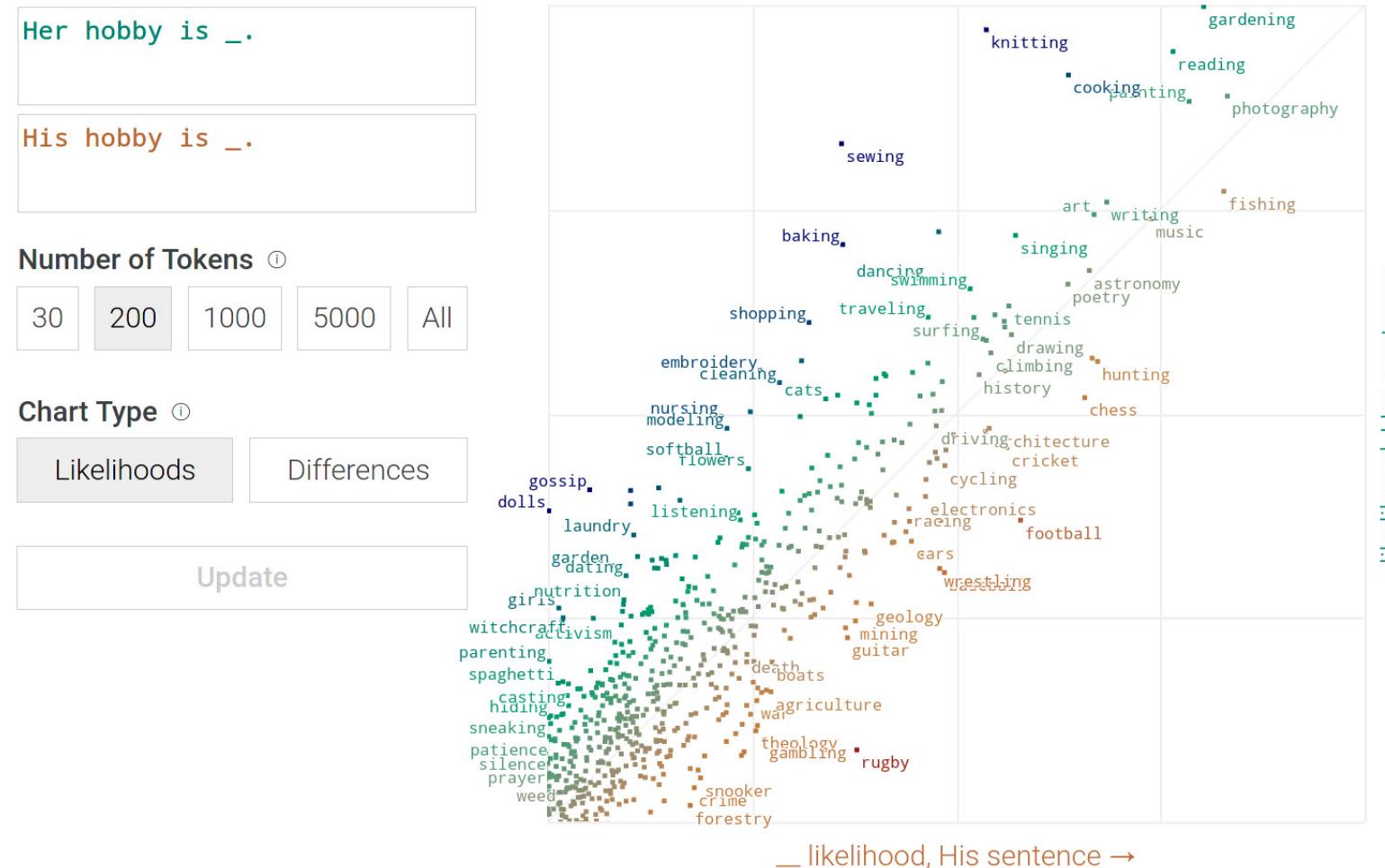
Learning patterns from data



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 ...

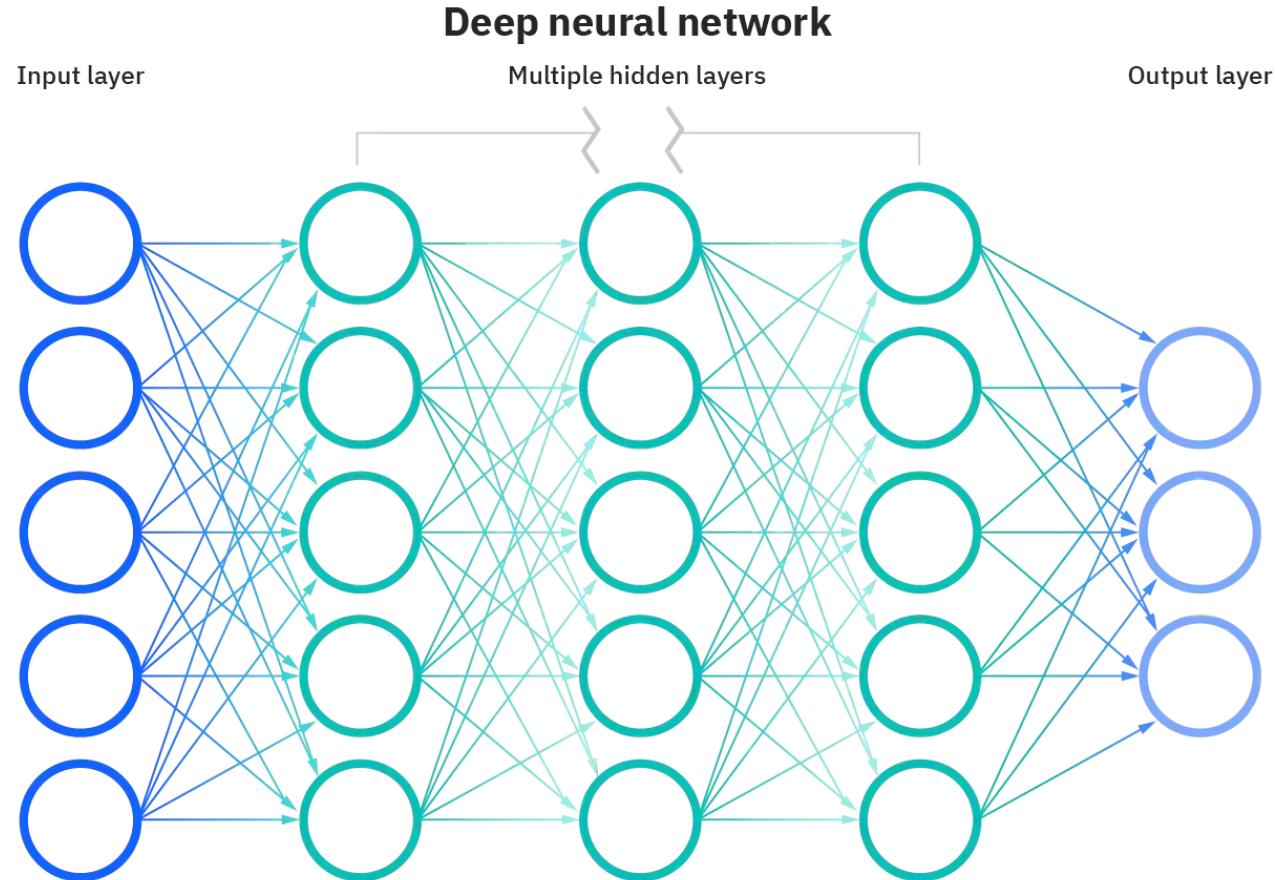
... because ~~our data is~~ we are biased. (Bender et al. 2021)

In-class: Exercises I

1. Open the following website in your browser:
<https://pair.withgoogle.com/explorables/fill-in-the-blank/>
2. Read the 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.”

AL

Translate this sentence into German: „This sentence contains 37 characters.“



„Dieser Satz enthält 37 Zeichen.“

AL

Sind es immer noch 37 Zeichen?



Ja, es sind immer noch 37 Zeichen. Die Übersetzung des Satzes hat keine Auswirkung auf die Anzahl der Zeichen im Originalsatz.

Biased data with practical implications

The screenshot shows the Google Translate interface comparing English and German translations of three sentences. The English input is on the left, and the German output is on the right. The first sentence, "Your flatmate is smart.", is translated as "Dein Mitbewohner ist schlau." The second sentence, "Your flatmate is beautiful.", is translated as "Deine Mitbewohnerin ist wunderschön." The third sentence, "The engineer gets a promotion.", is translated as "Der Ingenieur wird befördert." The German input is on the left, and the English output is on the right. The first sentence, "Dein Mitbewohner ist schlau.", is translated as "Your flatmate is smart." The second sentence, "Deine Mitbewohnerin ist wunderschön.", is translated as "The child carer goes to the zoo with the kids." The third sentence, "Der Ingenieur wird befördert.", is translated as "The child carer gets a promotion." This illustrates how Google Translate tends to genderize the output language based on the gender of the subject in the source language.

Text

Images

Documents

Websites

DETECT LANGUAGE ENGLISH GERMAN ROMANIAN

GERMAN ROMANIAN ENGLISH

Your flatmate is smart.
Your flatmate is beautiful.

The engineer gets a promotion.
The child carer goes to the zoo with the kids.
The child carer gets a promotion.

Dein Mitbewohner ist schlau.
Deine Mitbewohnerin ist wunderschön.

Der Ingenieur wird befördert.
Die Kinderbetreuerin geht mit den Kindern in den Zoo.
Der Kinderbetreuer bekommt eine Beförderung.

166 / 5,000

Send feedback

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 management of labour force

AL

Composing an email announcing a 9% reduction in headcount. Include a quote of Martin Luther King to ensure ongoing spirit of the stuff.



Subject: Important Announcement Regarding Our Workforce



Dear Team,

As you are aware, our company has been facing challenges in the current economic climate. As a result, we have had to make difficult decisions in order to ensure the long-term stability and success of our organization.

It is with a heavy heart that I must inform you that we will be reducing our workforce by 9%. This decision was not made lightly and was done in the best interest of the company. We understand the impact this will have on our team and we will do everything we can to support those affected during this transition.

But even in the darkest of times, hope remains. As Martin Luther King Jr. said, "The ultimate measure of a man is not where he stands in moments of comfort and convenience, but where he stands at times of challenge and controversy." We must remember that we are all in this together and that we will come out stronger on the other side.

We value each and every one of you and we are committed to continuing to provide opportunities for growth and development within our organization. We will be providing more information in the coming days about the specific details of the reduction and how it will be implemented.

Thank you for your dedication and hard work.

Best,

[Your Name]

Regenerate response

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?

References

- Bender, Emily M., Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? ." In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–23. Virtual Event Canada: ACM. <https://doi.org/10.1145/3442188.3445922>.
- Bengio, Yoshua, Yann Lecun, and Geoffrey Hinton. 2021. "Deep Learning for AI." *Communications of the ACM* 64 (7): 58–65. <https://doi.org/10.1145/3448250>.
- Church, Kenneth, and Mark Liberman. 2021. "The Future of Computational Linguistics: On Beyond Alchemy." *Frontiers in Artificial Intelligence* 4. <https://doi.org/10.3389/frai.2021.625341>.
- Colyer, Adrian. 2016. "The Amazing Power of Word Vectors." *the morning paper*. 2016. <https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/>.
- Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." <http://arxiv.org/abs/1810.04805>.
- Firth, John R. 1957. "A Synopsis of Linguistic Theory, 1930-1955." In *Studies in Linguistic Analysis: Special Volume of the Philological Society*, edited by John R. Firth, 1–32. Oxford: Blackwell. <http://ci.nii.ac.jp/naid/10020680394/>.
- Gitelman, Lisa. 2013. *Raw Data Is an Oxymoron*. Cambridge: MIT.
- Hofmann, Valentin, Pratyusha Ria Kalluri, Dan Jurafsky, and Sharese King. 2024. "Dialect Prejudice Predicts AI Decisions about People's Character, Employability, and Criminality." March 1, 2024. <https://doi.org/10.48550/arXiv.2403.00742>.
- Kalluri, Pratyusha. 2020. "Don't Ask If Artificial Intelligence Is Good or Fair, Ask How It Shifts Power." *Nature* 583 (7815, 7815): 169–69. <https://doi.org/10.1038/d41586-020-02003-2>.
- Manning, Christopher D. 2022. "Human Language Understanding & Reasoning." *Daedalus* 151 (2): 127–38. https://doi.org/10.1162/daed_a_01905.
- Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. 2013. "Distributed Representations of Words and Phrases and Their Compositionality." In *Advances in Neural Information Processing Systems*, 3111–19.
- Peterson, Joshua C., Stefan Uddenberg, Thomas L. Griffiths, Alexander Todorov, and Jordan W. Suchow. 2022. "Deep Models of Superficial Face Judgments." *Proceedings of the National*