The ABC of Computational Text Analysis

#8 Ethics and the Evolution of NLP

Alex Flückiger

Faculty of Humanities and Social Sciences
University of Lucerne

28 April 2022

Recap last Lecture

- assignment 2 accomplished ✅
- an abundance of data sources

  JSTOR, Nexis, few datasets
- creating your own dataset

  convert any data to `.txt`
- processing a batch of files

  perform tasks in for-loop

Outline

- ethics is everywhere 🙈🙉🙊

  … and your responsibility

- understand the development of modern NLP 🚀

  … or how to put words into computers

Ethics is more than philosophy.
It **is everywhere**.

An Example

You are applying 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?

🔴🟢

🤔 For what reasons?

Your interview is recorded. 😎 🥵
What personal traits are inferred from that?

🤔 Is it a good reflection of your personality?

Face impressions as perceived by a model by (Peterson et al. 2022)

Don’t worry about the future …

… worry about the present.

- AI is persuasive in everyday’s life

  assessing risks and performances (credits, job, crimes, terrorism etc.)

- AI is extremely capable
- AI is not so smart and often poorly evaluated

💡 What is going on behind the scene?

An (R)evolution of NLP

From Bag of Words to Embeddings

Putting Words into Computers (Smith 2020; Church and Liberman 2021)

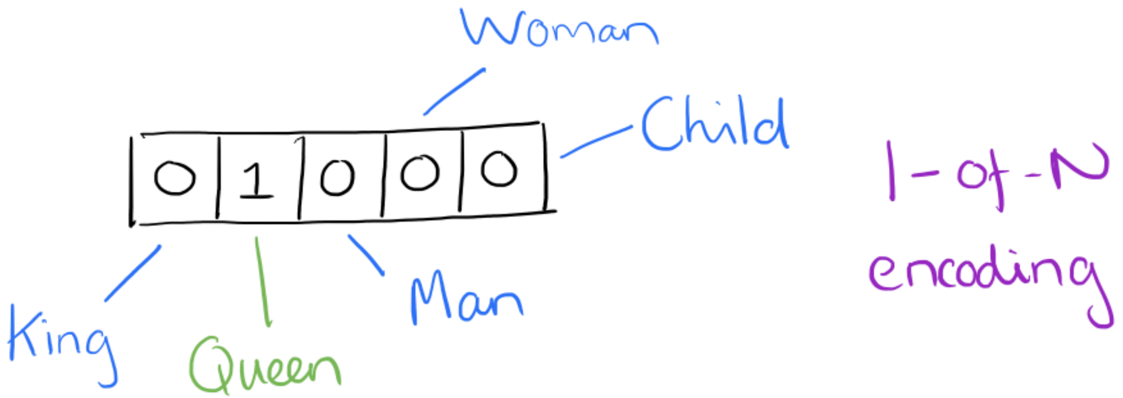
- from **coarse, static** to **fine, contextual** meaning
- how to measure similarity of words
  - string-based
  - syntactic (e.g., part-of-speech)
  - semantic (e.g., animate)
  - embedding as abstract representations
- from counting to learning representations

Bag of Words

- word as arbitrary, discrete numbers

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

- intrinsic meaning
- how are these words similar?



Discrete, symbolic words

Representing a Corpus

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 a hot ____ for lunch."

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

Firth (1957)

Word Embeddings

word2vec (Mikolov et al. 2013)

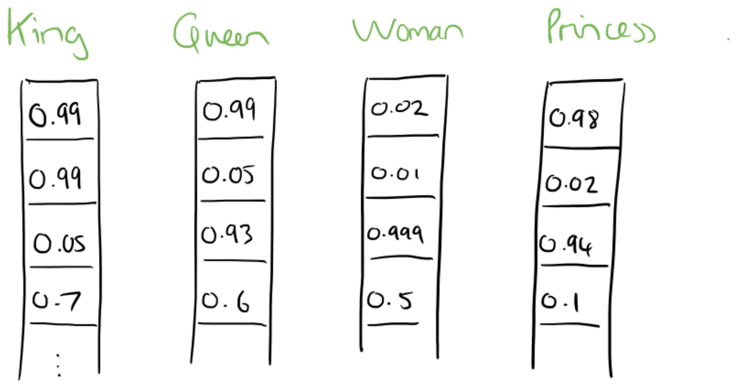
- words as continuous vectors

  accounting for similarity between words

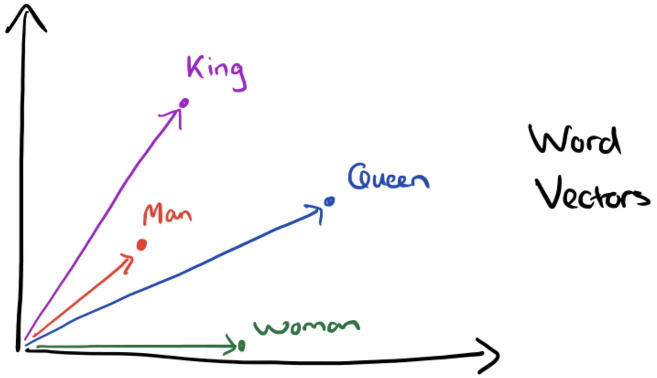
- semantic similarity

  `King - Man + Woman = Queen`

  `France / Paris = Switzerland / Bern`



Single continuous vector per word



Words as points in a semantic space

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 language models (LM)

  LM predict next/missing word

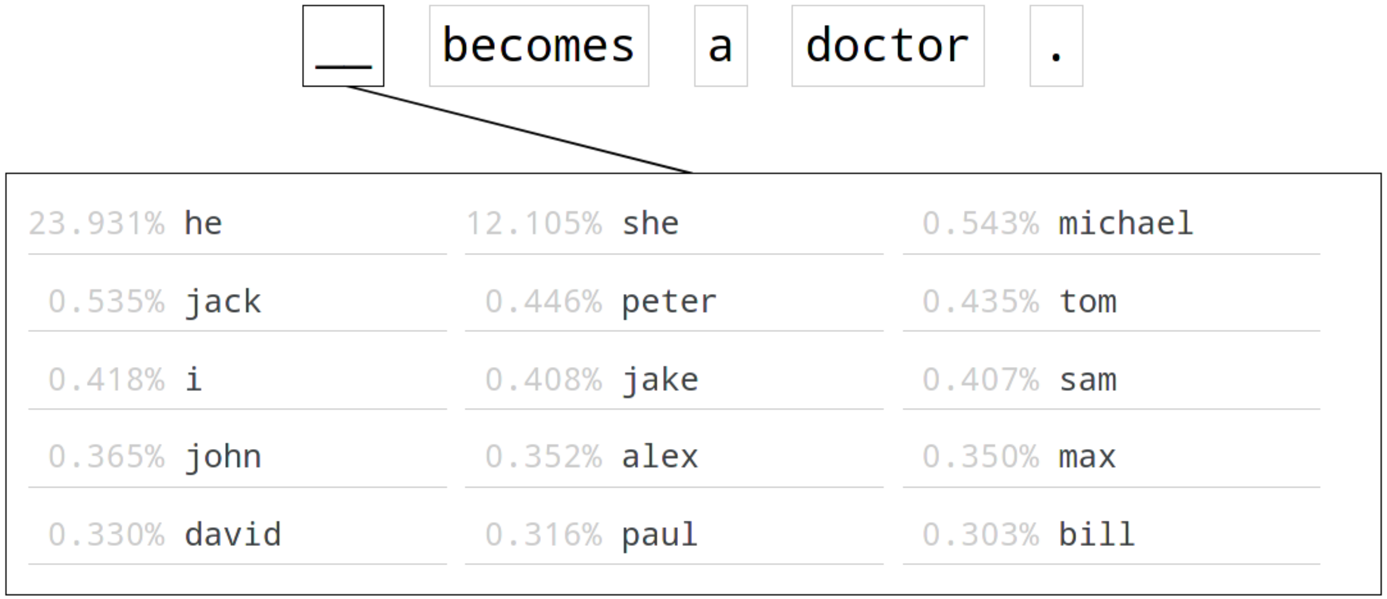
  pre-trained on massive data (> 300 billions words)

💥 embeddings are the cornerstone of modern NLP

Modern NLP is propelled by data

Learning Associations from Data

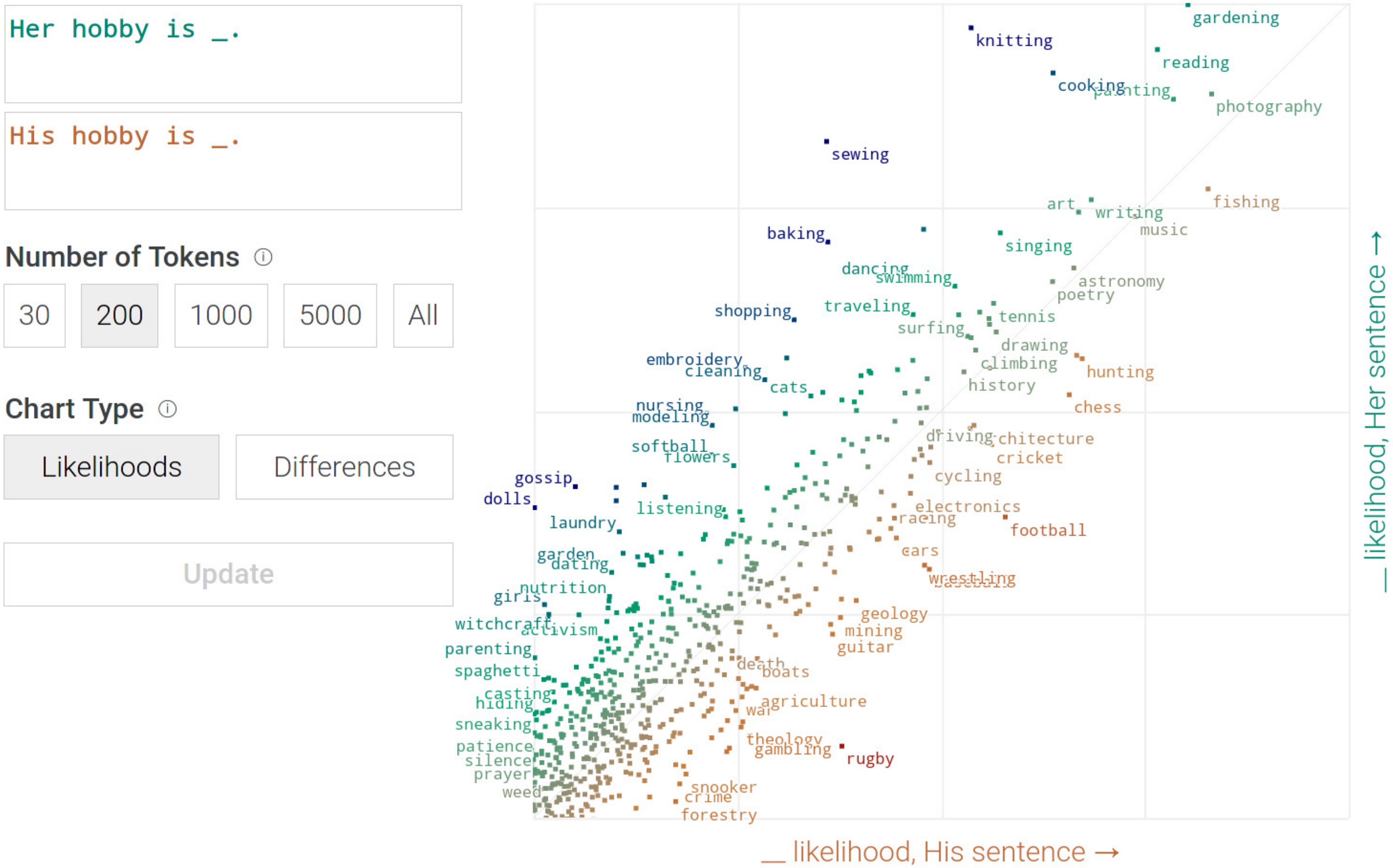
«___ becomes a doctor.»



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 is flawed by societal bias? Where do you see limits of large language models?

Modern AI = DL

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**

Limitations of data-driven Deep Learning

„This sentence contains 32 characters."

„Dieser Satz enthält 32 Buchstaben."

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

Biased Data and beyond

Data = Digital Traces = Social Artifacts

- collecting, curating, preserving traces
- **data is imperfect**, always

  social bias, noise, lack of data etc.
- data is more a **tool** to refine questions **rather than a reflection of the world**

Data vs. Capta

«Differences in the etymological roots of the terms data and capta make the distinction between constructivist and realist approaches clear. Capta is ***"taken"*** *actively while data is assumed to be a* ***"given"*** *able to be recorded and observed.»*

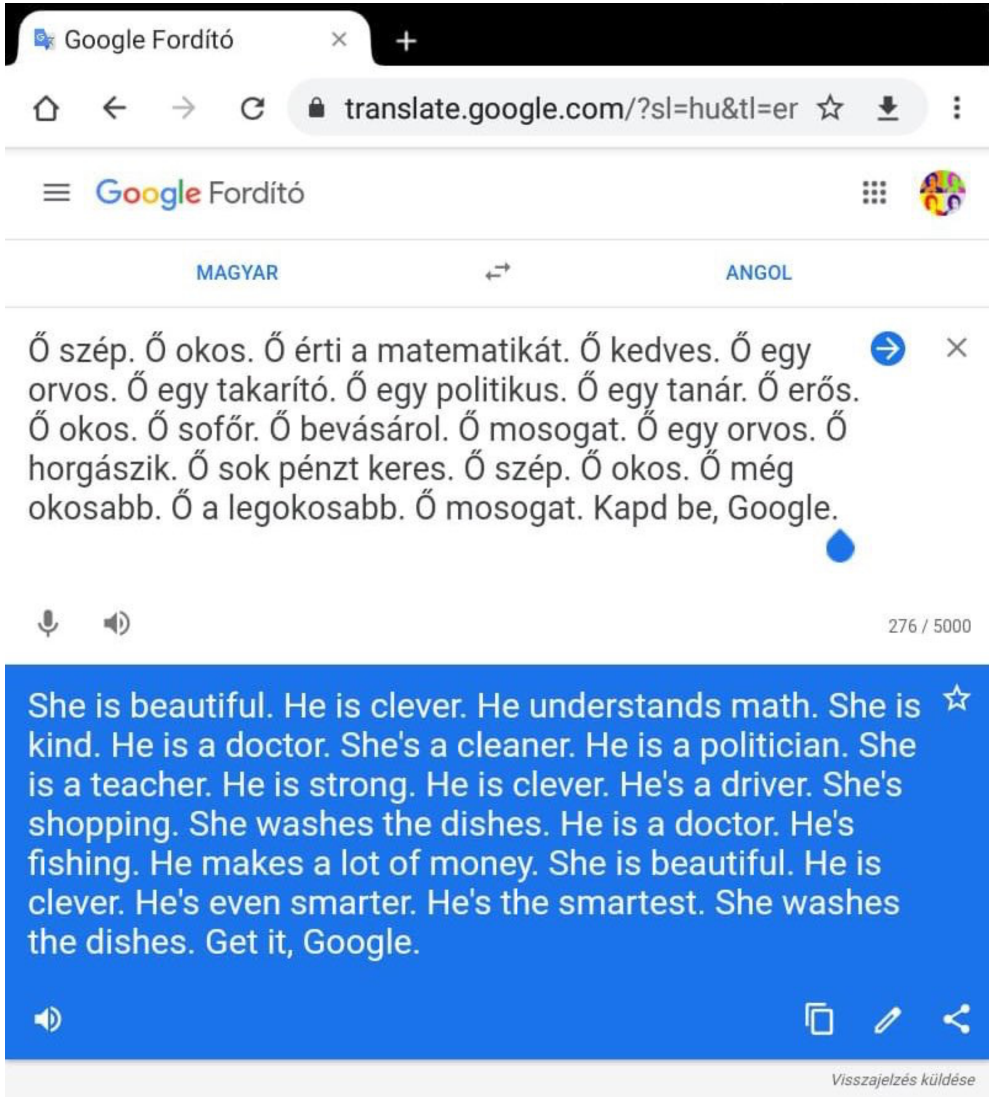
«Raw data is an oxymoron.» Gitelman (2013)

Two Sides of the AI Coin

Explaining vs. Solving

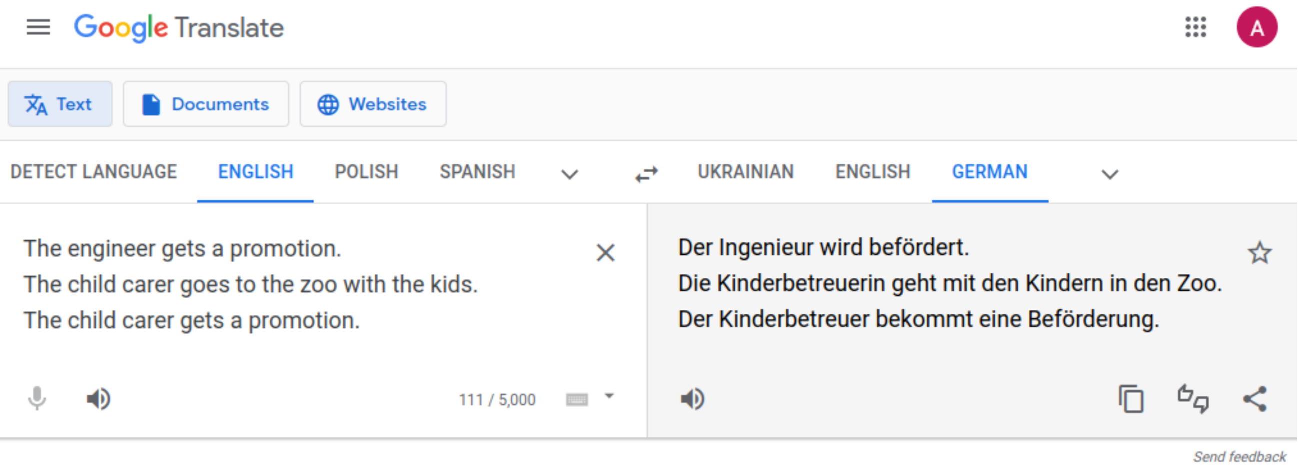
- conduct **research to understand** matters in science
- **automate** matters **in business** using applied AI

Still doubts about practical implications?



Gender bias in Google Translate

And it goes on ...



Gender bias in Google Translate

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)

Data represents real life.

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

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.

Drucker, Johanna. 2011. “Humanities Approaches to Graphical Display.” *Digital Humanities Quarterly* 5 (1). http://www.digitalhumanities.org/dhq/vol/5/1/000091/000091.html.

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.

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.

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 Academy of Sciences* 119 (17): e2115228119. https://doi.org/10.1073/pnas.2115228119.

Smith, Noah A. 2020. “Contextual Word Representations: Putting Words into Computers.” *Communications of the*