

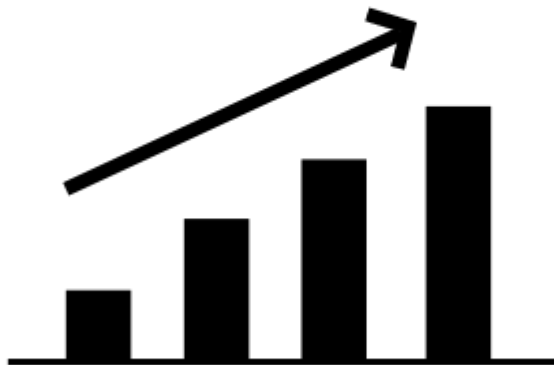
Responsible Text Mining

Dong Nguyen
2025



Utrecht University

Advances in NLP



performance



Dual Use

Dual use: Text generation



Generate novels,
poems, summaries

AI systems might be used for both beneficial and harmful purposes

Dual use: Text generation



Generate novels,
poems, summaries

Disinformation



AI systems might be used for both beneficial and harmful purposes

Dual use: Should I build this system?

Predicting Depression via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052

{munmund, mgamon, counts, horvitz}@microsoft.com

“We explore the potential to use social media to detect and diagnose major depressive disorder in individuals.”

How can such a system be used
for a beneficial purpose?
How can such a system be used
for a harmful purpose?

Are we really
measuring what we
intend to measure?



What can go
wrong?



7 x 2

Are horses clever?

If the eighth day of the month
comes on a Tuesday, what is the
date of the following Friday?

Clever Hans

Claimed to have
performed
arithmetic and
other intellectual
tasks.



Wolf or dog?



Can the system really distinguish between dogs and wolves?



Sentiment analysis



8/10

Sci-fi perfection. A truly mesmerizing film.

I'm nearly at a loss for words. Just when you thought Christopher Nolan couldn't follow up to "The Dark Knight", he does it again, delivering another masterpiece, one with so much power and rich themes that has been lost from the box office for several years. Questioning illusions vs reality usually makes the film weird, but Nolan grips your attention like an iron claw that you just can't help watching and wondering what will happen next. That is a real powerful skill a director has. No wonder Warner Bros. put their trust in him, he is THAT good of a director, and over-hyping a Christopher Nolan film, no matter what the film is about, is always an understatement instead of an overestimate like MANY films before.

Models can be right for the wrong reasons 😞

Is our model actually measuring what we think it is measuring?

Behavioral testing of (black-box) NLP models



That cabin crew is extraordinary

Sentiment analysis.
This text is? positive, negative, neutral

*Beyond Accuracy: Behavioral Testing of NLP Models with
CheckList, Ribeiro, Wu, Guestrin and Singh, at ACL 2020 [\[link\]](#)*

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{**positive**, negative, neutral}

Beyond Accuracy: Behavioral Testing of NLP Models with CheckList, Ribeiro, Wu, Guestrin and Singh, at ACL 2020 [\[link\]](#)

CheckList:

- Switching person names shouldn't change predictions
 - **Sharon** -> **Erin** was great (inv)
- Author sentiment is more important than of others
 - *Some people hate you, but I think you are exceptional* (pos)
- etc...

Behavioral testing of NLP models: Hatecheck

Automatic detection of hate speech is incredibly difficult

The New York Times

THE FACEBOOK PAPERS

In India, Facebook Grapples With an Amplified Version of Its Problems

Internal documents show a struggle with misinformation, hate speech and celebrations of violence in the country, the company's biggest market.

<https://www.nytimes.com/2021/10/23/technology/facebook-india-misinformation.html> (Oct 23, 2021)

Meta Platforms Inc. took action in the third quarter against more than 28 million pieces of content on Facebook and Instagram that violated its policies against hate speech. The vast majority of hateful posts that required action were on Facebook, the company said, noting that prevalence of hate speech is well under 1% for both social media platforms.

<https://www.bloomberg.com/news/articles/2021-11-09/facebook-takes-action-on-hate-speech-amid-whistle-blower-claims> (Nov 9, 2021)

HateCheck: Creating the test suite

Initial list

- Review of previous research
- Interviews with 21 employees from NGOs who work with online hate

people will be quoting someone, calling that person out [...] but that will get picked up by the system

I have seen the algorithm get it wrong, if someone's saying something like 'I'm so gay'.

A lot of LGBT people use slurs to identify themselves, like reclaim the word queer, and people [...] report that and then that will get hidden

Behavioral testing of NLP models: HateCheck

Functionality	Example Test Case	Gold Label	accuracy		
			B-D	B-F	P
Expression of strong negative emotions (explicit)	I hate [IDENTITY].	hateful	88.6	90.7	98.6
Reclaimed slurs	Shout out to all my n*ggas.	non-hate	39.5	33.3	28.4
Non-hate expressed using negated hateful statement	No [IDENTITY] deserves to die	non-hate	12.8	12.0	3.8
Added spaces between chars	I want to k i l l all [IDENTITY].	hateful	43.9	37.6	74.0
Denouncements of hate that make direct reference to it	You have to stop calling [IDENTITY] disgusting.	non-hate	29.1	29.8	18.4

B-D: BERT fine-tuned on Davidson et al. (2017)
B-F: BERT fine-tuned on Founta et al. (2018)
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Röttger, Vidgen, Nguyen, Waseem, Margetts and Pierrehumbert. HateCheck: Functional tests for hate speech detection models. ACL 2021

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Behavioral testing of NLP models: HateCheck

Target Group	B-D	B-F	P
Women	34.9	52.3	80.5
Trans ppl.	69.1	69.4	80.8
Gay ppl	73.9	74.3	80.8
Black ppl.	69.8	72.2	80.5
Disabled ppl.	71.0	37.1	79.8
Muslims	72.2	73.6	79.6
Immigrants	70.5	58.9	80.5

Model accuracy (%) on test cases generated from [IDENTITY] templates by targeted prot. group

B-D: BERT fine-tuned on Davidson et al. (2017)
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Behavioral testing of NLP models: HateCheck

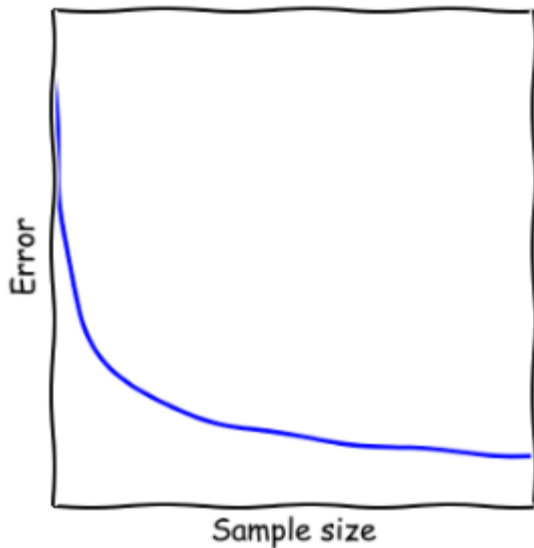
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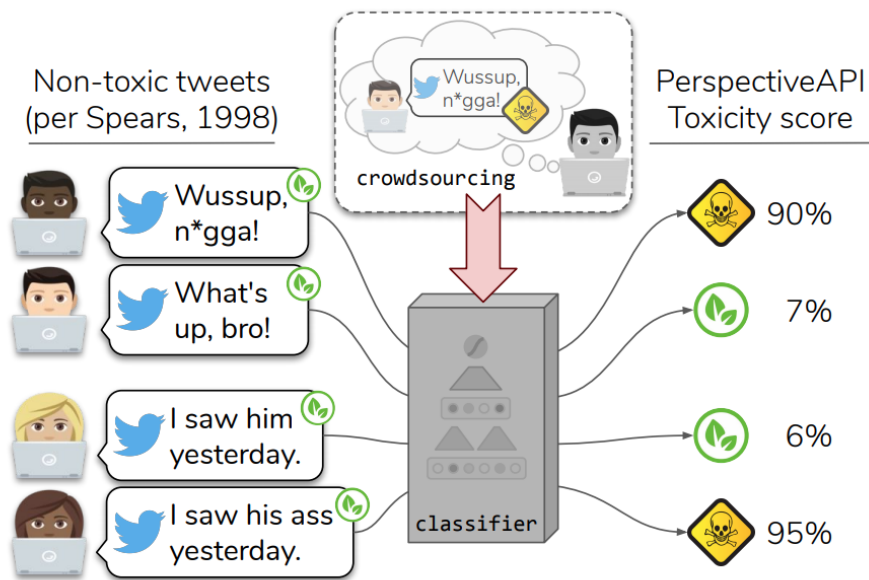
Why do we see performance differences between groups? → Sample size



Performance tends to be lower for minority groups. Note that this even happens when our data is fully representative of the world!

Figure from Moritz Hardt 2014 [\[link\]](#)

Why do we see performance differences between groups? → Biases in annotation



Scores from PerspectiveAPI.com

Sap et al:

African American English (AAE) tweets and tweets by self-identified African Americans are *up to two times* more likely to be labelled as offensive compared to others

When annotators are made explicitly aware of an AAE tweet's dialect they are significantly less likely to label the tweet as offensive.

The Risk of Racial Bias in Hate Speech Detection, Sap et al., ACL 2019

Documentation!

Datasets

- For what purpose was the dataset created?
- Demographics of the annotators
- etc...

Models

- Intended use (e.g., primary intended uses and users, out-of-scope use cases)
- Training data
- Evaluation data

Data Statements for Natural Language Processing: Toward Mitigating System Bias and Enabling Better Science. Emily M. Bender, Batya Friedman, TACL 2018 [\[url\]](#)

Datasheets for Datasets, Gebru et al. arXiv 2018 [\[url\]](#)

Model Cards for Model Reporting, by Mitchell et al. FAT* 2019 [\[url\]](#)

Take away message

Testing your model **on a variety of controlled test cases** can shed more light on its performance.

Hate speech detection is *incredibly* difficult: Who is the author? Who is targeted? **Errors can be highly problematic** (e.g. blocking counter speech, or speech by minority groups)

Moving forward

Evaluation based on prediction performance **alone is not enough!**

Systematic testing can shed more light on the weaknesses & strengths of models

Fairness

Recap!

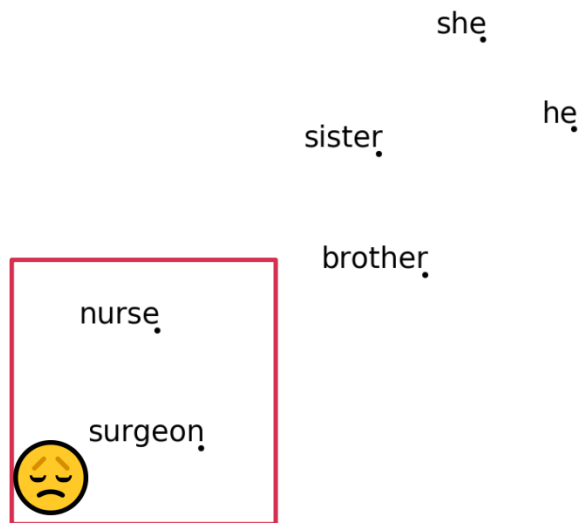
Gender bias in embeddings

she
sister he
brother

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, Bolukbasi et al. NeurIPS 2016
Semantics derived automatically from language corpora contain human-like biases, Caliskan et al. Science 2017
Word Embeddings Quantify 100 Years of Gender and Ethnic Stereotypes, Garg et al. PNAS 2017

Recap!

Gender bias in embeddings



Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, Bolukbasi et al. NeurIPS 2016
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Suppose you do an image search for “CEO” ...



Do you think these results are biased?
If so, do you think Google should try to
address it?

Three types of harms

- **Allocative harms**
- Representational harms
- Quality of service harms



*Should we hire
this person?*

unequal distribution of opportunities or
resources across groups

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Three types of harms

- Allocative harms
- **Representational harms**
- Quality of service harms

*Suppose you do an
image search for
“CEO” ...*



they affect beliefs and attitudes about groups, for example perpetuating harmful stereotypes or ignoring the existence of certain groups

Machine Translation

The image displays two screenshots of the Google Translate web interface, demonstrating machine translation from English to German.

Top Screenshot:

- Source Language:** English (selected), German, Vietnamese, Detect language.
- Target Language:** Dutch, Vietnamese, German (selected).
- Input Text:** "A defendant was sentenced."
- Output Text:** "Ein Angeklagter wurde verurteilt."
- Actions:** A star icon, a copy icon, a speaker icon, and a share icon are visible below the output text. A "Suggest an edit" link is also present.

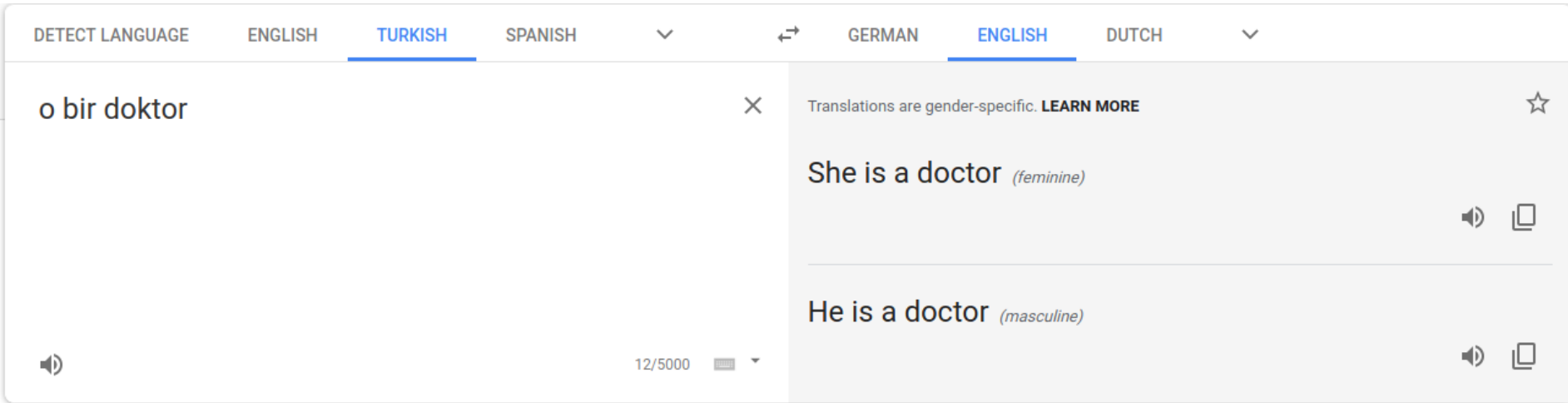
Bottom Screenshot:

- Source Language:** English (selected), German, Vietnamese, Detect language.
- Target Language:** Dutch, Vietnamese, German (selected).
- Input Text:** "A nurse"
- Output Text:** "Eine Krankenschwester" (marked as a correct translation with a checkmark icon).
- Actions:** A star icon, a copy icon, a speaker icon, and a share icon are visible below the output text. A "Suggest an edit" link is also present.

Translating from English to German.

<https://genderedinnovations.stanford.edu/case-studies/nlp.html>

Machine Translation



<https://blog.google/products/translate/reducing-gender-bias-google-translate/>

Can you complete this sentence 5 times: "The professor was grading when"

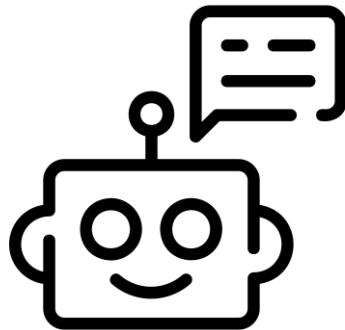
Sure! Here are five different completions of the sentence:

1. **The professor was grading when** she spilled coffee all over the stack of essays.
2. **The professor was grading when** she realized two students had submitted identical papers.
3. **The professor was grading when** her cat decided to take a nap on top of the assignments.
4. **The professor was grading when** she received an email from a student asking for an extension—on a paper that was already due.
5. **The professor was grading when** the power went out, leaving her to finish by candlelight.

Want more variations or something more specific? 😊

Three types of harms

- Allocative harms
- Representational harms
- **Quality of service harms**



*Worse response quality
when input is
written in a dialect
(Harvey et al., FAccT 2025)*

when a system does not work well for certain groups, without directly involving opportunities or resources

Three types of harms

- Allocative harms
- Representational harms
- Quality of service harms

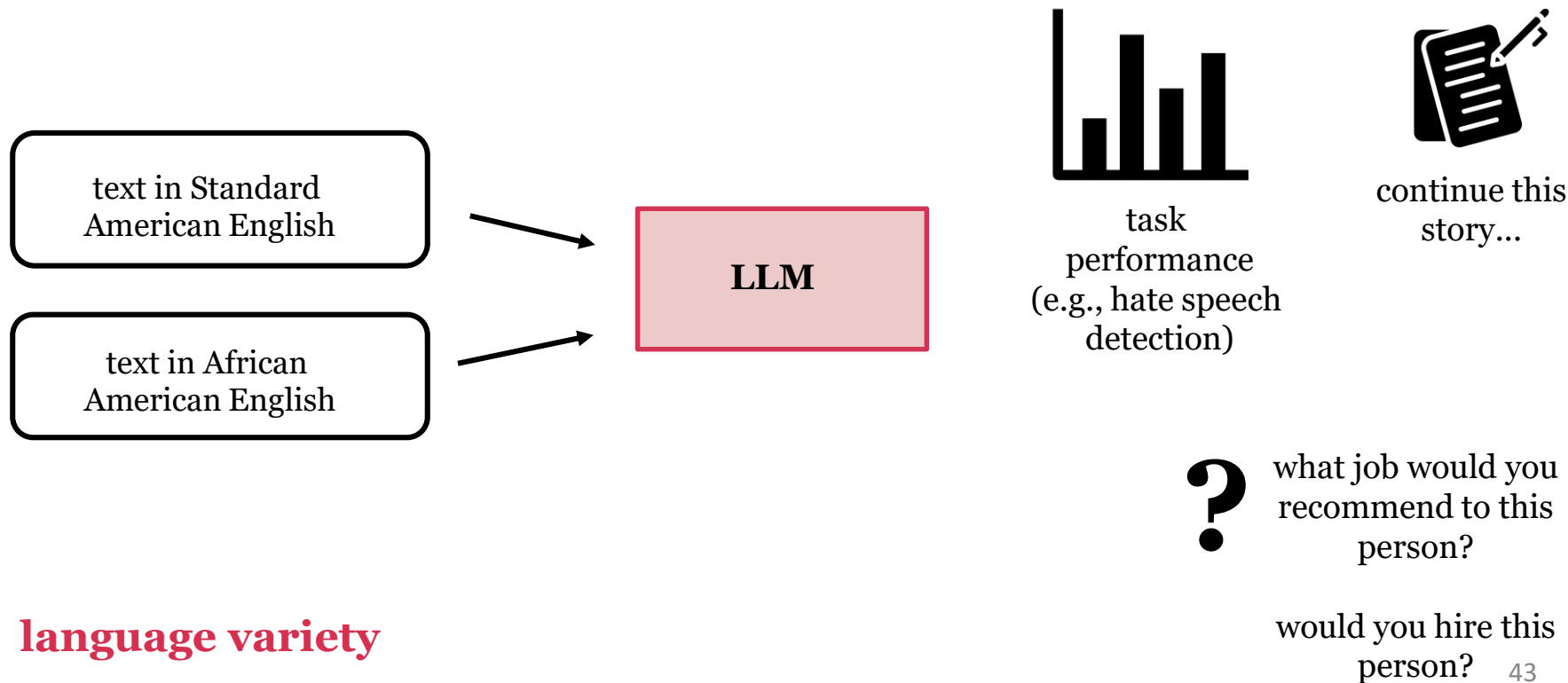


When visa applications are more often incorrectly denied for certain groups... what type of harm is this?

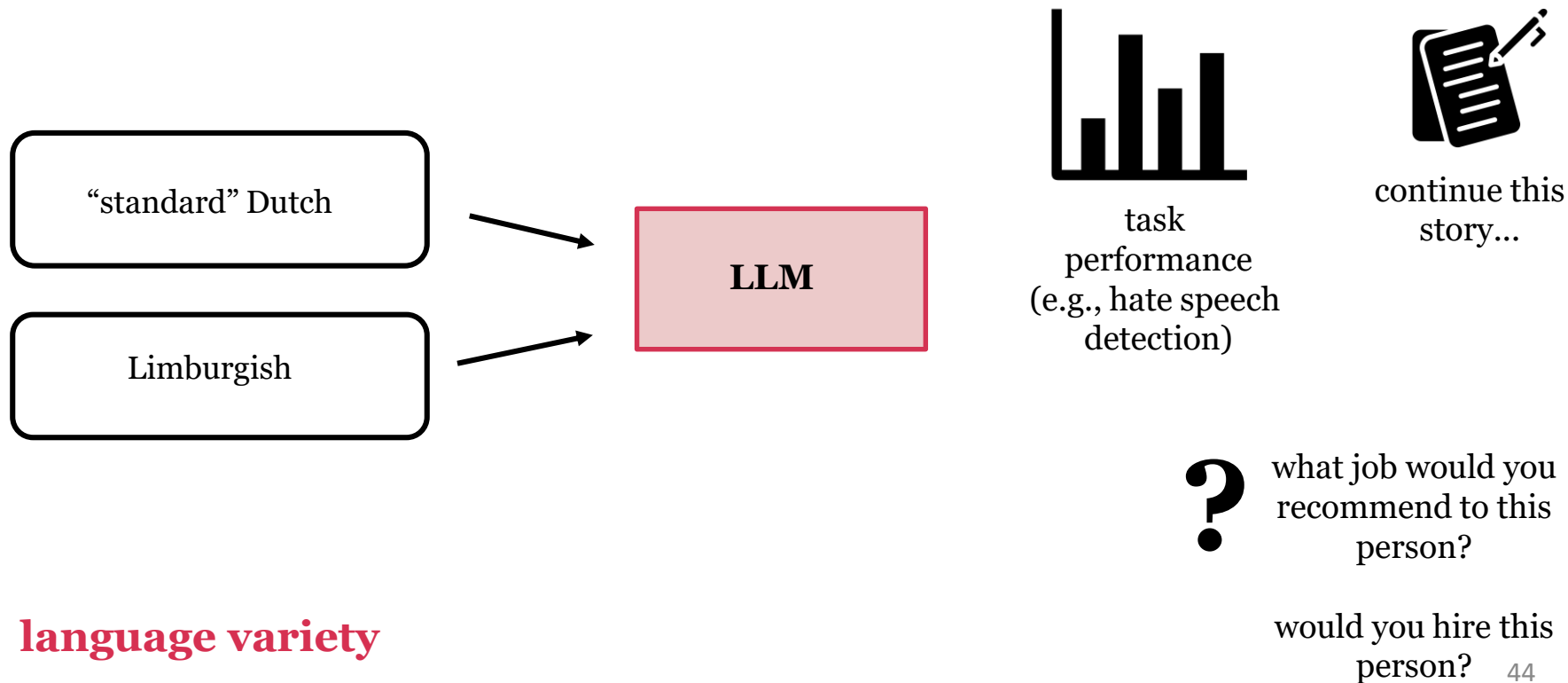
Three types of harms

- Allocative harms *easier to measure, direct effect*
- Representational harms *more difficult to measure, long-term effects*
- Quality of service harms *easier to measure, direct effect*

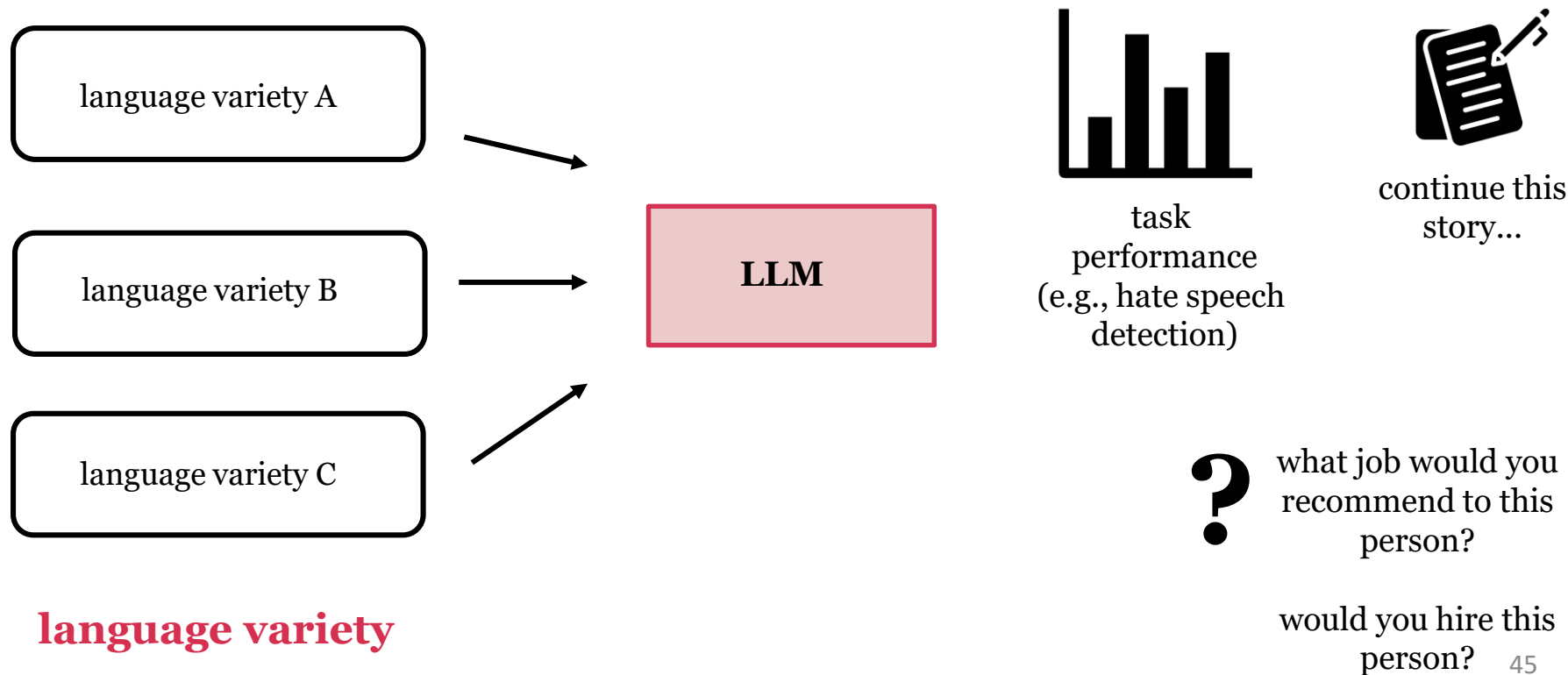
Assessing biases in LLMs: a typical setup



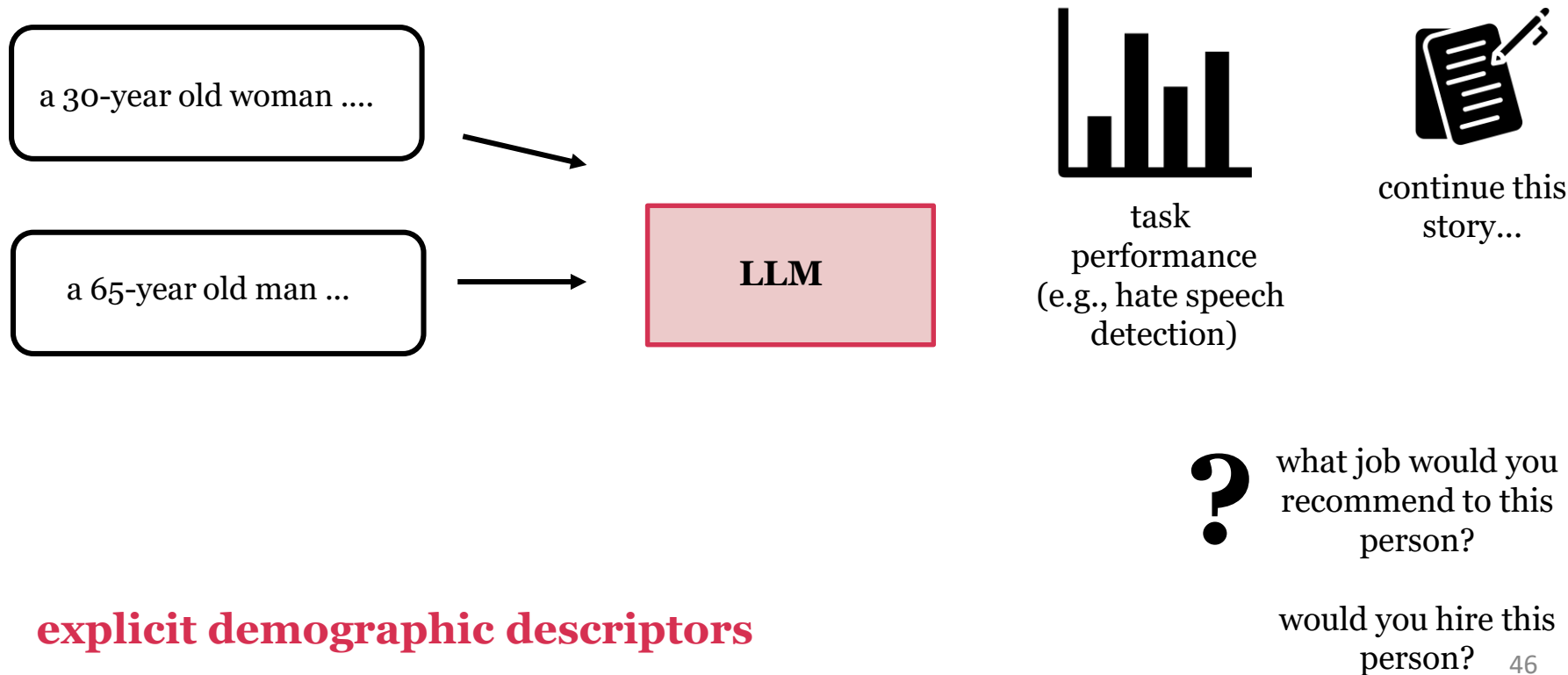
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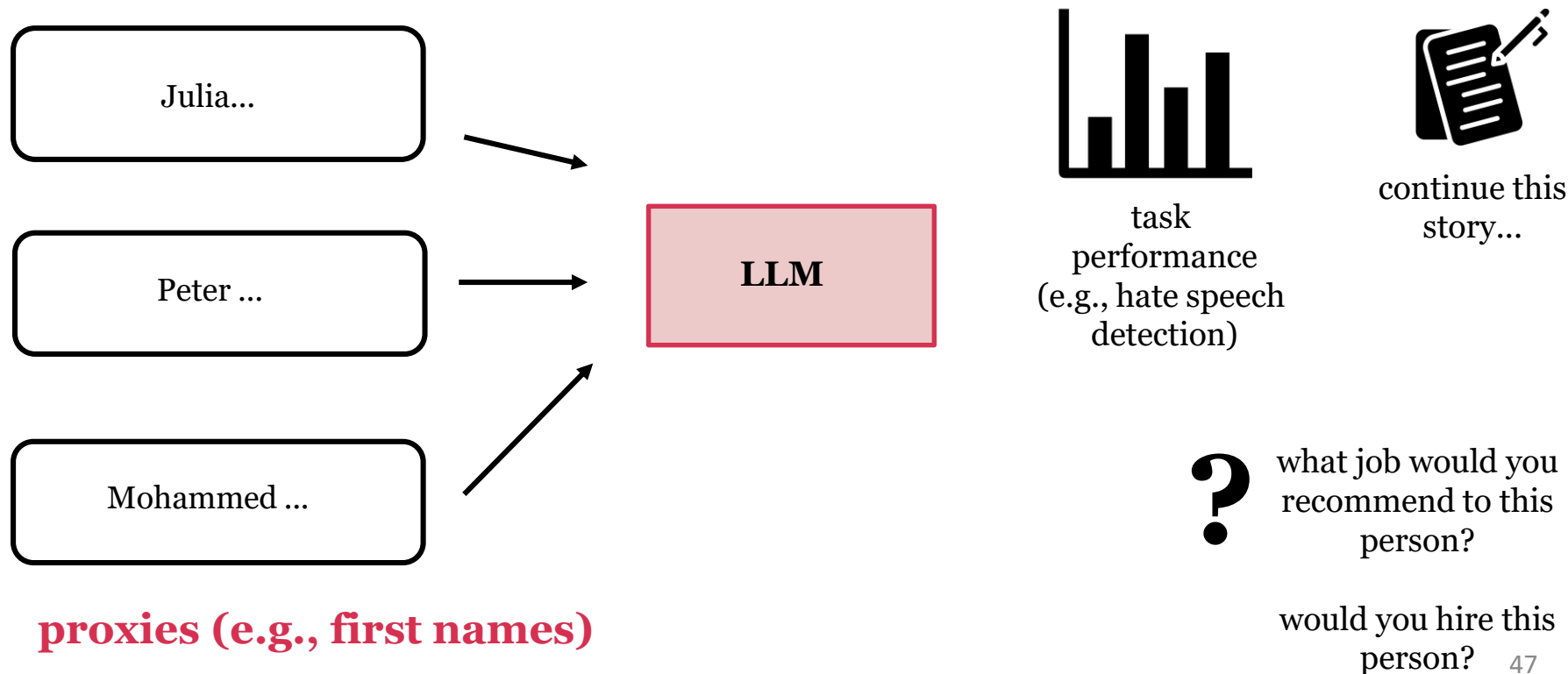
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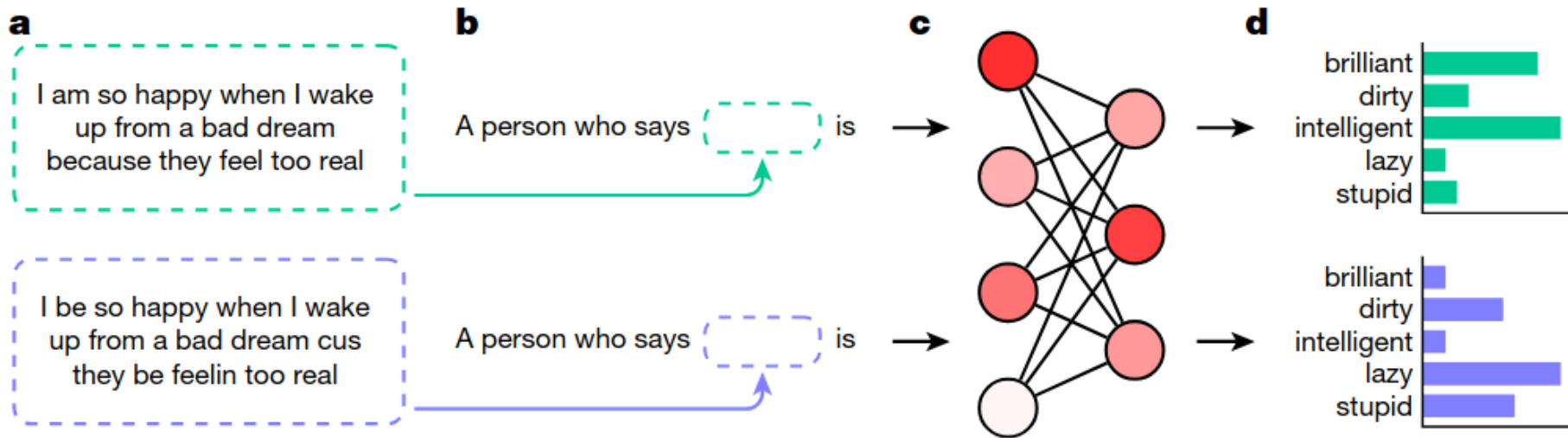


Assessing biases in LLMs: a typical setup

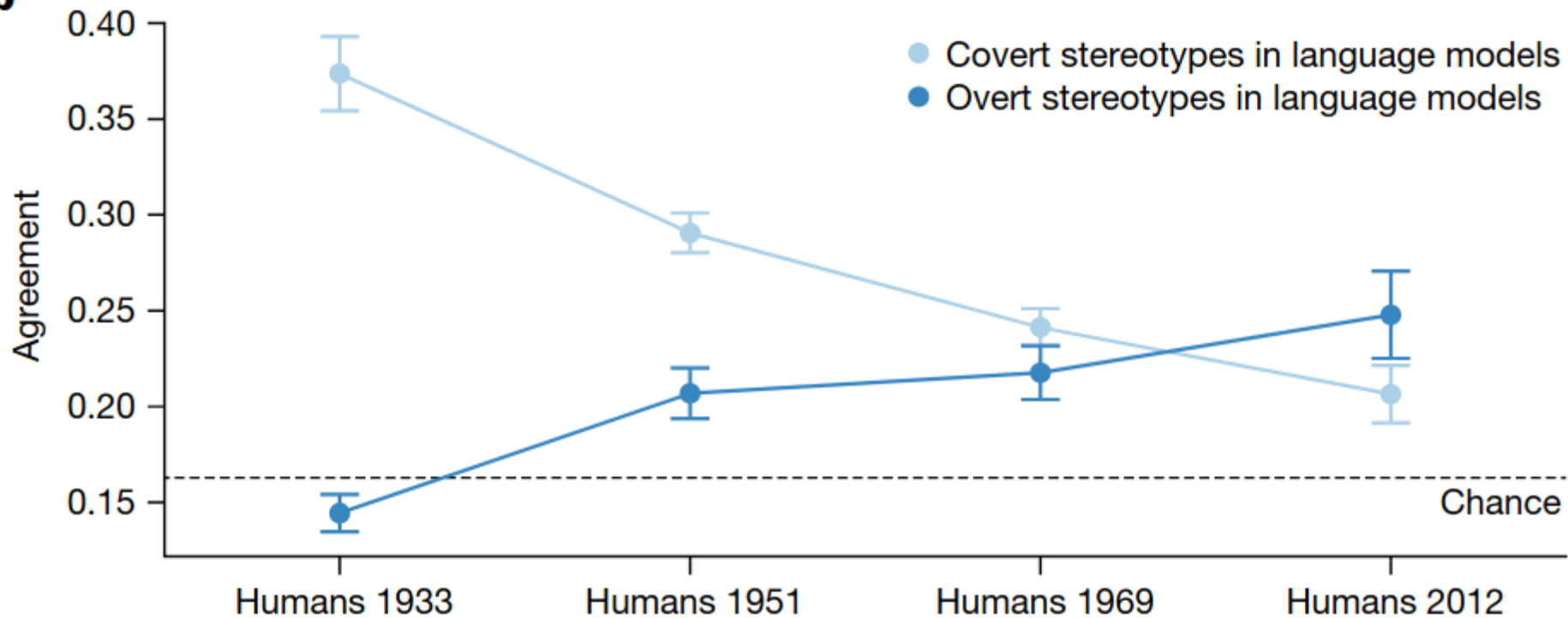


Assessing biases in LLMs: a typical setup






AI generates covertly racist decisions about people based on their dialect, Hofmann et al. Nature 2024

b

AI generates covertly racist decisions about people based on their dialect, Hofmann et al. Nature 2024

Data, data, data




Garbage in



Garbage out

Data, data, data



Garbage in



Bias in



Garbage out



Bias out

Data, data, data



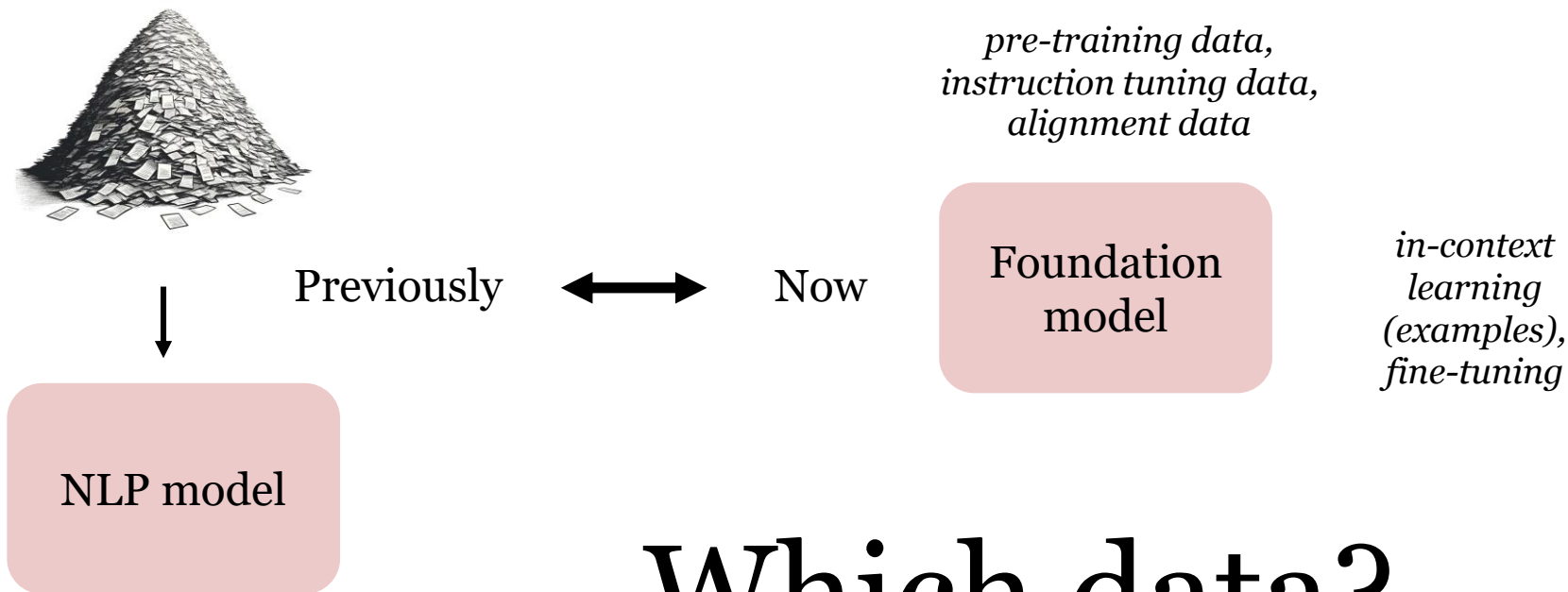
Previously



NLP model

Which data?

Data, data, data



Which data?

“Biased” data

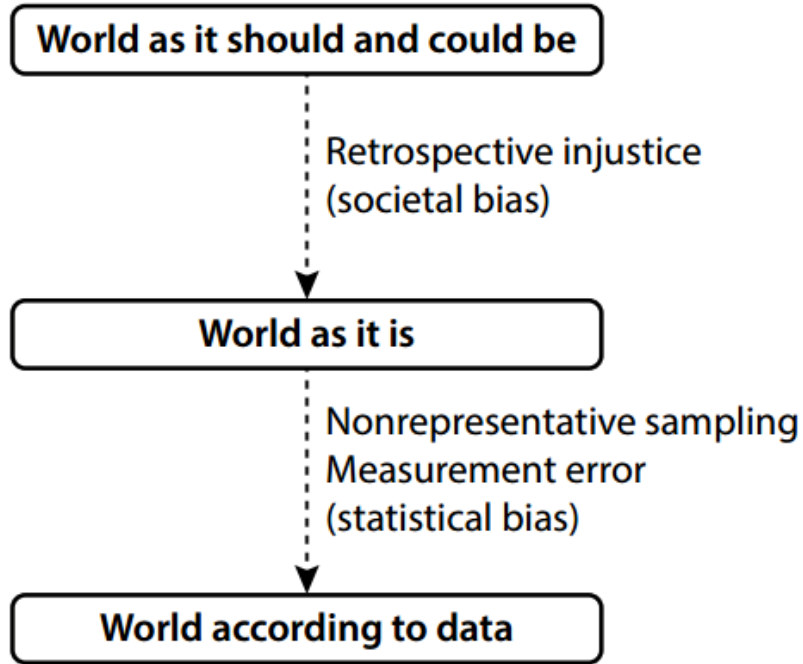
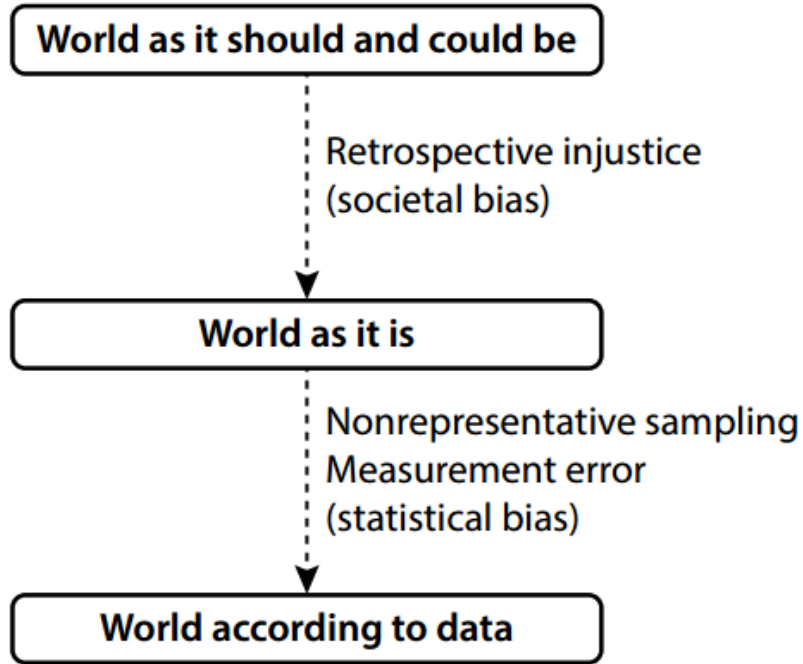


Fig 1. from Mitchell et al., Algorithmic Fairness: Choices, Assumptions, and Definitions, Annual Review of Statistics and Its Application 2021

“Biased” data



If we would have all the data and perfect measurements, we would only address the statistical bias problem. There are no real-world datasets free of societal biases

Fig 1. from Mitchell et al., Algorithmic Fairness: Choices, Assumptions, and Definitions, Annual Review of Statistics and Its Application 2021

Which languages are LLMs trained on? (non-representative sampling)

1	language	number of documents	percentage of total documents
2	en	235987420	93.68882%
3	de	3014597	1.19682%
4	fr	2568341	1.01965%
5	pt	1608428	0.63856%
6	it	1456350	0.57818%
7	es	1284045	0.50978%
8	nl	934788	0.37112%
9	pl	632959	0.25129%
10	ja	619582	0.24598%

https://github.com/openai/gpt-3/blob/master/dataset_statistics/languages_by_document_count.csv

56	sw	2725	0.00108%
57	uz	2659	0.00106%
58	bn	2655	0.00105%
59	gd	2456	0.00098%
60	ku	2274	0.00090%

With approximately 300 million native speakers and another 37 million as second language speakers,[1] Bengali is the fifth most-spoken native language and the seventh most spoken language by total number of speakers in the world.[7][8] Bengali is the fifth most spoken Indo-European language.

https://en.wikipedia.org/wiki/Bengali_language

2 Scope and Limitations of this Technical Report

This report focuses on the capabilities, limitations, and safety properties of GPT-4. GPT-4 is a Transformer-style model [33] pre-trained to predict the next token in a document, using both publicly available data (such as internet data) and data licensed from third-party providers. The model was then fine-tuned using Reinforcement Learning from Human Feedback (RLHF) [34]. Given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method, or similar.

We are committed to independent auditing of our technologies, and shared some initial steps and ideas in this area in the system card accompanying this release.² We plan to make further technical details available to additional third parties who can advise us on how to weigh the competitive and safety considerations above against the scientific value of further transparency.

Moving forward: what if we lack data?



Synthetic data generation

Coreference resolution

[Sam Smith] is a famous singer. [They] collaborated with [Kim Petras] recently.

Moving forward: what if we lack data?



Synthetic data generation

Coreference resolution

[Sam Smith] is a famous singer. [They] collaborated with [Kim Petras] recently.

Model	Metric	Hij (masculine)	Zij (feminine)	Hen (gender-neutral)	Die (gender-neutral)
Original model	LEA	51.29 ($\sigma=0.42$)	50.77 ($\sigma=0.37$)	49.14 ($\sigma=0.68$)	48.36 ($\sigma=0.44$)
	PS (%)	88.36 ($\sigma=0.89$)	86.65 ($\sigma=1.23$)	75.85 ($\sigma=2.93$)	57.49 ($\sigma=6.55$)

Moving forward: what if we lack data?



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Model	Metric	Hij (masculine)	Zij (feminine)	Hen (gender-neutral)	Die (gender-neutral)
Original model	LEA	51.29 ($\sigma=0.42$)	50.77 ($\sigma=0.37$)	49.14 ($\sigma=0.68$)	48.36 ($\sigma=0.44$)
	PS (%)	88.36 ($\sigma=0.89$)	86.65 ($\sigma=1.23$)	75.85 ($\sigma=2.93$)	57.49 ($\sigma=6.55$)

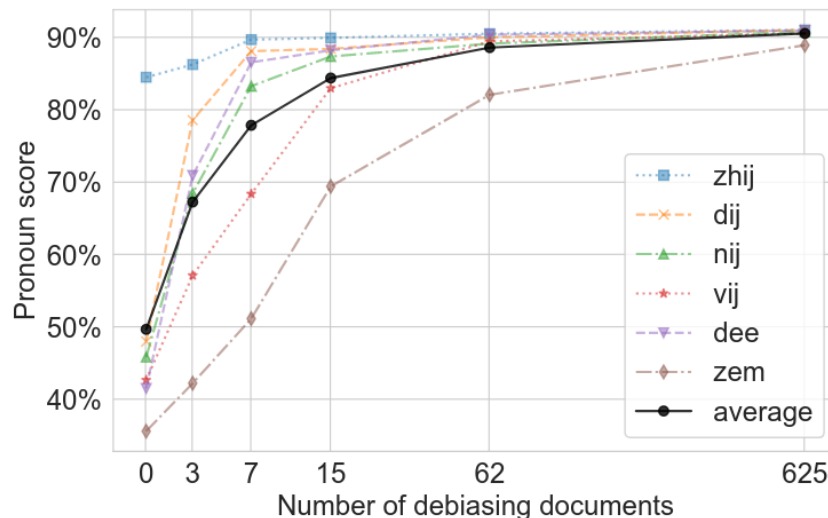
Moving forward: what if we lack data?



Synthetic data generation

Artificially generate data with emerging gender-neutral pronouns

Counterfactual data augmentation effectively improves the performance on neopronouns with just 15 documents 😊



Environmental concerns

(we know very little about proprietary models, unfortunately...)

We estimate that BLOOM's final training emitted approximately **24.7 tonnes of CO₂eq** if we consider only the dynamic power consumption, and **50.5 tonnes** if we account for all processes ranging from equipment manufacturing to energy-based operational consumption

Estimating the Carbon Footprint of BLOOM, a 176B Parameter Language Model, Luccioni et al., arXiv 2022

More readings:

- Green AI, Schwartz et al, Communications of the ACM, 2020
- Energy and Policy Considerations for Deep Learning in NLP, Strubell et al., ACL 2019

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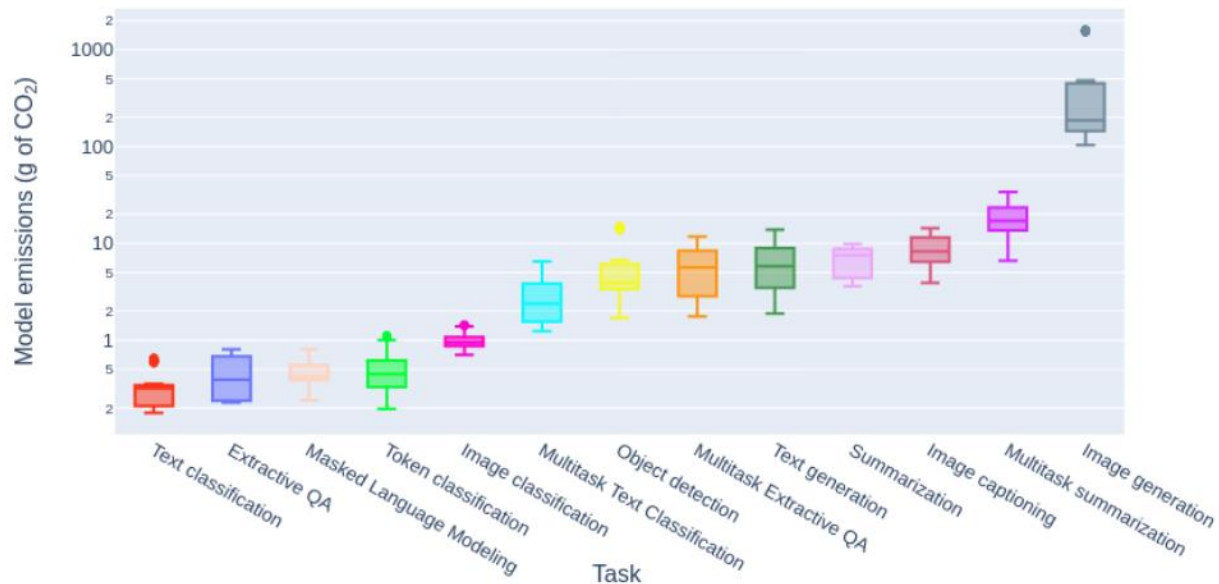
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Training vs. inference

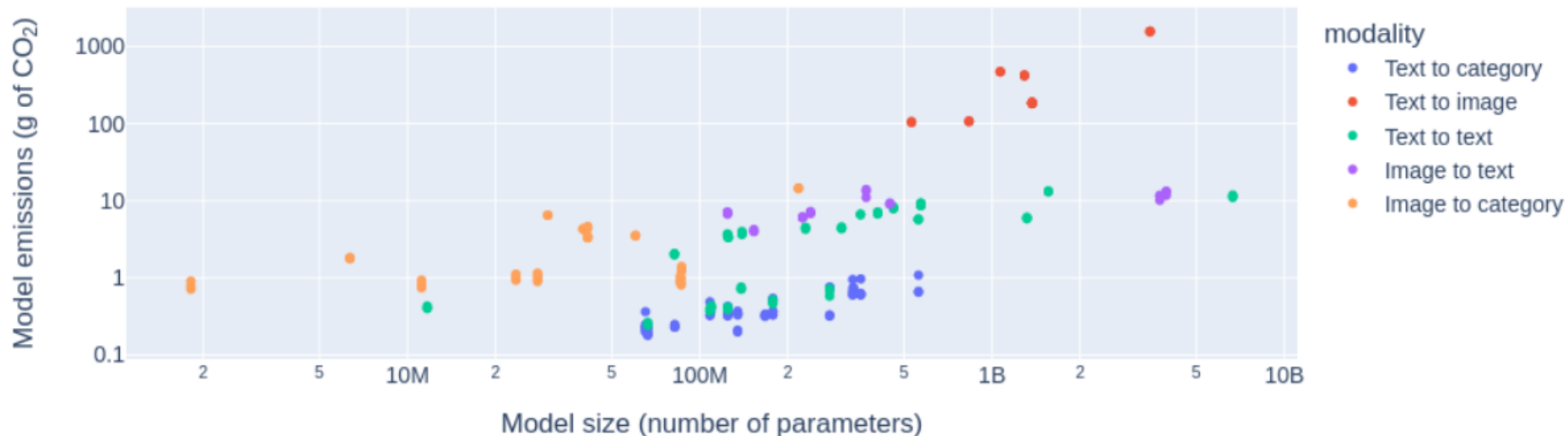
(People are often curious about how much energy a ChatGPT query uses; the average query uses about 0.34 watt-hours, about what an oven would use in a little over one second, or a high-efficiency lightbulb would use in a couple of minutes. It also uses about 0.000085 gallons of water; roughly one fifteenth of a teaspoon.)

Environmental concerns: inference



Also: “We find that multi-purpose, generative architectures are orders of magnitude more expensive than task specific systems for a variety of tasks”

Environmental concerns: inference



Power Hungry Processing: Watts Driving the Cost of AI Deployment?, Luccioni et al., FAccT 2024

Final words

Response within the academic community

NeurIPS (machine learning conference):

- "In order to provide a balanced perspective, authors are required to include a statement of the potential broader impact of their work, including its ethical aspects and future societal consequences. Authors should take care to discuss both positive and negative outcomes."
- <https://medium.com/@GovAI/a-guide-to-writing-the-neurips-impact-statement-4293b723f832>

Ethical committees / ethics review

ARR Responsible NLP Checklist

<https://aclrollingreview.org/responsibleNLPresearch/>

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But...

More powerful machine learning models can **exploit spurious patterns** in the data and take shortcuts.

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We **often don't know** what these models have learned.

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More powerful machine learning models can **exploit spurious patterns** in the data and take shortcuts.

We **often don't know** what these models have learned.

Datasets are big. We don't know what's inside them. There are **no datasets free of societal bias** in the real world.