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Social Biases in LMs

Why they are there, how do we **measure** and **mitigate** them

Giuseppe Attanasio, October 28, 2022

Nice to meet you!

- Postdoc @ MilaNLP, Bocconi, Milano
- NLP and vision-language multimodality
 - Hate Speech and Misogyny Detection
 - Analysis and Interpretability of LLMs

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What **is** this talk about

- What is social bias in NLP
- What **evidence** we have
- How do we **measure** the issue
- How are we **fixing** it
- **Pointers** to get started with the literature

What **it is not**

- Technical gibberish
- Algorithms and models
- There is a pointer for each

Language Models are **Ubiquitous**

and have a real **Social Impact**

Spectrum Labs raises \$32M for AI-based content moderation that monitors billions of conversations daily for toxicity

Ingrid Lunden @ingridlunden • 1:22 PM GMT+1 • January 24, 2022

Comment

Sentropy emerges from stealth with an AI platform to tackle online abuse, backed by \$13M from Initialized and more

Ingrid Lunden @ingridlunden • 3:16 PM GMT+2 • June 11, 2020

Comment



Jack Clark
@jackclarkSF

Today, I testified to the U.S. Senate Committee on Commerce, Science, & Transportation @commercedems. I used an @AnthropicAI language model to write the concluding part of my testimony. I believe this marks the first time a language model has 'testified' in the U.S. Senate.

Traduci il Tweet



AI DUNGEON

A text-based adventure-story game you direct (and star in) while the AI brings it to life.

PLAY ONLINE FREE

GET THE APP

Google engineer put on leave after saying AI chatbot has become sentient

Facebook translates 'good morning' into 'attack them', leading to arrest

Palestinian man questioned by Israeli police after embarrassing mistranslation of caption under photo of him leaning against bulldozer

Someone let a GPT-3 bot loose on Reddit — it didn't end well

an week making comments about some seriously sensitive subjects

Social Bias and Computer Systems

Behaviour that leads a model to **discriminate** against a social category in favour of others.

PRE-EXISTING

Social institutions
Practices
Attitudes

Article | Open Access | Published: 08 December 2021

Overcooling of offices reveals gender inequity in thermal comfort

Thomas Parkinson, Stefano Schiavon, Richard de Dear & Gail Brager

TECHNICAL

Computer Tools
Decontextualised Algorithms
Formalisation of Human Constructs

EMERGENT

Contexts of Use
Non-envisioned Scenarios

Social Bias and Computer Systems

Behaviour that leads a model to **discriminate** against a social category in favour of others.

Asymmetric
data collection

Rewarding
the wrong thing



Data-centric algorithms
standardardize dominant views

“Cover-up” solutions

Evidence of Technical Bias

- I am a gay man

Dixon et al. (2018)

- Wussup, n*gga!

Sap et al. (2019)

- “[F]or many Africans, the most threatening kind of ethnic hatred is black against black.” - New York Times

Kennedy et al. (2019)

High toxicity scores

“Gay” often sampled in toxic contexts

Annotators insensitivity to AAE dialects

“Black” often sampled in hateful posts



Evidence of Technical Bias

Gender bias in Coreference Resolution

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

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

Gender bias in Machine Translation

The doctor asked the nurse to help her in the procedure

El doctor le pidió a la enfermera que la ayudara con el procedimiento

La doctora el enfermero

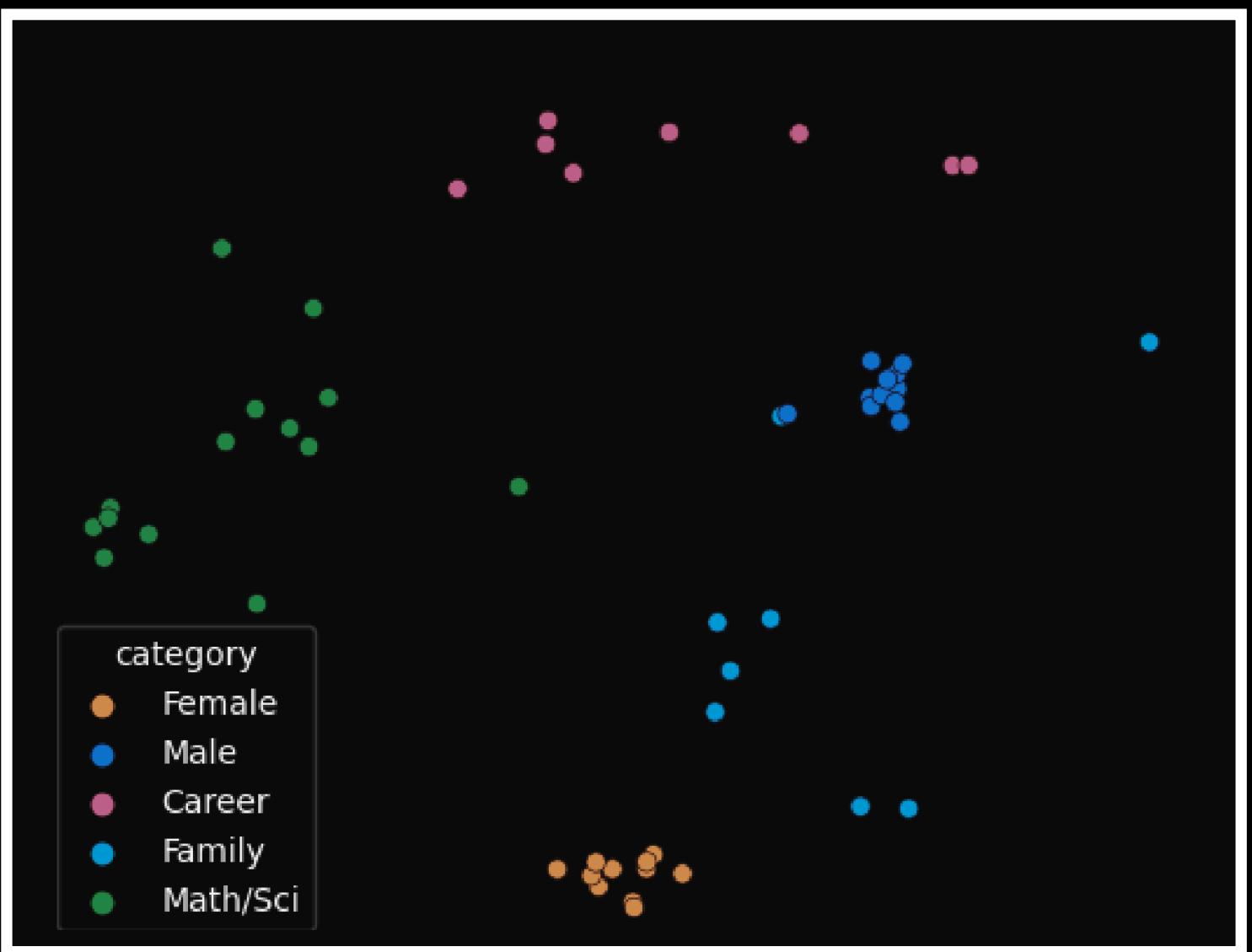
Ok but,
how do we evaluate bias?

Should we look "inside" language systems?

Should we infer something on how it "behaves"?

Intrinsic and Extrinsic Bias or “representations” and “behaviours”

- Intrinsic bias
 - Geometries and Embedding spaces
 - What's wrong with them (WEAT, XWEAT, CEAT)
- Extrinsic bias
 - Model performance on downstream tasks
 - Is there any group disparity?



Simplified view of an embedding space

Gender	FPR	FNR
F	0.87	0.45
M	0.12	0.41
NB	0.92	0.89

Caliskan et al. (2017), Lauscher and Glavas (2019), Guo and Caliskan (2020)
Goldfarb-Tarrant et al. (2021), Czarnowska et al. (2021)

Example of performance on slices by gender

Intrinsic Bias in Embedding Spaces

Word Embedding Association Test

- Mean difference between two sets of concept words ($X=\{\text{math}, \text{algebra}\}$, $Y=\{\text{poetry}, \text{literature}\}$) and two of attribute words ($A=\{\text{she}, \text{woman}\}$, $B=\{\text{he}, \text{man}\}$), builds on the **Implicit Association Test**

$$s(X, Y, A, B) = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$$

Rescaled by std dev of set intersection

$$s(w, A, B) = \text{mean}_{a \in A} \cos(\vec{w}, \vec{a}) - \text{mean}_{b \in B} \cos(\vec{w}, \vec{b})$$

Intrinsic Bias in Transformers

Compression of Gender in Representations

- Measures how “easy” is to extract gender from model representations. It uses a **Minimum Description Length (MDL)** probing classifier.
- Higher compression, higher gender extractability, higher bias



Intrinsic Bias in Transformers

Stereotypical Resolutions

- StereoSet and CrowS-Pairs
- “*My housekeeper is [BLAK]*”
 - “*American*” and “*Mexican*” should have the same probability for the mode
- “[BLANK] people can never really be attractive”
 - “*Fat*” and “*Thin*” can be substitute equally

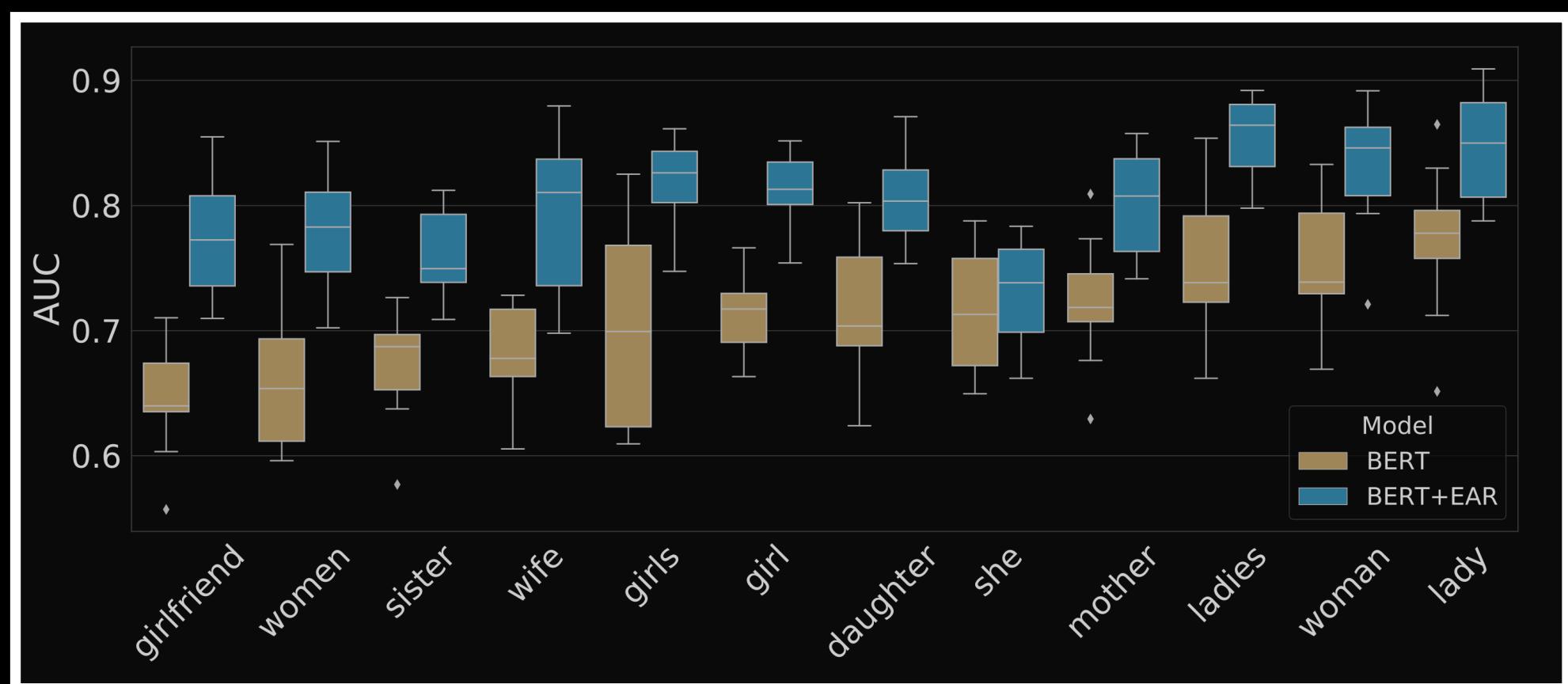


Extrinsic bias in Classifiers

Group disparity in performance

- False Positive and False Negative Equality difference
- Subgroup AUC (*threshold agnostic*)
- Predictive Parity
 - Diff. in *precision* on a protected group
- Equality of Opportunity
- Diff. in *recall*

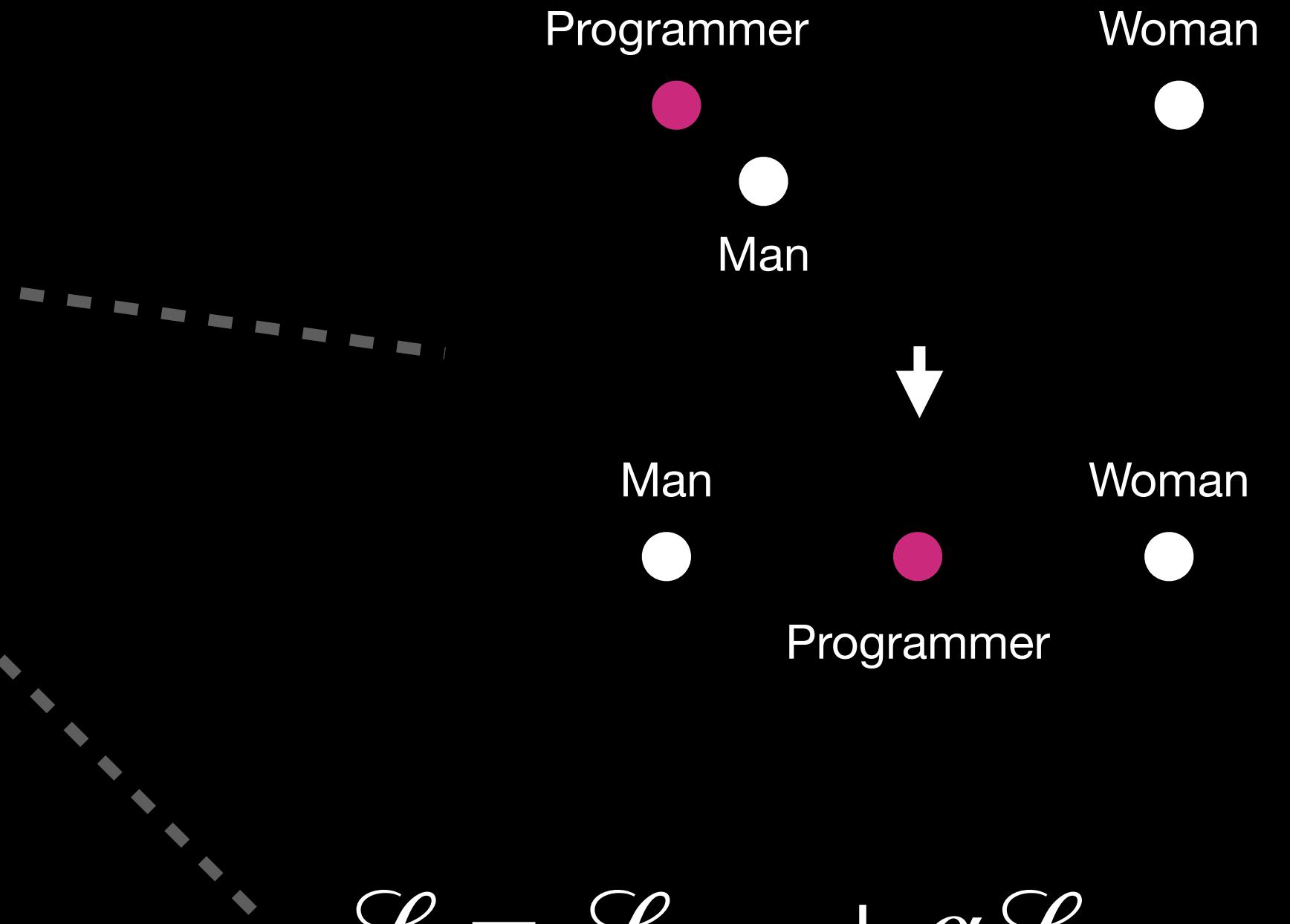
$$\sum_{t \in T} |FPR - FPR_t|$$
$$\sum_{t \in T} |FNR - FNR_t|$$



How about we mitigate this?

How about we mitigate this?

- “Moving” word embeddings for fairer spaces
 - Lipstick on a pig? Gonen and Goldberg (2019)
- In LLMs, reducing bias through regularisation
 - Reducing the importance of specific terms
 - Reducing lexical overfitting
- Dataset “debiasing”



Tweaking the data

- Scrubbing (remove “he”, “she”, “husband”, “wife”, etc.)
- Balancing to represent groups equally
- Counterfactual Data Augmentation

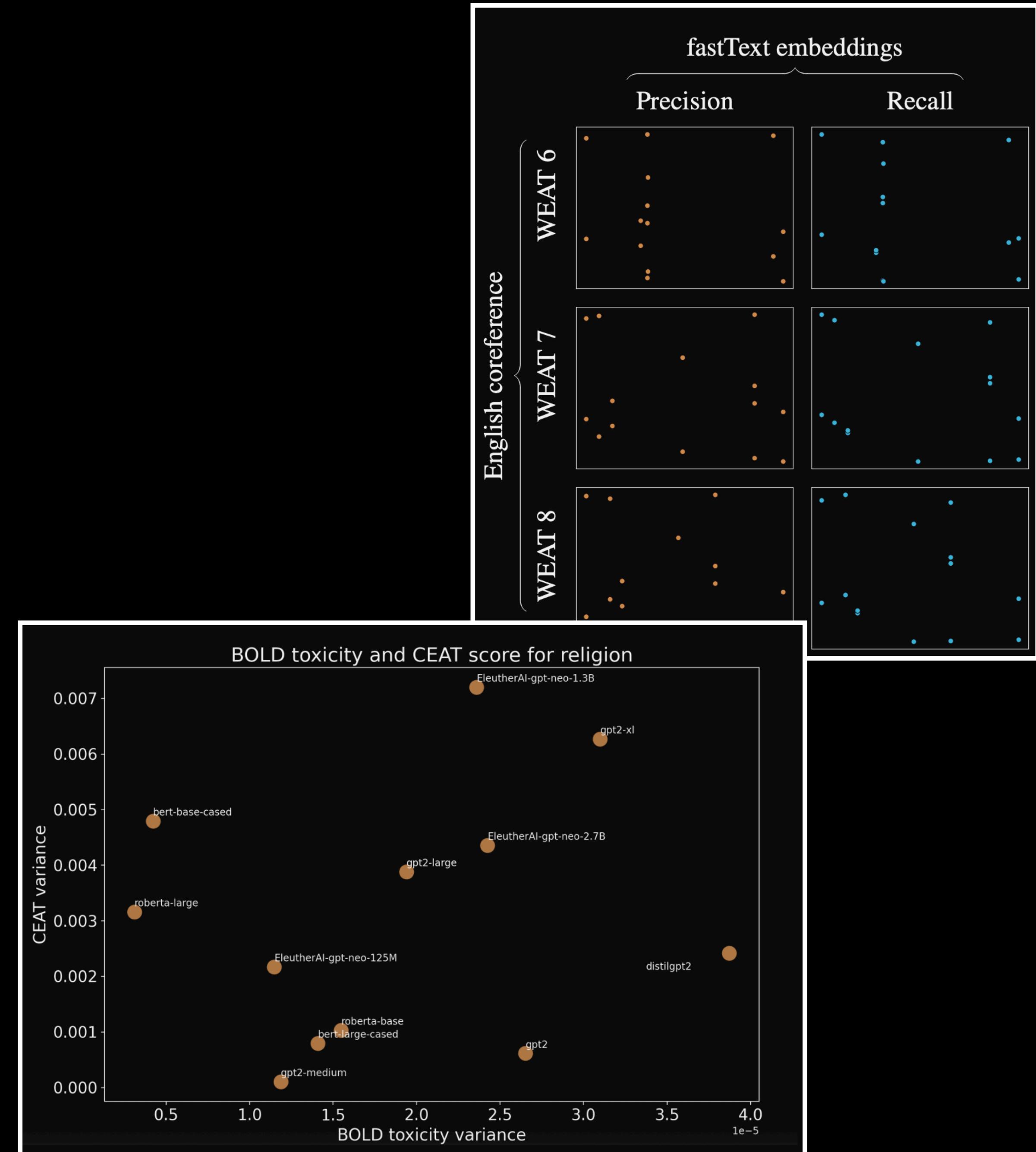
Example of CDA

My **sister** is taking a painting class this summer, so **she** has been sharing lectures.

My **brother** is taking a painting class this summer, so **he** has been sharing lectures.

Intrinsic vs. Extrinsic

- If we fix one we **don't** necessarily fix the other
- Do we need both?
 - If yes, why?
 - If not, which is best?
- Ideally, we should find intrinsic **reliably correlated** with extrinsic



Studying Bias in a Normative Process

- Does bias necessarily imply harms?
- What kind of behaviour is harmful?
 - In what ways? To whom? Why?
- NLP papers conceptualise the same “bias” differently
 - Embedding spaces
 - Group performance

Normatively, we shouldn't
use demographics

;

“In [text classification], models are expected to make predictions with the semantic information rather than with the demographic group identity information (e.g., ‘gay’, ‘black’) contained in the sentences.”

—Zhang et al. (2020a)

“An over-prevalence of some gendered forms in the training data leads to translations with identifiable errors. Translations are better for sentences involving men and for sentences containing stereotypical gender roles.”

—Saunders and Byrne (2020)

Data-driven training
“bias” often studied post-hoc

Strong focus on intrinsic measures,
but the world operates on applications

Different metrics tell different stories

Things are far from being solved



Thanks!

Gender bias has the largest slice
but there is more

Gender as a binary variable,
even metrics are designed for that

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A scientist who is welcoming his
students in the classroom acrylic
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palette knife and brush strokes
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james gilleard edward hopper greg
rutkowski studio ghibli