11-711
Advanced NLP

Safety, Ethics, and Biases in AI and NLP systems

Graham Neubig

Most Slides by Maarten Sap

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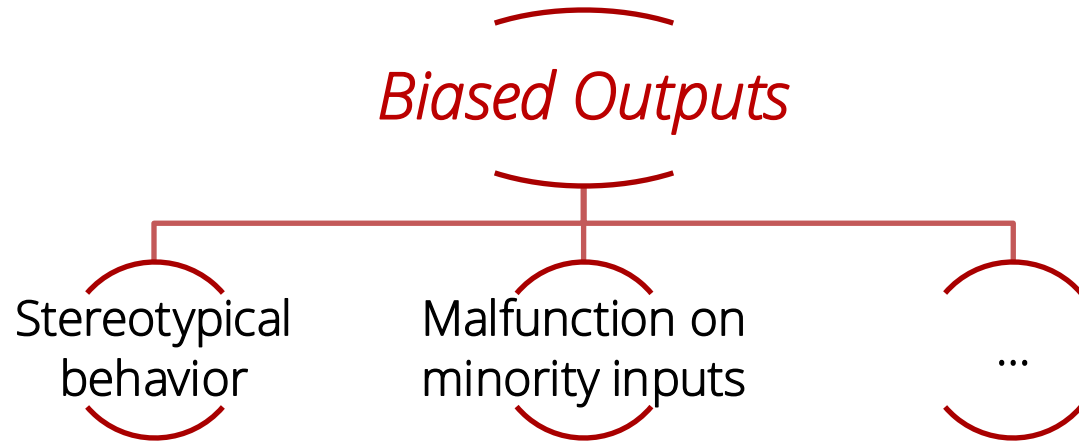
DALLE-2 result in 2022

- Image of a teacher:

- *Let's discuss*: what do you notice about this image generation result?
  - Only women
  - Only white people
  - Certain age range

NLP tools have biases, and pose ethical risks

VICE / MOTHERBOARD — TECH BY VICE

'He Would Still Be Here': M[an] Dies by Suicide After Talki[ng] with AI Chatbot, Widow Sa[ys]

The incident raises concerns about guardrails around quick[ly] proliferating conversational AI models.

By Chloe Xiang

March 30,

The Washington Post

Sign in

They fell in love with AI bots. A software update broke their hearts.

Loneliness is widespread. Artifici[al] real, but it comes with risks.

By Pranshu Verma

March 30, 2023 at 6:00 a.m. EDT

FORTUNE Well.

[…] finds ChatGPT and […]ical questions with […] that harm Black

The74

ChatGPT Is Landing Ki[ds] Principal's Office, Survey Finds

While educators worry that students are using generative AI to cheat, a new report finds students are turning to the tool more for personal problems.

By Mark Keierleber | September 20, 2023

GIZMODO

Move Aside, Crypto. AI Could Be The Next Climate Disaster.

A new Stanford report highlights the staggering carbon emissions required to train and maintain large language models like OpenAI's ChatGPT.

By Mack DeGeurin

Published April 3, 2023 | Comments (6)

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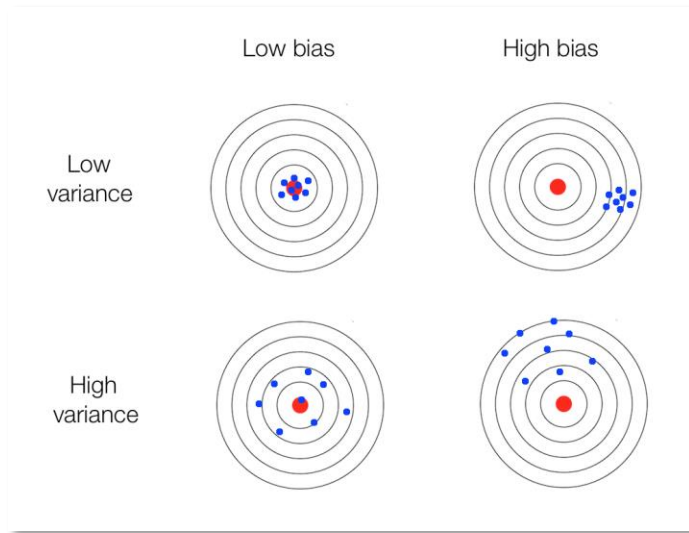
Today: a story in two parts

Biased Outputs

- Stereotypical behavior
- Malfunction on minority inputs
- …

Harmful Content

- Toxicity
- Unsafe content
- …

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Part 1 – Bias

Some definitions of bias

- Bias [*statistics*]: systematic tendency causing differences between model estimates / predictions
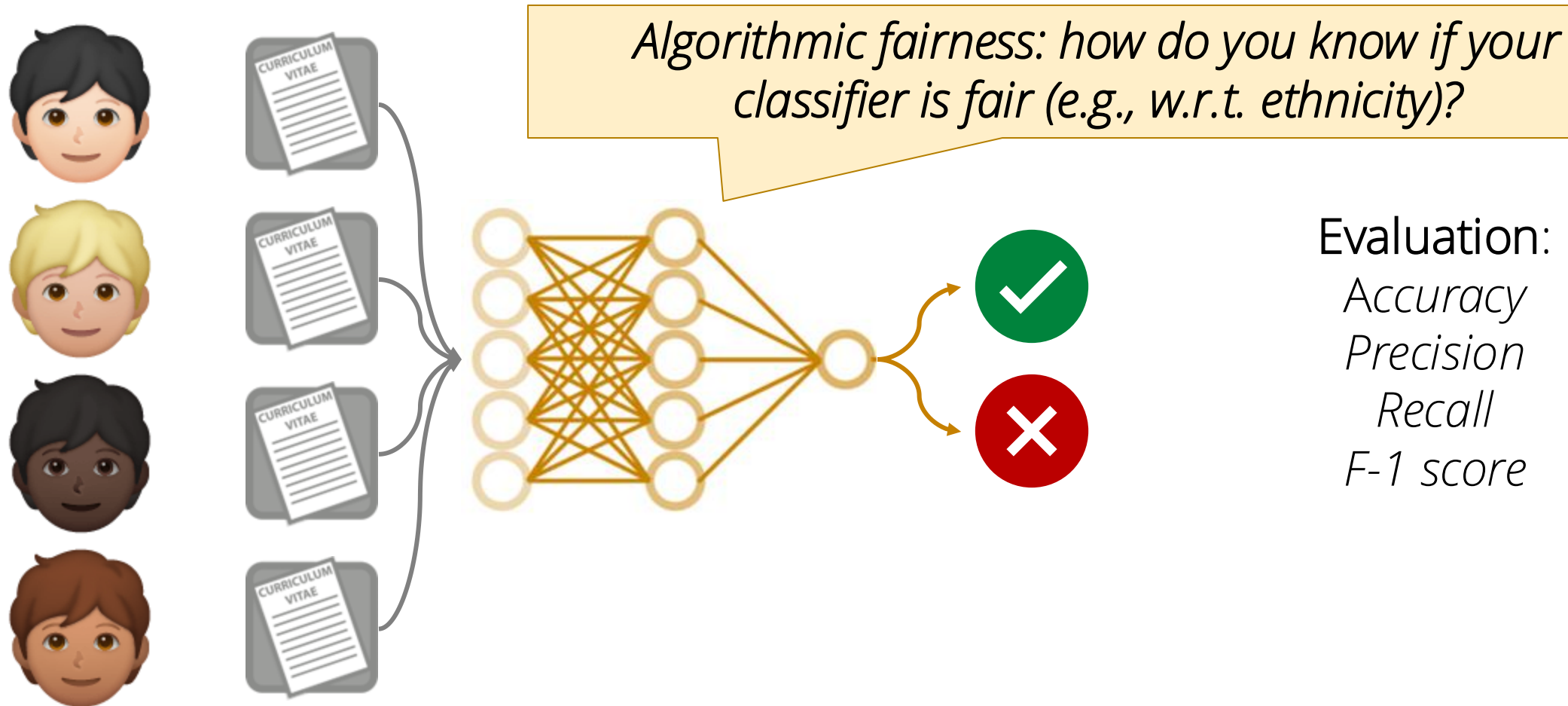

- Bias [*general*]: "*disproportionate weight in favor of or against an idea or thing, usually in a way that is closed-minded, prejudicial, or **unfair***" – Wikipedia

Presence of bias ≃ absence of fairness
Algorithmic fairness: attempts to correct biases in ML systems
But... how is fairness defined?

Algorithmic fairness

Let's assume a toy task: given a resumé, predict whether a candidate is qualified

Algorithmic fairness: how do you know if your classifier is fair (e.g., w.r.t. ethnicity)?

Evaluation:
Accuracy
Precision
Recall
F-1 score

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Fairness metrics

- **Accuracy quality**: a classifier is fair if the people from different groups have the same accuracy

- **Statistical parity**: groups should have the same probability of being assigned positive class

Accuracy

=

Accuracy

=

Accuracy

=

Accuracy

$p(\text{✅} | \text{👤})$

=

$p(\text{✅} | \text{👤})$

=

$p(\text{✅} | \text{👤})$

=

$p(\text{✅} | \text{👤})$

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Equalized odds criterion [Hardt et al '16]

A classifier c is fair if the *false positive (FP)* and
true positive (TP) rates are the same for different groups

o *False positives*

$$p\big(c(\text{🧑}) = \text{✅} \mid l(\text{🧑}) = \text{✖}\big)$$
$$=$$
$$p\big(c(\text{🧑}) = \text{✅} \mid l(\text{🧑}) = \text{✖}\big)$$

o *True positives*

$$p\big(c(\text{🧑}) = \text{✅} \mid l(\text{🧑}) = \text{✅}\big)$$
$$=$$
$$p\big(c(\text{🧑}) = \text{✅} \mid l(\text{🧑}) = \text{✅}\big)$$

		Predicted class	
		Positive	Negative
Actual class	Positive	TP	FN
	Negative	FP	TN

Other fairness metrics

- *Treatment equality*
  - Ratio of false negatives and false positives should be the same for groups
- *Fairness through unawareness*
  - Models should not employ sensitive attributes when making decisions
- *Causality-based*
  - *Counterfactual fairness*: outcome of the classifier would not changed if the sensitive attribute (e.g., race) were the only thing changed
- Many more…
  - https://en.wikipedia.org/wiki/Fairness_(machine_learning)
  - https://fairmlbook.org/

FAIRNESS AND MACHINE LEARNING

Limitations and Opportunities

Solon Barocas, Moritz Hardt, Arvind Narayanan

CONTENTS

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Other fairness metrics

- *Treatment equality*
  - Ratio of false negatives and false positives should be the same for groups

- *Fairness through unawareness*
  - Models should not employ sensitive attributes when ~~making decisions~~

FAIRNESS AND MACHINE LEARNING

Limitations and Opportunities

Solon Barocas, Moritz Hardt, Arvind Narayanan

> But, do these definitions really matter if no harms are caused? Many argue that unfairness/bias should be measured in terms of the harms that it causes

We explore what makes automated decision making a matter of normative concern, situated in bureaucratic decision making and its mechanical application of formalized rules.

3 CLASSIFICATION   PDF

We introduce formal non-discrimination criteria in a decision-theoretic setting, establish their relationships, and illustrate their limitations.

4 RELATIVE NOTIONS OF FAIRNESS   PDF

- Many more…
  - https://en.wikipedia.org/wiki/Fairness_(machine_learning)
  - https://fairmlbook.org/

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Bias in terms of the harms it causes

Bias in
AI systems

Allocational harms — Giving higher credit limit to men vs. women

Representational harms
(social biases)
- Stereotypical portrayals or associations
- Negative or dehumanized representations

Recognition harms — Poor performance on minority inputs

Most of NLP bias literature

Spurious biases (not aligned with social biases) — Cat = contradiction, dog = entailment

https://machinesgonewrong.com/bias_i/

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"Bias" is an overloaded term

- [Blodgett et al 2020](#) examined ~150 NLP papers with "bias" in the title, found that many papers use term "bias" in ill-defined or vague ways

Some recommendations

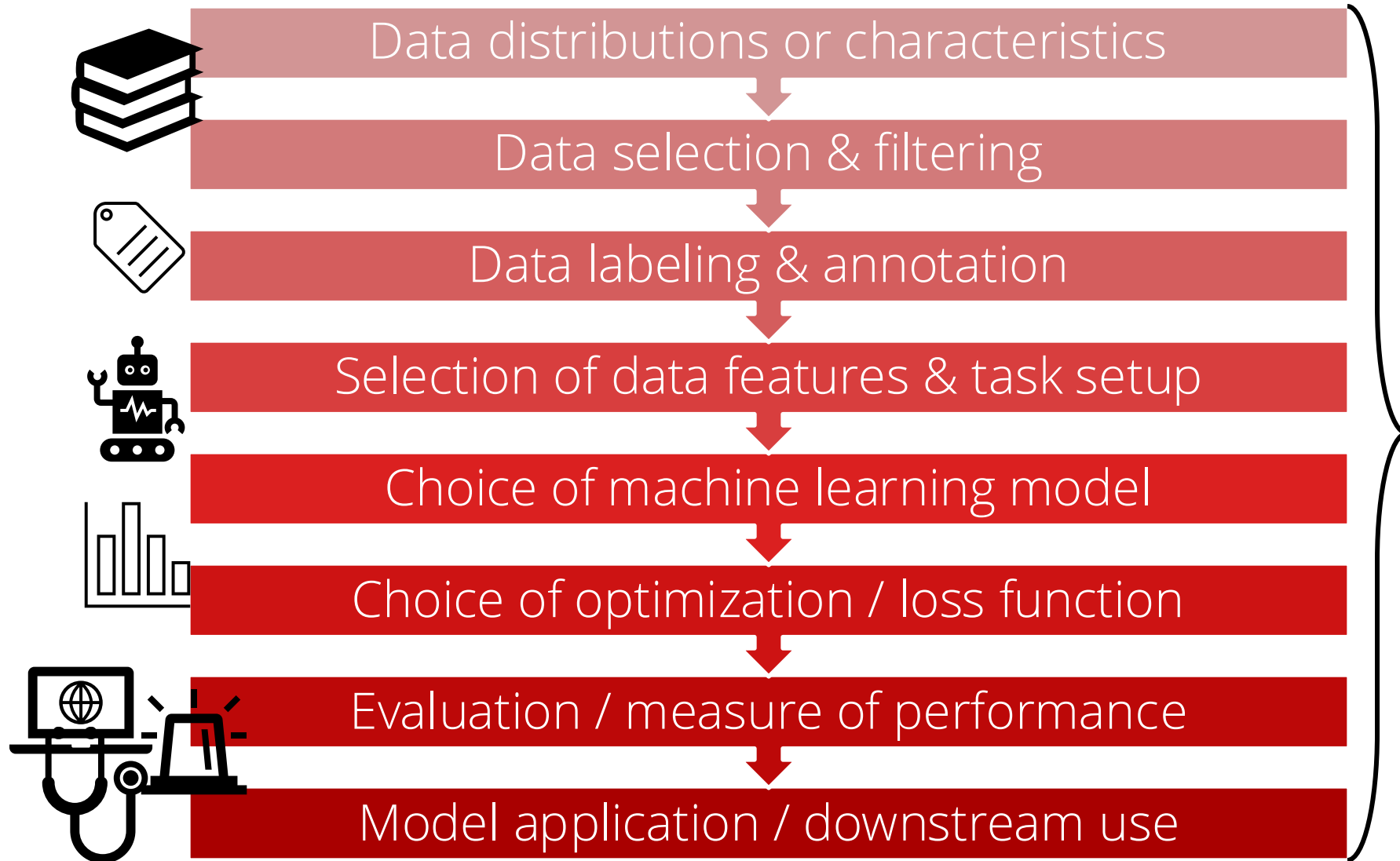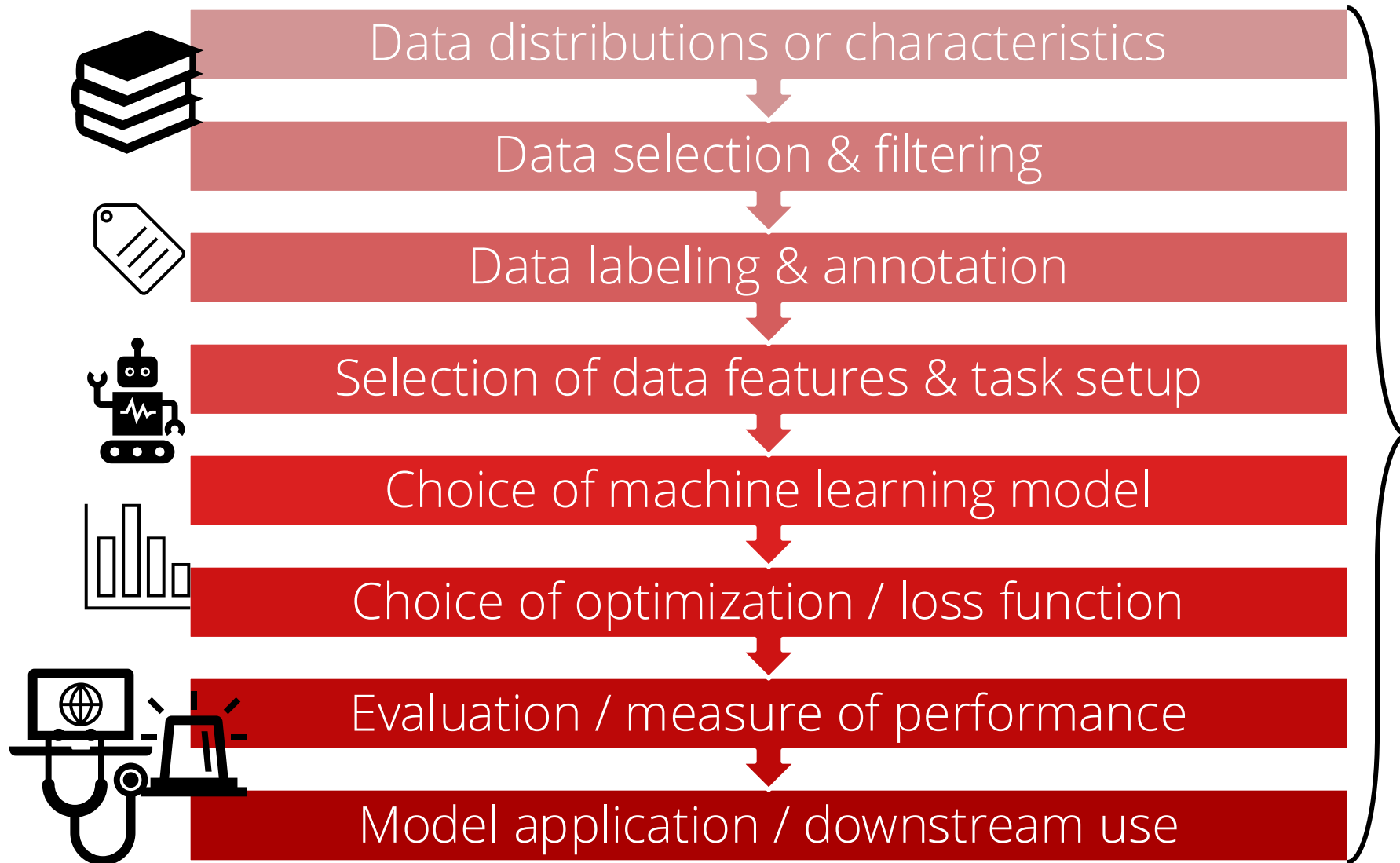| Biased behavior	Harms from biases	Social values
• What kinds of system behaviors are described as "bias"? What are their potential sources (e.g., general assumptions, task definition, data)?	• In what ways are these system behaviors harmful, to whom are they harmful, and why?	• What are the social values (obvious or not) that underpin this conceptualization of "bias?"

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Where does bias come from?

Machine learning pipeline

Data distributions or characteristics

↓

Data selection & filtering

↓

Data labeling & annotation

↓

Selection of data features & task setup

↓

Choice of machine learning model

↓

Choice of optimization / loss function

↓

Evaluation / measure of performance

↓

Model application / downstream use

Bias can arise from *any* of these design decisions

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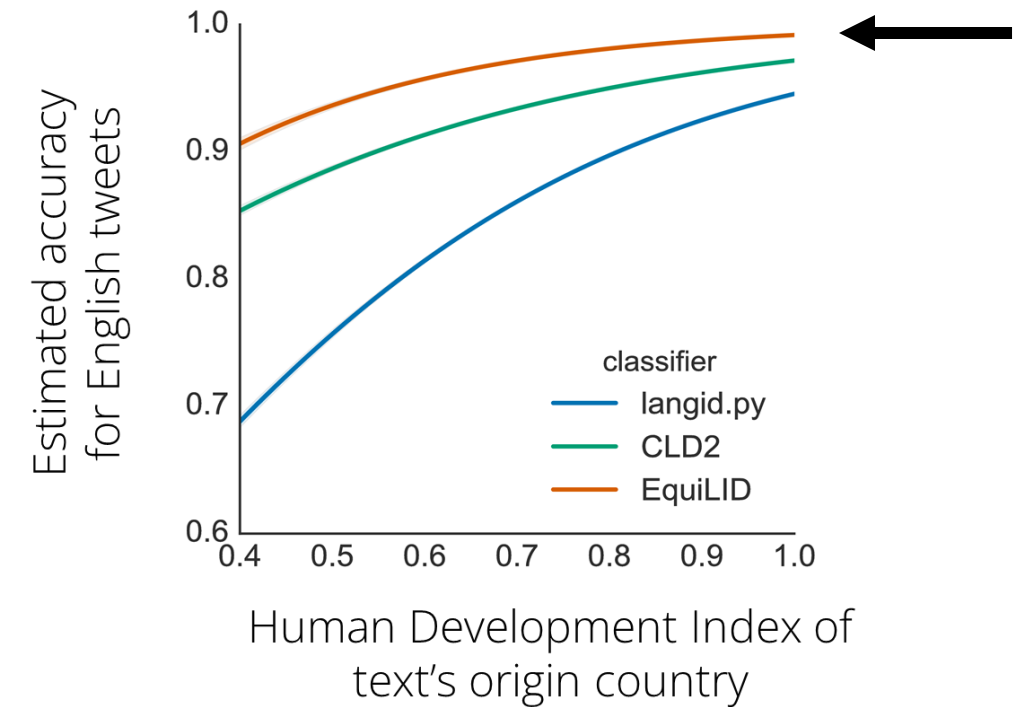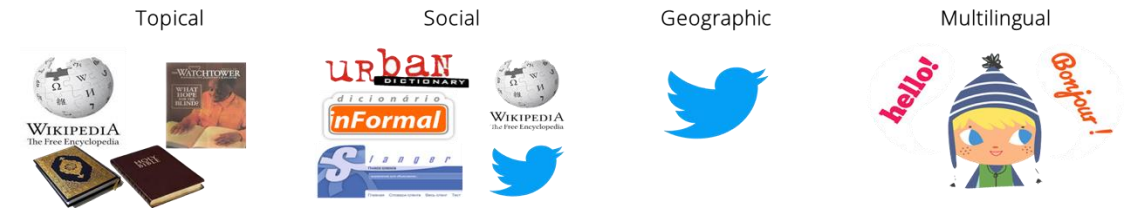
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Example of bias from data: LangID tool

- LangID task: determine which language an input text is in
  - Considered a "*a solved problem* suitable for undergraduate instruction" (McNamee, 2005)
- Often a first step in most NLP and CSS preprocessing pipelines
  - e.g., filtering LLM pretraining data
- *But*, many variations of English in the world
  - *Int'l*: Nigerian English, Indian English, etc.
  - *Within US*: African American English, etc.
- Jurgens et al. (2017) found that accuracy of LID tool correlated with wealth/development level of country; **works worse for low HDI countries**
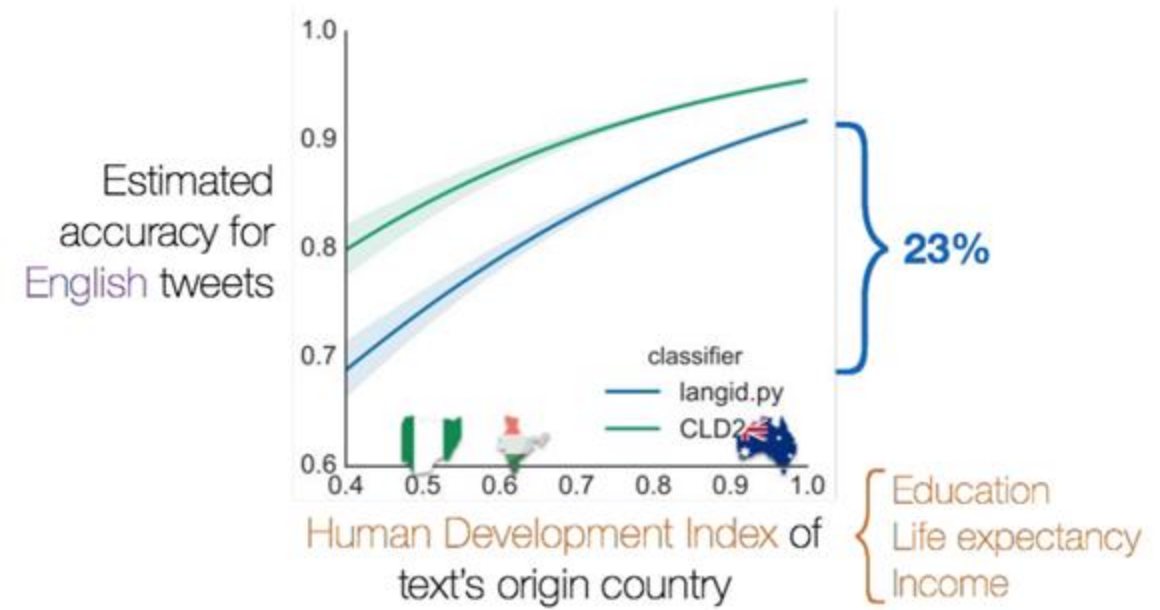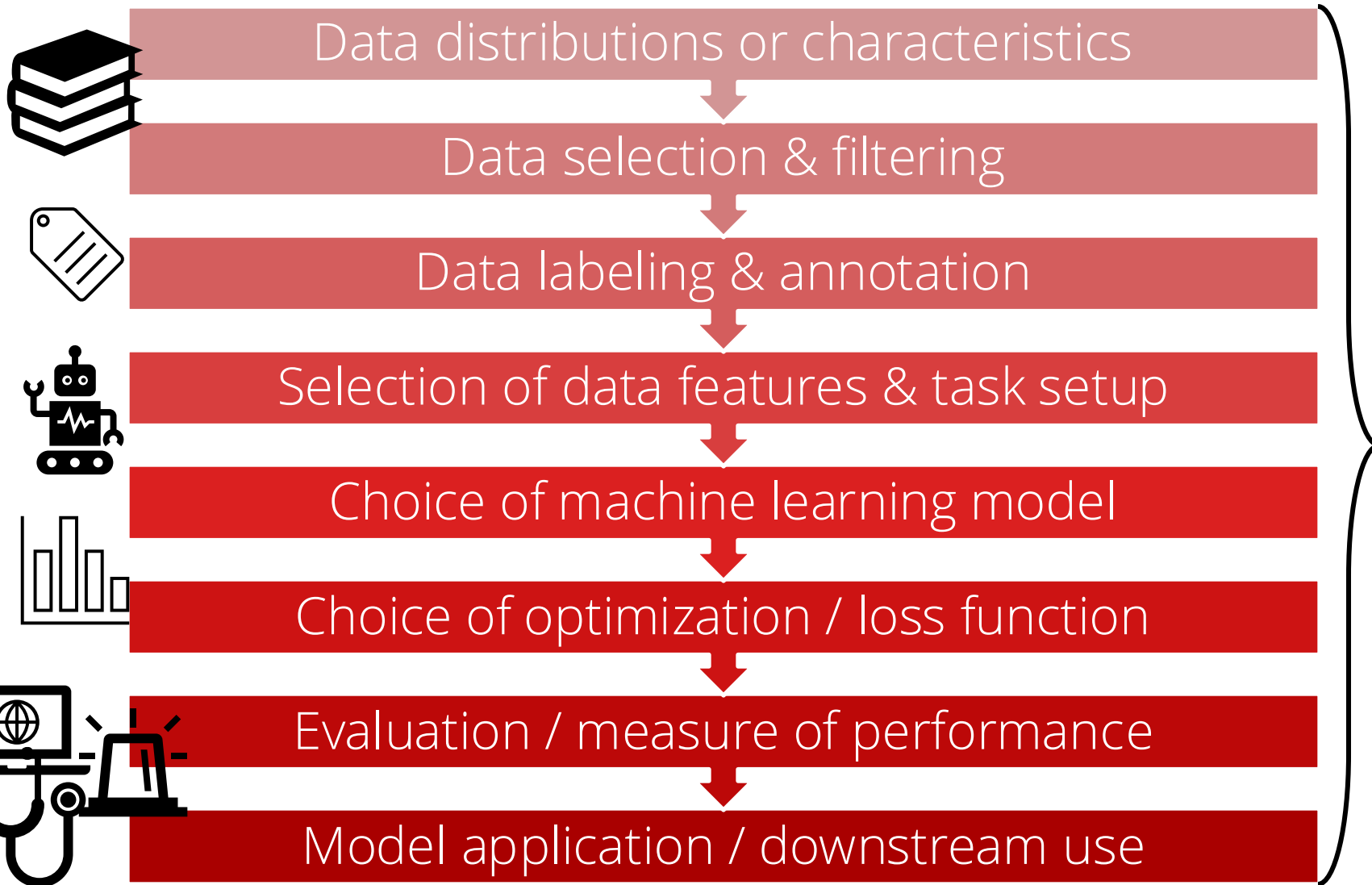
Example of bias from data: LangID tool (2)

- Jurgens et al (2017) introduce **EquiLID**
  - o Trained by sampling more variety of data, topically, socially, geographically diverse, and even multilingual data
- Find that tool works much better than original LID systems
  - o Bonus: even improved accuracy on highly developed countries!
- **Takeaway**: bias can be mitigated by making better data choices
 - o But that's not the only source of bias…

Topical   Social   Geographic   Multilingual

classifier
— langid.py
— CLD2
— EquiLID

Estimated accuracy for English tweets

Human Development Index of text's origin country

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Bias amplification from models

- [Zhao et al (2017)](#) examined visual semantic role labeling task
  - Given an image, predict various semantic roles, including agent (person doing the action)
- Found skews in training dataset
  - E.g., 66% of training cooking images had agent=woman
- Found that models *amplified* biases
  - E.g., 84% of test cooking images predicted as agent=woman (~18% men mis-labeled)
- Showed that prediction / inference functions can mitigate this bias
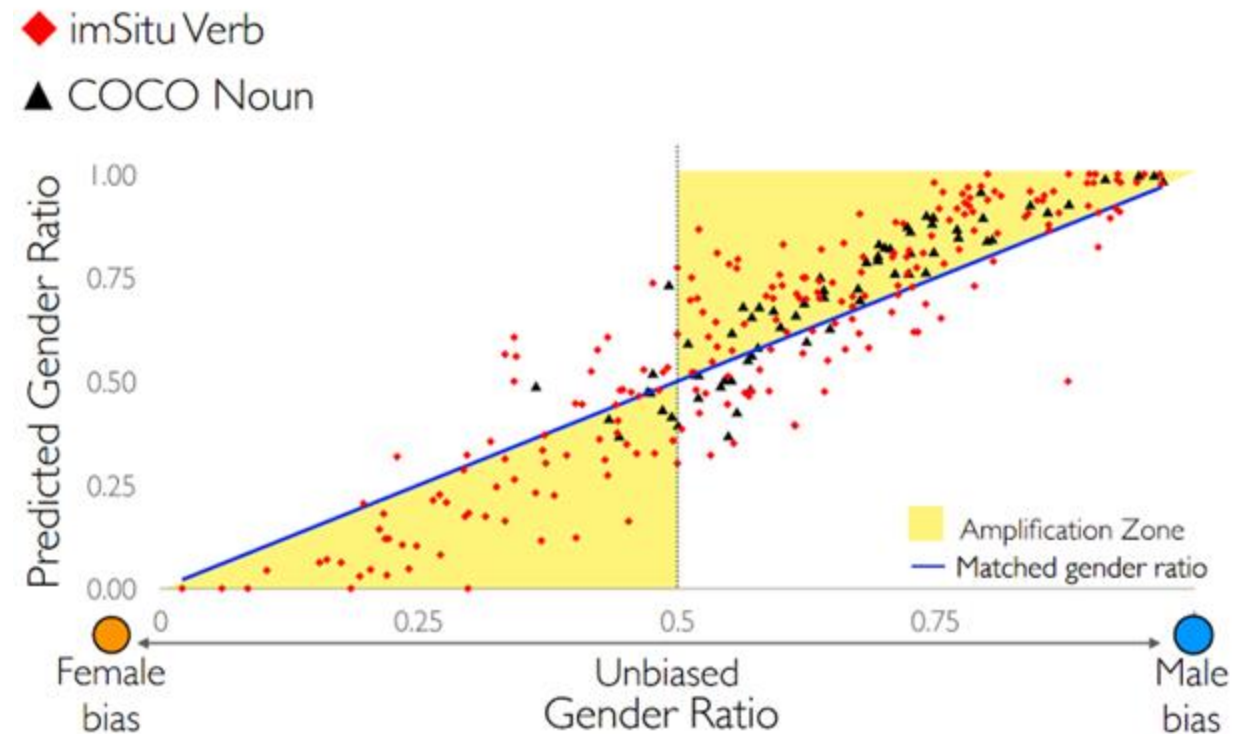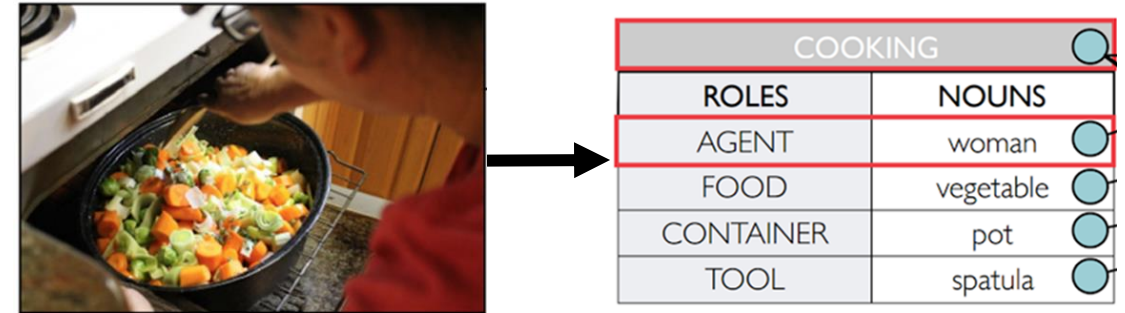
Model biases: mathematical links

- *Competing losses*: objective functions aim to minimize loss globally → learns to predict most frequent class
  - o Often at the expense of less frequent classes (e.g. minority groups)

- *Simplicity bias*: neural networks biased towards learning simpler functions [Valle Pérez et al. 2019]

- Intuitively, if a model has limited learning capacity, makes sense that it learns shortcuts first
  - o Shortcuts are often stereotypes or majority biases; e.g., CEOs are men

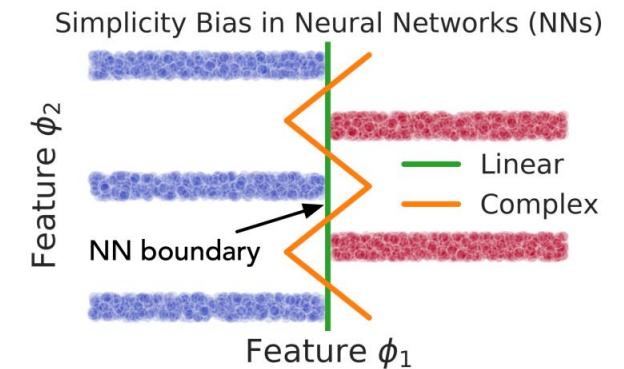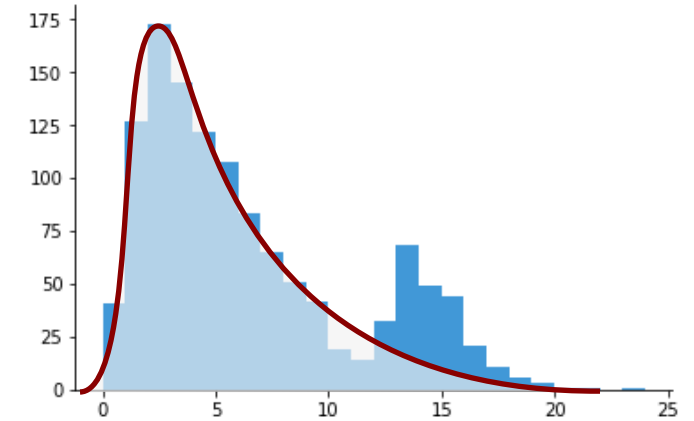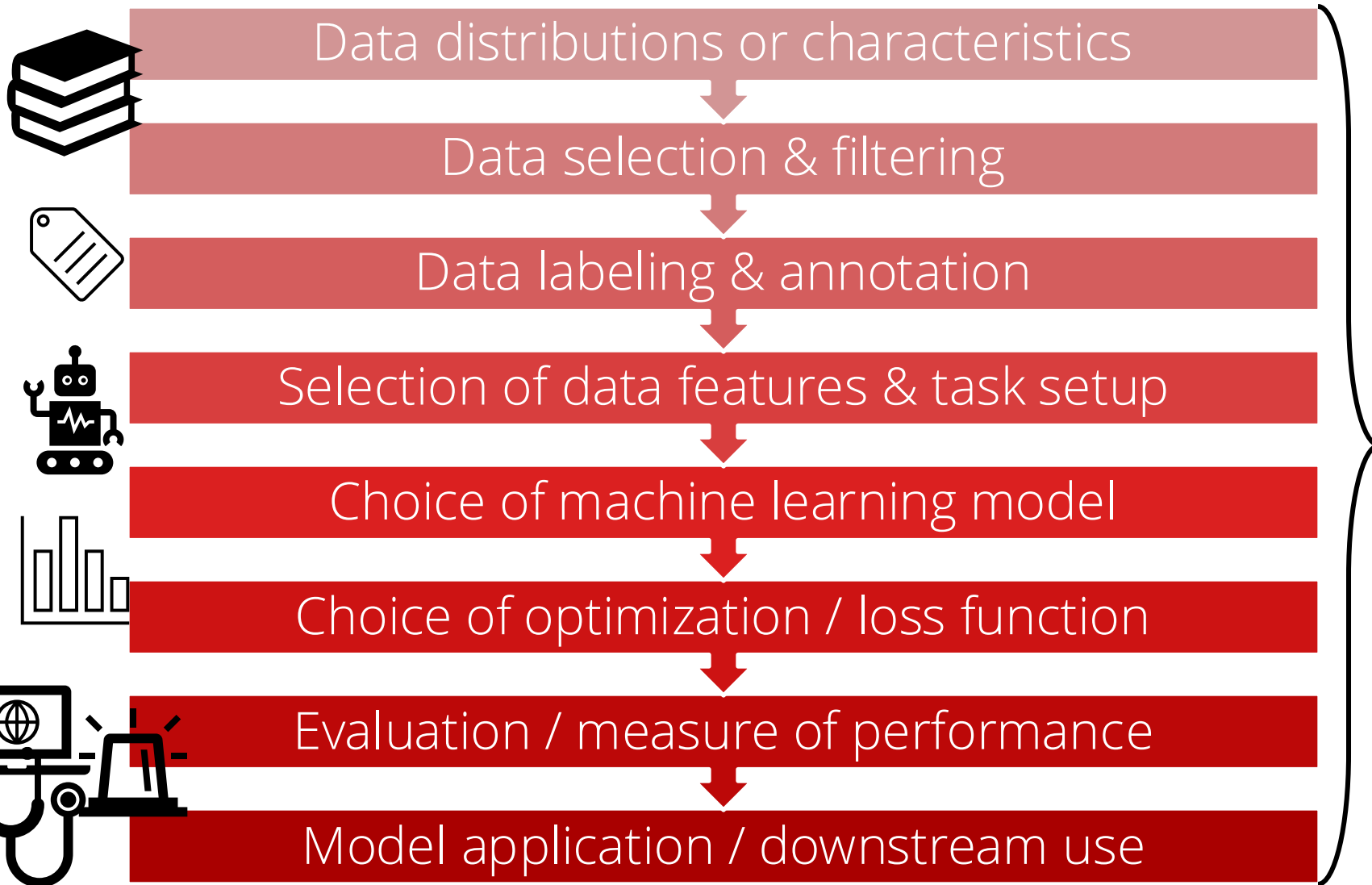- **Takeaway**: ML/optimization choices also affect biases

Figure 1: Simple vs. complex features

Figure from Shah et al 2020

Machine learning pipeline

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Google Translate issue

Before

After

Input in non-gendered language (e.g., Turkish)

Stereotypical gender assigned in translation
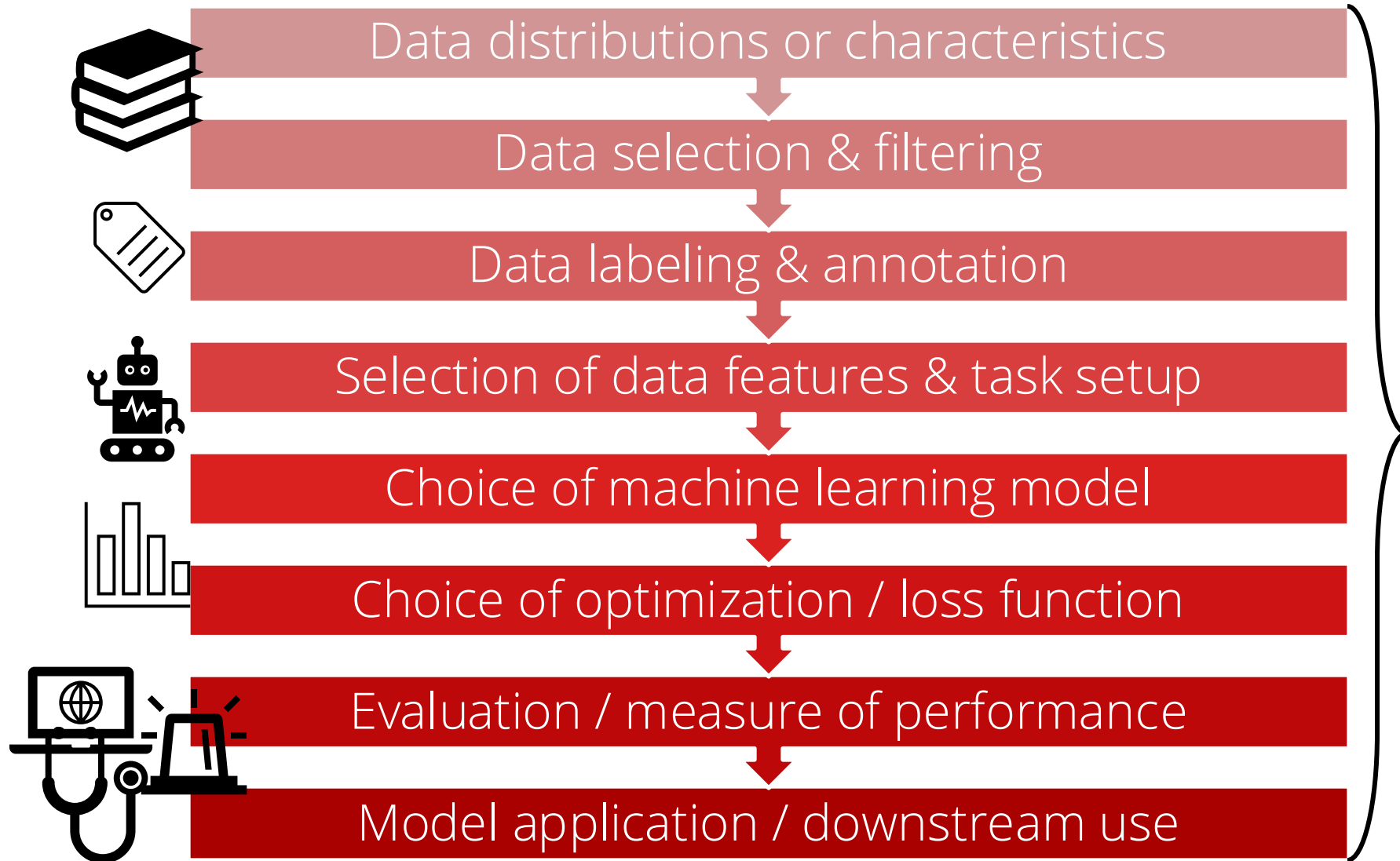
Google's fix: translate twice, with male & female pronouns

- Takeaways: mitigating bias may involve *system-level changes* to UI, input processing, output formatting, etc. while underlying AI model is similar

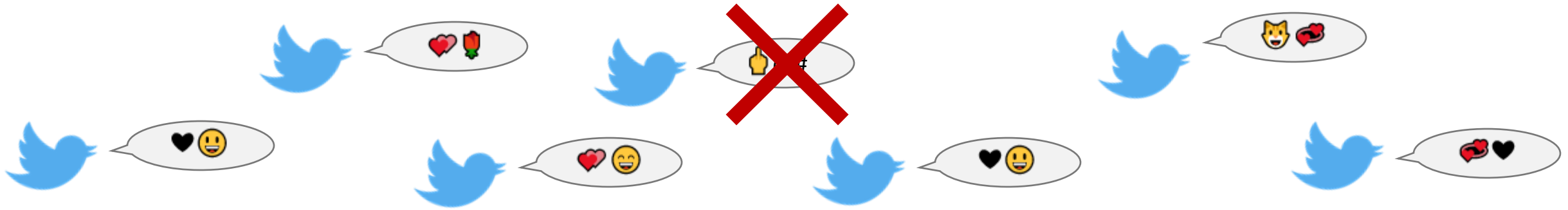- *Let's discuss*: what do you think of this approach? What are some possible issues?

https://ai.googleblog.com/2018/12/providing-gender-specific-translations.html

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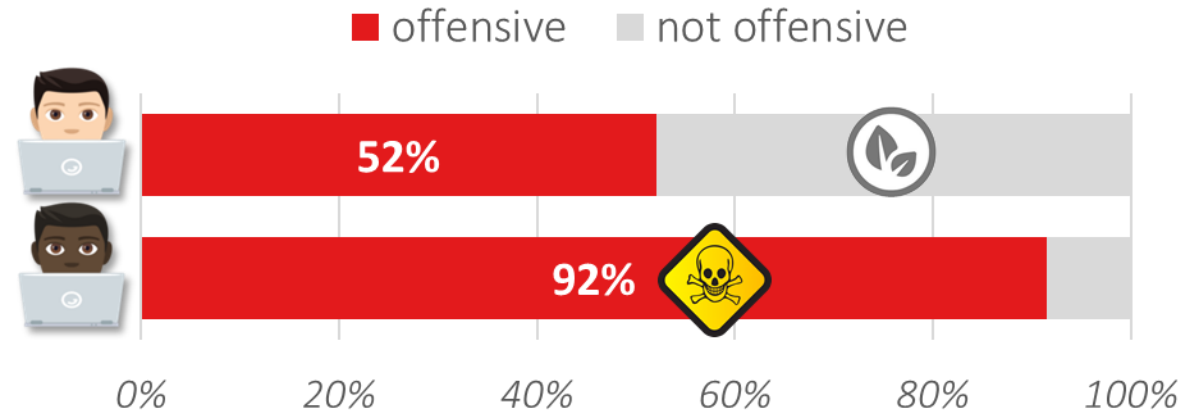
Model application / downstream use

Bias can arise from *any* of these design decisions
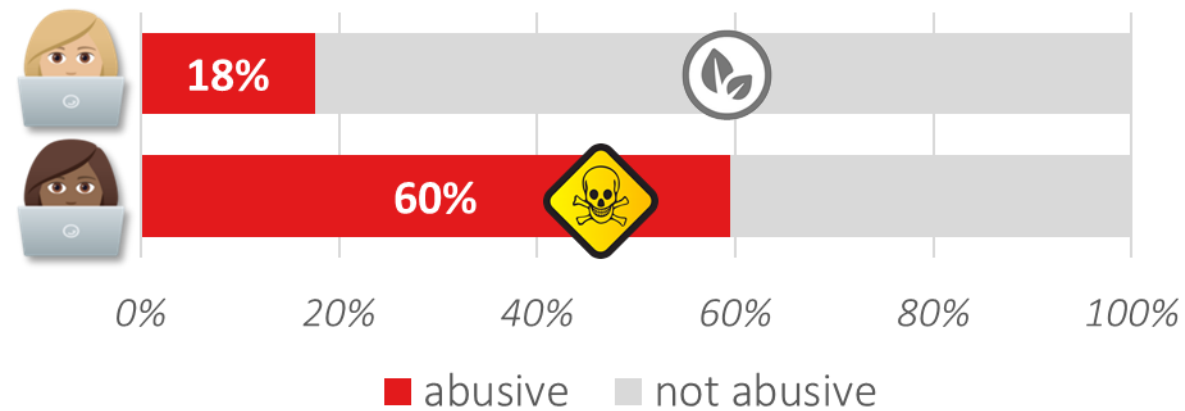
Hate Speech or Toxic Language Detection

Goal: find and flag hateful or toxic content online, to make the internet less toxic

Racial biases in two popular datasets [Sap et al 2019]

TWT-HATEBASE
(Davidson et al., 2017)

Both datasets have biases w.r.t. AAE tweets

TWT-BOOTSTRAP
(Founta et al., 2018)

Enhancing the labeling interface [Sap et al 2019]
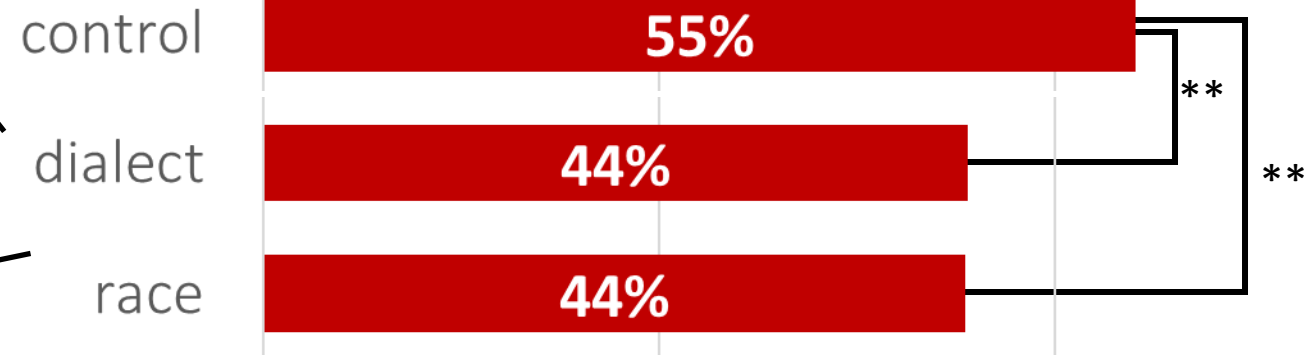
Control condition

Text-only, no context, prior work

Dialect priming

"Our AI thinks this tweet is in African American English"

Race priming

"A Twitter user that is likely Black/African American tweeted..."

MTurk study:
- 350 AAE tweets, ~50% labeled toxic
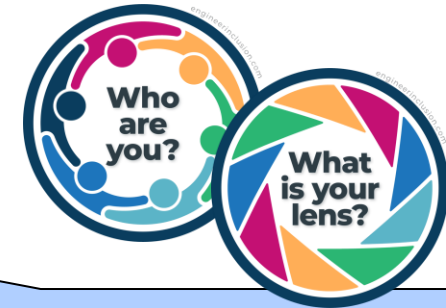- 3 (re-)annotators per tweet

Could this tweet be **offensive to** *anyone?*

control	**55%**
dialect	**44%**
race	**44%**

**

**

Takeaway: adding social context to labeling mitigated bias

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Why did these biases occur?
Why didn't NLP system designers think about these issues beforehand?

The world itself is biased

System designers have our own biases because of their *positionality*, i.e., set of perspectives that we hold due to our lived experiences and identity.

Positionality affects all our choices (e.g., assuming 1-1 mapping between languages and gendered pronouns, assuming toxicity looks the same in different dialects)

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Debiasing AI systems

Is it even possible?

DALLE-2 vs. Gemini

- DALLE-2 generated images were shown to have social biases, later fixed by adding identity keywords to the input prompts (e.g., `prompt+" Asian"`; Sparkes 2022)
- Gemini generations also shown to have skews
- *Let's discuss*: what do you think of this? How are these two generations different?

Limits of debiasing

- Gender debiasing doesn't work
  - Breaks down for non-binary genders, racial categories or other social identity types
- Intrinsic debiasing ≠ actual debiasing
  - Finetuning often reintroduces biases
  - Out-of-distribution data often still show biases
- *Real world vs. ideal world*: is reflecting the (biased) status quo the goal? or do we want to build a more fair or just world?
- Justice and fairness go beyond data & model fairness
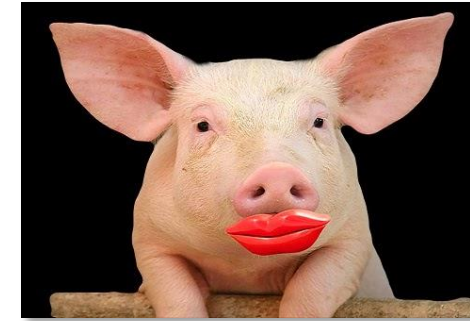
"Lipstick on a pig" paper,
Gonen & Goldberg 2019

On the Intrinsic and Extrinsic Fairness Evaluation Metrics for Contextualized Language Representations

Yang Trista Cao[*1], Yada Pruksachatkun[*2], Kai-Wei Chang[2,3], Rahul Gupta[2]
Varun Kumar[2], Jwala Dhamala[2], Aram Galstyan[2,4]
[1]University of Maryland, College Park

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A lot of people have understood that we need to have more diverse datasets, but unfortunately, I felt like that's kind of **where the understanding has stopped**. It's like '*let's diversify our datasets. And that's kind of ethics and fairness, right?*' But you **can't ignore social and structural problems**.

Timnit Gebru, PhD

Socio-technical view on bias & fairness

- You can have an "fair" NLP/ML model (e.g., facial recognition system)
  - o 95% accuracy/error rate on white & Black faces
- But if the system is used by law enforcement, bias creeps in w.r.t. who the system is used on
  - o Black people more often arrested, due to racial biases
- Actual error rates are a function of deployment
- Algorithm's fairness ≠ fairness of treatment

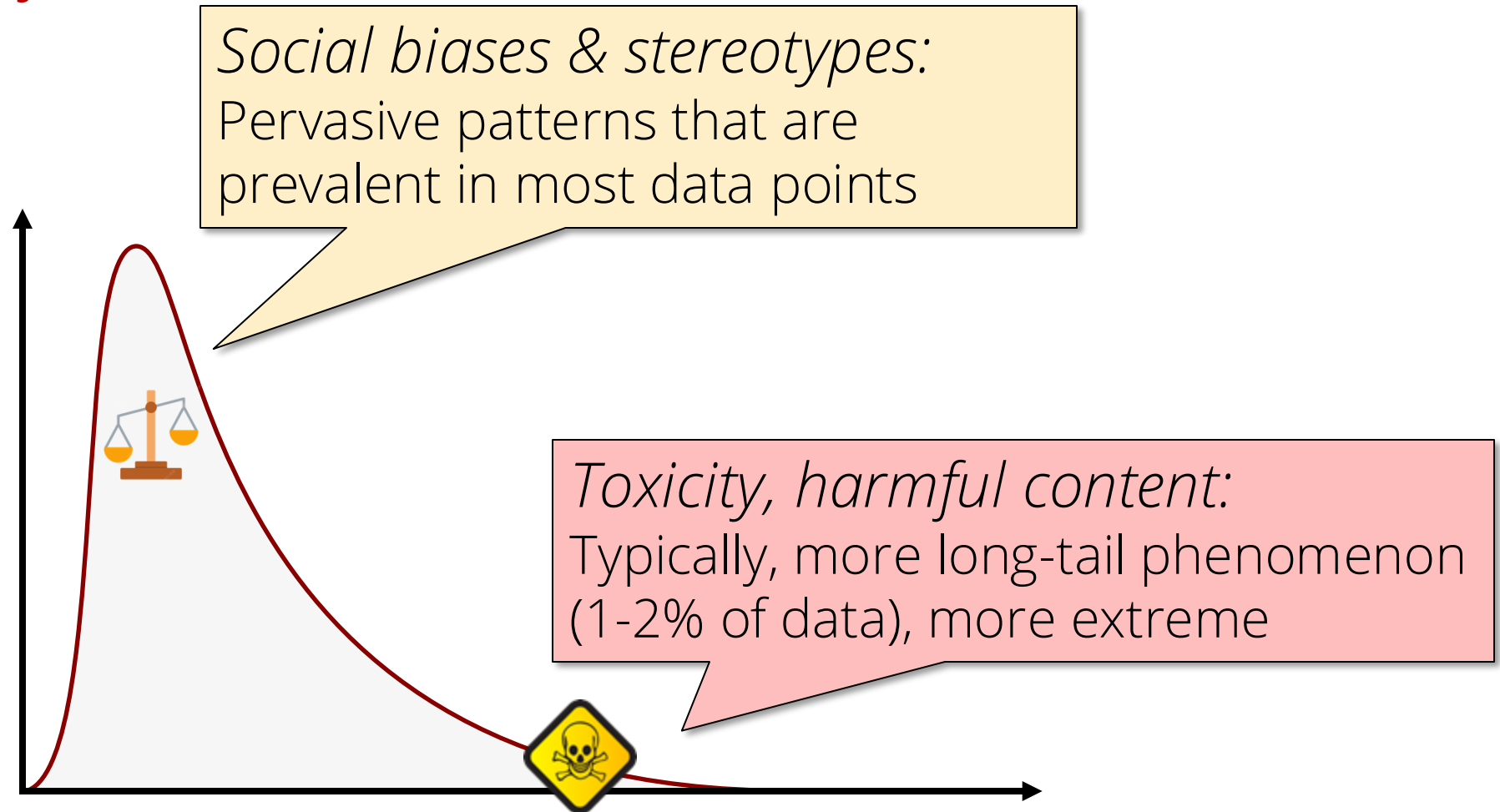

Black people are more likely to be arrested, charged and killed by police in Toronto, new report finds

By Scottie Andrew, CNN

Published 3:15 PM EDT, Wed August 12, 2020

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Part 2: Harmful content & toxicity

Toxicity in LLMs, how bad is the problem really?

- Gehman et al (2020) introduced concept of *neural toxic degeneration* in LLMs

- Out of a 100 generations sampled from models, at least one toxic sentence
  - 65-70% toxicity from GPT2, GPT3
  - 85% toxicity from GPT1

- Model size affects toxicity: larger models have more toxicity [Touvron et al 2023]
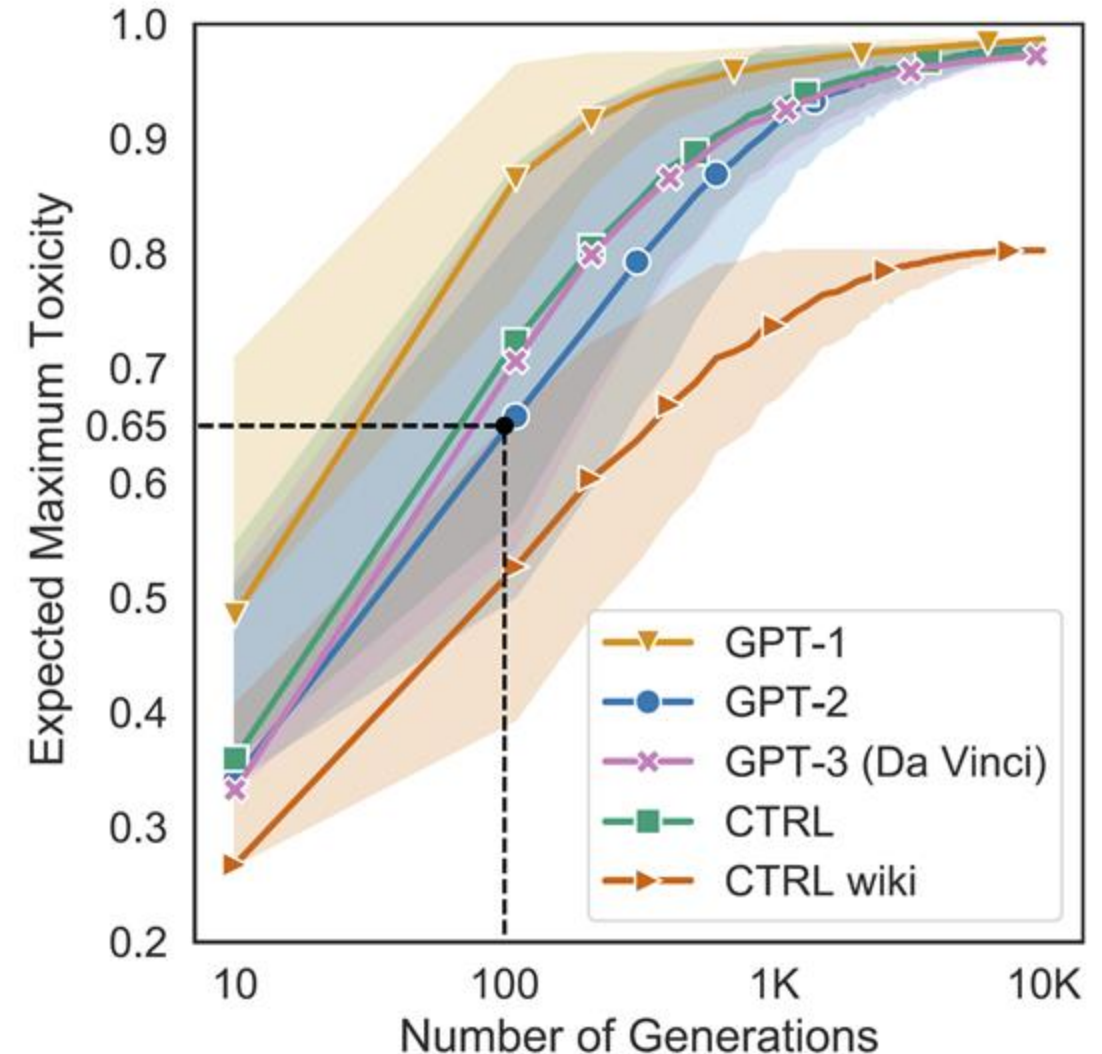
Why are these models learning so much undesirable content?

Problems with self-supervised pretraining

*"Feeding AI systems on the world's **beauty, ugliness, and cruelty**, but expecting it to reflect only the beauty is a fantasy"*

Prof. Ruha Benjamin, PhD

- **Recipe**: scrape as much pretraining data as you can to train your LM
- **Consequence**: LM ends up learning toxicity, biases, extremism, hate speech…

Toxicity in GPT-2's pretraining data

- Gehman et al (2020) also accessed the actual GPT-2 training corpus (OpenAI-WT)
  - o   8 million documents, 38Gb of text
  - o   Outbound links from Reddit posts with Karma>=3
- Scored it with PerspectiveAPI toxicity
- Found >4% of documents (340,000) are toxic
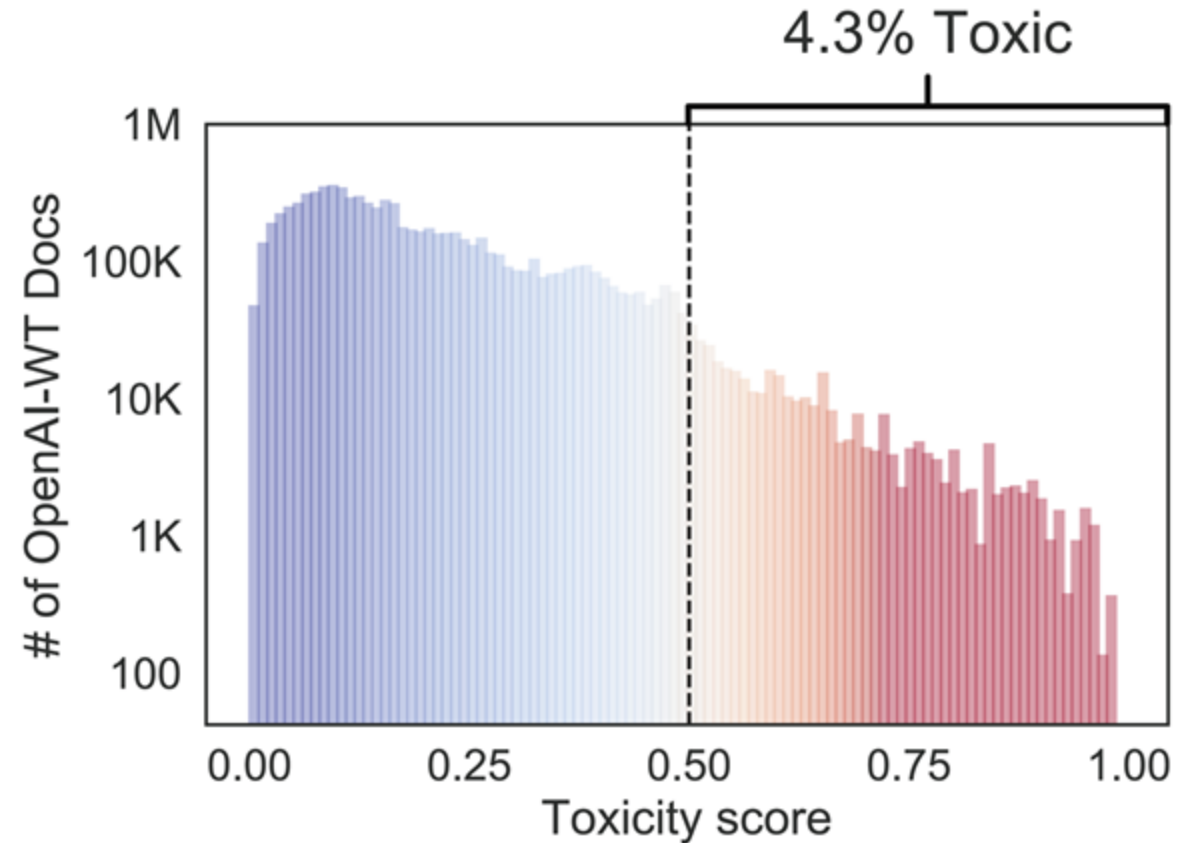
Fake news in GPT-2's pretraining data

- Also looked at sources of documents in training data
- Cross-referencing sources of documents with known factual reliability categorization
  - \>272K (3.4%) docs from low/mixed reliability sources
- Examining source where document is shared
  - \>200K (3%) docs linked from banned/quarantined subreddits, which typically are more toxic docs
- Important to examine training data
  - Can only do that if publicly released!

- *So... need approaches to safeguard your model against this undesirable content, knowledge, and text.*
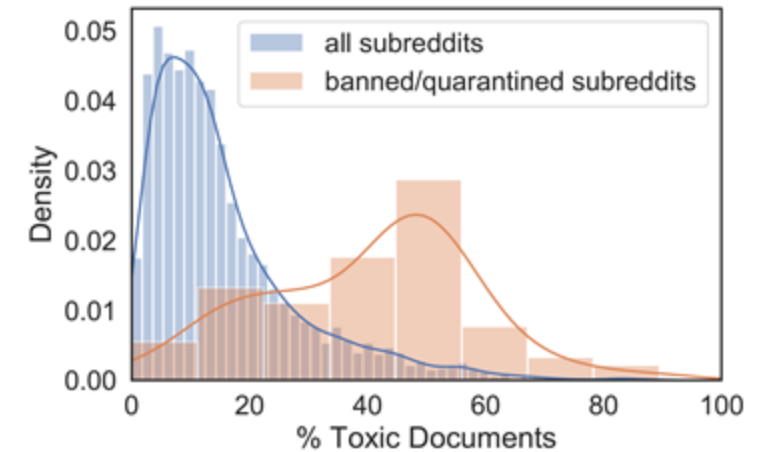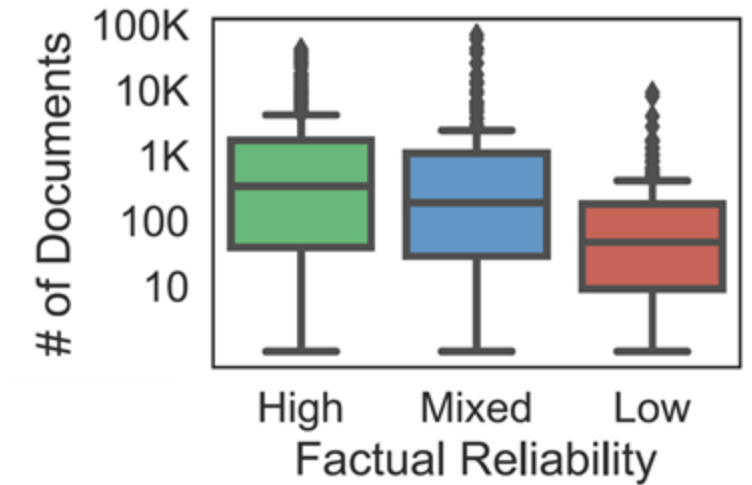
How to safeguard your LLMs

Overview – LLM safeguarding

Safeguards from training data	• Filtering out toxic training data
Safeguards from input prompt classification	• Topic-based filters • Toxic content detection
Safeguards from instruction-tuning & RLHF	• Write demonstrations for refusing to answer • RLHF models to prefer non-toxic generations
Safeguards at the output level	• Generate-then-classify • Controllable text generation

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Dataset filtering

- *Argument*: if you don't want your model to generate toxicity/hate speech, do not train it on such data (garbage in, garbage out)
- *Approach*: data filtering to ensure "high quality"
- How do you know what is "high quality" ?
  - GPT-2: Reddit "Karma" score as signal
  - T5, BERT: "blocklist" of "bad words"
  - GPT-3: "quality" classifier
- Often, those backfire! Let's investigate!
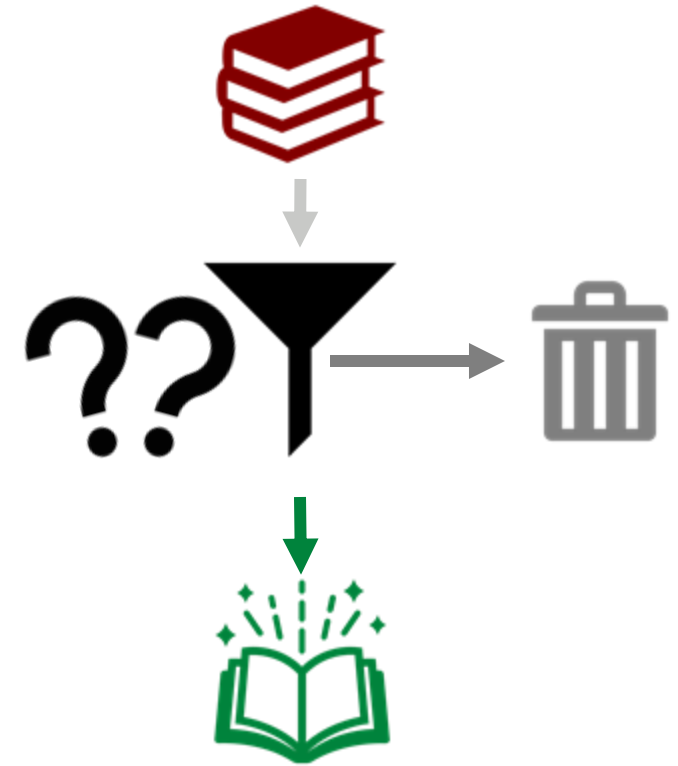
Blocklist of "bad" words

- "[List of Dirty, Naughty, Obscene, or Otherwise Bad Words](#)" originally by Shutterstock employees
  - Meant to prevent words in autocomplete settings
- Has been used by most companies creating LLMs
  - BERT, T5, GPT-2, etc.
- If document contains a "bad" word, remove it from training data
  - F*ck, sh*t, sex, vagina, viagra, n*gga, f*g, b*tch, etc.
- *Let's discuss*: what are issues with this?
  - Strong risk of over-deleting bio, legal, minority content

≡ WIRED SUBSCRIBE

TOM SIMONITE BUSINESS FEB 4, 2021 7:00 AM

AI and the List of Dirty, Naughty, Obscene, and Otherwise Bad Words

It started as a way to restrict autocompletes on Shutterstock. Now it grooms search suggestions on Slack and influences Google's artificial intelligence research.

Effect of "bad word" blocklist filtering

- Dodge et al examined the effect of blocklist filtering on the C4 corpus
- When looking at 100k documents that were excluded due to "bad words"
  - Found only 31% related to porn/explicit sex
  - Remaining was biology, medicine, legal
- Also examined the effect on which minority identities were removed
  - Found queer/LGBTQ identity terms removed more
- Examined dialects removed due to "bad words"
  - Found AAE, Hispanic English more likely to be removed
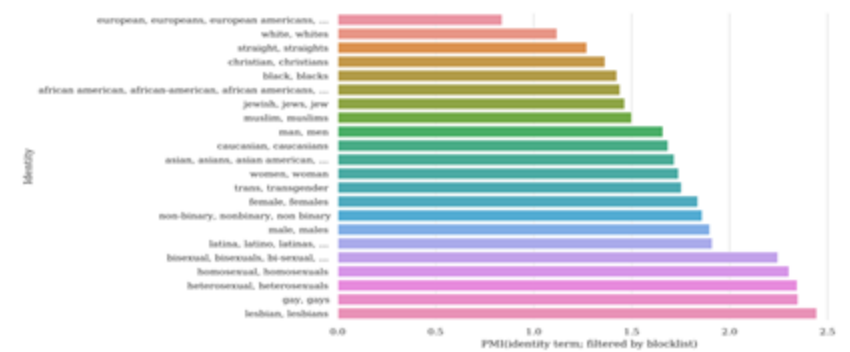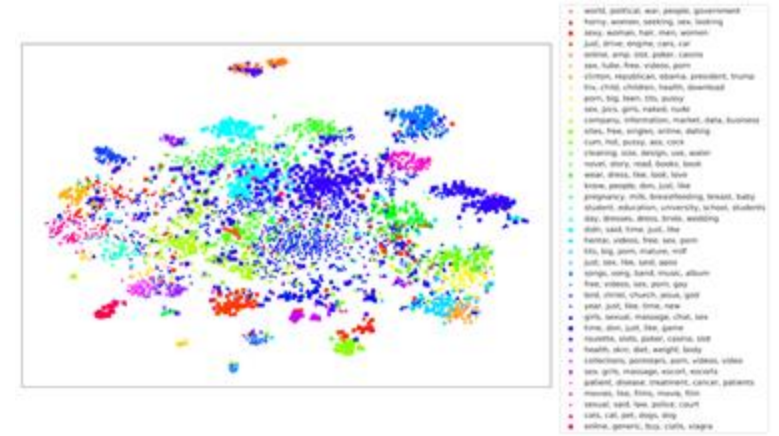
Less likely to be removed
- White-aligned English (6%)
- Other English (7%)

More likely to be removed
- African-American English (42%)
- Hispanic-aligned English (32%)

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GPT3 Quality filter backfires

- GPT3 quality filter: similar to GPT2 data

- [Gururangan et al. (2022)](#) re-implemented GPT-3 quality filter

- Ran it on articles from school newspapers, which have metadata

- Filter assigns higher quality to articles from
  - Richer counties 💰
  - Counties with more educated adults 👨‍🎓
  - More liberal counties 🗳️ DEMOCRAT
  - More urban counties 🏙️

- Raises language ideology question: Whose English is "good English"?

"In order to improve the quality of Common Crawl, we developed an automatic filtering method to remove low quality documents. Using the original WebText as a proxy for high-quality documents, we trained a classifier to distinguish these from raw Common Crawl." – Brown et al. 2020
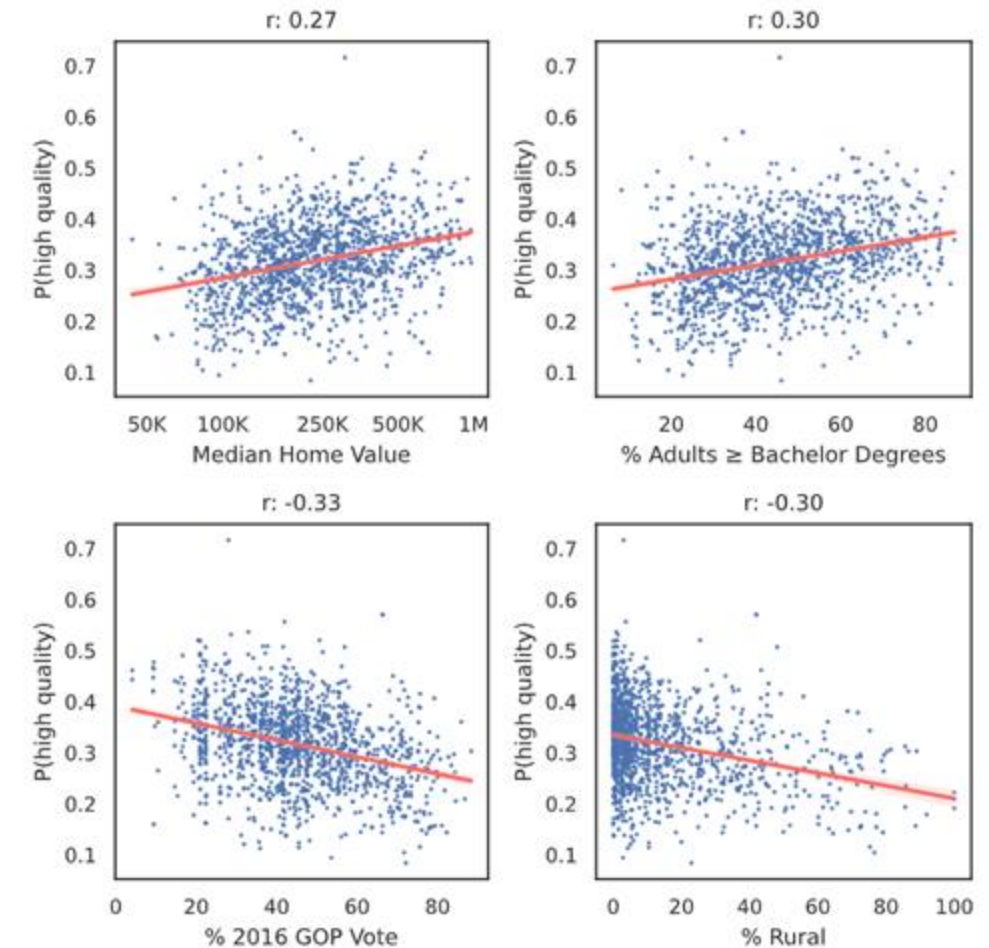
So… maybe filtering isn't a good idea since it'll backfire?

GPT4Chan controversy

- Yannic Kilchner finetuned GPT-J on 4chan posts
  - Trained on subforum /pol/ known to contain racist, sexist, white supremacist, antisemitic, anti-Muslim, anti-LGBT views
- Trolled 4chan users with bots powered by his model
  - 30,000 posts over the span of a few days
- Faced massive criticism
  - initially hosted on Huggingface, was taken down quickly
- *Let's discuss...*
  - Was this an ethical model to train? Given that the dataset was publicly available?
  - Was deploying the bots on 4chan okay?
  - Are there any useful/positive applications of the model?
  - What if Kilchner's intent was to raise awareness of ethical issues of LLMs, instead of doing it for Youtube views?

≡ FORTUNE

TECH · 4CHAN

'This breaches every principle of human research ethics': A YouTuber trained an A.I. bot on toxic 4Chan posts then let it loose — and experts aren't happy

BY SOPHIE MELLOR

June 10, 2022 at 5:23 AM EDT

https://thegradient.pub/gpt-4chan-lessons

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Why LLMs might want to have seen toxic content

- Detecting hate speech [Chiu et al 2022]
  - o Longpre et al. (2023) showed that LLMs trained on more toxicity are better toxicity detections
  - o Improving hate speech models with data augmentation: ToxiGen [Hartvigsen et al 2022]
- Counter speech generation [Saha et al 2022, Kim et al 2022, Mun et al 2023]

- *If we train on toxicity, something else must be done at a different time!*
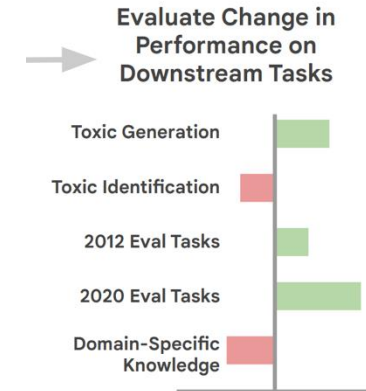
Evaluate Change in
Performance on
Downstream Tasks

Toxic Generation

Toxic Identification

2012 Eval Tasks

2020 Eval Tasks

Domain-Specific
Knowledge

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Overview – LLM safeguarding

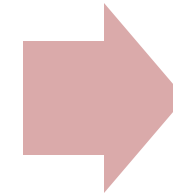|	
Safeguards from training data	• Filtering out toxic training data
Safeguards from input prompt classification	• Topic-based filters • Toxic content detection
Safeguards from instruction-tuning & RLHF	• Write demonstrations for refusing to answer • RLHF models to prefer non-toxic generations
Safeguards at the output level	• Generate-then-classify • Controllable text generation

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RLHF safeguarding – assumptions
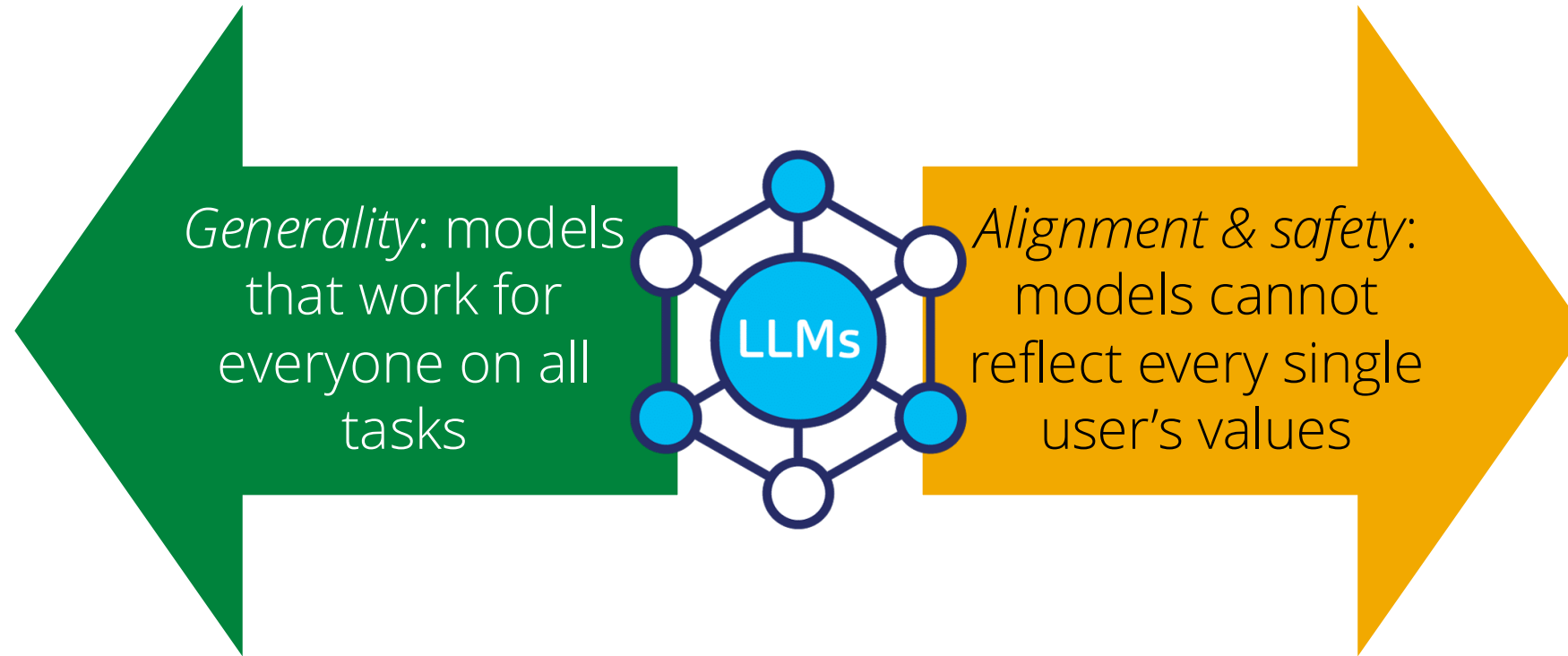
- PPO & family:

| Obtain preference data: which generation is **good** vs. bad? | → | RL is done to encourage more like "**preferred** output" |

- Big question: what does it mean for a generation to be **better/preferred**?
  - How to balance harmless and helpful? [Bai et al '23; Liu et al '24]
    - *E.g., "help me create a poisonous drink."*
  - What if people's preferences are biased or gameable?
    - *E.g., people prefer certainty over uncertainty in answers to questions [Zhou et al. 24]*
  - Fundamental issue: cannot represent all values and cultures into one ranking.
    - *Casper et al. 2023. "Open Problems and Fundamental Limitations of Reinforcement Learning from Human Feedback." arXiv [cs.AI]. arXiv. http://arxiv.org/abs/2307.15217*

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Big unresolved tension

Generality: models that work for everyone on all tasks

LLMs

Alignment & safety: models cannot reflect every single user's values

- Let's discuss: what do y'all think we should do?
- It's complicated!

So... what can we do?

- Need to keep studying what models can and can't do, who they work for and don't work for

- Narrow scope of model users

  o Community-specific models (e.g., Masakhane Initiative)

- Specialize models' abilities / away from one-size-fits-all

  o E.g., toxicity explanation generation model needs to generate stereotypes, but story generation models might not

- In line with many legislative efforts:
  legislate the application or task, not the model

Masakhane
A grassroots NLP community for Africa, by Africans

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University
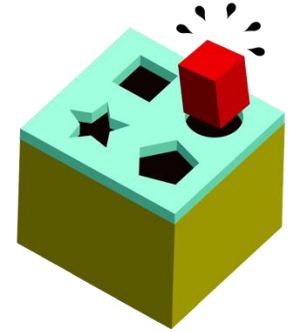
Takeaways

- AI systems are biased
  - o Real world is biased, data is biased
  - o ML objectives play a role
  - o Annotation interfaces, context plays a role
  - o Debiasing is challenging, requires socio-technical lens
- Toxicity and undesirable content
  - o Longer-tail phenomenon, present in training data
  - o Filtering data can backfire
  - o Safeguarding to all people is impossible
- *Any questions?*

Bias can arise from *any* of these design decisions

Social biases & stereotypes

Toxicity, harmful content

Safeguards from training data	· Filtering out toxic training data
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