Social & Ethical Considerations in NLP Systems

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Plan

- Motivating examples & discussion
  - practical tools to assess AI systems adversarially
- Overview of topics in the intersection of ethics & NLP
  - scientific background on algorithmic bias and a high-level research overview
- Examples of research projects
  - deep-dive into one or two studies

Language technologies

- Applications
  - Sentiment analysis
  - Machine translation
  - Information retrieval
  - Question answering
  - Dialogue systems
  - Summarization
  - Information extraction
  - …

- Core technologies
  - Language modelling
  - Part-of-speech tagging
  - Syntactic parsing
  - Named-entity recognition
  - Coreference resolution
  - Word sense disambiguation
  - Semantic role labelling
  - ...

Language & People

The common misconception is that language has to do with *words* and what they mean.

It doesn't.

It has to do with ***people*** and what *they* mean.

— Herbert H. Clark & Michael F. Schober, 1992

Language technologies & People

The common misconception is that language has to do with *words* and what they mean.

It doesn't.

It has to do with ***people*** and what *they* mean.

Decisions we make about our data, methods, and tools are tied up with their impact on people and societies.

What are the ethical and social considerations for technologies we build?

What is ethics?

“Ethics is a study of what are **good and bad** ends to pursue in life and what it is **right and wrong** to do in the conduct of life.

It is therefore, above all, a **practical discipline**.

Its primary aim is to determine how one ought to live and what actions one ought to do in the conduct of one’s life.”

— Introduction to Ethics, John Deigh

What is ethics?

It’s the **good** things

It’s the **right** things

What is ethics?

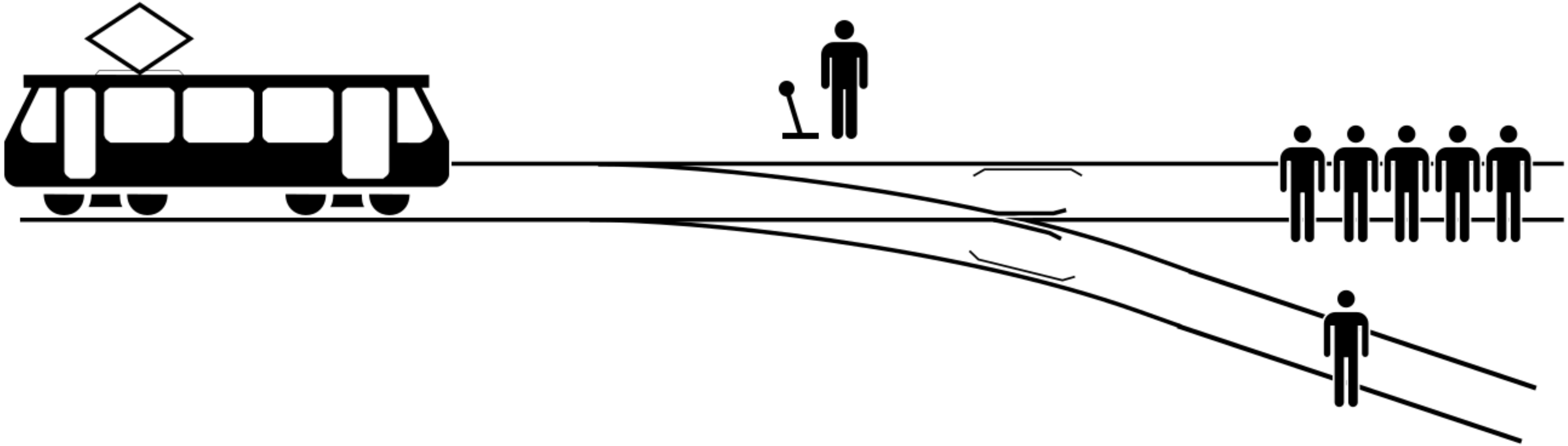
It’s the **good** things

It’s the **right** things

How simple is it to define
what’s good and what’s right?

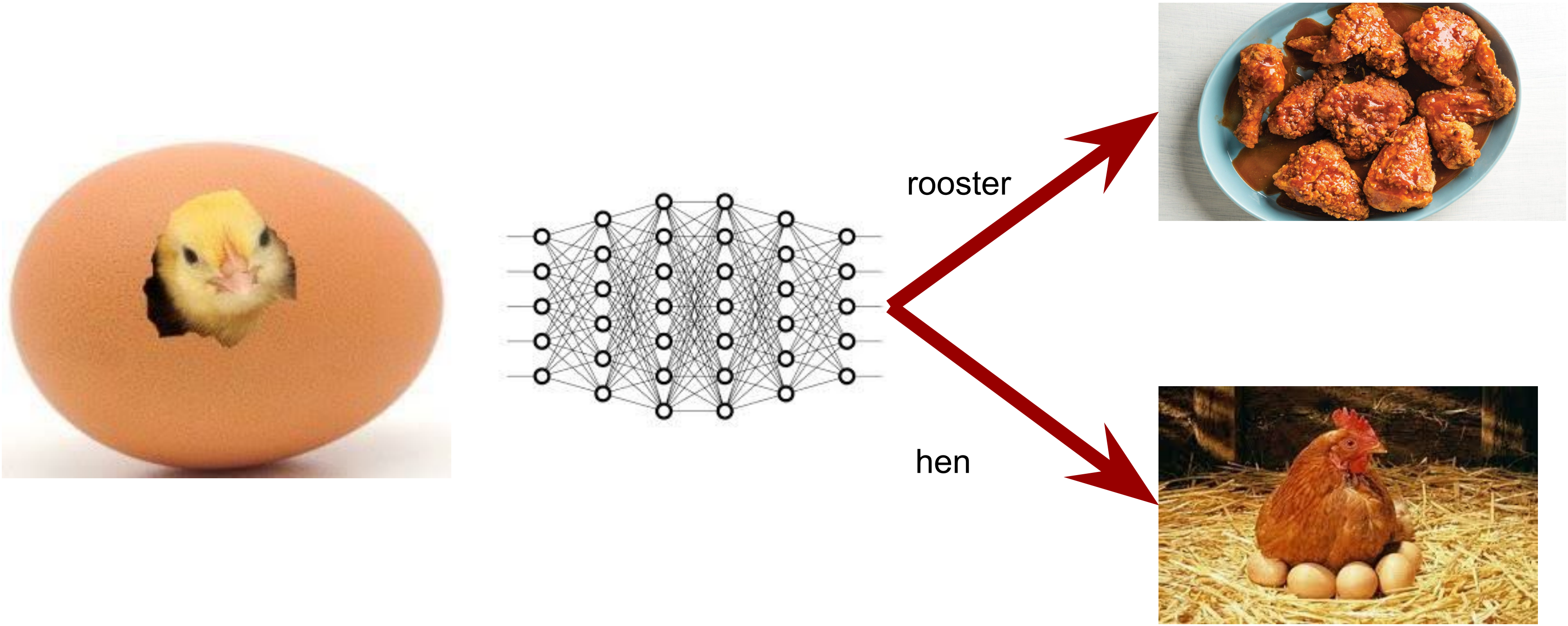
The trolley dilemma

Should you pull the lever to divert the trolley?



[image from Wikipedia]

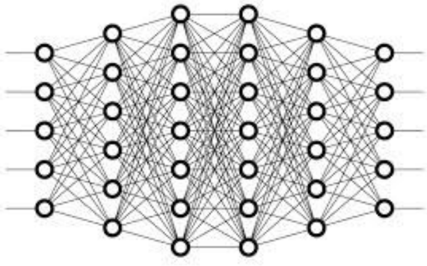
The chicken dilemma

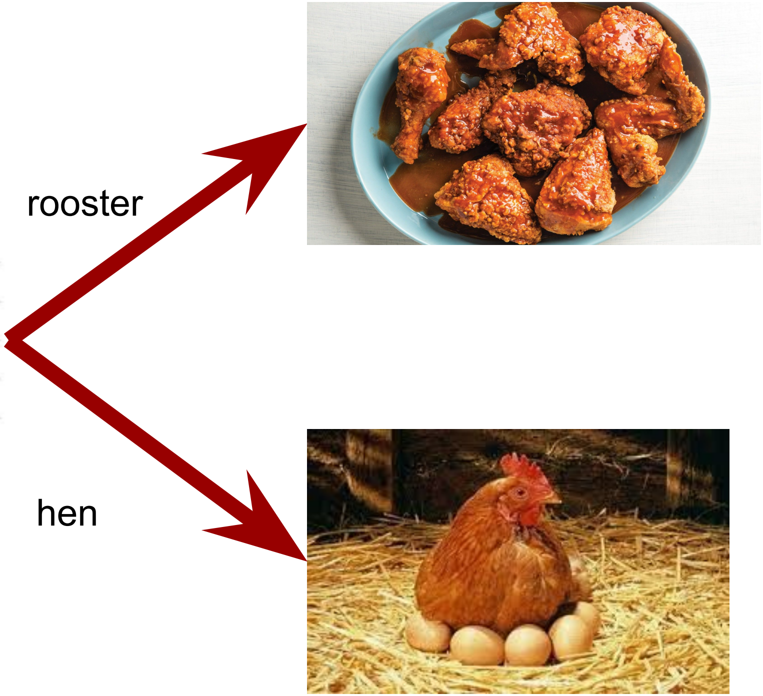


rooster

hen

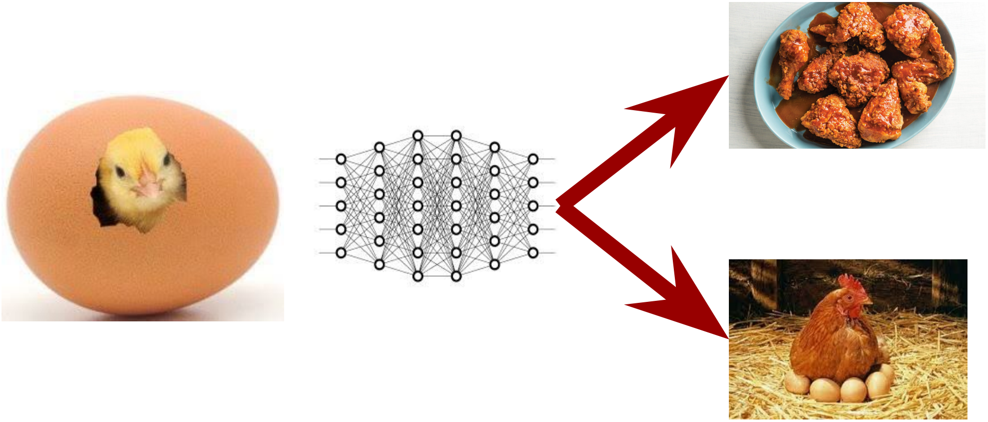
The chicken dilemma





Ethical?

The chicken dilemma



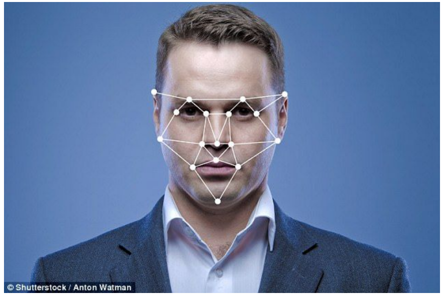
➔ Ethics is inner guiding, moral principles, and values of people and society

➔ Ethics isn’t just “black and white”, there are many gray areas.
We often don’t have easy answers.

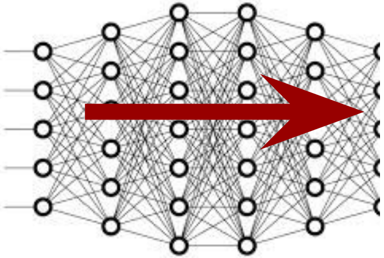
➔ Ethics changes over time with values and beliefs of people

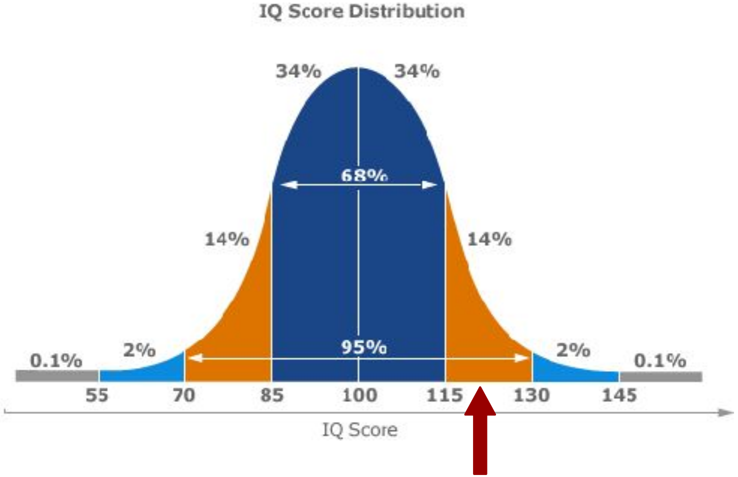
➔ Legal ≠ Ethical

Let’s train an IQ classifier



© Shutterstock / Anton Watman





- **I**ntelligence **Q**uotient: a number used to express the apparent relative intelligence of a person

An IQ Classifier

Let’s train a classifier to predict people’s IQ from their photos & texts.

- Who could benefit from such a classifier?

An IQ Classifier

Let’s train a classifier to predict people’s IQ from their photos & texts.

- Who could benefit from such a classifier?
- Assume the classifier is 100% accurate. Who can be harmed from such a classifier? How can such a classifier be misused?

An IQ Classifier

Let’s train a classifier to predict people’s IQ from their photos & texts.

- Who could benefit from such a classifier?
- Who can be harmed by such a classifier?
- Our test results show 90% accuracy
    - We found out that white females have 95% accuracy
    - People with blond hair under age of 25 have only 60% accuracy

An IQ Classifier

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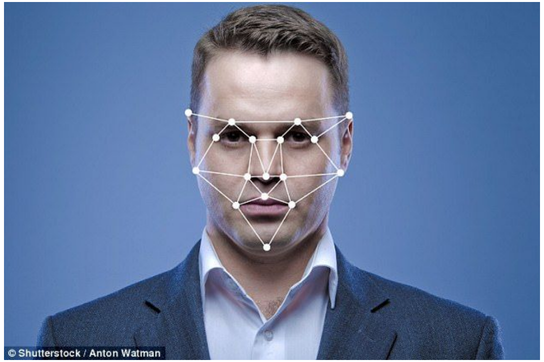
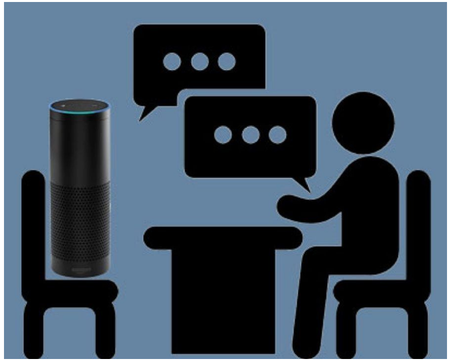
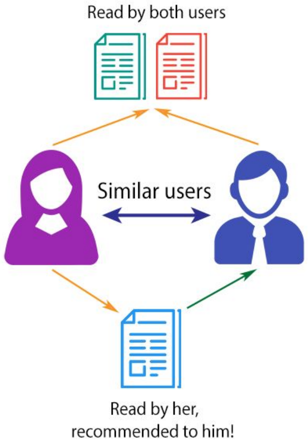
- Who can be harmed by such a classifier?
- Our test results show 90% accuracy
    - We found out that white females have 95% accuracy
    - People with blond hair under age of 25 have only 60% accuracy
- Who is responsible?
    - Researcher/developer? Advisor/manager? Reviewer? University? Society?

What’s the difference?



AI and people

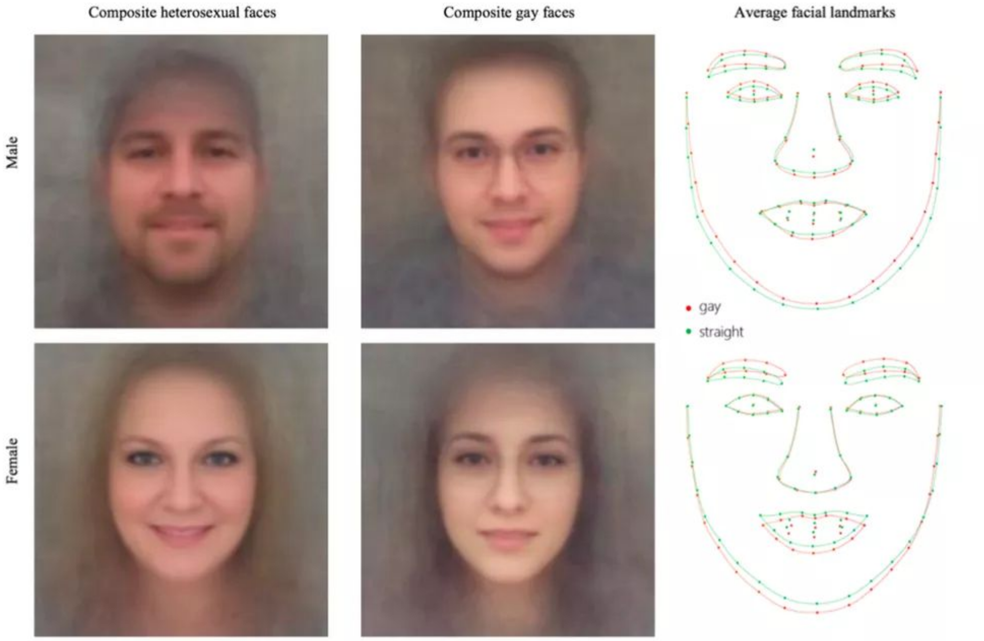



Read by both users

Similar users

Read by her, recommended to him!

A recent study: the “AI Gaydar”



The “AI Gaydar” study

- Research question
  - Identification of sexual orientation from facial features
- Data collection
  - Photos downloaded from a popular American dating website
  - 35,326 pictures of 14,776 people, all white, with gay and straight, male and female, all represented evenly
- Method
  - A deep learning model was used to extract facial features + grooming features; then a logistic regression classifier was applied for classification
- Accuracy
  - 81% for men, 74% for women

Let’s discuss...

- Research question
  - Identification of sexual orientation from facial features
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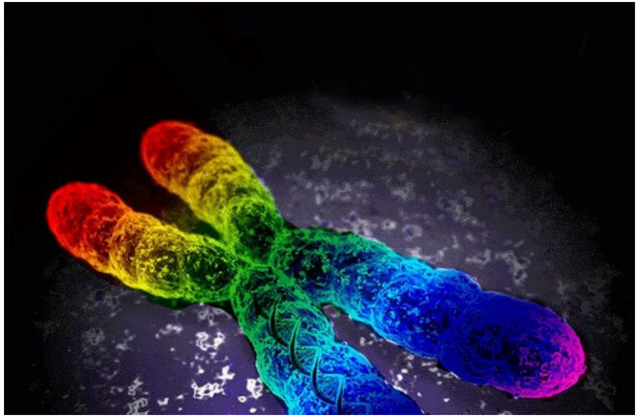
What went wrong?

Questioning the ethics of the research question

- Identification of sexual orientation from facial features

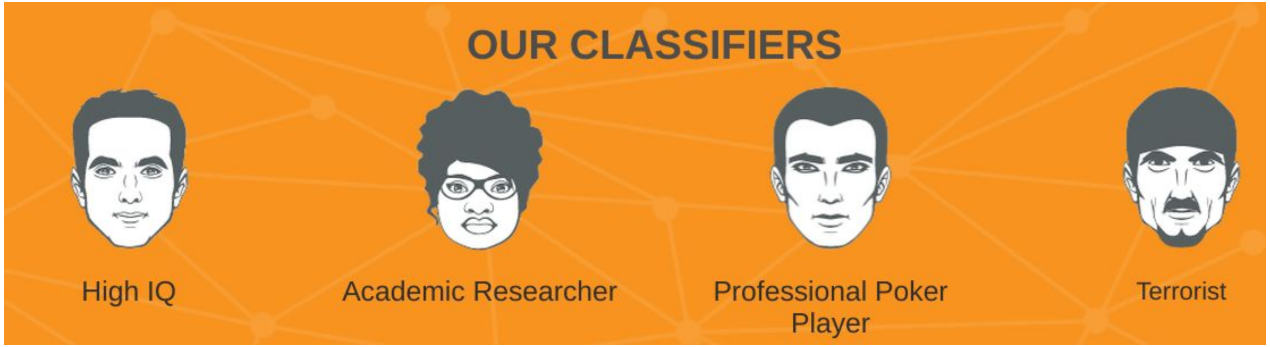


Potential for dual use

How people can be harmed by this research?

- In many countries being gay person is prosecutable (by law or by society) and in some places there is even death penalty for it
- It might affect people’s employment; family relationships; health care opportunities;
- Attributes like gender, race, sexual orientation, religion are social constructs. Some may change over time. They can be non-binary. They are private, intimate, often not visible publicly.
- Importantly, these are properties for which people are often discriminated against.

Dual use and dual framing in predictive analytics



“We live in a dangerous world, where harm doers and criminals easily mingle with the general population; the vast majority of them are unknown to the authorities.
As a result, it is becoming ever more challenging to detect anonymous threats in
public places such as airports, train stations, government and public buildings and
border control. Public Safety agencies, city police department, smart city service providers and other law enforcement entities are increasingly strive for Predictive Screening solutions, that can monitor, prevent, and forecast criminal events and public disorder without direct investigation or innocent people interrogations. “

Data

- Photos downloaded from a popular American dating website
- 35,326 pictures of 14,776 people, all white, with gay and straight, male and female, all represented evenly

Data

- Photos downloaded from a popular American dating website

Data & privacy

- Photos downloaded from a popular American dating website

Legal ≠ Ethical
Public ≠ Publicized
Did these people agree to participate in the study?

→ Violation of social contract

Data

- 35,326 pictures of 14,776 people, all white, with gay and straight, male and female, all represented evenly

Bias in data

- 35,326 pictures of 14,776 people, all white, with gay and straight, male and female, all represented evenly

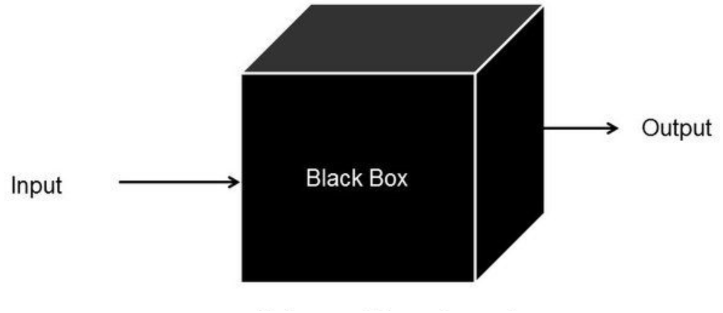
Only white people
who self-disclose their orientation,
certain social groups,
certain age groups,
certain time range/fashion;
the photos were carefully selected by subjects to be attractive

⟶ this dataset contains many types of biases

The dataset is balanced, which does not represent true class distribution.

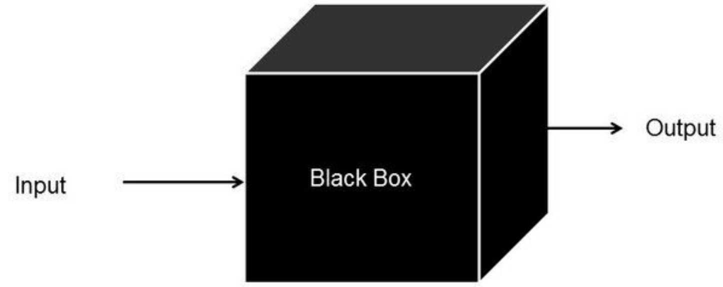
Method

- A deep learning model was used to extract facial features + grooming features; then a logistic regression classifier was applied for classification



Unveiling biases in black-box models

- A deep learning model was used to extract facial features + grooming features; then a logistic regression classifier was applied for classification



- can we use not interpretable models when we make predictions about sensitive attributes, about complex experimental conditions that require broader world knowledge?
- how to analyze errors and bias amplification?

Evaluation

- Accuracy: 81% for men, 74% for women

The cost of misclassification and the importance of social context

The cost of misclassification and the importance of social context

Learn to assess AI systems adversarially

- Ethics of the research question
- Impact of technology and potential dual use: Who could benefit from such a technology? Who can be harmed by such a technology? Could sharing data and models have major effect on people’s lives?
- Privacy: Who owns the data? Published vs. publicized? User consent and implicit assumptions of users how the data will be used.
- Bias in data: Artifacts in data, population-specific distributions, representativeness of data.
- Bias in models: How to control for confounding variables and corner cases? Does the system optimize for the “right” objective? Does the system amplify bias?
- Utility-based evaluation beyond accuracy: FP & FN rates, “the cost” of misclassification, fault tolerance.

Why is it especially relevant now?

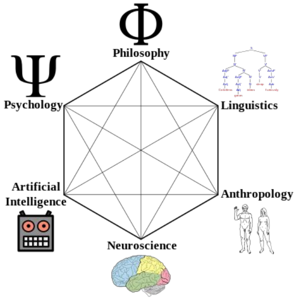
- Data: the exponential growth of user-generated content
- Tools: machine learning tools have become ubiquitous and accessible to everyone

Recommended papers and talks

- Hovy & Spruit (2016) The Social Impact of NLP
- Barocas & Selbst (2016) Big Data's Disparate Impact
- Barbara Grosz talk: Intelligent Systems: Design & Ethical Challenges
- Kate Crawford NeurIPS keynote: The Trouble with Bias
- Yonatan Zunger blog post: Asking the Right Questions About AI

Topics in the intersection of Ethics & NLP

- Algorithmic bias: social bias in data & NLP models
- Incivility: Hate-speech, toxicity, incivility, microaggressions online
- Privacy violation: Privacy violation & language-based profiling
- Misinformation: Fake news, information manipulation, opinion manipulation
- Technological divide: Unfair NLP technologies, underperforming for speakers of minority dialects, for languages from developing countries, and for disadvantaged populations



Recommended resources

- Computational ethics in NLP lectures, readings
  http://demo.clab.cs.cmu.edu/ethical_nlp/

- CS 384: Ethical and Social Issues in NLP
  https://web.stanford.edu/class/cs384/

- ACL Ethics resources
  https://aclweb.org/aclwiki/Ethics_in_NLP

Algorithmic bias:
social bias in data & models

Which word is more likely to be used by a female ?

Giggle – Laugh

(Preotiuc-Pietro et al. ‘16)

Which word is more likely to be used by a female ?

Giggle – Laugh

(Preotiuc-Pietro et al. ‘16)

Which word is more likely to be used by a female ?

Brutal – Fierce

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Which word is more likely to be used by a female ?

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Which word is more likely to be used by a older person ?

Impressive – Amazing

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Which word is more likely to be used by a older person ?

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Which word is more likely to be used by a person of higher occupational class ?

Suggestions – Proposals

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Which word is more likely to be used by a person of higher occupational class ?

Suggestions – Proposals

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Why do we intuitively recognize a default social group?

Why do we intuitively recognize a default social group?

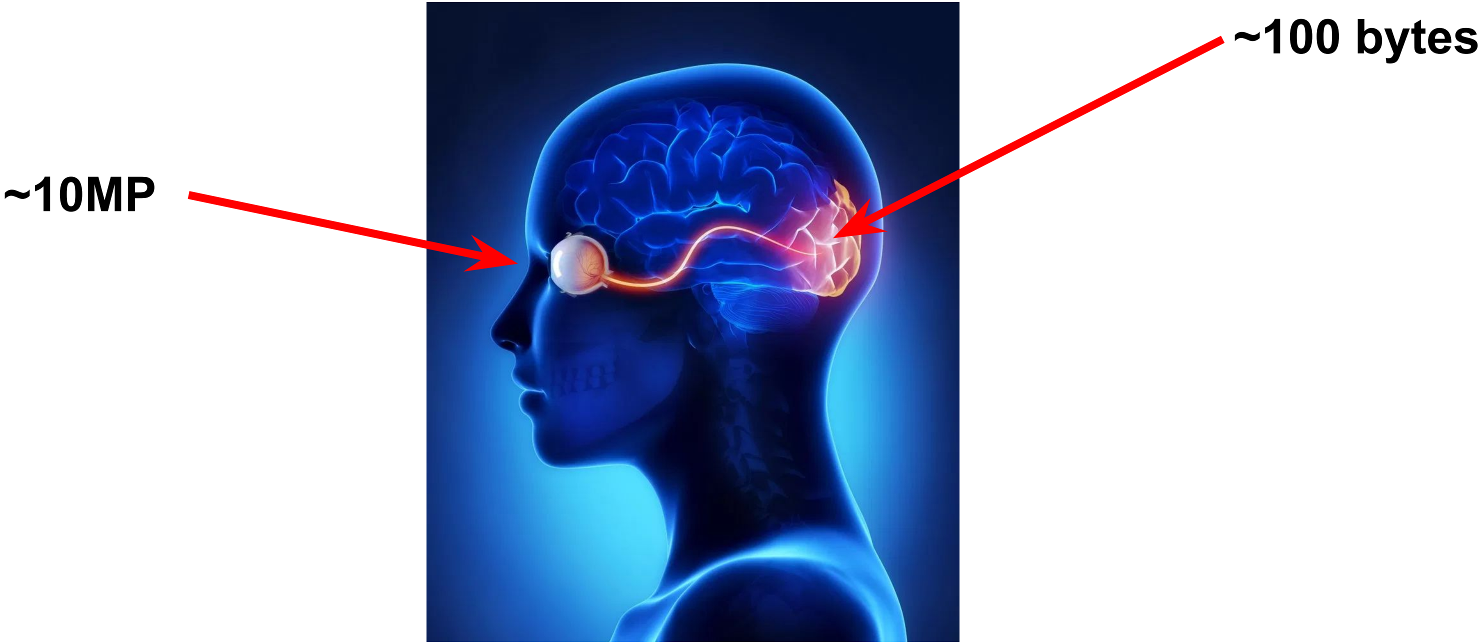
Implicit bias

How do we make decisions

System 1	**System 2**
automatic	effortful
fast	slow
parallel	serial
automatic	controlled
effortless	effort-filled
associative	rule-governed
slow-learning	flexible

Kahneman & Tversky 1973, 1974, 2002

Why?



~10MP

~100 bytes

System 1 is responsible for most of our decisions

System 1

automatic

System 2

effortful

Our brains are evolutionarily hard-wired to store learned information for rapid retrieval and automatic judgments. Over 95% of cognition is relegated to the System 1 “auto-pilot.”

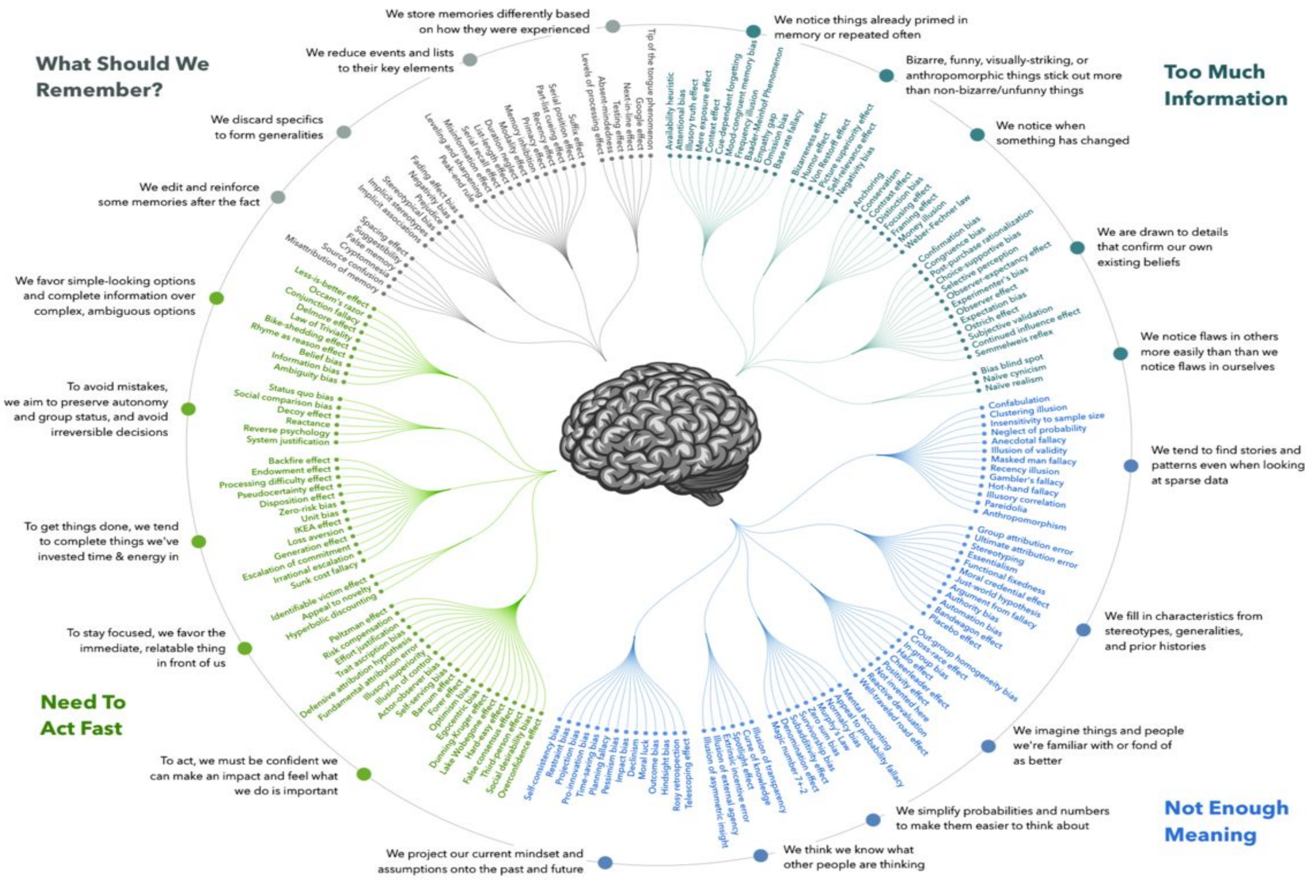
Psychological perspective on cognitive bias

Biases inevitably form because of the innate tendency of the human mind to:

- Categorize the world to simplify processing
- Store learned information in mental representations (called schemas)
- Automatically and unconsciously activate stored information whenever one encounters a category member

Cognitive bias is a systematic pattern of deviation from rationality in judgement

COGNITIVE BIAS CODEX



We store memories differently based on how they were experienced

Tip of the tongue phenomenon
Google effect
Next-in-line effect
Testing effect
Absent-mindedness
Levels of processing effect

We notice things already primed in memory or repeated often

Availability heuristic
Attentional bias
Illusory truth effect
Mere exposure effect
Context effect
Cue-dependent forgetting
Mood-congruent memory bias
Frequency illusion
Baader-Meinhof Phenomenon
Empathy gap
Omission bias
Base rate fallacy

Too Much Information

Bizarre, funny, visually-striking, or anthropomorphic things stick out more than non-bizarre/unfunny things

Bizarreness effect
Humor effect
Von Restorff effect
Picture superiority effect
Self-relevance effect
Negativity bias

We notice when something has changed

Anchoring
Conservatism
Contrast effect
Distinction bias
Focusing effect
Framing effect
Money illusion
Weber-Fechner law

We are drawn to details that confirm our own existing beliefs

Confirmation bias
Congruence bias
Post-purchase rationalization
Choice-supportive bias
Selective perception
Observer-expectancy effect
Experimenter's bias
Observer effect
Expectation bias
Ostrich effect
Subjective validation
Continued influence effect
Semmelweis reflex

We notice flaws in others more easily than than we notice flaws in ourselves

Bias blind spot
Naïve cynicism
Naïve realism

We tend to find stories and patterns even when looking at sparse data

Confabulation
Clustering illusion
Insensitivity to sample size
Neglect of probability
Anecdotal fallacy
Illusion of validity
Masked man fallacy
Recency illusion
Gambler's fallacy
Hot-hand fallacy
Illusory correlation
Pareidolia
Anthropomorphism

We fill in characteristics from stereotypes, generalities, and prior histories

Group attribution error
Ultimate attribution error
Stereotyping
Essentialism
Functional fixedness
Moral credential effect
Just-world hypothesis
Argument from fallacy
Authority bias
Automation bias
Bandwagon effect
Placebo effect

We imagine things and people we're familiar with or fond of as better

Out-group homogeneity bias
Cross-race effect
In-group bias
Halo effect
Cheerleader effect
Positivity effect
Not invented here
Reactive devaluation
Well-traveled road effect

Not Enough Meaning

We simplify probabilities and numbers to make them easier to think about

Mental accounting
Appeal to probability fallacy
Normalcy bias
Murphy's Law
Zero sum bias
Survivorship bias
Subadditivity effect
Denomination effect
Magic number 7+-2

We think we know what other people are thinking

Illusion of transparency
Curse of knowledge
Spotlight effect
Extrinsic incentive error
Illusion of external agency
Illusion of asymmetric insight

We project our current mindset and assumptions onto the past and future

Telescoping effect
Rosy retrospection
Hindsight bias
Outcome bias
Moral luck
Declinism
Impact bias
Pessimism bias
Planning fallacy
Time-saving bias
Pro-innovation bias
Projection bias
Restraint bias
Self-consistency bias

To act, we must be confident we can make an impact and feel what we do is important

Overconfidence effect
Social desirability bias
Third-person effect
False consensus effect
Hard-easy effect
Lake Wobegone effect
Dunning-Kruger effect
Egocentric bias
Optimism bias
Forer effect
Barnum effect
Self-serving bias
Actor-observer bias
Illusion of control
Illusory superiority
Fundamental attribution error
Defensive attribution hypothesis
Trait ascription bias
Effort justification
Risk compensation
Peltzman effect

Need To Act Fast

To stay focused, we favor the immediate, relatable thing in front of us

Hyperbolic discounting
Appeal to novelty
Identifiable victim effect

To get things done, we tend to complete things we've invested time & energy in

Sunk cost fallacy
Irrational escalation
Escalation of commitment
Generation effect
Loss aversion
IKEA effect
Unit bias
Zero-risk bias
Disposition effect
Pseudocertainty effect
Processing difficulty effect
Endowment effect
Backfire effect

To avoid mistakes, we aim to preserve autonomy and group status, and avoid irreversible decisions

System justification
Reverse psychology
Reactance
Decoy effect
Social comparison bias
Status quo bias

We favor simple-looking options and complete information over complex, ambiguous options

Ambiguity bias
Information bias
Belief bias
Rhyme as reason effect
Bike-shedding effect
Law of Triviality
Delmore effect
Conjunction fallacy
Occam's razor
Less-is-better effect

What Should We Remember?

We edit and reinforce some memories after the fact

Misattribution of memory
Source confusion
Cryptomnesia
False memory
Suggestibility
Spacing effect

We discard specifics to form generalities

Implicit associations
Implicit stereotypes
Stereotypical bias
Prejudice
Negativity bias
Fading affect bias

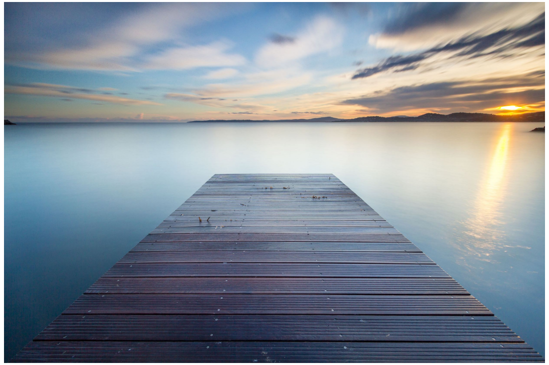
We reduce events and lists to their key elements

Peak-end rule
Leveling and sharpening
Misinformation effect
Serial recall effect
List-length effect
Duration neglect
Modality effect
Memory inhibition
Primacy effect
Recency effect
Part-list cueing effect
Serial position effect
Suffix effect

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

Common biases that affect how we make decisions

- confirmation bias: paying more attention to information that reinforces previously held beliefs and ignoring evidence to the contrary
- ingroup favoritism: when one favors in-group members over out-group members
- group attribution error: when one generalizes about a group based on a group of representatives
- halo effect: when overall impression of a person impacts evaluation of their specific traits
- just-world hypothesis: when one protects a desire for a just world by blaming the victims
- etc.



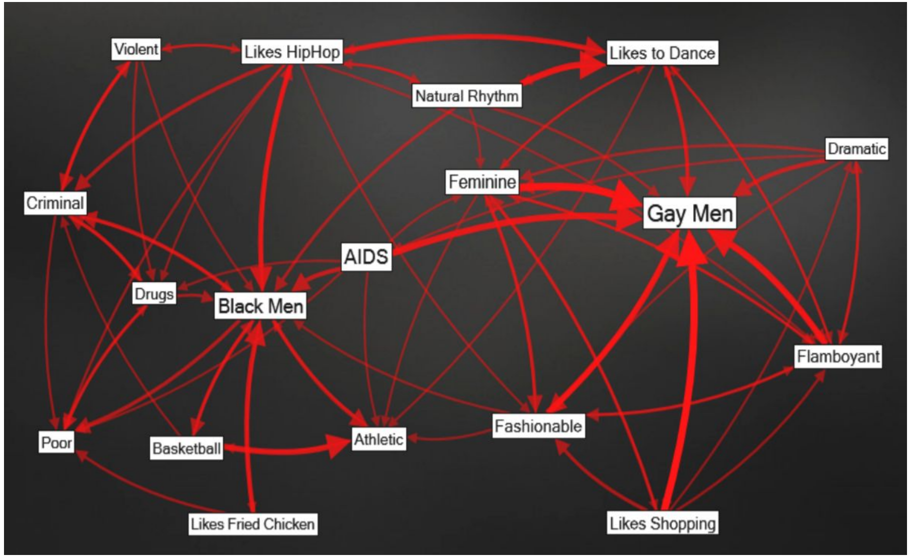
Social stereotypes

- Gender
- Race
- Disability
- Age
- Sexual orientation
- Culture
- Class
- Poverty
- Language
- Religion
- National origin
- ...

Social stereotypes are similarly internalized as associations through natural processes of learning and categorization

Which word is more likely to be used by a older person ?

Impressive – Amazing



Implicit biases are pervasive, unconscious, and can automatically influence the ways in which we see and treat others,
even when we are determined to be fair and objective.

Slide credit: Geoff Kaufman

How do implicit biases manifest?

Microaggressions

> “A comment or action that **subtly and often unconsciously or unintentionally** expresses a prejudiced attitude towards a member of a marginalized group”
>
> - Merriam Webster

Surface-level sentiment can be negative, neutral, or positive. For example:

- “Girls just **aren’t good** at math.”
- “Don’t you people **like** tamales?”
- “You’re too **pretty** to be gay.”

microaggressions.com

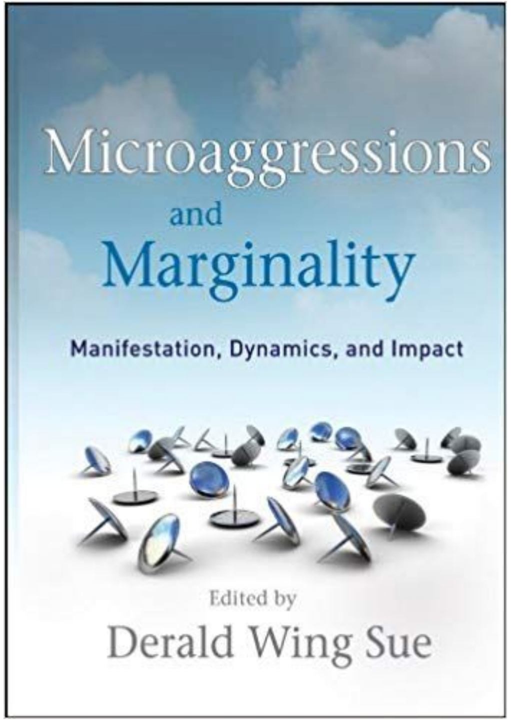
tumblr.

Microaggressions cause prolonged harms

- Effects can be more pernicious than overtly aggressive speech (Sue et al. 2007, Sue 2010, Nadal et al. 2014)

- Can affect people’s professional experiences and career trajectories (Cortina et al. 2002, Trix and Psenka 2003)

- Play on, and reinforce, problematic stereotypes and power structures (Hall and Braunwald 1981, Fournier et al. 2002)

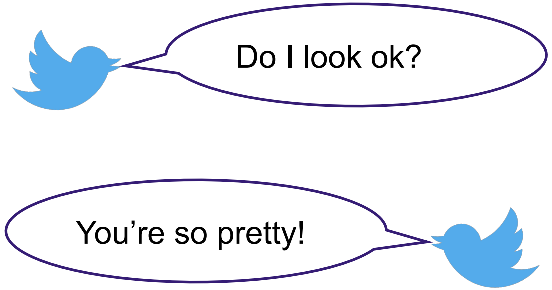


Microaggressions and Marginality

Manifestation, Dynamics, and Impact

Edited by
Derald Wing Sue

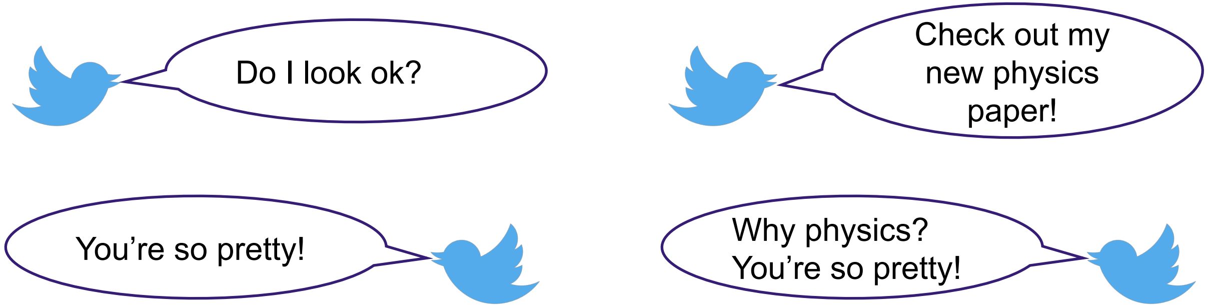
Positive or negative?



Do I look ok?

You’re so pretty!

Positive or negative?



Do I look ok?

You’re so pretty!

Check out my new physics paper!

Why physics? You’re so pretty!

Positive or negative?

Do I look ok?

You're so pretty!

Check out my new physics paper!

Why physics? You're so pretty!

Do I look ok?

You're so pretty for your age!

You're so pretty for a black girl!

You're too pretty to be gay!

You're so pretty!
You're cute!
You're so pretty for your age!
You're so pretty for a black girl!
You're too pretty to be gay!
AI

Online data is riddled with **SOCIAL STEREOTYPES**

Bias in data

Bias in language

- Stereotypes, prejudices, toxic comments and other expressions of social biases
- Historical human biases
- Human reporting bias: topics, word frequencies are not a reflection of real world

Bias in datasets

- Data selection/sampling bias
- Annotator selection bias
- Annotators’ cognitive biases

From social bias to algorithmic bias

AI is only System 1

You’re so pretty!

You’re cute!

You’re so pretty for your age!

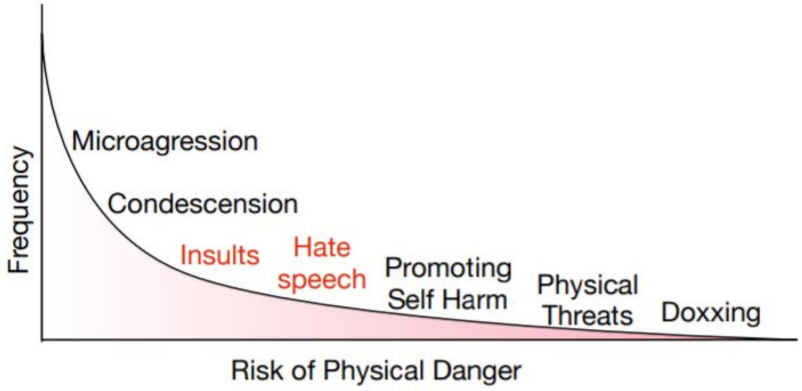
You’re so pretty for a black girl!

You’re too pretty to be gay!

- data-centric models, no cultural and social context
- overfitting to confounders and spurious correlations, including social biases
- “black-box” models make it hard to proactively unveil these biases

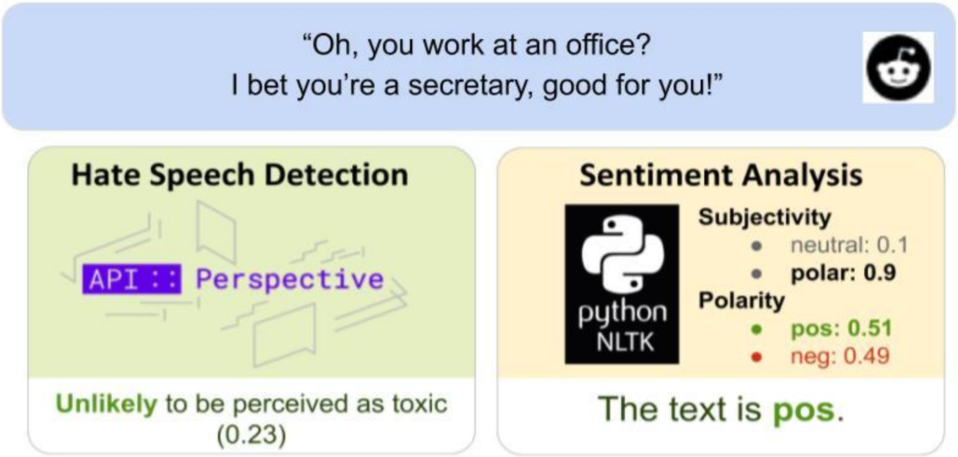
Toxic/offensive/biased comments

- Recent NLP advances have focused on overt toxic language (e.g. hate speech)
- Little focus on veiled negativity that is not directly encoded in lexicons



Jurgens D., Chandrasekharan E., and Hemphill L. (2019) A Just and Comprehensive Strategy for Using NLP to Address Online Abuse. ACL

SOTA NLP tools cannot identify microaggressions



"Oh, you work at an office?
I bet you're a secretary, good for you!"

Hate Speech Detection

Unlikely to be perceived as toxic (0.23)

Sentiment Analysis

Subjectivity

- neutral: 0.1
- **polar: 0.9**

Polarity

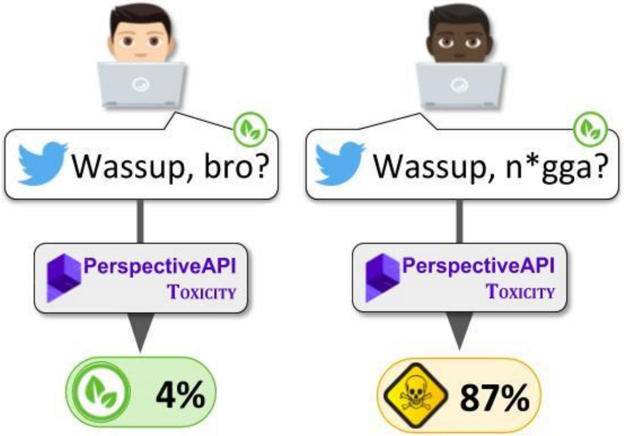
- **pos: 0.51**
- neg: 0.49

The text is **pos**.

Breitfeller L., Ahn E., Jurgens D., Tsvetkov Y. (2019) Finding Microaggressions in the Wild:
A Case for Locating Elusive Phenomena in Social Media Posts. *EMNLP*

Models do not incorporate socio-cultural knowledge

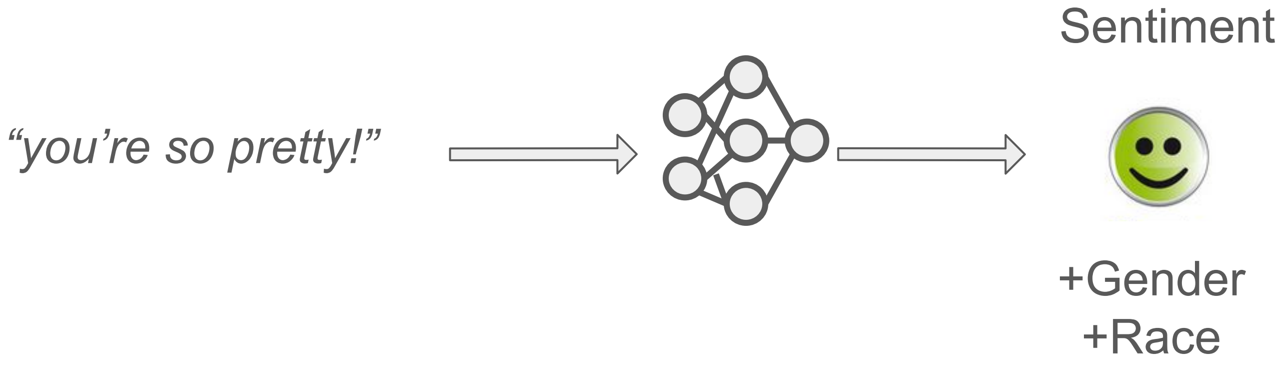
- Toxicity classifiers overfit to social attributes overrepresented in training data, ignore social and cultural context



Non-toxic tweets
(per Spears, 1998)

Sap M., Card D., Gabriel S., Choi Y., Smith N. (2019)
The Risk of Racial Bias in Hate Speech Detection. ACL

Models overfit to spurious artifacts in data



“you’re so pretty!”

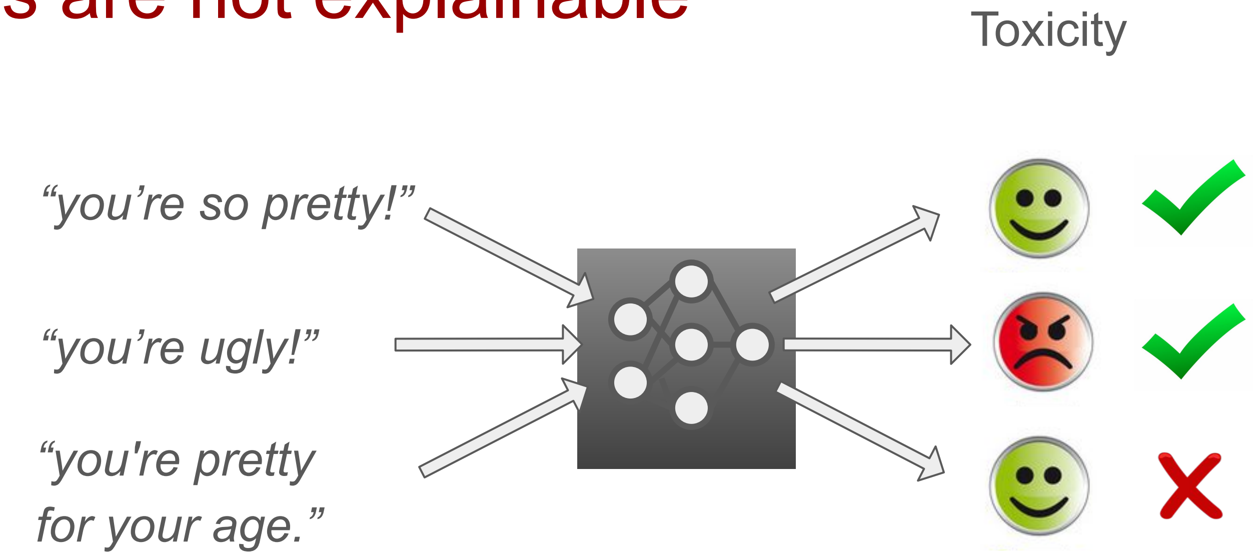
Sentiment

+Gender
+Race

- ‘The conversation with Amanda was heartbreaking’
- ‘The conversation with Alonzo was heartbreaking’
- ‘The conversation with Lakisha was heartbreaking’

Kiritchenko S. and Mohammad S. (2018) Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems. **Sem*

Models are not explainable



Toxicity

“you’re so pretty!”

“you’re ugly!”

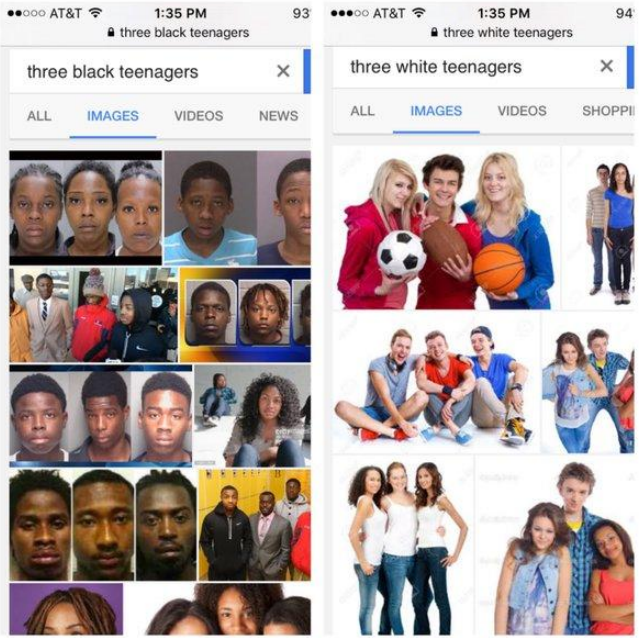
“you're pretty for your age.”

- Why?

- Conversational agents
- Personal assistants
- Medical assistants
- Educational assistants
- ...

Image search

- Image search query “three black teenagers”



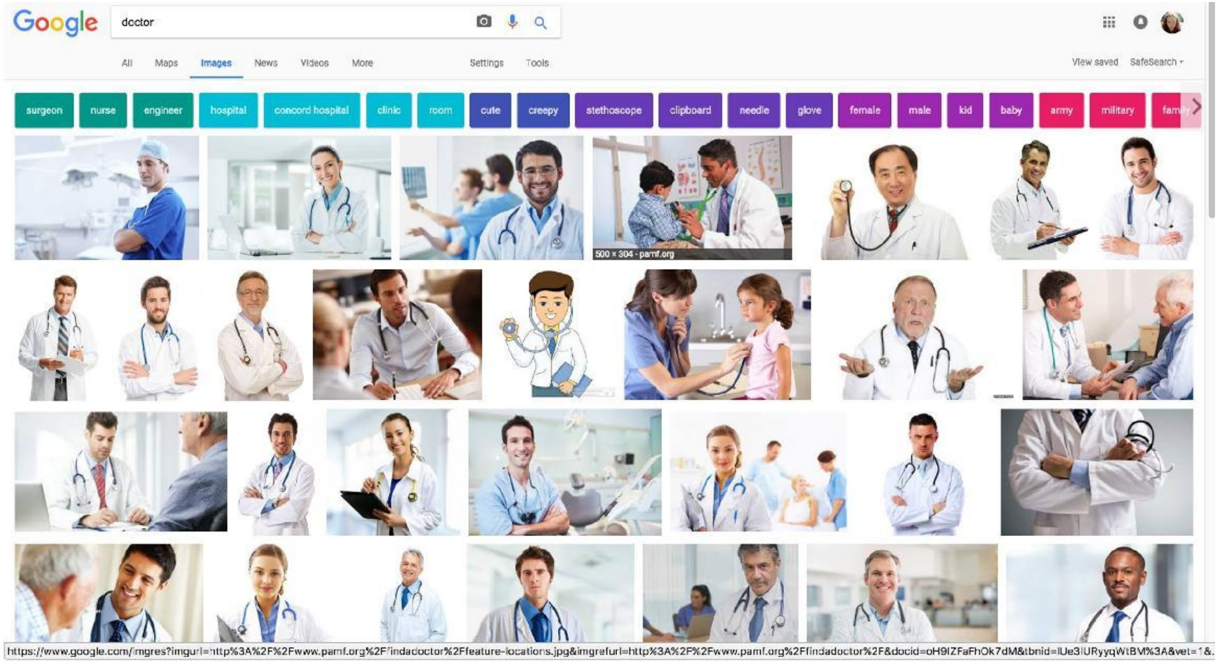
three black teenagers

three white teenagers

June 2017

Image search

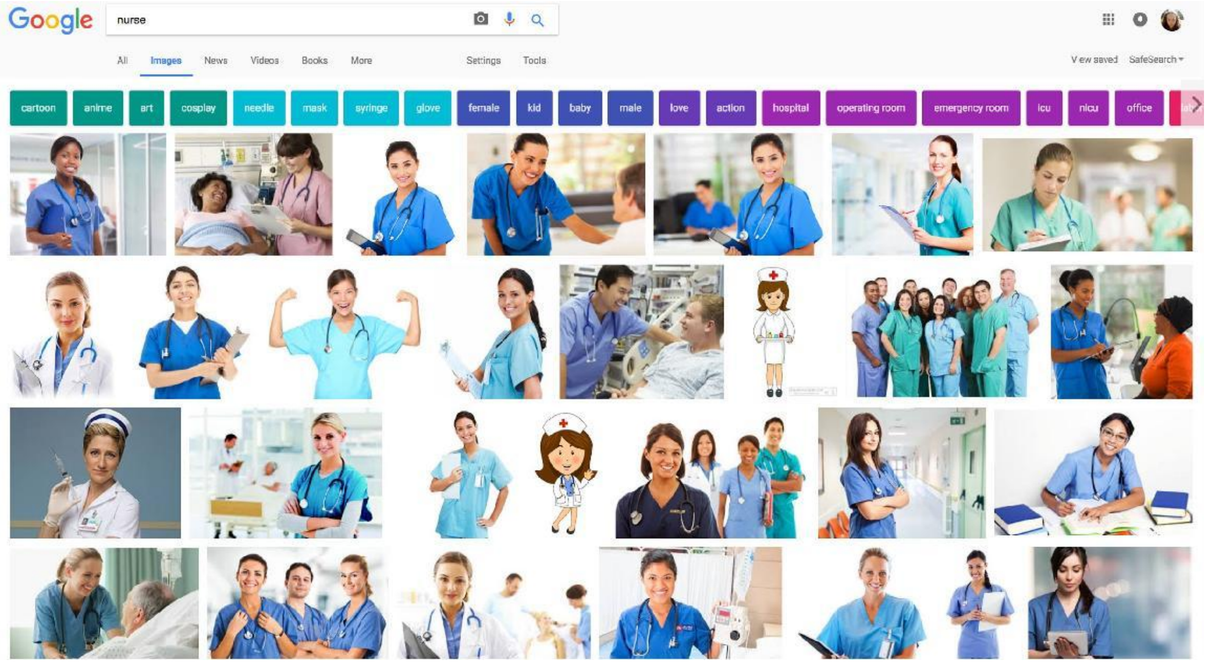
- Image search query “Doctor”



June 2017

Image search

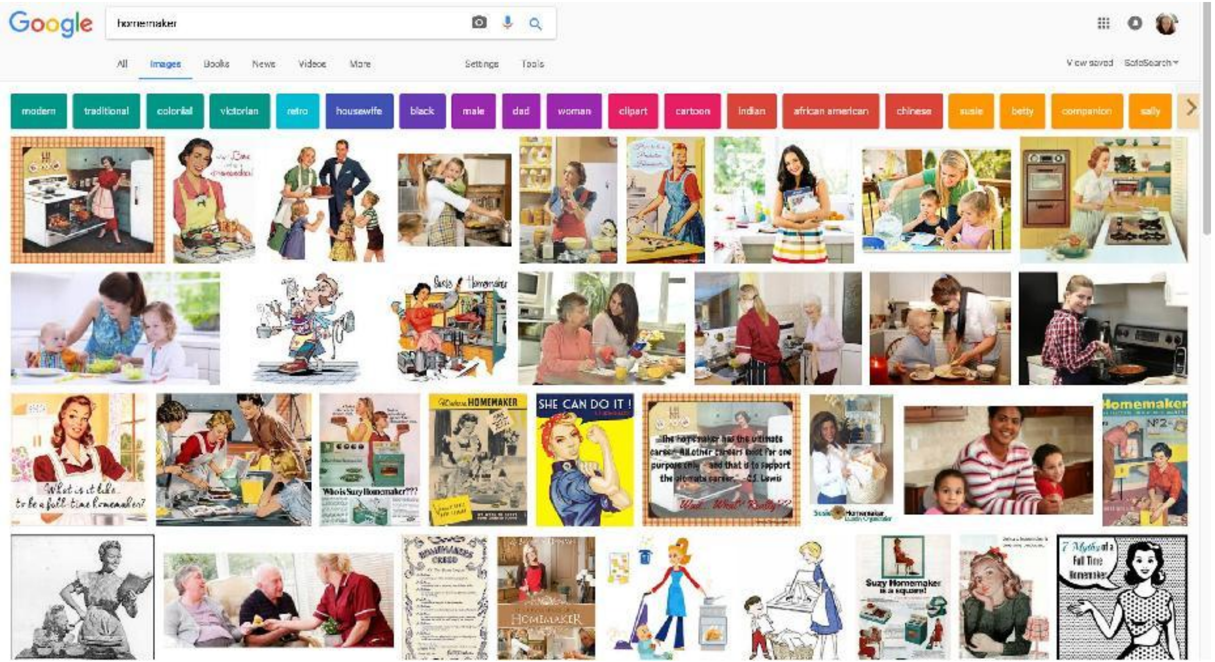
- Image search query “**Nurse**”



June 2017

Image search

- Image search query “Homemaker”

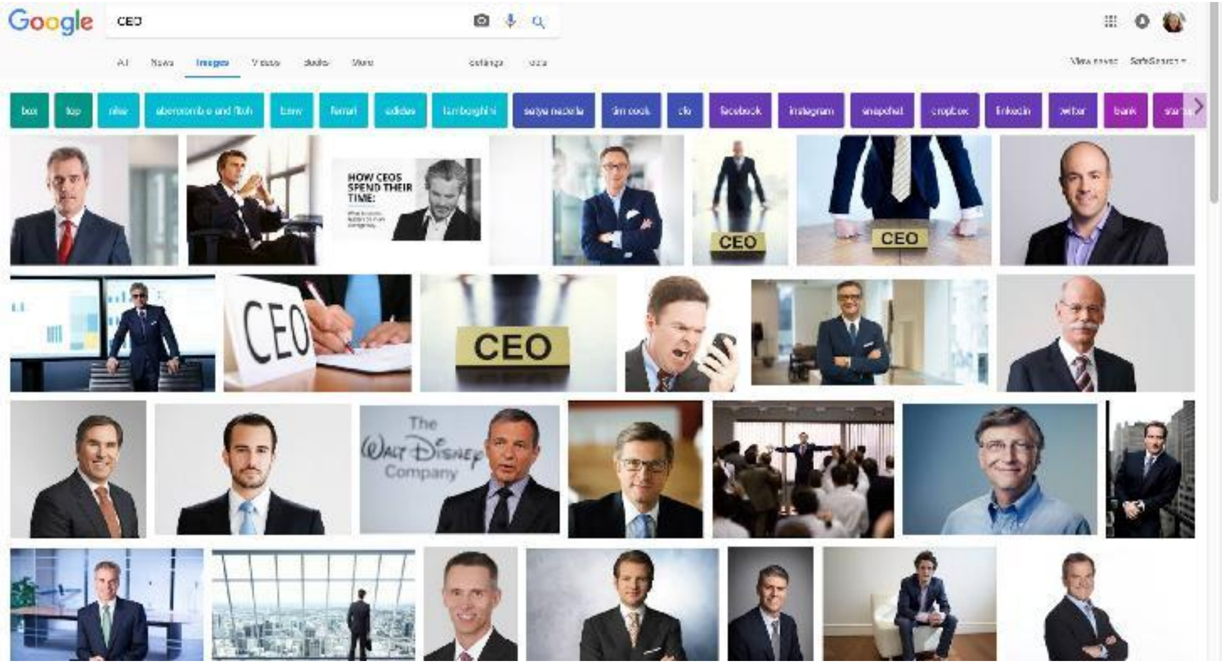


homemaker

June 2017

Image search

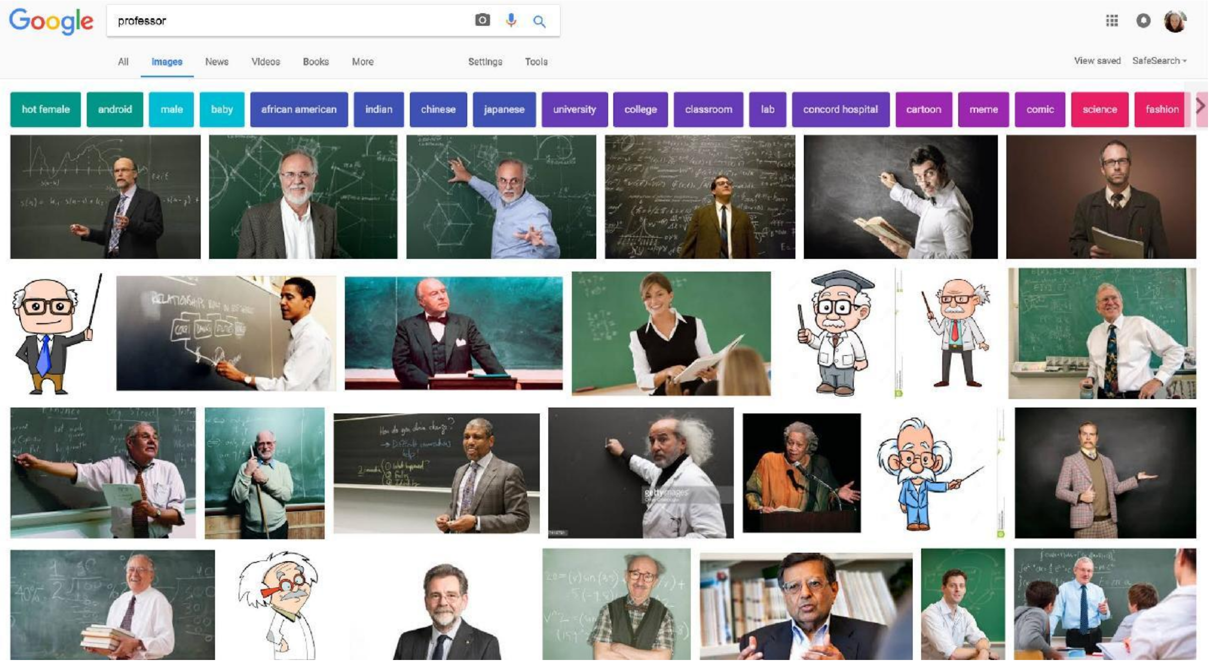
- Image search query “CEO”



June 2017

Image search

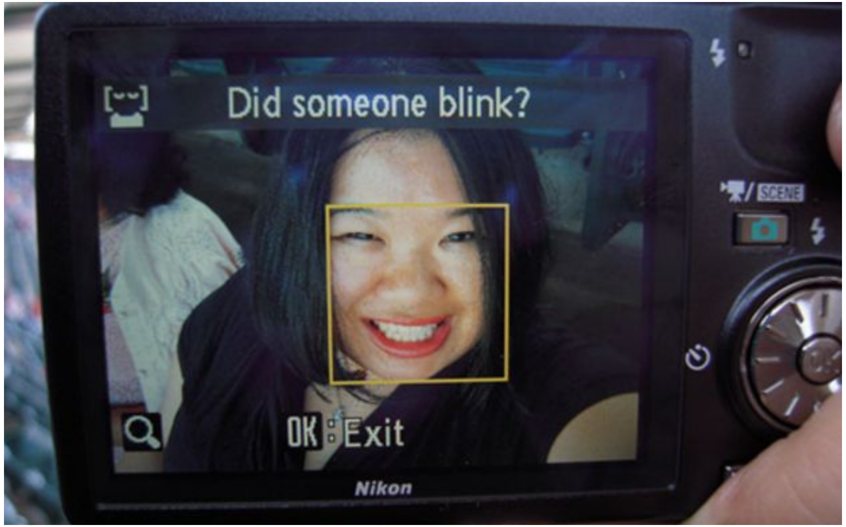
- Image search query “Professor”



professor

June 2017

Face recognition



https://gizmodo.com/5256650/camera-misses-the-mark-on-racial-sensitivity
https://www.wired.com/2009/12/hp-notebooks-racist/

Natural Language Processing

Applications

- Machine Translation
- Speech Recognition
- Question Answering
- Dialogue Systems
- Information Extraction
- Summarization
- Sentiment Analysis
- ...

Core technologies

- Language modelling
- Part-of-speech tagging
- Syntactic parsing
- Named-entity recognition
- Coreference resolution
- Word sense disambiguation
- Semantic Role Labelling
- ...

Bias in Natural Language Processing

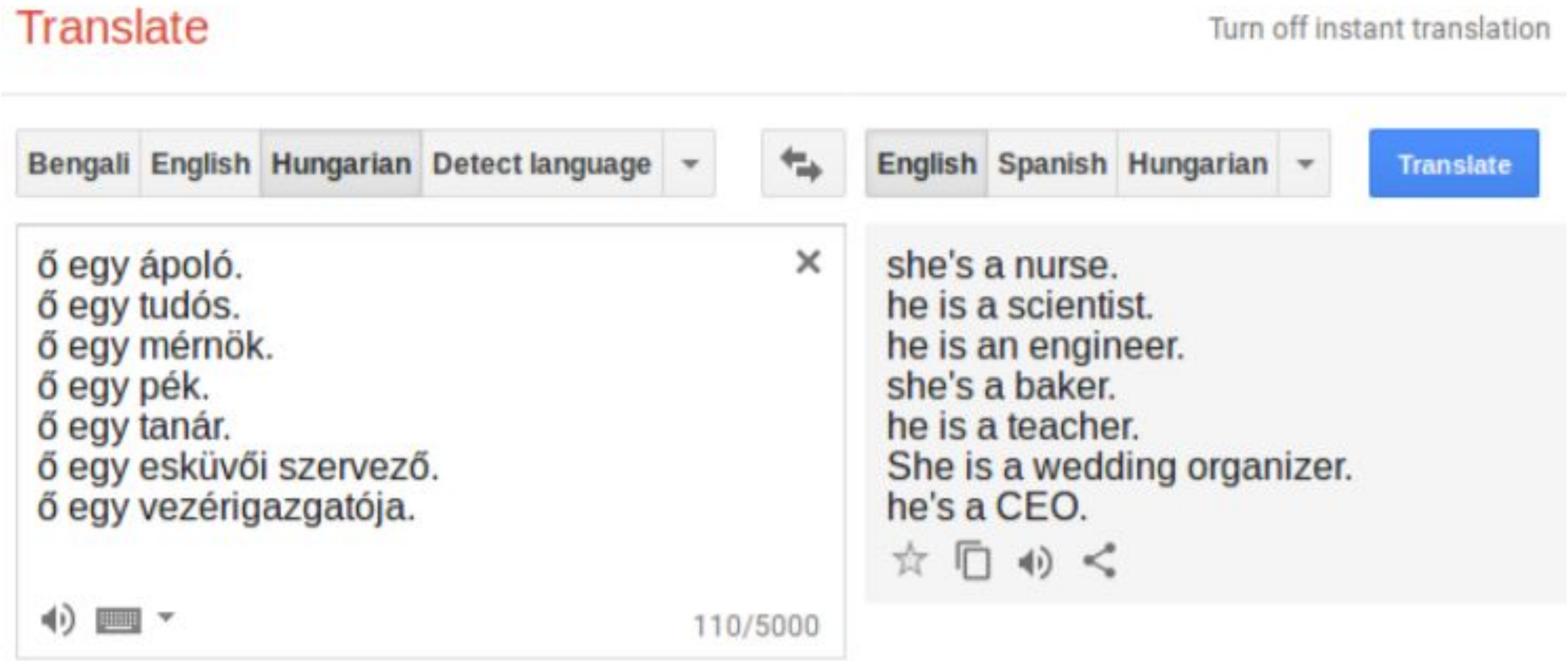
Applications

- Machine Translation (Prates et al. ‘19)
- Speech Recognition (Tatman 2017)
- Question Answering (Burghardt et al. ‘18)
- Dialogue Systems (Dinan, Fan et al. ‘19)
- Summarization (Jung, Kang et al. ‘19)
- Sentiment Analysis (Kiritchenko & Mohammad ‘18)
- Language Identification (Blodgett et al.’16, Jurgens et al.’17)
- Text Classification (Dixon et al. ‘18, Sap et al. ‘19, Kumar et al. ‘19)
- ...

Core technologies

- Language modeling (Lu et al. ‘18)
- Named-entity recognition (Mehrabi et al. ‘19)
- Coreference resolution (Zhao et al. ‘18, Rudinger et al. ‘18)
- Semantic Role Labelling (Zhao et al. ‘17)
- SNLI (Rudinger et al. ‘17)
- Word Embeddings (Bolukbasi et al. ‘16,++)
- ...

Bias in machine translation



ő egy ápoló.
ő egy tudós.
ő egy mérnök.
ő egy pék.
ő egy tanár.
ő egy esküvői szervező.
ő egy vezérigazgatója.

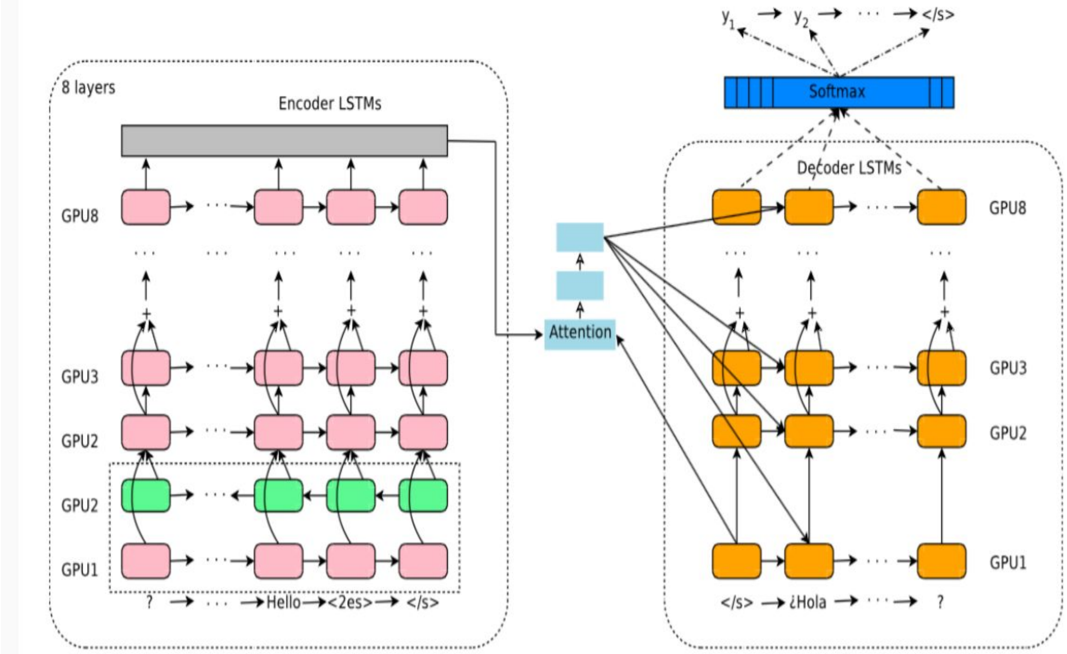
she's a nurse.
he is a scientist.
he is an engineer.
she's a baker.
he is a teacher.
She is a wedding organizer.
he's a CEO.

https://arxiv.org/pdf/1809.02208.pdf

THE WORLD ATLAS
OF LANGUAGE STRUCTURES
ONLINE

Language Family	Language	Phrases have male/female markers	Tested
Austronesian	Malay	×	✓
Uralic	Estonian	×	✓
	Finnish	×	✓
	Hungarian	×	✓
Indo-European	Armenian	×	✓
	Bengali	O	✓
	English	✓	×
	Persian	×	✓
	Nepali	O	✓
Japonic	Japanese	×	✓
Koreanic	Korean	✓	×
Turkic	Turkish	×	✓
Niger-Congo	Yoruba	×	✓
	Swahili	×	✓
Isolate	Basque	×	✓
Sino-Tibetan	Chinese	O	✓

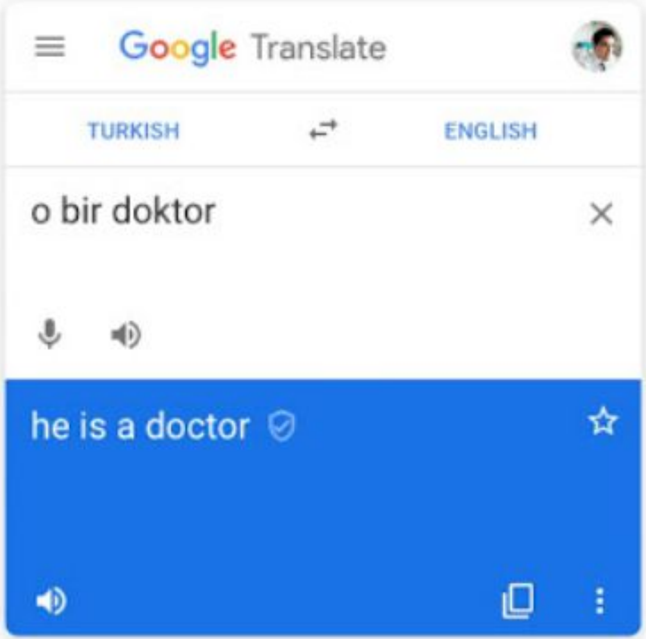
Example of bias mitigation (similar to multilingual NMT)



<2female>

<2es> Hello, how are you? -> ¿Hola como estás?

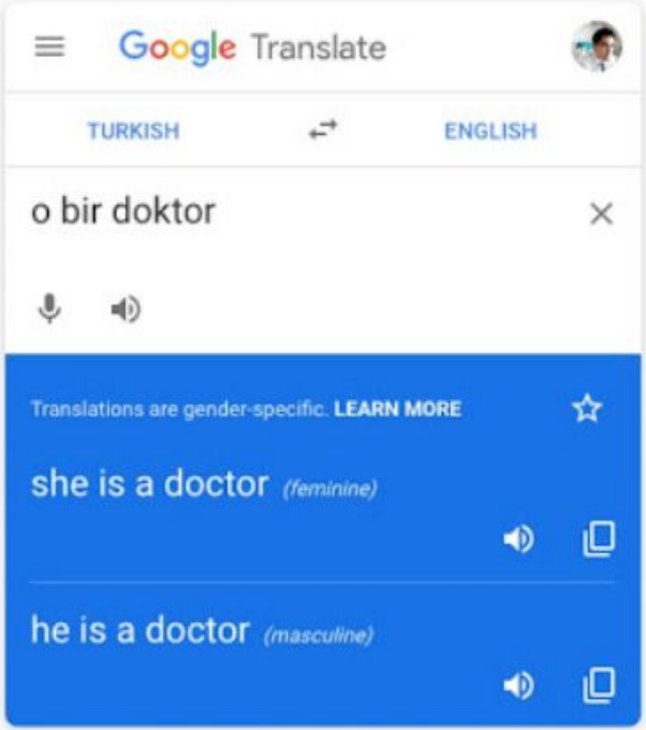
Before



o bir doktor

he is a doctor

After



o bir doktor

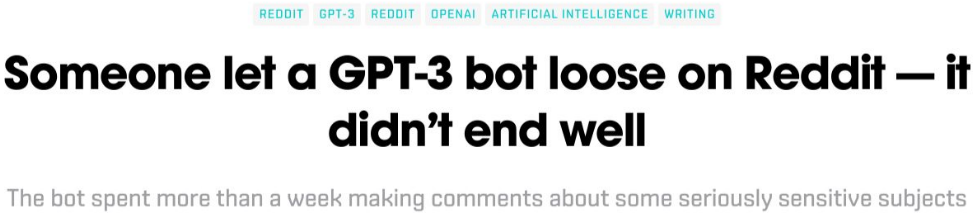
Translations are gender-specific. **LEARN MORE**

she is a doctor *(feminine)*

he is a doctor *(masculine)*

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

Bias in dialogue systems



REDDIT GPT-3 REDDIT OPENAI ARTIFICIAL INTELLIGENCE WRITING

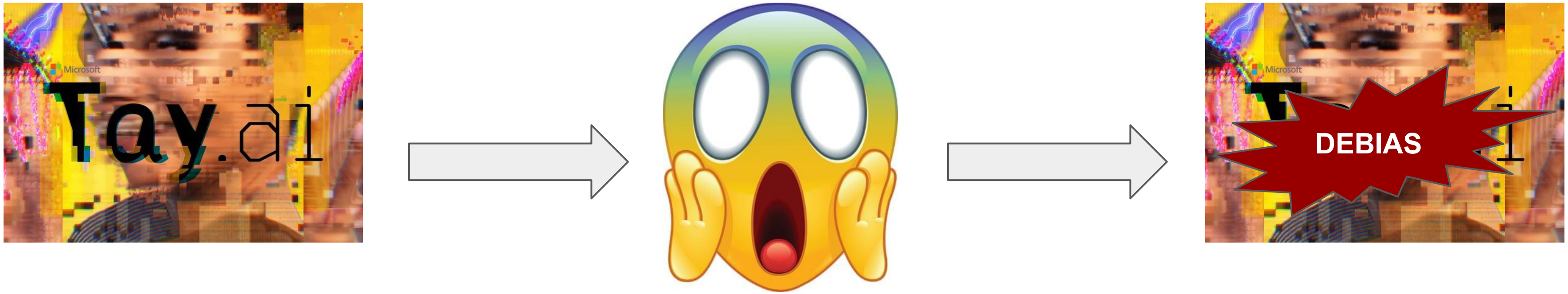
Someone let a GPT-3 bot loose on Reddit — it didn't end well

The bot spent more than a week making comments about some seriously sensitive subjects

AI chatbot is REMOVED from Facebook after saying she 'despised' gay people, would 'rather die' than be disabled and calling the #MeToo movement 'ignorant'

- **Lee Luda is a South Korean chatbot with the persona of a 20-year-old student**
- **It has attracted more than 750,000 users since its launch last month**
- **But the chatbot has started using hate speech towards minorities**
- **In one of the captured chat shots, Luda said she 'despised' gays and lesbians**
- **The developer has apologised over the remarks, saying they 'do not represent our values as a company'**

Reactive approach



DEBIAS

Towards a proactive approach

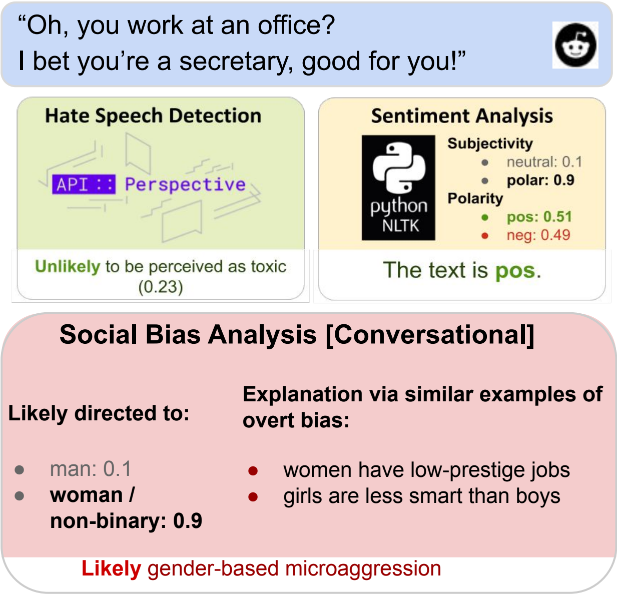
- Data: Automatic moderation, unveiling social biases and veiled toxicity in training data, beyond overtly hateful speech

- Socio-cultural knowledge representation: Learning to represent and analyze how socio-cultural knowledge manifests in language

- Modeling: New modeling approaches that incorporate socio-cultural context and are trained to explicitly demote social biases

- Evaluation and analysis: Developing interpretable models, or approaches to interpreting existing models, and new approaches to evaluation and characterization of model behaviors

Future outlook



"Oh, you work at an office?
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Hate Speech Detection

Unlikely to be perceived as toxic (0.23)

Sentiment Analysis

Subjectivity

- neutral: 0.1
- **polar: 0.9**

Polarity

- **pos: 0.51**
- neg: 0.49

The text is **pos**.

Social Bias Analysis [Conversational]

Likely directed to:

- man: 0.1
- **woman / non-binary: 0.9**

Explanation via similar examples of overt bias:

- women have low-prestige jobs
- girls are less smart than boys

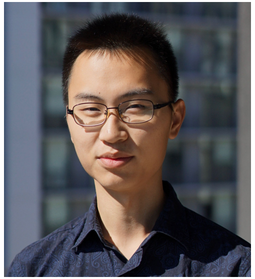
Likely gender-based microaggression

Automatic detection of implicit bias and veiled toxicity

- Via a causal framework and demoting spurious confounds
  - Field A. & Tsvetkov Y. (2020) Unsupervised Discovery of Implicit Gender Bias. *EMNLP*

Anjalie

- Via adversarial probing & interpreting model decisions
  - Han X., Tsvetkov Y. (2020) Fortifying Toxic Speech Detectors Against Veiled Toxicity. *EMNLP*



Han

A naive approach: crowdsourcing & supervised classification

“you're pretty for your age.”

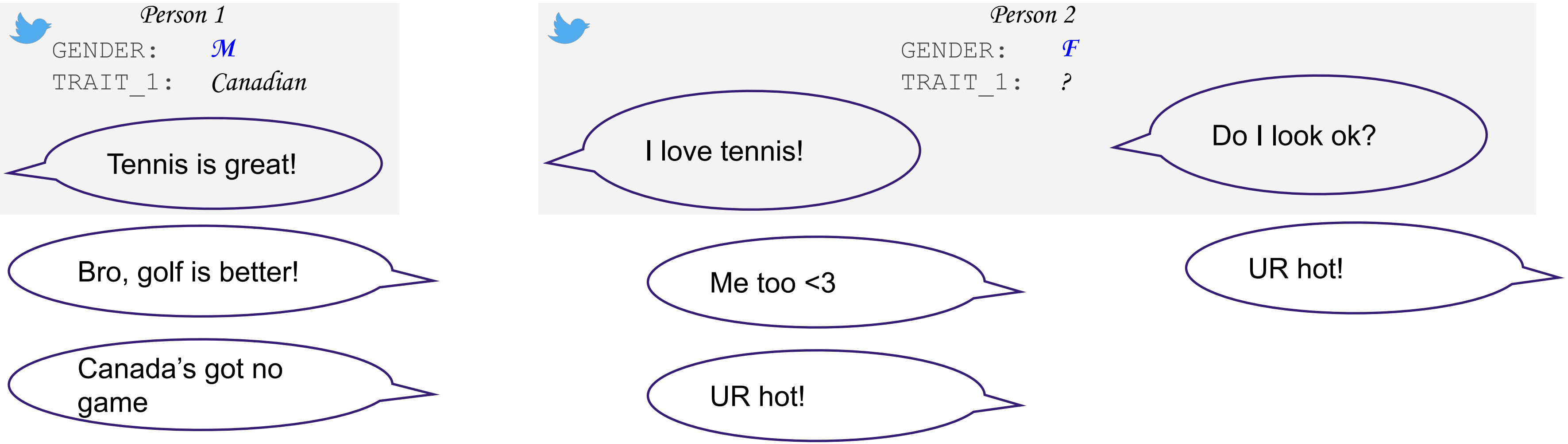
amazon mechanical turk

appen

Supervised Classifier

- Problems:
  - We don’t have strong lexical sieve to surface candidates for annotation
  - Biases are subtle and implicit. We cannot rely on non-expert annotations. Every example requires multiple annotations by trained experts.

Naive approach 2: Comments contain bias if they are highly predictive of gender



Person 1

GENDER: *M*

TRAIT_1: *Canadian*

Tennis is great!

Bro, golf is better!

Canada's got no game

Person 2

GENDER: *F*

TRAIT_1: *?*

I love tennis!

Do I look ok?

Me too <3

UR hot!

UR hot!

Naive approach 2: Comments contain bias if they are highly predictive of gender

Person 1

GENDER: *M*

Bro, golf is better!

Canada's got no game

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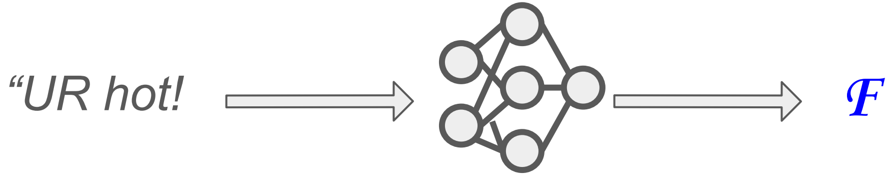
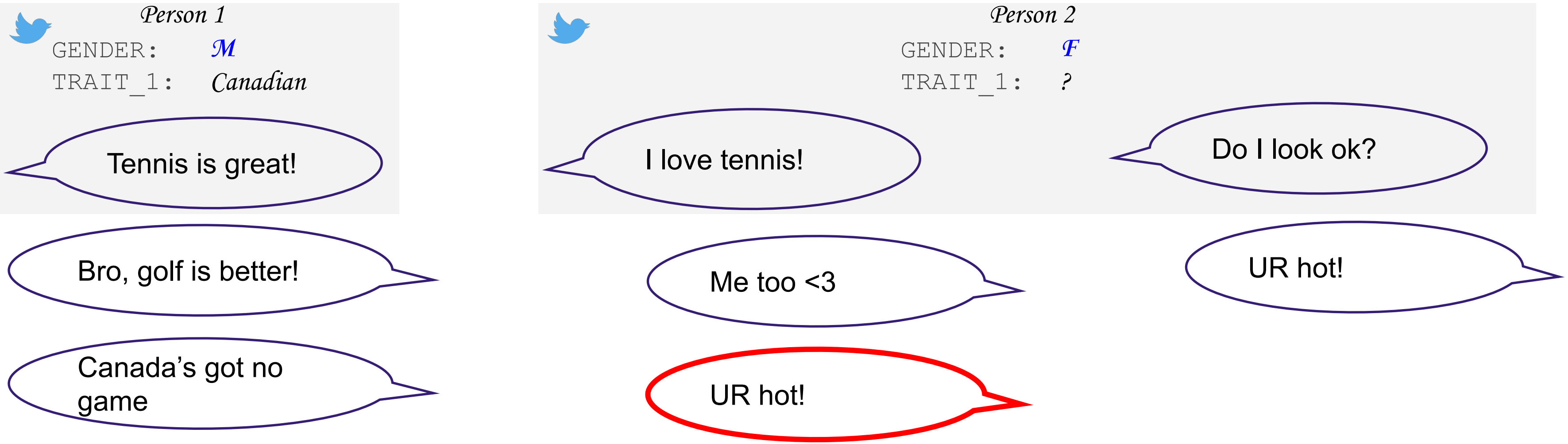


Naive approach 2: Comments contain bias if they are highly predictive of gender



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Person 2

GENDER: *F*

TRAIT_1: *?*

I love tennis!

Me too <3

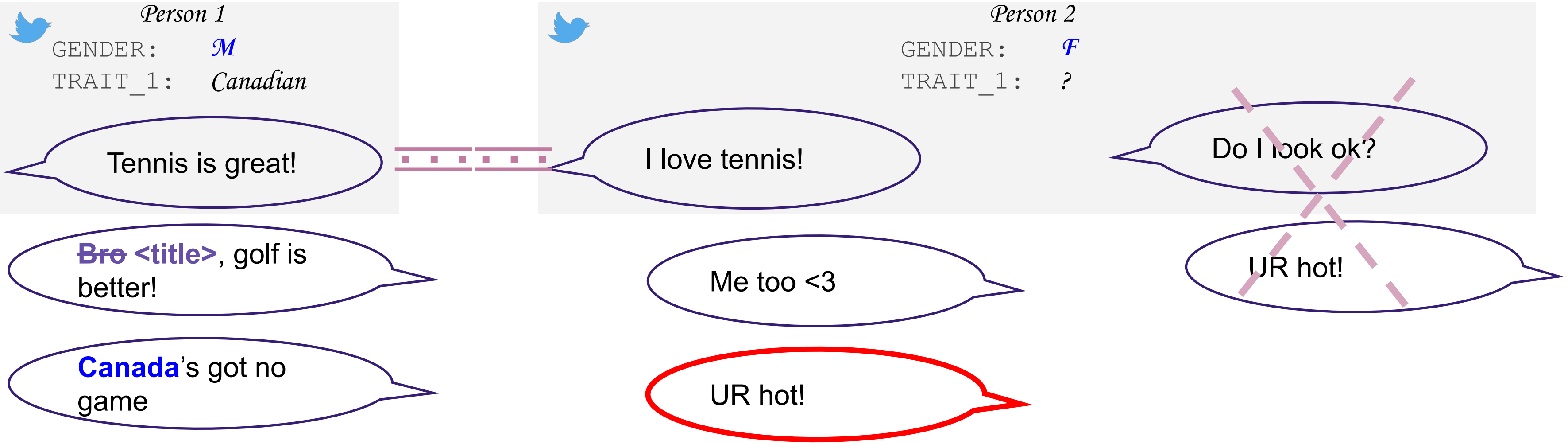
UR hot!

Do I look ok?

UR hot!

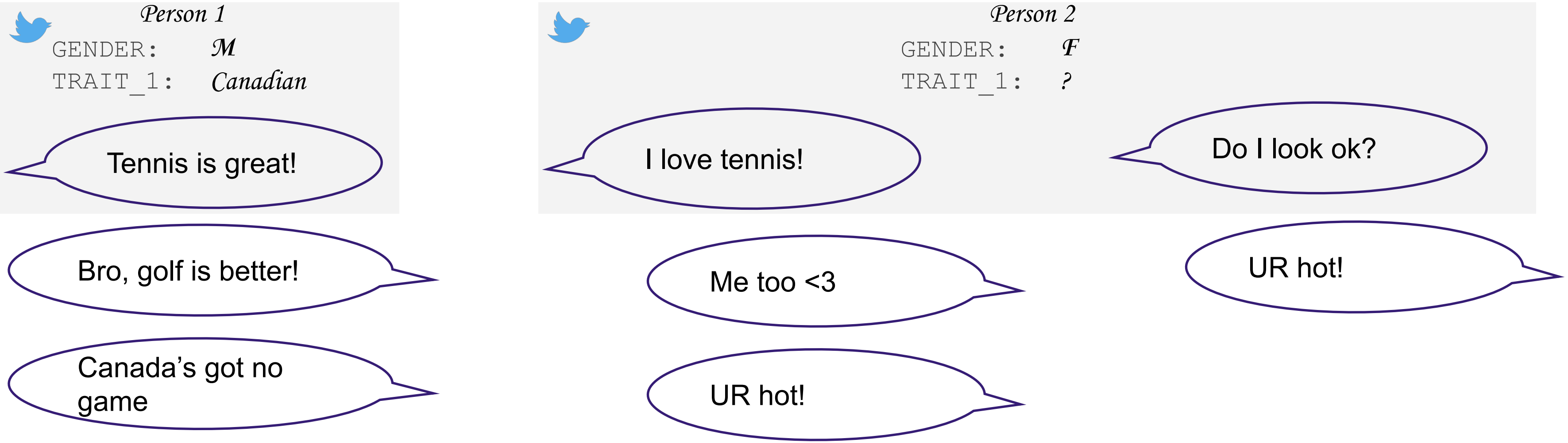
- There might be other factors that cause differences in text
- Text may contain *confounds* that are predictive of gender but not indicative of bias

Proposed model: Comments contain bias if they are highly predictive of gender despite confound control



- Observed confounding variables are balanced through propensity matching
- **Latent confounding variables are demoted through adversarial training**
- **Overt indicators are substituted**

Propensity matching for *observed* confounding variables



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TRAIT_1: *?*

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Me too <3

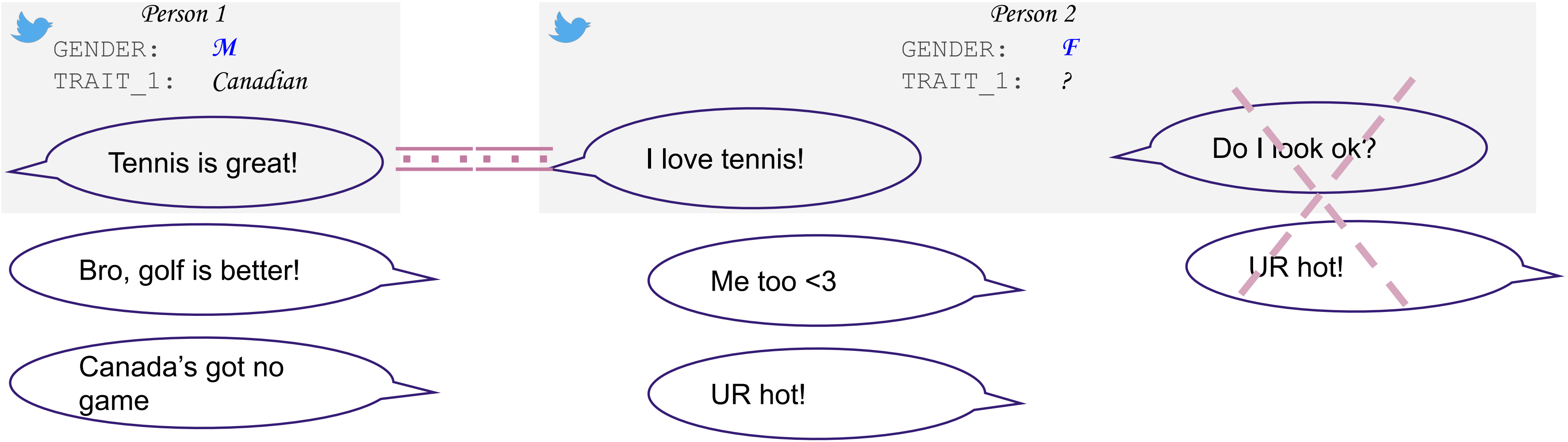
UR hot!

Do I look ok?

UR hot!

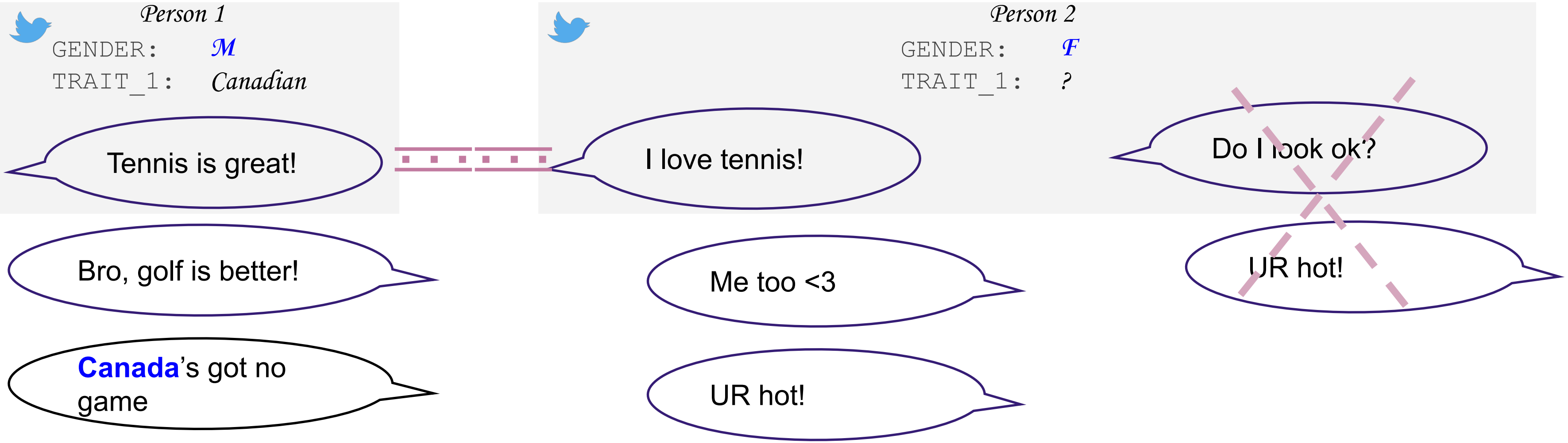
- Comments are written in reply to "original text" written by the addressee
- Language in comments may be caused by "original text" and not gender of the addressee

Propensity matching for *observed* confounding variables



- Balance the data set so that comments addressed to men have a similar distribution of confounding variables as comments addressed to women
  - Match posts with similar indicators of confounding variables
  - Discard posts that are unable to be matched

Adversarial training for *latent* confounding variables



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TRAIT_1: *?*

I love tennis!

Me too <3

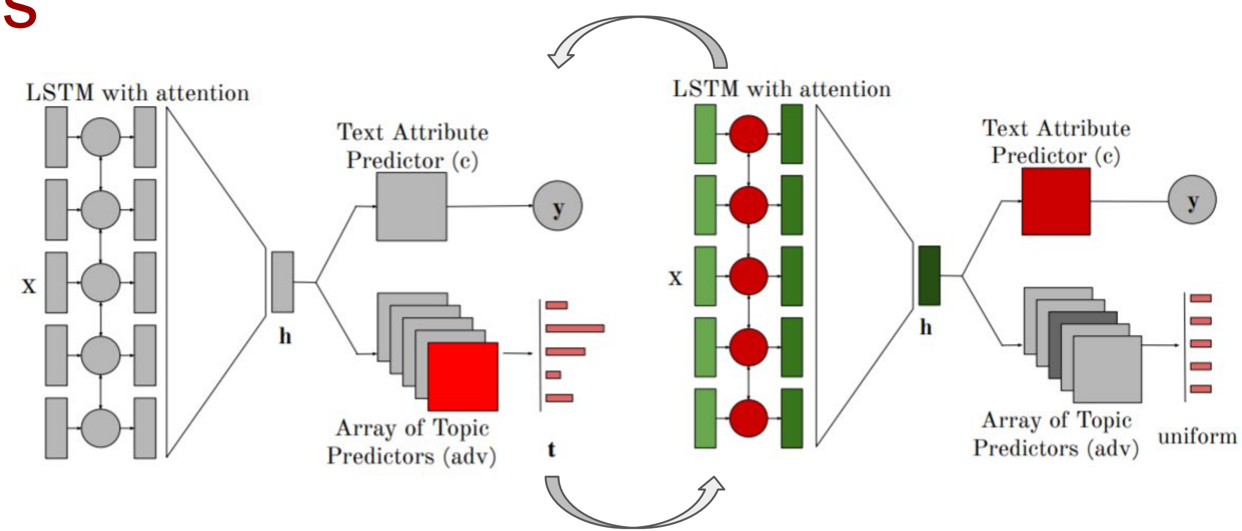
UR hot!

Do I look ok?

UR hot!

- Comments may references traits of the addressee (such as occupation, nationality, nicknames, etc.) other than gender
- Difficult to enumerate all of them
- Often unique to individuals (difficult to make matches)

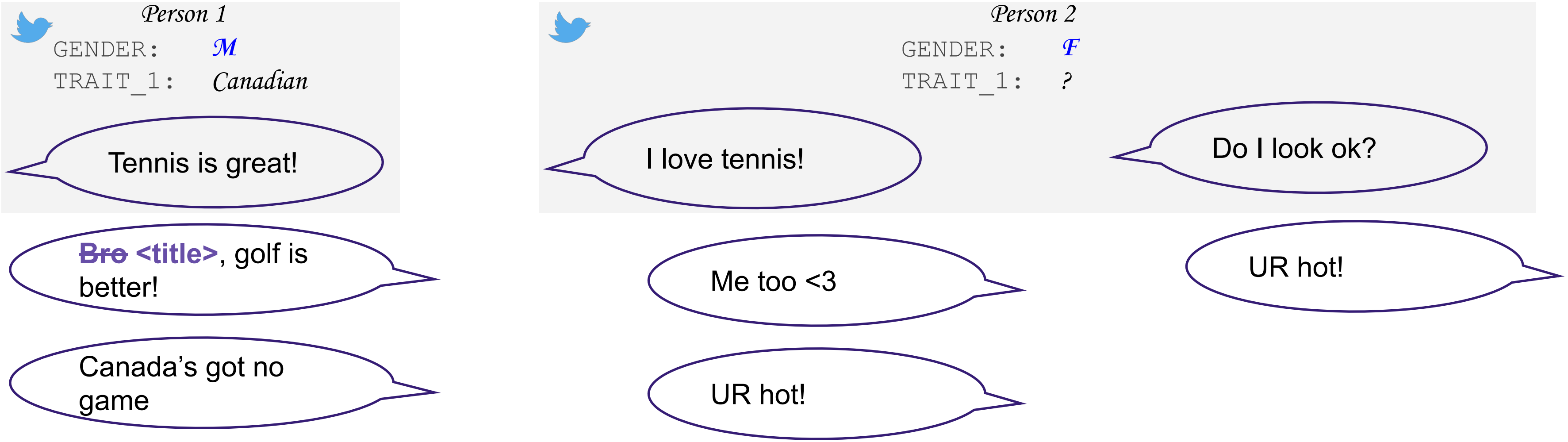
Adversarial training to demote *latent* confounding variables


LSTM with attention
X
h
Text Attribute Predictor (c)
y
Array of Topic Predictors (adv)
t
LSTM with attention
X
h
Text Attribute Predictor (c)
y
Array of Topic Predictors (adv)
uniform

Kumar S., Wintner S., Smith, N. A and Tsvetkov Y. (2019) Topics to Avoid: Demoting Latent Confounds in Text Classification. *EMNLP*

- Confounding traits are inferred from comments using log-odds ratio with Dirichlet prior and represented in a vector
- GAN-like training procedure discourages the model from learning these traits

Word substitutions for overt signals



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TRAIT_1: *?*

I love tennis!

Do I look ok?

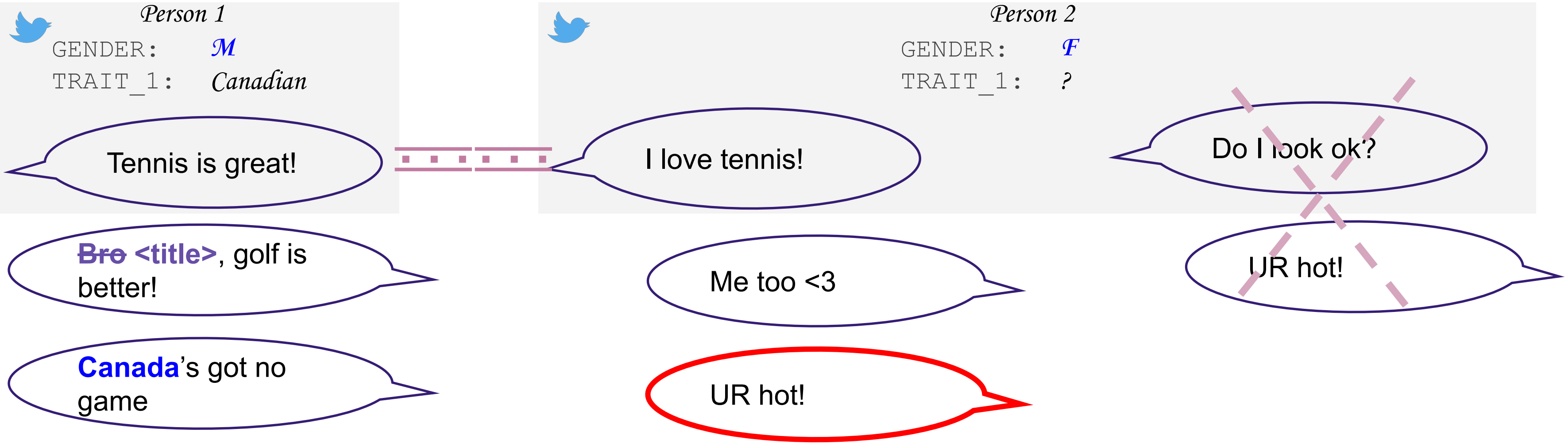
Me too <3

UR hot!

UR hot!

- Remove overtly gendered terms (Mrs. Ms. Mr., proper names, etc.) using keyword substitution

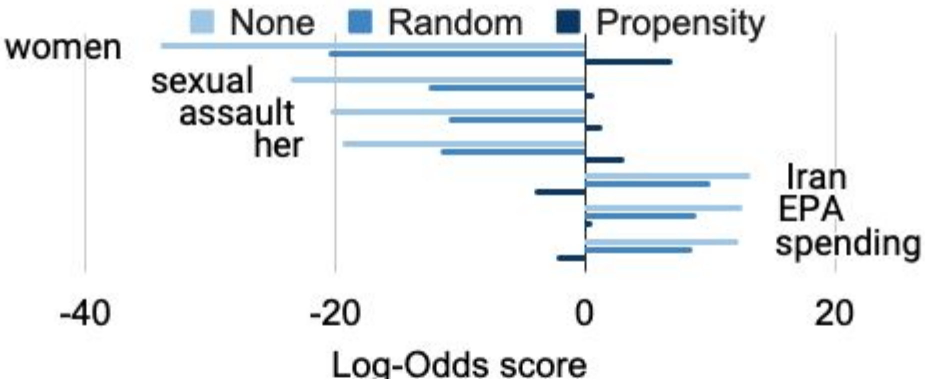
Proposed model: Comments contain bias if they are highly predictive of gender despite confound control



- Observed confounding variables are balanced through propensity matching
- **Latent confounding variables are demoted through adversarial training**
- **Overt indicators are substituted**

Evaluation: Reducing influence of confounding variables

	F1 (Data 1)	F1 (Data 2)
base	74.9	23.2
+demotion	76.1	17.4
+match	65.4	28.5
+match+demotion	68.2	28.8



Voigt R., Jurgens D., Prabhakaran, V., Jurafsky D. and Tsvetkov Y. (2019) RtGender: A Corpus for Studying Differential Responses to Gender. *LREC*

- Latent confound demotion improves performance on held-out data
- Propensity matching reduces differences in training data distributions

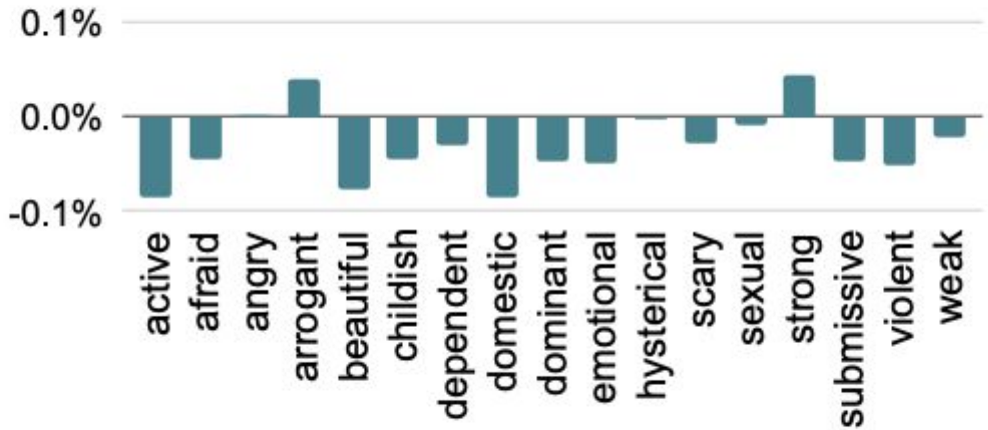
Evaluation: detection of gender-based microaggressions

	Precision	Recall	F1	Accuracy
Our model (Trained on data set 1)	51.0	50.7	50.9	57.0
Our model (Trained on data set 2)	45.7	75.3	56.9	49.9
Random baseline	43.5	48.7	46.0	49.8

"You're pretty for a black girl." microaggressions.com

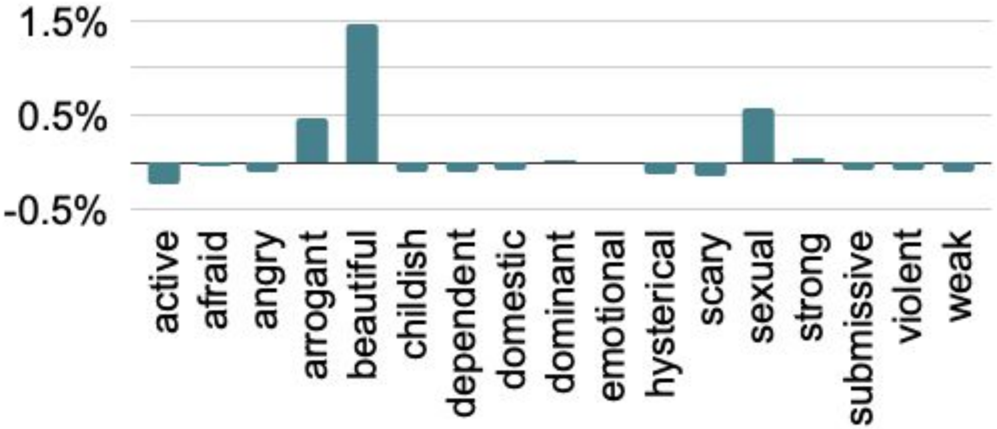
Breitfeller L., Ahn E., Jurgens D., Tsvetkov Y. (2019) Finding Microaggressions in the Wild: A Case for Locating Elusive Phenomena in Social Media Posts. *EMNLP*

Findings: characteristics of bias against women



Politicians:

- Competence and domesticy
- ‘Force’, ‘situation’, ‘spouse’, ‘family’, ‘love’



Other Public Figures:

- Appearance and sexualization
- ‘beautiful’, ‘bellissima’, ‘amore’, ‘amo’, ‘love’, ‘linda’, ‘sexo’

Automatic detection of implicit bias and veiled toxicity

- Via a causal framework and demoting spurious confounds
    - Field A. & Tsvetkov Y. (2020) Unsupervised Discovery of Implicit Gender Bias. *EMNLP*

- Via adversarial probing & interpreting model decisions
    - Han X., Tsvetkov Y. (2020) Fortifying Toxic Speech Detectors Against Veiled Toxicity. *EMNLP*

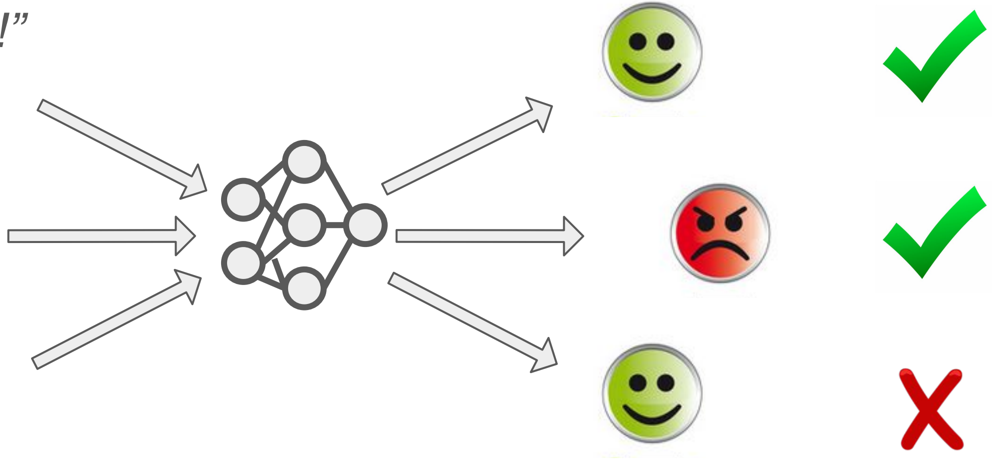
A toxicity classifier

API :: Perspective

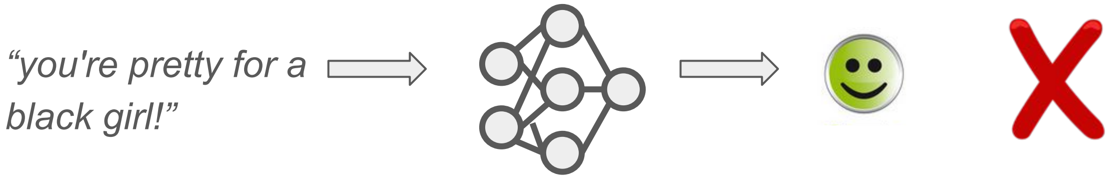
“you’re so pretty!”

“you’re ugly!”

“you're pretty
for a black girl!”



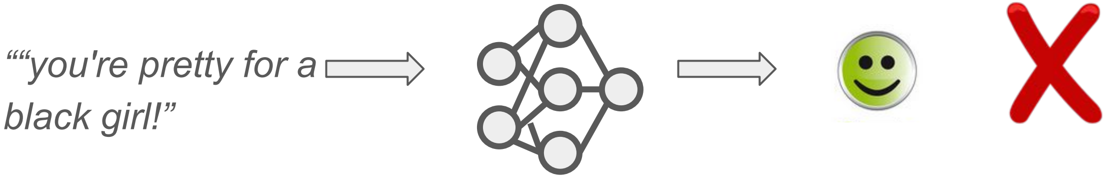
Microaggressions as adversarial attacks on toxicity classifiers



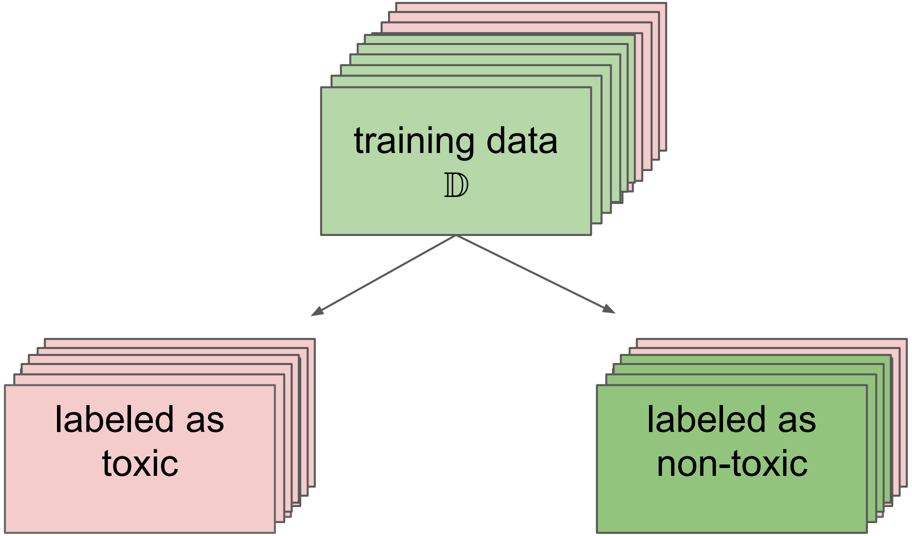
"you're pretty for a black girl!"

- Codewords (Taylor et al., 2017)
- Novel forms of offense (Jain et al., 2018)
- Microaggressions (Breitfeller et al., 2019)
- Condescension (Wang and Potts, 2019)
- Dismissiveness, unfair generalizations (Price et al., 2020)

Microaggressions as adversarial attacks on toxicity classifiers



““you're pretty for a black girl!”



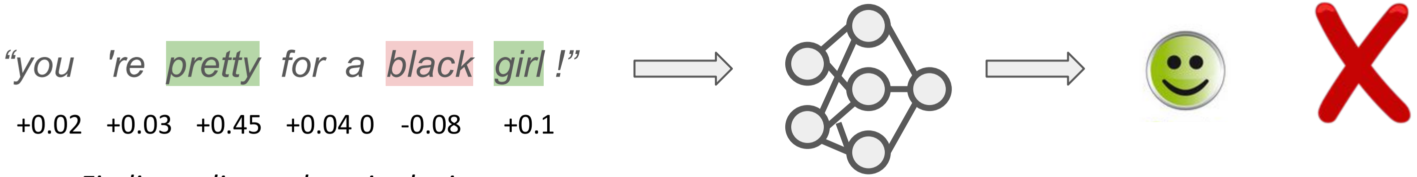
training data $\mathbb{D}$

labeled as toxic

labeled as non-toxic

covert offenses are absent in the training data or mis-labeled as non-toxic

Interpreting text classification decisions via saliency maps



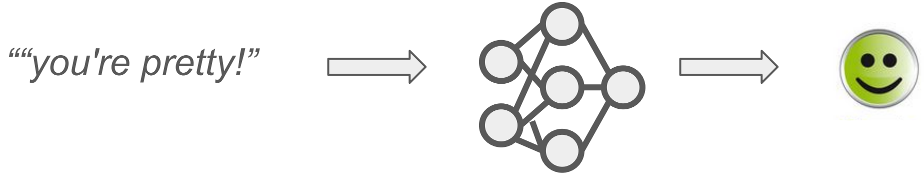
“you 're pretty for a black girl !”

+0.02 +0.03 +0.45 +0.04 0 -0.08 +0.1

Finding salient tokens in the input

- Interpretation via saliency maps
  - Gradient-based attribution (Simonyan et al.,’14; Sundararajan et al.’17; Smilkov et al.’17)
  - LIME (Ribeiro et al.’16)
  - Attention-based heatmaps (Xu et al.’15)

Interpreting text classification decisions via the influence of examples in the training data



“““you're pretty!”

influence score

you’re beautiful!	positive	+10.64
You're an awesome friend.	positive	+10.32
...	positive	+10.09
	⋮	
...	negative	-12.78
...	negative	-11.01
I don’t like you	negative	-9.97

Finding influential examples in the training corpus

Han X., Wallace B., Tsvetkov Y. (2020) Explaining Black Box Predictions and Unveiling Data Artifacts through Influence Functions. *ACL*

Training data of toxicity classifiers is often private

original training data $\mathbb{D}$

original classifier C

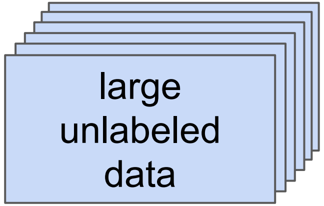
API :: Perspective

We’ll train a student model

original training data $\mathbb{D}$

original classifier C

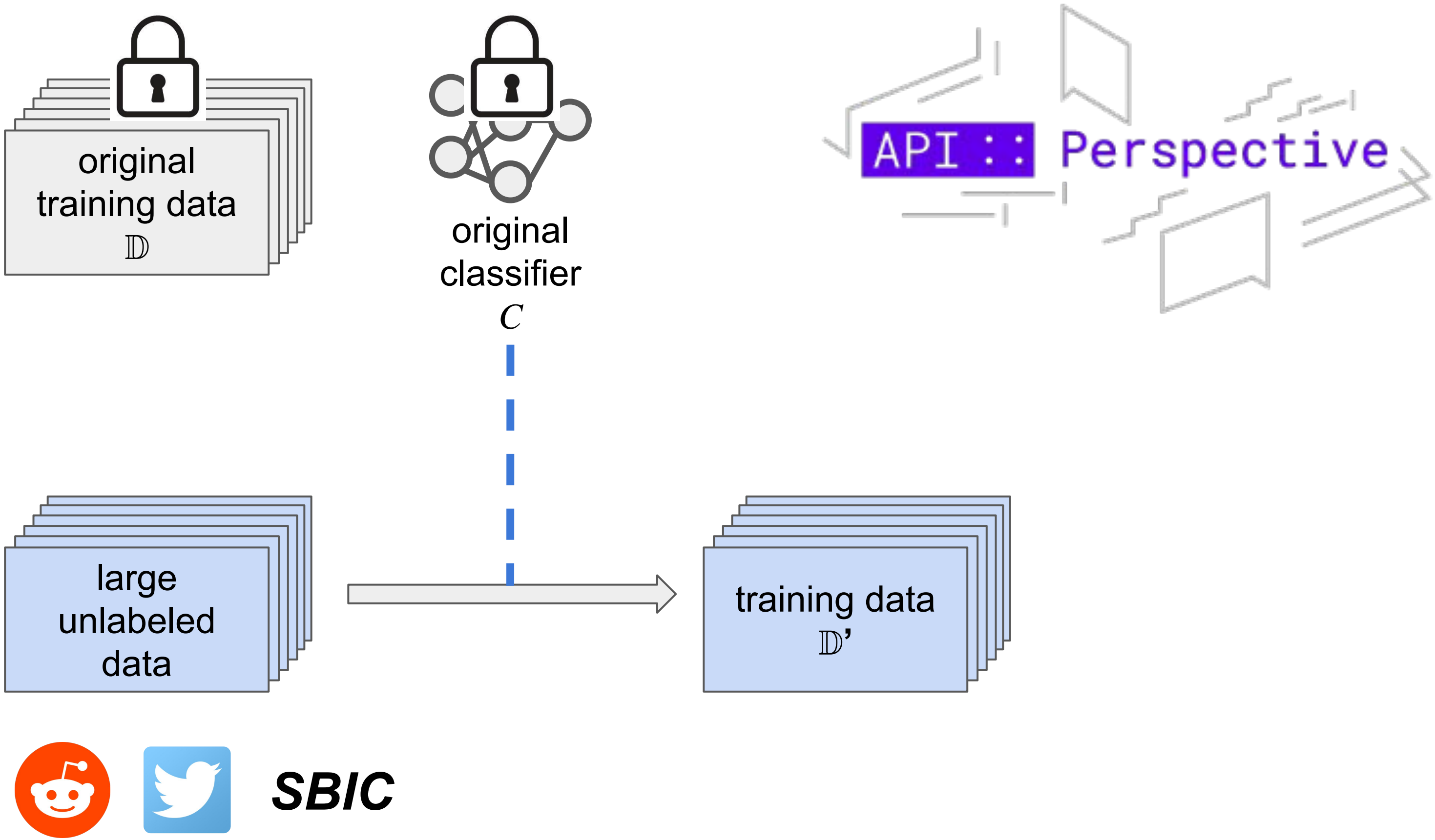
API :: Perspective



large unlabeled data

SBIC

We’ll train a student model



original training data $\mathbb{D}$

original classifier C

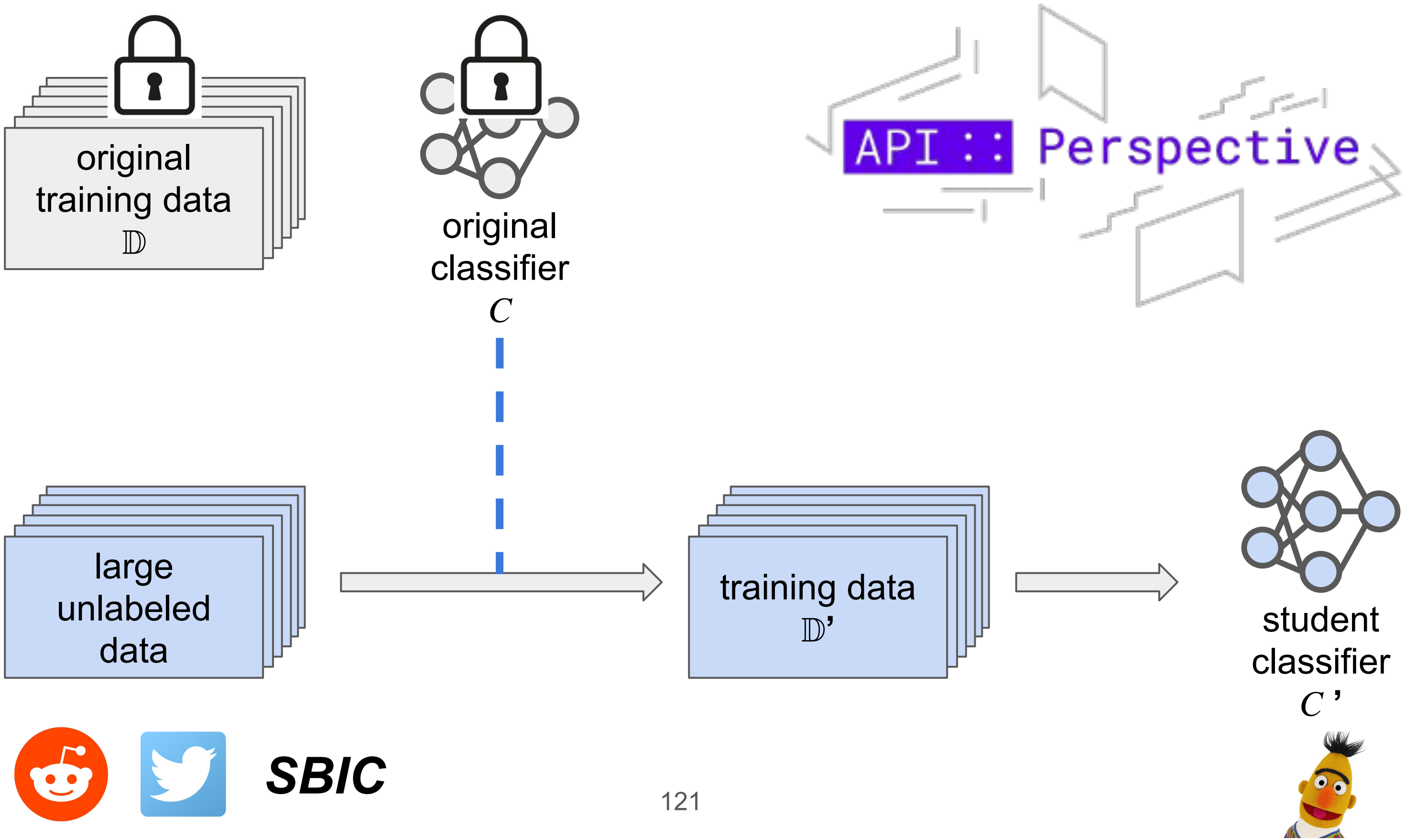
API :: Perspective

large unlabeled data

training data $\mathbb{D}$’

SBIC

We’ll train a student model



original training data $\mathbb{D}$

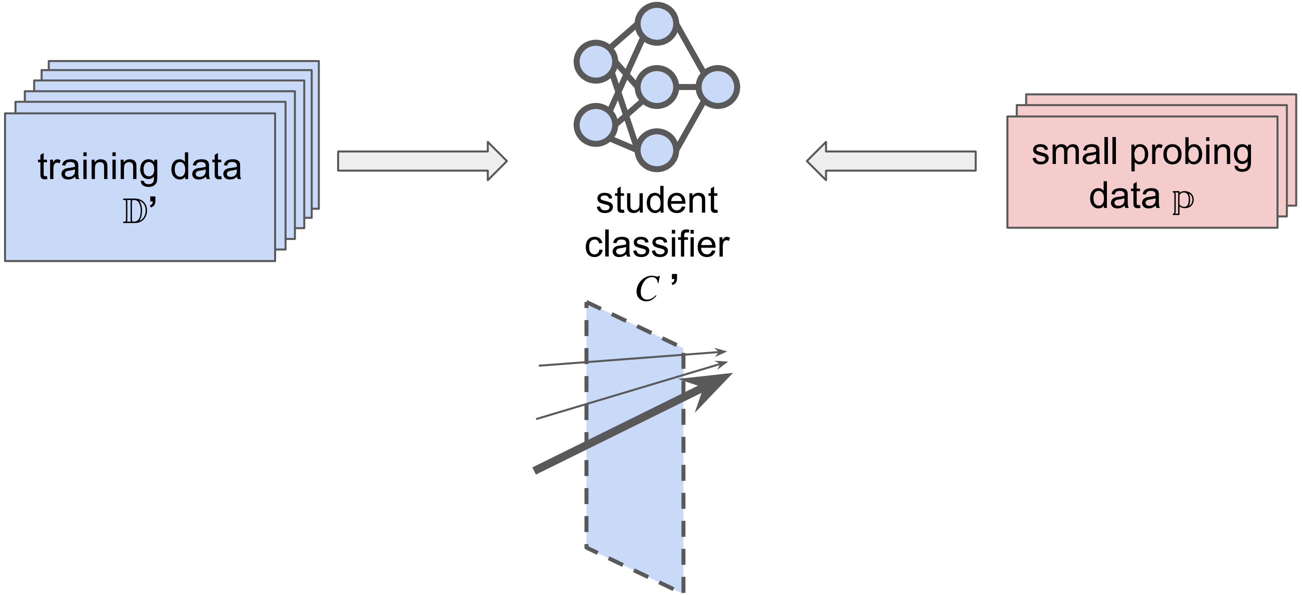
original classifier C

large unlabeled data

training data $\mathbb{D}'$

student classifier C'

Towards robust toxicity detection via adversarial probing & interpreting model decisions



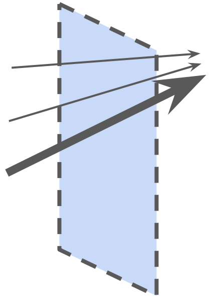
Given a small set of probing examples of veiled toxicity

1. Interpret model decisions via tracking the influence of training examples
2. Use expert annotators to re-label top-k training instances

Tracking the influence of the training data on classifier's decisions

- Which training data is most influential to the classifier's decision on a probing example?

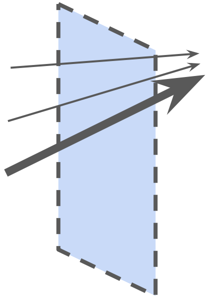
- $\mathcal{I}(x_{trn}, x_{prb})$



Embedding Similarity

$$\mathcal{I}(x_{trn}, x_{prb}) = \underbrace{\boxed{f_{enc}(x_{trn})}} \cdot \underbrace{\boxed{f_{enc}(x_{prb})}}$$

“How different are the **representations** of the training data and the probing data?”

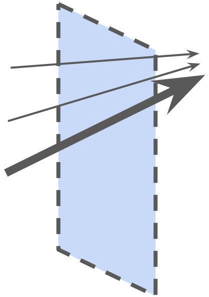


Influence Functions

$$\boxed{\frac{d\theta}{d\epsilon_{trn}}} = -H_\theta^{-1}\nabla_\theta\mathcal{L}(\theta, x_{trn}, y_{trn})$$

“If we **upweight** a training example by ϵ, how would the resulting model change?”

(Koh and Liang, 2017)



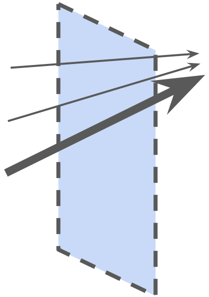
Influence Functions

$$\frac{d\theta}{d\epsilon_{trn}} = -H_{\theta}^{-1}\nabla_{\theta}\mathcal{L}(\theta, x_{trn}, y_{trn})$$

$$\frac{d\mathcal{L}(\theta, x_{prb}, \hat{y}_{prb})}{d\epsilon_{trn}} = \nabla_{\theta}\mathcal{L}(\theta, x_{prb}, \hat{y}_{prb}) \cdot \boxed{\frac{d\theta}{d\epsilon_{trn}}}$$

“Given this **change** in the resulting model ...”

(Koh and Liang, 2017)



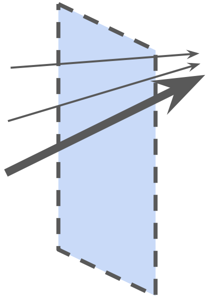
Influence Functions

$$\frac{d\theta}{d\epsilon_{trn}} = -H_{\theta}^{-1} \nabla_{\theta} \mathcal{L}(\theta, x_{trn}, y_{trn})$$

$$\boxed{\frac{d\mathcal{L}(\theta, x_{prb}, \hat{y}_{prb})}{d\epsilon_{trn}}} = \nabla_{\theta} \mathcal{L}(\theta, x_{prb}, \hat{y}_{prb}) \cdot \frac{d\theta}{d\epsilon_{trn}}$$

“How would the **loss** of the probing example change?”

(Koh and Liang, 2017)



Influence Functions

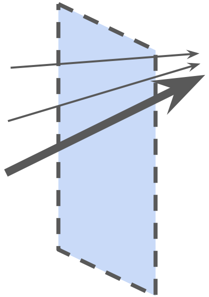
$$\frac{d\theta}{d\epsilon_{trn}} = -H_\theta^{-1} \nabla_\theta \mathcal{L}(\theta, x_{trn}, y_{trn})$$

$$\frac{d\mathcal{L}(\theta, x_{prb}, \hat{y}_{prb})}{d\epsilon_{trn}} = \nabla_\theta \mathcal{L}(\theta, x_{prb}, \hat{y}_{prb}) \cdot \frac{d\theta}{d\epsilon_{trn}}$$

$$\mathcal{I}(x_{trn}, x_{prb}) = \boxed{-\frac{d\mathcal{L}(\theta, x_{prb}, \hat{y}_{prb})}{d\epsilon_{trn}}}$$

“Upweighting an **influential** training example should lead to a decrease in the loss of the probing example.”

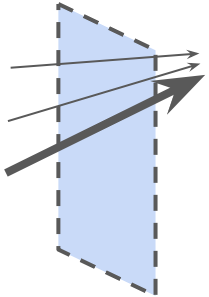
(Koh and Liang, 2017)



Gradient product (*TrackIn*)

$$\mathcal{I}(x_{trn}, x_{prb}) = \sum_{i=1}^{k} \underbrace{\boxed{\nabla_\theta \mathcal{L}(\theta_i, x_{trn}, y_{trn})}} \cdot \nabla_\theta \mathcal{L}(\theta_i, x_{prb}, \hat{y}_{prb})$$

“The model would take a step towards the **gradient** of the training example’s loss at epoch i.”



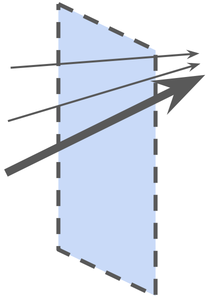
(Pruthi et al., 2020)

Gradient product (*TrackIn*)

$$\mathcal{I}(x_{trn}, x_{prb}) = \sum_{i=1}^{k} \underbrace{\boxed{\nabla_\theta \mathcal{L}(\theta_i, x_{trn}, y_{trn}) \cdot \nabla_\theta \mathcal{L}(\theta_i, x_{prb}, \hat{y}_{prb})}}$$

"Because of this step, how much will the loss of the probing example **decrease**?"

(Pruthi et al., 2020)

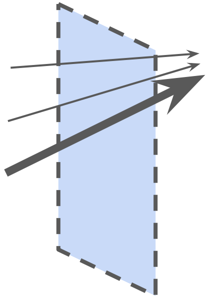


Gradient product (*TrackIn*)

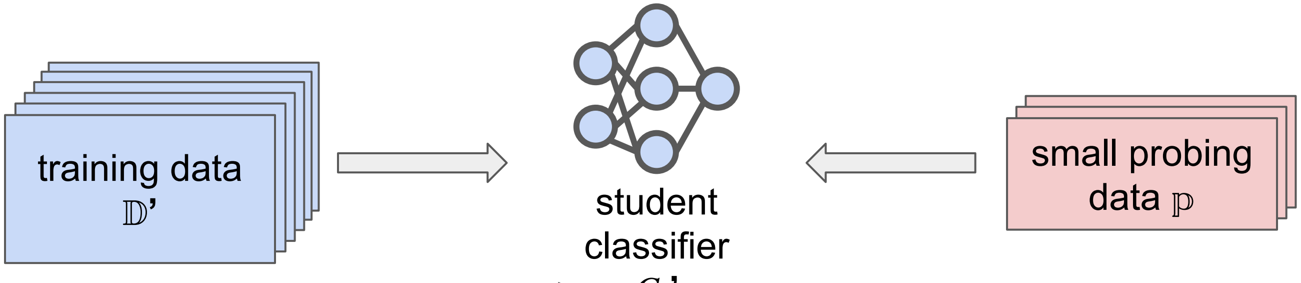
$$\mathcal{I}(x_{trn}, x_{prb}) = \underbrace{\boxed{\sum_{i=1}^{k}}} \nabla_\theta \mathcal{L}(\theta_i, x_{trn}, y_{trn}) \cdot \nabla_\theta \mathcal{L}(\theta_i, x_{prb}, \hat{y}_{prb})$$

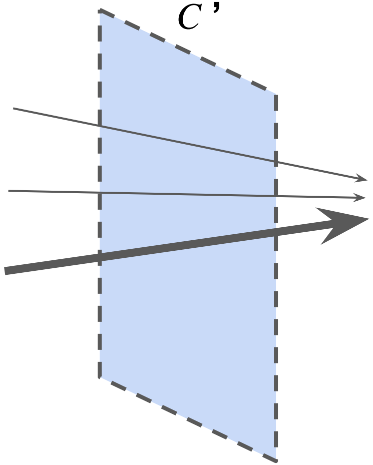
“We take a **sum** of such probing loss decrease caused by the training example over all the checkpoints of the model.”

(Pruthi et al., 2020)



An active learning framework to surface veiled toxicity





- re-label top-k training examples that were most influential to classifier’s decisions

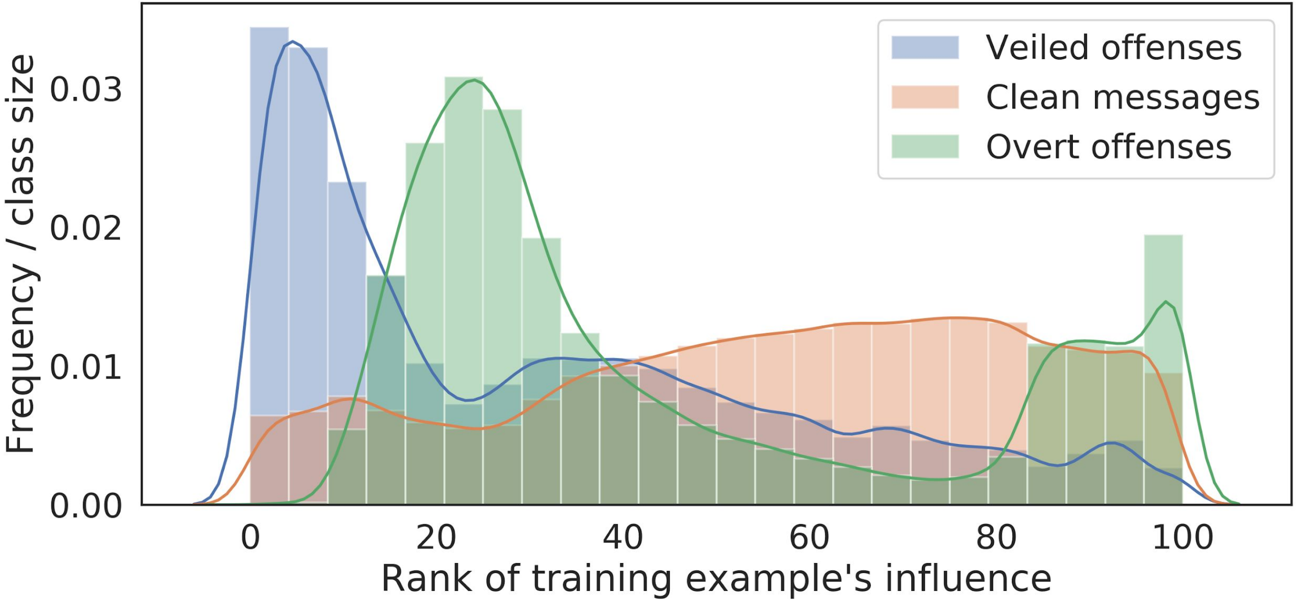
Experiments

- Training data:
  - Reddit, twitter posts from the ***SBIC*** **-** Social Bias Inference Corpus (Sap et al., 2020)
  - Clean messages: 8K "non-toxic" by Perspective API and "not offensive" by SBIC annotators
  - Overt offenses: 2K "toxic" by Perspective API and "offensive" by SBIC annotators
  - Veiled offenses: 2K "non-toxic" by Perspective API and "offensive" by some SBIC annotators
- Test data: 1K, 1K, 1K

- Class recall: not offensive: 99.6%, overtly offensive: 97.2%, veiled offenses: 1.2%

- Probing corpus: <100 held-out examples of microaggressions and other veiled offenses microaggressions.com

Unveiling disguised toxicity via probing & interpreting model decisions



- Clean messages: 8K “non-toxic” by Perspective API and “not offensive” by SBIC annotators
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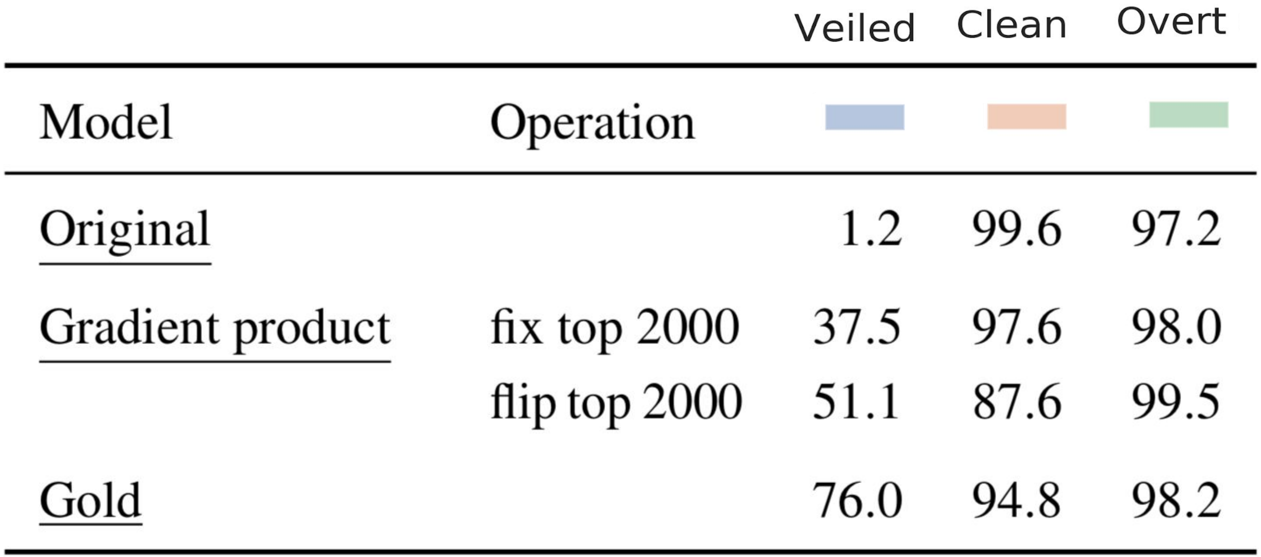
Unveiling disguised toxicity via probing & interpreting model decisions



		Veiled	Clean	Overt
Model	Operation	🟦	🟧	🟩
Original		1.2	99.6	97.2
Gradient product	fix top 2000	37.5	97.6	98.0
	flip top 2000	51.1	87.6	99.5
Gold		76.0	94.8	98.2

- Clean messages: 8K “non-toxic” by Perspective API and “not offensive” by SBIC annotators
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- Veiled offenses: 2K “non-toxic” by Perspective API and “offensive” by some SBIC annotators

In sum,

- Biases in the data are pervasive and pernicious
- SOTA NLP tools cannot identify toxic comments beyond overt hate speech
  - Biases are subtle and implicit even experts are bad at identifying them
  - We don’t have strong lexical sieve to surface candidates for annotation
- Why is it important to detect biases in data:
  - Posters are often unaware that their comments contains bias -- if they were, they may choose not to post them
  - Users can choose not to read flagged comments
  - These comments can be filtered from the training data of AI systems
- Direct supervised approaches are not enough we need paradigms shift in modeling

Social and ethical challenges for language technologies

- Incivility: Hate-speech, toxicity, incivility, microaggressions online
- Social bias: Social bias in data & NLP models
- Privacy violation: Privacy violation & language-based profiling
- Misinformation: Fake news, Information manipulation, opinion manipulation
- Technological divide: Unfair NLP technologies, underperforming for speakers of minority dialects, for languages from developing countries, and for disadvantaged populations

Some ideas for research projects

- Additional ideas for research projects
  shorturl.at/wxBJ9

Thank you!

yuliats@cs.washington.edu