Bias in the Vision and Language of Artificial Intelligence

Margaret Mitchell
Senior Research Scientist
Google AI

Conversation AI

Andrew Zaldivar | Me | Simone Wu | Parker Barnes | Lucy Vasserman | Ben Hutchinson | Elena Spitzer | Deb Raji | Timnit Gebru

Adrian Benton | Brian Zhang | Dirk Hovy | Josh Lovejoy | Alex Beutel | Blake Lemoine | Hee Jung Ryu | Hartwig Adam | Blaise Agüera y Arcas

What do you see?

What do you see?

- Bananas

What do you see?

- Bananas
- Stickers

What do you see?

- Bananas
- Stickers
- Dole Bananas

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas
- Bananas with stickers on them

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas
- Bananas with stickers on them
- Bunches of bananas with stickers on them on shelves in a store

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas
- Bananas with stickers on them
- Bunches of bananas with stickers on them on shelves in a store

...We don’t tend to say

Yellow Bananas

What do you see?

Green Bananas

Unripe Bananas

What do you see?

Ripe Bananas

Bananas with spots

What do you see?

Ripe Bananas

Bananas with spots

Bananas good for banana bread

What do you see?

Yellow Bananas

Yellow is prototypical for bananas

Prototype Theory

One purpose of categorization is to **reduce the infinite differences** among stimuli **to** behaviourally and **cognitively usable proportions**

There may be some central, prototypical notions of items that arise from stored typical properties for an object category (Rosch, 1975)

May also store exemplars (Wu & Barsalou, 2009)

Fruit

Bananas
“Basic Level”

Unripe Bananas, Cavendish Bananas

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

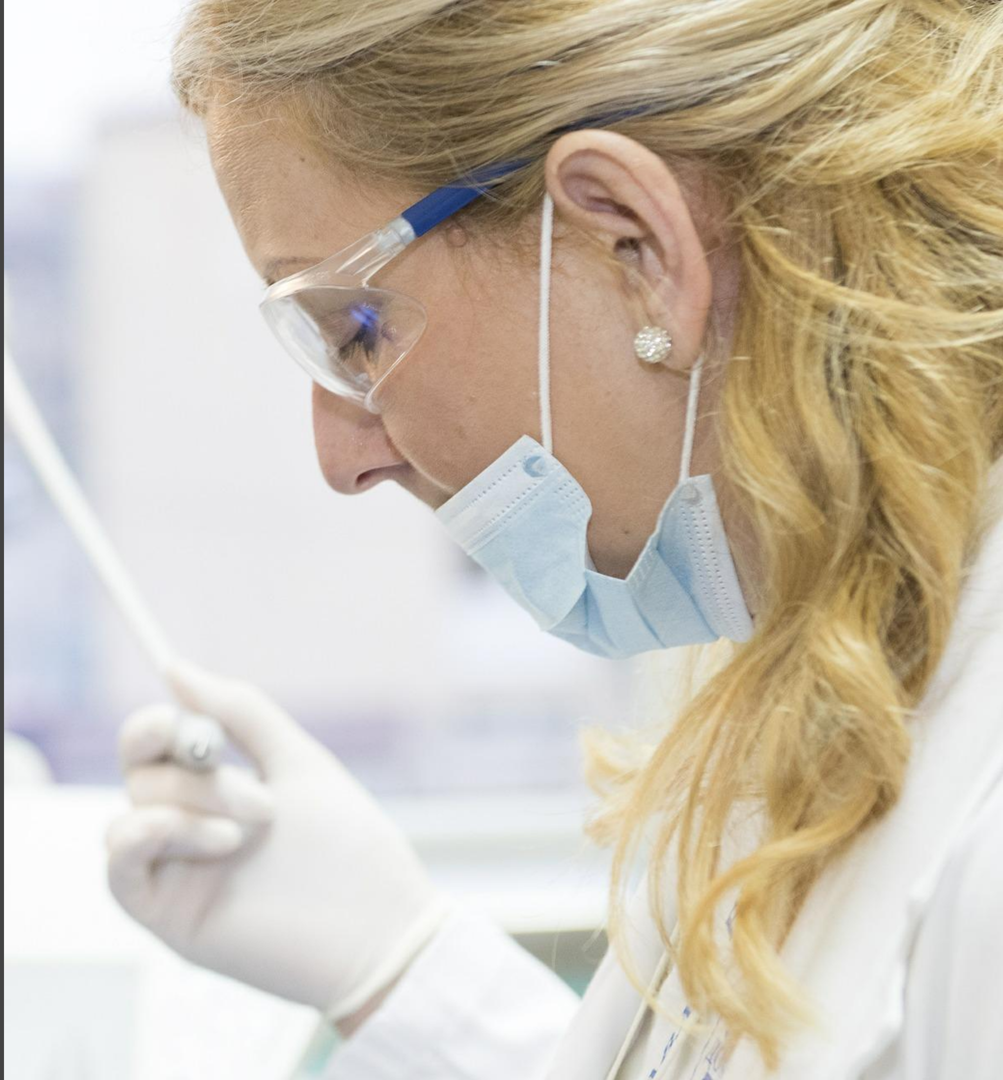
The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?



A man and his son are in a terrible accident and are rushed to the hospital in critical care.

The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?


“Doctor”

“Female doctor”

The majority of test subjects overlooked the possibility that the doctor is a she - including men, women, and self-described feminists.

Wapman & Belle, Boston University

World learning from text

Gordon and Van Durme, 2013

Word	Frequency in corpus
“spoke”	11,577,917
“laughed”	3,904,519
“murdered”	2,834,529
“inhaled”	984,613
“breathed”	725,034
“hugged”	610,040
“blinked”	390,692
“exhale”	168,985

World learning from text

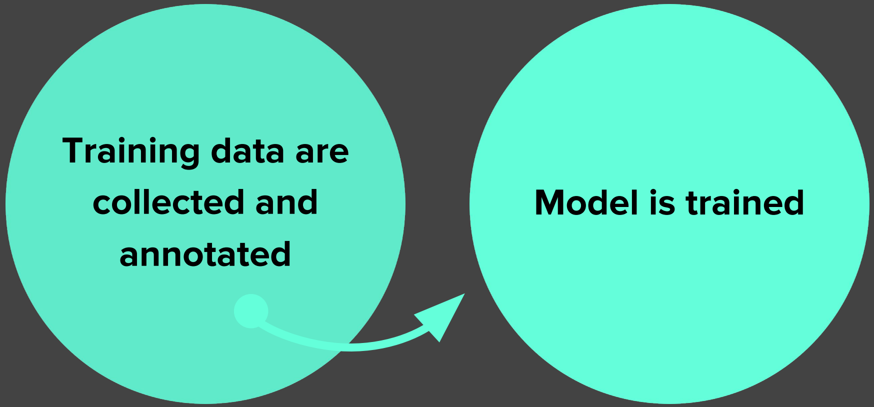
Gordon and Van Durme, 2013

Word	Frequency in corpus
“spoke”	11,577,917
“laughed”	3,904,519
“murdered”	2,834,529
“inhaled”	984,613
“breathed”	725,034
“hugged”	610,040
“blinked”	390,692
“exhale”	168,985

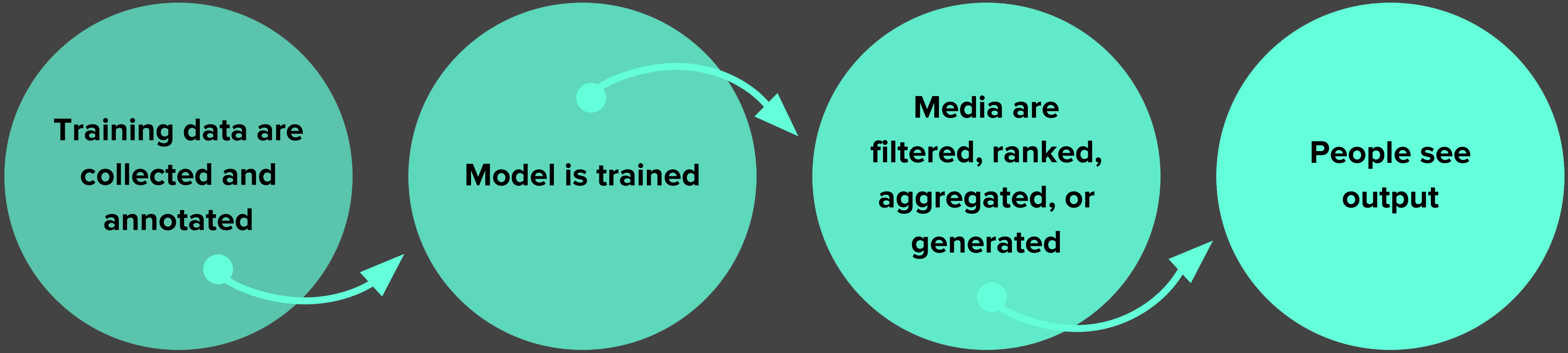
Human Reporting Bias

The **frequency** with which **people write** about actions, outcomes, or properties is **not a reflection of real-world frequencies** or the degree to which a property is characteristic of a class of individuals

Training data are collected and annotated


Training data are collected and annotated
Model is trained


Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated


Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated
People see output

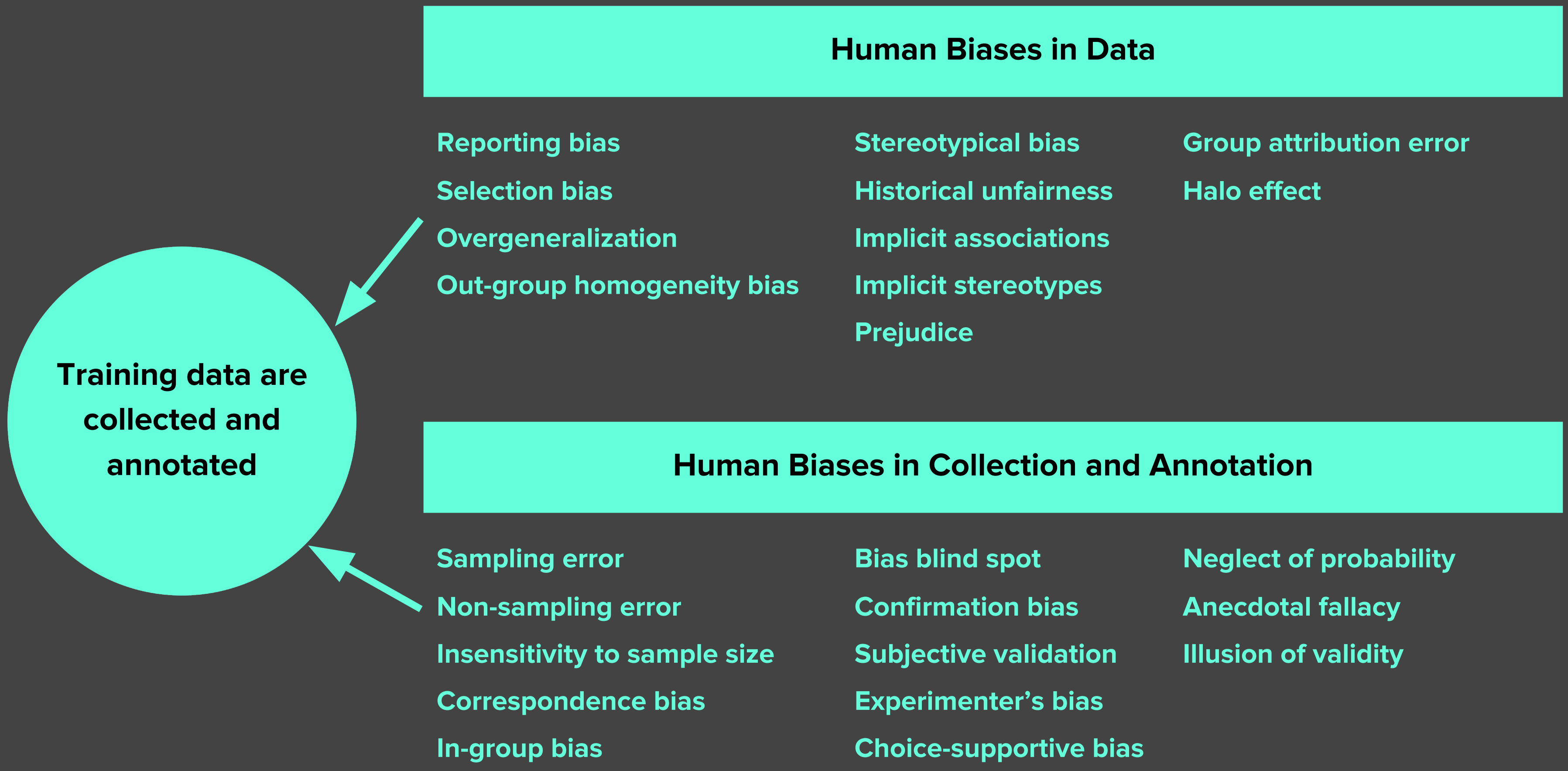
Human Biases in Data

Reporting bias
Selection bias
Overgeneralization
Out-group homogeneity bias

Stereotypical bias
Historical unfairness
Implicit associations
Implicit stereotypes
Prejudice

Group attribution error
Halo effect

Training data are collected and annotated


Training data are collected and annotated
Human Biases in Data
Reporting bias
Selection bias
Overgeneralization
Out-group homogeneity bias
Stereotypical bias
Historical unfairness
Implicit associations
Implicit stereotypes
Prejudice
Group attribution error
Halo effect
Human Biases in Collection and Annotation
Sampling error
Non-sampling error
Insensitivity to sample size
Correspondence bias
In-group bias
Bias blind spot
Confirmation bias
Subjective validation
Experimenter's bias
Choice-supportive bias
Neglect of probability
Anecdotal fallacy
Illusion of validity

Data

Interpretation

Reporting bias: What people share is not a reflection of real-world frequencies

Selection Bias: Selection does not reflect a random sample

Out-group homogeneity bias: People tend to see outgroup members as more alike than ingroup members when comparing attitudes, values, personality traits, and other characteristics

Confirmation bias: The tendency to search for, interpret, favor, and recall information in a way that confirms one's preexisting beliefs or hypotheses

Overgeneralization: Coming to conclusion based on information that is too general and/or not specific enough

Correlation fallacy: Confusing correlation with causation

Automation bias: Propensity for humans to favor suggestions from automated decision-making systems over contradictory information without automation

More at: https://developers.google.com/machine-learning/glossary/

Biases in Data

Biases in Data

Selection Bias: Selection does not reflect a random sample

Map of Amazon Mechanical Turk Workers

CREDIT

Biases in Data

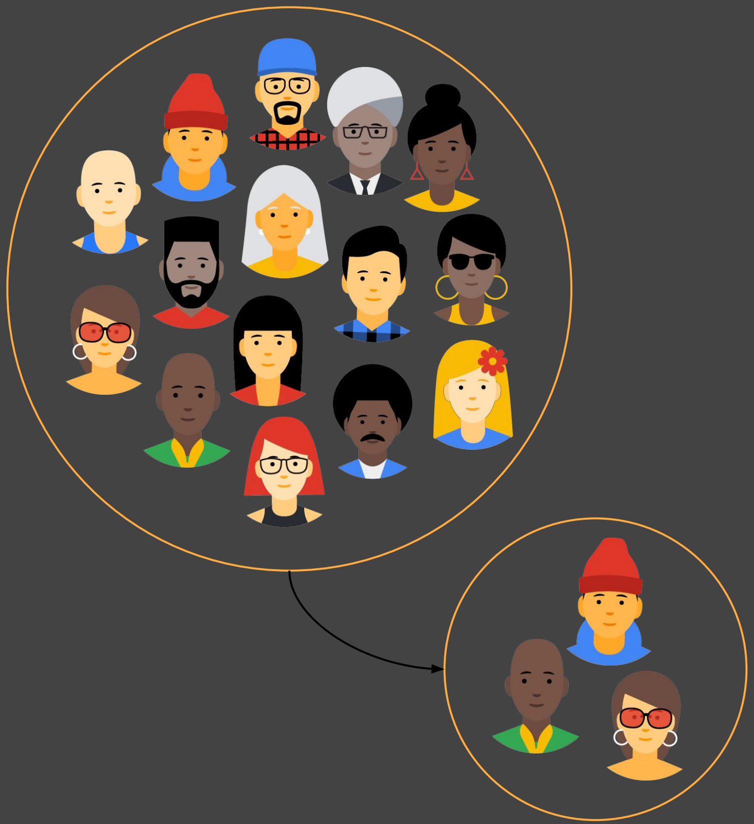
Out-group homogeneity bias: Tendency to see outgroup members as more alike than ingroup members





Biases in Data → Biased Data Representation

It's possible that you have an appropriate amount of data for every group you can think of but that some groups are represented less positively than others.



Biases in Data → Biased Labels

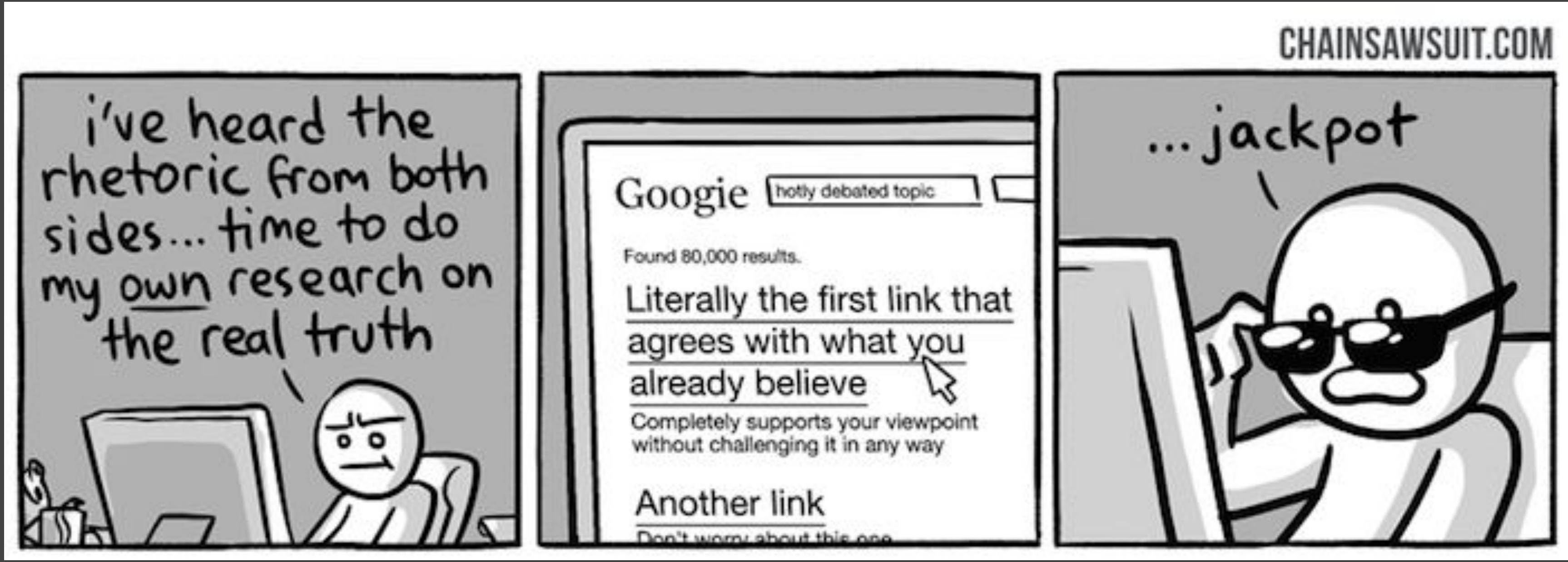
Annotations in your dataset will reflect the worldviews of your annotators.

https://ai.googleblog.com/2018/09/introducing-inclusive-images-competition.html

Biases in Interpretation

Biases in Interpretation

Confirmation bias: The tendency to search for, interpret, favor, recall information in a way that confirms preexisting beliefs



CREDIT

Biases in Interpretation

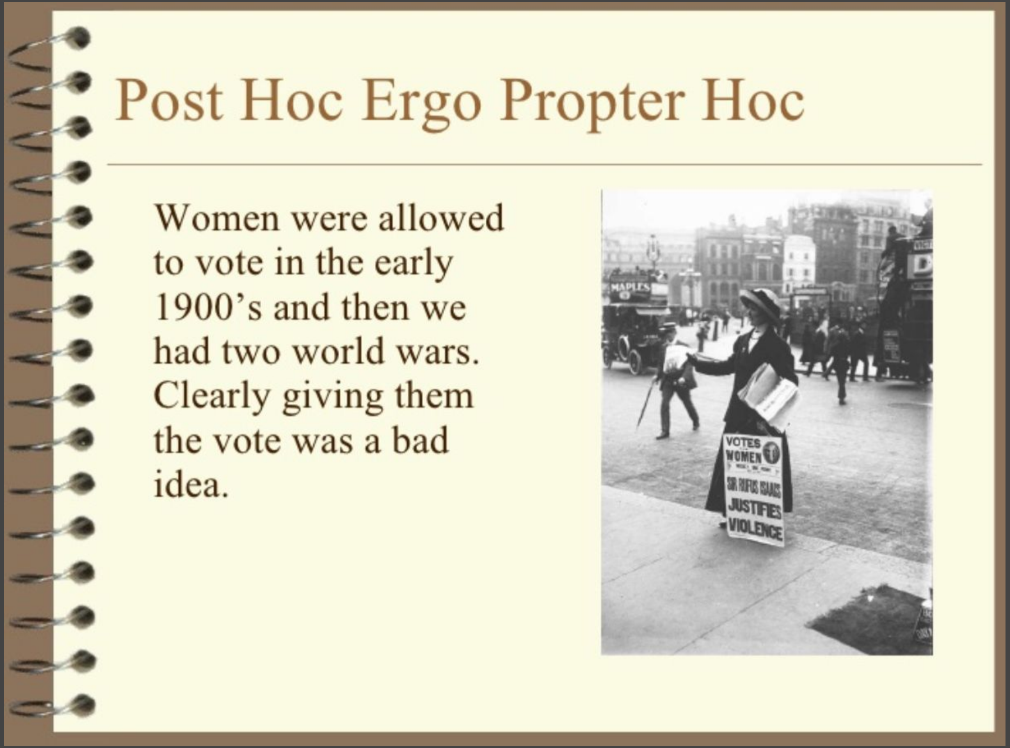
Overgeneralization: Coming to conclusion based on information that is too general and/or not specific enough (related: **overfitting**)

CREDIT

Sidney Harris

Biases in Interpretation

Correlation fallacy: Confusing correlation with causation



CREDIT

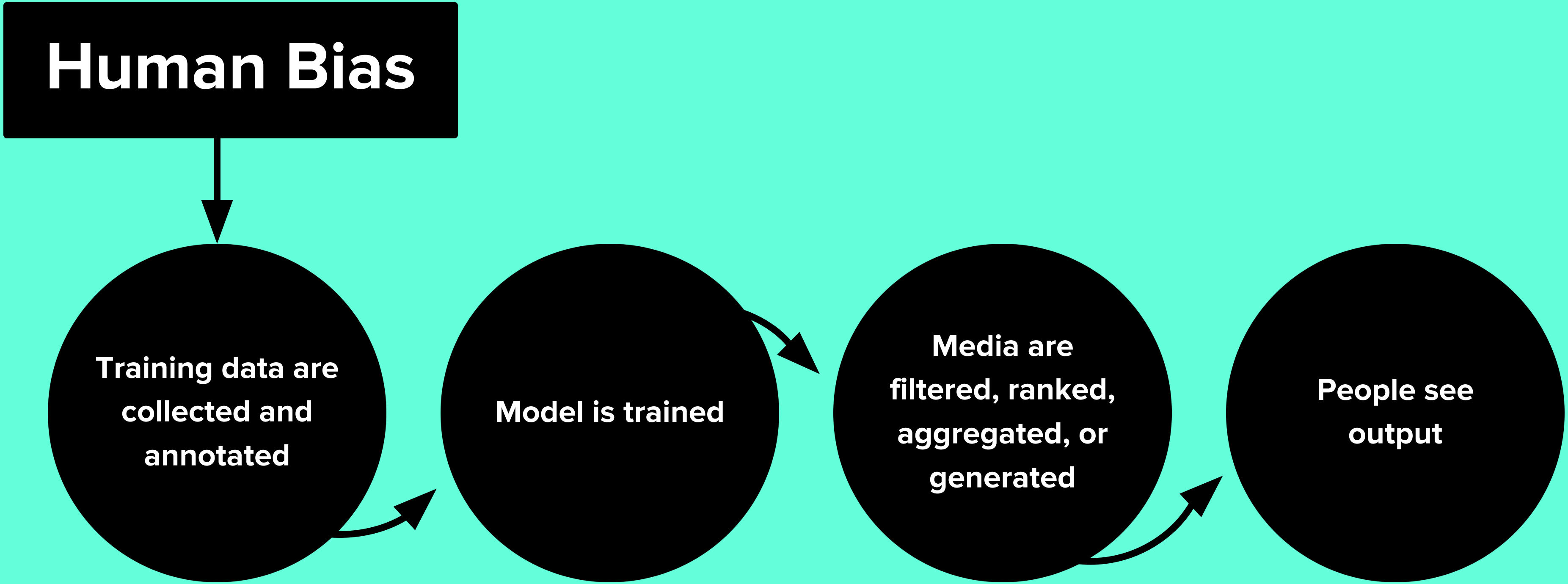
[© mollysdad - Slideshare - Introduction to Logical Fallacies]

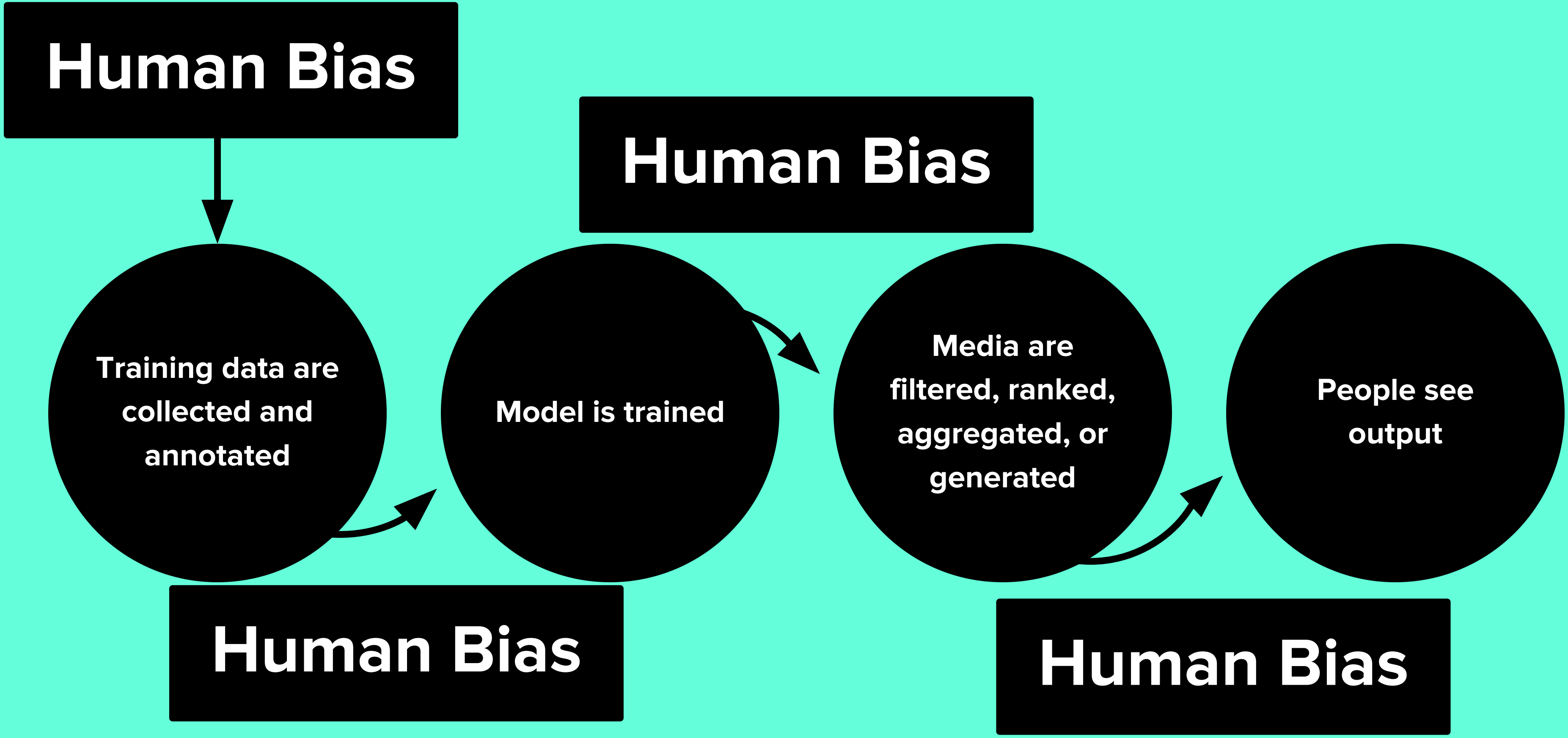
Biases in Interpretation

Automation bias: Propensity for humans to favor suggestions from automated decision-making systems over contradictory information without automation

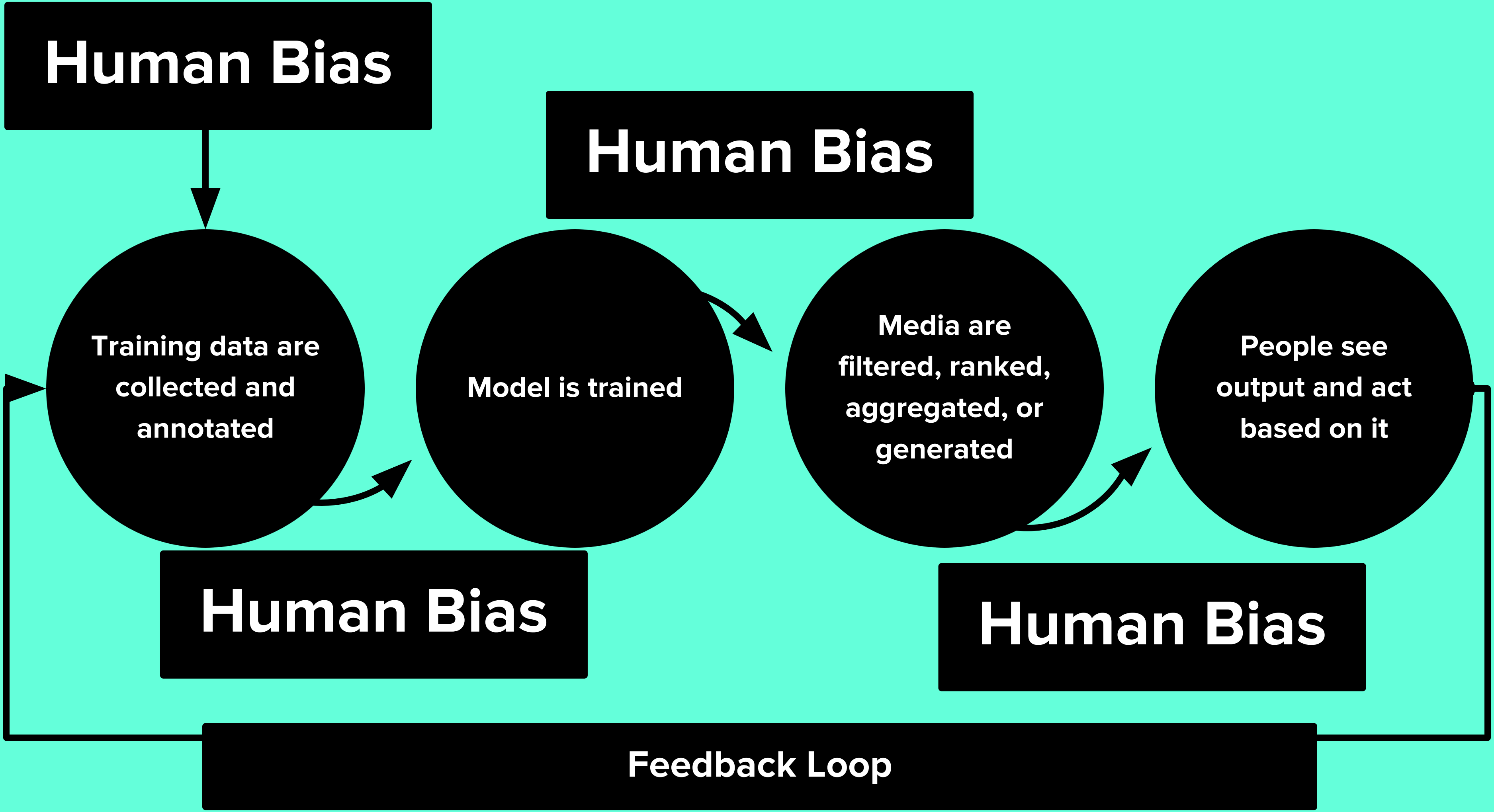
CREDIT

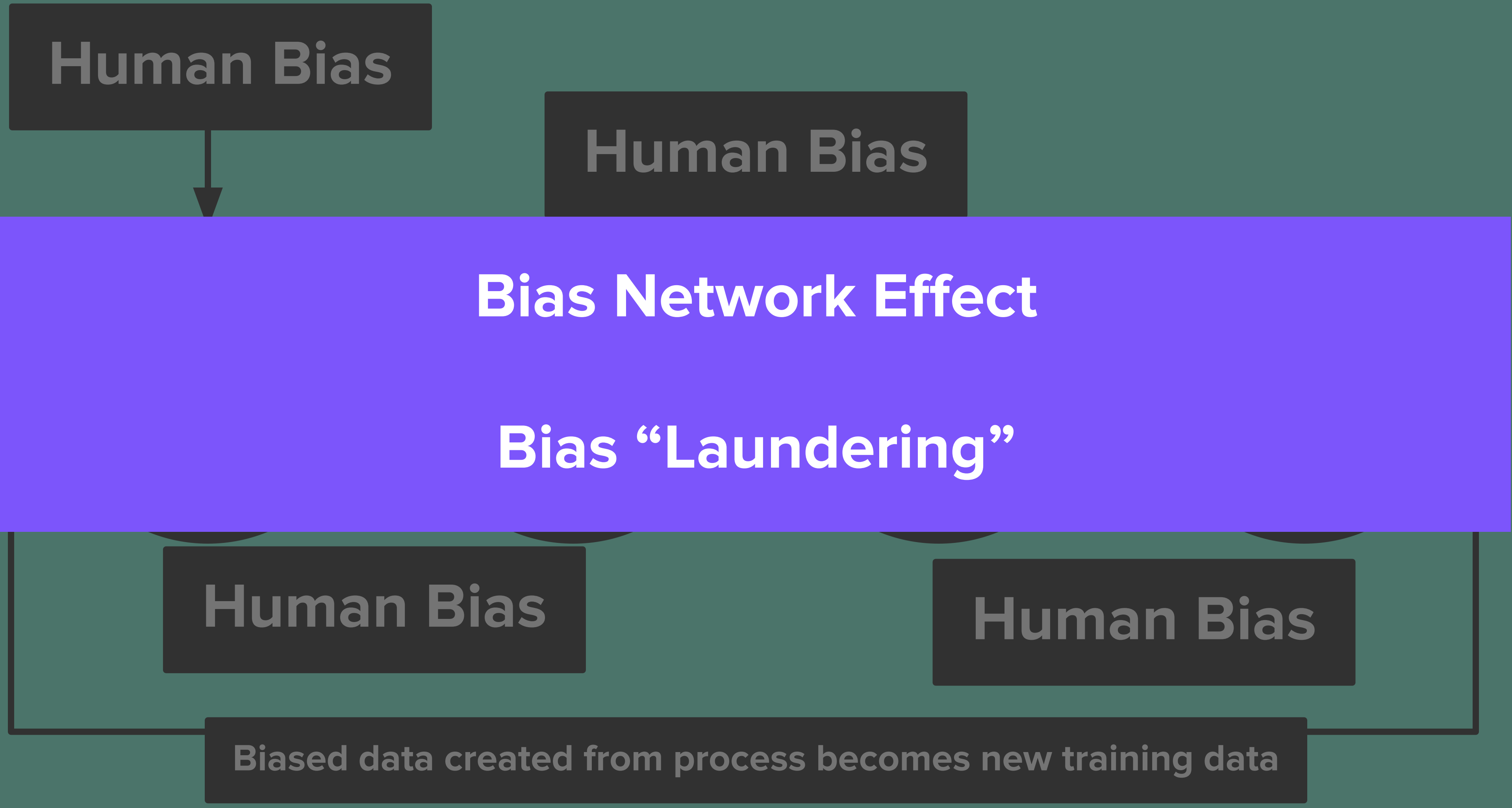

Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated
People see output


Human Bias
Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated
People see output



Human Bias
Human Bias
Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated
People see output
Human Bias
Human Bias


Human Bias
Human Bias
Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated
People see output and act based on it
Human Bias
Human Bias
Feedback Loop


Human Bias
Human Bias
Bias Network Effect
Bias “Laundering”
Human Bias
Human Bias
Biased data created from process becomes new training data

Human data perpetuates human biases.

As ML learns from human data, the result is a **bias network effect**.

BIAS = BAD ??

“Bias” can be Good, Bad, Neutral

- Bias in statistics and ML
  - Bias of an estimator: Difference between the predictions and the correct values that we are trying to predict
  - The "bias" term b (e.g., $y = mx + b$)
- Cognitive biases
  - Confirmation bias, Recency bias, Optimism bias
- Algorithmic bias
  - Unjust, unfair, or prejudicial treatment of people related to race, income, sexual orientation, religion, gender, and other characteristics historically associated with discrimination and marginalization, when and where they manifest in algorithmic systems or algorithmically aided decision-making

“Bias” can be Good, Bad, Neutral

- Bias in statistics and ML
  - Bias of an estimator: Difference between the predictions and the correct values that we are trying to predict
  - The "bias" term b (e.g., $y = mx + b$)
- Cognitive biases
  - Confirmation bias, Recency bias, Optimism bias
- **Algorithmic bias**
  - **Unjust, unfair, or prejudicial treatment of people** related to race, income, sexual orientation, religion, gender, and other characteristics historically associated with discrimination and marginalization, when and where they manifest in algorithmic systems or algorithmically aided decision-making

“Although neural networks might be said to write their own programs, they do so towards goals set by humans, using data collected for human purposes. If the data is skewed, even by accident, the computers will amplify injustice.”

— The Guardian

CREDIT

The Guardian view on machine learning: people must decide

"Although neural networks might be said to write their own programs, they do so towards goals set by humans, using data collected for human purposes. If the data is skewed, even by accident, the computers will amplify injustice."

— The Guardian

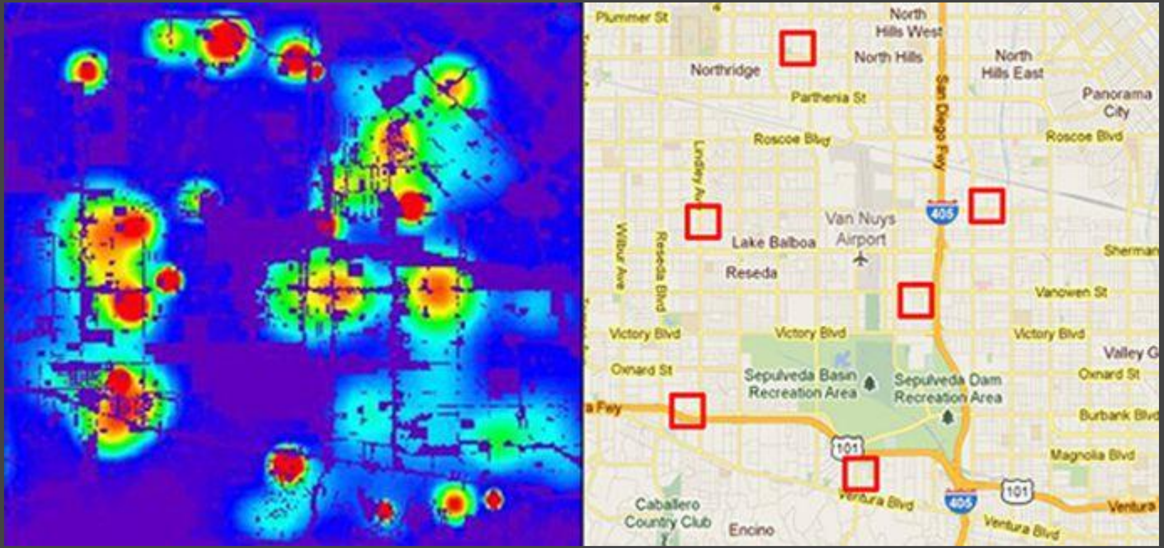
CREDIT

The Guardian view on machine learning: people must decide

Predicting Future Criminal Behavior

Predicting Policing

- Algorithms identify potential crime hot-spots
- Based on where crime is previously reported, not where it is known to have occurred
- Predicts future events from past



CREDIT

Smithsonian. *Artificial Intelligence Is Now Used to Predict Crime. But Is It Biased?* 2018

Predicting Sentencing

- Prater (who is white) rated **low risk** after shoplifting, despite two armed robberies; one attempted armed robbery.
- Borden (who is black) rated **high risk** after she and a friend took (but returned before police arrived) a bike and scooter sitting outside.
- Two years later, Borden has not been charged with any new crimes. Prater serving 8-year prison term for grand theft.

CREDIT

ProPublica. Northpointe: Risk in Criminal Sentencing. 2016.

Automation Bias in face of:

- Overgeneralization
- Feedback Loops
- Correlation Fallacy

Predicting Criminality

Israeli startup, Faception

> *"Faception is first-to-technology and first-to-market with proprietary computer vision and machine learning technology for profiling people and **revealing their personality based only on their facial image**."*

Offering specialized engines for recognizing "High IQ", "White-Collar Offender", "Pedophile", and "Terrorist" from a face image.

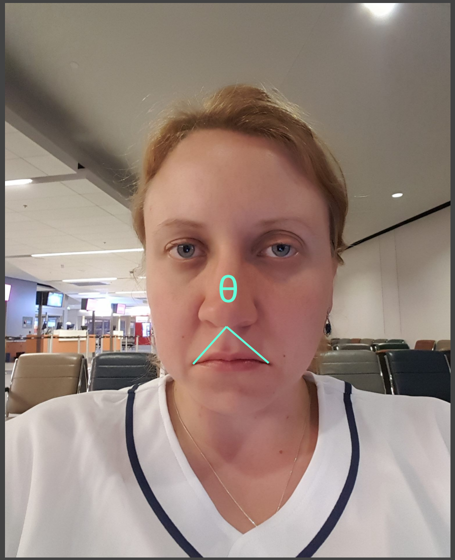
Main clients are in homeland security and public safety.

Predicting Criminality

"Automated Inference on Criminality using Face Images" Wu and Zhang, 2016. arXiv

1,856 closely cropped images of faces; Includes "wanted suspect" ID pictures from specific regions.

"[…] angle θ from nose tip to two mouth corners is on average 19.6% smaller for criminals than for non-criminals …"



See our longer piece on Medium, "Physiognomy's New Clothes"

Selection Bias + Experimenter's Bias + Confirmation Bias + Correlation Fallacy + Feedback Loops

Predicting Criminality - The Media Blitz

arXiv Paper Spotlight: Automated Inference on Criminality Using Face ...
www.kdnuggets.com/.../arxiv-spotlight-automated-inference-criminality-face-images....
A recent paper by Xiaolin Wu (McMaster University, Shanghai Jiao Tong University) and Xi Zhang (Shanghai Jiao Tong University), titled "**Automated Inference** ...

Automated Inference on Criminality Using Face Images | Hacker News
https://news.ycombinator.com/item?id=12983827
Nov 18, 2016 - The **automated inference on criminality** eliminates the variable of meta-accuracy (the competence of the human judge/examiner) all together.

A New Program Judges If You're a Criminal From Your Facial Features ...
https://motherboard.vice.com/.../new-program-decides-criminality-from-facial-feature...
Nov 18, 2016 - In their paper '**Automated Inference on Criminality** using Face Images', published on the arXiv pre-print server, Xiaolin Wu and Xi Zhang from ...

Can face classifiers make a reliable inference on criminality?
https://techxplore.com › Computer Sciences
Nov 23, 2016 - Their paper is titled "**Automated Inference on Criminality** using Face Images ... face classifiers are able to make reliable inference on criminality.

Troubling Study Says Artificial Intelligence Can Predict Who Will Be ...
https://theintercept.com/.../troubling-study-says-artificial-intelligence-can-predict-who...
Nov 18, 2016 - Not so in the modern age of Artificial Intelligence, apparently: In a paper titled "**Automated Inference on Criminality** using Face Images," two ...

Automated Inference on Criminality using Face Images (via arXiv ...
https://computationallegalstudies.com/.../automated-inference-on-criminality-using-fa...
Dec 6, 2016 - Next Next post: A General Approach for Predicting the Behavior of the Supreme Court of the United States (Paper Version 2.01) (Katz, ...

(Claiming to) Predict Internal Qualities Subject To Discrimination

Predicting Homosexuality

Composite Straight Faces Composite Gay Faces

Male

Female

- Wang and Kosinski, Deep neural networks are more accurate than humans at detecting sexual orientation from facial images, 2017.

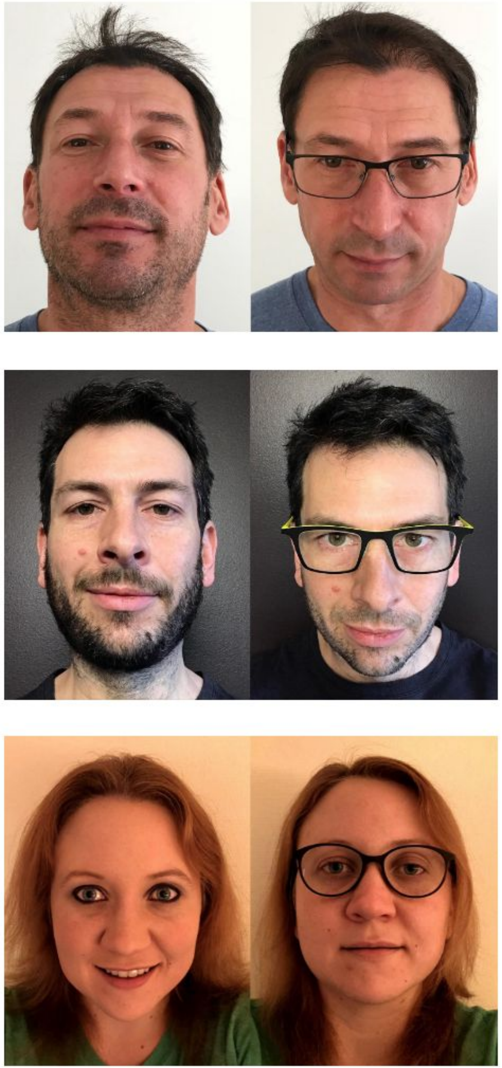
- “Sexual orientation detector” using 35,326 images from public profiles on a US dating website.

- “Consistent with the prenatal hormone theory [PHT] of sexual orientation, gay men and women tended to have gender-atypical facial morphology.”

Predicting Homosexuality

Differences between lesbian or gay and straight faces in selfies relate to grooming, presentation, and lifestyle — that is, **differences in culture, not in facial structure**.

See our longer response on Medium, [“Do Algorithms Reveal Sexual Orientation or Just Expose our Stereotypes?”]



Selection Bias + Experimenter's Bias + Correlation Fallacy

Measuring Algorithmic Bias

Evaluate for Fairness & Inclusion

Disaggregated Evaluation

Create for each (subgroup, prediction) pair.
Compare across subgroups.

Evaluate for Fairness & Inclusion

Disaggregated Evaluation

Create for each (subgroup, prediction) pair.
Compare across subgroups.

Example: women, face detection
men, face detection

Evaluate for Fairness & Inclusion

Intersectional Evaluation

Create for each (subgroup1, subgroup2, prediction) pair. Compare across subgroups.

Example: black women, face detection
white men, face detection

Evaluate for Fairness & Inclusion: Confusion Matrix

Model Predictions

References

Evaluate for Fairness & Inclusion: Confusion Matrix

		Model Predictions	
		Positive	Negative
References	Positive		
	Negative		

Evaluate for Fairness & Inclusion: Confusion Matrix

		Model Predictions	
		Positive	**Negative**
References	**Positive**	• Exists • Predicted **True Positives**	
	Negative		• Doesn’t exist • Not predicted **True Negatives**

Evaluate for Fairness & Inclusion: Confusion Matrix

		Model Predictions	
		Positive	**Negative**
References	**Positive**	• Exists • Predicted **True Positives**	• Exists • Not predicted **False Negatives**
	Negative	• Doesn’t exist • Predicted **False Positives**	• Doesn’t exist • Not predicted **True Negatives**

Evaluate for Fairness & Inclusion: Confusion Matrix

		Model Predictions		
		Positive	**Negative**	
References	**Positive**	• Exists • Predicted **True Positives**	• Exists • Not predicted **False Negatives**	Recall, False Negative Rate
	Negative	• Doesn’t exist • Predicted **False Positives**	• Doesn’t exist • Not predicted **True Negatives**	False Positive Rate, Specificity
		Precision, False Discovery Rate	Negative Predictive Value, False Omission Rate	LR+, LR-

Evaluate for Fairness & Inclusion

Female Patient Results

True Positives (TP) = 10	**False Positives (FP) = 1**
False Negatives (FN) = 1	**True Negatives (TN) = 488**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{10}{10 + 1} = 0.909$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{10}{10 + 1} = 0.909$$

Male Patient Results

True Positives (TP) = 6	**False Positives (FP) = 3**
False Negatives (FN) = 5	**True Negatives (TN) = 48**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{6}{6 + 3} = 0.667$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{6}{6 + 5} = 0.545$$

Evaluate for Fairness & Inclusion

Female Patient Results

True Positives (TP) = 10	**False Positives (FP) = 1**
False Negatives (FN) = 1	**True Negatives (TN) = 488**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{10}{10 + 1} = 0.909$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{10}{10 + 1} = 0.909$$

Male Patient Results

True Positives (TP) = 6	**False Positives (FP) = 3**
False Negatives (FN) = 5	**True Negatives (TN) = 48**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{6}{6 + 3} = 0.667$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{6}{6 + 5} = 0.545$$

“Equality of Opportunity” fairness criterion:
Recall is equal across subgroups

Evaluate for Fairness & Inclusion

Female Patient Results

True Positives (TP) = 10	**False Positives (FP) = 1**
False Negatives (FN) = 1	**True Negatives (TN) = 488**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{10}{10 + 1} = 0.909$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{10}{10 + 1} = 0.909$$

Male Patient Results

True Positives (TP) = 6	**False Positives (FP) = 3**
False Negatives (FN) = 5	**True Negatives (TN) = 48**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{6}{6 + 3} = 0.667$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{6}{6 + 5} = 0.545$$

"Predictive Parity" fairness criterion:
Precision is equal across subgroups

Choose your evaluation metrics in light of acceptable tradeoffs between **False Positives** and **False Negatives**

False Positives Might be Better than False Negatives

Privacy in Images

False Positive: Something that doesn't need to be blurred gets blurred.

Can be a bummer.

False Negative: Something that needs to be blurred is not blurred.

Identity theft.

False Negatives Might Be Better than False Positives

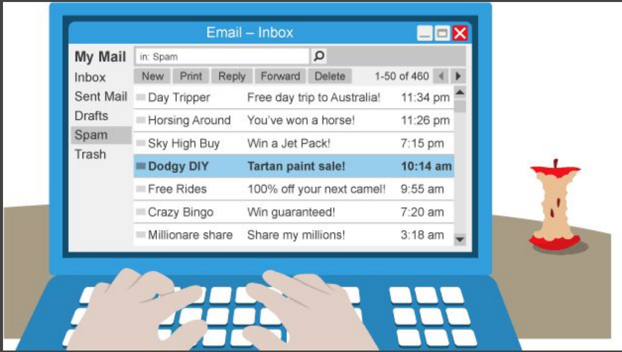
Spam Filtering

False Negative: Email that is SPAM is not caught, so you see it in your inbox.

Usually just a bit annoying.

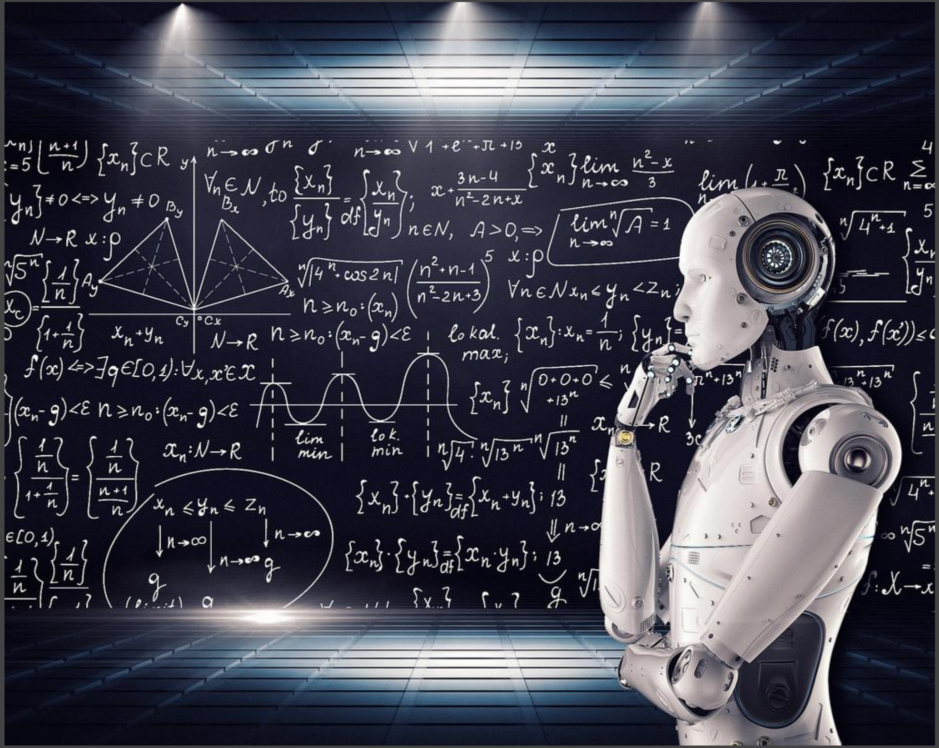
False Positive: Email flagged as SPAM is removed from your inbox.

If it's from a friend or loved one, it's a loss!

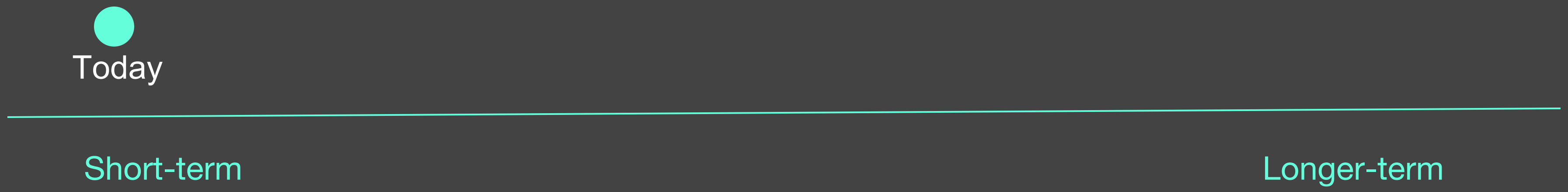


AI Can Unintentionally Lead to Unjust Outcomes

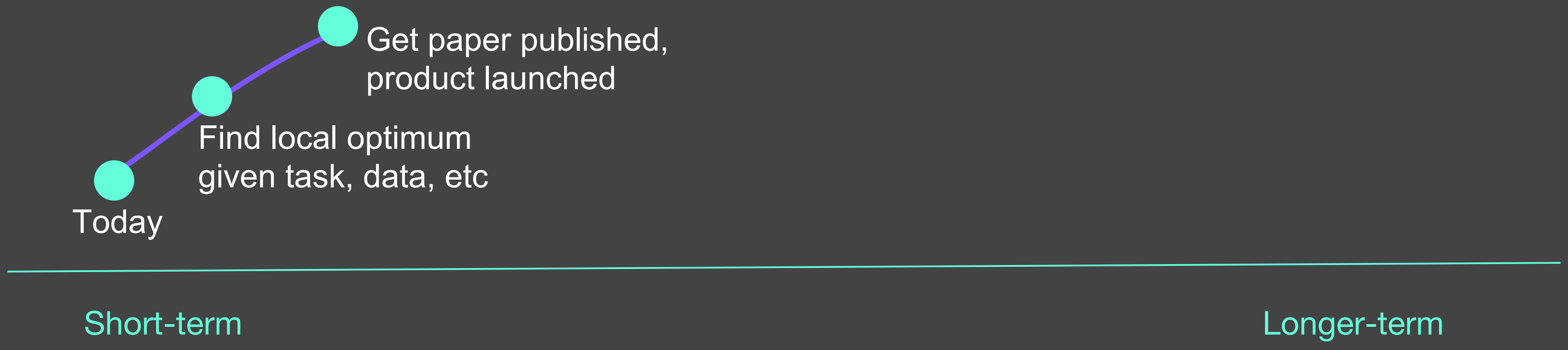
- Lack of insight into **sources of bias in the data** and model
- Lack of insight into the **feedback loops**
- Lack of careful, **disaggregated evaluation**
- Human **biases in interpreting and accepting results**

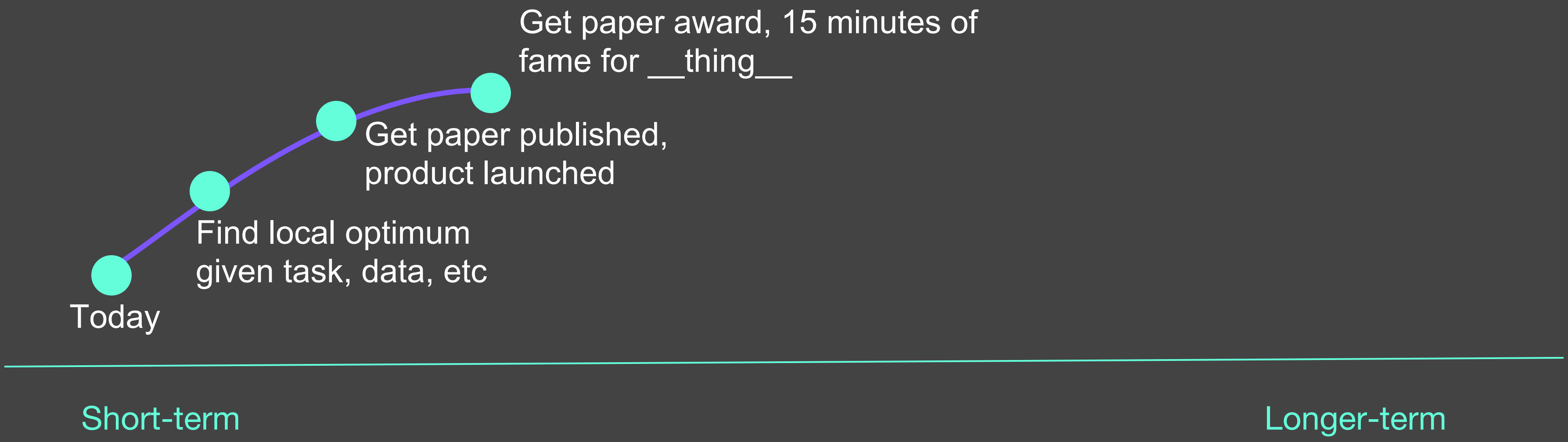


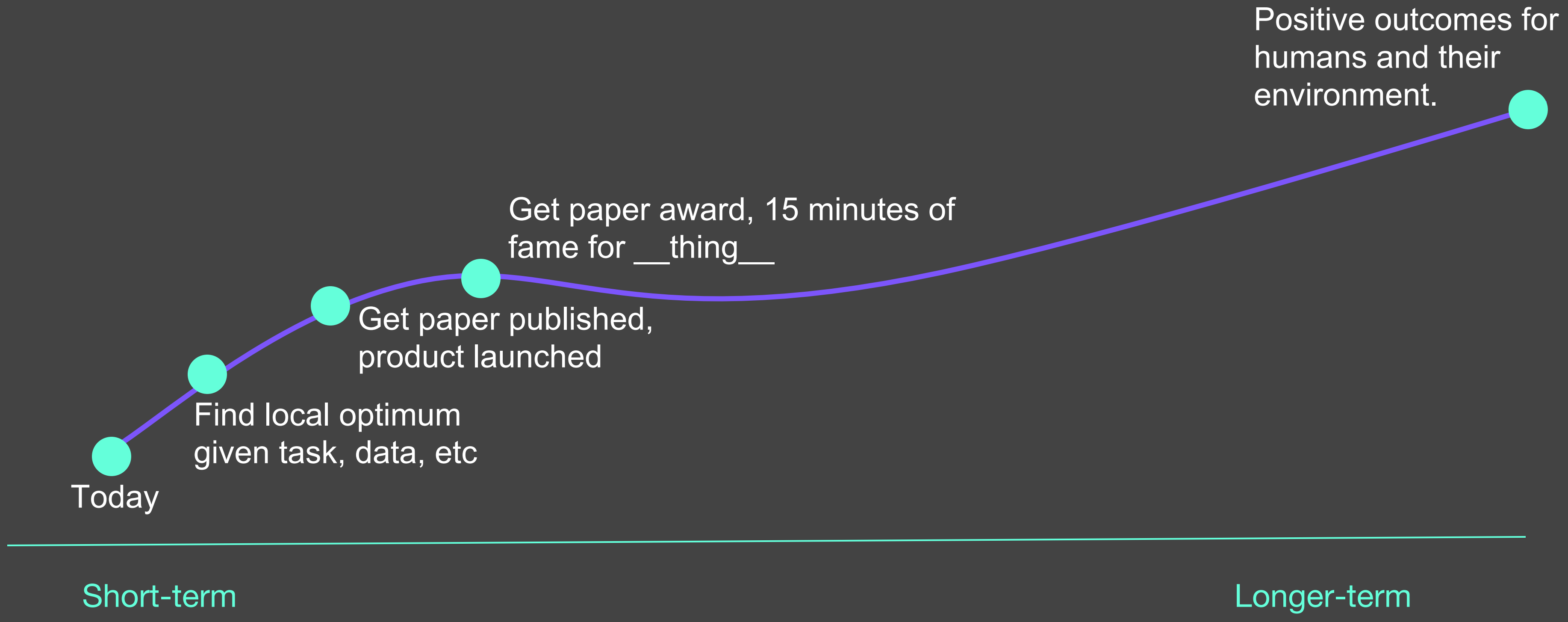
It’s up to **us** to influence how AI evolves.


Today
Short-term
Longer-term

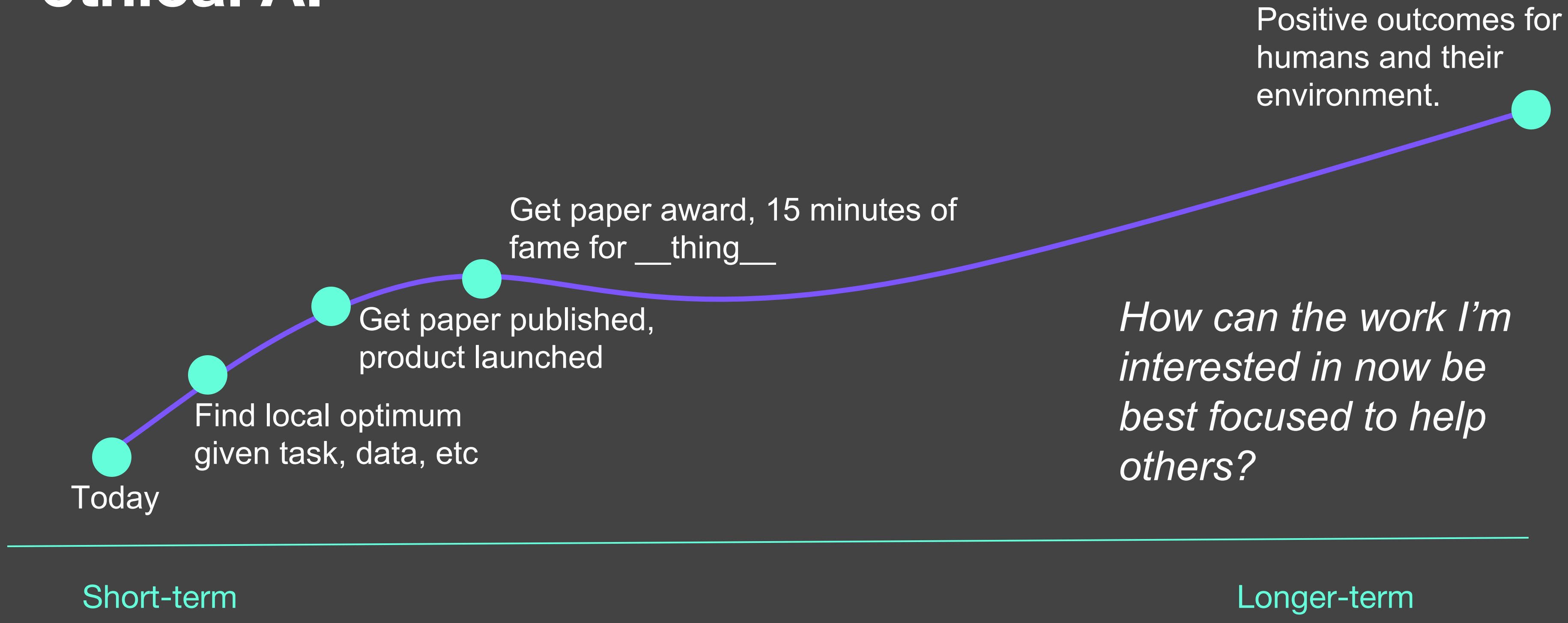

Find local optimum
given task, data, etc
Today
Short-term
Longer-term


Get paper published,
product launched
Find local optimum
given task, data, etc
Today
Short-term
Longer-term


Get paper award, 15 minutes of
fame for __thing__
Get paper published,
product launched
Find local optimum
given task, data, etc
Today
Short-term
Longer-term


Positive outcomes for humans and their environment.
Get paper award, 15 minutes of fame for __thing__
Get paper published, product launched
Find local optimum given task, data, etc
Today
Short-term
Longer-term

Begin tracing out paths for the evolution of ethical AI



How can the work I'm interested in now be best focused to help others?

It’s up to **us** to influence how AI evolves.

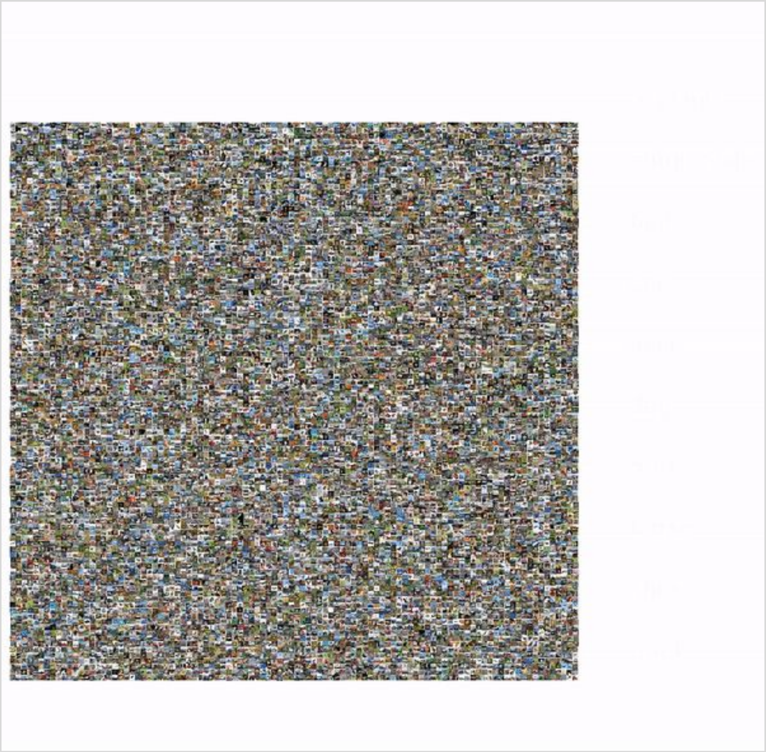
Here are some things we can do.

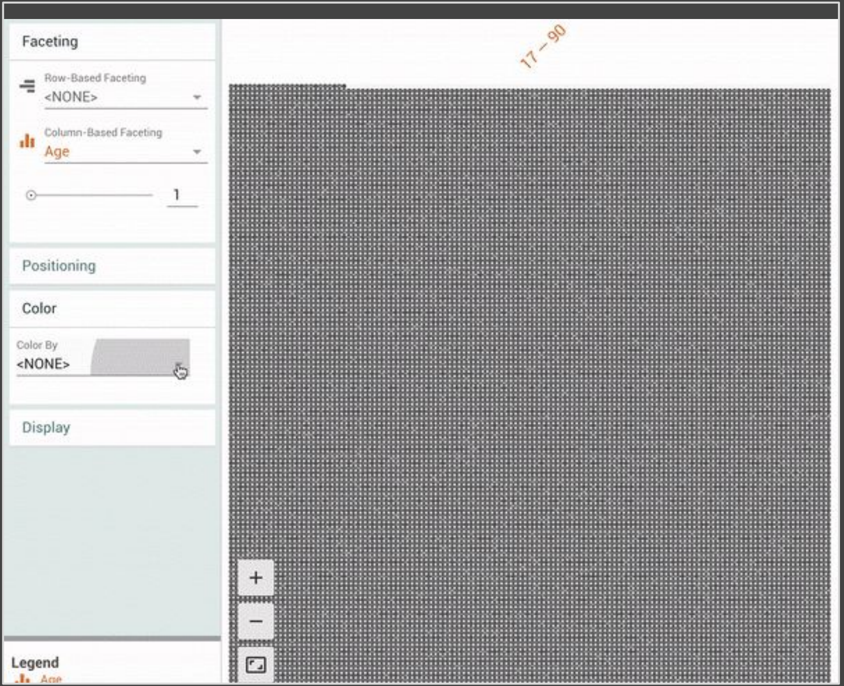
Data

Data Really, Really Matters

- Understand your Data: skews, correlations
- Abandon single training-set / testing-set from similar distribution
- Combine inputs from multiple sources
- Use **held-out test set** for hard use cases
- Talk to experts about additional signals

Understand Your Data Skews





Facets: pair-code.github.io

Datasheets for Datasets

Timnit Gebru [1] Jamie Morgenstern [2] Briana Vecchione [3] Jennifer Wortman Vaughan [1] Hanna Wallach [1]
Hal Daumé III [1 4] Kate Crawford [1 5]

Motivation for Dataset Creation

Why was the dataset created? (e.g., were there specific tasks in mind, or a specific gap that needed to be filled?)

What (other) tasks could the dataset be used for? Are there obvious tasks for which it should *not* be used?

Has the dataset been used for any tasks already? If so, where are the results so others can compare (e.g., links to published papers)?

Who funded the creation of the dataset? If there is an associated grant, provide the grant number.

Any other comments?

Dataset Composition

What are the instances? (that is, examples; e.g., documents, images, people, countries) Are there multiple types of instances? (e.g., movies, users, ratings; people, interactions between them; nodes, edges)

Are relationships between instances made explicit in the data (e.g., social network links, user/movie ratings, etc.)?

How many instances of each type are there?

Data Collection Process

How was the data collected? (e.g., hardware apparatus/sensor, manual human curation, software program, software interface/API; how were these constructs/measures/methods validated?)

Who was involved in the data collection process? (e.g., students, crowdworkers) How were they compensated? (e.g., how much were crowdworkers paid?)

Over what time-frame was the data collected? Does the collection time-frame match the creation time-frame?

How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part of speech tags; model-based guesses for age or language)? If the latter two, were they validated/verified and if so how?

Does the dataset contain all possible instances? Or is it, for instance, a sample (not necessarily random) from a larger set of instances?

If the dataset is a sample, then what is the population? What was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)? Is the sample representative of the larger set (e.g., geographic coverage)? If not, why not (e.g., to cover a more diverse range of instances)? How does this affect possible uses?

Dataset Fact Sheet

Metadata

Cj CC-0 .csv

Title COMPAS Recidivism Risk Score Data

Author Broward County Clerk's Office, Broward County Sherrif's Office, Florida

Email browardcounty@florida.usa

Description Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat.

DOI 10.5281/zenodo.1164791

Time Feb 2013 - Dec 2014

Keywords risk assessment, parole, jail, recidivism, law

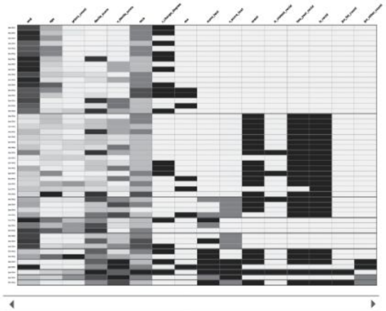
Records	7214
Variables	25

priors_count: *Ut enim ad minim veniam, quis nostrud exercitation* **numerical**

Probabilistic Modeling

Analysis

12



Dependency Probability **Pearson R**

Machine Learning

Use ML Techniques for Bias Mitigation and Inclusion

Bias Mitigation

- Removing the signal for problematic output
  - Stereotyping
  - Sexism, Racism, *-ism
  - “Debiasing”

Use ML Techniques for Bias Mitigation and Inclusion

Bias Mitigation

- Removing the signal for problematic output
  - Stereotyping
  - Sexism, Racism, *-ism
  - “Debiasing”

Inclusion

- Adding signal for desired variables
  - Increasing model performance
  - Attention to subgroups or data slices with worst performance

Multi-task Learning to Increase Inclusion

Multiple Tasks + Deep Learning for Inclusion: Multi-task Learning Example

- Collaboration with UPenn WWP
- Working directly with clinicians
- **Goals:**
  - System that can alert clinicians if suicide attempt is **imminent**
  - Feasibility of diagnoses when few training instances are available

Penn | World Well-Being Project
... advancing understanding of human flourishing using language analysis

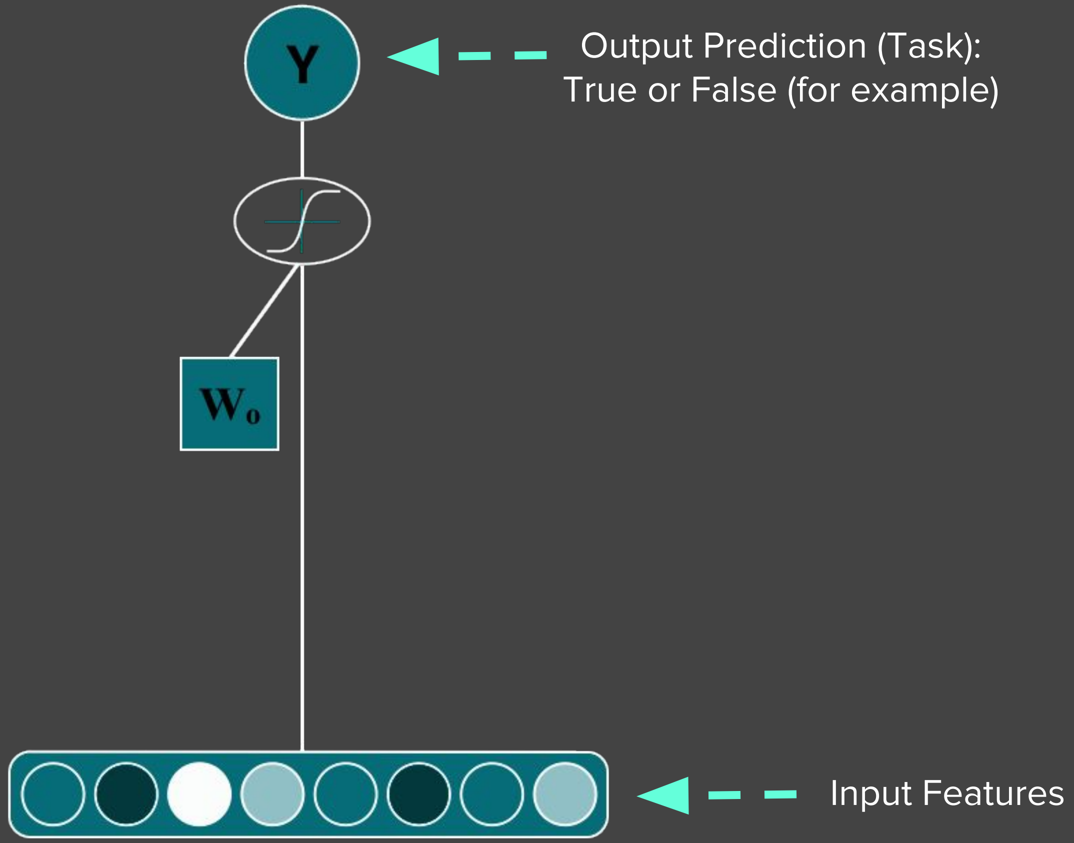
Benton, Mitchell, Hovy. [Multi-task learning for Mental Health Conditions with Limited Social Media Data](). *EACL, 2017.*

Multiple Tasks + Deep Learning for Inclusion: Multi-task Learning Example

- **Internal Data:**
  - Electronic Health Records
    - Patient or patient family provided
    - Including mental health diagnoses, suicide attempts, and completions
  - Social Media data
- **Proxy Data:**
  - Twitter media data
  - Proxy mental health diagnoses using self-declared diagnoses in tweets
    - “I’ve been diagnosed with X”
    - “I tried to commit suicide”

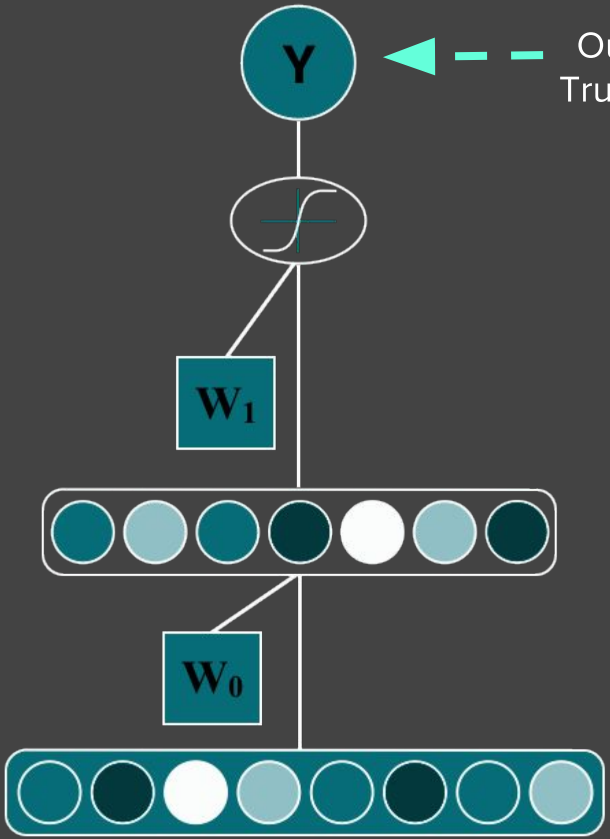
Benton, Mitchell, Hovy. Multi-task learning for Mental Health Conditions with Limited Social Media Data. *EACL, 2017.*

Single-Task: Logistic Regression



Single-Task: Deep Learning

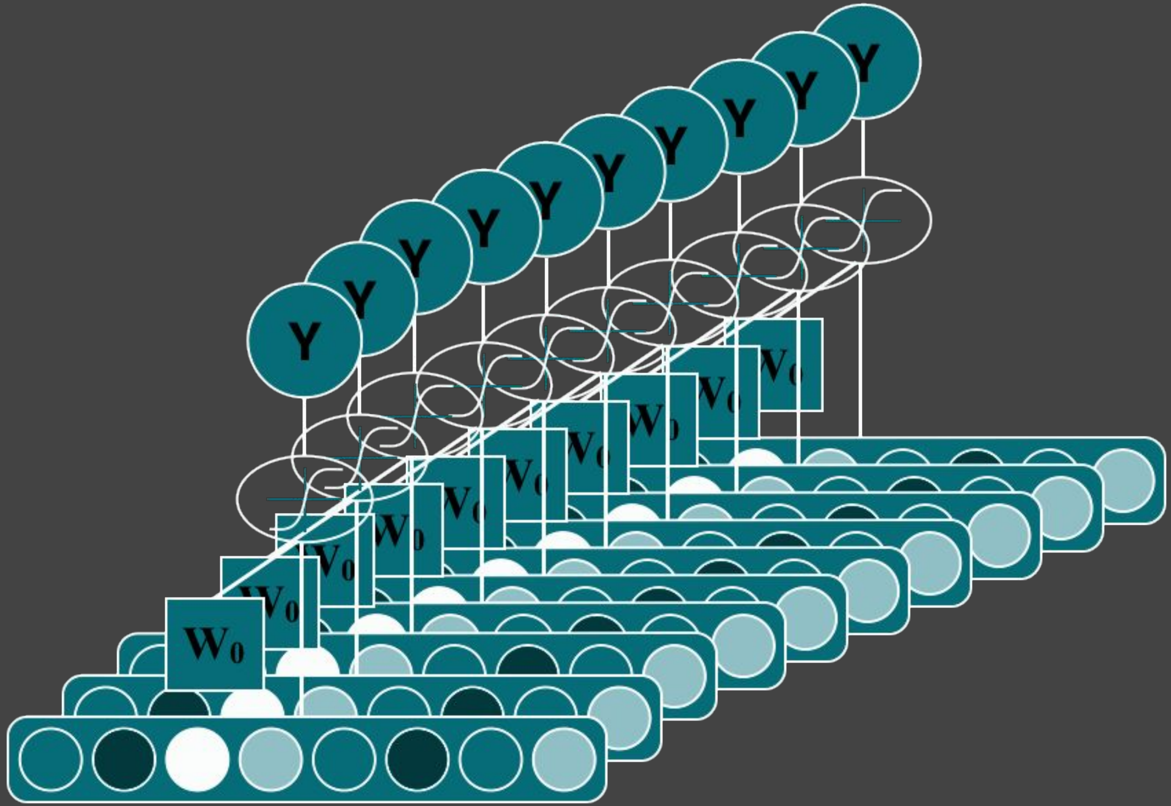
Fancier!!



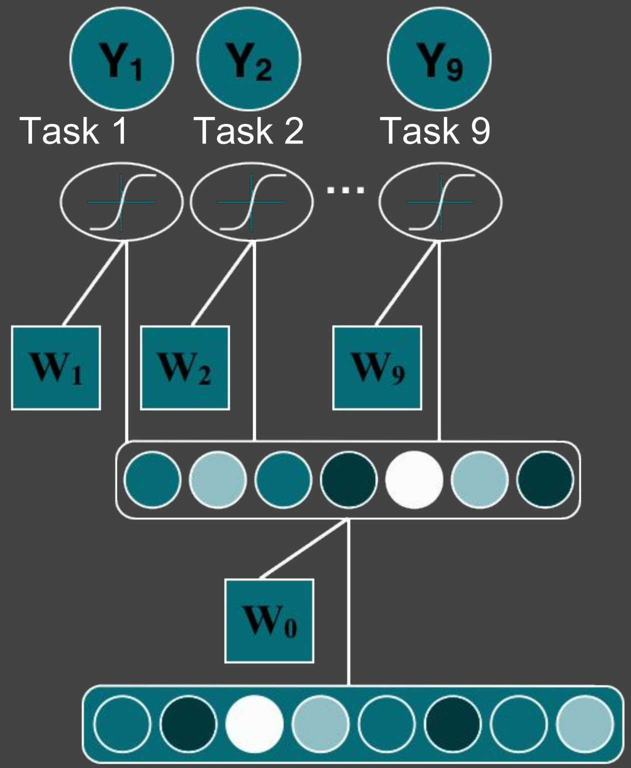
Output Prediction (Task):
True or False (for example)

Input Features

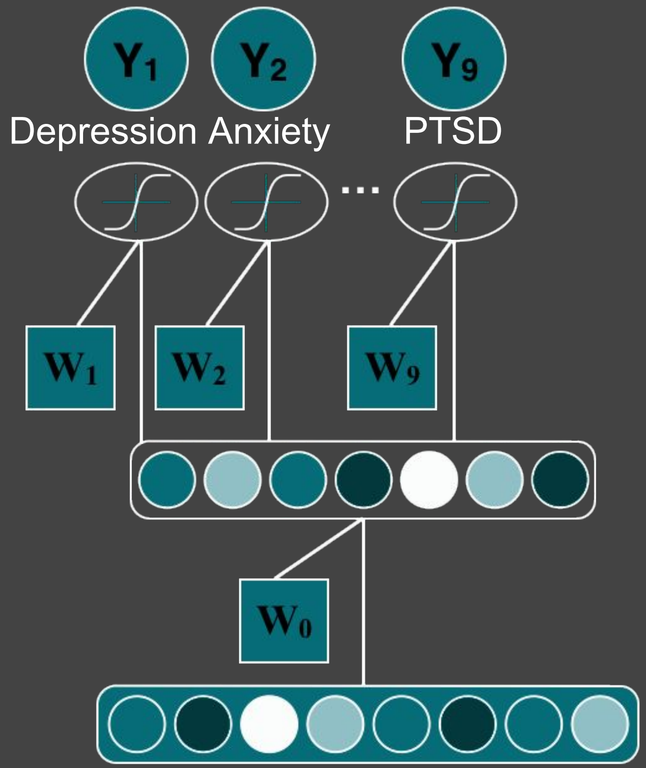
Multiple Tasks with Basic Logistic Regression



Multi-task Learning



Multi-task Learning

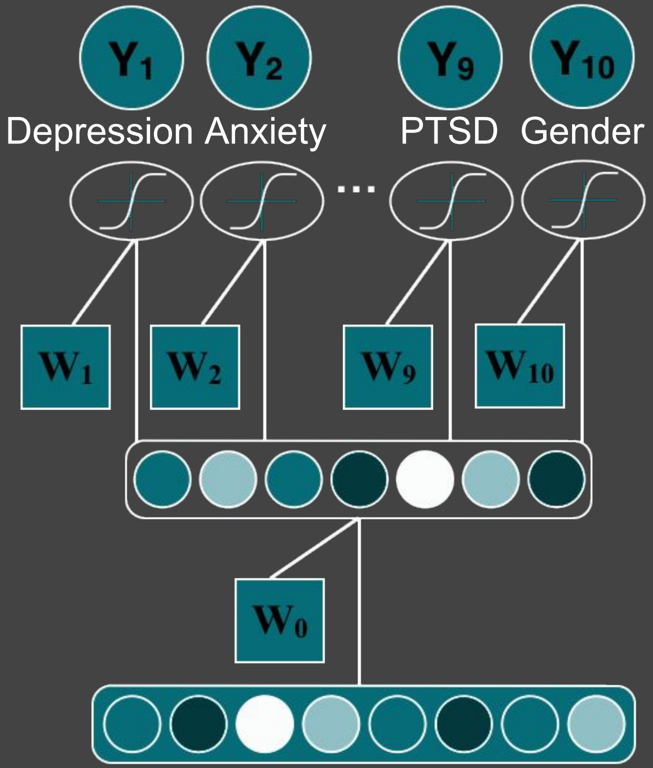


Task	N
Neurotypicality	4791
Anxiety	2407
Depression	1400
Suicide attempt	1208
Eating disorder	749
Schizophrenia	349
Panic disorder	263
PTSD	248
Bipolar disorder	191
All	**9611**

<5% positive examples

Benton, Mitchell, Hovy. Multi-task learning for Mental Health Conditions with Limited Social Media Data. *EACL, 2017.*

Multi-task Learning



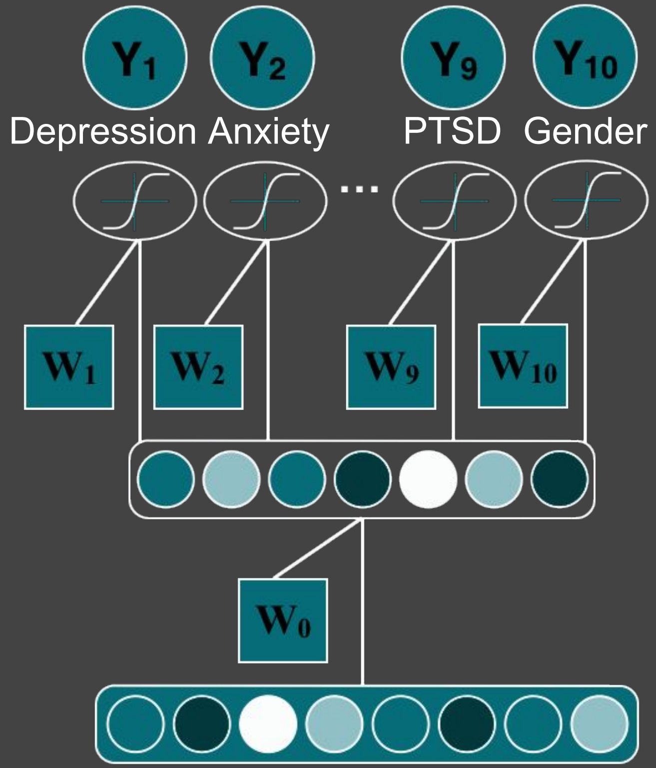
Task	N
Gender	1101
Neurotypicality	4791
Anxiety	2407
Depression	1400
Suicide attempt	1208
Eating disorder	749
Schizophrenia	349
Panic disorder	263
PTSD	248
Bipolar disorder	191
All	**9611**

<5% positive examples

Benton, Mitchell, Hovy. Multi-task learning for Mental Health Conditions with Limited Social Media Data. *EACL, 2017.*

Multi-task Learning

Multitask, given **cormorbidity**

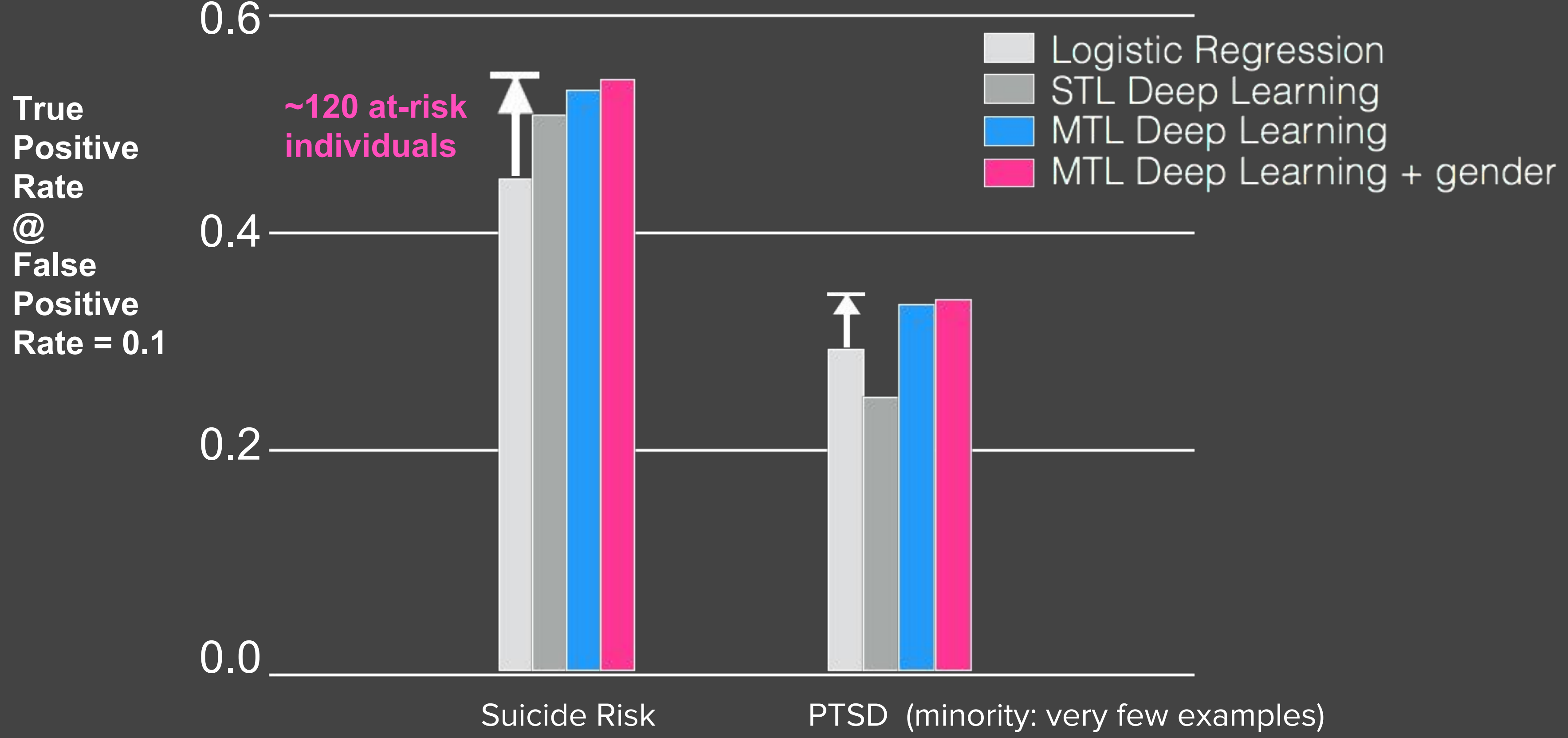


Task	N
Gender	1101
Neurotypicality	4791
Anxiety	2407
Depression	1400
Suicide attempt	1208
Eating disorder	749
Schizophrenia	349
Panic disorder	263
PTSD	248
Bipolar disorder	191
All	**9611**

<5% positive examples

Benton, Mitchell, Hovy. Multi-task learning for Mental Health Conditions with Limited Social Media Data. *EACL, 2017.*

Improved Performance across Subgroups



Benton, Mitchell, Hovy. Multi-task learning for Mental Health Conditions with Limited Social Media Data. *EACL, 2017.*

Reading for the masses….

Multi-Task Learning for Mental Health using Social Media Text

Adrian Benton
Johns Hopkins University
adrian@cs.jhu.edu

Margaret Mitchell
Microsoft Research*
mmitchellai@google.com

Dirk Hovy
University of Copenhagen
mail@dirkhovy.com

2 Ethical Considerations

As with any author-attribute detection, there is the danger of abusing the model to single out people (*overgeneralization*, see Hovy and Spruit (2016)). We are aware of this danger, and sought to minimize the risk. For this reason, we don't provide a selection of features or representative examples. The experiments in this paper were performed with a clinical application in mind, and use carefully matched (but anonymized) data, so the distribution is not representative of the population as a whole. The results of this paper should therefore *not* be interpreted as a means to assess mental health conditions in social media in general, but as a test for the applicability of MTL in a well-defined clinical setting.

Contextualizing and considering ethical dimensions

Benton, Mitchell, Hovy. [Multi-task learning for Mental Health Conditions with Limited Social Media Data](). *EACL, 2017.*

Adversarial Multi-task Learning to Mitigate Bias

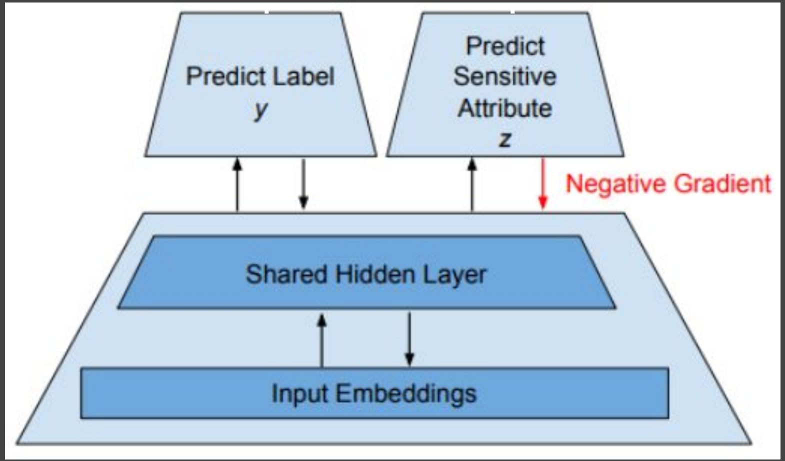
Multitask Adversarial Learning

- Basic idea: Jointly predict:
  - Output decision *D*
  - Attribute you'd like to remove from decision *Z*
  - Negate the effect of the undesired attribute

$$P(\hat{Y} = 1|Y = 1, Z = 1) = P(\hat{Y} = 1|Y = 1, Z = 0)$$

$Z \perp D \mid Y$

Get promoted **Gender**



Beutel, Chen, Zhao, Chi. [Data Decisions and Theoretical Implications when Adversarially Learning Fair Representations](). *FAT/ML, 2017.*
Zhang, Lemoine, Mitchell. [Mitigating Unwanted Biases with Adversarial Learning](). *AIES, 2018*.

Equality of Opportunity in Supervised Learning

A classifier's output decision should be the same **across sensitive characteristics**, given what the correct decision should be.

Hardt, Price, Srebro. Equality of Opportunity in Supervised Learning. *NIPS, 2016.*

Case Study: Conversation AI Toxicity

Measuring and Mitigating Unintended Bias in Text Classification

Lucas Dixon
ldixon@google.com

John Li
jetpack@google.com

Jeffrey Sorensen
sorenj@google.com

Nithum Thain
nthain@google.com

Lucy Vasserman
lucyvasserman@google.com

AIES, 2018 and FAT*, 2019

Conversation-AI

ML to improve online conversations at scale

Research Collaboration

Jigsaw, CAT, several Google-internal teams, and external partners (NYTimes, Wikimedia, etc)

Perspective API

perspectiveapi.com

Unintended Bias

Model falsely associates frequently attacked identities with toxicity: *False Positive Bias*

Sentence	model score
"i'm a proud **tall** person"	0.18
"i'm a proud **lesbian** person"	0.51
"i'm a proud **gay** person"	0.69

Bias Source and Mitigation

Bias caused by dataset imbalance

- Frequently attacked identities are overrepresented in toxic comments
- Length matters

Add *assumed non-toxic data* from Wikipedia articles to fix the imbalance.

- Original dataset had 127,820 examples
- 4,620 non-toxic examples added

	Comment Length				
Term	**20-59**	**60-179**	**180-539**	**540-1619**	**1620-4859**
ALL	17%	12%	7%	5%	5%
gay	88%	77%	51%	30%	19%
queer	75%	83%	45%	56%	0%
homosexual	78%	72%	43%	16%	15%
black	50%	30%	12%	8%	4%
white	20%	24%	16%	12%	2%
wikipedia	39%	20%	14%	11%	7%
atheist	0%	20%	9%	6%	0%
lesbian	33%	50%	42%	21%	0%
feminist	0%	20%	25%	0%	0%
islam	50%	43%	12%	12%	0%
muslim	0%	25%	21%	12%	17%
race	20%	25%	12%	10%	6%
news	0%	1%	4%	3%	3%
daughter	0%	7%	0%	7%	0%

Measuring Unintended Bias - Synthetic Datasets

Challenges with real data:

- Existing datasets are small and/or have false correlations
- Each example is completely unique: not easy to compare for bias

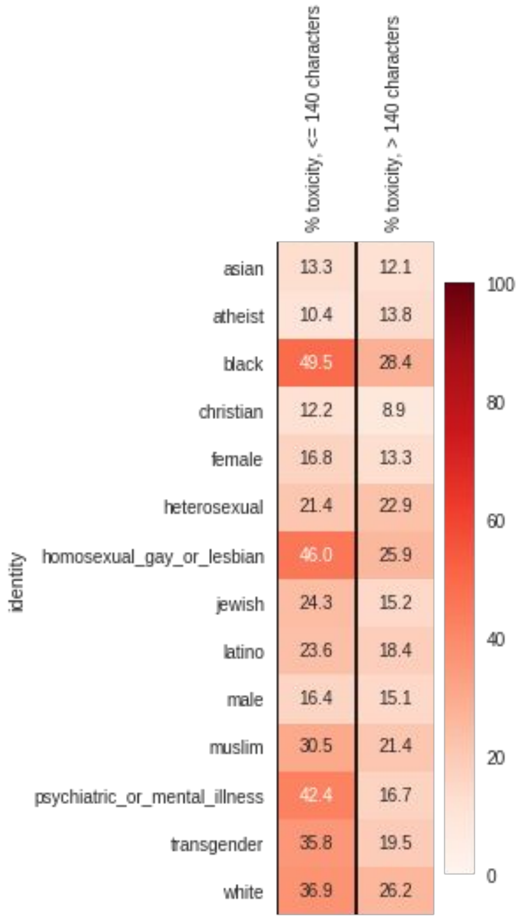
Approach: "bias madlibs": a synthetically generated 'templated' dataset for evaluation

Sentence	model score
"i'm a proud **tall** person"	0.18
"i'm a proud **lesbian** person"	0.51
"i'm a proud **gay** person"	0.69
"audre is a **brazilian** computer programmer"	0.02
"audre is a **muslim** computer programmer"	0.08
"audre is a **transgender** computer programmer"	0.56

Assumptions

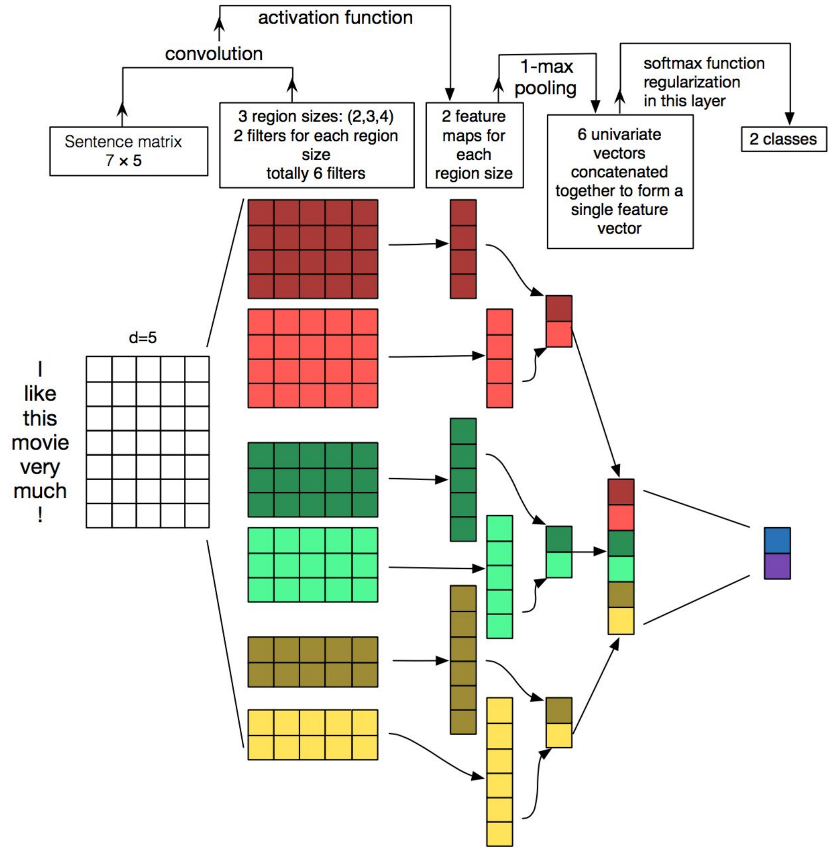
Dataset is reliable:

- Similar distribution as application
- Ignores annotator bias
- No causal analysis



Deep Learning Model

- CNN architecture
- Pretrained GloVe Embeddings
- Keras Implementation

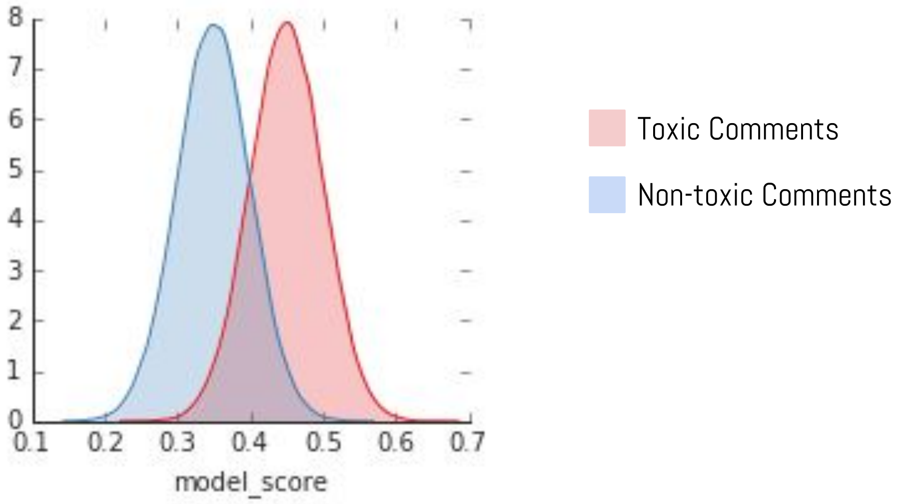


Source: Zhang, Y., & Wallace, B. (2015). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. arXiv preprint arXiv:1510.03820.

Measuring Model Performance

How good is the model at distinguishing good from bad examples? (ROC-AUC)

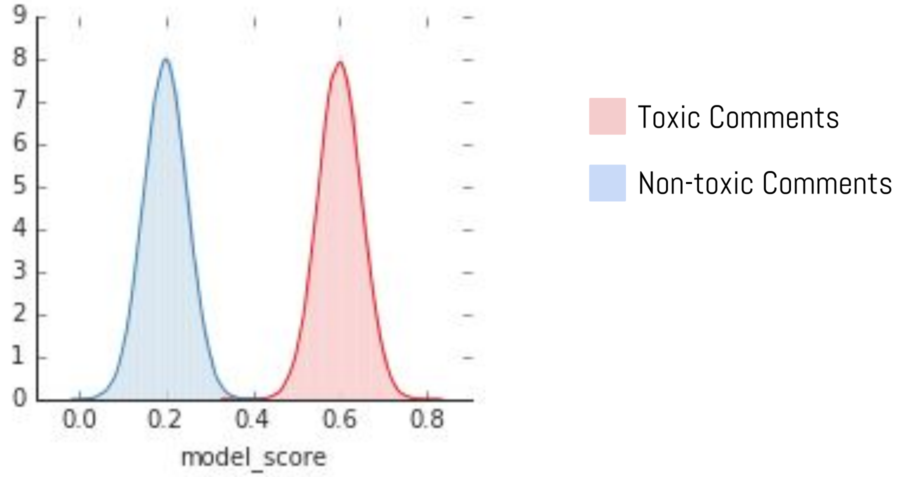
AUC (for a given test set) = Given two randomly chosen examples, one in-class (e.g. one is toxic and the other is not), AUC is the probability that the model will give the in-class example the higher score.



Measuring Model Performance

How good is the model at distinguishing good from bad examples? (ROC-AUC)

AUC (for a given test set) = Given two randomly chosen examples, one in-class (e.g. one is toxic and the other is not), AUC is the probability that the model will give the in-class example the higher score.

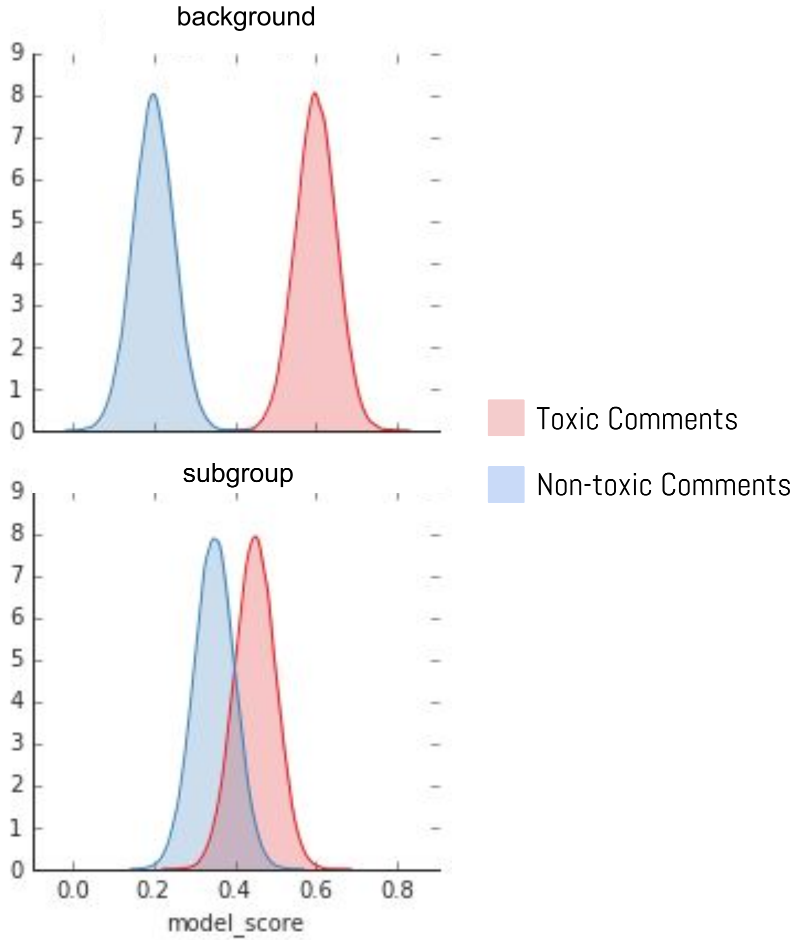


Types of Bias

Low Subgroup Performance

The model performs worse on subgroup comments than it does on comments overall.

Metric: Subgroup AUC



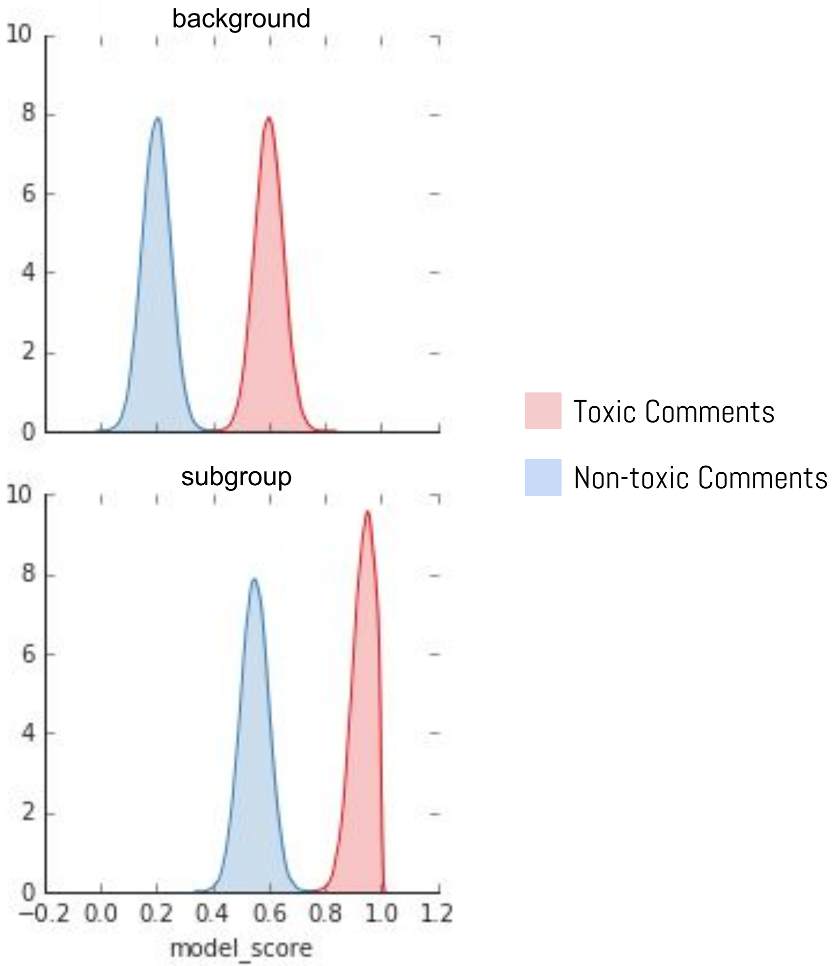
Types of Bias

Subgroup Shift (Right)

The model systematically scores comments from the subgroup higher.

Metric: BPSN AUC

(Background Positive Subgroup Negative)



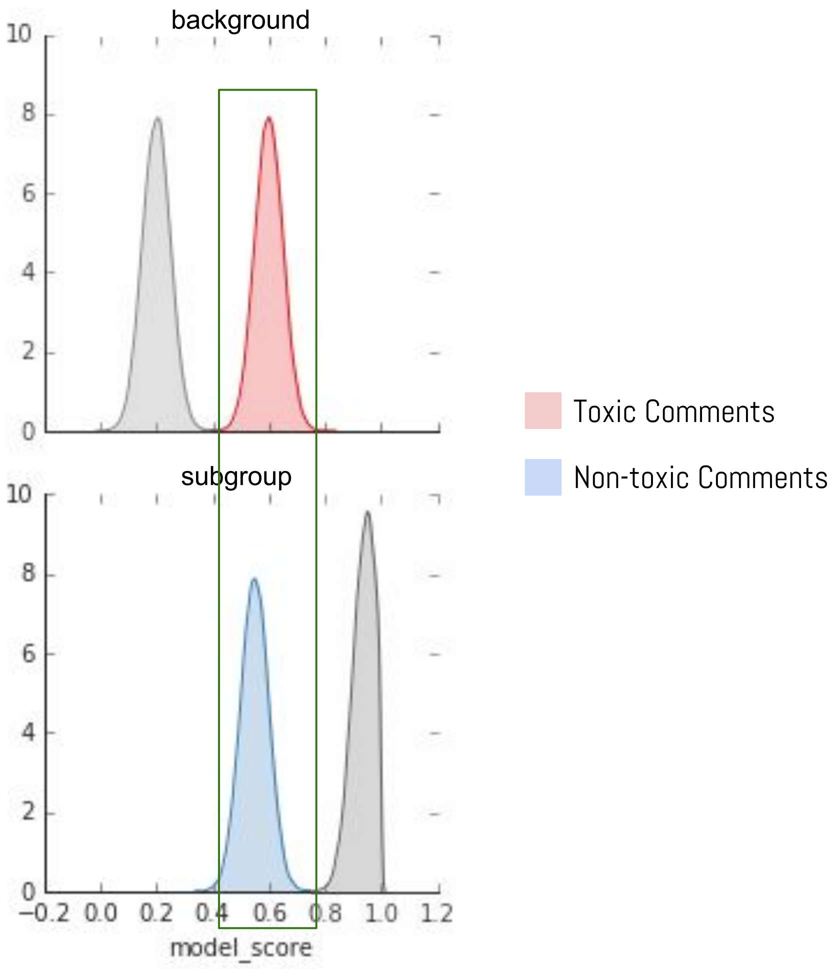
Types of Bias

Subgroup Shift (Right)

The model systematically scores comments from the subgroup higher.

Metric: BPSN AUC

(Background Positive Subgroup Negative)



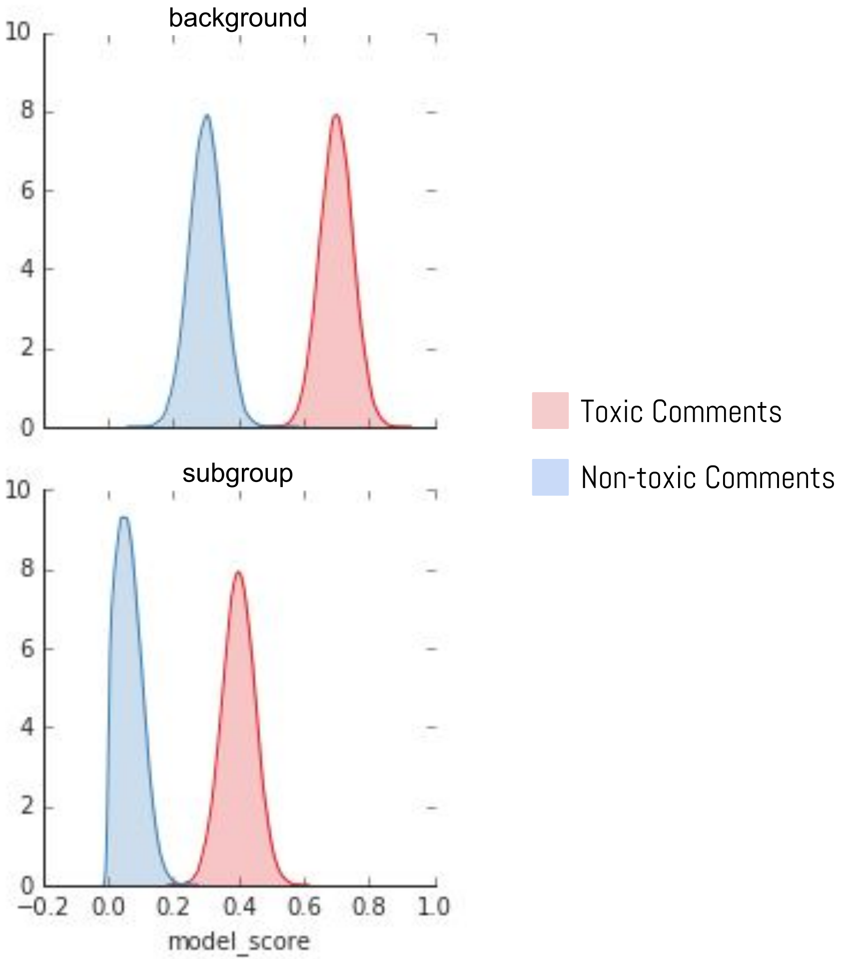
Types of Bias

Subgroup Shift (Left)

The model systematically scores comments from the subgroup lower.

Metric: BNSP AUC

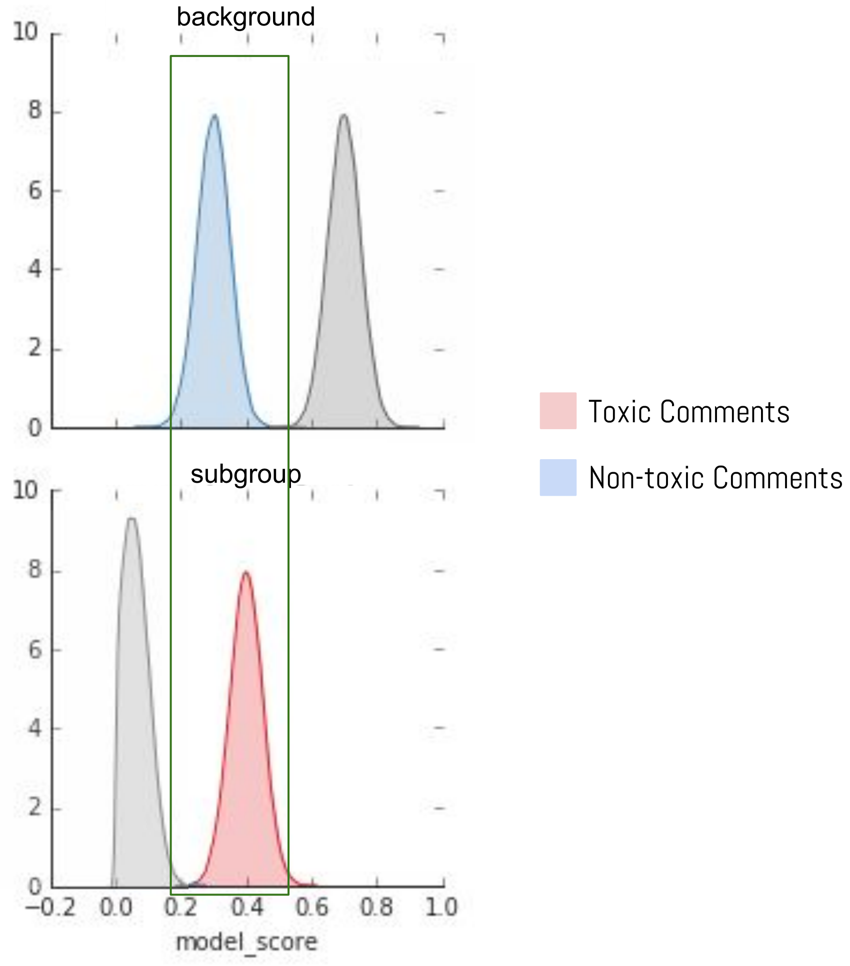
(Background Negative Subgroup Positive)



Types of Bias

Subgroup Shift (Left)

The model systematically scores comments from the subgroup lower.



Metric: BNSP AUC

(Background Negative Subgroup Positive)

Results

Toxicity @1

Identity groups	Subgroup AUC	BPSN AUC	BPSP AUC
lesbian	0.93	0.74	0.98
gay	0.94	0.65	0.99
queer	0.98	0.96	0.93
straight	0.99	1.00	0.87
bisexual	0.96	0.95	0.92
homosexual	0.87	0.53	0.99
heterosexual	0.96	0.94	0.92
cis	0.99	1.00	0.87
trans	0.97	0.96	0.91
nonbinary	0.99	0.99	0.90
black	0.91	0.85	0.95
white	0.91	0.88	0.94

0.5 0.6 0.7 0.8 0.9 1.0

Toxicity @6

Identity groups	Subgroup AUC	BPSN AUC	BPSP AUC
lesbian	1.00	0.98	1.00
gay	1.00	0.94	1.00
queer	0.99	0.98	0.99
straight	1.00	1.00	0.97
bisexual	0.98	0.98	0.99
homosexual	1.00	0.96	1.00
heterosexual	1.00	0.99	1.00
cis	1.00	1.00	0.98
trans	1.00	1.00	1.00
nonbinary	1.00	1.00	0.98
black	0.98	0.97	1.00
white	0.99	0.99	0.99

0.5 0.6 0.7 0.8 0.9 1.0

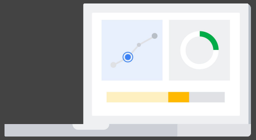
Release Responsibly

Model Cards for Model Reporting

- Currently no common practice of reporting how well a model works when it is released

Model Cards for Model Reporting

Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, Timnit Gebru
{mmitchellai,simonewu,andrewzaldivar,parkerbarnes,lucyvasserman,benhutch,espitzer,tgebru}@google.com
deborah.raji@mail.utoronto.ca



What It Does

A report that focuses on transparency in model performance to encourage responsible AI adoption and application.

How It Works

It is an easily discoverable and usable artifact presented at important steps of a user journey for a diverse set of users and public stakeholders.

Why It Matters

It keeps model developer accountable to release high quality and fair models.

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

Intended Use, Factors and Subgroups

Example Model Card - Toxicity in Text	
Model Details	Developed by Jigsaw in 2017 as a convolutional neural network trained to predict the likelihood that a comment will be perceived as toxic.
Intended Use	Supporting human moderation, providing feedback to comment authors, and allowing comment viewers to control their experience.
Factors	Identity terms referencing frequently attacked groups focusing on the categories of sexual orientation, gender identity and race.

Mitchell et al. Model Cards for Model Reporting. FAT*, 2019.

Metrics and Data

Metrics	*Pinned AUC*, which measures threshold-agnostic separability of toxic and non-toxic comments for each group, within the context of a background distribution of other groups.
Evaluation Data	A synthetic test set generated using a template-based approach, where identity terms are swapped into a variety of template sentences.
Training Data	Includes comments from a variety of online forums with crowdsourced labels of whether the comment is “toxic”. “Toxic” is defined as, “a rude, disrespectful, or unreasonable comment that is likely to make you leave a discussion”.

Mitchell et al. Model Cards for Model Reporting. FAT*, 2019.

Considerations, Recommendations

Ethical Considerations	A set of values around community, transparency, inclusivity, privacy and topic-neutrality to guide their work.
Caveats & Recommendations	Synthetic test data covers only a small set of very specific comments. While these are designed to be representative of common use cases and concerns, it is not comprehensive.

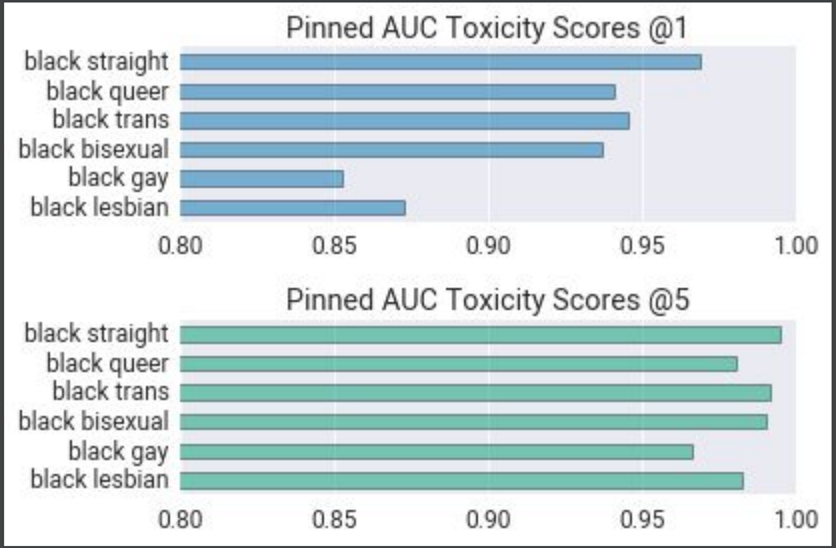
Mitchell et al. Model Cards for Model Reporting. FAT*, 2019.

Disaggregated Intersectional Evaluation

Toxicity @1

Identity groups	Subgroup AUC	BPSN AUC	BNSP AUC
lesbian	0.93	0.74	0.98
gay	0.94	0.65	0.99
queer	0.98	0.96	0.93
straight	0.99	1.00	0.87
bisexual	0.96	0.95	0.92
homosexual	0.87	0.53	0.99
heterosexual	0.96	0.94	0.92
cis	0.99	1.00	0.87
trans	0.97	0.96	0.91
nonbinary	0.99	0.99	0.90
black	0.91	0.85	0.95
white	0.91	0.88	0.94

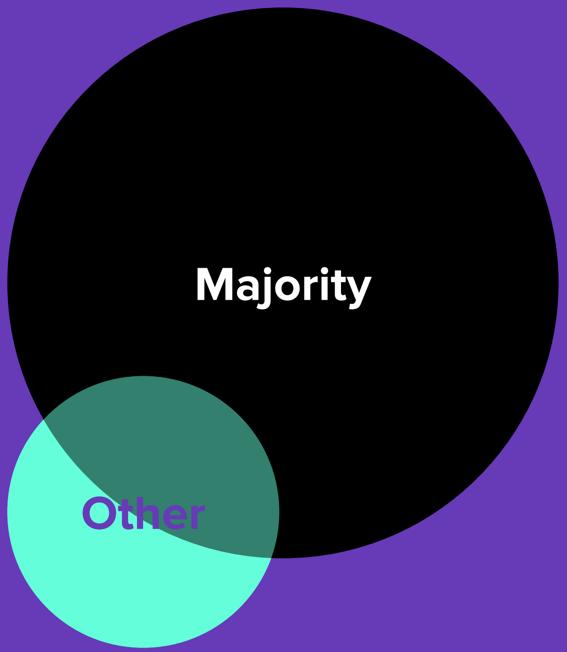
0.5 0.6 0.7 0.8 0.9 1.0



Jigsaw

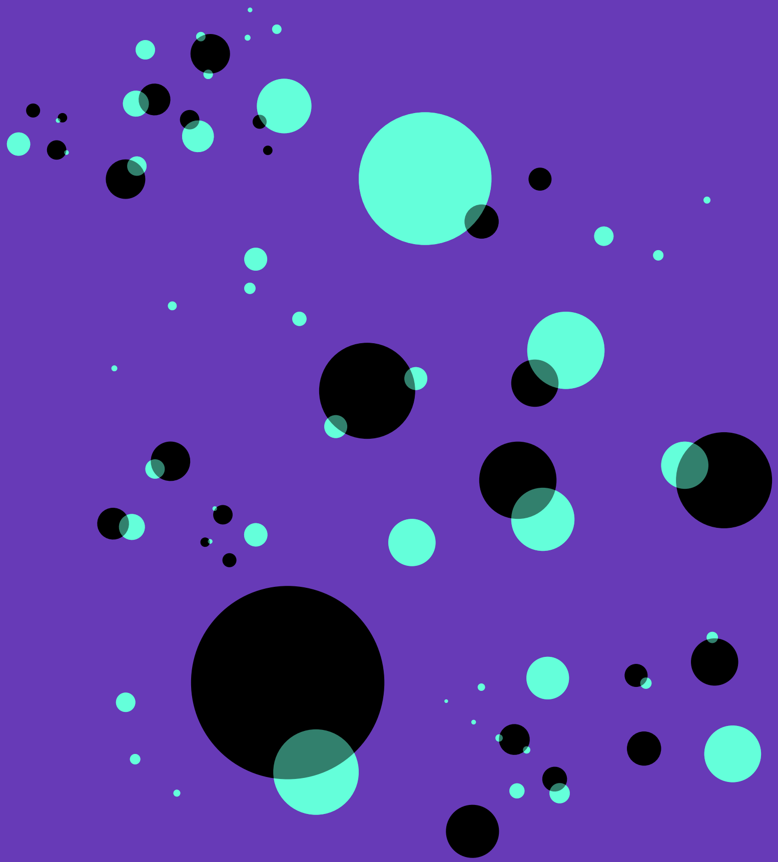
The False Positive

Moving from majority representation...



Moving from majority representation…

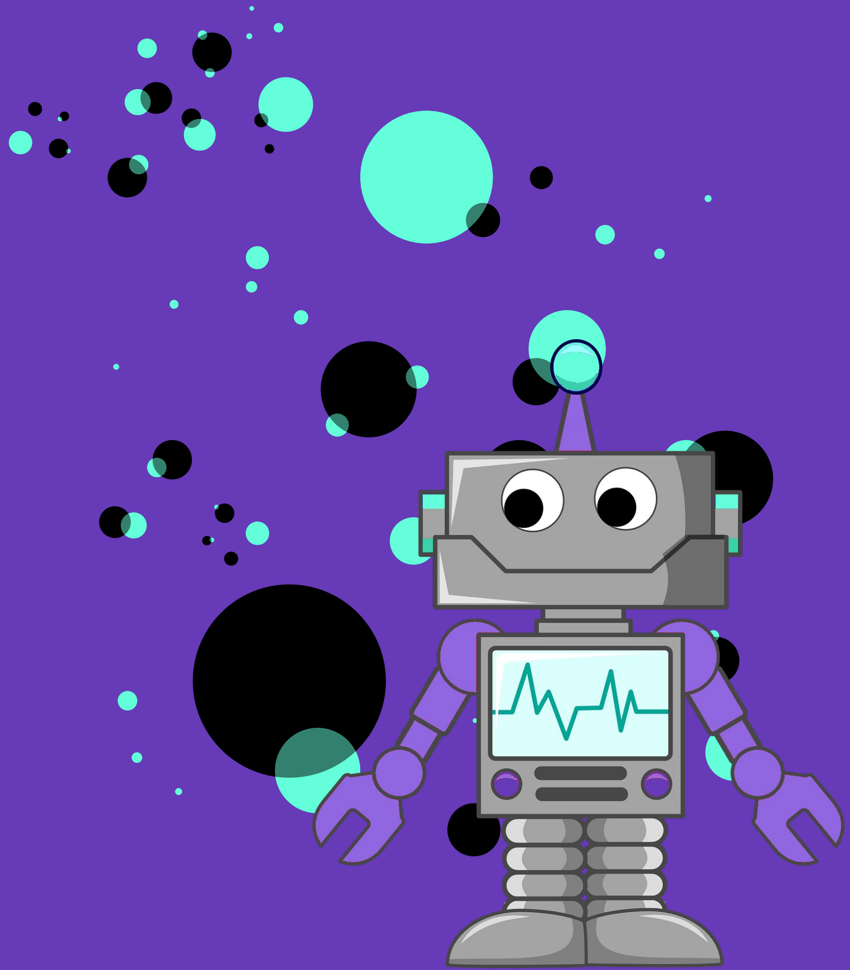
…to diverse representation



Moving from majority representation…

…to diverse representation

…for ethical AI



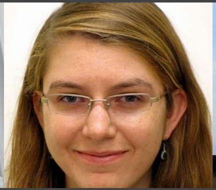
Thanks!

margarmitchell@gmail.com
m-mitchell.com

Need MOAR? ml-fairness.com

Andrew Zaldivar

Me



Simone Wu

Parker Barnes

Lucy Vasserman

Ben Hutchinson

Elena Spitzer

Deb Raji

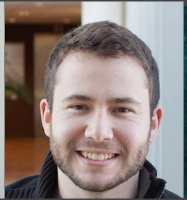
Timnit Gebru

Adrian Benton

Brian Zhang

Dirk Hovy

Josh Lovejoy



Alex Beutel

Blake Lemoine

Hee Jung Ryu

Hartwig Adam

Blaise Agüera y Arcas

More free, hands-on tutorials on how to build more inclusive ML

Measuring and Mitigating Unintended Bias in Text Classification

John Li
jetpack@google.com

Lucas Dixon
ldixon@google.com

Nithum Thain
nthain@google.com

Lucy Vasserman
lucyvasserman@google.com

Jeffrey Sorensen
sorenj@google.com

CO pinned_auc_demo.ipynb

File Edit View Insert Runtime Tools Help

CODE TEXT CELL CELL COPY TO DRIVE DISCARD CHANGES CONNEC

Table of contents Code snippets

- Conversation AI's Pinned AUC Unintended Model Bias Demo
  - Model Families - capture training variance
  - Data Format
- Unintended Bias Metrics
  - Pinned AUC
  - Pinned AUC Equality Difference
  - Pinned AUC Graphs
- SECTION

Conversation AI's Pinned AUC Unintended Model Bias Demo

Author: ldixon@google.com, jetpack@google.com, sorenj@google.com, nthain@google.com, lucyvasserman@google.com

Click here to run this colab interactively at on colab.research.google.com.

Summary

This notebook demonstrates Pinned AUC as an unintended model bias metric for Conversation AI wikipedia models.

See the paper Measuring and Mitigating Unintended Bias in Text Classification for background, detailed explanation, and experimental results.

Also see https://developers.google.com/machine-learning/fairness-overview for more info on Google's Machine Learning Fairness work.

Disclaimer

- This notebook contains experimental code, which may be changed without notice.
- The ideas here are some ideas relevant to fairness - they are not the whole story!

We start by loading some libraries that we will use and customizing the visualization parameters.

```
[ ] !pip install -U -q git+https://github.com/conversationai/unintended-ml-bias-analysi
```

Mitigating Unwanted Biases with Adversarial Learning

Brian Hu Zhang
Stanford University
Stanford, CA
bhz@stanford.edu

Blake Lemoine
Google
Mountain View, CA
lemoine@google.com

Margaret Mitchell
Google
Mountain View, CA
mmitchellai@google.com

CO Debiasing Word Embeddings using Fair Adversa...

File Edit View Insert Runtime Tools Help

CODE TEXT CELL CELL COPY TO DRIVE DISCARD CHANGES <HEAD> CONNECTED

Table of contents Code snippets

- Word analogies using a pretrained version of the adversarial model
  - Analogy task: A is to B as C is to ??
  - Analogy generation using a pretrained debiasing adversarial model
    - Analogy using unbiasing: A is to B as C is to ??
- Fair Adversarial Networks (FANs)
  - Defining the Protected Variable of Embeddings
    - Project words onto gender direction
  - Training the model
  - Analogy generation using the trained debiasing adversarial model
    - **Analogy using trained model: A is to B as C is to ??**
- SECTION

Debiasing Word Embeddings using Fair Adversarial Networks (FANs)

go/debias-word-embeddings-adversarial

Authors: lemoine@, zhangbrian@, benhutch@, guajardo@

Contributors: mmitchellai@, andrewzaldivar@

Summary of this Notebook

This Colab was put together as part of the ML-fairness inpired hackathon in late August 2017 to demonstrate how to mitigate bias in word embeddings using an adversarial network.

Disclaimer

- This notebook contains experimental code, which may be changed without notice.
- The ideas here are some ideas relevant to fairness -- they are not the whole story!

Intro statement of problem

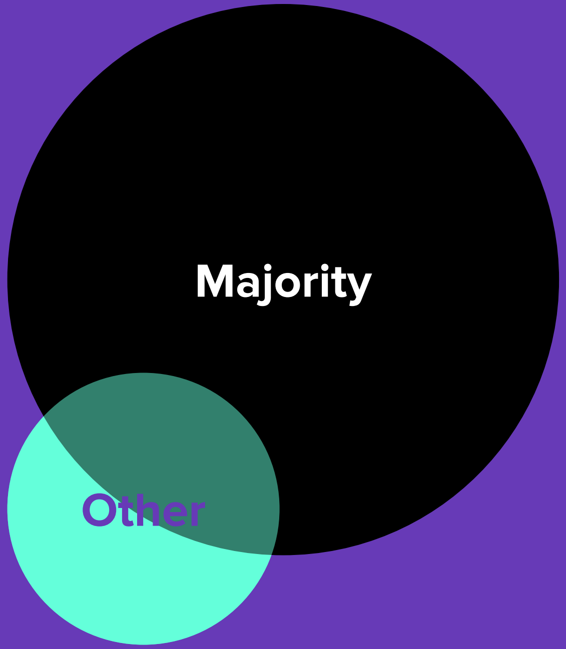
Embeddings are a powerful mechanism for projecting a discrete variable (e.g. words, locales, urls) into a multi-dimensional real valued space. Several strong methods have been developed for learning embeddings. One example is the Skipgram algorithm. In that algorithm the surrounding context is used to predict the presence of a word. Unfortunately, when you train embeddings on real world textual data the embeddings pick up bias from

ml-fairness.com

Get Involved

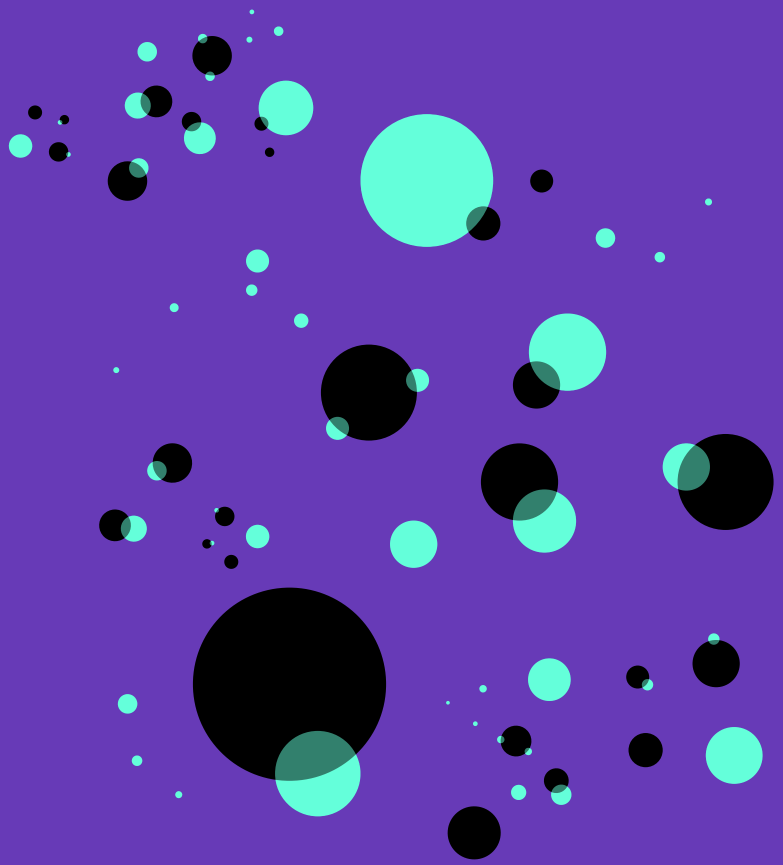
- Find free machine-learning tools open to anyone at **ai.google/tools**
- Check out Google's ML Fairness codelab at **ml-fairness.com**
- Explore educational resources at **ai.google/education**
- Take a free, hands-on Machine Learning Crash Course at **https://developers.google.com/machine-learning/crash-course/**
- Share your feedback: **acceleratewithgoogle@google.com**

Moving from majority representation...



Moving from majority representation...

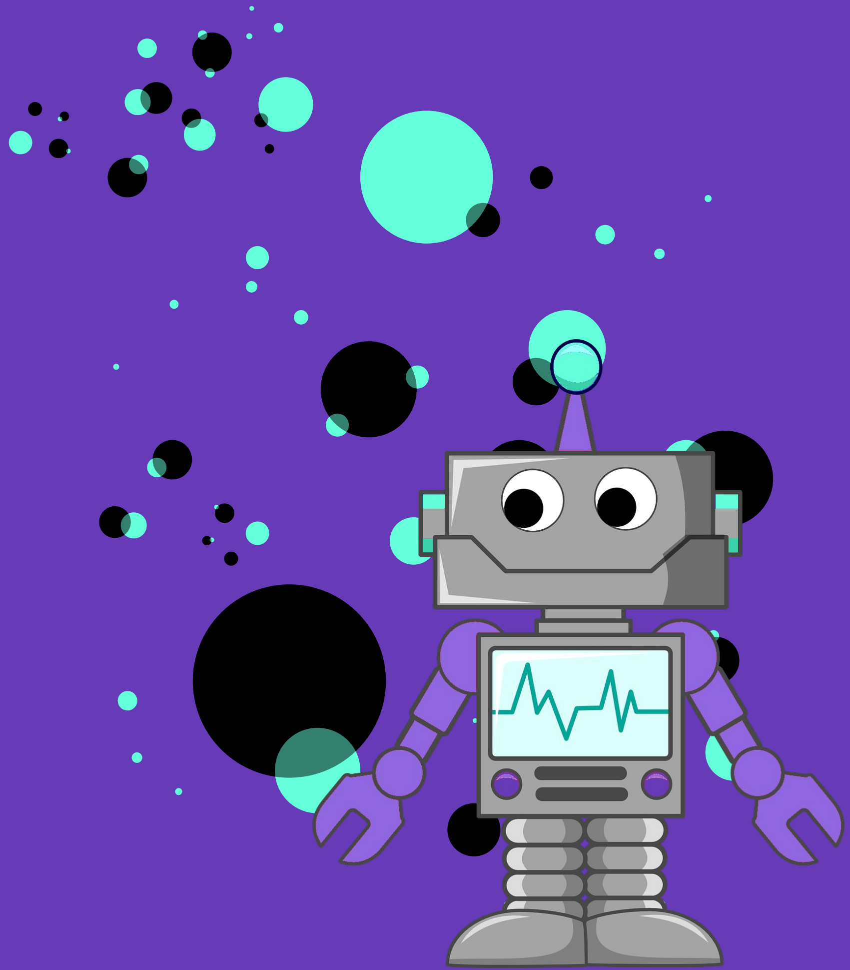
...to diverse representation



Moving from majority representation...

...to diverse representation

...for ethical AI



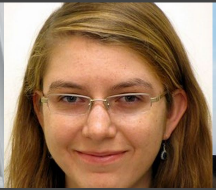
Thanks!

margarmitchell@gmail.com
m-mitchell.com

Need MOAR? ml-fairness.com


Andrew Zaldivar


Me


Simone Wu


Parker Barnes


Lucy Vasserman

Ben Hutchinson


Elena Spitzer

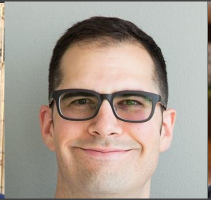

Deb Raji

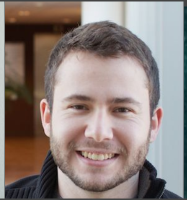

Timnit Gebru


Adrian Benton


Brian Zhang


Dirk Hovy


Josh Lovejoy


Alex Beutel


Blake Lemoine


Hee Jung Ryu


Hartwig Adam


Blaise Agüera y Arcas