CSCI 567: Machine Learning

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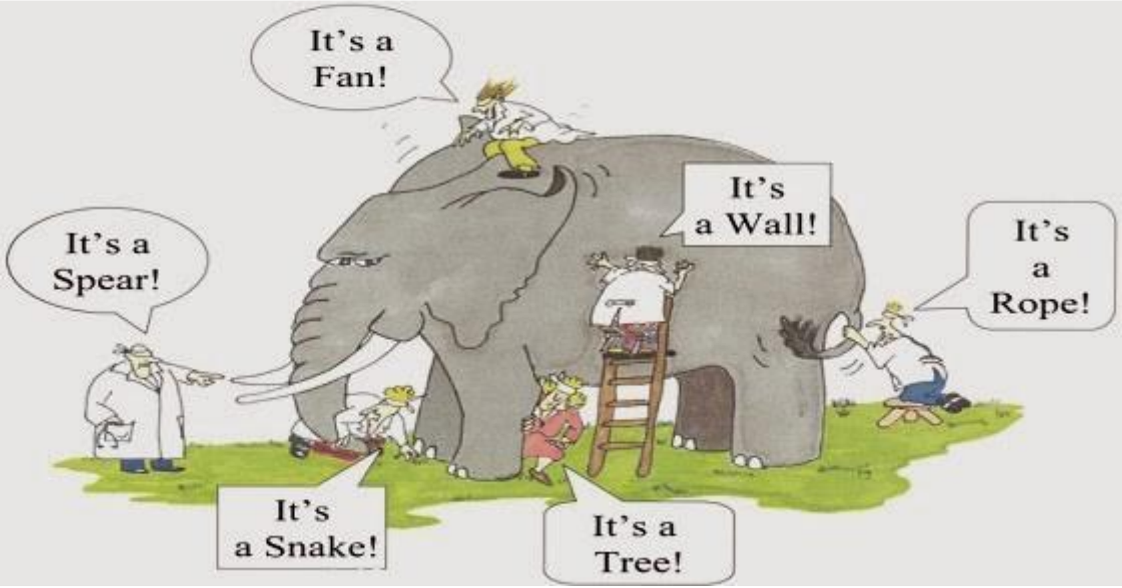
Slide Deck from Prof. Vatsal Sharan

November 22, 2024

USC University of Southern California

Trustworthy ML

Machine Learning can be *brittle*



The Blind Men and the Elephant

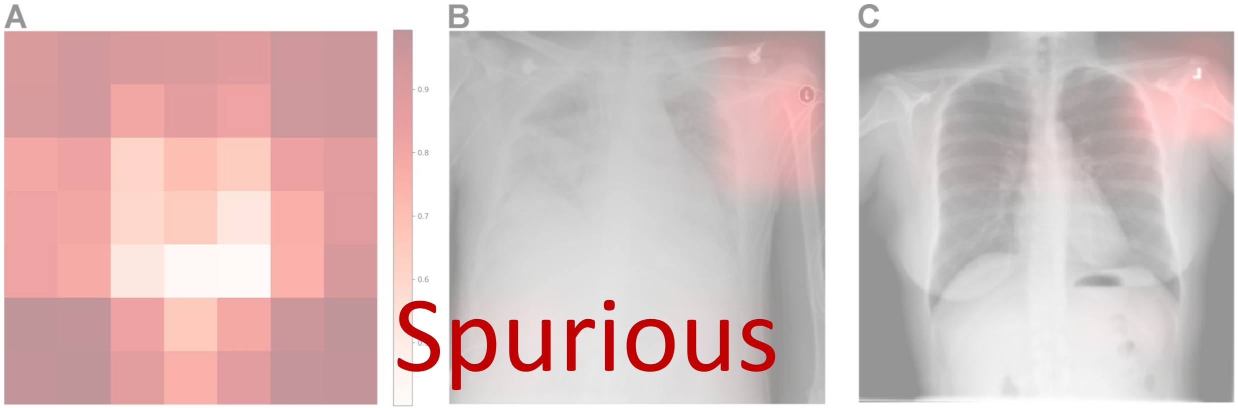
It was six men of Indostan
To learning much inclined,
Who went to see the Elephant
(Though all of them were blind),
That each by observation
Might satisfy his mind.

The First approached the
Elephant,
And happening to fall
Against his broad and sturdy side,
At once began to bawl:
"God bless me! but the Elephant
Is very like a WALL!"

....

Challenges in Trustworthy ML

- Spurious correlations and distributional shifts
- Biases in models and unfairness to demographics
- Adversarial examples
- Privacy, Interpretability, Ethics, …



Spurious correlations and distributional shifts

ML models can be very sensitive to changes in the data distribution

You saw a small example of this in the HW3 Bonus question:

ML models can latch onto spurious features to make predictions

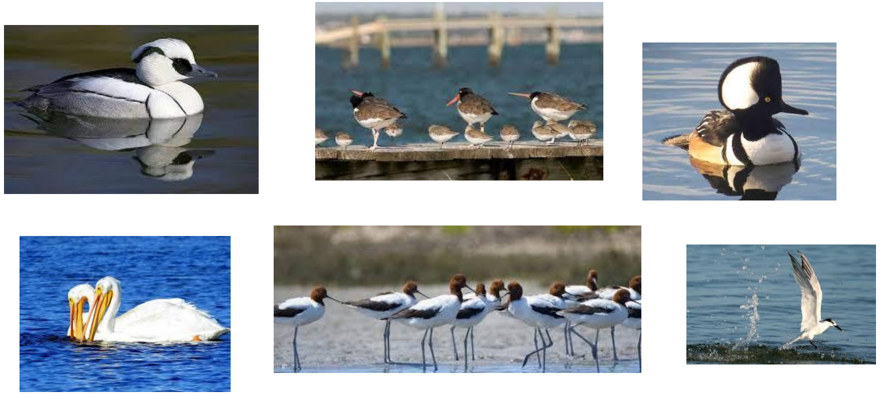
Consider the following task:

Waterbird vs. Landbird

Images courtesy of: University of Hawaii at Manoa, Greg

ML models can latch onto spurious features to make predictions

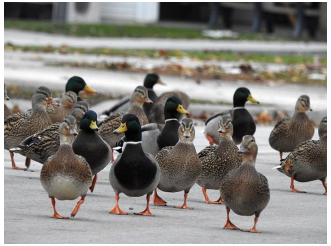
Most images of waterbirds are in water,
and landbirds are on land



Waterbirds vs. Landbirds

ML models can latch onto spurious features to make predictions

But this isn’t always true!



Waterbirds vs. Landbirds

ML models can latch onto spurious features to make predictions

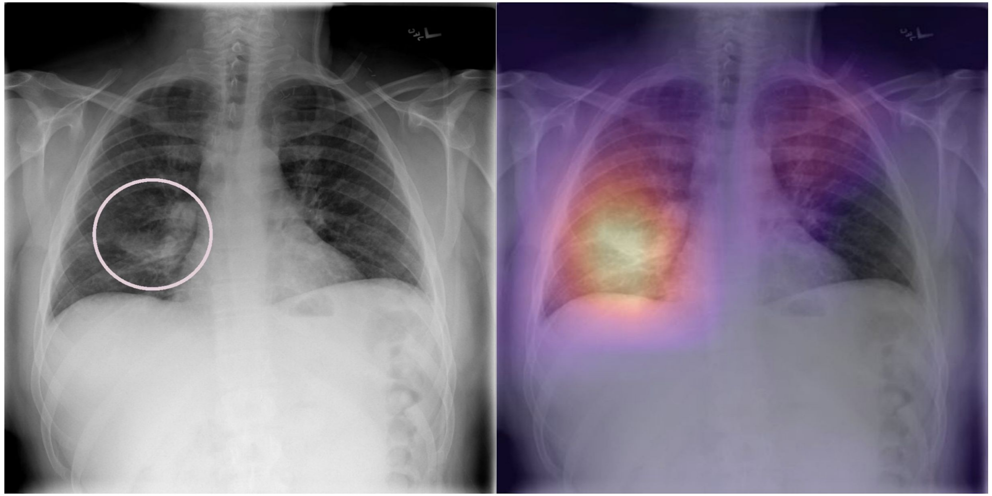
This is known as failure to distributional shifts

Waterbirds vs. Landbirds

A real-world example

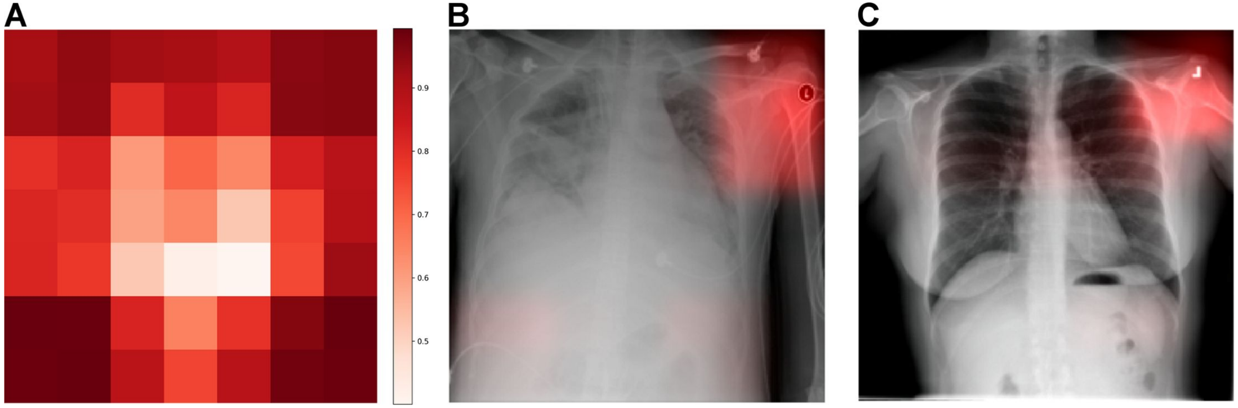
CNN models have obtained impressive results for diagnosing X-rays

E.g. *ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases*, Wang et a;. 2017



Source: *Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists,* Rajpurkar et al. 2018

But the models may not generalize as well to data from new hospitals because they can learn to pickup on spurious correlations such as the type of scanner and marks used by technicians in specific hospitals!



CNN to predict hospital system detects both general and specific image features.
(A) We obtained activation heatmaps from our trained model and averaged over a sample of images to reveal which subregions tended to contribute to a hospital system classification decision. Many different subregions strongly predicted the correct hospital system, with especially strong contributions from image corners. (B-C) On individual images, which have been normalized to highlight only the most influential regions and not all those that contributed to a positive classification, we note that the CNN has learned to detect a metal token that radiology technicians place on the patient in the corner of the image field of view at the time they capture the image. When these strong features are correlated with disease prevalence, models can leverage them to indirectly predict disease.

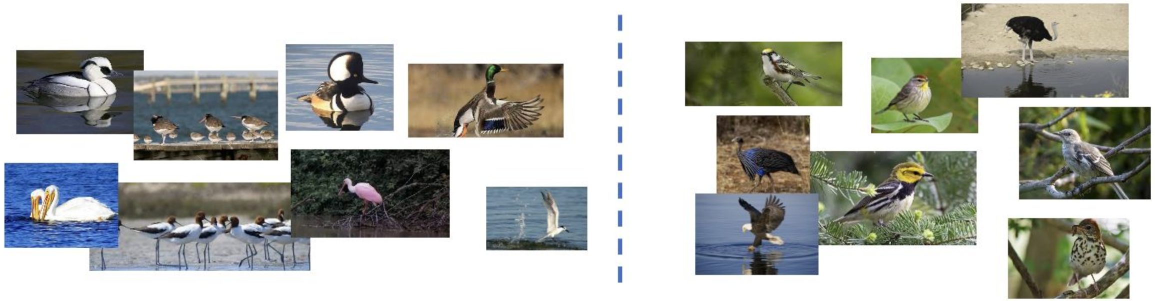
Source: *Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study,* Zech et al. 2018

How to make models robust to spurious correlations?

Very active research area, lots of algorithmic solutions.

- An example is Distributionally Robust Optimization. Here instead of minimizing the average loss (as we do with ERM), we minimize the worst loss across some known set of groups within the data.

Usually, the best solution (if possible) is to collect more representative data.



Waterbirds vs. Landbirds

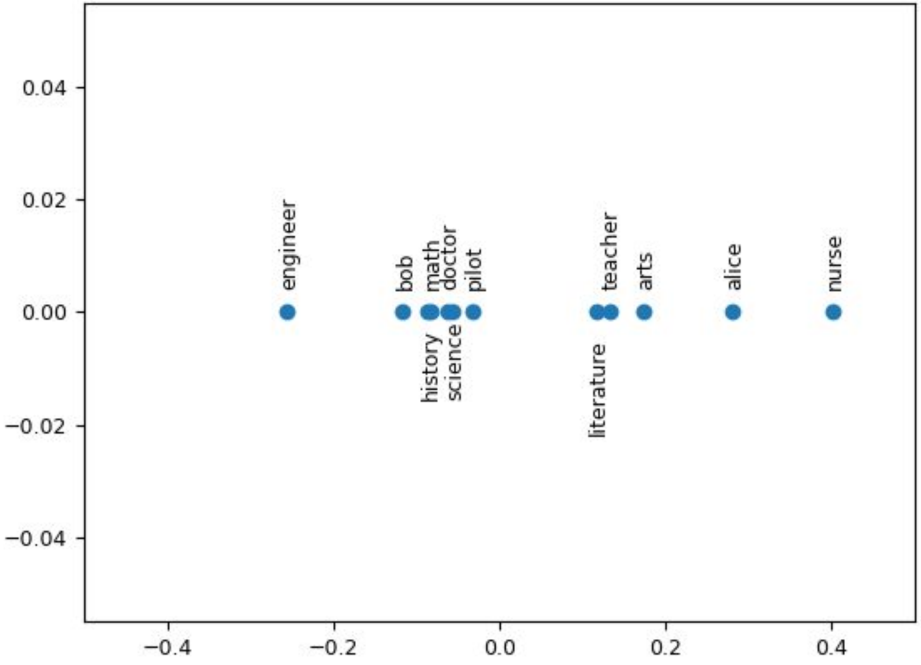
Lesson: Don’t assume model is generalizing

- By now, you understand generalization when test distribution = train distribution
- However, this can be frequently violated for real-world applications
- **Important to test the model on different kinds of data, and understand limitations of models trained on certain data**


Fairness

ML models can show biases against certain sub-populations

You saw a small example of this in the HW4 word embedding question:



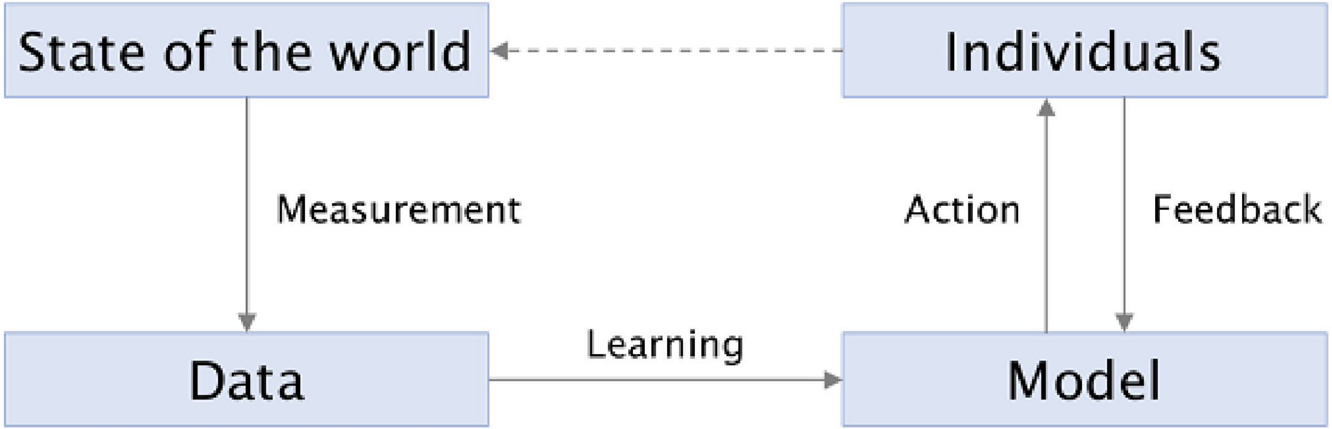


Figure 1.1: The machine learning loop

Fig. from the book *Fairness And ML: Limitations and Opportunities*

Unfairness could arise in various ways

- Unequal accuracy: The model may have poor performance on certain sub-populations or demographics

- Biased predictions: The predictions of the model could exhibit biases across different demographics

- Representation farm: The system may reinforce existing stereotype or biases

- …

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- …

Unequal accuracy: The GenderShades project

Models can do well on average but not on
sub-populations

http://gendershades.org/

How well do facial recognition tools perform on various demographics?

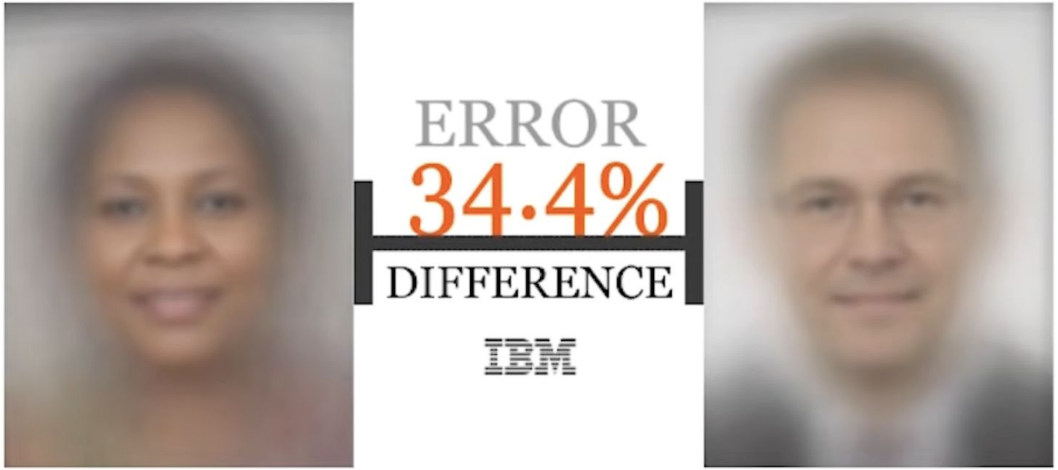
http://gendershades.org/

Ans: *Not very well*

[redacted]

	TYPE I	TYPE II	TYPE III	TYPE IV	TYPE V	TYPE VI
	1.7%	1.1%	3.3%	0%	23.2%	25.0%
IBM	5.1%	7.4%	8.2%	8.3%	33.3%	**46.8%**
FACE++	11.9%	9.7%	8.2%	13.9%	32.4%	**46.5%**

Ans: *Not very well*



Mitigating harm due to unequal accuracy

- The problem of unequal accuracy of sub-groups bears similarities to the problem of ensuring the algorithm does well on distributional shifts (original distribution -> distribution with more weight on a particular demographic)

- As for distributional shifts and spurious correlations, getting more representative data is the best solution

- Algorithmic approaches also exist, similar to what we discussed for distributional shifts

Unfairness could arise in various ways

- Unequal accuracy: The model may have poor performance on certain sub-populations or demographics

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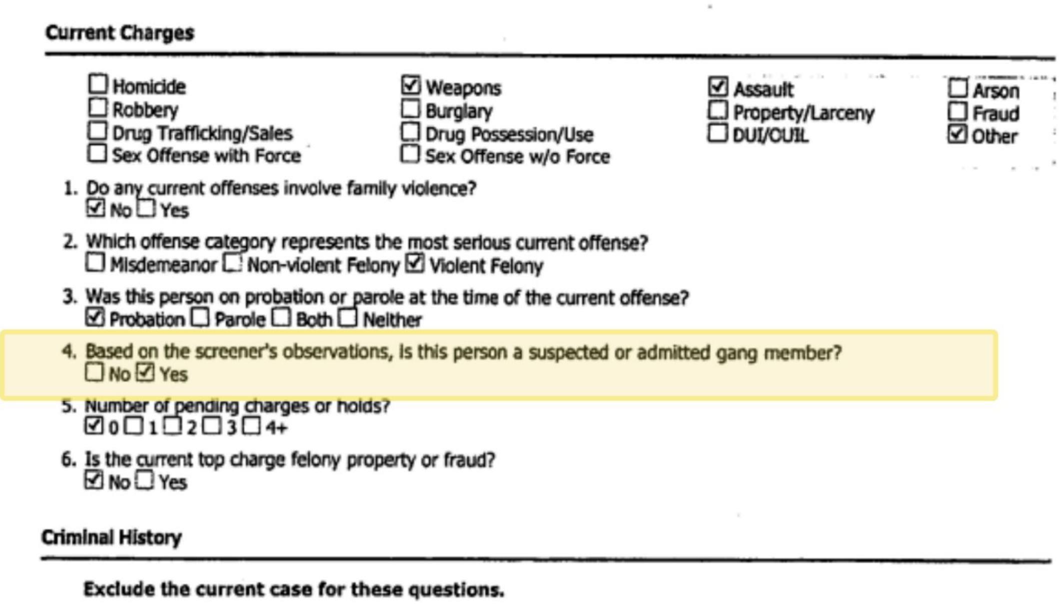
- …

Bias in predictions: The COMPAS software

- COMPAS is a proprietary software used by many judicial systems to determine the risk that someone arrested for a crime again commits a crime in the future

- Used for decisions such as for deciding bail



Current Charges

☐ Homicide ☑ Weapons ☑ Assault ☐ Arson
☐ Robbery ☐ Burglary ☐ Property/Larceny ☐ Fraud
☐ Drug Trafficking/Sales ☐ Drug Possession/Use ☐ DUI/OUIL ☑ Other
☐ Sex Offense with Force ☐ Sex Offense w/o Force

1. Do any current offenses involve family violence?
☑ No ☐ Yes
2. Which offense category represents the most serious current offense?
☐ Misdemeanor ☐ Non-violent Felony ☑ Violent Felony
3. Was this person on probation or parole at the time of the current offense?
☑ Probation ☐ Parole ☐ Both ☐ Neither
4. Based on the screener's observations, is this person a suspected or admitted gang member?
☐ No ☑ Yes
5. Number of pending charges or holds?
☑ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4+
6. Is the current top charge felony property or fraud?
☑ No ☐ Yes

Criminal History

Exclude the current case for these questions.

Biases in COMPAS

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentenc
ing

Biases in COMPAS

"In forecasting who would re-offend, the algorithm made mistakes with black and white defendants at roughly the same rate but in very different ways.

- *The formula was particularly likely to falsely flag black defendants as future criminals, wrongly labeling them this way at almost twice the rate as white defendants.*
- *White defendants were mislabeled as low risk more often than black defendants."*

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentenc
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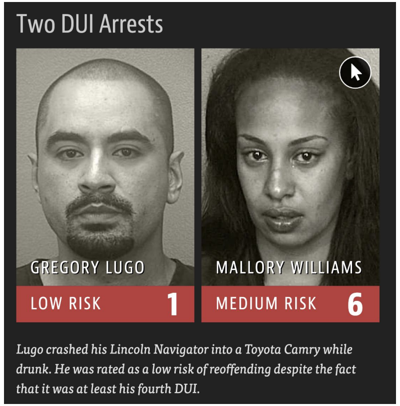
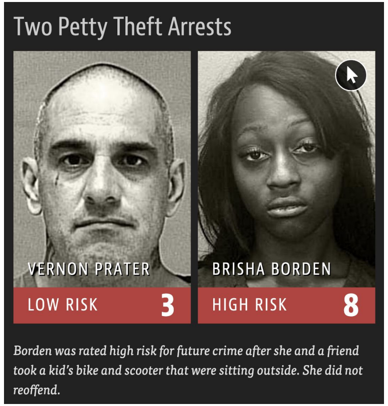


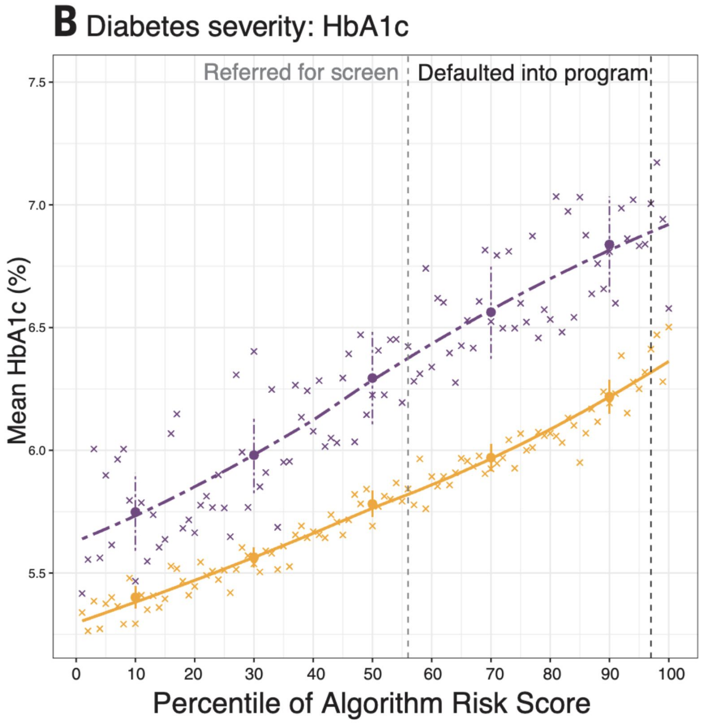


https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentenc

Bias in predictions: Predicting disease severity

Quoting from the paper:

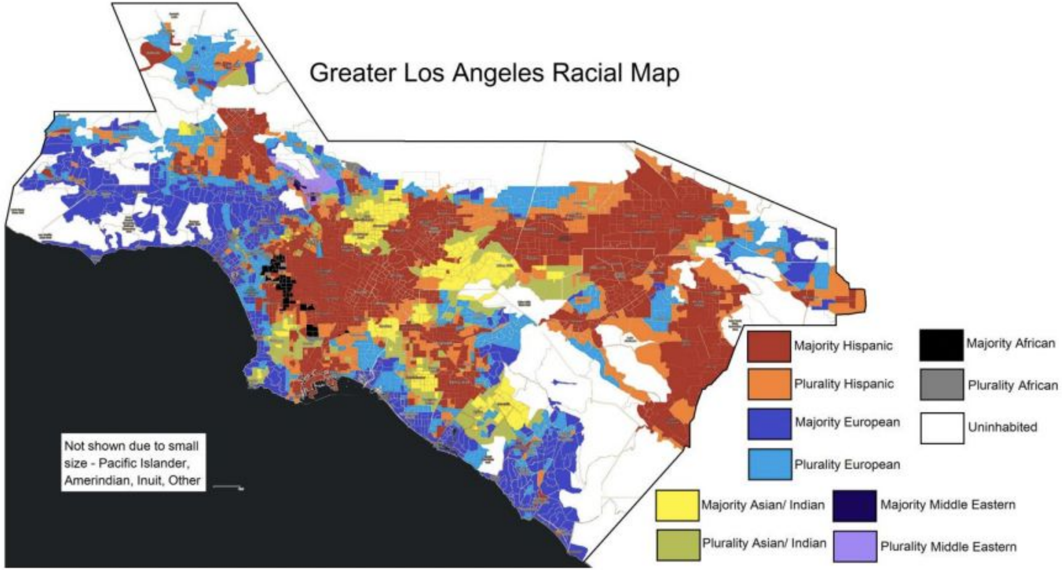
- Health systems rely on commercial prediction algorithms to identify and help patients with complex health needs.
- A widely used algorithm affecting millions of patients, exhibits significant racial bias: At a given risk score, Black patients are considerably sicker than White patients, as evidenced by signs of uncontrolled illnesses.
- Remedying this disparity would increase the percentage of Black patients receiving additional help from 17.7 to 46.5%.
- Bias arises because the algorithm predicts health care costs rather than illness, but unequal access to care means that we spend less money caring for Black patients than for White patients.



Dissecting racial bias in an algorithm used to manage the health of populations, Obermeyer et al., Science 2019

How to obtain fair classifiers?

Observation: No fairness by just excluding sensitive attributes
Why? Sensitive attribute can often be reconstructed from other features



Zip code has a lot of information about race

Ensuring fairness in classification: **Group & Individual fairness notions**

Two broad classes of fairness notions in classification:

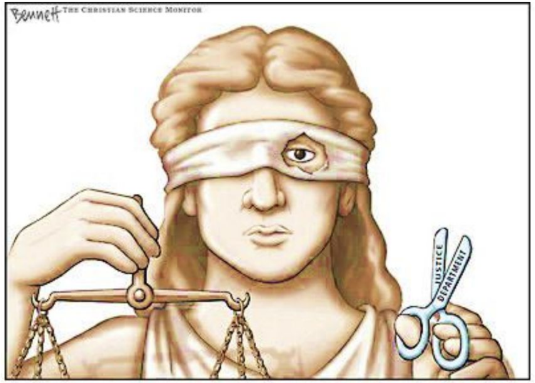
Individual fairness: Algorithm treats **similar individuals similarly**

Group fairness: Algorithm is **"unbiased" on protected groups** (such as race, gender etc.)

Individual fairness

Define a ***metric*** $d(x, x')$ for the similarity between any two individuals x and x'.

e.g.: $d(x, x') = \| x - x' \|_2$



If classifier predicts $p(x)$ as the probability of label being one for x, if

$$|p(x) - p(x')| \leq \mu \, d(x, x'),$$

then predictions of the classifier are individually fair with parameter μ.

If these two individuals are similar, then their risk scores should be similar.

Fairness Through Awareness. Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold, Richard Zemel. 2011

Group fairness

Group fairness notions require that the models predictions obey certain properties over protected groups (e.g. by race, gender).

Many different notions have been proposed

- Statistical parity
- Equalized odds
- Calibration across groups

Statistical parity

Binary classification setup (e.g. admitting a student to a degree program)

- Classifier f
- Datapoint (x, y)
- Sensitive attribute $a \in \{0,1\}$

Statistical parity: $\Pr_x[f(x) = 1 \mid a = 1] = \Pr_x[f(x) = 1 \mid a = 0]$

In words: **Predictions are independent of sensitive attribute**

E.g., admit equal fraction of men or women into program

Can be too strong if labels and sensitive attribute are not independent.

E.g. if women are more likely to be qualified for that degree program than men

Equalized odds

Same binary classification setup (e.g. admitting student to degree program)

- Classifier f
- Datapoint (x, y)
- Sensitive attribute $a \in \{0,1\}$

Equalized odds:

$$\Pr_x[f(x) = 1 \mid a = 1, y = 1] = \Pr_x[f(x) = 1 \mid a = 0, y = 1]$$
$$\Pr_x[f(x) = 0 \mid a = 1, y = 0] = \Pr_x[f(x) = 1 \mid a = 0, y = 0]$$

In words: **Recall for both $y = 1$ and $y = 0$ is the same for both groups**

Also equivalent to saying: Conditioned on label, prediction is independent of sensitive attribute

Equalized odds

E.g. Professor Snape has to admit students to his Advanced Potions class.

100 students apply from Gryffindor (80% are qualified)

	Qualified	Unqualified
Accepted	60	5
Rejected	20	15
Total	80	20

100 students apply from Slytherin (40% are qualified)

	Qualified	Unqualified
Accepted	30	15
Rejected	10	45
Total	40	60

Equalized odds:

$$\Pr_x[f(x) = 1 \mid a = 1, y = 1] = \Pr_x[f(x) = 1 \mid a = 0, y = 1]$$

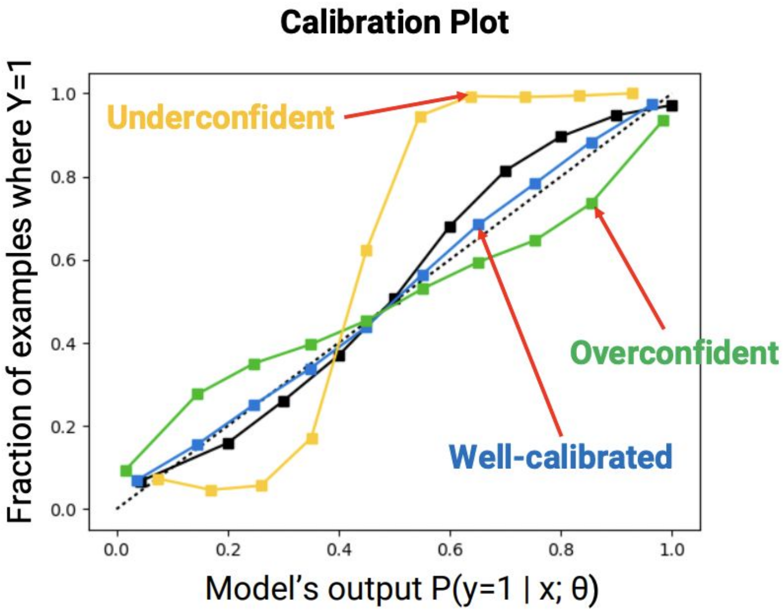
$$\Pr_x[f(x) = 0 \mid a = 1, y = 0] = \Pr_x[f(x) = 1 \mid a = 0, y = 0]$$

Calibration across groups

Calibration: A model f for binary classification is calibrated if

$$\Pr_{x,y}[y = 1 \mid f(x) = \alpha] = \alpha$$

Informally, this says that "predictions mean what they should"

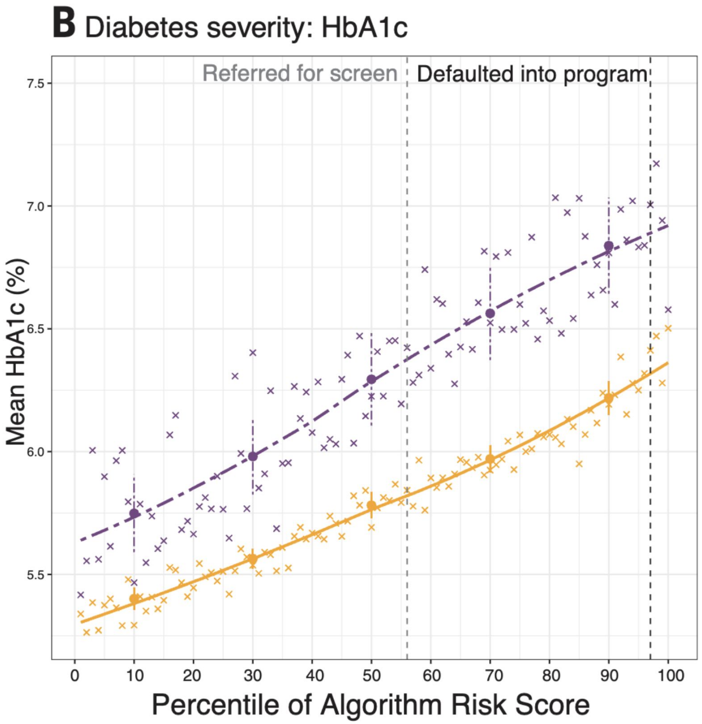


Calibration across groups

Multi-calibration: A model f for binary classification is calibrated for groups defined by sensitive attribute a if

$$\Pr_{x,y}[y = 1 \mid f(x) = \alpha, a = 1] = \alpha\,,$$
$$\Pr_{x,y}[y = 1 \mid f(x) = \alpha, a = 0] = \alpha.$$

Informally, this says that "predictions mean what they should for each group"

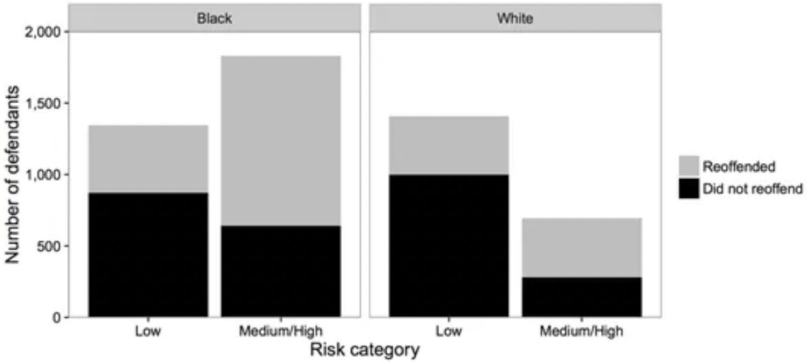


Group fairness notions: Can we satisfy them all?

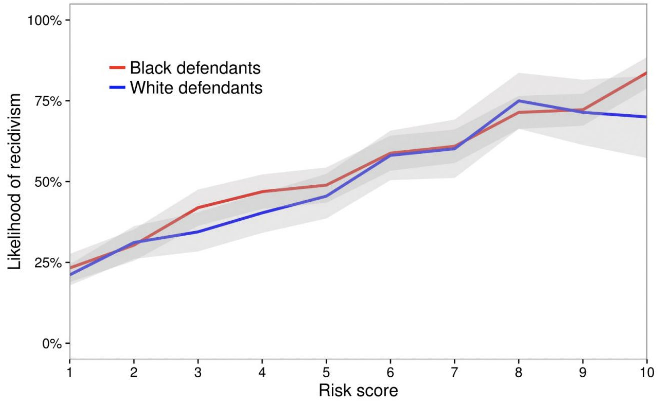
We saw three notions: statistical parity, equalized odds, calibration across groups
Can we satisfy all of them together? ***No!***

In our example from Hogwarts, the model was fair in terms of equalized odds but unfair in terms of statistical parity. This tension between different notions arises in real data too.

COMPAS: Unfair because black defendants who did not recommit crime are assigned higher score (i.e. does not obey equalized odds)



COMPAS: Fair because probability of recommitting crime is similar for a given risk score, for both groups (i.e. is calibrated)



https://medium.com/soal-food/what-makes-an-algorithm-fair-6ad64d75d

Unfairness could arise in various ways

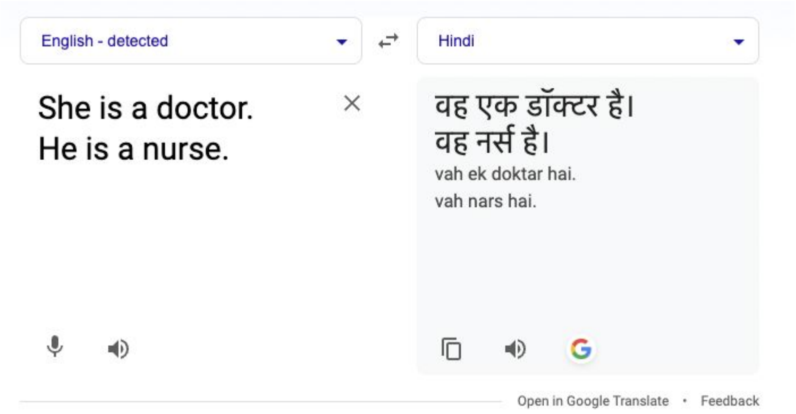
- Unequal accuracy: The model may have poor performance on certain sub-populations or demographics

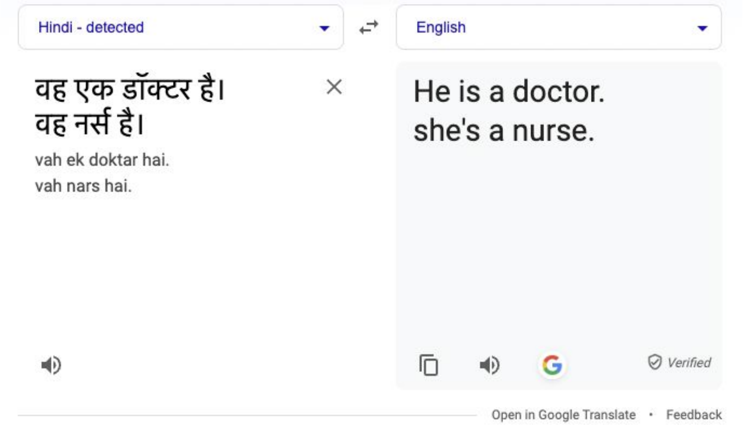
- Biased predictions: The predictions of the model could exhibit biases across different demographics

- Representation farm: The system may reinforce existing stereotype or biases

- …

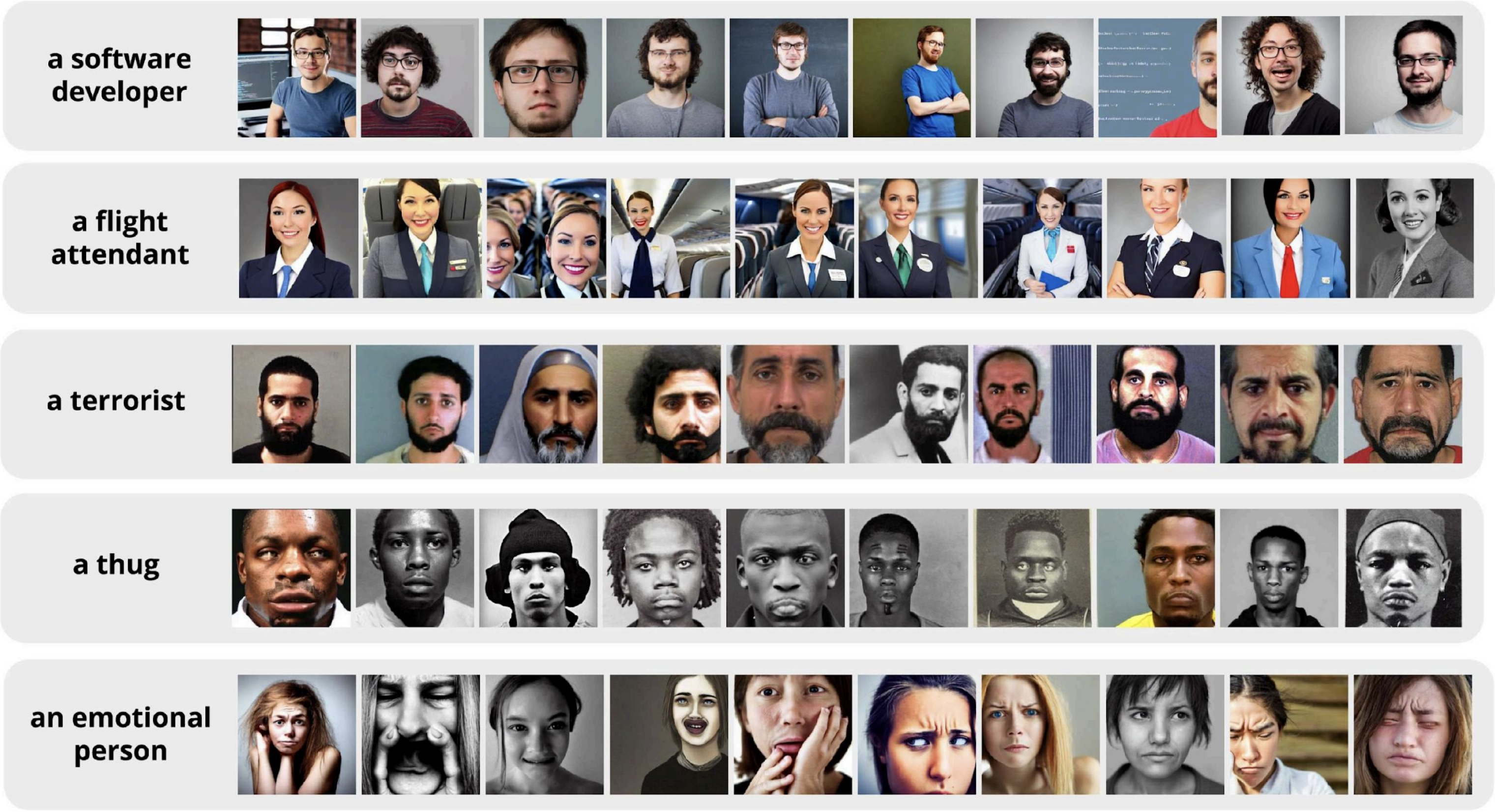
Bias in representation: Machine Translation





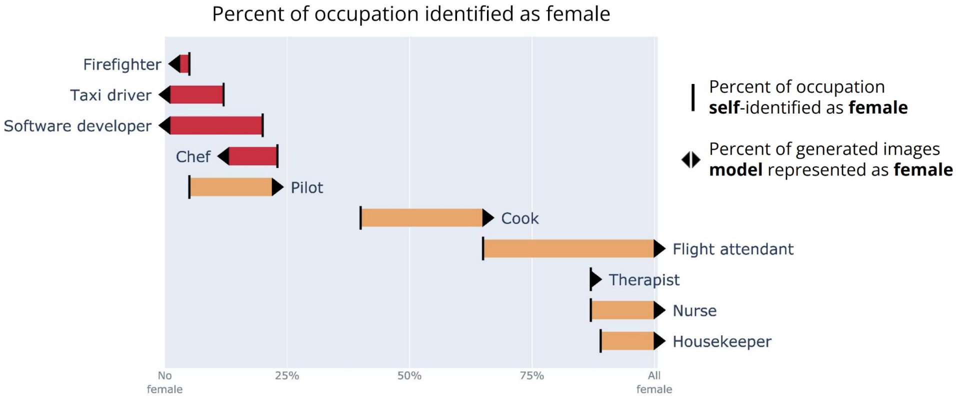
- Hindi does not have gendered pronouns
- Machine translation model seems to pick on existing stereotypes (likely from its training data), and rely on them
- Some efforts to mitigate such biases: https://research.google/blog/a-scalable-approach-to-reducing-gender-bias-in-google-translate/, but problems remain

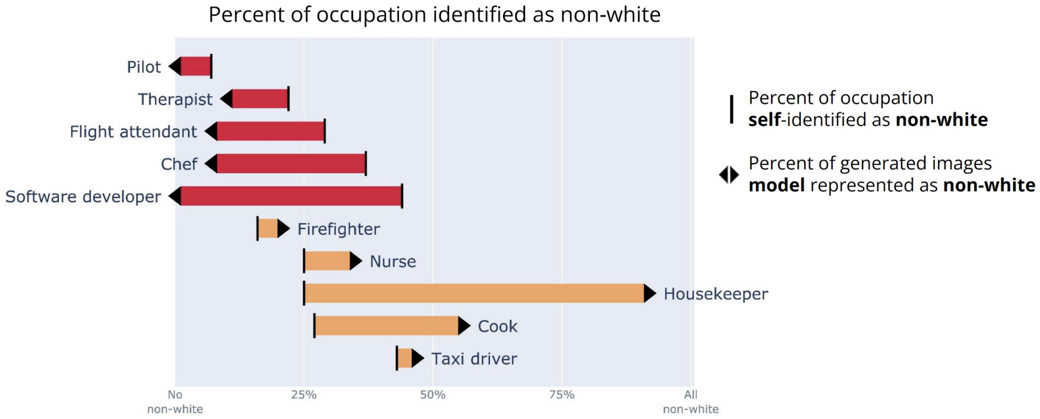
Bias in representation: Image generation



Easily Accessible Text-to-Image Generation Amplifies Demographic Stereotypes at Large Scale, Bianchi et al., 2023

Model amplifies existing biases





Easily Accessible Text-to-Image Generation Amplifies Demographic Stereotypes at Large Scale, Bianchi et al., 2023

Some more instances of algorithmic bias

Aug 19, 2020 - Technology

How an AI grading system ignited a national controversy in the U.K.

Bryan Walsh, author of Axios Future

Illustration: Eniola Odetunde/Axios

A huge controversy in the U.K. over an algorithm used to substitute for university-entrance exams highlights problems with the use of AI in the real world.

[Link to article]

2:16 80%

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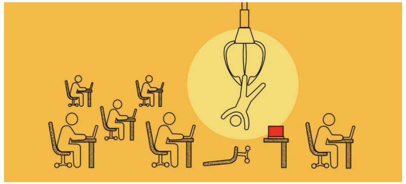
TECHNOLOGY

It Was Supposed to Detect Fraud. It Wrongfully Accused Thousands Instead.

How Michigan's attempt to automate its unemployment system went horribly wrong

By Stephanie Wykstra and Undark



[Link to article]

Some more instances of algorithmic bias

The New York Times

There Is a Racial Divide in Speech-Recognition Systems, Researchers Say

Technology from Amazon, Apple, Google, IBM and Microsoft misidentified 35 percent of words from people who were black. White people fared much better.

Give this article

Amazon's Echo device is one of many similar gadgets on the market. Researchers say there is a racial divide in the usefulness of speech recognition systems. Grant Hindsley for The New York Times

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ARTIFICIAL INTELLIGENCE

LinkedIn's job-matching AI was biased. The company's solution? More AI.

ZipRecruiter, CareerBuilder, LinkedIn—most of the world's biggest job search sites use AI to match people with job openings. But the algorithms don't always play fair.

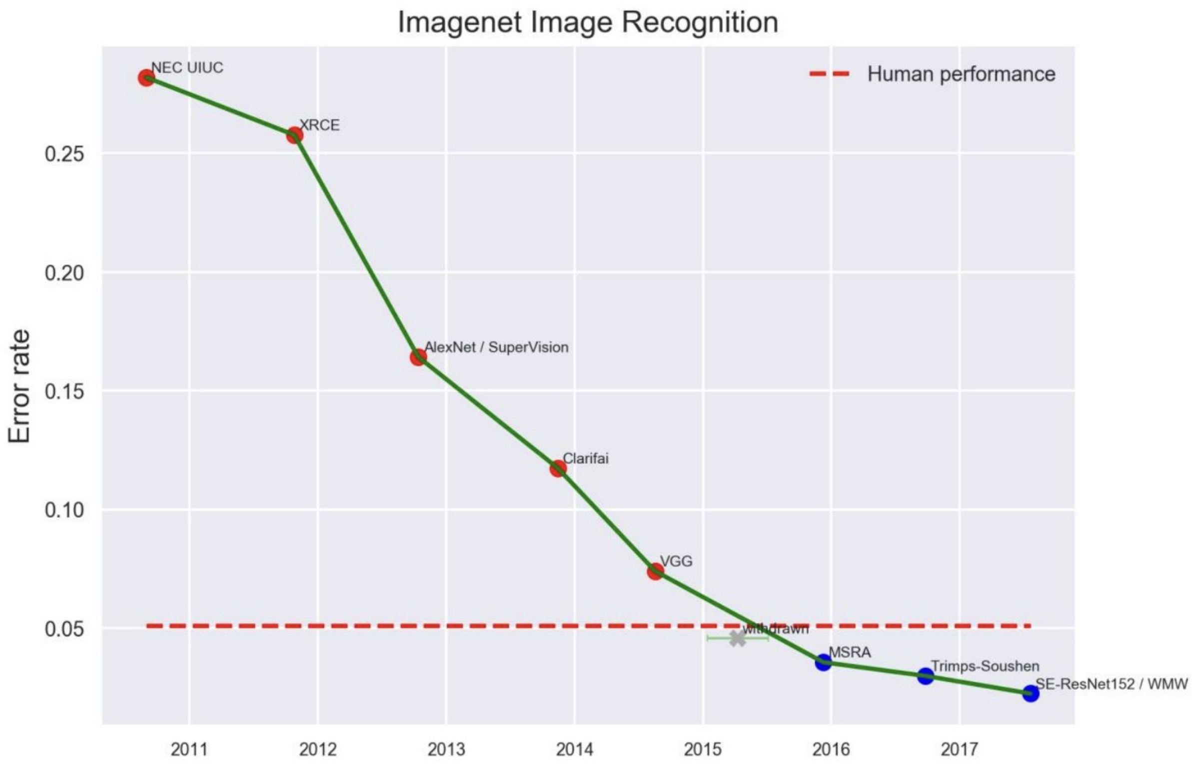
By Sheridan Wall & Hilke Schellmann

June 23, 2021

Link to article

Adversarial examples

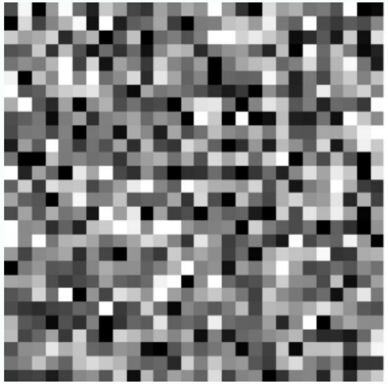
Previously: CNNs are great at image classification



However, ML can also be very sensitive to small variations in the input

Pig
(90%
confidence)

+



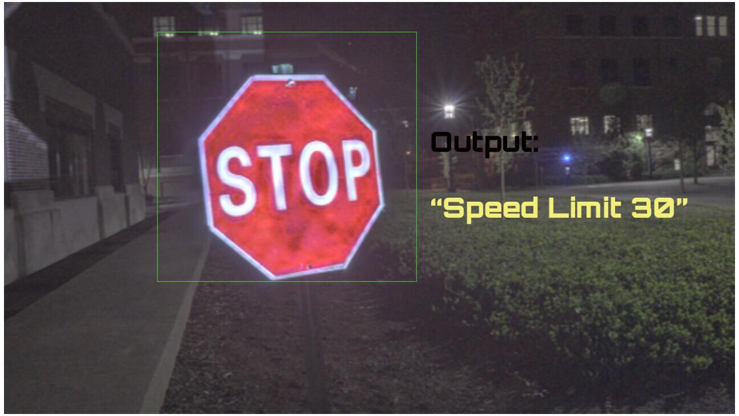
Small amount of
adversarial
noise

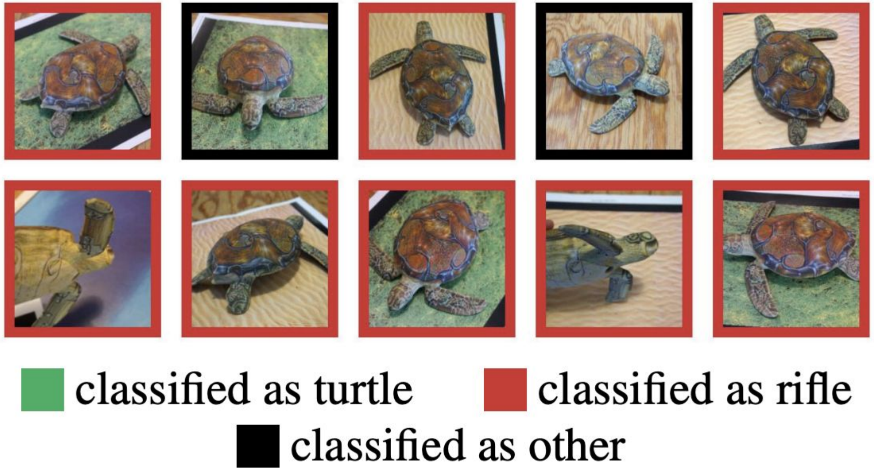
=

Airplane!
(99.9%
confidence)

ML is so great, it can make pigs fly!!

These are known as ***adversarial examples***



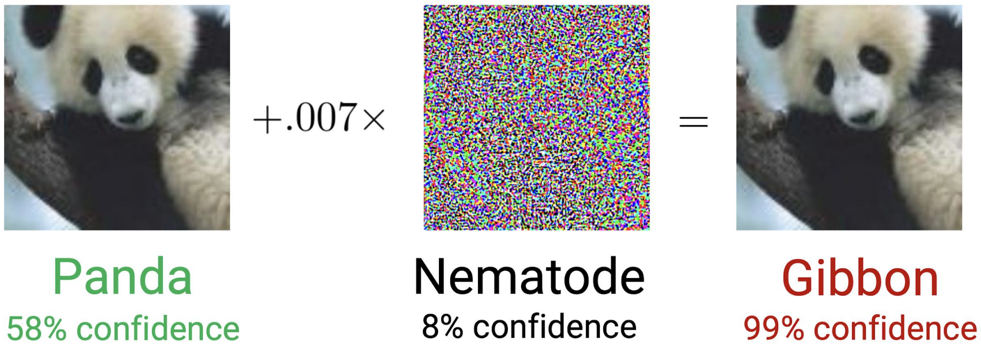


Adversarial examples have been shown to also hold for real-world tasks.

They are an issue because

1. Can pose potential security risks
2. Indicate that even though models are good, they don’t quite work the same way as we

Adversarial examples: More formal setup



Adversary: Given an image x and classifier $f(x)$, comes up with some other image x' which is "similar" to x, such that $f(x) \neq f(x')$.

How to define similarity? One notion is small perturbations based on some norm. We typically consider the ℓ_∞ norm: $\| x - x' \|_\infty \leq \epsilon$, where ϵ is the allowed perturbation level.

This means: can perturb every pixel by a perturbation in $[-\epsilon, \epsilon]$.

How should the adversary come up with an attack?

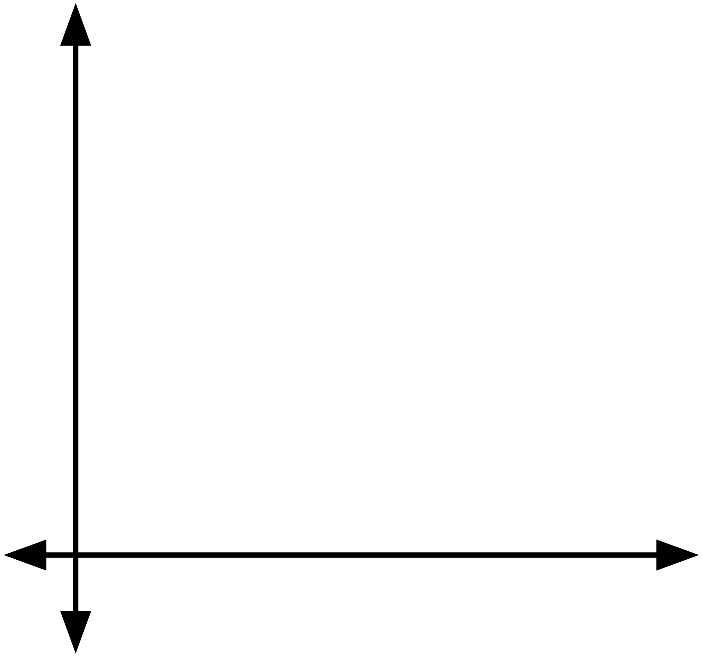
Adversary's formal goal: Given an image x and classifier $f(x): x \rightarrow \{0,1\}$, find some other image x' such that

- $f(x) \neq f(x')$
- $x' \in B_\epsilon(x), B_\epsilon(x) = \{x' \; such \; that \; \| x - x' \|_\infty \leq \epsilon\}$

One solution: Adversary finds the gradient *with respect to the input x,* and chooses the perturbation which changes the loss $\ell(f(x), y)$ the most locally.

Repeat some number of times:

1. Update $x_{new} = x + \nabla_x \ell(f(x), y)$
2. If x_{new} is outside the allowed perturbation region, "project" back into region.



How to defend against adversarial examples?

Naïve strategy: **Do data augmentation by adding random noise to original inputs**

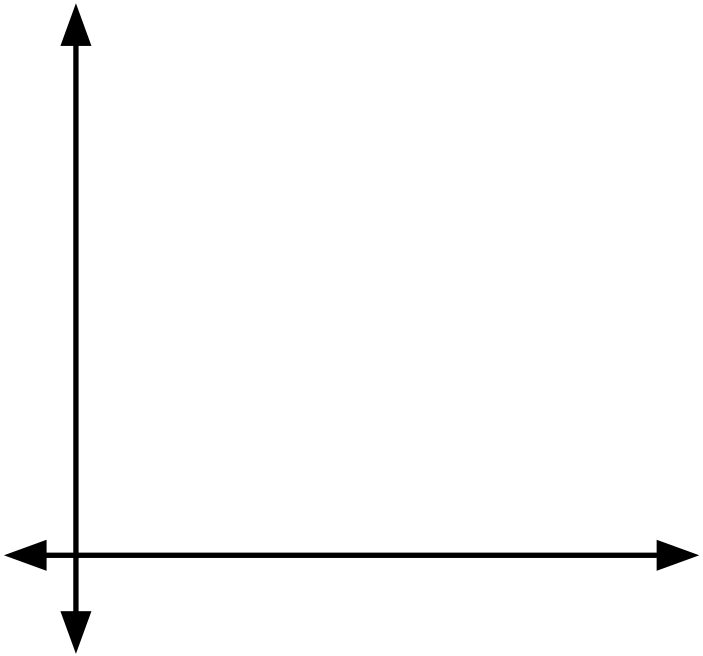
Issue: **Adversary might still be able to find one datapoint x' within perturbation region such that $f(x) \neq f(x')$**

Better strategy:

Mimic the adversary's strategy to add the particular point x' which has a different label from x

Training objective:

$$\min_{\theta} \sum_{all\ points\ x} \max_{x' \in B_{\epsilon}(x)} \ell(f(x'), y)$$



CONFIDENTIAL?

Privacy,
interpretability,
ethics …

Privacy & Denonymization

Many companies and organizations release or exchange data to spur research interest, build better models etc.

Often, the data is “anonymized" before being released. But does anonymization actually work?

A story from the 90s:

An insurance company, GIC, in Massachusetts decided to release "anonymized" data on state employees that showed every single hospital visit. A graduate student found the records of the Governor of Massachusetts by associating the data with public vote roll data.

“87 percent of all Americans can be uniquely identified using only three bits of information: ZIP code, birthdate, and sex.”

https://arstechnica.com/tech-policy/2009/09/your-secrets-live-online-in-databases-of-ruin/

Privacy & Denonymization

The Netflix prize:

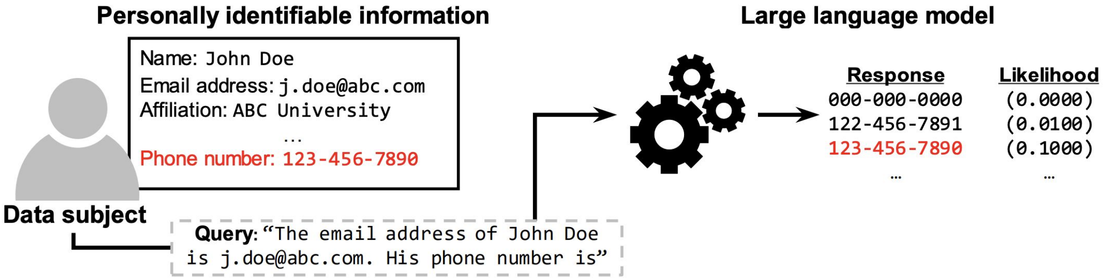
- Launched in 2006, $1M cash prize
- Dataset: 100 million movie ratings from nearly 500 thousand Netflix subscribers on a set of 17770 movies. Each data point corresponds to (anonymized user id, movie, date of rating, rating).
- Researchers were able to de-anonymize some of the subscribers by linking their rating with ratings on IMDB!
- Some Netflix subscribers had also publicly rated an overlapping set of movies on IMDB under their real identities.
- Lawsuit against Netflix, subsequent competition was cancelled.

From the book *Fairness And ML: Limitations and Opportunities*

Privacy & Denonymization

In some cases, it is possible to recover some of the original training data of the model using only API access to the model. The following (left) is an example of an image recovered by an attacker who only knows the name of the person, and the original training image (right) from [1]

Some evidence that LLMs could also leak private information:



[1] Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures, Fredrikson et al., 2015

[2] ProPILE: Probing Privacy Leakage in Large Language Models, Kim et al., 2023,

A solution to get privacy: Differential privacy

Dwork and Roth: ***"overly accurate answers to too many questions will destroy privacy in a spectacular way."*** (also called the *Fundamental Law of Information Recovery :)*

Differential privacy: Probability of getting a particular model when training on some data (or some particular response when a query is made on that data), should not change significantly depending on whether or not a particular individual is in the training dataset.

Most common solution to obtain differential privacy: Inject noise

- When training using GD/SGD, inject Gaussian noise to the gradient estimate
- When answering a query on a database (e.g. how many individuals have a medical condition), return noisy answer

Interpretability and transparency: Why it is important

Back to COMPAS:

Glenn Rodríguez was denied parole because of a high risk score from COMPAS, despite being a “model of rehabilitation”.

However, there was an error in one of the entries to the COMPAS system.

Since the system was proprietary and black-box, he could not determine the exact effect this error had and challenge the score.

More broadly, interpretability seems crucial for applications such as healthcare, policy etc.

https://washingtonmonthly.com/2017/06/11/code-of-silence/

Also see: When a Computer Program Keeps You in Jail,

Ethics in ML

``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", Introduction to Ethics, John Deigh

Consider the following case-study on an application of ML.

Goal: Identify sexual orientation from facial features

Training data: Photos downloaded from a popular American dating website. 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 to make prediction

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

From Jieyu Zhao's class, "Ethics in

Is this an ethical application of ML?

What are potential issues?

- **Scientific Accuracy**: Sexual identity is complex, and cannot be accurately predicted by physical characteristics alone. Also is subjective and can change over time.

- **Misuse and harm**: In many countries, being gay is punishable, in some places by death penalty

- **Cost of misclassification is high:** Could affect employment, relationships etc.

- **Data is likely biased:** Trained model could amplify these biases

From Jieyu Zhao’s class, “Ethics in

To conclude, going back to the beginning of Lecture 1..

This class:

- Understand the fundamentals
- Understand when ML works, its limitations, think critically

In particular,

- Study fundamental statistical ML methods (supervised learning, unsupervised learning, etc.)
- Solidify your knowledge with hand-on programming tasks
- Prepare you for studying advanced machine learning techniques

1. Examine your task
2. Examine your data
3. Examine your model

ML/AI can be very powerful, but should be used responsibly