

Applying AI for Hate Speech Detection

Xiang Ren
Department of Computer Science
USC



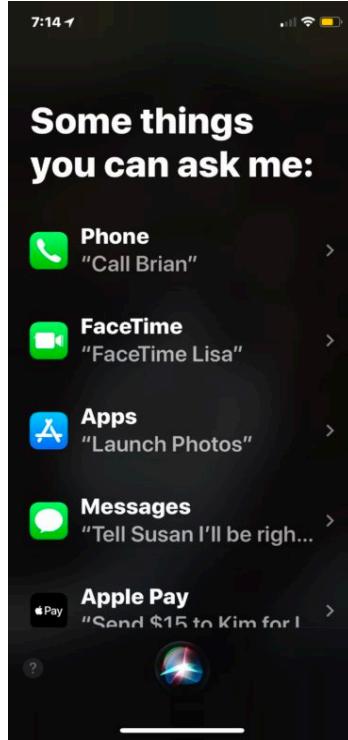
USC



About Me

- Assistant professor at USC Computer Science Department
- Did my doctoral study at University of Illinois at Urbana Champaign (Computer Science); spent time at Stanford University; consult for Snapchat
- I teach & do research on *natural language processing (NLP)*

Example of NLP in “AI” Application: Siri



- Speech recognition: voice → text
- Language analysis
- Question answering
- Dialog processing
- Text to speech

Applying NLP to determine sentiment of text



"This is frustrating", "Never works",
"Not once again", "will wait for
next release"



Negative
Sentiment



Lower Satisfaction



"Wow", "Amazing", "Saved me a
lot", "More than happy to"



Positive
Sentiment



Higher Satisfaction



"How do I", "Ohh is it", "Never
knew this works this way", "Ohh, I
missed that step"



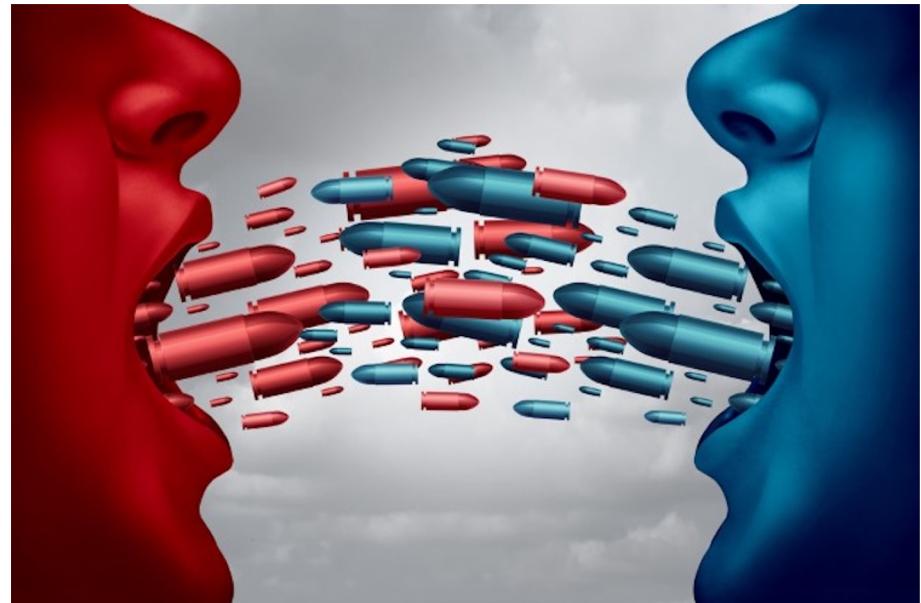
Model

Can we apply NLP to help moderate hate speech on social media?



First, what is Hate Speech?

Hate speech expresses *prejudice* against someone's race, ethnicity, gender identity, religion, sexual orientation, nationality, or mental and physical disability.



Warning: This presentation contains
offensive language

Examples: hate speech on twitter



All [national origin] are cockroaches who live off of welfare benefits and need to be taken away.



People who are [race] are leeches and only good for one thing.



[Ethnicity] are mail-order bride scum.



There are too many [national origin/race/ethnicity] maggots in our country and they need to leave!



Source: twitter hate conduct policy
<https://help.twitter.com/en/rules-and-policies/hateful-conduct-policy>

Examples: hate speech on twitter



All [Age Group] are leeches and don't deserve any support from us.



People with [Disease] are rats that contaminate everyone around them.



People with [Disability] are subhuman and shouldn't be seen in public.



[Religious Group] should be punished. We are not doing enough to rid us of those filthy animals.



Source: twitter hate conduct policy
<https://help.twitter.com/en/rules-and-policies/hateful-conduct-policy>

Hate speech online is hard to combat...

- People can act anonymously and without retribution online
- Governments have been slow to develop laws against online hate speech



The harms of online hate speech

In 2018, a white supremacist posted his rants against Jews on his “Gab” social media account shortly before murdering 11 people in a synagogue.



Shannon Martinez of the [Free Radicals Project](#), says:

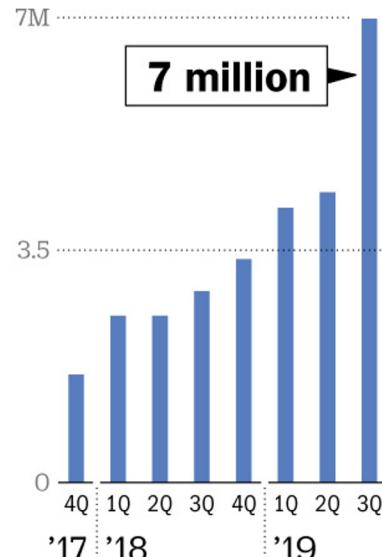
The digital world gives white supremacists a safe space to explore extreme ideologies and intensify their hate without consequence.

Upward Trend

- More hate speech on Facebook is being flagged over time
- Even in 2020, companies have had a difficult time handling the problem of hate speech being used on their platforms ([Vox, 2020](#))

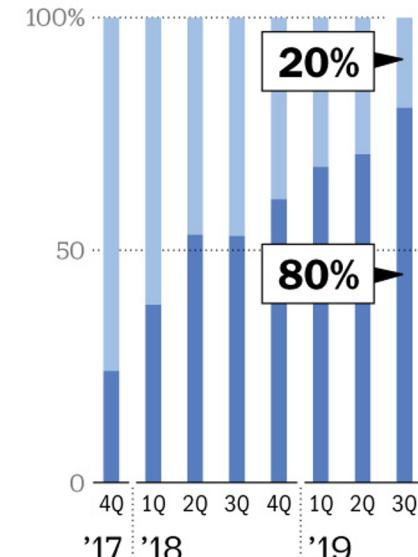
Hate speech on Facebook

Amount of hate speech acted on by Facebook



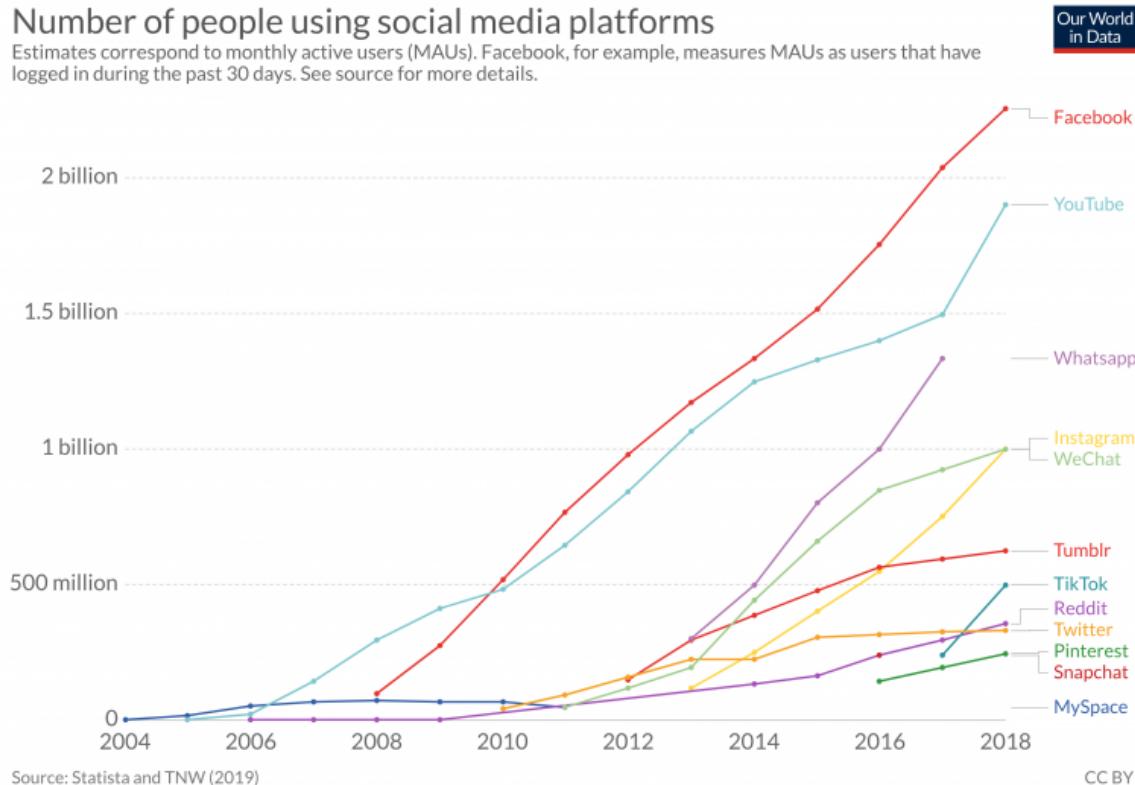
Of this, percentage flagged first by

■ USERS ■ FACEBOOK



SOURCES: FACEBOOK

Can we only rely on human moderators?



The human cost of flagging hate speech

When human annotators are charged with poring over hate speech and depictions or threats of violence, the results can be catastrophic.

In 2019, many human content moderators reported severe psychological trauma, PTSD, and one worker even committed suicide

[The Verge, 2019](#)

The logistic cost of flagging hate speech

The sheer volume of content that human moderators must process is impossible under even healthy conditions:

- 7 millions posts per quarter
- 28 million per year
- If one post requires ~10 seconds to moderate, this amounts to > 75,000 hours of emotionally draining labor per year.

“Automating” Hate Speech Detection?

Jews must be expelled, by force if need be	?
Jewish holidays occur on the same dates every year in the Hebrew calendar	?
African music consists of complex rhythmic patterns	?
Africans will always be savages	?

Note: Hate examples taken from the “Gab” Hate Corpus (GHC; Kennedy et al., 2020)

“Automating” Hate Speech Detection?

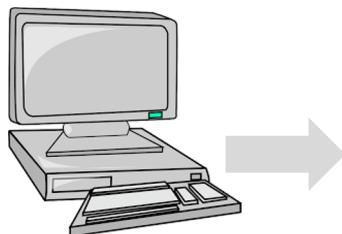
[Jews] must be expelled, by force if need be	Hate
Jewish holidays occur on the same dates every year in the Hebrew calendar	Not-hate
African music consists of complex rhythmic patterns	Not-hate
[Africans] will always be savages	Hate



Note: Hate examples taken from the “Gab” Hate Corpus (GHC; Kennedy et al., 2020)

“Automating” Hate Speech Detection?

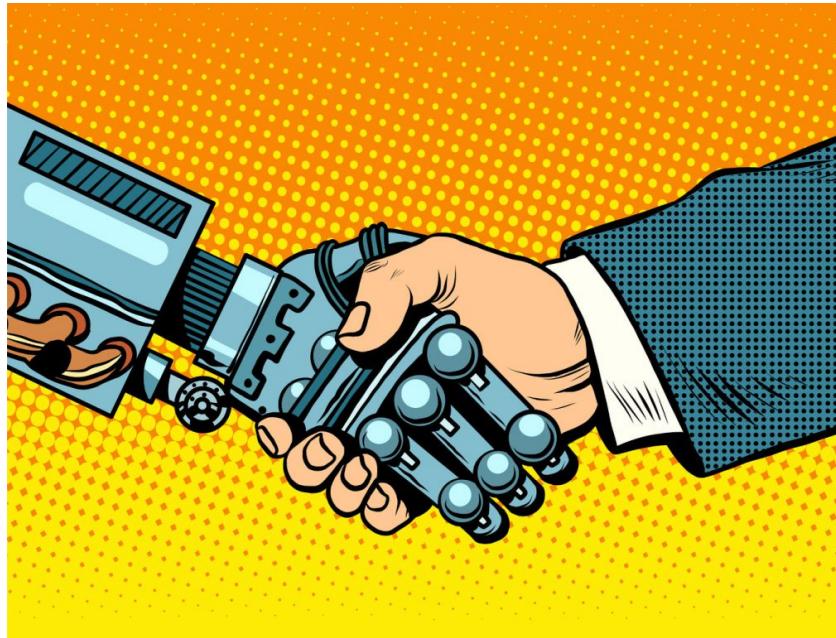
Instead of having human laborers label millions of messages, we build AI algorithms to detect hate speech



[Jews] must be expelled, by force if need be	Hate
Jewish holidays occur on the same dates every year in the Hebrew calendar	Not-hate
African music consists of complex rhythmic patterns	Not-hate
[Africans] will always be savages	Hate

Note: Hate examples taken from the “Gab” Hate Corpus (GHC; Kennedy et al., 2020)

How can AI (NLP) help on this problem?

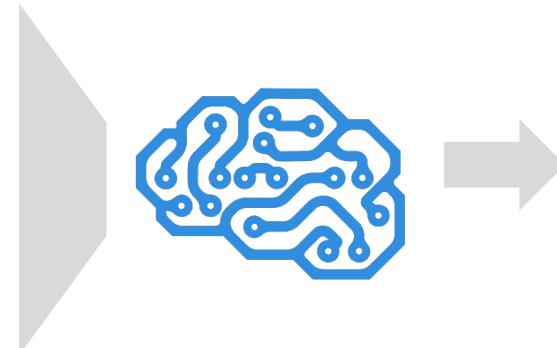


NLP for hate speech detection

Data collection

Text	Label
We respect the elderly	Non-hate
We respect the deaf	Non-hate
...	...
We hate the elderly	Hate

Model “training”

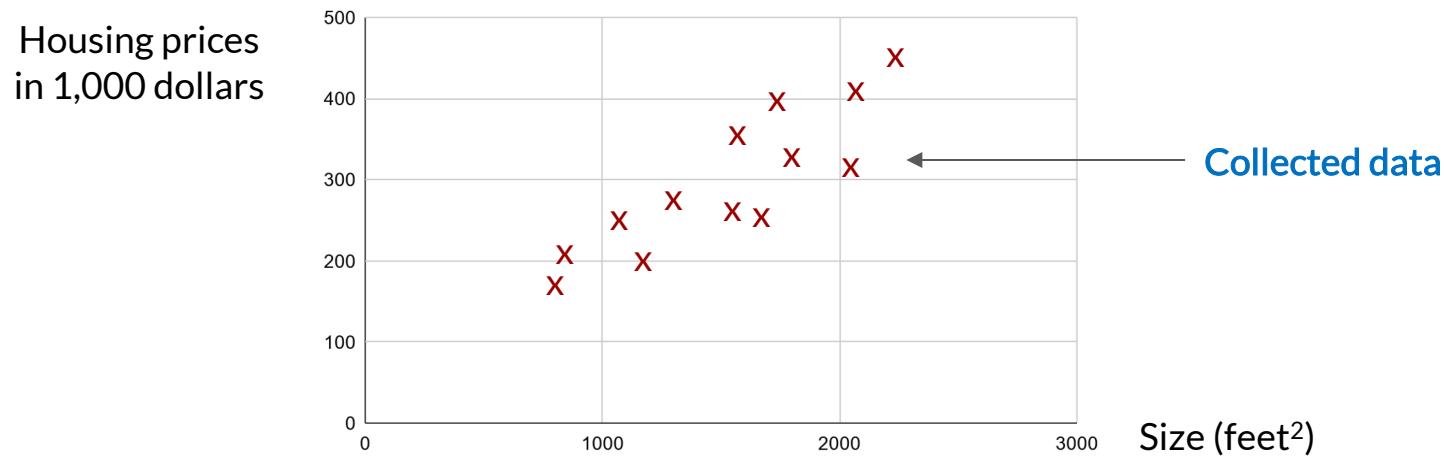


Prediction

We hate the deaf
Hate speech

The science and math in NLP

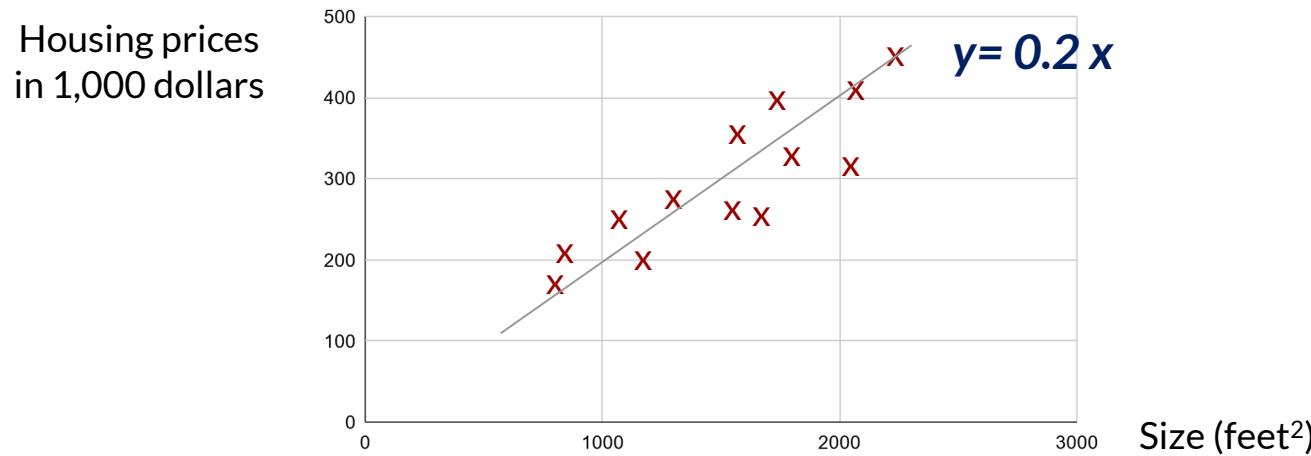
- Machine “learns” from experience/examples



Can we estimate the price of a house of size 1,000 feet²?

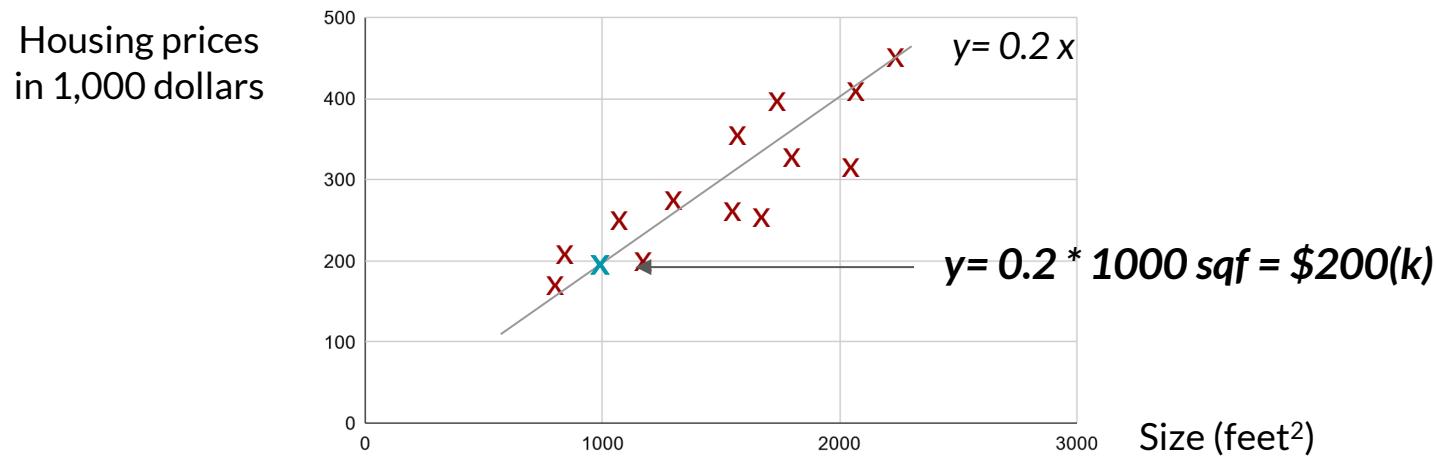
The science and math in NLP

- We can build a “model” using the collected data



The science and math in NLP

- With the model, we can **infer / predict** the housing price on the requested size



Similarly, we can predict whether the housing price is above \$200,000 or below (**classification**)

Similarly, for hate speech detection

- A model based on *word presence*
 - The prediction is sum of binary “weights” of the words in a sentence

$$y = w_{we}x_{we} + w_{the}x_{the} + w_{deaf}x_{deaf} + w_{elderly}x_{elderly} + w_{respect}x_{respect} + w_{hate}x_{hate}$$

Similarly, for hate speech detection

“We hate the **elderly**” →

Word	We	The	Deaf	Elderly	Respect	Hate
Presence (X)	1	1	1	0	0	1

$$y = w_{\text{we}} * 1 + w_{\text{the}} * 1 + w_{\text{deaf}} * 0 + w_{\text{elderly}} * 1 + w_{\text{respect}} * 0 + w_{\text{hate}} * 1$$

Similarly, for hate speech detection

A simple model:

Classify a sentence as “hate” if the word “hate” is mentioned in the sentence

Word	We	The	Deaf	Elderly	Respect	Hate
Weight (W)	0	0	0	0	0	1

Similarly, for hate speech detection

A simple model:

Classify a sentence as “hate” if the word “hate” is mentioned in the sentence

Word	We	The	Deaf	Elderly	Respect	Hate
Weight (W)	0	0	0	0	0	1

“We hate the elderly” →

$$y = w_{\text{we}} * 1 + w_{\text{the}} * 1 + w_{\text{deaf}} * 0 + w_{\text{elderly}} * 1 + w_{\text{respect}} * 0 + w_{\text{hate}} * 1$$

$$1 (\text{hate}) = 0 * 1 + 0 * 1 + 0 * 0 + 0 * 1 + 0 * 0 + 1 * 1$$

So, is hate speech detection “solved”?

Issues of hate speech detection models



Issues of hate speech detection models

- Some social group terms frequently co-occur with the “hate” sentences

Text	Label
We hate the elderly	Hate
Being elderly is awful	Hate
...	...

Bias in hate speech detection

the model performs differently on text related to different social groups, and the difference may cause harms to the corresponding group



I respect the **elderly**

I am an **elderly** person

Hate speech



Hate speech

Negative consequence of bias

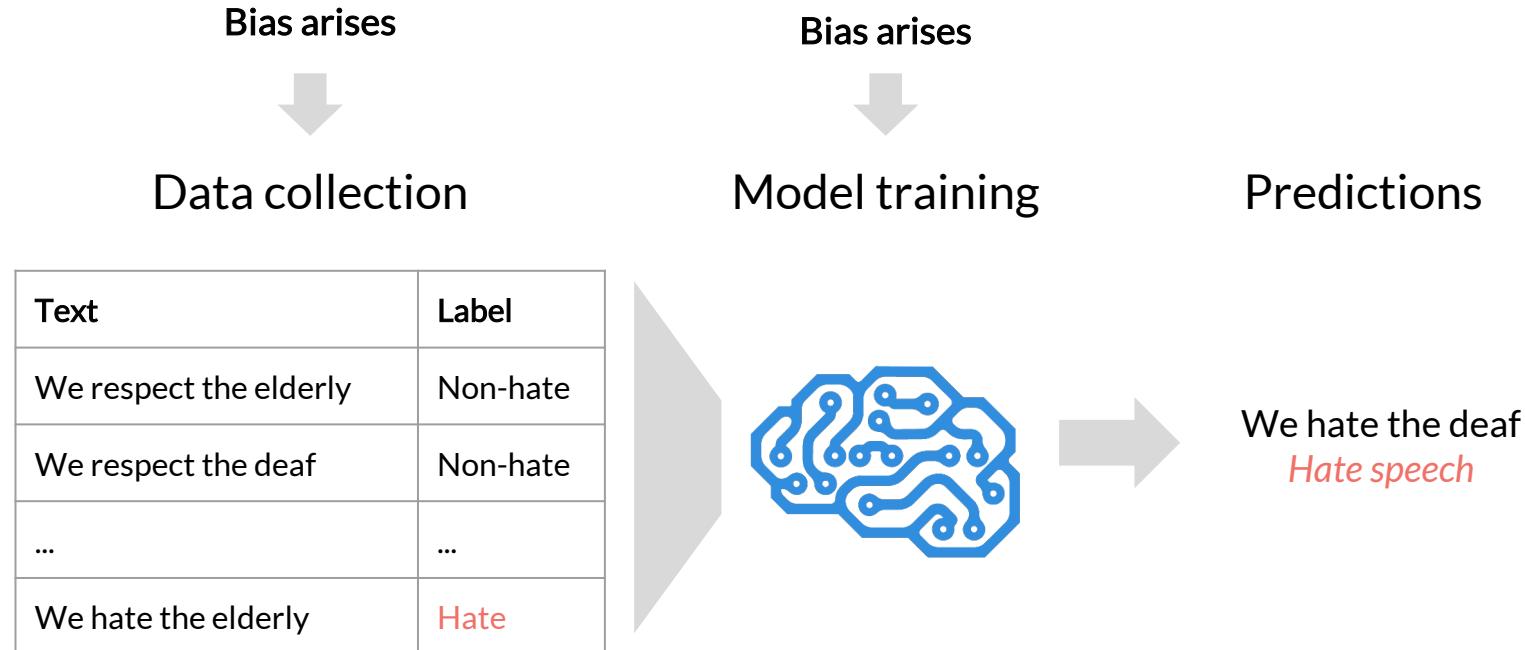
- **Disproportionate removal of posts**
mentioning / written by certain
communities, impeding their
participation in online platforms
- **Yield negative perceptions** of text
mentioning / written by certain
communities
- ...



Bias in hate speech detection - real world

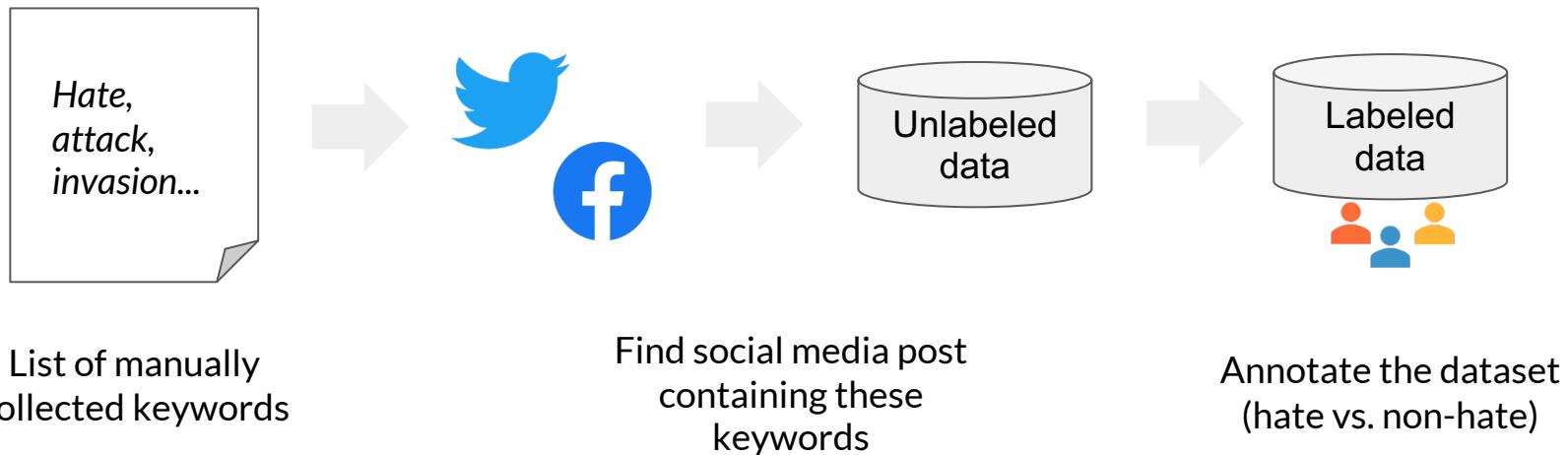
- Bias in hate speech detection is an **open problem**
- Even very powerful hate speech detectors
 - Classify **28% of New York Times articles** with social group names as hate speech
- Hate speech detectors can also be biased in many other ways
 - Overly sensitive to some dialects, mentions of gender identity, etc.

Where does bias arise?



Bias in data collection

- Hate speech is scarce in practice - to effectively constructing a hate speech detection dataset, data collection relies on a predefined set of **keywords**



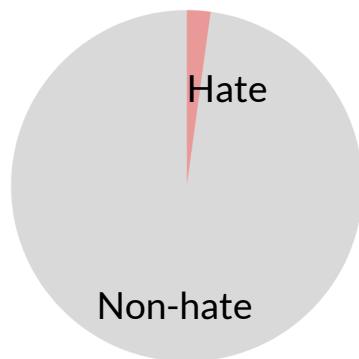
List of manually collected keywords

Find social media post containing these keywords

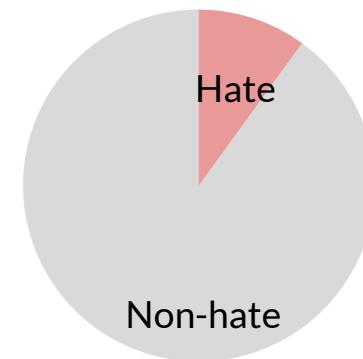
Annotate the dataset (hate vs. non-hate)

Bias in data collection

- The portion of hate speech related to a certain group can be higher / lower than the “real data distribution”



Real data mentioning “*elderly*” that are hate speech



Data mentioning “*elderly*” that are hate speech *in the collected data*

Bias in data collection

- Labels themselves can be incorrect



None of them are hate speech in right situations



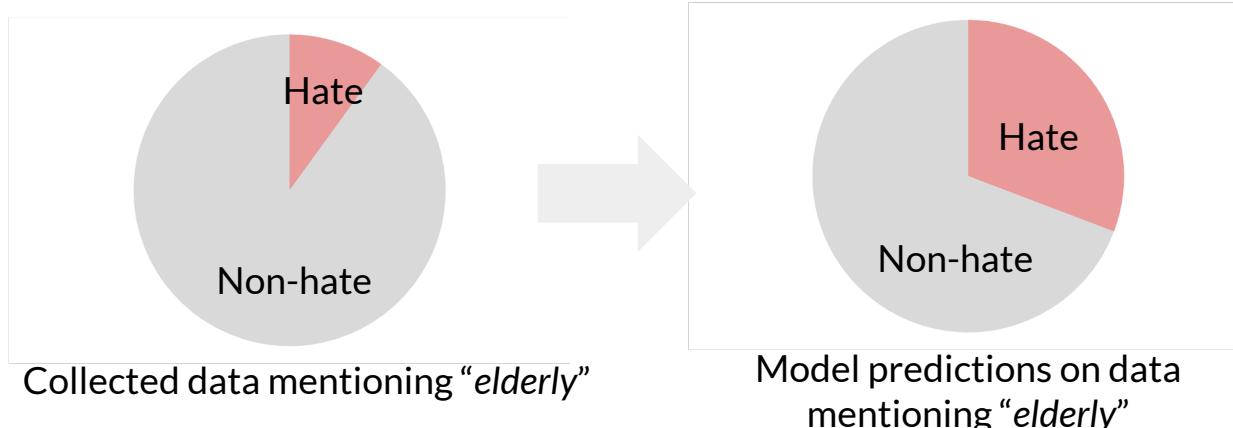
Annotators imagine speakers, audience, and situations by themselves



Model inherit mistakes from annotators

Bias in model training

- **Amplification of Bias**
 - Model may amplify a small differences in the dataset for different groups



Why?

It depends on multiple factors: the choice of model type, data distribution...

Mitigating bias in model

- While how bias arises is complicated, there can be (simple) ways to **mitigate bias**
- For example: reducing the weights of tokens related to some protected groups

Word	We	The	Deaf	Elderly	Respect	Hate
Weight	0	0	0	0	0	1

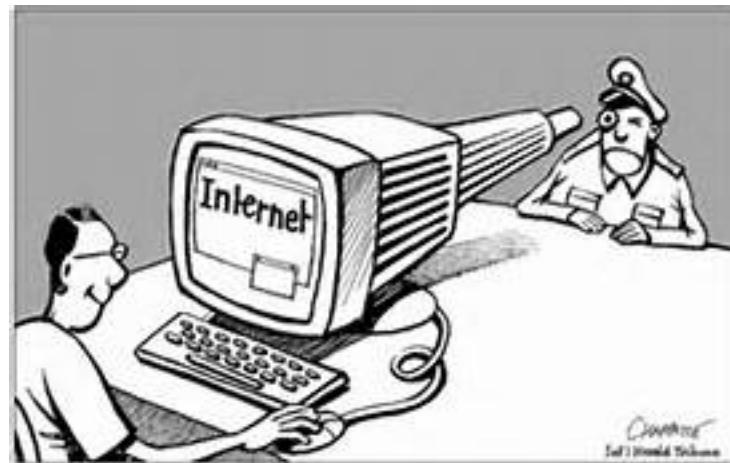


Fix weights as 0 for group related terms

Implications & Discussion

Issues of automatic hate speech detection

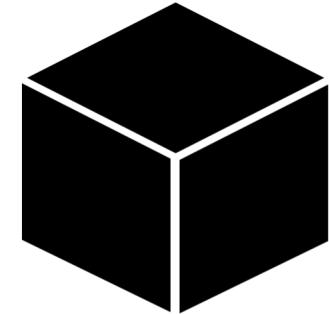
- Bias in hate speech detection model will cause negative societal impact
- Freedom of speech?



NLP models are like “black box”

Today's NLP models are often called “Black Boxes”:

- They learn “features” and their “weights” from data and can perform very well, but often it is hard to understand *how* they are performing so well



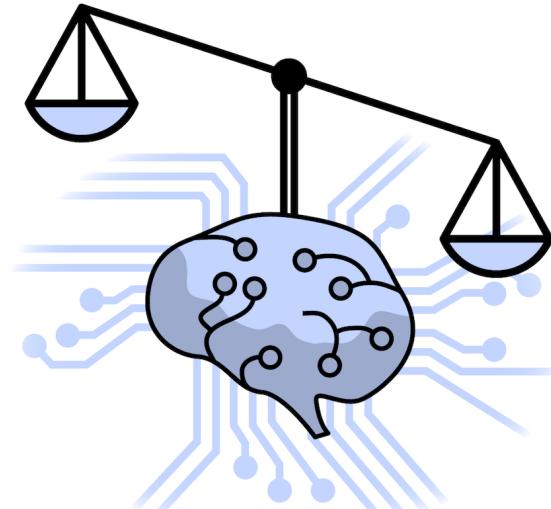
Emerging topics:

- Explaining what the models are doing --> open the black box
- Examine the potential bias in the model
- Mitigate the bias

"Fairness" of NLP models

Take **bias and fairness** as major metrics for evaluating a model

- instead of pursuing only accuracy



FAQ

xiangren@usc.edu