Hate Alert

IDSS
MIT INSTITUTE FOR DATA, SYSTEMS, AND SOCIETY

Hate speech: Detection, Mitigation and beyond

Tutorial at ICWSM 2021

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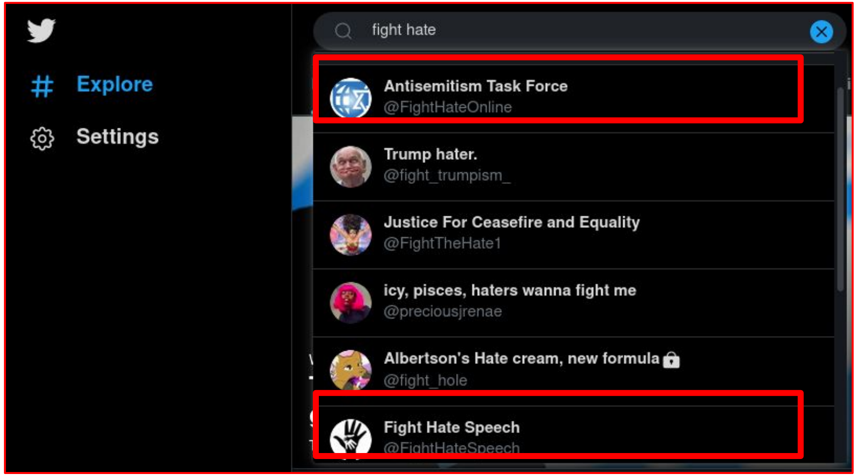
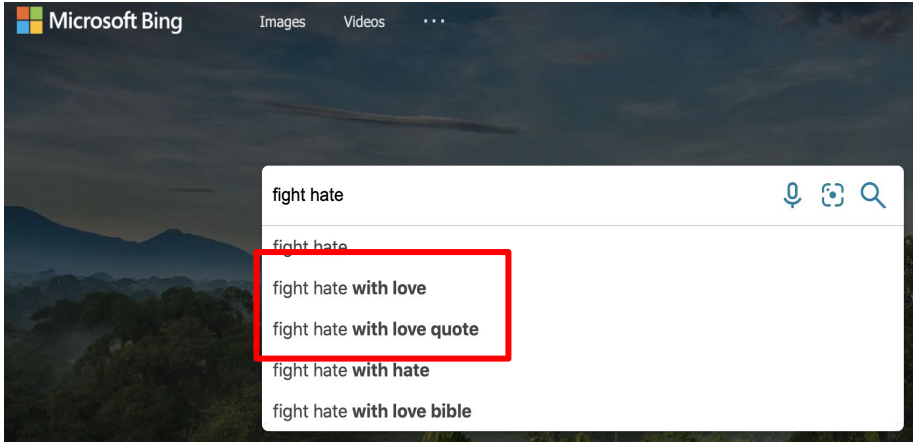
Find more about us here!
https://hate-alert.github.io/

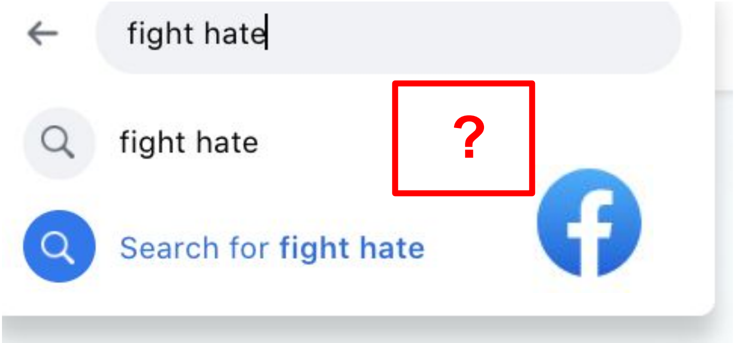
“

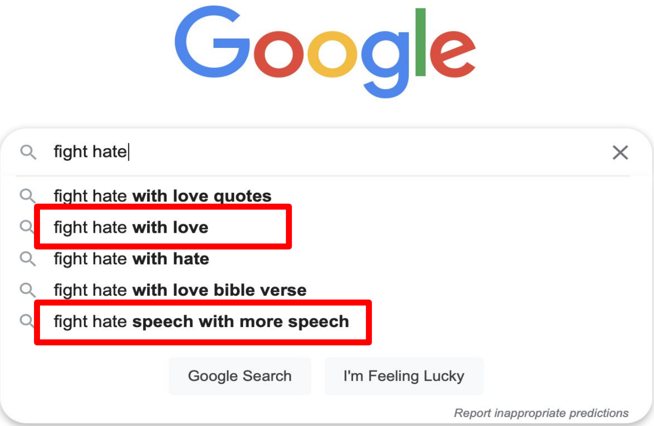
⚠️ This presentation contains material that many will find **offensive** or **hateful**; however this cannot be avoided owing to the nature of the talk.

Hate speech: A growing concern?



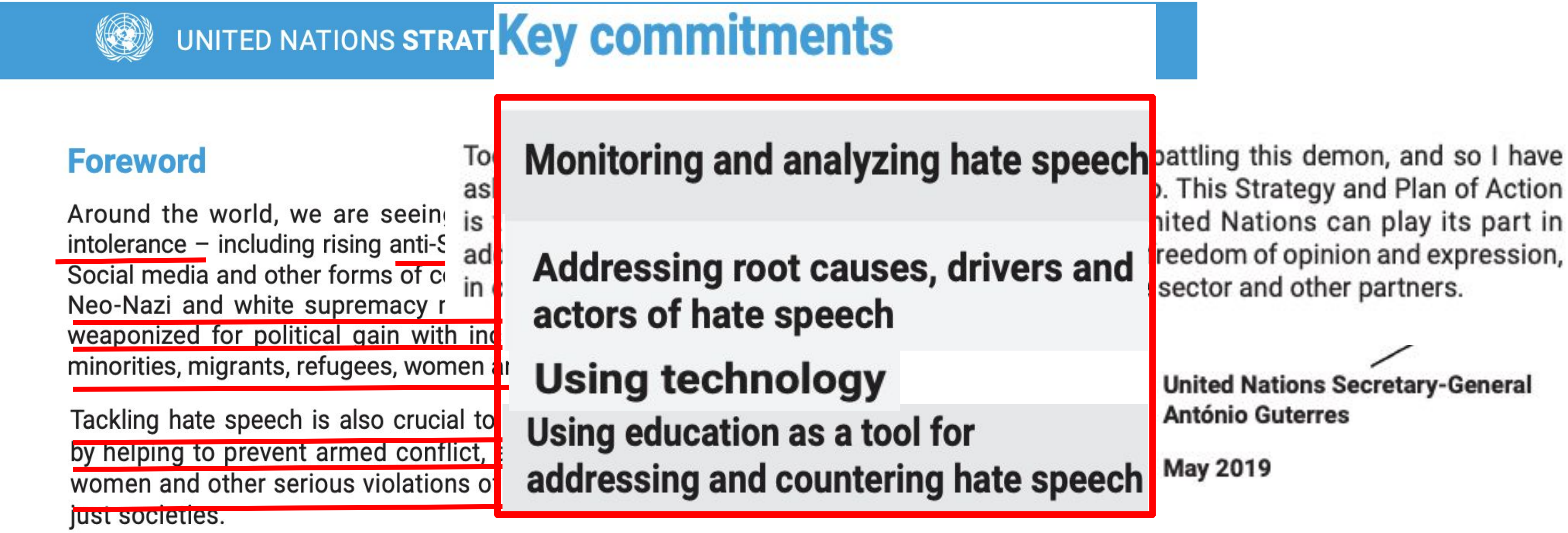






What to expect from this tutorial?

- What is the problem? Is it really important? How deep are the repercussions?



What to expect from this tutorial?

- Tutorial Part I:
  - **UN Key Commitment:** **Monitoring and analysing hate speech**
- How does hate speech **spread** in the online world?
- Can one comment on the **speed** and the **depth** using computational approaches?
- What are the long lasting effects?

What to expect from this tutorial?

- Tutorial Part II:
  - UN Key Commitment: **Addressing the root causes/drivers/technology**
- What could be the first step to handle this issue? Can we **detect** hate speech using computer algorithms?
- Can the detection results obtained from the model be **explained**?
- Are there **biases** in evaluation? Of what sort?

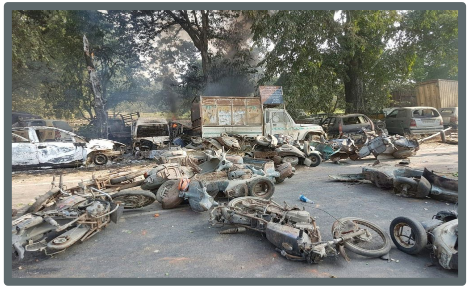
What to expect from this tutorial?

- Tutorial Part III:
  - UN Key Commitment: **Countering hate speech**
- How does one contain online hate?
- Conflicts with freedom of speech?
- Can one use more speech to counter hate speech (aka **counterspeech**)?
- Is counterspeech generic or specific to target communities?
- Can one use technology to **automatically generate** counterspeech?

What to expect from this tutorial?

- Bonus:
  - SWOT analysis
  - Resources: A topically organised notion page consisting of publications, links to codes and dataset.
  - Some hands-on.

Negative consequences



Bulandshahr Violence

Pittsburg Shooting

Christchurch Shooting

Rohingya Genocide

Sri Lanka Riots

Delhi Riots

Related tutorials

- [The battle against online harmful information: The cases of fake news and hate speech CIKM '20]

- [Characterization, Detection, and Mitigation of Cyberbullying, ICWSM '18]

Table of contents

Working definition of hate speech

Direct and **serious attacks** on any **protected category of people** based on their **race, ethnicity, national origin, religion, sex, gender, sexual orientation, disability or disease**

Directed hate: hate language towards a **specific individual** or **entity**.
Example "*@usr4 your a f*cking queer f*gg*t b*tch*".

Generalized hate: hate language towards a **general group of individuals who share a common protected characteristic**, e.g., ethnicity or sexual orientation.
Example: "*— was born a racist and — will die a racist! — will not rest until every worthless n*gger is rounded up and hung, n*ggers are the scum of the earth!! wPww WHITE America*".

Harmful content online -- a taxonomy

What we will be covering in this tutorial.

Concept	Definition of the concept	Distinction from hate speech
Hate	Expression of hostility without any stated explanation for it [68].	Hate speech is hate focused on stereotypes, and not so general.
Cyberbullying	Aggressive and intentional act carried out by a group or individual, using electronic forms of contact, repeatedly and over time, against a victim who can not easily defend him or herself [10].	Hate speech is more general and not necessarily focused on a specific person.
Discrimination	Process through which a difference is identified and then used as the basis of unfair treatment [69].	Hate speech is a form of discrimination, through verbal means.
Flaming	Flaming are hostile, profane and intimidating comments that can disrupt participation in a community [35]	Hate speech can occur in any context, whereas flaming is aimed toward a participant in the specific context of a discussion.
Abusive language	The term abusive language was used to refer to hurtful language and includes hate speech, derogatory language and also profanity [58].	Hate speech is a type of abusive language.
Profanity	Offensive or obscene word or phrase [23].	Hate speech can use profanity, but not necessarily.
Toxic language or comment	Toxic comments are rude, disrespectful or unreasonable messages that are likely to make a person to leave a discussion [43].	Not all toxic comments contain hate speech. Also some hate speech can make people discuss more.
Extremism	Ideology associated with extremists or hate groups, promoting violence, often aiming to segment populations and reclaiming status, where outgroups are presented both as perpetrators or inferior populations. [55].	Extremist discourses use frequently hate speech. However, these discourses focus other topics as well [55], such as new members recruitment, government and social media demonization of the in-group and persuasion [62].
Radicalization	Online radicalization is similar to the extremism concept and has been studied on multiple topics and domains, such as terrorism, anti-black communities, or nationalism [2].	Radical discourses, like extremism, can use hate speech. However in radical discourses topics like war, religion and negative emotions [2] are common while hate speech can be more subtle and grounded in stereotypes.

Fortuna et al. 2018

Hate speech in different contexts

- Targets of hate speech depends on **platform**, **demography** and **language & culture** (Mondal, 2017 and Ousidhoum, 2020)
- Focused research on characterising such diverse types.
  - **Racism** against blacks in Twitter (Kwok, 2013)
  - **Misogyny** across manosphere in Reddit (Farell, 2019)
  - **Sinophobic** behaviour w.r.t COVID-19 (Schild, 2021)
- Often becomes part of different communities
  - **Genetic Testing** Conversations (Mittos, 2020)
  - **QAnon** Conversations (Papasavva,2021)

Analysis and Spread

- Definitions and related concepts
- Analysis of hate speech
  - Prevalence
  - Effect
- Detection of hate speech
  - Datasets
  - Traditional methods
  - Sequential models
  - Transformer based models
  - Challenges
- Mitigation of hate speech
  - Campaigns
  - Counterspeech detection
  - Counterspeech generation
- SWOT analysis

Prevalence of hate speech

- Moderation free platforms like Gab, 4chan and Bitchute preferred.

gab =

4chan =

BITCHUTE =

Inside the UK-based site that has become the far right's YouTube

BitChute describes itself as a 'free speech' website but report accuses it of platforming 'hate and terror', Lizzie Dearden reports

Internet Culture

Gab, the social network that has welcomed Qanon and extremist figures, explained

Gab, a social-networking site popular among the far right, seems to be capitalizing on Twitter bans and Parler being forced offline. It says it's gaining 10,000 new users an hour.

Prevalence of hate speech

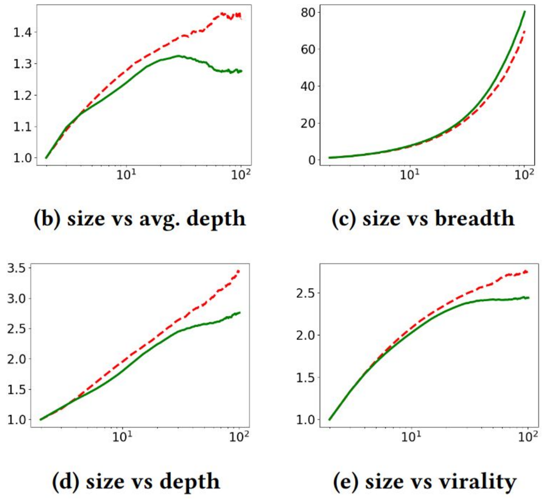
- **Gab**
- In Gab, early signals show **Alt-right**, **BanIslam** as popular hashtags (Zannettou,2018)

Hashtag	(%)	Mention	(%)
MAGA	6.06%	a	0.69%
GabFam	4.22%	TexasYankee4	0.31%
Trump	3.01%	Stargirlx	0.26%
SpeakFreely	2.28%	YouTube	0.24%
News	2.00%	support	0.23%
Gab	0.88%	Amy	0.22%
DrainTheSwamp	0.71%	RaviCrux	0.20%
AltRight	0.61%	u	0.19%
Pizzagate	0.57%	BlueGood	0.18%
Politics	0.53%	HorrorQueen	0.17%
PresidentTrump	0.47%	Sockalexis	0.17%
FakeNews	0.41%	Don	0.17%
BritFam	0.37%	BrittPettibone	0.16%
2A	0.35%	TukkRivers	0.15%
maga	0.32%	CurryPanda	0.15%
NewGabber	0.28%	Gee	0.15%
CanFam	0.27%	e	0.14%
BanIslam	0.25%	careyetta	0.14%
MSM	0.22%	PrisonPlanet	0.14%
1A	0.21%	JoshC	0.12%

Dataset: collected 22M posts from 336k users, between August 2016 and January 2018
Method: Frequency count

Prevalence of hate speech

- **Gab**
- In Gab, early signals show **Alt-right**, **BanIslam** as popular hashtags. (Zannettou,2018)
- The posts of hateful users diffuse significantly **farther**, **wider**, **deeper** and **faster** than the non hateful users. (Mathew, 2019)



X-axis vs Y-axis

Dataset: collect 21M posts from 340k users, between August 2016 and January 2018
Method: Hate user extraction + diffusion method on repost network

Prevalence of hate speech

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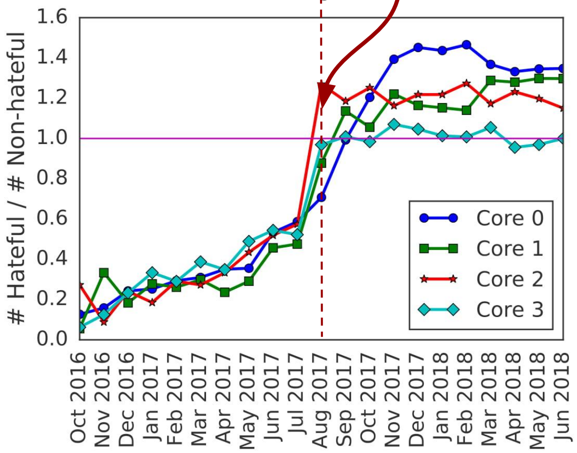
- The posts of hateful users diffuse significantly **farther**, **wider**, **deeper** and **faster** than the non hateful users.(Mathew, 2019)
- Further, **fraction of hateful users** in inner core increased through time in Gab (Mathew, 2020)

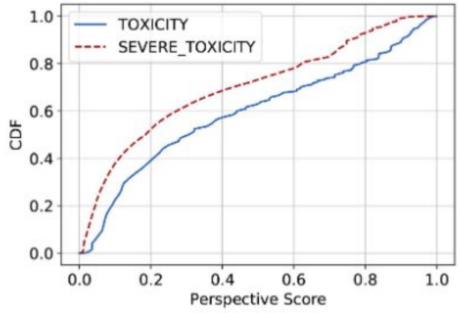
Unite the right rally
White supremacist rally at Charlottesville, Virginia

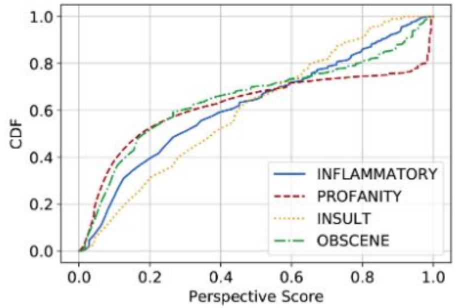


Dataset: collect 21M posts from 340k users, between August 2016 and January 2018
Method: Hate user extraction + Temporal k-core analysis

Prevalence of hate speech

- 4chan
- In 4chan's /pol/ thread (Papasavva,2020)
    - 37% → TOXICITY
    - **27% → SEVERE TOXIC**
    - 36% → INFLAMMATORY
    - 33% → PROFANITY
    - 35% → INSULT
    - 30% → OBSCENE





Dataset: Crawling from 4chan's /pol/ thread, June 29, 2016 to November 1, 2019.
Method: Perspective api then CDF

Prevalence of hate speech

- Bitchute
- In Bitchute-
  - 75% of the comments are hate speech
  - 21% of the videos have hate speech as a comment.
- Only 12% channels (in green) receive 87% comments. Out of this **55% are hate speech** (Trujilo,2020)

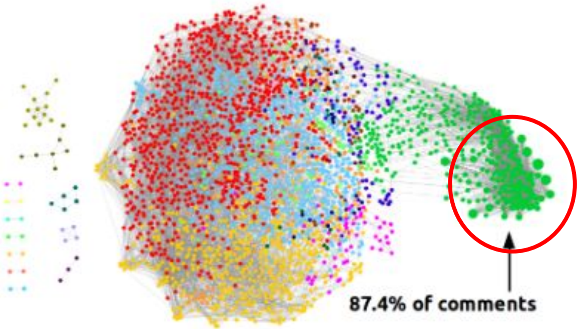


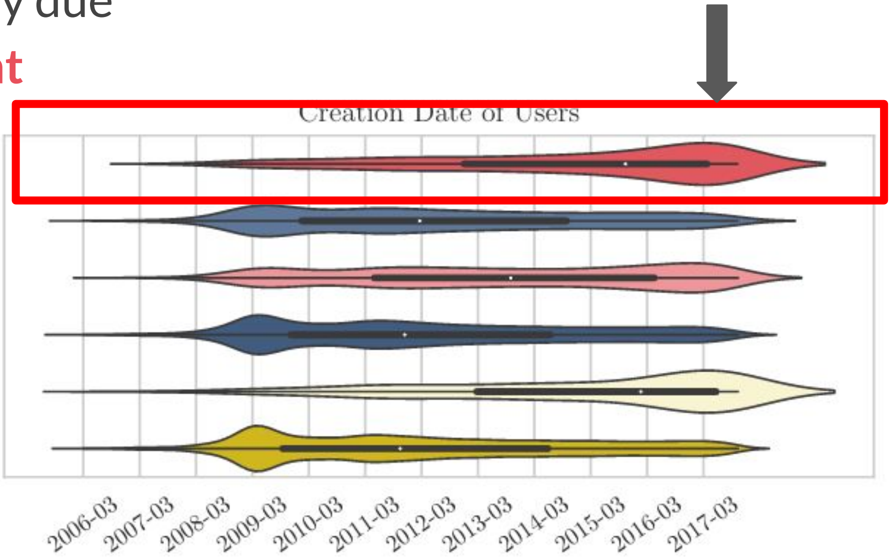
Figure 3: The layout is created using Allegro Edge-Repulsive Clustering in Cytoscape [23]

Dataset: 854K comments from 38K unique commenters
Method: Each node is a channel, edge represent commenters overlap. Community detection using modularity.

Prevalence of hate speech (Platforms with moderation)

Study on characterising hateful users in Twitter
(Riberio,2018)

- Spread of hatespeech difficult to study due to moderation of **hateful user/content**



Dataset: Data collected from Twitter, keyword based extraction
Method: Degroot method. Frequency based analysis

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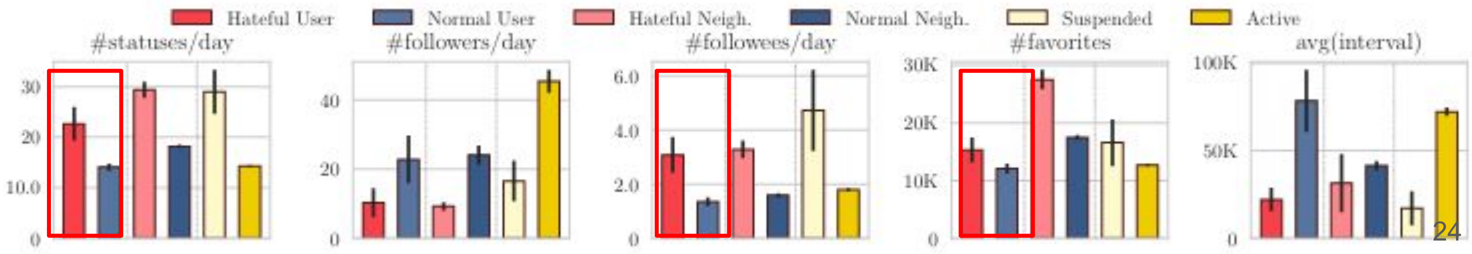

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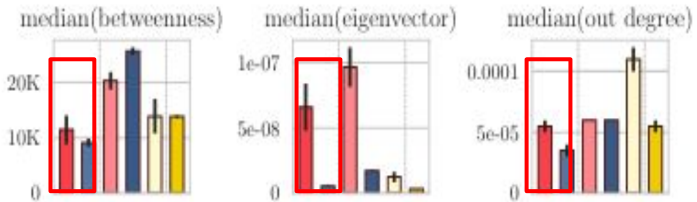
- Median hate user is **more central** to the network



Prevalence of hate speech (Platforms with moderation)

- Study on misogyny in reddit [(Farrell,2019)]
- ***r/Braincels*** was the main subreddit after ***r/incel*** was banned in 2015

Dataset: Pushshift reddit, lexicons, incel subreddits
Method: Degroot method. Frequency based analysis

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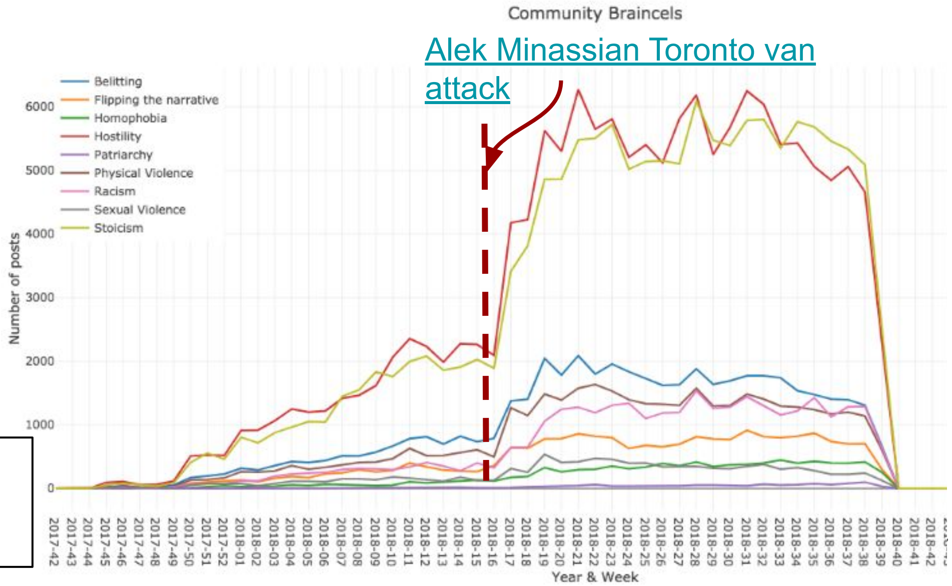
- *r/Braincels* was the main subreddit after *r/incel* was banned.
- **Increase** in misogynistic content across all categories after April’18



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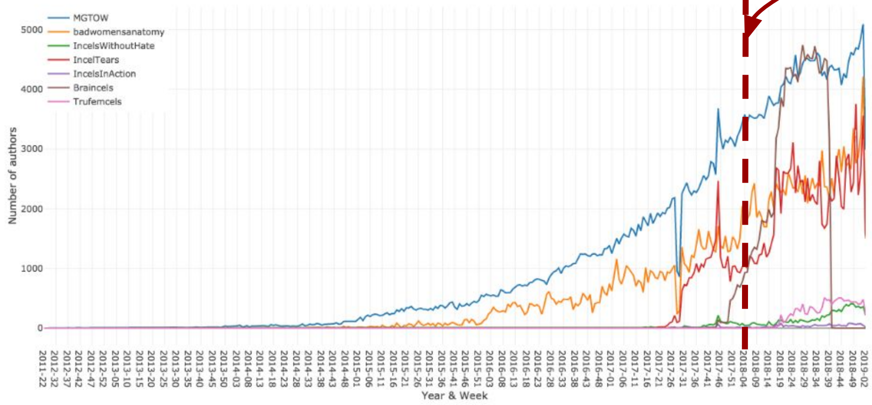
Prevalence of hate speech (Platforms with moderation)

- Study on misogyny in Reddit [(Farrell,2019)]
- *r/Braincels* was the main incel after *r/incel* was banned.
- **Increase** in misogynistic content across all categories after April'18
- **Users joining** in r/Braincels had a **sudden increase** after April'18

[Alek Minassian Toronto van attack]



Dataset: Pushshift reddit, lexicons, incel subreddits
Method: Degroot method. Frequency based analysis

Targets of hate speech

- Proportion of hate speech towards a target may vary across platforms. (Silva 2016)

Twitter		*Whisper*	
Categories	**% posts**	**Categories**	**% posts**
Race	48.73	Behavior	35.81
Behavior	37.05	Race	19.27
Physical	3.38	Physical	14.06
Sexual orientation	1.86	Sexual orientation	9.32
Class	1.08	Class	3.63
Ethnicity	0.57	Ethnicity	1.96
Gender	0.56	Religion	1.89
Disability	0.19	Gender	0.82
Religion	0.07	Disability	0.41
Other	6.50	Other	12.84

Table 4: Hate categories distribution.

Dataset: Crawling with a given template from whisper and twitter
Method: Target based keyword extraction

Targets of hate speech

- Proportion of hate speech towards a target may vary across platforms. (Silva, 2016)
- Recent study found difference in framing of hate groups towards different targets (Phadke,2021)
    - Diagnostic
    - Prognostic
    - Motivation

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  - Prognostic
  - Motivation

Here the main problem is identified

For e.g for climate change:
“The main problem behind climate change is inaction and silence”
- Greta Thunberg

Murray, Sofia. *"Framing a Climate Crisis: A descriptive framing analysis of how Greta Thunberg inspired the masses to take to the streets."* (2020).

Targets of hate speech

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    - **Prognostic**
    - Motivation

Here the solution to the problem is identified

For climate change:
"We want you to follow the Paris agreement and the IPCC reports…"

- Greta Thunberg

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Targets of hate speech

- Proportion of hate speech towards a target may vary across platforms. (Siilva, 2016)
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    - Diagnostic
    - Prognostic
    - **Motivation**

Here the motivation for finding solution is identified

For climate change:
"I want you to panic, I want you to feel the fear I feel every day…"
- Greta Thunberg

Murray, Sofia. *"Framing a Climate Crisis: A descriptive framing analysis of how Greta Thunberg inspired the masses to take to the streets."* (2020).

Targets of hate speech

- Proportion of hate speech towards a target may vary across platforms. (Siilva, 2016)
- Recent study found difference in framing of posts by hate groups towards different targets (Phadke,2021).

Anti-muslim hate groups

Diagnostic framing as **oppression**

"Wow... Muslim prison gangs are forcing inmates to convert and follow religious practices or face violent repercussions"

Anti-LGBT hate groups

Diagnostic framing as **immorality** and oppression

"Homosexuality is a socially immoral act in our society."

Dataset: 1440 post from 72 groups from Twitter and Facebook
Method: Framing based coding

Targets of hate speech

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Anti-muslim hate groups

Prognostic framing as **policy changes**

“ilhanomar has connections with cair supporting hamas terrorists. Sign our petition demanding her resignation and share with everyone!”

Anti-LGBT hate groups

Prognostic framing as **call for membership** and policy change

“Come and meet like-minded people … We want to restore honor, respect, civility…”

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Anti-muslim hate groups

Motivational framing as **fear**

"The movement is worse than you think, and it's entrenched in our culture, government, media, our corporations and into our churches.."

Anti-LGBT hate groups

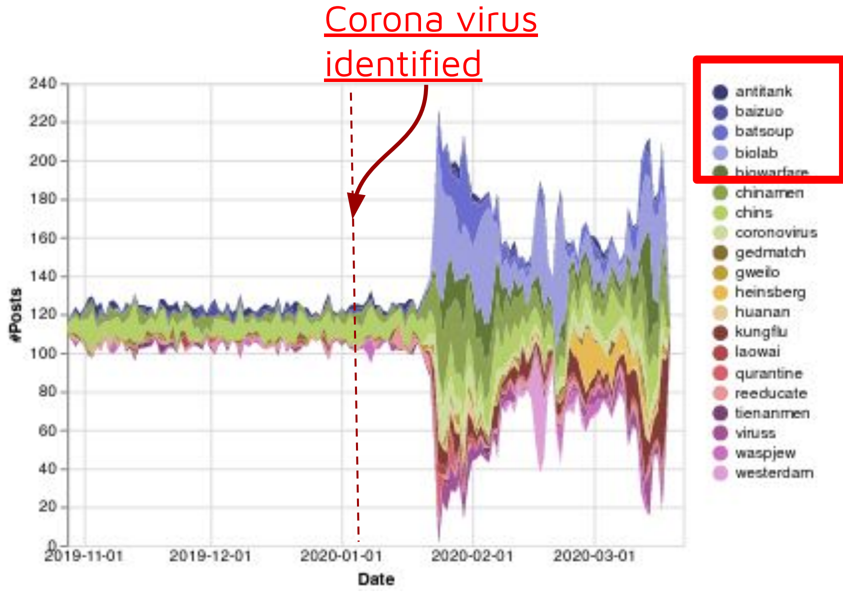
Motivational framing as **fear**

"If the "Equality Act" becomes law, women and girls would instantly forfeit equality rights and opportunities gained over decades."

Dataset: 1440 post from 72 groups from Twitter and Facebook
Method: Framing based coding

Targets of hate speech

- Proportion of hate speech towards a target may vary across platforms. (Mondal,2016)
- Recent study found difference in framing of posts by hate groups towards different targets (Phadke,2021).
- One major problem in studying hate speech is emerging of new racial slurs - **sinophobia due to COVID-19** (Tahmasbi,2021)



Dataset: Data collected from Twitter and 4chan
Method: word2vec model used to find new words.

Effect of hate speech

- It is important to understand the **psychological effect** of hate speech

Dataset: Interviews with the participants, hate speech (anti-semtism and anti-gay) statements shown as stimulus
Method: Frequency of different codes followed by significance analysis.

Effect of hate speech

- It is important to understand the **psychological effect** of hate speech
- **Pre-social media -** Interview based study revealed **short-term** → **emotional** & **long term** → **attitudinal** (Leets, 2002)

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- **Ignorance** and **repressed hostility** were most common speculated motives(Leets, 2002).

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Effect of hate speech

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- **Ignorance** and **repressed hostility** were most common speculated motives(Leets, 2002).
- Most participants prefer **passive response** (Leets, 2002).

Dataset: Interviews with the participants, hate speech (anti-semtism and anti-gay) statements shown as stimulus
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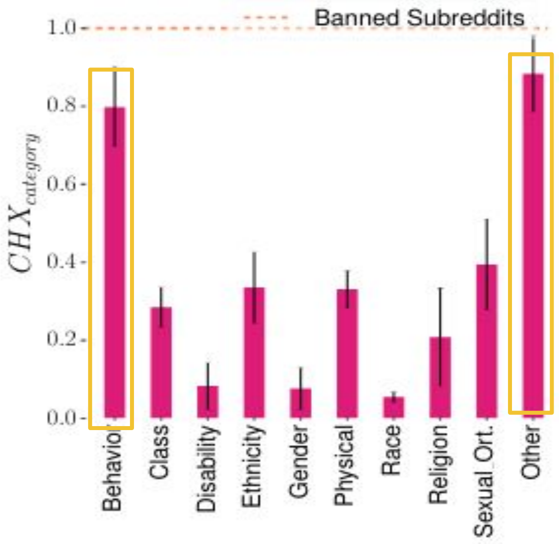
Effect of hate speech

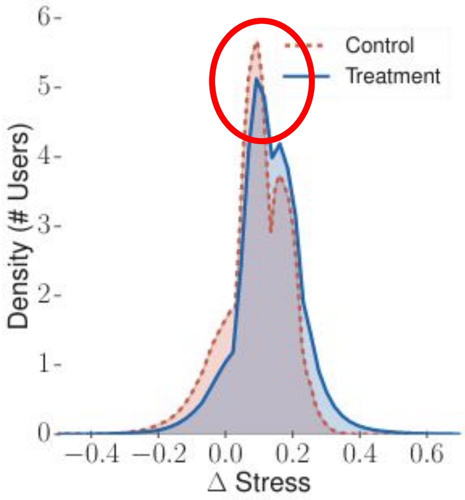
- In a large scale study, the authors found prevalence of hate speech in **college subreddits**. (Saha, 2019)



(a)

Effect of hate speech

- In a large scale study, the authors found prevalence of hate speech in **college subreddits.** (Saha, 2019)
- **Significant difference** exist between the hate exposed (treatment) and not hate exposed group's (control) stress level. (Saha, 2019)



Dataset: Subreddits of different college groups
Method: Hate identifying using keywords, Stress detector used to measure stress between hate exposed vs not group

Dataset: Interviews with the participants based on anti-LGBT hate speech
Method: Coding strategy with significance analysis

Effect of offline events

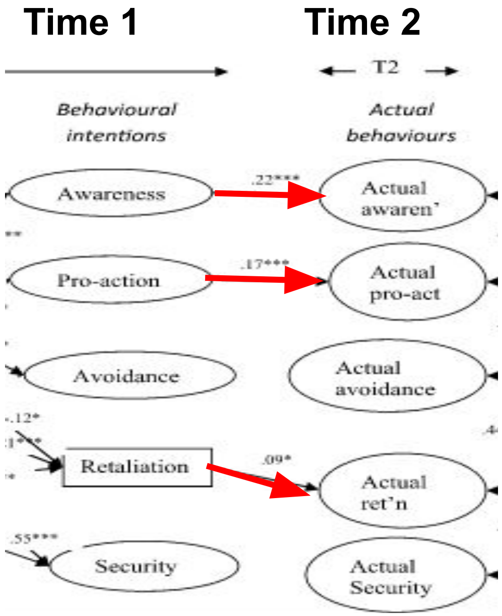
- An interview based further looked into the pathways of effect and response in a longitudinal study of impact of hate crimes (Patterson, 2018)
- Direct victims were **less empathetic** towards other victims.

Effect of offline events

Dataset: Interviews with the participants based on anti-LGBT hate speech
Method: Coding strategy with significance analysis

- An interview based looked into the pathways of effect and response in a longitudinal study of impact of **hate crimes** (Patterson, 2018)
- Direct victims were **less empathetic** towards other victims.
- Longitudinal study show not all **behavioural intentions** transformed to **actual actions**

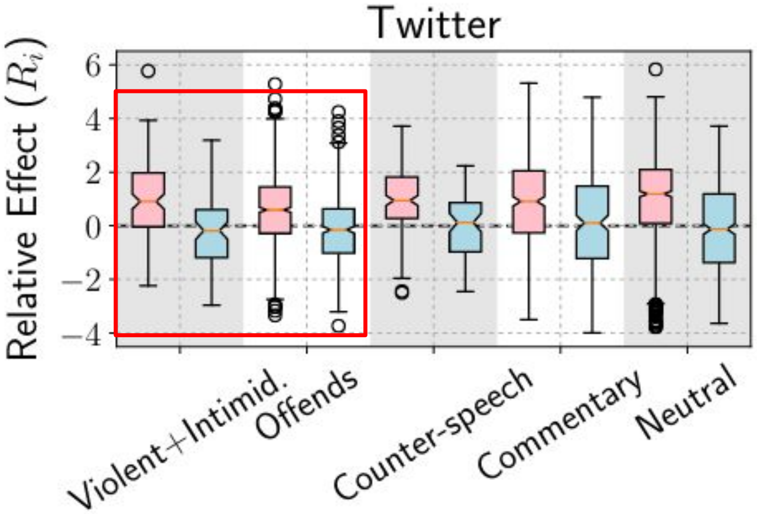
Gap of 3 months



Effect of offline events

Dataset: Collected from twitter using islamic keywords
Method: Framing annotations with impact analysis

- A study on different social media platforms measured the effect of **hate crime** and **terrorism** on **hate** and **counter speech** (Olteanu, 2018).
- Terms with violence and offense increased after **terrorism** but **not after hate crime**



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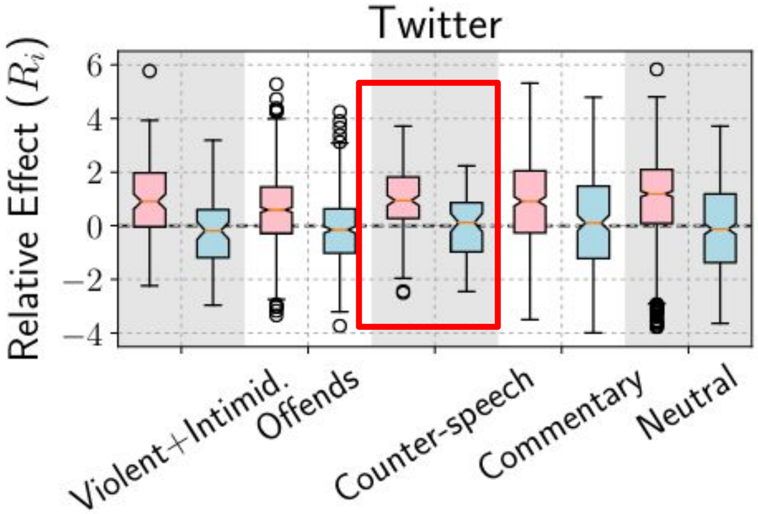
- Terms with violence and offense increased after terrorism but not after hate crime
- Terms with counterspeech increased after terrorism but not after hate crime



Detecting Hate Speech

- Definitions and related concepts
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    - Campaigns
    - Counterspeech detection
    - Counterspeech generation
    - Effect of counter speech
- SWOT Analysis

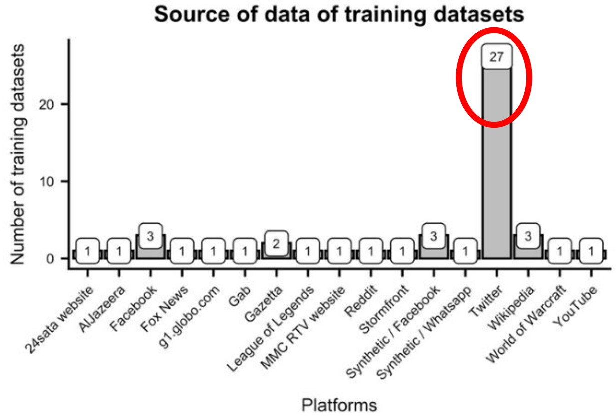
Datasets

- Different datasets have different **taxonomies**.
    - Binary classification (hate/not, targeting group or not) [(Zampieri,2019)]
    - Specific binary (Misogyny/not, Racism/not) ([Pamungkas, 2020])
    - Multiclass/labels datasets. ([Davidson,2017] , [Basile,2019])

Vidgen B, Derczynski L (2020) *Directions in abusive language training data, a systematic review: Garbage in, garbage out*. PLoS ONE 15(12): e0243300. https://doi.org/10.1371/journal.pone.0243300.

Datasets

- Different datasets have different **taxonomies**.
- Different datasets have different **sources**.
  Twitter is one of the major sources.
  - The works by Davidson ([Davidson,2017]) and Founta ([Founta, 2018]) are two highly used dataset from Twitter
  - Twitter is easily accessible.
  - Alt-right platforms are often taken down, hence studies are limited ([Voat], [Parler])



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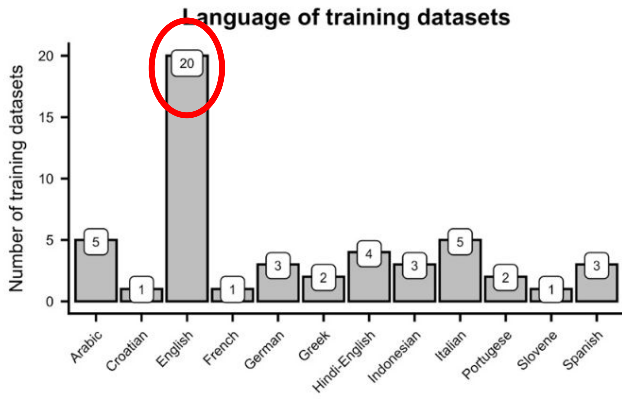
Datasets

- Different datasets have different **taxonomies.**
- Different datasets have different **sources.** Twitter is one of the major sources.
- Different datasets have different **languages**, English being the prominent one.
    - Arabic (Mulki,2019), Italian (Sanguinetti,2018), Spanish (Basile,2019) and Indonesian (Ibrohim,2019) has more than 3 datasets
    - Quality is often questionable for these datasets.
    - Can we benefit from english language datasets ?



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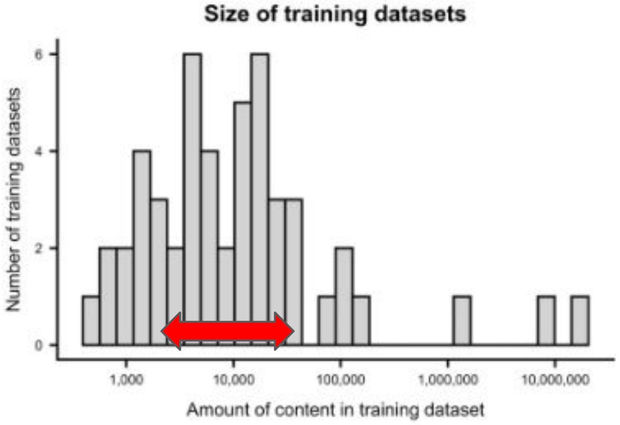
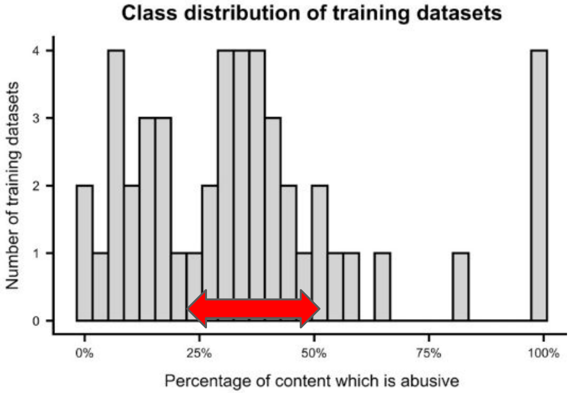
Datasets

- Different datasets have different **taxonomies.**
- Different datasets have different **sources.** Twitter is one of the major sources.
- Different datasets have different **languages**, English being the prominent one.
- **Training size** and **amount of hate/abuse** also varies across datasets





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Earlier Detection Methods

- Features used :-
  - TF-IDF vectors
  - Parts-of-speech tags
  - Linguistic features
    - Sentiment lexicons
    - Frequency counts of URL, username
    - Readability scores

(Davidson,2017)

Earlier Detection Methods

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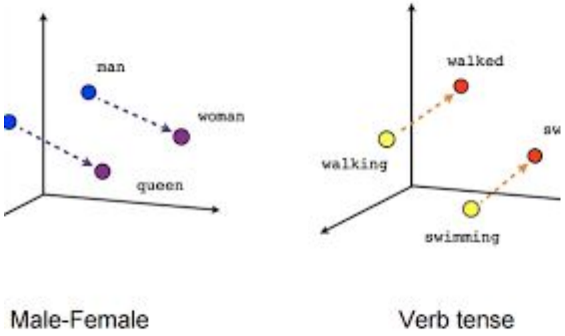
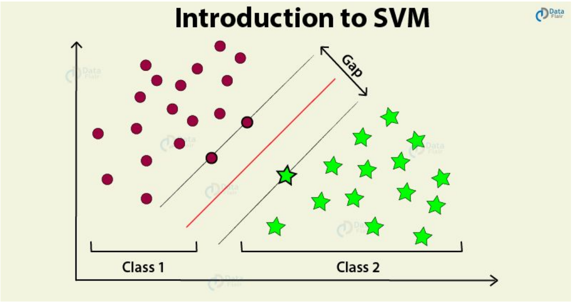
  - TF-IDF vectors
  - Parts-of-speech tags
  - Linguistic features
    - Sentiment lexicons
    - Frequency counts of URL, username
    - Readability scores

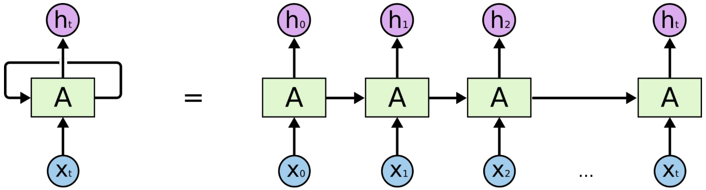
    (Davidson,2017)
  - **Word embeddings**
    - Twitter word embeddings (Zimmerman, 2018). Click here
  - **Sentence embeddings**
    - Google's universal embeddings (Saha, 2018). Click here



Earlier Detection Methods

- Features used
- Detection method
  - Logistic regression
  - **SVM** (Canós,2018)
  - XGboost (Saha, 2018)
  - **LSTM/GRU** (Gao,2017)
  - CNN-GRU (Zhang, 2018)





Earlier Detection Methods

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  - SVM ([Canós,2018](#))
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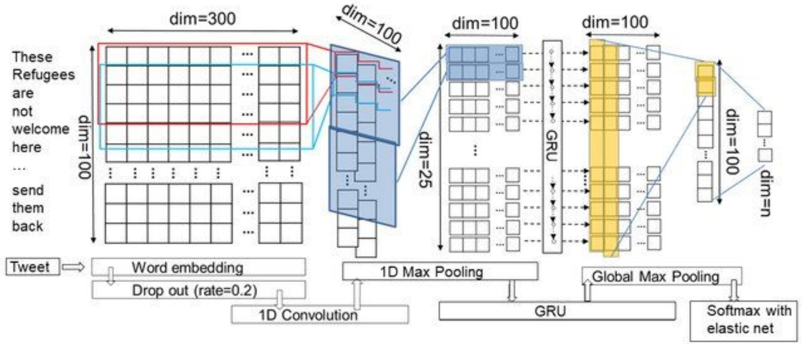
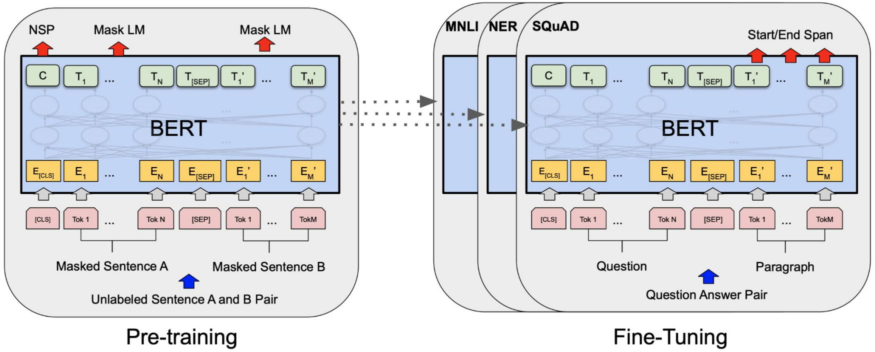


Dataset	SVM	SVM+	CNN	CNN+ GRU$_B$	CNN+ GRU	State of the art
WZ-L	0.74	0.74	0.80	0.81	**0.82**	.74 Waseem [26], best F1
WZ-S.amt	0.86	0.87	0.91	**0.92**	**0.92**	.84 Waseem [25], Best features
WZ-S.exp	0.89	0.90	0.90	0.91	**0.92**	.91 Waseem [25], Best features
WZ-S.gb	0.86	0.87	0.91	0.92	**0.93**	.90 Gamback [10], best F1
WZ-LS	0.72	0.73	0.81	0.81	0.82	.82 Park [20], WordCNN .81 Park [20], CharacterCNN **.83** Park [20], HybridCNN
DT	0.87	0.89	**0.94**	**0.94**	**0.94**	.87 SVM, Davidson [7]
RM	0.86	0.89	0.90	0.91	**0.92**	.86 SVM, Davidson [7]

Current Models

- Earlier models cannot completely capture context
- **BERT** and other transformers model helped in getting improved performance across different datasets [(Mozafari,2019)](#)



Method	Datasets	Precision(%)	Recall(%)	F1-score(%)
Waseem and Hovy [22]	Waseem	72.87	77.75	73.89
Davidson et al. [3]	Davidson	91	90	90
Waseem et al. [23]	Waseem	-	-	80
	Davidson	-	-	89
BERT$_{base}$	Waseem	81	81	81
	Davidson	91	91	91
BERT$_{base}$ + Nonlinear Layers	Waseem	73	85	76
	Davidson	76	78	77
BERT$_{base}$ + LSTM	Waseem	87	86	86
	Davidson	91	92	92
BERT$_{base}$ + CNN	Waseem	**89**	**87**	**88**
	Davidson	**92**	**92**	**92**

Current Models

- Earlier models cannot completely capture context
- **BERT** and other transformers model helped in getting improved performance across different datasets (Mozafari,2019)
- Incorporating lexicon into the BERT architecture → HurtBERT (Koufakou,2020).

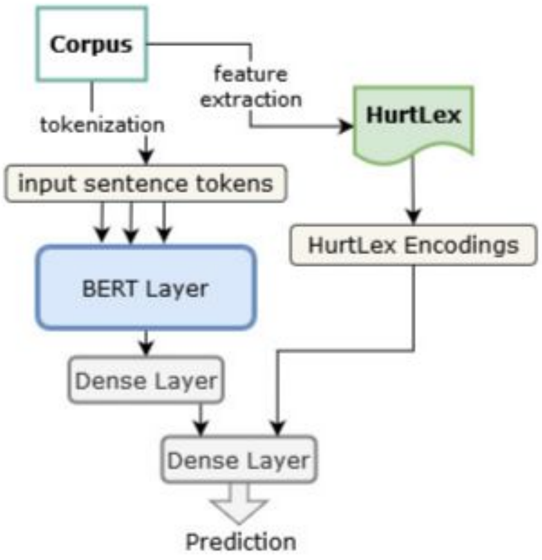
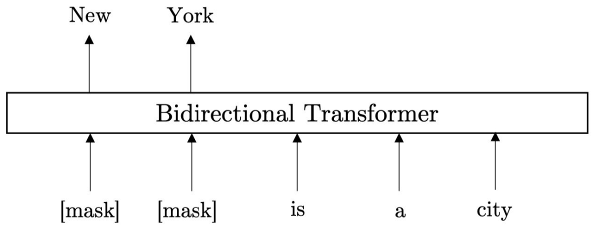


Figure 1: HurtBERT-Enc, our model using HurtLex Encodings

Current Models



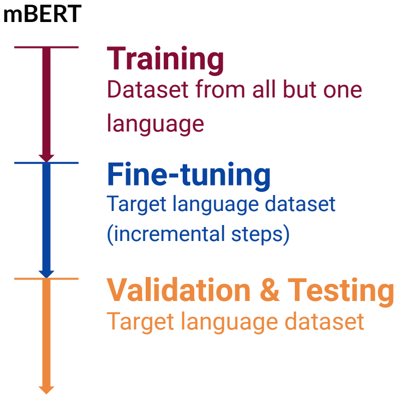
- Earlier models cannot completely capture context
- **BERT** and other transformers model helped in getting improved performance across different datasets (Mozafari,2019)
- Incorporating lexicon into the BERT architecture → HurtBERT (Koufakou,2020).
- Re-training BERT with banned subreddit data → HateBERT (Caselli,2021).

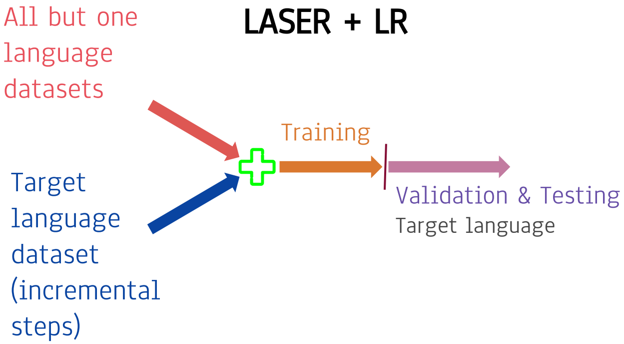
Dataset	Model	Macro F1	Pos. class - F1
OffensEval 2019	BERT	.803±.006	.715±.009
	HateBERT	**.809±.008**	**.723±.012**
	Best	.829	.599
AbusEval	BERT	.727±.008	.552±.012
	HateBERT	**.765±.006**	**.623±.010**
	Caselli et al. (2020)	.716±.034	.531
HatEval	BERT	.480±.008	.633±.002
	HateBERT	**.516±.007**	**.645±.001**
	Best	.651	–

Multilingual Hate speech

- Analysis of multilingual models across 9 different languages and 16 datasets (Aluru,2020).

Language	Low resource	High resource
Arabic	Monolingual, LASER + LR	Multilingual, mBERT
English	Multilingual, LASER + LR	Multilingual, mBERT
German	Monolingual, LASER + LR	Translation + BERT
Indonesian	Multilingual, LASER + LR	Monolingual, mBERT
Italian	Multilingual, LASER + LR	Monolingual, mBERT
Polish	Multilingual, LASER + LR	Translation + BERT
Portuguese	Multilingual, LASER + LR	Monolingual, LASER+LR
Spanish	Monolingual, LASER + LR	Multilingual, mBERT
French	Monolingual, LASER + LR	Translation + BERT



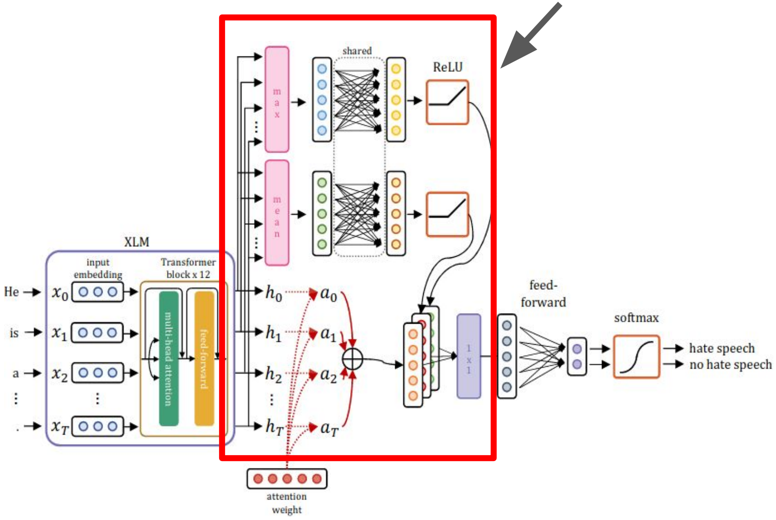


Click logo for demo

Multilingual Hate speech

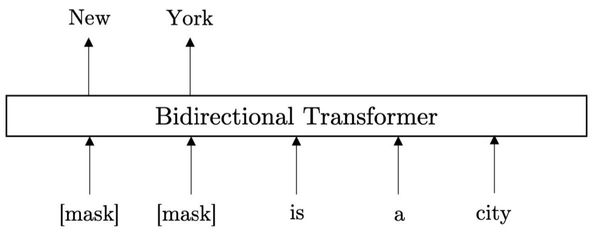
- Benchmarking multilingual models across 9 different languages and 16 datasets (Aluru,2020).
- A novel classification block -AXEL to improve cross lingual transfer (Stappen,2020) on Hateval data.

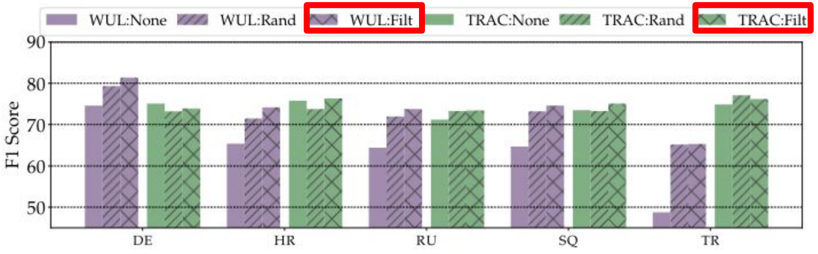
	Dense	Att	AXEL
EN⇒ES	41.31	34.37	**53.42**
ES⇒EN	**60.83**	48.47	52.48
ES⇒EN-S	49.38	39.10	**53.24**
EN⇒(ES→EN)	60.59	62.40	**64.39**
ES⇒(EN→ES)	56.89	49.17	**58.31**
ES⇒(EN-S→ES)	56.57	49.17	**65.04**



Multilingual Hate speech

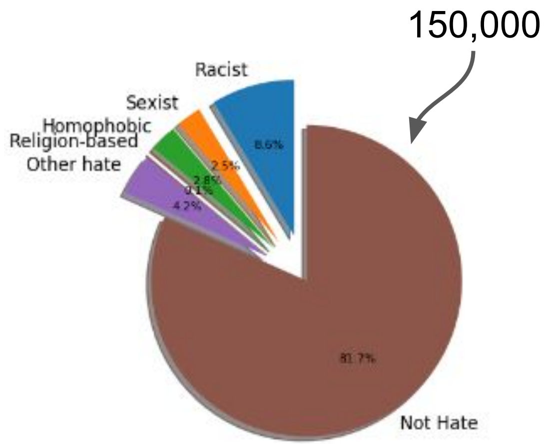
- Benchmarking multilingual models across 9 different languages and 16 datasets (Aluru,2020).
- A novel classification block -AXEL to improve cross lingual transfer (Stappen,2020) on Hateval data.
- **Pre-training** on keyword based filtered data also can help in cross lingual transfer (Glavaš,2020)





More Modalities

- **MMHS150K** is one of the largest dataset. image-text pair in hate speech research (Gomez,2019).
- Text based models are at par with multimodal models.



Shared tasks timeline

EVALITA AMI 2018

Task- Misogyny
Best- Feature based XGBoost

SemEval-2019

Task-Multilingual
Best- SVM with RBF

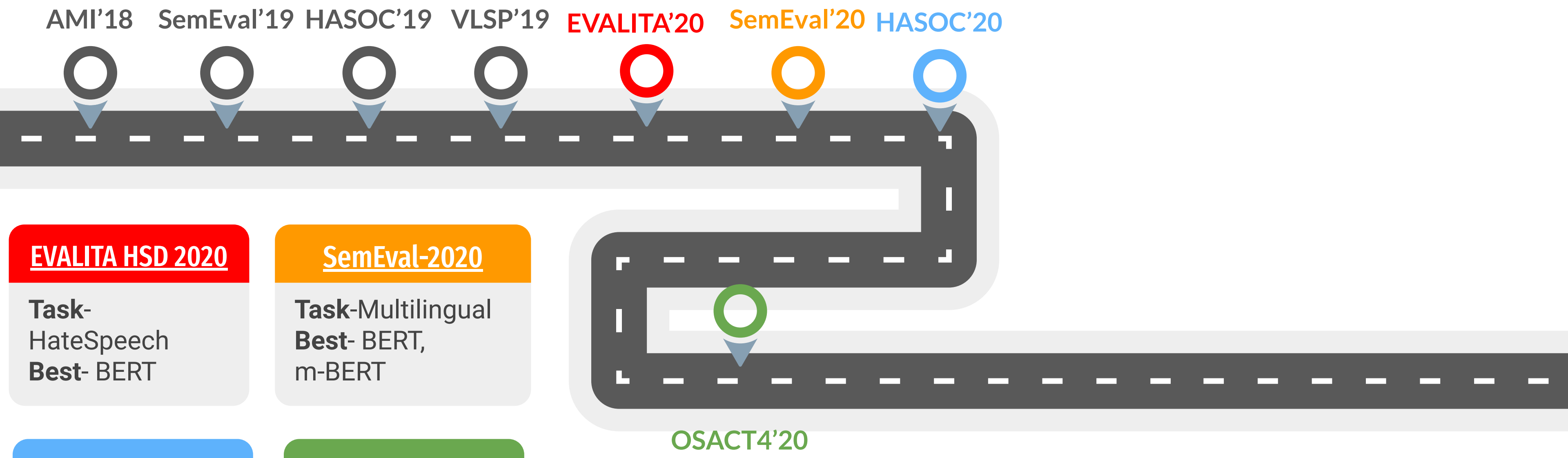
HASOC 2019

Task- Hate/Offensive
Best- Ensemble

VLSP HSD 2019

Task- Hate Speech
Best- LR + ngram

Shared tasks timeline



EVALITA HSD 2020

Task-
HateSpeech
Best- BERT

SemEval-2020

Task-Multilingual
Best- BERT,
m-BERT

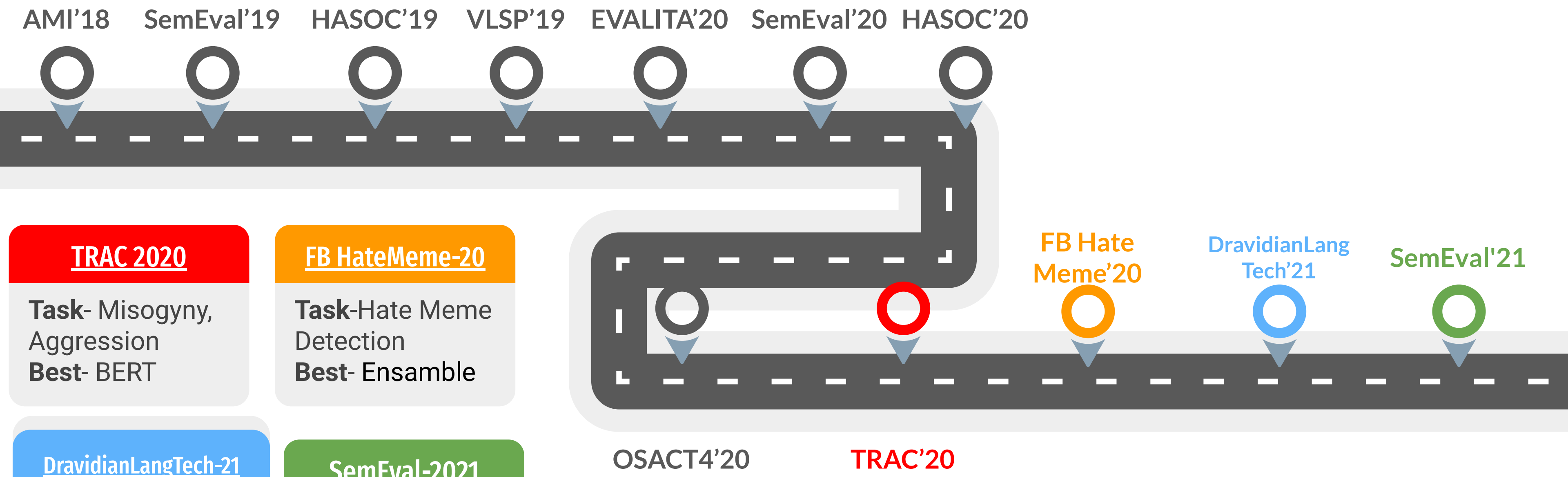
HASOC 2020

Task-
Multilingual
Best- CNN, BERT

OSACT4 HSD 2020

Task- Arabic
Hate Speech
Best- CNN

Shared tasks timeline



TRAC 2020

Task- Misogyny, Aggression
Best- BERT

FB HateMeme-20

Task-Hate Meme Detection
Best- Ensamble

DravidianLangTech-21

Task-Multilingual
Best- BERT-ensemble

SemEval-2021

Task- Toxic Span Detection
Best- N/A

Pitfalls of Model Evaluation

- Two of the previous studies had spurious evaluations (Badjatiya,2017 and Agrawal,2018)
- Types of **wrong evaluations**
  - Oversampling before train-test split (Agrawal,2018)
  - Feature extraction using the whole train and test split (Badjatiya,2017)

Method	Class	Prec.	Rec.	F1
Badjatiya et al. [2] Emb. over all dataset	Neither	95.5	96.8	96.1
	Racist	94.5	93.5	94.0
	Sexist	91.2	87.5	89.3
	Micro avg.	94.6	94.6	94.6
	Macro avg.	93.7	92.6	$\boxed{93.1}$
Agrawal and Awekar [1] Oversamp. all dataset	Neither	95.1	91.7	93.4
	Racist	94.9	96.0	95.4
	Sexist	92.5	97.0	94.6
	Micro avg.	94.4	94.4	94.4
	Macro avg.	94.2	94.9	94.5

After correcting the errors

Drop of 20% in Macro F1!

Method	Class	Prec.	Rec.	F1
Badjatiya et al. [2] Emb. over train set	Neither	82.3	94.7	88.1
	Racist	78.0	64.0	70.2
	Sexist	84.5	47.8	60.9
	Micro avg.	82.3	82.1	80.7
	Macro avg.	81.6	68.9	$\boxed{73.1}$
Agrawal and Awekar [1] Oversamp. train set	Neither	90.3	86.5	88.3
	Racist	69.6	81.3	75.0
	Sexist	74.0	77.4	75.5
	Micro avg.	84.7	84.1	84.3
	Macro avg.	78.0	81.7	79.6

Dataset: Waseem and Hovy dataset
Method: LSTM+GBDT , BiLSTM with attention

Aymé Arango, Jorge Pérez, and Barbara Poblete. 2019. Hate Speech Detection is Not as Easy as You May Think: A Closer Look at Model Validation. *SIGIR'19*

Pitfalls of Model Evaluation

- Two of the previous studies had spurious evaluations (Badjatiya,2017 and Agrawal,2018)
- Wrong evaluations
    - Oversampling before train-test split (Agrawal,2018)
    - Feature extraction using the whole train and test split (Badjatiya,2017)
- **Removing user overlap** between train and test set.

Method	Class	Prec.	Rec.	F1
Badjatiya et al. [2]	None	49.6	93.4	64.3
	Hateful	68.8	15.4	23.5
	Micro avg.	63.8	54.1	46.1
	Macro avg.	59.2	54.4	43.9
Agrawal and Awekar [1]	None	47.5	98.0	63.0
	Hateful	75.3	03.5	06.7
	Micro avg.	62.3	48.4	35.1
	Macro avg.	61.4	50.8	34.9

Dataset: Waseem and Hovy dataset
Method: LSTM+GBDT , BiLSTM with attention

Aymé Arango, Jorge Pérez, and Barbara Poblete. 2019. *Hate Speech Detection is Not as Easy as You May Think: A Closer Look at Model Validation. SIGIR'19*

Pitfalls of Model Evaluation

- Datasets lack testing in the **wild**, train-test comes from the same distribution.
- Different test suites generated to test the classifiers. (Röttger,2020)
- Error in neutral and positive statement about group

Models
DistilBERT-Davidson - **DB-D**
DistilBERT-Founta - **DB-F**
Perspective api - **PERS**

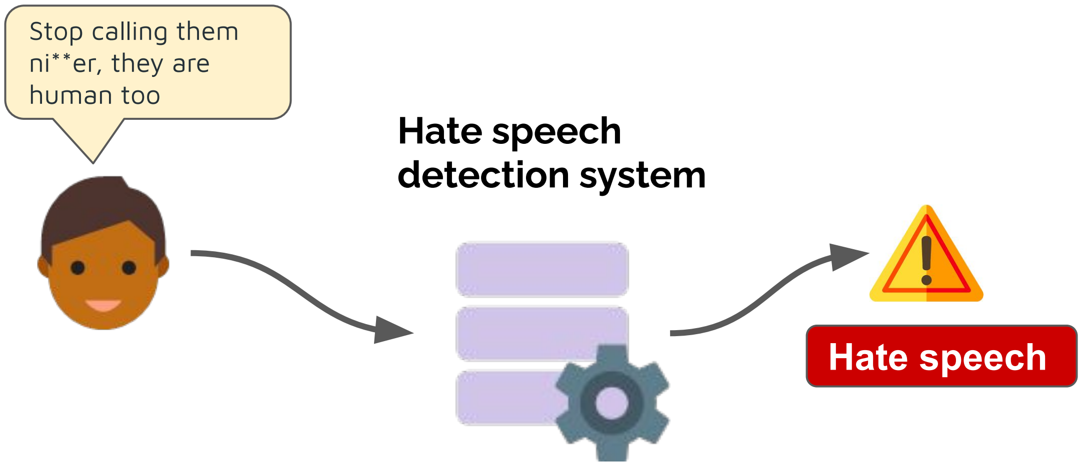
	Functionality	Example	Gold Label	n	Accuracy (%) DB-D	DB-F	PERS
Group identifier	**F18**: Neutral statement using protected group identifier	"We are a group of [IDENTITY]." "I live with two [IDENTITY]."	non-hateful	126	61.1	76.2	**84.1**
	F19: Positive statement using protected group identifier	"I love [IDENTITY]." "[IDENTITY] are great."	non-hateful	189	**86.2**	79.9	54.0

Explainability of Models

Explainability

Rationales | Free text

- Explainability is a crucial aspect more so in these social dimensions



Explainability of Models

- **Explainability** is a crucial aspect more so in these social dimensions
- **Hatexplain** - first dataset to include rationales along with labels. [(Mathew,2020)]

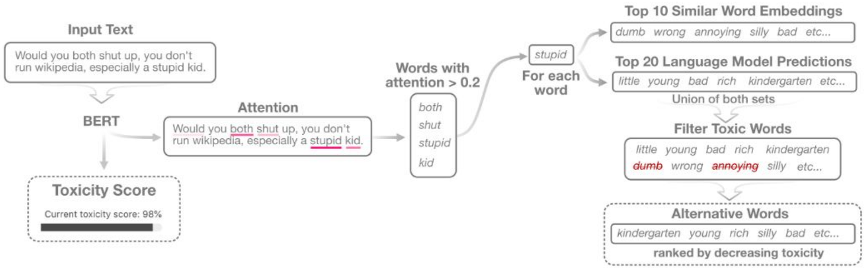
Models	Accuracy	F1 Score	AUROC
CNN-GRU	0.627	0.606	0.793
BERT	0.690	0.674	0.843
BERT-HateXplain	**0.698**	**0.687**	**0.851**

Models performance is better !

Click logo for demo

Explainability of Models

- **Explainability** is a crucial aspect more so in these social dimensions
- **Hatexplain** - first dataset to include rationales as well as target along with labels.(Mathew,2020)
- **RECAST - ** tool to suggest alt wordings based on attention scores. (Wright,2021)

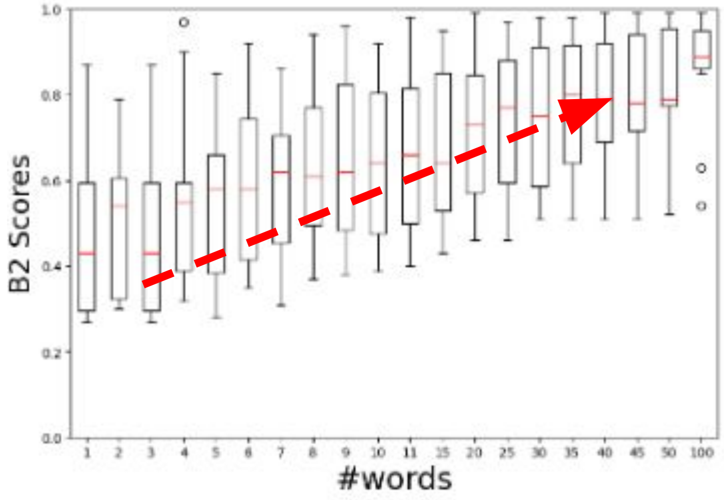


Advantage - reduce toxicity, way of debugging model
Disadvantage - malicious users might game the system.

Bias in Data/Models

- Bias from different directions
  - How is **data selected** ?
  - Who is the annotator?
  - Who is the speaker/target ?
- Often hate speech dataset can carry bias related to some identity words [(Ousidhoum,2020)](#)
- Increase in semantic relatedness between corpus and keywords as number of keywords are increased

No of topics kept fixed at 8



(b) $\mathbf{B_2}$ variations per number of words.

B2 measures how frequently keyword appear in topics

Bias in Data/Models

- Bias from different directions
  - How is data selected ?
  - Who is the **annotator**?
  - Who is the speaker/target ?
- Data using expert annotators (activists) performs better than amateurs (crowdsource) (Waseem,2016)

Feature Set	Amateur F1	Amateur Recall	Amateur Precision	Expert F1	Expert Recall	Expert Precision
Close	86.39	88.60%	87.59%	91.24	92.49%	92.67%
Middling	84.07	86.76%	85.43%	87.81	90.10%	88.53%
Distant	71.71	80.17%	82.05%	77.77	84.76%	71.85%
All	86.39	88.60%	87.59%	90.77	92.20%	92.23%
Best	83.88	86.68%	85.54%	91.19	92.49%	92.50%
Baseline	70.84	79.80%	63.69%	77.77	84.76%	71.85%

Table 5: Scores obtained for each of the feature sets.

Bias in Data/Models

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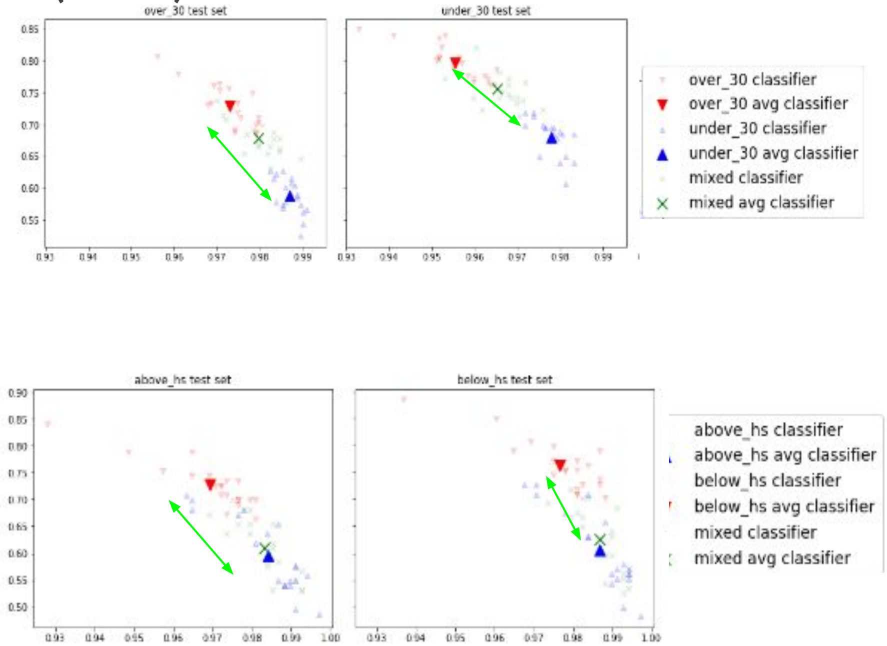
  - How is data selected ?
  - Who is the **annotator**?
  - Who is the speaker/target ?
- Data using expert annotators (activists) performs better than amateurs (crowdsource) [(Waseem,2016)]
- A study found significant bias for age and education of the annotators. [(Kuwatly,2020)]

Specificity (X-axis) vs sensitivity (Y-axis)



Method - Trained different classifiers on data annotated by different group and evaluated them

Community not annotated

Bias in Data/Models

- Bias from different directions
  - How is data selected ?
  - Who is the annotator?
  - Who is the **speaker/target** ?
- Often hate speech model can detect false positives for tweets written by different community (Davidson,2019)

Dataset	Class	$\widehat{p_{i_{black}}}$	$\widehat{p_{i_{white}}}$	t	p	$\frac{\widehat{p_{i_{black}}}}{\widehat{p_{i_{white}}}}$
Waseem and Hovy	Racism	0.001	0.003	-20.818	***	0.505
	Sexism	0.083	0.048	101.636	***	1.724
Waseem	Racism	0.001	0.001	0.035		1.001
	Sexism	0.023	0.012	64.418	***	1.993
	Racism and sexism	0.002	0.001	4.047	***	1.120
Davidson et al.	Hate	0.049	0.019	120.986	***	2.573
	Offensive	0.173	0.065	243.285	***	2.653
Golbeck et al.	Harassment	0.032	0.023	39.483	***	1.396
Founta et al.	Hate	0.111	0.061	122.707	***	1.812
	Abusive	0.178	0.080	211.319	***	2.239
	Spam	0.028	0.015	63.131	***	1.854

Table 2: **Experiment 1**

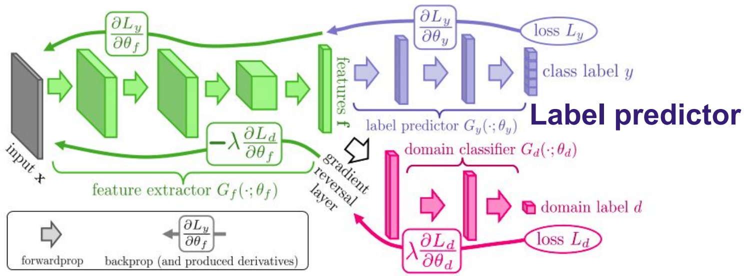
Values greater than 1 indicate that black-aligned tweets are classified as belonging to class at a higher rate than white

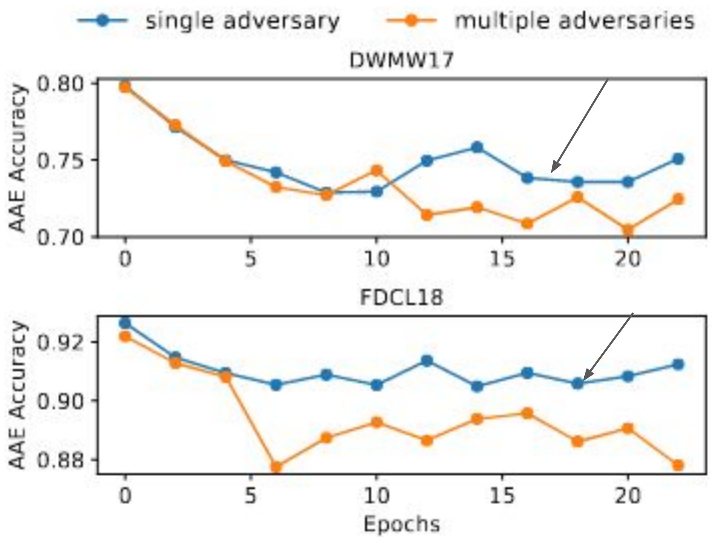
Dataset and model used for dialect identification (Blodgett,2016)

Community not annotated

Bias in Data/Models

- Bias from different directions
  - How is data selected ?
  - Who is the annotator?
  - Who is the **speaker/target** ?
- Often hate speech model can detect false positives for tweets written by different community (Davidson,2019).
- Training with adversarial loss can help reduce the bias (Xia,2020).





Dataset and model used for dialect identification (Blodgett,2016)

Community annotated

Bias in Data/Models

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  - Who is the annotator?
  - Who is the **speaker/target** ?
- Often hate speech model can detect false positives for tweets written by different community (Davidson,2019).
- Training with adversarial loss can help reduce the bias (Xia,2020).
- Using rationales can make the models less biased towards different targets (Mathew,2020)

Models	GMB-Sub	GMB-BPSN	GMB-BNSP
CNN-GRU	0.654	0.623	0.659
BERT	0.762	0.709	0.757
BERT-HateXplain	**0.807**	**0.745**	**0.763**

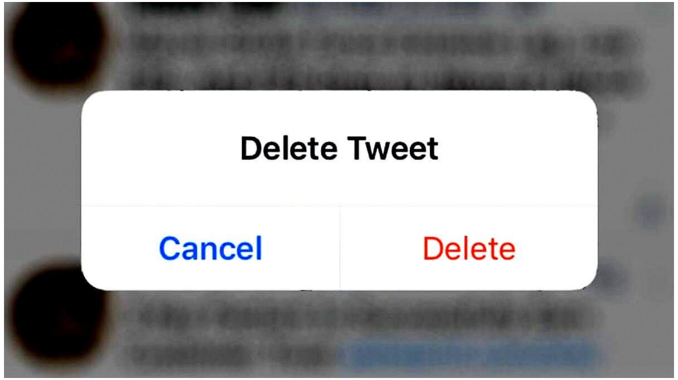
Models less biased !

Mitigating Hate Speech

- Definitions and related concepts
- Analysis of hate speech
  - Prevalence
  - Effect
- Detection of hate speech
  - Datasets
  - Traditional methods
  - Sequential models
  - Transformer based models
  - Challenges
- Mitigation of hate speech
  - Campaigns
  - Counterspeech detection
  - Counterspeech generation
  - Effect of counter speech
- SWOT analysis

What is done after detecting hate speech?

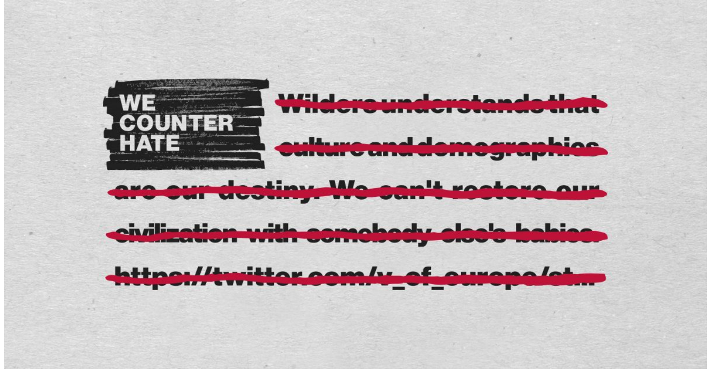
- Deletion of posts
- Suspension of user accounts
- Shadow banning



Campaign to deter hate

Counterspeech.fb

[ADL](ADL)



WeCounterHate

NoHateSpeechMovement

Hate speech laws

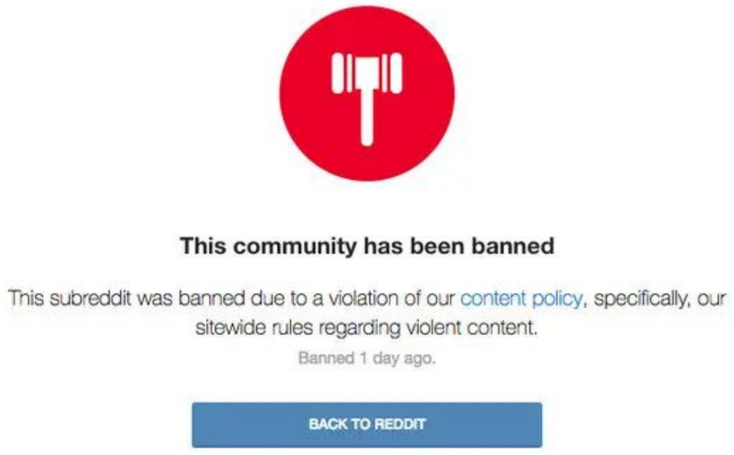
- Several countries have laws that prohibit hate speech

- The definition of hate speech varies according to the country

- Models which detect hate speech will need to take these nuances into account

Reddit Ban [2015]

- In 2015, Reddit closed several subreddits due to violations of Reddit's anti-harassment policy.
- Foremost among them were r/fatpeoplehate and r/CoonTown
- How effective was the ban?



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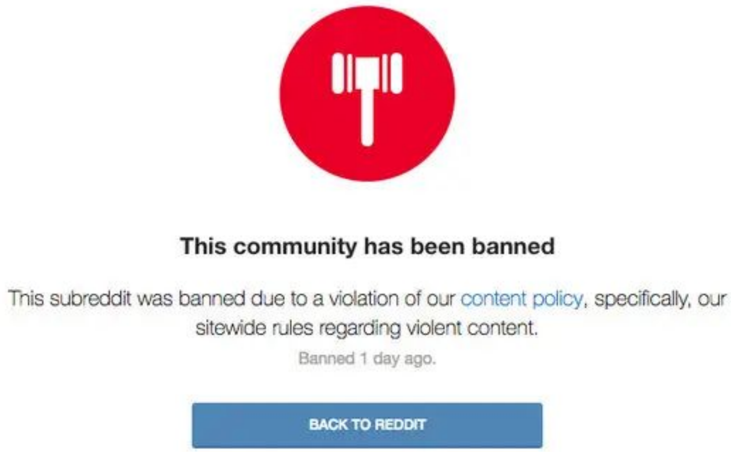
***You Can't Stay Here*: The Efficacy of Reddit's 2015 Ban Examined Through Hate Speech [Chandrasekharan 2017]**



The Efficacy of Reddit’s 2015 Ban

User-level Effects of the Ban

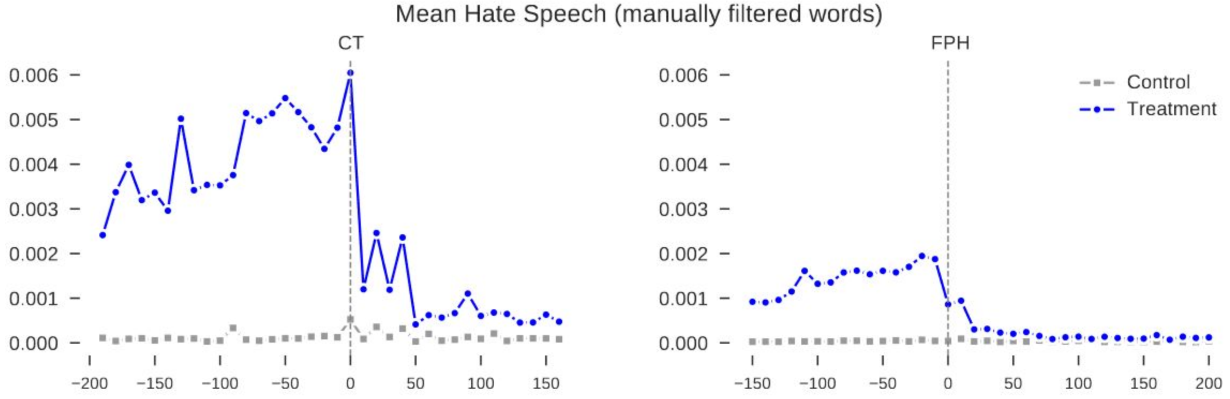
- Following Reddit’s 2015 ban, a large, significant percentage of users from banned communities left Reddit

- Following the ban, Reddit saw a decrease of over 80% in the usage of hate words by r/fatpeoplehate and r/CoonTown users

The Efficacy of Reddit's 2015 Ban

User-level Effects of the Ban

- For the banned community users that remained active, the ban drastically reduced the amount of hate speech they used across Reddit by a large and significant amount.



The Efficacy of Reddit's 2015 Ban

Community-level Effects of the Ban

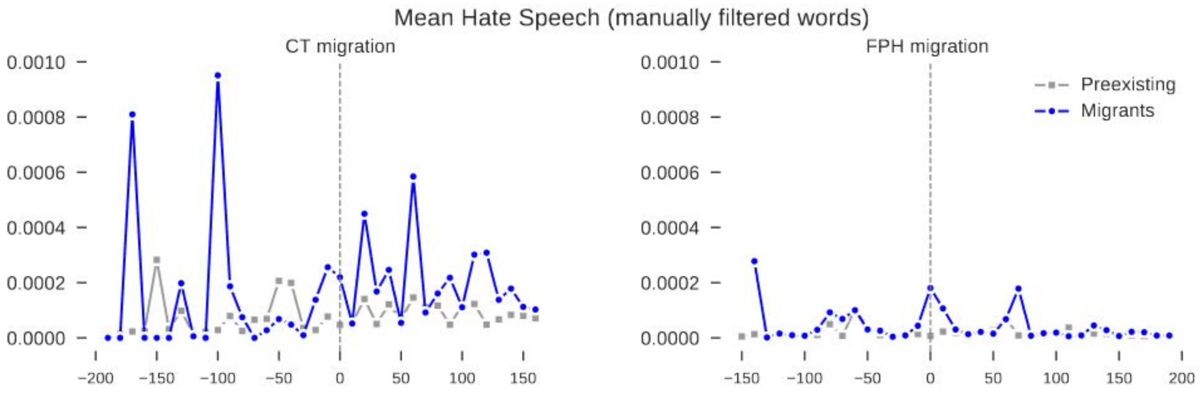
- Following the banning of r/fatpeoplehate and r/CoonTown, the affected users migrated to other parts of Reddit.

- The majority of r/CoonTown users migrated to other subreddits (like r/The_Donald, r/homeland, r/BlackCrimeMatters) where racist behavior has either been noted or is prevalent.

The Efficacy of Reddit's 2015 Ban

Community-level Effects of the Ban

- The migrant users did not bring hate speech with them to their new communities, nor did the longtime residents pick it up from them. **Reddit did not "spread the infection"**.



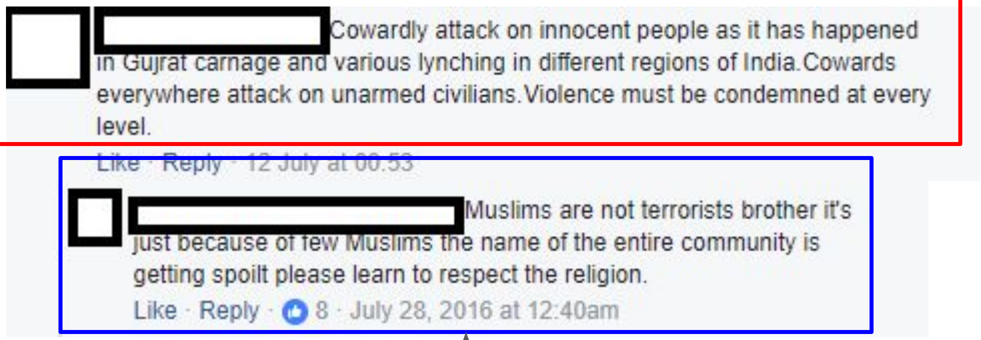
Doctrine of Counterspeech/Counter-Narrative

- The counterspeech doctrine posits that the proper response to negative speech is to counter it with positive expression.

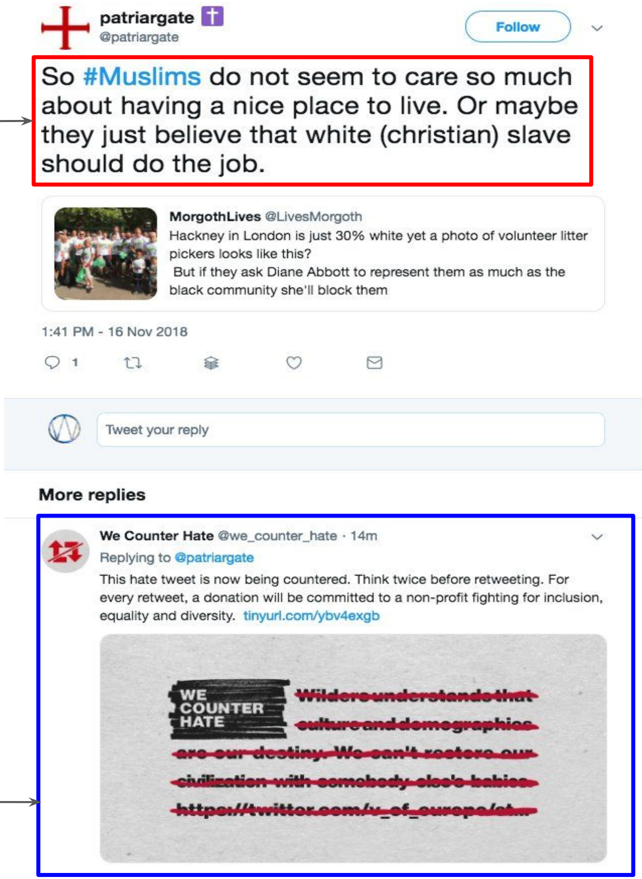
- Combating hate speech in this way has some advantages: it is faster, more flexible and responsive, capable of dealing with extremism from anywhere and in any language and it does not form a barrier against the principle of free and open public space for debate.

Counterspeech Examples

Hate Speech



Counterspeech



Taxonomy of counterspeech Benesch 2016

1. **Presenting facts to correct misstatements or mis-perceptions**

   "Actually homosexuality is natural. Nearly all known species of animal have their gay commu-nities. Whether it be a lion or a whale, they have or had(if they are endangered) a gay community. Also marriageis an unnatural act. Although there are some species that do have longer relationships with a partner most known do not".

   This comment was in response to a interview video in which the interviewee says that homosexuality is unnatural, detrimental and destructive to the society

Taxonomy of counterspeech Benesch 2016

1. Presenting facts to correct misstatements or mis-perceptions
2. **Pointing out hypocrisy or contradictions**

[redacted]

Whn Muslims tweet #KillAllChristians its called a terrorist threat,whn a Christian say #KillAllMuslims its called freedm of speech
Hypocrisy

1:39 PM · Nov 14, 2015 · Twitter for BlackBerry

Taxonomy of counterspeech Benesch 2016

1. Presenting facts to correct misstatements or mis-perceptions
2. Pointing out hypocrisy or contradictions
3. **Warning of offline or online consequences**

   “I’m not gay but nevertheless, whether You are beating up some-one gay or straight, it is still an assault and by all means, this preacher should be arrested for sexual harassment and instigating!!!”

Taxonomy of counterspeech Benesch 2016

1. Presenting facts to correct misstatements or mis-perceptions
2. Pointing out hypocrisy or contradictions
3. Warning of offline or online consequences
4. **Affiliation**

   "Hey I'm Christian and I'm gay and this guy is so wrong. Stop the justification and start the accepting. I know who my heart and soul belong to and that's with God: creator of heaven and earth. We all live in his plane of consciousness so it's time we started accepting one another. That's all"

Taxonomy of counterspeech Benesch 2016

5. Visual Communication

Taxonomy of counterspeech Benesch 2016

5. Visual Communication
6. **Denouncing hateful or dangerous speech**

   “*Maybe you are not a racist. But that’s a racist thing to say*”

   “*#KillAllMuslims is literally the most disgraceful thing I've seen on Twitter*”

Taxonomy of counterspeech [Benesch 2016]

5. Visual Communication
6. Denouncing hateful or dangerous speech
7. **Humor and sarcasm**

Taxonomy of counterspeech Benesch 2016

5. Visual Communication
6. Denouncing hateful or dangerous speech
7. Humor and sarcasm
8. **Tone**

   "I am a Christian, and I believe we're to love everyone!! No matter age, race, religion, sex, size, disorder… whatever!! I LOVE PEOPLE!! treat EVERYONE with respect"

Considerations for Successful Counterspeech. Benesch 2016

- When do you call a counterspeech as successful?

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- First is when the speech has a favorable impact on the original (hateful) user, shifting his or her discourse if not also his or her beliefs. This is usually indicated by an apology or recanting, or the deletion of the original tweet or account.

Considerations for Successful Counterspeech. Benesch 2016

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- First is when the speech has a favorable impact on the original (hateful) user, shifting his or her discourse if not also his or her beliefs. This is usually indicated by an apology or recanting, or the deletion of the original tweet or account.
- Second type of success is to positively affect the discourse norms of the 'audience' of a counterspeech conversation: all of the other users or 'cyberbystanders' who read one or more of the relevant exchange of tweets.

Considerations for Successful Counterspeech. Benesch 2016

Recommended Strategies

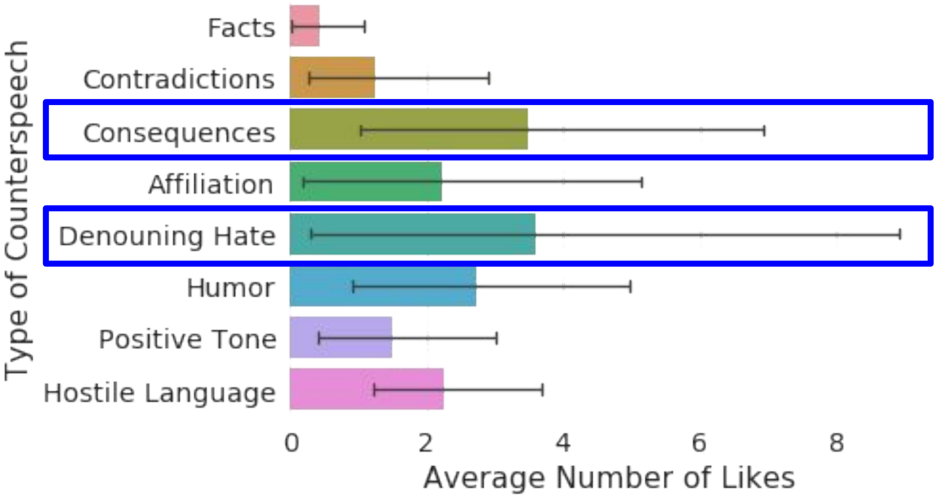
- Warning of Consequences
- Shaming/Labeling
- Empathy and Affiliation
- Humor
- Images

Discouraged Strategies

- Hostile or Aggressive Tone, Insults
- Fact-Checking
- Harassment and Silencing

Thou Shalt Not Hate: Countering Online Hate Speech [Mathew 2019]

Click logo for demo



In case of the African-American community, the counterspeakers call out for racism and talk about consequences of their actions

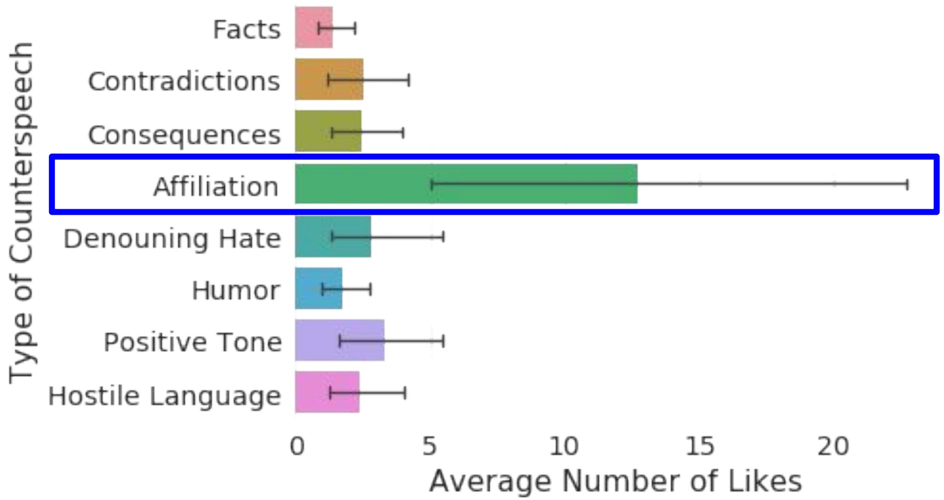
Example:

“i hope these cops got fired! this is bullshit”

“Sad to see the mom teaching her children to be racist and hateful. The way the guy handled it was great.”

Thou Shalt Not Hate: Countering Online Hate Speech [Mathew 2019]

Click logo for demo



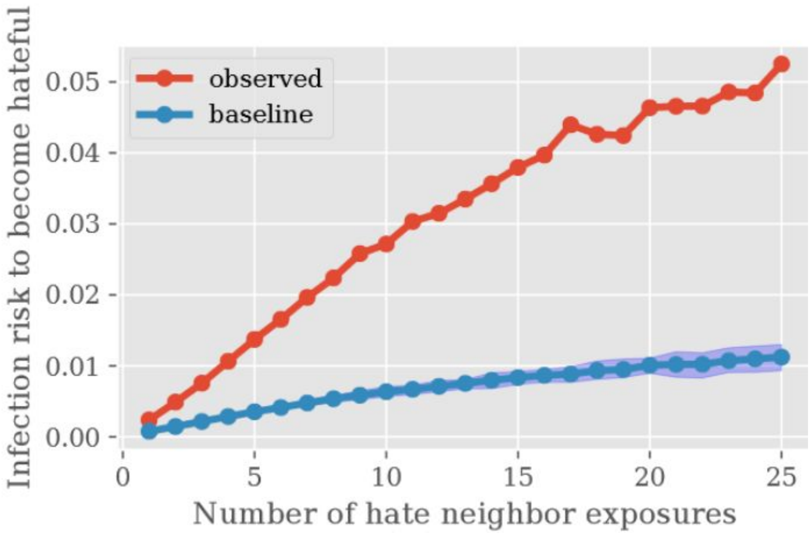
In case of the Jews community, we observe that the people affiliate with both the target and the source community ('Muslims', 'Christians') to counter the hate message.

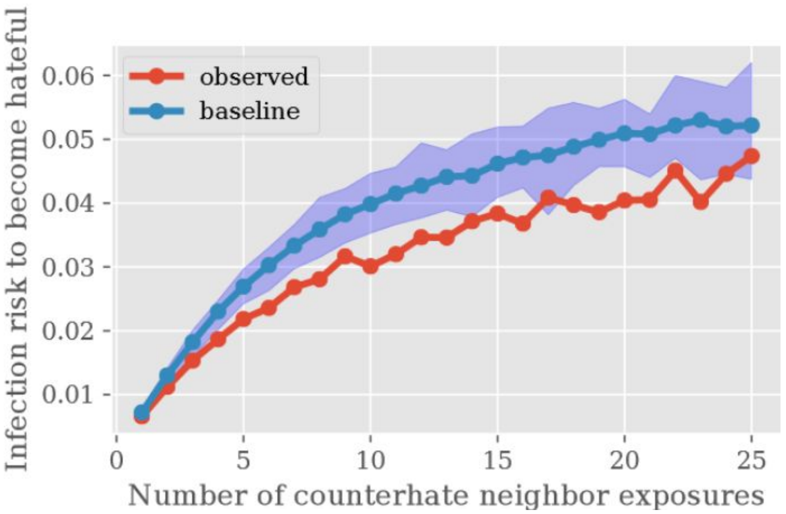
Example:

"I'm Jewish And I'm really glad there some people that stand up for us And I have no problems with Muslims. We're all brothers and sisters"

Racism is a Virus: Anti-Asian Hate and Counterhate in Social Media during the COVID-19 Crisis [Ziems 2020]

Analysis reveals that counterhate messages can discourage users from turning hateful in the first place.





Datasets

- Counterspeech YouTube [Mathew 2019]
- Counterspeech Twitter Dataset[Ziems 2020, Mathew 2020, Garland 2020]
- Hope Speech and Help Speech [Palakodety 2019] (YouTube Comments)
- CONAN Dataset [Chung 2019] (NGO Trainers)
- Intervene Dataset [Qian 2019] (Gab & Reddit)

Counterspeech Generation

The core idea is to directly intervene in the discussion with textual responses that are meant to counter the hate content and prevent it from further spreading

Manual intervention against hate speech is not scalable

Counterspeech Generation

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Qian, Jing, Anna Bethke, Yinyin Liu, Elizabeth Belding, and William Yang Wang. "A Benchmark Dataset for Learning to Intervene in Online Hate Speech." EMNLP-IJCNLP, pp. 4757-4766. 2019.

Counterspeech Generation

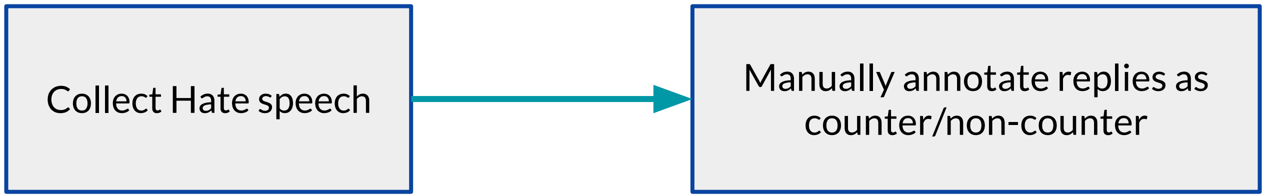
The core idea is to directly intervene in the discussion with textual responses that are meant to counter the hate content and prevent it from further spreading

Issues: lack of sufficient amount of quality data and tend to produce generic/repetitive responses.

Counterspeech collection Strategy Tekiroglu 2020

Crawling (CRAWL) :Mathew 2019 focuses on the intuition that Counterspeech can be found on social media as responses to hateful expressions. The proposed approach is a mix of automatic hate speech collection via linguistic patterns, and a manual annotation of replies to check if they are responses that counter the original hate content.

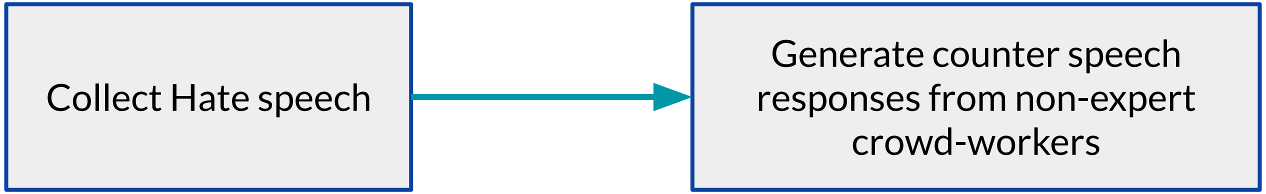
All the material collected is made of natural/real occurrences of hate-counter pairs.



Counterspeech collection Strategy Tekiroglu 2020

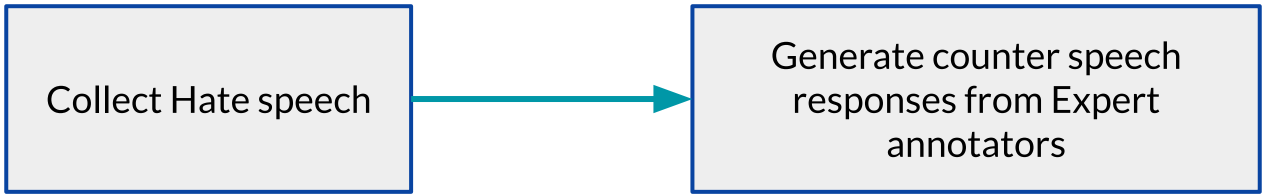
Crowdsourcing (CROWD) : Qian 2019 propose that once a list of hate speech is collected and manually annotated, we can briefly instruct crowd-workers (non-expert) to write possible responses to such hate content.

In this case the content is obtained in controlled settings as opposed to crawling approaches.



Counterspeech collection Strategy Tekiroglu 2020

Nichesourcing (NICHE): Chung 2019 still relies on the idea of outsourcing and collecting counterspeech in controlled settings. However, in this case the counterspeech is written by NGO operators, i.e. persons specifically trained to fight online hatred via textual responses that can be considered as experts in counterspeech production.

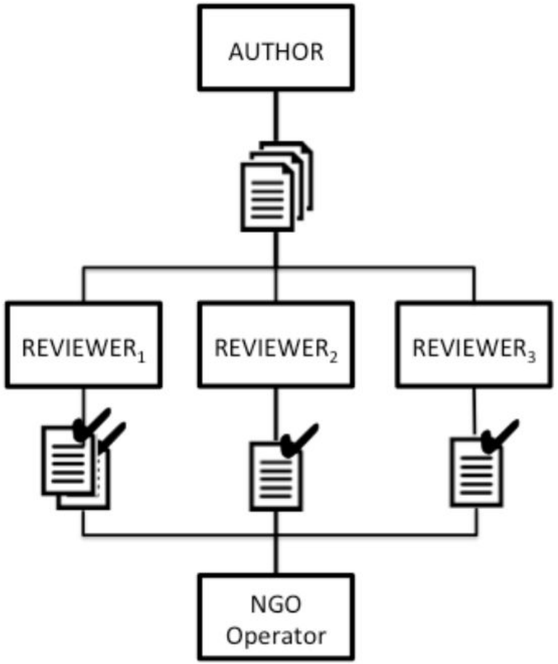


Counterspeech collection Strategy [Tekiroglu 2020]

Author-Reviewer framework [Tekiroglu 2020]: An author is tasked with text generation and a reviewer can be a human or a classifier model that filters the produced output.

A validation/post-editing phase is conducted with NGO operators over the filtered data.

This framework is scalable allowing to obtain datasets that are suitable in terms of diversity, novelty, and quantity.



Machine Generated Counterspeech

Conversation	Seq2Seq	VAE	RL
User 1: Ok. Keep White Knighting for a sand ni**er who f**ks tons of White women. You're entitled to your opinion.	This is is not allowed and un time to treat people by their skin color	Use of the r-word is unacceptable in our discourse as it demeans and insults people with mental disabilities	I do not use derogatory racial slurs
User 1: Feminists are f**king ret***ed, why are they so pissed about manspreading shit makes no difference in space. I'm gonna start throwing things in womens cleavage as they walk by.	Using talking about someones character to describe a woman is insulting to hateful	I don't think using words that are sexist in nature contribute to a productive conversation	Your post uses speech that denigrates sex and gender, which is in violation of our Community Guidelines and TOS Agreement
User 1: Only a nig****ick could reach that c**t User 2: I bet a midget football team could hide under her overhang during a rainstorm and not get wet. User 3: Ni**er probably uses her as a waterbed	Use of the c-word is unacceptable in our discourse as it demeans and insults women	Please do not use derogatory language for intellectual disabilities	If you don't agree with you, there 's no need to resort to name calling

Qian, Jing, Anna Bethke, Yinyin Liu, Elizabeth Belding, and William Yang Wang. "A Benchmark Dataset for Learning to Intervene in Online Hate Speech." EMNLP-IJCNLP, pp. 4757-4766. 2019.

Generate, Prune, Select: A Pipeline for Counterspeech Generation against Online Hate Speech [Zhu 2021]

Hate Speech:	I am done with Islam and isis. All Muslims should be sent to their homeland. Britain will be better without their violence and ideology.
Expert:	I agree that ISIS is an evil aberration, but to extend this to include up to 3 million people just in the UK is just plain silly.
Common-place:	Hate speech is not tolerated. Please review our user policies. Thank you for your cooperation.
Not rele-vant:	Use of the r-word is unacceptable as it de-means and insults people with disabilities.

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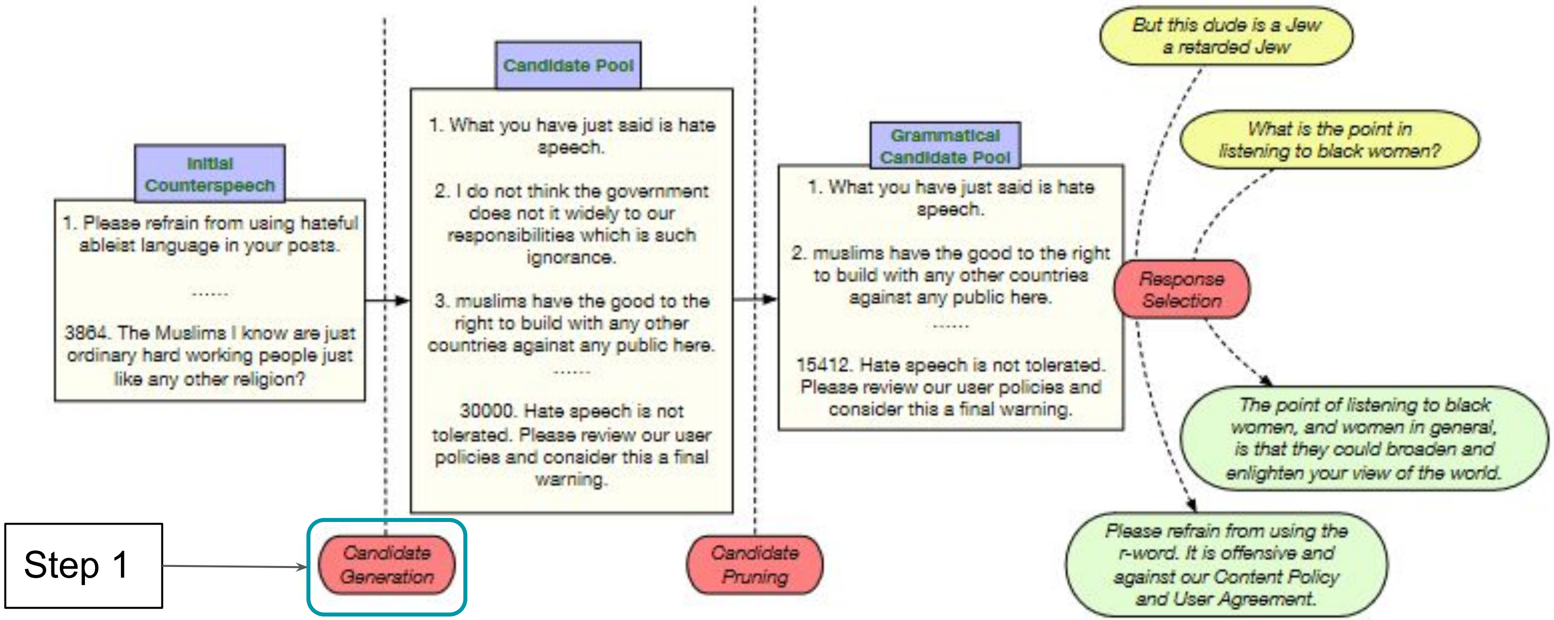

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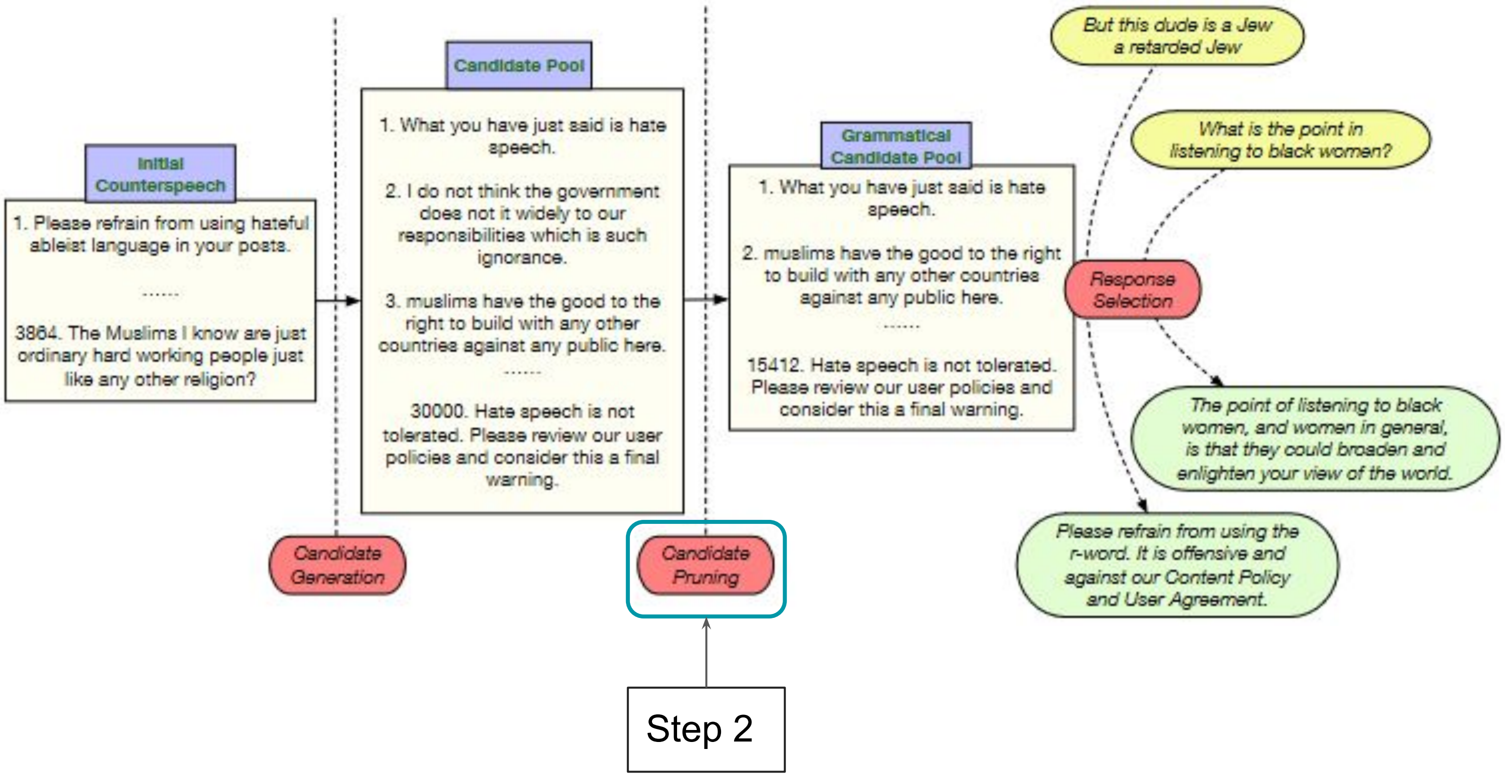

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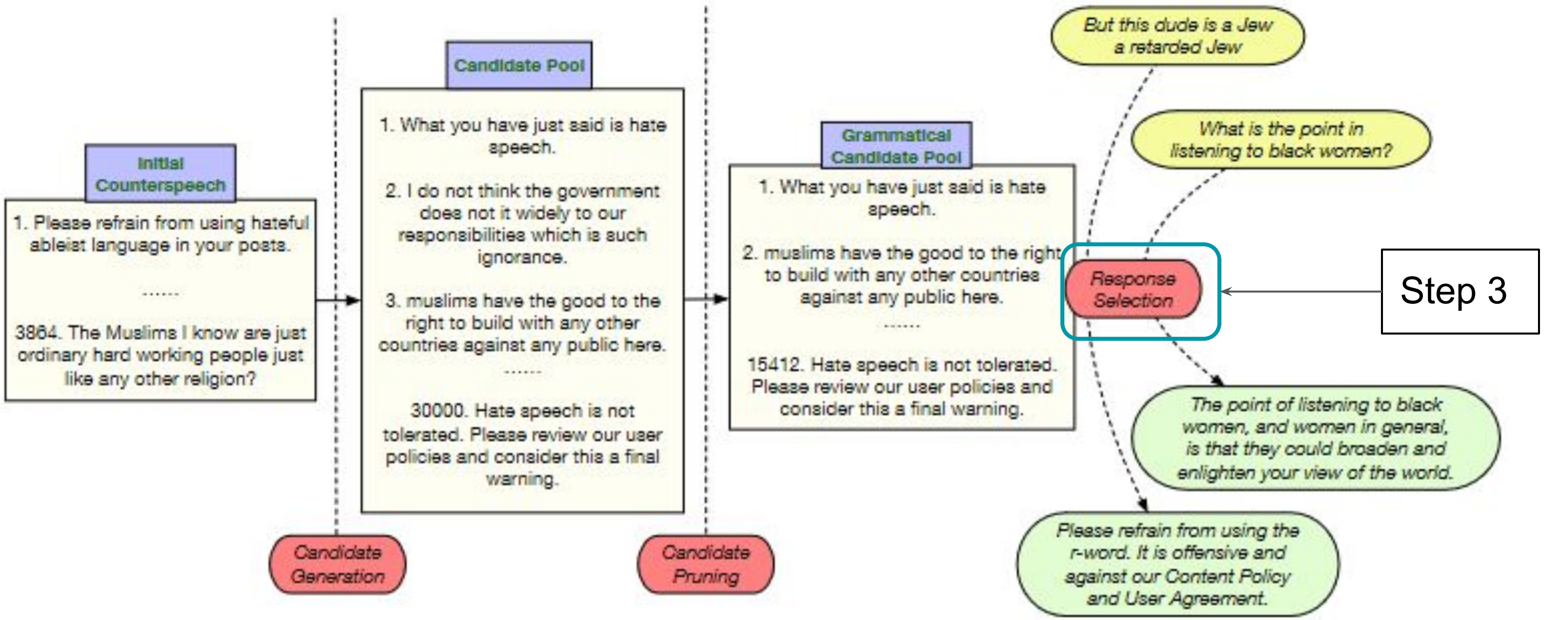

Generate, Prune, Select: A Pipeline for Counterspeech Generation against Online Hate Speech [Zhu 2021]

Hate Speech	Generated Counterspeech by GPS
(a): All the Muslims should have been punished for yesterday, not only a few. Citizen will take action if the government does not do anything.	You cannot blame all people for actions of a few. Banning something altogether will not solve anything.
(b): The world would be a better place without Muslims. They are only killing and raping our children.	The world would actually be a very dark place without Muslims who contribute a lot to our society. What about our Muslim doctors, scientists, philanthropists, actors, job-creators?
(c): What is the point in listening to black women? They are all retarded.	The point of listening to black women, and women in general, is that they could broaden and enlighten your view of the world.

Tweetment Effects on the Tweeted: Experimentally Reducing Racist Harassment Munger 2016

- Collected a sample of Twitter users who have harassed other users and use control accounts ("bots") to sanction the harassers.

Tweetment Effects on the Tweeted: Experimentally Reducing Racist Harassment [Munger 2016]

- By varying the identity of the bots between in-group (white man) and out-group (black man) and by varying the number of Twitter followers each bot has, the author found that subjects who were countered by a high-follower white male significantly reduced their use of a racist slur.

SWOT

- Definitions and related concepts
- Analysis of hate speech
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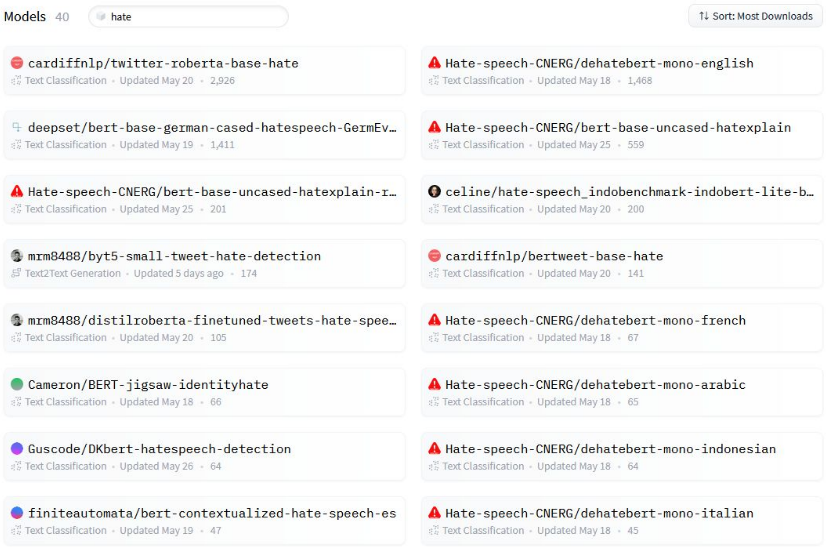

huggingface.co

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- Counterspeech initiatives by various NGOs and tech giants
- **Theme research grants, competitions, shared tasks and dedicated workshops**

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- Bias in data as well as in models
- **Lack of explainability in models**

Opportunities

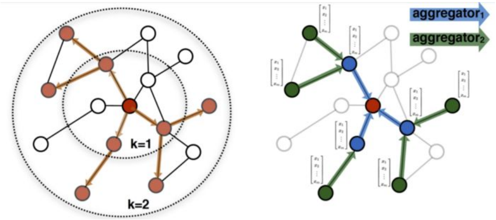
- Hateful user detection

Timesup, yall getting w should have happened long ago

Which was in reply to another tweet that mentioned the holocaust. Although the tweet, whose author's profile contained white-supremacy imagery, incited violence, it is hard to conceive how this could be detected as hateful with only textual features. Furthermore, the lack of hate-related words makes it difficult for this kind of tweet to be sampled.

Ribeiro, Manoel, Pedro Calais, Yuri Santos, Virgílio Almeida, and Wagner Meira Jr. "Characterizing and detecting hateful users on twitter." In Proceedings of the International AAAI Conference on Web and Social Media, vol. 12, no. 1. 2018.

Opportunities



Graph sage algorithm

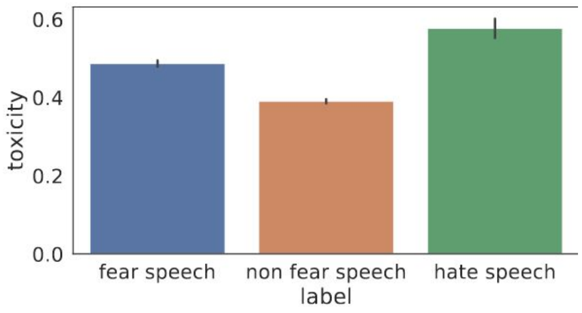
- User as another aspect
  - Helps in contextualising some tweets
  - User moderation more feasible from a practical perspective
  - **Issue -** Annotation guidelines
- On twitter dataset , GraphSage is the best model (Riberio,2018).

		Hateful/Normal			Suspended/Active		
Model	Features	Accuracy	F1-Score	AUC	Accuracy	F1-Score	AUC
GradBoost	user+glove	84.6 ± 1.0	52.0 ± 2.2	88.4 ± 1.3	81.5 ± 0.6	48.4 ± 1.1	88.6 ± 0.1
	glove	84.4 ± 0.5	52.0 ± 1.3	88.4 ± 1.3	78.9 ± 0.7	44.8 ± 0.7	87.0 ± 0.5
AdaBoost	user+glove	69.1 ± 2.4	37.6 ± 2.4	85.5 ± 1.4	70.1 ± 0.1	38.3 ± 0.9	84.3 ± 0.5
	glove	69.1 ± 2.5	37.6 ± 2.4	85.5 ± 1.4	69.7 ± 1.0	37.5 ± 0.8	82.7 ± 0.1
GraphSage	user+glove	$\mathbf{90.9 \pm 1.1}$	$\mathbf{67.0 \pm 4.1}$	$\mathbf{95.4 \pm 0.2}$	$\mathbf{84.8 \pm 0.3}$	$\mathbf{55.8 \pm 4.0}$	$\mathbf{93.3 \pm 1.4}$
	glove	90.3 ± 1.9	65.9 ± 6.2	94.9 ± 2.6	84.5 ± 1.0	54.8 ± 1.6	93.3 ± 1.5

https://towardsdatascience.com/an-intuitive-explanation-of-graphsage-6df9437ee64f

Opportunities

- Lot of new problems coming up
  - Interaction of **fake news with hate speech** (Ameur,2021)
  - Emergence of **fear speech** (Saha, 2021), **dangerous speech** (Alsheri,2020)



Message (original in hindi)	**Label**
Leave chatting and read this post or else all your life will be left in chatting. In 1378, a part was separated from India, became an Islamic nation - named Iran .. People who do love jihad --- is a Muslim. If you want to give muslims a good answer, please share!!	**Fear speech**
That's why I hate Islam! See how these mu**ahs are celebrating. Seditious traitors!!	**Hate speech**

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- **Newer methods of promoting hate -- e.g., hate codes which are very difficult to identify automatically**

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- Many new platforms cropping up as alternatives -- Parler (used to be a small scale initiative with few million uses, but from the last week of June 2020, 1.5M daily users)
- **Govt agencies and political parties weaponizing hate speech**

Resources

- Notion page containing hate speech papers.
- Demo codes for using our open source models
- A dataset resource created and maintained by Leon Derczynski and Bertie Vidgen. Click the link here
- This resource collates all the resources and links used in this information hub, for both teachers and young people. Click the link here

Thank You

Contacts:

https://hate-alert.github.io

https://twitter.com/hate_alert