Hate speech: Detection, Mitigation and beyond

Tutorial at AAAI 2022

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

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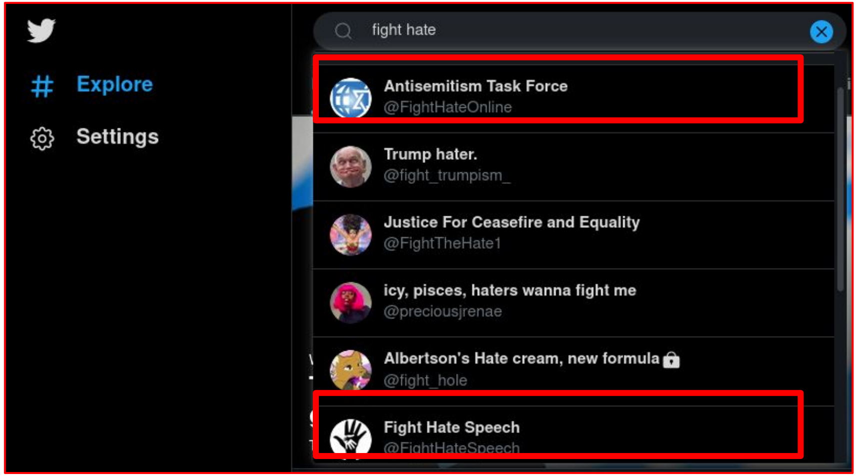
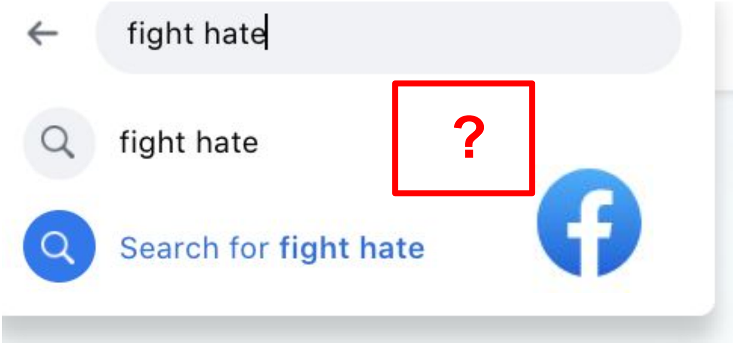
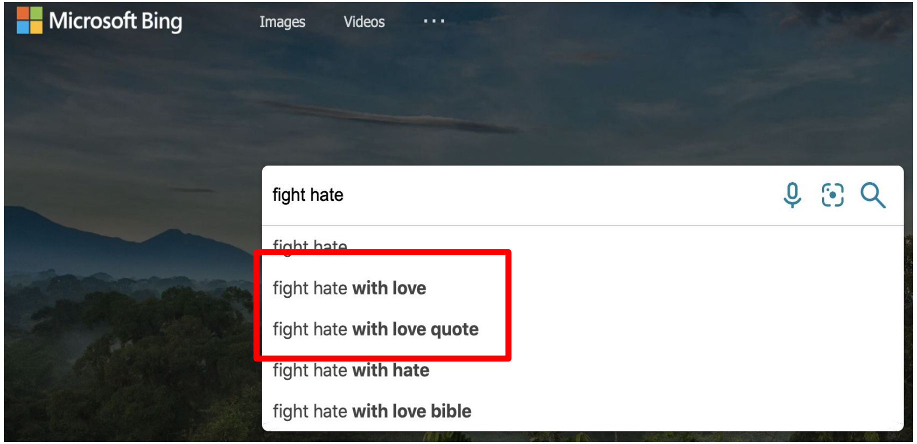
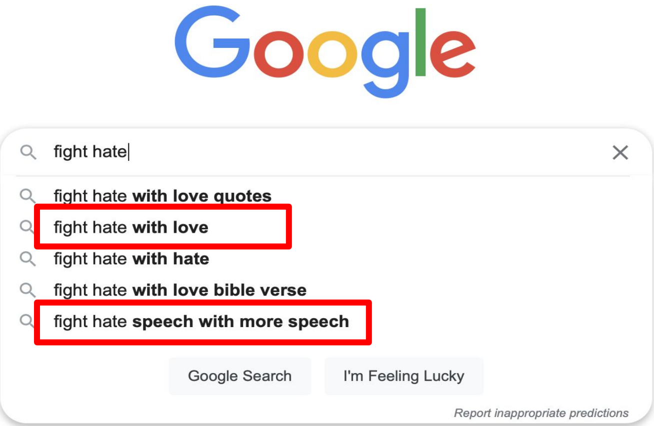
Find more about us here!
https://hate-alert.github.io/

Hate speech: A growing concern?









What to expect from this tutorial?

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

UNITED NATIONS STRAT

Key commitments

Monitoring and analyzing hate speech

Addressing root causes, drivers and actors of hate speech

Using technology

Using education as a tool for addressing and countering hate speech

Foreword

Around the world, we are seein
intolerance – including rising anti-S
Social media and other forms of c
Neo-Nazi and white supremacy r
weaponized for political gain with in
minorities, migrants, refugees, women a

Tackling hate speech is also crucial to
by helping to prevent armed conflict,
women and other serious violations o
just societies.

To
as
is
ad
in

battling this demon, and so I have
. This Strategy and Plan of Action
nited Nations can play its part in
reedom of opinion and expression,
sector and other partners.

United Nations Secretary-General
António Guterres

May 2019

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?

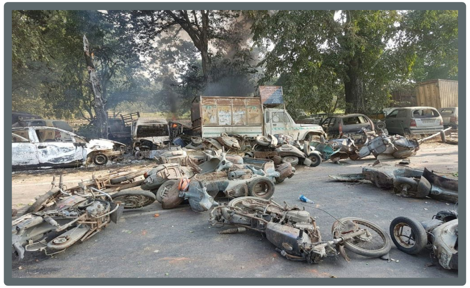
What to expect from this tutorial?

- 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

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.

What we will be covering in this tutorial.

Fortuna et al. 2018

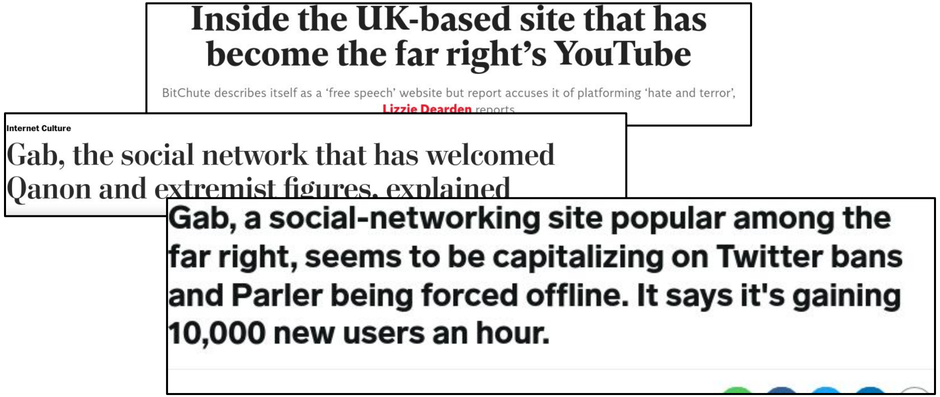
Hate speech in different contexts

- 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

Prevalence of hate speech

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


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

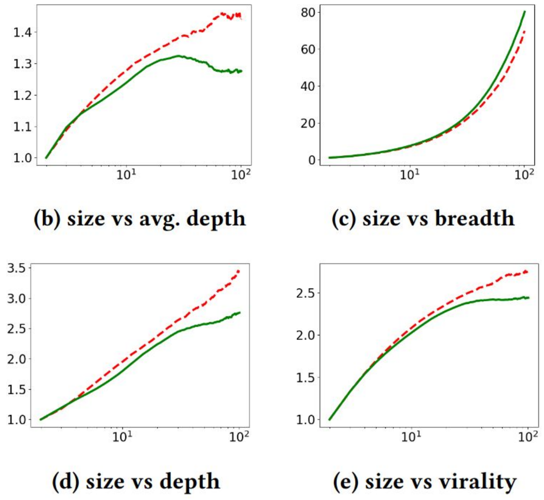
- **Gab**
- In Gab, early signals show **Alt-right**, **BanIslam** as popular hashtags (Zannettou,2018)

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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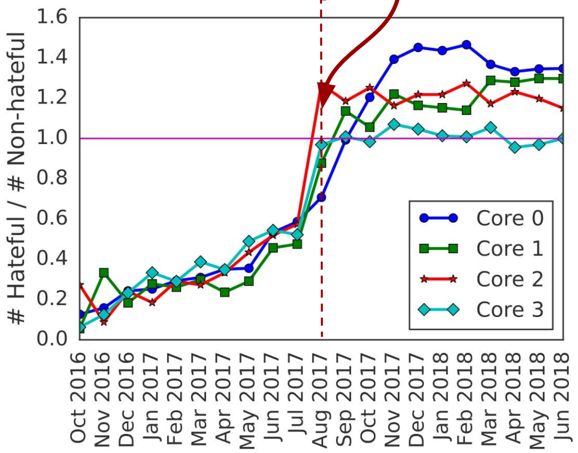
- Further, **fraction of hateful users** in inner core increased through time in Gab (Mathew, 2020)

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

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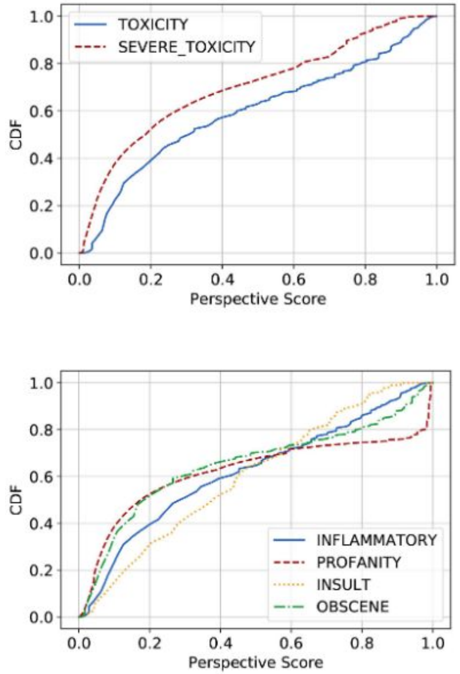
Prevalence of hate speech

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

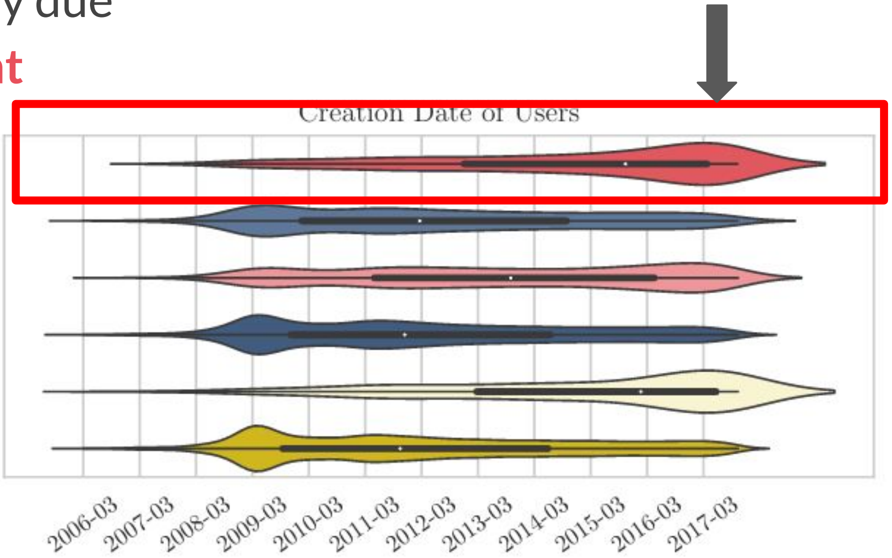


Dataset: Crawling from 4chan's /pol/ thread, June 29, 2016 to November 1, 2019.
Method: Perspective api then CDF

Prevalence of hate speech (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

Prevalence of hate speech (Platforms with moderation)

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

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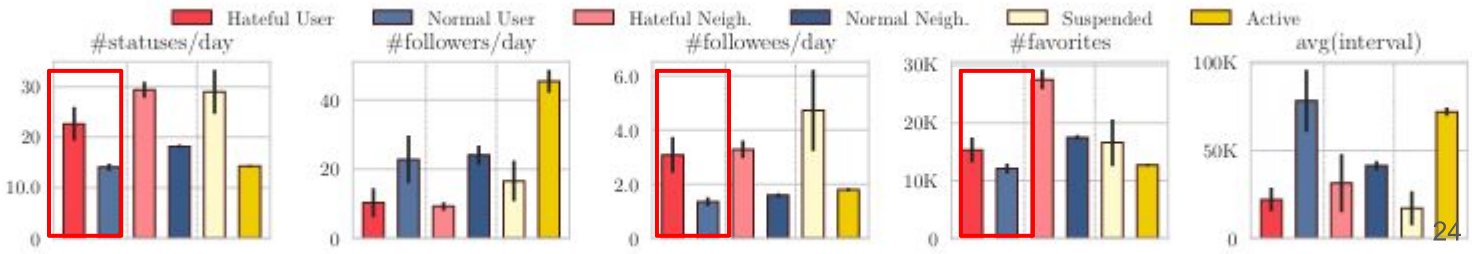
- Hateful users are **power users** (post more, favourite more).



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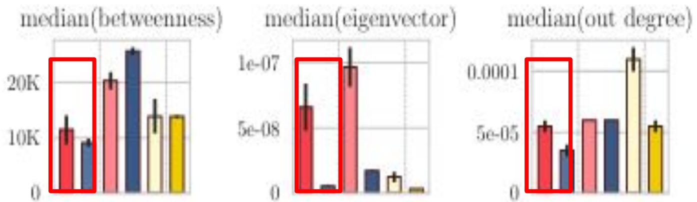
- Hateful users are **power users** (post more, favourite more).
- Median hate user is **more central** to the network



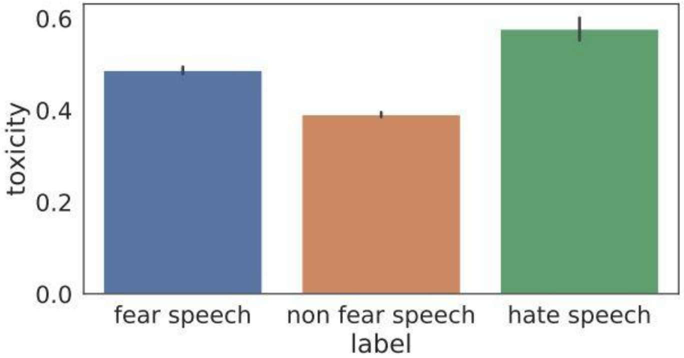
Prevalence of hate speech (Platforms with moderation)

- 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

Not Hateful?? Not Normal?? What's Then ?

- Fear speech used elements from **history**, and contains **misinformation** to vilify Muslims. At the end, they ask the readers, to take action by **sharing the post**(Saha.2021).



Text (translated from 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 ...and now Uttar Pradesh, Assam and Kerala are on the verge of becoming an Islamic state ...People who do *love jihad* – is a Muslim. Those who think of ruining the country – Every single one of them is a Muslim !!!! Everyone who does not share this message forward should be a Muslim. If you want to give muslims a good answer, please share!! We will finally know how many Hindus are united today !!	FS
That's why I hate Islam! See how these mullahs are celebrating. Seditious traitors!!	HS
A child's message to the countrymen is that Modi ji has fooled the country in 2014, distracted the country from the issues of inflationary job development to Hindu-Muslim and patriotic issues.	NFS

Detecting 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
  - Effects of Ban
  - Counterspeech detection
  - Counterspeech generation
  - Effect of counter speech
- SWOT Analysis

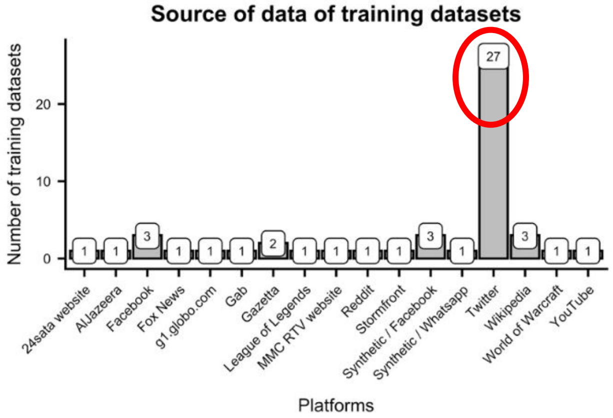
Datasets

- 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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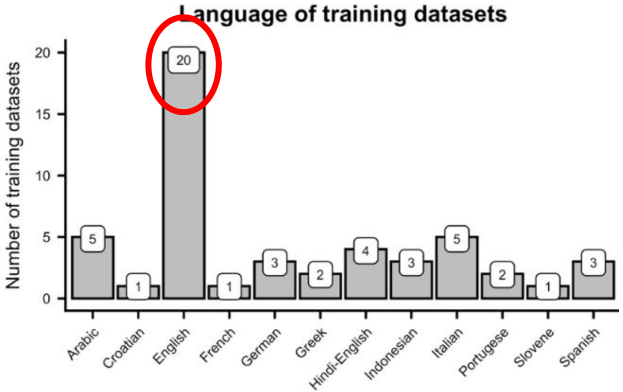
Datasets

- 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

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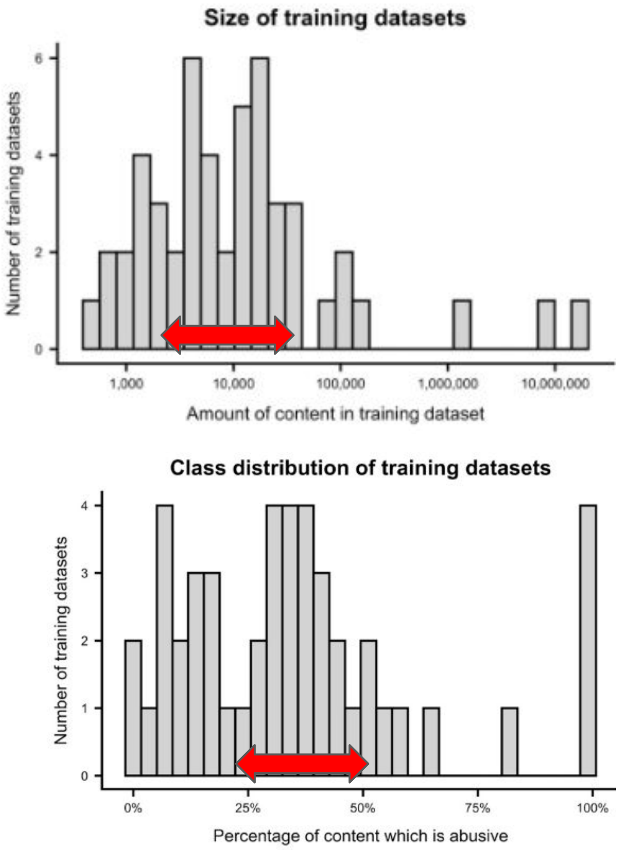
- Different datasets have different **sources.** Twitter is one of the major sources.
- Different datasets have different **languages**, English being the prominent one.
- **Training size** and **amount of hate/abuse** also varies across datasets



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Earlier Detection Methods

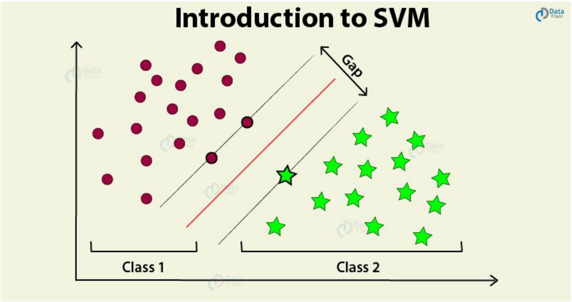
- Features used :-
  - TF-IDF vectors
  - Parts-of-speech tags
  - Linguistic features
    - Sentiment lexicons
    - Frequency counts of URL, username
    - Readability scores

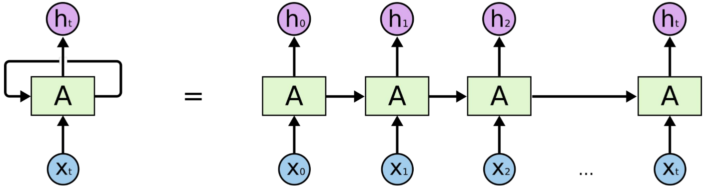
(Davidson,2017)

  - **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

- Features used
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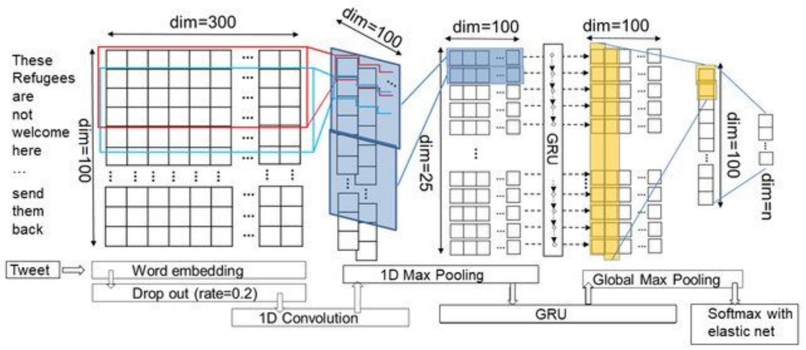
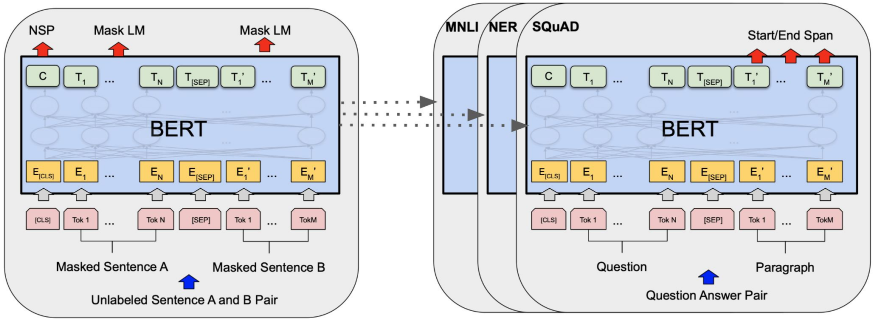


Dataset	SVM	SVM+	CNN	CNN+GRU$_B$	CNN+GRU	State of the art
WZ-L	0.74	0.74	0.80	0.81	**0.82**	0.74 Waseem [26], best F1
WZ-S.amt	0.86	0.87	0.91	**0.92**	**0.92**	0.84 Waseem [25], Best features
WZ-S.exp	0.89	0.90	0.90	0.91	**0.92**	0.91 Waseem [25], Best features
WZ-S.gb	0.86	0.87	0.91	0.92	**0.93**	0.90 Gamback [10], best F1
WZ-LS	0.72	0.73	0.81	0.81	0.82	0.82 Park [20], WordCNN 0.81 Park [20], CharacterCNN **0.83** Park [20], HybridCNN
DT	0.87	0.89	**0.94**	**0.94**	**0.94**	0.87 SVM, Davidson [7]
RM	0.86	0.89	0.90	0.91	**0.92**	0.86 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)]



Pre-training Fine-Tuning

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

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- **BERT** and other transformers model helped in getting improved performance across different datasets (Mozafari,2019)
- Incorporating lexicon into the BERT architecture → HurtBERT (Koufakou,2020).

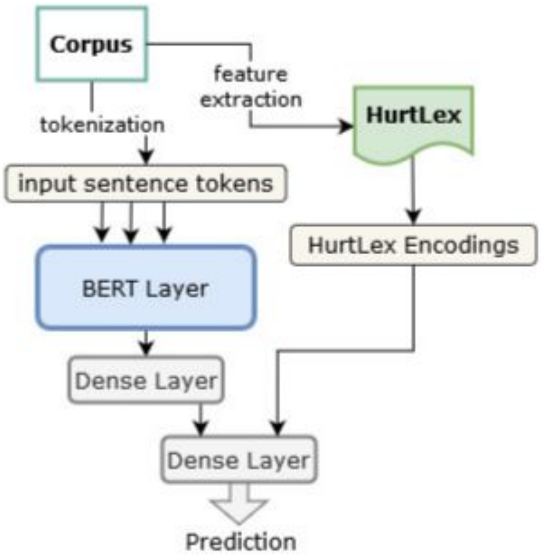

Figure 1: HurtBERT-Enc, our model using HurtLex Encodings

Current Models

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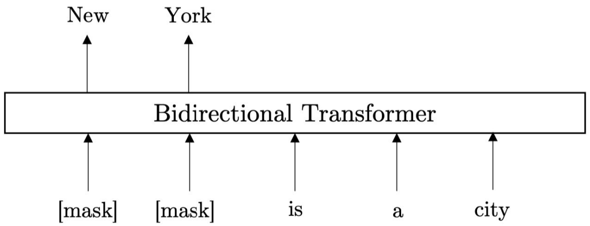
- **BERT** and other transformers model helped in getting improved performance across different datasets (Mozafari,2019)
- Incorporating lexicon into the BERT architecture → HurtBERT (Koufakou,2020).
- Re-training BERT with banned subreddit data → HateBERT (Caselli,2021).

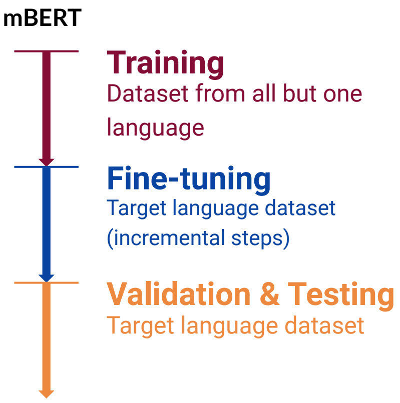


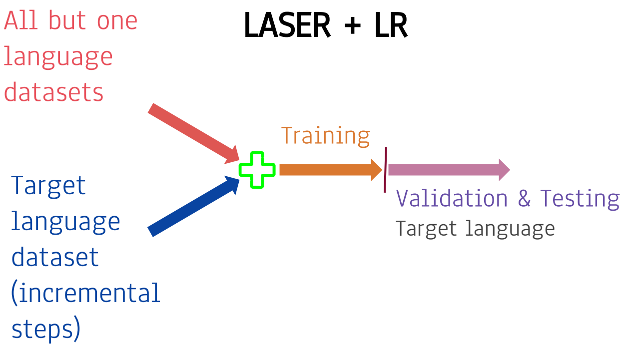
Dataset	Model	Macro F1	Pos. class - F1
OffensEval 2019	BERT	.803±.006	.715±.009
	HateBERT	**.809±.008**	**.723±.012**
	Best	.829	.599
AbusEval	BERT	.727±.008	.552±.012
	HateBERT	**.765±.006**	**.623±.010**
	Caselli et al. (2020)	.716±.034	.531
HatEval	BERT	.480±.008	.633±.002
	HateBERT	**.516±.007**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





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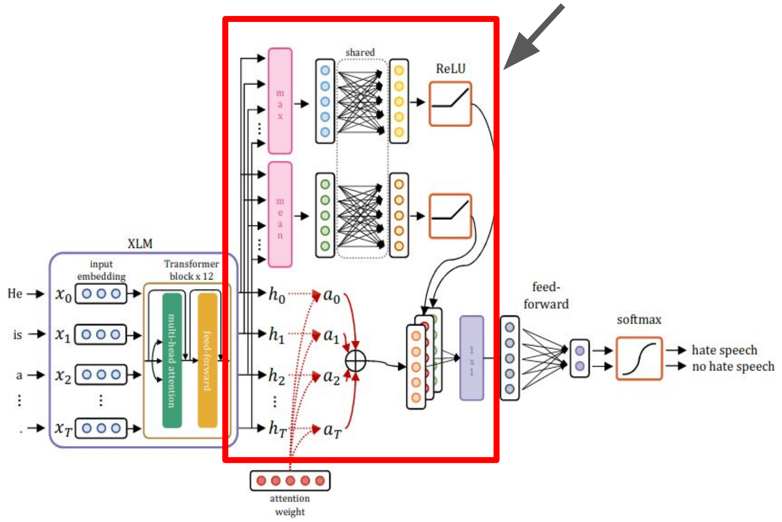
Multilingual Hate speech

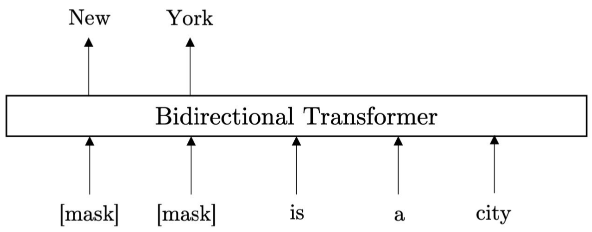
- Benchmarking multilingual models across 9 different languages and 16 datasets (Aluru,2020).
- A novel classification block -AXEL to improve cross lingual transfer (Stappen,2020) on Hateval data.

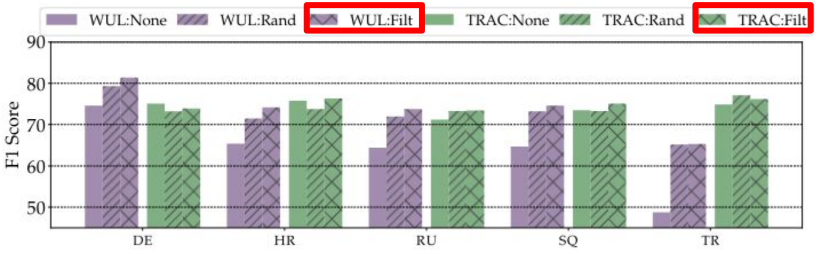
	Dense	Att	AXEL
EN⇒ES	41.31	34.37	**53.42**
ES⇒EN	**60.83**	48.47	52.48
ES⇒EN-S	49.38	39.10	**53.24**
EN⇒(ES→EN)	60.59	62.40	**64.39**
ES⇒(EN→ES)	56.89	49.17	**58.31**
ES⇒(EN-S→ES)	56.57	49.17	**65.04**



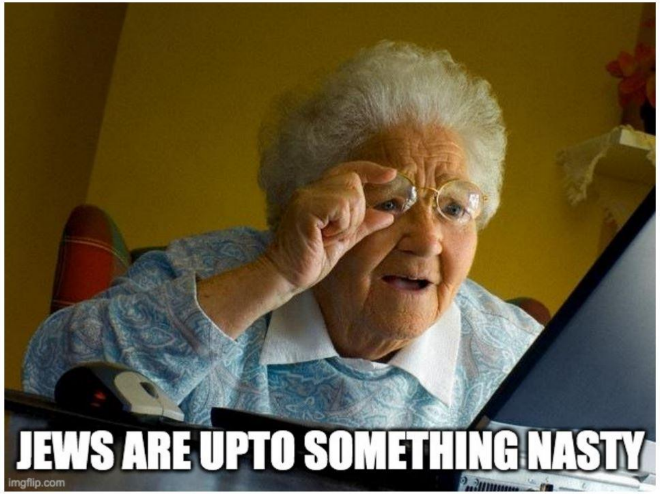
Multilingual Hate speech

- 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



Multimodal Datasets

- **MMHS150K** is one of the largest dataset. image-text pair in hate speech research (Gomez,2019).
- **Hateful Memes** is another dataset of 10K+ posts created by Facebook AI. (Goswami.2021)
- Automated multimodal detection of online **antisemitism**.(Chandra.2021)
- **HarMeme** is another dataset consisting of 3,544 memes related to COVID-19.(Pramanick.2021)

Models

- **Text Based**
  - Glove, Fastext Embedding with Dense ANN layer
  - BERT, RoBERTa
- **Image Based model**
  - ResNet-152, VGG19, ResNeXt-101 etc.
- **Multimodal model**
  - ViLBERT CC, V-BERT COCO
  - VisualBERT, MMBT, UNITER

Modality	Model	2-Class Classification					
		Acc ↑	P ↑	R ↑	F1 ↑	MAE ↓	MMAE ↓
	Human†	90.68	84.35	84.19	83.55	0.1760	0.1723
	Majority	64.76	32.38	50.00	39.30	0.3524	0.5000
Text Only	TextBERT	70.17	65.96	66.38	66.25	0.3173	0.2911
Image Only	VGG19	68.12	60.25	61.23	61.86	0.3204	0.3190
	DenseNet-161	68.42	61.08	62.10	62.54	0.3202	0.3125
	ResNet-152	68.74	61.86	62.89	62.97	0.3188	0.3114
	ResNeXt-101	69.79	62.32	63.26	63.68	0.3175	0.3029
Image + Text (Unimodal Pre-training)	Late Fusion	73.24	70.28	70.36	70.25	0.3167	0.2927
	Concat BERT	71.82	71.58	72.23	71.82	0.3033	0.3156
	MMBT	73.48	68.89	68.95	67.12	0.3101	0.3258
Image + Text (Multimodal Pre-training)	ViLBERT CC	78.53	78.62	**81.41**	78.06	0.2279	0.1881
	V-BERT COCO	**81.36**	**79.55**	81.19	**80.13**	**0.1972**	**0.1857**

Shared tasks timeline

AMI’18 SemEval’19 HASOC’19 VLSP’19

EVALITA AMI 2018

Task- Misogyny
Best- Feature based XGBoost

SemEval-2019

Task-Multilingual
Best- SVM with RBF

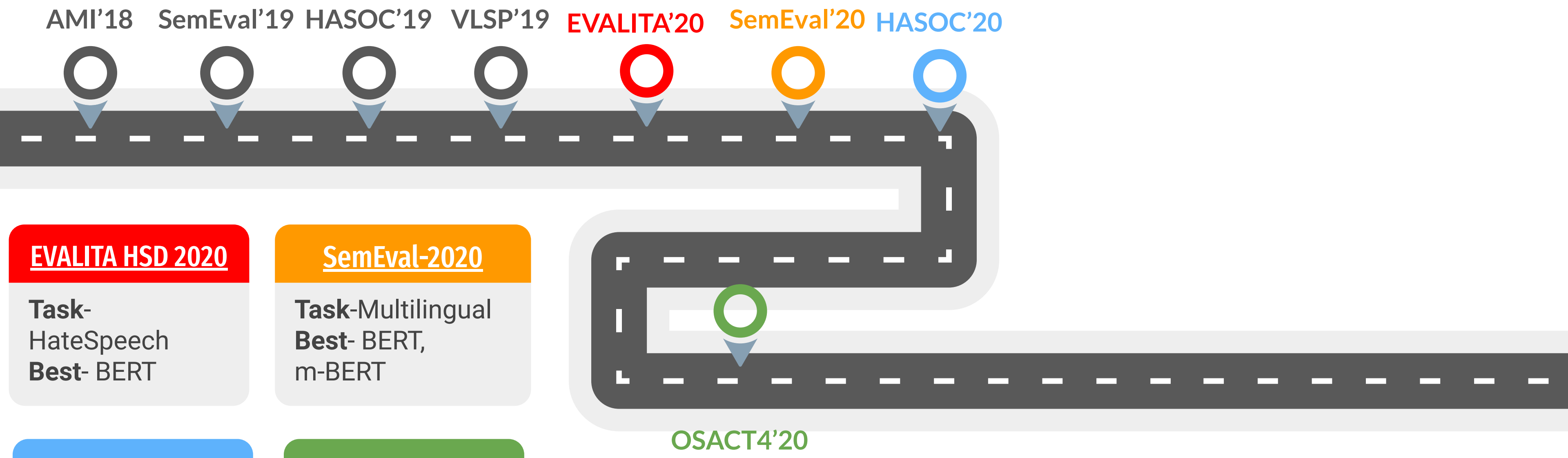
HASOC 2019

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

AMI’18
SemEval’19
HASOC’19
VLSP’19
EVALITA’20
SemEval’20
HASOC’20
OSACT4’20
TRAC’20
FB Hate Meme’20
DravidianLang Tech’21
SemEval'21

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**

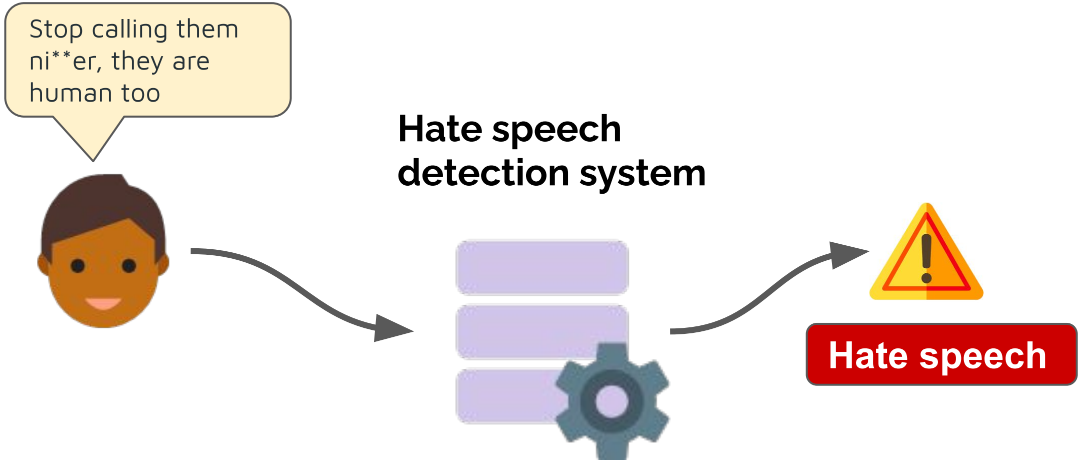
	Functionality	Example	Gold Label	n	Accuracy (%) DB-D	DB-F	PERS
Group identifier	**F18**: Neutral statement using protected group identifier	"We are a group of [IDENTITY]." "I live with two [IDENTITY]."	non-hateful	126	61.1	76.2	**84.1**
	F19: Positive statement using protected group identifier	"I love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

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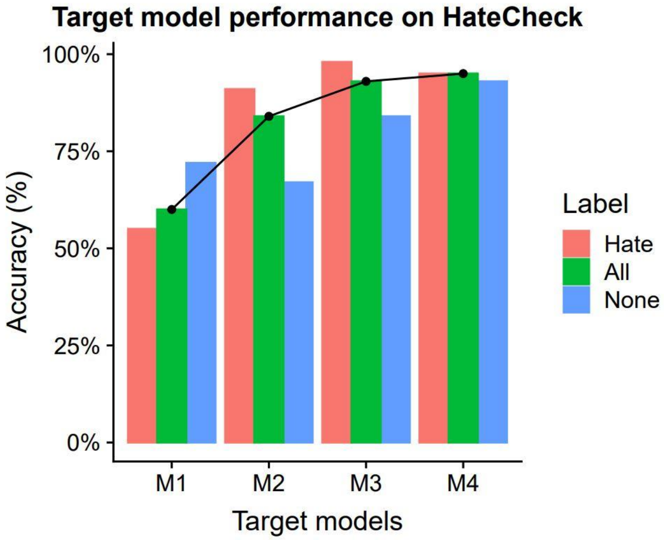
Dynamically Generated Data

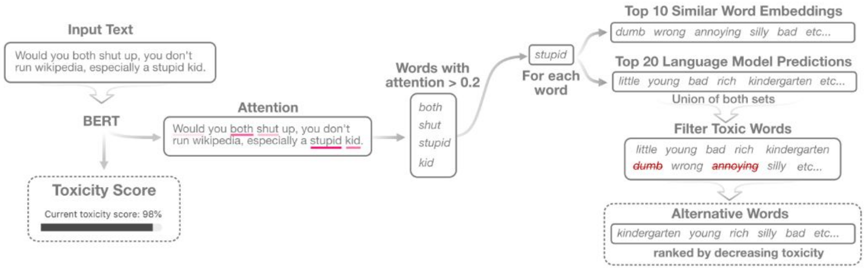
- A human-and model-in-the-loop process for training online hate detection models. (Vidgen.2021)

Round	Total	Not	Hate
R1	54.7%	64.6%	49.2%
R2	34.3%	38.9%	29.7%
R3	27.8%	20.5%	35.1%
R4	27.7%	23.7%	31.7%



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)

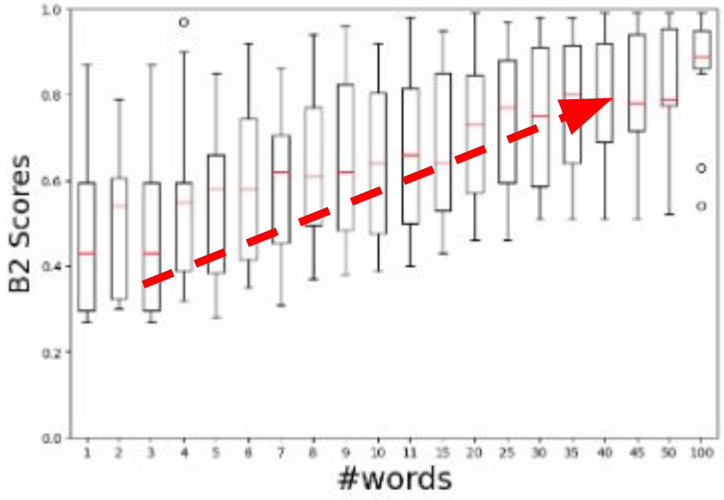


Advantage - reduce toxicity, way of debugging model
Disadvantage - malicious users might game the system.

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)]

	Amateur			Expert		
Feature Set	F1	Recall	Precision	F1	Recall	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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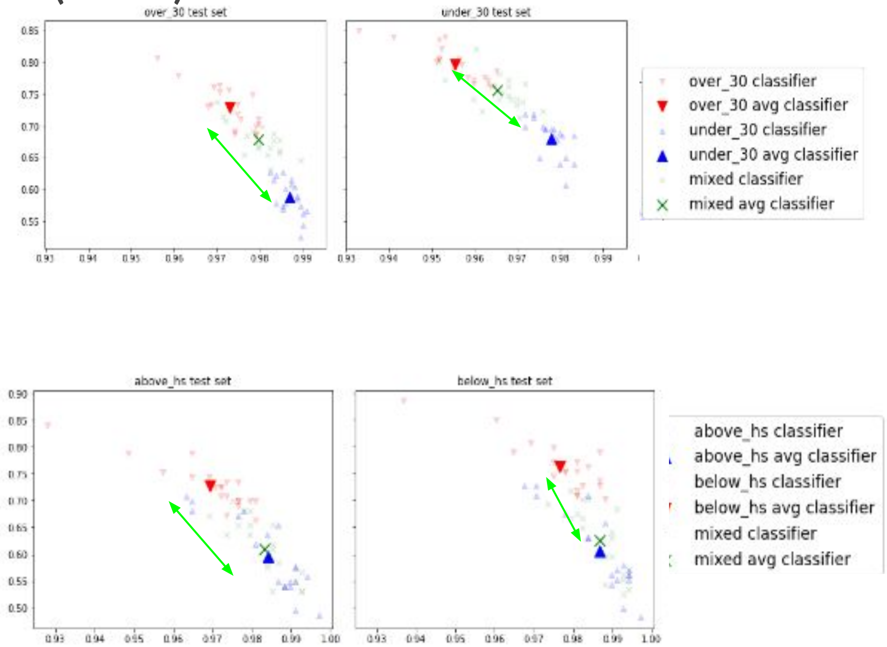
  - How is data selected ?
  - Who is the **annotator**?
  - Who is the speaker/target ?
- Data using expert annotators (activists) performs better than amateurs (crowdsource) (Waseem,2016)
- A study found significant bias for age and education of the annotators. (Kuwatly,2020)

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

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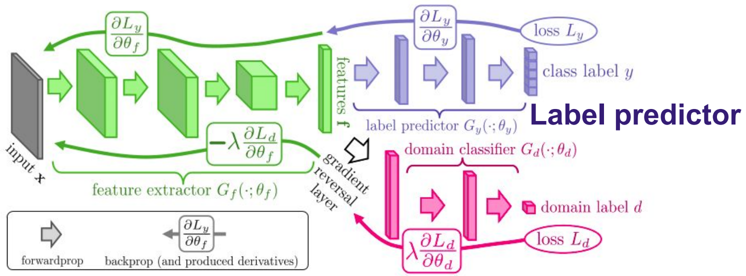
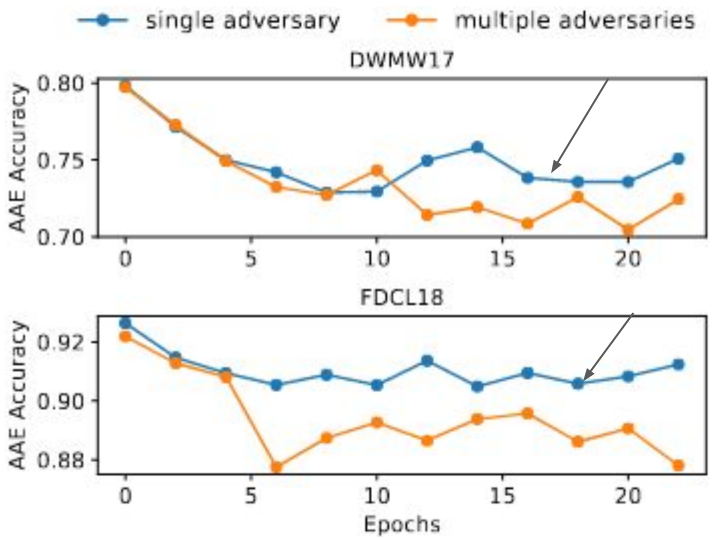
- Training with adversarial loss can help reduce the bias (Xia,2020).





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  - 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)

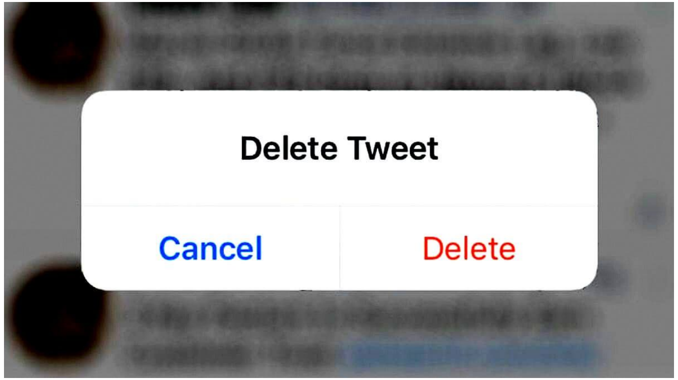
Models	GMB-Sub	GMB-BPSN	GMB-BNSP
CNN-GRU	0.654	0.623	0.659
BERT	0.762	0.709	0.757
BERT-HateXplain	**0.807**	**0.745**	**0.763**

Models less biased !

Mitigating Hate Speech

What is done after detecting hate speech?

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

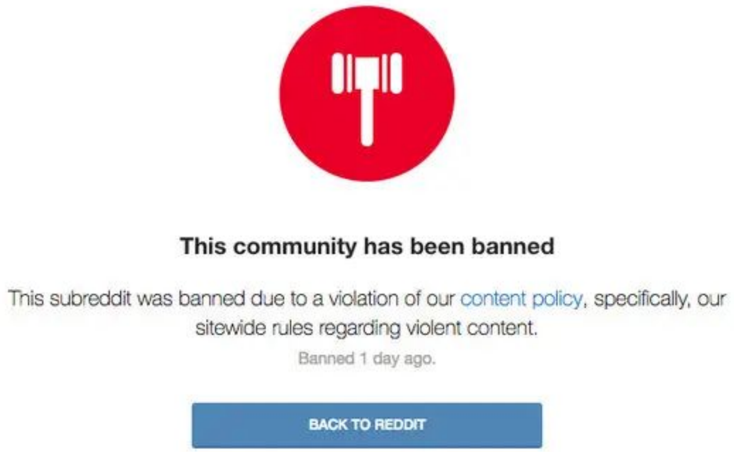


Is banning effective?

Is banning effective?

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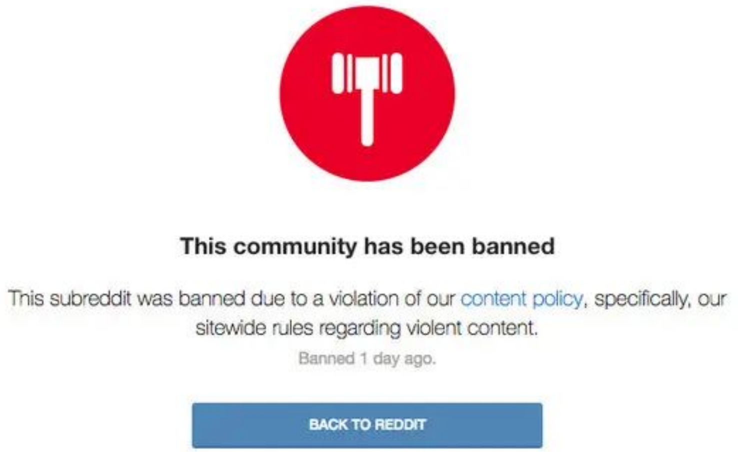
You Can't Stay Here: The Efficacy of Reddit's 2015 Ban Examined Through Hate Speech [Chandrasekharan 2017]

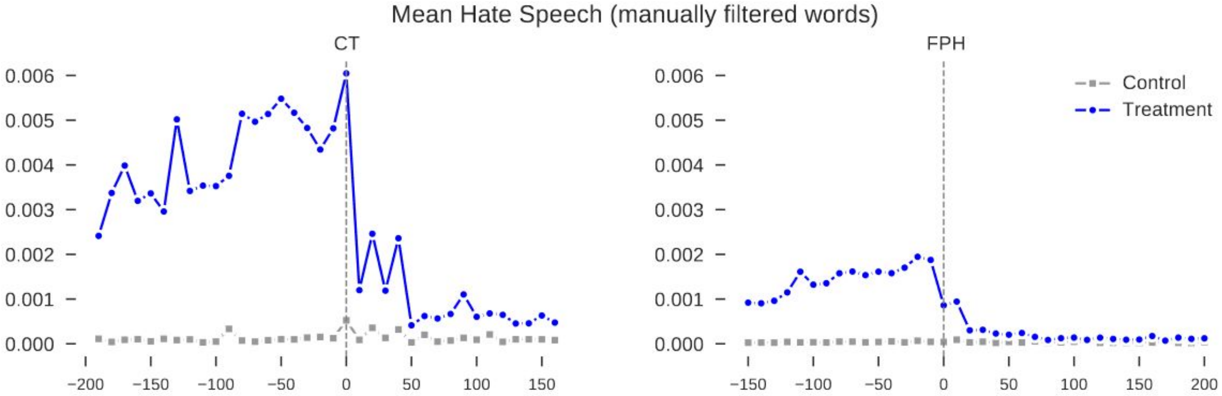


The Efficacy of Reddit's 2015 Ban

- **User-level -** Following Reddit's 2015 ban, a large, significant percentage of users from banned communities left Reddit. Others migrated to other sub-reddits where hate was prominent

The Efficacy of Reddit's 2015 Ban

- User-level - Following Reddit's 2015 ban, a large, significant percentage of users from banned communities **left Reddit.** Others migrated to other sub-reddits where hate was prominent
- Community-level - 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"**.

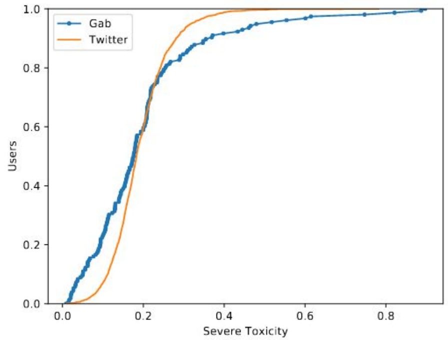


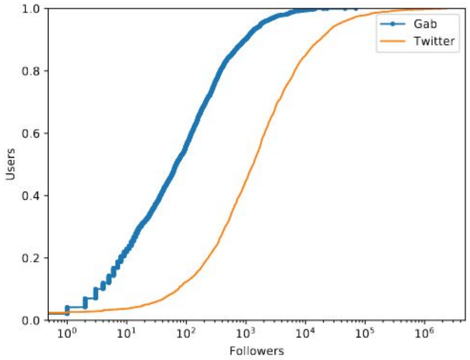
What about the users who left?

What about the users who left ?

Users who get banned on Twitter/Reddit exhibit an **increased level** of activity and toxicity on Gab, although the **audience** they potentially reach **decreases**

***Understanding the Effect of Deplatforming on Social Networks* [Ali 2021]**





Are there any alternatives?

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

[redacted] Cowardly attack on innocent people as it has happened in Gujrat carnage and various lynching in different regions of India.Cowards everywhere attack on unarmed civilians.Violence must be condemned at every level.

Like · Reply · 12 July at 00:53

[redacted] Muslims are not terrorists brother it's just because of few Muslims the name of the entire community is getting spoilt please learn to respect the religion.

Like · Reply · 8 · July 28, 2016 at 12:40am

Counterspeech

patriargate
@patriargate
Follow

So #Muslims do not seem to care so much about having a nice place to live. Or maybe they just believe that white (christian) slave should do the job.

MorgothLives @LivesMorgoth
Hackney in London is just 30% white yet a photo of volunteer litter pickers looks like this?
But if they ask Diane Abbott to represent them as much as the black community she'll block them

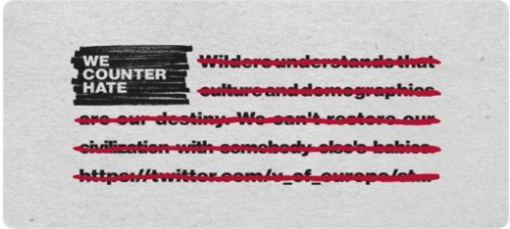
1:41 PM - 16 Nov 2018

1

Tweet your reply

More replies

We Counter Hate @we_counter_hate · 14m
Replying to @patriargate
This hate tweet is now being countered. Think twice before retweeting. For every retweet, a donation will be committed to a non-profit fighting for inclusion, equality and diversity. tinyurl.com/ybv4exgb



Taxonomy of counterspeech Benesch 2016

1. Presenting facts to correct misstatements or mis-perceptions
2. Pointing out hypocrisy or contradictions
3. Affiliation
4. Visual Communication
5. Humor and sarcasm
6. Denouncing hateful or dangerous speech
7. Tone

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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]

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

Counterspeech in Web

Counterspeech in Web

Data collected and annotated from comments of youtube videos showing hate towards some communities

	Target community			Total
Type of counterspeech	*Jews*	*Blacks*	*LGBT*	
Presenting facts	308	85	359	752
Pointing out hypocrisy or contradictions	282	230	526	1038
Warning of offline or online consequences	112	417	199	728
Affiliation	206	159	200	565
Denouncing hateful or dangerous speech	376	482	473	1331
Humor	227	255	618	1100
Positive tone	359	237	268	864
Hostile	712	946	1083	2741
Total	2582	2811	3726	9119

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

Counterspeech in Web

Data collected and annotated from comments of youtube videos showing hate towards some communities

	Target community			Total
Type of counterspeech	*Jews*	*Blacks*	*LGBT*	
Presenting facts	308	85	359	752
Pointing out hypocrisy or contradictions	282	230	526	1038
Warning of offline or online consequences	112	$\boxed{417}$	199	728
Affiliation	206	159	200	565
Denouncing hateful or dangerous speech	376	$\boxed{482}$	473	1331
Humor	227	255	618	1100
Positive tone	359	237	268	864
Hostile	712	946	1083	2741
Total	2582	2811	3726	9119

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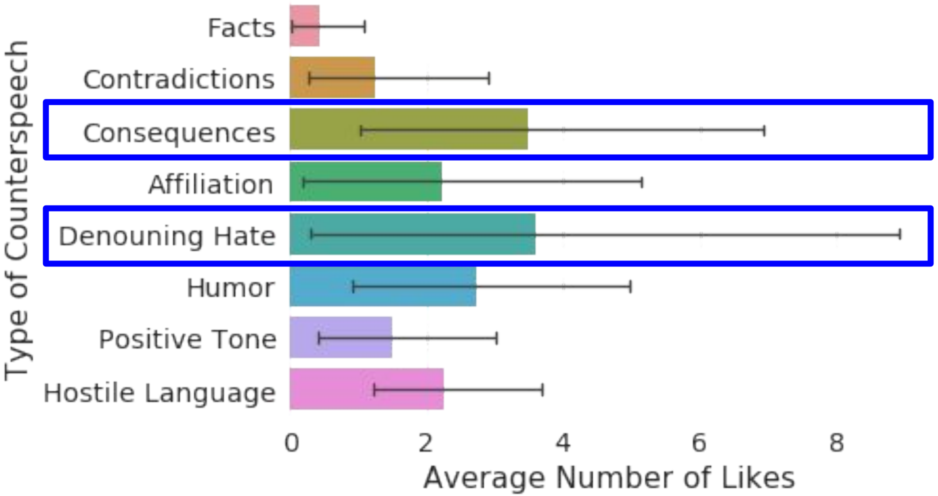
Click logo for demo

colab

Counterspeech in Web



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."

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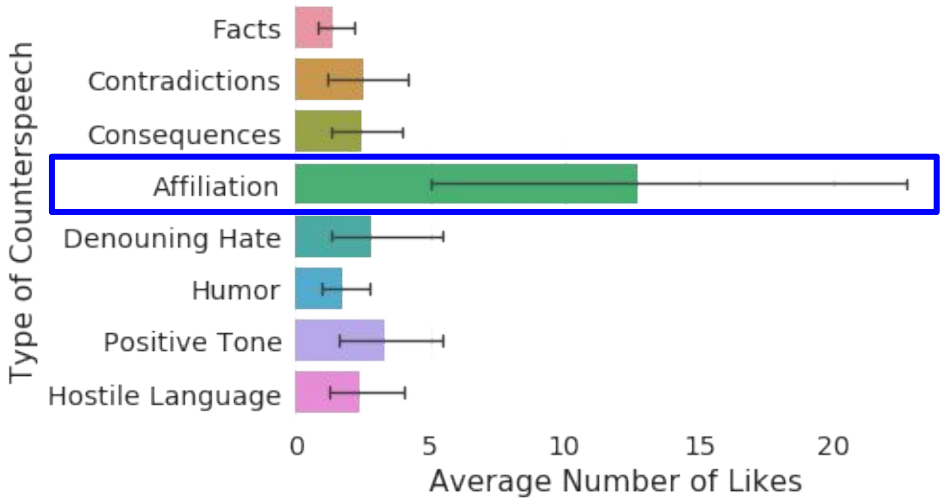
Click logo for demo

Counterspeech in Web



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"

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Can we generate counterspeech ?

Can we generate counterspeech ?

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**

Datasets for counterspeech generation

- CONAN Dataset [Chung 2019] (NGO Trainers)
- Intervene Dataset [Qian 2019] (Gab & Reddit)
- Multitarget CONAN Dataset [Fanton 2021] (Synthetic + NGO Trainers)

Counterspeech collection Strategy

Type	Hate speech source	Counter speech source	Annotation	Annotators
Crawling (Mathew 2019)	Online	Online	Labeling	Crowd
Crowdsourcing (Qian 2019)	Online	Synthetic	Response Generation	Crowd
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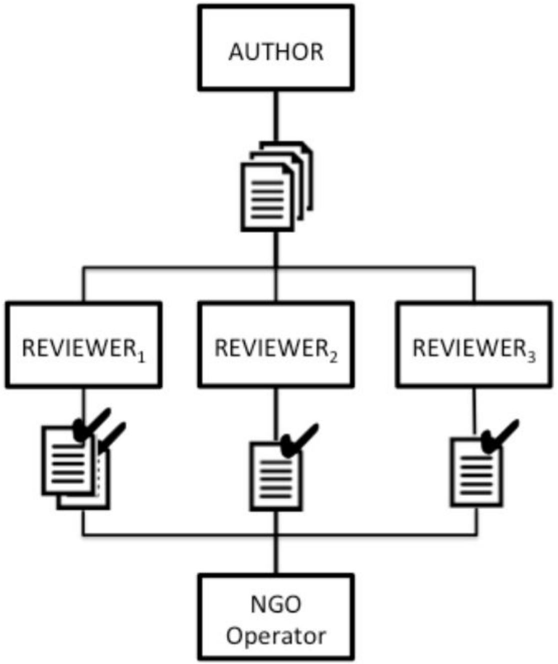
Counterspeech collection Strategy [Tekiroglu 2020]

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.

Example - Multitarget CONAN [Fanton et.al]



Generation models

VAE - RNN

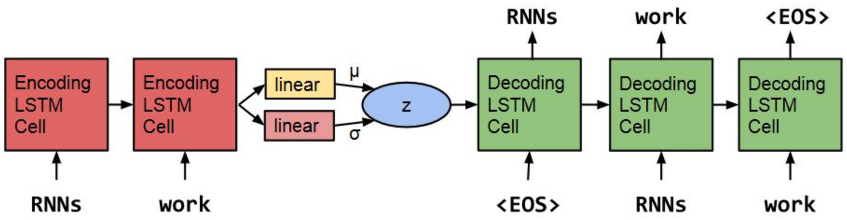
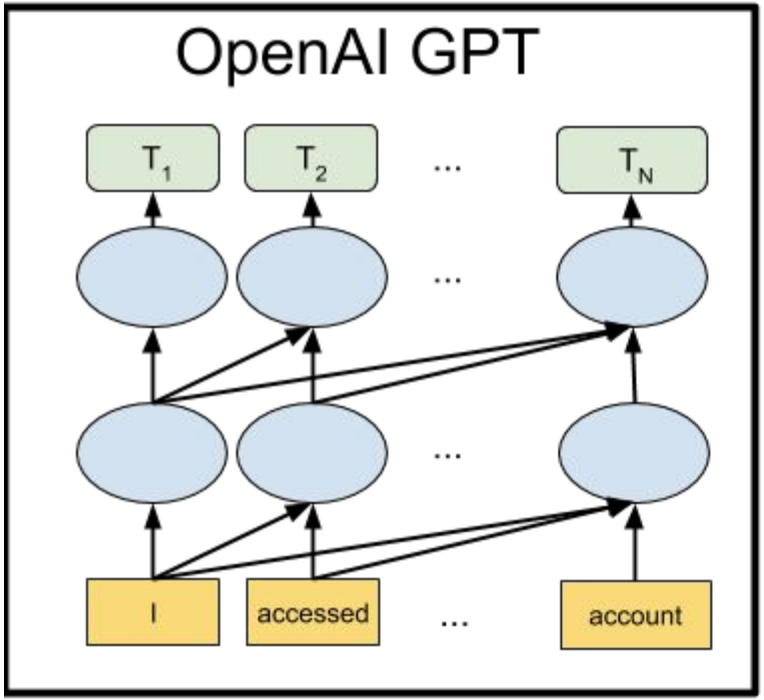
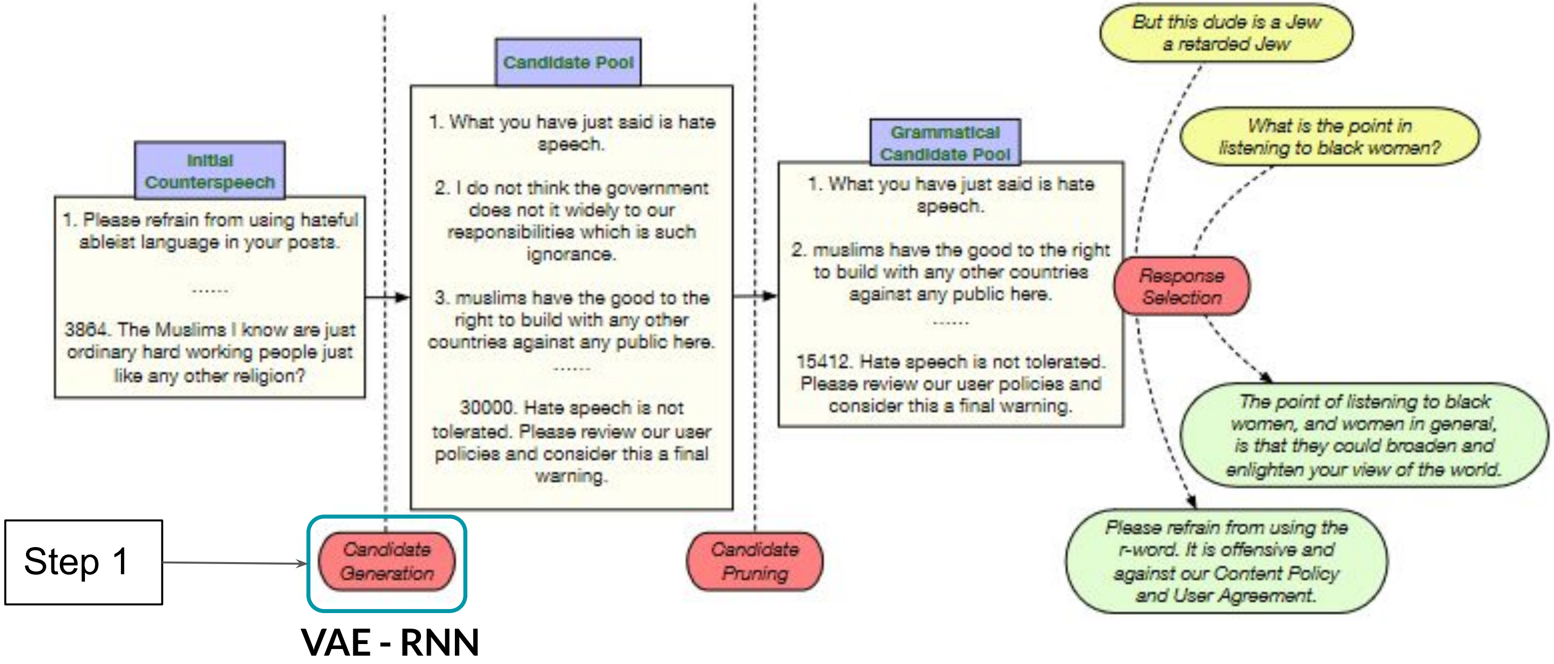


Figure 1: The core structure of our variational autoencoder language model. Words are represented using a learned dictionary of embedding vectors.

Generation models



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



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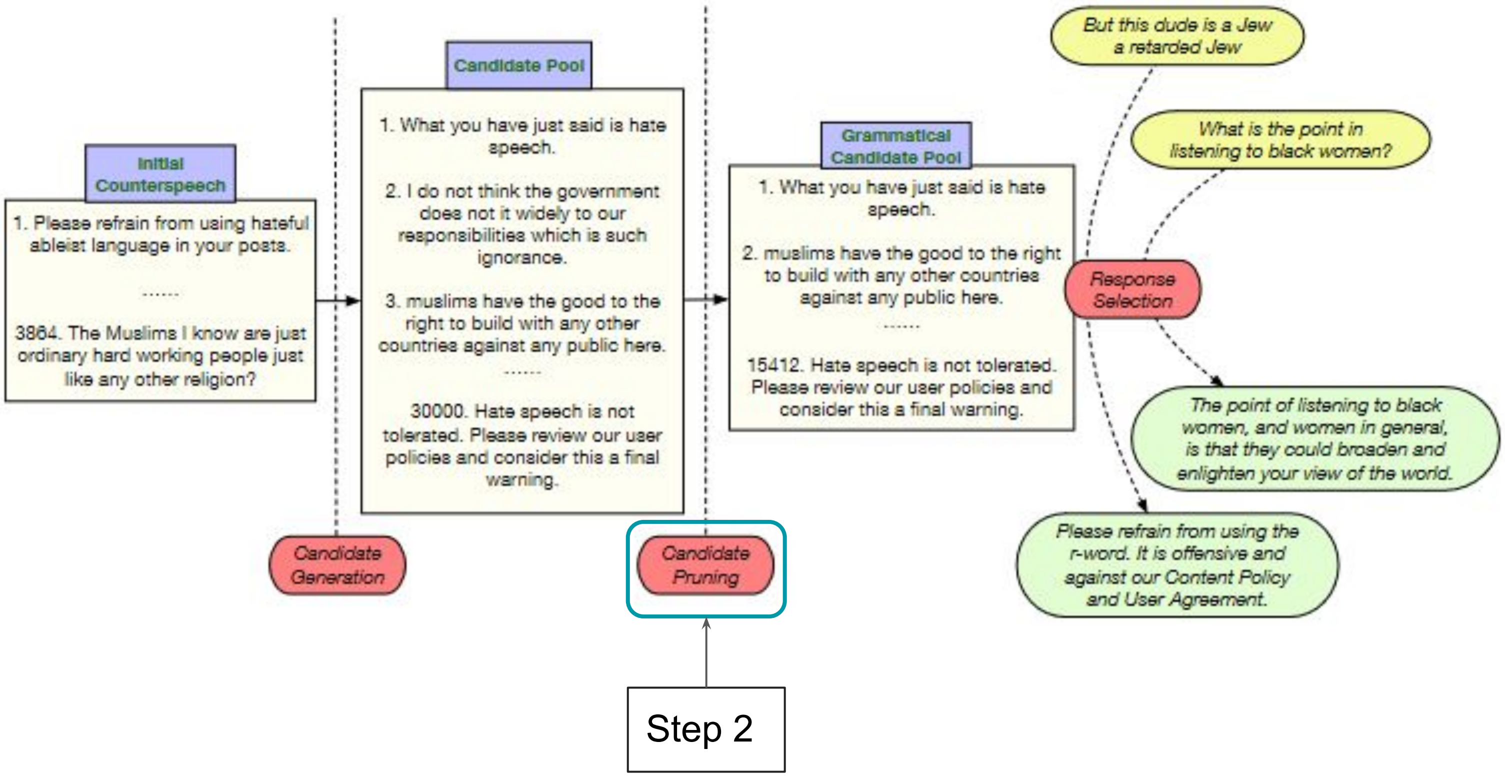

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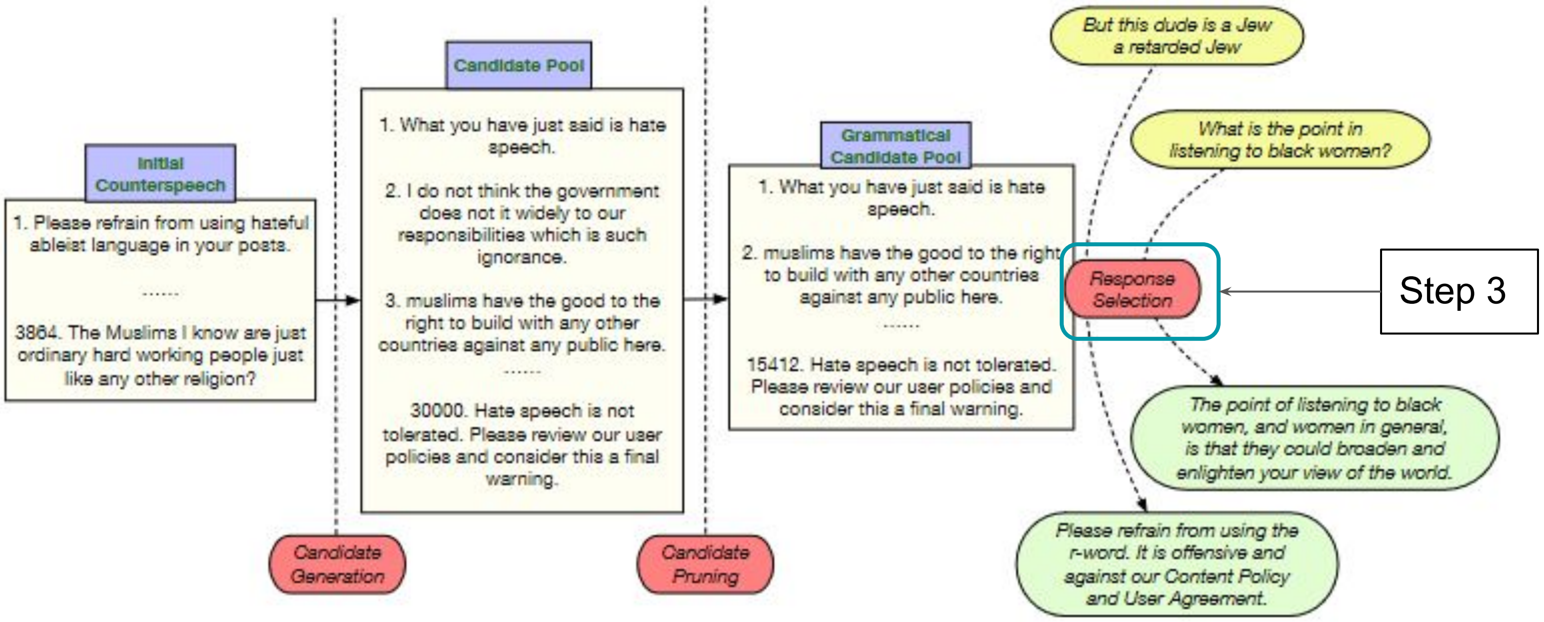

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		Diversity						Relevance					LQ.
		Dist-1	Dist-2	Ent-1	Ent-2	SB1*	SB2*	B2	R2	MS	BS	BM25	GR
CONAN	Seq2Seq	**0.06**	0.23	5.12	6.63	0.54	0.30	3.4	3.0	4.4	0.83	2.66	0.38
	MMI	**0.06**	0.23	4.88	6.41	0.57	0.35	2.9	2.3	3.9	0.82	1.63	0.33
	SpaceFusion	0.00	0.00	1.06	1.86	0.98	0.98	0.0	0.0	-14.2	0.76	0.12	0.38
	BART	0.04	0.23	**5.98**	**7.80**	0.52	0.26	3.9	3.6	7.1	0.84	1.86	**0.71**
	GPS	**0.06**	**0.27**	5.77	7.41	**0.43**	**0.19**	**7.1**	**6.5**	**10.9**	**0.85**	**5.43**	**0.71**
Reddit	Seq2Seq	0.04	0.24	5.07	6.61	0.58	0.31	6.5	4.0	6.8	0.85	0.14	0.64
	MMI	0.05	0.32	5.11	6.76	0.56	0.29	6.4	4.0	6.9	0.85	0.14	0.56
	SpaceFusion	0.00	0.02	2.73	4.16	0.87	0.76	0.9	0.0	-2.5	0.79	0.16	0.26
	BART	0.03	0.19	5.08	6.63	0.69	0.55	7.8	6.9	**7.8**	0.86	0.83	0.72
	GPS	**0.09**	**0.53**	**5.74**	**7.61**	**0.41**	**0.15**	**8.1**	**7.1**	**7.8**	**0.87**	**2.58**	**0.75**
Gab	Seq2Seq	0.02	0.17	5.14	6.71	0.56	0.30	7.5	5.0	6.7	0.86	0.14	0.67
	MMI	0.02	0.17	5.28	6.82	0.55	0.30	5.8	3.6	6.2	0.85	0.18	0.65
	SpaceFusion	0.00	0.01	3.72	4.84	0.81	0.73	1.8	0.1	0.0	0.82	0.17	0.21
	BART	0.03	0.17	5.42	7.25	0.60	0.38	6.9	6.4	6.8	0.86	0.81	0.72
	GPS	**0.06**	**0.40**	**5.82**	**7.83**	**0.39**	**0.15**	**7.6**	**6.4**	**6.8**	**0.87**	**1.94**	**0.76**

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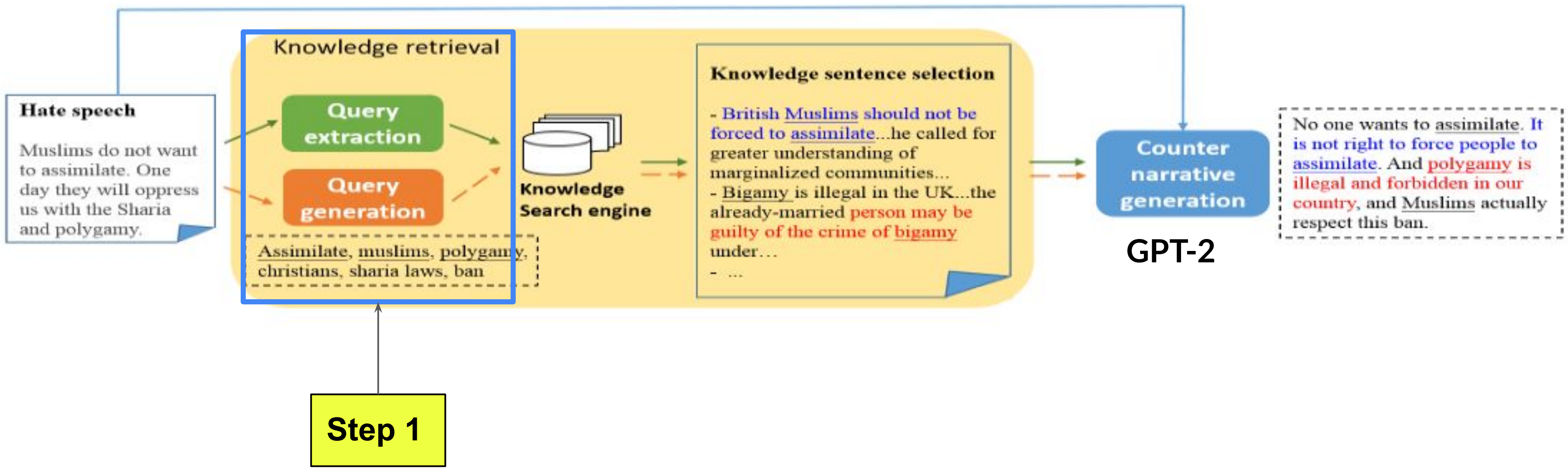
Hate Speech	Generated Counterspeech by GPS
(a): All the Muslims should have been punished for yesterday, not only a few. Citizen will take action if the government does not do anything.	You cannot blame all people for actions of a few. Banning something altogether will not solve anything.
(b): The world 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.

Problems: Hallucination

HS: *Muslims are invading our country*
CN: *Actually, there were 16,938,000 Muslims in the UK in 2016, so if you exclude London, that is actually increasing by 2%, which doesn't seem very significant.*

Table 2: Hallucinated CN generated by GPT-2 that is fluent and credible (according to Office for National Statistics, the Muslim population is just above 3M).

Towards Knowledge-Grounded Counter Narrative Generation for Hate Speech [Chung 2021]



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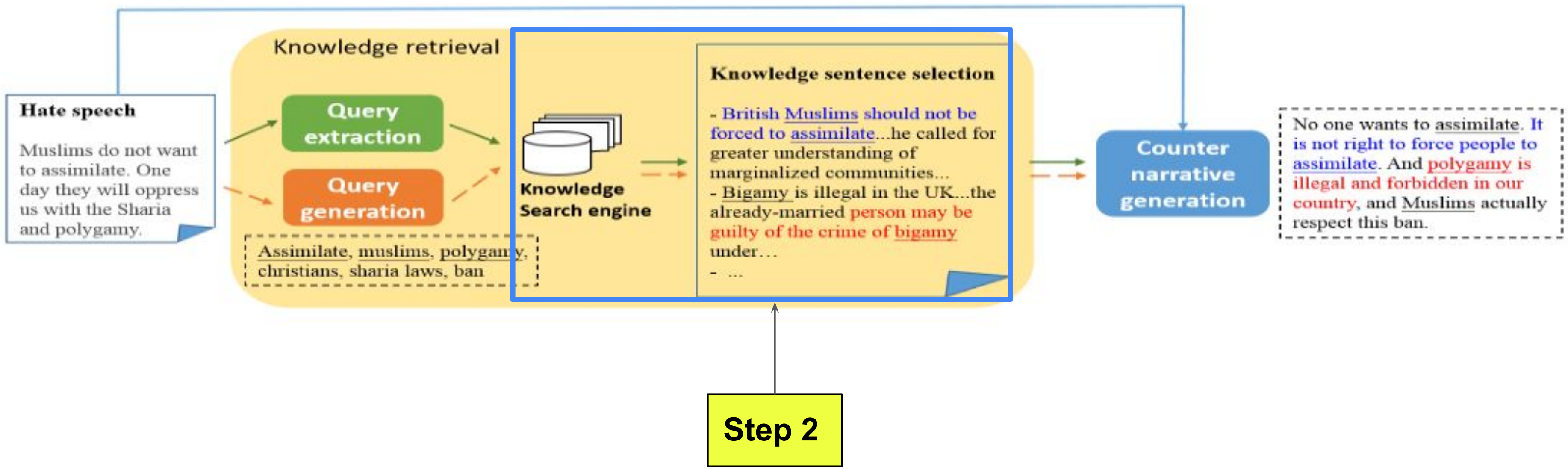

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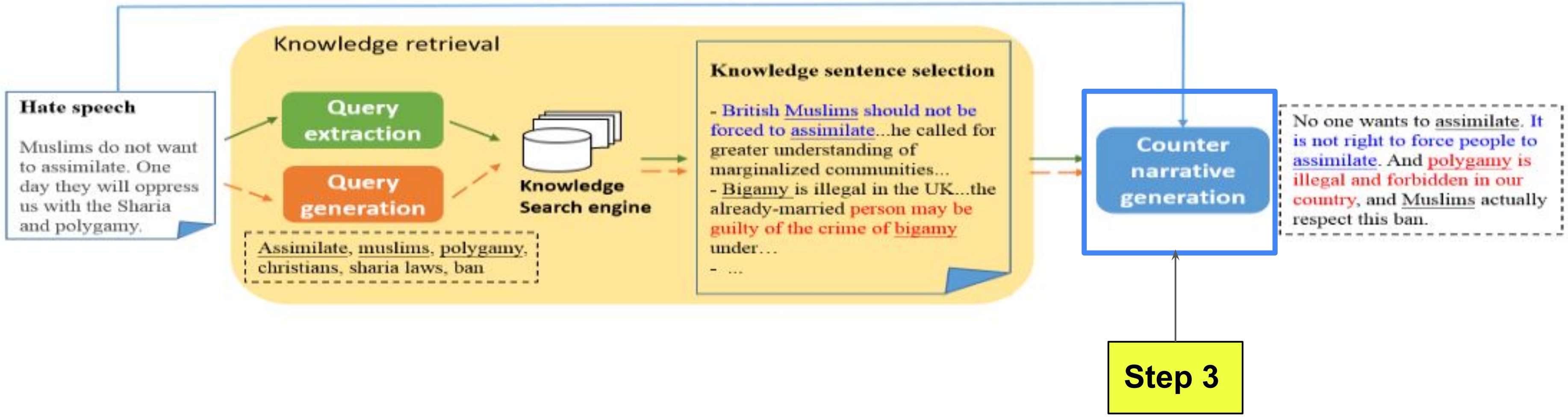

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without knowledge									
TRF	0.467	7.72	0.082	0.094	21.47	1.70	-	-	-
GPT-2	0.688	9.04	0.045	0.100	15.95	1.35	-	-	-
Train_{cn}	-	3.91	-	-	21.79	1.87	0.307	0.054	0.016
with knowledge									
Candela (Q_{hs})	0.692	21.87	0.040	0.098	23.85	2.47	0.173	0.008	0.001
GPT-2_{KN}									
w/ Q_{hs}	0.723	8.13	0.082	0.094	15.60	1.32	0.258	0.023	0.008
w/ Q_{gen}	0.728	7.48	0.067	0.091	12.75	1.17	0.260	0.050	0.019
w/ $Q_{hs \cup gen}$	0.735	6.30	0.085	0.103	15.35	1.59	0.358	0.068	0.024
w/ $Q_{hs \cup cn}$	0.727	7.17	**0.166**	0.110	13.10	1.16	0.282	0.058	0.022
$\text{GPT-2}_{KN,MT}$									
w/ Q_{hs}	0.744	11.69	0.050	0.090	13.35	1.17	0.269	0.049	0.017
w/ Q_{gen}	0.731	10.37	0.052	0.092	13.34	1.14	0.253	0.044	0.017
w/ $Q_{hs \cup gen}$	0.747	7.59	0.091	0.090	16.91	1.26	0.269	0.033	0.009
w/ $Q_{hs \cup cn}$	0.731	9.56	0.048	0.107	13.05	1.13	0.276	0.057	0.023
XNLG									
w/ Q_{hs}	**0.824**	14.42	0.073	0.084	55.51	3.71	0.841	0.650	0.558
w/ Q_{gen}	0.819	6.88	0.097	0.084	55.64	3.64	0.849	0.656	0.558
w/ $Q_{hs \cup gen}$	0.812	6.98	0.074	0.089	57.58	3.00	0.828	0.579	0.475
w/ $Q_{hs \cup cn}$	0.819	**5.69**	0.076	**0.116**	55.69	3.42	0.840	0.631	0.529

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w/ $Q_{hs \cup cn}$	0.731	9.56	0.048	0.107	13.05	1.13	0.276	0.057	0.023
XNLG									
w/ Q_{hs}	**0.824**	14.42	0.073	0.084	55.51	3.71	0.841	0.650	0.558
w/ Q_{gen}	0.819	6.88	0.097	0.084	55.64	3.64	0.849	0.656	0.558
w/ $Q_{hs \cup gen}$	0.812	6.98	0.074	0.089	57.58	3.00	0.828	0.579	0.475
w/ $Q_{hs \cup cn}$	0.819	**5.69**	0.076	**0.116**	55.69	3.42	0.840	0.631	0.529

Challenges ahead

- Generating diverse types of counterspeech.
- Lack of generalisation vs cost of building dataset.
- Evaluation of generative models.
- From generation models to tools.

Is counterspeech effective?

Considerations for Successful Counterspeech. Benesch 2016

- When do you call a counterspeech as successful?
- 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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- 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

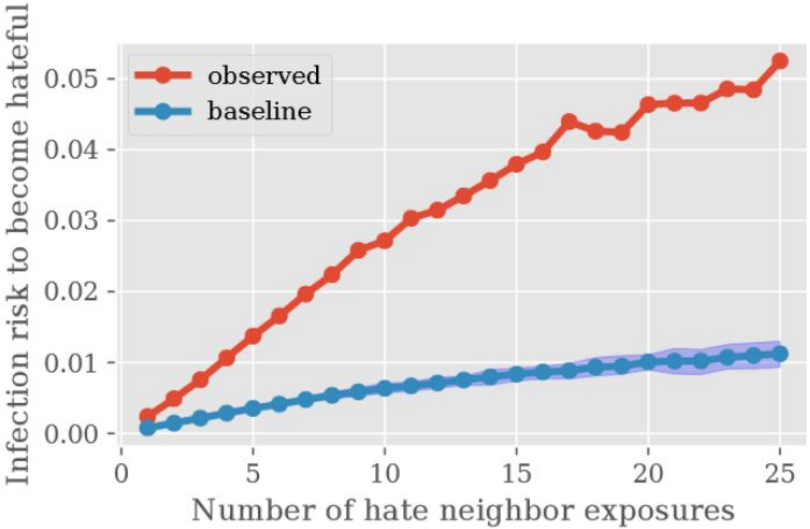
- Warning of Consequences
- Shaming/Labeling
- Empathy and Affiliation
- Humor
- Images

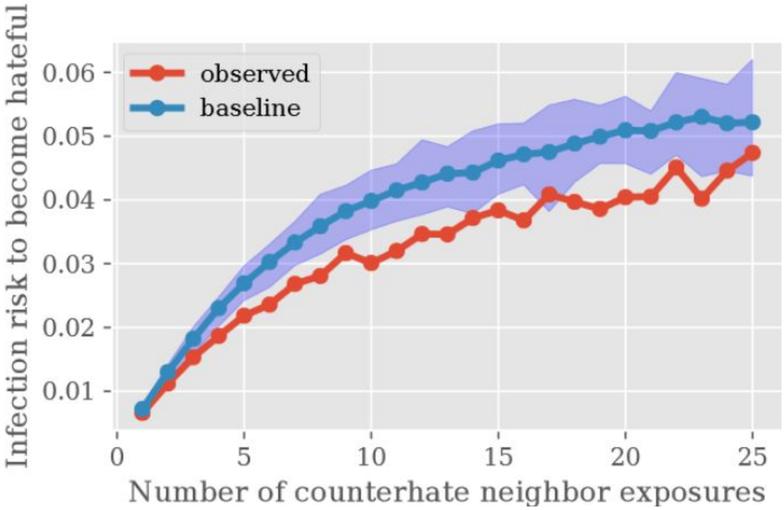
Discouraged Strategies

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

Evidence from social media platforms

Analysis reveals that **counterhate messages can discourage users from turning hateful** in the first place. [Ziem 2020]





Evidence from social media platforms

Their findings suggest that organized hate speech is associated with changes in public discourse and that counter speech—**especially when organized**—may help **curb hateful rhetoric** in online discourse [Garland 2020]

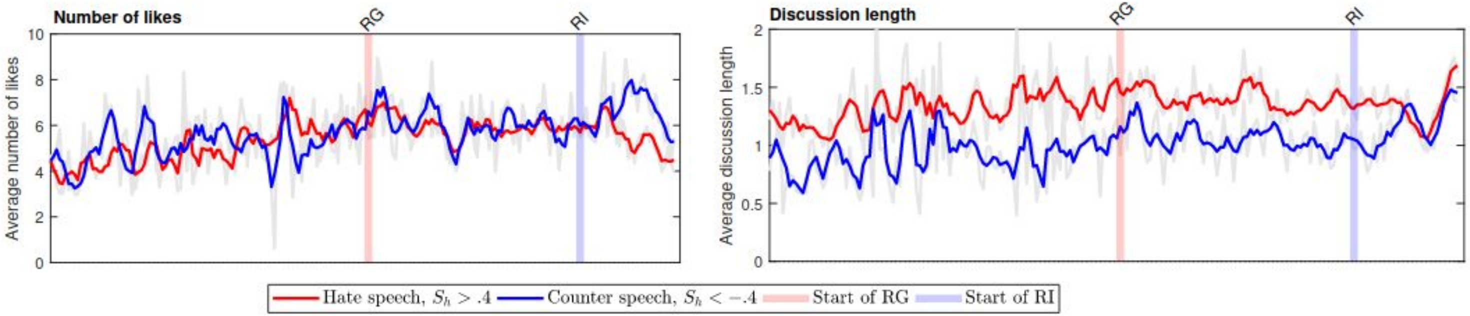


Figure 5: **Impressions of hate and counter speech.** Impact of hate and counter speech messages over time as quantified by the average number of likes and length of conversation they initiate. The emergence of organized counter speech (RI, blue vertical line). Results are for 181,370 reply trees from January 2015 to December 2018. Each data point is a week average and trends are smoothed over a month-long window. The timeline on the x-axis is the same as in other figures but was omitted for space, except for markers of the emergence of RG and RI.

Does type of counterspeech matter?

Does type of counterspeech matter?

Affiliation - Control accounts ("bots") to sanction the harassers. The author found that subjects who were countered by a **high-follower white male** significantly **reduced** their use of a racist slur.

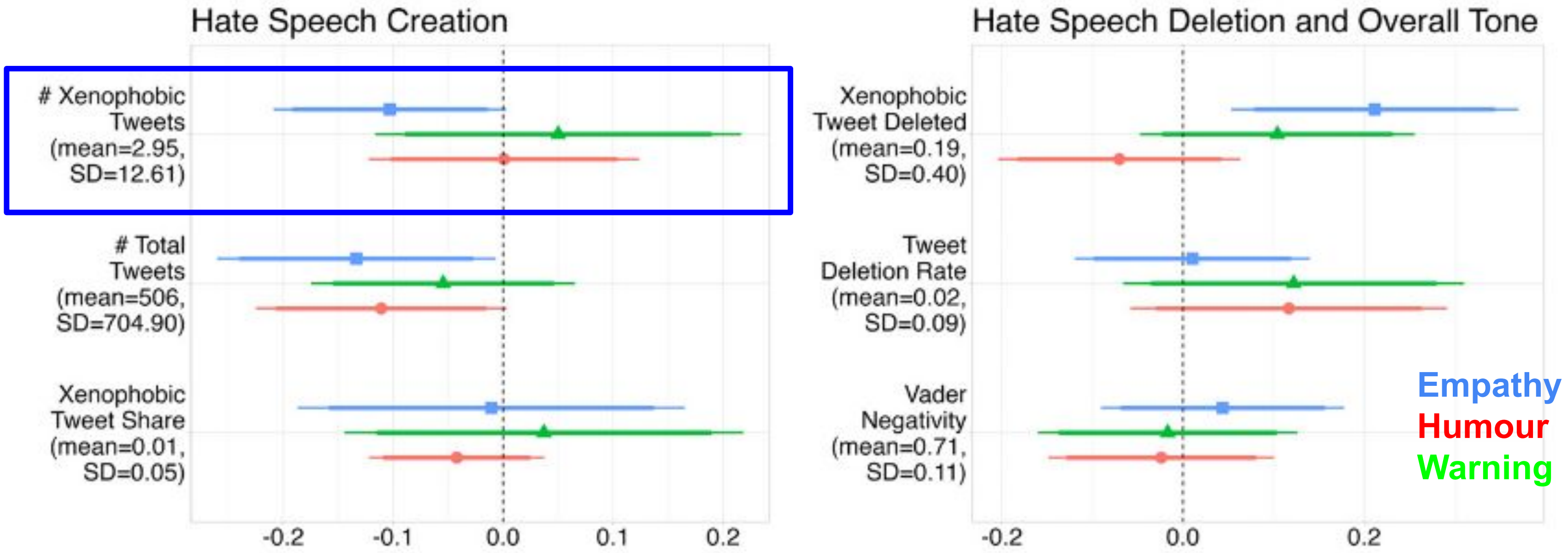
Tweetment Effects on the Tweeted: Experimentally Reducing Racist Harassment [Munger 2016](#)

Does type of counterspeech matter?

- The authors compared different types of counter speech - Warning of consequences, Humour and Empathy [Hangartnera,2021]

Does type of counterspeech matter?

Empathy based counter speech increase the **retrospective deletion of xenophobic hate speech**(0.2 SD) and reduce the prospective creation of xenophobic hate speech over a 4-wk follow-up period by 0.1 SD. [[Hangartnera,2021]]



Does type of counterspeech matter ?

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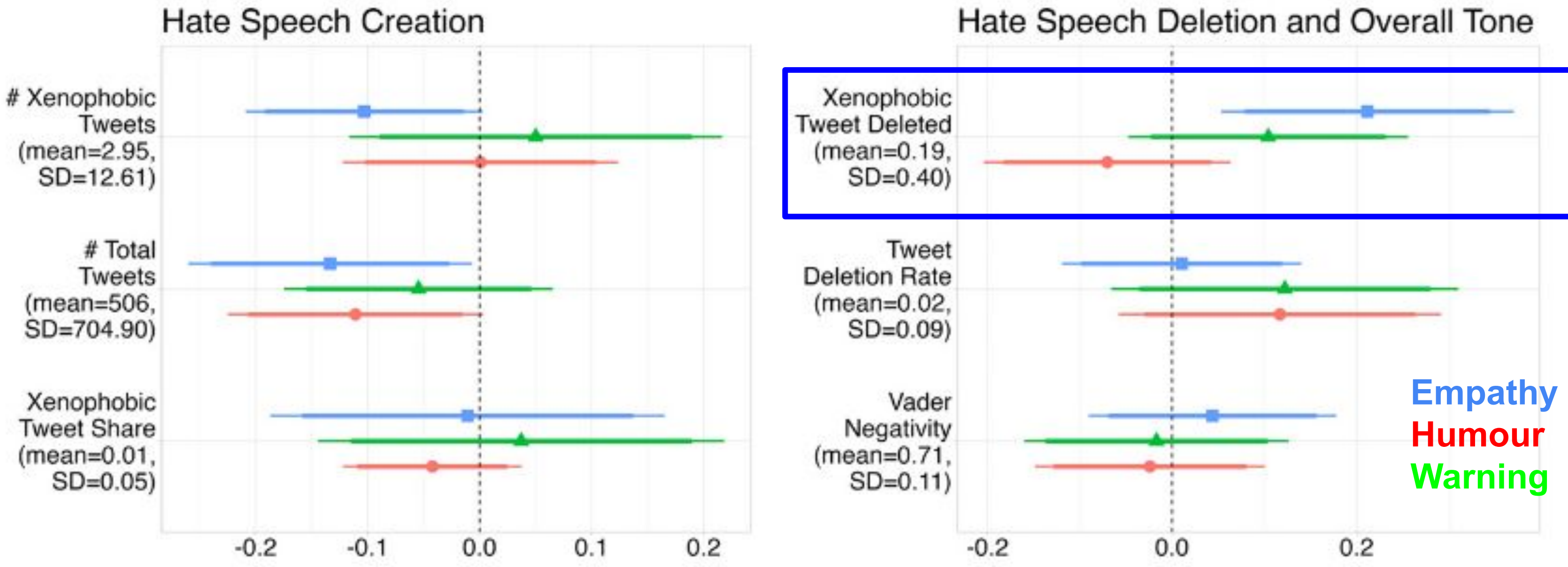


Potential extensions

- Hope Speech and Help Speech [Palakodety 2019] (YouTube Comments)

SWOT

- 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

Strengths

Weakness

Opportunity

Threat

Strengths

- Advancement in NLP i.e. Transformers
- Multilinguality
- NGO Initiatives
- Multiple datasets
- Theme, Research grants etc.

Weakness

Opportunity

Threat

Strengths

Weakness

- Inconsistent annotations
- Diverse tasks
- Lack of generalisability
- Bias in data as well as in models
- Lack of explainability

Opportunity

Threat

Strengths

Weakness

Opportunity

- Multimodal datasets
- User as an important aspect
- New variants coming up - Fearspeech, Dangerous speech
- Counter speech as mitigation

Threat

Strengths

Weakness

Opportunity

Threat

- Users vs detection
- Alternative (echo chamber) platforms - Gab
- Govt agencies weaponizing hate
- Laws used to silence dissent

Campaigns to deter hate

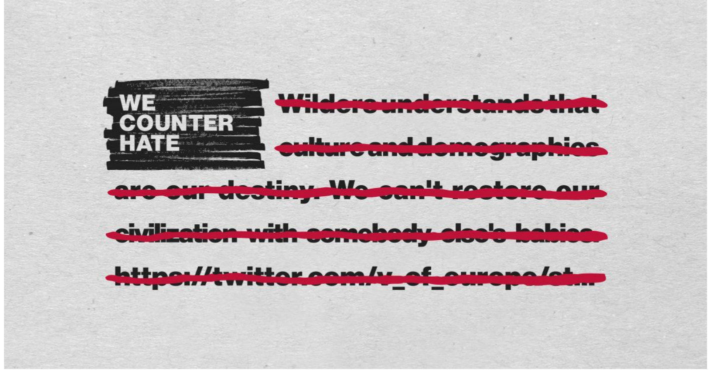
FACEBOOK

[Counterspeech.fb]

ADL

FIGHTING HATE FOR GOOD

[ADL]



[WeCounterHate]

NO HATE

NO HATE SPEECH MOVEMENT

[NoHateSpeechMovement]

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