Hate and Abuse Detection

An Overview

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How do we define "hate speech" and "abuse"?

• bn:00629957n • NOME • Concetto • Categorie: Censorship, Ethically disputed political practices, Freedom of speech, Hate crime...

EN hate speech

Hate speech is speech which attacks a person or group on the basis of attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender. *Wikipedia* *Più definizioni*

• bn:00000521n • NOME • Concetto • Categorie: Abuse, Bullying, Psychological abuse

EN abuse · insult · revilement · contumely · vilification

A rude expression intended to offend or hurt *WordNet* *Più definizioni*

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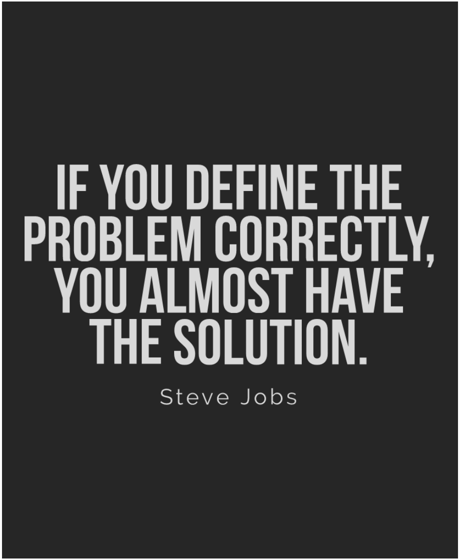

Difficulties in annotating abuse:

- Lack of standard definitions
- Differences in annotators' cultural background
- Ambiguity in the annotation guidelines

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Issues in data annotation

Figure: "Il bambino con lo zerbino" by Federico Clapis

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Figure: "Il bambino con lo zerbino" by Federico Clapis

- Is this artwork racist?

Figure: "Il bambino con lo zerbino" by Federico Clapis

- Is this artwork racist?
- **Only the target gets to decide**

Issues in data annotation (2)

Some Tweets may appear to be hateful when viewed in isolation, but may not be when viewed in the context of a larger conversation. For example, members of a protected category may refer to each other using terms that are typically considered as slurs. When used consensually, the intent behind these terms is not abusive, but a means to reclaim terms that were historically used to demean individuals.

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- We need:
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- We need:
  - Context
  - Information about author and target
- Good luck with ethical issues..

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But we must have something! ..right?

- Datasets characterised by:
  - **Source:** Twitter, Facebook, Reddit, Wikipedia
  - **Composition:** e.g., racism and sexism, or personal attack and racism, or hate speech and profanity
  - **Language:** English, followed by German, Hindi and Dutch.

name	publication	source	microposts	%abusive
Kaggle†	(Wulczyn et al., 2017)	Wikipedia	312,737	9.6
Founta	(Founta et al., 2018)	Twitter	59,357	14.1
Razavi	(Razavi et al., 2010)	diverse	1,525	31.9
Warner	(Warner and Hirschberg, 2012)	diverse	3,438	14.3
Waseem	(Waseem and Hovy, 2016)	Twitter	16,165	35.3
Kumar	(Kumar et al., 2018)	Facebook	15,000	58.1

Figure: Table from [Wiegand et al., 2019]

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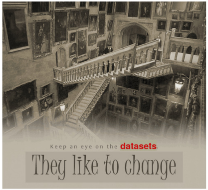

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The Problem of Biased Datasets [Wiegand et al., 2019]

- There are issues in data collection as well!
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Founta	(Founta et al., 2018)	Twitter	59,357	14.1	boosted random sampling	75.9
Razavi	(Razavi et al., 2010)	diverse	1,525	31.9	boosted random sampling	64.7
Warner	(Warner and Hirschberg, 2012)	diverse	3,438	14.3	biased sampling	51.3
Waseem	(Waseem and Hovy, 2016)	Twitter	16,165	35.3	biased sampling	44.4
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- There are issues in data collection as well!
  - Can't rely on random sampling: only 0.1% to 3% of posts are abusive
- What about **focused sampling**?
  - Boosted random sampling: random sampling + heuristics (fails at capturing implicit abuse)
  - Biased sampling: manual selection of query words and topics

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→ High classification scores are likely to be the result of modeling the bias in the datasets

→ We won't talk about SOTA

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  - Rules: noun phrases used as appositions ("you flamers"), imperative statements, bad-words, condescending statements ("isn't it?"), etc.
  - Limitations: sarcasm, complex sentences and errors in spelling, punctuation and grammar

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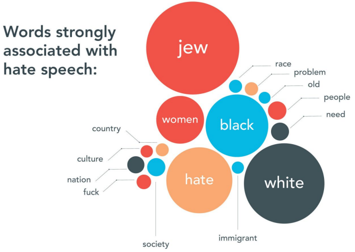
Lexicon-Based Approaches

- Razavi et al. [2010]:
  - IALD: Collect 2700 words and phrases and associate them with weights indicating their abusive impact



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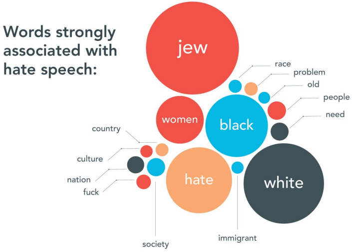

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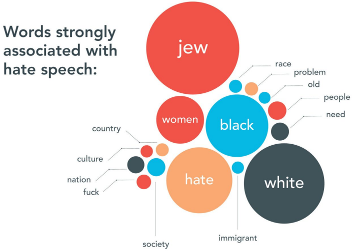

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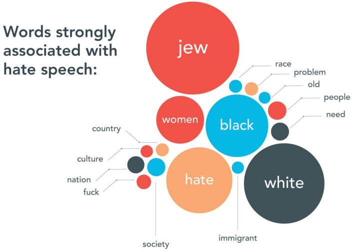

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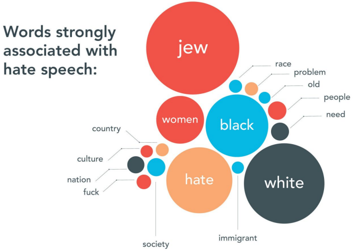

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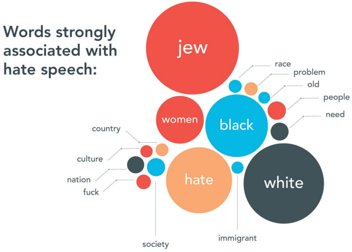

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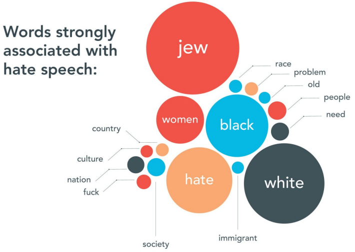

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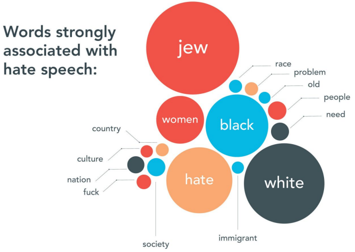

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- Work well on explicit posts, **limitations on implicit abuse**

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Exploiting User Profiling [Mishra et al., 2019a]

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- Employ NN to extract features for users instead of manually leveraging gender, location, etc.
- Capture structure of online communities and linguistic behaviour of users
  - *Homophily*: people tend to cluster with those who appear similar to themselves

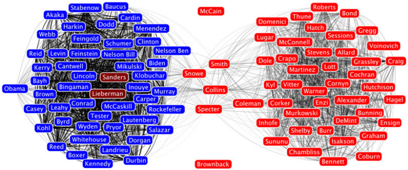

Figure: Graph by Human-computer Interaction Lab: nodes are senators (red for Republicans, blue for Democrats) and edges indicate the similarity of voting records

Exploiting User Profiling (2) [Mishra et al., 2019a]

- Data:
  - 16,202 tweets out of the 16,907 from Waseem and Hovy [2016]
  - 1,875 unique users
  - Classes: 12% racist, 19.4% sexist, 68.6% clean

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  - Heterogeneous **extended graph**: additionally contains nodes representing tweets, each tweet is connected to his author
- Graph-based **semi-supervised** problem:
  - Only tweet nodes have labels!
  - The model should distribute gradient information from the supervised loss on the labeled nodes
  - How? **Graph Convolutional Network**

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Exploiting User Profiling (3) [Mishra et al., 2019a]

- Graph Convolutional Networks (informal):
  - Classic NNs would process nodes independently: $O = \sigma(F\,W)$
  - Can't use Convolutional layers: nodes have different number of neighbours
  - GCNs take into account the adjacency matrix A: $O = \sigma(A\,F\,W)$

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- Authors apply a 2-layer GCN to the extended graph:
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  - Tweet as binary BOW, author as sum over all composed tweets
  - Extract **node embeddings**: $E = \sigma(A\,F\,W^1)$

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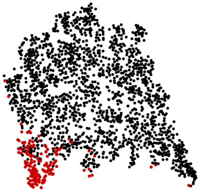
Exploiting User Profiling (4) [Mishra et al., 2019a]

- How do they classify tweets?
  - **GCN**: assign the label provided by the GCN



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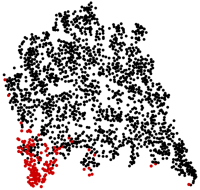
  - **GCN**: assign the label provided by the GCN
  - **LR + GCN**: author embedding is appended onto the tweet's character n-gram representation for training a Linear Regression classifier



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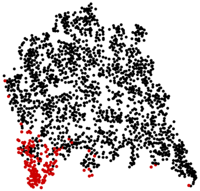
Exploiting User Profiling (4) [Mishra et al., 2019a]

- How do they classify tweets?
  - **GCN**: assign the label provided by the GCN
  - **LR + GCN**: author embedding is appended onto the tweet's character n-gram representation for training a Linear Regression classifier

- LR + GCN performs better (or better models the bias in the dataset..)

Method	Racism			Sexism			Overall		
	P	R	F_1	P	R	F_1	P	R	F_1
GCN†	74.12	64.95	69.23	82.48	**82.22**	82.35	81.90	79.42	80.56
LR + GCN†	79.08	**79.90**	**79.49**	**88.24**	80.95	**84.44**	**86.23**	**84.73**	**85.42**



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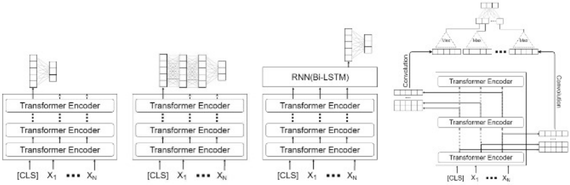
Where is BERT? [Mozafari et al., 2019]



(a) $\text{BERT}_{\text{base}}$ fine-tuning (b) Insert nonlinear layers (c) Insert Bi-LSTM layer (d) Insert CNN layer

- Pre-trained $\text{BERT}_{\text{base}}$ model
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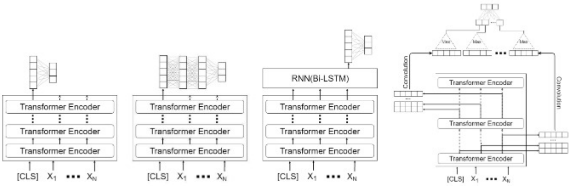

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- Pre-trained $\text{BERT}_{\text{base}}$ model
- Fine-tuning datasets: Waseem and Hovy [2016] and Davidson et al. [2017]
- Best performing model: BERT + CNN

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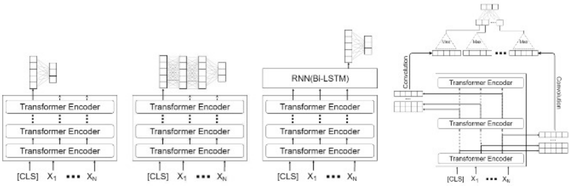

(a) $\text{BERT}_{\text{base}}$ fine-tuning (b) Insert nonlinear layers (c) Insert Bi-LSTM layer (d) Insert CNN layer

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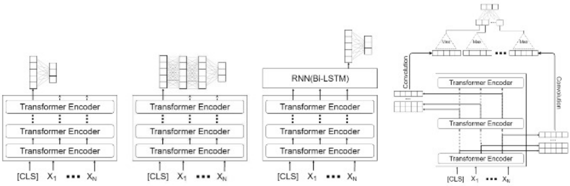

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Open Problems [Mishra et al., 2019b]

- **Ethical challenges** in user profiling:
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- Continuous **evolution of the Internet jargon**:
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- Abuse is inherently **contextual**:
  - Sophisticated techniques are needed to capture the history of the conversation and the behavior of the users as it develops over time

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- **Explainability**:
  - Establish intent of abuse or lack of it
  - Highlight instances of abuse if present, be they explicit or implicit
  - Identify the target(s) of abuse

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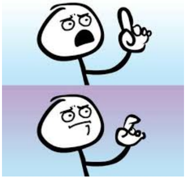

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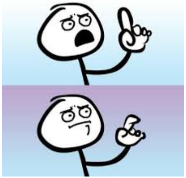

- Proposed solution:
  - Introduce **evidence-based** abuse detection
  - Evidences: collection of documents (from, e.g., social media guidelines, blog posts about social issues, etc.)

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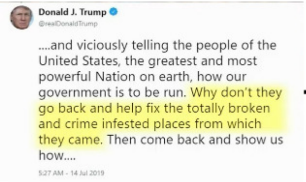

Donald J. Trump
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....and viciously telling the people of the United States, the greatest and most powerful Nation on earth, how our government is to be run. Why don't they go back and help fix the totally broken and crime infested places from which they came. Then come back and show us how....

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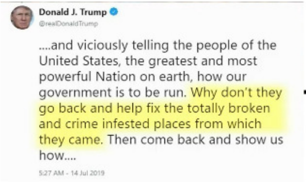

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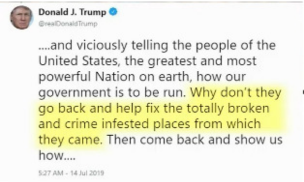
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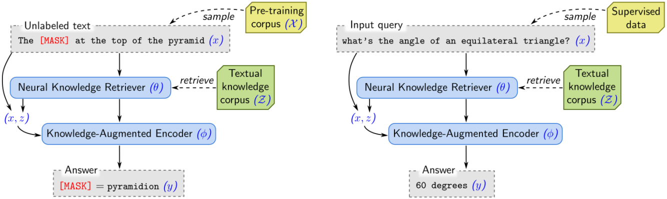

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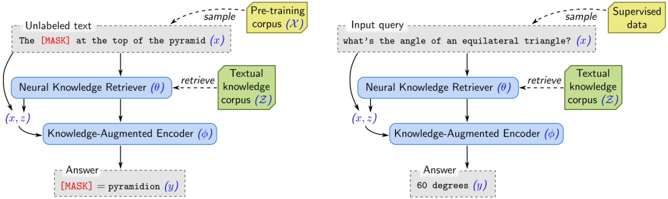

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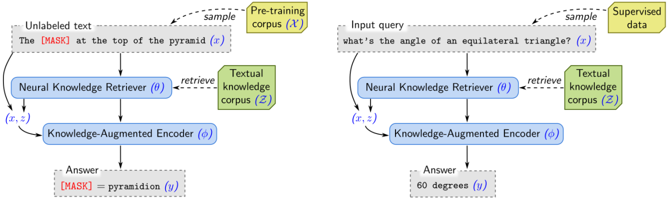

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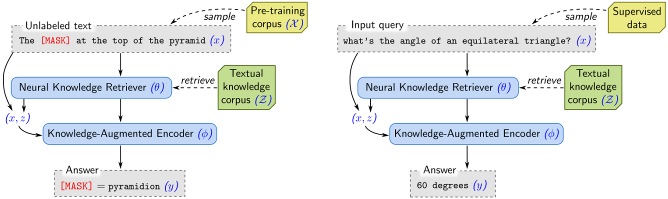

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- Evaluation through adversarial attacks, as in [Schiller et al., 2020]

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Thank you! Questions?

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