ZEERAK TALAT I UNIVERSITY OF SHEFFIELD

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PROGRESS IN HATE SPEECH DETECTION AND THE THINGS WE LOST IN THE FIRE

STATING OUR AIMS

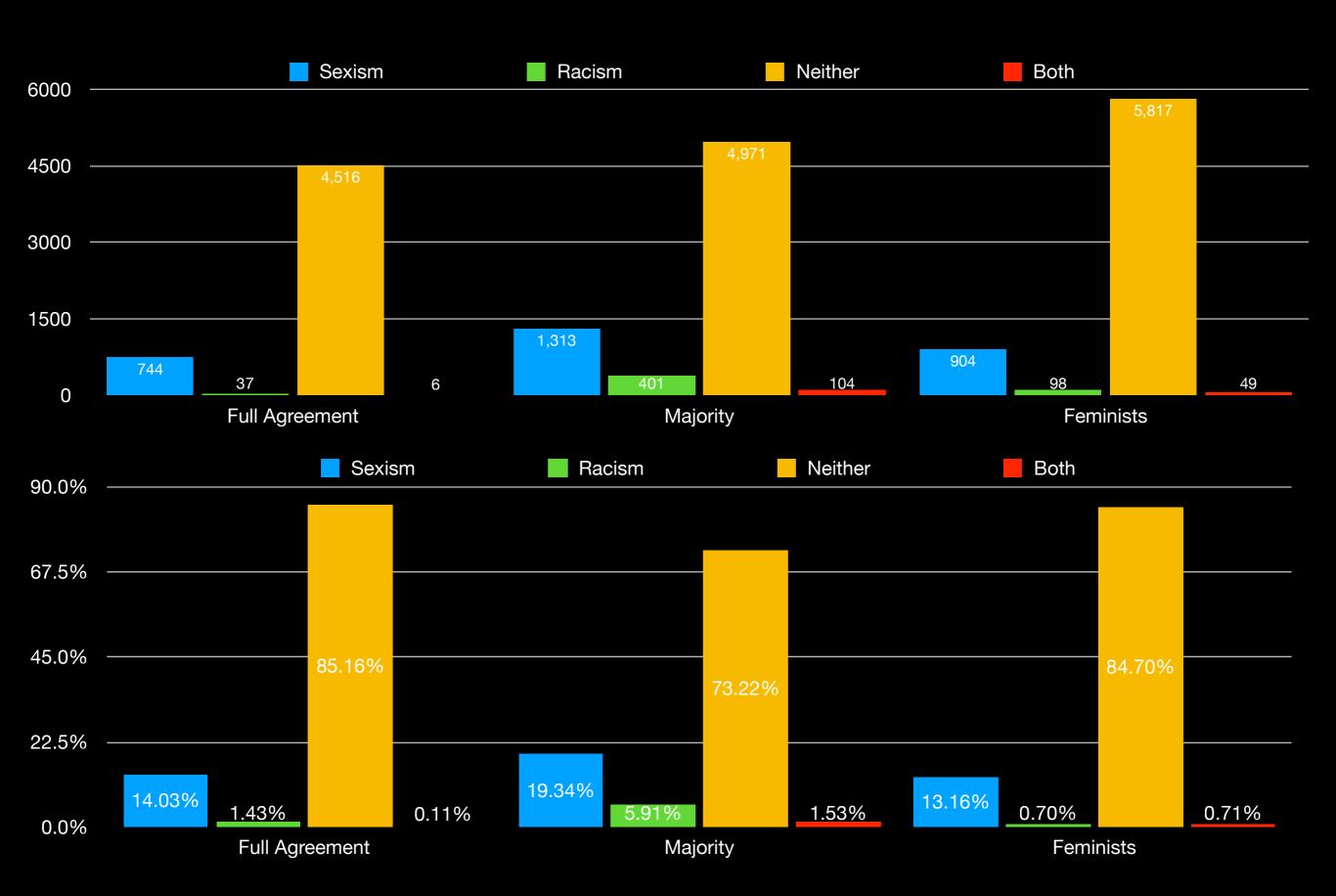
- High level:
 - Protection of people
 - Without coinciding with societal discrimination
 - and allowing for dissent
- Low Level
 - Removal of content
 - Find means of dealing with hate speech as it occurs on online platforms.

STATING OUR AIMS

- Which means...
 - A. Remove candidates of abuse; or
 - B. Understanding societal contexts to allow for dealing with abuse and hate.

ANNOTATION

- 1. uses a sexist or racial slur.
- 2. attacks a minority.
- 3. seeks to silence a minority.
- 4. criticizes a minority (without a well founded argument).
- 5. promotes, but does not directly use, hate speech or violent crime.
- 6. criticizes a minority and uses a straw man argument.
- 7. blatantly misrepresents truth or seeks to distort views on a minority with unfounded claims.
- 8. shows support of problematic hash tags. E.g. "#BanIslam", "#whoriental", "#whitegenocide"
- 9. negatively stereotypes a minority.
- 10. defends xenophobia or sexism.
- 11. contains a screen name that is offensive, as per the previous criteria, the tweet is ambiguous (at best), and the tweet is on a topic that satisfies any of the above criteria.



HOW WELL DO OUR ANNOTATORS AGREE

	Majority v. Feminists	Full Agreement v. Feminists	All CF Annotaators		
Cohen's kappa	0.34	0.70	0.57		
Krippendorf's alpha	0.32	0.70			

WHAT DOES OUR CLASSIFIER THINK

F1-Scores

	Majority	Feminists
Character n-gram	86.41	91.24
Token n-gram	86.37	91.55
Binary Gender	76.64	77.77
GenderProbability	86.37	81.30
Brown Clusters	84.50	87.74
AHST	71.71	55.40

Waseem et al. (2017)	Explicit	Implicit			
Directed	Unambiguous in its potential to be abusive, i.e. use of slurs directed at an individual/entity.	Not immediately clearly abusive. Often obscured by ambiguous terms, sarcasm, lack of profanity, etc. Directed at an entity/individual.			
Generalized	Unambiguous in its potential to be abusive, i.e. use of slurs directed at a generalised <i>other</i> .	Not immediately clearly abusive. Often obscured by ambiguous terms, sarcasm, lack of profanity, etc. Directed at an generalised other.			

Training Objective		F_1 -Scores of Predictions on Test Sets								
Primary	Aux	Feats	$\mathrm{W/W}\mathrm{+H}$			Davidson				
Aux	Aux		R	S	N	Avg	Н	О	N	Avg
W/W+H	-	BoW	0.70	0.65	0.88	0.82	0.00	0.64	0.42	0.57
W/W+H	-	Emb	0.30	0.42	0.85	0.71	0.01	0.04	0.29	0.08
W/W+H	-	B+E	0.00	0.00	0.82	0.57	0.00	0.00	0.29	0.05
Davidson	-	BoW	0.22	0.29	0.69	0.56	0.32	0.94	0.84	0.89
Davidson	-	Emb	0.00	0.32	0.60	0.48	0.19	0.92	0.69	0.84
Davidson	-	B+E	0.25	0.33	0.70	0.58	0.39	0.82	0.94	0.89
Both	-	BoW	0.21	0.54	0.81	0.70	0.20	0.92	0.77	0.86
Both	-	Emb	0.21	0.45	0.76	0.64	0.05	0.90	0.64	0.80
Both	-	B+E	0.17	0.53	0.81	0.69	0.31	0.92	0.77	0.86
W/W+H	Davidson	BoW	0.64	0.63	0.87	0.80	0.39	0.94	0.84	0.89
W/W+H	Davidson	Emb	0.32	0.50	0.84	0.72	0.10	0.91	0.64	0.82
W/W+H	Davidson	B+E	0.51	0.53	0.86	0.75	0.16	0.93	0.78	0.86
Davidson	W/W+H	BoW	0.66	0.62	0.86	0.79	0.37	0.94	0.83	0.89
Davidson	W/W+H	Emb	0.39	0.49	0.84	0.73	0.09	0.91	0.62	0.81
Davidson	W/W+H	B+E	0.60	0.57	0.85	0.77	0.14	0.93	0.78	0.86

Waseem et al. (2018)

CURRENT TRENDS

- Reducing gender bias (Park et al. EMNLP 2018).
- Expanding on crowd-sourced annotation (Founta et al., ArXiv 2018).
- Deep Learning Models (Badjatiya et al., WWW 2017).







- Waseem et al. (2017): Understanding abuse: A typology of abusive language detection subtasks; Zeerak Waseem, Thomas Davidson, Dana Warmsley, and Ingmar Weber; ALW 2017.
- Waseem et al. (2018): Bridging the Gaps: Multi Task Learning for Domain Transfer of Hate Speech Detection; Zeerak Waseem, James Thorne, Joachim Bingel; Online Harassment 2018.
- Park et al. (2018): Reducing Gender Bias in Abusive Language Detection; Ji Ho Park, Jamin Shin, Pascale Fung; EMNLP 2018.
- ▶ Founta et al. (2018): Large Scale Crowdsourcing and Characterization of Twitter Abusive Behavior; Antigoni-Maria Founta, Constantinos Djouvas, Despoina Chatzakou, Ilias Leontiadis, Jeremy Blackburn, Gianluca Stringhini, Athena Vakali, Michael Sirivianos, Nicolas Kourtellis; ArXiv 2018.
- Badjatiya et al. (2017): Deep learning for hate speech detection in tweets; Pinkesh Badjatiya, Shashank Gupta, Manish Gupta, and Vasudeva Varma; WWW 2017