Does BERT Pay Attention To Cyberbullying? Fatma Elsafoury¹, Stamos Katsigiannis², Steven R. Wilson³, and Naeem Ramzan¹ ¹University of the West of Scotland, ²Durham University, ³University of Edinburgh

2. BERT vs. RNNs for cyberbullying detection 1. Cyberbullying detection We compared BERT's performance on cyberbullying-related datasets to RNN models. Results show **Cyberbullying** is a form of spreading insults using mobile or internet technology that BERT significantly improves cyberbullying detection. The datasets contain comments col-• Victims could suffer from depression, anxiety, low self-esteem, self-harm. lected from Kaggle, Twitter, and Wikipedia Talk Pages (WTP). Automated cyberbullying detection can prevent these risks by banning the bullies and pro-BERT (Fine Tuned) 0.768 viding support to the victims. 0.760 0.757 Recent attention-based language models, like BERT, have improved cyberbullying detection but 0.753 the model's inner-workings have not been studied. 0.786 d for each dataset • This work attempts to explain BERT's performance for cyberbullying detection.

3. What is the role that attention weights play in BERT's performance?

We analysed BERT's attention weights to inspect if they are the reason behind its performance. We compared attention weights between BERT with and without fine-tuning on cyberbullying datasets. Then, we compared attention weights and feature importance scores measured using Integrated Gradients.







4. What are the features that BERT relies on for its performance?

We analysed BERT's importance scores for the part-of-speech (POS) tags in the datasets. We hypothesised that BERT assigns the highest importance scores to informative POS tags for the task of cyberbullying detection, e.g. Nouns, and Adjectives. Results show that the most important POS according to BERT are **Auxiliaries** and **Punctuation**. This suggests that BERT does not rely on semantic features related to cyberbullying but instead relies on syntactic biases in the datasets.









Dataset	No. Samples	No. Positive	LSTM	Bi-LST
Kaggle-insults	7425	2578 (35%)	0.6420	0.653
Twitter-sexism	14742	3370 (23%)	0.6569	0.649
Twitter-racism	13349	1969 (15%)	0.6400	0.678
WTP-aggression	114649	14641 (13%)	0.7110	0.679
WTP-toxicity	157671	15221 (10%)	0.7230	0.737
Table 1. [)atasat inform	ation and F1-c	cores a	chiovod

Attention weights vs. importance scores

 Table 2 shows that no positive correlation was found between the tokens' attention weights and importance scores.

 Consequently, attention weights do not play a direct role in BERT's performance.

Dataset

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Kaggle-insults Twitter-sexism Twitter-racism WTP-aggression WTP-toxicity

Table 2: Pearson's corr weights of fine-tuned BEF portance

5. Take away messages

- **BERT's performance**.



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o. tokens	PCC (attention vs importance)
4452	0.171
3878	0.108
3991	0.056
4457	0.125
4524	0.163
4524 elation betw RT and mean	0.163 een mean attention absolute feature im-

BERT performs significantly better than **RNNs** on cyberbullying detection tasks.

 Although the pattern of attention weights changes when fine-tuning BERT, we found that attention weights do not play a role in

 Results suggest that BERT does not rely on semantic features related to the task at hand, but **BERT relies on syntactical biases** in the datasets to achieve the high performance.