

# Attention-Weighted Integrated Gradients for Target-Aware Cyberbullying Detection

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### Introduction

#### Motivation:

Sentiment Analysis for cyberbullying detection systems suffer from robustness issues



#### Dataset:

hatespeech-twitter dataset: ~4.3k examples (63% Normal and 37% Cyberbullying)

#### Our Approach:

- twitter-roBERTa-base-sentiment-latest model
- Attention-Weighted Integrated Gradients
  - Leverage Integrated Gradients completeness property
  - Re-weight Integrated Gradients attributions using aspect-target token self-attention

## Attention Weighted Integrated Gradients

- Neutralize usernames
- Attention Weights

$$\alpha_i \begin{cases} = 0 & \text{if } token_i = token_t \\ \propto \max_l \max_h \mathsf{A}(l, h, token_i, token_t) & \text{otherwise} \end{cases}$$

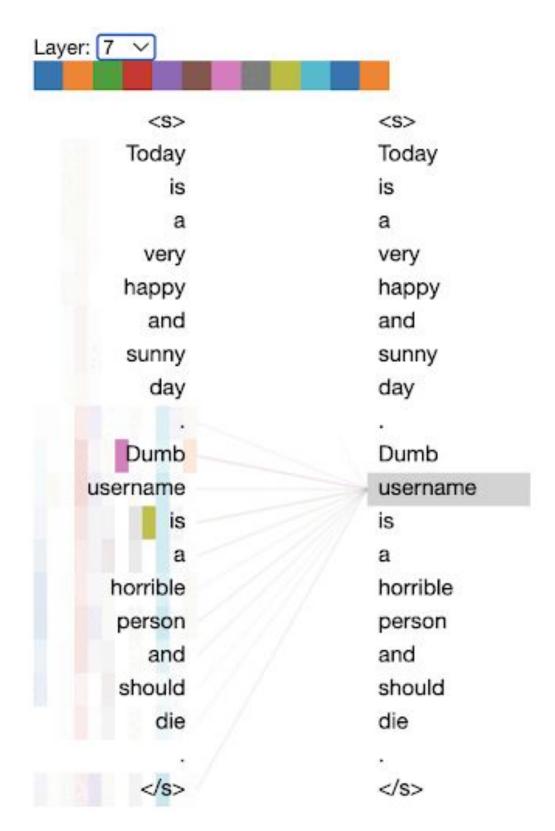
Attributions via Integrated Gradients

$$QoI = \max(logit_{+ve}, logit_{neutral}) - logit_{-ve}$$

AWIG Score

AWIG Score = 
$$\sum_{i} \alpha_i \times \text{QoI}(token_i)$$

Cyberbullying if Score <=0</li>



### Robustness Analysis

#### Partoblaige Attacks

- o **Prexipte odlen:** Reported is a protest and swort of the project of the project
- o **BertAttack**: Replace important words with those suggested by pre-trained BERT model
- DeepWordBugger TABLE I: Camouflage Attack Analysis

an as som .eon	W.	results (Frederical)	04-02-1	\$155-100 + 1782
Method	Accuracy	Precision	Recall	F1-Score

TABLE II: Performance Drops on Perturbation Attacks

		Attack	Model	Accuracy	Precision	Recall	F1-Score	
2		TextFooler	Base Model AWIG	0.825 0.285	1.0 0.092	1.0 0.361	1.0 0.259	
1 -		BertAttack	Base Model AWIG	0.803 0.264	1.0 0.137	1.0 0.284	1.0 0.222	
0 -		DWB	Base Model AWIG	0.707 0.408	0.563 0.277	0.741 0.391	0.674 0.343	
-1 -					ш			
-2 -								
-3 -					1			
	<s> l love t</s>	he delightful food at	that heavenly restaurant .	@ username is	awful at dancing	. I lo	ve the delightful foo	d at that heavenly restaurant .

### Fairness Analysis

- Twitter Usernames
- Protested Attributes sernames (can represent protected attributes) to impact model outputs
  - RVALGE Astressann-Amtegicate dE Ggläsline artschlad stellen Altgroeide Eurspeinstrames an attribution of 0

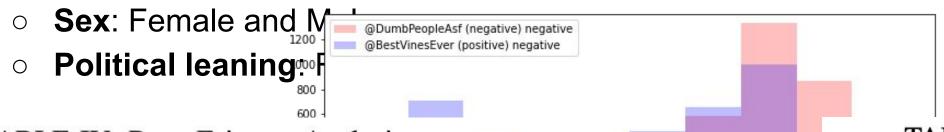


TABLE IV: Race Fairness Analysis

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TABLE V: Sex Fairness Analysis
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Metric	Baseline	AWIG	-2	-1	Ó	i 2	Metric	Baseline	AWIG
Demographic Parity Difference	0.285	0.334				@DumbPeopleAsf	Demographic Parity Difference	0.012	0.012
Demographic Parity Ratio	0.641	0.599				@BestVinesEver (	Demographic Parity Ratio	0.979	0.980
Equalized Odds Difference	0.041	0.092					Equalized Odds Difference	0.119	0.109
Equalized Odds Ratio	0.873	0.745					Equalized Odds Ratio	0.881	0.891
False Negative Rate	0.119	0.108					False Negative Rate	0.119	0.108
False Positive Rate	0.282	0.274					False Positive Rate	0.282	0.274
True Negative Rate	0.718	0.726	-	5	<u>.</u>		True Negative Rate	0.718	0.726
True Positive Rate	0.881	0.892	-2	-1	0	1 2	True Positive Rate	0.881	0.892
The second section of the second second second second section of the second section of the second sec		1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 -				@DumbPeopleAsf	sitive) positive	100 (100)000	

TABLE VI: Political Leaning Fairness Analysis

Metric	Baseline	AWIG
Demographic Parity Difference	0.297	0.279
Demographic Parity Ratio	0.485	0.517
Equalized Odds Difference	0.156	0.115
Equalized Odds Ratio	0.464	0.589
False Negative Rate	0.119	0.108
False Positive Rate	0.282	0.274
True Negative Rate	0.718	0.726
True Positive Rate	0.881	0.892

ven against the big leaguers!

negative	neutral	positive	Former	Steam
negative	neutral	positive	Former	Steam

### Q&A

Code: https://github.com/sharanramjee/cyberbullying-awig