Can attention-based transformers explain or interpret cyberbullying detection?

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Abstract

Automated textual cyberbullying detection is known to be a challenging task. It is sometimes expected that messages associated with bullying will either be a) abusive, b) targeted at a specific individual or group, or c) have a negative sentiment. Transfer learning by fine-tuning pre-trained attention-based transformer language models (LMs) has achieved near state-of-the-art (SOA) precision in identifying textual fragments as being bullying-related or not. This study looks closely at two SOA LMs, BERT and HateBERT, fine-tuned on real-life cyberbullying datasets from multiple social networking platforms. We intend to determine whether these finely calibrated pre-trained LMs learn textual cyberbullying attributes or syntactical features in the text. The results of our comprehensive experiments show that despite the fact that attention weights are drawn more strongly to syntactical features of the text at every layer, attention weights cannot completely account for the decision-making of such attention-based transformers.

1 Introduction

Repeated hostile and aggressive online behaviour to intentionally hurt or embarrass someone through digital communication technologies are generally understood as Cyberbullying. (Patchin and Hinduja, 2006). Recent research findings by (B et al., 2021) and (Milosevic, 2021), indicate that 44% children in 11 European countries and nearly 50% children in Ireland have reported an increase in cyberbullying during the COVID-19 lockdown restrictions across multiple social networking sites (SNS) and multiplayer online gaming (MOG) platforms. This growing amount of cyberbullying content emerging across multiple SNS and MOG platforms is alarming and necessitates more effective content moderation, as earlier studied by (Gillespie et al., 2020; Milosevic, 2018; Gillespie, 2018). Therefore, one crucial step toward efficient and effective content moderation is the ability to recognize and define the basis for automated cyberbullying detection systems to classify a textual expression or phrase as cyberbullying.

Recent computational cyberbullying research claim to have outstanding accuracy and precision in automating the identification of cyberbullying using state-of-the-art (SOA) deep learning algorithms like attention-based Transformers, Gated Recurrent Units (GRUs), Long-Short Term Memory (LSTMs). However, upon close examination of such research, including those by (Paul and Saha, 2020; Yadav et al., 2020; Behzadi et al., 2021; Tripathy et al., 2020; Pradhan et al., 2020; Fang et al., 2021) among others, reveal that they rely on datasets for hate-speech or personal-attacks by (Founta et al., 2018; Waseem and Hovy, 2016; Wulczyn et al., 2017) for cyberbullying identification. In reality, despite their inventive attempts, these studies can only determine whether a text is abusive or hateful. We consider it a poor decision to detect cyberbullying using such out-of-domain datasets.

Additionally, work by (Ruder et al., 2019; Howard and Ruder, 2018; Dodge et al., 2020) has demonstrated the efficacy of transfer learning by fine-tuning pre-trained deep layered language models (LMs) for a variety of natural language processing (NLP) tasks, such as text classification, thereby yielding impressive results. (Verma et al., 2022), have demonstrated that fine-tuning LMs like $BERT_{base-uncased}$ by (Devlin et al., 2018), and $Hate-BERT_{base-uncased}$ by (Caselli et al., 2020) outperform traditional machine learning algorithms and aid in more accurate detection of textual cyberbullying across multiple SNS platforms. Research by (Vaswani et al., 2017; Devlin et al., 2018) demonstrates that the attention-based mechanisms within the deeply layered architecture of such pre-trained LMs can display dependencies between input and output. High attention weights for
inputs (such as words) are frequently referred to be accountable for the output, which provides the model’s interpretability (Mullenbach et al., 2018; Xie et al., 2017; Martins and Astudillo, 2016; Lei et al., 2017; Choi et al., 2016; Xu et al., 2015). To our knowledge, these assertions and presumptions have not undergone a formal evaluation for user-generated content (UGC) datasets collected from various SNS and MOG platforms categorically labelled for cyberbullying. (Kitchin, 2017; Ananny and Crawford, 2018; Katzenbach and Ulbricht, 2019) question the existing opaqueness of automated algorithmic content moderation and decision-making practices by SNS and MOG platforms. It has thus become necessary to design and develop transparent and equitable algorithms for moderation and regulation. To that effect, we attempt to extend the work by (Verma et al., 2022) on multiple platform cyberbullying detection, by addressing the following research question,

• RQ.1 Can attention-weights of attention-based LMs fine-tuned on real-life cyberbullying datasets be relied upon to detect and explain cyberbullying in an interpretable and understandable way?

Hence, we hypothesize that if attention-based LMs fine-tuned on real-life cyberbullying datasets learn textual cyberbullying traits for detecting cyberbullying; they would have higher attention weights for a) Parts-of-speech (POS) tags like adjectives, nouns, proper nouns, pronouns, and b) words with more negative sentiment. We also hypothesize that this assumption will be valid for text samples categorically annotated as cyberbullying across different datasets sourced from varied SNS and MOG platforms.

Content Warning: This article contains examples of abusive language in Section 5.4. All examples are taken from existing datasets (Section 3) to illustrate its composition.

2 Related Work

2.1 Cyberbullying Detection on Multiple platforms

There has been research on cross-platform cyberbullying detection, but they have had a narrow focus. (Edwards et al., 2020) devise a dataset from direct messages (SMS) shared between participants across multiple SNS platforms, social media posts collected from now-defunct Formspring.me 1 and tweets from Twitter 2 focusing only on one topic (2016 USA elections). However, despite their novel attempts at developing a cross-platform cyberbullying dataset and devising supervised machine learning classifiers to identify cyberbullying, their focus on a specific type of text-based communication like SMS and only on two types of SNS platforms, of which one is now defunct. On the other hand, (Nikhila et al., 2020; Yi and Zubiaga, 2022) also devise novel techniques to identify textual cyberbullying using adversarial neural network algorithms. Nevertheless, for training the classifiers, they rely on datasets by (Waseem and Hovy, 2016; Wulczyn et al., 2017) marked for either personal attacks or hate speech. On the contrary, work by (Van Bruwaene et al., 2020) is both novel and apt for cyberbullying research. They devise a high-quality dataset and experiment with Support Vector Machines (SVM), Convolutional neural networks (CNNs), and XGBOOST algorithms to develop a cross-platform cyberbullying detection system. To our knowledge, the work by (Van Bruwaene et al., 2020) is the only one that leverages real-life cyberbullying datasets. However, due to proprietary reasons, it is not yet made publicly available. (Verma et al., 2022) leverage real-life cyberbullying datasets collected by computational researchers from multiple SNS and MOG platforms such as Instagram 3, Twitter, ASK.fm 4, now-defunct SNS platforms Formspring.me, and Vine 5. On training multiple binary cyberbullying classifiers on single platforms and benchmarking their efficacy on different platforms, they found that attention-based LMs could achieve better precision and recall than traditional machine learning algorithms at classifying cyberbullying samples as cyberbullying. However (Verma et al., 2022) were unable to determine why these phenomena occur, and were also unable to establish whether the attention-based LMs were dependent on any textual cyberbullying traits (eg. profanities or negative sentiment words).

1an anonymous question-answering SNS
2https://twitter.com
3https://www.instagram.com
4ASK.fm - https://ask.fm; is an anonymous question-answering SNS platform
5Video-sharing platform like TikTok https://en.wikipedia.org/wiki/Vine_(service)
2.2 Analysing Attention in attention-based language models

Attention-based transformer LMs developed by (Devlin et al., 2018; Yang et al., 2019; Caselli et al., 2020) consists of a deep architecture with many hidden layers stacked on top of one another. Within these layers are many attention-heads or sub-layers that assign attention-weights to a token (word) for learning the importance of the token. Substantial research conducted by (Zhang et al., 2019; Adadi and Berrada, 2018; Sundararajan et al., 2017) and others have demonstrated frameworks for explaining and interpreting these deep-layered LMs by analyzing these attention-weights at every layer. Moreover, (Vig, 2019a; Vig and Belinkov, 2019) have developed tools and resources that aid in visualizing the attention weights. This allows human users to comprehend and trust the results of such deep-layered LMs. However, studies by (Jain and Wallace, 2019; Serrano and Smith, 2019; Sun and Lu, 2020; Vashishth et al., 2019) have demonstrated that these attention-based mechanisms solely cannot be relied upon for interpreting and explaining the intricate workings of LMs. The work by (Elsafoury et al., 2021) for interpreting the attention mechanism of BERT for cyberbullying is closest to our research. We thank the authors (Elsafoury et al., 2021) for their contributions and for making the code repository reproducible. However, they a) rely on out-of-domain datasets like hate speech and personal attack datasets and b) lack in-depth analysis of LMs decision-making for both textual cyberbullying and non-cyber bullying samples. Moreover, they do not report the attention-based LM(s) interpretation for real-world binary instances of cyberbullying in text.

3 Datasets

To overcome current dataset-related gaps in cyberbullying research, we select datasets that are a) annotated by either cyberbullying domain experts or b) clear and precise annotation guidelines aided the annotation for cyberbullying. To our knowledge, there are only seven real-life datasets in English language that have been devised for cyberbullying markers with such annotations. We categorise the seven datasets into four groups based on a) type of SNS or MOG platform and b) average length of tokens observed from each of the seven platforms (See Figure 1). These groups include,

- **Question-answering SNS:** Question-answering SNS are both anonymous and non-anonymous platforms like ASK.fm, Reddit\(^6\), and Quora\(^7\) that allow platform users to respond to questions posted by other users. Dataset devised by (Van Hee et al., 2018) from the ASK.fm platform is available in both English and Dutch. Annotations in this dataset are both binary and fine-grained, i.e., it is annotated for different cyberbullying forms and varied cyberbullying participant roles. (Reynolds et al., 2011) collected English language dataset from now-defunct Formspring.me. Annotations in this dataset are binary, i.e., textual samples are labelled as cyberbullying and non-cyber bullying.

- **Twitter SNS:** (Xu et al., 2012) formulated a dataset by collecting tweets\(^8\) from Twitter in the English language. Their dataset annotations are annotated as binary textual cyberbullying samples and for varied author roles such as victim, bully, reporter, and others. (Salawu et al., 2020) formulated a dataset from tweets in the English language. They have various labels such as profanity, insult, spam, sarcasm, threat, exclusion, and bullying.

- **User-comment SNS:** User-comment SNS are platforms that allow users to comment on images or videos posted by other platform users. Such platforms include but are not limited to Instagram, Facebook, TikTok, Vine, etc. (Hosseinmardi et al., 2015) collected multi-modal data (inclusive of images and textual comments) from Instagram. The annotations in this dataset are for both cyberbullying and cyber aggression. (Rafiq et al., 2015) also collected multi-modal data (inclusive of videos and textual comments) from now-defunct Vine platform. The annotation in this dataset includes both cyberbullying and cyber-aggression.

- **MOG platforms:** On MOG platforms, players communicate on forums, in-game chats, or via voice (either in-built or by plug-in voice-call platforms like Discord). (Bretschneider and Peters, 2016) collected text from fo-

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\(^6\)https://www.reddit.com
\(^7\)https://www.quora.com
\(^8\)https://help.twitter.com/en/resources/twitter-guide/topics/how-to-join-the-conversation-on-twitter/how-to-tweet
rums of highly popular MOG platforms like World-of-Warcraft (WoW)\(^9\) and League-of-Legends (LoL)\(^10\). The annotations in this dataset are of two types a) role-based binary annotations, i.e., bully and victim, and b) binary labels for cyberbullying for each text sample.

As seen in Table 1, number of sentences for cyberbullying content is very low across all seven datasets. Each of the four grouped datasets were split into training, validation, and test sets. The training set makes up 80% for each of the grouped dataset, while the validation set and test set each make up for 10% of the datasets. The test set was further broken into two parts a) 90% was used to evaluate performance of fine-tuned LMs performed, and b) 10% was used to analyze attention weights and gradient-based feature importance scores for each layer and head in the architecture of the LMs.

4 Experiment Setup

Tasks depicted in the first block of Figure 7 (See Appendix A.3) are described in detail in sections 4.1 and 4.3. As depicted in other two blocks of the Figure 7, we discuss the strategies for fine-tuning, hyper-parameter optimization strategies, and the attention-weight and gradient-based feature importance scores for each layer for both bullying and non-bullying sentences in Sections 4.2 and 4.4. The code repository for reproducing this study can be found online\(^11\).

4.1 Data anonymization, pre-processing and handling data imbalance

4.1.1 Data Anonymization

Adhering to General Data Protection Regulation (GDPR) directive (Council of European Union, 2016), we fully anonymised and normalised the datasets for any Personally Identifiable Information (PII) data. Such data included but was not limited to email-address, user names, geographical locations, and user-profile details, among others. Using GATE Cloud (Tablan et al., 2013) and the TwitIE API (K. Bontcheva, 2013), PII data was de-identified by masking and replacing the original words with masked value. For example, the sentence “mary@gmail.com is based in London”, was masked as "email-address is based in location”.

4.1.2 Pre-processing

Due to the abundance of non-standard language in the datasets, including lexical variants like supa → super, and acronyms, e.g., tbh → to be honest, and spelling errors, we applied several normalization heuristics for spelling and slang corrections. We removed a) URLs, user mentions, and non-ASCII characters for all datasets, b) retweet (RT) markers in text for twitter datasets, and c) lower-cased all text, and d) converted contractions to formal format. We also gathered a list of slang words and acronyms with their standardized forms from an online website\(^12\). Finally, we developed an algorithm (See Appendix A.1 for details) to fix spelling errors with the most accurate semantic corrections.

4.1.3 Data Imbalance

The percentage of cyberbullying content in Table 1 shows a high imbalance skewed towards the non-bullying class. Handling the imbalance was paramount to avoid learning the bias towards the majority class in imbalanced datasets. Due to the limited nature of the dataset and to avoid the risk of losing context and sequence of words in a sentence, we leveraged the simple random oversampling technique (Moreo et al., 2016) over Synthetic Minority Oversampling Technique (SMOTE) (Bunkhumpornpat et al., 2009). It is worth noting

\(^9\)https://us.forums.blizzard.com/en/wow/
\(^10\)https://www.leagueoflegends.com/en-us/news/community/
\(^11\)https://gitlab.computing.dcu.ie/vermak3/xai-cyberbullying-attention
\(^12\)https://www.webopedia.com/reference/text-abbreviations/
Table 1: Dataset Description.

| Platform-Type | Study                                      | % Cyberbullying Content | # of Sentences |
|---------------|--------------------------------------------|-------------------------|----------------|
| Question-Answering | (Van Hee et al., 2018)                      | 4.73                    | 113,698        |
|               | (Reynolds et al., 2011)                    | 9.42                    | 25,802         |
| User-Comment  | (Hosseinmardi et al., 2015)                | 41.28                   | 32,074         |
|               | (Rafiq et al., 2015)                       | 34.58                   | 78,249         |
| Twitter       | (Xu et al., 2012)*                         | 5.99                    | 9,965          |
|               | (Salawu et al., 2020)*                     | 4.67                    | 4,009          |
| Gaming        | (Bretschneider and Peters, 2016)           | 2.3                     | 34,229         |

* Numbers vary to original dataset, as the tweet is unavailable due to deletion by tweet authors.

that the random oversampling was done in only one training set, and data imbalance was not handled in the validation and test set to match real-life scenarios. Also, to verify if over-sampling techniques affect the classification models’ accuracy, we run experiments with imbalanced and over-sampled datasets.

4.2 Language Models and Hyper-parameters

To ascertain which SOA LMs is able to a) better capture dependencies and b) learn better representation of cyberbullying text from noisy UGC data, we leverage pre-trained BERT$_{base-uncased}$ by (Devlin et al., 2018), and Hate-BERT$_{base-uncased}$ by (Caselli et al., 2020). BERT$_{base-uncased}$ is a bi-directional auto-encoding attention-based transformer with twelve layered transformer blocks, with each block containing twelve self-attention layers and a total of 768 hidden layers, resulting in approximately 110 M parameters. Hate-BERT$_{base-uncased}$ is a BERT LM re-trained on hateful comments from RAL-E Reddit’s banned communities (Chandrasekharan et al., 2017). We utilized the implementation provided by HuggingFace’s Transformer Library (Wolf et al., 2019) and by (Caselli et al., 2020), and follow (Verma et al., 2022) experiments to fine-tune the pre-trained LMs. To find optimal hyper-parameters, we used the Weights & Biases (Biewald, 2020) plug-ins to conduct multiple grid-based experiments with a varied range of hyper-parameters and optimized it to achieve maximum validation accuracy. The range of hyper-parameters includes,

- Maximum Token Length(s): [128, 256]
- Batch-size(s): [8, 16, 32]
- Epochs: [2, 3, 4]
- Loss Function: Binary Cross Entropy
- Optimizer Function: Adam Weighted
- Learning Rate(s): $1e^{-5}$, $2e^{-5}$, $3e^{-5}$, $4e^{-5}$, $5e^{-5}$

4.3 Collecting Parts-of-speech (POS) Tags & Sentiment Scores

To formally evaluate our hypothesis and assumptions addressed in Section 1. As the datasets leveraged in this study are a) sourced from SNS and MOG platforms, b) are not in formal language, and c) do not include POS tags or sentiment scores, we leveraged Spacy’s POS tagger 13 (Honnibal and Montani, 2017) to collect POS tags and VADER by (Hutto and Gilbert, 2014) to collect sentiment scores. Please note that both POS tags and sentiment scores were collected only for 10% of the test-set, (See Table 4 in Appendix A.2).

4.4 Attention-weights and gradient-based importance scores

To address our RQ.1 and compare with other experiments (Jain and Wallace, 2019; Serrano and Smith, 2019; Sun and Lu, 2020; Vashishth et al., 2019), we extract attention-weights of the fine-tuned LM(s) on 10 % of test-set reserved for attention analysis. Many experiments on transformer-based attention-analysis refer to gradient-based feature importance scores as a measure for providing importance of individual features with known semantics (Clark et al., 2019; Serrano and Smith, 2019; Sun and Lu, 2020). We leveraged the Integrated Gradients algorithm by (Sundararajan et al., 2017) for pytorch 14 to model interpretability by (Kokhlikyan et al., 2020) to compute the gradient-based feature importance scores on 10% of the test-set reserved for attention analysis. As the pre-trained LMs used

13https://spacy.io/usage/linguistic-features#pos-tagging
14A python language framework for deep learning https://pytorch.org/
in this study have 12 transformer block layers and 12 attention heads, we computed the mean attention weights for each head of every layer. Extending (Jain and Wallace, 2019)’s work, we use Pearson’s correlation coefficient (PCC) to measure the linear correlation between mean importance scores and mean attention weights. Moreover, we also a) compute mean-attention weights and gradient-based feature importance scores for every token for every POS tag of the reserved test-set and b) observe both mean-attention weights and gradient-based feature importance scores for tokens in the reserved test-set that have a greater negative sentiment.

5 Results

5.1 Impact of Data Imbalance

To assess if our simple oversampling strategy on training data referred to in Section 4.1.3 yields any significant improvement over the no-sampling strategy on training data, we check the model’s validation accuracy on the non-sampled validation dataset. As depicted in Table 5 (See Appendix A.4), we find no significant differences in the performance of either oversampling or no-sampling when both BERT and HateBERT LMs are fine-tuned on user-comment, twitter, and question-answering datasets, except for the gaming dataset. Both LMs fine-tuned on over-sampled gaming dataset perform better than fine-tuning on no-sampled datasets. We believe this is because, as seen in Table 1, there are only 2.3% bullying samples in the gaming dataset, and it is highly skewed towards non-bullying samples.

5.2 Hyper-parameters Finetuning

As discussed in Section 4.2, we experiment with different combinations of hyper-parameters with the help of the Weights & Biases plug-in for grid-based experiments. Table 2 represents the results of optimal hyper-parameters on validation-set for both fine-tuned LMs on each of the four datasets. We find that hyper-parameters vary for each model on every dataset. Overall, optimal hyper-parameters include, token-length of 128, batch-sizes ranging from 8 to 32, learning-rates between 1e-5, 2e-5, 3e-5, and 5e-5, and with 2 Epochs. With the help of these hyper-parameters, maximum accuracy can be achieved on validation sets.

5.3 Cyberbullying Detection

After training and validating both BERTbase−uncased and HateBERTbase−uncased with the optimal hyper-parameters (See Table 2) for every dataset, we assessed both LMs performance for their F1-scores for a) bullying, and b) non-bullying samples. In cyberbullying detection, false negatives and false positives are crucial, especially in cases of imbalanced data. We believe that F1 scores for each class are an apt metric for evaluating classifiers. As depicted in the Table 3 fine-tuning the HateBERT LM for each of the four platform datasets, does perform better than just fine-tuning the BERT LM. Moreover, these generalized LMs perform better with the grouped Twitter datasets.

5.4 Attention-weights & Gradient-based feature analysis

5.4.1 Correlation between attention-weights & gradient-based feature importance scores

As observed in the Figure 2, the Pearson’s correlation coefficient (PCC) between attention-weights and gradient-based feature importance scores for fine-tuned HateBERT ranges from 0.0129 for bullying-samples in user-comment dataset to 0.1202 for bullying-samples in gaming datasets. Whereas, for fine-tuned BERT the PCC between attention-weights and gradient-based feature importance scores ranges from 0.0042 for bullying-samples in question-answering datasets to 0.19 in twitter dataset. Overall, as depicted in the Figure 2, this PCC is close to zero for both BERT and HateBERT LMs fine-tuned on user-comment dataset. For BERT LM fine-tuned on twitter and gaming datasets, the PCC between attention-weights and gradient-based feature importance scores is in the range of 0.08 to 0.19. However, for HateBERT LM fine-tuned on twitter datasets, this is not the case; the PCC between attention-weights and gradient-based feature importance for this data is nearly zero (0.070-0.078).

From Table 3, we can deduce that HateBERT LM fine-tuned on twitter datasets has better F-scores than BERT LM fine-tuning on the same dataset. The near zero-correlation observed between mean attention-weights and gradient-based importance scores for both generalized LMs, especially for better performing HateBERT LM fine-tuned on twitter datasets, helps us substantiate
Table 2: Optimal Hyper-parameters for every model with every dataset

| Model       | Dataset | Token length | Batch-size | Learning Rate | Epochs | Val-Accuracy |
|-------------|---------|--------------|------------|---------------|--------|--------------|
| BERT+       | Gaming  | 128          | 8          | 5e$^{-5}$     | 4      | 0.7746       |
| UC          | 128     | 32           | 3e$^{-5}$  | 2             |        | 0.7476       |
| QA          | 128     | 8            | 5e$^{-5}$  | 2             |        | 0.9496       |
| Twitter     | 128     | 32           | 2e$^{-5}$  | 2             | 0.94   |
| Gaming      | 128     | 8            | 1e$^{-5}$  | 2             | 0.7478 |
| UC          | 128     | 16           | 3e$^{-5}$  | 2             | 0.7497 |
| QA          | 128     | 16           | 1e$^{-5}$  | 2             | 0.9498 |
| Twitter     | 128     | 32           | 5e$^{-5}$  | 2             | 0.939  |

Table 3: Cyberbullying Classification Results

| Model       | Dataset | Bullying F1 | Non-Bullying F1 | Average F1  |
|-------------|---------|-------------|-----------------|-------------|
| BERT+       | QA      | 0.62        | 0.68            | 0.65        |
| UC          | 0.65    | 0.77        | 0.71            |             |
| Twitter     | 0.75    | 0.79        | 0.77            |             |
| Gaming      | 0.68    | 0.79        | 0.72            |             |
| HateBERT+   | QA      | 0.73        | 0.73            | 0.73        |
| UC          | 0.68    | 0.84        | 0.76            |             |
| Twitter     | 0.78    | 0.84        | 0.81            |             |
| Gaming      | 0.74    | 0.78        | 0.76            |             |

Figure 2: Pearson’s Correlation between Mean Attention Weights and Mean Gradient-Importance Score for all LMs and Datasets

5.4.2 Layer-wise attention Analysis

In this section, we examine the mean-attention weights at each layer for each POS tag as well as sentences with both stronger negative & positive sentiment that were taken from fine-tuned LMs that had a) a higher positive correlation between the mean attention weights and the mean gradient-based feature importance scores and b) a higher classification F-1 score. To make their models more interpretable, they propose attention weights for interpretation, which is questionable at best, holds true even for real-life SNS and MOG cyberbullying datasets.

The claims by (Jain and Wallace, 2019; Serrano and Smith, 2019; Sun and Lu, 2020; Vashishth et al., 2019). They claim that while attention-mechanisms improve classification performance, relying on attention-weights for interpretation is questionable at best, holds true even for real-life SNS and MOG cyberbullying datasets.

- Layer-wise Attention for Parts-of-speech Tags &

In Figures 3 and 4, we represent mean-attention weights at each layer for every POS tag in the twitter and gaming datasets. For adjectives in both bullying and non-bullying samples in these datasets, fine-tuned BERT and HateBERT models have mean attention weights ranging from 0.051 to 0.062. For verbs in bullying samples, fine-tuned BERT has 0.1 mean attention weight at layer 6, and at the end of layer 12, it drops to 0.09, whereas in the fine-tuned HateBERT model for bullying samples, the mean attention weight is as low as it is for adjectives. For nouns in bullying samples, fine-tuned BERT has a mean attention weight of 0.051, and fine-tuned HateBERT has a much higher mean attention weight of 0.14 at the starting layers, but by layers 11 and 12, it drops down to 0.074. For proper nouns, fine-tuned BERT and HateBERT have a much higher mean attention weight for bullying samples. However, in non-bullying samples, fine-tuned HateBERT has a lower mean attention weight of 0.051 throughout all layers. This, in a way, disproves our hypothesis that words that are adjectives, verbs, nouns, and proper nouns will have higher mean attention weights. As depicted in Figures 3 and 4, mean
attention weights for auxiliaries, determiners, ad-positions, conjunctions, and interjections in comparison to adjectives, verbs and nouns are consistently higher at almost all layers for fine-tuned BERT and HateBERT models in both bullying and non-bullying samples.

• Negative Words & Attention
As discussed in an earlier section, we assume that negative sentiment words will have greater mean attention weights, so we compare these weights with the mean attention weights of positive sentiment words. Also, as mentioned in Section 4.3, we leveraged Vader to generate sentiment scores for all tokens in the reserved test set. We selected four words with greater negative sentiment (f*ck, a*s, b*tch, stu*id) and four words with greater positive sentiment (like, cute, pretty, truth). The Figures 5 and 6 represent mean-attention weights per layer for each of the words. We find that the positive sentiment word pretty has a similar mean attention weight as the negative sentiment words b*tch and a*s at all layers for both fine-tuned BERT and HateBERT models. This disproves our second assumption that negative sentiment words will have greater mean attention weights. For brevity, our analysis on two sample sentences at every layer and head are briefly discussed in Appendix A.5.

6 Conclusion & Future Work
Our comprehensive experiments using two LMs and four grouped real-life cyberbullying datasets from various SNS and MOG platforms revealed that: a) a fine-tuned HateBERT is better at classifying cyberbullying samples as cyberbullying; b) there is almost no correlation between the attention-weights and gradient-based feature importance scores; and c) an attention-based transformer model tuned for cyberbullying classification relies more on syntactical features in text, and d) attention-based transformer model fine-tuned for cyberbullying classification have similar “attention” for both negative and positive sentiment words. While our experiments show that to some level, attention-based transformers fine-tuned on real-life cyberbullying datasets do aid in interpreting and explaining its decision-making based on cyberbullying features, there is still a lot more work to be done in devising transparent and fair LM(s) for cyberbullying.
detection. While we demonstrate comprehensive methods to interpret and explain fine-tuned LMs on real-life SNS and MOG text cyberbullying classification, we acknowledge that due to the diverse forms and roles of cyberbullying, our work is limited by binary cyberbullying categories. Due to the current paucity of fine-grained cyberbullying datasets, in the future, we will attempt to use the learned representation of these fine-tuned LM(s) on fine-grained pre-adolescent datasets by (Sprugnoli et al., 2018).

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A Appendix

A.1 Data Normalisation Algorithm

As SNS and MOG text is short, an incorrect replacement of misspelt words can make the sentence lose its context. For example, if in the sentence "i got a tkn to play" "tkn" is replaced as "taken" instead of "token", the sentence will lose its meaning. So, to avoid such an incorrect spell correction, it is important to understand the context of the sentence. To that effect we developed an algorithm 1 to fix spelling spelling errors with the most accurate semantic corrections by leveraging the existing python library py-spell-checker and (Goldberg and Levy, 2014)'s word2vec word embedding technique. The python spell-check library py-spell-checker checks every word for a misspelling and suggests two or more possible correct words. The original sentence is then parsed through the word2vec (Goldberg and Levy, 2014) model to get obtain its word embedding. The candidate words suggested by the spell check library are then replaced in the original sentence, and the new sentence is parsed through the word2vec model again. We then calculate the cosine distances between the original and possible replacement sentences, and the sentence with the highest cosine score or cosine score above 0.9 i.e., most similar to the original sentence, replaces the original sentence in the dataset.

Algorithm 1 Algorithm for contextual misspelled word correction using Word2Vec

1: import spellcheck() ▷ Python Package
2: import slang word dictionary ▷ Python dictionary of slang words
3: import word2vec ▷ Word2Vec Model
4: for sentence in list sentences do
5: spellcheck ← sentence
6: word2vec ← sentence
7: wordoptions ← spellcheck(sentence)
8: newsentence ← wordoptions+sentence
9: newword2vec ← new sentence
10: similarity = word2vec.cosine - newword2vec.cosine
11: if similarity > threshold (0.90) then sentence = newsentence
12: return sentences

A.2 Dataset Split

The table 4 represents each grouped dataset’s training, validation, and test-set size.

A.3 Experiment Schema

A.4 Imbalance Handling Results

Table 5 presents the results of no-sampling and over-sampling techniques leveraged in this study
| Dataset-Type          | Total Size | Training-set | Validation-set | Test-set | 90% for Performance | 10% for Attention |
|-----------------------|------------|--------------|----------------|----------|---------------------|--------------------|
| Question-Answering    | 139,500    | 111,600      | 13,950         | 12,555   | 1,395               |                    |
| User-Comment          | 110,323    | 88,259       | 11,032         | 9,929    | 1,103               |                    |
| Twitter               | 13,974     | 11,179       | 1,397          | 1,258    | 140                 |                    |
| Gaming                | 34,229     | 27,383       | 3,423          | 3,081    | 342                 |                    |

Table 4: Dataset split-size

for fine-tuning pre-trained LMs.

A.5 Sentiment Attention Analysis

To analyse if negative and positive sentiment words have more attention in a text sequence. We selected the following two sentences, "f*ck the st*pid b*tch" (negative sentiment), and "i love this person" (positive sentiment), and visualized the sequence to sequence attention by leveraging BertViz (Vig, 2019b). Our findings for both positive and negative words in sample sentences for almost all layers and attention-heads on both fine-tuned BERT and HateBERT are depicted in Figure 8 and 9. As seen in Figure 8, the word "love" in positive sentence "i love this person", has higher attention distribution with neutral words like "the" and "person". As seen in Figure 9, the word "b*tch" in negative sentence has higher attention distribution with neutral words like "i, the" and "person". This too disproves our hypothesis, and shows attention is not fully at negative sentiment words, instead its similar for positive sentiment words and at times higher for neutral sentiment words.
| Model     | Dataset | No-sampling | Oversampling |
|-----------|---------|-------------|--------------|
| BERT+     | Gaming  | 0.7478      | 0.7746       |
|           | UC      | 0.8476      | 0.8224       |
|           | QA      | 0.9496      | 0.939        |
|           | Twitter | 0.94        | 0.365        |
| HateBERT+ | Gaming  | 0.6857      | 0.7468       |
|           | UC      | 0.8497      | 0.8261       |
|           | QA      | 0.9498      | 0.9076       |
|           | Twitter | 0.939       | 0.938        |

Table 5: Model’s performance on balanced and imbalanced training datasets
Note: UC → user-comment; QA → question-answering