HaT5: Hate Language Identification using Text-to-Text Transfer Transformer

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Abstract—We investigate the performance of a state-of-the-art (SoTA) architecture T5 (available on the SuperGLUE) and compare it with 3 other previous SoTA architectures across 5 different tasks from 2 relatively diverse datasets. The datasets are diverse in terms of the number and types of tasks they have. To improve performance, we augment the training data by using an autoregressive model. We achieve near-SoTA results on a couple of the tasks - macro F1 scores of 81.66% for task A of the OLID 2019 dataset and 82.54% for task A of the hate speech and offensive content (HASOC) 2021 dataset, where SoTA are 82.9% and 83.05%, respectively. We perform error analysis and explain why one of the models (Bi-LSTM) makes the predictions it does by using a publicly available algorithm: Integrated Gradient (IG). This is because explainable artificial intelligence (XAI) is essential for earning the trust of users. The main contributions of this work are the implementation method of T5, which is discussed; the data augmentation using a new conversational AI model checkpoint, which brought performance improvements; and the revelation on the shortcomings of HASOC 2021 dataset. It reveals the difficulties of poor data annotation by using a small set of examples where the T5 model made the correct predictions, even when the ground truth of the test set were incorrect (in our opinion). We also provide our model checkpoints on the HuggingFace hub[2] to foster transparency.

Index Terms—Hate Speech Detection, Data Augmentation, Transformers, T5, XAI,

I. INTRODUCTION

Hate speech is usually viewed as any communication that disparages any person or group of people [1], [2]. It is an unethical behaviour and has legal repercussions in many countries [2], [3]. The increasing importance of detecting hate speech automatically has come to the fore with the increasing influence of social media, in addition to mainstream media. For example, xenophobia and other social vices have been encouraged as a result of online/social media comments [4]. Examples of hate speech, which may incite others in the offensive language identification dataset (OLID) [5] training data are given below.

• @USER If Jamie Oliver fucks with my £3 meal deals at Tesco I’ll kill the cunt

1https://huggingface.co/sana-ngu/Hat5_augmentation
https://huggingface.co/sana-ngu/Hat5
https://huggingface.co/sana-ngu/Hat5-Roberta

• @USER She is worthless why is she not checked out by secret service she is irresponsible in trying to generate hste to have somone kill thre president

• @USER Regarding the story I think I’m going to kill the president”, why is it reporters “never” follow up on how a convicted felon could obtain, in this case, 6 guns? What’s the police doing about, or would that bring light to the gun control issue? Bias?”

For societies to be peaceful and promote equality, it is crucial to (automatically) detect hate speech and address it. This is also important to prevent perpetuating such undesirable behaviour or characteristics in new technologies, such as conversational systems and other AI technologies [6], [7]. Automatic hate speech detection is imperative because of the herculean task of doing it manually and the delay that manual detection involves[4]. Besides, a manual approach is more likely to be subjective while a trained, automated approach is more objective [8], [9].

Our work spans 5 English tasks from 2 publicly available datasets. The datasets are OLID [5] and HASOC 2021 [10]. The tasks are Tasks A & B of the HASOC 2021 and tasks A, B & C of the OLID dataset. Details of the datasets are provided in the Data section [III]. These datasets were selected because of their importance and the subtasks covered with regards to hate speech. This work compares the performance of different SoTA architectures over these datasets. The architectures include the Bi-Directional Long Short Term Memory Network (Bi-LSTM), the Convolutional Neural Network (CNN), Robustly optimized BERT approach (RoBERTa) and Text-to-Text-Transfer Transformer (T5). We use pretrained models for both the RoBERTa and T5 from the HuggingFace library [11].

In addition, we perform data augmentation on the training set of HASOC and evaluate the performance. We investigate two types of data augmentation in this work and achieve near-SoTA result on task A of the HASOC dataset by using one of these approaches. To promote transparency, we provide our model checkpoints for public access on the HuggingFace

2bbc.com/news/world-europe-35105003
platform and part of our code. Other key contributions of this paper are summarized as follows: 1) insight into the autoregressive data augmentation technique, 2) argument for more credible data annotation, and 3) investigation of the Bi-LSTM with regards to explainability using IG and error analysis for the T5 model.

The rest of the paper is divided as follows: section II provides an overview of prior work in automatic hate speech detection within the field of deep learning. The datasets used in this work are described in section III. Later, section IV explains the methods used in this study. Lastly, the results obtained, along with their critical analysis and discussion, are reported in section V.

II. RELATED WORK

The prevalence of hate speech has probably increased with advancements in technology, making it easier and faster to spread on social media platforms. This has motivated researchers to put significant efforts into creating datasets and designing intelligent algorithms for hate speech detection. Linguists, in addition, have analyzed contents and defined different categories of hate speech data. Reference [12] introduced the hate speech-offensive (HSO) dataset. A logistic regression model with L2 regularization gave the best performance (F1 score of 0.9) during experimentation with the dataset.

Reference [4] experimented with only the HSO dataset using different Transformer-based architectures. Their preprocessing approach involved removing low frequency words from the dataset, though this may result in newly introduced terms of hate speech escaping detection. Their best model (DistilBERT) achieved 0.75 F1 score.

The Transformer by [14] has gained fast adoption in the NLP community since its introduction. It is based solely on the attention mechanism and is, therefore, able to handle long-term dependencies [14], [15]. This advantage of models based on the attention mechanism makes dependency modeling possible regardless of distance in the sequence of input or output. Therefore, the Transformer-based models have gained much attention in hate speech detection. Among the many Transformer-based models are: BERT [18], RoBERTa [19], and T5 [20].

New datasets have been introduced since HSO while some have also been extended. This shows the growing awareness of the importance of hate speech detection. Besides extending the OLID dataset by [5], [21] performed cross-domain experiments on HatEval [22] after training on two different datasets. Their reason for extending the OLID dataset was to annotate the distinction between messages deemed as explicit (containing slur or profanity) and implicit (having no slur).

III. DATA

The following datasets are considered in this work:

1) HASOC 2021

This is the third edition of HASOC [10]. Reference [10] provided another set of tweets dataset with the same tasks as HASOC 2020. The dataset includes the following subtasks: 1) Task A, which is to identify hate speech and offensive text and 2) Task B, which is a further classification for the previous task to categorize the hateful and offensive content into either hate content (HATE), offensive (OFFN) or profane (PRFN). The English dataset consists of 3,843 training samples and 1,281 samples in the test set. They gathered the data during the Covid-19 wave, therefore the text has Covid-related topics. We split 10% of the training set as the dev (validation) set in this work for evaluation after each epoch.

2) OLID

The dataset of OffensEval 2019 (Task 6 of SemEval 2019) is based on OLID. It contains 14,200 annotated English tweets and encompasses the following three subtasks: a) offensive language detection, b) categorization of offensive language as to whether it’s targeted at someone (or a group) or not, and c) offensive language target identification such that distinction is made among individual, group and other entities, like an organisation or event [5]. OLID is derived from Twitter. Crowdworkers performed its data annotation and the original data-split was into training and test sets only. Similarly with HASOC 2021, we split 10% of the training set as the dev (validation) set for evaluation after each epoch in this study.

IV. METHODOLOGY

The following subsections describe the different parts of the methodology. All experiments were conducted on a shared DGX-1 machine with 8 × 32GB Nvidia V100 GPUs. The server runs on Ubuntu 18 and has 80 CPU cores. Each experiment was conducted 3 times and the average results (including standard deviation) obtained. Each experiment was run for 6 epochs but the model checkpoint with the lowest validation loss is saved and used for evaluation of the test set.

Dev set results are also based on the model with the lowest validation loss. We use a linear schedule with warm up for the learning rate adjustment for both RoBERTa and T5. We experimented with only very limited hyperparameters for all the models due to time and resource constraints.

A. Models

1) Bi-LSTM: LSTM is one form of Recurrent Neural Network (RNN) [23]. RNN is used with sequential data and can capture long-term dependencies in text. Bi-Directional Long Short Term Memory Network (Bi-LSTM) is another improved variant of RNN that comprises of two LSTMs where the input text flows forward and backwards, thereby providing more
contextual information and, as a result, improves the network performance [24].

First, we used an embedding layer to convert input text to its corresponding word embeddings. Word and subword embeddings have been shown to improve performance of downstream tasks [25]–[27]. We used Glove pre-trained word embedding [26] of vector size 100 to capture the semantics of words with the surrounding context. Then we applied a dropout layer to prevent overfitting. We used 2 bi-directional layers; the dimension of the hidden state is 20. Finally, a fully connected layer follows the last Bi-LSTM layer to classify the text. This model has 1,317,721 parameters.

2) CNN: CNN was initially used for image processing. Reference [28] shows the effectiveness of the CNN in capturing the local patterns in text on different NLP tasks. Both the Bi-LSTM and CNN were used as feature-based models, where for each tweet, we computed embeddings using pre-trained Glove, then we used the sequence of embeddings as an input to the model. For the CNN, the model is composed of 3 convolution layers with 100 filters each. The filter size for the first layer is 2*100 (100 is the size for the word embeddings), the filter size for the second layer is 3*100 and for the third layer it is 4*100. We used a Rectified Linear Unit (ReLU) activation function and max-pooling after each convolution layer. Finally, we perform dropout on the outputs and fully connected layer for final classification. The total trainable parameters for the CNN are 1,386,201

3) RoBERTa: RoBERTa is the product of a replication study of BERT. It makes changes to BERT in the following ways: (1) training for longer over more data; (2) removing the next sentence prediction objective; (3) using longer sequences for training; and (4) changing the masking pattern dynamically when applied to the training data [19]. The base version of the model has 12 layers and 110M parameters. For our study, we use RoBERTa-Base, a batch size of 32, initial learning rate of 1e-5 and maximum sequence length of 256. We restricted the number of tasks to only binary tasks for this model.

4) T5: The T5 [20] follows the originally proposed transformer architecture by [14]. It maps input sequence of tokens to embeddings before passing it to the encoder, comprising an alternating series of multi-head attention layer and feedforward linear layer. A different layer normalization is applied, where there’s no additive bias applied and the activations are only rescaled. The decoder includes a standard attention mechanism in addition to each self-attention layer. Causal or autoregressive self-attention is used in the decoder for it to attend to past outputs. Relative position embeddings are used instead of the original sinusoidal position signal, since self-attention is order-independent. The T5-Base model has about twice the number of parameters as that of BERT-Base. Its training method uses teacher forcing (i.e. standard maximum likelihood) and a cross-entropy loss. It was pretrained on 34B tokens, cutting the computational budget considerably when compared to BERT or RoBERTa, which were trained on 137B and 2.2T tokens, respectively.

Its base model has 220M parameters and 12 layers each in the encoder and decoder blocks [20]. Using this instead of the T5-Small model required more memory and would not fit on a single V100 GPU for the batch size of 64, hence we lowered the batch size to 16. The task prefix we use is ‘classification’ for all the tasks, as the model takes a hyperparameter called a task prefix.

B. Preprocessing

Preprocessing was carried out on all the data to remove duplicates and unwanted strings or characters. For example, for OLID (task C), there are nans (empty entries) in some columns of the labels. The nans cause problems for the models, increasing the total number of categories and dropping model performance. We, therefore, dropped all such rows during the preprocessing step. Furthermore, tweets are noisy and unstructured, which can affect the performance of the models. To prepare the text for each model, the following preprocessing steps were applied to the datasets:

- URLs are excluded.
- Uppercase characters are changed to lowercase.
- Emails are removed.
- Spaces more than 2 characters long are replaced as one space.
- Special characters such as hashtags(#) emojis and mention symbols (@) are removed.
- Numbers are removed.
- IP addresses are removed

C. Data Augmentation

We experimented with two data augmentation techniques: 1) a simple token-level deletion of the start and end tokens for each sample and 2) autoregressive text generation using the model checkpoint by [7]. It was fine-tuned on the MultiWOZ dataset by [29]. The autoregressive model is originally a pretrained DialoGPT (medium) model [6]. The second technique effectively doubled the training set size. In the first technique, samples ending or starting with offensive words are kept as they are in the new augmented training data and are therefore dropped when merged with the original, to avoid duplicates.

Examples from HASOC 2021 of the original sample and the augmented sample, using the second technique, are given below.

- Bloody hell is that all they can do ?
  https://t.co/JQOiOw8nPs
- bloody hell is that all they can do It is. Have a great day.

- He voted against migration by voting brexit the wanker
  https://t.co/5t419W0iq9
- he voted against migration by voting brexit the wanker
  I’m confused. Are you saying you don’t have a single moderate priced hotel in the centre of town with free parking?

- SHOOT NOW ASSHOLE
• shoot now asshole Booking was successful. Reference number is : N0LQRA43.

For the first technique, we use the list of offensive words available from the online resource at Carnegie Mellon University\(^5\) to ensure offensive or hate speech tokens are not dropped. The document originally contains almost 1,400 English terms that could be found offensive. However, we removed some words (160), which are nationalities/geographical locations or adjectives of emotions. We consider that these may not qualify as offensive words. Examples of such words are: african, american, arab, canadian, european, angry and many non-harmful words. There are 1,223 words left in the document we used for our experiment. The first technique was found to be less effective in improving model performance so we did not report its results in the next section.

D. Metrics

The F1 score is the harmonic mean of the precision and recall. The relative contribution to the F1 from precision and recall are equal. Micro F1 calculates globally by counting the total true positives, false negatives and false positives. Macro F1 does not take label imbalance into account unlike weighted recall. The relative contribution to the F1 from precision and recall are equal. Micro F1 calculates globally by counting the labels' true instances \([30]\). F1 does not take label imbalance into account unlike weighted recall. The relative contribution to the F1 from precision and recall are equal. Micro F1 calculates globally by counting the labels' true instances \([30]\).

We report both weighted and macro F1 scores because of past studies’ reported metrics.

V. Results and Discussion

Table I shows the results obtained across the models and datasets, and those from \([31]\) and \([10]\). We report both weighted and macro F1 scores for the dev and test sets, where applicable. Also, the standard deviation (sd) is reported. Considering the test set results, it is perhaps not surprising that the Transformer-based models outperform both the Bi-LSTM and CNN models, in almost all instances. The Bi-LSTM obtains better results than the CNN in the tasks A of both HASOC and OLID but the CNN outperforms it with a smaller margin in the tasks B % C of OLID. It also outperforms the Bi-LSTM in task B of HASOC. T5 outperforms RoBERTa on all tasks. It has near-SoTA performance in task A of OLID, given the result in \([31]\). The T5+Augmented Data version shows improved scores in both tasks of HASOC when compared with the plain T5. This makes the result near-SoTA when compared with \([10]\). Adequate exploration of hyperparameter tuning may have produced better scores with the models but we did not have sufficient time to do this.

We observe the performance of the LSTM trails behind that of the T5. Indeed, the T5 may have performed even better but for a certain shortcoming. Text classification in T5 outputs a prediction of a single word of the target label. However, in our experiments, we found out that the model is more stable with predictions when fine-tuned with target labels of numbers, explicitly type-cast as string. Otherwise, some predictions during fine-tuning can be an empty string or expressions from the training set, especially in the early epochs of the training. This problem is noted as a possibility by \([20]\) though they did not experience this behaviour in their trained models. Using target labels of numbers, explicitly type-cast as string greatly reduces this occurrence.

A. Error Analysis

We investigate the errors made by the T5 model on the HASOC 2021 test set. Figure[1] reveals the distribution of the predictions in a confusion matrix. 33.13% (160) of the ‘NOT’ class (not offensive) was misclassified while only 7.52% of the ‘HOF’ (hate or offensive) class was misclassified. This may not be unconnected to the fact that the training set had more ‘HOF’ samples, so the model is better at identifying such. This is because the training set has 2,251 ‘HOF’ samples and 1,207 ‘NOT’ samples. Improving the model’s ability on identifying ‘NOT’ samples (and the overall performance) may involve using a balanced training set or stratifying the categories during training.

A strong case for better annotation of data is evident when one considers some interesting cases in the HASOC 2021 test set. The examples below were annotated (with the ground truth) of being not offensive (NOT), however, the model was intelligent enough to predict them as hate or offensive (HOF). This issue has implications for the assessments done during the competitions organized. Furthermore, it is certain the T5

\(^{5}\)cs.cmu.edu/ biglou/resources/
\(^{6}\)scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html
and other models would have reported better scores if not for the issue raised here.

![Confusion Matrix of T5 on Hasoc 2021 Test Set](image)

**Fig. 1. Confusion matrix of T5 on Hasoc 2021 test set**

**TABLE II**

| id      | text                                                                 | task 1 | task 2 |
|---------|----------------------------------------------------------------------|--------|--------|
| ea565f0e1c | miya four creeps into every thought i have                         | NOT    | None   |
| ea565f0e1c | what the fuck                                                         | NOT    | None   |
| ea565f0b13 | At least we’re being freed from the shambles of the evangelical, but damn y’all couldn’t just go w the flow? Y’all just had to find jebus through crystals and astrology? Smdh | NOT    | None   |
| ea565f0c9e | These terrorists are more dangerous than #chinesevirus https://t.co/iazlTYm8St | NOT    | None   |
| ea565f0b13 | @kumarmbayar @Actor_Siddharth He is mentally Upset, Why He’s not talking about #BengalBurning and why stupid talks about Tejasvi_Surya | NOT    | None   |

### B. Explanability (XAI)

Explainable AI (XAI) is essential for trust, and the purpose of this section is to understand why the Bi-LSTM model misclassified specific tweets and what makes the model struggle in making the correct prediction. There are many ways to explain NLP models, and several researchers have proposed different methods to explain the output of the ML black box [32], [33]. In this study, we use Integrated Gradient (IG). IG is a simple but powerful axiomatic attribution originally proposed by [34]. It is an attribution method that attributes a model’s prediction to the input features (attributing the text classification to individual words in this case). We have computed the attribution compared to a baseline sequence of tokens by creating a path from the baseline to the input text. At each step on that path, we aggregate the gradient and finally, we calculate the path integral for the aggregated gradients. The attribution showed which word of the text input to the model affects the model prediction and how strongly.

In both Figures 2 and 3, the important words are highlighted. The words in green contribute to non-hate speech; those highlighted in red contribute to hate speech. Figure 3 shows examples of wrongly classified tweets. The second tweet has offensive words but it is annotated wrongly as ‘NOT’ (not offensive). The Bi-LSTM, however, predicts this correctly. In the third example, the model makes the prediction ‘NOT’ mainly because of the hashtag ‘indiacovidcrisis’, which is strongly associated with non-hate in both figures. This is very likely because, in the training set, most of the tweets containing this hashtag are classified as non-hateful content. In the fourth tweet, the most important words to the model for considering the tweet as hateful are ‘shag’ and ‘blood’. However, the model may have misunderstood the context of the tweet. For the last example, the model appears completely oblivious to the word ‘bombing’ and paid attention to other words, which ended in its wrong prediction.

### VI. CONCLUSION

Automatically detecting hate speech is a very important task and we show in this study that progress has been made, especially with the Transformer-based architectures. We also show that the quality of annotated data is crucial for the success of automatically detecting hate speech (and other offensive communication). We compared the performance of different SoTA architectures over multiple tasks in 2 datasets. The T5 pretrained model outperformed the LSTM, CNN and...
RoBERTa architectures/models. Data augmentation provided additional performance gains, establishing near-SoTA result on tasks A of the HASOC 2021 datasets while the plain T5 achieved near-SoTA performance on task A of OLID 2019.

Future direction may include using a voting ensemble method. Although this is potentially powerful, it may suffer due to poor votes from weak models. Another direction is improving the predictive power of models in cross-domain or zero-shot inference. Finally, it is also important to study the performance of models on raw data, even though preprocessing is an important step in obtaining better performance [35]. This is because some offensive messages may contain only disparaging emojis or special characters or other expressions of hate speech and not text.

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Fig. 3. Visualize attributions for Bi-LSTM on Hasoc 2021 test set (miss-classification)
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