**Abstract**

We conduct relatively extensive investigations of automatic hate speech (HS) detection using different state-of-the-art (SoTA) baselines over 11 subtasks of 6 different datasets. Our motivation is to determine which of the recent SoTA models is best for automatic hate speech detection and what advantage methods like data augmentation and ensemble may have on the best model, if any. We carry out 6 cross-task investigations. We achieve new SoTA on two subtasks - macro F1 scores of 91.73% and 53.21% for subtasks A and B of the HASOC 2020 dataset, where previous SoTA are 51.52% and 26.52%, respectively. We achieve near-SoTA on two others - macro F1 scores of 81.66% for subtask A of the OLID 2019 dataset and 82.54% for subtask A of the HASOC 2021 dataset, where SoTA are 82.9% and 83.05%, respectively. We perform error analysis and use two explainable artificial intelligence (XAI) algorithms (IG and SHAP) to reveal how two of the models (Bi-LSTM and T5) make the predictions they do by using examples. Other contributions of this work are 1) the introduction of a simple, novel mechanism for correcting out-of-class (OOC) predictions in T5, 2) a detailed description of the data augmentation methods, 3) the revelation of the poor data annotations in the HASOC 2021 dataset by using several examples and XAI (buttressing the need for better quality control), and 4) the public release of our model checkpoints and codes to foster transparency.¹

1 Introduction

Any disparaging remark targeted at an individual or group of persons is usually considered as hate speech (HS) (Nockleby, 2000; Brown, 2017). It is considered unethical in many countries and illegal in some (Brown, 2017; Quintel and Ullrich, 2020; Fortuna and Nunes, 2018). Manual detection of HS content is a tedious task that can result in delays in stopping harmful behaviour.² Automatic hate speech detection is, therefore, crucial and has been gaining increasing importance because of the rising influence of social media in many societies. It will facilitate the elimination/prevention of undesirable characteristics in data, and by extension AI technologies, such as conversational systems (Zhang et al., 2020; Adewumi et al., 2021). HS examples that may incite others to violence in the offensive language identification dataset (OLID) data (Zampieri et al., 2019a) are given in Table 1.

| id | tweet |
|----|-------|
| 23352 | @USER Antifa simply wants us to k*ll them. By the way. Most of us carry a back up. And a knife |
| 61110 | @USER @USER Her life is crappy because she is crappy. And she’s threatening to k*ll everyone. Another nut job...Listen up FBI! |
| 68130 | @USER @USER @USER @USER @USER Yes usually in THOSE countries people k*ll gays cuz religion advise them to do it and try to point this out and antifa will beat you. No matter how u try in america to help gay in those countries it will have no effect cuz those ppl hate america. |

Table 1: Inciteful examples from the OLID 2019 training set. (parts of offensive words masked with "*")

Short details of the datasets in this work are provided in appendix A. The datasets were selected based on the important subtasks covered with regards to HS or abusive language. The architectures employed include the Bi-Directional Long Short Term Memory Network (Bi-LSTM), the Convolutional Neural Network (CNN), Robustly optimized BERT approach (RoBERTa)-Base, Text-to-Text-Transfer Transformer (T5)-Base, where the last two are pretrained models from the HuggingFace hub. As the best-performing baseline model, T5-Base is then used on the augmented data for the HASOC 2021 subtasks A & B and for an ensemble. In addition, we compare result from HateBERT, a re-trained BERT model for abusive language detec-

¹available after anonymity period

²bbc.com/news/world-europe-35105003
tion (Caselli et al., 2021).

The rest of this paper is structured as follows: Section 2 explains the methods used in this study. The results, critical analysis with XAI and discussion are in Section 3. Section 4 provides an overview of HS and prior work in the field. Section 5 gives the conclusion and possible future work.

2 Methodology

All the experiments were conducted on a shared DGX-1 machine with 8 × 32GB Nvidia V100 GPUs. The operating system (OS) of the server is Ubuntu 18 and it has 80 CPU cores. Each experiment is conducted 3 times and the average results computed. Six is the total number of epochs for each experiment and the model checkpoint with the lowest validation loss is saved and used for evaluation of the test set, where available. Linear schedule with warm up is used for the learning rate (LR) adjustment for T5 and RoBERTa. Only limited hyperparameters are explored, through manual tuning, for all the models due to time and resource constraints.

Short details about all the models used are discussed in appendix B. Appendix C gives more information on the data preprocessing, metrics for evaluation, the ensemble, and cross-task training. Average time per epoch for training and evaluation on the validation set is 83.52, 7.82 & 22.29 seconds for the OLID, HASOC 2020 & HASOC 2021 datasets, respectively.3

2.1 Solving OOC Predictions in T5

Raffel et al. (2020) introduced T5 and noted the possibility of OOC predictions in the model. This is when the model predicts text (or empty string) seen during training but is not among the class labels. This issue appears more common in the initial epochs of training and may not even occur sometimes. We experienced this challenge in the two libraries we attempted to develop with.4 In order to solve this, first we introduced integers (explicitly type-cast as string) for class labels, which appear to make the model predictions more stable. The issue reduced by about 50% in pilot studies, when they occur. For example, for the HASOC datasets, we substituted "1" and "0" for the labels "NOT" and "HOF", respectively. As a second step, a simple correction we introduced is to replace the OOC prediction (if it occurs) with the label of the largest class in the training set.

2.2 Data Augmentation

The objective of data augmentation is to increase the number of training data samples in order to improve performance of models on the evaluation set (Feng et al., 2021). We experimented with 2 techniques: 1) word-level deletion of the start and end words per sample and 2) conversational AI text generation (Table 2). Our work may be the first to use conversational AI for data augmentation. It doubles the amount of samples and provides diversity. The average new words generated per sample prompt is around 16 words. More details about the 2 techniques are found in appendix C.3.

Table 2: Original and conversational AI-augmented examples from the HASOC 2021 dataset. (offensive words masked with "***")

| Type       | Sample                                                                 |
|------------|------------------------------------------------------------------------|
| original   | Son of a *** wrong 'you're'                                            |
| augmented  | son of a *** wrong yours No, that’s Saint Johns Chop House. I need a taxi to take me from the hotel to the restaurant, leaving the first at 5:45. |
| original   | SO EXCITED TO GET MY CovidVaccine I hate you covid!                    |
| augmented  | so excited to get my covidvaccine i hate you covid                     |
| original   | ModiKaVaccineJumla Who is responsible for oxygen? ModiResign Do you agree with me? â¤ï¸ Don’t you agree with me? |
| augmented  | modikavaccinejumla who is responsible for oxygen modiresign do you agree with me âï dont you agree with me Yes, I definitely do not want to work with them again. I appreciate your help. |

3 Results and Discussion

Tables 3, 4 and 5 (Appendix E) show baseline results, additional results using the best model: T5, and the cross-task with T5, respectively. Table 6 (Appendix E), shows results for other datasets and the HateBERT model (Caselli et al., 2021). The HatEval task is the only comparable one in our work and that by Caselli et al. (2021).

The Baselines : The Transformer-based models (T5 and RoBERTa) generally perform better than the other baselines (LSTM and CNN) (Zampieri et al., 2019b), except for RoBERTa on the OLID subtask B and HASOC 2021 subtask A. The T5 outperforms RoBERTa on all tasks. Based on the test set results, the LSTM obtains better results than...
| Task       | Weighted F1 (%) | Macro F1 (%) |
|------------|-----------------|--------------|
|            | Dev (sd) | Test (sd) | Dev (sd) | Test (sd) |
| Bi-LSTM    | OLID A  | 79.59 (0.89) | 83.39 (0.57) | 78.48 (1.52) | 79.49 (0) |
|            | OLID B  | 82.50 (1.70) | 83.86 (0) | 46.76 (0) | 47.32 (0) |
|            | OLID C  | 49.75 (3.95) | 43.82 (9.63) | 35.65 (2.81) | 36.82 (0) |
|            | Hasoc 2021 A | 78.05 (0.85) | 78.43 (0.84) | 77.99 (1.79) | 77.19 (0) |
|            | Hasoc 2021 B | 50.65 (1.34) | 52.19 (1.95) | 43.19 (2.09) | 42.25 (0) |
| CNN        | OLID A  | 79.10 (0.26) | 82.47 (0.56) | 77.61 (0.39) | 78.46 (0) |
|            | OLID B  | 82.43 (0.49) | 83.46 (0) | 46.76 (0) | 47.88 (0) |
|            | OLID C  | 47.54 (1.36) | 38.09 (3.91) | 35.65 (0) | 36.85 (0) |
|            | Hasoc 2021 A | 77.22 (0.52) | 78.63 (0.70) | 74.28 (0.58) | 75.67 (0) |
|            | Hasoc 2021 B | 55.60 (0.61) | 59.84 (0.41) | 50.41 (0.41) | 54.99 (0) |
| RoBERTa    | OLID A  | 82.70 (0.55) | 84.62 (0) | 80.51 (0.76) | 80.34 (0) |
|            | OLID B  | 82.43 (0.13) | 83.46 (0) | 46.76 (0) | 47.02 (0) |
|            | OLID C  | 92.90 (1.37) | 85.57 (0) | 92.93 (1.42) | 81.66 (0) |
|            | Hasoc 2021 A | 92.90 (3.27) | 85.57 (0) | 92.93 (2.20) | 82.54 (0) |
|            | Hasoc 2021 B | 64.74 (3.84) | 62.74 (0) | 33.09 (0.76) | 43.12 (0) |

Table 3: Mean scores of model baselines for different subtasks. (sd: standard deviation; bold values are best scores for a given task; '-.' implies no information available)

| Task       | Weighted F1 (%) | Macro F1 (%) |
|------------|-----------------|--------------|
|            | Dev (sd) | Test (sd) | Dev (sd) | Test (sd) |
| T5-Base    | Hasoc 2020 A | 96.77 (0.54) | 91.12 (0.2) | 96.76 (0.54) | 91.12 (0.2) |
|            | Hasoc 2020 B | 83.36 (1.59) | 79.08 (1.15) | 56.38 (5.09) | 53.21 (2.87) |
| T5-Base+Augmented Data | Hasoc 2021 A | 95.5 (3.27) | 83 (0) | 92.97 (2.20) | 82.54 (0) |
|            | Hasoc 2021 B | 64.74 (3.84) | 66.85 (0) | 65.56 (1.48) | 62.71 (0) |
| Ensemble   | Hasoc 2021 A | 80.78 (0) | 79.05 (0) |
|            | Hasoc 2021 A+Augmented | 51.52 (-) |
|            | Hasoc 2021 B+Augmented | 26.52 (-) |
| (Zampieri et al., 2019b) best scores | OLID A | 82.90 (-) |
|            | OLID B  | 75.50 (-) |
|            | OLID C  | 66 (-) |

Table 4: T5 variants’ mean scores over HASOC data. (sd: standard deviation; bold values are best scores for a given task; '-.' implies no information available)

The CNN in the OLID subtasks A, HASOC 2020 subtask A, and HASOC 2021 subtask A while the CNN does better than it on the others.

**T5 Variants & Augmentation**: The T5-Base model achieves new best scores on the HASOC 2020 subtasks. The augmented data, using the conversational AI technique, improves results on HASOC 2021.⁵

### 3.1 The Ensemble

The ensemble macro F1 result (79.05%) is closer to the T5-Base result (80.81%) and farther from the RoBERTa result (74%). The deciding factor is the T5-Small. Hence, a voting ensemble may not perform better than the strongest model in the collection if the other models are weaker at prediction.

### 3.2 Cross-Task Training

We obtain new SoTA result (91.73%) for the HASOC 2020 subtask A after initial training on the OLID subtask A. The reason we outperform the previous SoTA is that they used an LSTM with GloVe embeddings (Mandl et al., 2020), instead of a pre-trained deep model with the attention mechanism (Bahdanau et al., 2015) that gives transfer learning advantage. The p-value (p < 0.0001) obtained for the difference of two means of the two-sample t-test is smaller than the alpha (0.05), showing that the results are statistically significant.

³The first technique is not reported because there was no improvement. This may be because the number of total samples is smaller than that of the conversational AI technique.
3.3 HASOC 2021 Annotation Issues

Inspection of some of the samples predicted by the T5 model reveal challenges with the quality of data annotation in the HASOC 2021 dataset. Table 7 (Appendix E) gives several (10) examples of tweets incorrectly labeled as “NOT” (‘1’) by the annotators but which are clearly offensive (HOF (‘0’)), in our view, and are also correctly predicted as such by the model. More cases like these exist within the dataset than shown in the table. This issue makes a strong case for having better quality control (QC) with data annotation, given the possible implications, including the poor assessments that may result from the competitions organized using such dataset. We provide SHAP explanations of the T5 model predictions for some of these suspicious examples (Appendix E.3).

3.4 Error Analysis

The confusion matrix for the T5 on HASOC 2021 is given by Figure 1. It reveals that 33% (160) of the “NOT” class (not offensive) was misclassified as offensive while only 8% (60) of the “HOF” (hate or offensive) was misclassified as “NOT”. The higher percentage of misclassification for the “NOT” class is very likely due to the fact that the training set is imbalanced, as there are more “HOF” samples (2,251) compared to ”NOT” (1,207). Hence, the model is better at identifying samples of “HOF”.

![Figure 1: Confusion matrix of T5 on Hasoc 2021 test set](image)

3.5 Explainable Artificial Intelligence (XAI)

XAI helps us understand how a model arrives at a prediction and identify any incompleteness in the model (Doshi-Velez and Kim, 2017). This can add to the justification for using ML models and the trust in their predictions. In this study, rather than compare two XAI algorithms on one model, we focus on separate explanations from two XAI algorithms on two different models, using the same examples from the HASOC 2021 test set subtask A (Appendix E, Table 8). The XAI algorithms are IG and SHAP, which are discussed in detail in appendix D with examples.

4 Related Work

Significant efforts have gone into addressing automatic HS detection (Davidson et al., 2017; Mathew et al., 2021). Zampieri et al. (2019a) extended the OLID dataset to annotate the distinction between explicit and implicit messages. Caselli et al. (2020) performed cross-domain experiments on HatEval (Basile et al., 2019). Mutanga et al. (2020) experimented with different Transformer-based architectures using only the HSO dataset. However, their preprocessing approach, which involves removing low frequency words, may result in newly introduced hate terms escaping detection.

The Transformer architecture by Vaswani et al. (2017) has been very influential in recent progress with various NLP tasks. The attention mechanism on which it is based makes it possible for it to handle long-term dependencies (Bahdanau et al., 2015; Vaswani et al., 2017). Hence, Transformer-based models have gained increased attention in HS detection and classification (Mutanga et al., 2020; Mathew et al., 2021; Kovács et al., 2021; Elsafoury et al., 2021b). Despite the introduction of these models, there seems to be a gap where recent SoTA models are not compared across many HS datasets. We address that in this work.

5 Conclusion

In this study, we solve the OOC problem in T5 using a simple two-step approach, demonstrate the benefits of data augmentation through conversational AI and cross-task training for automatic HS detection. We achieve new SoTA results on the HASOC 2020 subtasks A and B. We also achieve near-SoTA results for both the subtask A of the OLID 2019 and HASOC 2021 datasets. We reveal, with examples and XAI, the shortcomings of the HASOC 2021 dataset and make a case for better quality control with data annotation. IG and SHAP are also used to explain predictions of some of the same examples from the HASOC 2021 dataset. Future work that compares performance with models, which are pretrained on large volumes of tweet,
such as BERTweet (Nguyen et al., 2020), may be a worthwhile investigation. Releasing our source codes and model checkpoints provides the opportunity for the community to reproduce our results and foster transparency.

Limitations

The datasets used in this study are all in the English language. The results are, therefore, limited to the English language. It is unclear how the models will perform with other languages. Many of the datasets are also based on tweets, which are usually short. Hence, there might be low scalability of the models to long text. Furthermore, none of the models has 100% performance on the short tweets. Also, all the models were trained on GPU and this requirement is necessary to train the models to speed up training time.

Ethics Statement

The results obtained in this work are factual and reproducible. Conscious effort was made by the authors to avoid harm in the presentation of this study though some data samples contain offensive or hate speech content. For example, many of the offensive words or characters have been masked with "*". Although we have used XAI, we acknowledge it may lead to the potential risk of undue trust in models and therefore provided more than one XAI algorithm explanations for more than one model. In fairness to other users of the shared system where the experiments were run, restrictions (cpuLimit) were implemented during the experiments to avoid overloading the server.

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Appendix

A Data

Following are the datasets considered in this work:

1. HASOC 2020

The English dataset is composed of 3,708 tweets for training and 1,592 for testing. The dataset includes the following subtasks: 1) task_1 (A), which identifies hate and offensive text and 2) task_2 (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). Mandl et al. (2020) collected the dataset and used a trained SVM classifier and human judgment to label the data.

2. HASOC 2021

This third edition of HASOC Mandl et al. (2021) provided another set of tweets dataset with the same subtasks as HASOC 2020. The English dataset consists of 3,843 training samples and 1,281 samples in the test set. The dataset has Covid-related topics since the data was gathered during the Covid-19 pandemic. 10% of the training set is split as the dev set in this work for evaluation after each epoch.

3. HatEval 2019

Basile et al. (2019) prepared this dataset of tweets to detect hateful content against women and immigrants. It contains 13,000 English tweets, distributed as 9,000 for training, 1,000 for development and 3,000 for testing. The dataset includes two subtasks: subtask A identifies the presence of hate speech while subtask B is the average of three binary classification tasks. The 3 binary subtasks under subtask B include 1) HS, 2) whether the hate speech targets group of people or an individual (TR), and if the HS contains aggressive content or not (AG).

4. OLID 2019

The SemEval 2019 shared task 6 dataset is based on the OLID dataset. It has 14,200 annotated English tweets and encompasses the following three sub-tasks: 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, where distinction is made among individual, group and other entities, like an organisation (Zampieri et al., 2019a). Crowd-workers performed its data annotation and the original data-split was into training and test sets only. As we did with HASOC 2021, we split 10% of the training set as the dev set for evaluation after each epoch.

5. HSO

Davidson et al. (2017) gathered tweets based on a hate speech lexicon and employed crowdsourcing effort to annotate them. They make a distinction between hate speech and offensive language, choosing a narrower definition of hate speech, as opposed to some general view like Zampieri et al. (2019a). Three categories are present in the labeled data: hate speech, only offensive language, and neither. Of the 24,802 labeled tweets, resulting in the
HSO data, 5% were labeled as containing hate speech while 1.3% were by unanimous decision.

6. TRAC

Kumar et al. (2020) introduced TRAC and the second version, in 2020, contains two sub-tasks. Three categories are present in the first subtask: Overtly Aggressive, Covertly Aggressive and Non-aggressive. The English version of this task contains 5,000 samples for training and evaluation, just like the Bangla and Hindi versions. The second subtask is a binary classification to identify gendered or non-gendered text. Our focus was on the first subtask only in this work. Elsafoury et al. (2021a) distinguish this dataset from other HS datasets. However, they also acknowledge that there are some similarities (like abusive language) between aggression and HS. It is based on this that we selected the dataset.

B Models

B.1 Bi-LSTM

The Bi-LSTM is one form of Recurrent Neural Network (RNN) (Hochreiter and Schmidhuber, 1997). It is an improved variant of the vanilla RNN. Its input text flows forward and backwards, thereby providing more contextual information, thereby improving the network performance (Graves and Schmidhuber, 2005). We used 2 bi-directional layers and a pretrained Glove (Pennington et al., 2014) word embeddings of 100 dimensions. We also applied a dropout layer to prevent overfitting. This model has 1,317,721 parameters. Word and subword embeddings have been shown to improve performance of downstream tasks (Mikolov et al., 2013; Pennington et al., 2014; Adewumi et al., 2022).

B.2 CNN

The CNN is common in computer vision or image processing. (Kim, 2014) shows the effectiveness of CNN to capture text local patterns on different NLP tasks. Both the Bi-LSTM and CNN architectures are used as feature-based models, where for each tweet, we computed embeddings using pre-trained Glove, before using the embeddings as an input to the baseline model. The CNN model is composed of 3 convolution layers with 100 filters each. The filter size for the first layer is $2 \times 100$, and the filter size for the second layer is $3 \times 100$ and $4 \times 100$ for the third layer. We use ReLU activation function and max-pooling after each convolution layer. We perform dropout for regularization. The total trainable parameters for the CNN are 1,386,201

B.3 RoBERTa

RoBERTa is based on the replication study of BERT. It differs from BERT in the following ways: (1) training for longer over more data, (2) removing the next sentence prediction objective, and (3) using longer sequences for training (Liu et al., 2019). The base version of the model, which we use, has 12 layers and 110M parameters. For our study, we use 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.

B.4 T5

The T5 (Raffel et al., 2020) is based on the transformer architecture by Vaswani et al. (2017). However, a different layer normalization is applied, where there’s no additive bias applied and the activations are only rescaled. Causal or autoregressive self-attention is used in the decoder for it to attend to past outputs. The T5-Base model has about twice the number of parameters as that of BERT-Base. Its has 220M parameters and 12 layers each in the encoder and decoder blocks while the small version has 60M parameters (Raffel et al., 2020). The T5 training method uses teacher forcing (i.e. standard maximum likelihood) and a cross-entropy loss. T5-Base 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 but kept the batch size at 64 for T5-Small. The task prefix we use is ‘classification’ for all the tasks, as the model takes a hyperparameter called a task prefix.

C Methods

C.1 Preprocessing

We carried out preprocessing on all the data to remove duplicates and unwanted strings or characters. In some of the datasets, such as OLID (task C), there are "nans" (empty entries) in some columns of the labels. These cause problems for the models by dropping model performance. We, therefore, dropped such rows during the preprocessing step. To prepare the text for the models, the following
standard preprocessing steps are applied to all the datasets:

- URLs are removed.
- emails are removed.
- IP addresses are removed.
- Numbers are removed.
- All characters are changed to lowercase.
- Excess spaces are removed.
- Special characters such as hashtags(#) and mention symbols (@) are removed.

C.2 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. We report both weighted and macro F1 scores because of past studies. Macro-F1 does not take label imbalance into account unlike weighted-F1, which accounts for label imbalance by finding the labels’ mean weighted by support (each label’s true instances) (Pedregosa et al., 2011).

C.3 Augmentation

C.3.1 Word-Level Deletion

The first technique involves the use of the list of offensive words available from the online resource at Carnegie Mellon University. This list is used to ensure offensive tokens are not deleted during the pass through the training set. From the original list of 1,383 English words, we removed 160 words, which we considered may not qualify as offensive words because they are nationalities/geographical locations or adjectives of emotions. 1,223 words are left in the document used for our experiment. Examples of words removed are: european, african, canadian, american, arab, angry and many unharmful words. 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.

C.3.2 Conversation Generation

The second technique involves the use of the dialogue (conversation) model checkpoint by Adewumi et al. (2021), which was finetuned on the Multi-Domain Wizard-of-Oz (MultiWOZ) dataset by Eric et al. (2020). It is an autoregressive model based on the pretrained DialoGPT-medium model by Zhang et al. (2020). An autoregressive model conditions each output word on previously generated outputs sequentially (Zou et al., 2021). Every sample from the training data is used as prompt to the model to generate a response, which is then concatenated to the prompt to form a new version of the prompt that was supplied. This ensures the original label of each sample is unchanged, as the offensive content, if any, is still retained in the new sample. As demonstrated by Adewumi (2022), the possibility of generating an offensive token is small for this model because the MultiWOZ dataset it is trained on is reputed to be non-toxic.

This second technique literally doubled the training set size of the HASOC 2021 dataset. Random quality inspection was carried out on the augmented data. Examples of the original and augmented samples from the HASOC 2021 dataset, using this second technique, are given in Table 2. The offensive words (masked with ***) are retained in the new samples. The top-p and top-k variables of the decoding algorithm for the model were set as p=0.7 and k=100, respectively. Additional hyperparameters include maximum decoding length, set as 200 tokens, temperature, set as 0.8, and maximum ngram repeat limit, set as 3. These hyperparameters are based on previous work, as they have been shown to perform well (Adewumi et al., 2021).

C.4 The Ensemble

The ensemble is a majority-voting system comprising of T5-Base, T5-Small and RoBERTa-Base models. The saved model checkpoint from each trained model is used to make prediction on each sample of the test set of the HASOC 2021 dataset for subtask A. The prediction (“HOF” or “NOT”) with more than one vote (2 or 3) is recorded as the prediction for that sample. The weighted and macro F1 scores are then calculated with the scikit-learn library (Pedregosa et al., 2011), as in all other cases.

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6 scikit-learn.org//generated/sklearn.metrics.f1_score.html
7 cs.cmu.edu//biglou/resources/
C.5 Cross-Task Training

We performed cross-task training to ascertain if there will be performance gains on a target subtask. We discover cross-task training can improve performance, however, not always. Six subtasks from three datasets are selected for this purpose because of time and resource constraints. The subtasks are all subtasks A (binary classification) from 3 datasets: OLID, HASOC 2020, and HASOC 2021. Only the T5 model is used for these experiments. We finetune an initial (source) subtask and then further finetune on a final (target) subtask of a different dataset before evaluating the test set of the target subtask.

D XAI

D.1 Integrated Gradient (IG)

We apply IG to the Bi-LSTM. It is an attribution method that is based on two fundamental axioms—Sensitivity and Implementation Invariance (Sundararajan et al., 2017). Generally, integrated gradients aggregate the gradients along the straight line between the baseline and the input. A good baseline (of a zero input embedding vector, in this case) is very important. Models trained using gradient descent are differentiable and IG can be applied to these. IG has the advantage of being relatively faster than SHAP computationally. Section E.2, in the appendix, show IG explanations for examples of 5 correctly classified (Figure 12) and 5 incorrectly classified (Figure 13) samples, based on the provided annotations. The attribution shows which input words affect the model prediction and how strongly. Important words are highlighted in shades of green or red, such that words in green contribute to non-hate speech while those in red contribute to hate speech. In Figure 13, the second tweet has what may be considered an offensive word but it is incorrectly annotated as "NOT". The Bi-LSTM, however, predicts this correctly.

D.2 SHapley Additive exPlanations (SHAP)

SHAP assigns each feature an importance value for a particular prediction (Lundberg and Lee, 2017). The exact computation of SHAP values is challenging. However, by combining insights from current additive feature attribution methods, one can approximate them. Its novel components include: (1) the identification of a new class of additive feature importance measures, and (2) theoretical results showing there is a unique solution in this class with a set of desirable properties (Lundberg and Lee, 2017). It unifies six existing methods: LIME, DeepLIFT, Layer-Wise Relevance Propagation, Shapley regression values, Shapley sampling values and Quantitative Input Influence. The last three are based on classic cooperative game theory (Shapley, 1951). This provides improved performance and consistency with human intuition. SHAP has the advantage that it can be applied to models whose training algorithm is differentiable as well as those based on non-differentiable algorithm, such as trees.

SHAP functionality is employed in this work by passing the supported HuggingFace transformers T5 pipeline (text2text-generation) to SHAP. Important words or subwords are highlighted in shades of red or blue, such that words in red are those that contribute to a resulting prediction while those in blue contribute to what would be an alternative prediction. The thicker the shade, the stronger the contribution, as also indicated by the real values above each word or subword. Figures 2 to 6 present examples using the same samples from Table 8. Additional examples are provided in Section E.1, in the appendix. We observe that 7 out of the 10 are correctly predicted by the T5, as explained by SHAP, compared to the 5 correct predictions by the Bi-LSTM.

D.3 SHAP Explanations

E Additional Results
### Table 5: Cross-Task inference using T5

| Cross-task | Weighted F1 (%) | Macro F1 (%) |
|-------------|-----------------|--------------|
|             | Dev (sd) | Test (sd) | Dev (sd) | Test (sd) |
| Hasoc 2020 A -> OLID A | 90.35 (0.01) | 83.94 (0.72) | 88.82 (0.01) | 79.81 (0.85) |
| Hasoc 2021 A -> OLID A | 91.82 (0.01) | 83.52 (0.48) | 90.57 (0.01) | 79.22 (1.01) |
| Hasoc 2021 A -> Hasoc 2020 A | 95.87 (0.0) | 83.52 (0.85) | 92.97 (0.0) | 79.22 (0.06) |
| OLID A -> Hasoc 2021 A | 86.82 (0.01) | 80.91 (0.53) | 84.91 (0.02) | 79.32 (0.55) |
| Hasoc 2020 A -> Hasoc 2021 A | 87.2 (0.03) | 81.75 (0.29) | 87.37 (0.01) | 80.4 (0.3) |

### Table 6: Model comparison of mean scores for other HS datasets. (sd: standard deviation; '-' implies no information available)

| Task | Weighted F1 (%) | Macro F1 (%) |
|------|-----------------|--------------|
|      | Dev (sd) | Test (sd) | Dev (sd) | Test (sd) |
| Bi-LSTM |        |          |        |          |
| HatEval SemEval 2019 A | - | 72.38 (0.54) | - | 72.12 (0.72) |
| HatEval SemEval 2019 B | - | 77.74 (2.8) | - | 73.11 (0.44) |
| Hasoc 2020 A | 88.6 (0.15) | 89.20 (0.15) | 89.47 (1.47) | 90.08 (0.46) |
| Hasoc 2020 B | 76.38 (0.56) | 74.39 (2.31) | 42.99 (0.15) | 42.97 (0.06) |
| HSO | 90.19 (0.03) | - | 68.77 (1.93) | - |
| T5-Base |        |          |        |          |
| HatEval SemEval 2019 A | - | 87.07 (4.81) | - | 86.52 (4.11) |
| HatEval SemEval 2019 B | - | 79.93 (0) | - | 99.88 (0) |
| TRAC | 71.01 (1.73) | - | 40.24 (0.43) | - |
| CNN |        |          |        |          |
| HatEval SemEval 2019 A | - | 73.95 (0.64) | - | 71.67 (0.43) |
| HatEval SemEval 2019 B | - | 78.88 (0.55) | - | 71.13 (0.43) |
| Hasoc 2020 B | 88.06 (0.41) | 89.76 (0.44) | 88.21 (0.41) | 90.08 (0.46) |
| Hasoc 2021 B | 76.38 (0.63) | 74.78 (0.61) | 49.15 (1.25) | 47.58 (0.85) |
| HSO | 88.52 (0.62) | - | 68.77 (1.93) | - |
| T5-Base |        |          |        |          |
| HatEval SemEval 2019 A | - | 87.07 (4.81) | - | 86.52 (4.11) |
| HatEval SemEval 2019 B | - | 79.93 (0) | - | 99.88 (0) |
| TRAC | 71.01 (1.73) | - | 40.24 (0.43) | - |

### Table 7: Hasoc 2021 test set samples with suspicious labels but correctly classified, in our view, as HOF by T5. (parts of offensive words masked with "*")

| id | text | task_1 | task_2 |
|----|------|--------|--------|
| 60c5d68f579ca2c535dfe18b | When you're the main b*tch https://t.co/HWlNpEUiwS | NOT | NONE |
| 60c5d68f579ca2c535dfe242 | miya four creeps into every thought i have what the f*ck | NOT | NONE |
| 60c5d68f579ca2c535dfe55 | At least we're being freed from the shambles of the evangelical, but d*mn y'all couldn't just go w the flow? Y'all just had to find jebus through crystals and astrology? Smdh | NOT | NONE |
| 60c5d68f579ca2c535dfe2e | #kumarubhyar #Actor_MdSudharth He is mentally Upset, Why he's not talking about BengalBurning and why stupid talks about Tejasvi_Surya | NOT | NONE |
| 60c5d68f579ca2c535dfe20 | #rape | NOT | NONE |
| 60c5d68f579ca2c535dfe18b | LIKE this tweet for a DM SC: jayjayson4225 #dime #bony #boymdm #instawriter #nsfw #wristeraferdik #whitecock #cockrate #nudes #naughty #dmopen #cowcock #dick #nsfw #sexpen #dickjock #cockpics #cumshot #cumshot #cumshot | NOT | NONE |
| 60c5d68f579ca2c535dfe28 | happy p*s off old people month | NOT | NONE |
| 60c5d68f579ca2c535dfe19 | China is such a worst country first they unleashed #Chinesevirus on whole world and #ChinaLedPeopleDied and now india is struggling with #ChineseVirus but they are mocking people who are dieing of #ChinesVirus in India https://t.co/V0AiuJV3lm | NOT | NONE |
| 60c5d68f579ca2c535dfe1a | @globaltimesnews Communist must feel shame God is watching you what you did with world. #CommunistVirus | NOT | NONE |
| 60c5d68f579ca2c535dfe70 | @RapidWolfReturn @Utd_76 @MenachooManuel1 @HHeKeTrain @UnitedStandMUCFC Yeah... sh*t move, but as has been said; heat of the moment, stupid comment he probably doesn't really back... should've just explained it, owned it, and moved on. He's a w*nker, regar | NOT | NONE |

### E.1 Cherry-picked Examples from the HASOC 2021 Test Set for T5 Explained by SHAP

### E.2 Cherry-picked Examples from the HASOC 2021 Test Set for Bi-LSTM Explained by IG

### E.3 Some Incorrect HASOC 2021 Annotations Correctly Classified by T5 & Explained by SHAP
holy shit i have to pack up and move to a new house in less than 30 days. یہ巨额
a large proportion of people all across the globe still feel that vaccines might be risky and have various doubts surrounding the same. To address these concerns we are here with an interactive live webinar on covid vaccine safety covidvaccine covid

indiacovidcrisis remember this stop spreading fake news

one thing which epitomises the level of incompetency of delhi amp centre is that both gvs failed to utilise existing healthcare infra built by earlier gvs to its capacity even failed to supply required oxygen this is sheer incompetency amp negligence both should resign resignmodi

matthancock this may all be true but what did you do to piss off big dom

on a pandemic situation our odisha disaster management team help west bengal people in amphan our chief minister personally call n congratulate wb cm on return gift these morons hurt our people because they r hindu bengalburning

cancelboardexams resign_pm_modi pmindia because of your overconfidence and ignorance hundreds of indian citizens are dying everyday and now you are ignoring lakhs of students daily plea to cancel exam cancelthboardexams

china must be punished for unleashing the chinesevirus starting a biological war ban and boycott everything sources from the animal country covidsecondwave

globaltimessnews china is not at all a trustworthy nation the epidemic caused by chinesevirus have wreaked havoc worldwide and not only in india if china really wants to help it should accept its blunder of creating this chinesevirus and spreading it all over intentionally boycotchina

table 8 cherry-picked (pre-processed) examples from hasoc 2021 test set for xai in sections e.1 & e.2.

Figure 7: SHAP explanation of an incorrect T5 model prediction

Figure 8: SHAP explanation of the T5 model prediction

Figure 9: SHAP explanation of the T5 model prediction
Figure 10: SHAP explanation of an incorrect T5 model prediction

Figure 11: SHAP explanation of an incorrect T5 model prediction

Figure 12: Visualize attributions for Bi-LSTM on HASOC 2021 test set (correct-classification)

Figure 13: Visualize attributions for Bi-LSTM on Hasoc 2021 test set (miss-classification)

Figure 14: Incorrectly annotated but correctly classified by T5, as explained by SHAP
Figure 15: Incorrectly annotated but correctly classified by T5, as explained by SHAP

Figure 16: Incorrectly annotated but correctly classified by T5, as explained by SHAP

Figure 17: Incorrectly annotated but correctly classified by T5, as explained by SHAP

Figure 18: Incorrectly annotated but correctly classified by T5, as explained by SHAP