VL-BERT+: Detecting Protected Groups in Hateful Multimodal Memes

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Abstract

This paper describes our submission (winning solution for Task A) to the Shared Task on Hateful Meme Detection at WOAH 2021. We build our system on top of a state-of-the-art system for binary hateful meme classification that already uses image tags such as race, gender, and web entities. We add further metadata such as emotions and experiment with data augmentation techniques, as hateful instances are underrepresented in the data set.

1 Introduction

In this work, we present our submission to the Shared Task on Hateful Memes at WOAH 2021: Workshop on Online Abuse and Harms. Detecting hateful memes that combine visual and textual elements is a relatively new task (Kiela et al., 2020). However, research can build on earlier work on the classification of hateful, abusive, or offending textual statements targeting individuals or groups based on gender, nationality, or sexual orientation (Basile et al., 2019; Burnap and Williams, 2014).

Shared Task Description We only tackle Task A, which is predicting fine-grained labels for protected categories that are attacked in the memes, namely RACE, DISABILITY, RELIGION, NATIONALITY, and SEX. The memes are provided in a multi-label setting. Table 1 shows the label distribution of the provided data set.2

| Labels                  | Train | Dev | %  |
|-------------------------|-------|-----|----|
| NONE                    | 5495  | 394 | 64.4|
| RELIGION                | 888   | 78  | 10.6|
| RACE                    | 801   | 59  | 9.4 |
| SEX                     | 552   | 44  | 6.5 |
| NATIONALITY             | 191   | 19  | 2.3 |
| DISABILITY              | 184   | 16  | 2.2 |
| RACE+SEX                | 66    | 4   | 0.8 |
| RELIGION+SEX            | 52    | 2   | 0.6 |
| RACE+RELIGION           | 53    | 10  | 0.7 |
| NATIONALITY+RELIGION    | 38    | 3   | 0.4 |
| DISABILITY+RELIGION     | 36    | 4   | 0.4 |
| NATIONALITY+RACE        | 52    | 2   | 0.6 |
| NATIONALITY+SEX         | 20    | 1   | 0.2 |
| DISABILITY+RACE        | 16    | 1   | 0.2 |
| Other                   | 56    | 3   | 0.5 |
| Total                   | 8,500 | 640 | 100 |

Table 1: Overview of categories in WOAH 2021 data set. ‘Other’ refers to the remaining (very infrequent) instances annotated with different combinations of protected group labels.

In addition, we consider emotion tags which are extracted from facial expressions available in the hateful meme detection task. Zhu (2020) fine-tuned a visual-linguistic transformer-based pre-trained model called VL-BERT\textsubscript{LARGE} and showed that metadata information of meme images such as race, gender, and web entity tags (recommended textual tags for the image based on data collected from the web) improved the performance of the hateful meme classification system. We replicate this system for a more fine-grained categorization of hateful memes, as proposed by the current shared task. Considering the data scarcity in this novel task, we also propose several data augmentation strategies and examine the effects on our classification problem. The evaluation metric used by the shared task is the (micro-averaged) area under the receiver operating characteristic curve AUROC.

2In the data set, memes are labeled as PC\textsubscript{EMPTY} if they are not hateful and none of the protected categories can be applied. In this paper, we use NONE instead of PC\textsubscript{EMPTY} for better intuition.
meme images. Based on experimental results and the shared task leaderboard scores, the inclusion of emotion tags along with VL-BERT\textsubscript{LARGE} model equipped with race, gender, and web entity tags exhibits the best performance for Task A. We make our source code publicly available.\footnote{https://github.com/aggarwalpiush/HateMemeDetection}

2 Related Work

Multi-modal hateful meme detection is the task of identifying hate in the combination of textual and visual information.

Textual Information In most previous works, hate speech detection has been performed solely in textual form. Despite many challenges (Vidgen et al., 2019), there have been several automatic detection systems developed to filter hateful statements (Waseem et al., 2017; Benikova et al., 2017; Wiegand et al., 2018; Kumar et al., 2018; Nobata et al., 2016; Aggarwal et al., 2019). One state-of-the-art model is BERT (Devlin et al., 2019). BERT is a contextualized transformer (Vaswani et al., 2017) based on a pre-trained language model which can be further fine-tuned for downstream applications such as hate speech classification.

Visual Information For hateful meme classification, the Facebook challenge team\footnote{https://ai.facebook.com/blog/hateful-memes-challenge-and-data-set/} proposed a unimodal training where a ResNet (He et al., 2015) encoder is used for image feature extraction. Apart from this, there has been a plenitude of work on extracting information from images, which is potentially useful for hateful meme detection. Image processing systems such as Faster R-CNN or Inception V3 models (Ren et al., 2016; Szegedy et al., 2015) are useful for detecting available objects in images. Smith (2007) and EasyOCR\footnote{https://github.com/JaidedAI/EasyOCR} can optically recognize the text embedded in an image.

Visual-linguistic Information There have been several ML-based approaches to solve the task of hateful meme detection. Blandfort et al. (2018) extracted textual features such as n-grams, affine dictionary along with local (Faster R-CNN) and global (Inception V3) visual features to train the SVM-based classification model. Sabat et al. (2019) proposed the fusion of vgg16 Convolutional Neural Network (Simonyan and Zisserman, 2015) based image features with BERT (Devlin et al., 2019) based contextualized text features to train a Multi-Layer Perceptron (MLP) based model. Earlier work (Liu et al., 2018; Gomez et al., 2019) proposed either early or late fusion strategies for the integration of textual and visual feature vectors. However, Chen et al. (2020); Li et al. (2020); Su et al. (2020); van Aken et al. (2020) and Yu et al. (2021) extracted visual-linguistic relationships by introducing cross-attention networks between textual transformers and transformers trained on visual features. Such networks deliver promising results on a variety of visual-linguistic tasks such as Image Captioning, Visual Question Reasoning (VQR), and Visual Commonsense Reasoning (VCR). Zhu (2020) and Lippe et al. (2020) exploited these networks for the binary classification of memes as hateful or non-hateful. The incorporation of additional metadata information as race, gender, and
web entity tags, which are extracted from meme images, increased performance significantly in hateful meme classification (Zhu, 2020).

Hitherto, meme classification, having been introduced only recently, has been a binary task. Except for the VisualBERT (Li et al., 2019) based baseline provided by the WOAH 2021 Shared Task, to our knowledge, there has been no work on detecting protected groups in hateful memes.

3 System Description

In this paper, we exploit the analysis proposed by Zhu (2020) for the fine-grained categorization of hateful memes.

3.1 Pre-processing

Both the visual and the textual parts of the memes are pre-processed. The data provided by the shared task consist of memes with their corresponding meme text. In this paper, we follow the steps proposed by Zhu (2020) to pre-process the provided input memes.

Text Pre-processing For text pre-processing, a BERT-based tokenizer (Devlin et al., 2019) is applied. This is also an integral part of the VL-BERT LARGE system (Su et al., 2020) (see Section 3.3).

Image Pre-processing The image part of the memes poses several challenges. First, meme images may consist of multiple sub-images, so-called patches. In this case, we segregate these patches using an image processing toolkit (Chen et al., 2019). Second, the text embedded in the images may add noise to the image features. Therefore, we aim to recover the original meme image before the text was added. To do so, we first apply EasyOCR-based Optical Character Recognition, which results in an image with black masked regions corresponding to the meme text as shown in Figure 1b. Then, inpainting, a process where damaged, deteriorating, or missing parts are filled in to present a complete image, is applied to these regions using the MMediting Tool (Contributors, 2020) (see Figure 1c).

3.2 Metadata

Understanding memes often requires implicit knowledge (e.g. cultural prejudice, clichés, historical knowledge) that human readers must have to understand the content. Such knowledge might be a big help for the classifier if explicitly provided. Zhu (2020) used meme image metadata, such as race, gender, and web entity tags to enhance binary classification performance on hateful memes. We utilized the same metadata and, in addition to that, emotion tags for the fine-grained categorization into protected groups.

Race and Gender We apply the pre-trained FairFace (Karkkainen and Joo, 2021) model to the provided meme images to extract the bounding boxes of detected faces with their corresponding race and gender metadata.

Web Entities Web entities are web-recommended textual tags associated with an image. They add contextual information to the images, making it easier for the model to establish the relationship between the meme text and image. We use Google’s Web Entity Detection service to extract these web entities.

Emotion Emotions are promising features for hate speech detection (Martins et al., 2018). Awal et al. (2021) investigated the positive impact of emotions in textual hate speech detection where emotion features are shared using a multi-task learning network. We exploit this in our system by extracting emotions based on facial expressions available in the meme image together with their corresponding bounding boxes. For this purpose, we use the Python-based emotion detection API which classifies a face into the seven universal emotions described by Ekman (1992)—ANGER, FEAR, DISGUST, HAPPINESS, SADNESS, SURPRISE, and CONTEMPT.

3.3 VL-BERT LARGE

VL-BERT LARGE (Su et al., 2020) demonstrates state-of-the-art performance on binary hateful meme classification Zhu (2020). Therefore, we investigate it for the detection of protected groups in hateful memes. VL-BERT LARGE is a transformer (Vaswani et al., 2017) back-boned visual-linguistic model pre-trained on the Conceptual Captions data set (Sharma et al., 2018) and some other text corpora (Zhu et al., 2015). It provides generic representations for visual-linguistic downstream tasks.

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https://github.com/facebookresearch/mmft/tree/master/projects/hateful_memes/fine_grained

https://cloud.google.com/vision/docs/detecting-web

https://pypi.org/project/facial-emotion-recognition
One of the model training requirements is to identify objects and their location in the image. To do that, we use Google’s Inception V2 Object Detection model.\(^9\)

We extract features from both modalities (image and text) in the provided data set to fine-tune the pre-trained VL-BERT\(^9\) LARGE representation. Afterward, these features are used to train a multi-layer feedforward network (also called a downstream network) to generate the final classifier. We train the model for a maximum of 10 epochs with the other default hyperparameters provided by Su et al. (2020).

### 3.4 Data Augmentation

Data scarcity often leads to model overfitting. As shown in the training set distribution in Table 1, non-hateful memes comprise the majority of the data set. The non-uniform distribution of labels makes this data set quite small for model training. Therefore, we artificially augment the samples labeled with the protected groups. For image augmentation, we use the image augmentation toolkit by Jung et al. (2020) which alters images by adding effects like blur, noise, hue/saturation changes, etc. Additionally, we use Google’s Web Entity Detection service to obtain visually similar images. For text augmentation, we generate semantically related statements using nlpaug (Ma, 2019). Furthermore, since we have original and augmented versions of images and texts, we combine them in three different ways: i) the original image with augmented text, ii) augmented image with the original text, and iii) augmented image with augmented text (see Figure 2).

![Figure 2: Data augmentation: (a) Original meme (b) Image augmentation with effects (c) Image augmentation with a visually similar image (d) Text augmentation (e) Image and text augmentation](image)

### 3.5 Ensemble

The predictions of a single system may not be generalized enough to be used on unseen data due to high variance, bias, etc. However, relying on multiple systems can overcome these technical challenges. Therefore, we choose our best three systems based on their AUROC scores. We apply the majority voting scheme on the prediction labels provided by each system. The label with the highest number of votes will be selected as the final prediction for the ensemble system. In cases when all systems disagree, we choose the label with the highest prediction probability.

### 4 Results and Discussion

Table 2 shows the results for Task A on the provided development data set. We also compare our results with the VisualBERT (Li et al., 2019) based baseline as provided by the shared task organizers. Among the different configurations of our system, VL-BERT\(^9\) LARGE model with race, gender, emotion, and web entity tags (called +W,RG,E in the table) achieves the best AUROC score. We find that the inclusion of emotion tags has a positive effect on the overall performance when compared to other systems. To analyze the statistical significance among the approaches, we apply the Bowker test (Bowker, 1948) on the contingency matrices created on the number of agreements and disagreements between the systems. To compensate for the chance significance, we apply the Bonferroni correction (Abdi, 2007) on \(p\) value. We find that approaches marked with * are statistically significant compared to the best-performing solution.

When the model is trained on the train set along with augmented data, hardly any significant performance improvement is encountered. This is
Table 2: Classification results of hateful memes target (protected groups) classes on provided development data set. Abbreviations are as follows: RG: Race and Gender, W: Web Entities, E: Emotion, T: Text Augmentation, I: Image Augmentation, IT: Image and Text Augmentation, and U: Undersampling. * denotes that the approach is significantly different from the best performing system (+W,RG,E)) using the Bowker significance test, considering $p < 0.004$ after Bonferroni correction.

| Approach          | sign. | RACE  | SEX   | REL.  | DIS.  | NAT.  | NONE | F1   | AUROC | Leader Board AUROC |
|-------------------|-------|-------|-------|-------|-------|-------|------|------|-------|-------------------|
| Baseline          |       | .71   | .84   | .75   | .84   | .70   | .78  | .62  | .85   |                   |
| +W                |       | .79   | .86   | .87   | .90   | .92   | .71  | .64  | .91   |                   |
| +W,RG             |       | .81   | .87   | .91   | .91   | .85   | .80  | .70  | .92   | .912              |
| +W,E              |       | .77   | .85   | .90   | .89   | .77   | .75  | .68  | .91   |                   |
| +W,RG,E           |       | .76   | .89   | .91   | .94   | .81   | .79  | .70  | .92   | .914              |
| U | +W     |       | .81   | .87   | .90   | .90   | .91   | .71  | .60  | .87   |                   |
| U | +W,RG  |       | .83   | .88   | .90   | .91   | .87   | .74  | .62  | .90   |                   |
| I | +W     |       | .79   | .86   | .89   | .93   | .91   | .74  | .67  | .91   |                   |
| I | +W,RG  |       | .81   | .86   | .91   | .88   | .88   | .77  | .68  | .92   |                   |
| T | +W     |       | .75   | .82   | .90   | .84   | .83   | .76  | .70  | .91   |                   |
| T | +W,RG  |       | .75   | .86   | .86   | .91   | .83   | .78  | .70  | .90   |                   |
| IT | +W    |       | .72   | .80   | .89   | .81   | .87   | .75  | .70  | .88   |                   |
| IT | +W,RG  |       | .77   | .88   | .83   | .79   | .84   | .77  | .68  | .90   |                   |
| Ensemble          |       | .75   | .89   | .92   | .93   | .79   | .80  | .71  | .92   |                   |

contrary to our expectations. We analyze the approaches with image and text augmentation (IT|+W and IT|+W,RG) (statistically significant from the best-performing system) and found a notable increase in False Negative errors, especially for RELIGION.

During post-experiment analysis, we find that the predictions for DISABILITY and RELIGION labels are better compared to others when the model is at a low False Positive rate. However, NATIONALITY performs relatively well at a high False Positive rate (see Figure 3). From the confusion matrices (Table 3), we find that the number of False Negatives is dominant in all classes. We believe that class imbalance is responsible for this behavior. To verify this, we train models on the undersampled training data set and found significant improvement on labels with low sample size. However, we also find a huge performance drop on the NONE label.

For the final submission, we generate predictions on the test set using our two best-performing models based on their AUROC score — VL-BERT\_LARGE +W,RG,E (winning solution) and +W,RG (2nd rank) (see Table 2 for Shared Task leaderboard scores).

5 Summary

In this paper, we presented our approach to identify and categorize attacked protected groups in hateful memes. We performed experiments using a visual-linguistic pre-trained model called VL-BERT\_LARGE along with metadata information extracted from the meme image and text. Results show that the inclusion of metadata helps to improve system performance. However, the final system still lacks a robust understanding of hateful memes targeting protected groups.

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Figure 3: AUROC analysis for individual protected groups for configuration VL-BERT\_LARGE (+W,RG,E).
Predictions | Gold Values | Total
--- | --- | ---
False | 531 | 14 | 545
True | 43 | 52 | 95
Total | 574 | 66 | 640

(a) RELIGION

Predictions | Gold Values | Total
--- | --- | ---
False | 608 | 6 | 614
True | 22 | 4 | 26
Total | 630 | 10 | 640

(c) NATIONALITY

Predictions | Gold Values | Total
--- | --- | ---
False | 617 | 1 | 618
True | 13 | 9 | 22
Total | 630 | 10 | 640

(e) DISABILITY

Predictions | Gold Values | Total
--- | --- | ---
False | 546 | 16 | 562
True | 36 | 22 | 58
Total | 584 | 38 | 622

(b) RACE

Predictions | Gold Values | Total
--- | --- | ---
False | 579 | 5 | 584
True | 37 | 19 | 56
Total | 616 | 24 | 640

(d) SEX

Predictions | Gold Values | Total
--- | --- | ---
False | 108 | 138 | 246
True | 40 | 354 | 394
Total | 148 | 492 | 640

(f) NONE

Table 3: Confusion matrices for configuration VL-BERT_{LARGE} (+W,RG,E).

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