KAREN: Unifying Hate Speech Detection and Benchmarking

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Abstract

Hate speech has existed for a very long time within our societies, but the recent development of the internet and social media has boosted the prevalence and visibility of hate speech and facilitated its spread. The call for automatized hate speech detection tools has seen a growing response from both the industry and academia, but many problems like the lack of a baseline dataset and a standardisation of evaluation metrics makes it hard to compare the different proposed solutions. This has lead to many models experiencing poor generalisability when applied to different datasets, or used in the real world.

Inspired by (Cen et al., 2021), we propose **KAREN**, a new and extensible framework that provides an easy to use toolkit containing different datasets and baseline models, together with an NLP toolkit containing different tools ready to be used. With this easy to use environment, implementation of models using KAREN is extremely easy and fast, thus allowing researchers to spend less time writing the evaluation environment and directly compare the results in their own system. KAREN is publicly available on our GitHub[1].

1 Introduction

Hate speech is defined as "any communication that disparages a person or a group on the basis of some characteristic such as race, color, ethnicity, gender, sexual orientation, nationality, religion, or other characterstic" (Nockleby, 2000). The increasing accessibility of the internet and the popularity of social media and online forums has enabled more people to express themselves online, while also facilitating the spread of inappropriate content, including hate speech.

With the massive volume of online traffic, automated hate speech detection is not only essential for maintaining a healthy environment in online platforms, but also has deeper social implications in terms of crime incident prediction and prevention, e.g. (Wang et al., 2012).

Interest and studies in the field of hate speech detection have emerged in the past decade. Both traditional methods such as SVM, LDA, Logistic Regression, and deep learning methods, such as CNN, RNN and Transformer-based architectures have been explored by researchers. Such works have been developed using a wide range of datasets collected from the Internet, often private and only specific to the task presented in the work, leading to lack of generalizability for such methods (Yin and Zubiaga, 2021).

In this work, we propose **KAREN**, a benchmark framework that enables the training and evaluation of deep-learning models using a selection of datasets on various metrics. We believe such a framework can benefit researchers by providing insights on the performance of their models on a set of benchmark datasets with standardized metrics, alongside providing an easy comparison to other methods.

KAREN provides and intuitive model/dataset implementation that allows researchers and enthusiasts alike to focus on their models and theory, rather than spending hours on setting up a whole system to test and validate their experiments. We also allow completely customizable user defined dataset parsing for any new datasets they wish to implement – though this is of course not necessary, as they can use the datasets already implemented. It also tackles the previously mentioned problems by providing a compatibility evaluation system, filtering which models can run on each dataset and providing an intuitive way of accessing the required data. To give a general baseline for researchers to compare with, we have implemented many models. Simple models have been

[1] https://github.com/TiagoMAntunes/KAREN

implemented as well as some other, more complex ones.

This work is organised as follows: in section 2 we analyse recent work in hate speech and highlight its current problems; in section 3 we introduce our framework's architecture, how it has been designed and how it can be extended; in section 4 we analyse and compare the obtained results from the currently available models and datasets; in section 5 we discuss our findings and highlight key points in hate speech detection performance.

2 Related Work

Continuous effort has been put into this topic. Surveys from (Fortuna and Nunes, 2018) and (Schmidt and Wiegand, 2017) provide an overview of the history of the task and summarize the methods investigated. Their work highlights different problems in current research, such as word sparsity and the lack of context (which can highlight the hate, such as when someone uses sarcasm), and also points to some findings of current research such as the importance of having meta-data (by, for example, performing sentiment analysis on the content, as it is done in (Awal et al., 2021)) which can increase the accuracy of detection.

At the same time, multiple datasets were collected from online forums, such as Reddit (Mollas et al., 2020) and Twitter (Davidson et al., 2017a), and have been annotated by humans as categories of being hate speech, offensive speech, etc. Some datasets also included the rationale for the annotations, for better interpretability (Mathew et al., 2020) and it also serves as a way to justify its label. The datasets were used in conjunction with a variety of methods, including traditional machine learning models and deep neural network architectures, which resulted in an increased difficulty when comparing models. (Mollas et al., 2020) evaluated the proposed ETHOS dataset on methods such as naive bayes, random forest, logistic regression, deep neural networks, BERT, etc., achieving accuracies ranging from 48.3 (Bernoulli Naive Bayes) to 79.17 (BERT). With the widespread application of deep learning in natural language processing, multiple works proposed deep neural network architectures for hate speech detection. (Zhang, 2017) proposed a convolution-LSTM based network, yielding promising results on various public datasets (Davidson et al., 2017a), (Waseem, 2016), and (Waseem and Hovy, 2016). With the emergence of attention-based models, Transformers and BERT models have also been studied such as in (Awal et al., 2021) and (Caselli et al., 2020). The latter uses a large-scale dataset containing hate speech to pretrain BERT, yielding their solution called HateBERT, which is targeted towards abusive language detection. Recently, (Mathew et al., 2020) proposed HateXPlain, a dataset that they intend to be used a benchmark of hate speech detection, while (Aluru et al., 2021) proposed a collection of deep learning models that aim to generalise the problem of hate speech analysis and detection.

2.1 Problems in the Field

Despite the ongoing research, several problems persistently affect the obtained results. After looking into recent publications, we drew the following conclusions.

1) There is no standard benchmark dataset that allows for comparison across different models. Multiple works, such as (Zhang et al., 2018; Waseem and Hovy, 2016; Gaydhani et al., 2018) even provided a new dataset together with their solutions. The addition of new public datasets is of course beneficial for the growth of this area, but the unfortunate side effect is the **2) lack of generalisability**, as the performance of the model might be highly dependent on the dataset used and might perform better in another one, and vice-versa. This lack of generalisability is also related with the subjectivity of dataset annotation itself: hate speech is highly dependent on the social context and background of the specific individual choosing the category for each line of data (Waseem and Hovy, 2016), so what might be seen as hate speech by one individual, might seem acceptable to another individual. That is, **3) datasets contain an annotator bias** and so being able to test the model on multiple datasets would give a better idea of its real performance and quality. To also tackle this problem (Mathew et al., 2020) compiled HateXplain, a benchmark dataset containing hate speech and annotations that capture human rationale for the labeling of abusive words and phrases which is intended to be used as the standard dataset for evaluation on this topic. In addition, using several datasets to train and test a model reduces the bias, as different groups of people will have done the grading of each dataset.

Given these problems, we concluded that there is a unifying factor missing from this area of research, and that by providing an easy to use framework that allows for easy implementation, training and evaluation, we hope to greatly improve the quality of both existing research, and future developments in this area.

3 Framework Structure

KAREN was designed with two main objectives: easy implementation of both models and datasets for the user, as well an in-built mechanism that could filter which models can be run on some datasets (what we have previously called *compatibility*).

Definition 3.1 (Compatibility) *For a model M with a set of data requirements S_M and a dataset D with a set of available data S_D, we say that M is compatible with D iif. $S_M \subset S_D$.*

This notion of compatibility is the main property that allows KAREN to become scalable without having to worry about keeping track of whether or not a particular model or dataset are compatible. KAREN automatically validates if the set of model properties are a subset of the dataset's available data. This restriction on the models causes two restrictions to happen:

1. A model cannot access any other data that is not explicit in its data requirements. This is a safety measure to guarantee the consistency of the available models.

2. A model that requires a specific type of data will not be able to run on the vast majority of the datasets if they do not also contain this information. This effectively has to do with the available datasets being limited and it provides a new work direction – allowing the community to contribute and extend these datasets to hold more information from the basic data that is available. One could, for example, develop sentiment analysis for previous datasets to allow others models that use this data to be run on a previously unavailable dataset.

Although this concept might seem limiting at first, we have come to realize that its benefits are way more valuable. After we successfully developed the core of the framework, implementing all the models was very fast and easy to do, since all the validations were already handled by KAREN and the model just had to select the type of data that it wanted to use.

As it is seen in Figure 1, there are 4 main pieces that build KAREN: model, dataset, toolkit and training.

Training is carried out on our default training cycle, which we have used for all the results that are available in section 4. Due to the usage of different datasets and the nature of the task, we consider the task to be, at all times, a **Multi Class Classification Task**, even if the dataset is made for binary classification. This training cycle also handles the split of the datasets into train, dev and test datasets, hence allowing the users to evaluate the bias and variance of models easily. In addition, KAREN handles and manages all memory that needs to be transferred to the GPU to make use of GPU acceleration, another thing the user does not have to worry about. The training loop automatically saves the model with the best validation accuracy to be run on the testing data. After training, the best saved model is used to test the model against the test dataset, yielding its **accuracy, precision, recall and F1-score**. Although the last 3 metrics are only for binary classification, it is possible to do a class-wise analysis and select the relevant class for our analysis (the one that yields the results for hate speech).

Toolkit is where KAREN provides its NLP related tools. At the time of writing, this toolkit consists of three different types of Glove embeddings, each trained on a different dataset. This toolkit can be extended to add any other relevant tools. Due to the size of the pretrained embeddings we use, we present a default download method. On the first time using a specific type of embeddings, KAREN will download it to a local folder, unzip it and convert to binary format for reduced storage size.

Models are the models that are available in KAREN. Each model is required to extend the *BaseModel* class that defines its interface. Defining a model is as easy as defining its *init*, *forward* and *data requirements* functions, so implementing a full model from scratch is a very short and simple process.

Datasets are the datasets which models will be trained on. Similar to models, datasets need to extend a *BaseDataset* class and override the corresponding selection of methods for it to be able to

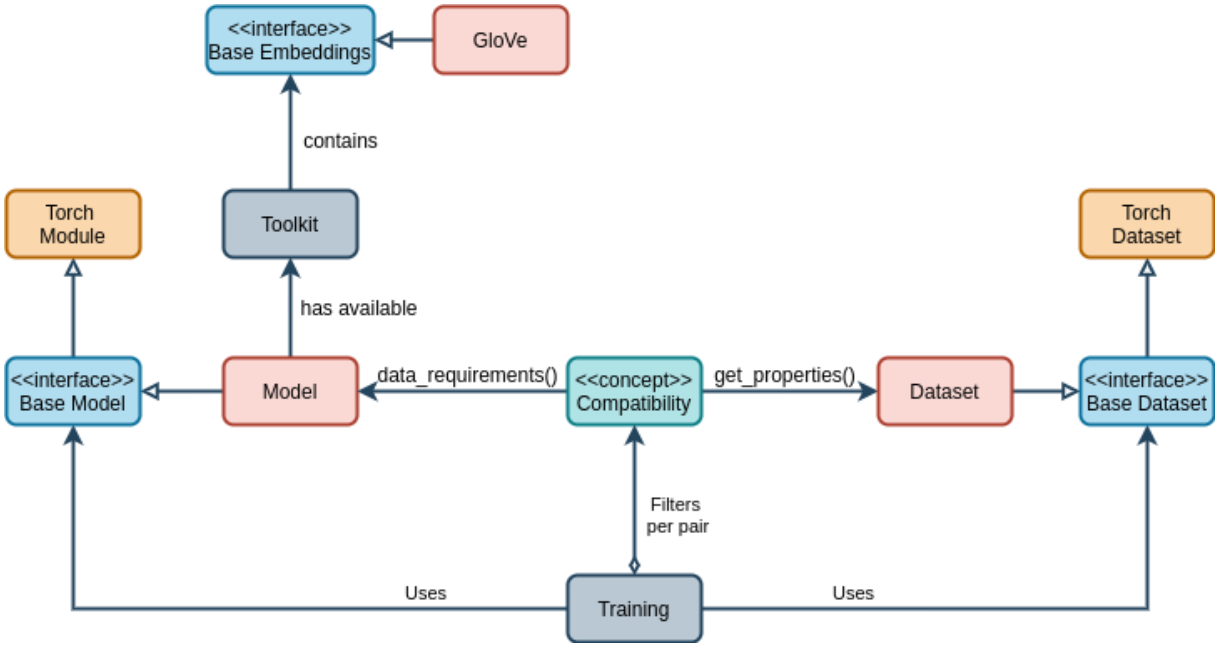

Figure 1: KAREN framework architecture

```python
@RegisterModel()
class ModelName(BaseModel):
    """
        This is a template file of a model implementation
    """

    def __init__(self):
        super(ModelName, self).__init__()

    def forward(self, data):
        pass

    @staticmethod
    def add_required_arguments(parser):
        pass

    @staticmethod
    def make_model(args):
        pass

    @staticmethod
    def data_requirements():
        pass
```

Figure 2: The interface of a model in KAREN. The user only needs to write this set of functions to easily and quickly implement a model in the framework.

run on the training script. Implementing datasets is a little more time consuming than models, as it must include some more information. One problem that was raised when developing was the way data was being sent to the models. Not all data can be transformed into a tensor, and some of the data is independent of the batch that is currently being run (for example, user metadata). For this, we designed datasets to output 3 types of data: tensor-like data, non-tensor data, always present data. We managed to shift the complex logic to the training instead of complicating the dataset, and implementing datasets is simple enough for anyone to quickly contribute theirs. We also implement a download logic for the datasets.

One thing that is not shown in Figure 1 is the run script. This script eases the manipulation of the framework by connecting all of its components together. Models and datasets both have a set of arguments that are customizable, and this script eases that configuration by allowing the users to run the framework from the command line by adding a set of parameters to a parser. To run, for example, a transformer model with 1 layer and dropout of 0.15 on the HateXPlain dataset using embeddings trained on twitter of size 100, the user simply needs to input `python3 run.py --model Transformer --dataset HateXPlain --transformer-n-layers 2 --dropout 0.15 --embeddings twitterglove --embedding-dim 100` which highly simplifies the testing method.

4 Results

4.1 Metrics and Datasets

In this section we will discuss the results obtained from our experiments, shown in Table 1, Table 2 and Table 3. To get an approximate baseline of performance so that we may compare models, we implemented three different datasets. These

Model	Accuracy	Precision	Recall	F1
Bert	**0.689**	**0.777**	**0.752**	**0.764**
CNN	0.613	0.711	0.69	0.7
Softmax Regression	0.366	0.298	0.087	0.135
RNN	0.55	0.684	0.654	0.669
BiLSTM	0.59	0.662	0.764	0.71
NetLSTM	0.61	0.678	0.76	0.716
GRU	0.609	0.666	0.777	0.72
Transformer (1 layer)	0.486	0.495	0.6	0.543
Transformer (2 layers)	0.532	0.551	0.732	0.629
CharCNN	0.552	0.65	0.61	0.63
AngryBERT	**0.649**	**0.736**	**0.695**	**0.764**
DistilBERT	**0.646**	**0.766**	**0.704**	**0.734**
RNN + GloVe	0.546	0.59	0.779	0.672
CNN + GloVe	**0.644**	**0.69**	**0.767**	**0.726**
BiLSTM + GloVe	**0.637**	**0.677**	**0.781**	**0.73**
GRU + GloVe	**0.64**	**0.699**	**0.736**	**0.717**
NetLSTM + GloVe	0.616	0.679	0.756	0.715
Transformer (1 layer) + GloVe	0.564	0.581	0.785	0.668
Transformer (2 layers) + GloVe	0.572	0.751	0.609	0.672
CharCNN + Glove	0.573	0.631	0.753	0.686
AngryBERT + Glove	**0.660**	**0.75**	**0.771**	**0.76**
UNet + Glove	0.602	0.714	0.670	0.691
UNet	0.548	0.646	0.670	0.657
VDCNN	0.552	0.694	0.653	0.673
VDCNN + Glove	0.601	0.681	0.694	0.688

Table 1: Results for the HateXPlain dataset. Precision, Recall and F1 score are showing for the hate speech label

Model	Accuracy	Precision	Recall	F1
CNN	0.644	0.639	0.548	0.590
Softmax Regression	0.467	0.465	0.952	0.625
RNN	0.522	0.4	0.048	0.085
BiLSTM	0.589	0.619	0.310	0.413
NetLSTM	0.544	0.6	0.071	0.128
GRU	0.6	0.588	0.476	0.526
Transformer (1 layer)	0.556	0.6	0.143	0.231
Transformer (2 layers)	0.478	0.468	0.881	0.612
UNet	0.478	0.471	0.976	0.636
DistilBERT	**0.744**	**0.757**	**0.667**	**0.709**
AngryBERT	**0.711**	**0.674**	**0.738**	**0.705**
RNN + GloVe	0.544	0.514	0.429	0.468
CNN + GloVe	0.644	0.639	0.548	0.590
BiLSTM + GloVe	0.656	0.628	0.643	0.635
GRU + GloVe	**0.711**	**0.674**	**0.738**	**0.705**
NetLSTM + GloVe	0.644	0.614	0.643	0.628
Transformer (1 layer) + GloVe	0.611	0.569	0.690	0.624
Transformer (2 layers) + GloVe	0.489	0.463	0.595	0.521
UNet + Glove	**0.722**	**0.707**	**0.690**	**0.699**
AngryBERT + Glove	**0.733**	**0.75**	**0.643**	**0.692**
Bert	**0.756**	**0.763**	**0.690**	**0.725**
CharCNN + GloVe	0.533	0	0	0
CharCNN + GloVe	0.533	0	0	0
VDCNN	0.5	0.459	0.405	0.430
VDCNN + Glove	**0.755**	**0.708**	**0.810**	**0.756**

Table 2: Results for the Ethos dataset.

datasets are HateXPlain (Mathew et al., 2020), HSAOL (Davidson et al., 2017b) and Ethos (Mollas et al., 2020). The datasets were designed specifically to be used for the detection of online hate speech. The data is mainly obtained from popular social media websites where users communicate via text, such as Twitter and Reddit.

We collect four different metrics in order to assess performance: accuracy, precision, recall and F1 score. To obtain the last three measures in a multi-class setting, we extract the metrics corresponding to the *hatespeech* class that is present in all datasets.

During our experiments we found that assessing performance based purely on accuracy was not sufficient, since some of the datasets we used (and indeed many datasets in this field) show a high degree of imbalance. An example of this is the HSAOL dataset, where the proportion of hate speech in the dataset is only around 10%.

Model	Accuracy	Precision	Recall	F1
CNN	**0.908**	**0.5**	**0.218**	**0.304**
Softmax Regression	0.757	0	0	0
RNN	0.865	0	0	0
BiLSTM	0.896	0	0	0
NetLSTM	0.897	0.377	0.168	0.233
GRU	0.904	0	0	0
Transformer (1 layer)	0.876	0.448	0.104	0.169
Transformer (2 layers)	0.887	0.4	0.192	0.26
UNet	0.897	0.475	0.224	0.304
DistilBERT	0.908	0.441	0.345	0.387
AngryBERT	0.908	0.3	0.024	0.044
RNN + GloVe	0.898	0	0	0
CNN + GloVe	**0.915**	**0.518**	**0.244**	**0.331**
BiLSTM + GloVe	0.906	0	0	0
GRU + GloVe	0.909	0	0	0
NetLSTM + GloVe	0.906	0.397	0.193	0.260
Transformer (1 layer) + GloVe	0.892	0.471	0.128	0.201
Transformer (2 layers) + GloVe	0.907	0.474	0.216	0.287
UNet + Glove	**0.912**	**0.524**	**0.264**	**0.351**
AngryBERT + Glove	0.913	0.385	0.12	0.183
Bert	**0.918**	**0.552**	**0.384**	**0.453**

Table 3: Results for the HSAOL dataset. Due to the dataset being quite unbalanced, our choice of using Precision, Recall and F1 score proves reliable.

Let us consider the binary classification problem, where we classify a sentence as either hate speech or not hate speech. In this setting, a model that predicts just the "not hate speech" label every single time already achieves an accuracy of 90% on the HSAOL dataset.

Since we are trying to measure a model's performance in detecting hate speech content, datasets that contain a low amount of hate speech labels might hide their poor performance detecting hate speech with a very high accuracy. As mentioned, this kind of behaviour is particularly prevalent in the HSAOL dataset, where most recurrent neural network (RNN) based models achieved very low F1 scores (models got an F1 score of 0) but achieved around 90% accuracy (in the multi-class detection setting).

In the following discussion, we will not go into much detail on any of the models unless necessary, since our task is creating a baseline and comparing models, not designing new models.

4.2 Results and Discussion

It is easy to see from the tables that use BERT models for hate speech detection achieve the best performance across nearly all datasets and metrics. The default BERT (Devlin et al., 2018) for sequence classification, which consists of a pre-trained BERT followed by a Feed Forward Network, is the best model (in terms of accuracy) across all datasets. It is nearly always first place in terms of the other metrics too. We also ex-

perimented with AngryBERT (primary only, since our datasets do not include sentiment detection labels yet), which uses a combination of BiLSTM with BERT in parallel followed by a trainable gate to give different contributions to each side of the computation. Its performance is lower than the default BERT, and the same goes for DistilBERT. We believe that this is related to the low amount of data available, which does not allow the BiLSTM structure to train as well, since for fine-tuning a BERT model we need to use a very low learning rate.

Compared to these models, one that performed surprisingly well was CNN, a very small and lightweight model. It uses a CNN structure to model N-grams. It consistently performs well on all datasets, and is always highlighted as one of the top models. It achieved almost equal performance to BERT on HSAOL and is one of the fastest models to train. For any researchers in the field, we would strongly suggest running this model as a baseline as it is fast and very flexible. In addition, the RAM usage is very small unlike BERT and the hyperparameters allow the model to scale very easily, so a user can make the model as deep and complicated as they like very easily. However, we found that for our datasets, adding more layers did not increase performance.

To go into more detail, we found that nearly all models performed well with a low number of layers. RNN based models performed best with only two layers in the RNN, the Transformer models worked the best with two layers and the CNN mentioned above separately passes the input to just three separate convolutional layers and concatenates the results. UNet similarly performed best when its depth was small (we will discuss this model later).

It is a current trend nowadays to use huge models by increasing the number of trainable parameters, but these very big models also require a very large amount of data to perform well. The datasets available for hate speech detection are in general very small as they require manual (and subjective) labelling. Therefore training very deep models often leads to bad results. This is likely why the transformer models in particular did not perform very well in this environment. The one exception to this is trend is VDCNN: Very Deep Convolutional Neural Network for Text Classification (Conneau et al., 2016).

VDCNN comes with four depth options: 9, 17, 29, 49 and the convolutional layers go up to 512 feature channels. In our experiments, there wasn't actually much difference using the different layer sizes. The results in the tables above are from the model with a depth of 17, which we found to perform the best, but the results using the other depths were very close. Interestingly, this model comes closest to beating BERT on the Ethos dataset. In fact, VDCNN actually performs better than BERT if we go by Recall or F1 score, and the accuracy only differs at the third decimal place. We were very pleased with this model's performance.

In addition to using NLP techniques, we also experimented with a model designed for image segmentation. See UNet (Ronneberger et al., 2015). UNet is a popular image classification model, first developed for the image segmentation of biomedical images. Recently, UNet has been adapted to work in the audio denoising setting as with UNetDNP (Michelashvili and Wolf, 2019). To give a very simplified overview, UNetDNP uses 1D convolutional layers instead of 2D convolutions. We further adapt this model to re-purpose it for sentence classification. After passing the batch through the embeddings layer, we need to convert the final dimension to a power of two so that the dimensions of the downsampling and upsampling convolutional layers match. This can be done with a linear layer, or a simple upscaling transformation – the later of the two offering the best performance. After passing through UNet, the output needs to be transformed using a linear layer to get the required number of output classes. In addition, inspired by ResNet (He et al., 2015), we sum the residual connections instead of concatenating. The results of this adapted version of UNet were also very pleasing. It came very close to BERT on the ETHOS dataset, and gave some of the best results on the HSAOL dataset – even achieving first place in terms of F1 score on HSAOL. Unfortunately, similar to VDCNN, the performance of UNet on HateXplain was only slightly above average.

Finally, we also implemented pretrained embeddings to increase training speed and model performance. For this task, we used the pretrained GloVe embeddings (Pennington et al., 2014), a very popular choice among researchers. For our results specifically, we use the glove embeddings collected from the Twitter crawl, but the

other GloVe embeddings are available for use in KAREN and are equally viable. With the GloVe embeddings, a noticeable increase in performance is seen across all models and datasets. We recommend its usage to maximize the detection performance of models, as well as greatly decreasing the training time.

5 Conclusion

Overall, we are very pleased with both KAREN and our findings. We have simplified the process of implementing and testing models and datasets by providing a unified architecture that allows researchers to quickly try out new ideas on different datasets. We showcased the framework to several acquaintances and received very positive feedback due to its simplicity and ease of use. Personally, all our members found that extending the framework to adapt to any new model was a very simple and efficient process, despite the fact that we were expecting to run into design barriers. We got some interesting results and many different model baselines for this field. We feel the unification and simplification of the model implementation process is a solid contribution to this research topic.

Regarding models, we have concluded that using pretrained models like BERT yield the best results. In addition, convolutional models also seem to work very well, likely due to the fact that they model N-gram behaviour internally. Also, using shallow models works best as a general rule since the available datasets do not have enough data to train deep models well. We have also analysed the dataset imbalance problem and how it can affect the results of a model, thus attaching importance to using other metrics such as precision, recall and F1 score. We also analyse the impact of using pretrained word embeddings, which we conclude to increase the performance of all models that use it, even if just a little.

As a final note, we welcome any contribution to KAREN. We think it would be relevant for more people to contribute to this repository and fill it in with more papers from this area, so that we can attract more people to use this contribution and become a standard across this research field. In the future, we also hope KAREN is used to analyse models that use meta-data in hate speech detection, since KAREN allows a very clean and intuitive meta-data implementation interface.

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