Bidirectional Recurrent Models for Offensive Tweet Classification

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Abstract

In this paper we propose four deep recurrent architectures to tackle the task of offensive tweet detection as well as further classification into targeting and subject of said targeting. Our architectures are based on LSTMs and GRUs, we present a simple bidirectional LSTM as a baseline system and then further increase the complexity of the models by adding convolutional layers and implementing a split-process-merge architecture with LSTM and GRU as processors. Multiple pre-processing techniques were also investigated. The validation F1-score results from each model are presented for the three subtasks as well as the final F1-score performance on the private competition test set. It was found that model complexity did not necessarily yield better results. Our best-performing model was also the simplest, a bidirectional LSTM; closely followed by a two-branch bidirectional LSTM and GRU architecture.

1 Introduction

The main task of OffensEval-2019 (Zampieri et al., 2019b) is to detect and classify offensive language in social media, specifically tweets. This task is partitioned into three subtasks, involving the classification of anonymised tweets.

- Task A: Offensive/Not Offensive
- Task B: Of those that are offensive, whether they are targeted or not targeted.
- Task C: Of those that are targeted, whether they are targeted at an individual, at an organisation or other.

For these, several recurrent neural network architectures were implemented, as presented in Section 3. The models were subsequently optimised and their performances compared in order to converge to the best model for each task. The data was also pre-processed before being fed to the model as discussed in Section 2. The results are given in Section 4 and discussion of these as well as of challenges encountered is presented in Section 5.

2 Data

2.1 Data Handling and Preprocessing

Training data for the competition (Zampieri et al., 2019a) was given in a plaintext format of tab-separated values consisting of tweet ID and tweet content, labelled with 3 values for task A = \{OFF, NOT\}, task B = \{TIN, UNT\} and task C = \{IND, GRP, OTH\}.

Prior to training the models, we preprocessed the data extensively. The primary aim of this is to ensure that models were trained on the most normalized representation of tweets possible, allowing us to take full advantage of our pretrained word embeddings, with the overall goal of increasing model performance as much as possible.

This section outlines all the data handling and processing techniques carried out.

2.1.1 User mentions and URLs

Tweet content data consisted of anonymised Twitter user mentions in the form of @USER. For example, the trial data (without anonymized mentions) contained this row: Hey @LIRR, you are disgusting.

One could add a module to the classifier that initially looks up @LIRR on Twitter, learns that it is the Long Island Rail Road, and helps with the classification that this tweet was targeted at an organization and offensive. Unfortunately, the training data anonymised all of these user mentions which intuitively would be of little value to the model, and thus all such mentions were
Similarly, all instances of real URLs were removed and changed into URL. One could argue that a more complicated classifier could make use of such information, but in its anonymized form we have decided to remove these as well.

2.1.2 HTML entities
The dataset contained certain HTML entities such as &gt; that represent certain special characters. These do not contribute to the meaning of the tweets, and thus were removed.

2.1.3 Hashtags
Even though hashtags can contain relevant information, their verbal form is complex to deal with. We decided to simply remove them - with the amount of data we have, it is unlikely that we have a lot of tweets where the hashtag influences the meaning of the tweet.

2.1.4 Lowercasing
One could argue that uppercase words could have a more offensive meaning than its lowercase version. Given this small dataset, this would not occur very frequently; we have therefore decided to reduce the noise by normalising each word to be lowercase, rather than introducing extra noise for the model to deal with.

2.1.5 Non-ASCII filtering
The next step was to delete all non-ASCII characters. Tweets could contain all kinds of non-ASCII characters: primarily emojis and non-Latin characters. For the former, we decided to not consider these in the model, following similar reasoning as before - emojis would not occur often enough to warrant a more sophisticated approach. Non-Latin characters were also found very rarely, as the data set given was intended to contain only English tweets, hence these characters can be discarded as noise.

Further, we wanted to avoid having the same word once alone and once followed by a Non-Latin character, which would not be considered as the same word, and tagged as unknown. To alleviate this issue, we partitioned and added spaces around non-Latin characters, such as symbols. For instance, me+you=forever would be transformed into me + you = forever.

2.1.6 Apostrophe handling
Most of the the tweets contain contract verbal forms. This creates noise and hides negation which is important for offensive detection. For instance we transformed aren’t into are not or i’m into i am. Then the verbs were also fed in the lemmatiser, detailed later on.

2.1.7 Punctuation removal
We removed punctuation such as question marks, commas, colons and periods.

2.1.8 Number removal
Numbers are irrelevant for this problem so we decided to remove them completely. For instance Obama2020 is transformed into Obama.

2.1.9 Stop word removal
We removed all stop words such as is, that, the etc. as they contribute little meaning to the tweets. The NLTK stop-word set\(^1\) was used.

2.1.10 Reduction of word lengths
Following tokenisation, we used a technique known was word length reduction based on the fact that all English words allow a maximum of two consecutive character repetitions. For example, we correct words such as reallllllly to really or aaaaaaaaaaaaah to aah. This allows us to normalize such occurrences of words prior to the following dictionary-based pre-processing techniques.

2.1.11 Word segmentation and spelling correction
We perform word segmentation using a fast state-of-the-art library SymSpell\(^2\). This uses a Triangular Matrix approach to correct words such as thecatontheimat to the cat on the mat with extremely good accuracy and high performance.

We then use the same SymSpell library and its Symmetric Delete approach to very quickly correct word spellings. We pick the closest matching word within an edit distance of 2.

As a pre-requisite to both the word segmentation and spelling correction, we use our corpus of words to create a frequency-aware dictionary that SymSpell uses to guide its segmentation and spell-checking processes.

\(^1\)https://gist.github.com/sebleier/554280
\(^2\)https://github.com/mammothb/symspellpy
2.1.12 Lemmatisation

Finally, we lemmatise all words to their base representation, such as **killing** to **kill** or **eating** to **eat**. This is important in ensuring that the meaning of words is maintained regardless of their exact form displayed in the sentence, increasing model performance. The NLTK package (Loper and Bird, 2002) was used for this step.

2.1.13 Sentence padding

A requirement for our LSTM models was that the input sentence length has to be fixed for all training examples. We therefore had to pick an appropriate sentence padding/truncation length \( p \). All sentences with more than \( p \) words would be truncated to \( p \) and all sentences with less than \( p \) words would be padded with a reserved padding token.

After the aforementioned data processing tasks, we plotted the distribution of tweet lengths on a histogram in order to guide our decision on \( p \). This showed that a majority of the sentences had sentence lengths in the 3-50 words range, as shown in Figure 1.

![Figure 1: Distribution of sentence lengths after pre-processing all tweets.](http://nlp.stanford.edu/data/glove.twitter.27B.zip)

The decision on \( p \) represents a trade-off: a low value of \( p \) means that we lose a lot of words in the longer sentences, but the shorter sentences need less padding. It was unclear whether amount of padding in shorter sentences would have a significant effect on the models; however, we knew that truncating a lot of long sentences would lose a lot of information. We took a conservative approach by setting \( p \) to 50, which captured most of our sentence lengths.

2.2 Data Representation: Word-embeddings

We tried two approaches for our data representation.

- Learnt word embeddings:
  
  We trained our own word embeddings during the execution of the whole model, with a randomly initialised embedding layer.

- Pre-trained GloVe Embeddings (Pennington et al., 2014):
  
  We used GloVe Twitter 27B embeddings\(^3\). These were trained from a corpus of 2 billion tweets, with 27 billion tokens. The vocabulary size is 1.2 million words, and the embedding dimensionality was 100.

All of our models seemed to perform much better using the pre-trained GloVe word embeddings. One explanation for this is that such embeddings are much richer in content and embed inter-word semantical correlations much better than what could be learnt during learning the classifiers using the limited provided dataset.

3 Model Design and Training

We devised four different deep recurrent network architectures, which we tested on all three tasks. Keras (Chollet et al., 2015) was used as the high-level library to implement these, with a TensorFlow (Abadi et al., 2015) backend.

The simplest model we trained was a recurrent bidirectional LSTM model. LSTM (Hochreiter and Schmidhuber, 1997) was chosen over RNN in order to alleviate the vanishing gradient problem and so the network is able to learn long-term dependencies between different words. A similar reasoning is used to justify the need for a Bidirectionality (Schuster and Paliwal, 1997), in so that there is no algorithmic bias towards later regions of the tweet. The other three architectures build upon this one are of increasing complexity.

3.1 biLSTM

This model, depicted in Figure 2, as well as the other three, takes as input the word embeddings as a matrix which is comprised of the vertically stacked embedding vectors corresponding to the words present in the tweet. This matrix can be thought of a sequence of embedded words. Each of these embedding vectors is fed to the bidirectional LSTM at their respective timestep and the final timestep output is then connected to a dense layer with sigmoidal or softmax-activated neurons depending on the Task. One-dimensional Spatial dropout was added between the embedding layer and the LSTM. This type of dropout scheme drops\(^3\)

\(^3\)http://nlp.stanford.edu/data/glove.twitter.27B.zip
entire rows of the embedded matrix, equivalent to dropping words from the sequence. The rationale behind this is to discourage the network to rely on specific words from the training set and therefore introduce more language-specific regularisation. This is in contrast to normal dropout which would randomly drop connections from specific elements in the embedded matrix which has no grammatical interpretation.

![Figure 2: Schematic of the bi-LSTM Architecture.](image)

### 3.2 CNN-biLSTM

The CNN-biLSTM is depicted in Figure 3. In this case, a 1D convolutional layer was used to convolve the embedding vectors along the temporal dimension with a kernel of size 4 and 64 output filters. This layer uses ReLU activation and was therefore initialised with a He uniform weight distribution. This convolutional layer is followed by pooling with pool size 4 and stride 4, which decreases dimensionality before feeding the resultant sequences to the Bidirectional LSTM layer. Again, the output vector is then fed to a dense layer with 1 sigmoidal output neuron (Tasks A and B) or 3 softmaxed output neurons (Task C). Adding this convolutional layer first means the inputs to the LSTM are local combinations of words, rather than individual words. While this adds complexity to the network, it is not a linguistically motivated change. CNN-LSTMs have been found to be useful for tasks with spatial inputs such as image sequences or 3-D point cloud sequences, in which local features are very relevant.

![Figure 3: Schematic of the CNN-biLSTM Architecture.](image)

### 3.3 biLSTM-CNN

The biLSTM-CNN, depicted in Figure 4 has the convolutional layer moved after the bidirectional LSTM. For this architecture, the LSTM was set to output its state for each timestep in order for the convolutional layer to be able to convolve along a temporal axis. This is in contrast to the previous two architectures, in which only the latest timestep output was used. No pooling was used after convolution, so to not unnecessarily lose meaningful information. The reasoning behind convolving after the LSTM is to further combine the long-term dependencies the LSTM has uncovered and add expressivity to the network. Therefore it is expected that this will perform better than the limiting CNN-biLSTM architecture.

![Figure 4: Schematic of the biLSTM-CNN Architecture.](image)

### 3.4 biGRU ⊕ biLSTM

Finally, introduced gated recurrent units (GRUs) (Cho et al., 2014), as they have been shown to, in some cases, improve performance relative to LSTMs as well as being computationally more efficient (Chung et al., 2014). Since it is inconclusive in the literature which is to perform best, we devised an architecture which combines both. This is depicted in Figure 5. The embedded words are processed in parallel through two branches
of biLSTM-CNN and biGRU-CNN. Global max pooling and global average pooling is then applied to each CNN output and the four resulting vectors are concatenated to form a 1D array which is then fed to a dense layer with 1 sigmoidal unit or 3 softmaxed units depending on the task. This architecture adds more expressivity to the network as well as allowing it to squeeze the best from both types of recurrent cells.

Figure 5: Schematic of the bi GRU LSTM Architecture.

4 Training procedure

4.1 Addressing class imbalance

For all tasks, our training dataset was very unbalanced: e.g. for Task B, 88% of all labels were the TIN class. We tackled this using class weighting. The loss function was weighted by the inverse of the proportion of each class in the training set; this means that weight updates during any single pass in our networks would have a greater effect when training under-represented classes. This technique worked well to improve overall performance by reducing overfitting.

Prior to this, we considered other approaches. Down-sampling is a technique which would discard examples from over-represented classes. Here, the gain in balancing the data-set did not outweigh the loss in having a very small number of examples to train on (due to the small data set), and thus resulted in very poor performance.

We also thought about using naive over-sampling, which would replicate examples in under-represented classes - intuitively, this likely would have had a similar effect to class weighting, but would be harder to implement and performant.

A more interesting technique is over-sampling using Smote, which involves generating synthetic training examples from real-valued vectors. We could use the embedding matrices for under-represented sentences in order to generate similar, new vectors not present in our dataset labelled under the same class. Generating synthetic data in this way has potential to allow the model to generalise better and can be investigated in further work.

4.2 Validation set

We used an 80%-20% split of our dataset into the training and validation sets. We used stratification during this process, which ensures that both sets have a roughly equal proportion of every class, to allow for more representative validation.

4.3 Optimisation

We used the Adam optimizer, which improves on the RMS-prop and AdaGrad back-propagation algorithms. We used the binary cross-entropy loss function for tasks A and B, as well as categorical cross-entropy for task C, since it is a multi-class classification problem.

We also used an early stopping strategy based on a long-term moving-average of the F1 score evaluated at the end of every epoch.

4.4 Hyperparameter optimization

Our set of hyperparameters consisted of the following:
- Learning rate
- Learning rate decay
- Number of epochs
- Batch size
- Dropout rate
- Recurrent units

We performed hyperparameter optimization using manual tweaking over successive runs on the validation set. We found that the following parameters yielded the best validation performance:

| Parameter     | Value |
|---------------|-------|
| LR            | 0.001 |
| LR_DECAY      | 0.001 |
| EPOCHS        | 50    |
| BATCH_SIZE    | 32    |
| DROPOUT       | 0.5   |
| BIDIRECTIONAL | True  |
| RECURRENT_UNITS | 50    |

Given more compute power and time, we would have preferred to run an extensive grid search over the entire hyperparameter space.
Table 1: Holdout-validation macro F1 scores and accuracy of all models for the three different tasks.

|           | Task A | Task B | Task C |
|-----------|--------|--------|--------|
|           | F1     | Acc    | F1     | Acc    | F1     | Acc    |
| biLSTM    | 0.7382 | 0.7801 | 0.6115 | 0.5753 | 0.5001 | 0.6966 |
| CNN-biLSTM| 0.6346 | 0.6473 | 0.5521 | 0.5068 | 0.4322 | 0.6142 |
| biLSTM-CNN| 0.7170 | 0.7562 | 0.5496 | 0.4903 | 0.4738 | 0.6863 |
| biGRU ⊕ biLSTM | 0.7285 | 0.7544 | 0.5963 | 0.5722 | 0.5052 | 0.7012 |

5 Results and Discussion

We gained a few key insights from our results, which are shown in Table 1. For most tasks, the most simple biLSTM model outperformed the other architectures, with the more complex biGRU ⊕ biLSTM closely following. We learned that, at least for this task and data set, more complex models did not necessarily result in better performance. The biLSTM model’s macro F1 scores on the OffensEval private test set were 0.77 for Task A, 0.64 for Task B and 0.52 for Task C. In hindsight, however, the model submitted was not optimal as it was not re-trained on the entire dataset and therefore only used 80% of the training data. We speculate that re-training the model on 100% of the provided dataset would have yielded significantly better results.

The key to any machine learning model is quantity and quality of data. Perhaps this 18,000 sample dataset has an insufficient amount of data for the networks to be able to generalise to the wider population of tweets, especially more the complex ones. The dataset was also highly unbalanced, which is one factor we can use to explain the lower performance attained in Task B and C when compared to Task A.

During training, we monitored how F1 score changed between epochs for both the training set and the validation set. We observed that the F1 score oscillated for a majority of epochs and often stabilized during later epochs (see Figure 7). One explanation is that while learning on successive mini-batches, the model gets pushed in different directions, but trends towards better performance with the progression of epochs. The F1-score also seldom correlated with the accuracy or loss. One explanation for this lack of correlation is that the F1-score into account the inherent imbalance in our classes by averaging per-class metrics, but the accuracy metric is the product of our loss function minimization which is more vulnerable to the imbalance. This imbalance originally resulted in models which only or over-predicted the class which was over-represented in the training set, which is a common failure resulting from having cross-entropy as a loss function and getting stuck in a local optimum, an example confusion matrix of this happening is shown in 6. This was alleviated by weighting the cross-entropy loss function by the inverse of the class support in the training dataset, therefore penalising incorrect predictions of the under-represented classes more harshly and avoiding an “all-on-red” situation.

Given the instability of the F1 score, settling on an architecture and a set of optimal hyperparameters was very tedious and challenging. Given more computational resources and time, we would have liked to run a substantial grid search across a suffi-
Figure 7: Example of F1 score profile during training for Task B. Blue: Training; Orange: Validation

ciently extensive hyperparameter space as a more reliable way of picking the best model.

6 Future work

Several paths for further work are possible, here are some which are interesting and could yield significant performance improvements.

- Gather more data or utilize other datasets
- Investigate learning rate scheduling, decay and decrease-on-plateau
- Further investigate Over-sampling both at language-level and at vector-level with SMOTE
- Automated sequential hyperparameter optimisation using bayesian optimisation. Or fine-grain grid search if computationally feasible. Since the dataset is not extensive, this approach could potentially be nested within k-fold cross-validation to get a good estimate of the generalisation error.
- Work at character-level (robust against misspellings and obscure words)
  - Simple: char-CNN or char-LSTM.
  - Better: char-CNN as word encoder then feed each char-encoded word to a Bidirectional LSTM, use last LSTM output to classify.
- Ensembling of different models. An ensemble of very different architectures could prove beneficial. The weak learners could be word-level biLSTMs, character-level LSTMs, more complex models such as BERT or ELMO, traditional approaches such as SVMs, etc.

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