PERFORMANCE COMPARISON OF SIMPLE TRANSFORMER AND RES-CNN-BiLSTM FOR CYBERBULLYING CLASSIFICATION

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ABSTRACT

The task of text classification using Bidirectional based LSTM architectures is computationally expensive and time consuming to train. For this, transformers were discovered which effectively give good performance as compared to the traditional deep learning architectures. In this paper we present a performance based comparison between simple transformer based network and Res-CNN-BiLSTM based network for cyberbullying text classification problem. The results obtained show that transformer we trained with 0.65 million parameters has significantly being able to beat the performance of Res-CNN-BiLSTM with 48.82 million parameters for faster training speeds and more generalized metrics. The paper also compares the 1-dimensional character level embedding network and 100-dimensional glove embedding network with transformer.

Keywords Character Embedding · Glove Embedding · Transformers · Res-CNN-BiLSTM

1 Introduction

The Natural Language Processing abbreviated as NLP [1, 2, 3] has shown a lot of advancement using Deep Learning [4, 5] system in recent years. The tasks of NLP are varied in terms of applications, viz. Sentiment Analysis [6], Machine Translation [7], Named Entity Recognition [8, 9, 10] etcetera. Machine Learning [11, 12] significantly played an important role earlier in the area of NLP before use of Deep Learning was normalized like modern state-of-the-art models. The NLP performs text preprocessing and generates word representations [13] which are the root of the language vocabulary. Then the word representations that hold the meaning of sentences are given to Machine Learning algorithms for task of prognostication. Initially the word representations like bag-of-words [14] and TF-IDF [15, 16, 17] were used which lacked in providing the semantics in deeper context. These were used for generating moderate level word representations and how the words are linked with each other but were inefficient for providing the literal meaning of a sentence. This was later replaced with advanced form of word representation mechanisms like word embeddings [18] and Word2Vec [19]. These consisted of word representations on very higher level where sparse matrix representations are used with one hot encoding [20] system for linkage of the words. These embeddings were high dimensional and used deep learning procedures in itself for better understanding of the semantics of language. The representations held the association of word linkage on multi-dimensional level. Later these representations were replaced by Glove [21] which is considered as global vectors for word representations which used context of latent semantic analysis [22] at a very different level which falls under the category of topic modeling [23]. These embeddings were related to word level embeddings and later the concept of character level embedding [24] also started to gain popularity which states that learning characters and making a random word out of context can also generate some semantics of the words respectively. This uses a 1-dimensional character level embedding [25] for capturing the character level representations. These all embeddings constitute the major preprocessing phase and prognostication phase is not limited to machine learning algorithms viz. logistic regression [26], support vector machines [27, 28], k neighbors [29], bagging ensemble methods [30, 31, 32], boosting ensemble methods [33, 34, 35, 36], discriminant analysis [37, 38], stacked generalization [39, 40] and much more. Deep Learning was leveraged for the same reason where the use of Recurrent Neural Network [41] became evident for sequence learning procedures. This is prominently
used for time series forecasting and NLP tasks. It can be also used for audio processing tasks too, basically wherever there is a data in sequential manner. The use of it was good but it ran into loss of information and vanishing gradient problem [42] while backward propagation [43]. For this Long Short Term Memory abbreviated as LSTM [44, 45, 46] was developed which held the necessary amount of information required for the sequence. This actually resolved the vanishing gradient problem but was quite slow to train and computationally expensive back then. Later it was discovered that learning the sequences ahead in time is also possible using Bidirectional [47] LSTM architecture which links back the learning blocks in forward propagation which turned out to be efficient way more than expected yet turned out to be computationally expensive and time consuming. For this reason the Transformers [48] were introduced which were one of the most promising learning systems developed in the area of NLP. These were extremely cost efficient and effective that focus on self-attention mechanism which will be discussed in further sections of the paper. The use of transformers ensure much promising results which we are presenting in this paper for cyberbullying [49] application. The use of transformers and how the difference can be made for our custom trained combination of traditional techniques condensed neural network, Res-CNN-BiLSTM [50] for cyberbullying text classification. We provide a detailed comparison of training and testing in results section of this paper respectively.

2 Methodology

This section of the paper discusses the various approaches used in this paper. These include a concise explanation of the models used along with their respective parameters.

2.1 1-D Character Embedding Network

Character level embedding [24] is performed with 1-dimensional convolutional neural network [25] that learns the parameters using character level representations. The model starts with embedding layer from input that learns 4830 parameters. Followed by this 1-dimensional convolutional layer is used with 256 filters have 7x7 size each with 3x3 strides which learns 123904 parameters. This uses Rectified Linear Unit abbreviated as ReLU [51] as its activation function. Followed by this 1-dimensional max-pooling layer [52] is used. Once again then 1-D Convolutional layer is used with same features which learns 459008 parameters. Followed by this is again one more, 1 dimensional max-pooling layer for dimension reduction. This process is repeated 4 times again where the convolutional layers have features of 256 filters with 3x3 dimensions and learn parameters 196864, 196864, 196864 and 196864 respectively. The output from this is flattened for further layers and a dense layer with 1024 hidden neurons, activation function as ReLU with L2 activity and bias regularizers [53] is used. This learns 8913920 parameters. Followed by this one dropout [54] regularization layer is used with 50% dropout ratio. This process is repeated again and the dense layer learns 1049600 parameters. The prediction mechanism then uses final 2 layers, one with 32 hidden neurons, activation function as ReLU which learns 32800 parameters followed by final layer of 5 hidden neurons for 5 categories of the output classes with softmax [55] activation function that yields probabilities of each class. This layer learns 165 parameters and entire network at the end learns 11,371,683 parameters that roughly translates to 11.3 million parameters. The model uses sparse categorical cross-entropy [56] loss function along with Adam [57] loss optimizer with learning rate of 3e-4 and decay rate of 5e-6. The batch size of data used is 128 and model runs for 10 epochs respectively.

2.2 Glove Embedding Network

The Glove [21] embeddings have their respective embeddings in different dimensions. The embedding dimensions we have used are 100 dimensions which is trained on 6 billion corpus of tokens. The input layer is given to 100-dimensional glove embedding that learns 2887000 parameters. Followed by the embeddings the LSTM layer is used with 512 hidden neurons in bidirectional state that learns 2510848 parameters. Following 2 layers are used for final predictions, one dense layer with 32 hidden neurons and ReLU activation function which learns 32800 parameters followed by final layer of 5 hidden neurons for 5 categories of the output classes with softmax [53] activation function that yields probabilities of each class. This layer learns 165 parameters and entire network at the end learns 11,371,683 parameters that roughly translates to 11.3 million parameters. The model uses sparse categorical cross-entropy [56] loss function along with Adam [57] loss optimizer with learning rate of 3e-4 and decay rate of 5e-6. The batch size of data used is 128 and model runs for 10 epochs respectively.

2.3 Res-CNN-BiLSTM Network

This network is combination and modification of 1-D Character Embedding Network and Glove Embedding Network. The Res-CNN-BiLSTM [50] is network which trains the 2 networks in parallel fashion and performs concatenation
The Accuracy is a commonly used metric for any classification problem and is not just limited to text classification problem. The accuracy is calculated for training and validation for all the respective networks used and can be visualized in the figure. The training accuracy in the last epoch for 1-D Character Embedding is 98.52% and validation accuracy is 91.81% respectively. Similarly the training accuracy in the last epoch for Glove Embedding Model is 93.65% and validation accuracy is 92.25% respectively. Following the training accuracy for Res-CNN-BiLSTM is 98.42% and validation accuracy is 91.81%. Finally the training accuracy for Transformer based network is 95.73% and validation accuracy is 92.63%. So practically the generalization of the training and validation accuracy is much better and efficient with transformer based architecture.

The accuracy for Res-CNN-BiLSTM in training is higher than
Transformer but the validation accuracy for transformer is more. The main noticeable point though for transformer is number of parameters that are around 600k or hardly 0.65 million whereas the parameters for Res-CNN-BiLSTM are around 48.82 million. This states that transformer is still more generalized than Res-CNN-BiLSTM effectively in very minute fraction of parameters. This will give effective outcome in other results in this paper respectively.

![Figure 1: Training Accuracy and Validation Accuracy](image1)

3.2 Training and Validation Loss

The Loss is another indication to what extent there has been a reduction in it. The comparison can be done in a very generalized manner for loss effectively with figure 2. The training loss for 1-D character embedding 5.59% whereas the validation loss is 35% which is not effectively generalized reduction. The training loss for glove embedding model is 16.81% and validation loss is 21.88% which is certainly good generalization as compared to 1-D character embedding model. The training loss for Res-CNN-BiLSTM is 5.31% and validation loss is 29.33% which is again poor generalization considering the number of parameters involved. Finally the training loss for transformer is 15.43% and validation loss is 34.47% which is much better generalized as compared to 1-D character embedding and Res-CNN-BiLSTM but not as efficient as Glove embedding. But consider just 0.65 million parameters for transformer and 5.4 million parameters for Glove, which is almost 9 times, the loss reduction is effectively considerable. Increasing the loss optimization for transformer with adding more multi-head attention can definitely give appropriate performance.

![Figure 2: Training Loss and Validation Loss](image2)

3.3 Training Time

The best feature of the transformer is time taken for training and it was one of the primary reasons for which transformer was developed. The time taken by LSTM based architectures were very slower to train. Bidirectional system makes
Table 1: Training Time Comparison for Epochs

| Algorithm      | 1\textsuperscript{st} Epoch | 5\textsuperscript{th} Epoch | 10\textsuperscript{th} Epoch |
|----------------|-----------------------------|-----------------------------|-------------------------------|
| 1-D Char       | 29s 96ms                    | 24s 96ms                    | 23s 94ms                      |
| Glove          | 21s 72ms                    | 17s 71ms                    | 18s 72ms                      |
| Res-CNN-BiLSTM | 359s 690ms                  | 334s 677ms                  | 325s 659ms                    |
| Transformer    | 10s 43ms                    | 8s 36ms                     | 6s 29ms                       |

it much slower as the amount of embeddings taken and sentence processed is word based. The transformer leverages this by using an entire sequence of sentence making training very effectively fast. All the networks were trained for 10 epochs under observation and this can be seen on intervals of 1\textsuperscript{st}, 5\textsuperscript{th} and 10\textsuperscript{th} epoch respectively in table 1.

From the table it can be inferred that time taken for training the transformer is the fastest. The parameters are one aspect but the nature of the algorithm also makes sense. The time taken by Res-CNN-BiLSTM is highest, then 1-D character embedding model and more faster than it is glove but transformer is almost half times the glove which clearly specifies that using Transformer considering the training time and accuracy trade-off is the best choice.

4 Conclusion

Res-CNN-BiLSTM network for Cyberbullying Text Classification had been a good network but had some drawbacks which we wanted to resolve. The use of transformer based architecture was definitely a sure shot move for solving the issue and we did present that in this paper along with results. The transformers have a lot to be explored in near future but proving a small point through a simple application does tingle the curiosity of many researchers. Many advance state-of-the-art transformers have already been developed and used evidently but the main task for us in this in paper was hypothesizing our own custom made Res-CNN-BiLSTM model and we were successful in that. This paper does open many doors to other research with cyberbullying concept and we would like to a part of it with our best belief and understanding.

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