
A Hybrid Framework using Hierarchical Analysis for Classification of Mental Health Information

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Abstract.

Social media has become one of the most important platforms to share the experiences of users. Reddit, A famous social networking site has facilities to express mental health problems. It can assist with medical decisions, public health policies, and improving health care. In a recent study, using Hierarchical approach mental health Reddit posts were evaluated and grouped into 11 disorder themes with Attention mechanisms in a recurrent neural network[24]. However, some posts were misclassified as existing approaches did not give importance to sequential characteristics of the text. In this paper, proposed a hybrid framework of hierarchical attention neural network to accurately classify the posts and to maintain the positional information in the sequence using attention mechanisms such as Multi head with global attention, Directional Self-attention. The results of the proposed system is evaluated using the PubMed medical abstracts and Reddit posts. The comparative analysis is done against other neural networks with Attention mechanism and each approach is evaluated using F- Measure.

Keywords. Hierarchical Attention network (HAN), Multi-head attention, Directional Self Attention, mentalhealth,hierarchicalapproach

1. INTRODUCTION

Text in the form of unstructured data is present everywhere like email, reviews, etc. But extracting the information from it is difficult due to its unstructured nature. The knowledge extracted from that large amount of data is useful for many applications and text classification helps to achieve that by classifying the problems into its predefined categories. It is one of the most significant jobs in Natural Language Processing (NLP), with applications in sentiment analysis, subject labelling, spam detection, and many other areas. Machine learning-based text classification learns to make classification decisions based on previous observations. The algorithm used the labelled dataset to train and based on that it will predict the label for particular unseen input.

Recent research in deep learning and machine learning provide solutions for a large dataset of health information. The approach not only used the data available from the medical organization such as Electronic Health Records (EHR) but also used the patient-generated text available on social media sites such as Twitter, Reddit, etc[17][18]. Mostly patient reports for health problem identification or drug suggestion and any user-generated reviews are used to classify in the healthcare field so it will be in document format. To classify the long sequence of text, existing approach lack accuracy and efficiency as it will not consider the overall characteristics of the sequence.

In this paper, how to categorize mental health-related reddit posts as well as medical abstracts is discussed. For a short sequence of text, a convolutional neural network and a recurrent neural network already exhibited good performance [16]. Moreover, to capture the long sequence of text Long Short Term Memory (LSTM) and Hierarchical approach used with attention mechanisms as attention helps to get the important words related to the sentence [9]. This approach works well for many sentences/document, but some misclassification occurs and computation speed is decreased. Also, the word order in the sentence is important to find the correct classification so positional information is added into this hierarchical network and parallel computation also utilized to improve the performance.

We apply a hierarchical attention network with two types of attention:

- Multi-head global attention to enhance computation performance by incorporating multiple heads.
- Directional Self Attention to capture positional information.

2. RELATED WORK

In this section, most of the traditional approach used for multiclass text classification in healthcare and other, as well as new research in hierarchical attention networks and their disadvantages, are described in this section.

2.1 The Traditional approach for multiclass text classification

The majority of previous text categorization research used a variety of machine learning classifiers, including logistic regression, Support Vector Machines (SVM) (Cortez and Vapnik, 1995), Nave Bayes, and Random Forest,Rule-based and many other approaches with different typesof features (eg: bag of words, TF-IDF, Topicmodeling (LDA) (Resnik et.al, 2015; Rumshinsky et.al).However, the accuracy in predicting the predefined categories isnot efficient. For the small dataset, thetraditional approach works well. As the size of the datasetincreases, then it will not be able to work well and alsoconsume more time while executing thealgorithm.

2.2 By applying Deep Learning Techniques

Convolutional neural network (CNN)generally used for computer vision (images), however, theyhave recently been applied to various NLP tasks (YoonKim, 2014)[21]in themedical domain. Recurrent neural network for shorttext developed to maintain the order of the describedevents for some time step. But the drawbacks in RNN is thatitcannot have the memory to storelong-

range dependencies in the text as sequential characteristics of text is important in predicting the class for document/sentence classification and it also has a vanishing gradient or exploding gradient problem. Long Short Time Memory (LSTM) networks [1] are a type of RNN extension that allows the RNN to retain its inputs for a longer length of time while using more memory. Gated Recurrent Units (GRU)[2] overcome the memory inefficiency problem in LSTM as well as the vanishing gradient problem to reach state-of-the-art performance in deep learning applications such as speech recognition, speech synthesis, natural language understanding, and so on. These above techniques can use the one-hot encoder to get the integer representation and feed into any of the above neural networks or any types of embedding techniques (Word2vec[3], Glove[4], fasttext[5], Universal sentence encoder[6], Elmo[7] and ULMfit[8]) can be incorporated into it. Furthermore, the attention mechanism [22] developed for the above architecture to interpret the relevant information based on the context and this attention layer used on top of the neural network layers (CNN, LSTM, GRU, etc.)

2.3 By applying the Hierarchical approach

Initially, attention mechanism developed for machine translation then it is also used for image caption generation to focus only in the relevant region of the image (Xu et.al, 2015). In NLP, it is incorporated with RNN/CNN based architectures in text classification [22] to predict words which contribute more importance to the sentence. The approach done in a sequential manner for document classification consumes more time and accuracy in predicting the classes tend to decrease significantly. Hierarchical approach captures the accurate information because of the hierarchical structure from word level to sentence level and then to document [9] shown in Figure 1. The attention mechanism is added on top of the word level and sentence level to focus only on the relevant information. So the hierarchical classification methods not only increase accuracy but also increase greater understanding of the document from word and sentence level. Hierarchical network used for food recommendations [20] to find the similar users tend to eat and learning user preferences in various recipes. Multi-head Attention mechanism with residual gated recurrent unit [19] to capture contextual information within long range and positional embedding is added to know the sequence of text. Bullying detection using hierarchical network [10] to find the representation of comments in Instagram.

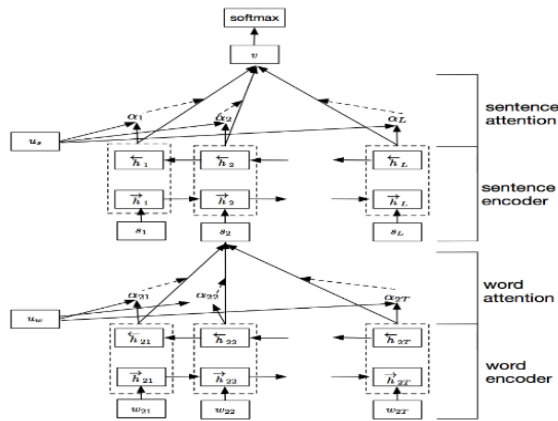


Figure 1. Hierarchical Attention Network [9]

3. PROPOSED METHODOLOGY

Apply the base diagram [1] the proposed changes are done as indicated in Figure 2. The dataset is preprocessed and converted to integer representation, then the hierarchical network approach is used along with attention mechanisms. The classification is done to get the predefined categories. Each module in the diagram is explained below.

3.1 Preprocessing

Dataset from different sources or user-written text is not in standard format to process that text. To improve the data quality, the dataset needs to be preprocessed. So, the first thing to do is to remove the special characters and convert to lowercase letters. The algorithm should learn the structure of the text as the machine cannot understand words. So, it is represented in numerical form. This can be done by using the `kerastokenizer` function. The function splits the sentence into words and keeps the most occurring words in the text corpus. Then the tokenizer also keeps an index of words which can be accessed by the tokenizer. `word_index` to specify the maximum number of words. The `maxlen` parameter should be specified so that each sentence will be of the same length.

3.2 Embedding

To represent each word with its similar context, embedding should be performed for the input sentence. In this approach, we have used Glove and fastText Pre-trained vectors. Glove embedding learns by creating a co-occurrence matrix (words X context) that counts the number of times a word appears in a context. It is trained on the Wikipedia corpus with a dimension of 300 and length of this dictionary is around billion, fastText[11] is an extension of word2vec model. It represents each word in input sentence as n-gram of characters. Pre-trained word vectors are generated by training with 2 million word vectors from common crawl. We match these two pre-trained word vectors with input sentence and extracted only the embedding of words that are in our word index and created an embedding matrix. We have compared the performance of two vectors in this approach.

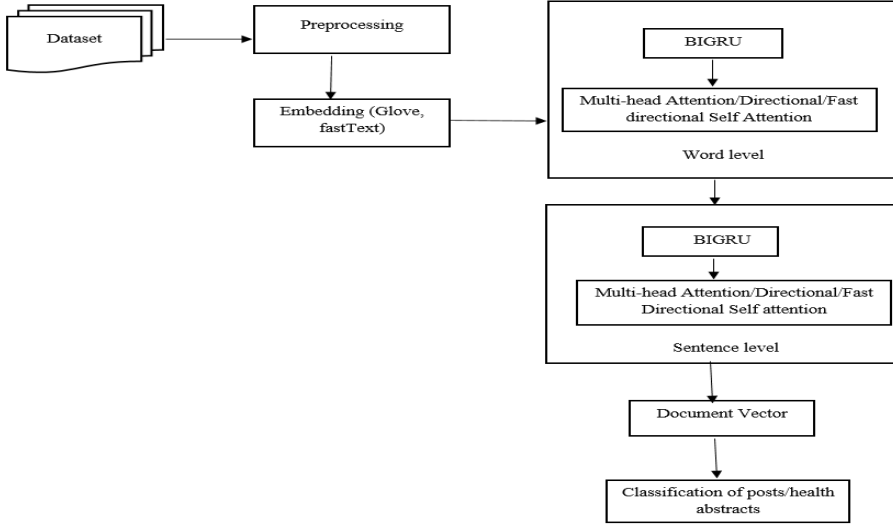


Figure 2. System design for the proposed method

3.3 Word Encoder

3.3.1 Bidirectional Gated Recurrent Unit (BI GRU)

In this step, the output obtained from the previous module is passed i.e) embedding word vectors in the embedding matrix. Then, to gather both forward and backward information, we employed bidirectional Gated Recurrent Units (BIGRU) and attention processes, as well as a gating mechanism to recall the sequences. Reset gate r_t and update gate z_t determine the data that should be transmitted to the output referred from [9].

3.3.2 Attention Mechanisms

The attention mechanism is important to focus only on the relevant information in the sentence. The information from the preceding layer (BIGRU) is transmitted to word-level attention mechanisms including multi-head and directional self-attention and combine the representations of those words to get a sentence vector. The traditional attention mechanism used cannot exploit the positional information of the input sentence. (Ex: I like dogs more than cats and I like cats more than dogs, here both looks similar but here the sentence compares two different entities). To solve this problem proposed attention mechanism used instead of traditional attention mechanisms.

3.3.2.1 Multi-head Attention

The multi-head attention [12] method repeats the standard attention process many times in parallel to increase the computation speed. It then separated into several heads, each of which executes parallel computations. Each head's attention outputs are simply added together and linearly translated into the required dimensions. It enables the overall context of the sentence to be derived from information from several representations at various points.

3.3.2.2 Directional Self Attention

Directional Self-attention [13], the input sentence is transformed into hidden state and then the multidimensional token2token [13] self-attention is used to compute the dependence between x_i and x_j for all elements in the input sentence to handle the diversity of contexts surrounding the same word. Then, positional masks is employed to attention distribution in both directions, i.e. forward mask and backward mask, to encode earlier structural knowledge, such as temporal order and dependency parsing. This design overcomes the disadvantage in traditional attention mechanism by modeling order information and takes full advantage of parallel computing. The architecture of Directional self-attention have a fewer parameters, less computation and easier parallelization.

3.4 Sentence Encoder

The sentence vector obtained from the word encoder is given as an input. We can get the document vector in a similar way by applying the attention that was applied in the word encoder to obtain the relevant information in sentence level. The sentence level attention in HAN is calculated by [9],

$$u_i = \tanh(W_s h_i + b_s) \quad (1)$$

$$\alpha_i = \frac{\exp(u_i^T u_s)}{\sum_i \exp(u_i^T u_s)} \quad (2)$$

$$v = \sum_i \alpha_i h_i \quad (3)$$

Where U_s is the context vector obtained by (1) and overall sentence level attention α_i obtained by (2) and v the document vector, which encapsulates all of the data from sentence to document.

3.5 Classification

The output from the sentence encoder v , i.e) the document vector with a representation of the document can be used as a feature to the softmax classifier to get the probability and normalize the value to get the classification label for the document

4. Experiments

4.1. Dataset

We have used two datasets: 1) Socialmedia Reddit posts, 2) Pubmed medical abstracts. The user posted their problem or suggestion in reddit under a particular subreddit. i.e topic-specific community within the platform. Total file of posts around 24GB JSON data is publicly available. We have downloaded the data and then extract only the health-related posts that are relevant to the 10 categories mentioned in Table 1. After retrieving, the dataset consists of 96147 posts. Then another dataset of PubMed medical abstracts is downloaded². It consists of 210176 medical abstracts with attributes, label and text.

Table 1. Number of rows in each subreddit

| Total Categories: 10 | |
|----------------------|------------|
| Subreddit | No of rows |
| Anxiety | 11304 |
| BPD | 2970 |
| Addiction | 341 |
| Autism | 1573 |
| Bipolar | 9622 |
| crippling alcohol | 11758 |
| Depression | 25909 |
| Opiates | 28154 |
| Schizophrenia | 1919 |
| Selfharm | 1414 |

4.2 Training the model

The dataset is preprocessed and converted into integer representation and it is passed as an input into the word encoder and then the sentence vector passed to the sentence encoder and it outputs the document vector and the classification is done using softmax classifier. We have used keras toolkit for the implementation. The hierarchical attention network architecture [9] is implemented. The dataset is split into two parts: 80 percent training and 20 percent testing. The input vocabulary was set to 30k, the maximum sentence length was set to 15, and the maximum number of words in a sentence was set to 100. The glove pre-trained vectors were used to construct the embedding matrix with a dimension of 100 and were trained using our data set (40000-word vectors with 100 dimensions). We train the model for 15 epochs and utilised early stopping to establish the halting condition for the iteration (epoch). Usually, loss tends to decrease after each epoch and accuracy get an increase. When val_loss tends to rise in some epochs and stays in the same condition for a long period of time, the training will come to an end. By using this we can find the correct number of epochs to train the model. We used Adam optimizer because it works best compared to other optimizers. We have used categorical cross entropy to output the probability for multiple class.

5. RESULT AND ANALYSIS

We implemented the hierarchical attention network with the attention mechanism such as multi-head attention and directional self-attention. The evaluation is done for both reddit posts and PubMed medical abstracts and compares the results with the traditional neural network approach. The results are presented in Table 2 and Table 3. The experimental results for reddit dataset with Glove word vector shows that multi-head with GRU/LSTM layer achieves 0.68 Precision (PR) more than the existing HAN approach because of multiple heads incorporated into the hierarchical structure. i.e) each head performs computation in parallel. But without using the GRU/LSTM layer in the hierarchical structure yields less performance because the features are not captured effectively. While applying directional self-attention to the hierarchical structure, it achieves comparable performance with existing approaches because of maintaining the order information in the sentence. The result for PubMed dataset achieves 0.83 precision in multi-head attention and while applying directional self-attention to this dataset achieves 0.82 precision and it performs faster computation than the multi-head attention. Misclassification of the post can occur because some post may fall under two categories, but in our approach, it is reduced between the categories. Another Word embedding used for the same attention mechanism i.e) fastText word vectors. The fastText embedding with simple BiGRU layer produced 0.60 precision for reddit dataset and 0.77

| Approach | Precision | Recall | F1-Score | Accuracy |
|--|-----------|--------|----------|----------|
| Convolutional Neural Network | 0.82 | 0.82 | 0.82 | 0.82 |
| Recurrent Neural Network | 0.84 | 0.84 | 0.84 | 0.84 |
| Hierarchical Attention Network with GRU | 0.8 | 0.8 | 0.8 | 0.8 |
| Hierarchical Attention Network with LSTM | 0.81 | 0.82 | 0.82 | 0.81 |
| Approach | Precision | Recall | F1-Score | Accuracy |
| Convolutional Neural Network | 0.55 | 0.53 | 0.52 | 0.53 |
| Recurrent Neural Network | 0.61 | 0.6 | 0.58 | 0.6 |
| Hierarchical Attention Network with GRU | 0.61 | 0.61 | 0.59 | 0.58 |
| Hierarchical Attention Network with LSTM | 0.61 | 0.61 | 0.59 | 0.58 |
| Multi-head Attention in HAN with GRU /LSTM | 0.68 | 0.64 | 0.64 | 0.64 |
| Multi-head Attention in HAN without GRU /LSTM | 0.59 | 0.59 | 0.58 | 0.58 |
| Directional self-attention Network with RNN | 0.6 | 0.6 | 0.6 | 0.6 |
| Directional self-attention Network with HAN (GRU) | 0.6 | 0.6 | 0.6 | 0.6 |
| Directional self-attention Network with HAN (LSTM) | 0.6 | 0.6 | 0.59 | 0.58 |

precision for pubmed medical abstracts. Multi-head with GRU/LSTM layer achieved 0.79 precision for pubmed abstracts higher than Reddit dataset. fastText word vectors with directional self-attention achieved 0.58 precision for both datasets. Comparing both word vectors Glove with different attention mechanism achieved higher performance for both datasets.

Table 2. Result of Reddit Dataset
Table 3. Result of Pubmed Dataset

| | | | | |
|---|------|------|------|------|
| Multi-head Attention in HAN with GRU /LSTM | 0.83 | 0.82 | 0.83 | 0.83 |
| Multi-head Attention in HAN without GRU /LSTM | 0.8 | 0.8 | 0.8 | 0.8 |
| Directional self-attention Network with RNN | 0.83 | 0.83 | 0.83 | 0.83 |
| Directional self-attention Network in HAN with GRU/LSTM | 0.82 | 0.82 | 0.82 | 0.82 |

6. CONCLUSION

Text categorization is an important task in Natural Language Processing (NLP) since it allows to classify the problems based on the predefined categories. The most difficult aspect of multiclass text classification is properly predicting the categories and having positional information in the sentence. The attention mechanism is incorporated to focus only on the relevant words within the word level to be passed to the sentence level and predict the categories. Together with the positional information and to improve the computation efficiency multi-head with global attention and directional/fast directional self-attention is implemented with the hierarchical approach. The proposed approach achieves comparative performance with the existing approach. In future, directional attention mechanism performance needs to be improved for reddit dataset. Fast directional self-attention and other different types of attention mechanism can be used along with the hierarchical structure and compared with the existing approaches. To reduce dependability on the balance of training data, background knowledge extracted from external corpus can be used in hierarchical attention network

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