Keyword Extraction by Deep Learning
Mid Term Report

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1 Introduction

As the goal of our project, we plan to do keyword extraction using deep learning. We are aiming to improve the performance of keyword extraction by deep learning techniques as compared to other techniques used previosuly. We believe that Deep learning techniques can improve the performance because when it has been applied to other similar tasks, a significant improvement has been observed. For example , Google speech recognizer uses Deep Neural Networks and accuracy is extremely high[cite].The area of applying deep learning to keyword extraction has not been explored much, hence we are trying to apply it and see how it performs.

2 Related Work

Before diving into the details of our model and algorithm, we want to summarize the related work that has been done in the field of Keyword Extractions, how they can be applied to our project and how deep learning can be applied to solve this particular problem and our thoughts on why deep learning should give better performance compared to other algorithms.

2.1 Baseline Algorithms of Keyword extraction

A survey was done by Lott.B[cite], and he summarizes that whenever he have a large corpus of data already available(as in our case), TF-IDF is the most accurate algorithms of the existing ones.

In TF-IDF model, we assign weight to each term in the model, and we choose the top'n' weighted words as the keywords for the text. The weight of each word is computed by taking into account the Term Frequency(TF) and Inverse Domain Frequency(IDF), where Term Frequency indicates how significant is the term to a spcicif document, and IDF takes into account how common the word is in the domain. We have implemented the benchmarks for this algorithms on our dataset.

Other algorithms presently being used are some variant of TF-IDF with domain specific modifications. For example , one technique uses a Bayes classifier with TF-IDF to compute the weights and extract the keywords. There are techniques which are to be used when we dont have a corpus of text available to us. Frequency based single Document Keyword Extraction is one such technique. This techniques coputes word weights by measuring the frequency of text occurence within two punctuation marks in the text. Since we have text corpus available, we did not want to be compared against these classes of algorithms.

2.2 Deep Learning Intution

3 Model Description

3.1 Neural language model

In traditional NLP model, the input of the classifer is just one-hot features or TF-IDF features of text. However, this model suffers from the curse of dimensionality. When the number of documents in the corpus becomes large, the matrix of features will become sparse. Therefore, Bengio et al.[1] proposed a new neural language model which generates distributed representations for each word in the corpus. That means each word in the documents has a fixed length of feature vector. With the feature vectors of each term, we can measure the similarity between different words or generate the vector representation of each document.

In our model, each word will be first transformed to word vector by the tool named word2vec[2]. The tool will first train the neural language model on our data set and then generate the word vector of each term.

3.2 Recursive Autoencoder

Autoencoder is a neural network model that learns the function $f(x) = x$ in order to learn the reduced representation of the input text. As we can see in the figure 1, autoencoder is only a three-layer neural network. We want to utilize the hidden layer to generate the similar vector as the input vector. And after traning the model, the hidden layer can be treated as the condensed feature of the input vectors. Therefore, the training objective is to minimize the distance which is known as reconstruction error between the input and the output of NN. When applying such structure into our model, the input of the autoencoder is word vectors of two terms. After traning the model, the vector of hidden layer can be seen as the condensed feature of these two words.

However, only using the structure of autoencoder may not effectively model the text. If we set the input of autoencoder as the vectors of all terms in one document and try to generate the condensed features of the document, there will be so many parameters to optimize and the structure of the text is not utilized. In order to solve the problem, the structure of recursive autoencoder was proposed to model the hierarchical structure. Figure 2 shows the structure of recursive autoencoder.

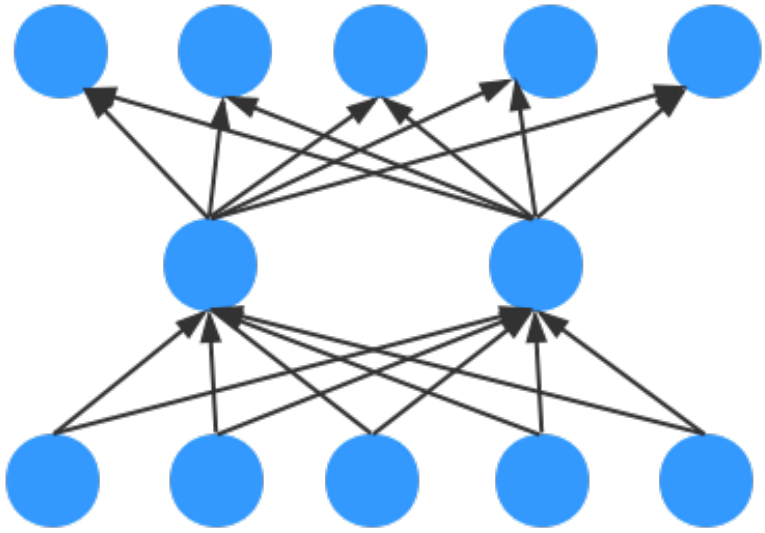


Figure 1: Autoencoder

In each layer, several terms are combined to generate the condensed features which will be utilized as the input of the next layer. At the final layer of recursive autoencoder, the vector of hidden layer will be the vector representation of the whole documents.

One of the key problem in such structure is how to combine different terms. There are mainly two ways. One way is to adopt the grammer tree which generated in advance. Each word will be combined in the same way as they are merge in the grammer tree. Another way is to utilize the greedy algorithm. At each layer, each pair of the adjacent words will be first combined and output reconstruction error. Then the pair of words with smallest error will be first combined. Using this greedy algorithm, the vector of each document can also be generated. In the experimental part, the effectiveness of the two structured will be compared.

3.3 Semi-supervised Recursive Autoencoder

In the traditional recursive autoencoder model, the network is trained only by the document itself. Therefore, it is the unsupervised model. In certain scenario, the label information of documents can be incorporated into the model and turn the model into a semi-supervised model.

One of the semi-superivised recursive autoencoder model has been proposed by socher et

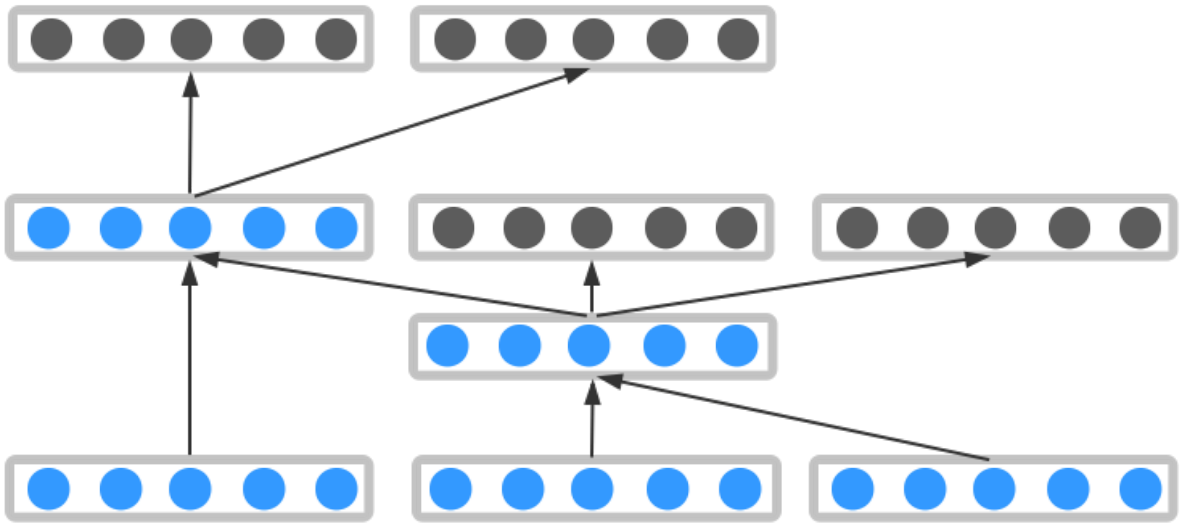


Figure 2: Recursive Autoencoder

al.[3] in order to handle the issue of sentiment analysis. The structure of recursive autoencoder is presented as follows:

As we can see from the figure, the input of the model is also the distributed representation. After being processed by the hidden layer, the output layer reconstructs the input vector. In order to measure the performance of the representation, the reconstruction error is computed as the distance between the input vector and output vector. Also we can assign different terms with different weights. So

$$\begin{aligned} &E_{rec}([c_1; c_2]; \theta) \\ &= \frac{n_1}{n_1 + n_2}||c_1 - c_1'||^2 + \frac{n_2}{n_1 + n_2}||c_2 - c_2'||^2 \end{aligned} \tag{1}$$

, where n denote the number of words. In addition, c denotes the vector of input and c' present the vector of output.

Also, in order to predict the sentiment of the sentence, an extra output unit is added to generate the sentiment label. And this generated label will be compared with the correct label. A softmax function is utilized in this scenario to generate the probability of each label. And author use the cross-entropy error to measure the correctness of the model.

$$\begin{aligned} &E_{cE}(p, t; \theta) \\ &= -\sum_{k=1}^{K} t_k \log d_k(p; \theta) \end{aligned} \tag{2}$$

, where t_k denotes the target label and d_k denotes the probability of each label.

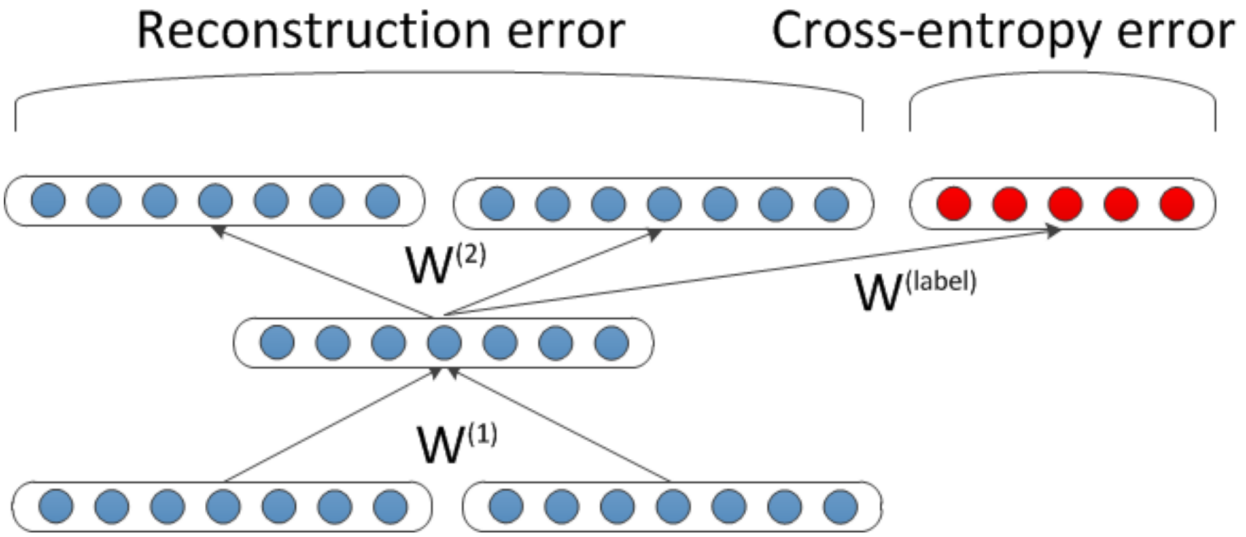


Figure 3: Semi-supervised Autoencoder

After combining the two process, we can compute the reconstruction error and cross-entropy error. And the objective is to minimize the weighted sum of the two errors as follows:

$$\begin{aligned} &E([c_1; c_2]s, ps, t,) = \\ &= \alpha E_{rec}([c_1; c_2]_s; \theta) + (1 - \alpha) E_{cE}(p_s, t; \theta). \end{aligned} \tag{3}$$

4 Experiment and Results

4.1 Baseline Algorithm Results

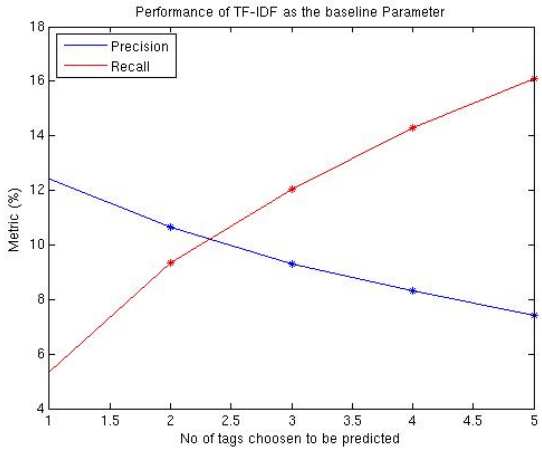
To evaluate the performance of our approach compared to existing techniques, we have used Precision and Recall rates as our benchmarking standards. We have formally defined these parameters as

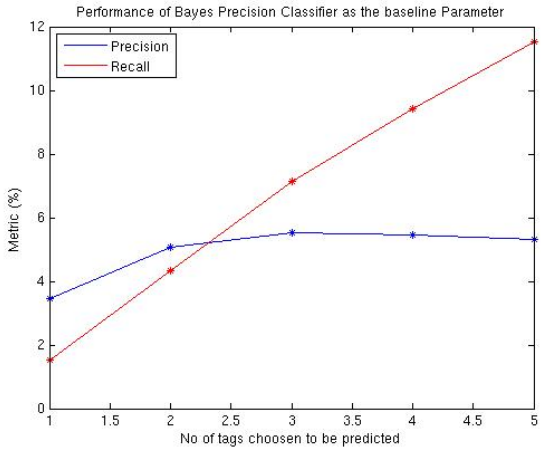
$Precision = \frac{sizeof(A \bigcap B)}{sizeof(A)}$

$Recall = \frac{sizeof(A \bigcap B)}{sizeof(A)}$

where A is the set of predicted tags and B is the set of actual tags.

We have implemnted TF-IDF and Bayseian Classifier approach as described by the survey for Keyword Extraction on our data set. With plain vanilla TF-IDF, the average precision and recall rates were less than 10 %. However, after preprocessing the data by using a stemmer, the accuracy is a modest 15-20% on topics in our data set for as the best performer. We have used portland stemmer, available as part of open source NLTK(Natural Language Processing Toolkit) project. The Bayesian Classifier is similar to TF-IDF apporach except that it takes into account the position of the word in text. The weight of each term is reduced as the log of the its position from the begining of the sentence.





As part of survey paper[6], we found out that the existing standard for key word extraction uses Lexical Tree approach and we are coming up with the precision and recall rates for Lexical Trees approach
{Report exact figures here}.

4.2 Dataset

We had identified data from stackexchange(`https://archive.org/download/stackexchange/stackexchange_archive.torrent`) to be a suitable data set for our project.

Of the 20 GB, available to us, we are using only 500 MB of data, on about 20 topics for our evaluation. We felt this was enough for testing purposes, and once we decide on the model, we will make use of all the data set available to us. Working with bigger datasets is a hassle when no concrete model is available and hence we stopped at 500MB. All our results and observations have been made on this 500MB of dataset, which we have cleaned and formatted for our applications.

5 Pending Work

References

[1] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Janvin. A neural probabilistic language model. *J. Mach. Learn. Res.*, 3:1137–1155, March 2003.

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[3] Richard Socher, Jeffrey Pennington, Eric H Huang, Andrew Y Ng, and Christopher D Manning. Semi-supervised recursive autoencoders for predicting sentiment distributions. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 151–161. Association for Computational Linguistics, 2011.