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Automatic Academic Paper Rating Based on Convolutional Neural Network

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ABSTRACT

As an ever increasing number of academic papers are being submitted to journals and conferences, assessing every one of these papers by experts is tedious and can cause imbalance because of the personal factors of the reviewers. In this system, in order to help professionals in assessing academic papers, here propose a task: Automatic Academic Paper Rating (AAPR), which automatically determine whether to accept academic papers. We build a convolutional neural network (CNN) model to achieve automatic academic paper rating task. It has two phases, first phase is identifying abstract part of source paper and generate rating score using CNN model and second phase is taking decision based on the score to accept or decline papers. This model takes word embedding of the abstracts as the input and learns useful features. The word embedding used for training the model is a semantically enriched set of Word2Vec word embedding. After the training phase, the proposed model will be able to generate the score of a new abstract. And find that the title and abstract parts have the most influence on whether the source paper quality when setting aside the other part of source papers. The proposed system outperforms the state-of-art technique.

Keywords: Convolutional Neural Network, Word2vec

I. INTRODUCTION

Consistently there are a large number of academic papers submitted to journals and conferences. Rating every one of these papers can be debilitating, and then rating scores can be influenced by the personal factor of the reviewer, prompting imbalance problem. Therefore, there is an essential requirement for rating academic papers naturally. In this system, investigate how to naturally rate the academic papers dependent on their title or abstract part, which is more impact some portion of the source papers.

An undertaking that is like the AAPR (Automating Academic Paper Rating) is Automatic Essay scoring (AES). Automatic Essay Scoring (AES) is the assignment of score or grade a computer based reviewing framework, with the point of diminishing, the inclusion of human raters as far as could be allowed. It tends to be profoundly testing, requiring not just knowledge on spelling and grammars, but also on semantics, discourse and pragmatics. Conventional models utilize inadequate highlights, for example, bag of words, part of speech, language structure intricacy measures, word mistake rates and essay lengths, which can experience the will effects of the disadvantages of time-consuming feature engineering and information sparsity. Traditionally Automatic Essay Scoring treated as classification [1], Regression [2] or ranking classification problem ,addressing AES by supervised learning [3]. Features are typically bag-of-words, spelling errors and lengths, such word length, sentence length and essay length, etc. A disadvantage is feature engineering, which can be tedious process.

So, late examination deep learning methods use to solve AES system problems. Deep learning model avoid the heavy feature engineering. [3] also applied recurrent neural networks to process the essay, except that they put a convolutional layer ahead of the recurrent layer to extract local features. [4] proposed to apply a two-layer convolutional neural network (CNN) to model the essay. The first layer is responsible for encoding the sentence and the second layer is to encode the whole essay. Further suggested adding the pooling layer attention mechanism to automatically determine which part is more important in determining the quality of the essay.

Despite the fact that there has been a great deal of work managing with AES task. The feature extract from Automatic Eassy Scoring(AES) is different from the Automatic Academic Paper Rating , researchers have not endeavored the AAPR task . An academic paper consisting much content like title, abstract, introduction , related work etc. Therefore system propose only abstract content of the source paper because that is more influenced part of the source Paper.

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks. CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually refer to fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. CNN is feed forward neural network, consist input layer, hidden layer and output layer. The hidden layers contain mainly convolution layer, pooling layer and fully connected layer. It is different from other neural network is the number of layers and its functionality, that is convolution layer and pooling layer. Convolutional neural network are one of the most successful deep learning model, And it is highly successful in various NLP tasks. Such as sequence labeling [6], sentences modeling [7], sentences classification [8] etc. Compare to other neural network, convolutional neural network are more powerful and its more capable of learning features automatically. Therefore, system mainly focused on convolutional neural network in this work.

The organization of this document is as follows. In Section 2 (**Automatic Academic Paper Rating**), a detailed explanation of the paper is given. The description of the dataset is also given. In Section 3 (**Result and Discussion**), the result analysis is explained with the results. Discussed in Section 4(**Conclusion**), it is explained with the future scope.

II. AUTOMATIC ACADEMIC PAPER RATING

This section talks about the system architecture of Automatic Academic Paper Rating (AAPR) in detail. The designing and implementation of the proposed system are discussed along with the data that the framework works with.

A. SYSTEM DESIGN AND IMPLEMENTATION

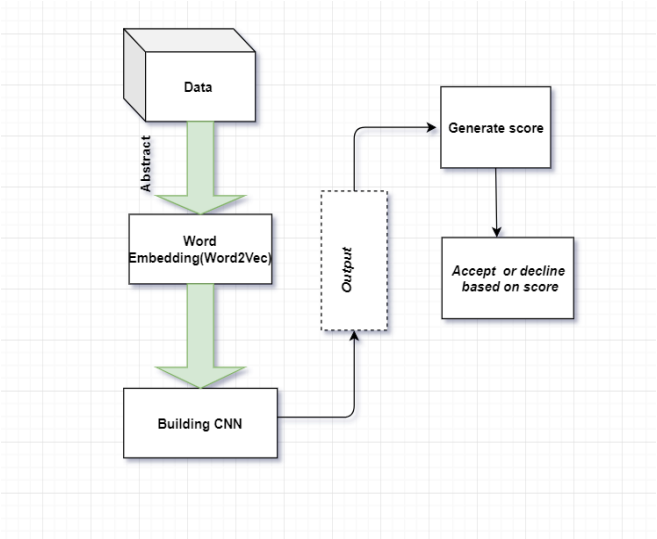

Figure 1

Figure1 shows the basic architecture of proposed automatic academic paper rating based on CNN. The main three stages of the system, word-embedding generation, training the convolution neural network and make a decision based on rating score for accept or decline academic papers. The dataset collection

deals with the input collection and the preprocessing steps. The proposed model takes word embedding of the abstracts of manuscripts as the input and learns useful features for identifying the score. The word embedding used for training the model is a semantically enriched set of Word2Vec word embedding. Then building the CNN model and train the model. After training process, generate rating score corresponding to abstract given by the journals . In our proposed system CNN model takes as regression task. Finally, rating score obtained in the range [0-1]. The rest of this chapter explains each stages in detail.

B. Dataset collection

The proposed automatic academic paper rating system based on abstract. Here using AIcorpus dataset it contain 1000+ Papers, which are published between 2001 to 2016. This dataset is in CSV (comma-separated values) format. This dataset contains paper related to area computer society conferences on computer vision and pattern recognition and some other related papers, The dataset include title , abstract , author details and other information about the papers. Finally, the processed dataset is given to word embedding generation phase.

C. Word Embedding Generation

In this system, Text Corpus as input of word2vec model. Model identifies the each unique word in the corpus and assigned corresponding vector. Using word embedding, embedding matrix is generated, the output of word embedding is embedding matrix. Word embedding (using word2vec) representation of the ith word w_i is embedded to a dense vector x_i through an embedding matrix.

D. Building Convolutional Neural Network Model

The word embedding vectors are given as the input to the convolutional neural network model framework. This model identifies abstract and model learns a rich number of feature representations by passing the input vectors through various neural network layers. The model type that using here is Sequential. Sequential is the easiest way to build a model in Keras. It builds a model layer by layer. Each layer has weights and bias vector that correspond to the layer the follows it. In our proposed system CNN model treated as regression task. The layers included in this framework are convolutional layer, max pooling layer, a gain followed by convolutional layer and global average pooling, and, dropout layer, dense layer. Here convolutional layer is the first layer to extract the features of abstarct data. **convolution layer** : Sequence of vector of length n is represented as the row concatenation of n k-dimensional vectors:X =$\{x_1; x_2; \ldots..; x_n\}$. Filter W convolves with the window vector generate each position of feature map c. Each element zj of feature map calculated as zj = f ($[w_x$ o $x_j : x_j$+ h] + b_x) b is a bias term and f is nonlinear activation function . Here we choose f to be tanh . m different filters can be used multiple feature map $z_1, z_2 \ldots\ldots z_m$. These features pass to next layer max pooling layer. Every convolution have a pooling layer that is different from the other neural network compare to CNN. A pooling layer is another building block of a CNN. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. Pooling layer operates on each feature map independently. The most common approach used in pooling is max pooling. Max pooling is selecting maximum value in the filter. An average pooling layer performs down-sampling by dividing the input into rectangular pooling regions and computing the average values of each region. In the dense layer, all nodes in the previous layer connect to the nodes in the current layer. The activation function will be using here is tanh and sigmoid . Non linear activation function tanh value ranged by [-1-1]and sigmoid activation function value ranged by [0-1] The dropout layer is

used for avoiding overfitting. The final dense layer using sigmoid activation function to generate a score.

Parameter	Value
Layers	Convolutional layer, Max pooling, Convolutional layer, Global average pooling, Drop out layer, Dense layer
Drop out	0.5
Activation	tanh,sigmoid
optimser	rmsprop
Epoch , Batch size	100,16

T Table 1: Model Specification

Training

Here we use the RMSProp optimization algorithm (Dauphin et al., 2015) to minimize the mean squared error (MSE) loss function over the training data. Mean squared error widely use in regression task. which measures the average value of square error between gold standard scores y_i^* and prediction scores y_i assigned by the academic rating system among all abstract data of the source paper. Given N source paper abstract data, we calculate MSE according to equation:

$$mse(y, y^*) = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i^*)$$

We train the neural network model for a fixed number of epochs and monitor the performance of the model on the development set after each epoch. Additionally, we make use of dropout regularization to avoid overfitting.

Acceptance Based On Rating Score

Our CNN model take task as a regression, it produce real number or continuous number. Building CNN model last layer is dense with sigmoid activation layer. Therefore, that layer output is [0-1] ranged value. Based on this value, obtained above 0.5 the paper can be accepted otherwise declined.

III. RESULTS AND DISCUSSION

This section talks about the experimental setup, evaluation and results obtained for the proposed system.

A. EVALUATION MEASURES

Data : The AI scopus dataset by kaggle is used as evaluation data of our AAPR system. We use accuracy as our evaluation metric rather than F-score, accuracy, and recall because our dataset favorable and negative examples are well balanced. Our task is novel task, so we cannot comparison with other system. Dataset of this system are not publicly available comparison with this system become impossible. Here 80 percentage data used as our traning set and 20 percenatage data used test set. For a fixed number of epochs, we train the model and then select the best model based on the development set.

B. RESULT

The proposed building convolutional neural network model is implemented using Keras with Tensorflow as the back end. The models are trained using a batch size of 16 for 10 epochs. The performance metrics used to evaluate the model accuracy. The accuracy of model will be almost above 90 percentage. Graph shown figure 2. Mean square error is measure the error squares average that is, the square average

difference between the estimated values and the estimated values. Graph given below figure 3.

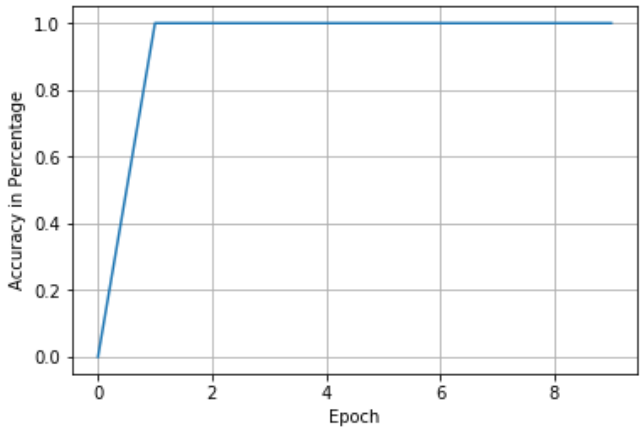

Figure 2 : Accuracy graph

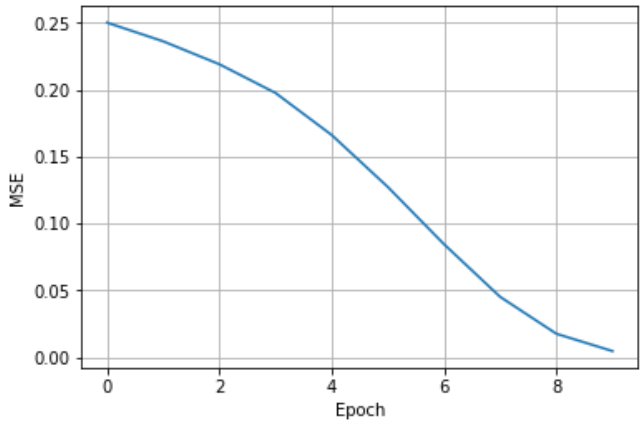

Figure 3 : MSE curve

Figure 4 shows Rating score can generate after 10 epochs. Each epoch will shows change in mean square error and accuracy. Here we are tested 100 abstract data's. Rating score shows that paper can accepted or rejected.

```
Epoch 1/10
 2/2 [==============================] - 0s 137ms/step - loss: 0.6933 - acc: 0.0000e+00 - mean_squared_error: 0.2501
Epoch 2/10
2/2 [==============================]  - 0s 684us/step - loss: 0.6925 - acc: 0.5000 - mean_squared_error: 0.2497
Epoch 3/10
 2/2 [==============================] - 0s 2ms/step - loss: 0.6917 - acc: 1.0000 - mean_squared_error: 0.2493
Epoch 4/10
 2/2 [==============================] - 0s 774us/step - loss: 0.6911 - acc: 1.0000 - mean_squared_error: 0.2490
Epoch 5/10
 2/2 [==============================] - 0s 1ms/step - loss: 0.6906 - acc: 1.0000 - mean_squared_error: 0.2487
Epoch 6/10
 2/2 [==============================] - 0s 775us/step - loss: 0.6901 - acc: 1.0000 - mean_squared_error: 0.2485
Epoch 7/10
 2/2 [==============================] - 0s 1ms/step - loss: 0.6896 - acc: 1.0000 - mean_squared_error: 0.2482
Epoch 8/10
 2/2 [==============================] - 0s 1ms/step - loss: 0.6891 - acc: 1.0000 - mean_squared_error: 0.2480
Epoch 9/10
 2/2 [==============================] - 0s 755us/step - loss: 0.6886 - acc: 1.0000 - mean_squared_error: 0.2477
Epoch 10/10
 2/2 [==============================] - 0s 957us/step - loss: 0.6881 - acc: 1.0000 - mean_squared_error: 0.2475
 2/2 [==============================] - 0s 17ms/step
The score is: 0.85
```

Figure 4 : Rating Score

IV. CONCLUSION

We have proposed an academic paper rating system for computer science and technology. Key feature of our proposal is that it requires only abstract of paper. This feature can be very important in practice from the point of view of both users (even in the early stages of the authoring process, the system may be queried) and developers (building and maintaining the knowledge base is much simpler than previous proposals require). We have assessed this proposal experimentally on a large and challenging dataset composed of more than 1000 papers. The entire working is divided into two phases. In first phase, generating score based on abstract of the source paper by using CNN model in deep learning approach. The second phase, making decisions based on score where it accepted or not. The score will above 50 percentage then it can be accepted otherwise rejected. The proposed automatic academic paper rating method for accepted papers outperforms the state-of-art method.

In future In order to apply this system for getting validated in other domains beyond the computer science this system can be modified with complex

neural networks. As of now this system can rating the papers, journals or conferences and it can be resolved in future. Here we are using abstract data of source paper, In future more contents are added like introduction, related work, methods etc. Academic paper rating system can also be improved by adding features like grammar checking, use of technical words. More complex deep learning models using CNN and Bi-LSTM with memory networks can be also used for building model.

V. REFERENCES

[1] Valenti, S., Neri, F., and Cucchiarelli, A. (2003). An overview of current research on automated essay grading. Journal of Information Technology Education: Research, 2(1):319–330.

[2] Attali, Y. and Burstein, J. (2004). Automated essay scoring with e-rater® v. 2.0. ETS Research Report Series, 2004(2):i–21.

[3] Yannakoudakis, H., Briscoe, T., and Medlock, B. (2011). A new dataset and method for automatically grading esol texts. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 180–189. Association for Computational Linguistics.

[4] Taghipour, K. and Ng, H. T. (2016). A neural approach to automated essay scoring. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1882–1891.

[5] Dong, F. and Zhang, Y. (2016). Automatic features for essay scoring–an empirical study. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1072–1077.

[6] Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. Journal of machine learning research, 12(Aug):2493–2537.

[7] Kalchbrenner, N., Grefenstette, E., and Blunsom, P. (2014). A convolutional neural network for modelling sentences. arXiv preprint arXiv:1404.2188.

[8] Kim, Y. (2014). Convolutional neural networks for sentence classification. arXiv preprint arXiv:1408.5882

[9] Gulli, A. and Pal, S. (2017). Deep Learning with Keras. Packt Publishing Ltd.

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