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Effect of Sentiment Embeddings in Sentiment Analysis

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Abstract— **Sentiment analysis is the most influencing factors in understanding the users' behavior. Word representation attempts to respect aspects of word meanings. Word representation is a critical component of many natural language processing systems as word is usually the basic computational unit of texts. To solve this problem, many studies represent each word as continuous, low dimensional, and real-valued vector, also known as word embeddings. Word embeddings have been leveraged as inputs or extra word features for a variety of natural language processing tasks, including machine translation, syntactic parsing, question answering, discourse parsing, etc. Due to the large volume of sentimental data, it is essential to mine such data and find sentiments in order to the overall sentiments on the uploaded dataset of products, politics, sports, education reforms, and so on. Existing system used the concept of pattern recognition for extracting the polarity of the sentences or words. The drawback of this system is that it will not be that much effective to classify or evaluate the datasets. So by using the concept of neural network models, we can evaluate the accuracy metric to find the effectiveness of sentiment embeddings in sentiment analysis.**

***Keywords- Natural Language Processing, Word Embeddings, Sentiment Analysis, Neural Networks*.**

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I. INTRODUCTION

Sentiment analysis, also known as opinion mining is a fundamental task in natural language processing and computational linguistics. Sentiment analysis is crucial to understanding user generated text in social networks or product reviews, and has drawn a lot of attentions from both industry and academic communities. In this paper, we focus on target-dependent sentiment classification, which is a fundamental and extensively studied task in the field of sentiment analysis. Given a sentence and a target mention, the task calls for inferring the sentiment polarity (e.g. positive, negative, neutral) of the sentence towards the target. For example, let us consider the sentence: “I bought a new camera. The picture quality is amazing but the battery life is too short”. If the target string is picture quality, the expected sentiment polarity is “positive” as the sentence expresses a positive opinion towards picture quality. If we consider the target as battery life, the correct sentiment polarity should be “negative”.Target-dependent sentiment classification is typically regarded as a kind of text classification problem in literature. Majority of existing studies build sentiment classifiers with supervised machine learning approach, such as feature based Supported Vector Machine or neural network approaches. Despite the effectiveness of these approaches, we argue that target-dependent sentiment classification remains a challenge: how to effectively model the semantic relatedness of a target word with its context words in a sentence. One straight forward way to address this problem is to manually design a set of target-dependent features, and integrate them into existing feature-based SVM. However, feature engineering is labor intensive and the “sparse” and “discrete” features are clumsy in encoding side information like target-context relatedness. In addition, a person asked to do this task will naturally “look at” parts of relevant context words which are helpful to determine the sentiment polarity of a sentence towards the target. These motivate us to develop a powerful neural network approach, which is capable of learning continuous features (representations)without feature engineering and meanwhile capturing the intricate relatedness between target and context words. We present neural network models to deal with target dependent sentiment classification. The approach is an extension on long short-term memory (LSTM) by incorporating target information. Such target-dependent LSTM approach models the relatedness of a target word with its context words, and selects the relevant parts of contexts to infer the sentiment polarity towards the target. The model could be trained in an end-to-end way with standard backpropagation, where the loss function is cross-entropy error of supervised sentiment classification. We apply the neural model to target-dependent sentiment classification on a benchmark dataset . We compare with feature-based SVM adaptive recursive neural network and lexicon-enhanced neural network. Empirical results show that the proposed approach without using syntactic parser or external sentiment lexicon obtains state-of the-art classification accuracy. In addition, we find that modeling sentence with standard LSTM does not perform well on this target-dependent task. Integrating target information into LSTM could significantly improve the classification accuracy. [7] proposed a work, in this work, a framework of feature distribution scheme is proposed for object matching. In this approach, information is distributed in such a way that each individual node maintains only a small amount of information about the objects seen by the network. Nevertheless, this amount is sufficient to efficiently route queries through the network without any degradation of the matching performance. Digital image processing approaches have been investigated to reconstruct a high resolution image from aliased low resolution images.

II.RELATED WORK

In order to learn sentiment embeddings effectively, we develop a number of neural networks with tailoring loss functions, and collect massive texts automatically with sentiment signals like emoticons as the training data. Sentiment embeddings can be naturally used as word features for a variety of sentiment analysis tasks without feature engineering. Here experimental results show that sentiment embeddings consistently outperform context-based

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language processingtasks[1]
To obtain large scale training corpora, we learn the sentiment-specific word embedding from massive distant-supervised tweets collected by positive and negative emotions. Experiments on applying SSWE to a benchmark Twitter sentiment classification dataset in SemEval 2013 show that the SSWE feature performs comparably with hand-crafted features in the top-performed system; and the performance is further improved by concatenating SSWE with existing feature set.[2]

Developed supervised learning framework by concatenating the sentiment-specific word embedding (SSWE) features with the state-of-the-art hand-crafted features. We develop a neural network with hybrid loss function 1 to learn SSWE, which encodes the sentiment information of tweets in the continuous representation of words. To obtain large-scale training corpora, we train SSWE from 10M tweets collected by positive and negative emotions, without any manual annotation.[4]

Presenting the results of machine learning algorithms for classifying the sentiment of Twitter messages using distant supervision. Our training data consists of Twitter messages with emoticons, which are used as noisy labels. This type of training data is abundantly available and can be obtained through automated means. We show that machine learning algorithms (Naive Bayes, Maximum Entropy, and SVM)have accuracy above 80% when trained with emoticon data. It describes the preprocessing steps needed in order to achieve high accuracy. The main idea is using tweets with emoticons for distant supervised learning.

Investigate whether the signals can potentially help sentiment analysis by providing a unified way to model two main categories of emotional signals, i.e., emotion indication and emotion correlation. We further incorporate the signals into an unsupervised learning framework for sentiment analysis. In the experiment, we compare the proposed framework with the state-of-the-art methods on two Twitter datasets and empirically evaluate our proposed framework to gain a deep understanding of the effects of emotional signals.[9]

A new learning procedure, back-propagation, for networks of neuron-like units. This procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal „hidden" units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure.[12]

We cast sentiment lexicon learning as a phrase-level sentiment classification task. The challenges are developing effective feature representation of phrases and obtaining training data with minor manual annotations for building the sentiment classifier. Specifically, we develop a dedicated neural architecture and integrate the sentiment information of text(e.g. sentences or tweets) into its hybrid emotions, without any manual annotation. Furthermore, we introduce the Urban Dictionary to expand a small number of sentiment seeds to obtain more training data for building the phrase-level sentiment classifier. We evaluate our sentiment lexicon (TS-Lex) by applying it in a supervised learning framework for Twitter sentiment classification. Experiment results on the benchmark dataset of SemEval 2013 show that, TS-Lex yields better performance than previously introduced sentiment lexicons.[3].

III. EXISTING SYSTEM

A. Data Analysis model

The existing system deals with data analysis model. Even still data analysis model for social network are done by manual only. These analysis reports are not much accurate while comparing with our proposed architecture. So still we a need a tool or an analysis model to find out the accurate sentimental variations about the users comments.

Still many companies are struggling to produce the sentimental variations for their applications like, New Company opening, new product launch, Introducing new techniques and etc. But they still employed a person to monitor the social marking and sentimental analysis about the company.

Some companies are depending excel or some UML models. But using these methods data sheet can be calculated but accurate sentimental variation is not possible. This is major impact factor in the global market. So still companies are assuming their result but not in accurate.

IV. PROPOSED SYSTEM

We describe the proposed approach for target-dependent sentiment classification in this section. We first present a basic long short-term memory (LSTM) approach, which models the semantic representation of a sentence without considering the target word being evaluated. Afterwards, we extend LSTM by considering the target word, obtaining the Target-Dependent Long Short-Term Memory (TD-LSTM)model. Finally, we extend TD-LSTM with target connection, where the semantic relatedness of target with its context words are incorporated.

A.Approach

B.Long Short-Term Memory (LSTM)

In this part, we describe a long short-term memory (LSTM) model for target-dependent sentiment classification. It is a basic version of our approach In this setting, the target to be evaluated is ignored so that the task is considered in a target independent way. We use LSTM as it is a state-of-the-art performer for semantic composition in the area of sentiment analysis. It is capable of computing the representation of a longer expression (e.g. a sentence) from the representation of

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contains three additional neural gates: an input gate, a forget gate and an output gate. These gates adaptively remember input vector, forget previous history and generate output vector. LSTM cell is calculated as follows.

it = _(Wi · [ht−1;wt] + bi) (1)
ft = _(Wf · [ht−1;wt] + bf) (2)
ot = _(Wo · [ht−1;wt] + bo) (3)
gt = tanh(Wr · [ht−1;wt] + br) (4)
ct = it _ gt + ft _ ct−1 (5)
ht = ot _ tanh(ct) (6)

C.Target-Dependent LSTM (TD-LSTM)

The aforementioned LSTM model solves target-dependent sentiment classification in a target independent way. That is to say, the feature representation used for sentiment classification remains the same without considering the target words. Let us again take "I bought a new camera. The picture quality is amazing but the battery life is too short" as an example. The representations of this sentence with regard to picture quality and battery life are identical. This is evidently problematic as the sentiment polarity labels towards these two targets are different. To take into an account of the target information, we make a slight modification on the aforementioned LSTM model and introduce a target-dependent LSTM (TD-LSTM) in this subsection. The basic idea is to model the preceding and following contexts surrounding the target string, so that contexts in both directions could be used as feature representations for sentiment classification. We believe that capturing such target-dependent context information could improve the accuracy of target-dependent sentiment classification.

Specifically, we use two LSTM neural networks, a left one LSTML and a right one LSTMR, to model the preceding and following contexts respectively. The input of LSTML is the preceding contexts plus target string, and the input of LSTMR is the following contexts plus target string. We run LSTML from left to right, and run LSTMR from right to left. We favour this strategy as we believe that regarding target string as the last unit could better utilize the semantics of target string when using the composed representation for sentiment classification. Afterwards, we concatenate the last hidden vectors of LSTML and LSTMR, and feed them to a softmax layer to classify the sentiment polarity label. One could also try averaging or summing the last hidden vectors of LSTML and LSTMR as alternatives

D.Target-Connection LSTM (TC-LSTM)

Compared with LSTM model, target-dependent LSTM (TD-LSTM) could make better use of the target information. However, we think TD-LSTM is still not good enough because it does not capture the interactions between target word and its contexts. Furthermore, a person asked to do target-dependent sentiment classification will select the relevant context words which are helpful to determine the sentiment polarity of a sentence towards the target.

Based on the consideration mentioned above, we go one step further and develop a target-connection long short-term memory (TC-LSTM). This model extends TD-LSTM by incorporating an target connection component, which explicitly utilizes the connections between target word and each context word when composing the representation of a sentence.

V. TRAINING DATA AND PARAMETER LEARNING

We describe the training datasets and the parameter estimation strategy for learning sentiment embeddings in this part.

A.Datasets

We collect sentence level sentiment information automatically from Twitter. This is based on the consideration that larger training data usually leads to more powerful word representation, and it is not practical to manually label sentiment polarity for huge number of sentences.

Specifically, we leverage massive tweets containing emoticons as weakly supervised corpora without any manual annotations. We crawl tweets from April 1st, 2013 to April 30th, 2013 with T witter API.

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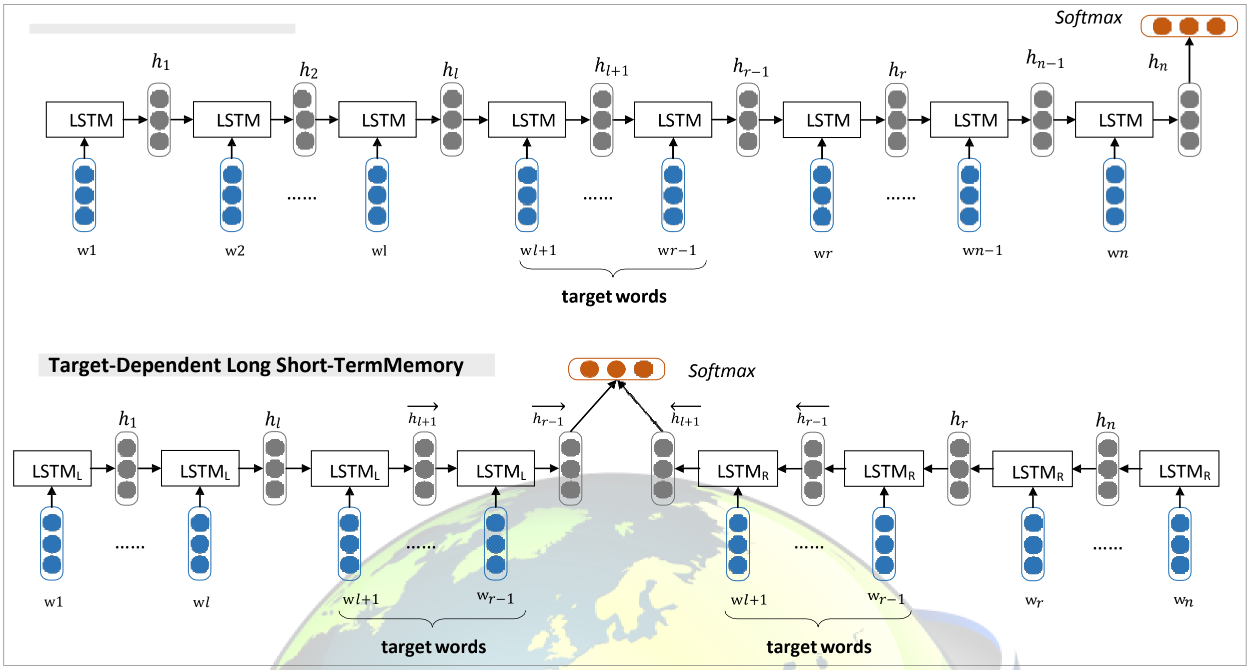

Figure 4.1:LSTM approach

Figure4.2:TD-LSTM approach

VI. IMPLEMENTATION

A.DATASET: SEMEVAL 2013

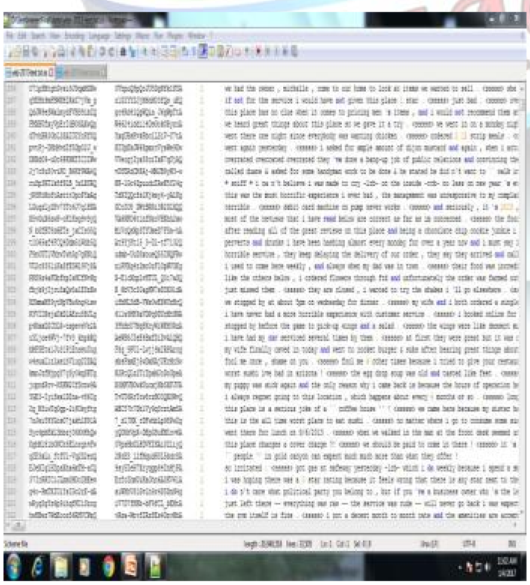

Figure 6.1: Dataset SemEval 2013

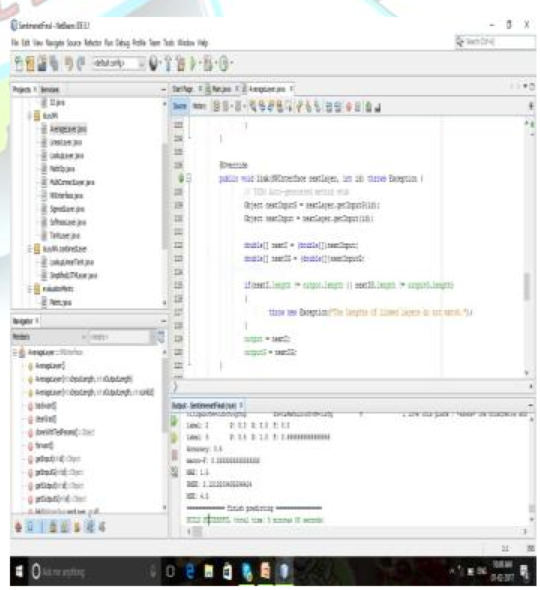

Figure 6.2: Accuracy and Macro-F Evaluation Metric

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By retrieving the SemEval 2013 dataset, there the positive, negative and neutral reviews are classified. The training and test dataset are used for evaluating the accuracy and macro-f1 evaluation metric to evaluate how the sentiment embeddings concept is efficient for the sentiment analysis domain.

The accuracy and evaluation metric is calculated by precision and recall values for the chosen labels. Since it is a LSTM methodology, there is a back-propagation process involved to have the outliers. The outliers can be measured by RMSE, MSE and MAE.

VII. CONCLUSION

We develop target-specific long short term memory models for target-dependent sentiment classification.

The approach captures the connection between target word and its contexts when generating the representation of a sentence. We train the model in an end-to-end way on a benchmark dataset, and show that incorporating target information could boost the performance of a long short-term memory model. The target-dependent LSTM model obtains state-of-the-art classification accuracy.

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