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A Deep Learning Framework for Online Product Review Sentiment Summarization

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ABSTRACT:

Reviews of a product are useful to future consumers in assisting them to make choices. Different opinion mining methods have been suggested to judge the orientation of the review sentence (e.g. positive, negative and spam) is one of their main problems. Deep learning has appeared as an efficient means of solving the issues of classification of feelings. Intrinsically, a neural network learns helpful representation automatically without human effort. However, the achievement of "Deep Learning" depends heavily on the accessibility of large-scale training data. We suggest a novel, deep-learning structure for product review sentiment classification, which uses prevalently accessible scores as weak surveillance signals. The structure consists of two steps: (1) learning a high-level representation (i.e. an embedding space) that captures the general sentiment distribution of phrases through rating data; (2) adding a classification layer to the top of the embedding layer and using marked phrases for monitored fine tuning.

We investigate two types of low-level network structure for sentence modeling, namely convolution features extractors and long-term memory. In order to evaluate the proposed framework, we construct a dataset containing 2 M weakly labeled review phrases and 11,754 labeled review phrases from all websites. Experimental findings indicate the efficacy and superiority of the suggested system over baselines.

***Index Terms—* Deep Learning, Sentiment, Opinion mining, classification, large-scale;**

1. INTRODUCTION

We force phrases with the same weak labels to be close to each other, while phrases with distinct soft labels are kept away from each other. In order to decrease the effect of phrases with a rating-inconsistent orientation (hereafter referred to as wrong-marked phrases), we suggest to penalize comparative distances between phrases in an embedding room by means of a ranking loss. In the second step, a classification layer is added to the top of the embedding layer, and we use marked phrases to fine-tune the profound network. The framework is called Weakly-supervised Deep Embedding (WDE). As far as network structure is concerned, two common systems are implemented to learn how to extract fixed-length vector features from review phrases, namely convolutionary feature extractors and Long Short-Term Memory (LSTM). With a slight abuse of concept, the former model is referred to as the K-Neural Network based WDE (WDE-KNN); the latter is referred to as the LSTM based WDE (WDE-LSTM). We then calculate the high-level characteristics (embedding) by synthesizing the extracted features, as well as the contextual aspect data (e.g. cell phone screen) of the item.. The input element reflects previous understanding of the orientation of the sentence.

The primary contributions of this article are summarized as follows:

1) We suggest a fresh WDE deep learning structure that can leverage a large number of weakly labeled review

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phrases for sentiment analysis. The framework first seeks to capture the data distribution of sentiment by embedding training on weakly marked phrases. It then utilizes a few marked phrases for profound network fine-tuning, as well as for forecast model learning.

We empirically show that this "weakly pre-training+ controlled fine-tuning" concept is viable. The concept could also be helpful for the exploitation of other types of weakly marked information (e.g. tagging information).

2) We develop a particular neural network architecture for WDE and instantiate it with two common neural network models for text information modeling: KNN and LSTM. We compare WDE-KNN and WDE-LSTM in terms of their efficacy, efficiency and specialties in this assignment of sentiment classification.

3) To evaluate WDE, we construct a dataset containing 2 M weakly labeled review phrases and 11,754 labeled review phrases from three Amazon domains, i.e. digital cameras, cell phones and laptops. The dataset can be downloaded from https:/www.dropbox.com/s/aji68llxmtcuu5l/data.zip. Experimental findings indicate that WDE is efficient and exceeds basic techniques.

Sentiment analysis is a long-standing subject of studies. Readers can refer to a latest study. Sentiment classification is one of the main duties of sentiment assessment and can be classified as document level, phrase level and aspect level. Traditional machine learning techniques for the classification of feelings can usually be implemented to three levels. Our job falls into the last category because we consider the data aspect. In the next one, we will examine two subtopics strongly linked to our job.

2. PROPOSED SYSTEM

In order to decrease the effect of phrases with a rating-inconsistent orientation (hereafter referred to as wrong-marked phrases), we suggest to penalize comparative distances between phrases in an embedding room by means of a ranking loss. In the second step, a classification layer is added to the top of the embedding layer, and we use marked phrases to fine-tune the profound network. The framework is called Weakly-supervised Deep Embedding (WDE). With regard to network structure, two common systems are implemented to know how to extract fixed-length vector features from review phrases, namely convolutionary feature extractors and Long Short-Term Memory (LSTM)]. With a slight abuse of notion, the former model is referred to as K-Neural Network based WDE (WDE-KNN); latter is referred to as LSTM derived WDE (WDE-LSTM). We then calculate the high-level features (embedding) by synthesizing the extracted features, as well as the contextual aspect information (e.g. cell phone screen) of the product. The input element reflects previous understanding of the orientation of the sentence.

3. IMPLEMENTATION

Weakly-supervised Deep Embedding:

- Two common systems are implemented to learn how to extract fixed-length vector features from review phrases.
- Convolution feature extractors and Long Short-Term Memory.
- A fresh profound learning framework WDE
- Leverage a large number of weakly labeled review phrases.
- The framework first seeks to capture the distribution of sentimental information by embedding instruction in weakly marked phrases.

Sentiment analysis:

- Researchers have studied various profound models of sentiment classification.
- Sentiment analysis and may be categorized as document level, sentence level and aspect level.

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- In sentimental assessment, the term co-occurrence data is generally not well correlated with sentimental forecast.

Aspect-based models for sentiment classification:-

- A set of composition tasks and syntactic interactions between phrases to regulate the spread of feelings to objectives.
- LSTM for the classification of aspect level sentiment.
- Two LSTM-based models for this assignment.
- Preceding and succession of target word contexts and constructing target specific representation.
- The destination vector was explicitly used as an input for each time step.

Phrases Identification:-

- Two kinds of sentences have been recognized, namely negation-of-adjective (NOA) and negation-of-verb (NOV).
- Most common negative prefixes, such as not, no, or nothing, are treated as adverbs by the POS tag.
- The algorithm was capable of identifying 21,586 distinct sentences.
- Total occurrence of more than 0.68 million, each of which has a adverse prefix.

4. RESULTS

The suggested research is carried out in java and the findings are evaluated in terms of precision and time of execution. Various parameters are used to calculate the precision or time of execution.

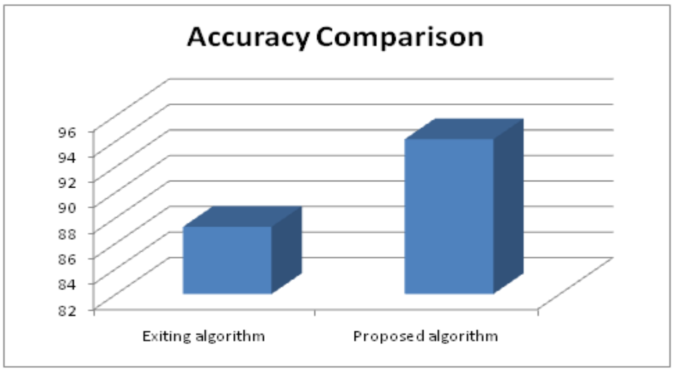

Figure 1: Accuracy Comparison

As shown in Figure 1, the precision of the suggested and current algorithms is compared for performance analysis. It is evaluated that the precision of the current wde-lstm algorithm is less than the suggested WDE-KNN algorithm.

Method	Accuracy
Exiting algorithm	87.26
Proposed algorithm	94.12

Table 1: Accuracy Comparison

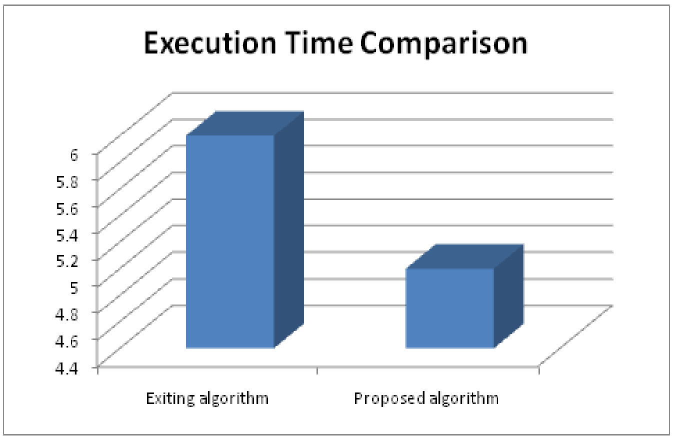

Figure 2: Execution Time Comparison

As shown in Figure 2, the execution time of the suggested and current algorithms is compared for performance analysis. It is evaluated that the execution time of the current wde-lstm algorithm is large compared to the suggested WDE-KNN algorithm.

Method	Execution time
Exiting algorithm	6.02 sec
Proposed algorithm	5.09sec

Table 2: Execution Time Comparison

5. CONCLUSION

In this job, we suggested a novel, profound learning structure called Weakly-supervised Deep Embedding for analysis of phrase sentiment classification. WDE trains profound neural networks by exploiting the rating data of reviews that is widely accessible on many merchant / review websites. Training is a two-step method: first we learn an embedding room that seeks to capture the sentimental distribution of phrases by penalizing relative

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distances between phrases according to weak labels inferred from scores; then we add a softmax classifier to the embedding layer and fine-tune the network with marked information. The review experiments gathered from Amazon.com demonstrate that WDE is efficient and outperforms basic techniques. Two particular snapshots of the structure, the novel WDE-KNN and the novel WDE-LSTM, are suggested..

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