2017 IEEE International Conference on Information Reuse and Integration

Deep Learning for Sentiment Analysis on Google Play Consumer Review

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***Abstract*— In recent years, there has been an increasing interest in sentiment analysis on consumer reviews to understand the opinion polarity on social media. However, little attention has been paid to the development of deep learning for sentiment analysis on consumer reviews in Chinese. The research objective of this paper is to explore the impact of deep learning for sentiment analysis on Google Play consumer reviews in Chinese. A web mining technique was implemented for collecting 196,651 reviews on Google Play. We used Long Short Term Memory (LSTM) deep learning model, Naïve Bayes (NB), and support vector machine (SVM) approaches for sentiment analysis on consumer reviews and compared the experimental results. The experimental results suggest that the accuracy of deep learning for sentiment analysis on Google Play consumer review achieves 94% and deep learning approach outperforms Naïve Bayes (74.12%) and Support Vector Machine (76.46%) in the present study. Our finding confirmed that sentiment analysis on Google Play consumer review with deep learning is outstanding. The contributions of this paper are three-fold. First, the present study confirmed sentiment analysis with deep learning on Google Play consumer review may improve the accuracy of prediction. Second, we create a sentiment dictionary named iSGoPaSD for Google Play review. Third, the study compared the result of average sampling data and non-average sampling data. We found that deep learning method with non-average sampling data reached the better performance.**

Keywords- Deep Learning, Sentiment Analysis, Consumer Review, Recurrent Neural Network (RNN), Long Short Term Memory (LSTM)

I. INTRODUCTION

Social media, defined as a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content [1].

Therefore, when living in a time that the social media is extremely flourishing, a large number of people are enthusiastically using social media to share their comments, feelings and experiences. In addition, the online retailer also provides consumers a platform to discuss the product testing, product quality and product reviews. Nevertheless, there is a great deal of difference between online retail and traditional retail industry. For example, in the past, the consumer could know and check the quality of product before buying; however, the online retailer only provides the consumer with product pictures in order to make them know the product's quality. Under such circumstances, the consumer tends to rely on the word-of-mouth publicity and user-generated reviews [2].

In order to study and analyze a great amount of consumer reviews, the application of sentiment analysis seems to be even more crucial. Currently, this analysis is often used to evaluate the rating of product and the preference of the public. Consequently, researches and techniques accompanying with such analysis became more and more prevalent and mature.

In recent years, opinion mining and sentiment analysis are abundantly used in documents to find out subjective opinions of the public and understand how they feel, how they think. Liu [3] defined sentiment orientation can be divided into three categories: positive, negative and neutral. For the subjectivity and sentiment analysis, we have to categorize if the reviews' orientation is positive, negative, but not neutral, because the neutral category represents only the neutrality of opinions and also statements of fact.

Recently, as the usage rate of social media becomes higher, the consumer can acquire the product reviews easily and quickly. However, there is no doubt that the consumer will take a lot of time to obtain the useful information from such abundant data.

For this reason, there are many researches applying sentimental analysis to consumer review survey, even SemEval-2016 uses consumer reviews in competitions. Still, there are few researches applying deep learning methods to consumer reviews survey in Chinese. Sun et al. [4] used sentiment analysis to study Weibo during their research and discovered that the performance of deep learning is higher than traditional methods such as NB and SVM.

As a result, we apply the deep learning to sentiment analysis in this study and focus on consumer reviews in smartphone domain. Moreover, we are going to use the sentiment dictionary, deep learning method and the opinion dictionary to evaluate and analyze the consumer reviews in smartphone domain and try to discover the opinion polarity of the consumer.

In this study, we collected the consumer reviews for mobile applications as the basis of the polarity analysis. And by accompanying with deep learning method, it allows us to have a higher accuracy.

The main objectives of this study include:

1. Use many sorts of relevant polarity analysis with deep learning method and compare it with the result of general machine learning. In this way, we can see if there are differences in performance between these methods.

978-1-5386-1562-1/17 $31.00 © 2017 IEEE
DOI 10.1109/IRI.2017.79

2. In the sentiment analysis research, the existence of opinion dictionary has a great impact on the accuracy. However, there were few researches applying the sentiment dictionary to mobile applications in Chinese in the past. Thus, we are going to extend the sentiment dictionary in mobile application domain while conducting the corpus analysis.

The remainder of this paper is organized as follows. Selection 2 describes the literature on sentiment analysis and deep learning. Section 3 shows the methodology. Section 4 shows the experimental results and discussion. Finally, Section 5 presents conclusions.

II. RELATED WORKS

A. Sentiment Analysis

Sentiment analysis or opinion mining is the computational study of people's opinions, sentiments, attitudes, and emotions expressed in written language [3].

Nowadays, due to the fact that the Internet is very well developed, there are more and more consumers post their comments on the Internet to express their own opinions about products. Yet, the sentiment analysis needs to collect a great deal of consumer reviews, to see if the opinions are positive or negative and to apply it to business purposes. The analysis methods can be divided into two main categories: sentiment classification and feature-based opinion mining. More than that, the sentiment classification can also be divided into two groups: corpus-based approach and dictionary-based approach [5].

- Corpus-Based Approach

The most commonly used way is to obtain the information by putting some emotional words in a large corpus and acquire the emotional score from these words. For example, the researches in the past put the word such as "happy" and "sad" in the corpus to evaluate the happiness factor of blogs.

- Dictionary-Based Approach

This approach is to find out the emotional adjectives in an article and use lexicon in order to obtain the emotional score of such adjectives and judge the polarity of the article.

- Feature Based Opinion Mining

In the sentiment analysis, the feature engineering is the most basic and important factor. Feature extraction can be divided into 6 different groups:

1) Term Frequency: Classify by the word usage frequency

2) Part of Speech (POS): Feature on the basis of grammatical properties of words

3) Opinion Words and Phrases: Consider opinion words and phrases as the feature.

4) Rules of Opinions: Use grammatical rules of self-defining words to find out features.

5) Negation: Negative words

6) Syntactic Dependency: Syntax tree

B. Opinion Dictionary

The opinion dictionary is mainly to evaluate the emotional words of corpus and adverbs which emphasize on emotions. In addition, the corpus can be divided into three different levels: articles, sentences and words. Among these three groups, words are the smallest but the most meaningful unit in the corpus. Therefore, to calculate the polarity of the corpus, we need to dismantle the articles into words. Then, the result can be sorted out after we checked the opinion dictionary.

- HowNet

HowNet [6] is an on-line common-sense knowledge base unveiling inter-conceptual relations and inter-attribute relations of concepts as connoting in lexicons. It contains 4,566 positive terms (including 3,730 positive opinion terms and 836 positive sentimental terms), 4,589 negative terms (including 1,254 negative opinion terms and 219 negative sentimental terms) and 219 adverbs.

- NTUSD:

NTUSD (National Taiwan University Sentiment Dictionary) is a Chinese sentiment dictionary provided by National Language Processing Laboratory of National Taiwan University. It consists of General Inquirer (GI) in Chinese version and Chinese Network Sentiment Dictionary (CNSD). It contains 2,810 positive terms and 8,275 negative terms in total. The opinions words only can be divided into positive and negative words, and these words don't possess degrees of attribute and polarity, which belong to single opinion tendency.

C. Neural Network

The origin of neural network can be traced back to 1943. McCulloch & Pitts believed that neural network consists of neuron, soma, axon and synapses [7]. It is also called neural computing and artificial neural networks, a parallel computing of biological neural network simulation [8]. It is connected by massive neurons and it allows us not only to conduct parallel computing but to learn from the samples [9].

American psychologists Rumelhart, McClelland, and Group proposed back-propagation neural networks in 1986 [9]. The advantages of this method include the simplicity, and it doesn't need the perceptron as general neural network. It can be utilized in any nonlinear network [11].

Besides, the accuracy of back-propagation neural networks depends on the volume of learning data. For this reason, it has been applied to a variety of domains in recent years [10].

D. Activation Function

Activation function is a nonlinear function in which we place input of each neuron and do the weight aggregation. Without a nonlinear activation function, the result of deep learning will be the same as that of general neural network.

The following examples are the most commonly used nonlinear activation functions:

1. Sigmoid Function: the most common activation function in back-propagation neural networks. The input range is from 0 to 1.

2. Tanh Function: It is a rescaled version of Sigmoid Function, the input range of this function is from -1 to 1.

3. Rectified Linear Unit (ReLU): The input range of ReLU is $[0, \infty]$. It means that any input is less than 0, the output will be 0; otherwise the output will be exactly as the input. Because

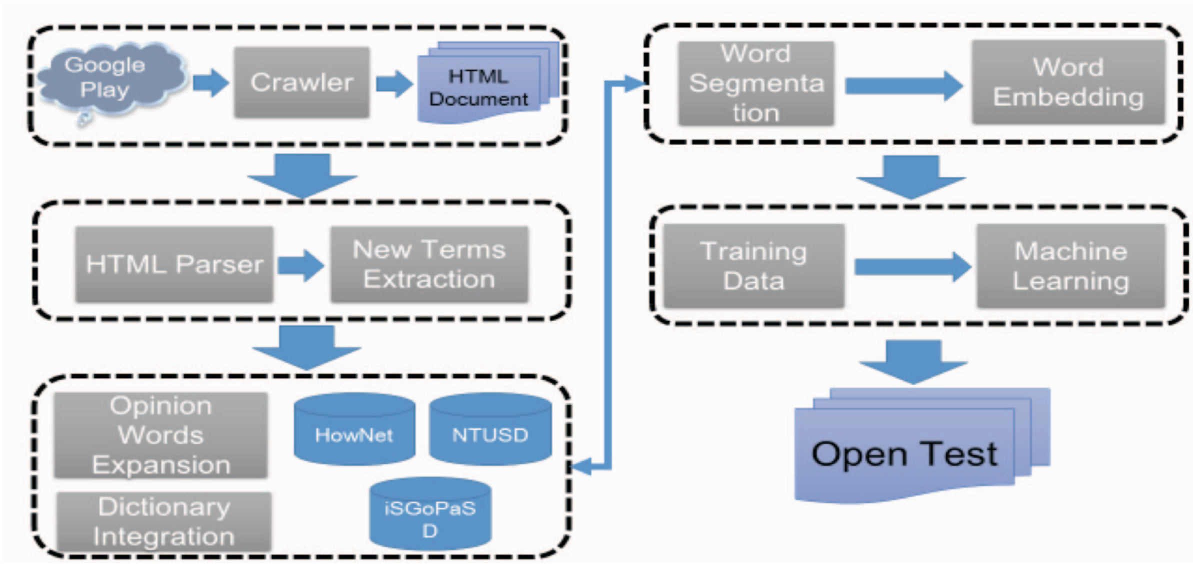

Figure 1. System Architecture of Deep Learning for Sentiment Analysis on Google Play Consumer Review

this linear function effectively improves the speed, ReLU has become the most commonly used function in recent years [15].

E. Deep Learning

As the researches of Natural Language Processing (NLP) developed quickly these days, some scholars found out that the traditional analysis methods are not quite sufficient or the results are not very satisfied. For example, joint learning might cause problems such as excessively long time training and overfitting [12]. The developed techniques of deep learning had a great impact on the performance of NLP.

Since the concept of deep learning came out [13], it has been successfully applied to NLP, image recognition and voice recognition technologies. Researches in the past, for example, Bourlard and Morgan [14] combined the Hidden Markov Model (HMM) with Automatic Speech Recognition (abbrev. ASR) [14]. After the potential of deep learning is discovered, the studies proved that Recurrent Neural Networks (RNN) did show satisfying results when it is used in sequential data, linguistic analysis, word recognition and also word prediction [15].

F. Long Short Term Memory

The developed Internet technology led us to the time of social network big data, and then a great deal of consumers uses social networks to share their own comments and reviews. To find out the messages in the corpus, it seems that recurrent neural network is too limited for NLP. The studies also showed that, during the long-time recurrent neural network, the gradient vector keeps to grow or decline [16], and it eventually results in vanishing gradient and exploding gradient [17]. To solve the insufficiency of recurrent neural network, Hochreiter and Schmidhuber [18] proposed the model of long short term memory (LSTM) in 1997 [18]. LSTM is one sort of recurrent neural network. It consists of three parts: input layer, output layer and forgot gate. LSTM uses forgot gate to choose those data which need to be memorized or forgotten in order to solve the problems for insufficient long-term learning of recurrent neural network.

III. 3. METHODOLOGY

In this study, we use "Systems Development Research Methodology" from information system research field as our research methodology [19].

A. System Architecture

Figure 1 shows the system architecture of deep learning for sentiment analysis on Google Play consumer review. The system architecture of this study, Sentiment Analysis with Deep Learning for Consumer Review on Social Media, is shown as follows:

- Mobile Application Information Extraction and Collection of Consumer Reviews: We have developed a crawler to collect the information of mobile, such as its name, star rating, developer and the comments, reviews and the text content from consumers.
- Data Preprocessing: In data preprocessing stage, we have implemented the processing the corpus content and word segmentation.
- Integration of Dictionaries: We have integrated opinion words in HowNet and NTUSD, and the Google Play domain sentiment dictionary named iSGoPaSD created by this study.

- Model development: We used Word2vec to generate training data, which is necessary for machine learning.
- Machine Learning: We used training data for machine learning in order to generate a training model.
- Validation and Test: We utilized the training model to analyze the test data and lead to a result.

B. Consumer Review collecting

The resources of corpus for this study come from the consumer reviews on Google Play. This website is a platform created by Google for mobile application developers to share or sell their mobile applications. There is a great amount of users on this website and its searching engines are clearly classified according to various mobile applications.

The information for all the products is complete in this platform, including the title of the application, name of developer, star rating, etc. Consumers are allowed to share their reviews on the platform for other users after using the product. The website counts automatically the rating, consumer reviews and the number of users to give a score for overall rating.

In this study, we create a web crawler by the technique of web mining. From the classification of Google Play, there are 53,172 results of free education applications, 1,456 results of paid education applications, 138,622 results of free tools applications and 3,401 results of paid tools applications, 196,651 results in total. The consumer comments in these four categories will be seen as the language of experiment analysis.

C. Data pre-processing

The information taken from Google Play is all belonging to semi-structured data or unstructured data. Therefore, we need to normalize the data before analyzing it to obtain an effective result.

- Remove HTML Tag: Remove the HTML data on the web page data and only keep the application information.
- Take Useful Information: Take the information that needs to be analyzed; for example, the title of mobile application, the name of developer, star rating of application, the classification of application, name of consumer, star rating of consumer and content of reviews.
- Number the Reviews: Number the reviews according to the category of applications.

D. New-Term Extraction

Regarding new term extraction, we use Yet Another Suffix Array (YASA) in this study to search for unknown emotional words in mobile application domain. The principles of YASA are to use suffix array for analyzing massive words, and find out the words appearing with a high frequency and how many time they appeared in the corpus. YASA only needs to configure the minimum of alphabets and the threshold limit value of frequency to obtain the combination of alphabets and the frequency.

TABLE 1. FEATURES USED IN MACHINE LEARNING APPROACH

ID	Future Name	Feature Description
F01	HowNet_Positive	Positive words in HowNet
F02	HowNet_Negative	Negative words in HowNet
F03	HowNet_PNDiff	The difference between Positive and Negative words in HowNet
F04	HowNet_Ratio	The opinion words ratio in HowNet
F05	NTUSD_Positive	Positive words in NTUSD
F06	NTUSD_Negative	Negative words in NTUSD
F07	NTUSD_PNDiff	The difference between Positive and Negative words in NTUSD
F08	NTUSD_Ratio	The opinion words ratio in NTUSD
F09	iSGoPaSD_Positive	Positive words in iSGoPaSD
F10	iSGoPaSD_Negative	Negative words in iSGoPaSD
F11	iSGoPaSD_PNDiff	The difference between Positive and Negative words in iSGoPaSD
F12	iSGoPaSD_Ratio	The opinion words ratio in iSGoPaSD
F13	iSGoPaSD_ HN_Pos	Positive words in HowNet, iSGoPaSD
F14	iSGoPaSD_ HN_Neg	Negative words in HowNet, iSGoPaSD
F15	iSGoPaSD_ HN_PNDiff	The difference between Positive and Negative words in HowNet, iSGoPaSD
F16	iSGoPaSD_ HN_Ratio	The opinion words ratio in HowNet, iSGoPaSD
F17	iSGoPaSD_ NTUSD_Pos	Positive words in NTUSD, iSGoPaSD
F18	iSGoPaSD_ NTUSD_Neg	Negative words in NTUSD, iSGoPaSD
F19	iSGoPaSD_ NTUSD_PNDiff	The difference between Positive and Negative words in NTUSD, iSGoPaSD
F20	iSGoPaSD_ NTUSD_Ratio	The opinion words ratio in NTUSD, iSGoPaSD
F21	iSGoPaSD_ HN_NTUSD_Pos	Positive words in HowNet, iSGoPaSD, NTUSD
F22	iSGoPaSD_HN_ NTUSD_Neg	Negative words in HowNet, iSGoPaSD, NTUSD
F23	iSGoPaSD_HN_ NTUSD_PNDiff	The difference between Positive and Negative words in NTUSD, iSGoPaSD, HowNet
F24	iSGoPaSD_HN_ NTUSD_Ratio	The opinion words ratio in NTUSD, iSGoPaSD, HowNet

After the information is settled, we conduct the cross-reference among word TF-IDF results, NTUSD and HowNet, and we remove repetitive and general opinion words. Eventually, we choose manually 18 positive words and 25 negative words and put them into the emotional words in mobile application domain, so-called "iSGoPaSD".

E. Feature Generation

After the data preprocessing and new term extraction of Google Play mobile application reviews are finished, we can start to generate and calculate the features. This experiment is based on three dictionaries: NTUSD, HowNet and iSGoPaSD in order to have 24 features eventually as the basis of positive and negative words. Table 1 shows the 24 features used in machine learning approach.

F. Word Embedding Generation

Word embedding is also known as word representation or word embedding. The origin of word embedding can be traced back to 1986, known as distributed representation proposed by Hinton. The word embedding is able to change the words into the low dimensional real vector and it allows us to discover the similarity of words based on cosine method.

Mikolov et.al [20] proposed CBOW and Skip-gram in his research. It allows us not only to simplify the complexity and reduce the time for calculation, but to change trillions of billions of words into word embedding [20].

G. Deep Learning

LSTM cell in recurrent neural network (RNN) is used as a way to conduct sentiment analysis in this study, and we utilized Keras (https://keras.io/) as the deep learning tool.

Keras is high-level neural networks which support Tensorflow and Theno as backend. Moreover, Keras is an easy-to-learn deep learning tool and allows us to use GPU to speed up the process.

There are three steps for this experiment:

1. Word Segmentation: Within the recognizable range of Nature Language Processing (NLP), the « word » is the minimum unit. In order to judge the emotions of consumer, we have to turn the corpus into minimum units in this study.

The tool of word segmentation we usedd in this study is Jieba, a source code that assists Python to segment words in Chinese (https://github.com/fxsjy/jieba). Then, we use the prefix dictionary with dynamic programming word segmentation based on Viterbi of HMM (Hidden Markov Model) to segment new Chinese words. In addition, the consumer can add their own defined dictionaries to elevate the accuracy of word segmentation.

2. Word Embedding Generation: In this step, we use Gensim in Python to build up a word embedding model accompanying with Word2Vec to calculate the similarity and the term frequency between a word and the another word.

(https://radimrehurek.com/gensim/install.html)

3. Deep Learning Model Training: Use the word embedding generation as the training data of LSTM during the deep learning. Applying different activation functions helps us to find out the best learning result.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The experiment result of this study will be discussed and depicted in details in this chapter. The experiments include the distribution of experiment data and the assessment methods of experiment result.

A. Data Distribution

The consumer reviews on Google Play mobile application website are the language of experiment for this study. After removing the neutral data with 0 and 3 stars (the rating of reviews is from 1 to 5) from 196,651 reviews, there are 195,651 reviews left. The training data research of Tomar indicates that the data volume of each category influences the accuracy of the result. However, collected positive reviews in this study are more than those are negative. To solve this problem, Tomar proposed the solutions such as under-sampling and over-sampling. Under-sampling method is to decrease the large-volume classification data in order to balance out the small-volume classification data; whereas over-sampling method is to increase the small-volume classification data in order to balance out the large-volume classification data [21]. The under-sample method is used in this study; thus, we decreased the positive reviews for keeping a precise accuracy.

B. Experiment Design

In this study, the machine learning is used to analyze emotions and to compare and evaluate the results.

- Experiment 1: Use Naïve Bayes to find out the review data.
- Experiment 2: Generate the review features in Google Play mobile application website. Then use support vector machine (SVM) to build up a model and then to predict.
- Experiment 3: Use deep learning LSTM to train a prediction data model of reviews.

C. Sentiment Analysis with Naïve Bayes (NB)

In this experiment, we divided the language of experiment into positive data and negative data. And we use three opinion dictionaries: HowNet, NTUSD and iSGoPaSD to build up prediction model by Naïve Bayes

Table 2 shows the accuracy of sentiment analysis using Naïve Bayes (NB). From this experiment, it suggests that the specific modeling and prediction data of Naïve Bayes. The accuracy of NTUSD is 74.08% and HowNet is 74.12%. The integrated accuracy of both NTUSD and Hownet is 73.95%

TABLE 2. ACCURACY OF SENTIMENT ANALYSIS USING NAÏVE BAYSE (NB)

Dictionary used in Naïve Base	Accuracy
NTUSD	74.08%
HowNet	**74.12%**
NTUSD+HowNet	73.95%
iSGoPaSD+NTUSD+HowNet	73.85%

TABLE 3. 10-FOLD CROSS VALIDATION RESULTS OF SUPPORT VECTOR MACHINES (SVM)

K-Fold Cross Validation	Accuracy
01	**71.13%**
02	77.04%
03	77.05%
04	77.03%
05	77.05%
06	77.13%
07	77.04%
08	77.03%
09	77.04%
10	77.03%
Average Accuracy	**76.46%**

and the integrated accuracy of three dictionaries, iSGoPaSD, NTUSD and HowNet is only 73.85%. The result shows that using HowNet achieve the highest accuracy.

In the experimental results, we found that the decreased accuracy is due to the fact that polarity of rating and the consumer reviews are not identical, which can easily cause the misjudge of model prediction.

D. Sentimental Analysis with Support Vector Machine (SVM)

We used the generated features based on opinion dictionaries in the training data for the sentimental analysis with support vector machine. The prediction data generated after the training is mainly for exanimating learning results based on the same database but with different machine learning. We found out that the optimization parameter of c is 32.0 and g is 0.5. Then we use 10-fold cross validation to find out the average accuracy. Table 3 shows the 10-fold cross validation results of support vector machines (SVM)

E. Sentiment Analysis with Deep Learning (DL)

In the experiment, we use LSTM cell in recurrent neural network (RNN) for modeling the opinion tendency of consumer reviews. At first, we need to change the corpus into the word embedding through Word2vec. After that, we build up a prediction model according to the positive and negative training. The objective of this experiment is to see the differences of result by comparing LSTM and other machine learning prediction models. Therefore, the prediction model with the best accuracy can thus be found out by cross testing. Table 4 shows the accuracy of deep learning with long short term memory (LSTM). The experimental result of sentiment analysis with deep learning achieve 94% accuracy.

In summary, Table 4 provides the comparison of the accuracy of three approaches (LSTM, NB, and SVM) for sentiment analysis. Figure 2 shows the accuracy of machine learning and deep learning for sentiment analysis on Google Play consumer review.

TABLE 4. ACCURACY OF DEEP LEARNING WITH LONG SHORT TERM MEMORY (LSTM)

Activation Function	Accuracy
ReLu	83.23%
Sigmoid	77.65%
Tanh	**94.00%**

TABLE 4. COMPARISON OF THE ACCURACY OF THREE ARROACHES FOR SENTIMENT ANALYSIS

Machine Learning Approaches	Accuracy
Naïve Bayes (NB)	75.12%
Support Vector Machin (SVM)	76.46%
Deep Learning with Bi-LSTM	**94.00%**

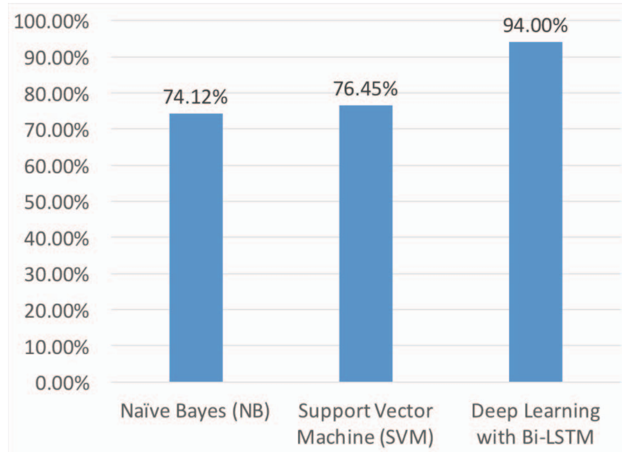

Figure 2. Accuracy of Machine Learning and Deep Learning for Sentiment Analysis on Google Play Consumer Review

V. CONCLUSION

In this study, different machine learning methods are used by accompanying with the review data of Google Play. For this reason, we can conclude as follows: the study can prove the prediction models trained by deep learning through experiments in order to elevate the prediction accuracy for the classification of sentiment analysis.

The contributions of this paper are three-fold. First, the present study confirmed sentiment analysis with deep learning on Google Play consumer review may improve the accuracy of prediction. Second, we create a sentiment dictionary named iSGoPaSD for Google Play review. Third, the study compared the result of average sampling data and non-average sampling data. We found that deep learning method with non-average sampling data reached the better performance.

As the usage rate of smartphone is becoming higher, the consumer also often uses a lot mobile applications to improve their quality of life; for this reason, the reviews from the public raised accordingly. However, it is difficult and it takes quite a long time to analyze such massive review data.

From the result of this study, we can prove that the deep learning increases the accuracy of prediction. The developers of mobile application can thus come up with a better solution to meet the needs of consumer; moreover, they can improve their own application by comparing the advantages and disadvantages of others. Even though we only analyzed the reviews under two categories: education and tools application in this study, it can be applied to other reviews as well.

For the research in the future, we propose the following points with regards to the research above:

- The collected review data in Google Play only include education and tools application categories. We suggest to collect more data in different categories as the experiment corpus for the future research.
- From the Chinese Google Play review data in Taiwan, there are many people using emotion to express their opinions and comments. If we can include this element in the research, the sentiment analysis will be more complete.

ACKNOWLEDGMENT

This research was supported in part of TKU research grant and Ministry of Science and Technology, Taiwan. We would like to thank the support of IASL, IIS, Academia Sinica, Taiwan.

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