Sentiment Analysis on Customer's Comments of Myanmar Cosmetic Products

Yu Mon Win Myint
Information Technology Supporting and Maintenanc, University of Computer Studies (Taunggyi)
yumonwinmyint247@gmail.com

War War Cho
Faculty of Computer Science, University of Computer Studies (Maubin)
warwarcho@ucsmub.edu.mm

Tin Nilar Win
Information Technology Supporting and Maintenance, University of Computer Studies (Taunggyi)
tinnilarwin.sushwnwady@gmail.com

Abstract

Today, people don't necessarily go outside for buying their daily use products. There are many door-to-door delivery services and online shopping to fulfill their needs. However, the expectation of the products and the reality will not be the same every time. In such cases, honest reviews comments of real customers will help to avoid buying poor quality products. This paper emphasizes classifying the customer's sentiment on Myanmar cosmetic products and we identified three sentiment polarities: positive, negative, and neutral. We collected and annotated the customer's comments from Facebook pages of the most popular cosmetic products in Myanmar. The experiment is performed by Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) model on the customer's comments datasets. According to the experiment, the LSTM model performs better than the RNN model. The average accuracy of the LSTM model is 91% and the RNN model is 89%.

Keywords: Sentiment, Recurrent Neural Network, Long Short Term Memory, Cosmetics

1. Introduction

Sentiment analysis of the cosmetic product plays an important role in decision making to buy a good quality product without time-consuming and much effort. The product review comments can help customers and the products without any review comment are not popular among customers. This review comments also affect any business company and negative customer's comments lead to financial loss and positive comments bring success. In Myanmar, most of people use Facebook social media and the customer's comments on Facebook can influence most of the people and it can even change the life of some people. The cosmetic products are daily-use products and important for most of the people. The good quality cosmetic products can help people to be smart and confident in their routine. Most of the customers decide to purchase a cosmetic product in many factors such as price, quality, and brand. Although there are many cosmetic websites and Facebook pages that allow customers to write comments, most of the customers cannot read all the comments because there are many comments by many customers and some are confused to make the decision. The sentiment classification system can help to decide to purchase the cosmetic product. It can calculate the positive and negative probability of each product to save time for reading many comments. In this paper, the sentiment of customers on cosmetic products is analyzed by using Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) model on customer's comments in the Myanmar language. The detail of the paper is described as follows, section 2 describes some related works of sentiment analysis in lexicon-based, machine learning, and deep learning approaches for both Myanmar and English text. Section 3 explains the details of collecting cosmetics reviews comments in Myanmar text. Section 4 describes the pre-processing step and section 5 discusses the word embedding technique. Section 6 presents the sentiment analysis on cosmetic products by comparing the performance of Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) models. Section 7 concludes the paper.

2. Related Work

Sentiment analysis is one of the important application areas in Natural Language Processing and text mining. It was implemented by many researchers by using Machine learning, deep learning, and variant models. In this section, we investigate some of the related work for sentiment analysis on both Machine learning and deep learning models. TT Zin et al. [7] constructed a domain-specific sentiment lexicon for classification in Myanmar language by using word correlation and chi-square statistics. NEE Kyaw et al. [4] implemented a recommender system using feature-based sentiment analysis that extracts semantically related features for finding users' preferences from review text. WLK Khine et al. [8] applied deep learning models to targeted aspect-based sentiment analysis in the restaurant domain. HMS Aung et al. [2] presented the comparison of three different machine learning models for sentiment analysis of the Facebook page's comments in the Myanmar language. R Moraes et al. [5] presented an empirical comparison between Support Vector Machine (SVM) and Artificial Neural Network (ANN) for document-level sentiment classification. YM Aye et al. [9] constructed sentiment lexicon in Myanmar language for the food and restaurant domain and calculated the sentiment polarity. KZ Aung et al. [3] presented a lexicon-based sentiment analysis to evaluate teaching performance by using student's comments.

This paper aims to show the empirical comparison of Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) model to analyze sentiment on Cosmetics products by using comments of the customers.

3. Data Collection

There are many popular cosmetic brands on Facebook social media in Myanmar, *Bella, Nature Republic, SAI Cosmetix*, and so on. Among them, Bella's and Nature Republic's cosmetics got attention in most of the Myanmar people and many positive comments can be seen in most of their cosmetics products. The main difficulty of collecting comments on Facebook social media is to collect negative reviews comments. Most of the negative reviews comments are deleted by the page admin because it can entirely affect their business. Such kind of Facebook has very few comments to analyze their products and avoid by most of the customers. In this paper, we collect positive, negative, and neutral comments from various sources of Facebook pages of cosmetic products. Most of the positive and neutral comments are collected from Bella [11] and the Nature Republic [12] Facebook page.

Table 1. Example of positive comments

No	Positive Comment	Label
1	အရမ်းတန်ချက် (Very Reasonable price)	Positive
2	EyeSerumလေးကိုအရမ်းကြိုက်ပါတယ်။ (I like EyeSerum very much.)	Positive
3	အမယ်လေးနော် လိုချင်လိုက်တာအမောပဲ (Wow! I want it)	Positive

Table 2. Example of neutral comments

No	Neutral Comment	Label
1	သန်လျင်ဆိုဘယ်မှာဝယ်လို့ရလဲရှင် (Where can I buy in Thalyin?)	Neutral
2	နှစ်မျိုးကိုဘယ်လောက်ကျမလဲ (How much is it for two products?)	Neutral
3	တောင်ကြီးမှာဘယ်မှာရနိုင်လဲ(Where can I buy in Taunggyi?)	Neutral

Table 3. Example of negative comments

No	Negative Comment	Label
1	ဈေးအရမ်းယူထားတယ် (Very Expensive)	Negative
2	ထုတ်ပိုးမှုကလည်းဖြစ်ကတတ်ဆန်း (Bad packaging)	Negative
3	တော်တော်ဆိုးဆိုးပဲနော် (Very bad)	Negative

The negative comments are collected from some of the notorious cosmetics that were disproved by the Food and Drug Administration (FDA), Myanmar and they had many customers complain. These pages were reported on Facebook by many customers and the negative comments are collected from some of the customer's bad feeling posts regarding these cosmetics. The samples of positive, negative, and neutral comments are listed in Tables 1, 2, 3. Table 1 lists the positive opinion of the customers, the first comment shows the recommendation of a customer in the price of the product, and the second comment shows the satisfaction of a customer on *Eye Serum* products and the next one express that the product is desirable for a customer. Table 2 describes the neutral comments that do not express the positive and negative feelings and just only the query for purchasing products. Table 3 expresses the negative feeling for a product. The negative feeling can be originated from many points of view such as bad packaging, poor quality, unreasonable price, and bad customer service. The positive, negative, and neutral dataset for cosmetic products are annotated by three Myanmar native annotators. The total number of comments on the cosmetic product is listed in Table 4 and train and test data are separated into 80% and 20%.

Table 4. Customer's comments dataset

Sentiment	No. of Comments
Positive	4,553
Neutral	1,517
Negative	502

4. Pre-processing

The unnecessary characters such as emoji, sticker, punctuation marks, English character, and the number are removed from the collection of customer's comments. The Myanmar text is segmented into words by a tokenizer.

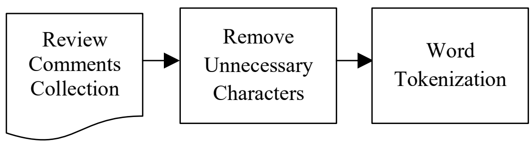


Figure 1. Pre-processing process flow of customer's comments

5. Word Embedding

In the word embedding phase, we use the word vector that was trained by using FastText [1] Skip-gram model, an extension of the *Word2vec* model. The distinction of FastText skip-gram model over word2vec model is the conversion of sub-word to vector instead of the word to vector to detect rare words. Word2vec model contains two models: the Skip-gram model and the Continuous Bag of Word (CBOW) model and FastText also contain these two models. In the Skip-gram model, the context words (w_{c-2}, w_{c-1}, w_{c+1}, w_{c+2})

can be predicted by a target word (w_t). Figure 1 illustrates the basic structure of the Skip-gram model. The conditional probability of the context words for a target word is calculated by Softmax function in the Skip-gram model. In this paper, the word vectors trained on Wikipedia text data by the FastText Skip-gram model with 300 dimensions and the size of the word vector is 91,497. The tokenized words from section 4 are converted into word vectors by matching vocabulary from the FastText Skip-gram model.

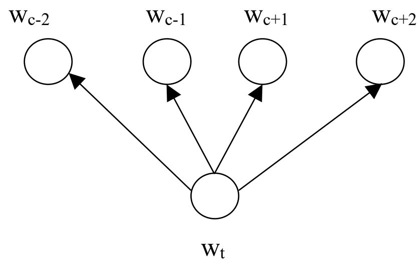


Figure 2. Skip-gram model

6. Sentiment Analysis on Customer's Comments of Cosmetic Products

In this paper, the sentiment of customers on cosmetic products is classified by using Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) model.

6.1. Recurrent Neural Network (RNN)

RNN is the extension of the Artificial Neural Network that contains memory to understand sequential data. In traditional Neural networks, all input and output are independent. In the RNN model, the output depends on previous inputs and performs the same task for all input and output data recurrently. In this paper, the sentiment of the cosmetic comments is predicted by the RNN model and compares the performance result with the LSTM model.

6.2. Long Short Term Memory (LSTM)

LSTM model is the special kind of RNN model that capable of long term dependencies. The nature of the LSTM model is the ability to remember long periods of information as to its default behavior. It contains three processes states: forget gate, input gate, and output gate.

Table 5. Software requirements

Name	Version
Bpemb	0.3.0
Jupyter notebook	6.0.3
Keras	2.3.1
Tensorflow-gpu	2.1.0
Gensim	3.8.1
Conda	4.8.3
Conda-env	2.6.0

6.3. System Requirements

Sentiment analysis on customer's comment of cosmetics product is implemented on Jupyter notebook with Conda environment. Table 5 describes the most important library and the related version. Table 6 shows the hardware status to implement the system.

Table 6. Hardware requirements

Processor	Intel® Core ™ i51035G1 Processor
RAM	4GB
Graphic	NVIDIA® GeForce® MX230
Hard Drive	1TB 5400 rpm 2.5" SATA Hard Drive

6.2. Performance Comparison

The performance of the sentiment analysis of RNN and LSTM model on cosmetic reviews comments are compared in terms of precision, recall, F1 score metrics, and average accuracy for each metrics are illustrated in Figures 3, 4, 5, 6. The overall accuracy for all comments by the RNN model is 89 % and the LSTM model is 91%. According to the experiment, the LSTM model performs 3% and 1% better than the RNN model in precision and f1-score of positive comments dataset. In the neutral comments dataset, the LSTM model performs better in all metrics with 3%, 4%, and 3% respectively. In the negative comment dataset, the RNN model performs 4% better than the LSTM model in precision, and the LSTM model performs better than the RNN model in recall and f1-score. The hyper-parameters used in the comparison model are set equally as listed in Table 7.

Table 7. Hyper-parameter Setting for Comparison Models

Embedding Dim	300
Optimizer	Adam
Epoch	10
Batch Size	128
Activation	Sigmoid
Dropout	0.5

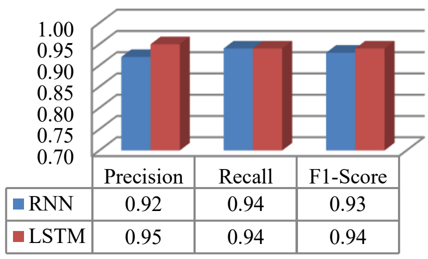
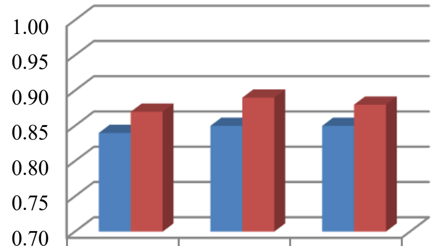


Figure 3. Performance comparison of positive comments

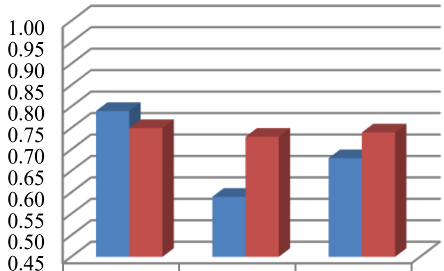


	Precision	Recall	F1-Score
RNN	0.84	0.85	0.85
LSTM	0.87	0.89	0.88

Figure 4. Performance comparison of neutral comments

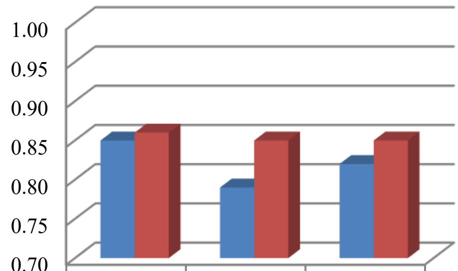
7. Conclusion

In this study, we collected and annotated the cosmetics reviews comments dataset in Myanmar text and performed a comparative analysis of RNN and LSTM on this dataset. According to both our knowledge and the experiment results, the LSTM model performs better than the RNN model in most conditions with an equal hyper-parameters setting. The performance of both models little degrade on negative comments data because of the small number of training and testing negative text data. We will collect more data and perform experiments with other machine learning and deep learning models in the future.



	Precision	Recall	F1-Score
RNN	0.79	0.59	0.68
LSTM	0.75	0.73	0.74

Figure 5. Performance comparison of negative comments



	Precision	Recall	F1-Score
RNN	0.85	0.79	0.82
LSTM	0.86	0.85	0.85

Figure 6. Average Performance comparison on all comments

References

[1] A Joulin, É Grave, P Bojanowski, T Mikolov. "Bag of Tricks for Efficient Text Classification". In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers 2017 Apr (pp. 427-431).

[2] HMS Aung, WP Pa. "Analysis of Word Vector Representation Techniques with Machine-Learning Classifiers for Sentiment Analysis of Public Facebook Page's Comments in Myanmar Text". In 2020 IEEE Conference on Computer Applications (ICCA) 2020 Feb 27 (pp. 1-7). IEEE.

[3] KZ Aung, NN Myo. "Sentiment analysis of students' comment using lexicon-based approach". In 2017 IEEE/ACIS 16th international conference on computer and information science (ICIS) 2017 May 24 (pp. 149-154). IEEE.

[4] NEE Kyaw, TT Wai. "Implementation of Recommender System Using Feature-Based Sentiment Analysis". The 2nd International Conference on Advanced Information Technology (ICAIT 2018). Yangon, Myanmar.

[5] R Moraes, JF Valiati, WP Neto. Document-level sentiment classification: An empirical comparison between SVM and ANN. Expert Systems with Applications. 2013 Feb 1;40(2):621-33.

[6] T Mikolov, K Chen, G Corrado, J Dean. "Efficient estimation of word representations in vector space". arXiv preprint arXiv:1301.3781. 2013 Jan 16.

[7] TT Zin, KT Yar, SS Htay, KK Htwe, NTT Aung, WW Thant,"Domain-Specific Sentiment Lexicon for Classification", the 1st International Conference on Advanced Information Technologies, 2017.

[8] WLK Khine, NTT Aung. "Applying Deep Learning Approach to Targeted Aspect-based Sentiment Analysis for Restaurant Domain". In 2019 International Conference on Advanced Information Technologies (ICAIT) 2019 Nov 6 (pp. 206-211). IEEE.

[9] YM Aye, SS Aung. "Sentiment analysis for reviews of restaurants in Myanmar text". In the 2017 18th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing (SNPD) 2017 Jun 26 (pp. 321-326). IEEE.

[10] https://nlp.h-its.org/bpemb/

[11] https://web.facebook.com/BellaBeAStar/

[12] https://web.facebook.com/NatureRepublicMyanmar/