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Analyzing Amazon Customer Sentiments using Recurrent Neural Network Architecture

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Abstract— With the exponential growth of e-commerce, understanding customer sentiments has become increasingly crucial for businesses. As one of the largest online retailers, Amazon generates a vast volume of customer reviews daily, offering valuable insights for companies to enhance their products and services. In this research, a system for analyzing customer sentiments on the Amazon platform is proposed to manage valuable insights into customer preferences and opinions. The main goal of this paper was to find effective marketing strategies to drive profit growth, monitor market trends, and perform competitive analysis. The achieved results by the proposed system were accurate in predicting the sentiments of Amazon customers. The size of the testing set was 1200 for positive reviews and 1200 for negative reviews. The system predicted 995 true positives and 205 false positives for positive reviews, while for negative reviews, it predicted 861 true negatives and 339 false negatives.

Keywords: Sentiments Analysis; Web Scraping; Natural Language Processing.

I. INTRODUCTION

Amazon is a competitive platform. sellers and brand managers face the challenge of making sense of big data and finding ways to outperform their competitors, expand their market share, and drive sales [1]. It is no longer sufficient for sellers to rely solely on cost advantages; instead, understanding customer demands has become a crucial strategy. To achieve e-commerce success, sellers must delve into detailed data that provides valuable insights for enhancing performance and making informed strategic decisions [2]. One significant source of data in e-commerce platforms like Amazon is the abundance of customer-generated content, including reviews, ratings, and feedback. These sources collectively hold a wealth of information that, if properly analyzed, can reveal critical patterns, preferences, and sentiments of customers. Sentiment analysis emerges as a powerful tool that enables businesses to extract meaningful insights from this vast amount of customer-generated

data. Sentiment analysis, also known as opinion mining, is a field of study within natural language processing (NLP) that focuses on analyzing and understanding sentiments, opinions, and attitudes expressed in text. By applying sentiment analysis techniques to customer-generated data on platforms like Amazon, businesses can gain valuable insights into customer sentiments, preferences, and satisfaction levels. This information is invaluable for understanding customer needs, improving products and services, and making data-driven decisions to enhance overall performance.

II. OVERVIEW OF LSTM NEURAL NETWORK

LSTM, short for Long Short-Term Memory, is a type of recurrent neural network (RNN) architecture that addresses the limitations of traditional RNNs when it comes to handling long sequences and capturing long-term dependencies [3]. LSTMs are particularly well-suited for tasks that involve sequential or time-dependent data, such as natural language processing, speech recognition, and time series analysis [4]. "Fig. 1" shows the LSTM architecture.

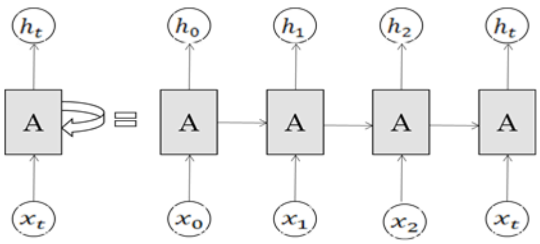

Fig. 1: LSTM Architecture

III. SENTEMINTS ANALYSIS SYSTEM

The comprehensive system consists of two main stages, each serving a specific purpose in the overall process. These stages are:

A. Data Processing Stage

To gain a thorough understanding of data processing, we recommend referring to our previous research titled "Sentiments Analysis: Web Scraping and Natural Language Processing" [5]. This study established a web scraping system that gathered raw data from Amazon and implemented natural language processing techniques to clean and prepare the data for pattern analysis.

B. Pattern Analysis Stage

For this research, we will use the Long-Short-Term Memory (LSTM) architecture to capture the sequential nature of text data, allowing for a more comprehensive understanding of patterns and sentiments in the text.

IV. PATTERN ANALYSIS

The next step in the sentiment analysis process is to analyze the data patterns and extract relevant features that can help in predicting whether a review is positive or negative. This step involves building and training an LSTM neural network model on the preprocessed data. this model takes the preprocessed text data as input and learn to identify patterns and relationships between the words and the sentiment labels positive or negative. The LSTM model architecture consists of several key layers, each serving a specific purpose in the analysis process, as shown in "Fig. 2".

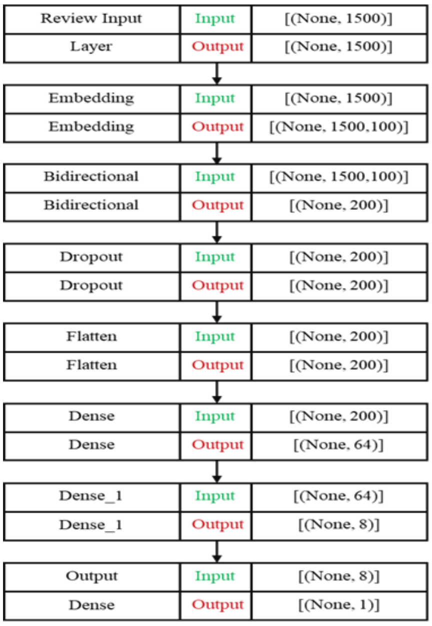

Fig. 2: LSTM Architecture

The steps below illustrate how the layers and parameters of an LSTM architecture interact to generate sentiment analysis predictions as follows:

1. **Review Input Layer:** The input layer expects input data in the form of sequences, where each sequence represents a review, indicating that each review is represented by a sequence of (1500) values.

2. **Embedding Layer:** The embedding layer converts the input word indices into dense vector representations. It maps each word index to a corresponding dense vector of fixed size (100), capturing semantic relationships between words.

3. **Bidirectional LSTM Layer:** The bidirectional LSTM layer processes the input sequence in both the forward and backward directions. It captures information from both past and future contexts, allowing the LSTM model to effectively capture long-term dependencies and context in the text data.

4. **Dropout Layer:** The dropout layer helps prevent over fitting by randomly dropping out a fraction of the input units during training. It introduces regularization and helps the system generalize better to unseen data. In the LSTM model, a dropout rate of 0.5 was used.

5. **Flatten Layer:** The flatten layer reshapes the output from the previous layer into 1D vector. It collapses the multi-dimensional output into a flat representation, preparing it for the subsequent dense layers.

6. **Dense Layers:** The dense layers are fully connected layers that apply a linear transformation to the input data, followed by an activation function. In this system, two dense layers with 64 and 8 units, respectively. They introduce non-linearity and enable the system to learn complex relationships in the data.

7. **Output Layer:** The output layer produces the final prediction of sentiment. In sentiment analysis, the sigmoid activation function was used to obtain a probability value between 0 and 1. This probability represents the predicted sentiment score for the input review.

V. PREPARING DATA for TRAINING and TESTING

A training is a dataset that is used to train system. It consists of the sample output data and the corresponding sets of input data that have an influence on the output. The training is used to run the input data through the algorithm to correlate the processed output against the sample output. The result from this correlation is used to modify the neural network model. This iterative process is called “model fitting”. The accuracy of the training dataset or the validation dataset is critical for the precision of the neural network model. Training a neural network simply means learning (determining) good values for all the weights and the bias from labeled examples. In supervised learning, a machine learning algorithm builds a model by examining many examples and attempting to find a model that minimizes loss, this process is called empirical risk minimization. Loss is the penalty for a bad prediction. That is, the loss is a number indicating how bad the neural network model's prediction is. If the model's prediction is perfect, the loss is zero, otherwise, the loss is greater [6].

VI. SUPERVISED LEARNING

Supervised learning, a popular approach in machine learning, to train the neural network model. Supervised learning involves providing the system with labelled data as shown in "Fig. 3". Where each data point is associated with a known sentiment label (positive or negative). This allows the neural network model to learn the patterns and relationships between the input text and their corresponding sentiments. The training process involves iteratively presenting the labeled data to the model, calculating the prediction error, and updating the model's parameters using optimization [7].

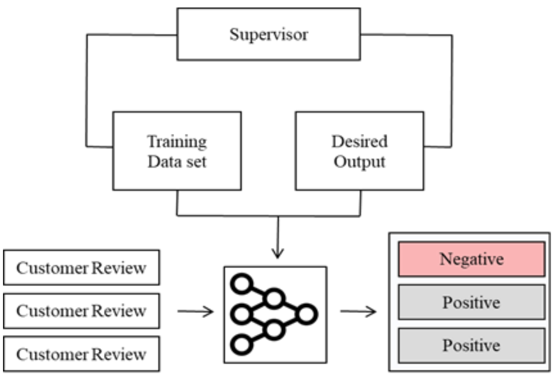

Fig. 3: Supervised Learning

VII. SPLITTING DATASET

Splitting a dataset into a training set and a testing set is a fundamental step in machine learning. The goal of this step is to ensure that the system can perform well on new, unseen data. During this process, the dataset is divided into two sets: one for training the system and the other for evaluating its performance. The testing set is subsequently used to assess the system's performance on new, unseen data. The original dataset was divided into a training set consisting of 5600 rows and a testing set comprising 2400 rows. The size of the testing set was determined to be 0.3, indicating that 30% of the data was allocated for testing, while the remaining 70% was used for training the system, as shown in "Fig. 4".

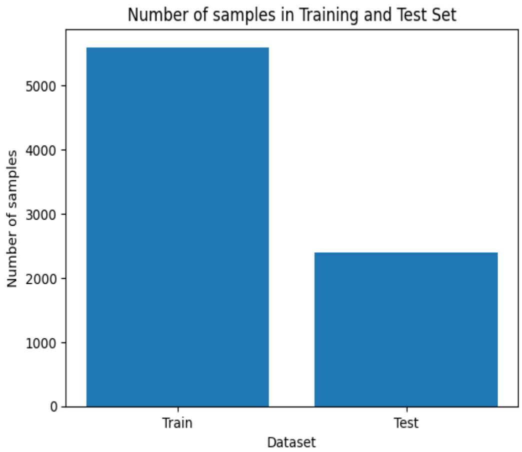

Fig. 4: Testing and Training Samples

VIII. SEPARATING TARGET VARIABLES

In sentiment analysis, it is crucial to segregate the target variable from the input features to ensure an accurate prediction of sentiment based on the provided text. The target variable represents the sentiment or polarity associated with each input text. In this particular context, the target variable corresponds to the "rating" column in the dataset, which contains the sentiment labels or ratings for each text review.

The following steps are performed to separate the target variable:

- The "rating" column is extracted from the dataset and assigned to the variable "y_train" for the training set and "y_test" for the testing set. This step creates two separate datasets for the target variable, each corresponding to the training and testing data.
- The target variable column is then removed from the input feature datasets to ensure that the system does not have access to the sentiment labels during the training process.

IX. SYSTEM TRAINING

The training of a system involves feeding input data to the LSTM model and adjusting its parameters so that it produces the desired output. The training results show the system's performance at each epoch during the training process. The system was trained for 20 epochs, with each epoch consisting of 88 batches of data. The training process took a total of 94 minutes (approximately 1.5 hours) to complete. The training results show that the system's accuracy gradually improved as the epochs progressed. In the first epoch, the system had an accuracy of 59.86%, which improved to 95.68% in the final epoch. Similarly, the loss decreased gradually from 0.7742 in the first epoch to 0.1331 in the final epoch. This indicates that the system is learning from the training data and becoming more accurate in its predictions. The validation accuracy also shows a similar trend, gradually increasing from 61.54% in the first epoch to 77.33% in the final epoch. This indicates that is performing well. Overall, the training results show that the system is learning from the data and improving its accuracy over time as shown in "Fig. 5".

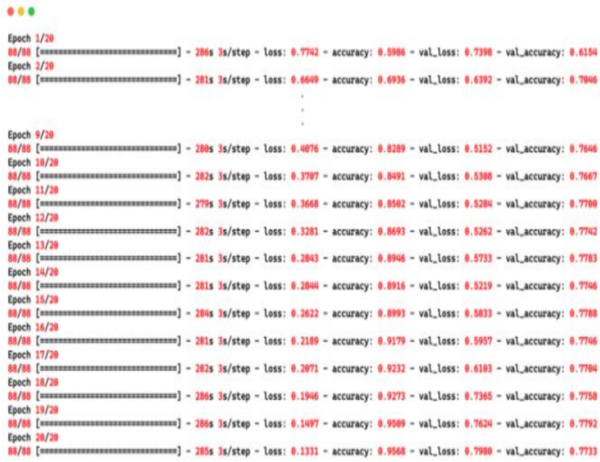

Fig. 5: System Training

X. SYSTEM TESTING

In order to assess the performance of the sentiment analysis system, the accuracy score was used, a commonly used metric for evaluating classification neural network models. The system's accuracy on the test set was found to be 0.773, indicating that it correctly classified approximately 77% of the reviews in the test set. This suggests that the system was successful in predicting the sentiments of Amazon customers with a good level of accuracy. It is important to note that there are additional techniques that can be employed to further enhance the system's performance. These techniques include hyper parameter tuning, and feature engineering. Overall, these results provide valuable insights into the sentiments expressed by Amazon customers and can be utilized to improve customer experience.

XI. SYSTEM EVALUATION

In neural network models and statistical analysis, a confusion matrix is a table used to evaluate the performance of a classification system. In a binary classification problem, the confusion matrix is a 2x2 matrix that shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for a given set of predictions. In this case, the confusion matrix cn is a (2x2) matrix that shows the number of true positives, true negatives, false positives, and false negatives for a set of reviews, as shown in "Fig. 6".

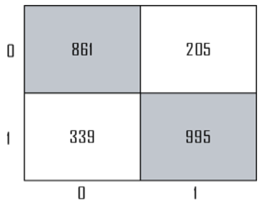

Fig. 6: Confusion Matrix

- **[0,0] = 861: True negative.**
- **[0,1] = 205: False positive.**
- **[1,0] = 339: False negative.**
- **[1,1] = 995: True positive**.

By analysing the confusion matrix and calculating these variables, the performance of a classification system can be evaluated and determine how well it is able to predict positive and negative reviews. In this case, the system predicted 995 positive reviews and 861 negative reviews, while the actual number of positive reviews was 1334 and the actual number of negative reviews was 1066, as shown in "Fig. 7 ".

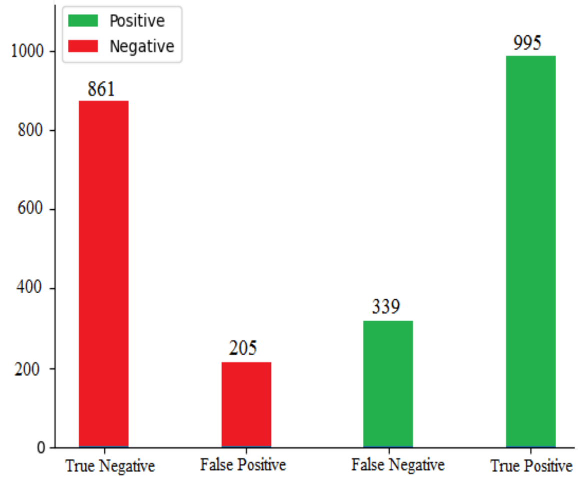

Fig. 7: Predication Result

XII. CONCLUSIONS

In conclusion, this research has focused on developing a powerful sentiment analysis system for Amazon customer reviews using artificial intelligence, specifically neural network models, and natural language processing techniques. The conclusions can be listed as follows:

- The exponential growth of e-commerce has made it increasingly important for businesses to understand customer sentiments to enhance their products and services. Through the utilization of advanced technologies and tools such as Python, Google Colab, Jupyter notebooks, and Amazon SageMaker, we successfully developed and fine-tuned a robust sentiment analysis system. The system effectively analyzed customer sentiments and preferences, providing valuable insights for companies to make informed decisions and improve customer experience.
- This research based on Long Short-Term Memory (LSTM), a type of recurrent neural network, for sentiment analysis of Amazon customer reviews. LSTM has gained

popularity for its ability to capture sequential information in text data, making it well-suited for analyzing the sentiments expressed in reviews.

- By training the system with effectively processed and prepared data, the results demonstrated that the LSTM-based sentiment analysis system achieved a high accuracy score of 0.773 on the test data. This indicates that the system correctly classified approximately 77% of the reviews, showcasing the effectiveness of the LSTM model in predicting the sentiments of Amazon customers. The flexibility of LSTM allowed us to explore and fine-tune different model architectures and hyperparameters to improve the system's performance further.
- Comparing this approach with other neural network models used in sentiment analysis on Amazon reviews, this system outperformed traditional systems which based on Naive Bayes and Support Vector Machines. LSTM's ability to handle sequential data gives it an advantage in understanding the context and dependencies present in customer reviews, leading to more accurate sentiment predictions.

XIII. FUTURE WORK

While the current system has demonstrated promising results in analysing the sentiment of Amazon customer reviews using LSTM, there is still room for further improvement and exploration. Here are some potential areas for future work:

Fine-tuning hyperparameters: While tuned some of the hyperparameters such as the number of LSTM units and the dropout rate, there are still many other hyperparameters that can be fine-tuned to achieve better performance. For instance, the different learning rates, batch sizes, and optimization algorithms can be used.

Future work could explore the use of higher-dimensional pre-trained embeddings, as this current approach utilized a 100-dimensional embedding matrix.

Analyzing misclassified reviews: While the system achieved a decent accuracy on the test set, there were still some misclassified reviews. It would be interesting to analyze these misclassified reviews to identify any patterns or common themes that system may have missed. This can provide insights into the limitations of system and guide further improvements.

Expanding the dataset: The dataset was used in this work consists of about 8000 datasets. It would be worthwhile to expand the dataset to include a wider range of products and categories. This can help to improve the generalization of system and make it more robust to new and unseen data.

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