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Comparative Analysis of Artificial Neural Network and Recurrent Neural Network for Sentiment Analysis in Movie Reviews

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ABSTRACT

The ability to recognize and extract sentiments from text data depends heavily on sentiment analysis. We use the dataset of IMDb movie reviews in this work to investigate the use of machine learning and deep learning approaches for sentiment analysis. Using the sentiments indicated in the text, the goal is to categorize movie reviews as positive or negative. To extract pertinent features for the machine learning methodology from the movie reviews, we use conventional feature engineering techniques. These characteristics include sentiment lexicons, bag-of-words, and n-grams. Train well-known machine learning algorithms on these features to create sentiment classifiers, including Naive Bayes, Support Vector Machines, and Logistic Regression. The deep learning approach, in contrast, uses the strength of neural networks to automatically uncover representations from unprocessed text data. We use a recurrent neural network (RNN), more specifically an LSTM network, to capture the sequential flow of language and extract contextual information from the movie reviews. The LSTM network is then used to learn sentiment representations on the IMDb movie review dataset. split the data into test and learn sets so we could compare different approaches. We use several metrics, including accuracy, precision, recall, and F1-score, to evaluate the performance of the sentiment classifiers. We also compare the results of the machine learning and deep learning models to identify the benefits and drawbacks of each approach. Different machine learning models were analyzed for their performance, with Linear SVM coming out on top with an accuracy of 89.57%. Other top performers included Multinomial Naive Bayes, Linear SVM, and XGboost.

INTRODUCTION

Sentiment analysis, also known as opinion mining, is a field of natural language processing (NLP) that aims to determine the sentiment or subjective information expressed in text. With the explosive growth of social media platforms, online review websites, and user-generated content, sentiment analysis has gained significant attention. It plays a vital role in understanding public opinion, consumer feedback, and market trends.

In the realm of movie reviews, sentiment analysis holds particular importance. Moviegoers often express their opinions and emotions about films through written reviews, which can greatly influence the success or failure of a movie. Analyzing these reviews can provide valuable insights into audience reactions, enabling filmmakers, producers, and distributors to make informed decisions. Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs) are two widely used deep learning models that have shown remarkable success in various NLP tasks, including sentiment analysis. ANNs are feedforward neural networks composed of multiple layers of interconnected artificial neurons, while RNNs are specialized neural networks designed to process sequential data by capturing temporal dependencies. This study aims to compare the performance of ANN and RNN models in sentiment analysis specifically applied to movie reviews. By analyzing and classifying movie reviews as positive or negative, we can assess the effectiveness of these models in capturing the sentiment expressed in textual data.

BENEFITS OF SENTIMENT ANALYSIS

Sentiment analysis offers several benefits across various domains and industries. Here are some key advantages of sentiment analysis:

Customer Insights: Sentiment analysis helps businesses gain valuable insights into customer opinions, preferences, and experiences. By analyzing sentiment in customer feedback, reviews, and social media posts, companies can understand customer satisfaction levels, identify areas for improvement, and make data-driven decisions to enhance products, services, and customer support.

Brand Reputation Management: Monitoring sentiment around a brand is crucial for reputation management. Sentiment analysis allows businesses to track online mentions, reviews, and social media conversations related to their brand. By identifying negative sentiment early on, companies can address customer concerns, mitigate potential crises, and maintain a positive brand image.

Market Research and Competitive Analysis: Sentiment analysis provides valuable market research data by analyzing public opinion and sentiment towards products, services, and competitors. Businesses can uncover consumer preferences, emerging trends, and gaps in the market, enabling them to make informed strategic decisions and stay ahead of the competition.

Customer Sentiment Tracking: Sentiment analysis enables continuous monitoring of customer sentiment over time. By tracking sentiment trends, businesses can identify patterns, spot changes in customer sentiment, and proactively address issues before they escalate. This helps in building long-term customer relationships and loyalty.

Product Feedback and Improvement: Sentiment analysis helps companies gather feedback on their products or services. By analyzing sentiment in customer reviews, surveys, and feedback forms, businesses can gain insights into what customers like or dislike about their offerings. This information can be used to drive product improvements, enhance user experience, and meet customer expectations.

Social Media Campaign Analysis: Sentiment analysis plays a crucial role in measuring the effectiveness of social media campaigns. By analyzing sentiment around campaign hashtags, mentions, and user interactions, businesses can gauge audience sentiment, identify campaign impact, and make adjustments to optimize their social media strategies.

Financial Market Analysis: Sentiment analysis has applications in financial markets, where understanding market sentiment can be valuable for investors and traders. By analyzing sentiment in news articles, social media posts, and financial reports, investors can gauge market sentiment and make informed investment decisions.

sentiment analysis empowers businesses and organizations to harness the power of customer feedback, public opinion, and textual data to make data-driven decisions, enhance customer experiences, manage brand reputation, and gain a competitive edge in the market.

Methodology

The methodology that has been developed for conducting sentiment analysis on IMDb reviews consists of a number of essential phases that are meant to examine and categorize the sentiment that is conveyed in the reviews. The following is a condensed explanation of the research methodology:

DATA COLLECTION

The IMDB dataset contains 50,000 different movie reviews, making it useful for natural language processing and text analytics. When compared to earlier benchmark datasets, this one for classifying binary attitudes contains a substantial amount of additional information. There are 25,000 highly polar critiques of movies offered for instruction, and another 25,000 are provided for testing. Make a decision between using categorization methods or machine learning techniques to make a forecast regarding the amount of positive and negative reviews. For additional information regarding this dataset, please visit the following URL: http://ai.stanford.edu/amaas/data/sentiment/.

DATA PREPROCESSING

In the process of data mining, one of the most important steps is known as "data preprocessing," which can mean either the alteration of data or the deleting of data before it is used to ensure or improve efficiency. Projects involving data mining and machine learning are excellent illustrations of how the proverb "garbage in, garbage out" might be applicable. Remove any more punctuation, put a stop to the birds, activate the limiter and tokenizer, or remove any data that isn't necessary.

PERFORM EDA

Exploratory data analysis, often known as EDA, is a process that needs to be carried out before one can completely analyze and investigate a dataset. The process of analyzing data comprises summarizing the most important aspects, locating correlations, and identifying outliers. The steps involved in the EDA process are outlined in this section.

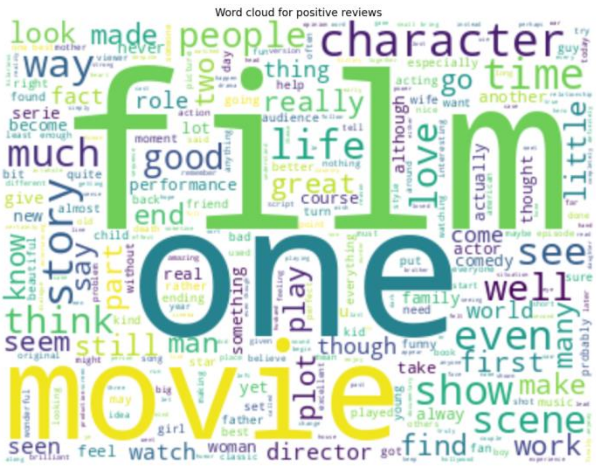

Figure 1 shows the word clouds of positive reviews

Figure 2 Shows the word clouds of Negative reviews

RESULTS AND DISCUSSION

You can determine how well your taught machine learning models performed by using performance evaluation measures. This makes it easier to assess the likelihood that your machine learning and deep learning model will work with new data sets. The ideas that should be often specified include the following:

1) TN/TP/FN/FP

- True Positive - It was anticipated to be successful, and it did succeed.
- False Positive - It was supposed to be uplifting, but the outcome was depressing.
- True Negative - Unfavourable outcomes were predicted to occur, and they have now happened.
- False Negative - Despite negative projections, the outcome was favorable.

2) Confusion Matrix

The first thing we do with the data after cleaning, prepping, and otherwise handling it is feeding it into a fantastic model, which by definition produces outputs in the form of probabilities. Wait a moment! How on earth will we know whether or not our model is successful? A higher standard of effectiveness and performance is exactly what we seek. Now we can see the full meaning of the Confusion Matrix. One type of performance measure used in machine learning classification is the confusion matrix.

3) Accuracy

The percentage of data instances that have been correctly classified relative to the total number of data instances is known as accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

4) Loss

If your prediction is off, you'll lose money. In these other contexts, loss is used to quantify the model's failure to accurately anticipate a given instance. If a model's prediction is incorrect, losses will be higher than if the prediction is accurate. Models need to be trained in order to discover a balanced collection of biases and weights.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} yi.\log(yi) \qquad (2)$$

5) Precision

A good classifier should have the precision of one, which is an extremely high precision. When the numerator and denominator are identical, as in the formula TP = TP + FP, the level of precision increases to 1 while the FP decreases to 0. When FP increases, the denominator value increases while the accuracy value decreases, which is the exact opposite of what we want to happen.

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

6) Recall

For a classifier to be successful, it must have a recall value of one (high). The need for this is unquestionable. Only when the denominator and numerator are the same will the and when TP = TP + FN, which also means that FN is zero, will recall ever rise to 1. In addition to the denominator's value rising as FN rises, recall's value falls, which is the exact opposite of what we desire. Its capacity to discern between negative and positive examples serves as a gauge of a machine learning model's sensitivity. Depending on the situation, it may also go by the names recall and true positive rate (TPR). Sensitivity is one aspect that is taken into account when assessing the performance of a model since it allows us to observe how many successful detections the system was able to make.

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

7) F1 Score

Precision and recall ratings must both be one for the F1 Score to be one. Only at extremely high recall and precision levels will the F1 score increase. The harmonic mean of recall and precision is the optimal statistic to use to maximize the F1 score.

$$F1-score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \quad (5)$$

Table 1 Performance Evaluation of Models

Model	Accuracy	Precision	recall	F1-score
LR	89.03%	87.86%	90.68%	89.24%
Multinomial Naive Bayes	86.79%	87.29%	86.24%	86.76%
Linear SVM	89.57%	88.56%	90.98%	89.75%
XGBOOST	84.63%	82.93%	87.36%	85.09%

Table 1 displays the performance evaluation of a variety of machine learning models, including LR, Multinomial Naive Bayes, Linear SVM, and XGboost, with Linear SVM achieving the greatest accuracy of 89.57% when compared to the other models. For comparative study, Linear SVM improved by 5% over XGboost and 3% over Multinomial Naive Bayes.

Table.2 Shows LSTM model Accuracy, Loss, Validation accuracy, and Validation loss.

Model	Accuracy	Loss	Val Acc	Val Loss
Hybrid LSTM	0.879	0.676	87.98	0.676

Table.3 exhibits LSTM Loss is 0.676, Accuracy is 0.879, Validation Accuracy is 87.98, and Validation Loss is 0.676.

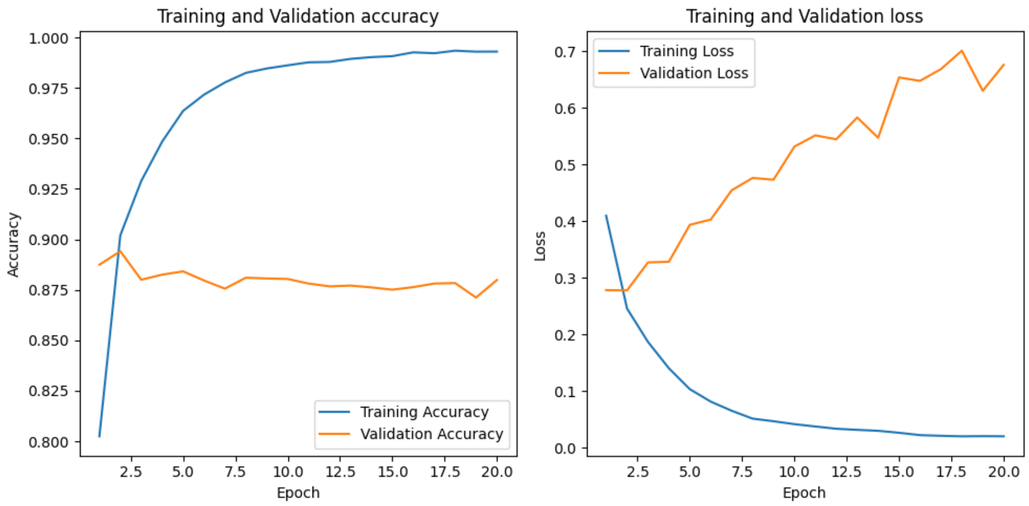

Figure 3 shows the training and validation accuracy and loss graph

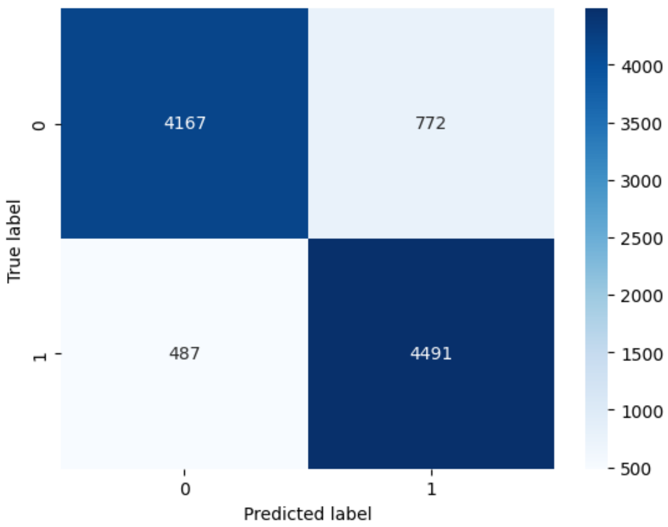

Figure 4 shows the confusion matrix of true and predicted labels of LSTM

Figure 2 and 3 shows the loss and accuracy of the LSTM model and Figure 4 shows the confusion matrix of the true and predicted label.

CONCLUSION

IMDb movie reviews were used as the dataset for the research project, and machine learning and deep learning techniques were studied for their potential utility in sentiment analysis. Both approaches showed potential when it came to determining if a movie review was positive or unfavorable based on the opinions expressed within the text of the review. The machine learning methodology utilized well-known feature engineering techniques such as bag-of-words, n-grams, and sentiment lexicons as its foundation. These features were used to train a number of different machine learning methods, such as Naive Bayes, Support Vector Machines, or Xgboost, which were then used to generate sentiment classifiers. These models exhibited a high degree of accuracy, but they were unable to recognize the nuanced expressions of emotion contained within the text. On the other hand, the deep learning method automatically learned representations from raw text data by employing a recurrent neural network (RNN), more precisely an LSTM network. The LSTM network was able to successfully extract the contextual information from the movie reviews while also successfully capturing the sequential character of the language. Because of this, it performed significantly better than traditional machine learning algorithms in terms of precision and its ability to recognize complex patterns of emotion. In conclusion, the research demonstrates that sentiment analysis using IMDb movie reviews may be conducted using either machine learning or deep learning methods. The findings contribute to our understanding of different methods for classifying emotions and offer insights into the benefits and drawbacks of various approaches.Deep learning finds that the validation loss for hybrid cars is 0.676, the accuracy is 0.879, the validation accuracy for hybrid cars is 87.98, and the validation loss for hybrid cars is 0.676 for the comparison research. Linear SVM improves by 5% over XGboost and by 3% over Multinomial Naive Bayes.

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