Sentiment Analysis for Restaurant Reviews

by

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GitHub Link:

https://github.com/aman4computing/Sentiment_Analysis_for_Restaurant_Reviews

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1. ABSTRACT:

Sentiment analysis of customer reviews has a crucial impact on a business's development strategy. The evolution of the internet in the past decade resulted the in generation of voluminous data in all sectors. Due to this advent, people have new ways of expressing their opinions about anything in the form of Google Reviews, Tweets, Blog Posts, etc. Sentiment analysis deals with the process of computationally identifying and categorizing opinions expressed in a piece of text, especially in order to determine whether the writer's attitude toward a particular topic is positive, negative, or neutral. Knowing the opinion of customers is very important for any business. Hence, in this project, we analyze the reviews given by the customers of the restaurant with the help of Machine learning models and Deep learning models and their comparison.

2. INTRODUCTION:

Sentiment analysis, also known as opinion mining, is a branch of natural language processing (NLP) that focuses on determining the sentiment or subjective information expressed in text data. With the exponential growth of user-generated content on the internet, sentiment analysis has gained significant importance in understanding public opinion and customer feedback. In the domain of the restaurant industry, sentiment analysis plays a crucial role in understanding customer satisfaction, identifying areas for improvement, and making informed business decisions. Analyzing restaurant reviews allows restaurant owners and managers to gain insights into customer experiences, identify popular dishes or services, and address any negative feedback promptly.

In this project, we aim to perform sentiment analysis on restaurant reviews using various machine learning and deep learning techniques. We compare the performance of traditional machine learning models such as Naive Bayes and Decision Trees, as well as advanced deep learning models such as BI-LSTM with word2vec/fasttext word embedding and a Transformer-based model with BERT-based word embedding. Machine learning models have been widely used in sentiment analysis tasks. Naive Bayes classifiers leverage probabilistic algorithms to predict sentiment based on feature probabilities. Decision Trees use a tree-like model to make decisions based on features and their thresholds. These models have been effective in sentiment analysis tasks and provide a baseline for comparison.

Deep learning models, on the other hand, have demonstrated remarkable performance in various NLP tasks, including sentiment analysis. Bidirectional LSTM (BI-LSTM) models are capable of capturing the context and dependencies of words in a sentence. Word embedding techniques such as word2vec and fasttext help represent words as numerical vectors, capturing semantic relationships. These models can capture the nuanced meaning and context of words, potentially improving sentiment analysis accuracy. Transformer-based models, particularly the BERT (Bidirectional Encoder Representations from Transformers) model, have revolutionized NLP tasks. BERT-based word embedding allows for a deeper understanding of the context and semantics of sentences. Fine-tuning BERT on specific tasks has shown promising results in sentiment analysis.

In this project, we compare the performance of these models on a dataset of restaurant reviews. By evaluating their accuracy, precision, recall, and F1 score, and analyzing the results using appropriate plots, we aim to determine the most effective approach for sentiment analysis in the context of restaurant reviews. The findings from this project can provide valuable insights for restaurant owners, managers, and researchers seeking to extract sentiment information from customer feedback and make data-driven decisions to enhance customer satisfaction and business performance.

3. DATASET OVERVIEW:

Restaurant Reviews Dataset:

https://www.kaggle.com/datasets/akram24/restaurant-reviews

This dataset is available on Kaggle, is titled "Restaurant Reviews" and is curated by a user named Akram24. Here is an overview of the dataset:

Dataset Description:

The dataset consists of restaurant reviews, where each review is labeled with a sentiment category: 0, 1(Liked). The reviews are written in English and reflect customers' opinions and experiences with various restaurants.

Dataset Contents:

The dataset contains two columns: "Review" and "Liked".

The "Review" column consists of text data, representing the restaurant reviews.

The "Liked" column contains categorical labels indicating the sentiment of each review.

Potential Use Cases:

The dataset can be used for sentiment analysis tasks, specifically analyzing sentiment in restaurant reviews. It provides an opportunity to train machine learning or deep learning models to classify reviews based on sentiment. The dataset can be utilized to gain insights into customer satisfaction, identify common sentiments, and extract actionable information for restaurant owners and managers.

Dataset Availability:

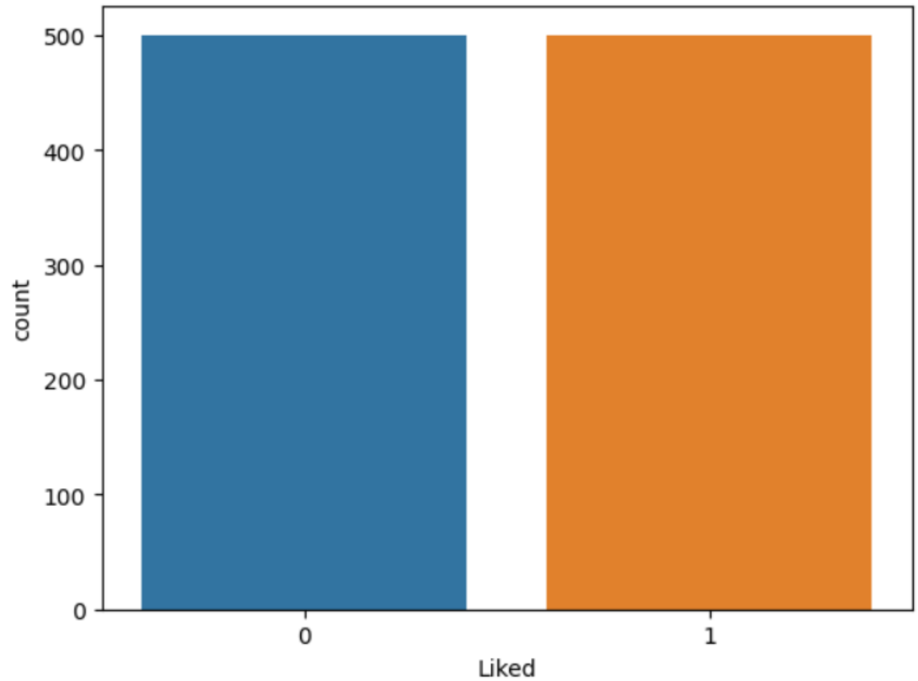
The dataset is available for download in TSV format on Kaggle.

```
[ ]  data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Review  1000 non-null   object
 1   Liked   1000 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 15.8+ KB
```

```
[ ]  sns.countplot(x = data['Liked'],data = data)
```

```
<Axes: xlabel='Liked', ylabel='count'>
```



4. MODEL'S OVERVIEW AND INTRODUCTION:

Here's an overview of the machine learning models and deep learning techniques that I will be comparing for sentiment analysis on restaurant reviews:

1. Naive Bayes:

Naive Bayes is a probabilistic machine learning model commonly used for text classification tasks, including sentiment analysis. It assumes that the features (words or n-grams) are conditionally independent given the class label. Naive Bayes calculates the probability of each sentiment category for a given review and assigns the label with the highest probability. It is computationally efficient and works well with high-dimensional data. However, it may oversimplify the relationships between features and may not capture the dependencies between words.

Algorithm Steps:

1. Data Preprocessing: Convert the text data into numerical feature vectors

2. Training: Calculate the prior probabilities and likelihoods of each class based on the training data.
3. Prediction: For a new review, calculate the posterior probabilities of each class using Bayes' theorem and select the class with the highest probability as the predicted sentiment.
4. Evaluation: Compare the predicted sentiments with the actual sentiments in the testing set to assess the model's performance using metrics such as accuracy, precision, recall, and F1-score.

2. Decision Tree:

Decision Tree is a popular machine-learning model that builds a tree-like structure to make decisions based on feature thresholds. It recursively splits the dataset based on the most informative features to maximize the separation of different sentiment categories. Decision Trees are interpretable and can handle both categorical and numerical features. However, they may suffer from overfitting, especially if the tree becomes too complex.

Algorithm Steps:

1. Data Preprocessing: Convert the text data into numerical feature vectors, similar to Naive Bayes.
2. Training: Build a decision tree by recursively splitting the data based on the selected features and their thresholds. The splits are determined using metrics like Gini impurity or information gain.
3. Prediction: For a new review, traverse the decision tree based on the feature values to reach a leaf node, which represents the predicted sentiment.
4. Evaluation: Compare the predicted sentiments with the actual sentiments in the testing set to assess the model's performance using metrics such as accuracy, precision, recall, and F1-score.

3. BI-LSTM with Word Embedding:

Bidirectional LSTM (BI-LSTM) is a type of recurrent neural network (RNN) architecture that can capture the contextual information and dependencies between words in a sentence. Word embedding techniques such as word2vec or fasttext are used to convert words into dense numerical vectors, capturing semantic relationships. BI-LSTM processes the input sequence in both forward and backward directions, enabling it to capture information from the entire sentence. It can handle variable-length sequences and has been successful in capturing the sequential nature of text data. However, training BI-LSTM models can be computationally expensive, especially with large datasets

Algorithm Steps:

1. Data Preprocessing: Convert the text data into word vectors using word embedding techniques like word2vec or fasttext.
2. Model Architecture: Build a BI-LSTM model with an input embedding layer, LSTM layers (forward and backward), and output layers for sentiment classification.
3. Training: Feed the training data into the model and optimize the model's parameters using backpropagation and gradient descent.
4. Prediction: For a new review, pass it through the trained BI-LSTM model to obtain the predicted sentiment.
5. Evaluation: Compare the predicted sentiments with the actual sentiments in the testing set to assess the model's performance using metrics such as accuracy, precision, recall, and F1-score.

4. Transformer-based model with BERT-based Word Embedding:

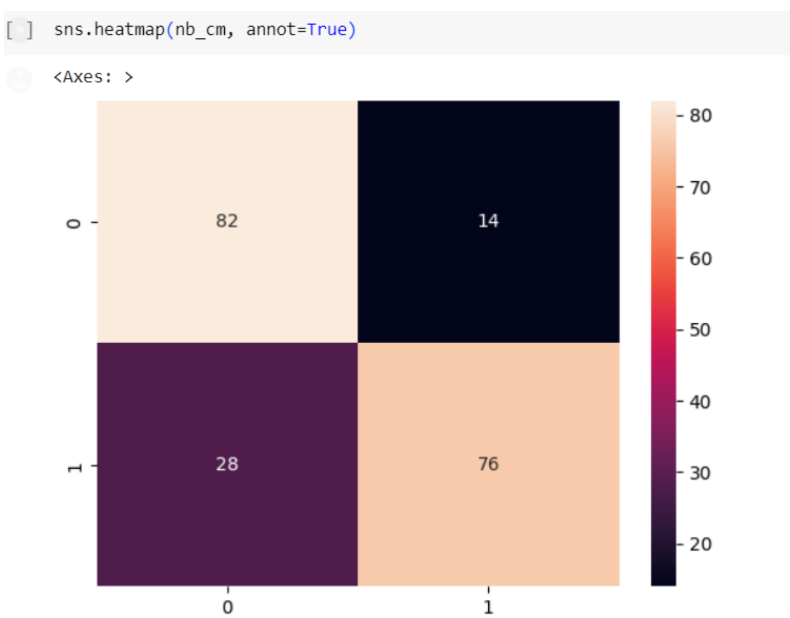
Transformers, especially the BERT (Bidirectional Encoder Representations from Transformers) model, have revolutionized NLP tasks. BERT-based word embedding allows for a deep understanding of the context and semantics of sentences. Fine-tuning a pre-trained BERT model on the specific sentiment analysis task has shown state-of-the-art performance. Transformers capture long-range dependencies and exhibit strong contextual understanding, leading to accurate sentiment analysis results. However, they require substantial computational resources and training time, and inference can be slower compared to other models.

Algorithm Steps:

1. Data Preprocessing: Convert the text data into BERT-based word embeddings.
2. Model Architecture: Build a Transformer model with BERT layers and additional layers for sentiment classification.
3. Training: Fine-tune the pre-trained BERT model using the training data specific to the sentiment analysis task.
4. Prediction: For a new review, pass it through the fine-tuned Transformer model to obtain the predicted sentiment.
5. Evaluation: Compare the predicted sentiments with the actual sentiments in the testing set to assess the model's performance using metrics such as accuracy, precision, recall, and F1-score.

5. KEY RESULTS & CONCLUSION:

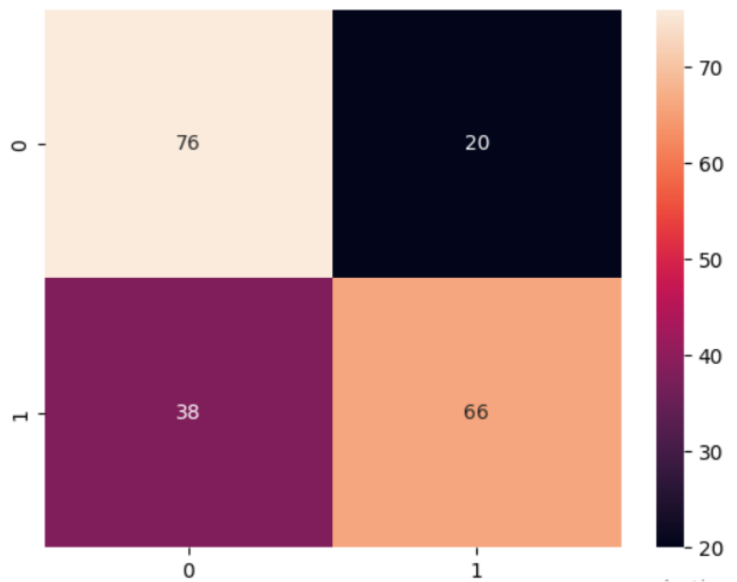
1. Naive Bayes:



	precision	recall	f1-score	support
0	0.75	0.85	0.80	96
1	0.84	0.73	0.78	104
accuracy			0.79	200
macro avg	0.79	0.79	0.79	200
weighted avg	0.80	0.79	0.79	200

(Accuracy for Naive Bayes Model= 79%)

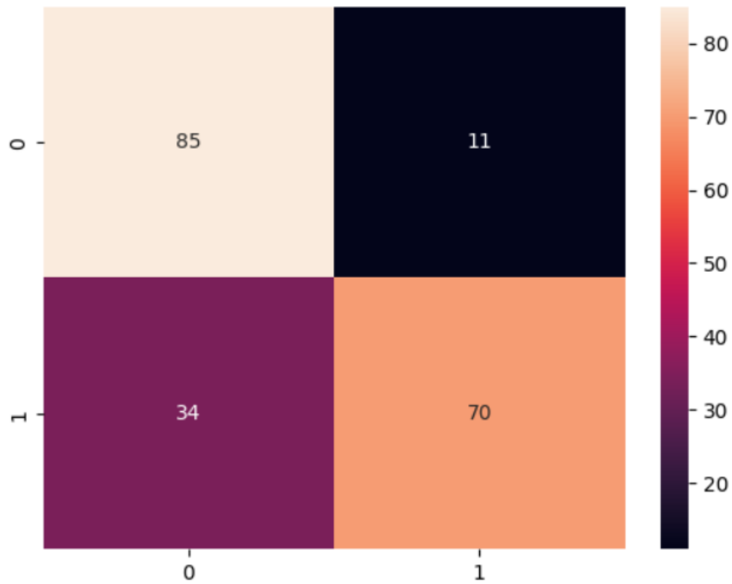
2. Decision Tree:



	precision	recall	f1-score	support
0	0.67	0.79	0.72	96
1	0.77	0.63	0.69	104
accuracy			0.71	200
macro avg	0.72	0.71	0.71	200
weighted avg	0.72	0.71	0.71	200

(Accuracy for Decision Tree Model= 71%)

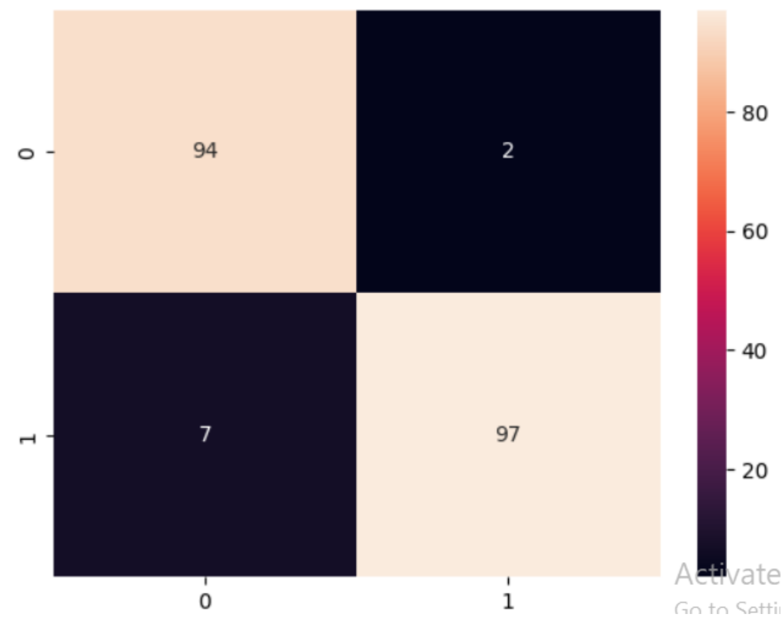
3. BI-LSTM with Word Embedding:



	precision	recall	f1-score	support
0	0.71	0.89	0.79	96
1	0.86	0.67	0.76	104
accuracy			0.78	200
macro avg	0.79	0.78	0.77	200
weighted avg	0.79	0.78	0.77	200

(Accuracy for BI-LSTM with Word2Vec/FastText Model= 78%)

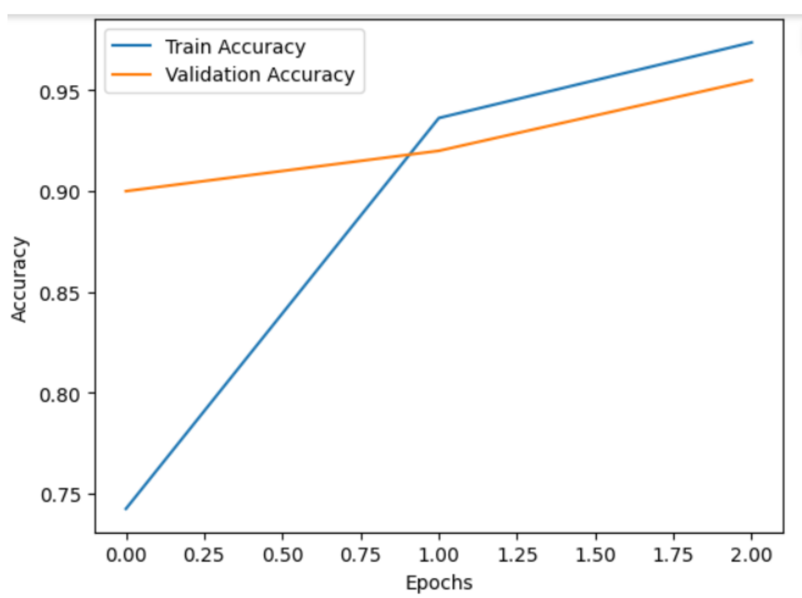
4. Transformer-based model with BERT-based Word Embedding:




```
Accuracy: 0.955
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.98      0.95        96
           1       0.98      0.93      0.96       104

    accuracy                           0.95       200
   macro avg       0.96      0.96      0.95       200
weighted avg       0.96      0.95      0.96       200
```



(Accuracy for Transformer based model with BERT-based word embedding Model= 95%)

After applying the above ML & DL Models to Restaurant Reviews Dataset, we can draw the following conclusions:

Model	Avg. Accuracy	Avg. Precision	Avg. Recall	Avg. F1-score
N.B.	0.79	0.80	0.79	0.79
D.T.	0.71	0.72	0.17	0.71
BI-LSTM	0.78	0.79	0.78	0.77
Transformer-based model with BERT	0.95	0.96	0.95	0.96

The Classification Report of the four models shows that the Transformer based model with BERT performed best and achieved an accuracy rate of 95% Furthermore, all four Models achieved outstanding results.

6. FUTURE SCOPE:

The field of sentiment analysis and restaurant reviews presents several exciting avenues for future research and development. Here are some potential future scopes to explore:

1. Fine-grained Sentiment Analysis: Current sentiment analysis models typically classify reviews into broad sentiment categories such as positive, negative, or neutral. Future research could focus on developing models that can capture more fine-grained sentiments, such as detecting specific aspects of a restaurant experience that contribute to positive or negative sentiments (e.g., food quality, service, ambiance).

2. Aspect-based Sentiment Analysis: Along similar lines, aspect-based sentiment analysis involves identifying and analyzing sentiment towards specific aspects or features of a restaurant, such as menu items, cleanliness,

pricing, or customer service. This approach provides more detailed insights for restaurant owners and allows for targeted improvements in specific areas.

3. Multilingual Sentiment Analysis: Extending sentiment analysis to multiple languages would enable analyzing reviews from diverse cultural contexts and expanding the scope of insights gained. Developing models that can handle multiple languages and adapt to language-specific nuances and expressions would be a valuable future direction.

4. Handling Sarcasm and Irony: Sentiment analysis models often struggle with identifying sarcasm and irony in the text. Future research can focus on improving models to better understand and interpret such linguistic nuances, enabling more accurate sentiment classification.

5. Domain Adaptation: Restaurants and food-related experiences vary greatly across different cultures and regions. Developing techniques for domain adaptation in sentiment analysis would enhance model performance in specific restaurant contexts, accounting for cultural differences, regional preferences, and local sentiments.

6. User-level Sentiment Analysis: Traditional sentiment analysis focuses on aggregating sentiments across reviews. Future work could explore user-level sentiment analysis, tracking individual users' sentiments over time and understanding their evolving preferences and experiences with different restaurants.

7. Incorporating Contextual Information: Context plays a vital role in sentiment analysis. Future research can explore techniques to incorporate contextual information, such as user demographics, location, or time of the review, to provide more personalized and context-aware sentiment analysis.

8. Interpretability and Explainability: As deep learning models become increasingly complex, ensuring interpretability and explainability of sentiment analysis results becomes essential. Future work can focus on developing methods to provide transparent explanations of model predictions, enabling users to understand the reasoning behind sentiment classifications.

9. Real-time Sentiment Analysis: The ability to perform sentiment analysis in real time can provide immediate insights for restaurants, allowing them to respond promptly to customer feedback and address concerns. Future research can explore efficient algorithms and architectures for real-time sentiment analysis.

10. Transfer Learning and Pre-training: Leveraging transfer learning and pre-training techniques, similar to BERT, can improve sentiment analysis models' performance, especially in scenarios where labeled data is scarce. Future research can investigate pre-training on larger datasets and fine-tuning on specific restaurant review datasets to enhance model capabilities.

These future directions hold great potential for advancing sentiment analysis in the context of restaurant reviews, enabling more accurate, context-aware, and detailed insights for restaurant owners, managers, and customers alike.