“ Sentiment-Driven Personalized Restaurant Recommendations: A DistilBert Approach”

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Abstract

Recommender systems are used to provide users with information and services. Opinions are important in recommendation systems because they affect the success or failure of applications, restaurants, and other tech-driven services in today's world. Positive or negative reviews can have a big impact on user engagement. Analyzing these reviews is essential to understand user experiences and enhance service quality.In traditional recommendation system star ratings provide a basic overview, while delving into text-based reviews offers valuable insights into the reasons behind the ratings. However, manually processing numerous reviews is impractical. Various methods, such as TF-IDF and Word2Vec, have been employed for sentiment analysis. However, these methods faced challenges in comprehending emotions and the genuine meaning embedded in sentences. Moreover, earlier methods lacked personalization, making it crucial to evolve the approach.This work employs the DistilBert model to analyze sentiments. The method integrates two datasets: a business dataset with details about shops, addresses, and features, and a review dataset containing user-generated review texts. Through the combination of these datasets, the framework aims to provide personalized recommendations considering both city and cuisine preferences. The proposed method combines Sentiment Analysis and Recommendation Systems to provide users with tailored suggestions. Sentiment Analysis is used to classify the reviews of restaurants based on the text. The results from Sentiment Analysis are then sent to a recommendation system, which generates a list of the top-n restaurants for the user. This approach has shown better results compared to existing recommendation process.

Keywords: Recommendation System, Restaurant Recommendation System,TF-IDF,Word2vec,Sentiment Analysis.

1. Introduction

The exponential rise of social media platforms has led to an overwhelming arrival of unstructured data, making it difficult for users to go through and find those high quality services. Most users often find themselves in a situation when they need to answer some questions:which place, restaurant is best for thai food, mexican food stc. To tackle this challenge head-on, this paper endeavours to construct a fine-tuned, user preference-centric framework. By harnessing user reviews, comments, and sentiment analysis, our objective is to distil meaningful insights and furnish personalized recommendations of restaurants. This framework's significance lies in its ability to predict restaurant ratings from Yelp data based on user sentiments, furnish an intuitive graphical interface for predicting top eateries in a city and cuisine, uncover restaurant services, and restrain information overload. Focused on carefully analysing restaurant-related reviews and comments, our scope centers on a transfer learning model, merging datasets, preprocessing, tokenizing, and employing sentiment analysis to provide individualized suggestions. This initiative stems from the necessity to navigate the vast social media landscape effortlessly, presenting tailored restaurant recommendations and an enriched user experience. Our ultimate motivation is to ensure that everyone gains access to a tailored recommendation system, simplifying every dining quest by aligning with their distinct city and cuisine preferences.

2. Literature review

Research on sentiment analysis[26] in restaurant reviews has been extensive. [1] examine how sentiment analysis[26] techniques are used to determine customers' sentiments on several aspects of dining experiences, like meal quality, service, and ambience.on fact, texting remains one of the most popular ways to communicate on social networks, despite the availability of other channels. The goal of the work described is to identify, analyse, and utilise the sentiment and emotion that people express through text in their Twitter messages in order to generate recommendations. [2]. [2] gathered tweets and responses on a few specific subjects and created a dataset containing text, user, emotion, sentiment, and other data. [3] employ cosine similarity and term frequency-inverse document frequency (TF-IDF) and Cosine Similarity to offer other hotel selections based on their reviews. The weight value of terms or documents is found using TF-IDF, and comparable types of values are extracted from the sample set using cosine similarity. Customers are frequently observed to display inconsistent rating behaviour, which results in less accurate preferences being gathered for the recommendation task. In order to alleviate this issue [4], take into consideration using the sentiment data gathered from user-posted comments on the channels as a stand-in for user ratings. [4] experimented with different sentiment analysis[26] classifiers, such as the responsive neural network-based sentiment analysis[26], to assess the effectiveness of substituting sentiment data for user ratings. [5] research dining establishment recommendation systems for patron preference and services according to amenities and rating. The proposed sentiment score measure natural language processing technology is utilised to determine the sentiments and perspectives of user comments. Instead, it is much more practical to train an algorithm to perform this task, and advancements in machine learning make this possible. Many machine learning algorithms, such as Random Forest Classifier, Multinomial Naïve Bayes, and Bernoulli's Naïve Bayes, have been analysed, and their behaviour has been examined in [6].The study of feelings towards an object or entity is known as sentiment analysis[26] (SA) or opinion mining [7]. sentiment analysis[26] Classification problems can be addressed; sentiment analysis[26] will determine whether the sentiment expresses a positive or negative opinion [7][8].Product reviews are the most significant use of sentiment analysis[26]; these reviews are crucial for business owners because they allow them to make decisions based on customer feedback, as well as for users because they can be advised for products based on the feedback left by other customers [7].

Numerous researchers have attempted to address the issue of personalised social media research using a variety of techniques. [8] gave a thorough overview of the work being done in the field of social media sentiment analysis[26]. Improvements in a number of recently proposed algorithms and sentiment analysis[26] (SA) applications were thoroughly examined and presented in this survey effort. Many strategies, including non-machine learning-based techniques and machine learning-based techniques (probabilistic classifiers, such as Naive Bayes, Maximum Entropy and Linear, Support Vector Machines (SVM), and neural networks) were looked into.Developing a recommendation system is an interesting concept, which includes techniques that combine the short text content with existing knowledge, based on the sentiments and opinions that are now available. [10] Investigate a novel use of Recursive Neural Networks (RNN) in conjunction with deep learning systems for sentiment analysis[26] of interviews. provide a deep learning model to process user feedback and generate a potential user rating for user recommendations [11]. Ultimately, data learning for the recommendations is achieved by a deep belief network and sentiment analysis[26] (DBNSA). A variety of research has been actively conducted on sentiment analysis techniques such as an approach using word frequency or morphological analysis, and the method of using a complex neural network. Study of Convolutional Neural Networks and Recurrent Neural Networks is done to find out if deep learning algorithms perform better. Numerous studies have been actively carried out on sentiment analysis[26] techniques, including the use of a complex neural network and word frequency or morphological analysis. Convolutional and recurrent neural networks are studied to determine whether deep learning algorithms work better. [12] Provide a four-step procedure for users to recommend the best book. The levels are referred to as collections of related sentences by the semantic network, sentiment analysis[26] (SA), recommendation system, and reviewers. A two-step efficient resource recommendation model is introduced in order to raise the level of learning resource efficiency [13].The model relies on unsupervised deep learning machines to identify learning styles and user examples, as well as a sentiment analysis[26] bonus system based on user experience to enhance or modify the recommendation system's list classification of items.

3. Dataset Description

3.1 Overview

The data utilized in this project constitutes a segment of the Yelp Dataset Challenge [14], comprising a collection of JSON files encompassing diverse information. These files contain data regarding business details, reviews, tips (brief reviews), user profiles, and check-ins. Within the business objects, key information includes the business name, location, operating hours, category, average star rating, review count, and various attributes such as noise level or reservation policies. Review objects comprise star ratings, review text, review date, and the number of votes received. The dataset [14] comprises six sub-datasets, each serving a distinct purpose and described briefly as follows: Business Dataset ,Check-In Dataset, Photo Dataset, Review Dataset, Tips Dataset, Users Dataset. Specifically, this paper emphasizes two primary types of objects: Business Objects entail essential details like name, location, opening hours, category, average star rating, review count, and a multitude of attributes that delineate the business characteristics. Review Objects encompass crucial information such as star ratings, review text, review date, and the count of received votes.

3.2 Dataset Preprocessing

The Figure 1 provides a visual representation of the preprocessing steps undertaken in this study. The process involves three key stages: Business Dataset Preprocessing, Review Dataset Processing, and the subsequent merging of Business and Review Datasets. Each of these steps plays a crucial role in preparing and organizing the data for further analysis.

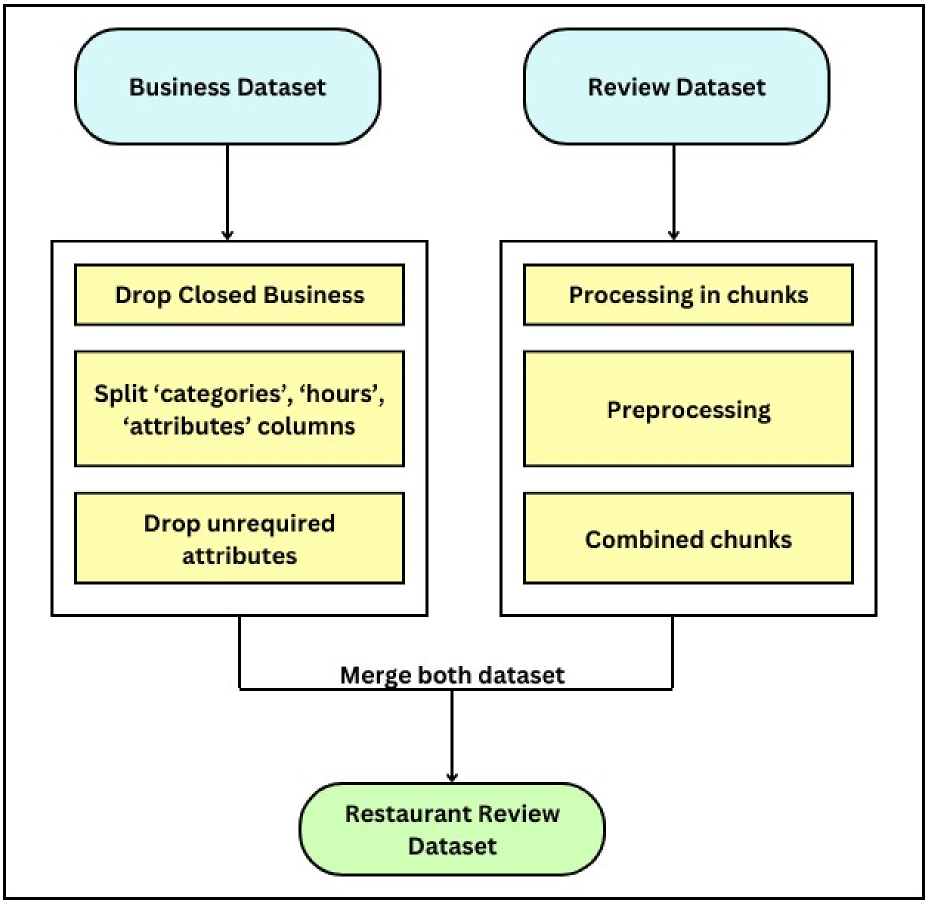

Figure 1. Steps of data preprocessing

Here's step-by-step detailed explanation of the process:

3.2.2 Business Dataset Preprocessing:

The first step involves filtering out businesses that are currently closed. This is done by selecting only the records where the 'is_open' flag is equal to 1. This ensures that the analysis focuses on actively operating businesses, providing more relevant insights.

The preprocessing likely aims to organize the data for further analysis or visualization. This includes splitting certain columns into separate columns to make the data more structured and easier to work with.

a) Splitting 'categories' Column

The 'categories' column contains an array of strings representing the business's categories. To make this information more accessible, the column is split into separate columns, using commas as separators. This allows for easier analysis of the different categories associated with each business.

b) Splitting 'hours' Column

The 'hours' column is assumed to be in nested form, meaning it contains a dictionary within each record. To extract the hour information, the column is split into separate columns, each representing a specific day of the week and its corresponding hours of operation. This makes the hour information more organized and easier to analyze.

c) Splitting 'attributes' Column

Similar to the 'hours' column, the 'attributes' column is also assumed to be in nested form. It contains various business attributes, such as parking options and takeout availability. To make this information more accessible, the column is split into separate columns, each representing a specific attribute.

d) Dropping Redundant Columns

After splitting the 'attributes' column, two redundant columns, 'BikeParking' and 'BusinessParking', are dropped from the resulting DataFrame. These columns contain overlapping information, and keeping them would introduce unnecessary duplication.

3.2.3 Review Dataset Processing:

The review dataset is quite large, with approximately 69,90,280 rows. To handle this large amount of data efficiently, the code employs a chunking approach. This involves processing the dataset in smaller chunks, allowing for better memory management and faster processing.The code performs date-related processing on each chunk of the review dataset. This likely involves extracting and formatting date information from the reviews, such as the date of the review or the reviewer's joining date on the platform.After processing each chunk of the review dataset, the processed chunks are combined into a final dataframe. This creates a unified DataFrame containing all the processed review data for further analysis.

3.2.4 Merging Business and Review Datasets

After preprocessing both datasets, the business and review datasets are merged to create a new merged dataset. This merged dataset combines information about businesses with the corresponding reviews, providing a comprehensive view of each business and its associated customer feedback.

4. Exploratory Data Analysis

Primary features of a business being used in data analysis are business category and location (state and city). The preliminary exploratory analysis Figure 2 of the dataset includes study of distribution of reviews with respect to category of the business and its location. Figure 3 present the frequency distribution of Category 1 versus count. These graphical representations showcase the relationship between the categories and their corresponding counts, providing a visual insight into the distribution patterns within each category.

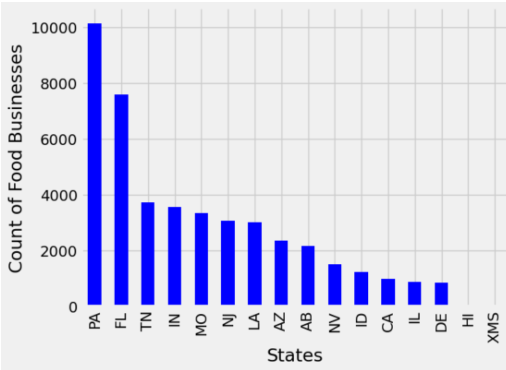

Figure 2 Frequency distribution of State v/s Number of food businesses

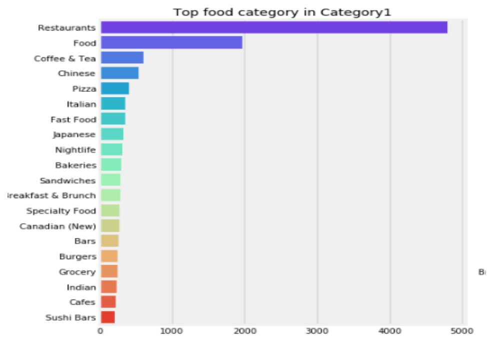

Figure 3 : Frequency distribution of category1 v/s count

5. Proposed methodology

Overview

The suggested method incorporates the outcomes of the Sentiment Analysis process. Figure 4 illustrates the primary components and interactions of the proposed system. The Yelp Restaurants Reviews [14] dataset serves as input for the sentiment analyzer, generating a sentiment score as output. This score is then forwarded to the recommender system to generate a top-n items recommendation list.

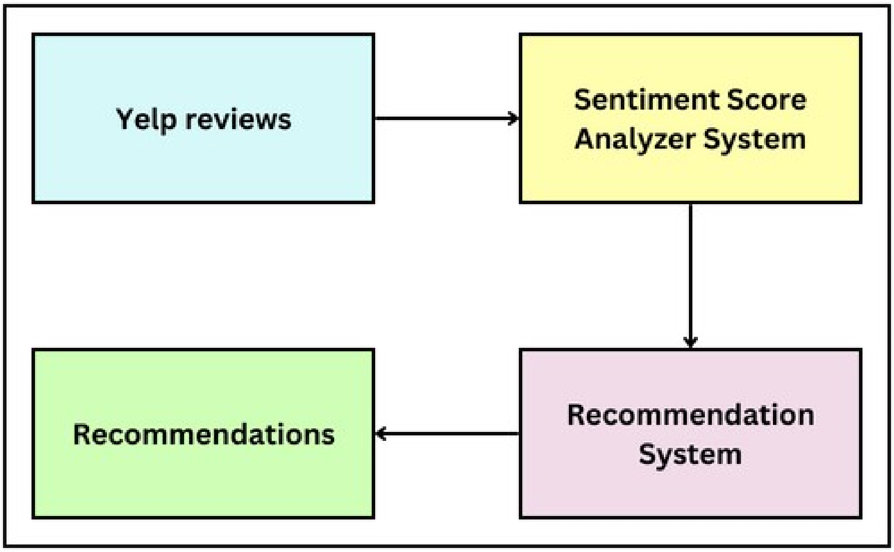

Figure 4. Overall System Architecture

5.1 Sentiment Analysis on Restaurants Reviews

5.1.1 Flowchart:

The visual representation Figure 5 provides a clear depiction of the sequential stages involved in the sentiment analysis process. Each step is outlined, starting with data collection from the Yelp Restaurants Reviews dataset[14] and progressing through filtration based on user preferences, text preprocessing, sentiment score calculation using the "DistilBert" model[15], prediction of ratings based on sentiment scores, and concluding with the evaluation of the model's performance using metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE). This visual guide serves as a concise and informative overview of the entire sentiment analysis workflow.

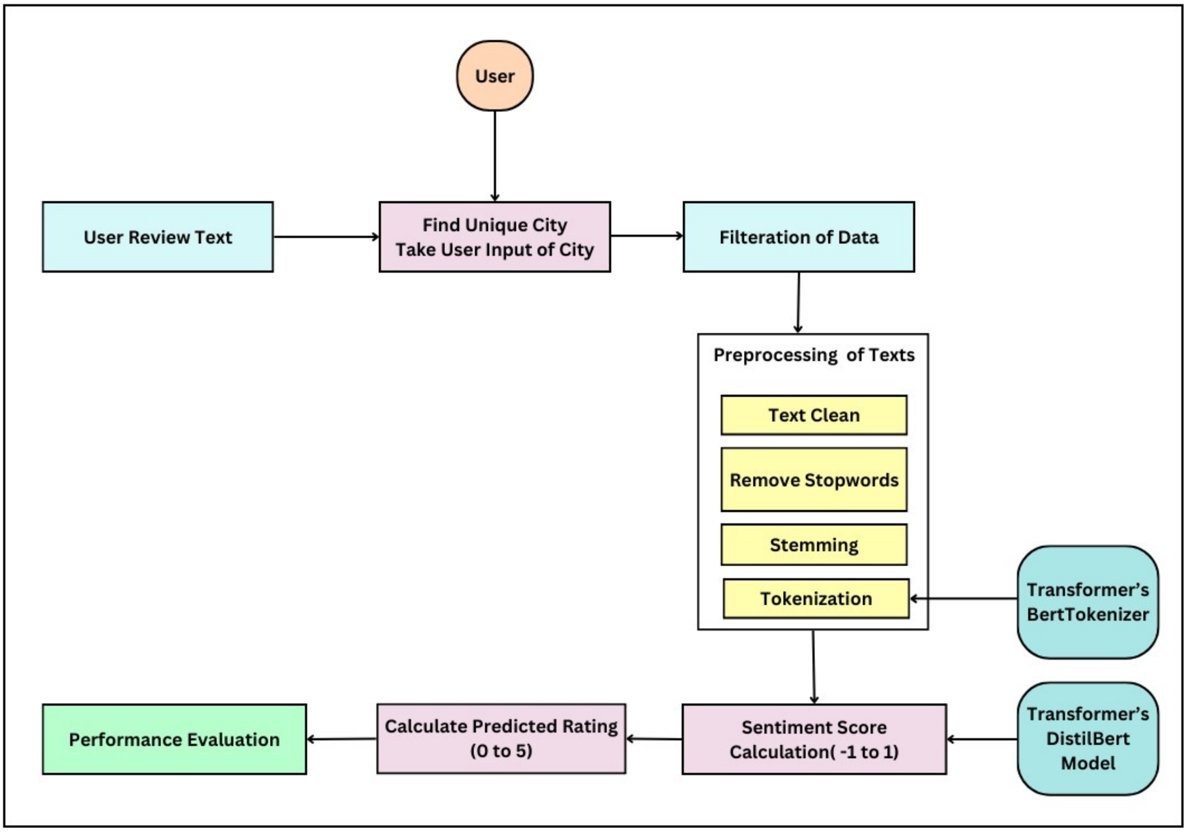

Figure 5 . Steps for Sentiment Analysis of Review text

- **Data Collection:**
  Our primary dataset is derived from a preprocessed dataset that includes extensive reviews and business information. We pay attention to the Yelp Restaurant Reviews dataset [14]. This dataset includes important information like the business ID, review date, review ID, user-assigned star ratings (from one to five), unique user IDs, and user-provided veterinarian review text. These data sets are combined to provide a strong basis for our sentiment analysis task, which enables us to comprehend user sentiments towards different businesses.

- **Filtration:**
  Understanding user preferences is key to tailoring this analyses.Engaging with users involves seeking their input on restaurant reviews for their chosen city of interest. This user-driven filtration process ensures that subsequent analyses are region-specific, providing a more personalized and relevant perspective on restaurant reviews.

- **Preprocessing of Text**:
  After user-driven filtration, text preprocessing is a vital step to refine and enhance the quality of our review texts. This involves several sub-steps:

a. Text Cleaning:
Carefully reviewing the texts involves removing any odd formatting, superfluous punctuation, and unnecessary whitespace, ensuring that the text data is consistent, noise-free, and ready for analysis.

b. Removal of Stopwords:
Stopwords are words that are frequently used in a language but typically don't mean much by themselves. Conjunctions ("and," "but"), articles ("the," "a"), and common prepositions ("in," "on") are a few examples.The sentiment analysis model can focus on the words that convey sentiment and user opinions

by removing stopwords[16] from reviews. This preprocessing step helps to streamline the analysis process, which is especially useful when working with limited computational resources..

c. Stemming:

Using the Porter stemming algorithm, we perform word stemming [17], a process that involves removing suffixes to extract the root or stem of each word. This aids in standardizing words, reducing dimensionality, and capturing the core meaning of words.

d. Lowercasing:

For consistency and simplicity in analysis, process converts all characters in the dataset to lowercase. This normalization ensures that there is no distinction between uppercase and lowercase letters, streamlining subsequent analyses.

e. Tokenization:

Leveraging the BertTokenizer [18] from the transformers library to tokenize the cleaned and preprocessed text. Tokenization breaks down the text into individual units, or tokens, enabling more granular analysis and understanding of the text.

- **Sentiment score calculation:**

  The sentiment score of a review text functions as a numerical indicator, providing a quantitative depiction of the emotional tone contained within the content. Sentiment analysis, a sophisticated natural language processing technique created to assess and decipher sentiments expressed in written or spoken language, is applied to this scoring [25]. The sentiment score, which is typically positioned on a spectrum between positive and negative or measured on a scale from 0 to 1, offers a precise assessment of the emotional landscape present in textual expressions.

  Our chosen methodology for deriving these sentiment scores involves leveraging the powerful "DistilBert" model [15]. This cutting-edge model employs advanced language understanding techniques to analyze the words, phrases, and contextual nuances of a given text. Trained on extensive datasets, DistilBert [15] excels in discerning sentiments, classifying them as positive, negative, or neutral. The resulting sentiment score not only furnishes a quantitative measure of the emotional context but also facilitates a nuanced comprehension of user sentiments and attitudes.

  For practical illustration, a sentiment score nearing 1 implies a positive and contented tone, while a score closer to 0 signifies a more critical or discontented sentiment. This sentiment analysis, driven by the DistilBert model [15], proves invaluable for businesses, researchers, and analysts aiming to gauge public opinion, evaluate customer satisfaction, or make informed, data-driven decisions based on the emotional undercurrents within textual data. The implementation of DistilBert [15] enhances the precision and depth of sentiment analysis, contributing to a more comprehensive understanding of user sentiments in diverse contexts, including product reviews, social media interactions, and restaurant feedback.

- **Predicting Rating Based on Sentiment Score:**

  In this step, the sentiment score, which ranges from -1 to 1, is transformed into a more interpretable and applicable range of 0 to 5 using mathematical transformations. This conversion ensures alignment with common rating scales and facilitates the interpretation of sentiment in the context of ratings.

  Mathematical Transformation:The sentiment score (S) is mapped to the range [0, 5] using the following transformation:

  $$\text{Predicted Rating}=(S+1)/2*5$$

  This transformation ensures that a sentiment score of -1 corresponds to a predicted rating of 0, a sentiment score of 0 corresponds to a predicted rating of 2.5, and a sentiment score of 1 corresponds to a predicted rating of 5.

- **Performance of sentiment analysis:**

  The performance of the sentiment analysis model is assessed through various metrics to gauge its effectiveness in predicting sentiment accurately. Several commonly used metrics include:

  - **MAE:** The Mean Absolute Error, or MAE, measures the precision of the model by computing the average absolute differences between predicted and actual ratings.

$$\text{MAE}=\frac{1}{N}\Sigma\left|y_i - \hat{y}\right|$$

where,

$\hat{y}$= predicted rating of calculated

y=actual rating provided by users

- **MSE:** Mean Squared Error is similar to RMSE but without the square root operation. It penalizes larger errors more significantly, offering insights into the model's overall performance.

$$\text{MSE}=\frac{1}{N}\Sigma\left|y_i - \hat{y}\right|^2$$

where,

$\hat{y}$= predicted rating of calculated

y=actual rating provided by users

- **RMSE:** Root Mean Squared Error, or RMSE, quantifies the average magnitude of the differences between predicted and actual ratings. Better accuracy is indicated by lower RMSE values.

$$\text{RMSE}=\sqrt{MSE}=\sqrt{\frac{1}{N}\Sigma\left|y - \hat{y}\right|^2}$$

where,

$\hat{y}$= predicted rating of calculated

y=actual rating provided by users

5. 2 Restaurant Recommendation System

5.2.1 Flowchart

In Figure 6, different steps for recommending the restaurants are shown:

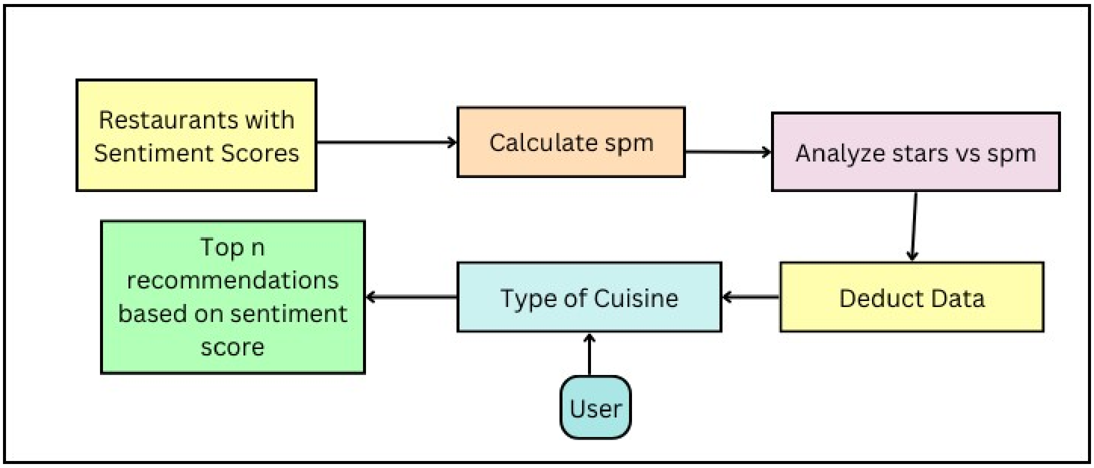

Figure 6. Steps for restaurant recommendation

- **Sentiment Score Integration:** Each restaurant in our dataset is now associated with a sentiment score, reflecting the overall sentiment derived from customer reviews.
- **Mean Sentiment Polarity Calculation(spm):** We calculate the mean sentiment polarity by grouping entries based on their unique business ID. This allows for a comprehensive analysis of sentiment trends across restaurants.
- **Stars vs. Sentiment Polarity Analysis:** We analyze the relationship between star ratings and mean sentiment polarity. Figure 7 illustrates the relationship between stars and spm for values within the range of (1, 1.5). Similarly, Figure 8 depicts the correlation between stars and spm for values falling within the range of (2, 2.5). Moving forward, Figure 9 showcases the stars versus spm dynamics for the range of (3,

3.5). Lastly, Figure 10 provides insights into the interplay between stars and spm for values encompassing the range of (4, 4.5, 5). These figures collectively offer a comprehensive visual representation of the variations in stars and spm across different specified ranges, contributing to a deeper understanding of the underlying data patterns.

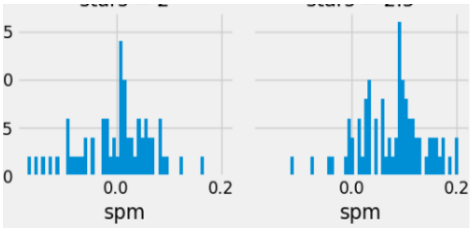

Figure7 . stars vs spm of (1,1.5)

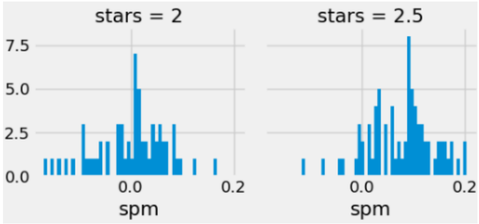

Figure 8. stars vs spm of (2,2.5)

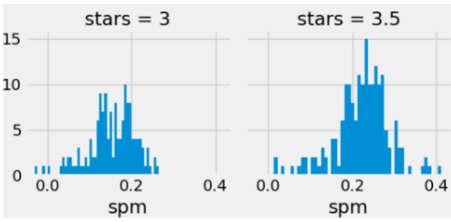

Figure 9 . stars vs spm of (3,3.5)

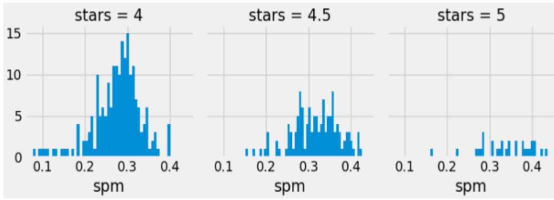

Figure 10. stars vs spm of (4,4.5,5)

Analysis from the Graph:

- **Star Distribution Above 3.5:**
  The graph analysis reveals that restaurants with star ratings surpassing 3.5 are predominantly found within the range of 0 to 0.5 on the sentiment polarity scale.
- **Refined Dataset Criteria:**
  To narrow our analysis and concentrate on particularly positive sentiments and highly rated establishments, we refine our focus. Specifically, we isolate rows where the star rating exceeds 3.5, indicating notable customer satisfaction, and the sentiment polarity value is greater than 0.

- **Dataset Refinement:**
  To focus on positive sentiments and higher-rated establishments, we narrow down the dataset. This involves considering only rows where the star rating exceeds 3.5, and the sentiment polarity is greater than 0.
- **User-Centric Top N Recommendation System:**
  Upon receiving user input specifying a cuisine , our recommendation system employs a two-tiered approach: city and cuisine. This system recommends top establishments based on cuisine preferences and the specified city. Leveraging city-based information, our recommendation system ensures a personalized experience. Recommendations prioritize establishments with the highest sentiment polarity, contributing to a positive and enjoyable dining experience.

6. Experimental results

In our relentless pursuit of refining sentiment analysis, we meticulously compared various models, starting with TF-IDF and incorporating n-grams and tokenization. Using a Linear Support Vector Machine (SVM) resulted in an accuracy of 59.6%. Another model, combining a Random Forest algorithm with a Tokenizer and Word2Vec embeddings, achieved 66% accuracy, showcasing proficiency in complex data tasks.Venturing into deep learning, an LSTM model with advanced features and early stopping achieved 69% accuracy. However, the pinnacle of our exploration was the application of DistilBert, which excelled with a remarkable 83% accuracy. This underscores the superiority of DistilBert over traditional approaches like TF-IDF, LSTM, and word2vec-based methodologies, highlighting its unparalleled effectiveness in sentiment analysis."

Model	Tokenizer	Accuracy	MSE	RMSE	MAE
distilbert-base-uncased	DistilBertTokenizer	0.83	0.34	0.58	0.45
LSTM	keras Tokenizer	0.69	0.41	0.64	0.51
Random forest	word2vec	0.66	0.69	0.83	0.45

Figure 11.Comparison of result and error

7. Conclusion & Future Work

In the past, methods like TF-IDF and Word2Vec had trouble understanding emotions in text. They struggled with seeing how words related to each other and understanding the real meaning behind sentences. Word2Vec had issues with uncommon words and didn't pay attention to the order of words in a sentence. These problems made them not very good at figuring out how people felt in what they wrote. . In a comparison, models like random forest and LSTM showed decent accuracies, but the game-changer was DistilBert, achieving an impressive 83% accuracy. User input on city and cuisine preferences serves as a crucial filtration step, tailoring our analyses to specific geographic locations and culinary tastes, amplifying the relevance of our recommendations and catering to diverse user preferences.Strategic result filtering based on user-specified criteria, combined with top polarity values, elevates our recommendation system's effectiveness. This approach ensures recommendations aren't just highly rated but also align with positive sentiments expressed by users, refining the selection process for establishments that consistently evoke positive experiences.The integration of DistilBert, with its streamlined architecture and impressive performance, aligns with our commitment to efficiency and user satisfaction. Its role in extracting sentiment from reviews, paired with user-focused filtering and recommendation strategies, emphasizes our dedication to a tailored and enjoyable dining experience.

The implementation of the DistilBert model has yielded promising results, with an accuracy rate of 83%. Additionally, the Mean Squared Error (MSE) stands at 0.34, the Root Mean Squared Error (RMSE) at 0.58, and the Mean Absolute Error (MAE) at 0.45. These metrics collectively indicate a high level of precision and reliability in the model's predictions.

Looking ahead in our future work, exploring larger and diverse datasets could unveil more insights into model adaptability across linguistic variations and domains. Leveraging multiple filtration criteria holds promise for enhancing accuracy. Domain-specific pre-training for models like DistilBert[15] could tailor sentiment analysis to specific industries, while continuous refinement to evolving language patterns and user behaviors remains crucial for maintaining efficacy in real-world scenarios. Sentiment analysis beckons further research, promising ongoing advancements in natural language processing[25].

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