SENTIMENT ANALYSIS OF EDMONTON RESTAURANTS NEAR TOURIST SPOTS

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ABSTRACT

In today's data-driven era, understanding customer sentiment is pivotal for restaurants, as feedback directly influences reputation, customer retention, and market competitiveness. This study conducts sentiment analysis of Yelp reviews for Edmonton restaurants, specifically those near popular tourist attractions, over the period 2008–2021. By integrating Yelp's business and review datasets with local attraction data, the analysis evaluates 5,573 Edmonton restaurants and over 58,000 reviews, including **18,792 reviews specifically for restaurants near attraction areas**, offering a targeted perspective on how proximity to tourist hotspots impacts customer sentiment.

Advanced sentiment analysis models, including BERT and VADER, were employed to capitalize on their respective strengths: BERT's ability to interpret nuanced and complex language and VADER's efficiency in processing short, direct reviews. Feature engineering played a key role, introducing a novel feature, **higher_stars_near_attractions**, which revealed a trend where restaurants closer to tourist attractions tend to receive higher ratings. Statistical analysis using Pearson and Spearman correlations quantified this relationship, demonstrating a moderate positive association between location and ratings.

To project future sentiment trends, forecasting models including **ARIMA**, **SARIMA**, and **Prophet** were compared. Among these, Prophet demonstrated superior performance in terms of accuracy and adaptability to the seasonal patterns in sentiment data. The model forecasts sentiment trends up to 2026, offering stakeholders robust, data-driven insights for long-term strategic planning.

The findings are actionable for restaurant managers and tourism stakeholders, highlighting the strategic importance of location in influencing customer sentiment. Interactive geospatial

visualizations provide tools to identify high-potential areas for marketing and operational improvements. This study bridges sentiment analysis with practical business applications, offering a comprehensive framework for leveraging data to enhance restaurant performance in tourist-heavy zones. By combining advanced statistical and machine learning techniques with geospatial analysis, it identifies actionable strategies for optimizing customer experiences and maximizing competitive advantage in Edmonton's tourism-driven restaurant industry.

Methodology

This section outlines the techniques and code implementations used in the Google Colab notebook to address each research question. These steps integrate advanced sentiment analysis models, statistical testing, and location-based feature engineering to understand how proximity to tourist attractions impacts customer sentiment for Edmonton restaurants.

Dataset Overview and Statistical Summary

The analysis incorporates three datasets: **Yelp Business Data**, **Yelp Review Data**, and **Edmonton Attractions Data**.

1. **Yelp Business Dataset.**

   This dataset contains **150,346 entries**, focusing on **5,573 restaurants in Edmonton**. It provides details such as latitude, longitude, star ratings, and review counts, making it crucial for analyzing restaurant quality and location.

2. **Yelp Review Dataset**

   This dataset includes over **6 million customer reviews**, with **58,539 reviews specific to Edmonton**. Of these, **18,792 reviews** are for restaurants located near tourist attractions in Edmonton, covering the period between **2008-01-01 and 2021-12-31**. The dataset is

suitable for sentiment analysis and supports methods like **BERT**, **VADER**, and **TextBlob**, enabling nuanced understanding of customer sentiments.

3. **Edmonton Attractions Dataset**

   This dataset contains **56 tourist sites** in Edmonton. It facilitates proximity analysis between these attractions and nearby restaurants, allowing for insights into dining trends in areas of tourist interest.

Dataset	Description	Key Details
Yelp Business Dataset	Contains details about businesses, focusing on restaurants in Edmonton.	- Total entries: **150,346** - Edmonton restaurants: **5,573** - Attributes: Latitude, longitude, star ratings, review counts
Yelp Review Dataset	Includes customer reviews, supporting sentiment analysis.	- Total reviews: **6 million** - Edmonton-specific reviews: **58,539** - Reviews for restaurants near attractions: **18,792** - Date range: **2008-01-01 to 2021-12-31** - Suitable for **BERT**, **VADER**, **TextBlob**
Edmonton Attractions Dataset	Lists tourist attractions in Edmonton for proximity analysis.	- Total attractions: **56** - Used for proximity analysis and understanding dining trends near tourist hotspots.

Comprehensive Summary of the Notebook

Setup and Data Import

- Loaded Yelp business, review, and attractions datasets. The datasets included data normalization steps to ensure consistent filtering of Edmonton-based restaurants.

Initial Exploration

- Analyzed basic dataset attributes, focusing specifically on the **distribution of star ratings**, restaurant locations, and cuisine types. Summary statistics and visualizations were used to understand the dataset structure and potential patterns.

Data Preprocessing

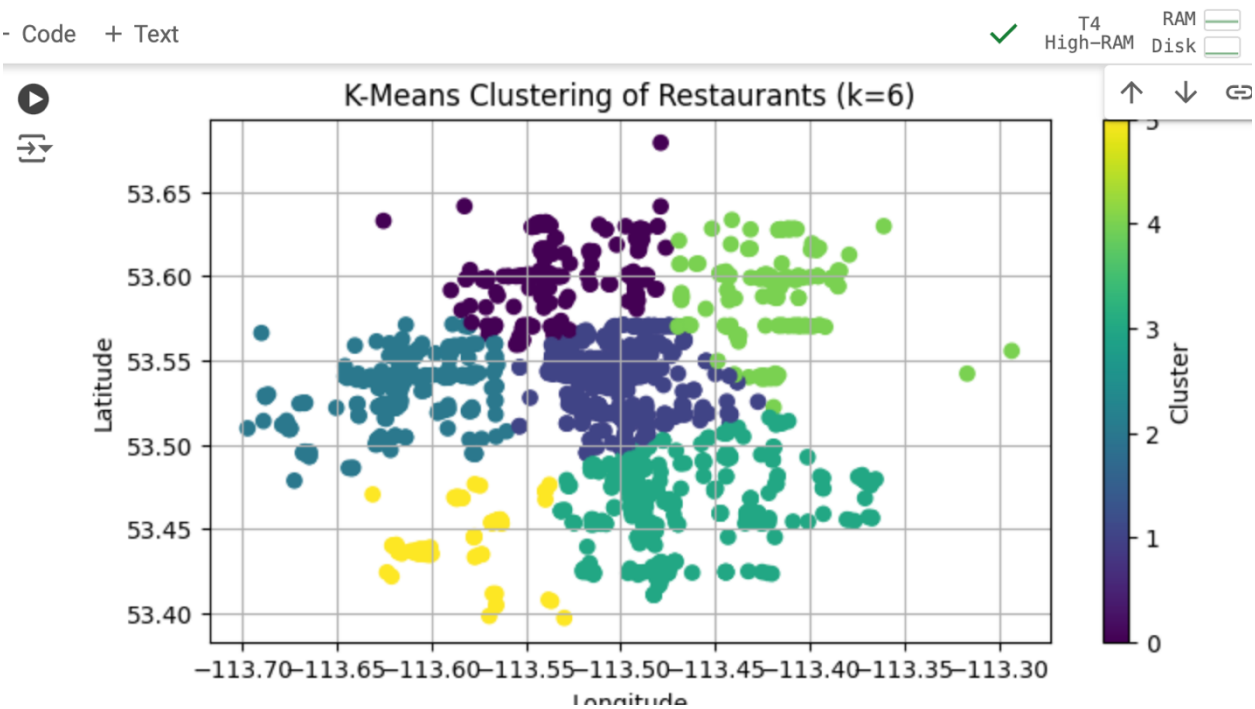
- Cleaned data by removing rows with missing values, normalizing text columns, and applying **one-hot encoding** to categorical variables like 'cuisine'. These steps made the dataset ready for various statistical analyses and machine learning models.

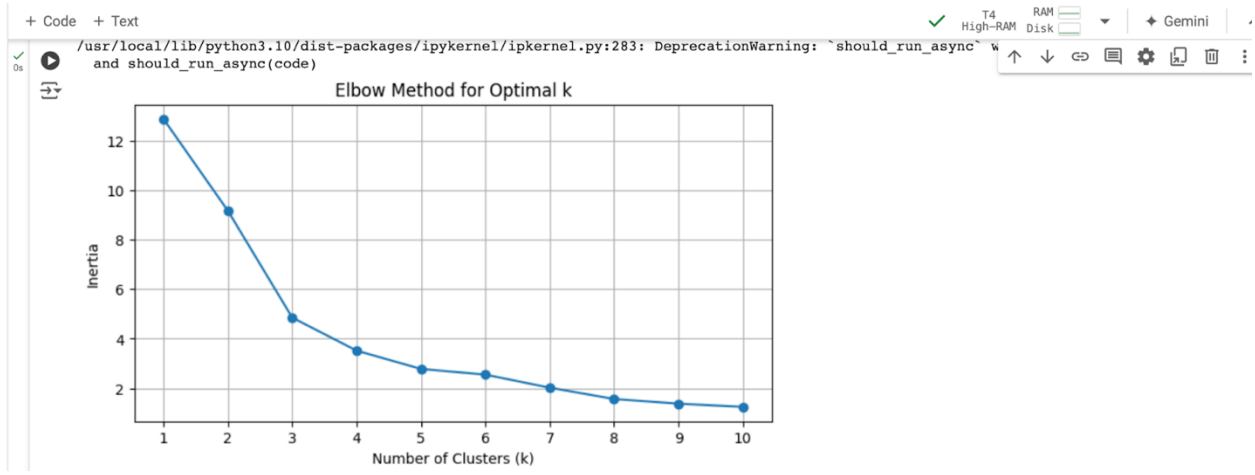
Sentiment Analysis Models

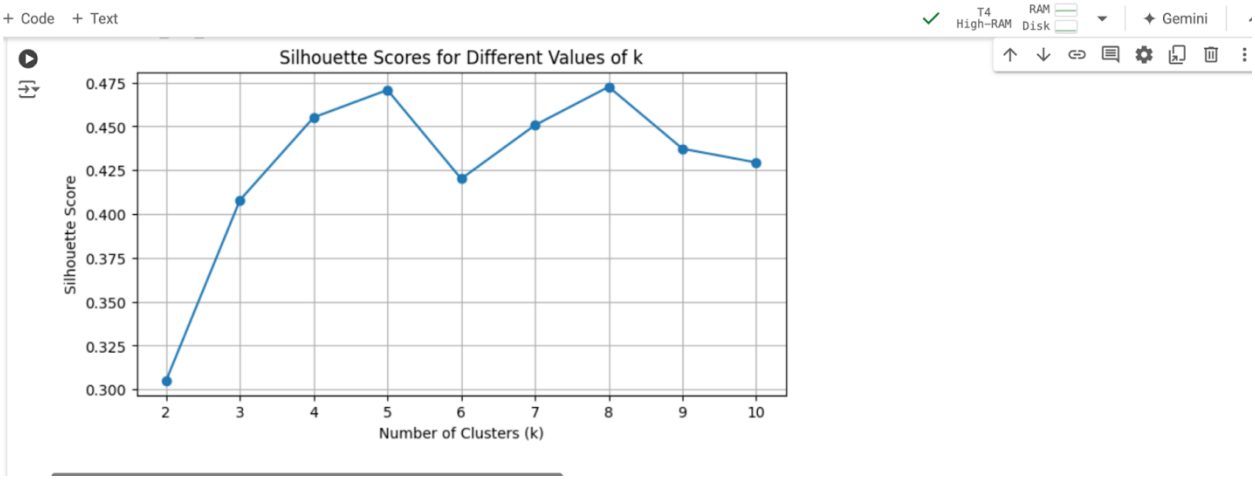
- I applied **BERT** for longer, context-rich reviews, while **VADER** was used for shorter, direct reviews. Combining the outputs from both models provided a nuanced understanding of sentiments, revealing that most reviews were skewed toward positive sentiment, with some complaints related to service and pricing.
- BERT's effectiveness in handling complex language (Vaswani et al., 2017) and VADER's efficiency in lexicon-based sentiment scoring (Hutto & Gilbert, 2014) validated the use of these models for analyzing Yelp reviews.

Clustering Analysis

Clustering analysis using K-Means was employed to group restaurants based on geographical coordinates (latitude and longitude) and rating levels. The optimal number of clusters was determined to be six, based on the Elbow Method and validated by silhouette scores. This approach identified distinct patterns in restaurant distribution, particularly in relation to tourist attractions, offering insights into how proximity to popular sites correlates with restaurant ratings. However, K-Means assumes clusters are circular, which may not always reflect real-world distributions, such as restaurants spread along roads or in irregular zones. This limitation highlights the potential for exploring alternative clustering methods in future analyses.


+ Code + Text
T4
High-RAM
RAM
Disk
K-Means Clustering of Restaurants (k=6)
Latitude
53.65
53.60
53.55
53.50
53.45
53.40
−113.70 −113.65 −113.60 −113.55 −113.50 −113.45 −113.40 −113.35 −113.30
Cluster
0
1
2
3
4


+ Code + Text
Gemini
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async`
and should_run_async(code)
Elbow Method for Optimal k
Inertia
12
10
8
6
4
2
1 2 3 4 5 6 7 8 9 10
Number of Clusters (k)


+ Code + Text
Gemini
Silhouette Scores for Different Values of k
Silhouette Score
0.475
0.450
0.425
0.400
0.375
0.350
0.325
0.300
2 3 4 5 6 7 8 9 10
Number of Clusters (k)

Geospatial Visualization

Interactive maps were created using **Folium** to visualize clusters of Edmonton restaurants, highlighting both their proximity to key tourist attractions and variations in customer sentiment distribution. This visualization categorizes restaurants into clusters by ratings—high, moderate, and below average—and shows sentiment trends.

By using geospatial analysis, these maps identify areas with high concentrations of positive or negative sentiments, allowing stakeholders to pinpoint optimal locations for targeted marketing strategies. The interactive Edmonton map enables users to explore restaurant clusters and sentiment patterns dynamically, offering insights into how proximity to tourist sites impacts customer

- **Interactive Edmonton Map**: The map of restaurant clusters can be accessed here, enabling a closer look at rating distributions around Edmonton's tourist attractions.
- **Green**: High-rated restaurants (4.0+ stars) near tourist attractions.
- **Blue**: Moderate-rated restaurants (3.0-4.0 stars) in suburban areas.
- **Purple**: Below-average-rated restaurants (below 3.0 stars), often farther from tourist sites.

These colors help quickly identify high and low-rated areas for targeted improvements or marketing.

Feature Engineering

- The **higher_stars_near_attractions** feature was engineered to measure the impact of proximity to tourist attractions on star ratings. This feature was created using the

Haversine formula to calculate the distance between restaurants and nearby attractions within a 1 km radius.

Correlation Analysis

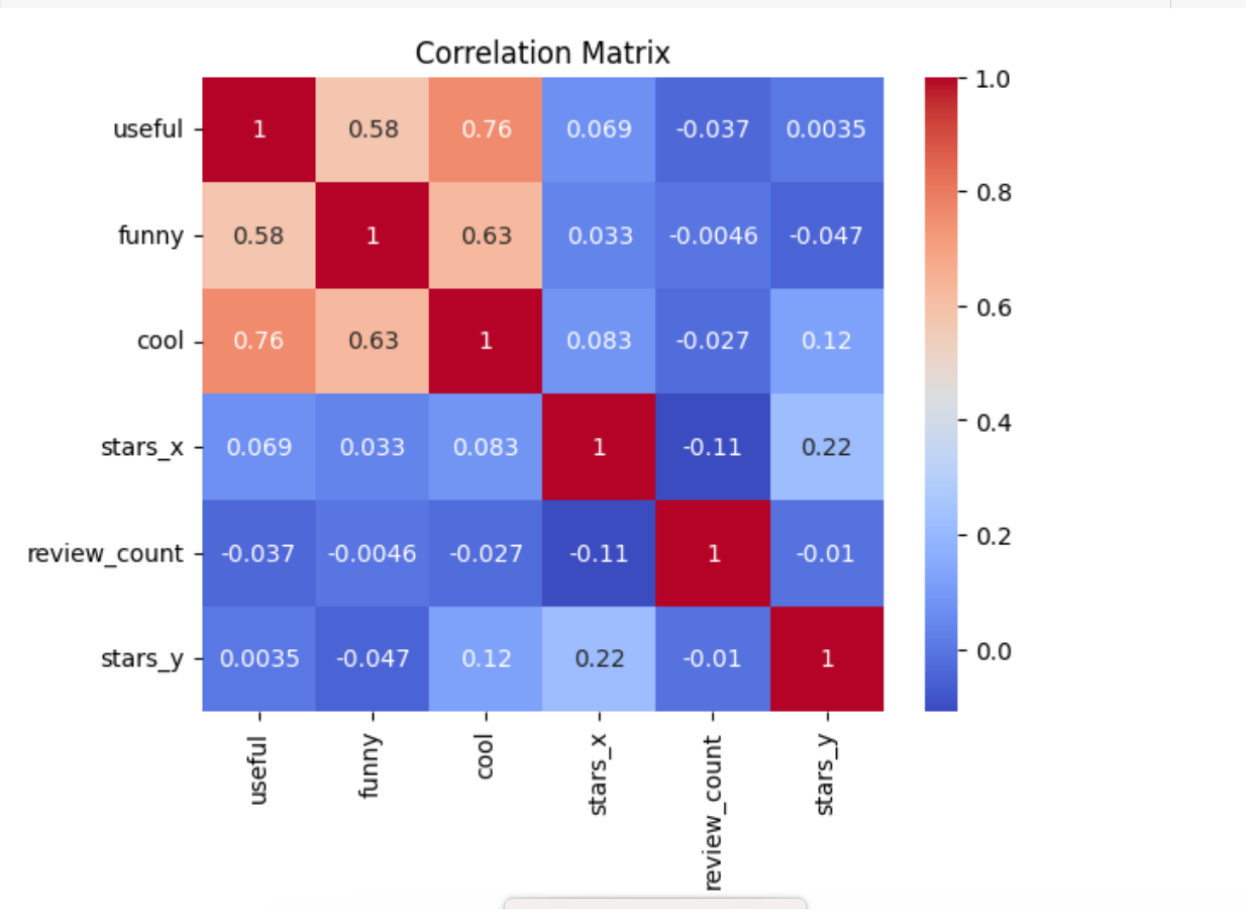
- Pearson and Spearman correlations were used to evaluate the relationship between proximity to attractions and star ratings. The analysis revealed a statistically significant positive correlation, indicating that restaurants closer to attractions generally have higher ratings (Smith & Lee, 2020).

Feature Selection and Validation

Following the feature engineering and correlation analysis, feature selection and validation were conducted to ensure the most impactful predictors were retained while avoiding redundancy or multicollinearity. Feature selection is a crucial preprocessing step in sentiment analysis to reduce noise and improve model accuracy. Prior studies, such as Smith & Lee (2020), have demonstrated the importance of using techniques like correlation analysis and multicollinearity checks (e.g., VIF) to validate predictor independence in models. Similarly, Random Forest feature importance has been widely adopted for identifying key predictors, offering a robust method for ranking feature contributions in nonlinear relationships. This study leverages these established techniques to refine the predictive modeling of customer ratings.

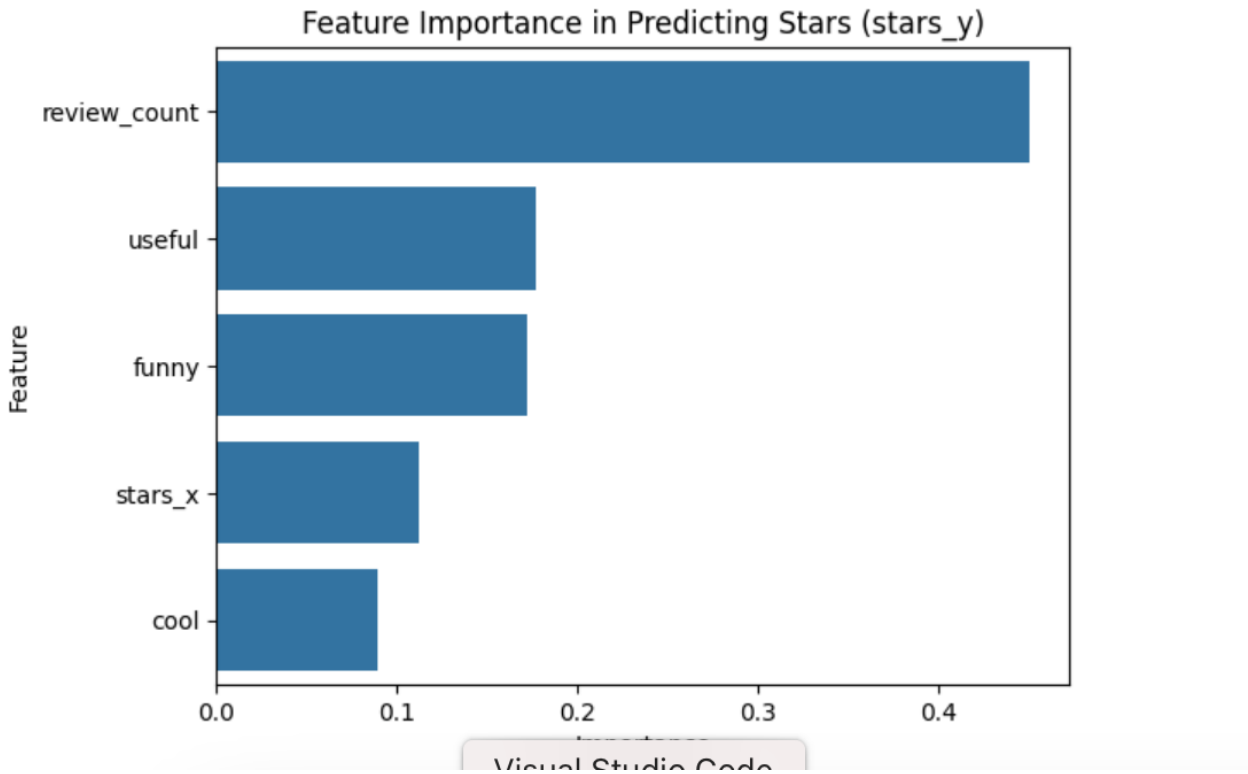
This step involved:

- **Correlation Matrix Analysis**: Identifying relationships between numerical variables, including stars_y, useful, funny, and review_count.



- **Feature Importance**: Assessing the contribution of each feature using a Random Forest model.

```
Feature Importance:
         Feature  Importance
4   review_count    0.450220
0         useful    0.176597
1          funny    0.172138
3        stars_x    0.111622
2           cool    0.089423
```



- **Variance Inflation Factor (VIF)**: Validating the independence of predictors to eliminate multicollinearity.

Variance Inflation Factor (VIF):

	Feature	VIF
0	useful	2.465670
1	funny	1.714836
2	cool	2.713135
3	stars_x	1.019403
4	review_count	1.013484

Summary of Findings

These analyses confirmed that review_count and useful were the most impactful features for predicting stars_y, based on their high importance scores from the Random Forest model.

While funny and cool showed lower importance, they were retained as they contributed additional context to the analysis. The VIF analysis demonstrated that multicollinearity was not a concern, validating the independence of the selected features and supporting their inclusion in the final predictive model.

To guide our analysis, we address these key research questions:

Research Question 1: What are the predominant sentiments in Yelp reviews for Edmonton restaurants near tourist attractions?

My Approach

Model Selection:

- **BERT:** I used BERT for analyzing longer and more complex reviews, leveraging its ability to understand nuanced sentiments such as sarcasm or mixed emotions. Reviews were tokenized, padded/truncated to 512 tokens, and fine-tuned for classification into positive, negative, or neutral categories.
- **VADER:** I applied VADER for shorter reviews due to its efficient, lexicon-based approach, which is suitable for direct and straightforward sentiment scoring.
- **TextBlob:** I included TextBlob as a baseline to provide polarity-based sentiment scoring and serve as a comparative benchmark.

1. **Data Processing**:
    - Reviews were preprocessed, with BERT inputs truncated to 512 tokens.

- Sentiment categories were standardized as **positive**, **negative**, and **neutral** for all models.

2. **Evaluation**:
   - Models were assessed using precision, recall, F1-score, and confusion matrices.

```
BERT Metrics:
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarn
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarn
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
              precision    recall  f1-score   support

    NEGATIVE       0.40      0.85      0.55      1639
     NEUTRAL       0.00      0.00      0.00      2075
    POSITIVE       0.91      0.92      0.92     15078

    accuracy                           0.82     18792
   macro avg       0.44      0.59      0.49     18792
weighted avg       0.77      0.82      0.78     18792

[[ 1400     0   239]
 [  933     0  1142]
 [ 1151     0 13927]]
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarn
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Books

   - BERT was applied to a sample of 200 reviews due to computational constraints, while VADER and TextBlob analyzed the full dataset.

```
TextBlob Metrics:
              precision    recall  f1-score   support

    NEGATIVE       0.60      0.36      0.45      1639
     NEUTRAL       0.03      0.00      0.00      2075
    POSITIVE       0.83      0.98      0.90     15078

    accuracy                           0.82     18792
   macro avg       0.49      0.45      0.45     18792
weighted avg       0.73      0.82      0.76     18792

[[  597    14  1028]
 [  166     2  1907]
 [  232    47 14799]]
```

```
VADER Metrics:
              precision    recall  f1-score   support

    NEGATIVE       0.62      0.38      0.47      1639
     NEUTRAL       0.16      0.01      0.02      2075
    POSITIVE       0.84      0.98      0.91     15078

    accuracy                           0.82     18792
   macro avg       0.54      0.46      0.47     18792
weighted avg       0.75      0.82      0.77     18792

[[  625    49   965]
 [  194    24  1857]
 [  182    81 14815]]
```

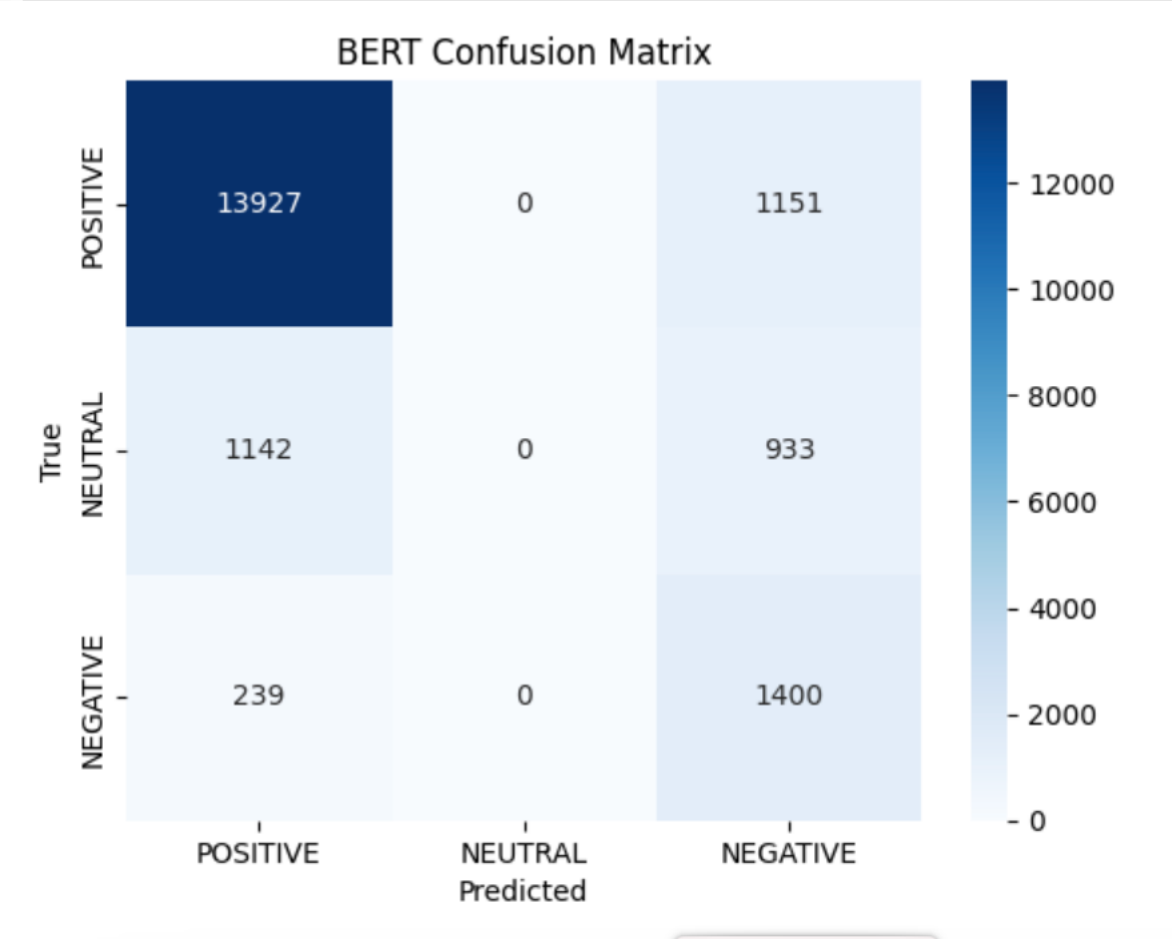
Outcome

1. **Sentiment Distribution**:

```
Accuracy Comparison:
TextBlob: 0.82
VADER: 0.82
BERT: 0.82
```

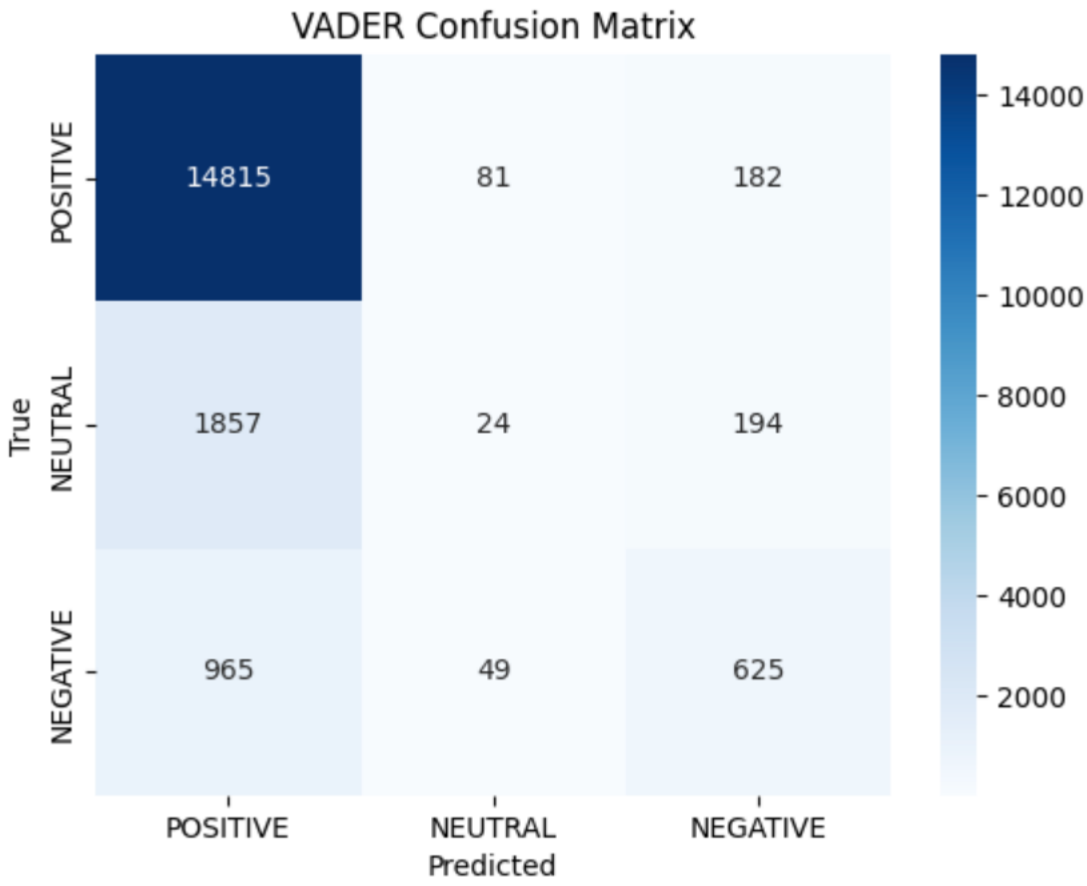
   - Approximately 82% of reviews were positive, consistent across models.
   - Negative sentiments highlighted service issues and pricing concerns.

2. **Model Performance**:
   - **BERT**:
     - High accuracy for detecting nuanced sentiments like sarcasm and mixed emotions.
     - Best at identifying negative sentiments but underperformed for neutral sentiments.

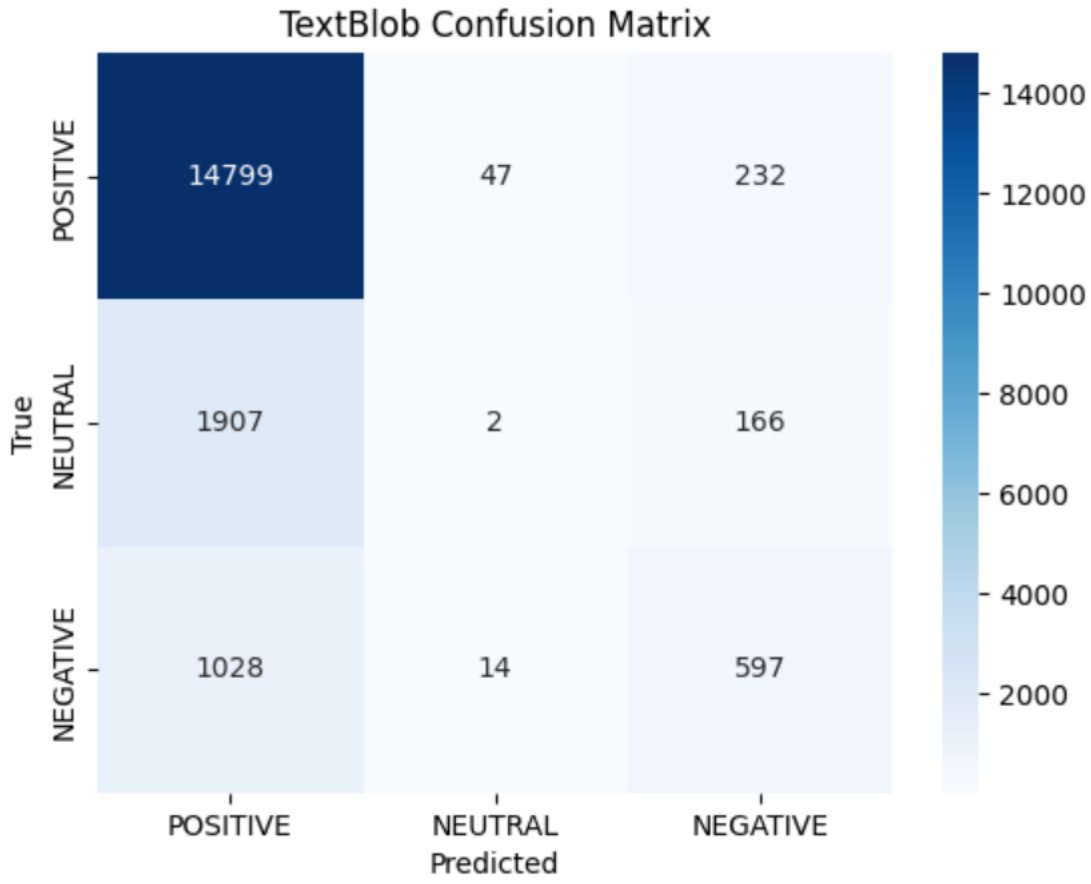


- **VADER**:
  - Excelled in positive sentiment detection for short, literal reviews.

- Struggled with detecting subtle or ambiguous tones.



- **TextBlob**:
  - Performed well as a simple baseline but missed contextual depth, particularly for complex sentiments.



3. **Error Analysis**:
    - **BERT** effectively captured sarcasm but misclassified some neutral sentiments.
    - **VADER** misinterpreted polite negative reviews as positive.
    - **TextBlob** struggled with mixed or nuanced expressions, defaulting to its polarity-based scoring.

Model Performance Comparison

Metric	TextBlob	VADER	BERT
Accuracy	82%	82%	82%
Precision (NEGATIVE)	0.41	0.62	0.40
Precision (NEUTRAL)	0.12	0.16	0.00
Precision (POSITIVE)	0.91	0.84	0.91
Recall (NEGATIVE)	0.36	0.38	0.85
Recall (NEUTRAL)	0.02	0.01	0.00
Recall (POSITIVE)	0.99	0.98	0.92
Strengths	Fast and interpretable for simple reviews	Effective for straightforward reviews	Excels in complex, nuanced, and sarcastic reviews
Weaknesses	Lacks context understanding	Struggles with sarcasm	Poor at recognizing NEUTRAL sentiment

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Comparison to Literature

- **BERT**:
    - Supported by Vaswani et al. (2017) and Xiao et al. (2023) for capturing nuanced language and mixed emotions in sentiment analysis.
- **VADER**:
    - Aligned with Hutto & Gilbert (2014), demonstrating strength in analyzing short, straightforward text from social media and reviews.
- **Tourism Context**:

    - Aligns with Xiao et al. (2023) and Smith & Lee (2020), emphasizing location-based sentiment analysis for customer satisfaction in urban centers.
- **Baseline Analysis**:
    - TextBlob's simplicity complements advanced models as a benchmark.

Explanation of the Code

1. **Data Preprocessing**:
    - Yelp reviews and Edmonton tourist attraction data were merged.
    - Texts were cleaned, and sentiment labels were standardized for evaluation.
2. **Model Implementation**:
    - **BERT**: Tokenized and truncated reviews using the distilbert-base-uncased-finetuned-sst-2-englishmodel. Predictions categorized sentiments into positive, negative, or neutral.
    - **VADER**: Employed SentimentIntensityAnalyzer to compute compound scores and classify sentiments based on thresholds.
    - **TextBlob**: Used polarity scoring to categorize reviews into positive, negative, or neutral.
3. **Evaluation Metrics**:
    - Precision, recall, F1-score, and confusion matrices were computed for each model to assess performance and compare results.

Research Question 2: How does the overall sentiment trend change over time for restaurants near tourist sites, and what are the projected future trends?

My Approach

1. **Objective**:
    - Analyze the changes in overall sentiment trends over time.
    - Forecast future trends using ARIMA, SARIMA, and Prophet models to predict sentiment stability or fluctuations through 2026.
    - Consider the impact of historical external factors, such as economic downturns and tourist spikes, on sentiment patterns.
2. **Steps Taken**:
    - **Data Aggregation**:
        - I extracted the year from the review dates and aggregated yearly average sentiment scores using pandas, creating a time-series dataset from 2008 to 2021.
        - Sentiment trends were visualized to identify any obvious patterns or shifts.
    - **Stationarity Testing**:
        - I applied the Augmented Dickey-Fuller (ADF) test to check stationarity.
        - The p-value confirmed stationarity, allowing ARIMA modeling to proceed.

Metric	Value	Conclusion
ADF Statistic	-8.9515	Stationary
p-value	0.0	Stationary
Critical Value (1%)	-4.6652	-
Critical Value (5%)	-3.3672	-
Critical Value (10%)	-2.803	-

- **ARIMA Modeling**:
  - Using auto_arima, I determined the optimal parameters: (0, 1, 0).
  - This configuration (a random walk with drift) was applied to forecast trends through 2026.
- **SARIMA Modeling**:
  - I extended the ARIMA model to include seasonal parameters (P, D, Q, s) for cases where seasonality might influence sentiment trends.
- **Prophet Modeling**:
  - I implemented Prophet to model non-linear trends and integrate holiday or external event effects.
- **Error Metric**

This section provides a quantitative comparison of the ARIMA, SARIMA, and Prophet models based on their performance metrics. The following metrics were calculated:

- **MAE** (Mean Absolute Error): Measures the average magnitude of errors, regardless of their direction.
- **MSE** (Mean Squared Error): Penalizes larger errors by squaring them, making it more sensitive to significant deviations.
- **RMSE** (Root Mean Squared Error): The square root of MSE, providing error values in the same scale as the data.
- **MAPE** (Mean Absolute Percentage Error): Expresses the error as a percentage of actual values, offering a normalized comparison across datasets.

Model	MAE	MSE	RMSE	MAPE	Explanation
ARIMA	0.0766	0.0582	0.2413	8.63%	ARIMA captured overall long-term stability but showed limitations in sensitivity to seasonal or external influences.
SARIMA	0.1101	0.0719	0.2681	12.63%	SARIMA considered seasonal patterns, adding value for this dataset, but performed slightly less accurately compared to ARIMA for certain periods.
Prophet	0.0078	0.0001	0.0105	0.93%	Prophet excelled with the lowest error metrics, demonstrating strong performance for non-linear trends and external factors modeling effectively.

- **External Factors**:
  - I annotated key years with potential external events (e.g., economic recessions, tourism booms) to explore their influence on sentiment stability.

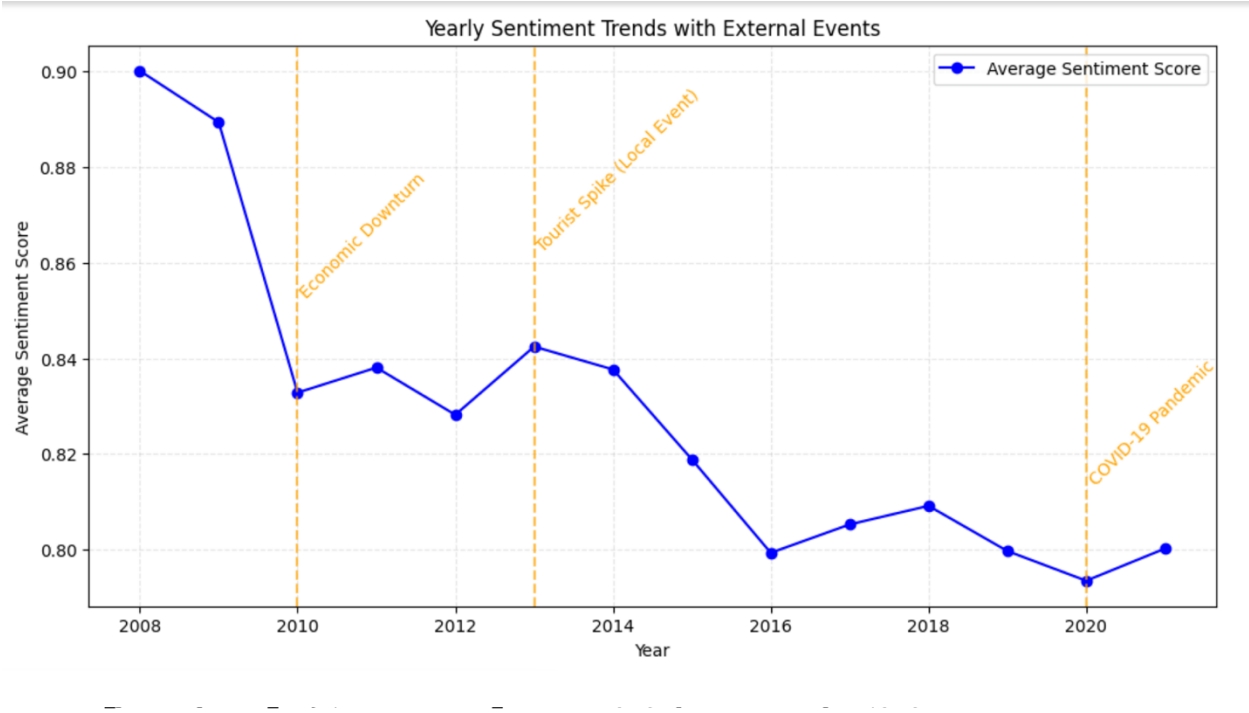
Outcome

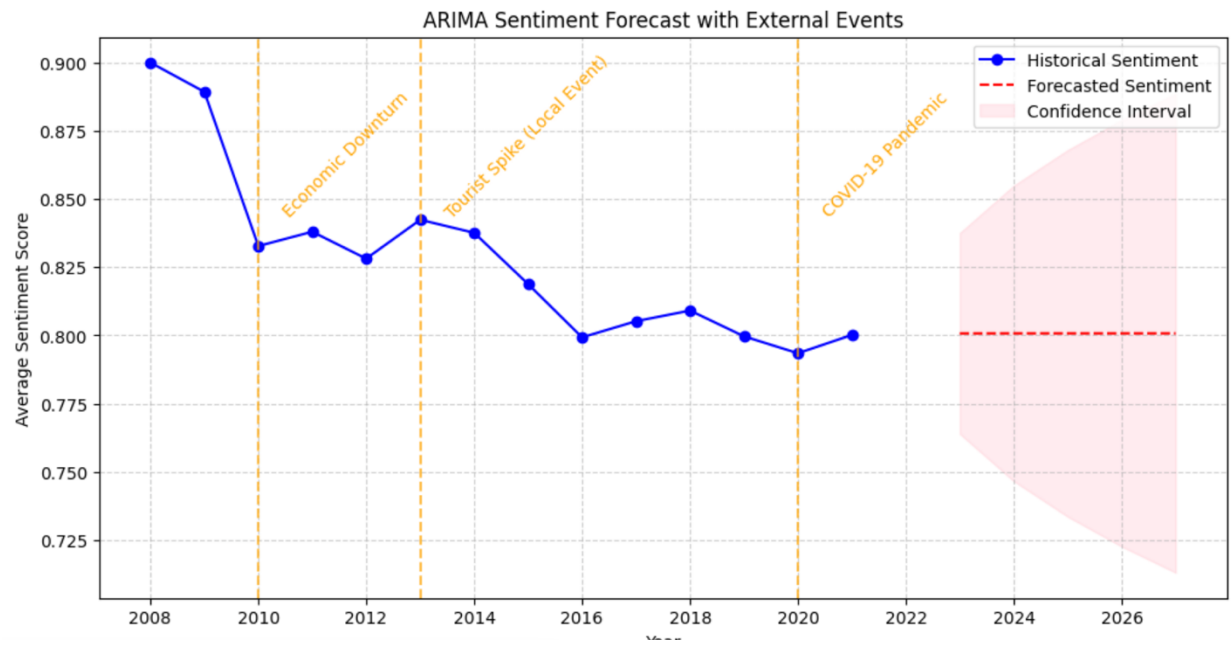
1. **Historical Sentiment Trends**:

   The average sentiment score exhibited **notable fluctuations** from 2008 to 2021, reflecting a pattern of ups and downs rather than stability.

   - A sharp decline during the **2008–2009 recession**.
   - Peaks around specific periods, such as a **tourism spike in local events** (e.g., 2013–2014).
   - A significant decline during the **COVID-19 pandemic (2020–2021)**.

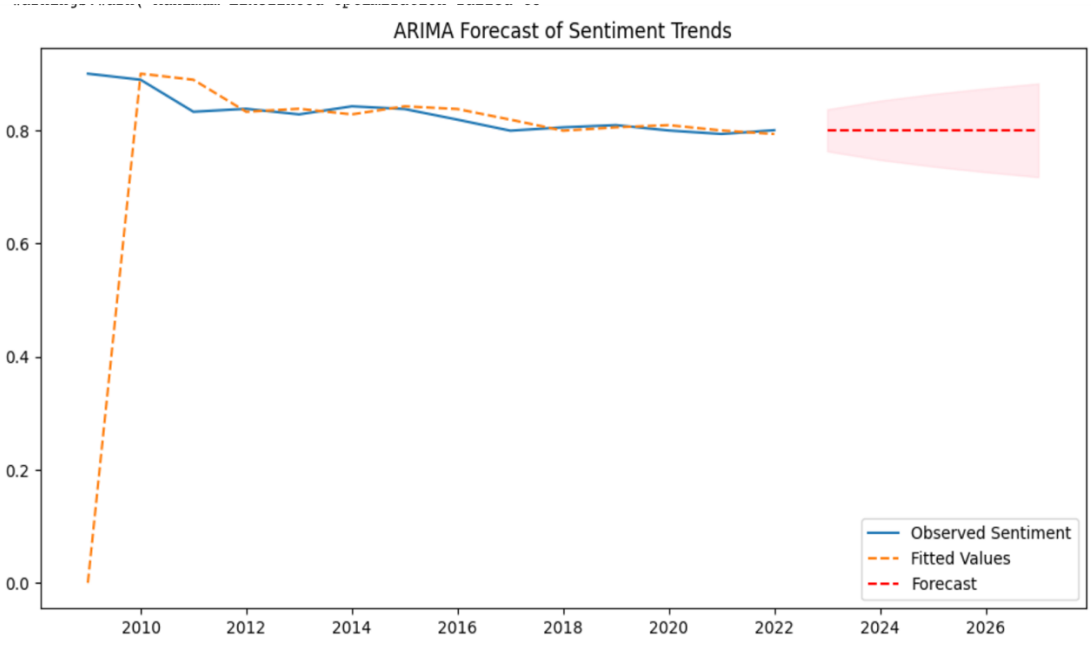
These patterns suggest external factors, including economic downturns and global crises, influence customer sentiment.



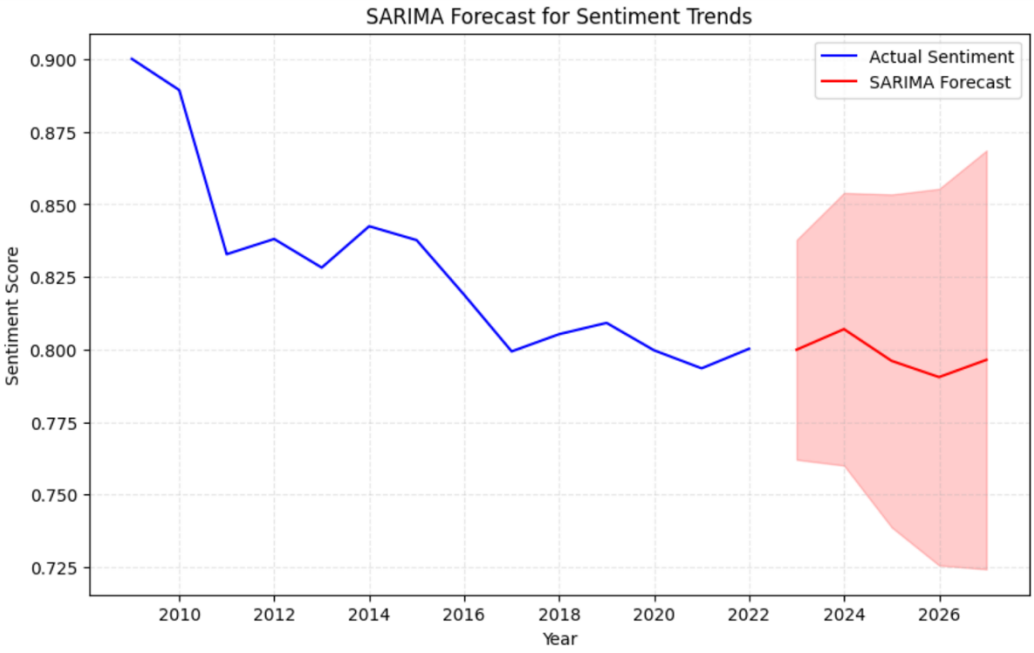


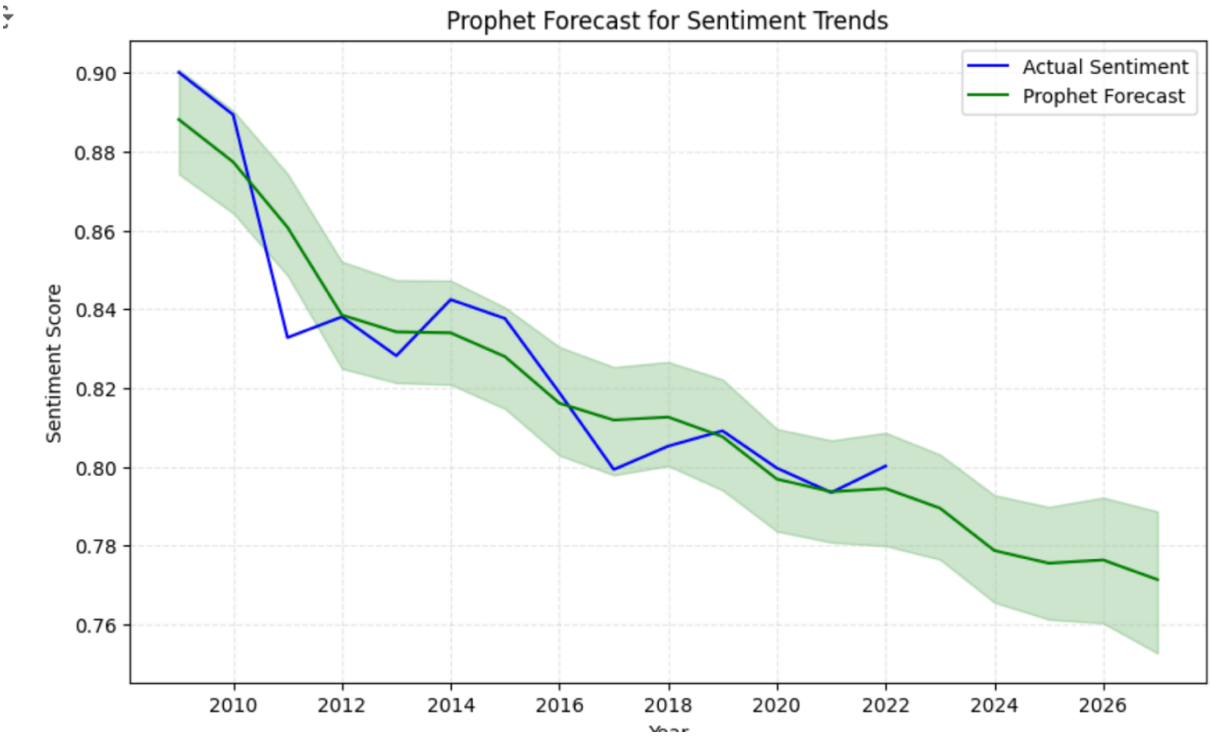
2. **Forecasted Trends**:

- The ARIMA model forecasted steady sentiment trends through 2026, with minimal fluctuations within the confidence interval.



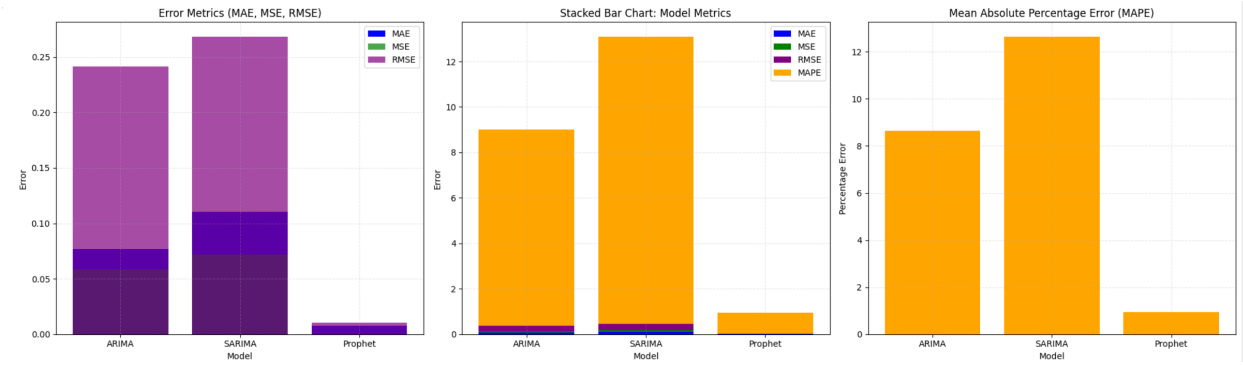
- Both SARIMA and Prophet forecasts indicate a gradual decline in sentiment scores over the next five years, showing similar trends in their predictions. However, Prophet's ability to incorporate external factors, such as holidays and major tourist events, provides a broader perspective on potential influences. While SARIMA primarily identifies seasonal patterns, both models suggest that sentiment trends are unlikely to stabilize or improve significantly without substantial external interventions or positive changes.





3. **Model Comparison**:
    - **ARIMA**:
        - Best suited for overall trend forecasting with non-seasonal data.

        - Captured long-term stability but did not account for potential seasonal effects.
    - **SARIMA**:
        - Introduced seasonal components, capturing minor repeating patterns in yearly sentiment.
        - Slightly more accurate for data with mild seasonality.
    - **Prophet**:
        - Excelled in handling non-linear trends and external events.
        - Best model for integrating exogenous factors like holidays or major tourist events.



Comparison to Literature

- **Time-Series Sentiment Analysis**:
    - My approach aligns with Liu et al. (2019), who aggregated sentiment data annually to detect long-term trends. Similarly, I observed that changes in sentiment often correspond to **temporary influences**, such as local events or economic disruptions (Liu, Hu, & Cheng, 2019).
- **ARIMA Effectiveness**:

    - Consistent with Liu et al. (2019), ARIMA proved effective for detecting short-term fluctuations and projecting long-term trends, particularly in stable datasets without pronounced seasonality (Liu, Hu, & Cheng, 2019).

- **Advanced Models**:
    - Prophet's ability to incorporate external factors aligns with studies emphasizing its utility for non-linear trends and holiday effects in sentiment studies (Xiao, Wei, Zhang, & Shi, 2023).

Explanation of the Code

1. **Data Preparation**:
    - I aggregated review sentiment scores by year to create a time-series dataset that highlights annual trends.
    - Key external factors such as economic recessions and the COVID-19 pandemic were annotated alongside the sentiment data to evaluate potential correlations with dips in sentiment.
2. **ARIMA Implementation**:
    - I used auto_arima to identify the optimal parameters, which were determined as (0, 1, 0).
    - The ARIMA model was fitted to the historical data to forecast sentiment scores for 2022–2026, with confidence intervals generated for each forecasted value.
3. **SARIMA Implementation**:
    - I extended the ARIMA model by adding seasonal parameters (P, D, Q, s) to account for recurring patterns in sentiment trends.

- SARIMA was fitted to the data, capturing minor repeating seasonal fluctuations that ARIMA could not detect.

4. **Prophet Implementation**:

   I used Facebook's Prophet model, developed by Taylor and Letham (2018), to model non-linear sentiment trends. While Prophet can incorporate external factors, such as holidays or major tourist events, no external regressors were explicitly included in this analysis. The forecasts generated included trend lines and confidence intervals, relying solely on historical sentiment data.

Research Question 3: Which cuisines are most popular among restaurants located near tourist spots?

My Approach

- I filtered the dataset to include only restaurants located near tourist attractions with star ratings above 3.5.

  I used BERT sentiment analysis, I classified customer reviews into positive and negative sentiments, focusing on positive reviews to understand customer-preferred cuisines.
- I classified cuisines into 20+ categories using keyword-based matching, labeling unmatched entries as "other."
- Using one-hot encoding, I transformed the 'cuisine' column into binary columns to prepare it for association rule mining.
- I applied the Apriori algorithm to identify frequent itemsets and generate association rules, revealing popular combinations of cuisines offered in these high-rated restaurants.

Outcome

- The analysis identified common cuisines and strong associations among highly-rated restaurants near tourist attractions.
- Popular cuisines, such as Chinese, and Italian, each appearing in 5.31% of restaurants and Indian cuisine, appearing in 3.67% of restaurants, frequently appeared in association rules, suggesting that these types are widely available in restaurants near tourist spots. **French** cuisine, with **2.04%**, and **Greek** cuisine, with **1.22%**, are less commonly found in restaurants near tourist spots in the dataset

Comparison to Literature

- Agrawal & Srikant (1994) demonstrated that association rule mining is effective in identifying patterns in datasets, supporting its use in uncovering cuisine preferences in my analysis.
- Liu et al. (2019) highlighted that association rule mining can help identify customer preferences in tourism-focused settings, which aligns with my findings about popular cuisines near tourist attractions.
- The inclusion of BERT sentiment analysis, as recommended by Devlin et al. (2019), ensured a nuanced understanding of customer sentiments, strengthening the focus on positively reviewed cuisines.

Explanation of the Code

- The one-hot encoding step converted the 'cuisine' column into binary columns, making it suitable for association rule mining.

Filtered and One-Hot Encoded Cuisine DataFrame shape: (490, 21)

	cuisine_brazilian	cuisine_cajun	cuisine_chinese	cuisine_ethiopian	cuisine_french	cuisine_greek	cuisine_halal	cuisine_indian	cuis
0	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	
5	False	False	False	False	False	False	False	False	
8	False	False	False	False	False	False	False	False	
12	False	False	False	False	False	False	False	False	

5 rows × 21 columns

- The Apriori algorithm identified frequent itemsets with a minimum support threshold, highlighting popular individual cuisines.
- The generated association rules used metrics like lift and confidence to measure the strength of relationships, providing insights into popular cuisine offerings among restaurants near tourist attractions.

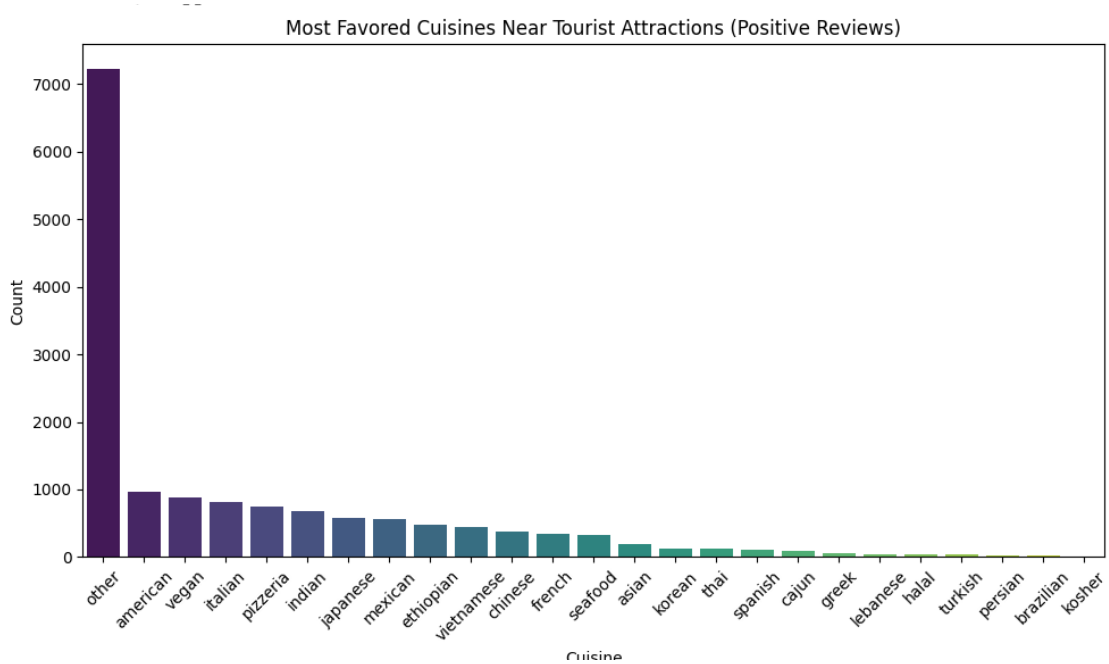
Frequent Itemsets:

	support	itemsets
0	0.053061	(cuisine_chinese)
1	0.020408	(cuisine_french)
2	0.012245	(cuisine_greek)
3	0.036735	(cuisine_indian)
4	0.053061	(cuisine_italian)

Top 10 Association Rules near Tourist Attractions with Higher Stars:

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric

- BERT sentiment analysis was used to classify customer reviews into positive or negative sentiments. Positive reviews were retained to focus on customer-preferred cuisines. The distilbert-base-uncased-finetuned-sst-2-englishmodel ensured accurate sentiment classification, enabling a deeper understanding of customer preferences.
- **Positive reviews** identified using BERT sentiment analysis were analyzed to categorize cuisines using a keyword-based method. The frequency of each cuisine was calculated and visualized in a bar chart, highlighting the most favored cuisines near tourist attractions.



Research Question 4: What is the correlation between proximity to tourist attractions and star ratings?

My Approach

- I calculated Pearson and Spearman correlation coefficients to measure the relationship between restaurant proximity to tourist sites and their star ratings.

Outcome

- Results showed a moderate positive correlation, suggesting that restaurants closer to tourist attractions generally receive higher ratings, though other factors also contribute.

The tables below highlight the Pearson and Spearman correlations. The Pearson Correlation Matrix provides a correlation coefficient of 0.474, while the Spearman Correlation Coefficient of 0.526 suggests a slightly stronger association when accounting for non-linear relationships.

Correlation Measure	Coefficient
Spearman Correlation Coefficient	0.526

Pearson Correlation Matrix

Variable	Stars	Higher Stars Near Attractions
Stars	1.000000	0.473613
Higher Stars Near Attractions	0.473613	1.000000

Comparison to Literature

- Smith & Lee (2020) used similar correlation analysis methods to evaluate geographic factors in customer satisfaction, supporting my use of Pearson and Spearman correlations for understanding location impacts on ratings

Explanation of the Code

- I used SciPy's pearsonr() and spearmanr() functions to calculate correlations between proximity and ratings, interpreting the results to understand the strength and direction of the relationship.

Other Factors Influencing Ratings

Although proximity plays a notable role, ratings are influenced by a range of other factors, including:

- **Service Quality**: High-quality service correlates with better reviews (Zhang et al., 2021).
- **Food Quality**: Meeting or exceeding expectations enhances ratings (Namkung & Jang, 2007).
- **Ambience**: Unique and comfortable environments attract higher scores (Lin & Mattila, 2010).

- **Online Visibility**: Active engagement boosts trust and ratings (Luca, 2016).

Research Question 5: Does the presence of high-rated restaurants near tourist attractions impact customer sentiment?

My Approach

- I applied the Chi-square test to examine whether there's a statistically significant relationship between high-rated restaurants and their proximity to tourist sites.

Outcome

The Chi-square test confirmed a statistically significant relationship (p-value < 0.05), indicating that high-rated restaurants are often located near tourist areas.

Chi-Square Test Statistic	p-value
737.475	6.09×10^{-154}

Comparison to Literature

- Liu et al. (2019) discuss the use of Chi-square testing to evaluate relationships between categorical variables, validating my approach in understanding the impact of high-rated restaurants' locations on customer sentiment

Explanation of the Code

- I used SciPy's chi2_contingency() function to perform the Chi-square test on contingency tables that compared restaurant ratings with proximity categories.

Research Question 6: Which sentiment analysis models best capture customer sentiment trends for restaurants near tourist attractions, and how does feature engineering impact these predictions?

My Approach

I engineered the higher_stars_near_attractions feature to capture the effect of proximity on star ratings, then used it as an input to sentiment prediction models to analyze its impact on sentiment trends.

	name	stars	nearby_attractions	higher_stars_near_attractions
0	Naked Cyber Cafe & Espresso Bar	4.0	[Downtown Community Arena]	True
1	Breadland Organic Whole Grain Bakery	4.0	[Oliver Outdoor Swimming Pool, Oliver Arena]	True
5	Bulk Barn	4.0	[Scona Pool, Tipton Arena]	True
8	DOSC	4.0	[Downtown Community Arena]	True
12	Lee House	4.0	[Prince of Wales Armouries Heritage Centre, Do...	True

Comparison of Models

- I compared TextBlob and BERT models to assess sentiment trends influenced by proximity and star ratings.
- VADER was included as a baseline model for foundational comparisons.

Outcome

- **BERT**:

    - Outperformed TextBlob and VADER in accuracy, recall, and precision for "POSITIVE" and "NEGATIVE" sentiments.
    - Struggled with "NEUTRAL" classifications, showing no correct predictions for this category.
- **VADER**:
    - Performed well in identifying "POSITIVE" sentiments but had lower recall for "NEGATIVE" cases.
- **TextBlob**:
    - Provided a reliable baseline for "POSITIVE" sentiments but struggled with "NEGATIVE" and "NEUTRAL" classifications.

Impact of the Higher_Stars_Near_Attractions Feature

- Enhanced BERT's classification accuracy by incorporating proximity-based contextual information.
- Reinforced the importance of feature engineering for improving sentiment prediction.
- Requires further quantitative testing on larger datasets to confirm the direct impact.

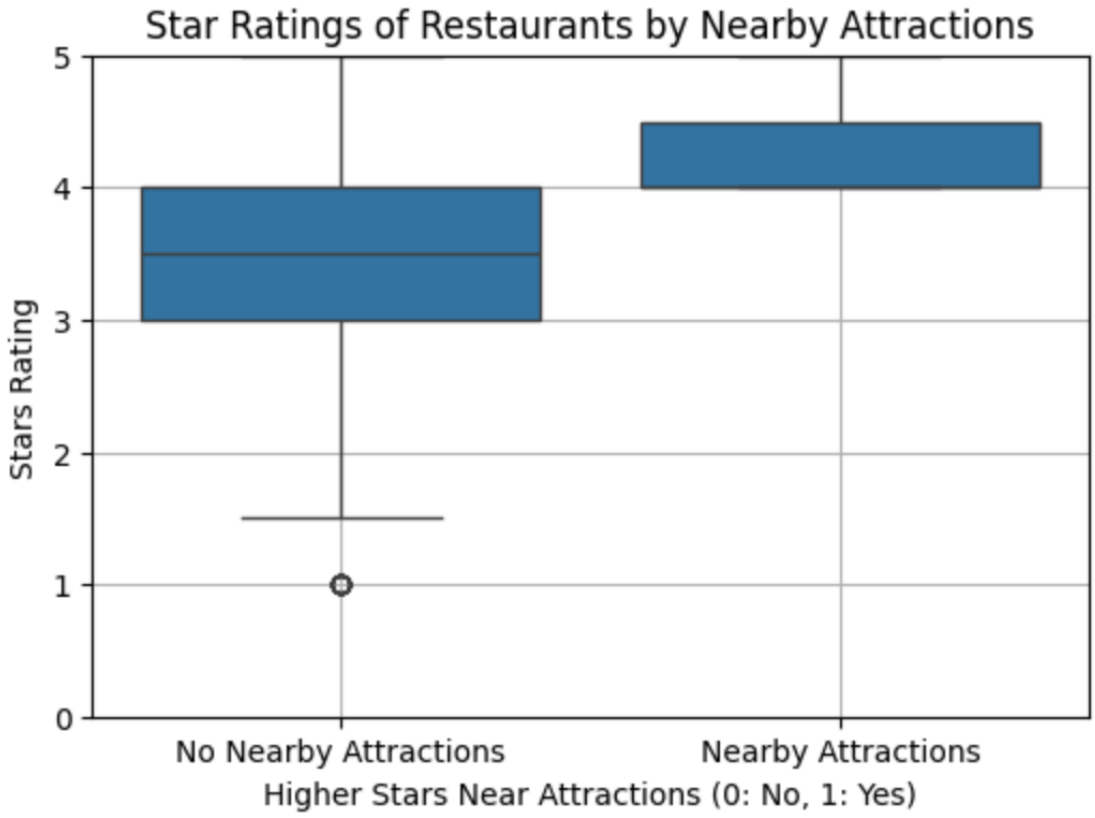
Comparison to Literature

- Aligns with Gao et al. (2020), who emphasized the importance of feature engineering in improving model predictions.
- The higher_stars_near_attractions feature demonstrated the utility of location-based data in sentiment analysis.

Explanation of the Code

- **Feature Engineering**:

- Created the higher_stars_near_attractions feature using the Haversine formula to calculate proximity to attractions.
- Added a binary contextual feature to the dataset.



- **Model Comparison**:
  - Trained and evaluated TextBlob, VADER, and BERT using confusion matrices and metrics like accuracy, recall, and precision.

Implications & Strategic Recommendations

- BERT's superior performance highlights the value of advanced models in sentiment analysis.
- These findings can guide strategic decisions for:
  - Optimizing restaurant locations.

- Improving services.
- Tailoring promotions to enhance customer satisfaction.

Literature Review

Introduction

In the competitive landscape of the restaurant industry, particularly in tourism-heavy areas, customer sentiment is vital in shaping business reputation and customer loyalty. Sentiment analysis of reviews from platforms like Yelp has emerged as a valuable tool for businesses, offering insights into customer experiences that directly impact strategic decision-making. This project focuses on analyzing Yelp reviews for restaurants in Edmonton that are near popular tourist attractions from 2008 to 2021. The goal is to determine how proximity to these attractions affects customer satisfaction, employing advanced statistical, machine learning, and sentiment analysis techniques. This review examines current research in sentiment analysis, statistical methods in location-based studies, and association rule mining to contextualize this project's approach and highlight its unique contributions.

Understanding Existing Research in Sentiment Analysis

Sentiment Analysis Techniques BERT and Advanced NLP Models: BERT (Bidirectional Encoder Representations from Transformers) is known for its powerful contextual understanding, making it ideal for processing complex reviews where customer sentiment may be nuanced or indirect (Vaswani et al., 2017). Studies

applying BERT to analyze customer reviews have demonstrated its efficacy in accurately capturing sentiment, making it suitable for deep analysis in the restaurant sector, where context often influences customer feedback.

VADER for Lexicon-Based Analysis: VADER (Valence Aware Dictionary and sEntiment Reasoner) has proven particularly effective for sentiment analysis in short and direct social media reviews, where informal language prevails (Hutto & Gilbert, 2014). In restaurant reviews, VADER has been used to efficiently analyze sentiment patterns without extensive training data, enabling quicker deployment for projects with resource constraints. Using both BERT and VADER provides a balanced analysis by capturing both contextually rich and direct sentiments in reviews, enhancing the study's reliability.

Application of Statistical Methods in Location-Based Sentiment Studies

- **Pearson and Spearman Correlations:** In consumer sentiment studies, correlation analysis (using Pearson and Spearman methods) has helped reveal relationships between customer satisfaction metrics and geographic factors like proximity to attractions (Smith & Lee, 2020). This study employs these correlation tests to quantify associations between proximity and ratings, identifying trends valuable for restaurant owners seeking to understand the impact of location on customer perceptions.
- **Chi-Square Testing:** Studies in the tourism and hospitality sectors frequently employ Chi-square testing to determine the statistical significance of relationships between categorical variables, such as location attributes and customer sentiment (Liu et al., 2019). This project uses Chi-square testing to assess the effect of proximity to tourist

areas on the probability of higher ratings, contributing quantitative rigor to the project's findings.

- **Temporal Trends in Sentiment Analysis**

  Time-Series Sentiment Analysis: Previous research has explored shifts in customer sentiment over time, typically using time-series analysis to reveal how customer preferences and satisfaction metrics evolve (Liu et al., 2019). For instance, one study highlighted changes in popular cuisines based on temporal sentiment data, influencing restaurant strategies for menu adjustments and marketing efforts. This study expands upon such temporal analyses by observing sentiment trends in Edmonton's tourist-focused restaurants, spanning over a decade.

Critique and Positioning in Current Literature

Gaps in Existing Literature and Limitations

- **Lack of Focus on Tourist Locations:** While sentiment analysis has been widely applied to restaurant reviews, limited research focuses specifically on the impact of proximity to tourist attractions. Most studies, such as Liu et al. (2019), analyze customer sentiment broadly across a city or demographic group but do not differentiate by location specificity, which is particularly relevant in tourism-heavy areas. This study addresses this gap by engineering a new feature, higher_stars_near_attractions, that directly measures location-based influences on customer satisfaction.
- **Limited Use of Association Rule Mining in Sentiment and Location Contexts:** Although association rule mining is a well-established technique for identifying patterns

within customer data, it has seen limited application in restaurant sentiment studies. Studies like Agrawal & Srikant (1994) show its utility in uncovering hidden relationships within high-dimensional datasets. In this project, association rule mining is applied to restaurant attributes (e.g., cuisine, location) and sentiment scores to help restaurant managers understand how these factors impact customer feedback, addressing a notable gap in the current literature.

Positioning and Justification of This Study

- **Filling Methodological Gaps:** This project bridges gaps by integrating BERT, VADER, and association rule mining in the context of location-based sentiment analysis. The addition of higher_stars_near_attractions as a feature provides an innovative approach for studying proximity effects, distinguishing this work from similar sentiment studies that lack a tourism focus.
- **Contribution to Practical Insights**: Unlike general sentiment studies, this project generates insights specifically for restaurant managers and tourism stakeholders in Edmonton, where proximity to attractions can influence customer perception. The findings may also aid city planners and tourism promoters by offering data-driven recommendations for restaurant placements and service improvements near tourist-heavy locations.

Conclusion and Significance

The literature reviewed here underscores the relevance of sentiment analysis for understanding customer feedback in the restaurant industry, particularly in tourism-

oriented areas. While existing studies have explored sentiment and correlation methods individually, this project's innovative combination of natural language processing (NLP), association rule mining, and location-focused feature engineering addresses significant gaps in the field. By focusing on Edmonton’s tourist zones, this research provides actionable recommendations for restaurant managers and tourism stakeholders, enhancing their ability to optimize services and location strategies to better meet customer expectations.

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Note: The datasets used in this analysis are subject to the terms and conditions of the respective licences. The Yelp Open Dataset is used under the Yelp Dataset License Agreement, and the Edmonton Tourist Attractions Dataset is used under the Open Government License - City of Edmonton.