CMPE 255

Analyzing User Feedback on Yelp Reviews: A Natural Language Processing and Data Mining Approach

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MOTIVATION

Customer feedback is essential for businesses as it provides insights into customer experiences, opinions, and preferences, which can help improve services and retain customers.

OBJECTIVES

- To develop models that can classify user comments as positive or negative sentiments using natural language processing and data mining techniques.
- To analyze the sentiment in greater detail to understand the reasoning behind positive or negative reviews.

ALGORITHMS USED

We used several classification algorithms, including

- **Naive Bayes** is a probabilistic algorithm that assumes independence among the features.
- **Decision Tree** algorithm splits the data into branches based on the most significant attribute.
- **Support Vector Classifier** tries to find the best hyperplane that separates the data into two classes.
- **Random Forest** is an ensemble learning algorithm that creates multiple decision trees and combines their results.

DATASETS USED

- **Yelp Academic Dataset Business:** 160585 rows and 14 columns (1.21 GB) (business_id, name, address, city, state, postal code, latitude, longitude, stars, review_count, is open, attributes, categories, hours)
- **Yelp Academic Dataset Review:** 879878 rows and 9 columns (6.25 GB) (review_id, user_id, business_id, stars, useful, funny, cool, text, date)

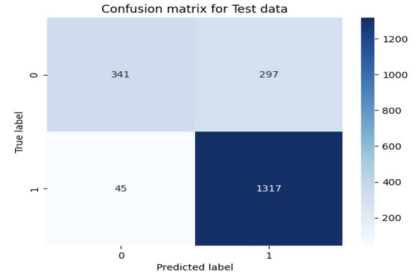
Methodology – Part-I Predicting user sentiment

1. Loading and Merging Datasets
2. Preprocessing
3. Filtering and Adding a New Column
4. Assigning Sentiment Values
5. Normalization: The next step was to perform tf-idf normalization of the rows to ensure that the dataset was scaled properly.
6. Splitting the Dataset: The dataset was split into an 80:20 ratio.
7. Finally, several machine learning models were used to predict the sentiment of the review.

RESULTS

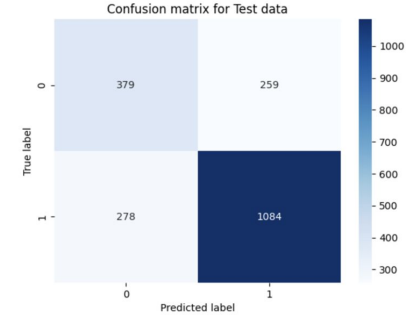
Naive Bayes

Precision Score of the model: 81.59851301115242
Recall Score of the model: 96.69603524229075
Accuracy score of the model: 82.89999999999999
F1 score of the model: 88.50806451612902



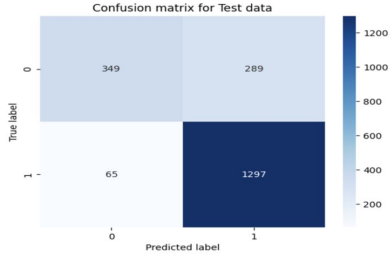
Decision Tree

Precision Score of the model: 80.71481757259866
Recall Score of the model: 79.58883994126285
Accuracy score of the model: 73.15
F1 score of the model: 80.1478743068392



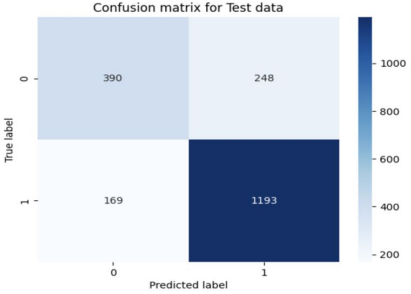
Support vector classifier

Precision Score of the model: 81.7780580075662
Recall Score of the model: 95.22760646108664
Accuracy score of the model: 82.3
F1 score of the model: 87.99185888738127



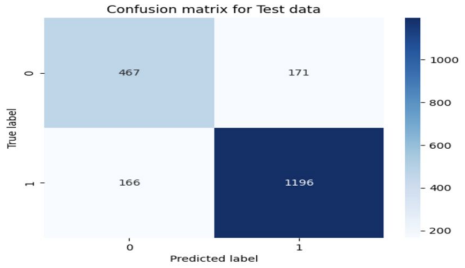
Random forest

Precision Score of the model: 82.78972935461485
Recall Score of the model: 87.59177679882526
Accuracy score of the model: 79.14999999999999
F1 score of the model: 85.12308241170174

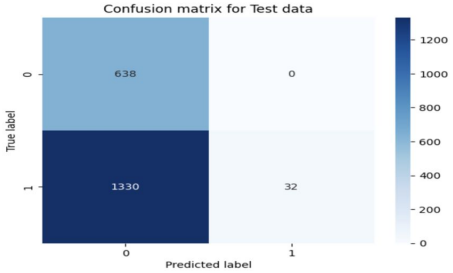


To improve the results, we performed oversampling and hypertuning grid search cross validation

Naive Bayes
Best parameters for the algorithm - Alpha = 0.001
Precision Score of the model: 87.4908558888076
Recall Score of the model: 87.81204111600587
Accuracy score of the model: 83.15
F1 score of the model: 87.651154268963

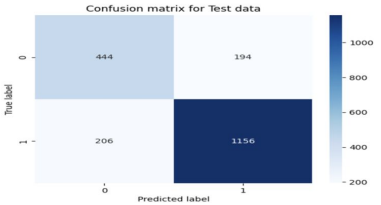


Decision Tree
Best parameters for the algorithm DecisionTreeClassifier (max_depth=8, max_features=5,min_samples_leaf=5, min_samples_split=3)
Precision Score of the model: 100.0
Recall Score of the model: 2.3494860499265786
Accuracy score of the model: 33.5
F1 score of the model: 4.591104734576758



Support vector classifier

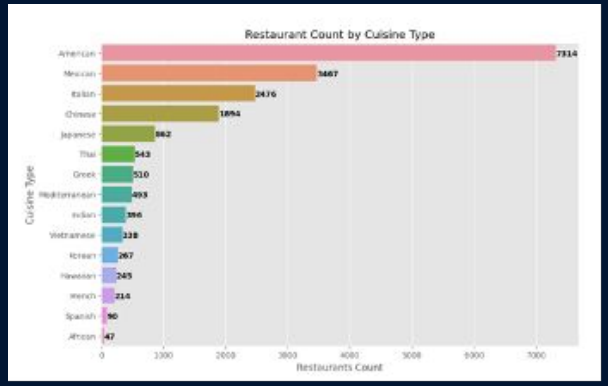
Best parameters for the algorithm SGDClassifier(alpha=0.0001, max_iter=20)
Precision Score of the model: 85.62962962962963
Recall Score of the model: 84.87518355359765
Accuracy score of the model: 80.0
F1 score of the model: 85.25073746312685

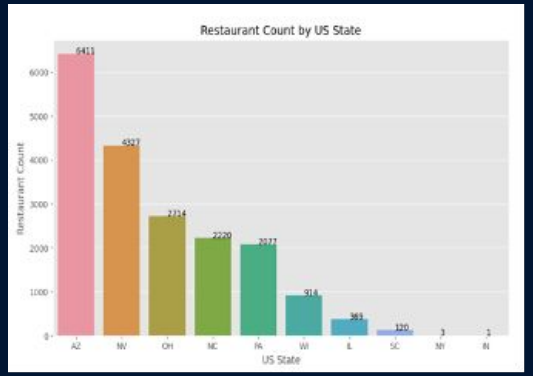


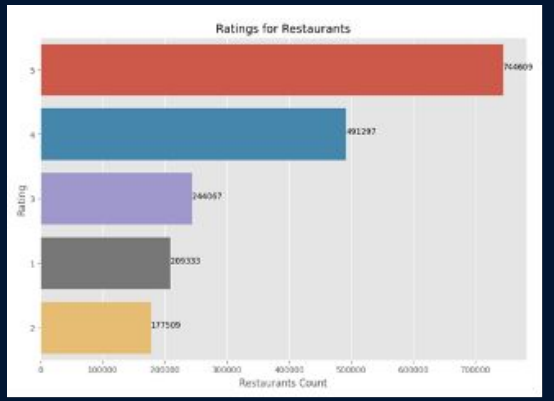
Part 2 - Analyzing the polarity of positive and negative sentiment

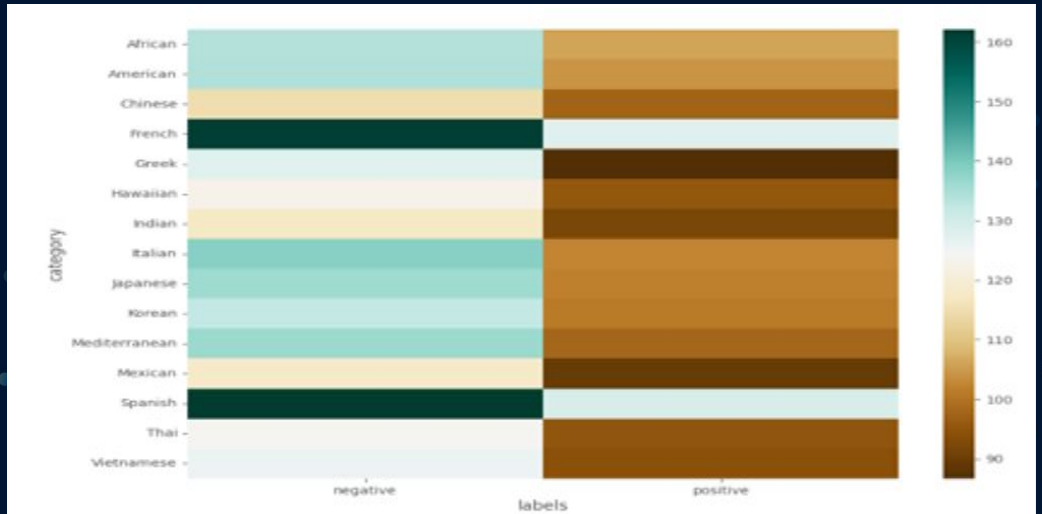
1. We analyzed Yelp restaurant reviews to understand factors contributing to positive or negative reviews.
2. We used Count Vectorizer and SVC classifier to obtain the score of each word.
3. Polarity score of a word indicates its contribution to the sentiment of that review.
4. We dropped obvious polarity words and identified top 10 words contributing to each cuisine type.
5. We reinforced our analysis through exploratory data analysis.

RESULTS


Restaurant Count by Cuisine Type
American
Mexican
Italian
Chinese
Japanese
Thai
Greek
Mediterranean
Indian
Vietnamese
Korean
Hawaiian
French
Spanish
African
7314
3467
2476
1894
982
543
510
493
386
238
267
245
214
90
47
Cuisine Type
0
1000
2000
3000
4000
5000
6000
7000
Restaurants Count

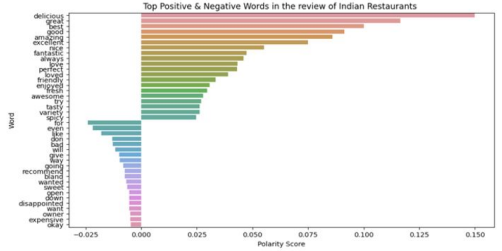

Restaurant Count by US State
6411
4327
2714
2220
2077
914
363
120
3
1
AZ
NV
OH
NC
PA
WI
IL
SC
NY
IN
Restaurant Count
0
1000
2000
3000
4000
5000
6000
US State


Ratings for Restaurants
5
4
3
2
1
764609
491297
244067
209333
177509
Rating
0
100000
200000
300000
400000
500000
600000
700000
Restaurants Count

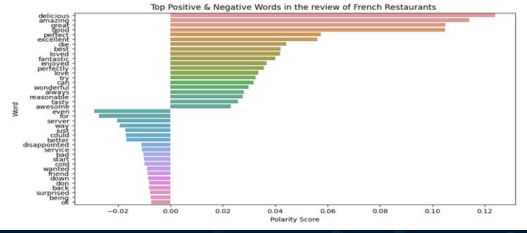

African
American
Chinese
French
Greek
Hawaiian
Indian
Italian
Japanese
Korean
Mediterranean
Mexican
Spanish
Thai
Vietnamese
category
negative
positive
labels
160
150
140
130
120
110
100
90

POLARITY RESULTS

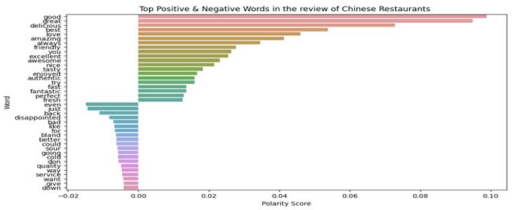
Indian



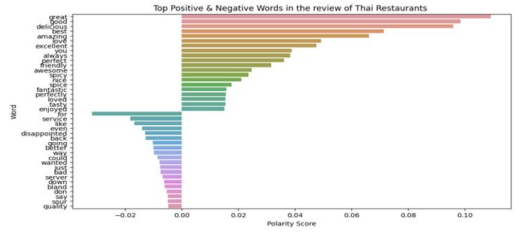
French



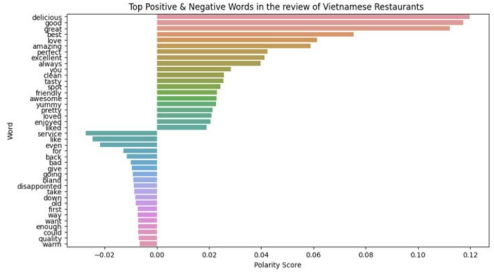
Chinese



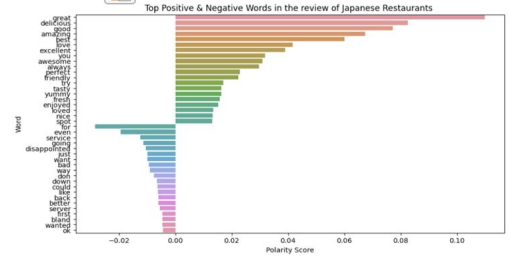
Thai



Vietnamese



Japanese



Positive and Negative sentiment polarity

cuisine	0	1	2	3	4	5	6	7	8	9
Japanese	friendly	fresh	recommend	fun	reasonable	creative	clean	variety	attentive	tasty
Chinese	friendly	fresh	authentic	reasonable	hot	fun	fast	tender	recommend	yummy
Vietnamese	friendly	fresh	recommend	reasonable	variety	attentive	fast	comfortable	yummy	authentic
Thai	fresh	clean	fast	recommend	reasonable	tender	fancy	refreshing	generous	yummy
French	sweet	tender	impeccable	recommend	rich	attentive	romantic	perfection	incredible	friendly

cuisine	0	1	2	3	4	5	6	7	8
Japanese	hard	cold	wrong	slow	bland	dark	expensive	rude	overpriced
Chinese	sour	bland	cold	greasy	hard	slow	wrong	rude	overpriced
Vietnamese	bland	greasy	expensive	weird	wrong	slow	hard	cold	sour
Thai	bland	wrong	hard	slow	expensive	rude	greasy	dirty	weird
French	cold	expensive	slow	bland	overpriced	mediocre	wrong	poor	squash

RESULTS/OUTCOMES

- We used default parameters to predict the sentiment of user reviews and found that Naïve Bayes had the highest accuracy of 82.89%.
- We performed oversampling and hyper tuning grid search cross-validation to calculate the best parameters for each algorithm.
- The best performing algorithm was Naive Bayes with an accuracy of 83.15%.
- We identified the words that contributed significantly to the positive and negative sentiment of each cuisine type that we showed in previous slide.

CHALLENGES FACED AND OVERCOMING THEM

Challenge: Large dataset size (6 million rows, 6GB)

Solution: Filtered dataset to only include US-based restaurant reviews

Benefits of filtering dataset:

1. Reduced dataset size
2. Focused on relevant data
3. Increased efficiency of analysis
4. Derivation of valuable insights from data

Despite the challenges, we were able to overcome them and carry out our analysis effectively

Our approach can be applied to similar large datasets to extract insights and make informed decisions.

CONCLUSION

- The study highlights the importance of customer feedback in the food industry and how businesses can use it to improve their services.
- By developing models to classify customer sentiment and analyzing the factors contributing to positive and negative reviews, businesses can gain a better understanding of their customers.

THANK YOU!