# Final Report: Sentiment Analysis on Restaurant Reviews

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## Introduction

Sentiment analysis has become a major part of natural language processing because of how often people express opinions online. Businesses especially rely on tools that can automatically sort through customer reviews and extract what people actually think. The goal of this project was to build a working sentiment-analysis system that could look at restaurant reviews and determine not only whether a review is positive or negative overall, but also what the reviewer thought about specific aspects such as food, service, and price. Instead of using only one approach, the project uses a traditional machine-learning model on top of a lexicon system, which makes it possible to understand both the overall tone of a review and the reviewer's opinions about specific parts of their experience.

## Dataset and Preprocessing

The project uses a set of short restaurant reviews stored in a TSV file, each labeled as either liked or not liked. Because the reviews are written informally, the text needs to be cleaned before it can be used by the model. The preprocessing pipeline starts by splitting each review into sentences and then into tokens using NLTK. A small but important improvement is the merging of clitics, which fixes cases where contractions like *"didn't"* get split into *"did"* and *"n't"*. Handling these correctly properly helps keep the actual sentiment of each review.

After tokenization, punctuation is removed and all words are converted to lowercase so the text is consistent. The stop-word list is also adjusted so that negation and intensifier words such as, *not*, *never*, and *very* are kept instead of removed, since they play a major role in determining sentiment. The end result is a clean, standardized version of each review that can be used for vectorization and later classification.

## Feature and Model

Once the text has been cleaned, it is turned into numerical features using a TF-IDF vectorizer. This method captures which words appear in each review and how important they are compared to the rest of the dataset. The vectorizer also includes bigrams so that simple two-word phrases can be recognized as meaningful patterns. After vectorization, the data is split into training and testing sets.

The main model used for overall sentiment is a Multinomial Naive Bayes classifier. After being trained, the model is evaluated on the test set, and the project prints out its accuracy along with a classification report. This gives a clear view of how well the system can identify positive and negative reviews.

## Aspect Lexicon and Analysis

To go beyond overall sentiment, the project loads a lexicon file that contains words related to food, service, and price, along with whether each word is typically used in a positive or negative way. Before the lexicon is used, the terms are cleaned and lemmatized to create a consistent set of entries. The system then builds an internal configuration that groups keywords and phrases under each aspect. This structure makes it easy to check whether a review contains content related to a particular aspect.

The aspect-based analysis works by first detecting whether an aspect is mentioned in a review. This is done by checking for the presence of aspect-specific keywords or phrases. If none are found, that aspect is marked as not present.

If an aspect is present, the system uses the lexicon to count how many positive and negative terms appear. The analysis also checks for nearby negation words, which can reverse the meaning of a sentiment term, and looks for common intensifiers like “very” or “really”. These adjustments help the system read phrases in a more natural way.

In cases where the lexicon does not provide enough information, the system uses smaller aspect-specific Naive Bayes models trained only on reviews that mention that aspect. This provides a fallback option so the system can still make a prediction when the lexicon alone is not enough.

## Results

The overall sentiment model performed well, reaching about 81.5 percent accuracy on the test set. The classifier handled both classes consistently, with negative reviews showing slightly higher recall and positive reviews showing slightly higher precision. The scores suggest the model can reliably separate positive and negative opinions in these short restaurant reviews.

The aspect analysis adds more detail about what customers talk about. Food appears the most often, though only a small number of these mentions clearly lean positive or negative. Negative food comments usually focus on bland or stale dishes, while positive ones often describe flavor or freshness. Service is mentioned less often and ranges from complaints about slow or rude behavior to compliments about friendly staff. Price shows up the least, with negative comments focusing on high costs and smaller positives tied to deals or value. Even with fewer examples, the aspect breakdown gives a useful picture of what people tend to care about.

## Limitations

Although the system works well, there are several ways it could be improved. Applying full lemmatization to all reviews, not just the lexicon terms, would reduce the number of unique word forms and likely improve the classifier's performance. The project also relies on Naive Bayes, which is simple and fast, but more advanced models like BERT or other transformer-based architectures would likely achieve higher accuracy. Expanding the lexicon or weighting its terms could help capture more nuanced sentiment. Finally, the negation handling could be made more precise by using dependency parsing instead of a simple window around each word.

## Conclusions

This project created a functional system that can classify the overall sentiment of restaurant reviews and also point out how customers feel about specific aspects like food, service, and price. The overall accuracy is strong for a simple model, and the aspect summaries help highlight the main themes that show up in the reviews.

There is still room to improve, especially by expanding the lexicon or using more advanced models, but the current system offers a clear and practical way to understand customer feedback. It provides a solid starting point for anyone looking to build more detailed or more powerful sentiment-analysis tools in the future.

## References

Dataset: https://www.kaggle.com/datasets/d4rklucif3r/restaurant-reviews/data