NLP ANALYSIS OF RESTAURANT REVIEWS

INTRODUCTION

Online customer reviews have become a critical source of business intelligence in the food and hospitality industry. Platforms such as Zomato, Yelp, TripAdvisor, and Google Reviews generate massive volumes of unstructured textual data that directly influence customer perception, brand reputation, and revenue outcomes. Extracting actionable insights from this data manually is neither scalable nor consistent.

This project presents an end-to-end Restaurant Review Sentiment Analysis system built using Natural Language Processing (NLP) and Machine Learning techniques. The objective is to automatically classify restaurant reviews as positive or negative based on the semantic content of the text. By transforming raw, unstructured reviews into numerical representations, the system enables supervised learning models to identify sentiment patterns with measurable accuracy.

The project implements a structured NLP pipeline that includes text cleaning, lemmatization, TF-IDF based feature extraction with n-gram modeling, and the training of multiple classification algorithms. To ensure robustness and generalization, hyperparameter tuning and cross-validation are applied across models such as Multinomial Naive Bayes, Logistic Regression, and Linear Support Vector Machines.

Beyond prediction accuracy, the project emphasizes model evaluation, interpretability, and reproducibility, making it suitable for real-world analytical use cases. The resulting system demonstrates how sentiment analysis can support data-driven decision making by helping restaurants monitor customer satisfaction, identify recurring issues, and improve overall service quality.

This repository reflects an iterative improvement over a baseline sentiment analysis approach and showcases practical machine learning design choices aligned with industry-standard NLP workflows.

OBJECTIVE

The objective of this project is to design and implement an end-to-end **sentiment analysis pipeline** capable of automatically classifying restaurant reviews as **positive** or **negative** using Natural Language Processing and Machine Learning techniques.
The project aims to:

- Transform unstructured textual reviews into meaningful numerical representations.
- Build and compare multiple supervised learning models for sentiment classification.
- Optimize model performance using systematic hyperparameter tuning.
- Evaluate models using standard classification metrics to ensure robustness and reliability.
- Provide interpretability to understand which textual features influence sentiment predictions.
- Demonstrate a scalable and reproducible NLP workflow suitable for real-world analytical use cases.

Data Description:

The dataset used in this project consists of 1000 restaurant reviews, each labeled with a binary sentiment outcome.

- Input Feature: Customer review text (free-form natural language)
- Target Variable:
  - 1 → Positive sentiment
  - 0 → Negative sentiment
- File Format: Tab-Separated Values (TSV)
- Data Quality:
  - No missing values
  - Contains noise such as punctuation, numbers, and mixed casing
  - Requires preprocessing before modeling

The dataset represents a realistic scenario of customer feedback data commonly found on online review platforms.

TECH STACK:

Programming Language

- Python

Libraries & Tools

- Pandas, NumPy – Data handling and numerical operations
- NLTK – Text preprocessing (stopwords removal, lemmatization)
- Scikit-learn – Feature extraction, modeling, evaluation
- Matplotlib, Seaborn – Data visualization
- re – Text cleaning using regular expressions

Techniques Used

- Text preprocessing (cleaning, tokenization, lemmatization)
- TF-IDF Vectorization with n-grams
- Supervised Machine Learning
- Hyperparameter tuning with GridSearchCV
- Model evaluation and interpretability

METHODOLOGY:

1. Text Preprocessing

Raw review text was cleaned and normalized through the following steps:

- Removal of non-alphabetic characters using regular expressions
- Conversion to lowercase
- Tokenization of text into words
- Removal of English stopwords
- Lemmatization to reduce words to their base form

This step ensured consistency and reduced noise in the textual data.

2. Feature Engineering
Text data was transformed into numerical form using TF-IDF (Term Frequency–Inverse Document Frequency) with the following configuration:

- Maximum features: 2000
- N-gram range: (1, 2) to capture contextual word pairs

TF-IDF helps emphasize informative words while reducing the impact of commonly occurring but less meaningful terms.

3. Train-Test Split

- Dataset split into 75% training and 25% testing
- Stratified sampling applied to maintain class balance
- Fixed random state used to ensure reproducibility

4. Model Training and Tuning
Three classification models were trained and optimized using GridSearchCV with 5-fold cross-validation:

- Multinomial Naive Bayes
  Tuned using smoothing parameter (alpha)
- Logistic Regression
  Tuned using regularization strength and solver
- Linear Support Vector Machine (SVM)
  Tuned using regularization parameter (C)

F1-score was used as the primary optimization metric.

MODEL EVALUATION:

Model performance was evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC score (for probabilistic models)
- Confusion Matrix

This multi-metric evaluation ensured balanced assessment beyond accuracy alone.

RESULTS AND OBSERVATIONS:

Key observations from the experiments include:

- Text preprocessing significantly improved classification performance.
- TF-IDF with bigrams captured sentiment context better than unigram-only models.
- Hyperparameter tuning improved generalization across all models.
- Naive Bayes demonstrated stable and balanced performance across sentiment classes.

- Logistic Regression showed strong ROC-AUC performance and interpretability.
- Linear SVM performed competitively but does not provide probability estimates.

CONFUSION MATRIX ANALYSIS:

The confusion matrix analysis revealed:

- High true positive predictions for positive reviews.
- Slightly lower recall for negative reviews, which is common in sentiment datasets.
- Overall balanced classification behavior with minimal bias toward a single class.

Visualization of the confusion matrix helped identify misclassification patterns and validate model reliability.

MODEL INTERPRETABILITY:

To enhance transparency, the Naive Bayes model was analyzed to identify the most influential words for each sentiment class.

- Positive sentiment indicators: Words associated with satisfaction, quality, and positive experience
- Negative sentiment indicators: Words linked to dissatisfaction, poor service, or negative experience

This interpretability step provides actionable insights and increases trust in the model's predictions.

CONCLUSION:

This project successfully demonstrates the development of a production-ready sentiment analysis system using NLP and machine learning techniques. By combining structured text preprocessing, TF-IDF based feature extraction, and systematic model tuning, the system achieves reliable and interpretable sentiment predictions.

The solution can be effectively used by restaurant businesses and review platforms to:

- Monitor customer sentiment at scale
- Identify recurring service or quality issues
- Support data-driven decision making

Overall, the project highlights the practical application of NLP in extracting value from unstructured text data and provides a strong foundation for future extensions such as deep learning models, multilingual analysis, or real-time deployment.