Sentiment Analysis: Restaurant Reviews

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Motivation

Restaurants receive thousands of online reviews, too many for manual analysis.

Businesses need automated tools to understand:

- Overall customer sentiment
- Specific aspects such as food, service, and price
- Trends, recurring complaints, or frequently praised features

Traditional star ratings don’t capture why a review is positive or negative.

NLP enables turning raw, unstructured text into structured data businesses can act on.

Plan

1) Preprocess review text
- Clean and tokenize reviews

2) Build a baseline sentiment classifier
- Convert reviews to TF-IDF vectors with n-grams
- Train a Multinomial Naive Bayes model to classify positive vs. negative sentiment

3) Perform aspect-based sentiment analysis
- Detect whether a review contains food, service, or price terms
- Use a restaurant sentiment lexicon to score aspect-specific sentiment
- Apply rules for negation and intensifiers

4) Evaluate the system
- Measure overall accuracy
- Show example predictions
- Compare lexicon-based and ML-based aspect results

Dataset

Restaurant_Reviews.tsv - Kaggle

1,000 restaurant reviews

Typical review length: short, 5–25 words

Two columns:

- Review - customer-written text
- Liked - overall sentiment label (1 = positive, 0 = negative)

Text is informal and contains:

- Contractions (“didn’t”, “I’ve”)
- Punctuation and typos
- Short, opinion-heavy sentences

Methods

Traditional NLP preprocessing:

- Sentence and word tokenization, Punctuation removal
- Clitic merging (didn’t, won’t), Lowercasing, Stopword filtering

Vectorization:

- CountVectorizer for the baseline model
- TF-IDF with 1–2 gram features for the model

Classification - Multinomial Naive Bayes for overall review sentiment

Aspect-based sentiment:

- Lexicon-based scoring for food, service, and price
- Negation and intensifier handling
- Optional aspect-specific Naive Bayes models

Pipeline

- Load and inspect the dataset
- Split each review into sentences
- Tokenize sentences into words
- Merge clitics (didn’t, I’ll)
- Remove punctuation tokens
- Convert all words to lowercase
- Create TF-IDF feature vectors
- Train the Naive Bayes sentiment model
- Detect food, service, and price aspects using the lexicon
- Produce aspect-level sentiment outputs

Preprocessing

Tokenization

- Sentence splitting with nltk.sent_tokenize()
- Word tokenization with nltk.word_tokenize()

Stopword Strategy

- Remove common stopwords
- Keep key words such as not, no, never, very, too, but
- These words influence sentiment direction, especially negation and intensity

Clitic merging

- Examples: “did + n’t” → “didn’t”, “I + ’m” → “I’m”
- Make sure negations and contractions are treated as single meaningful tokens

Vectorization

Baseline approach:

- CountVectorizer (bag-of-words)
- Works well for short review texts but treats all terms equally

Improved approach:

- TF-IDF with 1–2 gram features
- Uses sublinear term frequency and binary weighting
- Captures short phrases and reduces the influence of very common words

Benefits

- Highlights meaningful expressions such as “not good,” “very tasty,” and “too expensive”
- Produces clearer sentiment signals and improves model performance

Sentiment Classifier

Model - Multinomial Naive Bayes

Performs well with sparse TF-IDF features

Fast, simple, and easy to interpret

Training setup - 80/20 train–test split

Accuracy printed during model evaluation

Aspect-Based Sentiment

Restaurant lexicon

- CSV file containing aspect terms such as “tasty,” “slow service,” “overpriced”
- Covers three aspects: food, service, and price

Aspect detection

- Keyword matching
- Phrase matching for multi-word expressions
- Lemmatization to improve matching across word forms

Aspect sentiment scoring

- Count positive and negative terms
- Handle negation and intensifiers
- Fall back to aspect-specific Naive Bayes if no lexicon match appears

Output

The system produces an overview of sentiments including:

- Overall sentiment (positive or negative)
- Aspect-level sentiment for food, service, and price
    - Each labeled as positive, negative, or none
    - Top drivers for positive and negative sentiments
    - Examples of sentiments

Demo Output

```
## Aspect Sentiment Summary
### Food
- Positive: 96 (9.6%)
- Negative: 27 (2.7%)
- None: 877 (87.7%)
- Top negative drivers: bland, dry, gross, stale, soggy, awful, overcooked, lukewarm, undercooked, raw
- Top positive drivers: amazing, delicious, fresh, fantastic, tasty, tender, flavorful, seasoned, crispy, rich
- Examples (negative):
  - The turkey and roast beef were bland.
  - It was pretty gross!
  - Crostini that came with the salad was stale.
  - Unfortunately, we must have hit the bakery on leftover day because everything we ordered was STALE.
  - The burger had absolutely no flavor - the meat itself was totally bland, the burger was overcooked and there was no charcoal flavor.

### Service
- Positive: 42 (4.2%)
- Negative: 17 (1.7%)
- None: 941 (94.1%)
- Top negative drivers: slow, rude, rushed, ignored, unprofessional
- Top positive drivers: friendly, fast, attentive, helpful, professional, courteous, polite
- Examples (negative):
  - Waitress was a little slow in service.
  - The management is rude.
  - He was extremely rude and really, there are so many other restaurants I would love to dine at during a weekend in Vegas.
  - The menu is always changing, food quality is going down & service is extremely slow.
  - The service was a little slow , considering that were served by 3 people servers so the food was coming in a slow pace.

### Price
- Positive: 30 (3.0%)
- Negative: 7 (0.7%)
- None: 963 (96.3%)
- Top negative drivers: overpriced, expensive, pricey
- Top positive drivers: special, deal, reasonable, inexpensive, cheap, discount, worth it, affordable, good value, happy hour
- Examples (negative):
  - The cashier had no care what so ever on what I had to say it still ended up being wayyy overpriced.
  - This place is way too overpriced for mediocre food.
  - And it was way to expensive.
  - Food is way overpriced and portions are fucking small.
  - Some may say this buffet is pricey but I think you get what you pay for and this place you are getting quite a lot!
```

Accuracy Results

	precision	recall	f1-score	support
0	0.781	0.854	0.816	96
1	0.853	0.779	0.814	104
accuracy			0.815	200
macro avg	0.817	0.817	0.815	200
weighted avg	0.818	0.815	0.815	200

Thank You