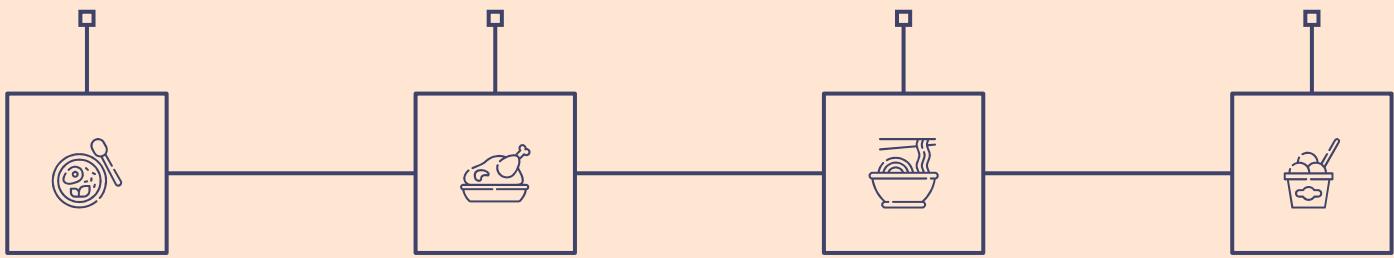


Predicting Restaurant Review Sentiment From Text

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Motivation &
Question

Data &
Methods

Modeling

Results &
Implications

Motivation & Research Question

Why predict sentiment from review text?

- Online reviews influence consumer and business decisions
- Star ratings are easy, but **text explains why**
- Automating sentiment analysis allows businesses to analyze thousands of reviews efficiently

Can the language used in restaurant reviews reliably predict whether a customer rated their dining experience positively or negatively?



Hypothesis & Modeling Approach

The sentiment analysis model will predict with at least 70% accuracy:

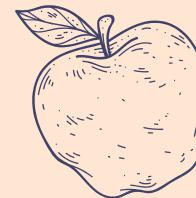
★☆☆☆: Negative review

★★☆☆: Neutral review

★★★★☆: Positive review

Model:

- Supervised text classification
- Star ratings mapped to sentiment labels
- Baseline NLP models trained on text features



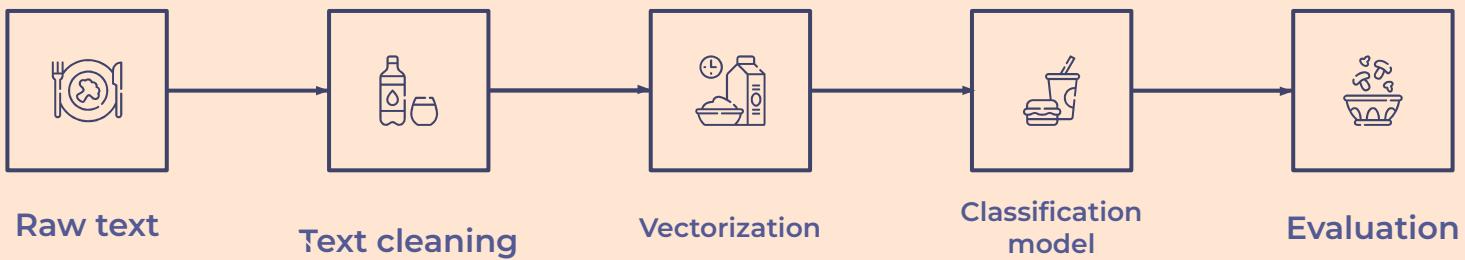
Data Overview

- Restaurant reviews with written text & star ratings
- Star ratings mapped to sentiment labels
- Reviews without written text removed
- Class distribution skewed toward positive sentiment

	Restaurant	Review	Rating
0	Beyond Flavours	The ambience was good, food was quite good . h...	5.0
1	Beyond Flavours	Ambience is too good for a pleasant evening. S...	5.0
2	Beyond Flavours	A must try.. great food great ambience. Thnx f...	5.0
3	Beyond Flavours	Soumen das and Arun was a great guy. Only beca...	5.0
4	Beyond Flavours	Food is good.we ordered Kodi drumsticks and ba...	5.0

Rating_num	Sentiment
5.0	positive

Analysis Pipeline



- Logistic Regression
- Naive Bayes
- Train/Test Split

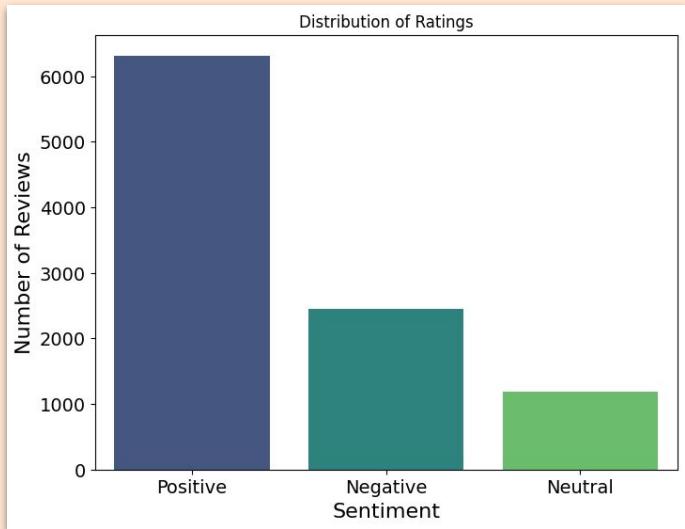
Tricky Analysis Decision

Class Imbalance

- Majority of reviews are positive
- Accuracy alone can be misleading
- Reviews without written text removed
- Decision: use class-weighted models

Impact

- Prevents majority-class dominance
- Improves fairness across sentiment categories



Bias & Uncertainty

Potential biases

- Overrepresentation of positive experiences
- Self-selection bias in who leaves reviews

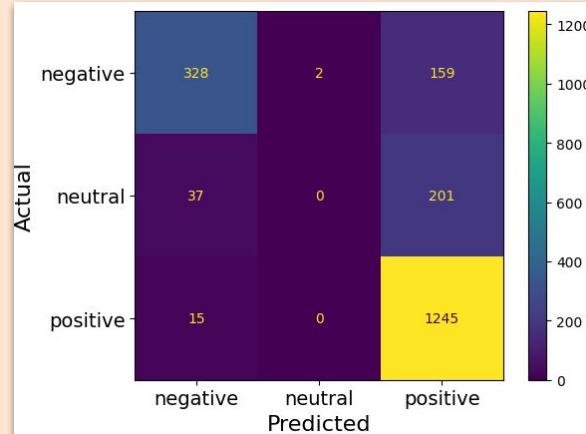
Sources of uncertainty

- Ambiguous language
- Neutral sentiment hardest to classify

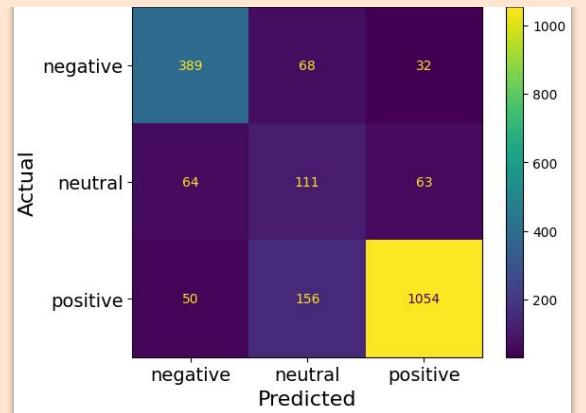
Validation

- Model comparison
- Weighted evaluation metrics

Naive Bayes Confusion Matrix



Logistic Regression Confusion Matrix



Results & Conclusions



Logistic regression

78%

Best Model

Accuracy

LR classification report				
	precision	recall	f1-score	support
negative	0.77	0.80	0.78	489
neutral	0.33	0.47	0.39	238
positive	0.92	0.84	0.88	1260
accuracy			0.78	1987
macro avg	0.67	0.70	0.68	1987
weighted avg	0.81	0.78	0.79	1987

The model achieved 78% accuracy, exceeding our 70% benchmark. Therefore, our hypothesis is supported.

Next Steps



Incorporate bigrams and trigrams to capture word context



Improve neutral sentiment classification



Evaluate more advanced models

References

- [1] “Restaurant Reviews,” www.kaggle.com.
<https://www.kaggle.com/datasets/joebeachcapital/restaurant-reviews>
- [2] B. Pang and L. Lee, “Opinion mining and sentiment analysis,” *Foundations and Trends in Information Retrieval*, vol. 2, no. 1–2, pp. 1–135, 2008, Available:
<https://www.cs.cornell.edu/home/llee/omsa/omsa.pdf>
- Github:
<https://github.com/benshults22/ds4002-project1-DataDawgs/tree/main>

Questions?

