Data Scientist II Technical Challenge

Task 3: Natural Language Processing

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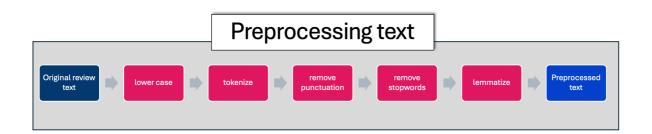
Using the Customer Reviews dataset:

- Preprocess the text data (e.g., tokenization, stopword removal, stemming/lemmatization).
- Perform sentiment analysis on the reviews.
- Visualize the distribution of sentiment scores.

Deliverables:

- Preprocessed text data.
- Sentiment analysis results.
- Visualizations of sentiment distribution.

Preprocessed text data



		review_text	preprocessed_review
	1	Terrible service, will not buy from here again.	terrible service buy
	2	Average quality, you get what you pay for.	average quality get pay
İ	3	Great product, very satisfied with the quality and performance.	great product satisfied quality performance
	4	Very disappointed with the product, not as described.	disappointed product described
	5	Excellent service, highly recommend!	excellent service highly recommend
	6	The item arrived damaged and customer service was unhelpful.	item arrived damaged customer service unhelpful
	7	Fast delivery and the product works perfectly!	fast delivery product work perfectly
	8	The item arrived damaged and customer service was unhelpful.	item arrived damaged customer service unhelpful
	9	The service was acceptable, but could be improved.	service acceptable could improved
ı	10	Decent product, but there are better options available.	decent product better option available

See complete file in GitHub.

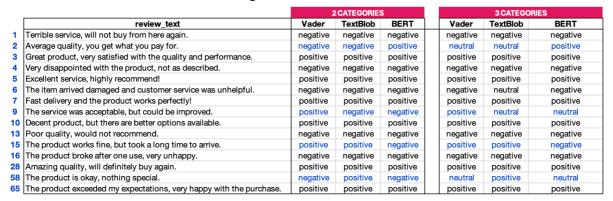
Sentiment analysis results

I use lexicon-based methods (Vader and TextBlob) and a Large Language Model (distilled BERT) on the provided data.

Lexicon-based methods require preprocessing the review text while LLMs are less sensitive.

Since the reviews are repeated, I removed duplicates before running the clustering since duplicate reviews can skew the clustering results by giving more weight to the repeated texts.

The results are summarized in the following table:



The three libraries manage to classify the reviews that have a strong positive/negative sentiment. The differences arise when the review

- has a more impartial tone:
 - #2. Average quality, you get what you pay for.
 - #58. The product is okay, nothing special.
- is composed of two parts, one positive and the other negative:
 - #9. The service was acceptable, but could be improved.
 - #15. The product works fine, but took a long time to arrive.

With two categories, BERT model correctly classifies the reviews, even the four aforementioned. The two lexicon-based methods struggle with at least one of them.

I run a more deeper classification in three categories, adding a new one named "neutral":

- Vader classifies reviews 2 and 58 as neutral
- Textblob has two reviews (6, 9) with score 0. With three categories, review 6 is assigned a neutral sentiment what is clearly incorrect.
- The BERT model I applied is specifically trained for binary sentiment analysis, so it would be better to use another model trained for multiclass classification.

As future work:

- The classification is strongly dependent on thresholds. It should be convenient to experiment with different thresholds
- Use a LLM specifically trained on multiclass sentiment analysis
- Get labeled data and run a ML (Naive Bayes, SVMs, RNNs, LSTM).

Visualizations of sentiment distribution.







BERT



