

Predict Potential Usefulness and Positivity of Product Reviews

DS4A Women's Summit Fall 2020 Capstone Project | **Team 10 - CleaReview**

Romane Goldmuntz, Hanh Nguyen, Mansi Parikh, Joyce Yu, Jane Zhang

Background

MOTIVATION

- "Ratings and review content is having greater impact on consumer behavior in the **COVID-19 era**, providing the **validation** and **social proof** necessary to drive sales" (PowerReviews, 2020)
- Research suggests that consumers are seeking validation for their purchases in such uncertain times more than ever, yet the length of their **review periods** have **shortened** with increased stress and/or the greater need to multitask (PowerReviews, 2020)
- *Quality* product reviews can aid both the consumer and the business:
- Improve the product/service(s) offered and the overall customer experience based on feedback extracted, which would likely boost consumer confidence in purchases from the brand
- Reduce friction in the review engagement process of the consumer journey by identifying and presenting high-quality user-generated information about the product/service based on various indicators as opposed to helpful votes alone

FOCUS

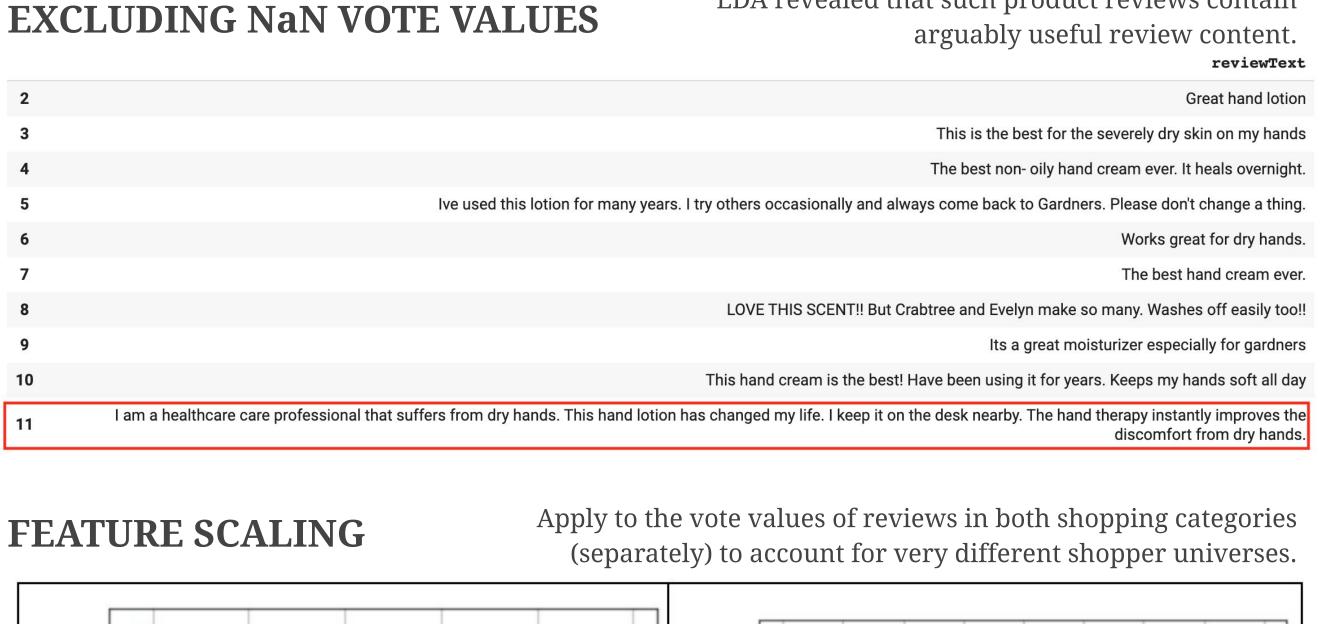
To predict the helpfulness and sentiment of product reviews independent of the (helpful) vote value.

DATA

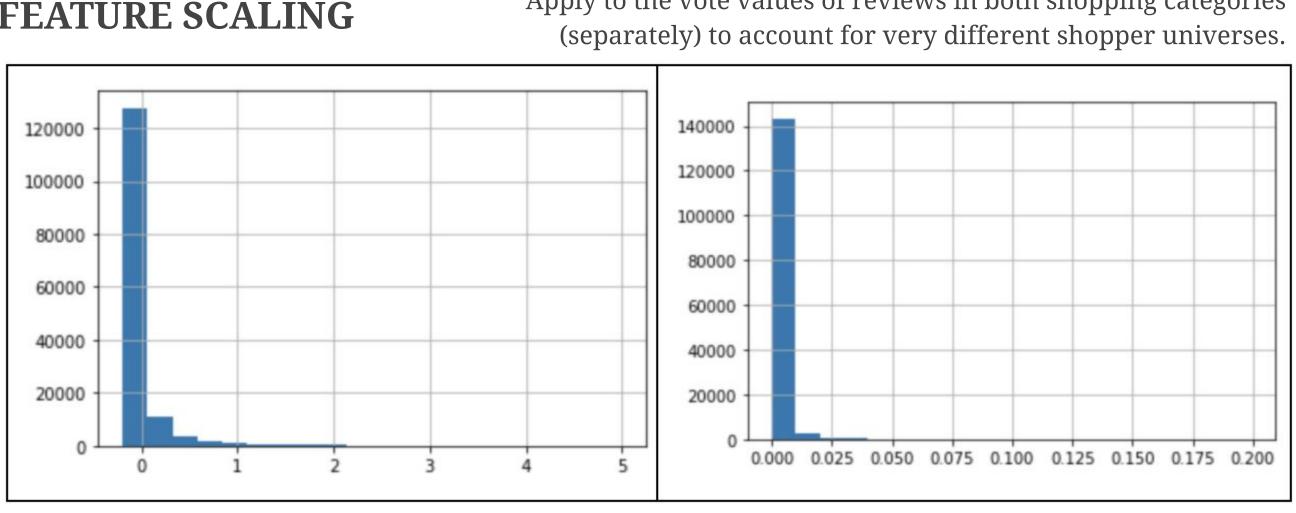
Amazon Product Reviews and Metadata

- All Beauty (UCSD) 370K reviews that represent 33K products
- Luxury Beauty (UCSD) 575K reviews that represent 12K products

Construct Training Data

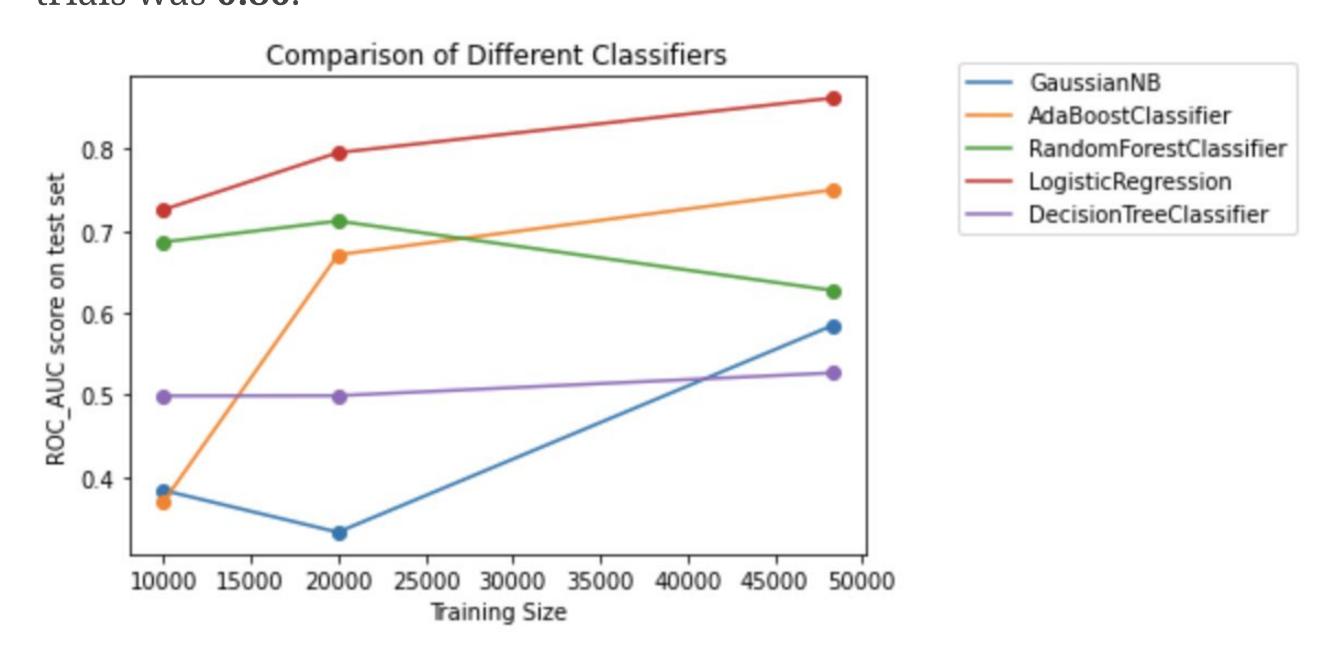


EDA revealed that such product reviews contain



Predicting Helpfulness

We determined the features of a review that deem it most helpful by users, which we assessed by vote counts. Each word in the reviews became its own independent attribute which would be used as the predictor variables in determining if a post is helpful (1) or not (0). Unfortunately, helpfulness itself is still considered a rather subjective quality of a post, but if several people hold the same belief (as seen by the vote count), we can safely assume that the post is indeed helpful. **Logistic regression** performed the best in terms of ROC so we pursued that to the finish. Not only was the ROC of this classifier better than the rest, but also the **average AUC under the ROC** from 100 simulated trials was **0.86**.



Predicting Sentiment

APPLYING LINEAR SVM

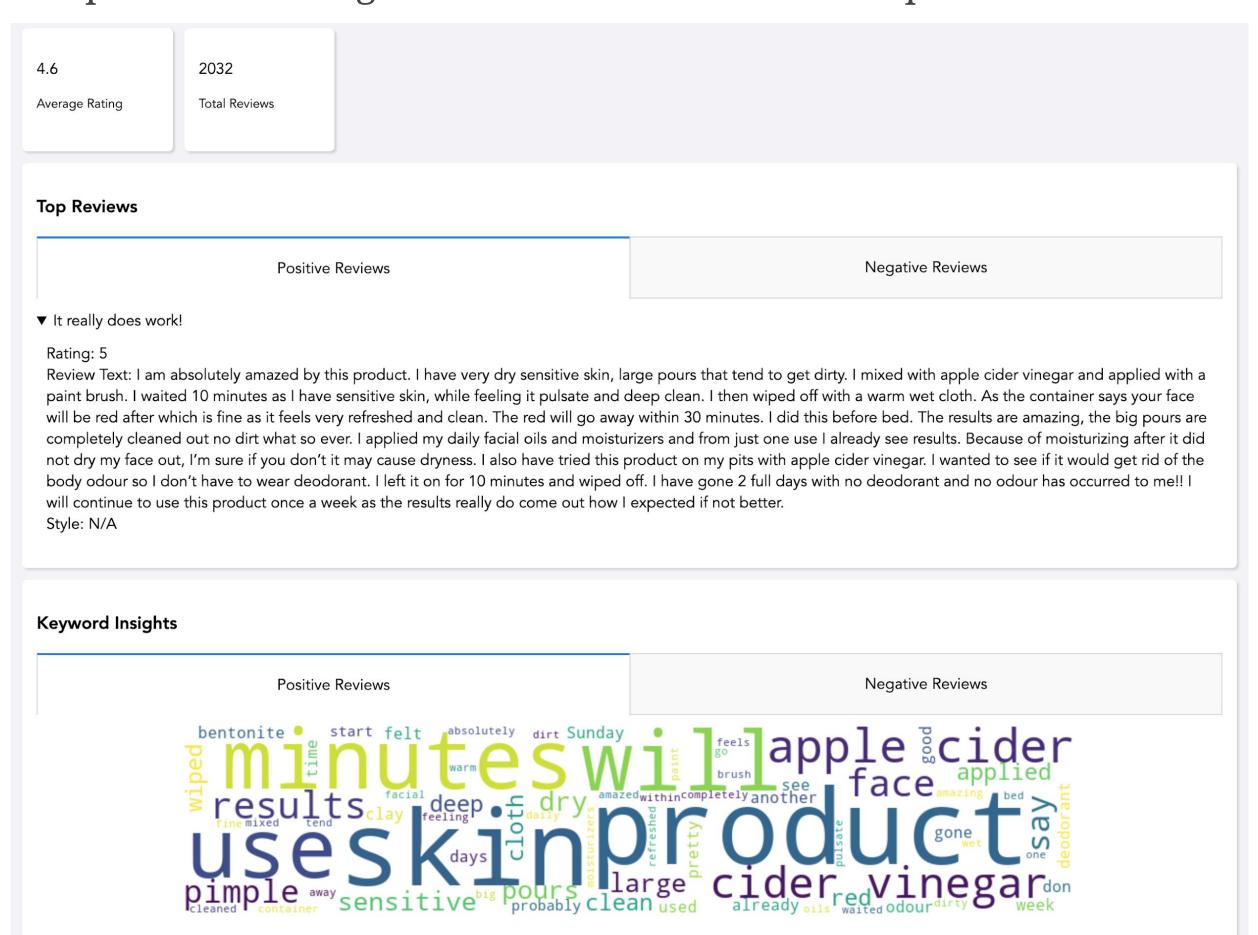
True value/predicted value	negative	positive
negative	1946	422
positive	264	10360
prec	ision recall f1-score	support
0.0	0.88 0.82 0.85 0.96 0.98 0.97	
accuracy	0.95	12992

Overall, the selected model performs very well, but with bias towards the positive class that is likely due to the imbalance in the dataset used. This issue was tentatively addressed by oversampling the negative reviews using **SMOTE** and combining the latter with a **biased SVM**. The resulting models were either not performing as well as the first one or were inverting the bias. For business reasons, we favored the initial bias and the first model was selected and used in the dashboard. In the worst case scenario, a negative review being considered highly helpful will be labelled positive and be under the Positive Reviews tab. This will only give more information to the vendor about what is strongly disliked by their customers and give them a chance to fix it before it drives new potential customers away.

Dashboard

Primary components:

- *Summary Info*: the average review rating and the total number of reviews available for the selected product;
- *Top Reviews*: the most helpful positive and negative reviews for the product, categorized and ranked based on the models;
- *Keyword Insights*: word clouds to present the keywords found in positive and negative reviews for the selected product.



Insights and Recommendations

TAKEAWAYS

The English language is varied where a single word can have many meanings depending on the phrasing. This makes it hard to isolate words and work with the resulting features independently as done. However, this only makes it more necessary to incorporate important phrasing and slang into models to account for different interpretations. Furthermore, many assumptions were made given the suboptimal datasets used, but the models still performed adequately and could effectively classify reviews as intended.

FUTURE WORK

To create a reliable technical solution to businesses that will provide them real-time analysis of customer reviews across their products, the current MVP may be improved by:

Dashboard

- Powered by a dynamic database
- Other visuals that offer deep insights into product performance
 Model
- Explore different ways of constructing the outcome variable
- Statistical soundness throughout the modeling process