

Biased Review Detection

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Abstract—This project which we call “Biased Review Detection” is our attempt to solve the hot issue of veracity of online data, specifically for online customer reviews. Opportunity to write online reviews has provided a never before power to customers and has actually made the customer, the god of the business world. According to an analysis, a 1 star change in customer review rating of a business on Yelp can affect its performance by 5-7%. Also, according to a report, after price, previous customer rating is the second most important factor a buyer considers while making a purchase on Amazon. While some of these online customer reviews may be true experiences of the customer with the product, some of them might be biased. Meaning, the dealers or their friends/someone they paid may post positive reviews about the product with an intention to make benefit the business. Also, a competitor or someone else with malicious intent may post negative reviews to harm the business. Such users will possibly have no purchase records of the product and yet contribute to the review section, diluting the whole purpose of the review platform. In the interest of online businesses and their customers, it is very important to identify and filter such reviews. Our project takes into consideration the above need and tries to fulfill it. As per our understanding, the topic of finding the veracity or the truthfulness of online reviews is still under research. Some of the businesses like Amazon have done some work in this regard but it is still under development. Our aim is to use the labeled dataset provided by amazon for biased reviews and build a model that can be used to identify biased reviews.

1. INTRODUCTION

While brainstorming on what was taught to us about how the veracity of data (or the opposite) is affecting election results, spreading rumors and even big businesses these days, we started discussing how sometimes we end up watching movies that got good reviews online but were a mere waste of time and money. It occurred to us that if we could somehow determine if a review is genuine or not, then we could actually solve a big present-day issue of online fake reviews.

We started digging into it and found that nothing concrete has been achieved in this field as of now. This excited us even more and we decided to work towards achieving veracity in data. We found the Amazon labelled data for biased reviews very intriguing and relevant as we all buy from Amazon almost every week and sometimes end up buying a product for which the reviews were good but the product actually didn't turn up that well. Also, reference from the book, by Prof. Vishnu Pendyala: 'Veracity of Big Data: Machine Learning and Other Approaches to Verifying Truthfulness', is behind our further inspiration.

2. METHODOLOGY

- Obtained labeled customer reviews data from Amazon with over 20 thousand records. This dataset is not openly available. It is provided for research purposes only.
- Preprocessing of data- We did data cleaning and structuring to get data in a readable format.
- Data exploration- We plotted graphs between various attributes which are given in the data to understand how each one of them is affecting the target variable (label).

- Feature engineering - We identified three of the factors which are substantially affecting the target variable. These factors are - verified purchaser/not, the polarity of the review text (+ve/-ve) and length of the review (number of words in the review).
- Model building - Using the above 3 factors, we tried out 3 classification models (logistic regression, SVM, K-NN and decision trees) and till now we have been able to achieve ~78% accuracy on test data.

3 FEATURES ENGINEERING

Features in our dataset are DOC_ID, LABEL, RATING, VERIFIED_PURCHASE, PRODUCT_CATEGORY, PRODUCT_ID, PRODUCT_TITLE, REVIEW_TITLE, REVIEW_TEXT. We chose count of words in the REVIEW_TEXT attribute, the sentiment polarity, the length of the review text and the VERIFIED_PURCHASE as our features base. We transformed the VERIFIED_PURCHASE field from categorical to a binomial field in order to make it easy for the model training.

Various other features that we explored in this regard are, semantics of the review text like count of Nouns, Verbs, Adjectives, Adverbs. We also created few more features like finding the Modality of the text, subjectivity, sentiments of the text - (negative, positive, neutral and compound).

We also created a word cloud to make note of most frequent words.

Below are the features that we have used for building our machine learning models:

3.1 Verified Purchase

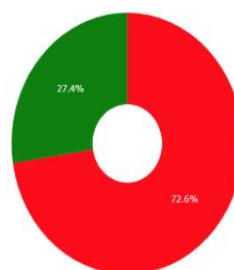
VERIFIED_PURCHASE is the major game-changer in the analysis. This field gave us valuable insights in determining whether the reviews are biased or not. As shown in the below graphical representation, we understand that the data that was labeled as biased had around 73% of users whose purchases were not recorded/no purchases were made. Only 27% of the users actually purchased the item and then provided reviews about the product. In contradiction, the unbiased data had a higher number of reviews from verified users (84% of users' purchases were verified) and low records by un-verified users(16%).

On Amazon, when the system associates a product review with a product purchase, that review is from a "verified purchaser". Reviews from a verified purchase tend to be reliable since Amazon has already confirmed an actual purchase of the product being reviewed. On the flip side, if an Amazon review is not from a "verified purchaser" there is no way of knowing for sure if the reviewer purchased or even used the product. While it is possible that a reviewer could have purchased the product elsewhere and left a review on Amazon at a later date, without purchase verification, it is impossible to tell. According to our analysis, dishonesty is likely when an Amazon review is not associated with a verified purchase. [[Fakespot-Fake Review Analysis](#)]

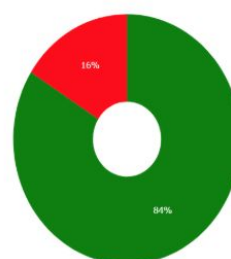
Biased Data: **Yes- 27%; No- 73%**

Unbiased Data: **Yes- 84%; No- 16%**

BIASED verified Purchase

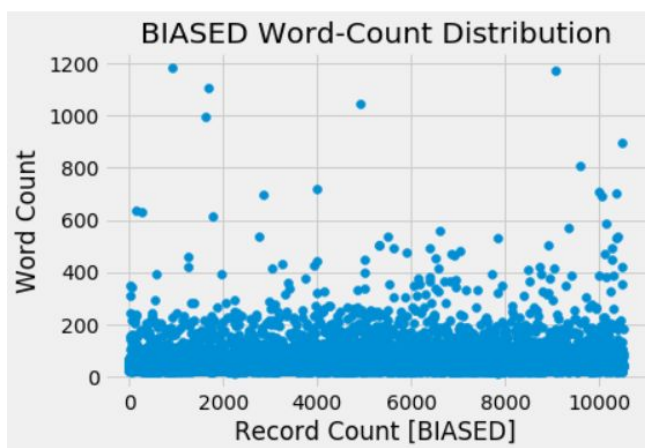


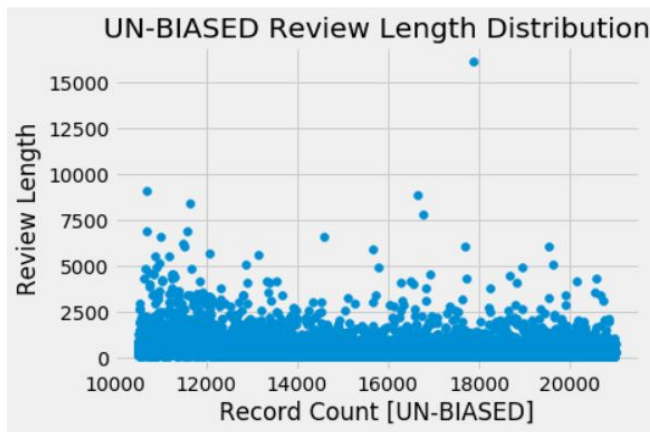
UN-BIASED verified Purchase



3.2 Word count in text reviews

According to the plots below, the average word count(or the baseline) for unbiased reviews is around 500 and that for biased reviews is around 200. Thus the biased reviews are shorter.

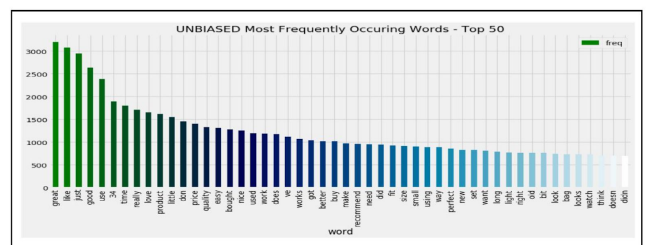
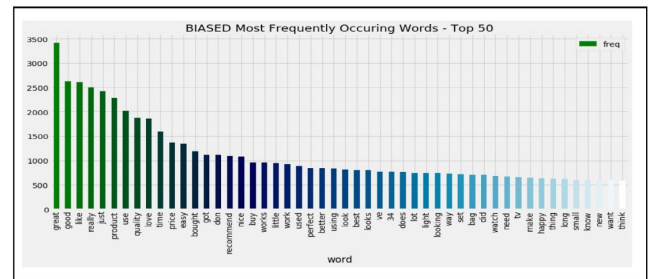




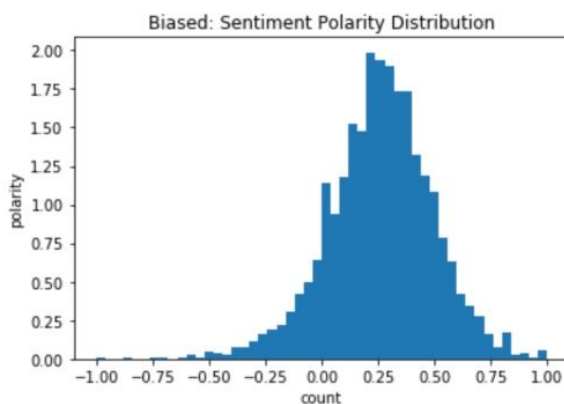
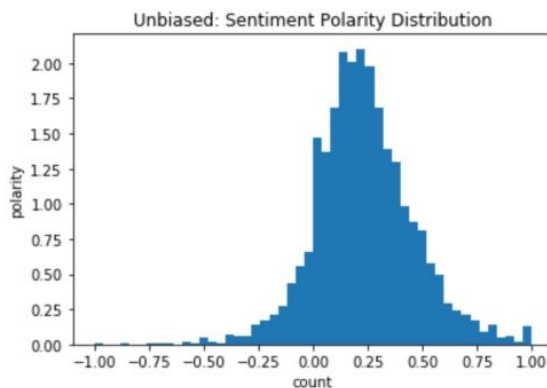
3.4. Word Frequency Distribution

The Word frequency distribution chart helped us identify the words that our model must look for in order to predict whether a review must be categorized as biased or unbiased.

Also when we calculated the length of the reviews, we observed that the unbiased reviews were lengthier than the biased reviews.



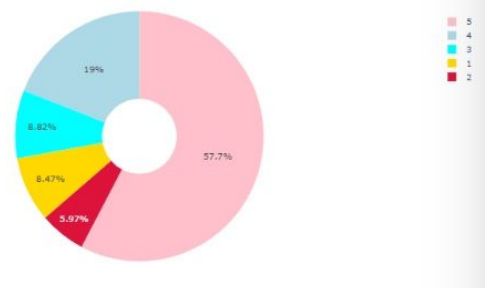
3.3. Sentiment polarity of review text



3.4. Rating

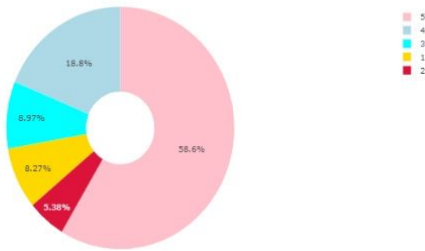
1-5 Rating Frequency Distribution.

BIASED Ratings Distribution



The above plots show that the polarity for biased reviews is skewed towards the positive side.

UNBIASED Ratings Distribution

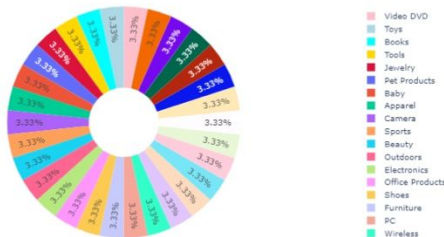


The above two pie charts represent rating distribution for both biased and unbiased data. Though this field hasn't played any role in our model training, it gave us useful insights on how the review texts are correlated with the ratings.

3.5. Product Category

Product Categories Frequency Distribution. There are 30 product categories for Biased and Unbiased data each.

BIASED Product Category



The dataset that we received has equal proportions of both biased and unbiased data covering reviews for 30 different product categories. This field just provides the dataset distribution information so as to know what type of dataset we are working with. As we can see from below dispersion, each product contributes 3.33% of the dataset.

4. Models Used

4.1 Logistic Regression:

Applied this statistical model that in its basic form uses a **logistic** function to model a binary dependent variable.

Accuracy: 80.54

4.2 SVM: Accuracy: 67.38

4.3 KNN: Accuracy: 61.82

4.4 XGBoost: Accuracy: 79.54

4.5 Gradient Boosting: Accuracy: 80.69

4.6 Bagging: Accuracy: 75.76

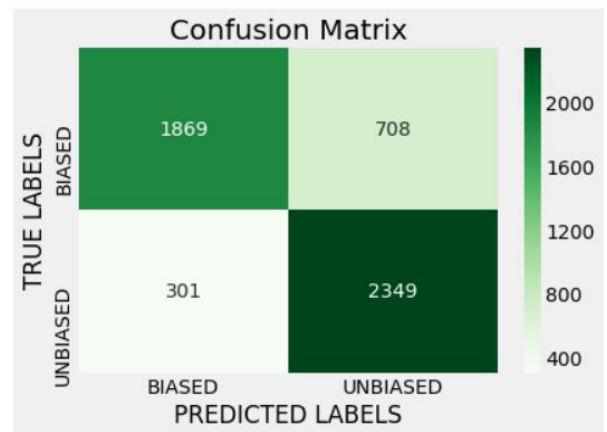
4.7 Adaptive Boosting: Accuracy: 80.60

4.8 Random Forest: Accuracy: 75.76

4.9 Decision Tree: Accuracy: 80.68

4.10 NGrams: Accuracy: 65.90 %

	f1-score	precision	recall	support
__label1__	0.79	0.86	0.73	2577
__label2__	0.82	0.77	0.89	2650
accuracy	0.81	0.81	0.81	0.81
macro avg	0.81	0.81	0.81	5227
weighted avg	0.81	0.81	0.81	5227



5. CONCLUSION AND FUTURE WORK

Data preprocessing and attribute selection are the two major challenges with real-life datasets. While some attributes show a direct relationships with the target class, certain attributes have inherent correlations with the label class.

This project implements various methods to find new features like analysing the semantics

and sentiments of the review text, obtaining the semantic score of the text and letting the model learn based on these features for accurate classification.

Future work in this stream includes collecting data from various websites, computer assisted labelling of biased reviews and more efficient machine learning algorithms that can improve the classification accuracy.

6. ACKNOWLEDGMENT

We wish to thank Prof. Vishnu Pendyala for his support throughout the project.

7. REFERENCES

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- [2] Nitin Jindal, Bing Liu, "Review Spam Detection" (WWW 2007 / Poster Paper)
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- [4] a) Understanding and Overcoming Biases in Customer Reviews:
- [5] <https://pdfs.semanticscholar.org/a5fd/ec50edbbe193e23e93c28e9b803c39583500.pdf>
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To identify the 'semantic orientation' of words we will be referring to this paper.
- [7] Learning from the cloud: Regression discontinuity estimates of the effects of an online review database: https://are.berkeley.edu/~jmagruder/yelp-11_05_23.pdf
- [8] Towards understanding and detecting fake reviews in app stores: <https://link.springer.com/article/10.1007/s10664-019-09706-9>
- [9] A Systematic Review on the Profiling of Digital News Portal for Big Data Veracity <https://www.sciencedirect.com/science/article/pii/S1877050915036157>
This Paper talks about determining the truthfulness of the literature.