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Article Title

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Abstract

In this paper data gathered from product reviews on the e-commerce site Amazon.com is assessed to discover if the helpfulness of a review can be determined from the frequency of words used. Using the amount of votes a review has received as an indicator of helpfulness, text classification is done to group a review into one of two classes – helpful or unhelpful. We argue that parameterizing text data by term-frequency vastly improves predictions compared to an inverse term-frequency statistic, and that some classifiers perform better when only a few features are used, but that involving more features would likely improve performance overall. Finally, we find that predicting the helpfulness of a review based on votes is difficult, as the dataset provided is biased in the favor of unhelpful reviews, making the likelihood of helpful terms appearing in reviews with no votes very high.

I. Introduction

In the globalized economy of today, consumers are presented with a range of products to choose from when shopping. This can present some difficulty, as quality of the product is not always clear from its presentation. The customer review seeks to solve this by providing feedback on the purchase. Still, determining the value of a review can be difficult, as reviews can be misleading or provide little information.

Voting systems are often set in place to identify helpful reviews, and help consumers circumvent this issue, yet these reviews still get lost in the sheer number of unlabeled reviews. Our machine learning model aims to further filter reviews mainly by analyzing use of words, verbosity, among other aspects, to discover what makes a review helpful.

II. Problem Formulation

The main focus of this paper is to analyze Amazon review data across different categories and answer the question: “To what extent can the helpfulness of an Amazon review be predicted?” through the use of classification models.

III. Methods

Our research aims at creating a predictive model for identifying helpful Amazon reviews. Therefore, the data used in this study is a subset of Amazon product reviews divided into categories, with each product and reviewer having at least 5 reviews.

As our model is primarily trained on text data, common Natural Language Processing techniques have been used in the preprocessing of data and the subsequent structuring of this data into input data.

For converting our text data into parametric data for use in building our model, we have chosen to use document-term matrices through Count Vectorization and TF-IDF Vectorization. By employing two methods of text vectorization, we can more easily determine which term weighing factor improves the most upon the performance metrics of our model.

Since we are dealing with a binary classification problem due to separation of reviews into two groups - helpful and unhelpful - we make use of several different classifiers in training our model. We are labelling each review on its helpfulness feature to make supervised learning through each of these classifiers possible.

For our model evaluation we make use of primarily two statistics. A confusion matrix is used in summarizing the performance of the classifier algorithms used in training our model. As mentioned, we are dealing with a binary classification problem, and as in many problems of this nature, the two groups are not symmetric. Therefore we also apply Youden's Index to make up for our unbalanced dataset, using this statistic as a final measure of our model's predictive power.

i. Data exploration

With the cleaned up dataset and the research question in mind, columns with relevance are explored. To explore, we plot different columns of interest to identify any patterns in the data in connection to review helpfulness. We plot the distribution between reviews with votes and no votes. As seen in Figure1, the distribution is

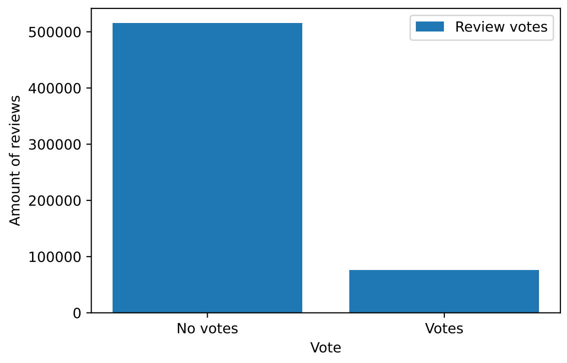


Figure 1: *Upvote distribution*

very uneven in favor of reviews with no votes. This is relevant when evaluating performance metrics of our model, as it indicates that a statistic like Youden's Index might be useful to counteract random guessing. To get another perspective on review votes we plot the data into a heatmap in relation to ratings. Figure2 shows the ratings binned with the amount of votes. This heatmap only shows reviews with votes. The heatmap gives an indication of how

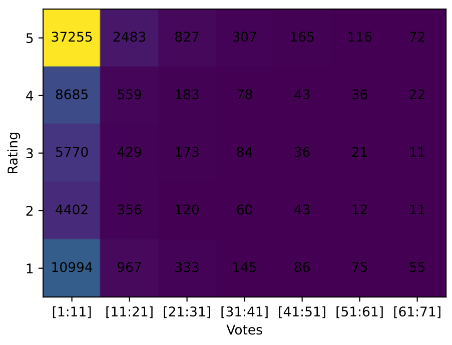


Figure 2: *Votes in relation to rating*

votes combined with ratings are distributed in our dataset in a more specific way with the binned votes compared to Figure1.

IV. Analysis

i. Ethics and bias

As our model seeks to highlight helpful reviews, and distinguish - or filter - these from the unhelpful ones, ethics regarding censorship must be considered. Specific associations with words can often be attributed to bias, making NLP models whose purpose it is to filter undesired text prime censorship tools in the wrong hands[1]censorship. In the context of our model, a very real use-case would be as a tool for preventing unhelpful reviews from being submitted. However, unhelpfulness is subject to opinion, and controversial statements can quickly be tagged as bad and subsequently filtered out.

ii. Data Preprocessing

Our starting point of data preparation was to understand what an Amazon review consists of. The raw data can be seen in Figure4.

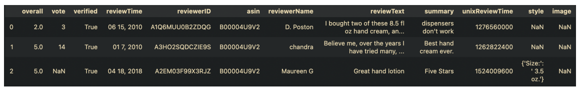
Initial data preparation was carried out on the whole dataset, dropping review time, image, style, ASIN, and reviewer id columns, as

[1][

],

Count/TF-IDF	Classifier	Train-set size	Parameters	Time spend	Youden's Index
Count	MLP	876.132	LBFGS, 1x50	23min 5sec (i7 8700k)	0.25646
Count	MLP	241.209	Adam, 2x100	184min 24sec (M1 Air)	0.23941
Count	MLP	107.302	LBFGS, 1x100	2min 3sec (M1 Air)	0.23504
Count	LogisticReg	107.302	max iter=10000	17 sec (i7 6700k)	0.22513
Count	MLP	107302	LBFGS, 1x50	2min 25sec(M1 Air)	0.22214
Count	SVC	107.302	max iter=5000	58sec (M1 Air)	0.21384
Count	MLP	107.302	Adam, 1x100	63min 2sec (M1 Air)	0.18065
TF-IDF	LogisticReg	107.391	max iter=10000	0.3sec (i7 6700k)	0.12344
TF-IDF	SVC	107.391	max iter=5000	1.4sec (i7 6700k)	0.06107

Figure 3: *Model test runs*



	overall	vote	verified	reviewTime	reviewerID	asin	reviewerName	reviewText	summary	unixReviewTime	style	image
0	2.0	3	True	06 15, 2010	A1Q6MUU0B2ZDQG	B00004U9V2	D. Poston	I bought two of these 8.5 fl oz hand cream, an...	dispensers don't work	1276560000	NaN	NaN
1	5.0	14	True	01 7, 2010	A3HO2SQDCZIE9S	B00004U9V2	chandra	Believe me, over the years I have tried many, ...	Best hand cream ever.	1262822400	NaN	NaN
2	5.0	NaN	True	04 18, 2018	A2EM03F99X3RJZ	B00004U9V2	Maureen G	Great hand lotion	Five Stars	1524009600	{'Size:': ' 3.5 oz.'}	NaN

Figure 4: *Unclean data*

these were not needed. Unverified reviews were also filtered out, to avoid reviews from customers who did not purchase the product. Finally, null values were removed from the review text column.

As our input data mainly consists of unstructured text reviews, text normalization[2]as done on the review text column to reduce randomness and reach a more uniform structure. This was done in accordance with common NLP data cleaning guidelines. Steps in this process involved removing non-word elements from the text – punctuation, symbols -, along with transforming each remaining word into lowercase. Because our model concerns itself with classification rather than sentiment, stop words like "not" did not provide any additional information to our model and were subsequently removed, as with other stop words contained in the NLTK "stopwords" library.

Each review was then tokenized into separate words using whitespace as a delimiter, as part of lemmatization to reduce morphological variation. Shortening some words to their root was thought important to improve model training efficiency. Lemmatization was chosen over stemming, as the accuracy of a lemmatizer in properly shortening words was more important than the speed of a stemmer.

As the next step of our data cleanup a column "voteSuccess" was added to the dataframe, calculating helpfulness of a review by dividing number of votes from the "votes"-column by quarters elapsed since the review was submitted. This was done to create a fairer indicator of helpfulness, since newer reviews would have had less time to accumulate helpfulness-votes and therefore appear less helpful.

For training our model, a numeric representation of our text corpus was needed for providing our models with input data. This was the final part of data preprocessing. Document-term matrices were created from two different vectorizations – Count[3]nd TF-IDF[4] Count vectorization parses a text corpus into a matrix based on the frequency of each term occurring in that corpus. This method was therefore the easiest way for us to present our data as something our classifiers could use. To discover if any less informative words not removed as part of our data cleanup were negatively impacting the performance of our model, we also opted for TF-IDF vectorization of our text data. TF-IDF favors unique terms appearing in documents higher, likely leading to a difference in model accuracy and precision metrics, and F1

[2]w

[3]a

[4].

scores.

iii. Model Building

To begin our model building LinearSVC was chosen as the initial classifier for our dataset. LinearSVC tries to classify our data into two groups, helpful and unhelpful since our problem is of a binary nature, and tries to find the optimal split between these two[**?**]. Initially the model did not converge in time. We therefore tried different max iterations to see when the model would converge and avoid overfitting and find the best fit for classifying a review as helpful/unhelpful. Performance does take a hit as the data size increases, see Figure3.

After trying SVM as our first classifier, we wanted to try a neural network on the dataset. Both SVM and neural network seemed like a great place to start, since they can be used in most machine learning tasks and yield decent results.

We've used the Multi-layer Perceptron classifier with different amounts of hidden layers, nodes and solvers.

During our testing the performance scaled positively as the size of the dataset increased. The cost of using the Adam solver over the LBFGS is higher, increasing the fitting dramatically as the training set grows, which matches scikit-learn's documentation[scikit-learn MLPClassifier].

Playing around with the nodes and layers got us to the ideal spot of 1 layer of 50 nodes, which scored highest on the Youden's Index3.

Logistic Regression is the last classifier we built upon[**?**]. Just as with the SVM max iterations need to be tweaked. As seen in Figure3, Logistic Regression fits a lot faster, but with a slightly lower Youden's Index score with the CountVectorizer.

iv. Model Evaluation

To get a reliable estimate of how well the models are doing, we run all the predictions through our summary report-function, which consists of metrics such as accuracy, recall and f1-score, and a confusion matrix.

As seen in the confusion matrix5, the model performs well at predicting the unhelpful reviews, but fail to predict the helpful reviews at a decent rate. This is the case for every model. Youden's Index makes up for this by taking chance into account and applying the same weight to both groups, measuring how well helpfulness was predicted in a review. Our Youden's Index scores have all been low since the models haven't been able to predict the helpful reviews at a rate higher than a third, which while being better than true randomness still is very low.

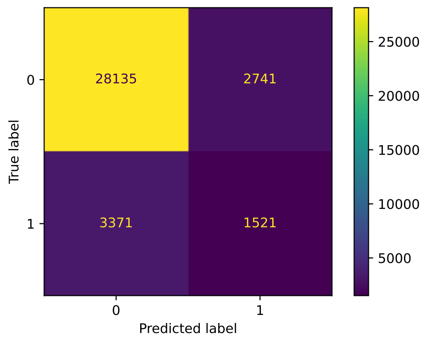


Figure 5: *Confusion Matrix*

As the final step of our data cleanup a column "voteSuccess" was added to the dataframe, calculating helpfulness of a review by dividing number of votes from the "votes"-column by quarters elapsed since the review was submitted. This was done to create a fairer indicator of helpfulness, since newer reviews would have had less time to accumulate helpfulness-votes and therefore appear less helpful.

V. Findings

Looking at our table of model test runs3, no model was fully able to predict, with any certainty, which reviews were helpful. The Count document-term matrix using an MLP classifier with the LBFGS algorithm on a neural network of 1 layer of 50 nodes, with a training-set size of 876132, reached the best performance, with a Youden's Index of 0.25646. Comparatively, other classifiers did worse, with LinearSVC doing only slightly worse than LBFGS on smaller training-sets, and the Adam Solver MLP classifier doing slightly worse on bigger training-sets.

When comparing the performance metrics of the models using different types of input data, Count or TF-IDF, Count did remarkably better. This could be interpreted as Count doing better when facing a classification problem, since some terms that would normally help distinguish between the two groups likely being suppressed by the IDF, removing valuable terms. Further examination is required to discover if this is the case, and if so, if another approach to parameterizing our dataset, like Bi-Normal Separation[5]Jean-Thomas Baillargeon, Luc Lamontagne, and Étienne Marceau, 2018. would perform better than Count.

Overall, our model was able to predict a helpful review in 1/3 of the cases, indicating that a more in-depth approach, possibly involving more features than the two currently provided, to training our model is required.

VI. Conclusion

In this paper we have analyzed to what extent we can use classification models to predict the helpfulness of an Amazon review based on the review text and upvotes.

Based on the analysis we find that the features used are not sufficient in determining the helpfulness of a review when using common classification tools. The inclusion of several other features contained in our dataset would likely improve upon the predictive power of our models.

Solely classifying reviews based on term-frequency may not be enough to properly distinguish between helpful and unhelpful, as the review text can be nearly identical in both cases. This can be due to the fact that many reviews containing terms that would be labeled as helpful get lost in the large volume of unvoted reviews as seen in Figure1.

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[scikit-learn Count Vectorizer] https://scikit-learn.org/stable/modules/generated/sklearn.feature$_{e}$*xtraction*

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[5] ,