



Book Review Analysis

Goodreads + Barnes and Noble



AGENDA

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 - 3 Natural Language Processing**
 - 4 Modeling Process**
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Business Problem

eCommerce has taken over the retail space making it close to impossible for brick and mortar stores to compete with larger retailers such as Amazon, Target, or Walmart. Over the years we have seen stores begin to close their doors due to the inability to keep up with online competitors.

Goodreads is an online social platform which gives readers the ability to share and rank their most recent books read. Once a user marks a book read or rates the book, the platform will recommend a new book to the user. A recent study was done which showed 93% of customers will read online reviews prior to purchasing.

Barnes and Noble is looking to understand what books should be showcased in their stores. They are looking to get ahead of the game by utilizing a model which can predict the rating of a book on the most popular book reviewed site.

Data Understanding

This dataset contains more than 1.3M book reviews about 25,475 books and 18,892 users. It was found through the Kaggle Goodreads Competition. The dataset of this competition is taken from UCSD Book Graph.

Sample Data:

A sample of 100,000 was used from the overall dataset to create the models.

The rating column was then weighted to help with class imbalance.

A zero rating was removed since this is not an actual rating on the Goodreads website. Two approaches were taken with this sample data.

First Approach:

The first approach with modeling utilized all ratings individually. Value counts below:

- **5 Rating:** 17,195
- **4 Rating:** 20,215
- **3 Rating:** 23,560
- **2 Rating:** 20,834
- **1 Rating:** 18,196

Second Approach:

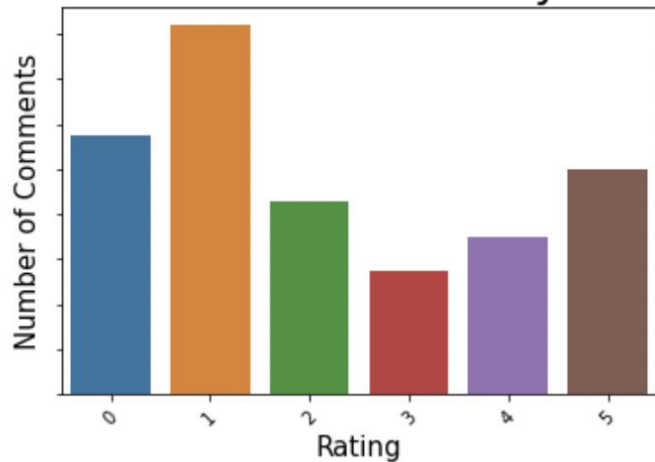
The second approach grouped ratings into two categories. Where a rating of 5 & 4 were labeled as 1 and a rating of 3, 2, & 1 were labeled as 0. Value counts below:

- **1 (5 & 4 Rating):** 37,410
- **0 (3, 2, & 1 Rating):** 62,590

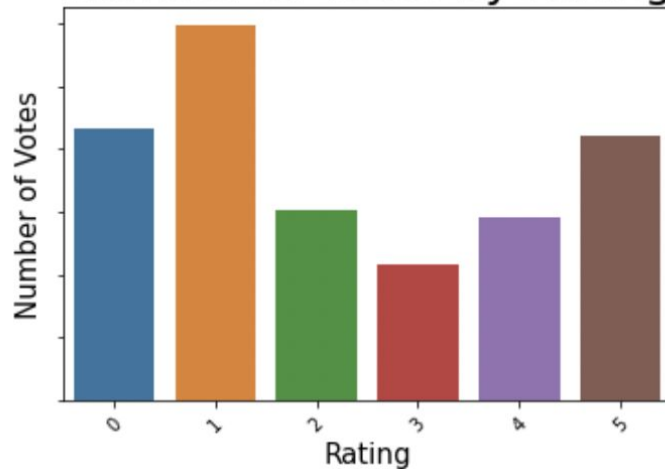
Data Understanding

EDA was performed with a focus on the Rating column. Looked to see if the average number of comments or votes impacted the rating given during a review.

Number of Comments by Rating



Number of Votes by Rating



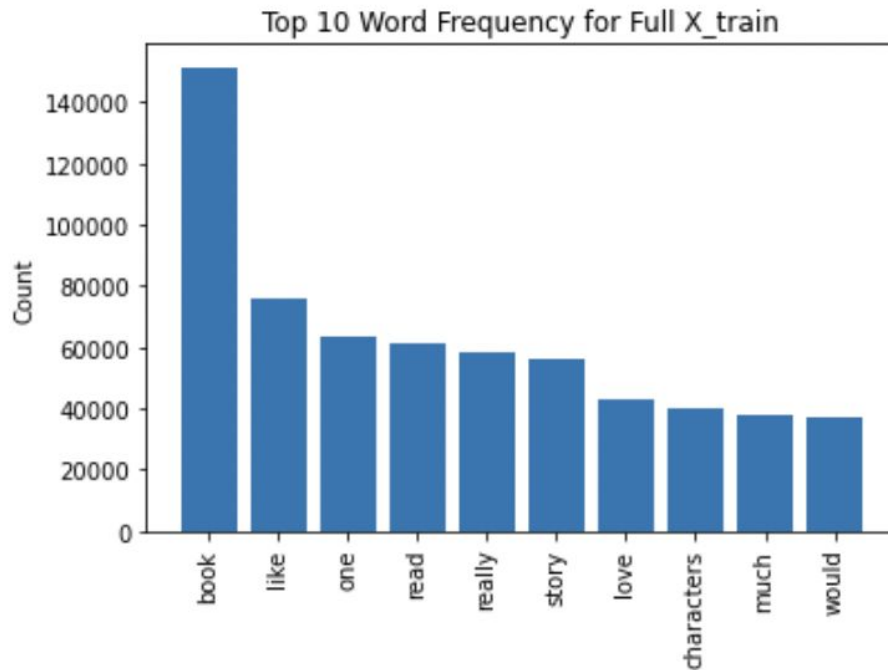
Natural Language Processing

Natural Language Processing was utilized to clean the book review data.

This process included:

- Standardizing
- Tokenizing

After cleaning the text data, you could look at frequency of words in the full dataset:



Modeling

The same modeling process was done on both versions of rating.

Started modeling with the ratings separated 1 through 5 and to see if it would improve model performance the ratings were then grouped into two labels, 0 and 1.

Three different models were created before choosing the best fit model. Before modeling was done, the data was vectorized using TF-IDF Vectorizer.

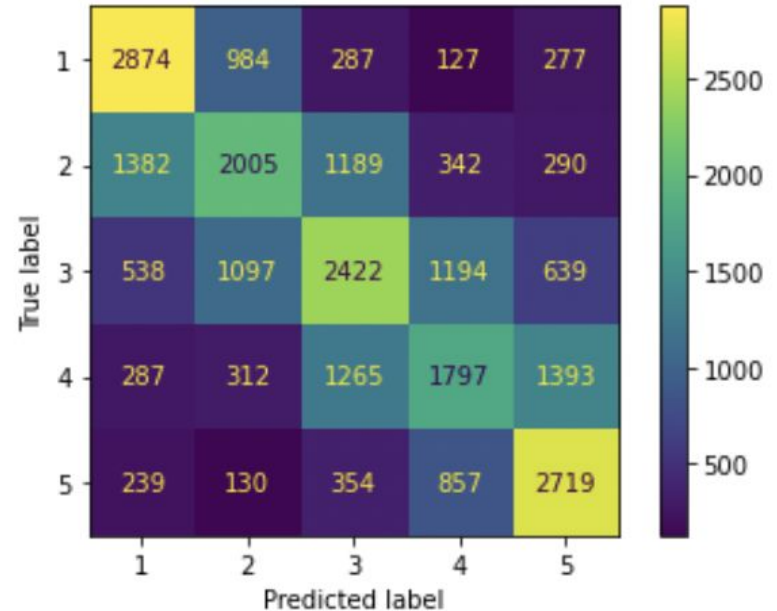
Modeling Types:

- Baseline Model with Multinomial NB
- Random Forest
- XGBoost

Final Model Version One

- The first approach with modeling utilized all ratings individually. (Ratings 1 through 5).
- The best performing model was Multinomial NB with grid search best parameters.
- A confusion matrix was utilized to showcase largest area of mislabeled reviews.
- A classification report was run on the best model. This model has an accuracy of 47%.

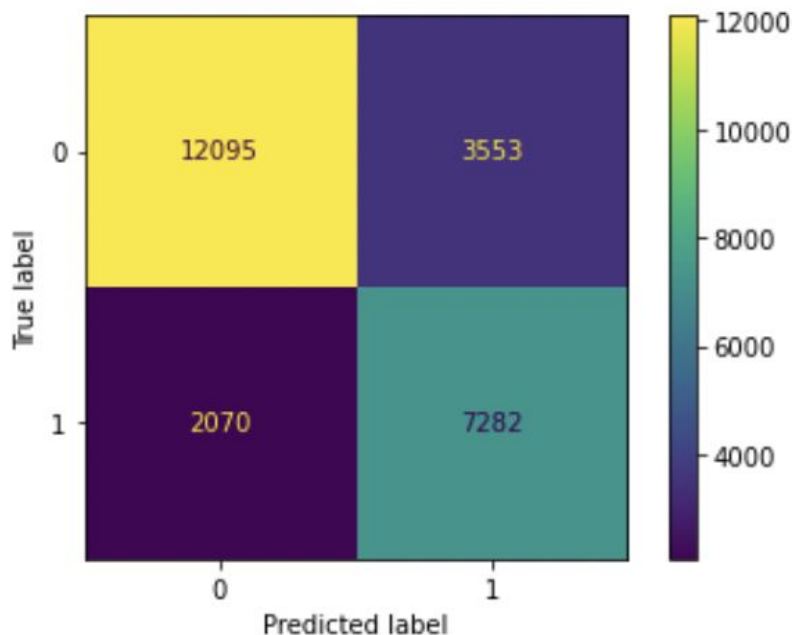
Confusion Matrix



Final Model Version Two

- The second approach grouped ratings into two categories. Where a rating of 5 & 4 were labeled as 1 and a rating of 3, 2, & 1 were labeled as 0.
- The best performing model was Multinomial NB with grid search best parameters.
- A confusion matrix was utilized to showcase largest area of mislabeled reviews.
- A classification report was run on the best model. This model has an accuracy of 78%.

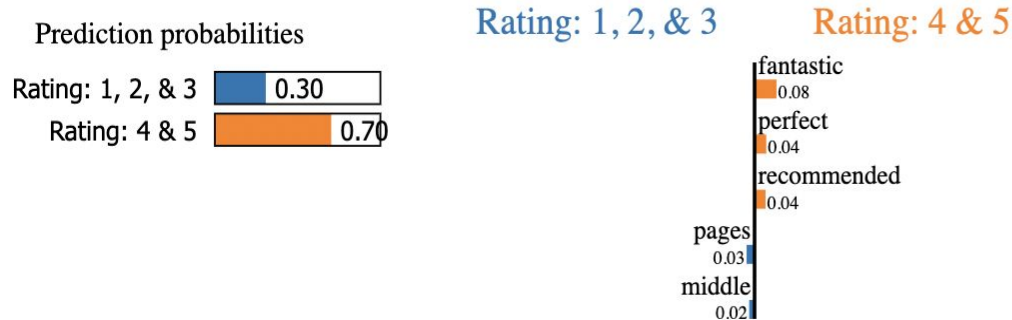
Confusion Matrix



Utilizing Lime (High Rating)

Lime was utilized with the version two best fit model. Lime was utilized to showcase the predictions within our best fit model.

Lime on High Rating (4 & 5)



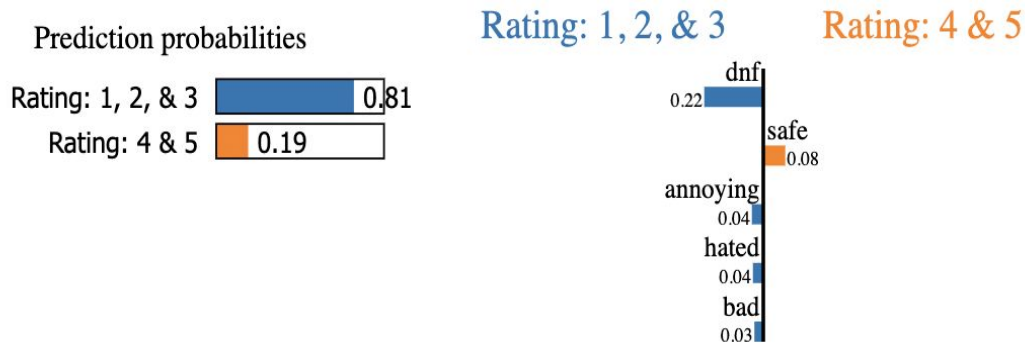
Text with highlighted words

sat read book one fast sitting stop turning **pages** story
fantastic well done really captures emotion changes
friendships personal interests often occur around **middle**
school especially graphic novel art **perfect** story helped
convey emotion personal note best friend ironically also
named nicole lost age changed interests book really means
lot plus great introduction roller derby totally **recommended**

Utilizing Lime (Low Rating)

Lime was utilized with the version two best fit model. Lime was utilized to showcase the predictions within our best fit model.

Lime on Low Rating (1, 2, & 3)



Text with highlighted words

big dnf hated characters awfull amelia annoying transitions
really bad blue got attacked next second safe door could safe
really bad people nop follow decisions amelia made think
thoughts missing

Conclusion & Next Steps

Two versions of modeling was concluded utilizing the dataset. Prior to modeling a sample of 100,000 was taken from the data and the ratings were weighted to help with class imbalance.

Version One: Utilizing all ratings 1-5. The best fit model was the Multinomial NB which accurately predicted the correct rating 47% of the time. With a score so low it was decided to create a second version, grouping the ratings together to see if it helped with the overall score.

Version Two: Grouped Rating 4 & 5 with the label of 1. Grouped Rating 1, 2, & 3 with the label 0. The best fit model was again Multinomial utilizing Gridsearch to find the best parameters. This model accurately predicted the grouped rating 78% of the time.

It is the recommendation to continue to use version 2 of model with Multinomial NB while utilizing gridsearch best parameters. This will help identify which books are higher rated and should be showcased more prominently in the physical storefronts.

Next Steps would be to continue to build upon the model to be able to increase the amount of reviews which can be inputted while shortening the overall run time.