CS 506 - Midterm Report - Kaggle Competition

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The goal of this competition was to predict the star rating (score) associated with user reviews from Amazon Movie/product Reviews using the available features - 'Id', 'ProductId', 'UserId', 'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Time', 'Summary', 'Text', 'Score'

1 Preliminary Analysis:

The following major steps I followed to understand the data provided:

1. Understood the numeric data columns from the basic plots provided in the starter code.
2. Plotted the correlation matrix with the helpfulness values and time to check how related they were with the score. (Figure 1)
3. Plotted the distribution of review scores which showed that the data is imbalanced with over 80% of the data having scores 4 and 5. (Figure 2)
4. Plotted the HelpfulnessRatio with Score which showed that the ratio is a constantly increasing curve with the Score which I considered to be a great feature to use for predictions. (Figure 3)
5. Plotted the mean summary length against the score which helped me conclude that the summary and text review lengths have no correlation with the score (Figure 4)
6. Plotted the Average score per UserId which showed no relation between the UserId and the score. (Figure 5)
7. Plotted the change of review score for a ProductId over time on multiple products which showed no clear insights on how the ProductId or Time affects the score. (Figure 6)

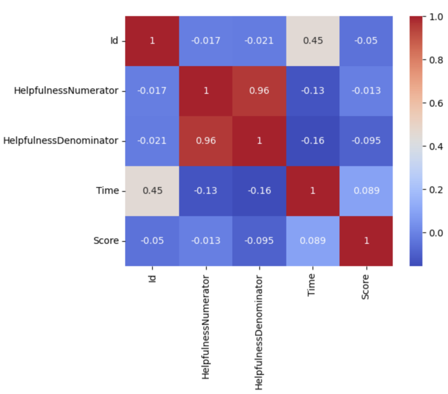


Figure 1: Correlation matrix

Figure 2: Distribution of Review Scores

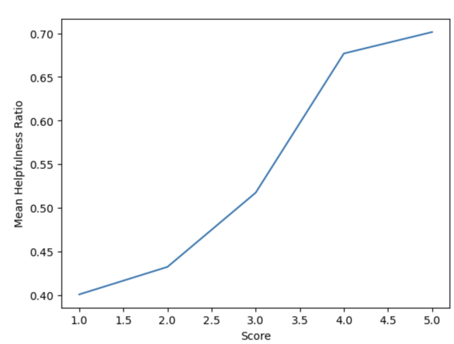


Figure 3: Mean Helpfulness Ratio

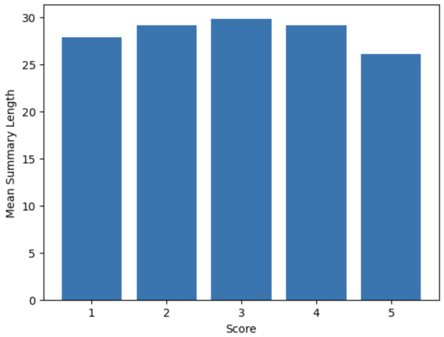


Figure 4: Mean Summary Length

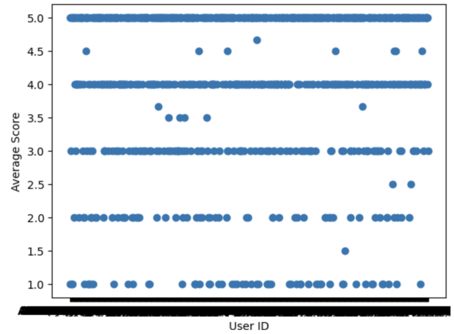


Figure 5: Average Score per UserId

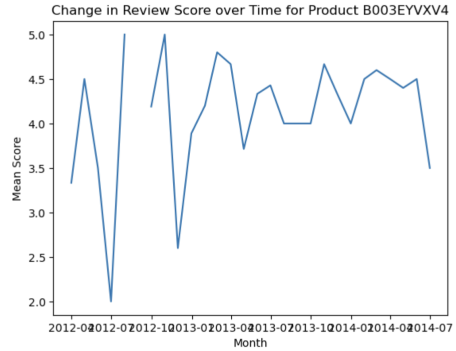


Figure 6: Change in Review Score over Time for Product

2 Dataset understanding:

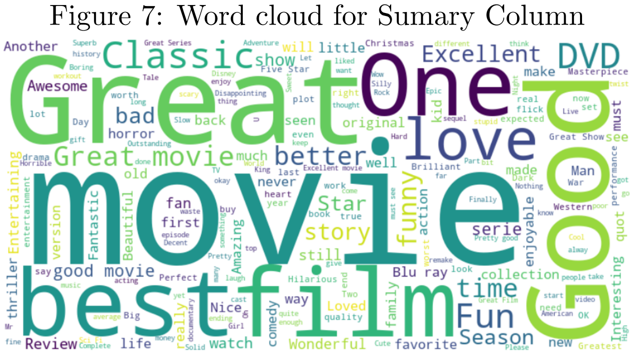
From the above plots and the word cloud below (Figure 7), I understood that

1. The dataset mostly deals with movie reviews in Amazon.
2. Looking at the distribution of scores, we can see a trend of how most users either rate 4 or 5 stars.
3. Initial look at the word cloud gives us an idea that most of the reviews are probably positive or leaning towards positive.
4. Looking at the helpfulness ratio, we can see a very clear trend of how people rate products which are helpful with higher stars, which is also intuition, but the dataset confirms it.

3 Experiment Setup:

Model:
From figure 2, I concluded that the **data is imbalanced**, as we see almost 80 % of the dataset has reviews with scores of either 4 or 5. This made to choose the **boosting algorithms** like LightGBM, Adaboost, XGBoost, as they are designed to train a series of weak learners on the dataset iteratively, so misclassified samples or samples with higher error rates in one iteration are given more weight which is used as the updated dataset by the next weak learner.

Figure 7: Word cloud for Sumary Column



Text Pre-processing:
For
correlating the **Summary** and **Text** columns with the score, reducing the sentences to just a collection of characters/words is important to make a more meaningful analysis by reducing the noise. I plotted the word cloud of the word used in Summary first to better understand the words. (Figure 7) After looking at the word cloud, I used **TfidfVectorizer** to extract the commonly occurring words which differentiate samples from each other, meanwhile paying less attention to words that frequently occur across most samples. I chose to **retain the stop words** as words like *but, no, good, great* defnitely makes a difference in determining the final scores.
As the output of Tfidf is very sparse, I used **MaxAbsScaler** to **normalize** the features, as it **preserves the sparsity**, reducing computational time
Feature Pre-processing:
From Figure 3, I concluded that, although HelpfulnessNumerator and HelpfulnessDenominator have huge correlation to the review score, the **HelpfulnessRatio** definitely has a significant impact on the score, as we see that the **HelpfulnessRatio** value keeps increasing with the score.
Hyper-parameter tuning:

I tried applying GridSearchCV for finding the best possible hyperparameters for every model but I couldn't achieve that because the kernel kept crashing. So, I resorted to reading the documentation to understand the purpose of every parameter to figure out whether to change the default value or not. For instance, for LightGBM, I changed the *num_leaves* value from 31 to 30 and *learning_rate* from 0.05 to 0.06, although compromises on the training speed/time, gives better accurate models according to the documentation.

4 Experiments:

Iteration 1: (Model selection)
To narrow down to the best working model for the task, I focused on creating a **simplified version of my envisioned pipeline** and run it against all the different boosting algorithms. The steps of the simplified pipeline were: *Extract tfidf character and word n-grams for both Text and Summary columns - normalize the values using MaxAbsScaler - use this as the features to train.* The models I tried are:

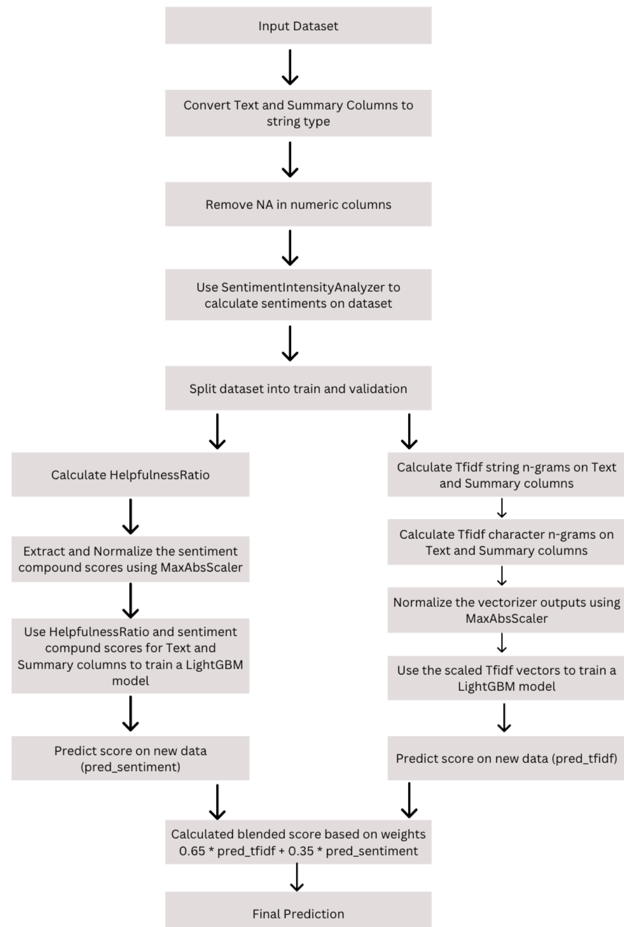
1. XGBoost
2. LightGBM
3. ElasticNet
4. AdaBoost
5. StackingEnsemble
6. VotingEnsemble

The models I tried are:

1. MaxAbsScaler
2. StandardScaler
3. SMOTE
4. MinMaxScaler

Results Validation:
Using **RMSE** scores, I figured out that **LightGBM** worked better than other models with **MaxAbsScaler**
Iteration 2 (Best submission):
For the actual pipeline which produced my best submission, refer to **Figure 8 for the design**. The columns from the input dataset I utilized are: HelpfulnessNumerator, HelpfulnesssDenominator, Summary, Text, ProductId

Figure 8: Pipeline design followed for best submission



5 Challenges:

1. Compute was a major issue as a lot of models/pipelines kept crashing. Due to the same reason I could only train my models on a fraction of the dataset.
2. As there were a plethora of techniques and models at our disposal, i definitely spent a lot of time trying to figure out if what I am planning on using is relevant to the problem and if it makes sense logically as a solution, irrespective of its performance.