Write-Up

I don't have extensive knowledge about NLP, so I essentially approached this competition as a general classification challenge.

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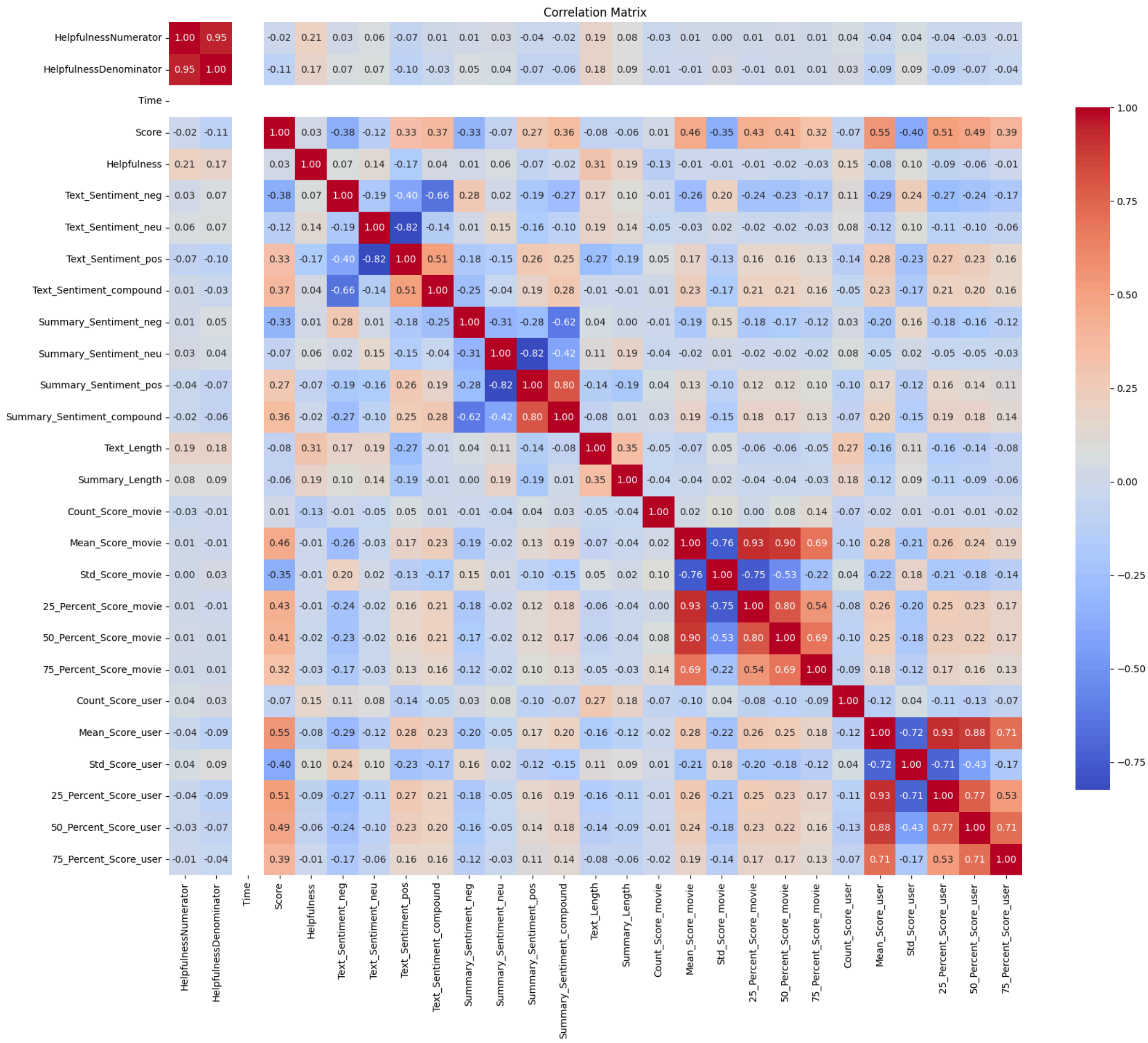
Data Analysis

I explore the dataset by using `df.dtypes` to see the data type of each column, using `df.describe` to get the information about the distribution of the data, and then using `df.head` to get a few examples of the samples so I could have an initial thought about how to make each column into usable features.

```
Id   ProductId         UserId  HelpfulnessNumerator  \
0   914403  B0009W5KHM   AV6QDP8Q0ONK4                     2
1   354887  6303079709  A2I8RXJN80A2D2                     0
2  1407653  B004H0M2XC  A3FHV3RV8Z12E6                     0
3  1377458  B003ZJ9536  A12VLTA3ZHVPUY                     1
4   475323  630574453X  A13NM1PES9OXVN                     2

   HelpfulnessDenominator        Time  \
0                       2  1341014400
1                       0  1168819200
2                       0  1386201600
3                       1  1348704000
4                       3   970012800

                                      Summary  \
0                               GOOD FUN FILM
1                                Movie Review
2             When is it a good time to Consent?
3                                       TRUTH
4  Intelligent and bittersweet -- stays with you

                                               Text  Score
0  While most straight to DVD films are not worth...    5.0
1  I have wanted this one for sometime, also.  I ...    5.0
2  Actually this was a pretty darn good indie fil...    4.0
3  Episodes 37 to 72 of the series press on in a ...    5.0
4  I was really impressed with this movie, but wa...    3.0

        Id  Score
0  1323432    NaN
1  1137299    NaN
2  1459366    NaN
3   931601    NaN
4  1311995    NaN

                   Id  HelpfulnessNumerator  HelpfulnessDenominator  \
```

```
count  1.697533e+06          1.697533e+06          1.697533e+06
mean   8.487660e+05          3.569048e+00          5.301422e+00
std    4.900357e+05          1.727883e+01          2.024445e+01
min    0.000000e+00          0.000000e+00          0.000000e+00
25%    4.243830e+05          0.000000e+00          0.000000e+00
50%    8.487660e+05          1.000000e+00          1.000000e+00
75%    1.273149e+06          3.000000e+00          5.000000e+00
max    1.697532e+06          6.084000e+03          6.510000e+03

               Time         Score
count  1.697533e+06  1.485341e+06
mean   1.262422e+09  4.110517e+00
std    1.289277e+08  1.197651e+00
min    8.793792e+08  1.000000e+00
25%    1.164413e+09  4.000000e+00
50%    1.307491e+09  5.000000e+00
75%    1.373242e+09  5.000000e+00
max    1.406074e+09  5.000000e+00
```

I also draw a correlation matrix after feature processing to see if any of the features are strongly related.



Feature Engineering

Helpfulness

The first feature I added was "Helpfulness" since it’s easy to implement and free!

User Preference and Movie Averages

One of the most important tasks I undertook was grouping the ratings by `userID` and `movieID`. This allowed me to derive several features:

- **Movie Features:**
  - **Average Rating:** This reflects the general quality of the movie.
  - **Count of Ratings:** This indicates the popularity of the movie.
  - **Standard Deviation (STD):** This measures the variability in ratings, helping the model to discern whether to weight the semantic analysis of individual reviews more heavily or to rely on the average rating.
- **User Features:**
  - **Average Rating:** This reflects the user’s personal rating tendencies.
  - **Count of Ratings:** This provides insight into the user’s experience and qualifications.
  - **Standard Deviation (STD):** This indicates the range of ratings a user typically gives. For instance, some users, like myself, tend to score movies between 2 and 4, categorizing films as either masterpieces or total failures.

Label Encoding

I label-encoded `ProductId` and `UserId` since they were originally strings. I hoped this would aid in classification, although ultimately, it didn’t significantly impact the results.

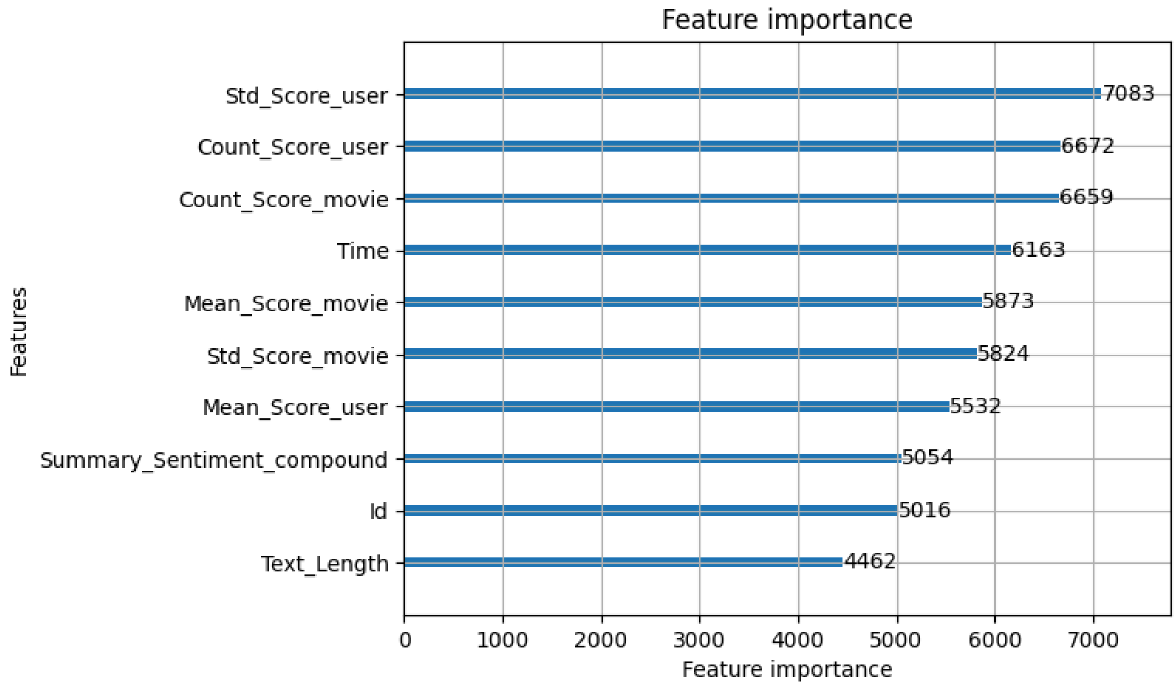
Time as a Feature

By analyzing feature importance plots and correlation matrices, I found that `Time` emerged as an important feature. My current hypothesis is that it may reflect the economic conditions when the movie was released, which could correlate with the quality of the movies.

NLP Features

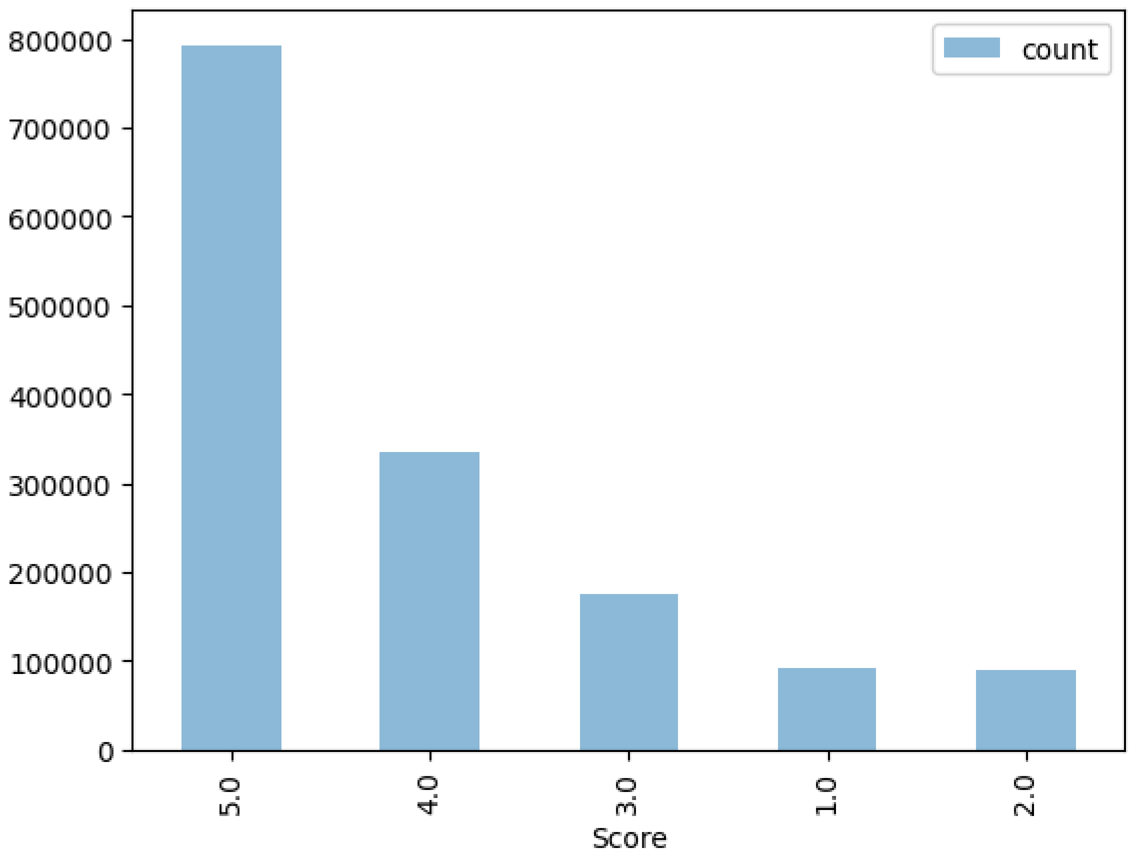
The only NLP features I included were the sentiment scores of the `Summary` and `Text` calculated by Vader Sentiment, as well as their lengths. I believe that longer reviews are often more thoughtful and serious.

Here is a plot showing the importance of each feature in my XGBoost model.



Addressing Class Imbalance

Oversample



Upon observing the distribution plot, I discovered that the dataset was extremely imbalanced. To address this, I employed SMOTE to oversample the features mentioned earlier in the 1 to 4 star comments, aligning their numbers with those of the 5-star ratings. Fortunately, this strategy improved model performance.

Training the model

Models Used

I experimented with XGBoost, LightGBM, and Extra Trees, applying aggressive hyperparameter tuning throughout the competition. The best results came from XGBoost. While I generally prefer LightGBM due to its advantages, it is also prone to overfitting. Given the time constraints, I focused more on feature engineering rather than model selection.

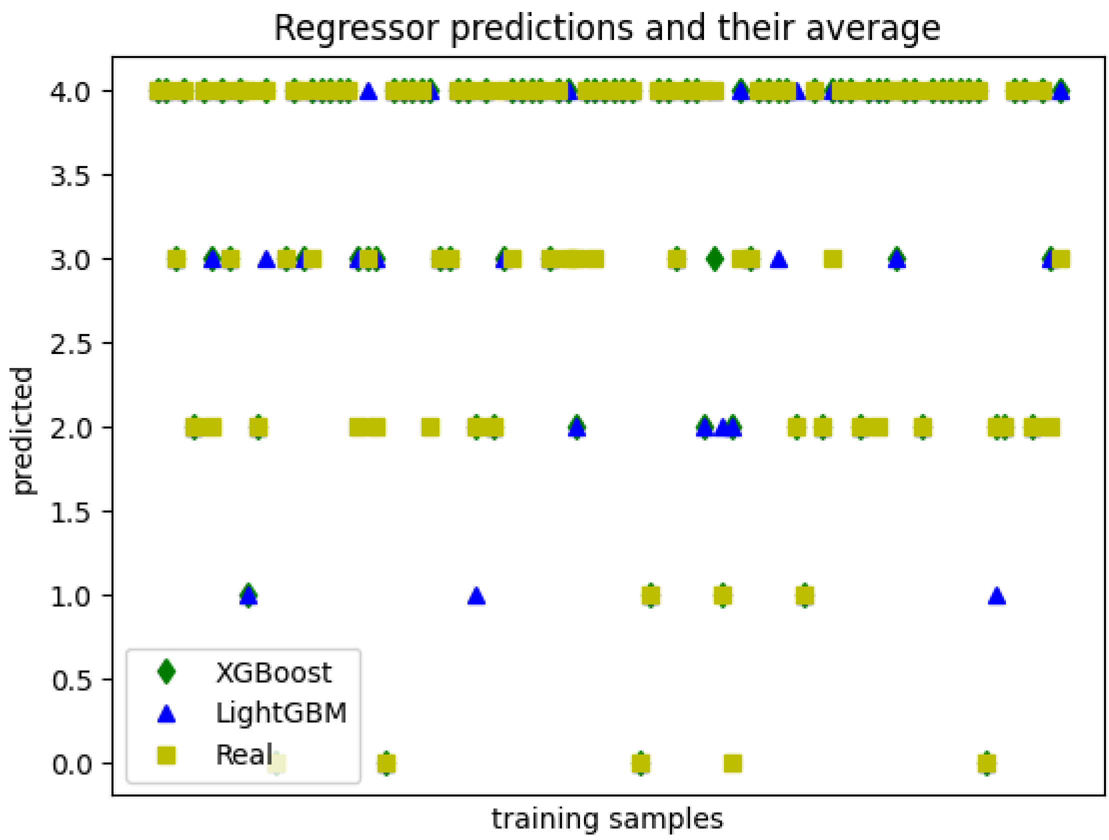
The benefit of XGBoost lies in its layer-by-layer development, which can help mitigate overfitting compared to other methods, and that's important because I had already overfitting my model with only 10% of the dataset or many time.

Classification vs. Regression

I typically prefer regression techniques, clamping scores into integers since discrete ratings often maintain a meaningful relationship. However, for this competition, I opted for classification. My previous models tended to categorize 4-star ratings as 5 stars, which misrepresented their distinctiveness. By treating them as separate categories, the model learned that predicting an actual 5-star rating as 4 stars wouldn’t yield any credit, as there’s no concept of partial correctness in this context.

Attempt to Combine Multiple Models

I attempted to use another vote classifier (I don't want to train 3 heavy models in a row), but it resulted in the worst performance. The combined predictions were even less accurate than those made by the individual models, LGBM and XGBoost. I had hoped that these models would balance out each other’s biases, but it seems they ended up making the same mistakes together!



Hyperparameter Tuning

I utilized `GridSearchCV` for tuning, exploring the relationships between key parameters like `n-estimators`, `max-depth`, and `learning_rate`, which are crucial for optimizing XGBoost.

```
Best Parameters:  {'learning_rate': 0.1, 'max_depth': 10, 'n_estimators': 200}
Best Score:  0.715226335924629
```

Validation Strategy

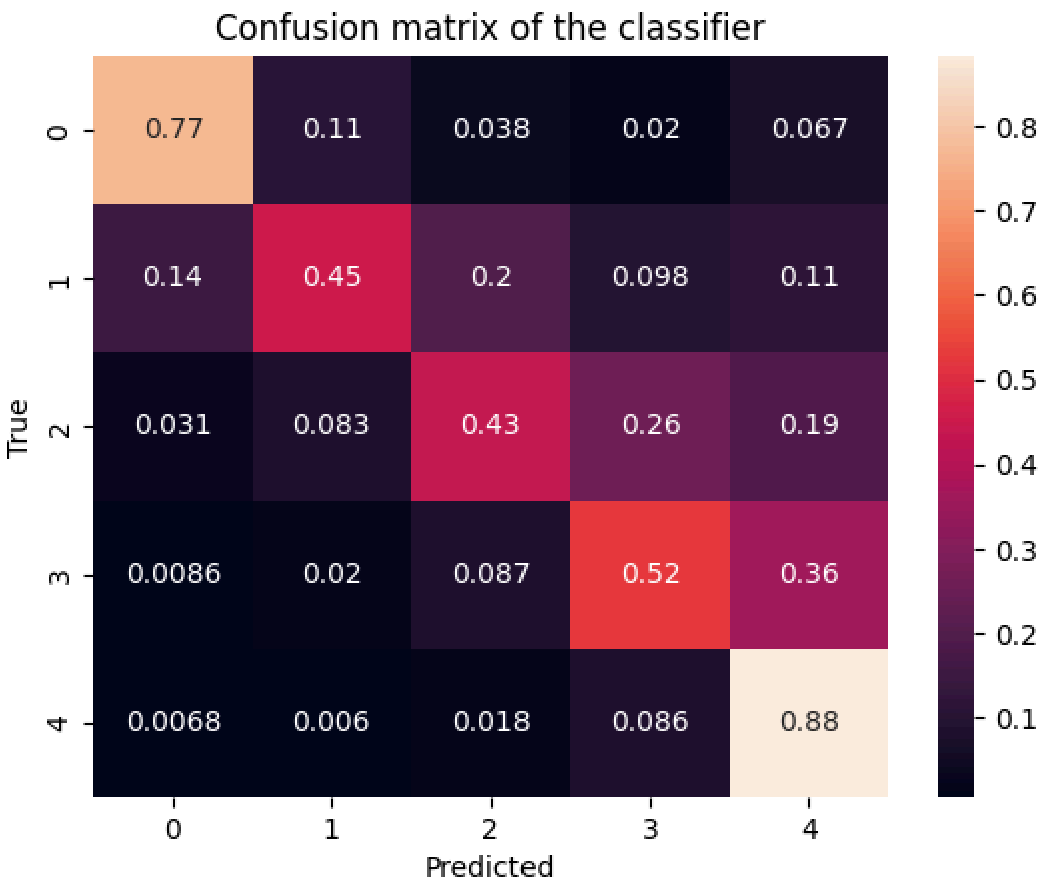
Cross-Validation with K-Folds

Since `GridSearchCV` handled hyperparameter tuning, cross-validation was integrated into the grid search process, making additional manual 5 folds stratified cross-validation unnecessary. Following tuning, the model achieved an average cross-validation score of **0.715** on the full training dataset and an accuracy score of **0.7165** when trained on 80% of the data and tested on the remaining 20%. However, on the Kaggle public test dataset, the score dropped significantly to **0.6332**. This discrepancy indicated that the dataset is very prone to overfitting, especially since my CV and test accuracy were so close. As a result, I intentionally simplified the complexity of my XGBoost model in the latest version, but unfortunately, this led to worse results.

Evaluation with Confusion Matrix

Later, I visualized a confusion matrix to assess the model's performance, which helped identify classification tendencies. The matrix revealed inconsistencies in predicting mid-range scores, indicating potential overfitting to higher ratings (4-5 stars). I'm still struggling to find an effective way to address this issue.

> All ratings are aligned to 0 here; add 1 to make them the real ratings.



Citation

XGBoost: XGBoost is a popular gradient boosting framework that iteratively builds models to minimize error, often improving accuracy by reducing overfitting with built-in regularization.

LightGBM': LightGBM is a fast, efficient gradient boosting model optimized for large datasets. It is a tree-based gradient boosting framework that uses a "leaf-wise" growth strategy, unlike XGBoost, which grows level by level. This means LightGBM may be more likely to overfit without careful tuning.

ExtraTrees: Extra Trees is an ensemble learning technique that constructs multiple decision trees with additional randomness, significantly enhancing generalization.

SMOTE: SMOTE (Synthetic Minority Over-sampling Technique) is a technique to balance datasets by generating synthetic samples for minority classes.

Label Encoding: Label Encoding assigns numerical labels to categorical variables, which would not increase the dimension of the data like One Hot Encoding, even though it does not create significant performance gains.

VaderSentiment: Vader Sentiment (Valence Aware Dictionary and sEntiment Reasoner) is an NLP library for carrying out sentiment analysis.

VotingClassifier: The Voting Classifier combines predictions from multiple models to improve accuracy by mitigating individual model biases.

GridSearchCV: GridSearchCV uses a brute force approach to search all possible parameter combinations in order to optimize the performance of the model.