Capstone Project

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Definition

Project Overview:

This project work is from yelp data challenge. Many businesses collect reviews of their services or products. Along with reviews text, reviewer is also asked to enter rating in the range of one to five, five being excellent. Sometimes, there is discrepancy between the numeric value of the rating and reviews text. In fact many start-ups evolved to understand and interpret this data and provide good insight to the business. Yelp provides data set for this challenge. In their data challenge page, they also put some ideas to consider. I have chosen the idea of predicting numeric rating from the reviews text alone. They also provided example code to use for this datasets.

Problem Statement

Predict numeric rating from reviews text.

We are given labeled training data, which has reviews text, and it's rating. Rating is considered as label or class that is to be predicted. Each review was given a rating on a discrete label in the scale 1 to 5.

Although the rating is for that particular product or service, here I have not considered that relationship. Reviews text is tokenized with TF-IDF Vector. Then Logistic Regression Classifier is used to train the model. I persist the model with pickle. The predict API is used to predict for unseen reviews text.

Metrics

F1 score which is defined as harmonic mean of precision and recall used to measure the performance of the model, where best value reaches at 1 and the worst score at 0. This project is not a binary classifier. This is a multi-class and multi-label case. By default, parameter search uses the `score` function of the estimator to evaluate a parameter setting. But in this case, alternate scoring function F1_MACRO used to address class imbalance. This is specified as scoring parameter to GridSearchCV constructor.

Analysis

Data Exploration

If a dataset is present, features and calculated statistics relevant to the problem have been reported and discussed, along with a sampling of the data. In lieu of a dataset, a thorough description of the input space or input data has been made. Abnormalities or characteristics about the data or input that need to be addressed have been identified.

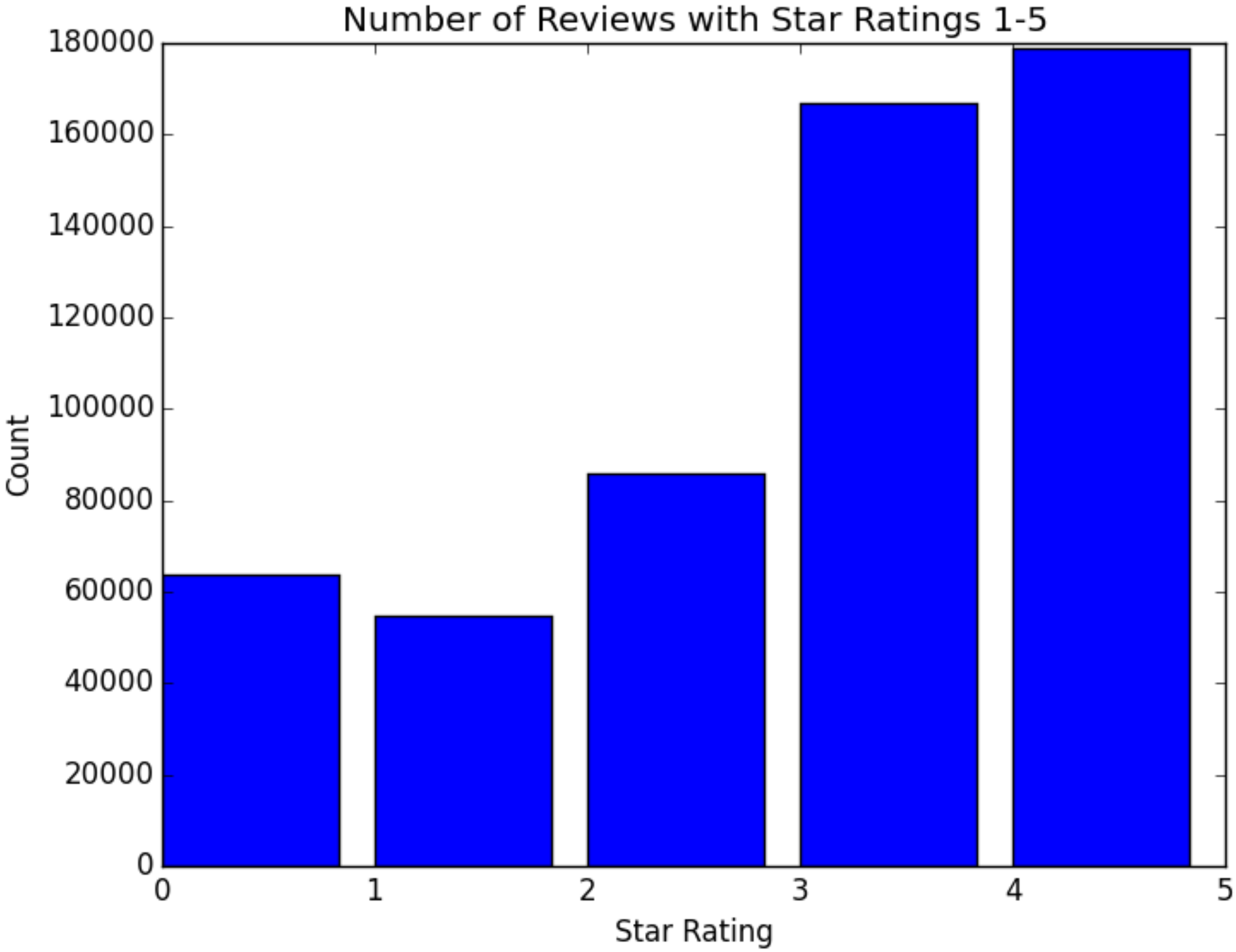
Yelp business review data set consists five data files. For this project, I considered only reviews file.

Found relationship between each of the vote types (cool/useful/funny) and the number of stars as follows.

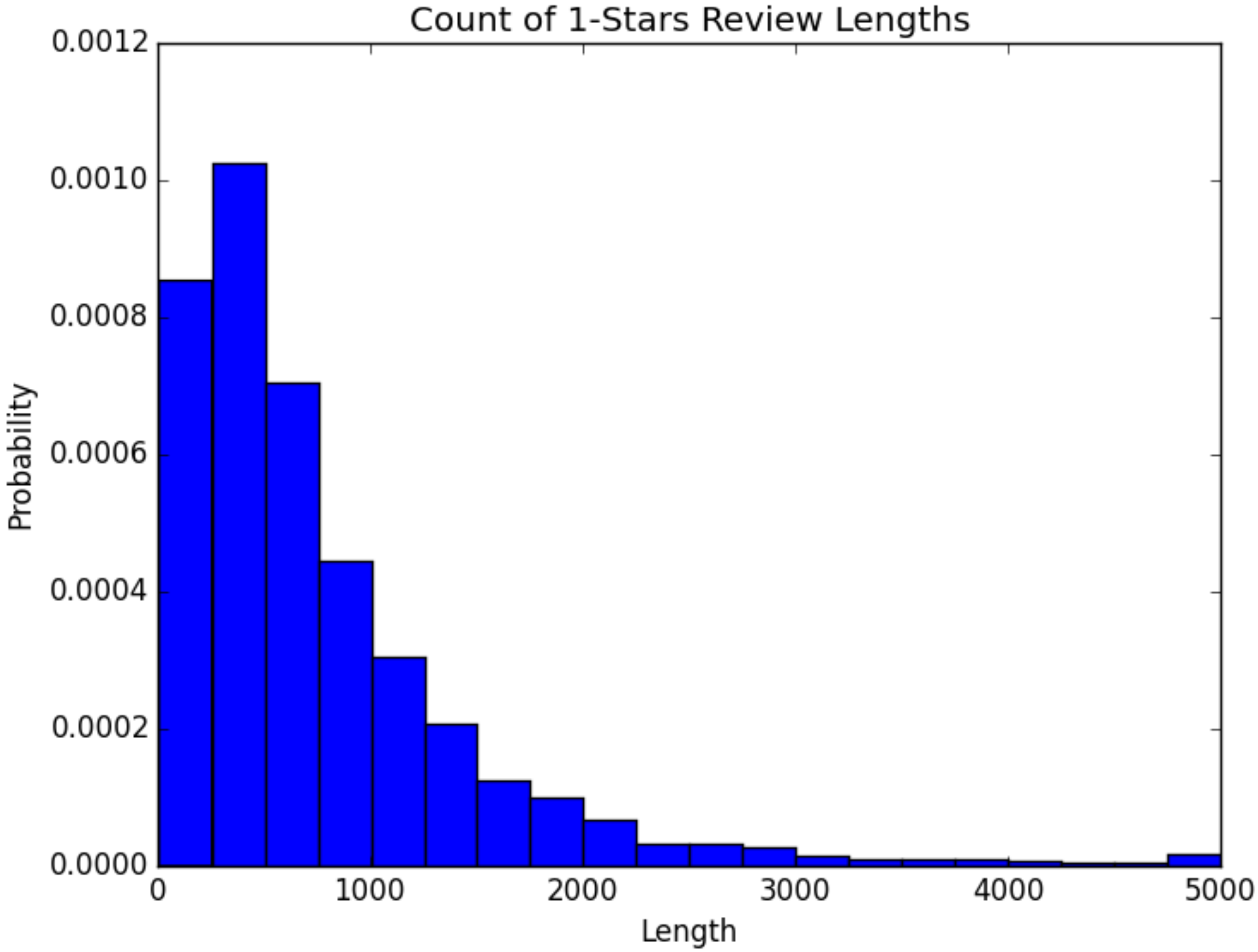
	cool	useful	funny
Stars			
1	0.268	1.289	0.547
2	0.404	1.192	0.567
3	0.578	1.055	0.521
4	0.714	1.064	0.481

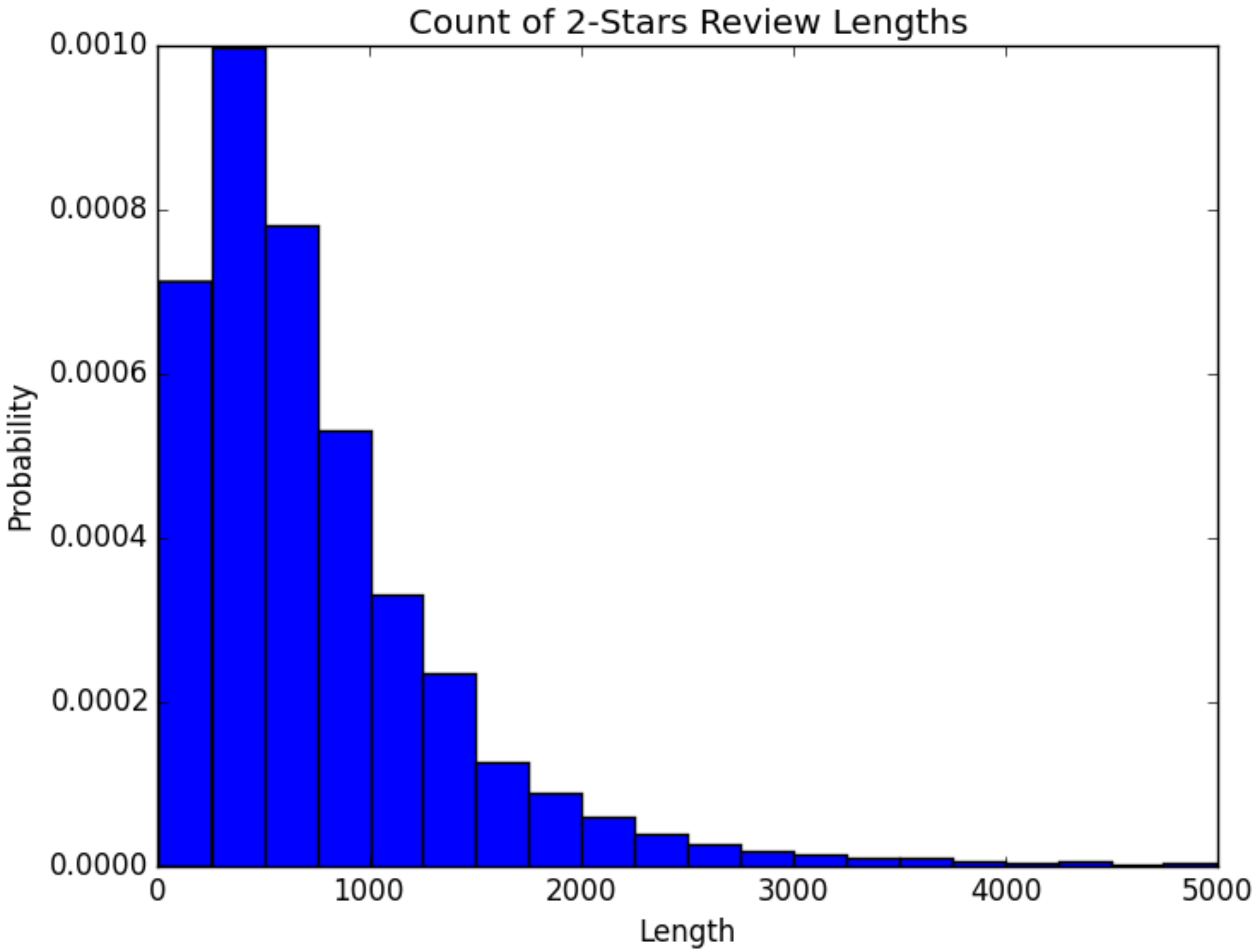
5	**0.545**	**0.869**	**0.333**

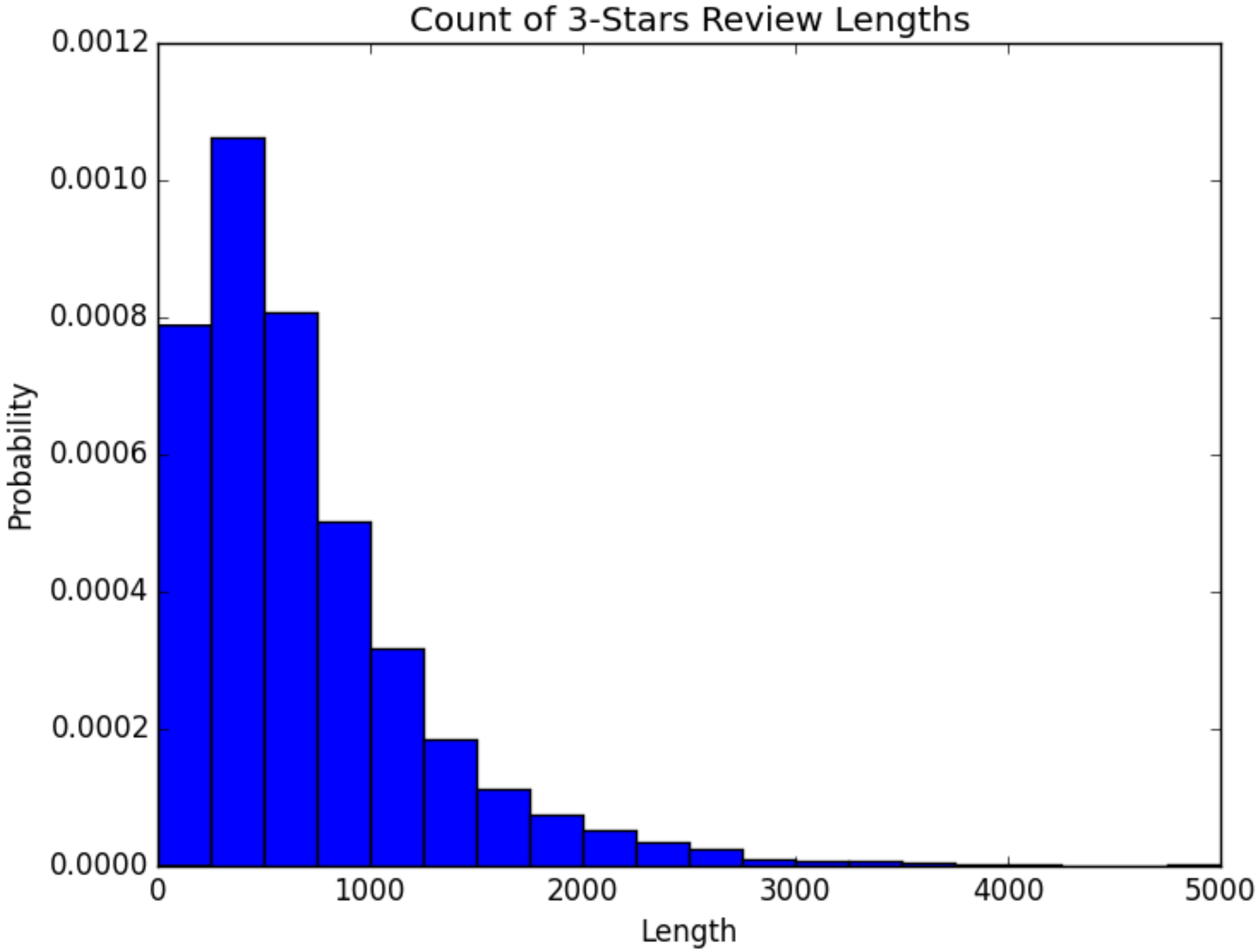
Looked at rating (stars) distribution. Distribution is obviously skewed. People tend to write positive reviews

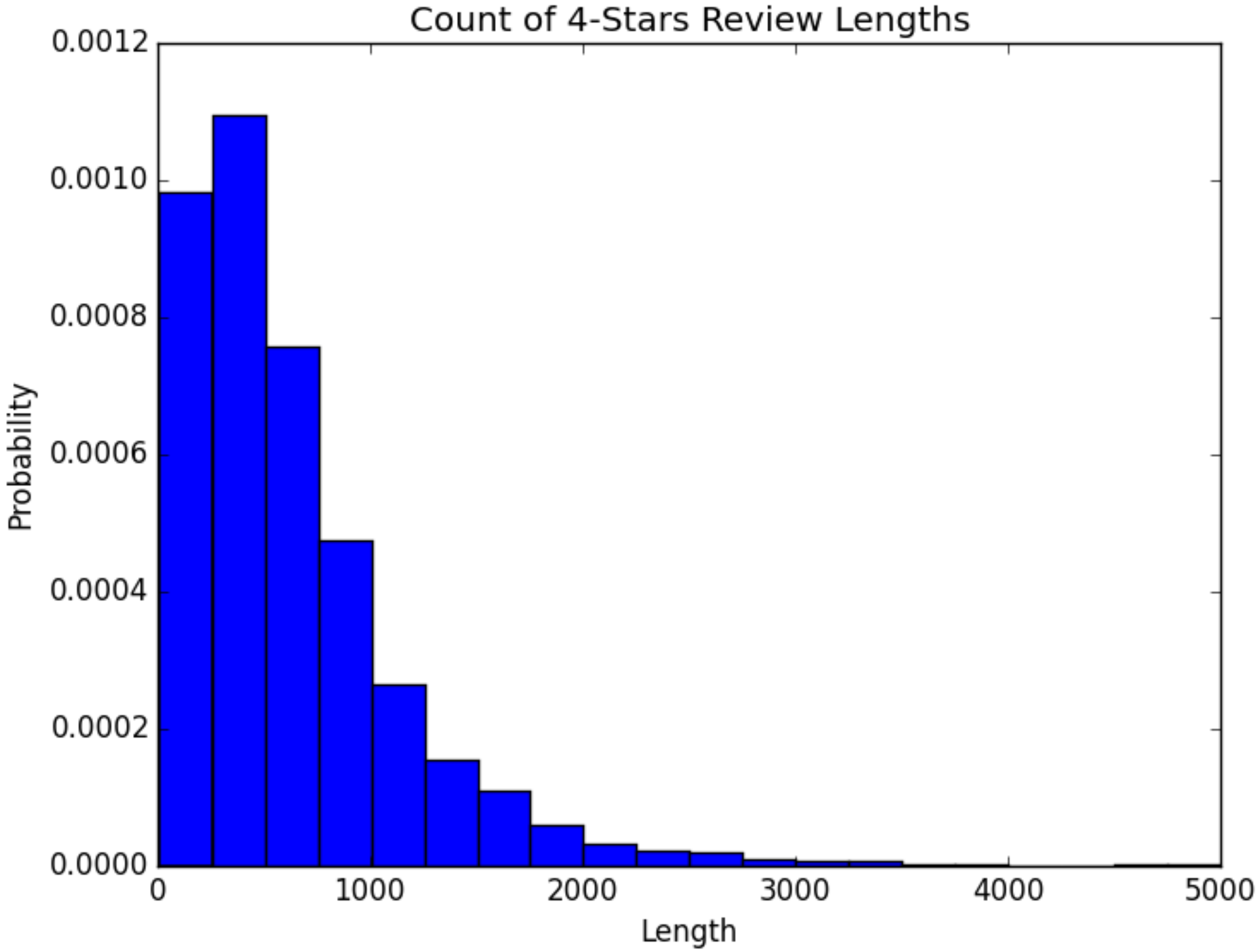

Number of Reviews with Star Ratings 1-5
Count
180000
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
2
3
4
5
Star Rating

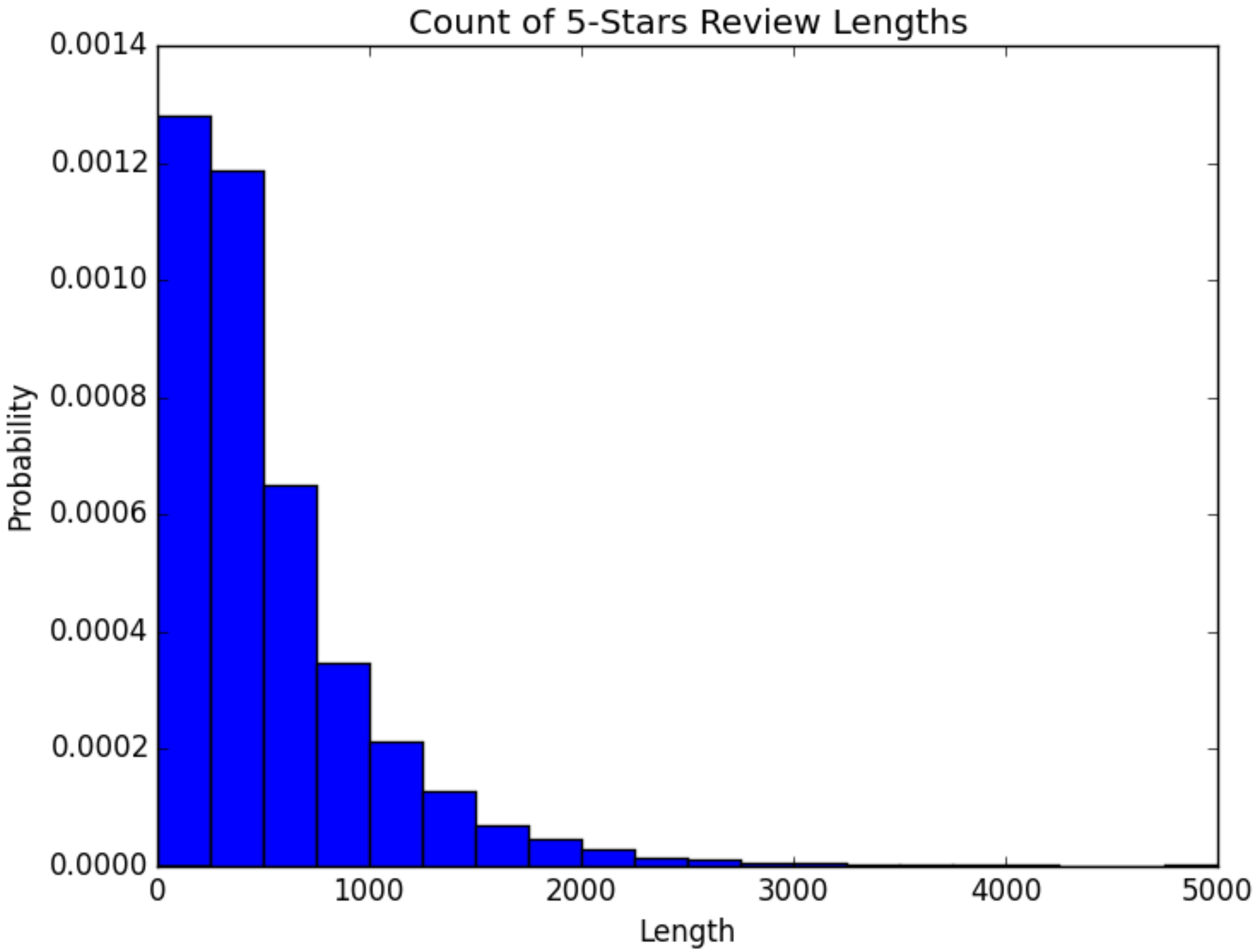
Identified correlation between review length and star rating if any, and plotted as histogram for each rating as below:


Count of 1-Stars Review Lengths
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Probability
0
1000
2000
3000
4000
5000
Length


Count of 2-Stars Review Lengths
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Probability
0
1000
2000
3000
4000
5000
Length


Count of 3-Stars Review Lengths
Probability
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
1000
2000
3000
4000
5000
Length


Count of 4-Stars Review Lengths
Probability
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
1000
2000
3000
4000
5000
Length


Count of 5-Stars Review Lengths
Probability
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
1000
2000
3000
4000
5000
Length

Data set size is 2.2 million.

Exploratory Visualization

Visualization has been provided that summarizes or extracts a relevant characteristic or feature about the dataset or input data with thorough discussion. Visual cues are clearly defined.

There are 2225213 reviews. Reviews are for a business or any properties of business. Business types range from restaurants to home improvement to automotive services. I do see new line character \n in most of the place and were removed.

Star Rating	Mean	Standard Deviation
1	6.257	0.914
3	6.22	0.861
5	5.93	0.88

Please see explore_data ipython notebook for code details.
Total documents in the data set: 2225213

1 rated reviews = 11.71%
2 rated reviews = 8.54%
3 rated reviews = 12.68%
4 rated reviews = 26.59%
5 rated reviews = 40.49%

Data Format

review

```
{
   'type': 'review',
   'business_id': (encrypted business id),
   'user_id': (encrypted user id),
   'stars': (star rating, rounded to half-stars),
   'text': (review text),
   'date': (date, formatted like '2012-03-14'),
   'votes': {(vote type): (count)},
}
```

Algorithms and Techniques

We have an array of algorithms like Naive Bayes, decision trees, Random Forests, Support Vector Machines, and many others. Logistic regression classifier classifies text documents by using a bag-of-words approach, efficiently handles sparse features. I have chosen Logistic Regression, as it is fast, easy to regularize and it outputs well-calibrated predicted probabilities. It also works with categorical features.

Raw reviews data cannot be directly feed to Logistic Regression algorithm as it expects numerical feature vector with a fixed size rather than the raw text documents of variable length. In order to address this, sci-kit learn provides utilities to extract numerical features from text content, namely

- **tokenizing** strings and giving an integer id for each possible token, for instance by using white spaces and punctuation as token separators.
- **counting** the occurrences of tokens in each document.
- **normalizing** and weighting with diminishing importance tokens that occur in the majority of samples / documents.

I used tf-idf vectorizer to generate features from reviews text. I set the parameter to remove English stop words.

Tuned Parameters

min_df : float in range [0.0, 1.0] or int, default=1 (Tuned to 0.1)

When building the vocabulary ignore terms that have a document frequency strictly lower than the given threshold. This value is also called cut-off in the literature. If float, the parameter represents a proportion of documents, integer absolute counts. This parameter is ignored if vocabulary is not None.

Stop word English is used.

Simple Logistic Regression Classifier with GridSearchCV to train the model. GridsearchCV searches over parameter values for logistic regression. Parameters that are not directly learnt, also called hyper parameters can be set by searching a parameter space for the best score. A search consists of:

- a classifier
- a parameter space;
- a method for searching or sampling candidates;
- a cross-validation scheme; and
- a score function.

By default, parameter search uses the score function of the estimator to evaluate a parameter setting.

Following parameters were tuned with GridsearchCV

```
grid = {'C': 10.0 ** np.arange(-2, 3),
                        'penalty': ['l1', 'l2'],
                        'class_weight': [None, 'auto']}
```

C Inverse of regularization strength

Penalty whether L1 or L2 regularization

class_weight   Weights associated with classes

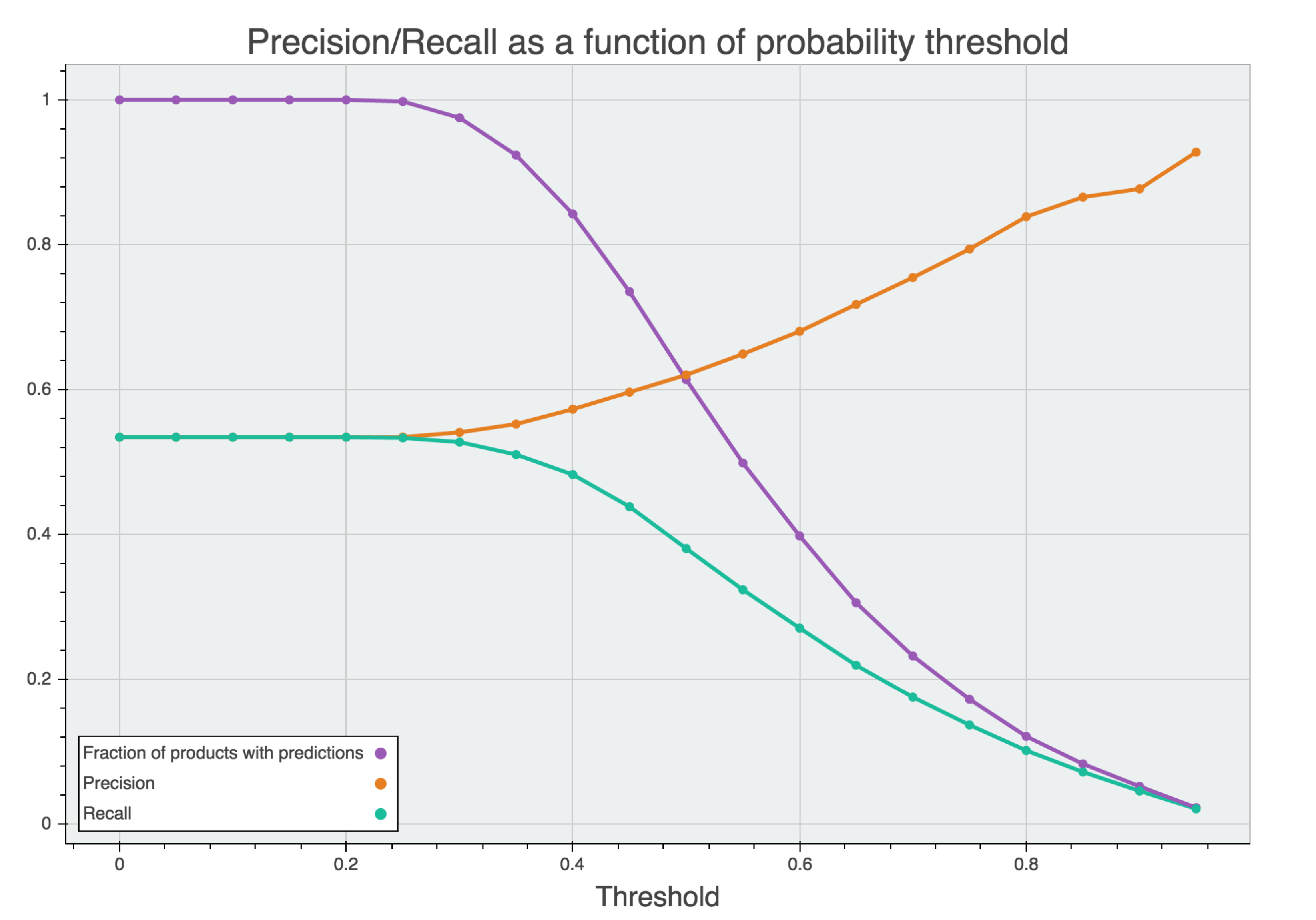
Benchmark

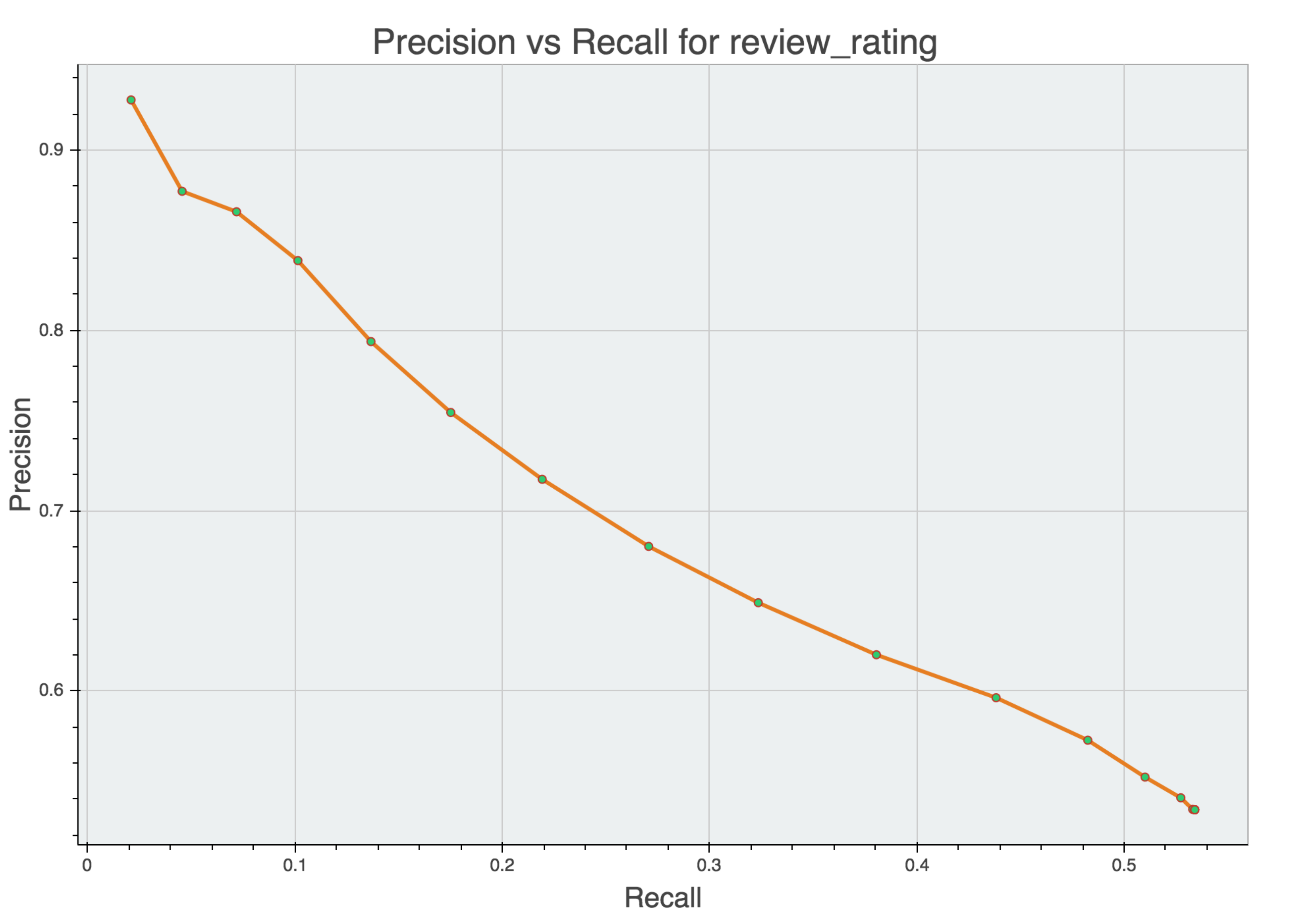
Student clearly defines a benchmark result or threshold for comparing performances of solutions obtained.

Multinomial Naïve Bayes performance result:

```
Best estimator MultinomialNB(alpha=0.10000000000000001, class_prior=None,
fit_prior=False)

Precision on training data = 0.98121875
Precision on test data = 0.534125
Accuracy on training data = 0.98121875
Accuracy on test data = 0.534125

Classification Report
         Star    precision    recall  f1-score   support

          1       0.60      0.71      0.65       948
          2       0.45      0.22      0.30       810
          3       0.42      0.28      0.33      1306
          4       0.45      0.62      0.52      2348
          5       0.66      0.62      0.64      2588

avg / total       0.53      0.53      0.52      8000

Printing model stats
```

```
Overall precision = 0.534125
```

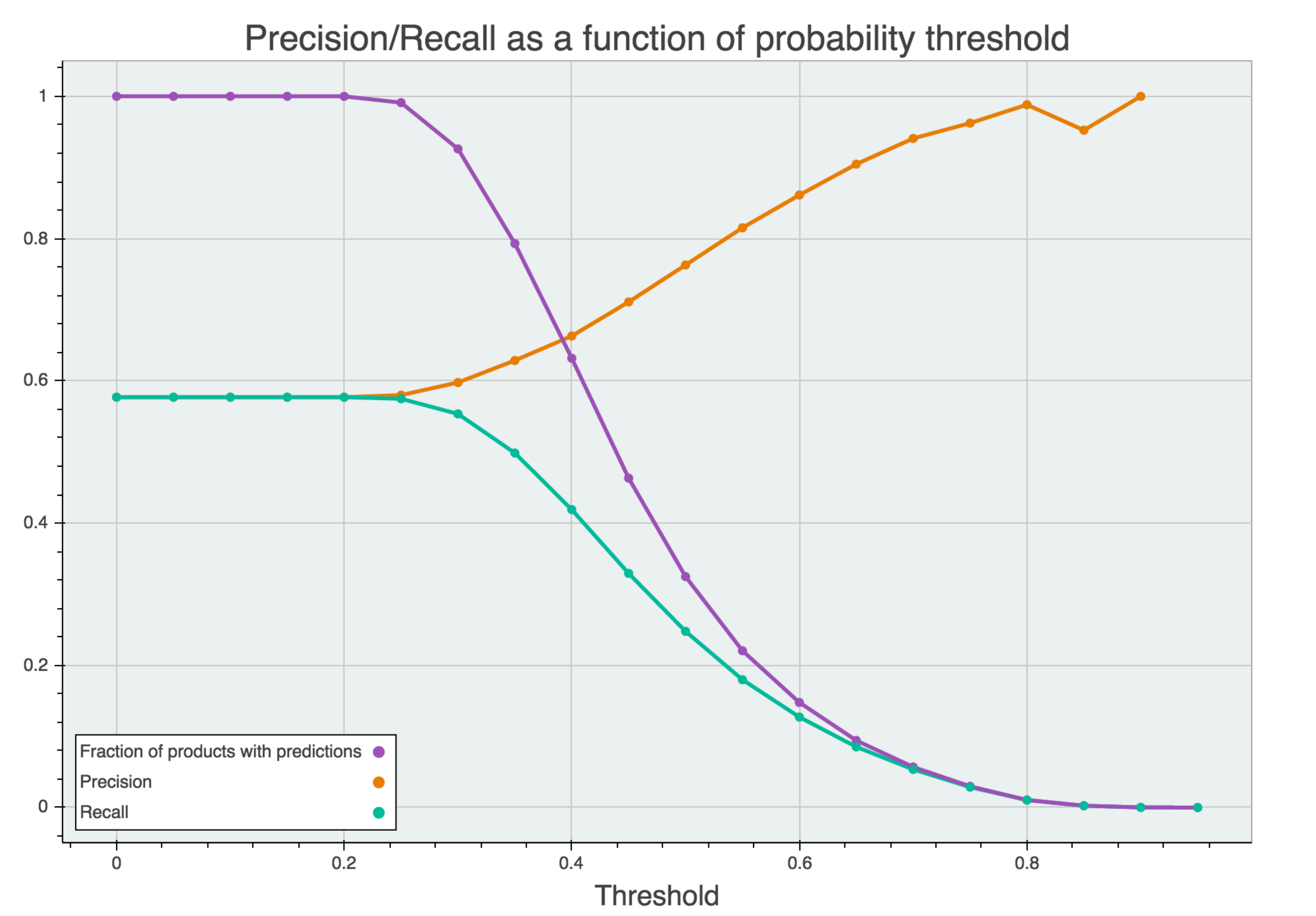
Precision/Recall as a function of probability threshold
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
Threshold
Fraction of products with predictions ●
Precision ●
Recall ●


Precision vs Recall for review_rating
Precision
Recall
0.9
0.8
0.7
0.6
0
0.1
0.2
0.3
0.4
0.5

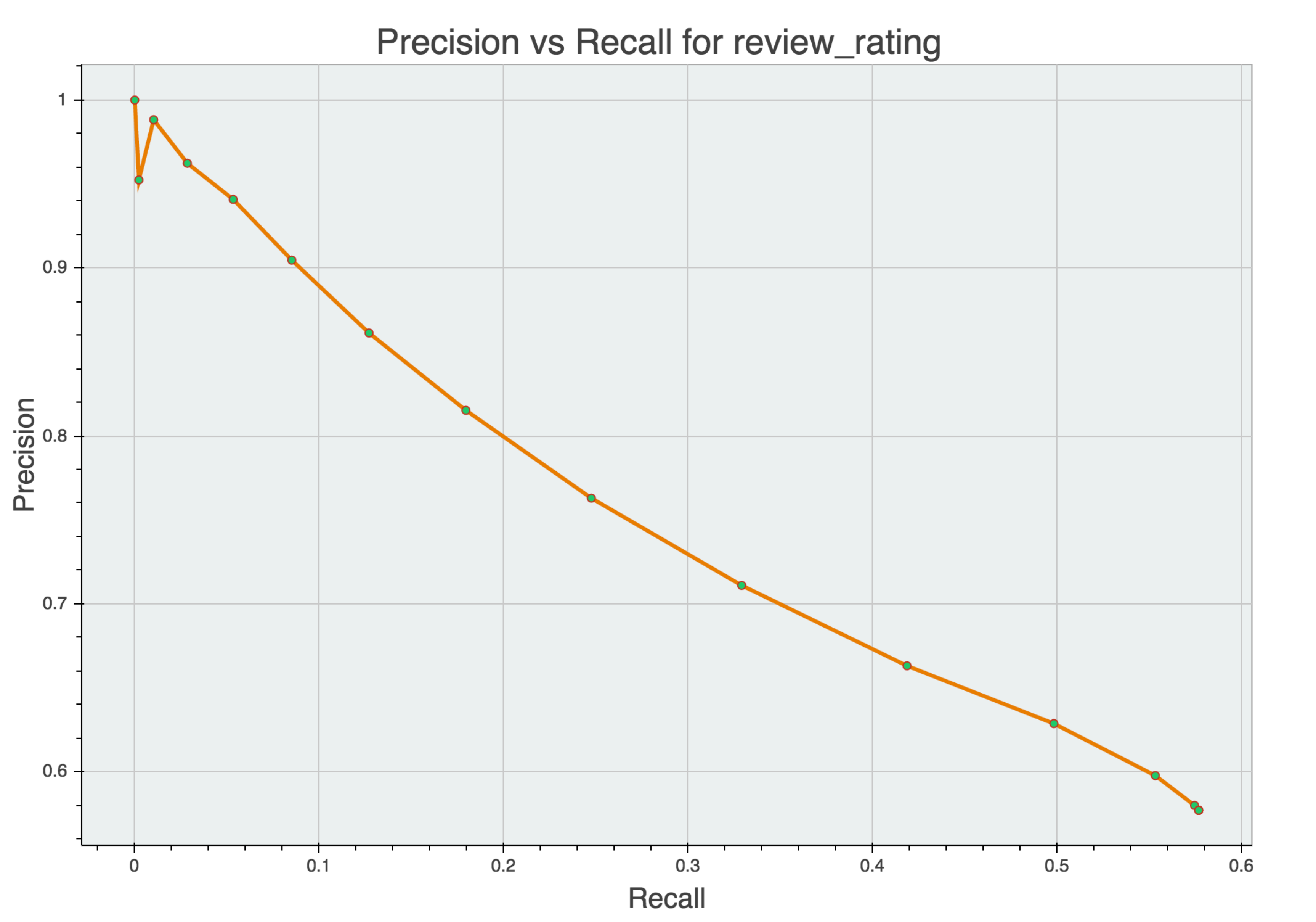
Logistic Regression:

```
Best estimator LogisticRegression(C=1.0, class_weight='auto', dual=False,
fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr',
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0)
Precision on training data = 0.82665625
Precision on test data = 0.577
Accuracy on training data = 0.82665625
Accuracy on test data = 0.577

Classification Report
        Stars   precision    recall  f1-score   support

          1       0.60      0.77      0.67       948
          2       0.43      0.38      0.40       810
          3       0.50      0.40      0.44      1306
          4       0.54      0.52      0.53      2348
          5       0.67      0.71      0.69      2588

avg / total       0.57      0.58      0.57      8000
```

```
Printing model stats:
Overall precision = 0.577
```



Precision/Recall as a function of probability threshold


Precision vs Recall for review_rating
Precision
1
0.9
0.8
0.7
0.6
Recall
0
0.1
0.2
0.3
0.4
0.5
0.6

Methodology

Data Preprocessing

During preprocessing, I extracted only relevant fields required for the algorithm. They are

Review_id

Review_text

Votes (funny, useful and cool)

Stars (i.e. numeric rating) this is the class label.

Each observation in this dataset is a review of a particular business by a user.

Added a new feature, reviews text length. Instead of absolute length, I made it a range, because adding absolute length in fact reduced precision and recall.

Explored the relationship between each of the vote types (cool/useful/funny) and the number of stars.
“stars” field is a categorical variable. Looking the difference between each vote types.

Implementation

The process for which metrics, algorithms, and techniques were implemented with the given datasets or input data has been thoroughly documented. Complications that occurred during the coding process are discussed.

Finally, based on the model evaluation as explained above, selected logistic regression classifier.

Preprocessed input data set as explained above in the data preprocessing section. After preprocessing, an output file, yelp_reviews_train.txt is generated.

Four modules:

Extract.py : This is responsible for reading parameter file and input data.

Model.py : which holds model object for persistence using pickle

Train.py: Has all algorithms that is used for model evaluation. All possible algorithms can be specified in the config file, without changing code. This will create a persistence model using training data set. I persist using pickle.

Predict.py: This has interface predict which takes input reviews text and returns numeric rating.

In the config file, I specify evaluation metrics to be used, training data folder, algorithm used to create model, threshold value below that value, do not predict any rating. Performance metrics used are F1-Matric (Precision, Recall and F1 Score)

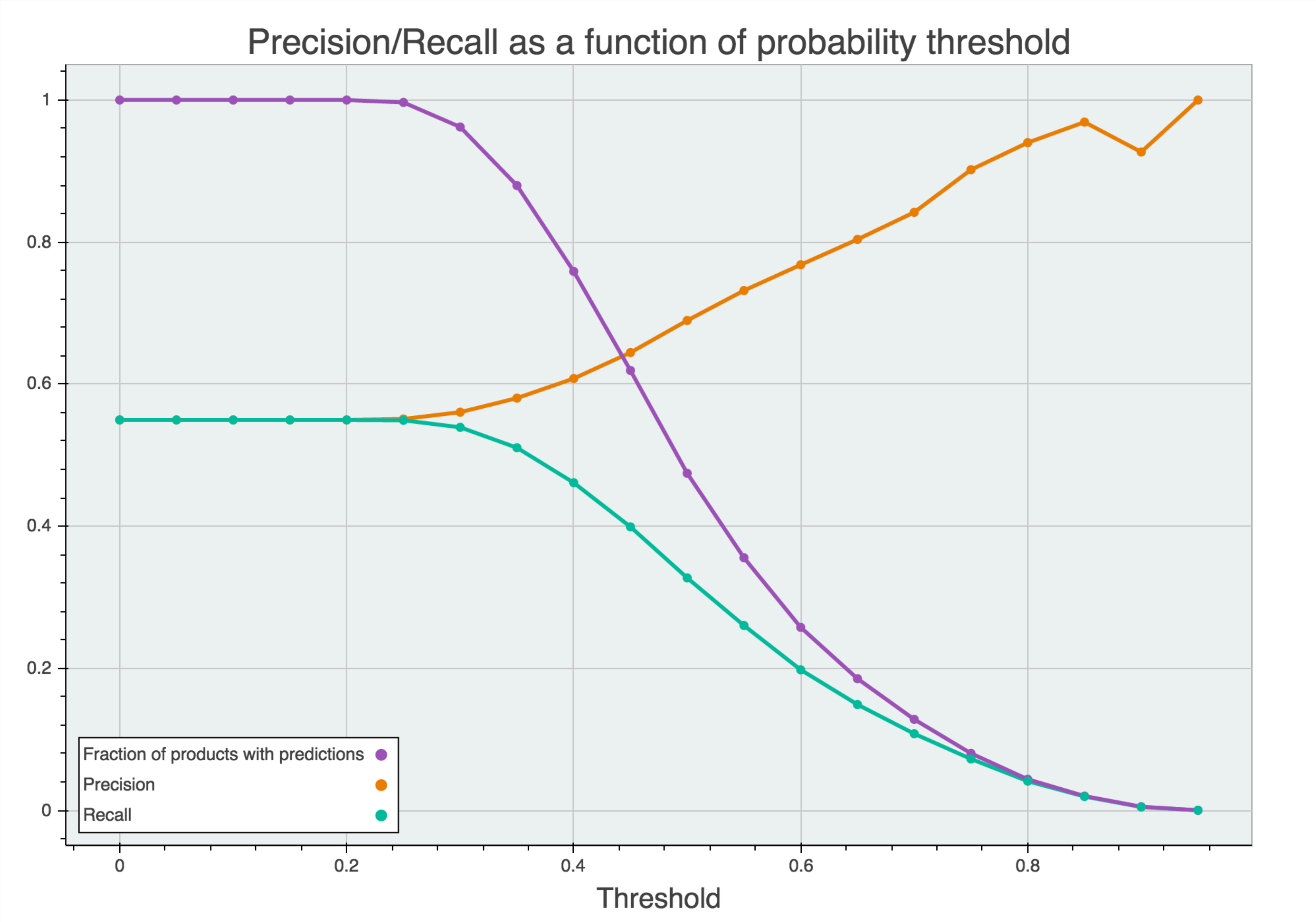
Refinement

The process of improving upon the algorithms and techniques used is clearly documented. Both the initial and final solutions are reported, along with intermediate solutions, if necessary.

Added review length feature, below are the result of experiment:

```
Best estimator LogisticRegression(C=1.0, class_weight='auto', dual=False,
fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr',
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0)
Precision on training data = 0.63115625
Precision on test data = 0.549625
Accuracy on training data = 0.63115625
Accuracy on test data = 0.549625
Classification Report
       Stars    precision    recall  f1-score   support

          1       0.58      0.76      0.66       948
          2       0.37      0.37      0.37       810
          3       0.45      0.40      0.43      1306
          4       0.53      0.45      0.49      2348
          5       0.65      0.69      0.67      2588

avg / total       0.54      0.55      0.54      8000

Printing model stats
Overall precision = 0.549625
```

Actually, after adding text length and votes feature, model performance did not increase.


Precision/Recall as a function of probability threshold
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
Threshold
Fraction of products with predictions ●
Precision ●
Recall ●

Results

Model Evaluation and Validation

The final model's qualities — such as parameters — are evaluated in detail. Some type of analysis is used to validate the robustness of the model's solution.

Evaluated the model by splitting it into training and testing sets 80:20 and K-fold validation. CV takes tunes hyper parameters and chooses best estimates.

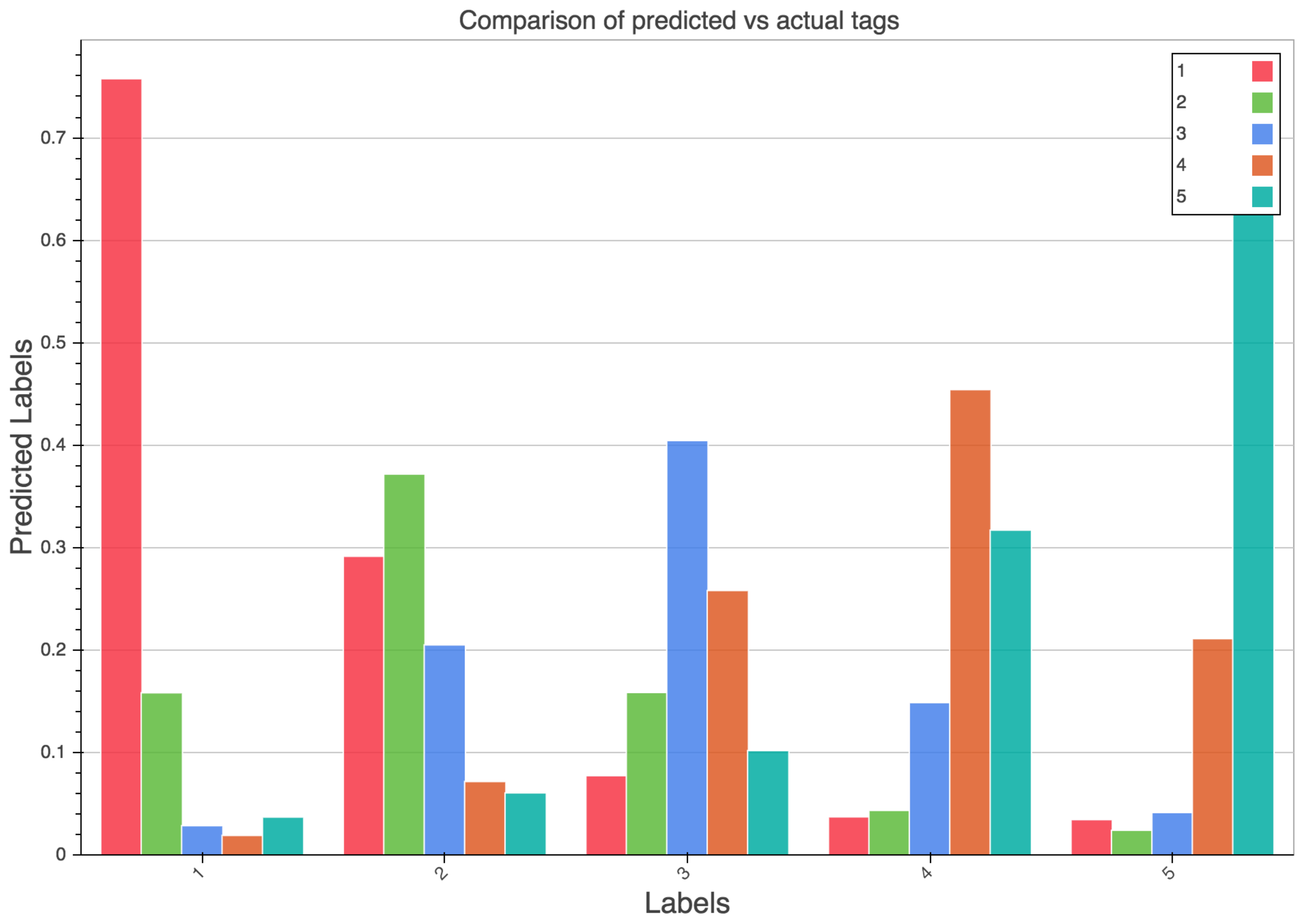
```
cv = KFold(self.x_train.shape[0], n_folds=5, shuffle=True, random_state=0)
```

random_state: When shuffle=True, pseudo-random number generator state used for shuffling. If None, use default numpy RNG for shuffling.

shuffle : Whether to shuffle the data before splitting into batches.

```
Best estimator LogisticRegression(C=1.0, class_weight='auto', dual=False,
fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr',
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0)

Precision on training data = 0.82665625
Precision on test data = 0.577
Accuracy on training data = 0.82665625
Accuracy on test data = 0.577

 Classification Report
        Stars   precision   recall  f1-score   support

          1       0.60      0.77      0.67       948
          2       0.43      0.38      0.40       810
          3       0.50      0.40      0.44      1306
          4       0.54      0.52      0.53      2348
          5       0.67      0.71      0.69      2588

avg / total       0.57      0.58      0.57      8000
```

```
Confusion matrix plot:
```


Comparison of predicted vs actual tags
Predicted Labels
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Labels
1
2
3
4
5
1 🟥
2 🟩
3 🟦
4 🟧
5 🟦

Un normalized confusion Matrix:

```
               Predicted labels
                    1      2      3      4       5
A  1    [[ 718   236   101     87     89]
c  2     [ 150   301   207   102     62]
t  3     [   27   166   528   349   107]
u  4     [   18     58   337 1066   546]
a  5     [   35     49   133   744 1784]]
l
```

Justification

The final results are compared to the benchmark result or threshold with some type of statistical analysis. Justification is made as to whether the final model and solution is significant enough to have adequately solved the problem.

I have analyzed two algorithms a) Multinomial Naïve Bayes and b) Logistic Regression. For training data set size 10K, 20K and 40K are tabulated below:

	Precision on Training data	Precision on Test data	Average precision (all labels)	Average recall (all labels)	F1-Score	Overall Precision
10K	0.61925	0. 5265	0.52	0.53	0.52	0.5496
20K	0.6315625	0.5455	0.54	0.55	0.54	0.5455
40K	0.63115625	0.549625	0.54	0.55	0.54	0.5496
Above 40K	Out of CPU limit					

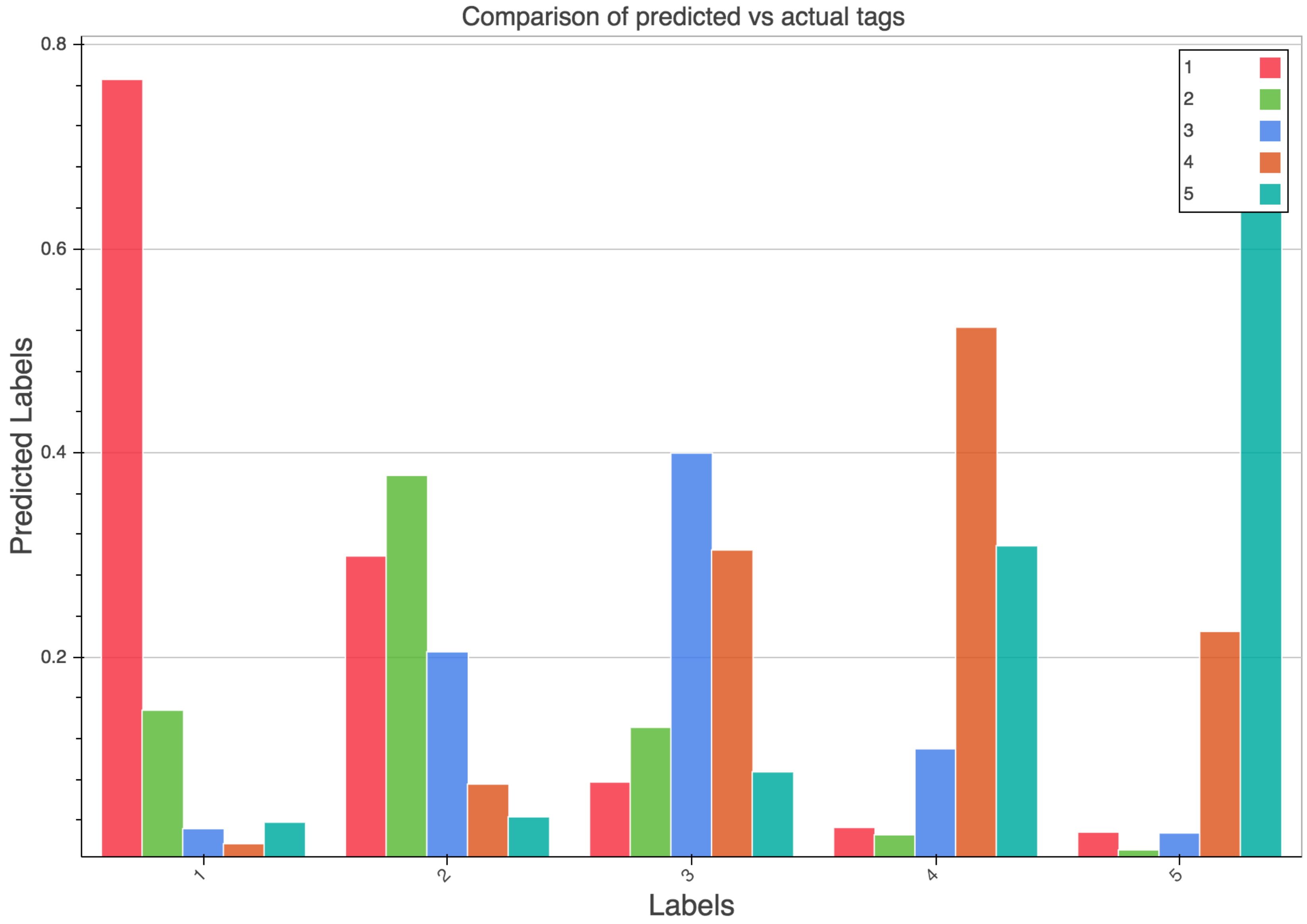
CPU usage exceeds, could not run for training data more than 40K.

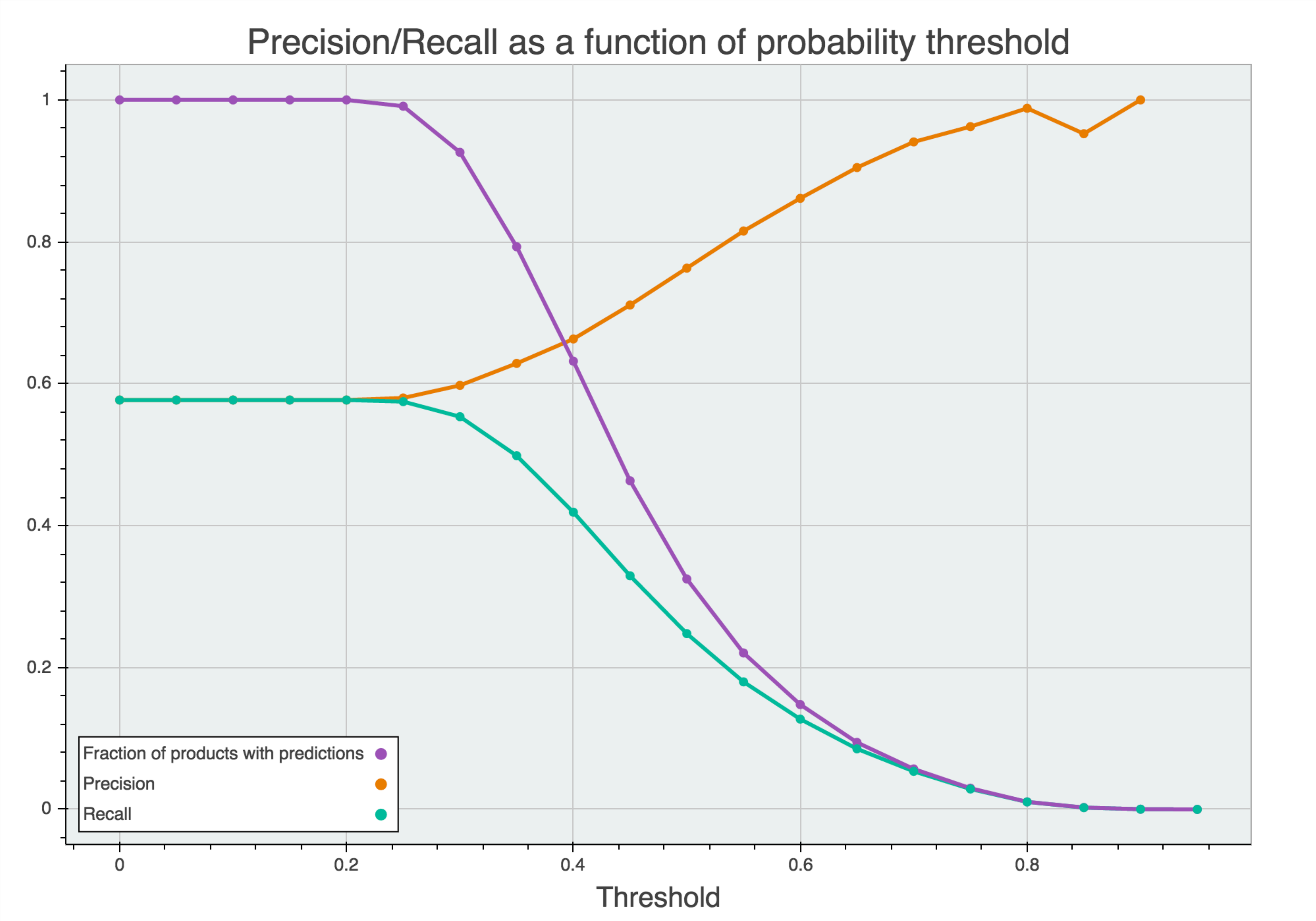
Conclusion

Free-Form Visualization

Visualization has been provided that emphasizes an important quality about the project with thorough discussion. Visual cues are clearly defined.

Below is a graph of final confusion matrix, comparison of predicted rating with actual rating. Interestingly, many actual 5 ratings misclassified as 1. Similarly, many actual “4” ratings misclassified as “5”.


Comparison of predicted vs actual tags
Predicted Labels
0.8
0.6
0.4
0.2
Labels
1
2
3
4
5
1 🟥
2 🟩
3 🟦
4 🟧
5 🟦


Precision/Recall as a function of probability threshold
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
Threshold
Fraction of products with predictions ●
Precision ●
Recall ●

In the precision recall curve above, I determine at what point prediction probability is optimal that means precision and recall both have optimal value. From the above plot, precision increases to a certain point. Recall graph is constant after certain value. At 0.8 both precision and recall has maximum optimal value beyond this point precision decreases and recall remains constant.

Reflection

Student adequately summarizes the end-to-end problem solution and discusses one or two particular aspects of the project they found interesting or difficult.

In conclusion, adding new features did not improve accuracy. It might work to find out popular words in one rating reviews and five review ratings and use them as feature, might improve model performance. Another problem I faced was adding more training data above 50K, training process dies. How to improve the precision to at least 90%?

Improvement

Discussion is made as to how one aspect of the implementation could be improved. Potential solutions resulting from these improvements are considered and compared/contrasted to the current solution

Feature selection with the help of PCA algorithm might help to add more training data and possibly improve precision.

Reference:

Yelp Data challenge
https://www.yelp.com/dataset_challenge

Get start code
https://github.com/Yelp/dataset-examples