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Capstone Project II – Milestone Report 2

Problem Statement: Classifying Amazon reviews based on customer ratings using NLP

Machine Learning

We'll further process our finalized `model_df` dataframe in order to make it compatible and easy to pipe into our Machine Learning model.

Dealing with NaNs

It is important that we impute NaN values before we feed them into a model because machine learning algorithms can only work with *real* numbers. Our dataframe was derived from employing a *Word2Vec* model and so the only way we could have invalid entries that would become NaN values is when we have empty documents.

If a review contains no tokens then every dimension would become NaN. And so to find out the indices of NaN documents, we just have to filter reviews that have a NaN on the first dimension (or any dimension at all).

```
nan_list = model_df[model_df[0].isna()].index
nan_list = nan_list.tolist()

print(nan_list[0:50])
```

```
[149, 293, 1212, 4534, 4633, 8246, 10697, 12187, 17951, 18876, 21171, 21704, 36627, 39350,
41099, 42082, 43641, 44684, 49161, 49449, 62350, 62736, 64575, 64972, 65469, 66077, 66516,
66641, 67469, 67476, 67801, 67953, 70700, 70720, 70752, 74554, 76078, 78490, 84984, 86130,
88623, 89665, 92247, 96398, 98872, 100055, 100095, 103207, 107213, 108672]
```

Indeed, inspecting these documents brings us empty lists which tell us that there are no tokens in the review.

```
print(*[tokenized[blank] for blank in nan_list[0:5]])
```

```
[] [] [] [] []
```

Imposing these indices to our `df`, we can extract what these reviews originally looked like before tokenization and before all the pre-processing steps were performed. We see that, other than blanks, reviews that would become NaNs contain only minimal characters. The fourth entry is invalidated because in our steps, we have dropped all characters that are not alphanumeric leaving us with just the letter *A*. We have also chosen in our pre-processing that single-characters would not be tokenized. The fourth review would therefore end up as an empty list after our NLP steps.

```
for blank in nan_list[0:5]:
    display(df["reviewText"].iloc[blank])
```

```
''

''

''

'A+++++++'

''
```

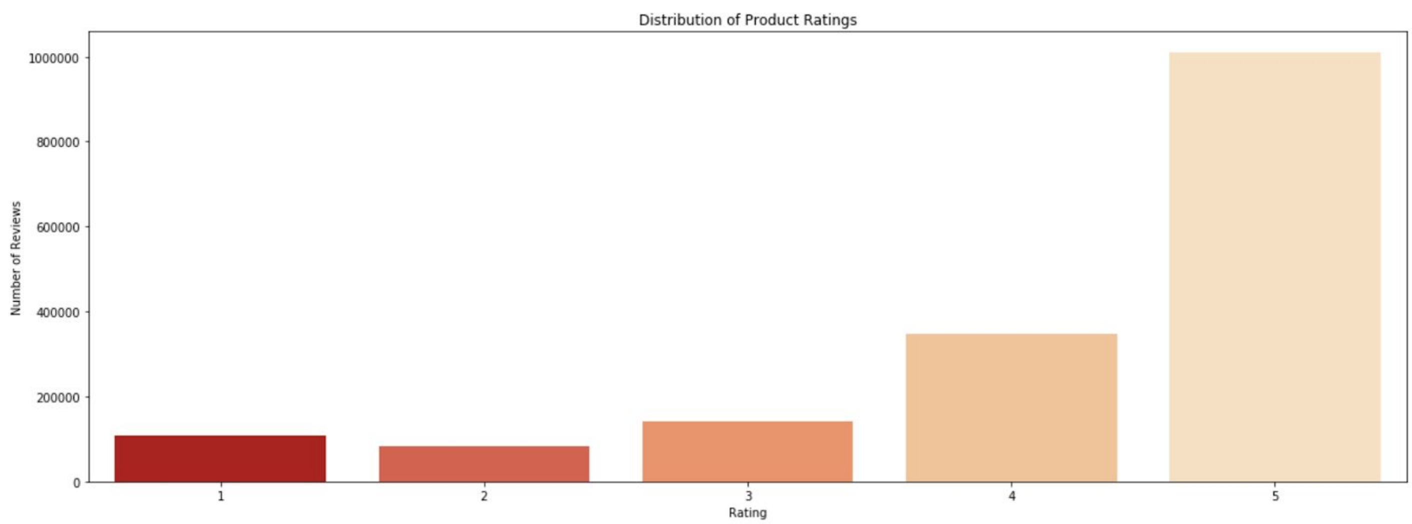
The `model_df` is updated by dropping the NaN documents.

```
Original 'model_df' count: 1689188
Final 'model_df' count: 1688086
```

Dealing with Unbalanced Data

The distribution of ratings shows that, in general, users highly approve of products bought on Amazon. This however gives us a highly imbalanced dataset.

```
import seaborn as sns

f, axes = plt.subplots(figsize=(20,7))
ax = sns.countplot(x=df["overall"], palette="OrRd_r")
ax.set(title="Distribution of Product Ratings", \
       xlabel="Rating", ylabel="Number of Reviews")
plt.show()
```



If the model simply classified every review as `5`, then an accuracy of around 60% can be achieved given this exact dataset. Since this would outperform predictions made by chance, we should therefore ensure that we stratify the testing set where we base the final score of the model.

To deal with this we will have to take into account underrepresenting the majority and/or overrepresenting the minority.

```
majority = df["overall"] == 5
majority_ratio = len(df[majority]) / len(df)

print(f"{majority_ratio*100:.2f}%")
```

```
59.73%
```

Underrepresentation vs. Overrepresentation

Performing over-representation is possible by bootstrapping the minority classes to match the size of the majority classes. This can be done using K-Nearest Neighbors (*KNN*) or via Support Vector Machine (*SVM*) by clustering a given class first before generating random samples within the decision boundaries of the class. A popular module called `SMOTE`, or *Synthetic Minority Over-sampling Technique*, does exactly this. However, since the imbalance in our classes is massive, and because we have 100 dimensions for each one of our almost 1.7 million observations, this approach is extremely computationally expensive.

Because our dataset is huge, we can afford to perform sampling in every class and still have a significant amount of data for the model. This way, we can then opt to *underrepresent* the majority class according to our most minority class.

```
count = len(model_df[model_df["label"] == 2])
print(f"Size of the most underrepresented class: {count}")
```

```
Size of the most underrepresented class: 82139
```

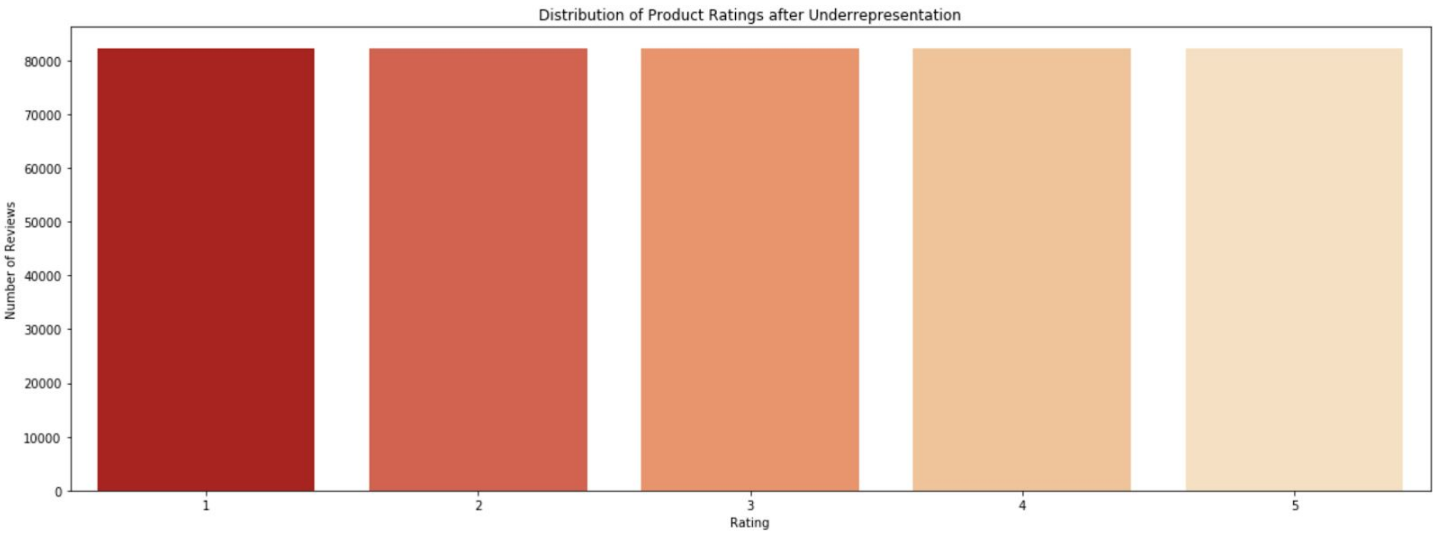
In choosing this route to deal with imbalance, we create a trimmed version of our dataframe, `trimmed_df`. Each class is trimmed to have the same number of entries as the smallest class which is *Class 2*.

```
#trim the majority class
condition = model_df["label"] == 5
trimmed_df = model_df[condition].sample(n=count, random_state=42)

#trim other class and add on to the trimmed_df
for rating in [1, 2, 3, 4]:
    condition = model_df["label"] == rating
    if len(model_df[condition]) >= count:
        add_df = model_df[condition].sample(n=count, random_state=42)
    else:
        add_df = model_df[condition]
    trimmed_df = pd.concat([trimmed_df, add_df], ignore_index=False)

#display new class sizes of trimmed_df
for rating in [1, 2, 3, 4, 5]:
    class_size = len(trimmed_df[trimmed_df["label"] == rating])
    print(f"Size of Class {rating}: {class_size}")
```

```
Size of Class 1: 82139
Size of Class 2: 82139
Size of Class 3: 82139
Size of Class 4: 82139
Size of Class 5: 82139
```

We see that we now have a perfectly balanced dataset after we performed underrepresentation.

```
f, axes = plt.subplots(figsize=(20,7))
ax = sns.countplot(x=trimmed_df["label"], palette="OrRd_r")
ax.set(title="Distribution of Product Ratings after Underrepresentation", \
       xlabel="Rating", ylabel="Number of Reviews")
plt.show()
```



Train-Test Split

The `y` is our target variable or the labels for the data. The `X` constitutes the features and are the predictor variables.

We evenly split the training and testing sets and *stratify* to ensure the ratio of classes in both sets are identical.

```
from sklearn.model_selection import train_test_split

X = trimmed_df.iloc[:, :-1]
y = trimmed_df.iloc[:, -1]

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.5, random_state=42)
```

Scoring and Baseline

In our study, we will make use of two metrics to measure the model performance:

- Accuracy
- F1 Score

Accuracy will identify how many reviews are correctly labeled by the model. There are five ratings and thus five classes. No review can have two or more ratings and so the probability that a correct prediction is made from pure guesswork is `20%`.

The F1 score is taking *precision* and *recall* into consideration. Taking into account false positives and false negatives for each class is especially important in inherently imbalanced datasets.

The baseline scores below are for when a model only randomly guesses the output labels – in this case, when every prediction is the same class. The scores are also based on an evenly distributed dataset.

```python
from sklearn import metrics

label_shape = np.shape(y_test)
y_baseline = np.full(label_shape, 5)

accuracy_baseline = metrics.accuracy_score(y_test, y_baseline)
f1_score_baseline = metrics.f1_score(y_test, y_baseline, average="micro")

print(f"Baseline Accuracy: {accuracy_baseline*100:.3f}%")
print(f"Baseline F1 Score: {f1_score_baseline:.3f}")
```

```
Baseline Accuracy: 20.000%
Baseline F1 Score: 0.200
```

Random Forest

Random Forest actually has a native way of supporting datasets that have class imbalance. We will therefore be able to use the original `model_df` instead of the sample `trimmed_df`:

```python
from sklearn.model_selection import train_test_split

X = model_df.iloc[:, :-1]
y = model_df.iloc[:, -1]

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.5, random_state=42)
```

The `class_weight` attribute is provided with a dictionary that represents the associated weight of each class – the majority class is given a *1* and the rest are given the multiplying factor at which they would level with the largest class.

The criteria chosen is `entropy` which is similar to `gini` but instead of splitting nodes until there are pure classes, the nodes are split until the classes within have equal probability.

```python
from sklearn.ensemble import RandomForestClassifier

forest = RandomForestClassifier(n_estimators=25, class_weight={1:10, 2:12, 3:7, 4:9, 5:1}, \
                                criterion="entropy", random_state=42)
forest.fit(X_train, y_train)
```

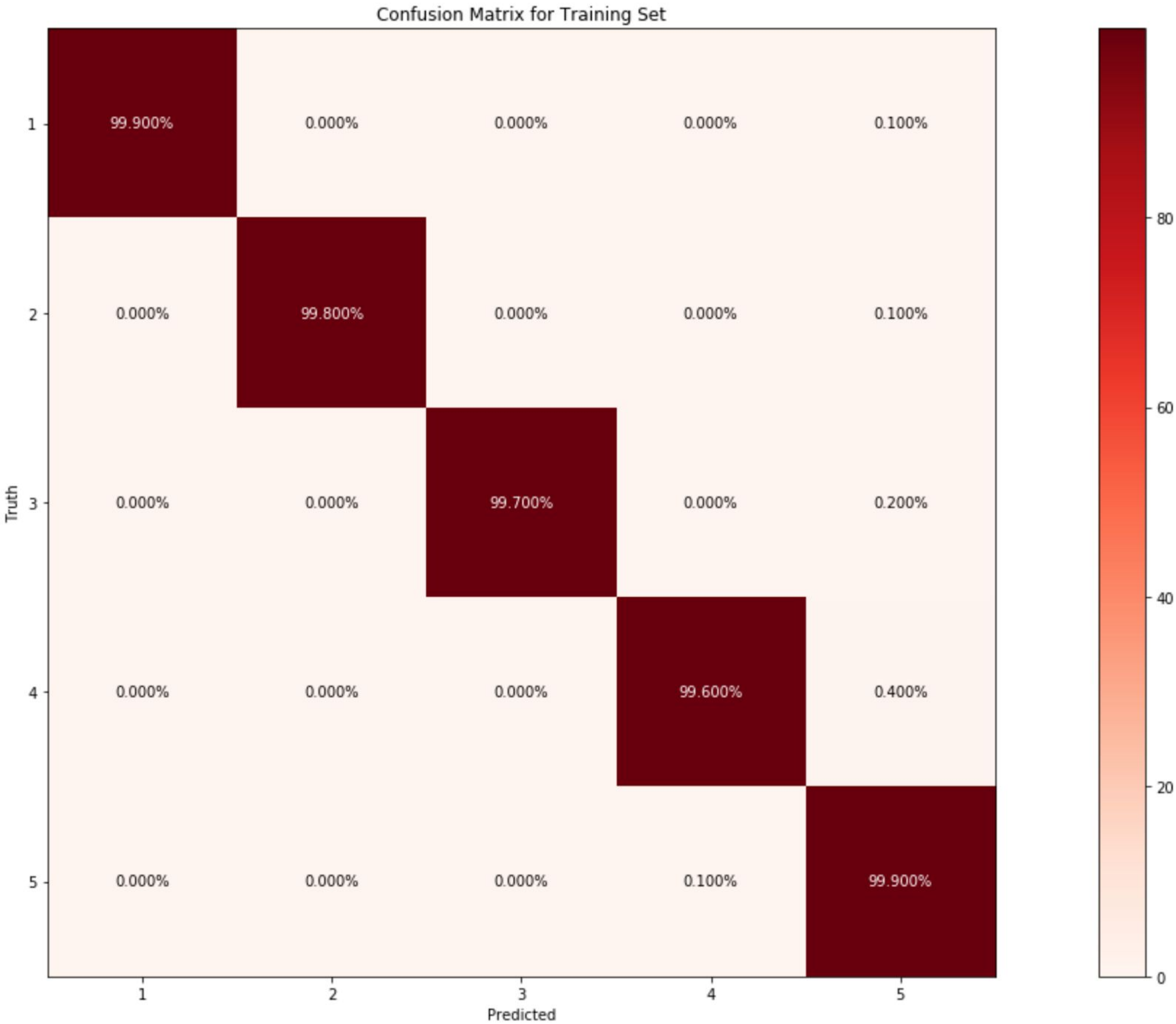
Our tuned Random Forest model got a very high score on the training data. The confusion matrix plotted below highlighted how the model almost perfectly classified each Amazon review accordingly.

However, these scores may be misleading since they are based on the data that the model were trained on. This is highly likely a result of *overfitting*. It is then important to rate our model more effectively without digging into our reserved test set.

```python
y_pred = forest.predict(X_train)

accuracy = metrics.accuracy_score(y_train, y_pred)
f1_score = metrics.f1_score(y_train, y_pred, average="micro")

print(f"Training Set Accuracy: {accuracy*100:.3f}%")
print(f"Training Set F1 Score: {f1_score:.3f}")
```

```
Training Set Accuracy: 99.839%
Training Set F1 Score: 0.998
```

```python
from sklearn.metrics import confusion_matrix

#create the confusion matrix of the training set
confusion_train = confusion_matrix(y_train, y_pred)
confusion_train = confusion_train.astype("float") / \
                   confusion_train.sum(axis=1)[:, np.newaxis]
confusion_train = np.around(confusion_train, decimals=3)*100

#create confusion matrix heat map
f, axes = plt.subplots(figsize=(20,10))
im = axes.imshow(confusion_train, interpolation="nearest", cmap=plt.cm.Reds)

axes.figure.colorbar(im, ax=axes)
axes.set(title="Confusion Matrix for Training Set", \
         xticks=np.arange(confusion_train.shape[1]), \
         yticks=np.arange(confusion_train.shape[0]), \
         xticklabels=range(1, 6), yticklabels=range(1, 6), \
         xlabel="Predicted", ylabel="Truth")

#add clear annotations to the confusion matrix
threshold = confusion_train.max()/1.5
for i in range(confusion_train.shape[0]):
    for j in range(confusion_train.shape[1]):
        axes.text(j, i, f"{confusion_train[i, j]:.3f}%",
                ha="center", va="center",
                color="white" if confusion_train[i, j] > threshold else "black")
f.tight_layout()
plt.show()
```



Cross-Validation

Cross-validation makes the most of the training data by splitting the training set into *folds* and further subjecting each fold to train-test splits. Cross-validation can thus test against overfitting and the resulting scores can better reflect how the model performs on data it has not seen before.

```
from sklearn.model_selection import cross_val_score

cross_val_accuracy = cross_val_score(forest, X_train, y_train, \
                                     cv=3, scoring="accuracy")
cross_val_f1 = cross_val_score(forest, X_train, y_train, \
                               cv=3, scoring="f1_micro")

cross_val_accuracy = np.mean(cross_val_accuracy)
cross_val_f1 = np.mean(cross_val_f1)

print(f"Training Set Accuracy: {cross_val_accuracy*100:.3f}%")
print(f"Training Set F1 Score: {cross_val_f1:.3f}")
```

```
Training Set Accuracy: 61.722%
Training Set F1 Score: 0.617
```

XGBoost

Let's now try to create a model based on a popular boosting technique and see how it compares with our Random Forest model (which is a tree-based bagging approach). XGBoost has become a staple in Kaggle competitions because of its high rate of success and its ease-of-use.

The class notation for our *XGBoost* object `boost` begins from 0, and so we perform an element-wise shift of our labels from *1* to *0*, from *2* to *1*, from *3* to *2*, etc. We tune our model using the maximum number of depths, the learning rate (*eta*), the number of classes, etc. We expect our outputs to be multi-class and so we select `softprob` as our *objective*.

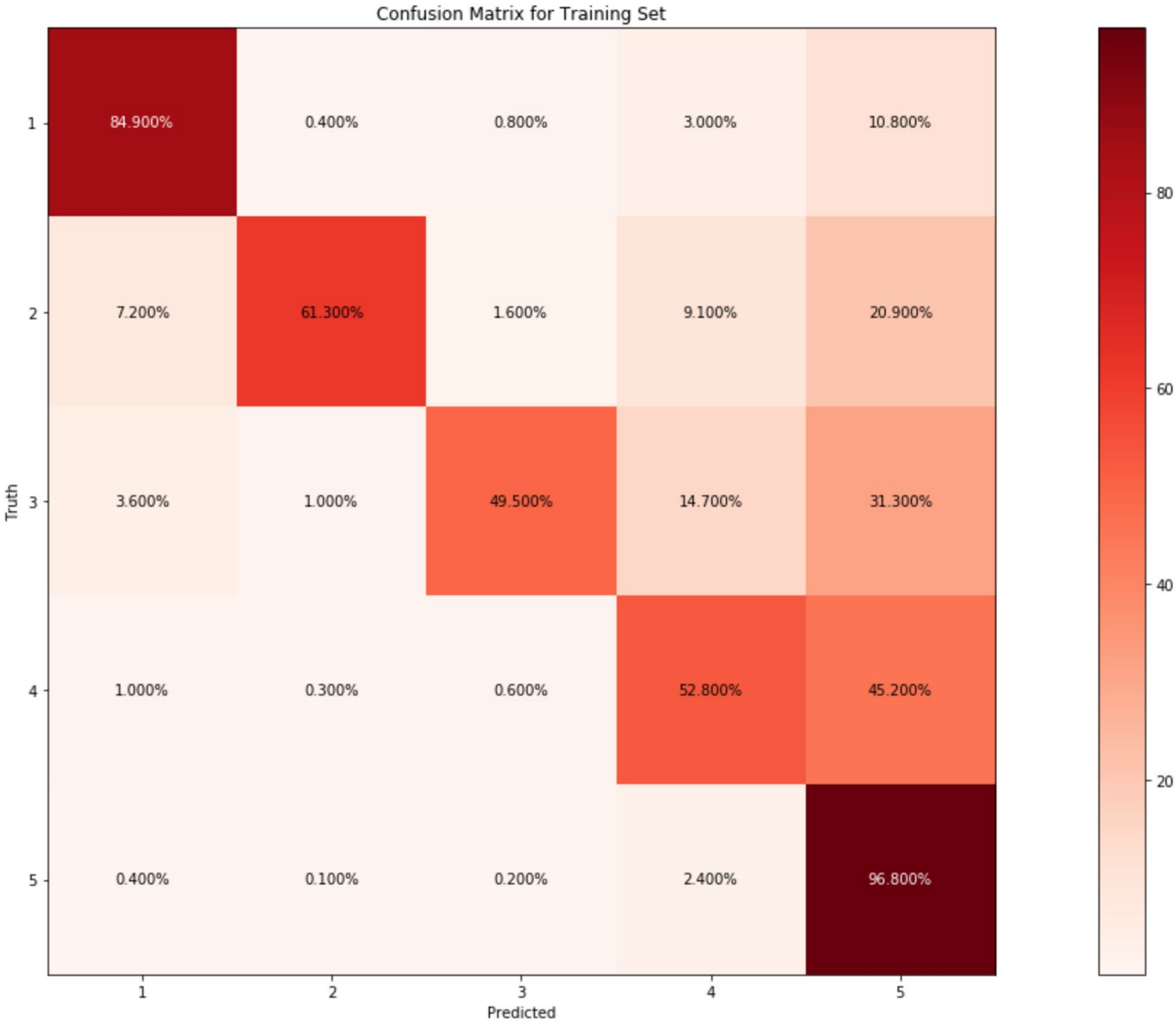
```
import xgboost as xgb

y_train_shifted = y_train-1
y_test_shifted = y_test-1

train_set = xgb.DMatrix(X_train, label=y_train_shifted)
test_set = xgb.DMatrix(X_test, label=y_test_shifted)

parameters = {"max_depth": 10, "eta": 0.2, "silent": 1, \
              "objective": "multi:softprob", "num_class": 5}

boost = xgb.train(parameters, train_set, 100)
```

The array of predicted labels `y_pred` contains lists of probabilities for each class per product review. The class that is deemed most likely is chosen by the *argmax* and the labels are shifted back to their original state.

The `micro` approach in averaging the F1 score means that the false positives, true positives, and false negatives are taken into account across all classes. This is in contrast with the `macro` approach that instead averages the F1 scores of each class independently.

```
y_pred = boost.predict(train_set)
y_pred = y_pred.argmax(axis=1)
y_pred = y_pred+1

accuracy = metrics.accuracy_score(y_train, y_pred)
f1_score = metrics.f1_score(y_train, y_pred, average="micro")

print(f"Training Set Accuracy: {accuracy*100:.3f}%")
print(f"Training Set F1 Score: {f1_score:.3f}")
```

```
Training Set Accuracy: 81.303%
Training Set F1 Score: 0.813
```



To fairly compare our boosting results with our Random Forest outcome, we perform cross-validation on three folds of the training data set as well.

However, since the XGBoost implementation we used is not supported by *scikit-learn*'s `.fit` method, the cross-validation must be done using `xgboost`'s own API. The output `boost_cv` is actually a *pandas* dataframe that tabulates the results of the cross-validation.

```
boost_cv = xgb.cv(dtrain=train_set, params=parameters, nfold=3, \
                  num_boost_round=50, early_stopping_rounds=10, \
                  metrics="merror", as_pandas=True, seed=42)

display(boost_cv.head())
```

	train-merror-mean	train-merror-std	test-merror-mean	test-merror-std
0	0.366273	0.000547	0.385373	0.000749
1	0.360975	0.000926	0.379174	0.000721
2	0.358772	0.000521	0.377226	0.000836
3	0.356486	0.000489	0.375637	0.000913
4	0.354330	0.000464	0.374665	0.000778

We get the training set cross-validation score by getting the *merror* mean on the 50th `num_boost_round`, which is the final boosting phase. The *merror* is an accuracy error rate metric meant for multi-class labels.

We can get a sense of how accurate the model is by subtracting the *merror* value from a perfect score of 100%.

```
cross_val_accuracy = boost_cv.iloc[-1,2]
cross_val_accuracy = 1-cross_val_accuracy

print(f"Training Set Accuracy: {cross_val_accuracy*100:.3f}%")
```

```
Training Set Accuracy: 64.617%
```

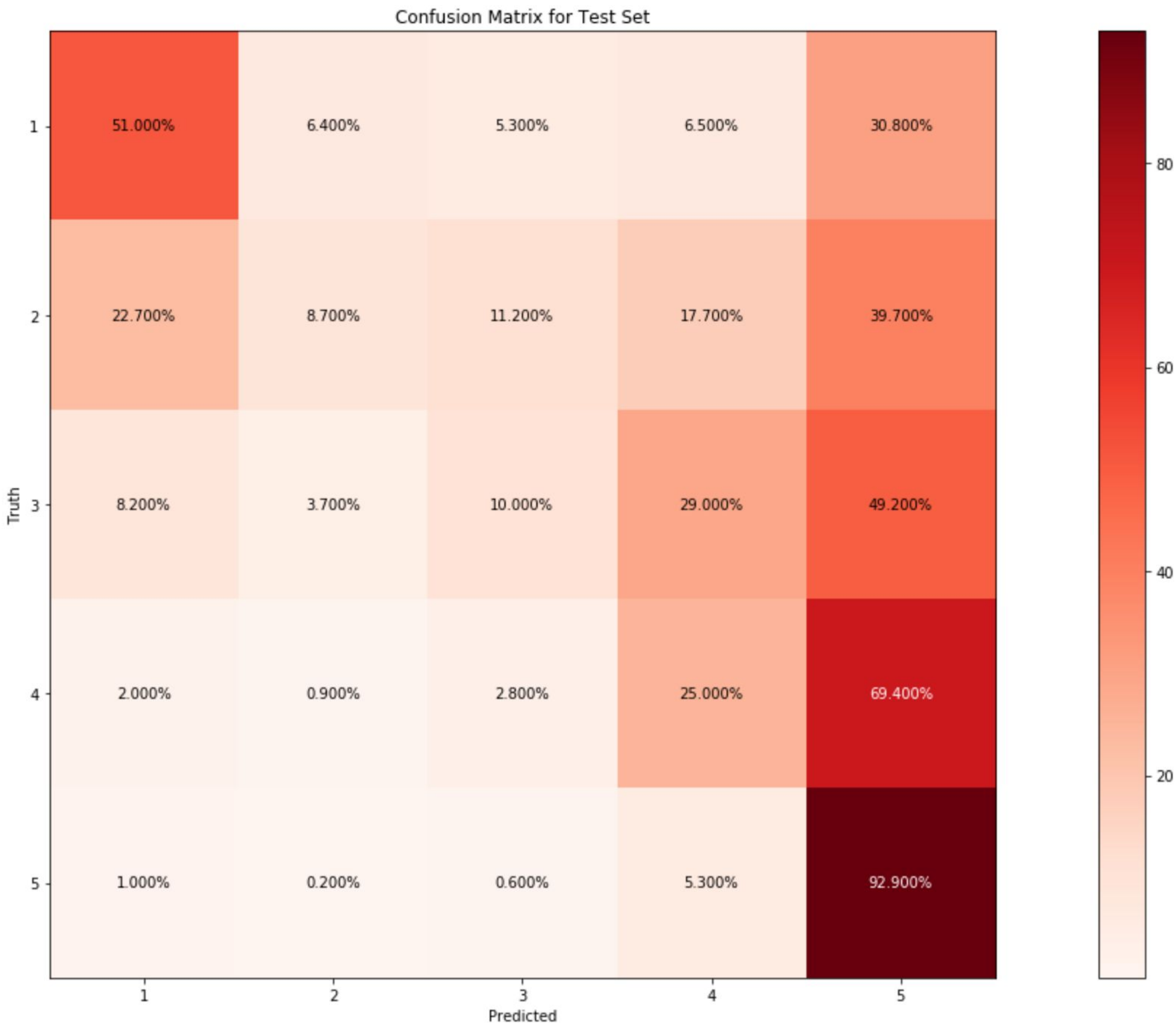
Final Scores

Seeing that the boosting model outperformed the Random Forest approach in the three-fold cross validation, we can now apply our model on the testing set that we have put aside early on.

```
y_pred = boost.predict(test_set)
y_pred = y_pred.argmax(axis=1)
y_pred = y_pred+1

accuracy = metrics.accuracy_score(y_test, y_pred)
f1_score = metrics.f1_score(y_test, y_pred, average="micro")

print(f"Test Set Accuracy: {accuracy*100:.3f}%")
print(f"Test Set F1 Score: {f1_score:.3f}")
```

```
Test Set Accuracy: 65.161%
Test Set F1 Score: 0.652
```

```python
#create the confusion matrix of the test set
confusion_train = confusion_matrix(y_test, y_pred)
confusion_train = confusion_train.astype("float") / \
                   confusion_train.sum(axis=1)[:, np.newaxis]
confusion_train = np.around(confusion_train, decimals=3)*100

#create confusion matrix heat map
f, axes = plt.subplots(figsize=(20,10))
im = axes.imshow(confusion_train, interpolation="nearest", cmap=plt.cm.Reds)

axes.figure.colorbar(im, ax=axes)
axes.set(title="Confusion Matrix for Test Set", \
         xticks=np.arange(confusion_train.shape[1]), \
         yticks=np.arange(confusion_train.shape[0]), \
         xticklabels=range(1, 6), yticklabels=range(1, 6), \
         xlabel="Predicted", ylabel="Truth")

#add clear annotations to the confusion matrix
threshold = confusion_train.max()/1.5
for i in range(confusion_train.shape[0]):
    for j in range(confusion_train.shape[1]):
        axes.text(j, i, f"{confusion_train[i, j]:.3f}%",
                ha="center", va="center",
                color="white" if confusion_train[i, j] > threshold else "black")
f.tight_layout()
plt.show()
```



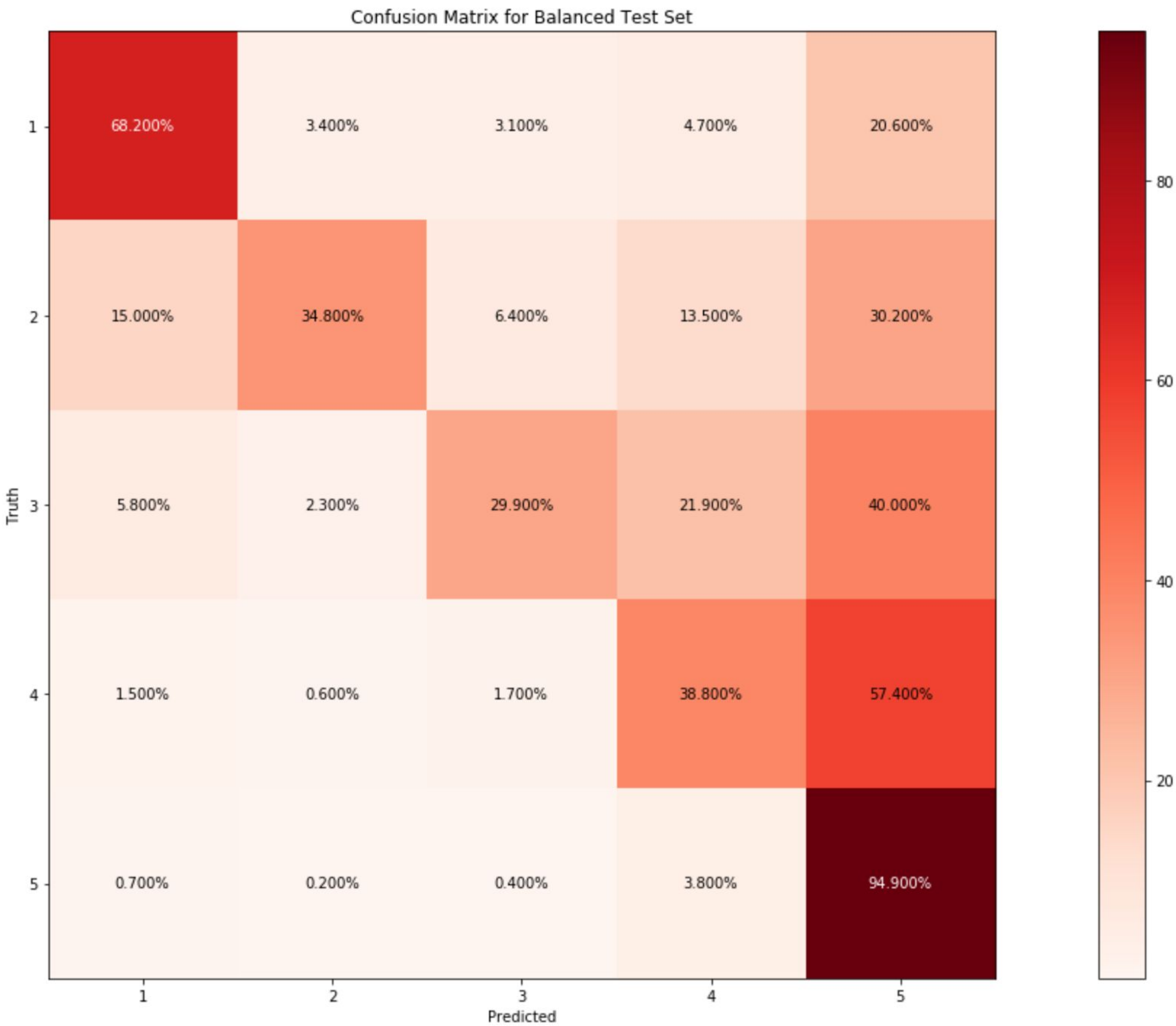
Our results above were actually based on the original `model_df` dataset that had the massive class imbalance. Let's now reassign our `X` and `y` variables to the balanced `trimmed_df` sample dataset we've created.

```
X = trimmed_df.iloc[:, :-1]
y = trimmed_df.iloc[:, -1]

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.5, random_state=42)
```

```python
y_train_shifted = y_train-1
y_test_shifted = y_test-1

train_set = xgb.DMatrix(X_train, label=y_train_shifted)
test_set = xgb.DMatrix(X_test, label=y_test_shifted)

y_pred = boost.predict(test_set)
y_pred = y_pred.argmax(axis=1)
y_pred = y_pred+1

accuracy = metrics.accuracy_score(y_test, y_pred)
f1_score = metrics.f1_score(y_test, y_pred, average="micro")

print(f"Balanced Test Set Accuracy: {accuracy*100:.3f}%")
print(f"Balanced Test Set F1 Score: {f1_score:.3f}")
```

```
Balanced Test Set Accuracy: 53.336%
Balanced Test Set F1 Score: 0.533
```

```python
#create the confusion matrix of the balanced test set
confusion_train = confusion_matrix(y_test, y_pred)
confusion_train = confusion_train.astype("float") / \
                  confusion_train.sum(axis=1)[:, np.newaxis]
confusion_train = np.around(confusion_train, decimals=3)*100

#create confusion matrix heat map
f, axes = plt.subplots(figsize=(20,10))
im = axes.imshow(confusion_train, interpolation="nearest", cmap=plt.cm.Reds)

axes.figure.colorbar(im, ax=axes)
axes.set(title="Confusion Matrix for Balanced Test Set", \
         xticks=np.arange(confusion_train.shape[1]), \
         yticks=np.arange(confusion_train.shape[0]), \
         xticklabels=range(1, 6), yticklabels=range(1, 6), \
         xlabel="Predicted", ylabel="Truth")

#add clear annotations to the confusion matrix
threshold = confusion_train.max()/1.5
for i in range(confusion_train.shape[0]):
    for j in range(confusion_train.shape[1]):
        axes.text(j, i, f"{confusion_train[i, j]:.3f}%",
                ha="center", va="center",
                color="white" if confusion_train[i, j] > threshold else "black")
f.tight_layout()
plt.show()
```



At 53.3% on a perfectly balanced training data set, we have achieved a better result compared to the 20% accuracy of our baseline.

Word Cloud

Using the true labels of the reviews, we can take the fifty most salient words in every rating and produce a word cloud. The same `stop_words` we derived from the NLTK library are excluded.

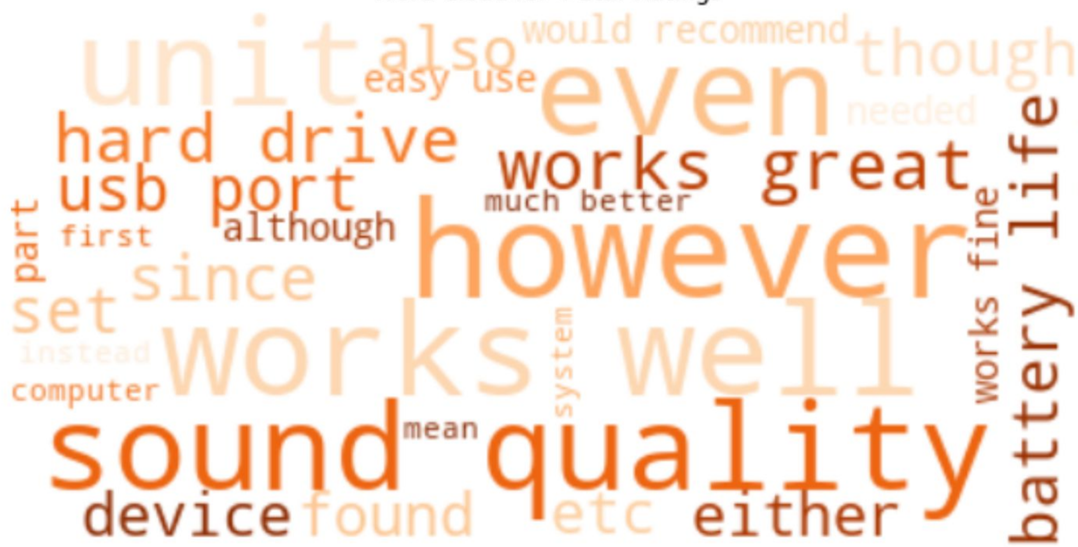
We see that some of the words are quite descriptive of the rating, with "problem" and "issue" frequently appearing in one-star reviews, and "quality" and "highly recommend" in top reviews.

Word Cloud for 1-Star Ratings

Word Cloud for 2-Star Ratings

Word Cloud for 3-Star Ratings

Word Cloud for 4-Star Ratings



Conclusion

A lot of Natural Language Processing techniques were covered in the study. Just some of the concepts explored include topic modeling – where similar texts were clustered together according to topic, named entity recognition (NER) – where nouns were given identifying labels like *place* or *time*, and dependency trees – where parts-of-speech tags and sentence structure were discerned. Though the *Word2Vec* phase was central to our final model, the pre-processing steps were perhaps just as crucial. Prior to tokenization, each document had to be decoded from UTF and encoded to ASCII, and converted to lowercase. The texts were stripped of accents, stop words and punctuation, and multiple whitespaces were dropped. Words were simplified to their root words in order to compact the vocabulary as much as possible. Tokens that were often used together were also singularized through phrase modeling.

Beyond word use and word frequency, our model actually extracts and quantifies *context*. Every token in all the reviews are understood by their neighboring words and embedded in a given number of dimensions. All the interactions of a word with all the other words it has been associated with are expressed in vectors. And all the words in a given review are averaged according to each of the dimensions to create its 100 features. So the essence of a review by its words make up the final dataframe.

What we have is a multi-class model where each of the five classes correspond to a review's star rating. This is then a discrete approach where each class is independent of each other. In a situation where a 5-star rating is misinterpreted by the model as a 1-star review, then the model has simply misclassified – it is agnostic to how far off *1* and *5* are. This is in contrast with a *continuous* approach whereas a misclassification of a 5-star review as a 1-star review would be more penalizing. Our model then is reliant on the distinction of each kind of review. It is more concerned in asking "What makes a 5-star review different from a 4-star review?" than asking "Is this review *more* approving than criticizing?"

Limitations and Recommendations

Though we have observed satisfactory results in our model compared to the baseline, there are several limitations in the way the model handles data. These could serve as areas of improvement. First, despite a rich vocabulary, the model will not be able to handle words that it has not encountered during training. In fact, if an unknown word appears in a review, the word is dropped from the dimension-averaging step since has not been referenced in our `word_vec_df`.

Because each word is simplified by lemmatization during pre-processing, then alternate forms of a token shouldn't necessarily be a concern. However, the model cannot identify if a word is misspelled and will identify one simply as a new word. Incorporating a spellchecker would add to the computational cost and will certainly add to the model's complexity.

Finally, as is usually the case in NLP, sarcasm or text that is intended to be ironic is interpreted by what is literally in the text and not by its underlying context. Because sarcasm is usually detected by readers through the mood and sentiment of the document, it takes adding another layer of NLP just to approximate whether the review is sarcastic or not in order to properly work with such text. This supplement layer will not only utilize tagged sarcastic text as supervised labels, but must also consider the review's given product rating in its judgment to detect sarcasm.