

Importing Libraries

```
1 import pandas as pd
2 import numpy as np
3 # Ignore Warnings
4 import warnings
5 warnings.filterwarnings("ignore")
```

Load the dataset

```
1 # Load and view the training data
2 data = pd.read_csv("/content/goodreads_train.csv", skiprows=[641293], error_bad_lines=False)
3 data.sample(5, random_state=42)
```

		user_id	book_id		review_id	rating	review_text	date_
9008	d76881f6f75216d6f25479114c66b62c	27158835	3b69be2b412ede8328e34ca758e35bf1			4	"Have you ever wanted something so badly that ...	Sat 11:00 -0700
23940	af941aae76ff1b9c9b256cbb8ebc2aef	18283798	43ff471669735c1ae345ffc6ba459592			5	I am really, really glad I gave this book a go...	Sat 11:23 -0700
29264	08d805375530cc208801531ca7fdefbc	15857227	25f908270c36865cd2667915cf01ca0a			3	The only way Aria can leave the Pods and save ...	Sun 11:10 -0700
843	4672eb229c808b792b8ea95f01f19784	18339662	e91c170da6bc07ea204d080b9cb32aa2			1	1.5 stars? If I were to describe this book in ...	Wed 11:18 -0800
14697	a9091e712f89280c3012684ec029d2a5	10319826	024ee2c8802cee4ca44815098bf0192c			3	I have to hand it to Susan Mallery. By inventi...	Tue 11:19 -0800



```
1 # Count the unique users in data
2 data["user_id"].nunique()
```

418

```
1 # Count the unique books in data
2 data["book_id"].nunique()
```

14431

Finding null values in the dataset

```
1 # Check for null values in our data
2 data.isnull().sum()
```

```
user_id      0
book_id      0
review_id    0
rating       0
review_text  0
date_added   0
date_updated 1
read_at      3258
started_at   12161
n_votes      1
```

```
n_comments      1
dtype: int64
```

```
1 books_data= data['book_id'].value_counts(normalize=False).reset_index()
2 books = books_data.fillna(0.0)
3 books= books.sort_values('book_id', ascending=False)
```

1 books

	index	book_id	
0	11870085	59	
1	2767052	51	
2	11235712	47	
3	18007564	45	
4	10194157	40	
...	
9733	16298	1	
9732	68930	1	
9731	18278085	1	
9730	929	1	
14430	22609307	1	

14431 rows × 2 columns

Calculating mean and standard deviation for rating variable

```
1 # remove non-numeric values from n_votes and n_comments columns
2 data['n_votes'] = pd.to_numeric(data['n_votes'], errors='coerce')
3 data['n_comments'] = pd.to_numeric(data['n_comments'], errors='coerce')
4 decider = data.groupby(by=['book_id']).agg({
5     'rating': ['mean', 'std'],
6     'n_votes': ['sum'],
7     'n_comments': ['sum'],
8     'user_id': ['count']
9 }).reset_index()
10
11 # flatten column names
12 decider.columns = ['_'.join(col) for col in decider.columns.values]
13 decider
14
```

	book_id_	rating_mean	rating_std	n_votes_sum	n_comments_sum	user_id_count	
0	1	4.642857	0.841897	30.0	6.0	14	
1	2	4.652174	0.831685	302.0	93.0	23	
2	3	4.772727	0.528413	96.0	4.0	22	
3	5	4.578947	0.768533	25.0	1.0	19	
4	6	4.650000	0.587143	110.0	12.0	20	
...	
14426	36107506	5.000000	NaN	171.0	13.0	1	
14427	36135327	4.000000	NaN	0.0	0.0	1	
14428	36158863	5.000000	NaN	1.0	0.0	1	
14429	36252773	4.666667	0.577350	31.0	0.0	3	
14430	36328685	5.000000	NaN	0.0	0.0	1	

14431 rows × 6 columns

```
1 decider[decider['rating_std']>1.0].sort_values('rating_mean')
```

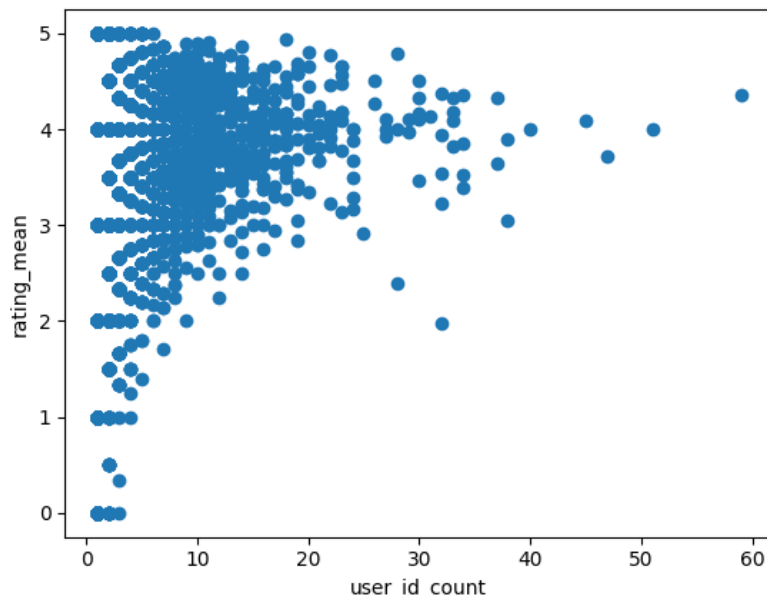
	book_id_	rating_mean	rating_std	n_votes_sum	n_comments_sum	user_id_count	
11452	23299513	1.000000	1.414214	67.0	15.0	2	
10950	22571552	1.000000	1.414214	2.0	0.0	2	
12462	25663595	1.000000	1.414214	0.0	0.0	2	
8356	17571907	1.000000	1.414214	1.0	0.0	2	
11875	24331115	1.000000	1.414214	2.0	0.0	2	
...	
4829	10644930	4.444444	1.333333	11.0	10.0	9	
6534	13600318	4.461538	1.050031	39.0	60.0	13	
8071	17317675	4.500000	1.080123	23.0	4.0	10	
7633	16163690	4.571429	1.089410	49.0	57.0	14	
7069	15818969	4.625000	1.060660	15.0	8.0	8	

2646 rows × 6 columns

```

1 import matplotlib.pyplot as plt
2 plt.scatter(decider['user_id_count'], decider['rating_mean'])
3 plt.xlabel('user_id_count')
4 plt.ylabel('rating_mean')
5 plt.show()

```



```

1 plt.scatter(decider['user_id_count'], decider['rating_std'])
2 plt.xlabel('user_id_count')
3 plt.ylabel('rating_std')
4 plt.show()

```



```

1 # identify problematic rows
2 mask = pd.to_datetime(data['date_added'], errors='coerce').isna()
3 problem_rows = data.loc[mask, 'date_added']
4 print(f"Rows with problematic data: {problem_rows}")
5 # drop problematic rows
6 data.drop(index=problem_rows.index, inplace=True)
7
8 # convert date_added to datetime format
9 datetime_format = '%a %b %d %H:%M:%S %z %Y'
10 data['date_added'] = pd.to_datetime(data['date_added'], format=datetime_format, utc=True)
11

```

```

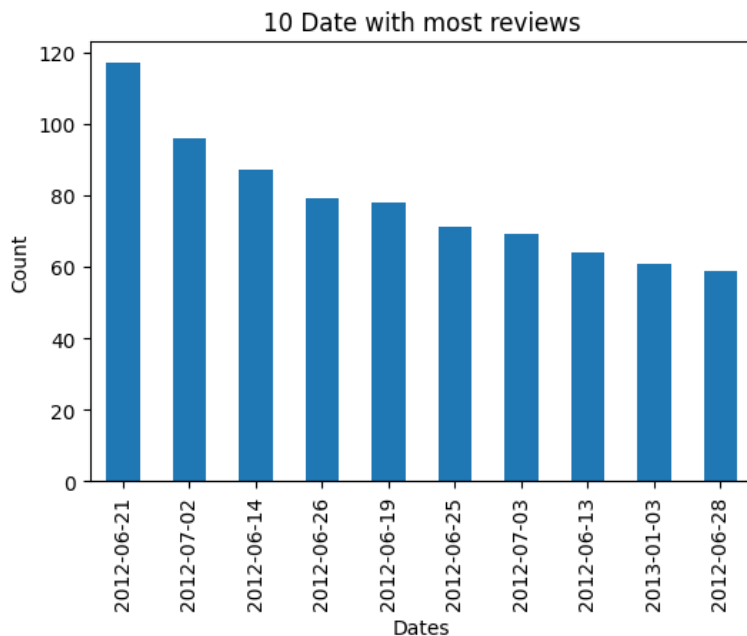
Rows with problematic data: 36263    Tue
Name: date_added, dtype: object

```

```

1 data_date = data['date_added'].dt.date
2 data_date.value_counts()[:10].plot(kind='bar',
3                                     figsize=(6, 4),
4                                     title='10 Date with most reviews',
5                                     xlabel='Dates',
6                                     ylabel='Count')
<Axes: title={'center': '10 Date with most reviews'}, xlabel='Dates', ylabel='Count'>

```

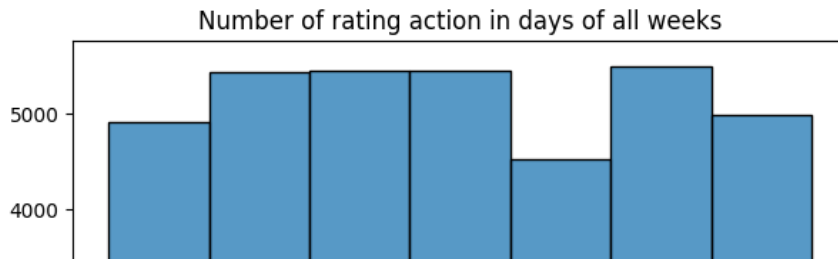


```

1
2 import seaborn as sns
3 plt.figure(figsize=(7, 5))
4 plt.title("Number of rating action in days of all weeks")
5 plt.xlabel("Day of week")
6 plt.ylabel("Count")
7 sns.histplot(data['date_added'].dt.day_name())

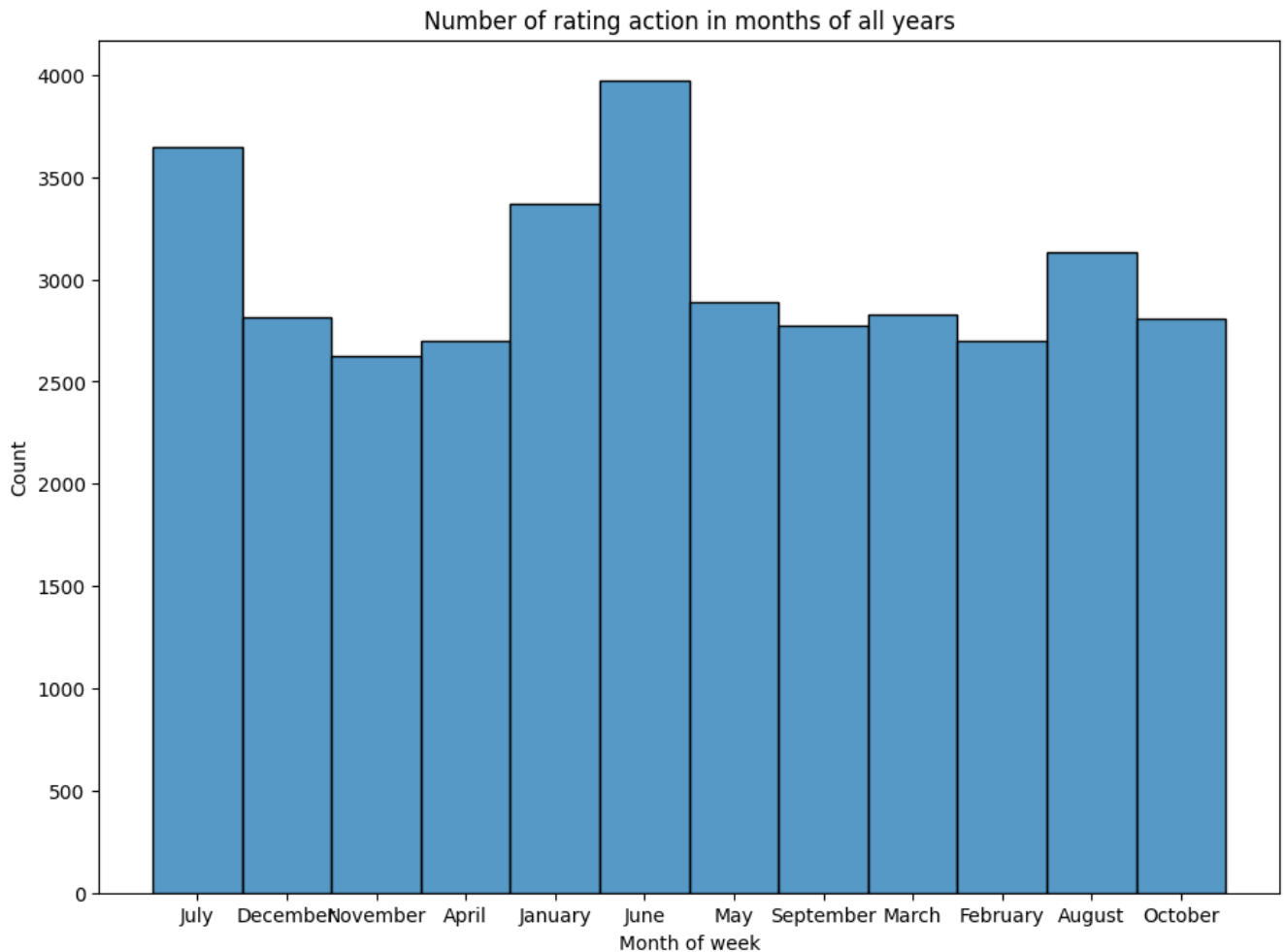
```

```
<Axes: title={'center': 'Number of rating action in days of all weeks'}, xlabel='Day of week', ylabel='Count'>
```



```
1 plt.figure(figsize=(11, 8))
2 plt.title("Number of rating action in months of all years")
3 plt.xlabel("Month of week")
4 plt.ylabel("Count")
5 sns.histplot(data['date_added'].dt.month_name())
```

```
<Axes: title={'center': 'Number of rating action in months of all years'}, xlabel='Month of week', ylabel='Count'>
```



```
1 # Dropping the columns of no use
2 data.drop(columns = ["book_id", "review_id", "date_added", "date_updated", "read_at", "started_at", "user_id", "n_votes", "n_

1 # View the new train_df
2 data.sample(5, random_state = 42)
```

	rating	review_text
16092	3	2.5-ish stars, leaning towards 3 because of th...
25031	5	What 'David Copperfield', always one of Dicken...
18036	4	3.5? Good because It's Rainbow Rowell and I'm ...
428	5	This dark and fantastic story completely and u...
34542	5	It's an awesome ending to this trilogy. If I S...

```
1 data['rating'].value_counts()
```

```

4    12384
5    11608
3     7365
2     2580
0      1166
1      1160
Name: rating, dtype: int64

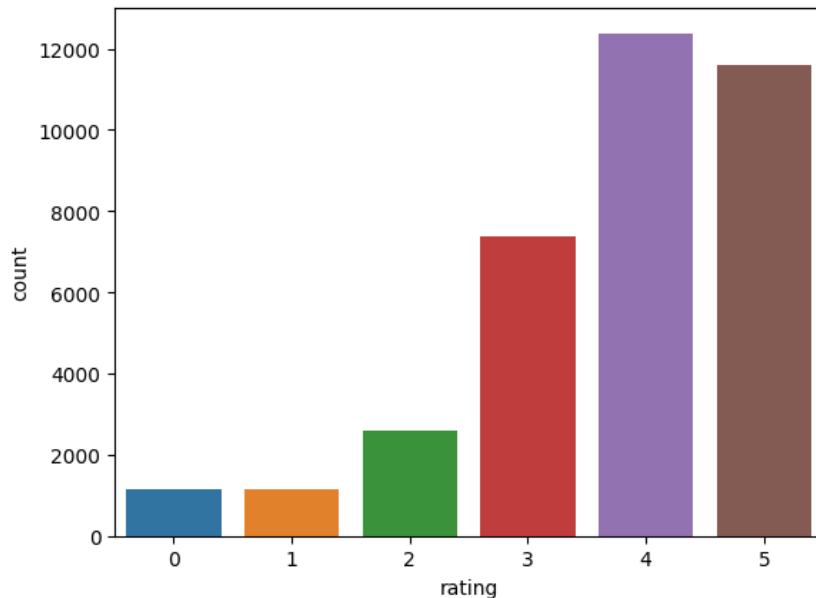
```

```

1 import seaborn as sns
2 sns.countplot(x = data.rating)

```

<Axes: xlabel='rating', ylabel='count'>



Applying all the preprocessing steps like stop words removal, links and extra spaces

```

1 # Lowercase the review text
2 data["review_text"] = data["review_text"].apply(lambda x: str(x).lower())

1 # Remove the line breaks and extra spaces
2 data["review_text"] = data["review_text"].apply(lambda x: " ".join(x.split()))

1 # re for matching and replacing patterns in string
2 import re
3
4 # Removing https links from the text
5 data["review_text"] = data["review_text"].apply(
6     lambda x: re.sub(
7         r'(https?:\/\/)(\s)*(www\.)?(\s)*((\w|\s)+\.)*([ \w\-\s]+\w)*([ \w\-\s]+)((\?)[\w\s]*=\s*[\w\%&]*)*', '',
8         x, flags=re.MULTILINE))
9
10 data["review_text"] = data["review_text"].apply(
11     lambda x: re.sub(
12         r'(https?:\/\/)(\s)*(www\.)?(\s)*((\w|\s)+\.)*([ \w\-\s]+\w)*([ \w\-\s]+)((\?)[\w\s]*=\s*[\w\%&]*)*', '',
13         x, flags=re.MULTILINE))

1 # Remove special charaters from the review text
2 data["review_text"] = data["review_text"].apply(lambda x: re.sub('\W+', ' ', x))

1 # Import nltk and download stopwords
2 import nltk
3 nltk.download('stopwords')
4 from nltk.corpus import stopwords
5
6 # Load the stop words
7 stop_words = list(stopwords.words('english'))
8 # View the count of stop_words
9 len(stop_words)

[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Unzipping corpora/stopwords.zip.

```

179

```

1 # Remove stop_words from reviews
2 data["review_text"] = data["review_text"].apply(lambda x: ' '.join([word for word in x.split() if word not in stop_words]))

1 data.sample(5, random_state = 42)

```

	rating	review_text
16092	3	2 5 ish stars leaning towards 3 first half som...
25031	5	david copperfield always one dickens beloved f...
18036	4	3 5 good rainbow rowell convinced wrong defini...
428	5	dark fantastic story completely utterly thrill...
34542	5	awesome ending trilogy die much better ending ...



As we discussed in project update meeting. I'm replacing 'read' and 'book' words as empty string.

```

1 # Replace 'read' with an empty string in review_text column
2 data['review_text'] = data['review_text'].apply(lambda x: re.sub(r'\bread\b', '', x, flags=re.IGNORECASE))
3
4 # Replace 'book' with an empty string in review_text column
5 data['review_text'] = data['review_text'].apply(lambda x: re.sub(r'\bbook\b', '', x, flags=re.IGNORECASE))

```

Visualizing Wordcloud on text data

```

1 # Wordcloud for text visualization - most used words throughout all reviews
2 from wordcloud import WordCloud
3 import matplotlib.pyplot as plt
4 def show_wordcloud(data, title = None):
5
6     wordcloud = WordCloud(
7         colormap      = "Spectral",
8         scale         = 3,
9         random_state  = 1
10    ).generate(str(data))
11
12    fig = plt.figure(1, figsize = (10, 10))
13    plt.axis('off')
14    if title:
15        fig.suptitle(title, fontsize = 20)
16        fig.subplots_adjust(top = 2.3)
17    plt.imshow(wordcloud)
18    plt.show()

1 # Train data word cloud
2 show_wordcloud(data["review_text"], title = "Wordcloud")

```



```
1 # Import Plotly for plots
2 import plotly.express as px
3 import plotly.graph_objects as go
4 from IPython.core.display import HTML
```

```
1 # Importing the CountVectorizer
2 from sklearn.feature_extraction.text import CountVectorizer
3 def get_top_n_words(corpus, n = None, ngram_range = (1, 1)):
4
5
6     vec = CountVectorizer(stop_words = 'english', ngram_range = ngram_range).fit(corpus)
7     bag_of_words = vec.transform(corpus)
8     sum_words = bag_of_words.sum(axis = 0)
9     words_freq = [(word, sum_words[word_idx]) for word, idx in vec.vocabulary_.items()]
10    words_freq = sorted(words_freq, key = lambda x: x[1], reverse=True)
11    return words_freq[:n]
```

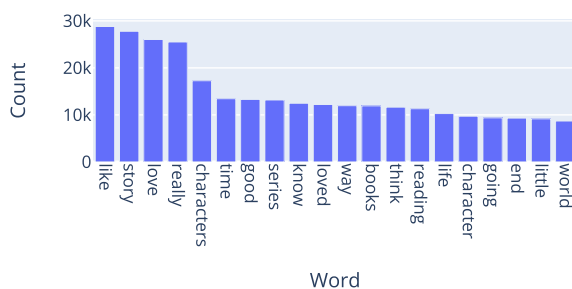
```
1 # Function to plot the top n words by frequency
2 def get_frequency_count_plot(df, title, n = 20, ngram_range = (1, 1)):
3     common_words = get_top_n_words(df['review_text'], n, ngram_range)
4     temp_df = pd.DataFrame(common_words, columns = ['review_text', 'count'])
5     temp_df = temp_df.groupby('review_text').sum()['count'].sort_values(ascending = False)
6     fig = go.Figure([
7         go.Bar(x = temp_df.keys(), y = temp_df.values)
8     ])
9     fig.update_layout(
10         title = title,
11         xaxis_title = "Word",
12         yaxis_title = "Count",
13         width = 500,
14         height = 300,
15     )
16     fig.update_xaxes(tickangle = 90)
17
18    return fig
```

Replace 'hide spoiler' and 'view spoiler' keywords with an empty string as we mentioned in project update meeting.

```
1 import re
2 data['review_text'] = data['review_text'].apply(lambda x: re.sub(r'\bhide\s+spoiler\b', '', x, flags=re.IGNORECASE))
3 data['review_text'] = data['review_text'].apply(lambda x: re.sub(r'\bview\s+spoiler\b', '', x, flags=re.IGNORECASE))
4
```

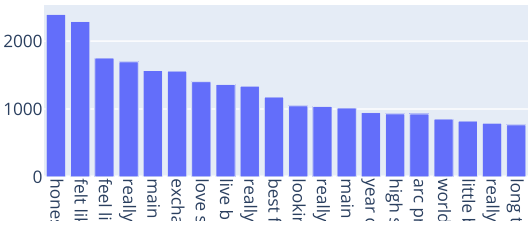
```
1 # Top 20 words - unigrams from data
2 get_frequency_count_plot(df = data, title = "Top 20 words - unigrams", n = 20, ngram_range = (1, 1))
```

Top 20 words - unigrams



```
1 # Top 20 words - bigram from data
2 get_frequency_count_plot(df = data, title = "Top 20 words - bigram ", n = 20, ngram_range = (2, 2))
```


Word
Top 20 words - bigram



1 data

	rating	review_text
0	5	special started slow first third middle third...
1	3	recommended katz avail free december
2	3	fun fast paced science fiction thriller 2 nig...
3	0	recommended reading understand going middle am...
4	4	really enjoyed lot recommend drag little end ...
...
36258	4	never child disappointing think would loved ...
36259	2	already familiar sisi looking forward reading ...
36260	3	story mostly engaging hard time connecting fee...
36261	5	recommend reading lunch break one books stay l...
36262	5	fun quick enjoyed somewhat bizarre unusual ty...

36263 rows × 2 columns

```
1
1 from sklearn.linear_model import LogisticRegression, SGDClassifier
2 from sklearn.naive_bayes import MultinomialNB
3 from xgboost import XGBClassifier
4 from sklearn.model_selection import train_test_split
5 from sklearn.feature_extraction.text import TfidfVectorizer
6 from sklearn.metrics import classification_report, confusion_matrix
7 X = data['review_text']
8 y = data['rating']
9 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=True, random_state=404)
10 print(np.isnan(y_train).sum())
11 y_train = y_train.fillna(0)
12 y_test = y_test.fillna(0)
13 tfidf_vectorizer = TfidfVectorizer(use_idf=True)
14 X_train_vectors = tfidf_vectorizer.fit_transform(X_train)
15 X_test_vectors = tfidf_vectorizer.transform(X_test)

0
```

Applying Naive Bayes Model

```
1 NaiveBayes_model = MultinomialNB()
2 NaiveBayes_model.fit(X_train_vectors, y_train)
```

▼ MultinomialNB

MultinomialNB()

```
1 #Predict y value for test dataset
2 y_predict_Naive = NaiveBayes_model.predict(X_test_vectors)
3 y_prob = NaiveBayes_model.predict_proba(X_test_vectors)[: ,1]
4 print("Accuracy", str(np.mean(y_test == y_predict_Naive)))
5 print("-"*60)
6 print(classification_report(y_test,y_predict_Naive))
```

```
7 print("-"*60)
8 print('Confusion Matrix:', confusion_matrix(y_test, y_predict_Naive))
```

Accuracy 0.4533296566937819

	precision	recall	f1-score	support
0	0.00	0.00	0.00	235
1	0.00	0.00	0.00	225
2	0.00	0.00	0.00	480
3	0.60	0.03	0.06	1486
4	0.38	0.82	0.52	2475
5	0.64	0.51	0.57	2352
accuracy			0.45	7253
macro avg	0.27	0.23	0.19	7253
weighted avg	0.46	0.45	0.38	7253

```
Confusion Matrix: [[ 0  0  0  2 170  63]
 [ 0  0  0  7 200  18]
 [ 0  0  0 18 434  28]
 [ 0  0  0 47 1322 117]
 [ 0  0  0  4 2030 441]
 [ 0  0  0  0 1141 1211]]
```

SVM Model

```
1 from sklearn.svm import SVC
2 svm_model = SVC(kernel='linear', probability=True)
3 svm_model.fit(X_train_vectors, y_train)

1 # predict y value for test dataset
2 y_predict_svm = svm_model.predict(X_test_vectors)
3 y_prob = svm_model.predict_proba(X_test_vectors)[: ,1]
4 # evaluate the performance of the model
5 print("Accuracy:", str(np.mean(y_test == y_predict_svm)))
6 print("-"*60)
7 print(classification_report(y_test, y_predict_svm))
8 print("-"*60)
9 print('Confusion Matrix:', confusion_matrix(y_test, y_predict_svm))
```

Applying Regression Models - Random Forest Model & Decision tree

```
1
2 from sklearn.ensemble import RandomForestClassifier
3 rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
4 rf_model.fit(X_train_vectors, y_train)
5 y_predict_rf = rf_model.predict(X_test_vectors)
6 y_prob_rf = rf_model.predict_proba(X_test_vectors)[: ,1]
7
8 print("Accuracy:", np.mean(y_test == y_predict_rf))
9 print("-"*60)
10 print(classification_report(y_test, y_predict_rf))
11 print("-"*60)
12 print('Confusion Matrix:', confusion_matrix(y_test, y_predict_rf))
```

Accuracy: 0.4763546118847374

	precision	recall	f1-score	support
0	0.60	0.17	0.27	235
1	0.44	0.04	0.07	225
2	0.40	0.01	0.02	480
3	0.45	0.15	0.23	1486
4	0.41	0.68	0.51	2475
5	0.58	0.63	0.61	2352
accuracy			0.48	7253
macro avg	0.48	0.28	0.28	7253
weighted avg	0.48	0.48	0.43	7253

```
Confusion Matrix: [[ 41  0  1  17  93  83]
 [ 4  8  2  36 127  48]
 [ 3  8  4 107 285  73]
 [ 3  1  1 229 1060 192]]
```

```
[ 5  0  2 102 1684 682]
[ 12  1  0  23  827 1489]]
```

Decision Tree Model

```
1
2 from sklearn.tree import DecisionTreeClassifier
3 dt_model = DecisionTreeClassifier(random_state=42)
4 dt_model.fit(X_train_vectors, y_train)
5 # Predict y value for test dataset
6 y_predict_dt = dt_model.predict(X_test_vectors)
7 print("Accuracy:", np.mean(y_test == y_predict_dt))
8 print("-"*60)
9 print(classification_report(y_test, y_predict_dt))
10 print("-"*60)
11 print('Confusion Matrix:', confusion_matrix(y_test, y_predict_dt))
```

Accuracy: 0.3761202261133324

```
-----
              precision    recall  f1-score   support

0             0.30      0.22      0.25       235
1             0.10      0.08      0.09       225
2             0.14      0.11      0.12       480
3             0.30      0.29      0.29      1486
4             0.38      0.42      0.40      2475
5             0.48      0.48      0.48      2352

accuracy          0.38      0.38      0.38      7253
macro avg         0.28      0.27      0.27      7253
weighted avg      0.37      0.38      0.37      7253

-----
```

```
Confusion Matrix: [[ 51  10  17  24  70  63]
 [ 9  19  40  48  63  46]
 [ 8  31  54 144 153  90]
 [ 25 42 102 430 592 295]
 [ 39 58 117 502 1037 722]
 [ 38 34  66 287 790 1137]]
```

Applying Logistic Regression Model

```
1 logistic_model=LogisticRegression(solver = 'liblinear', C=10, penalty = 'l2')
2 logistic_model.fit(X_train_vectors, y_train)
```

```
▼          LogisticRegression
LogisticRegression(C=10, solver='liblinear')
```

```
1 #Predict y value for test dataset
2 from sklearn.metrics import classification_report, confusion_matrix
3 y_predict_logistic = logistic_model.predict(X_test_vectors)
4 y_prob = logistic_model.predict_proba(X_test_vectors)[:,:1]
5
6 print("Accuracy", str(np.mean(y_test == y_predict_logistic)))
7 print("-"*60)
8 print(classification_report(y_test,y_predict_logistic))
9 print("-"*60)
10 print('Confusion Matrix:',confusion_matrix(y_test, y_predict_logistic))
```

Accuracy 0.48531642079139664

```
-----
              precision    recall  f1-score   support

0             0.60      0.22      0.32       235
1             0.39      0.16      0.23       225
2             0.31      0.17      0.22       480
3             0.40      0.38      0.39      1486
4             0.45      0.52      0.48      2475
5             0.59      0.64      0.61      2352

accuracy          0.49      0.49      0.49      7253
macro avg         0.46      0.35      0.38      7253
weighted avg      0.48      0.49      0.47      7253

-----
```

```
Confusion Matrix: [[ 52  13  14  23  69  64]
```

```
[ 5 36 51 64 40 29]
[ 5 21 80 201 119 54]
[ 8 12 73 562 653 178]
[ 6 7 32 401 1295 734]
[ 10 4 12 137 694 1495]]
```

In conclusion, Based on the results of the models trained on the dataset, the logistic regression model performed the best with an accuracy of 0.485. The random forest model also performed relatively well with an accuracy of 0.476. However, the other models, including the decision tree, support vector machine, and naive Bayes models, performed poorly with accuracies ranging from 0.376 to 0.453. It is important to note that the performance of the models may be improved by adjusting the hyperparameters or by using more advanced techniques such as neural networks. Overall, the project highlights the importance of using natural language processing and machine learning techniques to analyze and classify reviews.

1

Executing (6m 13s) <cell line: 3> > fit() > _sparse_fit()

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