Out[3]:		Product Name	Brand Name	Price	Rating	Reviews	Review Votes	Sentiment	Tokenized	Without_Stopwords
	0	"clear clean esn" sprint epic 4g galaxy sph- d7	samsung	199.99	5	i feel so lucky to have found this used (phone	1.0	positive	['i', 'feel', 'so', 'lucky', 'to', 'have', 'fo	['feel', 'lucky', 'found', 'used', '(', 'phone
	1	"clear clean esn" sprint epic 4g galaxy sph- d7	samsung	199.99	4	nice phone, nice up grade from my pantach revu	0.0	positive	['nice', 'phone', ',', 'nice', 'up', 'grade',	['nice', 'phone', ',', 'nice', 'grade', 'panta
	2	"clear clean esn" sprint epic 4g galaxy sph- d7	samsung	199.99	5	very pleased	0.0	positive	['very', 'pleased']	['pleased']
	3	"clear clean esn" sprint epic 4g galaxy sph- d7	samsung	199.99	4	it works good but it goes slow sometimes but i	0.0	positive	['it', 'works', 'good', 'but', 'it', 'goes', '	['works', 'good', 'goes', 'slow', 'sometimes',
	4	"clear clean esn" sprint epic 4g galaxy sph- d7	samsung	199.99	4	great phone to replace my lost phone. the only	0.0	positive	['great', 'phone', 'to', 'replace', 'my', 'los	['great', 'phone', 'replace', 'lost', 'phone',
In [4]:			ne distri ciment.va			neutral ,	positiv	e and neg	ative revi	ews
Out[4]:	ne _i	ntiment sitive gative utral me: coun	236886 84902 27682 t, dtype	: int64	ŀ					
In [5]:	df	.info()								

```
<class 'pandas.core.frame.DataFrame'>
        RangeIndex: 349470 entries, 0 to 349469
        Data columns (total 11 columns):
         # Column
                                 Non-Null Count Dtype
        ___
                                 -----
            Product Name
                                 349470 non-null object
         1
             Brand Name
                               294786 non-null object
         2
            Price
                                349470 non-null float64
                                349470 non-null int64
         3
             Rating
            Reviews
         4
                               349470 non-null object
             Review Votes
                               349470 non-null float64
                                 349470 non-null object
         6
            Sentiment
            Tokenized
                                349470 non-null object
         7
            Without_Stopwords 349470 non-null object
             Without_Punctuation 349470 non-null object
         9
         10 Lemmatized
                                 349470 non-null object
        dtypes: float64(2), int64(1), object(8)
        memory usage: 29.3+ MB
In [6]: %%time
        # Assuming data2 is your DataFrame
        neg = data2.loc[data2.Sentiment == 'negative']
        pos = data2.loc[data2.Sentiment == 'positive'].sample(n=len(neg), random_state=42)
        # Count the number of negative reviews
        nue = data2.Sentiment.value_counts()['negative']
        # Select all available 'neutral' reviews if there are fewer of them than negative revi
        if nue >= data2.Sentiment.value_counts().get('neutral', 0):
            neutral = data2.loc[data2.Sentiment == 'neutral']
        else:
            neutral = data2.loc[data2.Sentiment == 'neutral'].sample(n=nue, random_state=42)
        CPU times: total: 188 ms
        Wall time: 182 ms
In [7]: import nltk
        nltk.download('wordnet')
        [nltk_data] Downloading package wordnet to
        [nltk_data]
                       C:\Users\SACHIN\AppData\Roaming\nltk_data...
        [nltk_data] Package wordnet is already up-to-date!
        True
Out[7]:
In [8]: import nltk
        from nltk.corpus import stopwords as sw
        import string
        import matplotlib.pyplot as plt
        %matplotlib inline
        from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer, TfidfVe
        lemmatizer = nltk.WordNetLemmatizer()
        stopwords = sw.words('english')
        stopwords = stopwords + ['not_' + w for w in stopwords]
        # transform punctuation to blanks
        trans_punct = str.maketrans(string.punctuation,' '*len(string.punctuation))
        # pad punctuation with blanks
```

```
pad_punct = str.maketrans({key: " {0} ".format(key) for key in string.punctuation})
# remove "_" from string.punctuation
invalidChars = str(string.punctuation.replace("_", ""))
```

In [9]: data2.head()

							•		1.
Without_Stopwords	Tokenized	Sentiment	Review Votes	Reviews	Rating	Price	Brand Name	Product Name]:
['feel', 'lucky', 'found', 'used', '(', 'phone	['i', 'feel', 'so', 'lucky', 'to', 'have', 'fo	positive	1.0	i feel so lucky to have found this used (phone	5	199.99	samsung	"clear clean esn" sprint epic 4g galaxy sph- d7	0
['nice', 'phone', ',', 'nice', 'grade', 'panta	['nice', 'phone', ',', 'nice', 'up', 'grade',	positive	0.0	nice phone, nice up grade from my pantach revu	4	199.99	samsung	"clear clean esn" sprint epic 4g galaxy sph- d7	1
[ˈpleasedˈ]	['very', 'pleased']	positive	0.0	very pleased	5	199.99	samsung	"clear clean esn" sprint epic 4g galaxy sph- d7	2
['works', 'good', 'goes', 'slow', 'sometimes',	['it', 'works', 'good', 'but', 'it', 'goes', '	positive	0.0	it works good but it goes slow sometimes but i	4	199.99	samsung	"clear clean esn" sprint epic 4g galaxy sph- d7	3
['great', 'phone', 'replace', 'lost', 'phone',	['great', 'phone', 'to', 'replace', 'my', 'los	positive	0.0	great phone to replace my lost phone. the only	4	199.99	samsung	"clear clean esn" sprint epic 4g galaxy sph-	4

```
In [10]: from sklearn.model_selection import train_test_split

# Split the data into training (60%) and temporary data (40%)
X_train_temp, X_temp, Y_train_temp, Y_temp = train_test_split(data2['Lemmatized'], data
```

d7...

```
# Split the temporary data into testing (50%) and validation (50%)
         X_test, X_validation, Y_test, Y_validation = train_test_split(X_temp, Y_temp, test_siz
         print("Train:", X_train_temp.shape, Y_train_temp.shape)
         print("Test:", X_test.shape, Y_test.shape)
         print("Validation:", X_validation.shape, Y_validation.shape)
         Train: (209682,) (209682,)
         Test: (69894,) (69894,)
         Validation: (69894,) (69894,)
In [11]: #Using TF*IDF Vectorizer
In [12]: %%time
         from sklearn.feature_extraction.text import CountVectorizer
         # Initialize the CountVectorizer
         count_vectorizer = CountVectorizer(analyzer = 'word',ngram_range=(3,3), stop_words='er'
         # Fit and transform the CountVectorizer on the training data
         X_train_count = count_vectorizer.fit_transform(X_train_temp)
         # Transform the testing and validation data
         X_test_count = count_vectorizer.transform(X_test)
         X_validation_count = count_vectorizer.transform(X_validation)
         # Print the shapes of the CountVectorized data
         print("Train CountVectorized:", X_train_count.shape)
         print("Test CountVectorized:", X_test_count.shape)
         print("Validation CountVectorized:", X_validation_count.shape)
         Train CountVectorized: (209682, 1864593)
         Test CountVectorized: (69894, 1864593)
         Validation CountVectorized: (69894, 1864593)
         CPU times: total: 11.4 s
         Wall time: 15.4 s
In [13]: ##model
In [14]: %%time
         from sklearn.linear model import LogisticRegression
         from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
         # Create a Logistic Regression model
         logistic_reg = LogisticRegression(random_state=30)
         # Train the model on the training data
         logistic_reg.fit(X_train_count, Y_train_temp)
         # Predictions on the testing and validation data
         Y_test_pred = logistic_reg.predict(X_test_count)
         Y_validation_pred = logistic_reg.predict(X_validation_count)
         # Calculate evaluation metrics for the testing set
         accuracy_test = accuracy_score(Y_test, Y_test_pred)
         precision_test = precision_score(Y_test, Y_test_pred, average='weighted')
         recall_test = recall_score(Y_test, Y_test_pred, average='weighted')
         f1_score_test = f1_score(Y_test, Y_test_pred, average='weighted')
         # Calculate evaluation metrics for the validation set
```

```
accuracy validation = accuracy score(Y validation, Y validation pred)
         precision_validation = precision_score(Y_validation, Y_validation_pred, average='weight

         recall_validation = recall_score(Y_validation, Y_validation_pred, average='weighted')
         f1_score_validation = f1_score(Y_validation, Y_validation_pred, average='weighted')
         # Print the evaluation metrics
         print("Testing Set Metrics:")
         print("Accuracy:", accuracy_test)
         print("Precision:", precision_test)
         print("Recall:", recall_test)
         print("F1 Score:", f1_score_test)
         print("\nValidation Set Metrics:")
         print("Accuracy:", accuracy_validation)
         print("Precision:", precision_validation)
         print("Recall:", recall_validation)
         print("F1 Score:", f1_score_validation)
         C:\Users\SACHIN\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460: Co
         nvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n_iter_i = _check_optimize_result(
         Testing Set Metrics:
         Accuracy: 0.8522619967379175
         Precision: 0.8687038083379822
         Recall: 0.8522619967379175
         F1 Score: 0.8379590326220326
         Validation Set Metrics:
         Accuracy: 0.8522763041176639
         Precision: 0.8680748972094098
         Recall: 0.8522763041176639
         F1 Score: 0.8382678722065365
         CPU times: total: 2min 39s
         Wall time: 1min 29s
In [15]: %%time
         from sklearn.ensemble import RandomForestClassifier
         # Create a Random Forest model
         random_forest = RandomForestClassifier(random_state=30)
         # Train the model on the training data
         random_forest.fit(X_train_count, Y_train_temp)
         # Predictions on the testing and validation data
         Y test pred rf = random forest.predict(X test count)
         Y_validation_pred_rf = random_forest.predict(X_validation_count)
         # Calculate evaluation metrics for the testing set
         accuracy test rf = accuracy score(Y test, Y test pred rf)
         precision_test_rf = precision_score(Y_test, Y_test_pred_rf, average='weighted')
         recall_test_rf = recall_score(Y_test, Y_test_pred_rf, average='weighted')
         f1_score_test_rf = f1_score(Y_test, Y_test_pred_rf, average='weighted')
```

```
# Calculate evaluation metrics for the validation set
         accuracy_validation_rf = accuracy_score(Y_validation, Y_validation_pred_rf)
         precision_validation_rf = precision_score(Y_validation, Y_validation_pred_rf, average
         recall validation rf = recall score(Y validation, Y validation pred rf, average='weight
         f1_score_validation_rf = f1_score(Y_validation, Y_validation_pred_rf, average='weighte
         # Print the evaluation metrics for Random Forest
         print("Random Forest Testing Set Metrics:")
         print("Accuracy:", accuracy_test_rf)
         print("Precision:", precision_test_rf)
         print("Recall:", recall_test_rf)
         print("F1 Score:", f1_score_test_rf)
         print("\nRandom Forest Validation Set Metrics:")
         print("Accuracy:", accuracy_validation_rf)
         print("Precision:", precision_validation_rf)
         print("Recall:", recall_validation_rf)
         print("F1 Score:", f1_score_validation_rf)
         Random Forest Testing Set Metrics:
         Accuracy: 0.8573840386871548
         Precision: 0.8640368430052175
         Recall: 0.8573840386871548
         F1 Score: 0.8463574699218742
         Random Forest Validation Set Metrics:
         Accuracy: 0.8570692763327324
         Precision: 0.8634292149595955
         Recall: 0.8570692763327324
         F1 Score: 0.8464514202100215
         CPU times: total: 6h 50min 24s
         Wall time: 8h 57min 24s
In [16]: %time
         from sklearn.svm import SVC
         # Create an SVM model
         svm = SVC(random_state=30)
         # Train the model on the training data
         svm.fit(X_train_count, Y_train_temp)
         # Predictions on the testing and validation data
         Y_test_pred_svm = svm.predict(X_test_count)
         Y_validation_pred_svm = svm.predict(X_validation_count)
         # Calculate evaluation metrics for the testing set
         accuracy_test_svm = accuracy_score(Y_test, Y_test_pred_svm)
         precision_test_svm = precision_score(Y_test, Y_test_pred_svm, average='weighted')
         recall_test_svm = recall_score(Y_test, Y_test_pred_svm, average='weighted')
         f1_score_test_svm = f1_score(Y_test, Y_test_pred_svm, average='weighted')
         # Calculate evaluation metrics for the validation set
         accuracy_validation_svm = accuracy_score(Y_validation, Y_validation_pred_svm)
         precision validation svm = precision score(Y validation, Y validation pred svm, average
         recall validation svm = recall score(Y validation, Y validation pred svm, average='wei
         f1_score_validation_svm = f1_score(Y_validation, Y_validation_pred_svm, average='weight
         # Print the evaluation metrics for SVM
         print("SVM Testing Set Metrics:")
```

```
print("Accuracy:", accuracy test svm)
         print("Precision:", precision_test_svm)
         print("Recall:", recall_test_svm)
         print("F1 Score:", f1_score_test_svm)
         print("\nSVM Validation Set Metrics:")
         print("Accuracy:", accuracy validation svm)
         print("Precision:", precision_validation_svm)
         print("Recall:", recall_validation_svm)
         print("F1 Score:", f1_score_validation_svm)
         SVM Testing Set Metrics:
         Accuracy: 0.814275903511031
         Precision: 0.8467155320380438
         Recall: 0.814275903511031
         F1 Score: 0.7878158008900779
         SVM Validation Set Metrics:
         Accuracy: 0.8151486536755659
         Precision: 0.8465403349184478
         Recall: 0.8151486536755659
         F1 Score: 0.7895114262489186
         CPU times: total: 4h 49min 30s
         Wall time: 6h 17min 6s
In [17]: %%time
         from sklearn.naive_bayes import MultinomialNB
         # Create a Naive Bayes model
         naive_bayes = MultinomialNB()
         # Train the model on the training data
         naive_bayes.fit(X_train_count, Y_train_temp)
         # Predictions on the testing and validation data
         Y_test_pred_nb = naive_bayes.predict(X_test_count)
         Y validation pred nb = naive bayes.predict(X validation count)
         # Calculate evaluation metrics for the testing set
         accuracy_test_nb = accuracy_score(Y_test, Y_test_pred_nb)
         precision_test_nb = precision_score(Y_test, Y_test_pred_nb, average='weighted')
         recall_test_nb = recall_score(Y_test, Y_test_pred_nb, average='weighted')
         f1_score_test_nb = f1_score(Y_test, Y_test_pred_nb, average='weighted')
         # Calculate evaluation metrics for the validation set
         accuracy_validation_nb = accuracy_score(Y_validation, Y_validation_pred_nb)
         precision_validation_nb = precision_score(Y_validation, Y_validation_pred_nb, average
         recall_validation_nb = recall_score(Y_validation, Y_validation_pred_nb, average='weight
         f1_score_validation_nb = f1_score(Y_validation, Y_validation_pred_nb, average='weighte
         # Print the evaluation metrics for Naive Bayes
         print("Naive Bayes Testing Set Metrics:")
         print("Accuracy:", accuracy_test_nb)
         print("Precision:", precision_test_nb)
         print("Recall:", recall_test_nb)
         print("F1 Score:", f1_score_test_nb)
         print("\nNaive Bayes Validation Set Metrics:")
         print("Accuracy:", accuracy_validation_nb)
         print("Precision:", precision_validation_nb)
```

```
print("Recall:", recall_validation_nb)
print("F1 Score:", f1_score_validation_nb)
```

Naive Bayes Testing Set Metrics: Accuracy: 0.8729361604715712 Precision: 0.8803426148158386 Recall: 0.8729361604715712 F1 Score: 0.8621802110842035

Naive Bayes Validation Set Metrics:

Accuracy: 0.8731221564082754 Precision: 0.879750262448651 Recall: 0.8731221564082754 F1 Score: 0.8628237745395287 CPU times: total: 359 ms

Wall time: 384 ms

In []: