Amazon Alexa Review - Sentiment Analysis

Analyzing the Amazon Alexa dataset and building classification models to predict if the sentiment of a given input sentence is positive or negative.

Importing required libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
from nltk.stem.porter import PorterStemmer
nltk.download('stopwords')
from nltk.corpus import stopwords
STOPWORDS = set(stopwords.words('english'))

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import accuracy_score
from wordcloud import WordCloud
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
import pickle
import re
```

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

```
%pip install wordcloud
```

```
Requirement already satisfied: wordcloud in c:\users\user\anaconda3\lib\site-packages (1.9.2)
Requirement already satisfied: pillow in c:\users\user\anaconda3\lib\site-packages (from wordcloud) (9.
Requirement already satisfied: matplotlib in c:\users\user\appdata\roaming\python\python38\site-package
Requirement already satisfied: numpy>=1.6.1 in c:\users\user\anaconda3\lib\site-packages (from wordclou
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\user\anaconda3\lib\site-packages (from mat
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\user\anaconda3\lib\
Requirement already satisfied: python-dateutil>=2.1 in c:\users\user\anaconda3\lib\site-packages (from
Requirement already satisfied: cycler>=0.10 in c:\users\user\anaconda3\lib\site-packages (from matplotl
Requirement already satisfied: six in c:\users\user\anaconda3\lib\site-packages (from cycler>=0.10->mat
Note: you may need to restart the kernel to use updated packages.
```

Exploratory Data Analysis

```
#Load the data

data = pd.read_csv(r"/content/amazon_alexa.tsv", delimiter = '\t', quoting = 3)

print(f"Dataset shape : {data.shape}")
```

```
Dataset shape : (3150, 5)
```

```
data.head()
```

	rating	date	variation	verified_reviews	feedback
0	5	31-Jul-18	Charcoal Fabric	Love my Echo!	1
1	5	31-Jul-18	Charcoal Fabric	Loved it!	1
2	4	31-Jul-18	Walnut Finish	"Sometimes while playing a game, you can answe...	1
3	5	31-Jul-18	Charcoal Fabric	"I have had a lot of fun with this thing. My 4...	1
4	5	31-Jul-18	Charcoal Fabric	Music	1

Next steps: Generate code with `data` | View recommended plots | New interactive sheet

```
#Column names

print(f"Feature names : {data.columns.values}")
```

```
Feature names : ['rating' 'date' 'variation' 'verified_reviews' 'feedback']
```

```
#Check for null values

data.isnull().sum()
```

	0
rating	0
date	0
variation	0
verified_reviews	1
feedback	0

dtype: int64

There is one record with no 'verified_reviews' (null value)

```
#Getting the record where 'verified_reviews' is null

data[data['verified_reviews'].isna() == True]
```

	rating	date	variation	verified_reviews	feedback
473	2	29-Jun-18	White	NaN	0

```
#We will drop the null record

data.dropna(inplace=True)

print(f"Dataset shape after dropping null values : {data.shape}")
```

```
Dataset shape after dropping null values : (3149, 5)
```

```
#Creating a new column 'length' that will contain the length of the string in 'verified_reviews' column

data['length'] = data['verified_reviews'].apply(len)

data.head()
```

	rating	date	variation	verified_reviews	feedback	length
0	5	31-Jul-18	Charcoal Fabric	Love my Echo!	1	13
1	5	31-Jul-18	Charcoal Fabric	Loved it!	1	9
2	4	31-Jul-18	Walnut Finish	"Sometimes while playing a game, you can answe...	1	197
3	5	31-Jul-18	Charcoal Fabric	"I have had a lot of fun with this thing. My 4...	1	174
4	5	31-Jul-18	Charcoal Fabric	Music	1	5

Next steps: Generate code with `data` View recommended plots New interactive sheet

The 'length' column is new generated column - stores the length of 'verified_reviews' for that record. Let's check for some sample records

```
#Randomly checking for 10th record

print(f"'verified_reviews' column value: {data.iloc[10]['verified_reviews']}") #Original value
print(f"Length of review : {len(data.iloc[10]['verified_reviews'])}") #Length of review using len()
print(f"'length' column value : {data.iloc[10]['length']}") #Value of the column 'length'
```

```
'verified_reviews' column value: "I sent it to my 85 year old Dad, and he talks to it constantly."
Length of review : 65
'length' column value : 65
```

We can see that the length of review is the same as the value in the length column for that record

Datatypes of the features

```
data.dtypes
```

	0
rating	int64
date	object
variation	object
verified_reviews	object
feedback	int64
length	int64

dtype: object

- rating, feedback and length are integer values
- date, variation and verified_reviews are string values

Analyzing 'rating' column

This column refers to the rating of the variation given by the user

```
len(data)
```

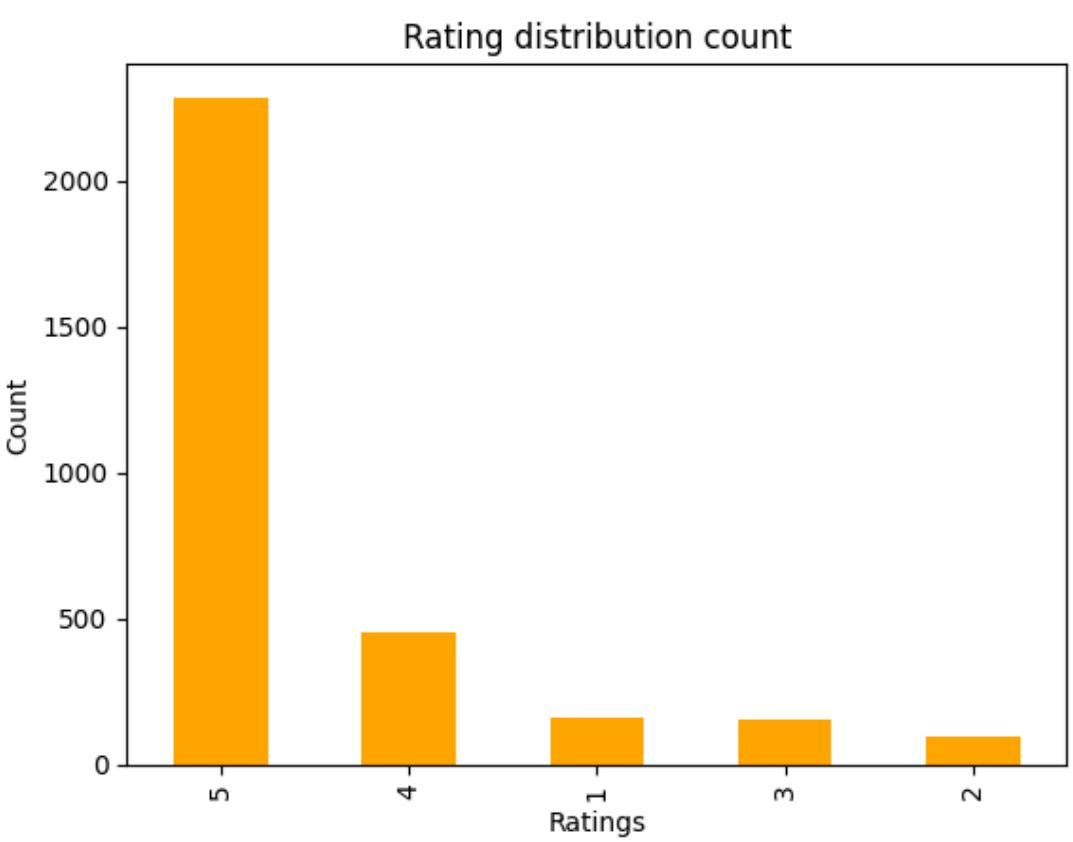
```
3149
```

```
#Distinct values of 'rating' and its count

print(f"Rating value count: \n{data['rating'].value_counts()}")
```

```
Rating value count:
rating
5    2286
4     455
1     161
3     152
2      95
Name: count, dtype: int64
```

Let's plot the above values in a bar graph

```
#Bar plot to visualize the total counts of each rating

data['rating'].value_counts().plot.bar(color = 'orange')
plt.title('Rating distribution count')
plt.xlabel('Ratings')
plt.ylabel('Count')
plt.show()
```

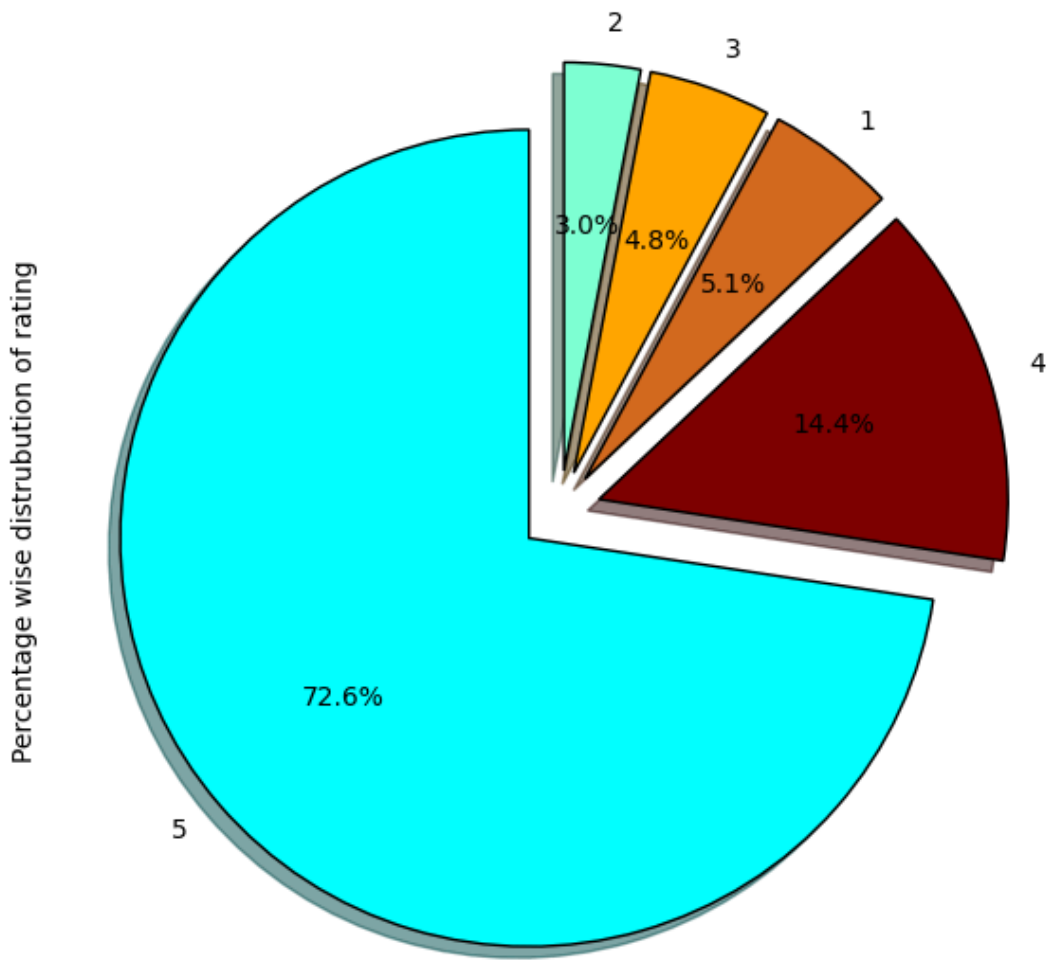



```
#Finding the percentage distribution of each rating - we'll divide the number of records for each rating by

print(f"Rating value count - percentage distribution: \n{round(data['rating'].value_counts()/data.shape[0]*
```

```
Rating value count - percentage distribution:
rating
5    72.59
4    14.45
1     5.11
3     4.83
2     3.02
Name: count, dtype: float64
```

Let's plot the above values in a pie chart

```
fig = plt.figure(figsize=(7,7))

colors = ('cyan', 'maroon', 'chocolate','orange','aquamarine')

wp = {'linewidth':1, "edgecolor":'black'}

tags = data['rating'].value_counts()/data.shape[0]

explode=(0.1,0.1,0.1,0.1,0.1)

tags.plot(kind='pie', autopct="%1.1f%%", shadow=True, colors=colors, startangle=90, wedgeprops=wp, explode=ex

from io import  BytesIO

graph = BytesIO()

fig.savefig(graph, format="png")
```



Analyzing 'feedback' column

This column refers to the feedback of the verified review

```
#Distinct values of 'feedback' and its count

print(f"Feedback value count: \n{data['feedback'].value_counts()}")
```

```
Feedback value count:
feedback
1    2893
0     256
Name: count, dtype: int64
```

There are 2 distinct values of 'feedback' present - 0 and 1. Let's see what kind of review each value corresponds to.

feedback value = 0

```
#Extracting the 'verified_reviews' value for one record with feedback = 0

review_0 = data[data['feedback'] == 0].iloc[1]['verified_reviews']
print(review_0)
```

```
Sound is terrible if u want good music too get a bose
```

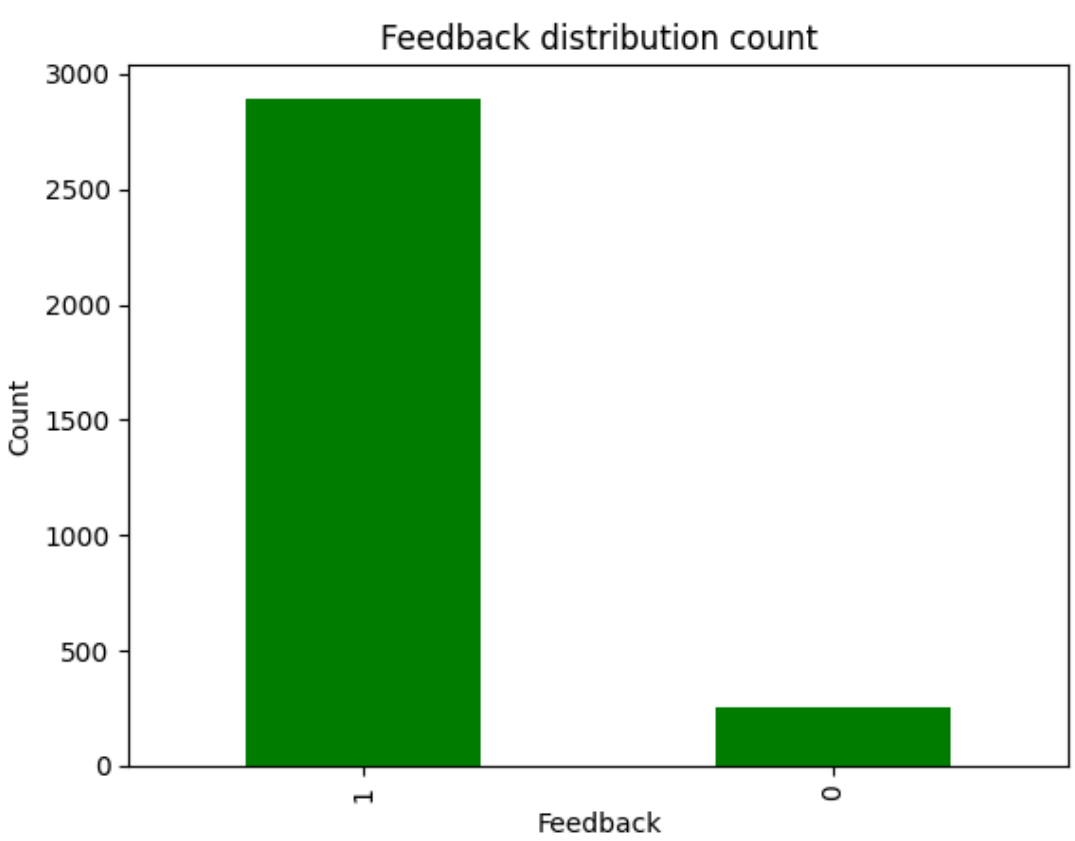
```
#Extracting the 'verified_reviews' value for one record with feedback = 1

review_1 = data[data['feedback'] == 1].iloc[1]['verified_reviews']
print(review_1)
```

```
Loved it!
```

From the above 2 examples we can see that feedback **0 is negative review** and **1 is positive review**

Let's plot the feedback value count in a bar graph

```
#Bar graph to visualize the total counts of each feedback

data['feedback'].value_counts().plot.bar(color = 'green')
plt.title('Feedback distribution count')
plt.xlabel('Feedback')
plt.ylabel('Count')
plt.show()
```




```
#Finding the percentage distribution of each feedback - we'll divide the number of records for each feedbac

print(f"Feedback value count - percentage distribution: \n{round(data['feedback'].value_counts()/data.shape
```

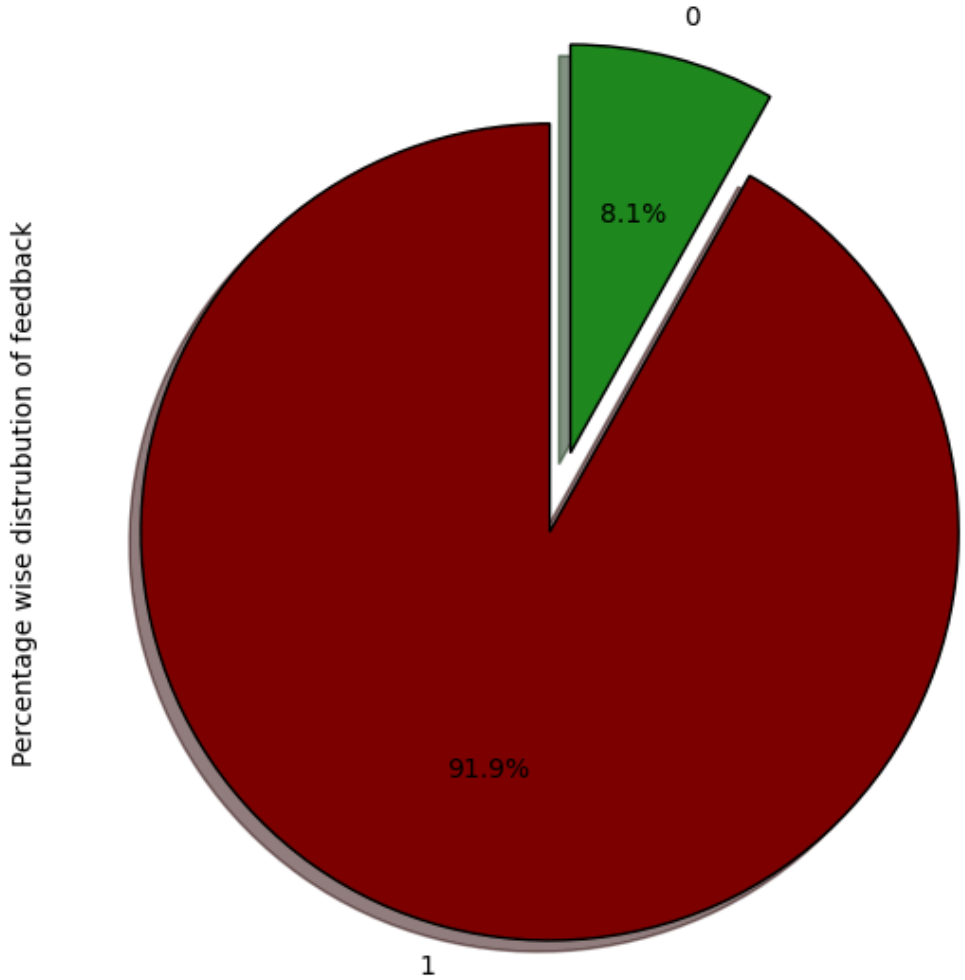
```
Feedback value count - percentage distribution:
feedback
1    91.87
0     8.13
Name: count, dtype: float64
```

Feedback distribution

- 91.87% reviews are positive
- 8.13% reviews are negative

```
fig = plt.figure(figsize=(7,7))

colors = ('maroon', 'forestgreen')

wp = {'linewidth':1, "edgecolor":'black'}

tags = data['feedback'].value_counts()/data.shape[0]

explode=(0.1,0.1)

tags.plot(kind='pie', autopct="%1.1f%%", shadow=True, colors=colors, startangle=90, wedgeprops=wp, explode=ex
```

```
<Axes: ylabel='Percentage wise distrubution of feedback'>
```



Let's see the 'rating' values for different values of 'feedback'

```
#Feedback = 0
data[data['feedback'] == 0]['rating'].value_counts()
```

rating	count
1	161
2	95

dtype: int64

```
#Feedback = 1
data[data['feedback'] == 1]['rating'].value_counts()
```

rating	count
5	2286
4	455
3	152

dtype: int64

If rating of a review is 1 or 2 then the feedback is 0 (negative) and if the rating is 3, 4 or 5 then the feedback is 1 (positive).

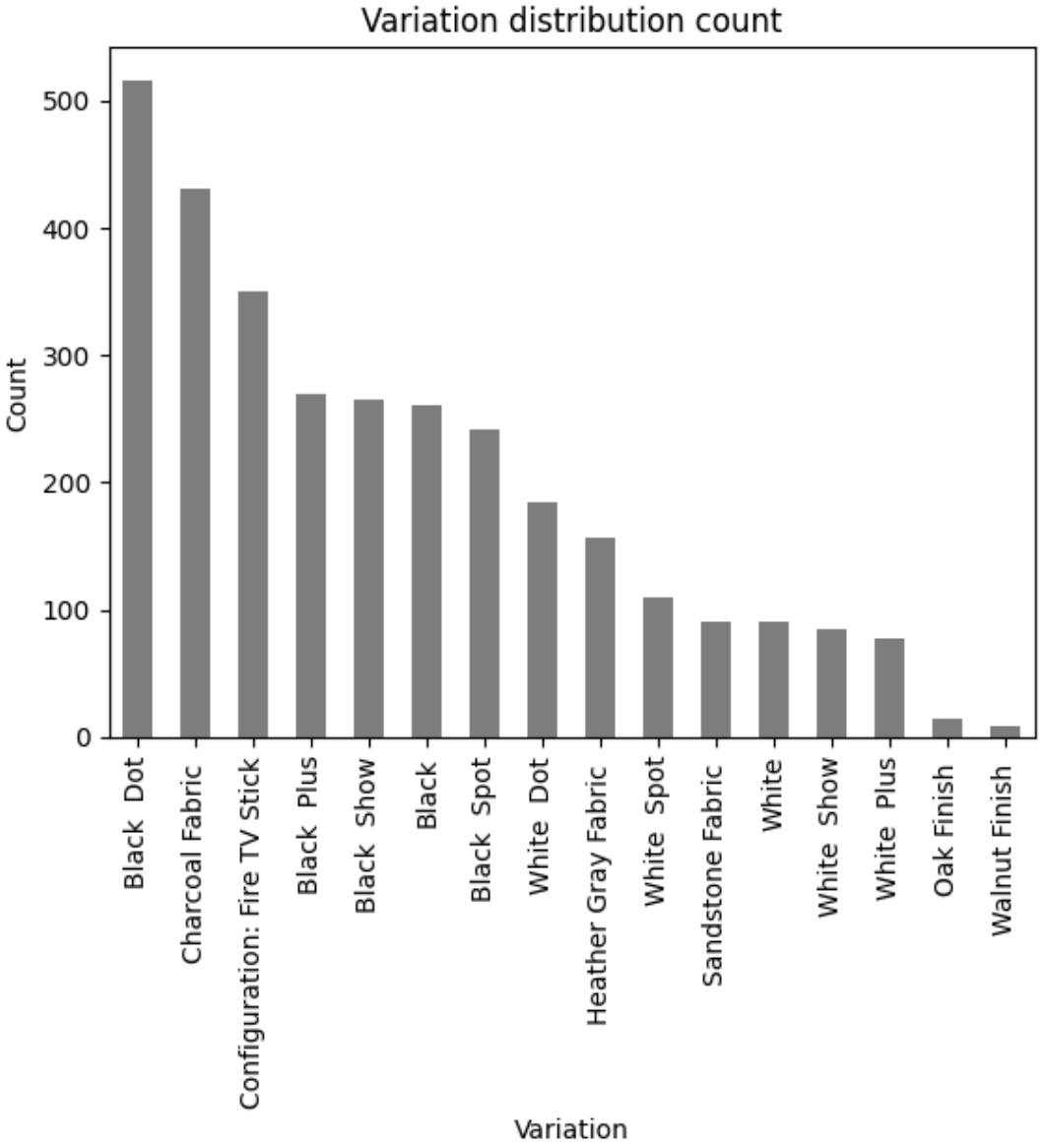
Analyzing 'variation' column

This column refers to the variation or type of Amazon Alexa product. Example - Black Dot, Charcoal Fabric etc.

```
#Distinct values of 'variation' and its count

print(f"Variation value count: \n{data['variation'].value_counts()}")
```

```
Variation value count:
variation
Black  Dot                      516
Charcoal Fabric                 430
Configuration: Fire TV Stick    350
Black  Plus                     270
Black  Show                     265
Black                           261
Black  Spot                     241
White  Dot                      184
Heather Gray Fabric             157
White  Spot                     109
Sandstone Fabric                 90
White                            90
White  Show                      85
White  Plus                      78
Oak Finish                       14
Walnut Finish                     9
Name: count, dtype: int64
```

```
#Bar graph to visualize the total counts of each variation

data['variation'].value_counts().plot.bar(color = 'grey')
plt.title('Variation distribution count')
plt.xlabel('Variation')
plt.ylabel('Count')
plt.show()
```




```
#Finding the percentage distribution of each variation - we'll divide the number of records for each variatio

print(f"Variation value count - percentage distribution: \n{round(data['variation'].value_counts()/data.shape
```

```
Variation value count - percentage distribution:
variation
Black  Dot                      16.39
Charcoal Fabric                 13.66
Configuration: Fire TV Stick    11.11
Black  Plus                      8.57
Black  Show                      8.42
Black                            8.29
Black  Spot                      7.65
White  Dot                       5.84
Heather Gray Fabric              4.99
White  Spot                      3.46
Sandstone Fabric                 2.86
```

```
White                          2.86
White  Show                    2.70
White  Plus                    2.48
Oak Finish                     0.44
Walnut Finish                  0.29
Name: count, dtype: float64
```

Mean rating according to variation

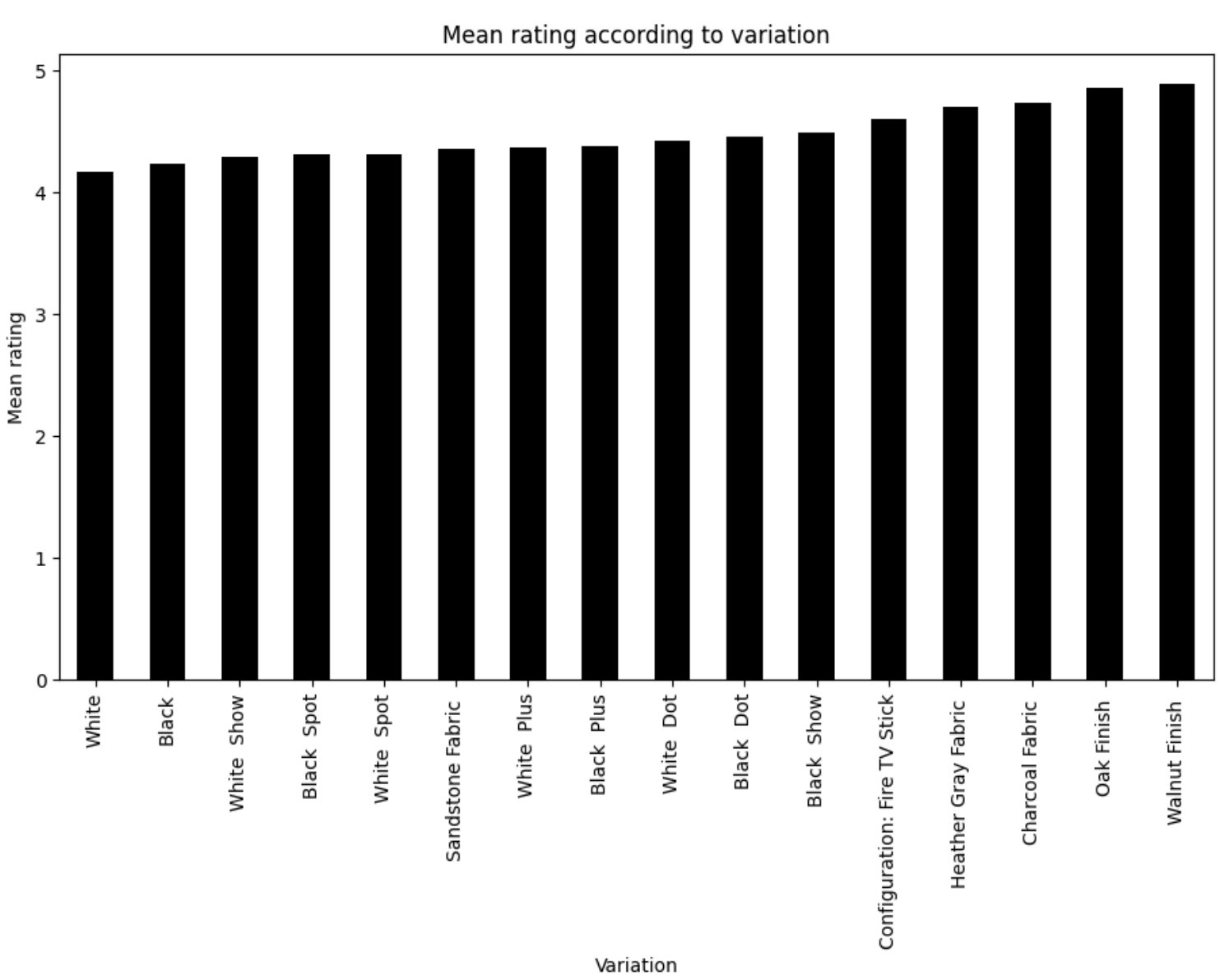
```
data.groupby('variation')['rating'].mean()
```

variation	rating
Black	4.233716
Black Dot	4.453488
Black Plus	4.370370
Black Show	4.490566
Black Spot	4.311203
Charcoal Fabric	4.730233
Configuration: Fire TV Stick	4.591429
Heather Gray Fabric	4.694268
Oak Finish	4.857143
Sandstone Fabric	4.355556
Walnut Finish	4.888889
White	4.166667
White Dot	4.423913
White Plus	4.358974
White Show	4.282353
White Spot	4.311927

dtype: float64

Let's analyze the above ratings

```
data.groupby('variation')['rating'].mean().sort_values().plot.bar(color = 'black', figsize=(11, 6))
plt.title("Mean rating according to variation")
plt.xlabel('Variation')
plt.ylabel('Mean rating')
plt.show()
```



Analyzing 'verified_reviews' column

This column contains the textual review given by the user for a variation for the product.

```
data['length'].describe()
```

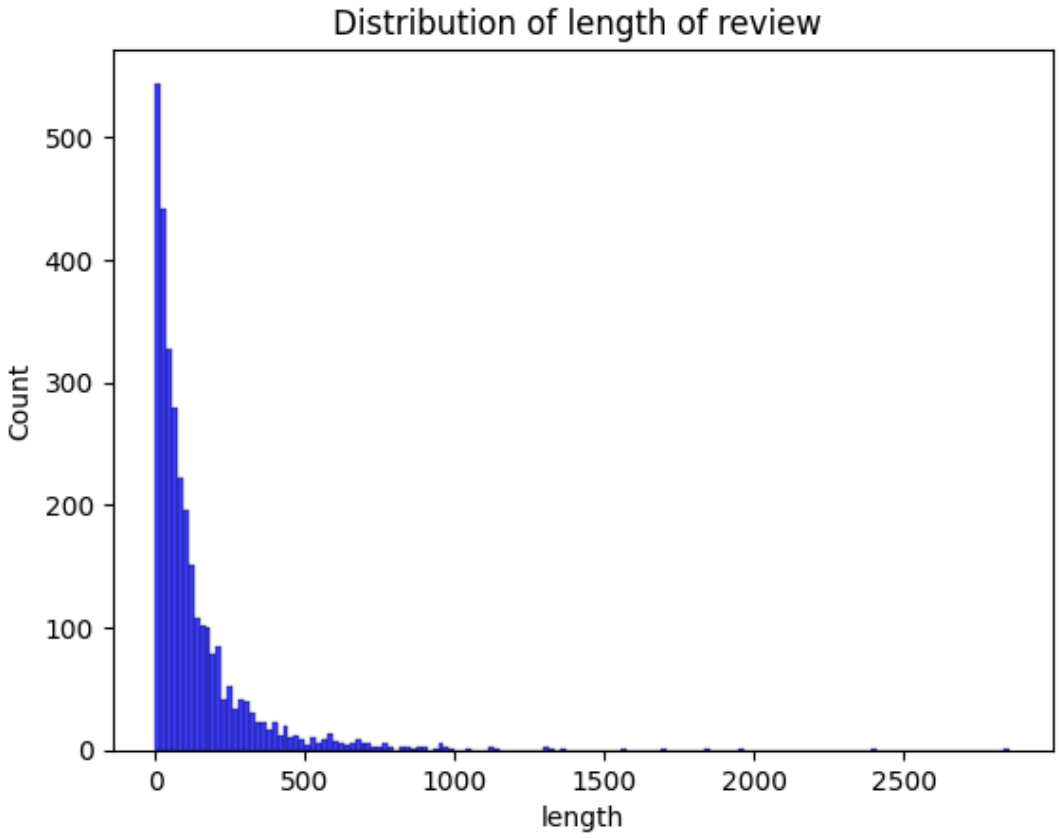
	length
count	3149.000000
mean	132.714513
std	182.541531
min	1.000000
25%	30.000000
50%	74.000000
75%	166.000000
max	2853.000000

dtype: float64

Length analysis for full dataset

```
sns.histplot(data['length'],color='blue').set(title='Distribution of length of review ')
```

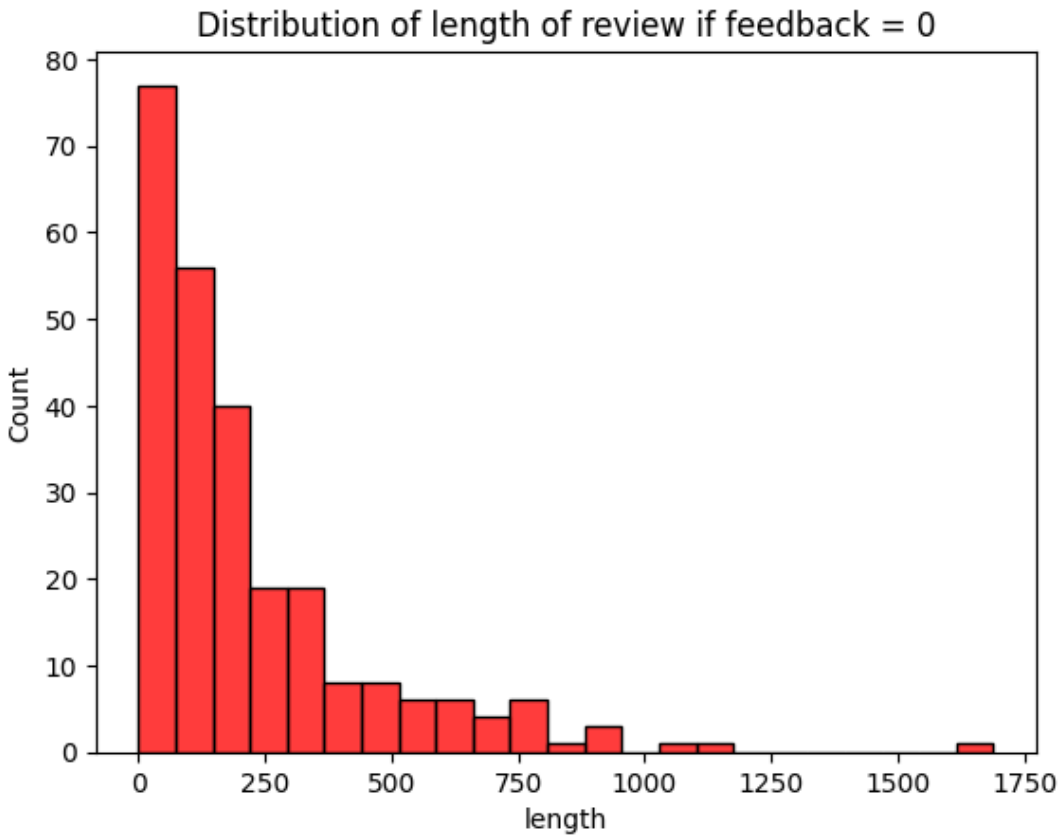
```
[Text(0.5, 1.0, 'Distribution of length of review ')]
```



Length analysis when feedback is 0 (negative)

```
sns.histplot(data[data['feedback']==0]['length'],color='red').set(title='Distribution of length of review if
```

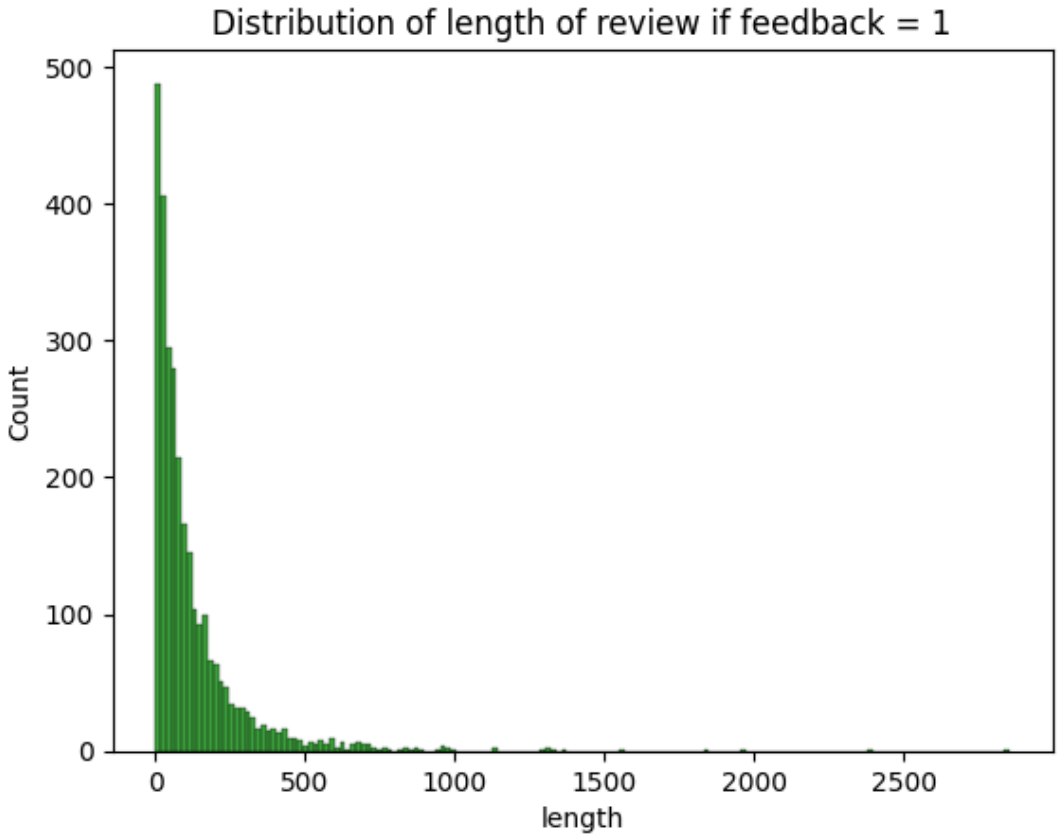
```
[Text(0.5, 1.0, 'Distribution of length of review if feedback = 0')]
```



Length analysis when feedback is 1 (positive)

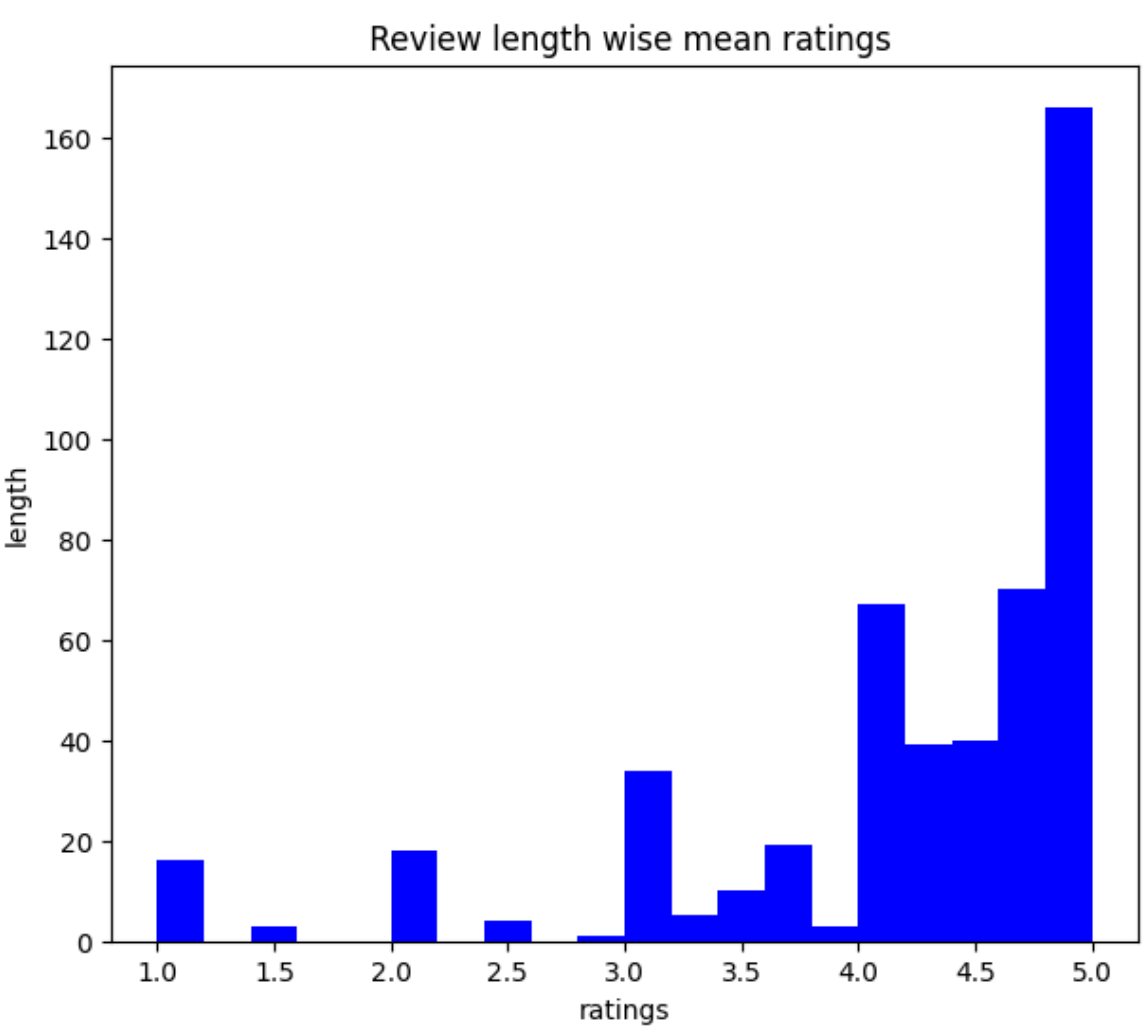
```
sns.histplot(data[data['feedback']==1]['length'],color='green').set(title='Distribution of length of review i
```

```
[Text(0.5, 1.0, 'Distribution of length of review if feedback = 1')]
```



Lengthwise mean rating

```
data.groupby('length')['rating'].mean().plot.hist(color = 'blue', figsize=(7, 6), bins = 20)
plt.title(" Review length wise mean ratings")
plt.xlabel('ratings')
plt.ylabel('length')
plt.show()
```




```
cv = CountVectorizer(stop_words='english')
words = cv.fit_transform(data.verified_reviews)
```

```
# Combine all reviews
reviews = " ".join([review for review in data['verified_reviews']])

# Initialize wordcloud object
wc = WordCloud(background_color='white', max_words=50)

# Generate and plot wordcloud
plt.figure(figsize=(10,10))
plt.imshow(wc.generate(reviews))
plt.title('Wordcloud for all reviews', fontsize=10)
plt.axis('off')
plt.show()
```

Lets find the unique words in each feedback category

```
# Combine all reviews for each feedback category and splitting them into individual words
neg_reviews = " ".join([review for review in data[data['feedback'] == 0]['verified_reviews']])
neg_reviews = neg_reviews.lower().split()

pos_reviews = " ".join([review for review in data[data['feedback'] == 1]['verified_reviews']])
pos_reviews = pos_reviews.lower().split()

#Finding words from reviews which are present in that feedback category only
unique_negative = [x for x in neg_reviews if x not in pos_reviews]
unique_negative = " ".join(unique_negative)

unique_positive = [x for x in pos_reviews if x not in neg_reviews]
unique_positive = " ".join(unique_positive)



wc = WordCloud(background_color='white', max_words=50)

# Generate and plot wordcloud
plt.figure(figsize=(10,10))
plt.imshow(wc.generate(unique_negative))
plt.title('Wordcloud for negative reviews', fontsize=10)
plt.axis('off')
plt.show()
```

Negative words can be seen in the above word cloud - garbage, pointless, poor, horrible, repair etc

```
wc = WordCloud(background_color='white', max_words=50)

# Generate and plot wordcloud
plt.figure(figsize=(10,10))
plt.imshow(wc.generate(unique_positive))
plt.title('Wordcloud for positive reviews', fontsize=10)
plt.axis('off')
plt.show()
```

Positive words can be seen in the above word cloud - good, enjoying, amazing, best, great etc

Preprocessing and Modelling

To build the corpus from the 'verified_reviews' we perform the following -

1. Replace any non alphabet characters with a space
2. Covert to lower case and split into words
3. Iterate over the individual words and if it is not a stopword then add the stemmed form of the word to the corpus

```
corpus = []
stemmer = PorterStemmer()
for i in range(0, data.shape[0]):
  review = re.sub('[^a-zA-Z]', ' ', data.iloc[i]['verified_reviews'])
  review = review.lower().split()
  review = [stemmer.stem(word) for word in review if not word in STOPWORDS]
  review = ' '.join(review)
  corpus.append(review)
```

Using Count Vectorizer to create bag of words

```
cv = CountVectorizer(max_features = 2500)

#Storing independent and dependent variables in X and y
X = cv.fit_transform(corpus).toarray()
y = data['feedback'].values
```

Checking the shape of X and y

```
print(f"X shape: {X.shape}")
print(f"y shape: {y.shape}")
```

```
X shape: (3149, 2500)
y shape: (3149,)
```

Splitting data into train and test set with 30% data with testing.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 15)

print(f"X train: {X_train.shape}")
print(f"y train: {y_train.shape}")
print(f"X test: {X_test.shape}")
print(f"y test: {y_test.shape}")
```

```
X train: (2204, 2500)
y train: (2204,)
X test: (945, 2500)
y test: (945,)
```

```
print(f"X train max value: {X_train.max()}")
print(f"X test max value: {X_test.max()}")
```

```
X train max value: 12
X test max value: 10
```

We'll scale X_train and X_test so that all values are between 0 and 1.

```
scaler = MinMaxScaler()

X_train_scl = scaler.fit_transform(X_train)
X_test_scl = scaler.transform(X_test)
```

Random Forest

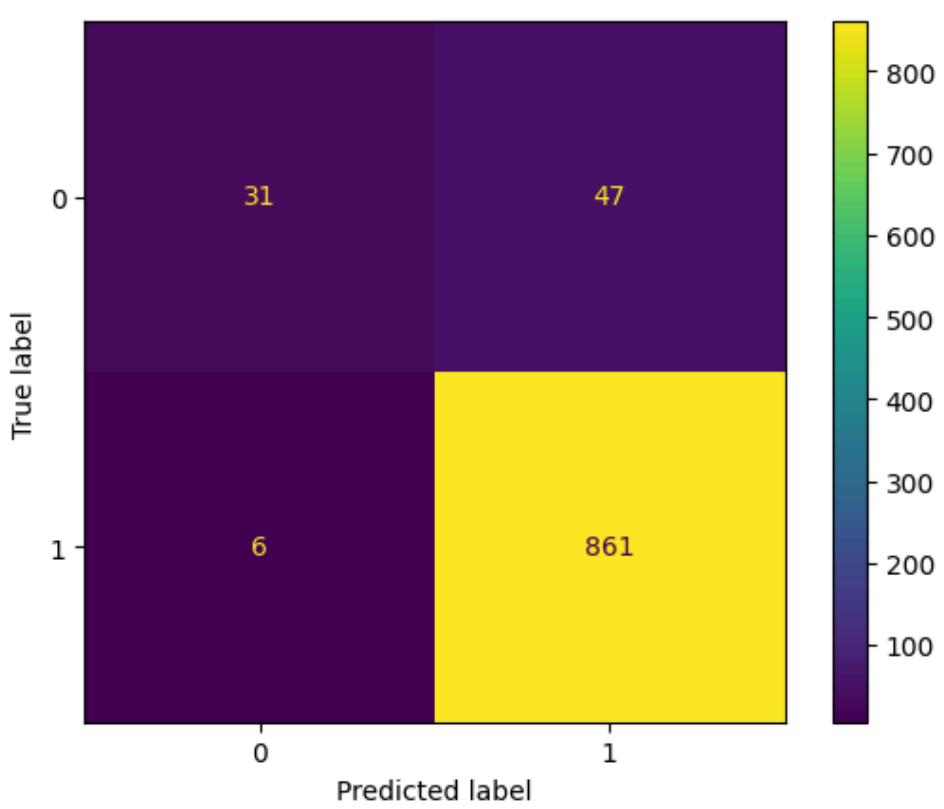
```
#Fitting scaled X_train and y_train on Random Forest Classifier
model_rf = RandomForestClassifier()
model_rf.fit(X_train_scl, y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
#Accuracy of the model on training and testing data

print("Training Accuracy :", model_rf.score(X_train_scl, y_train))
print("Testing Accuracy :", model_rf.score(X_test_scl, y_test))
```

```
Training Accuracy : 0.9945553539019963
Testing Accuracy : 0.9439153439153439
```

```
#Predicting on the test set
y_preds = model_rf.predict(X_test_scl)


#Confusion Matrix
cm = confusion_matrix(y_test, y_preds)


cm_display = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_rf.classes_)
cm_display.plot()
plt.show()
```



K fold cross-validation

```
accuracies = cross_val_score(estimator = model_rf, X = X_train_scl, y = y_train, cv = 10)

print("Accuracy :", accuracies.mean())
print("Standard Variance :", accuracies.std())
```

```
Accuracy : 0.9314890991361577
Standard Variance : 0.011381389796097078
```

Applying grid search to get the optimal parameters on random forest

```
params = {
    'bootstrap': [True],
    'max_depth': [80, 100],
    'min_samples_split': [8, 12],
    'n_estimators': [100, 300]
}


cv_object = StratifiedKFold(n_splits = 2)

grid_search = GridSearchCV(estimator = model_rf, param_grid = params, cv = cv_object, verbose = 0, return_t
grid_search.fit(X_train_scl, y_train.ravel())
```

```
GridSearchCV
estimator: RandomForestClassifier
RandomForestClassifier
```

```
#Getting the best parameters from the grid search


print("Best Parameter Combination : {}".format(grid_search.best_params_))
```

```
Best Parameter Combination : {'bootstrap': True, 'max_depth': 100, 'min_samples_split': 8, 'n_estimator
```

```
print("Cross validation mean accuracy on train set : {}".format(grid_search.cv_results_['mean_train_score']
print("Cross validation mean accuracy on test set : {}".format(grid_search.cv_results_['mean_test_score'].m
print("Accuracy score for test set :", accuracy_score(y_test, y_preds))
```

```
Cross validation mean accuracy on train set : 96.81261343012704
Cross validation mean accuracy on test set : 92.17899274047187
Accuracy score for test set : 0.9439153439153439
```

XgBoost

```
model_xgb = XGBClassifier()
model_xgb.fit(X_train_scl, y_train)
```

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

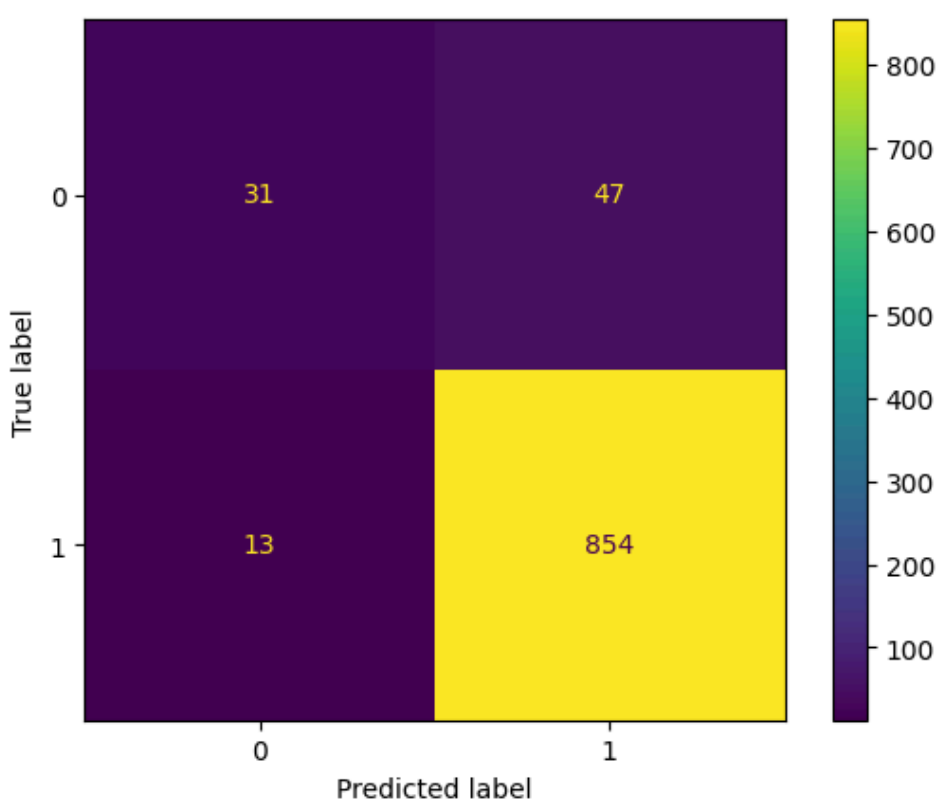
```
#Accuracy of the model on training and testing data

print("Training Accuracy :", model_xgb.score(X_train_scl, y_train))
print("Testing Accuracy :", model_xgb.score(X_test_scl, y_test))
```

```
Training Accuracy : 0.971415607985481
Testing Accuracy : 0.9417989417989417
```

```
y_preds = model_xgb.predict(X_test)


#Confusion Matrix
cm = confusion_matrix(y_test, y_preds)
print(cm)
```

```
[[ 31  47]
 [ 13 854]]
```

```
cm_display = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_xgb.classes_)
cm_display.plot()
plt.show()
```



Decision Tree Classifier

```
model_dt = DecisionTreeClassifier()
model_dt.fit(X_train_scl, y_train)
```

```
DecisionTreeClassifier
```