PROJECT: SENTIMENT ANALYSIS FOR MARKETING

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PHASE 3 : DEVELOPMENT PART

Start building the Sentiment Analysis for Marketing to analysis customers sentiments for competitor products.

Sentiment analysis is a marketing tool that helps you examine the way people interact with a brand online. This method is more comprehensive than traditional online marketing tracking, which measures the number of online interactions that customers have with a brand, like comments and shares.

APPLICABILITY:

AI powered to enhance products by understanding customers likes and dislikes.

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- ## INTRODUCTION:
- Sentiment Analysis, often referred to as opinion mining, is a powerful technique within the field of Natural Language Processing (NLP).
- At its core, sentiment analysis involves teaching machines to understand and interpret human emotions and opinions expressed within text data.
- By analyzing the sentiment behind words and phrases, Al models can classify text as positive, negative, or neutral, thus providing valuable insights into people's attitudes, feelings, and reactions.

TRAINING AL MODELS FOR SENTIMENT ANALYSIS:

Training AI models for sentiment analysis involves these steps:

- **Data Collection:**

  Gather a labeled dataset with text samples and sentiment labels (positive negative).

- **Text Preprocessing:**

  Clean text by removing punctuation, special characters, and lowercase conversion.

- **Tokenization:**

  Break text into smaller units (tokens) like words.

- **Feature Extraction:**

  Convert tokens into numerical representations using techniques like TF-IDF.

- **Model Selection:**
  Choose an algorithm like Naive Bayes, SVM, or RNN.
- **Model Training:**
  Train the model on labeled data to learn sentiment patterns.
- **Model Evaluation:**
  Measure model performance with metrics like accuracy and precision.
- **Deployment:**
  Deploy the model to predict sentiment in new text data.

IMPORTING ESSENTIAL LIBRARIES:

Data Analysis and Visualization Libraries:

- Pandas

- NumPy
- Seaborn and Matplotlib

Text Preprocessing Libraries:

- NLTK (Natural Language Toolkit)
- String and Word Cloud
- TidfVectorizer

Data Splitting and Model Training Libraries:

- train_test_split
- Logistic Regression and MultinomialNB
- Naive Bayes

Model Evaluation Libraries

- Metrics and Display Tools
- Classification reports and confusion matrices.

NECESSARY STEPS TO FOLLOWS:

IN [1]:

```
# Data Analysis and Visualization
    import pandas as pd
    import numpy as no
    import seaborn as ins
    import matplotlib.pyplot as plt

# Text Preprocessing
    import string from nitk.corpus
    import stopwords from nitk. stem import
    PorterStemme from wordcloud
    import WordCloud from sklearn. feature
    extraction.text
    import TfidfVectorizer
```

```
# Data Splitting and Model Training
      from sklearn.model selection import
train_test_split
      from sklearn.linear model import
LogisticRegression
      from sklearn.naive_bayes  import
MultinomialNB


#Model Evaluation
      from sklearn.metrics import (
accuracy score,
precision score,
recall score,
f1_score,
classification report,
confusion_matrix,
ConfusionMatrixDisplay)
```

IMPORT DATASETS:

IN [2]:

```
df pd.read_csv('amazon_reviews.csv')
```

IN [3]:

```
df.head(5)
```

OUTPUT:

	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 answer...	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

DATA INSPECTION:

IN [4]:

```
df.info()
```

Data Information

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3150 entries, 0 to 3149
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   rating            3150 non-null   int64
 1   date              3150 non-null   object
 2   variation         3150 non-null   object
 3   verified_reviews  3150 non-null   object
 4   feedback          3150 non-null   int64
dtypes: int64(2), object(3)
memory usage: 123.2+ KB
```

Display the first 5 full reviews with a space in between

IN [5]:

```
for index, row in df.head (5).iterrows():
    print (f"Review {index + 1}: {row[
'verified_reviews"]}\n")
```

```
Review 1: Love my Echo!

Review 2: Loved it!

Review 3: Sometimes while playing a game, you can answer a question correctly but Alexa says you got it wrong and answers the s
ame as you.  I like being able to turn lights on and off while away from home.

Review 4: I have had a lot of fun with this thing. My 4 yr old learns about dinosaurs, i control the lights and play games like
categories. Has nice sound when playing music as well.

Review 5: Music
```

DATA PREPROCESSING:

IN [6]:

```
null_mask = df.isnull()
null_values = null_mask.sum().sum()
print ("Number of null values:", null_values)
```

EXPLORATORY DATA ANALYSIS:

IN [7]:

```
print("\nSummary Statistics:")
summary_stats = df.describe()
print (summary_stats)
```

Summary Statistics:

	rating	feedback
count	3150.000000	3150.000000
mean	4.463175	0.918413
std	1.068506	0.273778
min	1.000000	0.000000
25%	4.000000	1.000000
50%	5.000000	1.000000
75%	5.000000	1.000000
max	5.000000	1.000000

DISTRIBUTION OF SENTIMENTS:

IN [8]:

```
Print ("\n Distribution of Sentiments:")
sentiment_counts =
df['feedback'].value_counts()
print (sentiment_counts)
```

```
Distribution of Sentiments:
1    2893
0     257
Name: feedback, dtype: int64
```

DISTRIBUTION OF RATINGS:

IN [9]:

Print ("\nDistribution of Ratings:")

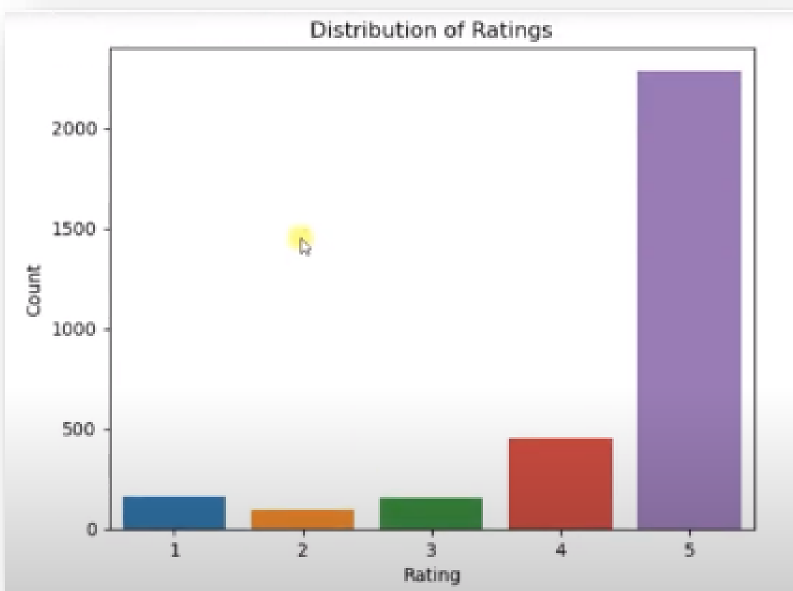
rating_counts = df['rating'].value_counts().sort_index()

print (rating_counts)

```
Distribution of Ratings:
1     161
2      96
3     152
4     455
5    2286
Name: rating, dtype: int64
```

IN [9.1]:

```
#plt.figure(figsize-(8, 6))
sns.countplot (data=df, x='rat Ing')
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.show()
```



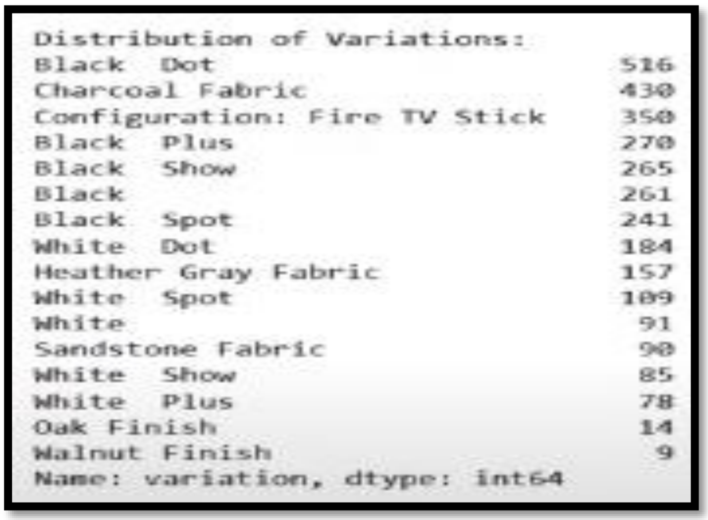
DISTRIBUTION OF VARIATIONS:

IN [10]:

Print ("\nDistribution of Variations:")

variation_counts=df["variation"]
.value_counts()

print (variation_counts)

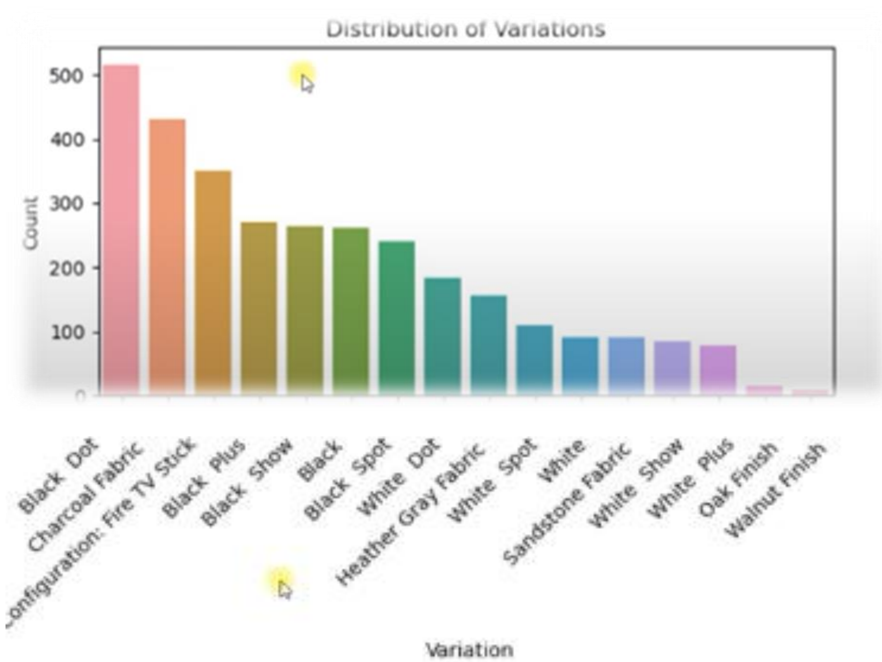


```
Distribution of Variations:
Black  Dot                       516
Charcoal Fabric                  430
Configuration: Fire TV Stick     350
Black  Plus                      270
Black  Show                      265
Black                            261
Black  Spot                      241
White  Dot                       184
Heather Gray Fabric              157
White  Spot                      109
White                             91
Sandstone Fabric                  90
White  Show                       85
White  Plus                       78
Oak Finish                        14
Walnut Finish                      9
Name: variation, dtype: int64
```

In [10.1]:

```
#plt.figure(figsize=(12, 6))
sns.countplot (data=df, x='variation',
order=df['variation'].value_counts().index)
plt.title('Distribution of Variations')
plt.xlabel('Variation')
plt.ylabel('Count')
```

```
plt.xticks (rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



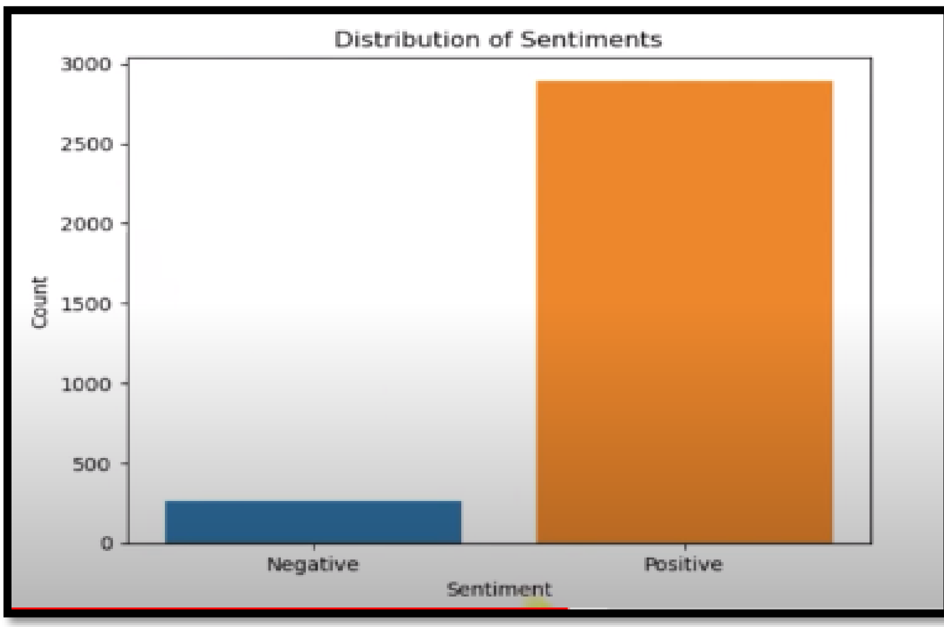
<u>DISTRIBUTION OF SENTIMENTS</u>:

IN [11]:

```
#plt.figure(figsize=(8, 6))
sns.countplot (data=df, x='feedback')
plt.title ('Distribution of Sentiments')
```

```
plt.xlabel ('Sentiment')
plt.ylabel ('Count')
plt.xticks ([0, 1], ['Negative', 'Positive'])
plt.show()
```

#Distribution of Sentiments (Feedback)

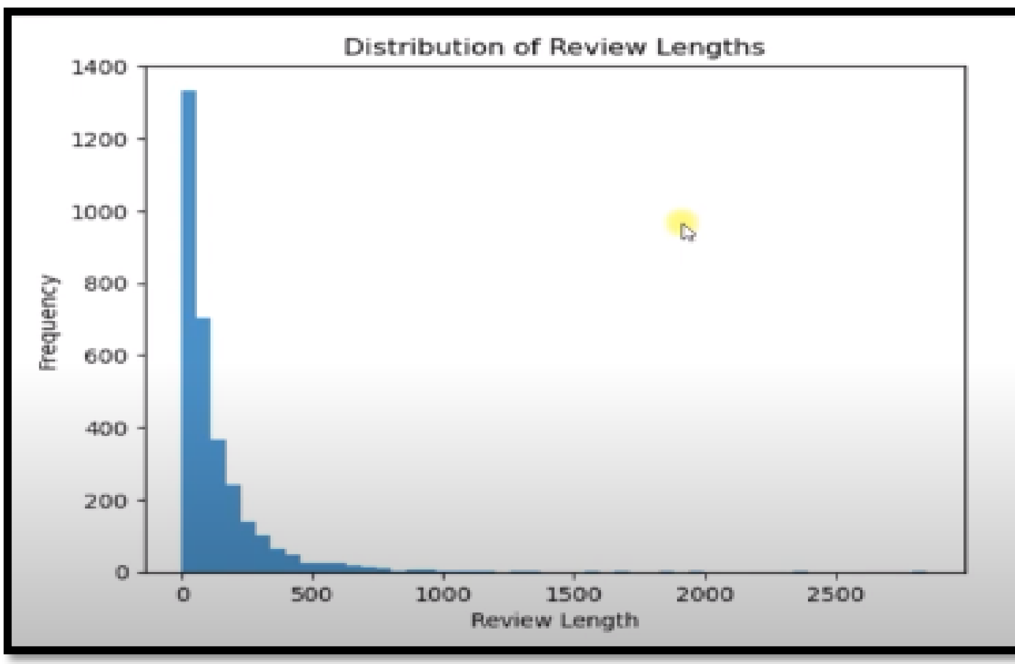


DISTRIBUTION OF REVIEW LENGTHS:

IN [12]:

```
# Calculate the Length of each review
df['review_length']=df['verified_reviews'].
apply(len)
```

```
#plt.figure(figsize=(10, 6))
plt.hist(df['review_length'],bins=50,
alpha=0.8)
plt.xlabel('Review Length')
plt.ylabel('Frequency')
plt.title('Distribution of Review Lengths')
plt.show()
```



TEXT PREPROCESSING :

- Tokenization
- Punctuation Removal and Lowercasing

- Stopword Removal
- Stemming

FEATURE EXTRACTION USING TF-IDF IN SENTIMENT ANALYSIS

- In sentiment analysis, feature extraction is a crucial step that converts processed text data into numbers, suitable for machine learning.
- One common technique is TF-IDF (Term Frequency-Inverse Document Frequency), which assigns weights to words in text documents.
- It measures word importance within a

document while considering its frequency across all documents.

MODEL SELECTION AND TRAINING:

- The models employed in this project- Logistic Regression and Multinomial Naive Bayes-and their significance in sentiment analysis.
  - Logistic Regression
  - Multinomial Naive Bayes

MODEL EVALUATION METRICS:

In the field of sentiment analysis, assessing how well our trained models perform is crucial. We use model evaluation metrics to measure their classification accuracy.

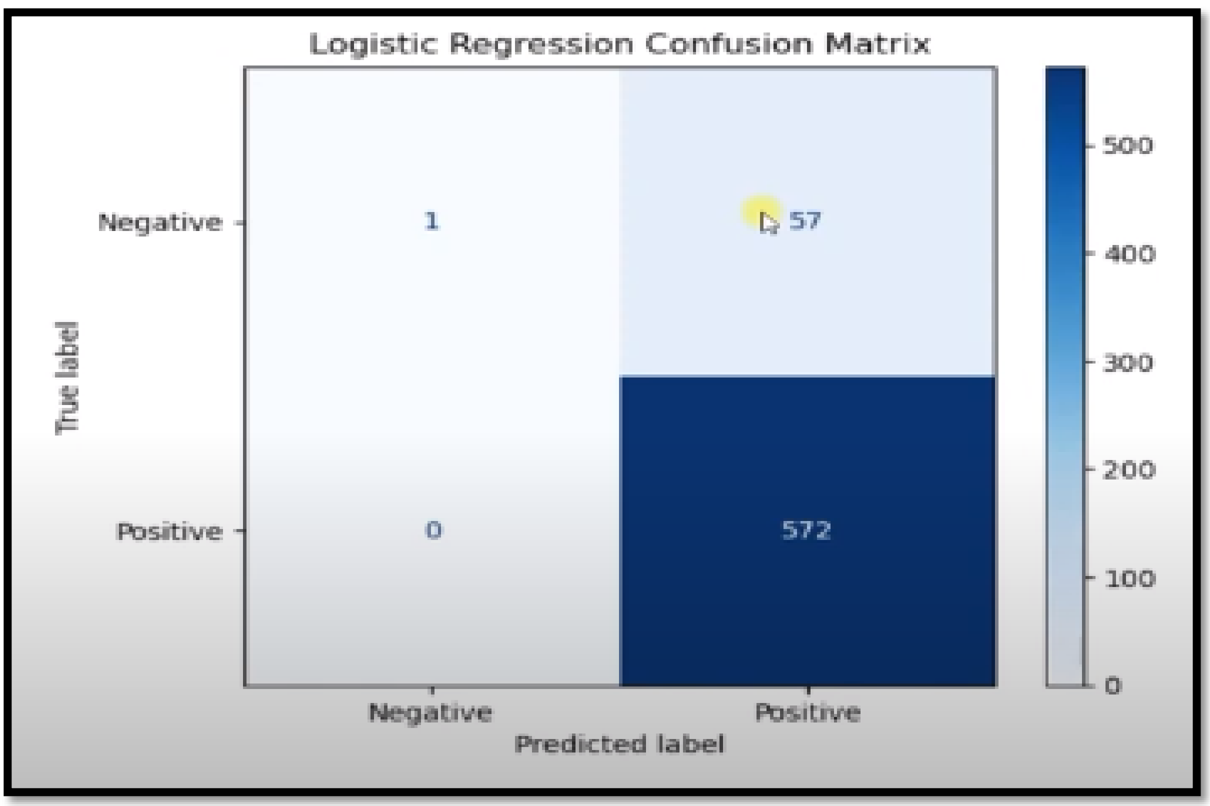
IMPORTANT MODEL EVALUATION METRICS:

- Accuracy
- Precision
- Recall (Sensitivity)

- F1-Score

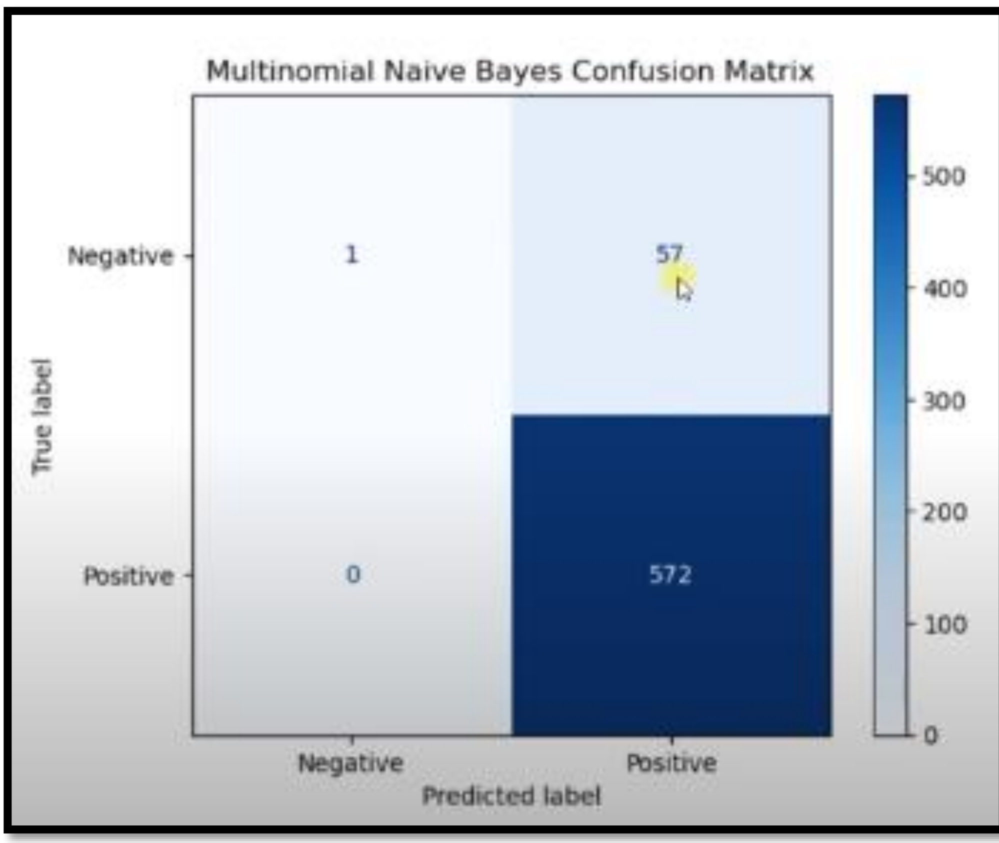
LOGISTIC REGRESSION CONFUSION MATRIX:

plot_confusion_matrix(logistic_regression model, X_test, y_test, title='Logistic Regression Confusion Matrix')



MULTINOMIAL NAIVE BAYES CONFUSION MATRIX

plot_confusion_matrix(multinomial_nb_model, X_test, y_test, title='Multinomial Naive Bayes Confusion Matrix')



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