Product Review Prediction with Multinomial Naive Bayes

The multinomial Naive Bayes is suitable for classification with discrete features(e.g., word counts for text classification). The multinomial distribution typically requires integer feature counts. However, in practice, fractional counts such as term frequency-inverse document frequency may also work.

Data Source: GitHub

Import Library

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

Import Dataset

Descibe Data

df.head()

<u>→</u> ▼	Clot	hing ID	Age	Title	Review	Rating	Recommended	Positive Feedback	Division	Departmen
	0	767	33	NaN	Absolutely wonderful - silky and sexy and comf	4	1	0	Initmates	Intimat
	1	1080	34	NaN	Love this dress! it's sooo pretty. i happene	5	1	4	General	Dresse
•										•
Next s	steps:	Gene	erate co	de with df		View reco	mmended plots			

df.tail()



噩

ılı.



df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 23486 entries, 0 to 23485 Data columns (total 10 columns):

Ducu	COTAMIS (COCAT TO	coramiis).	
#	Column	Non-Null Count	Dtype
0	Clothing ID	23486 non-null	int64
1	Age	23486 non-null	int64
2	Title	19676 non-null	object
3	Review	22641 non-null	object
4	Rating	23486 non-null	int64
5	Recommended	23486 non-null	int64
6	Positive Feedback	23486 non-null	int64
7	Division	23472 non-null	object
8	Department	23472 non-null	object
9	Category	23472 non-null	object

dtypes: int64(5), object(5) memory usage: 1.8+ MB

df.describe()

_						
$\overrightarrow{\Rightarrow}$		Clothing ID	Age	Rating	Recommended	Positive Feedback
	count	23486.000000	23486.000000	23486.000000	23486.000000	23486.000000
	mean	918.118709	43.198544	4.196032	0.822362	2.535936
	std	203.298980	12.279544	1.110031	0.382216	5.702202
	min	0.000000	18.000000	1.000000	0.000000	0.000000
	25%	861.000000	34.000000	4.000000	1.000000	0.000000
	50%	936.000000	41.000000	5.000000	1.000000	1.000000
	75%	1078.000000	52.000000	5.000000	1.000000	3.000000
	max	1205.000000	99.000000	5.000000	1.000000	122.000000

df.shape

→ (23486, 10)

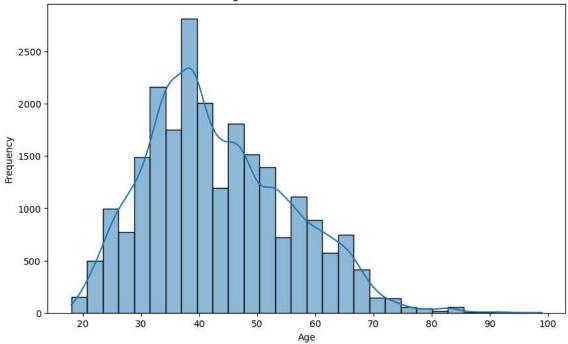
Data Visualization

Histogram of Age

plt.figure(figsize=(10, 6)) sns.histplot(df['Age'], bins=30, kde=True) plt.title('Age Distribution of Reviewers') plt.xlabel('Age') plt.ylabel('Frequency') plt.show()

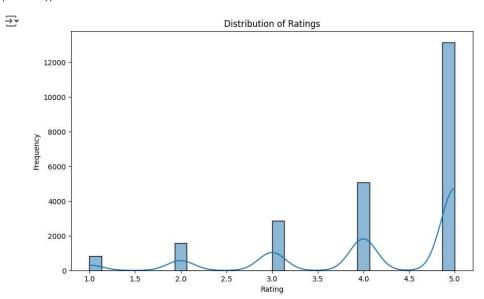




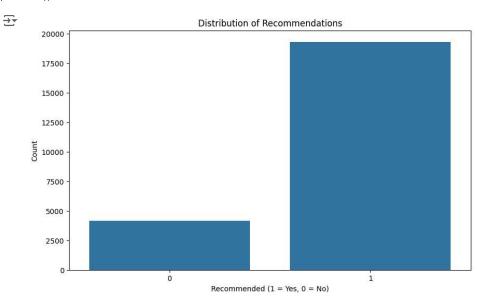


Bar Plot of Ratings

```
plt.figure(figsize=(10, 6))
sns.histplot(df['Rating'], bins=30, kde=True)
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```



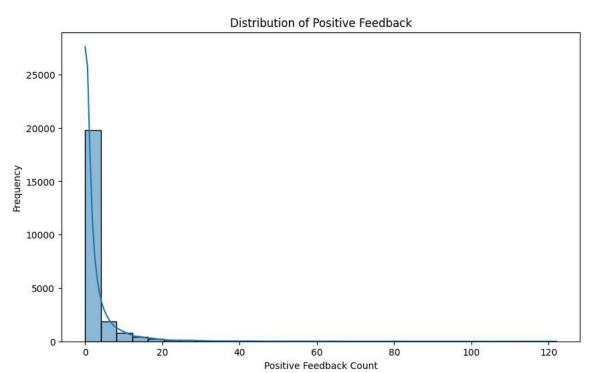
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Recommended', data=df)
plt.title('Distribution of Recommendations')
plt.xlabel('Recommended (1 = Yes, 0 = No)')
plt.ylabel('Count')
plt.show()
```



Histogram of Positive Feedback

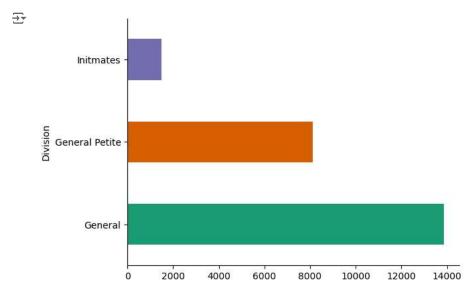
 $\overline{\Rightarrow}$

```
plt.figure(figsize=(10, 6))
sns.histplot(df['Positive Feedback'], bins=30, kde=True)
plt.title('Distribution of Positive Feedback')
plt.xlabel('Positive Feedback Count')
plt.ylabel('Frequency')
plt.show()
```



Division

```
# @title Division
df.groupby('Division').size().plot(kind='barh', color=sns.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```



Missing Values/Data Preprocessing

```
df.isna().sum()

→ Clothing ID
                             0
     Age
                             0
     Title
                          3810
     Review
                           845
     Rating
                             0
     Recommended
     Positive Feedback
                             a
     Division
                            14
     Department
     Category
                            14
     dtype: int64
df[df['Review']==""]=np.NaN
df['Review'].fillna("No Review",inplace=True)
df.isna().sum()

→ Clothing ID
                             0
     Age
                             0
     Title
                          3810
     Review
                             0
     Rating
                             a
     Recommended
                             0
     Positive Feedback
                            14
     Division
     Department
                            14
     Category
     dtype: int64
```

df['Review']

```
Absolutely wonderful - silky and sexy and comf...

Love this dress! it's sooo pretty. i happene...

I had such high hopes for this dress and reall...

I love, love, love this jumpsuit. it's fun, fl...

This shirt is very flattering to all due to th...

23481 I was very happy to snag this dress at such a ...

23482 It reminds me of maternity clothes. soft, stre...
```

```
23483 This fit well, but the top was very see throug...
23484 I bought this dress for a wedding i have this ...
23485 This dress in a lovely platinum is feminine an...
Name: Review, Length: 23486, dtype: object
```

→ Define Target Variable (y) and Feature Variables (X)

Train Test Split

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.7,stratify=y,random_state=2529)

x_train.shape,x_test.shape,y_train.shape,y_test.shape

((16440,), (7046,), (16440,), (7046,))
```

Get Features Text Conversion to Tokens

Get Model Train

```
from sklearn.naive_bayes import MultinomialNB
model=MultinomialNB()
model.fit(x_train,y_train)

...
...
...
MultinomialNB()
```

Get Model Prediction

```
y_pred=model.predict(x_test)

y_pred.shape

→ (7046,)

y_pred

→ array([1, 5, 5, ..., 5, 5, 5])
```

Get Probability of Each Predicted Class

Get Model Evaluation

print(classification_report(y_test,y_pred))

→	precision	recall	f1-score	support
1	0.02	0.06	0.03	253
2	0.08	0.09	0.09	470
3	0.14	0.13	0.14	861
4	0.25	0.22	0.23	1523
5	0.60	0.56	0.58	3939
accuracy			0.39	7046
macro avg	0.22	0.21	0.21	7046
weighted avg	0.42	0.39	0.40	7046

Recategories Ratings as Poor(0) and Good(1)

```
df['Rating'].value_counts()

→ Rating
5 13131
4 5977
3 2871
2 1565
1 842
Name: count, dtype: int64
```

Re-Rating as 1,2,3 as 0 and 4,5 as 1

```
df.replace({'Rating' : {1:0,2:0,3:0,4:1,5:1}},inplace=True)
y=df['Rating']
x=df['Review']
```

Train Test Split

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.7,stratify=y,random_state=2529)

x_train.shape,x_test.shape,y_train.shape,y_test.shape

$\frac{1}{2}$ ((16440,), (7046,), (16440,), (7046,))
```

Get Feature Text Conversion to Tokens

```
from sklearn.feature_extraction.text import CountVectorizer

cv=CountVectorizer(lowercase=True,analyzer='word',ngram_range=(2,3),stop_words='english',max_features=5000)

x_train=cv.fit_transform(x_train)

x_test=cv.fit_transform(x_test)
```

Get Model Re-Train

Get Model Prediction

```
y_pred=model.predict(x_test)

y_pred.shape

→ (7046,)

y_pred

→ array([1, 1, 1, ..., 1, 1, 1])
```

Get Model Evaluation

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

print(classification_report(y_test,y_pred))

	precision	recall	f1-score	support
0	0.31	0.28	0.30	1583
1	0.80	0.82	0.81	5463
accuracy			0.70	7046
macro avg	0.56	0.55	0.55	7046
weighted avg	0.69	0.70	0.69	7046

```
print(accuracy_score(y_test,y_pred))
```

→ 0.698694294635254

confusion_matrix(y_test,y_pred)

```
⇒ array([[ 449, 1134],
 [ 989, 4474]])
```

Explanation

The project predicts product reviews' sentiments using Multinomial Naive Bayes (MNB), starting with data preprocessing and feature extraction. Initially, the model predicts detailed ratings (1 to 5), but due to low accuracy, the task is simplified by categorizing ratings into binary classes: poor (0) and good (1). This retraining focuses on distinguishing between positive and negative reviews, significantly improving the model's performance. The final model achieves around 70% accuracy, effectively classifying reviews as positive or negative. The binary classification task reduces complexity, leading to better performance metrics. Retraining with this simplified target improves accuracy and provides more reliable predictions for review sentiment.