In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
```

In [2]:
```python
data = pd.read_csv("amazon.csv")
```

In [3]:
```python
data.head(5)
```

Out[3]:

	reviewText	Positive
0	This is a one of the best apps acording to a b...	1
1	This is a pretty good version of the game for ...	1
2	this is a really cool game. there are a bunch ...	1
3	This is a silly game and can be frustrating, b...	1
4	This is a terrific game on any pad. Hrs of fun...	1

Initial Observations

In [4]:
```python
df = data.copy()
```

In [5]:
```python
df.shape
```

Out[5]:
```
(20000, 2)
```

In [6]:
```python
# We have 20000 rows and 2 columns
```

In [7]:
```python
df.nunique()
```

Out[7]:
```
reviewText    20000
Positive          2
dtype: int64
```

In [8]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   reviewText  20000 non-null  object
 1   Positive    20000 non-null  int64 
dtypes: int64(1), object(1)
memory usage: 312.6+ KB
```

In [9]:
```python
df.describe()
```

Out[9]:

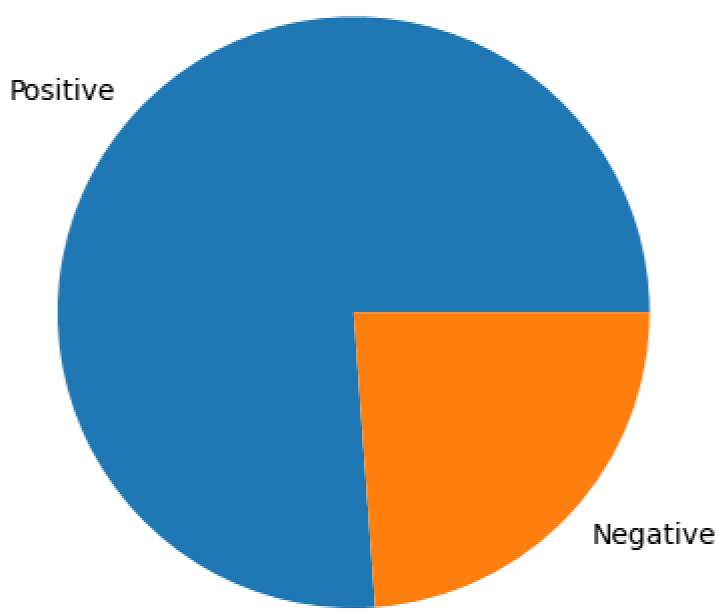
	Positive
count	20000.000000
mean	0.761650
std	0.426085
min	0.000000
25%	1.000000
50%	1.000000
75%	1.000000
max	1.000000

In [10]:
```
df.dtypes
```

Out[10]:
```
reviewText    object
Positive       int64
dtype: object
```

In [11]:
```
label = ["Positive","Negative"]
values = df["Positive"].value_counts()
plt.pie(labels = label, x = values)
```

Out[11]:
```
([<matplotlib.patches.Wedge at 0x20a85a92f50>,
  <matplotlib.patches.Wedge at 0x20a85a86d10>],
 [Text(-0.8057580416543408, 0.748835080848488, 'Positive'),
  Text(0.8057581117653374, -0.7488350054079725, 'Negative')])
```



We can clearly see class imbalance here

Word Cloud

In [12]:
```
positive_reviews = ' '.join(df[df['Positive'] == 1]['reviewText'])
negative_reviews = ' '.join(df[df['Positive'] == 0]['reviewText'])
```

In [13]:
```
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(pos
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title("Positive Reviews")
plt.show()
```

Positive Reviews

In [14]:
```
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(neg
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title("Negative Reviews")
plt.show()
```

Negative Reviews

Data Preprocessing

Null Handling

In [15]:

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

Out[15]:

```
reviewText    0
Positive      0
dtype: int64
```

Text Preprocessing

In [16]:

```
df["reviewText"][0]
```

Out[16]:

```
'This is a one of the best apps acording to a bunch of people and I agree it has b
ombs eggs pigs TNT king pigs and realustic stuff'
```

In [17]:

```
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import plotly.express as px
import string
```

In [18]:

```
stopwords.fileids()
```

Out[18]:
```
['arabic',
 'azerbaijani',
 'basque',
 'bengali',
 'catalan',
 'chinese',
 'danish',
 'dutch',
 'english',
 'finnish',
 'french',
 'german',
 'greek',
 'hebrew',
 'hinglish',
 'hungarian',
 'indonesian',
 'italian',
 'kazakh',
 'nepali',
 'norwegian',
 'portuguese',
 'romanian',
 'russian',
 'slovene',
 'spanish',
 'swedish',
 'tajik',
 'turkish']
```

In [19]:
```
stopword = stopwords.words("English")
```

In [20]:
```
punctuation = string.punctuation
```

In [21]:
```
def preprocess_text(text):

    preprocess_punctuation = "".join([char for char in text if char not in punctuat
    preprocess_stopword = [char for char in preprocess_punctuation.split() if char.
    return preprocess_stopword
```

In [22]:
```
df["reviewText"] = df["reviewText"].apply(preprocess_text)
```

In [23]:
```
df.head()
```

Out[23]:

	reviewText	Positive
0	[one, best, apps, acording, bunch, people, agr...	1
1	[pretty, good, version, game, free, LOTS, diff...	1
2	[really, cool, game, bunch, levels, find, gold...	1
3	[silly, game, frustrating, lots, fun, definite...	1
4	[terrific, game, pad, Hrs, fun, grandkids, lov...	1

Text Normalization/Scaling

In [24]:
```
lemmatizer = WordNetLemmatizer()
```

In [25]:
```
df["reviewText"][0]
```

Out[25]:
```
['one',
 'best',
 'apps',
 'acording',
 'bunch',
 'people',
 'agree',
 'bombs',
 'eggs',
 'pigs',
 'TNT',
 'king',
 'pigs',
 'realustic',
 'stuff']
```

In [26]:
```
def normalize_data(text):
    normalized_text = ' '.join([lemmatizer.lemmatize(word) for word in text])
    return normalized_text
```

In [27]:
```
df["reviewText"] = df["reviewText"].apply(normalize_data)
```

In [28]:
```
df.head()
```

Out[28]:

	reviewText	Positive
0	one best apps acording bunch people agree bomb...	1
1	pretty good version game free LOTS different l...	1
2	really cool game bunch level find golden egg s...	1
3	silly game frustrating lot fun definitely reco...	1
4	terrific game pad Hrs fun grandkids love Great...	1

Vectorization

In [29]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [30]:
```
vectorizer = TfidfVectorizer()
```

In [31]:
```
X = vectorizer.fit_transform(df["reviewText"])
y = df["Positive"]
```

In [32]:
```
X.shape
```

Out[32]:
```
(20000, 22617)
```

Data Spliting

In [33]:
```
from sklearn.model_selection import train_test_split
```

In [34]:
```
xtrain, xtest, ytrain, ytest = train_test_split(X, y, test_size=0.3, random_state=4
```

In [35]:
```
xtrain.shape
```

Out[35]:
```
(14000, 22617)
```

Model Training

In [36]:
```
from sklearn.naive_bayes import MultinomialNB, BernoulliNB # naive bayes classifier
from sklearn.linear_model import LogisticRegression
import sklearn.metrics as mt
```

In [37]:
```
mnbNB = MultinomialNB()
berNB = BernoulliNB()
lr = LogisticRegression()
```

In [38]:
```
models = [mnbNB, berNB, lr]
```

In [39]:
```python
def train_models(X_train,y_train, models):
    for model in models:
        model.fit(X_train,y_train)
        print(f"{model} : {mt.accuracy_score(y_train, model.predict(X_train))}")
```

In [40]:
```python
train_models(xtrain,ytrain,models)
```

```
MultinomialNB() : 0.8077857142857143
BernoulliNB() : 0.9132857142857143
LogisticRegression() : 0.9223571428571429
```

Model Evaluation

In [41]:
```python
def evaluate_model(X_test, y_test, models):

    y_predicted_list = []
    accuracy_scores = []

    for model in models:
        prediction = model.predict(X_test)
        y_predicted_list.append(prediction)
        accuracy_scores.append(mt.accuracy_score(y_test,prediction))

    for idx, prediction in enumerate(y_predicted_list):
        print(f"{models[idx]}")
        print()
        print("Test Accuracy Score: ",accuracy_scores[idx])
        print()
        print(mt.classification_report(y_test,prediction))
        print("---------------------------------------------------------------------

    return accuracy_scores, y_predicted_list
```

In [42]:
```python
accuracy_scores, predictions = evaluate_model(xtest,ytest,models)
```

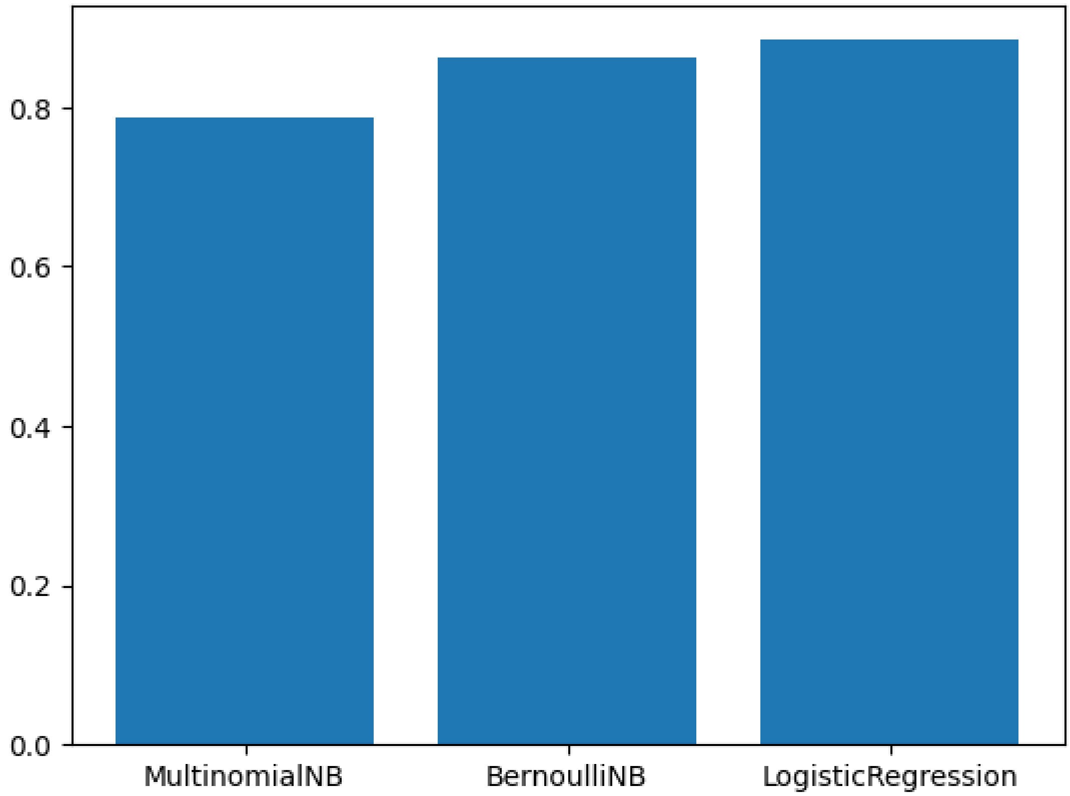
```
MultinomialNB()

Test Accuracy Score:  0.7873333333333333

              precision    recall  f1-score   support

           0       0.91      0.11      0.19      1411
           1       0.78      1.00      0.88      4589

    accuracy                           0.79      6000
   macro avg       0.85      0.55      0.53      6000
weighted avg       0.81      0.79      0.72      6000

------------------------------------------------------------------------
BernoulliNB()

Test Accuracy Score:  0.8635

              precision    recall  f1-score   support

           0       0.80      0.56      0.66      1411
           1       0.88      0.96      0.91      4589

    accuracy                           0.86      6000
   macro avg       0.84      0.76      0.79      6000
weighted avg       0.86      0.86      0.85      6000

------------------------------------------------------------------------
LogisticRegression()

Test Accuracy Score:  0.8843333333333333

              precision    recall  f1-score   support

           0       0.86      0.60      0.71      1411
           1       0.89      0.97      0.93      4589

    accuracy                           0.88      6000
   macro avg       0.88      0.79      0.82      6000
weighted avg       0.88      0.88      0.88      6000

------------------------------------------------------------------------
```

By analyzing the classification reports above, we can see that Logistic Regression has the best accuracy with 88%.

Accuracy Comparison

In [43]:
```
plt.bar(['MultinomialNB','BernoulliNB','LogisticRegression'], accuracy_scores)
```

Out[43]:
```
<BarContainer object of 3 artists>
```



Multinomial Naive Bayes:

- **Test Accuracy Score:** 78.73%
- **Precision-Recall-F1 Score:**
  - Class 0: Precision 91%, Recall 11%, F1-Score 19%
  - Class 1: Precision 78%, Recall 100%, F1-Score 88%

An interesting start with a good overall accuracy, though there's room for improvement in predicting Class 0.

Bernoulli Naive Bayes:

- **Test Accuracy Score:** 86.35%
- **Precision-Recall-F1 Score:**
  - Class 0: Precision 80%, Recall 56%, F1-Score 66%
  - Class 1: Precision 88%, Recall 96%, F1-Score 91%

Bernoulli Naive Bayes exhibits strong performance, particularly in correctly identifying instances of Class 1.

Logistic Regression:

- **Test Accuracy Score:** 88.43%

- **Precision-Recall-F1 Score:**
  - Class 0: Precision 86%, Recall 60%, F1-Score 71%
  - Class 1: Precision 89%, Recall 97%, F1-Score 93%

Logistic Regression takes the lead with the highest accuracy and robust performance across both classes.

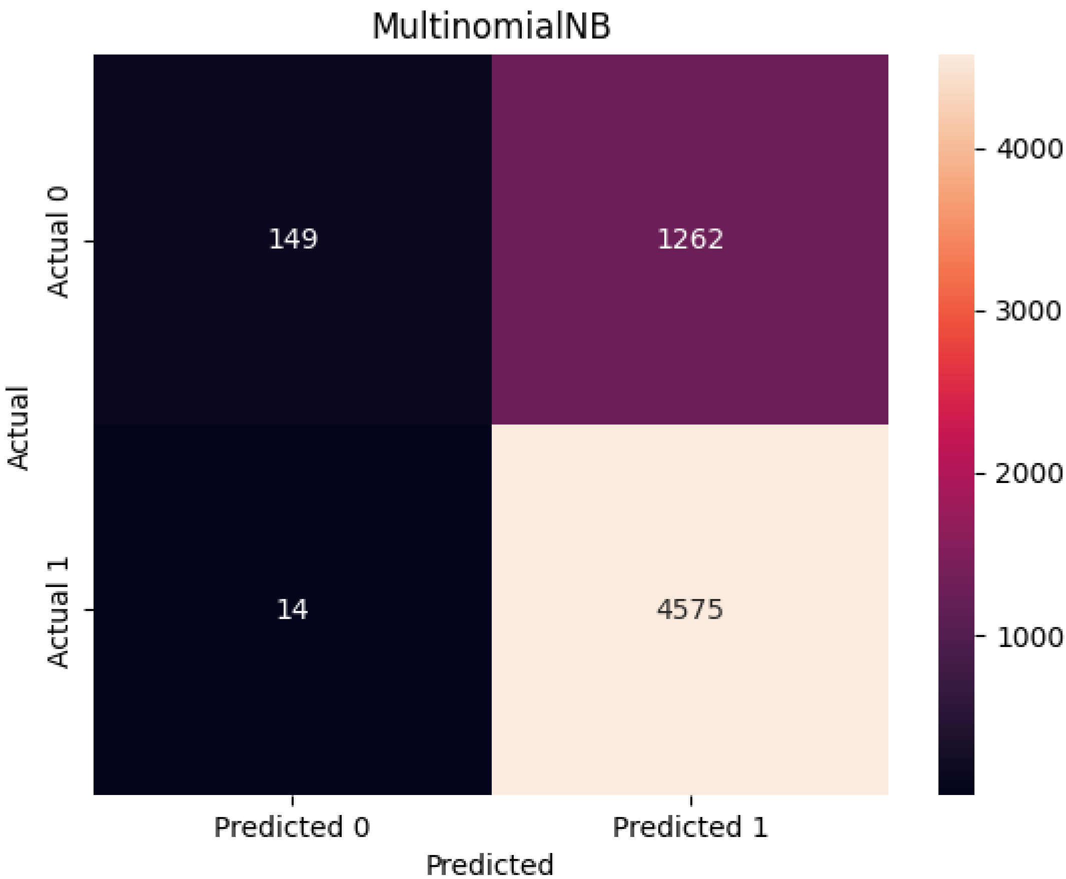
Insights:

- Multinomial Naive Bayes shows potential but may benefit from additional optimization, especially in predicting Class 0.
- Bernoulli Naive Bayes excels in predicting Class 1, indicating its effectiveness in capturing relevant patterns.
- Logistic Regression emerges as a strong contender, offering high accuracy and balanced performance.

Confusion Matrix

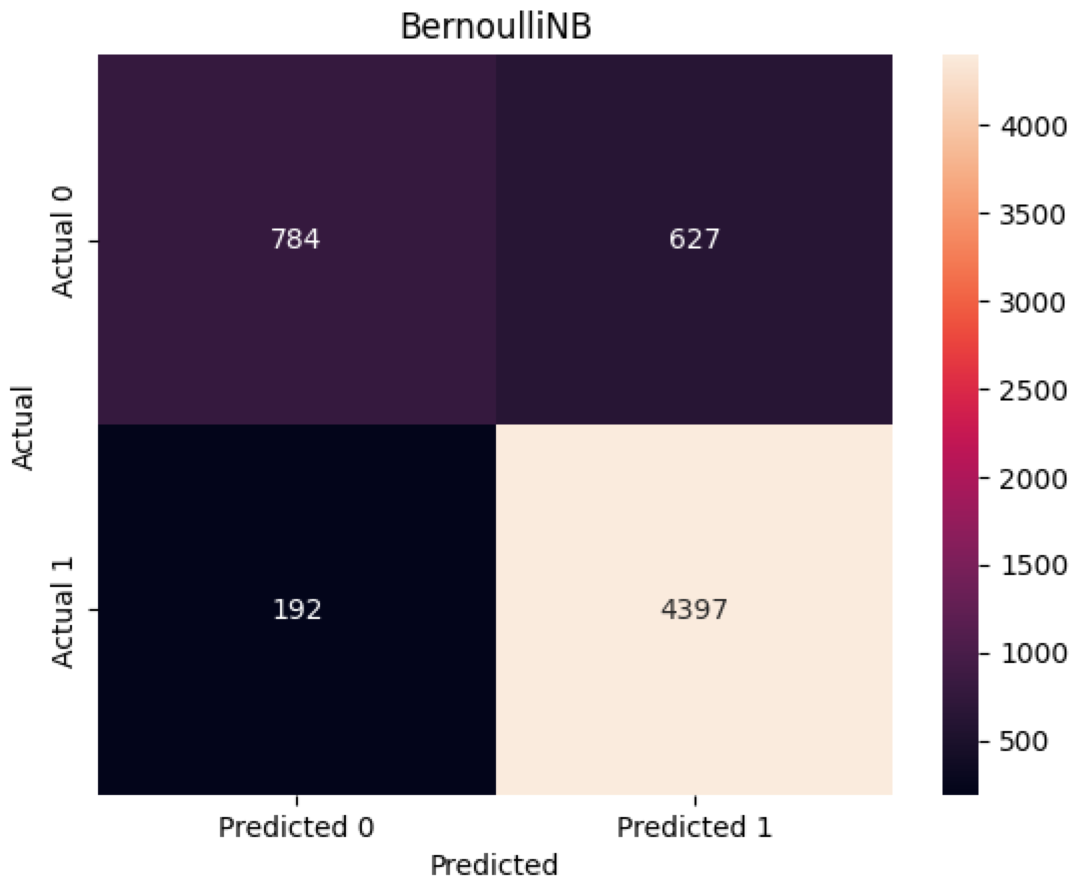
In [44]:
```
sns.heatmap(mt.confusion_matrix(ytest, predictions[0]),annot= True,fmt="d",yticklab
plt.title("MultinomialNB")
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[44]:
```
Text(50.722222222222214, 0.5, 'Actual')
```



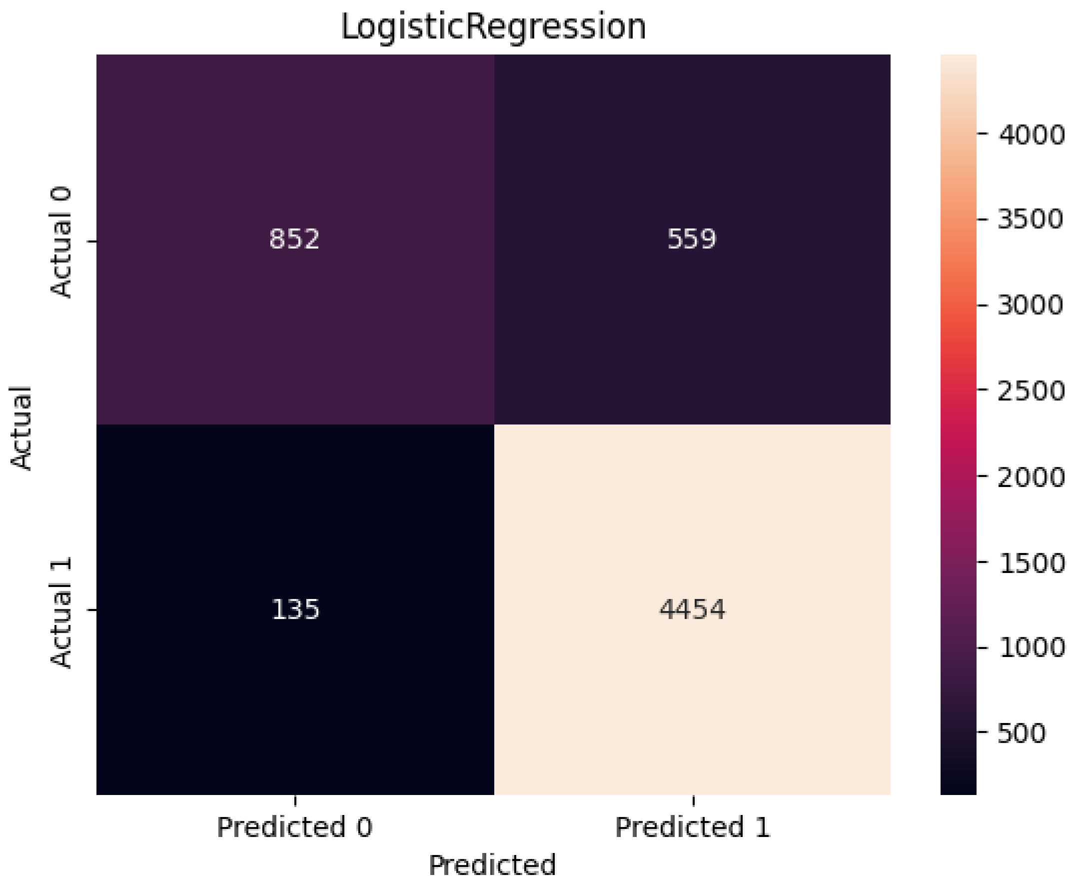
In [45]:
```
sns.heatmap(mt.confusion_matrix(ytest, predictions[1]),annot= True,fmt="d",yticklab
plt.title("BernoulliNB")
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[45]:
```
Text(50.722222222222214, 0.5, 'Actual')
```



In [46]:
```
sns.heatmap(mt.confusion_matrix(ytest, predictions[2]),annot= True,fmt="d",yticklab
plt.title("LogisticRegression")
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[46]: Text(50.722222222222214, 0.5, 'Actual')



Multinomial Naive Bayes:

- **True Positives (TP):** 4575
- **True Negatives (TN):** 149
- **False Positives (FP):** 1262
- **False Negatives (FN):** 14

Observations:

- The model performs well in correctly predicting Class 1 (heart attack occurrence) with a high True Positive count.
- However, it struggles in predicting instances of Class 0, as indicated by the low True Negative count and a relatively high False Positive count.

Bernoulli Naive Bayes:

- **True Positives (TP):** 4397
- **True Negatives (TN):** 784
- **False Positives (FP):** 627
- **False Negatives (FN):** 192

Observations:

- The model shows a strong ability to predict both Class 0 and Class 1, with high counts in both True Positives and True Negatives.
- The False Positive count is relatively low, indicating a good balance between precision and recall.

Logistic Regression:

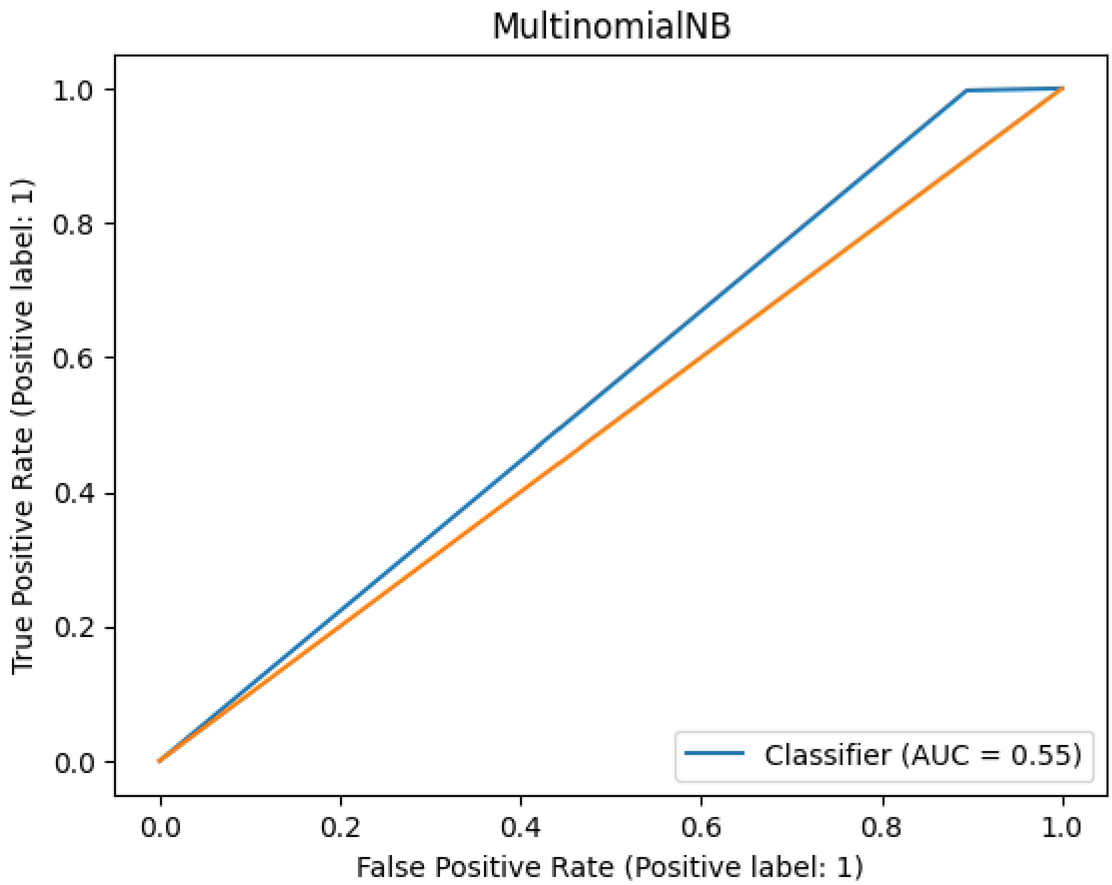
- **True Positives (TP):** 4454
- **True Negatives (TN):** 852
- **False Positives (FP):** 559
- **False Negatives (FN):** 135

Observations:

- Logistic Regression demonstrates a balanced performance in predicting both classes, with high counts in both True Positives and True Negatives.
- The False Positive count is relatively low, contributing to the model's high precision and accuracy.

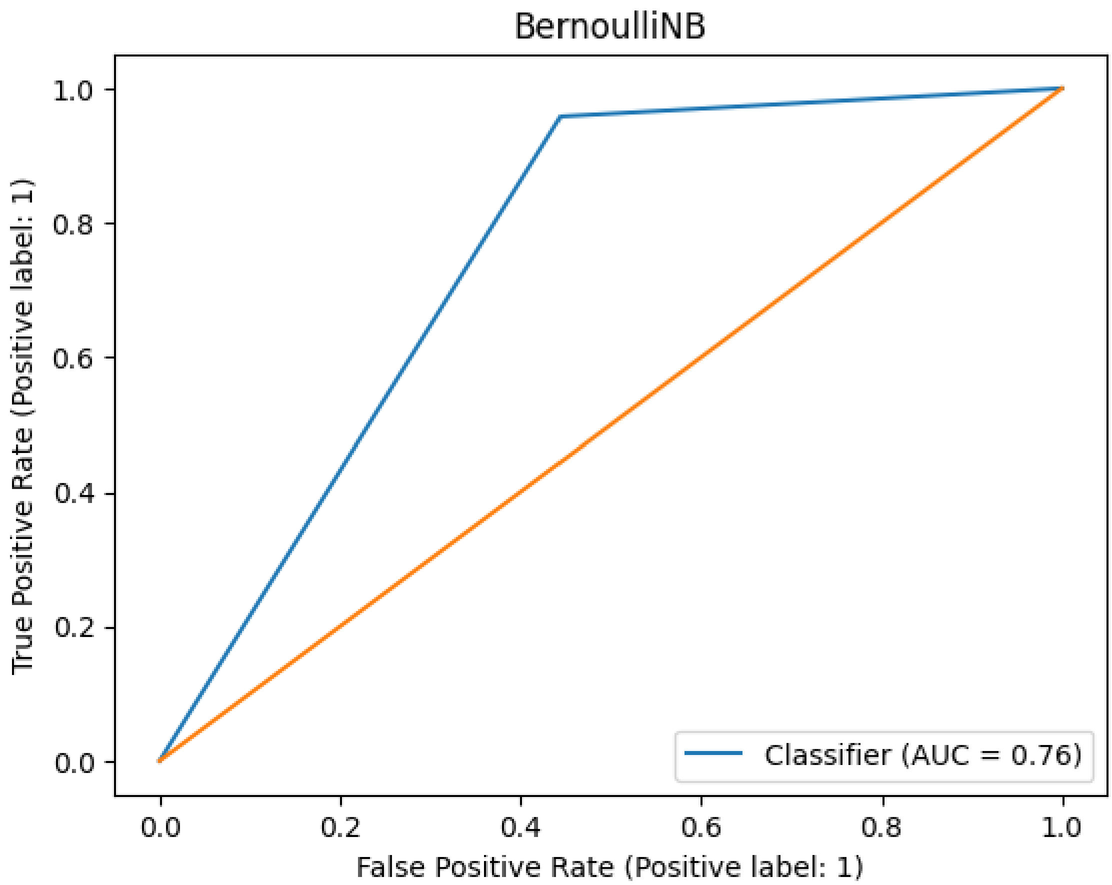
Roc Auc Curve

In [50]:
```
mt.RocCurveDisplay.from_predictions(ytest, predictions[0])
plt.plot([0,1],[0,1])
plt.title("MultinomialNB")
plt.show()
```

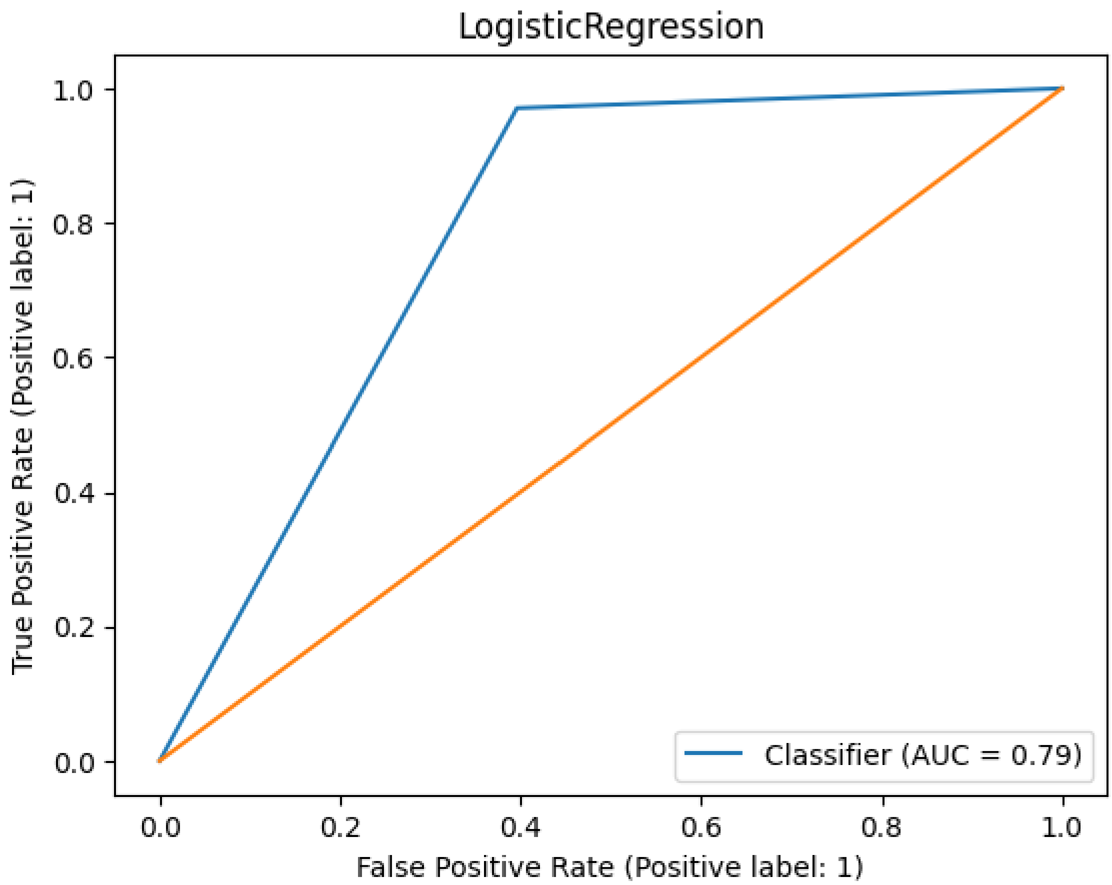


In [51]:

```
mt.RocCurveDisplay.from_predictions(ytest, predictions[1])
plt.plot([0,1],[0,1])
plt.title("BernoulliNB")
plt.show()
```



In [52]:
```
mt.RocCurveDisplay.from_predictions(ytest, predictions[2])
plt.plot([0,1],[0,1])
plt.title("LogisticRegression")
plt.show()
```



The Logistic Regression Model performs better compared to other two models in ROC AUC Curve with a coverage of 79% percent.

Summary:

- All three models perform well in predicting Class 1 (heart attack occurrence), with high True Positive counts.
- Multinomial Naive Bayes struggles more with predicting instances of Class 0, while Bernoulli Naive Bayes and Logistic Regression demonstrate better balance in predicting both classes.
- Logistic Regression stands out with the highest overall accuracy and balanced performance across both class

Recommendations:

- For Multinomial Naive Bayes, consider addressing the imbalance in predicting Class 0 through further optimization or sampling techniques.
- Continue fine-tuning hyperparameters and exploring feature engineering for all models to improve overall performance. es.

```
In [ ]:
```