In [1]:
```
import numpy as np
import sklearn
from sklearn.model_selection import train_test_split, KFold
from sklearn.preprocessing import PolynomialFeatures, StandardScaler

from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
import matplotlib.pyplot as plt

from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.metrics import confusion_matrix
```

Using Naive Bayes to predict outbreak

Getting the aggregated data

In [2]:
```
X = np.genfromtxt('data/aggregated_data.csv',delimiter = ",", usecols
=(1,3))[1:]
y = np.genfromtxt('data/aggregated_data.csv', delimiter=",", usecols =
(8))[1:]
print(X)
print(y)
```

```
[[ 0.   95.1]
 [ 0.   89.3]
 [ 0.   86.8]
 ...
 [ 1.   92.1]
 [ 1.   92.1]
 [ 1.   92.7]]
[0. 0. 0. ... 0. 0. 0.]
```

Split the dataset

In [3]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2
0, random_state=0)
```

MSE Function

In [4]:
```
def mse(y_pred,y):
    return np.mean((y_pred-y)**2)
```

Implementing the BernoulliNB

In [5]:
```
# Reference for Naive Bayes models: https://scikit-learn.org/stable/mo
dules/naive_bayes.html
# Reference for BernoulliNB model: https://scikit-learn.org/stable/mod
ules/generated/sklearn.naive_bayes.BernoulliNB.html#sklearn.naive_baye
s.BernoulliNB

bernNB = BernoulliNB(binarize=True)
bernNB.fit(X_train, y_train)
print(bernNB)

bern_y_pred = bernNB.predict(X_test)
score = accuracy_score(y_test,bern_y_pred)
print("Accuracy of BernoulliNB: " + str(score * 100) + "%")
```

```
BernoulliNB(alpha=1.0, binarize=True, class_prior=None, fit_prior=Tr
ue)
Accuracy of BernoulliNB: 96.33333333333334%
```

Computing the MSE for BernoulliNB

In [6]:
```
Ytr_pred = bernNB.predict(X_train)
Yte_pred = bernNB.predict(X_test)

print("Train MSE:", mse(Ytr_pred,y_train))
print("Train MSE:", mse(Yte_pred,y_test))
```

```
Train MSE: 0.05
Train MSE: 0.03666666666666667
```

Improving the BernoulliNB's binarize parameter

In [7]:
```
results = dict()

def improve_bernoulliNB():
    '''We can try to improve the bernoulliNB model by using different
value for the binarize function'''
    binarize_param = 0.1
    while binarize_param < 1:
        bernNB = BernoulliNB(binarize=binarize_param)
        bernNB.fit(X_train, y_train)
        #print(bernNB)

        y_pred = bernNB.predict(X_test)
        score = accuracy_score(y_test,y_pred)
        results[binarize_param] = score
        binarize_param += 0.01

def get_best_binarize_value():
    return sorted(results.items(), key = lambda x : x[1], reverse = Tr
ue)[0][0]

improve_bernoulliNB()

print("Best value for the binarize parameter: ",get_best_binarize_valu
e())
```

```
Best value for the binarize parameter:  0.1
```

In [8]:
```
bernNB = BernoulliNB(binarize=0.1)
bernNB.fit(X_train,y_train)
```

Out[8]:
```
BernoulliNB(alpha=1.0, binarize=0.1, class_prior=None, fit_prior=Tru
e)
```

Implementing the MultinomialNB

In [9]:
```
# Reference for MultinomialNB model: https://scikit-learn.org/stable/m
odules/generated/sklearn.naive_bayes.MultinomialNB.html#sklearn.naive_
bayes.MultinomialNB

multNB = MultinomialNB()

multNB.fit(X_train, y_train)
print(multNB)

mult_y_pred = multNB.predict(X_test)
score = accuracy_score(y_test,mult_y_pred)
print("Accuracy of BernoulliNB: " + str(score * 100) + "%")
```

```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
Accuracy of BernoulliNB: 96.33333333333334%
```

Computing the MSE for MultinomialNB

In [10]:
```
Ytr_pred = multNB.predict(X_train)
Yte_pred = multNB.predict(X_test)

print("Train MSE:", mse(Ytr_pred,y_train))
print("Train MSE:", mse(Yte_pred,y_test))
```

```
Train MSE: 0.05
Train MSE: 0.03666666666666667
```

Implementing the GaussianNB

In [11]:
```
# Reference for GaussianNB model: https://scikit-learn.org/stable/modu
les/generated/sklearn.naive_bayes.GaussianNB.html#sklearn.naive_bayes.
GaussianNB

gaussNB = GaussianNB()
gaussNB.fit(X_train,y_train)
print(gaussNB)

gauss_y_pred = multNB.predict(X_test)
score = accuracy_score(y_test,gauss_y_pred)
print("Accuracy of BernoulliNB: " + str(score * 100) + " %")
```

```
GaussianNB(priors=None)
Accuracy of BernoulliNB: 96.33333333333334 %
```

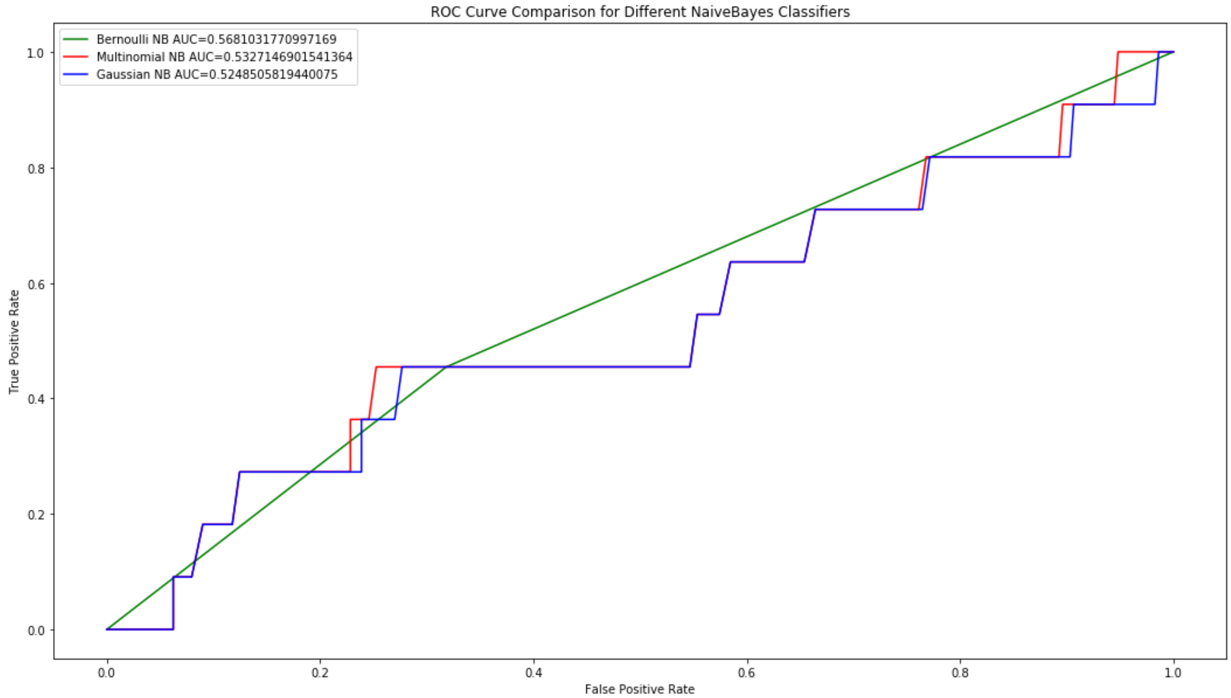
Computing the MSE

In [12]:
```
Ytr_pred = gaussNB.predict(X_train)
Yte_pred = gaussNB.predict(X_test)

print("Train MSE:", mse(Ytr_pred,y_train))
print("Train MSE:", mse(Yte_pred,y_test))
```

```
Train MSE: 0.05
Train MSE: 0.03666666666666667
```

Calculating the ROC Curve

In [13]:
```
# Reference used: https://scikit-learn.org/stable/modules/generated/sk
learn.metrics.roc_curve.html

def plot_roc_curve(prob, model, col):
    fpr, tpr, thresholds = roc_curve(y_test,prob)
    area = auc(fpr,tpr)
    plt.plot(fpr, tpr, color=col , label=model + " AUC="+ str(area))
    plt.legend()
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curve Comparison for Different NaiveBayes Classifie
rs")
plt.rcParams['figure.figsize'] = (18.0, 10.0)
bern_prob = bernNB.predict_proba(X_test)[:,1]
mult_prob = multNB.predict_proba(X_test)[:,1]
gauss_prob = gaussNB.predict_proba(X_test)[:,1]

plot_roc_curve(bern_prob,"Bernoulli NB","g")
plot_roc_curve(mult_prob, "Multinomial NB","r")
plot_roc_curve(gauss_prob, "Gaussian NB","b")
plt.show()
```

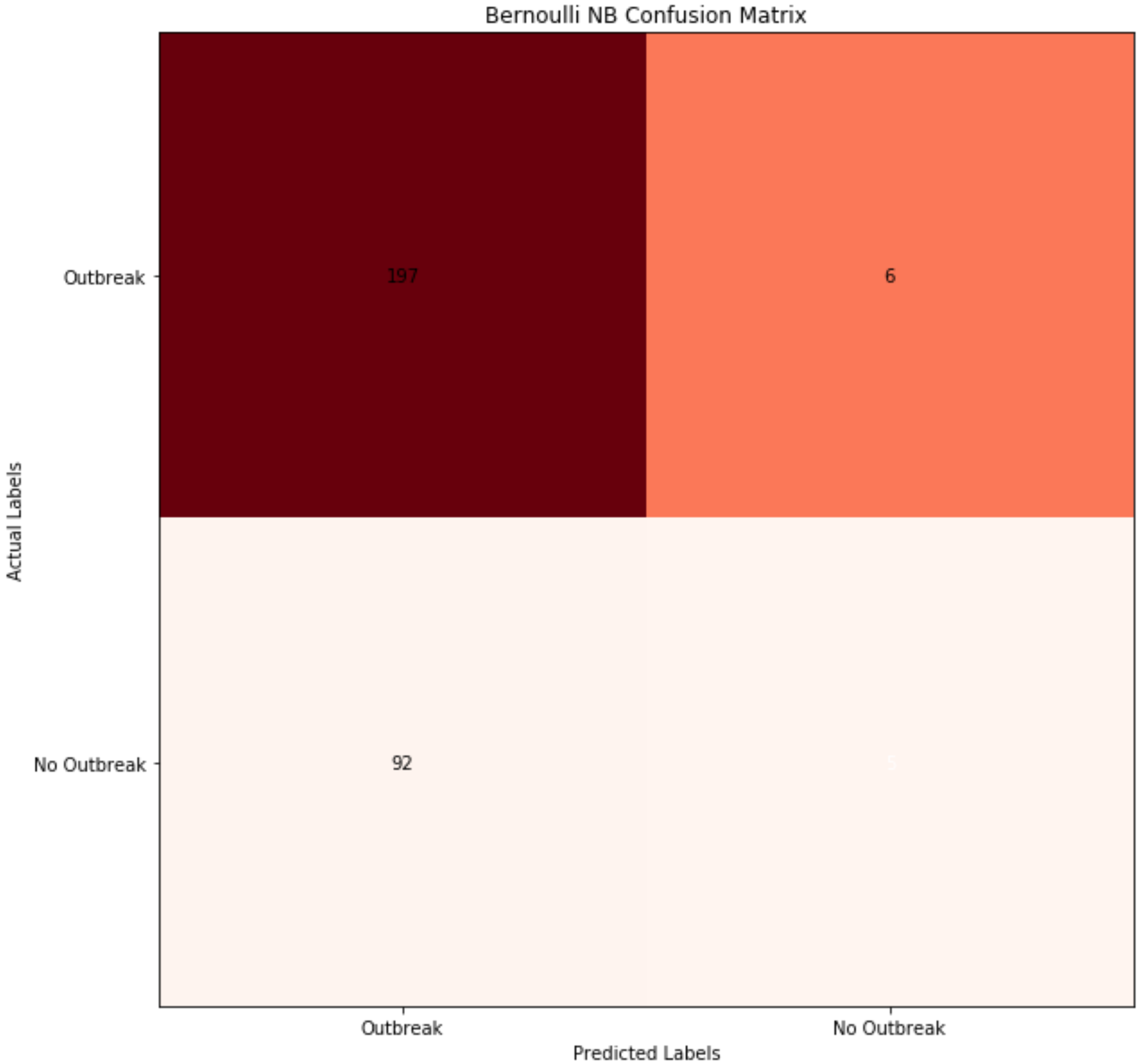


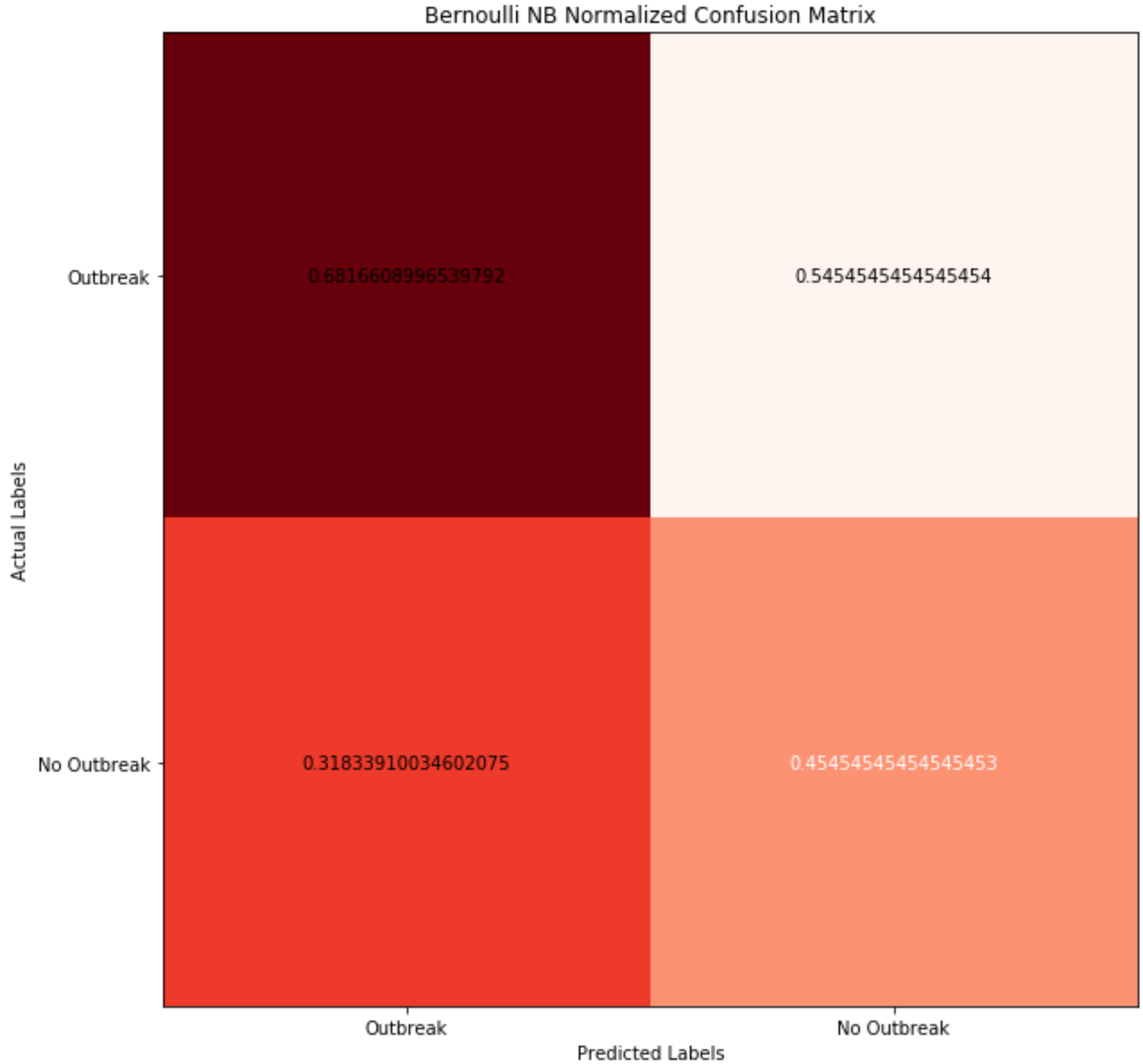
Confusion Matrix

In [14]:
```
def plotMatrix(confusionMatrix, title):
    classLabels = ["Outbreak", "No Outbreak"]
    plt.rcParams['figure.figsize'] = (18.0, 10.0)
    plt.imshow(confusionMatrix, cmap=plt.cm.Reds)
    plt.xticks([0,1], classLabels)
    plt.yticks([0,1], classLabels)
    plt.ylabel("Actual Labels")
    plt.xlabel("Predicted Labels")
    plt.title(title)
    plt.text(0, 0, str(confusionMatrix[0][0]), horizontalalignment="ce
nter", verticalalignment="center" ,color="black")
    plt.text(0, 1, str(confusionMatrix[0][1]), horizontalalignment="ce
nter", verticalalignment="center" ,color="black")
    plt.text(1, 0, str(confusionMatrix[1][0]), horizontalalignment="ce
nter", verticalalignment="center" ,color="black")
    plt.text(1, 1, str(confusionMatrix[1][1]), horizontalalignment="ce
nter", verticalalignment="center" ,color="white")
    plt.show()
```

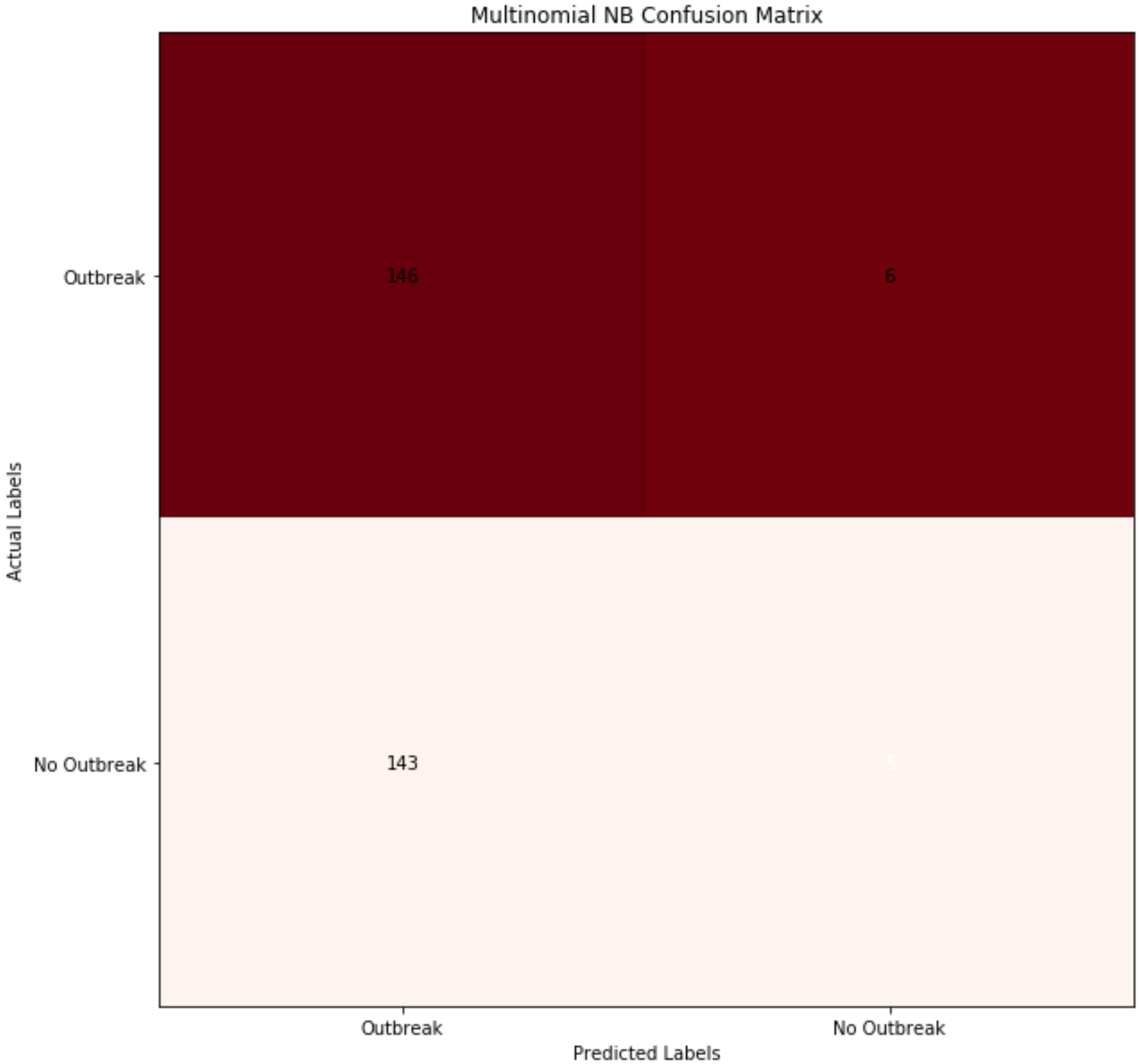
In [17]:
```
# Reference used: https://scikit-learn.org/stable/modules/generated/sk
learn.metrics.confusion_matrix.html

def generate_confusion_matrix(threshold, prob,label):
    predictions = []
    for i in range(0,prob.shape[0]):
        if prob[i][1] <= threshold:
            predictions.append(0)
        else:
            predictions.append(1)

    confusionMatrix = confusion_matrix(y_test, predictions)
    normalizedConfusionMatrix = confusionMatrix.astype('float') / conf
usionMatrix.sum(axis=1)[:, np.newaxis]
    plotMatrix(confusionMatrix, label + " Confusion Matrix")
    plotMatrix(normalizedConfusionMatrix, label + " Normalized Confusi
on Matrix")
```

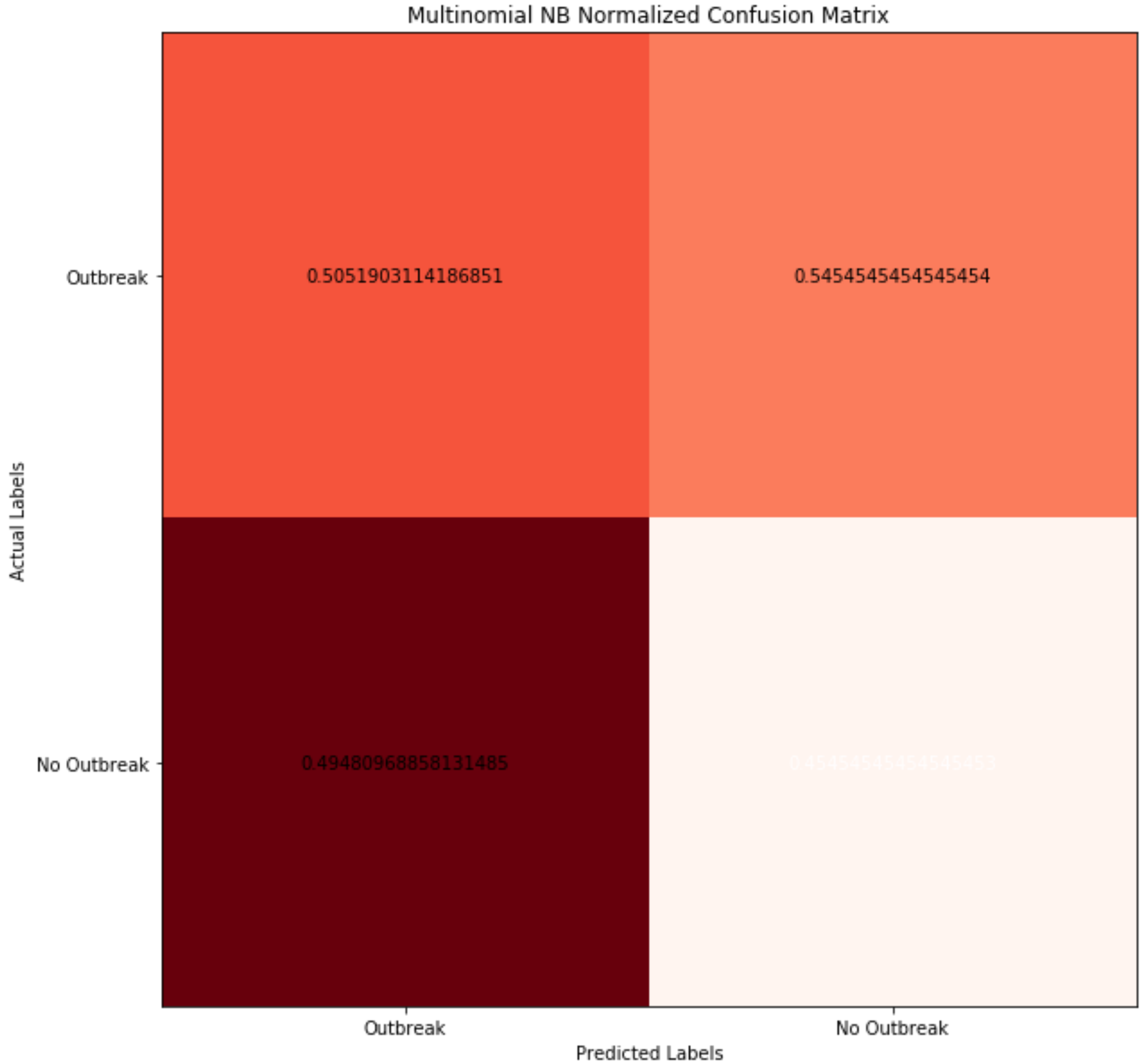
In [18]:
```
def generate_threshold(prob):
    return np.median(prob)


bern_prob = bernNB.predict_proba(X_test)
mult_prob = multNB.predict_proba(X_test)
gauss_prob = gaussNB.predict_proba(X_test)


generate_confusion_matrix(generate_threshold(bern_prob[:,1]),bern_prob
,"Bernoulli NB")
```


Bernoulli NB Confusion Matrix
Actual Labels
Outbreak
No Outbreak
197
6
92
5
Outbreak
No Outbreak
Predicted Labels

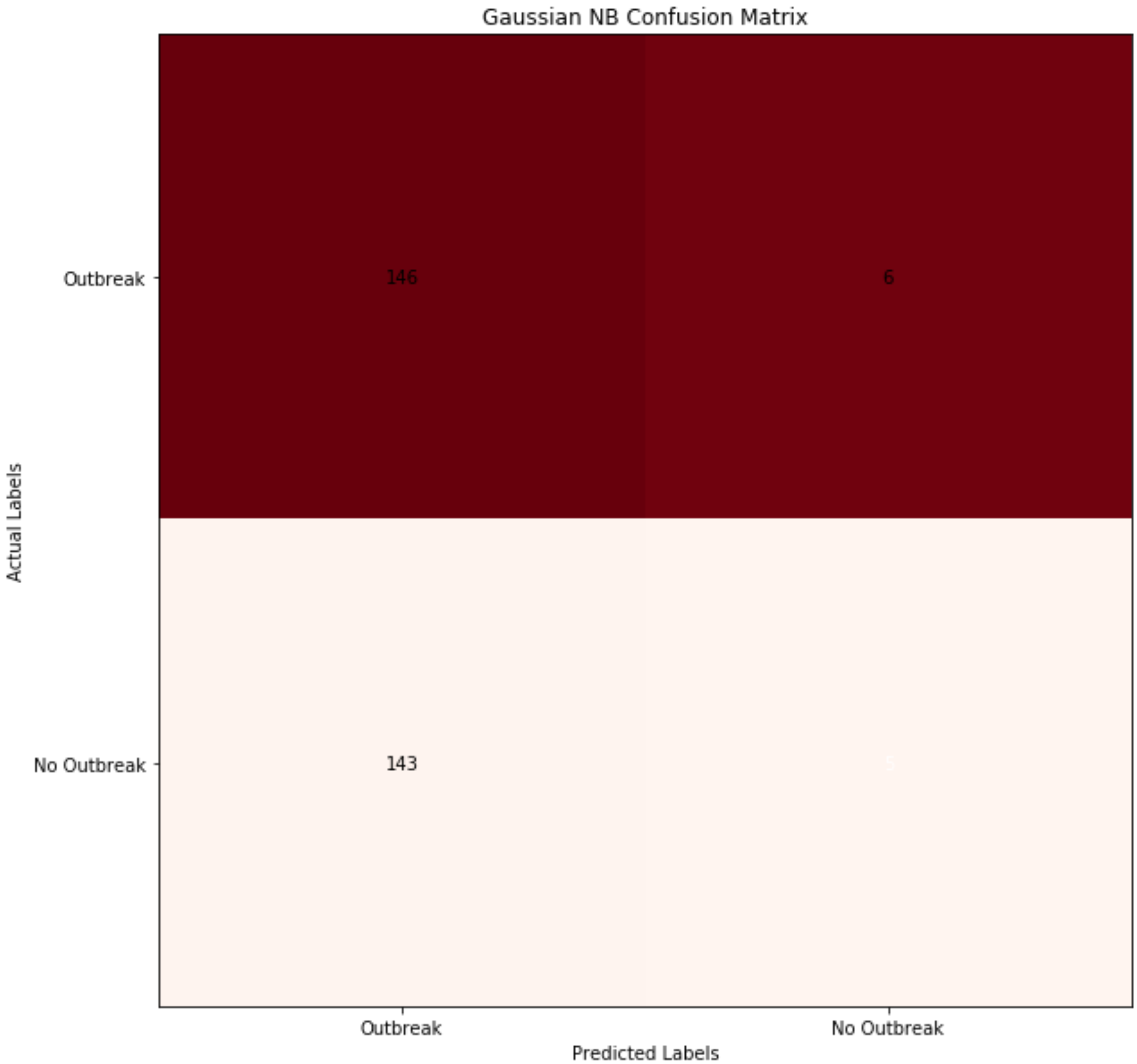


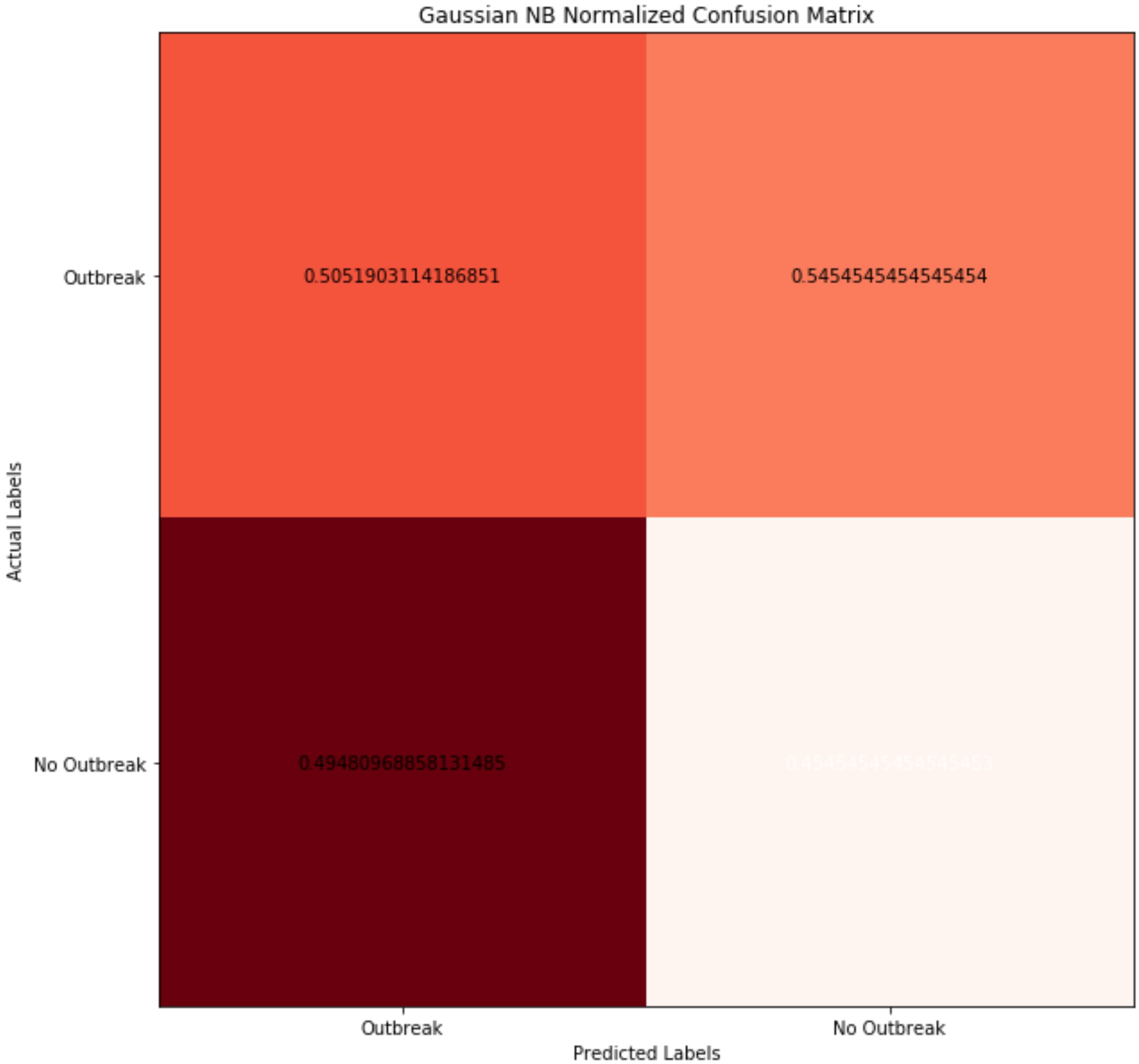
In [19]:
```
generate_confusion_matrix(generate_threshold(mult_prob[:,1]),mult_prob
,"Multinomial NB")
```


Multinomial NB Confusion Matrix
Outbreak
No Outbreak
146
6
143
5
Actual Labels
Outbreak
No Outbreak
Predicted Labels



In [20]:
```
generate_confusion_matrix(generate_threshold(gauss_prob[:,1]),gauss_pr
ob,"Gaussian NB")
```


Gaussian NB Confusion Matrix
Outbreak
No Outbreak
146
6
143
5
Actual Labels
Outbreak
No Outbreak
Predicted Labels


Gaussian NB Normalized Confusion Matrix
Outbreak
No Outbreak
Actual Labels
0.5051903114186851
0.5454545454545454
0.49480968858131485
0.4545454545454545453
Outbreak
No Outbreak
Predicted Labels