In [1]:
```
#!pip install spacy
```

In [2]:
```
#!python -m spacy download en_core_web_sm
```

In [3]:
```
import warnings
warnings.filterwarnings('ignore')

# From Example Code  https://github.com/Swathiu/Detecting-Fake-Reviews/blob/master/Deception_Detection.py
import pandas as pd
import numpy as np

from nltk.corpus import stopwords
from nltk.tokenize import RegexpTokenizer

from datetime import datetime
from time import time

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score, pairwise_distances
from sklearn.metrics import confusion_matrix

import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm

import spacy
```

In [4]:
```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', None)
```

In [5]:
```
file_path = "C:/Users/tsaie/OneDrive/Desktop/000 Resumes & Projects/# Projects/DS3 Fake Amazon Reviews/Dataset/"
# apparel = pd.read_csv(file_path + 'amazon_reviews_us_Apparel_v1_00.tsv.gz', compression='gzip', header=0, sep='\t', quo
electronics = pd.read_csv(file_path + 'amazon_reviews_us_Electronics_v1_00.tsv.gz', compression='gzip', header=0, sep='\t
print(f"The 'electronics' file has {electronics.shape[0]} rows and {electronics.shape[1]} columns")
electronics.head(3)
```

```
The 'electronics' file has 20000 rows and 15 columns
```

Out[5]:

	marketplace	customer_id	review_id	product_id	product_parent	product_title	product_category	star_rating	helpful_votes	total_vot
0	US	41409413	R2MTG1GCZLR2DK	B00428R89M	112201306	yoomall 5M Antenna WIFI RP-SMA Female to Male Extensionl Cable	Electronics	5	0	
1	US	49668221	R2HBOEM8LE9928	B000068O48	734576678	Hosa GPM-103 3.5mm TRS to 1/4" TRS Adaptor	Electronics	5	0	
2	US	12338275	R1P4RW1R9FDPEE	B000GGKOG8	614448099	Channel Master Titan 2 Antenna Preamplifier	Electronics	5	1	

In [6]:
```
electronics_small = electronics[['verified_purchase', 'review_body']]
electronics_small.head()
```

Out[6]:

	verified_purchase	review_body
0	Y	As described.
1	Y	It works as advertising.
2	Y	Works pissa
3	Y	Did not work at all.
4	Y	Works well. Bass is somewhat lacking but is present. Overall pleased with the item.

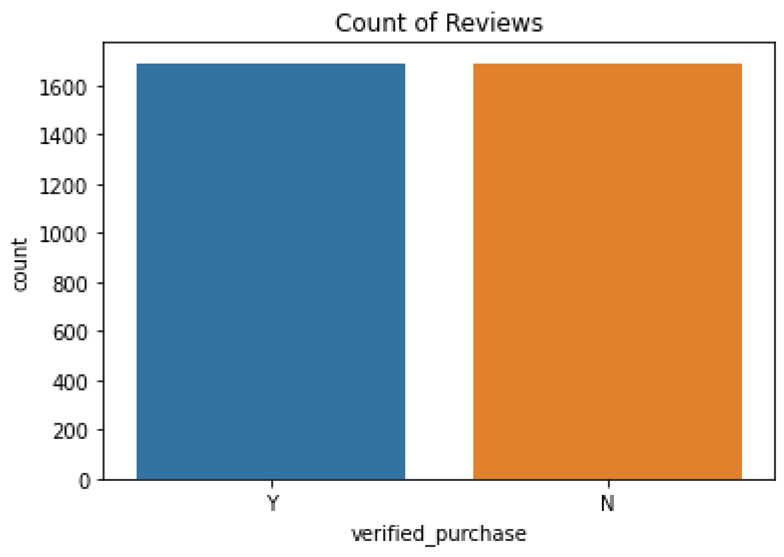
Create Balanced Dataset

- have same number of rows of verified and unverified reviews

In [7]:
```
def under_sampling(df):
    print("Under-Sampling Data")
    # Count of Reviews
    print("Verified:", sum(df['verified_purchase'] == 'Y'))
    print("Un-Verified:", sum(df['verified_purchase'] == 'N'))

    sample_size = sum(df['verified_purchase'] == 'N')

    authentic_reviews_df = df[df['verified_purchase'] == 'Y']
    fake_reviews_df = df[df['verified_purchase'] == 'N']

    authentic_reviews_us_df = authentic_reviews_df.sample(sample_size)
    under_sampled_df = pd.concat([authentic_reviews_us_df, fake_reviews_df], axis=0)

    print("Under-Sampled Verified", sum(under_sampled_df['verified_purchase'] == 'Y'))
    print("Under-Sampled Un-Verified", sum(under_sampled_df['verified_purchase'] == 'N'))


    # Graph of Data Distribution
    fig, ax = plt.subplots(figsize=(6, 4))
    sns.countplot(x='verified_purchase', data=under_sampled_df)
    plt.title("Count of Reviews")
    plt.show()
    print("Under-Sampling Complete")
    return under_sampled_df
```

In [8]:
```
electronics_equal_weight = under_sampling(electronics_small)
# electronics_equal_weight
```

```
Under-Sampling Data
Verified: 18309
Un-Verified: 1691
Under-Sampled Verified 1691
Under-Sampled Un-Verified 1691
```



```
Under-Sampling Complete
```

Data Cleaning

In [9]:

```python
# Pre-processing Text Reviews
def data_cleaning(df):
    # Removing emtpy cells
    df.dropna(inplace=True)
    df['review_body_cleaned'] = df['review_body']

    # Replace HTML keywords with blank space ("&quot;", "br", "&#34")
    remove_dict = {"<br /><br />": " ", "<br />": " ", "br": " ", "&quot;": " ", "&#34": " "}
    for key, val in remove_dict.items():
        df['review_body_cleaned'] = df['review_body_cleaned'].apply(
            lambda x: x.replace(key, val))

    print("\n######## Remove HTML Keywords Complete ########")

    # Remove Punctuations and numbers
    tokenizer = RegexpTokenizer(r'\w+')
    df['review_body_cleaned'] = df['review_body_cleaned'].apply(
        lambda x: ' '.join([word for word in tokenizer.tokenize(x)]))

    remove_dict = {"0": "", "1": "", "2": "", "3": "", "4": "", "5": "", "6": "", "7": "", "8": "", "9": "",
                   "(": "", ")":""}
    for key, val in remove_dict.items():
        df['review_body_cleaned'] = df['review_body_cleaned'].apply(
            lambda x: x.replace(key, val))

    print("\n######## Remove Punctuation and Numbers Complete ########")

    # Lowercase Words
    df['review_body_cleaned'] = df['review_body_cleaned'].str.lower()

    print("\n######## Lowercase Complete ########")

    # Remove Stop Words.
    stop = stopwords.words('english')
    stop += ["can't", "i'm", "I'm", "i'd", "i've", "i'll", "that's", "there's", "they're"]

    df['review_body_cleaned'] = df['review_body_cleaned'].apply(
        lambda x: ' '.join([word for word in x.split() if word.strip() not in stop]))

    print("\n######## Remove Stop Words Complete ########")

    # Lemmatization using .lemma_
    nlp = spacy.load('en_core_web_sm', disable=['parser', 'ner'])
    df['review_body_cleaned'] = df['review_body_cleaned'].apply(
        lambda x: ' '.join([token.lemma_ for token in nlp(x)]))

    print("\n######## Data Cleaning Complete ########")

    return df
```

In [10]:

```python
# Clean the dataset
electronics_cleaned = data_cleaning(electronics_equal_weight)
electronics_cleaned.head()
```

```

######## Remove HTML Keywords Complete ########

######## Remove Punctuation and Numbers Complete ########

######## Lowercase Complete ########

######## Remove Stop Words Complete ########

######## Data Cleaning Complete ########
```

Out[10]:

	verified_purchase	review_body	review_body_cleaned
12529	Y	typical	typical
2256	Y	It was cool howver I live in the hills and it did not work for me. However neither did the other one I bought. So I think its my location and nit the actual product.	cool howver live hill work however neither one buy think location nit actual product
1411	Y	Perfect for our movie theater sound system.	perfect movie theater sound system
3986	Y	I haven't been late to work since i bought this!	late work since buy

Feature Engineering + Prepare Data for Machine Learning

Add Bigrams

In [11]:
```
# https://stackoverflow.com/questions/48331315/how-to-extract-all-the-ngrams-from-a-text-dataframe-column-in-different-o

from collections import Counter
from nltk import ngrams
from itertools import chain

def find_ngrams(input_list, n):
    return list(zip(*[input_list[i:] for i in range(n)]))


electronics_cleaned['bigrams'] = electronics_cleaned['review_body_cleaned'].map(lambda x: find_ngrams(x.split(), 2))
electronics_cleaned.head()
```

Out[11]:

	verified_purchase	review_body	review_body_cleaned	bigrams
12529	Y	typical	typical	[]
2256	Y	It was cool howver I live in the hills and it did not work for me. However neither did the other one I bought. So I think its my location and nit the actual product.	cool howver live hill work however neither one buy think location nit actual product	[(cool, howver), (howver, live), (live, hill), (hill, work), (work, however), (however, neither), (neither, one), (one, buy), (buy, think), (think, location), (location, nit), (nit, actual), (actual, product)]
1411	Y	Perfect for our movie theater sound system.	perfect movie theater sound system	[(perfect, movie), (movie, theater), (theater, sound), (sound, system)]
3986	Y	I haven't been late to work since i bought this!	late work since buy	[(late, work), (work, since), (since, buy)]
14948	Y	Worked like a charm.	work like charm	[(work, like), (like, charm)]

In [12]:
```
electronics_un_verified = electronics_cleaned[electronics_cleaned['verified_purchase'] == 'N']
electronics_verified = electronics_cleaned[electronics_cleaned['verified_purchase'] == 'Y']

electronics_un_verified.tail(1)
```

Out[12]:

	verified_purchase	review_body	review_body_cleaned	bigrams
19952	N	I use them at work for my chargers. Keeps cords looking organized and I love it.	use work charger keep cord look organize love	[(use, work), (work, charger), (charger, keep), (keep, cord), (cord, look), (look, organize), (organize, love)]

In [13]:
```
verified_bigrams = electronics_verified['bigrams'].tolist()
verified_bigrams = list(chain(*verified_bigrams))

verified_bigram_counts = Counter(verified_bigrams)
verified_bigram_counts.most_common(20)
```

Out[13]:
```
[(('work', 'great'), 143),
 (('work', 'well'), 67),
 (('sound', 'quality'), 57),
 (('work', 'perfectly'), 42),
 (('great', 'sound'), 37),
 (('sound', 'great'), 37),
 (('work', 'fine'), 35),
 (('great', 'product'), 35),
 (('good', 'quality'), 34),
 (('good', 'price'), 29),
 (('great', 'price'), 26),
 (('easy', 'install'), 25),
 (('highly', 'recommend'), 25),
 (('well', 'make'), 24),
 (('stop', 'work'), 22),
 (('sound', 'good'), 22),
 (('hdmi', 'cable'), 21),
 (('last', 'long'), 21),
 (('good', 'product'), 21),
 (('work', 'like'), 20)]
```

In [14]:
```
un_verified_bigrams = electronics_un_verified['bigrams'].tolist()
un_verified_bigrams = list(chain(*un_verified_bigrams))

un_verified_bigram_counts = Counter(un_verified_bigrams)
un_verified_bigram_counts.most_common(20)
```

Out[14]:
```
[(('sound', 'quality'), 265),
 (('bluetooth', 'speaker'), 133),
 (('good', 'sound'), 99),
 (('work', 'well'), 98),
 (('work', 'great'), 94),
 (('exchange', 'honest'), 93),
 (('receive', 'product'), 88),
 (('listen', 'music'), 88),
 (('battery', 'life'), 84),
 (('honest', 'review'), 83),
 (('sound', 'good'), 80),
 (('sound', 'great'), 74),
 (('great', 'sound'), 69),
 (('easy', 'use'), 66),
 (('unbiased', 'review'), 60),
 (('honest', 'unbiased'), 56),
 (('highly', 'recommend'), 55),
 (('product', 'discount'), 52),
 (('can', 'not'), 50),
 (('quality', 'sound'), 49)]
```

Let's call the bigrams in vertified reviews "gold_bigrams" and the bigrams in unverified reviews "fake_bigrams"

count = number of gold/fake_bigrams in a review

percent = number of gold/fake_bigrams as a percentage of total number of bigrams in a review.

simple score = sum of the gold/fake_bigrams' popularity scores (calculated using the bigram's count in the Counter)

normalized score = simple score / total bigram count

In [15]:
```
def get_bigram_count(bigrams, bigram_dict):
    count = 0
    for bigram in bigrams:
        if bigram in bigram_dict.keys():
            count += 1
    return count

def get_bigram_simple_score(bigrams, bigram_dict):
    score = 0
    for bigram in bigrams:
        if bigram in bigram_dict.keys():
            score += bigram_dict[bigram]
    return score
```

In [16]:
```
electronics_cleaned['bigram_count'] = electronics_cleaned['bigrams'].apply(lambda x: len(x))
```

In [17]:
```
# fake

fake_bigram_dict = dict(un_verified_bigram_counts) # fake_bigram_dict = dict(un_verified_bigram_counts.most_common(30))

electronics_cleaned['fake_bigram_count'] = electronics_cleaned['bigrams'].apply(
    lambda x: get_bigram_count(x, fake_bigram_dict))

electronics_cleaned['fake_bigram_percent'] = electronics_cleaned['fake_bigram_count'] / electronics_cleaned['bigram_coun

electronics_cleaned['fake_bigram_simple_score'] = electronics_cleaned['bigrams'].apply(
    lambda x: get_bigram_simple_score(x, fake_bigram_dict))

electronics_cleaned['fake_bigram_normalized_score'] = electronics_cleaned['fake_bigram_simple_score'] / electronics_clea
```

In [18]:
```
# gold

gold_bigram_dict = dict(verified_bigram_counts) # gold_bigram_dict = dict(verified_bigram_counts.most_common(30))

electronics_cleaned['gold_bigram_count'] = electronics_cleaned['bigrams'].apply(
    lambda x: get_bigram_count(x, gold_bigram_dict))

electronics_cleaned['gold_bigram_percent'] = electronics_cleaned['gold_bigram_count'] / electronics_cleaned['bigram_coun

electronics_cleaned['gold_bigram_simple_score'] = electronics_cleaned['bigrams'].apply(
    lambda x: get_bigram_simple_score(x, gold_bigram_dict))

electronics_cleaned['gold_bigram_normalized_score'] = electronics_cleaned['gold_bigram_simple_score'] / electronics_clea
```

In [19]:
```
# Fill all the NaN values with zero
electronics_cleaned = electronics_cleaned.fillna(0)
electronics_cleaned.tail(1)
```

Out[19]:

	verified_purchase	review_body	review_body_cleaned	bigrams	bigram_count	fake_bigram_count	fake_bigram_percent	fake_bigram_simple_
19952	N	I use them at work for my chargers. Keeps cords looking organized and I love it.	use work charger keep cord look organize love	[(use, work), (work, charger), (charger, keep), (keep, cord), (cord, look), (look, organize), (organize, love)]	7	7	1.0	

Use Machine Learning to Make Predictions for Verified VS. Unverified

LABELS:

- 1 = verified review
- 0 = unverified review

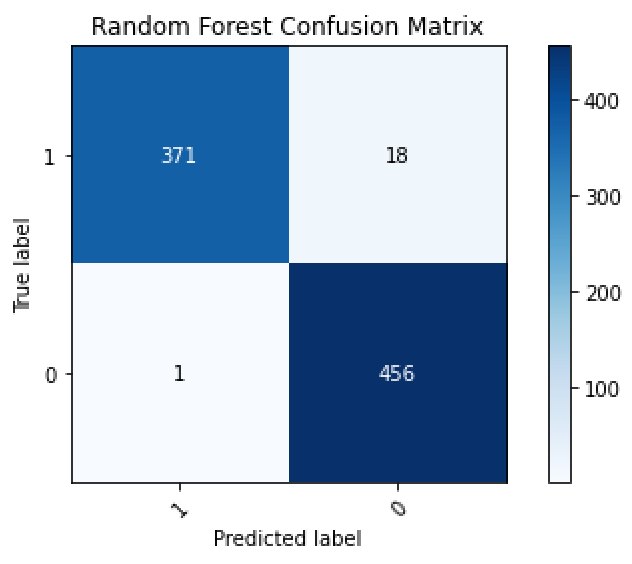
```
In [20]: def semi_supervised_learning(df, model, algorithm, threshold=0.8, iterations=40):
             df = df.copy()

             df_unlabled = df[['fake_bigram_count', 'fake_bigram_percent', 'fake_bigram_simple_score', 'fake_bigram_normalized_sc
                      'gold_bigram_count', 'gold_bigram_percent', 'gold_bigram_simple_score', 'gold_bigram_normalized_score']]

             df['verified_purchase'] = df['verified_purchase'].apply(lambda x: 1 if x == 'Y' else 0)
             print("Training " + algorithm + " Model")
             labels = df['verified_purchase']

             train_data, test_data, train_label, test_label = train_test_split(df_unlabled, labels, test_size=0.25, random_state=

             test_data_copy = test_data.copy()
             test_label_copy = test_label.copy()

             all_labeled = False

             current_iteration = 0

             pbar = tqdm(total=iterations)

             while not all_labeled and (current_iteration < iterations):
                 current_iteration += 1
                 model.fit(train_data, train_label)

                 probabilities = model.predict_proba(test_data)
                 pseudo_labels = model.predict(test_data)

                 indices = np.argwhere(probabilities > threshold)

                 for item in indices:
                     train_data.loc[test_data.index[item[0]]] = test_data.iloc[item[0]]
                     train_label.loc[test_data.index[item[0]]] = pseudo_labels[item[0]]
                 test_data.drop(test_data.index[indices[:, 0]], inplace=True)
                 test_label.drop(test_label.index[indices[:, 0]], inplace=True)

                 print("--" * 20)

                 if len(test_data) == 0:
                     print("Exiting loop")
                     all_labeled = True
                 pbar.update(1)

             pbar.close()
             predicted_labels = model.predict(test_data_copy)

             print(algorithm + ' Model Results')
             print('--' * 20)
             print('Accuracy Score : ' + str(accuracy_score(test_label_copy, predicted_labels)))
             print('Precision Score : ' + str(precision_score(test_label_copy, predicted_labels, pos_label=1)))
             print('Recall Score : ' + str(recall_score(test_label_copy, predicted_labels, pos_label=1)))
             print('F1 Score : ' + str(f1_score(test_label_copy, predicted_labels, pos_label=1)))
             print('Confusion Matrix : \n' + str(confusion_matrix(test_label_copy, predicted_labels)))
             plot_confusion_matrix(test_label_copy, predicted_labels, classes=[1, 0],
                                   title=algorithm + ' Confusion Matrix').show()


         def plot_confusion_matrix(y_true, y_pred, classes, title=None, cmap=plt.cm.Blues):
             # Compute confusion matrix
             cm = confusion_matrix(y_true, y_pred)
             # Only use the labels that appear in the data

             fig, ax = plt.subplots()
             im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
             ax.figure.colorbar(im, ax=ax)
             # We want to show all ticks...
             ax.set(xticks=np.arange(cm.shape[1]),
                    yticks=np.arange(cm.shape[0]),
                    xticklabels=classes,
                    yticklabels=classes,
                    title=title,
                    ylabel='True label',
                    xlabel='Predicted label')

             # Rotate the tick labels and set their alignment.
             plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
                      rotation_mode="anchor")

             # Loop over data dimensions and create text annotations.
             fmt = 'd'
             thresh = cm.max() / 2.
             for i in range(cm.shape[0]):
                 for j in range(cm.shape[1]):
                     ax.text(j, i, format(cm[i, j], fmt),
                             ha="center", va="center",
                             color="white" if cm[i, j] > thresh else "black")
             fig.tight_layout()
```

```
    return plt
```

ML Method #1: RandomForestClassifier

```
In [21]: start_time = time()
         rf = RandomForestClassifier(random_state=42, criterion='entropy', max_depth=14, max_features='auto', n_estimators=500)
         semi_supervised_learning(electronics_cleaned, model=rf, threshold=0.7, iterations=15, algorithm='Random Forest')
         end_time = time()

         print("Time taken : ", end_time - start_time)
```

```
Training Random Forest Model

  7%|█████▌                                                                              | 1/15 [00:03<00:52,  3.74s/it]

----------------------------------------

 13%|███████████                                                                         | 2/15 [00:05<00:31,  2.39s/it]

----------------------------------------

 20%|████████████████▌                                                                   | 3/15 [00:06<00:22,  1.88s/it]

----------------------------------------

 27%|██████████████████████▍                                                              | 4/15 [00:07<00:18,  1.66s/i
t]

----------------------------------------

 33%|███████████████████████████▋                                                         | 5/15 [00:09<00:15,  1.56s/i
t]

----------------------------------------

 40%|█████████████████████████████████▏                                                   | 6/15 [00:10<00:13,  1.46s/i
t]

----------------------------------------

 47%|██████████████████████████████████████▋                                              | 7/15 [00:11<00:11,  1.40s/i
t]

----------------------------------------

 53%|████████████████████████████████████████████▏                                        | 8/15 [00:13<00:09,  1.39s/i
t]

----------------------------------------

 60%|█████████████████████████████████████████████████▊                                   | 9/15 [00:14<00:08,  1.37s/i
t]

----------------------------------------

 67%|██████████████████████████████████████████████████████▋                             | 10/15 [00:16<00:07,  1.44s/i
t]

----------------------------------------

 73%|████████████████████████████████████████████████████████████▏                       | 11/15 [00:17<00:05,  1.39s/i
t]

----------------------------------------

 80%|██████████████████████████████████████████████████████████████████                 | 12/15 [00:18<00:04,  1.40s/it]

----------------------------------------

 87%|███████████████████████████████████████████████████████████████████████            | 13/15 [00:20<00:02,  1.37s/it]

----------------------------------------

 93%|█████████████████████████████████████████████████████████████████████████████      | 14/15 [00:21<00:01,  1.36s/it]

----------------------------------------

100%|██████████████████████████████████████████████████████████████████████████████████| 15/15 [00:22<00:00,  1.52s/it]

----------------------------------------
Random Forest Model Results
----------------------------------------
Accuracy Score : 0.9775413711583925
Precision Score : 0.9620253164556962
Recall Score : 0.9978118161925602
F1 Score : 0.979591836734694
Confusion Matrix :
[[371  18]
 [  1 456]]
```

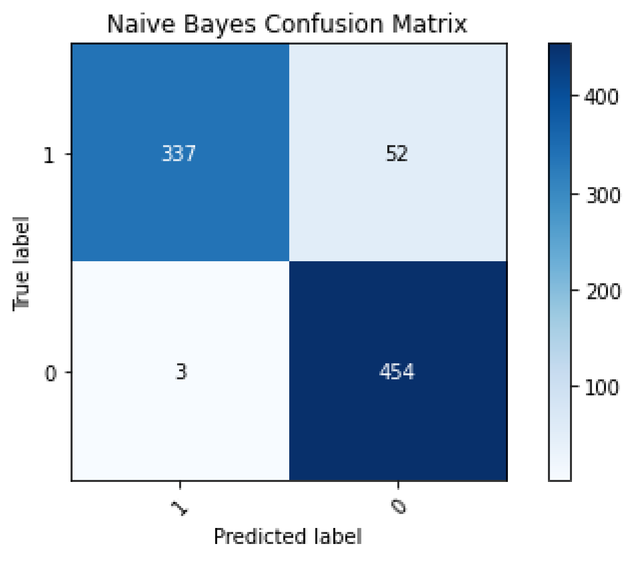


```
Time taken :  23.0534093379974 37
```

ML Method #2: GaussianNB

In [22]:
```
start_time = time()
nb = GaussianNB()
semi_supervised_learning(electronics_cleaned, model=nb, threshold=0.7, iterations=15, algorithm='Naive Bayes')
end_time = time()

print("Time taken : ", end_time - start_time)
```

```
Training Naive Bayes Model

100%|████████████████████████████████████████████████████████████████████| 15/15 [00:01<00:00,  8.45it/s]

----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
----------------------------------------
Naive Bayes Model Results
----------------------------------------
Accuracy Score : 0.9349881796690307
Precision Score : 0.8972332015810277
Recall Score : 0.99343544857776805
F1 Score : 0.9428868120456906
Confusion Matrix :
[[337  52]
 [  3 454]]
```



```
Time taken :  1.9174318313598633
```

END