NLP ASSIGNMENT

NAME: Dadireddy Jahnavi

ROLL NO: B190181EC

BATCH: ECE-A

Write the python code for sentiment analysis for the following dataset. Do the required pre-processing - stemming, punctuation removal, term frequency etc. - (whichever required). Then design a classifier to categorize the reviews / texts using logistic regression and naive bayes classifier. Also generate required plots and confusion matrix.

1) Use the twitter data from the nltk library in python

BASIC IMPORTS (MODULES AND DATA)

In [16]:

```
# importing modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import nltk
from nltk.corpus import twitter_samples

# importing twitter data using nltk
# downloads sample twitter dataset.
nltk.download('twitter_samples')

# download the stopwords for the process_tweet function
nltk.download('stopwords')

import re                                  # library for regular expression operations
import string                              # for string operations
from nltk.corpus import stopwords          # module for stop words that come with NLTK
from nltk.stem import PorterStemmer        # module for stemming
from nltk.tokenize import TweetTokenizer   # module for tokenizing strings
```

```
[nltk_data] Downloading package twitter_samples to
[nltk_data]     /home/kary/nltk_data...
[nltk_data]   Package twitter_samples is already up-to-date!
[nltk_data] Downloading package stopwords to /home/kary/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

FUNCTIONS

PRE-PROCESSING

In [17]:

```
def process_tweet(tweet):
    #Remove old style retweet text "RT"
    tweet2 = re.sub(r'^RT[\s]','', tweet)

    #Remove hyperlinks
    tweet2 = re.sub(r'https?:\/\/.*[\r\n]*','', tweet2)

    #Remove hastags
    #Only removing the hash # sign from the word
    tweet2 = re.sub(r'#','',tweet2)

    # instantiate tokenizer class
    tokenizer = TweetTokenizer(preserve_case=False,    strip_handles=True, reduce_len=True)

    # tokenize tweets
    tweet_tokens = tokenizer.tokenize(tweet2)

    #Import the english stop words list from NLTK
    stopwords_english = stopwords.words('english')

    #Creating a list of words without stopwords
    tweets_clean = []
    for word in tweet_tokens:
        if word not in stopwords_english and word not in string.punctuation:
            tweets_clean.append(word)

    #Instantiate stemming class
    stemmer = PorterStemmer()

    #Creating a list of stems of words in tweet
    tweets_stem = []
    for word in tweets_clean:
        stem_word = stemmer.stem(word)
        tweets_stem.append(stem_word)

    return tweets_stem
```

FREQUENCY GENERATING FUNCTION

In [18]:
```
def build_freqs(tweets, ys):
    yslist = np.squeeze(ys).tolist()

    freqs = {}
    for y, tweet in zip(yslist, tweets):
        for word in process_tweet(tweet):
            pair = (word, y)
            freqs[pair] = freqs.get(pair, 0) + 1

    return freqs
```

SIGMOID FUNCTION

In [19]:
```
def sigmoid(z):
    # calculate the sigmoid of z
    h = 1/(1 + np.exp(-z))

    return h
```

COST FUNCTION AND GRADIENT DESCENT

In [20]:
```
def gradientDescent(x, y, theta, alpha, num_iters):
    m = len(x)

    for i in range(0, num_iters):

        # get z, the dot product of x and theta
        z = np.dot(x,theta)

        # get the sigmoid of z
        h = sigmoid(z)

        # calculate the cost function
        J = (-1/m)*(np.dot(y.T,np.log(h)) + np.dot((1-y).T,np.log(1-h)))

        # update the weights theta
        theta = theta - (alpha/m)*np.dot(x.T, h-y)

    J = float(J)
    return J, theta
```

EXTRACTING TWEETS

In [21]:
```
def extract_features(tweet, freqs):
    # process_tweet tokenizes, stems, and removes stopwords
    word_l = process_tweet(tweet)

    # 3 elements in the form of a 1 x 3 vector
    x = np.zeros((1, 3))

    #bias term is set to 1
    x[0,0] = 1

    # loop through each word in the list of words
    for word in word_l:

        # increment the word count for the positive label 1
        x[0,1] += freqs.get((word,1),0)

        # increment the word count for the negative label 0
        x[0,2] += freqs.get((word,0),0)

    assert(x.shape == (1, 3))
    return x
```

TEST LOGISTIC REGRESSION

In [22]:
```
def predict_tweet(tweet, freqs, theta):
    # extract the features of the tweet and store it into x
    x = extract_features(tweet, freqs)

    # make the prediction using x and theta
    z = np.dot(x,theta)
    y_pred = sigmoid(z)

    return y_pred
```

```python
def test_logistic_regression(test_x, test_y, freqs, theta):
    # the list for storing predictions
    y_hat = []

    for tweet in test_x:
        # get the label prediction for the tweet
        y_pred = predict_tweet(tweet, freqs, theta)

        if y_pred > 0.5:
            # append 1.0 to the list
            y_hat.append(1)
        else:
            # append 0 to the list
            y_hat.append(0)
# With the above implementation, y_hat is a list, but test_y is (m,1) array
    # convert both to one-dimensional arrays in order to compare them using the '==' operator
    y_hat = np.array(y_hat)
    test_y = test_y.reshape(-1)
    accuracy = np.sum((test_y == y_hat).astype(int))/len(test_x)

    return accuracy
```

TRAIN NAIVE BAYES

In [23]:

```python
def train_naive_bayes(freqs, train_x, train_y):
    loglikelihood = {}
    logprior = 0
    # calculate V, the number of unique words in the vocabulary
    vocab = set([pair[0] for pair in freqs.keys()])
    V = len(vocab)
    # calculate N_pos and N_neg
    N_pos = N_neg = 0
    for pair in freqs.keys():
        # if the label is positive (greater than zero)
        if pair[1] > 0:
            # Increment the number of positive words by the count for this (word, label) pair
            N_pos += freqs.get(pair, 1)
        # else, the label is negative
        else:
            # increment the number of negative words by the count for this (word,label) pair
            N_neg += freqs.get(pair, 1)
    # Calculate D, the number of documents
    D = len(train_y)
    # Calculate D_pos, the number of positive documents (*hint: use sum(<np_array>))
    D_pos = sum(train_y)
    # Calculate D_neg, the number of negative documents (*hint: compute using D and D_pos)
    D_neg = D-D_pos
    # Calculate logprior
    logprior = np.log(D_pos) - np.log(D_neg)
    # For each word in the vocabulary...
    for word in vocab:
        # get the positive and negative frequency of the word
        freq_pos = freqs.get((word, 1),0)
        freq_neg = freqs.get((word, 0),0)
        # calculate the probability that each word is positive, and negative
        p_w_pos = (freq_pos + 1)/(N_pos + V)
        p_w_neg = (freq_neg + 1)/(N_neg + V)
        # calculate the log likelihood of the word
        loglikelihood[word] = np.log(p_w_pos/p_w_neg)
    return logprior, loglikelihood
# logprior, loglikelihood = train_naive_bayes(freqs, train_x, train_y)
```

TEST NAIVE BAYES

In [24]:

```python
def naive_bayes_predict(tweet, logprior, loglikelihood):
    # process the tweet to get a list of words
    word_l = process_tweet(tweet)
    # initialize probability to zero
    p = 0
    # add the logprior
    p += logprior
    for word in word_l:
    # check if the word exists in the loglikelihood dictionary
        if word in loglikelihood:
            # add the log likelihood of that word to the probability
            p += loglikelihood[word]
    return p

def test_naive_bayes(test_x, test_y, logprior, loglikelihood):
    accuracy = 0  # return this properly
    y_hats = []
    for tweet in test_x:
        # if the prediction is > 0
```

```
        if naive_bayes_predict(tweet, logprior, loglikelihood) > 0:
            # the predicted class is 1
            y_hat_i = 1
        else:
            # otherwise the predicted class is 0
            y_hat_i = 0
    # append the predicted class to the list y_hats
        y_hats.append(y_hat_i)

    # error is the average of the absolute values of the differences between y_hats and test_y
    error = np.mean(np.absolute(y_hats - test_y))
    # Accuracy is 1 minus the error
    accuracy = 1 - error
    return accuracy
```

SPLITTING THE DATA

In [25]:

```
# select the set of positive and negative tweets
all_positive_tweets = twitter_samples.strings('positive_tweets.json')
all_negative_tweets = twitter_samples.strings('negative_tweets.json')
tweets = all_positive_tweets + all_negative_tweets

# make a numpy array representing labels of the tweets
labels = np.append(np.ones((len(all_positive_tweets))), np.zeros((len(all_negative_tweets))))

# split the data into two pieces, one for training and one for testing (validation set)
test_pos = all_positive_tweets[4000:]
train_pos = all_positive_tweets[:4000]
test_neg = all_negative_tweets[4000:]
train_neg = all_negative_tweets[:4000]
train_x = train_pos + train_neg
test_x = test_pos + test_neg

# combine positive and negative labels
train_y = np.append(np.ones((len(train_pos), 1)), np.zeros((len(train_neg), 1)), axis=0)
test_y = np.append(np.ones((len(test_pos), 1)), np.zeros((len(test_neg), 1)), axis=0)
```

TRAINING YOUR MODEL

In [26]:

```
# create frequency dictionary
freqs = build_freqs(tweets, labels)

# collect the features 'x' and stack them into a matrix 'X'
X = np.zeros((len(train_x), 3))
for i in range(len(train_x)):
    X[i, :]= extract_features(train_x[i], freqs)
# training labels corresponding to X
Y = train_y
# Apply gradient descent
J, theta = gradientDescent(X, Y, np.zeros((3, 1)), 1e-9, 1500)
print(f"The cost after training is {J:.8f}.")
print(f"The resulting vector of weights is {[round(t, 8) for t in np.squeeze(theta)]}")
```

```
The cost after training is 0.19513844.
The resulting vector of weights is [7e-08, 0.00054223, -0.00054312]
```

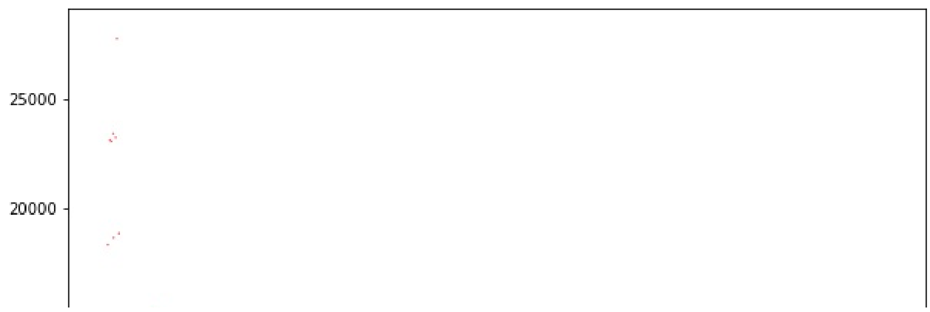
VISUALIZING TWEETS

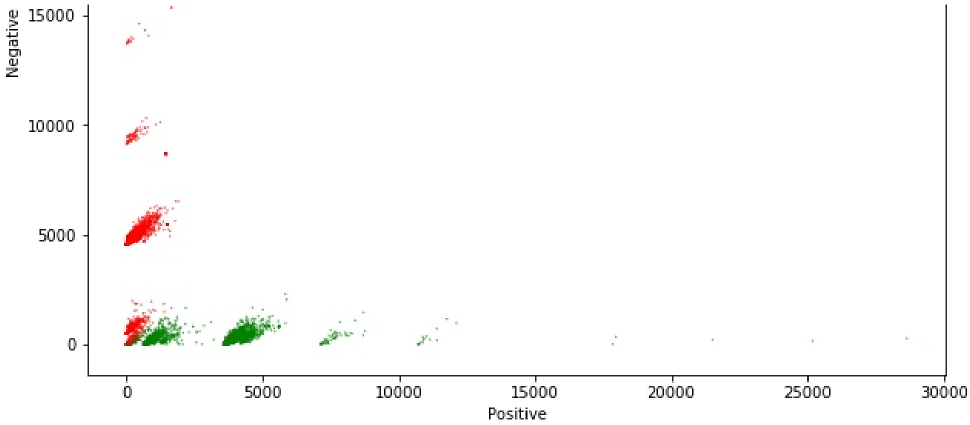
In [27]:

```
# Plot the samples using columns 1 and 2 of the matrix
fig, ax = plt.subplots(figsize = (10, 8))

colors = ['red', 'green']

# Color based on the sentiment Y
ax.scatter(X[:,1], X[:,2], c=[colors[int(k)] for k in Y], s = 0.1)  # Plot a dot for each pair of words
plt.xlabel("Positive")
plt.ylabel("Negative")
```

Out[27]:

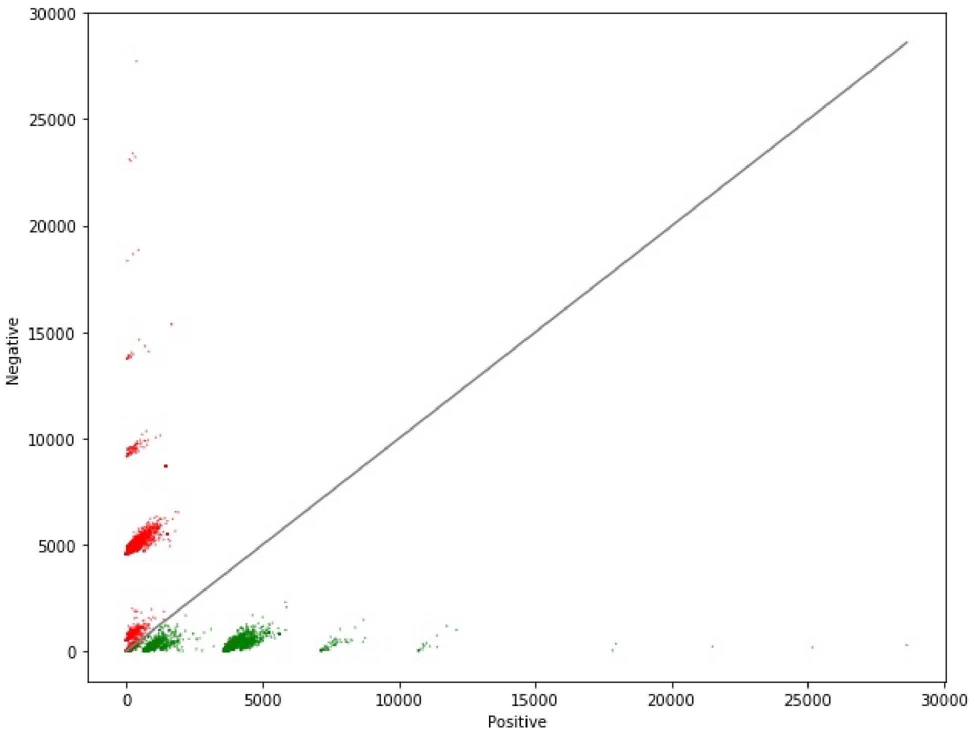
```
Text(0, 0.5, 'Negative')
```





In [28]:

```
# Equation for the separation plane
def neg(theta, pos):
    return (-theta[0] - pos * theta[1]) / theta[2]

fig, ax = plt.subplots(figsize = (10, 8))

colors = ['red', 'green']

# Color base on the sentiment Y
ax.scatter(X[:,1], X[:,2], c=[colors[int(k)] for k in Y], s = 0.1)  # Plot a dot for each pair of words
plt.xlabel("Positive")
plt.ylabel("Negative")

# Now lets represent the logistic regression model in this chart.
maxpos = np.max(X[:,1])          # max value in x-axis

# Plot a gray line that divides the 2 areas.
ax.plot([0,  maxpos], [neg(theta, 0),   neg(theta, maxpos)], color = 'gray')

plt.show()
```



LOGISTIC REGRESSION

In [29]:

```
test_accuracy = test_logistic_regression(test_x, test_y, freqs, theta)
print(f"Logistic regression model's accuracy = {test_accuracy:.4f}")
```

```
Logistic regression model's accuracy = 0.9965
```

NAIVE BAYES CLASSIFIER

In [43]:

```
logprior_naive, loglikelihood_naive = train_naive_bayes(freqs, train_x, train_y)
test_acc_naive = test_naive_bayes(test_x, test_y, logprior_naive, loglikelihood_naive)
print(f"Naive bayes classifier's accuracy = {test_acc_naive:.4f}")
```

```
Naive bayes classifier's accuracy = 0.5000
```