smsnlprajib_colab.ipynb

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Step 1: Data Analysis

```
#a = []
#while(1):
#a.append('1')
#import tensorflow.compat.v1 as tf
#tf.disable_v2_behavior()
import tensorflow as tf
print(tf.__version__)
```

```
1.5.0
```

```
#!pip uninstall tensorflow
#!pip uninstall tensorflow-gpu
#!pip install tensorflow==1.5
#!pip install tensorflow-gpu==1.5
#!pip install tensorflow-gpu==2.0.0-alpha0
```

```
# Import Required Library and sysnc with gib

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import nltk
#nltk.download('stopwords')
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import feature_extraction, model_selection, naive_bayes, metrics, svm
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import GaussianNB

# Try for RNN based on LSTM as per suggestion of SIR
from keras.models import Model
from keras.layers import SimpleRNN, LSTM, Activation, Dense, Dropout, Input, Embedding
from keras.models import Sequential
from keras.optimizers import RMSprop
```

```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing import sequence
from keras.utils import to_categorical
from keras.callbacks import EarlyStopping
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter(action='ignore', category=FutureWarning)

#import tensorflow.compat.v1 as tf
#tf.disable_v2_behavior()
```

```
Using TensorFlow backend.
```

```
[ ] # load the dataset of SMS messages
    #url = 'https://github.com/nsumlcse533/ctmnlp/blob/master/1935376/SMSSpamCollection'
    #df1 = pd.read_table(url)
    #df = pd.read_table(url, header=None, encoding='utf-8')
    #df = pd.read_table(io.StringIO(uploaded['SMSSPamCollection'].decode('utf-8')))
    from google.colab import files
    uploaded = files.upload()
```

Browse... SMSSpamCollection

SMSSpamCollection(n/a) - 483481 bytes, last modified: n/a - 100% done

```
Saving SMSSpamCollection to SMSSpamCollection (3)
```

```
[ ] import io
    df = pd.read_table(io.BytesIO(uploaded['SMSSpamCollection']))
```

```
[ ] # print useful information about the dataset
    print(df.info())
    print(df.head(5))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5571 entries, 0 to 5570
Data columns (total 2 columns):
ham                                                                                                  5571 non-null object
Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine there got amore wat...    5571 non-null object
dtypes: object(2)
memory usage: 87.2+ KB
None
    ham Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine there got amore wat...
0   ham                         Ok lar... Joking wif u oni...
1  spam  Free entry in 2 a wkly comp to win FA Cup fina...
2   ham  U dun say so early hor... U c already then say...
3   ham  Nah I don't think he goes to usf, he lives aro...
4  spam  FreeMsg Hey there darling it's been 3 week's n...
```

```
[ ] df.describe()
```

	ham	Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine there got amore wat...
count	5571	5571
unique	2	5168
top	ham	Sorry, I'll call later
freq	4824	30

```
[ ] df.columns
```

```
Index(['ham', 'Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine there got amore wat...'], dtype='object')
```

```
[ ] # Rename of Columns from 0,1 to type,sms for better understanding
    df.columns = ['type','sms']
```

```
[ ] #Check if the column rename completed
    df.columns
```

```
Index(['type', 'sms'], dtype='object')
```

```
[ ] #check the header data after column rename
    df.head(5)
```

	type	sms
0	ham	Ok lar... Joking wif u oni...
1	spam	Free entry in 2 a wkly comp to win FA Cup fina...
2	ham	U dun say so early hor... U c already then say...
3	ham	Nah I don't think he goes to usf, he lives aro...
4	spam	FreeMsg Hey there darling it's been 3 week's n...

```
[ ] #check the data type wise status
    df.groupby('type').describe()
```

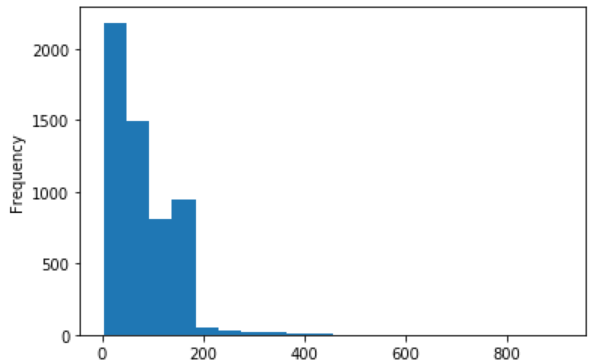
	sms			
	count	unique	top	freq
type				
ham	4824	4515	Sorry, I'll call later	30
spam	747	653	Please call our customer service representativ...	4

```
[ ] #check the character length for each message to analyze typical lengh of ham or spam messages
    df['length'] = df['sms'].map(lambda text: len(text))
    df.head()
```

	type	sms	length
0	ham	Ok lar... Joking wif u oni...	29
1	spam	Free entry in 2 a wkly comp to win FA Cup fina...	155
2	ham	U dun say so early hor... U c already then say...	49
3	ham	Nah I don't think he goes to usf, he lives aro...	61
4	spam	FreeMsg Hey there darling it's been 3 week's n...	147

```
[ ] #Plot the sms length in histogram for analyze the length nature
    df.length.plot(bins=20, kind='hist')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f02a729d128>
```




```
[ ] #Find the mean value for length
    df.length.describe()
```

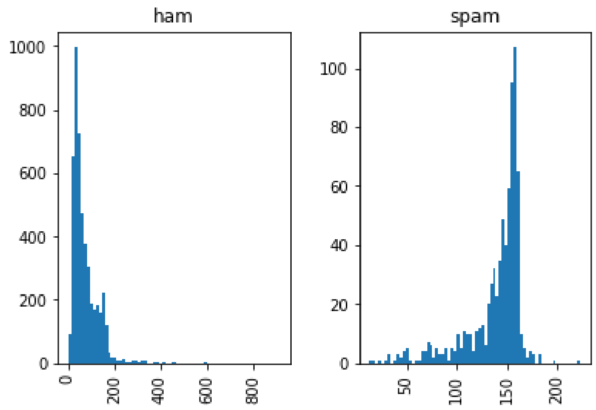
```
count    5571.000000
mean       80.484832
std        59.948514
min         2.000000
25%        36.000000
50%        62.000000
75%       122.000000
max       910.000000
Name: length, dtype: float64
```

```
[ ] #What is the long message?
    print(df.sms[df.length > 900])
```

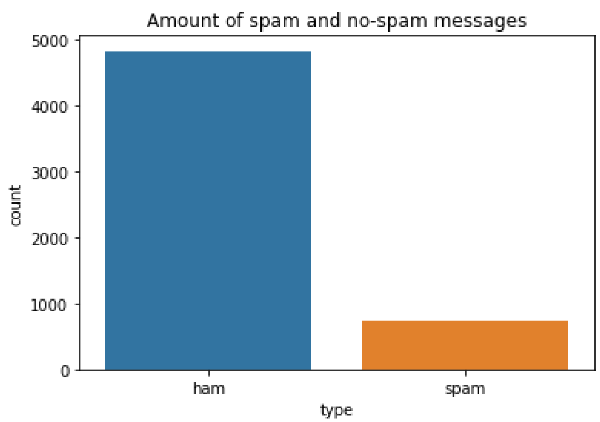
```
1084    For me the love should start with attraction.i...
Name: sms, dtype: object
```

```
[ ] # Difference in message length between spam and ham.
    df.hist(column='length', by='type', bins=70)
```

```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7f02a71fef60>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7f02a6da28d0>],
      dtype=object)
```




```
[ ] #compare the types of HAM (non SPAM) vs SPAM
    sns.countplot(data = df, x= df["type"]).set_title("Amount of spam and no-spam messages")
    plt.show()
```




```
[ ] # count number of records
    df.shape
```

```
(5571, 3)
```

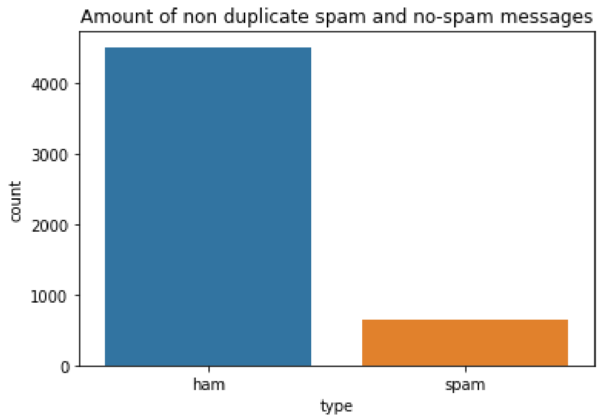
```
[ ] df[df==np.inf]=np.nan
    df.fillna(df.mean(), inplace=True)
```

```
[ ] # check and remove duplicate
    df.drop_duplicates(inplace=True)
```

```
[ ] # check after duplicate remove
    df.shape
```

```
(5168, 3)
```

```
[ ] #compare the types of HAM (non SPAM) vs SPAM after duplicate removal
    sns.countplot(data = df, x= df["type"]).set_title("Amount of non duplicate spam and no-spam messages")
    plt.show()
```




```
[ ] # Find for missing data
    df.isnull().sum()
```

```
type      0
sms       0
length    0
dtype: int64
```

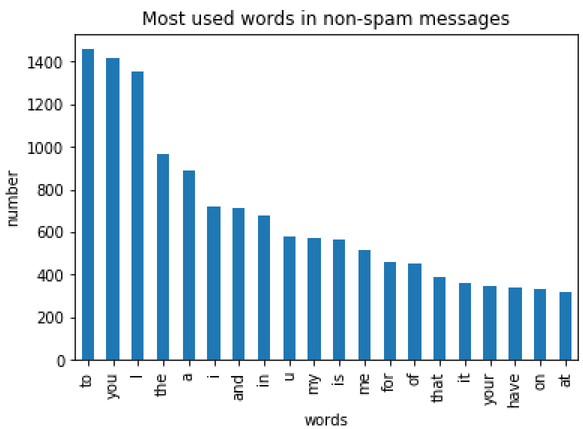
```
[ ] df["type"].value_counts()
```

```
ham     4515
spam     653
Name: type, dtype: int64
```

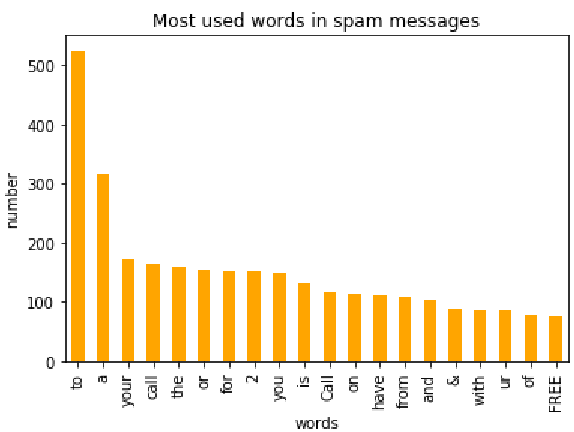
```
[ ] #Text Analytics find the frequencies of words in the spam and non-spam messages
    count1 = Counter(" ".join(df[df['type']=='ham']["sms"]).split()).most_common(20)
    df1 = pd.DataFrame.from_dict(count1)
    df1 = df1.rename(columns={0: "words in non-spam", 1 : "count"})
    count2 = Counter(" ".join(df[df['type']=='spam']["sms"]).split()).most_common(20)
    df2 = pd.DataFrame.from_dict(count2)
    df2 = df2.rename(columns={0: "words in spam", 1 : "count_"})
```

[ ]

```
[ ] #Most used words
    df1.plot.bar(legend = False)
    y_pos = np.arange(len(df1["words in non-spam"]))
    plt.xticks(y_pos, df1["words in non-spam"])
    plt.title('Most used words in non-spam messages')
    plt.xlabel('words')
    plt.ylabel('number')
    plt.show()
    df2.plot.bar(legend = False, color = 'orange')
    y_pos = np.arange(len(df2["words in spam"]))
    plt.xticks(y_pos, df2["words in spam"])
    plt.title('Most used words in spam messages')
    plt.xlabel('words')
    plt.ylabel('number')
```




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




```
[ ] # From above we find the majority of frequent words in both classes are stop words such as 'to', 'a', 'or' etc....
```

```
[ ] #converting categorical data in numeric labels || split a message into its individual words
    # 0=ham,1=spam
    from sklearn.preprocessing import LabelEncoder
    encoder=LabelEncoder()
    classes=df["type"]
    Y=encoder.fit_transform(classes)
```

```
[ ] text_messages=df["sms"]
    text_messages.sample(5)
```

```
3466    Actually fuck that, just do whatever, do find ...
280                                 You got called a tool?
1961                      LOL that would be awesome payback.
1823    Same as u... Dun wan... Y u dun like me alread...
5419                    I dont know oh. Hopefully this month.
Name: sms, dtype: object
```

```
[ ] # Remove regular expressions and stop words
    # using regular expressions to replace email addresses, URLs, phone numbers, other numbers

    # Replacing email addresses with 'email'
    processed = text_messages.str.replace(r'^.+@[^\.].*\.[a-z]{2,}$',
                                  'emailaddress')

    # Replacing URLs with 'webaddress'
    processed = processed.str.replace(r'^http\://[a-zA-Z0-9\-\.]+\.[a-zA-Z]{2,3}(/\S*)?$',
                                  'webaddress')

    # Replacing money symbols with 'moneysymb' (£ can by typed with ALT key + 156)
    processed = processed.str.replace(r'£|\$', 'moneysymbol')

    # Replacing 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber'
    processed = processed.str.replace(r'^\(?[\d]{3}\)?[\s-]?[\d]{3}[\s-]?[\d]{4}$',
                                  'phonenumber')

    # Replacing numbers with 'number'
    processed = processed.str.replace(r'\d+(\.\d+)?', 'number')

    # Removing punctuation
    processed = processed.str.replace(r'[^\w\d\s]', ' ')

    # Replacing whitespace between terms with a single space
    processed = processed.str.replace(r'\s+', ' ')

    # Removing leading and trailing whitespace
    processed = processed.str.replace(r'^\s+|\s+?$', '')
```

Step 2: Data preprocessing

```
[ ] # Convert the raw sms (sequence of characters) into vectors (sequences of numbers).
```

```
[ ] # remove the stop words in order to improve the analytics
    f = feature_extraction.text.CountVectorizer(stop_words = 'english')
    X = f.fit_transform(df["sms"]) #data set
    np.shape(X)
    #created more than 8400 new features. The new feature  j  in the row  i  is equal to 1 if the word  wj  appears in the text example  i . It is zero if ı
```

```
(5168, 8442)
```

```
[ ] # Here we transform the variable spam/non-spam into binary variable,
    Y=df["type"].map({'spam':1,'ham':0}) #target
    #df["type"]=df["type"].map({'spam':1,'ham':0})
    #df["type"].head(5)

    # then split target data set in training set (train test split function) and test set.we want 33% of data into the test set,
    # use randon_state=42 of same set of data every time and cosistent result

    X_train, X_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.33, random_state=42)
    print([np.shape(X_train), np.shape(X_test)])
    print([np.shape(y_train), np.shape(y_test)])
```

```
[(3462, 8442), (1706, 8442)]
[(3462,), (1706,)]
```

```
[ ] # Multinomial naive bayes classifier
```

```
[ ] MultiNB = MultinomialNB()
    MultiNB.fit(X_train, y_train)
    print(MultiNB)
    y_pred=MultiNB.predict(X_test)
    print (accuracy_score(y_test, y_pred))
```

```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
0.9759671746776084
```

```
[ ] #Bernoulli
    BernNB = BernoulliNB(binarize=True)
    BernNB.fit(X_train, y_train)
    print(BernNB)
    y_pred=BernNB.predict(X_test)
    print (accuracy_score(y_test, y_pred))
```

```
BernoulliNB(alpha=1.0, binarize=True, class_prior=None, fit_prior=True)
0.8704572098475967
```

```
[ ] # we found that the accuracy score of Multinomial is very high, So bellow we will try to analyze bayes based on Multinomial
```

```
[ ] array_alpha = np.arange(1/100000, 20, 0.11) #array creation routines based on numerical rangesnumpy.arange([start, ]stop, [step, ], dtype=None)
    # create some score set for test the result
    score_train = np.zeros(len(array_alpha))
    score_test = np.zeros(len(array_alpha))
    recall_test = np.zeros(len(array_alpha))
    precision_test= np.zeros(len(array_alpha))
    count = 0
    for alpha in array_alpha:
        bayes = naive_bayes.MultinomialNB(alpha=alpha)
        bayes.fit(X_train, y_train)
        score_train[count] = bayes.score(X_train, y_train)
        score_test[count]= bayes.score(X_test, y_test)
        recall_test[count] = metrics.recall_score(y_test, bayes.predict(X_test))
        precision_test[count] = metrics.precision_score(y_test, bayes.predict(X_test))
        count = count + 1
```

```
[ ] # Create matrix for test and pring different models
    matrix = np.matrix(np.c_[array_alpha, score_train, score_test, recall_test, precision_test])
    models = pd.DataFrame(data = matrix, columns = ['alpha', 'Train Accuracy', 'Test Accuracy', 'Test Recall', 'Test Precision'])
    models.head(n=20)
```

	alpha	Train Accuracy	Test Accuracy	Test Recall	Test Precision
0	0.00001	0.997400	0.965416	0.914027	0.834711
1	0.11001	0.996534	0.964244	0.941176	0.812500
2	0.22001	0.996245	0.966002	0.954751	0.814672
3	0.33001	0.996245	0.969519	0.950226	0.836653
4	0.44001	0.996245	0.970106	0.950226	0.840000
5	0.55001	0.995667	0.971278	0.950226	0.846774
6	0.66001	0.995378	0.972450	0.950226	0.853659
7	0.77001	0.995378	0.974209	0.936652	0.873418
8	0.88001	0.995378	0.973623	0.932127	0.872881
9	0.99001	0.995090	0.975381	0.932127	0.884120
10	1.10001	0.995378	0.977726	0.932127	0.899563
11	1.21001	0.995090	0.977726	0.927602	0.903084
12	1.32001	0.995090	0.978312	0.927602	0.907080
13	1.43001	0.994801	0.980070	0.927602	0.919283
14	1.54001	0.994223	0.980070	0.923077	0.923077
15	1.65001	0.994223	0.981243	0.923077	0.931507
16	1.76001	0.993645	0.981243	0.923077	0.931507
17	1.87001	0.993068	0.980657	0.918552	0.931193

18	1.98001	0.993068	0.981829	0.918552	0.939815
19	2.09001	0.993068	0.983001	0.918552	0.948598

```
[ ] #find the model with the most test precision and details relation with other model
    best_index = models['Test Precision'].idxmax()
    models.iloc[best_index, :]
```

```
alpha             11.770010
Train Accuracy     0.978914
Test Accuracy      0.971278
Test Recall        0.778281
Test Precision     1.000000
Name: 107, dtype: float64
```

```
[ ] # So the selected best model does not produce any false positive, which is our goal.
    #Now find if there is more than one model with 100% precision !
    models[models['Test Precision']==1].head(n=5)
```

	alpha	Train Accuracy	Test Accuracy	Test Recall	Test Precision
107	11.77001	0.978914	0.971278	0.778281	1.0
108	11.88001	0.978914	0.971278	0.778281	1.0
109	11.99001	0.978914	0.971278	0.778281	1.0
110	12.10001	0.978914	0.971278	0.778281	1.0
111	12.21001	0.978047	0.971278	0.778281	1.0

```
[ ] # Between these models with the highest possible precision, we are going to select which has more test accuracy.
    best_index = models[models['Test Precision']==1]['Test Accuracy'].idxmax()
    bayes = naive_bayes.MultinomialNB(alpha = array_alpha[best_index])
    bayes.fit(X_train, y_train)
    models.iloc[best_index, :]
```

```
alpha             11.770010
Train Accuracy     0.978914
Test Accuracy      0.971278
Test Recall        0.778281
Test Precision     1.000000
Name: 107, dtype: float64
```

```
[ ] #Confusion matrix with naive bayes classifier
    m_confusion_test = metrics.confusion_matrix(y_test, bayes.predict(X_test))
    pd.DataFrame(data = m_confusion_test, columns = ['Predicted 0', 'Predicted 1'],
                index = ['Actual 0', 'Actual 1'])
```

	Predicted 0	Predicted 1

Actual 0	1485	0
Actual 1	49	172

[ ]

```
# Out of the 1485 actual instances of 'ham' (not spam), it predicted correctly all of them;
# Out of the 172 actual instances of spam, it predicted correctly 136 of them.
# The accuracy obtained from the confusion matrix, as the sum of the diagonal divided by the sum of all matrix entries:
(m_confusion_test[0,0]+m_confusion_test[1,1])/np.sum(m_confusion_test)
```

```
0.9712778429073857
```

[ ]

[ ]

```
#Support Venctor Machine Test, we will evaluate the accuracy, recall and precision of the model with the test set.
# We train different models changing the regularization parameter C.
```

[ ]

```
# import warnings filter due to getting warning as "The default value of gamma will change from 'auto' to 'scale' in version 0.22 to account better for
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)

list_C = np.arange(500, 2000, 100) #100000
score_train = np.zeros(len(list_C))
score_test = np.zeros(len(list_C))
recall_test = np.zeros(len(list_C))
precision_test= np.zeros(len(list_C))
count = 0
for C in list_C:
    svc = svm.SVC(C=C)
    svc.fit(X_train, y_train)
    score_train[count] = svc.score(X_train, y_train)
    score_test[count]= svc.score(X_test, y_test)
    recall_test[count] = metrics.recall_score(y_test, svc.predict(X_test))
    precision_test[count] = metrics.precision_score(y_test, svc.predict(X_test))
    count = count + 1
```

[ ]

```
# Create matrix for test and pring different models
matrix = np.matrix(np.c_[list_C, score_train, score_test, recall_test, precision_test])
models = pd.DataFrame(data = matrix, columns =
             ['C', 'Train Accuracy', 'Test Accuracy', 'Test Recall', 'Test Precision'])
models.head(n=5)
```

	C	Train Accuracy	Test Accuracy	Test Recall	Test Precision
0	500.0	0.993356	0.981243	0.859729	0.994764
1	600.0	0.993934	0.981829	0.864253	0.994792
2	700.0	0.995667	0.981829	0.864253	0.994792

	C	Train Accuracy	Test Accuracy	Test Recall	Test Precision
3	800.0	0.996534	0.981829	0.864253	0.994792
4	900.0	0.997111	0.981829	0.864253	0.994792

```
[ ] # select the model with the most test precision
    best_index = models['Test Precision'].idxmax()
    models.iloc[best_index, :]
```

```
C                  600.000000
Train Accuracy       0.993934
Test Accuracy        0.981829
Test Recall          0.864253
Test Precision       0.994792
Name: 1, dtype: float64
```

```
[ ] # here also our best model does not produce any false positive, which is our goal.
    # we will find if there is more than one model with 100% precision !
    models[models['Test Precision']>0.99].head(n=5)
```

	C	Train Accuracy	Test Accuracy	Test Recall	Test Precision
0	500.0	0.993356	0.981243	0.859729	0.994764
1	600.0	0.993934	0.981829	0.864253	0.994792
2	700.0	0.995667	0.981829	0.864253	0.994792
3	800.0	0.996534	0.981829	0.864253	0.994792
4	900.0	0.997111	0.981829	0.864253	0.994792

```
[ ] # compare these models with the highest possible precision.
    best_index = models[models['Test Precision']>0.99]['Test Accuracy'].idxmax()
    svc = svm.SVC(C=list_C[best_index])
    svc.fit(X_train, y_train)
    models.iloc[best_index, :]
```

```
C                  600.000000
Train Accuracy       0.993934
Test Accuracy        0.981829
Test Recall          0.864253
Test Precision       0.994792
Name: 1, dtype: float64
```

```
[ ] # Confusion matrix with support vector machine classifier.
    svm_confusion_test = metrics.confusion_matrix(y_test, svc.predict(X_test))
    pd.DataFrame(data = svm_confusion_test, columns = ['Predicted 0', 'Predicted 1'],
                index = ['Actual 0', 'Actual 1'])
```

	Predicted 0	Predicted 1
Actual 0	1484	1

Actual 1	30	191

```
[ ] # Out of the 1482 actual instances of 'ham' (not spam), it predicted correctly all of them;
    # Out of the 189 actual instances of spam, it predicted correctly 154 of them.
    # The accuracy obtained from the confusion matrix, as the sum of the diagonal divided by the sum of all matrix entries:
    (svm_confusion_test[0,0]+svm_confusion_test[1,1])/np.sum(svm_confusion_test)
```

```
0.9818288393903869
```

```
[ ] After comparing the NB and SVM, we found that support vector machine with more than 98% accuracy(NB=0.9742086752637749 || SVM = 0.9894841735052755).
```

```
[ ] # we will now LSTM ''' Tensorflow
```

```
[ ]
```

```
[ ] #import tensorflow.compat.v1 as tf
    #tf.disable_v2_behavior()
```

```
[ ] max_words = 1000
    max_len = 150
    #tok = Tokenizer(num_words=max_words)

    #tok.fit_on_texts(X_train)
    #sequences = tok.texts_to_sequences(X_train)
    #sequences_matrix = sequence.pad_sequences(sequences,maxlen=max_len)
```

```
[ ] model = Sequential()
    model.add(Embedding(max_words, 32))
    model.add(LSTM(32))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
    history_ltsm = model.fit(X_train, y_train, epochs=5, batch_size=60, validation_split=0.2)
```

```
Train on 2769 samples, validate on 693 samples
Epoch 1/5
2769/2769 [==============================] - 307s 111ms/step - loss: 0.4307 - acc: 0.8693 - val_loss: 0.3284 - val_acc: 0.8990
Epoch 2/5
2769/2769 [==============================] - 306s 110ms/step - loss: 0.3904 - acc: 0.8693 - val_loss: 0.3318 - val_acc: 0.8990
Epoch 3/5
2769/2769 [==============================] - 302s 109ms/step - loss: 0.3884 - acc: 0.8693 - val_loss: 0.3321 - val_acc: 0.8990
Epoch 4/5
2769/2769 [==============================] - 301s 109ms/step - loss: 0.3907 - acc: 0.8693 - val_loss: 0.3335 - val_acc: 0.8990
Epoch 5/5
2769/2769 [==============================] - 298s 107ms/step - loss: 0.3882 - acc: 0.8693 - val_loss: 0.3309 - val_acc: 0.8990
```

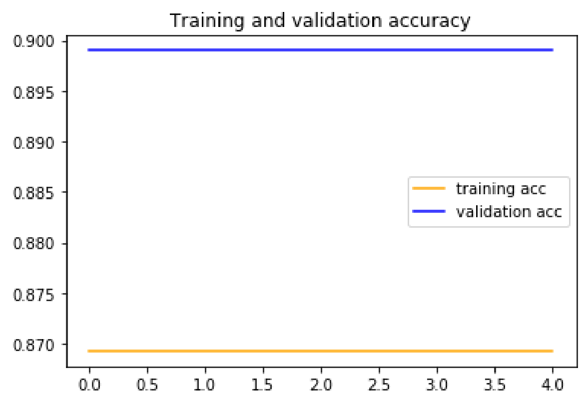
```
[ ] #def RNN():
    #    inputs = Input(name='inputs',shape=[max_len])
    #    layer = Embedding(max_words,50,input_length=max_len)(inputs)
```

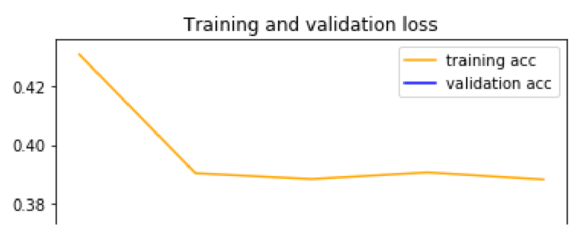
```
#     layer = LSTM(64)(layer)
#     layer = Dense(256,name='FC1')(layer)
#     layer = Activation('relu')(layer)
#     layer = Dropout(0.5)(layer)
#     layer = Dense(1,name='out_layer')(layer)
#     layer = Activation('sigmoid')(layer)
#     model = Model(inputs=inputs,outputs=layer)
#     return model
```

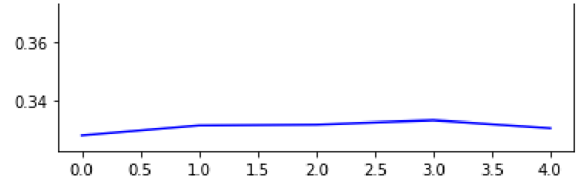
[ ]
```
#model = RNN()
#model.summary()
#model.compile(loss='binary_crossentropy',optimizer=RMSprop(),metrics=['accuracy'])
```

[ ]
```
acc = history_ltsm.history['acc']
val_acc = history_ltsm.history['val_acc']
loss = history_ltsm.history['loss']
val_loss = history_ltsm.history['val_loss']
epochs = range(len(acc))
plt.plot(epochs, acc, '-', color='orange', label='training acc')
plt.plot(epochs, val_acc, '-', color='blue', label='validation acc')
plt.title('Training and validation accuracy')
plt.legend()
plt.show()

plt.plot(epochs, loss, '-', color='orange', label='training acc')
plt.plot(epochs, val_loss,  '-', color='blue', label='validation acc')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```








```
[ ] pred = model.predict_classes(X_test)
    acc = model.evaluate(X_test, y_test)
    proba_ltsm = model.predict_proba(X_test)
    from sklearn.metrics import confusion_matrix
    print("Test loss is {0:.2f} accuracy is {1:.2f}  ".format(acc[0],acc[1]))
    print(confusion_matrix(pred, y_test))
```

```
1706/1706 [==============================] - 48s 28ms/step
Test loss is 0.39 accuracy is 0.87
[[1485  221]
 [   0    0]]
```

```
[ ] # After comparing the NB and SVM, we found that
    # support vector machine with more than 98% accuracy
    # NB= 97%| SVM = 98% || LSTM = 87%
    # summery is LSTM may give more accurate result, but for our run we have tried for epochs=5, i think epochs=30 should give above 98% accuracy.
```

```
[ ] ############# END OF THE PROJECT CODE ###########################
```