PROBLEM STATEMENT

- The SMS Spam Collection is a set of SMS tagged messages that have been collected for SMS Spam research. It contains one set of SMS messages in English of 5,574 messages, tagged according being ham (legitimate) or spam.
- The files contain one message per line. Each line is composed by two columns: v1 contains the label (ham or spam) and v2 contains the raw text.



STEP #0: LIBRARIES IMPORT

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

STEP #1: IMPORT DATASET

```
In [2]:
```

```
spam_df = pd.read_csv("emails.csv")
```

In [3]:

```
spam_df.head(10)
```

Out[3]:

	text	spam
0	Subject: naturally irresistible your corporate	1
1	Subject: the stock trading gunslinger fanny i	1
2	Subject: unbelievable new homes made easy im	1
3	Subject: 4 color printing special request add	1
4	Subject: do not have money , get software cds \dots	1
5	Subject: great nnews hello , welcome to medzo	1
6	Subject: here 's a hot play in motion homela	1
7	Subject: save your money buy getting this thin	1
8	Subject: undeliverable : home based business f	1
9	Subject: save your money buy getting this thin	1

In [4]:

```
spam_df.tail()
```

Out[4]:

	text	spam
5723	Subject: re : research and development charges	0
5724	Subject: re : receipts from visit jim , than	0
5725	Subject: re : enron case study update wow ! a	0
5726	Subject: re : interest david , please , call	0
5727	Subject: news : aurora 5 . 2 update aurora ve	0

```
In [5]:
```

```
spam_df.describe()
```

Out[5]:

	spam
count	5728.000000
mean	0.238827
std	0.426404
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

In [6]:

```
spam_df.info()
```

STEP #2: VISUALIZE DATASET

In [7]:

```
# Let's see which message is the most popular ham/spam message
spam_df.groupby('spam').describe()
```

Out[7]:

text

	count	unique	top	freq
spam				
0	4360	4327	Subject: re : term project : brian , no prob	2
1	1368	1368	Subject: considered unsolicited bulk email fro	1

In [8]:

```
# Let's get the length of the messages
spam_df['length'] = spam_df['text'].apply(len)
spam_df.head()
```

Out[8]:

	text	spam	length
0	Subject: naturally irresistible your corporate	1	1484
1	Subject: the stock trading gunslinger fanny i	1	598
2	Subject: unbelievable new homes made easy im	1	448
3	Subject: 4 color printing special request add	1	500
4	Subject: do not have money , get software cds	1	235

In [9]:

spam_df

Out[9]:

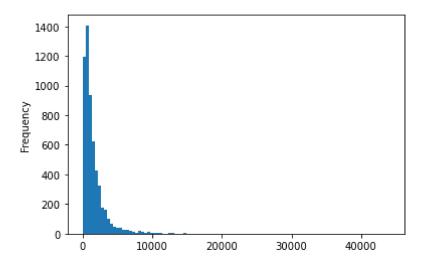
	text	spam	length
0	Subject: naturally irresistible your corporate	1	1484
1	Subject: the stock trading gunslinger fanny i	1	598
2	Subject: unbelievable new homes made easy im	1	448
3	Subject: 4 color printing special request add	1	500
4	Subject: do not have money , get software $\operatorname{cds} \ldots$	1	235
5723	Subject: re : research and development charges	0	1189
5724	Subject: re : receipts from visit jim , than	0	1167
5725	Subject: re : enron case study update wow ! a	0	2131
5726	Subject: re: interest david, please, call	0	1060

In [10]:

```
spam_df['length'].plot(bins=100, kind='hist')
```

Out[10]:

<AxesSubplot:ylabel='Frequency'>



In [11]:

```
spam_df.length.describe()
```

Out[11]:

count	5728.000000
mean	1556.768680
std	2042.649812
min	13.000000
25%	508.750000
50%	979.000000
75%	1894.250000
max	43952.000000

Name: length, dtype: float64

```
In [12]:
```

```
# Let's see the Longest message 43952
spam_df[spam_df['length'] == 43952]['text'].iloc[0]
```

Out[12]:

'Subject: from the enron india newsdesk - april 27 th newsclips fyi news forwarded by sandeep kohli / enron _ development on 04 / 27 / 2001 08 : 2 4 am - - - - - - - nikita varma 04 / 27 / 2001 07 : 51 am to : nikita varma / enron _ development @ enro n _ development cc : (bcc : sandeep kohli / enron _ development) subj ect : from the enron india newsdesk - april 27 th newsclips friday apr 2 7 2001 , http://www.economictimes.com/today/cmo3.htm dpc board empowers md to cancel mseb contract friday apr 27 2001 , http:/ / www . economictimes . com / today / 27 compl 1 . htm mseb pays rs 134 cr under \' protest \' to dpc friday , april 27 , 001 , http : / / www . businessstandard . com / today / economy 4 . asp ? menu = 3 enron india md authorised to terminate ppa friday , april 27 , 2001 , http : / / www . financial express . com / fe 20010427 / topl . html foreign lenders sla m brakes on disbursements to dpc , sanjay jog & raghu mohan global banks comfortable with enron pull - out friday , april 27 , 2001 , http : / / www . indian - express . com / ie 20010427 / nat 23 . html enron : dabho l chief gets powers to end deal with the mseb friday . april 27 . 2001 .

In [13]:

```
# Let's divide the messages into spam and ham
```

In [14]:

```
ham = spam_df[spam_df['spam']==0]
```

In [15]:

```
spam = spam_df[spam_df['spam']==1]
```

In [16]:

ham

Out[16]:

	text	spam	length
1368	Subject: hello guys , i ' m " bugging you " f	0	1188
1369	Subject: sacramento weather station fyi	0	1997
1370	Subject: from the enron india newsdesk - jan 1	0	7902
1371	Subject: re: powerisk 2001 - your invitation	0	3644
1372	Subject: re : resco database and customer capt	0	5535
5723	Subject: re : research and development charges	0	1189
5724	Subject: re : receipts from visit jim , than	0	1167
5725	Subject: re : enron case study update wow ! a	0	2131
5726	Subject: re : interest david , please , call	0	1060
5727	Subject: news : aurora 5 . 2 update aurora ve	0	2331

4360 rows × 3 columns

In [17]:

spam

Out[17]:

	text	spam	length
0	Subject: naturally irresistible your corporate	1	1484
1	Subject: the stock trading gunslinger fanny i	1	598
2	Subject: unbelievable new homes made easy im	1	448
3	Subject: 4 color printing special request add	1	500
4	Subject: do not have money , get software cds	1	235
1363	Subject: are you ready to get it? hello! v	1	347
1364	Subject: would you like a \$ 250 gas card ? do	1	188
1365	Subject: immediate reply needed dear sir , i	1	3164
1366	Subject: wanna see me get fisted ? fist bang	1	734
1367	Subject: hot stock info : drgv announces anoth	1	9342

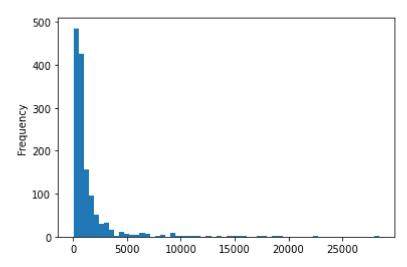
1368 rows × 3 columns

In [18]:

```
spam['length'].plot(bins=60, kind='hist')
```

Out[18]:

<AxesSubplot:ylabel='Frequency'>

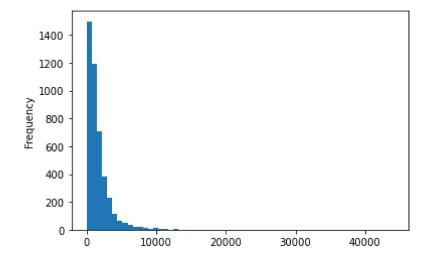


In [19]:

```
ham['length'].plot(bins=60, kind='hist')
```

Out[19]:

<AxesSubplot:ylabel='Frequency'>



In [20]:

```
print( 'Spam percentage =', (len(spam) / len(spam_df) )*100,"%")
```

Spam percentage = 23.88268156424581 %

```
In [21]:
```

```
print( 'Ham percentage =', (len(ham) / len(spam_df) )*100,"%")
```

Ham percentage = 76.11731843575419 %

In [22]:

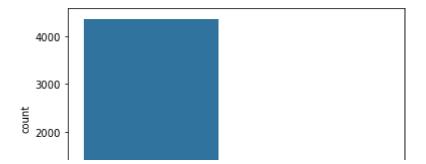
```
sns.countplot(spam_df['spam'], label = "Count")
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn_decorators.py:36: Fut ureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing othe r arguments without an explicit keyword will result in an error or misint erpretation.

warnings.warn(

Out[22]:

<AxesSubplot:xlabel='spam', ylabel='count'>



STEP #3: CREATE TESTING AND TRAINING DATASET/DATA CLEANING

STEP 3.1 EXERCISE: REMOVE PUNCTUATION

```
In [23]:
```

```
import string
string.punctuation
```

Out[23]:

```
'!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

In [24]:

```
Test = 'Hello Mr. Future, I am so happy to be learning AI now!!'
```

```
In [25]:
Test_punc_removed = [char for char in Test if char not in string.punctuation]
Test_punc_removed

Out[25]:
['H',
    'e',
    '1',
    '1',
    'v',
    'r',
    'r',
    'u',
    't',
    'u',
    'r',
    'e',
    ''',
    'I',
    '''
In [26]:
# Join the characters again to form the string.
Test_punc_removed_join = ''.join(Test_punc_removed)
```

Out[26]:

Test_punc_removed_join

'Hello Mr Future I am so happy to be learning AI now'

STEP 3.2 EXERCISE: REMOVE STOPWORDS

```
import nltk
nltk.download('stopwords')

[nltk_data] Downloading package stopwords to
[nltk_data] C:\Users\saile\AppData\Roaming\nltk_data...
[nltk_data] Unzipping corpora\stopwords.zip.

Out[28]:
True
```

```
In [29]:
# You have to download stopwords Package to execute this command
from nltk.corpus import stopwords
stopwords.words('english')
Out[29]:
['i',
 'me',
 'my',
 'myself',
 'we',
 'our',
 'ours',
 'ourselves',
 'you',
 "you're",
 "you've",
 "you'11",
 "you'd",
 'your',
 'yours',
 'yourself',
 'yourselves',
 'he'.
In [30]:
Test_punc_removed_join
Out[30]:
'Hello Mr Future I am so happy to be learning AI now'
In [31]:
Test_punc_removed_join_clean = [word for word in Test_punc_removed_join.split() if word.low
In [32]:
Test_punc_removed_join_clean # Only important (no so common) words are Left
Out[32]:
```

STEP 3.3 EXERCISE: COUNT VECTORIZER EXAMPLE

['Hello', 'Mr', 'Future', 'happy', 'learning', 'AI']

```
In [33]:
from sklearn.feature_extraction.text import CountVectorizer
sample_data = ['This is the first document.','This document is the second document.','And t

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(sample_data)

In [34]:

print(vectorizer.get_feature_names())

['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']

In [35]:

print(X.toarray())

[[0 1 1 1 0 0 1 0 1]
[0 2 0 1 0 1 1 0 1]
[1 0 0 1 1 0 1 1 1]
```

LET'S APPLY THE PREVIOUS THREE PROCESSES TO OUR SPAM/HAM EXAMPLE

```
In [36]:
```

[0 1 1 1 0 0 1 0 1]]

```
# Let's define a pipeline to clean up all the messages
# The pipeline performs the following: (1) remove punctuation, (2) remove stopwords

def message_cleaning(message):
    Test_punc_removed = [char for char in message if char not in string.punctuation]
    Test_punc_removed_join = ''.join(Test_punc_removed)
    Test_punc_removed_join_clean = [word for word in Test_punc_removed_join.split() if word return Test_punc_removed_join_clean
```

```
In [ ]:
```

```
# Let's test the newly added function
spam_df_clean = spam_df['text'].apply(message_cleaning)
```

```
In [ ]:
```

```
print(spam_df_clean[0])
```

```
In [39]:
```

```
print(spam_df['text'][0])
```

Subject: naturally irresistible your corporate identity lt is really hard t o recollect a company: the market is full of suggestions and the informati on isoverwhelming; but a good catchy logo, stylish statlonery and outstan ding website will make the task much easier . we do not promise that havin q ordered a iogo your company will automatically become a world leader : it isguite ciear that without good products, effective business organization and practicable aim it will be hotat nowadays market; but we do promise th at your marketing efforts will become much more effective . here is the lis t of clear benefits : creativeness : hand - made , original logos , special ly done to reflect your distinctive company image . convenience : logo and stationery are provided in all formats; easy - to - use content management system letsyou change your website content and even its structure . promptn ess : you will see logo drafts within three business days . affordability : your marketing break - through shouldn 't make gaps in your budget . 100 % satisfaction guaranteed : we provide unlimited amount of changes with no ex tra fees for you to be surethat you will love the result of this collaborat ion . have a look at our $\,$ portfolio $\,$ _ _ _ _ _ _ _ _ _ _ _ _____ not interest

LET'S APPLY COUNT VECTORIZER TO OUR MESSAGES LIST

In [40]:

```
from sklearn.feature_extraction.text import CountVectorizer
# Define the cleaning pipeline we defined earlier
vectorizer = CountVectorizer(analyzer = message_cleaning)
spamham_countvectorizer = vectorizer.fit_transform(spam_df['text'])
```

```
In [41]:
```

```
print(vectorizer.get_feature_names())
```

In [42]:

```
print(spamham_countvectorizer.toarray())
```

```
[[0 0 0 ... 0 0 0]

[0 0 0 ... 0 0 0]

[0 0 0 ... 0 0 0]

...

[0 0 0 ... 0 0 0]

[0 0 0 ... 0 0 0]
```

In [43]:

```
spamham_countvectorizer.shape
```

Out[43]:

(5728, 37229)

STEP#4: TRAINING THE MODEL WITH ALL DATASET

```
In [44]:
from sklearn.naive_bayes import MultinomialNB
NB_classifier = MultinomialNB()
label = spam_df['spam'].values
NB_classifier.fit(spamham_countvectorizer, label)
Out[44]:
MultinomialNB()
In [45]:
testing_sample = ['Free money!!!', "Hi Kim, Please let me know if you need any further info
testing_sample_countvectorizer = vectorizer.transform(testing_sample)
In [46]:
test_predict = NB_classifier.predict(testing_sample_countvectorizer)
test_predict
Out[46]:
array([1, 0], dtype=int64)
DIVIDE THE DATA INTO TRAINING AND TESTING
PRIOR TO TRAINING
In [49]:
X = spamham_countvectorizer
y = label
In [50]:
X.shape
Out[50]:
(5728, 37229)
In [51]:
y.shape
Out[51]:
(5728,)
In [52]:
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [53]:

```
from sklearn.naive_bayes import MultinomialNB

NB_classifier = MultinomialNB()
NB_classifier.fit(X_train, y_train)
```

Out[53]:

MultinomialNB()

In [54]:

```
# from sklearn.naive_bayes import GaussianNB
# NB_classifier = GaussianNB()
# NB_classifier.fit(X_train, y_train)
```

STEP#5: EVALUATING THE MODEL

In [55]:

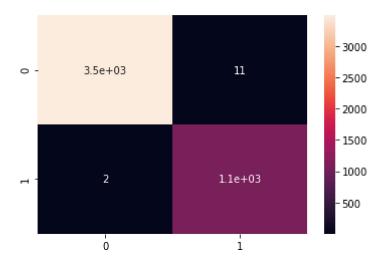
from sklearn.metrics import classification_report, confusion_matrix

In [56]:

```
y_predict_train = NB_classifier.predict(X_train)
y_predict_train
cm = confusion_matrix(y_train, y_predict_train)
sns.heatmap(cm, annot=True)
```

Out[56]:

<AxesSubplot:>

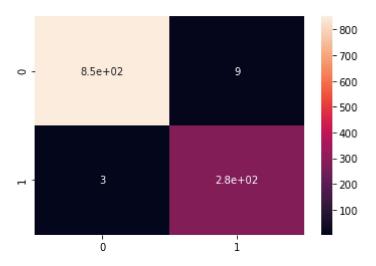


In [57]:

```
# Predicting the Test set results
y_predict_test = NB_classifier.predict(X_test)
cm = confusion_matrix(y_test, y_predict_test)
sns.heatmap(cm, annot=True)
```

Out[57]:

<AxesSubplot:>



In [58]:

print(classification_report(y_test, y_predict_test))

	precision	recall	f1-score	support
0	1.00	0.99	0.99	860
1	0.97	0.99	0.98	286
accuracy			0.99	1146
macro avg	0.98	0.99	0.99	1146
weighted avg	0.99	0.99	0.99	1146

STEP #6: LET'S ADD ADDITIONAL FEATURE TF-IDF

- Tf-idf stands for "Term Frequency-Inverse Document Frequency" is a numerical statistic used to reflect how important a word is to a document in a collection or corpus of documents.
- TFIDF is used as a weighting factor during text search processes and text mining.
- The intuition behing the TFIDF is as follows: if a word appears several times in a given document, this word might be meaningful (more important) than other words that appeared fewer times in the same document. However, if a given word appeared several times in a given document but also appeared many times in

other documents, there is a probability that this word might be common frequent word such as 'l' 'am'..etc. (not really important or meaningful!).

- TF: Term Frequency is used to measure the frequency of term occurrence in a document:
 - TF(word) = Number of times the 'word' appears in a document / Total number of terms in the document
- IDF: Inverse Document Frequency is used to measure how important a term is:
 - IDF(word) = log_e(Total number of documents / Number of documents with the term 'word' in it).
- Example: Let's assume we have a document that contains 1000 words and the term "John" appeared 20 times, the Term-Frequency for the word 'John' can be calculated as follows:
 - TFljohn = 20/1000 = 0.02
- Let's calculate the IDF (inverse document frequency) of the word 'john' assuming that it appears 50,000 times in a 1,000,000 million documents (corpus).
 - IDF|john = log (1,000,000/50,000) = 1.3
- · Therefore the overall weight of the word 'john' is as follows
 - TF-IDF|john = 0.02 * 1.3 = 0.026

In [59]:

```
spamham_countvectorizer
```

Out[59]:

In [60]:

```
from sklearn.feature_extraction.text import TfidfTransformer

emails_tfidf = TfidfTransformer().fit_transform(spamham_countvectorizer)
print(emails_tfidf.shape)
```

(5728, 37229)

In [61]:

```
print(emails_tfidf[:,:])
# Sparse matrix with all the values of IF-IDF
```

```
(0, 36565)
              0.06908944889543289
(0, 36432)
              0.06757047739651872
(0, 36430)
              0.059679365326344706
(0, 36025)
              0.1319392730989776
(0, 35034)
              0.05233428188145157
(0, 34800)
              0.09384305652743173
(0, 33562)
              0.06921203533637368
(0, 33037)
              0.09490328795519132
(0, 32843)
              0.06073679014431701
(0, 32617)
              0.11152518721878715
(0, 32602)
              0.11962021118089677
(0, 32319)
              0.11962021118089677
(0, 32263)
              0.0789584619498058
(0, 31968)
              0.11850864343422601
(0, 31959)
              0.08499360588016656
(0, 31547)
              0.10454173100334828
(0, 30218)
              0.04607380847274443
(0, 29858)
              0.09333645170409068
(0, 28879)
              0.07691781511072393
```

In [62]:

```
X = emails_tfidf
y = label

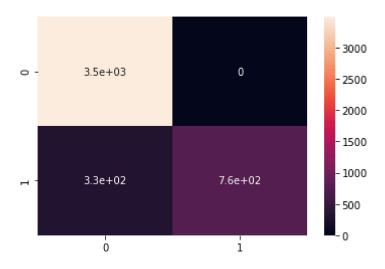
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

from sklearn.naive_bayes import MultinomialNB
NB_classifier = MultinomialNB()
NB_classifier.fit(X_train, y_train)

from sklearn.metrics import classification_report, confusion_matrix
y_predict_train = NB_classifier.predict(X_train)
y_predict_train
cm = confusion_matrix(y_train, y_predict_train)
sns.heatmap(cm, annot=True)
```

Out[62]:

<AxesSubplot:>



In [63]:

print(classification_report(y_test, y_predict_test))

	precision	recall	f1-score	support
0	0.77	0.76	0.76	867
1	0.27	0.29	0.28	279
accuracy			0.64	1146
macro avg	0.52	0.52	0.52	1146
weighted avg	0.65	0.64	0.64	1146