## Problem Statement

The objective of this task is to:

1) Build lexicon based spam filter on Twitter data set using AFINN

2) Build a spam filterusing Naïve Bayes on Text Blob

3) Compare the classification accuracies of two approaches (AFINN/Lexicon, Naïve Bayes)

In [1]:

```
import re
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import string
import nltk
```

In [2]:

```
%matplotlib inline
```

In [3]:

```
data  = pd.read_csv(r'C:\Users\Akanksha\REVA\Text Analytics\Assignment 3\train_t
weets.csv')
```

In [4]:

```
data.head(10)
```

Out[4]:

| | id | label | tweet |
|---|---|---|---|
| **0** | 1 | 0 | @user when a father is dysfunctional and is s... |
| **1** | 2 | 0 | @user @user thanks for #lyft credit i can't us... |
| **2** | 3 | 0 | bihday your majesty |
| **3** | 4 | 0 | #model i love u take with u all the time in ... |
| **4** | 5 | 0 | factsguide: society now #motivation |
| **5** | 6 | 0 | [2/2] huge fan fare and big talking before the... |
| **6** | 7 | 0 | @user camping tomorrow @user @user @user @use... |
| **7** | 8 | 0 | the next school year is the year for exams.ðŸ˜... |
| **8** | 9 | 0 | we won!!! love the land!!! #allin #cavs #champ... |
| **9** | 10 | 0 | @user @user welcome here ! i'm it's so #gr... |

### 1) Removing @user

In [5]:

```
def remove_pattern(input_txt, pattern):
    r = re.findall(pattern, input_txt)
    for i in r:
        input_txt = re.sub(i, '', input_txt)
    return input_txt
```

In [6]:

```
data['clean_tweet'] = np.vectorize(remove_pattern)(data['tweet'], "@[\w]*")

# np.vectorize takes a nested sequence of objects or numpy arrays as inputs and
 returns a
#single numpy array or a tuple of numpy arrays.
# src: https://docs.scipy.org/doc/numpy/reference/generated/numpy.vectorize.html

# Here we are using regular expression "@[\w]* to find the pattern of words begi
nning with @
```

In [7]:

```
data['clean_tweet'].head()
```

Out[7]:

```
0      when a father is dysfunctional and is so sel...
1      thanks for #lyft credit i can't use cause th...
2                                  bihday your majesty
3    #model   i love u take with u all the time in ...
4                factsguide: society now    #motivation
Name: clean_tweet, dtype: object
```

### 2) Removing Punctuations, Numbers, and Special Characters

In [8]:

```
data['clean_tweet'] = data['clean_tweet'].str.replace("[^a-zA-Z#]", " ")

#Here we will replace everything except characters and hashtags with spaces.
```

### 3) Removing Short Words

In [9]:

```
data['clean_tweet'] = data['clean_tweet'].apply(lambda x: ' '.join([w for w in x
.split() if len(w)>3]))

# Here we remove all the words having length 3 or less. The reason for removing
 the short words are, there are multiple words with "oh" and "hmm" in the given
 document
# these words are very less useful for further analysis.
```

In [10]:

```
data.head()
```

Out[10]:

| | id | label | tweet | clean_tweet |
|---|---|---|---|---|
| **0** | 1 | 0 | @user when a father is dysfunctional and is s... | when father dysfunctional selfish drags kids i... |
| **1** | 2 | 0 | @user @user thanks for #lyft credit i can't us... | thanks #lyft credit cause they offer wheelchai... |
| **2** | 3 | 0 | bihday your majesty | bihday your majesty |
| **3** | 4 | 0 | #model i love u take with u all the time in ... | #model love take with time |
| **4** | 5 | 0 | factsguide: society now #motivation | factsguide society #motivation |

#### 4) Normalization

In [11]:

```
data['clean_tweet'] = data['clean_tweet'].apply(lambda x: " ".join(x.lower() for
x in x.split()))
data['clean_tweet'].head()
```

Out[11]:

```
0    when father dysfunctional selfish drags kids i...
1    thanks #lyft credit cause they offer wheelchai...
2                                  bihday your majesty
3                           #model love take with time
4                       factsguide society #motivation
Name: clean_tweet, dtype: object
```

#### 5) Sopword Removal

In [12]:

```
from nltk.corpus import stopwords
stopwords = nltk.corpus.stopwords.words('english')
```

In [13]:

```
data['clean_tweet'] = data['clean_tweet'].apply(lambda x: " ".join(x for x in x.
split() if x not in stopwords))
data['clean_tweet'].head()
```

Out[13]:

```
0    father dysfunctional selfish drags kids dysfun...
1    thanks #lyft credit cause offer wheelchair van...
2                                    bihday majesty
3                               #model love take time
4                         factsguide society #motivation
Name: clean_tweet, dtype: object
```

### 4) Tokenization

In [14]:

```
import nltk
from nltk.tokenize import word_tokenize
```

In [15]:

```
tokenized_tweet = data['clean_tweet'].apply(lambda x: x.split())
tokenized_tweet.head()
```

Out[15]:

```
0    [father, dysfunctional, selfish, drags, kids, ...
1    [thanks, #lyft, credit, cause, offer, wheelcha...
2                                  [bihday, majesty]
3                         [#model, love, take, time]
4                    [factsguide, society, #motivation]
Name: clean_tweet, dtype: object
```

### 6) Stemming

Stemming work by cutting off the end or the beginning of the word, taking into account a list of common prefixes and suffixes that can be found in an inflected word. This indiscriminate cutting can be successful in some occasions, but not always, and that this approach presents some limitations.

In [16]:

```
#from nltk.stem import PorterStemmer
#ps = PorterStemmer()
#stemmed_words = tokenized_tweet.apply(lambda x: " ".join([ps.stem(word) for wor
d in x]))
#stemmed_words.head()
```

In [17]:

```
#In the above output, dysfunctional has been transformed into dysfunct, among ot
her changes.
```

### 7) Lematization

In [18]:

```
from nltk.stem import WordNetLemmatizer
wnl = WordNetLemmatizer()
lemma_words = tokenized_tweet.apply(lambda x: " ".join([wnl.lemmatize(word) for
word in x]))
lemma_words.head()
```

Out[18]:

```
0    father dysfunctional selfish drag kid dysfunct...
1    thanks #lyft credit cause offer wheelchair van...
2                                       bihday majesty
3                                #model love take time
4                         factsguide society #motivation
Name: clean_tweet, dtype: object
```

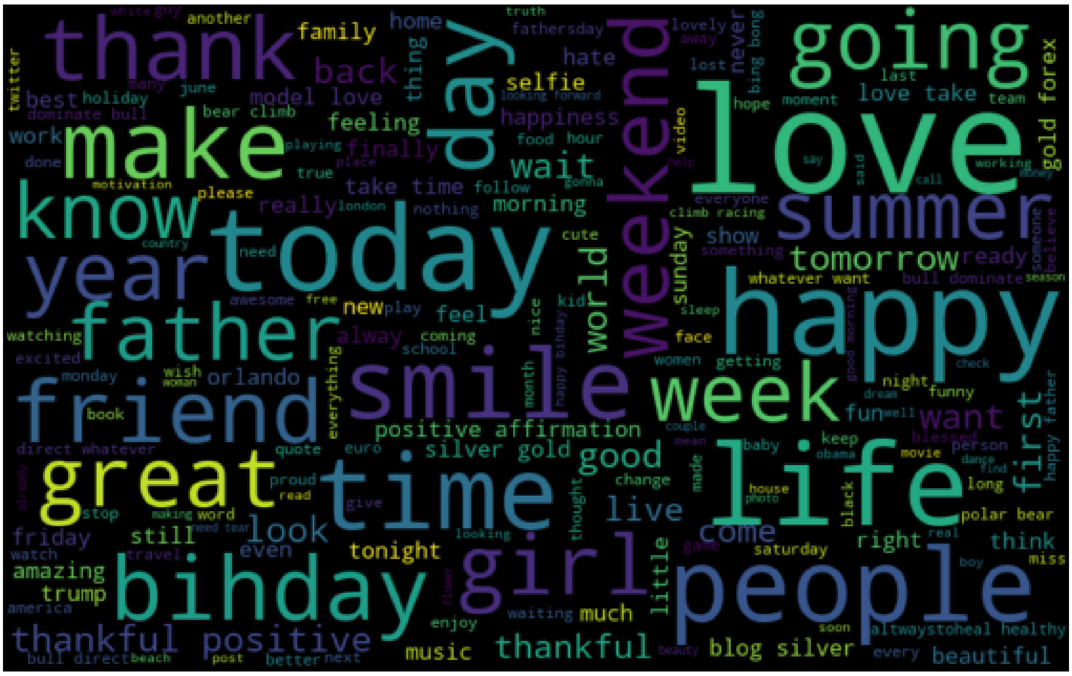
In [19]:

```
#Now let’s stitch these tokens back together.

for i in range(len(tokenized_tweet)):
    tokenized_tweet[i] = ' '.join(tokenized_tweet[i])

data['clean_tweet'] = tokenized_tweet
```

### 8) WordCloud

In [20]:

```
all_words = ' '.join([text for text in data['clean_tweet']])
from wordcloud import WordCloud
wordcloud = WordCloud(width=800, height=500, max_font_size=110).generate(all_wor
ds)

plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```




We can see most of the words are positive or neutral. With happy and love being the most frequent ones. It doesn’t give us any idea about the words associated with the racist/sexist tweets. Hence, we will plot separate wordclouds for both the classes(racist/sexist or not).

#### a) Words in ham tweets

In [21]:

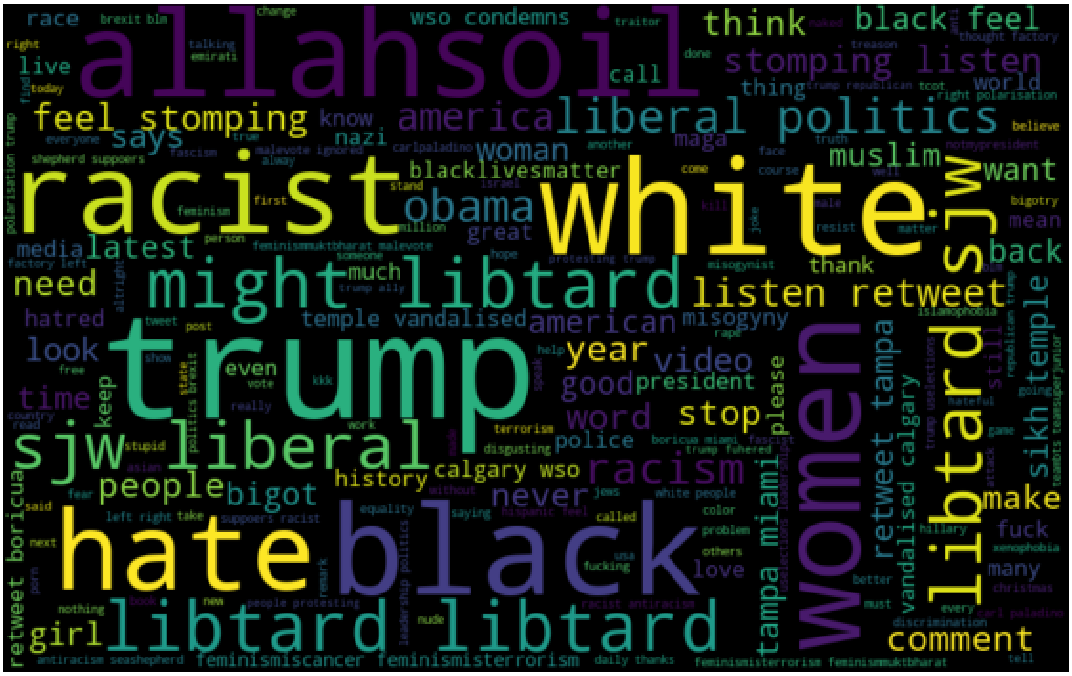
```
normal_words =' '.join([text for text in data['clean_tweet'][data['label'] == 0
]])

wordcloud = WordCloud(width=800, height=500, random_state=21, max_font_size=110)
.generate(normal_words)
plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```


We can see most of the words are positive or neutral. With happy, smile, and love being the most frequent ones. Hence, most of the frequent words are compatible with the sentiment which is non racist/sexists tweets. Similarly, we will plot the word cloud for the other sentiment. Expect to see negative, racist, and sexist terms.

#### b) Words in Spam Tweets

In [22]:

```
negative_words = ' '.join([text for text in data['clean_tweet'][data['label'] ==
1]])
wordcloud = WordCloud(width=800, height=500,
random_state=21, max_font_size=110).generate(negative_words)
plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```




## 9) Understanding the impact of Hashtags on tweets

In [23]:

```
# function to collect hashtags
def hashtag_extract(x):
    hashtags = []
    # Loop over the words in the tweet
    for i in x:
        ht = re.findall(r"#(\w+)", i)
        hashtags.append(ht)

    return hashtags
```

In [24]:

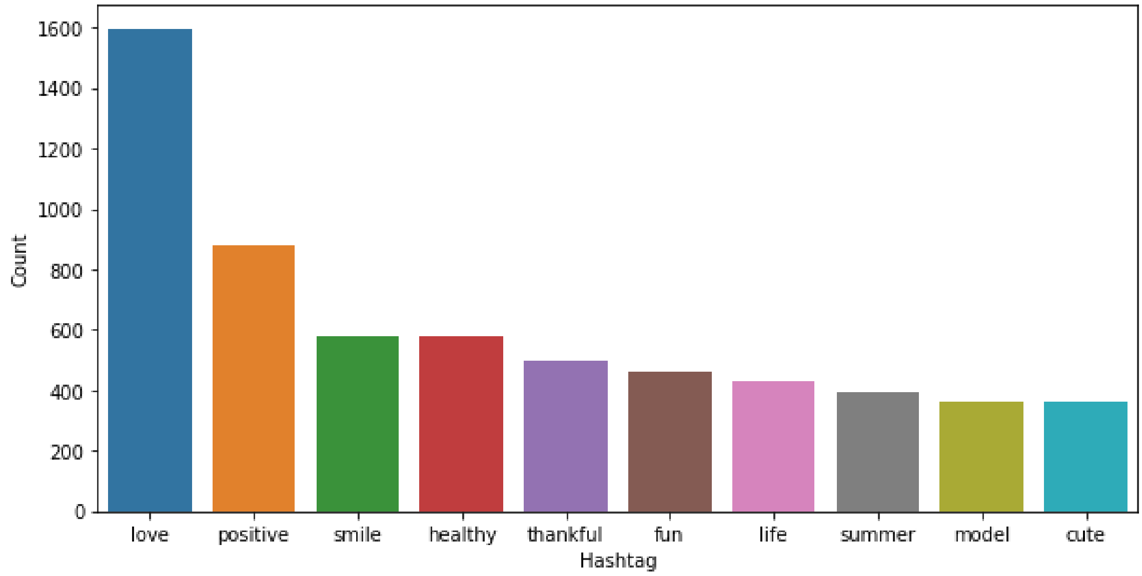
```
# extracting hashtags from non racist/sexist tweets
HT_regular = hashtag_extract(data['clean_tweet'][data['label'] == 0])

# extracting hashtags from racist/sexist tweets
HT_negative = hashtag_extract(data['clean_tweet'][data['label'] == 1])

# unnesting list
HT_regular = sum(HT_regular,[])
HT_negative = sum(HT_negative,[])
```

Now that we have prepared our lists of hashtags for both the sentiments, we can plot the top n hashtags. So, first let's check the hashtags in the non-racist/sexist tweets.

### *Non-Racist/Sexist (Ham) Tweets*

In [25]:

```
a = nltk.FreqDist(HT_regular)
d = pd.DataFrame({'Hashtag': list(a.keys()),
                  'Count': list(a.values())})
# selecting top 10 most frequent hashtags
d = d.nlargest(columns="Count", n = 10)
plt.figure(figsize=(10,5))
ax = sns.barplot(data=d, x= "Hashtag", y = "Count")
ax.set(ylabel = 'Count')
plt.show()
```

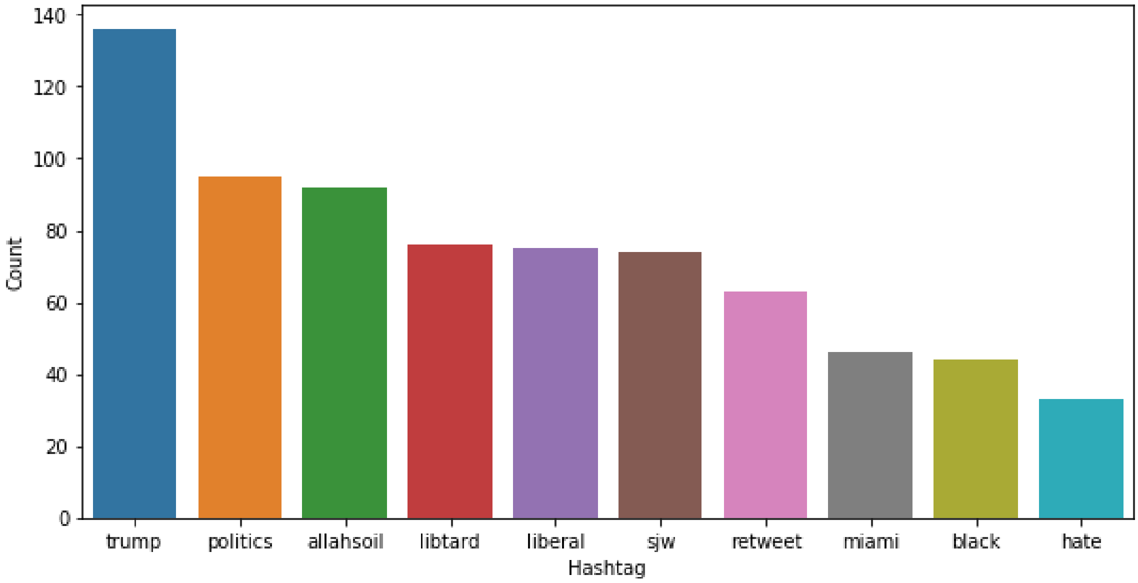



All these hashtags are positive and it makes sense. I am expecting negative terms in the plot of the second list. Let's check the most frequent hashtags appearing in the racist/sexist tweets.

### *Racist/Sexist (Spam) Tweets*

In [26]:

```
b = nltk.FreqDist(HT_negative)
e = pd.DataFrame({'Hashtag': list(b.keys()), 'Count': list(b.values())})
# selecting top 10 most frequent hashtags
e = e.nlargest(columns="Count", n = 10)
plt.figure(figsize=(10,5))
ax = sns.barplot(data=e, x= "Hashtag", y = "Count")
ax.set(ylabel = 'Count')
plt.show()
```




As expected, most of the terms are negative with a few neutral terms as well. So, it’s not a bad idea to keep these hashtags in our data as they contain useful information. Next, we will try to extract features from the tokenized tweets.

### Splitting Train and Test Datasets

In [27]:

```
x = data['clean_tweet']
y = data['label']
```

In [28]:

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x[0:5000], y[0:5000], test_s
ize=0.2)
```

In [32]:

```
len(x_train)
```

Out[32]:

```
4000
```

In [33]:

```
len(x_test)
```

Out[33]:

1000

#### Vectorization

In [34]:

```
from sklearn.feature_extraction.text import CountVectorizer

vect = CountVectorizer(max_features=1000, binary=True)

x_train_vect = vect.fit_transform(x_train)
```

## Spam Filtering

#### Multinomial Naive Bayes Classifier

In [59]:

```
from sklearn.naive_bayes import MultinomialNB

nb = MultinomialNB()

#Fitting the Multinomial Naive Bayes model
nb.fit(x_train_vect, y_train)

nb.score(x_train_vect, y_train)
```

Out[59]:

0.9565

In [60]:

```
x_test_vect = vect.transform(x_test)

y_pred = nb.predict(x_test_vect)

y_pred
```

Out[60]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 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, 0,
       1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 1, 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, 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,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 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, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 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, 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, 0, 1, 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, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 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, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 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, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

```
0, 0,
        0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 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, 0, 0,
0, 0,
        0, 0, 0, 1, 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, 0, 0, 0, 1, 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, 0, 0, 1, 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, 1, 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, 0,
0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 1, 0, 0,
0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
        0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 1,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

In [61]:

```python
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix

print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred) * 100))
print("\nF1 Score: {:.2f}".format(f1_score(y_test, y_pred) * 100))
print("\nCOnfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

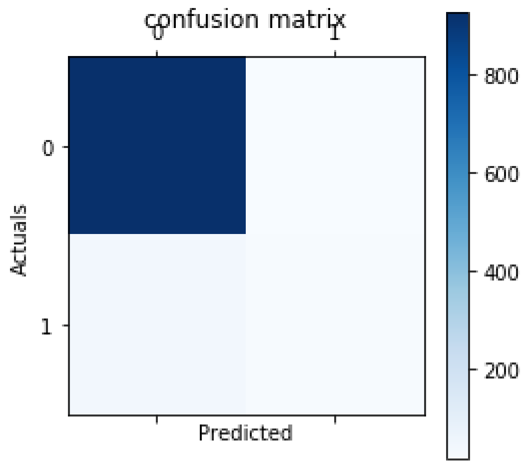
```
Accuracy: 94.70%

F1 Score: 43.01

COnfusion Matrix:
 [[927  15]
 [ 38  20]]
```

In [78]:

```
plt.matshow(confusion_matrix(y_test, y_pred), cmap='Blues', interpolation='neare
st')
plt.title('confusion matrix')
plt.colorbar()
plt.ylabel('Actuals')
plt.xlabel('Predicted')
```

Out[78]:

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




For a breakdown of the confusion matrix, we have:

927 predicted positive (0), and was positive (0). True Positive. 20 predicted negative (1), and was negative (1). True Negative. 38 predicted positive (0), but was negative (1). False Positive. 15 predicted negative (1), but was positive (0). False Negative.

From the above results, it is very clear that Multinomial Naive Bayes classifier performed great with 94.70% accuracy. The classifier was able to predict 947 (=927+20) tweets correctly out of 1000 tweets.

#### Using Naive Bayes Classifier Available in TextBlob

In [43]:

```
from textblob import TextBlob
from textblob.classifiers import NaiveBayesClassifier

train = list(zip(x_train, y_train))
test = list(zip(x_test, y_test))
#test_tweet, test_labels = map(list, zip(*test))
```

In [44]:

```
cl = NaiveBayesClassifier(train)
```

In [45]:

```
print(cl.accuracy(test))
cl.show_informative_features(5)
```

```
0.949
Most Informative Features
        contains(racism) = True                1 : 0      =     91.6
: 1.0
       contains(liberal) = True                1 : 0      =     60.2
: 1.0
        contains(racist) = True                1 : 0      =     50.5
: 1.0
         contains(bigot) = True                1 : 0      =     48.0
: 1.0
      contains(equality) = True                1 : 0      =     39.3
: 1.0
```

### with AFINN Lexicon

In [79]:

```
# initialize afinn sentiment analyzer
from afinn import Afinn
af = Afinn()

# compute sentiment scores (polarity) and labels
sentiment_scores = [af.score(tweet) for tweet in x_test]
sentiment_category = ['1' if score > 0
                          else '0'
                              for score in sentiment_scores]
```

In [80]:

```
#test_tweet, test_labels = map(list, zip(*test))
df2 = pd.DataFrame([list(x_test), list(y_test), sentiment_scores, sentiment_cate
gory]).T
df2.columns = ['tweet', 'label','sentiment_score', 'sentiment_category']
df2['sentiment_score'] = df2.sentiment_score.astype('float')
```

In [81]:

```
type(x_test)
```

Out[81]:

```
pandas.core.series.Series
```

In [82]:

```
#df2[['label', 'sentiment_category']] = df[['label', 'sentiment_category']].appl
y(pd.to_numeric)
#df2['label'] = pd.to_numeric(df["label"])
y_test = df2['label']
y_pred = df2['sentiment_category']
y_pred = y_pred.astype(int)
y_test = y_test.astype(int)
```

In [83]:

```
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred) * 100))
```

```
Accuracy: 46.60%
```

In [84]:

```
print("\nF1 Score: {:.2f}".format(f1_score(y_test, y_pred) * 100))
print("\nCOnfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

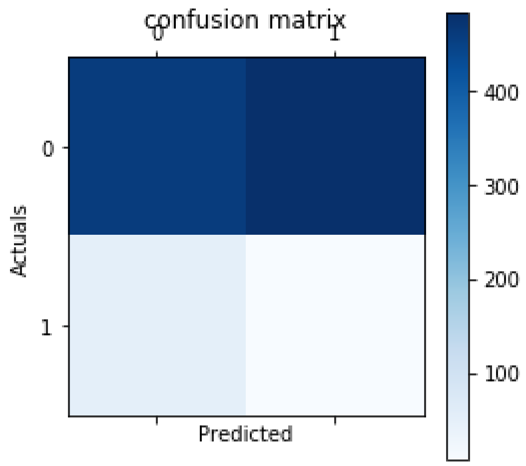
```
F1 Score: 2.55

COnfusion Matrix:
 [[459 483]
 [ 51   7]]
```

In [85]:

```
plt.matshow(confusion_matrix(y_test, y_pred), cmap="Blues", interpolation='neare
st')
plt.title('confusion matrix')
plt.colorbar()
plt.ylabel('Actuals')
plt.xlabel('Predicted')
```

Out[85]:

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




We can see that our model has predicted the sentiment with a 46.60% accuracy. Also, looking at the confusion matrix we can see that it's not doing that great of a job classifying.

For a breakdown of the confusion matrix, we have:

459 predicted positive (0), and was positive (0). True Positive. 7 predicted negative (1), and was negative (1). True Negative. 51 predicted positive (0), but was negative (1). False Positive. 483 predicted negative (1), but was positive (0). False Negative.

The classifier was able to predict 466 (=459+7) tweets correctly out of 1000 tweets. and 534 (=51+483) tweets classified incorrectly.

#### ***From the results from Multinomial NB classifer and Afinn based classifier, MNB classifier outperformed Afinn based classifier***