# HW4

October 29, 2019

```
In [5]: import io
        import sys
        import numpy as np
```

```
In [6]: vocab = np.loadtxt('./hw4_vocab.txt',dtype = str)
        uni_count = np.loadtxt('./hw4_unigram.txt',dtype = float)
        uni_prob  = np.zeros(uni_count.shape)
        total = uni_count.sum()
        uni_prob = uni_count/total
        vocab_m = []
        m_prob  = []
```

## 1 unigram

```
In [7]: for i in range(len(vocab)):
            if vocab[i][0] == 'M':
                #print(vocab[i])
                vocab_m.extend([vocab[i]])
                m_prob.extend([uni_prob[i]])
```

```
In [8]: for i in range(len(vocab_m)):
            print('Token: ',vocab_m[i],'      Uni-Prob: ',np.round(m_prob[i],6))
```

```
Token:  MILLION       Uni-Prob:  0.002073
Token:  MORE       Uni-Prob:  0.001709
Token:  MR.       Uni-Prob:  0.001442
Token:  MOST       Uni-Prob:  0.000788
Token:  MARKET       Uni-Prob:  0.00078
Token:  MAY       Uni-Prob:  0.00073
Token:  M.       Uni-Prob:  0.000703
Token:  MANY       Uni-Prob:  0.000697
Token:  MADE       Uni-Prob:  0.00056
Token:  MUCH       Uni-Prob:  0.000515
Token:  MAKE       Uni-Prob:  0.000514
Token:  MONTH       Uni-Prob:  0.000445
Token:  MONEY       Uni-Prob:  0.000437
```

```
Token:  MONTHS       Uni-Prob:  0.000406
Token:  MY       Uni-Prob:  0.0004
Token:  MONDAY       Uni-Prob:  0.000382
Token:  MAJOR       Uni-Prob:  0.000371
Token:  MILITARY       Uni-Prob:  0.000352
Token:  MEMBERS       Uni-Prob:  0.000336
Token:  MIGHT       Uni-Prob:  0.000274
Token:  MEETING       Uni-Prob:  0.000266
Token:  MUST       Uni-Prob:  0.000267
Token:  ME       Uni-Prob:  0.000264
Token:  MARCH       Uni-Prob:  0.00026
Token:  MAN       Uni-Prob:  0.000253
Token:  MS.       Uni-Prob:  0.000239
Token:  MINISTER       Uni-Prob:  0.00024
Token:  MAKING       Uni-Prob:  0.000212
Token:  MOVE       Uni-Prob:  0.00021
Token:  MILES       Uni-Prob:  0.000206
```

## 2 BIGRAM

```
In [9]: bi_count = np.loadtxt('./hw4_bigram.txt',dtype = float)
```

```
In [10]: bigram_the = bi_count[bi_count[:,0]==4]
```

```
In [11]: THE_count = uni_count[3]
         THE_count
```

```
Out[11]: 3855375.0
```

```
In [14]: sorted_bigram_the[::-1][:20]
```

```
Out[14]: array([[  4., 270.,   1.],
                [  4., 140.,   1.],
                [  4., 145.,   1.],
                [  4., 139.,   1.],
                [  4., 150.,   1.],
                [  4., 157.,   1.],
                [  4., 120.,   1.],
                [  4., 164.,   1.],
                [  4., 386.,   1.],
                [  4.,  44.,   1.],
                [  4., 358.,   1.],
                [  4., 195.,   1.],
                [  4.,  37.,   1.],
                [  4., 200.,   1.],
                [  4., 109.,   1.],
                [  4., 301.,   1.],
```

```
       [  4., 343.,   1.],
       [  4., 470.,   1.],
       [  4., 318.,   1.],
       [  4.,  93.,   1.]])
```

```
In [13]: sorted_bigram_the = bigram_the[bigram_the[:,2].argsort()[::-1]]
         bigram_top_10 = sorted_bigram_the[:10]
         top_10_vocab_index = np.subtract(bigram_top_10[:,1].astype(int),np.ones(10)) # gives us
         top_10_words = top_10_words = vocab[top_10_vocab_index.astype(int)]
         top_10_counts = bigram_top_10[:,2]
         top_10_prob   = top_10_counts/THE_count
```

```
In [15]: import pandas as pd
         probs = {'words': top_10_words,'probability': top_10_prob}

         pd.DataFrame(data = probs)
```

```
Out[15]:    probability       words
         0     0.615020       <UNK>
         1     0.013372          U.
         2     0.011720       FIRST
         3     0.011659     COMPANY
         4     0.009451         NEW
         5     0.008672      UNITED
         6     0.006803  GOVERNMENT
         7     0.006651    NINETEEN
         8     0.006287        SAME
         9     0.006161         TWO
```

### 2.1 The stock market fell by one hundred points last week

```
In [16]: ######### UNIGRAM ############
         string = 'THE STOCK MARKET FELL BY ONE HUNDRED POINTS LAST WEEK'
         sentence = string.split(' ')
         sentence
```

```
Out[16]: ['THE',
          'STOCK',
          'MARKET',
          'FELL',
          'BY',
          'ONE',
          'HUNDRED',
          'POINTS',
          'LAST',
          'WEEK']
```

```
In [17]: total = uni_count.sum()
         uni_prob = uni_count/total
```

```
vocab_ind = []
word_prob = []
word_count = []
cummu_prob = []
for i in range(len(sentence)):
    vocab_ind.extend([np.where(vocab==sentence[i])])

    prob = uni_prob[vocab_ind[i]][0]
    word_prob.extend([prob])
    word_count.extend([])
    if i == 0:
        cummu_prob.extend([word_prob[i]])
    else:
        cummu_prob.extend([cummu_prob[i-1]*word_prob[i]])
```

In [18]:
```
print('log cummulative probabilty: ',np.log(cummu_prob[-1]))
```

```
log cummulative probabilty:  -64.50944034364878
```

In [257]:
```
.047*.000668
```

Out[257]: 3.1395999999999996e-05

In [20]:
```
prob_dict = {'prob': word_prob,'word': sentence}
pd.DataFrame(columns = ['word','prob'], data = prob_dict)
```

Out[20]:

| | word | prob |
|---|---|---|
| 0 | THE | 0.047152 |
| 1 | STOCK | 0.000668 |
| 2 | MARKET | 0.000780 |
| 3 | FELL | 0.000265 |
| 4 | BY | 0.004180 |
| 5 | ONE | 0.006006 |
| 6 | HUNDRED | 0.004021 |
| 7 | POINTS | 0.000221 |
| 8 | LAST | 0.001161 |
| 9 | WEEK | 0.000572 |

In [21]:
```
########## BIGRAM APPROACH ###############
string = '<s> THE STOCK MARKET FELL BY ONE HUNDRED POINTS LAST WEEK'
sentence = string.split(' ')
sentence


vocab_ind = []
bigram_num = [] #equals the vocab index +1
bigram_count = []
```

```
bigram_prob  = []
word_count = []
cummu_prob = []


# first pass start loggin word indexes and total occurances

for i in range(len(sentence)):

    vocab_ind.extend([np.where(vocab==sentence[i])])
    bigram_num.extend([vocab_ind[i][0]+1])
    word_count.extend([uni_count[vocab_ind[i][0]]])

for i in range(len(sentence)-1):

    parent = bigram_num[i][0]
    child  = bigram_num[i+1][0]
    cond_count = bi_count[(bi_count[:,0] == parent) & (bi_count[:,1]==child)][0][-1]
    bigram_count.extend([cond_count])
    bigram_prob.extend([cond_count/word_count[i]])
    if i == 0:
        cummu_prob.extend([bigram_prob[i]])
    else:
        cummu_prob.extend([cummu_prob[i-1]*bigram_prob[i]])


print('log likelihood:',np.log(cummu_prob[-1]))
```

```
log likelihood: [-40.91813213]
```

### 2.2 "The sixteen officials sold fire insurance"

#### UNIGRAM

In [22]:
```
######### UNIGRAM ############
string = 'THE SIXTEEN OFFICIALS SOLD FIRE INSURANCE'
sentence = string.split(' ')
sentence

total = uni_count.sum()
uni_prob = uni_count/total

vocab_ind = []
word_prob = []
word_count = []
cummu_prob = []
for i in range(len(sentence)):
    vocab_ind.extend([np.where(vocab==sentence[i])])
```

```
            prob = uni_prob[vocab_ind[i]][0]
            word_prob.extend([prob])
            word_count.extend([])
            if i == 0:
                cummu_prob.extend([word_prob[i]])
            else:
                cummu_prob.extend([cummu_prob[i-1]*word_prob[i]])

        print('log likelihood:',np.log(cummu_prob[-1]))
```

```
log likelihood: -44.291934473132606
```

**BIGRAM**

```
In [23]: string = '<s> THE SIXTEEN OFFICIALS SOLD FIRE INSURANCE'
         sentence = string.split(' ')
         sentence


         vocab_ind = []
         bigram_num = [] #equals the vocab index +1
         bigram_count = []
         bigram_prob  = []
         word_count = []
         cummu_prob = []
         faulty_pairs = []


         # first pass start loggin word indexes and total occurances

         for i in range(len(sentence)):

             vocab_ind.extend([np.where(vocab==sentence[i])])
             bigram_num.extend([vocab_ind[i][0]+1])
             word_count.extend([uni_count[vocab_ind[i][0]]])

         for i in range(len(sentence)-1):

             parent = bigram_num[i][0]
             child  = bigram_num[i+1][0]
             try:
                 cond_count = bi_count[(bi_count[:,0] == parent) & (bi_count[:,1]==child)][0][-1
                 bigram_count.extend([cond_count])
                 bigram_prob.extend([cond_count/word_count[i]])

             except:
```

```
            # there is no conditional probability, child is independent of the parent,
            # calculate unigram probability for the child

            faulty_pairs.extend([(vocab[vocab_ind[i]][0],vocab[vocab_ind[i+1]][0])]) # voca
            cond_count = 0
            bigram_count.extend([cond_count])
            bigram_prob.extend([cond_count/word_count[i]])

        if i == 0:
            cummu_prob.extend([bigram_prob[i]])
        else:
            cummu_prob.extend([cummu_prob[i-1]*bigram_prob[i]])


    print('log likelihood:',np.log(cummu_prob[-1]))
```

```
log likelihood: [-inf]


C:\Users\Steve\Anaconda2\envs\Conda36\lib\site-packages\ipykernel_launcher.py:48: RuntimeWarning
```

```
In [26]: bigram_prob
```

```
Out[26]: [array([0.15865263]),
          array([0.00022851]),
          array([0.]),
          array([9.16220773e-05]),
          array([0.]),
          array([0.0030524])]
```

```
In [ ]: #### PAIRS NOTE SEEN ###

        'SIXTEEN OFFICIALS'
        'SOLD FIRE'
```

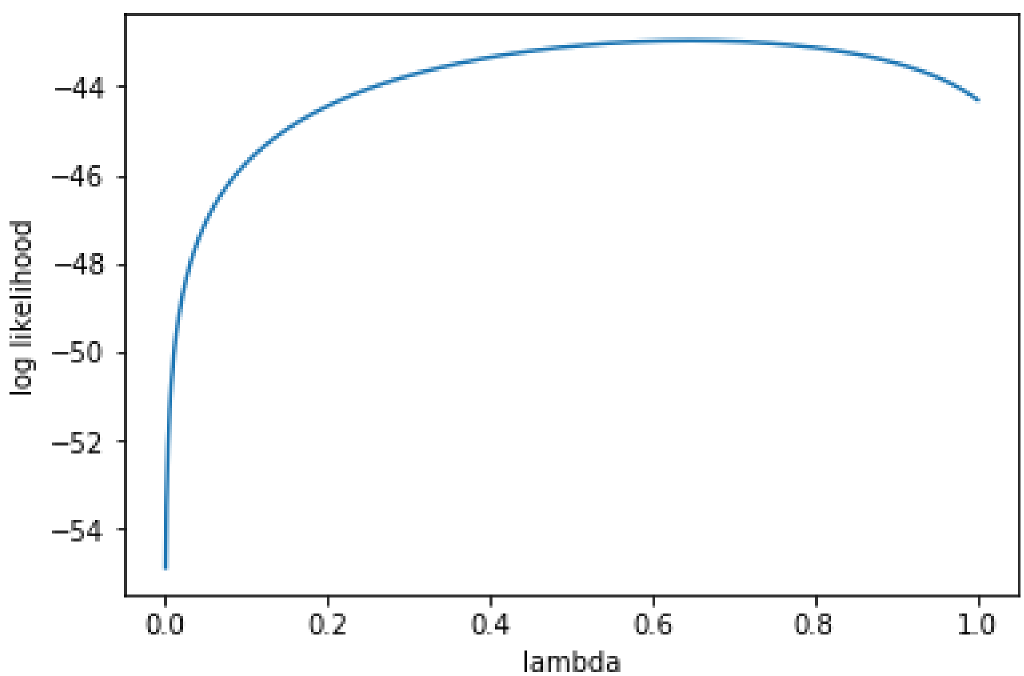
**MIXTURE MODEL**

```
In [31]: # for each model, the probability of each element was tallied in the word_prob and bigr
         # we will use these while tuning the lambda function
         uni_prob = word_prob # unigram model P(ith element)
         bi_prob = bigram_prob # bigram model P(child|parent)
         lmbda_score = []

         for lmbda in np.linspace(0,1.001,1000):
             prob = 1
             for i in range(len(word_prob)):
```

```
                prob = prob*(uni_prob[i]*lmbda + (1-lmbda)*bi_prob[i])

            lmbda_score.extend([prob])
```

```
In [32]: lmbda_score = np.log(lmbda_score)
         lmbda_val   = np.linspace(0,1.001,1000)
         import matplotlib.pyplot as plt
         plt.xlabel('lambda')
         plt.ylabel('log likelihood')
         plt.plot(np.linspace(0,1.001,1000),lmbda_score)
         plt.show()
```

```
C:\Users\Steve\Anaconda2\envs\Conda36\lib\site-packages\ipykernel_launcher.py:2: RuntimeWarning:
```




```
In [33]: np.where(lmbda_score == np.max(lmbda_score))
         max_lambda = lmbda_val[647]
         print(max_lambda,np.max(lmbda_score))
```

```
0.6482952952952953 -42.9641380716605
```

# 3 4.4 Stock Market Prediction

## 3.1 part a

The model is essentially a time lag model that predicts the value at the next time step to be equivalent to the current time step, as evidenced by the heavy weight on a3. This is a poor model because it essentially admits that it does not know if the price will go up or down, so the safest bet is to predict the same as the previous step in order to minimize the prediction loss.

```
In [34]: nasdaq_train = np.loadtxt('./nasdaq00.txt',dtype = float)
         nasdaq_test  = np.loadtxt('./nasdaq01.txt',dtype = float)


         # condition the data
         nasdaq_train_three_step = []
         train_y = []
         for i in range(2,len(nasdaq_train)-1):
             nasdaq_train_three_step.append([nasdaq_train[i-2],nasdaq_train[i-1],nasdaq_train[i]
             train_y.extend([nasdaq_train[i+1]])

         train_y = np.array([train_y])

         nasdaq_test_three_step = []
         test_y = []
         for i in range(2,len(nasdaq_test)-1):
             nasdaq_test_three_step.append([nasdaq_test[i-2],nasdaq_test[i-1],nasdaq_test[i]])
             test_y.extend([nasdaq_test[i+1]])

         test_y = np.array([test_y])
```

```
In [36]: import numpy as np
         A_inv = np.linalg.pinv(nasdaq_train_three_step)
         weights = A_inv@train_y.T
         print(weights[:])
```

```
[[0.03189569]
 [0.01560133]
 [0.95067337]]
```

### 3.1.1 WEIGHTS a1,a2,a3

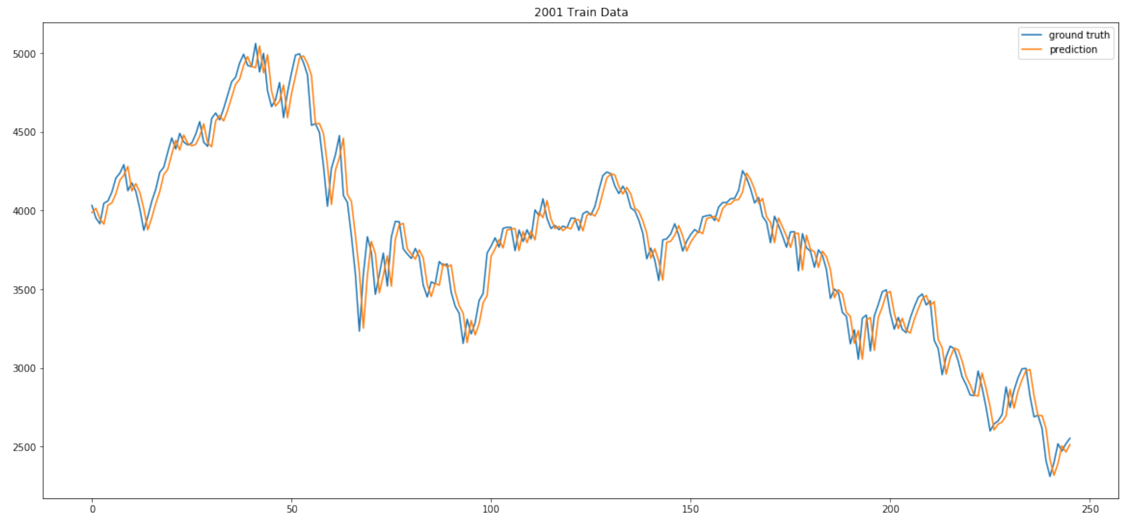
```
In [38]: for i in range(3):
             print('a%i : %f'%(i+1,weights[i]))
```

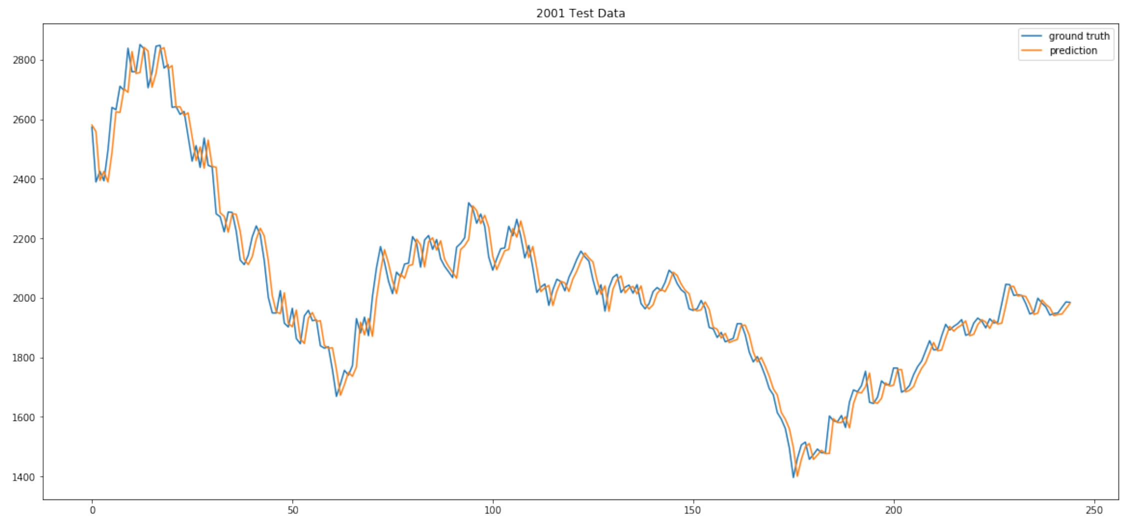
```
a1 : 0.031896
a2 : 0.015601
a3 : 0.950673
```

# 4 Part b

In [420]:
```
# test the data
y_pred=[]
for i in range(test_y.shape[1]):
    pred = nasdaq_test_three_step[i]@weights
    y_pred.extend([pred])

# vector form
y_pred_tr = nasdaq_train_three_step@weights
```

In [419]:
```
plt.figure(figsize=(20,20))
plt.subplot(2,1,1)
plt.plot(range(train_y.shape[1]),train_y.flatten())
plt.plot(range(train_y.shape[1]),nasdaq_train_three_step@weights)
plt.legend(['ground truth','prediction'])
plt.title('2001 Train Data')

plt.subplot(2,1,2)
plt.plot(range(test_y.shape[1]),test_y.flatten())
plt.plot(range(test_y.shape[1]),y_pred)
plt.legend(['ground truth','prediction'])
plt.title('2001 Test Data')
plt.show()
```




### 4.0.2 Mean Squared Error

In [428]:
```
squared_error_tr = 0 # tr = train
error_tr = 0
squared_error_t  =0      # t = test
error_t =0
for i in range(test_y.shape[1]):

    squared_error_t     += (test_y[0][i]-y_pred[i])**2
    error_t             += test_y[0][i]-y_pred[i]
    squared_error_tr    += (train_y[0][i]-y_pred_tr[i])**2
    error_tr            += train_y[0][i]-y_pred_tr[i]
```

```
mse_t = squared_error_t/test_y.shape[1]
mse_tr = squared_error_tr/train_y.shape[1]
print('MSE Test: ',np.round(mse_t[0],2),'  MSE Train: ',np.round(mse_tr[0],2))
```

```
MSE Test:  2985.1   MSE Train:  13895.86
```

## 5 Recommendation: Don't Use

The model is essentially a time lag model that predicts the value at the next time step to be equivalent to the current time step, as evidenced by the heavy weight on a3. This is a poor model because it essentially admits that it does not know if the price will go up or down, so the safest bet is to predict the same as the previous step in order to minimize the prediction loss.