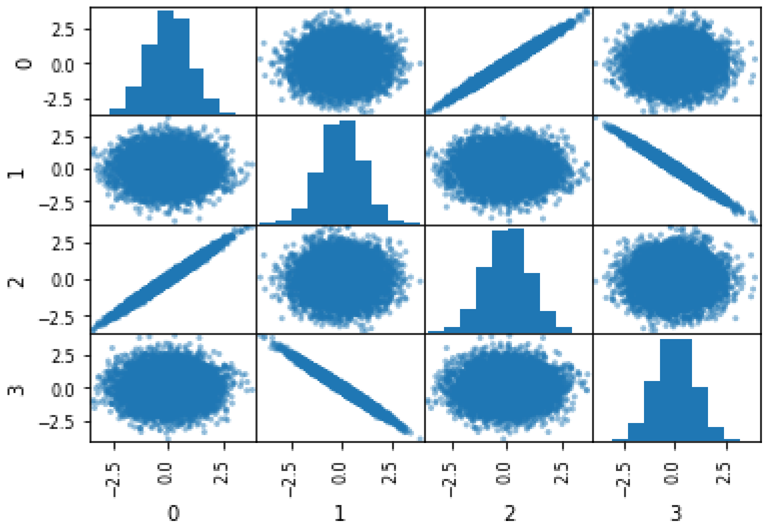
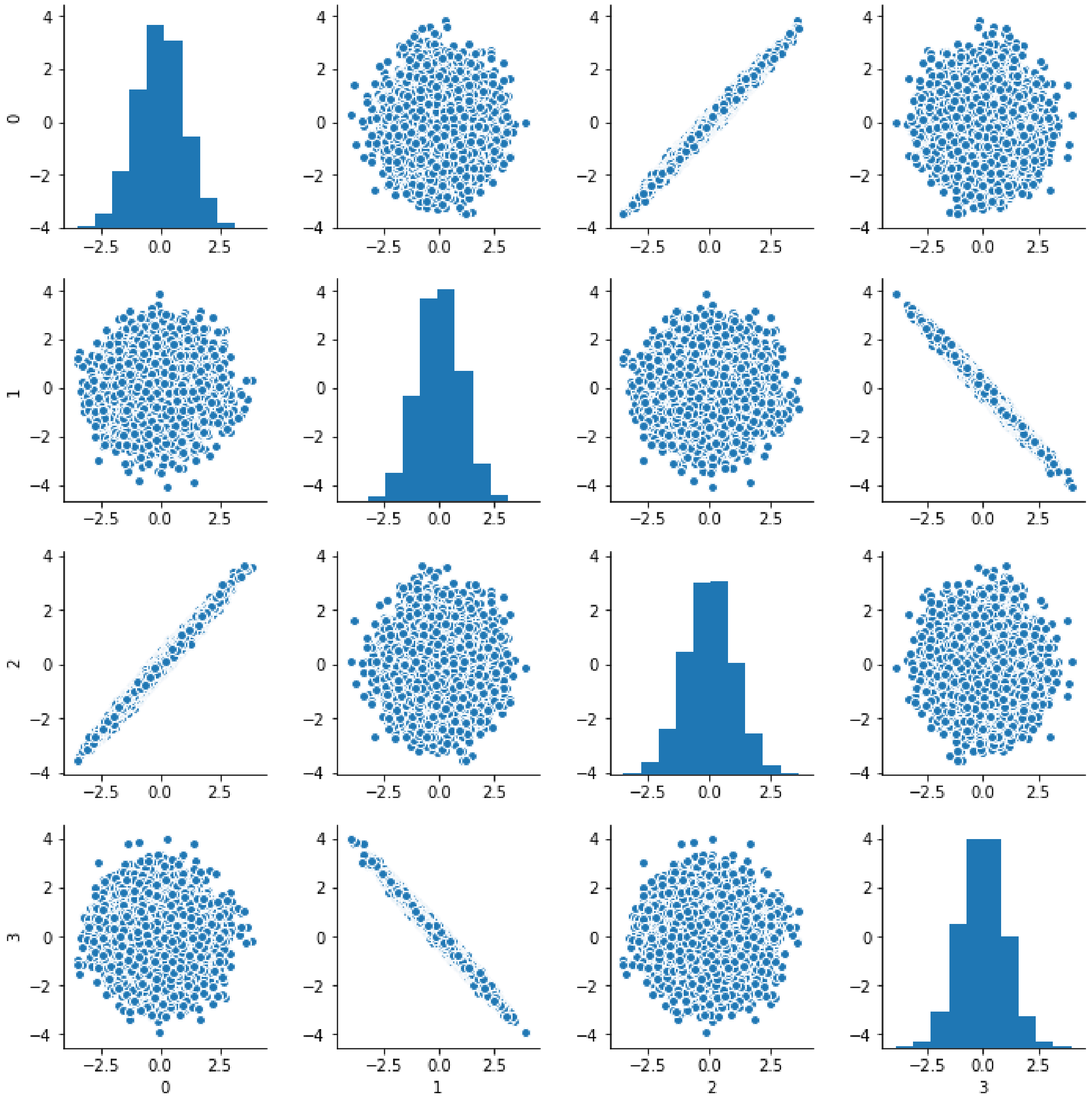
Andriy Dashko - ard2682
Justin Hoang - jah7399

In [1]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from pandas.plotting import scatter_matrix
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import scipy
from sklearn import linear_model
```

```
In [2]: #Problem 1a)

        df = pd.read_csv('Lab2_Data/DF1', header=0, index_col=0)

        scatter_matrix(df)
        sns.pairplot(df)
```

```
Out[2]: <seaborn.axisgrid.PairGrid at 0x12cf7eb6320>
```





From the scatter plots, we can see that columns 0 and 2 and columns 3 and 1 are very correlated

In [3]:
```
#Problem 1b)

df.cov()
```

Out[3]:

	0	1	2	3
0	1.001558	-0.004012	0.991624	0.004125
1	-0.004012	1.005378	-0.004099	-0.995457
2	0.991624	-0.004099	1.001589	0.004081
3	0.004125	-0.995457	0.004081	1.005168

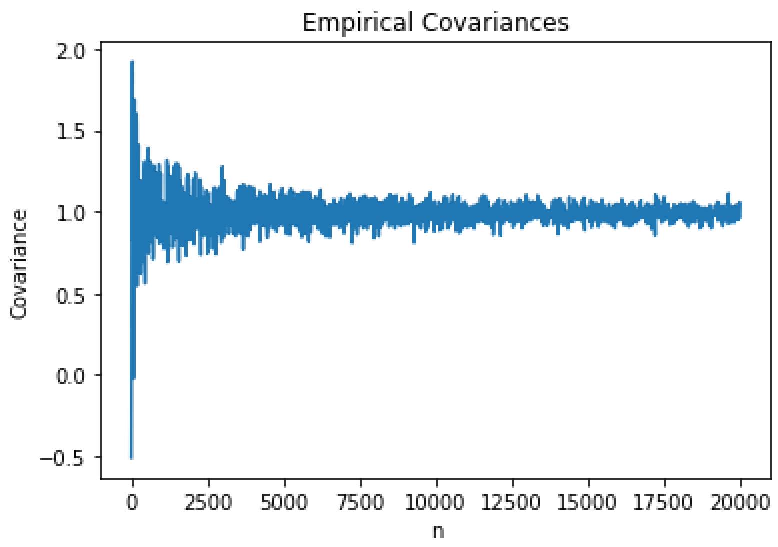
image.png

http://users.stat.umn.edu/~helwig/notes/datamat-Notes.pdf (http://users.stat.umn.edu/~helwig/notes/datamat-Notes.pdf)

The covariance of a matrix is defined with the formula above. Looking at our dataset, we see columns 0 and 2 have a correlation of 0.99 and columns 1 and 3 have a correlation of -0.99. This leads us to believe these sets of columns are correlated.

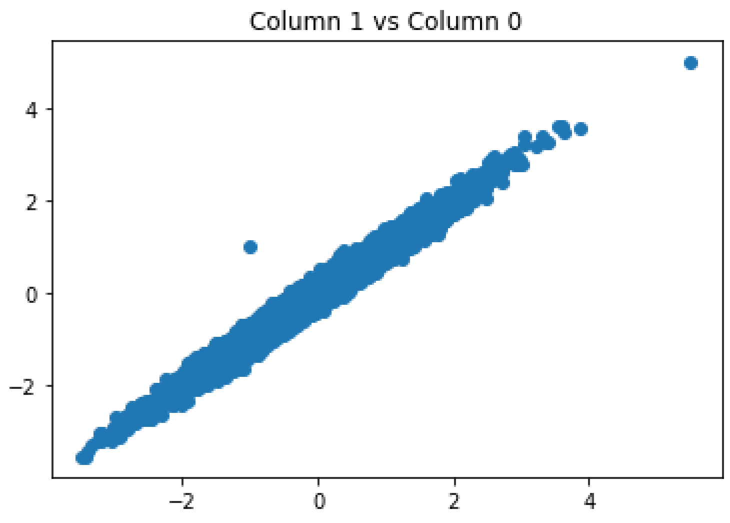
```
In [4]: #Problem 1c)

        mean = [0, 0, 0]
        cov = [[5, 0, 0],
                [0, 5, 0.99],
                [0, 0.99, 5]]

        rv = np.random.multivariate_normal(mean, cov, 100000)
        df = pd.DataFrame(rv, columns = ['X1', 'X2', 'X3'])

        samples = []
        covariances = []

        for numsamples in range(0, 20000, 10):
            rv = np.random.multivariate_normal(mean, cov, numsamples)
            covar23 = pd.DataFrame(rv, columns = ['X1', 'X2', 'X3']).cov().loc['X2'][
        'X3']
            samples.append(numsamples)
            covariances.append(covar23)

        plt.title('Empirical Covariances')
        plt.xlabel('n')
        plt.ylabel('Covariance')
        plt.plot(samples, covariances)
```

```
Out[4]: [<matplotlib.lines.Line2D at 0x12cf8a6fcc0>]
```



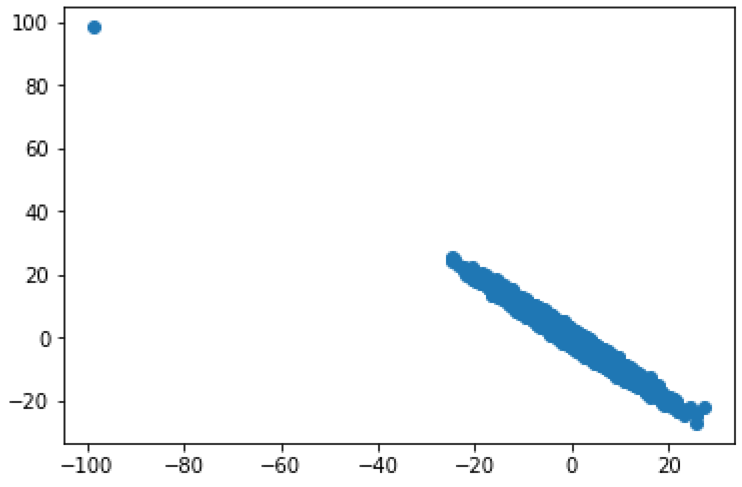
```
In [5]: df = pd.read_csv('Lab2_Data\DF2', header=0, index_col=0)

        plt.scatter(df['0'], df['1'])
        plt.title("Column 1 vs Column 0")
```

```
Out[5]: Text(0.5,1,'Column 1 vs Column 0')
```



```
In [6]: cov = df.cov()
        cov_inverse = pd.DataFrame(np.linalg.pinv(cov.values))

        #transform data
        data = pd.DataFrame(np.dot(df, cov_inverse))
        column_names = ['A', 'B']
        data.columns = column_names

        plt.scatter(data['A'], data['B'])
```

```
Out[6]: <matplotlib.collections.PathCollection at 0x12cf7f207f0>
```



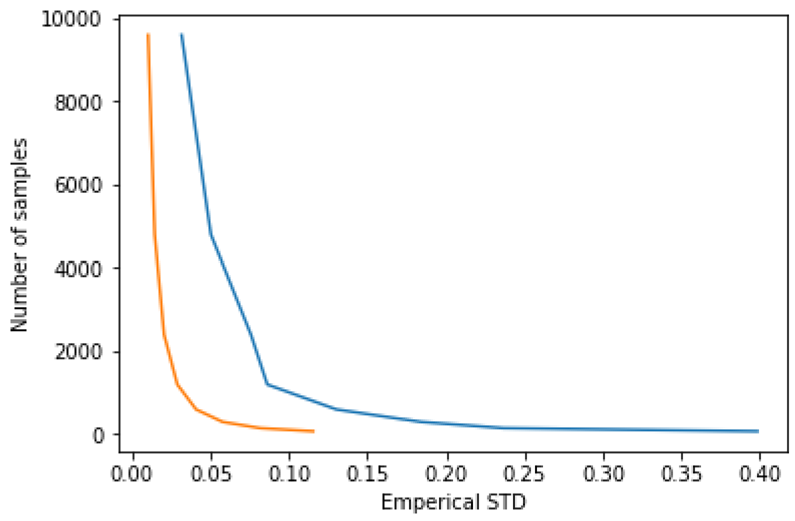
From the graph, we see (-1, 1) is the outlier. We used the Mahalanobis distance to scale distances so that the distances along a direction where the dataset is very spread out are scaled down, and distances along directions where the dataset is tightly packed are scaled up. So, the value of much higher variance will be farther away with this transformation. We see:

image.png

Source(page 222):https://books.google.com/books/about/Fundamentals_of_Machine_Learning_for_Pre.html?id=3EtQCgAAQBAJ&printsec=frontcover&source=kp_read_button#v=onepage&q&f=false (https://books.google.com/books/about/Fundamentals_of_Machine_Learning_for_Pre.html?id=3EtQCgAAQBAJ&printsec=frontcover&source=kp_read_button#v=onepage&q&f=false)

In [33]:
```
#Problem 3
def empStdDev(n):
    errors = []

    for i in range(100):
        xi = np.random.randn(n)
        ei = np.random.randn(n)
        yi = -3 + xi*0 + ei
        betahat = np.dot(xi,yi) / np.dot(xi,xi)
        errors.append(betahat-0)

    return np.std(errors)

print("Emperical STD (150):",empStdDev(150))

print("The standard deviation is well above 0.15, so that beta hat is not very
 significant at all.")

nvals = [75,150,300,600,1200,2400,4800,9600]
devs = []
inv = []
for n in nvals:
    devs.append(empStdDev(n))
    inv.append(1/(n**(1/2)))

plt.plot(devs, nvals)
plt.plot(inv, nvals)
plt.ylabel("Number of samples")
plt.xlabel("Emperical STD")
plt.show()

print("The blue curve is of the emperical STDs for different n and the orange
 curve is 1/sqrt(n). The fit is pretty close, they follow the same general tre
nd, but 1/sqrt(n) has sharper transitions. ")
```

```
Emperical STD (150): 0.234602873705
The standard deviation is well above 0.15, so that beta hat is not very signi
ficant at all.
```



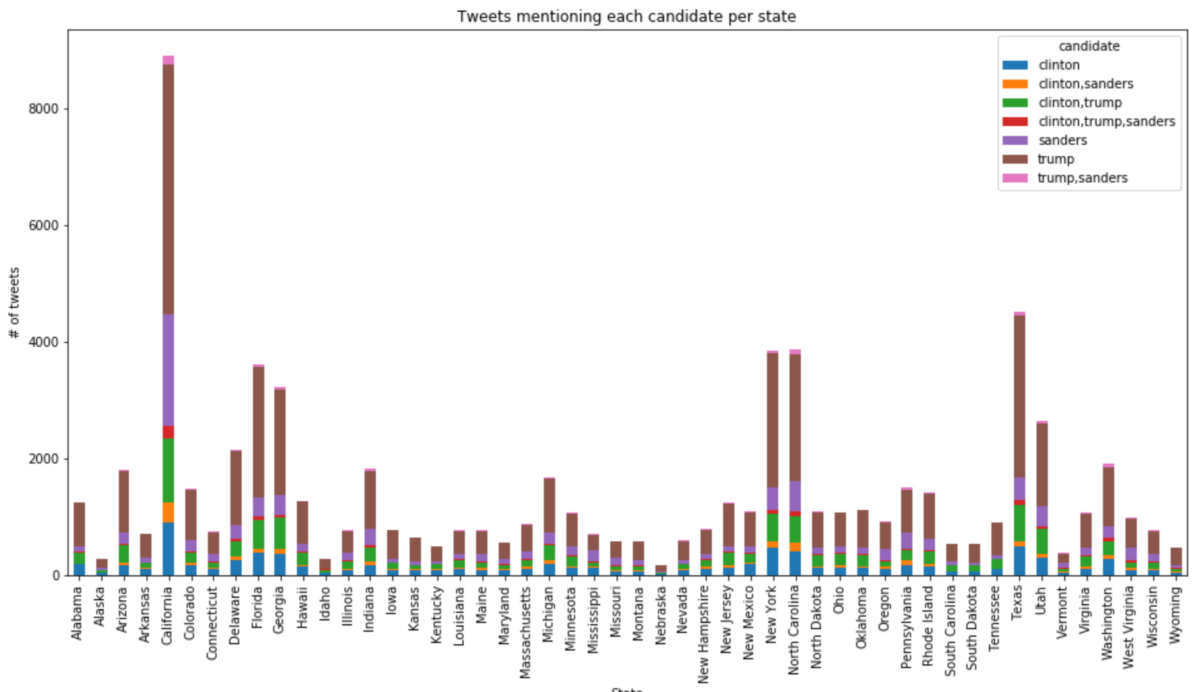
```
The blue curve is of the emperical STDs for different n and the orange curve
is 1/sqrt(n). The fit is pretty close, they follow the same general trend, bu
t 1/sqrt(n) has sharper transitions.
```

In [ ]:
```
#Problem 4


#Program 1

def topNames (k, year):
    data = pd.read_csv('Names/Names/yob'+str(year)+'.txt', sep=",", header=Non
e)
    names = data.iloc[0:k,0]
    return names.values

#print(topNames(4,1880))

#Program 2
numYears = (2015+1)-1880;

def nameFreq (name):

    fFreq = []
    mFreq = []

    for i in range(1880,2015+1):
        data = pd.read_csv('Names/Names/yob'+str(i)+'.txt', sep=",", header=No
ne)
        dataN = data[data[0] == name]

        for j in range(0,dataN.shape[0]):
            if(dataN.iloc[j,1] == 'F'):
                fFreq.append(dataN.iloc[j,2])
            else:
                mFreq.append(dataN.iloc[j,2])


    return [mFreq, fFreq]

#print(nameFreq('Mary'))

#Program 2 (relative)
totalNames = [0] * numYears
for i in range(numYears):
        data = pd.read_csv('Names/Names/yob'+str(i+1880)+'.txt', sep=",", head
er=None)
        tN = 0
        for j in range(0,data.shape[0]):
            tN+=data.iloc[j,2]
        totalNames[i] = tN


def nameRelFreq (name):

    fFreq = [0] * numYears
    mFreq = [0] * numYears

    for i in range(numYears):
        data = pd.read_csv('Names/Names/yob'+str(i+1880)+'.txt', sep=",", head
er=None)
```

```
        dataN = data[data[0] == name]

        for j in range(0,dataN.shape[0]):
            if(dataN.iloc[j,1] == 'F'):
                fFreq[i] = dataN.iloc[j,2]/totalNames[i]
            else:
                mFreq[i] = dataN.iloc[j,2]/totalNames[i]

    result = np.array([mFreq, fFreq])
    return result

s=nameRelFreq('Mary')
#print(s.shape)
#print(s[0,0])


#All Names switching popularity

nameSwitched = []
namesT = []

for i in range(numYears):
    data = pd.read_csv('Names/Names/yob'+str(i+1880)+'.txt', sep=",", header=N
one)
    for j in range(0,data.shape[0]):
        name = data.iloc[j,0]
        duplicate = 0
        for k in range(0, len(namesT)):
            if(namesT[k] == name):
                duplicate = 1
                break
        if(duplicate == 1):
            break
        namesT.append(name)
        freqs = nameRelFreq(name)
        popularity = 0
        if(freqs[0,0] > freqs[1,0]):
            popularity = 1
        for k in range(numYears):
            if popularity == 0 and freqs[0,k] > freqs[1,k]:
                 nameSwitched.append(name)
            if popularity == 1 and freqs[0,k] < freqs[1,k]:
                 nameSwitched.append(name)

print(nameSwitched)

print("The code for nameSwitched should work, but it runs too slow on a laptop
 to get the results in a reasonable time.")
```

```
In [34]: #Problem 5
         #Tutorial code from https://www.dataquest.io/blog/matplotlib-tutorial/
         #We looked through the code, ran it, and understand it
         import pandas as pd

         tweets = pd.read_csv("tweets.csv")
         tweets.head()

         def get_candidate(row):
             candidates = []
             text = row["text"].lower()
             if "clinton" in text or "hillary" in text:
                 candidates.append("clinton")
             if "trump" in text or "donald" in text:
                 candidates.append("trump")
             if "sanders" in text or "bernie" in text:
                 candidates.append("sanders")
             return ",".join(candidates)

         tweets["candidate"] = tweets.apply(get_candidate,axis=1)

         from datetime import datetime

         tweets["created"] = pd.to_datetime(tweets["created"])
         tweets["user_created"] = pd.to_datetime(tweets["user_created"])

         tweets["user_age"] = tweets["user_created"].apply(lambda x: (datetime.now() -
         x).total_seconds() / 3600 / 24 / 365)

         stateName = ["Alabama","Alaska","Arizona","Arkansas","California","Colorado",
           "Connecticut","Delaware","Florida","Georgia","Hawaii","Idaho","Illinois",
           "Indiana","Iowa","Kansas","Kentucky","Louisiana","Maine","Maryland",
           "Massachusetts","Michigan","Minnesota","Mississippi","Missouri","Montana",
           "Nebraska","Nevada","New Hampshire","New Jersey","New Mexico","New York",
           "North Carolina","North Dakota","Ohio","Oklahoma","Oregon","Pennsylvania",
           "Rhode Island","South Carolina","South Dakota","Tennessee","Texas","Utah",
           "Vermont","Virginia","Washington","West Virginia","Wisconsin","Wyoming"]

         stateAbbrv = ["AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DC", "DE", "FL", "GA"
         ,
                   "HI", "ID", "IL", "IN", "IA", "KS", "KY", "LA", "ME", "MD",
                   "MA", "MI", "MN", "MS", "MO", "MT", "NE", "NV", "NH", "NJ",
                   "NM", "NY", "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
                   "SD", "TN", "TX", "UT", "VT", "VA", "WA", "WV", "WI", "WY"]

         #Aggregating Results by States
         def get_state(row):
             states = [];
             text = str(row);
             appended = 0;

             for i in range(50):
                 if stateName[i] in text or stateAbbrv[i] in text:
                     states.append(stateName[i])
                     #states.append(i+1)
                     appended = 1;
```

```
            break

        #if appended == 0:
         #states.append("N/A")
         #states.append(0)

    return ",".join(states)

tweets["state"] = tweets["user_location"].apply(get_state)

tweets2 = tweets.groupby(['state', 'candidate'])['state'].count().unstack('can
didate').fillna(0)
tweets3 = tweets2.iloc[1:tweets2.shape[0],1:tweets2.shape[1]]
tweets3.plot(kind='bar', stacked=True, figsize=[16,8])
plt.title("Tweets mentioning each candidate per state")
plt.xlabel("State")
plt.ylabel("# of tweets")
plt.show()

print("This state prediction is fairly poor. It assigns states to tweets based
 on the user_location information, searching for the first full state name or
 abbreviation. Most of the tweets in the set are missing because many have no
 user_location or one that doesn't explicitly mention their state")
```



```
This state prediction is fairly poor. It assigns states to tweets based on th
e user_location information, searching for the first full state name or abbre
viation. Most of the tweets in the set are missing because many have no user_
location or one that doesn't explicitly mention their state
```

Lab 2

1. $P(Z_{AVG} > c)$

$P(S_n > cn)$

$P\left[\frac{S_n}{\sqrt{n}\,\theta} > \frac{0.1n}{\sqrt{n}\,\theta}\right)$ by Central Limit Thm

$P(Z_n > 0.1\sqrt{n})$

$1 - P(Z_n < c\sqrt{10000})$ Standard Normal

For $c = 0.1$

$P(Z_{avg} > 0.1)$

$1 - P(Z_n < 10) = 0$

For $c = 0.01$

$P(Z_{avg} > 0.01)$

$1 - P(Z_n < 1) = 0.16$

For $c = 0.001$

$P(Z_{avg} > 0.001)$

$1 - P(Z_n < 0.1) = 0.46$

General Case: $P(Z_{avg} > c)$

$$P\left(\frac{S_n - (n\mu)}{\sqrt{n}\,\theta} > \frac{cn - (n\mu)}{\sqrt{n}\,\theta}\right)$$

For $c = n^{-1/3}$

$$P(Z_{avg} - \mu > n^{-1/3})$$

$$\hat{x} = n^{-1/3} + \mu$$

$$Z_n = \frac{n^{-1/3} + \mu - \mu}{\delta / \sqrt{n}} = P\left(Z < \frac{-n^{1/6}}{\delta}\right)$$

For $c = n^{-1/2}$

$$P(Z_{avg} - \mu > n^{-1/2})$$

$$\hat{x} = n^{-1/2} + \mu$$

$$Z = \frac{n^{-1/2} + \mu - \mu}{\delta / \sqrt{n}}$$

$$Z = \frac{n^{-1/2}}{\delta} n^{1/2} = \frac{n^{-1/2}}{\delta} = P\left(Z < \frac{-1}{\delta}\right)$$

For $c = n^{-2/3}$

$$P(Z_{avg} - \mu > n^{-2/3})$$

$$\hat{x} = n^{-2/3} + \mu$$

$$Z = \frac{n^{-2/3} + \mu - \mu}{\delta / \sqrt{n}}$$

$$Z = \frac{n^{-2/3}}{\delta} n^{1/2} = \frac{n^{-1/6}}{\delta} = P\left(Z < \frac{-n^{-1/6}}{\delta}\right)$$

2. a) $\min \beta \cdot \frac{1}{n}\sum_{i=1}^{n}(x_i\beta - y_i)^2$

$\min\beta = \frac{1}{n}\left[\sum_{i=1}^{n}(x_i^2\beta^2 - 2x_i\beta y_i + y_i^2)\right]$

$\min\beta = \beta^2\frac{1}{n}\sum_{i=1}^{n}x_i^2 - \beta\frac{2}{n}\sum_{i=1}^{n}2x_iy_i + \frac{1}{n}\sum_{i=1}^{n}y_i^2$

where $A = \frac{1}{n}\sum_{i=1}^{n}x_i^2$

$B = \frac{2}{n}\sum_{i=1}^{n}2x_iy_i$

Note that A is quadratic with $A \geq 0$

$C = \frac{1}{n}\sum_{i=1}^{n}y_i^2$

b) $\frac{d}{d\beta}\left(\frac{1}{n}\sum_{i=1}^{n}(X_i\beta - y_i)^2\right) = \frac{2}{n}\sum_{i=1}^{n}(X_i\beta - y)X_i) = 0$

$\sum_{i=1}^{n}(X_i^2\beta - X_iY_i) = 0$

$$\boxed{\therefore \beta = \frac{\sum_{i=1}^{n}X_iY_i}{\sum_{i=1}^{n}X_i^2}}$$

c) Plugging in $y_i = X_i\beta + e_i$

$$\hat{\beta} = \beta + \frac{X^T * e}{X^TX}$$

Using $\hat{\beta} = \beta + Ze$

$$\boxed{Z = \frac{X^T}{X^TX}}$$