Assignment 2: Applied data science

PROBLEMS:

1. In words, the "standard normal distribution" is a normal distribution with mean zero and variance one, denoted here as N(0,1). For a random variable X that is distributed as a standard normal, mathematically we write $X \sim N(0,1)$. [5 points]
    a. Using R or Python, write code to draw at random 10 observations from a N(0,1) random variable. Instruct the machine to calculate the mean, variance and standard deviation of your draws.
    b. Repeat this exercise using 10,000 draws from a N(0,1), instructing again the machine to calculate the mean, variance and standard deviation of your draws.
    c. Repeat this exercise with 1,000,000 draws from a N(0,1), instructing again the machine to calculate the mean, variance and standard deviation of your draws.
    d. What conclusions, if any, do you draw from increasing the sample size?
    e. Submit your code and results.

ANSWERS:

a. Output:

Mean = 0.123408348806

Variance = 1.34614414078

Standard Deviation = 1.16023451973

b. Output:

Mean = 0.00445184390789

Variance = 0.987748960347

Standard Deviation = 0.993855603369

c. Output:

Mean = 0.00106250329193

Variance = 0.999348641121

Standard Deviation = 0.99967426751

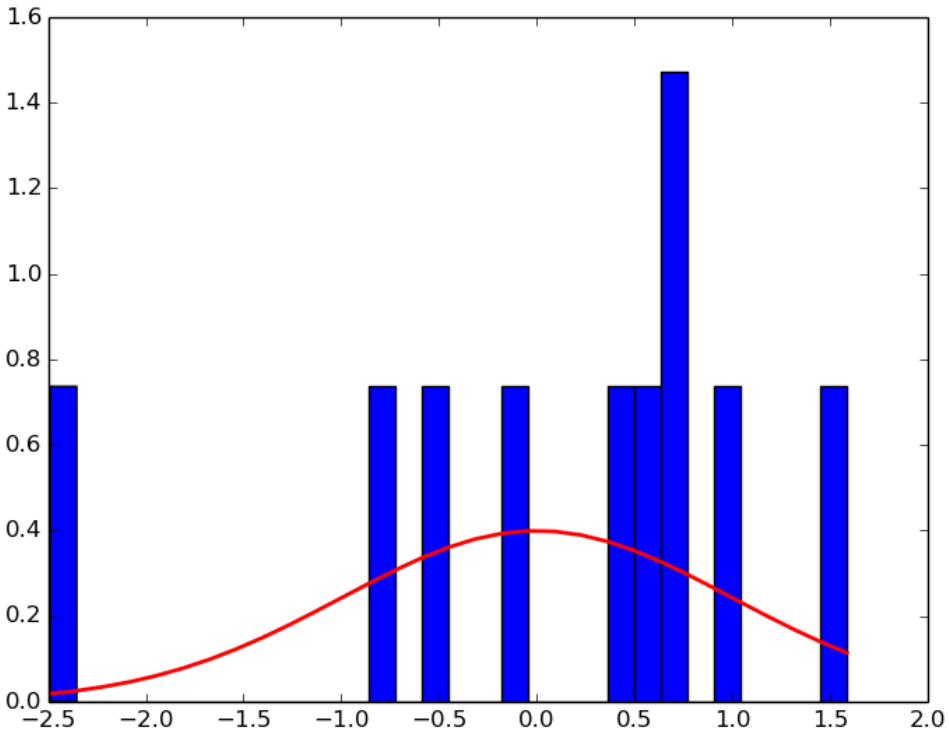
d. Random values that are normally distributed shows more accurate distribution in larger number of sample.

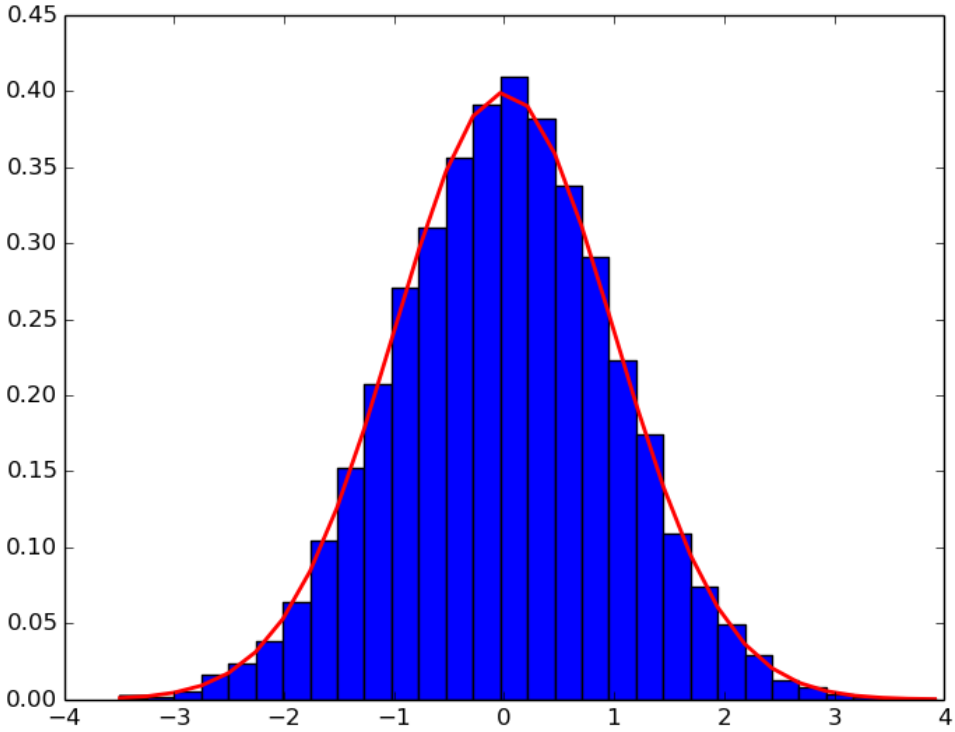
e. Source code:

Source Code (with num_samples being adjusted to number of samples a-c):

```
################################################
################################################
#       Applied Data Science GX5004            #
#       Assignment 2                           #
#       Dimas Rinarso Putro | drp354@nyu.edu   #
################################################
import argparse,csv, sys, os
import numpy as np
from matplotlib import pyplot as plt
import pylab

###No.1a-1c, just by changing the num_samples###
########################################
#variable initialization
mu, sigma = 0, 1
num_samples = 10 #change to the desired sample numbers in 1a-1c

#generate random numbers
nor = np.random.normal(mu, sigma, num_samples)

#calculate mean
print 'Mean = ',str(np.mean(nor))
#verify the standard deviation
print 'Variance = ',str(np.var(nor, ddof=1))
#verify the standard deviation
print 'Standard Deviation = ',str(np.std(nor, ddof=1))

#plot histogram
count, bins, ignored = plt.hist(nor, 30, normed=True)
plt.plot(bins, 1/(sigma * np.sqrt(2 * np.pi)) *
```

```
                np.exp( - (bins - mu)**2 / (2 * sigma**2) ),
         linewidth=2, color='r')
plt.show()
```

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0.40
0.35
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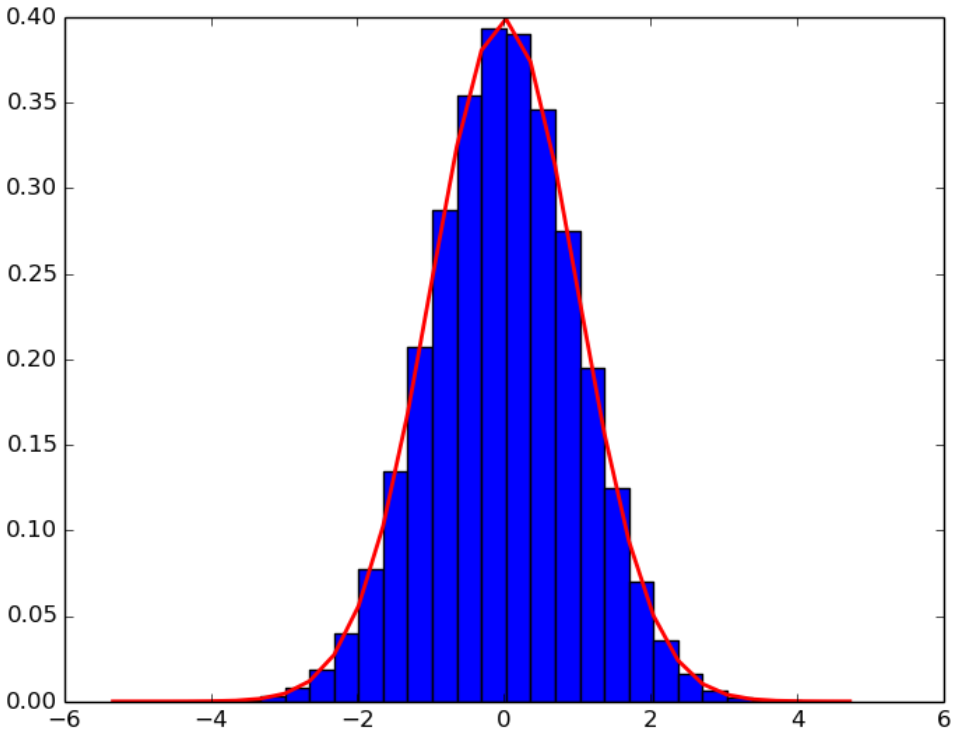
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6

PROBLEMS:

2. We discussed at some length the bivariate linear regression model,

   $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$.

   [5 points]

   a. Go to http://www.random.org/integers/ and generate two series of 1,000 random integers with values between 0 and 9. Call one series y and the other x.

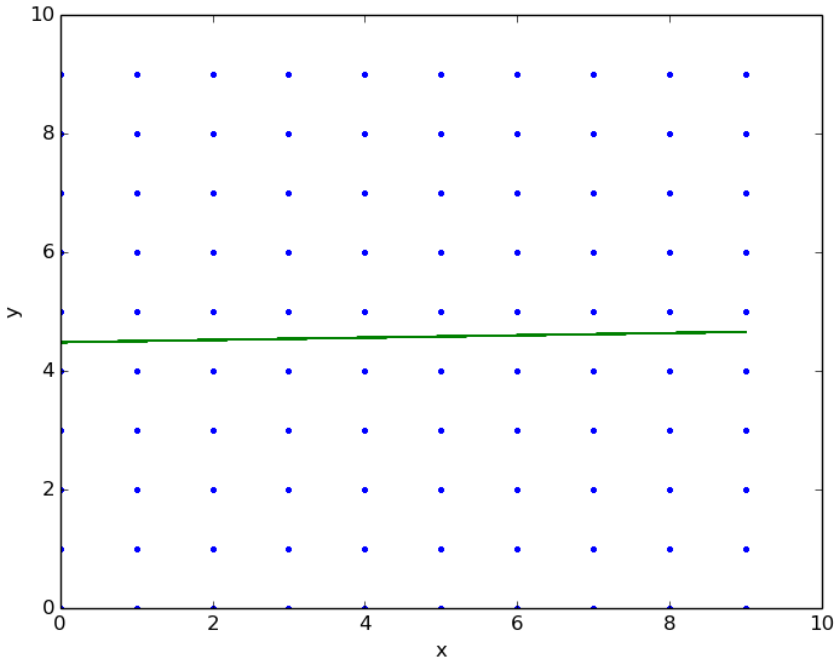
   b. Using Python or R, fit the bivariate linear regression model.

   c. Examine your t-statistic to evaluate whether it is greater than two in absolute value. Would you reject or fail to reject that there is *any relationship* between these two series?

   d. Submit your series, your code, and your results.

ANSWERS

2.b. Plotting bivariate linear regression model:



2.c. t-statistic of the x and y

OLS Regression Results

Dep. Variable:	y	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	0.3881
Date:	Sat, 20 Sep 2014	Prob (F-statistic):	0.533
Time:	18:54:34	Log-Likelihood:	-2451.8
No. Observations:	1000	AIC:	4908.
Df Residuals:	998	BIC:	4917.
Df Model:	1		

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
const	4.4763	0.168	26.671	0.000	4.147	4.806
x1	0.0195	0.031	0.623	0.533	-0.042	0.081

Omnibus:	507.754	Durbin-Watson:	1.910
Prob(Omnibus):	0.000	Jarque-Bera (JB):	55.096
Skew:	-0.017	Prob(JB):	1.09e-12
Kurtosis:	1.851	Cond. No.	10.4

As shown on the OLS regression result, the value of t is 0.623. This means that the absolute value is less than 2 ($|0.623|<2$) so we should reject that there is a relation between two variables.

2.d. Source code and output:

```
################################################
################################################
#       Applied Data Science GX5004            #
#       Assignment 2                           #
#       Dimas Rinarso Putro | drp354@nyu.edu   #
################################################

import argparse,csv, sys, os
import numpy as np
from matplotlib import pyplot as plt
import pylab
import statsmodels.api as sm

###No.2###
```

```
##########################################
#variable initialization
mu, sigma = 0, 1
num_samples = 1000000
filename='no-2.csv'
x = []
y = []

with open(filename, 'rb') as f:
    csvReader = csv.reader(f)
    headers = next(csvReader)
    for row in csvReader:
        x.append(int(row[0]))
        y.append(int(row[1]))

print x
print y

##t-statistic
# Fit regression model
x = sm.add_constant(x)
results = sm.OLS(y, x).fit()
# Inspect the results
print results.summary()
```

Output:

X = [8, 9, 9, 1, 6, 8, 8, 4, 7, 6, 9, 6, 1, 4, 1, 5, 9, 0, 7, 7, 2, 2, 1, 1, 4, 2, 7, 5, 3, 0, 2, 1, 8, 4, 0, 4, 7, 6, 4, 6, 4, 5, 1, 3, 1, 9, 7, 3, 0, 0, 9, 7, 5, 9, 2, 6, 6, 9, 9, 8, 5, 7, 5, 6, 5, 3, 8, 8, 0, 0, 0, 2, 0, 2, 4, 6, 6, 3, 1, 7, 5, 9, 5, 8, 2, 2, 1, 2, 6, 6, 0, 1, 9, 6, 3, 6, 1, 7, 8, 6, 5, 3, 5, 0, 5, 7, 2, 5, 7, 1, 5, 5, 7, 4, 2, 7, 9, 1, 0, 0, 2, 7, 3, 6, 9, 5, 6, 8, 9, 0, 8, 1, 2, 0, 3, 5, 2, 9, 4, 9, 8, 0, 8, 1, 3, 0, 2, 0, 1, 7, 3, 2, 7, 2, 3, 9, 7, 5, 3, 2, 2, 4, 2, 1, 1, 2, 3, 9, 4, 7, 5, 0, 5, 6, 3, 5, 9, 1, 9, 1, 0, 4, 9, 9, 9, 5, 1, 6, 9, 2, 2, 4, 4, 4, 4, 4, 1, 2, 5, 8, 2, 1, 5, 1, 2, 6, 0, 1, 6, 0, 8, 1, 6, 5, 8, 4, 7, 3, 1, 0, 9, 9, 0, 9, 6, 2, 3, 7, 4, 8, 4, 5, 7, 4, 8, 5, 8, 3, 6, 8, 7, 0, 8, 7, 2, 1, 5, 1, 6, 4, 0, 2, 2, 6, 2, 6, 8, 2, 2, 2, 5, 4, 7, 9, 5, 0, 6, 8, 6, 1, 3, 1, 1, 1, 5, 8, 7, 2, 3, 6, 9, 8, 9, 6, 3, 4, 6, 6, 3, 7, 4, 9, 3, 2, 4, 3, 1, 4, 4, 5, 1, 0, 5, 7, 6, 9, 0, 2, 0, 4, 8, 6, 5, 7, 4, 6, 5, 6, 7, 9, 4, 0, 6, 2, 1, 7, 7, 5, 5, 8, 2, 8, 0, 5, 4, 9, 1, 4, 4, 0, 3, 7, 5, 1, 5, 6, 8, 5, 2, 3, 2, 6, 9, 2, 1, 9, 4, 1, 6, 3, 6, 5, 7, 2, 1, 7, 2, 2, 7, 6, 0, 3, 4, 3, 7, 6, 7, 8, 6, 8, 3, 0, 5, 6, 6, 9, 4, 5, 0, 4, 4, 0, 3, 8, 8, 3, 6, 4, 9, 7, 0, 4, 9, 7, 4, 9, 0, 2,

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Y = [1, 7, 8, 4, 9, 5, 6, 6, 1, 3, 1, 7, 0, 8, 8, 6, 5, 5, 0, 7, 1, 0, 5, 2, 2, 5, 2, 0, 7, 5, 3, 6, 7, 6, 4, 0, 1, 5, 4, 6, 3, 4, 6, 4, 8, 4, 5, 0, 2, 3, 3, 6, 3, 0, 2, 4, 3, 6, 2, 2, 0, 8, 2, 3, 4, 1, 6, 8, 9, 6, 4, 4, 5, 1, 9, 3, 5, 5, 3, 8, 9, 8, 9, 1, 4, 5, 2, 6, 5, 4, 4, 0, 1, 1, 1, 9, 4, 3, 8, 1, 6, 0, 3, 4, 0, 4, 5, 2, 4, 5, 5, 9, 2, 9, 5, 0, 6, 6, 1, 1, 7, 3, 0, 6, 9, 3, 5, 9, 0, 0, 1, 4, 2, 2, 7, 0, 6, 7, 5, 5, 6, 9, 0, 5, 1, 2, 3, 9, 0, 7, 1, 4, 0, 5, 8, 1, 4, 5, 0, 3, 3, 4, 3, 0, 8, 9, 1, 7, 8, 4, 6, 7, 8, 2, 6, 1, 2, 8, 7, 9, 6, 1, 5, 6, 9, 9, 7, 4, 1, 2, 2, 7, 7, 1, 2, 3, 3, 2, 5, 3, 7, 7, 4, 5, 5, 9, 1, 5, 4, 2, 7, 4, 0, 3, 9, 2, 5, 4, 9, 4, 6, 7, 5, 8, 6, 2, 1, 8, 1, 9, 5, 3, 7, 1, 5, 6, 4, 7, 9, 8, 3, 9, 6, 6, 7, 9, 5, 4, 6, 4, 8, 9, 9, 1, 8, 3, 5, 8, 3, 7, 5, 6, 2, 9, 9, 7, 1, 0, 3, 4, 2, 5, 7, 9, 2, 0, 2, 7, 0, 6, 5, 8, 6, 7, 1, 3, 4, 5, 3, 1, 9, 2, 3, 6, 2, 5, 4, 4, 8, 3, 4, 5, 9, 4, 2, 4, 5, 7, 2, 7, 7, 1, 4, 7, 3, 9, 6, 0, 1, 1, 5, 6, 2, 6, 1, 0, 1, 8, 9, 7, 8, 3, 7, 1, 2, 2, 2, 4, 8, 6, 7, 1, 8, 9, 0, 5, 1, 5, 8, 1, 1, 7, 5, 5, 3, 6, 6, 6, 2, 0, 3, 5, 4, 5, 2, 5, 8, 7, 3, 7, 0, 9, 7, 0, 8, 5, 1, 3, 7, 5, 9, 6, 8, 7, 8, 2, 8, 2, 2, 2, 6, 4, 2, 0, 8, 7, 7, 2, 2, 5, 2, 6, 3, 1, 8, 9, 9, 4, 7, 6, 1, 6, 0, 9, 7, 5, 2, 9, 1, 9, 5, 5, 6, 0, 9, 4, 5, 3, 3, 8, 3, 6, 9, 8, 7, 4, 8, 3, 1, 2, 1, 0, 7, 9, 5, 1, 9, 8, 0, 6, 5, 3, 5, 3, 7, 4, 1, 6, 8, 4, 3, 8, 8, 2, 4, 1, 4, 1, 6, 8, 1, 1, 6, 9, 9, 8, 6, 3, 3, 6, 4, 4, 0, 5, 3, 7, 9, 1, 9, 9, 1, 2, 9, 9, 9, 8, 5, 9, 3, 1, 1, 7, 2, 0, 4, 1, 3, 9, 5, 8, 6, 1, 6, 6, 6, 2, 4, 3, 8, 4, 2, 5, 2, 7, 5, 0, 0, 5, 4, 8, 6, 2, 8, 3, 0, 3, 3, 0, 7, 4, 4, 5, 7, 8, 9, 7, 7, 9, 9, 7, 1, 3, 4, 8, 6, 9, 5, 8, 4, 3, 3, 1, 4, 7, 0, 5, 1, 9, 7, 9, 3, 8, 9, 6, 9, 3, 4, 0, 4, 2, 0, 6, 4, 2, 9, 9, 3, 6, 2, 2, 8, 3, 5, 9, 9, 0, 0, 7, 5, 2, 5, 6, 9, 2, 5, 7, 0, 4, 5, 0, 3, 4, 0, 9, 6, 2, 2, 6, 0, 9, 6, 4, 9, 4, 4, 9, 0, 5, 0, 8, 8, 2, 0, 7, 1, 8, 4, 5, 6, 5, 1, 7, 1, 9, 4, 1, 6, 9, 2, 3, 7, 1, 9, 6, 5, 1, 3, 2, 2, 5, 1, 9, 9, 6, 0, 5, 0, 5, 4, 0, 1, 3, 0, 8, 5, 8, 3, 0, 6, 1, 8, 5, 7, 5, 7, 7, 2, 4, 6, 3, 1, 6, 2, 9, 9, 9, 3, 4, 3, 0, 2, 2, 3, 7, 7, 0, 3, 0, 4, 7, 8, 9, 0, 3, 4, 8, 5, 9, 3, 5, 7, 0, 0, 7, 6, 4, 7, 7, 3, 6, 4, 0, 7, 0, 5, 0, 0, 1, 1, 2, 2, 2, 7, 8, 5, 4, 5, 9, 2, 7, 5, 2, 3, 3, 2, 4, 9, 8, 9, 2, 9, 8, 7, 6, 1, 7, 3, 9, 2, 8, 4, 2, 0, 0, 2, 5, 2, 5, 4, 8, 1, 1, 7, 4, 4, 0, 9, 1, 6, 7, 2, 5, 5, 7, 5, 9, 7, 5, 4, 4, 2, 5, 4, 6, 0, 6, 2, 7, 4, 6, 4, 5, 8, 8, 3, 3, 1, 7,

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PROBLEMS

3. Go to Yahoo!Finance (or the source of your choice, such as Bloomberg) and download a daily price series for a particular publicly-traded stock of your choice for a ten-year time period (don't use Apple), as well as the daily price series on the exchange on which it trades. [5 points]
   a. Using R or Python, calculate the log returns of each series as the natural log of the ratio of (price today/price yesterday). Use the reported closing price for this exercise.
   b. Using R or Python, generate a histogram of log returns of the stock of your choice.
   c. Using R or Python, generate a scatterplot that relates the log returns of your stock of choice to the log returns of the exchange on which it is traded.
   d. Finally, using R or Python, fit a linear model to obtain estimates of what finance folks call the "alpha" and the "beta". Is "alpha" significantly different than zero at a 95% level? Does a 95% confidence level for "beta" include one?
   e. Submit all code and results.

ANSWERS

3.a. Plotting bivariate linear regression model:

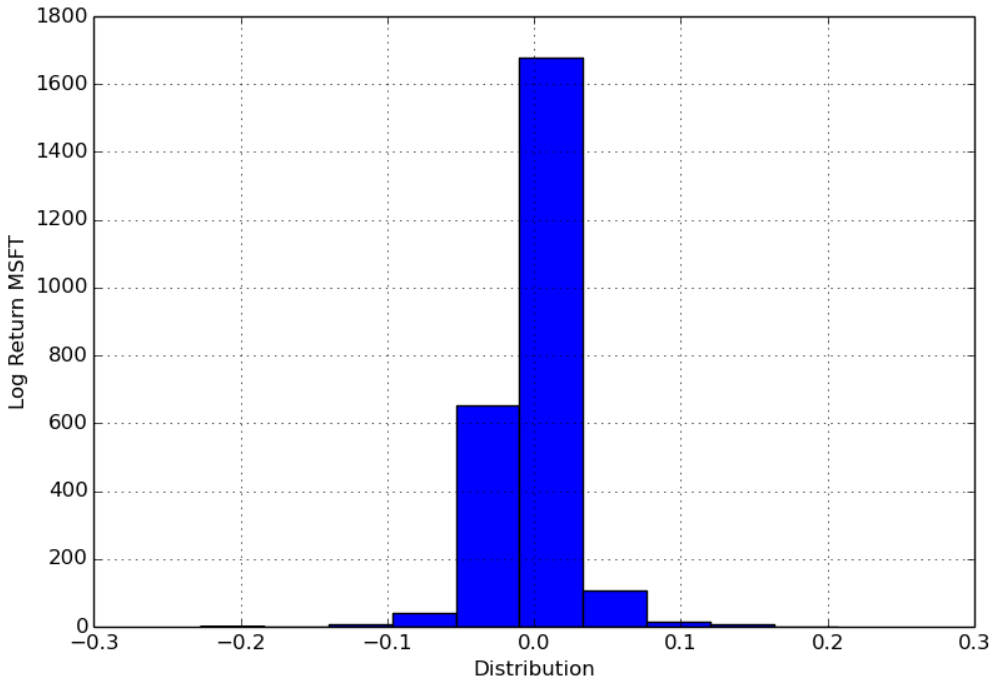
Microsoft:

Date	Open	High	Low	Close	Volume	Adj Close	Return
2004-09-20	27.44	27.65	27.33	27.51	51513600	20.07	NaN
2004-09-21	27.45	27.53	27.25	27.26	73874400	19.89	-0.009129
2004-09-22	27.28	27.74	27.07	27.12	68409000	19.79	-0.005149
2004-09-23	27.19	27.39	27.17	27.35	52155800	19.96	0.008445
2004-09-24	27.39	27.46	27.19	27.29	49859800	19.91	-0.002196
2004-09-27	27.17	27.32	27.13	27.19	47813600	19.84	-0.003671
2004-09-28	27.21	27.36	27.04	27.27	62055100	19.90	0.002938
2004-09-29	27.26	27.69	27.23	27.58	61529300	20.12	0.011304
2004-09-30	27.59	27.79	27.52	27.65	71218000	20.18	0.002535
2004-10-01	27.82	28.32	27.78	28.25	66302800	20.61	0.021468

Nasdaq

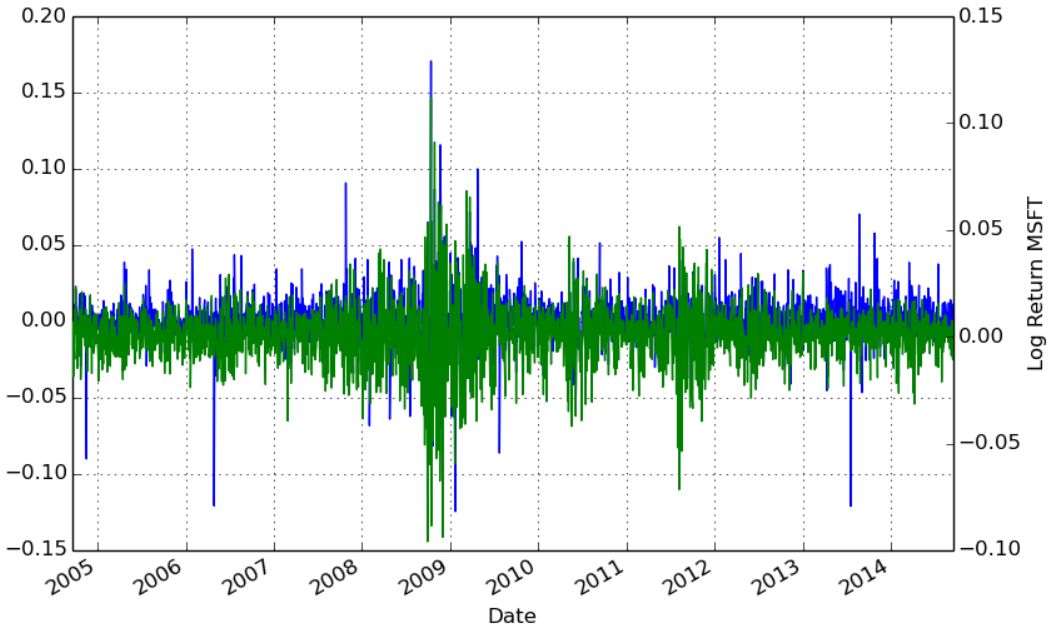
Date	Open	High	Low	Close	Volume	Adj Close	Return
……..(shortened to oldest records)							
……..							
2004-09-20	1903.02	1921.50	1900.24	1908.07	1565540000	1908.07	NaN
2004-09-21	1913.13	1925.85	1909.43	1921.18	1531560000	1921.18	0.006847
2004-09-22	1910.23	1910.23	1884.85	1885.71	1588290000	1885.71	-0.018635
2004-09-23	1887.02	1894.67	1883.32	1886.43	1396810000	1886.43	0.000382
2004-09-24	1888.89	1897.42	1879.48	1879.48	1360090000	1879.48	-0.003691
2004-09-27	1871.16	1871.94	1858.88	1859.88	1316790000	1859.88	-0.010483
2004-09-28	1865.88	1873.86	1852.59	1869.87	1536980000	1869.87	0.005357
2004-09-29	1870.61	1894.06	1869.95	1893.94	1637280000	1893.94	0.012790
2004-09-30	1892.60	1902.25	1887.68	1896.84	1656620000	1896.84	0.001530
2004-10-01	1909.59	1942.23	1908.57	1942.20	1820300000	1942.20	0.023632

3.b. Histogram of the log returns of MSFT stocks:

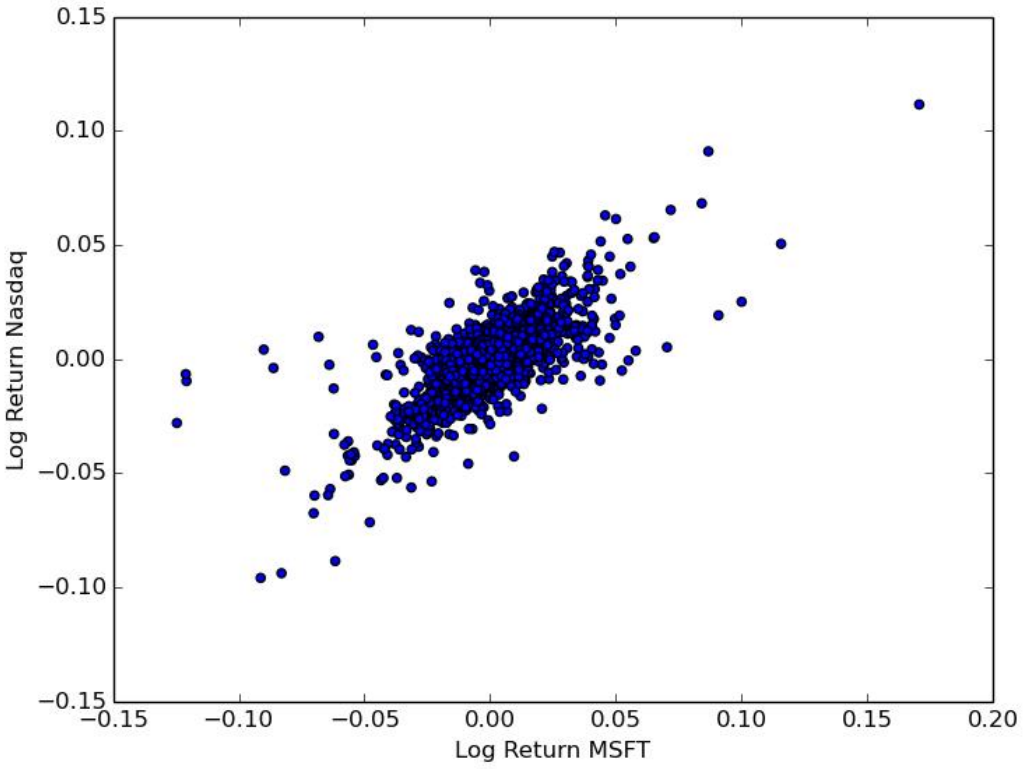


3.c. Scatterplot that relates the log returns of MSFT stock to the log returns of the exchange on

which it is plotted agains the time :



And consequently Microsoft stock value log return VS Nasdaq stock value log return:



3.d. a linear model to obtain “Alpha” and “Beta”:

With the summary of t statistic of both log returns:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Return   R-squared:                       0.516
Model:                            OLS   Adj. R-squared:                  0.516
Method:                 Least Squares   F-statistic:                     2684.
Date:                Mon, 22 Sep 2014   Prob (F-statistic):               0.00
Time:                        15:01:11   Log-Likelihood:                 8137.0
No. Observations:                2517   AIC:                        -1.627e+04
Df Residuals:                    2515   BIC:                        -1.626e+04
Df Model:                           1
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const          0.0002      0.000      1.196      0.232        -0.000      0.001
Return         0.5781      0.011     51.812      0.000         0.556      0.600
==============================================================================
Omnibus:                      276.730   Durbin-Watson:                   1.972
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2325.002
Skew:                           0.126   Prob(JB):                         0.00
Kurtosis:                       7.702   Cond. No.                         58.6
==============================================================================
```

Here we could observe that “Beta” is 0.5871 and “Alpha” is 0.011.

3.e source code

```
################################################
################################################
#       Applied Data Science GX5004            #
#       Assignment 2                           #
#       Dimas Rinarso Putro | drp354@nyu.edu   #
################################################

import argparse,csv,sys, os
import numpy as np
from matplotlib import pyplot as plt
import pylab
from pandas.io.data import DataReader
import pandas as pd
from pandas.tools.plotting import scatter_matrix as scatter
from datetime import date,datetime
```

```
from matplotlib.dates import date2num
import statsmodels.api as sm

###No.3###
##########################################

#Read data
df_mic = DataReader('MSFT','yahoo',start='09/18/2004',end='09/18/2014')
df_nas =
DataReader('^IXIC','yahoo',start='09/18/2004',end='09/18/2014')

#calculate log returns
df_mic['Return'] = np.log(df_mic['Close']/df_mic['Close'].shift(1))
df_nas['Return'] = np.log(df_nas['Close']/df_nas['Close'].shift(1))

#print to screen
print df_mic['Return'].describe()
print df_nas['Return'].describe()

#histogram of Microsoft stock
plt.figure();
df_mic['Return'].diff().hist()
plt.xlabel('Distribution')
plt.ylabel('Log Return MSFT')
plt.show()

#scatterplot of both log returns
df_mic['Return'].plot()
df_nas['Return'].plot(secondary_y=True, style='g')
plt.xlabel('distribution')
plt.ylabel('Log Return MSFT')
plt.show()

##calculate alpha
X=df_mic.Return[1:]
y=df_nas.Return[1:]
```

```
X = sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit()
print(results.summary())

#scatterplot of both log returns
plt.scatter(df_mic['Return'],df_nas['Return'])
plt.xlabel('Log Return MSFT')
plt.ylabel('Log Return Nasdaq')
plt.show()
```

PROBLEMS

4. Download the file train.dta from the course website. These data are formatted as a Stata dataset. [5 points]

    a. Read this dataset into R or Python. (For R, you may find the "foreign" library of use. For Python, check out Pandas. The goal here is to get you familiar with reading datasets with alternative formats.)
    b. Generate summary statistics for the following variables in the data:
        - d, which is an indicator for whether a particular email is spam
        - x1, which is an attribute of the email
    c. Using least squares, regress d on x1. (For R, check out lm. For Python, check out StatsModels.) Congratulations, you have created a support vector machine that you will use to forecast whether an incoming email with a different attribute is spam.
    d. Suppose you set the threshold that an email is spam if the predicted value exceeds 1.[1] I give you a new email with an attribute value 0.65. Would you classify it as spam or not spam?
    e. I give you another new email with an attribute value of 0.99. Would you classify it as spam or not spam?

ANSWERS

a. Read the dataset using pandas (`pandas.io.stata`) in python (see source code)

b. The summary of both the d and x1 respectively:

d=

count	1000.000000
mean	0.477000
std	0.499721
min	0.000000
25%	0.000000
50%	0.000000
max	1.000000

dtype: float64

x1=

count	1000.000000
mean	0.487376
std	0.283345
min	0.000286
25%	0.249382
50%	0.484645
75%	0.732494
max	0.999006

dtype: float64

4.c. The summary of the regression d on x1:

OLS Regression Results

Dep. Variable:	d	R-squared:	0.332
Model:	OLS	Adj. R-squared:	0.331
Method:	Least Squares	F-statistic:	495.0
Date:	Mon, 22 Sep 2014	Prob (F-statistic):	2.21e-89
Time:	14:44:23	Log-Likelihood:	-523.32
No. Observations:	1000	AIC:	1051.
Df Residuals:	998	BIC:	1060.
Df Model:	1		

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
const	-0.0180	0.026	-0.698	0.486	-0.068	0.033
x1	1.0155	0.046	22.250	0.000	0.926	1.105

Omnibus:	28.836	Durbin-Watson:	2.011
Prob(Omnibus):	0.000	Jarque-Bera (JB):	14.710
Skew:	0.061	Prob(JB):	0.000639
Kurtosis:	2.419	Cond. No.	4.43

4.d. From the summary it is given the coef, that is the estimated coefficient is 1.0155 so if the there is an additional email attribute with the value of 0.65, then the predicted value is Mx which is 1.0155(0.65) which is equal to 0.66. Since it's smaller than the threshold, it should be classified as **non-spam email**.

4.e. if the there is an additional email attribute with the value of 0.99, then the predicted value is

should be classified **as spam email** because at 1.0155(0.99) is 1.0053 which is greater than the threshold.

4.f. source code:

```
################################################
################################################
#       Applied Data Science GX5004            #
#       Assignment 2                           #
#       Dimas Rinarso Putro | drp354@nyu.edu   #
#       No.4                                   #
################################################

import argparse,csv,sys,os
import numpy as np
from matplotlib import pyplot as plt
import pandas as pd
from pandas.tools.plotting import scatter_matrix as scatter
from pandas.io.stata import read_stata as rd_stata
import statsmodels.api as sm

###No.4###
################################################

#Read data
filename = 'train.dta'
df = rd_stata(filename)

#print the summary for each column
print 'd='
print df['d'].describe()
print 'x1='
print df['x1'].describe()

#sorting
print df.head()
result =df.sort(['x1'], ascending=[1])
```

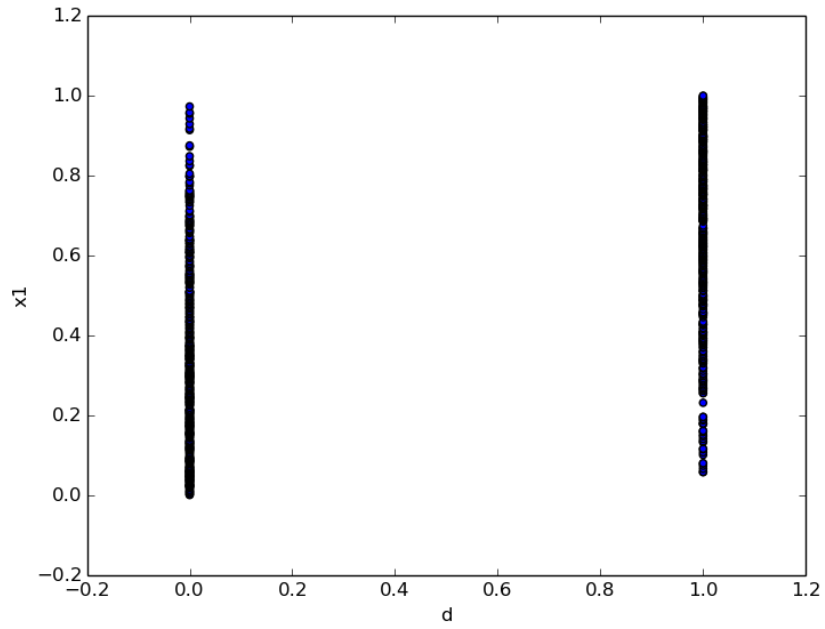
```
X = df.x1
y = df.d

#linear regression d on x1
X = sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit()
print(results.summary())

#plot sorted column into scatterplot
#for better understanding

plt.scatter(result['d'],result['x1'])
plt.xlabel('d')
plt.ylabel('x1')
plt.show()
```

Output:



PROBLEMS

5. This is a very challenging question, but it addresses several key topics in data analytics. You should work collectively on a solution with the recognition that you may not complete it. The phrase "data generating process" (or DGP) is often used to describe the hypothetical process by which observations arise in the real world. We discussed at some length the bivariate linear regression model, $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$. In this problem, we will work with a specific DGP and evaluate features of $\widehat{\beta_1}$, the least squares estimate of β_1. [5 points]
    a. Suppose your DGP is $y_i = 1 + 2x_i + \epsilon_i$, where $x \sim N(0,1)$ and $\epsilon \sim N(0,1)$.
    b. Using R or Python, write code to generate 1,000 draws for x and ϵ. Use these draws to generate y in accordance with the DGP in a.
    c. Using R or Python, write code to estimate the bivariate model, $y_i = \beta_0 + \beta_1 x_i$ and summarize the findings.
    d. Repeat b. and c. above five times for a new set of random draws for each replication. (This effort is called Monte Carlo simulation.)
    e. Given what you've done in d., Suppose you wrote code to repeat b. and c. above 1,000 times, each time recording the estimated value of β_1. What do you think a histogram of these 1,000 replications of the estimate value of β_1 would show?
    f. Suppose that you were not interested in the estimate of β_1 per se, but instead in some functional transformation, such as the estimate of $\exp(\beta_1)$. What might you do with your 1,000 replications from e. above to inform you about the distribution of the estimate of $\exp(\beta_1)$?
    g. Submit code and results.

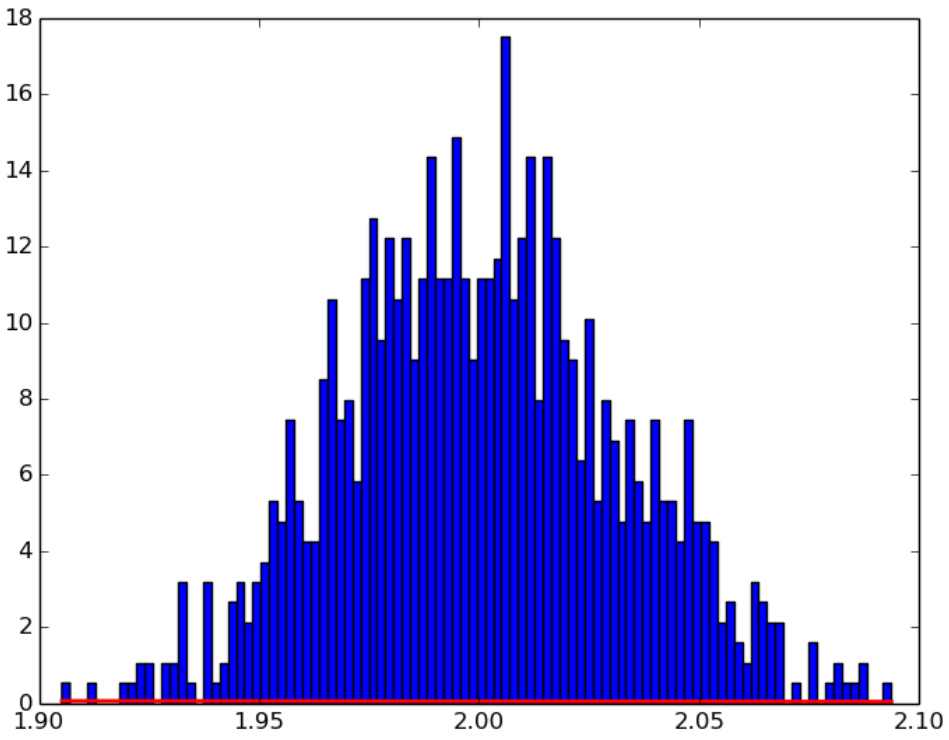
ANSWERS:

For no.5a-b please refer to the source code.

c.-d. the summary and the result of the 5 times iterations:

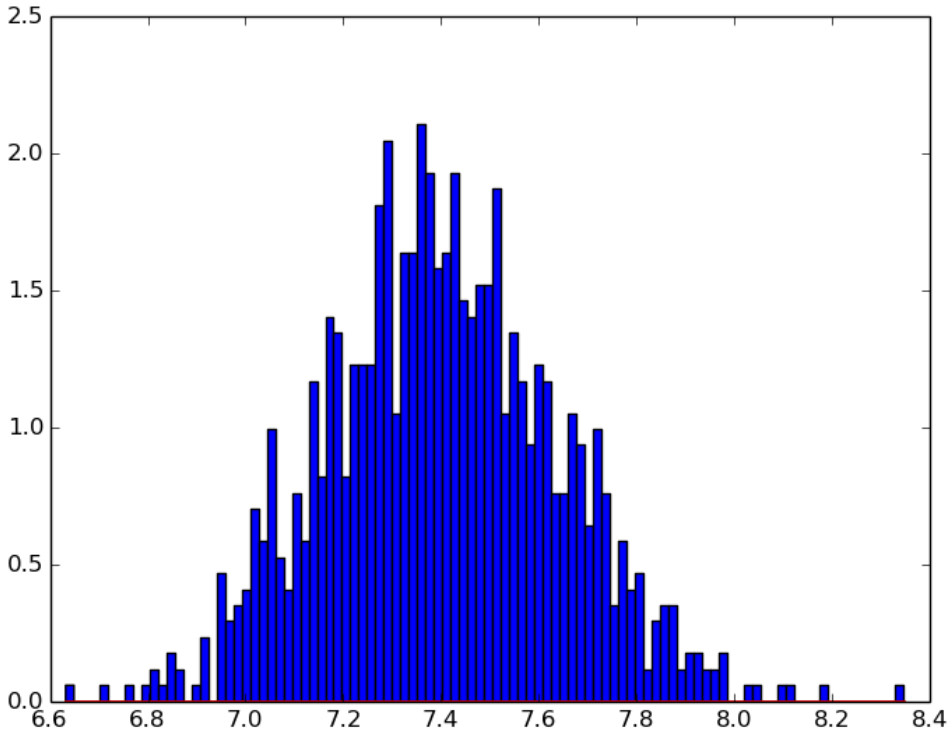
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.808
Model:                            OLS   Adj. R-squared:                  0.807
Method:                 Least Squares   F-statistic:                     4186.
Date:                Mon, 22 Sep 2014   Prob (F-statistic):               0.00
Time:                        16:19:07   Log-Likelihood:                -1409.6
No. Observations:                1000   AIC:                             2823.
Df Residuals:                     998   BIC:                             2833.
Df Model:                           1
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const          1.0285      0.031     32.795      0.000         0.967     1.090
x1             2.0206      0.031     64.703      0.000         1.959     2.082
==============================================================================
Omnibus:                        1.940   Durbin-Watson:                   1.914
Prob(Omnibus):                  0.379   Jarque-Bera (JB):                1.852
Skew:                           0.042   Prob(JB):                        0.396
Kurtosis:                       2.806   Cond. No.                         1.00
==============================================================================
Beta value for 5 iterations: [1.9747836037299731, 2.0165703320766091, 2.0261041963974651, 1.9617479696364135]
```

5.e. the histogram of 1000 iterations for Beta estimation:



Conclusion: it can be observed that by 1 time iteration the value of beta is 2.02 and by 1000 times iteration and its histogram plot the value of beta can vary from 1.90 to 2.1.

5.f. The histogram of 1,000 iterations of $\exp(\beta_1)$:



5.g. source code and result

```
################################################
################################################
#       Applied Data Science GX5004            #
#       Assignment 2                           #
#       Dimas Rinarso Putro | drp354@nyu.edu   #
################################################

import argparse,csv, sys, os
import numpy as np
from matplotlib import pyplot as plt
import pylab
import statsmodels.api as sm

###No.5###
##########################################
```

```
#variable initialization
mu, sigma = 0, 1
num_samples = 1000

#generate random numbers
x = np.random.normal(mu, sigma, num_samples)
e = np.random.normal(mu, sigma, num_samples)
y = 1+2*x+e

#regression
x = sm.add_constant(x)
model = sm.OLS(y, x)
results = model.fit()
print(results.summary())

##########################################
###########NOW WITH MONTE CARLO############
#---------5 iterations
m = []
for i in xrange (0,4):
  #generate random numbers
  x = np.random.normal(mu, sigma, num_samples)
  e = np.random.normal(mu, sigma, num_samples)
  y = 1+2*x+e

  #regression
  regression = np.polyfit(x, y, 1)
  m.append(regression[0]) #adding beta into list

print 'Beta value for 5 iterations: '+str(m)

##########################################
###########NOW WITH MONTE CARLO############
#---------1000 iterations
m_1000 = []
for i in xrange (0,999):
```

```
  #generate random numbers
  x = np.random.normal(mu, sigma, num_samples)
  e = np.random.normal(mu, sigma, num_samples)
  y = 1+2*x+e

  #regression
  regression = np.polyfit(x, y, 1)
  m_1000.append(regression[0]) #adding beta into list

#plot histogram
acount, bins, ignored = plt.hist(m_1000, 100, normed=True)
plt.plot(bins, 1/(sigma * np.sqrt(2 * np.pi)) *
               np.exp( - (bins - mu)**2 / (2 * sigma**2) ),
         linewidth=2, color='r')
plt.show()

##########################################
###########NOW WITH MONTE CARLO############
#---------1000 iterations on exp(Beta)
m_1000 = []
for i in xrange (0,999):
  #generate random numbers
  x = np.random.normal(mu, sigma, num_samples)
  e = np.random.normal(mu, sigma, num_samples)
  y = 1+2*x+e

  #regression
  regression = np.polyfit(x, y, 1)
  m_1000.append(np.exp(regression[0])) #adding beta into list

#plot histogram
acount, bins, ignored = plt.hist(m_1000, 100, normed=True)
plt.plot(bins, 1/(sigma * np.sqrt(2 * np.pi)) *
               np.exp( - (bins - mu)**2 / (2 * sigma**2) ),
         linewidth=2, color='r')
plt.show()
```