lab2

September 20, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
import seaborn as sns
import os
import re
```

0.0.1 The dataset spaghetti.txt contains the weight (in oz) of 20 spaghetti boxes of a famous pasta brand.

[2]:
```
os.getcwd() # check current location
```

[2]:
```
'/Users/jimin/Desktop/    -
MacBook\xa0Air/ /ewha/2023-2/Regression/week2'
```

txt ” ” , pd.readtable() . .

[3]:
```
with open('spaghetti.txt', 'r') as file:
    lines = file.readlines() # ['"spaghetti"\n','"1"15.3133500408265\n',

indices = []
elements = []

for line in lines:
    match = re.match(r'"(\d+)"([\d.]+)', line)
    if match:
        index = int(match.group(1))
        element = float(match.group(2))
        indices.append(index)
        elements.append(element)
```

[4]:
```
data_1 = pd.DataFrame({'spaghetti' : elements})
data_1.head(5)
```

```
[4]:    spaghetti
     0  15.313350
     1  15.283792
     2  15.905021
     3  16.751270
     4  15.893500
```

0.0.2 A consumers' association would like to sue the company, affirming that the mean box weight is lower than the nominal one (16 oz). To be sure about their statement, they ask you to perform a suitable test with level 1%.

First compute the sample mean and the standard deviation of the box weight.

```
[59]: data_1['spaghetti'].describe()
```

```
[59]: count    20.000000
      mean     15.489846
      std       0.882175
      min      14.041929
      25%      14.867575
      50%      15.458736
      75%      16.143848
      max      16.950836
      Name: spaghetti, dtype: float64
```

```
[5]: mean_spa = data_1['spaghetti'].mean()
     std_spa = data_1['spaghetti'].std()

     print(f'mean : {mean_spa}')
     print(f'std : {std_spa}')
```

```
mean : 15.489845631427375
std : 0.8821747119189167
```

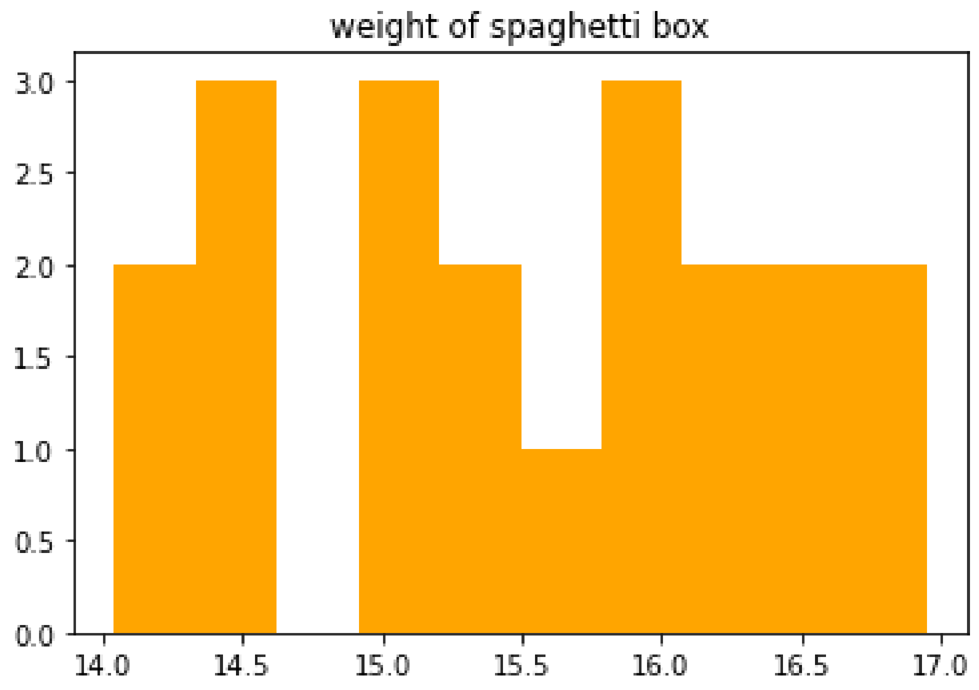
Perform the test for the consumers' association.

What is your null hypothesis H0? H0 : M $= 16$

What is your alternative hypothesis H1? H1 : M < 16

What distribution can you assume for the test statistic (type of distribution and parameters), and why?

```
[6]: plt.hist(data_1['spaghetti'], color='orange')
     plt.title('weight of spaghetti box')
     plt.show()
```



Compute the test statistic.

```
[7]: def cal_TestStatistic(mean_hat, mu, s, n):
         return ((mean_hat - float(mu)) / (s / np.sqrt(float(n))))

     t = cal_TestStatistic(mean_spa, 16, std_spa, data_1.count())
     t
```

```
[7]: -2.58619938144797
```

Compute the test p-value.

```
[8]: tstat, pval = stats.ttest_1samp(data_1['spaghetti'], popmean=16,␣
       ↪alternative='less')
     pval
```

```
[8]: 0.009055174905033336
```

Do you reject the null hypothesis, at significance level 1%? Yes, since t value is less than p value.

Compute the 99% two-sided confidence interval for the mean of the box weight.

```
[9]:
```

```
std_sample = stats.sem(data_1['spaghetti']) #   ,         .
stats.t.interval(alpha=0.99, df=data_1['spaghetti'].shape[0]-1, loc=mean_spa,␣
  ↪scale=std_sample) #
```

```
[9]: (14.925496920283585, 16.054194342571165)
```

0.0.3 Consider again the dataset record.txt that you used for Lab 1. This dataset contains running records obtained from athletes from different countries in various types of athletics events (sprints and middle-distance).

We have data about 55 countries (observations) and 6 records (variables): 100 meters, 200 meters, 400 meters, 800 meters, 1500 meters and 3000 meters.

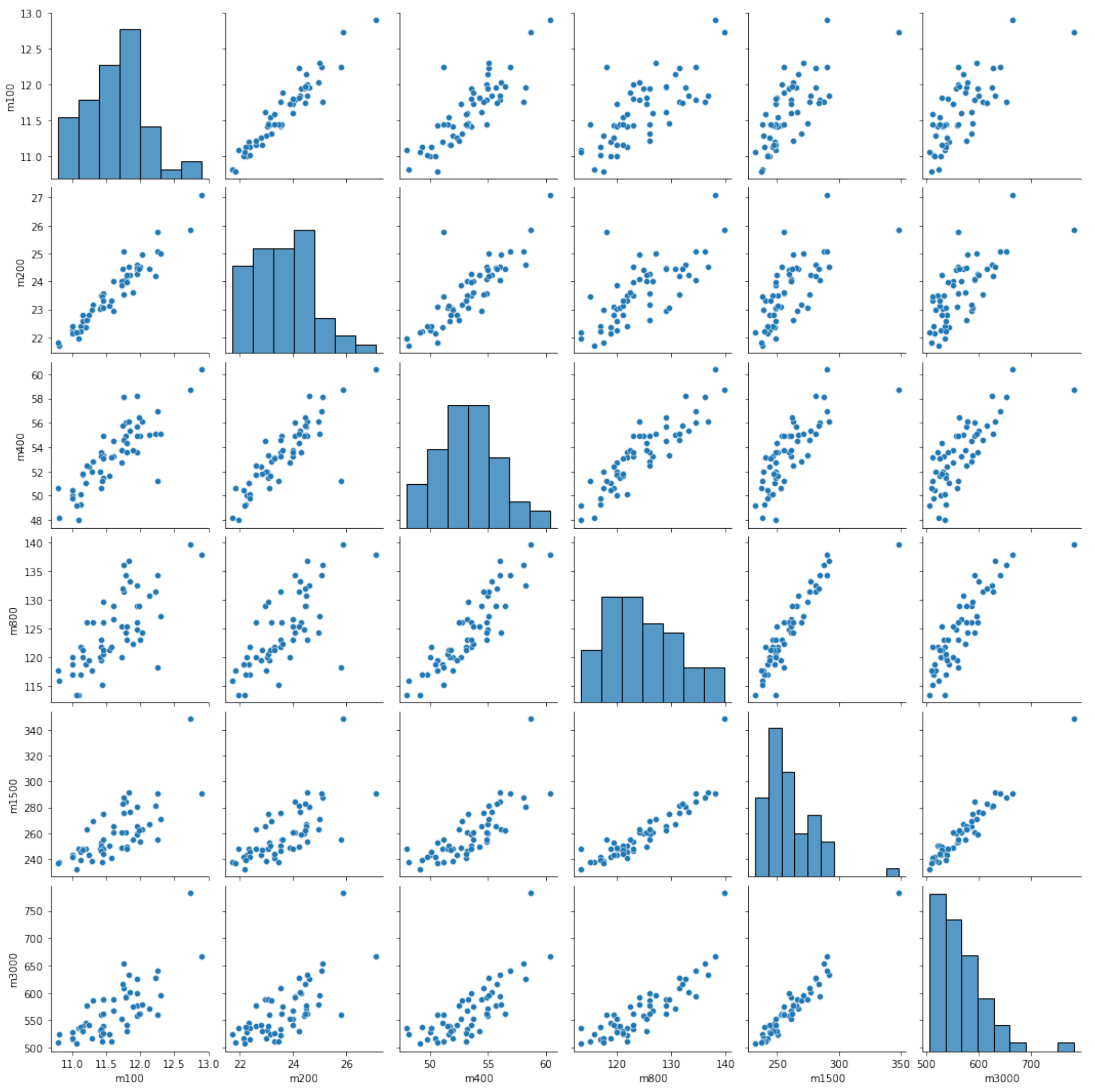
Load the dataset record.txt in R, using the function read.table (remember to set sep=' ')

```
[10]: data_2 = pd.read_table('record.txt', sep='\s+')
      data_2.head(10)
```

```
[10]:           m100   m200   m400   m800  m1500  m3000
      argentin  11.61  22.94  54.50  129.0  265.8  587.4
      australi  11.20  22.35  51.08  118.8  247.8  544.8
      austria   11.43  23.09  50.62  119.4  253.2  560.4
      belgium   11.41  23.04  52.00  120.0  248.4  532.8
      bermuda   11.46  23.05  53.30  129.6  274.8  588.6
      brazil    11.31  23.17  52.80  126.0  269.4  586.2
      burma     12.14  24.47  55.00  130.8  267.0  570.6
      canada    11.00  22.25  50.06  120.0  243.6  528.6
      chile     12.00  24.52  54.90  123.0  253.8  562.2
      china     11.95  24.41  54.97  124.8  259.8  558.6
```

Draw a scatterplot and compute the correlation for all pairs of variables in the dataset. Interpret the results you obtained: what can you observe about the relationship among the variables?

```
[11]: sns.pairplot(data_2)
      plt.show()
```



0.0.4 Consider the variables m100 and m400.

Using the equations(not lm function or matrix equation in r), compute the least square estimators for the coefficients of a single linear regression model, with response m100 and predictor m400. How do you interpret the slope or the regression line?

[12]:
```
x = np.array(data_2['m100']).reshape(-1,1) # x.shape = (55,1)
y = np.array(data_2['m400']).reshape(-1,1) # y.shape = (55,1)
```

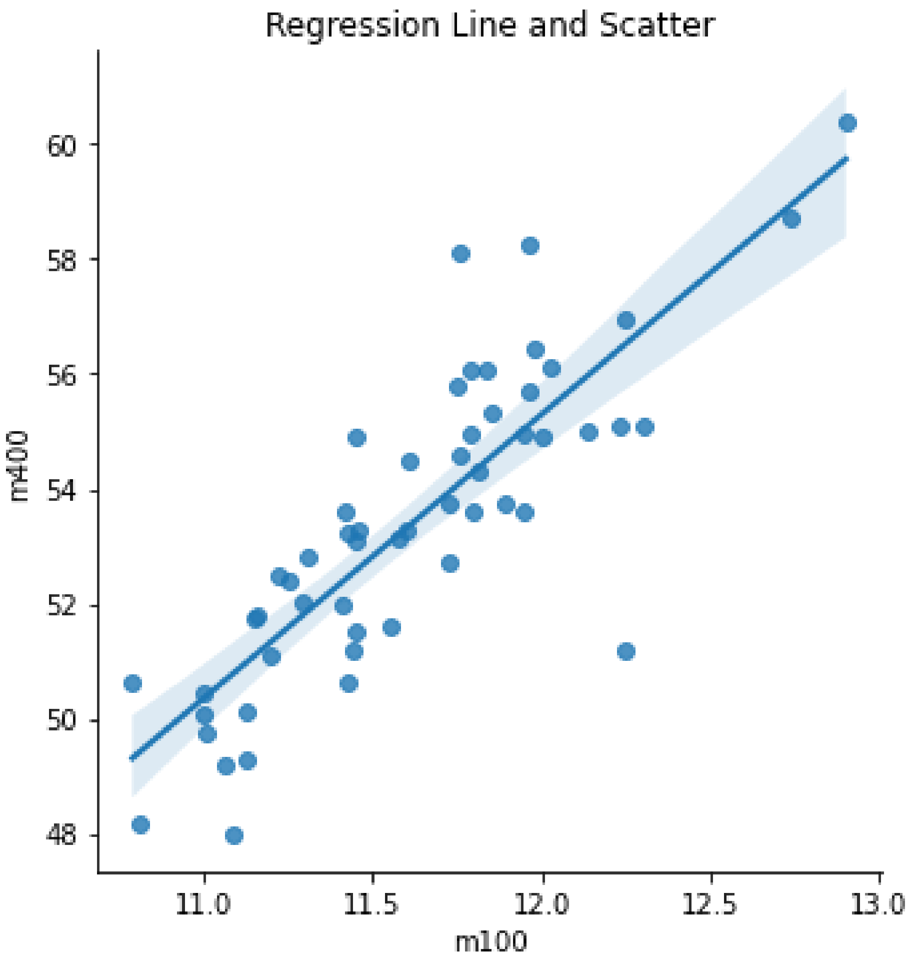
[13]:
```
b1 = np.sum((y- np.mean(y))*(x-np.mean(x))) / np.sum((x-np.mean(x))**2)
b0 = np.mean(y) - np.mean(x)*b1

print('b0 : ',b0)
print('b1 : ',b1)
```

```
b0 :  -4.0326275398140865
b1 :  4.943686449077924
```

Produce a scatter plot for m100 vs m400 with the fitted regression line superimposed.

[14]:
```
sns.lmplot(data=data_2, x='m100', y='m400')
plt.title("Regression Line and Scatter")
plt.show()
```



Re-compute the least square estimators of beta0 and beta1 using the matrix equation.

[15]:
```
def cal_beta(x,y):
    '''
    b matrix
      b0, b1, ...
    '''
    mat_x = np.hstack((np.ones(x.shape), x))
    return np.linalg.inv(mat_x.T@mat_x)@mat_x.T@y
```

```
cal_beta(x,y) #    b0, b1
```

```
[15]: array([[-4.03262754],
              [ 4.94368645]])
```

Re-compute the least square estimators of beta0 and beta1 using the R function lm, and visualize the summary of the regression.

```
[16]: # from sklearn.linear_model import LinearRegression

lr = LinearRegression()
lr.fit(x, y)
cof = lr.coef_
intercept = lr.intercept_

beta = np.vstack((intercept, cof)) # intercept :   ,      b0, cof : b1
beta
```

```
[16]: array([[-4.03262754],
              [ 4.94368645]])
```

```
[18]: # summary           (   )
results = sm.OLS(y, x).fit()
print(results.summary())
```

```
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:                      y   R-squared (uncentered):
0.999
Model:                            OLS   Adj. R-squared (uncentered):
0.999
Method:                 Least Squares   F-statistic:
7.142e+04
Date:                Thu, 21 Sep 2023   Prob (F-statistic):
5.58e-86
Time:                        02:05:13   Log-Likelihood:
-99.223
No. Observations:                  55   AIC:
200.4
Df Residuals:                      54   BIC:
202.5
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
x1             4.5971      0.017    267.243      0.000       4.563       4.632
==============================================================================
Omnibus:                        7.121   Durbin-Watson:                   2.304
Prob(Omnibus):                  0.028   Jarque-Bera (JB):                9.940
Skew:                          -0.336   Prob(JB):                      0.00694
Kurtosis:                       4.971   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Which are n and p for the considered regression model? n : total num of observations p : total num of parameters

Compute the fitted values and the residuals, using the estimated regression line.

[21]:
```python
# the fitted values
fitted_values = lr.predict(x)
fitted_values[:10]
```

[21]:
```
array([[53.36357213],
       [51.33666069],
       [52.47370857],
       [52.37483484],
       [52.62201917],
       [51.8804662 ],
       [55.98372595],
       [50.3479234 ],
       [55.29160985],
       [55.04442553]])
```

[23]:
```python
residuals = y - fitted_values
residuals[:10]
```

[23]:
```
array([[ 1.13642787],
       [-0.25666069],
       [-1.85370857],
       [-0.37483484],
       [ 0.67798083],
       [ 0.9195338 ],
       [-0.98372595],
       [-0.2879234 ],
       [-0.39160985],
       [-0.07442553]])
```

Consider the 25th and 75th percentiles of the variable m100 on the dataset.Use the estimated regression line to estimate the fitted value of the variable m100 at each of these two percentiles. percentile vs quantitle

[57]:
```
m100_25 = np.quantile(a=x, q=0.25)
m100_75 = np.quantile(a=x, q=0.75)

percent_vec = np.vstack((m100_25, m100_75))
percent_vec
```

[57]:
```
array([[11.27],
       [11.92]])
```

[58]:
```
lr.predict(percent_vec)
```

[58]:
```
array([[51.68271874],
       [54.89611493]])
```