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In [1]: import pandas as pd
         import numpy as np
In [2]: h = open('X.txt', 'r')
         P1 = []
         P2 = []
         P3 = []
         for line in h:
             currentline = line.split(",")
             P1.append(float(currentline[0]))
             P2.append(float(currentline[1]))
             P3.append(float(currentline[2]))
         X_df = pd.DataFrame(
                                                    you can use pd. read cosu
             {'X_1': P1,
              'X_2': P2,
              'X_3': P3
             })
         # Add a column of 1s (First column) to the observations matrix as it will help us estimate the parameter that
         # corresponds to the intercept of the model — the matrix X
         X_df.insert(0, 'X_0', 1)
         X_Final = X_df.to_numpy()
In [3]: h = open('Y.txt', 'r')
         Y_list = []
         for line in h:
             Y_list.append(float(line))
         Y_temp = pd.Series(Y_list)
         Y = Y temp.values.reshape(201, 1)
         Estimate of \hat{\beta} = (X^T X)^{-1} X^T Y
In [4]: X_T = X_Final.transpose()
         temp 1 = np.dot(X T, X df) # (X^T * X)
         temp_2 = np.linalg.inv(temp_1) # (X^T * X)^(-1)
         temp_3 = np.dot(X_T, Y) # X^T * Y
                                                                                          chech X has fell column
         Beta_hat = np.dot(temp_2, temp_3) # (X^T * X)^(-1) * X^T
                                                                                                                   ranh (1)
In [5]: print(Beta_hat)
         [[-0.00800698]
          [ 0.88161162]
          [-2.45938171]
          [-0.97715699]]
         Here \beta_0 = -0.00800698, \beta_1 = 0.88161162, \beta_2 = -2.45938171, \beta_3 = -0.97715699, for them \beta_0 is the slope.
         The ML-estimator of the unknown parameters \sigma^2 is \hat{\sigma}_{ML}^2=rac{\hat{\epsilon}\hat{\epsilon}}{n} where \hat{\epsilon}=y-X\hat{eta}
In [6]: n = 201
         epsilon = Y - np.dot(X_Final, Beta_hat) # y - X * beta_hat
         epsilon_mul = np.vdot(epsilon, epsilon) # dot product of epsilon and epsilon
         sigma_square_ML = epsilon_mul / n # divided by n
In [7]: print(sigma_square_ML)
         0.9548405627555108
         The estimate of \sigma is called the sample standard error of the residuals.
         A high standard error shows that sample means are widely spread around the population mean i.e. sample may not closely represent the
         population. A low standard error shows that sample means are closely distributed around the population mean i.e. sample is
         representative of the population.
         For our case, the value is 0.955, accroding to this artcile [1] the value is acceptable.
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[1] Tighe, J., McManus, I., Dewhurst, N.G. et al. The standard error of measurement is a more appropriate measure of quality for postgraduate medical assessments than is reliability: an analysis of MRCP(UK) examinations. BMC Med Educ 10, 40 (2010). https://doi.org/10.1186/1472-6920-10-40

The adjusted estimator $\hat{\sigma}_{ad}^2 = rac{y^T y - \hat{eta}^T X^T y}{n-p-1}$

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In [8]: p = 3

Y_T = Y.transpose()

Beta_hat_T = Beta_hat.transpose()

t_1 = np.matmul(Y_T, Y) # Y^T * Y

t_2 = np.matmul(Beta_hat_T, X_T) # Beta^T * X^T

t_3 = np.matmul(t_2, Y) # Beta^T * X^T * y

t_4 = n - p - 1

sigma_ad = ((t_1 - t_3) / t_4).squeeze() #squeeze() for convert dataframe to series
```

In [9]: print(sigma_ad)
0.9742281883952163

We got the $\hat{\sigma}^2_{ad}$ = 0.974, which is also very small and acceptable.