

Honors by Contract Homework - MATH 425

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April 19, 2021

1 Least-Squares Linear Optimization Proof

We are tasked with proving the following theorem: Given n points $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$, the straight line $y = a + bx$ minimizing

$$L = \sum_{i=1}^n [y_i - (a + bx_i)]^2$$

has slope

$$b = \frac{n \sum_{i=1}^n x_i y_i - \left(\sum_{i=1}^n x_i \right) \left(\sum_{i=1}^n y_i \right)}{n \sum_{i=1}^n x_i^2 - \left(\sum_{i=1}^n x_i \right)^2}$$

and y-intercept

$$a = \frac{\sum_{i=1}^n y_i - b \sum_{i=1}^n x_i}{n}$$

1.1 Proof

Assume we have n points $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$, and let

$$L = \sum_{i=1}^n [y_i - (a + bx_i)]^2$$

We know that

$$\frac{\partial L}{\partial a} = 0 = -2 \sum_{i=1}^n [y_i - (a + bx_i)]$$

and

$$\frac{\partial L}{\partial b} = 0 = -2 \sum_{i=1}^n x_i [y_i - (a + bx_i)]$$

Rearrange $\frac{\partial L}{\partial a}$ to obtain

$$\begin{aligned} 0 &= \sum_{i=1}^n y_i - \sum_{i=1}^n a - \sum_{i=1}^n bx_i \\ \sum_{i=1}^n a &= na = \sum_{i=1}^n y_i - \sum_{i=1}^n bx_i \end{aligned}$$

Therefore,

$$a = \frac{\sum_{i=1}^n y_i - \sum_{i=1}^n bx_i}{n}$$

Rearrange $\frac{\partial L}{\partial b}$ to obtain

$$\begin{aligned} a \sum_{i=1}^n x_i &= \sum_{i=1}^n x_i y_i - \sum_{i=1}^n bx_i^2 \\ a &= \frac{\sum_{i=1}^n x_i y_i - \sum_{i=1}^n bx_i^2}{\sum_{i=1}^n x_i} \end{aligned}$$

Plugging in the a value:

$$\begin{aligned} \frac{\sum_{i=1}^n y_i - \sum_{i=1}^n bx_i}{n} &= \frac{\sum_{i=1}^n x_i y_i - \sum_{i=1}^n bx_i^2}{\sum_{i=1}^n x_i} \\ \sum_{i=1}^n y_i - \sum_{i=1}^n bx_i &= \frac{n \sum_{i=1}^n x_i y_i - n \sum_{i=1}^n bx_i^2}{\sum_{i=1}^n x_i} \end{aligned}$$

More rearranging:

$$bn \sum_{i=1}^n x_i^2 - b \left(\sum_{i=1}^n x_i \right) \left(\sum_{i=1}^n x_i \right) = n \sum_{i=1}^n x_i y_i - \left(\sum_{i=1}^n y_i \right) \left(\sum_{i=1}^n x_i \right)$$

Therefore:

$$b = \frac{n \sum_{i=1}^n x_i y_i - \left(\sum_{i=1}^n y_i \right) \left(\sum_{i=1}^n x_i \right)}{n \sum_{i=1}^n x_i^2 - \left(\sum_{i=1}^n x_i \right)^2}$$

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2 Least-Squares Linear Fit on Example Data

The data for this section is drawn from Case Study 11.2.1 in the Larsen and Marx textbook. For this portion, I simply plugged in the values from the data into the following equation for a linear model:

$$y = a + bx$$

where,

$$b = \frac{n \sum_{i=1}^n x_i y_i - \left(\sum_{i=1}^n x_i \right) \left(\sum_{i=1}^n y_i \right)}{n \sum_{i=1}^n x_i^2 - \left(\sum_{i=1}^n x_i \right)^2}$$

$$a = \frac{\sum_{i=1}^n y_i - b \sum_{i=1}^n x_i}{n}$$

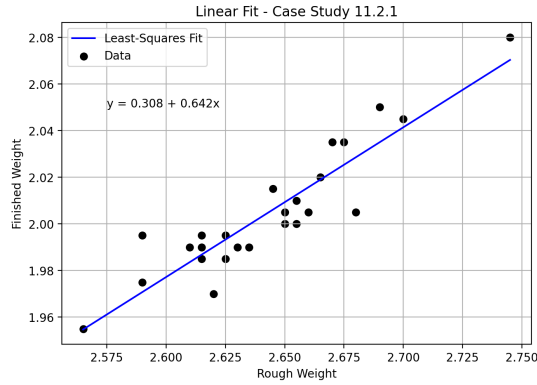


Figure 1: The least-squares fit for the data on a linear model seems to match the data from a visual standpoint.

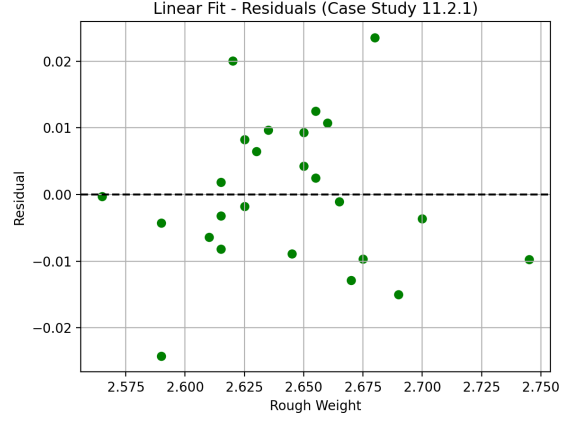


Figure 2: Residual plot for the data. All residuals are contained within a roughly $[-0.03, 0.03]$ range.

3 Least-Squares Non-Linear Fit on Example Data

For this portion, I simply plugged the values of the data in section 11.2.4 into the following nonlinear model:

$$y = ae^{bx}$$

where,

$$b = \frac{n \sum_{i=1}^n x_i \ln y_i - \left(\sum_{i=1}^n x_i \right) \left(\sum_{i=1}^n \ln y_i \right)}{n \sum_{i=1}^n x_i^2 - \left(\sum_{i=1}^n x_i \right)^2}$$

$$\ln a = \frac{\sum_{i=1}^n \ln y_i - b \sum_{i=1}^n x_i}{n}$$

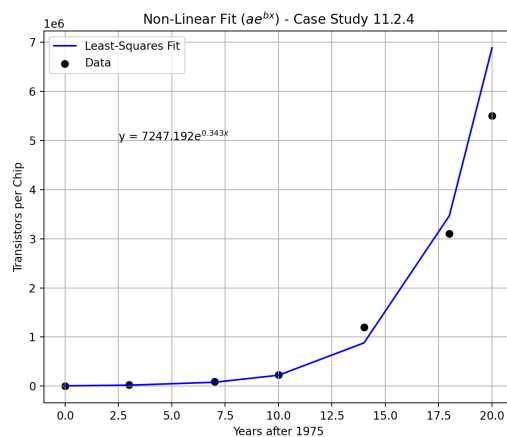


Figure 3: Exponential curve seems to fit the data very well. Note the y-axis has a 10^6 scale.

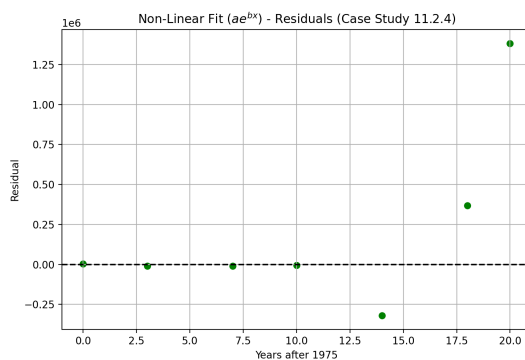


Figure 4: Residuals seem to increase with later years, which is expected since the scale grows exponentially.