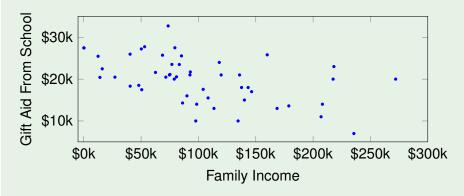
Least Squares Regression

Colby Community College

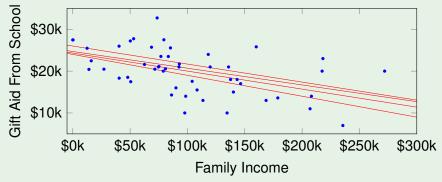
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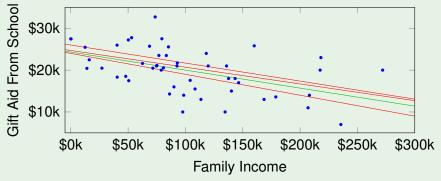
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Which of the lines best fits the data?

Without an objective definition of measure of "best", the answer will vary from person to person.

A reasonable idea of best, is if we make the sum of the residuals as small as possible:

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Note

In many applications, a residual twice as large as another is more than twice as bad. Squaring the residuals helps account for this discrepancy.

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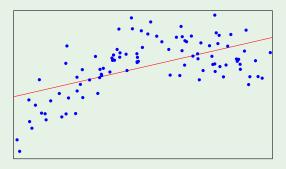
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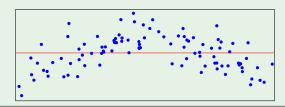
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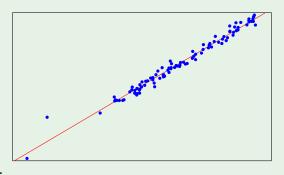
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- Independent Observations: Be careful about applying regression to **time series** data, which are sequential observations in time such as a stock price each day.

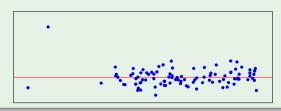
Scatter plot where the linearity condition fails:



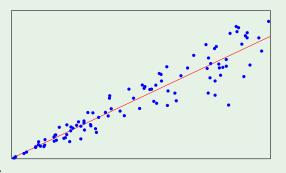


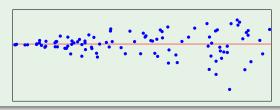
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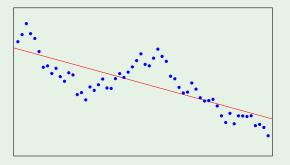


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Scatter plot using time series data:





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Note

Recall from Algebra that if we know the slope, m, of a line and a point, (x_0, y_0) , on that line, then:

$$y-y_0=m(x-x_0)$$

The summary statistics of the Elmhurst College data set are:

	Family	Income (x)	Gift	Aid (y)
mean	$\bar{x} =$	\$101,780	$\bar{y} =$	\$19,940
std. dev.	$s_x =$	\$63,200	$s_y =$	\$5,460

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The intercept, b_0 , describes the average outcome of y if x = 0 and the linear model is valid all the way to x = 0.

Example 6 (Continued)

The slope, $b_1 = -0.0431$, means that for each \$1,000 family income, we would expect a student to receive a net difference of

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Note

We must be cautious about interpreting a causal connection between these variables because this data is observational, not experimental.

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The financial aid a school gives a student can never be less than zero!

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The R^2 of a linear model describes what percent of the variation in the response that is explained by the least squares line.

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Note that for this data set we have R = -0.499 and

$$R^2 = (-0.4999)^2 \approx 0.25$$