

ML Week

Linear Regression

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23–24 novembre 2016

Linear models

Problem: $\{(x_i, y_i)\}$.

Given x , predict \hat{y} .

Linear models

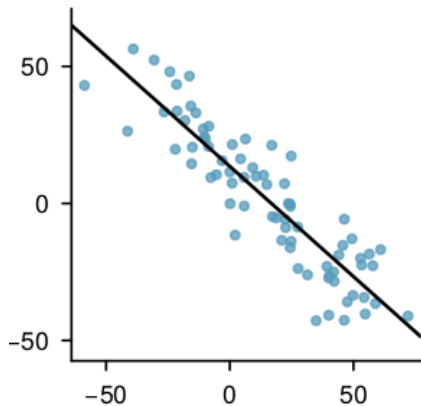
x : **explanatory** or **predictor** variable.

y : **response** variable.

For some reason, we believe a linear model is a good idea.

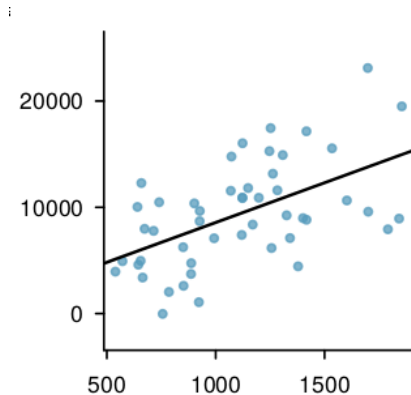
Linear models

Example:



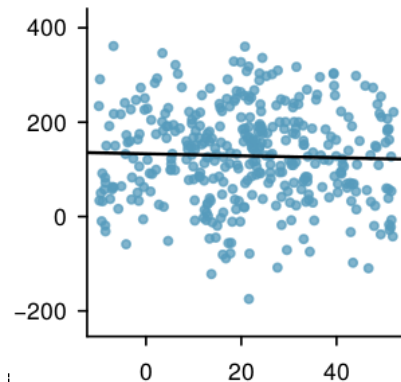
Linear models

Example:



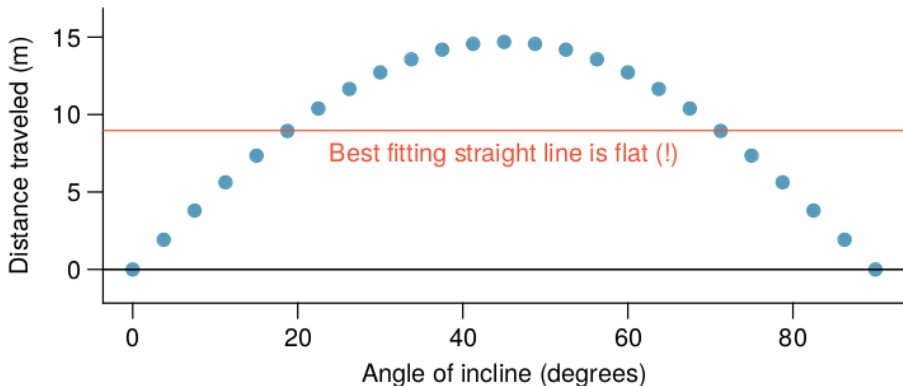
Linear models

Example:



Linear models

Example:



Residuals

What's left over.

$$\text{data} = \text{fit} + \text{residual}$$

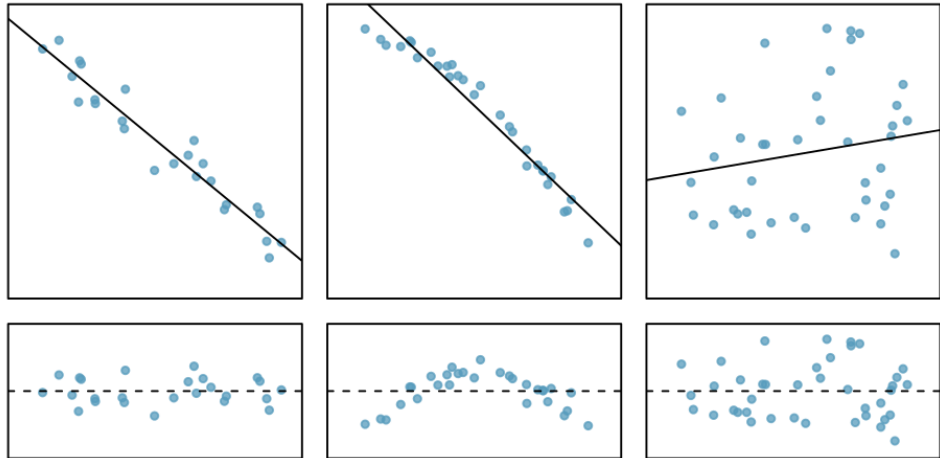
Residuals

What's left over.

$$y_i = \hat{y}_i + e_i$$

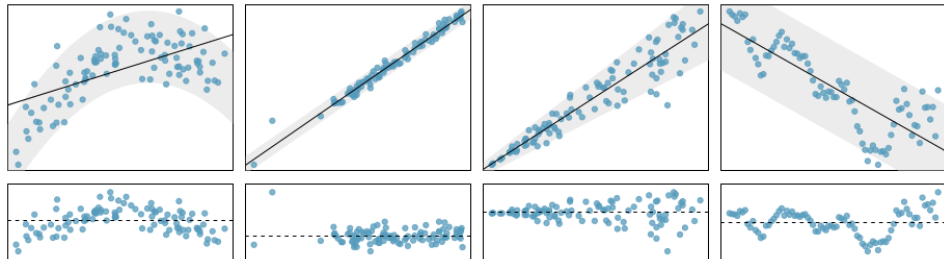
Residuals

What's left over.



Residuals

What's left over.



Residuals

What's left over.

Goal: small residuals.

$$\sum |e_i|$$

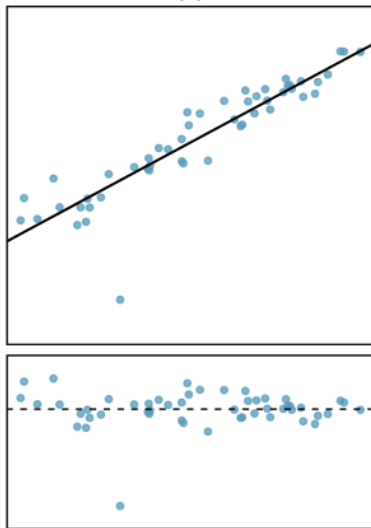
Residuals

What's left over.

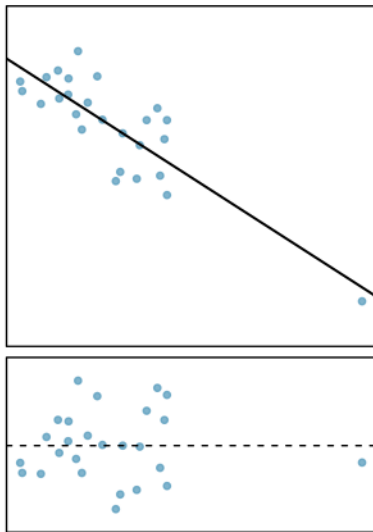
Goal: small residuals.

$$\sum e_i^2$$

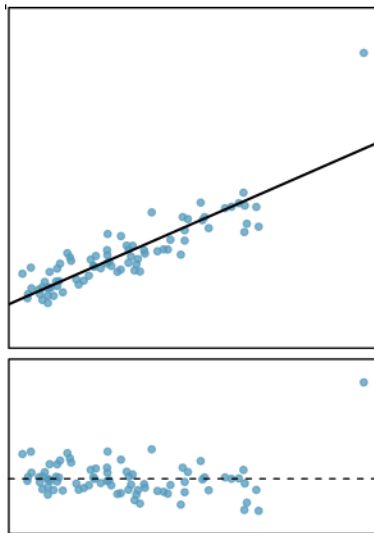
Outliers



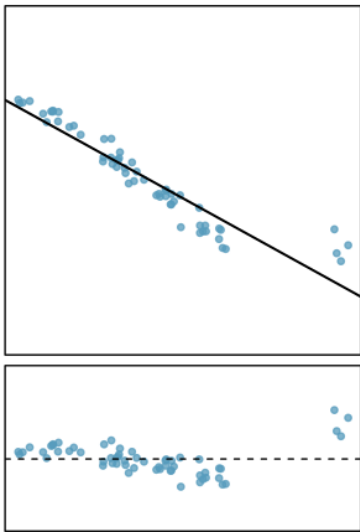
Outliers



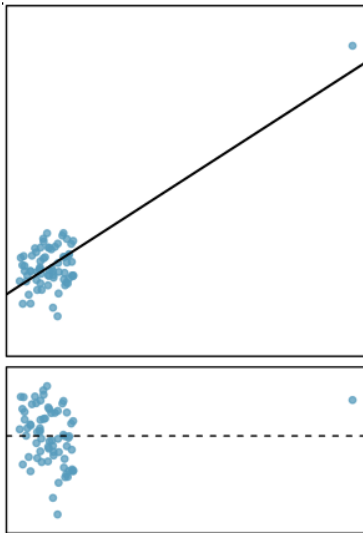
Outliers



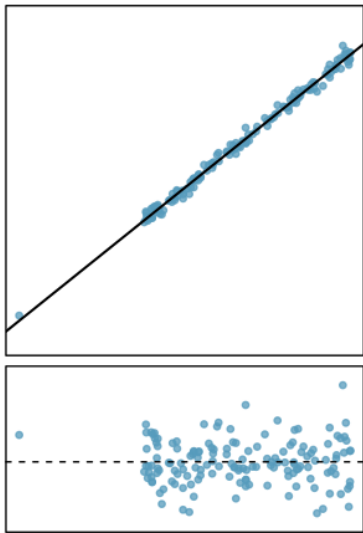
Outliers



Outliers

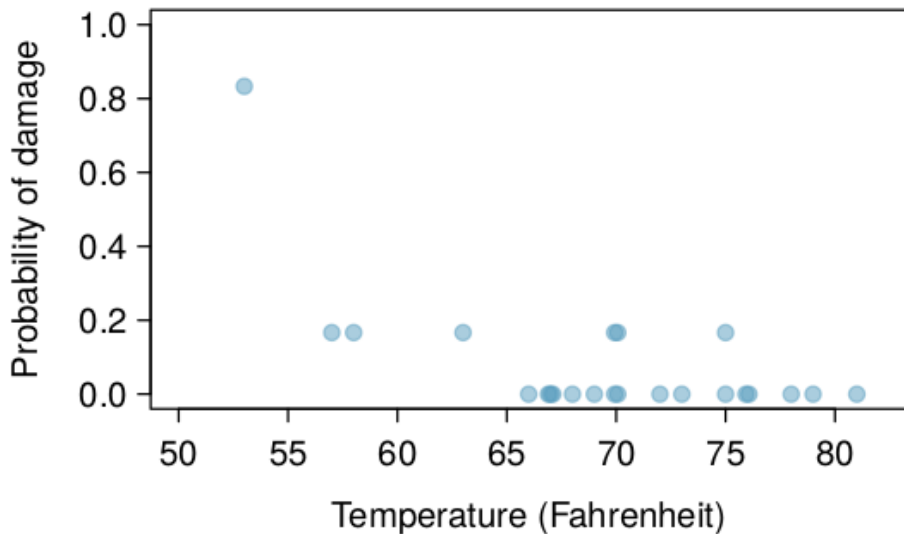


Outliers

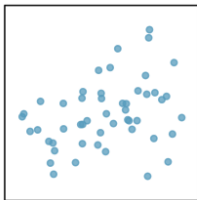


Don't ignore outliers.

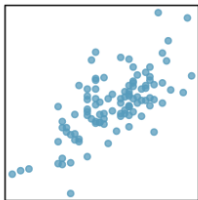
Outliers



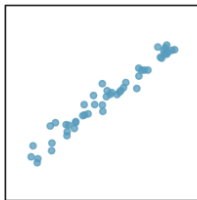
Correlation



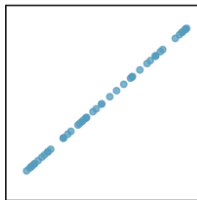
$R = 0.33$



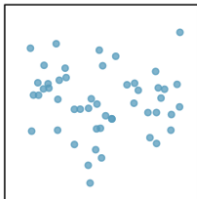
$R = 0.69$



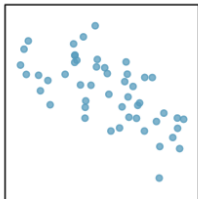
$R = 0.98$



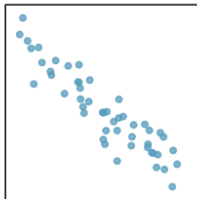
$R = 1.00$



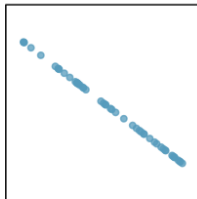
$R = -0.08$



$R = -0.64$

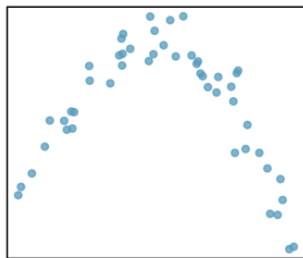


$R = -0.92$

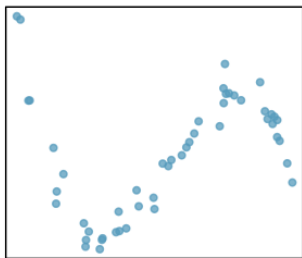


$R = -1.00$

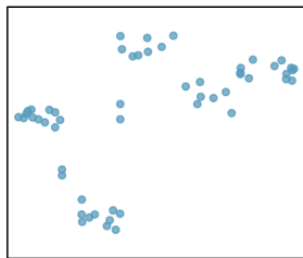
Correlation



$R = -0.23$



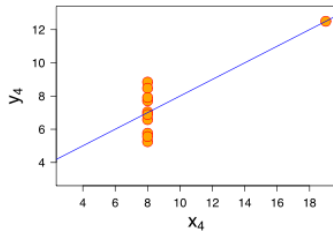
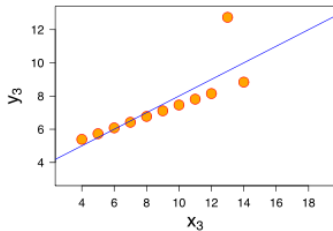
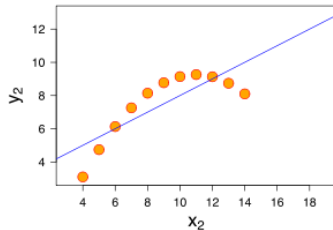
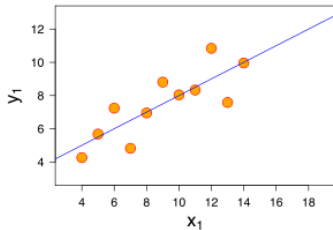
$R = 0.31$



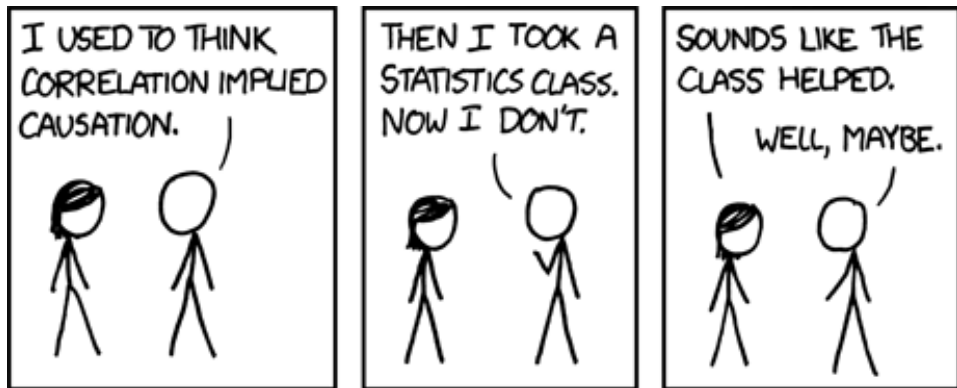
$R = 0.50$

Correlation

Anscombe's Quartet



Correlation does not imply causation



<https://xkcd.com/552/>

Hypothesis (model)

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

Cost function

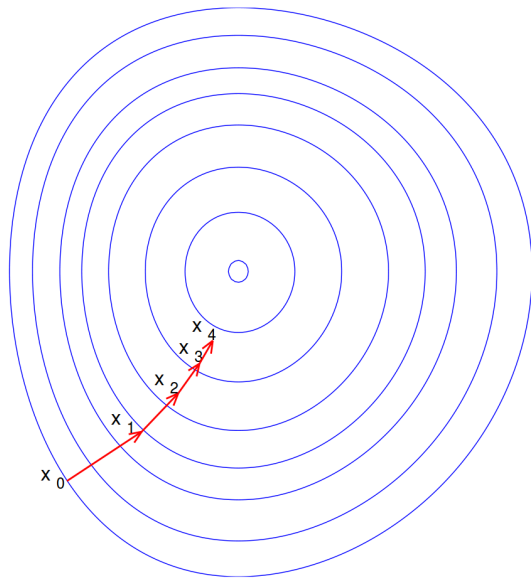
$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x_i) - y_i)^2$$

Gradient descent

$$\begin{cases} \theta_0 & \leftarrow \theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1) \\ \theta_1 & \leftarrow \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1) \end{cases}$$

Gradient descent

$$\begin{cases} \theta_0 \leftarrow \theta_0 - \frac{\alpha}{m} \sum_{i=1}^m (h_{\theta}(x_i) - y_i) \\ \theta_1 \leftarrow \theta_1 - \frac{\alpha}{m} \sum_{i=1}^m (h_{\theta}(x_i) - y_i) \end{cases}$$



Hypothesis again

$$\begin{aligned}h_{\theta}(x) &= \theta_0 + \theta_1 x_1 \\&= \theta_0 + \sum_{i=1}^1 \theta_i x_i \\&= [\theta_0, \theta_1] \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} \\&= \theta^T x\end{aligned}$$

Hypothesis (multiple regression)

$$\begin{aligned}h_{\theta}(x) &= \theta_0 + \sum_{i=1}^n \theta_i x_i \\&= [\theta_0, \dots, \theta_n] \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \\&= \theta^T x\end{aligned}$$

Hypothesis (multiple regression)

$$\begin{aligned}h_{\theta}(x) &= \theta^T x \\ &= \theta^T x^{(1)}\end{aligned}$$

Hypothesis (multiple regression)

$$X = \begin{bmatrix} \begin{array}{c} | \\ x^{(1)} \\ | \end{array} & \begin{array}{c} | \\ x^{(2)} \\ | \end{array} & \cdots & \begin{array}{c} | \\ x^{(m)} \\ | \end{array} \end{bmatrix} = \begin{bmatrix} x_0^{(1)} & x_0^{(2)} & \cdots & x_0^{(m)} \\ x_1^{(1)} & x_1^{(2)} & \cdots & x_1^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ x_n^{(1)} & x_n^{(2)} & \cdots & x_n^{(m)} \end{bmatrix}$$

Hypothesis (multiple regression)

$$\begin{aligned}h_{\theta}(X) &= \theta^T X \\&= [h_0(x^{(1)}), h_0(x^{(2)}), \dots, h_0(x^{(m)})] \\&= \theta^T X\end{aligned}$$

Hypothesis (multiple regression)

or $X\theta$ if row vectors. . .

Cost function (multiple regression)

$$\begin{aligned} J(\theta) &= \frac{1}{2m} \sum_{i=1}^m \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^2 \\ &= \frac{1}{2m} (X\theta - Y)^T (X\theta - Y) \end{aligned}$$

Gradient descent (multiple regression)

$$\theta_j \leftarrow \theta_j - \frac{\alpha}{m} \sum_{i=1}^m \left(h_{\theta}(x^{(i)}) - y^{(i)} \right) \cdot x_j^{(i)}$$

for $j = 1, \dots, n$

Gradient descent (multiple regression)

$$\theta \leftarrow \theta - \nabla J(\theta)$$

$$\text{where } \nabla = \begin{bmatrix} \frac{\partial}{\partial \theta_0} \\ \frac{\partial}{\partial \theta_1} \\ \vdots \\ \frac{\partial}{\partial \theta_n} \end{bmatrix}$$

Questions?

`purple.com/talk-feedback`