

Evaluating Regression Models

A simple example

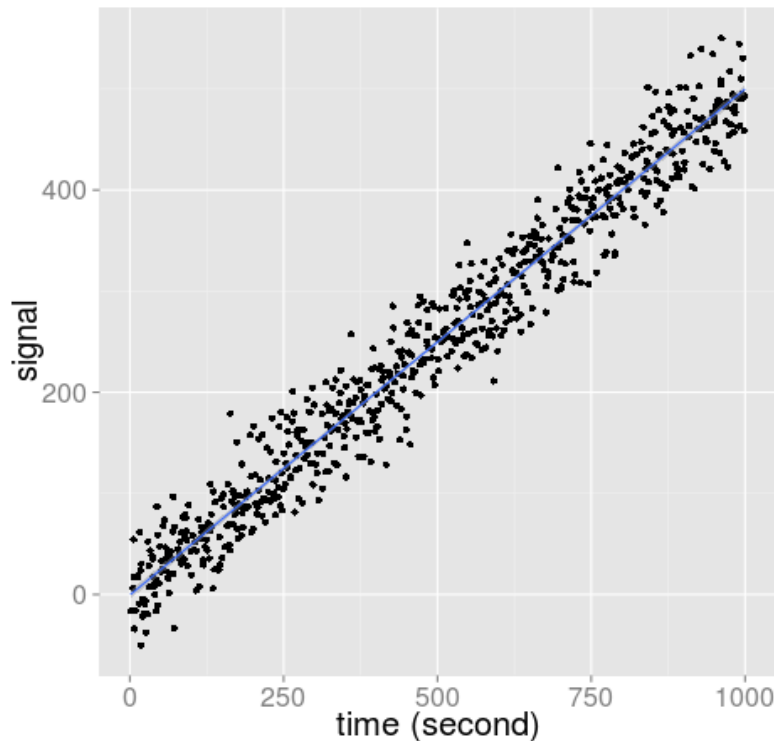
▪ A **linear regression model** is built based on the training data set:

$signal =$

$$h(time) = -0.498 + 0.500 \times time$$

How to evaluate this model?

What are the evaluation metrics for such regression models?



Basic metrics

Root-mean-square deviation (RMSE)

Mean Absolute Error(MAE)

Coefficient of determination (R Squared)

RMSE

Formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - h(\mathbf{x}_i))^2}{n}}$$

for data set i , \mathbf{x}_i is a vector of all the predictors,

y_i is the corresponding response;

$h(\mathbf{x}_i)$ is the prediction using a certain model;

n is the number of data in the test data set.

RMSE

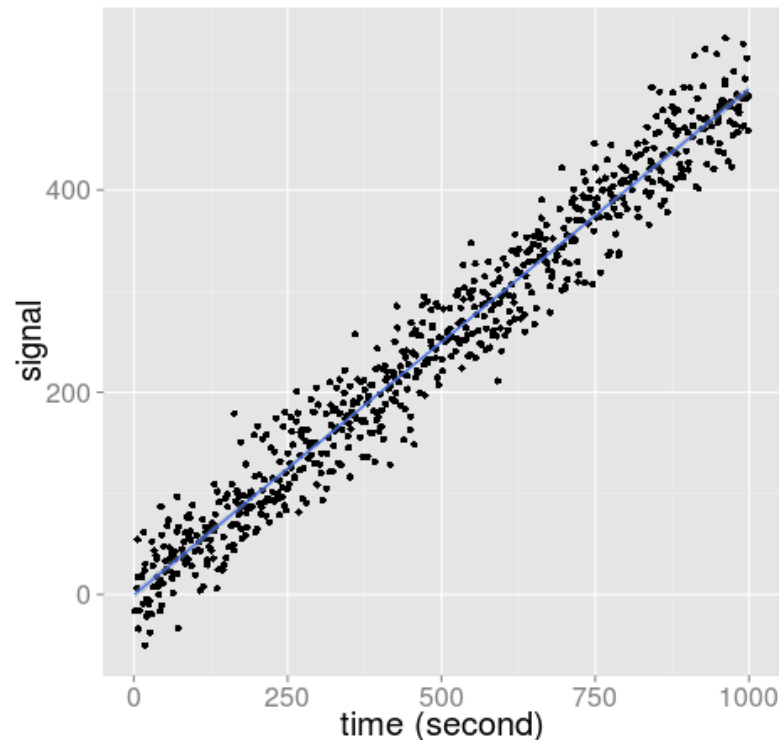
▪ Back to our simple **linear regression model**:

signal =

$$h(\text{time}) = -0.498 + 0.500 \times \text{time}$$

700 data items are used to **train** this model;

Another 300 data items in **testing data set** are used to measure this model.



RMSE

Using the testing data set with $n = 300$ data items:

$$y_i: -5.905, 48.261, 4.115, -8.370, 42.222, 10.320, \dots$$

$$h_{(x_i)}: 0.502, 1.003, 1.503, 4.505, 5.005, 6.507, \dots$$

$$h_{(x_i)} - y_i: 6.408, -47.259, -2.612, 12.875, -37.217, -3.814, \dots$$

$$(h_{(x_i)} - y_i)^2: 41.059, 2233.367, 6.823, 165.766, 1385.102, 14.546, \dots$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - h(\mathbf{x}_i))^2}{n}} = 29.17852$$

MAE

Formula:
$$MAE = \frac{\sum_{i=1}^n |residual_i|}{n} = \frac{\sum_{i=1}^n |y_i - h(\mathbf{x}_i)|}{n}$$

for data set i , \mathbf{x}_i is a vector of all the predictors,
 y_i is the corresponding response;
 $h(\mathbf{x}_i)$ is the prediction using a certain model;
 n is the number of data in the test data set.

MAE

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$$y_i: -5.905, 48.261, , 4.115, -8.370, 42.222, 10.320, \dots$$

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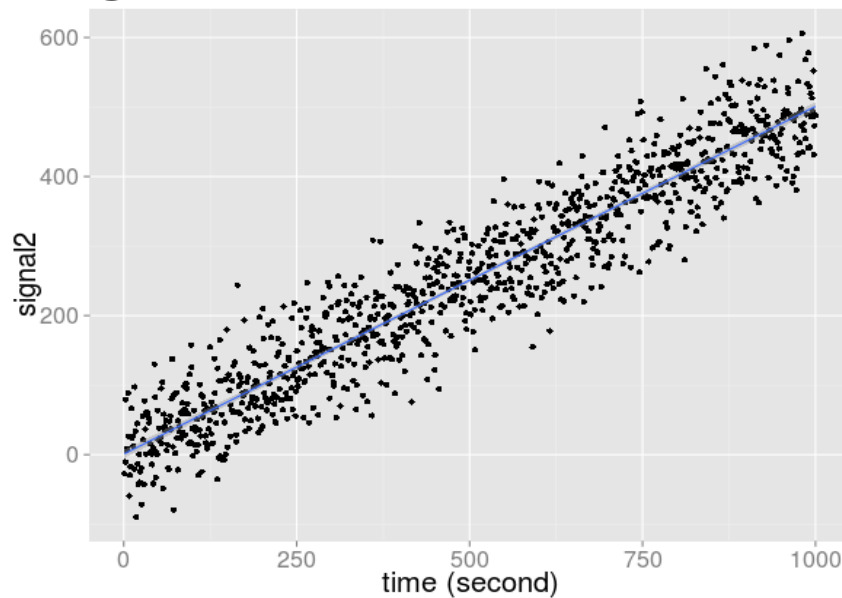
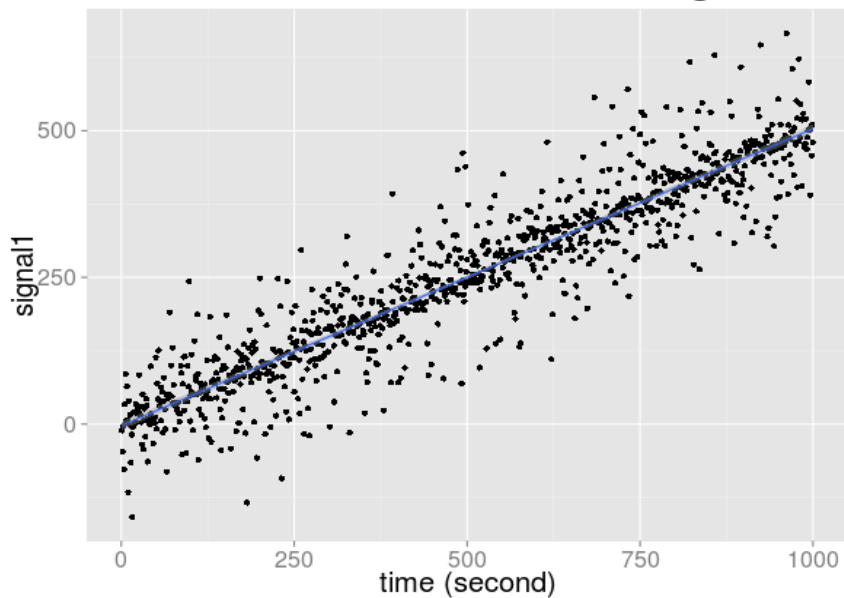
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$$|h_{(x_i)} - y_i|: 6.408, 47.259, 2.612, 12.875, 37.217, 3.814, \dots$$

$$MAE = \frac{\sum_{i=1}^n |y_i - h(\mathbf{x}_i)|}{n} = 23.02094$$

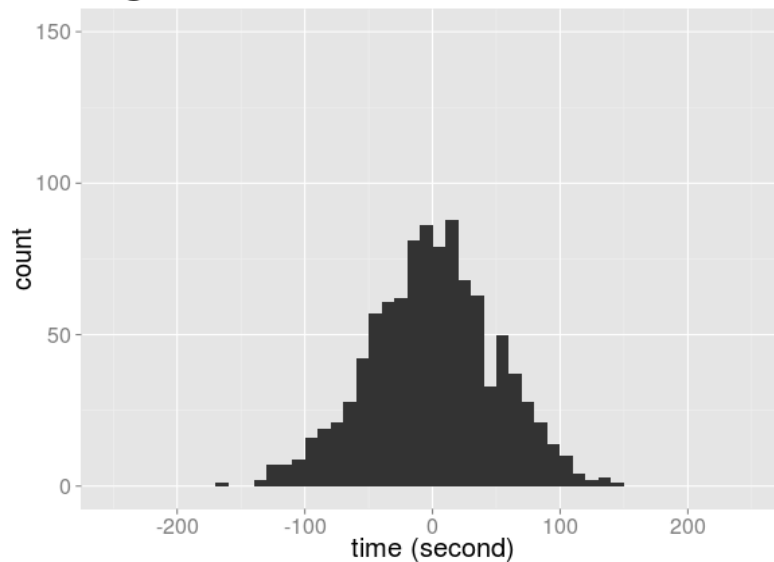
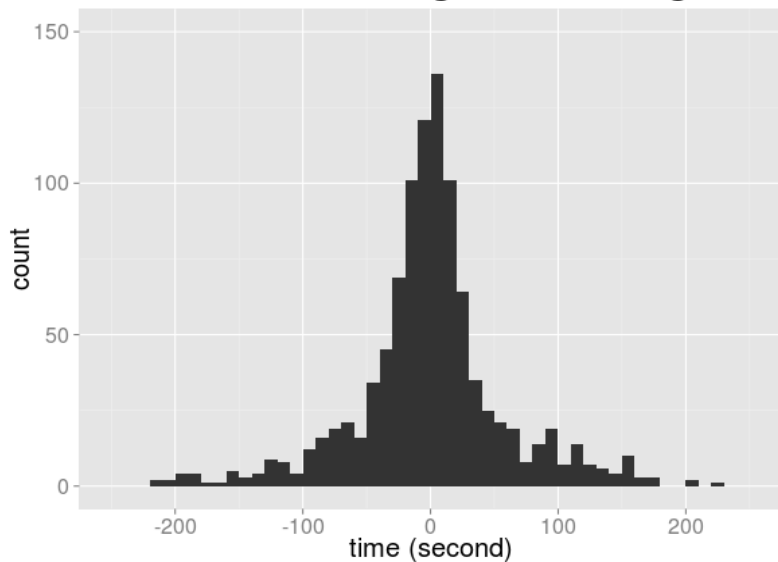
MAE *vs.* RMSE

Signal1 and signal2

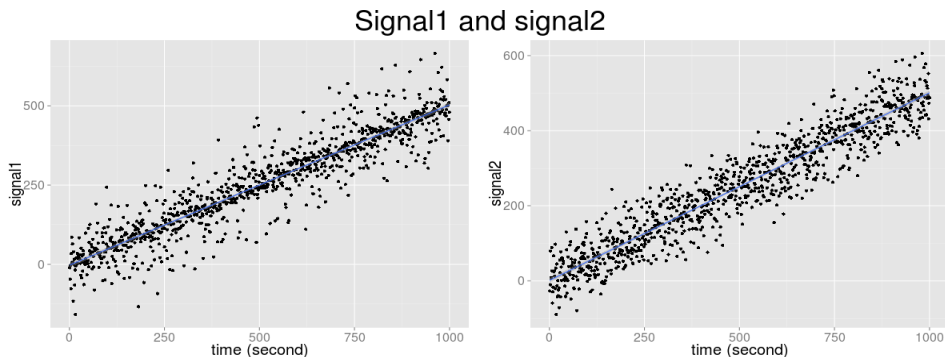


MAE *vs.* RMSE

Histograms of signal1 and signal2's residuals



MAE *vs.* RMSE



MAE: 41.926 (better) < 43.199

RMSE: 61.458 > 54.516 (better)

In RMSE, larger deviation cost more

Coefficient of Determination (R squared)

Formula:
$$R^2 = 1 - \frac{VAR_{res}}{VAR_{tot}}$$

(the proportion of variance explained by the model!)

where
$$VAR_{res} = \sum_{i=1}^n (y_i - h(\mathbf{x}_i))^2 / n, \quad VAR_{tot} = \sum_{i=1}^n (y_i - \bar{y})^2 / n$$

for data set i , \mathbf{x}_i is a vector of all the predictors,

y_i is the corresponding response;

$h(\mathbf{x}_i)$ is the prediction using a certain model.

\bar{y} is the mean of all responses;

n is the number of data in the test data set.

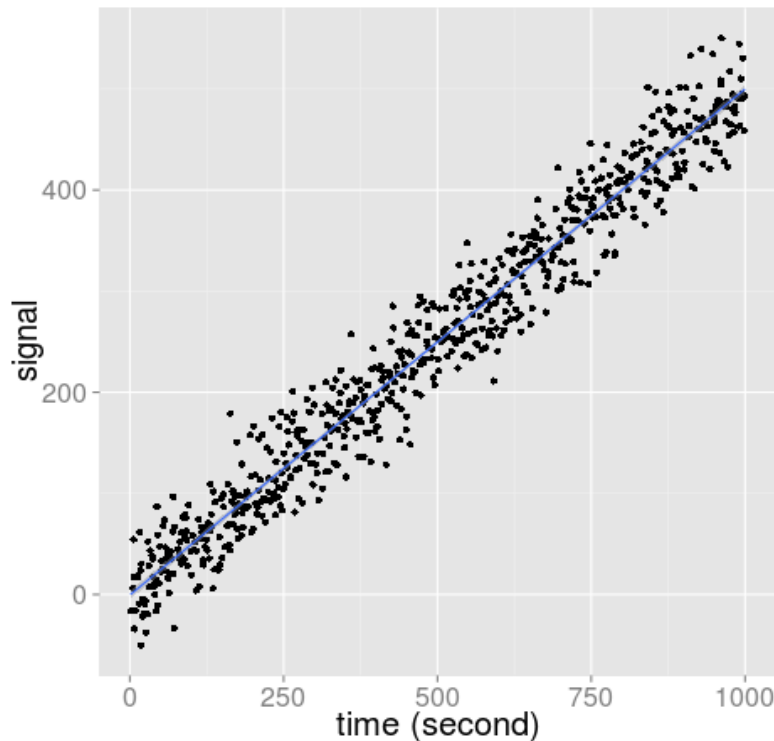
The simple example

$$R^2 = 0.958$$

The model built by real-world data
is usually not that good.

$$R^2 = 0.6$$

can be a good model.



Adjusted R squared

$$R_{adj}^2 = 1 - (1 - R^2) \frac{n-1}{n-p-1}$$

Where p is the total number of predictors in the model (not counting the constant term),

n is the sample size.

Penalized by the more predictors

QUESTIONS