

# **Multiple Linear Regression**

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#### **REGRESSION ANALYSIS**

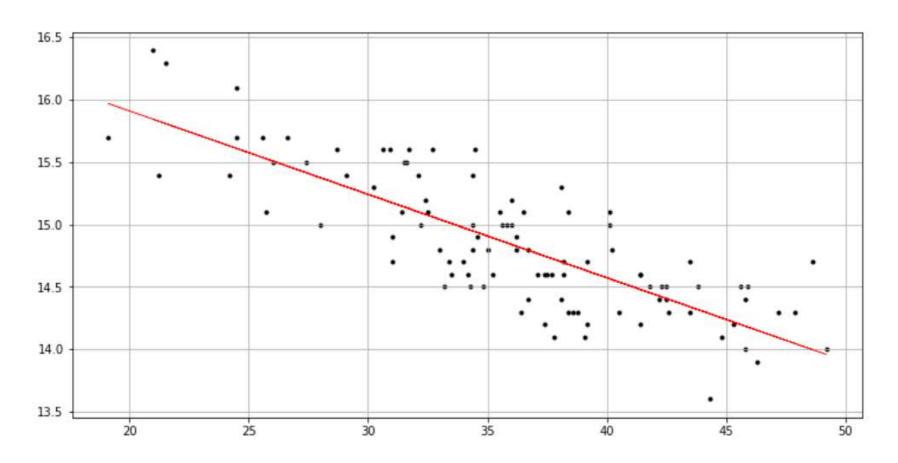
Regression analysis is useful to find a relationship between a response and a set of predictors

Two Regression Models

- Simple linear regression (SLR)
- Multiple linear regression (MLR)

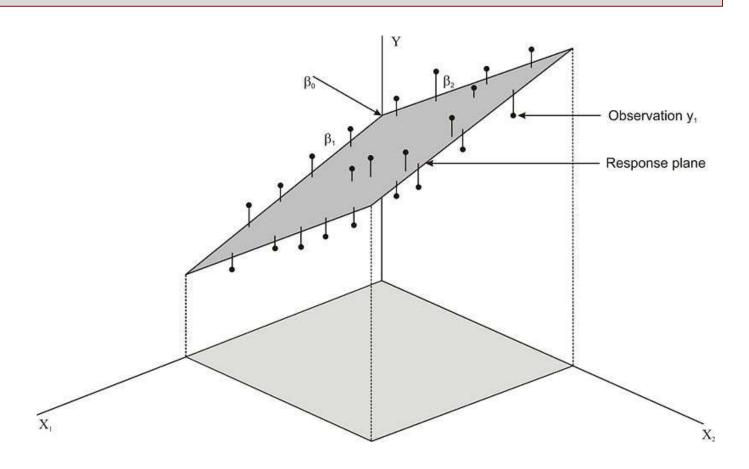


# **OLS line – one predictor**





# 2 predictors





# **OLS plane**

Closest plane to dataset Average relation Observation y, between (X1,X2) and Y Response plane



# **Multiple Linear Regression**

Consider predictors X<sub>1</sub>, X<sub>2</sub>,...,X<sub>p</sub>

Regression plane 
$$E[Y] = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p$$



# **Multiple Linear Regression**

Consider predictors X<sub>1</sub>, X<sub>2</sub>,...,X<sub>p</sub>

Regression plane

$$E[Y] = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$$

Fitted plane

$$\hat{Y} = b_0 + b_1 X_1 + \cdots + b_p X_p$$



# How good is the regression model?



# How good is the regression model?

How well the model fits the data?

How well the model predicts the data?



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SSE R<sup>2</sup>

How well the model predicts the data?

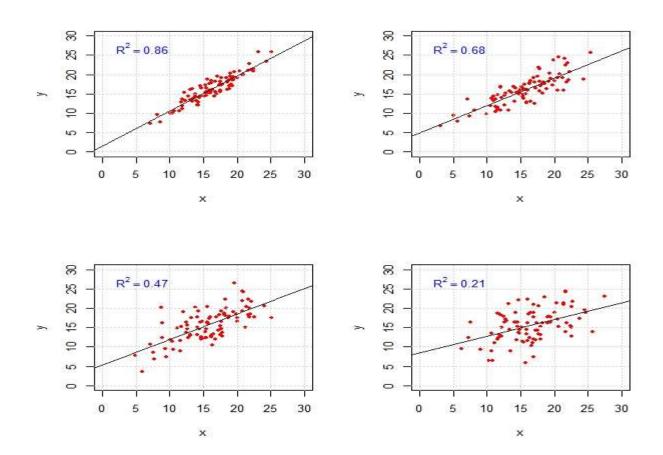


## **Model adequacy**

# $R^2$ is the proportion of the variation in Y that is explained by $X_1, X_2,..., X_p$



# One predictor





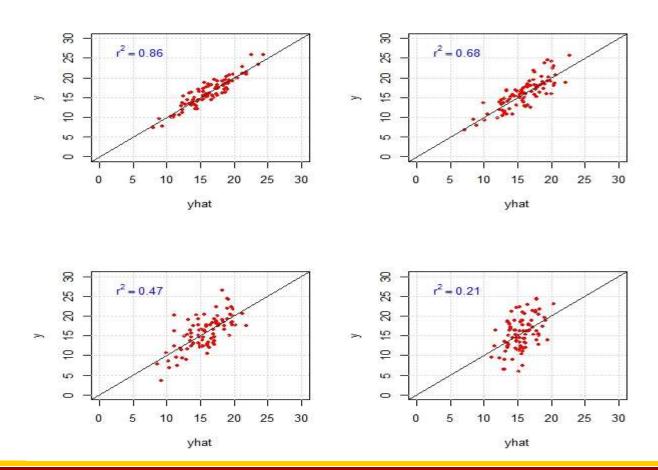
# R-squared vs correlation (y, yhat)

# If r is the correlation between y and yhat

$$R^2 = r^2$$



# y vs. yhat plot





We say that *p* increases

when more predictors (features)

are added to the model



We say that *p* decreases

when some predictors (features)

are removed from the model



# Given a set of *p* predictors

- What is the best predictor?
- What is the best set of predictors?`



Fact 1

If *p* increases, SSE decreases, always



Fact 1

If *p* increases, SSE decreases, always

Therefore,

$$R^2 = 1 - \frac{SSE}{SST}$$

if p increases,  $R^2$  increases



# $R^2$ useful to compare models with the same number p of predictors



R<sup>2</sup> useful to compare models

with the same number *p* of predictors

R<sup>2</sup> not useful to compare models

R<sup>2</sup> not useful to compare models

with different number p of predictors



How to compare models with different number of predictors?



How to compare models with different number of predictors?

- Adjusted R<sup>2</sup>
- AIC (Information Criteria)



How to compare models with different number of predictors?

- Adjusted R<sup>2</sup> (larger is better)
- AIC (smaller is better)



Fact 2

If p increases, MSE may increase or decrease

$$MSE = \frac{SSE}{n - p - 1}$$



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Therefore, if p increases

adjusted-
$$R^2 = 1 - \frac{MSE}{MST}$$

adjusted-R<sup>2</sup> may increase or decrease



Fact 2

If p increases, MSE may increase or decrease

Therefore, if p increases

$$adjusted-R^2 = 1 - \frac{MSE}{MST}$$

select number of predictors s.t. adj-R<sup>2</sup> is smallest



# Adj-R<sup>2</sup> useful to compare models with different number of predictors



## **MS formulas for Simple Linear Regression**

$$SSTotal = \sum_{i=1}^{n} (y - \overline{y})^2 \qquad \qquad MSTotal = \frac{SSTotal}{n-1} \quad \text{ sample variance Y}$$

$$MSTotal = \frac{SSTotal}{n-1}$$

$$SSR = \sum_{i=1}^{n} (\hat{y} - \overline{y})^2 \qquad MSR = \frac{SSR}{1}$$

$$MSR = \frac{SSR}{1}$$

$$SSE = \sum_{i=1}^{n} (y - \hat{y})^{2} \qquad MSE = \frac{SSE}{n-2}$$

$$MSE = \frac{SSE}{n-2}$$



# **MS formulas for Multiple Linear Regression**

$$SSTotal = \sum_{i=1}^{n} (y_i - \overline{y})^2$$
  $MSTotal = \frac{SSTotal}{n-1}$  sample variance Y

$$MSTotal = \frac{SSTotal}{n-1}$$

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \overline{y})^2 \qquad MSR = \frac{SSR}{p}$$

$$MSR = \frac{SSR}{p}$$

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$
  $MSE = \frac{SSE}{n - p - 1}$ 

$$MSE = \frac{SSE}{n - p - 1}$$



# ANOVA DECOMPOSITION, R-squared

$$SSTotal =$$

$$SSE + SSR$$

$$\frac{SSE}{SST}$$

SSE

$$+ \frac{SSR}{SST}$$

$$+ R^2$$



# ANOVA DECOMPOSITION, R-squared

$$SSTotal =$$

$$SSE + SSR$$

$$\frac{SSE}{SST}$$

$$+ \frac{SSI}{SSI}$$

$$\frac{SSE}{SST}$$



# ANOVA DECOMPOSITION, R-squared

$$SSTotal =$$

$$SSE + SSR$$

$$\frac{SSE}{SST}$$

$$+ \frac{SSR}{SST}$$

$$\frac{SSE}{SST}$$

$$-R^2$$



# R-squared vs adj R-squared

$$R^2 = 1 - \frac{SSE}{SST}$$

$$adj R^2 = 1 - \frac{MSE}{MST}$$



## R-squared vs adj R-squared - interpretation

- 100R<sup>2</sup> is the percentage of variation in Y that is explained by the model
- Adjusted R<sup>2</sup> has no interpretation



# R-squared vs adj R-squared

$$R^2 = 1 - \frac{SSE}{SST}$$

$$adj R^2 = 1 - \frac{MSE}{MST}$$



$$adj R^2 = 1 - \frac{MSE}{MST}$$

$$= 1 - \frac{\frac{SSE}{n-p-1}}{\frac{SST}{n-1}}$$



$$adj R^2 = 1 - \frac{MSE}{MST}$$

$$= 1 - \frac{\frac{SSE}{n-p-1}}{\frac{SST}{n-1}}$$

$$= 1 - \frac{n-1}{n-p-1} \frac{SSE}{SST}$$



$$adj R^2 = 1 - \frac{n-1}{n-p-1} \frac{SSE}{SST}$$

$$1 \quad - \quad adj \ R^2 \qquad = \quad \quad \frac{n-1}{n-p-1} \ \frac{SSE}{SST}$$



$$adj R^2 = 1 - \frac{n-1}{n-p-1} \frac{SSE}{SST}$$

$$1 - adj R^2 = \frac{n-1}{n-p-1} \frac{SSE}{SST}$$

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



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# **Akaike Information Criteria**

Measures the lost of information by fitting a model from a sample.

$$AIC = n \log \left(\frac{SSE}{n}\right) + 2p$$



# As the number *p* of predictors increases

SSE decreases

$$AIC = n \log \left(\frac{SSE}{n}\right) + 2p$$

AIC may increase or decrease