Multiple Linear Regression

- features/predictors: $X_1, \ldots, X_p$
- response/outcome variable: Y

The linear regression model assumes

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p + e$$

where

β_0 is the intercept

β_j is the regression coefficient associated with X_j

e is the error term often assumed to have mean zero

and variance σ^2.

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Housing Data

Y: sale price of a house

X_1: # of bedrooms

X_2: # of bathrooms

X_3: square feet

$\ldots\ldots$

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Training Data $(x_{i1}, \dots, x_{ip}, y_i)_{i=1}^n$

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + e_i$$

$$i = 1, \dots, n$$

Matrix Representation

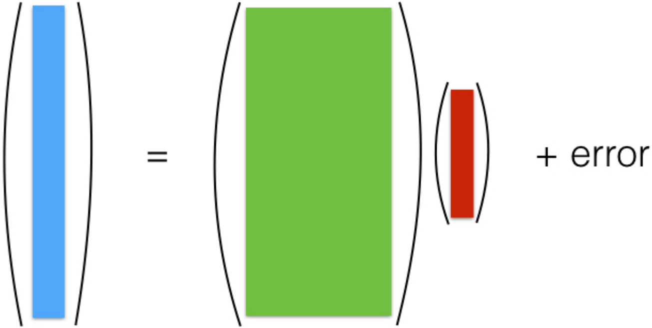
Express the regression model on $(x_{i1}, \ldots, x_{ip}, y_i)_{i=1}^n$ in the following matrix form

$$\begin{pmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{pmatrix} = \begin{pmatrix} \beta_0 + x_{11}\beta_1 + x_{12}\beta_2 + \cdots + x_{1p}\beta_p + e_1 \\ \beta_0 + x_{21}\beta_1 + x_{22}\beta_2 + \cdots + x_{2p}\beta_p + e_2 \\ \cdots \\ \beta_0 + x_{n1}\beta_1 + x_{n2}\beta_2 + \cdots + x_{np}\beta_p + e_n \end{pmatrix}$$

$$= \begin{pmatrix} 1 & x_{11} & \cdots & x_{1p} \\ 1 & x_{21} & \cdots & x_{2p} \\ 1 & \cdots & \cdots & \cdots \\ 1 & x_{n1} & \cdots & x_{np} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \cdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \\ \cdots \\ e_n \end{pmatrix}$$

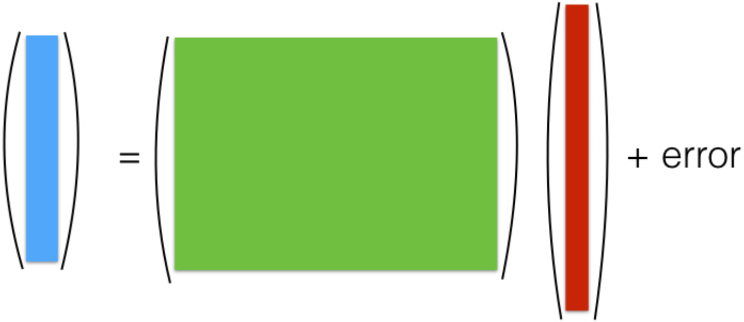
$$\mathbf{y}_{n\times 1} = \mathbf{X}_{n\times(p+1)}\boldsymbol{\beta}_{(p+1)\times 1} + \mathbf{e}_{n\times 1}$$

The classical large n small p regression model:



Focus of **this** week

The modern large p small n regression model:



Focus of **next** week