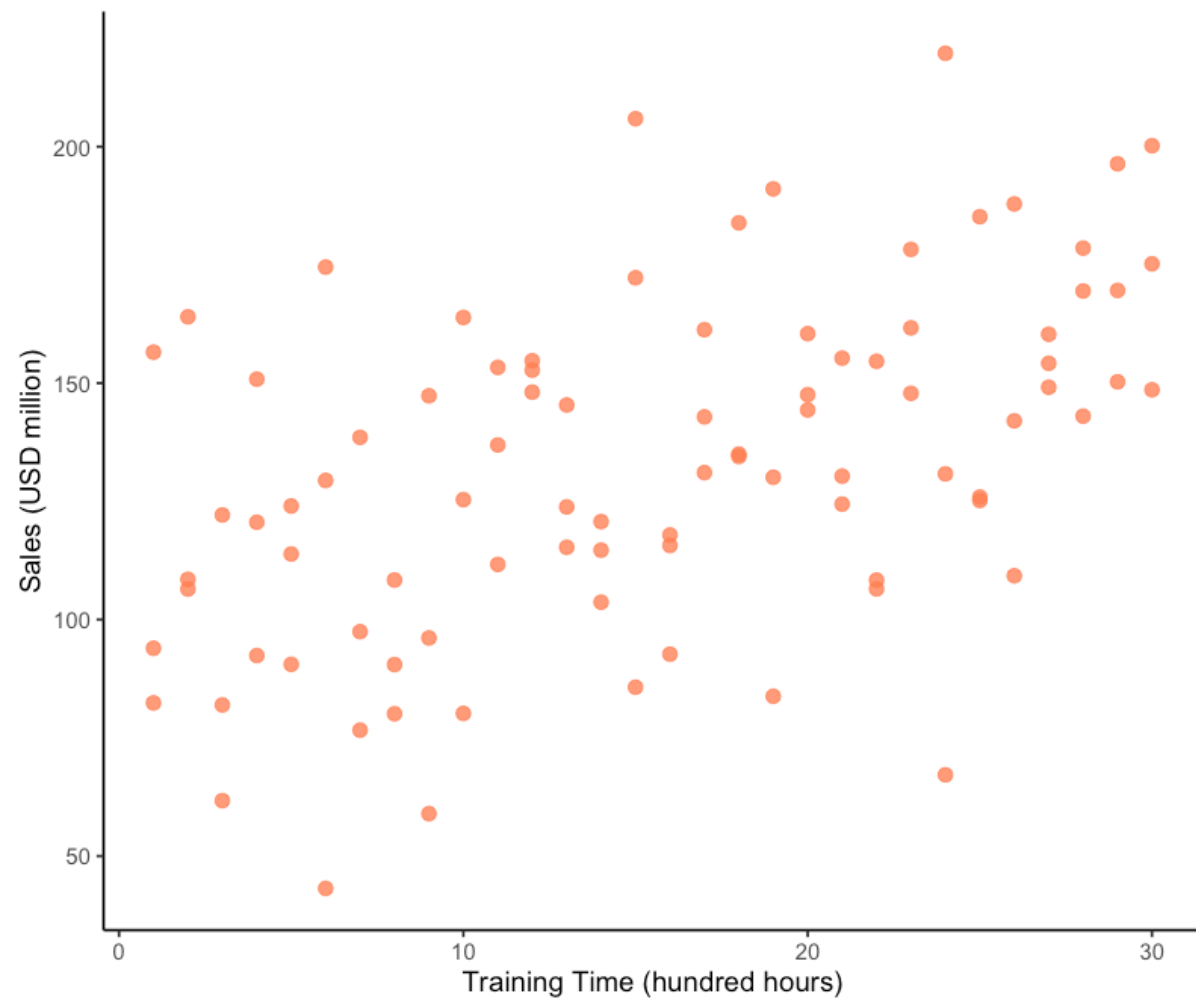
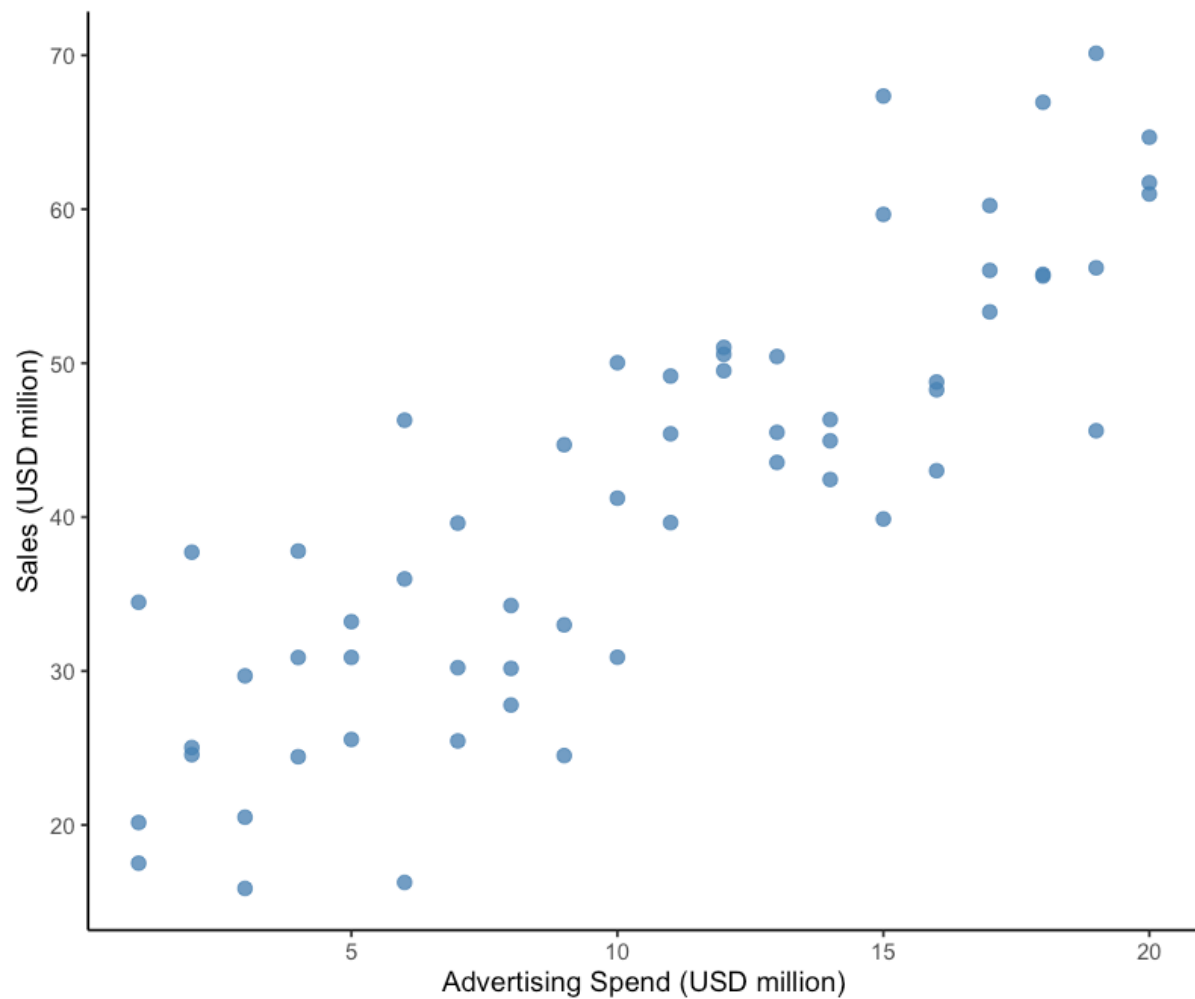


# Regression Part A

Ulink MM Club  
Alan, Frank



# Introduction



# Linear Regression

## General formula

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

where  $\beta_0$  denotes the intercept,  $\beta_1$  denotes the gradient, and  $\epsilon_i$  denotes the error term (or residue).

## Key Assumptions

- ◆ Observations are independent of each other.
- ◆ The residue is normally distributed.

# Likelihood Functions

A likelihood function measures how well a statistical model explains observed data by calculating the probability of seeing that data under different parameter values of the model, written as:

$$\mathcal{L}(\theta|x)$$

which denotes the probability of obtaining parameter  $\theta$  given observation  $x$ .

# Maximum Likelihood Estimation

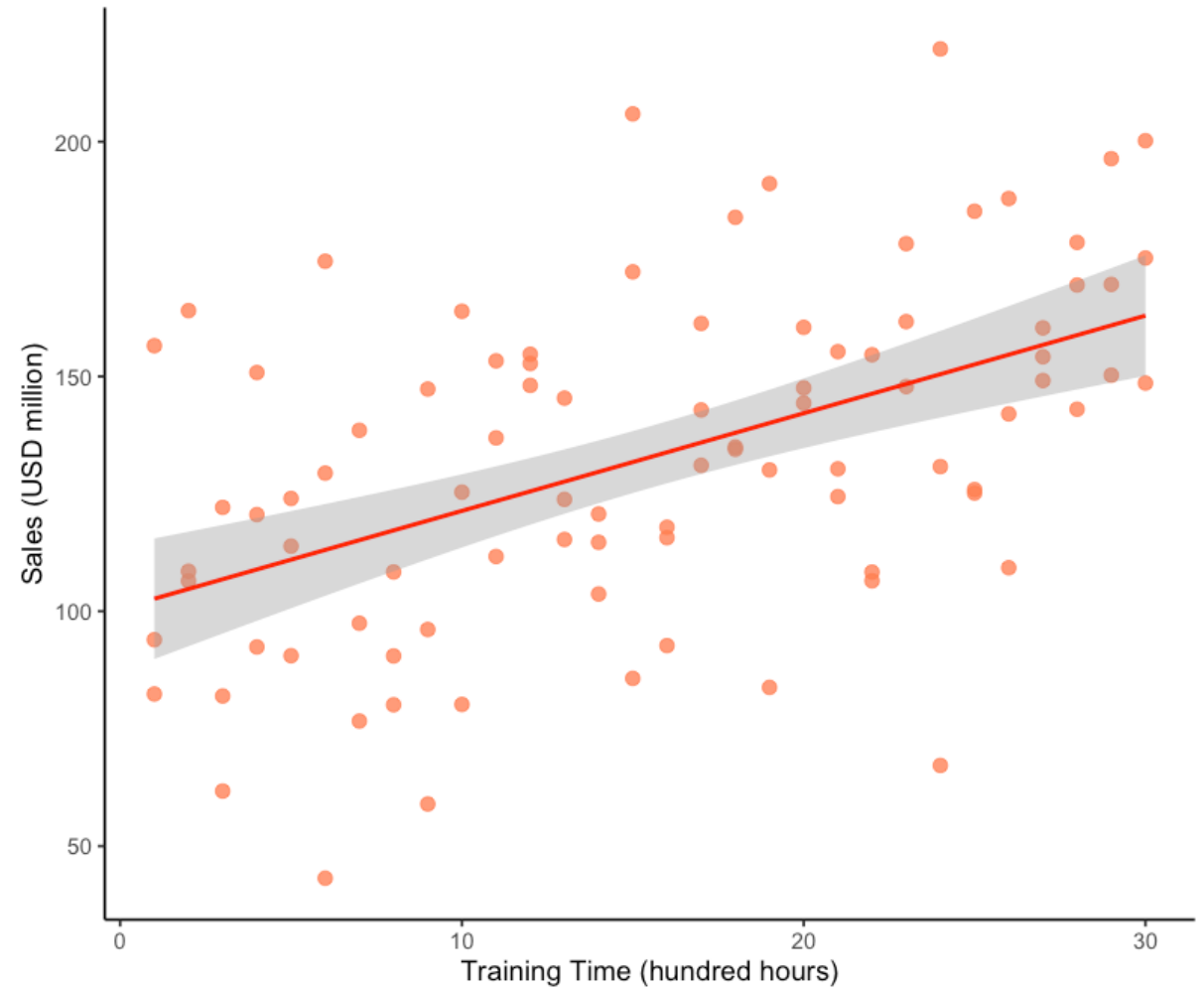
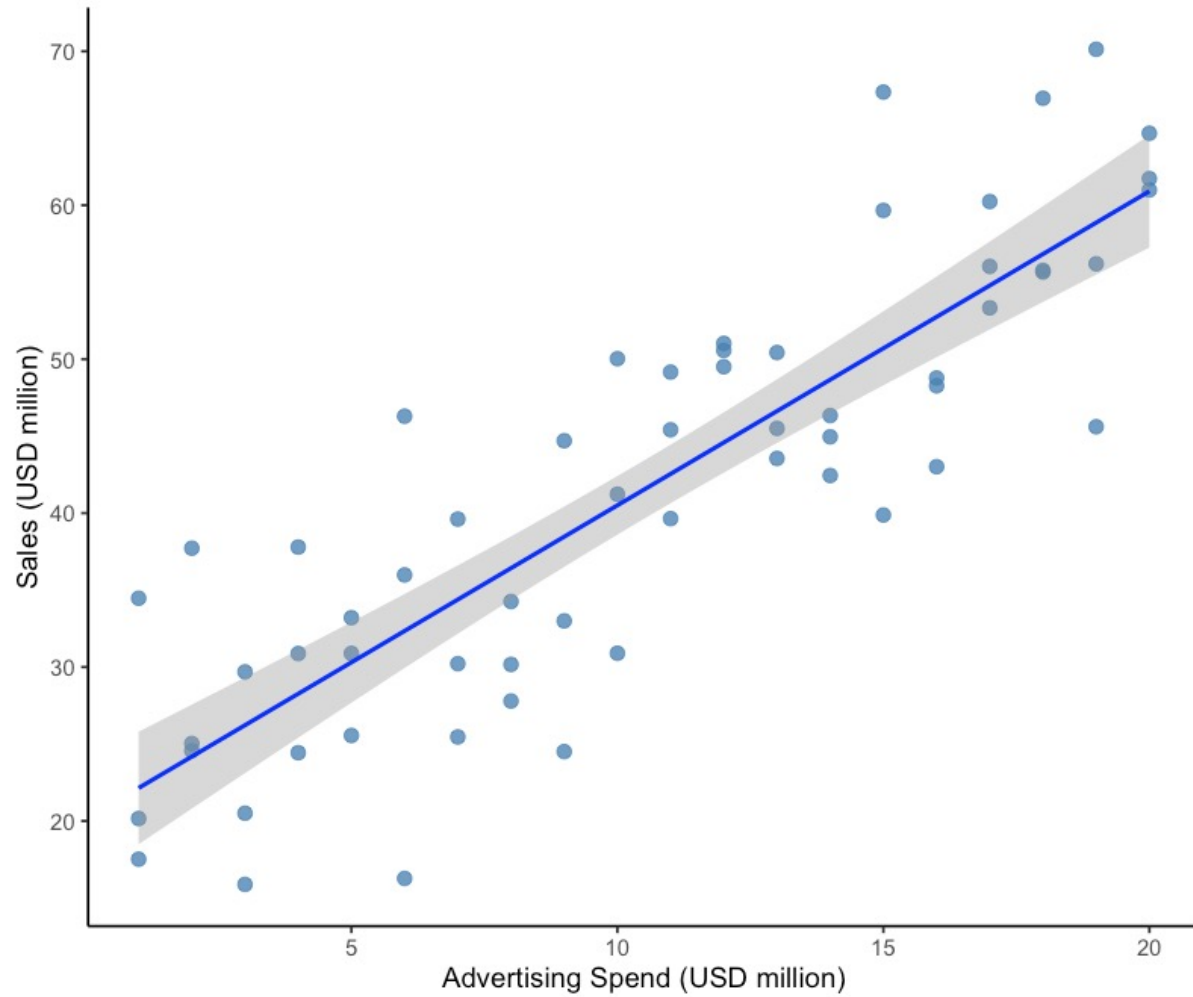
We aim to maximise this  $\mathcal{L}(\theta|x)$ , so that we have high probability of getting  $\theta$  given  $x$ , that is to say, the parameter  $\theta$  best fits the observations.

## Conclusion for Linear Regressions

Maximum likelihood estimation is identical to least square estimation.

Mean squared error (MSE):  $MSE(\beta_0, \beta_1) = \frac{1}{n} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$ .

# Results



# Evaluating the Models

Coefficient of determination  $R^2$

$$SS_{res} = \sum_{i=1}^n (y_i - \widehat{y}_i)^2, SS_{tot} = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

If the model exactly fits the data,  $SS_{res} = 0$  and  $R^2 = 1$ ,

If the model always estimates output to be  $\bar{y}$ ,  $SS_{res} = SS_{tot}$  and  $R^2 = 0$ .

# Evaluating the Models

## Adjusted $R^2$

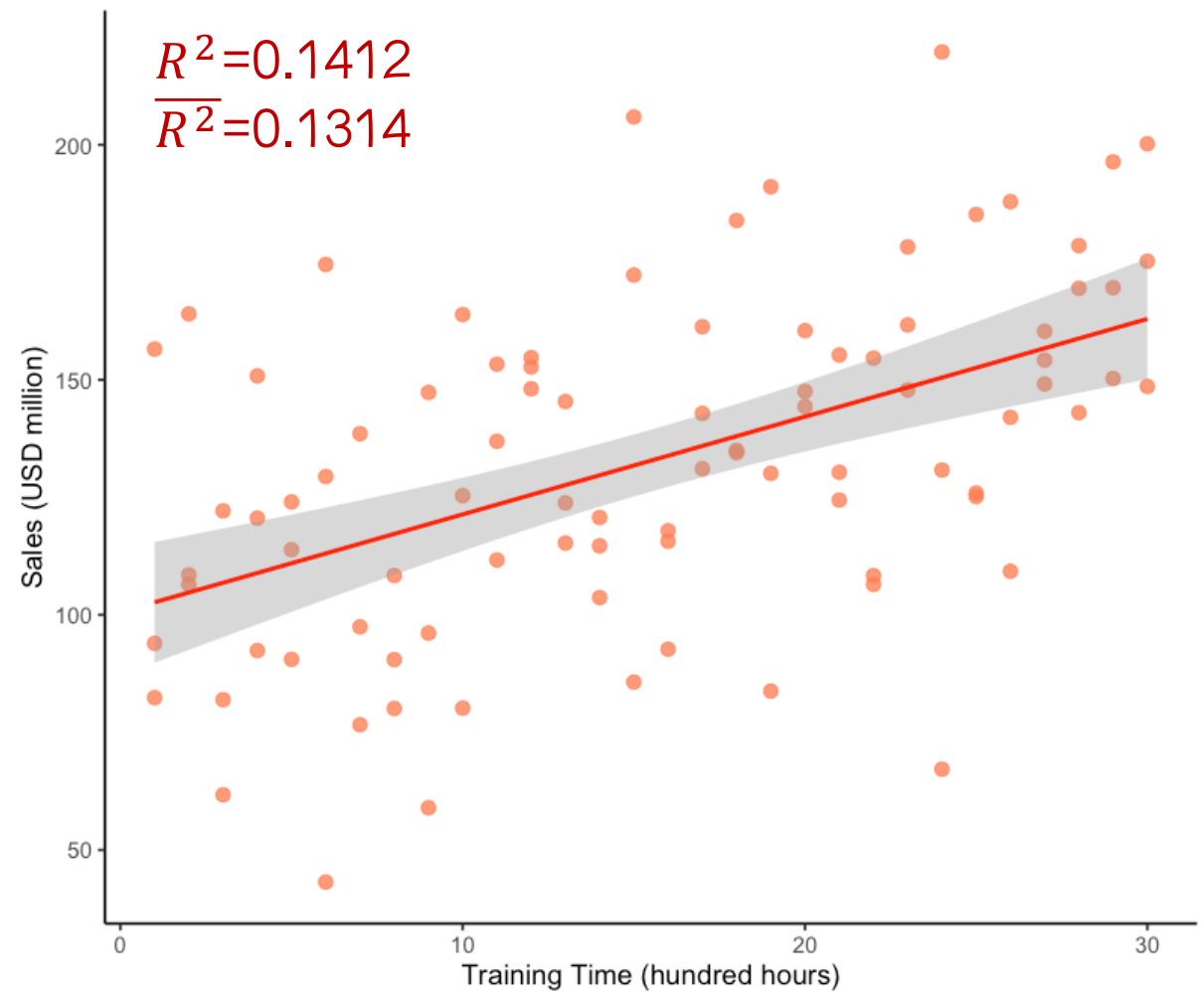
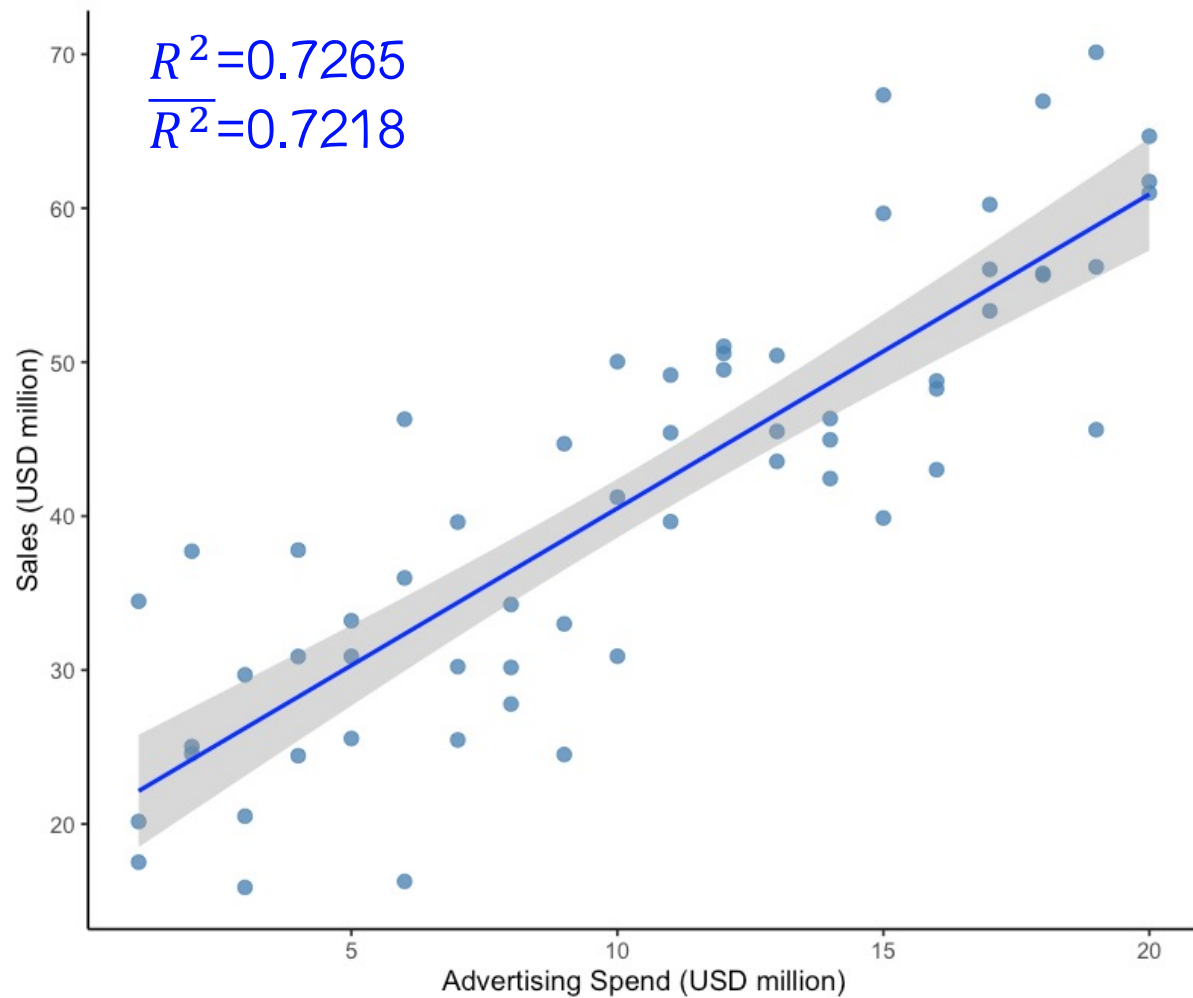
$R^2$  measures how well the model fits the historical data, but not how well the model will forecast future data. In addition, adding any variable tends to increase the value of  $R^2$ , even if that variable is irrelevant.

$$\overline{R^2} = 1 - (1 - R^2) \frac{T - 1}{T - k - 1}$$

where  $T$  denotes the number of observations and  $k$  denotes the number of predictors (independent variables).



# Results



# Strengths and Weaknesses

## Strengths:

- ◆ The model gives a direct relationship between predictors and the target (e.g. each 1 unit increase in  $X$  adds 2.5 units to  $Y$ );
- ◆ Fast to train and test, even on large datasets, as it has a closed-form solution;

## Weaknesses:

- ◆ Sensitive to Outliers;
- ◆ When the number of predictors is large relative to observations, it can overfit unless regularization (e.g., Ridge, Lasso) is applied.



Thank you