

$$J(w_0, w_1) = \frac{1}{2} \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \frac{1}{2} (y - \hat{y})^T (y - \hat{y}) = \frac{1}{2} (y - (w_0 + w_1 x))^T (y - (w_0 + w_1 x))$$

Linear Regression

- output y is continuous
- learned Model: linear function mapping input to output (a weight for each feature + bias)
- Goal: minimize the RSS or SSE (sum of squared errors)

Why are models useful?

- Visualizing data, drawing conclusions
- make predictions

Linear Models? (continuous, not discrete)

- which of the features x are associated with the response variable y ?
- relationship b/w x & y ?
- Given x can we predict y ?
- is it enough?

Linear Regression:

output is continuous

Weights/params

Ex: $h_{\vec{w}} = w_0 + w_1 x = \hat{y}$ $\vec{w} = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}$

minimize $\sum_{i=1}^n (y_i - \hat{y}_i)^2$

actual predicted

Board:

cost function

$$J(w_0, w_1) = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad \& \quad h_{\vec{w}} = w_0 + w_1 x = \hat{y}$$

$$= \sum_{i=1}^n (y_i - (w_0 + w_1 x))^2$$

Analytical solution: $\frac{\partial J}{\partial w_0} = 0$; $\frac{\partial J}{\partial w_1} = 0$



$$J, \text{ with } \frac{1}{2} = J(w_0, w_1) = \frac{1}{2} \sum_{i=1}^n (y_i - (w_0 + w_1 x_i))^2$$

$$a) \frac{\partial J}{\partial w_0} = 0$$

$$2 \cdot \frac{1}{2} \sum_{i=1}^n (y_i - w_0 - w_1 x_i) (-1) = 0$$

$$= - \sum_{i=1}^n y_i + \sum_{i=1}^n w_0 + \sum_{i=1}^n w_1 x_i = 0$$

$$\downarrow$$

$$nw_0 = \sum_{i=1}^n y_i - \sum_{i=1}^n w_1 x_i$$

$$w_0 = \frac{1}{n} \sum_{i=1}^n y_i - \frac{1}{n} \sum_{i=1}^n w_1 x_i$$

$$= \frac{1}{n} \sum_{i=1}^n y_i - w_1 \frac{1}{n} \sum_{i=1}^n x_i$$

$$w_0 = \bar{y} - w_1 \bar{x}$$

$$b) \frac{\partial J}{\partial w_1} = 0$$

$$2 \cdot \frac{1}{2} \sum_{i=1}^n (y_i - w_0 - w_1 x_i) (-x_i) = 0$$

$$= \sum_{i=1}^n (y_i - \bar{y} + w_1 \bar{x} - w_1 x_i) (-x_i)$$

$$= - \sum_{i=1}^n y_i x_i + \sum_{i=1}^n \bar{y} x_i - \sum_{i=1}^n w_1 \bar{x} x_i + \sum_{i=1}^n w_1 x_i^2 = 0$$

$$= w_1 \left(- \sum_{i=1}^n \bar{x} x_i + \sum_{i=1}^n x_i^2 \right) - \sum_{i=1}^n y_i x_i + \sum_{i=1}^n \bar{y} x_i$$

$$w_1 = \frac{- \sum_{i=1}^n (y_i x_i) + \sum_{i=1}^n (\bar{y} x_i)}{\sum_{i=1}^n \bar{x} x_i - \sum_{i=1}^n x_i^2}$$

$$w_1 = \frac{\sum_{i=1}^n (y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})} = \frac{\sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\text{cov}(X, Y)}{\text{var}(X)}$$

for cov, we care about magnitude & sign, but only magnitude for var.