

# CSCE 633: Machine Learning

## Lecture 4: Linear Regression

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# Goals For This Lecture

- Motivate a simple supervised learning problem
- Introduce a linear machine learning method (Linear regression)
- Develop a Loss Function
- Ordinary Least Squares - Optimally solve the learning problem
- Interpret model
- Understanding Accuracy and Error
- Acknowledgements: example and figure sources: James, Witten, Hastie, Tibshirani (ISLR)

# Notation and Modeling

- $D = \{(x_i, y_i)\}_{i=1}^n$
- $x_i$  a column vector of length  $p$ , with  $n$  samples
- $y_i$  a scalar
- for  $p = 1$ , linear regression is fitting line to data in 2-dimensional space
- in general, linear regression is about fitting a hyperplane to a scatter of points in a  $p + 1$  dimensional space

# Notation and Modeling

- Consider the p dimensional case
- The objective is determining intercept  $\beta_0$  and p slope weights  $\beta_i$ 's so that for all n datapoints:

$$\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} \approx y_i$$

- Putting it into the vector form:

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}, \dot{x}_i = \begin{bmatrix} 1 \\ x_{i1} \\ \vdots \\ x_{ip} \end{bmatrix}$$

- $\dot{x}_i$  obtained by stacking a 1 on top of  $x_i$
- Our linear equation would be

$$\beta^T \dot{x}_i \approx y_i, i = 1, \dots, n$$

# An Important Example: Advertising

- How do I make a useful Market Plan for the coming fiscal year to increase sales?
- My budget includes advertising in:
  - TV
  - Radio
  - Newspapers
- How much should I add or subtract from each to increase sales?

# Important Questions to Ask

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- Is there a relationship between budget and sales?
- If there is a relationship, how strong is it?
- Which of the three media contribute to sales?
- How accurately can we estimate the effect of each medium on sales?
- Is the relationship linear?
- Is there synergy among the advertising media?

# Simple Linear Regression

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- We want to predict  $y$  based upon a single predictor  $x$ , we want to regress  $y$  on to  $x$ :

$$\beta_0 + \beta_1 x \approx y$$

# Simple Linear Regression

- We want to predict  $y$  based upon a single predictor  $x$ , we want to regress  $y$  on to  $x$ :

$$\begin{aligned}\beta_0 + \beta_1 x &\approx y \\ \beta_0 + \beta_1 TV &\approx Sales\end{aligned}$$



# Parameters

- We want to learn (trained by existing data) the parameters of the model, also known as the coefficients,  $\beta$

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

- Where  $\hat{y}$  indicates a prediction of  $y$  on the basis of  $x$

# Estimating the Coefficients

- We do not know  $\beta_0$  or  $\beta_1$
- So, assume we have a training set  $D = \{(x_1, y_1), \dots, (x_n, y_n)\}$
- Assume  $n = 200$  markets of sales and tv budget
- Goal: set  $\hat{\beta}_0$  and  $\hat{\beta}_1$  so we are as close to  $y_i$  from  $x_i$  for all  $i$

# Residual Sum of Squares

- Let  $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$  be the prediction for  $y$  based on the  $i$ 'th value of  $x$
- Then the residual error is

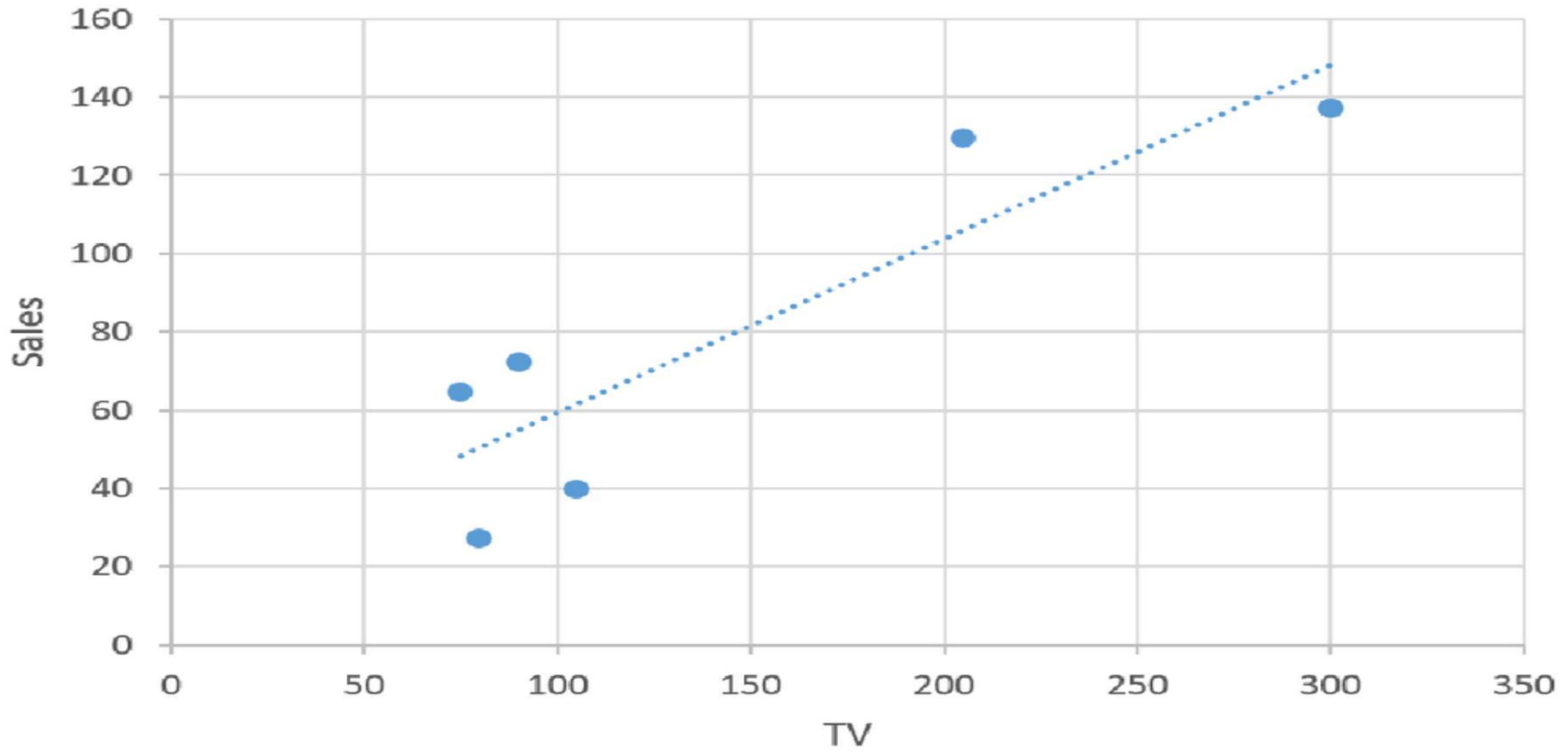
$$e_i = y_i - \hat{y}_i$$

- So, we define Residual Sum of Squares as:

$$RSS = e_1^2 + e_2^2 + \cdots + e_n^2$$

- and in least squares, the objective is minimize RSS

# Residual Sum of Squares



# Least Squares

The residual sum of squares

$$\begin{aligned} RSS &= e_1^2 + e_2^2 + \cdots + e_n^2 \\ &= (y_1 - \hat{\beta}_0 - \hat{\beta}_1 x_1)^2 + \cdots + (y_N - \hat{\beta}_0 - \hat{\beta}_1 x_n)^2 \end{aligned}$$

# Least Squares: Learning Coefficients

The residual sum of squares

$$\begin{aligned} RSS &= e_1^2 + e_2^2 + \cdots + e_n^2 \\ &= (y_1 - \hat{\beta}_0 - \hat{\beta}_1 x_1)^2 + \cdots + (y_N - \hat{\beta}_0 - \hat{\beta}_1 x_n)^2 \end{aligned}$$

if  $RSS$  is our total sum of squared error, what do we need to learn?

# Differentiation

To minimize RSS, need to differentiate with respect to both unknowns

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

- Calculate  $\frac{\partial RSS}{\partial \hat{\beta}_0}$
- Calculate  $\frac{\partial RSS}{\partial \hat{\beta}_1}$

# Differentiation: $\hat{\beta}_0$

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$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$



# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-1)$$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\begin{aligned} \frac{\partial RSS}{\partial \hat{\beta}_0} &= \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-1) \\ &= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) \end{aligned}$$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-1)$$

$$= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)$$

$$= -2 \sum_{i=1}^n y_i + 2 \sum_{i=1}^n \hat{\beta}_0 + 2 \hat{\beta}_1 \sum_{i=1}^n x_i$$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-1)$$

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**Note:**  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  is the sample mean

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-1)$$

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**Note:**  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  is the sample mean

$$= -2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x}$$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-1)$$

$$= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)$$

$$= -2 \sum_{i=1}^n y_i + 2 \sum_{i=1}^n \hat{\beta}_0 + 2 \hat{\beta}_1 \sum_{i=1}^n x_i$$

**Note:**  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  is the sample mean

$$= -2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x}$$

To minimize, set  $\frac{\partial RSS}{\partial \hat{\beta}_0} = 0$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = -2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x}$$

To minimize, set  $\frac{\partial RSS}{\partial \hat{\beta}_0} = 0$

$$-2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x} = 0$$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = -2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x}$$

$$\text{To minimize, set } \frac{\partial RSS}{\partial \hat{\beta}_0} = 0$$

$$-2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x} = 0$$

$$2n\hat{\beta}_0 = 2n\bar{y} - 2n\hat{\beta}_1 \bar{x}$$



# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = -2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x}$$

To minimize, set  $\frac{\partial RSS}{\partial \hat{\beta}_0} = 0$

$$-2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x} = 0$$

$$2n\hat{\beta}_0 = 2n\bar{y} - 2n\hat{\beta}_1 \bar{x}$$

$$\cancel{2n}\hat{\beta}_0 = \cancel{2n}\bar{y} - \cancel{2n}\hat{\beta}_1 \bar{x}$$

# Differentiation: $\hat{\beta}_0$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_0} = -2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x}$$

To minimize, set  $\frac{\partial RSS}{\partial \hat{\beta}_0} = 0$

$$-2n\bar{y} + 2n\hat{\beta}_0 + 2n\hat{\beta}_1 \bar{x} = 0$$

$$2n\hat{\beta}_0 = 2n\bar{y} - 2n\hat{\beta}_1 \bar{x}$$

$$\cancel{2n}\hat{\beta}_0 = \cancel{2n}\bar{y} - \cancel{2n}\hat{\beta}_1 \bar{x}$$

$$\hat{\beta}_0^* = \bar{y} - \hat{\beta}_1 \bar{x}$$

# Differentiation: $\hat{\beta}_1$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_1} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-x_i)$$

# Differentiation: $\hat{\beta}_1$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_1} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-x_i)$$

$$= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(x_i)$$

# Differentiation: $\hat{\beta}_1$

$$RSS = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial RSS}{\partial \hat{\beta}_1} = \sum_{i=1}^n 2(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(-x_i)$$

$$= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)(x_i)$$

set equal to 0:

$$-2 \sum_{i=1}^n y_i x_i + 2 \hat{\beta}_0 \sum_{i=1}^n x_i + 2 \hat{\beta}_1 \sum_{i=1}^n x_i^2 = 0$$

# Differentiation: $\hat{\beta}_1$

$$\begin{aligned} & -2\sum_{i=1}^n y_i x_i + 2\beta_0 \sum_{i=1}^n x_i + 2\beta_1 \sum_{i=1}^n x_i^2 = 0 \\ & = -\cancel{2}\sum_{i=1}^n y_i x_i + \cancel{2}\beta_0 \sum_{i=1}^n x_i + \cancel{2}\beta_1 \sum_{i=1}^n x_i^2 = 0 \end{aligned}$$

# Differentiation: $\hat{\beta}_1$

$$\begin{aligned} & -2\sum_{i=1}^n y_i x_i + 2\beta_0 \sum_{i=1}^n x_i + 2\beta_1 \sum_{i=1}^n x_i^2 = 0 \\ & = -\cancel{2}\sum_{i=1}^n y_i x_i + \cancel{2}\beta_0 \sum_{i=1}^n x_i + \cancel{2}\beta_1 \sum_{i=1}^n x_i^2 = 0 \\ & = -\sum_{i=1}^n y_i x_i + (\bar{y} - \beta_1 \bar{x}) \sum_{i=1}^n x_i + \beta_1 \sum_{i=1}^n x_i^2 = 0 \end{aligned}$$

# Differentiation: $\hat{\beta}_1$

$$-2\sum_{i=1}^n y_i x_i + 2\beta_0 \sum_{i=1}^n x_i + 2\beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$= -\cancel{2}\sum_{i=1}^n y_i x_i + \cancel{2}\beta_0 \sum_{i=1}^n x_i + \cancel{2}\beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$= -\sum_{i=1}^n y_i x_i + (\bar{y} - \beta_1 \bar{x}) \sum_{i=1}^n x_i + \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$-\sum_{i=1}^n y_i x_i + \bar{y} \sum_{i=1}^n x_i - \hat{\beta}_1 \bar{x} \sum_{i=1}^n x_i + \hat{\beta}_1 \sum_{i=1}^n x_i^2$$



# Differentiation: $\hat{\beta}_1$

$$\begin{aligned} & -2\sum_{i=1}^n y_i x_i + 2\beta_0 \sum_{i=1}^n x_i + 2\beta_1 \sum_{i=1}^n x_i^2 = 0 \\ & = -\cancel{2}\sum_{i=1}^n y_i x_i + \cancel{2}\beta_0 \sum_{i=1}^n x_i + \cancel{2}\beta_1 \sum_{i=1}^n x_i^2 = 0 \\ & = -\sum_{i=1}^n y_i x_i + (\bar{y} - \beta_1 \bar{x}) \sum_{i=1}^n x_i + \hat{\beta}_1 \sum_{i=1}^n x_i^2 = 0 \\ & -\sum_{i=1}^n y_i x_i + \bar{y} \sum_{i=1}^n x_i - \hat{\beta}_1 \bar{x} \sum_{i=1}^n x_i + \hat{\beta}_1 \sum_{i=1}^n x_i^2 \\ & \hat{\beta}_1^* = \frac{\bar{y} \sum_{i=1}^n x_i - \sum_{i=1}^n y_i x_i}{\bar{x} \sum_{i=1}^n x_i - \sum_{i=1}^n x_i^2} \end{aligned}$$

# Differentiation: $\hat{\beta}_1$

$$\hat{\beta}_1^* = \frac{\bar{y} \sum_{i=1}^n x_i - \sum_{i=1}^n y_i x_i}{\bar{x} \sum_{i=1}^n x_i - \sum_{i=1}^n x_i^2}$$

$$\hat{\beta}_1^* = \frac{\bar{y} \bar{x} n - \sum_{i=1}^n y_i x_i}{\bar{x}^2 n - \sum_{i=1}^n x_i^2}$$

$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n y_i x_i - \bar{y} \bar{x} n}{\sum_{i=1}^n x_i^2 - \bar{x}^2 n}$$

# Differentiation: $\hat{\beta}_1$

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

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

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

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

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

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

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

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

# Differentiation: $\hat{\beta}_1$

$$\hat{\beta}_1^* = \frac{\bar{y} \sum_{i=1}^n x_i - \sum_{i=1}^n y_i x_i}{\bar{x} \sum_{i=1}^n x_i - \sum_{i=1}^n x_i^2}$$

$$\hat{\beta}_1^* = \frac{\bar{y} \bar{x} n - \sum_{i=1}^n y_i x_i}{\bar{x}^2 n - \sum_{i=1}^n x_i^2}$$

$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n y_i x_i - \bar{y} \bar{x} n}{\sum_{i=1}^n x_i^2 - \bar{x}^2 n}$$

$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n x_i^2 - \bar{x}^2 n}$$

# Differentiation: $\hat{\beta}_1$

$$\begin{aligned} & \sum_{i=1}^n x_i^2 - \bar{x}^2 n \\ &= \sum_{i=1}^n x_i^2 - \bar{x}^2 n - \bar{x}^2 n + \bar{x}^2 n \\ &= \sum_{i=1}^n x_i^2 - 2\bar{x}^2 n + \bar{x}^2 n \\ &= \sum_{i=1}^n x_i^2 - 2\bar{x}\bar{x}n + \bar{x}^2 \sum_{i=1}^n 1 \\ &= \sum_{i=1}^n x_i^2 - 2\bar{x} \sum_{i=1}^n x_i + \sum_{i=1}^n \bar{x}^2 \\ &= \sum_{i=1}^n (x_i^2 - 2\bar{x}x_i + \bar{x}^2) \\ &= \sum_{i=1}^n (x_i^2 - \bar{x}x_i - \bar{x}x_i + \bar{x}^2) \\ &= \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x}) \\ &= \sum_{i=1}^n (x_i - \bar{x})^2 \end{aligned}$$

# Differentiation: $\hat{\beta}_1$

$$\hat{\beta}_1^* = \frac{\bar{y} \sum_{i=1}^n x_i - \sum_{i=1}^n y_i x_i}{\bar{x} \sum_{i=1}^n x_i - \sum_{i=1}^n x_i^2}$$

$$\hat{\beta}_1^* = \frac{\bar{y} \bar{x} n - \sum_{i=1}^n y_i x_i}{\bar{x}^2 n - \sum_{i=1}^n x_i^2}$$

$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n y_i x_i - \bar{y} \bar{x} n}{\sum_{i=1}^n x_i^2 - \bar{x}^2 n}$$

$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n x_i^2 - \bar{x}^2 n}$$

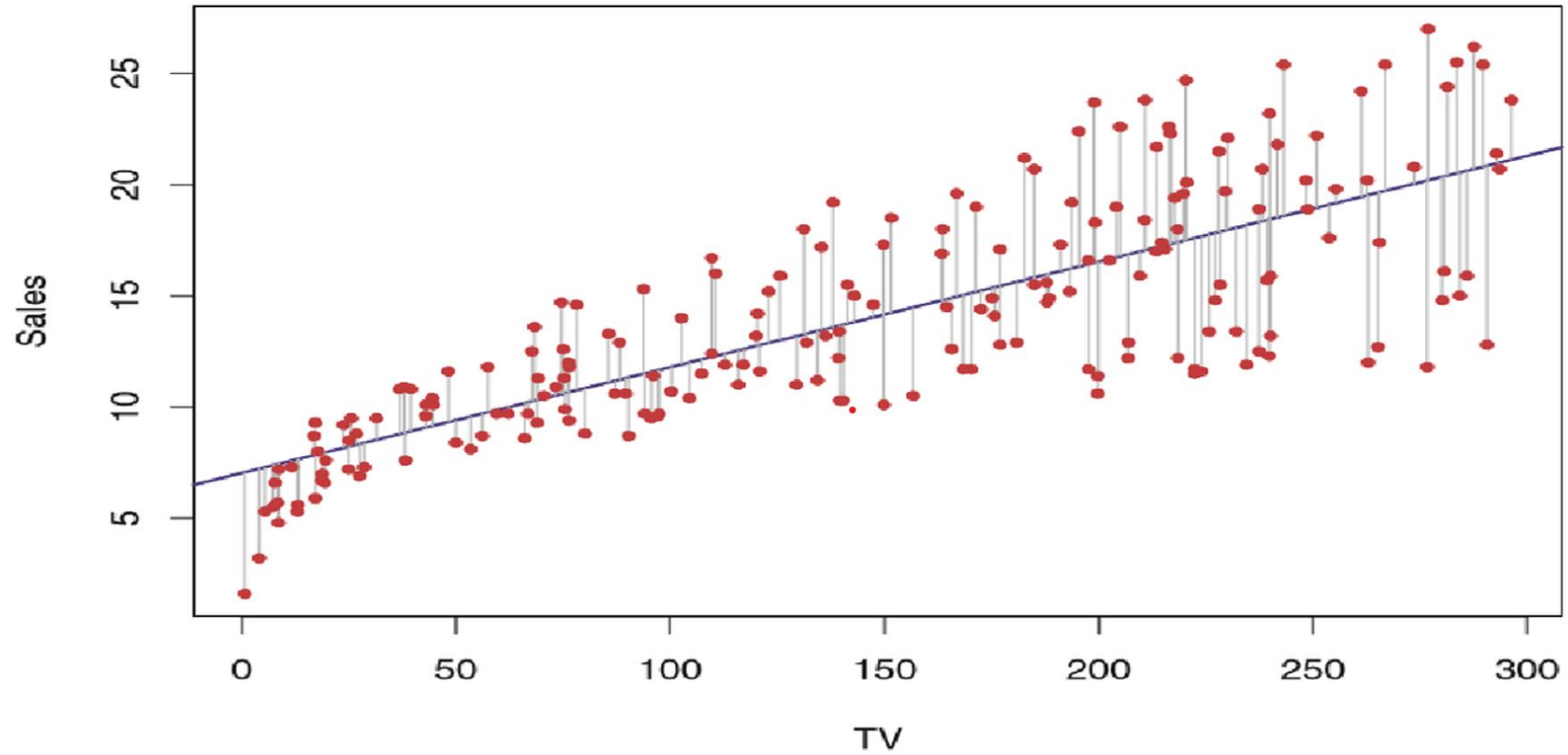
$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

## Optimal Coefficients: $\hat{\beta}_0, \hat{\beta}_1$

$$\hat{\beta}_0^* = \bar{y} - \hat{\beta}_1^* \bar{x}$$

$$\hat{\beta}_1^* = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

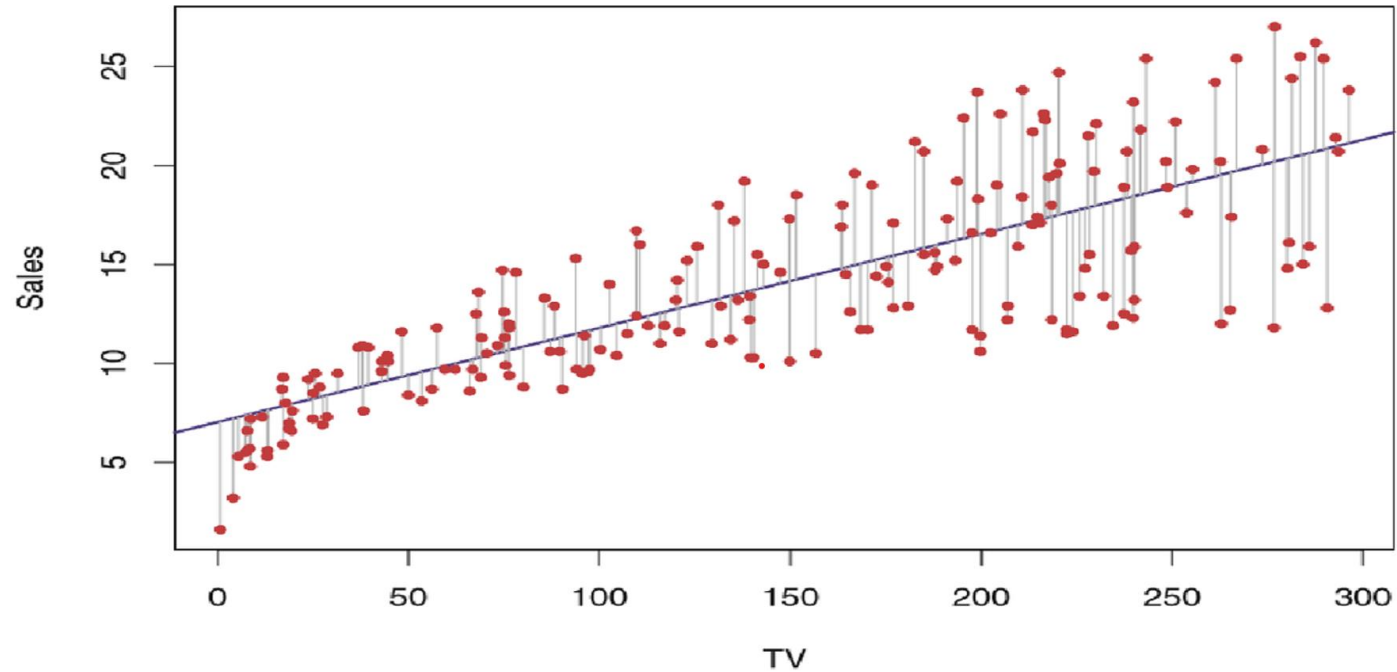
# Advertising Solution



- $\hat{\beta}_0 = 7.03$
- $\hat{\beta}_1 = 0.0475$
- Source: ISLR



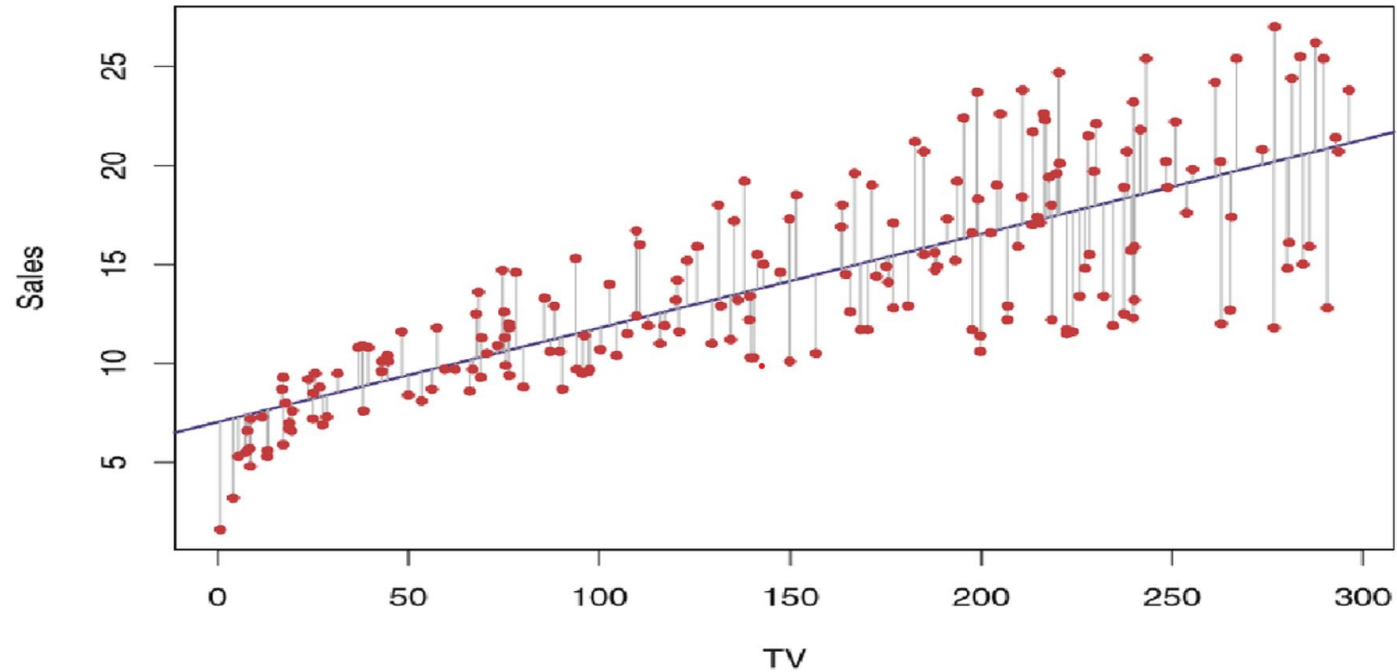
# Advertising Solution



$\hat{\beta}_0 = 7.03$  and  $\hat{\beta}_1 = 0.0475$ . If we had no TV advertising, how many units would we sell? What if we had \$1000 budgeted for TV?

- A. 703,  $475 + 703$
- B. 7.03,  $47.5 + 7.03$
- C.  $47.5 + 7.03$ , 7.03
- D.  $475 + 703$ , 703

# Advertising Solution



$\hat{\beta}_0 = 7.03$  and  $\hat{\beta}_1 = 0.0475$ . If we had no TV advertising, how many units would we sell? What if we had \$1000 budgeted for TV?

- A. 703,  $475 + 703$
- B. 7.03,  $47.5 + 7.03$
- C.  $47.5 + 7.03$ , 7.03
- D.  $475 + 703$ , 703

# Takeaways

- Understanding key notation
- Important questions to ask for supervised learning problem
- Ordinary Least Squares
- Simple Linear Regression
- Optimizing RSS
- Next Time: Interpret model and Understanding Accuracy and Error