

# CS 383: Machine Learning

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Lecture 06

# Announcements

HW02 is due Sunday night

- **Reading quiz: Thursday**
  - Duame 7.6 (2+ pages)
  - ISL 59-63 (4+ pages)
- Midterm 1: Thursday October 3rd

# Outline

Expectation & Variance

Bias-Variance Tradeoff

Linear regression

# Loss Function

$\ell(y, \hat{f}(x))$  quantifies how far our prediction is from the true value

We want to minimize Expected Loss:

$$\mathbb{E}_{(x,y)} \left[ \ell(y, \hat{f}(x)) \right]$$

# Expected Values



Weight

$$\mathbb{E}[X] = \sum_{v \in X} p(X = v) v$$

Handout

$$\text{Var}(X) = \sigma_x^2 = \mathbb{E}[(X - \mu_x)^2]$$

$$\text{SD}(X) = \sigma_x = \sqrt{\mathbb{E}[(X - \mu_x)^2]}$$

# Expected Value Rules

## Additivity of Expectation

$$\begin{aligned}\mathbb{E}[X + Y] &= \\ &= \mathbb{E}[X] + \mathbb{E}[Y]\end{aligned}$$

## Linearity of Expectation

$$\begin{aligned}\mathbb{E}[\alpha X] &= \\ &= \alpha \mathbb{E}[X]\end{aligned}$$

[https://prob140.org/textbook/content/Chapter\\_08/04\\_Additivity.html](https://prob140.org/textbook/content/Chapter_08/04_Additivity.html)

# Expected Values



## Quick Check

Let  $X$  and  $Y$  be random variables on the same space, with  $E(X) = 5$  and  $E(Y) = 3$ .

(a) Find  $E(X - Y)$ .

(b) Find  $E(2X - 8Y + 7)$ .

[https://prob140.org/textbook/content/Chapter\\_08/04\\_Additivity.html](https://prob140.org/textbook/content/Chapter_08/04_Additivity.html)

# Expected loss

Read it as (x,y) has  
distribution  $\mathcal{D}$

$$(x, y) \sim \mathcal{D}$$

Expected Loss

Probability of (x,y)  
occurring

$$\sum_{x,y \in \mathcal{D}} D(x, y) \ell(y, \hat{f}(x))$$

loss

$$\frac{1}{n} \sum_i^n \ell(y_i, \hat{f}(x_i))$$



# Mean Squared Error

Squared error:

$$\ell(y, \hat{y}) = (y - \hat{y})^2$$

Mean Square Error (MSE):

$$\frac{1}{n} \sum_i^n (y_i - \hat{y}_i)^2$$

$$\mathbb{E}[MSE] = \frac{1}{n} \sum_i^n \mathbb{E}[(y_i - \hat{y}_i)^2]$$

# Mean Squared Error

$$\mathbb{E}[(y - \hat{y})^2]$$

$$= \mathbb{E}[(y - \hat{f})^2]$$

$$= \mathbb{E}[(y - f + f - \hat{f})^2]$$

$$= \text{Var}(\varepsilon) + \mathbb{E}[(f - \hat{f})^2]$$

error  $\varepsilon$

model  
issue

# Mean Squared Error

$$\mathbb{E}[(y - \hat{y})^2] = \text{Var}(\varepsilon) + \mathbb{E}[(f - \hat{f})^2]$$

$$\begin{aligned}\mathbb{E}[(f - \hat{f})^2] &= \mathbb{E}[(f - \mathbb{E}[\hat{f}] + \mathbb{E}[\hat{f}] - \hat{f})^2] \\ &= \mathbb{E}[(f - \mathbb{E}[\hat{f}])^2 + 2(\hat{f} - \mathbb{E}[\hat{f}])(\mathbb{E}[\hat{f}] - \hat{f}) + (\mathbb{E}[\hat{f}] - \hat{f})^2] \\ &= \mathbb{E}[(f - \mathbb{E}[\hat{f}])^2] + \mathbb{E}[2(\hat{f} - \mathbb{E}[\hat{f}])(\mathbb{E}[\hat{f}] - \hat{f})] + \mathbb{E}[(\mathbb{E}[\hat{f}] - \hat{f})^2] \\ &= \text{var}(\hat{f}(x)) + 0 + \text{bias}(\hat{f})^2\end{aligned}$$

$$\mathbb{E}[MSE] = \text{var}(\varepsilon) + \text{var}(\hat{f}) + \text{bias}(\hat{f})^2$$

# Mean Squared Error

$$\mathbb{E}[MSE] = \text{bias}(\hat{f})^2 + \text{var}(\hat{f}) + \text{var}(\varepsilon)$$

Bias: approximation error

error introduced by approximated a real-life problem

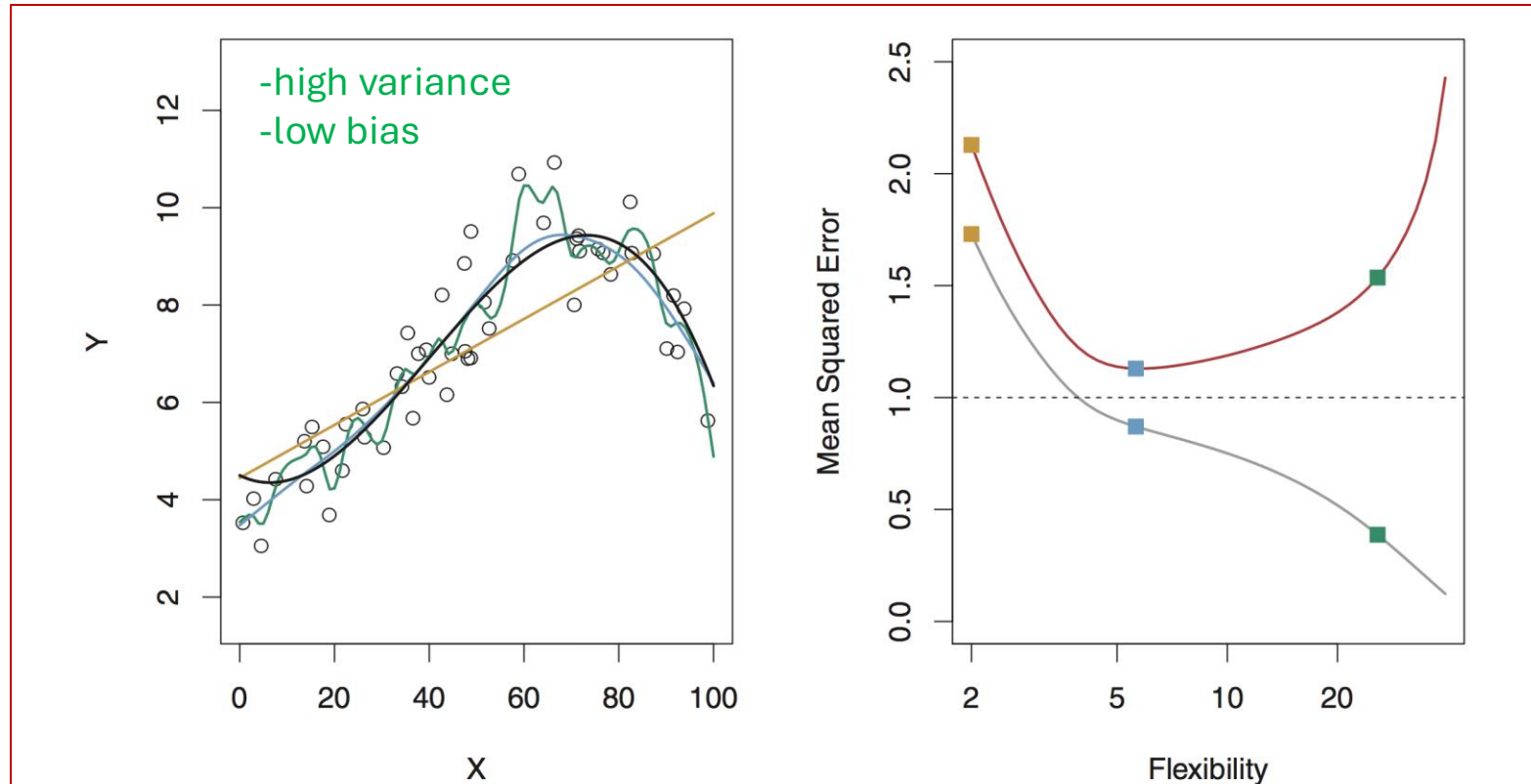
$$\hat{f} - f$$

Variance: estimation error

amount  $\hat{f}$  would change if we trained on different data

# Bias Variance Tradeoff

# Assessing Model Accuracy



**FIGURE 2.9.** Left: Data simulated from  $f$ , shown in black. Three estimates of  $f$  are shown: the linear regression line (orange curve), and two smoothing spline fits (blue and green curves). Right: Training MSE (grey curve), test MSE (red curve), and minimum possible test MSE over all methods (dashed line). Squares represent the training and test MSEs for the three fits shown in the left-hand panel.

# Outline

Continuous Features in Decision Trees

Learning problem so far + terminology

Bias-Variance Tradeoff

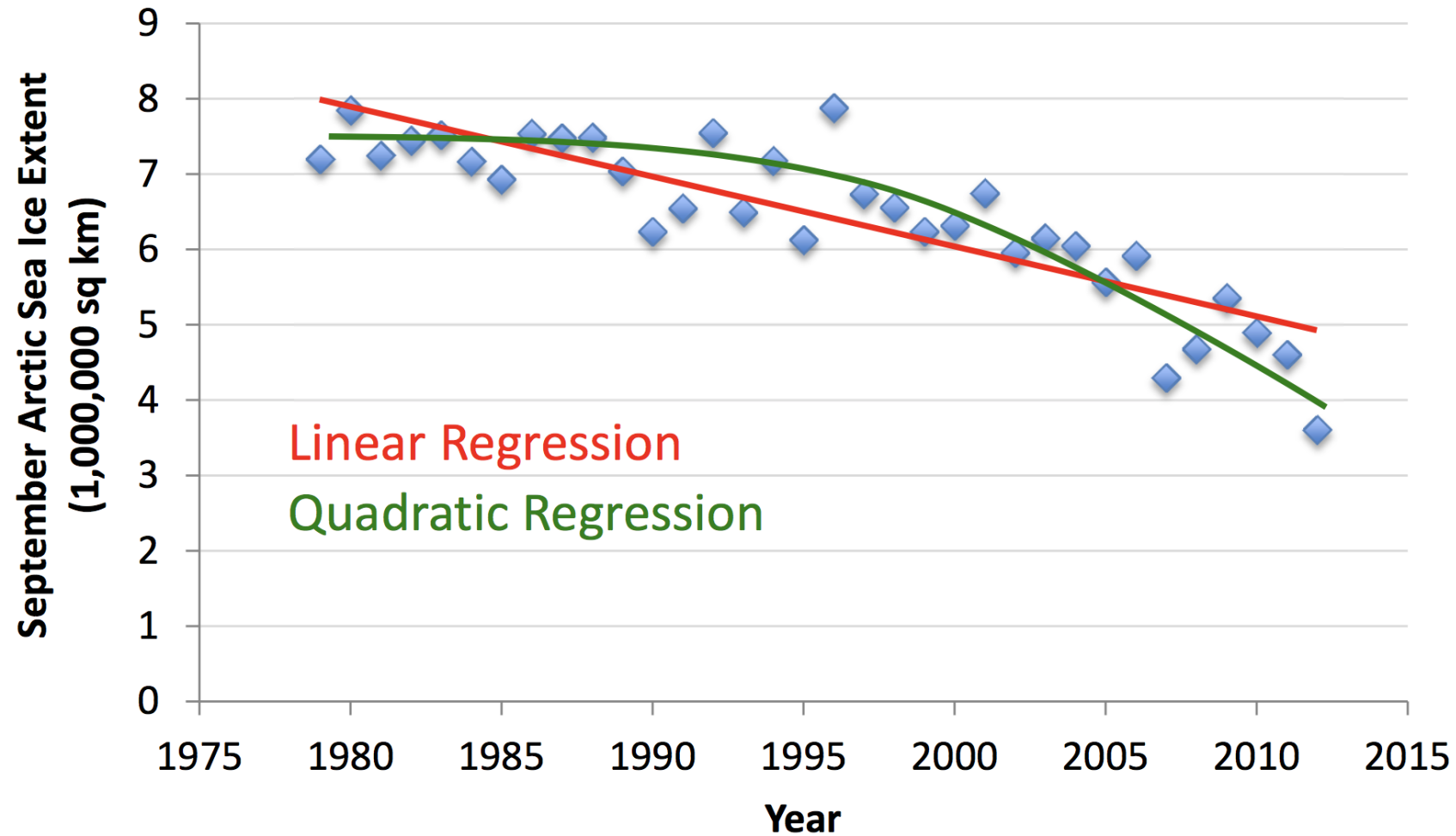
Linear regression

# Goals of Inference

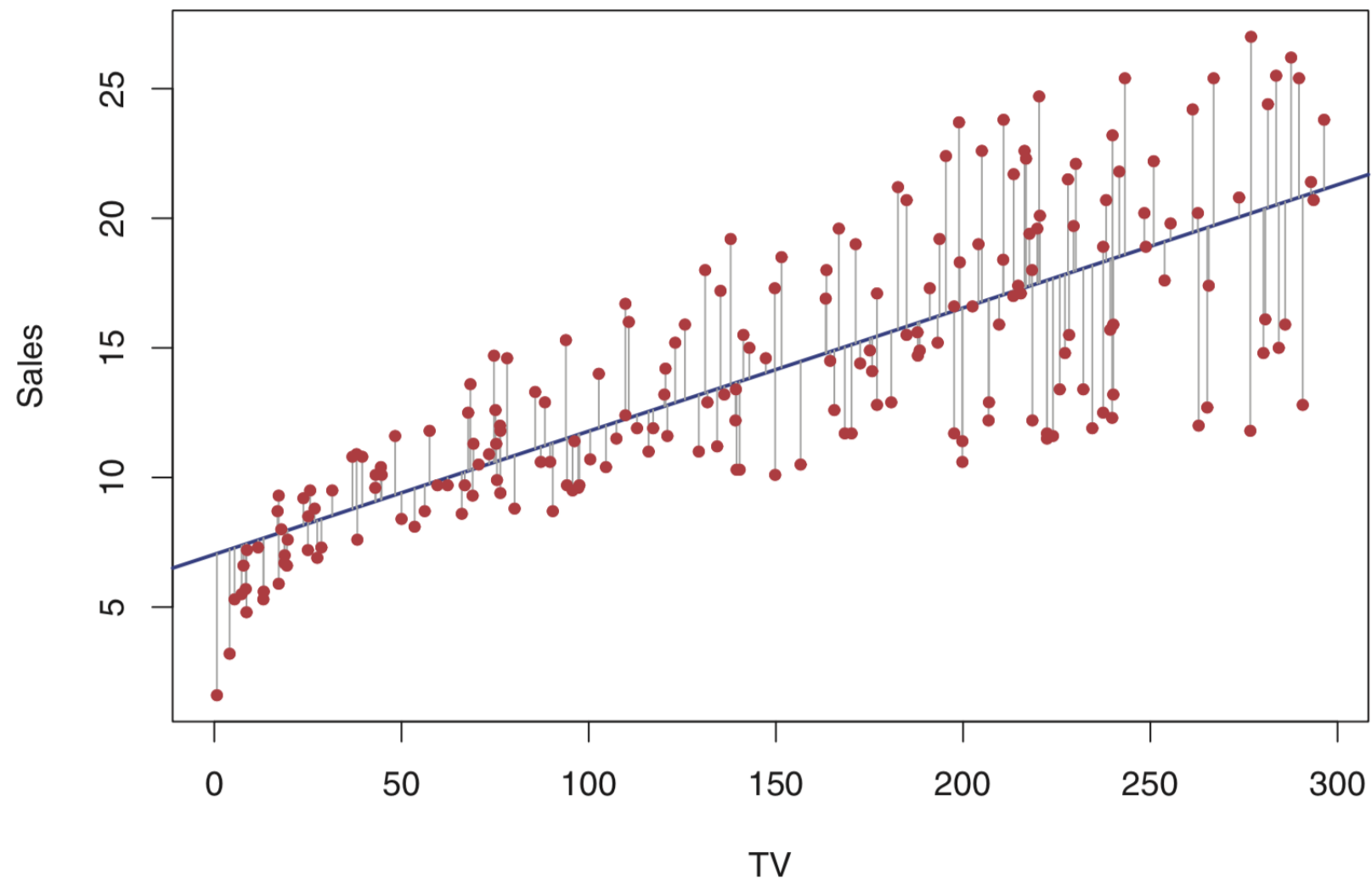
- 1) Which of the features/explanatory variables/predictors ( $x$ ) are associated with the response variable ( $y$ )?
- 2) What is the relationship between  $x$  and  $y$ ?
- 3) Is a linear model enough?
- 4) Can we predict  $y$  given a new  $x$ ?



# Regression Example



## Example: predict sales from TV advertising budget



# Cost Function: sum of squared errors

