

Ch3 Reg to ML

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Textbook: James et al. 1ed.

A Regression to Statistical Learning

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A.1 Statistical Learning

- General Model

$$Y = f(X) + \epsilon$$

- We don't want to assume that $f(X)$ is linear function.
- Motivation:
 - Model Estimation
 - Prediction
- Pattern recognition

A.2 How do we find 'overall pattern'? - Inference

- Want to understand the relationship between X and Y
- Which predictors are associated with the response?
- What is the relationship between the response and each predictor?
- Can the relationship between Y and each predictor be adequately summarized using a linear equation, or is the relationship more complicated?

A.3 Prediction

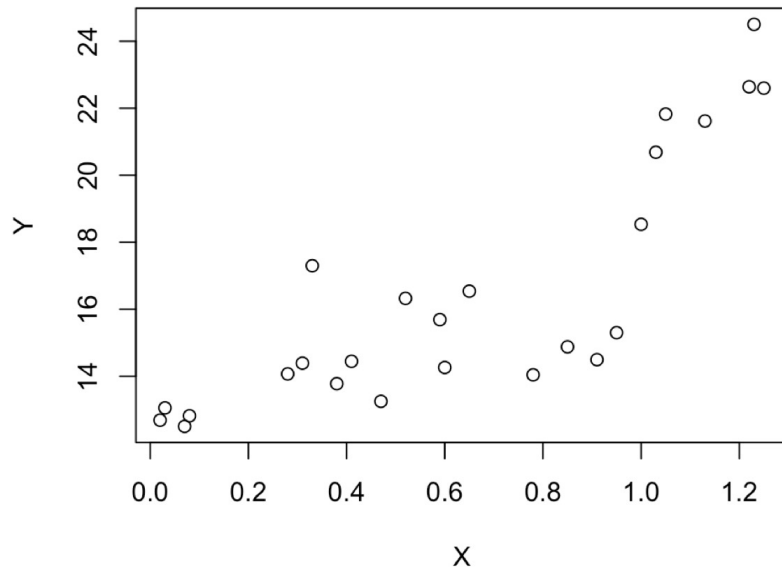
- Want to guess the next Y as accurate as possible

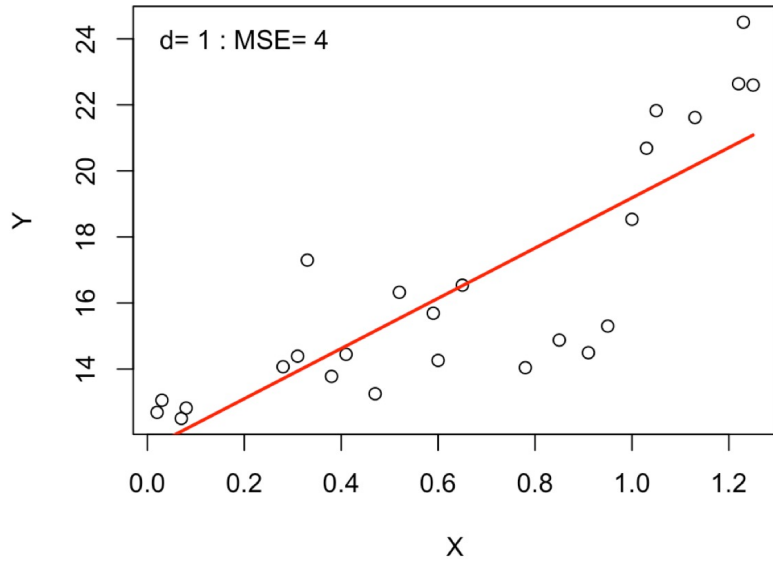
$$\hat{Y} = \hat{f}(X)$$

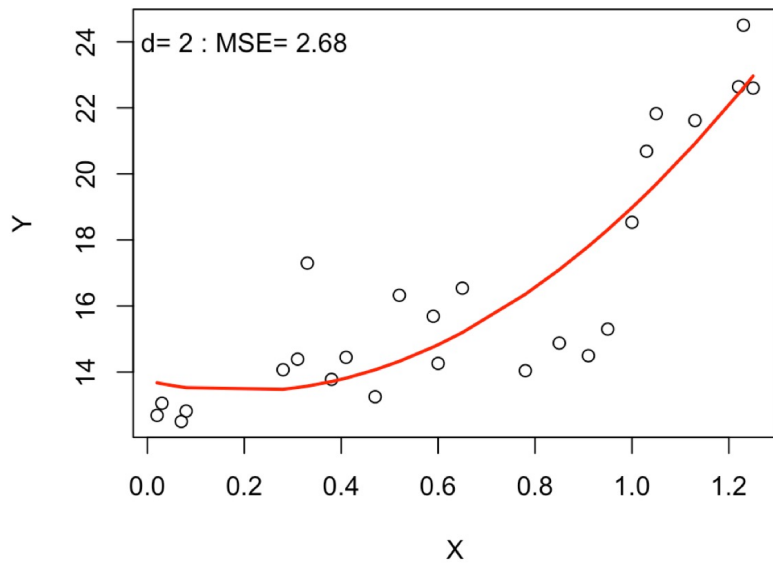
- f can be a black box
- reducible error and irreducible error in prediction
- Want to reduce prediction Mean Squared Error:

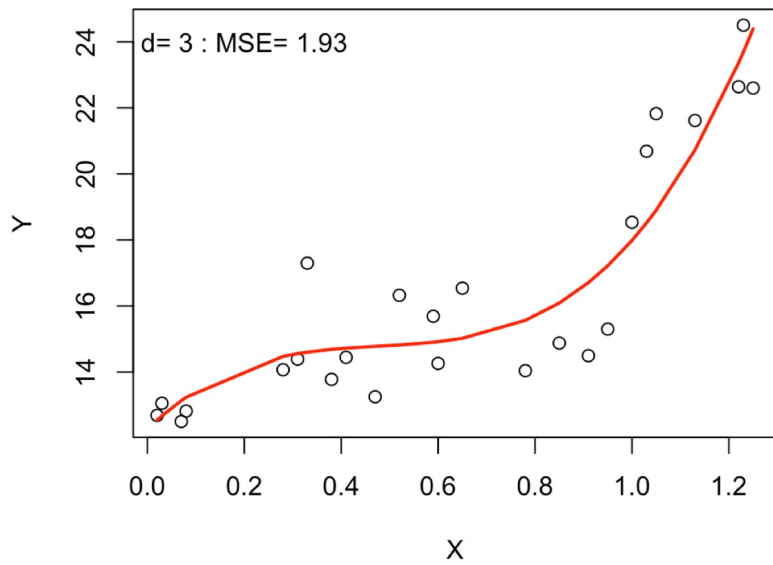
$$MSE = E(Y - \hat{Y})^2 = E(Y - \hat{f}(X))^2$$

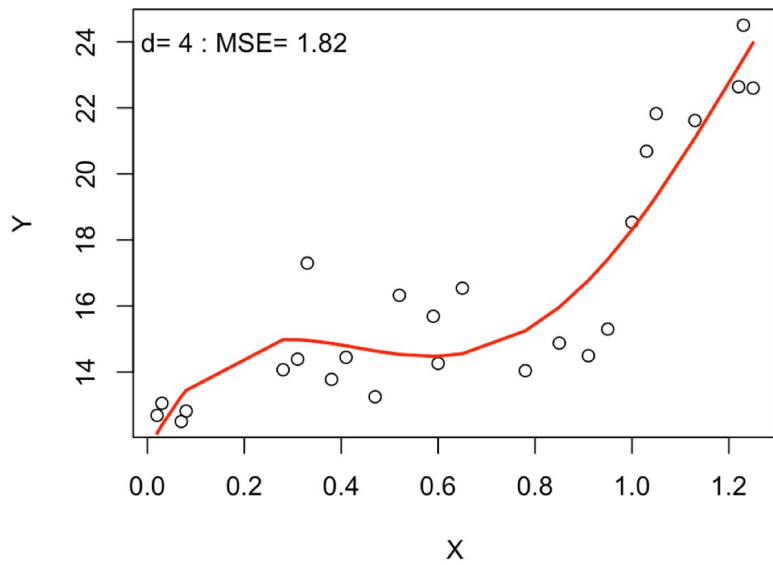
A.4 Polynomial Regression 1

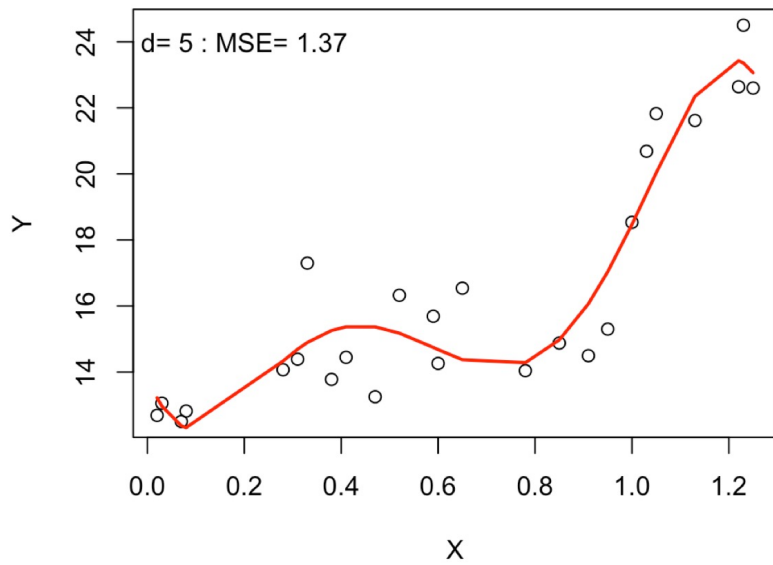


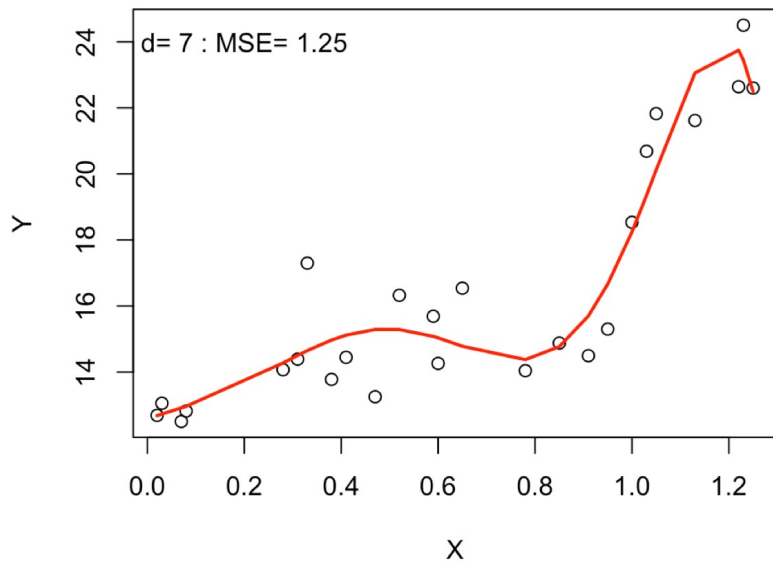


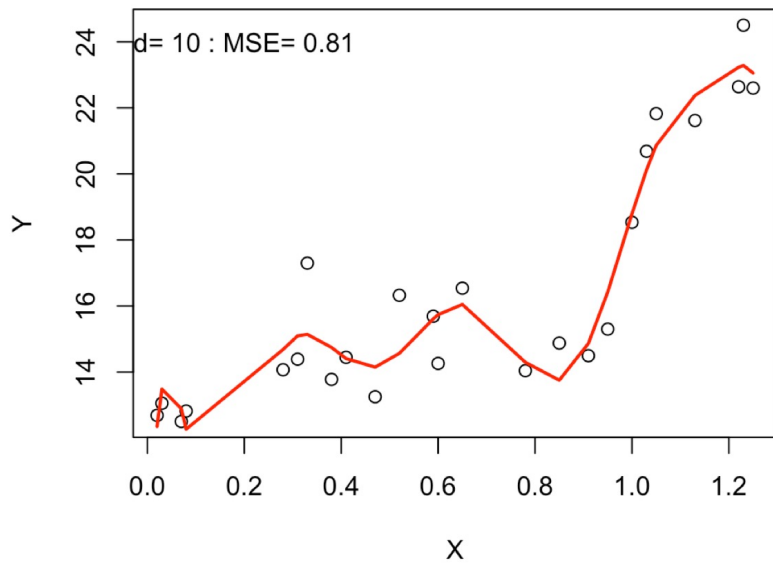


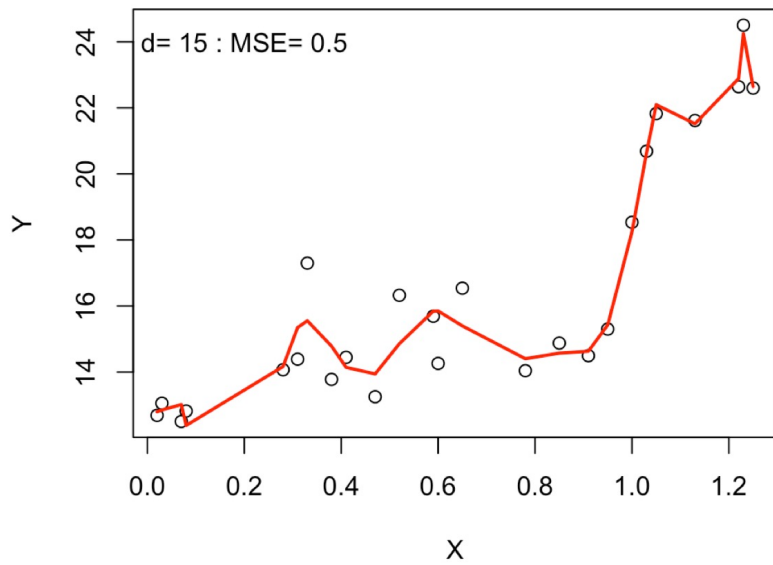


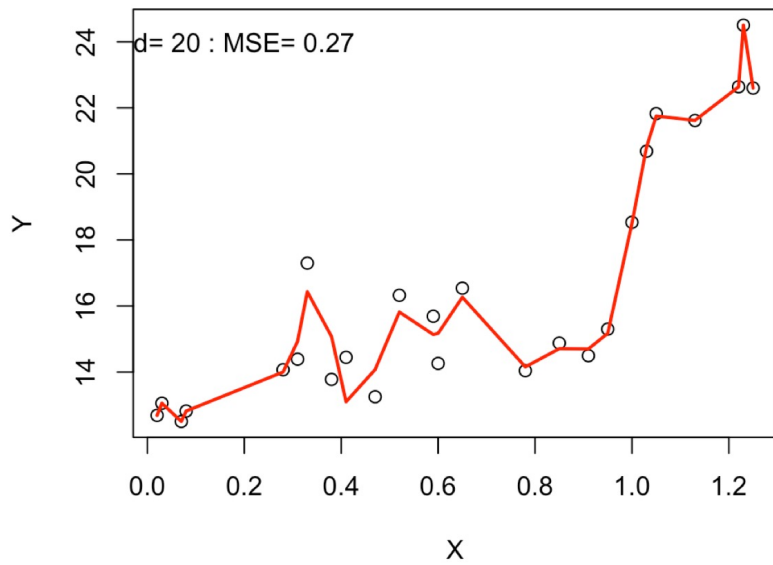




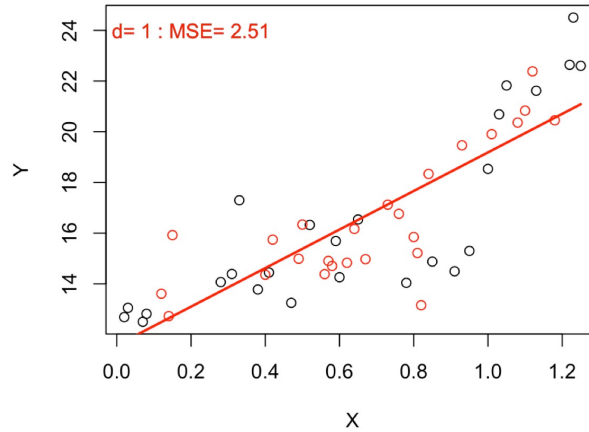
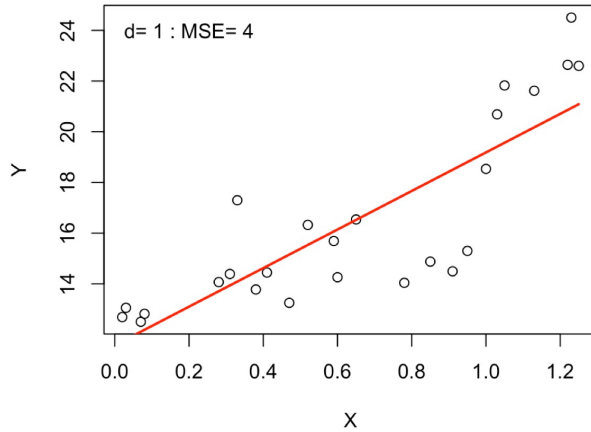


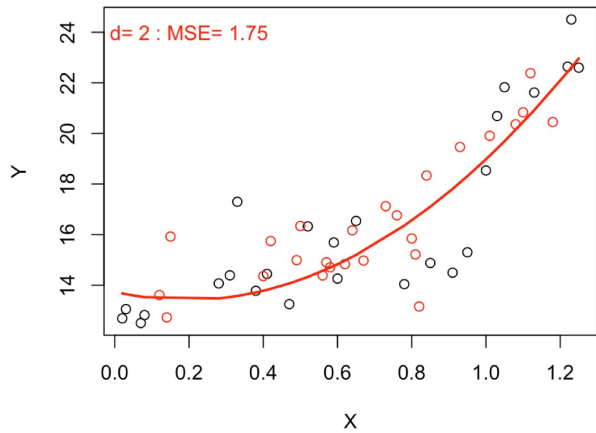
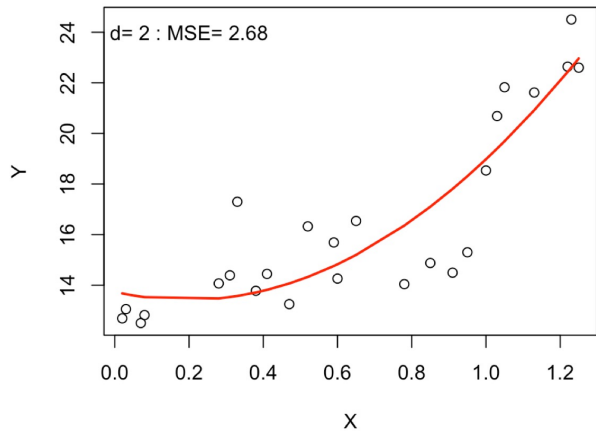


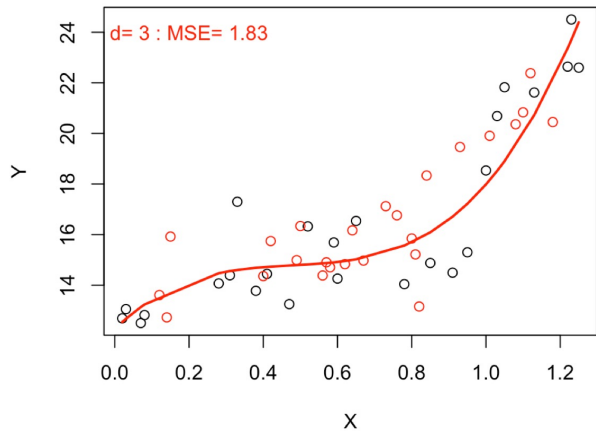
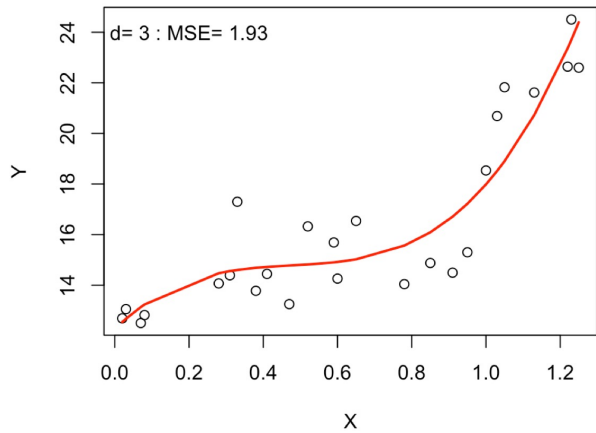


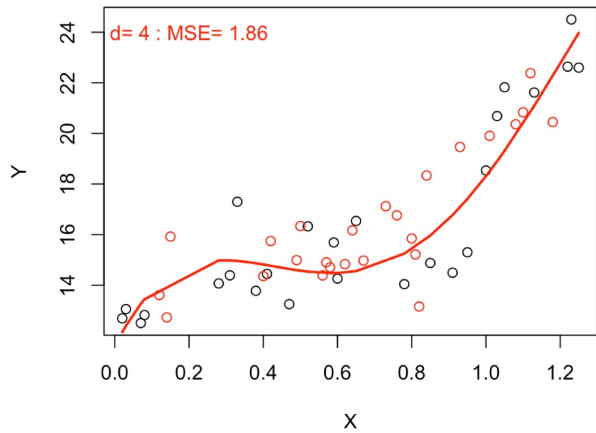
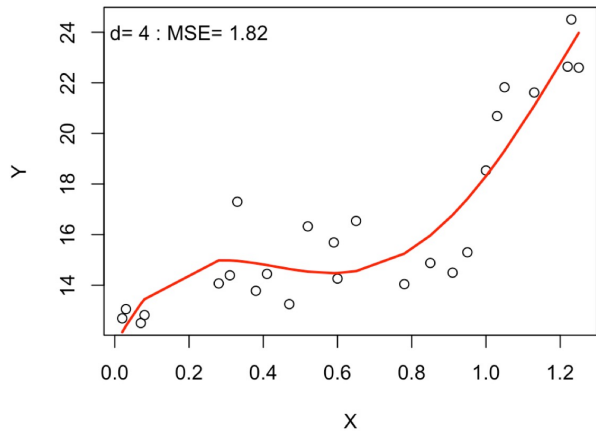


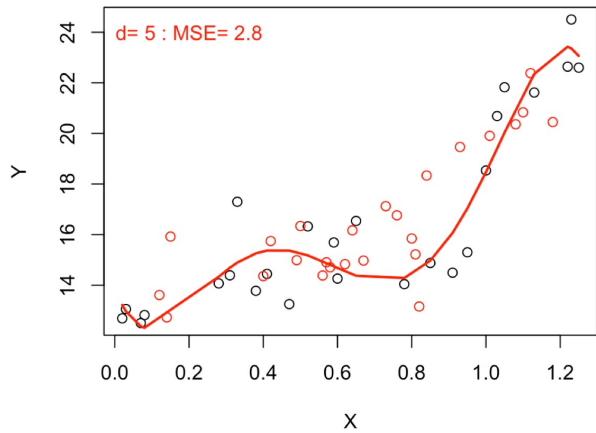
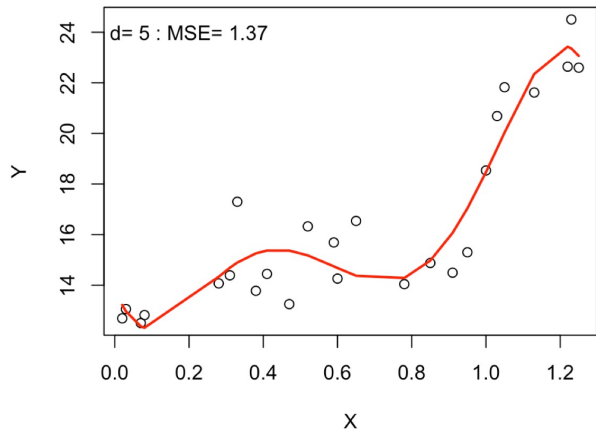
A.5 Prediction

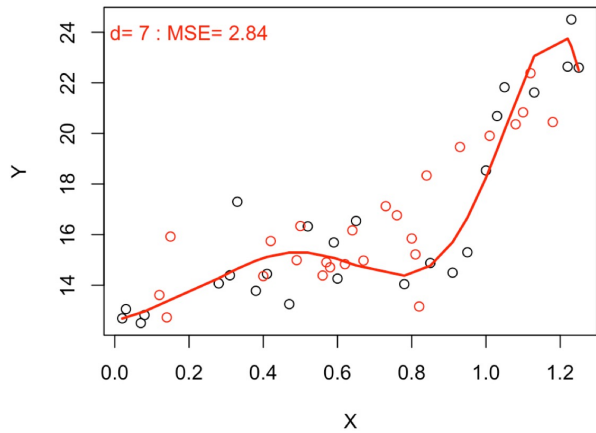
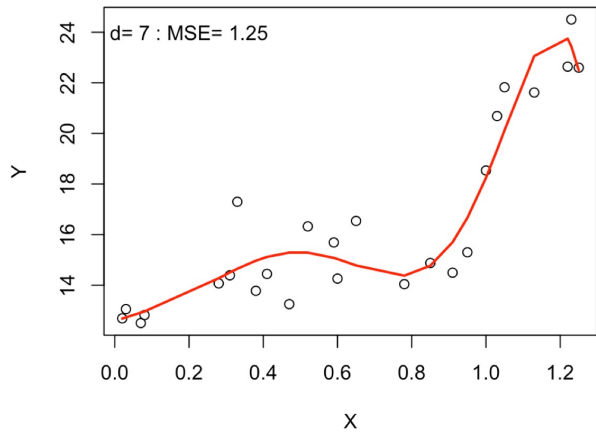


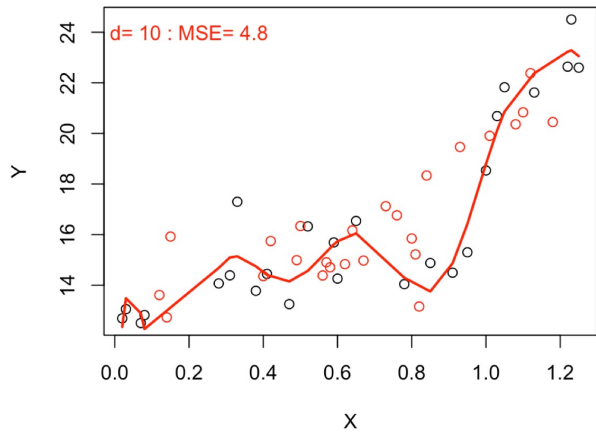
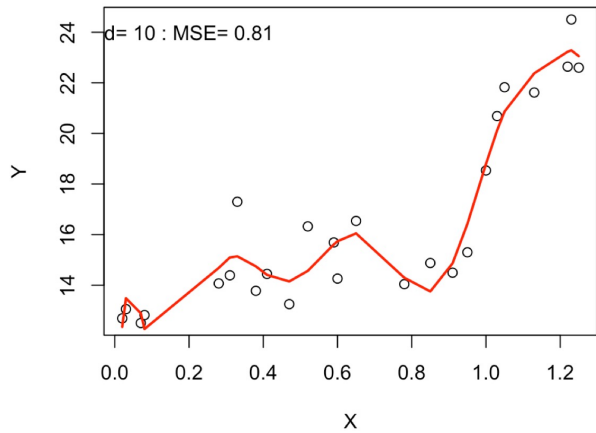


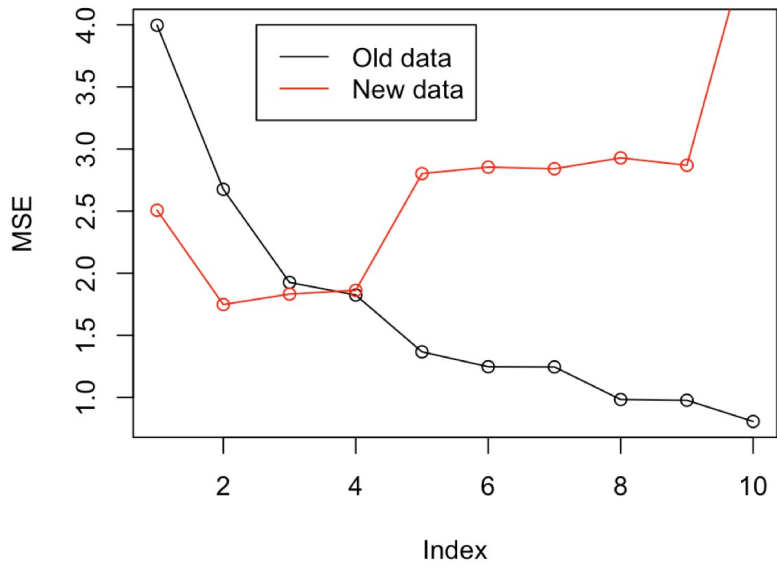






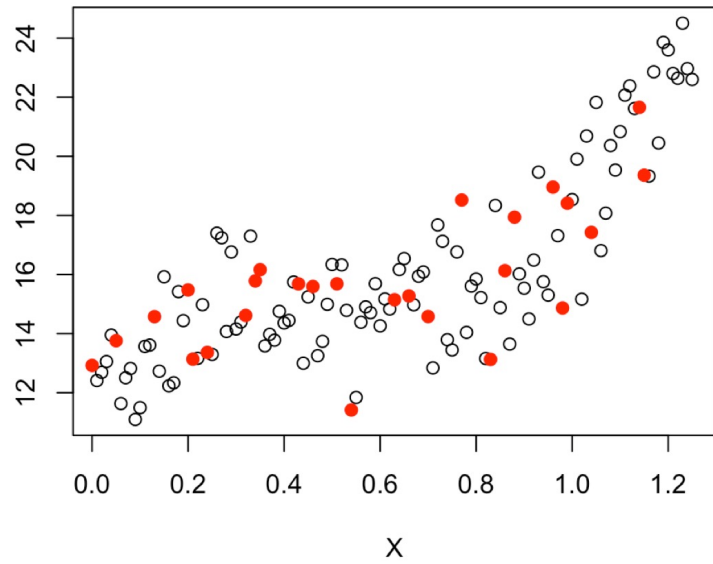
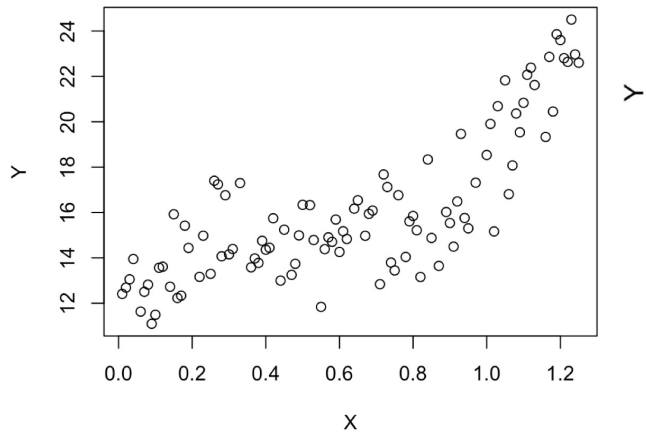


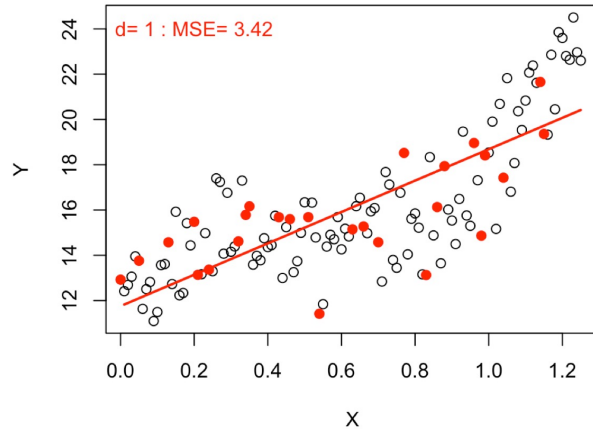
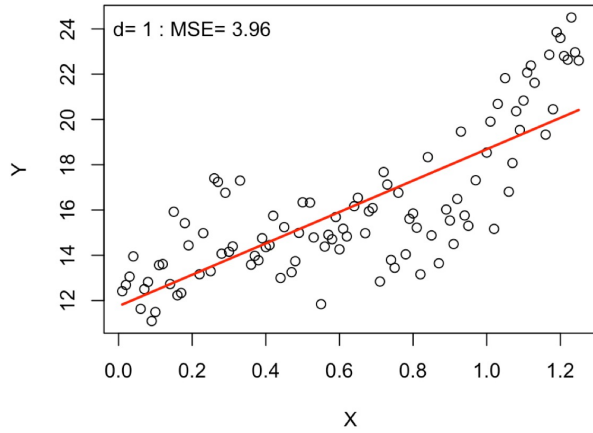


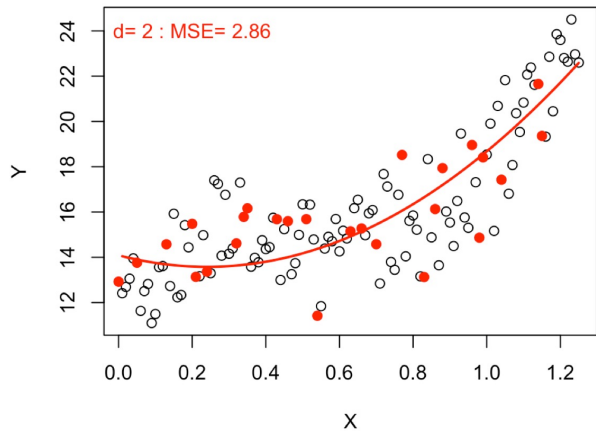
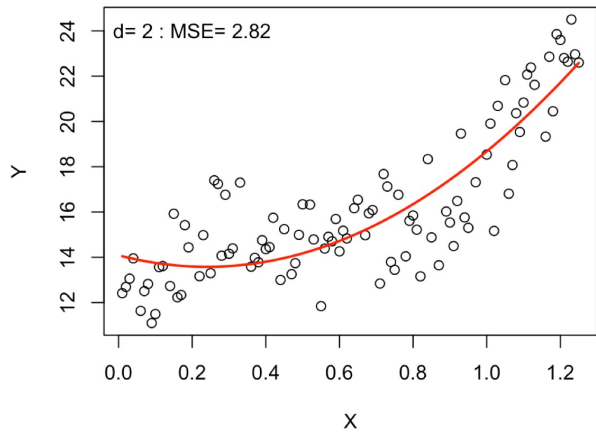


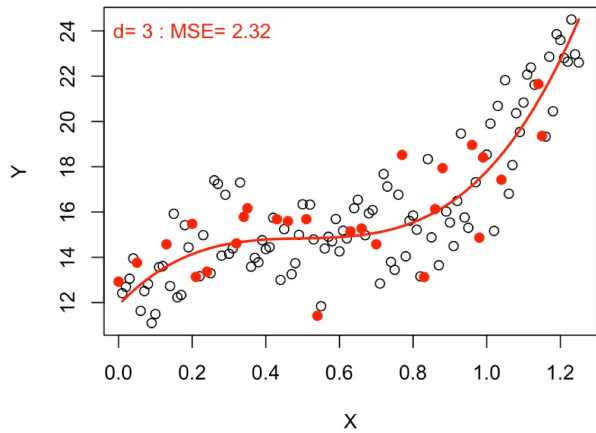
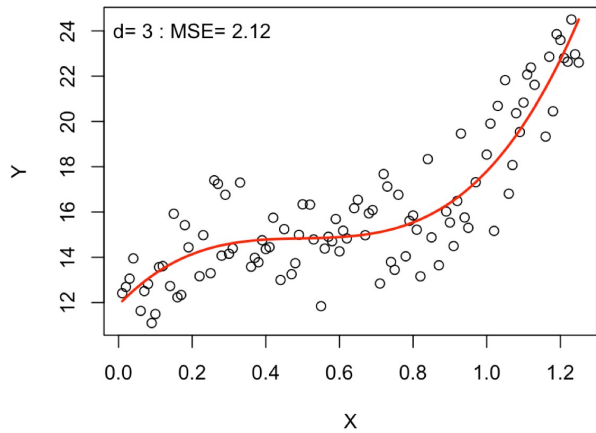
A.6 Polynomial Regression 2

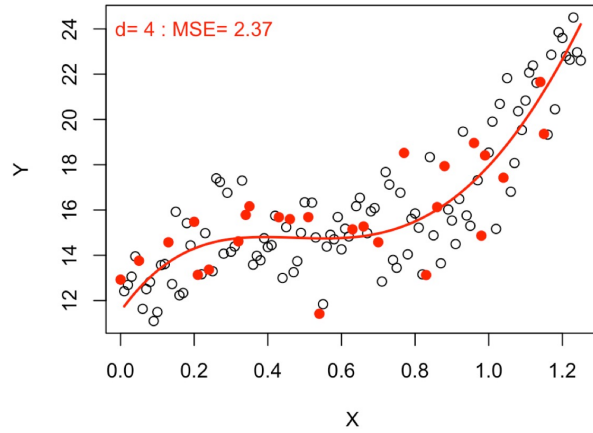
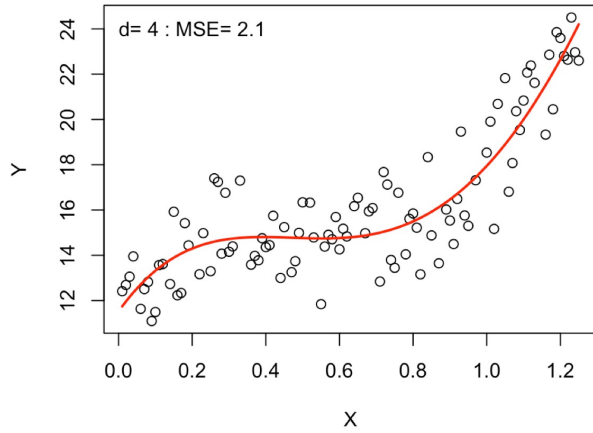
Larger dataset. $n = 100$ and $m = 26$.

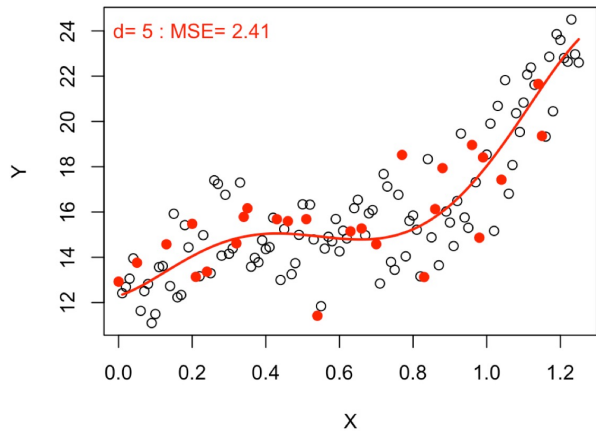
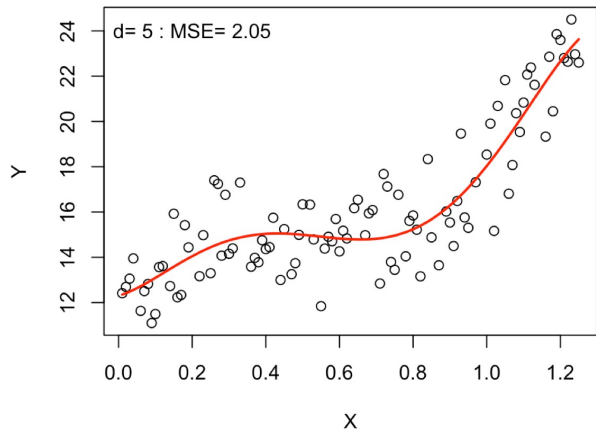


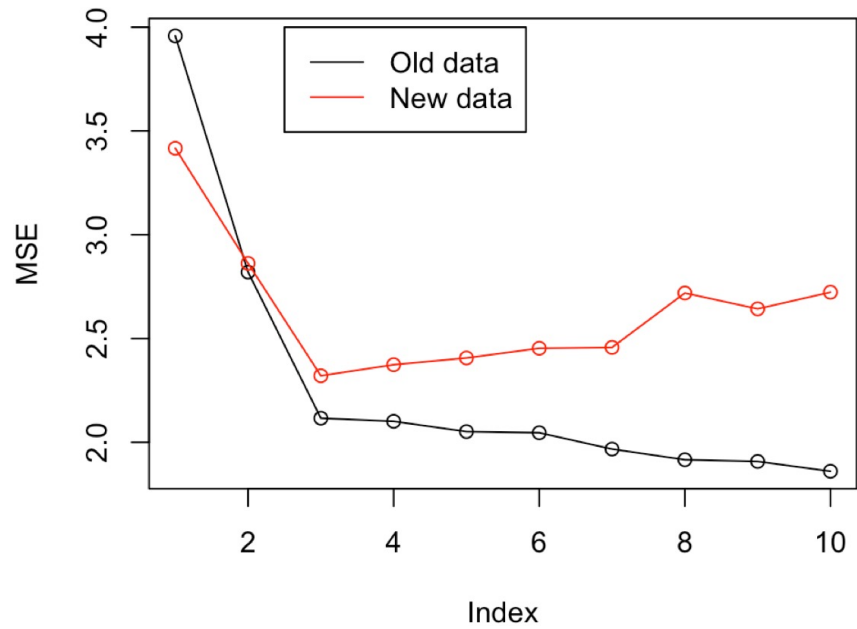












B Training Set and Testing Set

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C Training, Validation, and Testing Set

[\[ToC\]](#)

-
- k-fold Cross Validation

C.1 How do we estimate f ?

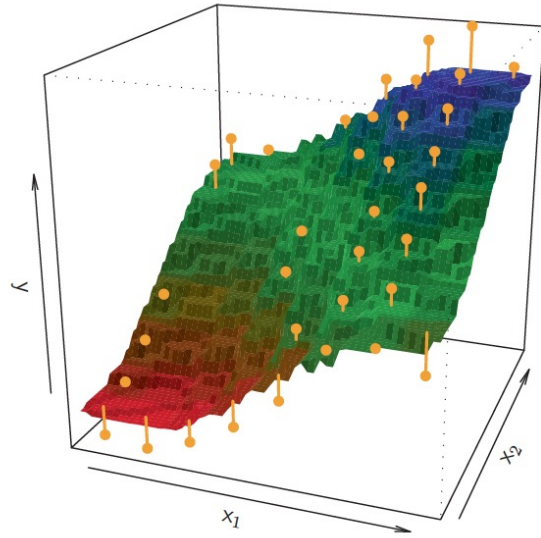
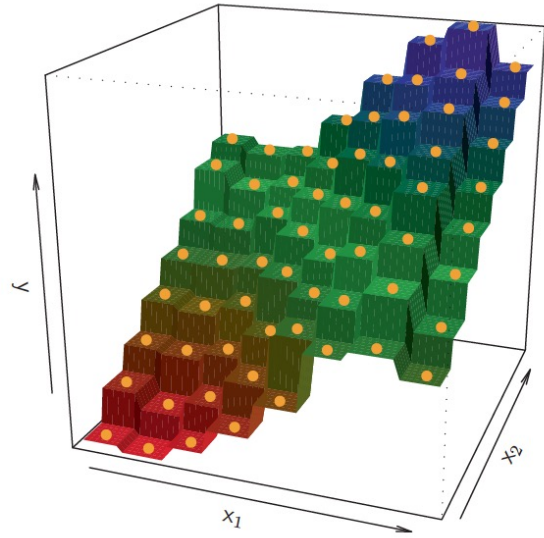
- Hyperparameter

C.2 K-Nearest Neighbor

- Pick a point x_0
- Find K nearest observations
- $f(x_0)$ is estimated by the average of all K neighbors

$$\hat{f}(x_0) = \frac{1}{K} \sum y_i$$

- K=1 (left) and K=9 (right)



D Assessing Model Prediction Accuracy

[\[ToC\]](#)

D.1 Measure of Quality of Fit

- Training MSE (sample)

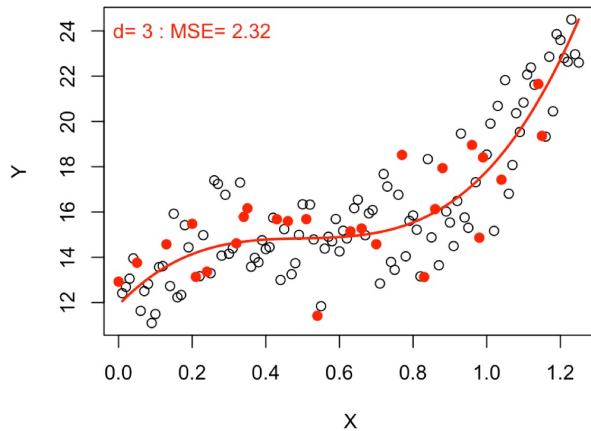
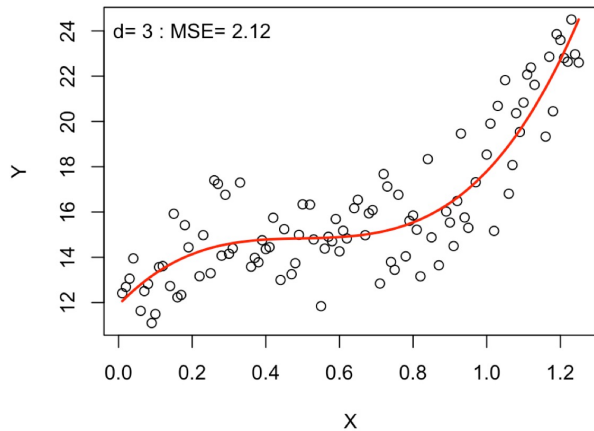
$$\text{MSE}_{tr} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2$$

- But we want minimum Prediction MSE

$$\text{MSE} = E(Y - \hat{f}(X))^2$$

- Solution: look at Test MSE (sample) as estimator

$$\text{MSE}_{test} = \frac{1}{m} \sum_{j=1}^m (y_j - \hat{f}(x_j))^2$$



E Bias-Variance Trade-Off

[\[ToC\]](#)

E.1 Prediction MSE

$$E(Y - \hat{f}(X))^2 = \text{Var}(\hat{f}(X)) + \text{Bias}(\hat{f}(X))^2 + \text{Var}(\epsilon)$$

- can't have low variance and low bias
- has lower bound

Bias-Variance Trade-off

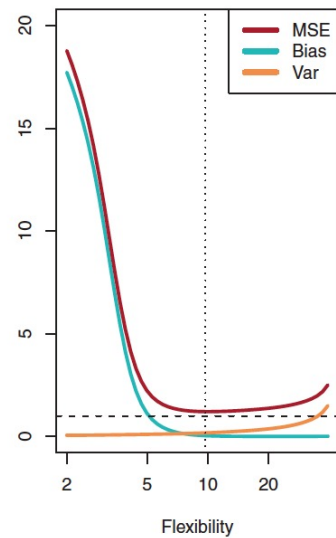
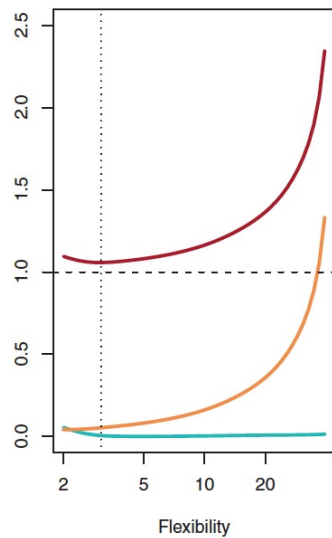
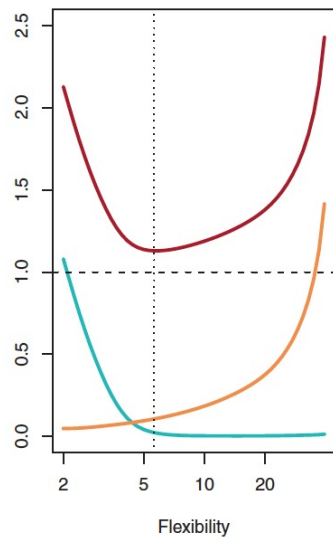
Prediction MSE can be decomposed as

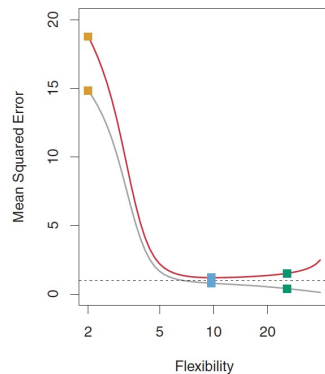
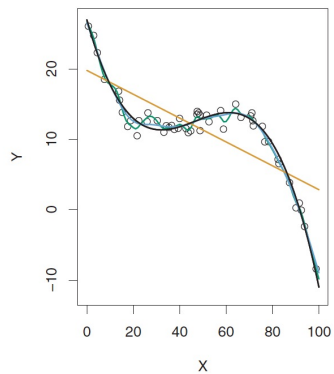
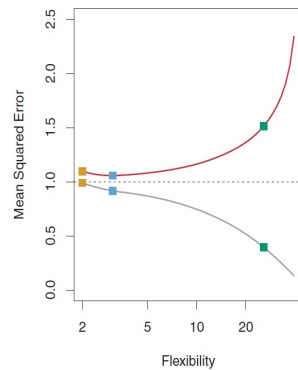
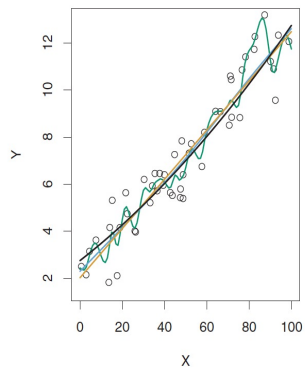
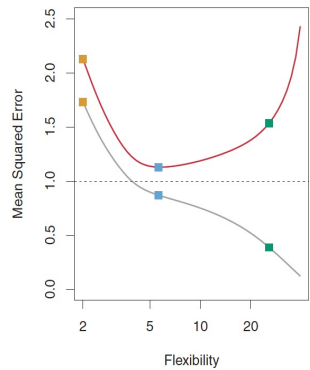
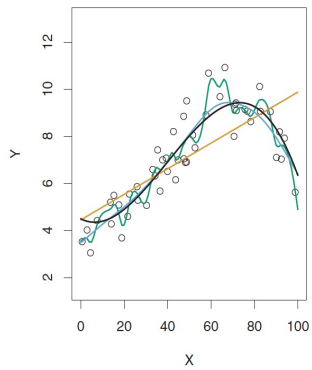
$$\begin{aligned} E(Y - \hat{f}(X))^2 &= E\left(f(X) + \epsilon - \hat{f}(X)\right)^2 \\ &= E\left(f(X) - E(\hat{f}(X)) + E(\hat{f}(X)) - \hat{f}(X) + \epsilon\right)^2 \\ &= E\left(f(X) - E(\hat{f}(X))\right)^2 + E\left(E(\hat{f}(X)) - \hat{f}(X)\right)^2 + E(\epsilon^2) \\ &= \text{Var}(\hat{f}(X)) + \text{Bias}(\hat{f}(X))^2 + \text{Var}(\epsilon) \end{aligned}$$

F Regression vs Classification

[\[ToC\]](#)

F.1 Plot

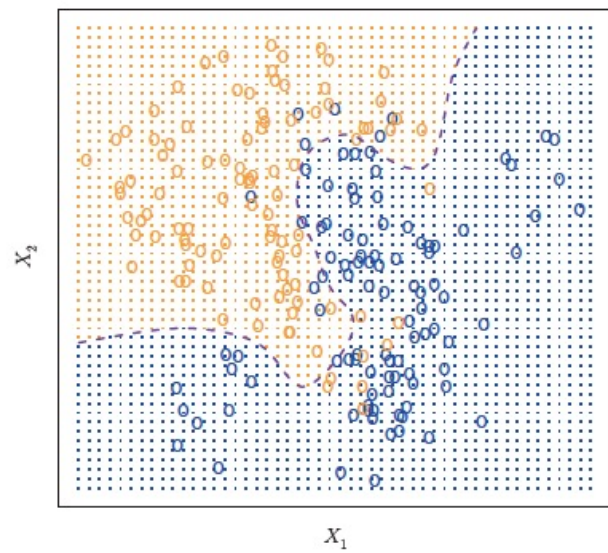


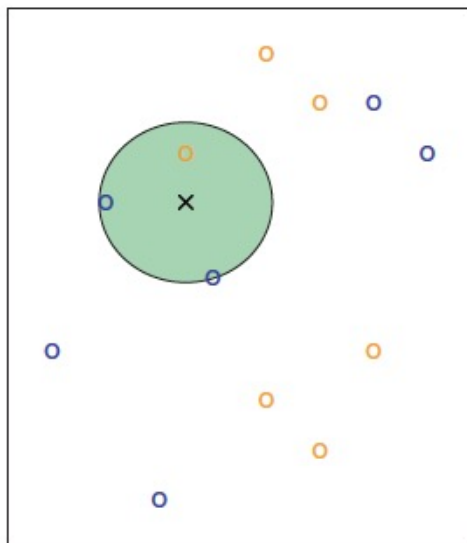


F.2 Classification Setting

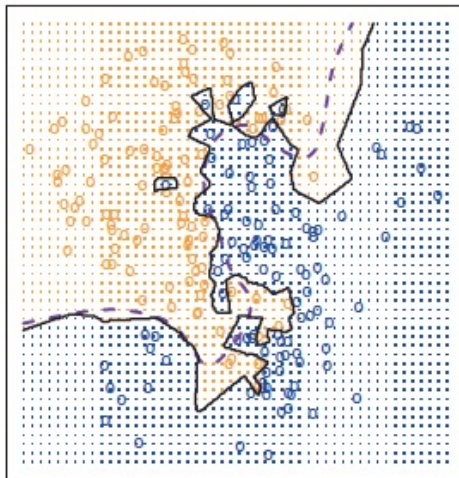
- Instead of MSE, work with Error Rate:

$$\frac{1}{n} \sum_{i=1}^n I(y_i \neq \hat{y}_i)$$





KNN: K=1



KNN: K=100

