

Statistical Modeling 2

Exercise 3

February 14, 2017

Basic concepts

$$\begin{aligned}\text{MSE}(\hat{f}, f) &= E\{[f(x) - \hat{f}(x)]^2\} \\ &= E[f(x)^2 + \hat{f}(x)^2 - 2f(x)\hat{f}(x)] \\ &= f(x)^2 + E[\hat{f}(x)^2] - E[\hat{f}(x)]^2 + E[\hat{f}(x)]^2 - 2f(x)E[\hat{f}(x)] \\ &= \{E[\hat{f}(x)^2] - E[\hat{f}(x)]^2\} + \{f(x)^2 + E[\hat{f}(x)]^2 - 2f(x)E[\hat{f}(x)]\} \\ &= V + B^2\end{aligned}$$

Curve fitting by linear smoothing

A

In the least square estimate, we minimize:

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

We take the derivative and set to 0:

$$\begin{aligned}\partial L / \partial \hat{\beta} &= \sum_{i=1}^n 2(\hat{\beta}x_i - y_i)x_i = 0 \\ \implies \hat{\beta}(\sum_{i=1}^n x_i^2) - \sum_{i=1}^n y_i x_i &= 0 \\ \implies \hat{\beta} &= \frac{\sum_{i=1}^n y_i x_i}{\sum_{i=1}^n x_i^2}\end{aligned}$$

We have that the prediction is:

$$\begin{aligned}\hat{f}(x^*) &= \hat{\beta}x^* \\ &= \frac{\sum_{i=1}^n x_i x^* y_i}{\sum_{i=1}^n x_i^2} \\ &= \sum_{i=1}^n w(x_i, x^*) y_i\end{aligned}$$

where

$$w(x_i, x^*) = \frac{x_i x^*}{\sum_{i=1}^n x_i^2}$$

B

Code: kernel.r

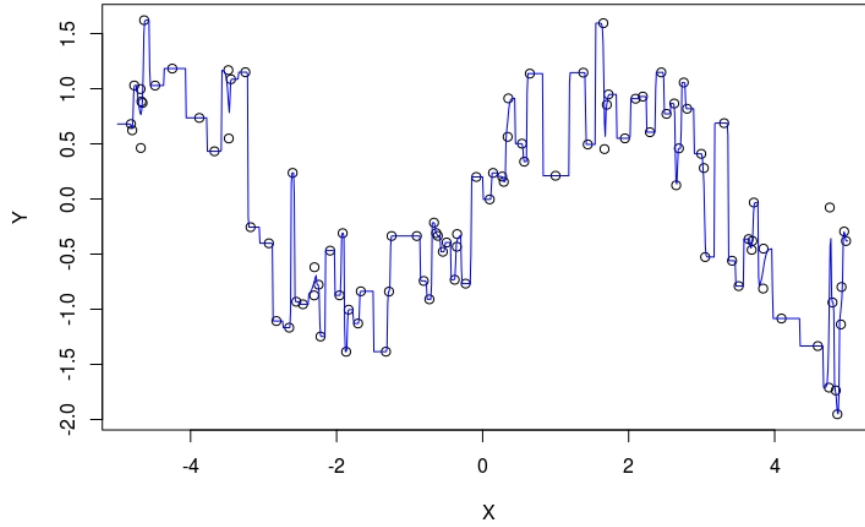


Figure 1: Bandwidth $h = 0.01$

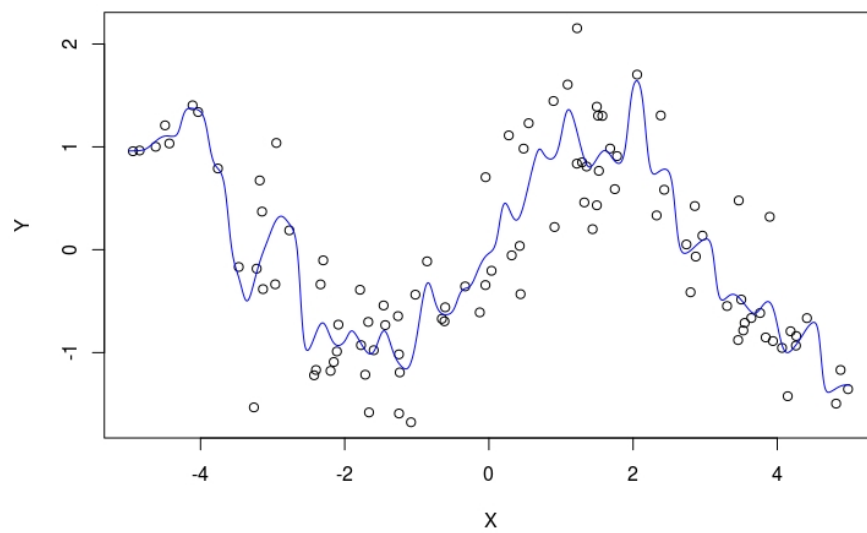


Figure 2: Bandwidth $h = 0.1$

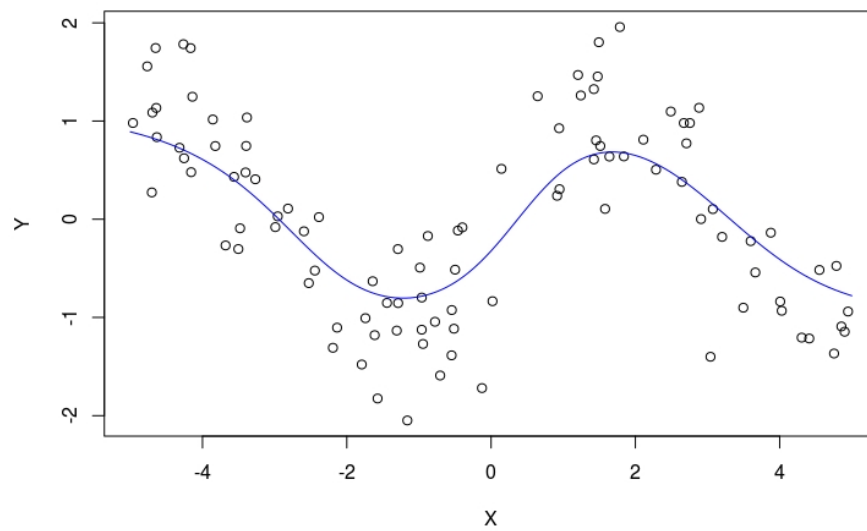


Figure 3: Bandwidth $h = 1$