

Prob: Predict  $\hat{y}(z)$  at  $z$  using MSE

$$MSE(\hat{y}(z)) = \frac{1}{N} \sum_{i=1}^N \left( \frac{z - x_i}{w} \right) (y_i - \hat{y}(z))^2$$

Take derivative wrt  $\hat{y}(z)$  and set equal to 0

$$\text{let } w = \frac{1}{w} \left( \frac{z - x_i}{w} \right) \quad [\text{weight for point } i]$$

then,

$$MSE(\hat{y}(z)) = \frac{1}{N} \sum_{i=1}^N w_i (y_i - \hat{y}(z))^2$$

Differentiate wrt  $\hat{y}(z)$ ,

$$\frac{\partial}{\partial \hat{y}(z)} MSE(\hat{y}(z)) = \underbrace{\frac{1}{N} \sum_{i=1}^N w_i \cdot \cancel{\frac{1}{w} (y_i - \hat{y}(z))}}_0 = 0$$

$$\sum_{i=1}^N w_i (\hat{y}(z) - y_i) = 0$$

isolate  $\hat{y}(z)$ ,

$$\Rightarrow \sum_{i=1}^N w_i \cdot \hat{y}(z) - \sum_{i=1}^N w_i y_i = 0$$

$$\hat{y}(z) \sum_{i=1}^N w_i = \sum_{i=1}^N w_i y_i$$

$$\hat{y}(z) = \frac{\sum_{i=1}^N w_i y_i}{\sum_{i=1}^N w_i}$$

$$\text{Sub back in } w_i = \frac{1}{h} k \left( \frac{z - x_i}{h} \right)$$

$$\tilde{y}(z) = \frac{\sum_{i=1}^N \frac{1}{h} k \left( \frac{z - x_i}{h} \right) y_i}{\sum_{i=1}^N \frac{1}{h} k \left( \frac{z - x_i}{h} \right)} //$$

This is the LLS estimator