

Prob 4

Nadaraya waston kernel regression estimator is given by.

$$\hat{f}(x) = \frac{\sum \left(K\left(\frac{x-x_i}{h}\right) y_i \right)}{\sum \left(K\left(\frac{x-x_i}{h}\right) \right)}$$

Gaussian kernel is given by

~~$$K(u) = \left(\frac{1}{\sqrt{2\pi}} \right)^2 \exp$$~~

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} \quad \text{where} \quad u = \frac{(x-x_i)}{h}$$

By differentiating Nadaraya waston kernel using Gaussian kernel.

$$\hat{f}(x) = \frac{\sum \left(K\left(\frac{x-x_i}{h}\right) \cdot y_i \right)}{\sum \left(K\left(\frac{x-x_i}{h}\right) \right)} \quad \text{d}x.$$

Gaussian kernel differentiation with x .

$$\frac{dK(u)}{dx} = \frac{d}{dx} \left(\frac{1}{\sqrt{2\pi}} \right) e^{-\frac{u^2}{2}} \quad \text{d}x$$

$$= \left(\frac{u}{h} \right) \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{u^2}{2}}$$

From Nadaraya - waston estimator
lets differentiate Numerator & denominator
with respect to x .

Numerator =

$$\sum \left(d \left(k \left(\frac{x - x_i}{\lambda} \right) \right) y_i \right) dx$$

$$= \sum \left(-\frac{y}{\lambda} \right) \left(\frac{1}{\sqrt{2\pi}} \right) e^{-\frac{u^2}{2}} \cdot y_i$$

Denominator =

$$\sum \left(d \left(k \left(\frac{x - x_i}{\lambda} \right) \right) dx \right)$$

$$= \sum \left(-\frac{y}{\lambda} \right) \left(\frac{1}{\sqrt{2\pi}} \right) e^{-\frac{u^2}{2}} \cdot 1$$

Now we apply quotient rule to find $f'(x)$

$$f'(x) = \left(\sum \left(-\frac{y}{\lambda} \right) \left(\frac{1}{\sqrt{2\pi}} \right) e^{-\frac{u^2}{2}} \cdot y_i \right) \sum \left(k \left(\frac{x - x_i}{\lambda} \right) y_i \right)$$

$$\frac{\sum \left(-\frac{y}{\lambda} \right) \left(\frac{1}{\sqrt{2\pi}} \right) e^{-\frac{u^2}{2}}}{\sum k \left(\frac{x - x_i}{\lambda} \right)^2}$$

Since above expression involves continuous f & sums of continuous f , we can conclude that Nadaraya-Watson kernel smooth with Gaussian kernel is differentiable.

As for Epanechnikov kernel is given by

$$K(u) = \frac{3}{4} (1 - u^2) \text{ for } |u| \leq 1 \text{ and } 0 \text{ otherwise}$$

Regarding Epanechnikov kernel with an adaptive nearest-neighbor bandwidth $\lambda(x_0)$

Since kernel f_u itself is not differentiable at $u = \pm 1$, the same conclusion applies.

Nadaraya-Watson estimator using Epanechnikov kernel with an adaptive bandwidth is not guaranteed to be differentiable everywhere.

— x ————— b ————— b —————