

R Notebook

Q1

Question 1.

Let \hat{f}_h be a kernel estimator of the unknown density f with a bandwidth h . Show that $\int \hat{f}_h(y) dy = 1$.

$$\begin{aligned}\hat{f}_h(y) &= \frac{1}{nh} \sum_{i=1}^n K\left(\frac{y_i - y}{h}\right) \\ \int \hat{f}_h(y) dy &= \int \frac{1}{nh} \sum_{i=1}^n K\left(\frac{y_i - y}{h}\right) dy = \sum_{i=1}^n \frac{1}{nh} \int K\left(\frac{y_i - y}{h}\right) dy \\ &\quad \text{substitute } u = \frac{y - y_i}{h} \\ \int \hat{f}_h(y) dy &= \sum_{i=1}^n \frac{1}{nh} \int K(u) h du = \sum_{i=1}^n \frac{1}{n} \int K(u) du = \sum_{i=1}^n \frac{1}{n} = 1\end{aligned}$$

Q2

Question 2.

Let $Y_1, \dots, Y_n \sim f(y)$, where the density f is unknown.

1. We want to estimate $\mu = EY$. An obvious (?) estimator is \bar{Y} . Suppose however that we decided to estimate first f by a kernel estimator $\hat{f}_h(y)$ based on a symmetric kernel and a bandwidth h , and then estimate μ by $\hat{\mu} = \int y \hat{f}_h(y) dy$. What is the resulting $\hat{\mu}$? Is it a consistent estimator for μ ? Does it depend on a specific kernel and on a chosen bandwidth?
2. Return to the previous paragraph but for estimating the second moment $\mu_2 = EY^2$ by $\hat{\mu}_2 = \int y^2 \hat{f}_h(y) dy$.
3. How will $\hat{\mu}_2$ change if we use a *third* order kernel instead? Generalize these results for estimating the p -th moment $\mu_p = EY^p$ by $\hat{\mu}_p = \int y^p \hat{f}_h(y) dy$.

a

$$\hat{\mu} = \sum_{i=1}^n \frac{1}{nh} \int y K\left(\frac{y_i - y}{h}\right) dy$$

using the substitute as before and the fact that: $\int u K(u) du = 0$ we get the following expression:

$$\sum_{i=1}^n \frac{1}{nh} \int (uh - y_i) K(u) h du = \sum_{i=1}^n \frac{1}{n} \int y_i K(u) du = \bar{y}$$

as we already know this estimator is consistent

also we didn't assume anything about K (beside what we assumed in class) so the result does not depend on the kernel or bandwidth

b

$$\hat{\mu}_2 = \sum_{i=1}^n \frac{1}{nh} \int y^2 K\left(\frac{y_i - y}{h}\right) dy$$

using the substitute as before and the fact that: $\int u K(u) du = 0$ we get the following expression:

$$\begin{aligned}\sum_{i=1}^n \frac{1}{nh} \int (uh - y_i)^2 K(u) h du &= \sum_{i=1}^n \frac{1}{nh} \int (u^2 h^2 - 2y_i u h + y_i^2) K(u) h du = \sum_{i=1}^n \frac{1}{n} \left[h \int u^2 h^2 K(u) du - 2y_i \int u K(u) du + y_i^2 \int K(u) du \right] \\ &= \sum_{i=1}^n \frac{1}{n} \left[y_i^2 + h^2 \int u^2 K(u) du \right] = h^2 \int u^2 K(u) du + \sum_{i=1}^n \frac{y_i^2}{n} \\ \sum_{i=1}^n \frac{y_i^2}{n} &\text{ is a consistent estimator for } \mu_2 \text{ Law of large numbers}\end{aligned}$$

but $h^2 \int u^2 K(u) du$ does not converge to zero unless $h \rightarrow 0$

and the estimator depends both on h and K

C

if we use a Kernel of order 3 then:

$$\int u^2 K(u) du = 0 \text{ thus in this case the precious estimator is consistent}$$

i will show the general case for a kernel of order p by induction that: $\hat{\mu}_p = h^p \int u^p K(u) du + \sum_{i=1}^n \frac{y_i^p}{n}$

we saw that this is true for the case where p=2, now assume its true for p=m-1 and prove for p=m

$$\begin{aligned} \hat{\mu}_m &= \sum_{i=1}^n \frac{1}{nh} \int y^m K\left(\frac{y_i - y}{h}\right) dy = \sum_{i=1}^n \frac{1}{n} \int (uh - y_i)^m K(u) du = \sum_{i=1}^n \frac{1}{n} \int (uh - y_i)^{m-1} (uh - y_i) K(u) du = \\ &= \sum_{i=1}^n \frac{1}{n} \int (uh - y_i)^{m-1} K(u) (uh - y_i) du = (h^{m-1} \int u^{m-1} K(u) du + \sum_{i=1}^n \frac{y_i^{m-1}}{n}) y_i + \sum_{i=1}^n \frac{h}{n} \int (uh - y_i)^{m-1} u K(u) du \end{aligned}$$

lets break down this expression:

$$\begin{aligned} (1) & (h^{m-1} \int u^{m-1} K(u) du + \sum_{i=1}^n \frac{y_i^{m-1}}{n}) y_i = h^{m-1} \int u^{m-1} K(u) du y_i + \sum_{i=1}^n \frac{y_i^m}{n} \quad \text{K is of order m} \quad \sum_{i=1}^n \frac{y_i^m}{n} \\ (2) & \sum_{i=1}^n \frac{h}{n} \int (uh - y_i)^{m-1} u K(u) du = \sum_{i=1}^n \frac{h}{n} \int (uh - y_i)^{m-2} (uh - y_i) u K(u) du = \sum_{i=1}^n \frac{h^2}{n} \int (uh - y_i)^{m-2} u^2 K(u) du = \\ & \dots = \sum_{i=1}^n \frac{h^m}{n} \int u^m K(u) du \end{aligned}$$

i used the fact that K is of order m, m-2 times

plugging it back in we get :

$$\hat{\mu}_m = \sum_{i=1}^n \frac{y_i^m}{n} + h^m \int u^m K(u) du$$

as in the previous case we get that $\hat{\mu}_m$ is consistent if K is of order p+1 and the estimator depends both on K and h

Q3

Question 3.

Consider kernel estimation of the unknown (univariate) density f given a random sample $Y_1, \dots, Y_n \sim f(y)$. Assume that $f \in H^m$, $m \geq 1$, where $H^m = \{f : \int f^{(m)}(y)^2 dy < \infty\}$ and choose the kernel $K(\cdot)$ of the order m . Show that

1. $IMSE(\hat{f}_h, f) \leq C_1(K) h^{2m} + \frac{C_2(K)}{nh}$
2. the optimal choice for a bandwidth is $h_0 = O(n^{-\frac{1}{2m+1}})$
3. the optimal $IMSE(\hat{f}_{h_0}, f) = O(n^{-\frac{2m}{2m+1}})$

a

$$IMSE(\hat{f}_h, f) = \int MSE(\hat{f}_h, f)$$

$$\begin{aligned} bias(y_0) &= E(\hat{f}_h(y_0)) - f(y_0) = \int f(y_0 + uh) K(u) du - f(y_0) = \int [f(y_0 + uh) - f(y_0)] K(u) du = \\ &\stackrel{Taylor}{=} \int [f(y_0) + h u f'(y_0) + \dots + \frac{1}{m} h^m u^m f^{(m)}(y_0) + O(h^{m+1}) - f(y_0)] K(u) du \quad \text{K is of order m} \quad \frac{1}{m} h^m f^{(m)}(y_0) \int u^m K(u) du + O(h^{m+1}) \end{aligned}$$

$$\text{thus: } bias(y_0)^2 = \frac{1}{m^2} h^{2m} (f^{(m)}(y_0))^2 \left(\int u^m K(u) du \right)^2 + O(h^{2m+2})$$

$$\begin{aligned} Var(\hat{f}_h(y_0)) &= Var\left[\frac{1}{nh} \sum_{i=1}^n K\left(\frac{y_i - y_0}{h}\right)\right] = \frac{1}{n^2 h^2} Var\left[\sum_{i=1}^n K\left(\frac{y_i - y_0}{h}\right)\right] = \frac{1}{n h^2} Var\left[K\left(\frac{y_1 - y_0}{h}\right)\right] = \\ &= \frac{1}{n h^2} (E([K(\frac{y_1 - y_0}{h})]^2) - E^2[K(\frac{y_1 - y_0}{h})]) \leq \frac{1}{n h^2} E([K(\frac{y_1 - y_0}{h})]^2) = \\ &= \frac{1}{n h^2} \int (K(\frac{y - y_0}{h}))^2 f(y) dy = \frac{1}{n h} \int K(u)^2 f(y_0 + uh) du \stackrel{Taylor}{=} \frac{1}{n h} \int K(u)^2 [f(y_0) + O(h)] du = \\ &= \frac{f(y_0)}{n h} \int K(u)^2 du + O\left(\frac{1}{n}\right) \end{aligned}$$

$$MSE(\hat{f}_h, f) \leq \frac{f(y_0)}{n h} \int K(u)^2 du + O\left(\frac{1}{n}\right) + \frac{1}{m^2} h^{2m} (f^{(m)}(y_0))^2 \left(\int u^m K(u) du \right)^2 + O(h^{2m+2})$$

$$\begin{aligned} IMSE(\hat{f}_h, f) &\leq \int \left[\frac{f(y)}{n h} \int K(u)^2 du + O\left(\frac{1}{n}\right) + \frac{h^{2m}}{m^2} (f^{(m)}(y))^2 \left(\int u^m K(u) du \right)^2 + O(h^{2m+2}) \right] dy = \\ &= O\left(\frac{1}{n}\right) + O(h^{2m+2}) + \frac{1}{n h} \int K(u)^2 du + \frac{h^{2m}}{m^2} \left[\int (f^{(m)}(y))^2 dy \right] \left[\int u^m K(u) du \right]^2 = C_1(K) h^{2m} + C_2(K) \frac{1}{n h} \end{aligned}$$

b

$$\frac{\partial IMSE}{\partial h} = 2mC_1(K)h^{2m-1} - C_2(K)\frac{1}{nh^2} = 0 \iff h^{2m+1} = C_2(K)\frac{1}{n2mC_1(K)} \iff h = O(n^{-\frac{1}{2m+1}})$$

$$\frac{\partial^2 IMSE}{\partial^2 h} = 2m(2m-1)C_1(K)h^{2m-2} + C_2(K)\frac{1}{nh^3} > 0 \forall h$$

thus the optimal bandwidth is $h_0 = O(n^{-\frac{1}{2m+1}})$

c

plug h_0 back in the IMSE we get:

$$C_1(K)O(n^{-\frac{1}{2m+1}})^{2m} + C_2(K)\frac{1}{nO(n^{-\frac{1}{2m+1}})} = O(n^{-\frac{2m}{2m+1}}) + O(n^{2m}) = O(n^{-\frac{2m}{2m+1}})$$