Lecture course Statistics II
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## Exercise sheet 9

Exercise 1. Given $\left(X_{1}, \ldots, X_{n}\right) \sim \mathbb{P}^{\otimes n}$ and for each $\theta \in \Theta$ a function $m_{\theta}: \mathcal{X} \rightarrow \mathbb{R}$ belonging to $L_{\mathbb{P}}^{1}$ consider $M_{n}(\theta)=\overline{\mathbb{P}}_{n} m_{\theta}=\frac{1}{n} \sum_{i=1}^{n} m_{\theta}\left(X_{i}\right)$ and $M(\theta)=\mathbb{P} m_{\theta}$. Show that any estimator $\widehat{\theta}_{n}$ such that $M_{n}\left(\widehat{\theta}_{n}\right) \leqslant M_{n}\left(\theta_{o}\right)+o_{\mathbb{P}}(1)$ converges in probability to $\theta_{o}$, if the following conditions are satisfied
(a) $\Theta$ is compact,
(b) $M\left(\theta_{o}\right)<M(\theta)$ for all $\theta \neq \theta_{o}$,
(c) $\theta \rightarrow m_{\theta}(x)$ is continuous for all $x$,
(d) $\sup \left\{\left|m_{\theta}(X)\right|: \theta \in \Theta\right\}$ belongs to $L_{\mathbb{P}}^{1}$.

Exercise 2. Consider a real-valued r.v. $X$ and a r.v. $Z \sim \mathfrak{U}([0,1])$ obeying a nonlinear regression model $\mathbb{E}_{f_{\theta}}(X \mid Z)=f_{\theta}(Z)$, where the regression function $f_{\theta}$ belongs to a parametric subset $\left\{f_{\theta}, \theta \in \Theta\right\}$ of $L^{2}([0,1])$. We assume further that $\varepsilon=X-f_{\theta}(Z)$ has a finite second moment and it is independent of $Z$. Given for each $n \in \mathbb{N}$ i.i.d. copies $\left(X_{i}, Z_{i}\right), i \in \llbracket 1, n \rrbracket$, of $(X, Z)$ denote by $\widehat{\theta}_{n}=\arg \min _{\theta \in \Theta} \sum_{i=1}^{n}\left(X_{i}-f_{\theta}\left(Z_{i}\right)\right)^{2}$ the least squares estimator (LSE), if it exists. Determine sufficient conditions on the parametric family $\left\{f_{\theta}, \theta \in \Theta\right\}$ to ensure the consistency of the LSE.

Exercise 3. For $n \in \mathbb{N}$ consider the uniform distributions $\mathbb{P}_{n}=\mathfrak{U}([0,1])$ and $\mathbb{Q}_{n}=$ $\mathfrak{U}\left(\left[0,1+\frac{1}{n}\right]\right)$ on the common measurable space $(\mathbb{R}, \mathscr{B})$. Show that $\mathbb{P}_{n} \triangleleft \triangleright \mathbb{Q}_{n}$ holds. Is this also true for the product probability measures $\mathbb{P}_{n}=\mathfrak{U}^{\otimes n}([0,1])$ and $\mathbb{Q}_{n}=\mathfrak{U}^{\otimes n}\left(\left[0,1+\frac{1}{n}\right]\right)$ on the common measurable space $\left(\mathbb{R}^{n}, \mathscr{B}^{\otimes n}\right)$ ?

Exercise 4. Considering the product experiment $\left(\mathbb{R}^{n}, \mathscr{B}^{\otimes n},\left\{\operatorname{Exp}^{\otimes n}(\theta), \theta>0\right\}\right)$ test the null hypothesis $H_{0}: \theta=\theta_{o}$ against the alternative $H_{1}: \theta>\theta_{o}$ using the test $\phi_{n}=\mathbb{1}_{\left\{Z_{n}>c_{n}\right\}}$ with $Z_{n}:=-\frac{1}{n} \sum_{i=1}^{n} X_{i}^{2}$.
(i) Show that the sequence of product experiments is LAN for each $\theta_{o}>0$ and derive its central sequence.
(ii) Determine a sequence $c_{n}$ such that $\phi_{n}$ is an asymptotic level $\alpha$ test.
(iii) Show that the asymptotic power of $\phi_{n}$ under a local alternative $\theta_{o}+h / \sqrt{n}$ is given by $\lim _{n \rightarrow \infty} \beta_{\varphi_{n}}\left(\theta_{o}+h / \sqrt{n}\right)=\mathbb{F}_{\mathfrak{N}(0,1)}\left(-z_{1-\alpha}+h \frac{2}{\theta_{o} \sqrt{5}}\right)$.
(iv) Calculate the relative asymptotic efficiency of $\phi_{n}$ w.r.t. an asymptotic optimal test $\phi_{n}^{*}$. Which sample size $n$ is needed, such that $\phi_{n}$ has the same asymptotic power than $\phi_{n^{\prime}}^{*}$ with sample size $n^{\prime}=100$.

Hint: If $X \sim \mathfrak{E x p}(\theta)$, then $\mathbb{E}\left(X^{k}\right)=\frac{k!}{\lambda^{k}}$ for each $k \in \mathbb{N}$.

Exercise 5. Given an i.i.d. sample $X_{1}, \ldots, X_{n} \sim \mathbb{p}$ consider a kernel density estimator $\widehat{\mathrm{p}}_{h}=\frac{1}{h n} \sum_{i=1}^{n} K\left(\frac{X_{i}-x}{h}\right)$ of $\mathfrak{p}(x)$ at a given point $x$, where $K$ is a kernel and $h$ is bandwidth. Assuming that $\mathfrak{p}$ belongs to the Hölder class $\mathcal{H}(\beta, L)$ and that $K$ is a kernel of order $l=\lfloor\beta\rfloor$ with $\lambda\left(|\operatorname{id}|^{\beta}|K|\right)<\infty$, show that for each $x \in \mathbb{R}, h>0$ and $n \in \mathbb{N}$ it holds $\left|\operatorname{bias}_{\mathfrak{p}}(x)\right| \leqslant$ $h^{\beta} \frac{L}{l!} \lambda\left(|\mathrm{id}|^{\beta}|K|\right)$.

Exercise 6. Consider r.v.'s $Y$ and $Z$ obeying $Y=\sigma(Z) \varepsilon$, where $\varepsilon$ is centred with variance 1 and independent of $Z \sim \mathfrak{U}([0,1])$. Let $\left(X_{i}, Z_{i}\right), i \in \llbracket 1, n \rrbracket$, be an i.i.d. sample of $(X, Z)$. Given a kernel $K$ and a bandwidth $h$ consider at a point $z \in[0,1]$ the kernel estimator $\widehat{\sigma}_{h}^{2}(z)=\frac{1}{n h} \sum_{i=1}^{n} Y_{i}^{2} K\left(\frac{Z_{i}-z}{h}\right)$ of the variance function $\sigma^{2}(z)$.
(a) Derive an upper bound for $\operatorname{bias}(z)=\mathbb{E}\left(\widehat{\sigma}_{h}^{2}(z)\right)-\sigma^{2}(z)$ if $\sigma^{2}$ belongs to an Hölder class and $K$ is a kernel of appropriate order.
(b) Derive an upper bound for $\operatorname{Var}\left(\widehat{\sigma}_{h}^{2}(z)\right)$ assuming that $\mathbb{E}\left(\varepsilon^{4}\right)<\infty,\left\|\sigma^{2}\right\|_{L^{\infty}}<\infty$ and $\|K\|_{L^{2}}<\infty$.
(c) Find an upper bound for $\operatorname{MSE}(z)=\mathbb{E}\left|\widehat{\sigma}_{h}^{2}(z)-\sigma^{2}(z)\right|^{2}$ depending on the bandwidth. Select an optimal value for the bandwidth and derive the associated upper bound.

Exercise 7. Consider an ONB $\left\{\mathbb{1}_{[0,1]}\right\} \cup\left\{u_{j}, j \in \mathbb{N}\right\}$ in $L^{2}[0,1]$ and the sieve $(\llbracket 1, m \rrbracket)_{m \in \mathbb{N}}$ in $\mathbb{N}$. Given for each $n \in \mathbb{N}$ an observable quantity $[\widehat{\mathbb{p}}]=\left(\overline{\mathbb{P}}_{n} u_{j}\right)_{j \in \mathbb{N}}$ using an i.i.d. sample $X_{i} \sim \mathbb{p}, i \in \llbracket 1, n \rrbracket$, let $\left\{\widehat{\mathbb{p}}_{m}=\mathbb{1}_{[0,1]}+\sum_{j=1}^{m}[\widehat{\mathbb{p}}]_{j} u_{j}, m \in \mathbb{N}\right\}$ be a family of OSE's of $\mathbb{p}=\mathbb{1}_{[0,1]}+\sum_{j \in \mathbb{N}}[\mathbb{p}]_{j} u_{j} \in L^{2}([0,1])$. Assuming that $0<\mathbb{p}_{0}^{-1} \leqslant \mathbb{p} \leqslant$ $\mathbb{p}_{0}<\infty \lambda$-a.s. for some finite constant $\mathbb{p}_{0} \geqslant 1$ show that the $\operatorname{OSE}\left(\widehat{\mathbb{p}}_{m_{n}}\right)_{n \in \mathbb{N}}$ with $m_{n}:=\arg \min \left\{\max \left(n^{-1} m, \sum_{j>m}\left|[\mathbb{p}]_{j}\right|^{2}\right), m \in \mathbb{N}\right\}$ is oracle optimal (up to a constant) for the integrated means squared error, i.e., $\mathbb{E}\|\widehat{\mathbb{p}}-\mathbb{p}\|_{L^{2}}^{2}$.

Exercise 8. Consider r.v.'s $Y$ and $Z$ obeying $Y=\sigma(Z) \varepsilon$, where $\varepsilon$ is centred with variance 1 and independent of $Z \sim \mathfrak{U}([0,1])$. Let $\left(X_{i}, Z_{i}\right), i \in \llbracket 1, n \rrbracket$, be an i.i.d. sample of $(X, Z)$. Given an ONB $\left\{u_{j}, j \in \mathbb{N}\right\}$ in $L^{2}[0,1]$, the sieve $(\llbracket 1, m \rrbracket)_{m \in \mathbb{N}}$ in $\mathbb{N}$, and for $j \in \mathbb{N}$ the observable quantity $\left[\hat{\sigma}^{2}\right]_{j}=\frac{1}{n} \sum_{i=1}^{n} Y_{i}^{2} u_{j}\left(Z_{i}\right)$ let $\left\{\widehat{\sigma}_{m}^{2}:=\sum_{j=1}^{m}\left[\widehat{\sigma}^{2}\right]_{j} u_{j}, m \in \mathbb{N}\right\}$ be a family of OSE's of $\sigma^{2}=\sum_{j \in \mathbb{N}}\left[\sigma^{2}\right]_{j} u_{j} \in L^{2}([0,1])$. Assuming for some finite constant $\sigma_{o}^{2} \geqslant 1$ that $0<\sigma_{o}^{-2} \leqslant \sigma^{2} \leqslant \sigma_{o}^{2}<\infty \lambda$-a.s. show that the $\operatorname{OSE}\left(\widehat{\sigma}_{m_{n}}^{2}\right)_{n \in \mathbb{N}}$ with $m_{n}:=$ $\arg \min \left\{\max \left(n^{-1} m, \sum_{j>m}\left|\left[\sigma^{2}\right]_{j}\right|^{2}\right), m \in \mathbb{N}\right\}$ is oracle optimal (up to a constant) for the integrated means squared error, i.e., $\mathbb{E}\left\|\widehat{\sigma}^{2}-\sigma^{2}\right\|_{L^{2}}^{2}$.

