# Assignment 10 <br> Mathematics for Machine Learning 

Submission due on 01.02.21, 8:00

Justify all your claims.
Exercise 1 (Multivariate distributions, $3+2$ points).
a) Consider the joint density

$$
f(x, y)=\frac{1}{Z} \exp \left(-2 x^{2}-y^{2}-x^{2} y^{2}\right), \quad x, y \in \mathbb{R}
$$

of two real-valued random variables $X$ and $Y$, where $Z=\int_{\mathbb{R}^{2}} \exp \left(-2 x^{2}-y^{2}-x^{2} y^{2}\right) d(x, y)$ is the normalizing constant. Compute the marginal densities $f_{X}(x)$ and $f_{Y}(y)$, as well as the conditional densities $f_{X \mid Y=y}(x)$ and $f_{Y \mid X=x}(y)$. What is the name of the distributions given by the conditional densities?
Hint: Use the formula $\int_{\mathbb{R}} \exp \left(-a(x+b)^{2}\right) d x=\sqrt{\frac{\pi}{a}}$ for $a>0, b \in \mathbb{R}$.
b) Consider a positive joint density $f(x, y)$ of two real-valued random variables $X$ and $Y$. Prove the continuous versions of Bayes' formula and the law of total probability for all $x, y \in \mathbb{R}$ :

$$
f_{Y \mid X=x}(y)=\frac{f_{X \mid Y=y}(x) f_{Y}(y)}{f_{X}(x)}
$$

(Bayes' formula)
and

$$
f_{Y}(y)=\int_{\mathbb{R}} f_{Y \mid X=x}(y) f_{X}(x) d x \quad \text { (Law of total probability) }
$$

Exercise 2 (Concentration inequalities, $2+3+3+2$ points). Let $\left(X_{1}, Y_{1}\right), \ldots,\left(X_{n}, Y_{n}\right)$ be i.i.d. random variables taking values in $\mathbb{R}^{d} \times \mathbb{R}$. For a function $g: \mathbb{R}^{d} \times \mathbb{R} \rightarrow[0,1]$, define

$$
R(g):=\mathbb{E}_{(X, Y)}[g(X, Y)] \quad \text { and } \quad R_{n}(g)=\frac{1}{n} \sum_{i=1}^{n} g\left(X_{i}, Y_{i}\right)
$$

Let $\mathcal{G}=\left\{g_{1}, \ldots, g_{m}\right\}$ be a finite set of $m \in \mathbb{N}$ such functions. Define

$$
g_{n}:=\underset{g \in \mathcal{G}}{\arg \min } R_{n}(g) \quad \text { and } \quad g^{*}:=\underset{g \in \mathcal{G}}{\arg \min } R(g)
$$

a) Let $Z_{1}, \ldots, Z_{n}$ be i.i.d random variables taking values in $[0,1]$ with $\mu=\mathbb{E}\left[Z_{1}\right]$. Use Hoeffding's inequality to prove that for any $\varepsilon>0$, it holds

$$
P\left(\left|\frac{1}{n} \sum_{i=1}^{n} Z_{i}-\mu\right| \geq \varepsilon\right) \leq 2 \exp \left(-2 n \varepsilon^{2}\right)
$$

b) Use part a) on $Z_{i}:=g\left(X_{i}, Y_{i}\right)$ to prove that for any $\varepsilon>0$, it holds

$$
P\left(\sup _{g \in \mathcal{G}}\left|R_{n}(g)-R(g)\right| \geq \varepsilon\right) \leq 2 m \exp \left(-2 n \varepsilon^{2}\right)
$$

c) Prove that for any $\varepsilon>0$, it holds

$$
P\left(\left|R\left(g_{n}\right)-R\left(g^{*}\right)\right| \geq \varepsilon\right) \leq P\left(\sup _{g \in \mathcal{G}}\left|R_{n}(g)-R(g)\right| \geq \frac{\varepsilon}{2}\right)
$$

Hint: prove the implication $\left(\left|R\left(g_{n}\right)-R\left(g^{*}\right)\right| \geq \varepsilon\right) \Rightarrow\left(\sup _{g \in \mathcal{G}}\left|R_{n}(g)-R(g)\right| \geq \frac{\varepsilon}{2}\right)$ by using the decomposition

$$
R\left(g_{n}\right)-R\left(g^{*}\right)=\left[R\left(g_{n}\right)-R_{n}\left(g_{n}\right)\right]+\left[R_{n}\left(g_{n}\right)-R_{n}\left(g^{*}\right)\right]+\left[R_{n}\left(g^{*}\right)-R\left(g^{*}\right)\right] .
$$

d) Combine the inequalities from part b) and c) to prove that $R\left(g_{n}\right) \rightarrow R\left(g^{*}\right)$ almost surely as $n \rightarrow \infty$.
Hint: Use the Borel-Cantelli lemma and the following characterization (compare Assignment 9, Exercise 2c)

$$
X_{n} \xrightarrow[n \rightarrow \infty]{\longrightarrow} X \text { almost surely } \quad \Leftrightarrow \quad \forall \varepsilon>0: P\left(\left\{\left|X_{n}-X\right| \geq \varepsilon\right\} \text { i.o. }\right)=0 .
$$

Exercise 3 (Variance bounds, $3+2$ points). The Efron-Stein inequality is stated as follows. Let $X_{1}, \ldots, X_{n}$ be independent random variables taking values in $\mathbb{R}$ and let $Z=f\left(X_{1}, \ldots, X_{n}\right)$ be a square-integrable function, that is, $\mathbb{E}\left[Z^{2}\right]<\infty$. Moreover, let $X_{1}^{\prime}, \ldots, X_{n}^{\prime}$ be independent copies of $X_{1}, \ldots, X_{n}$, that is, they are jointly independent and $X_{i}^{\prime}$ has the same distribution as $X_{i}$ for every $i \in\{1, \ldots, n\}$. For every $i$, define $Z_{i}^{\prime}$ as the random variable obtained by replacing $X_{i}$ with $X_{i}^{\prime}$, that is,

$$
Z_{i}^{\prime}=f\left(X_{1}, \ldots, X_{i-1}, X_{i}^{\prime}, X_{i+1}, \ldots, X_{n}\right) .
$$

Then it holds

$$
\operatorname{Var}[Z] \leq \sum_{i=1}^{n} \mathbb{E}\left[\left(Z-Z_{i}^{\prime}\right)_{+}^{2}\right], \quad \text { where } x_{+}:=\left\{\begin{array}{ll}
x, & \text { if } x \geq 0 \\
0, & \text { otherwise }
\end{array} .\right.
$$

Now consider the following scenario. Let $A \in \mathbb{R}^{n \times n}$ be a symmetric real matrix whose entries $A_{i, j}=X_{i, j}$ for $1 \leq i \leq j \leq n$ are independent random variables taking values in $[-1,1]$. Let $Z=Z(A)$ denote the largest eigenvalue of $A$.
a) For $1 \leq i \leq j \leq n$, let $X_{i, j}^{\prime}$ be an independent copy of $X_{i, j}$. Consider the symmetric matrix $A_{i, j}^{\prime}$ obtained by replacing $X_{i, j}$ in $A$ with $X_{i, j}^{\prime}$, and let $Z_{i, j}^{\prime}$ denote the corresponding largest eigenvalue. Let $v=\left(v_{1}, \ldots, v_{n}\right)^{T} \in \mathbb{R}^{n}$ denote an eigenvector of $A$ corresponding to the largest eigenvalue $Z$ with $\|v\|=1$. Prove that

$$
\left(Z-Z_{i, j}^{\prime}\right)_{+} \leq 4\left|v_{i} v_{j}\right|
$$

Hint: Use the fact that the largest eigenvalue $Z$ satisfies

$$
\begin{equation*}
Z=v^{T} A v=\sup _{u \in \mathbb{R}^{n}:\|u\|=1} u^{T} A u \tag{*}
\end{equation*}
$$

b) Use part a) to prove that $\operatorname{Var}[Z] \leq 16$.

Hint: You may assume that $\mathbb{E}\left[Z^{2}\right]<\infty$ without a proof.

