## 4. Norms and inequalities

4.1. $L^{p}$-norms. Let $(E, \mathcal{E}, \mu)$ be a measure space. For $1 \leq p<\infty$, we denote by $L^{p}=L^{p}(E, \mathcal{E}, \mu)$ the set of measurable functions $f$ with finite $L^{p}$-norm:

$$
\|f\|_{p}=\left(\int_{E}|f|^{p} d \mu\right)^{1 / p}<\infty
$$

We denote by $L^{\infty}=L^{\infty}(E, \mathcal{E}, \mu)$ the set of measurable functions $f$ with finite $L^{\infty}$ norm:

$$
\|f\|_{\infty}=\inf \{\lambda:|f| \leq \lambda \text { a.e. }\}
$$

Note that $\|f\|_{p} \leq \mu(E)^{1 / p}\|f\|_{\infty}$ for all $1 \leq p<\infty$. For $1 \leq p \leq \infty$ and $f_{n} \in L^{p}$, we say that $f_{n}$ converges to $f$ in $L^{p}$ if $\left\|f_{n}-f\right\|_{p} \rightarrow 0$.
4.2. Chebyshev's inequality. Let $f$ be a non-negative measurable function and let $\lambda \geq 0$. We use the notation $\{f \geq \lambda\}$ for the set $\{x \in E: f(x) \geq \lambda\}$. Note that

$$
\lambda 1_{\{f \geq \lambda\}} \leq f
$$

so on integrating we obtain Chebyshev's inequality

$$
\lambda \mu(f \geq \lambda) \leq \mu(f)
$$

Now let $g$ be any measurable function. We can deduce inequalities for $g$ by choosing some non-negative measurable function $\phi$ and applying Chebyshev's inequality to $f=\phi \circ g$. For example, if $g \in L^{p}, p<\infty$ and $\lambda>0$, then

$$
\mu(|g| \geq \lambda)=\mu\left(|g|^{p} \geq \lambda^{p}\right) \leq \lambda^{-p} \mu\left(|g|^{p}\right)<\infty
$$

So we obtain the tail estimate

$$
\mu(|g| \geq \lambda)=O\left(\lambda^{-p}\right), \quad \text { as } \lambda \rightarrow \infty
$$

4.3. Jensen's inequality. Let $I \subseteq \mathbb{R}$ be an interval. A function $c: I \rightarrow \mathbb{R}$ is convex if, for all $x, y \in I$ and $t \in[0,1]$,

$$
c(t x+(1-t) y) \leq t c(x)+(1-t) c(y)
$$

Lemma 4.3.1. Let $c: I \rightarrow \mathbb{R}$ be convex and let $m$ be a point in the interior of $I$. Then there exist $a, b \in \mathbb{R}$ such $c(x) \geq a x+b$ for all $x$, with equality at $x=m$.
Proof. By convexity, for $m, x, y \in I$ with $x<m<y$, we have

$$
\frac{c(m)-c(x)}{m-x} \leq \frac{c(y)-c(m)}{y-m}
$$

So, fixing an interior point $m$, there exists $a \in \mathbb{R}$ such that, for all $x<m$ and all $y>m$

$$
\frac{c(m)-c(x)}{m-x} \leq a \leq \frac{c(y)-c(m)}{y-m}
$$

Then $c(x) \geq a(x-m)+c(m)$, for all $x \in I$.

Theorem 4.3.2 (Jensen's inequality). Let $X$ be an integrable random variable with values in $I$ and let $c: I \rightarrow \mathbb{R}$ be convex. Then $\mathbb{E}(c(X))$ is well defined and

$$
\mathbb{E}(c(X)) \geq c(\mathbb{E}(X))
$$

Proof. The case where $X$ is almost surely constant is easy. We exclude it. Then $m=\mathbb{E}(X)$ must lie in the interior of $I$. Choose $a, b \in \mathbb{R}$ as in the lemma. Then $c(X) \geq a X+b$. In particular $\mathbb{E}\left(c(X)^{-}\right) \leq|a| \mathbb{E}(|X|)+|b|<\infty$, so $\mathbb{E}(c(X))$ is well defined. Moreover

$$
\mathbb{E}(c(X)) \geq a \mathbb{E}(X)+b=a m+b=c(m)=c(\mathbb{E}(X))
$$

We deduce from Jensen's inequality the monotonicity of $L^{p}$-norms with respect to a probability measure. Let $1 \leq p<q<\infty$. Set $c(x)=|x|^{q / p}$, then $c$ is convex. So, for any $X \in L^{p}(\mathbb{P})$,

$$
\|X\|_{p}=\left(\mathbb{E}|X|^{p}\right)^{1 / p}=\left(c\left(\mathbb{E}|X|^{p}\right)\right)^{1 / q} \leq\left(\mathbb{E} c\left(|X|^{p}\right)\right)^{1 / q}=\left(\mathbb{E}|X|^{q}\right)^{1 / q}=\|X\|_{q}
$$

In particular, $L^{p}(\mathbb{P}) \supseteq L^{q}(\mathbb{P})$.
4.4. Hölder's inequality and Minkowski's inequality. For $p, q \in[1, \infty]$, we say that $p$ and $q$ are conjugate indices if

$$
\frac{1}{p}+\frac{1}{q}=1
$$

Theorem 4.4.1 (Hölder's inequality). Let $p, q \in(1, \infty)$ be conjugate indices. Then, for all measurable functions $f$ and $g$, we have

$$
\mu(|f g|) \leq\|f\|_{p}\|g\|_{q} .
$$

Proof. The cases where $\|f\|_{p}=0$ or $\|f\|_{p}=\infty$ are obvious. We exclude them. Then, by multiplying $f$ by an appropriate constant, we are reduced to the case where $\|f\|_{p}=1$. So we can define a probability measure $\mathbb{P}$ on $\mathcal{E}$ by

$$
\mathbb{P}(A)=\int_{A}|f|^{p} d \mu
$$

For measurable functions $X \geq 0$,

$$
\mathbb{E}(X)=\mu\left(X|f|^{p}\right), \quad \mathbb{E}(X) \leq \mathbb{E}\left(X^{q}\right)^{1 / q}
$$

Note that $q(p-1)=p$. Then
$\mu(|f g|)=\mu\left(\frac{|g|}{|f|^{p-1}}|f|^{p}\right)=\mathbb{E}\left(\frac{|g|}{|f|^{p-1}}\right) \leq \mathbb{E}\left(\frac{|g|^{q}}{|f|^{q(p-1)}}\right)^{1 / q}=\mu\left(|g|^{q}\right)^{1 / q}=\|f\|_{p}\|g\|_{q}$.

Theorem 4.4.2 (Minkowski's inequality). For $p \in[1, \infty)$ and measurable functions $f$ and $g$, we have

$$
\|f+g\|_{p} \leq\|f\|_{p}+\|g\|_{p}
$$

Proof. The cases where $p=1$ or where $\|f\|_{p}=\infty$ or $\|g\|_{p}=\infty$ are easy. We exclude them. Then, since $|f+g|^{p} \leq 2^{p}\left(|f|^{p}+|g|^{p}\right)$, we have

$$
\mu\left(|f+g|^{p}\right) \leq 2^{p}\left\{\mu\left(|f|^{p}\right)+\mu\left(|g|^{p}\right)\right\}<\infty .
$$

The case where $\|f+g\|_{p}=0$ is clear, so let us assume $\|f+g\|_{p}>0$. Observe that

$$
\left\||f+g|^{p-1}\right\|_{q}=\mu\left(|f+g|^{(p-1) q}\right)^{1 / q}=\mu\left(|f+g|^{p}\right)^{1-1 / p} .
$$

So, by Hölder's inequality,

$$
\begin{aligned}
\mu\left(|f+g|^{p}\right) & \leq \mu\left(|f||f+g|^{p-1}\right)+\mu\left(|g||f+g|^{p-1}\right) \\
& \leq\left(\|f\|_{p}+\|g\|_{p}\right)\left\||f+g|^{p-1}\right\|_{q} .
\end{aligned}
$$

The result follows on dividing both sides by $\left\||f+g|^{p-1}\right\|_{q}$.

