

L^2 [§ 10.5 in Driver]

Given a measure space $(\Omega, \mathcal{F}, \mu)$,

$$L^2(\Omega, \mathcal{F}, \mu) = \left\{ f: \Omega \rightarrow \mathbb{R} \text{ measurable s.t. } \int_{\Omega} f^2 d\mu < \infty \right\}.$$

Note: for any real numbers f, g ,

$$(|f| - |g|)^2 =$$

Thus, if $f, g \in L^2$, then

I.e. Prop: If $f, g \in L^2$ then

Cor: If μ is a finite measure, then $L^2(\mu) \subseteq L^1(\mu)$.

Cauchy-Schwarz

For $f, g \in L^2(\Omega, \mathcal{F}, \mu)$, define:

$$\|f\|_{L^2} := \left(\int_{\Omega} f^2 d\mu \right)^{1/2}, \quad \langle f, g \rangle_{L^2} := \int_{\Omega} fg d\mu$$

Theorem: If $f, g \in L^2(\Omega, \mathcal{F}, \mu)$, then

$$|\langle f, g \rangle_{L^2}| \leq \int |fg| d\mu \leq \|f\|_{L^2} \|g\|_{L^2}.$$

Pf.

Cor: $L^2(\Omega, \mathcal{F}, \mu)$ is a vector space, and $\|f\|_{L^2} = \sqrt{\langle f, f \rangle_{L^2}}$
is a norm on it.

Pf.

Fact: L^2 is actually a **Hilbert space**: it is (Cauchy) complete.

I.e. If $f_n \in L^2$ s.t. $\|f_n - f_m\|_{L^2} \rightarrow 0$ as $n, m \rightarrow \infty$,

then $\exists ! f \in L^2$ s.t. $\|f_n - f\|_{L^2} \rightarrow 0$.

(The same holds true in L^1 , and in general in L^p for $1 \leq p \leq \infty$.)

We'll return to prove this important fact in the near future.

This will be very important when we make a serious study of **conditional probability**.

Covariance

In a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, $L^2 \subseteq L^1$. In fact

$$\|X\|_{L^1} = \int_{\Omega} |X| d\mathbb{P}$$

Def. For $X, Y \in L^2$, let $\overset{\circ}{X} = X - \mathbb{E}[X]$, $\overset{\circ}{Y} = Y - \mathbb{E}[Y]$

Their **covariance** is

$$\text{Cov}(X, Y) := \mathbb{E}[\overset{\circ}{X}\overset{\circ}{Y}]$$

For $X \in L^2$, its **variance** is

$$\text{Var}(X) := \text{Cov}(X, X) = \mathbb{E}[\overset{\circ}{X}^2]$$

Lemma: If $X \in L^2(\Omega, \mathcal{F}, \mathbb{P})$ and $\text{Var}(X) = 0$,
then $X \equiv \text{Const. a.s.}$

Pf.

E.g. $X \stackrel{d}{=} \mathcal{N}(\alpha, t)$. $X \stackrel{d}{=} \sqrt{t}Z + \alpha$, $Z \stackrel{d}{=} \mathcal{N}(0, 1)$

$$\text{Var}(X) =$$

E.g. $T \stackrel{d}{=} \text{Exp}(\alpha)$, $\mathbb{E}[T] = \frac{1}{\alpha}$

E.g. $N \stackrel{d}{=} \text{Pois}(\alpha)$, $\mathbb{E}[N] = \alpha$

Def: $X, Y \in L^2(\Omega, \mathcal{F}, \mathbb{P})$ are **uncorrelated** if $\text{Cov}(X, Y) = 0$.

In general, their **correlation** is $\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$

Prop: $\text{Cov}(X + \alpha, Y) = \text{Cov}(X, Y + \alpha) = \text{Cov}(X, Y)$

for any $\alpha \in \mathbb{R}$. As a result,

if X_1, \dots, X_n are all (pairwise)

uncorrelated, then

$$\text{Var}(X_1 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n).$$

Pf.

What Does "Uncorrelated" Mean?

Eg. Let $A, B \in \mathcal{F}$, and consider $\mathbb{1}_A, \mathbb{1}_B$

$$\begin{aligned} & \text{Cov}(\mathbb{1}_A, \mathbb{1}_B) \\ &= \mathbb{E}(\mathbb{1}_A \mathbb{1}_B) - \mathbb{E}(\mathbb{1}_A) \mathbb{E}(\mathbb{1}_B) \end{aligned}$$

Eg. Toss a fair coin n times. $X_j = \begin{cases} 1 & \text{if the } j^{\text{th}} \text{ toss is Heads} \\ 0 & \text{if the } j^{\text{th}} \text{ toss is Tails} \end{cases}$

$$\Omega = \{ (\omega_1, \dots, \omega_n) : \omega_j \in \{0, 1\} \}$$

$$\mathcal{F} = 2^\Omega$$

$$\mathbb{P}(A) = \frac{\#A}{2^n}$$