

X inner space (with a norm $\|\cdot\|$)

(\cdot, \cdot) scalar product associated to the norm $\|\cdot\|$

$$\cdot : X \times X \rightarrow \mathbb{R}$$

$$x, y \rightarrow (x, y) = x \cdot y = \langle x, y \rangle \in \mathbb{R}$$

1) symmetric $(x, y) = (y, x)$

2) linear $(x+z, y) = (x, y) + (z, y)$, $(\lambda x, y) = \lambda(x, y)$, $\lambda \in \mathbb{R}$

3) continuous $\text{if } x_n \rightarrow x \text{ in } X \text{ (} \|x_n - x\| \rightarrow 0 \text{)}$

$$(x_n, y) \rightarrow (x, y)$$

4) $|(x, y)| \leq \|x\| \|y\|$ (Cauchy-Schwarz inequality)

it is associated with the norm if

$$(x, x) = \|x\|^2$$

$$\|x\| = \sqrt{(x, x)}$$

Example:

$I \subseteq \mathbb{R}$

$(L^2(I), \|\cdot\|_2)$ is a Hilbert space

$f, g \in L^2(I)$ by Hölder inequality

$$(f, g) = \int_I f(x)g(x) dx < +\infty$$

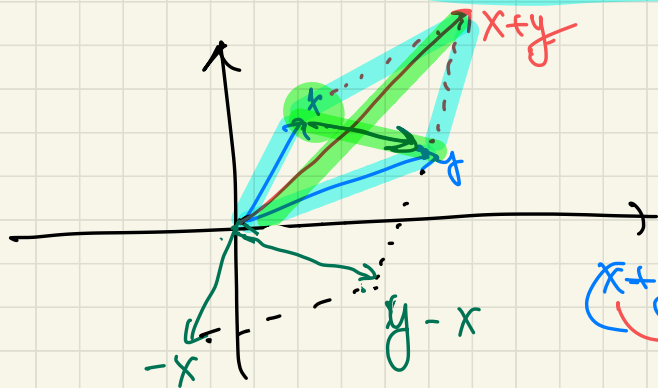
$$|(f, g)| = \left| \int_I f(x)g(x) dx \right| \leq \int_I |f(x)g(x)| dx \stackrel{\text{Hölder}}{\leq} \|f\|_2 \|g\|_2$$

Hölder inequality coincides with the Cauchy-Schwarz inequality

Prop Let $(X, \|\cdot\|)$ be a Banach space.

Then the norm $\|\cdot\|$ is associated to a scalar product if and only if it satisfies the PARALLELOGRAM IDENTITY

$$\forall x, y \in X \quad \|x+y\|^2 + \|x-y\|^2 = 2\|x\|^2 + 2\|y\|^2$$



$X = \mathbb{R}^2$

$$(x+y, x+y) + (x-y, x-y) = 2(x, x) + 2(y, y)$$

Examples of Banach spaces

$$I \subseteq \mathbb{R}$$

$$L^p(I), \|\cdot\|_p$$

$$f \in L^p(I) \Leftrightarrow \int_I |f(x)|^p dx < +\infty$$

$$\|f\|_p = \left[\int_I |f(x)|^p dx \right]^{1/p}$$

$$L^\infty(I), \|\cdot\|_\infty$$

$$f \in L^\infty(I) \quad \exists C \quad \sup_{x \in I} |f(x)| \leq C$$

$$\|f\|_\infty = \sup_{x \in I} |f(x)|$$

$$\underline{C(I)}, \|\cdot\|_\infty$$

$$f \in C(I) \text{ if } f \text{ is continuous in } \overline{I}, \quad \|f\|_\infty = \max_{x \in \overline{I}} |f(x)|$$

THE UNIQUE HILBERT SPACE is $(L^2(I), \|\cdot\|_2)$

Example of Borel spaces.

$(\Omega, \mathcal{F}, \mathbb{P})$ a probability space

\mathcal{F} filtration (a σ -algebra collecting all events)

Ω is a set

\mathbb{P} is a probability measure on Ω

$$\mathbb{P} : \mathcal{F} \rightarrow [0, +\infty]$$

$$A \mapsto \mathbb{P}(A)$$

$$X : (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow \mathbb{R}$$

measurable
(RANDOM VARIABLE)

X is "transporting" \mathbb{P} measure to a measure on \mathbb{R} . $B \in \mathcal{B}(\mathbb{R})$

$$\underbrace{\mathbb{P}_X(B)}_{\text{Borel measure on } \mathbb{R}} = \mathbb{P} \{ \omega \mid X(\omega) \in B \} = \mathbb{P}(X^{-1}(B))$$

$\underline{M}^1 = \{ X \text{ random variables on } (\Omega, \mathcal{F}, \mathbb{P}) \text{ such that } \mathbb{E}(X) < +\infty \}$ (it is a vectorial space on \mathbb{R})

$$\mathbb{E}(X) = \int_{\mathbb{R}} x d\mathbb{P}_X(x)$$

What is $\mathbb{E}(X)$?

→ X is discrete (with a finite number of values)

$$\mathbb{P}(\omega \mid X(\omega) = i) = \underbrace{\mathbb{P}_X\{i\}}_{\text{}} \quad i = 1 \dots k$$

$$\mathbb{E}(X) = \sum_{i=1}^k \mathbb{P}_X\{i\} \cdot i$$

$$\mathbb{P}_X = \sum_{i=1}^k \mathbb{P}(\omega \mid X(\omega) = i) \cdot \delta_{\{i\}}$$

→ X is absolutely continuous

$\mathbb{P}_X \ll \mathcal{L}$ (Lebesgue m.)

\mathbb{P}_X has a density f_X

$$\mathbb{E}(X) = \int_{\mathbb{R}} x f_X(x) dx$$

$M^1 = \{ X \text{ random variables, } \mathbb{E}(X) < +\infty \}$

is a vectorial space

$$X_1, X_2 \quad \lambda X_1 + \mu X_2 \in M^1$$

$$\mathbb{E}(X_1 + X_2) = \mathbb{E}(X_1) + \mathbb{E}(X_2) \dots$$

$\|X\|_1 = \mathbb{E}(|X|)$ this is a norm on M^1

1) $\mathbb{E}|X| = 0 \iff |X| = 0$ with probability 1.

2) $\mathbb{E}|\lambda X| = |\lambda| \mathbb{E}(|X|) \quad \forall \lambda \in \mathbb{R}$.

3) $\mathbb{E}(|X+Y|) \leq \mathbb{E}(|X| + |Y|) = \mathbb{E}|X| + \mathbb{E}|Y|$.

Def. $X_n \rightarrow X$ in mean if $X_n \rightarrow X$ in M^1 , that is $E(|X_n - X|) \rightarrow 0$

$(M^1, \|\cdot\|_1)$ is a Banach space.

Obs $\|\cdot\|_1$ is NOT ASSOCIATED TO any scalar product

It is sufficient to show that the parallelogram identity is not satisfied for some $X, Y \in M^1$.

Example

X Bernoulli of parameter $p \in (0, 1)$, $X: \Omega \rightarrow \{0, 2\} \subseteq \mathbb{R}$
 $\{\omega \mid X(\omega) = 0\} = \mathcal{A}$ $\{\omega \mid X(\omega) = 2\} = \mathcal{A}^c$
 $P(\mathcal{A}) = p$ $P(\mathcal{A}^c) = 1 - p$

$$E|X| = E(X) = p \cdot 0 + (1-p) \cdot 2 = 2(1-p) = 2 - 2p$$

Y Bernoulli of parameter $p \in (0, 1)$, $Y: \Omega \rightarrow \{1, 3\} \subseteq \mathbb{R}$

$$\{\omega \mid Y(\omega) = 1\} = p \quad \{\omega \mid Y(\omega) = 3\} = 1-p$$

$$E(Y) = E(Y) = p \cdot 1 + (1-p) \cdot 3 = p + 3 - 3p = 3 - 2p$$

$$X+Y: \Omega \rightarrow \{1, 3, 5\}$$

$$Y-X: \Omega \rightarrow \{1, -1, 3\} \quad |Y-X|: \Omega \rightarrow \{1, 2\}$$

$$P(\omega \mid X+Y=1) = P(X(\omega)=0) P(Y(\omega)=1) = p^2$$

$$P(\omega \mid X+Y=3) = P(X(\omega)=0) P(Y(\omega)=3) + P(X(\omega)=2) P(Y(\omega)=1) \\ = p \cdot (1-p) + (1-p) p = 2p - 2p^2$$

$$P(\omega \mid X+Y=5) = P(X(\omega)=2) P(Y(\omega)=3) = (1-p)(1-p) \\ = (1-p)^2$$

$$E(X+Y) = E|X+Y| = 1 \cdot p^2 + 3 \cdot (2p - 2p^2) + 5(1-p)^2 =$$

$$= \cancel{p^2} + 6p - \cancel{6p^2} + 5 + \cancel{5p^2} - 10p = 5 - 4p$$

$$\begin{aligned} P(Y-X=1) &= P(Y(\omega)=1)P(X(\omega)=0) + P(Y(\omega)=3)P(X(\omega)=2) \\ &= p \cdot p + (1-p)(1-p) = p^2 + 1 + p^2 - 2p = \\ &= 2p^2 + 1 - 2p \end{aligned}$$

$$P(Y-X=-1) = P(Y(\omega)=1)P(X(\omega)=2) = p \cdot (1-p) = p - p^2$$

$$\begin{aligned} P(|Y-X|=1) &= P(Y-X=1) + P(Y-X=-1) = \\ &= 2p^2 + 1 - 2p + p - p^2 = p^2 - p + 1 \end{aligned}$$

$$P(|Y-X|=3) = P(Y=3)P(X=0) = (1-p) \cdot p = p - p^2$$

$$\begin{aligned} E(|Y-X|) &= 1 \cdot (p^2 - p + 1) + 3(p - p^2) = \\ &= p^2 - p + 1 + 3p - 3p^2 = 2p - 2p^2 + 1 \end{aligned}$$

$$\begin{aligned} [\mathbb{E}(|X+Y|)]^2 + [\mathbb{E}(|X-Y|)]^2 &= \|X+Y\|_1^2 + \|X-Y\|_1^2 = \\ &= (5-4p)^2 + (2p-2p^2+1)^2 \end{aligned}$$

$$\begin{aligned} &\neq 2(2-2p)^2 + 2(3-2p)^2 = 2\|X\|_1^2 + 2\|Y\|_1^2 \\ &= 2[\mathbb{E}(|X|)]^2 + 2(\mathbb{E}(|Y|))^2 \end{aligned}$$

So the parallelogram identity is NOT VERIFIED

$\|\cdot\|_1$ is NOT ASSOCIATED TO A SCALAR

PRODUCT $\Rightarrow (M^1, \|\cdot\|_1)$ is NOT Hilbert!

We introduce the following space:

$$M^2 = \{ X \text{ random variables} \mid \begin{array}{l} \mathbb{E}(X^2) < +\infty \\ \mathbb{E}(X) < +\infty \end{array} \}$$

$$\downarrow \\ \|X\|_2 = \left[\mathbb{E}(|X|^2) \right]^{1/2}$$

this is a NORM on the space M^2 .

Def: We say that $X_n \rightarrow X$ in **MEAN SQUARE** if

$$\|X_n - X\|_2 \rightarrow 0 \quad \text{that is} \quad \mathbb{E}[(X_n - X)^2] \rightarrow 0 \quad \text{as } n \rightarrow +\infty$$

Note that:

$$\mathbb{E}(X \cdot X) = \|X\|_2^2.$$

We define the scalar product $M^2 \times M^2 \rightarrow \mathbb{R}$

$$X, Y \rightarrow \mathbb{E}(X \cdot Y)$$

We need to prove that $\forall X, Y \in M^2, \mathbb{E}(X \cdot Y) < +\infty$.

proof:

$$a = \frac{|x|}{[\mathbb{E}|x|^2]^{1/2}}$$

$$b = \frac{|y|}{[\mathbb{E}|y|^2]^{1/2}}$$

YOUNG $ab \leq \frac{1}{2} a^2 + \frac{1}{2} b^2$

$$\frac{|x||y|}{([\mathbb{E}|x|^2]^{1/2} [\mathbb{E}|y|^2]^{1/2})} \leq \frac{1}{2} \frac{|x|^2}{\mathbb{E}|x|^2} + \frac{1}{2} \frac{|y|^2}{\mathbb{E}|y|^2}$$

→ take the expected values

$$\frac{\mathbb{E}(|x||y|)}{([\mathbb{E}|x|^2]^{1/2} [\mathbb{E}|y|^2]^{1/2})} \leq \frac{1}{2} \frac{\mathbb{E}|x|^2}{\mathbb{E}|x|^2} + \frac{1}{2} \frac{\mathbb{E}|y|^2}{\mathbb{E}|y|^2} = \frac{1}{2} + \frac{1}{2} = 1$$

$$|\mathbb{E}(xy)| \leq \mathbb{E}|xy| \leq [\mathbb{E}|x|^2]^{1/2} [\mathbb{E}|y|^2]^{1/2} < +\infty \quad \text{since } x, y \in M^2$$

So $(M^2, \|\cdot\|_2)$ is a HILBERT SPACE

~~Def~~ $X, Y \in M^2$ X is orthogonal to Y if

$$\mathbb{E}(X \cdot Y) = 0$$

$$C \subseteq M^2 \quad C^\perp = \{ Y \in M^2 \text{ such that } \mathbb{E}(X \cdot Y) = 0 \\ \forall X \in C \}$$

Example $C = \{ X \in M^2 \mid \mathbb{E}(X) = 0 \}$

$C^\perp = ?$ We prove that $C^\perp = \{ \text{constant random variables} \}$.

1) if $Y \equiv c$ constant then

$$\mathbb{E}(X \cdot Y) = c \mathbb{E}(X) = 0 \quad \forall X \in C.$$

2) if Y is such that $\mathbb{E}(X \cdot Y) = 0 \quad \forall X \in C \Rightarrow$

$$\Rightarrow \mathbb{E}(X \cdot (Y - \mathbb{E}(Y))) = \underbrace{\mathbb{E}(X \cdot Y)}_0 - \mathbb{E}(Y) \cdot \underbrace{\mathbb{E}(X)}_0 = 0$$

$\forall X \in \mathcal{C}$



but $Y - \mathbb{E}(Y) \in \mathcal{C}$ since $\mathbb{E}(Y - \mathbb{E}(Y)) = 0!$

$$\text{so } \mathbb{E}((Y - \mathbb{E}(Y))(Y - \mathbb{E}(Y))) = 0$$

$$\mathbb{E}(|Y - \mathbb{E}(Y)|^2) = 0 \Rightarrow |Y - \mathbb{E}(Y)|^2 = 0 \text{ with probability 1}$$

$\Rightarrow Y = \mathbb{E}(Y)$ with probability one

$\rightarrow Y$ is constant.

$(\Omega, \mathcal{F}, \mathbb{P})$

\mathcal{G} filtration

$\mathcal{G} \subseteq \mathcal{F}$

\mathcal{G} a sub filtration

\mathcal{G} is a σ -algebra

$M^2_{\mathcal{G}} = \{ \bar{X} \in M^2 \text{ such that } X \text{ is meas. with resp to } \mathcal{G} \}$

$\bar{X}: (\Omega, \underline{\mathcal{G}}, \mathbb{P}) \rightarrow \mathbb{R}$ is a measurable function:

$\forall B \in \mathcal{B}(\mathbb{R}) \quad X^{-1}(B) = \{ \omega \mid X(\omega) \in B \} \in \mathcal{G} \subseteq \mathcal{F} \} \subseteq M^2$

($M^2_{\mathcal{G}}$ is a closed subspace of M^2).

ORTHOGONAL PROJECTION THEOREM.

$$M^2 = (M^2_{\mathcal{F}}, \|\cdot\|_2)$$

$\mathcal{G} \subseteq \mathcal{F}$ (\mathcal{G} is a σ -algebra contained in \mathcal{F}).

$M^2_{\mathcal{G}}$ is a closed subspace of M^2 .

$\forall \underline{X} \in M^2 \quad \exists \underline{Y} \in M^2_{\mathcal{G}}$ such that

$$d(\underline{X}, \underline{Y}) = \|\underline{X} - \underline{Y}\|_2 = \left[\mathbb{E} (\underline{X} - \underline{Y})^2 \right]^{1/2} =$$

$$= \min_{\underline{Z} \in M^2_{\mathcal{G}}} \left[\mathbb{E} (\underline{X} - \underline{Z})^2 \right]^{1/2} = \min_{\underline{Z} \in M^2_{\mathcal{G}}} d(\underline{X}, \underline{Z}).$$

$\underline{X} - \underline{Y}$ is orthogonal to M_g^2

$$(\underline{X} = Y + W \quad W \in (M_g^2)^\perp)$$

$\underline{Y} = E(X | \mathcal{G})$ = conditional expectation of X given \mathcal{G}

= best estimator of X , given the information contained in the filtration \mathcal{G} .

Y is MEASURABLE with respect to \mathcal{G} .

$X - \mathbb{E}(X|G)$ is orthogonal to every element
of M^2_G

$$\left[\begin{array}{l} X - \mathbb{E}(X|G) \perp \mathbb{E}(X|G) \in M^2_G \\ \Rightarrow \mathbb{E}((X - \mathbb{E}(X|G)) \cdot \mathbb{E}(X|G)) = 0 \\ \mathbb{E}(X \mathbb{E}(X|G)) = \mathbb{E}([\mathbb{E}(X|G)]^2) \end{array} \right.$$

$\forall Z \in M^2_G$

$$\mathbb{E}((X - \mathbb{E}(X|G))Z) = 0$$

observe that every constant random variable
is in M^2_G for every G σ -algebra

take Z constant r.v.

$$\boxed{Z(\omega) \equiv c \quad \forall \omega}$$

$$\forall B \in \mathcal{B}(\mathbb{R}) \quad Z^{-1}(B) = \{\omega \mid \overbrace{Z(\omega)}^c \in B\} = \{\omega \mid c \in B\}$$

$$= \begin{cases} \emptyset & \text{if } c \notin B \\ \Omega & \text{if } c \in B \end{cases}$$

if Z is constant $\Rightarrow Z \in M^2_{\mathcal{G}}$ $\forall \mathcal{G}$ σ -algebra

because $\forall \mathcal{G}$ σ -algebra, $\emptyset, \Omega \in \mathcal{G}$

$$\mathbb{E}((X - \mathbb{E}(X|\mathcal{G})) \cdot c) = 0 \Rightarrow \mathbb{E}(X) = \mathbb{E}(\mathbb{E}(X|\mathcal{G}))$$

(apply the orthogonality cond to $Z(\omega) \equiv c$)

A particular case is the following.

$$\text{fix } Z \in M^2$$

$$Z^{-1}(B) = \{\omega \mid Z(\omega) \in B\} \in \mathcal{F}$$

$\mathcal{G}(Z)$ = filtration generated by $Z =$

= smallest σ -algebra which contains

all the elements $Z^{-1}(B)$ for $B \in \mathcal{B}(\mathbb{R})$

Example:

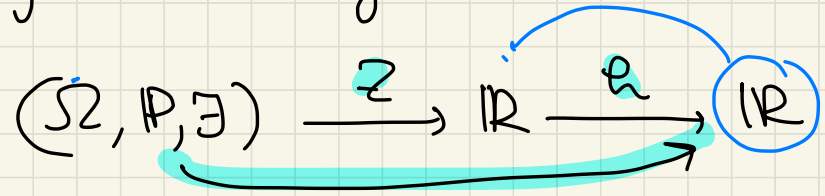
if $Z \equiv c$ (Z constant)

$$\mathcal{G}(Z) = \{\emptyset, \Omega\}$$

So for $X \in M^2$ $\exists!$ $\mathbb{E}(X | \mathcal{G}(Z)) = \mathbb{E}(X | Z)$ CONDITIONAL EXPECTATION

The orthogonal projection of X on

$M^2_{\mathcal{G}(Z)}$.



$$M^2_{\mathcal{G}(Z)} = \left\{ Y \in M^2 \text{ such that } Y \text{ is measurable w.r. to } \mathcal{G}(Z). \right.$$

$$\left. Y^{-1}(B) = \{ \omega \mid Y(\omega) \in B \} \in \mathcal{G}(Z) \right\} =$$

$$= \left\{ \underbrace{h(Z)}_{\text{Borel measurable}}, \text{ for } h: \mathbb{R} \rightarrow \mathbb{R} \text{ Borel measurable} \right\}$$

$$\mathbb{E}((h(Z))^2) < +\infty.$$

Since $M^2_{\mathcal{G}}(Z) = \{h(Z), \quad h: \mathbb{R} \rightarrow \mathbb{R} \text{ Borel measurable}\}$

$\mathbb{E}(X|Z) = h(Z)$ where $h: \mathbb{R} \rightarrow \mathbb{R}$ is the

function which minimizes:

$$\underbrace{\mathbb{E}(|X - h(Z)|^2)}_{[\text{dist}(X, h(Z))]^2} = \min_{\substack{g: \mathbb{R} \rightarrow \mathbb{R} \\ g \text{ measurable}}} \underbrace{\mathbb{E}(|X - g(Z)|^2)}_{(\text{dist}(X, g(Z)))^2}$$

$h(Z) = \mathbb{E}(X|Z)$ is the BEST ESTIMATOR of X given Z : it is a function of Z which has minimal distance (in $\|\cdot\|_2$ sense) from X .

$E(X|Z) = h(Z)$ where

$$\frac{E(|X - E(X|Z)|^2)}{E|X - h(Z)|^2} = \min_{\substack{g: \mathbb{R} \rightarrow \mathbb{R} \\ \text{measurable}}} E(|X - g(Z)|^2)$$

instead of MINIMIZING AMONG ALL POSSIBLE MEASURABLE functions g , I RESTRICT the set (IMPOSING a CONSTRAINT).

↓
I impose the constraint that g is LINEAR:

$$g: \mathbb{R} \rightarrow \mathbb{R} \text{ linear} \Leftrightarrow g(x) = Ax + B \quad \forall x \\ \text{for } A, B \in \mathbb{R}.$$

I consider this other problem

$$\min_{g(z)=Az+B} \mathbb{E}(|X-g(z)|^2) = \min_{(A,B) \in \mathbb{R}^2} \mathbb{E}(|X-Az-B|^2)$$

$$= \mathbb{E}(|X-\bar{A}z-\bar{B}|^2) \quad (\bar{A} \ \bar{B} \text{ MINIMUM})$$

$\bar{A}z + \bar{B}$ is the BEST LINEAR ESTIMATOR of X given z (it is not the best possible estimator of X , which is $\mathbb{E}(X|Z) = h(Z)$ h in general NOT LINEAR..)

$$\therefore \bar{A} = \frac{\text{Cov}(X, Z)}{\text{Var}(Z)} \quad \bar{B} = \mathbb{E}(X) \cdot \begin{bmatrix} 1 - \frac{\text{Cov}(X, Z)}{\text{Var}(Z)} \\ \dots \\ \text{Var}(Z) \end{bmatrix}$$

How to find \bar{A}, \bar{B} ?

$$E(X - AZ - B)^2 =$$

$$E(X)^2 + A^2 E(Z)^2 + B^2 - 2A E(XZ) - 2B E(X) + 2AB E(Z)$$

$$F(A, B) = E(X)^2 + A^2 E(Z)^2 + B^2 - 2A E(XZ) - 2B E(X) + 2AB E(Z)$$

$$F: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$\frac{\partial F}{\partial A} = 0$$

$$\frac{\partial F}{\partial B} = 0$$

$$D^2 F = \begin{pmatrix} \frac{\partial^2 F}{\partial A^2} & \frac{\partial^2 F}{\partial A \partial B} \\ \frac{\partial^2 F}{\partial A \partial B} & \frac{\partial^2 F}{\partial B^2} \end{pmatrix}$$

$$\text{If } z \equiv c \quad \underbrace{g(z) = \{\Omega, \phi\}}$$

$$\mathbb{E}(X | g(z)) = \mathbb{E}(X).$$

$$M^2 \quad g(z) = \{\text{constant random variable}\}$$