Mathematics and numerics for data assimilation and state estimation – Lecture 7

Summer semester 2020

Summary of lecture 6

- Recurrence and construction of invariant distributions for finite discrete-time Markov chains.

- Prediction, filtering and smoothing of Markov Chains

Overview

1. Random variables on $\mathbb{R}^d$

2. Conditional probability density functions

3. $L^2(\Omega)$, sub-σ-algebras and projections

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1. Random variables on $\mathbb{R}^d$

2. Conditional probability density functions

3. $L^2(\Omega)$, sub-σ-algebras and projections

Extending definitions from discrete to continuous state-space rv

- Given $(\Omega, \mathcal{F}, \mathbb{P})$, recall that a discrete rv $X : \Omega \to A$ was defined by measurability constraint

$$X^{-1}(a) \in \mathcal{F} \quad \forall a \in A.$$

- And $\mathbb{P}_X(a) := \mathbb{P}(X = a)$ is a probability measure on the measurable space $(A, \mathcal{A})$ where

$$\mathcal{A} = \sigma(\{a_k\}) := \text{smallest } \sigma\text{-algebra containing the sets } \{a_1\}, \{a_2\}, \ldots$$

- Example elements of $C \in \mathcal{A} : \{a_1, a_2\}, \ldots$
- An equivalent definition of discrete rv that extends to the continuous state-space setting: X is a **measurable** mapping between measurable spaces $X : (\Omega, \mathcal{F}) \to (A, \mathcal{A})$, meaning that

$$X^{-1}(C) \in \mathcal{F} \quad \forall C \in \mathcal{A}.$$

Random values/vectors (rv) on $\mathbb{R}^d$

- For a mapping $X : \Omega \to \mathbb{R}^d$ what sets $C \subset \mathbb{R}^d$ are relevant, in the sense that we seek the probability of events

$$\{X \in C\} = \{\omega \in \Omega \mid X(\omega) \in C\}?$$

- If all open sets in $\mathbb{R}^d$ are relevant, then we should be able to evaluate

$$\mathbb{P}_X(C) = \mathbb{P}(X \in C) \quad \text{for all open } C \subset \mathbb{R}^d,$$

- and $\mathbb{P}_X$ should be a probability measure on $(\mathbb{R}^d, \sigma(\text{all open sets in } \mathbb{R}^d))$.
- the above is called the Borel σ-algebra:

$$\mathcal{B}^d := \text{smallest } \sigma\text{-algebra containing all open sets in } \mathbb{R}^d.$$

Random variables/vectors on $\mathbb{R}^d$

Definition 1

An rv on $\mathbb{R}^d$ is a measurable mapping $X : (\Omega, \mathcal{F}) \to (\mathbb{R}^d, \mathcal{B}^d)$ satisfying,

$$\{X \in C\} = X^{-1}(C) \in \mathcal{F} \quad \forall C \in \mathcal{B}^d.$$

Comments:

- The definition extends to measurable mappings $X : (\Omega, \mathcal{F}) \to (\mathbb{S}, \mathcal{S})$ for any measurable space $(\mathbb{S}, \mathcal{S})$.
- We will only consider rv on $(\mathbb{R}^d, \mathcal{B}^d)$, and often just write

$$X : \Omega \to \mathbb{R}^d.$$

Example 2 (Uniform distribution)

- Let $X \sim U[0,1]^d$ denote the rv on $\mathbb{R}^d$ with

$$\mathbb{P}(X \in C) = \mathrm{Leb}(C \cap [0,1]^d) = \int_C \mathbb{1}_{[0,1]^d}(x)\, \mathrm{Leb}(dx) \qquad (1)$$

for any $C \subset \mathbb{R}^d$ and with $\mathrm{Leb}(\cdot)$ being the Lebesgue measure on $\mathbb{R}^d$.

- This measure associates to volumes of sets: for instance, for any $C = (a_1, b_1) \times (a_2, b_2) \times \ldots \times (a_d, b_d)$,

$$\mathrm{Leb}(C) = \prod_{k=1}^{d} (b_k - a_k).$$

- From now on $dx := \mathrm{Leb}(dx)$, and we rewrite (1) with a density:

$$\mathbb{P}(X \in C) = \int_C \mathbb{1}_{[0,1]^d}(x)\, dx$$

Probability density function (pdf)

Definition 3

- Consider an rv $X \sim \mathbb{P}_X$ on $\mathbb{R}^n$.
- If there exists a mapping $\pi : \mathbb{R}^d \to [0, \infty)$ such that

$$\mathbb{P}_X(C) = \int_C \pi(x)\, dx \quad \forall C \in \mathbb{R}^d,$$

  then π is called the **pdf** of X.
- X has a pdf whenever $\mathbb{P}_X$ is absolutely continuous wrt the Lebesgue measure, meaning that for all $C \in \mathcal{B}^d$,

$$\text{if} \quad dC = \text{Leb}(C) = 0, \qquad \text{then also} \qquad \mathbb{P}_x(C) = 0.$$

- And then

$$\pi(x) = \frac{\mathbb{P}_X(dx)}{dx}, \quad dx\text{"} = \text{"tiny set surrounding } x \in \mathbb{R}^d.$$

- An rv with a pdf is called a **continuous** rv.

Example 4 (Uniform rv)

For $X \sim U[0,1]^d$, we have

$$\mathbb{P}_X(C) = \int_C \mathbb{1}_{[0,1]^d}(x)\, dx$$

pdf derived from the Radon-Nikodym derivative:

$$\pi(x) = \frac{\mathbb{P}_X(dx)}{dx} = \frac{\mathbb{1}_{[0,1]^d}(x)dx}{dx} = \begin{cases} 0 & x \in (-\infty, 0) \cup (1, \infty) \\ ? & x \in \{0,1\} \\ 1 & \in (0,1) \end{cases}$$

Value of $\pi|_{\{0,1\}}$ does not matter, whatever value we assign on this measure 0 set, π will be the very same pdf:

$$\mathbb{P}(X \in C) = \int_C \pi(y)\, dy \quad \forall C \in \mathcal{B}^d.$$

So let us write $\pi(x) = \mathbb{1}_{[0,1]^d}(x)$.

Example 5 (Real-valued normal distribution)

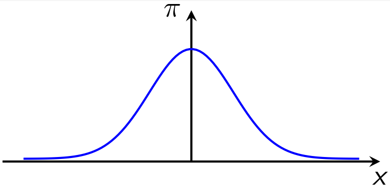
- Let $X \sim N(\mu, \sigma^2)$ denote the normal disribution on $\mathbb{R}$ with

$$\mathbb{P}(X \in C) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_C \exp\left(-\frac{(x-\mu)^2}{2\sigma^2} \right) dx$$

where $\mu \in \mathbb{R}$ and $\sigma > 0$.

pdf:

$$\pi(x) = \frac{\exp\left(-\frac{(x-\mu)^2}{2\sigma} \right)}{\sqrt{2\pi\sigma^2}}$$



Example 6 (Multivariate normal distribution)

- Let $X \sim N(\mu, \Sigma)$ denote the rv on $\mathbb{R}^d$ with

$$\mathbb{P}(X \in C) = \frac{1}{(2\pi)^{d/2}\sqrt{\det(\Sigma)}} \int_C \exp\Big(- \frac{(x-\mu)\cdot \Sigma^{-1}(x-\mu)}{2}\Big)\, dx$$

- With the pdf:

$$\pi(x) = \frac{1}{(2\pi)^{d/2}\sqrt{\det(\Sigma)}} e^{-|x-\mu|^2_{\Sigma}/2}$$

Consider $X \sim N((0,0), \Sigma)$ on $\mathbb{R}^2$ with

$$\Sigma = [u_1 \ u_2] \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} [u_1 \ u_2]^T$$

u_1, u_2 orthonormal basis.

Contour plot:

Cumulative distribution function (cdf)

Definition 7

The cdf of a d-dimensional rv $X = (X_1, X_2, \ldots, X_d)$ is defined by

$$F_X(x) = F_X(x_1, \ldots, x_d) = \mathbb{P}(X_1 \leq x_1, X_2 \leq x_2, \ldots, X_d \leq x_d) \quad \text{for } x \in \mathbb{R}^d.$$

Whenever X is continuous F_X is a primitive of π:

$$F_X(x) = \int_{-\infty}^{x_1} \ldots \int_{-\infty}^{x_d} \pi(y_1, \ldots, y_d)\, dy_1 \ldots dy_d$$

And in general, the cdf has the following properties:

- F_X is non-decreasing and right continuous in each of its variables
- $$\lim_{x_1, x_2, \ldots, x_d \to -\infty} F_X(x) = 0 \quad \text{and} \quad \lim_{x_1, x_2, \ldots, x_d \to \infty} F_X(x) = 1.$$

Example 8 (Discrete rv)

$X \sim \mathit{Bernoulli}(1/2)$ yields

$$F(x) = \begin{cases} 0, & x < 0 \\ 1/2, & x \in [0, 1) \\ 1, & x > 1 \end{cases}$$

and formally

$$\pi(x) = F'(x) = 0.5\delta_0(x) + 0.5\delta_2(x).$$

Example 9 (Sum of discrete and continuous rv that becomes ...)

Let $X = Y + 2Z$ where $Y \sim U[0,1]$ and $Z \sim \mathit{Bernoulli}(1/2)$ are independent. Then

$$F(x) = \mathbb{P}(Y + 2Z \leq x) = \begin{cases} 0 & \text{if } x < 0 \\ x/2 & \text{if } x \in [0,1] \\ 1/2 & \text{if } x \in [1,2) \\ (x-1)/2 & \text{if } x \in [2,3) \\ 1 & \text{if } x \geq 3 \end{cases}$$

and

$$\pi(x) = F'(x) = \frac{1}{2}\mathbb{1}_{[0,1]\cup[2,3]}(x).$$

(Formally,

$$\pi(x) = \pi_Y * \pi_{2Z}(x)$$

where $\pi_{2Z} = 0.5\delta_0(x) + 0.5\delta_2(x)$.)

Joint pdfs and cdfs

For rv $X : \Omega \to \mathbb{R}^d$ and $Y : \Omega \to \mathbb{R}^k$,

- the mapping $(X, Y) : (\Omega, \mathcal{F}) \to (\mathbb{R}^{d+k}, \mathcal{B}^{d+k})$ is also an rv
- with joint cdf
$$F_{XY}(x, y) = \mathbb{P}(X \leq x, Y \leq y)$$
where $X \leq x$ etc. should be read component-wise for vectors
- and, whenever (X, Y) is continuous, the joint pdf
$$\pi_{XY}(x, y) = \frac{\mathbb{P}(X \in dx, Y \in dy)}{dx\, dy}.$$
- To avoid clutter, one often suppresses XY subscripts.

Joint pdfs and cdfs

The notation extends naturally to the joint distribution of a sequence of rv $\{X_k\}$,

$$\begin{aligned} F(x_1, \ldots, x_n) &:= \mathbb{P}(X_1 \leq x_1, \ldots, X_n \leq x_n) \\ &= \int_{y_1 \leq x_1, \ldots, y_n \leq x_n} \pi(y_1, \ldots, y_n) dy_1 \ldots dy_n, \end{aligned}$$

where the last equality with the pdf π is valid when $(X_1, \ldots, X_n)$ is continuous.

Independence of rv

A finite sequence of rv $X_k : (\Omega, \mathcal{F}) \to (\mathbb{R}^d, \mathcal{B}^d)$ for $k = 1, \dots, n$ is independent if

- $$\mathbb{P}(X_1 \in C_1, \dots, X_n \in C_n) = \prod_{k=1}^{n} \mathbb{P}(X_k \in C_k)$$

  for all $C_1, \dots, C_n \in \mathcal{B}^d$.
- or equivalently, if

  $$F(x_1, x_2, \dots, x_n) = \prod_{k=1}^{n} F_{X_k}(x_k) \quad \forall x_1, x_2, \dots, x_n \in \mathbb{R}^d,$$

- or, if all X_k are continuous, equivalently if

  $$\pi(x_1, x_2, \dots, x_n) = \prod_{k=1}^{n} \pi_{X_k}(x_k) \quad \text{for almost all} \quad x_1, x_2, \dots, x_n \in \mathbb{R}^d$$

- A countable sequence of rv $\{X_k\}$ is independent if any of the above conditions hold for any finite subsequence.

Expectations of rv

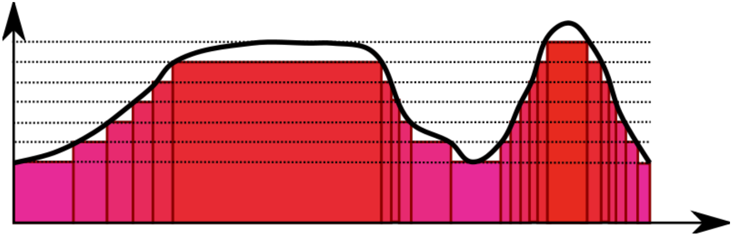
The expectation of $X : \Omega \to \mathbb{R}^d$ is defined by

$$\mathbb{E}[X] = \int_\Omega X(\omega)\,\mathbb{P}(d\omega)$$

where for non-negative $X = (X_1, \ldots, X_d)$, each component of the right side is defined by

$$\int_\Omega X_j \, d\mathbb{P} := \sup_{Y \leq X_j, Y \text{ simple}} \int_\Omega Y \, d\mathbb{P}$$

where "simple" $= \{ Y : (\Omega, \mathcal{F}) \to (\mathbb{R}, \mathcal{B}) \mid Y \text{ is simple } \}$.



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where "simple" $= \{ Y : (\Omega, \mathcal{F}) \to (\mathbb{R}, \mathcal{B}) \mid Y \text{ is simple } \}$.
And in general,

$$\int_\Omega X_j \, d\mathbb{P} := \underbrace{\int_\Omega X_j^+ \, d\mathbb{P}}_{I_j^+} - \underbrace{\int_\Omega X_j^- \, d\mathbb{P}}_{I_j^-}$$

where

$$X_j^+ = \max\{X_j, 0\} \quad \text{and} \quad X_j^- = \max\{-X_j, 0\}.$$

Observation: $\mathbb{E}[X_j]$ exists whenever at least one of I_j^+ and I_j^- are finite.

Covariance function

- The definition extends straightforwardly to functions of rv:
$$\mathbb{E}\left[g(X)\right] = \int_{\Omega} g(X(\omega))\,\mathbb{P}(d\omega)$$
- Whenever $\mathbb{E}\left[g(X)\right]$ exists, the change of variables formula yields the equivalent representations (Durrett, Theorem 1.6.9)
$$\mathbb{E}\left[g(X)\right] = \int_{\mathbb{R}^d} g(x) dF_x(x) = \int_{\mathbb{R}^d} g(x)\pi_X(x)\,dx$$
(last equality valid when π_X exists).

Main idea of proof:

1. In the $1D$ setting with $g(X) = \sum_{a\in A} g(a)\mathbb{1}_{X=a}$, then

$$\mathbb{E}\left[g(X)\right] =$$

2. For non-discrete rv, approximate by sequence of simple functions.

Covariance function

- In what remains, we will assume that the rvs are continuous so that we can employ pdfs in the expectations of rv.
- The covariance of the d-dimensional rv X with mean μ is the $d \times d$ matrix defined by

$$\mathrm{Cov}(X) = \mathbb{E}\left[(X-\mu)(X-\mu)^T\right] = \int_{\mathbb{R}}^{d} (x-\mu)(x-\mu)^T \pi_X(x)dx$$

- In the special case of 1-dimensional rv, $\mathrm{Cov}(X) = \mathrm{Var}(X)$

Example 10

$X \sim U[0,1]$, yields

$$\mathbb{E}[X] = \int_{\mathbb{R}} x\mathbb{1}_{[0,1]}(x)dx = 1/2$$

and

$$\mathrm{Var}(X) = \int_{\mathbb{R}} (x-1/2)^2 \mathbb{1}_{[0,1]}(x)dx = 1/12.$$

Example 11 (Multivariate normal distribution)

For $X \sim N(\mu, \Sigma)$ with

$$\pi_X(x) = \frac{1}{(2\pi)^{d/2}\sqrt{\det(\Sigma)}} e^{-(x-\mu)\cdot\Sigma^{-1}(x-\mu)/2},$$

one can show that

$$\mathbb{E}\left[X\right] = \mu$$

and

$$\mathrm{Cov}(X) = \Sigma.$$

Overview

1. Random variables on $\mathbb{R}^d$
2. Conditional probability density functions
3. $L^2(\Omega)$, sub-σ-algebras and projections

Marginal and conditional densities

For a continuous rv $(X, Y) : \Omega \to \mathbb{R}^d \times \mathbb{R}^k$, we define

- the marginal pdf for X by

$$\pi_X(x) := \int_{\mathbb{R}^k} \pi_{XY}(x, y) dy$$

- and the conditional density of X given $Y = y$ by

$$\pi_{X|Y}(x|y) := \frac{\pi_{XY}(x, y)}{\pi_Y(y)} \quad \text{(using division-by-zero convention).}$$

Properties:

- $\pi_{X|Y}(\cdot|y)$ is a density whenever $\pi_Y(y) > 0$
- the disintegration property holds

$$\pi_{XY}(x, y) = \pi_{X|Y}(x|y)\pi(y)$$

- and it extends to multiple rv (X, Y, Z):

$$\pi(x, y, z) = \pi(x|y, z)\pi(y|z)\pi(z) \quad \text{etc}$$

Formal motivation for scalar-valued Y : For any $C \in \mathcal{B}^d$,

$$\mathbb{P}(X \in C \mid Y \in [y, y + \Delta y]) = \frac{\int_y^{y+\Delta y} \int_C \pi_{XY}(x, y)\, dx\, dy}{\int_{\Delta y} \pi_Y(y)\, dy}$$

$$\approx$$

So when π_{XY} is continuous, we have the relation

$$\lim_{\Delta y \to 0} \mathbb{P}(X \in C \mid Y \in \Delta y) = \int_C \pi_{X|Y}(x \mid y) dx,$$

for neighborhoods Δy of y.

Expectation of X given Y

Definition 12 (Conditional expectation)

For continuous rv $(X, Y) : \Omega \to \mathbb{R}^d \times \mathbb{R}^k$ and mapping $g(X)$ such that $\mathbb{E}[|g(X)|] < \infty$, we define

$$\mathbb{E}[g(X) \mid Y = y] := \int_{\mathbb{R}^d} g(x)\,\pi_{X|Y}(x|y)\,dx,$$

and the related continuous rv

$$\mathbb{E}[g(X) \mid Y](\omega) := \mathbb{E}[g(X) \mid Y = Y(\omega)].$$

Properties

For integrable $g(X, Y)$, the **tower property** holds:

$$\mathbb{E}[\mathbb{E}[g(X,Y) \mid Y]] := \mathbb{E}[g(X,Y)]$$

and if $g(X, Y) = f(X)h(Y)$, then

$$\mathbb{E}[\mathbb{E}[g(X,Y) \mid Y]] := \mathbb{E}[h(Y)\mathbb{E}[f(X) \mid Y]].$$

Verification:

Example 13

Let $Y, Z \sim U[0,1]$ and independent, and $X = Y + Z$.

Then for $y \in [0,1]$,

$$\text{shortcut: } X|\{Y = y\} = Z + y \sim U[y, 1+y]$$

giving

$$\pi_{X|Y}(x|y) = \mathbb{1}_{[y,y+1]}(x)$$

and

$$\mathbb{E}\left[X \mid Y = y\right] = \int_{\mathbb{R}} x \mathbb{1}_{[y,y+1]}\, dx = \frac{y+1}{2}.$$

Proper argument:

$$\pi_{XY}(x,y) = \pi_{ZY}(x-y,y) = \mathbb{1}_{[0,1]}(x-y)\mathbb{1}_{[0,1]}(y) \quad \text{etc.}$$

Overview

General definition for conditional expectation

- Random variables may also be mixed, meaning neither discrete nor continuous.

Example 14

$X = YZ$ where $Y \sim \mathit{Bernoulli}(1/2)$ and $Z \sim U[0,1]$ with $Y \perp Z$.
Then formally,

$$\pi_X(x) = \frac{\delta_0(x) + \mathbb{1}_{[0,1]}(x)}{2}$$

- Mixed rv do not have a pdf, so Definition 12 does not apply to conditional expectations of mixed rv.

- **Objective:** obtain a unifying definition for conditional probability.

Conditional expectations

- For a discrete rv
$$Y(\omega) = \sum_{k=1}^{k} b_k \mathbb{1}_{B_k}(\omega)$$
on $(\Omega, \mathcal{F}, \mathbb{P})$, with $B_k = \{Y = b_k\}$ we define

$$\sigma(Y) := \sigma(\{B_k\}) = \text{smallest } \sigma\text{-algebra containing all events } B_1, B_2, \ldots$$

- By construction Y is $\sigma(Y)$-measurable and $\sigma(Y) \subset \mathcal{F}$.
- Then, if X is either continuous or discrete, it holds that

$$\mathbb{E}\left[X|Y\right](\omega) = \begin{cases} \frac{1}{\mathbb{P}(B_1)} \int_{B_1} X d\mathbb{P} & \text{if } \omega \in B_1 \\ \frac{1}{\mathbb{P}(B_2)} \int_{B_2} X d\mathbb{P} & \text{if } \omega \in B_2 \\ \vdots & \end{cases}$$

Observations: $\mathbb{E}[X|Y]$ is a $\sigma(Y)$-measurable discrete rv for which

$$\int_B X\,d\mathbb{P} = \int_B \mathbb{E}[X \mid Y]\,d\mathbb{P} \quad \forall B \in \sigma(Y).$$

(hint: verify first for sets B_k, and extend to general $B \in \sigma(Y)$ by recalling the properties of a σ-algebra).

Seeking to preserve these properties, observe first that for $Y : (\Omega, \mathcal{F}) \to (\mathbb{R}^k, \mathcal{B}^k)$,

$$\sigma(Y) := \text{smallest } \sigma\text{-algebra containing } Y^{-1}(C) \quad \forall C \in \mathcal{B}^k$$

similarly satisfies $\sigma(Y) \subset \mathcal{F}$ and that Y is $\sigma(Y)$-measurable.

Definition 15 (Conditional expectation for general rv)

For rv $X : \Omega \to \mathbb{R}^d$ and $Y : \Omega \to \mathbb{R}^k$ defined on the same probability space, the conditional expectation of X given Y is defined as any $\sigma(Y)$-measurable rv Z satisfying

$$\int_B X d\mathbb{P} = \int_B Z\,d\mathbb{P} \quad \forall B \in \sigma(Y).$$

Conditioning on a $\sigma-$algebra

One may relate $\mathbb{E}[X \mid Y]$ to another kind of conditional expectation:

Definition 16 (Expectation of X given $\mathcal{V} \subset \mathcal{F}$.)

Let $X : \Omega \to \mathbb{R}^d$ be an integrable rv on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and assume $\mathcal{V}$ is a σ-algebra $\mathcal{V} \subset \mathcal{F}$. Then we define $\mathbb{E}[X \mid \mathcal{V}]$ as any $\mathcal{V}$-measurable rv Z satisfying

$$\int_B X dP = \int_B Z\, dP \quad \forall B \in \mathcal{V}.$$

Observation: Setting $\mathcal{V} = \sigma(Y)$ implies that $\mathbb{E}[X \mid Y]$ satisfies the constraints of $\mathbb{E}[X \mid \sigma(Y)]$.

Question: Does $\mathbb{E}[X \mid \mathcal{V}]$ exist and is it unique?

Yes, $\mathbb{E}[X \mid \mathcal{V}] = \mathrm{Proj}_{L^2(\Omega,\mathcal{V})} X$ is a.s. unique.

Function space $L^2(\Omega, \mathcal{F})$

As an extension of $L^2(\Omega)$ for discrete rv, we introduce the Hilbert space

$$L^2(\Omega, \mathcal{F}) = \left\{ X : (\Omega, \mathcal{F}) \to (\mathbb{R}^d, \mathcal{B}^d) \,\middle|\, \quad \int_\Omega |X(\omega)|^2 \, dP < \infty \right\}$$

with the scalar product

$$\langle X, Y \rangle = \int_\Omega X \cdot Y dP = \int_{\mathbb{R}^d \times \mathbb{R}^d} X \cdot Y dF(x, y)$$

and norm

$$\|X\|_{L^2(\Omega, \mathcal{F})} = \sqrt{\langle X, Y \rangle}.$$

This is a Hilbert space: it is complete and for any sub-σ-algebra $\mathcal{V} \subset \mathcal{F}$, $L^2(\Omega, \mathcal{V})$ is a closed subspace of $L^2(\Omega, \mathcal{F})$.

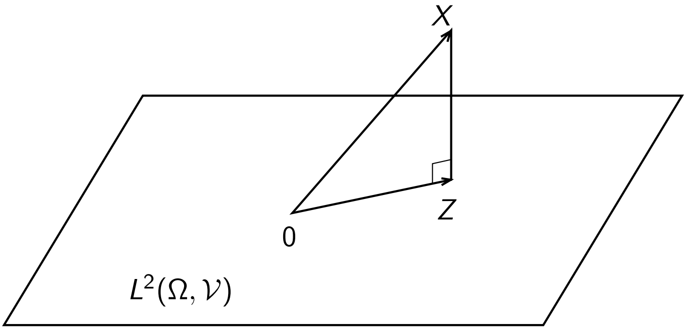
Orthogonal projections onto subspaces

Definition 17

The orthogonal projection of $X \in L^2(\Omega, \mathcal{F})$ onto the closed subspace $L^2(\Omega, \mathcal{V})$ is defined as any rv $Z \in L^2(\Omega, \mathcal{V})$ satisfying

$$\langle X - Z, W \rangle = 0 \quad \forall W \in L^2(\Omega, \mathcal{V}). \tag{2}$$

$$\text{We write} \quad Z = \mathrm{Proj}_{L^2(\Omega,\mathcal{V})} X.$$



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$$\text{We write} \quad Z = \mathrm{Proj}_{L^2(\Omega,\mathcal{V})} X.$$

Exercise: verify that $\mathrm{Proj}_{L^2(\Omega,\mathcal{V})} X$ satisfies the constraints of $\mathbb{E}[X \mid \mathcal{V}]$.
Hint: consider $W = \mathbb{1}_B$ for $B \in \mathcal{V}$

Exercise: verify that $Z = \mathrm{Proj}_{L^2(\Omega,\mathcal{V})} X$ is unique in $L^2(\Omega, \mathcal{V})$ (and thus a.s. unique).

Last step: take as a fact that $\mathbb{E}[X \mid \mathcal{V}]$ satisfies the constraint (2) of $\mathrm{Proj}_{L^2(\Omega,\mathcal{V})} X$, and conclude that $\mathbb{E}[X \mid \mathcal{V}]$ is a.s. unique.

What describes an rv fully?

- An rv can be discrete, mixed or continuous.
- Regardless of that, X is uniquely described by its distribution $\mathbb{P}_X$, and also by its cdf
$$F_X(x) = \mathbb{P}(X \leq x)$$
and, if it exists, also by its pdf
$$\pi_X(x) = \frac{\mathbb{P}(X \in dx)}{dx}.$$
- every rv generates a sigma algebra $\sigma(Y) \subset \mathcal{F}$ which relates to conditional expectations for rv defined on the same probability space:
$$\mathbb{E}[X \mid Y] = \mathbb{E}[X \mid \sigma(Y)]$$

Next time

Bayesian inverse problems and well-posedness.