

1 More RVs and distributions

Corollary 1.1. *Given a PM μ on $S \times \mathbb{R}$.*

Given a RV $X : \Omega \rightarrow S$ where $\text{dist}(X) = \mu_1 = \text{marginal of } \mu$.

Given a RV $U : \Omega \rightarrow [0, 1]$, $\text{dist}(U)$ is $U[0, 1]$, U independent of X .

Then $\exists f : S \times [0, 1] \rightarrow \mathbb{R}$ such that, with $Y = f(X, U)$, then $\text{dist}(X, Y) = \mu$.

Proof. Let Q be a kernel from S to \mathbb{R} associated with μ .

Let $f(s, u)$ be the inverse distribution function of PM $Q(s, \cdot)$

$f(s, U)$ has distribution $Q(s, \cdot)$ since $Q(s, B) = \lambda\{u : f(s, u) \in B\}$ for all $B \in \mathcal{B}$ ($U \sim U[0, 1]$ has distribution $\lambda = \text{Lebesgue measure}$).

Check that this f works:

$$P(X \in A, Y \in B) = P(X \in A, f(X, U) \in B) \quad (1.1)$$

$$= \int \int 1_{X \in A} 1_{f(X, U) \in B} \mu(dx) \otimes \lambda(du) \quad (1.2)$$

$$\stackrel{\text{Fubini}}{=} \int 1_{X \in A} \left(\int 1_{f(X, U) \in B} \lambda(du) \right) \mu(dx) = \int_A Q(x, B) \mu(dx) \quad (1.3)$$

$$\stackrel{\text{Def of } Q}{=} \mu(A \times B) \quad (1.4)$$

□

This theorem, along with the following, justifies Markov chains in MT setting.

Notation: Let $1 \leq m < n < \infty$, $\tilde{\pi}_{n,m} : (x_1, x_2, \dots, x_n) \rightarrow (x_1, \dots, x_m)$, $\pi_{n,m}$ the associated map $\mathcal{P}(\mathbb{R}^n) \rightarrow \mathcal{P}(\mathbb{R}^m)$ such that $\text{dist}(X_1, \dots, X_n) \rightarrow \text{dist}(X_1, \dots, X_m)$.

Theorem 1.2 (Kolmogorov Extension (Consistency) Theorem). *Given PMs μ_n on \mathbb{R}^n , $1 \leq n < \infty$, which are consistent in the sense $\pi_{n,m} \mu_n = \mu_m$, $1 \leq m < n < \infty$.*

Then \exists a PM μ_∞ on \mathbb{R}^∞ such that $\pi_{\infty,m} \mu_\infty = \mu_m$, $1 \leq m < \infty$.

Proof. Take U_1, U_2, \dots independent $U[0, 1]$. Define $X_1 = F_{\mu_1}^{-1}(U_1)$. Inductively, suppose we have defined $X = (X_1, \dots, X_n)$ as functions of (U_1, \dots, U_n) such that $\text{dist}(X_n) = \mu_n$.

We can show $\exists f_{n+1}$ such that defining $X_{n+1} = f_{n+1}(X_n, U_{n+1})$ we have $\text{dist}(X_{n+1} = (\tilde{X}_n, X_{n+1})) = \mu_{n+1}$. To do that, apply the corollary with $S = \mathbb{R}^n$, $X = \tilde{X}_n$, $U = U_{n+1}$, $\mu = \mu_{n+1}$ on $\mathbb{R}^n \times \mathbb{R}$.

This constructs infinite $(X_n, 1 \leq n < \infty)$. Define $\mu_\infty = \text{dist}(X_n, 1 \leq n < \infty)$. □

Example 1.3. Given measurable $h : \mathbb{R} \rightarrow \mathbb{R}$ and a PM μ that is invariant under h , i.e. $\text{dist}(X) = \mu \implies \text{dist}(h(X)) = \mu$.

For each n , take $\text{dist}(X_n) = \mu$. Define $X_i = h(X_{i+1})$, $1 \leq i \leq n-1$, $\mu_n = \text{dist}(X_1, \dots, X_n)$.

Theorem $\implies \mu_\infty = \text{dist}(Y_1, Y_2, \dots)$ such that $\text{dist}(Y_1, \dots, Y_n) = \text{dist}(X_1, \dots, X_n) \quad \forall n$. $Y_i = h(Y_{i+1})$ for all $1 \leq i < \infty$.

2 Intermission: example relevant to data

Hypothesis: Probabilities from gambling odds are indistinguishable from “true probabilities” as formalized in math.

Question: Does this hyp make predictions that can be checked against data?

Model: Z_1 = point difference at half time. Z_2 = point difference in second half. Home team wins $\iff Z_1 + Z_2 > 0$. Assume $Z_2 \stackrel{d}{=} -Z_1$ (symmetric), $Z_1 \perp Z_2$, Z_1 has continuous dist.

$$P(\text{home team wins} \mid Z_1 = z) = P(Z_2 \geq -z \mid Z_1 = z) \quad (2.1)$$

$$= P(Z_2 \geq -z) \text{ by indep.} \quad (2.2)$$

$$= P(Z_2 \leq z) \text{ by symmetry} \quad (2.3)$$

$$= F_Z(z) \quad (2.4)$$

$$P(\text{home team wins} \mid Z_1) = F_Z(Z_1) \stackrel{d}{=} U[0, 1] \quad (2.5)$$

3 Conditional Expectation in measure theory setting

3.1 Undergraduate version

X, Y \mathbb{R} -valued, A an event.

$\mathbb{E}X$ is a number.

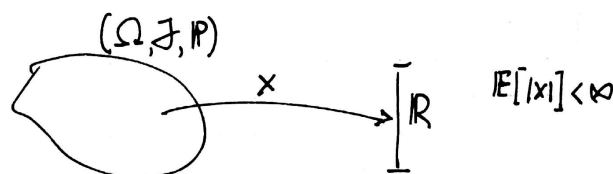
$\mathbb{E}[X \mid A]$ is a number.

$\mathbb{E}[X \mid Y = y]$ is a number depending on y i.e. a function of y , say $= h(y)$.

Write $E[X \mid Y] = h(Y)$, view as a RV. Useful because of tower property: $\mathbb{E}\mathbb{E}[X \mid Y] = \mathbb{E}X$.

Another way to define it is as a best least-squares estimator.

3.2 Measure theory setup



Consider a sub- σ -field $\mathcal{G} \subset \mathcal{F}$. We will define $\mathbb{E}[X \mid \mathcal{G}]$ to be a certain \mathcal{G} -measurable RV.

Suppose know information in \mathcal{G} . Fair stake now $= Y$, say

(a) Y is \mathcal{G} -measurable

(b) $\mathbb{E}Y1_G = \mathbb{E}X1_G \quad \forall G \in \mathcal{G}$

(b) is because of the following betting strategy: Choose $G \in \mathcal{G}$, bet if G happens, not if G^c happens, gain $(X - Y)1_G$. Fair $\iff \mathbb{E}(\text{gain}) = 0 \forall \text{strategies} \iff \mathbb{E}(X - Y)1_G = 0 \forall G$.

Define $\mathbb{E}[X | \mathcal{G}]$ to be the RV Y satisfying (a) and (b).

Existence: For $G \in \mathcal{G}$, define $\nu(G) = \mathbb{E}X1_G$. $P(G) = 0 \implies \nu(G) = 0$. $\nu \ll P$ as PMs on (Ω, \mathcal{G}) .

RN works for ν a signed-measure. Defining property of RN density is (b).

Radon-Nikodym $\implies \exists$ density $\frac{d\nu}{dP}(\omega) = Y(\omega)$.

Radon-Nikodym $\implies \mathcal{G}$ -measurable.

Uniqueness:

Lemma 3.1. If Y is \mathcal{G} -measurable, if $\mathbb{E}|Y| < \infty$. If $\mathbb{E}(Y1_G) \geq 0, \forall G \in \mathcal{G}$, then $Y \geq 0$ a.s.

Proof. If not, $G := \{Y < 0\}$ has $P(G) > 0$ and $\mathbb{E}Y1_G < 0$. Contradiction. \square

Corollary 3.2. If Y_1 and Y_2 each satisfy (a) and (b), then $Y_1 \stackrel{\text{a.s.}}{=} Y_2$.

Proof.

$$\mathbb{E}(Y_1 - Y_2)1_G = 0 \forall G \xRightarrow{\text{Lemma}} Y_1 \geq Y_2 \text{ a.s. and } Y_1 \leq Y_2 \text{ a.s.} \implies Y_1 \stackrel{\text{a.s.}}{=} Y_2 \quad (3.1)$$

\square

Lemma 3.3 (Technical Lemma). (a) If $Z = \mathbb{E}[X | \mathcal{Y}]$ then $\mathbb{E}[VZ] = \mathbb{E}[VX]$ for all bounded \mathcal{G} -measurable V .

(b) If Z is \mathcal{G} -measurable, then to prove $Z = \mathbb{E}[X | \mathcal{Y}]$ it suffices to prove $\mathbb{E}Z1_A = \mathbb{E}X1_A \forall A \in \mathcal{A}$ where \mathcal{A} is a π -class such that $\mathcal{G} = \sigma(\mathcal{A})$.

Proof. (a) Use def for $V = 1_G$, monotone class theorem

(b) Dynkin $\pi - \lambda$ lemma

\square