

INFORMATION FLOW AND σ -ALGEBRAS

Example Binomial model + information flow

$T=3$ (3 periods)

$$\Omega = \{ \omega = (\xi_1, \xi_2, \xi_3) : \xi_i = u \text{ or } d, 1 \leq i \leq 3 \}$$

Ω is market state space, ω is one "path"

$t=0$: $\omega \in \Omega$, $\mathcal{F}_0 := \{ \emptyset, \Omega \}$
(simplest possible σ -algebra for this Ω)

$t=1$: We know $\omega \in A_u$ or A_d

$$A_u = \{ \underline{uuu}, \underline{uud}, \underline{udu}, \underline{udd} \}$$

$$= \{ (u\xi_2\xi_3) : \xi_i = u \text{ or } d, i=2,3 \}$$

$$A_d = \{ \underline{duu}, \underline{dud}, \underline{ddu}, \underline{ddd} \}$$

$$\mathcal{F}_1 := \{ \emptyset, \Omega, A_u, A_d \} \supset \mathcal{F}_0$$

$t=2$: Told outcome of market moves up to $t=2$. Then

$$A_{uu} = \{ \underline{uud}, \underline{uuu} \}$$

$$A_{du} = \{ \underline{duu}, \underline{dud} \}$$

$$A_{ud} = \{ \underline{udu}, \underline{udd} \}$$

$$A_{dd} = \{ \underline{ddu}, \underline{ddd} \}$$

Include all unions + complements to make a σ -algebra:

$$\mathcal{F}_2 = \left\{ \emptyset, \Omega, A_{uu}, A_{du}, A_{ud}, A_{dd}, A_{uu}^c, A_{du}^c, A_{ud}^c, A_{dd}^c, A_{ud} \cup A_{du}, A_{uu} \cup A_{dd}, A_{ud} \cup A_{dd}, A_{du} \cup A_{uu}, A_u, A_d \right\}$$

$$A_u = A_{uu} \cup A_{ud}, \quad A_d = A_{du} \cup A_{dd}$$

$$A_{uu}^c = A_{ud} \cup A_{du} \cup A_{dd}, \text{ etc.}$$

$$|\mathcal{F}_2| = 2^{2^2} = 16$$

t=3: $\mathcal{F}_3 = \{ \text{all subsets of } \Omega \}$

$$|\mathcal{F}_3| = 2^{2^3} = 256 \text{ elements}$$

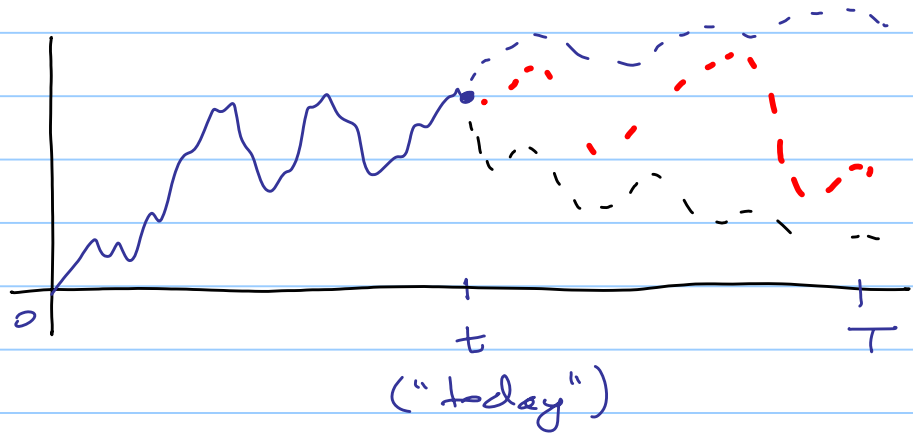
Obtain: $\mathcal{F}_0 \subset \mathcal{F}_1 \subset \mathcal{F}_2 \subset \mathcal{F}_3 \subset \dots$ (if $T > 0$)

Sequence $\{ \mathcal{F}(n) \}_{n=0,1,\dots}$ is called a filtration of \mathcal{F} .

Defn Given Ω (non-empty set), let $T > 0$, s.t. $\forall t \in [0, T]$, you have a σ -algebra $\mathcal{F}(t)$ such that $\mathcal{F}(s) \subset \mathcal{F}(t) \forall s \leq t$. Then $\{ \mathcal{F}(t) \}_{t \in [0, T]}$ is called a filtration.

Example $\Omega = C_0[0, T]$, the set of all cont's functions, $\omega: [0, T] \rightarrow \mathbb{R}$ such that $\omega(0) = 0$.

Spec $\bar{\omega} \in \Omega$. Can observe $\bar{\omega}(s)$, $0 \leq s \leq t$ but we do not know $\bar{\omega}(s)$, $t < s \leq T$.



$M := \{ \omega \in \Omega : \max_{0 \leq s \leq t} \omega(s) \leq 1 \}$ "known @ t "

$P := \{ \omega \in \Omega : \omega(T) > 0 \}$ "unknown @ t "

Can decide @ t whether $\bar{\omega} \in M$ (or not) but we cannot decide @ t whether $\bar{\omega} \in P$.

Information Learned by Observing a Random Variable

Defn: Spec X is a random variable. Then $\sigma(X)$, the sigma algebra generated by X is

$$\sigma(X) := \{ \{ X \in B \} : B \in \mathcal{B}(\mathbb{R}) \}$$

where $\{X \in \mathcal{B}\} := \{\omega \in \Omega; X(\omega) \in \mathcal{B}\}$

$\mathcal{B}(\mathbb{R}) =$ Borel σ -algebra generated
by unions, complements
of intervals, $[\epsilon, b] \subset \mathbb{R}$.
closed.

Example 3-period binomial model.

$$u = 2, d = 1/2, S_0 = 4$$

$$S(2, \omega) = \begin{cases} 16, & \omega = uud, uuu \\ 4, & \omega = udu, udd, duu, dud \\ 1, & \omega = ddu, ddd \end{cases}$$

$\mathcal{B} = \{16\} \in \mathcal{B}(\mathbb{R})$; $S(2)$ is a random variable
on Ω

$$\begin{aligned} \Rightarrow \{S(2) \in \mathcal{B}\} &= \{\omega \in \Omega; S(2, \omega) = 16\} \\ &= \{uud, uuu\} = A_{uu} \end{aligned}$$

$\mathcal{B} = \{4\} \in \mathcal{B}(\mathbb{R})$

$$\begin{aligned} \Rightarrow \{S(2) \in \mathcal{B}\} &= \{\omega \in \Omega; S(2, \omega) = 4\} \\ &= \{udu, udd, duu, dud\} \\ &= A_{ud} \cup A_{du} \end{aligned}$$

$\mathcal{B} = \{1\} \in \mathcal{B}(\mathbb{R})$

$$\begin{aligned} \Rightarrow \{S(2)\} &= \{\omega \in \Omega; S(2, \omega) = 1\} \\ &= \{ddd, ddu\} = A_{dd} \end{aligned}$$

$$B = \emptyset \Rightarrow \{S(z) \in B\} = \emptyset$$

$$B = \mathbb{R} \Rightarrow \{S(z) \in B\} = \Omega$$

$$B = [4, 16] \Rightarrow \{S(z) \in B\} = A_{uu} \cup A_{ud} \cup A_{du}$$

$$\sigma(S_2) = \{ \emptyset, \Omega, A_{uu}, A_{ud} \cup A_{du}, A_{dd}, + \text{all unions and complements} \}$$

$$\subsetneq \mathcal{F}(z)$$

Reason: " $\sigma(S_2)$ contains less information than $\mathcal{F}(z)$ "

Eg. If we know $S(z, \omega) = 4$, then $\omega \in A_{ud} \cup A_{du}$ but we do not know whether $\omega \in A_{ud}$ or $\omega \in A_{du}$

ie $A_{ud} \cup A_{du} \in \sigma(S_2)$ but

$$A_{ud} \notin \sigma(S_2), \quad A_{du} \notin \sigma(S_2)$$

measurability? • $S(z, \omega)$ is not $\mathcal{F}(z)$ measurable.

Reason: $\mathcal{F}(z) = \{ \emptyset, \Omega, A_u, A_d \}$, $S(z, \omega)$ unknown any $\omega \in \mathcal{F}(z)$

• $S(z, \omega)$ is $\sigma(S_2)$ -measurable

$A_{ud} \cup A_{du} \in \sigma(S_2)$, $\omega \in A_{ud} \cup A_{du}$

$\Rightarrow S(z, \omega)$ known ($= 4$).

• $S(z, \omega)$ is $\mathcal{F}(z)$ -measurable

$\omega \in A_{du}$ or $\omega \in A_{ud} \Rightarrow S(z, \omega)$ known (=4).

Adapted Stochastic Processes + Portfolio Processes

Defn (Ω, \mathcal{F}) given. A collection of random variables, $\{X(t)\}_{t \in [0, T]}$, is a stochastic process. (Implicit in definition is fact that each $X(t)$ is \mathcal{F} -measurable function, $X(t): \Omega \rightarrow \mathbb{R}$.) Call $X(t)$ an adapted process if $X(t)$ is $\mathcal{F}(t)$ -measurable w.r.t. a filtration $\{\mathcal{F}(t)\}_{t \in [0, T]}$.

Example: S^n is binomial tree model stock price process and $\mathcal{F}(n)$, $n = 0, 1, 2, \dots$ is filtration defined for this model, then S^n is $\mathcal{F}(n)$ -measurable + so is adapted.

Example: $V(t) = \Delta(t) S(t) + \underbrace{(V(t) - \Delta(t) S(t))}_{\text{cash}}$

$\Delta(t)$ ↗ # shares of stock $S(t)$

Replicating portfolio value

matching an option price (payoff $X(t)$ @ $t = T$.)

$\Delta(t)$ should be an adapted process (to $\mathcal{F}(t)$).

Independent Random Variables

Defn: $(\Omega, \mathcal{F}, \mathbb{P})$. Call sets $A, B \in \mathcal{F}$
independent $\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$

Example: Binomial model, $T=2$

$$A = A_{uu} \cup A_{ud} \quad (= \text{"up @ } t=1 \text{"})$$

$$B = A_{uu} \cup A_{du} \quad (= \text{"up @ } t=2 \text{"})$$

$$\mathbb{P}\{u\} = 1-q, \quad \mathbb{P}\{d\} = q, \quad 0 < q < 1$$

$$\mathbb{P}\{uu\} = (1-q)^2, \quad \mathbb{P}\{ud\} = \mathbb{P}\{du\} = (1-q)q$$

$$\mathbb{P}\{dd\} = q^2$$

Defines $\mathbb{P}: \mathcal{F} \rightarrow [0,1]$, as usual.

Are A, B independent or not?

$$\begin{aligned} \text{Soln: } \mathbb{P}(A) &= \mathbb{P}\{uu, ud\} = \mathbb{P}\{uu\} + \mathbb{P}\{ud\} \\ &= (1-q)^2 + q(1-q) = (1-q)\{(1-q) + q\} = 1-q \end{aligned}$$

$$\mathbb{P}(B) = \mathbb{P}\{uu, du\} = 1-q$$

$$\mathbb{P}(A) \cdot \mathbb{P}(B) = (1-q)^2$$

$$A \cap B = \{uu\}, \quad \mathbb{P}(A \cap B) = (1-q)^2 = \mathbb{P}(A)\mathbb{P}(B) \checkmark.$$

Defn: $(\Omega, \mathcal{F}, \mathbb{P})$ probability space.

Given $\mathcal{G}, \mathcal{H} \subset \mathcal{F}$ σ -algebras.

Call \mathcal{G}, \mathcal{H} independent σ -algebras

$$P(A \cap B) = P(A) \cdot P(B) \quad \forall A \in \mathcal{G}, B \in \mathcal{H}$$

ie A, B independent sets $\forall A \in \mathcal{G}, B \in \mathcal{H}$

Defn: If X, Y random variables on ^{random} variables
(Ω, \mathcal{F}, P), call X, Y independent,
if $\sigma(X), \sigma(Y)$ independent σ -algebras

Example: Binomial model. Are $S(1), S(2)$
independent? $T=2$

Soln: Heuristic: usually, expect no: $S(1) = 8$
 $\Rightarrow S(2) = 16$ or 4 but not $S(2) = 1$.

$$P\{S(1) = 8 \text{ and } S(2) = 16\} \stackrel{?}{=} P\{S(1) = 8\} P\{S(2) = 16\}?$$

Observe: X, Y are independent random
variables \Leftrightarrow

$$P\{X \in B \text{ and } Y \in C\} = P\{X \in B\} \cdot P\{Y \in C\}$$

$\forall B, C \in \mathcal{B}(\mathbb{R})$ (essentially, closed intervals)

$$\begin{aligned} \{S(1) = 8\} &= \{uu, ud\}, & \{S(1) = 8 \text{ and } S(2) = 16\} \\ \{S(2) = 16\} &= \{uu\} & = \{uu\} \end{aligned}$$

$$\Rightarrow P\{S(1) = 8\} = 1 - q$$

$$P\{S(2) = 16\} = (1 - q)^2$$

$$P\{S(1) = 8 \text{ and } S(2) = 16\} = (1 - q)^2$$

$$\neq P\{S(1) = 8\} \cdot P\{S(2) = 16\} = (1 - q)^3, \quad (0 < q < 1).$$

Pairs of random variables

Defn: X, Y are random variables on $(\Omega, \mathcal{F}, \mathbb{P})$
then $(X, Y): \Omega \rightarrow \mathbb{R}^2$ is a (vector-valued) random variable. It has a joint distribution measure

$$\mu_{X,Y}(C) := \mathbb{P}\{(X, Y) \in C\} \quad \forall C \in \mathcal{B}(\mathbb{R}^2)$$

where $\mathcal{B}(\mathbb{R}^2)$ is σ -algebra of subsets of \mathbb{R}^2 generated by all closed rectangles $[a_1, a_2] \times [b_1, b_2]$ & their unions & complements.

$\mu_{X,Y}: \mathcal{B}(\mathbb{R}^2) \rightarrow [0, 1]$ is a probability measure.

the joint cumulative distribution function is

$$F_{X,Y}(a, b) := \mathbb{P}\{X \leq a, Y \leq b\}, \quad a, b \in \mathbb{R}$$

Call $f_{X,Y} \geq 0$ a density function for $\mu_{X,Y}$ if

$$\mu_{X,Y}(C) = \iint_C f_{X,Y}(x, y) dx dy$$

Equivalently:

$$F_{X,Y}(a, b) = \int_{-\infty}^a \int_{-\infty}^b f_{X,Y}(u, v) dv du$$

$$\text{(i)} \quad \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x,y) = f_{X,Y}(x,y).$$

Marginal Probability Distribution

Given $\mu_{X,Y}$, $F_{X,Y}$, $f_{X,Y}$, how do we determine μ_X , μ_Y , F_X , F_Y , f_X , f_Y ?

$$f_X(x) = \int_{\mathbb{R}} f_{X,Y}(x,y) dy; \text{ similarly } f_Y(y)$$

$$\begin{aligned} F_X(x) &= P\{X \leq x\} = P\{X \leq x, Y \in \mathbb{R}\} \\ &= F_{X,Y}(x, \infty) \end{aligned}$$

$$\begin{aligned} \mu_X(A) &= P\{X \in A\} = P\{X \in A, Y \in \mathbb{R}\} \\ &= \mu_{X,Y}(A \times \mathbb{R}) \end{aligned}$$

Thm X, Y random variables on (Ω, \mathcal{F}, P) .
The following are equivalent:

(i) X, Y independent

$$(ii) \mu_{X,Y}(A \times B) = \mu_X(A) \mu_Y(B) \quad \forall A, B \in \mathcal{B}(\mathbb{R})$$

$$(iii) F_{X,Y}(a,b) = F_X(a) F_Y(b), \quad \forall a, b \in \mathbb{R}$$

$$(iv) f_{X,Y}(a,b) = f_X(a) f_Y(b), \quad \forall a, b \in \mathbb{R}$$

(if densities)

$$(v) \mathbb{E}[e^{uX + vY}] = \mathbb{E}[e^{uX}] \mathbb{E}[e^{vY}]$$

$\forall u, v \in \mathbb{R}$

$$\Rightarrow (vi) \mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$$

Conditional Expectation

Example Binomial tree model, $T=N$.
 $(\Omega, \mathcal{Q}, \mathbb{F})$ usual one;

$$\Omega = \{(\xi_1, \dots, \xi_N) : \xi_i = u \text{ or } d, 1 \leq i \leq N\}$$

$$\mathcal{F} = \mathcal{P}(\Omega) = \{\text{Set of all subsets of } \Omega\}$$

$$\mathcal{F}_n := \{(\xi_1, \dots, \xi_n) : \xi_i = u \text{ or } d, 1 \leq i \leq n\}$$

$$\mathcal{F}_0 \subset \mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots \subset \mathcal{F}_N = \mathcal{F}$$

$$\omega = (\xi_1, \dots, \xi_N), \text{ then } \mathbb{Q}^P[\omega] = (1-q)^k q^{N-k},$$

$$k = \# \xi_i = u.$$

Conditional expectation of a random variable $X : \Omega \rightarrow \mathbb{R}$, given $\mathcal{F}(n)$:

$$\mathbb{E}[X | \mathcal{F}(n)](\omega) := \sum_{\omega_n^c} (1-q)^{\#u(\omega_n^c)} \cdot q^{\#d(\omega_n^c)} X(\omega)$$

where:

$$\omega = (\underbrace{\xi_1, \dots, \xi_n}_{\omega_n}, \underbrace{\xi_{n+1}, \dots, \xi_N}_{\omega_n^c})$$

$$\#u(\omega_n^c) = \# \text{ up moves in } (\xi_{n+1}, \dots, \xi_N)$$

$$\#d(\omega_n^c) = \# \text{ down } \dots \dots \dots$$

$$\mathbb{E}[X | \mathcal{F}(n)](\omega) = \mathbb{E}[X | \mathcal{F}(n)](\omega_n, \omega_n^c)$$

$$= \mathbb{E}[X | \mathcal{F}(n)](\omega_n),$$

$$\omega_n \in \mathcal{F}(n).$$

This is an $\mathcal{F}(n)$ -measurable random variable.

$$\underline{n=0}: \mathbb{E}[X | \mathcal{F}(n)] = \mathbb{E}[X | \mathcal{F}(0)]$$

$$= \sum_{\omega \in \Omega} Q(\omega) X(\omega) = \mathbb{E}[X]$$

$$\underline{n=N}: \mathbb{E}[X | \mathcal{F}(N)] = X, \text{ an } \mathcal{F}\text{-measurable random variable.}$$

Defn Given $(\Omega, \mathcal{F}, \mathbb{P})$, $\mathcal{G} \subset \mathcal{F}$, and random variable X , then

$\mathbb{E}[X | \mathcal{G}]$ is the conditional expectation of X given \mathcal{G} if

(i) $\mathbb{E}[X | \mathcal{G}]$ is \mathcal{G} -measurable

$$(ii) \int_A \mathbb{E}[X | \mathcal{G}](\omega) d\mathbb{P}(\omega) = \int_A X(\omega) d\mathbb{P}(\omega)$$

(Partial averaging property)

When $\mathcal{G} = \sigma(Y)$, some random variable Y , then

$$\mathbb{E}[X | \mathcal{G}] = \mathbb{E}[X | Y].$$

Example Binomial model, $T=2$, $\mathcal{F} = \mathcal{F}(2)$,

$$y = \sigma(S(1))$$

Show that $\mathbb{E}[S(2)|S(1)]$ is an $\mathcal{F}(1)$ measurable random variable.

Soln: $\sigma(S(1)) = \{\emptyset, \Omega, A_u, A_d\} = \mathcal{F}(1)$

$$\begin{aligned}\mathbb{E}[S(2)|S(1)] &= \mathbb{E}[S(2)|\mathcal{F}(1)] \\ &\stackrel{\text{formula}}{=} (1-q)S(2; \omega_{1,u}) + qS(2; \omega_{1,d})\end{aligned}$$

$\mathbb{E}[S(2)|S(1)](\omega)$ is determined by ω_1

\hat{c} is $\mathcal{F}(1)$ -measurable random variable.

Properties of Conditional Expectation

Theorem $(\Omega, \mathcal{F}, \mathbb{P})$ and $\mathcal{G} \subset \mathcal{F}$

(i) $\mathbb{E}[\alpha X + \beta Y | \mathcal{G}] = \alpha \mathbb{E}[X | \mathcal{G}] + \beta \mathbb{E}[Y | \mathcal{G}]$
("Linearity")

(ii) $\mathbb{E}[XY | \mathcal{G}] = X \mathbb{E}[Y | \mathcal{G}]$ if X \mathcal{G} -measurable

("Taking out what is known")

(iii) $\mathbb{E}[\mathbb{E}[X | \mathcal{G}] | \mathcal{H}] = \mathbb{E}[X | \mathcal{H}]$ if $\mathcal{H} \subset \mathcal{G}$

("Tower property")

(iv) $\mathbb{E}[X | \mathcal{G}] = \mathbb{E}[X]$ if X independent of \mathcal{G}

(v) Jensen's inequality:

$$\mathbb{E}[\varphi(X) | \mathcal{G}] \geq \varphi(\mathbb{E}[X | \mathcal{G}])$$

where f is a convex function:

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$

$$\forall \lambda \in [0, 1], \quad x_1 < x_2$$

