

## Lecture 12. Fubini, Bounds, Convergence

Wednesday, October 18, 2017 9:50 AM

HW4

min and max confusion  
 $E(\max X_i) < \infty$  not true

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Plan for the nearest future  
HW5 due on Friday  
No new HW until next Wednesday  
30th Wednesday  $\rightarrow$  Midterm  
Topics all the way until convergence

Next Monday No in-class lecture

I will post a practice Mid-term

$\downarrow$   
Posted Panopto lecture capture on  
Solutions for the practice exam

I will make more office hours

No office hours next Monday

New Office hours on Friday 20th 1-2 pm  
Tuesday 24th 5-6 pm

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Previous lecture

Independence intersections  
probabilities of  $\bigvee$  any # of events  
factorize

r.v.s and sets  
CDFs will also factorize

$X$  is  $\sigma(Y)$ -measurable then  $X$  and  $Y$

are functionally related

Copulae

$$C(u, v)$$

↳ joint uniform CDF

Grounded

$$C(0, v) = C(u, 0) = 0$$

With margins

$$C(1, v) = v$$

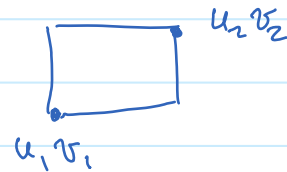
$$C(u, 1) = u$$

$$(u, v) \in [0, 1] \times [0, 1]$$

↓  
Cartesian Product  
of sets

(DF)  $C(u_2, v_2) + C(u_1, v_1) - C(u_1, v_2) - C(u_2, v_1) \geq 0$

$$u_1 \leq u_2$$
$$v_1 \leq v_2$$



(Th) Sklar

Any joint distribution of r.v.  $(X, Y)$   
can be represented as

$$F_{(X, Y)} = C(F_X, F_Y)$$

↓  
joint CDF

↓ ↓  
marginal CDFs  
w/o proof.

$X \perp Y$   
 $C(u, v) = u \cdot v$

Note: Copulae are not the only way to model dependence

Conditional specifications:

$\left. \begin{matrix} [X | Y] \\ [Y | X] \end{matrix} \right\}$  define conditional  
models simultaneously

(TH)

Fréchet - Hoeffding bounds

↓ any Copula satisfies the  
bounds



any Copula satisfies the bounds

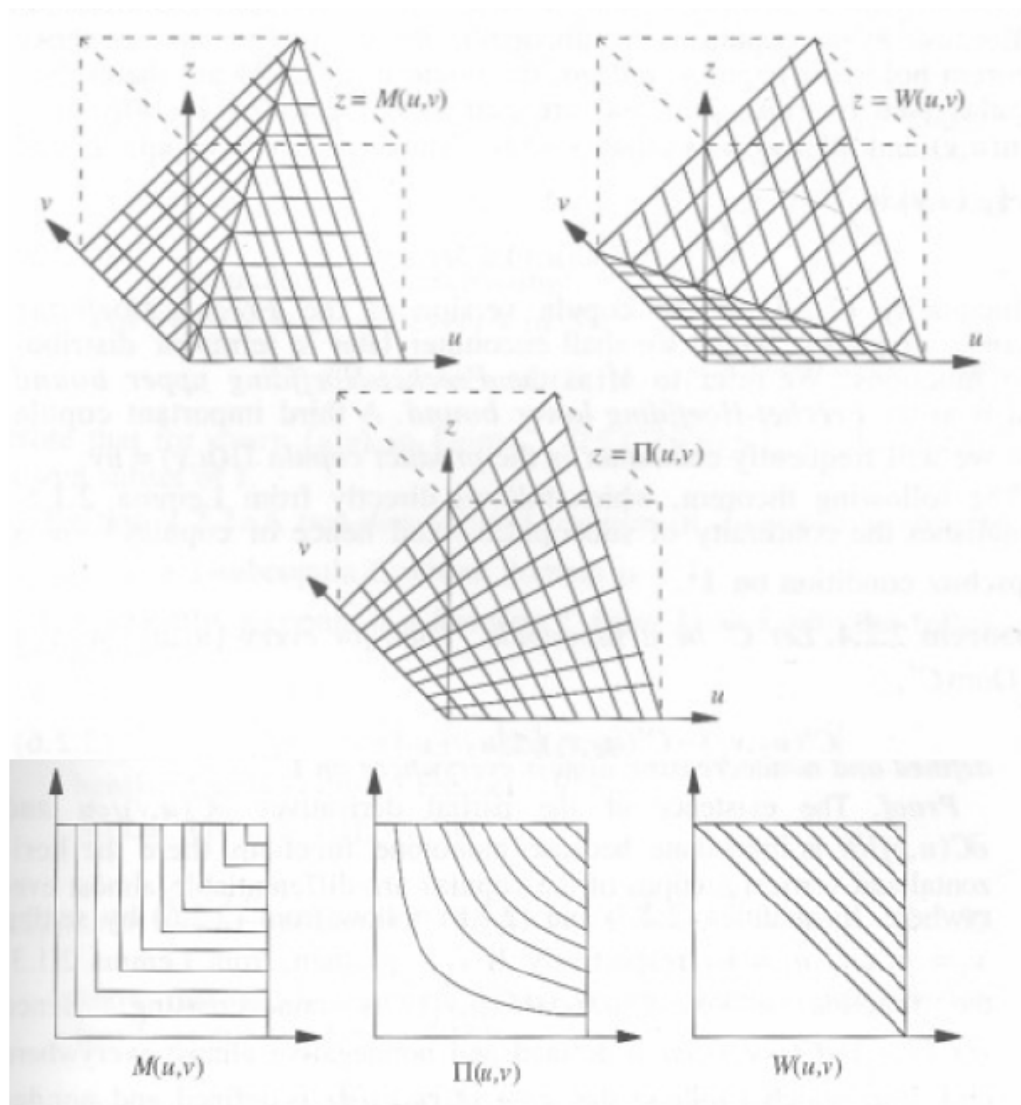
$$\max(0, u+v-1) \leq C(u,v) \leq \min(u,v)$$

$\leq u \cdot v \leq$

extreme neg. dep. Copula

extreme positive dep.

$x = \varphi(t)$   
 $y = \psi(t)$



## Iterated Expectations

# Expectations of functions of independent random variables

↓ r.v.

$$X(\omega) = (X_1(\omega), \dots, X_n(\omega))^T$$

defined on a sample space  
 $(\mathbb{R}^n, \mathcal{B}^n, P_X)$

## Lebesgue Integral

$$\int_{A \in \mathbb{R}^n} g(x) dP_X(x) := E(g(X); A)$$

$A \in \mathbb{R}^n$

some function

$$A = \{ (x_1, \dots, x_n)^T, x_1 \in A_1, \dots, x_n \in A_n \} = A_1 \times A_2 \times \dots \times A_n$$

If  $X_1, \dots, X_n$  are mutually independent

$$P_X(x) = \prod_i P_{X_i}(x_i)$$

$(x_1, \dots, x_n)^T$

(TH)

$X_1 \perp X_2$ , r.v.s  $X = (X_1, X_2)^T$

Fubini

If  $\int g(x) dP_X(x)$  exists then

$$\int g(x) dP_X(x) = \int \left[ \int g(x_1, x_2) dP_{X_2}(x_2) \right] dP_{X_1}(x_1)$$

over the plane

order of 1  $\leftrightarrow$  2 can be interchanged

w/o proof. You can find the proof usually in Appendices to Probability or Measure Theory textbooks

Example:  $X_1 \perp X_2$   
 $X_1 + X_2 \sim ?$  Convolution

$$\begin{aligned}
 F_{X_1+X_2} &= P_X(X_1+X_2 \leq x) = \int_{x_1+x_2 \leq x} dP_X(x_1, x_2) = \\
 &\stackrel{\text{Fubini}}{=} \int_{x_1 \in \mathbb{R}} \left[ \int_{x_2 \leq x-x_1} dP_{X_2}(x_2) \right] dP_{X_1}(x_1) = \\
 &= \int_{-\infty}^{\infty} F_{X_2}(x-x_1) dF_{X_1}(x_1) \rightarrow \text{Convolution}
 \end{aligned}$$


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Convergence of random sequences

(DF) Convergence in probability (Consistency)

$$X_n \xrightarrow[n \rightarrow \infty]{P} X \text{ if}$$

$$\forall \varepsilon > 0 \quad P(|X_n - X| > \varepsilon) \xrightarrow[n \rightarrow \infty]{} 0$$

Any  $\varepsilon$ -deviation of  $X_n$  from  $X$   
 becomes increasingly unlikely

In  $\varepsilon$ - $\delta$  language

$$\forall \varepsilon > 0, \forall \delta > 0 \quad \exists N:$$

$$P(|X_n - X| > \varepsilon) < \delta, \quad \forall n > N$$

$$\sup_{k > N} P(|X_k - X| > \varepsilon) \rightarrow 0$$

DF

Almost sure convergence  
everywhere

a.s. (Strong  
consistency)  
a.e.

$$X_n \xrightarrow{\text{a.s.}} X \quad \text{wrt measure } P$$

when  $X_n(\omega) \rightarrow X(\omega)$  for  
all  $\omega$ , except perhaps a set  
of measure 0.

Will connect both definitions to limits of sets

Will show that conv. a.s. implies conv in prob.