

Lecture 22: Martingale convergence

(1)

Under mild conditions subM_ns converge a.e.

Dobbs upcrossing inequality is the key to the proof.

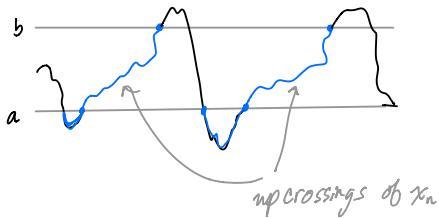
Here is a motivation in terms of how to

check a sequence of numbers x_1, x_2, x_3, \dots converges.

x_n does not converge

$$\text{iff } \liminf_n x_n < \limsup_n x_n$$

$$\text{iff } \exists a, b \in \mathbb{Q} \text{ s.t. } a < b \\ x_n > b \text{ & } x_n < a \text{ infinitely often.} \\ \text{i.e.}$$



iff $\exists a, b \in \mathbb{Q}$ s.t. x_n has infinitely many upcrossings of $[a, b]$

Dobbs upcrossings

Let (X_1, X_2, \dots, X_n) be adapted to the filtration $(\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_n)$.

Fix $-\infty < a < b < \infty$ and define

$$\alpha_1 = \min \left(\{k \geq 1 : X_k \leq a\} \cup \{n\} \right) \left\{ \begin{array}{l} \text{upcrossings} \\ \text{of } [a, b] \end{array} \right\}$$

$$\beta_1 = \min \left(\{k > \alpha_1 : X_k \geq b\} \cup \{n\} \right) \left\{ \begin{array}{l} \text{upcrossings} \\ \text{of } [a, b] \end{array} \right\}$$

$$\alpha_2 = \min \left(\{k > \beta_1 : X_k \leq a\} \cup \{n\} \right) \left\{ \begin{array}{l} \text{upcrossings} \\ \text{of } [a, b] \end{array} \right\}$$

$$\beta_2 = \min \left(\{k > \alpha_2 : X_k \geq b\} \cup \{n\} \right) \left\{ \begin{array}{l} \text{upcrossings} \\ \text{of } [a, b] \end{array} \right\}$$

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The number of upcrossings of $[a, b]$, denoted $U_{a,b}$, is defined as

$$U_{a,b} := \sum_{j=1}^n \mathbb{I}_{\{\alpha_j \leq a, \beta_j \geq b\}} \quad \leftarrow \text{can't be more than } \frac{n}{2} \text{ terms}$$

Proposition:

$\alpha_1, \dots, \alpha_n, \beta_1, \dots, \beta_n$ are stopping times w.r.t $(\mathcal{F}_1, \dots, \mathcal{F}_n)$ and U_{ab} is \mathcal{F}_n -measurable

Proof:

We've already shown that α_i is a ST.

To show β_i is a stopping time notice that

- If $1 \leq m < n$ then

$$\begin{aligned} \{\beta_i = m\} &= \{\alpha_i < m, \beta_i = m\} \\ &= \bigcup_{j=1}^{m-1} \{\alpha_i = j, \beta_i = m\} \\ &= \bigcup_{j=1}^{m-1} \{\alpha_i = j, X_{j+1} < b, \dots, X_{m-1} < b, X_m \geq b\} \\ &\quad \uparrow \qquad \qquad \qquad \uparrow \qquad \qquad \qquad \uparrow \\ &\in \mathcal{F}_j \subset \mathcal{F}_m \qquad \qquad \qquad \qquad \qquad \in \mathcal{F}_m \\ &\in \mathcal{F}_m \end{aligned}$$

- If $m = n$ then

$$\{\beta_i = n\} = \{\beta_i < n\}^c = \left(\bigcup_{j=1}^{n-1} \{\beta_i = j\} \right)^c \in \mathcal{F}_n$$

An induction argument shows $\alpha_1, \beta_1, \dots, \alpha_n, \beta_n$ are ST.

$\therefore X_{\alpha_j}$ is \mathcal{F}_{α_j} -measurable &

X_{β_j} is \mathcal{F}_{β_j} -measurable

Since \mathcal{F}_{α_j} & \mathcal{F}_{β_j} are sub σ -fields of \mathcal{F}_n

U_{ab} is \mathcal{F}_n -measurable.

QED.

Theorem: (Doob's upcrossing ineq)

Suppose (X_1, X_2, \dots, X_n) is a non-negative subM w.r.t filtration $(\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_n)$.

Let $c > 0$ & $\mathcal{U}_{0,c}$ denote the upcrossings of $[0, c]$. Then

$$E(\mathcal{U}_{0,c}) \leq \frac{E(X_n) - E(X_1)}{c}.$$

Proof: The idea is to write $X_n - X_1$ as a telescoping sum: must be X_n

$$\begin{aligned} X_n - X_1 &= (X_{\beta_n} - X_{\alpha_n}) + (X_{\alpha_n} - X_{\beta_{n-1}}) \\ &\quad + (X_{\beta_{n-1}} - X_{\alpha_{n-1}}) + (X_{\alpha_{n-1}} - X_{\beta_{n-2}}) \\ &\quad + \vdots \\ &\quad + (X_{\beta_2} - X_{\alpha_2}) + (X_{\alpha_2} - X_{\beta_1}) \\ &\quad + (X_{\beta_1} - X_{\alpha_1}) + (X_{\alpha_1} - X_1) \\ &\quad \text{set } \beta_0 = 1 \end{aligned}$$

Notice that

$$\begin{aligned} E(\text{a red term}) &= E(X_{\alpha_j} - X_{\beta_{j-1}}) \\ &= E(E(X_{\alpha_j} - X_{\beta_{j-1}} | \mathcal{F}_{\beta_{j-1}})) \\ &= E(E(X_{\alpha_j} | \mathcal{F}_{\beta_{j-1}}) - X_{\beta_{j-1}}) \\ &\quad \underbrace{\geq}_{\geq X_{\beta_{j-1}} \text{ by the}} \\ &\quad \text{Final optional Sampling Thm} \\ &> 0 \end{aligned}$$

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Moreover

$$(X_{\beta_j} - X_{\alpha_j}) \begin{cases} > c & \text{if } (X_{\alpha_j}, X_{\beta_j}) \text{ an upcrossing} \\ 0 & \text{if } \beta_j = \alpha_j = n \\ > 0 & \text{if } \beta_j = n \text{ but } \alpha_j < n \\ & \text{since } X_{\alpha_j} = 0 \text{ & } X_{\beta_j} > 0 \text{ by} \\ & \text{non-negativity} \end{cases}$$

\therefore The sum of all blue terms $\geq c \mathcal{U}_{0,c}$

$$\begin{aligned} \therefore E(X_n - X_1) &\geq E(\text{blue}) + E(\text{red}) \geq c E(\mathcal{U}_{0,c}). \\ &\geq c \mathcal{U}_{0,c} \xrightarrow{> 0} \end{aligned}$$

QED

Corollary:

If (X_1, \dots, X_n) is a subM w.r.t. $(\mathcal{F}_1, \dots, \mathcal{F}_n)$ and $-\infty < a < b < \infty$ then

$$E(\mathcal{U}_{a,b}) = \frac{E(X_n - a)^+ - E(X_1 - a)^+}{b - a} \leq \frac{E(X_n^+) + a^-}{b - a}.$$

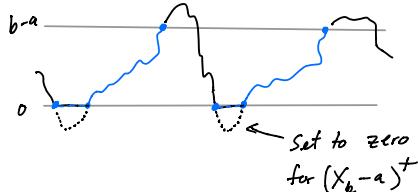
Proof:

For the first inequality:

upcrossings of $[a, b]$ in (X_1, \dots, X_n)

upcrossings of $[a, b-a]$ in $(X_1 - a, \dots, X_n - a)$

upcrossings of $[0, b-a]$ in $(X_1 - a)^+, \dots, (X_n - a)^+$



By Doob's result we therefore have

$$E(\mathcal{U}_{a,b-a}) \leq \frac{E(X_n - a)^+ - E(X_1 - a)^+}{b - a}$$

For the second inequality just notice (5)

$$\begin{aligned} E(X_{n-a})^+ - E(X_1-a)^+ &\leq E(X_n-a)^+ \\ &= E(X_n + (-a))^+ \\ &\leq E(X_n^+ + (-a)^+) \\ &\quad \text{since } (-\cdot)^+ \text{ is convex} \\ &= E(X_n^+) + a^- \end{aligned}$$

QED

a.e. Convergence of martingales

For this section let

$$\mathcal{F}_\infty := \sigma(\mathcal{F}_1, \mathcal{F}_2, \dots)$$

for a filtration $(\mathcal{F}_n)_{n \geq 1}$.

Theorem: $(E(X_n^+) \text{ bdd} \Rightarrow \text{a.e. conv})$

Let $(X_n)_{n \geq 1}$ be a subM w.r.t. filtration $(\mathcal{F}_n)_{n \geq 1}$.

If $\sup_n E(X_n^+) < \infty$ then $\exists X_\infty \in L_1(\Omega, \mathcal{F}_\infty, P)$

s.t. $X_n \xrightarrow{P\text{-a.e.}} X_\infty$

Proof:

For $-\infty < a < b < \infty$ let $U_{a,b}^n$ denote the number of crossings of $[a, b]$ from (X_1, \dots, X_n) , with $U_{a,b}^\infty$ for $(X_n)_{n \geq 1}$.

We must have that

$$0 \leq U_{a,b}^n \uparrow U_{a,b}^\infty \text{ as } n \rightarrow \infty$$

$$\begin{aligned} \therefore E(U_{a,b}^\infty) &\stackrel{\text{Bd}^3}{=} \lim_n E(U_{a,b}^n) \\ &\leq \lim_n \frac{E(X_n^+) + a^-}{b-a} \\ &= \frac{\sup_n E(X_n^+) + a^-}{b-a} < \infty \end{aligned}$$

$$\therefore U_{a,b}^\infty < \infty \text{ P-a.e.}$$

Now

$$P\left(\liminf_n X_n < \limsup_n X_n\right)$$

$$\leq P\left(\bigcup_{\substack{a < b \\ a, b \in \mathbb{R}}} \{U_{a,b}^\infty = \infty\}\right)$$

$= 0$ since

$$U_{a,b}^\infty < \infty \text{ P-a.e.}$$

must $\exists a, b$ with an infinite # of crossings.

$$\therefore X_n \xrightarrow{P\text{-a.e.}} \limsup_n X_n =: X_\infty$$

must be $\in \mathcal{F}_\infty$ by closure Thm.

To see why $X_\infty \in L_1(\Omega, \mathcal{F}_\infty, P)$

$$E|X_\infty| = E|\liminf_n X_n| = E\left(\liminf_n |X_n|\right)$$

$$\stackrel{\text{Fatou}}{\leq} \liminf_n E|X_n|$$

$$\leq \sup_n E|X_n|$$

$$= \sup_n E(2X_n^+ - X_n)$$

$$\leq \sup_n (2E(X_n^+) - E(X_n)) \stackrel{\text{since } E(X_n) \leq E(X_n^+)}{\leq} \sup_n 2E(X_n^+) < \infty \quad \text{by subM}$$

QED

Remark: Note the analog to monotonic sequences where $\sup_n E(X_n^+) < \infty$ plays the role of $\sup_n X_n^+ < \infty$

Another bold type condition is that the X_n^+ 's are UI.

Proposition: $(X_n^+)_n \text{ UI} \Rightarrow E(X_n^+) \text{ bdd}$

If $X_1, X_2, \dots \in L_1(\mathcal{R}, \mathcal{F}, P)$ and $(X_n^+)_n$ are UI then $\sup_n E(X_n^+) < \infty$.

Proof:

$$\sup_n E(X_n^+) \leq \sup_n E(X_n^+ I_{X_n^+ \geq c}) + \sup_n E(X_n^+ I_{X_n^+ < c})$$

↓
 $c \rightarrow \infty$ by definition of UI
 ↓
 So for a large enough c this is $< \infty$.

QED.

Here is an application of the above proposition which comes in handy for subsequent results.

Theorem: (Lévy's Smoothing Martingale)

If $X \in L_1(\mathcal{R}, \mathcal{F}, P)$ & $(\mathcal{F}_n)_{n \geq 1}$ is a filtration then

$$E(X|\mathcal{F}_n) \xrightarrow{n \rightarrow \infty} E(X|\mathcal{F}_\infty) \text{ a.e. \& in } L_1$$

where $\mathcal{F}_\infty = \sigma(\mathcal{F}_1, \mathcal{F}_2, \dots)$.

Proof:

$$\text{Let } X_n := E(X|\mathcal{F}_n).$$

We first show the X_n 's are UI.

Since $|X_n| = |E(X|\mathcal{F}_n)| \leq E(|X||\mathcal{F}_n)$ it will be sufficient to show the $E(|X||\mathcal{F}_n)$'s are UI.

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i.e. show

$$\lim_{c \rightarrow \infty} \sup_n \int E(|X||\mathcal{F}_n) dP = 0$$

$E(|X||\mathcal{F}_n) \geq c$
 ↓
 $\int |X| dP \quad \text{since } \{E(|X||\mathcal{F}_n) \geq c\}$
 $E(|X||\mathcal{F}_n) \geq c \quad \text{is a } \mathcal{F}_n\text{-set}$

$$\text{Let } A_{n,c} := \{E(|X||\mathcal{F}_n) \geq c\}$$

we then want to bound $\int_{A_n} |X| dP$

Note $\int_{A_n} |X| dP \ll P(\cdot)$ on \mathcal{F}_n

∴ by HWK 3 in 235A

$$\lim_{\delta \downarrow 0} \sup \left\{ \int_F |X| dP : F \in \mathcal{F}_n, P(F) \leq \delta \right\} = 0$$

i.e. $\forall \varepsilon > 0, \exists \delta_\varepsilon > 0$ s.t.

$$P(F) \leq \delta_\varepsilon \Rightarrow \int_F |X| dP \leq \varepsilon$$

Now since

$$\begin{aligned} P(A_{n,c}) &= P(E(|X||\mathcal{F}_n) \geq c) \\ &\leq \frac{E(E(|X||\mathcal{F}_n))}{c} = \frac{E|X|}{c} \end{aligned}$$

we have $\forall \varepsilon > 0, \exists C > 0$ s.t.

$$c \geq C \Rightarrow P(A_{n,c}) \leq \delta_\varepsilon \quad \text{by (*)}$$

$$\Rightarrow \int_{A_{n,c}} |X| dP \leq \varepsilon$$

$$\Rightarrow \sup_n \int_{A_{n,c}} |X| dP \leq \varepsilon$$

∴ the X_n 's are indeed UI

∴ the X_n^+ 's are UI so the $E(X_n^+)$'s bdd

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$\therefore \exists X_n \in L_1(\Omega, \mathcal{F}_n, P)$ s.t.

$$X_n \xrightarrow{\text{a.e.}} X_\infty \quad \text{by subM a.e. Thm}$$

$\therefore X_n \xrightarrow{L_1} X_\infty$ by the L_p convergence
Thm since the X_n 's are UI

To finish we show $X_\infty = E(X|\mathcal{F}_\infty)$.

In particular show:

- (i) X_∞ is \mathcal{F}_∞ -measurable ✓
- (ii) $X_\infty \in L_1(\Omega, \mathcal{F}_\infty, P)$ ✓
- (iii) Integrates like X over \mathcal{F}_∞ -sets.
i.e. $E(X\mathbf{1}_A) = E(X_\infty \mathbf{1}_A) \forall A \in \mathcal{F}_\infty$

For (iii) notice that $\forall A \in \bigcup_{n=1}^{\infty} \mathcal{F}_n$

$$E(X\mathbf{1}_A) \stackrel{(*)}{=} E(X_n \mathbf{1}_A) \quad \text{if large } n
 \text{since } X_n = E(X|\mathcal{F}_n)$$

$\therefore \forall A \in \bigcup_{n=1}^{\infty} \mathcal{F}_n \leftarrow$ a field generating \mathcal{F}_∞

$$\begin{aligned} E(X_\infty \mathbf{1}_A) &= E\left(\lim_n X_n \mathbf{1}_A\right) \quad \text{since } X_n \xrightarrow{\text{a.e.}} X_\infty \\ &= \lim_n E(X_n \mathbf{1}_A) \quad \text{by UI and for } \lim f = \lim \\ &\stackrel{(*)}{=} E(X\mathbf{1}_A) \quad \text{by } (*) \end{aligned}$$

To show $E(X_\infty \mathbf{1}_A) = E(X\mathbf{1}_A) \forall A \in \mathcal{F}_\infty$

Let

$$\mathcal{Y} = \{A \in \mathcal{F}: E(X_\infty \mathbf{1}_A) = E(X\mathbf{1}_A)\}$$

By $(*)$ we have

$$\begin{array}{c} \text{field} \xrightarrow{\text{a.s. sys}} \bigcup_{n=1}^{\infty} \mathcal{F}_n \subset \mathcal{Y} \xleftarrow{\text{a } \lambda\text{-system}} \\ \therefore \text{a } \sigma\text{-sys} \end{array}$$

$$\therefore \lambda \left\langle \bigcup_{n=1}^{\infty} \mathcal{F}_n \right\rangle \subset \mathcal{Y} \quad (10)$$

"Dynkin's Th"

$$\sigma \left\langle \bigcup_{n=1}^{\infty} \mathcal{F}_n \right\rangle$$

$$\therefore E(X_\infty \mathbf{1}_A) = E(X\mathbf{1}_A) \quad \forall A \in \mathcal{F}_\infty$$

by "Good sets".

QED

Example

Let's use Levy Thm to deduce the Kolmogorov 0-1 law.

Let $\mathcal{O}_1, \mathcal{O}_2, \dots$ be indep sub- σ -fields of \mathcal{F} .

The tail σ -field is defined as

$$\Sigma = \bigcap_{n=1}^{\infty} \sigma(\mathcal{O}_1, \mathcal{O}_2, \dots)$$

We want to show

$$P(A) \in \{0, 1\} \quad \forall A \in \Sigma.$$

Set $\mathcal{F}_n = \sigma(\mathcal{O}_1, \dots, \mathcal{O}_n)$ and notice that for $A \in \Sigma$,

$$\begin{aligned} E(\mathbf{1}_A | \mathcal{F}_n) &\xrightarrow{\text{a.e.}} E(\mathbf{1}_A | \mathcal{F}_\infty) \\ &\sim = E(\mathbf{1}_A) \quad \text{since } A \in \sigma(\mathcal{O}_{n+1}, \dots) \perp \mathcal{F}_n \\ &\qquad \qquad \qquad \text{by ANOVA} \\ &= P(A) \end{aligned}$$

$$\therefore P(A) = E(\mathbf{1}_A | \mathcal{F}_\infty) \stackrel{\text{a.e.}}{=} \mathbf{1}_A$$

since $A \in \Sigma \subset \sigma(\mathcal{O}_1, \mathcal{O}_2, \dots) = \mathcal{F}_\infty$

$$\therefore P(A) = 0 \text{ or } 1.$$

Another way to quantify "boldness" of subMs is with "closers".

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r.v. sub σ -field of \mathcal{F}

Definition: A pair (X_0, \mathcal{F}_0) closes

a subM $(X_n)_{n \geq 1}$ on the right if

$$X_1, X_2, \dots, X_n, \dots X_0.$$

is a subM w.r.t. $\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_n, \dots, \mathcal{F}_0$, i.e if

$$E(X_0 | \mathcal{F}_n) \stackrel{\text{prac.}}{\geq} X_n \quad \forall n \in \mathbb{N}.$$

Definition: (X_0, \mathcal{F}_0) is a nearest closer of $(X_n)_{n \geq 1}$ if

$$X_1, X_2, \dots, X_n, X_0.$$

is a subM w.r.t. $\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_0, \mathcal{F}_0$

for every closer (X_0, \mathcal{F}_0) of $(X_n)_{n \geq 1}$.

The existence of a closer is equivalent to the UI condition:

Theorem: $(\exists \text{closer} \Leftrightarrow X_n^+ \text{'s are UI})$

If $(X_n)_{n \geq 1}$ is a subM w.r.t. filt $(\mathcal{F}_n)_{n \geq 1}$ then

\exists a closer for $(X_n)_{n \geq 1} \Leftrightarrow (X_n^+)_{n \geq 1}$ are UI

Proof:

(\Rightarrow) : Suppose (X_0, \mathcal{F}_0) closes $(X_n)_{n \geq 1}$.

$\therefore (X_0^+, \mathcal{F}_0)$ closes the subM $(X_n^+)_{n \geq 1}$ by trans of Ms.

$\therefore E(X_0^+ | \mathcal{F}_n) \stackrel{\text{a.e.}}{\geq} X_n^+ \quad \forall n \in \mathbb{N}$

These are UI by proof of Lévy's thm

\therefore these are too.

(\Leftarrow) Suppose $(X_n^+)_{n \geq 1}$ are UI.

$\therefore \exists X_\infty \in L_1(\Omega, \mathcal{F}_\infty, P)$ s.t.

$$X_n \xrightarrow{\text{a.e.}} X_\infty$$

we show that $(X_\infty, \mathcal{F}_\infty)$ is a closer.

Case 1: $X_n \geq c > -\infty \quad \forall n \in \mathbb{N}$.

\therefore The X_n^- 's are UI & hence the X_n^1 's are UI.

$\therefore X_n \xrightarrow{L_1} X_\infty$ by the L_p -convergence Thm.

Now to show $E(X_\infty | \mathcal{F}_n) \stackrel{\text{a.e.}}{\geq} X_n$ let $A \in \mathcal{F}_n$ so that

$$\begin{aligned} \int_A X_n dP &\stackrel{\text{subM}}{\leq} \int_A E(X_{n+m} | \mathcal{F}_n) dP \\ &= \int_A X_{n+m} dP \\ &\xrightarrow{n \rightarrow \infty} \int_A X_\infty dP \quad \text{since } X_{n+m} \xrightarrow{L_1} X_\infty \\ &= \int_A E(X_\infty | \mathcal{F}_n) dP \end{aligned}$$

$\therefore X_n \stackrel{\text{a.e.}}{\leq} E(X_\infty | \mathcal{F}_n)$ by our results on indefinite integrals.

$\therefore (X_\infty, \mathcal{F}_\infty)$ closes $(X_n)_{n \geq 1}$.

Case 2: $X_n \in L_1(\Omega, \mathcal{F}, P)$.

Now Case 1 applies to $\underbrace{X_n + c}_{\text{a subM since } \max(X_n, c)}$ where

$c > -\infty$. \therefore $X_n + c$ is a subM, also

UI and bold below. Also $X_n + c \xrightarrow{L_1} X_\infty + c$

$\therefore E(X_\infty | \mathcal{F}_n) \stackrel{\text{a.e.}}{\geq} X_n$ by taking limits as $c \rightarrow -\infty$ by MCT for $L_1(\mathcal{F}_n)$

QED

Now we get the "closeness" condition for a.e. convergence almost as a corollary.

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Theorem: (\exists closer \Rightarrow a.e. convergence)

If the subM $(X_n)_{n \geq 1}$ has a closer then $\exists X_\infty \in L_1(\Omega, \mathcal{F}_\infty, P)$ s.t. $X_n \xrightarrow{\text{a.e.}} X_\infty$

and $(X_\infty, \mathcal{F}_\infty)$ is the nearest closer.

Proof:

By the previous result

$$\begin{aligned} \exists \text{ closer} &\Leftrightarrow (X_n^+)'s \text{ are uI} \\ &\Rightarrow E(X_n^+)'s \text{ are bdd} \\ &\Rightarrow \exists X_\infty \in L_1(\Omega, \mathcal{F}_\infty, P) \text{ s.t.} \\ &\quad X_n \xrightarrow{\text{a.e.}} X_\infty. \end{aligned}$$

The proof of the previous Thm also establishes that $(X_\infty, \mathcal{F}_\infty)$ closes $(X_n)_{n \geq 1}$.

Now we just show $(X_\infty, \mathcal{F}_\infty)$ is the nearest closer.

Let $(X_\infty, \mathcal{F}_\infty)$ be some closer.

We need to show

$X_1, X_2, \dots, X_\infty, X_\infty$ is a subM

w.r.t. filtration $\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_\infty, \mathcal{F}_\infty$

it's a filtration
since $\cup_{i=1}^n \mathcal{F}_i \subset \mathcal{F}_\infty$
 $\cap_{i=1}^n \mathcal{F}_i = \emptyset$

Notice it is sufficient to show

$$(*) \quad E(X_\infty | \mathcal{F}_\infty) \stackrel{\text{a.e.}}{\geq} X_\infty$$

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To show (*) use Lévy's smoothing result as follows

$$\begin{aligned} E(X_\infty | \mathcal{F}_n) &\stackrel{\text{a.e.}}{\geq} X_n \quad \text{since } (X_n, \mathcal{F}_n) \\ &\quad \text{is a closer} \\ &\downarrow \text{a.e.} \quad \downarrow \text{a.e.} \\ E(X_\infty | \mathcal{F}_\infty) &\stackrel{\text{a.e.}}{\geq} X_\infty \end{aligned}$$

as way to be shown.

QED

Likelihood ratio Example from last Lecture

Two models P & Q for a random ω generating an infinite sequence of r.v.s

$$X = (X_1, X_2, \dots)$$

$$\begin{array}{ccc} (X_1, X_2, \dots) @&& \\ \downarrow \text{P or Q} & \longrightarrow & \bigcirc \mathbb{R}^\infty \\ \mathbb{P} & & \mathcal{B}(\mathbb{R}^\infty) \end{array}$$

where

P & Q are distinguishable (a.e.) $\Leftrightarrow P X^{-1} \perp Q X^{-1}$
from one sample of X

$$\Leftrightarrow Q_\infty \perp P_\infty$$

$$\text{where } \mathcal{F}_\infty := \sigma\langle X_i : i \geq 1 \rangle$$

$$Q_\infty := Q|_{\mathcal{F}_\infty}$$

$$\Leftrightarrow \frac{dQ_\infty}{dP_\infty} = 0$$

$$\Leftrightarrow \frac{dQ_n}{dP_n} \xrightarrow{\text{a.e.}} 0$$

$$\text{where } \mathcal{F}_n := \sigma\langle X_1, \dots, X_n \rangle$$

$$Q_n := Q|_{\mathcal{F}_n}$$

where $\frac{dQ_n}{dP_n}$ & $\frac{dQ_\infty}{dP_\infty}$ represents the finite & infinite data likelihood ratio

Recall that we showed $\frac{dQ_n^a}{dP_n}$ is a sup M wrt $(\mathcal{F}_n)_{n \geq 1}$ under P. We will

use this to show $\frac{dQ_n^a}{dP_n}$ converge

Theorem: $\frac{dQ_n^a}{dP_n} \xrightarrow{\text{P-a.e.}} \frac{dQ_\infty^a}{dP_\infty}$ as $n \rightarrow \infty$.

Proof:

$\frac{dQ_n^a}{dP_n}$ is a sup M and non-neg by construction

$\therefore \left(-\frac{dQ_n^a}{dP_n}\right)_{n \geq 1}$ is a non-positive subM

$\therefore (0, \mathcal{F}_\infty)$ closes $\left(-\frac{dQ_n^a}{dP_n}\right)_{n \geq 1}$ on the right:

i.e. $-\frac{dQ_1^a}{dP_1}, -\frac{dQ_2^a}{dP_2}, \dots, 0$

is a subM w.r.t. $\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_\infty$ because

$$0 = E(0 | \mathcal{F}_n) \geq -\frac{dQ_n^a}{dP_n} \quad \forall n \in \mathbb{N}.$$

By the closer Thm $\exists X_\infty \in L_1(\mathcal{D}, \mathcal{F}_\infty, P)$ s.t.

$\frac{dQ_n^a}{dP_n} \xrightarrow{\text{a.e.}} X_\infty$ & $(-X_\infty, \mathcal{F}_\infty)$ is the nearest closer of
note $X_\infty \geq 0$ $\left(-\frac{dQ_n^a}{dP_n}\right)_{n \geq 1}$.

We show $X_\infty = \frac{dQ_\infty^a}{dP_\infty}$

(show $X_\infty \leq \frac{dQ_\infty^a}{dP_\infty}$)

Use that $-X_\infty$ closes $\left(-\frac{dQ_n^a}{dP_n}\right)_{n \geq 1}$ on the right.

Since X_∞ closes we have

$$E(X_\infty | \mathcal{F}_n) \stackrel{\text{P-a.e.}}{\leq} \frac{dQ_n^a}{dP_n}$$

15
16
 $\therefore \int_A X_\infty dP \leq \int_A \frac{dQ_n^a}{dP_n} dP \leq Q_n^a(A) \quad \forall A \in \bigcup_{k=1}^n \mathcal{F}_k$

Since $\bigcup_{k=1}^n \mathcal{F}_k$ is a field generating \mathcal{F}_∞

& $X_\infty \xrightarrow{\text{a.e.}}$ we can apply "Good sets" to show

$$\int_A X_\infty dP \leq Q_\infty(A) \quad \forall A \in \mathcal{F}_\infty$$

a finite measure

but $\frac{dQ_\infty^a}{dP_\infty}$ is the P-largest (by Lab 3 prop)

such, so we have

$$X_\infty \stackrel{\text{P-a.e.}}{\leq} \frac{dQ_\infty^a}{dP_\infty}$$

(show $X_\infty \geq \frac{dQ_\infty^a}{dP_\infty}$)

Use that $-\frac{dQ_\infty^a}{dP_\infty}$ closes $\left(-\frac{dQ_n^a}{dP_n}\right)_{n \geq 1}$ on the right.

Indeed this follows from the same method

used to show $\left(\frac{dQ_n^a}{dP_n}\right)_{n \geq 1}$ is a supM.

nearest closer

i.e. $-\frac{dQ_1^a}{dP_1}, -\frac{dQ_2^a}{dP_2}, \dots, -X_\infty, -\frac{dQ_\infty^a}{dP_\infty}, 0$

is a subM w.r.t. $\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_\infty, \mathcal{F}_\infty, \mathcal{F}_\infty$

$$\therefore E\left(-\frac{dQ_\infty^a}{dP_\infty} | \mathcal{F}_\infty\right) \stackrel{\text{a.e.}}{\geq} -X_\infty$$

!! a.e.

$$-\frac{dQ_\infty^a}{dP_\infty}$$

QED

L_p convergence

To summarize what we know so far for subM's:

$$\sup_n E(X_n^+) < \infty \implies X_n \xrightarrow{a.e.} X_\infty \in L_1(\Omega, \mathcal{F}, P)$$

\uparrow

X_n^+ are UI \iff X_n is closable

X_n have a closer $\implies X_n \xrightarrow{a.e.} X_\infty \in L_1$ &
 X_∞ is the nearest closer.

The next result shows that for $p \geq 1$

$$|X_n|^p \text{ UI} \implies X_n \xrightarrow{L_p} X_\infty \in L_p(\Omega, \mathcal{F}, P)$$

where X_∞ is the nearest closer.

Theorem: (subM L_p convergence Thm for $1 \leq p < \infty$)

Suppose $1 \leq p < \infty$ and $(X_n)_{n \geq 1}$ is a subM wrt filtration $(\mathcal{F}_n)_{n \geq 1}$.

If $|X_n|^p$ is UI then $\exists X_\infty \in L_p(\Omega, \mathcal{F}, P)$ s.t.

$$X_n \rightarrow X_\infty \quad p\text{-a.e. \& } L_p$$

where $(X_\infty, \mathcal{F}_\infty)$ is the nearest closer of $(X_n)_{n \geq 1}$

$= \sigma(\mathcal{F}_1, \mathcal{F}_2, \dots)$

Proof:

Clearly $|X_n|$'s are UI by the dilation criterium.

$\therefore (X_n^+)_{n \geq 1}$ are UI since $X_n^+ \leq |X_n|$

$\therefore X_n \xrightarrow{a.e.} X_\infty \in L_1(\Omega, \mathcal{F}, P)$ with

X_∞ being the nearest closer.

Now all we need is to show

$$X_n \xrightarrow{L_p} X_\infty$$

but this follows immediately by the L_p convergence Thm, since $(|X_n|^p)_{n \geq 1}$ are UI. QED.

Theorem: (Checking $|X_n|^p$ UI for $X_n \geq 0$ subM)

If $(X_n)_{n \geq 1}$ is a subM, $X_n \geq 0$ f/n & $p > 1$

then

$$X_n^p \text{ are UI} \iff \sup_n E(X_n^p) < \infty$$

$$\iff E(\sup_n X_n^p) < \infty$$

Proof:

$$(X_n^p \text{ UI} \implies \sup_n E(X_n^p) < \infty)$$

Follows by UI properties

$$\left(\sup_n E(X_n^p) < \infty \implies E(\sup_n X_n^p) < \infty \right)$$

Let $M_n = \max_{1 \leq k \leq n} X_k$ & $q > 1$ satisfy $\frac{1}{p} + \frac{1}{q} = 1$

Now

$$\begin{aligned} E M_n^p &= \int_0^\infty P(M_n^p \geq t) dt \\ &= \int_0^\infty P(M_n \geq t^{1/p}) dt \quad \begin{matrix} w = t^{1/p} \\ dw = \frac{1}{p} t^{-1/p} dt \\ \therefore dw = \frac{1}{p} t^{-1/p} dt \end{matrix} \\ &= \int_0^\infty P(M_n \geq w) \cdot p w^{p-1} dw \\ &\stackrel{\text{Fubini}}{\leq} \int_0^\infty w^{-1} E(X_n I_{\{M_n \geq w\}}) p w^{p-1} dw \end{aligned}$$

$$= p E \left[\int_0^\infty X_n I_{\{M_n \geq w\}} w^{p-2} dw \right]$$

$$= p E \left[X_n \left[\frac{w^{p-1}}{p-1} \right]_0^{M_n} \right]$$

(19)

$$\begin{aligned}
 \therefore E(M_n^p) &= \frac{p}{p-1} E(X_n M_n^{p-1}) \\
 &\stackrel{\text{Holder}}{\leq} \frac{p}{p-1} \|X_n\|_p \|M_n^{p-1}\|_q \\
 &= \frac{1}{1-\frac{1}{p}} [E(X_n^p)]^{\frac{1}{p}} [E(M_n^{sp-p})]^{\frac{1}{q}} \\
 &= \frac{1}{q} [E(X_n^p)]^{\frac{1}{p}} [E(M_n^p)]^{\frac{1}{q}} \\
 \therefore [E(M_n^p)]^{1-\frac{1}{q}} &\leq q [E(X_n^p)]^{\frac{1}{p}} \quad \text{since } E(M_n^p) < \infty \\
 &\quad \text{because } M_n = \underbrace{X_1 + \dots + X_n}_{\in L_p} \\
 \therefore E(M_n^p) &\leq q^p E(X_n^p) \leq q^p \sup_k E(X_k^p) \quad (\star)
 \end{aligned}$$

Now since $M_n^p = \max_{1 \leq k \leq n} X_k^p \uparrow \sup_n X_n^p$

we can take a limit in n in (\star)
to obtain

$$E(\sup_n X_n^p) \leq q^p \sup_k E(X_k^p).$$

$E(\sup_n X_n^p) < \infty \Rightarrow X_n^p$ are UI

$$X_n^p \leq \sup_n X_n^p =: Y$$

Since $Y \in L_1$, the single Y is UI.

$\therefore X_n^p$'s are UI.

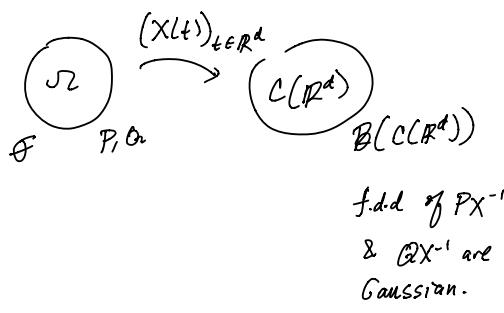
QED

Application of QLP & $Q \ll P$
for Gaussian random fields (GRF)

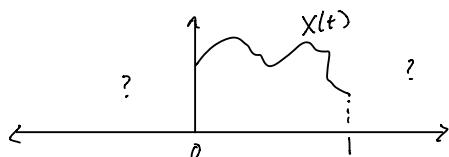
(20)

Let (Ω, \mathcal{F}) be a measure space &
 P, Q be two probability measures on (Ω, \mathcal{F}) .

Suppose $(X(t))_{t \in \mathbb{R}^d}$ is a collection of
r.v.s defined on (Ω, \mathcal{F}) s.t. under both
 P & Q , $(X(t))_{t \in \mathbb{R}^d}$ induces a measure
on $C(\mathbb{R}^d)$ s.t. $\forall t_1, \dots, t_n \in \mathbb{R}^d$
 $(X(t_1), \dots, X(t_n))$ is multivariate Gaussian.



Suppose I sample $w \in \Omega$ according to
 P or Q & show you $X(t)(w) \quad \forall t \in [0, 1]^d$



You need to determine if I used P or Q
to sample $w \in \Omega$.

The information available to you is
encoded in $\sigma\langle X(t) : t \in [0, 1]^d \rangle$.

If we let P, Q denote the restriction
to $\sigma\langle X(t) : t \in [0, 1]^d \rangle$ then

$P \perp Q \iff$ perfect discrimination
possible (w.p. 1)

$P = Q \iff$ impossible to distinguish
 P from Q

Example: GRF's are characterized
by $m(t) := E(X(t))$ &
 $K(t, s) := \text{cov}(X(t), X(s))$.

Suppose that $X(t)$ is defined on \mathbb{R} &

Under P : $m(t) = 0$, $K(t, s) = e^{-|t-s|}$

Under Q : $m(t) = 0$, $K(t, s) = (1 + |t-s|)e^{-|t-s|}$

Now let

$$X_n = n(X(\frac{1}{n}) - X(0))$$

$$\begin{aligned} \therefore \text{var}_P(X_n) &= n^2(K(\frac{1}{n}, \frac{1}{n}) - 2K(\frac{1}{n}, 0) + K(0, 0)) \\ &= 2n^2(1 - e^{-\frac{1}{n}}) \sim n \rightarrow \infty \end{aligned}$$

$$\begin{aligned} \text{var}_Q(X_n) &= 2n^2(1 - e^{-\frac{1}{n}}(1 + \frac{1}{n})) \\ &= 2n^2\left(1 - \left(1 - \frac{1}{n} + \frac{1}{2n^2} + O(\frac{1}{n^3})\right)\left(1 + \frac{1}{n}\right)\right) \\ &= 2n^2\left(1 - \left(1 - \frac{1}{n} + \frac{1}{2n^2} + O(\frac{1}{n^3})\right)\right. \\ &\quad \left.- \left(\frac{1}{n} - \frac{1}{n^2} + O(\frac{1}{n^3})\right)\right) \\ &\rightarrow 1 \end{aligned}$$

(21)

\therefore under P : $X_n \sim N(0, \theta(n))$

under Q : $X_n \sim N(0, \theta(1))$

\therefore one can find $F_n \in \mathcal{F}$ s.t.

$$\begin{aligned} P(F_n) &\xrightarrow{n \rightarrow \infty} 0 & \text{scale } X_n \text{ so} \\ && \text{var}(c_n X_n) \\ && \rightarrow 0 \text{ under } P \\ Q(F_n) &\xrightarrow{n \rightarrow \infty} 1 & \text{and } \rightarrow 0 \text{ under} \\ && Q \end{aligned}$$

$\therefore P \perp Q$ & perfect discrimination
is possible from "one sample" of
 $X(t)$ on $t \in [0,1]$.

Now choose an infinite sequence of r.v.s
 $X_1, X_2, \dots \in \text{finite linear span } \{X(t): t \in [0,1]^d\}$

which are linearly independent under both
 P & Q (if no such sequence exists then
 $P \perp Q$).

Let $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$

$\mathcal{F}_{\infty} = \sigma(X_1, X_2, \dots)$

$P_n = P \Big|_{\mathcal{F}_n}, Q_n = Q \Big|_{\mathcal{F}_n} \text{ then } \mathcal{N}(\{\mathcal{F}_n\})$

Note: Since the sample paths of X are continuous we can choose X_n 's so that

$P_{\infty} = Q_{\infty} \Leftrightarrow P \equiv Q$ &

$P_{\infty} \perp Q_{\infty} \Leftrightarrow P \perp Q$

remember these
are defined on
 $\{X(t): t \in [0,1]^d\}$

(22)

Let p_n & q_n be the density of

$P(X_1, \dots, X_n)^{-1}$ & $Q(X_1, \dots, X_n)^{-1}$ w.r.t

Lebesgue measure on \mathbb{R}^n .

Let

$$\begin{aligned} KL(P_n, Q_n) &= E_P \log \frac{dp_n}{dq_n} - E_Q \log \frac{dq_n}{dp_n} \\ &= E_P \log \frac{p_n(X_1, \dots, X_n)}{q_n(X_1, \dots, X_n)} \\ &\quad - E_Q \log \frac{q_n(X_1, \dots, X_n)}{p_n(X_1, \dots, X_n)} \end{aligned}$$

Claim: For GRF models $P \neq Q$

(i) $KL(P_n, Q_n)$ is monotonic

(ii) $KL(P_n, Q_n) \rightarrow \infty \Rightarrow P_{\infty} \perp Q_{\infty}$

(iii) $KL(P_n, Q_n) \rightarrow c < \infty \Rightarrow P_{\infty} = Q_{\infty}$

Proof:

(i) Follows since

a martingale
under P w.r.t.
 $(\mathcal{F}_n)_{n \geq 1}$

a martingale
under Q w.r.t.
 $(\mathcal{F}_n)_{n \geq 1}$

$$KL(P_n, Q_n) = E_P \left(-\log \underbrace{\frac{dQ_n}{dP_n}}_{\text{a subM under } P} \right) + E_Q \left(-\log \underbrace{\frac{dP_n}{dQ_n}}_{\text{a subM under } Q} \right)$$

\therefore a subM under P
since $-\log(x)$
is convex.

For (ii) Suppose $KL(P_n, Q_n) \rightarrow \infty$.

For each n find a linear transformation
of (X_1, \dots, X_n) to $(Z_{1,n}, \dots, Z_{n,n})$ s.t.

under Q : $(Z_{1,n}, \dots, Z_{n,n}) \sim N(0, I)$

under P : $(Z_{1,n}, \dots, Z_{n,n}) \sim N\left(\begin{pmatrix} m_{1,n} \\ \vdots \\ m_{n,n} \end{pmatrix}, \begin{pmatrix} \lambda_{1,n}^2 & & \\ & \ddots & \\ & & \lambda_{n,n}^2 \end{pmatrix}\right)$

(23)

Now

$$\begin{aligned} \frac{dP_n}{dQ_n} &= \frac{P_n(X_1, \dots, X_n)}{Q_n(X_1, \dots, X_n)} \\ &= \frac{\prod_{k=1}^n \lambda_{kn}^{-1} \exp\left(-\frac{1}{2} \frac{(z_{kn} - m_{kn})^2}{\lambda_{kn}^2}\right)}{\prod_{k=1}^n \exp\left(-\frac{1}{2} z_{kn}^2\right)} \end{aligned}$$

so that

$$E_p\left(\log \frac{dP_n}{dQ_n}\right) = E_p\left(-\frac{1}{2} \sum_{k=1}^n \left[\frac{(z_{kn} - m_{kn})^2}{\lambda_{kn}^2} - z_{kn}^2 \right]\right) - \sum_{k=1}^n \log \lambda_{kn}$$

$$= -\frac{1}{2} \sum_{k=1}^n \left[1 - m_{kn}^2 - \lambda_{kn}^2 \right] - \sum_{k=1}^n \log \lambda_{kn}$$

$$\begin{aligned} E_Q\left(\log \frac{dP_n}{dQ_n}\right) &= -\frac{1}{2} \sum_{k=1}^n \left[\frac{1 + m_{kn}^2}{\lambda_{kn}^2} - 1 \right] - \sum_{k=1}^n \log \lambda_{kn} \end{aligned}$$

∴

$$\begin{aligned} KL(P_n, Q_n) &= E_p\left(\log \frac{dP_n}{dQ_n}\right) - E_Q\left(\log \frac{dP_n}{dQ_n}\right) \\ &= -\frac{1}{2} \sum_{k=1}^n \left[2 - m_{kn}^2 - \lambda_{kn}^2 - \frac{1 + m_{kn}^2}{\lambda_{kn}^2} \right] \\ &= \frac{1}{2} \sum_{k=1}^n \left[\frac{(1 - \lambda_{kn}^2)^2}{\lambda_{kn}^2} + m_{kn}^2 + \frac{m_{kn}^2}{\lambda_{kn}^2} \right] \end{aligned}$$

(24)

Also

$$\text{var}_Q\left(\log \frac{dP_n}{dQ_n}\right) = \frac{1}{2} \sum_{k=1}^n \left[\frac{(1 - \lambda_{kn}^2)^2 + 2 m_{kn}^2}{\lambda_{kn}^4} \right]$$

$$\text{var}_P\left(\log \frac{dP_n}{dQ_n}\right) = \frac{1}{2} \sum_{k=1}^n \left[(1 - \lambda_{kn}^2)^2 + 2 m_{kn}^2 \lambda_{kn}^2 \right]$$

If $\inf_{k,n} \lambda_{kn}^2 = 0$, $\exists k_n$ s.t. $\lambda_{k_n, n}^2 \rightarrow 0$ then

$$\text{var}_Q(z_{k_n, n}) = 1 \text{ but } \text{var}_P(z_{k_n, n}) = \lambda_{k_n, n}^2 \rightarrow 0$$

which implies $P \perp Q$. Similarly $P \perp Q$

$$\text{if } \sup_{k,n} \lambda_{kn}^2 = \infty.$$

So suppose

$$0 < \inf_{k,n} \lambda_{kn}^2 \leq \sup_{k,n} \lambda_{kn}^2 < \infty$$

In this case

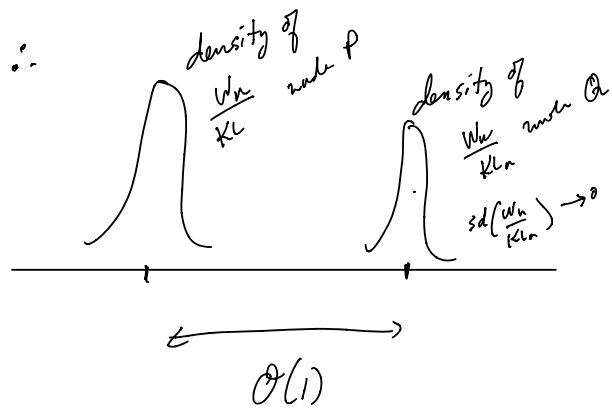
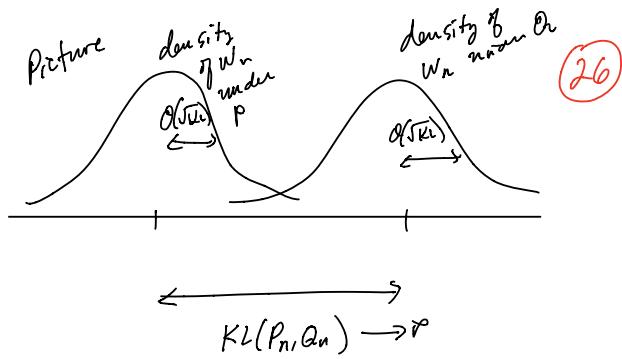
$$KL(P_n, Q_n) \asymp \text{var}_P\left(\log \frac{dP_n}{dQ_n}\right) \asymp \text{var}_Q\left(\log \frac{dP_n}{dQ_n}\right)$$

Now setting $w_n := \log \frac{dP_n}{dQ_n}$

$$KL(P_n, Q_n) = \underbrace{E_p(w_n) - E_Q(w_n)}_{\text{same order as}} \rightarrow \infty$$

$$\text{var}_p(w_n) \text{ & } \text{var}_Q(w_n)$$

(25)



$$\therefore P \perp Q_n$$

For (iii) Suppose $KL(P_n, Q_n) \rightarrow c < \sigma$

and show $P_\infty \equiv Q_\infty$

Suppose $P_\infty \neq Q_\infty$ so $\exists A \in \mathcal{F}_\infty$ s.t.

$P(A) > 0$ but $Q(A) = 0$

Approximate A with $A_n \in \bigcup_{k=1}^{\infty} \Theta_k$ such that

$$P(A_n) \rightarrow P(A) > 0$$

$$Q(A_n) \rightarrow Q(A) = 0$$

$$\text{Let } \mathcal{Q}_n := \{\emptyset, \mathcal{R}, A_n, A_n^c\}$$

Now

$$KL(P_n, Q_n) = E_p \log \frac{dp_n}{dQ_n} - E_q \log \frac{dq_n}{dP_n}$$

$$\text{since } -E_Q \log \frac{dq_n}{dQ_n} \stackrel{\text{jensen}}{\geq} -\log E_Q \frac{dq_n}{dQ_n} = -\log \int \frac{dq_n}{dQ_n} dQ_n = 0$$

we have

$$KL(P_n, Q_n) \geq E_p \log \frac{dp_n}{dQ_n}$$

$$= -E_p \log \frac{dQ_n}{dP_n}$$

$$= E_p \left(E_p \left(-\log \frac{dQ_n}{dP_n} | \mathcal{Q}_n \right) \right)$$

$$\geq E_p \left(-\log \underbrace{E_p \left(\frac{dQ_n}{dP_n} | \mathcal{Q}_n \right)}_{\text{jensen}} \right)$$

$$= \begin{cases} Q(A_n)/P(A_n) & \text{on } A_n \\ Q(A_n^c)/P(A_n^c) & \text{on } A_n^c \end{cases}$$

$$= -E_p \left(\log \left(\frac{Q(A_n)}{P(A_n)} \right) I_{A_n} + \log \left(\frac{Q(A_n^c)}{P(A_n^c)} \right) I_{A_n^c} \right)$$

$$= -P(A_n) \log \left(\frac{Q(A_n)}{P(A_n)} \right) - P(A_n^c) \log \left(\frac{Q(A_n^c)}{P(A_n^c)} \right)$$

$\rightarrow \sigma$

contradiction.

$$\therefore P_\infty \equiv Q_\infty.$$

QED