

MAS550 Probability Theory HW4, 2020/30 Yujun Kim

#4.1.2

$$a^2 \mathbb{1}_{|X| \geq a} \leq X^2 \Rightarrow \mathbb{1}_{|X| \geq a} \leq a^{-2} X^2.$$

$$\text{By thm 4.1.9, } \mathbb{P}(|X| \geq a | \mathcal{F}) = \mathbb{E}(\mathbb{1}_{|X| \geq a} | \mathcal{F})$$

$$\leq \mathbb{E}(a^{-2} X^2 | \mathcal{F}) \quad (\text{by (b)})$$

$$= a^{-2} \mathbb{E}(X^2 | \mathcal{F}). \quad (\text{by (a)})$$

#4.1.3

$(X + \theta Y)^2 \geq 0$. Thus, for θ ,

$$0 = \mathbb{E}[0 | \mathcal{G}] \leq \mathbb{E}[(X + \theta Y)^2 | \mathcal{G}]$$

$$= \underbrace{\mathbb{E}(X^2 | \mathcal{G})}_c + 2\theta \underbrace{\mathbb{E}(XY | \mathcal{G})}_b + \theta^2 \underbrace{\mathbb{E}(Y^2 | \mathcal{G})}_a \quad (\text{By linearity})$$

$$\Rightarrow b^2 - ac \leq 0$$

$$\text{Thus, } \mathbb{E}(XY | \mathcal{G})^2 \leq \mathbb{E}(X^2 | \mathcal{G}) \mathbb{E}(Y^2 | \mathcal{G})$$

#4.1.6

$$\begin{aligned} \mathbb{E}((X - \mathbb{E}(X | \mathcal{G}))^2) &= \mathbb{E}((X - \mathbb{E}(X | \mathcal{F}) + \mathbb{E}(X | \mathcal{F}) - \mathbb{E}(X | \mathcal{G}))^2) \\ &= \mathbb{E}((X - \mathbb{E}(X | \mathcal{F}))^2) + \mathbb{E}((\mathbb{E}(X | \mathcal{F}) - \mathbb{E}(X | \mathcal{G}))^2) \\ &\quad + 2 \mathbb{E}((X - \mathbb{E}(X | \mathcal{F}))(\mathbb{E}(X | \mathcal{F}) - \mathbb{E}(X | \mathcal{G}))) \end{aligned}$$

and so it suffices to show $(*) = 0$.

As $\mathcal{G} \subseteq \mathcal{F}$, $\mathbb{E}(X | \mathcal{G}) = \mathbb{E}(\mathbb{E}(X | \mathcal{G}) | \mathcal{F}) = \mathbb{E}(\mathbb{E}(X | \mathcal{F}) | \mathcal{G})$.
and $\mathbb{E}(X | \mathcal{G}), \mathbb{E}(X | \mathcal{F}) \in \mathcal{F}$.

Using $Z = \mathbb{E}(X | \mathcal{F}) - \mathbb{E}(X | \mathcal{G}) \in \mathcal{F}$ and thm 4.1.14,

$$Z \mathbb{E}(X | \mathcal{F}) = \mathbb{E}(ZX | \mathcal{F})$$

$$\Rightarrow \mathbb{E}(Z \mathbb{E}(X | \mathcal{F})) = \mathbb{E}(\mathbb{E}(ZX | \mathcal{F})) = \mathbb{E}(ZX).$$

$$\Rightarrow \mathbb{E}(Z(X - \mathbb{E}(X | \mathcal{F}))) = 0 \Leftrightarrow (*)$$

Hence, we are done.

#4.1.7

Note that $\mathcal{G} = \{\emptyset, \Omega\}$ is independent to any R.V.
Thus, $\mathbb{E}(X|\mathcal{G}) = \mathbb{E}(X)$.

From #4.1.6, $\mathbb{E}(\{X - \mathbb{E}(X|\mathcal{G})\}^2) = \mathbb{E}(\{X - \mathbb{E}(X)\}^2)$
 $= \text{Var}(X)$ ①

$$\begin{aligned}\mathbb{E}(\{X - \mathbb{E}(X|\mathcal{F})\}^2) &= \mathbb{E}(X^2) - 2\mathbb{E}(X\mathbb{E}(X|\mathcal{F})) \\ &\quad + \mathbb{E}(\mathbb{E}(X|\mathcal{F})^2)\end{aligned}\dots ②$$

$$\begin{aligned}\mathbb{E}(X\mathbb{E}(X|\mathcal{F})) &= \mathbb{E}(\mathbb{E}(X\mathbb{E}(X|\mathcal{F}))|\mathcal{F}) \\ &= \mathbb{E}(\mathbb{E}(X|\mathcal{F})\mathbb{E}(X|\mathcal{F})) \\ &= \mathbb{E}(\mathbb{E}(X|\mathcal{F})^2)\end{aligned}\dots ③$$

Using ③ to ①, $\mathbb{E}(\{X - \mathbb{E}(X|\mathcal{F})\}^2) = \mathbb{E}(X^2) - \mathbb{E}(\mathbb{E}(X|\mathcal{F})^2)$
 $= \mathbb{E}(\mathbb{E}(X^2|\mathcal{F})) - \mathbb{E}(\mathbb{E}(X|\mathcal{F})^2)$
 $= \mathbb{E}(\mathbb{E}(X^2|\mathcal{F}) - \mathbb{E}(X|\mathcal{F})^2)$
 $= \mathbb{E}(\text{Var}(X|\mathcal{F}))$ ④

$$\mathbb{E}(\mathbb{E}(X|\mathcal{F})) = \mathbb{E}(X) = \mathbb{E}(X|\mathcal{G}) \text{ so that}$$

$$\text{Var}(\mathbb{E}(X|\mathcal{F})) = \mathbb{E}(\{\mathbb{E}(X|\mathcal{F}) - \mathbb{E}(X|\mathcal{G})\}^2)$$
. ... ⑤

①, ④, ⑤ on #4.1.6 gives desired equality:

$$\text{Var}(X) = \mathbb{E}(\text{Var}(X|\mathcal{F})) + \text{Var}(\mathbb{E}(X|\mathcal{F}))$$

#4.1.8

$$\text{Var}(X) = \mathbb{E}(\text{Var}(X|N)) + \text{Var}(\mathbb{E}(X|N))$$

i) $\mathbb{E}(X|N) = \mu N$

$$\int_{N=n} X dP = \int_{N=n} Y_1 + \dots + Y_n dP$$

$$= n\mu \int 1_{N=n} dP = \mu \int_{N=n} N dP$$

$\{N=n\}$ generate $\sigma(N)$. Thus, $\mathbb{E}(X|N) = \mu N$.

ii) $\text{Var}(X|N) = \sigma^2 N$.

$$\int_{N=n} X^2 dP = \int_{N=n} (Y_1 + \dots + Y_n)^2 dP$$

$$= \sum_i \int_{N=n} Y_i^2 dP + \sum_{i \neq j} \int_{N=n} Y_i Y_j dP$$

$$= \{n(\sigma^2 + \mu^2) + n(n-1)\mu^2\} \int 1_{N=n} dP$$

$$= \int_{N=n} N\sigma^2 + N^2\mu^2 dP.$$

$$\Rightarrow \mathbb{E}[X^2 - N\mu^2 | N] = \mathbb{E}[X^2 | N] - \mathbb{E}[X | N]^2 = N\sigma^2.$$

The formula follows from #4.1.7

#4.1.9

$$\mathbb{E}(XY) = \mathbb{E}(\mathbb{E}(XY|\mathcal{G})) = \mathbb{E}(X\mathbb{E}(Y|\mathcal{G})) = \mathbb{E}(X^2).$$

as $X = \mathbb{E}(Y|\mathcal{G}) \in \mathcal{G}$

$$\begin{aligned} \text{Thus, } \mathbb{E}(X-Y)^2 &= \mathbb{E}X^2 + \mathbb{E}Y^2 - 2\mathbb{E}XY \\ &= \mathbb{E}X^2 + \mathbb{E}X^2 - 2\mathbb{E}X^2 = 0. \end{aligned}$$

#4.2.4

$$\sup X_n < \infty, \quad S_n = X_n - X_{n-1}, \quad \mathcal{F}_n = \sigma(X_1, \dots, X_n)$$

Let $N = \inf\{n \mid X_n^+ \geq M\}$. $X_{N \wedge n}$ is subMG, $X_{N \wedge n}^+ \leq M + \sup S_n^+$.

Then, $\mathbb{E}[X_{N \wedge n}^+] \leq M + \mathbb{E}[\sup S_n^+] < \infty$.

Hence, $X_{N \wedge n}$ conv. a.s. $\{N=\infty\} \cap \Omega$ as $M \rightarrow \infty$.

Thus, $N = \infty$ a.s. i.e. X_n converges a.s. as well.

#4.2.5

$$\xi_i = \begin{cases} -1 & \text{with probability } \frac{i^2}{i^2+1} \\ 1 & \text{with probability } \frac{1}{i^2+1}. \end{cases}$$

ξ_1, ξ_2, \dots independent.

Then, $\mathbb{E}\xi_i = 0$. Let $X_n = \xi_1 + \dots + \xi_n$, $\{\mathcal{F}_n\}$: canonical filtration

$$\begin{aligned}\mathbb{E}(X_{n+1} | \mathcal{F}_n) &= \mathbb{E}(X_n + \xi_{n+1} | \mathcal{F}_n) \\ &= X_n + \mathbb{E}(\xi_{n+1} | \mathcal{F}_n) \\ &= X_n + \mathbb{E}(\xi_{n+1}) = X_n.\end{aligned}$$

Hence, X_n is \mathcal{F}_n -MG.

$$\sum P(\xi_i \neq -1) = \sum \frac{1}{i^2+1} < \infty.$$

By 1st B-C, $P(\xi_i \neq -1 \text{ i.o.}) = 0$, i.e. $\xi_i = -1$ eventually a.s.

Hence, $X_n = -\infty$ a.s.

#4.2.6

(i) X_n is MG. $\exists x$ s.t. $X_n \rightarrow x$ a.s.

$$P(|X_{n+1} - X_n| > \varepsilon^2) \geq P(X_n > \varepsilon) P(|Y_{n+1} - 1| > \varepsilon) \rightarrow 0 \text{ as } n \rightarrow \infty.$$

As Y_n is iid, $P(Y_n = 1) < 1$, $P(|Y_{n+1} - 1| > \varepsilon) = \delta_\varepsilon > 0$.

Thus, $P(X_n > \varepsilon) \rightarrow 0$ as $n \rightarrow \infty$. i.e. $X_n \xrightarrow{P} 0$. Hence, $X_n \rightarrow 0$ a.s.

\nearrow neg. strict, as $P(Y > 1) > 0$, $P(Y < 1) > 0$.

(ii) $\mathbb{E} \log Y < \log \mathbb{E} Y = \log 1 = 0$.

By strong law of large nbrs,

$$\frac{1}{n} \log X_n = \frac{1}{n} \sum_{m=1}^n \log Y_m \rightarrow \mathbb{E} \log Y < 0.$$

#4.2.8

Let $Z_n = \prod_{i=1}^n (1 + Y_n) \in \mathcal{F}_n \Rightarrow Z_n \geq 0$

$$\text{Then, } \mathbb{E}\left(\frac{X_{n+1}}{Z_n} | \mathcal{F}_n\right) = \frac{1}{Z_n} \mathbb{E}(X_{n+1} | \mathcal{F}_n)$$

$$\leq \frac{1}{Z_n} (1 + Y_n) X_n = \frac{X_n}{Z_{n-1}}.$$

Thus, $\frac{X_{n+1}}{Z_n}$ is \mathcal{F}_n -super MG, $\frac{X_{n+1}}{Z_n} \geq 0$.

By thm 4.2.12, $\frac{X_{n+1}}{Z_n} \rightarrow W$ a.s.

$$Z_n \leq e^{\sum_{i=1}^n Y_i} \leq e^{\sum Y_n} < \infty \text{ a.s.}$$

Z_n is monotone increasing bounded above a.s. $\Rightarrow Z_n \rightarrow Z$ a.s.

Hence, $X_{n+1} = \frac{X_{n+1}}{Z_n} Z_n \rightarrow WZ$ a.s.

#4.3.3

Let $N = \inf \{k \mid \sum_{m=1}^k Y_m > M\}$, which is a stopping time.

$$Z_n = X_n - \sum_{k=1}^n Y_k \in \mathcal{F}_n$$

$$\begin{aligned} \mathbb{E}[Z_{n+1} \mid \mathcal{F}_n] &= \mathbb{E}\left[X_{n+1} - \sum_{k=1}^n Y_k \mid \mathcal{F}_n\right] \\ &= \mathbb{E}[X_{n+1} \mid \mathcal{F}_n] - \sum_{k=1}^n Y_k \\ &\leq X_n + Y_n - \sum_{k=1}^n Y_k = X_n - \sum_{k=1}^{n-1} Y_k = Z_n \end{aligned}$$

Hence, Z_{n+1} is \mathcal{F}_n -super MG

By thm, $Z_{n \wedge N}$ is superMG.

$$Z_{n \wedge N} + M = X_{n \wedge N} - \sum_{k=1}^{n \wedge N} Y_k + M \geq 0 \text{ is nonnegative superMG.}$$

By MG convergence thm, $Z_{n \wedge N} + M$ converges a.s.

$\Rightarrow Z_{n \wedge N}$ converges a.s.

$\{\sum Y_m \leq M\} \uparrow \Omega$ as $M \uparrow$. Thus, $\{N = \infty\}$ a.s. $\Rightarrow Z_{n \wedge N} = Z_n$ a.s.

Thus, $Z_n = X_n - \sum_{k=1}^{n-1} Y_k$ converges a.s. to Z_∞

$$\Rightarrow X_n = Z_n + \sum_{k=1}^{n-1} Y_k \rightarrow Z_\infty + \sum Y_k \text{ a.s.}$$

#4.3.12

$P_k = P(S_i^m = k)$, $\varphi(p) = p$ for $p < 1$.

① p^{2n} is MG.

$$\begin{aligned} E(p^{2n+1} | F_{1,n}) &= E(p^{S_1^{m+1} + \dots + S_{2n}^{m+1}} | F_{1,n}) \\ &= \prod_{i=1}^{2n} (E(p^{S_i^{m+1}} | F_{1,n})) \\ &= \prod_{i=1}^{2n} \varphi(p) \\ &= p^{2n} \end{aligned}$$

② If $Z_0 = \lambda$, $Z_n = Z_n^1 + \dots + Z_n^\lambda$, a sum of λ indep.

Galton Watson process. $P(Z_n^i = 0 \text{ for some } n) = p^{H_i} \quad \forall 1 \leq i \leq \lambda$.

$Z_n = 0 \text{ for some } n \iff Z_n^i = 0 \text{ for some } n_i \quad \forall 1 \leq i \leq \lambda$.

By independence, $P(Z_n = 0 \text{ for some } n) = \prod_{i=1}^{\lambda} (Z_n^i = 0 \text{ for some } n_i)$
 $= p^\lambda$ (thm 4.3.12)