

## Solution for HW 9

1. We first consider  $h(x, y) = 1_{x \in A} 1_{y \in B}$  where  $A, B$  are measurable sets in  $\mathbb{R}$ . On one hand,  $\mathbb{E}(h(X, Y)|\mathcal{G})(w) \stackrel{(*)}{=} 1_{Y(w) \in B} \mathbb{P}(X \in A|\mathcal{G})(w) = 1_{Y(w) \in B} \mu(w, A)$ , where  $(*)$  is due to the fact that  $Y$  is  $\mathcal{G}$ -measurable. On the other hand,  $\int h(x, Y(w)) \mu(w, dx) = 1_{Y(w) \in B} \mu(w, A)$ . Thus,  $\mathbb{E}(1_{X \in A} 1_{Y \in B}|\mathcal{G})(w) = \int 1_{x \in A} 1_{Y(w) \in B} \mu(w, dx)$ . Next by  $\pi - \lambda$  lemma, the equality holds for all indicator functions in  $\mathbb{R}^2$  (not necessarily decomposable). Finally the result also holds for bounded measurable functions by usual extension argument.
2. (b) $\Rightarrow$ (a) by taking  $h_1 = 1_{A_1}$  and  $h_2 = 1_{A_2}$ . (a) $\Rightarrow$ (b) follows usual extension argument. Now we prove that (c) $\Rightarrow$ (b). By tower property of conditional expectation,  $\mathbb{E}(h_1(X_1)h_2(X_2)|\mathcal{G}) = \mathbb{E}[\mathbb{E}(h_1(X_1)h_2(X_2)|\mathcal{G}, X_2)|\mathcal{G}] = \mathbb{E}[h_2(X_2)\mathbb{E}(h_1(X_1)|\mathcal{G}, X_2)|\mathcal{G}] = \mathbb{E}[h_2(X_2)\mathbb{E}(h_1(X_1)|\mathcal{G})|\mathcal{G}] = \mathbb{E}(h_1(X_1)|\mathcal{G})\mathbb{E}(h_2(X_2)|\mathcal{G})$ . Finally, we show that (b) $\Rightarrow$ (c). Take  $Y$  a  $\mathcal{G}$ -measurable random variable. (b) implies that  $\mathbb{E}(h_1(X_1)h_2(X_2)Y) = \mathbb{E}[\mathbb{E}(h_1(X_1)|\mathcal{G})\mathbb{E}(h_2(X_2)|\mathcal{G})Y] = \mathbb{E}[\mathbb{E}(h_1(X_1)|\mathcal{G})h_2(X_2)Y]$  (\*), where the last equality is due to the fact that  $\mathbb{E}(h_1(X_1)|\mathcal{G})Y$  is  $\mathcal{G}$ -measurable. To simplify the notation, denote  $Z := \mathbb{E}(h_1(X_1)|\mathcal{G}, X_2)$ . Since  $h_2(X_2)Y$  is  $\sigma(\mathcal{G}, X_2)$ -measurable,  $\mathbb{E}(Zh_2(X_2)Y) = \mathbb{E}(h_1(X_1)h_2(X_2)Y) \stackrel{(*)}{=} \mathbb{E}[\mathbb{E}(h_1(X_1)|\mathcal{G})h_2(X_2)Y]$ . Thus,  $\mathbb{E}[(Z - \mathbb{E}(h_1(X_1)|\mathcal{G}))h_2(X_2)Y] = 0$  for all measurable functions  $h_2$  and  $\mathcal{G}$ -measurable random variables  $Y$ . Again using  $\pi - \lambda$  argument,  $\mathbb{E}[(Z - \mathbb{E}(h_1(X_1)|\mathcal{G}))\mathcal{X}] = 0$  for all  $\sigma(\mathcal{G}, X_2)$ -measurable random variable  $\mathcal{X}$ , which permits to conclude.
3. We use extensively the property (c) in **Q2**. Denote  $f$  a bounded measurable function.  $X$  and  $Y$  are conditionally independent given  $Z$  means that  $\mathbb{E}(f(X)|Y, Z) \stackrel{(*)}{=} \mathbb{E}(f(X)|Z)$ .  $X$  and  $Z$  are conditionally independent given  $\mathcal{F}$  suggests that  $\mathbb{E}(f(X)|Z) \stackrel{(**)}{=} \mathbb{E}(f(X)|\mathcal{F})$  since  $\mathcal{F} \subset \sigma(Z)$ . By tower property of conditional expectation,  $\mathbb{E}(f(X)|Y, \mathcal{F}) = \mathbb{E}[\mathbb{E}(f(X)|Y, Z)|Y, \mathcal{F}] \stackrel{(\#)}{=} \mathbb{E}[\mathbb{E}(f(X)|\mathcal{F})|Y, \mathcal{F}] = \mathbb{E}(f(X)|\mathcal{F})$ , where  $(\#)$  follows  $(*)$  and  $(**)$ . Therefore,  $X$  and  $Y$  are conditionally independent given  $\mathcal{F}$ .
4. Suppose that  $(X_n)_{n \in \mathbb{N}}$  and  $(Y_n)_{n \in \mathbb{N}}$  are submartingales with respect to  $\mathcal{F}_n$ . Then  $\mathbb{E}(X_{n+1} + Y_{n+1}|\mathcal{F}_n) = \mathbb{E}(X_{n+1}|\mathcal{F}_n) + \mathbb{E}(Y_{n+1}|\mathcal{F}_n) \geq X_n + Y_n$ .  $(X_n + Y_n)_{n \in \mathbb{N}}$  is submartingale with respect to  $\mathcal{F}_n$ . In addition, observe that  $(x, y) \rightarrow \max(x, y)$  is convex. Apply Jensen's inequality (for conditional expectation), we get  $\mathbb{E}(\max(X_{n+1}, Y_{n+1})|\mathcal{F}_n) \geq \max(\mathbb{E}(X_{n+1}|\mathcal{F}_n), \mathbb{E}(Y_{n+1}|\mathcal{F}_n)) \geq \max(X_n, Y_n)$ .  $(\max(X_n, Y_n))_{n \in \mathbb{N}}$  is submartingale with respect to  $\mathcal{F}_n$ .
5. Denote  $(\xi_i)_{i \in \mathbb{N}}$  i.i.d such that  $\mathbb{P}(\xi_i = 1) = \mathbb{P}(\xi_i = -1) = \frac{1}{2}$ . Consider  $X_n := \sum_{i=1}^n \xi_i$  and  $Y_n := -\sum_{i=1}^{n+1} \xi_i$ . It is immediate that  $(X_n)_{n \in \mathbb{N}}$  is (sub)martingale with respect to filtration  $\mathcal{F}_n := \sigma(\xi_1, \dots, \xi_n)$  and  $(Y_n)_{n \in \mathbb{N}}$  is (sub)martingale with respect to filtration  $\mathcal{G}_n := \sigma(\xi_1, \dots, \xi_{n+1})$ . Suppose by contradiction that  $X_n + Y_n = -\xi_{n+1}$  is submartingale with respect to some filtration. According to martingale convergence theorem,  $\xi_n$  converges to some random variable  $\xi_\infty$  a.s. This is impossible by the construction of  $(\xi_n)_{n \in \mathbb{N}}$ .