

Stochastic analysis, fall 2014, Exercises-6, 29.10.2014

Consider a probability space (Ω, \mathcal{F}, P) equipped with the discrete-time filtration $\mathbb{F} = (\mathcal{F}_t : t \in \mathbb{N})$

1. In discrete time, show that a \mathbb{F} -predictable (P, \mathbb{F}) -martingale is constant, i.e $M_n(\omega) = M_0(\omega) \forall n$.

Solution

$$M_n = E(M_n | \mathcal{F}_{n-1}) = M_{n-1}$$

then $M_n(\omega) = M_0(\omega) \forall n$.

2. A *potential* $(Z_n : n \in \mathbb{N})$ is a non-negative (P, \mathbb{F}) -supermartingale with

$$\lim_{n \rightarrow \infty} E(Z_n) = 0$$

Show that a potential is uniformly integrable.

Solution

Note that, since Z_n is non-negative, then Z_n converges to 0 in L^1 . Then, by theorem 12 in the lecture notes, we have that it is uniformly integrable.

3. An (\mathbb{F}, P) -supermartingale $(X_n : n \in \mathbb{N})$ has *Riesz decomposition* if it can be written as

$$X_n = Y_n + Z_n$$

where Y_n is a martingale and Z_n is a potential.

- (a) Show that if $\sup_{n \in \mathbb{N}} E_P(X_n^-) < \infty$ then X_n has Riesz decomposition with

$$Y_n = M_n - E(A_\infty | \mathcal{F}_n), \quad Z_n = E(A_\infty | \mathcal{F}_n) - A_n,$$

where $X_n = M_n - A_n$ is the Doob decomposition of X into a martingale part M and a predictable part with A non-decreasing and $A_0 = 0$.

- (b) Show that the Riesz decomposition is unique.

Solution

- (a) By the Doob convergence theorem and Doob decomposition we have that there exist almost surely

$$\lim_{n \rightarrow \infty} X_n = X_\infty = M_\infty - A_\infty \in L^1$$

Furthermore, note that

$$E(A_n) = E(M_n) - E(X_n) \leq E(M_0) + E(X_n^-)$$

so we get

$$\sup_n E(A_n) < \infty$$

By linearity we get

$$\begin{aligned} X_n &= M_n + E(M_\infty - A_\infty | \mathcal{F}_n) - E(M_\infty - A_\infty | \mathcal{F}_n) - A_n = \\ &= M_n - E(A_\infty | \mathcal{F}_n) + E(A_\infty | \mathcal{F}_n) - A_n = Y_n + Z_n \end{aligned}$$

We check that Y_n is a martingale: it is integrable since M_n is a martingale

$$E(|M_n - E(A_\infty | \mathcal{F}_n)|) \leq E|M_n| + E(E(A_\infty | \mathcal{F}_n)) = E|M_n| + E(A_\infty) < \infty$$

and by the tower property the martingale property holds

$$E(M_n - E(A_\infty|\mathcal{F}_n)|\mathcal{F}_{n-1}) = M_{n-1} - E(E(A_\infty|\mathcal{F}_n)|\mathcal{F}_{n-1}) = M_{n-1} - E(A_\infty|\mathcal{F}_{n-1}).$$

Now we check that Z_n is a potential: it is clearly non negative and it is integrable

$$E|Z_n| = E(E(A_\infty|\mathcal{F}_n) - A_n) \leq E(E(A_\infty|\mathcal{F}_n)) = E(A_\infty) < \infty$$

and the super-martingale property holds

$$E(Z_n|\mathcal{F}_{n-1}) = E(E(A_\infty|\mathcal{F}_n) - A_n|\mathcal{F}_{n-1}) \leq E(A_\infty|\mathcal{F}_{n-1}) - A_{n-1}$$

Finally we check that $\lim_{n \rightarrow \infty} E(Z_n) = 0$:

$$\lim_{n \rightarrow \infty} E(Z_n) = \lim_{n \rightarrow \infty} E(E(A_\infty|\mathcal{F}_n) - A_n) = E(A_\infty) - E(\lim_{n \rightarrow \infty} A_n) = 0$$

where we used monotone convergence in the last equality.

(b) Let be $X_n = Y'_n + Z'_n = Y_n + Z_n$, then we have

$$Y'_n - Y_n = Z_n - Z'_n$$

We know that both Z_n and Z'_n converge to 0 both in probability and in L^1 since they are uniformly integrable, then $(Y'_n - Y_n)$ converges to 0 both in probability and in L^1 . But $(Y'_n - Y_n)$ is a martingale, so almost surely $\forall n$

$$(Z_n - Z'_n) = (Y'_n - Y_n) = E(Y'_n - Y_n|\mathcal{F}_n) = 0$$

4. Show that a martingale $(X_t : t \in \mathbb{N})$ has *Krickeberg decomposition*

$$X_t = L_t - M_t$$

where L_t and M_t are non-negative (P, \mathbb{F}) -martingales, if and only if

$$\sup_{t \in \mathbb{N}} E_P(|X_t|) < \infty$$

Hints: You can always assume without loss of generality that $M_0 = 0$, otherwise consider the martingale $(M_t - M_0)$.

For sufficiency show take the decomposition $X_t = X_t^+ - X_t^-$, and show first that $(-X_t^-)$ is a supermartingale and which admits a Riesz decomposition

$$(-X_t^-) = Y_t + Z_t$$

where Y_t is a martingale and Z_t is a potential. Show then that X_t has Krickeberg decomposition with

$$L_t = (X_t - Y_t) = X_t^+ + Z_t \geq 0, \quad \text{and} \quad M_t = -Y_t = X_t^- + Z_t \geq 0.$$

Solution

For sufficiency, we start by showing that $-X_t^-$ is a super-martingale: since the map $f : x \mapsto -x^-$ is concave, then the Jensen inequality for conditional expectation implies

$$E(f(X_t)|\mathcal{F}_{t-1}) \leq f(E(X_t|\mathcal{F}_{t-1})) = -X_{t-1}^-$$

Then we get immediately that $-X_t^-$ has a Riesz decomposition $-X_t^- = Y_t + Z_t$, for the hypothesis $\sup_{t \in \mathbb{N}} E_P(|X_t|) < \infty$.

Now write

$$X_t = X_t - Y_t + Y_t$$

and define $L_t := X_t - Y_t$ and $M_t := -Y_t$, which are non-negative martingales. To show the necessity we need to show that if $X_t = L_t - M_t$, where L_t, M_t are non-negative martingales, then

$$\sup_t E(|X_t|) < \infty$$

and this is true because $\forall t$

$$E(|X_t|) \leq E(L_t) + E(M_t) = E(L_0) + E(M_0) < \infty$$

5. Suppose we have an urn which contains at time $t = 0$ two balls, one black and one white. At each time $t \in \mathbb{N}$ we draw uniformly at random from the urn one ball, and we put it back together with a new ball of the same colour.

We introduce the random variables

$$X_t(\omega) = \mathbf{1}\{ \text{the ball drawn at time } t \text{ is black} \}$$

and denote $S_t = (1 + X_1 + \dots + X_t)$,

$M_t = S_t/(t + 2)$, the proportion of black balls in the urn.

We use the filtration $\{\mathcal{F}_n\}$ with $\mathcal{F}_n = \sigma\{X_s : s \in \mathbb{N}, s \leq t\}$.

- Compute the Doob decomposition of (S_t) , $S_t = S_0 + N_t + A_t$, where (N_t) is a martingale and (A_t) is predictable.
- Show that (M_t) is a martingale and find the representation of (M_t) as a martingale transform $M_t = (C \cdot N)_t$, where (N_t) is the martingale part of (S_t) and (C_t) is predictable.
- Note that the martingale $(M_t)_{t \geq 0}$ is uniformly integrable (Why?). Show that P a.s. and in L^1 exists $M_\infty = \lim_{t \rightarrow \infty} M_t$. Compute $E(M_\infty)$.
- Show that $P(0 < M_\infty < 1) > 0$.

Since $M_\infty(\omega) \in [0, 1]$, it is enough to show that $0 < E(M_\infty^2) < E(M_\infty)$ with strict inequalities.

Hint: compute the Doob decomposition of the submartingale (M_t^2) , and then take expectations before going to the limit to find the value of $E(M_\infty^2)$.

Solution

- We recall that according to the Doob decomposition we have

$$N_t = \sum_{r=1}^t (S_r - E(S_r | \mathcal{F}_{r-1})) \quad A_t = \sum_{r=1}^t (E(S_r | \mathcal{F}_{r-1}) - S_{r-1})$$

where

$$E(S_t | \mathcal{F}_{t-1}) = S_{t-1} + E(X_t | \mathcal{F}_{t-1}) = S_{t-1} + M_{t-1} = S_{t-1} \left(1 + \frac{1}{t+1}\right)$$

So the Doob decomposition is

$$S_t = 1 + \sum_{r=1}^t S_{r-1} \frac{1}{t+1} + \sum_{r=1}^t (X_r - M_{r-1})$$

Since the predictable part is non-decreasing, we see that S_t is a submartingale.

(b) M_t is a martingale because

$$E(M_t | \mathcal{F}_{t-1}) = \frac{1}{t+2} E(S_t | \mathcal{F}_{t-1}) = \frac{1}{t+2} \left(1 + \frac{1}{t+1}\right) S_{t-1} = \frac{S_{t-1}}{t+1} = M_{t-1}$$

and in order to find its representation as a martingale transform we consider

$$\begin{aligned} M_t - M_{t-1} &= \frac{S_t}{t+2} - \frac{S_{t-1}}{t+1} = \frac{S_{t-1} + X_t}{t+2} - \frac{S_{t-1}}{t+1} = \frac{1}{t+2} \left(X_t + S_{t-1} \left(1 - \frac{t+2}{t+1}\right) \right) \\ &= \frac{1}{t+2} \left(X_t - \frac{S_{t-1}}{t+1} \right) = \frac{1}{t+2} (X_t - M_{t-1}) \end{aligned}$$

Therefore

$$M_t = \frac{1}{2} + \sum_{r=1}^t \frac{1}{r+2} (X_r - M_{r-1}) = \frac{1}{2} + (C \cdot N)_t$$

with $C_t = \frac{1}{t+2}$ (deterministic).

(c) M_t is uniformly integrable because

$$|M_t| = \frac{|S_t|}{t+2} \leq \frac{t+1}{t+2} < 1$$

By Doob's martingale convergence theorem $M_t(\omega) \rightarrow M_\infty(\omega)$ P -almost surely, and by uniform integrability also in $L^1(P)$. Since M_t is uniformly integrable, then $E(M_\infty) = E(M_t) = E(M_0) = 1/2$.

(d) First we show that if $0 < E(M_\infty^2) < E(M_\infty)$ then $P(0 < M_\infty < 1) > 0$.

Note that $0 < E(M_\infty^2)$ is always true because, via the Jensen inequality, we have

$$E(M_\infty^2) \geq (E(M_\infty))^2 = 1/4 > 0$$

Moreover, note that $E(M_\infty^2) \leq E(M_\infty)$ because $0 \leq M_\infty^2 \leq M_\infty$.

Thus, we actually want to prove that if $E(M_\infty^2) < E(M_\infty)$ then $P(0 < M_\infty < 1) > 0$. Suppose that $P(0 < M_\infty < 1) = 0$, then we get

$$\begin{aligned} E(M_\infty^2) &= E[M_\infty^2 (\mathbf{1}(0 < M_\infty < 1) + \mathbf{1}(M_\infty = 0) + \mathbf{1}(M_\infty = 1))] = P(M_\infty = 1) \\ &= E[M_\infty (\mathbf{1}(0 < M_\infty < 1) + \mathbf{1}(M_\infty = 0) + \mathbf{1}(M_\infty = 1))] = E(M_\infty) \end{aligned}$$

so we got a contradiction.

Now we will show the inequality $E(M_\infty^2) < E(M_\infty)$: by the discrete integration by parts we have

$$M_t^2 - M_{t-1}^2 = 2M_{t-1}(M_t - M_{t-1}) + (M_t - M_{t-1})^2$$

and since by the martingale property

$$E\left(2M_{t-1}(M_t - M_{t-1})\right) = E\left(E(2M_{t-1}(M_t - M_{t-1}) | \mathcal{F}_{t-1})\right) = E\left(2M_{t-1}E(M_t - M_{t-1} | \mathcal{F}_{t-1})\right) = 0$$

it follows

$$E(M_t^2) = \frac{1}{4} + E\left(\sum_{r=1}^t ((M_r - M_{r-1})^2)\right) = \frac{1}{4} + \sum_{r=1}^t E\left(E((M_r - M_{r-1})^2 | \mathcal{F}_{r-1})\right)$$

Recall that $\Delta M_r = \frac{1}{r+2}(X_r - M_{r-1})$, thus

$$\begin{aligned} E((X_r - M_{r-1})^2 | \mathcal{F}_{r-1}) &= E(X_r^2 | \mathcal{F}_{r-1}) + M_{r-1}^2 - 2M_{r-1}E(X_r | \mathcal{F}_{r-1}) \\ &= E(X_r | \mathcal{F}_{r-1}) + M_{r-1}^2 - 2M_{r-1} \\ &= M_{r-1} - M_{r-1}^2 \end{aligned}$$

So we have

$$\begin{aligned} E(M_t^2) &= \frac{1}{4} + \sum_{r=1}^t \frac{1}{(r+2)^2} \left(E(M_{r-1}) - E(M_{r-1}^2) \right) = \frac{1}{4} + \sum_{r=1}^t \frac{1}{(r+2)^2} \left(\frac{1}{2} - E(M_{r-1}^2) \right) \\ &< \frac{1}{4} + \frac{1}{2} \sum_{r=1}^t \frac{1}{(r+2)^2} \end{aligned}$$

By Fatou's lemma

$$E(M_\infty^2) \leq \liminf_{t \rightarrow \infty} E(M_t^2) \leq \frac{1}{4} + \frac{1}{2} \sum_{r=1}^{\infty} \frac{1}{(r+2)^2} = \frac{1}{4} + \frac{1}{2} \sum_{r=3}^{\infty} \frac{1}{r^2} < \frac{1}{4} + \frac{1}{4} = E(M_\infty)$$

where $\sum_{r=3}^{\infty} r^{-2} < \int_2^{\infty} x^{-2} dx = 1/2$ with strict inequality.

6. Consider an i.i.d. random sequence $(U_t : t \in \mathbb{N})$ with uniform distribution on $[0, 1]$, $P(U_1 \in dx) = \mathbf{1}_{[0,1]}(x)dx$. Note that $E_P(U_t) = 1/2$.

Consider also the random variable $-\log(U_1(\omega))$ which is 1-exponential w.r.t. P .

$$P(-\log(U_1) > x) = \begin{cases} \exp(-x) & \text{kun } x \geq 0 \\ 1 & \text{kun } x < 0 \end{cases}$$

$-\log(U_1) \in L^1(P)$ with $E_P(-\log(U_1)) = 1$.

- (a) Let $Z_0 = 1$, and

$$Z_t(\omega) = 2^t \prod_{s=1}^t U_s(\omega)$$

Show that (Z_t) is a martingale in the filtration $\mathbb{F} = (\mathcal{F}_t : t \in \mathbb{N})$, with $\mathcal{F}_t = \sigma(Z_1, Z_2, \dots, Z_t) = \sigma(U_1, U_2, \dots, U_t)$.

- (b) Show that $E_P(Z_t) = 1$.
(c) Show that the limit $Z_\infty(\omega) = \lim_{t \rightarrow \infty} Z_t(\omega)$ exists P almost surely.
(d) Show that

$$Z_\infty(\omega) = 0 \quad P\text{-a.s.}$$

Hint Compute first the P -a.s. limit

$$\lim_{t \rightarrow \infty} \frac{1}{t} \log(Z_t(\omega))$$

(remember Kolmogorov's strong law of large numbers!).

- (e) Show that the martingale $(Z_t(\omega) : t \in \mathbb{N})$ is not uniformly integrable.
(f) Show that $\log(Z_t(\omega))$ is a supermartingale, does it satisfy the assumptions of Doob's martingale convergence theorem?
(g) At every time $t \in \mathbb{N}$, define the probability measure

$$Q_t(A) := E_P(Z_t \mathbf{1}_A) \quad \forall A \in \mathcal{F}_t$$

on the probability space (Ω, \mathcal{F}) .

Show that the random variables (U_1, \dots, U_t) are i.i.d. also under Q_t , compute their probability density under Q_t .

Solution

- (a) Note that $0 \leq Z_t \leq 2^t \forall t \in \mathbb{N}$, then Z_t is integrable $\forall t \in \mathbb{N}$ and it enjoys the martingale property

$$E(Z_t | \mathcal{F}_{t-1}) = 2^t \prod_{s=1}^{t-1} U_s(\omega) E(U_t) = Z_{t-1}$$

- (b) $E_P(Z_t) = E_P(Z_0) = Z_0 = 1$.
(c) $(Z_t : t \in \mathbb{N})$ is a non-negative martingale, by Doob's martingale convergence theorem $\lim_{t \rightarrow \infty} Z_t(\omega)$ exists a.s.
(d) Via the strong law of large numbers

$$\begin{aligned} \frac{1}{t} \log(Z_t) &= \frac{1}{t} \left(t \log(2) + \sum_{s=1}^t \log(U_s) \right) \\ &= \log(2) + \frac{1}{t} \sum_{s=1}^t \log(U_s) \rightarrow \log(2) + E(\log(U_1)) = \log(2) - 1 < 0. \end{aligned}$$

with convergence P a.s., then P a.s. as $t \rightarrow \infty$ $Z_t(\omega) = \mathcal{O}(\exp(t(\log(2) - 1))) \rightarrow 0$, that is $Z_\infty(\omega) = 0$.

- (e) Since $E(Z_1) = 1 > E(Z_\infty) = 0$, so the martingale property does not hold at infinity, so Z_t is not uniformly integrable.
(f) By Jensen' inequality for the conditional expectation:

$$\log Z_{t-1} = \log \left(E_P(Z_t | \mathcal{F}_{t-1}) \right) \geq E_P(\log Z_t | \mathcal{F}_{t-1})$$

therefore $\log(Z_t)$ is a supermartingale. We see that the hypothesis of the Doob convergence theorem does not hold, in fact

$$E_P(\log Z_t) = t \log 2 + \sum_{s=1}^t E(\log U_s) = t(\log 2 - 1) < 0$$

and

$$\sup_{t \in \mathbb{N}} E_P(|\log(Z_t)|) \geq \sup_{t \in \mathbb{N}} \left| E_P(\log(Z_t)) \right| = (1 - \log 2) \sup_{t \in \mathbb{N}} t = +\infty$$

Therefore the collection $\{\log(Z_t) : t \in \mathbb{N}\}$ is not bounded uniformly in $L^1(P)$.

- (g) For bounded measurable test functions $g_i(x)$, $i = 1, \dots, t$,

$$\begin{aligned} E_{Q_t}(g_1(U_1) \dots g_t(U_t)) &= E_P(Z_t g_1(U_1) \dots g_t(U_t)) = E_P \left(2^t \prod_{s=1}^t U_s g_s(U_s) \right) = \prod_{s=1}^t E_P(2U_s g(U_s)) \\ &= \prod_{s=1}^t E_P(Z_s g(U_s)) = \prod_{s=1}^t E_P(Z_t g_s(U_s)) = \prod_{s=1}^t E_{Q_t}(g_s(U_s)) \end{aligned}$$

which means that U_1, \dots, U_t are independent under Q_t .

For $t \in [0, 1]$

$$Q(U \leq t) = E_P(2U \mathbf{1}(U \leq t)) = 2 \int_0^t u du = t^2$$

and $Q(U \in dt) = 2tdt$.

7. (Paley's and Littlewood's maximal function) Consider a function in $f(x) \in L^1(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d), dx)$.

Define the σ -algebra

$$\mathcal{F}_k = \sigma\{Q_{k,z} = (z2^{-k}, (z+1)2^{-k}], z \in \mathbb{Z}^d\} \subseteq \mathcal{B}(\mathbb{R}^d), \quad k \in \mathbb{Z}$$

and the two sided filtration $\mathbb{F} = (\mathcal{F}_k : k \in \mathbb{Z})$ where the dyadic cubes $(Q_{k,z} : z \in \mathbb{Z}^d)$ form a partition of \mathbb{R}^d , and the functions

$$f_k(x) = \sum_{z \in \mathbb{Z}^d} \mathbf{1}(x \in Q_{k,z}) \frac{1}{|Q_{k,z}|} \int_{Q_{k,z}} f(y) dy$$

where for $k \in \mathbb{Z}$, $|Q_{k,z}| = 2^{-kd}$ is the Lebesgue measure of the d -dimensional dyadic cube

- (a) Show that $f_k(x)$ is an \mathbb{F} -martingale w.r.t. Lebesgue measure. Note that the definition of conditional expectation martingales extends directly to the case where we integrate with respect to σ -finite positive measures, where the martingale property in this case means

$$\int_{\mathbb{R}^d} f(x) g_k(x) dx = \int_{\mathbb{R}^d} f(x) g_k(x) dx$$

$\forall k \in \mathbb{Z}$ and $g_k(x)$ bounded and \mathcal{F}_k -measurable.

To work with a probability measure, we could take instead with $f(x) \in L^1([0, 1]^d, \mathcal{B}([0, 1]^d), dx)$.

- (b) Show that

$$\lim_{k \rightarrow -\infty} f_k(x) = 0, \quad \forall x \in \mathbb{R}^d,$$

but it does not converge in L^1 .

In particular this means that the Doob's martingale backward convergence theorem does NOT extend to the case of σ -finite measures.

- (c) Show that $\lim_{k \rightarrow +\infty} f_k(x) = f(x)$ almost everywhere and in L^1 .
 (d) Define the *maximal function*

$$f^\square(x) := \sup_{k \in \mathbb{Z}} f_k(x)$$

Use the martingale maximal inequalities to show that for $1 < p < \infty$

$$\|f^\square(x)\|_{L^p(\mathbb{R}^d)} \leq \frac{p}{p-1} \sup_{k \in \mathbb{Z}} \|f_k\|_{L^p(\mathbb{R}^d)} \leq \frac{p}{p-1} \|f\|_{L^p(\mathbb{R}^d)}$$

and

$$cP(|f^\square(x)| > c) \leq \sup_{k \in \mathbb{Z}} \|f_k\|_{L^1(\mathbb{R}^d)} \leq \|f\|_{L^1(\mathbb{R}^d)}$$

Solution

- (a) Note that $f_k \in \mathcal{F}_k$ and that $\mathcal{F}_k \subseteq \mathcal{F}_{k+1}$. We want to show that f_k is a martingale, so first we see that f_k is integrable $\forall k \in \mathbb{Z}$.

$$\begin{aligned} \int_{\mathbb{R}^d} dx |f_k(x)| &= \int_{\mathbb{R}^d} dx \sum_{z \in \mathbb{Z}^d} \mathbf{1}(x \in Q_{k,z}) 2^{kd} \left| \int_{Q_{k,z}} f(y) dy \right| \\ &\leq \int_{\mathbb{R}^d} dx \sum_{z \in \mathbb{Z}^d} \mathbf{1}(x \in Q_{k,z}) 2^{kd} \int_{Q_{k,z}} |f(y)| dy \\ &\leq \sum_{z \in \mathbb{Z}^d} \int_{Q_{k,z}} |f(y)| dy = \|f\|_1 < \infty \end{aligned}$$

where we used the monotone convergence theorem to switch the order between the sum and the integral.

Note that every $A \in \mathcal{F}_k$ is a disjoint union of squares Q_k , i.e. $A = \cup_{i \in I} Q_{k,i}$ for some set $I \subseteq \mathbb{Z}$, and each $Q_{k,i}$ is clearly the union of four squares of size $2^{-(k+1)}$. Then we can check the martingale property by using the Kolmogorov's definition of conditional expectation just for a generic Q_k

$$\begin{aligned} \int_{\mathbb{R}^d} dx f_{k+1}(x) \chi_{Q_k}(x) &= \int_{\mathbb{R}^d} dx \sum_{i: \cup_{j=1}^4 Q_{k+1,i} = Q_k} \frac{\chi_{Q_{k+1,i}}(x)}{|Q_{k+1,i}|} \int_{Q_{k+1,i}} f(y) dy = \\ &= \int_{Q_k} f(y) dy = \int_{\mathbb{R}^d} dx f_k(x) \chi_{Q_k}(x) \end{aligned}$$

(b) Note that

$$|f_k(x)| \leq 2^{kd} \|f\|_{L^1(\mathbb{R}^d)} \rightarrow 0, \quad \text{as } k \rightarrow -\infty$$

On the other hand we have

$$E|f_k| = \sum_{z \in \mathbb{Z}} \left| \int_{Q_{z,k}} f(x) dx \right| \rightarrow |E(f)|$$

as $k \rightarrow -\infty$, then $f_k \rightarrow f$ in L^1 as $k \rightarrow -\infty$ only if $|E(f)| = 0$

(c) To show convergence in L^1 convergence, we split the integral into two parts. Let $\epsilon > 0$. Then there exists a dyadic cube Q , such that

$$\int_{\mathbb{R}^d \setminus Q} |f(x)| dx < \epsilon$$

Then also

$$\int_{\mathbb{R}^d \setminus Q} |f_k(x) - f(x)| dx < \int_{\mathbb{R}^d \setminus Q} (|f_k(x)| + |f(x)|) dx < 2\epsilon$$

because $\int_{\mathbb{R}^d \setminus Q} |f_k(x)| \leq \int_{\mathbb{R}^d \setminus Q} |f(x)|$ when k is large enough so that the cubes on the level k tile the set $\mathbb{R}^d \setminus Q$.

On the other hand, Q has finite measure (which we can normalize to be 1), and $f_k|_Q$ is uniformly integrable because

$$f_k = E(f|\mathcal{F}_k)$$

Therefore $f_k|_Q \rightarrow f|_Q$ in L^1 .

The result follows since

$$\int_{\mathbb{R}^d} |f_k(x) - f(x)| dx \leq \int_Q |f_k(x) - f(x)| dx + \int_{\mathbb{R}^d \setminus Q} |f_k(x) - f(x)| dx < 3\epsilon$$

for k large enough.

On the other hand the convergence almost surely follows from the Doob martingale convergence theorem.

(d) For $n \in \mathbb{N}$, the process $(|f_k(x)| : k = -n, \dots, 0, \dots, n)$ is a submartingale as one can see by the Jensen's inequality.

We want to apply the maximal Doob inequality, so we need to consider a probability measure: for each $z \in \mathbb{Z}^d$, consider the probability space $Q_{-n,z}$ equipped with the normalized Lebesgue measure $2^{-nd} dx$.

Then $\forall z \in \mathbb{Z}$, $c > 0$, by using Doob's martingale maximal inequalities

$$\begin{aligned} c \int_{Q_{-n,z}} \mathbf{1} \left(\sup_{-n \leq k \leq n} |f_k(x)| > c \right) dx &\leq \int_{Q_{-n,z}} |f_n(x)| \mathbf{1} \left(\sup_{-n \leq k \leq n} |f_k(x)| > c \right) dx \\ &\leq \int_{Q_{-n,z}} |f_n(x)| dx \end{aligned}$$

and we can sum over $z \in \mathbb{Z}^d$ obtaining

$$\begin{aligned} c \int_{\mathbb{R}^d} \mathbf{1} \left(\sup_{-n \leq k \leq n} |f_k(x)| > c \right) dx &\leq \int_{\mathbb{R}^d} |f_n(x)| \mathbf{1} \left(\sup_{-n \leq k \leq n} |f_k(x)| > c \right) dx \\ &\leq \int_{\mathbb{R}^d} |f_n(x)| dx \leq \|f\|_{L^1(\mathbb{R})} \end{aligned} \quad (1)$$

This implies easily that

$$c \int_{\mathbb{R}^d} \mathbf{1} \left(\sup_{-n \leq k \leq n} |f_k(x)| > c \right) dx \leq \int_{\mathbb{R}^d} |f_n(x)| dx \leq \sup_{n \in \mathbb{Z}} \|f_n\|_1 \leq \|f\|_1$$

Moreover, by monotone convergence we get that

$$\begin{aligned} \lim_{n \rightarrow \infty} c \int_{\mathbb{R}^d} \mathbf{1} \left(\sup_{-n \leq k \leq n} |f_k(x)| > c \right) dx &= c \int_{\mathbb{R}^d} \mathbf{1} \left(\sup_{k \in \mathbb{Z}} |f_k(x)| > c \right) dx \\ &\geq c \int_{\mathbb{R}^d} \mathbf{1} \left(\left| \sup_{k \in \mathbb{Z}} f_k(x) \right| > c \right) dx =: cP(|f^\square(x)| > c) \end{aligned}$$

so we finally get the second inequality from 1

$$cP(|f^\square(x)| > c) \leq \sup_{k \in \mathbb{Z}} \|f_k\|_{L^1(\mathbb{R}^d)} \leq \|f\|_{L^1(\mathbb{R}^d)}$$

Now, if $f \in L^p$, then $\|f_k\|_p \leq \|f\|_p \forall k \in \mathbb{Z}$. Equation 1 means that the hypothesis of Lemma 20 are satisfied in the probability space specified above and for $X = \sup_{k \in \mathbb{Z}} |f_k(x)| \geq f^\square(x)$ and $Y = f_n(x) \forall n \in \mathbb{N}$.

Thus we get

$$\int_{Q_{-n,z}} |f^\square(x)|^p dx \leq \left(\frac{p}{p-1} \right)^p \int_{Q_{-n,z}} |f_n(x)|^p dx$$

By summing all over $z \in \mathbb{Z}^d$ we get finally

$$\|f^\square(x)\|_p \leq \frac{p}{p-1} \|f_n\|_p \leq \frac{p}{p-1} \sup_{k \in \mathbb{Z}} \|f_k\|_p \leq \frac{p}{p-1} \|f\|_p$$