

mas651 exercises

Jaemin Oh

April 7, 2021

Problem (5.1.1).

Let (S, \mathcal{S}) be a state space of X_n where $S = \{1, 2, \dots, N\}$ and $\mathcal{S} = 2^S$. Note that N is an absorbing state. And $X_1 = 1$ with probability 1. For fixed k such that $1 \leq k < N$, $k \leq n$,

$$P(X_{n+1} = k + 1 | X_n = k) = \frac{N - k}{N}$$

and

$$P(X_{n+1} = k | X_n = k) = \frac{k}{N}.$$

If $k > n$, then the above are all 0. So it is a temporally inhomogeneous. The Markov property is trivial since the very next state only depends on the current state.

□

Problem (5.1.2).

$$P(X_4 = 2 | X_3 = 1, X_2 = 1, X_1 = 1, X_0 = 0) = (1/16)/(1/4) = 1/4$$

but

$$P(X_4 = 2 | X_3 = 1, X_2 = 0, X_1 = 0, X_0 = 0) = (1/16)/(1/8) = 1/2.$$

Thus X_n is not a Markov chain.

□

Problem (5.1.5).

$$P(X_{n+1} = k + 1 | X_n = k) = \frac{m - k}{m} \frac{b - k}{m}$$

because we must choose a white ball in the left urn and a black ball in the right urn.

$$P(X_{n+1} = k | X_n = k) = \frac{k}{m} \frac{b - k}{m} + \frac{m - k}{m} \frac{m + k - b}{m}$$

since there are two cases, choosing both black or both white.

$$P(X_{n+1} = k - 1 | X_n = k) = \frac{k}{m} \frac{m + k - b}{m}$$

since we must choose a black ball in the left urn and a white ball in the right urn. Note that the sum of the above is 1, so there is no other transition probability.

□

Problem (5.1.6).

$$P(S_{n+1} = k + 1 | S_n = k) = \frac{P(X_{n+1} = 1, S_n = k)}{P(S_n = k)}$$

where the denominator is

$$\int_{\theta \in (0,1)} P(S_n = k|\theta) dP = \binom{n}{x} \frac{x!y!}{(n+1)!} = \frac{1}{n+1}$$

for $x =$ the number of i such that $U_i \leq \theta$ and $y = n - x$. Note that $x = (n+k)/2$ and $y = (n-k)/2$ since $x + y = n$ and $x - y = k$. The numerator is

$$\int_{\theta \in (0,1)} P(X_{n+1} = 1, S_n = k|\theta) dP = \binom{n}{x} \frac{(x+1)!y!}{(n+2)!}$$

These are because $P(S_n = k|\theta) = \theta^x(1-\theta)^y \binom{n}{x}$ and $P(X_{n+1} = 1, S_n = k|\theta) = P(X_{n+1} = 1|\theta)P(S_n = k|\theta) = \binom{n}{x} \theta^{x+1}(1-\theta)^y$ and using the kernel of beta distribution.

Thus, the probability what we want is $(n+k+2)/(2n+4)$ which depends on n . So X_n is temporally inhomogeneous.

$$P(S_{n+1} = k+1 | S_1 = t_1, \dots, S_n = k) = P(X_{n+1} = 1 | X_1 = t_1, \dots, X_n = t_n)$$

where $\sum_{i=1}^n t_i = k$. We can show the above is equal to $P(S_{n+1} = k+1 | S_n = k) = (n+k+2)/(2n+4)$ similarly, by omitting the $\binom{n}{x}$ term of both denominator and numerator.

□

Problem (5.2.1).

By the given hint,

$$E(1_A 1_B | \mathcal{F}_n) = E(1_A E(1_B | \mathcal{F}_n) | X_n)$$

so it suffices to show that $E(1_B | \mathcal{F}_n) = E(1_B | X_n)$.

Let $Y = 1_{B_n}(\omega_0) \cdots 1_{B_{n+k}}(\omega_k)$. Then $Y \circ \theta_n =$ the indicator function of $\{X_n \in B_n, \dots, X_{n+k} \in B_{n+k}\} = B$. By the markov property,

$$P(B | \mathcal{F}_n) = E_{X_n} Y.$$

Let $\varphi(x) = E_x Y$ then $\varphi(X_n)$ is $\sigma(X_n)$ -measurable mapping. Thus, when B has a form of $\{X_n \in B_n, \dots, X_{n+k} \in B_{n+k}\}$ for some nonnegative integer k ,

$$P(B | \mathcal{F}_n) = P(B | X_n).$$

Note that a collection of such B generates $\sigma(X_n, X_{n+1}, \dots)$.

Now let $\mathcal{G} = \{C : P(C | \mathcal{F}_n) = P(C | X_n)\}$. By putting $B_{n+i} = S$ for $0 \leq i \leq k$, we earn $\Omega_0 \in \mathcal{G}$. If $C, D \in \mathcal{G}$ and $C \subset D$, then by properties of conditional expectation, $D \setminus C \in \mathcal{G}$. If $C_i \in \mathcal{G}$ and $C_i \uparrow C$ then by monotone convergence theorem for conditional expectation, $C \in \mathcal{G}$. Thus \mathcal{G} is a lambda system containing a collection of B 's which generates $\sigma(X_n, \dots)$. Therefore, by Dynkin's theorem, the third equation is satisfied by any $B \in \sigma(X_n, \dots)$. By the first equation, we can derive the conclusion. □

Problem (5.2.4).

First, claim that

$$P_x(X_n = y | T_y = m) = P_y(X_{n-m} = y).$$

This is because

$$\begin{aligned} P_x(X_n = y | T_y = m) &= \frac{P_x(X_n = y, T_y = m)}{P_x(T_y = m)} \\ &= \frac{\int_{T_y=m} 1_{(X_n=y)} dP_x}{P_x(T_y = m)} \\ &= \frac{\int_{T_y=m} E(1_{(X_n=y)} | \mathcal{F}_m) dP_x}{P_x(T_y = m)} \\ &= \frac{\int_{T_y=m} E_{X_m} 1_{(X_{n-m}=y)} dP_x}{P_x(T_y = m)} \\ &= \frac{P_x(T_y = m) P_y(X_{n-m} = y)}{P_x(T_y = m)}. \end{aligned}$$

Now, note that $P_x(X_n = y) = \sum_{m=1}^n P_x(X_n = y, T_y = m)$. From this and

the above discussion,

$$\begin{aligned} p^n(x, y) &= P_x(X_n = y) = \sum_{m=1}^n P_x(X_n = y | T_y = m) P_x(T_y = m) \\ &= \sum_{m=1}^n P_y(X_{n-m} = y) P_x(T_y = m) = \sum_{m=1}^n P_x(T_y = m) p^{n-m}(y, y). \end{aligned}$$

□

Problem (5.2.6).

Fix $x \in S \setminus C$. Since $P_x(T_C = \infty) = \lim_{M \rightarrow \infty} P_x(T_C > M) < 1$, we can choose N_x and ε so that

$$P_x(T_C > M) \leq 1 - \varepsilon$$

whenever $M \geq N_x$. Note that we can choose N_x as an integer. Put $N = \max_{x \in S \setminus C} N_x$. Now we get

$$\begin{aligned} P_y(T_C > 2N) &= \sum_{x \in S \setminus C} P_y(T_C > 2N, T_C > N, X_N = x) \\ &= \sum_{x \in S \setminus C} P_y(T_C > 2N | X_N = x, T_C > N) P_y(X_N = x, T_C > N) \\ &\leq \sum_{x \in S \setminus C} P_x(T_C > N) P_y(X_N = x, T_C > N) \\ &\leq (1 - \varepsilon) \sum_{x \in S \setminus C} P_y(X_N = x, T_C > N) \\ &\leq (1 - \varepsilon)^2. \end{aligned}$$

By induction, the result follows.

Remark 1. By $k \rightarrow \infty$, we can say that $P_y(T_C = \infty) = 0$. That is, $P_y(T_C < \infty) = 1$.

□

Problem (5.2.7).

1. It is similar to the manipulation of problem 5.2.4:

$$\begin{aligned} P_x(V_A < V_B) &= \sum_y P_x(V_A < V_B, X_1 = y) = \sum_y P_x(V_A < V_B | X_1 = y) P_x(X_1 = y) \\ &= \sum_y p(x, y) P_x(V_A < V_B | X_1 = y) = \sum_y p(x, y) P_y(V_A < V_B) \end{aligned}$$

where the first term is $h(x)$ and the last term is $\sum_y p(x, y)h(y)$.

2. I think we must further assume that h is bounded and measurable. For convenience, let $\tau = V_A \wedge V_B = V_{A \cup B}$. By the equation (5.2.2) of our textbook, we get

$$\begin{aligned} E_x(h(X_{n+1})|\mathcal{F}_n) &= \sum_y p(X_n, y)h(y) \\ &= h(X_n) \end{aligned}$$

for $X_n \notin A \cup B$.

Now, put $Y_n = h(X_n)$. Then

$$Y_{n \wedge \tau} - Y_0 = h(X_{n \wedge \tau}) - h(X_0) = \sum_{k=1}^n 1_{(\tau \geq k)} (Y_k - Y_{k-1}).$$

By using the above,

$$\begin{aligned} E_x(Y_{n+1 \wedge \tau} - Y_0|\mathcal{F}_n) &= \sum_{k=1}^{n+1} 1_{(\tau \geq k)} E_x(Y_k - Y_{k-1}|\mathcal{F}_n) \\ &= 1_{(\tau \geq n+1)} (Y_n - Y_0) + 1_{(\tau < n+1)} (Y_\tau - Y_0) \\ &= 1_{(\tau > n)} (Y_n - Y_0) + 1_{(\tau \leq n)} (Y_\tau - Y_0) \\ &= Y_{n \wedge \tau} - Y_0. \end{aligned}$$

So $h(X_{n \wedge \tau})$ is a martingale. Note that the first equality is due to (5.2.2), and the last is due to optional stopping.

3. We assumed that h is bounded. Thus, our martingale is uniformly bounded, so the optional stopping theorem can be applied:

$$x = E_x h(X_0) = E_x h(X_\tau) = E_x [E_x(h(X_\tau)|\mathcal{F}_\tau)]$$

where the last term is equal to

$$E_x [E_{X_\tau} h(X_0)] = E_x [1_{(X_\tau \in A)} + 0 \cdot 1_{(X_\tau \in B)}] = E_x [1_{(X_\tau \in A)}].$$

The above is because $P_x(\tau < \infty) = 1$ and h is 1 on A and 0 on B . Note that this implies the result, since $X_\tau \in A$ is equivalent to $V_A < V_B$.

□

Problem (5.2.8).

Let $\tau = V_0 \wedge V_N$. Then $X_{n \wedge \tau}$ is an uniformly bounded martingale since the state space of X_n is finite. By the optional stopping theorem, we get

$$E_x X_0 = E_x X_\tau$$

where the LHS is equal to x . Note that, by the remark 1, we can say that $P_x(\tau < \infty) = 1$. Then the RHS of the above eqn is equal to $0P_x(V_0 < V_N) + NP_x(V_N < V_0)$. Thus,

$$x = NP_x(V_N < V_0).$$

□

Problem (5.2.11).

1. It is similar to the manipulation of problem 5.2.7:

$$\begin{aligned}
E_x V_A &= \sum_{k \geq 1} P_x(V_A \geq k) \\
&= P_x(V_A \geq 1) + \sum_{k \geq 2} P_x(V_A \geq k) \\
&= 1 + \sum_{k \geq 2} P_x(V_A \geq k) \\
&= 1 + \sum_{k \geq 2} \sum_y P_x(V_A \geq k | X_1 = y) P_x(X_1 = y) \\
&= 1 + \sum_y p(x, y) \sum_{k \geq 2} P_y(V_A \geq k - 1) = 1 + \sum_y p(x, y) E_y V_A
\end{aligned}$$

where $P_x(V_A \geq 1) = 1$ since x lies outside of A .

Also, $E_x V_A < \infty$ because

$$\begin{aligned}
E_x \frac{V_A}{N} &= \sum_{k \geq 1} P_x(V_A \geq kN) \\
&\leq \sum_{k \geq 1} (1 - \varepsilon)^k < \infty.
\end{aligned}$$

2. I think we should assume the measurability, and boundedness of g . By the manipulation used in problem 5.2.7, we get:

$$\begin{aligned}
E_x(g(X_{n+1}) + n + 1 | \mathcal{F}_n) &= n + 1 + \sum_y p(X_n, y) g(y) \\
&= n + g(X_n)
\end{aligned}$$

for $X_n \notin A$.

Now put $Y_n = g(X_n) + n$ and $\tau = V_A$ for convenience. Then

$$\begin{aligned}
E_x(Y_{n+1 \wedge \tau} - Y_0 | \mathcal{F}_n) &= \sum_{k=1}^{n+1} 1_{(\tau \geq k)} E_x(Y_k - Y_{k-1} | \mathcal{F}_n) \\
&= 1_{(\tau \geq n+1)}(Y_n - Y_0) + 1_{(\tau < n+1)}(Y_\tau - Y_0) \\
&= Y_{n \wedge \tau} - Y_0.
\end{aligned}$$

So $X_{n \wedge V_A} + n \wedge V_A$ is a martingale.

3. From the boundedness of g and the fact that V_A is L^1 function, our martingale is uniformly integrable. Thus we can apply optional stopping theorem:

$$E_x g(X_0) = E_x [V_A + g(X_{V_A})]$$

where the first term is $g(x)$ and the second term is $E_x V_A + E_x g(X_{V_A})$. But X_{V_A} lies in A and g is 0 on A . Thus the second term of the equation is $E_x V_A$.

□

Problem (5.3.1).

Abbreviation of notation: $P(X_1 \leq x_1, \dots, X_n \leq x_n)$ as $P(X \leq x)$, which is a distribution function of a random vector.

First, let's see that they are identically distributed. Since y is recurrent, the strong Markov property always holds when we are considering \mathcal{F}_{R_k} .

$$P_y(\nu_k \leq x) = E_y P_y(\nu_k \leq x | \mathcal{F}_{R_{k-1}}) = E_y E_{X_{R_{k-1}}} 1_{(\nu_1 \leq x)} = P_y(\nu_1 \leq x).$$

So ν_k are identically distributed.

Now, let's see that they are independent.

$$\begin{aligned} P_y(\nu_1 \leq x_1, \dots, \nu_n \leq x_n) &= E_y P_y(\nu_1 \leq x_1, \dots, \nu_n \leq x_n | \mathcal{F}_{R_{n-1}}) \\ &= E_y [1_{(\nu_1 \leq x_1)} \cdots 1_{(\nu_{n-1} \leq x_{n-1})} P_y(\nu_n \leq x_n)] \\ &= P_y(\nu_1 \leq x_n) P_y(\nu_1 \leq x_1, \dots, \nu_{n-1} \leq x_{n-1}) \\ &= \dots \\ &= P_y(\nu_n \leq x_n) \cdots P_y(\nu_1 \leq x_1) \end{aligned}$$

since they are identically distributed. Note that ν_1, \dots, ν_{n-1} are $\mathcal{F}_{R_{n-1}}$ measurable. This is because $\{X_{R_{n-2}+i} \in B\} \cap \{R_{n-1} = k\} \in \mathcal{F}_k$. □

Problem (5.3.2).

On $\{T_y < \infty\}$, by the strong Markov property,

$$\rho_{xy} = P_y(T_z < \infty) = E_x (1_{(T_y + T_z < \infty)} | \mathcal{F}_{T_y}).$$

Thus,

$$\begin{aligned} \rho_{xy} \rho_{yz} &= E_x 1_{(T_y < \infty)} E_x (1_{(T_y + T_z < \infty)} | \mathcal{F}_{T_y}) \\ &= E_x 1_{(T_y < \infty)} 1_{(T_y + T_z < \infty)} \\ &= P_x(T_y + T_z < \infty) \leq P_x(T_z < \infty) = \rho_{xz}. \end{aligned}$$

Problem (5.3.5).

As in the proof of theorem 5.3.8, $\varphi(X_{n \wedge \tau})$ is a nonnegative supermartingale. So the supermartingale converges to Y a.s. From the modified condition $\varphi \rightarrow 0$, we know that $\{x : \varphi(x) > M\}$ is a finite set. So X_n visits $\{x : \varphi(x) > M\}$ only finitely many times for all $M > 0$. Thus $\varphi(X_n) \rightarrow 0$ as $n \rightarrow \infty$. If $\tau < \infty$ almost surely, then $\varphi(X_{n \wedge \tau}) \rightarrow \varphi(X_\tau) = 0$. But we have the other condition: $\varphi > 0$ on F . So $\varphi(X_\tau) = 0$ cannot happen; thus $P_x(\tau = \infty) > 0$.

If the chain is recurrent, then $\tau < \infty$ a.s. But our case is not the case, so the chain must be transient. □

Problem (5.3.7).

First assume the recurrence. Let f be a superharmonic function, so $f(X_n)$ is a nonnegative supermartingale. By the martingale convergence theorem, $f(X_n) \rightarrow$

Y a.s. By the recurrence, $P(X_n = x \text{ i.o.}) = 1$ for all $x \in S$. So $P(f(X_n) = f(x) \text{ i.o.}) = 1$, which says $f(X_n) \rightarrow f(x) = Y$ a.s. But $x \in S$ is arbitrary, f must be a constant.

Now, assume the transience. Fix $z \in S$. Let $V = \inf \{n \geq 0 : X_n = z\}$. Let $f(x) = P_x(V < \infty)$. We will show that f is a nonconstant superharmonic function. For $x \neq z$,

$$f(x) = P_x(V < \infty) = \sum_y p(x, y) P_y(V < \infty) = \sum_y p(x, y) f(y).$$

For $x = z$,

$$\sum_y p(z, y) f(y) \leq \sum_y p(z, y) = 1 = f(z)$$

since $f \leq 1$. Thus, f is superharmonic.

Now claim that there is $y \in S$ such that $f(y) < 1$. If no such y exists, then $f(y) = 1$ for all $y \in S$. This says that $P_y(V < \infty) = 1$ for all y which is equivalent to the recurrence of z . But we assumed the transience of our chain. So there is $y \in S : f(y) < 1$. And this says f is nonconstant. □

Problem (5.5.2).

Let N_y^x be the number of hittings to y before returning to x . Then $\mu_x(y) = E_x N_y^x$. Also, we can write

$$N_y^x = \sum_{k=1}^{\infty} 1_{(T_y, \dots, T_y^k < T_x)} = \sum_{k=1}^{\infty} 1_{(T_y^k < T_x)}.$$

By using the strong Markov property and the induction, we get

$$\begin{aligned} E_x N_y^x &= \sum_{k=1}^{\infty} P_x(T_y^k < T_x) \\ &= \sum_{k=1}^{\infty} E_x [P_x(T_y, T_y^k < T_x | \mathcal{F}_{T_y})] \\ &= \sum_{k=1}^{\infty} E_x [1_{(T_y < T_x)} P_y(T_y^{k-1} < T_x)] \\ &= \dots \\ &= \sum_{k=1}^{\infty} P_x(T_y < T_x) P_y(T_y < T_x)^{k-1} \\ &= \frac{P_x(T_y < T_x)}{1 - P_y(T_y < T_x)} = \frac{w_{xy}}{w_{yx}}. \end{aligned}$$

□

Problem (5.5.3).

Irreducibility and recurrence implies the existence of unique (up to constant multiple) stationary measure. The recurrence implies that $y \mapsto \mu_x(y)$ is the stationary measure. Thus, for some $c > 0$, $\mu_y(z) = \mu_x(z) \cdot c$. So $\mu_y(z)p(z, y) = c\mu_x(z)p(z, y)$. By adding over z ,

$$1 = \mu_y(y) = \sum_z \mu_y(z)p(z, y) = c \sum_z \mu_x(z)p(z, y) = c\mu_x(y).$$

Thus $c = 1/\mu_x(y)$ and this leads the result.

□

Problem (5.5.4).

$E_x T_y = \infty$ says that the chain is expected to not reach the state y . So $\mu_x(y) = 0$, contradiction. Also

$$\sum_x E_x T_y p(x, y) + 1 = E_y T_y < \infty$$

by positive recurrence. Therefore $E_x T_y$ should be finite.

□

Problem (5.5.5).

On the contrary, assume that p is positive recurrent. Then, with irreducibility, the existence of stationary distribution π is guaranteed. Also, any stationary measure is constant multiple of π by theorem 5.5.9. Thus $c\pi(x) = \mu(x)$ for some constant $c > 0$. Then,

$$\infty = \sum_x \mu(x) = c \sum_x \pi(x) = c < \infty,$$

which is a contradiction. Hence p cannot be positive recurrent. □

Problem (5.5.9).

Note that $Y_{n \wedge \tau} - Y_0 = \sum_{k=1}^n 1_{(\tau \geq k)} (Y_k - Y_{k-1})$. Using this,

$$\begin{aligned} E_x(Y_{n+1 \wedge \tau} - Y_0 | \mathcal{F}_n) &= \sum_{k=1}^n 1_{(\tau \geq k)} (Y_k - Y_{k-1}) + 1_{(\tau \geq n+1)} [E_x(X_{n+1} | \mathcal{F}_n) - X_n + \varepsilon] \\ &\leq \sum_{k=1}^n 1_{(\tau \geq k)} (Y_k - Y_{k-1}) + 1_{(\tau \geq n+1)} [X_n - \varepsilon - X_n + \varepsilon] \\ &= Y_{n \wedge \tau} - Y_0. \end{aligned}$$

Thus $Y_{n \wedge \tau}$ is a nonnegative supermartingale. Now, by theorem 4.8.4, we have

$$x = E_x[Y_0] \geq E_x[Y_\tau] = E_x[X_\tau + \tau\varepsilon] \geq \varepsilon E_x[\tau]$$

since $X_n \geq 0$. By dividing both sides by ε , we earn the result. □

Problem (5.6.1).

For $n = 1$,

$$P_\mu(X_1 = 0) = \mu(0)p(0, 0) + (1 - \mu(0))p(1, 0) = (1 - \alpha - \beta)\mu(0) + \beta.$$

Now,

$$\begin{aligned} P_\mu(X_{n+1} = 0) &= E_\mu P_\mu(X_{n+1} = 0 | \mathcal{F}_n) \\ &= E_\mu [P_0(X_1 = 0) 1_{(X_n=0)} + P_1(X_1 = 0) 1_{(X_n=1)}] \\ &= P_\mu(X_n = 0)p(0, 0) + P_\mu(X_n = 1)p(1, 0) \\ &= (1 - \alpha)P_\mu(X_n = 0) + \beta(1 - P_\mu(X_n = 0)) \\ &= (1 - \alpha - \beta)P_\mu(X_n = 0) + \beta \\ &= (1 - \alpha - \beta)^{n+1} \left[\mu(0) - \frac{\beta}{\alpha + \beta} \right] + \frac{\beta(1 - \alpha - \beta)}{\alpha + \beta} + \beta \end{aligned}$$

where the last term is what we desired. □

Problem (5.6.2).

Aperiodicity of state x is defined only when the state x is recurrent. So aperiodicity of the chain necessarily contains recurrence of the chain. Note that recurrent chain has stationary measure, $\mu_x(y)$. With finiteness of the state space, by normalizing, we can earn the stationary distribution π . With irreducibility of the chain, by existence of the stationary measure, the chain is positive recurrent. Now, for any $x, y \in S$, by convergence theorem,

$$p^m(x, y) \rightarrow \pi(y) > 0.$$

So we can find M_{xy} such that $m \geq M_{xy}$ implies $p^m(x, y) > \pi(y)/2 > 0$. Take $M = \max_{x, y} M_{xy}$. Then $M < \infty$ because of the finiteness. For any $x, y \in S$,

$$p^M(x, y) > \pi(y)/2 > 0. \quad \square$$

Problem (5.6.3).

By the previous problem, there is $m > 0$ such that $p^m(x, y) > 0$ for all $x, y \in S$. Fix $y \in S$. Let $p = \min_{x \in S} p^m(x, y)$. Then

$$P(X_{n+m} = Y_{n+m} = y | X_n = x_1, Y_n = x_2) \geq p^2$$

for all $x_1, x_2 \in S$ by the definition of \bar{p} . So $P(X_{n+m} = Y_{n+m} | X_n, Y_n) \geq p^2$,

which is equivalent to $P(X_{n+m} \neq Y_{n+m} | X_n, Y_n) \leq 1 - p^2$. Now, consider

$$\begin{aligned}
& P(T > km) \\
&= P(X_1 \neq Y_1, \dots, X_{km} \neq Y_{km}) \\
&= EP(\cdot | \mathcal{F}_{(k-1)m}) \\
&= EP_{X_{(k-1)m}, Y_{(k-1)m}}(X_{km} \neq Y_{km}, \dots, X_{(k-1)m+1} \neq Y_{(k-1)m+1}) 1_{(X_{(k-1)m} \neq Y_{(k-1)m}, \dots, X_1 \neq Y_1)} \\
&\leq (1 - p^2)P(X_1 \neq Y_1, \dots, X_{(k-1)m} \neq Y_{(k-1)m}) \\
&\leq \dots \\
&\leq (1 - p^2)^k.
\end{aligned}$$

Therefore

$$P(T > n) \leq P(T > \left\lfloor \frac{n}{m} \right\rfloor m) \leq (1 - p^2)^{\left\lfloor \frac{n}{m} \right\rfloor} \leq (1 - p^2)^{\frac{n}{m}}$$

where $\lfloor \cdot \rfloor$ is the floor function. So the convergence occurs at least exponentially fast. □

Problem (5.6.5).

Note that $P_x(T_x^k < \infty) = 1$. Let $V_k^f = V_k$, and $V_k^{|f|} = V_k'$.

1. By the strong Markov property,

$$\begin{aligned}
P(V_k \leq a) &= EP(V_k \leq a | \mathcal{F}_{T_x^k}) \\
&= P_x(f(X_0) + \dots + f(X_{T_x^k-1}) \leq a) = P_x(V_0 \leq a).
\end{aligned}$$

Thus $\{V_k^f\}_{k=1}^\infty$ is an identically distributed sequence.

By the strong Markov property,

$$\begin{aligned}
P(V_k \leq a_0, \dots, V_{k+m} \leq a_m) &= EP(\cdot | \mathcal{F}_{T_x^{k+m}}) \\
&= EP_x(V_1 \leq a_m) 1_{(V_k \leq a_0, \dots, V_{k+m-1} \leq a_{m-1})} \\
&= \dots \\
&= \prod_{n=0}^m P_x(V_0 \leq a_n) \\
&= P(V_k \leq a_0) \dots P(V_{k+m} \leq a_m)
\end{aligned}$$

where the last equality is due to the previous result. So they are independent.

Now, consider $E|V_1|$.

$$\begin{aligned}
&\leq E \sum_{k \geq 1} 1_{(T_x^1 < k \leq T_x^2)} |f(X_k)| (= EV_1') \\
&= E \sum_{k \geq 1} 1_{(T_x^1 < k \leq T_x^2)} \sum_y |f(y)| 1_{(X_k=y)} \\
&= \sum_y |f(y)| E \sum_{k \geq 1} 1_{(T_x^1 < k \leq T_x^2)} 1_{(X_k=y)} \\
&= \sum_y |f(y)| \mu_x(y) = \sum_y |f(y)| \pi(y) E_x T_x^1 < \infty.
\end{aligned}$$

Similarly, we can get $EV_1 = \sum_y f(y) \pi(y) E_x T_x^1$.

2. Note that $N_n(x) = \sup \{k : T_x^k \leq n\}$. So $N_n(x) \leq K_n$. If $N_n(x) < K_n$, then $K_n = N_n(x) + 1$. By SLLN and theorem 5.6.1, as $n \rightarrow \infty$,

$$\frac{1}{n} \sum_{m=1}^{K_n} V_m = \frac{N_n(x)}{n} \frac{K_n}{N_n(x)} \frac{1}{K_n} \sum_{m=1}^{K_n} V_m \rightarrow \frac{EV_1}{E_x T_x^1} = \sum_y f(y) \pi(y)$$

P_μ almost surely since $N_n(x) \rightarrow \infty$.

3. Refer to problem 2.3.17, sufficient (in fact, necessary also) condition for $\max_{m \leq n} V'_m/n \rightarrow 0$ is $EV_m'^+ < \infty$ for all m . This is because

$$\sum_{n \geq 1} P(V'_n \geq n\delta) < \infty$$

for all $\delta > 0$. Thus, by Borel Cantelli lemma, $P(V'_n \geq n\delta \text{ i.o.}) = 0$. So

$$P(V'_n/n < \delta \text{ all but finitely many } n) = 1.$$

Also,

$$\frac{1}{n} \max_{m \leq n} V'_m \leq \frac{1}{n} \left(\max_{m \leq M} V'_m + \max_{M < m \leq n} V'_m \right) \leq \frac{\max_{m \leq M} V'_m}{n} + \max_{M < m \leq n} \frac{V'_m}{m}$$

where the last term $\leq \delta$ as $n \rightarrow \infty$. Since δ is arbitrary, we can get $\max_{m \leq n} V'_m/n \rightarrow 0$ a.s.

Now, note that $K_n \leq n$. Then

$$\frac{1}{n} \left| \sum_{m=1}^n f(X_m) - \sum_{m=1}^{K_n} V_m \right| \leq \frac{1}{n} \max_{m \leq n} V'_m \rightarrow 0$$

as $n \rightarrow \infty$.

□