MATH 8170, Fall 2016 HW 1 Shuai Wei

1.

$$P(N(t) = k) = P(T_k \le t < T_{k+1})$$

= $P(T_k \le t) - P(T_{k+1} \le t)$

 $\{T_1 = X_1\}$ may be interpreted as the rewarded recieved after conducted one bernoulli trail. $X_1 = 1$ if trial fails and $X_1 = 2$ if it succeeds. $\{T_n = X_n\}$ may be interpreted as the rewards n recieved after conducting k bernoulli trails, and then we have n - k success and k - (n - k) = 2k - n fails. Moreover, the rewards n range from k to 2k.

$$P(T_k = n) = \binom{k}{n-k} 0.2^{n-k} 0.8^{2k-n}, n = k, k+1, ..., 2k$$

So

$$P(N(t) = k) = \sum_{n=k}^{\min(\lfloor t \rfloor, 2k)} P(T_k = n) - \sum_{n=k+1}^{\lfloor t \rfloor} P(T_{k+1} = n)$$

$$= \sum_{n=k}^{\min(\lfloor t \rfloor, 2k)} {k \choose n-k} 0.2^{n-k} 0.8^{2k-n} - \sum_{n=k+1}^{\min(\lfloor t \rfloor, 2k+2)} {k+1 \choose n-k-1} 0.2^{n-k-1} 0.8^{2k+2-n}$$

Assume $T_0 = 0$.

$$E(A(t)B(t)) = \int_0^\infty E(A(t)B(t)|T_1 = s)dF(s)$$

$$= \int_0^t E(A(t)B(t)|T_1 = s)dF(s) + \int_t^\infty E(A(t)B(t)|T_1 = s)dF(s)$$

$$= \int_0^t E(A(t-s)B(t-s)dF(s) + E((t-T_{N(t)})(T_{N(t)+1} - t)|T_1 \ge t)$$

$$= \int_0^t E(A(t-s)B(t-s)dF(s) + E(t(T_1 - t)|T_1 \ge t)$$

Then $h(t) = E(t(T_1 - t)|T_1 \ge t)$, so h is continuous a.e on $[0, \infty)$. so for t > 1

$$|h(t)| = E(t(T_1 - t)|T_1 \ge t) \le E(T_1/2(T_1 - T_1/2)|T_1 \ge t)$$

$$= E(T_1^2/4|T_1 \ge t)$$

$$= \frac{1}{4}E(T_1^2|T_1 \ge t) = b(t).$$

It is obvious that b(t) is directly Riemann integrable since F has finite second moment

Besides, F is nonarithmetic.

So the key renewal theorem is applicable, and

$$\lim_{t \to \infty} E(A(t)B(t)) = \frac{1}{E(X_1)} \int_0^\infty E(t(T_1 - t)|T_1 \ge t) dt$$

$$= \frac{1}{E(X_1)} \int_0^\infty E(tT_1 - t^2|T_1 \ge t) dt$$

$$= \frac{1}{E(X_1)} \int_0^\infty \int_t^\infty E(tT_1 - t^2|T_1 = s) dF(s) dt$$

$$= \frac{1}{E(X_1)} \int_0^\infty \int_t^\infty E(ts - t^2) dF(s) dt$$

$$= \frac{1}{E(X_1)} \int_0^\infty \int_t^\infty ts - t^2 dF(s) dt$$

$$= \frac{1}{E(X_1)} \int_0^\infty \left(t \int_t^\infty s dF(s) - t^2 \int_t^\infty dF(s) \right) dt$$

$$= \frac{1}{\int_0^\infty s dF(s)} \int_0^\infty \left(t \int_t^\infty s dF(s) - t^2 (1 - F(t)) \right) dt$$

3.

$$P(N(t) \text{ is odd }) = P(N(t) \text{ is odd }, T_1 > t) + P(N(t) N(t) \text{ is odd }, T_1 \le t)$$

$$= P(N(t) \text{ is odd }, T_1 \le t)$$

$$= \int_0^t P(N(t) \text{ is odd } | T_1 = s) dF(s)$$

$$= \int_0^t P(N(t-s) \text{ is even }) dF(s)$$

$$= \int_0^t \left(1 - P(N(t-s) \text{ is odd })\right) dF(s)$$

$$= \int_0^t dF(s) - \int_0^t P(N(t-s) \text{ is odd }) dF(s)$$

$$= F(t) - \int_0^t P(N(t-s) \text{ is odd }) dF(s)$$

Let H(t)=P(N(t) is odd), then H(0)=0 and $F(t)=1-e^{-\lambda t}$ and $dF(s)=\lambda e^{-\lambda s}ds$.

$$H(t) = F(t) - \int_0^t H(t - s)dF(s)$$
$$= 1 - e^{-\lambda t} - \int_0^t H(t - s)\lambda e^{-\lambda s}ds$$
$$= 1 - e^{-\lambda t} - \lambda e^{-\lambda t} \int_0^t H(x)e^{\lambda x}dx$$

Take derivatives on both sides, we have

$$H'(t) = \lambda e^{-\lambda t} + \lambda^2 e^{-\lambda t} \int_0^t H(x) e^{\lambda x} dx - \lambda e^{-\lambda t} H(t) e^{\lambda t}$$

$$= \lambda e^{-\lambda t} + \lambda^2 e^{-\lambda t} \int_0^t H(x) e^{\lambda x} dx - \lambda H(t)$$

$$= \lambda e^{-\lambda t} + \lambda (1 - e^{-\lambda t} - H(t)) - \lambda H(t)$$

$$= \lambda - 2\lambda H(t)$$

So

$$H'(t) + 2\lambda H(t) = \lambda$$

It can be found that $\frac{\lambda}{2}$ is the special solution and $Ce^{-2\lambda t}, C \neq 0$ are the general solutions.

So $H(t) = Ce^{-2\lambda t} + \frac{1}{2}$ is the general form of the solution.

Since $H(0) = C + \frac{1}{2} = 0$, we have $C = -\frac{1}{2}$.

Thus.

$$H(t) = -\frac{1}{2}e^{-2\lambda t} + \frac{1}{2}.$$

4.

Proof. (a)

$$\lim_{n \to \infty} \frac{T_n^D}{n} = \lim_{n \to \infty} \frac{X_1 + \sum_{i=2}^n X_i}{n}$$

$$= \lim_{n \to \infty} \frac{\sum_{i=2}^n X_i}{n}$$

$$= \lim_{n \to \infty} \frac{\sum_{i=2}^n X_i}{n-1} \frac{n-1}{n}$$

$$= \lim_{n \to \infty} \frac{\sum_{i=2}^n X_i}{n-1} \lim_{n \to \infty} \frac{n-1}{n}$$

$$= E[X_2] \quad w.p.1$$

by central limit theorem since $X_n, n \geq 2$ are *iid*.

Then there exists an event $A \subseteq \Omega$ with P(A) = 1 and $\lim_{t\to\infty} \frac{T_n^D(\omega)}{n} = \mu$ for each $\omega \in A$.

We observe that $T_n^D(\omega) < \infty$ for each n and $T_n^D(\omega) \to \infty$ as $n \to \infty$, which implies $\lim_{t\to\infty} N^D(t,\omega) = \infty$. Fix an $\omega \in A$. For each t>0,

$$T^D_{N^D(t)}(\omega) \leq t < T^D_{N^D(t)+1}(\omega).$$

Let t large enough such that $N^D(t,\omega) \geq 1$, and divide the above equalities by $N^D(t,\omega)$, so we have

$$\frac{T_{N^D(t)}^D(\omega)}{N^D(t,\omega)} \le \frac{t}{N^D(t,\omega)} < \frac{T_{N^D(t)}^D(\omega) + 1}{N^D(t,\omega)}$$

Namely,

$$\frac{T_{N^D(t)}^D(\omega)}{N^D(t,\omega)} \leq \frac{t}{N^D(t,\omega)} < \frac{T_{N^D(t)}^D(\omega) + 1}{N^D(t,\omega) + 1} \frac{N^D(t,\omega) + 1}{N^D(t,\omega)}$$

Let $t \to \infty$, then

$$\frac{T^D_{N^D(t)}(\omega)}{N^D(t,\omega)} \to E[X_2] \text{ and } \frac{T^D_{N^D(t)}(\omega)+1}{N^D(t,\omega)+1} \frac{N^D(t,\omega)+1}{N^D(t,\omega)} \to E[X_2].$$

So

$$\lim_{t \to \infty} \frac{N_D(t)}{t} = \frac{1}{E[X_2]}$$

(b) Step1:

Note that the r.v $N^D(t) + 1$ is a stopping time w.r.t $\{X_n\}_{n=1}^{\infty}$. Since

$$1(N^D(t) + 1 \ge k) = 1 - 1(N^D(t) + 1 < k) = 1 - 1(N^D(t) + 1 \le k - 1),$$

 $1(N^D(t)+1 \ge k)$ is a function of $X_0, X_1, ... X_{k-1}$, and $1(N^D(t) \ge k)$ is independent of X_k .

Therefore,

$$\begin{split} E\big(T^D_{N^D(t)+1}\big) &= E\bigg(\sum_{k=1}^{N^D(t)+1} X_k\bigg) \\ &= E\Big(\sum_{k=1}^{\infty} X_k \mathbf{1} \big(N^D(t) + 1 \ge k\big)\Big) \\ &= \sum_{k=1}^{\infty} E\bigg(X_k \mathbf{1} \big(N^D(t) + 1 \ge k\big)\Big) \\ &= \sum_{k=1}^{\infty} E(X_k) P\big(N^D(t) + 1 \ge k\big) \\ &= E(X_1) P\big(N^D(t) + 1 \ge 1\big) + \sum_{k=2}^{\infty} E(X_k) P\big(N^D(t) + 1 \ge k\big) \\ &= E(X_1) + \sum_{k=1}^{\infty} E(X_{k+1}) P\big(N^D(t) + 1 \ge k + 1\big) \\ &= E(X_1) + \sum_{k=1}^{\infty} E(X_{k+1}) P\big(N^D(t) \ge k\big) \\ &= E(X_1) + E(X_2) \sum_{k=1}^{\infty} P\big(N^D(t) \ge k\big) \\ &= E(X_1) + E(X_2) E\big(N^D(t)\big). \end{split}$$

So

$$t < E(T_{N^D(t)+1}^D) = E(X_1) + E(X_2)E(N^D(t)).$$

Then

$$\frac{E(N^{D}(t))}{t} > \frac{1}{E(X_{2})} - \frac{E(X_{1})}{E(X_{2})} \frac{1}{t}.$$

Thus,

$$\lim_{t \to \infty} \frac{E(N^D(t))}{t} \ge \frac{1}{E(X_2)}.$$

Fix a > 0, and define $X_n^{(a)} = \min\{X_n, a\}$. Let $T_n^{D(a)} = \sum_{k=1}^n X_n^{(a)}$, and define a new renewal process $\{N^{D(a)}(t)\}$ whose points are given by $\{T_n^{D(a)}\}.$

Then

$$E\Big(T_{N^{D(a)}(t)+1}^{D(a)}\Big) = E\Big(X_1^a\Big) + E\Big(X_2^{(a)}\Big) E\Big(N^{D(a)}(t)\Big).$$

by following the similar process with Step 1.

Next we note that

$$T_{N^{D(a)}(t)+1}^{D(a)} = T_{N^{D(a)}(t)}^{D(a)} + X_{N^{D(a)}(t)+1}^{(a)} \leq t+a.$$

So

$$\begin{split} E\Big(T_{N^{D(a)}(t)+1}^{D(a)}\Big) &\leq t+a \implies E(X_1^a) + E(X_2^{(a)}) E\big(N^{D(a)}(t)\big) \leq t+a \\ &\implies \frac{E\big(N^{D(a)}(t)\big)}{t} \leq \frac{1}{E\big(X_2^{(a)}\big)} + \frac{a-E\big(X_1^a\big)}{E\big(X_2^{(a)}\big)} \frac{1}{t} \\ &\implies \lim_{t \to \infty} \sup \frac{E\big(N^{D(a)}(t)\big)}{t} \leq \frac{1}{E\big(X_2^{(a)}\big)} \end{split}$$

Since $N^D(t) < N^{D(a)}(t)$, we have

$$\lim_{t\to\infty} \sup \frac{E\left(N^D(t)\right)}{t} \leq \frac{1}{E\left(X_2^{(a)}\right)}.$$

Let $a \to \infty$, and we have

$$\lim_{t \to \infty} \sup \frac{E(N^D(t))}{t} \le \frac{1}{E(X_2)}$$

According to the above two steps, we have

$$\lim_{t \to \infty} \frac{E(N^D(t))}{t} = \frac{1}{E(X_2)}$$

5.

(a) Define X_i as how long it takes the miner to make the *i*-th journey. Define the stopping time N as the first journey which takes the miner 2 days. Verify:

$$1(N = n) = 1(X_1 = 4 \text{ or } 6 \text{ for } i = 1, 2, ... n - 1, X_{n-1} = 2)$$

$$P(N=i) = \left(\frac{2}{3}\right)^{i-1} \frac{1}{3}, \quad i = 1, 2, \dots$$

So $N \sim Geo\left(\frac{1}{3}\right)$ and

$$E(N) = 3$$

Morevoer,

$$P(X_i = j) = \frac{1}{3}$$
 for $j = 2, 4, 6$.

So for i = 1, 2, ...,

$$E(X_i) = \frac{1}{3}(2+4+6) = 4.$$

(b) By Wald's equality,

$$E(T) = E(N)E(X_i) = 3 * 4 = 12$$

$$E\left(\sum_{i=1}^{N} X_i | N = n\right) = E\left(\sum_{i=1}^{n} X_i\right)$$
$$= \sum_{i=1}^{n} E(X_i)$$
$$= 4n$$

since n is a constant and X_i are iid.

(d) By part (c), we have

$$E(T|N) = E\left(\sum_{i=1}^{N} X_i|N\right) = 4N.$$

So

$$E(T) = E(E(T|N)) = E(4N) = 4E(N) = 4 * 3 = 12.$$

6.

Let μ_G denote the mean service time. Then the mean time of a cycle is $\mu_G + \frac{1}{\lambda}$ by the memoryless property of the Poisson

So the proportion of time (on the average) the server is busy is $\frac{\mu_G}{\mu_G + \frac{1}{\lambda}}$.