

Solutions for HW2

(1)

6.5!

- a) Let T denote the interarrival time. Then T is exponentially distributed with rate λ . Therefore,

$$P(T > \tau) = 1 - P(T \leq \tau) = 1 - (1 - e^{-\lambda\tau/60}) = e^{-\lambda\tau/60}$$

(The division by 60 is necessary since λ is expressed in jobs/hr and τ in minutes).

- b) Let $N(\tau)$ denote the number of jobs arriving over an interval of length τ . Then, we are interested in the probability of the event.

$$N(a) = 0 \quad \wedge \quad N(60-b, 60) = 0$$

Since the arrival process is Poisson it has independent and stationary increments. Therefore,

$$\begin{aligned} P(N(a) = 0 \wedge N(60-b, 60) = 0) &= P(N(a) = 0) \cdot P(N(b) = 0) \\ &= e^{-\lambda a/60} e^{-\lambda b/60} = e^{-\lambda(a+b)/60} \end{aligned}$$

where the division by 60 is performed for the same reason as above.

- c) A compact expression for this probability is obtained by noticing that the complement of the considered event is that at most one job is submitted within the first a minutes. Hence,

$$\begin{aligned} P(N(a) \geq 2) &= 1 - P(N(a) \leq 1) = 1 - e^{-\lambda a/60} - \frac{\lambda a}{60} e^{-\lambda a/60} \\ &= 1 - \left(1 + \frac{\lambda a}{60}\right) e^{-\lambda a/60} \end{aligned}$$

(2)

6.6) Let E_n denote the event that exactly one event occurs in each of the intervals $(s_i, t_i]$, $i=1, \dots, n$. Then,

$$P[E_n \mid \text{exactly } n \text{ events occur in } (0, t]] =$$

$$= \frac{P[E_n \mid \text{exactly } n \text{ events occur in } (0, t)]}{P[\text{exactly } n \text{ events occur in } (0, t)]}$$

$$= \frac{P[N(s_1, t_1)=0 \wedge N(s_2, t_2)=1 \wedge N(t_2, s_3)=0 \wedge \dots \wedge N(s_n, t_n)=1 \wedge N(t_n, t)=0]}{\frac{(2t)^n}{n!} e^{-2t}}$$

$$= \frac{e^{-2s_1} (2\tau_1 e^{-2(t_1-s_1)}) \dots (2\tau_n e^{-2(t_n-s_n)}) e^{-2(t-t_n)}}{\frac{(2t)^n}{n!} e^{-2t}}$$

$$= \frac{2^n \tau_1 \tau_2 \dots \tau_n e^{-2[s_1+t_1-s_1+\dots+t_n-s_n+t-t_n]}}{\frac{(2t)^n}{n!} e^{-2t}}$$

$$= \frac{n! \left(\prod_{i=1}^n \tau_i \right) e^{-2t}}{t^n e^{-2t}} = n! \prod_{i=1}^n \left(\frac{\tau_i}{t} \right)$$

Remark: The above result when considered for $n=1$ implies that the distribution of the occurrence time of a single event that took place by time t according to a Poisson arrival process, is uniform over the interval $(0, t]$.

6.11) Let X denote the number of customers that arrive during a service time and S to the random length of the service time. Then,

$$P[X=k] = \int_0^{\infty} P[X=k|S=t] f_S(t) dt$$

where $f_S(t)$ is the density function of S , given by

$$f_S(t) = \mu e^{-\mu t}, \quad t \geq 0.$$

Also we have,

$$\begin{aligned} P[X=k|S=t] &= P[k \text{ customers arrive during the interval } [0, t]] = \\ &= \frac{(\lambda t)^k}{k!} e^{-\lambda t}, \quad t \geq 0, \quad k = 0, 1, 2, \dots \end{aligned}$$

Therefore,

$$P[X=k] = \int_0^{\infty} \frac{(\lambda t)^k}{k!} e^{-\lambda t} \mu e^{-\mu t} dt = \frac{\mu \lambda^k}{k!} \int_0^{\infty} t^k e^{-(\lambda+\mu)t} dt$$

For $k=0$:

$$P[X=0] = \mu \int_0^{\infty} e^{-(\lambda+\mu)t} dt = \frac{\mu}{\lambda+\mu} \quad (\text{which should look familiar!})$$

For $k \geq 1$:

$$\begin{aligned} P[X=k] &= \frac{\mu \lambda^k}{k!} \int_0^{\infty} \frac{[(\lambda+\mu)t]^k}{(\lambda+\mu)^k} e^{-(\lambda+\mu)t} \frac{d[(\lambda+\mu)t]}{\lambda+\mu} = \\ &= \frac{\mu \lambda^k}{k!} \frac{1}{(\lambda+\mu)^{k+1}} \int_0^{\infty} [(\lambda+\mu)t]^k e^{-(\lambda+\mu)t} d[(\lambda+\mu)t] = \\ &= \frac{\mu \lambda^k}{k!} \frac{1}{(\lambda+\mu)^{k+1}} \Gamma(k+1) = \frac{\mu \lambda^k}{(\lambda+\mu)^{k+1}} \end{aligned}$$

where in the next to last equality we have used the results provided in the hint.

Remark. The last result is also quite intuitive. To understand it, note that the event $\{X=k\}$ is equivalent to the event that the (Poisson) counting process that combines arrivals and departures must observe $k+1$ events, of which the first k must be arrivals. Hence, the corresponding probability is

$$\left(\frac{\lambda}{\lambda+\mu}\right)^k \frac{\mu}{\lambda+\mu}.$$

7

b) The conditional distribution of X , given that $X > 1$, is the same with the unconditional distribution of $1 + Y$, where Y is the residual life of X after the first unit. But since X is exponentially distributed, Y has the same statistics with X itself. Hence, the correct answer is 1.

c) Let T_i denote the time between the $(i-1)$ st and the i -th failure. Then the r.v.'s T_i are independent and exponentially distributed, each with rate $(101-i)/200 \text{ hrs}^{-1}$. Therefore

$$E[T] = E[T_1 + T_2 + T_3 + T_4 + T_5] = \sum_{i=1}^5 E[T_i] = \sum_{i=1}^5 \frac{200}{101-i}$$

Similarly

$$\text{Var}[T] = \sum_{i=1}^5 \text{Var}[T_i] = \sum_{i=1}^5 \frac{200^2}{(101-i)^2}$$

d) (1) The considered event is equivalent to the event that your processing time in ~~server~~ 1 will be smaller than the remaining processing time of A in server 2. Since these two random variables are exponentially distributed with corresponding rates μ_1 and μ_2 , the sought probability is equal to $\mu_1 / (\mu_1 + \mu_2)$.

(2) The complementary event to the event considered in this question is that we will have two service completions at server 2 before a service completion at server 1. Thinking as in the interpretation of the result of problem 6.11 in your textbook (see above), the prob. of this last event is equal to $\left(\frac{\mu_2}{\mu_1 + \mu_2}\right)^2$. Hence, the prob. of the considered event is equal to $1 - \left(\frac{\mu_2}{\mu_1 + \mu_2}\right)^2$.

d) (13) One way to answer this question is by noting (8)

that

$$E[T] = E[\text{Your own total processing time}] +$$

$$P_A \cdot E[\text{remaining time of A in server 2 when you arrive at station 2}] +$$

$$P_B \cdot E[\text{remaining time of B in server 2 when you arrive at station 2}] =$$

$$= \frac{1}{\mu_1} + \frac{1}{\mu_2} + P_A \cdot \frac{1}{\mu_2} + P_B \cdot \frac{1}{\mu_2}$$

where P_A and P_B are taken from the previous parts of this problem.

e) 1) A will obtain a new kidney simply if he arrives before he dies. This will occur with probability $\frac{2}{2+\mu_A}$

2) B will obtain a ^{new} kidney if A obtains a new kidney or dies while he is still alive, and subsequently a kidney arrives before B himself dies. Therefore, the corresponding probability is

$$\left(\frac{2+\mu_A}{2+\mu_A+\mu_B} \right) \left(\frac{2}{2+\mu_B} \right)$$

f) ~~First of all, let us observe that the sum of independent exponential random variables is a gamma random variable.~~

$$E[S] = \sum_{i=1}^n E[T_i] = \sum_{i=1}^n \frac{1}{\lambda} = n/\lambda$$

and

$$\text{Var}[S] = \sum_{i=1}^n \text{Var}[T_i] = \sum_{i=1}^n \frac{1}{\lambda^2} = n/\lambda^2$$

Also,

$$\text{SCV}[S] = \frac{\text{Var}[S]}{E[S]^2} = \frac{n/\lambda^2}{(n/\lambda)^2} = \frac{1}{n}$$

Finally, to compute the pdf and cdf of r.v. S , we work as follows:

First we establish the pdf formula by induction:

For $n=1$, the provided formula becomes:

$$f(s) = \begin{cases} \lambda e^{-\lambda s}, & \text{if } s > 0 \\ 0, & \text{o.w.} \end{cases}$$

which is correct since in that case $S = T_1$, i.e., exponentially distributed with rate λ .

Then suppose that the formula holds true for $n \leq k$. To prove it true for $n = k+1$, notice that the convolution integral which provides the cdf of the sum of two continuous independent r.v.'s (as discussed in class), implies that:

$$\begin{aligned} f_{T_1 + T_2 + \dots + T_k + T_{k+1}}(s) &= \int_0^s f_{T_k}(s-y) f_{T_1 + T_2 + \dots + T_k}(y) dy = \\ &= \int_0^s \lambda e^{-\lambda(s-y)} \lambda e^{-\lambda y} \frac{(\lambda y)^{k-1}}{(k-1)!} dy = \frac{\lambda e^{-\lambda s}}{(k-1)!} \int_0^s (\lambda y)^{k-1} d(\lambda y) = \frac{\lambda e^{-\lambda s}}{(k-1)!} \frac{(\lambda s)^k}{k} \\ &= \frac{\lambda^k e^{-\lambda s}}{k!} \end{aligned}$$

Finally, $F(s)$ can be obtained from $f(s)$ by

$$F(s) = \int_{-\infty}^s f(s) ds,$$

and integration by parts (formally, you can establish the result by induction).

An alternative way for getting $F(s)$ and $f(s)$:

$$1 - F(s) = P(S > s) = P(\text{at most } n-1 \text{ arrivals in } [0, s]) =$$

$$= \sum_{j=0}^{n-1} \frac{e^{-\lambda s} (\lambda s)^j}{j!} \rightsquigarrow$$

$$\rightsquigarrow F(s) = 1 - \sum_{j=0}^{n-1} \frac{e^{-\lambda s} (\lambda s)^j}{j!}$$

Then

$$f(s) = \frac{dF(s)}{ds} = \lambda e^{-\lambda s} \sum_{j=0}^{n-1} \frac{(\lambda s)^j}{j} - e^{-\lambda s} \sum_{j=1}^{n-1} \lambda \frac{(\lambda s)^{j-1}}{(j-1)!} =$$

$$= \lambda e^{-\lambda s} \left[\sum_{j=0}^{n-1} \frac{(\lambda s)^j}{j!} - \sum_{j=0}^{n-2} \frac{(\lambda s)^j}{j!} \right] =$$

$$= \begin{cases} \frac{\lambda^n s^{n-1} e^{-\lambda s}}{(n-1)!} & \text{if } s \geq 0 \\ 0 & \text{w.} \end{cases}$$

Another approach could be based on MGFs.

19

~~Problem 4 (25 points): Consider two independent exponentially distributed random variables X_1 and X_2 with corresponding rates μ_1 and μ_2 . Compute $E[X_2 | X_2 > X_1]$.~~

$$\begin{aligned}
 h) \quad \text{let } F_{X_2 > X_1}(x) &= P[X_2 \leq x | X_2 > X_1] = \\
 &= \frac{P[X_1 < X_2 \leq x]}{P[X_2 > X_1]} = \\
 &= \frac{\mu_1 + \mu_2}{\mu_1} \cdot \int_0^x P[X_1 < X_2 \leq x | X_2 = y] dP(X_2 = y) = \\
 &= \frac{\mu_1 + \mu_2}{\mu_1} \int_0^x P[X_1 < y] f_{X_2}(y) dy
 \end{aligned}$$

where $f_{X_2}(y)$ is the pdf of X_2 (exponential dist. with rate μ_2)

Then,

$$\begin{aligned}
 f_{X_2 > X_1}(x) &= \frac{d F_{X_2 > X_1}(x)}{dx} = \frac{\mu_1 + \mu_2}{\mu_1} P[X_1 < x] f_{X_2}(x) = \\
 &= \frac{\mu_1 + \mu_2}{\mu_1} (1 - e^{-\mu_1 x}) \mu_2 e^{-\mu_2 x}
 \end{aligned}$$

and

$$\begin{aligned}
 E[X_2 | X_2 > X_1] &= \int_0^\infty x f_{X_2 > X_1}(x) dx = \frac{\mu_2(\mu_1 + \mu_2)}{\mu_1} \int_0^\infty x e^{-\mu_2 x} (1 - e^{-\mu_1 x}) dx \\
 &= \frac{\mu_1 + \mu_2}{\mu_1} \int_0^\infty x \mu_2 e^{-\mu_2 x} dx - \frac{\mu_2}{\mu_1} \int_0^\infty x (\mu_1 + \mu_2) e^{-(\mu_1 + \mu_2)x} dx \\
 &= \frac{\mu_1 + \mu_2}{\mu_1} \frac{1}{\mu_2} - \frac{\mu_2}{\mu_1} \frac{1}{\mu_1 + \mu_2} = \frac{1}{\mu_2} + \frac{\mu_2}{\mu_1} \left(\frac{1}{\mu_2} - \frac{1}{\mu_1 + \mu_2} \right) =
 \end{aligned}$$

$$= \frac{1}{\mu_2} + \frac{1}{\mu_1} \frac{\mu_1}{\mu_1 + \mu_2} = \frac{1}{\mu_2} + \frac{1}{\mu_2 + \mu_1}$$

Notice that the above result makes perfect sense, since the second term (i.e., $\frac{1}{\mu_2 + \mu_1}$) is the expected time until X_1 expires (this is an "exponential race" between the two exponentials) and the first term (i.e., $\frac{1}{\mu_2}$) is the expected remaining time to the expiring of X_2 (due to its memoryless nature). So, with these insights, the above result could have also been derived ~~while~~ while arguing from the fundamental properties of the exponential distribution.