

3. Poisson Processes (9/10/04, cf. Ross)

Exponential Distribution

Poisson Processes

Poisson and Exponential Relationship

Generalizations

Exponential Distribution

Definition: The continuous RV X has the *exponential distribution* with parameter λ if its p.d.f. is $f(x) = \lambda e^{-\lambda x}$, $x \geq 0$.

Facts: $F(x) = 1 - e^{-\lambda x}$, $x \geq 0$.

$E[X] = 1/\lambda$, $\text{Var}(X) = 1/\lambda^2$,

$M_X(t) = \lambda/(\lambda - t)$, $t < \lambda$.

Theorem: The exponential distribution has the *memoryless property*. Namely, for $s, t > 0$,

$$\Pr(X > s + t | X > t) = \Pr(X > s).$$

Example: If $X \sim \text{Exp}(1/10)$, then

$$\Pr(X > 10 | X > 5) = \Pr(X > 5) = e^{-5/10} = 0.607.$$

Remark: The exponential is the only continuous distribution with this property.

3. Poisson Processes

Definition: For a continuous distribution, the *hazard function* (or *failure rate*) is

$$r(t) \equiv \frac{f(t)}{1 - F(t)}.$$

The hazard function is the conditional p.d.f. that X will fail at time t (given that X made it to t).

Why this interpretation?

$$\begin{aligned}
 r(t) dt &= \frac{f(t) dt}{1 - F(t)} \\
 &\approx \frac{\Pr(X \in (t, t + dt))}{\Pr(X > t)} \\
 &= \frac{\Pr(X \in (t, t + dt) \text{ and } X > t)}{\Pr(X > t)} \\
 &= \Pr(X \in (t, t + dt) | X > t).
 \end{aligned}$$

Example: $X \sim \text{Exp}(\lambda)$ implies that $r(t) = \lambda$. This makes sense in light of the memoryless property. In fact, the $\text{Exp}(\lambda)$ is the only RV with constant $r(t)$.

Remark: $r(t)$ (uniquely) determines $F(t)$.

“Proof:”

$$r(t) = \frac{f(t)}{1 - F(t)} = -\frac{d}{dt} \ln(1 - F(t)),$$

so that

$$F(t) = 1 - \exp\left(-\int_0^t r(s) ds\right). \quad \diamond$$

3. Poisson Processes

Theorem: $X_1, X_2, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Exp}(\lambda)$ implies that

$$\sum_{i=1}^n X_i \sim \text{Erlang}_n(\lambda) \sim \text{Gamma}(n, \lambda).$$

Many proofs — m.g.f.'s, induction, you name it. \diamond

Poisson Processes

Definition: Consider discrete (non-fractional) events occurring in continuous intervals (time, length, volume, etc.). The *counting process* $N(t) \equiv$ the number of events occurring in $[0, t]$. Let the *rate* $\lambda > 0$ be the average number of occurrences per unit time (or length or volume).

3. Poisson Processes

Examples: 1. Cars entering a shopping center (time);
 $\lambda = 5/\text{min}$.

2. Defects on a wire (length); $\lambda = 3/\text{ft}$.

3. Raisins in cookie dough (volume); $\lambda = 2.6/\text{in}^3$.

3. Poisson Processes

Definition: A counting process $N(t)$ satisfying the following three assumptions is called a *Poisson process* with rate λ (PP(λ)).

- (A-1) Arrivals occur one-at-a-time,
- (A-2) Independent increments, and
- (A-3) Stationary increments.

Details follow...

(A-1) For any interval of sufficiently small length h ,

(a) The prob of one arrival in that interval is

$$\Pr(N(t+h) - N(t) = 1) = \lambda h + o(h) \doteq \lambda h.$$

(b) The prob of no arrivals is

$$\Pr(N(t+h) - N(t) = 0) = 1 - \lambda h + o(h) \doteq 1 - \lambda h.$$

(c) The prob of more than one arrival is

$$\Pr(N(t+h) - N(t) \geq 2) = o(h) \doteq 0,$$

where $o(h)$ is a function that $\rightarrow 0$ faster than $h \rightarrow 0$.

(A-2) Independent Increments: The numbers of arrivals in two *disjoint* intervals are *independent*. I.e., if $a < b < c < d$, then $N(d) - N(c)$ and $N(b) - N(a)$ are independent.

(A-3) Stationary Increments: The number of arrivals in a time interval depends only on its length. Thus, $N(t + s) - N(t) \sim N(s) - N(0)$ for all t .

(A-4) (bonus assumption): $N(0) = 0$.

3. Poisson Processes

Example: People arriving to a restaurant is not a PP. Arrivals occur in groups (violating A-1), and arrival rates change throughout the day (violating A-3). \diamond

Theorem: If $N(t)$ is a PP(λ), then $N(t) \sim \text{Pois}(\lambda t)$. In particular, $N(1) \sim \text{Pois}(1)$. Further, $E[N(t)] = \text{Var}(N(t)) = \lambda t$.

Proof: See any reasonable probability text. \diamond

3. Poisson Processes

Remark: Be careful with units of time. For example, suppose that $X \sim \text{Pois}(3)$ is the number of phone calls in a one-minute period.

Then the number of calls in a 3-minute period is $\text{Pois}(9)$ and the number in a 30-sec. period is $\text{Pois}(1.5)$.

Poisson and Exponential Relationship

Definition: Let A_1 denote the time until the first arrival of a $PP(\lambda)$.

For $i \geq 2$, let A_i denote the time between the $(i - 1)$ st and i th arrivals.

The A_i 's are called *interarrival* times.

We can get the distributions of the A_i 's...

3. Poisson Processes

First of all, consider A_1 .

$A_1 > t$ iff no arrivals take place in $[0, t]$. Thus, for $t > 0$,

$$\Pr(A_1 > t) = \Pr(N(t) = 0) = \frac{e^{-\lambda t} (\lambda t)^0}{0!} = e^{-\lambda t},$$

and so $A_1 \sim \text{Exp}(\lambda)$.

Now A_2 . For $0 < s < t$, we have

$$\begin{aligned} & \Pr(A_2 > t | A_1 = s) \\ &= \Pr(\text{no arrivals in } (s, s + t] | A_1 = s) \\ &= \Pr(\text{no arrivals in } (s, s + t]) \\ &\quad (\text{by independent increments}) \\ &= \Pr(\text{no arrivals in } (s, s + t]) \\ &\quad (\text{by stationary increments}) \\ &= e^{-\lambda t} \quad (\text{by previous arguments}). \end{aligned}$$

3. Poisson Processes

Thus, $\Pr(A_2 > t | A_1 = s) = e^{-\lambda t}$ for all s .

So $\Pr(A_2 > t) = e^{-\lambda t}$, i.e., $A_2 \sim \text{Exp}(\lambda)$, independent of the value of A_1 .

This can be generalized...

Theorem: $A_1, A_2, \dots \stackrel{\text{iid}}{\sim} \text{Exp}(\lambda)$.

Definition: The n th arrival time is $S_n \equiv \sum_{i=1}^n A_i$, $n \geq 1$.

Theorem: $S_n \sim \text{Gamma}(n, \lambda) \sim \text{Erlang}_n(\lambda)$. Thus, $E[S_n] = n/\lambda$ and $\text{Var}(S_n) = n/\lambda^2$.

Example: A UGA student can read $X \sim \text{Pois}(1)$ pages of *Dick and Jane* a day. (a) The expected time until the 10th page is completed is $E[S_{10}] = n/\lambda = 10$ days. (b) The prob that it takes > 2 days to read the 11th page is $\Pr(A_{11} > 2) = e^{-2} \doteq 0.135$. \diamond

Theorem: Consider a $PP(\lambda)$, $N(t)$. Suppose arrivals are either Type I or II (e.g., male or female), with $\Pr(\text{Type I}) = p$, $\Pr(\text{Type II}) = 1 - p$. Let $N_1(t)$ and $N_2(t)$ denote the numbers of Type I and II events during $[0, t]$. Note that $N(t) = N_1(t) + N_2(t)$.

Then $N_1(t)$ and $N_2(t)$ are *independent* PP's with resp. rates λp and $\lambda(1 - p)$.

Proof: Long and tedious. See, e.g., Ross. \diamond

Example: Suppose cars entering a parking lot follow a $PP(5/\text{min})$. Further, suppose the prob that a driver is female is 0.6. Find the prob that exactly 3 cars driven by females will enter the lot in the next 2 minutes.

The # of cars entering in two min. $\sim \text{Pois}(\lambda t = 10)$.

The # driven by females is $\text{Pois}(\lambda t p = 6)$.

So the desired prob is

$$\Pr(\text{Pois}(6) = 3) = \frac{e^{-6} 6^3}{3!} = 0.0892. \quad \diamond$$

Conditional Distribution of Arrival Times

Theorem: $\Pr(A_1 < s | N(t) = 1) = \frac{s}{t}$.

In other words, suppose we *know* that one arrival has occurred by time t , i.e., $N(t) = 1$. What's the (conditional) distribution of the time of that arrival? Answer: $\text{Unif}(0, t)$!

Proof: We have

$$\begin{aligned} & \Pr(A_1 < s | N(t) = 1) \\ &= \frac{\Pr(A_1 < s \text{ and } N(t) = 1)}{\Pr(N(t) = 1)} \\ &= \frac{\Pr(1 \text{ arrival in } [0, s]; \text{ none in } (s, t])}{\Pr(N(t) = 1)} \\ &= \frac{\Pr(1 \text{ arrival in } [0, s]) \Pr(\text{none in } (s, t])}{\Pr(N(t) = 1)} \\ & \quad \text{(by independent increments)} \\ &= \frac{\Pr(N(s) = 1) \Pr(N(t) - N(s) = 0)}{\Pr(N(t) = 1)} \end{aligned}$$

Proof (cont'd): Then

$$\begin{aligned}
 & \Pr(A_1 < s | N(t) = 1) \\
 &= \frac{\Pr(N(s) = 1) \Pr(N(t-s) = 0)}{\Pr(N(t) = 1)} \\
 & \quad \text{(by stationary increments)} \\
 &= \frac{e^{-\lambda s} (\lambda s)^1}{1!} \frac{e^{-\lambda(t-s)} (\lambda(t-s))^0}{0!} \bigg/ \frac{e^{-\lambda t} (\lambda t)^1}{1!} \\
 &= s/t. \quad \diamond
 \end{aligned}$$

Can generalize above result. . .

Theorem: Given that $N(t) = n$, the joint probability distribution of the n arrival times S_1, S_2, \dots, S_n is the same as the joint distribution of n i.i.d. $\text{Unif}(0, t)$ RV's.

Thus, if we *know* that n arrivals have occurred by time t , the arrivals can be treated as if they were i.i.d. $\text{Unif}(0, t)$.

Bonus Theorem: Consider a $PP(\lambda)$, $N(t)$. Suppose there are k possible types of arrivals. Further suppose that the prob that an arrival is of Type i depends on the *time* that it occurs — if it occurs at time t , then the probability that it's a Type i is $P_i(t)$, where $\sum_{i=1}^k P_i(t) = 1$. If $N_i(t)$ denotes the number of Type i arrivals by time t , then the $N_i(t)$'s, $i = 1, 2, \dots, k$, are *independent* Poisson RV's with means

$$E[N_i(t)] = \lambda \int_0^t P_i(s) ds.$$

Proof: Ross. \diamond

Generalizations

Definition: The counting process $N(t)$ is a *nonhomogeneous PP* with *intensity function* $\lambda(t)$ if it satisfies:

(A-1') Arrivals occur one-at-a-time. In particular,

$$\Pr(N(t+h) - N(t) = 1) = \lambda(t)h + o(h) \quad \text{and}$$

$$\Pr(N(t+h) - N(t) = 0) = 1 - \lambda(t)h + o(h)$$

(A-2) Independent increments.

(A-4) $N(0) = 0$.

Note: We don't require stationary increments.

3. Poisson Processes

Fact: $N(t + s) - N(t) \sim \text{Pois} \left(\int_t^{t+s} \lambda(x) dx \right)$.

Remark: Arrivals may be more (or less) likely to occur as time progresses in a NHPP, since there is no stationarity requirement.

Example: Distribution of cars arriving to a lot as the day progresses is a NHPP. From 8:00–11:00 a.m., cars arrive at a steadily increasing rate: 5 cars/hr at 8:00 a.m. to 20 cars/hr at 11:00 a.m. I.e., $\lambda(t) = 5 + 5t$, $0 \leq t \leq 3$ hrs.

Number of arrivals between 8:30–9:30 a.m. is

$$N(1.5) - N(0.5) \sim \text{Pois} \left(\int_{0.5}^{1.5} (5 + 5x) dx \right) \sim \text{Pois}(10).$$



Definition: A stochastic process $X(t)$ is a *compound PP* if it can be written as

$$X(t) = \sum_{i=1}^{N(t)} Y_i, \quad t \geq 0,$$

where $N(t)$ is a $PP(\lambda)$ and the Y_i 's are i.i.d. and independent of $N(t)$.

Facts: $E[X(t)] = E[N(t)]E[Y_1] = \lambda t E[Y_1]$ and
 $\text{Var}(X(t)) = \lambda t E[Y_1^2]$.

3. Poisson Processes

Example: If the Y_i 's all equal 1, then $X(t) = N(t)$, the usual PP.

Example: Customers leave a market according to a PP. Let Y_i be the amount spent by customer i . If $X(t)$ is the total amount spent by time t , then $X(t)$ is a compound PP.

Example: A FB player makes $\text{Pois}(\lambda = 2)$ scores/game.

$$\Pr(\text{score} = x) = \begin{cases} 1/6 & \text{if } x = 1 \\ 1/3 & \text{if } x = 3 \\ 1/2 & \text{if } x = 6 \end{cases}$$

Let Y_i be the value of the i th score. $E[Y_i] = \frac{25}{6}$,
 $E[Y_i^2] = \frac{127}{6}$. Let $X(t)$ be the total points scored in t games.

$$E[X(5)] = \lambda t E[Y_1] = 125/3,$$

$$\text{Var}(X(t)) = \lambda t E[Y_1^2] = 635/3. \quad \diamond$$