

More Discrete Distributions

Poisson

Suppose X counts occurrences of some observable event in an interval $[0, T]$ of time, and that we partition this interval into n subintervals. Let us assume further that

- the event count in any subinterval is independent of those in others.
- by making time subintervals small enough (i.e., large enough n), the number of occurrences in any subinterval is limited to 0 or 1. This assumption is tantamount to saying we can take X_j , the number of occurrences in subinterval j , to be a Bernoulli random variable.
- the probability of an occurrence in subinterval j is proportional to the length of the subinterval. Let us denote this probability by λ/n , making it basically true that each $X_j \sim \text{Binom}(1, \lambda/n)$.

Under these assumptions, then the total count X of occurrences is roughly

$$X = X_1 + X_2 + \cdots + X_n \sim \text{Binom}(n, \lambda/n),$$

which means

$$P(X = x) \approx \binom{n}{x} \left(\frac{\lambda}{n}\right)^x \left(1 - \frac{\lambda}{n}\right)^{n-x} = \frac{n!}{x!(n-x)!} \frac{\lambda^x}{n^x} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-x}$$

potential pmf

$= \boxed{e^{-\lambda} \frac{\lambda^x}{x!}}$ for large n .

Handwritten notes: The expression is annotated with circles and arrows. A purple circle around $n!$ has an arrow pointing to 1. A red circle around λ^x has an arrow pointing to λ . An orange circle around $(1 - \lambda/n)^n$ has an arrow pointing to $e^{-\lambda}$. A green circle around $(1 - \lambda/n)^{-x}$ has an arrow pointing to 1.

What we have done here is "invent" a possible pmf, and state conditions under which counts might be accurately modeled by it.

Claim 1: The function $f_X(x) = e^{-\lambda} \frac{\lambda^x}{x!}$, defined for nonnegative integers x , is a pmf.

Two things to check

① Sum $\sum_{x=0}^{\infty} e^{-\lambda} \frac{\lambda^x}{x!} = 1$

② $f_X(x) \geq 0$.

$$X \sim \text{Pois}(\lambda)$$

$\lambda = \text{rate parameter}$

Claim 2: (actually Lemma 2.7.2) If $X \sim \text{Pois}(\lambda)$, then

(a) $E(X) = \lambda$.

(B) $\text{Var}(X) = \lambda.$

NCAA Fumbles. Do NCAA fumble counts seem to follow a Poisson model?

There are an average of 1.75 fumbles per game during Week 1

```
mean(~ week1, data=Fumbles)
```

```
[1] 1.75
```

so it seems like the Poisson model with $\lambda = 1.75$ would make for the closest fit.

```
myTab <- tally(~week1, data=Fumbles)
xcoords <- as.numeric( row.names( myTab ) )
ycoords <- as.numeric( myTab ) / 120
gf_point( ycoords ~ xcoords ) %>%
  gf_dist( "pois", params = list(lambda=1.75), color="blue" ) %>%
  gf_segment(0 + dpois(0:10, lambda=1.75) ~ (0:10) + (0:10), color="blue" )
```

Assume $X = \# \text{ of arrivals} \sim \text{Pois}$

Example: Arrivals at the bank.

Suppose that, during the noon hour (noon - 1 pm), the average number of customers coming inside for help with a bank teller is 60. What is the probability that

- (a) a 10-minute period elapses during the noon hour without customers?

$$\text{count} \sim \text{Pois}(\lambda = 10)$$

$$P(\text{count} = 0) = e^{-10} \cdot \frac{10^0}{0!} \\ = \text{dpois}(0, \text{lambda} = 10)$$

- (b) 100 or more customers come in a single day during the noon hour?

Still assuming count $X \sim \text{Pois}(\lambda = 60)$

$$1 - \text{sum}(\text{dpois}(0:99, \text{lambda} = 60))$$

$$= 1 - \text{ppois}(99, \text{lambda} = 60)$$