

APM1110: Probability and Probability Distributions
Formative Assessment 9

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Question 1: Show that the mean and variance of the gamma distribution are given by.

(a) $\mu = \beta\alpha$, (b) $\sigma^2 = \alpha\beta^2$

The gamma probability distribution function is the following:

$$f(x) = \begin{cases} \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

while the definition of the Gamma function is the following:

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx = (\alpha - 1)!$$

Show that, for the gamma probability distribution, $\mu = \alpha\beta$, and $\sigma^2 = \alpha\beta^2$

$$\begin{aligned} \mu = E(X) &= \int_0^\infty \frac{x}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} dx \\ &= \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty x^\alpha e^{-\frac{x}{\beta}} dx \end{aligned}$$

let $u = \frac{x}{\beta}$, $x = u\beta$

then $du = \frac{1}{\beta} dx$, $dx = \beta du$

then we'll have:

$$\longrightarrow \frac{\beta^{\alpha+1}}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty (u)^\alpha e^{-u} du$$

using the definition of a Gamma function:

$$\frac{\beta}{\Gamma(\alpha)} \int_0^\infty (u)^{\alpha+1-1} e^{-u} du = \frac{\beta}{\Gamma(\alpha)} \Gamma(\alpha + 1) = \frac{\beta}{\Gamma(\alpha)} \alpha \Gamma(\alpha)$$

cancelling out terms gives us:

$$\beta\alpha = E(X) = \mu$$

The definition of σ^2 is $Var(X) = E(X^2) - E(X)^2$

looking for $E(X^2)$ gives us:

$$E(X) = \int_0^\infty \frac{x^2}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} dx$$

$$== \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty x^{\alpha+1} e^{-\frac{x}{\beta}} dx$$

again, let $u = \frac{x}{\beta}$, $x = u\beta$

then $du = \frac{1}{\beta} dx$, $dx = \beta du$

then we'll have:

$$\longrightarrow \frac{\beta^{\alpha+2}}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty (u)^{\alpha+1+1-1} e^{-u} du$$

note that we have already added 0 to the exponent of u, this makes the integral more familiar: the Gamma Function:

$$\longrightarrow \frac{\beta^2}{\Gamma(\alpha)} \Gamma(\alpha + 2)$$

this gives us:

$$\begin{aligned} &\longrightarrow \frac{\beta^2}{\Gamma(\alpha)} (\alpha + 1) \alpha \Gamma(\alpha) = \beta^2 (\alpha + 1) \alpha \\ &== \beta^2 \alpha^2 + \beta^2 \alpha = E(X^2) \end{aligned}$$

solving for the variance:

$$\begin{aligned} \sigma^2 &= E(X^2) - E(X)^2 = \beta^2 \alpha^2 + \beta^2 \alpha - (\beta \alpha)^2 \\ &== \beta^2 \alpha \end{aligned}$$

\therefore for a gamma probability distribution, $\mu = \beta \alpha$ and $\sigma^2 = \beta^2 \alpha$ \square

Question 2: Prove that the mean and variance of a binomially distributed random variable are, respectively.

$\mu = np$ and $\sigma^2 = npq$.

$$\mu = np$$

Let U_1, \dots, U_n be independent Bernoulli random variables.

$E(U_i) = p$ and $Var(U_i) = p(1 - p)$, where p is the mean (μ) or the expectation and $p(1 - p)$ is the variance (σ)

$X = U_1 + \dots + U_n$, where the binomial random variable X is the sum of these n random variables.

$E(X) = E(U_1 + \dots + U_n)$, where the expectation of our binomial random variable X denoted as E is the expectation of the sum of the n Bernoulli random variables.

Using the properties of expectation, this is simply the sum of the expectation,

$$\begin{aligned} E(X) &= E(U_1) + \dots + E(U_n) \\ &= p + \dots + p \\ &= np, \text{ where } n \text{ represents the number of times } (p) \text{ occurs} \quad \square. \end{aligned}$$

$$\sigma^2 = npq$$

In a binomial distribution, success and failure are complementary probabilities, let p be the probability of success and q be the probability of failure, then:

$$q(\text{failure}) = 1 - p(\text{success}) \quad (2)$$

Let U_1, \dots, U_n be independent Bernoulli random variables.

$E(U_i) = p$ and $Var(U_i) = p(1 - p)$, where p is the mean (μ) or the expectation and $p(1-p)$ is the variance (σ)

$X = U_1 + \dots + U_n$, where the binomial random variable X is the sum of these n Bernoulli random variables.

$Var(X) = Var(U_1 + \dots + U_n)$, where the variance of X is the variance of the sum of these n independent Bernoulli random variables.

When random variables are independent, the variance of the sum is the sum of the variances.

$$\begin{aligned} Var(X) &= Var(U_1) + \dots + Var(U_n) \\ &= p(1 - p) + \dots + p(1 - p) \\ &= np(1 - p), \text{ where } n \text{ represents the number of times } p(1 - p) \text{ occurs} \end{aligned}$$

Now, recall from equation ((2)) that $q = 1 - p$

Substituting $q = 1 - p$ into $np(1 - p)$, we get npq . Therefore,

$$Var(X) = npq \quad \square.$$

Question 3: Establish the validity of the Poisson approximation to the binomial distribution.

The PMF of the Binomial Distribution

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x} \quad (3)$$

The PMF of the Poisson Distribution

$$P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!} \quad (4)$$

We know that the mean (μ) of the binomial random variable is np and the μ of the poisson random variable is λ . If we set $np = \lambda$ and through algebraic manipulation, $p = \frac{\lambda}{n}$,

We can substitute p into the binomial PMF:

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

Using the binomial coefficient properties,

$$\binom{n}{x} = \frac{n!}{x!(n-x)!}$$

Substituting this value into the equation, we get:

$$\frac{n!}{x!(n-x)!} \left(\frac{\lambda}{n}\right)^x \left(1 - \frac{\lambda}{n}\right)^{n-x}$$

Taking λ^x to the front so that it will resemble the PMF poisson formula from equation (4) ,

$$\frac{\lambda^x}{x!} \frac{n!}{(n-x)!} \frac{1}{n^x} \left(1 - \frac{\lambda}{n}\right)^{n-x}$$

Now all we need to show is that the,

$$\frac{n!}{(n-x)!} \frac{1}{n^x} \left(1 - \frac{\lambda}{n}\right)^{n-x} = e^{-\lambda}, \text{ of the PMF poisson formula as } n \rightarrow \infty$$

Let's simplify first this term, $\frac{n!}{(n-x)!} \frac{1}{n^x}$

$$\begin{aligned} &= \frac{n(n-1)(n-2) \dots (n-x+1)(n-x)!}{(n-x)!n^x} \\ &= \frac{n(n-1)(n-2) \dots (n-x+1)}{n^x} \\ &= \frac{n}{n} \cdot \frac{n-1}{n} \cdot \frac{n-2}{n} \dots \frac{n-x+1}{n} \\ &= 1\left(1 - \frac{1}{n}\right)\left(1 - \frac{2}{n}\right) \dots \left(1 - \frac{x+1}{n}\right) \end{aligned}$$

We now have,

$$\frac{\lambda^x}{x!} \left(1 - \frac{1}{n}\right)\left(1 - \frac{2}{n}\right) \dots \left(1 - \frac{x+1}{n}\right) \left(1 - \frac{\lambda}{n}\right)^{n-x}$$

Simplifying the last term, $\left(1 - \frac{\lambda}{n}\right)^{n-x}$ using the properties of exponent, we have:

$$\frac{\lambda^x}{x!} \left(1 - \frac{1}{n}\right)\left(1 - \frac{2}{n}\right) \dots \left(1 - \frac{x+1}{n}\right) \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-x}$$

Now, we have rewritten the PMF binomial formula into this:

$$\binom{n}{x} p^x (1-p)^{n-x} = \frac{\lambda^x}{x!} \left(1 - \frac{1}{n}\right) \left(1 - \frac{2}{n}\right) \dots \left(1 - \frac{x+1}{n}\right) \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-x}$$

We'll restructure this a bit to make it easier to get the $\lim_{n \rightarrow \infty}$

$$\begin{aligned} \lim_{n \rightarrow \infty} \binom{n}{x} p^x (1-p)^{n-x} &= \frac{\lambda^x}{x!} \\ &\times \lim_{n \rightarrow \infty} \left(1 - \frac{1}{n}\right) \left(1 - \frac{2}{n}\right) \dots \left(1 - \frac{x+1}{n}\right) \\ &\times \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n \\ &\times \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^{-x} \end{aligned}$$

$$\begin{aligned} \lim_{n \rightarrow \infty} \binom{n}{x} p^x (1-p)^{n-x} &= \frac{\lambda^x}{x!} \\ &\times \lim_{n \rightarrow \infty} (1-0)(1-0) \dots (1-0) = 1 \\ &\times \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n = e^{-\lambda} \\ &\times \lim_{n \rightarrow \infty} (1-0)^{-x} = 1 \end{aligned}$$

As $n \rightarrow \infty$, $p \rightarrow 0$ and $\lambda = np$ stays constant:

$$\begin{aligned} \lim_{n \rightarrow \infty} \binom{n}{x} p^x (1-p)^{n-x} &= \frac{\lambda^x}{x!} \times 1 \times e^{-\lambda} \times 1 \\ &= \frac{\lambda^x e^{-\lambda}}{x!} \quad \square. \end{aligned}$$