

# *Inference in a Poisson model*

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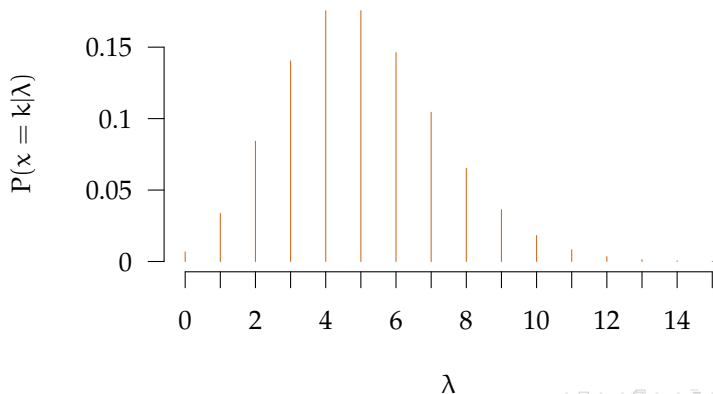
🔗 <https://github.com/lawsofthought/psbayes>

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## *Inference in Poisson models*

- ▶ The Poisson distribution can be used to model the rare occurrences in fixed intervals.
- ▶ If  $x$  is a Poisson random variable with rate  $\lambda$ , then

$$P(x = k|\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}.$$



## *Inference in Poisson models*

- ▶ Let's say that the number of emails I get per hour, in  $n = 10$  hours, is

$$D = 6, 8, 12, 7, 11, 14, 10, 12, 11, 16.$$

- ▶ We can assume that these frequencies are generated according to a Poisson process with rate  $\lambda$  per hour.
- ▶ Given this assumption and this observed data, what is the probable value of  $\lambda$ ?
- ▶ In other words, what is

$$P(\lambda|D)?$$

## *Likelihood of a Poisson model*

- Given a known value for  $\lambda$ , the probability of  $x_1, x_2 \cdots x_n$  is

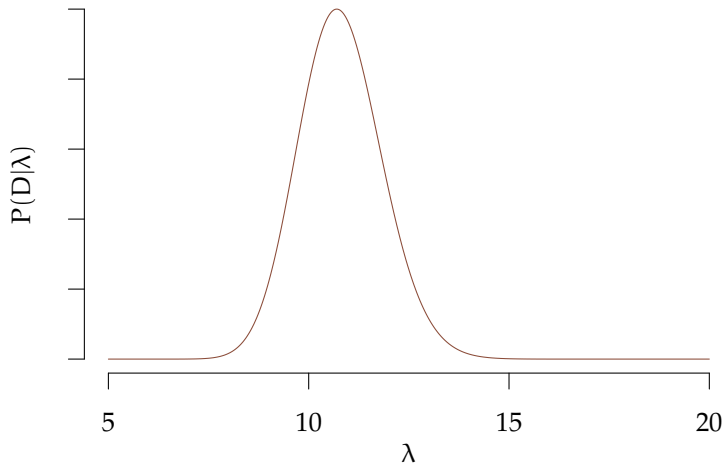
$$\begin{aligned} P(x_1, x_2 \cdots x_n | \lambda) &= \prod_{i=1}^n P(x_i | \lambda), \\ &= \prod_{i=1}^n \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}, \\ &\propto e^{-n\lambda} \prod_{i=1}^n \lambda^{x_i} = e^{-n\lambda} \lambda^{\sum_{i=1}^n x_i}. \end{aligned}$$

When  $D = x_1, x_2 \cdots x_n = 6, 8 \cdots 16$ , the likelihood of  $\lambda$  is

$$P(D | \lambda) = e^{-n\lambda} \lambda^S,$$

where  $S = \sum_{i=1}^n x_i = 107$ .

## *Likelihood of a Poisson model*

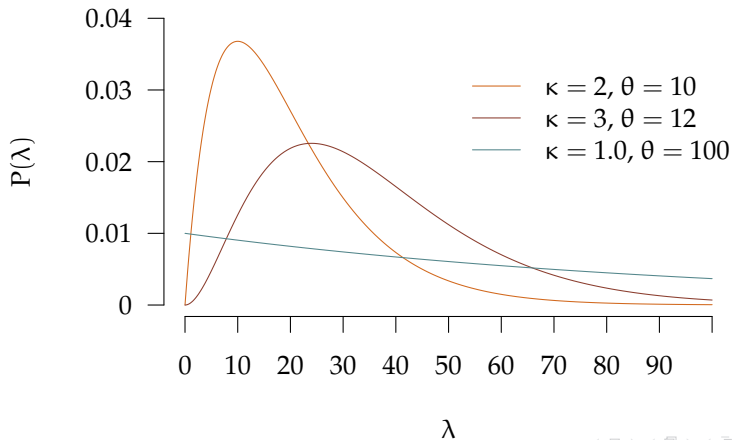


The likelihood of  $\lambda$  given the sufficient statistics  $S = 107$  and  $n = 10$ .

## Conjugate prior for the Poisson model

- The Gamma distribution with shape  $\kappa$  and scale  $\theta$  is a conjugate prior for the Poisson model:

$$\text{Gamma}(\lambda|\kappa, \theta) = \frac{\lambda^{\kappa-1} e^{-\lambda/\theta}}{\theta^{\kappa} \Gamma(\kappa)}.$$



## Posterior distribution

- With the Poisson likelihood, the Gamma prior leads to

$$\begin{aligned} P(\lambda|D, \kappa, \theta) &\propto e^{-n\lambda} \lambda^S \times \frac{\lambda^{\kappa-1} e^{-\lambda/\theta}}{\theta^{\kappa} \Gamma(\kappa)}, \\ &\propto e^{-\lambda\left(n + \frac{1}{\theta}\right)} \lambda^{S+\kappa-1}. \end{aligned}$$

Given that

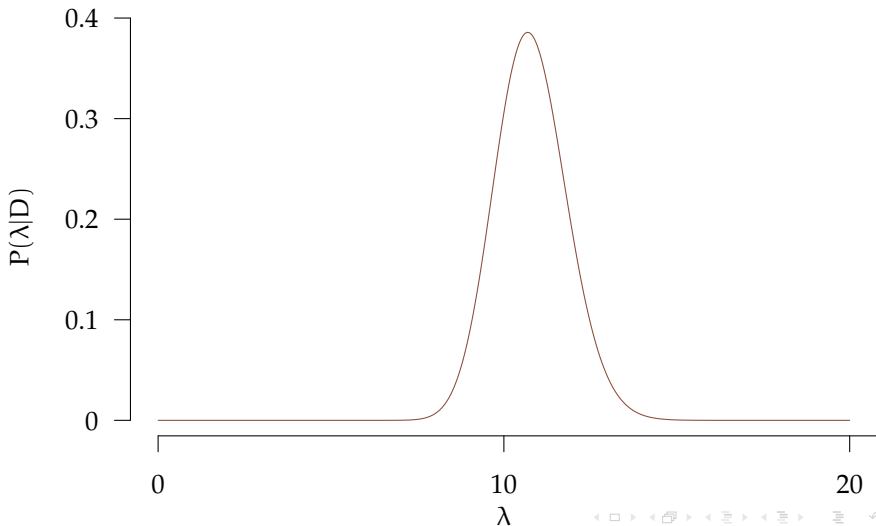
$$\int e^{-\lambda\left(n + \frac{1}{\theta}\right)} \lambda^{S+\kappa-1} d\lambda = \left(n + \frac{1}{\theta}\right)^{-(S+\kappa)} \Gamma(S+\kappa),$$

we have

$$P(\lambda|D, \kappa, \theta) = \text{Gamma}(\lambda|S + \kappa, (n + \frac{1}{\theta})^{-1}).$$

## Posterior distribution

- With prior hyper-parameters of  $\kappa = 1.0$ ,  $\theta = 100.0$ , and sufficient statistics of  $S = 107$  and  $n = 10$ , we have Gamma distribution with shape 108 and scale  $\approx 0.1$





## *Summarizing the posterior*

- The mean, variance and modes of any Gamma distribution with shape  $\kappa$  and scale  $\theta$  are as follows:

$$\langle \lambda \rangle = \kappa \theta,$$

$$V(\lambda) = \kappa \theta^2,$$

$$\text{mode}(\lambda) = (\kappa - 1)\theta.$$

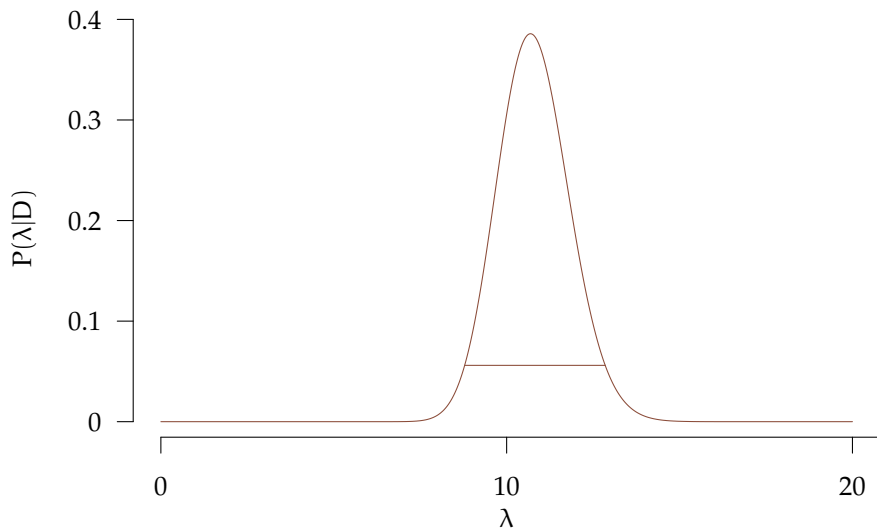
- Thus in our case, we have

$$\langle \lambda \rangle = 108.0,$$

$$V(\lambda) = 1.08, \quad \text{sd}(\theta) = 1.04,$$

$$\text{mode}(\lambda) = 10.69.$$

## *The 0.95 HPD interval*



The 0.95 HPD interval is from 8.78 to 12.86.

## Posterior predictive distribution

- Given that the number of emails every hour were

$$D = 6, 8, 12, 7, 11, 14, 10, 12, 11, 16,$$

what do we predict will be number of emails in the next hour?

- This is given by the posterior predictive distribution:

$$\begin{aligned} P(x_{\text{next}} = k | D, \kappa, \theta) &= \int P(x_{\text{next}} = k | \lambda) P(\lambda | D, \kappa, \theta) d\lambda, \\ &= \int \frac{e^{-k} \lambda^k}{k!} \times \frac{(n + \frac{1}{\theta})^{S+\kappa}}{\Gamma(S+\kappa)} e^{-\lambda(n + \frac{1}{\theta})} \lambda^{S+\kappa-1}, \\ &= \frac{\Gamma(S+\kappa+k)}{\Gamma(S+\kappa)\Gamma(k+1)} q^k (1-q)^{S+\kappa}, \\ &= \text{NegativeBinomial}(k | S+\kappa, q), \end{aligned}$$

with  $q = (n + \frac{1}{\theta} + 1)^{-1}$ .

## *Posterior predictive distribution*

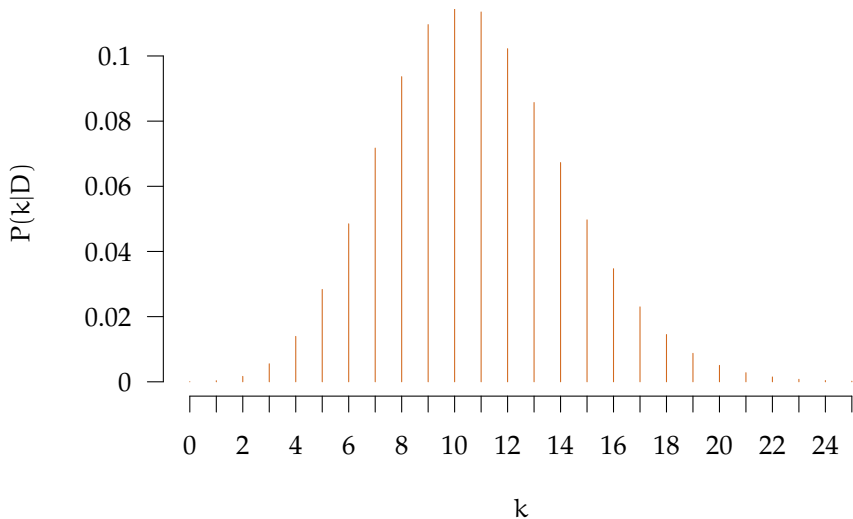
- ▶ The negative binomial distribution gives the number of “successes” until a predefined number  $r$  of “failures” have occurred, with the probability of a success being  $q$ .
- ▶ The mean and variance of the negative binomial are

$$\langle k \rangle = \frac{qr}{1-q}, \quad V(k) = \frac{qr}{(1-q)^2}.$$

- ▶ In our case,  $r = S + \kappa = 108$  and  $q = (n + \frac{1}{\theta} + 1)^{-1} = (10 + \frac{1}{100} + 1)^{-1} = 0.091$ .
- ▶ The mean and variance of the negative binomial are

$$\langle k \rangle = \frac{S + \kappa}{n + \frac{1}{\theta}} = 10.79, \quad V(k) = \frac{S + \kappa}{n + \frac{1}{\theta}} (n + \frac{1}{\theta} + 1) = 11.87.$$

## Posterior predictive distribution



The posterior predictive distribution  $P(x_{\text{next}} = k|D, \kappa, \theta)$  is a negative binomial distribution with  $r = 108$ ,  $q = 0.091$ .