

# Stuff I Should Know for Bayesian Statistics

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## Normal Distribution

A normal distribution has two parameters: the mean ( $\theta$ ) and the variance ( $\sigma^2$ ).  $x$  can go from  $-\infty$  to  $\infty$ . Its density is given by

$$p(x) \propto e^{-\frac{(x-\theta)^2}{2\sigma^2}}$$

For that to integrate to 1, the normalizing constant is

$$\frac{1}{\sqrt{2\pi\sigma^2}}$$

The conjugate prior of the mean of a normal distribution is another normal distribution. Specifically, if  $x_1, \dots, x_n$ , are identical and independent with a normal distribution  $\mathcal{N}(\theta, \sigma^2)$  and the prior is  $\theta \sim N(\theta_0, \sigma_0^2)$ ,

$$\theta|x_1, \dots, x_n \sim \mathcal{N}\left(\frac{\frac{\sigma^2}{n}\theta_0 + \sigma_0^2\bar{x}}{\frac{\sigma^2}{n} + \sigma_0^2}, \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2}\right)^{-1}\right)$$

The conjugate prior of the variance of a normal distribution is an inverse gamma distribution.

## Gamma Distribution

The gamma distribution has two parameters:  $\alpha$  and  $\beta$ .  $x$  can go from 0 to  $\infty$ . Its density is given by

$$p(x) \propto x^{\alpha-1} e^{-\beta x} \quad \text{for } x > 0 \text{ and } \alpha, \beta > 0,$$

For that to integrate to 1, the normalizing constant is

$$\frac{\beta^\alpha}{\Gamma(\alpha)}$$

The mean of the distribution is

$$E[x] = \frac{\alpha}{\beta}$$

If  $\alpha \geq 1$ , the mode is

$$\frac{\alpha - 1}{\beta}$$

## Inverse Gamma Distribution

An inverse gamma distribution has two parameters:  $\alpha$  and  $\beta$ .  $x$  can go from 0 to  $\infty$ . Its density is given by

$$p(x) \propto (1/x)^{\alpha+1} e^{(-\frac{\beta}{x})}$$

For that to integrate to 1, the normalizing constant is

$$\frac{\beta^\alpha}{\Gamma(\alpha)}$$

If  $\alpha > 1$ , the mean of the distribution is

$$E[x] = \frac{\beta}{\alpha - 1}$$

The mode is

$$\frac{\beta}{\alpha + 1}$$

## Binomial Distribution

The binomial distribution is a discrete distribution that takes one parameter:  $\pi$  is the probability of one success in one try. The probability of getting exactly  $k$  successes in  $n$  trials is given by

$$p(k) = \binom{n}{k} \pi^k (1 - \pi)^{n-k}$$

The mean is  $n\pi$ .

Its conjugate prior of  $\pi$  is the Beta distribution.

## Beta Distribution

The beta distribution takes two parameters:  $\alpha$  and  $\beta$ . Its density is given by

$$p(x) \propto x^{\alpha-1} (1-x)^{\beta-1}$$

For that to integrate to 1, the normalizing constant is

$$\frac{1}{Beta(\alpha, \beta)}$$

The mode is

$$\frac{\alpha - 1}{\alpha + \beta - 2}$$

## Poisson Distribution

The Poisson Distribution is a discrete distribution that takes one parameter:  $\lambda$ . Its distribution is given by

$$p(x) = \frac{\lambda^x}{x!} \quad x \in \{0, 1, \dots\}$$

To normalize it, the constant is

$$e^{-\lambda}$$

$\lambda$  is both its mean and its variance.

The conjugate prior for  $\lambda$  is the gamma distribution

## Pareto Distribution

The Type 1 Pareto Distribution has two parameters  $\alpha$  and  $x_m$ , where  $x_m$  is the minimum possible value. Both  $x_m$  and  $\alpha$  must be positive. Its density is

$$p(x) = \begin{cases} \frac{\alpha x_m^\alpha}{x^{\alpha+1}} & x \geq x_m, \\ 0 & x < x_m. \end{cases}$$

The mean of the distribution is

$$E(X) = \begin{cases} \infty & \alpha \leq 1, \\ \frac{\alpha x_m}{\alpha - 1} & \alpha > 1. \end{cases}$$

Its cumulative distribution function is

$$F(x) = \begin{cases} 1 - \left(\frac{x_m}{x}\right)^\alpha & x \geq x_m, \\ 0 & x < x_m. \end{cases}$$

## Gamma Function

The gamma function is a generalization of factorial. That is, if  $n$  is a positive integer

$$\Gamma(n) = (n - 1)!$$

But the gamma function is defined:

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

## Beta Function

The beta function is

$$\text{Beta}(x, y) = \int_0^1 t^{x-1} (1-t)^{y-1} dt = \frac{\Gamma(x) \Gamma(y)}{\Gamma(x+y)}$$

## Choose Function

The choose function is:

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

## Linear Regression

If you are trying to use  $p$  inputs  $(x_1, \dots, x_p)$  to predict an output  $y$ , you could create a vector of coefficients  $(\beta_0, \dots, \beta_p)$  such that

$$y \approx \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p$$

So how do you figure out what the  $\beta$  is? You use the  $n$  data points you have: The column vector  $\mathbf{y} = (y_1, y_2, \dots, y_n)'$  is the outcomes. The matrix  $\mathbf{X}$  is the inputs. Row  $i$  of  $\mathbf{X}$  starts with 1 and has the inputs  $(x_{i,1}, x_{i,2}, \dots, x_{i,p})$  that correspond to  $y_i$ . Thus  $X$  has  $n$  rows and  $p+1$  columns.

Given the data you have, the sum of the squares of the errors for a vector  $\beta$  is given by

$$\mathbf{y}^T \mathbf{y} - 2\beta^T \mathbf{X}^T \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{X} \beta$$

To minimize that, you set  $\beta$  to be:

$$\beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$