

# Conjugate Bayesian analysis

**Matthew Stephens**

University of Chicago

January 8, 2026

See [here](#) for a PDF version of this vignette.

## Overview

This vignette introduces the idea of “conjugate prior” distributions for Bayesian inference for a continuous parameter. You should be familiar with [Bayesian inference for a binomial proportion](#).

## Conjugate Priors for binomial proportion

### Background

In [this example](#) we considered the following problem.

Suppose we sample 100 elephants from a population, and measure their DNA at a location in their genome (“locus”) where there are two types (“alleles”), which it is convenient to label 0 and 1.

In my sample, I observe that 30 of the elephants have the “1” allele and 70 have the “0” allele. What can I say about the frequency,  $q$ , of the “1” allele in the population?

The example showed how to compute the posterior distribution for  $q$ , using a *uniform prior distribution*. We saw that, conveniently, the posterior distribution for  $q$  is a Beta distribution.

Here we generalize this calculation to the case where the prior distribution on  $q$  is a Beta distribution. We will find that, in this case, the posterior distribution on  $q$  is again a Beta distribution. The property where the posterior distribution comes from the same family as the prior distribution is very convenient, and so has a special name: it is called “conjugacy”. We say “The Beta distribution is the conjugate prior distribution for the binomial proportion”.

### Details

As before we use Bayes Theorem which we can write in words as

$$\text{posterior} \propto \text{likelihood} \times \text{prior},$$

or in mathematical notation as

$$p(q|D) \propto p(D|q)p(q),$$

where  $D$  denotes the observed data.

In this case, the likelihood  $p(D|q)$  is given by

$$p(D|q) \propto q^{30}(1-q)^{70}$$

If our prior distribution on  $q$  is a Beta distribution, say  $\text{Beta}(a, b)$ , then the prior density  $p(q)$  is

$$p(q) \propto q^{a-1}(1-q)^{b-1} \quad (q \in [0, 1]).$$

Combining these two we get:

$$p(q|D) \propto q^{30}(1-q)^{70} q^{a-1}(1-q)^{b-1} \propto q^{30+a-1}(1-q)^{70+b-1}$$

At this point we again apply the “trick” of recognizing this density as the density of a Beta distribution - specifically, the Beta distribution with parameters  $(30 + a, 70 + b)$ .

### Generalization

Of course, there is nothing special about the 30 “1” alleles and 70 “0” alleles we observed here. Suppose we observed  $n_1$  of the “1” allele and  $n_0$  of the “0” allele. Then the likelihood becomes

$$p(D|q) \propto q^{n_1}(1-q)^{n_0},$$

and you should be able to show (Exercise) that the posterior is

$$q|D \sim \text{Beta}(n_1 + a, n_0 + b).$$

### Summary

When doing Bayesian inference for a binomial proportion,  $q$ , if the prior distribution is a Beta distribution then the posterior distribution is also Beta.

We say “the Beta distribution is the conjugate prior for a binomial proportion”.

### Exercise

Show that the Gamma distribution is the conjugate prior for a Poisson mean.

That is, suppose we have observations  $X$  that are Poisson distributed,  $X \sim \text{Poi}(\mu)$ . Assume that your prior distribution on  $\mu$  is a Gamma distribution with parameters  $n$  and  $\lambda$ . Show that the posterior distribution on  $\mu$  is also a Gamma distribution.

Hint: you should take the following steps. 1. write down the likelihood  $p(X|\mu)$  for  $\mu$  (look up the Poisson distribution if you cannot remember it). 2. Write down the prior density for  $\mu$  (look up the density of a Gamma distribution if you cannot remember it). 3. Multiply them together to obtain the posterior density (up to a constant of proportionality), and notice that it has the same form as the gamma distribution.