

# Classical and Bayesian inference

AMS 132

January 18, 2018

# Sampling from a Bernoulli Distribution

## Theorem (Beta-Bernoulli model)

Suppose that  $X_1, \dots, X_n$  form a random sample from the Bernoulli distribution with parameter  $\theta$ , which is unknown ( $0 < \theta < 1$ ). Suppose also that the prior distribution of  $\theta$  is the beta distribution with parameters  $\alpha > 0$  and  $\beta > 0$ . Then the posterior distribution of  $\theta$  given that  $X_i = x_i$ , ( $i = 1, \dots, n$ ), is the beta distribution with parameters  $\alpha + \sum_{i=1}^n x_i$  and  $\beta + n - \sum_{i=1}^n x_i$ .

## Example (Beta-Bernoulli model)

Consider a large shipment of iPhone has arrive, and the proportion of defective iPhone,  $\theta$ , is unknown. A  $Beta(\alpha, \beta)$  prior is assumed and  $n$  randomly selected items are inspected.

- Find the posterior distribution of  $\theta$ .
- How is the posterior distribution updated?

# Sampling from a Bernoulli Distribution

## Definition (Conjugate Family and Hyperparameters)

Let  $X_1, X_2, \dots$  be conditionally i.i.d. given  $\theta$  with common p.f. or p.d.f.  $f(x | \theta)$ . Let  $\Psi$  be a family of possible distributions over the parameter space  $\Omega$ . Suppose that, no matter which prior distribution  $\xi$  we choose from  $\Psi$ , no matter how many observations  $\mathbf{X} = (X_1, \dots, X_n)$  we observe, and no matter what are their observed values  $\mathbf{x} = (x_1, \dots, x_n)$ , the posterior distribution  $\xi(\theta | \mathbf{x})$  is a member of  $\Psi$ . Then  $\Psi$  is called a *conjugate family* of prior distributions for samples from the distributions  $f(x | \theta)$ . It is also said that the family  $\Psi$  is *closed under sampling* from the distributions  $f(\mathbf{x} | \theta)$ .

Finally, if the distributions in  $\Psi$  are parametrized by further parameters, then the associated parameters for the prior distribution are called the *prior hyperparameters* and the associated parameters of the posterior distribution are called the *posterior hyperparameters*.

# Sampling from a Poisson Distribution

## Theorem (Gamma-Poisson model)

*Suppose that  $X_1, \dots, X_n$  form a random sample from the Poisson distribution with mean  $\theta > 0$ , which is unknown. Suppose also that the prior distribution of  $\theta$  is the gamma distribution with parameters  $\alpha > 0$  and  $\beta > 0$ . Then the posterior distribution of  $\theta$  given that  $X_i = x_i$ , ( $i = 1, \dots, n$ ), is the gamma distribution with parameters  $\alpha + \sum_{i=1}^n x_i$  and  $\beta + n$ .*

## Example (Gamma-Poisson model)

Suppose that customers arrive to a store at an unknown rate,  $\theta$ , per hour. Assume that  $\theta$  follows a gamma distribution with parameters  $\alpha$  and  $\beta$ .

a) Find the posterior distribution of  $\theta$ .

# Sampling from a Normal Distribution

## Theorem (Normal-Normal model)

Suppose that  $X_1, \dots, X_n$  form a random sample from the Normal distribution with unknown mean  $\theta$  and known variance  $\sigma^2 > 0$ . Suppose also that the prior distribution of  $\theta$  is the normal distribution with mean  $\mu_0$  and variance  $v_0^2$ . Then the posterior distribution of  $\theta$  given that  $X_i = x_i, (i = 1, \dots, n)$ , is the normal distribution with mean and variance given by

$$\mu_1 = \frac{\sigma^2 \mu_0 + n v_0^2 \bar{x}_n}{\sigma^2 + n v_0^2}, \quad v_1^2 = \frac{\sigma^2 v_0^2}{\sigma^2 + n v_0^2}.$$

# Sampling from a Normal Distribution

## Example (Normal-Normal model)

Suppose that  $X_i | \theta, \sigma^2 \stackrel{i.i.d.}{\sim} N(\theta, \sigma^2)$ , with  $\sigma^2$  known. Assume that  $\theta$  follows a normal distribution with parameters  $\mu_0$  and  $v_0^2$ .

- Find the posterior distribution of  $\theta$ .
- Show that the posterior mean can be written as

$$\mu_1 = \frac{\sigma^2}{\sigma^2 + nv_0^2} \mu_0 + \frac{nv_0^2}{\sigma^2 + nv_0^2} \bar{X}_n.$$

- Find an expression for computing  $P(\theta > 1 | \mathbf{x})$ .

# Sampling from a Exponential Distribution

## Theorem (Gamma-Exponential model)

Suppose that  $X_1, \dots, X_n$  form a random sample from the exponential distribution with unknown parameter  $\theta > 0$ . Suppose also that the prior distribution of  $\theta$  is the gamma distribution with parameters  $\alpha > 0$  and  $\beta > 0$ . Then the posterior distribution of  $\theta$  given that  $X_i = x_i$ , ( $i = 1, \dots, n$ ), is the gamma distribution with parameters  $\alpha + n$  and  $\beta + \sum_{i=1}^n x_i$ .

## Example (Gamma-Exponential model)

Suppose that  $X_i \mid \theta \stackrel{i.i.d.}{\sim} \exp(\theta)$ ,  $i = 1, \dots, n$ ,  $\theta > 0$ , where  $X_i$  describes the lifetime of component  $i$ , and  $\theta \sim \text{Gamma}(\alpha, \beta)$ .

a) Find the posterior distribution of  $\theta$ .

# Improper Prior Distributions

- Recall that improper priors capture the idea that there is much more information in the data than is captured in our prior distribution.
- Each of the conjugate families that we have seen has an improper prior as a limiting case.

## Definition

Let  $\xi$  be a nonnegative function whose domain includes the parameter space of a statistical model. Suppose that  $\int_{\Omega} \xi(\theta) d\theta = \infty$ . If we pretend as if  $\xi(\theta)$  is the prior p.d.f. of  $\theta$ , then we are using an improper prior for  $\theta$ .



# Improper Prior Distributions

## Example (Improper Prior Distributions)

- Consider a large shipment of iPhone has arrive, and the proportion of defective iPhone,  $\theta$ , is unknown. A  $Beta(\alpha, \beta)$  prior is assumed and  $n$  randomly selected items are inspected. What happens when  $\alpha = \beta = 0$ ?
- Suppose that customers arrive to a store at an unknown rate,  $\theta$ , per hour. Assume that  $\theta$  follows a gamma distribution with parameters  $\alpha$  and  $\beta$ . What happens when  $\alpha = \beta = 0$ ? What happens if no customers arrive in an hour?
- Suppose that  $X_i | \theta, \sigma^2 \stackrel{i.i.d.}{\sim} N(\theta, \sigma^2)$ , with  $\sigma^2$  known. Assume that  $\theta$  follows a normal distribution with parameters  $\mu_0$  and  $v_0^2$ . What happens if  $v_0^2 = \infty$ ?