

# STA 6360, Report 1.6

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## Example 1.12

Suppose we observe  $y \sim \mathcal{N}(\mu, \sigma^2)$ ,  $\sigma^2$  known, and use prior  $\mu \sim \mathcal{N}(\xi, \tau^2)$  for  $\mu \neq 0$  and  $\rho = 1/2$ . We want to test  $H_0 : \mu = 0$  vs.  $H_1 : \mu \neq 0$ . In the absence of prior information to the contrary, we set  $\xi = 0$ . Then, we have that our prior is

$$\pi(\mu) = \rho I_{\{\mu=0\}}(\mu) + \rho \pi_1(\mu) I_{\{\mu \neq 0\}}.$$

Under  $H_1$ , the prior for  $\mu$  is  $\mu \sim \mathcal{N}(0, \tau^2)$ . Thus, the posterior distribution of  $y$  given  $\mu$  and  $H_1$  is  $y | \mu, H_1 \sim \mathcal{N}(\mu, \sigma^2)$ . To obtain the marginal likelihood  $m(y | H_1)$ , we integrate out  $\mu$  with respect to its prior:

$$m(y | H_1) = \int_{-\infty}^{\infty} f(y | \mu) \pi_1(\mu) d\mu.$$

Since  $y | \mu \sim \mathcal{N}(\mu, \sigma^2)$  and  $\mu \sim \mathcal{N}(0, \tau^2)$ ,  $y$  marginally follows a normal distribution with mean 0 and variance  $\sigma^2 + \tau^2$ . Therefore,  $y | H_1 \sim \mathcal{N}(0, \sigma^2 + \tau^2)$ , and thus,

$$m(y | H_1) = \frac{1}{\sqrt{2\pi(\sigma^2 + \tau^2)}} \exp\left(-\frac{y^2}{2(\sigma^2 + \tau^2)}\right).$$

The Bayes factor  $BF$  against  $H_0$  is given by

$$BF = \frac{m(y | H_1)}{m(y | H_0)}.$$

Substitute the expressions for  $m(y | H_1)$  and  $m(y | H_0)$ :

$$BF = \frac{\frac{1}{\sqrt{2\pi(\sigma^2 + \tau^2)}} \exp\left\{-\frac{y^2}{2(\sigma^2 + \tau^2)}\right\}}{\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{y^2}{2\sigma^2}\right\}}.$$

Simplify this expression yields

$$BF = \sqrt{\frac{\sigma^2}{\sigma^2 + \tau^2}} \exp\left\{\frac{y^2}{2} \left(\frac{1}{\sigma^2 + \tau^2} - \frac{1}{\sigma^2}\right)\right\}.$$

Rearrange the exponent term, we have

$$BF = \sqrt{\frac{\sigma^2}{\sigma^2 + \tau^2}} \exp\left\{\frac{\tau^2 y^2}{2\sigma^2(\sigma^2 + \tau^2)}\right\}.$$

Then, we compute the posterior probability. To calculate the posterior probability of the null hypothesis,  $H_0 : \mu = 0$ , we use Bayes' theorem for model probabilities. Given prior probabilities  $P(H_0) = \rho$  and  $P(H_1) = 1 - \rho$ , the posterior probability of  $H_0$  is

$$P(H_0 | y) = \frac{P(H_0) m(y | H_0)}{P(H_0) m(y | H_0) + P(H_1) m(y | H_1)},$$

where:

- $m(y | H_0)$  and  $m(y | H_1)$  are the marginal likelihoods under  $H_0$  and  $H_1$ , respectively.
- $BF$  is the Bayes factor in favor of  $H_1$  over  $H_0$ .

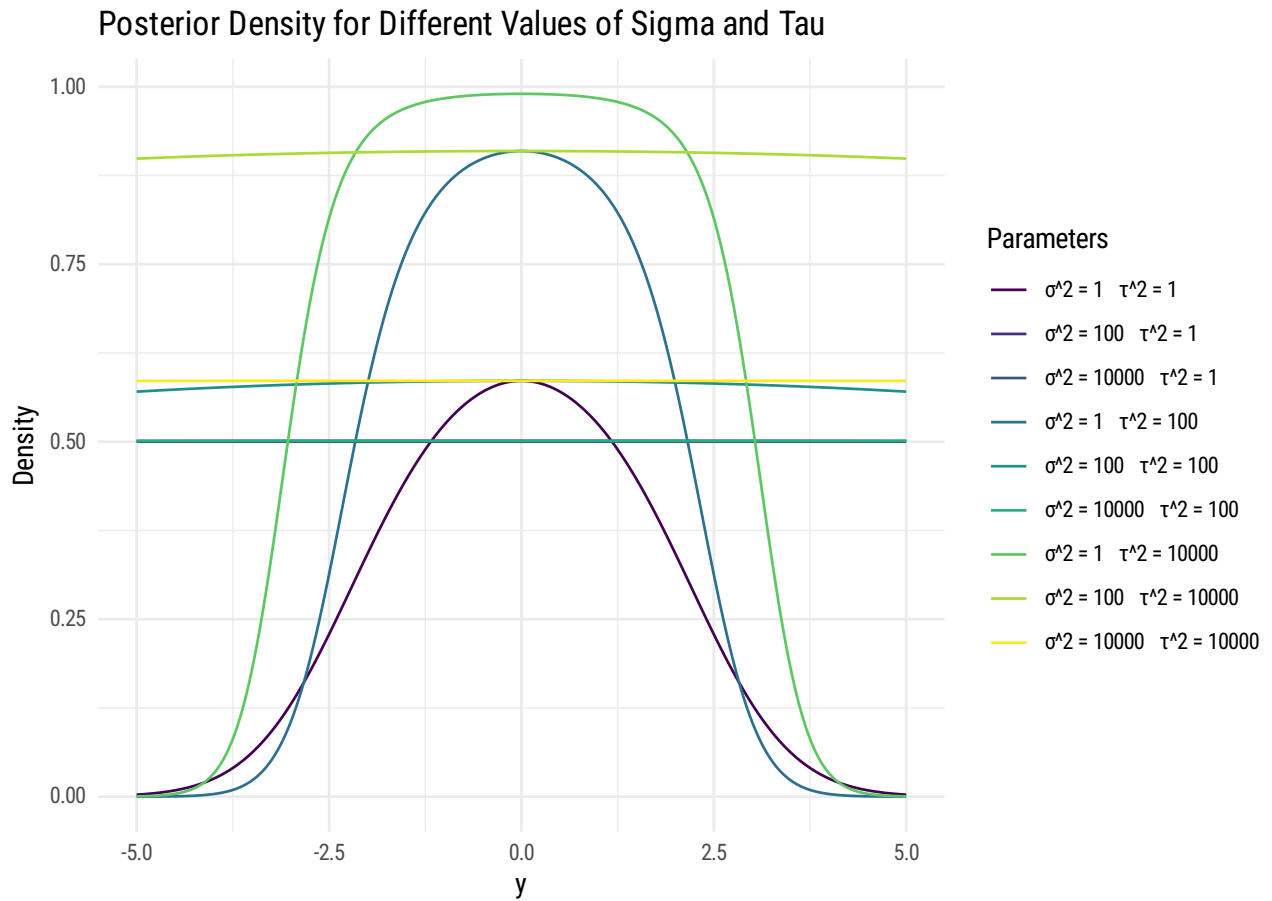
Since  $m(y | H_1) = BF \cdot m(y | H_0)$ , we can rewrite the posterior probability of  $H_0$  as:

$$P(H_0 | y) = \frac{\rho}{\rho + (1 - \rho)BF}$$

Substituting the Bayes factor we derived, we obtain the posterior probability of  $H_0$ :

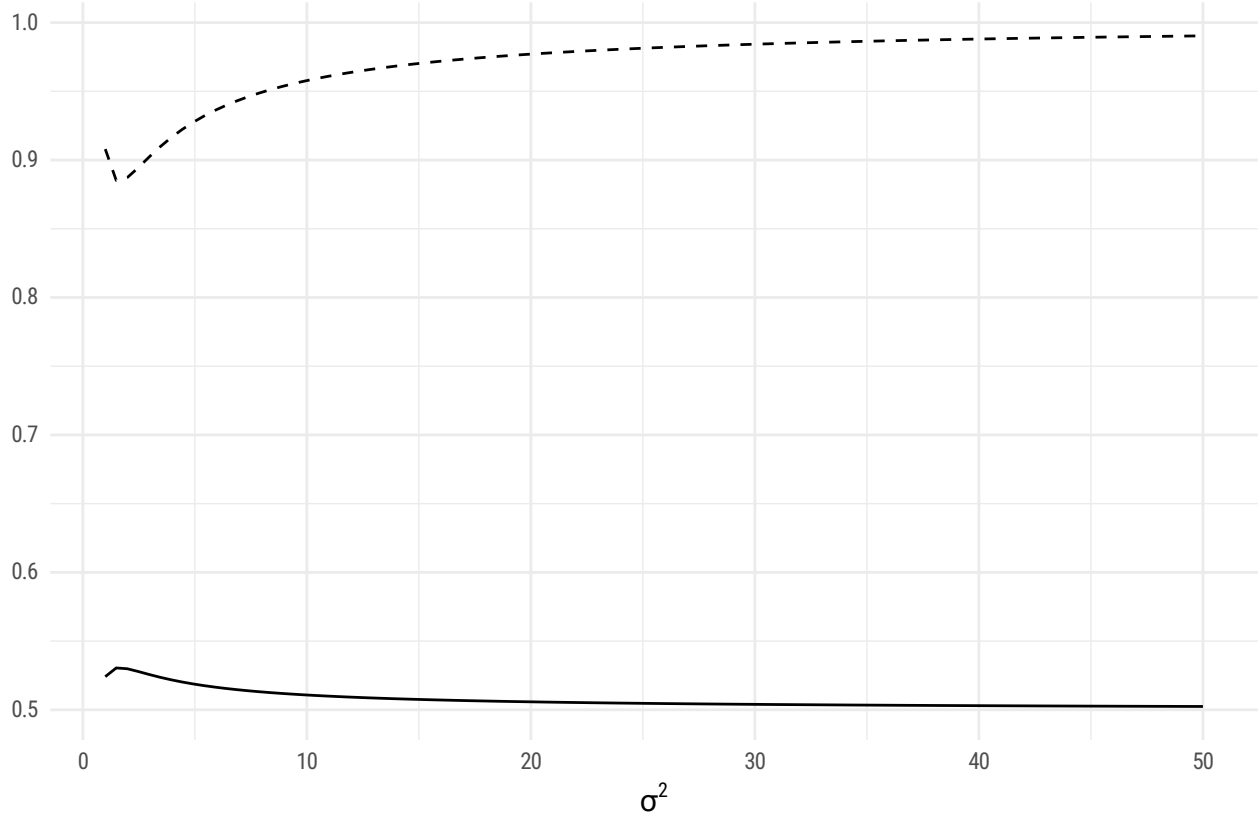
$$P(H_0 | y) = \left[ 1 + \frac{1 - \rho}{\rho} \sqrt{\frac{\sigma^2}{\sigma^2 + \tau^2}} \exp \left\{ \frac{\tau^2 y^2}{2\sigma^2(\sigma^2 + \tau^2)} \right\} \right]^{-1}$$

### Assessing Relationship



*Other Investigation*

### Bayes Factor and Posterior Probability



Bayes factor (dashed) and posterior probability (dotted) as variance increases.