

The importance of priors

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Bayesian inference

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(\theta|data) = \frac{P(data|\theta)P(\theta)}{P(data)}$$

$$P(\theta|data) \propto P(data|\theta)P(\theta)$$

The posterior **is proportional to** the likelihood and the prior

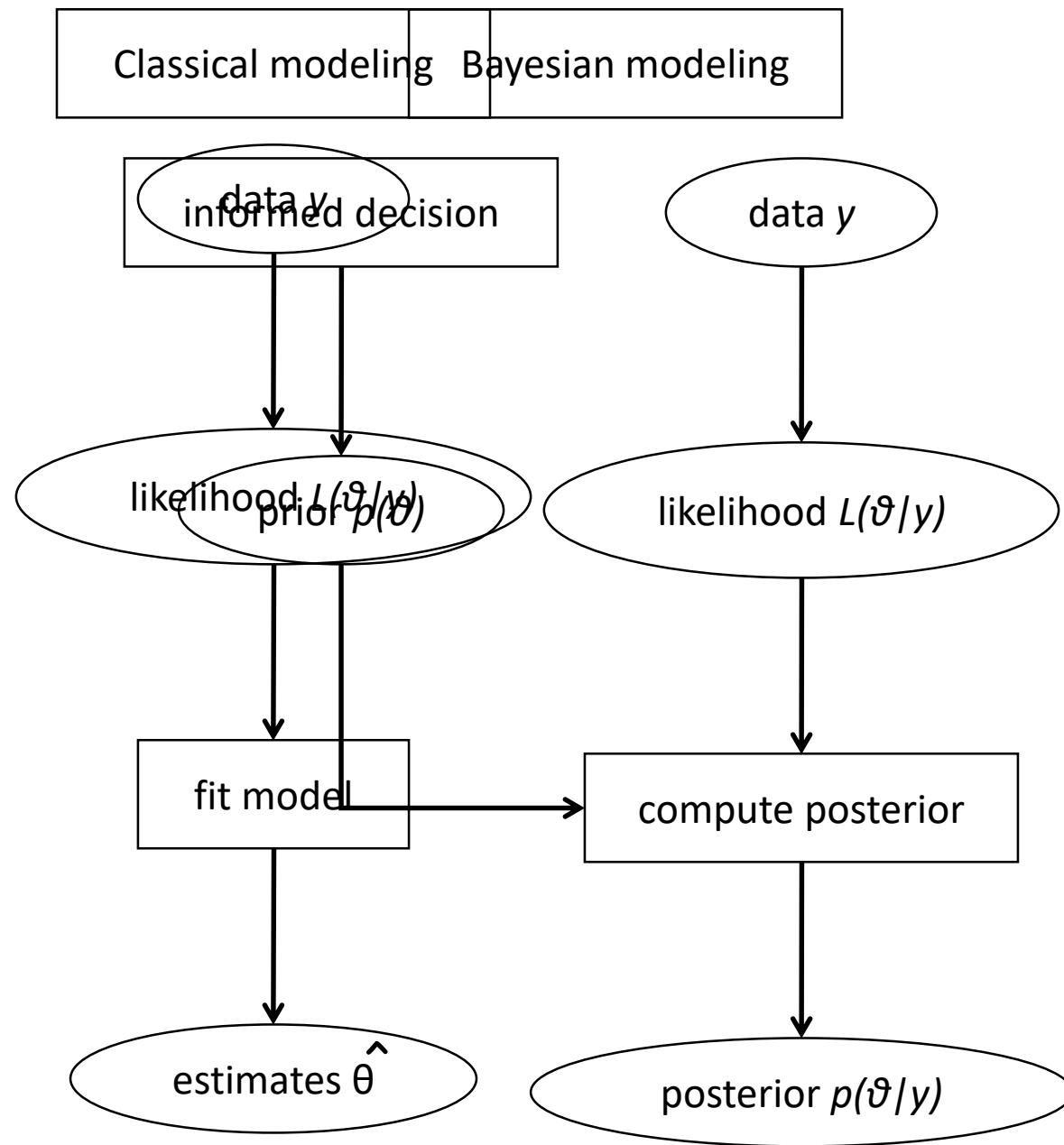
Bayesian inference

We estimate the posterior $L(\vartheta | data)$

We need to

- i. define the **likelihood of the data $L(data | \vartheta)$**
assumption about the underlying distribution that the observed data follow
- ii. **specify prior information on the parameters ϑ**
choice of a distribution for the prior on ϑ





Classical estimation for binomial data

- Estimate an unknown population proportion (θ) from the results of a sequence of Bernoulli trials; data y_1, \dots, y_n , each of which is either 0 or 1.

$$p(y|\theta) = \text{Bin}(y | n, \theta) = \binom{n}{y} \theta^y (1 - \theta)^{n-y}$$

$$\theta = \frac{y}{n}$$

$$\theta \pm z_{\left(1-\frac{\alpha}{2}\right)} * \sqrt{\frac{\theta(1-\theta)}{n}}$$

TB prevalence – Classical approach

Suppose that we are interested in estimating the prevalence of tuberculosis (TB) among hospitalized men in Greece. Data from a retrospective study indicated that 5 men out of a random sample of 1000 were TB+.

$$p(y|\theta)=Bin(y | n, \theta) = \binom{n}{y} \theta^y (1 - \theta)^{n-y}$$

$$\theta = \frac{y}{n} = \frac{5}{1000} = 0.005$$

$$\theta \pm z_{\left(1-\frac{\alpha}{2}\right)} * \sqrt{\frac{\theta(1-\theta)}{n}}$$

$$\theta = 0.005 \pm 1.96 * \sqrt{0.005 * 0.995 / 1000}$$

$$\theta = 0.005 \pm 0.004$$

$$\theta = 0.005(0.001;0.009)$$



Bayesian inference for binomial data

We estimate the posterior $L(\vartheta | data)$

We need to

- i. define the **likelihood of the data $L(data | \vartheta)$**
assumption about the underlying distribution that the observed data follow
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choice of a distribution for the prior on ϑ



Bayesian inference for binomial data

$$P(\theta|y) \propto P(y|\theta)P(\theta)$$

$$p(y|\theta) = \text{Bin}(y | n, \theta) = \binom{n}{y} \theta^y (1 - \theta)^{n-y}$$

$$p(\theta) = \text{Beta}(a, b) \propto \theta^{a-1} (1 - \theta)^{b-1}$$

$$p(y|\theta) \propto \theta^y (1 - \theta)^{n-y}$$

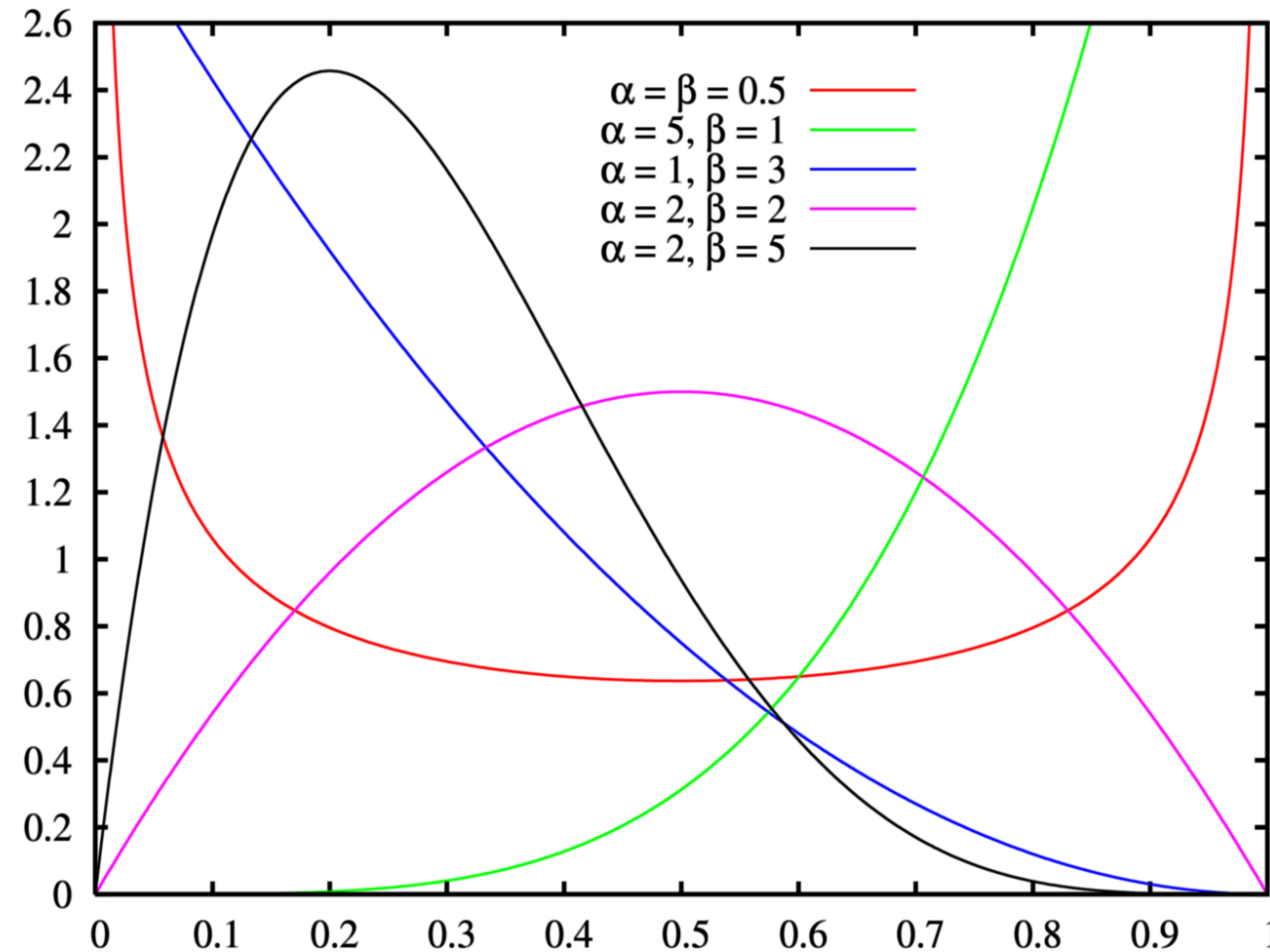
$$p(\theta|y) \propto p(y|\theta)p(\theta)$$

$$p(\theta|y) \propto \theta^y (1 - \theta)^{n-y} \theta^{a-1} (1 - \theta)^{b-1}$$

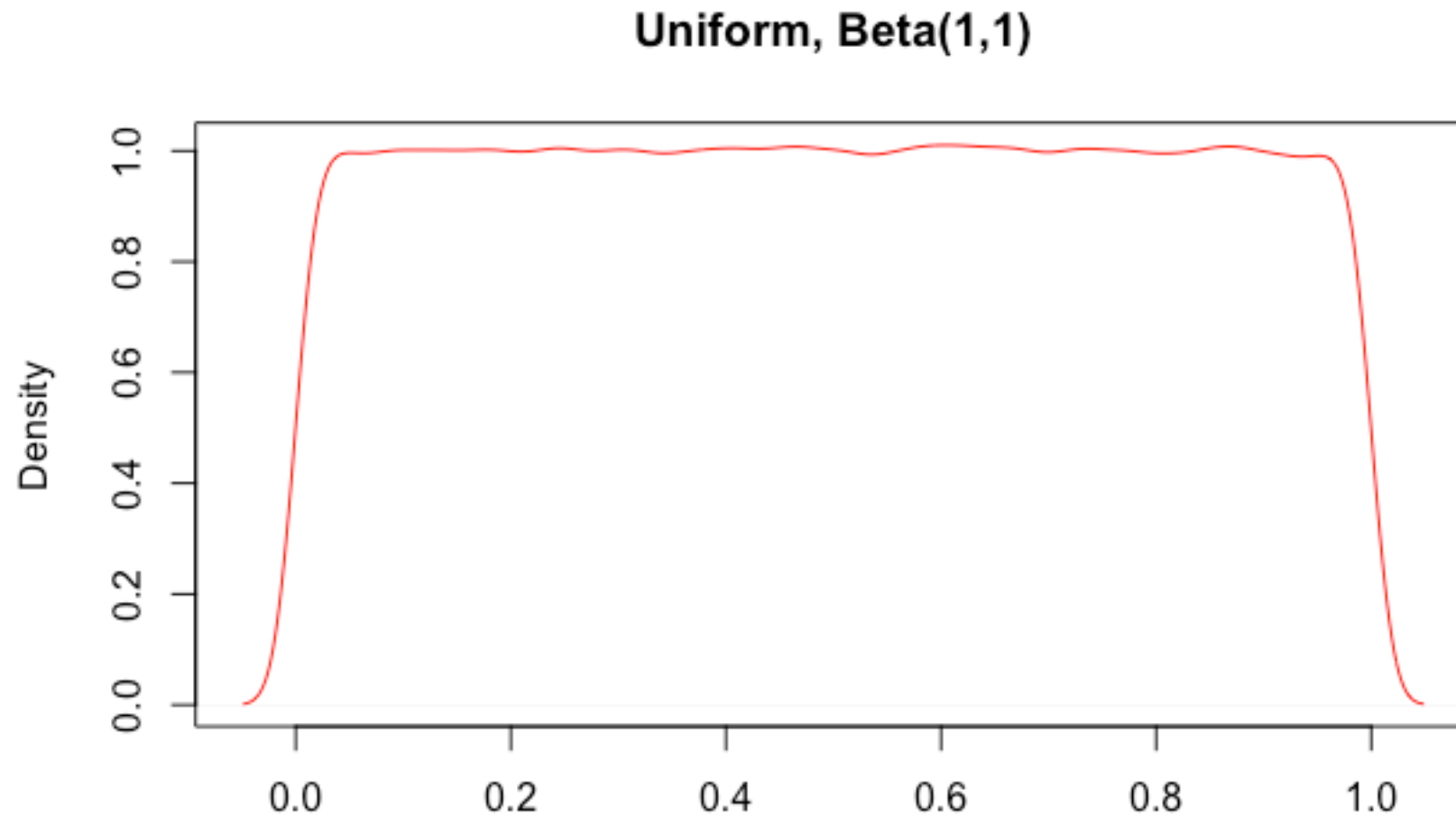
$$p(\theta|y) \propto \theta^{y+a-1} (1 - \theta)^{n-y+b-1}$$

$$p(\theta|y) = \text{Beta}(\theta | y + \alpha, n - y + \beta)$$

Beta distribution



Uniform beta distribution



TB prevalence – Bayesian Inference

Suppose that we are interested in estimating the prevalence of tuberculosis (TB) among hospitalized men in Greece. Data from a retrospective study indicated that 5 men out of a random sample of 1000 were TB+.

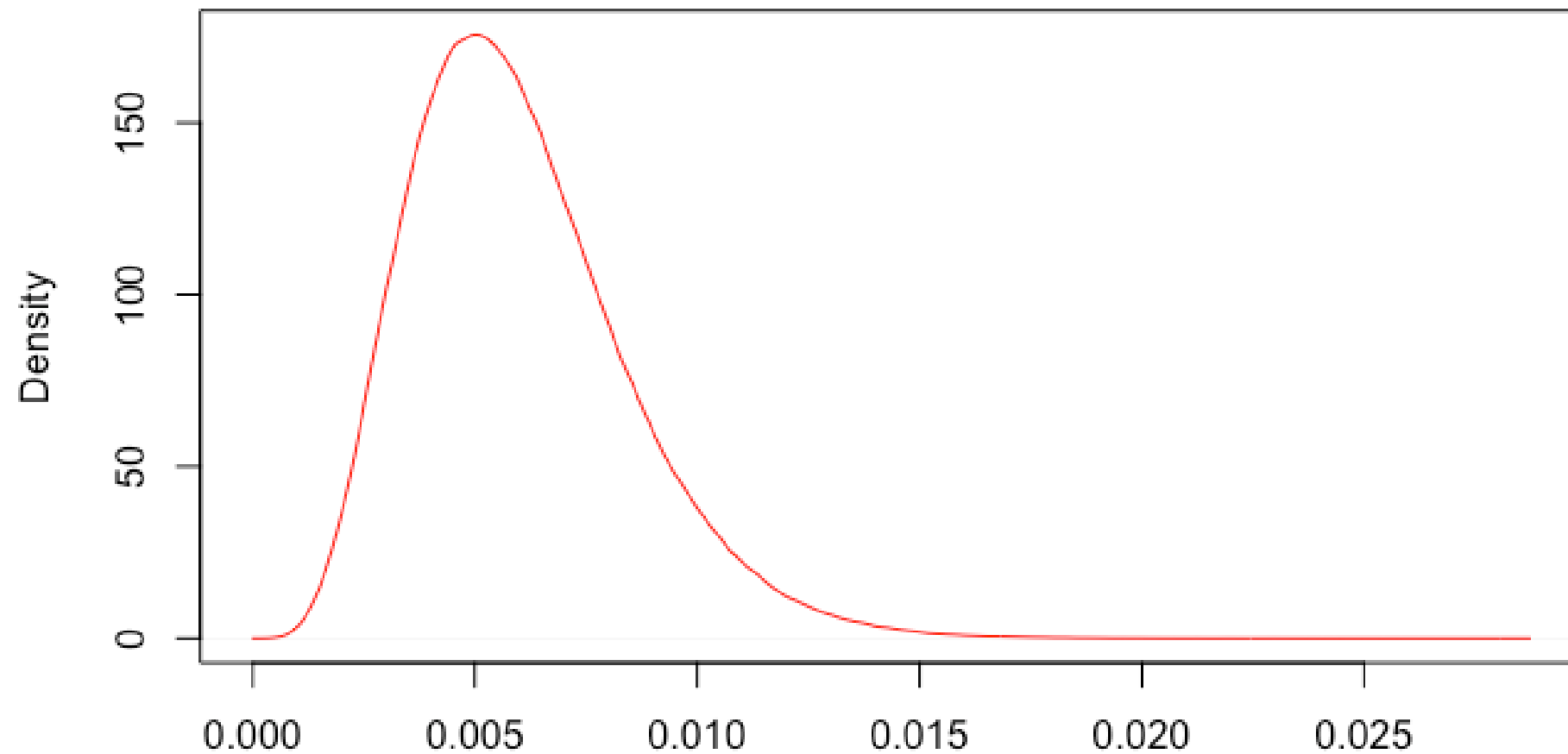
Using a non-informative Beta(1,1) prior we estimate the prevalence of TB as:

$$p(\theta|y) = \text{Beta}(\theta \mid \alpha + y, \beta + n - y)$$

$$p(\theta|y) = \text{Beta}(1 + 5, 1 + 1000 - 5)$$

$$p(\theta|y) = \text{Beta}(6, 996)$$

Beta(6,996)



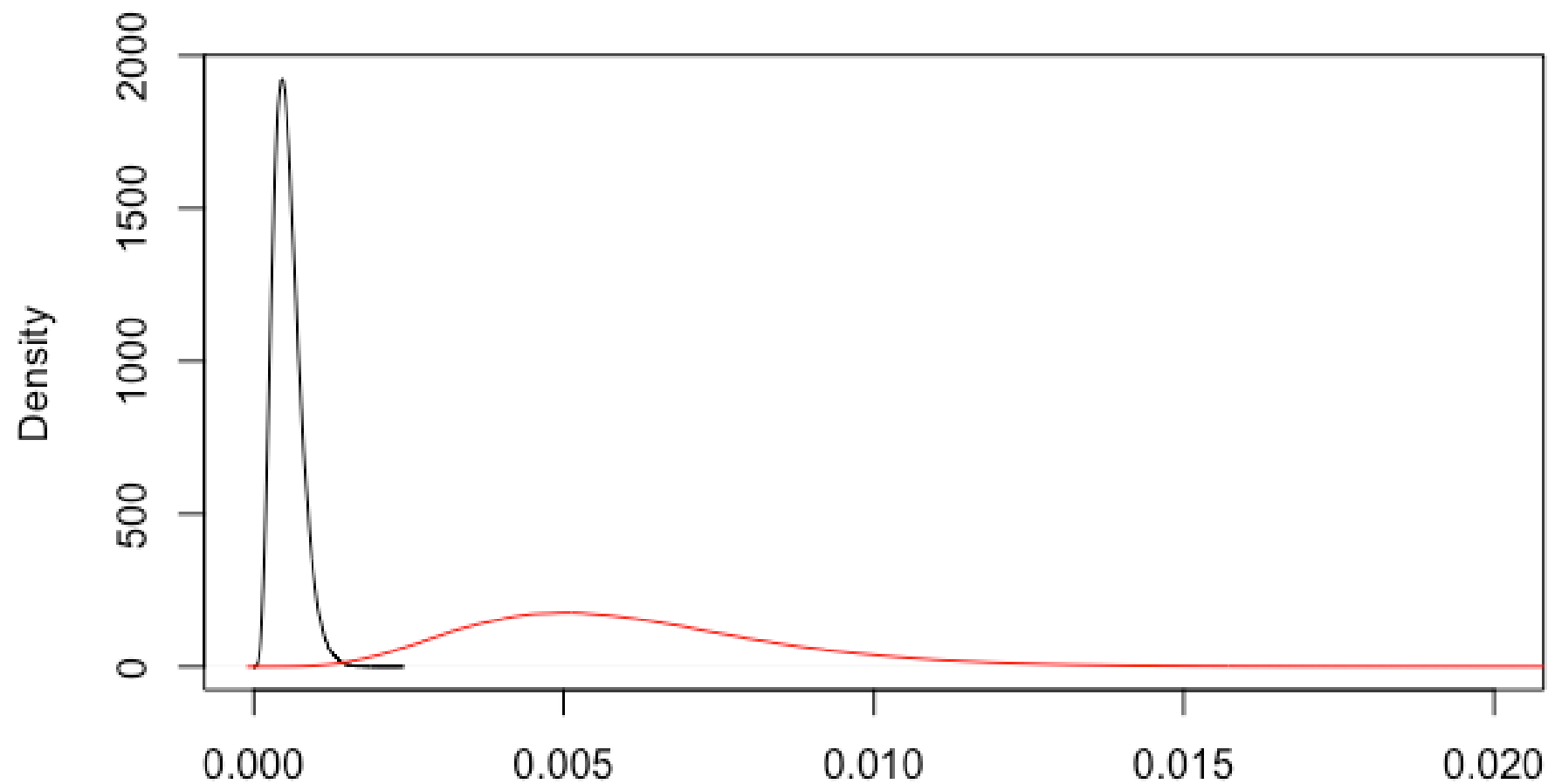
TB prevalence – Bayesian Inference

Let's use a very narrow informative Beta(1,10000) prior:

$$P(\theta|y) = \text{Beta}(\theta|\alpha + y, \beta + n - y)$$

$$P(\theta|y) = \text{Beta}(1 + 5, 10000 + 1000 - 5)$$

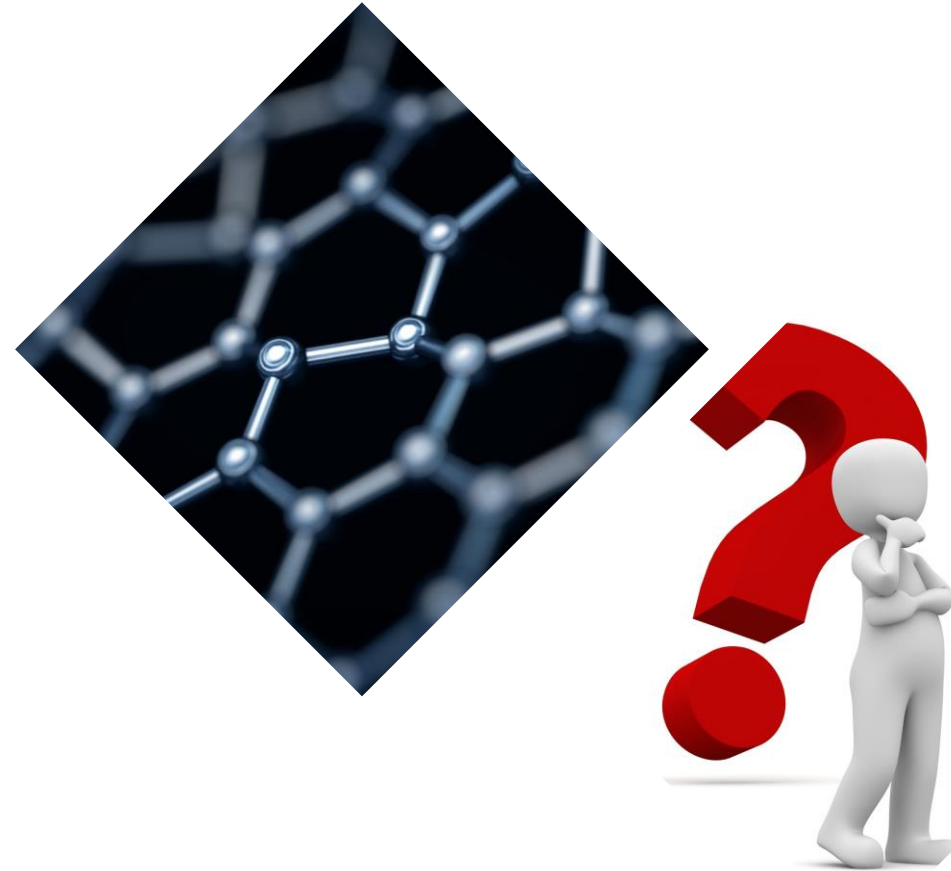
$$P(\theta|y) = \text{Beta}(6, 10995)$$



Prior + Data

IDENTIFIABLE MODELS

NON-IDENTIFIABLE MODELS



HARMONY
Novel tools for test evaluation and
disease prevalence estimation





HARMONY

Novel tools for test evaluation and
disease prevalence estimation

Thank you!