

Parameter estimation

Dr. Jarad Niemi

STAT 544 - Iowa State University

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Outline

- Parameter estimation
 - Beta-binomial example
 - Point estimation
 - Interval estimation
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Parameter estimation

For point or interval estimation of a parameter θ in a model M based on data y , Bayesian inference is based off

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} = \frac{p(y|\theta)p(\theta)}{\int p(y|\theta)p(\theta)d\theta} \propto p(y|\theta)p(\theta)$$

where

- $p(\theta)$ is the **prior** distribution for the parameter,
- $p(\theta|y)$ is the **posterior** distribution for the parameter,
- $p(y|\theta)$ is the statistical **model** (or **likelihood**), and
- $p(y)$ is the **prior predictive distribution** (or **marginal likelihood**).

Obtaining the posterior

The hard way:

1. Derive $p(y)$.
2. Derive $p(\theta|y) = p(y|\theta)p(\theta)/p(y)$.

The easy way:

1. Derive $f(\theta) \propto p(y|\theta)p(\theta)$.
2. Recognize $f(\theta)$ as the **kernel** of some distribution.

Definition

The **kernel** of a probability density (mass) function is the form of the pdf (pmf) with any terms not involving the random variable omitted.

For example, $\theta^{a-1}(1-\theta)^{b-1}$ is the kernel of a beta distribution.

Derive the posterior - the hard way

Suppose $Y \sim \text{Bin}(n, \theta)$ and $\theta \sim \text{Be}(a, b)$, then

$$\begin{aligned}
 p(y) &= \int p(y|\theta)p(\theta)d\theta \\
 &= \int \binom{n}{y} \theta^y (1-\theta)^{n-y} \frac{\theta^{a-1}(1-\theta)^{b-1}}{\text{Beta}(a,b)} d\theta \\
 &= \binom{n}{y} \frac{1}{\text{Beta}(a,b)} \int \theta^{a+y-1} (1-\theta)^{b+n-y-1} d\theta \\
 &= \binom{n}{y} \frac{\text{Beta}(a+y, b+n-y)}{\text{Beta}(a,b)}
 \end{aligned}$$

which is known as the Beta-binomial distribution.

$$\begin{aligned}
 p(\theta|y) &= p(y|\theta)p(\theta)/p(y) \\
 &= \binom{n}{y} \theta^y (1-\theta)^{n-y} \frac{\theta^{a-1}(1-\theta)^{b-1}}{\text{Beta}(a,b)} \bigg/ \binom{n}{y} \frac{\text{Beta}(a+y, b+n-y)}{\text{Beta}(a,b)} \\
 &= \frac{\theta^{a+y-1} (1-\theta)^{b+n-y-1}}{\text{Beta}(a+y, b+n-y)}
 \end{aligned}$$

Thus $\theta|y \sim \text{Be}(a+y, b+n-y)$.

Derive the posterior - the easy way

Suppose $Y \sim \text{Bin}(n, \theta)$ and $\theta \sim \text{Be}(a, b)$, then

$$\begin{aligned} p(\theta|y) &\propto p(y|\theta)p(\theta) \\ &\propto \theta^y(1-\theta)^{n-y}\theta^{a-1}(1-\theta)^{b-1} \\ &= \theta^{a+y-1}(1-\theta)^{b+n-y-1} \end{aligned}$$

Thus $\theta|y \sim \text{Be}(a+y, b+n-y)$.

Example data

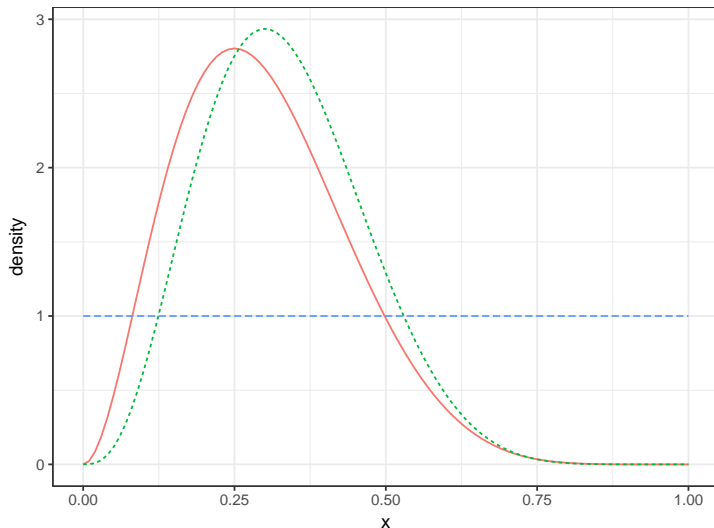
Assume $Y \sim \text{Bin}(n, \theta)$ and $\theta \sim \text{Be}(1, 1)$ (which is equivalent to $\text{Unif}(0, 1)$). If we observe three successes ($y = 3$) out of ten attempts ($n = 10$). Then our posterior is $\theta|y \sim \text{Be}(1 + 3, 1 + 10 - 3) \stackrel{d}{=} \text{Be}(4, 8)$.

Remark Note that a $\text{Be}(1, 1)$ is equivalent to $p(\theta) = \text{I}(0 < \theta < 1)$, i.e.

$$p(\theta|y) \propto p(y|\theta)p(\theta) = p(y|\theta)\text{I}(0 < \theta < 1)$$

so it may seem that a reasonable approach to a default prior is to replace $p(\theta)$ by a 1 (times the parameter constraint). We will see later that this depends on the parameterization.

Posterior distribution



Distribution — normalized likelihood — posterior - - prior

Point and interval estimation

Nothing inherently Bayesian about obtaining point and interval estimates.

Point estimation requires specifying a loss (or utility) function.

A $100(1 - \alpha)\%$ credible interval is any interval in the posterior that contains the parameter with probability $(1 - \alpha)$.

Point estimation

Define a loss (or utility) function $L(\theta, \hat{\theta}) = -U(\theta, \hat{\theta})$ where

- θ is the parameter of interest
- $\hat{\theta} = \hat{\theta}(y)$ is the estimator of θ .

Find the estimator that minimizes the expected loss:

$$\hat{\theta}_{Bayes} = \operatorname{argmin}_{\hat{\theta}} E \left[L(\theta, \hat{\theta}) \middle| y \right]$$

or maximizes expected utility.

Common estimators:

- Mean: $\hat{\theta}_{Bayes} = E[\theta|y]$ minimizes $L(\theta, \hat{\theta}) = (\theta - \hat{\theta})^2$
- Median: $\int_{\hat{\theta}_{Bayes}}^{\infty} p(\theta|y) d\theta = \frac{1}{2}$ minimizes $L(\theta, \hat{\theta}) = |\theta - \hat{\theta}|$
- Mode: $\hat{\theta}_{Bayes} = \operatorname{argmax}_{\theta} p(\theta|y)$ is obtained by minimizing $L(\theta, \hat{\theta}) = -\mathbf{I}(|\theta - \hat{\theta}| < \epsilon)$ as $\epsilon \rightarrow 0$, also called **maximum a posterior (MAP)** estimator.

Mean minimizes squared-error loss

Theorem

The mean minimizes expected squared-error loss.

Proof.

Suppose $L(\theta, \hat{\theta}) = (\theta - \hat{\theta})^2 = \theta^2 - 2\theta\hat{\theta} + \hat{\theta}^2$, then

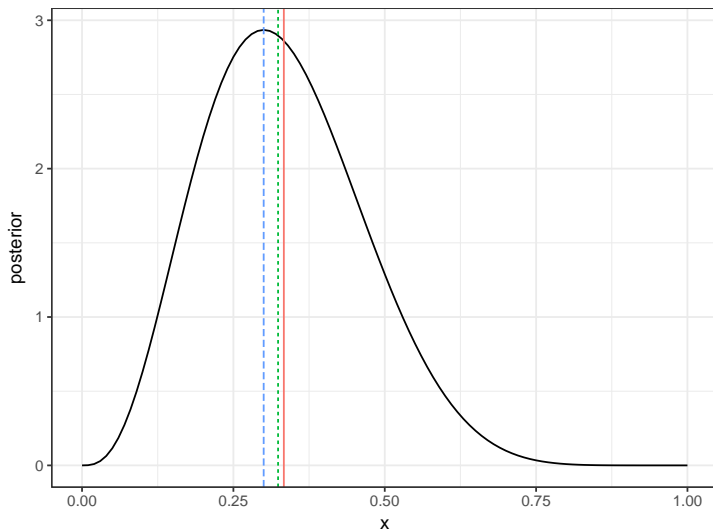
$$E \left[L(\theta, \hat{\theta}) \middle| y \right] = E [\theta^2 | y] - 2\hat{\theta}E[\theta | y] + \hat{\theta}^2$$

$$\frac{d}{d\hat{\theta}} E \left[L(\theta, \hat{\theta}) \middle| y \right] = -2E[\theta | y] + 2\hat{\theta} \stackrel{set}{=} 0 \implies \hat{\theta} = E[\theta | y]$$

$$\frac{d^2}{d\hat{\theta}^2} E \left[L(\theta, \hat{\theta}) \middle| y \right] = 2$$

So $\hat{\theta} = E[\theta | y]$ minimizes expected squared-error loss. □

Point estimation



estimator | mean | median | mode

Interval estimation

Definition

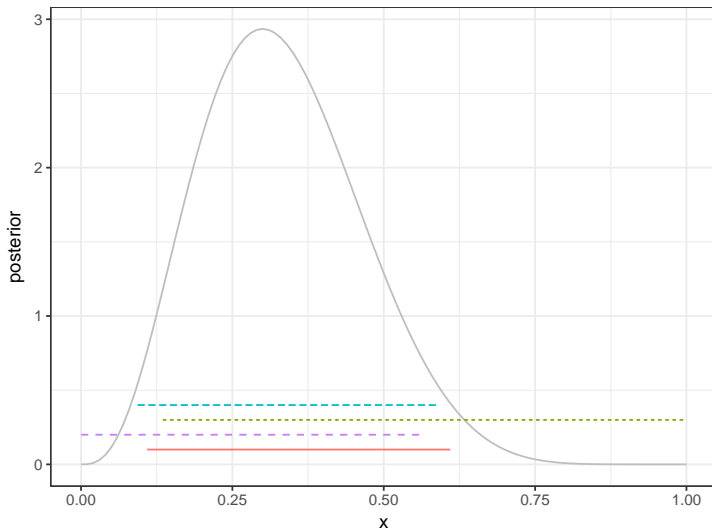
A $100(1 - a)\%$ **credible interval** is any interval (L, U) such that

$$1 - a = \int_L^U p(\theta|y) d\theta.$$

Some typical intervals are

- Equal-tailed: $a/2 = \int_{-\infty}^L p(\theta|y) d\theta = \int_U^{\infty} p(\theta|y) d\theta$
- One-sided: either $L = -\infty$ or $U = \infty$
- **Highest posterior density (HPD)**: $p(L|y) = p(U|y)$ for a uni-modal posterior which is also the shortest interval

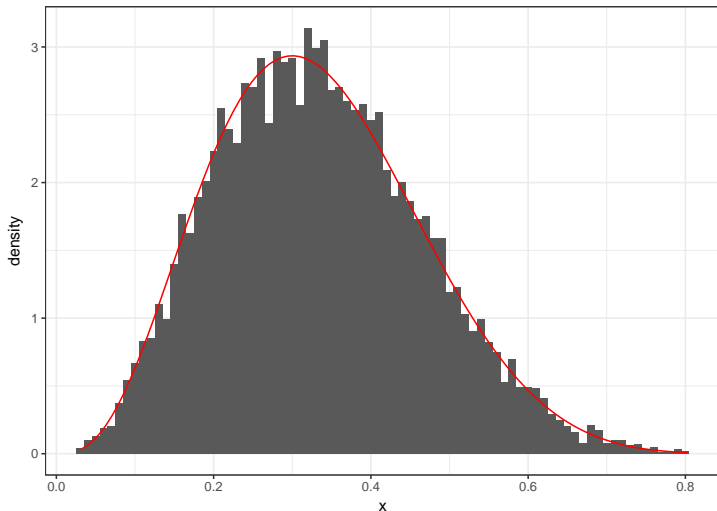
Interval estimation



type — equal-tail ··· higher tail - · - highest posterior density (HPD) - - lower tail

Simulation from the posterior

An estimate of the full posterior can be obtained via simulation, i.e.



Estimates via simulation

We can also obtain point and interval estimates using these simulations

```
c(mean = mean(sim$x), median = median(sim$x))
```

```
      mean      median  
0.3351243 0.3270852
```

```
quantile(sim$x, c(.025,.975)) # Equal-tail
```

```
      2.5%      97.5%  
0.1095259 0.6112486
```

```
quantile(sim$x, .05) # Upper
```

```
      5%  
0.1347931
```

```
quantile(sim$x, .95) # Lower
```

```
      95%  
0.5653678
```


Guess the probability

- A coin spins heads.
- Seattle Seahawks win 2015 Super Bowl.
- The first base pair on my genome is A.

What are priors?

Definition

A **prior probability distribution**, often called simply the **prior**, of an uncertain quantity θ is the probability distribution that would express one's uncertainty about θ before the “data” is taken into account.

http://en.wikipedia.org/wiki/Prior_distribution

Priors

Definition

A prior $p(\theta)$ is **conjugate** if for $p(\theta) \in \mathcal{P}$ and $p(y|\theta) \in \mathcal{F}$, $p(\theta|y) \in \mathcal{P}$ where \mathcal{F} and \mathcal{P} are families of distributions.

For example, the beta distribution (\mathcal{P}) is conjugate to the binomial distribution with unknown probability of success (\mathcal{F}) since

$$\theta \sim \text{Be}(a, b) \quad \text{and} \quad \theta|y \sim \text{Be}(a + y, b + n - y).$$

Definition

A **natural** conjugate prior is a conjugate prior that has the same functional form as the likelihood.

For example, the beta distribution is a natural conjugate prior since

$$p(\theta) \propto \theta^{a-1}(1-\theta)^{b-1} \quad \text{and} \quad L(\theta) \propto \theta^y(1-\theta)^{n-y}.$$

Discrete priors are conjugate

Theorem

Discrete priors are conjugate.

Proof.

Suppose $p(\theta)$ is discrete, i.e.

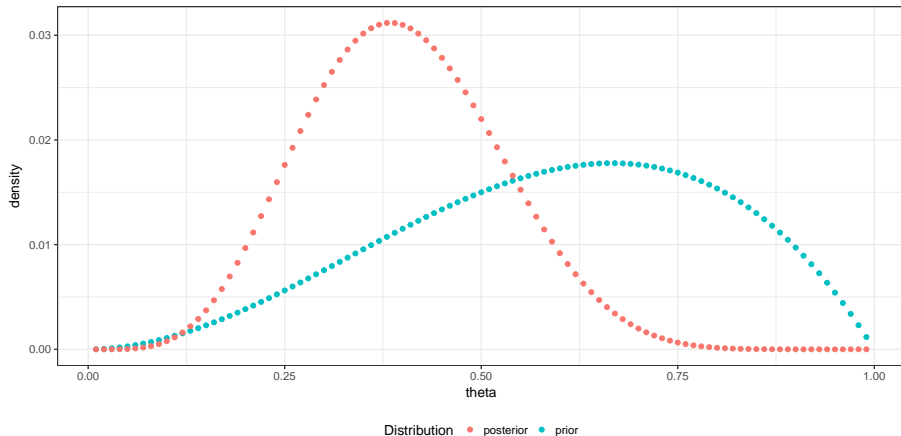
$$P(\theta = \theta_i) = p_i \quad \sum_{i=1}^I p_i = 1$$

and $p(y|\theta)$ is the model. Then, $P(\theta = \theta_i|y) = p'_i$ is the posterior with

$$p'_i = \frac{p_i p(y|\theta_i)}{\sum_{j=1}^I p_j p(y|\theta_j)} \propto p_i p(y|\theta_i).$$



Discrete prior



Mixtures of conjugate priors are conjugate

Theorem

Mixtures of conjugate priors are conjugate.

Proof.

Let $p_i = P(H_i)$ and $p_i(\theta) = p(\theta|H_i)$,

$$\theta \sim \sum_{i=1}^I p_i p_i(\theta) \quad \sum_{i=1}^I p_i = 1,$$

and $p_i(y) = \int p(y|\theta)p_i(\theta)d\theta$, then

$$\begin{aligned} p(\theta|y) &= \frac{1}{p(y)} p(y|\theta) p(\theta) = \frac{1}{p(y)} p(y|\theta) \sum_{i=1}^I p_i p_i(\theta) \\ &= \frac{1}{p(y)} \sum_{i=1}^I p_i p(y|\theta) p_i(\theta) = \frac{1}{p(y)} \sum_{i=1}^I p_i p_i(y) p_i(\theta|y) \\ &= \sum_{i=1}^I \frac{p_i p_i(y)}{p(y)} p_i(\theta|y) = \sum_{i=1}^I \frac{p_i p_i(y)}{\sum_{j=1}^I p_j p_j(y)} p_i(\theta|y) \end{aligned}$$

Mixtures of conjugate priors are conjugate

Bottom line: if

$$\theta \sim \sum_{i=1}^I p_i p_i(\theta) \quad \sum_{i=1}^I p_i = 1$$

and $p_i(y) = \int p(y|\theta)p_i(\theta)d\theta$, then

$$\theta|y \sim \sum_{i=1}^I p'_i p_i(\theta|y) \quad p'_i \propto p_i p_i(y)$$

where $p_i(\theta|y) = p(y|\theta)p_i(\theta)/p_i(y)$.

Mixture of beta distributions

Recall, if $Y \sim \text{Bin}(n, \theta)$ and $\theta \sim \text{Be}(a, b)$, then

$$\begin{aligned}
 p(y) &= \int p(y|\theta)p(\theta)d\theta \\
 &= \int \binom{n}{y} \theta^y (1-\theta)^{n-y} \frac{\theta^{a-1}(1-\theta)^{b-1}}{\text{Beta}(a,b)} \\
 &= \binom{n}{y} \frac{1}{\text{Beta}(a,b)} \int \theta^{a+y-1} (1-\theta)^{b+n-y-1} d\theta \\
 &= \binom{n}{y} \frac{\text{Beta}(a+y, b+n-y)}{\text{Beta}(a,b)} \quad y = 0, \dots, n
 \end{aligned}$$

If $Y \sim \text{Bin}(n, \theta)$ and

$$\theta \sim p \text{Be}(a_1, b_1) + (1-p) \text{Be}(a_2, b_2),$$

then

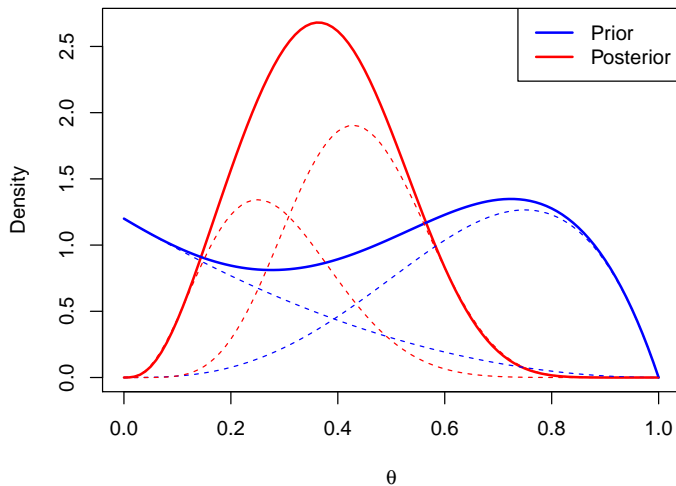
$$\theta|y \sim p' \text{Be}(a_1 + y, b_1 + n - y) + (1 - p') \text{Be}(a_2 + y, b_2 + n - y)$$

with

$$p' = \frac{p p_1(y)}{p p_1(y) + (1-p) p_2(y)} \quad p_i(y) = \binom{n}{y} \frac{\text{Beta}(a_i + y, b_i + n - y)}{\text{Beta}(a_i, b_i)}$$

Mixture priors

Binomial, mixture of betas



Default priors

Definition

A **default** prior is used when a data analyst is unable or unwilling to specify an informative prior distribution.

Default priors

Can we always use $p(\theta) \propto 1$?

Suppose we use $\phi = \log(\theta/[1 - \theta])$, the log odds as our parameter, and set $p(\phi) \propto 1$, then the implied prior on θ is

$$\begin{aligned} p_{\theta}(\theta) &\propto 1 \left| \frac{d}{d\theta} \log(\theta/[1 - \theta]) \right| \\ &= \frac{1-\theta}{\theta} \left[\frac{1}{1-\theta} + \frac{\theta}{[1-\theta]^2} \right] \\ &= \frac{1-\theta}{\theta} \left[\frac{[1-\theta] + \theta}{[1-\theta]^2} \right] \\ &= \theta^{-1} [1 - \theta]^{-1} \end{aligned}$$

a $\text{Be}(0,0)$, if that were a proper distribution, and is different from setting $p(\theta) \propto 1$ which results in the $\text{Be}(1,1)$ prior.

Jeffreys prior

Definition

Jeffreys prior is a prior that is invariant to parameterization and is obtained via

$$p(\theta) \propto \sqrt{\det \mathcal{I}(\theta)}$$

where $\mathcal{I}(\theta)$ is the Fisher information.

For example, for a binomial distribution $\mathcal{I}(\theta) = \frac{n}{\theta[1-\theta]}$, so

$$p(\theta) \propto \theta^{-1/2}(1-\theta)^{-1/2} = \theta^{1/2-1}(1-\theta)^{1/2-1}$$

a $\text{Be}(1/2, 1/2)$ distribution.

Fisher information

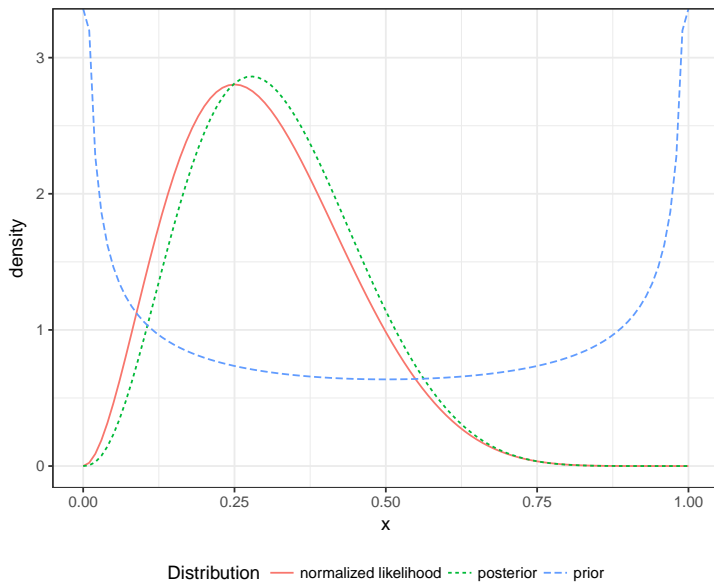
Theorem

The Fisher information for $Y \sim \text{Bin}(n, \theta)$ is $\mathcal{I}(\theta) = \frac{n}{\theta(1-\theta)}$.

Proof.

Since the binomial is an exponential family, we can use Lemma 7.3.11 of Casella and Berger (2nd ed).

$$\begin{aligned}
 \mathcal{I}(\theta) &= -E_{y|\theta} \left[\frac{\partial^2}{\partial \theta^2} \log p(y|\theta) \right] \\
 &= -E_{y|\theta} \left[\frac{\partial^2}{\partial \theta^2} \log \binom{n}{y} + y \log \theta + (n-y) \log(1-\theta) \right] \\
 &= -E_{y|\theta} \left[\frac{\partial}{\partial \theta} \frac{y}{\theta} - \frac{n-y}{1-\theta} \right] \\
 &= -E_{y|\theta} \left[-\frac{y}{\theta^2} - \frac{n-y}{(1-\theta)^2} \right] \\
 &= - \left[-\frac{n\theta}{\theta^2} - \frac{n-n\theta}{(1-\theta)^2} \right] = \frac{n}{\theta} + \frac{n}{(1-\theta)} \\
 &= \frac{n}{\theta(1-\theta)}
 \end{aligned}$$



Non-conjugate priors

If $Y \sim \text{Bin}(n, \theta)$ and $p(\theta) = e^\theta / (e - 1)$, then

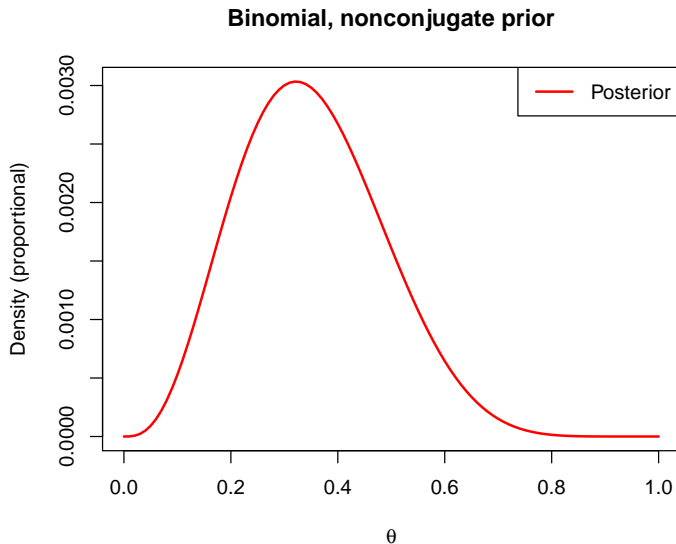
$$p(\theta|y) \propto f(\theta) = \theta^y (1 - \theta)^{n-y} e^\theta$$

which is not a known distribution.

Options

- Plot $f(\theta)$ (possibly multiplying by a constant).
- Find $i = \int f(\theta) d\theta$, so that $p(\theta|y) = f(\theta)/i$.
- Evaluate $f(\theta)$ on a grid and normalize by the grid spacing.

Plot of $f(\theta)$



Numerical integration

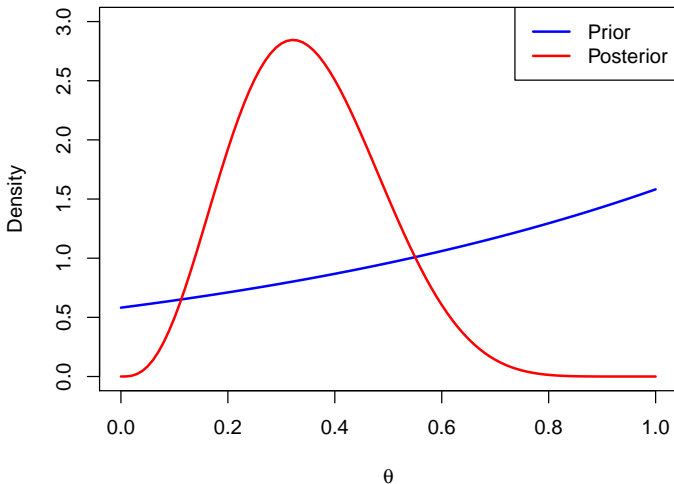
Find $i = \int f(\theta)d\theta$, so that $p(\theta|y) = f(\theta)/i$.

```
(i = integrate(f, 0, 1))
```

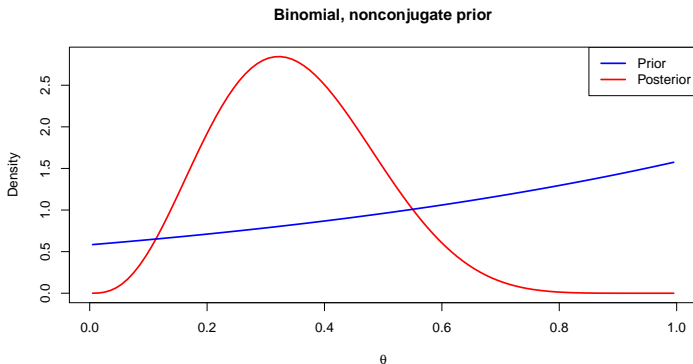
```
0.001066499 with absolute error < 1.2e-17
```

Nonconjugate prior, numerical integration

Binomial, nonconjugate prior



Nonconjugate prior, evaluated on a grid



```
theta[c(which(cumsum(d)*w>0.025)[1]-1, which(cumsum(d)*w>0.975)[1])] # 95% CI
```

```
[1] 0.105 0.625
```

Improper priors

Definition

An unnormalized density, $f(\theta)$, is **proper** if $\int f(\theta)d\theta = c < \infty$, and otherwise it is **improper**.

To create a normalized density from a proper unnormalized density, use

$$p(\theta|y) = \frac{f(\theta)}{c}$$

to see that $p(\theta|y)$ is a proper normalized density note that $c = \int f(\theta)d\theta$ is not a function of θ , then

$$\int p(\theta|y)d\theta = \int \frac{f(\theta)}{\int f(\theta)d\theta}d\theta = \int \frac{f(\theta)}{c}d\theta = \frac{1}{c} \int f(\theta)d\theta = \frac{c}{c} = 1$$

Be(0,0) prior

Recall that $\text{Be}(a, b)$ is a proper probability distribution if $a > 0, b > 0$.

Suppose $Y \sim \text{Bin}(n, \theta)$ and $p(\theta) \propto \theta^{-1}(1 - \theta)^{-1}$, i.e. the kernel of a $\text{Be}(0, 0)$ distribution. This is an improper distribution.

The posterior, $\theta|y \sim \text{Be}(y, n - y)$, is proper if $0 < y < n$.