



# Bayesian inference

Statistical Inference

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# Bayesian analysis

- Bayesian statistics posits a *prior* on the parameter of interest
- All inferences are then performed on the distribution of the parameter given the data, called the posterior
- In general,  $\text{Posterior} \propto \text{Likelihood} \times \text{Prior}$
- Therefore (as we saw in diagnostic testing) the likelihood is the factor by which our prior beliefs are updated to produce conclusions in the light of the data

# Prior specification

- The beta distribution is the default prior for parameters between 0 and 1.
- The beta density depends on two parameters  $\alpha$  and  $\beta$  
$$\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha - 1} (1 - p)^{\beta - 1} \text{ for } 0 \leq p \leq 1$$
- The mean of the beta density is  $\alpha / (\alpha + \beta)$
- The variance of the beta density is  $\frac{\alpha \beta}{(\alpha + \beta)^2 (\alpha + \beta + 1)}$
- The uniform density is the special case where  $\alpha = \beta = 1$

```
## Exploring the beta density
library(manipulate)
pvals <- seq(0.01, 0.99, length = 1000)
manipulate(
  plot(pvals, dbeta(pvals, alpha, beta), type = "l", lwd = 3, frame = FALSE),
  alpha = slider(0.01, 10, initial = 1, step = .5),
  beta = slider(0.01, 10, initial = 1, step = .5)
)
```

# Posterior

- Suppose that we chose values of  $\alpha$  and  $\beta$  so that the beta prior is indicative of our degree of belief regarding  $p$  in the absence of data
- Then using the rule that  $\text{Posterior} \propto \text{Likelihood} \times \text{Prior}$  and throwing out anything that doesn't depend on  $p$ , we have that 
$$\text{Posterior} \propto p^x (1 - p)^{n-x} \times p^{\alpha-1} (1 - p)^{\beta-1} \propto p^{x + \alpha - 1} (1 - p)^{n - x + \beta - 1}$$
- This density is just another beta density with parameters  $\tilde{\alpha} = x + \alpha$  and  $\tilde{\beta} = n - x + \beta$

# Posterior mean

$$\begin{aligned} E[p \sim X] &= \frac{\tilde{\alpha}}{\tilde{\alpha} + \tilde{\beta}} \quad \&= \frac{x + \alpha}{x + \alpha + n - x + \beta} \quad \&= \frac{x + \alpha}{n + \alpha + \beta} \quad \&= \frac{x}{n} \times \frac{n}{n + \alpha + \beta} + \frac{\alpha}{\alpha + \beta} \times \frac{\beta}{n + \alpha + \beta} \quad \&= \\ &\text{MLE} \times \pi + \text{Prior Mean} \times (1 - \pi) \end{aligned}$$

# Thoughts

- The posterior mean is a mixture of the MLE ( $\hat{p}$ ) and the prior mean
- $\lambda$  goes to 1 as  $n$  gets large; for large  $n$  the data swamps the prior
- For small  $n$ , the prior mean dominates
- Generalizes how science should ideally work; as data becomes increasingly available, prior beliefs should matter less and less
- With a prior that is degenerate at a value, no amount of data can overcome the prior

# Example

- Suppose that in a random sample of an at-risk population 13 of 20 subjects had hypertension. Estimate the prevalence of hypertension in this population.
- $x = 13$  and  $n=20$
- Consider a uniform prior,  $\alpha = \beta = 1$
- The posterior is proportional to (see formula above)  $p^x (1 - p)^{n - x}$  That is, for the uniform prior, the posterior is the likelihood
- Consider the instance where  $\alpha = \beta = 2$  (recall this prior is humped around the point .5) the posterior is  $p^{x + 1} (1 - p)^{n - x + 1}$
- The "Jeffrey's prior" which has some theoretical benefits puts  $\alpha = \beta = .5$



```

pvals <- seq(0.01, 0.99, length = 1000)
x <- 13; n <- 20
myPlot <- function(alpha, beta){
  plot(0 : 1, 0 : 1, type = "n", xlab = "p", ylab = "", frame = FALSE)
  lines(pvals, dbeta(pvals, alpha, beta) / max(dbeta(pvals, alpha, beta)),
        lwd = 3, col = "darkred")
  lines(pvals, dbinom(x,n,pvals) / dbinom(x,n,x/n), lwd = 3, col = "darkblue")
  lines(pvals, dbeta(pvals, alpha+x, beta+(n-x)) / max(dbeta(pvals, alpha+x, beta+(n-x))),
        lwd = 3, col = "darkgreen")
  title("red=prior,green=posterior,blue=likelihood")
}
manipulate(
  myPlot(alpha, beta),
  alpha = slider(0.01, 100, initial = 1, step = .5),
  beta = slider(0.01, 100, initial = 1, step = .5)
)

```

# Credible intervals

- A Bayesian credible interval is the Bayesian analog of a confidence interval
- A 95% credible interval,  $[a, b]$  would satisfy  $P(p \in [a, b] | x) = .95$
- The best credible intervals chop off the posterior with a horizontal line in the same way we did for likelihoods
- These are called highest posterior density (HPD) intervals

# Getting HPD intervals for this example

- Install the `binom` package, then the command

```
library(binom)
```

```
## Error: there is no package called 'binom'
```

```
binom.bayes(13, 20, type = "highest")
```

```
## Error: could not find function "binom.bayes"
```

gives the HPD interval.

- The default credible level is 95% and the default prior is the Jeffrey's prior.

```

pvals <- seq(0.01, 0.99, length = 1000)
x <- 13; n <- 20
myPlot2 <- function(alpha, beta, cl){
  plot(pvals, dbeta(pvals, alpha+x, beta+(n-x)), type = "l", lwd = 3,
    xlab = "p", ylab = "", frame = FALSE)
  out <- binom.bayes(x, n, type = "highest",
    prior.shape1 = alpha,
    prior.shape2 = beta,
    conf.level = cl)
  p1 <- out$lower; p2 <- out$upper
  lines(c(p1, p1, p2, p2), c(0, dbeta(c(p1, p2), alpha+x, beta+(n-x)), 0),
    type = "l", lwd = 3, col = "darkred")
}
manipulate(
  myPlot2(alpha, beta, cl),
  alpha = slider(0.01, 10, initial = 1, step = .5),
  beta = slider(0.01, 10, initial = 1, step = .5),
  cl = slider(0.01, 0.99, initial = 0.95, step = .01)
)

```