

VE414 Lecture 3

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- However, Bayes did not focus on point estimates because he argued a point estimate fail to fully incorporate and reflect what we can learn from the data.

Q: What would you have as \hat{p}_k and \tilde{p}_k if you had the following data

$$X_2 = 2; \quad X_{20} = 20; \quad x_{200} = 200$$

Q: What should you report instead of point estimates?

Definition

In Bayesian analysis, a **credible interval** is an interval within which an unobserved parameter/variable value falls with a particular probability. Let $F_{Y|X}$ be the CDF,

$$F_{Y|X}(y_u | x) > F_{Y|X}(y_l | x)$$

then the interval $\mathcal{I} = [y_l, y_u]$ is a credible interval with **coverage probability**

$$F_{Y|X}(y_u | X) - F_{Y|X}(y_l | X)$$

If exactly $(\alpha/2)100\%$ of the posterior probability lies above and below \mathcal{I} , then \mathcal{I} is known as the **central credible interval** with coverage probability of $1 - \alpha$.

```
> # Prior is taken to be beta(1,1), i.e. uniform
> # Prior Hyperparameters
> a.prior = 1; b.prior = 1

> # Inverse of cdf, aka quantile function
> qbeta(0.5, a.prior, b.prior)
```

```
[1] 0.5
```

```
> # Lower and upper limits
> l = qbeta(0.025, a.prior, b.prior)
> u = qbeta(0.975, a.prior, b.prior)

> # Print out the prior central credible interval
> cat(paste("(", l, sep = ""),
+     paste(u, ")", sep = ""), sep = ",")
```

```
(0.025,0.975)
```

```

> # Extreme case
> k.vec = c(2, 20, 200)    # Number of trials
> x.vec = c(2, 20, 200)    # Data
> n = length(k.vec)        # Number of cases

> for (i in 1:n){
+   # Posterior hyperparameters
+   a.posterior = a.prior + x.vec[i]
+   b.posterior = b.prior + (k.vec[i]-x.vec[i])
+
+   l = qbeta(0.025, a.posterior, b.posterior)
+   u = qbeta(0.975, a.posterior, b.posterior)
+   cat(paste("(", l, sep = ""),
+       paste(u, ")", sep = ""),
+       "\n", sep = ",")    # New line
+ }

```

```

(0.292401773821287,0.991596241340387)
(0.83890238478092,0.998795116551636)
(0.981814749945614,0.99987404868883)

```

```
> # Simulation study of posterior CCI
> set.seed(414)
> n = 5000
> k.vec = 1:n
> true.prob = 0.65

> # n Bernoulli trials
> x.vec = rbinom(n, size = 1, prob = true.prob)
> head(x.vec)
```

```
[1] 0 1 0 1 1 0
```

```
> # forming simulated the data
> x.vec = cumsum(x.vec)
> head(x.vec)
```

```
[1] 0 1 1 2 3 3
```

- Notice how the posterior central credible interval shrinks as k grows.

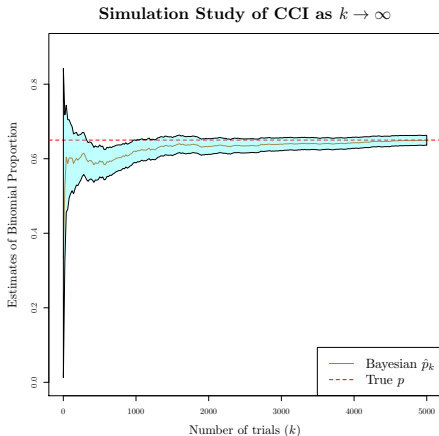


Figure: R Code: `central_credible_interval_binomial_beta.R`

```

> # Back to Bayes' data
> k.vec = 1:3
> x.vec = c(1, 2, 2)
> n = length(k.vec)           # Number of cases

> for (i in 1:n){
+   # Posterior hyperparameters
+   a.posterior = a.prior + x.vec[i]
+   b.posterior = b.prior + (k.vec[i]-x.vec[i])
+   l = qbeta(0.025, a.posterior, b.posterior)
+   u = qbeta(0.975, a.posterior, b.posterior)
+   cat(paste("(", l, sep = " "),
+       paste(u, ")", sep = " "),
+       "\n", sep = ",")      # New line
+ }

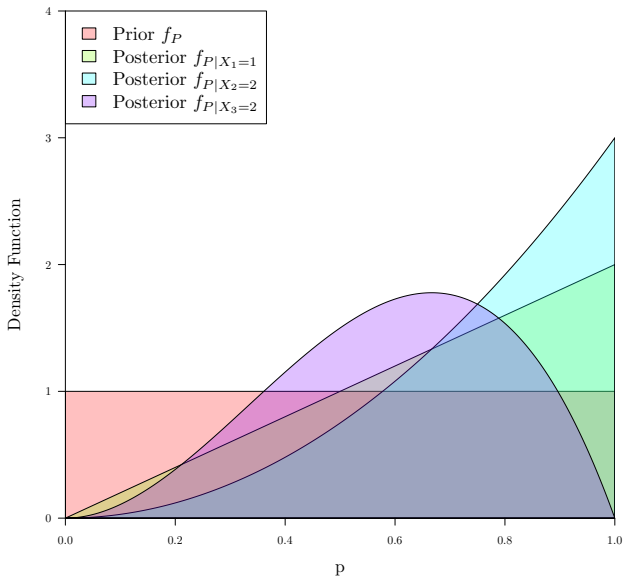
```

```

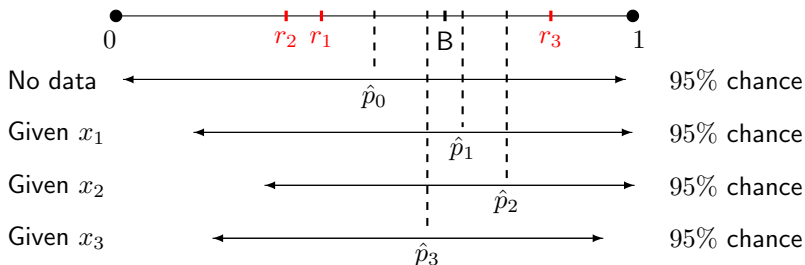
(0.158113883008419, 0.987420882906575)
(0.292401773821287, 0.991596241340387)
(0.194120449683243, 0.932414013511457)

```

Prior/Posterior Densities



- In the Bayes' study, 95% credible intervals have a 95% chance of correctly capturing the true p , thus the black ball, at various stage of the experiment.



- Notice those intervals are different from typical confidence intervals (CI).

Q: What is the difference? How can we compute a typical confidence interval?

- Recall confidence intervals for binomial proportion p rely on the central limit theorem, and it is unreliable for a small number of trials. Hence suppose the experiment continues, and we have 3000 trials instead of just 3 trials.

- According to the central limit theorem, the following random variable

$$Z = (\tilde{p}_k - p) / \sqrt{\frac{\tilde{p}_k (1 - \tilde{p}_k)}{k}}$$

follows a standard normal distribution as $k \rightarrow \infty$.

- Thus the following can be used as the $(1 - \alpha)100\%$ confidence interval of p .

$$\left(\tilde{p}_k - z_{\alpha/2} \sqrt{\frac{\tilde{p}_k (1 - \tilde{p}_k)}{k}}, \tilde{p}_k + z_{\alpha/2} \sqrt{\frac{\tilde{p}_k (1 - \tilde{p}_k)}{k}} \right)$$

where $\alpha \in (0, 1)$ and $z_{\alpha/2}$ is a real number such that $\Pr(Z \leq -z_{\alpha/2}) = \frac{\alpha}{2}$.

- To understand a 95% confidence interval,
 1. consider $2^{16} = 65536$ samples of size 3000
 2. compute the 95% confidence interval for each sample
 3. check whether the true p is inside each of the confidence intervals

- Roughly 95% of the 95% confidence intervals contain the true p for large n

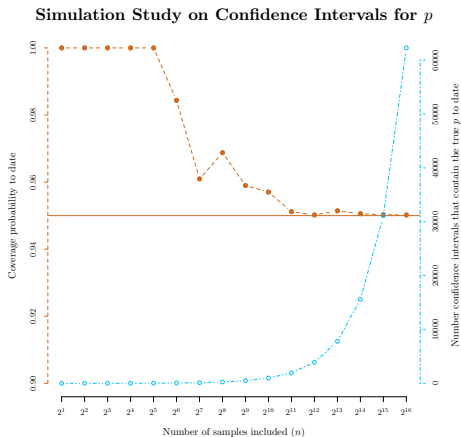


Figure: R Code: `bayes_ball_table_414.R`

- We can conduct something similar to a hypothesis test,

$$H_0 : p > 0.8$$

```
> a.prior = 1; b.prior = 1  
> pbeta(0.8, a.prior, b.prior)           # cdf
```

```
[1] 0.8
```

```
> k.vec = 1:3; x.vec = c(1, 2, 2); n = length(k.vec)  
> for (i in 1:n){  
+   # Posterior hyperparameters  
+   a.posterior = a.prior + x.vec[i]  
+   b.posterior = b.prior + (k.vec[i]-x.vec[i])  
+   cat(pbeta(0.8, a.posterior, b.posterior),  
+       ";\t", sep = "")  
+ }
```

```
0.64;    0.512;    0.8192;
```

Q: Is there any difference between Bayesian and Frequentist hypothesis testing?

- Recall p is considered to be a **nonrandom** parameter in the traditional sense, having an estimate of which allows us to predict X_k , for example, using MLE

$$\tilde{p}_3 = \frac{2}{3}$$

the following is sometime used to make point predictions

$$X_k^* \mid X_3 = 2 \sim \text{Binomial} \left(k, \frac{2}{3} \right)$$

since the exact sampling distribution of \tilde{p} is not available as usual.

Q: Do you see the Bayesian approach offers an easy and nature way around?

$$\begin{aligned} f_{X_k^* \mid X_3=2} (x_k^* \mid 2) &= \int_{-\infty}^{\infty} f_{\{X_k^*, P\} \mid X_3=2} (x_k^*, p \mid 2) dp \\ &= \int_{-\infty}^{\infty} f_{X_k^* \mid P} (x_k^* \mid p) f_{P \mid X_3=2} (p \mid 2) dp \end{aligned}$$

Definition

In Bayesian analysis, given a prior of some parameter Y

$$f_Y(y)$$

and a likelihood of some observed data $X = x$,

$$\mathcal{L}(y; x) = f_{X|Y}(x | y)$$

the **posterior predictive distribution** of a future observation, X^* , is given by

$$\begin{aligned} f_{X^*|X}(x^* | x) &= \int_{-\infty}^{\infty} f_{\{X^*, Y\}|X}(x^*, y | x) dy \\ &= \int_{-\infty}^{\infty} f_{X^*|\{Y, X\}}(x^* | y, x) f_{Y|X}(y | x) dy \\ &= \int_{-\infty}^{\infty} f_{X^*|Y}(x^* | y) f_{Y|X}(y | x) dy \end{aligned}$$

Similarly, the **prior predictive distribution** $f_{X^*}(x^*) = \int_{-\infty}^{\infty} f_{X^*|Y}(x^* | y) f_Y(y) dy$

Q: In terms of Bayes' original problem, given $X_3 = 2$, the binomial likelihood and the uniform prior, what is the posterior predictive distribution for X_3^* ?

$$\begin{aligned}
 f_{X_k^*|X_3=2} &= \int_0^1 f_{X_k^*|P} \cdot f_{P|X_3=2} dp \\
 &= \int_0^1 \frac{k^*!}{x_k^*!(k^* - x_k^*)!} p^{x_k^*} (1-p)^{k^* - x_k^*} \quad \text{where } k^* = 3 \\
 &\quad \frac{\Gamma(\alpha^* + \beta^*)}{\Gamma(\alpha^*) \Gamma(\beta^*)} p^{\alpha^* - 1} (1-p)^{\beta^* - 1} dp \quad \text{and } \alpha^* = 3; \beta^* = 2 \\
 &= \frac{k^*!}{x_k^*!(k^* - x_k^*)!} \cdot \frac{\Gamma(\alpha^* + \beta^*)}{\Gamma(\alpha^*) \Gamma(\beta^*)} \int_0^1 p^{x_k^* + \alpha^* - 1} (1-p)^{k^* - x_k^* + \beta^* - 1} dp \\
 &= \frac{k^*!}{x_k^*!(k^* - x_k^*)!} \cdot \frac{\Gamma(\alpha^* + \beta^*)}{\Gamma(\alpha^*) \Gamma(\beta^*)} \cdot \frac{\Gamma(x_k^* + \alpha^*) \Gamma(k^* - x_k^* + \beta^*)}{\Gamma(k^* + \alpha^* + \beta^*)}
 \end{aligned}$$

- This distribution of X_k^* is known as the **Beta-Binomial** distribution.