

$$X_1, \dots, X_n | \theta, \sigma^2 \sim N(\theta, \sigma^2)$$

$$\theta \sim N(\mu_0, \tau^2)$$

$$\sigma^2 \sim \text{Inverse}(\frac{\nu_0}{2}, \frac{\nu_0 s_0^2}{2})$$

$$\Rightarrow P(\theta, \sigma^2 | x) = N(\theta_p, \sigma_p^2) K(\sigma^2 | x)$$

difficult to deal with !!

same thing, easy though

Gauss, Gauss, Gauss?

## Recall

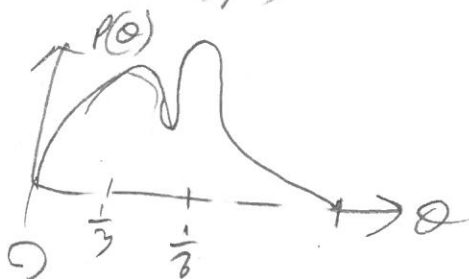
$$X | \theta \sim \text{Bin}(n, \theta)$$

$$\theta \sim \text{Beta}(\alpha, \beta)$$

$$\theta | x \sim \text{Beta}(x + \alpha, n - x + \beta)$$

Beta is the conjugate prior for the binomial likelihood.

But... what if  $H_0$  has no  $\text{Beta}(\alpha, \beta)$  which captured your prior belief? e.g.



There is no beta that could do this!!! why?

Can we use this prior? Sure... numerically. How?  $P(\theta | x) \propto P(x | \theta) P(\theta) = k(\theta | x)$

$\theta_{\min} = 0, \theta_{\max} = 1$ , set  $\Delta\theta$ ... the resolution. Assume you have interval from  $\theta$ .

Sample... use  $G = \langle \theta_{\min}, \theta_{\min} + \Delta\theta, \theta_{\min} + 2\Delta\theta, \dots, \theta_{\max} \rangle$

① Calculate  $k(\theta | x) = P(x | \theta) P(\theta) \quad \forall \theta \in G$

② Compute  $C \approx \frac{1}{\sum_{\theta \in G} k(\theta | x)}$

③ Return  $P(\theta | x) \approx C k(\theta | x)$

$\hat{\theta}_{\text{mp}} \approx \arg\max_{\theta} k(\theta | x), \quad \hat{\theta}_{\text{mmse}} \approx \frac{\sum_{\theta \in G} \theta P(\theta | x)}{\sum_{\theta \in G} P(\theta | x)}$

suffers from  
same  
drawbacks

Can we still use conjugacy? Yes...

Imagine  $P(\theta)$  as a mixture / compound distribution with conjugate components.

e.g.

$$P(\theta) = \frac{1}{2} \text{Beta}(3, 3) + \frac{1}{2} \text{Beta}(2, 4)$$

$$E(\theta) = \frac{1}{2}$$

$$E(\theta) = \frac{1}{2}$$

this produces something close to our intended prior.

Is  $P(\theta)$  "conjugate"? No... but close. Consider

$$P(\theta) = \sum_{m=1}^M \gamma_m P_m(\theta)$$

where  $\gamma_1 + \gamma_2 + \dots + \gamma_M = 1$  and  $P_m(\theta) \sim \text{Beta}(\alpha_m, \beta_m)$  i.e. all components

In the case where  $M=2$ ,  $\gamma_1 = \frac{1}{2}$ ,  $\gamma_2 = \frac{1}{2}$ ,  $\alpha_1 = 1, \beta_1 = 3$ ,  $\alpha_2 = 2, \beta_2 = 4$

we have two different parameters.

$$X|\theta \sim \text{Bin}(L, \theta)$$

$$P(\theta) = \sum \gamma_m P_m(\theta)$$

$\theta|X \sim ?$  let's see...

$$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)} = \frac{P(X|\theta) \sum \gamma_m P_m(\theta)}{P(X)} = \sum_{m=1}^M \gamma_m \frac{P(X|\theta) P_m(\theta)}{P(X)}$$

$$\frac{P(\theta|X)}{\sum_{m=1}^M \gamma_m \frac{P(X|\theta) P_m(\theta)}{P(X)}} = \frac{\gamma_m \text{Beta}(\alpha_m, \beta_m)}{P_m(X)}$$

Posterior has the same form! Thus, it's conjugate.

Recall

$$p(x) = \int p(x|\theta) p(\theta) d\theta = \int p(x|\theta) \sum_{m=1}^M \gamma_m p_m(\theta) d\theta = \sum_{m=1}^M \gamma_m \int p(x|\theta) p_m(\theta) d\theta$$

If  $\gamma_m = \frac{1}{M}$  for equal mixing,  $p_m(x) = \sum_{m=1}^M \gamma_m p_m(x)$

Let's do an example.

Let  $p(\theta) = \frac{1}{2} \text{Beta}(3,3) + \frac{1}{2} \text{Beta}(2,4)$  as before

$n=10, x=$

$p_m(x) = \text{BetaBinom}(n, \alpha_m, \beta_m)$   
prior pred. distr!

$p(\theta|x) = \frac{1}{p(x)} \sum_{m=1}^M \gamma_m p_m(x) p_m(\theta|x) = \frac{1}{\sum_{m=1}^M p_m(x)} \sum_{m=1}^M p_m(x) p_m(\theta|x)$

$= \frac{1}{p_1(.5) p_2(.5)} \left( p_1(.5) p_1(\theta|x=.5) + p_2(.5) p_2(\theta|x=.5) \right)$

$= \frac{1}{\text{dbb}(5,10,3,3) + \text{dbb}(5,10,2,4)} \left( \text{dbb}(5,10,3,3) \text{dbb}(\theta, 7,10) + \text{dbb}(5,10,2,4) \text{dbb}(\theta, 6,9) \right)$   
distribution  $(x,n,\alpha,\beta) \rightarrow$  calc value abbr. dbb

How to plot  $p(\theta|x)$ . Pick  $\Delta\theta$ ; calc above. graph  $\forall \theta \in \mathcal{G}$ . Plot.

OR -

- 1) Sample  $\theta_1$  from  $\text{Beta}(7,10)$  (use `rbeta(7,10)`)
- 2) Sample  $\theta_2$  from  $\text{Beta}(6,9)$  (use `rbeta(6,9)`)
- 3) Keep  $\theta_0 = \gamma_1 \theta_1 + \gamma_2 \theta_2$
- 4) repeat 1-3 many times, plot histogram.

$\frac{1}{0.112 + 0.147}$   
 $= .43 \text{dbb}(\theta)$   
 $+ .57 \text{dbb}(\theta)$

Point Estimator

$$\hat{\theta}_{MLE} = E[\theta|x] = \int \theta \sum \gamma'_m P_m(\theta|x) d\theta$$

(1)

$$= \sum \gamma'_m \int \theta P_m(\theta|x) d\theta$$

$$= \sum \gamma'_m E_m[\theta|x]$$

$$= \sum \gamma'_m \frac{\gamma_m}{\alpha'_m + \beta'_m}$$

In our example

$$\hat{\theta}_{MLE} = .43 \frac{7}{17} + .57 \frac{6}{15} = .405$$

$\hat{\theta}_{MAP} = ?$  No closed form. Algorithm?

use code

$$\theta_{min} = 0, \theta_{max} = 1, \Delta\theta = ?$$

$$\theta_0 = 0, F = 0$$

repeat {

$$\theta_0 = \theta_0 + \Delta\theta$$

$$F = F + P(\theta_0|x) \Delta\theta$$

if  $F \geq 0.5$  then  $\theta_0$

}



Same algorithm to get CR's.

Look for e.g.  $F \geq 0.025, F \geq 0.975$

How to get  $\hat{\theta}_{MAP}$

$$\hat{\theta}_{MAP} := \underset{\theta}{\operatorname{argmax}} \{ p(\theta|x) \} = \underset{\theta}{\operatorname{argmax}} \{ k\theta(x) \}$$

$$p(\theta|x) \propto \sum_{m=1}^M \gamma_m p_m(x) p(\theta|x) = k\theta(x) \propto \sum_{m=1}^M p_m(x) p_m(\theta|x) \quad \text{if } \gamma_m = \frac{1}{M} \gamma_m$$

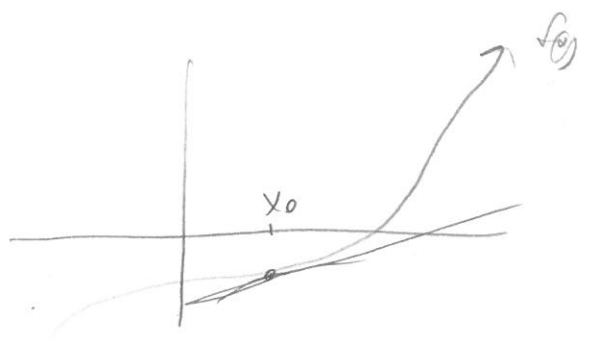
$\uparrow$   $\uparrow$   
 Bernoulli Bernoulli

$$\frac{d}{d\theta} \left[ \sum \binom{n}{x} \frac{\beta(x+\alpha_m, n-x+\beta_m)}{\beta(\alpha_m, \beta_m)} \right] \left( \frac{1}{\beta(x+\alpha_m, n-x+\beta_m)} \theta^{x+\alpha_m-1} (1-\theta)^{n-x+\beta_m-1} \right)$$

$$= \sum_{m=1}^M \frac{d}{d\theta} \left[ \frac{\theta^{x+\alpha_m-1} (1-\theta)^{n-x+\beta_m-1}}{\beta(\alpha_m, \beta_m)} \right] = \sum_{m=1}^M \frac{1}{\beta(\alpha_m, \beta_m)} \left( (x+\alpha_m-1) \theta^{x+\alpha_m-2} (1-\theta)^{n-x+\beta_m-1} - (n-x+\beta_m-1) \theta^{x+\alpha_m-1} (1-\theta)^{n-x+\beta_m-2} \right) = 0$$

$\Rightarrow$  No closed form solution

Global problem. Find the zero  $f(x)=0$  if  $f$  is continuous and has no zero.



Step 1: guess  $x_0$  to be the root

Step 2: draw tangent line to  $f(x_0)$

Step 3: find the x-intercept of line and call it  $x_1$

Step 4: repeat steps 1-3 until

$$|x_{t+1} - x_t| < \epsilon, \text{ a pre-specified accuracy level (AKA tolerance)}$$

Step 2:  $y - b = m(x - a)$

$$y - f(x_0) = f'(x_0) (x - x_0)$$

Step 3. To find  $x$ -intercept, solve for  $x = x_1, y = 0$

$$-f(x_0) = f'(x_0) (x_1 - x_0) \Rightarrow x_1 - x_0 = -\frac{f(x_0)}{f'(x_0)} \Rightarrow x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$$

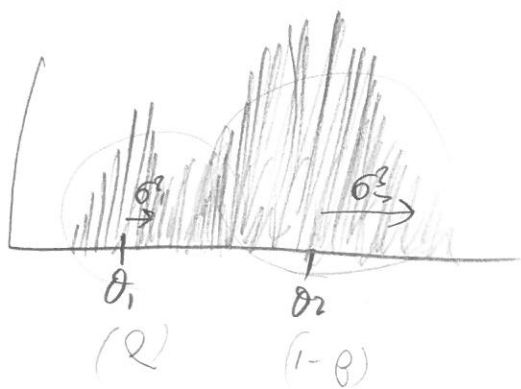
Step 4: 
$$x_{t+1} = x_t - \frac{f(x_t)}{f'(x_t)}$$

We just did the case where the prior was a mixture but the likelihood was a single bernoulli. Now, imagine the prior as single but the likelihood is a mixture!

e.g.  $M=2: \delta_1 = p, \delta_2 = 1-p$

$$X_1, \dots, X_n | \dots \sim \sum_{m=1}^M \delta_m N(\theta_m, \sigma_m^2)$$

$$X_1, \dots, X_n | \theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p \sim p N(\theta_1, \sigma_1^2) + (1-p) N(\theta_2, \sigma_2^2)$$



$$P(\theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p | X_1, \dots, X_n) \propto P(X_1, \dots, X_n | \theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p) P(\theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p)$$