

$$H_0: \theta = \theta_0, H_1: \theta \neq \theta_0$$

Two ideas

(a)  $\alpha = 5\%$ , declare  $\hat{\theta} = 1.01$ , the margin of evidence, the margin that you assume is a fair coin. makes sense since there is a <sup>extra</sup> ~~little~~ <sup>weight</sup> on heads or tails.

$$H_0: \theta \in [\theta_0 \pm \hat{\theta}] \Rightarrow \theta \in [0.99, 0.51] \quad \text{New def of fair}$$

$$H_1: \theta \notin [\theta_0 \pm \hat{\theta}] \Rightarrow \theta \in [0, 0.99) \cup (0.51, 1]$$

$$p_{\text{val}} = P(H_0 | \alpha) = F_{\theta | \alpha}(.51) - F_{\theta | \alpha}(.99) = p_{\text{beta}}(.51, .99, .50) - p_{\text{beta}}(.99, .99, .50) = 0.06 \Rightarrow \text{Fail to reject } H_0 \Rightarrow$$

not enough evidence coin is unfair

Downside: need  $\hat{\theta}$ ! Subjective!

(b) If  $\theta_0 \in CR_{1-\alpha} \Rightarrow \text{Retain } H_0 \text{ else Reject } H_0$

This is highly correct. Downside: No  $p$ -val!

$$CR_{1-\alpha} = [q_{\text{beta}}(.025, .99, .50), q_{\text{beta}}(.975, .99, .50)] = [.337, .520]$$

$$\theta_0 = 0.5$$

$$\theta_0 \in CR_{1-\alpha} \Rightarrow \text{FTR } H_0$$

There is another way of comparing models called Bayes Factors. We will do after midterm. Now I want to move towards prediction, another goal of statistics besides for inference.

See  $X_1, \dots, X_n$  but there will be a new  $X^{n+1}$  realization

You don't know what it is... but you want to know its distr.  
 Let  $X \sim \text{Binomial}$ . Let  $x^*$  have length  $n^* = 1$ . Prediction for 1 future obs.  
 $P(X^* | x)$ . Frequentist... what can you do?

$X^* \sim \text{Bin}(\hat{\theta}_{MLE})$ . Good idea! But can fail badly if  $\hat{\theta}_{MLE} = 0$  or 1  
 Another problem:  
 what if  $n^* > 1$

$X^* \sim \text{Bin}(n^*, \hat{\theta}_{MLE})$  correct? No... wrongness in  $\hat{\theta}_{MLE}$   
 not taking into account  
 we will do this right now  
 we do the  $n^* > 1$  case.

Bayesian approach: posterior predictive distr.

$$P(X^* | x) = \int P(X^*, \theta | x) d\theta = \int P(X^* | \theta, x) P(\theta | x) d\theta = \int P(X^* | \theta) P(\theta | x) d\theta$$

if  $P(\theta | x)$  discrete

$$= \sum_{\theta \in \Theta} P(X^* | \theta) P(\theta | x)$$

This integral is an average of  $P(X^* | \theta)$  weighted by the different probabilities of  $\theta | x$ .  
 Posterior: anything known about  $\theta$  after data is seen

$$\Theta = \{0.5, 0.75\}$$

$$X = (0, 1, 1)$$

$$P(\theta = 0.75 | x) = 0.53, \quad P(\theta = 0.5 | x) = 0.47$$

$$X^* \sim ?$$

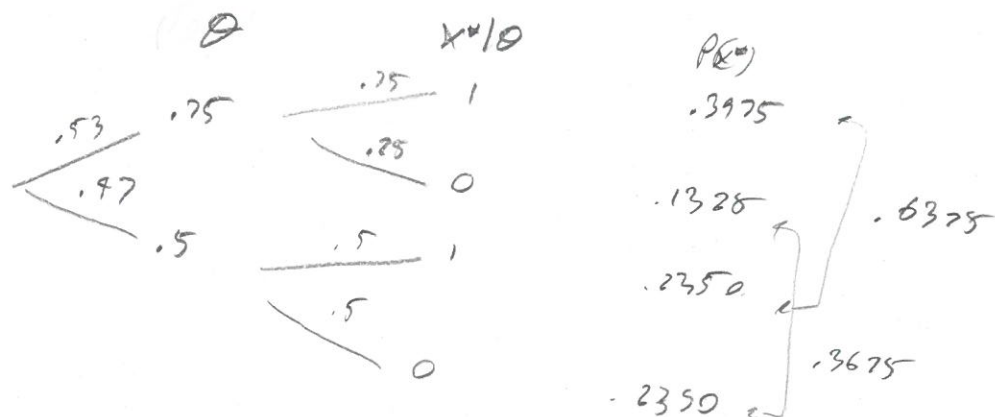
$$P(X^* | x) = P(X^* | \theta = 0.75) P(\theta = 0.75 | x) + P(X^* | \theta = 0.5) P(\theta = 0.5 | x)$$

$$= (0.5)^{x^*} (0.25)^{1-x^*} (0.53) + (0.5)^{x^*} (1-0.5)^{1-x^*} (0.47)$$

that's the answer... we can simplify it by plugging in 1.0  
 we know  $\text{supp}(x^*|x) = \{0, 1\}$   
 $\Rightarrow$  If  $x^* = 1$

$$P(x^*=1|x) = 0.75 \cdot 0.53 + 0.5 \cdot 0.97 = .6325$$

$$\Rightarrow P(x^*|x) = \text{Bern}(.6325)$$



Generally...  $P(\theta) = \text{Beta}(\alpha, \beta)$ ,  $\tilde{T}$  = Binomial from  $n$ , length of  $x^*$  is  $n^*=1$ ,  
 predicting for one obs.

$$\begin{aligned}
 P(x^*|x) &= \int P(x^*|\theta) P(\theta|\alpha) d\theta = \int_0^1 \theta^{x^*} (1-\theta)^{1-x^*} \frac{1}{B(x+\alpha, n-x+\beta)} \theta^{x+\alpha-1} (1-\theta)^{n-x+\beta-1} d\theta \\
 &= \frac{1}{B(x+\alpha, n-x+\beta)} \int_0^1 \theta^{(x^*+x+\alpha)-1} (1-\theta)^{(n-x+\beta-x^*+1)-1} d\theta = \frac{B(x^*+x+\alpha, n-x+\beta-x^*+1)}{B(x+\alpha, n-x+\beta)}
 \end{aligned}$$

that's the answer... but we can simplify...

$$\text{we know } \text{supp}(x^*|x) = \{0, 1\}$$

LA

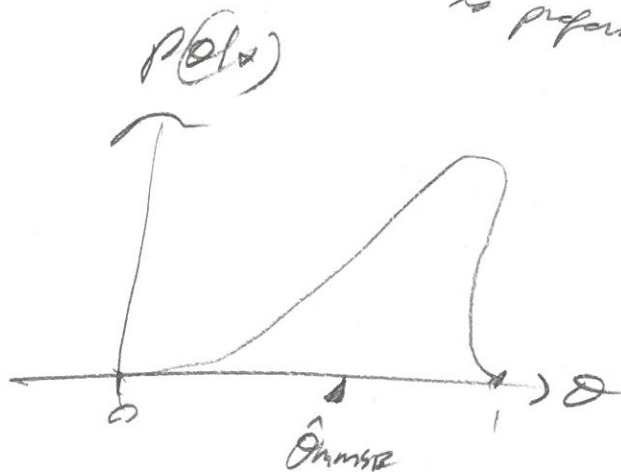
If  $x^* = 1 \dots$

$$P(x^* = 1 | x) = \frac{B(x + \alpha + 1, n - x + \beta)}{B(x + \alpha, n - x + \beta)} = \frac{\frac{\Gamma(x + \alpha + 1) \Gamma(n - x + \beta)}{\Gamma(n + \alpha + \beta + 1)}}{\frac{\Gamma(x + \alpha) \Gamma(n - x + \beta)}{\Gamma(n + \alpha + \beta)}}$$

$$= \frac{\frac{(x + \alpha) \Gamma(x + \alpha) \Gamma(n - x + \beta)}{(n + \alpha + \beta) \Gamma(n + \alpha + \beta)}}{\frac{\Gamma(x + \alpha) \Gamma(n - x + \beta)}{\Gamma(n + \alpha + \beta)}}$$

$$= \frac{x + \alpha}{n + \alpha + \beta} = \hat{\theta}_{MSE} \dots \text{quicker version why this estimate is preferred}$$

$$\Rightarrow P(x^* | x) = \text{Bern}\left(\frac{x + \alpha}{n + \alpha + \beta}\right)$$



Best guess of  $\theta$  for next obs.

Modem I  
Modem II

What if  $n^* > 1$  See  $n = 7$  data pts and new data for  $n^* = 5$  new observations

Would it be  $x^* \sim \text{Bin}(n^*, \frac{x + \alpha}{n + \alpha + \beta})$ ? No...