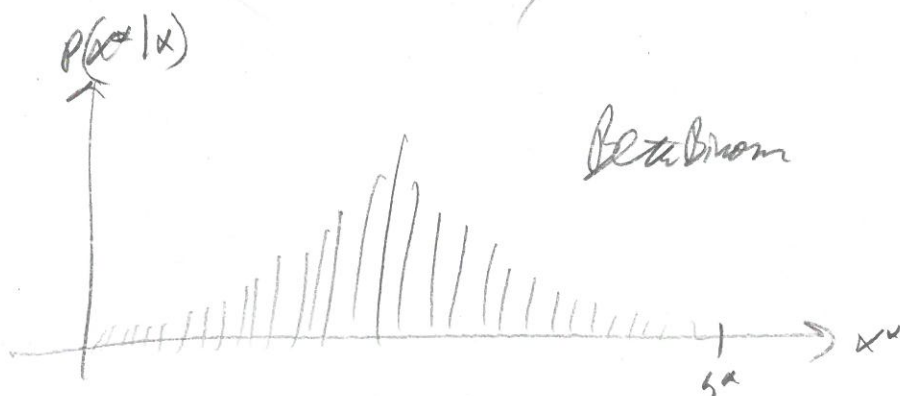


If you average over all  $\theta$ 's



See 19 Aug  
 Out of  $n=25$   
 What is the prob. of  
 the last 10 flips  
 of  $B$  HT?  $p(\theta) = U(0,1)$

$$p(x^*|x) \propto \text{Beta Bin}(10, 20, B)$$

$$=$$

$$p(x^*=6|x) = d_{\text{beta bin}}(6, 10, 20, B)$$

$$= .17$$

Prob of 6 or less HT?

$$P(x^* \leq 6|x) = p_{\text{beta bin}}(6, 10, 20, B)$$

$$= .33$$

## Improper Priors

$$p(\theta) = \text{Beta}(\alpha, \beta), \quad p(x|\theta) = \text{Bin}(n, \theta) \Rightarrow p(\theta|x) = \text{Beta}(x+\alpha, n-x+\beta)$$

$n_0 = \alpha + \beta$  # pseudosamples. If  $p(\theta) = U(0,1) \Rightarrow n_0 = 2$ . What if we want prior so have no weight at all?

$p(\theta) = \text{Beta}(0,0)$  but this is not a true beta dist!  $\alpha \neq 0, \beta \neq 0$   
 $\Rightarrow$  "Improper Prior", "Haldane prior" (1932)

Complete ignorance  $\pi_0 = 0$ . Unknown if success / failure is even possible. (2)

However,  $p(\theta|x) = \text{Beta}(x, n-x)$  which is proper if  $x > 0$   
and  $x < n$ .

$$\hat{\theta}_{\text{muse}} = \frac{x}{n} = \hat{\theta}_{\text{MLE}}$$

Informative?

This is okay to use as long as posterior is proper.

### Informative priors.

Imagine you are trying to infer a baseball player's true batting ability,  $\theta$ , the prob(hit). Assume  $F = \text{binomial}$   
 $\Rightarrow$  all at bats independent, prob(hit) should be unknown.

$$\hat{\theta}_{\text{MLE}} = \frac{x}{n}$$

# Hits                      # At Bats

$\hat{\theta}_{\text{MLE}}$  performs poorly at inferring  $\theta$  if  $n$  is small.

$n=3, x=2$      $\hat{\theta}_{\text{MLE}} = .667$     Is that possible ??? No!

=  $\hat{\theta}_{\text{muse}}$  under ignorance

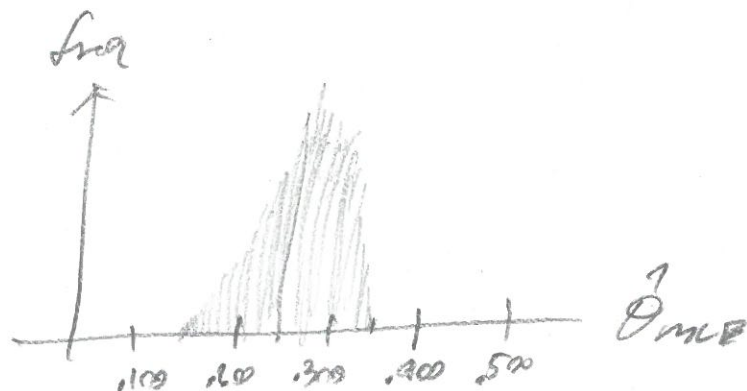
Ref: Ty Cobb  
.366

If we use Bayesian estimator with  $p(\theta) = U(0,1) \Rightarrow \hat{\theta}_{\text{muse}} = 0.6$  ~~not better~~

Solution? Shrink towards previous data!! All time avg  
batting avg is  $\approx .260$ ,                      informativeness and high

Let's design a prior with high shrinkage  $\Rightarrow \alpha, \beta$  large.

Method: look at previous data. Subset where each player has  $n \geq 500$  at bats. Plot all  $\hat{\theta}_{MLE}$ 's:



Now... fit a beta distr. to it. How? Calc.  $\hat{\alpha}_{MLE}$ ,  $\hat{\beta}_{MLE}$ .

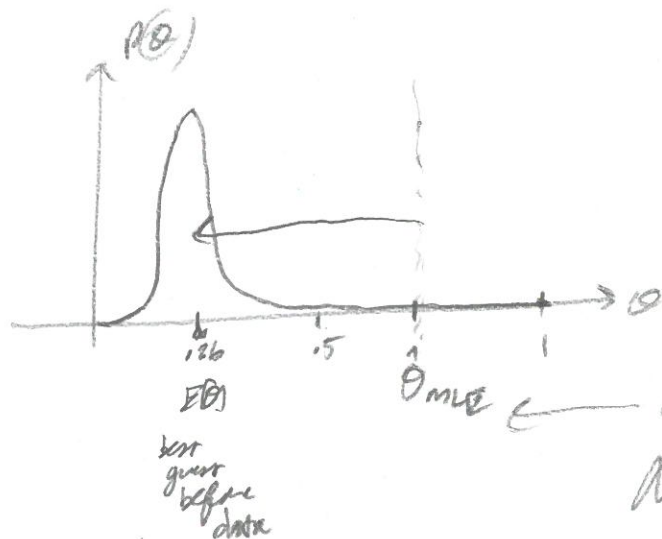
$$\Rightarrow P(\theta) = \text{Beta}(78.7, 227.8) \Rightarrow E[\theta] = 0.26 \Rightarrow n_0 = 303.5$$

empirical  
bays!

For  $n=3$  at bats  $R = \frac{303.5}{303.5+3} = 99\%$

$$\hat{\theta}_{muse} = (1\%)(.667) + (99\%)(.26) = 0.263$$

Why is this smart?



do you really believe it??

No... it is an artifact of randomness in small datasets. Shrink it back.

Is it possible this guy bats .667? Yes... but the ~~threshold~~ <sup>threshold</sup> is we need a lot of data to prove it.

Even with a strong prior. If  $n$  is large  $\Rightarrow p \rightarrow 0$  and since is  $\approx$  our estimate.

3 topics in prob.

$$\text{Odds}(A) := \text{Odds}(A, A^c)$$

$$\text{e.g. } P(A) = 0.2$$

$$:= \frac{P(A)}{P(A^c)} = \frac{P(A)}{1-P(A)} = \frac{0.2}{0.8} = \frac{1}{4} = 1:4 \quad \leftarrow \text{usually like}$$

$$\text{Odds Against } (A) = \text{Odds}(A)^{-1} = 4:1$$

$$P(A) \in [0, 1] \text{ but...}$$

$$\text{Odds}(A) \in [0, \infty)$$

$$\text{Odds}(A, B) = \frac{P(A)}{P(B)} \quad \text{prob. ratio of two events,} \quad \text{Imagine you want to compare two O's:}$$

$$P(\theta = \theta_1 | x) = \frac{P(x | \theta = \theta_1) P(\theta = \theta_1)}{P(x)}$$

$$P(\theta = \theta_0 | x) = \frac{P(x | \theta = \theta_0) P(\theta = \theta_0)}{P(x)}$$

$$\Rightarrow \frac{P(\theta = \theta_1 | x)}{P(\theta = \theta_0 | x)} = \frac{P(x | \theta = \theta_1) P(\theta = \theta_1)}{P(x | \theta = \theta_0) P(\theta = \theta_0)}$$

posterior odds

prior odds

$$\Rightarrow \text{Odds}(\theta_1, \theta_0 | x) = \frac{P(x | \theta = \theta_1)}{P(x | \theta = \theta_0)} \text{Odds}(\theta_1, \theta_0)$$

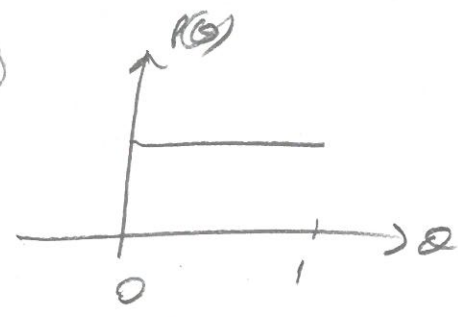
$$\Rightarrow \frac{\text{Odds}(\theta_1, \theta_0 | x)}{\text{Odds}(\theta_1, \theta_0)} = \frac{P(x | \theta = \theta_1)}{P(x | \theta = \theta_0)}$$

$$\text{Odds}(\theta_1, \theta_0) \xrightarrow{x} \text{Odds}(\theta_1, \theta_0 | x)$$

$$1:1$$

$$5:1$$

$F = \text{Bernoulli}$   $P(\theta) = U(\theta, 1) = \text{Beta}(1, 1)$



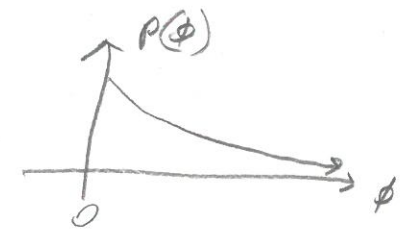
principle of indifference

But is it indifferent on the odds scale? Let  $\phi(\theta) = \frac{\theta}{1-\theta} \in [0, \infty)$

$P(\theta) = U(\theta, 1) \Rightarrow P(\phi(\theta)) = U(\phi, \infty)$ ? No since  $U(\phi, \infty)$  doesn't make sense!!

$\Rightarrow$  the principle of indifference has a big problem!

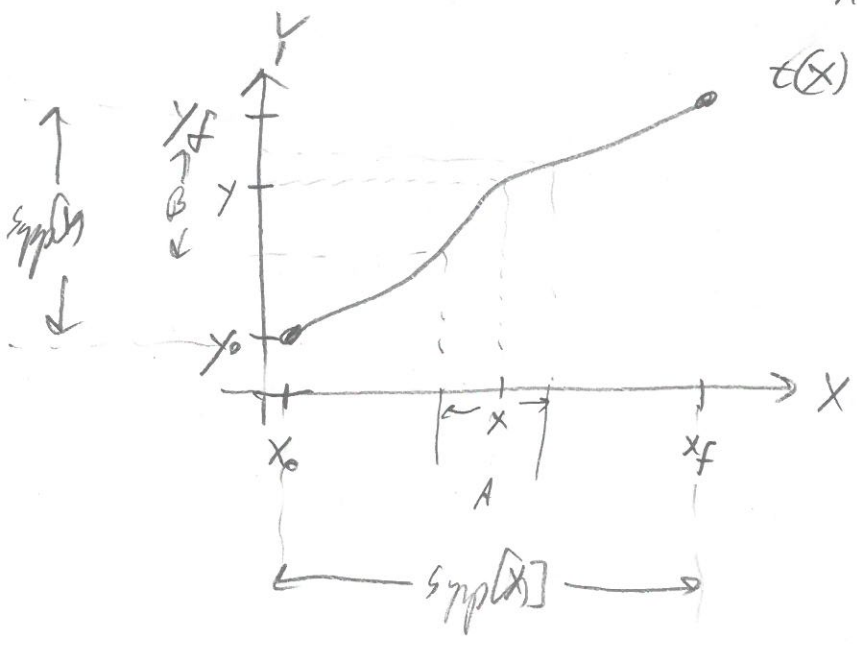
To see the problem clearly we need  $P(\phi)$ .



Math 621 (not covered here).

Imagine <sup>cont.</sup> r.v.'s  $X, Y$  with densities  $f_X, f_Y$ .  $f_X$  known

Let  $Y = t(X)$  where  $t$  is <sup>known</sup> an invertible function. Find  $f_Y$ .



$$P(X \in A) = P(Y \in B)$$

If  $A, B$  small...

$$P(X \in A) \approx f_X(x) |dx|$$

$$P(Y \in B) \approx f_Y(y) |dy|$$

$$\Rightarrow f_Y(y) = f_X(x) \left| \frac{dx}{dy} \right|$$

$$y = t(x) \Rightarrow x = t^{-1}(y)$$

$$\Rightarrow f_Y(y) = f_X(t^{-1}(y)) \left| \frac{d}{dy} [t^{-1}(y)] \right|$$