

# 341 Lec10

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## Birth ratios

- 6115 mothers, each has  $\geq 13$  children, but only consider the first 12 children. Count the number of boys for each mother.

| # of Boys | 0 | 1  | 2   | 3   | 4   | 5    | 6    | 7    | 8   | 9   | 10  | 11 | 12 | total |
|-----------|---|----|-----|-----|-----|------|------|------|-----|-----|-----|----|----|-------|
| x         | 3 | 24 | 104 | 206 | 670 | 1033 | 1343 | 1112 | 829 | 478 | 181 | 45 | 7  | 6115  |
| Binom     | 1 | 12 | 72  | 259 | 628 | 1085 | 1367 | 1266 | 854 | 410 | 152 | 26 | 2  | 6115  |
| BetaBin   | 2 | 23 | 105 | 311 | 656 | 1036 | 1258 | 1182 | 854 | 462 | 178 | 44 | 5  | 6115  |

## Binomial

- Modeling this data ( $\mathcal{F}$ ) is beyond the course. If the mother has a baby, what is the probability it will have a boy?  $X \sim \text{Binomial}(12, 50\%)$  does not accurately capture the data.  $\mathbb{P}(\text{boy}) \approx 51\%$ .

## Beta Binomial

- Solving alpha and beta through maximum likelihood:

$$n = 12, \alpha_{MLE} = 34, \beta_{MLE} = 32 \rightarrow X \sim \text{BetaBinomial}(12, 34, 32), \mathbb{E}[X] = 12 \frac{34}{34 + 32} = 0.511 = 51\%$$

- The BetaBinomial fits better.
- $\mathbb{P}(\theta) = \text{Beta}(34, 32), \text{Quantile}[\theta, 0.5\%] = 36\%, \text{Quantile}[\theta, 99.5\%] = 67\%$

## Generalized:

- After seeing  $n$  bernoulli trials, what is the *next future*  $n_*$  trials not seen?
- Consider:  $\mathbb{P}(x_* | X = x) \stackrel{?}{=} \text{Binomial}(n_*, \hat{\theta}_{MLE})$  It is reasonable to use MLE but the problem is that  $\hat{\theta}_{MLE}$  is not  $\theta$
- With  $\gg 0, \theta$  is approximately normally distributed.
- For small  $n$  we need Bayesian statistics

## Posterior predictive distribution

- $\mathbb{P}(X_* | x) = \int_{\Theta} \mathbb{P}(X_*, \theta | x) d\theta = \int_{\Theta} \mathbb{P}(X_* | \theta, x) \mathbb{P}(\theta | x) d\theta \rightarrow \int_{\Theta} \mathbb{P}(X_*) \mathbb{P}(\theta | x) d\theta$  (a mixture/compound distribution)

- For  $\mathcal{F} : \text{Bin}(n, \theta) : \int \underbrace{\mathbb{P}(X_* | \theta)}_{\text{Bin}(n, \theta)} \underbrace{\mathbb{P}(\theta | x)}_{\text{prior } \mathbb{P}(\theta) \text{ beta}} d\theta = \text{BetaBinomial}(n_*, \alpha + x, \beta + n - x)$

- $\mathbb{P}(\theta) \xrightarrow{x} \mathbb{P}(\theta | x)$  and  $\mathbb{P}(x_*) \xrightarrow{x} \mathbb{P}(X_* | x)$

## Example:

- $n = 10$  at bats for a new baseball player and  $x = 6$  hits assuming each at bat is  $\overset{iid}{\sim}$  Bernoulli( $\theta$ ) what is the probability he will have  $x_* = 17$  hits in the next  $n_* = 32$  at bats? Assume uniform prior.

$$\mathbb{P}(X_*|x) = \text{BetaBinomial}(32, 7, 5), \mathbb{P}(X_* = 17|x = 6) = \frac{\binom{32}{17}}{\beta(7,5)}\beta(24, 20) = \text{dbetabinom}(17, 32, 7, 5)$$

## Probability 17 or less hits on the next 32 at bats?

- $\mathbb{P}(X_* < 17|x = 6) = \sum_{y=0}^{17} \frac{\binom{32}{y}}{\beta(7,5)}\beta y + 7, 32 - y + 5 = \text{pbetabinom}(17, 32, 7, 5)$

## Probability theory

- Let  $X, Y$  be continuous rv's where  $f_x, f_X$  are known and  $y = t(X)$  where  $t$  is a known invertible function. Derive  $f_Y$  using  $f_X$  and  $t$
- $\mathbb{P}(x \in A) = \mathbb{P}(y \in B)$
- If  $A, B$  small  $\mathbb{P}(x \in A) \approx f_x(x)|dx|, \mathbb{P}(y \in B) \approx f_y(y)|dy| \Rightarrow f_x(x)|dx| \approx f_y(y)|dy| \Rightarrow f_y(y) = f_x(x) \left| \frac{dx}{dy} \right|$

$$= f_y(y) \overset{y=t(x), x=t^{-1}(y)}{=} f_x(t^{-1}(y)) \left| \frac{d}{dy}[t^{-1}(y)] \right|$$