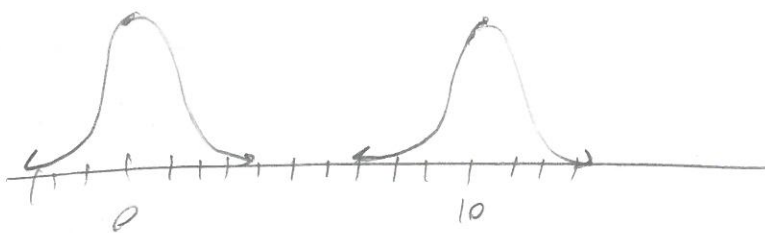


Mixture Dists

$$X \sim \begin{cases} N(0,1) & \text{w.p. } \frac{1}{2} \\ N(10,1) & \text{w.p. } \frac{1}{2} \end{cases}$$

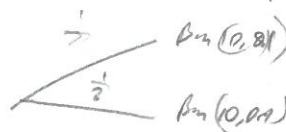


What is the PPF of X ?

$$\begin{aligned} P(X) &= \sum_{\theta \in \{0,10\}} P(X|\theta) P(\theta) = \frac{1}{2} N(0,1) + \frac{1}{2} N(10,1) \\ &= \frac{1}{2} \frac{1}{\sqrt{2\pi}} \left(e^{-\frac{1}{2}(X-0)^2} + e^{-\frac{1}{2}(X-10)^2} \right) \end{aligned}$$

this is called a "mixture dist"

Imagine $X_1 \sim \text{Bin}(10, 0.1)$, $X_2 \sim \text{Bin}(10, 0.9)$ where each w.p. $\frac{1}{2}$



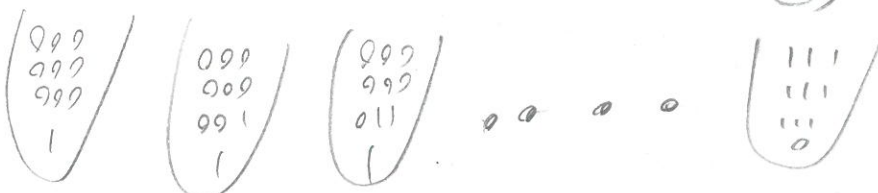
$$P(X) = \sum_{\theta \in \{0.1, 0.9\}} P(X|\theta) P(\theta) = \frac{1}{2} \binom{10}{x} \left(0.1^x 0.9^{10-x} + 0.9^x 0.1^{10-x} \right)$$

Imagine... $\text{Bin}(n, \theta)$



Hierarchical Model

$\text{Bin}(n, \theta)$ but...
 $\theta \sim U(0,1)$



Now let's go back to $X|O \sim \text{Bern}(y, \theta)$, $O \sim \text{Beta}(1,1) = U(0,1) \dots$
and look at the marginal again:

2

$$p(x) = \int_0^1 p(x|\theta) p(\theta) d\theta$$

$$= \int_0^1 \binom{n}{x} \theta^x (1-\theta)^{n-x} (1) d\theta$$

$$= \binom{n}{x} \frac{1}{n-x+1}$$

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

$$p(x) = \int_0^1 p(x|\theta) p(\theta) d\theta = \int_0^1 \binom{n}{x} \theta^x (1-\theta)^{n-x} \frac{1}{B(\alpha, \beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1} d\theta$$

$$= \binom{n}{x} \frac{1}{B(\alpha, \beta)} \int_0^1 \theta^{x+\alpha-1} (1-\theta)^{n-x+\beta-1} d\theta = \binom{n}{x} \frac{B(x+\alpha, n-x+\beta)}{B(\alpha, \beta)}$$

$$X \sim \text{Beta-Bin}(n, \alpha, \beta) := \binom{n}{x} \frac{B(x+\alpha, n-x+\beta)}{B(\alpha, \beta)}$$

"Overdispersed"
Binomial

$\text{supp}(X) = \{0, \dots, n\}$ wr?
Parameter $n \in \mathbb{N}$, $\alpha, \beta > 0$ wr?

hard after the
hierarchy / mixture

$$E(X) = n \frac{\alpha}{\alpha+\beta}, \text{Var}(X) = \frac{n\alpha\beta(\alpha+\beta+1)}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

if $\frac{\alpha}{\alpha+\beta} = \theta \Rightarrow E(X) = n\theta$

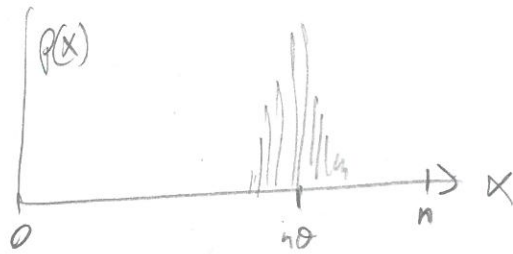
$$\Rightarrow \frac{\alpha}{\alpha+\beta} = \theta \Rightarrow 1 + \frac{\beta}{\alpha} \cdot \frac{1}{\theta} \Rightarrow \frac{\beta}{\alpha} = \frac{1}{\theta} - 1 \Rightarrow \beta = \frac{\alpha}{\theta} - \alpha$$

Now let $\alpha \rightarrow \infty$

$$\lim_{\alpha \rightarrow \infty} E(X) = \lim_{\alpha \rightarrow \infty} n \underbrace{\left(\frac{\alpha}{\alpha+\beta} \right)}_{\theta} \underbrace{\left(\frac{\beta}{\alpha+\beta} \right)}_{(1-\theta)} = \frac{\frac{\alpha}{\theta} - \alpha}{\frac{\alpha}{\theta} + 1} = \frac{\frac{\alpha}{\theta} + 1}{\frac{\alpha}{\theta} + 1} = \frac{\alpha + \theta}{\alpha + \theta} = 1$$

In the limit of $\alpha \rightarrow \infty$, this is a binomial ... why should this be?

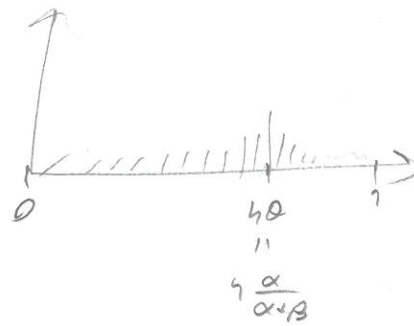
Bin (n, θ)



$E(X) = n\theta$
 $Var(X) = n\theta(1-\theta)$

if n fixed, var fixed

Let $Bin(n, \alpha, \beta)$, $\theta := \frac{\alpha}{\alpha+\beta}$



$E(X) = n\theta$
 $Var(X) = n\theta(1-\theta) \frac{\alpha+\beta+1}{\alpha+\beta}$

if α, β small $Var(X) \uparrow$
 if α, β big $Var(X) \rightarrow Var(Binomial)$

overdispersion
 (flexibility)

you can control the spread

if α, β large $Bin(\alpha, \beta) \rightarrow \text{Log}(\frac{\alpha}{\alpha+\beta})$

$= \text{Log}(\theta)$
 i.e. are prob
 i.e. a binomial

$P(13|6) = 0.511 \neq 0.5$
 why? No one knows

Is this useful?

Gender birth data, 6115 families with ≥ 13 children, genders of first 12 children...

# Boys	0	1	2	3	4	5	6	7	8	9	10	11	12
X	3	24	104	285	670	1033	1243	1112	829	470	181	95	7
$Bin(12, 0.511)$	1	12	72	259	628	1045	1367	1266	854	410	132	26	2
$betaBin(12, 34, 32)$	2	23	195	311	656	1036	1258	1182	854	462	170	44	5

$\frac{34}{34+32} = .515$

via MLE

Does it all fit in this (example)

Meaning?

Women have different preferences for their babies?

Recall the Bayesian arg
 $X|\theta \sim \text{Bin}(n, \theta)$
 $\theta \sim \text{Beta}(\alpha, \beta)$
 $\Rightarrow \theta|X \sim \text{Beta}(\alpha+X, \beta+n-X)$

~~$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)}$~~

Now, what if we are $X^*|X$ where X^* is k th obs.
 we have shown that

$X^*|X \sim \text{Beta}\left(\frac{X+\alpha}{n+\alpha+\beta}\right)$

But what if X^* is n^* th obs? $X^*|X \sim ?$

if θ known... $X^*|\theta \sim \text{Bin}(n^*, \theta)$ but θ unknown...
 but we have idea on θ represented by $\theta|X$, the posterior...

$P(X^*|X) = \int P(X^*|\theta) P(\theta|X) d\theta$ mixture distr!!

$= \int \binom{n^*}{x^*} \theta^{x^*} (1-\theta)^{n^*-x^*} \frac{1}{B(\alpha+X, \beta+n-X)} \theta^{\alpha+X-1} (1-\theta)^{\beta+n-X-1} d\theta$

same thing as before!!!

$= \text{BetaBin}\left(n^*, \underbrace{\alpha+X}_{\alpha'}, \underbrace{\beta+n-X}_{\beta'}\right) = \binom{n^*}{x^*} \frac{B(\alpha'+x^*, \beta'+n^*-x^*)}{B(\alpha', \beta')}$
 $= \binom{n^*}{x^*} \frac{B(\alpha'+x^*, \beta'+n^*-x^*)}{B(\alpha', \beta')}$

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

$\Rightarrow P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)}$

→ prior predictive distr.

$X \sim ?$ $P(X) = \int P(X|\theta) P(\theta) d\theta$ same thing!!!

$= \int \binom{n}{x} \theta^x (1-\theta)^{n-x} \frac{1}{B(\alpha, \beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1} d\theta = \text{BetaBin}(n, \alpha, \beta)$