

Hierarchical and mixture models

Introduction (see Section 4.4 of Casella & Berger)

Key idea: joint distributions specified by thinking hierarchically (or conditionally)

$$f(x, y) = f_X(x)f(y|x)$$

Motivations:

1. a model building technique

(e.g. number of questions answered correctly is Binomial(n, p) but p varies from respondent to respondent)

$$\left\{ \begin{array}{l} X|Y \text{ has some dist.} \\ Y \text{ has a dist.} \end{array} \right. \Rightarrow \text{What is the dist. of } X ?$$

2. Bayesian statistics

$$f(\theta|x) = \frac{f(\theta, x)}{f_X(x)} = \frac{f(x|\theta)f(\theta)}{\int f(x|\theta)f(\theta)d\theta}$$

3. Mixed discrete-continuous models

(e.g., can take X discrete and $Y|X$ continuous)

Our approach to this topic: consider some examples

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Examples

Example 1: pdf $f(x, y) = 1/x$, $0 < y < x < 1$.

We've seen $X \sim \text{uniform}(0, 1)$ and that, given $X = x \in (0, 1)$, $Y|X=x \sim \text{uniform}(0, x)$.

$$f_X(x) = 1 \quad \checkmark \quad 0 < x < 1, \quad f(y|x) = \frac{1}{x} \quad \checkmark \quad 0 < y < x \\ f_{(x,y)} = f(x)f(y|x) = \begin{cases} \frac{1}{x} & 0 < x < 1, 0 < y < x \\ 0 & \text{otherwise} \end{cases}$$

Example 2: Beta-Binomial model

- $X = \# \text{ of male children in } n\text{-child family}$ $x = 0, 1, 2, \dots, n$
 $n-x \geq 0$
 - $P = \text{probability of male child for a random woman}$
 - Consider $X|P=p \sim \text{Binomial}(n, p)$
 - Consider $P \sim \text{Beta}(\alpha, \beta)$
 - Marginal distribution of X
- $\rightarrow X|P = P \sim \text{Bin}(n, p)$
 $P \sim \text{Beta}(\alpha, \beta)$
 $\Rightarrow \text{What is the dist. of } X?$

Recall:

$$\begin{aligned} P(A) &= \sum_{i=1}^n P(A \cap B_i) \\ &= \sum_{i=1}^n P(A|B_i)P(B_i) \\ &\quad \text{Diagram: A large oval labeled } B \text{ containing several smaller overlapping ovals labeled } B_1, B_2, \dots, B_n. } \\ P(X=x) &= E[P(X=x|P)] \\ &= \int_0^1 P(X=x|P=p)f_P(p)dp \\ &= \int_0^1 \binom{n}{x} p^x (1-p)^{n-x} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha, \beta)} dp \\ &= \binom{n}{x} \frac{1}{B(\alpha, \beta)} \int_0^1 p^{x+\alpha-1} (1-p)^{n+\beta-x-1} dp \\ &= \binom{n}{x} \frac{B(x+\alpha, n+\beta-x)}{B(\alpha, \beta)} \\ &\quad \text{Diagram: A large oval labeled } P \text{ containing several smaller overlapping ovals labeled } B_1, B_2, \dots, B_n. } \\ \bullet \text{ Expected value of } X &= E(X) = E(E(X|P)) = \mathbb{E}(nP) = nE(P) = \frac{n\alpha}{\alpha+\beta} \quad \uparrow P(X=x) \end{aligned}$$

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Examples (cont'd)

Example 3: Poisson-binomial hierarchical model

- Consider $Y|N \sim \text{Binomial}(N, p)$

- Consider $N \sim \text{Poisson}(\lambda)$

- Marginal mean of Y

$$E(Y) = E(E(Y|N)) = E(Np) = pE(N) = \lambda p$$

- Marginal distribution of Y

$$P(Y = y) = \sum_{n=0}^{\infty} P(Y = y, N = n)$$

$$P(Y = y | N = n) = 0$$

$y > n$
 $n > y$

$$\frac{n-y}{n} := z$$

$$\begin{aligned}
 P(Y = y) &= \sum_{n=0}^{\infty} P(Y = y | N = n) P(N = n) \\
 &= \sum_{n=y}^{\infty} P(Y = y | N = n) P(N = n) \\
 &= \sum_{n=y}^{\infty} \binom{n}{y} p^y (1-p)^{n-y} \frac{e^{-\lambda} \lambda^n}{n!} \\
 &= \frac{p^y e^{-\lambda}}{y!} \sum_{n=y}^{\infty} (1-p)^{n-y} \frac{\lambda^n}{(n-y)!} \\
 &\quad \frac{p^y e^{-\lambda}}{y!} \sum_{z=0}^{\infty} (1-p)^z \frac{\lambda^{z+y}}{z!} \\
 &= \frac{(\lambda p)^y e^{-\lambda}}{y!} \sum_{z=0}^{\infty} \frac{[(1-p)\lambda]^z}{z!} \\
 &= \frac{(\lambda p)^y e^{-\lambda}}{y!} e^{(1-p)\lambda} \\
 &= \frac{e^{-\lambda} \lambda^y}{y!} (\lambda p)^y
 \end{aligned}$$

Recall: $e^x = \sum_{n=0}^{\infty} \frac{x^n}{n!}$

$$\begin{aligned}
 &e^{\lambda(1-p)} \frac{(\lambda p)^y e^{-\lambda}}{y!} \sum_{z=0}^{\infty} \frac{[(1-p)\lambda]^z}{z!} = 1 \\
 &= \frac{e^{\lambda(1-p)}}{y!} \frac{(\lambda p)^y e^{-\lambda}}{y!} = \frac{e^{-\lambda} \lambda^y (\lambda p)^y}{y!}
 \end{aligned}$$

$$\Rightarrow Y \sim \text{Poisson}(\lambda p)$$

$$E(Y) = \lambda p$$

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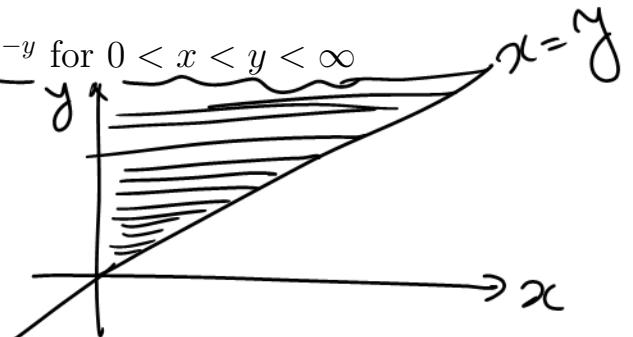
Examples (cont'd)

Example 4: continuous X, Y with pdf $f(x, y) = e^{-y}$ for $0 < x < y < \infty$

Where does such a distribution come from?

View 1:

- marginal: $\underline{f_X(x) = e^{-x}}$ for $0 < x < \infty$
- conditional: $\underline{f(y|x) = e^{-(y-x)}}$ for $x \leq y < \infty$
- X is Exponential(1)
- $Y|X = x$ is a location shifted exponential or $(Y - x)|X = x$ is Exponential(1)
- draw an Exponential(1) r.v. to determine X and then, given $X = x$, obtain Y by adding x to another Exponential(1) r.v.



$$f(y|x) = \frac{f(x,y)}{f(x)}$$

$$\Rightarrow f(y|x) = \frac{e^{-y}}{e^{-x}} = e^{-(y-x)}$$

View 2:

- marginal $f_Y(y) = ye^{-y}$ for $0 < y < \infty$
- conditional: $\underline{f(x|y) = y^{-1}}$ for $0 < x \leq y$
- Y is Gamma(2, 1)
- $X|Y = y$ is Uniform(0, y)
- given $Y = y$, pick X randomly on $(0, y)$

$$f(x|y) = \frac{f(x,y)}{f(y)}$$