

## Lecture 20

$$Y \sim \text{Pois}(\lambda)$$

$$X | Y=y \sim \text{Bin}(y, p)$$

note:  $X \leq Y$

What is the dist of  $X$ ?

$$f(x) = \sum_y \overbrace{f(x|y)}^{\text{Bin}(y,p)} \overbrace{f(y)}^{\text{Pois}(\lambda)}$$

$$= \sum_{y=x}^{\infty} \left( \frac{y}{x} \right) p^x (1-p)^{y-x} \frac{\lambda^y e^{-\lambda}}{y!}$$

$$= \frac{p^x e^{-\lambda}}{x!} \sum_{y=x}^{\infty} \frac{1}{(y-x)!} (1-p)^{y-x} \lambda^{y-x} \frac{y!}{x!(y-x)!} \frac{1}{y!}$$

$$= \frac{\lambda^x p^x e^{-\lambda}}{x!} \sum_{y=0}^{\infty} \frac{1}{y!} [\lambda(1-p)]^y$$

$e^z = \sum_{i=0}^{\infty} \frac{z^i}{i!}$

$$= \frac{\lambda^x p^x e^{-\lambda}}{x!} e^{\lambda(1-p)}$$

$\text{Bin}(n, p)$

PDF:

$$\binom{n}{x} p^x (1-p)^{n-x}$$

$$= \frac{(p\lambda)^x e^{-p\lambda}}{x!} = f(x)$$

$\uparrow$  Pois( $p\lambda$ )

$X \sim \text{Pois}(p\lambda)$

Theorem: Iterated Expectation

If  $X$  and  $Y$  are RVs then

$$E[X] = E\left[E[X|Y]\right] \quad \begin{array}{l} \text{a RV} \\ \text{(a fn of } Y\text{)} \end{array}$$

Proof:  $E[X|Y=y] = \int_{\mathbb{R}} x f(x|y) dx$

= a number

For each  $y \in \mathbb{R}$  I get a different  
corresp val.

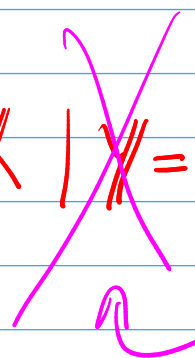
$$g(y) = E[X|Y=y] \quad \text{a number}$$

e.g.  $g(y) = y^2$  or  $g(y) = y+1$

Can plug  $Y$  into  $g$

e.s.  $g(Y) = Y^2$  or  $g(Y) = Y + 1$

$$g(Y) = E[X | Y = Y]$$

 weird notation

tend to use notation

$$g(Y) = E[X | Y]$$

e.s.  $E[X | Y] = Y^2 \leftarrow$  a RV.

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Ex. Prev.  $Y \sim \text{Pois}(\lambda)$

$$X | Y = y \sim \text{Bin}(y, p)$$

what is  $E[X]$ ?

$$\textcircled{1} E[X | Y = y] = yp$$

$$\textcircled{2} E[X|Y] = Yp$$

$$\textcircled{3} E[X] = E[E[X|Y]]$$

$$= E[Yp]$$

$$= p E[Y] = p\lambda.$$

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Ex.  $P \sim \text{Beta}(\alpha, \beta)$

$$X|P=p \sim \text{Bin}(n, p)$$

$$E[X]?$$

$$\textcircled{1} E[X|P=p] = np$$

$$\textcircled{2} E[X|P] = nP$$

$$\textcircled{3} E[X] = E[E[X|P]]$$

$$= E[nP]$$

$$= n E[P] = n \frac{\alpha}{\alpha + \beta}.$$

pf of theorem (cts)

$$\textcircled{1} \quad f(x) = \int_{\mathbb{R}} f(x, y) dy$$

$$\textcircled{2} \quad f(x|y) = \frac{f(x, y)}{f(y)} \Leftrightarrow f(x, y) = f(x|y) f(y)$$

$$\textcircled{3} \quad g(y) = E[X|Y=y] = \int_{\mathbb{R}} x f(x|y) dx$$

$$E[X] = \int_{\mathbb{R}} x f(x) dx$$

$$= \int_{\mathbb{R}} x \underbrace{\int_{\mathbb{R}} f(x, y) dy}_{\textcircled{1}} dx$$

$$= \int_{\mathbb{R}} x \underbrace{\int_{\mathbb{R}} f(x|y) f(y) dy}_{\textcircled{2}} dx$$

$$= \int_{\mathbb{R}} \underbrace{\int_{\mathbb{R}} x f(x|y) dx}_{g(y)} f(y) dy$$

$$= \int_{\mathbb{R}} g(y) f(y) dy$$

$$= E[g(Y)]$$

$$= E[E(X|Y)]$$

defn

Theorem: Law of total Variance

$$\text{Var}(X) = E[\underbrace{\text{Var}(X|Y)}] + \text{Var}(\underbrace{E[X|Y]})$$

similar defn

Ex.  $P \sim \text{Beta}(\alpha, \beta)$

$$X|P=p \sim \text{Bin}(n, p)$$

$$\text{Var}(X)?$$

$$\textcircled{1} \quad E[X|P=p] = np$$

$$\text{Var}(X|P=p) = np(1-p)$$

$$\textcircled{2} \quad E[X|P] = nP$$

$$\text{Var}(X|P) = nP(1-P)$$

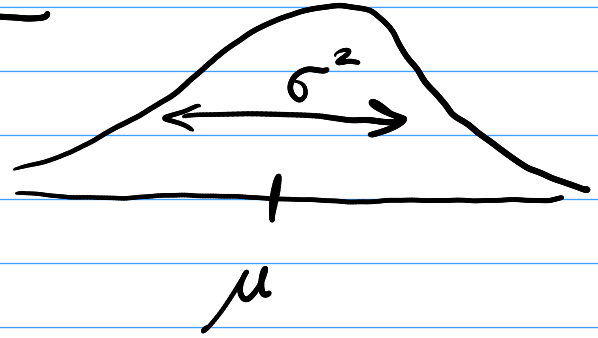
$$\textcircled{3} \quad \begin{aligned} \text{Var}(X) &= E[\text{Var}(X|P)] + \text{Var}(E[X|P]) \\ &= E[nP(1-P)] + \text{Var}(nP) \\ &= n(E[P] - E[P^2]) + n^2 \text{Var}(P) \\ &\quad \hookrightarrow \text{Var}(P) + E[P]^2 \end{aligned}$$

$$= \dots$$

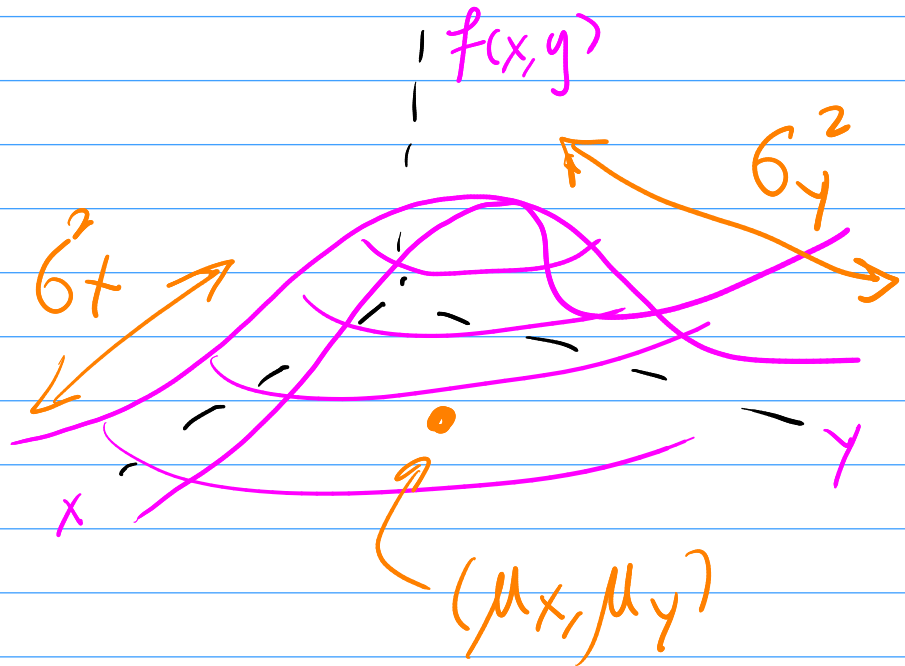
$$= n \frac{\alpha\beta}{(\alpha+\beta)(\alpha+\beta+1)} + n^2 \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

# Bivariate Normal

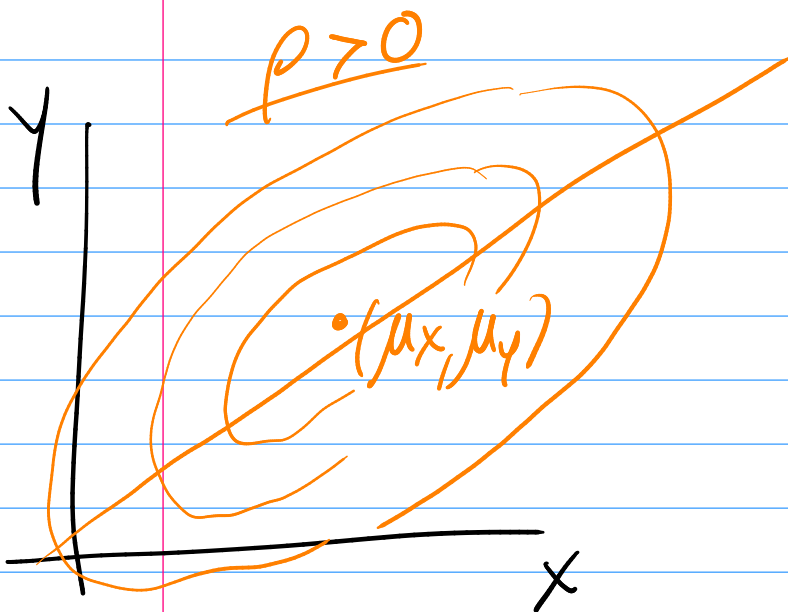
Uni:  $N(\mu, \sigma^2)$



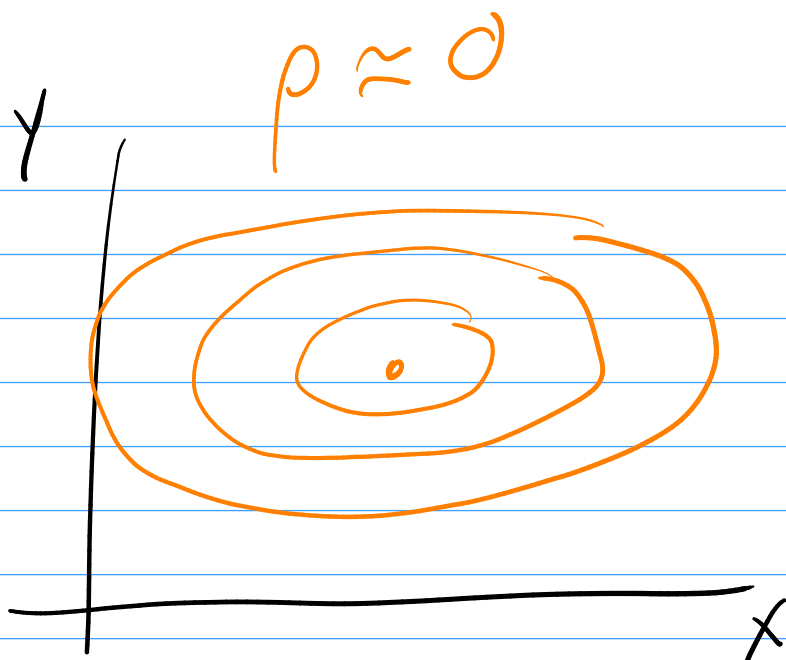
Bivariate:



need : correlation  $\rho$







Density:

$$f(x, y) = \frac{1}{2\pi \sigma_x \sigma_y \sqrt{1-\rho^2}}$$

$$\exp \left\{ -\frac{1}{2\sqrt{1-\rho^2}} \left[ \left( \frac{x-\mu_x}{\sigma_x} \right)^2 + \left( \frac{y-\mu_y}{\sigma_y} \right)^2 - 2\rho \left( \frac{x-\mu_x}{\sigma_x} \right) \left( \frac{y-\mu_y}{\sigma_y} \right) \right] \right\}$$

alt.  $\mu = (\mu_x, \mu_y)$  mean vector

$$\Sigma = \begin{bmatrix} \sigma_x^2 & \sigma_x \sigma_y \rho \\ \sigma_x \sigma_y \rho & \sigma_y^2 \end{bmatrix} = \begin{bmatrix} \text{Var}(X) & \text{Cov}(X, Y) \\ \text{Cov}(Y, X) & \text{Var}(Y) \end{bmatrix}$$

Covariance matrix

$$z = (x, y)$$

$$f(z) = \frac{1}{2\pi} \frac{1}{\sqrt{\det \Sigma}} \exp \left( -\frac{1}{2} (z - \mu)^T \Sigma^{-1} (z - \mu) \right)$$

a number

1x2   2x2   2x1

uni:

$$f(x) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{\sigma^2}} \exp \left( -\frac{1}{2} (x - \mu) (\sigma^2)^{-1} (x - \mu) \right)$$

## Properties

$$\textcircled{1} \quad X \sim N(\mu_x, \sigma_x^2)$$

$$Y \sim N(\mu_y, \sigma_y^2)$$

$$\textcircled{2} \quad \text{Cor}(X, Y) = \rho$$

$$\textcircled{3} \quad aX + bY$$

$$\sim N(\underline{a\mu_x + b\mu_y}, \underline{a^2\sigma_x^2 + b^2\sigma_y^2 + 2ab\sigma_x\sigma_y\rho})$$

$$\textcircled{4} \quad (X, Y) \sim \text{BivN} \Leftrightarrow \forall a, b \quad aX + bY \sim N$$

⑤ Prev: If  $X \perp Y$  then  $\text{Cor}(X, Y) = 0$

If  $(X, Y) \sim \text{Biv } N$  and  $\rho = 0$

then  $X \perp Y$ .

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