

DIY

$$f(y_1, y_2) = \frac{1}{\sqrt{2\pi}\sigma_1} \exp\left(-\frac{(y_1 - \mu_1)^2}{2\sigma_1^2}\right) \times \frac{1}{\sqrt{2\pi}\sigma_2} \exp\left(-\frac{(y_2 - \mu_2)^2}{2\sigma_2^2}\right)$$

$$= f(y_1) \times f(y_2)$$

Marginal

$$\begin{bmatrix} Y_1 \sim N(\mu_1, \sigma_1^2) \\ Y_2 \sim N(\mu_2, \sigma_2^2) \end{bmatrix}$$

$$\cdot \underline{Y} \sim N(\underline{\mu}, \Sigma)$$

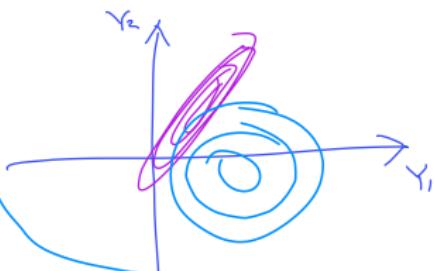
$$\cdot \underline{\alpha}' \underline{Y} \sim N(\underline{\alpha}' \underline{\mu}, \underline{\alpha}' \Sigma \underline{\alpha})$$

$$Y_1 = (1, 0) \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \underline{\alpha}' \underline{Y}$$

Show

$$\int_{-\infty}^{\infty} f(y_1, y_2) dy_2$$

$$= \frac{1}{\sqrt{2\pi}\sigma_1} \exp\left(-\frac{(y_1 - \mu_1)^2}{2\sigma_1^2}\right)$$



Conditional of $Y_1 | Y_2 = y_2$

$$f(y_1 | y_2) = \frac{f(y_1, y_2)}{f(y_2)} = \frac{\frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-p_2}} \exp\left(-\frac{1}{2}Q\right)}{\frac{1}{\sqrt{2\pi}\sigma_2} \exp\left(-\frac{(y_2 - \mu_2)^2}{2\sigma_2^2}\right)}$$

$$= \left\{ \begin{array}{c} \dots \\ \dots \\ \dots \\ \dots \end{array} \right.$$

$$E(Y_1 | Y_2 = y_2)$$

$$V(Y_1 | Y_2 = y_2)$$

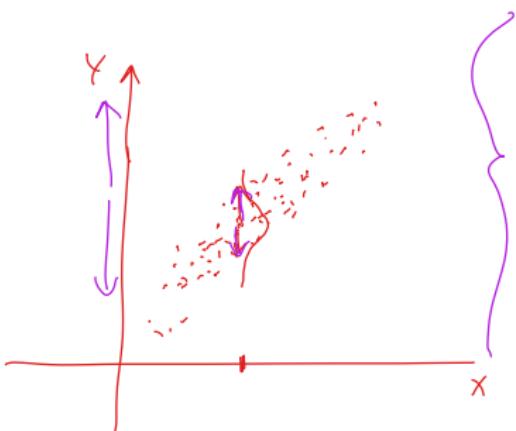
: density of

$$N\left(\mu_1 + \rho \cdot \frac{\sigma_1}{\sigma_2} (y_2 - \mu_2), \sigma_1^2 (1 - \rho^2)\right)$$

① Conditional mean \Rightarrow
a linear ft of y_2 .

② Conditional Variance does not
depend on y_2

③ Conditional Variance \leq Variance
of Y_1



Why we do regression.

Conditional Expectations

Conditional expectation of Y_1 , given that $Y_2 = y_2$

$$E[Y_1|Y_2 = y_2] = \int_{-\infty}^{\infty} y_1 f(y_1|y_2) dy_1$$

; mean of
conditional
distribution

* $E(Y_1|Y_2)$ is a function of Y_2 , thus a random variable. thus, it has a distribution itself.

$$E(Y_1) = E[E(Y_1|Y_2)] \quad (1)$$

w.r.t. marginal of Y_2

$$V(Y_1) = E[V(Y_1|Y_2)] + V[E(Y_1|Y_2)] \quad (2)$$

Total variance theorem .

$$\begin{aligned}
 \textcircled{1} \quad \text{RHS} &= \int E(Y_1|Y_2) f_2(y_2) dy_2 = \int \left[\int y_1 \cdot f(y_1|y_2) dy_1 \right] f_2(y_2) dy_2 \\
 &= \left\langle \int y_1 \cdot \frac{f(y_1, y_2)}{f_2(y_2)} dy_1 \right\rangle f_2(y_2) dy_2 \\
 &= \iint y_1 f(y_1, y_2) dy_1 dy_2 = E(Y_1)
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{2} \quad a &= E_{Y_2} \left(\underset{Y_1|Y_2}{E}(Y_1^2|Y_2) - E(Y_1|Y_2)^2 \right) \\
 &= E(E(Y_1^2|Y_2)) - E(E(Y_1|Y_2)^2) \\
 &= E(Y_1^2) - E(E(Y_1|Y_2)^2) \\
 b &= V(E(Y_1|Y_2)) = E(E(Y_1|Y_2)^2) - [E(E(Y_1|Y_2))]^2 \\
 &= \quad " \quad - E(Y_1)^2
 \end{aligned}$$

$$a+b = E(Y_1^2) - E(Y_1)^2 = V(Y_1) \quad \square$$

$$Y_1 \mid Y_1 = y_1 \sim \begin{pmatrix} y_1 & \text{w.p. 1} \\ 0 & \text{w.w.} \end{pmatrix}$$

$$V(Y_1 \mid Y_1 = y_1) = 0$$

$$E(Y_1 \mid Y_1 = y_1) = y_1$$

Eg 32] $Y : \# \text{ defectives out of } 10 \sim B(10, p)$

$p : \text{prob. defect.} \sim U(0, \frac{1}{4})$

$$\therefore Y \mid P \sim B(10, p)$$

$$\therefore E(Y) = E(E(Y \mid P)) = E(10p) = 10 \cdot \frac{1}{8}$$

$$\therefore V(Y) = V(E(Y \mid P)) + E(V(Y \mid P))$$

$$= V(10p) + E(10p(1-p)) = 100 \cdot \frac{\left(\frac{1}{4}\right)^2}{12} + 10 E(p) - 10 E(p^2)$$

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139

N : # jobs per week $\sim \text{Poisson}(\lambda)$

Y : no. hrs completing each job $\sim \text{Gamma}(\alpha, \beta)$

Total hours completing all jobs in a week

$$T = \sum_{i=1}^N Y_i, \quad Y_i \stackrel{iid}{\sim} \text{Gamma}(\alpha, \beta)$$

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

E(T) = E(E(T|N)) = E(N\alpha\beta) \quad T|N \sim \text{Gamma}(N\alpha, \beta)

$$= \alpha\beta\lambda$$

$$V(T)$$

$$= V(E(T|N)) + E(V(T|N))$$

$$= V(N\alpha\beta) + E(N\alpha\beta^2) = \alpha^2\beta^2\lambda + \alpha\beta^2\lambda$$