

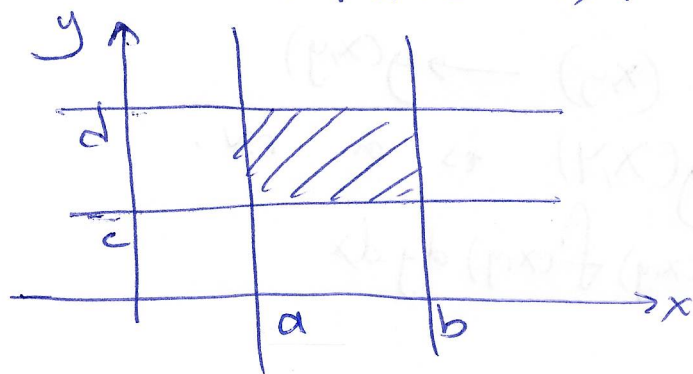
Lecture 4 - Joint Distributions

①

snow = $g(\text{temperature, humidity})$

Ex: $P(\text{snow} > 1 \text{ inch}) = P(\text{temp} \leq 30^\circ \text{F} \cap \text{humid} > 30\%)$

In general, $P(X \in (a, b) \cap Y \in (c, d))$
 $= P(X \in (a, b), Y \in (c, d))$



joint pdf

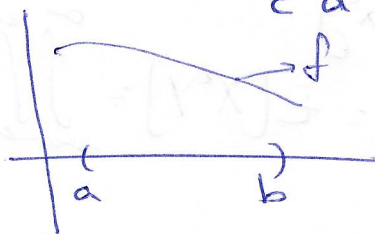
$$\int_a^b \int_c^d f_{X,Y}(x,y) dy dx$$

$$= \int_c^d \int_a^b f_{X,Y}(x,y) dx dy$$

Recall Single RV case

$$P(X \in (a, b))$$

$$= \int_a^b f(t) dt$$



Joint cdf $F_{X,Y}(\alpha, \beta) = P(X \leq \alpha, Y \leq \beta)$

$$= \int_{-\infty}^{\alpha} \left(\int_{-\infty}^{\beta} f(x,y) dy \right) dx$$

$$F(-\infty, -\infty) = 0$$

$$F(\infty, \infty) = 1$$

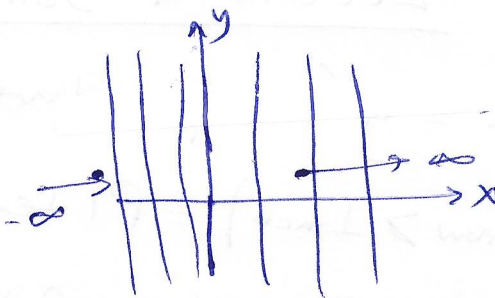
Validity: $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dy dx = 1$

$$\frac{\partial^2 F_{X,Y}(x,y)}{\partial x \partial y} = f_{X,Y}(x,y)$$

Marginal distributions

$$\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx = f_Y(y)$$

$$\int_{-\infty}^{\infty} f_{X,Y}(x,y) dy = f_X(x)$$



Expectation: Joint $(x,y) \rightarrow g(x,y)$

$$E[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f(x,y) dy dx$$

$g(X,Y)$ is a r.v.

Ex: $g(x,y) = x^2 y$

$$E[g(X,Y)] = E[X^2 Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^2 y f(x,y) dy dx$$

Ex: $g(x,y) = x$

$$E[g(X,Y)] = E[X] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x,y) dy dx$$

$$= \int_{-\infty}^{\infty} x \left(\int_{-\infty}^{\infty} f(x,y) dy \right) dx = \int_{-\infty}^{\infty} x f_X(x) dx$$

Linearity of Expectation (LOE)

$$E[X+Y] = E[X] + E[Y]$$

$$E[X+Y+Z] = E[X] + E[Y] + E[Z]$$

$$E[g(X) + h(Y)] = E[g(X)] + E[h(Y)]$$

Ex: $E[\ln^2(X) + \sin^3(Y)] = E[\ln^2(X)] + E[\sin^3(Y)]$

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Pf (of LOE) a) continuous case

$$E[X+Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x+y) f(x,y) dy dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x,y) dy dx + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f(x,y) dx dy$$

$$= \int_{-\infty}^{\infty} x \left(\int_{-\infty}^{\infty} f(x,y) dy \right) dx + \int_{-\infty}^{\infty} y \left(\int_{-\infty}^{\infty} f(x,y) dx \right) dy$$

$$= \int_{-\infty}^{\infty} x f_X(x) dx + \int_{-\infty}^{\infty} y f_Y(y) dy$$

$$= E[X] + E[Y]$$

(ii) Discrete case is similar with replacing integrals with sums.

Note: For LOE, X & Y need not to be independent!

Extension: $E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i]$

Ex: $X \sim \text{Binomial}(n, p)$ Show that $E[X] = np$

Soln: $X = \#$ of successes in n flips of a coin with $P(H) = p$

$$\Rightarrow X = \sum_{i=1}^n X_i \text{ where}$$

$$X_i = I_{F_i} = \begin{cases} 1 & \text{if } i\text{th flip is heads (or success)} \\ 0 & \text{" " " " tails (or failure)} \end{cases} \text{ for all } i=1, \dots, n$$

so, $X_i \sim \text{Bernoulli}(p)$ with pmf $f(x) = \begin{cases} p & \text{if } x=1 \\ 1-p & \text{if } x=0 \end{cases}$

$$\Rightarrow E[X_i] = E[I_{F_i}] = P(F_i) = p$$

Then $E[X] = E\left[\sum_{i=1}^n X_i\right]$

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$$= \sum_{i=1}^n E[X_i] = \sum_{i=1}^n p = np.$$

Note: $X_i = I_{F_i}$ where $F_i = i$ th flip is success will give the same result.

EX: (The Hat Problem)

n people throw their hats in a box and then each pick one at random.

X : # of people who get their own hat.

$E[X] = ?$

Sol'n:

$$X_i = I_{H_i} = \begin{cases} 1 & \text{if } i\text{th person gets his/her hat back} \\ 0 & \text{o.w.} \end{cases}$$

$$\Rightarrow X = \sum_{i=1}^n X_i = I_{H_1} + I_{H_2} + \dots + I_{H_n}$$

$$\Rightarrow E[X] = \sum_{i=1}^n E[X_i] = \sum_{i=1}^n P(H_i) = \sum_{i=1}^n \frac{1}{n} = n \cdot \frac{1}{n} = 1 \quad \Rightarrow$$

Note: $P(H_i) = \frac{1}{n}$ for all i

$$P(H_1) = \frac{1}{n}$$

$$P(H_2) = P(H_2 \mid \text{person 1 got hat 2}) \cdot P(\text{person 1 got hat 2})$$

$$+ P(H_2 \mid \text{person 1 did not get hat 2}) \cdot P(\text{person 1 did not get hat 2})$$

$$= 0 \cdot \frac{1}{n} + \frac{1}{n-1} \cdot \frac{n-1}{n} = \frac{1}{n}$$

Independence of RV's

Recall events $A \perp B \iff P(A \cap B) = P(A)P(B)$

(1) discrete case: $X \perp Y$ iff $f_{X,Y}(x,y) = f_X(x) f_Y(y)$

(ii) cts $\quad \quad \quad X \perp Y \quad \text{iff} \quad F_{X,Y}(x,y) = F_X(x) F_Y(y).$
 $\Leftrightarrow f_{X,Y}(x,y) = f_X(x) f_Y(y)$

Product of Expectation (POE)

If $X \perp Y$ then $E[XY] = E[X]E[Y]$

Pf: $E[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{X,Y}(x,y) dy dx$
 $\nearrow$
 $g(x,y) = xy$
 $= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_X(x) f_Y(y) dy dx$ $\nearrow$ indep of x & y
 $= \int_{-\infty}^{\infty} x f_X(x) \left(\int_{-\infty}^{\infty} y f_Y(y) dy \right) dx$
 $= E[Y] \int_{-\infty}^{\infty} x f_X(x) dx$
 $= E[Y] E[X]$ $\square$

Exer: Do the pf for discrete X & Y .

Extension (of POE)

Independence (of RVs)
If $X \perp Y$ then $E[g(X)h(Y)] = E[g(X)]E[h(Y)]$.

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Linearity of Variance (LOV) - for indep r.v.s

If $X \perp Y$, then $\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$.

Pf: $\text{Var}(X+Y) = E[(X+Y) - E(X+Y)]^2$

$$= E[(X - E(X) + Y - E(Y))]^2$$

$$= E[(X - E(X))^2] + E[(Y - E(Y))^2] + E[2(X - E(X))(Y - E(Y))]$$

$$= \text{Var}(X) + \text{Var}(Y) + 2 E[\underbrace{(X - E(X))}_{g(X)} \underbrace{(Y - E(Y))}_{h(Y)}]$$

where $E[(X - E(X))(Y - E(Y))]$

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

$$= (E(X) - E(X)) (E(Y) - E(Y)) = 0 \cdot 0 = 0$$

$$\Rightarrow \text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) \quad \square$$

Ex: $X \sim \text{Binomial}(n, p)$,

$$X = \sum_{i=1}^n X_i, \quad X_i = I_{F_i} = \begin{cases} 1 & \text{if flip } i \text{ is success} \\ 0 & \text{if flip } i \text{ is failure} \end{cases}$$

& X_i s are indep.

$$\Rightarrow E[X] = E\left(\sum X_i\right) \stackrel{\text{LoE}}{=} \sum_{i=1}^n E(X_i) = \sum_{i=1}^n P(F_i) = \sum_{i=1}^n p = np$$

$$\text{Var}(X) = \text{Var}\left(\sum X_i\right) \stackrel{\text{LoV}}{=} \sum \text{Var}(X_i) = \sum_{i=1}^n p(1-p) = np(1-p).$$

Ex: $X \sim F_X$ & $Y \sim F_Y$ & $X \perp Y$.

(a) Let $M = \max(X, Y)$. $F_M(\alpha) = ?$

$$\begin{aligned} F_M(\alpha) &= P(M \leq \alpha) = P(\max(X, Y) \leq \alpha) \\ &= P(X \leq \alpha, Y \leq \alpha) \\ &= P(X \leq \alpha) P(Y \leq \alpha) \quad \text{[X & Y]} \\ &= F_X(\alpha) F_Y(\alpha), \end{aligned}$$

(b) Let $W = \min(X, Y)$. $F_W(\alpha) = ?$

$$\begin{aligned} F_W(\alpha) &= P(W \leq \alpha) \\ &= P(\min(X, Y) \leq \alpha) \\ &= 1 - P(\min(X, Y) > \alpha) \\ &= 1 - P(X > \alpha, Y > \alpha) \\ &= 1 - P(X > \alpha) P(Y > \alpha) \quad \text{[X & Y]} \\ &= 1 - (1 - F_X(\alpha)) (1 - F_Y(\alpha)) \end{aligned}$$

Normal Distribution

Linear Transformation: If $X \sim N(\mu, \sigma^2)$ then
for $a, b \in \mathbb{R}$, $Y = aX + b \sim N(a\mu + b, a^2\sigma^2)$.

Weighted Sum (i.e. Linear Combination) of $\perp$ Normals

(i) If $X_1 \sim N(\mu_1, \sigma_1^2) \perp X_2 \sim N(\mu_2, \sigma_2^2)$
then $X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

(ii) If $X_i \sim N(\mu_i, \sigma_i^2)$ & X_i 's are $\perp$ then

$$\sum_{i=1}^n a_i X_i \sim N\left(\sum_{i=1}^n a_i \mu_i, \sum_{i=1}^n a_i^2 \sigma_i^2\right) \quad \text{where } a_i \text{'s are constant}$$

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Ex: $X \sim N(2, 4) \perp Y \sim N(1, 5)$

(1) $X+Y \sim N(2+1, 4+5) \equiv N(3, 9)$

(2) $X+3Y \sim N(2+3 \times 1, 4+9 \times 5)$
 $\equiv N(5, 49)$

(3) $X-Y = X + (-1)Y \sim N(1 \cdot 2 + (-1) \cdot 1, 1^2 \cdot 4 + (-1)^2 \cdot 5)$
 $= \underbrace{1}_{\tilde{\alpha}_1} X + \underbrace{(-1)}_{\tilde{\alpha}_2} Y = N(1, 9)$

iid $\equiv$ independent identically distributed

"X & Y are iid rv's" $\Leftrightarrow$ (i) $X \perp Y$ } $\Rightarrow f_{X,Y}(x,y) = f_X(x)f_Y(y)$
 (ii) $X \stackrel{d}{=} Y$ } $= f_X(x)f_X(y)$

Ex: $X \sim \text{Uniform}(0,1)$
 $Y \sim \text{Uniform}(0,2)$
 $W \sim \text{Uniform}(0,1)$

} $\Rightarrow X \stackrel{d}{=} W \Rightarrow$
 $E(X) = E(W)$
 $E(X^2) = E(W^2)$
 $\text{Var}(X) = \text{Var}(W)$
 $F_X(x) = F_W(x)$

Note: If $X=Y$ then $X \stackrel{d}{=} Y$ but not vice versa.

Ex: a) $X_1 = X_2$

$$E[X_1 + X_2] = E[X_1 + X_1]$$

$$= E[2X_1]$$

$$= 2E[X_1]$$

$$E[(X_1 + X_2)^2] = E[(2X_1)^2]$$

$$= E[4X_1^2]$$

$$= 4E[X_1^2]$$

b) $X_1 \stackrel{d}{=} X_2$

$$E[X_1 + X_2] \stackrel{L.O.E.}{=} E[X_1] + E[X_2]$$

$$= E[X_1] + E[X_1]$$

$$= 2E[X_1]$$

$$E[(X_1 + X_2)^2] = E[X_1^2 + 2X_1X_2 + X_2^2]$$

$$= E[X_1^2] + 2E[X_1X_2] + E[X_2^2]$$

$$= 2E[X_1^2] + 2E[X_1X_2]$$

Ex (iii) X_1 & X_2 are iid rv's. (i.e. $X_1 \stackrel{iid}{\sim} X_2$) ⑨

$$\begin{aligned}\text{Then } E[(X_1 + X_2)^2] &= 2E[X_1^2] + 2E[X_1 X_2] \quad (\text{from identical distr.}) \\ &= 2E[X_1^2] + 2E[X_1]E[X_2] \\ &= 2E[X_1^2] + 2(E[X_1])^2\end{aligned}$$

Exer: Find $\text{Var}(X_1 + X_2)$ in cases (i)-(iii) above

Ex: X & Y are iid rv's with $E(X) = \mu$ & $\text{Var}(X) = \sigma^2$

Find $E[X^2 + XY + Y^2]$ in terms of μ & σ^2 .

Sol'n: $E[X^2 + XY + Y^2] \stackrel{\text{LOE}}{=} E[X^2] + E[XY] + E[Y^2]$

$$= 2E[X^2] + E(X)E(Y)$$

$$= 2E(X^2) + (E(X))^2$$

$$\text{Recall } \text{Var}(X) = E(X^2) - (E(X))^2 \Rightarrow \sigma^2 = E(X^2) - \mu^2$$

$$\Rightarrow E(X^2) = \mu^2 + \sigma^2$$

$$\text{So, } E[X^2 + XY + Y^2] = 2(\mu^2 + \sigma^2) + \mu^2 = 3\mu^2 + 2\sigma^2$$

Ex: What if $X=Y$ in above Ex?

$$E[X^2 + XY + Y^2] = E[X^2 + XX + X^2] = E[3X^2]$$

$$= 3E[X^2] = 3(\mu^2 + \sigma^2)$$

Recap

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① LOE: $E(\sum X_i) = \sum E[X_i]$
or $E(\sum a_i X_i) = \sum a_i E[X_i]$

$\perp$ not needed

② POE: If $X \perp Y$, then
 $E(XY) = E(X)E(Y)$
also $E(g(X)h(Y)) = E(g(X))E(h(Y))$

③ LOV: If $X \perp Y$, then
 $\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$
also $\text{Var}(g(X) + h(Y)) = \text{Var}(g(X)) + \text{Var}(h(Y))$

Let X be any r.v. & c be a constant.

Then

- $E[c] = c$, $E[c^2] = c^2 \Rightarrow \text{Var}(c) = E[c^2] - (E[c])^2 = c^2 - c^2 = 0$
- $E[cX] = cE[X]$, $E[(cX)^2] = E[c^2 X^2] = c^2 E[X^2]$
 $\Rightarrow \text{Var}(cX) = E[(cX)^2] - (E[cX])^2 = c^2 E[X^2] - (cE[X])^2$
 $= c^2 E[X^2] - c^2 (E[X])^2$
 $= c^2 (E[X^2] - (E[X])^2)$

Let X & Y be two r.v's & $X \perp Y$, c a constant

Then $\text{Var}(X+cY) = \text{Var}(X) + c^2 \text{Var}(Y)$

$\text{Var}(X-cY) = \text{Var}(X) + c^2 \text{Var}(Y)$

$\underbrace{\text{Var}(X \pm cY)}_{X \pm cY}$

Recall

$$E[X_1 + X_2] = 2E[X_1] \quad \text{for all cases of } \begin{array}{l} X_1 = X_2 \\ X_1 \stackrel{d}{=} X_2 \\ \text{and } X_1 \stackrel{iid}{\sim} X_2 \end{array}$$

Consider $X_1 - X_2$ in these cases

(i) $X_1 = X_2$

- $E[X_1 - X_2] = E[X_1 - X_1] = E[0] = 0$
- $E[(X_1 - X_2)^2] = E[(X_1 - X_1)^2] = E[0] = 0$

(ii) $X_1 \stackrel{d}{=} X_2$

- $E[X_1 - X_2] = E[X_1] - E[X_2] = E[X_1] - E[X_1] = 0$
- $E[(X_1 - X_2)^2] = E[X_1^2 - 2X_1X_2 + X_2^2]$
 $= E[X_1^2] - 2E[X_1X_2] + E[X_2^2]$
 $= 2E[X_1^2] - 2E[X_1X_2]$

(iii) $X_1 \stackrel{iid}{\sim} X_2$

- $E[X_1 - X_2] = 0$
- $E[(X_1 - X_2)^2] = 2E[X_1^2] - 2E[X_1X_2]$
 $= 2E[X_1^2] - 2E[X_1]E[X_2]$
 $= 2E[X_1^2] - 2(E[X_1])^2$

Exer: Find $\text{Var}(X_1 - X_2)$ in cases (i)-(iii) above