

Suppose that $X \neq Y$ are independent. Stat 451
2-20-18

Then $f(x, y) = g(x) h(y)$. ①

$$\begin{aligned} \text{Then } E[XY] &= \int \int xy f(x, y) dy dx \\ &= \int \int xy \underbrace{g(x) h(y)} dy dx \end{aligned}$$

$$\begin{aligned} &= \int \left[x g(x) \underbrace{\int y h(y) dy}_{\mu_y} \right] dx \\ &= \mu_y \int x g(x) dx = \mu_y \mu_x \end{aligned}$$

$\therefore$ If $X \neq Y$ are independent, then ②

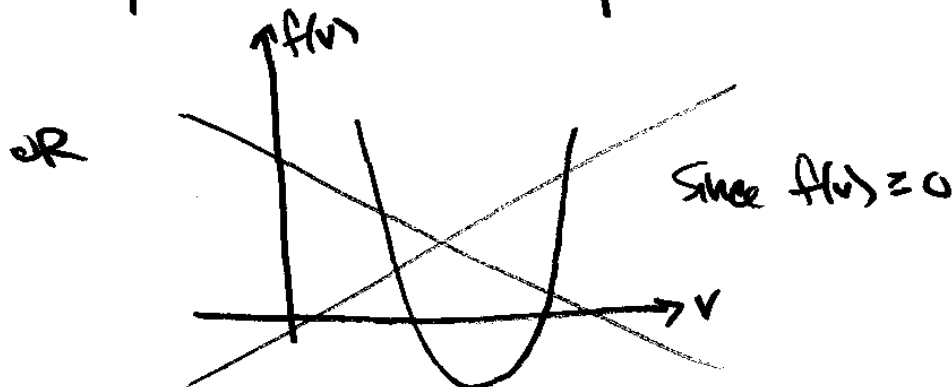
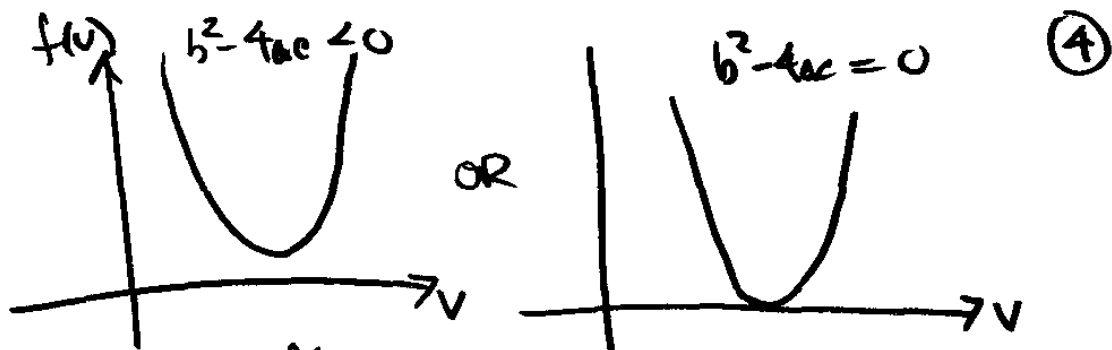
$$E[XY] = E[X] E[Y]$$

$$\alpha \text{ so } \sigma_{xy} = 0 \text{ and } \rho_{xy} = 0$$

Note: $\rho_{xy} = 0 \not\Rightarrow$ independence

$$E \left(\underbrace{[(X - \mu_x) + v(Y - \mu_y)]^2}_{f(v)} \right) \geq 0 \quad (3)$$

$$\begin{aligned} f(v) &= E \left[(X - \mu_x)^2 + v^2 (Y - \mu_y)^2 + 2v(X - \mu_x)(Y - \mu_y) \right] \\ &= E(X - \mu_x)^2 + v^2 E(Y - \mu_y)^2 + 2v E[(X - \mu_x)(Y - \mu_y)] \\ &= \sigma_x^2 + v^2 \sigma_y^2 + 2v \sigma_{xy} \\ &= \sigma_y^2 v^2 + 2\sigma_{xy} v + \sigma_x^2 \quad \text{this is a parabola in } v, \text{ opening up} \end{aligned}$$



$$\therefore b^2 - 4ac \leq 0$$

That is, $(2\sigma_{xy})^2 - 4\sigma_y^2\sigma_x^2 \leq 0$ (5)

$$\sigma_{xy}^2 - \sigma_x^2\sigma_y^2 \leq 0$$

$$\sigma_{xy}^2 \leq \sigma_x^2\sigma_y^2$$

$$\frac{\sigma_{xy}^2}{\sigma_x^2\sigma_y^2} \leq 1$$

$$-1 \leq \frac{\sigma_{xy}}{\sigma_x\sigma_y} \leq 1$$

$$\therefore -1 \leq \rho_{xy} \leq 1$$

The case where $\rho_{xy} = \pm 1$ (6)

corresponds to the case where $b^2 - 4ac = 0$

But $f(v) = E\left([(X - \mu_x) + v(Y - \mu_y)]^2\right)$

And it must have some v for which $f(v) = 0$.

If $f(v) = 0$, then

$$[(X - \mu_x) + v(Y - \mu_y)]^2 = 0 \quad \forall X, Y$$

$$X - \mu_x + v(Y - \mu_y) = 0 \quad \forall X, Y$$

$$X = -v(Y - \mu_Y) + \mu_X \quad \text{for some } v \quad (7)$$

$\therefore$ If $\rho_{xy} = \pm 1$ then X is exactly
a linear function of Y

3 important facts: ① Independence $\Rightarrow \rho_{xy} = 0$

$$\text{② } |\rho_{xy}| \leq 1$$

③ $\rho_{xy} = \pm 1$ means perfect
linear dependence between
 X & Y

Example of correlation in a discrete distribution (8)

Defn: The multinomial distribution

Run independent trials.

Assume r possible outcomes in each trial,

with probabilities $p_1, p_2, \dots, p_r$ such that

$$p_1 + p_2 + \dots + p_r = 1.$$

$X_1 = \# \text{ of type 1 outcomes}$

$\vdots$

$X_r = \# \text{ of type } r \text{ outcomes}$

$$\left. \begin{array}{l} X_1 = \# \text{ of type 1 outcomes} \\ \vdots \\ X_r = \# \text{ of type } r \text{ outcomes} \end{array} \right\} X_1 + \dots + X_r = n$$

(9)

$$P(X_1 = n_1 \cap X_2 = n_2 \cap \dots \cap X_r = n_r) \\ = \frac{n!}{n_1! n_2! \dots n_r!} p_1^{n_1} p_2^{n_2} \dots p_r^{n_r}$$

Find the correlation between X_i and X_j

X_i is a binomial random variable with parameters n and p_i

$$\text{So } E[X_i] = np_i \text{ and } V[X_i] = np_i q_i \\ (q_i = 1 - p_i)$$

(10)

$X_i + X_j$ is a binomial random variable with parameters n and $(p_i + p_j)$

$$V[X_i + X_j] = n(p_i + p_j)(1 - p_i - p_j) \\ \parallel$$

$$V[X_i] + V[X_j] + 2\text{Cov}(X_i, X_j)$$

$$\therefore \text{Cov}(X_i, X_j) = \frac{n(p_i + p_j)(1 - p_i - p_j) - V[X_i] - V[X_j]}{2}$$

$$\text{Cov}(X_i, X_j) = \frac{n[p_i p_j - p_i^2 - p_i p_j - p_j p_i + p_j^2] - n p_i (1 - p_i) - n p_j (1 - p_j)}{2} \quad (44)$$

$$= \frac{-2n p_i p_j}{2} = -n p_i p_j$$

$$\text{Corr}(X_i, X_j) = \frac{-n p_i p_j}{\sqrt{n p_i q_i} \sqrt{n p_j q_j}} = -\sqrt{\frac{p_i p_j}{q_i q_j}}$$