

# W1211 Introduction to Statistics

## Lecture 14

Wei Wang

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# Correlation

- The **correlation coefficient** of  $X$  and  $Y$ , denoted by  $\text{Corr}(X, Y)$  or  $\rho_{X,Y}$  is defined by

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \cdot \sigma_Y}$$

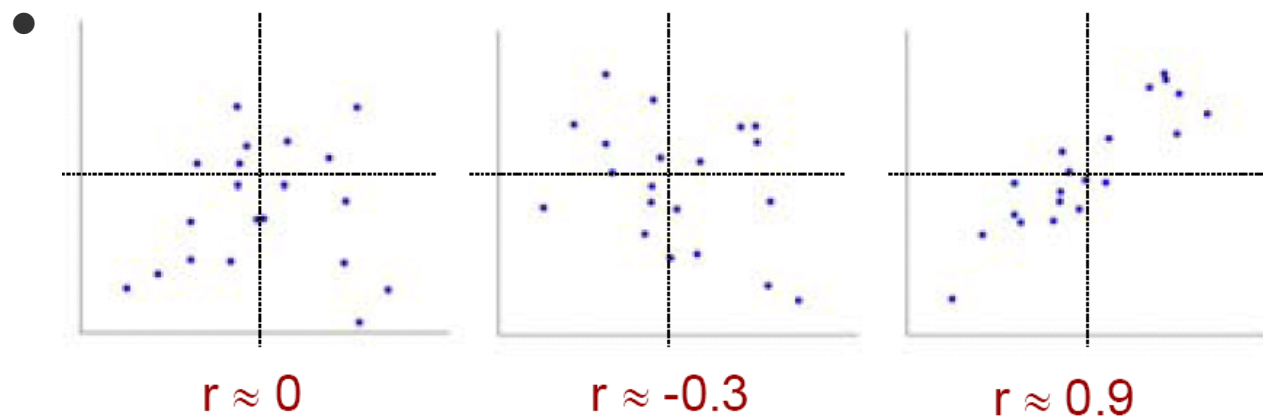
- Because of Cauchy-Schwarz inequality, we have

$$\text{Cov}^2(X, Y) \leq \text{Var}(X)\text{Var}(Y) \implies |\rho_{X,Y}| \leq 1$$

- The correlation coefficient  $\rho_{X,Y}$  is **NOT** a completely general measure of the strength of a relationship.  $\rho_{X,Y}$  is actually a measure of the degree of **linear** relationship between  $X$  and  $Y$ .

# Remarks

- If  $X$  and  $Y$  are independent, then  $\rho_{X,Y} = 0$  (why?). But  $\rho_{X,Y} = 0$  does **NOT** imply independence.
- $\rho_{X,Y} = 1$  or  $-1$  **iff**  $Y = aX + b$  for some numbers  $a$  and  $b$  with  $a \neq 0$ .



# Relationship Between Correlation and Independence

- ▶ Independence leads to uncorrelatedness.

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) = E(X)E(Y) - E(X)E(Y) = 0$$

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- ▶ But not vice versa!
- ▶ We will talk about this more in regression.