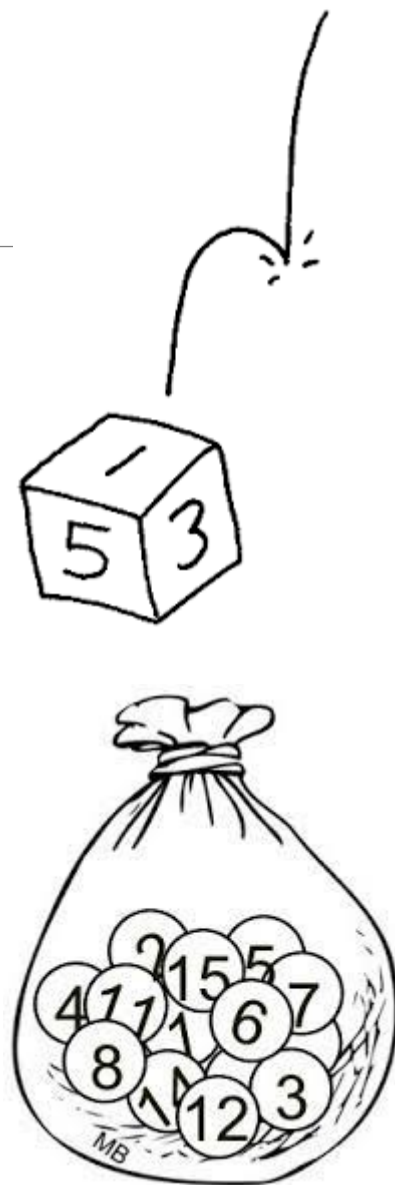


# Lecture 12

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- Covariance (协方差)
- Correlation Coefficient (相关系数)
- Moment (矩统计量)



# Covariance (协方差)

The covariance between  $X$  and  $Y$  is defined by

$$\text{Cov}(X, Y) = E\{[X - E(X)][Y - E(Y)]\}$$

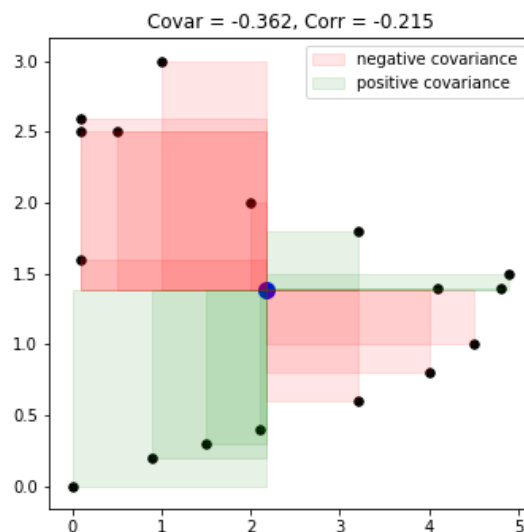
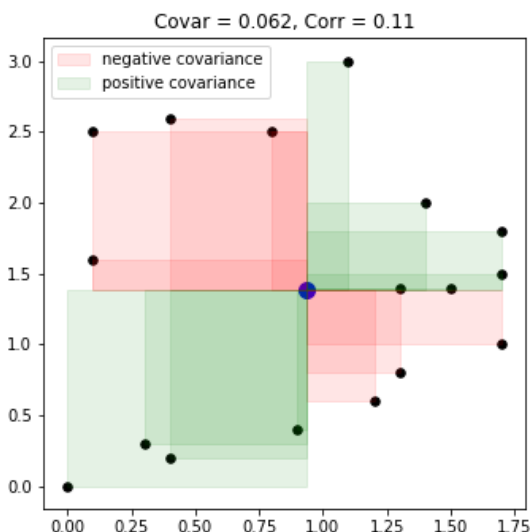
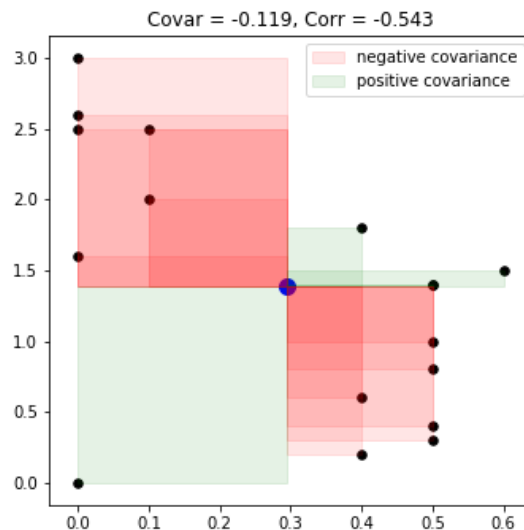
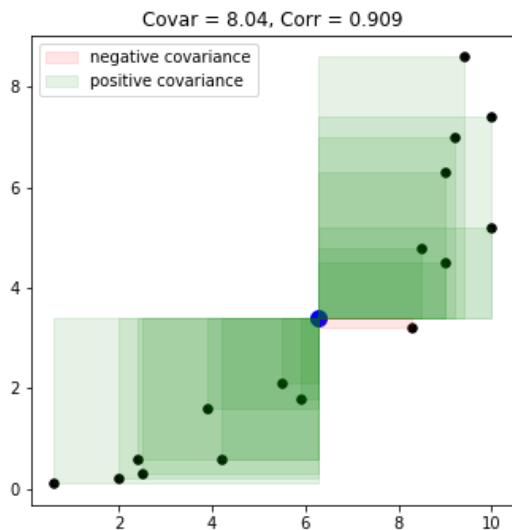
Two ways to calculate covariance:

$$\begin{aligned} 1. \quad \text{Cov}(X, Y) &= E\{XY - E[X]Y - XE[Y] + E[X]E[Y]\} \\ &= E[XY] - E[X]E[Y] - E[X]E[Y] + E[X]E[Y] \\ &= E[XY] - E[X]E[Y] \end{aligned}$$

$$\begin{aligned} 2. \quad D(X + Y) &= D(X) + D(Y) + 2 \cdot \text{Cov}(X, Y) \\ \Rightarrow \text{Cov}(X, Y) &= \frac{1}{2} [D(X + Y) - D(X) - D(Y)] \end{aligned}$$

# Covariance explained

$$\begin{aligned}\text{Cov}(X, Y) &= E\{[X - E(X)][Y - E(Y)]\} \\ &= E(XY) - E(X)E(Y)\end{aligned}$$



- **Blue point:**  $C[E(X), E(Y)]$
- **Sample point:**  $P(X, Y)$
- **Edge of square:**  
 $X - E(X)$  &  $Y - E(Y)$
- **Area of square:**  
 $|[X - E(X)][Y - E(Y)]|$
- **Color of square:**  
sign of  $[X - E(X)][Y - E(Y)]$

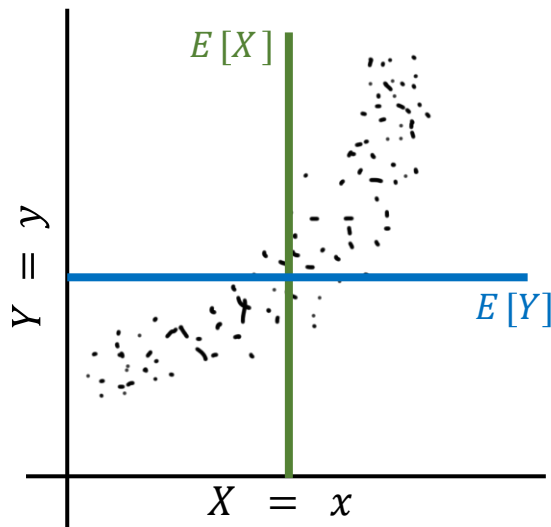
⇒ **Covariance:**  $\text{Cov}(X, Y)$   
 $= E\{[X - E(X)][Y - E(Y)]\}$   
 $= \frac{\text{green area} - \text{red area}}{\# \text{ data point}}$

# Quick test

$$\begin{aligned}\text{Cov}(X, Y) \\ = E\{[X - E(X)][Y - E(Y)]\}\end{aligned}$$

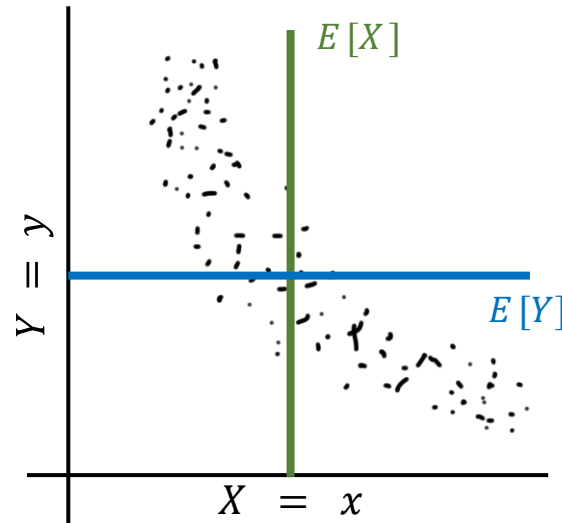
Is the covariance positive, negative, or zero?

1.



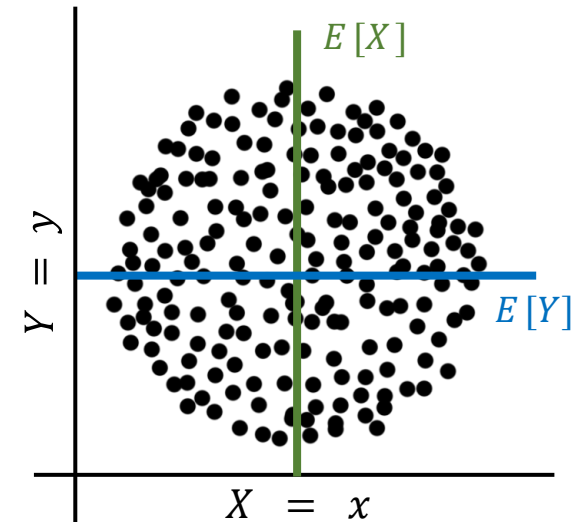
positive

2.



negative

3.



zero

# Properties of covariance

$$\begin{aligned}\text{Cov}(X, Y) &= E\{[X - E(X)][Y - E(Y)]\} \\ &= E(XY) - E(X)E(Y)\end{aligned}$$

1.  $\text{Cov}(X, Y) = \text{Cov}(Y, X)$ , exchangeable, symmetry
2.  $\text{Cov}(X, X) = D(X)$ , reduced to variance
3.  $\text{Cov}(aX, Y) = a \cdot \text{Cov}(X, Y)$  multiplicative rule  
 $\text{Cov}(aX + b, Y) = a \cdot \text{Cov}(X, Y)$ , non-linearity
4.  $\text{Cov}(X_1 + X_2, Y) = \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)$ , summation
5. If  $X$  and  $Y$  are independent,

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

Ex. Given R.V.s  $(X, Y)$  follows joint PDF

$$f(x, y) = \begin{cases} 8xy, & 0 \leq x \leq y \leq 1, \\ 0, & \text{otherwise} \end{cases}$$

Find  $\text{Cov}(X, Y)$ .      Hint:  $\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$ .

Ex. Given R.V.s  $(X, Y)$  follows joint PDF

$$f(x, y) = \begin{cases} 8xy, & 0 \leq x \leq y \leq 1, \\ 0, & \text{otherwise} \end{cases}$$

Find  $\text{Cov}(X, Y)$ . Hint:  $\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$ .

Sol.

$$E(X) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xf(x, y) dx dy = \int_0^1 dx \int_x^1 x \cdot 8xy dy = \frac{8}{15}$$

$$E(Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} yf(x, y) dx dy = \int_0^1 dx \int_x^1 y \cdot 8xy dy = \frac{4}{5}$$

$$E(XY) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xyf(x, y) dx dy = \int_0^1 dx \int_x^1 xy \cdot 8xy dy = \frac{4}{9}$$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) = \frac{4}{9} - \frac{4}{5} \cdot \frac{8}{15} = \frac{4}{225}$$

# Zero covariance does not imply independence

Let  $X$  take on values  $\{-1, 0, 1\}$   
with equal probability  $1/3$ .

Define  $Y = \begin{cases} 1 & \text{if } X = 0 \\ 0 & \text{otherwise} \end{cases}$

		$X$			
		-1	0	1	
$Y$	0	1/3	0	1/3	2/3
	1	0	1/3	0	1/3
		1/3	1/3	1/3	

Marginal  
PMF of  
 $Y$ ,  $p_Y(y)$

Marginal PMF of  $X$ ,  $p_X(x)$

Show that  $\text{Cov}(X, Y) = 0$   
but

$$P\{Y = y_0 | X = x_0\} \neq P(Y = y_0)$$

$$E[X] = \frac{1}{3} \times (-1 + 0 + 1) = 0$$

$$E[Y] = \frac{1}{3} \times 1 + \frac{2}{3} \times 0 = \frac{1}{3}$$

$$E[XY] = \frac{1}{3} \times (-1 \cdot 0 + 0 \cdot 1 + 1 \cdot 0) = 0$$

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

$\Rightarrow X, Y$  are with **zero covariance**.

$$P\{Y = 0 | X = 1\} = 1, P\{Y = 0 | X = 0\} = 0$$

$$\neq$$

$$P(Y = 0) = 2/3$$

$\Rightarrow X, Y$  are **not independent**.



# Covariance matrix

**Def.** The covariance matrix of a  $n$ -dimensional R.V.  $(X_1, X_2, \dots, X_n)$  can be written as

$$\mathbf{C} = \begin{pmatrix} c_{11} & c_{12} & \dots & c_{1n} \\ c_{21} & c_{22} & \dots & c_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ c_{n1} & c_{n2} & \dots & c_{nn} \end{pmatrix}$$

where  $c_{ij} = \text{Cov}(X_i, X_j) = E\{[X_i - E(X_i)][X_j - E(X_j)]\}$ ,  
 $i, j = 1, 2, \dots, n$ .

The element  $c_{ij} = c_{ji}$  indicates the covariance between the  $i$ -th and  $j$ -th dimensions of  $(X_1, X_2, \dots, X_n)$ .

# Lecture 12

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- Covariance (协方差)
- Correlation Coefficient (相关系数)
- Moment (矩统计量)



# Correlation Coefficient (相关系数)

The correlation coefficient between  $X$  and  $Y$  is defined by

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{D(X)}\sqrt{D(Y)}} = \frac{E\{[X - E(X)][Y - E(Y)]\}}{\sqrt{D(X)}\sqrt{D(Y)}}$$

where  $D(X) > 0, D(Y) > 0$ .

## Note:

1.  $\rho_{XY}$  only measures the **linear** correlation;
2.  $-1 \leq \rho_{XY} \leq 1$ ;
3.  $|\rho_{xy}| = 1 \Leftrightarrow P\{Y = a + bX\} = 1$ ;
4.  $X$  and  $Y$  are **independent**  $\Rightarrow X, Y$  are **uncorrelated** ( $\rho_{XY} = 0$ );
5.  $X, Y$  are **uncorrelated** ( $\rho_{XY} = 0$ )  $\Leftrightarrow \text{Cov}(X, Y) = 0$   
 $\Leftrightarrow E(XY) = E(X)E(Y)$   
 $\Leftrightarrow D(X + Y) = D(X) + D(Y)$

# Correlation Coefficient explained

$$\rho_{XY} = \frac{\text{Cov}(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \quad (\text{Given } D(X) = \sigma_X^2, D(Y) = \sigma_Y^2 \text{ are known constant.})$$

$$= \frac{E\{[X-E(X)][Y-E(Y)]\}}{\sigma_X \sigma_Y} = E \left\{ \left[ \frac{X-E(X)}{\sigma_X} \right] \left[ \frac{Y-E(Y)}{\sigma_Y} \right] \right\} = \text{Cov}(X^*, Y^*)$$

(The **covariance** of normalized variable  $X^*$  and  $Y^*$ )

Moreover:

$$\rho_{XY} = \frac{E\{[X-E(X)][Y-E(Y)]\}}{\sqrt{E\{[X-E(X)]^2\}}\sqrt{E\{[Y-E(Y)]^2\}}} = \pm \sqrt{\frac{E\{[X-E(X)][Y-E(Y)]\}^2}{E\{[X-E(X)]^2\}E\{[Y-E(Y)]^2\}}}$$

If  $X - E(X)$  and  $Y - E(Y)$  are with the same sign,  $\rho_{XY} = 1$ ;

If  $X - E(X)$  and  $E(Y) - Y$  are with the opposite sign,  $\rho_{XY} = -1$ ;

Otherwise,  $-1 < \rho_{XY} < 1$ .

# Covariance vs. Correlation

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{D(X)}\sqrt{D(Y)}}$$

	Covariance	Correlation
Definition	Measure of linear correlation	Scaled version of covariance
Values	$(-\infty, +\infty)$	$[-1, 1]$
Change in scale	Affects covariance	Does not affect correlation
Unit-free measure	No	Yes

**Differ only in scale!**

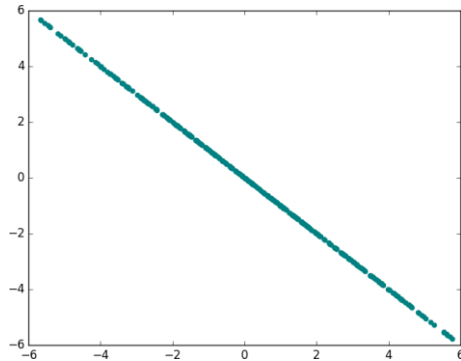
<https://www.wallstreetmojo.com/correlation-vs-covariance/>

# Quick test

What is the correlation coefficient  $\rho_{XY}$ ?

- A.  $\rho_{XY} = 1$
- B.  $\rho_{XY} = -1$
- C.  $\rho_{XY} = 0$
- D. Other

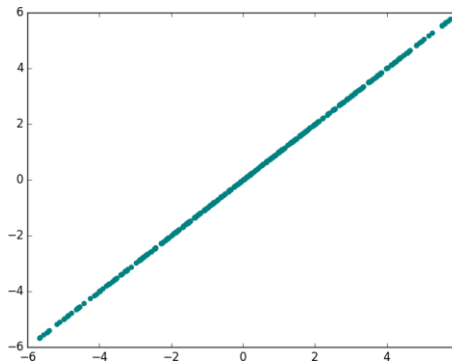
1.



$$Y = aX + b, a < 0$$

B

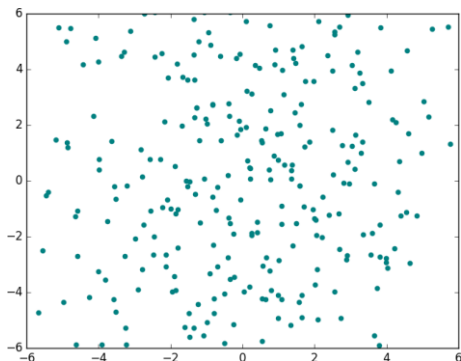
2.



$$Y = aX + b, a > 0$$

A

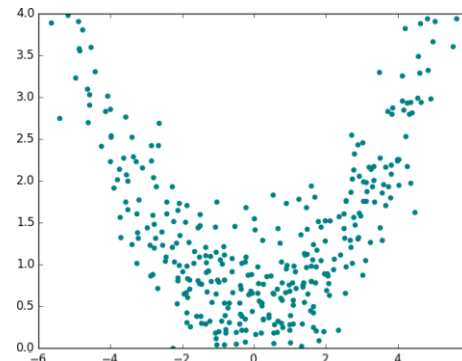
3.



uniformly distributed

C

4.



$$Y = X^2$$

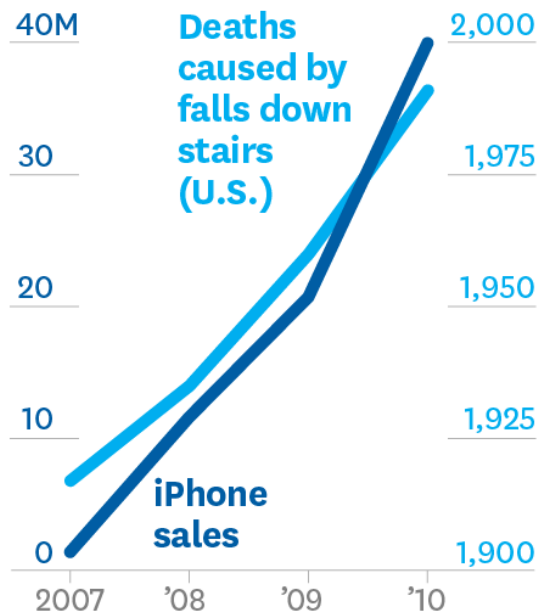
C

nonlinearly related  
even  $\rho_{XY} = 0$ .

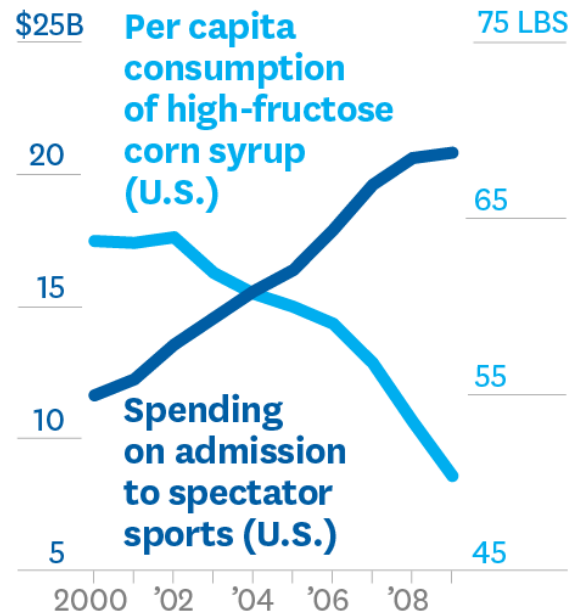
$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - E[X]E[Y] \\ &= E[X^3] - E[X]E[X^2] = 0 - 0 \cdot E[X^2] = 0. \end{aligned}$$

# Beware Spurious Correlations

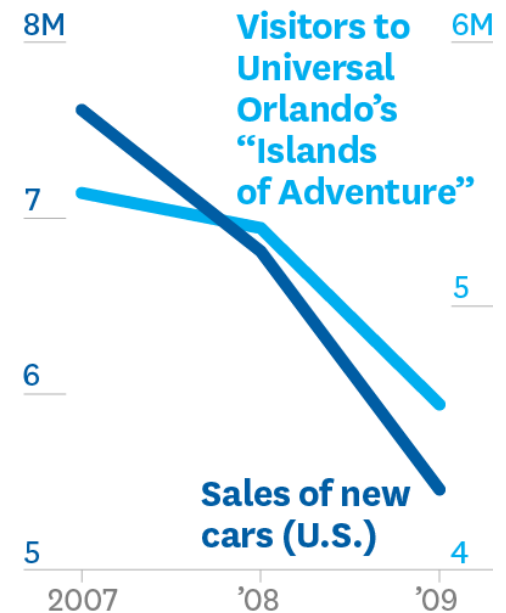
**MORE IPHONES MEANS  
MORE PEOPLE DIE FROM  
FALLING DOWN STAIRS**



**LET'S CHEER ON  
THE TEAM, AND  
WE'LL LOSE WEIGHT**



**TO INCREASE AUTO  
SALES, MARKET TRIPS  
TO UNIVERSAL ORLANDO**



SOURCE TYLERVIGEN.COM  
FROM "BEWARE SPURIOUS CORRELATIONS," JUNE 2015

© HBR.ORG

<https://hbr.org/2015/06/beware-spurious-correlations>

**Ex.** Given  $X \sim \mathcal{N}(1, 3^2)$ ,  $Y \sim \mathcal{N}(0, 4^2)$ ,  $\rho_{XY} = -\frac{1}{2}$ , and  $Z = \frac{X}{3} - \frac{Y}{2}$ , find  $D(Z)$ ,  $\rho_{XZ}$ .

$$D(Z) = D\left(\frac{X}{3} - \frac{Y}{2}\right) = D\left(\frac{X}{3}\right) - 2\text{Cov}\left(\frac{X}{3}, \frac{Y}{2}\right) + D\left(\frac{Y}{2}\right)$$

$$\rho_{XZ} = \frac{\text{Cov}(X, Z)}{\sqrt{D(X)}\sqrt{D(Z)}}$$

**Ex.** If  $\rho_{XY} = 0.5$ ,  $E(X) = E(Y) = 0$ ,  $E(X^2) = E(Y^2) = 2$ , find  $E[(X + Y)^2]$ .

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



**Ex.** Given  $X \sim \mathcal{N}(1, 3^2)$ ,  $Y \sim \mathcal{N}(0, 4^2)$ ,  $\rho_{XY} = -\frac{1}{2}$ , and  $Z = \frac{X}{3} - \frac{Y}{2}$ , find  $D(Z)$ ,  $\rho_{XZ}$ .

**Sol.**

$$\begin{aligned} D(Z) &= D\left(\frac{X}{3} - \frac{Y}{2}\right) = D\left(\frac{X}{3}\right) - 2\text{Cov}\left(\frac{X}{3}, \frac{Y}{2}\right) + D\left(\frac{Y}{2}\right) \\ &= \frac{1}{9}D(X) - 2 \cdot \frac{1}{2} \cdot \frac{1}{3} \text{Cov}(X, Y) + \frac{1}{4}D(Y) \\ &= \frac{1}{9}D(X) - \frac{1}{3}\rho_{XY}\sqrt{D(X)}\sqrt{D(Y)} + \frac{1}{4}D(Y) \\ &= \frac{1}{9} \cdot 9 - \frac{1}{3}\left(-\frac{1}{2}\right)\sqrt{9}\sqrt{16} + \frac{1}{4} \cdot 16 = 7 \end{aligned}$$

$$\begin{aligned} \rho_{XZ} &= \frac{\text{Cov}(X, Z)}{\sqrt{D(X)}\sqrt{D(Z)}} = \frac{1}{3 \cdot \sqrt{7}} \text{Cov}\left(X, \frac{X}{3} - \frac{Y}{2}\right) \\ &= \frac{1}{3 \cdot \sqrt{7}} \left[ \text{Cov}\left(X, \frac{X}{3}\right) - \text{Cov}\left(X, \frac{Y}{2}\right) \right] = \frac{1}{3 \cdot \sqrt{7}} \left[ \frac{1}{3} \text{Cov}(X, X) - \frac{1}{2} \text{Cov}(X, Y) \right] \\ &= \frac{1}{3 \cdot \sqrt{7}} \left[ \frac{1}{3} \cdot 9 - \frac{1}{2} \left(-\frac{1}{2}\right) \cdot 3 \cdot 4 \right] = \frac{2}{\sqrt{7}} \end{aligned}$$

**Ex.** If  $\rho_{XY} = 0.5$ ,  $E(X) = E(Y) = 0$ ,  $E(X^2) = E(Y^2) = 2$ , find  $E[(X + Y)^2]$ .

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

**Sol.**  $D(X) = E(X^2) - E(X)^2 = 2$ .

Similarly,  $D(Y) = 2$ .

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{D(X) \cdot D(Y)}} = \frac{E(XY) - E(X)E(Y)}{\sqrt{D(X) \cdot D(Y)}} = \frac{E(XY)}{2} = 0.5$$

$$\Rightarrow E(XY) = 1$$

$$E[(X + Y)^2] = E(X^2) + E(Y^2) + 2E(XY) = 2 + 2 + 2 = 6$$

# Uncorrelated but not independent

$X$  and  $Y$  are independent  $\Rightarrow X, Y$  are uncorrelated ( $\rho_{XY} = 0$ )

$X$  and  $Y$  are independent  $\nLeftarrow X, Y$  are uncorrelated ( $\rho_{XY} = 0$ )

Is this possible?

Ex. Let  $(X, Y)$  follow joint uniform distribution in a circle with radius  $R$  and center  $(0,0)$ . Show that  $X$  and  $Y$  are uncorrelated, but  $X$  and  $Y$  are not independent.

Sol.

$$f(x, y) = \begin{cases} \frac{1}{\pi R^2}, & x^2 + y^2 \leq R^2 \\ 0, & \text{otherwise} \end{cases}$$

1. Show that  $X, Y$  are uncorrelated, i.e.,  $\rho_{XY} = 0$

$$E(X) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} xf(x, y) dx dy = \int_{-R}^{+R} dy \int_{-\sqrt{R^2-y^2}}^{\sqrt{R^2-y^2}} x \frac{1}{\pi R^2} dx = 0$$

$$E(Y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} yf(x, y) dx dy = \int_{-R}^{+R} dx \int_{-\sqrt{R^2-x^2}}^{\sqrt{R^2-x^2}} y \frac{1}{\pi R^2} dy = 0$$

$$E(XY) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} xy \cdot f(x, y) dx dy = \int_{-R}^{+R} dx \int_{-\sqrt{R^2-x^2}}^{\sqrt{R^2-x^2}} xy \cdot \frac{1}{\pi R^2} dy = 0$$

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

$\Rightarrow X, Y$  are uncorrelated.

2. Show that  $X, Y$  are not independent, i.e.,  $f(x, y) \neq f_X(x)f_Y(y)$

$$f_X(x) = \int_{-\infty}^{+\infty} f(x, y) dy = \begin{cases} \frac{2\sqrt{R^2 - x^2}}{\pi R^2} & , \quad -R \leq x \leq R \\ 0 & , \quad \text{otherwise} \end{cases}$$

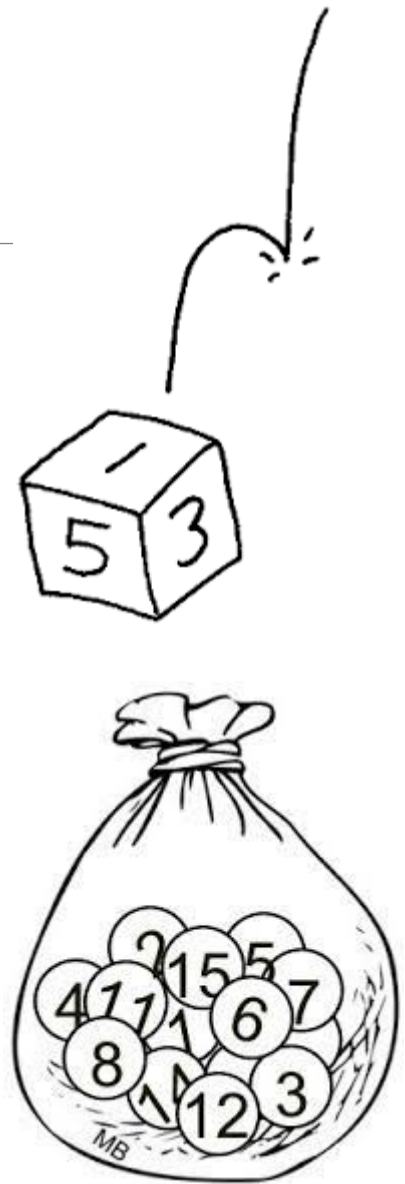
$$f_Y(y) = \int_{-\infty}^{+\infty} f(x, y) dx = \begin{cases} \frac{2\sqrt{R^2 - y^2}}{\pi R^2} & , \quad -R \leq y \leq R \\ 0 & , \quad \text{otherwise} \end{cases}$$

$\Rightarrow f(x, y) \neq f_X(x)f_Y(y) \Rightarrow X, Y$  are not independent

# Lecture 12

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- Covariance (协方差)
- Correlation Coefficient (相关系数)
- Moment (矩统计量)



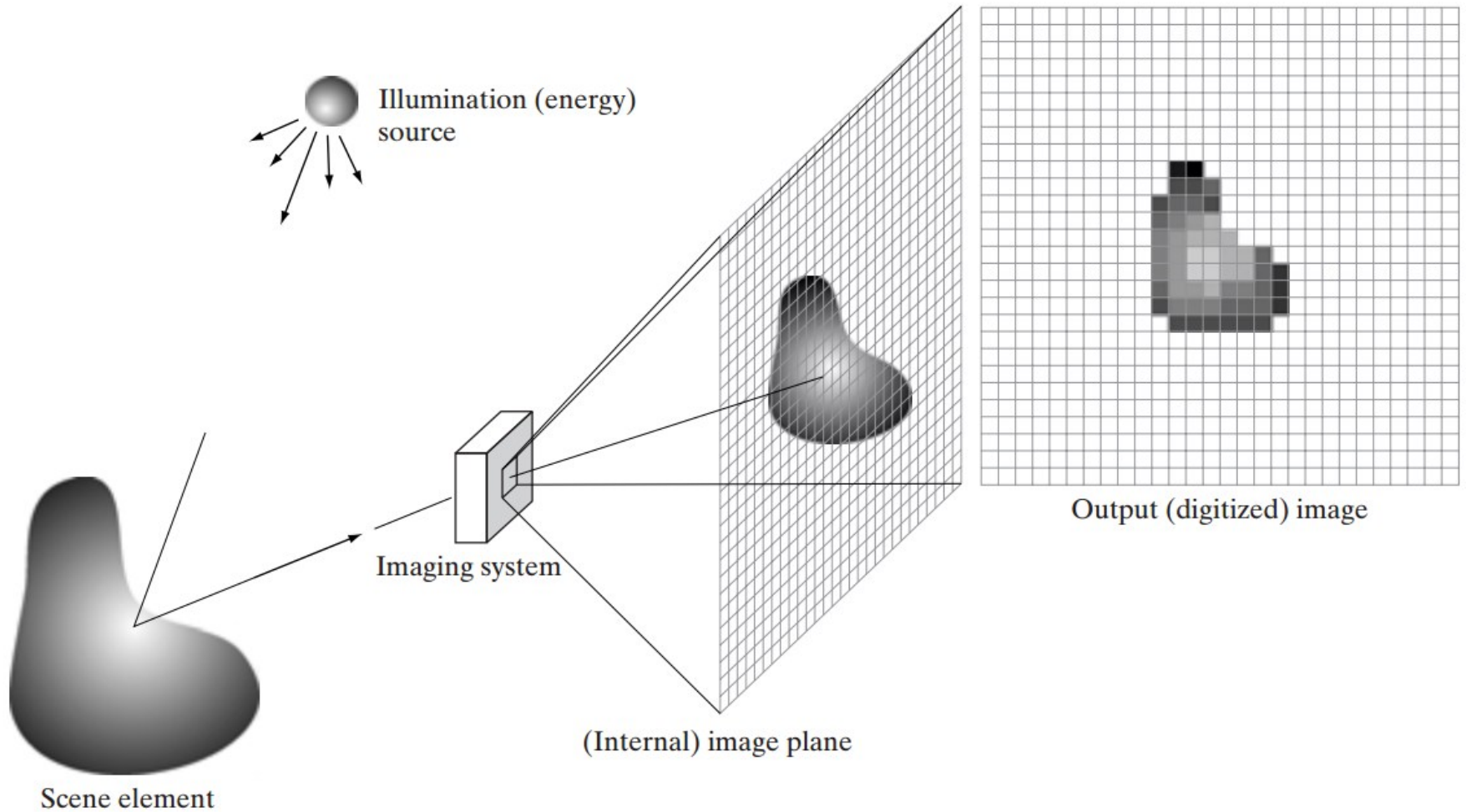
# Moment (矩)

**Def.** Let  $X, Y$  be two R.V.s, and  $k, l$  be two positive integers,

$E(X^k)$	the $k$ -th order <b>raw moment</b> (原点矩)
$E\{[X - E(X)]^k\}$	the $k$ -th order <b>central moment</b> (中心矩)
$E(X^k Y^l)$	the $k+l$ -th order <b>mixed</b> (混合) raw moment
$E\{[X - E(X)]^k [Y - E(Y)]^l\}$	the $k+l$ -th order mixed central moment

1.  $E(X)$  is the first order raw moment of  $X$ .
2.  $D(X)$  is the second order central moment.
3.  $\text{Cov}(X, Y)$  is the second order mixed moment of  $X$  and  $Y$ .
4. useful in **moment estimator** (to be covered in a few weeks).

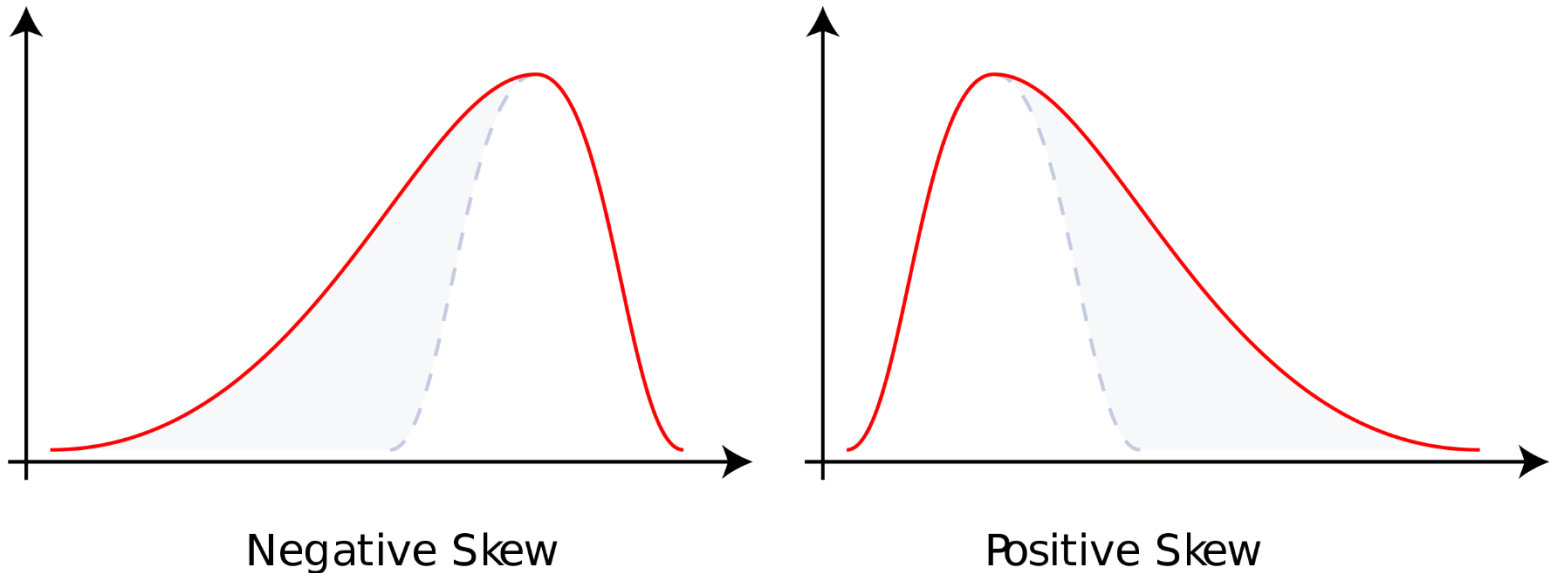
# Moment in a digital image





Moment ordinal	Moment		
	Raw	Central	Standardized
1	Mean	0	0
2	—	Variance	1
3	—	—	Skewness
4	—	—	(Non-excess or historical) kurtosis
5	—	—	Hyperskewness
6	—	—	Hypertailedness
7+	—	—	—

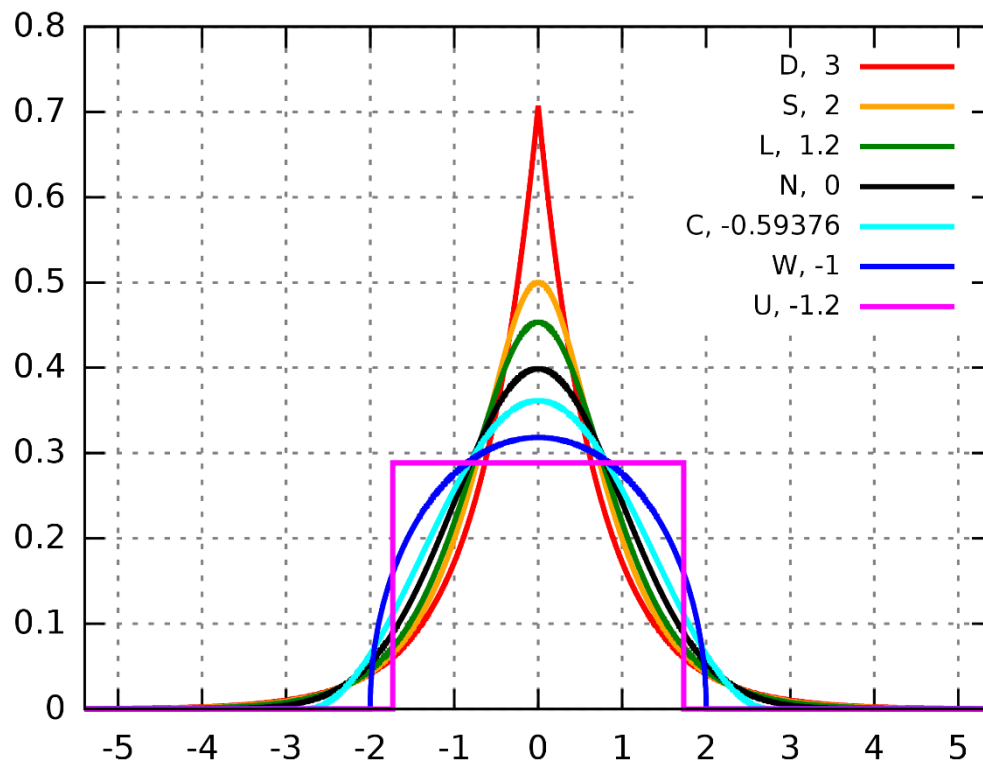
## [Significance of moments, Wikipedia](#)



$$\text{skew}(X) = E \left[ \left( \frac{X - \mu}{\sigma} \right)^3 \right]$$

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean.

[Skewness, Wikipedia](#)



$$\text{Kurt}(X) = E \left[ \left( \frac{X - \mu}{\sigma} \right)^4 \right]$$

Kurtosis is a measure of the **tailedness** of the prob. distribution of a real-valued random variable.

- **D: Laplace distribution**, also known as the double exponential distribution, red curve (two straight lines in the log-scale plot), excess kurtosis = 3
- **S: hyperbolic secant distribution**, orange curve, excess kurtosis = 2
- **L: logistic distribution**, green curve, excess kurtosis = 1.2
- **N: normal distribution**, black curve (inverted parabola in the log-scale plot), excess kurtosis = 0
- **C: raised cosine distribution**, cyan curve, excess kurtosis = -0.593762...
- **W: Wigner semicircle distribution**, blue curve, excess kurtosis = -1
- **U: uniform distribution**, magenta curve (shown for clarity as a rectangle in both images), excess kurtosis = -1.2.