

Review)

- If X is a RV of discrete type with PMF p_X , then

$$E(X) = \sum_{x \in S_X} x p_X(x).$$

- LOTUS tells that

$$E(u(X)) = \sum_{x \in S_X} u(x) p_X(x).$$

- $E(\cdot)$ satisfies

$$E(c) = c \quad \text{and} \quad E(c_1 X_1 + \dots + c_n X_n) = c_1 E(X_1) + \dots + c_n E(X_n)$$

for constants $c, c_1, \dots, c_n$ and RVs $X_1, \dots, X_n$.

Ex For each constant b ,

$$\begin{aligned} E[(X-b)^2] &= E[X^2 - 2bX + b^2] \\ &= E[X^2] - 2bE[X] + b^2 \\ &= (E[X] - b)^2 + (E[X^2] - E[X]^2). \end{aligned}$$

This is minimized when $b = E[X]$ with the minimum value $E[X^2] - E[X]^2$.

Ex Roll two 6-faced dices and let

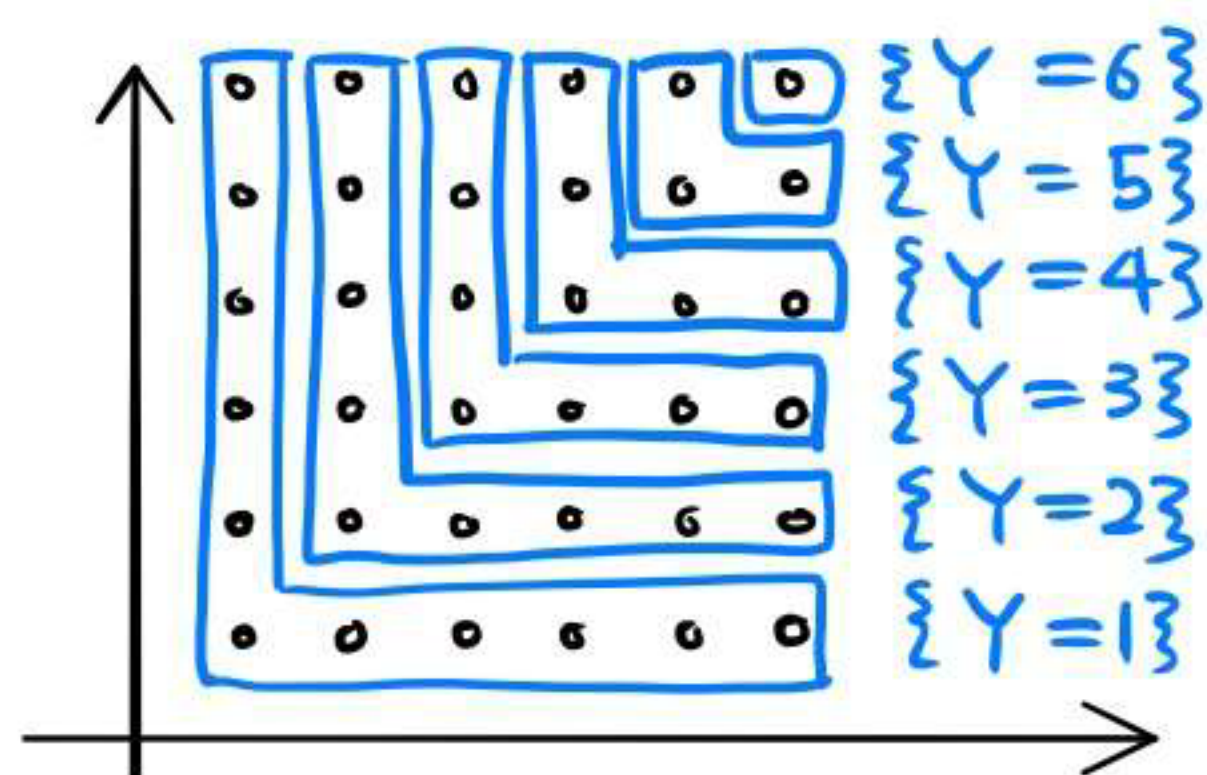
$X_1 = [\text{outcome of 1st dice}]$

$X_2 = [\text{outcome of 2nd dice}]$

also, set

$$Y = \min\{X_1, X_2\}, \quad Z = \max\{X_1, X_2\}, \quad W = X_1 + X_2.$$

Then



$$\Rightarrow P_Y(k) = \frac{13-2k}{36} \quad \text{for } k = 1, 2, \dots, 6.$$

$$\begin{aligned} \Rightarrow E(Y) &= \sum_{k=1}^6 k \cdot P_Y(k) = \sum_{k=1}^6 \frac{k(13-2k)}{36} \\ &= \frac{91}{36}. \end{aligned}$$

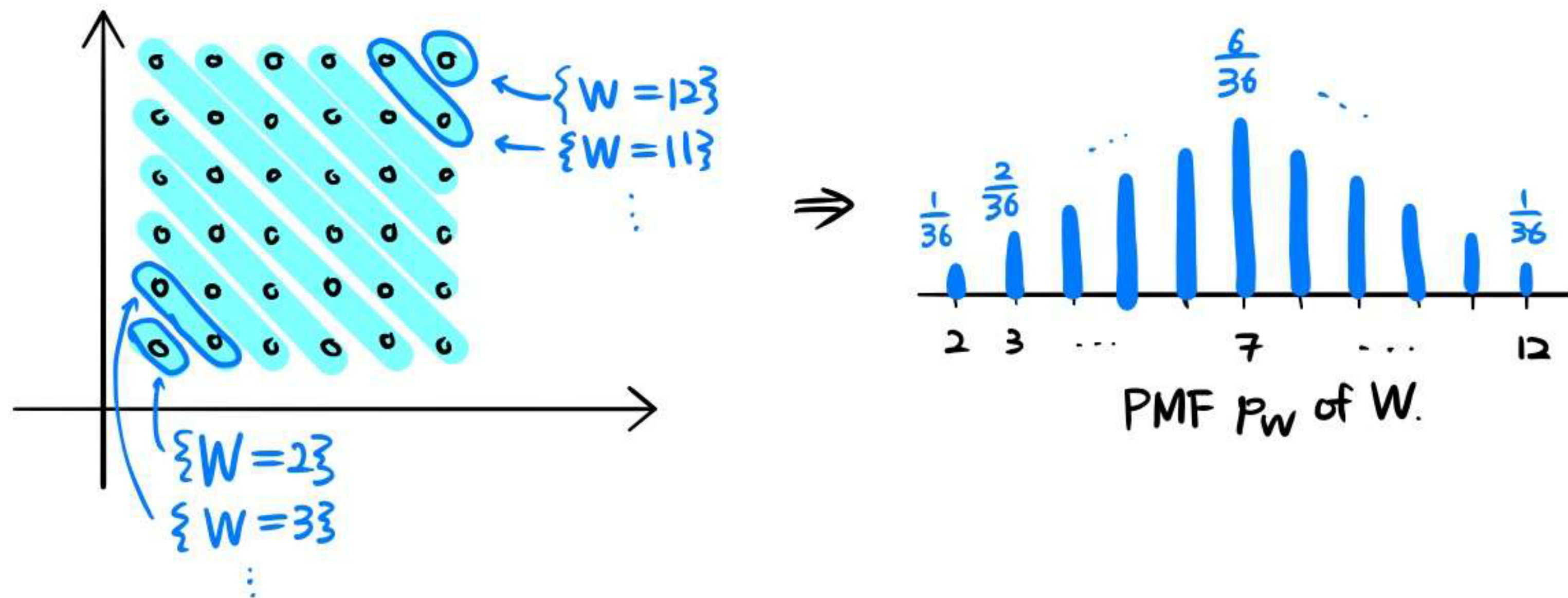
Similar argument shows $E(Z) = \frac{161}{36}$. Alternatively, using the identity $X_1 + X_2 = Y + Z$,

We get

$$E(Z) = E(X_1 + X_2 - Y) = E(X_1) + E(X_2) - E(Y).$$

Since $E(X_1) = \sum_{x=1}^6 x \cdot \frac{1}{6} = \frac{1+2+3+4+5+6}{6} = \frac{7}{2}$ and $E(X_2) = \frac{7}{2}$ likewise, we get $E(Z) = \frac{7}{2} + \frac{7}{2} - \frac{91}{36} = \frac{161}{36}$ as we have already confirmed.

Also, $E(W) = E(X_1) + E(X_2) = 7$. This can also be directly checked using



□

Ex (Geometric distribution) Assume:

- ▶ A random expr. yields $\begin{cases} \text{SUCCESS with prob } p \in (0,1), \\ \text{FAILURE with prob } q = 1-p. \end{cases}$
- ▶ Repeat this expr. indefinitely.
- ▶ $X = [\text{\# of trials until the 1st SUCCESS}]$.

Then

- $S_X = \{1, 2, 3, \dots\}$.
- For each $x \in S_X$, i.e., for $x = 1, 2, 3, \dots$,

$$\begin{aligned} P_X(x) &= P(X=x) \\ &= P((x-1) \text{ FAILURE then 1 SUCCESS}) \\ &= \underbrace{q \dots q}_{(x-1) \text{ times}} \cdot p = q^{x-1} p. \end{aligned}$$

(A sanity check: $\sum_{x \in S_X} P_X(x) = \sum_{x=1}^{\infty} q^{x-1} p = \frac{p}{1-q} = 1$. ☺)

- $E(X) = \sum_{x=1}^{\infty} x \cdot P_X(x) = \sum_{x=1}^{\infty} x q^{x-1} p$.

Using the formula

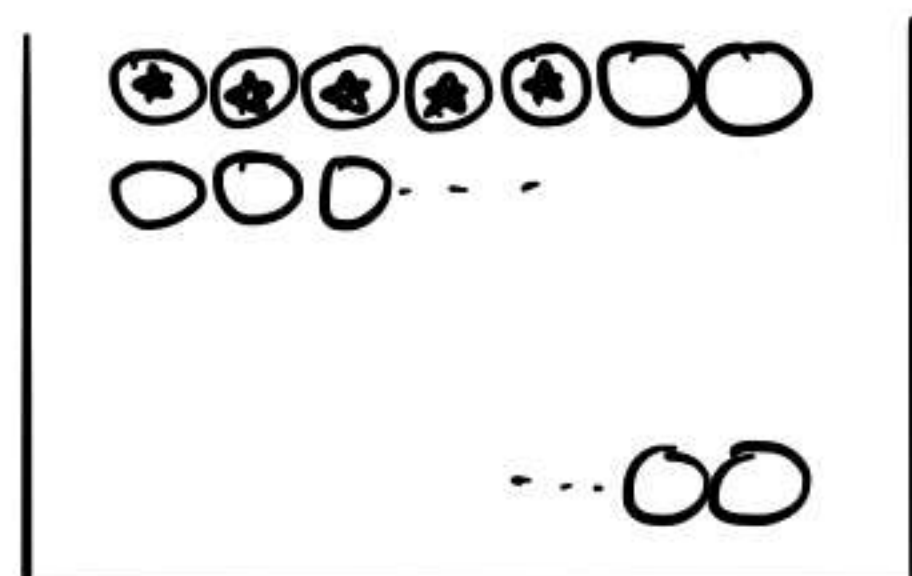
$$\frac{1}{(1-z)^2} = \frac{d}{dz} \frac{1}{1-z} = \frac{d}{dz} (1 + z + z^2 + \dots) = (1 + 2z + 3z^2 + \dots) = \sum_{n=1}^{\infty} n z^{n-1},$$

We get $E(X) = \frac{p}{(1-q)^2} = \frac{1}{p}$.

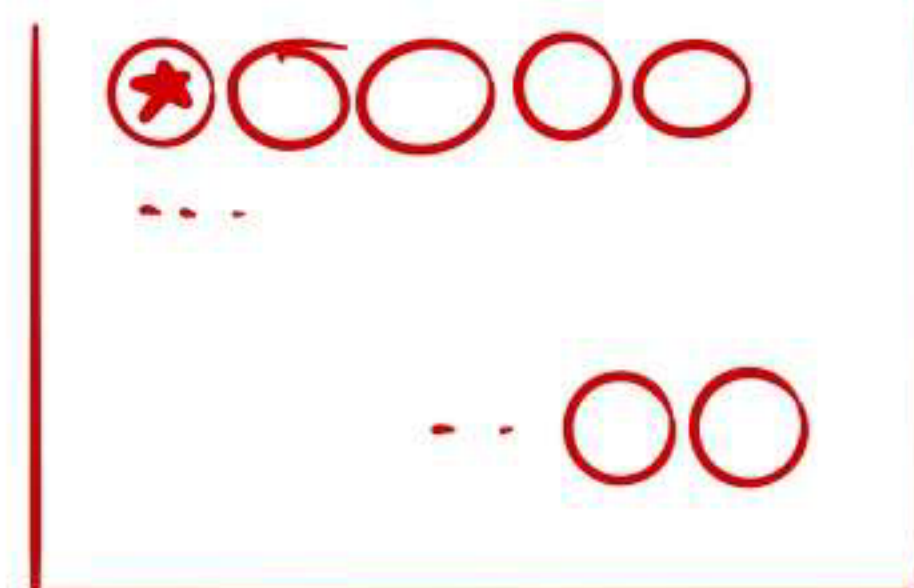
□

Ex

- Box 1 : 69 white balls,
5 of them are labeled with ★.



- Box 2 : 26 red balls,
one of them is labeled with ★.



- Pick 5 white balls from Box 1 w/o replacement,
Pick 1 red ball from Box 2
- The player wins a prize according to the following table:

Match	Prize	# of ways (out of total $\binom{69}{5}\binom{26}{1}$)
★ ★ ★ ★ ★ + ★	343m	$\binom{5}{5}\binom{64}{0}\binom{1}{1}\binom{25}{0} = 1$
★ ★ ★ ★ ★	1m	$\binom{5}{5}\binom{64}{0}\binom{25}{1} = 25$
★ ★ ★ ★ + ★	50k	$\binom{5}{4}\binom{64}{1}\binom{1}{1}\binom{25}{0} = 320$
★ ★ ★ ★	100	$\binom{5}{4}\binom{64}{1}\binom{25}{1} = 1,600$
★ ★ ★ + ★	100	8,000
★ ★ ★	7	504,000
★ ★ + ★	7	416,640
★ + ★	4	3,176,880
★	4	7,624,512

- The expected prize is then

$$343,000,000 \times \frac{1}{292,210,338} + 1,000,000 \times \frac{25}{292,210,338} + \dots$$

$$= 1.49372 \dots$$

It is unfair to pay \$2 to enter this game.

□

Section 2.3 . Special Mathematical Expectations

GOAL Study the quantities derived from RV which have certain statistical meanings.

- $E(X)$ of X is often called the **mean** of X (or of its distribution) and denoted as μ .
 $\mu \leftarrow \text{mu}$

- The "second moment of X about the mean μ "

$$E[(X-\mu)^2]$$

Is called the **variance** of X (or of its distribution) and denoted as **$\text{Var}(X)$** .

- The square root

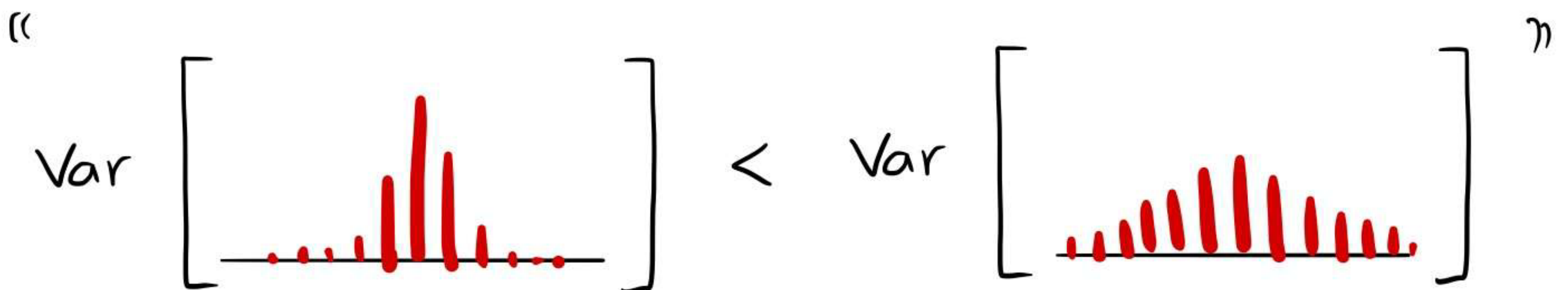
$$\sqrt{E[(X-\mu)^2]}$$

Is called the **standard deviation** of X and denoted as σ .
Accordingly,

$\sigma \leftarrow \text{sigma}$

$$\text{Var}(X) = \sigma^2.$$

σ (as well as $\text{Var}(X)$) is a measure of how the distribution of X is dispersed:



PROP $\text{Var}(X) = E[X^2] - \mu^2$ (where $\mu = E[X]$).

Pf) $\text{Var}(X) \stackrel{\text{by def.}}{=} E[(X - \mu)^2]$
 $= E[X^2 - 2\mu X + \mu^2]$
 $= E[X^2] - 2\mu E[X] + \mu^2$
 $= E[X^2] - \underbrace{2\mu \cdot \mu + \mu^2}_{= -\mu^2}$



Ex (Uniform distribution) Let X have the unif. dist. over $S = \{1, \dots, m\}$, i.e.,

$$P_X(x) = \begin{cases} \frac{1}{m} & \text{for } x=1, \dots, m \\ 0 & \text{o/w.} \end{cases}$$

Then

► The mean $\mu = E(X)$ is

$$\mu = \sum_{x \in S} x \cdot P_X(x) = \sum_{x=1}^m \frac{1}{m} \cdot x = \frac{1}{m} \cdot \frac{m(m+1)}{2}$$

$$= \frac{m+1}{2}$$

► The 2nd moment $E[X^2]$ is

$$E[X^2] = \sum_{x \in S} x^2 P_X(x) = \sum_{x=1}^m \frac{1}{m} \cdot x^2 = \frac{1}{m} \cdot \frac{m(m+1)(2m+1)}{6}$$

$$= \frac{(m+1)(2m+1)}{6}$$

So

$$\sigma^2 = E[X^2] - \mu^2 = \frac{m^2 - 1}{12}$$

► Indeed,

$$\text{Var} \left[\begin{array}{c} \text{"dispersion"} \\ \leftarrow \text{ } \rightarrow \\ \begin{array}{c} \text{1} \quad \text{2} \quad \dots \quad m \\ \text{---} \end{array} \end{array} \right] = \frac{m^2 - 1}{12}$$

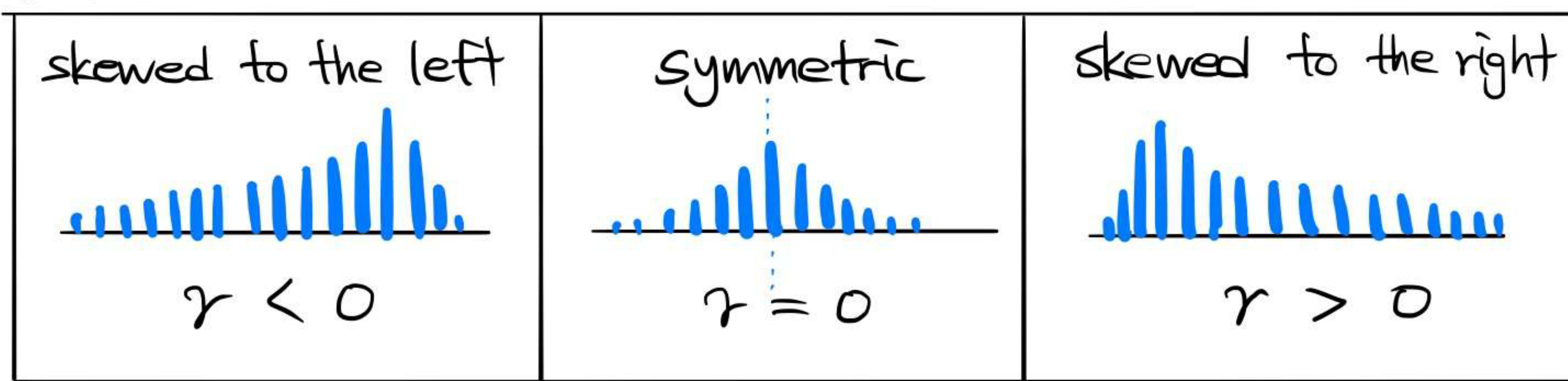
and large $\text{Var}(X)$ implies more dispersion. $\square$

PROP (1) $E(aX+b) = aE(X)+b$, i.e., $\mu_{aX+b} = a\mu_X + b$.
 (2) $\text{Var}(aX+b) = a^2 \text{Var}(X)$, i.e., $\sigma_{aX+b} = |a|\sigma_X$.

Pf (1) is obvious from the linearity of $E(\cdot)$.

$$\begin{aligned} (2) \quad \text{Var}(aX+b) &= E[(aX+b - E(aX+b))^2] \\ &= E[(aX - aE(X))^2] \\ &= a^2 E[(X - E(X))^2] \\ &= a^2 \text{Var}(X). \end{aligned} \quad \square$$

- $E(X^r) = \sum_{x \in S} x^r p(x)$ is called the **r-th moment** of X .
- $\gamma := \frac{E[(X-\mu)^3]}{\sigma^3}$ is called the **index of skewness** of X .
- In the "unimodal" case :



DEF Let X : RV of discrete type. Assume

$$E(e^{tX}) = \sum_{x \in S_X} e^{tx} \cdot p_X(x)$$

is finite near the origin $t=0$. Then

$$M_X(t) := E(e^{tX})$$

is called the **moment-generating function (MGF)** of X (or of the distribution of X).

• If we enumerate $S_X = \{b_1, b_2, \dots\}$, then

$$M_X(t) = e^{tb_1} p_X(b_1) + e^{tb_2} p_X(b_2) + \dots$$

$\Rightarrow$ (1) Reading out coef. of e^{tb} in $M_X(t)$ determines the value of $p_X(b)$.

(2) So, M_X uniquely determines PMF of X .

Ex Assume $M_X(t) = \frac{1}{6} (3e^t + 2e^{2t} + e^{3t})$. Then

► Support of X is $S_X = \{1, 2, 3\}$

► $p_X(1) = [\text{coef. of } e^t \text{ in } M_X(t)] = \frac{3}{6}$

$p_X(2) = [\text{coef. of } e^{2t} \text{ in } M_X(t)] = \frac{2}{6}$

$p_X(3) = \frac{1}{6}$.

Ex Recall: $e^x = \sum_{n=0}^{\infty} \frac{x^n}{n!}$ for any $x \in \mathbb{R}$. So, if

$$M_X(t) = e^{\lambda(e^t - 1)}, \quad (\lambda > 0)$$

then

$$\begin{aligned}
 M_X(t) &= e^{\lambda e^t} \cdot e^{-\lambda} \\
 &= \sum_{n=0}^{\infty} \frac{(\lambda e^t)^n}{n!} e^{-\lambda} \\
 &= \sum_{n=0}^{\infty} \left(\frac{\lambda^n}{n!} e^{-\lambda} \right) e^{tn}.
 \end{aligned}$$

$$\Rightarrow P_X(x) = \begin{cases} \frac{\lambda^x}{x!} e^{-\lambda} & \text{if } x = 0, 1, 2, \dots \\ 0 & \text{o/w.} \end{cases}$$

PROF $M^{(r)}(0) = E(X^r)$ is the r -th moment of X .

$$\begin{aligned}
 \text{PF)} \quad M^{(r)}(t) &= \left(\frac{d}{dt} \right)^r M(t) = \left(\frac{d}{dt} \right)^r \sum_{x \in S} e^{tx} p(x) \\
 &= \sum_{x \in S} x^r e^{tx} p(x) = E(X^r e^{tX}).
 \end{aligned}$$

Plug $t=0$. □

Ex If X has geom. dist. w/ PMF

$$P_X(x) = q^{x-1} p \quad \text{for } x = 1, 2, 3, \dots,$$

then

$$M_X(t) = E(e^{tX}) = \sum_{x=1}^{\infty} e^{tx} q^{x-1} p = \frac{pe^t}{1-qe^t},$$

provided $qe^t < 1$ ($\Leftrightarrow t < -\ln q$). Then

$$E(X) = M'(0) = \frac{pe^t}{(1-qe^t)^2} \Big|_{t=0} = \frac{1}{p}$$

and

$$E(X^2) = M''(0) = \frac{pe^t(1+\lambda e^t)}{(1-\lambda e^t)^3} \Big|_{t=0} = \frac{p(1+\lambda)}{(1-\lambda)^3}.$$

So

$$\text{Var}(X) = E(X^2) - (E(X))^2 = \frac{\lambda}{p^2}.$$

□