

Expectation (continued), Variance

February 28 - March 2

(Annotated Slides)

The expected value rule, for calculating $E[g(X)]$

- Let X be a r.v. and let $Y = g(X)$
- Averaging over y : $E[Y] = \sum_y y p_Y(y)$

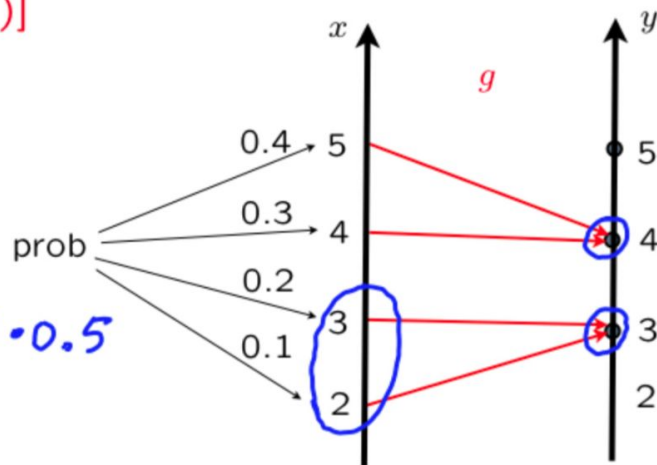
$$3 \cdot (0.1 + 0.2) + 4 \cdot (0.3 + 0.4)$$

- Averaging over x : $3 \cdot 0.1 + 3 \cdot 0.2 + 4 \cdot 0.3 + 4 \cdot 0.5$

$$E[Y] = E[g(X)] = \sum_x g(x) p_X(x)$$

Proof:

$$\begin{aligned} & \sum_y \sum_{x: g(x)=y} g(x) p_X(x) \\ &= \sum_y \sum_{x: g(x)=y} y p_X(x) = \sum_y y \sum_{x: g(x)=y} p_X(x) \\ &= \sum_y y p_Y(y) = E[Y] \end{aligned}$$



- $E[X^2] = \sum_x x^2 p_X(x)$
 $g(x) = x^2$

- Caution:** In general, $E[g(X)] \neq g(E[X])$

$$E[X^2] \neq (E[X])^2$$

Linearity of expectation: $E[aX + b] = aE[X] + b$

$X = \text{salary}$ $E[X] = \text{average salary}$

$Y = \text{new salary} = 2X + 100$ $E[Y] = E[2X + 100] = 2E[X] + 100$

- Intuitive

- **Derivation**, based on the expected value rule:

$$g(x) = ax + b$$

$$Y = g(X)$$

$$E[Y] = \sum_x g(x) p_X(x)$$

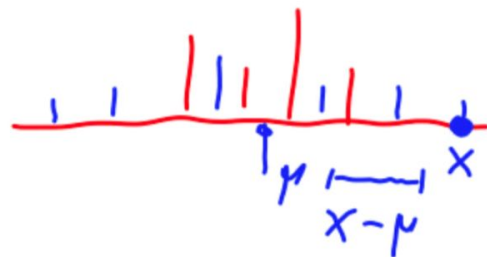
$$= \sum_x (ax + b) p_X(x) = a \sum_x x p_X(x) + b \underbrace{\sum_x p_X(x)}_1$$

$$E[g(X)] = g(E[X]) \quad \text{exceptional } g$$

Variance — a measure of the spread of a PMF

- Random variable X , with mean $\mu = \mathbb{E}[X]$
- Distance from the mean: $X - \mu$
- Average distance from the mean?

$$\mathbb{E}[X - \mu] = \mathbb{E}[X] - \mu = \mu - \mu = 0$$



- **Definition of variance:** $\text{var}(X) = \mathbb{E}[(X - \mu)^2]$ ≥ 0

- Calculation, using the expected value rule, $\mathbb{E}[g(X)] = \sum_x g(x)p_X(x)$

$$g(x) = (x - \mu)^2 \quad \text{var}(X) = \mathbb{E}[g(x)] = \sum_x (x - \mu)^2 p_X(x)$$

Standard deviation: $\sigma_X = \sqrt{\text{var}(X)}$

Properties of the variance

- Notation: $\mu = \mathbf{E}[X]$

$$\text{var}(aX + b) = a^2 \text{var}(X)$$

$$\begin{aligned}\text{var}(3-4x) \\ &= (-4)^2 \text{var}(x) \\ &= 16 \text{var}(x)\end{aligned}$$

- Let $Y = X + b$ $\gamma = \mathbf{E}[Y] = \mu + b$
$$\text{var}(Y) = \mathbf{E}[(Y - \gamma)^2] = \mathbf{E}[(X + b - (\mu + b))^2] = \mathbf{E}[(X - \mu)^2] = \text{var}(X)$$
- Let $Y = aX$ $\gamma = \mathbf{E}[Y] = a\mu$
$$\text{var}(Y) = \mathbf{E}[(aX - a\mu)^2] = \mathbf{E}[a^2(X - \mu)^2] = a^2 \mathbf{E}[(X - \mu)^2] = a^2 \text{var}(X)$$

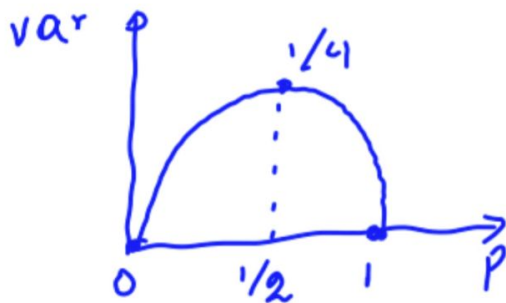
A useful formula:
$$\text{var}(X) = \mathbf{E}[X^2] - (\mathbf{E}[X])^2$$

$$\begin{aligned}\text{var}(X) &= \mathbf{E}[(X - \mu)^2] = \mathbf{E}[X^2 - 2\mu X + \mu^2] \\ &= \mathbf{E}[X^2] - 2\mu \mathbf{E}[X] + \mu^2 = \mathbf{E}[X^2] - (\mathbf{E}[X])^2\end{aligned}$$

Variance of the Bernoulli

$$X = \begin{cases} 1, & \text{w.p. } p \\ 0, & \text{w.p. } 1-p \end{cases}$$

$$E[X] = p$$



$$\begin{aligned} \text{var}(X) &= \sum_x (x - E[X])^2 p_X(x) = (1-p)^2 p + (0-p)^2 \cdot (1-p) \\ &= p - 2p^2 + \cancel{p^3} + p^2 - \cancel{p^3} = p - p^2 = p(1-p) \end{aligned}$$

$$\text{var}(X) = E[X^2] - (E[X])^2 = E[X] - (E[X])^2 = p - p^2 = \boxed{p(1-p)}$$

$$X^2 = X$$

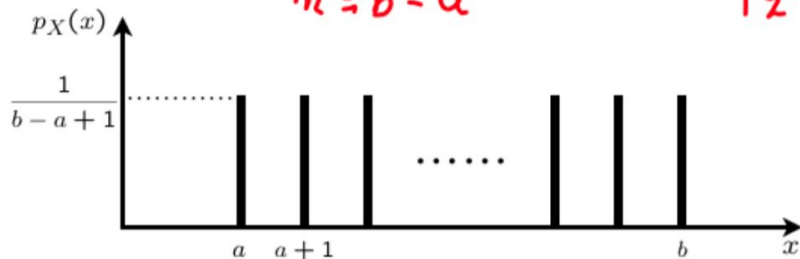
Variance of the uniform



$$\frac{1}{6} n(n+1)(2n+1)$$

$$\begin{aligned} \text{var}(x) &= E[x^2] - (E[x])^2 = \frac{1}{n+1} (0^2 + 1^2 + 2^2 + \dots + n^2) - \left(\frac{n}{2}\right)^2 \\ &= \frac{1}{12} n(n+2) \end{aligned}$$

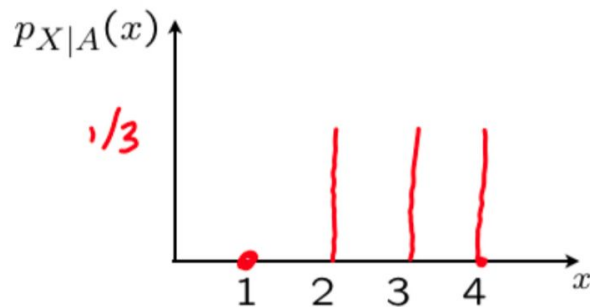
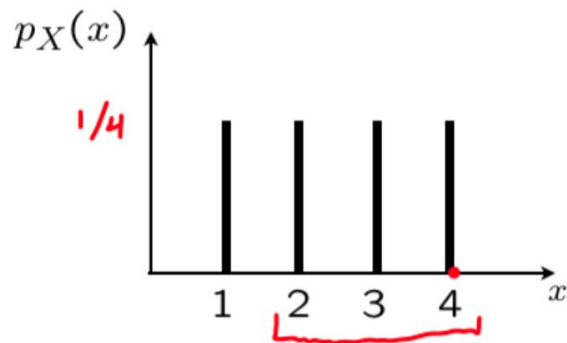
$$n = b - a$$



$$\text{Var}(x) = \frac{1}{12} (b-a)(b-a+2)$$

Example of conditioning

- Let $A = \{X \geq 2\}$



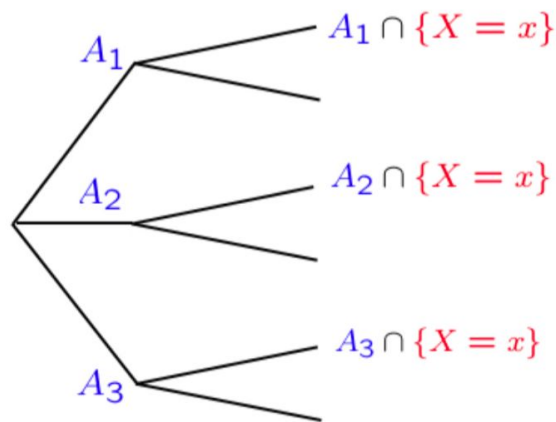
$$E[X] = 2.5$$

$$\begin{aligned} \text{var}(X) &= \frac{1}{12}(b-a)(b-a+1) \\ &= \frac{1}{12} 3 \cdot 5 = \frac{5}{4} \end{aligned}$$

$$E[X | A] = 3$$

$$\begin{aligned} \text{var}(X | A) &= \frac{1}{3}(4-3)^2 + \frac{1}{3}(3-3)^2 \\ &\quad + \frac{1}{3}(2-3)^2 = \frac{2}{3} \end{aligned}$$

Total expectation theorem



$$P(B) = P(A_1) P(B | A_1) + \cdots + P(A_n) P(B | A_n)$$

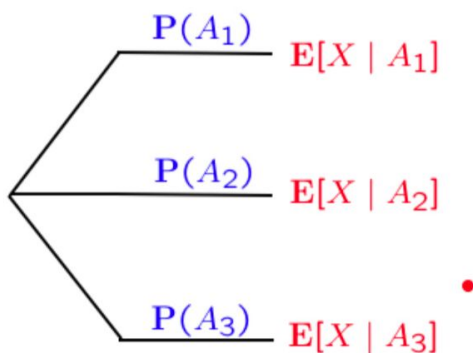
$$B = \{X = x\}$$

$$p_X(x) = P(A_1) p_{X|A_1}(x) + \cdots + P(A_n) p_{X|A_n}(x)$$

for all x

$$\sum_x x p_X(x) = P(A_1) \underbrace{\sum_x x p_{X|A_1}(x)}_{E[X|A_1]} + \cdots$$

" $E[X]$

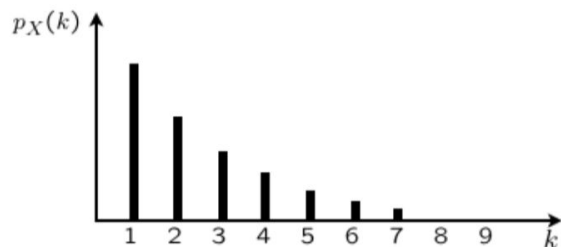


$$E[X] = P(A_1) E[X | A_1] + \cdots + P(A_n) E[X | A_n]$$

Conditioning a geometric random variable

- X : number of independent coin tosses until first head; $P(H) = p$

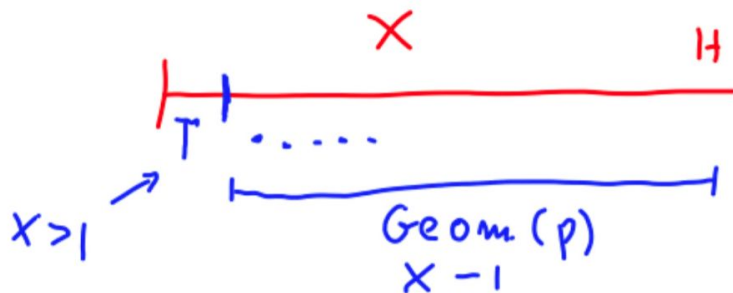
$$p_X(k) = (1 - p)^{k-1}p, \quad k = 1, 2, \dots$$



Memorylessness:

Number of **remaining** coin tosses, conditioned on Tails in the first toss, is **Geometric**, with parameter p

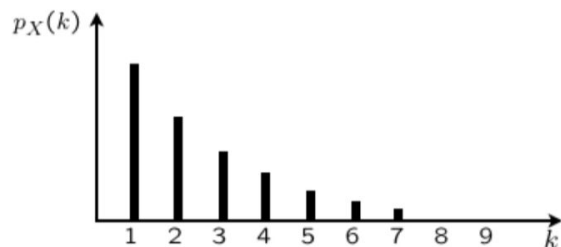
Conditioned on $X > 1$, $X - 1$ is geometric with parameter p



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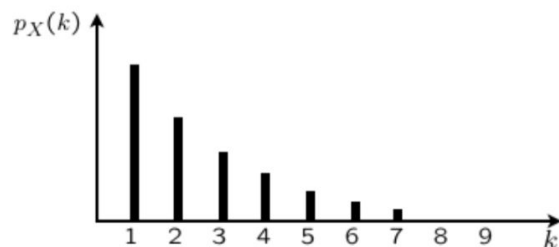
Conditioned on $X > 1$, $X - 1$ is geometric with parameter p

$$\begin{aligned} P_{X-1|X>1}(3) &= P(X-1=3 | X>1) = P(T_2 T_3 H_4 | T_1) = P(T_2 T_3 H_4) \\ &= (1-p)^2 p = p_X(3) \\ P_{X-1|X>1}(k) &= p_X(k) \end{aligned}$$

Conditioning a geometric random variable

- X : number of independent coin tosses until first head; $P(H) = p$

$$p_X(k) = (1-p)^{k-1}p, \quad k = 1, 2, \dots$$



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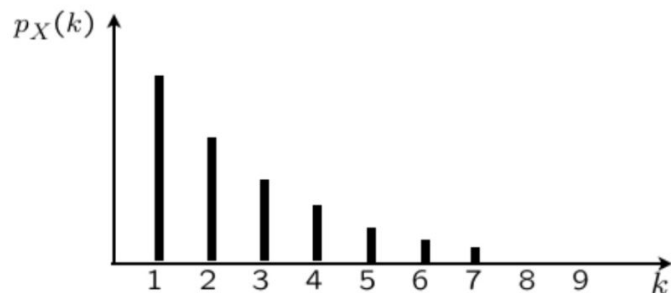
Conditioned on $X > \underline{n}$, $X - \underline{n}$ is geometric with parameter p

$$p_{X-1|X>1}(3) = P(X-1=3 | X>1) = P(T_2 T_3 H_4 | T_1) = P(T_2 T_3 H_4)$$

$$p_{X-1|X>1}(k) = p_X(k) = (1-p)^{k-1}p = p_X(3)$$

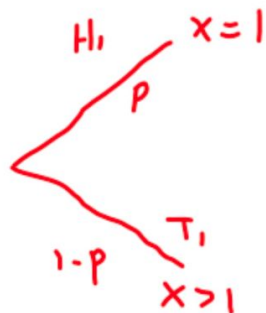
$$p_{X-n|X>n}(k)$$

The mean of the geometric



$$E[X] = \sum_{k=1}^{\infty} k p_X(k) = \sum_{k=1}^{\infty} k (1-p)^{k-1} p$$

$$E[X] = \frac{1}{p}$$



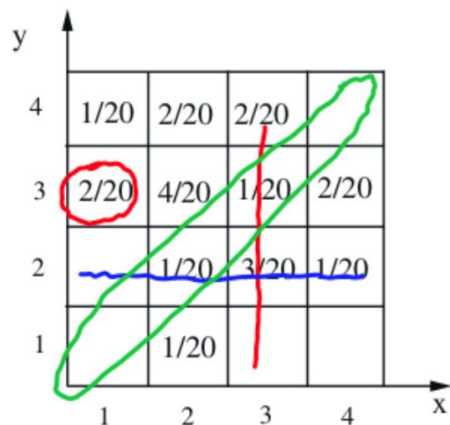
$$\begin{aligned} E[x] &= 1 + E[x-1] \\ &= 1 + p \cdot E[x-1 | x=1] + (1-p) E[x-1 | x>1] \\ &= 1 + 0 + (1-p) E[x] \end{aligned}$$

Multiple random variables and joint PMFs

$X : p_X$
 $Y : p_Y$

$$P(X = Y) = \frac{2}{20}$$

Joint PMF: $p_{X,Y}(x,y) = P(X = x \text{ and } Y = y)$



$p_X(3)$

$$p_{X,Y}(1,3) = \frac{2}{20}$$

$$p_X(4) = \frac{1}{20} + \frac{2}{20}$$

$$p_Y(2) = \frac{1}{20} + \frac{3}{20} + \frac{1}{20}$$

$$\sum_x \sum_y p_{X,Y}(x,y) = 1$$

$$p_X(x) = \sum_y p_{X,Y}(x,y)$$

$$p_Y(y) = \sum_x p_{X,Y}(x,y)$$

Linearity of expectations

$$\mathbf{E}[aX + b] = a\mathbf{E}[X] + b$$

$$\mathbf{E}[X + Y] = \mathbf{E}[X] + \mathbf{E}[Y]$$

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

$$(g(x, y) = x + y)$$

$$= \sum_x \sum_y (x + y) p_{X,Y}(x, y)$$

$$= \sum_x \underbrace{\sum_y x p_{X,Y}(x, y)} + \sum_x \sum_y y p_{X,Y}(x, y)$$

$$= \sum_x x \underbrace{\sum_y p_{X,Y}(x, y)} + \underbrace{\sum_x \sum_y y p_{X,Y}(x, y)}$$

$$= \sum_x x p_X(x) + \sum_y y p_Y(y) = E[X] + E[Y]$$

Linearity of expectations

$$\mathbf{E}[aX + b] = a\mathbf{E}[X] + b$$

$$\mathbf{E}[X + Y] = \mathbf{E}[X] + \mathbf{E}[Y]$$

$$\mathbf{E}[X_1 + \cdots + X_n] = \mathbf{E}[X_1] + \cdots + \mathbf{E}[X_n]$$

$$\mathbf{E}[2X + 3Y - Z] = E[2x] + E[3y] - E[z] = 2E[x] + 3E[y] - E[z]$$

The mean of the binomial

- X : binomial with parameters n, p
 - number of successes in n independent trials

$$E[X] = \sum_{k=0}^n k \underbrace{\binom{n}{k} p^k (1-p)^{n-k}}_{p_X(k)}$$

$$E[X] = np$$

$X_i = 1$ if i th trial is a success; $\swarrow p$
 $X_i = 0$ otherwise $\swarrow 1-p$ (indicator variable)

$$X = X_1 + \cdots + X_n$$

$$E[X] = \underbrace{E[X_1]}_p + \cdots + \underbrace{E[X_n]}_p = np$$

Independence

- of two events: $P(A \cap B) = P(A) \cdot P(B)$ $P(A | B) = P(A)$

- of a r.v. and an event: $P(\underline{X = x} \text{ and } \underline{A}) = P(X = x) \cdot P(A)$, for all x

$$P_{X|A}(x) = P_X(x), \text{ for all } x \quad P(A | X=x) = P(A), \text{ for all } x$$

- of two r.v.'s: $P(\underline{X = x} \text{ and } \underline{Y = y}) = P(X = x) \cdot P(Y = y)$, for all x, y

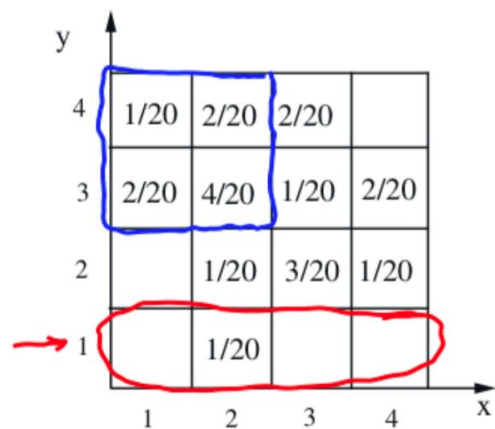
$$P_{X|Y}(x|y) = P_X(x) \quad p_{X,Y}(x, y) = p_X(x) p_Y(y), \text{ for all } x, y$$

$$P_{Y|X}(y|x) = P_Y(y)$$

X, Y, Z are **independent** if:

$$p_{X,Y,Z}(x, y, z) = p_X(x) p_Y(y) p_Z(z), \text{ for all } x, y, z$$

Example: independence and conditional independence



- Independent? *No*

$$P_X(1) = 3/20$$

$$P_{X|Y}(1|1) = 0$$

- What if we condition on $X \leq 2$ and $Y \geq 3$?

Yes .

1/3	1/9	2/9
2/3	2/9	4/9
	1/3	2/3

Independence and expectations

- In general: $E[g(X, Y)] \neq g(E[X], E[Y])$

always true

- Exceptions: $E[aX + b] = aE[X] + b$

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

If X, Y are **independent**: $E[XY] = E[X]E[Y]$

$g(X)$ and $h(Y)$ are also independent: $E[g(X)h(Y)] = E[g(X)] \cdot E[h(Y)]$

$$E[g(X, Y)] \quad g(x, y) = xy$$

$$= \sum_x \sum_y xy p_{x,y}(x, y) = \sum_x \sum_y \underbrace{xy}_{\text{circled}} p_x(x) p_y(y)$$

$$= \sum_x x p_x(x) \underbrace{\sum_y y p_y(y)}_{\text{underlined}} = E[X] E[Y]$$

Independence and variances

- Always true: $\text{var}(aX) = a^2 \text{var}(X)$ $\text{var}(X + a) = \text{var}(X)$
- In general: $\text{var}(X + Y) \neq \text{var}(X) + \text{var}(Y)$

If X, Y are independent: $\text{var}(X + Y) = \text{var}(X) + \text{var}(Y)$

assume

$$E[X] = E[Y] = 0$$

$$E[XY] = E[X]E[Y] = 0$$

$$\begin{aligned}\text{var}(X+Y) &= E[(X+Y)^2] = E[X^2 + 2XY + Y^2] \\ &= E[X^2] + 2E[XY] + E[Y^2] = \text{var}(X) + \text{var}(Y)\end{aligned}$$

- Examples:

– If $X = Y$: $\text{var}(X + Y) = \text{var}(2X) = 4\text{var}(X)$

– If $X = -Y$: $\text{var}(X + Y) = \text{var}(0) = 0$

– If X, Y independent: $\text{var}(X - 3Y) = \text{var}(X) + \text{var}(-3Y) = \text{var}(X) + 9\text{var}(Y)$

Variance of the binomial

- X : binomial with parameters n, p
 - number of successes in n independent trials

$X_i = 1$ if i th trial is a success;
 $X_i = 0$ otherwise

(indicator variable)

independent

$$X = X_1 + \cdots + X_n$$

$$\begin{aligned}\boxed{\text{var}(x)} &= \text{var}(X_1) + \cdots + \text{var}(X_n) \\ &= n \cdot \text{var}(X_1) = \boxed{np(1-p)}\end{aligned}$$