Review.

After Midterm content.

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See lecture 13, for pre-Midterm review.

First Rule: Enumerate objects with sequence of choices.

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Concept: Can programatically modify *text* of input program (to HALT).

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CS70: Review of Probability.

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Variance

► Variance: $var[X] := E[(X - E[X])^2] = E[X^2] - E[X]^2$

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- ► WLLN: X_m i.i.d. $\Rightarrow \frac{X_1 + \dots + X_n}{n} \approx E[X]$

Random Variables so far.

Probability Space: Ω , $Pr: \Omega \to [0,1]$, $\sum_{\omega \in \Omega} Pr(w) = 1$.

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- 6. Joint pdf: $Pr[X \in (x, x + \delta), Y = (y, y + \delta)) = f_{X,Y}(x, y)\delta^2$.
 - 6.1 Conditional Distribution: $f_{X|Y}(x,y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$.
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- $\begin{array}{ll} & X \sim Expo(\lambda) \\ & f_X(x) = \lambda \, e^{-\lambda x} \mathbf{1} \{ x \geq 0 \} \quad F_X(x) = 1 e^{\lambda x}. \\ & E[X] = \frac{1}{\lambda}. \\ & Var[X] = \frac{1}{\lambda^2} \\ & X = lim_{n \to \infty} \frac{1}{n} X \ G(\lambda/n) \\ & Pr[X > s + t | X > s] = Pr[X > t] \text{: Memoryless.} \end{array}$
- $X \sim N(\mu, \sigma). \ f(x) = \frac{1}{\sqrt{2\pi}} e^{-(x-\mu)^2} 2 \quad F(x) = \Phi(x) = \int_{-\infty}^{x} f(x) dx$ CLT: $A_n = \frac{X_1 + \cdots X_n}{n}, \ E[X] = \mu, \ \text{and} \ Var(X) = \sigma^2.$ $\lim_{n \to \infty} A_n \to N(\mu, \sigma)$ $\frac{X \mu}{\sigma} \sim N(0, 1).$

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- ▶ Calculating π : One finds $P\pi = \pi$ and π is distribution.

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- ▶ $Pr[|X-a| \ge b] \le \frac{E[(X-a)^2]}{b^2}$. True

- \triangleright Ω and A are independent. True
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$$\frac{\exp\{-\lambda 5\}}{\exp\{-\lambda 3\}} = \exp\{-\lambda 2\}.$$



Correct or not?

$$A_n = \frac{\sum_{i=0}^n X_i}{n}$$
, X_i i.i.d, mean μ and variance σ .

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$$A_n = \frac{\sum_{i=0}^{n} X_i}{n}$$
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$$A_n \in [\mu - 2\sigma \frac{1}{n}, \mu + 2\sigma \frac{1}{n}]$$
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▶ If
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$$Pr[|X - E[X]| \ge z] \le \frac{Var(X)}{z^2}$$
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[4]
$$Pr[|\frac{X_1+X_2+\cdots+X_n}{n}-E[X_1]| \geq \varepsilon] \rightarrow 0$$

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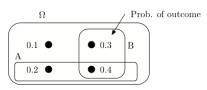
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$$Pr[|X - E[X]| \ge z] \le \frac{Var(X)}{z^2}$$
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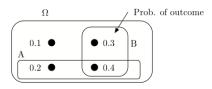
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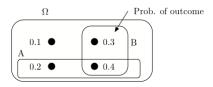
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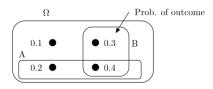
- ► WLLN (4) and (5)
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- E[Y|X=x] (3)



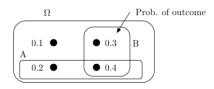




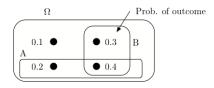
$$Pr[A|B] =$$



$$Pr[A|B] = \frac{Pr[A \cap B]}{Pr[B]} =$$

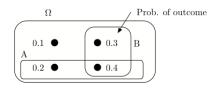


$$Pr[A|B] = \frac{Pr[A \cap B]}{Pr[B]} = \frac{0.4}{0.7}$$



1. What is P[A|B]?

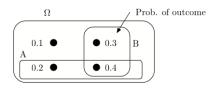
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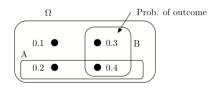
$$Pr[B|A] =$$



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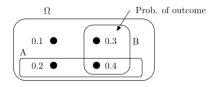
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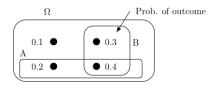
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2. What is Pr[B|A]?

$$Pr[B|A] = \frac{Pr[A \cap B]}{Pr[A]} = \frac{0.4}{0.6}$$

3. Are A and B positively correlated?



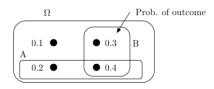
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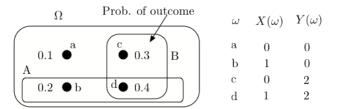
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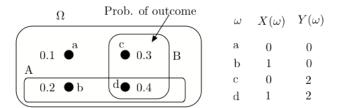
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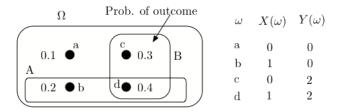
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$$Pr[A \cap B] = 0.4 < Pr[A]Pr[B] = 0.6 \times 0.7$$
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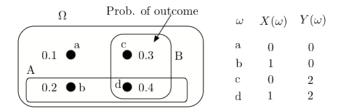




4. What is cov(X, Y)?

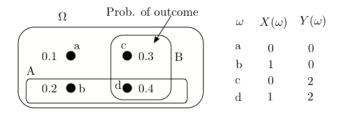


4. What is cov(X, Y)? cov(X, Y) =

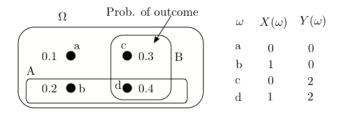


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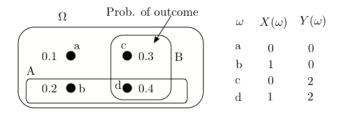
$$cov(X, Y) = E[XY] - E[X]E[Y]$$



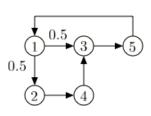
4. What is
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 $cov(X, Y) = E[XY] - E[X]E[Y]$
 $= 0.8 - 0.6 \times 1.4 =$

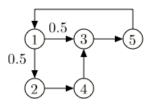


4. What is cov(X, Y)? cov(X, Y) = E[XY] - E[X]E[Y] $= 0.8 - 0.6 \times 1.4 = -0.04$

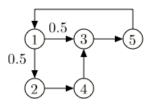


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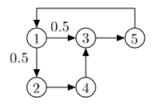




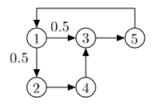
7. Is this Markov chains irreducible?



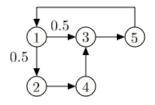
7. Is this Markov chains irreducible? Yes.



- 7. Is this Markov chains irreducible? Yes.
- 8. Is this Markov chain periodic?

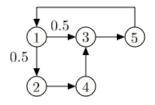


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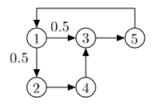
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No. The return times to 3 are

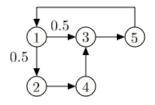


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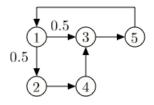
No. The return times to 3 are $\{3,5,..\}$:



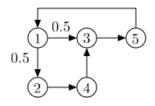
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 - No. The return times to 3 are {3,5,..}: coprime!
- 9. Does π_n converge to a value independent of π_0 ?

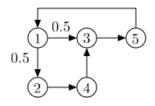


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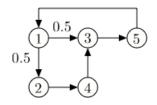
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- 10. Does $\frac{1}{n}\sum_{m=1}^{n-1}1\{X_m=3\}$ converge as $n\to\infty$?



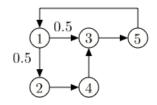
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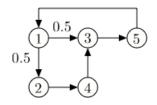
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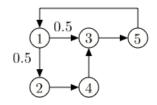
Let
$$a = \pi(1)$$
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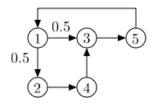
Let
$$a = \pi(1)$$
. Then $a = \pi(5)$,



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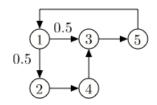
Let
$$a = \pi(1)$$
. Then $a = \pi(5), \pi(2) = 0.5a$,



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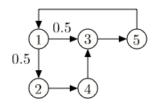
Let
$$a = \pi(1)$$
. Then $a = \pi(5), \pi(2) = 0.5a$, $\pi(4) = \pi(2) = 0.5a$,



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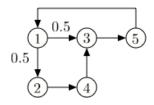
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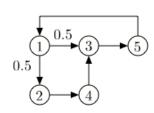
Let
$$a=\pi(1)$$
. Then $a=\pi(5), \pi(2)=0.5a$, $\pi(4)=\pi(2)=0.5a, \pi(3)=0.5\pi(1)+\pi(4)=a$. Thus, $\pi=[a,0.5a,a,0.5a,a]=[1,0.5,1,0.5,1]a$, so $a=1$

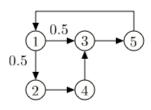


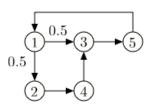
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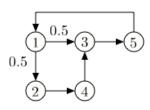
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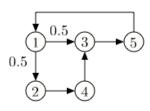


$$\beta(1) = 1 + 0.5\beta(2) + 0.5\beta(3)$$



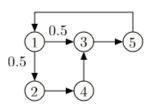
$$\beta(1) = 1 + 0.5\beta(2) + 0.5\beta(3)$$

 $\beta(2) = 1$



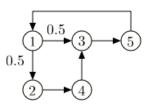
$$eta(1) = 1 + 0.5 \beta(2) + 0.5 \beta(3)$$

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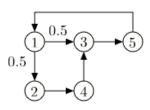


12. Write the first step equations for calculating the mean time from 1 to 4.

$$\beta(1) = 1 + 0.5\beta(2) + 0.5\beta(3)$$

 $\beta(2) = 1$
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13. Solve these equations.



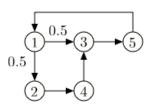
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$$\beta(1) = 1 + 0.5 \times 1 + 0.5 \times (1 + (1 + \beta(1)))$$



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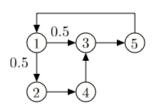
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= 2.5 + 0.5\beta(1).



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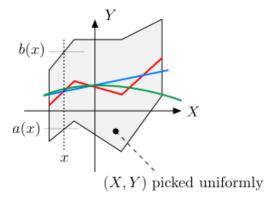
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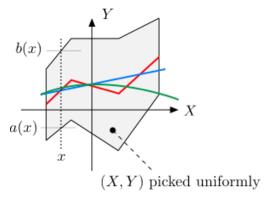
Hence, $\beta(1) = 5$.

14. Which is E[Y|X]? Blue, red or green?

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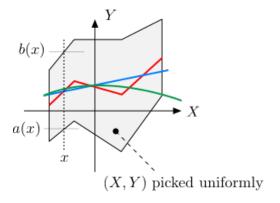


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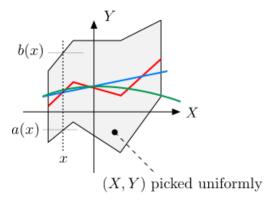
Answer: Red.

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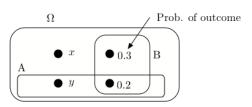


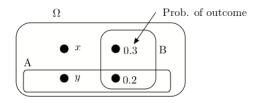
Answer: Red. Given X = x, Y = U[a(x), b(x)].

14. Which is E[Y|X]? Blue, red or green?

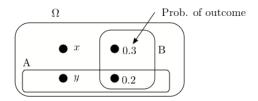


Answer: Red. Given X = x, Y = U[a(x), b(x)]. Thus, $E[Y|X = x] = \frac{a(x) + b(x)}{2}$.



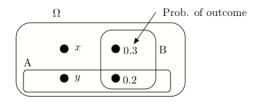


1. Find (x, y) so that A and B are independent.



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 We need

$$Pr[A \cap B] = Pr[A]Pr[B]$$

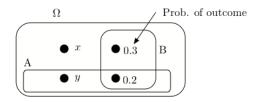


Find (x,y) so that A and B are independent.
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That is,

$$0.2 = (y + 0.2) \times 0.5 =$$



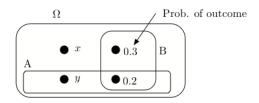
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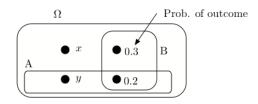
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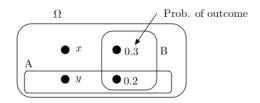
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$$y = 0.2 \text{ and } x =$$



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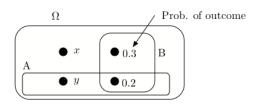
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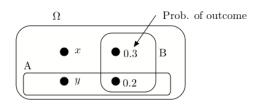
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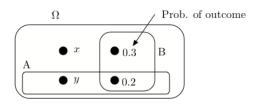
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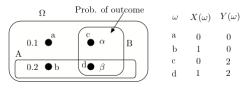
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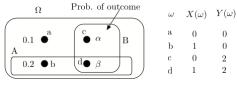
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Hence,

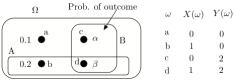
$$y = 0.2$$
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2. Find the value of x that maximizes Pr[B|A]. When x = 0.5, Pr[B|A] = 1.

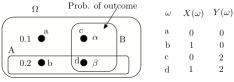




3. Find α so that X and Y are independent.

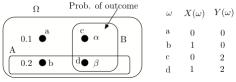


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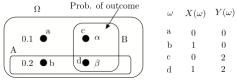
$$Pr[X = 0, Y = 0] = Pr[X = 0]Pr[Y = 0]$$



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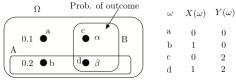


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$$Pr[X = 0, Y = 0] = Pr[X = 0]Pr[Y = 0]$$

That is,

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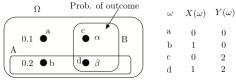
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We need

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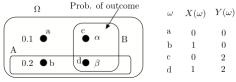
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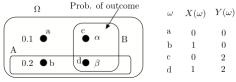
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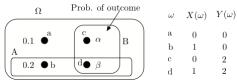
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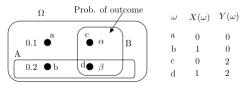
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Hence,

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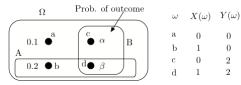
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But: A and B independent $\iff \overline{A}, B$ independent.

Take: A = "X = 0" and B = "Y = 0", since only two values for X, Y

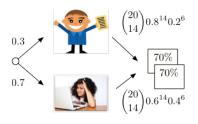
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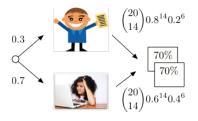
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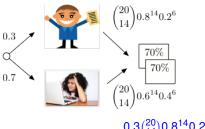
4. A CS70 student is great w.p. 0.3 and good w.p. 0.7. A great student solves each question correctly w.p. 0.8 whereas a good student does it w.p. 0.6. One student got right 70% of the 10 questions on Midterm 1 and 70% of the 10 questions on Midterm 2.



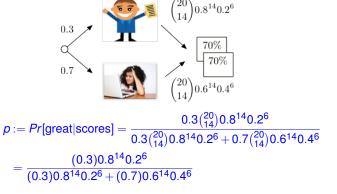
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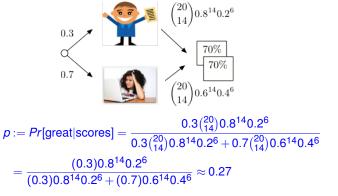


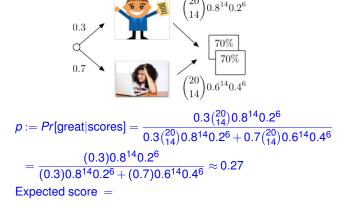
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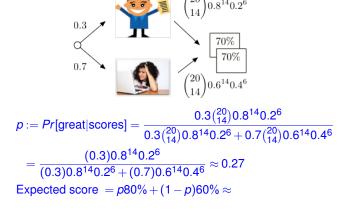


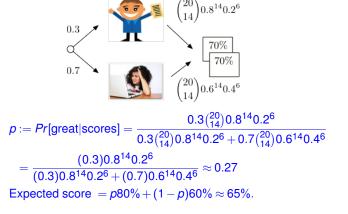
$$p := Pr[\text{great}|\text{scores}] = \frac{0.3\binom{20}{14}0.8^{14}0.2^{6}}{0.3\binom{20}{14}0.8^{14}0.2^{6} + 0.7\binom{20}{14}0.6^{14}0.4^{6}}$$











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Hence,

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$$E[\text{ lifespan of other bulb }] =$$

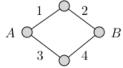
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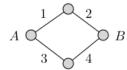
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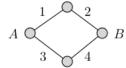
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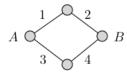


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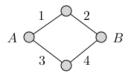
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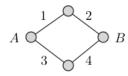
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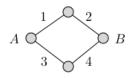
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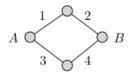
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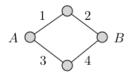
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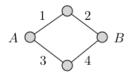


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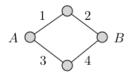


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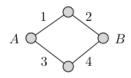
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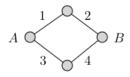
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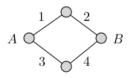
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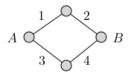
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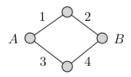
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 In the figure, 1,2,3,4 are links that fail after i.i.d. times that are U[0,1].

Find the average time until *A* and *B* are disconnected.

$$Pr[Y_1 > t] = Pr[X_1 > t]Pr[X_2 > t] = (1 - t)^2$$

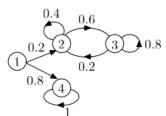
$$Pr[Z \le t] = Pr[Y_1 \le t]Pr[Y_2 \le t] = (1 - (1 - t)^2)^2$$

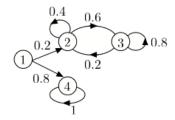
$$= (2t - t^2)^2 = 4t^2 - 4t^3 + t^4$$

$$f_Z(t) = 8t - 12t^2 + 4t^3$$

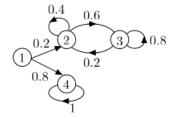
$$E[Z] = \int_0^1 tf_Z(t)dt = 8\frac{1}{3} - 12\frac{1}{4} + 4\frac{1}{5}$$

$$\approx 0.4667.$$

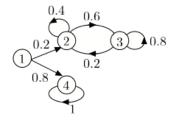




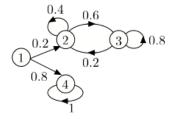
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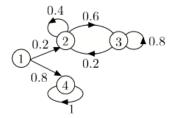
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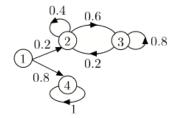
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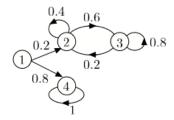
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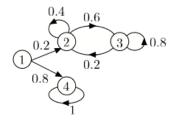
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