



Computer
Science

CSC380: Principles of Data Science

Probability Primer 3 Alon Efrat

Outline:

- Independence
- Random variables
- Distribution

Credit:

- Jason Pacheco,
- Kwang-Sung Jun,
- Chicheng Zhang
- Xinchen yu

1

1

Outline

2

- Independence
- Random variables
- Distribution

2

Independence

3

3

Independence

4

- Informally, given two events A and B, they are **independent** if the probability of A is not affected by whether B is true or false (and vice versa)
 - E.g., A = “die1=1” and B=“die2=1” are independent.
 \Rightarrow the probability of die1 being 1 would not be changed just because die2=1.
- Mathematically, this can be written as $P(A|B) = P(A)$ or $P(B|A) = P(B)$.
- E.g., A = “die1=1” and B=“two dice sum to 6” are **not independent**.

$\because P(A) = 1/6 = 0.166\dots$. However, $P(A|B) = 1/5 = 0.2$

quiz candidate

$A = \{(1,1), (1,2), (1,3), (1,4), (1,5), (1,6)\}$

$B = \{(1,5), (2,4), (3,3), (4,2), (5,1)\}$

4

Independence

5

- Informally, given two events A and B, they are **independent** if the probability of A is not affected by whether B is true or false (and vice versa)
- Mathematically, this can be written as $P(A|B) = P(A)$ or $P(B|A) = P(B)$.

$$P(A|B) = \frac{P(A, B)}{P(B)} = P(A)$$

$$P(B|A) = \frac{P(B, A)}{P(A)} = P(B)$$

$$P(A, B) = P(A)P(B)$$

$A \perp B$: A and B are independent

5

Independence

6

[Def] Two events A and B are **independent** if
 $P(A, B) = P(A)P(B)$

$A \perp B$ means A and B are independent

“joint probability is product of two marginal probabilities”

=> note: symmetric!

Also, a set of events $\{A_i\}_{i=1}^n$ (n can be ∞) are **mutually independent** if

for every $J \subseteq \{1, \dots, n\}$, we have $P(\cap_{i \in J} A_i) = \prod_{i \in J} P(A_i)$

6

Random Events and Probability

7

Rolling two fair dice

(2,2)	(3,5)		(6,2)	(1,6)	
(5,2)	(5,3)				(5,6)
(4,3)	(2,6)	(3,4)	(1,2)	(4,2)	(3,1)
(3,2)	(6,4)		(2,1)	(1,5)	(5,1)
(4,4)	(6,5)	(5,4)	(6,1)	(3,3)	
			(1,1)		(1,4)
(4,5)	(5,5)	(6,3)			
(3,6)	(2,5)	(6,6)	(1,3)	(4,1)	(2,3)

Each outcome is equally likely.
by the **independence**
=> 1/36

7

Independence

8

- Ex) recall two fair dice

- We took it for granted that $P((1,1))$ is 1/36.
- But why is it true, really?
- To be rigorous,

$$P(\text{die1} = 1, \text{die2} = 1) = P(\text{die1} = 1)P(\text{die2} = 1) = \frac{1}{6} \cdot \frac{1}{6}$$

due to independence.

- E.g., two biased coin **C1** and **C2**. Suppose $P(C1=H) = 0.3$ and $P(C2=H) = 0.4$. Compute the probability of $P(C1=H, C2=T)$.

$$0.3 \cdot 0.6 = 0.18$$

quiz candidate

8

Example: Dependent Coin Flips

9

- First coin (X1): fair coin
- Second coin (X2):
 - if $X1=H$, throw a **fair** coin.
 - If $X1=T$, throw an **unfair** coin $P(H) = 0.2$, $P(T) = 0.8$

- Q: Are $X1=H$ and $X2=H$ independent or not?

$$P(X1=H) = \underline{\hspace{2cm}} \quad 0.5$$

$$P(X2=H) = \underline{\hspace{2cm}} = P(X2=H, X1=H) + P(X2=H, X1=T) = 0.25 + 0.1 = 0.35$$

$$P(X1=H, X2=H) = \underline{\hspace{2cm}} \quad 0.25$$

$$P(X1=H) \cdot P(X2=H) = 0.175$$

Quiz candidate

9

Review

10

Axiom 3:

For any *finite* or *countably infinite* sequence of disjoint events E_1, E_2, E_3, \dots , $P\left(\bigcup_{i \geq 1} E_i\right) = \sum_{i \geq 1} P(E_i)$

Inclusion-exclusion rule:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

Law of total probability: For events B_1, B_2, \dots that partitions Ω ,

$$P(A) = \sum_i P(A \cap B_i)$$

Conditional probability:

$$P(A|B) := \frac{P(A \cap B)}{P(B)}$$

($P(A|B) \neq P(B|A)$ in general)

Probability chain rule:

$$P(A \cap B \cap C) = P(A|B \cap C)P(B|C)P(C)$$

Law of total probability + Conditional probability: $P(A) = \sum_i P(A \cap B_i) = \sum_i P(B_i)P(A|B_i) = \sum_i P(A)P(B_i|A)$

Bayes' rule:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

Independence:

(definition) A and B are independent if $P(A, B) = P(A)P(B)$

(property) A and B are independent if and only if $P(A|B) = P(A)$ (or $P(B|A) = P(B)$)

10

Random Variables and Probability

11

11

Random Variables

My own perspective:

A random variable is actually a **function**. This function assigns a numerical value to each outcome of the experiment.

These values do not need to "make sense". Any definition is legit.

Two outcomes could have the same value assigned to them by a random variable.

Example: Tossing a fair coin. Let's define a new random var Q .

If the coin shows Face, then we decide that $Q=15$.

If the coin shows HEAD, then we decide that $Q=3$.

Now we can ask what are the events that are correlated to each value of Q ? What is the probability of these events?

For example,

what is the probability $P(Q=12)$?

What is the probability $P(Q=15)$?

Harder: What is the probability $P(Q<16)$? First find which event corresponds to.

12

12

Random Variables and Probability

13

Suppose we are interested in probabilities about the sum of two dice...

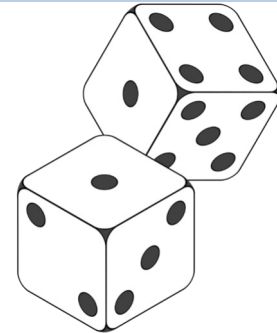
Option 1 Let E_i be event that the sum equals i

Two dice example:

$$E_2 = \{(1, 1)\} \quad E_3 = \{(1, 2), (2, 1)\} \quad E_4 = \{(1, 3), (2, 2), (3, 1)\}$$

$$E_5 = \{(1, 4), (2, 3), (3, 2), (4, 1)\} \quad E_6 = \{(1, 5), (2, 4), (3, 3), (4, 2), (5, 1)\}$$

Enumerate all possible outcomes obtaining the desired sum.
Gets cumbersome for $N > 2$ dice...



13

Random Variables and Probability

14

Suppose we are interested in probabilities about the sum of dice...

Option 2 Give it a name

Let X be the sum of two dice.

We can say the event " $X = i$ " to mean E_i .

X is called **random variable**.

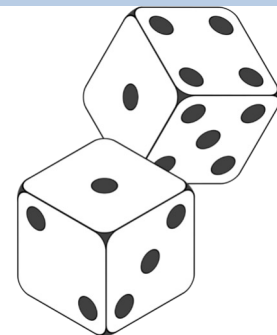
$$P(X = 2) = 1/36$$

$$P(X = 3) = 2/36$$

$$P(X = 4) = 3/36$$

...

$$P(X = 12) = 1/36$$



14

Random Variables and Probability

15

A random variable is a numerical description of the outcomes of a statistical experiment.

Example 1

- let X = sum of two dice;
- probability of X on different values:

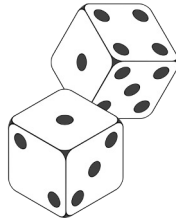
$$P(X = 2) = 1/36$$

$$P(X = 3) = 2/36$$

$$P(X = 4) = 3/36$$

$$\dots$$

$$P(X = 12) = 1/36$$

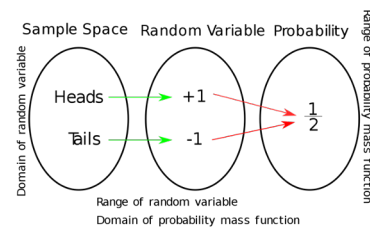


Example 2.

- let Y = outcomes of one coin toss;
- probability of Y on 1 (head) and -1 (tail):

$$P(Y = 1) = 1/2$$

$$P(Y = -1) = 1/2$$

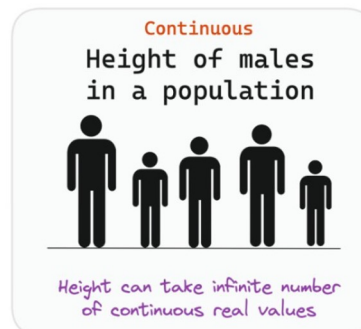
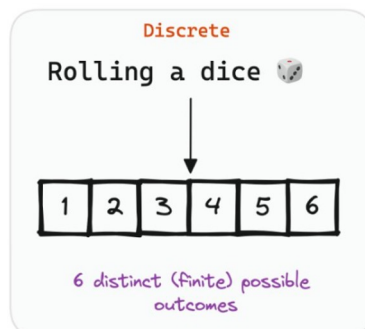


15

Random Variables and Probability

16

- A discrete random variable takes a finite or countable number of distinct values.
- A continuous random variable takes an infinite number of values within a specified range or interval.



16

Random Variables and Probability

17

- All the laws/rules about events applies to RVs.

The **law of total probability** for random variable is,

$$P(y) = \sum_i P(y, x_i) \quad P(Y = y) = \sum_x P(Y = y, X = x)$$

for all x : $P(X=x) > 0$

... you will also see people write down $p(Y) = \sum_x p(Y, X = x)$

This means $p(Y = y) = \sum_x p(Y = y, X = x)$ for all y

17

Random Variables and Probability

18

- I have three bags that each contain 100 marbles:

- Bag A has 75 red and 25 blue marbles;
- Bag B has 60 red and 40 blue marbles;
- Bag C has 45 red and 55 blue marbles.

$$P(Y = y) = \sum_x P(Y = y, X = x)$$

I choose one of the bags at random and then pick a marble from the chosen bag, also at random.
What is the probability that the chosen marble is red?

$$P(Y = 1|X = 1) = 0.75$$

$$P(Y = 1|X = 2) = 0.60$$

$$P(Y = 1|X = 3) = 0.45$$

Y: pick a marble
X: choose a bag

$$P(X = 1) = P(X = 2) = P(X = 3) = \frac{100}{300} = 1/3$$

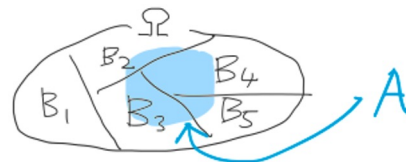
$$\begin{aligned} P(Y = 1) &= P(Y = 1, X = 1) + P(Y = 1, X = 2) + P(Y = 1, X = 3) \\ &= P(Y = 1|X = 1)P(X = 1) + P(Y = 1|X = 2)P(X = 2) + P(Y = 1|X = 3)P(X = 3) \\ &= 0.75 \times \frac{1}{3} + 0.60 \times \frac{1}{3} + 0.45 \times \frac{1}{3} \\ &= 0.60 \end{aligned}$$

18

Conditional Probability

19

$$P(Y) = \sum_x P(Y, X = x)$$



Also works for conditional probabilities,

$$p(Y | Z) = \sum_x p(Y, X = x | Z)$$

Rule: Any rules about the probability still works for the conditional probabilities!!

(just make sure you add the conditioning part for every p(!))

Proof:

$$P(Y|Z) = \frac{P(Y,Z)}{P(Z)} = \frac{\sum_x P(Y,Z,X=x)}{P(Z)} = \frac{\sum_x P(Y,X=x|Z)P(Z)}{P(Z)} = \sum_x P(Y, X = x|Z)$$

19

Conditional Probability

20

Conditional probability version

Conditional probability $p(X | Y) = \frac{p(X,Y)}{p(Y)}$

$$p(X|Y,Z) = \frac{p(X,Y|Z)}{p(Y|Z)}$$

Proof:

$$p(X|Y,Z) = \frac{p(X,Y,Z)}{p(Y,Z)} = \frac{p(X,Y|Z)p(Z)}{p(Y|Z)p(Z)}$$



20

Conditional Probability

21

Conditional probability version

Conditional probability $p(X | Y) = \frac{p(X, Y)}{p(Y)}$

$$p(X|Y, Z) = \frac{p(X, Y|Z)}{p(Y|Z)}$$

↑ there is no 'double' conditioning

Chain rule: $p(X, Y) = p(X|Y)p(Y)$

$$p(X, Y|Z) = p(X|Y, Z)p(Y|Z)$$

HW1, hint 4

Bayes rule: $p(X|Y) = \frac{p(Y|X)p(X)}{p(Y)}$

$$p(X|Y, Z) = \frac{p(Y|X, Z)p(X|Z)}{p(Y|Z)}$$

Proof:

$$p(X|Y, Z) = \frac{p(X, Y, Z)}{p(Y, Z)} = \frac{p(Y|X, Z)p(X, Z)}{p(Y, Z)} = \frac{p(Y|X, Z)p(X|Z)p(Z)}{p(Y|Z)p(Z)}$$

21

Tabular Calculations for Random Variables

22

Tabular representation of two binary RVs (joint probability)

Use K-by-K probability table for K-valued discrete RVs

Y

e.g., X = disease, Y = test result

$$P(Y) = \sum_x P(Y, X = x)$$

	X	Y	
		y 1	y 2
	x 1	0.04	0.36
	x 2	0.30	0.30

0.4
0.6
P(X)

$P(x_1)$
 $P(x_2)$

$P(y_1) = P(x_1, y_1) + P(x_2, y_1)$
 $P(y_2) = P(x_1, y_2) + P(x_2, y_2)$
 [i.e., sum down columns]

0.3
0.6
P(Y)

$P(y_1)$
 $P(y_2)$

$P(X=x_1) = P(x_1, y_1) + P(x_1, y_2)$
 $P(X=x_2) = P(x_2, y_1) + P(x_2, y_2)$
 [i.e., sum across rows]

22

Tabular Calculations for Random Variables

23

e.g., X = disease, Y = test result

We don't care about event $Y=y_2$

		Y	
		y	y
		1	2
X	x	0.04	Censored!
	x	0.30	
	2		

$P(X | Y = y_1)?$

0.3
4 \nearrow $P(y_1)$

23

Tabular Calculations for Random Variables

24

		Y=y ₁	
X	x	0.04	\rightarrow <div style="border: 1px solid orange; border-radius: 50%; padding: 10px; display: inline-block;"> $0.04 / 0.34$ $0.30 / 0.34$ </div> $P(X y_1)$
	x	0.30	
	2		

$P(X=x_1 | Y = y_1) = P(x_1, y_1)/P(y_1)$

0.3
4 \nearrow $P(y_1)$

These sum to one:
 A conditional probability is still a
 'probability'.

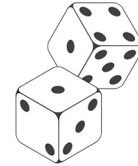
24

Independence

25

Definition Two random variables X and Y are independent given if and only if

$$p(X = x, Y = y) = p(X = x)p(Y = y)$$



for all values x and y , and we say $X \perp Y$.

- From now on, we will just write it down as $p(X, Y) = p(X)p(Y)$
- Property: X and Y are independent if and only if $p(X) = p(X|Y)$ (or $p(Y) = p(Y|X)$)

□ N RVs are independent if

$$p(X_1, \dots, X_N) = \prod_{i=1}^N p(X_i)$$

(Again, for all the possible values x_1, \dots, x_N)

25

Conditional Independence

26

Definition Two random variables X and Y are conditionally independent given Z if and only if,

$$p(X = x, Y = y \mid Z = z) = p(X = x \mid Z = z)p(Y = y \mid Z = z)$$

for all values x , y , and z , and we say that $X \perp Y \mid Z$.

□ N RVs conditionally independent, given Z , if and only if:

$$p(X_1, \dots, X_N \mid Z) = \prod_{i=1}^N p(X_i \mid Z)$$

Caveat: $X \perp Y \neq X \perp Y|Z$

26

Discrete Distributions

27

27

Distribution

28

- If X is a random variable, then we can talk about its 'distribution'
- **Distribution**: the set of values X can take and the probability assigned to each value.

- Examples:

X_1 : unfair coin

value	prob.
1	0.2
2	0.8

X_2 : unfair die

value	prob.
1	0.1
2	0.15
3	0.15
4	0.15
5	0.15
6	0.3

- Such a table can be viewed as a function $f(x)$. This is called **probability mass function (PMF)**.

28

Distribution

29

Another example.

- let S = sum of two dice;
- probability of S on different values:

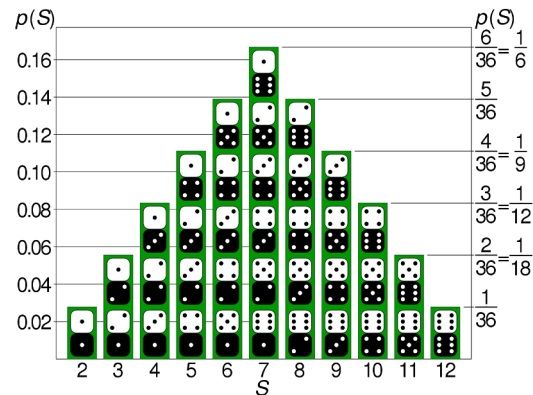
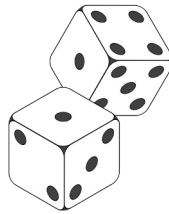
$$P(S = 2) = 1/36$$

$$P(S = 3) = 2/36$$

$$P(S = 4) = 3/36$$

...

$$P(S = 12) = 1/36$$



$$\text{PMF: } f_X(S) = \frac{\min(S-1, 13-S)}{36}, \text{ for } S \in \{2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12\}$$

29

Uniform Distribution

30

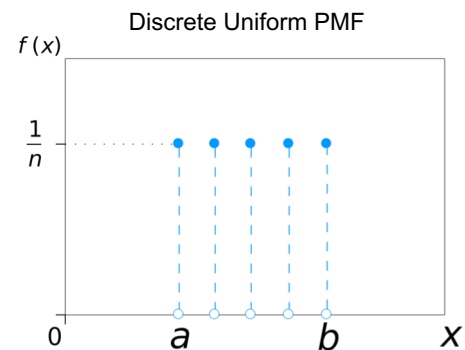
Generalization of fair die with N -faced die. Its PMF is:

$$p(X = k) = \frac{1}{N}$$

More generally, we define a set of numbers $\{v_1, v_2, \dots, v_N\}$

$$\text{Uniform}(X=k; \{v_1, v_2, \dots, v_N\}) = \begin{cases} \frac{1}{N} & \text{if } k \in \{v_1, v_2, \dots, v_N\} \\ 0 & \text{o.w} \end{cases}$$

↑ it's like $P(X=k)$
but being explicit
about 'what' distribution
 X follows.



30

Reminder: The number of combinations:

Assume we have 4 letters. How many permutations? Let's play. From the set ABCD, create a permutation $\pi = x_1 x_2 x_3 x_4$ by first picking for x_4 . There are 4 ways to pick x_4 . After this choice we are left with only 3 choices for x_3 , only 2 for x_3 and 1 for x_1 . Altogether $4 \cdot 3 \cdot 2 \cdot 1 = 4!$

The same holds if we discuss n letters, $\pi = x_1 x_2 x_3 x_4 \dots x_n$. The number of permutations is $n! = n(n-1)(n-2) \dots 1$.

What if after setting the order, we decide that we only care which letters appear in the blue and which in the red of $\pi = x_1 x_2 x_3 x_4 x_5 x_6$. We don't care about their order within the red and blue parts. Then the number of permutations $n!$ should be divided by the number of permutations of red, and then by the number of permutation of blue. So the **binomial coefficient** is

$$\binom{n}{k} = \frac{n!}{k! (n-k)!}$$

31

31

Bernoulli distribution

32

Bernoulli a.k.a. the **coin flip** distribution on binary RVs $X \in \{0, 1\}$

$$\text{PMF: } p(X = x) = \pi^x (1 - \pi)^{1-x}$$

Where π is the probability of **success** (e.g., heads)

Suppose we flip N independent coins X_1, X_2, \dots, X_N , what is the distribution over their sum $Y = \sum_{i=1}^N X_i$

Num. "successes" out of N trials

Num. ways to obtain k successes out of N

Binomial Dist.

$$p(Y = k) = \binom{N}{k} \pi^k (1 - \pi)^{N-k}$$



32

Binomial distribution

33

Binomial Dist. $p(Y = k) = \binom{N}{k} \pi^k (1 - \pi)^{N-k}$

Why is this true?

Say $N=5$. Compute $p(Y=3)$

$$p(\text{HTTTH}) = \pi(1 - \pi)(1 - \pi)\pi\pi$$

$$p(\text{TTHHH}) = (1 - \pi)(1 - \pi)\pi\pi\pi$$

...

$$\begin{aligned} p(Y=3) &= p(\text{HTTTH}, \text{TTHHH}, \text{HTTTH}, \dots, \text{HHHTT}) \\ &= p(\text{HTTTH}) + p(\text{TTHHH}) + \dots + p(\text{HHHTT}) \\ &= \binom{5}{3} \pi^3 (1 - \pi)^2 \end{aligned}$$

The values are the same: $\pi^3 (1 - \pi)^2$!

By axiom 3, just add up $\pi^3 (1 - \pi)^2$ over all possible outcomes with the # of H is 3.

⇒ count: **N choose k!**

You'll use the same argument for HW1

33

Homework 1

34

Law of total probability for conditional probability $p(Y | Z) = \sum_x p(Y, X = x | Z)$

$$P(W | S = (i, j)) = P(W, R_{i+j+1} = 1 | S = (i, j)) + P(W, R_{i+j+1} = 0 | S = (i, j))$$

Chain rule $p(X, Y | Z) = p(X | Y, Z) p(Y | Z)$

$$P(W, R_{i+j+1} | S = (i, j)) = P(W | R_{i+j+1}, S = (i, j)) P(R_{i+j+1} | S = (i, j)) \rightarrow \frac{1}{2}$$

round $i+j+1$ you win and you have already win i rounds, opponents win j rounds = you win $i+1$, opponents win j

$$P(W | R_{i+j+1} = 1, S = (i, j)) = P(W | S = (i + 1, j))$$

round $i+j+1$ you lose and you have already win i rounds, opponents win j rounds = you win i , opponents win $j+1$

$$P(W | R_{i+j+1} = 0, S = (i, j)) = P(W | S = (i, j + 1))$$

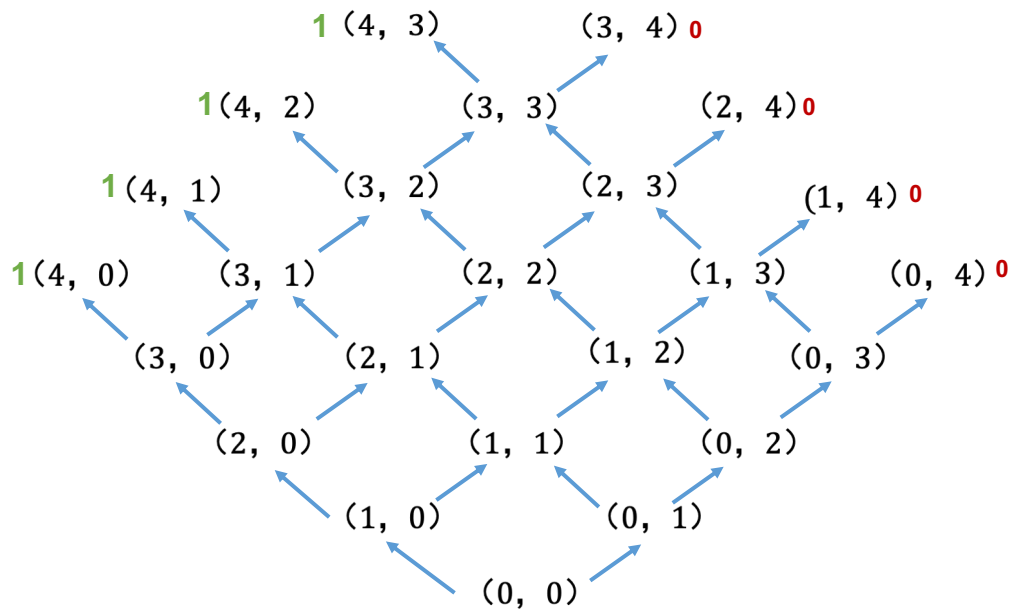
We can get the probability of win in this round based on the probabilities of next round (recursive)

$$P(W | S = (i, j)) = P(W | S = (i, j + 1)) \times 1/2 + P(W | S = (i + 1, j)) \times 1/2$$

34

Homework 1

35



35