

CS5314

Randomized Algorithms

Lecture 21: Markov Chains
(Definitions, Solving 2SAT)

Objectives

- Introduce **Markov Chains**
 - powerful model for special random processes
- Analyze a simple randomized algorithms for **2SAT** and **3SAT** problems

Stochastic Process

Definition: A collection of random variables $X = \{ X_t \mid t \in T \}$ is called a **stochastic process**. The index t often represents time; X_t is called the **state** of X at time t

E.g., A gambler is playing a fair coin-flip game: wins \$1 if head, loses \$1 if tail

Let X_0 = a gambler's initial money

X_t = a gambler's money after t flips

→ $\{ X_t \mid t \in \{0, 1, 2, \dots\} \}$ is a stochastic process

Stochastic Process (2)

Definition: If X_t assumes values from a finite set, then the process is a **finite** stochastic process

Definition: If T (where the index t is chosen) is countably infinite, the process is a **discrete time** process

Question: In the previous example about a gambler's money, is the process finite?
Is the process discrete time?

Markov Chain (Definition)

Definition: A discrete time stochastic process $X = \{X_0, X_1, X_2, \dots\}$ is a **Markov chain** if

$$\begin{aligned} & \Pr(X_t = a \mid X_{t-1} = b, X_{t-2} = a_{t-2}, \dots, X_0 = a_0) \\ &= \Pr(X_t = a \mid X_{t-1} = b) = P_{b,a} \end{aligned}$$

That is, the value of X_t depends on the value of X_{t-1} , but **not** the history how we arrived at X_{t-1} with that value

Question: In the example about a gambler's money, is the process a Markov chain?

Markov Chain (2)

In other words, if X is a Markov chain, then

$$\Pr(X_1 = a \mid X_0 = b) = P_{b,a}$$

$$\Pr(X_2 = a \mid X_1 = b) = P_{b,a}$$

...

$$\begin{aligned} \rightarrow P_{b,a} &= \Pr(X_1 = a \mid X_0 = b) \\ &= \Pr(X_2 = a \mid X_1 = b) \\ &= \Pr(X_3 = a \mid X_2 = b) = \dots \end{aligned}$$

Markov Chain (3)

- Next, we focus our study on Markov chain whose state space (the set of values that X_t can take) is **finite**
- So, without loss of generality, we label the states in the state space by $0, 1, 2, \dots, n$
- The probability $P_{i,j} = \Pr(X_t = j \mid X_{t-1} = i)$ is the probability that the process moves from **state i** to **state j** in one step

Transition Matrix

- The definition of Markov chain implies that we can define it using a **one-step transition matrix** P with

$$P_{i,j} = \Pr(X_t = j \mid X_{t-1} = i)$$

Question: For a particular i , what is $\sum_j P_{i,j}$?

Transition Matrix (2)

- The transition matrix representation of a Markov chain is very convenient for computing the distribution of future states of the process
- Let $p_i(t)$ denote the probability that the process is at state i at time t

Question: Can we compute $p_i(t)$ from the transition matrix P , assuming we know $p_0(t-1), p_1(t-1), \dots$?

Transition Matrix (3)

The value of $p_i(t)$ can be expressed as:

$$p_0(t-1) P_{0,i} + p_1(t-1) P_{1,i} + \dots + p_n(t-1) P_{n,i}$$

In other words, let $\langle p(t) \rangle$ denote the vector

$$(p_0(t), p_1(t), \dots, p_n(t))$$

Then, we have

$$\langle p(t) \rangle = \langle p(t-1) \rangle P$$

Transition Matrix (4)

- For any m , we define the m -step transition matrix $P^{(m)}$ such that

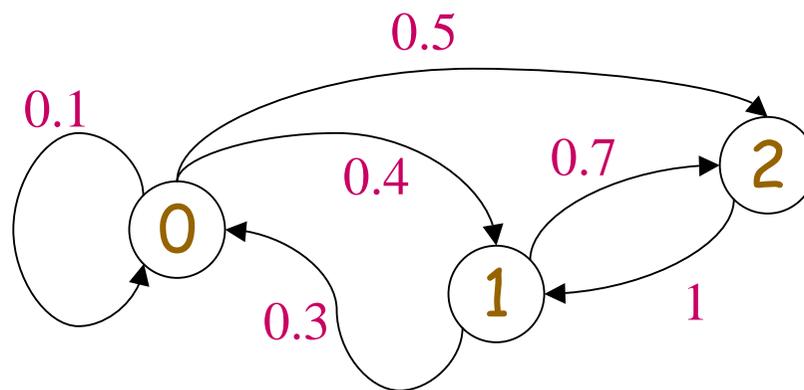
$$P^{(m)}_{i,j} = \Pr(X_{t+m} = j \mid X_t = i),$$

which is the probability that we move from state i to state j in exactly m steps

- It is easy to check that $P^{(2)} = P^2$,
 $P^{(3)} = P \cdot P^{(2)} = P^3$, and in general, $P^{(m)} = P^m$
 $\rightarrow \langle p(t+m) \rangle = \langle p(t) \rangle P^m$

Directed Graph Representation

- Markov chain can also be expressed by a directed weighted graph (V, E) , such that
 - V = state space
 - E = transition between states
 - weight of edge $(i, j) = P_{i,j}$



Application: Solving 2SAT

- Given a Boolean formula F , with each clause consisting exactly 2 literals. Our task is to determine if F has satisfiable
→ Can be solved in **linear** time! (how??)
- Let $n = \#$ variables in F
- In the next slide, we describe a randomized algorithm for solving this problem, which is **not** efficient...
 - However, we can modify the algorithm a bit to solve the case when each clause has 3 literals instead (3SAT is NP-complete!)

1. Start with an arbitrary assignment
2. Repeat $2cn^2$ times, terminating with all clauses satisfied
 - (a) Choose a clause that is currently not satisfied
 - (b) Choose uniformly at random one of the literals in the clause and switch its value
3. If valid assignment found, return it
4. Else, conclude that F is not satisfiable

Application: Solving 2SAT (3)

Questions:

(1) When will the algorithm make a wrong conclusion?

Ans. ... only when the formula is satisfiable, but the algorithm fails to find a satisfying assignment

(2) What is the success probability?

Ans. ... let's study it using Markov chain $\hat{_}$

Application: Solving 2SAT (4)

- Firstly, suppose that the formula F is satisfiable (for the other case, we don't care much since the algorithm must give correct answer)
- That means, a particular assignment to the n variables in F can make F true
- Let A^* = this particular assignment
- Also, let A_t = the assignment of variables after the t^{th} iteration of Step 2
- Let X_t = the number of variables that are assigned the same value in A^* and A_t

Application: Solving 2SAT (5)

E.g., suppose that

$$F = (x_1 \vee \neg x_2) \wedge (x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_3)$$

and A^* : $x_1 = T, x_2 = T, x_3 = F$

- Also, suppose that after 4 iterations of Step 2 in the algorithm, we have

$$A_4: x_1 = F, x_2 = T, x_3 = F$$

→ $X_4 = \#$ variables that are assigned the same value in A^* and A_4
 $= 2$

Application: Solving 2SAT (6)

- So, when $X_+ = n$, the algorithm terminates with a satisfying assignment
 - ... in fact, the algorithm may terminate before X_+ reaches n , as it is possible that we find another satisfying assignment
 - ... but for our analysis, we are very **pessimistic**, and we consider the algorithm only stops when $X_+ = n$
- Let us take a closer look of how X_+ changes over time, so that we can tell how long it takes for X_+ to reach n

Application: Solving 2SAT (7)

- First, when $X_t = 0$, any change in the current assignment A_t must increase the # of matching assignment with A^* by 1. So,

$$\Pr(X_{t+1} = 1 \mid X_t = 0) = 1$$

- When $X_t = j$, with $1 \leq j \leq n-1$, we will choose a clause that is false with the current assignment A_t , and change the assignment of one of its variable next ...

Application: Solving 2SAT (8)

Question: What can be the value of X_{t+1} ?

Ans. ... it can either be $j-1$ or $j+1$

Question: Which is more likely to be X_{t+1} ?

Ans. ... $j+1$. It is because the assignment A^* will make this clause true, which must mean that either one, or both the variables in this clause is assigned differently in $A_t \rightarrow$ If we change one variable randomly, at least $1/2$ of the time A_{t+1} will match more with A^*

Application: Solving 2SAT (9)

- So, for j , with $1 \leq j \leq n-1$ we have

$$\Pr(X_{t+1} = j+1 \mid X_t = j) \geq 1/2$$

$$\Pr(X_{t+1} = j-1 \mid X_t = j) \leq 1/2$$

- Note: the stochastic process X_0, X_1, X_2, \dots is not necessarily a Markov chain...
 - Reason : the transition probabilities, e.g., $\Pr(X_{t+1} = j+1 \mid X_t = j)$, is not a constant
(sometimes, it can be 1, sometimes, it can be 1/2 ...
in fact, this value depends on which j variables are matching with A^* , which in fact depends on the history of how we obtain A_t)

Application: Solving 2SAT (10)

- To simplify the analysis, we invent a true Markov chain Y_0, Y_1, Y_2, \dots as follows:

$$Y_0 = X_0$$

$$\Pr(Y_{t+1} = 1 \mid Y_t = 0) = 1$$

$$\Pr(Y_{t+1} = j+1 \mid Y_t = j) = 1/2$$

$$\Pr(Y_{t+1} = j-1 \mid Y_t = j) = 1/2$$

- When compared with the stochastic process X_0, X_1, X_2, \dots , it takes more time for Y_t to increase to n ... (why??)

Application: Solving 2SAT (11)

- Thus, the expected time to reach n from any point is larger for Markov chain Y than for the stochastic process X

→ So, we have

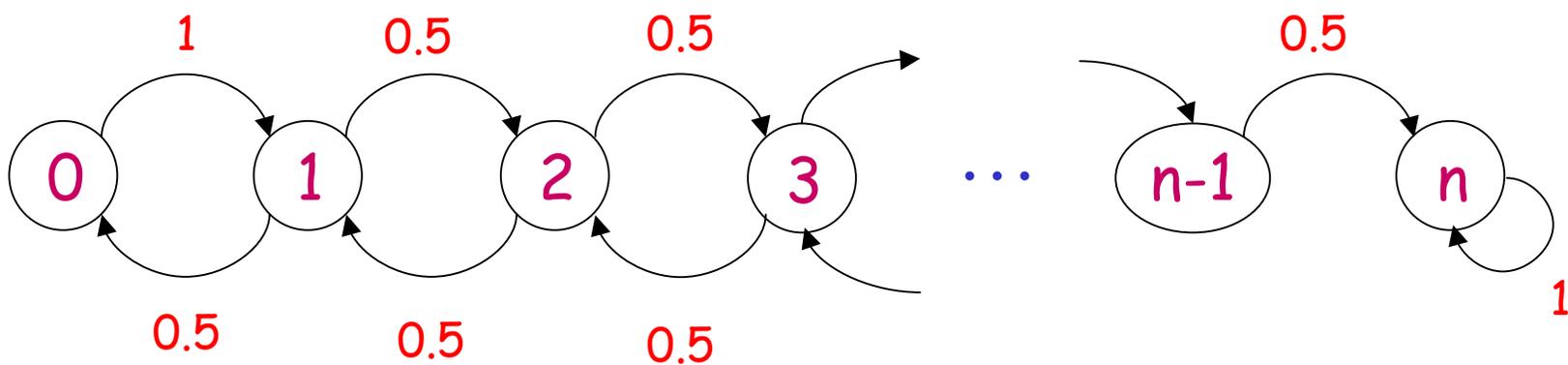
$$E[\text{time for } X \text{ to reach } n \text{ starting at } X_0] \\ \leq E[\text{time for } Y \text{ to reach } n \text{ starting at } Y_0]$$

Question: Can we upper bound the term $E[\text{time for } Y \text{ to reach } n \text{ starting at } Y_0]$?

Application: Solving 2SAT (12)

Let us take a look of how the Markov chain Y looks like in the graph representation

- Recall that vertices represents the state space, which are the values that any Y_t can take on:



Application: Solving 2SAT (13)

Let $h_j = E[\text{time to reach } n \text{ starting at state } j]$

Clearly,

$$h_n = 0 \quad \text{and} \quad h_0 = h_1 + 1$$

Also, for other values of j , we have

$$h_j = \frac{1}{2}(h_{j-1} + 1) + \frac{1}{2}(h_{j+1} + 1)$$

By induction, we can show that for all j ,

$$h_j = n^2 - j^2 \leq n^2$$

Application: Solving 2SAT (13)

- Combining with previous argument :
 $E[\text{time for } X \text{ to reach } n \text{ starting at } X_0]$
 $\leq E[\text{time for } Y \text{ to reach } n \text{ starting at } Y_0]$
 $\leq n^2$, which gives the following lemma:

Lemma: Assume that F has a satisfying assignment. Then, if the algorithm is allowed to run until it finds a satisfying assignment, the expected number of iterations is at most n^2

Application: Solving 2SAT (13)

- Since the algorithm runs for $2cn^2$ iterations, we can show the following:

Theorem: The 2SAT algorithm answers correctly if the formula is unsatisfiable. Otherwise, with probability $\geq 1 - 1/2^c$, it returns a satisfying assignment

How to prove?

(Hint: Break down the $2cn^2$ iterations into c groups, and apply Markov inequality)