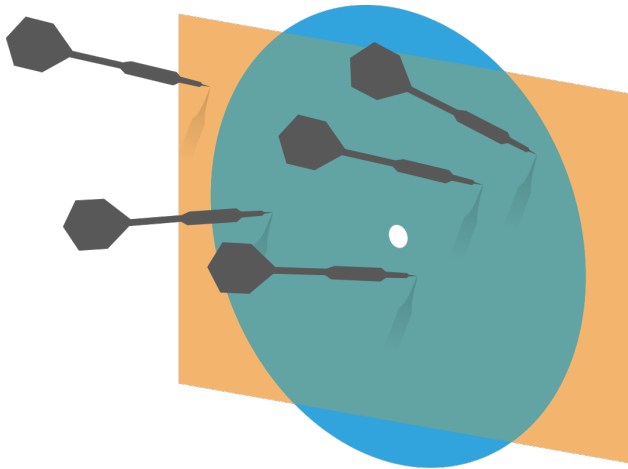


Probability and Statistics for Computer Science



Conditional probability comes
back in matrix!

Credit: wikipedia

Last Time

* Application of Clustering

Cluster center Histogram

* Markov chain (I)

conditional prob.
coming back is Matrix

Objectives

Markov Chain (II)

Recap

Transition Matrix

Stationary Markov Chain

Application of Stationary Markov chains

↳ Page Rank algo.

An example of dependent events in a sequence

I had a glass of wine with my grilled _____

An example of dependent events in a sequence

Google Books Ngram Viewer

Graph these comma-separated phrases: case-insensitive

between and from the corpus with smoothing of [Search lots of books](#)

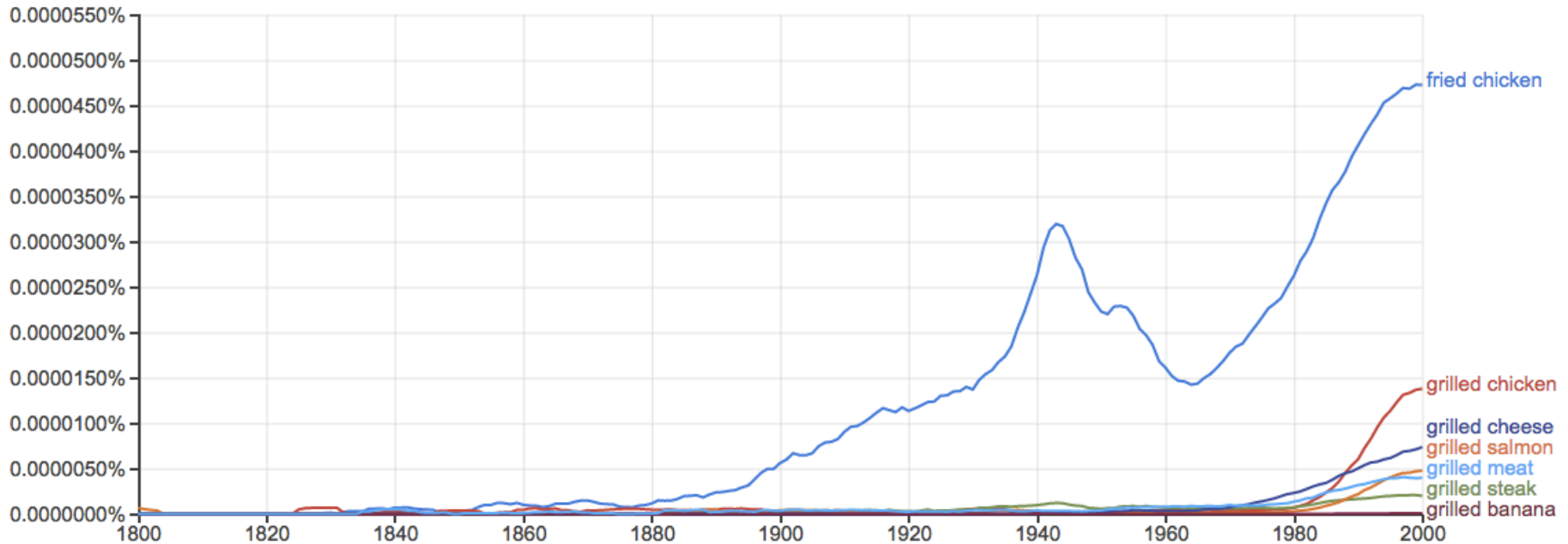


An example of dependent events in a sequence

Google Books Ngram Viewer

Graph these comma-separated phrases: case-insensitive

between and from the corpus with smoothing of . [Search lots of books](#)



(click on line/label for focus)

Markov chain

- ✱ Markov chain is a process in which outcome of any trial in a sequence is $X_n - X_{n+1}$ conditioned by the outcome of the trial immediately preceding, but not by earlier ones.



- ✱ Such dependence is called chain dependence

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

Andrey Markov (1856-1922)

$$P(X_{n+1} | X_n) = f(n) = P(X_{n+1} | X_n, X_{n-1}, \dots, X_1)$$

Markov chain in terms of probability

- ✱ Let X_0, X_1, \dots be a sequence of discrete finite-valued random variables
- ✱ The sequence is a Markov chain if the probability distribution X_t only depends on the distribution of the immediately preceding random variable X_{t-1}

$$P(X_t | X_0, \dots, X_{t-1}) = P(X_t | X_{t-1})$$

- ✱ If the conditional probabilities (transition probabilities) do **NOT change with time**, it's called **constant Markov chain**.

$$P(X_t | X_{t-1}) = P(X_{t-1} | X_{t-2}) = \dots = P(X_1 | X_0)$$

$= f(t) = c$

Coin example

- * Toss a fair coin until you see two heads in a row and then stop, what is the probability of stopping after exactly n flips?

↓
Random variable

* * * HH
n

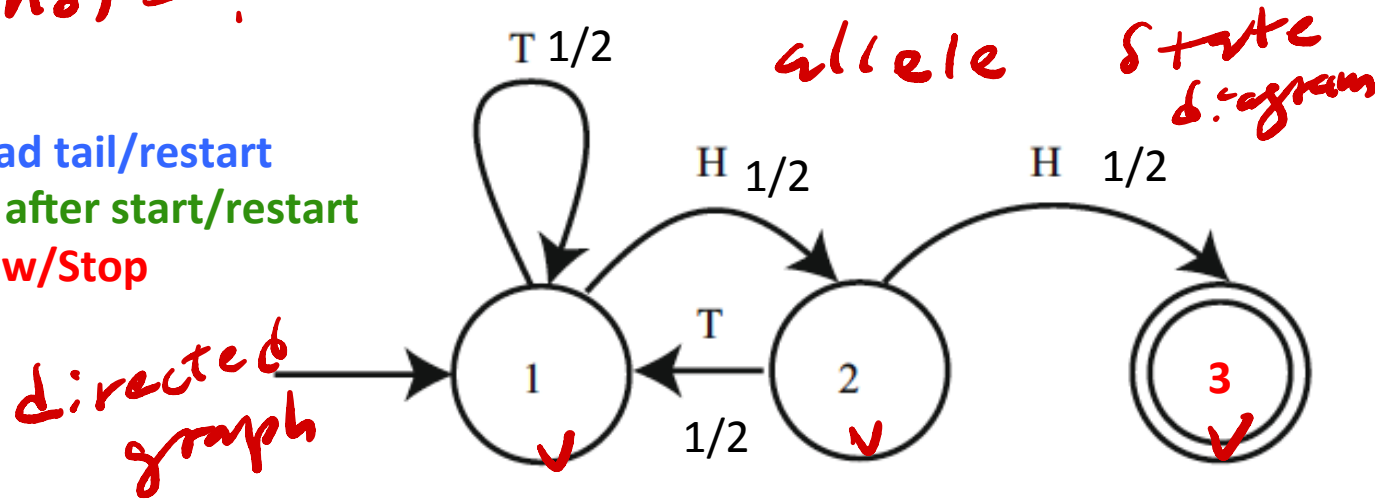
X_n

Geometric

T T T ... H

$$P(n = n_0) = ?$$

- 1 -> Start or just had tail/restart
- 2 -> had one head after start/restart
- 3 -> 2 heads in a row/Stop



$N =$	0	1	2	3	4	5	6
Trials	T	T	H	T	H	H	
$X_N =$	X_1	X_2	X_3	X_4	X_5	X_6	
State	1	1	2	1	2	3	

Markov property:

Given the current state
the past doesn't matter

$$P_{ij} = P(X_{n+1} = j \mid X_n = i)$$

$$= P(X_{n+1} = j \mid X_n = i, X_{n-1} = ? \dots X_0 = ?)$$

this part can be
any !!

The model helps form recurrence formula

✱ Let p_n be the probability of stopping after n flips

$$p_1 = 0 \quad p_2 = \frac{1}{4} \quad p_3 = \frac{1}{8} \quad p_4 = \frac{1}{8} \quad \dots$$

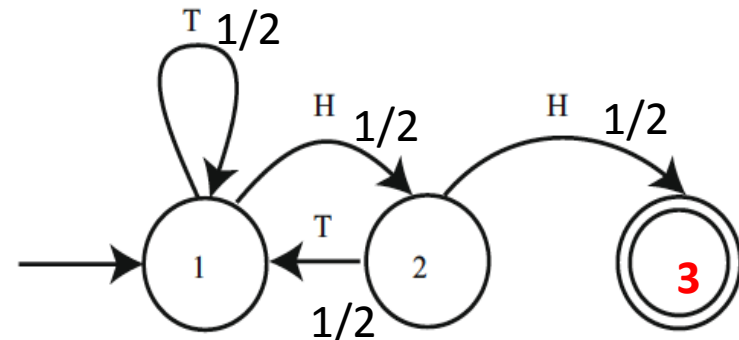
HTH

* HTH
T H H

* * HTH
T T H H
H T H H

$$P(n=n_0) =$$

$n \uparrow$



The model helps form recurrence formula

- Let p_n be the probability of stopping after n flips

$$p_1 = 0 \quad p_2 = 1/4 \quad p_3 = 1/8 \quad p_4 = 1/8 \quad \dots$$

- If $n > 2$, there are two ways the sequence starts

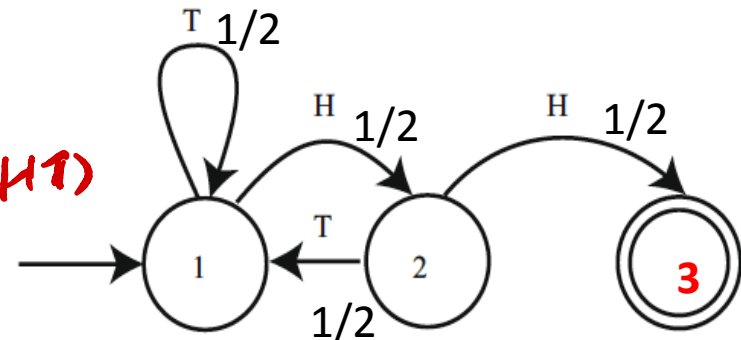
- Toss T and finish in $n-1$ tosses

- Or toss HT and finish in $n-2$ tosses

- So we can derive a recurrence relation

$$p_n = \frac{1}{2}p_{n-1} + \frac{1}{4}p_{n-2}$$

\uparrow \downarrow \uparrow
 $P(T)$ $P(n-1 | T)$ $P(n-2 | HT)$



Transition probability btw states

States

t

- ①
- ②
- ③
- ④
- ⑤
- ⑥

① 0
② 1
③ 0
④ 0
⑤ 0
⑥ 0

$\therefore \frac{1}{4}, \frac{3}{4}$

① 1
② 0
③ 0
④ 1
⑤ 0
⑥ 0

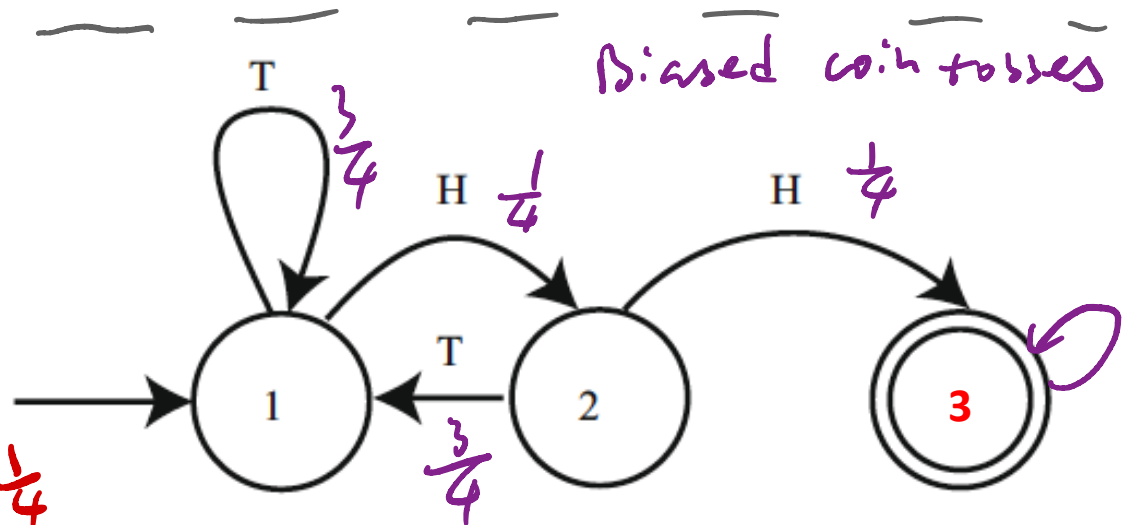
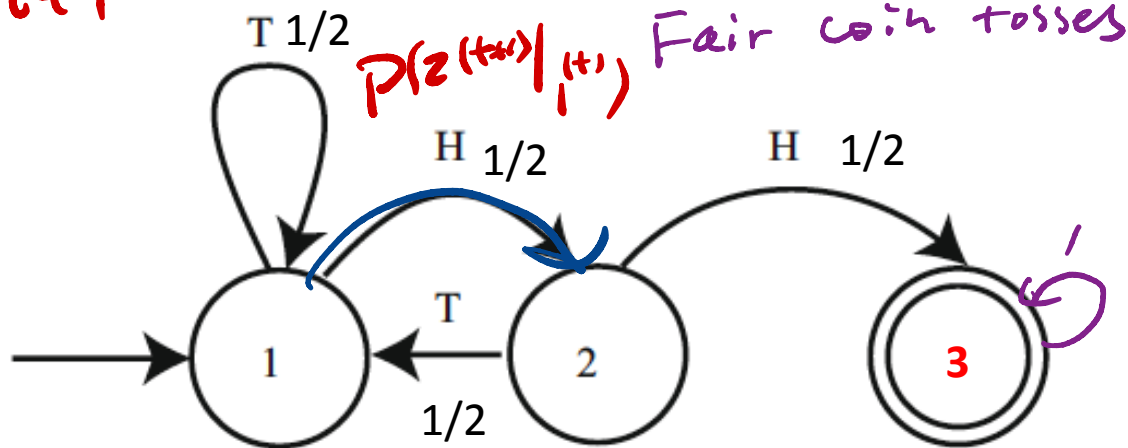
$\frac{1}{4}, \frac{3}{4}$

① 0
② 1
③ 0
④ 0
⑤ 1
⑥ 0

$\frac{1}{4}, \frac{3}{4}$

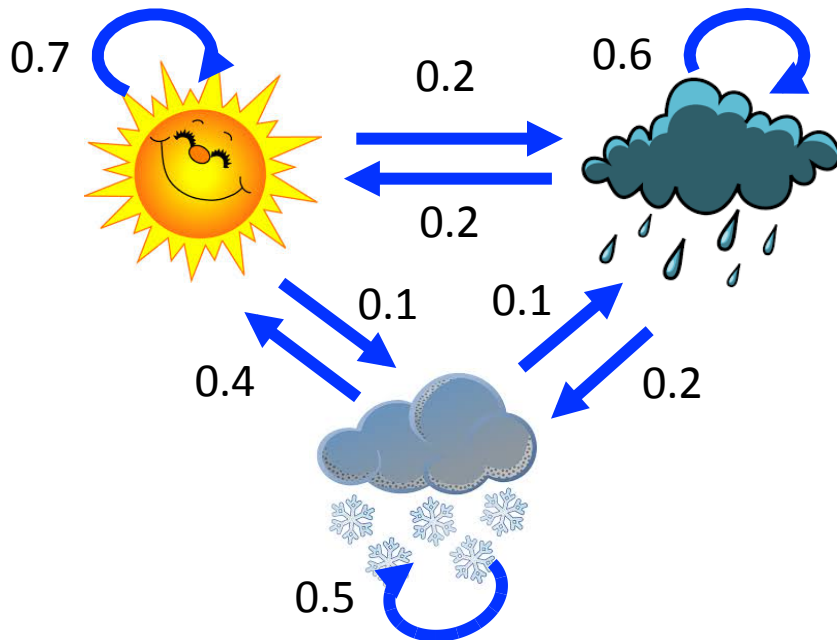
$t+1$

$P(③|①) = \frac{1}{4}$



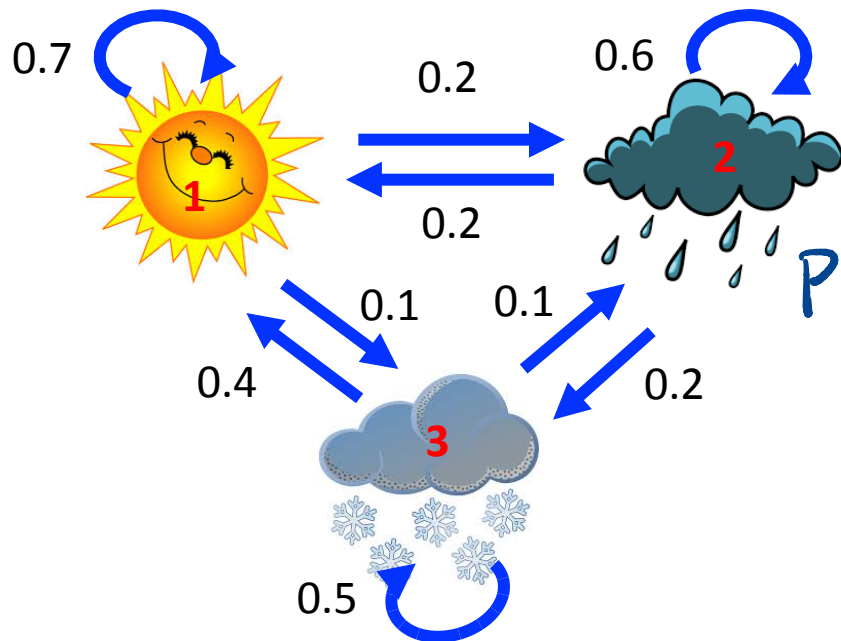
Transition probability matrix: weather model

- Let's model daily weather as one of the three states (Sunny, Rainy, and Snowy) with Markov chain that has the transition probabilities as shown here.



Transition probability matrix: weather model

- Let's model daily weather as one of the three states (Sunny, Rainy, and Snowy) with Markov chain that has the transition probabilities as shown here.



Stochastic matrix

i , the current state at time point t
 j , the next state at time point $t+1$

$P =$

	Sunny	Rainy	Snowy
Sunny	0.7	0.2	0.1
Rainy	0.2	0.6	0.2
Snowy	0.4	0.1	0.5

$P_{ij} \geq 0$

The transition probability matrix

Is this true?

For a constant Markov chain, at any step t , the probability distribution among the states remain the same.

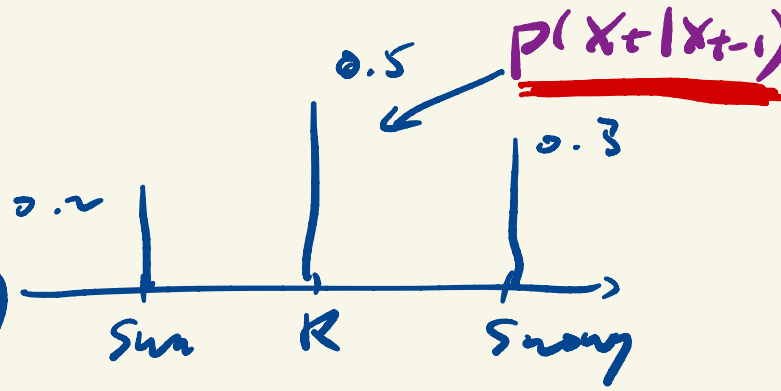
$P(X_t)$

A. True

B. False

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

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



Q: The transition probabilities for a node sum to 1

A. Yes.

B. No.

Transition probability matrix properties

* The transition probability matrix P is a square matrix with entries p_{ij}

* Since $p_{ij} = P(X_t = j | X_{t-1} = i)$

$$p_{ij} \geq 0 \quad \text{and} \quad \sum_j p_{ij} = 1$$

Stochastic matrix

$X_1 \quad X_2 \quad \dots \quad X_n$
 $P(X_n = i)$

$P(X_{n+k} = j) ?$

$$P = \begin{matrix} & \begin{matrix} \text{Sunny} & \text{Rainy} & \text{Snowy} \end{matrix} \\ \begin{bmatrix} 0.7 & 0.2 & 0.1 \\ 0.2 & 0.6 & 0.2 \\ 0.4 & 0.1 & 0.5 \end{bmatrix} & \begin{matrix} \text{Sunny} \\ \text{Rainy} \\ \text{Snowy} \end{matrix} \end{matrix}$$

The transition probability matrix

Probability distributions over states

- Let $\boldsymbol{\pi}$ be a row vector containing the probability distribution over all the finite discrete states at $t=0$

$$\pi_i = P(X_0 = i) \quad \text{3 states}$$

- For example: if it is rainy today, and today is $t=0$, then

$$\boldsymbol{\pi} = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \quad \text{prior}$$

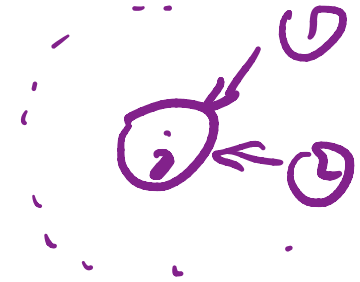
- Let $\mathbf{P}^{(t)}$ be a row vector containing the probability distribution over states at time point t

$$P_i^{(t)} = P(X_t = i) \quad \begin{bmatrix} ? & ? & ? \end{bmatrix}$$

Propagating the probability distribution

- ✱ Propagating from $t=0$ to $t=1$,

$$\begin{aligned} P_j^{(1)} &= P(X_1 = j) \\ &= \sum_i P(X_1 = j, X_0 = i) \\ &= \sum_i P(X_1 = j | X_0 = i) P(X_0 = i) \\ &= \sum_i p_{ij} \pi_i \end{aligned}$$



- ✱ In matrix notation,

$$\mathbf{p}^{(1)} = \boldsymbol{\pi} P$$

prior
conditional
↓
transition matrix

$$t? \quad P^{(t)} = P^{(t-1)} P$$

Probability distributions:

* Suppose that it is rainy, we have the initial probability distribution. $\boldsymbol{\pi} = [0 \quad 1 \quad 0]$

* What are the probability distributions for tomorrow and the day after tomorrow?

$$\boldsymbol{p}^{(1)} = \boldsymbol{\pi} P$$

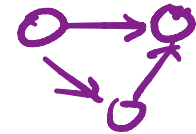
$$\boldsymbol{p}^{(2)} = \boldsymbol{p}^{(1)} P$$

Propagating to $t = \infty$

- * We have just seen that

$$\mathbf{p}^{(2)} = \mathbf{p}^{(1)} P = (\boldsymbol{\pi} P) P = \boldsymbol{\pi} P^2$$

- * So in general $\mathbf{p}^{(t)} = \boldsymbol{\pi} P^t$



- * If one state can be reached from any other state in the graph, the Markov chain is called irreducible (single chain).

- * Furthermore, if it satisfies:

$$\lim_{t \rightarrow \infty} \boldsymbol{\pi} P^t = \mathbf{S}$$

(Handwritten notes: $P^{(t)} \rightarrow S$)

then the Markov chain is stationary and **S** is the stationary distribution.

Stationary distribution

- * The stationary distribution \mathbf{s} has the following property: $\mathbf{s}P = \mathbf{s}$
- * \mathbf{s} is a row eigenvector of \mathbf{P} with eigenvalue 1
- * In the example of the weather model, regardless of the initial distribution,

$$\mathbf{S} = \lim_{t \rightarrow \infty} \pi \begin{bmatrix} 0.7 & 0.2 & 0.1 \\ 0.2 & 0.6 & 0.2 \\ 0.4 & 0.1 & 0.5 \end{bmatrix}^t = \left[\frac{18}{37} \quad \frac{11}{37} \quad \frac{8}{37} \right]$$

> 0

Chance of being up-to-date

In a class, students are either up-to-date or behind regarding progress. If a student is up-to-date, the student has 0.8 probability remaining up-to-date, if a student is behind, the student has 0.6 probability becoming up-to-date. Suppose the course is so long that it runs life long, what is the probability any student eventually gets up-to-date?

A) 25%

C) 75%

B) 50%

D) 95%

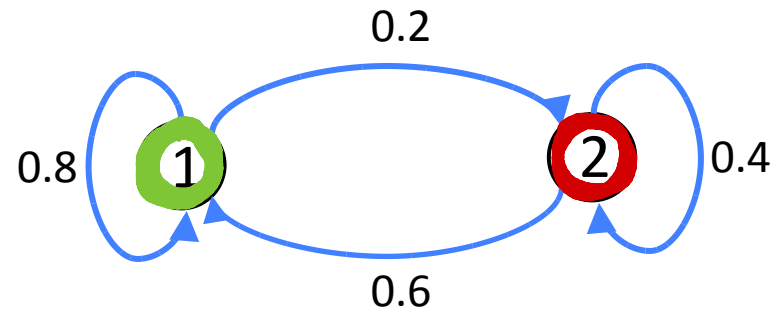
The Markov model



Example: Up-to-date or behind model

State 1: Up-to-date

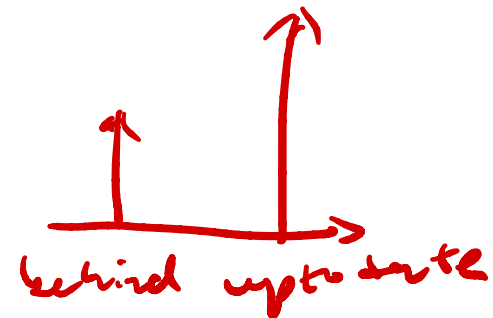
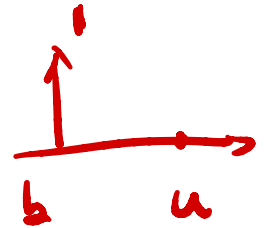
State 2: Behind



What's the transition matrix?

If I start with $\pi = [0, 1]$, what is my probability of being up-to-date eventually? $\frac{3}{4}$

$$P = \begin{matrix} & \begin{matrix} 1 & 2 \end{matrix} \\ \begin{matrix} 1 \\ 2 \end{matrix} & \begin{bmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{bmatrix} \end{matrix}$$



Solving the stationary Markov

$$SP = S$$

$$(SP)^T = S^T \Rightarrow P^T S^T = S^T$$

$$AX = X$$

$$\lambda = 1$$

$$S^T = u \quad A = P^T$$

$$\begin{bmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{bmatrix}^T u = u$$

$$(A - I)u = 0$$

$$u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\begin{bmatrix} -0.2 & 0.6 \\ 0.2 & -0.6 \end{bmatrix} u = 0$$

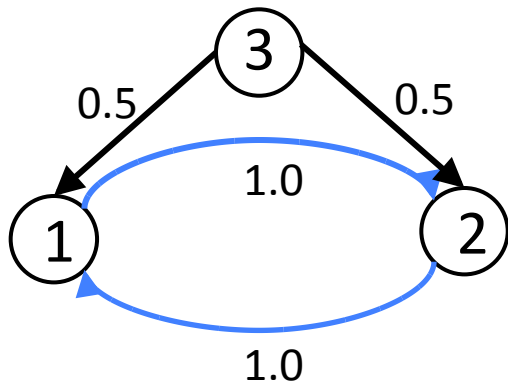
$$u_1 + u_2 = 1$$

$$u_1 = \frac{3}{4}$$

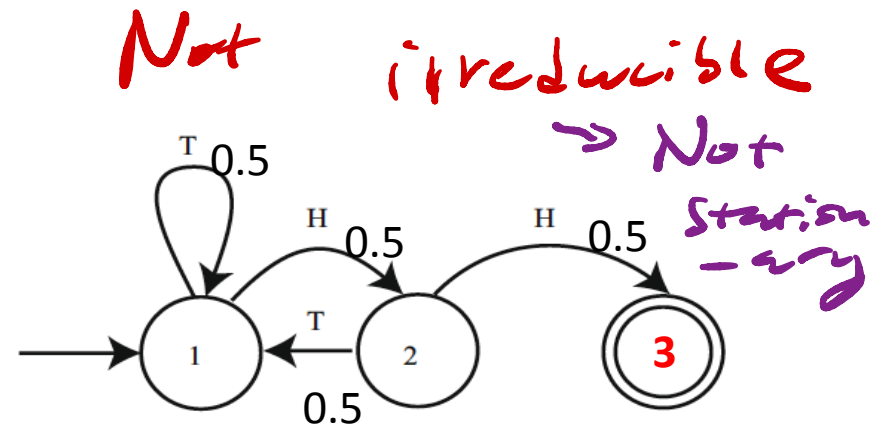
$$u_2 = \frac{1}{4}$$

75%
up to
date!

Examples of non-stationary Markov chains



Periodic



Absorbing

$$SP = S$$

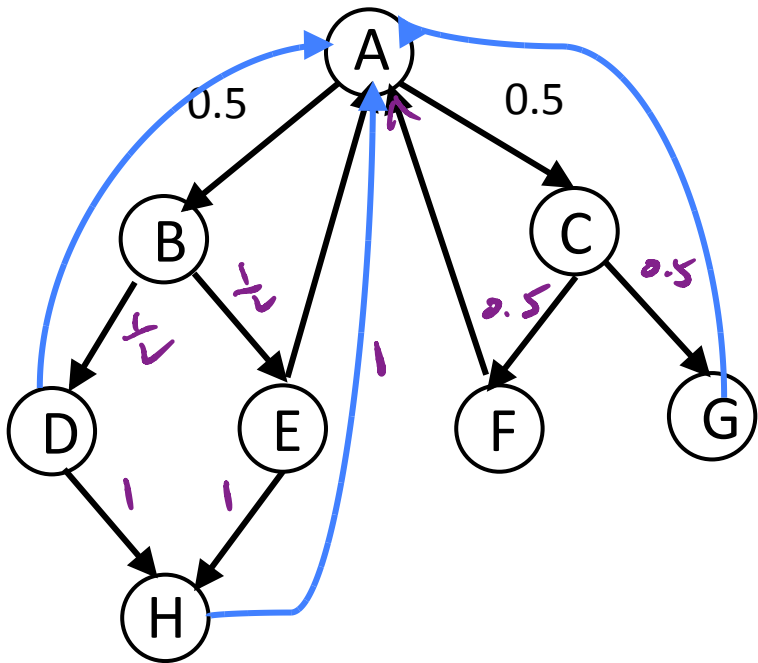
PageRank Example

- ✱ How to rate web pages objectively?
- ✱ The PageRank algorithm by Page et al. made **Google** successful
- ✱ The method utilized **Markov chain model** and applied it to the large list of webpages.
- ✱ To illustrate the point, we use a small-size example and assume a simple **stationary model**.

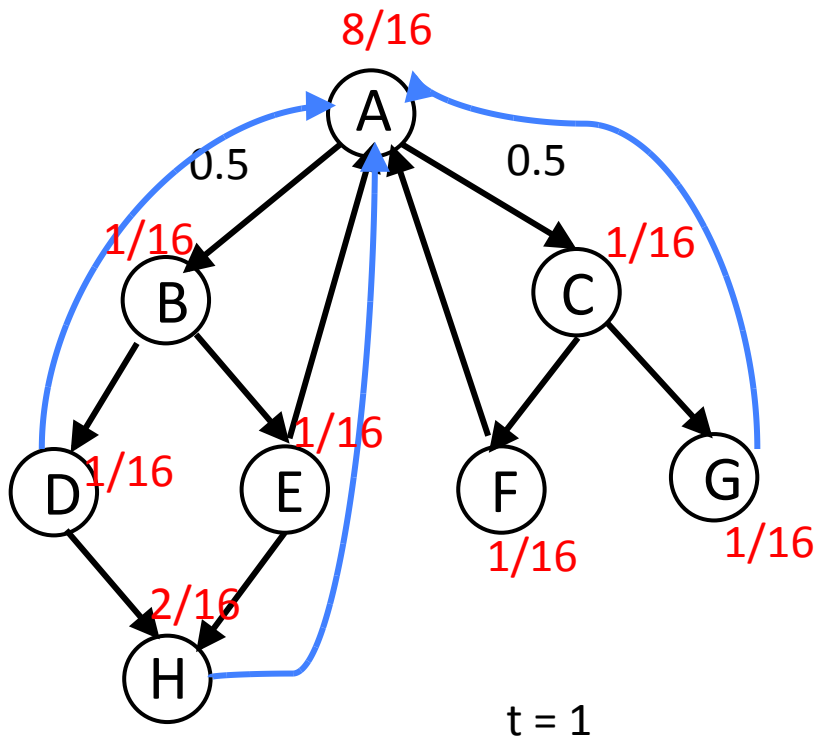
$$\lim_{t \rightarrow \infty} \pi P^t$$

Suppose we are randomly surfing a network of webpages

1/80



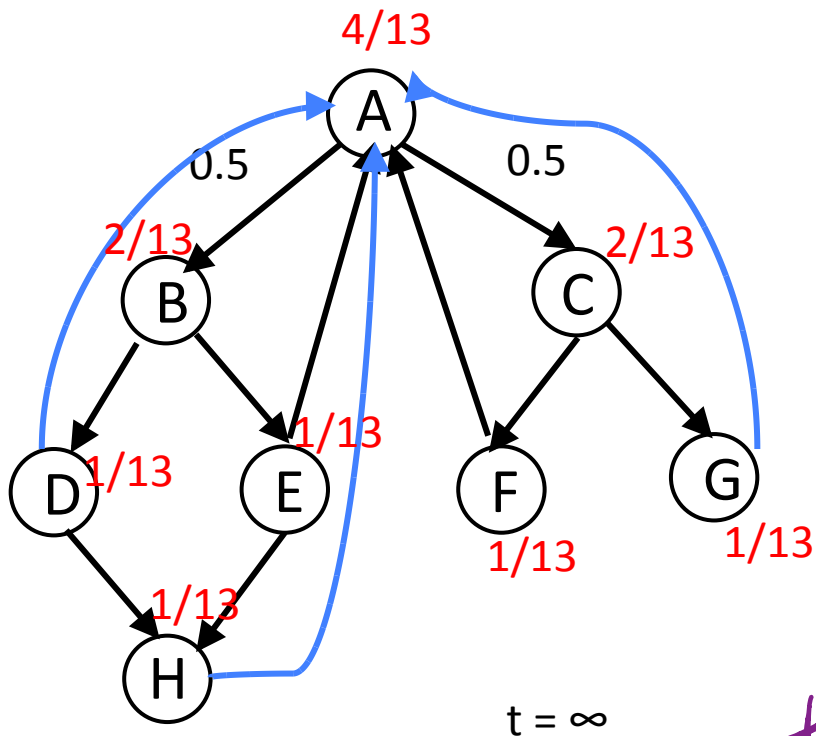
Update the distribution iteratively



$$\lim_{t \rightarrow \infty} \pi P^t = ?$$

$$\pi P^t$$

Until the stationary distribution

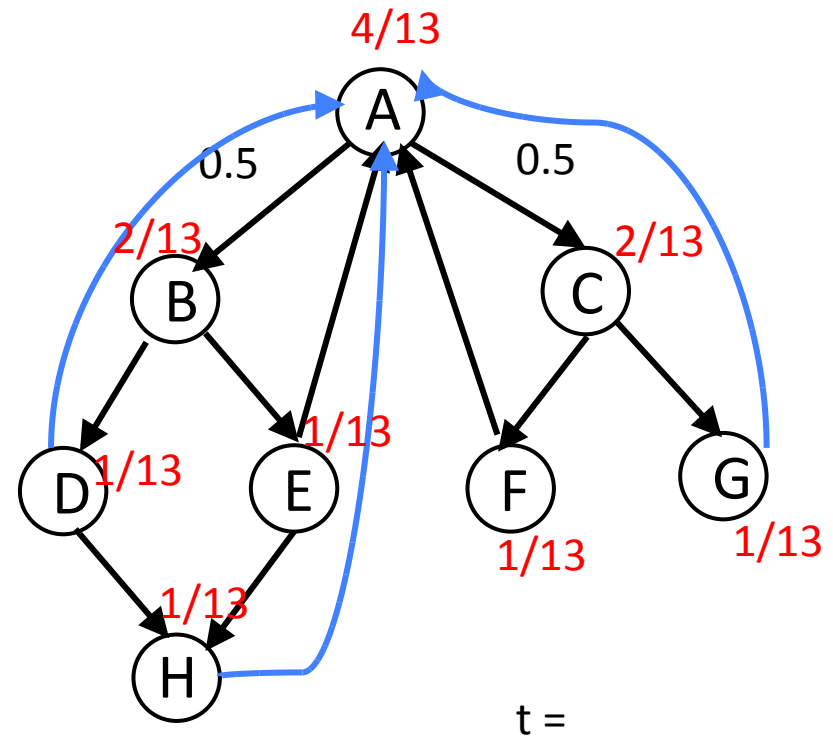


Why not
try $SP = S$?

the page $\sim 1.7 \times 10^9$

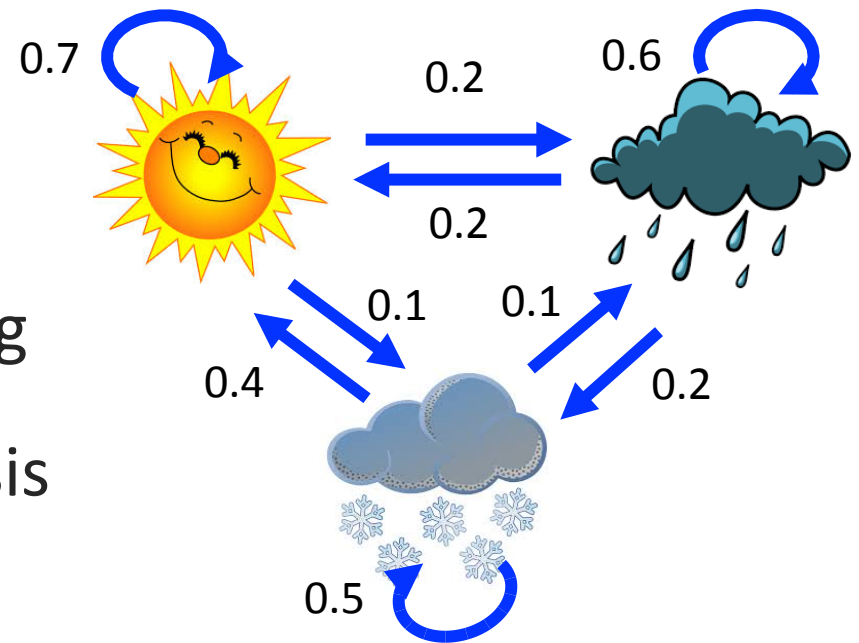
If the surfer get trapped

- ✱ Allow “teleport” with small probability from any page to another
- ✱ Or allow “teleport” with user input of URL



Diverse applications of Markov Model

- ✧ Communication network
- ✧ Queue modeling
- ✧ DNA sequence modeling
- ✧ Natural language processing
- ✧ Single-cell large data analysis
- ✧ Financial/Economic model
- ✧ Music



Final Exam

- * Time: 1:30pm-4:30pm 12/11 Fri. Central Time
- * Conflicts need to be requested 2 days ahead.
- * Duration: 3hrs
- * Content coverage: Ch1-14, except 8, details are on Compass
- * Open book and lecture notes
- * Format: 50 multiple choices

Additional References

- ✱ Robert V. Hogg, Elliot A. Tanis and Dale L. Zimmerman. “Probability and Statistical Inference”
- ✱ Kelvin Murphy, “Machine learning, A Probabilistic perspective”

Acknowledgement

*Thank
You!*

