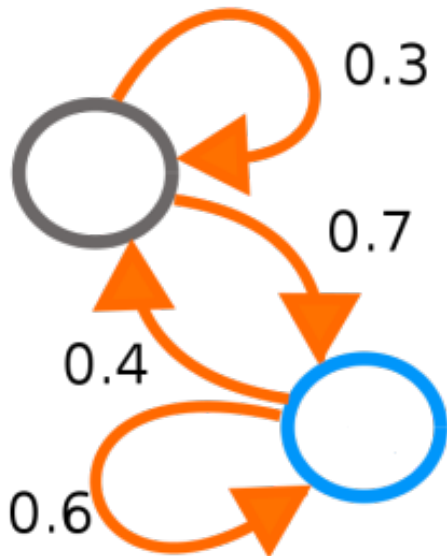


# 15-252

## More Great Ideas in Theoretical Computer Science

### Markov Chains

*April 27th, 2018*



# Markov Chain

Andrey Markov (1856 - 1922)

Russian mathematician.

Famous for his work on  
random processes.



( $\Pr[X \geq c \cdot \mathbf{E}[X]] \leq 1/c$  is Markov's Inequality.)

A model for the evolution of a random system.

*The future is independent of the past, given the present.*

# Cool things about Markov Chains

- It is a very general and natural model.

Applications in:

computer science, mathematics, biology, physics,  
chemistry, economics, psychology, music, baseball,...

- The model is simple and neat.

- Cilantro



# The plan

Motivating examples and applications

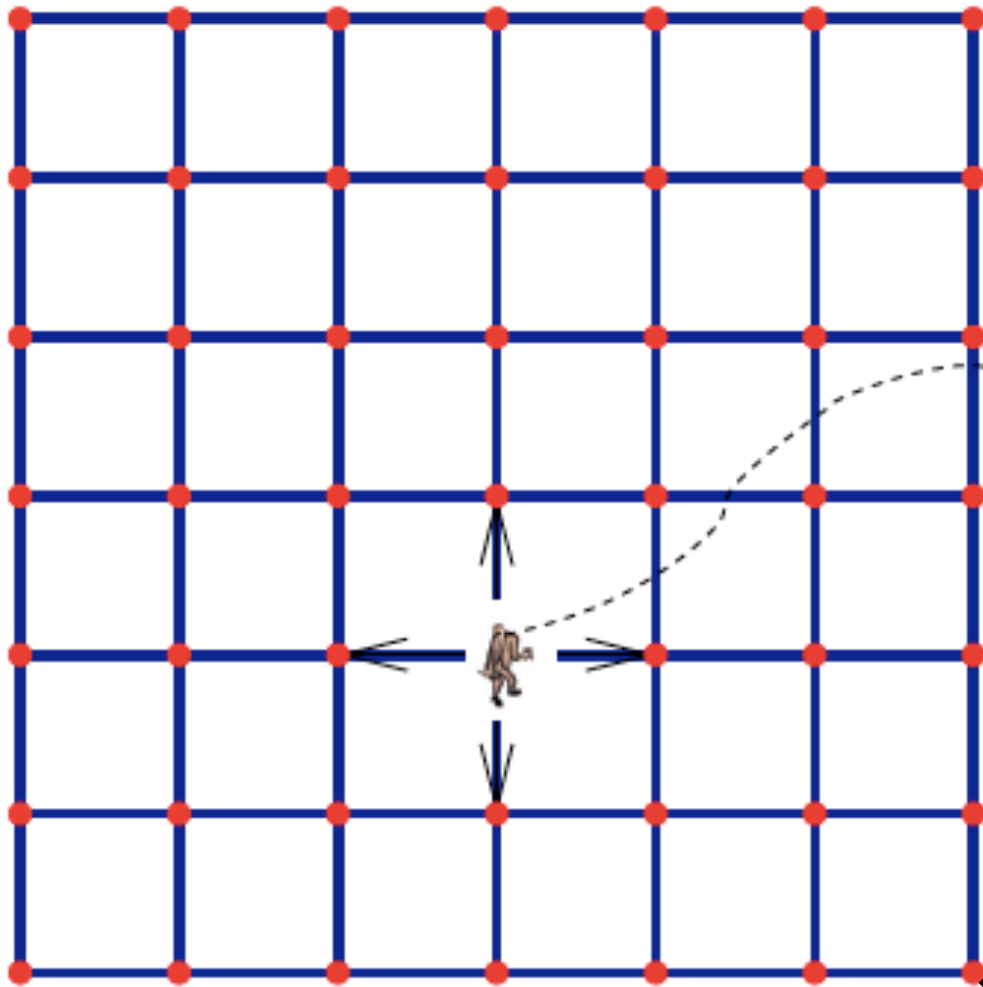
Basic mathematical representation and properties

A bit more on applications

*The future is independent of the past, given the present.*

# **Some Examples of Markov Chains**

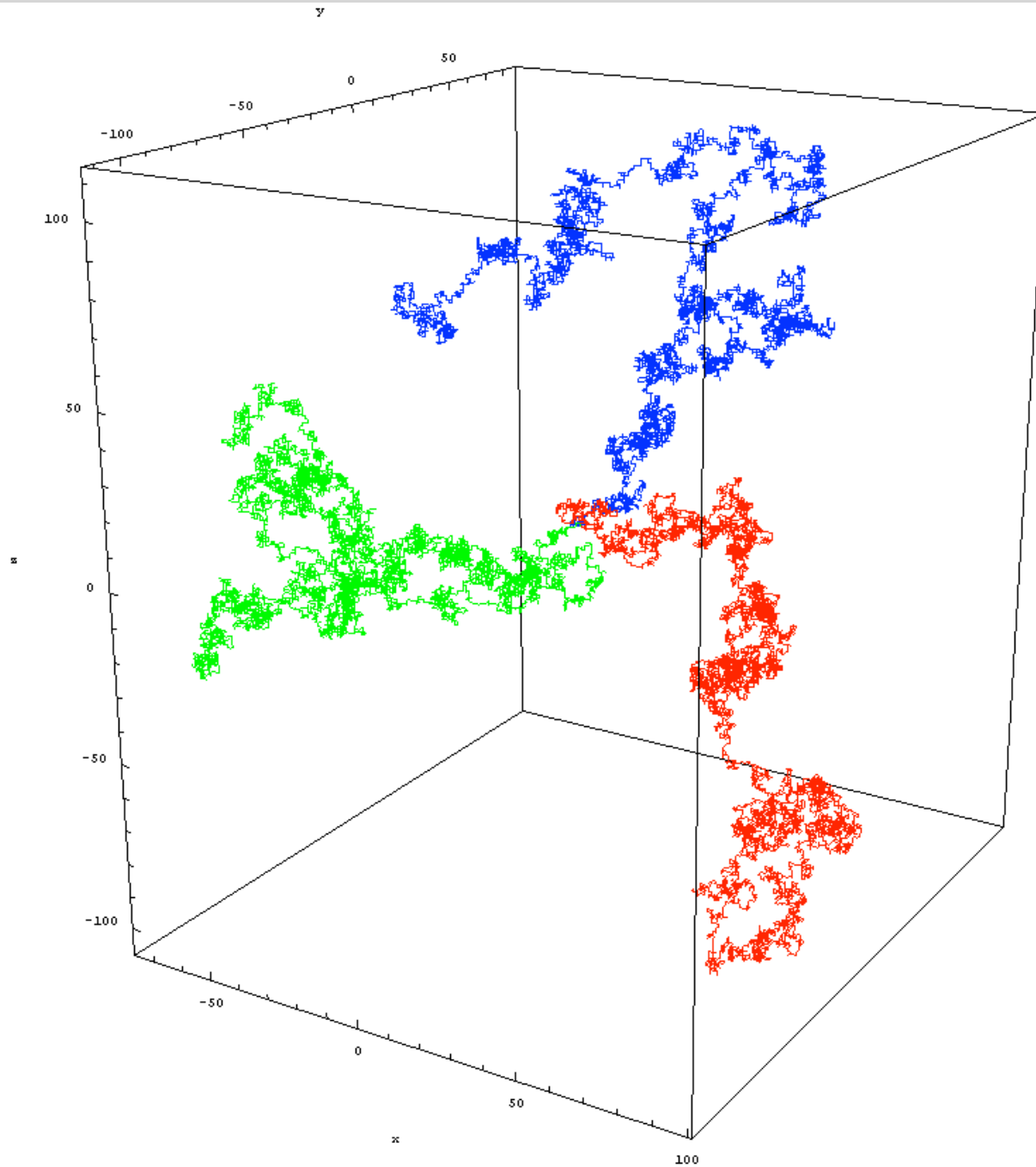
# Example: Drunkard Walk



**Salvador Dali (1922)  
The Drunkard**

Home

# Example: Diffusion Process





# Example: Weather

A very (!! ) simplified model for the weather.

Probabilities on a daily basis:

$$\Pr[\text{sunny to rainy}] = 0.1$$

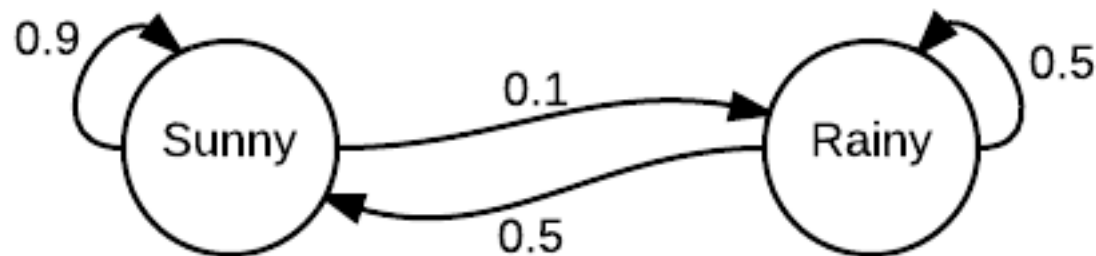
$$\Pr[\text{sunny to sunny}] = 0.9$$

$$\Pr[\text{rainy to rainy}] = 0.5$$

$$\Pr[\text{rainy to sunny}] = 0.5$$

**S = sunny**  
**R = rainy**

	<b>S</b>	<b>R</b>
<b>S</b>	0.9	0.1
<b>R</b>	0.5	0.5



Encode more information about current state for a more accurate model.

# Example: Life Insurance

Goal of life insurance company:

figure out how much to charge the clients.

Find a model for how long a client will live.

Probabilistic model of health on a monthly basis:

$$\text{Pr}[\text{healthy to sick}] = 0.3$$

$$\text{Pr}[\text{sick to healthy}] = 0.8$$

$$\text{Pr}[\text{sick to death}] = 0.1$$

$$\text{Pr}[\text{healthy to death}] = 0.01$$

$$\text{Pr}[\text{healthy to healthy}] = 0.69$$

$$\text{Pr}[\text{sick to sick}] = 0.1$$

$$\text{Pr}[\text{death to death}] = 1$$

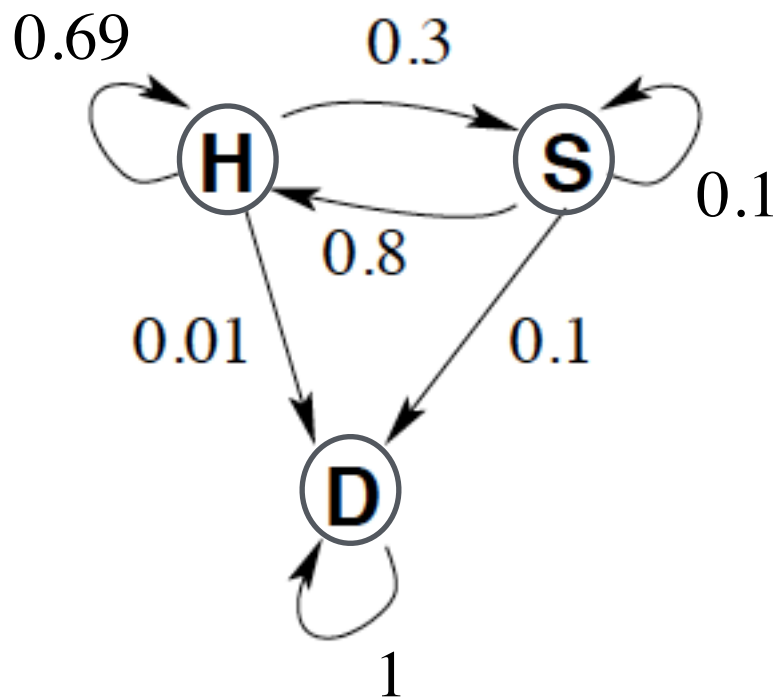
# Example: Life Insurance

Goal of life insurance company:

figure out how much to charge the clients.

Find a model for how long a client will live.

Probabilistic model of health on a monthly basis:



$$\begin{matrix} & \mathbf{H} & \mathbf{S} & \mathbf{D} \\ \mathbf{H} & \left[ \begin{array}{ccc} 0.69 & 0.3 & 0.01 \\ 0.8 & 0.1 & 0.1 \\ 0 & 0 & 1 \end{array} \right] \\ \mathbf{S} & & & \\ \mathbf{D} & & & \end{matrix}$$

# **Some Applications of Markov Models**

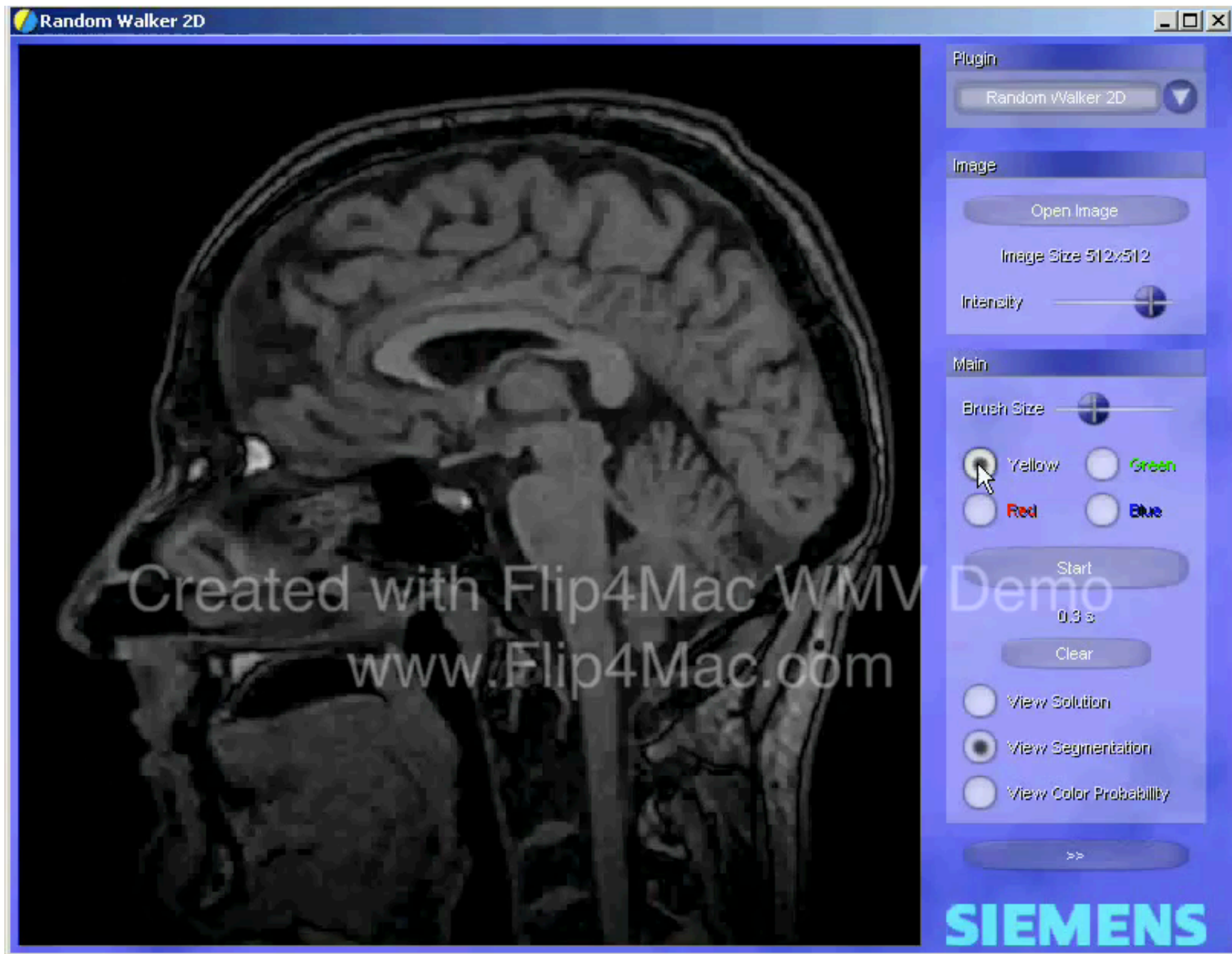
# Application: Algorithmic Music Composition

Nicholas Vasallo

***Megalithic Copier #2:  
Markov Chains  
(2011)***

written in Pure Data

# Application: Image Segmentation



# Application: Automatic Text Generation

Random text generated by a computer  
(putting random words together):

“While at a conference a few weeks back, I spent an interesting evening with a grain of salt.”

Google: Mark V Shaney

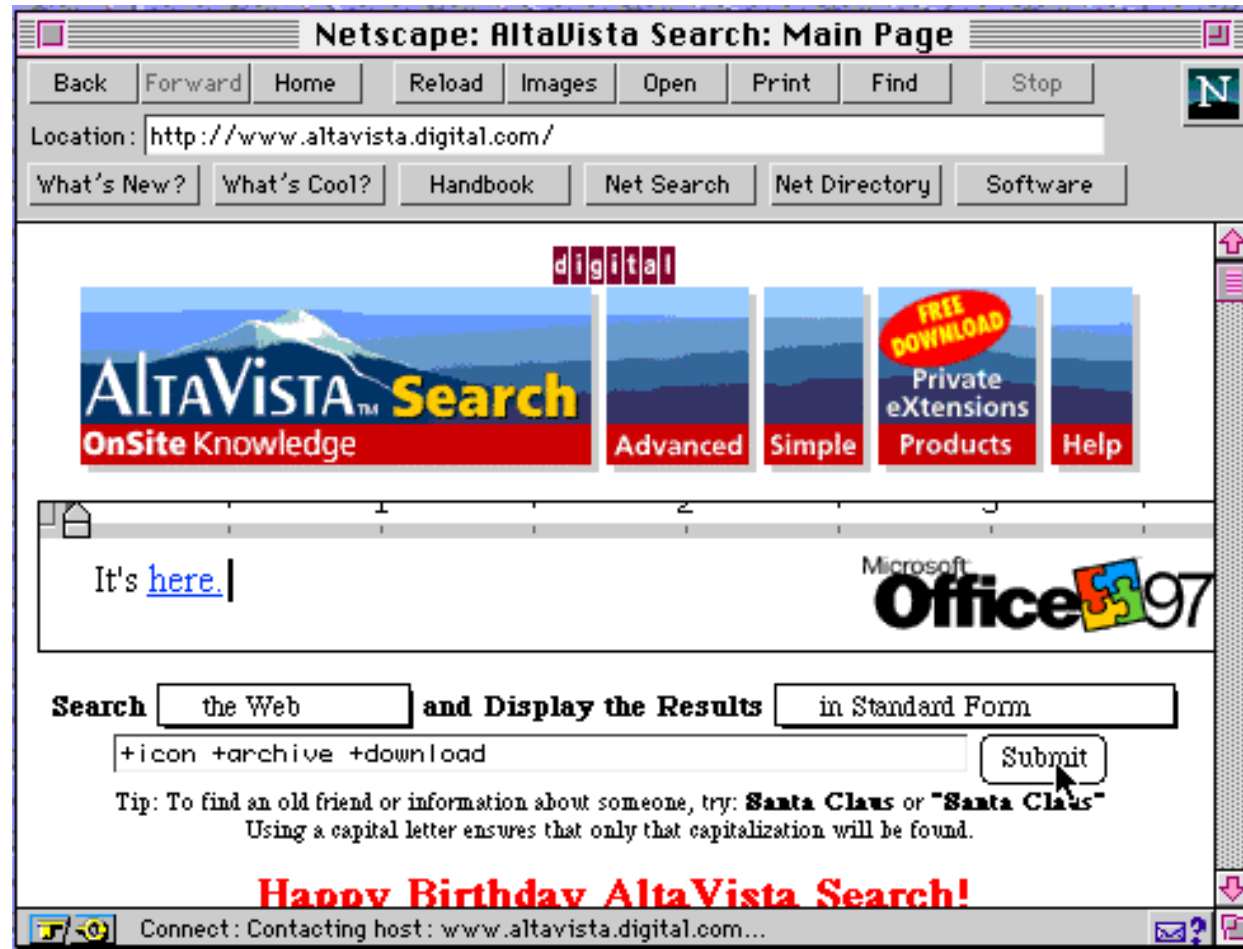
# Application: Speech Recognition

Speech recognition software programs use Markov models to listen to the sound of your voice and convert it into text.



# Application: Google PageRank

**1997:** Web search was horrible



Sorts webpages by number of occurrences of keyword(s).

# Application: Google PageRank

Founders of **Google**



Larry Page

Sergey Brin

**\$40Billionaires**

# Application: Google PageRank



Jon Kleinberg

Nevanlinna Prize

# Application: Google PageRank

How does Google order the webpages displayed after a search?

## 2 important factors:

- Relevance of the page.

- Reputation of the page.



*The number and reputation of links pointing to that page.*

Reputation is measured using **PageRank**.

**PageRank** is calculated using a Markov Chain.

# The plan

Motivating examples and applications

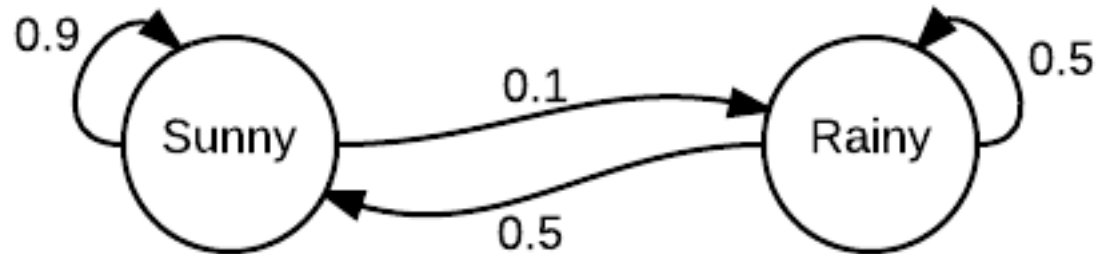
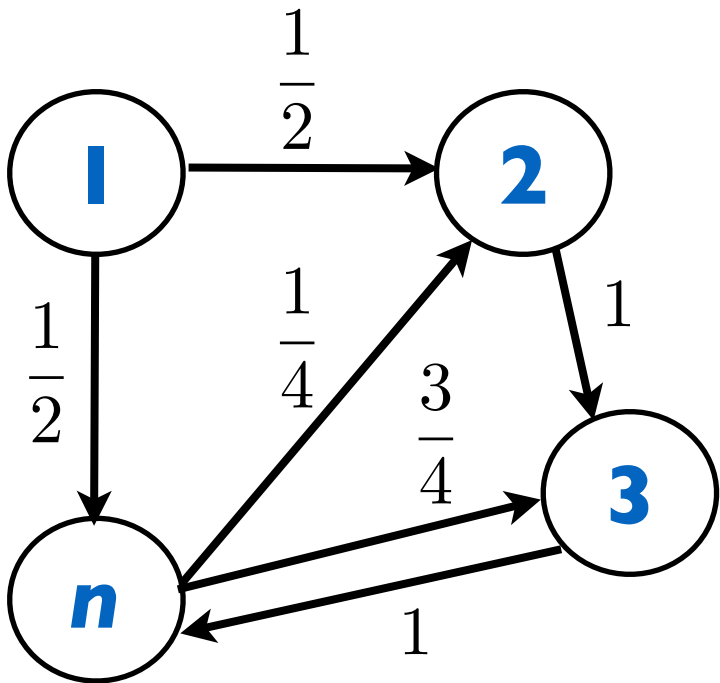
Basic mathematical representation and properties

A bit more on applications

# The Setting

There is a system with  $n$  possible states/values  $\{1, 2, \dots, n\}$ .

At each time step, the state changes probabilistically.



*Memoryless*

The next state only depends on the current state.

*Evolution of the system:* random walk on the graph.

# The Definition

A **Markov Chain** is a digraph with  $V = \{1, 2, \dots, n\}$  such that:

- Each edge is labeled with a value in  $(0, 1]$  (a probability).  
self-loops allowed
- At each vertex, the probabilities on outgoing edges sum to 1.

(We usually assume the graph is strongly connected.

i.e. there is a directed path from  $i$  to  $j$  for any  $i$  and  $j$ .)

The vertices of the graph are called **states**.

The edges are called **transitions**.

The label of an edge is a **transition probability**.

# Notation

## Given some Markov Chain with $n$ states:

Define

$\pi_t[i]$  = probability of being in state  $i$  after exactly  $t$  steps.

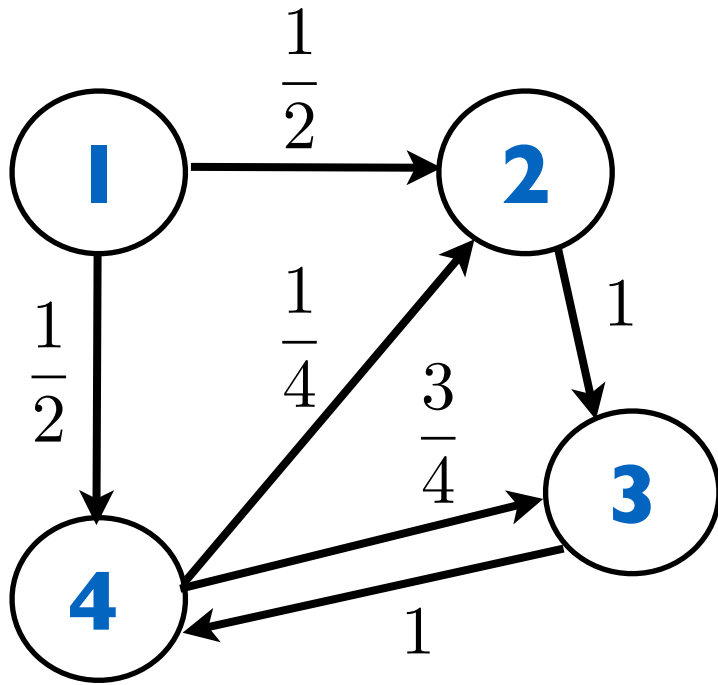
$$\pi_t = \begin{matrix} & \mathbf{1} & \mathbf{2} & & \mathbf{n} \\ \left[ p_1 & p_2 & \cdots & p_n \right] \end{matrix} \quad \sum_i p_i = 1$$

Note that someone has to provide  $\pi_0$ .

Once this is known, we get the distributions  $\pi_1, \pi_2, \dots$



# Notation



	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>
<b>1</b>	0	$\frac{1}{2}$	0	$\frac{1}{2}$
<b>2</b>	0	0	1	0
<b>3</b>	0	0	0	1
<b>4</b>	0	$\frac{1}{4}$	$\frac{3}{4}$	0

Transition Matrix

A Markov Chain with  $n$  states can be characterized by the  $n \times n$  **transition matrix**  $K$

$$\forall i, j \in \{1, 2, \dots, n\} \quad K[i, j] = \Pr[i \rightarrow j \text{ in one step}]$$

Note: rows of  $K$  sum to 1.

# Some Fundamental and Natural Questions

What is the probability of being in state  $i$  after  $t$  steps (given some initial state)?

$$\pi_t[i] = ?$$

What is the expected time of reaching state  $i$  when starting at state  $j$  ?

What is the expected time of having visited every state (given some initial state)?

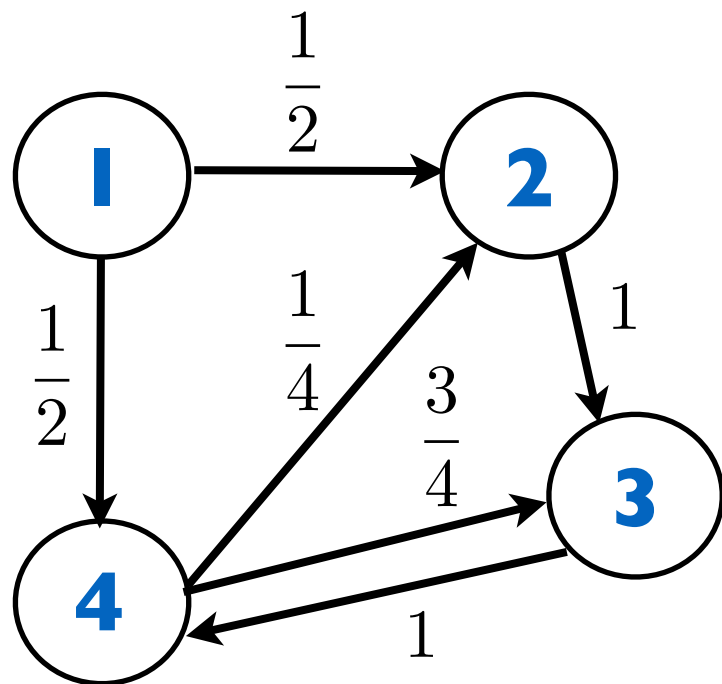


How do you answer such questions?

# Mathematical representation of the evolution

Suppose we start at state **1** and let the system evolve.

How can we mathematically represent the evolution?

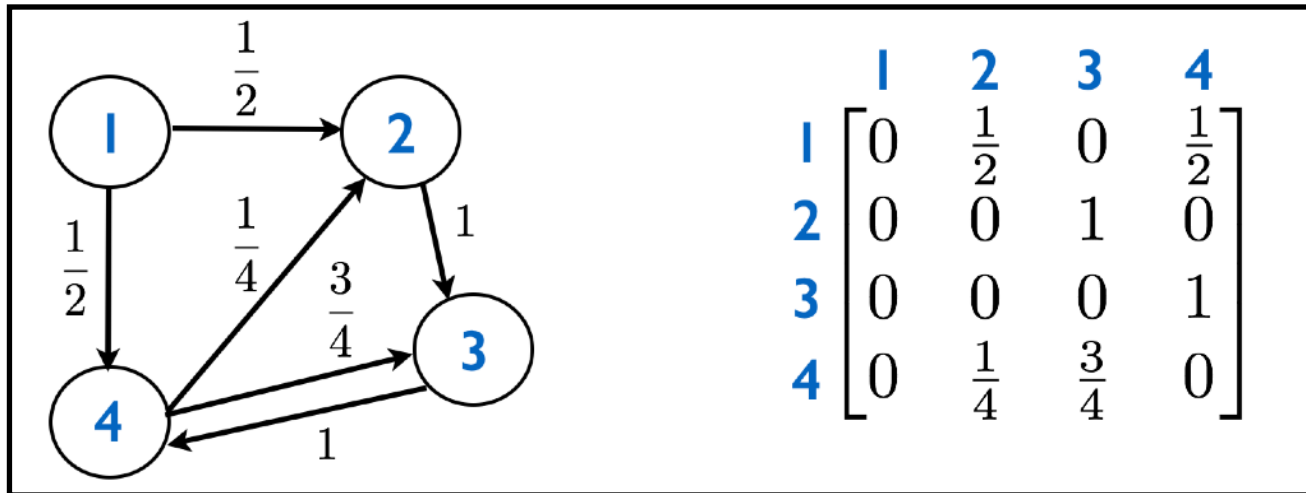


$$\begin{array}{c} \mathbf{1} \\ \mathbf{2} \\ \mathbf{3} \\ \mathbf{4} \end{array} \begin{bmatrix} \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{1}{4} & \frac{3}{4} & 0 \end{bmatrix}$$

$$\pi_0 = \begin{array}{c} \mathbf{1} \quad \mathbf{2} \quad \mathbf{3} \quad \mathbf{4} \\ [1 \quad 0 \quad 0 \quad 0] \end{array}$$

What is  $\pi_1$ ? By inspection,  $\pi_1 = \begin{array}{c} \mathbf{1} \quad \mathbf{2} \quad \mathbf{3} \quad \mathbf{4} \\ [0 \quad \frac{1}{2} \quad 0 \quad \frac{1}{2}] \end{array}$ .

# Mathematical representation of the evolution



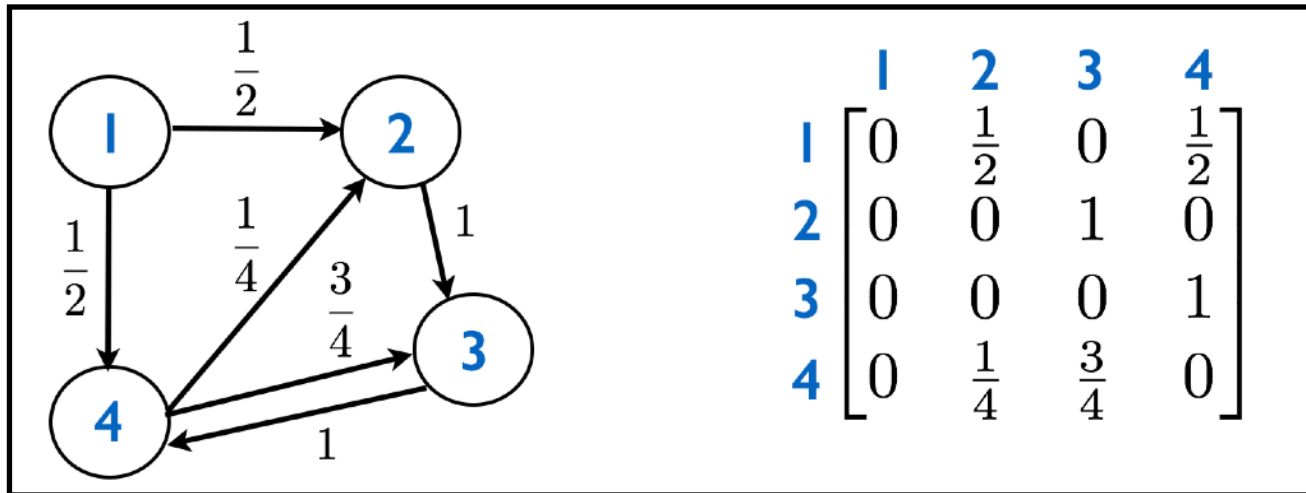
The probability of states after 1 step:

$$\begin{matrix} [1 & 0 & 0 & 0] \\ \pi_0 \end{matrix} \begin{matrix} \begin{bmatrix} 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{1}{4} & \frac{3}{4} & 0 \end{bmatrix} \\ K \end{matrix} = \begin{matrix} [0 & \frac{1}{2} & 0 & \frac{1}{2}] \\ \pi_1 \end{matrix}$$

the new state  
(probabilistic)

$K$

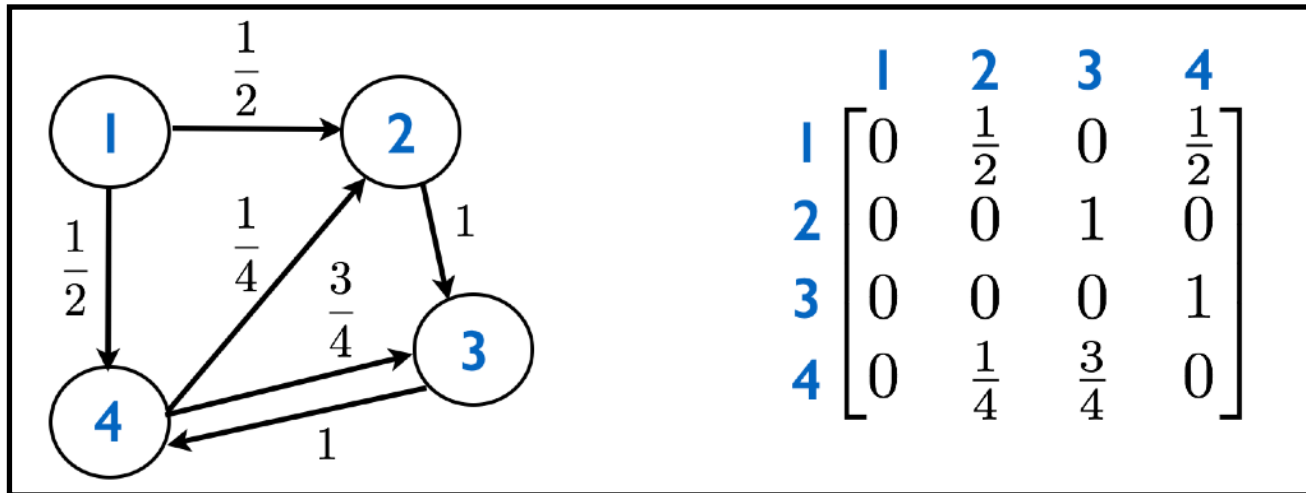
# Mathematical representation of the evolution



The probability of states after 2 steps:

$$\begin{bmatrix} 0 & \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix} \begin{matrix} \pi_1 \\ \\ \\ K \end{matrix} \begin{bmatrix} 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{1}{4} & \frac{3}{4} & 0 \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{8} & \frac{7}{8} & 0 \end{bmatrix} \begin{matrix} \pi_2 \\ \\ \\ \text{the new state} \\ \text{(probabilistic)} \end{matrix}$$

# Mathematical representation of the evolution



$$\pi_1 = \pi_0 \cdot K$$

$$\pi_2 = \pi_1 \cdot K$$

So

$$\begin{aligned} \pi_2 &= (\pi_0 \cdot K) \cdot K \\ &= \pi_0 \cdot K^2 \end{aligned}$$

# Mathematical representation of the evolution

## In general:

If the initial probabilistic state is  $[p_1 \ p_2 \ \cdots \ p_n] = \pi_0$

$p_i =$  probability of being in state  $i$ ,

$$p_1 + p_2 + \cdots + p_n = 1,$$

after  $t$  steps, the probabilistic state is:

$$[p_1 \ p_2 \ \cdots \ p_n] \begin{bmatrix} \text{Transition} \\ \text{Matrix} \end{bmatrix}^t = \pi_t$$

# Remarkable Property of Markov Chains

## What happens in the long run?

i.e., can we say anything about  $\pi_t$  for large  $t$  ?

Suppose the Markov chain is “aperiodic”.

Then, as the system evolves, the probabilistic state **converges** to a **limiting probabilistic state**.

As  $t \rightarrow \infty$ , for any  $\pi_0 = [p_1 \ p_2 \ \cdots \ p_n]$  :

$$[p_1 \ p_2 \ \cdots \ p_n] \begin{bmatrix} \text{Transition} \\ \text{Matrix} \end{bmatrix}^t \rightarrow \pi$$




# Remarkable Property of Markov Chains

In other words:

$$\pi_t \rightarrow \pi \quad \text{as} \quad t \rightarrow \infty.$$

Note:

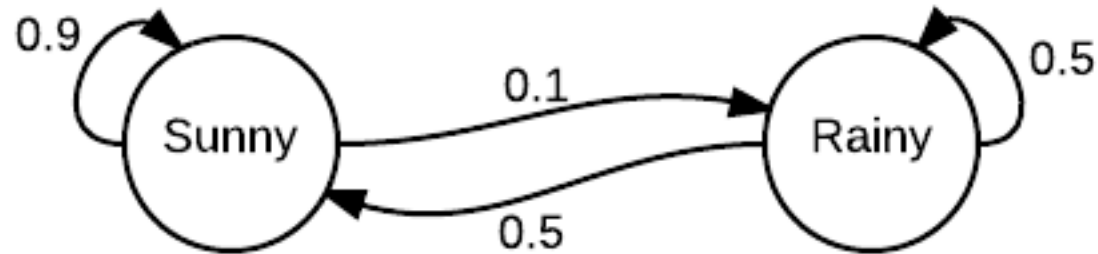
$$\pi \begin{bmatrix} \text{Transition} \\ \text{Matrix} \end{bmatrix} = \pi$$



**stationary/invariant  
distribution**

This  $\pi$  is unique.

# Remarkable Property of Markov Chains



Stationary distribution is  $\left[ \frac{5}{6} \quad \frac{1}{6} \right]$ .

$$\left[ \frac{5}{6} \quad \frac{1}{6} \right] \begin{bmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{bmatrix} = \left[ \frac{5}{6} \quad \frac{1}{6} \right]$$

*In the long run, it is Sunny **5/6** of the time,  
it is Rainy **1/6** of the time.*

# Remarkable Property of Markov Chains

How did I find the stationary distribution?

$$\begin{bmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{bmatrix}^2 = \begin{bmatrix} 0.86 & 0.14 \\ 0.7 & 0.3 \end{bmatrix}$$

$$\begin{bmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{bmatrix}^4 = \begin{bmatrix} 0.8376 & 0.1624 \\ 0.812 & 0.188 \end{bmatrix}$$

$$\begin{bmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{bmatrix}^8 = \begin{bmatrix} 0.833443 & 0.166557 \\ 0.832787 & 0.167213 \end{bmatrix}$$

**Exercise:** Why do the rows converge to  $\pi$  ?

# Things to remember

Markov Chains can be characterized by the **transition matrix**  $K$ .

$$K[i, j] = \Pr[i \rightarrow j \text{ in one step}]$$

What is the probability of being in state  $i$  after  $t$  steps?

$$\pi_t = \pi_0 \cdot K^t \qquad \pi_t[i] = (\pi_0 \cdot K^t)[i]$$

# Things to remember

## **Theorem** (Fundamental Theorem of Markov Chains):

Consider a Markov chain that is strongly connected and aperiodic.

- There is a unique invariant/stationary distribution  $\pi$  such that

$$\pi = \pi K.$$

- For any initial distribution  $\pi_0$ ,

$$\lim_{t \rightarrow \infty} \pi_0 K^t = \pi$$

- Let  $T_{ij}$  be the number of steps it takes to reach state  $j$  provided we start at state  $i$ . Then,

$$\mathbf{E}[T_{ii}] = \frac{1}{\pi[i]}.$$

# The plan

Motivating examples and applications

Basic mathematical representation and properties

A bit more on applications

# How are Markov Chains applied ?

## 2 common types of applications:

**1.** Build a Markov chain as a statistical model of a real-world process.

Use the Markov chain to simulate the process.

e.g. **text generation**, music composition.

**2.** Use a measure associated with a Markov chain to approximate a quantity of interest.

e.g. **Google PageRank**, image segmentation

# Automatic Text Generation

Generate a superficially real-looking text given a sample document.

## Idea:

From the sample document, create a Markov chain.

Use a random walk on the Markov chain to generate text.

## Example:

Collect speeches of Obama, create a Markov chain.

Use a random walk to generate new speeches.



# Automatic Text Generation

## The Markov Chain:

1. For each word in the document, create a node/state.
2. Put an edge **word1** ---> **word2** if there is a sentence in which **word2** comes after **word1**.
3. Edge probabilities reflect frequency of the pair of words.



# Automatic Text Generation

“I jumped up. I don't know what's going on so I am coming down with a road to opportunity. I believe we can agree on or do about the major challenges facing our country.”

# Automatic Text Generation

## Another use:

Build a Markov chain based on speeches of Obama.

Build a Markov chain based on speeches of Bush.

Given a **new** quote, can predict if it is by Obama or Bush.

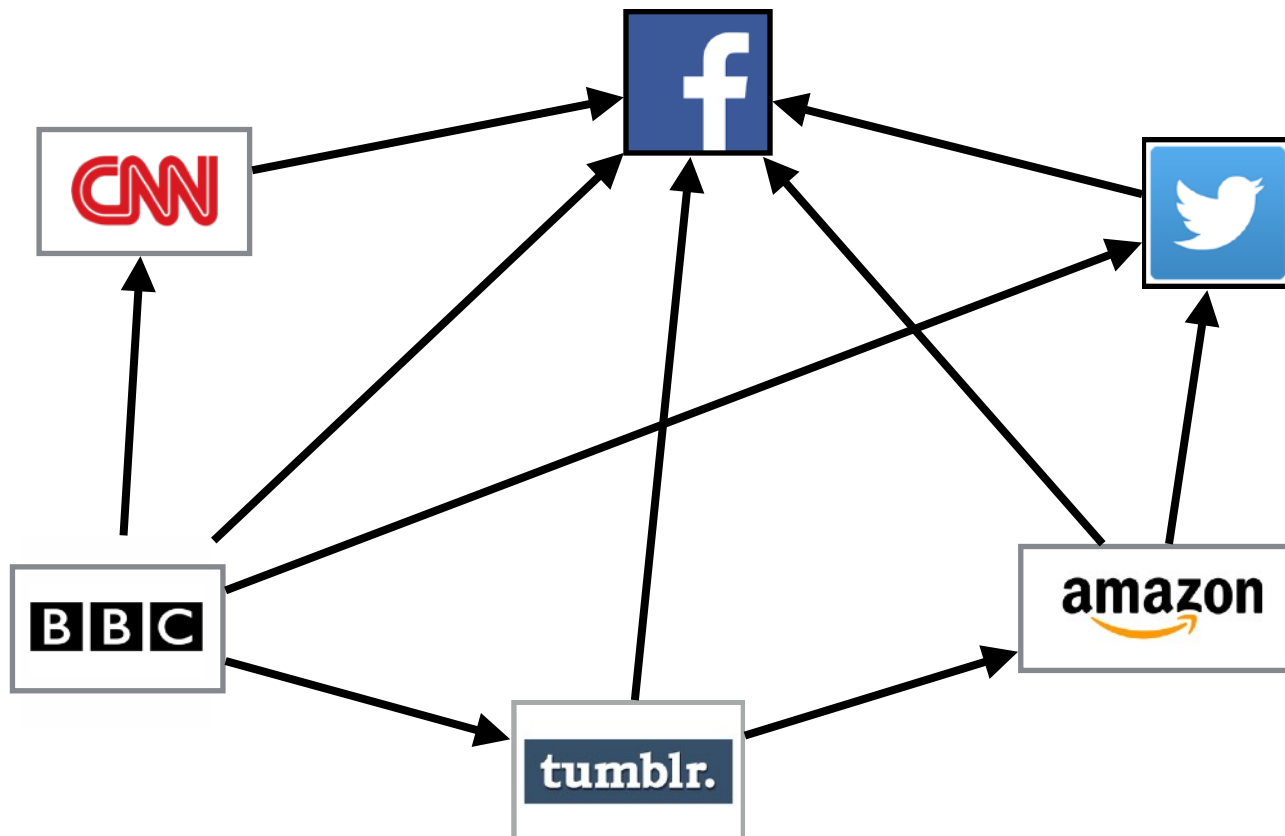
(by testing which Markov model the quote fits best)

# Google PageRank

PageRank is a measure of **reputation**:

The number and reputation of links pointing to you.

## The Markov Chain:



# Google PageRank

PageRank is a measure of **reputation**:

The number and reputation of links pointing to you.

## The Markov Chain:

1. Every webpage is a node/state.

2. Each hyperlink is an edge:

if webpage **A** has a link to webpage **B**,  $A \dashrightarrow B$

3a. If **A** has  $m$  outgoing edges, each gets label  $1/m$ .

3b. If **A** has no outgoing edges, put edge  $A \dashrightarrow B \quad \forall B$   
(jump to a random page)

# Google PageRank

A little tweak:

Random surfer jumps to a random page with 15% prob.

**Stationary distribution:**

probability of being at webpage **A** in the long run

PageRank of webpage **A**

=

The stationary probability of **A**



# Google PageRank

**Google:**

*“PageRank continues to be the heart of our software.”*



# The plan

Motivating examples and applications

Basic mathematical representation and properties

A bit more on applications