

Link Analysis

Introduction to Information Retrieval

INF 141/ CS 121

Donald J. Patterson

Content adapted from Hinrich Schütze

<http://www.informationretrieval.org>

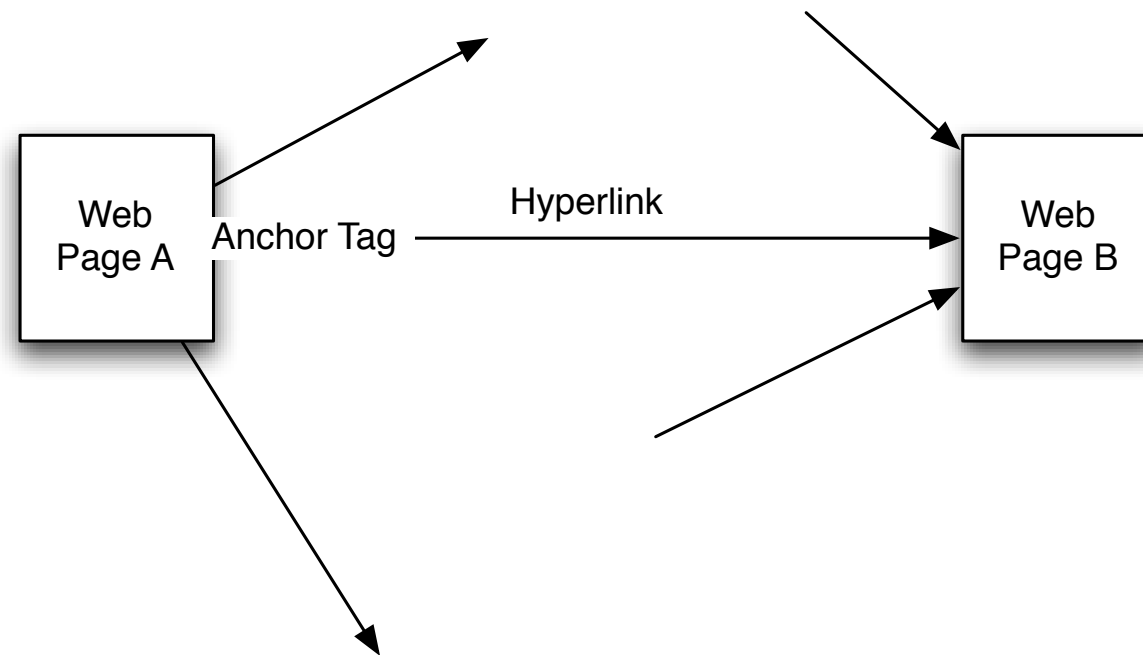


Outline

- The web as a directed graph



The web as a directed graph



- Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)
- Assumption 2: The anchor of the hyperlink describes the target page (textural context)

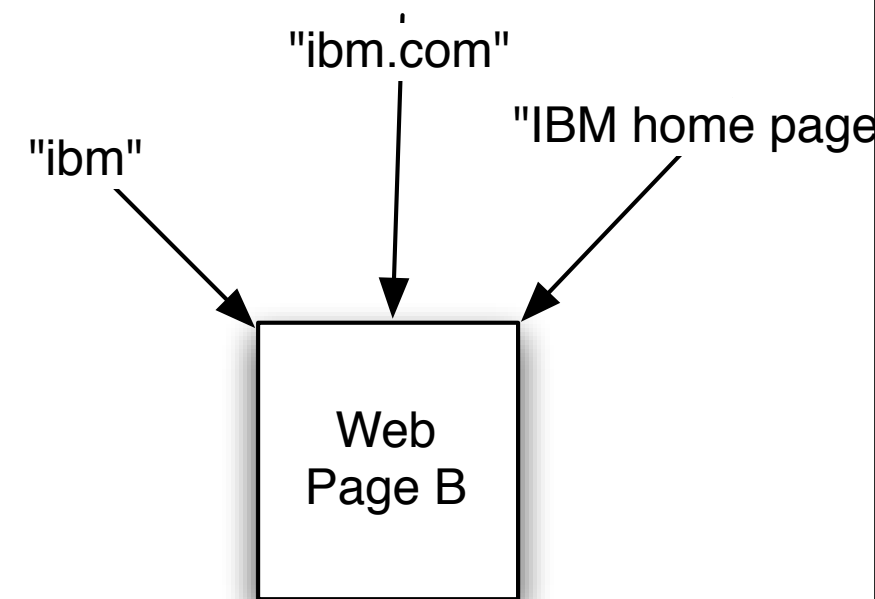
The web as a directed graph

- Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)
- Assumption 2: The anchor of the hyperlink describes the target page (textual context)
- Where might these assumptions not hold?



The web as a directed graph

- Anchor Text
 - WWW Worm -McBryan94
- For IBM how do you distinguish between
 - IBM's home page (mostly graphics)
 - IBM's copyright page (high TF for "ibm")
 - Rival spam page (high TF for "ibm")
 - ?
- A million pieces of anchor text with "ibm" send a strong



signal

Indexing anchor text also

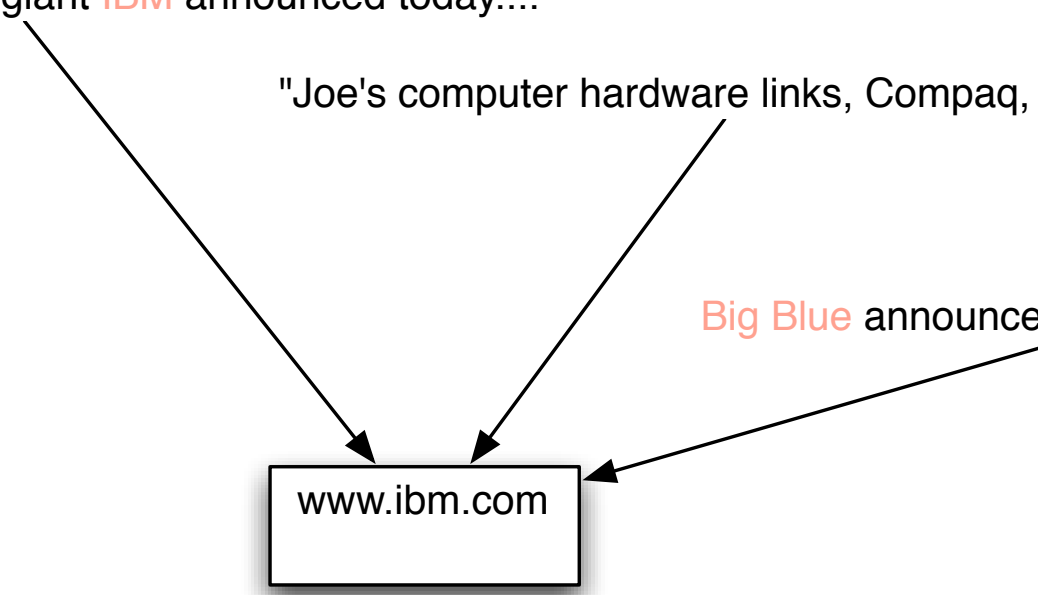
- When indexing a document D
- include anchor text from links **pointing** to D

"Armonk, NY-based computer giant **IBM** announced today...."

"Joe's computer hardware links, Compaq, HP, **IBM**"

Big Blue announced record profits for the quarter

www.ibm.com



Indexing anchor text

- Anchor text is often a better description of a page's content than the page itself.
- Can be weighted more highly than the text
 - If enough anchor text is available
 - Same technique as zone weighting
 - create a "zone" for anchor text
- Indexing anchor text can have unexpected side effects
 - Google bombs, miserable failure
 - nigrITUDE ultramarine follow-on



Anchor text

- Other applications
 - Weighting links in the graph
 - Generating page descriptions from anchor text



PageRank

- Citation analysis:
 - Analysis of citations in the scientific literature
 - Example citation:
 - “Miller (2001) has shown that physical activity alters the metabolism of estrogens”



The web as a directed graph

- Link Analysis/PageRank has its origins in bibliometrics
 - “Measurement of influence among publications based on citations”
 - Just as citing a paper confers authority upon it, linking to a page confers authority to it.

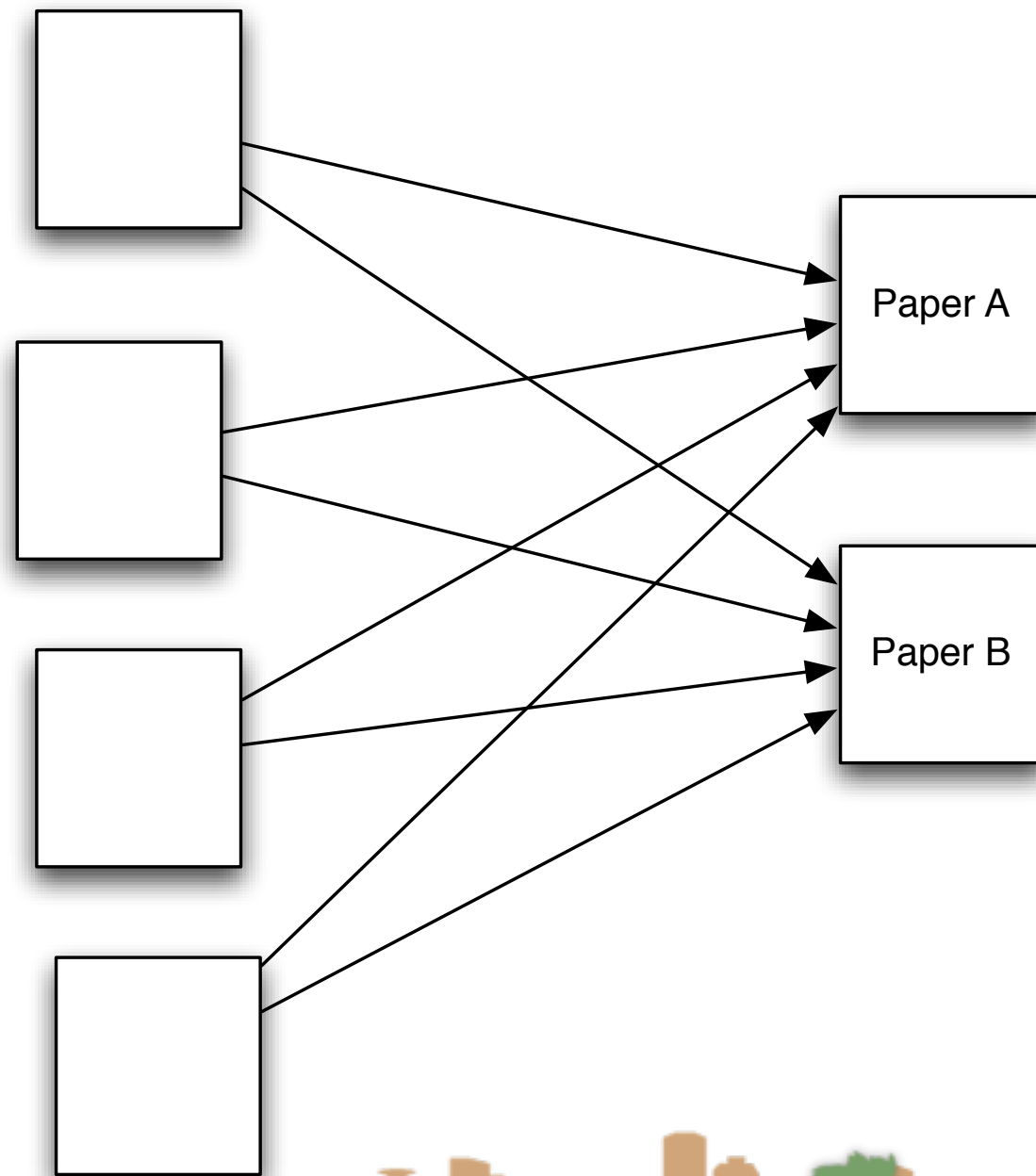


Bibliometrics

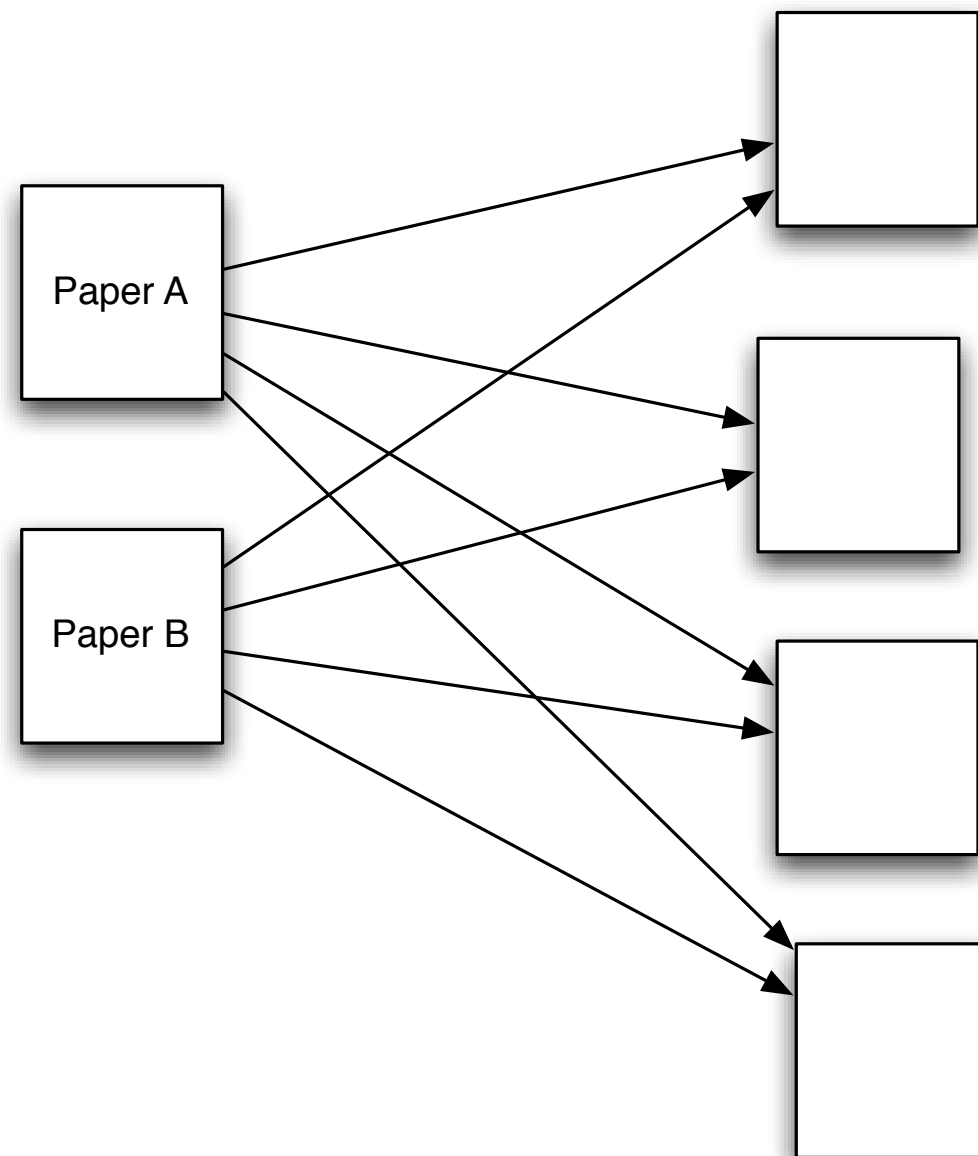
- Two ways of measuring similarity of scientific articles:
 - Cocitation similarity: The two articles are cited by the same articles
 - Bibliographic coupling similarity: The two articles cite the same articles



Co-citation similarity



Bibliographic coupling similarity



Bibliometrics

- Citation frequency can be used to measure impact
 - Each article gets one vote
 - Not a very accurate measure
- Better measure: weighted citation frequency/ citation rank
 - An article's vote is weighted according to its citation impact.
 - Sounds circular, but can be formalized in a well-defined way
 - This is basically PageRank
 - Invented for citation analysis in the 1960's by Pinsker and

Narin



Key Observation

- A citation in scientific literature is like a link on the web



Link Analysis

- A full search engine ranks based on many different scores
 - Cosine similarity
 - Term proximity
 - Zone scoring
 - Contextual relevance (implicit queries)
 - Link analysis



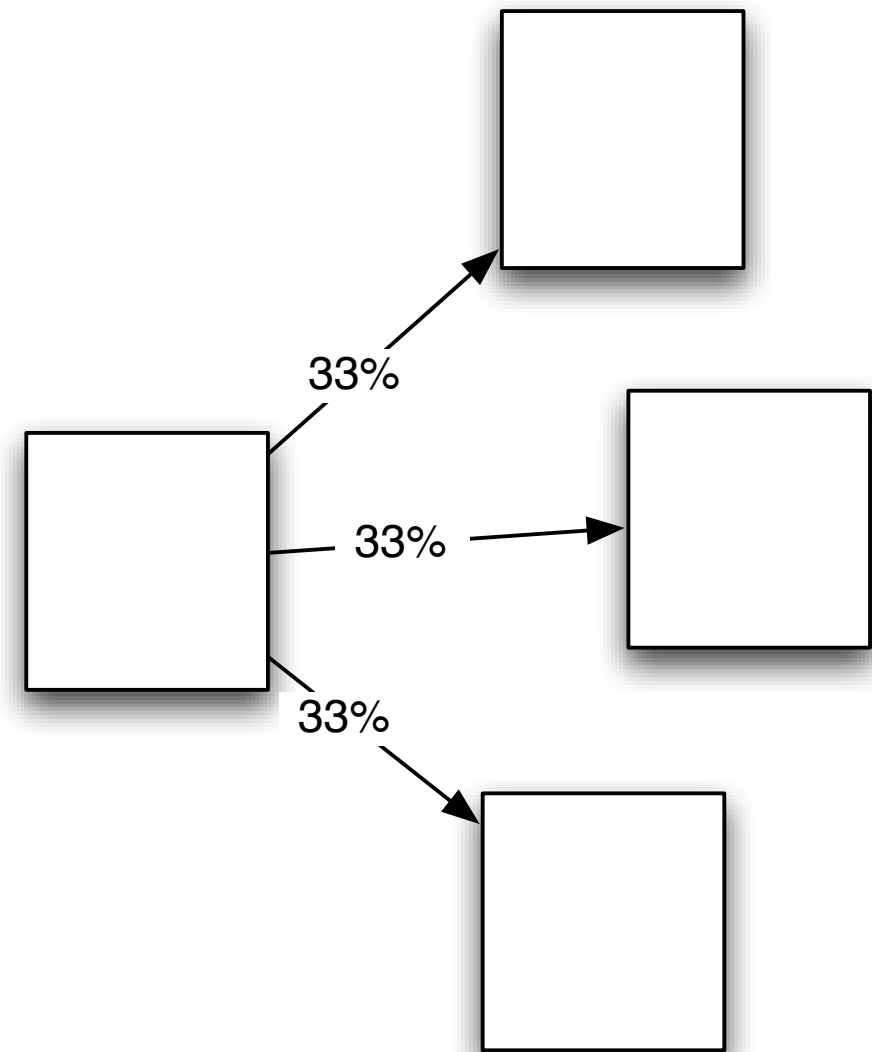
Link based query ranking

- Retrieve all pages meeting the query
- First generation:
 - Then order them by their link popularity
 - citation frequency
 - Easy to spam. Why?
- Second generation:
 - Order them by their weighted link popularity
 - PageRank



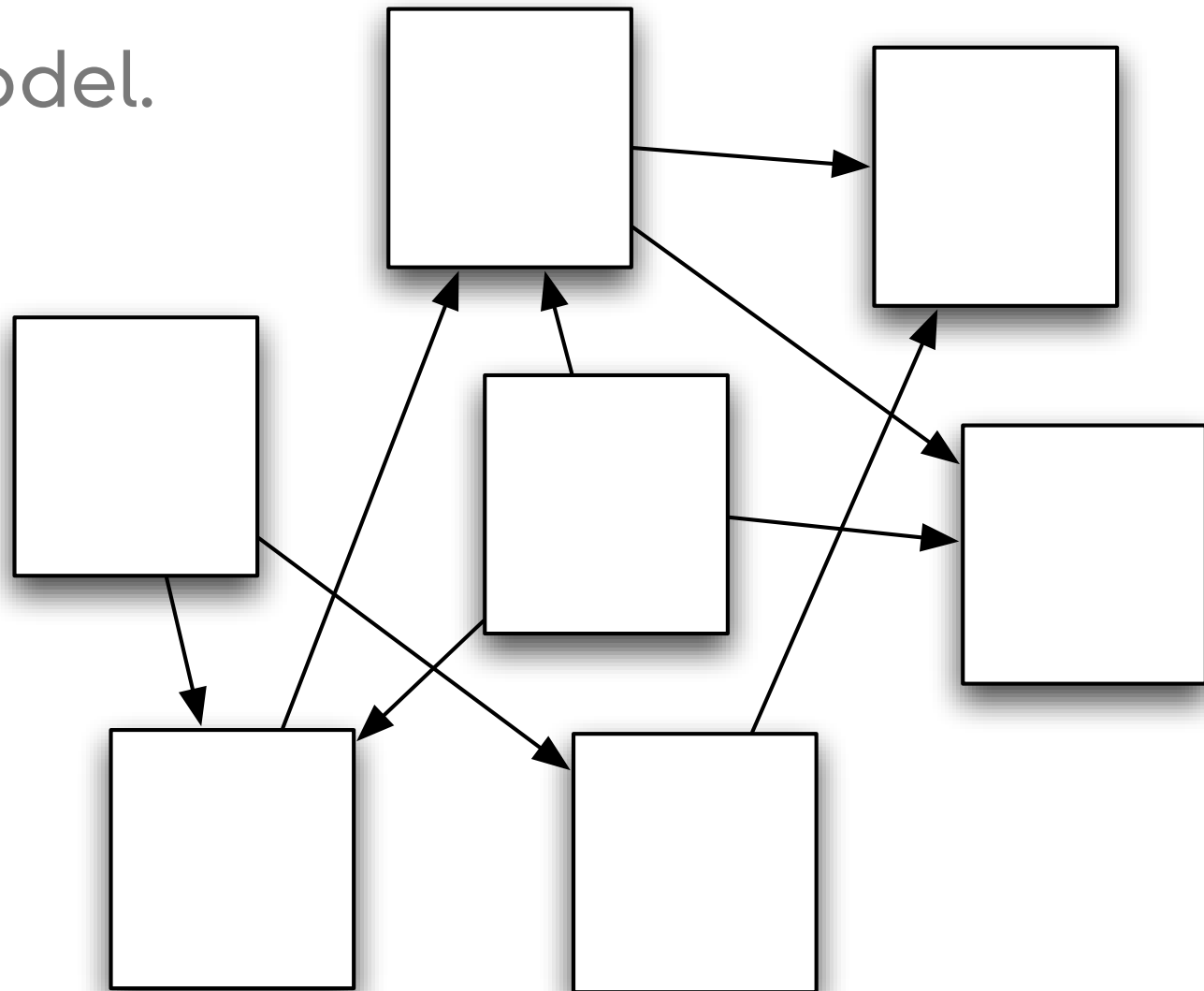
PageRank

- Every webpage gets a score
 - between 0 and 1
 - it's **PageRank**
- The random walk
 - Start at a random page
 - Follow an out edge with equal probability
- In the long run each page has a long-term visit rate.



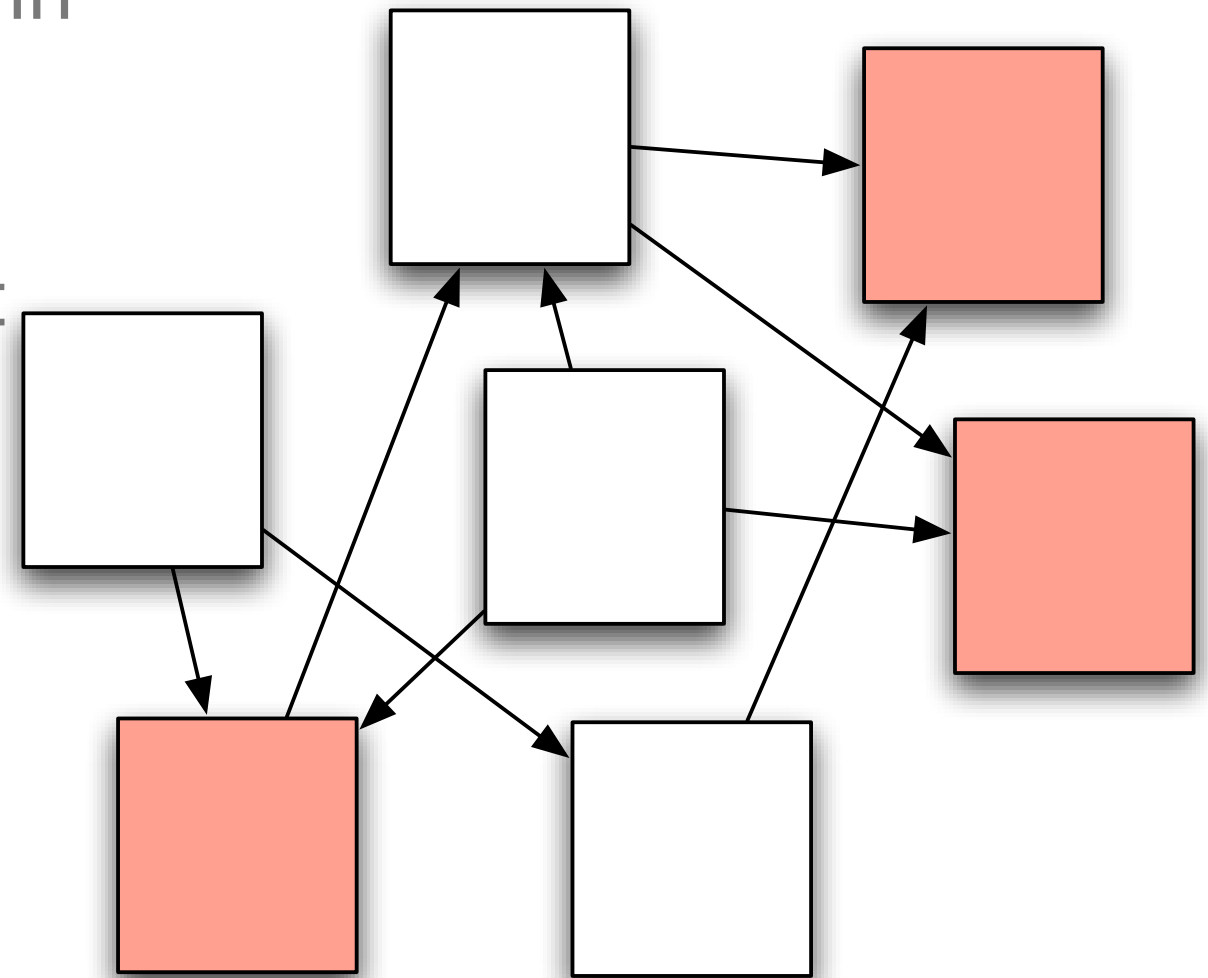
PageRank

- PageRank is a page's long-term steady state visit rate based on a random walk model.



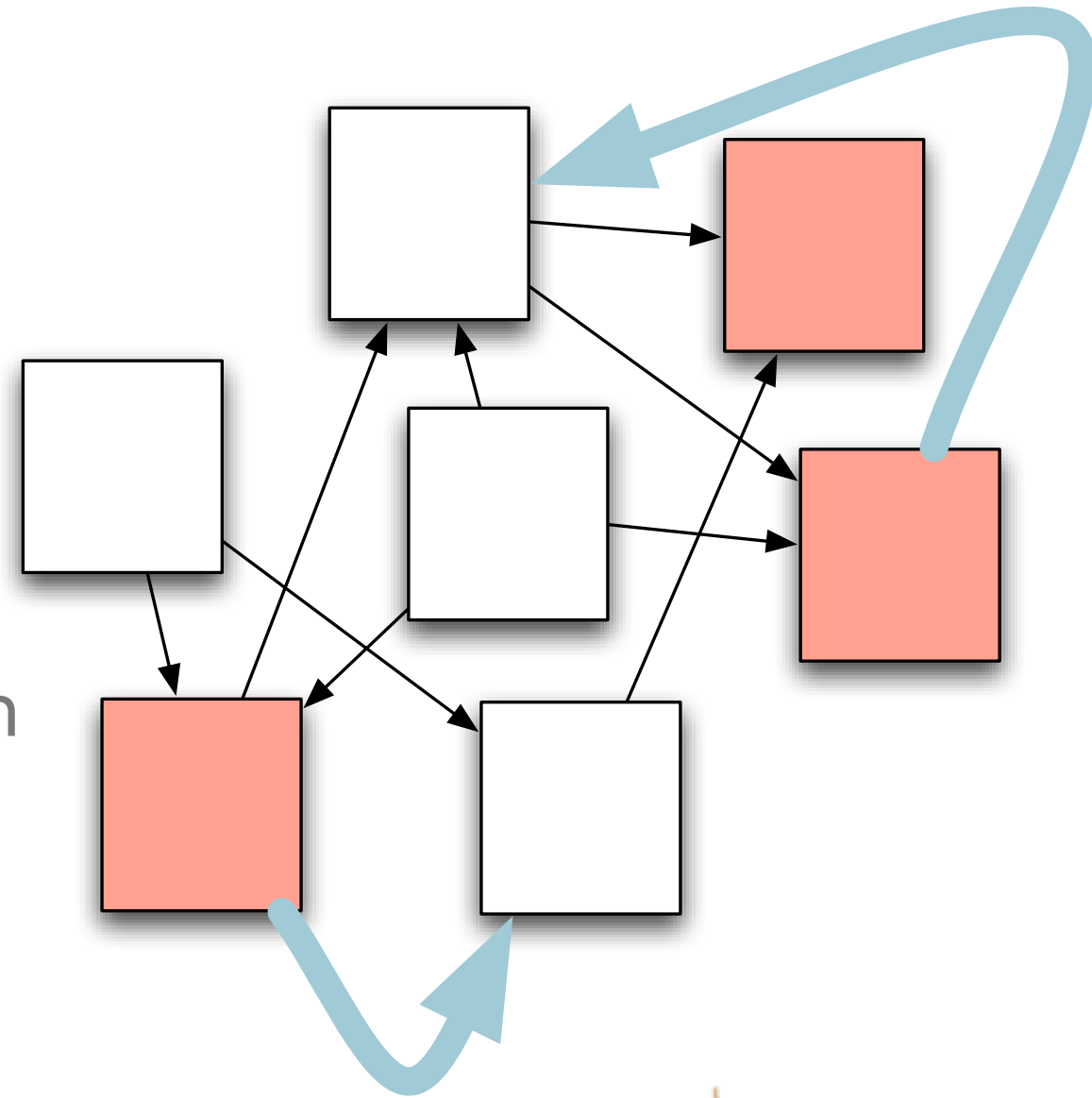
Visit Rate not quite enough

- The web is full of dead-ends
- A random walk can get stuck in dead-ends
- Makes no sense to talk about long-term visit rates



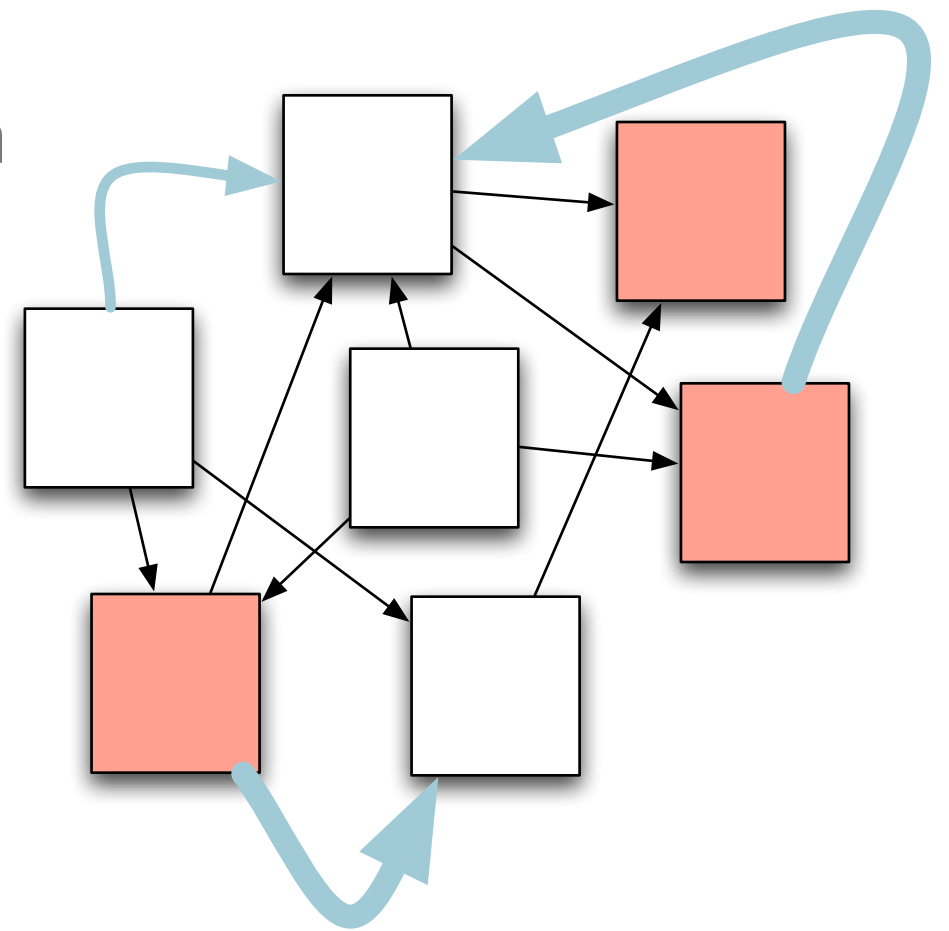
Teleporting

- At a dead end, jump to a random web page
- at any non-dead end, with probability 10% jump to a random web page anyway
- the other 90% choose a random out link
- “10%” is a tunable parameter



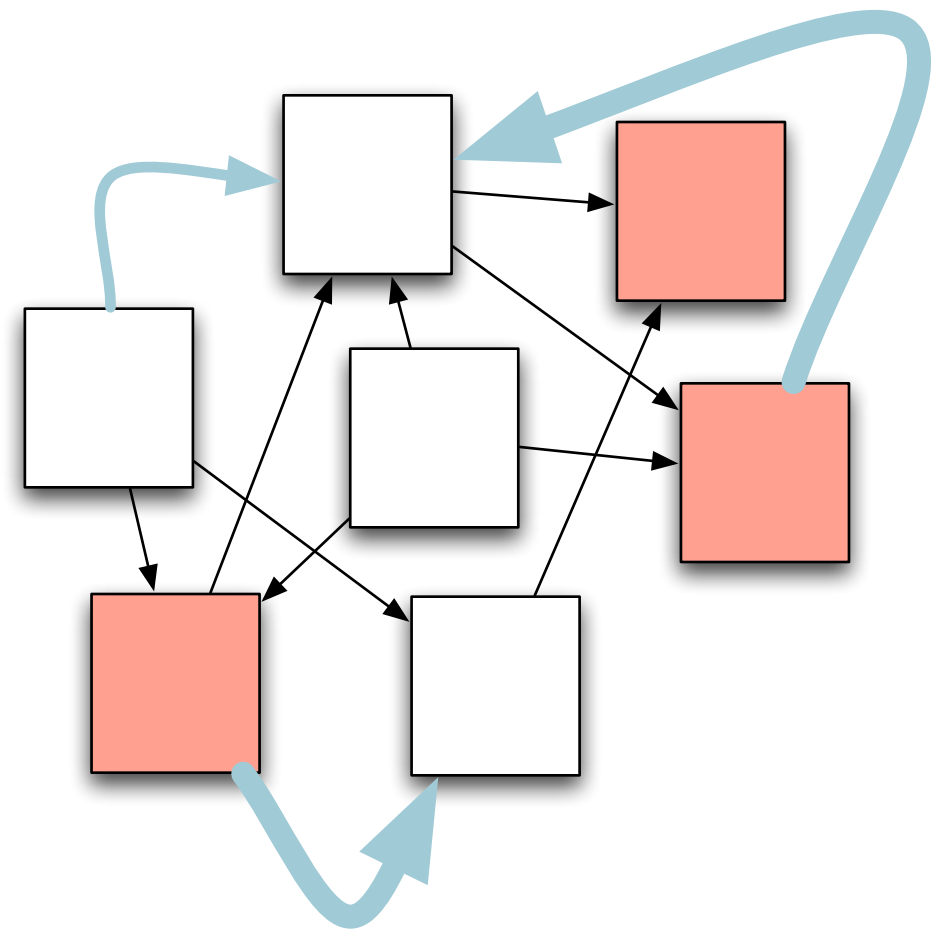
Teleporting

- Now we cannot get stuck locally
- There is a long-term visit rate at which any page is visited.
- How do we compute the visit rate?
 - How do we compute PageRank?
- (By the way this is a Markov Chain)



Markov Chains

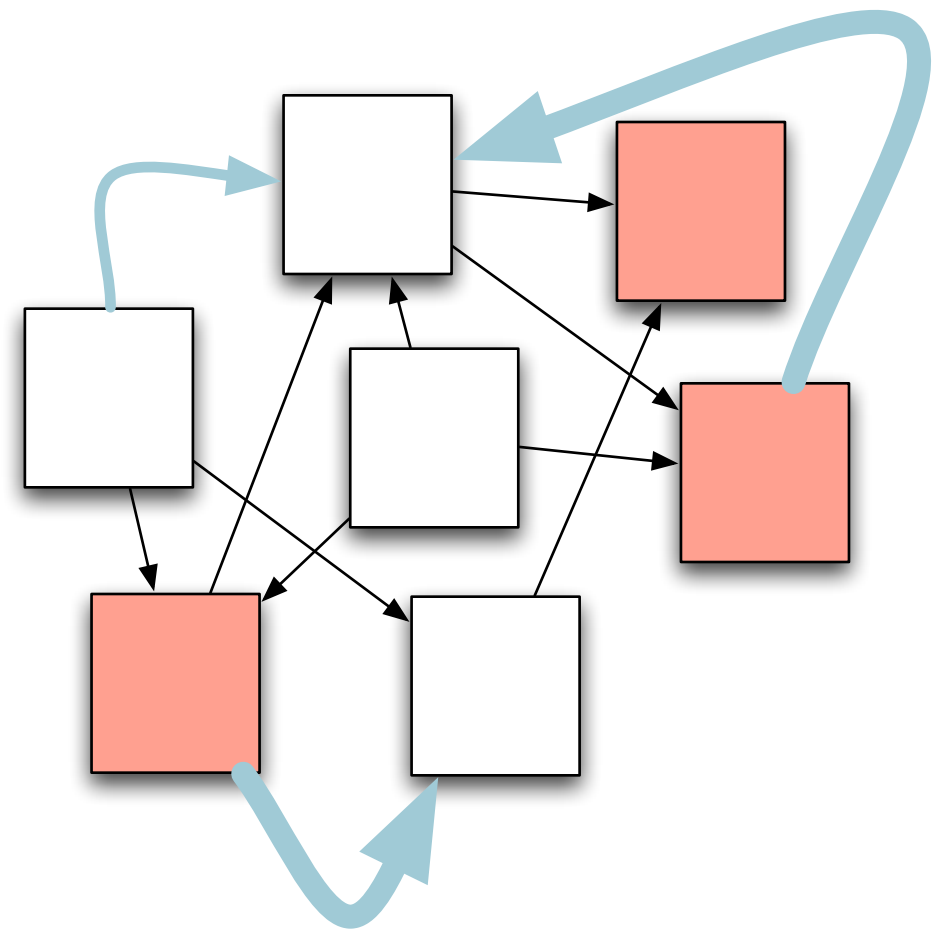
- A Markov Chain is a mathematical “game”
- It consists of n **states**
 - corresponds to web pages
- And a **transition probability matrix**
 - corresponds to links
 - it is like an adjacency matrix



Markov Chains

- At any moment in the game we are in one of the **states**
- In the next step we move to a new state
- We use the **transition matrix** to decide which state to move into.
- If you are in state "i" then the probability of moving into state "j" is

$$P(i \rightarrow j)$$



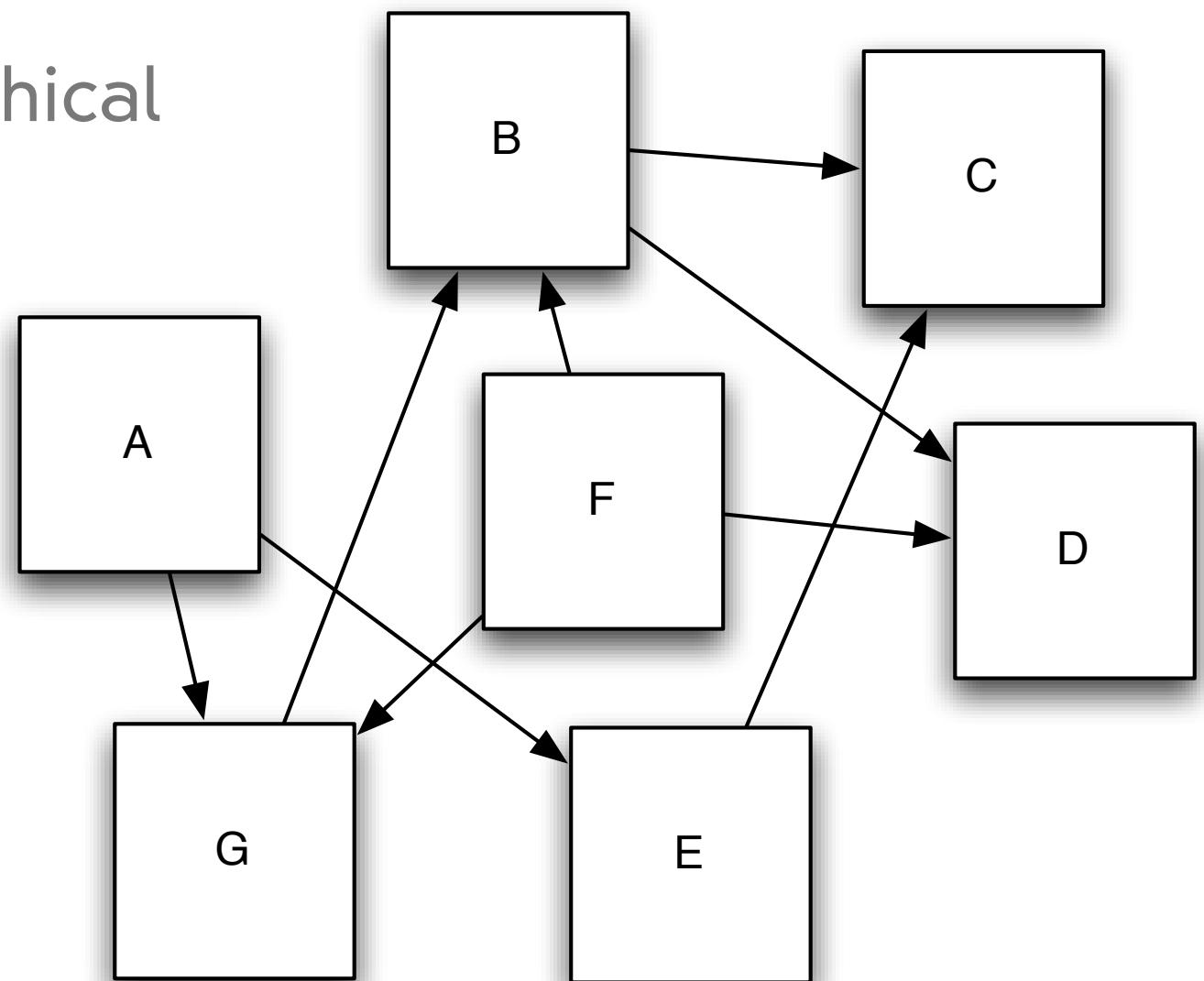
Markov Chains

- Markov Chains are described by two parameters:
 - A list of n **states**
 - An (n by n) **transition probability table**
- It's like a graph, except that links aren't boolean, they are real numbers.
 - A link doesn't just exist or not exist
 - It exists with a probability also



Exercise

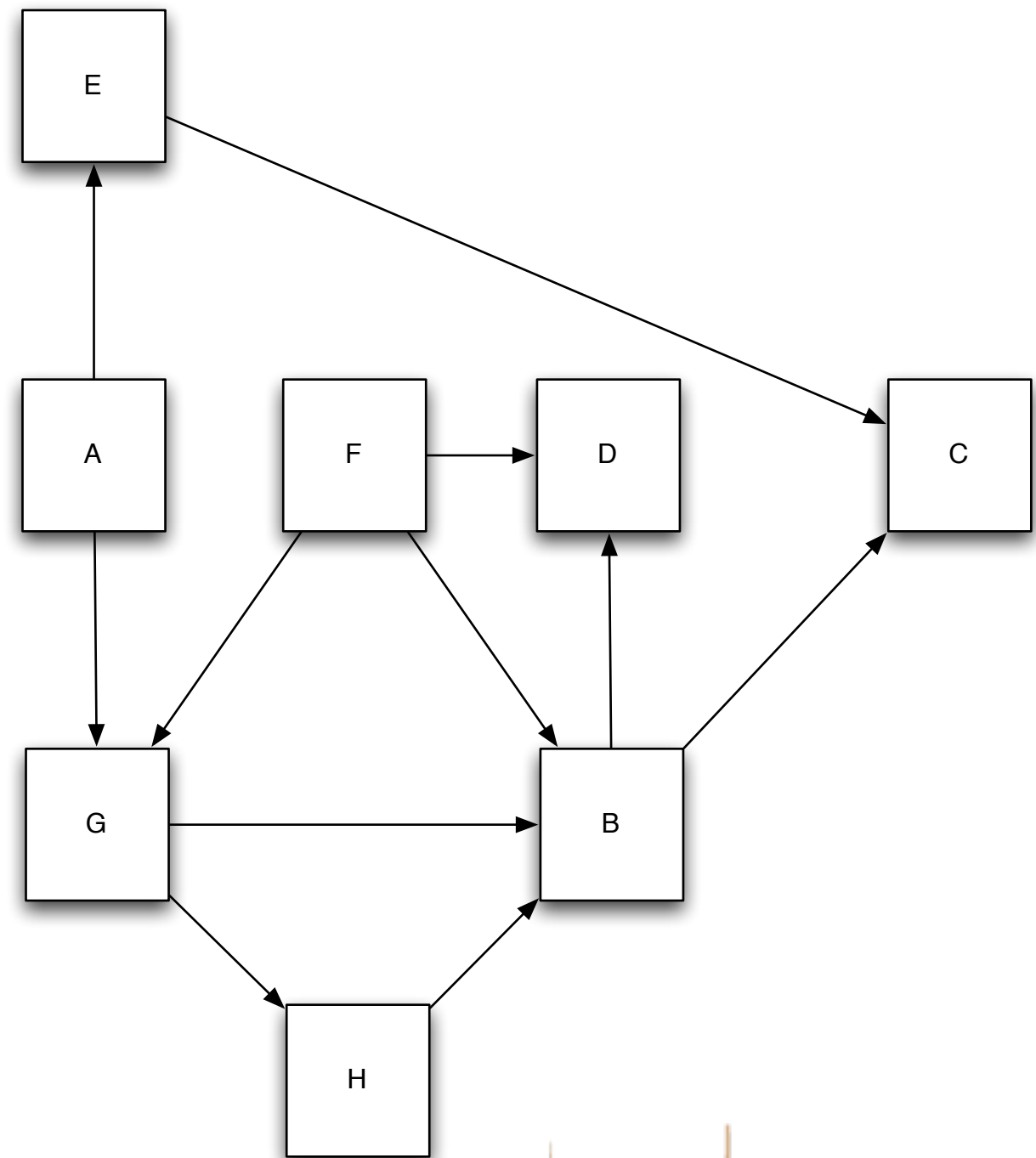
- Compute the parameters of the Markov Chain for this graphical model



Markov Chains

- Example:
 - 8 states
 - (web pages or whatever)
 - 8 by 8 transition prob. matrix

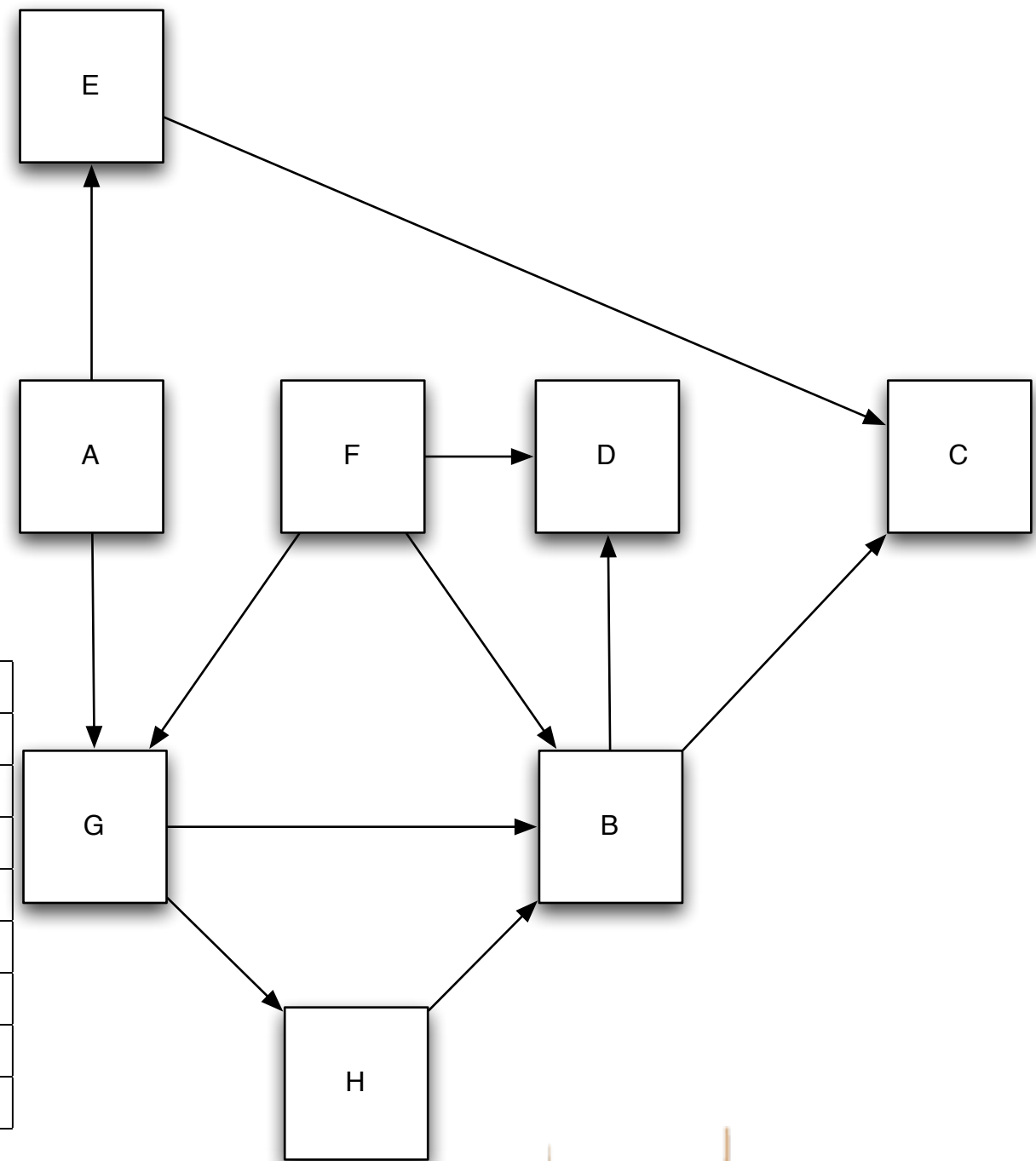
	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0	0	0	0	0	0	0	0
<i>D</i>	0	0	0	0	0	0	0	0
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



Markov Chains

- Example:
 - 8 states
 - 8 by 8 transition prob. matrix
 - Handle Dead-Ends also

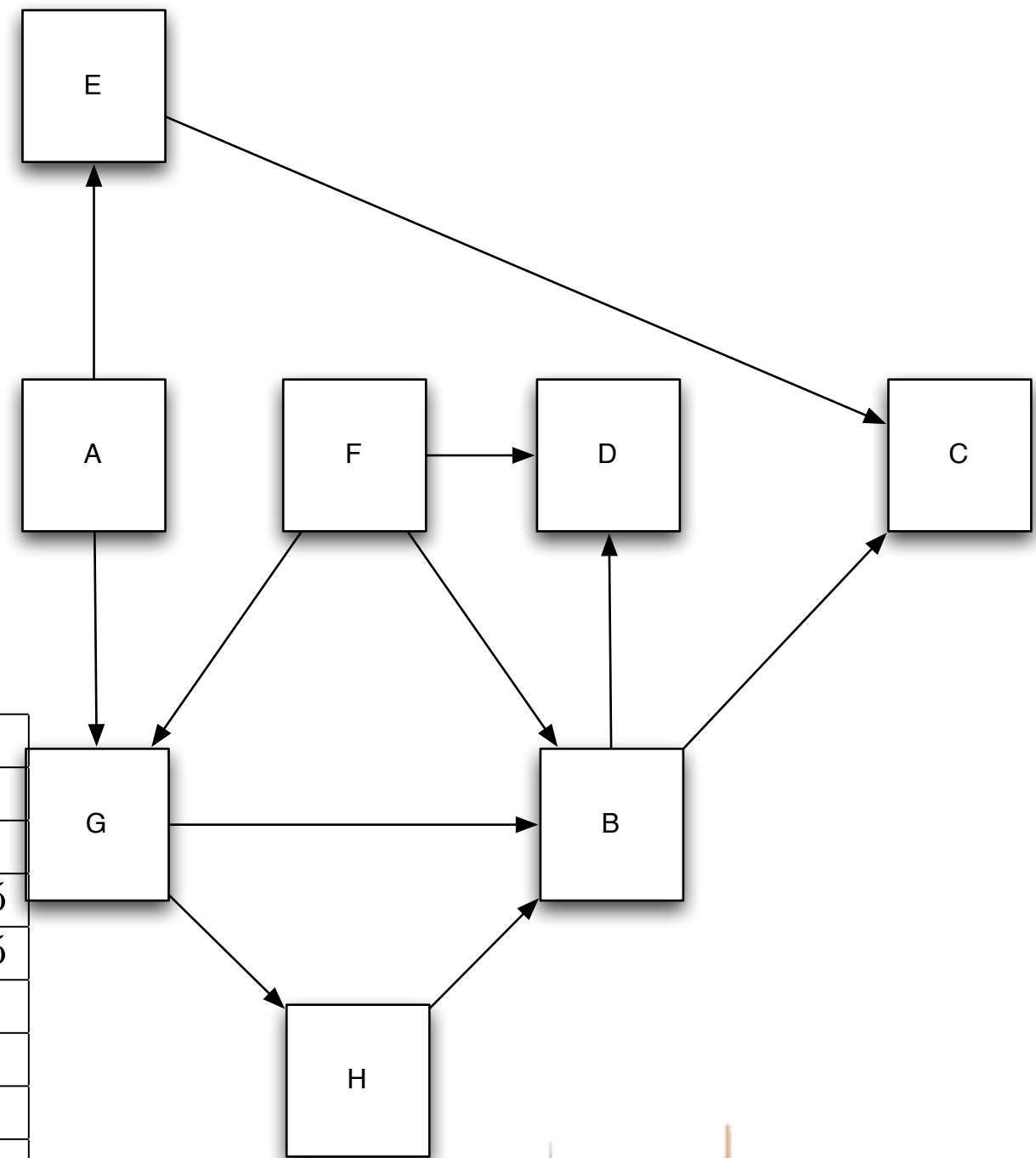
	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



Markov Chains

- Example:
 - 8 states
 - 8 by 8 transition prob. matrix
 - Handle Dead-Ends also
 - Handle teleports

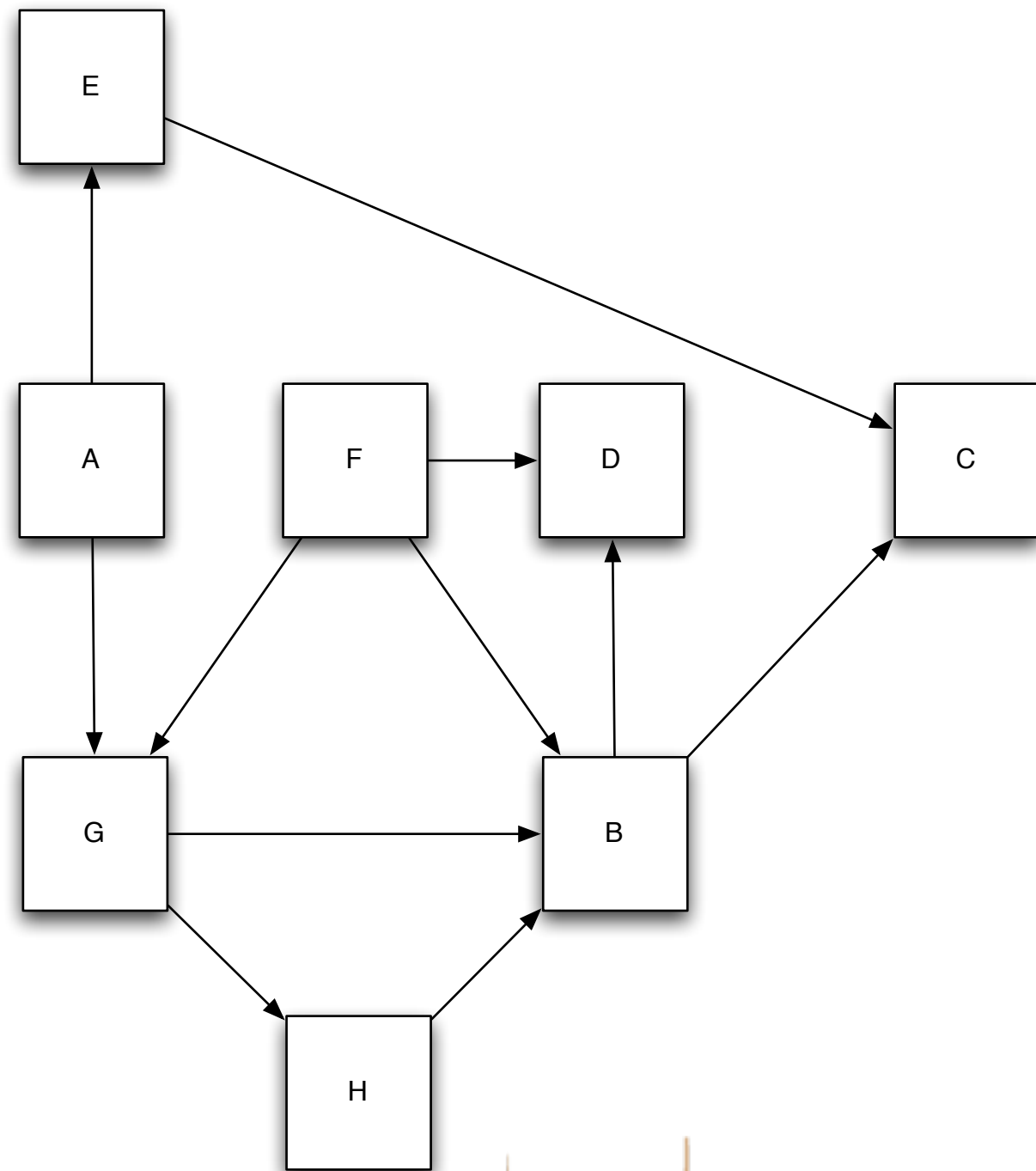
	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0.01	0.01	0.01	0.01	0.47	0.01	0.47	0.01
<i>B</i>	0.01	0.01	0.47	0.47	0.01	0.01	0.01	0.01
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0.01	0.01	0.93	0.01	0.01	0.01	0.01	0.01
<i>F</i>	0.01	0.32	0.01	0.32	0.01	0.01	0.32	0.01
<i>G</i>	0.01	0.47	0.01	0.01	0.01	0.01	0.01	0.47
<i>H</i>	0.01	0.93	0.01	0.01	0.01	0.01	0.01	0.01



Markov Chain : The Game

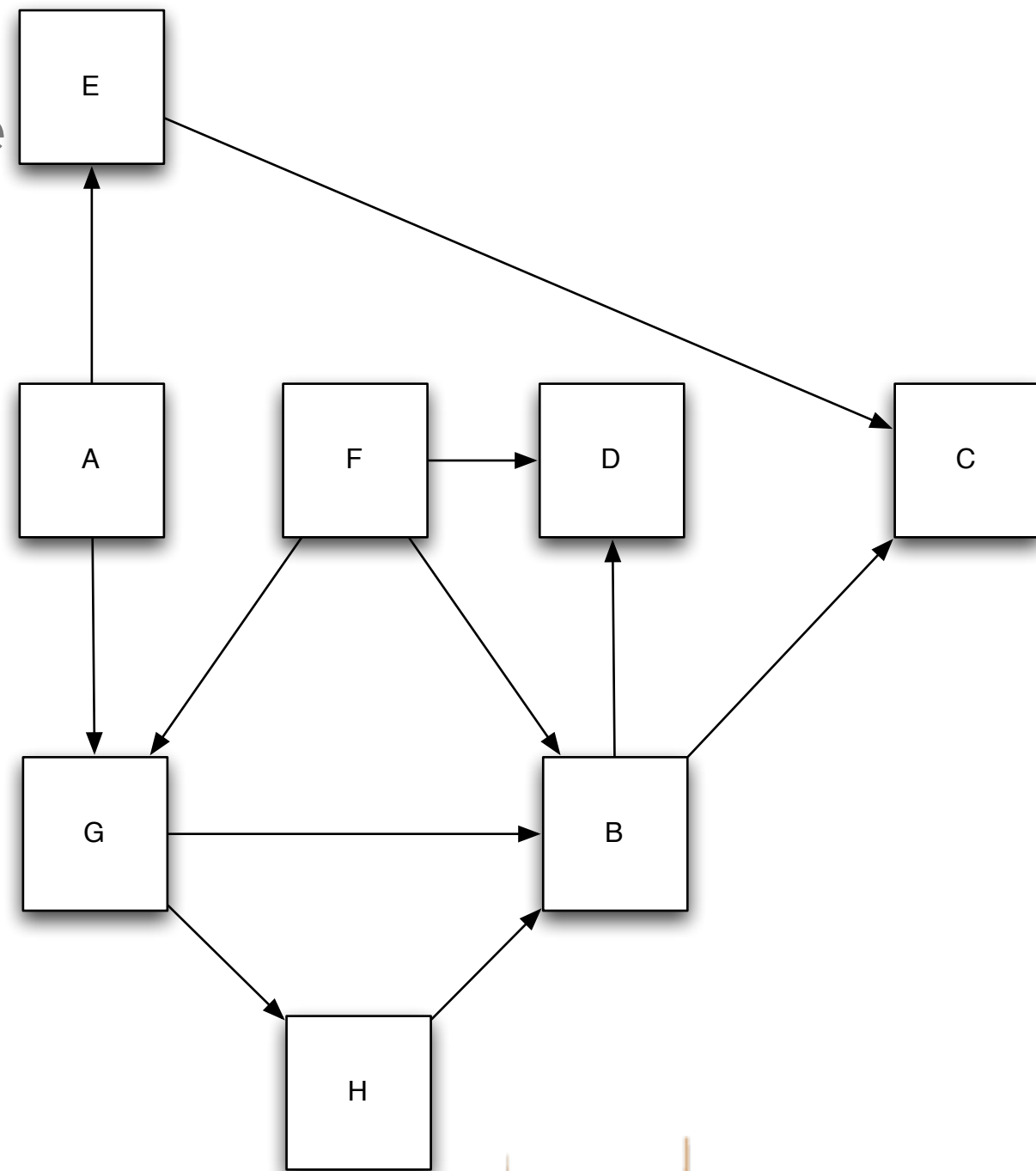
- You may be in one state at a time
- Every tick you move one step
chosen randomly from the
transition probability matrix

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



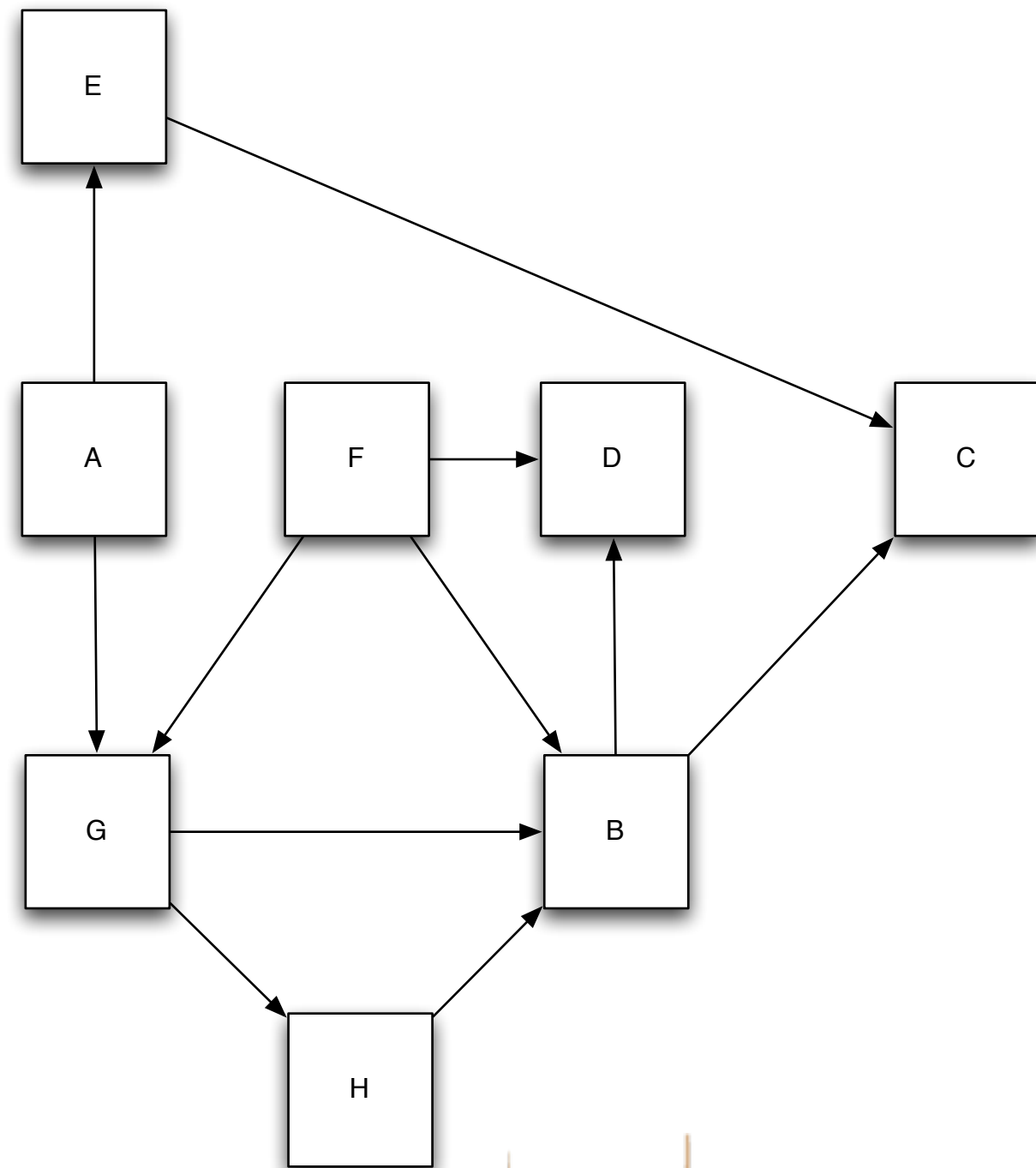
The Markov Property

- It doesn't matter where you came from.
- All information that you need to take the next step comes from your current state and the transition probability matrix
- History is irrelevant given your current state

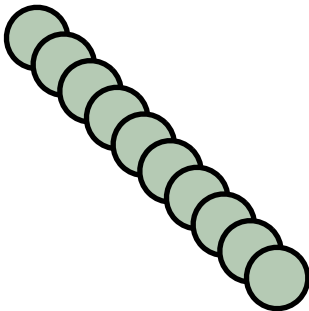


PageRank

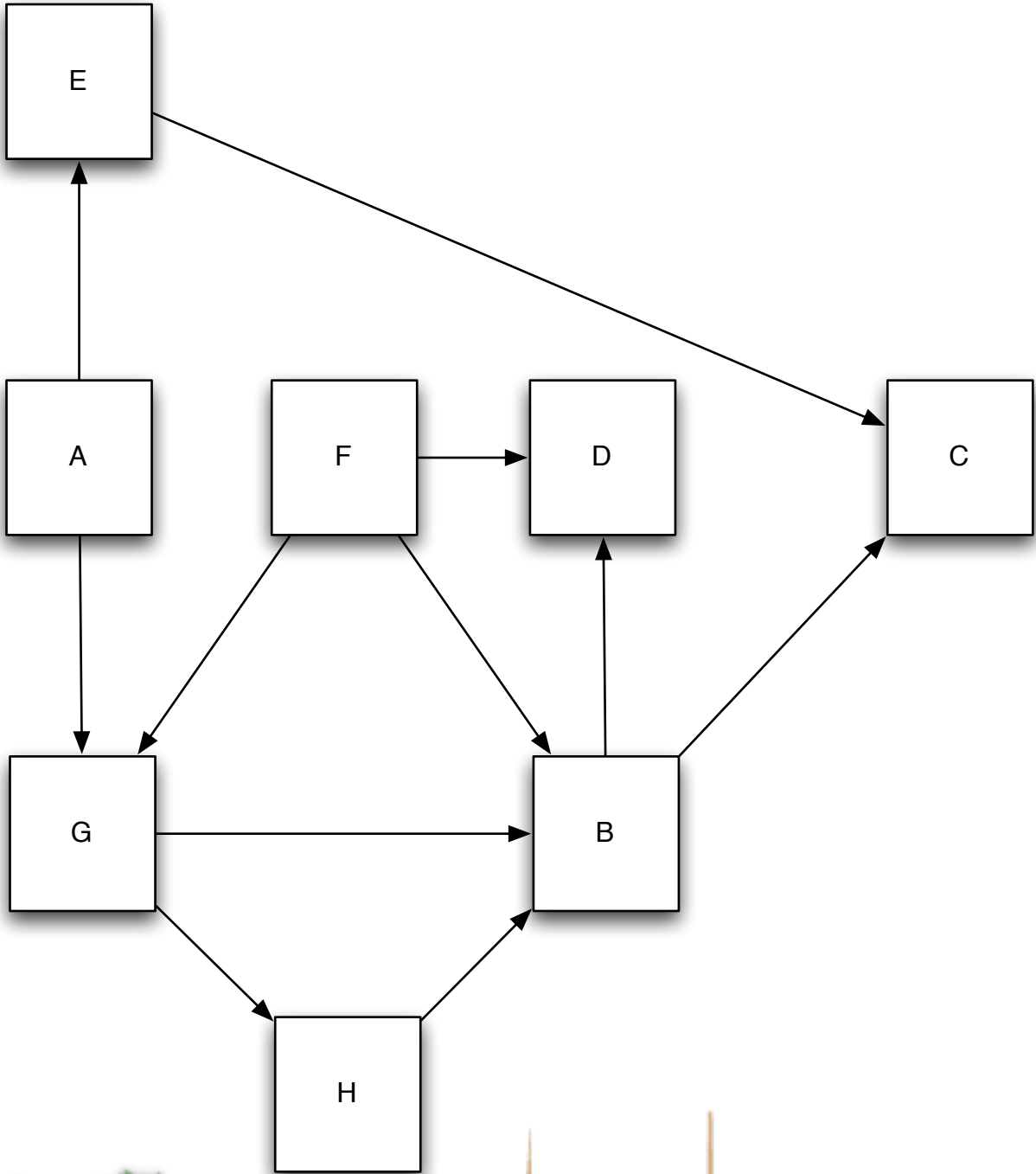
- PageRank is the long term visit rate of a random walk on the graph.
- With teleports



Long-Term visit rate

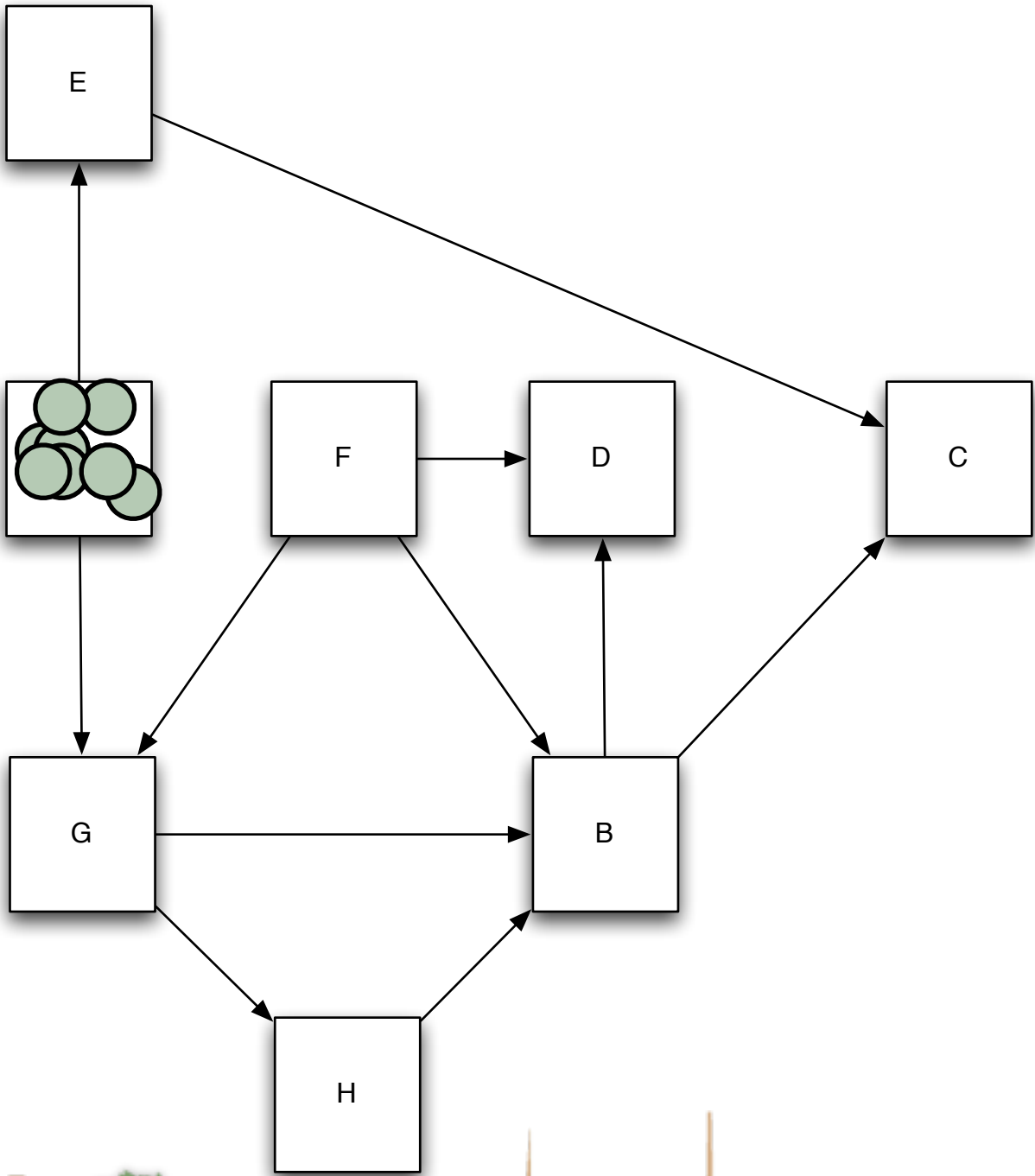


	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



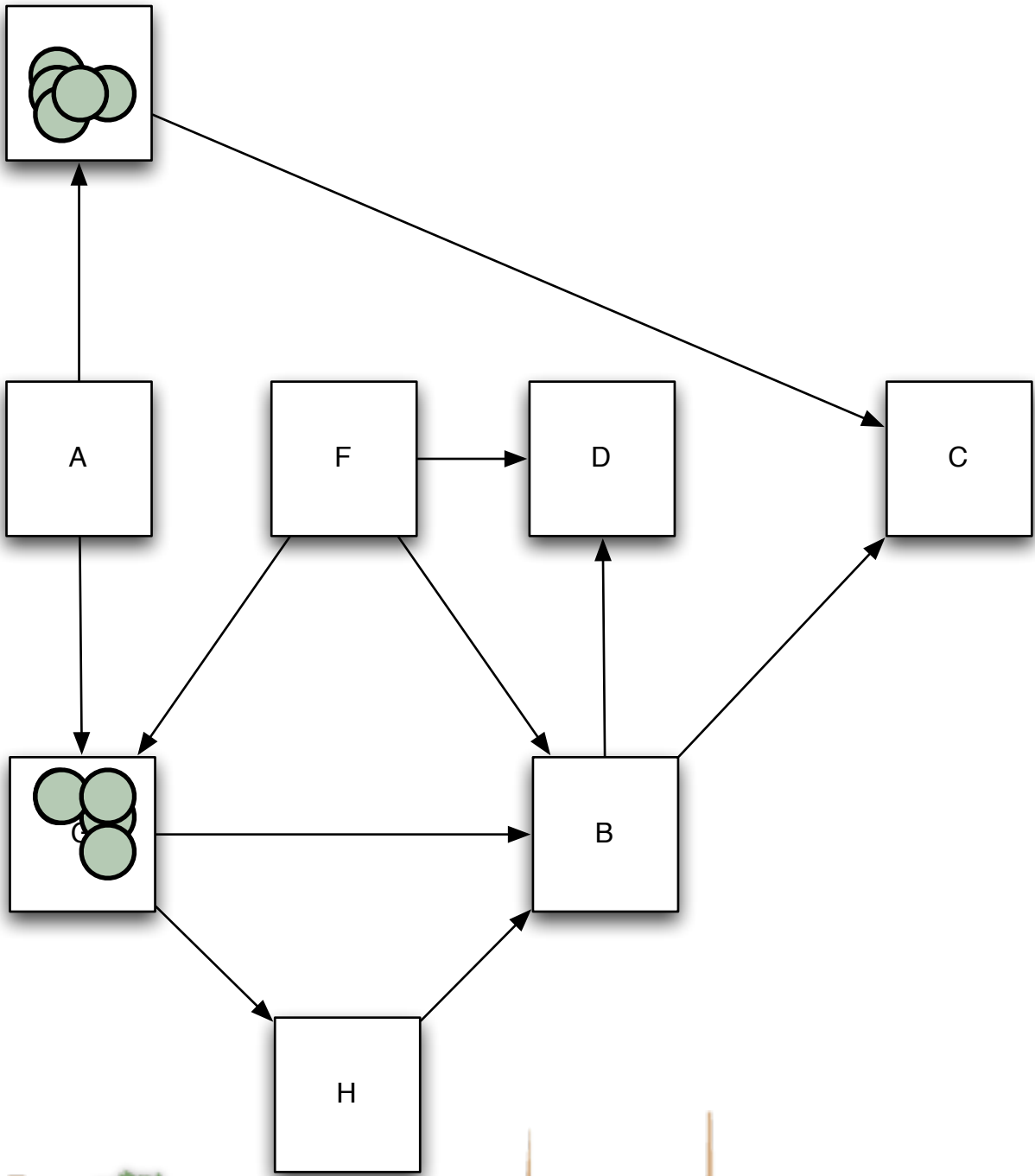
Long-Term visit rate

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



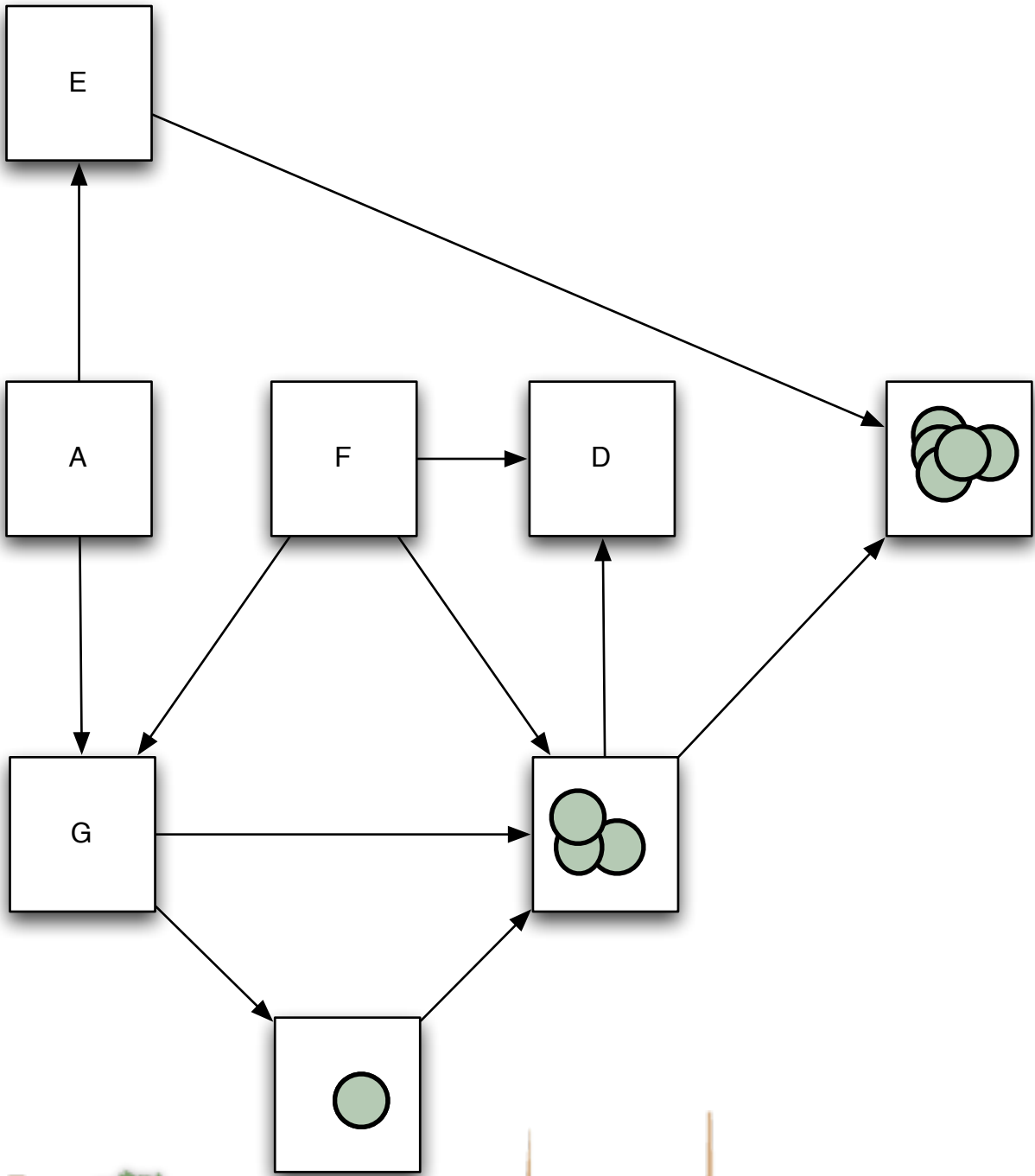
Long-Term visit rate

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



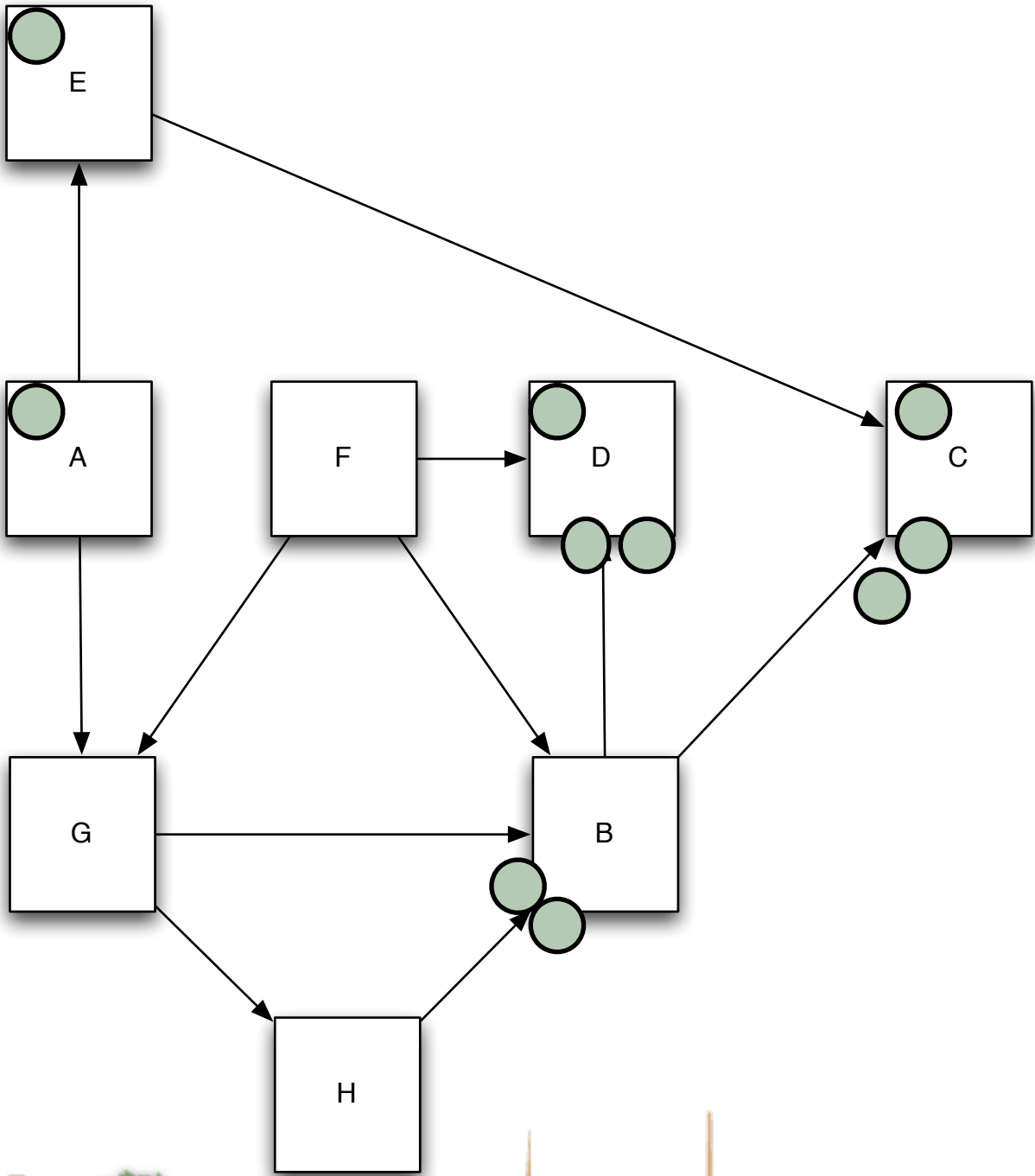
Long-Term visit rate

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



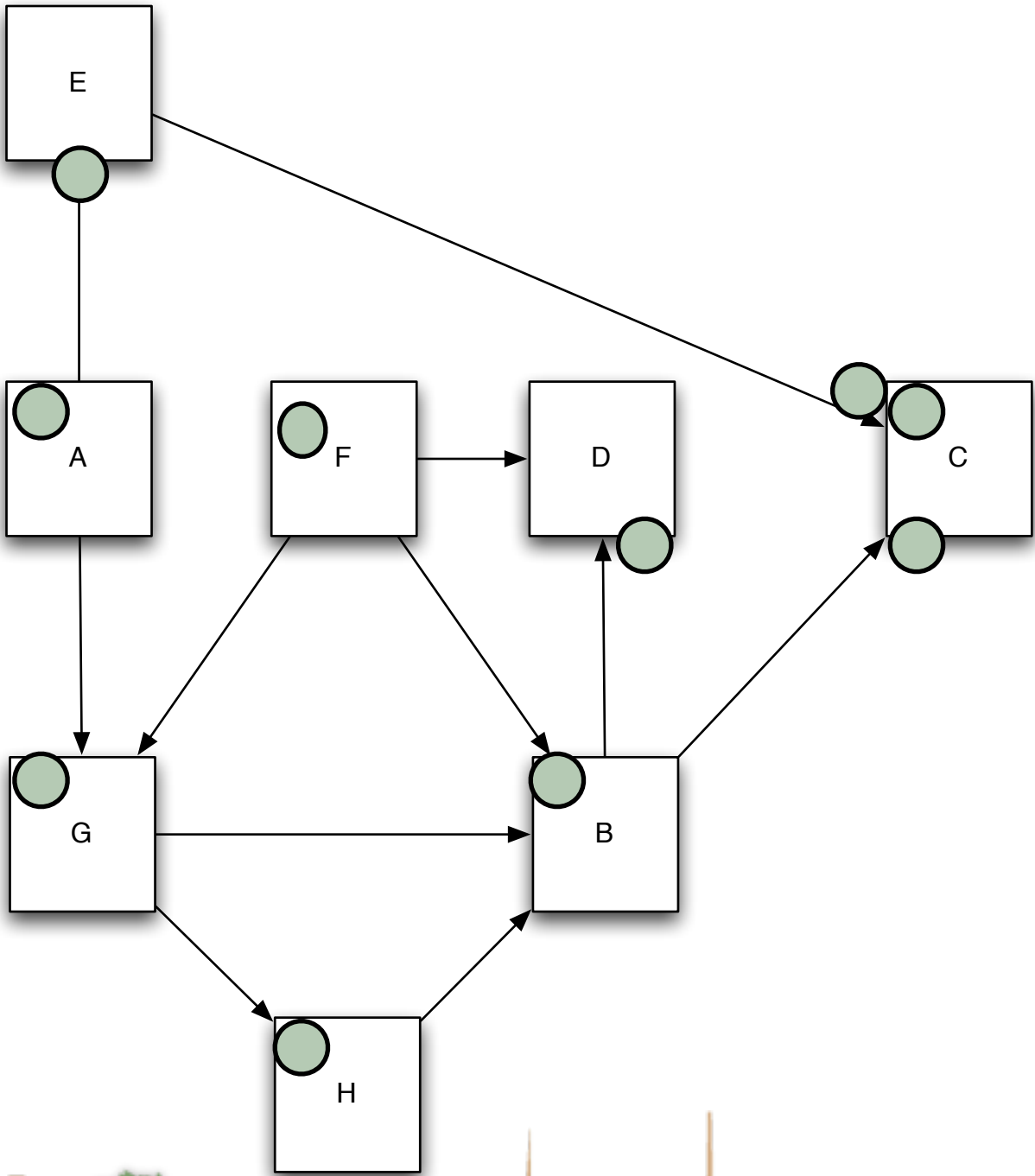
Long-Term visit rate

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



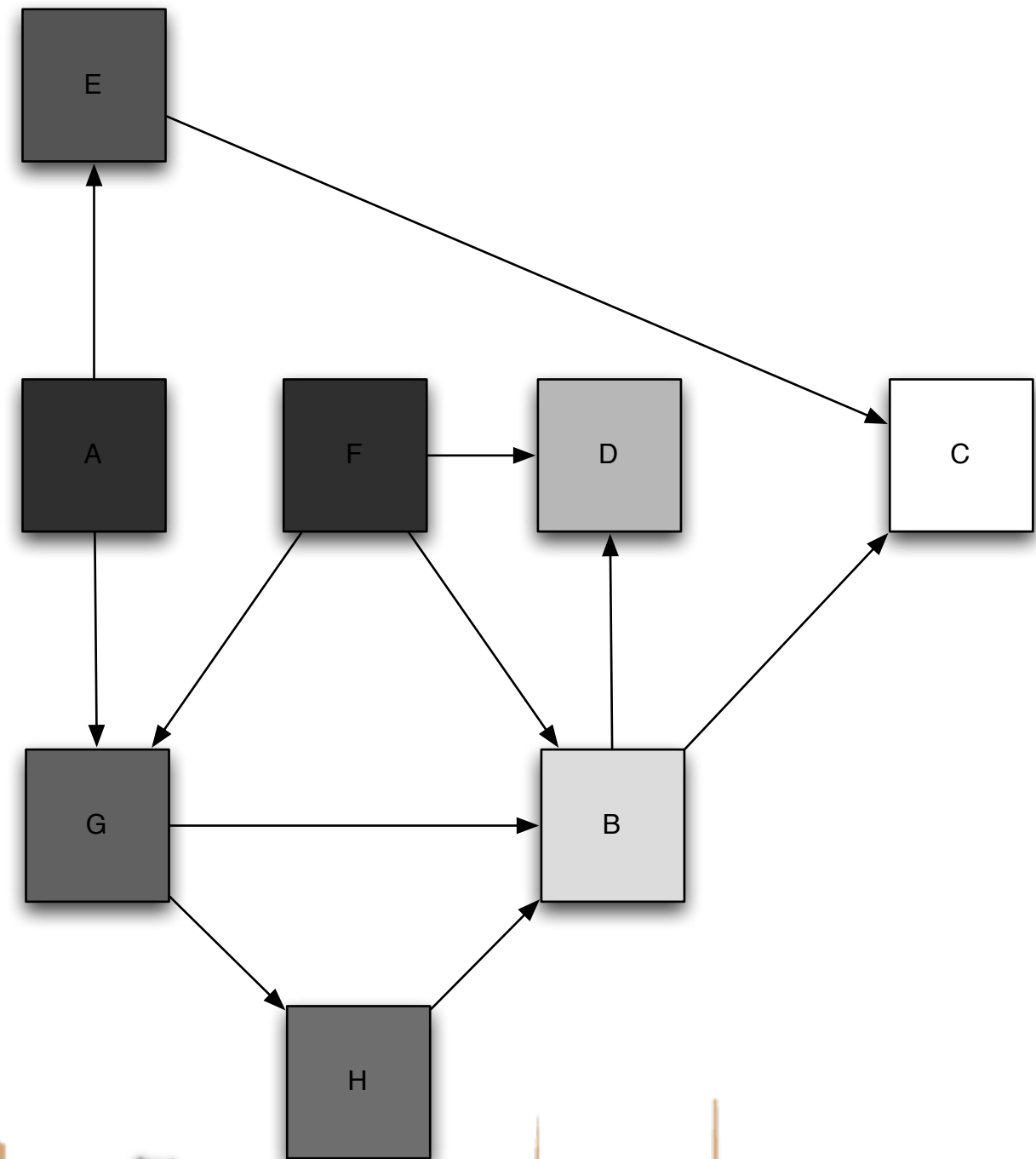
Long-Term visit rate

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



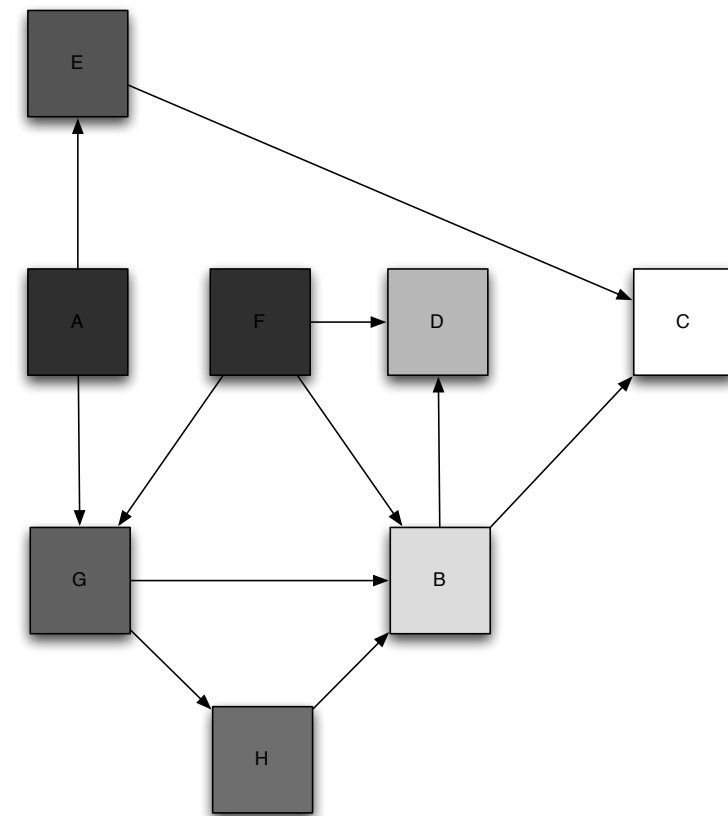
Long-Term visit rate

- A: 5%
- B: 21%
- C: 23%
- D: 18%
- E: 8%
- F: 5%
- G: 9%
- H: 10%



Some properties of Markov chains

- **Ergodic:**
 - All states can reach all states
 - What did we have to do to enable this for a web graph?
- **Steady State Theorem:**
 - Every ergodic markov chain has a steady state -> has a PageRank

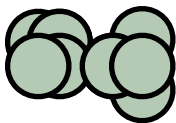


Calculating PageRank

- Visual representation to math representation

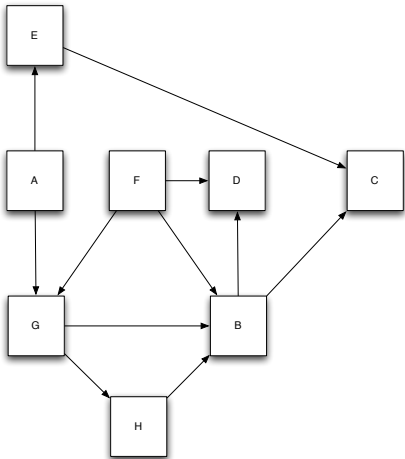
$\vec{x}_0$

<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
1.0	0	0	0	0	0	0	0



P

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
1.0	0	0	0	0	0	0	0

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0



Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

1.0	A
0	B
0	C
0	D
0	E
0	F
0	G
0	H

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	1.0	0	0	0	0	0	0

0



Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	0	0	0	0	0	0	0

0	0
---	---



Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	1.0	0	0	0	0	0	0

0	0	0
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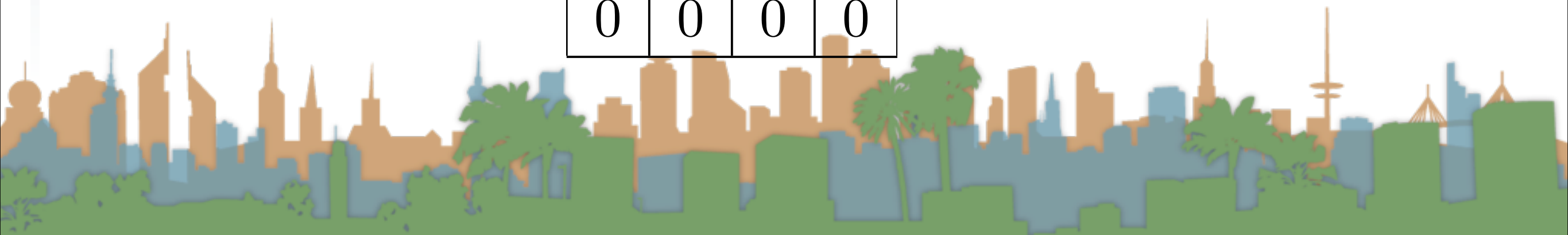
Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	1.0	0	0	0	0	0	0

0	0	0	0
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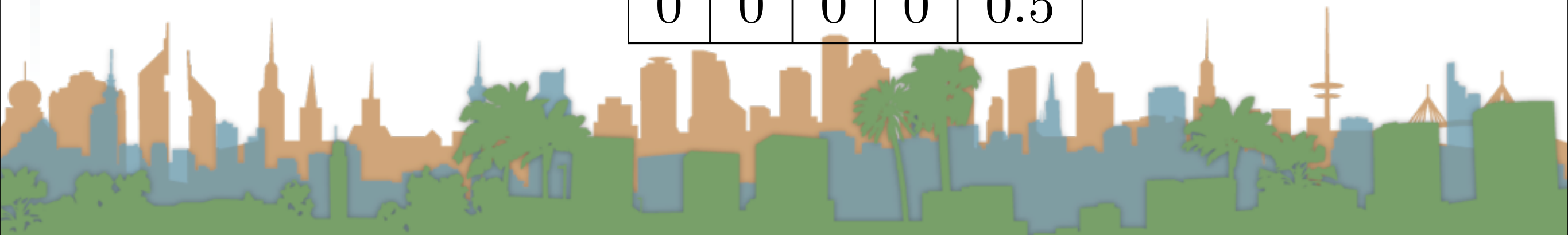
Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	1.0	0	0	0	0	0	0

0	0	0	0	0.5
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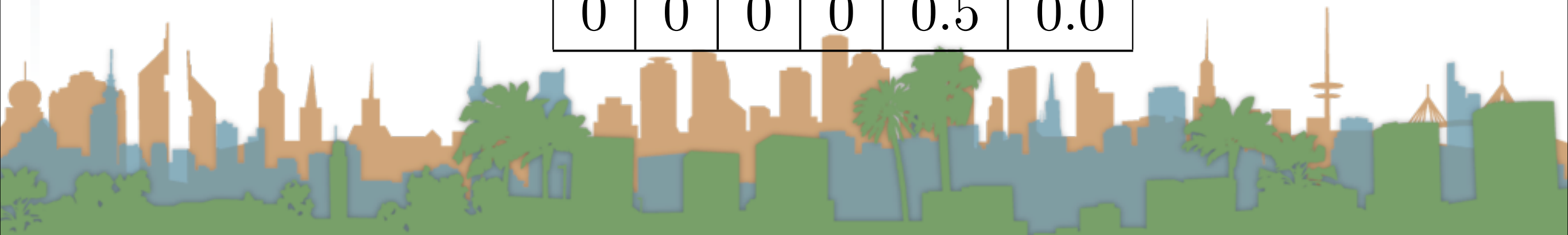
Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	1.0	0	0	0	0	0	0

0	0	0	0	0.5	0.0
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Calculating PageRank

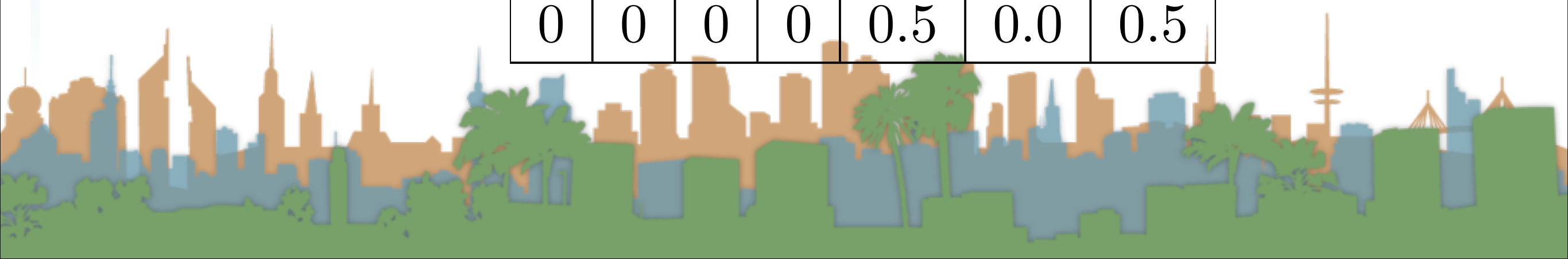
- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

1.0	A	B	C	D	E	F	G	H
0								
0.5								
0								
0.125								
0.125								
0								
0.33								
0								
0								

	A	B	C	D	E	F	G	H
A	0	0	0	0	0.5	0	0.5	0
B	0	0	0.5	0.5	0	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33	0
G	0	0.5	0	0	0	0	0	0.5
H	0	1.0	0	0	0	0	0	0

0	0	0	0	0.5	0.0	0.5
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Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

1.0	A	B	C	D	E	F	G	H
0								
0								
0								
0								
0								
0								
0								
0								

	A	B	C	D	E	F	G
A	0	0	0	0	0.5	0	0.5
B	0	0	0.5	0.5	0	0	0
C	0.125	0.125	0.125	0.125	0.125	0.125	0.125
D	0.125	0.125	0.125	0.125	0.125	0.125	0.125
E	0	0	1.0	0	0	0	0
F	0	0.33	0	0.33	0	0	0.33
G	0	0.5	0	0	0	0	0
H	0	1.0	0	0	0	0	0

0	0	0	0	0.5	0.0	0.5	0.0
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Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_0 P = \vec{x}_1$$

<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
1.0	0	0	0	0	0	0	0

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0

$$\vec{x}_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.5 & 0 & 0.5 & 0 \end{bmatrix}$$



Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_1 P = \vec{x}_2$$

0	0	0	0	0.5	0	0.5	0
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	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>
<i>A</i>	0	0	0	0	0.5	0	0.5	0
<i>B</i>	0	0	0.5	0.5	0	0	0	0
<i>C</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>D</i>	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
<i>E</i>	0	0	1.0	0	0	0	0	0
<i>F</i>	0	0.33	0	0.33	0	0	0.33	0
<i>G</i>	0	0.5	0	0	0	0	0	0.5
<i>H</i>	0	1.0	0	0	0	0	0	0

$$\vec{x}_2 =$$

0	0.25	0.5	0	0.0	0	0.0	0.25
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Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_1 P = \vec{x}_2$$

0	0.25	0.5	0	0.0	0	0.0	0.25		A	B	C	D	E	F	G	H
								A	0	0	0	0	0.5	0	0.5	0
								B	0	0	0.5	0.5	0	0	0	0
								C	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
								D	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
								E	0	0	1.0	0	0	0	0	0
								F	0	0.33	0	0.33	0	0	0.33	0
								G	0	0.5	0	0	0	0	0	0.5
								H	0	1.0	0	0	0	0	0	0

$$\vec{x}_3 = \begin{bmatrix} 0.0625 & 0.3125 & 0.1875 & 0.1875 & 0.0625 & 0.0625 & 0.0625 & 0.0625 \end{bmatrix}$$



Calculating PageRank

- Take one step is multiplying state vector times transition probability matrix

$$\vec{x}_1 P = \vec{x}_2$$

$$\lim_{(n \rightarrow \infty)} x_n = PageRank$$



Long-Term visit rate

- A: 5%
- B: 21%
- C: 23%
- D: 18%
- E: 8%
- F: 5%
- G: 9%
- H: 10%

