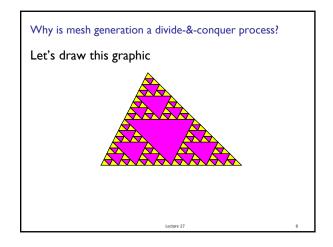
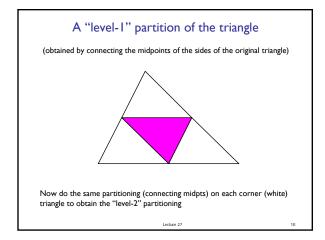
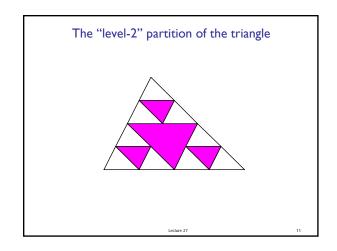
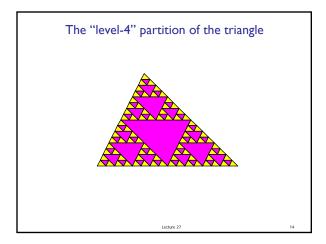
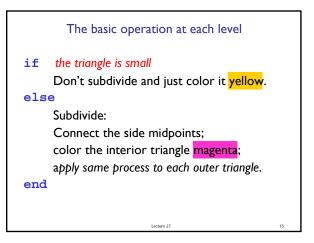
- Previous Lecture:
 - Comparing different sorting algorithms
 - Recursion
- Today's Lecture:
 - Recursion review
 - Efficiency: dealing with "expensive" function evaluation
 - A model to quantify importance: Google "Page Rank"
- Announcement:
 - Discussion this week in the computer lab (UP B7)
 - P6 due Thursday at I Ipm



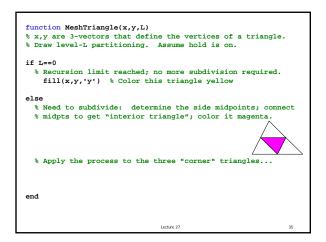


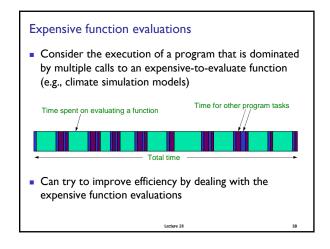




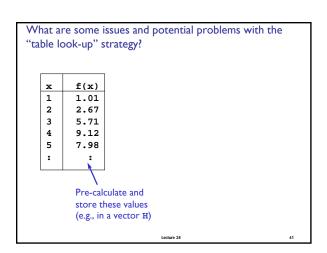


CS1112 Lecture 27





Dealing with expensive function evaluations
Can the function code be improved?
Can we do fewer function evaluations?
Can we pre-compute and store specific function values so that during the main program execution the program can just look up the values?
Consider function f(x). If there are many function calls and few distinct values of x, can get substantial speedup
Only speeds up main program execution—it still takes time to do the pre-computation



Quantifying Importance

How do you rank web pages for importance given that you know the link structure of the Web, i.e., the in-links and out-links for each web page?

A related question:

How does a deleted or added link on a webpage affect its "rank"?

Lecture 27

Background

Index all the pages on the Web from I to n. (n is around ten billion.)

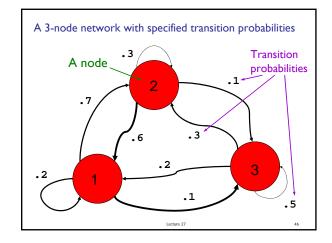
- The PageRank algorithm orders these pages from "most important" to "least important."
- It does this by analyzing links, not content.

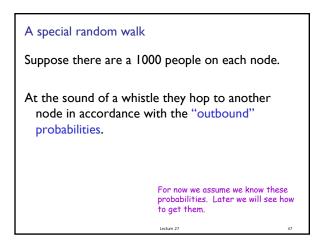
Key ideas

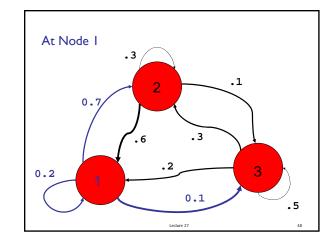
- There is a random web surfer—a special random walk
- The surfer has some random "surfing" behavior—a transition probability matrix
- The transition probability matrix comes from the link structure of the web—a connectivity matrix

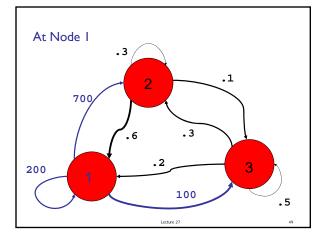
Lecture 27

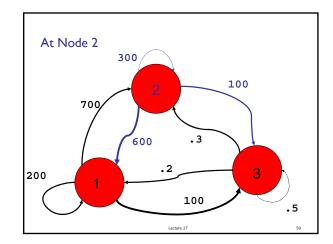
 Applying the transition probability matrix → Page Rank

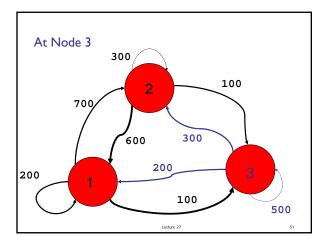


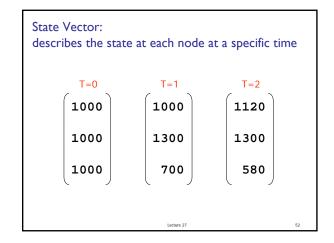


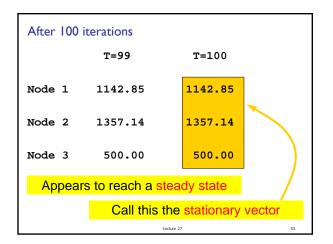


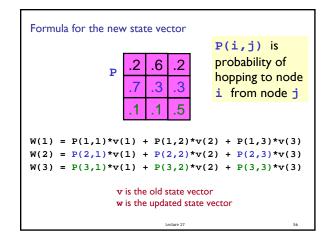


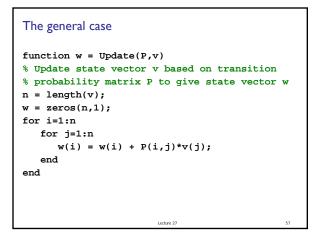


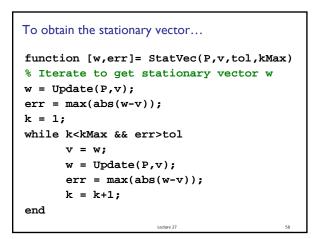


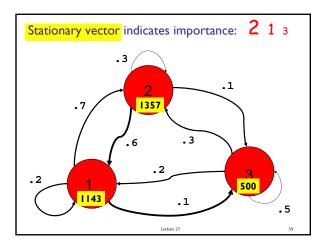


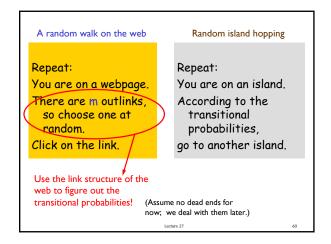


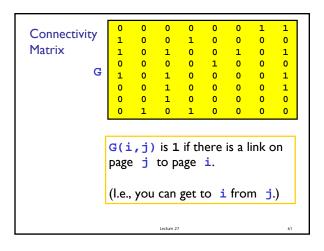




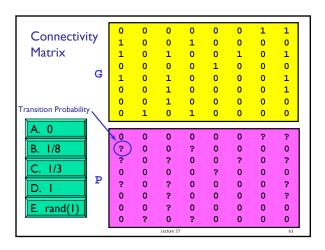


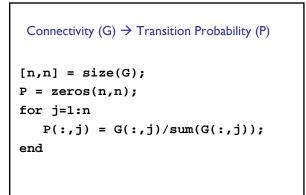






Connectivity	0	0	0	0	0	0	1	1	
	1	0	0	1	0	0	0	0	
Matrix	1	0	1	0	0	1	0	1	
-	0	0	0	0	1	0	0	0	
G	1	0	1	0	0	0	0	1	
	0	0	1	0	0	0	0	1	
	0	0	1	0	0	0	0	0	
	0	1	0	1	0	0	0	0	
Transition	0	0	0	0	0	0	?	?	
	?	0	0	?	0	0	0	0	
Probability	?	0	?	0	0	?	0	?	
Matrix _	0	0	0	0	?	0	0	0	
derived from P	?	0	?	0	0	0	0	?	
Connectivity	0	0	?	0	0	0	0	?	
Matrix	0	0	?	0	0	0	0	0	
	0	?	0	?	0	0	0	0	
Lecture 27					62	•			





Lecture 27

Stationary vector represents how "popular" the pages are \rightarrow PageRank						
0.5723	0.891	1 6	4			
0.8206	0.820	6 2	2			
0.7876	0.787	6 3	3			
0.2609	0.572	3 1	6			
0.2064	0.410	8 0	8			
0.8911	0.260	9 4	1			
0.2429	0.242	9 7	7			
0.4100	0.206	4 5	5			
statVec	sorted	l idz	c pR	pR		
	Lecture 27					

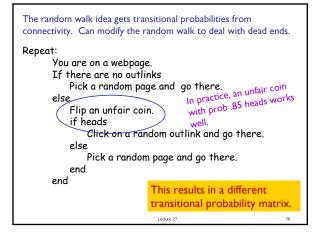
<pre>[sorted, idx] = sort(-statVec); for k= 1:length(statVec) j = idx(k); % index of kth largest pR(j) = k; end</pre>						
0.572	3	-0.8911	6		4	
0.8206		-0.8206	2		2	
0.7876		-0.7876	3		3	
0.2609		-0.5723	1		6	
0.2064		-0.4100	8		8	
0.8911		-0.2609	4		1	
0.2429		-0.2429	7		7	
0.4100		-0.2064	5		5	
statVec		sorted id		r pR		
Lecture 27					68	

The random walk idea gets the transitional probabilities from connectivity. So how to deal with dead ends?

Repeat:

You are on a webpage. There are m outlinks. Choose one at random. Click on the link.

What if there are no outlinks?





How do you rank web pages for importance given that you know the link structure of the Web, i.e., the in-links and out-links for each web page?

A related question:

How does a deleted or added link on a webpage affect its "rank"?