217		
3/7	/	
\mathcal{L}	LU	

e Title	<u>2016-04-</u>
	A common solution is to rank the pages in order of the number of links to that page (often called backlinks of the page), starting with the page that has the highest number
	of pointers into it. We refer to this strategy as citation counting.
	Question: Suppose that we could determine the number of backlinks of each pag
	(number of links pointing to the page). Why would that not necessarily be a goo measure of the importance of the page?

Goo high	gle's Solution: Google's solution is to define page rank recursively: "A page har rank if the sum of the ranks of its backlinks is high." Observe that this covers bot
the o	case when a page has many backlinks and when a page has a few highly ranker links.
Que	stion: It is easy to say that "a page has high rank if the sum of the ranks of it links is high," but how does that help us figure out the rank of a page?
	wer: The "aha" that the Google founders made was to realize that the recursive
	$\pi_j = \sum_{i=1}^n \pi_i P_{ij}.$
	i=1

Google's PageRank Algorithm:

- Create a DTMC transition diagram where there is one state for each web
 page and there is an arrow from state i to state j if page i has a link to
 page j.
- If page i has k > 0 outgoing links, then set the probability on each outgoing arrow from state i to be 1/k.
- Solve the DTMC to determine limiting probabilities. Pages are then ranked based on their limiting probabilities (higher probability first).

Example

Suppose the entire web consists of the three pages shown in Figure 10.1. Then the corresponding DTMC transition diagram is shown in Figure 10.2.

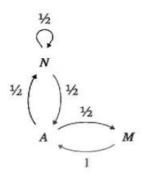


Figure 10.2. Corresponding DTMC transition diagram.

$$T_{A} = \frac{1}{2}T_{N} + 1.T_{M}$$

$$T_{A} = \frac{1}{2}T_{N} + \frac{1}{2}T_{A} = \frac{1}{2}T_{N} = \frac{1}{2}T_{A} = \frac{1}{2}T_{M} = \frac{1}{2}T_{A}$$

$$T_{A} = \frac{1}{2}T_{A} + \frac{1}{2}T_{A} = \frac{1}{2}T_{M} =$$

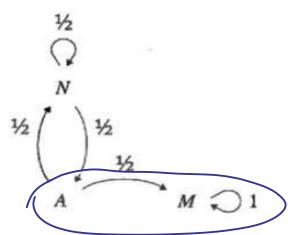




Figure 10.3. DTMC for a web graph with a dead end or spider trap at M.

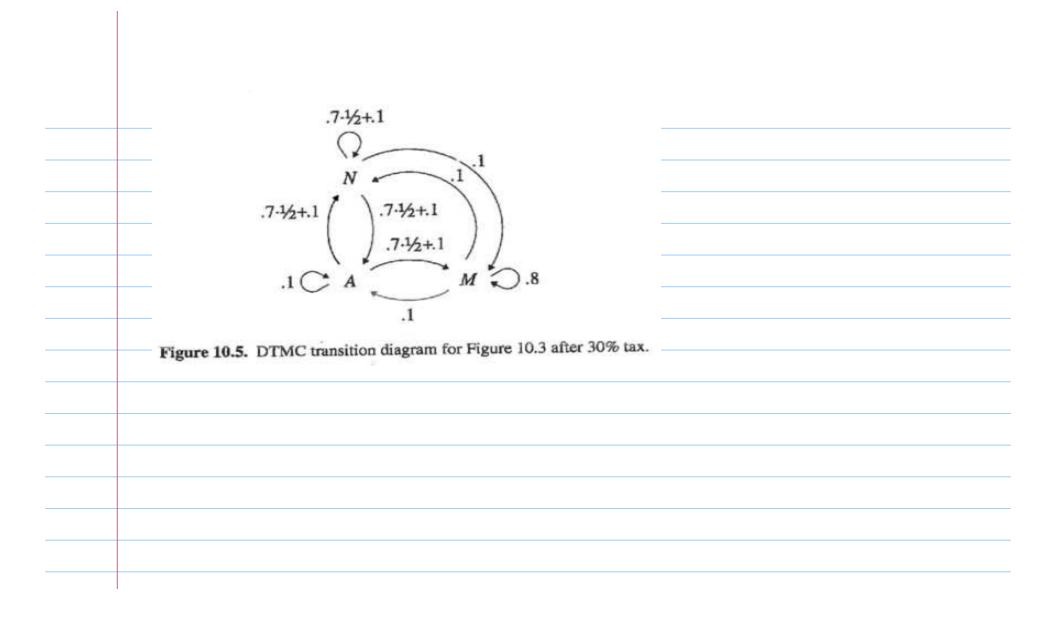
$$T_{N} = \frac{1}{2} \pi_{N} + \frac{1}{2} \pi_{A}$$

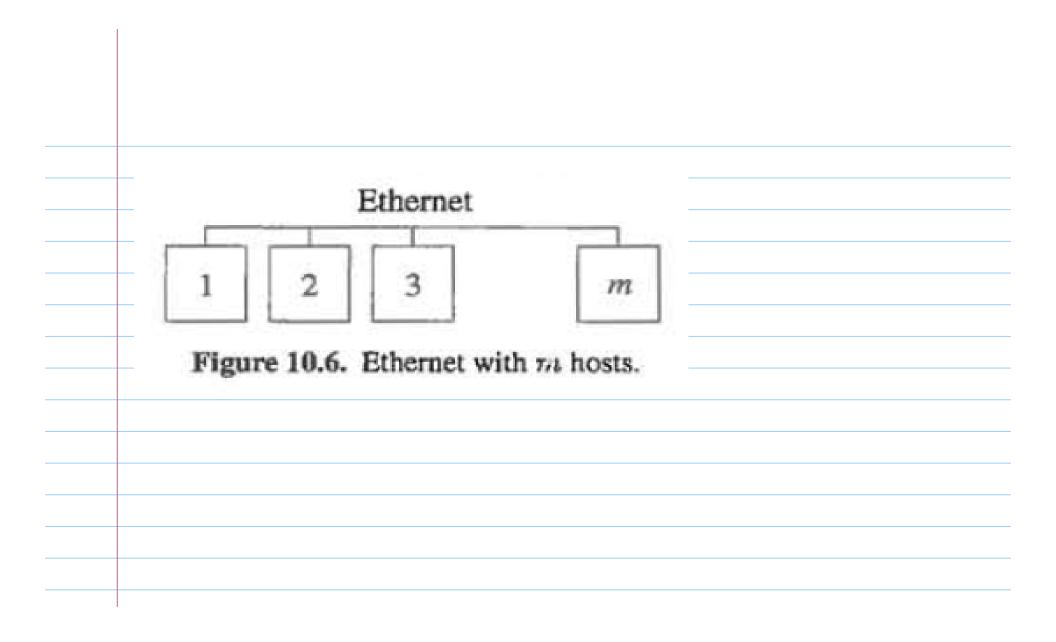
$$T_{A} : \frac{1}{2} \pi_{N}$$

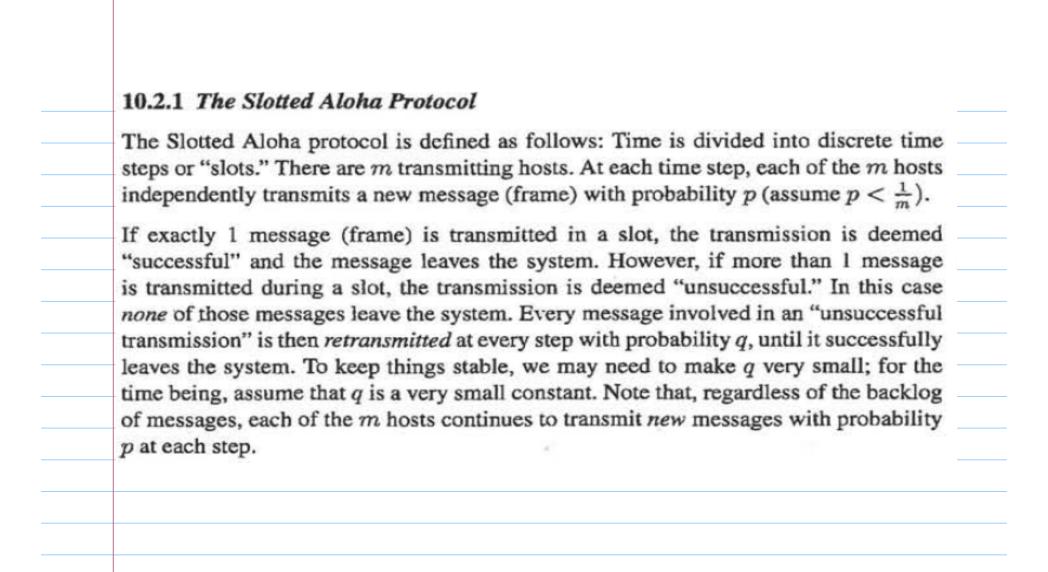
$$T_{N} = \frac{1}{2} \pi_{A}$$



Figure 10.4. DTMC for a web graph with two spider traps.



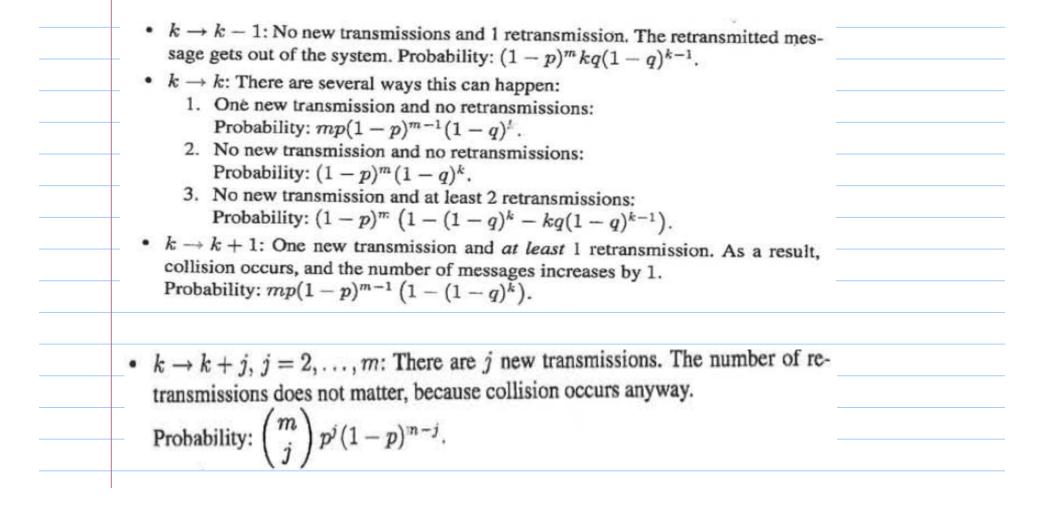




$$p_k = {m \choose k} p^k (1-p)^{m-k}, \forall k = 0, 1, ..., m.$$

$$q_k^n = \binom{n}{k} q^k (1-q)^{n-k}, \forall k = 0, 1, ..., n.$$

$P_{0.0} = (1-p)^m + mp(1-p)^{m-1}.$
$P_{0,1} = 0.$
$P_{0,j}=\left(egin{array}{c}m\j\end{array} ight)p^{j}(1-p)^{m-j},orall j=2,\ldots,m.$
$P_{0.j}=0$, $\forall j>m$.



 $P_{k,j} = 0, \quad \forall j \leq k - 2.$ $P_{k,k-1} = (1-p)^m kq(1-q)^{k-1}.$ $P_{k,k} = m(1-q)^k p(1-p)^{m-1} + (1-kq(1-q)^{k-1}) (1-p)^m.$ $P_{k,k+1} = mp(1-p)^{m-1} (1-(1-q)^k).$ $P_{k,k+j} = {m \choose j} p^j (1-p)^{m-j}, \quad \forall j = 2, ..., m.$ $P_{k,j} = 0, \quad \forall j > k+m.$