# Web Page Quality Ranking

Kai Shen



## Web Page Quality Ranking

- Inverted web indexes help locate matching pages of search words
  - But there are too many matches and humans can't read all
- Both relevance and quality are important in web search
- What is a high-quality web page?
- How to identify a high-quality web page?
  - Hard to spam
- Related to identifying high-quality scientific publications
  - But much bigger dataset



## PageRank

- PageRank …
  - "works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites."
- Count of in-links is important; the quality of the sources of in-links are also important
  - http://upload.wikimedia.org/wikipedia/commons/6/69/PageRank-hi-res.png
- Originated at Google, though may not be heavily relied upon by Google now



## PageRank

- PageRank scores each page
  - the score is the converged probability for a random web surfer to arrive at the page
- Scores transfer through links (random click by the surfer):
  - If pages B, C are the pages that link to A, then PR(A) = PR(B)/L(B) + PR(C)/L(C)
- Damping factor (for stability):
  - The surfer has a tendency to stay at where he/she is
  - PR(A) = (1-d)/N + d(PR(B)/L(B) + PR(C)/L(C))
- A linear system of equations (N variables, N linear equations)

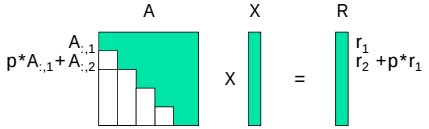
## How to compute it?

- How to solve a linear system of equations?
- Big data ⇨ large matrix (50billion × 50billion)
  - Parallelizing it is essential



## Gaussian Elimination

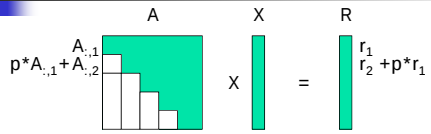
- Simplification – ignore final solving step and pivoting
- Reduce an equation matrix into an equivalent upper-diagonal




for c=1 to N
  for r=c+1 to N
    zero out $A_{c,r}$ by adding $p*A_{:,c}$ to $A_{:,r}$



## Parallelizing Gaussian Elimination




for c=1 to N
  for r=c+1 to N
    zero out $A_{c,r}$ by adding $p*A_{:,c}$ to $A_{:,r}$

- How to parallelize? Dependencies:
  - Outer loop instances (e.g., c=2 depends on c=1)?
  - Inner loop instances (e.g., r=3 depends on r=2)?
- MapReduce? Does it scale?
- Traditional parallel programming is fine, but hard to program correctly, robustly with high performance and scalability



## Iterative Solver

- PR(A) = (1-d)/N + d(PR(B)/L(B) + PR(C)/L(C))
- Iterative solver:
  - Start from an initial PR vector (1/N for each page)
  - Compute a new PR vector by the above linear transformation
  - Keep repeating the linear transformation until the PR converges (very small change after further linear transformation)
    - Even with the large, complex web graph, often converging after dozens of iterations
- Each iteration is a matrix-vector multiplication, so the whole computation is a series of matrix-vector multiplication

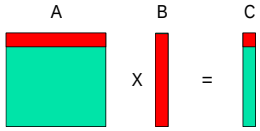
## Parallelizing the Iterative Solver

- The whole computation is a series of matrix-vector multiplication
- How to parallelize?
  - MapReduce?
  - Does it scale?

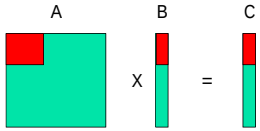


## Load Distribution

- One row (or a few rows) per task:



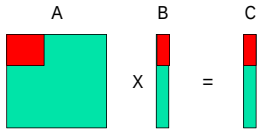

- Or one block per task:






## Load Balancing

- Matrix vector multiplication




- Load balancing by distributing equal-size blocks of A to each map task
- But matrix is extremely sparse ⇨ equal-size blocks doesn't mean equal amount of work
  - More map tasks than the number of nodes; rely on dynamic load balancing in MapReduce



## Topic-Sensitive PageRank

- Web page quality ranking is sometimes affected by interest on a particular topic
- Original PageRank score
  - Start from a PR vector (1/N for each page)
  - Compute a new PR vector by the link-based linear transformation
    - PR(A) = (1-d)/N + d(PR(B)/L(B) + PR(C)/L(C))
  - Keep repeating the above until the PR converges
- Topic-sensitive PageRank:
  - Start from a PR vector (1/n for each topic-matching page, 0 otherwise), n is the number of topic-matching page
  - In iterative computation, PR(A)'s damping factor is (1-d)/n if it is a topic-matching page, 0 otherwise
- Effect: the random surfer always starts from a topic-matching page, and has an extra staying probability if it is on such a page

## Topic-Sensitive PageRank

- A great way to return searches online searches
  - Can it be done that quickly?



## Hubs and Authorities

- Fundamentally wrong to think that web pages are of one kind
  - Existence of hubs, pages with many links to good pages (even though they are not linked by others very well)
  - In original PageRank computation, these pages have very low scores and their out-links are even less effective (since they have many links)
- HITS [Kleinberg 1999]
  - Each page has two scores---authority score is like the traditional quality score; hub score indicates the strength of the page linking to high-quality page
  - $a = L\ h$
  - $h = L^T\ a$
  - Solved iteratively, can use MapReduce



## Disclaimer

- Preparation of this class was helped by materials in the online book “Mining of Massive Datasets” by Rajaraman, Leskovec, and Ullman.