CAIM: Cerca i Anàlisi d’Informació Massiva
FIB, Grau en Enginyeria Informàtica

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5. Web Search. Architecture of simple IR systems
Searching the Web, I
When documents are interconnected

The World Wide Web is huge
- 100,000 indexed pages in 1994
- 10,000,000,000’s indexed pages in 2013
- Most queries will return millions of pages with high similarity.
- Content (text) alone cannot discriminate.
- Use the structure of the Web - a graph.
- Gives indications of the prestige - usefulness of each page.
How Google worked in 1998


Notation:
Some components

- **URL store**: URLs awaiting exploration
- **Doc repository**: full documents, zipped
- **Indexer**: Parses pages, separates text (to Forward Index), links (to Anchors) and essential text info (to Doc Index)
  - Text in an anchor very relevant for *target* page
    - `<a href="http://page">anchor</a>`
  - Font, placement in page makes some terms extra relevant
- **Forward index**: docid → list of terms appearing in docid
- **Inverted index**: term → list of docid’s containing term
The inverter (sorter), I

Transforms forward index to inverted index

First idea:

for every entry document d
  for every term t in d
    add docid(d) at end of list for t;

Lousy locality, many disk seeks, too slow
Better idea for indexing:

create in disk an empty inverted file, ID;
create in RAM an empty index IR;
for every document d
    for every term t in d
        add docid(d) at end of list for t in IR;
    if RAM full
        for each t, merge the list for t in IR
            into the list for t in ID;

Merging previously sorted lists is sequential access
Much better locality. Much fewer disk seeks.
The inverter (sorter), III

The above can be done concurrently on different sets of documents:
The inverter (sorter), IV

- Indexer ships barrels, fragments of forward index
- Barrel size = what fits in main memory
- Separately, concurrently inverted in main memory
- Inverted barrels merged to inverted index
- 1 day instead of estimated months
Searching the Web, I
When documents are interconnected

The internet is huge

- 100,000 indexed pages in 1994
- 10,000,000,000 indexed pages at end of 2011

To find content, it is necessary to search for it

- We know how to deal with the content of the webpages
- But.. what can we do with the structure of the internet?
Searching the Web, II
Meaning of a hyperlink

When page $A$ links to page $B$, this means

- $A$’s author thinks that $B$’s content is *interesting* or important
- So a link from $A$ to $B$, adds to $B$’s reputation

But not all links are equal..

- If $A$ is very important, then $A \rightarrow B$ “counts more”
- If $A$ is not important, then $A \rightarrow B$ “counts less”

In today’s lecture we’ll see two algorithms based on this idea

- *Pagerank* (Brin and Page, oct. 98)
- *HITS* (Kleinberg, apr. 98)
Intuition:

A page is important if it is pointed to by other important pages

- Circular definition ...
- not a problem!
The web is a graph $G = (V, E)$

- $V = \{1, \ldots, n\}$ are the nodes (that is, the pages)
- $(i, j) \in E$ if page $i$ points to page $j$
- we associate to each page $i$, a real value $p_i$ (i’s pagerank)
- we impose that $\sum_{i=1}^{n} p_i = 1$

How are the $p_i$’s related

- $p_i$ depends on the values $p_j$ of pages $j$ pointing to $i$

$$p_i = \sum_{j \rightarrow i} \frac{p_j}{\text{out}(j)}$$

- where $\text{out}(j)$ is $j$’s outdegree
Pagerank, III

Example

A set of $n + 1$ linear equations:

\[
\begin{align*}
    p_1 &= \frac{p_1}{3} + \frac{p_2}{2} \\
    p_2 &= \frac{p_3}{2} + p_4 \\
    p_3 &= \frac{p_1}{3} \\
    p_4 &= \frac{p_1}{3} + \frac{p_2}{2} + \frac{p_3}{2} \\
    1 &= p_1 + p_2 + p_3 + p_4
\end{align*}
\]

Whose solutions is:

$p_1 = 6/23$, $p_2 = 8/23$, $p_3 = 2/23$, $p_4 = 7/23$
Pagerank, IV

Formally

Equations

- \( p_i = \sum_{j: (j,i) \in E} \frac{p_j}{\text{out}(j)} \) for each \( i \in V \)
- \( \sum_{i=1}^{n} p_i = 1 \)

where \( \text{out}(i) = |\{j : (i,j) \in E\}| \) is the outdegree of node \( i \)

If \( |V| = n \)

- \( n + 1 \) equations
- \( n \) unknowns

Could be solved, for example, using Gaussian elimination in time \( O(n^3) \)
A set of linear equations:

\[
\begin{pmatrix}
 p_1 \\
p_2 \\
p_3 \\
p_4
\end{pmatrix} = \begin{pmatrix}
 \frac{1}{3} & \frac{1}{2} & 0 & 0 \\
 0 & 0 & \frac{1}{2} & 1 \\
 \frac{1}{3} & 0 & 0 & 0 \\
 \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 0
\end{pmatrix} \cdot \begin{pmatrix}
 p_1 \\
p_2 \\
p_3 \\
p_4
\end{pmatrix}
\]

namely: \( \vec{p} = M^T \vec{p} \) and additionally

\[\sum_i p_i = 1\]

Whose solutions is:

\( \vec{p} \) is the eigenvector of matrix \( M^T \) associated to eigenvalue 1
What does $M^T$ look like?

$M^T$ is the transpose of the row-normalized adjacency matrix of the graph!
Adjacency matrix

$$A = \begin{pmatrix} 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$M = \begin{pmatrix} 1/3 & 0 & 1/3 & 1/3 \\ 1/2 & 0 & 0 & 1/2 \\ 0 & 1/2 & 0 & 1/2 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

(rows add up to 1)

$$M^T = \begin{pmatrix} 1/3 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 1/2 & 1/2 & 0 \end{pmatrix}$$

(columns add up to 1)
Question:
Why do we need to row-normalize and transpose $A$?

Answer:

- **Row normalization**: because $p_i = \sum_{j: (j, i) \in E} \frac{p_j}{\text{out}(j)}$

- **Transpose**: because $p_i = \sum_{j: (j, i) \in E} \frac{p_j}{\text{out}(j)}$, that is, $p_i$ depends on $i$’s incoming edges.
Pagerank, IX

It is just about solving a system of linear equations!

.. but

- How do we know a solution exists?
- How do we know it has a single solution?
- How can we compute it efficiently?

For example, the graph on the left has no solution.. (check it!) but the one on the right does
How do we know a solution exists?

Luckily, we have some results from *linear algebra*

**Definition**

A matrix $M$ is stochastic, if

- All entries are in the range $[0, 1]$
- Each row adds up to 1 (i.e., $M$ is row normalized)

**Theorem (Perron-Frobenius)**

*If $M$ is stochastic, then it has at least one stationary vector, i.e., one non-zero vector $p$ such that*

$$M^T p = p.$$
Pagerank, XI
Equivalently: the random surfer view

Now assume $M$ is the transition probability matrix between states in $G$

Let $\vec{p}(t)$ be the probability over states at time $t$
  - E.g., $p_j(0)$ is the probability of being at state $j$ at time 0

Random surfer jumps from page $i$ to page $j$ with probability $m_{ij}$
  - E.g., probability of transitioning from state 2 to state 4 is $m_{24} = \frac{1}{2}$
Surfer starts at random page according to probability distribution $\vec{p}(0)$

At time $t > 0$, random surfer follows one of current page’s links uniformly at random

$$\vec{p}(t) := M^T \vec{p}(t - 1)$$

In the limit $t \to \infty$:

- $\vec{p}(t) = \vec{p}(t + 1) = \vec{p}(t + 2) = \ldots = \vec{p}$
- so $\vec{p}(t) = M^T \vec{p}(t - 1)$
- $\vec{p}(t)$ converges to a solution $p$ s.t. $p = M^T p$ (the pagerank solution)!
Pagerank, XIII
Random surfer example

$\vec{p}(0)^T = (1, 0, 0, 0)$

$\vec{p}(1)^T = (1/3, 0, 1/3, 1/3)$

$\vec{p}(2)^T = (0.11, 0.50, 0.11, 0.28)$

$\vec{p}(10)^T = (0.26, 0.35, 0.09, 0.30)$

$\vec{p}(11)^T = (0.26, 0.35, 0.09, 0.30)$

$M^T = \begin{pmatrix} \frac{1}{3} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & \frac{1}{2} & 1 \\ \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 0 \end{pmatrix}$
Pagerank, XIV

An algorithm to solve the eigenvector problem (find $p$ s.t. $p = M^T p$)

The Power Method

- Chose initial vector $\vec{p}(0)$ randomly
- Repeat $\vec{p}(t) \leftarrow M^T \vec{p}(t - 1)$
- Until convergence (i.e. $\vec{p}(t) \approx \vec{p}(t - 1)$)

We are hoping that

- The method converges
- The method converges fast
- The method converges fast to the pagerank solution
- The method converges fast to the pagerank solution regardless of the initial vector
Pagerank, XV

Convergence of the Power method: aperiodicity required

Try out the power method with \( \vec{p}(0) \):

\[
\begin{pmatrix}
\frac{1}{4} \\
\frac{1}{4} \\
\frac{1}{4} \\
\frac{1}{4}
\end{pmatrix}
, \text{ or }
\begin{pmatrix}
1 \\
0 \\
0 \\
0
\end{pmatrix}
, \text{ or }
\begin{pmatrix}
\frac{1}{2} \\
0 \\
\frac{1}{2} \\
0
\end{pmatrix}
\]

Not being able to break the cycle looks problematic!

- .. so will require graphs to be aperiodic
  - no integer \( k > 1 \) dividing the length of every cycle
Pagerank, XVI
Convergence of the Power method: strong connectedness required

What happens with the pagerank in this graph?

The sink hoards all the pagerank!

- need a way to leave sinks
- .. so we will force graphs to be strongly connected
Theorem

If a matrix $M$ is strongly connected and aperiodic, then:

- $M^T \vec{p} = \vec{p}$ has exactly one non-zero solution such that $\sum_i p_i = 1$
- $1$ is the largest eigenvalue of $M^T$
- the Power method converges to the $\vec{p}$ satisfying $M^T \vec{p} = \vec{p}$, from any initial non-zero $\vec{p}(0)$
- Furthermore, we have exponential fast convergence

To guarantee a solution, we will make sure that the matrices that we work with are strongly connected and aperiodic
Definition (The Google Matrix)

Given a damping factor $\lambda$ such that: $0 < \lambda < 1$:

$$G = \lambda M + (1 - \lambda) \frac{1}{n} J$$

where $J$ is a $n \times n$ matrix containing 1 in each entry

Observe that:

- $G$ is stochastic
  - .. because $G$ is a weighted average of $M$ and $\frac{1}{n} J$, which are also stochastic
  - for each integer $k > 0$, there is a non-zero probability path of length $k$ from every state to any other state of $G$
    - .. implying that $G$ is strongly connected and aperiodic
  - and so the Power method will converge on $G$, and fast!
The meaning of $\lambda$

- With probability $\lambda$, the random surfer follows a link in the current page.
- With probability $1 - \lambda$, the random surfer jumps to a random page in the graph (teleportation).
Compute the pagerank value of each node of the following graph assuming a damping factor $\lambda = 2/3$:

\[
\begin{bmatrix}
    p_1 \\
p_2 \\
p_3 \\
p_4
\end{bmatrix}
= \left[ \begin{array}{c}
    2 \\
    3 \\
    \frac{1}{3} \\
    \frac{1}{3}
\end{array} \right]
\begin{bmatrix}
    0 & 1 & 1 & 1 \\
    \frac{1}{3} & 0 & 0 & 0 \\
    \frac{1}{3} & 0 & 0 & 0 \\
    \frac{1}{3} & 0 & 0 & 0
\end{bmatrix}
+ \frac{1}{3} \cdot \frac{1}{4}
\begin{bmatrix}
    1 & 1 & 1 & 1 \\
    1 & 1 & 1 & 1 \\
    1 & 1 & 1 & 1 \\
    1 & 1 & 1 & 1
\end{bmatrix}
\begin{bmatrix}
p_1 \\
p_2 \\
p_3 \\
p_4
\end{bmatrix}
\]

Hint: solve the following system, using $p_2 = p_3 = p_4$.
Compute the pagerank vector $\vec{p}$ of graph with row-normalized matrix $M$ for damping factor $\lambda$ in closed matrix form.

Answer:

$$\vec{p} = (I - \lambda M^T)^{-1} \begin{pmatrix} \frac{1-\lambda}{n} \\ \vdots \\ \frac{1-\lambda}{n} \end{pmatrix}$$
Observe that pageranks are independent of user’s query

- Advantages
  - Computed off-line
  - Collective reputation
- Disadvantages
  - Insensitive to particular user’s needs
Topic-sensitive Pagerank, II

Assume there is a small set of $K$ topics (sports, science, politics, ...)

- Each topic $k \in \{1, .., K\}$ is defined by a subset of the web pages $T_k$
- For each $k$, compute pagerank of node $i$ for topic $k$:
  
  $$p_{i,k} = \text{“pagerank of node } i \text{ with teleportation reduced to } T_k\text{”}$$

- Finally compute ranking score of a page $i$ given query $q$

  $$score(i, q) = \sum_{k=1}^{K} \text{sim}(T_k, q) \cdot p_{i,k}$$
Interest of a web page due to two different reasons

- page content is interesting (authority), or
- page points to interesting pages (hub)

HITS main rationale

- hubs are important if they point to important authorities
- authorities are important if pointed to by important hubs
- .. but .. circular definition again .... not a problem!
HITS, II

Definition of authority and hub value \( (a_i \text{ and } h_i) \)

Associate to each page \( i \) an authority value \( a_i \) and a hub value \( h_i \)

- vector of all authority values is \( \vec{a} \)
- vector of all hub values is \( \vec{h} \)

Keep these vectors normalized (notice L2 norm!)

- \( \|\vec{a}\| = \sum_i a_i^2 = 1 \), and \( \|\vec{h}\| = \sum_i h_i^2 = 1 \)

For appropriate scaling constants \( c \) and \( d \)

- \( a_i = c \cdot \sum_{j \rightarrow i} h_j \), and \( h_i = d \cdot \sum_{i \rightarrow j} a_j \)

Notice not a linear system anymore!

- ... but still ok with a variant of the power method
HITS, III
Example

Our old graph

Adjacency matrix

\[ A = \begin{pmatrix} 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{pmatrix} \]

\[ a_1 = c \cdot (h_1 + h_2) \quad \text{// here we use A’s first column} \]

\[ a_1 \propto (1, 1, 0, 0) \cdot \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{pmatrix} = (1, 1, 0, 0) \cdot \vec{h} \]
**Example**

Our old graph

Adjacency matrix

$$
A = \begin{pmatrix}
1 & 0 & 1 & 1 \\
1 & 0 & 0 & 1 \\
0 & 1 & 0 & 1 \\
0 & 1 & 0 & 0
\end{pmatrix}
$$

$$
h_2 = d \cdot (a_1 + a_4) \quad \text{// here we use } A\text{'s second row}
$$

$$
h_2 \propto (1, 0, 0, 1) \cdot \begin{pmatrix}
a_1 \\
a_2 \\
a_3 \\
a_4
\end{pmatrix} = (1, 0, 0, 1) \cdot \vec{a}
$$
HITS, V
Update rule for $\vec{a}$ and $\vec{h}$

Written in compact matrix form

- To update authority values
  - $\vec{a} := A^T \cdot \vec{h}$
  - normalize afterwards $\vec{a} := \frac{\vec{a}}{\|a\|}$ so that $\|a\| = 1$

- To update hub values
  - $\vec{h} := A \cdot \vec{a}$
  - normalize afterwards $\vec{h} := \frac{\vec{h}}{\|h\|}$ so that $\|h\| = 1$
HITS, VI
The power method for finding $\vec{a}$ and $\vec{h}$

Given adjacency matrix $A$

- Initialize $\vec{a} = \vec{h} = (1, 1, \ldots, 1)^T$
- Normalize $\vec{a}$ and $\vec{h}$ so that $\|a\| = \|h\| = 1$
- Repeat until convergence
  - $\vec{a} := A^T \cdot \vec{h}$
  - normalize $\vec{a}$ so that $\|a\| = 1$
  - $\vec{h} := A \cdot \vec{a}$
  - normalize $\vec{h}$ so that $\|h\| = 1$
Query answering algorithm HITS

- Get query $q$ and run content-based searcher on $q$
- Let $RootSet$ be the top-$k$ ranked pages
- Expand pages to $BaseSet$ by adding all pages pointed to and by pages in $RootSet$
- Compute hub and authority values for the subgraph of web induced by $BaseSet$
- Rank pages in $BaseSet$ according to $\vec{a}$, $\vec{h}$, and content
Fig. 1. Expanding the root set into a base set.
HITS vs. Pagerank

Pros of HITS vs. Pagerank
  ▶ Sensitive to user queries

Cons of HITS vs. Pagerank
  ▶ Compute online, not offline!
  ▶ More vulnerable to webspamming