IR: Information Retrieval
FIB, Master in Innovation and Research in Informatics

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http://www.cs.upc.edu/~ir-miri
5. Web Search. Architecture of simple IR systems
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:

```plaintext
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!
Pagerank, II

Definitions

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:

$$p_1 = \frac{p_1}{3} + \frac{p_2}{2}$$
$$p_2 = \frac{p_3}{2} + p_4$$
$$p_3 = \frac{p_1}{3}$$
$$p_4 = \frac{p_1}{3} + \frac{p_2}{2} + \frac{p_3}{2}$$

$$1 = p_1 + p_2 + p_3 + p_4$$

Whose solutions is:

$$p_1 = \frac{6}{23}, p_2 = \frac{8}{23}, p_3 = \frac{2}{23}, p_4 = \frac{7}{23}$$
Pagerank, IV
Formally

Equations

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

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

If $|V| = n$

1. $n + 1$ equations
2. $n$ unknowns

Could be solved, for example, using Gaussian elimination in time $O(n^3)$
Pagerank, V
Example, revisited

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!

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

Example, revisited

Adjacency matrix

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

\[
M = \begin{pmatrix}
\frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\
\frac{1}{2} & 0 & 0 & \frac{1}{2} \\
0 & \frac{1}{2} & 0 & \frac{1}{2} \\
0 & 1 & 0 & 0
\end{pmatrix}
\]

(rows add up to 1)

\[
M^T = \begin{pmatrix}
\frac{1}{3} & \frac{1}{2} & 0 & 0 \\
0 & 0 & \frac{1}{2} & 1 \\
\frac{1}{3} & 0 & 0 & 0 \\
\frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 0
\end{pmatrix}
\]

(columns add up to 1)
Pagerank, VIII
Example, revisited

\[ A = \begin{pmatrix} 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{pmatrix}, \quad M = \begin{pmatrix} \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 1 & 0 & 0 \end{pmatrix}, \quad M^T = \begin{pmatrix} \frac{1}{3} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & \frac{1}{2} & 1 \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 0 \end{pmatrix} \]

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 $G$

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

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 $m_{24} = \frac{1}{2}$
Pagerank, XII
The random surfer view

- 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

\[
\begin{pmatrix}
\frac{1}{3} & \frac{1}{2} & 0 & 0 \\
0 & 0 & \frac{1}{2} & 1 \\
\frac{1}{3} & 0 & 0 & 0 \\
\frac{1}{3} & \frac{1}{2} & \frac{1}{2} & 0
\end{pmatrix}
\]

- \( \vec{p}(0)^T = (1, 0, 0, 0) \)
- \( \vec{p}(1)^T = (1/3, 0, 1/3, 1/3) \)
- \( \vec{p}(2)^T = (0.11, 0.50, 0.11, 0.28) \)
- ..
- \( \vec{p}(10)^T = (0.26, 0.35, 0.09, 0.30) \)
- \( \vec{p}(11)^T = (0.26, 0.35, 0.09, 0.30) \)
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
Try out the power method with $\vec{p}(0)$:

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

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
A useful theorem from Markov chain theory

**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!
Teleportation in the random surfer view

The meaning of $\lambda$

- With probability $\lambda$, the random surfer follows a link in 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 $\lambda = 2/3$:

Hint: solve the following system, using $p_2 = p_3 = p_4$

$$\begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 0 & 1 & 1 & 1 \\ \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{3} & 0 & 0 & 0 \end{bmatrix} + \frac{1}{3} \cdot \frac{1}{4} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix}$$
Pagerank, XXI

Exercise, II

Compute the pagerank vector \( \vec{p} \) of graph with row-normalized matrix \( M \) for damping factor \( \lambda \) in closed matrix form.

Answer:

\[
\vec{p} = (I - \lambda M^T)^{-1} \begin{pmatrix} \frac{1-\lambda}{n} \\ \vdots \\ \frac{1-\lambda}{n} \end{pmatrix}
\]
Topic-sensitive Pagerank, I

Observe that pageranks are independent of user’s query

- Advantages
  - Computed off-line
  - Collective reputation
- Disadvantages
  - Insensitive to particular user’s needs
Assume there is a small set of $K$ topics (sports, science, politics, ...)

- Each topic $k \in \{1, \ldots, K\}$ 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\"
- Finally compute ranking score of a page $i$ given query $q$
  \[
  \text{score}(i, q) = \sum_{k=1}^{K} \text{sim}(T_k, q) \cdot p_{i,k}
  \]
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!
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 \(d\)

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

Notice not a linear system anymore!

- ... but still ok with a variant of the power method
Our old graph

Adjacency matrix

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

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

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

Example

Our old graph

Adjacency matrix

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

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

\[ h_2 \propto (1, 0, 0, 1) \cdot \begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix} = (1, 0, 0, 1) \cdot \vec{a} \]
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 $\vec{a} := \frac{\vec{a}}{\|\vec{a}\|}$ so that $\|\vec{a}\| = 1$

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