Web Information Retrieval

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Acknowledgement

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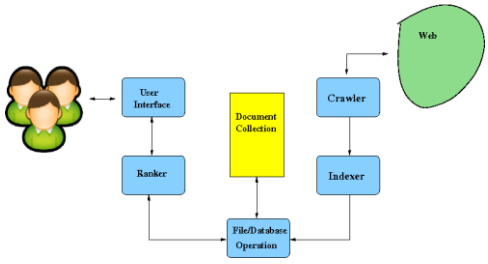
In this segment:

- Web search engine architecture
  - Text collection
  - Text processing
  - Indexing
  - Ranking
  - User interface
  - Storage
- Link analysis
  - Hubs and authorities: HITS
  - PageRank

Search Engine Architecture

System Architecture



Collecting Text

Basic algorithm:

- *Initialize queue with URLs of known seed pages*
- *Repeat*
  - *Take a URL from queue*
  - *Fetch and parse page specified by the URL*
  - *Extract URLs from page*
  - *Add URLs to queue*
- *Until the stop condition is met*

Possible stop conditions:

- Page count reached, time limit reached, or a combination of these conditions

Fundamental assumption: The web is well connected.

Processing Text

- Parsing text
- Removing stop words
- Selecting index terms
- Stemming terms

Processing Text – parsing text

- In English words are separated by delimiters such as space
- In Chinese, it is a bit more challenge to separate words (or characters)

和尚

The two characters can be treated as one word meaning 'monk' or as a sequence of two words meaning 'and' (和, 以及) and 'still, not yet (尚未).'

8

Chinese: No White Space

莎拉波娃现在居住在美国东南部的佛罗里达。今年４月９日，莎拉波娃在美国第一大城市纽约度过了１８岁生日。生日派对上，莎拉波娃露出了甜美的微笑。

Processing Text – selecting index term

- Converting documents to a collection of *index terms*, which is typically a subset of all terms.
- Why?
  - Matching the exact string of characters typed by the user is too restrictive
    - i.e., it doesn't work very well in terms of effectiveness
  - Not all words are of equal value in a search
  - Sometimes not clear where words begin and end
    - Not even clear what a word is in some languages
      - e.g., Chinese, Korean

Processing Text – removing stop words

- Function words, e.g., *the, so*, have little meaning on their own
- High occurrence frequencies, e.g., *computer* in a computer science textbook
- Treated as *stopwords* (i.e., removed)
  - reduce index space, improve response time, improve effectiveness
- Some special cases have to be considered
  - e.g., "to be or not to be"

Processing Text – removing stop words

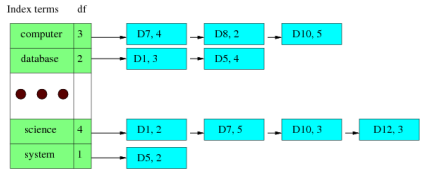
- Stopword list can be created from high-frequency words or based on a standard list
- Lists are customized for applications, domains, and even parts of documents
  - e.g., "click" is a good stopword for anchor text
- Best policy is to index all words in documents, make decisions about which words to use at query time

Text Processing -- stemming

- Many morphological variations of words
  - *inflectional* (plurals, tenses)
  - *derivational* (making verbs nouns etc.)
- In most cases, these have the same or very similar meanings
- Stemmers attempt to reduce morphological variations of words to a common stem
  - usually involves removing suffixes
- Can be done at indexing time or as part of query processing (like stopwords)

Building Inverted Index

- After selecting index terms and applying stemming algorithm, if necessary, an inverted indexing system is built



A simple inverted indexing system

14

Ranking

- Many results may "match" the query terms
- How to rank these results, possible solutions
  - No ranking
  - Ranking by the number of times a query term appears in documents
  - Ranking by some weighted average
  - …

15

User Interface

- Display one huge list 1 … n?
- Display k results per page? Allow the user to jump to certain pages directly?
- Allow user feedback for refining the search results?

16

Experiment with Code

- Let's now examine the code example for a simple server program that can take a user input

17

Link Analysis

18

Link Analysis

- Links are a key component of the Web
- Important for navigation, but also for search
  - e.g., Example website
  - "Example website" is the anchor text
  - "http://example.com" is the destination link
  - both are used by search engines

Anchor Text

- Used as a description of the content of the *destination page*
  - i.e., collection of anchor text in all links pointing to a page can be used as an additional text field
- Anchor text tends to be short, descriptive, and similar to query text
- Retrieval experiments have shown that anchor text has significant impact on effectiveness for *some types of queries*
  - i.e., more than PageRank

Authorities

- *Authorities* are pages that are recognized as providing significant, trustworthy, and useful information on a topic.
- *In-degree* (number of pointers to a page) is one simple measure of authority.
- However in-degree treats all links as equal.
- Should links from pages that are themselves authoritative count more?

Hubs

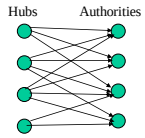
- *Hubs* are index pages that provide lots of useful links to relevant content pages (topic authorities).
- Hub pages for IR are included in the course home page:
  - http://www.cs.utexas.edu/users/mooney/ir-course
  - http://www.eg.bucknell.edu/~xmeng/webir-course/common-files/sortingWebIRCourses.html

HITS

- Hyperlink Induced Topic Search
- Algorithm developed by Kleinberg of Cornell in 1998.
- Attempts to computationally determine hubs and authorities on a particular topic through analysis of a relevant subgraph of the web.
- Based on mutually recursive facts:
  - Hubs point to lots of authorities.
  - Authorities are pointed to by lots of hubs.

Hubs and Authorities

- Together they tend to form a bipartite graph:



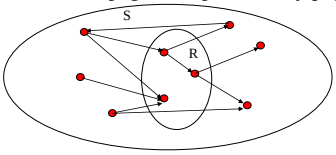
HITS Algorithm

- Computes hubs and authorities for a particular topic specified by a normal query.
- First determines a set of relevant pages for the query called the *base* set *S*.
- Analyze the link structure of the web subgraph defined by *S* to find authority and hub pages in this set.

25

Constructing a Base Subgraph

- For a specific query *Q*, let the set of documents returned by a standard search engine (e.g., google) be called the *root* set *R*.
- Initialize *S* to *R*.
- Add to *S* all pages pointed to by any page in *R*.
- Add to *S* all pages that point to any page in *R*.



26

Base Limitations

- To limit computational expense:
  - Limit number of root pages to the top 200 pages retrieved for the query.
  - Limit number of "back-pointer" pages to a random set of at most 50 pages returned by a "reverse link" query.
- To eliminate purely navigational links:
  - Eliminate links between two pages on the same host.
- To eliminate "non-authority-conveying" links:
  - Allow only m ($m \cong 4$–8) pages from a given host as pointers to any individual page.

27

Authorities and In-Degree

- Even within the base set *S* for a given query, the nodes with highest in-degree are not necessarily authorities (may just be generally popular pages like Facebook or Amazon).
- True authority pages are pointed to by a number of hubs (i.e., pages that point to lots of authorities).

28

Iterative Algorithm

- Use an iterative algorithm to slowly converge on a mutually reinforcing set of hubs and authorities.
- Maintain for each page $p \in S$:
  - Authority score: a_p (vector $\boldsymbol{a}$)
  - Hub score: h_p (vector $\boldsymbol{h}$)
- Initialize all $a_p = h_p = 1$
- Maintain normalized scores:

$$\sum_{p \in S} (a_p)^2 = 1 \qquad \sum_{p \in S} (h_p)^2 = 1$$

29

HITS Update Rules

- Authorities are pointed to by lots of good hubs:

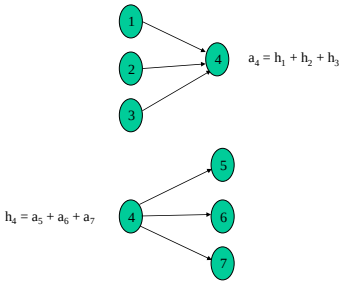
$$a_p = \sum_{q:q \to p} h_q$$

- Hubs point to lots of good authorities:

$$h_p = \sum_{q:p \to q} a_q$$

30

Illustrated Update Rules



31

HITS Iterative Algorithm

Initialize for all $p \in S$: $a_p = h_p = 1$

For i = 1 to k:

For all $p \in S$: $a_p = \sum_{q:q \to p} h_q$ *(update auth. scores)*

For all $p \in S$: $h_p = \sum_{q:p \to q} a_q$ *(update hub scores)*

For all $p \in S$: $a_p = a_p / c$ c: $\sum_{p \in S} (a_p / c)^2 = 1$ *(normalize **a**)*

For all $p \in S$: $h_p = h_p / c$ c: $\sum_{p \in S} (h_p / c)^2 = 1$ *(normalize **h**)*

32

Convergence

- Algorithm converges to a *fix-point* if iterated indefinitely.
- Define *A* to be the adjacency matrix for the subgraph defined by *S*.
  - $A_{ij} = 1$ for $i \in S, j \in S$ iff $i \to j$
- Authority vector, ***a***, converges to the principal eigenvector of $A^T A$
- Hub vector, ***h***, converges to the principal eigenvector of AA^T
- In practice, 20 iterations produces fairly stable results.

33

Results (late 1990s)

- Authorities for query: "Java"
  - java.sun.com
  - comp.lang.java FAQ
- Authorities for query "search engine"
  - Yahoo.com
  - Excite.com
  - Lycos.com
  - Altavista.com
- Authorities for query "Gates"
  - Microsoft.com
  - roadahead.com

34

Result Comments

- In most cases, the final authorities were not in the initial root set generated using Altavista.
- Authorities were brought in from linked and reverse-linked pages and then HITS computed their high authority score.

35

Finding Similar Pages Using Link Structure

- Given a page, *P*, let *R* (the root set) be *t* (e.g., 200) pages that point to *P*.
- Grow a base set *S* from *R*.
- Run HITS on *S*.
- Return the best authorities in *S* as the best similar-pages for *P*.
- Finds authorities in the "link neighbor-hood" of *P*.

36

Similar Page Results

- Given "honda.com"
  - toyota.com
  - ford.com
  - bmwusa.com
  - saturncars.com
  - nissanmotors.com
  - audi.com
  - volvocars.com

37

HITS for Clustering

- An ambiguous query can result in the principal eigenvector only covering one of the possible meanings.
- Non-principal eigenvectors may contain hubs & authorities for other meanings.
- Example: "jaguar":
  - Atari video game (principal eigenvector)
  - NFL Football team (2nd non-princ. eigenvector)
  - Automobile (3rd non-princ. eigenvector)

38

In-Class Work

- Working with your neighbor(s), compute the first round of result from the HITS algorithm for the graph represented by the following adjacency matrix

0	1	0	0
0	0	0	1
1	1	0	0
1	0	1	0

39

Work in Progress

- a1=a2=a3=a4=1, h1=h2=h3=h4=1
- a1 = h3 + h4 = 2
- a2 = h1 + h3 = 2
- a3 = h4 = 1
- a4 = h2 = 1
- $c^2 = \text{sum}(a_i^2) = 4 + 4 + 1 + 1 = 10$
- a1/c = a2/c = 2/3.16 = 0.632
- a3/c = a4/c = 1/3.16 = 0.316

40

PageRank

- Billions of web pages, some more informative than others
- Links can be viewed as information about the *popularity* (*authority*?) of a web page
  - can be used by ranking algorithm
- *Inlink* count could be used as simple measure
- Link analysis algorithms like PageRank provide more reliable ratings
  - less susceptible to link spam

Random Surfer Model

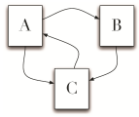
- Browse the Web using the following algorithm:
  - Choose a random number r between 0 and 1
  - If $r < \lambda$:
    - Go to a random page
  - If $r \geq \lambda$:
    - Click a link at random on the current page
  - Start again
- PageRank of a page is the probability that the "random surfer" will be looking at that page
  - links from popular pages will increase PageRank of pages they point to

Dangling Links

- Random jump prevents getting stuck on pages that
  - do not have links
  - contains only links that no longer point to other pages
  - have links forming a loop
- Links that point to the first two types of pages are called *dangling links*
  - may also be links to pages that have not yet been crawled

PageRank

- PageRank (*PR*) of page C = *PR*(A)/2 + *PR*(B)/1
- More generally,



$$PR(u) = \sum_{v \in B_u} \frac{PR(v)}{L_v}$$

  - where B_u is the set of pages that point to u, and L_v is the number of outgoing links from page v (not counting duplicate links)

PageRank

- Don't know PageRank values at start
- Assume equal values (1/3 in this case), then iterate:
  - first iteration: *PR*(C) = 0.33/2 + 0.33 = 0.5, *PR*(A) = 0.33, and *PR*(B) = 0.17
  - second: *PR*(C) = 0.33/2 + 0.17 = 0.33, *PR*(A) = 0.5, *PR*(B) = 0.17
  - third: *PR*(C) = 0.42, *PR*(A) = 0.33, *PR*(B) = 0.25
- Converges to *PR*(C) = 0.4, *PR*(A) = 0.4, and *PR*(B) = 0.2

PageRank

- Taking random page jump into account, 1/3 chance of going to any page when $r < \lambda$
- $PR(C) = \lambda/3 + (1 - \lambda) \cdot (PR(A)/2 + PR(B)/1)$
- More generally,

$$PR(u) = \frac{\lambda}{N} + (1 - \lambda). \sum_{v \in B_u} \frac{PR(v)}{L_v}$$

  - where N is the number of pages, λ typically 0.15

PageRank Algorithm

Let S be the total set of pages.

Let $\forall p \in S$: $E(p) = \alpha/|S|$ (for some $0<\alpha<1$, e.g. 0.15)

Initialize $\forall p \in S$: $R(p) = 1/|S|$

Until ranks do not change (much) (*convergence*)

For each $p \in S$:

$$R'(p) = \sum_{q:q \to p} \frac{R(q)}{N_q} + E(p)$$

$$c = 1/\sum_{p \in S} R'(p)$$

For each $p \in S$: $R(p) = cR'(p)$ (*normalize*)

In-Class Work

- Working with your neighbor(s), compute the first round of result from the PageRank algorithm for the graph specified by the following adjacency matrix

0	0	1	1
1	0	1	0
0	0	0	1
0	1	0	0

Work in Progress

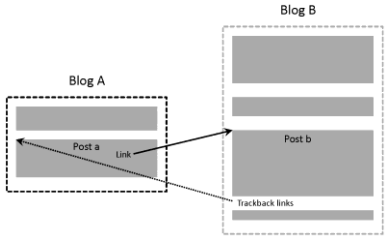
- $\alpha = 0.15$, S = 4, $E(p) = \alpha/S = 0.0375$
- $N_q = (2, 2, 1, 1)$
- Initially R' = 1/S = 0.25
- $R'(1) = \text{sum}(R_q/N_q) + E(p) = R_2/N_2 + E(p) = 0.25/2 + 0.0375 = 0.163$
- $R'(2) = \text{sum}(R_q/N_q) + E(p) = R_4/N_4 + E(p) = 0.25/1 + 0.0375 = 0.288$
- $R'(3) = \text{sum}(R_q/N_q) + E(p) = R_1/N_1 + R_2/N_2 + E(p) = 0.25/2 + 0.25/2 + 0.0375 = 0.288$
- $R'(4) = \text{sum}(R_q/N_q) + E(p) = R_1/N_1 + R_3/N_3 + E(p) = 0.25/2 + 0.25/1 + 0.0375 = 0.413$

49

Link Quality

- Link quality is affected by spam and other factors
  - e.g., *link farms* to increase PageRank
  - *trackback links* in blogs can create loops
  - links from comments section of popular blogs
    - Blog services modify comment links to contain `rel=nofollow` attribute
    - e.g., "Come visit my <a `rel=nofollow` href="http://www.page.com">web page."

Trackback Links



Information Extraction

- Automatically extract structure from text
  - annotate document using tags to identify extracted structure
- *Named entity recognition*
  - identify words that refer to something of interest in a particular application
  - e.g., people, companies, locations, dates, product names, prices, etc.

Named Entity Recognition

- Example showing semantic annotation of text using XML tags
- Information extraction also includes document structure and more complex features such as *relationships* and *events*

Fred Smith, who lives at 10 Water Street, Springfield, MA, is a long-time collector of **tropical fish.**

<PersonName><GivenName>Fred</GivenName> <Sn>Smith</Sn> </PersonName>, who lives at <address><Street >10 Water Street</Street>, <City>Springfield</City>, <State>MA</State></address>, is a long-time collector of tropical fish.

Named Entity Recognition

- *Rule-based*
  - Uses *lexicons* (lists of words and phrases) that categorize names
    - e.g., locations, peoples' names, organizations, etc.
  - Rules also used to verify or find new entity names
    - e.g., "<number> <word> street" for addresses
    - "<street address>, <city>" or "in <city>" to verify city names
    - "<street address>, <city>, <state>" to find new cities
    - "<title> <name>" to find new names

Named Entity Recognition

- Rules either developed manually by trial and error or using machine learning techniques
- *Statistical*
  - uses a probabilistic model of the words in and around an entity
  - probabilities estimated using *training data* (manually annotated text)
  - Hidden Markov Model (HMM) is one approach

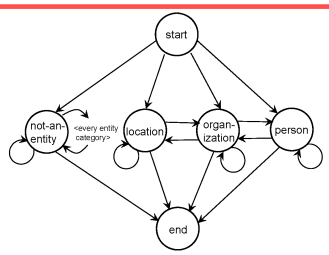
HMM for Extraction

- Resolve ambiguity in a word using *context*
  - e.g., "marathon" is a location or a sporting event, "boston marathon" is a specific sporting event
- Model context using a *generative* model of the sequence of words
  - *Markov property*: the next word in a sequence depends only on a small number of the previous words

HMM for Extraction

- *Markov Model* describes a process as a collection of states with transitions between them
  - each transition has a probability associated with it
  - next state depends only on current state and transition probabilities
- *Hidden Markov Model*
  - each state has a set of possible outputs
  - outputs have probabilities

HMM Sentence Model



- Each state is associated with a probability distribution over words (the output)

HMM for Extraction

- Could generate sentences with this model
- To recognize named entities, find sequence of "labels" that give highest probability for the sentence
  - only the outputs (words) are visible or observed
  - states are "hidden"
  - e.g., <start><name><not-an-entity><location><not-an-entity><end>
- *Viterbi* algorithm used for recognition

Named Entity Recognition

- Accurate recognition requires about 1M words of training data (1,500 news stories)
  - may be more expensive than developing rules for some applications
- Both rule-based and statistical can achieve about 90% effectiveness for categories such as names, locations, organizations
  - others, such as product name, can be much worse

Internationalization

- 2/3 of the Web is in English
- About 50% of Web users do not use English as their primary language
- Many (maybe most) search applications have to deal with multiple languages
  - *monolingual search*: search in one language, but with many possible languages
  - *cross-language search*: search in multiple languages at the same time

Internationalization

- Many aspects of search engines are language-neutral
- Major differences:
  - Text encoding (converting to Unicode)
  - Tokenizing (many languages have no word separators)
  - Stemming
- Cultural differences may also impact interface design and features provided

Chinese "Tokenizing"

1. Original text

旱灾在中国造成的影响

(the impact of droughts in China)

2. Word segmentation

旱灾 在 中国 造成 的 影响

drought at china make impact

3. Bigrams

旱灾 灾在 在中 中国 国造

造成 成的 的影 影响