Information Retrieval

Lecture 4: Web Search

Computer Science Tripos Part II

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(Lecture Notes after Stephen Clark)

Challenges of Web Search

- Distributed data
  - data is stored on millions of machines with varying network characteristics
- Volatile data
  - new computers and data can be added and removed easily
  - dangling links and relocation problems
- Large volume
- Unstructured and redundant data
  - not all HTML pages are well structured
  - much of the Web is repeated (mirrored or copied)

Challenges of Web Search

- Quality of data
  - data can be false, invalid (e.g. out of date), SPAM
  - poorly written, can contain grammatical errors
- Heterogeneous data
  - multiple media types, multiple formats, different languages
- Unsophisticated users
  - information need may be unclear
  - may have difficulty formulating a useful query

Web Challenges – Size of Vocabulary

- Heap's law: $V = Kn^{\beta}$
  - β is typically between 0.4 and 0.6, so vocabulary size V grows roughly with the square root of the text size n
- 99% of distinct words in the VLC2 collection are not dictionary head-words (Hawking, Very Large Scale Information Retrieval)

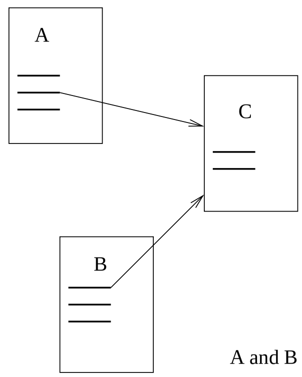
Link-Based Retrieval

- A characteristic of the Web is its hyperlink structure
- Web search engines exploit properties of the structure to try and overcome some of the web-specific challenges
- Basic idea: hyperlink structure can be used to infer the validity / popularity / importance of a page
  - similar to citation analysis in academic publishing
  - number of links to a page correspond with page's importance
  - links coming from an important page are indicators of other important pages
  - Anchor text describes the page
    - can be a useful source of text in addition to the text on the page itself, eg *Big Blue* → IBM

PageRank

- PageRank is *query-independent* and provides a global importance score for every page on the web
  - can be calculated once for all queries
  - but can't be tuned for any one particular query
- PageRank has a simple intuitive interpretation:
  - PageRank score for a page is the probability a random surfer would visit that page
- PageRank is/was used by Google
  - PageRank is combined with other measures such as TF×IDF

Link Structure for PageRank



A and B are backlinks of C

- Pages with many backlinks are typically more important than pages with few backlinks
- But pages with few backlinks can also be important
  - some links, e.g. from Yahoo, are more important than other links

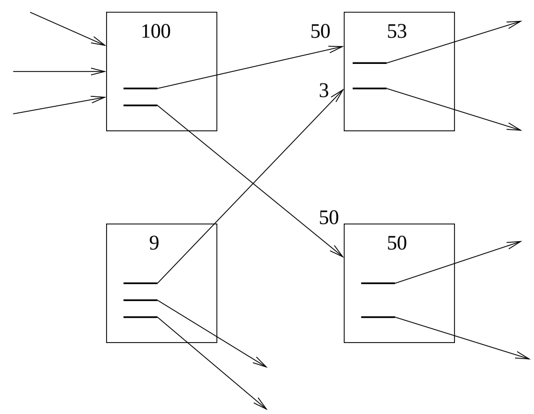
PageRank Scoring

- Consider a browser doing a random walk on the Web
  - start at a random page
  - at each step go to another page along one of the out-links, each link having equal probability
- Each page has a long-term visit rate (the “steady state”)
  - use the visit rate as the score

Simplified PageRank

$$R(u) = d \sum_{v:v \to u} \frac{R(v)}{N_v}$$

u is a web page
N_v is the number of links from v



Teleporting

- Web is full of dead-ends
  - "long-term visit rate" doesn't make sense
- A page may have no in-links
- *Teleporting*: jump to any page on the Web at random (with equal probability 1/N)
  - when there are no out-links use teleporting
  - otherwise use teleporting with probability α, or follow a link chosen at random with probability $(1 - \alpha)$

PageRank

$$R(u) = (1-\alpha) \sum_{v:v\rightarrow u} \frac{R(v)}{N_v} + \alpha E(u)$$

- $E(u)$ is a prior distribution over web pages
- Typical value of α is 0.1
- $R(u)$ can be calculated using an iterative algorithm

Probabilistic Interpretation of PageRank

- PageRank models the behaviour of a ”random surfer”
- Surfer randomly clicks on links, sometimes jumping to any page at random based on E
- Probability of a random jump is α
- PageRank for a page is the probability that the random surfer finds himself on that page

Markov Chains

- A Markov chain consists of n *states* plus an $n \times n$ *transition probability matrix* $\mathbf{P}$
- At each step, we are in exactly one of the states
- For $1 \leq i, j \leq n$, the matrix entry P_{ij} tells us the probability of j being the next state given the current state is i
- For all i, $\Sigma_{j=1}^{n} P_{ij} = 1$
- Markov chains are abstractions of random walks
  - crucial property is that the distribution over next states only depends on the current state, and not how the state was arrived at

Random Surfer as a Markov Chain

- Each state represents a web page; each transition probability represents the probability of moving from one page to another
  - transition probabilities include teleportation
- Let $\overline{x}^t$ be the probability vector for time t
  - x_i^t is the probability of being in state i at time t
- we can compute the surfer's distribution over the web pages at any time given only the initial distribution and the transition probability matrix $\mathbf{P}$

$$x_i^t = \overline{x}^0 P^t$$

Ergodic Markov Chains

- A Markov chain is *ergodic* if the following two conditions hold:
  - For any two states i, j, there is an integer $k \geq 2$ such that there is a sequence of k states $s_1 = i, s_2, \ldots, s_k = j$ such that $\forall l, 1 \leq l \leq k-1$, the transition probability $P_{s_l, s_{l+1}} > 0$
  - There exists a time T_0 such that for all states j, and for all choices of start state i in the Markov chain, and for all $t > T_0$, the probability of being in state j at time t is > 0

Ergodic Markov Chains

- Theorem: *For any ergodic Markov chain, there is a unique steady-state probability distribution over the states, $\overline{\pi}$, such that if $N(i,t)$ is the number of visits to state i in t steps, then*

$$\lim_{t \to \infty} \frac{N(i,t)}{t} = \pi(i),$$

where $\pi(i) > 0$ is the steady-state probability for state i.

(Introduction to IR, ch.21)

- $\pi(i)$ is the PageRank for state/web page i

Eigenvectors of the Transition Matrix

- The *left eigenvectors* of the transition probability matrix P are N-vectors $\overline{\pi}$ such that

$$\overline{\pi}\, P = \lambda\, \overline{\pi}$$

- We want the eigenvector with eigenvalue 1 (this is known as the *principal* left eigenvector of the matrix P, and it has the largest eigenvalue)
- This makes π the steady-state distribution we're looking for

PageRank Computation

- There are many ways to calculate the principal left eigenvector of the transition matrix
- One simple way:
  - Start with any distribution, eg $\overline{x} = (1, 0, \ldots, 0)$
  - After one step, distribution is $x\, P$
  - After two steps, distribution is $x\, P^2$
  - For large k, $x\, P^k = a$, where a is the steady state
  - Algorithm: keep multiplying x by P until the product looks stable

Personalised PageRank

- Putting all the probability mass from E onto a single page produces a personalised importance ranking relative to that page
- E gives the probabilities of jumping to pages via a random jump
- Putting all the mass on one page emphasises pages ”close to” that page

HITS

- Hypertext Induced Topic Search (Kleinberg)
  - “Hyperlinks encode a considerable amount of latent human judgement”
  - “The creator of page p, by including a link to page q, has in some measure *conferred authority* on q”
- Example: consider the query ”Harvard”
  - `www.harvard.edu` may not use *Harvard* most often
  - but many pages containing the term *Harvard* will point at `www.harvard.edu`
- But some links are created for reasons other than conferral of authority, e.g. navigational purposes, advertisements
- Need also to balance criteria of *relevance* and *popularity*
  - e.g. lots of pages point at `www.google.com`

Hubs and Authorities (for a given query)

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- An authority is a page which has many relevant pages pointing at it
  - authorities are likely to be relevant (precision)
  - there should be overlap between the sets of pages which point at authorities
- A hub is a page which links to many authorities
  - hubs help find relevant pages (recall)
  - hubs ”pull-together” authorities on a common topic
  - hubs allow us to ignore non-relevant pages with a high *in-degree*
- Relationship between hubs and authorities is mutually reinforcing:
  - a good hub points to many good authorities
  - a good authority is pointed at by many good hubs

Finding Hubs and Authorities

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- Suppose we are given some query σ
- We wish to find authoritative pages with respect to σ, restricting computation to a relatively small set of pages:
  - recover top-n pages using some search engine: the *root set*
  - add pages which link to the root set and pages which the root set link: the *base set*
- Base set might contain a few thousand documents, with many authorities
  - how do we find the authorities?

Finding Hubs and Authorities

- Each page p has a hub weight h_p and authority weight a_p
- Initially set all weights to 1
- Update weights iteratively:

$$h_p \leftarrow \sum_{q:p \rightarrow q} a_q$$

$$a_p \leftarrow \sum_{q:q \rightarrow p} h_q$$

  - $p \rightarrow q$ means p points at q
  - weights are normalised after each iteration
  - can prove this algorithm converges
- Pages for a given query can then be weighted by their hub and authority weights

Calculating Hub and Authority Weights

Loop(G,k):
G: a collection of n linked pages
K: a natural number
Let z denote the vector (1,1,1,...,1) $\in \mathcal{R}^n$
Set $\overline{a}_0 := z$
Set $\overline{h}_0 := z$
For i = 1,2,...,k
Update $\overline{a}_{i-1}$ obtaining new weights $\overline{a}_i^{'}$
Update $\overline{h}_{i-1}$ obtaining new weights $\overline{h}_i^{'}$
Normalise $\overline{a}_i^{'}$ obtaining $\overline{a}_i$
Normalise $\overline{h}_i^{'}$ obtaining $\overline{h}_i$
Return ($\overline{a}_k$,$\overline{h}_k$)

Example Results for HITS

Query	Top Authorities	
censorship	.378 http://www.eff.org/	The Electronic Frontier Foundation
	.344 http://www.eff.org/blueribbon.html	Campaign for online free speech
	.238 http://www.cdt.org/	Center for democracy & technology
	.235 http://www.vtw.org/	Voters telecommunications watch
”search engines”	.346 http://www.yahoo.com/	Yahoo
	.291 http://www.excite.com/	Excite
	.239 http://www.mckinley.com/	Welcome to Magellan
	.231 http://www.lycos.com/	Lycos home page
	.231 http://www.altavista.digital.com	AltaVista
Gates	.643 http://www.roadahead.com/	Bill Gates: The Road Ahead
	.458 http://www.microsoft.com/	Welcome to Microsoft
	.440 http://www.microsoft.com/corpinfo	

References

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