Technologies for Web Crawling, Indexing and Search

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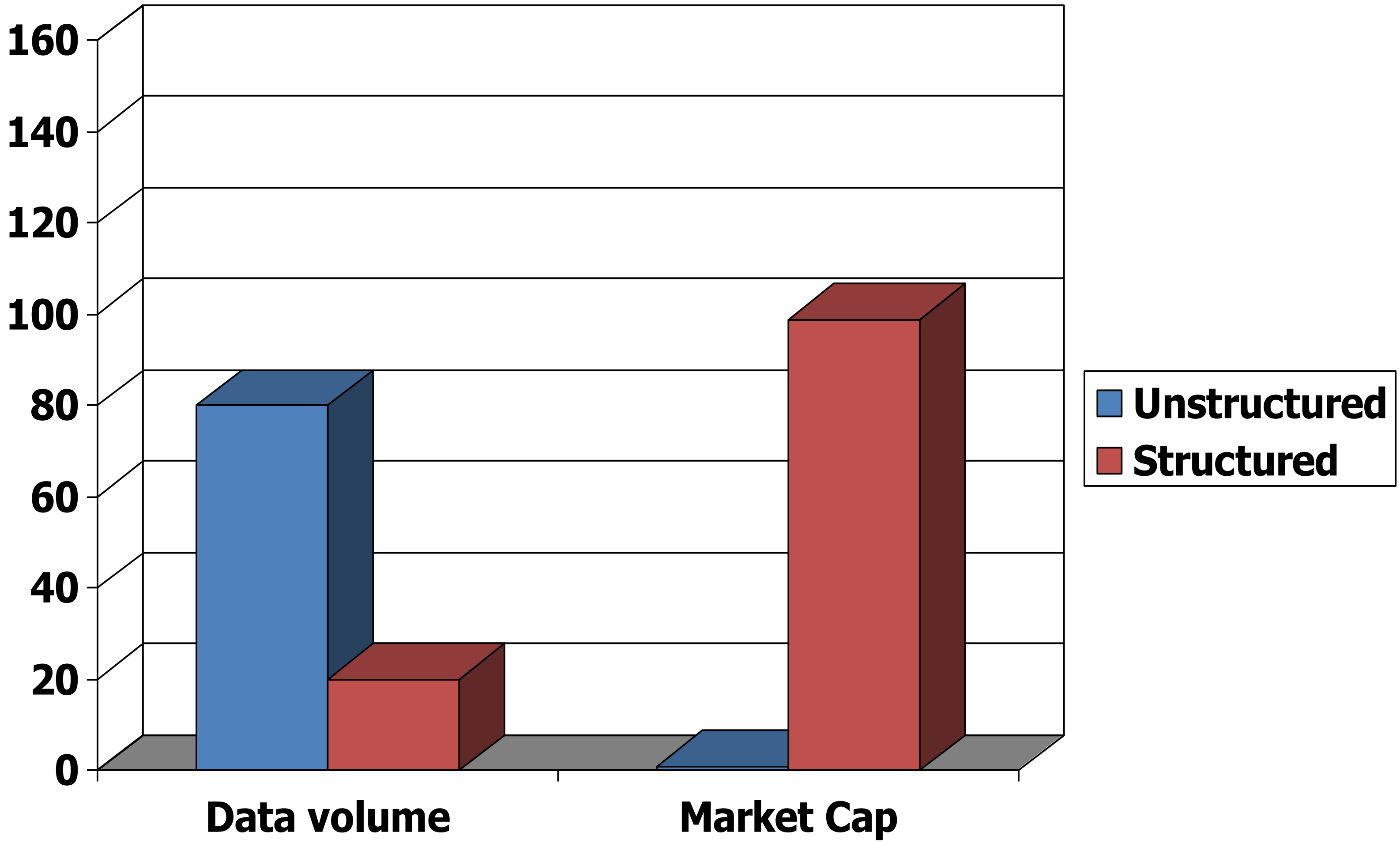
Information Retrieval
Search Basics

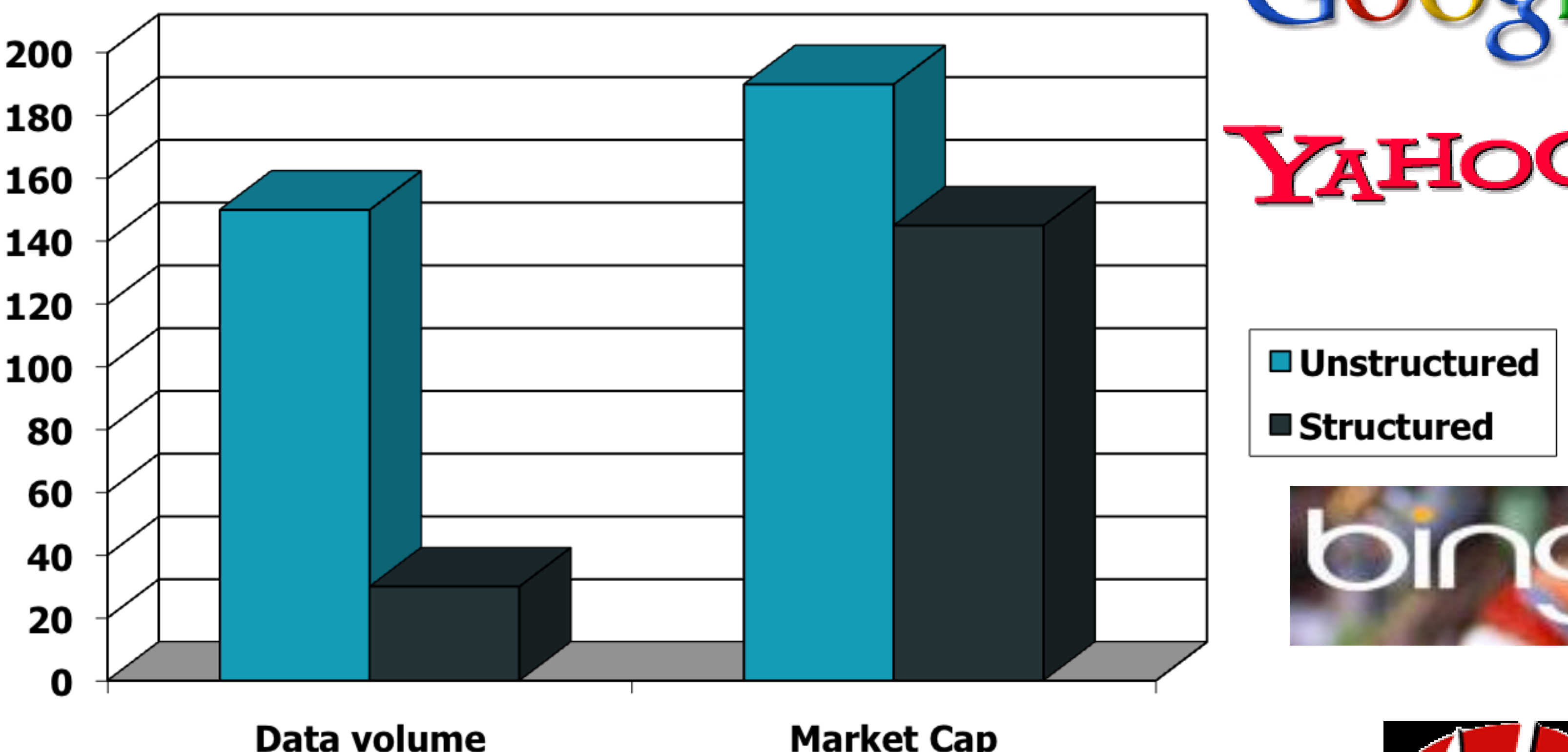
Information Retrieval

- Information Retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).
  - Librarians
  - Now also in XML and DB
  - Focus on user

Unstructured (text) vs. structured (database) data in 1996



Unstructured (text) vs. structured (database) data in 2009



Unstructured data in 1680

- Which plays of Shakespeare contain the words ***Brutus*** *AND* ***Caesar*** but *NOT* ***Calpurnia***?
- One could grep all of Shakespeare's plays for ***Brutus*** and ***Caesar,*** then strip out lines containing ***Calpurnia***?
  - Slow (for large corpora)
  - *NOT* ***Calpurnia*** is non-trivial
  - Other operations (e.g., find the word ***Romans*** near ***countrymen***) not feasible
  - Ranked retrieval (best documents to return) also hard

Solution: Term-document incidence

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

Brutus *AND* ***Caesar*** *but NOT* ***Calpurnia***

1 if play contains word, 0 otherwise

Incidence vectors

- So we have a 0/1 vector for each term.
- To answer query: take the vectors for ***Brutus, Caesar*** and ***Calpurnia*** (complemented) ➔ bitwise *AND*.
- 110100 *AND* 110111 *AND* 101111 = 100100.

Answers to query

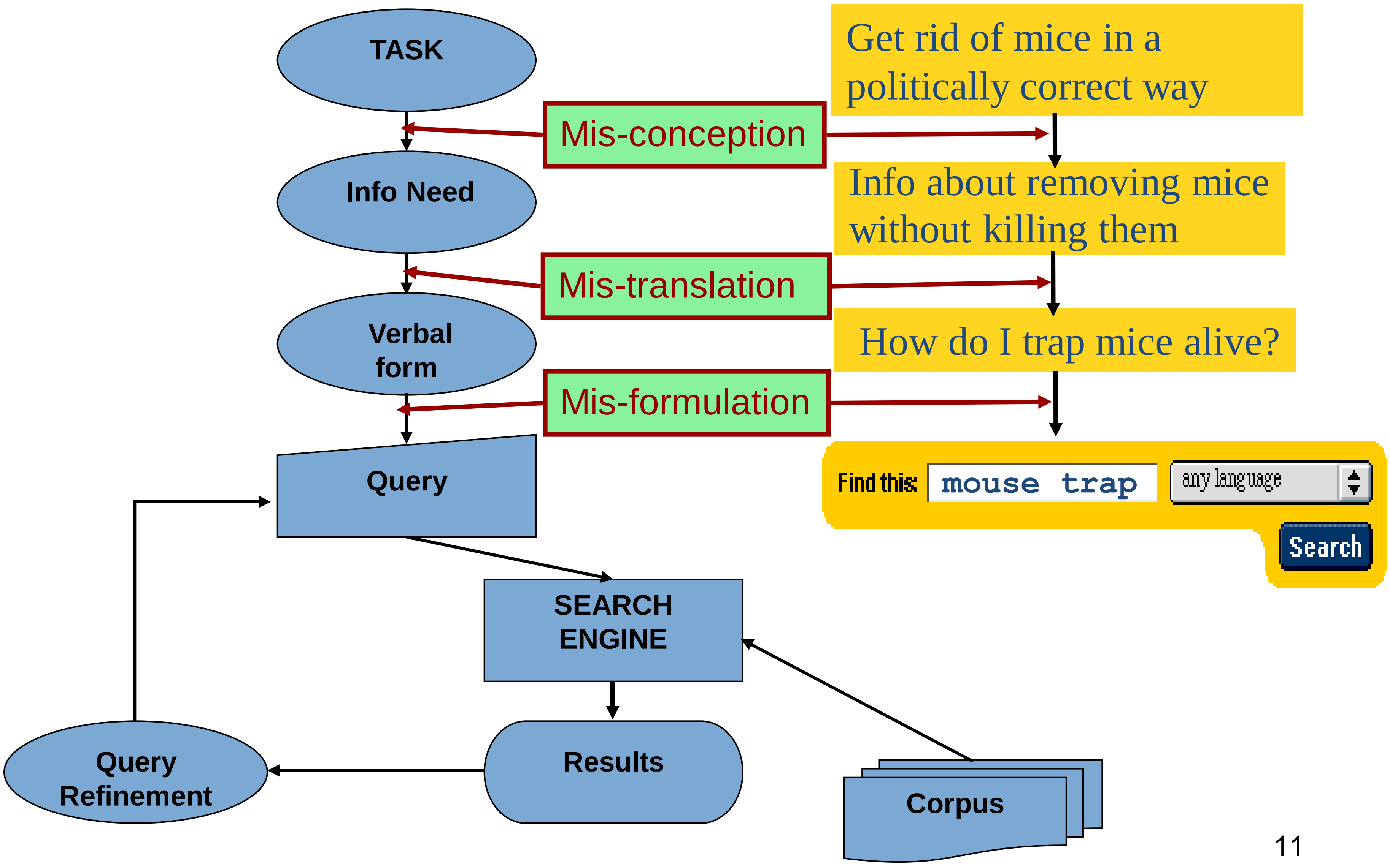
- Antony and Cleopatra, Act III, Scene ii
- *Agrippa* [Aside to DOMITIUS ENOBARBUS]: Why, Enobarbus,
- When Antony found Julius ***Caesar*** dead,
- He cried almost to roaring; and he wept
- When at Philippi he found ***Brutus*** slain.

- Hamlet, Act III, Scene ii
- *Lord Polonius:* I did enact Julius ***Caesar*** I was killed i' the
- Capitol; ***Brutus*** killed me.

Basic assumptions of Information Retrieval

- Corpus: Fixed document collection
- Goal: Retrieve documents with information that is relevant to user’s information need and helps him complete a task

The classic search model



How good are the retrieved docs?

- *Precision* : Fraction of retrieved docs that are relevant to user's information need
- *Recall* : Fraction of relevant docs in corpus that are retrieved
- More precise definitions and measurements to follow in later lectures

Bigger corpora

- Consider N = 1M documents, each with about 1K terms.
- Avg. 6 bytes/term incl. spaces/punctuation (EN)
  - 6GB of data in the documents.
- Say there are m = 500K *distinct* terms among these.

Can’t build the matrix

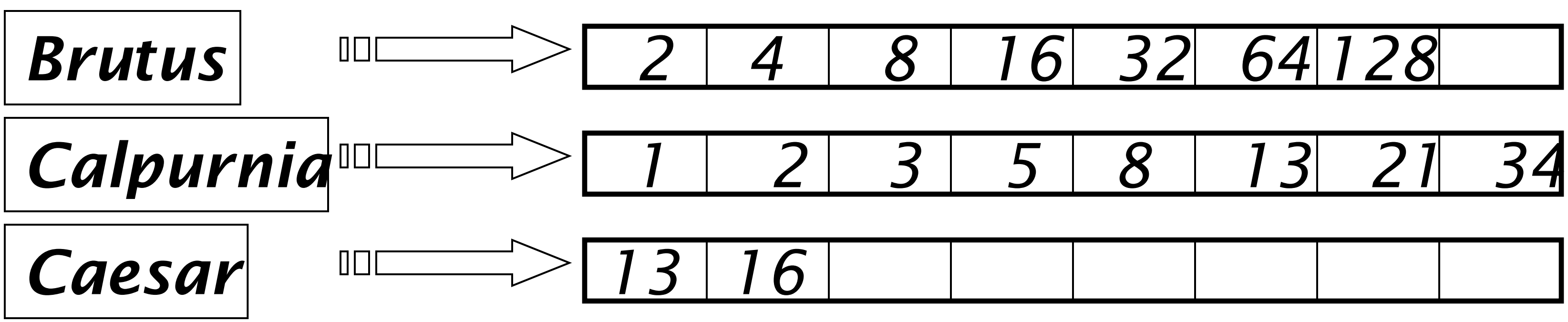
- 500K x 1M matrix has half-a-trillion 0’s and 1’s.
- But it has no more than one billion 1’s.
  - matrix is extremely sparse.

Why?

- What’s a better representation?
  - We only record the 1 positions.

Inverted index

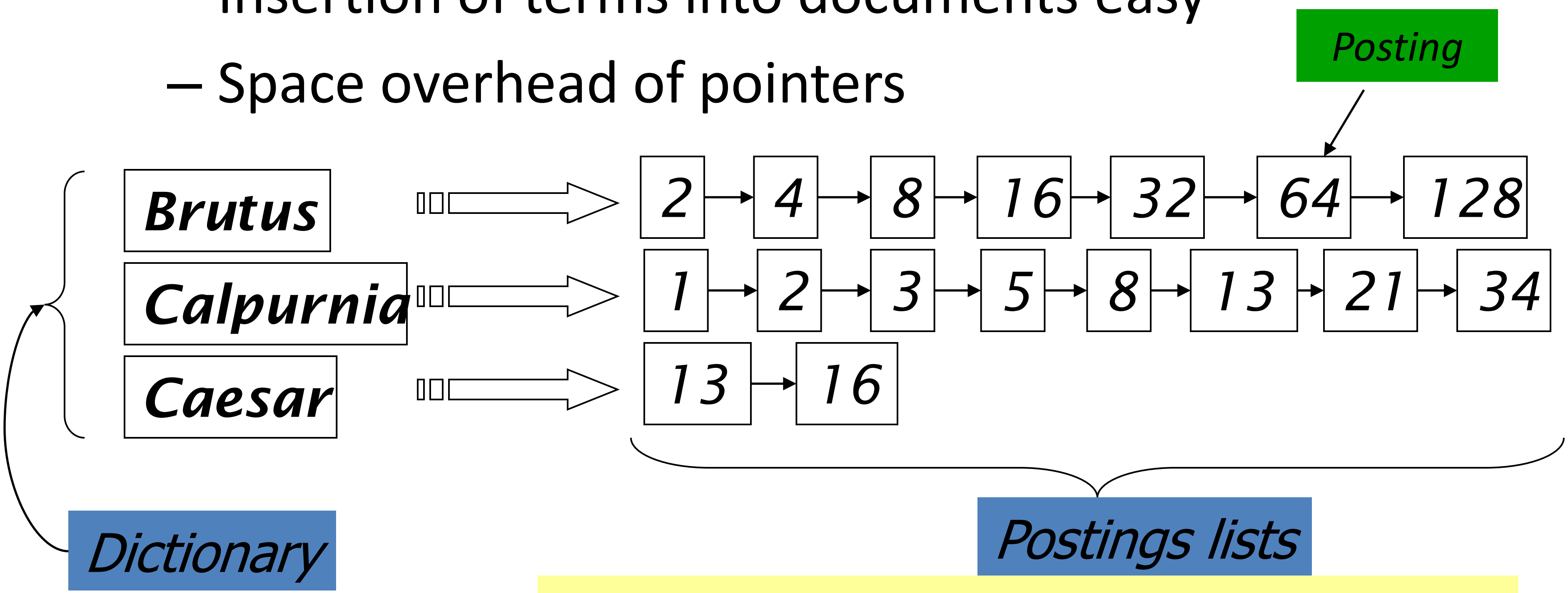
- For each term *T*, we must store a list of all documents that contain *T*.
- Do we use an array or a list for this?



*What happens if the word **Caesar** is added to document 14?*

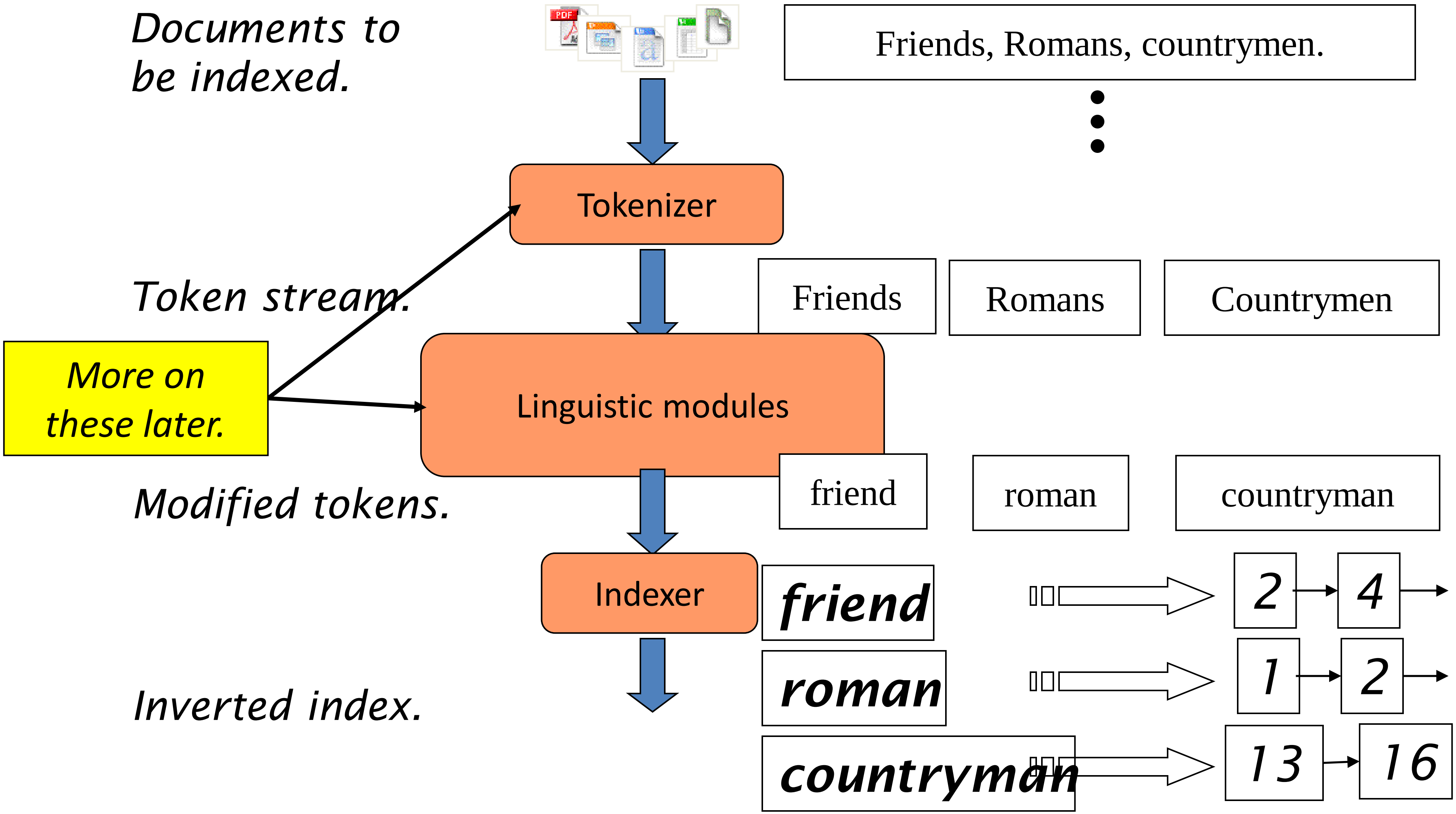
Inverted index

- Linked lists generally preferred to arrays
  - Dynamic space allocation
  - Insertion of terms into documents easy
  - Space overhead of pointers



Sorted by docID (more later on why).

Inverted index construction



Indexer steps

- Sequence of (Modified token, Document ID) pairs.

Doc 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Doc 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious

Term	Doc #
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

- Sort by terms.

<u>Core indexing step.</u>

Term	Doc #
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

$\rightarrow$

Term	Doc #
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Indexer steps: Dictionary & Postings

- Multiple term entries in a single document are merged.
- Split into Dictionary and Postings
- Doc. frequency information is added.

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

Why frequency?
Will discuss later.

- Where do we pay in storage?

Term	N docs	Coll freq
ambitious	1	1
be	1	1
brutus	2	2
capitol	1	1
caesar	2	3
did	1	1
enact	1	1
hath	1	1
I	1	2
i'	1	1
it	1	1
julius	1	1
killed	1	2
let	1	1
me	1	1
noble	1	1
so	1	1
the	2	2
told	1	1
you	1	1
was	2	2
with	1	1

Doc #	Freq
2	1
2	1
1	1
2	1
1	1
1	
2	
1	
1	
2	
1	
1	
2	1
1	1
1	2
2	1
1	1
2	1
2	1
1	1
2	1
2	1
2	1
1	1
2	1
2	1

Will quantify the storage, later.

Terms

Pointers

The index we just built

- How do we process a query?

Query processing: AND

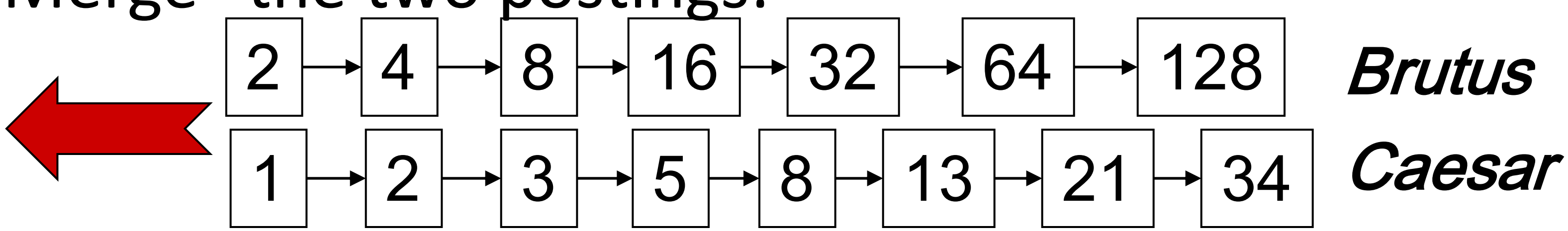
- Consider processing the query:

  Brutus *AND* ***Caesar***

  – Locate ***Brutus*** in the Dictionary;
    - Retrieve its postings.

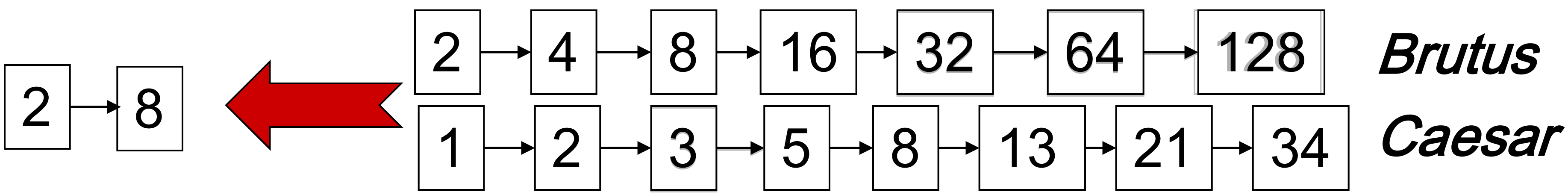
  – Locate *Caesar* in the Dictionary;
    - Retrieve its postings.

  – "Merge" the two postings:



The merge

- Walk through the two postings simultaneously, in time linear in the total number of postings entries



If the list lengths are x and y, the merge takes O(x+y) operations.

<u>Crucial</u>: postings sorted by docID.

Intersecting two postings lists (a "merge" algorithm)

```
INTERSECT(p1, p2)
answer ← ⟨ ⟩
while p1 ≠ NIL and p2 ≠ NIL
do if docID(p1) = docID(p2)
      then ADD(answer, docID(p1))
           p1 ← next(p1)
           p2 ← next(p2)
      else if docID(p1) < docID(p2)
              then p1 ← next(p1)
              else p2 ← next(p2)
return answer
```

Ranked Search

Ranked retrieval

- Thus far, our queries have all been Boolean.
  - Documents either match or don't.
- Good for expert users with precise understanding of their needs and the collection.
  - Also good for applications: Applications can easily consume 1000s of results.
- Not good for the majority of users.
  - Most users incapable of writing Boolean queries (or they are, but they think it's too much work).
  - Most users don't want to wade through 1000s of results.
    - This is particularly true of web search.

Facts

- The average query length on current search engines is 2.4 words
- Over 40% of the user queries are single words
- About 80+% of the users look only at the first page of results, 95% look at the first two pages, almost everybody looks only at the first three

Problem with Boolean search: feast or famine

- Boolean queries often result in either too few (=0) or too many (1000s) results.
- Query 1: "*standard user dlink 650*" → 200,000 hits
- Query 2: "*standard user dlink 650 no card found*": 0 hits
- It takes a lot of skill to come up with a query that produces a manageable number of hits.
  - AND gives too few; OR gives too many

Ranked retrieval models

- Rather than a set of documents satisfying a query expression, in ranked retrieval models, the system returns an ordering over the (top) documents in the collection with respect to a query
- Free text queries: Rather than a query language of operators and expressions, the user's query is just one or more words in a human language
- In principle, there are two separate choices here, but in practice, ranked retrieval models have normally been associated with free text queries and vice versa

Feast or famine: not a problem in ranked retrieval

- When a system produces a ranked result set, large result sets are not an issue
  - Indeed, the size of the result set is not an issue
  - We just show the top *k* (≈ 10) results
  - We don’t overwhelm the user
  - Premise: the ranking algorithm works

Scoring as the basis of ranked retrieval

- We wish to return in order the documents most likely to be useful to the searcher
- How can we rank-order the documents in the collection with respect to a query?
- Assign a score – say in [0, 1] – to each document
- This score measures how well document and query "match".

Query-document matching scores

- We need a way of assigning a score to a query/document pair
- Let's start with a one-term query
- If the query term does not occur in the document: score should be 0
- The more frequent the query term in the document, the higher the score (should be)
- We will look at a number of alternatives for this.

Term-document count matrices

- Consider the number of occurrences of a term in a document:
  - Each document is a count vector in $\mathbb{N}^{|V|}$: a column below

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

Bag of words model

- Vector representation doesn't consider the ordering of words in a document
- *John is quicker than Mary* and *Mary is quicker than John* have the same vectors
- This is called the bag of words model.
- In a sense, this is a step back: The positional index was able to distinguish these two documents.
- We will look at "recovering" positional information later in this course.
- For now: bag of words model

Term frequency tf

- The term frequency $tf_{t,d}$ of term *t* in document *d* is defined as the number of times that *t* occurs in *d*.
- We want to use tf when computing query-document match scores. But how?
- Raw term frequency is not what we want:
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence of the term.
  - But not 10 times more relevant.
- Relevance does not increase proportionally with term frequency.

NB: frequency = count in IR

Log-frequency weighting

- The log frequency weight of term t in d is

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d}, & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

- 0 → 0, 1 → 1, 2 → 1.3, 10 → 2, 1000 → 4, etc.
- Score for a document-query pair: sum over terms *t* in both *q* and *d*:
- score $= \sum_{t \in q \cap d} (1 + \log \mathrm{tf}_{t,d})$

- The score is 0 if none of the query terms is present in the document.

Document frequency

- Rare terms are more informative than frequent terms
  - Recall stop words
- Consider a term in the query that is rare in the collection (e.g., *arachnocentric*)
- A document containing this term is very likely to be relevant to the query *arachnocentric information*
- → We want a high weight for rare terms like *arachnocentric*.

Document frequency, continued

- Frequent terms are less informative than rare terms
- Consider a query term that is frequent in the collection (e.g., *high, increase, line*)
- A document containing such a term is more likely to be relevant than a document that doesn’t
- But it’s not a sure indicator of relevance.
- → For frequent terms, we want high positive weights for words like *high, increase, and line*
- But lower weights than for rare terms.
- We will use document frequency (df) to capture this.

idf weight

- df_t is the document frequency of t: the number of documents that contain t
  - df_t is an inverse measure of the informativeness of t
  - $\mathrm{df}_t \leq N$
- We define the idf (inverse document frequency) of t by
  - We use log (N/df_t) instead of N/df_t to "dampen" the effect of idf.

$$\mathrm{idf}_t = \log_{10}(N/\mathrm{df}_t)$$

Will turn out the base of the log is immaterial.

idf example, suppose N = 1 million

term	df_t	idf_t
calpurnia	1	
animal	100	
sunday	1,000	
fly	10,000	
under	100,000	
the	1,000,000	

$$\mathrm{idf}_t = \log_{10}\left(N/\mathrm{df}_t\right)$$

There is one idf value for each term t in a collection.

Effect of idf on ranking

- Does idf have an effect on ranking for one-term queries, like
  - iPhone
- idf has no effect on ranking one term queries
  - idf affects the ranking of documents for queries with at least two terms
  - For the query capricious person, idf weighting makes occurrences of capricious count for much more in the final document ranking than occurrences of person.

tf-idf weighting

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

$$w_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
  - Note: the “-” in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, tf x idf
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

Final ranking of documents for a query

$$\text{Score}(q,d) = \sum_{t \in q \cap d} \text{tf.idf}_{t,d}$$

Exercise 1

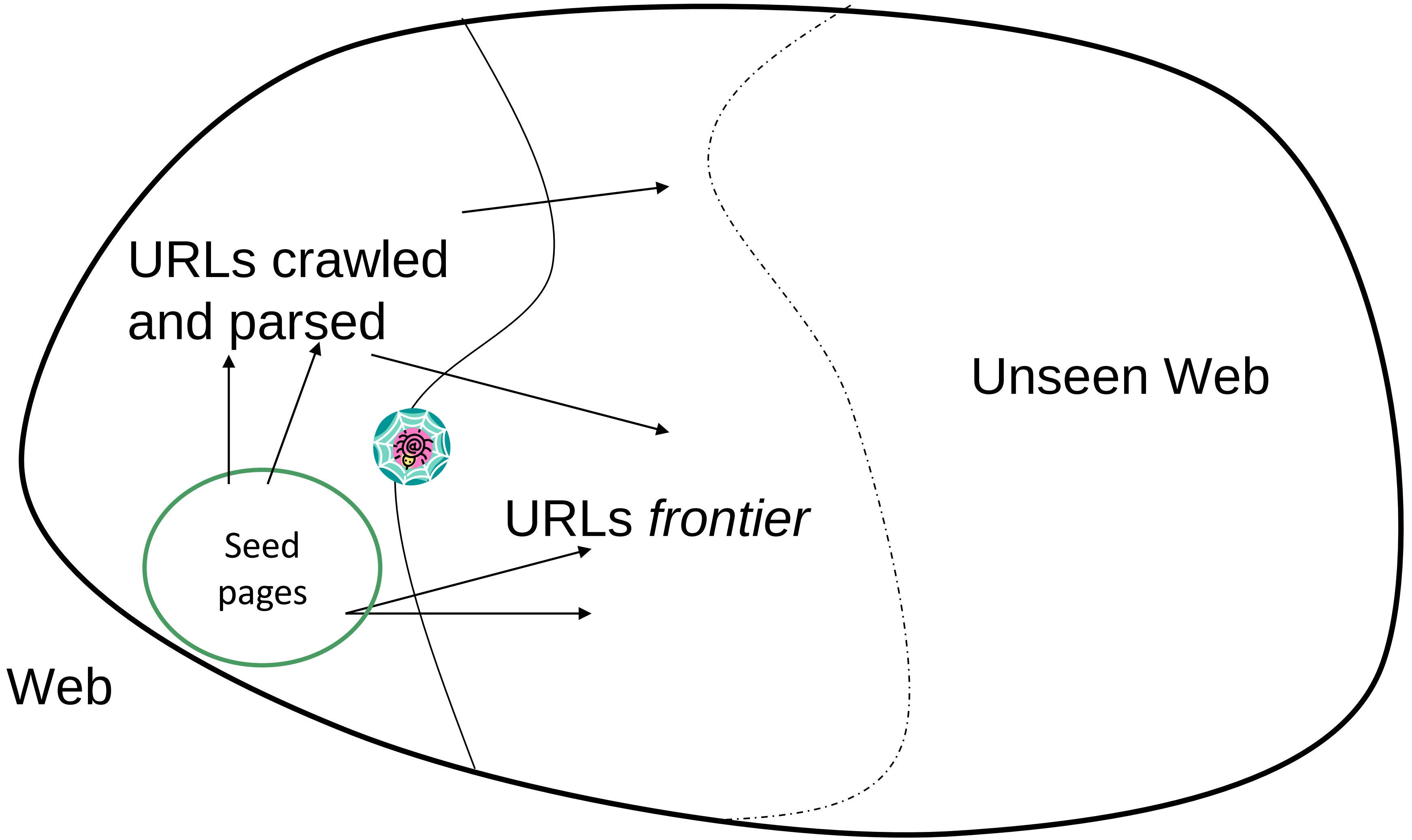
- Which is the ranking for the following example? (python code)
- Query: “haina cine departe”
- Document collection:
  - *D1 = “Cine împarte, parte își face”*
  - *D2 = “Cine se scoală de dimineață, departe ajunge”*
  - *D3 = “Așchia nu sare departe de trunchi”*
  - *D4 = “Omul face haina și nu haina pe om”*
  - *D5 = “Cămașa e mai aproape de piele decât haina”*

Web Crawling

Basic crawler operation

- Begin with known “seed” pages
- Fetch and parse them
  - Extract URLs they point to
  - Place the extracted URLs on a queue
- Fetch each URL on the queue and repeat

Crawling picture



Simple picture – complications

- Web crawling isn't feasible with one machine
  - All of the above steps distributed
- Even non-malicious pages pose challenges
  - Latency/bandwidth to remote servers vary
  - Webmasters' stipulations
    - How "deep" should you crawl a site's URL hierarchy?
  - Site mirrors and duplicate pages
- Malicious pages
  - Spam pages
  - Spider traps – including dynamically generated
- Politeness – don't hit a server too often

What any crawler *must* do

- Be <u>Polite</u>: Respect implicit and explicit politeness considerations for a website
  - Only crawl pages you're allowed to
  - Respect *robots.txt* (more on this shortly)
- Be <u>Robust</u>: Be immune to spider traps and other malicious behavior from web servers

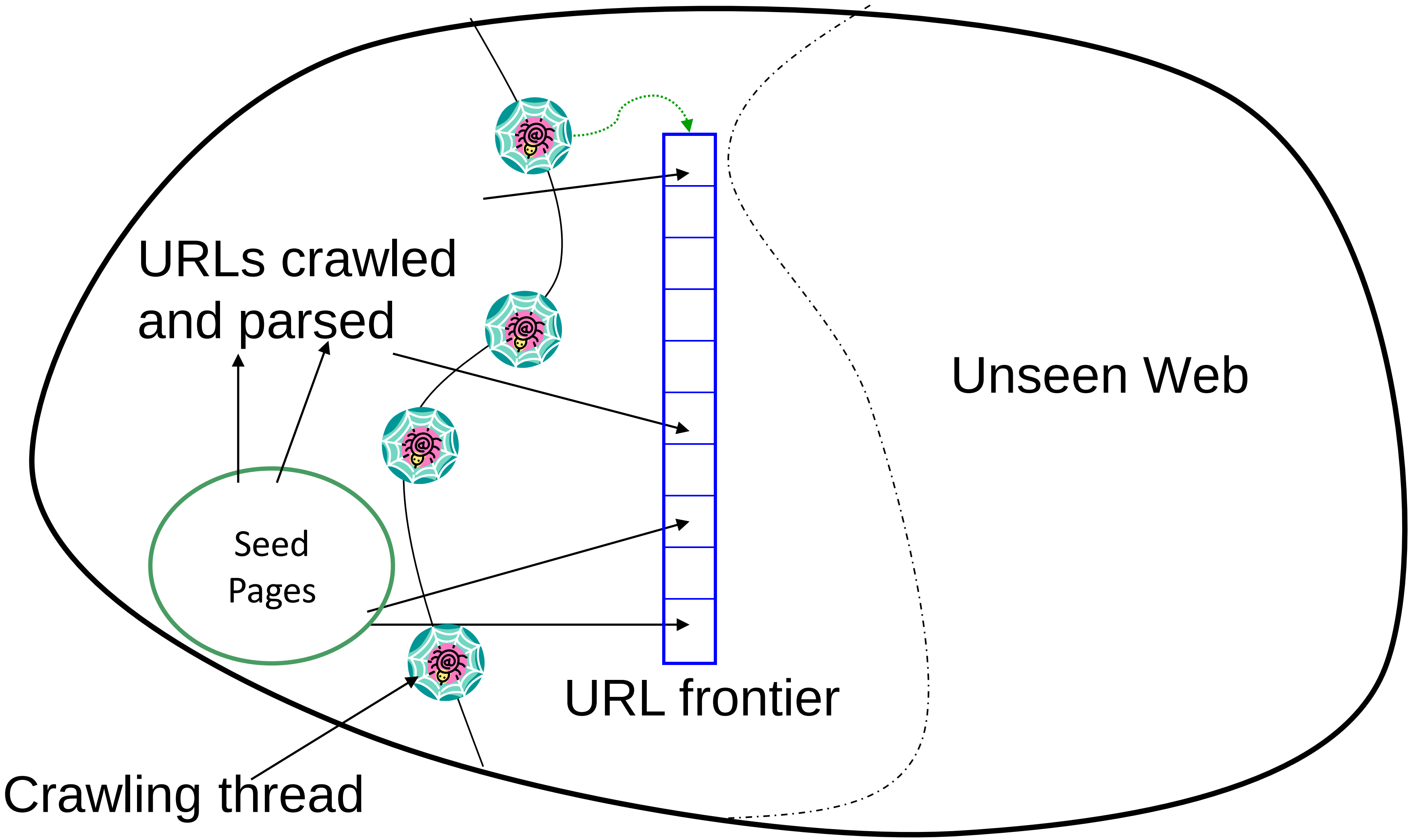
What any crawler *should* do

- Be capable of distributed operation: designed to run on multiple distributed machines
- Be scalable: designed to increase the crawl rate by adding more machines
- Performance/efficiency: permit full use of available processing and network resources

What any crawler *should* do

- Fetch pages of "higher quality" first
- Continuous operation: Continue fetching fresh copies of a previously fetched page
- Extensible: Adapt to new data formats, protocols

Updated crawling picture



URL frontier

- Can include multiple pages from the same host
- Must avoid trying to fetch them all at the same time
- Must try to keep all crawling threads busy

Explicit and implicit politeness

- Explicit politeness: specifications from webmasters on what portions of site can be crawled
  - robots.txt
- Implicit politeness: even with no specification, avoid hitting any site too often

Robots.txt

- Protocol for giving spiders ("robots") limited access to a website, originally from 1994
  - www.robotstxt.org/wc/norobots.html
- Website announces its request on what can(not) be crawled
  - For a URL, create a file `URL/robots.txt`
  - This file specifies access restrictions

Robots.txt example

- No robot should visit any URL starting with "/yoursite/temp/", except the robot called “searchengine":

```
User-agent: *
Disallow: /yoursite/temp/

User-agent: searchengine
Disallow:
```

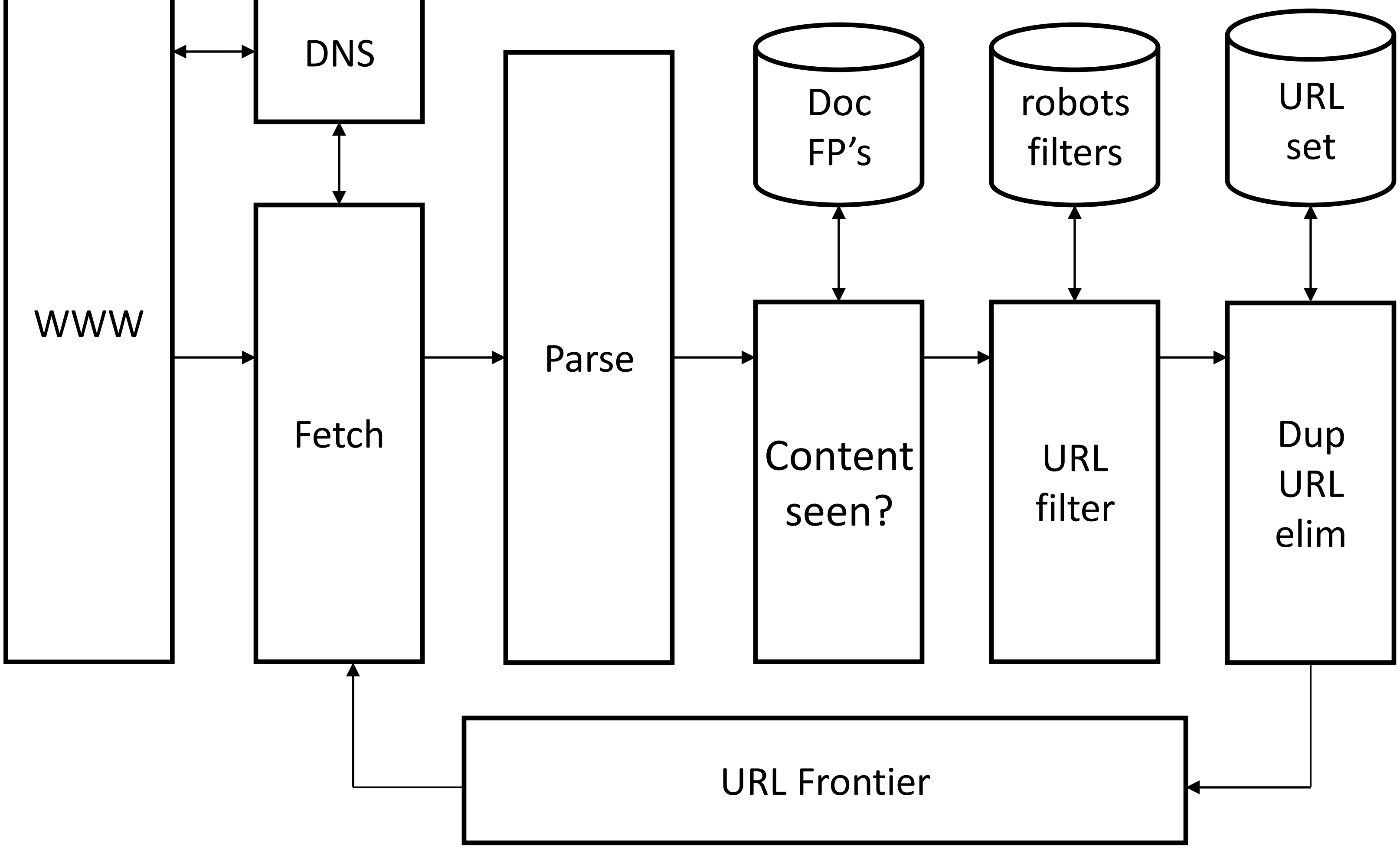
Processing steps in crawling

- Pick a URL from the frontier
- Fetch the document at the URL
- Parse the URL
  - Extract links from it to other docs (URLs)
- Check if URL has content already seen
  - If not, add to indexes
- For each extracted URL
  - Ensure it passes certain URL filters
  - Check if it is already in the frontier (duplicate URL elimination)

Which one?

E.g., only crawl .edu, obey robots.txt, etc.

Basic crawl architecture



DNS (Domain Name Server)

- A lookup service on the internet
  - Given a URL, retrieve its IP address
  - Service provided by a distributed set of servers – thus, lookup latencies can be high (even seconds)
- Common OS implementations of DNS lookup are *blocking*: only one outstanding request at a time
- Solutions
  - DNS caching
  - Batch DNS resolver – collects requests and sends them out together

Parsing: URL normalization

- When a fetched document is parsed, some of the extracted links are *relative* URLs
- E.g., at http://en.wikipedia.org/wiki/Main_Page

we have a relative link to /wiki/Wikipedia:General_disclaimer which is the same as the absolute URL http://en.wikipedia.org/wiki/Wikipedia:General_disclaimer

- During parsing, must normalize (expand) such relative URLs

Content seen?

- Duplication is widespread on the web
- If the page just fetched is already in the index, do not further process it
- This is verified using document fingerprints or shingles

Filters and robots.txt

- Filters – regular expressions for URL’s to be crawled/not
- Once a robots.txt file is fetched from a site, need not fetch it repeatedly
  - Doing so burns bandwidth, hits web server
- Cache robots.txt files

Duplicate URL elimination

- For a non-continuous (one-shot) crawl, test to see if an extracted+filtered URL has already been passed to the frontier
- For a continuous crawl – see details of frontier implementation

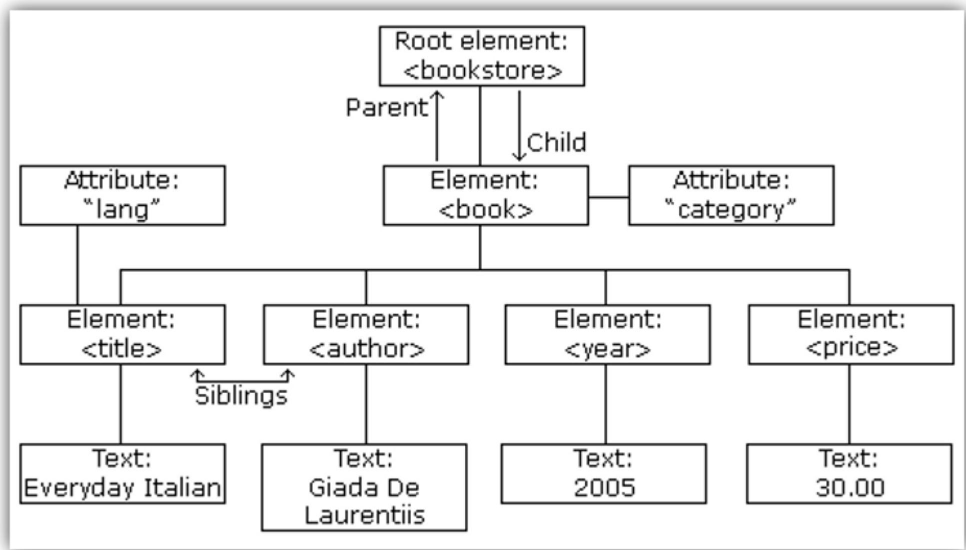
Practical Web Crawling

- Apache Nutch (http://nutch.apache.org/)
  - Java
  - Distributed / Hadoop
  - "Using Nutch for a one of scrape of a website is like aiming a Tank at a mouse.“
- Scrapy (http://scrapy.org/)
  - Python
  - Not distributed
  - Used for “scraping”, not for crawling

Practical Web Crawling (2)

- XPath is used to select elements form a DOM (Document Object Model) created from XML / HTML documents
- Example from http://vichargrave.com/xml-parsing-with-dom-using-c/

```xml
<bookstore>
    <book category="cooking">
        <title lang="en">Everyday Italian</title>
        <author>Giada De Laurentis</author>
        <year>2005</year>
        <price>30.00</price>
    </book>
    <book category="children">
        <title lang="en">Harry Potter and the Half-Blood Prince</title>
        <author>J. K. Rowling</author>
        <year>2005</year>
        <price>29.99</price>
    </book>
</bookstore>
```



XPath Examples

- /bookstore/book
- /bookstore/book[1]
- //book
- /bookstore/book/title[text()]
- /bookstore/book[1]/title

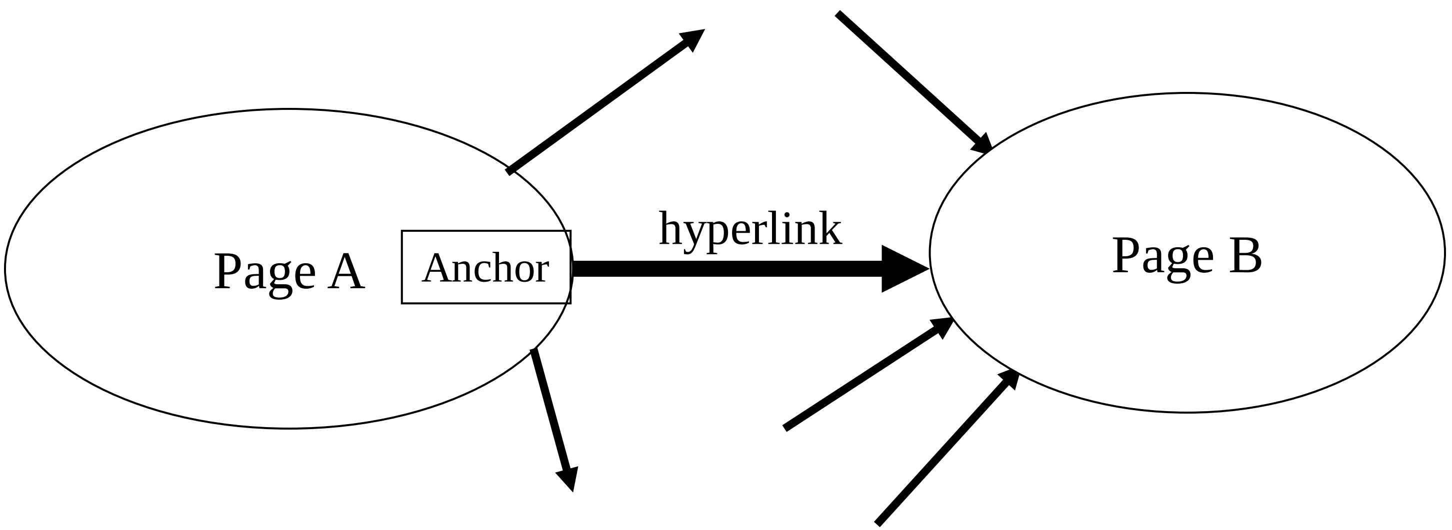
```
<bookstore>
    <book category="cooking">
        <title lang="en">Everyday Italian</title>
        <author>Giada De Laurentis</author>
        <year>2005</year>
        <price>30.00</price>
    </book>
    <book category="children">
        <title lang="en">Harry Potter and the Half-Blood Prince</title>
        <author>J. K. Rowling</author>
        <year>2005</year>
        <price>29.99</price>
    </book>
</bookstore>
```

Exercise 2

- Crawl/scrap the news from one of the following: BBC, CNN, Reuters, NY Times, Huffington Post, Washington Post, Gandul, Hotnews, Adevarul, …
- Install Scrapy for Python
- Read the tutorial: http://doc.scrapy.org/en/latest/intro/tutorial.html
- Write a program to extract the title and content of a news item
- Write each news item (title and content) in a different text file

Page Rank

The Web as a Directed Graph

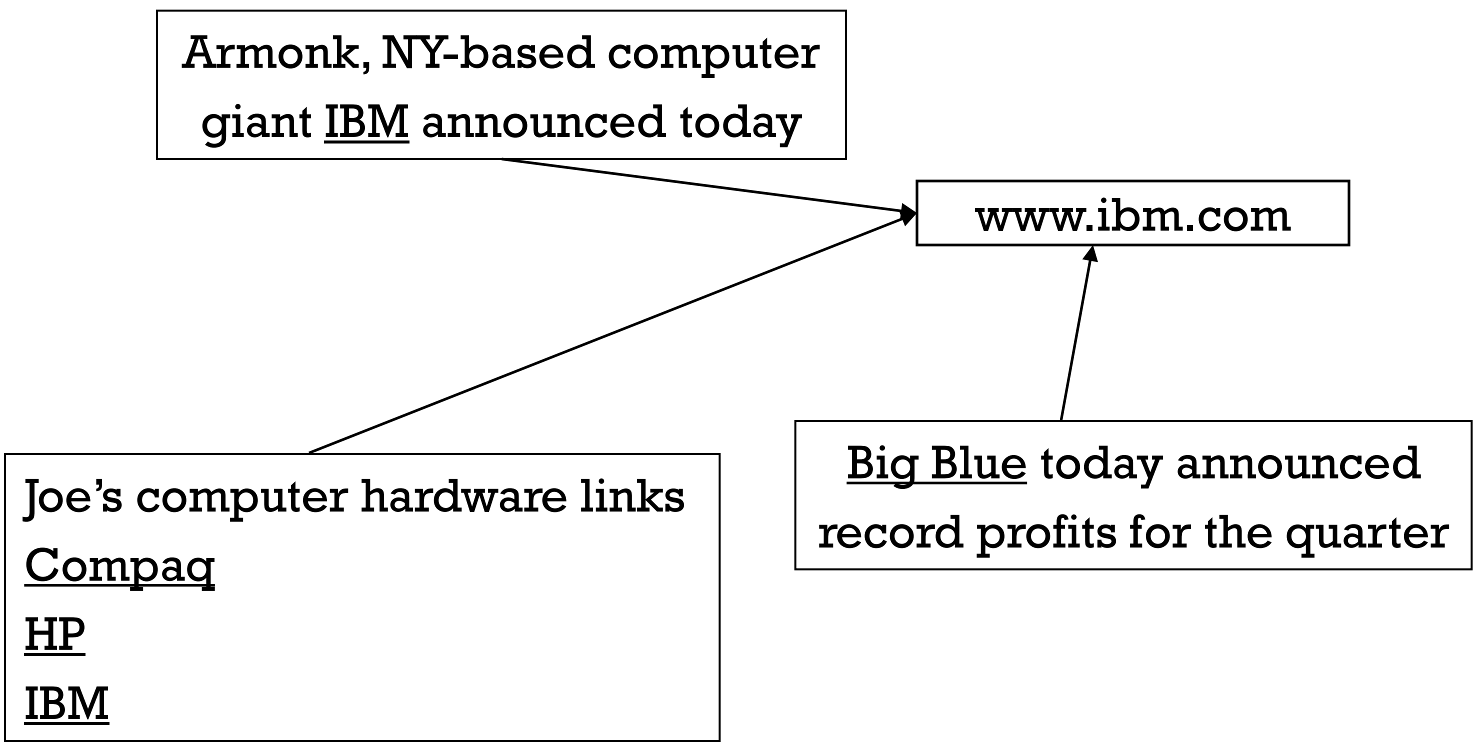


Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)

Assumption 2: The anchor of the hyperlink describes the target page (textual context)

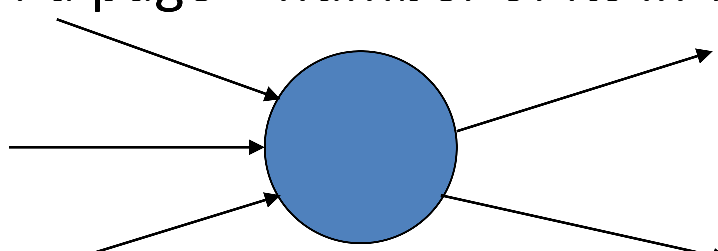
Indexing anchor text

- When indexing a document *D*, include anchor text from links pointing to *D*.



Query-independent ordering

- First generation: using link counts as simple measures of popularity.
- Two basic suggestions:
  - <u>Undirected popularity:</u>
    - Each page gets a score = the number of in-links plus the number of out-links (3+2=5).
  - <u>Directed popularity:</u>
    - Score of a page = number of its in-links (3).



Query processing

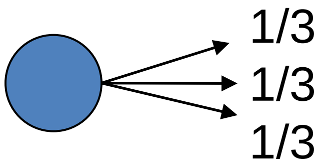
- First retrieve all pages meeting the text query (say ***venture capital***).
- Order these by their link popularity (either variant on the previous page).
- More nuanced – use link counts as a measure of static goodness, combined with text match score

Spamming simple popularity

- *Exercise*: How do you spam each of the following heuristics so your page gets a high score?
- Each page gets a score = the number of in-links plus the number of out-links.
- Score of a page = number of its in-links.

Pagerank scoring

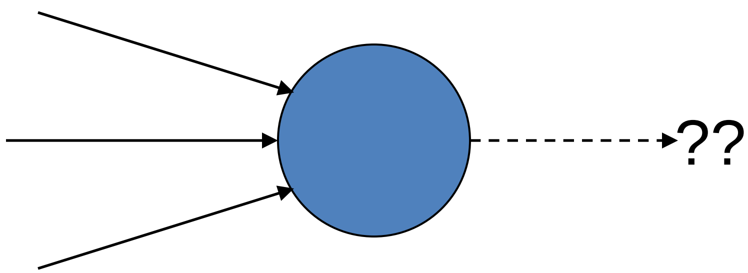
- Imagine a browser doing a random walk on web pages:
  – Start at a random page



  – At each step, go out of the current page along one of the links on that page, equiprobably
- "In the steady state" each page has a long-term visit rate - use this as the page's score.

Not quite enough

- The web is full of dead-ends.
  - Random walk can get stuck in dead-ends.
  - Makes no sense to talk about long-term visit rates.



Teleporting

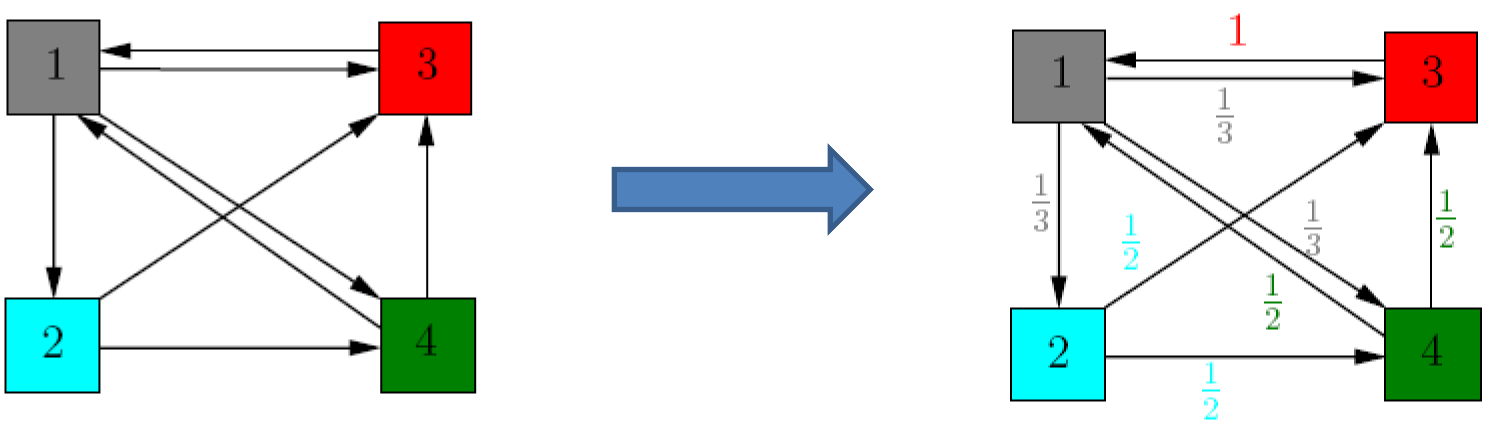
- At a dead end, jump to a random web page.
- At any non-dead end, with probability 10%, jump to a random web page.
  - With remaining probability (90%), go out on a random link.
  - 10% - a parameter.

Result of teleporting

- Now cannot get stuck locally.
- There is a long-term rate at which any page is visited.
- How do we compute this visit rate?

Web Graph

- Starting from the links, compute the weights
- This is the web graph matrix - **A**
- Example from: http://www.math.cornell.edu/~mec/Winter2009/RalucaRemus/Lecture3/lecture3.html



“Google” Matrix

- Developed by Larry Page & Sergey Brin
- Incorporates the “teleporting” solution
- Defined starting from the web graph matrix – A
- p – damping factor (usually between 0.05..0.15)

$$M = (1-p) \cdot A + \ p \cdot B$$

$$B = \frac{1}{n} \cdot \begin{bmatrix} 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

PageRank

- Compute the rank (importance of each page in the web graph)
- Larry Page & Sergey Brin
- Similar to citation analysis
- The rank of any page, **π**, is actually the left eigenvector of M, for the largest eigenvalue:

$$\boldsymbol{\pi}\,\mathbf{M} = \boldsymbol{\lambda}\,\mathbf{M}$$

Computing PageRank

- There are various methods to compute PageRank (**π**)
- The simplest method is called the **power (iterative) method**
- Start with an initial vector $\pi_0 = [1/n \dots 1/n]$
- Compute $\pi_{k+1} = \pi_k M$ $(k \geq 0)$
- Stop at convergence
  - Either $\pi_{k+1} = \pi_k$
  - Or $||\pi_{k+1} - \pi_k|| < \varepsilon$

Exercise 3

- Extend the previous program in order to save the URLs and the links between these URLs
- Build the matrix A of the crawled web graph
- Build the matrix M
- Compute the PageRank of each page
- Print the URLs of the pages sorted by PageRank

References and Further Reading

- Christopher Manning, Prabhakar Raghavan, Hinrich Schuetze: *Introduction to Information Retrieval*
- Free PDF:
  - http://nlp.stanford.edu/IR-book/information-retrieval-book.html
- Buy @ Amazon:
  - http://www.amazon.com/Introduction-Information-Retrieval-Christopher-Manning/dp/0521865719

- Most of the content in the slides has been taken from Stanford's CS276 course on Information Retrieval & Data Mining
  - http://www.stanford.edu/class/cs276/
- Many thanks to Prabhakar Raghavan for allowing the re-use of this content