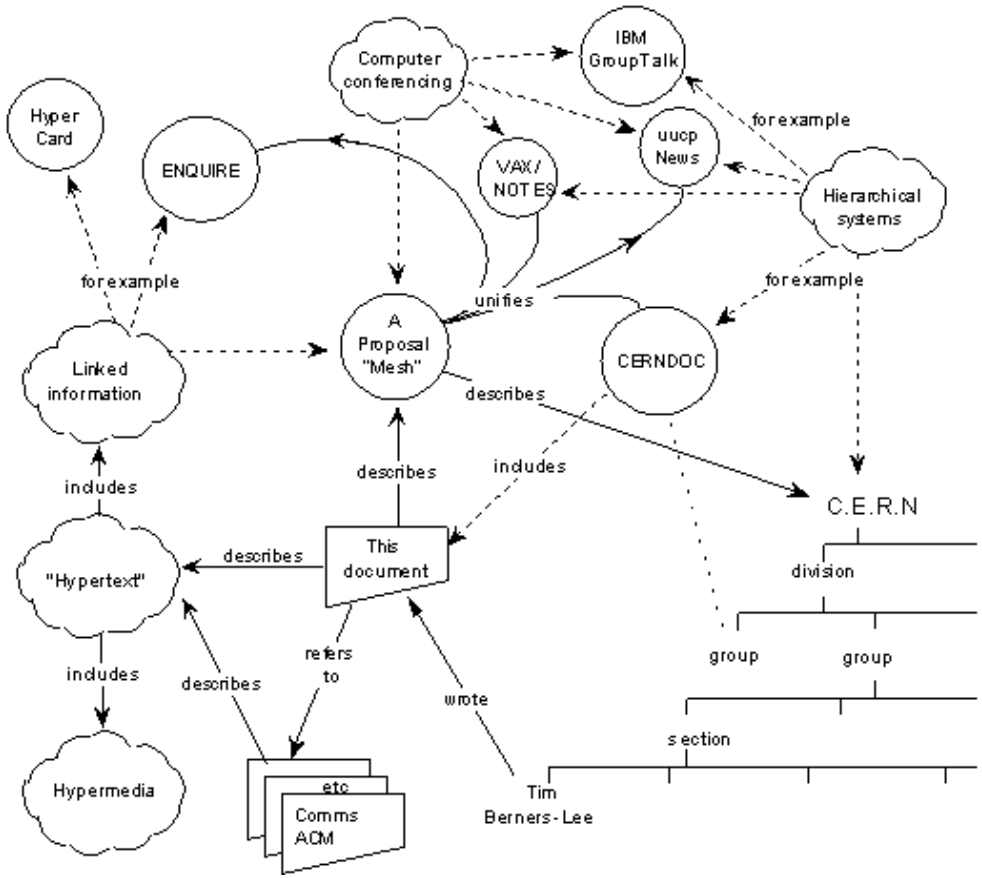
Part I: Web Structure Mining
Chapter 1: Information Retrieval and Web Search

- The Web Challenges
- Crawling the Web
- Indexing and Keyword Search
- Evaluating Search Quality
- Similarity Search

The Web Challenges

Tim Berners-Lee, Information Management: A Proposal, CERN, March 1989.



The Web Challenges

18 years later …

- The recent Web is huge and grows incredibly fast. About ten years after the Tim Berners-Lee proposal the Web was estimated to 150 million nodes (pages) and 1.7 billion edges (links). Now it includes more than 4 billion pages, with about a million added every day.

- Restricted formal semantics - nodes are just web pages and links are of a single type (e.g. “refer to”). The meaning of the nodes and links is not a part of the web system, rather it is left to the web page developers to describe in the page content what their web documents mean and what kind of relations they have with the documented they link to.

- As there is no central authority or editors relevance, popularity or authority of web pages are hard to evaluate. Links are also very diverse and many have nothing to do with content or authority (e.g. navigation links).

The Web Challenges

How to turn the web data into web knowledge

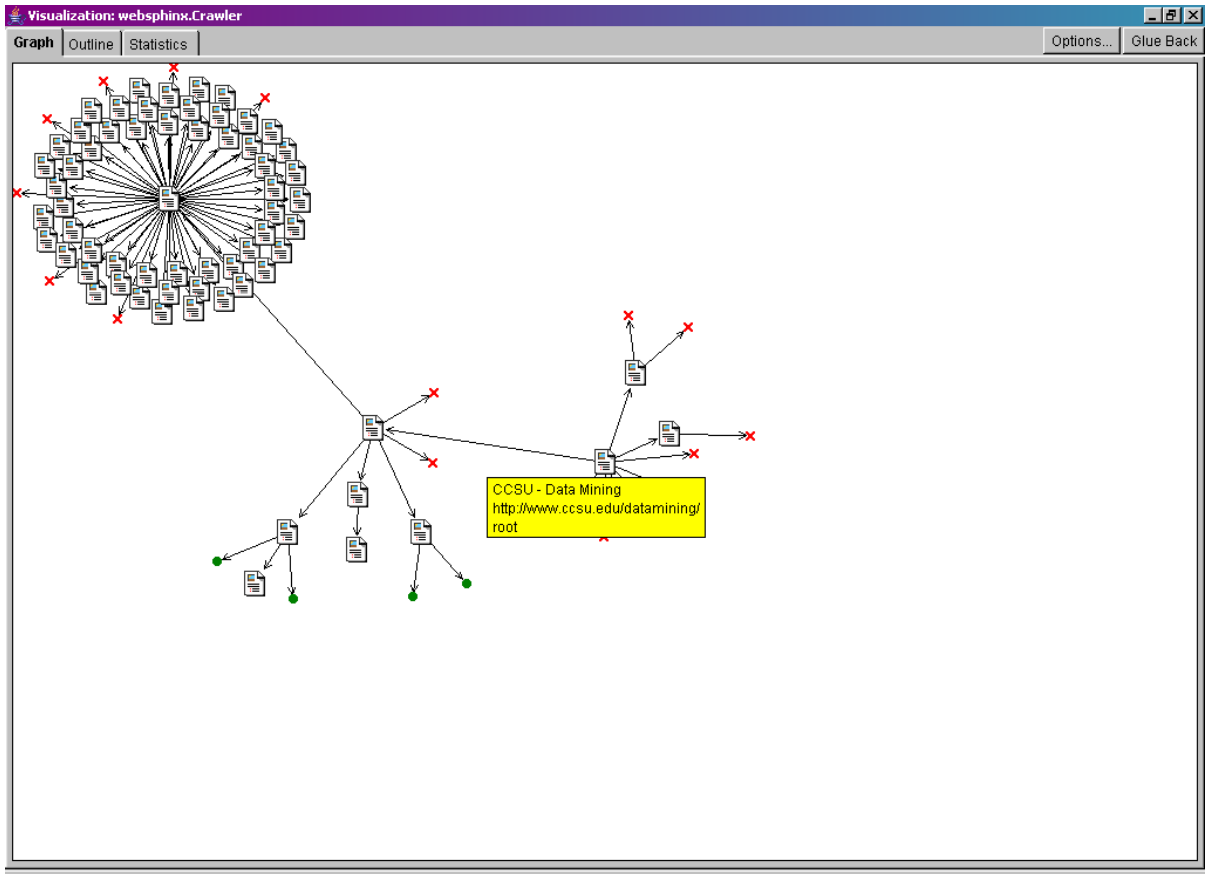
- Use the existing Web
  - Web Search Engines
  - Topic Directories
- Change the Web
  - Semantic Web

Crawling The Web

- To make Web search efficient search engines collect web documents and index them by the words (terms) they contain.
- For the purposes of indexing web pages are first collected and stored in a local repository
- *Web crawlers* (also called *spiders* or *robots*) are programs that systematically and exhaustively browse the Web and store all visited pages
- Crawlers follow the *hyperlinks* in the Web documents implementing graph search algorithms like *depth-first* and *breadth-first*

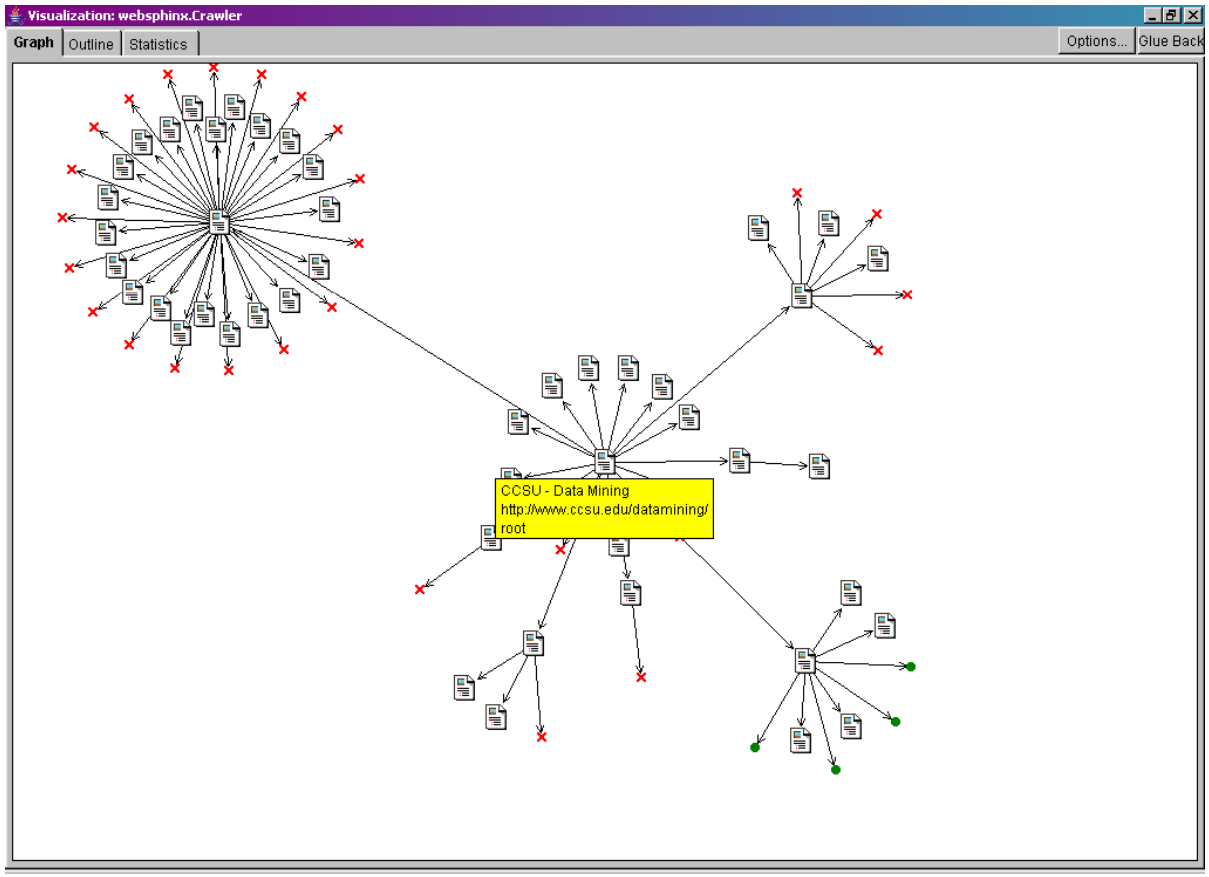
Crawling The Web

Depth-first Web crawling limited to depth 3



Crawling The Web

Breadth-first Web crawling limited to depth 3



Crawling The Web

Issues in Web Crawling:

- Network latency (multithreading)
- Address resolution (DNS caching)
- Extracting URLs (use canonical form)
- Managing a huge web page repository
- Updating indices
- Responding to constantly changing Web
- Interaction of Web page developers
- Advanced crawling by guided (informed) search (using web page ranks)

Indexing and Keyword Search

We need efficient content-based access to Web documents

- Document representation:
  - Term-document matrix (inverted index)
- Relevance ranking:
  - Vector space model

Indexing and Keyword Search

Creating term-document matrix (inverted index)

- Documents are tokenized (punctuation marks are removed and the character strings without spaces are considered as tokens)
- All characters are converted to upper or to lower case.
- Words are reduced to their canonical form (*stemming*)
- *Stopwords (a*, *an*, *the*, *on*, *in*, *at*, etc.) are removed.

The remaining words, now called *terms* are used as *features* (*attributes*) in the term-document matrix

CCSU Departments example

Document statistics

Document ID	Document name	Words	Terms
d_1	Anthropology	114	86
d_2	Art	153	105
d_3	Biology	123	91
d_4	Chemistry	87	58
d_5	Communication	124	88
d_6	Computer Science	101	77
d_7	Criminal Justice	85	60
d_8	Economics	107	76
d_9	English	116	80
d_{10}	Geography	95	68
d_{11}	History	108	78
d_{12}	Mathematics	89	66
d_{13}	Modern Languages	110	75
d_{14}	Music	137	91
d_{15}	Philosophy	85	54
d_{16}	Physics	130	100
d_{17}	Political Science	120	86
d_{18}	Psychology	96	60
d_{19}	Sociology	99	66
d_{20}	Theatre	116	80
Total number of words/terms		2195	1545
Number of different words/terms		744	671

CCSU Departments example

Boolean (Binary) Term Document Matrix

DID	lab	laboratory	programming	computer	program
d_1	0	0	0	0	1
d_2	0	0	0	0	1
d_3	0	1	0	1	0
d_4	0	0	0	1	1
d_5	0	0	0	0	0
d_6	0	0	1	1	1
d_7	0	0	0	0	1
d_8	0	0	0	0	1
d_9	0	0	0	0	0
d_{10}	0	0	0	0	0
d_{11}	0	0	0	0	0
d_{12}	0	0	0	1	0
d_{13}	0	0	0	0	0
d_{14}	1	0	0	1	1
d_{15}	0	0	0	0	1
d_{16}	0	0	0	0	1
d_{17}	0	0	0	0	1
d_{18}	0	0	0	0	0
d_{19}	0	0	0	0	1
d_{20}	0	0	0	0	0

CCSU Departments example

Term document matrix with positions

DID	lab	laboratory	programming	computer	program
d_1	0	0	0	0	[71]
d_2	0	0	0	0	[7]
d_3	0	[65,69]	0	[68]	0
d_4	0	0	0	[26]	[30,43]
d_5	0	0	0	0	0
d_6	0	0	[40,42]	[1,3,7,13,26,34]	[11,18,61]
d_7	0	0	0	0	[9,42]
d_8	0	0	0	0	[57]
d_9	0	0	0	0	0
d_{10}	0	0	0	0	0
d_{11}	0	0	0	0	0
d_{12}	0	0	0	[17]	0
d_{13}	0	0	0	0	0
d_{14}	[42]	0	0	[41]	[71]
d_{15}	0	0	0	0	[37,38]
d_{16}	0	0	0	0	[81]
d_{17}	0	0	0	0	[68]
d_{18}	0	0	0	0	0
d_{19}	0	0	0	0	[51]
d_{20}	0	0	0	0	0

Vector Space Model

Boolean representation

- documents $d_1, d_2, \ldots, d_n$
- terms $t_1, t_2, \ldots, t_m$
- term t_i occurs n_{ij} times in document d_j.
- *Boolean representation:*

$$\vec{d}_j = (d_j^1 \, d_j^2 \ldots d_j^m) \qquad d_j^i = \begin{cases} 0 & if \ n_{ij} = 0 \\ 1 & if \ n_{ij} > 0 \end{cases}$$

- For example, if the terms are: *lab*, *laboratory*, *programming*, *computer* and *program*. Then the Computer Science document is represented by the Boolean vector

$$\vec{d}_6 = (0 \quad 0 \quad 1 \quad 1 \quad 1)$$

Term Frequency (TF) representation

Document vector $\vec{d}_j = (d_j^1\, d_j^2 \ldots d_j^m)$ with components $d_j^i = TF(t_i, d_j)$

- Using the sum of term counts: $$TF(t_i, d_j) = \begin{cases} 0 & if\ n_{ji} = 0 \\ \dfrac{n_{ij}}{\sum_{k=1}^{m} n_{kj}} & if\ n_{ji} > 0 \end{cases}$$
- Using the maximum of term counts: $$TF(t_i, d_j) = \begin{cases} 0 & if\ n_{ji} = 0 \\ \dfrac{n_{ij}}{\max_k n_{kj}} & if\ n_{ji} > 0 \end{cases}$$
- Cornell SMART system: $$TF(t_i, d_j) = \begin{cases} 0 & if\ n_{ji} = 0 \\ 1 + \log(1 + \log n_{ji}) & if\ n_{ji} > 0 \end{cases}$$

Inverted Document Frequency (IDF)

Document collection: $D = \bigcup_{1}^{n} d_j$, documents that contain term t_i : $D_{t_i} = \{d_j \mid n_{ij} > 0\}$

- Simple fraction: $IDF(t_i) = \frac{|D|}{|D_{ti}|}$

or

- Using a log function: $IDF(t_i) = \log \frac{1+|D|}{|D_{t_i}|}$

TFIDF representation

$$d_j^i = TF(t_i, d_j) \times IDF(t_i)$$

For example, the *computer science* TF vector

$$\vec{d}_6 = (0 \quad 0 \quad 0.026 \quad 0.078 \quad 0.039)$$

scaled with the IDF of the terms

lab	laboratory	Programming	computer	program
3.04452	3.04452	3.04452	1.43508	0.559616

results in

$$\vec{d}_6 = (0 \quad 0 \quad 0.079 \quad 0.112 \quad 0.022)$$

Relevance Ranking

- Represent the query as a vector $q = \{computer, program\}$

  $\vec{q} = (0 \quad 0 \quad 0 \quad 0.5 \quad 0.5)$

- Apply IDF to its components

lab	laboratory	Programming	computer	program
3.04452	3.04452	3.04452	1.43508	0.559616

  $\vec{q} = (0 \quad 0 \quad 0 \quad 0.718 \quad 0.28)$

- Use *Euclidean norm* of the vector difference $\left\| \vec{q} - \vec{d}_j \right\| = \sqrt{\sum_{i=1}^{m} (q^i - d_j^i)^2}$

- or *Cosine similarity* (equivalent to *dot product* for normalized vectors)

$$\vec{q}.\vec{d}_j = \sum_{i=1}^{m} q^i d_j^i$$

Relevance Ranking

Cosine similarities and distances to $\vec{q} = (0\ 0\ 0\ 0.932\ 0.363)$ **(normalized)**

Doc	**TFIDF Coordinates (normalized)**					$\vec{q}.\vec{d}_j$ **(rank)**	$\left\|\vec{q}-\vec{d}_j\right\|$ **(rank)**
d_1	0	0	0	0	1	0.363	1.129
d_2	0	0	0	0	1	0.363	1.129
d_3	0	0.972	0	0.234	0	0.218	1.250
d_4	**0**	**0**	**0**	**0.783**	**0.622**	**0.956 (1)**	**0.298 (1)**
d_5	0	0	0	0	1	0.363	1.129
d_6	**0**	**0**	**0.559**	**0.811**	**0.172**	**0.819 (2)**	**0.603 (2)**
d_7	0	0	0	0	1	0.363	1.129
d_8	0	0	0	0	1	0.363	1.129
d_9	0	0	0	0	0	0	1
d_{10}	0	0	0	0	0	0	1
d_{11}	0	0	0	0	0	0	1
d_{12}	0	0	0	1	0	0.932	0.369
d_{13}	0	0	0	0	0	0	1
d_{14}	**0.890**	**0**	**0**	**0.424**	**0.167**	**0.456 (3)**	**1.043 (3)**
d_{15}	0	0	0	0	1	0.363	1.129
d_{16}	0	0	0	0	1	0.363	1.129
d_{17}	0	0	0	0	1	0.363	1.129
d_{18}	0	0	0	0	0	0	1
d_{19}	0	0	0	0	1	0.363	1.129
D_{20}	0	0	0	0	0	0	1

Relevance Feedback

- The user provides feed back:
  - Relevant documents D_+
  - Irrelevant documents D_-
- The original query vector $\vec{q}$ is updated (*Rocchio's method*)

$$\vec{q}' = \alpha \vec{q} + \beta \sum_{D_+ \; d_j \in D_+} \vec{d}_j - \gamma \sum_{d_j \in D_-} \vec{d}_j$$

- Pseudo-relevance feedback
  - Top 10 documents returned by the original query belong to D_+
  - The rest of documents belong to D_-

Advanced text search

- Using ”OR” or “NOT” boolean operators
- Phrase Search
  - Statistical methods to extract phrases from text
  - Indexing phrases
- Part-of-speech tagging
- Approximate string matching (using n-grams)
  - Example: match “program” and “prorgam”
    {pr, ro, og, gr, ra, am} ∩ {pr, ro, or, rg, ga, am} = {pr, ro, am}

Using the HTML structure in keyword search

- Titles and metatags
  - Use them as tags in indexing
  - Modify ranking depending on the context where the term occurs
- Headings and font modifiers (prone to spam)
- Anchor text
  - Plays an important role in web page indexing and search
  - Allows to increase search indices with pages that have never been crawled
  - Allows to index non-textual content (such as images and programs

Evaluating search quality

- Assume that there is a set of queries Q and a set of documents D, and for each query $q \in Q$ submitted to the system we have:
  - The response set of documents (retrieved documents) $R_q \subseteq D$
  - The set of relevant documents D_q selected manually from the whole collection of documents , i.e. $D_q \subseteq D$

- $$precision = \frac{\left|D_q \cap R_q\right|}{\left|R_q\right|}$$

- $$recall = \frac{\left|D_q \cap R_q\right|}{\left|D_q\right|}$$

Precision-recall framework (set-valued)

- Determine the relationship between the set of relevant documents (D_q) and the set of retrieved documents (R_q)
- Ideally $D_q == R_q$
- Generally $D_q \bigcap R_q \subset D_q$
- A very general query leads to recall = 1, but low precision
- A very restrictive query leads to precision =1, but low recall
- A good balance is needed to maximize both precision and recall

Precision-recall framework (using ranks)

- With thousands of documents finding D_q is practically impossible.
- So, let's consider a *list* $R_q = (d_1, d_2, ..., d_m)$ of *ranked documents* (highest rank first)
- For each $d_i \in R_q$ compute its relevance as $r_i = \begin{cases} 1 & if\ d_i \in D_q \\ 0 & otherwise \end{cases}$
- Then define *precision at rank k* as

$$precision\ (k) = \frac{1}{k} \sum_{i=1}^{k} r_i$$

- And *recall at rank k* as

$$recall\ (k) = \frac{1}{|D_q|} \sum_{i=1}^{k} r_i$$

Precision-recall framework (example)

Relevant documents $D_q = (d_4, d_6, d_{14})$

k	Document index	r_k	*recall* (k)	*precision* (k)
1	4	1	0.333	1
2	12	0	0.333	0.5
3	6	1	0.667	0.667
4	14	1	1	0.75
5	1	0	1	0.6
6	2	0	1	0.5
7	3	0	1	0.429

Precision-recall framework

$$\text{Average precision} = \frac{1}{|D_q|} \sum_{k=1}^{|D|} r_k \times precision(k)$$

- Combines precision and recall and also evaluates document ranking
- The maximal value of 1 is reached when all relevant documents are retrieved and ranked before any irrelevant ones.
- Practically to compute the average precision we first go over the ranked documents from R_q and then continue with the rest of the documents from D until all relevant documents are included.

Similarity Search

- *Cluster hypothesis* in IR: Documents similar to relevant documents are likely to be relevant too

- Once a relevant document is found a larger collection of possibly relevant documents may be found by retrieving similar documents.

- Similarity measure between documents
  - Cosine Similarity
  - Jaccard Similarity (most popular approach)
  - Document Resemblance

Cosine Similarity

- Given document *d* and collection *D* the problem is to find a number (usually 10 or 20) of documents $d_i \in D$, which have the largest value of cosine similarity to *d*.

- No problems with the small query vector, so we can use more (or all) dimensions of the vector space

- How many and which terms to use?
    - All terms from the corpus
    - Select the terms that best represent the documents (*Feature Selection*)
        - Use highest TF score
        - Use highest IDF score
        - Combine TF and IDF scores (e.g. TFIDF)

Jaccard Similarity

- Use Boolean document representation and only the nonzero coordinates of the vectors (i.e. those that are 1)

- *Jaccard Coefficient*: proportion of coordinates that are 1 in both documents to those that are 1 in either of the documents

$$sim(\vec{d}_1, \vec{d}_2) = \frac{\left|\{j \mid d_1^j = 1 \wedge d_2^j = 1\}\right|}{\left|\{j \mid d_1^j = 1 \vee d_2^j = 1\}\right|}$$

- Set formulation $sim(d_1, d_2) = \frac{\left|T(d_1) \bigcap T(d_2)\right|}{\left|T(d_1) \bigcup T(d_2)\right|}$

Computing Jaccard Coefficient

- Problems
  - Direct computation is straightforward, but with large collections it may lead to inefficient similarity search.
  - Finding similar documents at query time is impractical.

- Solutions
  - Do most of the computation offline
  - Create a list of all document pairs sorted by the similarity of the documents in each pair. Then the *k* most similar documents to a given document *d* are those that are paired with *d* in the first *k* pairs from the list.
  - Eliminate frequent terms
  - Pair documents that share at least one term

Document Resemblance

- The task is finding identical or nearly identical documents, or documents that share phrases, sentences or paragraphs.
- The *set of words* approach does not work.
- Consider the document as a sequence of words and extract from this sequence short subsequences with fixed length (*n-grams* or *shingles*).
- Represent document *d* as a set of *w*-grams $S(d, w)$
- Example: $T(d) = \{a, b, c, d, e\}$ $S(d, 2) = \{ab, bc, cd, de\}$
- Note that $T(d) = S(d, 1)$ and $S(d, |d|) = d$
- Use Jaccard to compute resemblance $r_w(d_1, d_2) = \frac{|S(d_1, w) \cap S(d_2, w)|}{|S(d_1, w) \cup S(d_2, w)|}$