Informatics 225
Computer Science 221

Information Retrieval

Lecture 20

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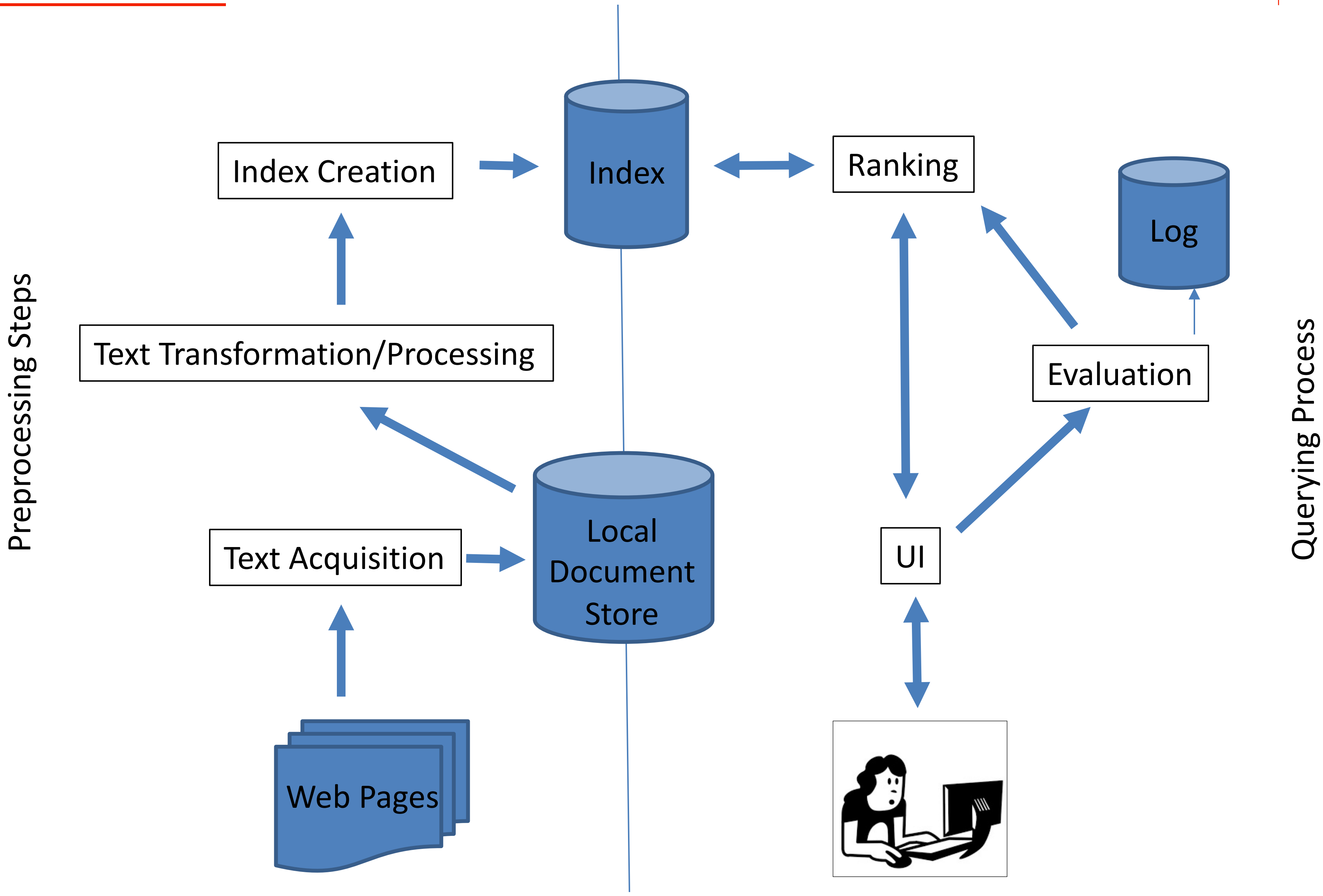
Architecture



Evolving from Boolean retrieval

Retrieval Models

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  - includes explanation of assumptions
  - basis of ranking algorithms
  - can be implicit

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- Theories about relevance

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- Retrieval models make various assumptions about relevance to simplify problem
  - e.g., *topical* vs. *user* relevance
  - e.g., *binary* vs. *continuous* vs. *multi-valued* relevance

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  - Documents either match or don't.
- Good for expert users with precise understanding of their needs and the collection.
  - Also good for applications.
- Not good for the majority of "generic" users.
  - Most users incapable of writing Boolean queries; *or they are capable, but they think it's too much work…*
  - Most users don't want to wade through 1000s of results.
    - *Particularly true for web search.*

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- It takes some skill to come up with a query that produces a manageable number of hits.
  - AND gives too few; OR gives too many.
  - Complex combinations are necessary, and except in specific cases (e.g. law), people happily trade deterministic results by ease of use.

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- Rather than a set of documents satisfying a query expression, in ranked retrieval, the system returns an ordering over the (top) documents in the collection for 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 has 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, or show them in the first “page”
  - We don’t overwhelm the user

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  - Strong assumption: the ranking algorithm "works" for the user

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- 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”.

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  - 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 some alternatives for this.

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- Good properties:
  - *A* and *B* don't have to be the same size.
  - Always assigns a number between 0 and 1.

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- More sophisticated heuristics to normalize for the length of the documents result in better scores
- Another option: $|A \cap B| / \sqrt{|A \cup B|}$
  instead of $|A \cap B|/|A \cup B|$ (Jaccard) for length normalization.

Recall the term-document incidence matrix

	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

Each document is represented by a binary vector $\in \{0,1\}^{|V|}$

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

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- In a sense, this is a temporary step back, since a positional index is able to distinguish these two documents.
  - We will see positional information later
  - For now: bag of words model

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- Relevance does not increase proportionally with term frequency.

Note: 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.

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- 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.

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  – e.g., *arachnocentric*
- A document containing this term is very likely to be relevant to the query *arachnocentric.*

→ We want a high weight for rare terms like *arachnocentric*!

We can do better than simple term frequencies…

Document frequency, continued

- Frequent terms in the collection 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
  - $0 < \mathrm{df}_t \leq N$

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- 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
  - $0 < \text{df}_t \leq N$
- We define the idf (inverse document frequency) of t by

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

  - We use log (N/df_t) instead of N/df_t to dampen the effect of idf.

Will turn out the base of the log is immaterial.

idf example, suppose *N* = 1 million

term	df_t	idf_t
calpurnia	1	6
animal	100	4
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

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- 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.

Collection vs. Document frequency

- The collection frequency of *t* is the number of occurrences of *t* in the collection, counting multiple occurrences.

- Example:

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

- Which word is a better search term (and thus should get a higher weight)?

tf-idf weighting

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

$$w_{t,d} = (1+\log(tf_{t,d})) \times \log(N/df_t)$$

Relevance or Score for a document *d* given a query *q*

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

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$$w_{t,d} = (1+\log(tf_{t,d})) \times \log(N/df_t)$$

- Best known and most used weighting scheme in IR
  - **Note: the "-" in tf-idf is a hyphen, not a minus sign!**
  - Alternative names: tf.idf, tf x idf, tfidf

- Good properties:
  - Increases with the number of occurrences within a document
  - Increases with the rarity of the term in the collection

Relevance or Score for a document *d* given a query *q*

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

- Many variants can be constructed
  - E.g. How “tf” is computed (e.g. with/without logs)
  - E.g. Whether the terms in the query are also weighted
  - … *pick and/or design your heuristics…*