Information Retrieval

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Outline

1. Introduction
   - Motivation
2. Document Retrieval
   - Inverted Index
3. Tokenization
   - Stopwords
   - Token Normalization
4. Scoring
   - Zone
   - Term Frequency
   - Inverse Document Frequency
   - Tf-idf
5. Document Vector
   - Vector Model
   - Document Similarity
6. Scalability
   - Skip List
   - Inexact Retrieval
7. System
8. Conclusions

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Definition

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Retrieval (finding) of information (e.g., documents) that is mostly unstructured (e.g., text) and is relevant to a particular need (query) from a large collection

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- Started with documents
- Has now extended to music, images, graphs

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- *Not* scalable (remember "large" collections)

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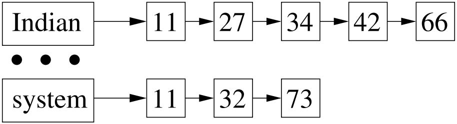

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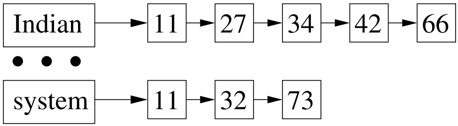

- Postings list is maintained as a linked list

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- OR is more time consuming
- Query with only NOT is impractical for large collections
  - All right with AND: “system” AND NOT “Indian”

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  - “isn’t New Delhi-Uttar Pradesh a good example?”

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- Removing stopwords from queries may sometimes be erroneous
  - “to be or not to be”
- Therefore, web search engines do not bother to remove stopwords

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  - Increases recall but decreases precision
- Character set is important
  - “pena” (sorrow) and “peña” (cliff) in Spanish

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- Fields are generalized to zones that may contain free text as well
- Separate inverted indexes can be built for each zone
- Or, zone may be mentioned *explicitly* in a single inverted index

Indian.title → 11 → 34 → 56

Indian.body → 11 → 27 → 42 → 66

Indian → 11.title → 11.body → 27.body → 34.title → 42.body → 56.title → 66.body

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- Weights of zones
  - Can be supplied by the application
  - Machine learned

Term Frequency

- Moving away from the binary model
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- This assumes the bag of words model
- *Context* and *sequence* are lost
  - I love butter but I hate cheese
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- Logarithmic to make it less drastic

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- Tf-idf has many different forms

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Document Vector

- Each document d has a score with each term t in the vocabulary
  - If t is absent in d, then this score is 0

Document Vector

- Each document d has a score with each term t in the vocabulary
  - If t is absent in d, then this score is 0
- Imagine a n-dimensional vector space where n is the total number of terms in the vocabulary
- Each document can be, thus, thought of as a vector (point) in this n-dimensional space
- Its coordinates are the scores correponding to the scores

$$d[t_i] = tf\text{-}idf(t_i, d)$$

- This is called the document vector model

Exercise

- d_1: Water, water everywhere, not a drop to drink
- d_2: I have filtered water
- d_3: Drinking and driving is not good
- d_4: Water quality is not good here
- d_5: Milk is not good for health
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- Find tf, idf (with $\log_2$) and tf-idf ($\log_2$) scores

Similarity between Documents

- What is the "similarity" between two documents (i.e., their vectors)?

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- *Euclidean distance* may not be suitable
    - Longer documents have larger distances

Cosine Similarity

- Consider two documents d_1 and d_2 with their corresponding document vectors $\vec{V}(d_1)$ and $\vec{V}(d_2)$
- Cosine similarity measures the *normalised* dot product

$$\text{sim}(d_1, d_2) = \frac{\vec{V}(d_1).\vec{V}(d_2)}{|\vec{V}(d_1)|.|\vec{V}(d_2)|}$$

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- Consider the length-normalised document vectors

$$\vec{v}(d_i) = \frac{\vec{V}(d_1)}{|\vec{V}(d_1)|}$$

- Then, cosine similarity is their dot product

$$\text{sim}(d_1, d_2) = \vec{v}(d_1).\vec{v}(d_2)$$

Example

Term	d_1	d_2	d_3
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ancient	10	7	11
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- Similarities between documents

$$\text{sim}(d_1, d_2) = \frac{115}{115.45} \cdot \frac{58}{58.42} + \frac{10}{115.45} \cdot \frac{7}{58.42} + \frac{2}{115.45} \cdot \frac{0}{58.42} = 0.99$$

- d_1 and d_2 is the closest pair

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- Brute-force method of computing scores with all the documents and ranking them is *not* scalable

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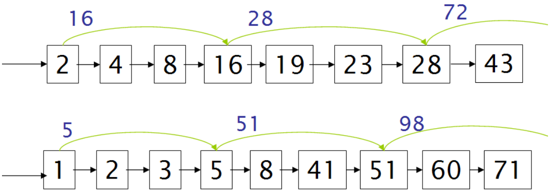
Skip Lists

- Skip lists are used to traverse linked lists faster



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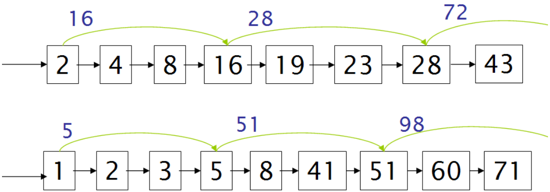

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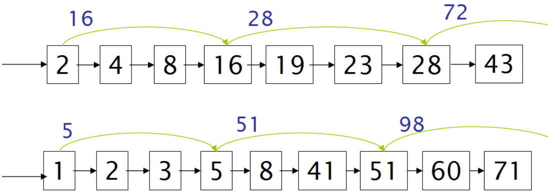

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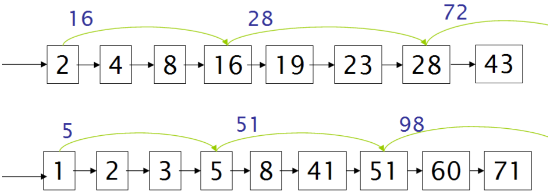

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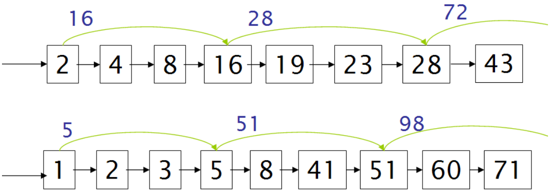

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- $\sqrt{l}$ equally spaced skips for a l-length list

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- Retrieval process becomes much faster
- Generally, a two-step process
  1. Retrieve *approximate* top-K documents where $k \leq K \ll m$
  2. Retrieve *exact* top-k from K

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  - Take union of top-r of every query term to get top-K
- Build tiered index
  - Each level (tier) lists only those documents whose *tf* for the term is greater than a threshold
  - Continue with tiers till top-K results are obtained

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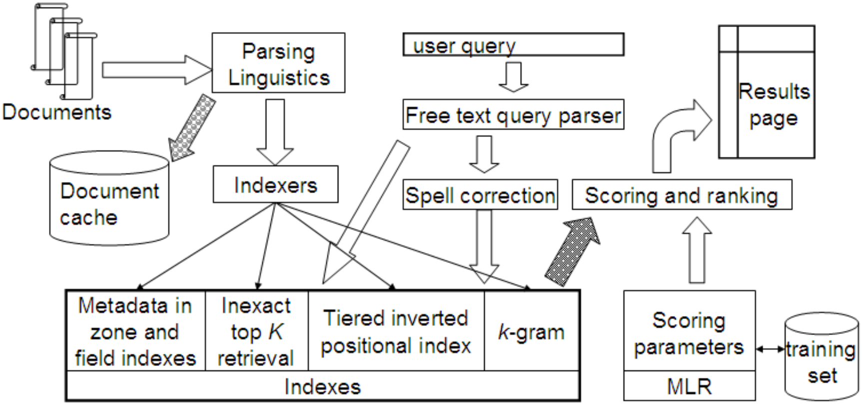
The Complete Information Retrieval System



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Questions?
Answers!