

Modern Information Retrieval

Dictionaries and tolerant retrieval

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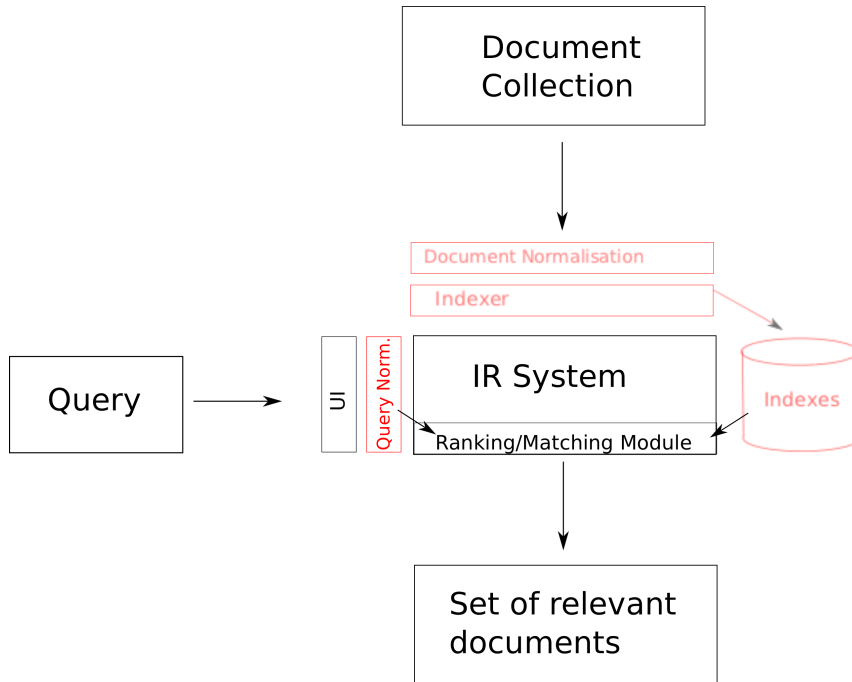
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Introduction





Brutus 8 → 1 → 2 → 4 → 11 → 31 → 45 → 173 → 174

Caesar 9 → 1 → 2 → 4 → 5 → 6 → 16 → 57 → 132 → 179

Calpurnia 4 → 2 → 31 → 54 → 101



1. Data structures for dictionaries

- Hash tables
- Trees
- k -term index
- Permuterm index

2. Tolerant retrieval: What to do if there is no exact match between query term and document term

3. Spelling correction

1. Inverted index

For each term t , we store a list of all documents that contain t .

BRUTUS	→	1	2	4	11	31	45	173	174
--------	---	---	---	---	----	----	----	-----	-----

CAESAR	→	1	2	4	5	6	16	57	132	...
--------	---	---	---	---	---	---	----	----	-----	-----

CALPURNIA	→	2	31	54	101
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⋮

⏟
dictionary

⏟
postings



1. **Dictionary:** the data structure for storing the term vocabulary.
2. For each term, we need to store a couple of items:
 - document frequency
 - pointer to postings list
3. How do we look up a query term q in the dictionary at query time?



1. Two different types of implementations:
 - hash tables
 - search trees
2. Some IR systems use [hash tables](#), some use [search trees](#).
3. Criteria for when to use [hash tables](#) vs. [search trees](#):
 - How many terms are we likely to have?
 - Is the number likely to remain fixed, or will it keep growing?
 - What are the relative frequencies with which various terms will be accessed?

Hash tables



1. **Hash table:** an array with a hash function
 - **Input:** a key which is a query term
 - **output:** an integer which is an index in array.
 - **Hash function:** determine where to store / search key.
 - Hash function that minimizes chance of collisions.
Use all info provided by key (among others).
2. Each vocabulary term (key) is hashed into an integer.
3. At query time: hash each query term, locate entry in array.



1. Advantages

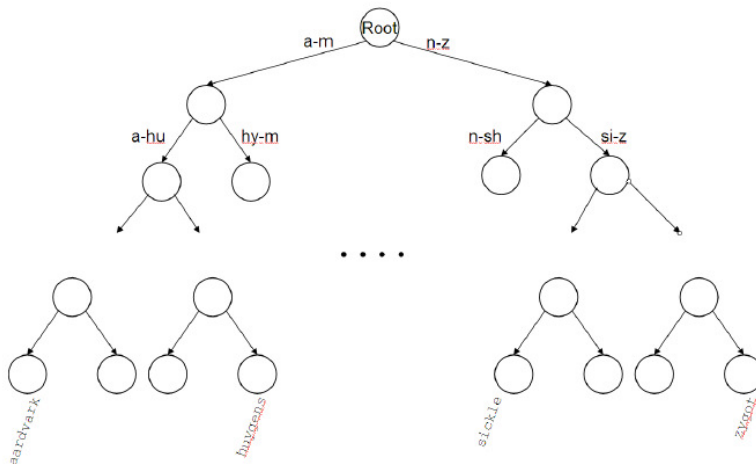
- Lookup in a hash is faster than lookup in a tree. (Lookup time is constant.)

2. disadvantages

- No easy way to find minor variants (*résumé* vs. resume)
- No prefix search (all terms starting with [automat](#))
- Need to rehash everything periodically if vocabulary keeps growing
- Hash function designed for current needs may not suffice in a few years' time

Search trees

1. Simplest search tree: [binary search tree](#)

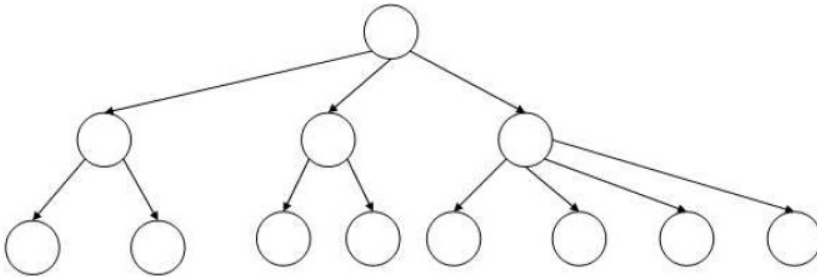


2. Partitions vocabulary terms into two subtrees, those whose first letter is between [a](#) and [m](#), and the rest (actual terms stored in the leaf).
3. Anything that is on the left subtree is smaller than what's on the right.
4. Trees solve the prefix problem (find all terms starting with [automat](#)).

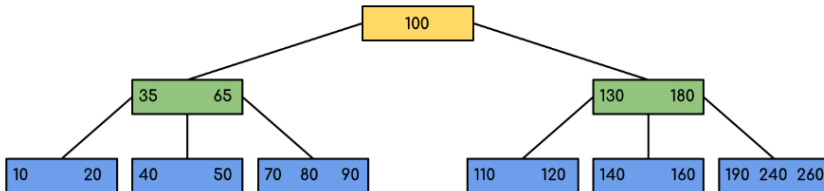


1. Cost of operations depends on height of tree.
2. Keep height minimum / keep binary tree balanced: for each node, heights of subtrees differ by no more than 1.
3. $O(\log M)$ search for balanced trees, where M is the size of the vocabulary.
4. Search is slightly slower than in hashes
5. But: re-balancing binary trees is expensive (insertion and deletion of terms).

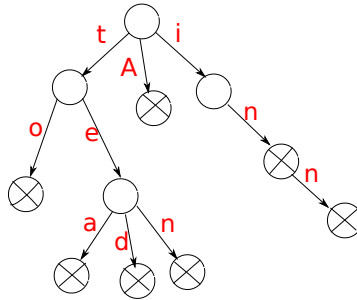
1. Need to mitigate re-balancing problem – allow the number of sub-trees under an internal node to vary in a fixed interval.
2. B-tree definition: every internal node has a number of children in the interval $[a, b]$ where a, b are appropriate positive integers, e.g., $[2, 4]$.



3. Every internal node has between 2 and 4 children.



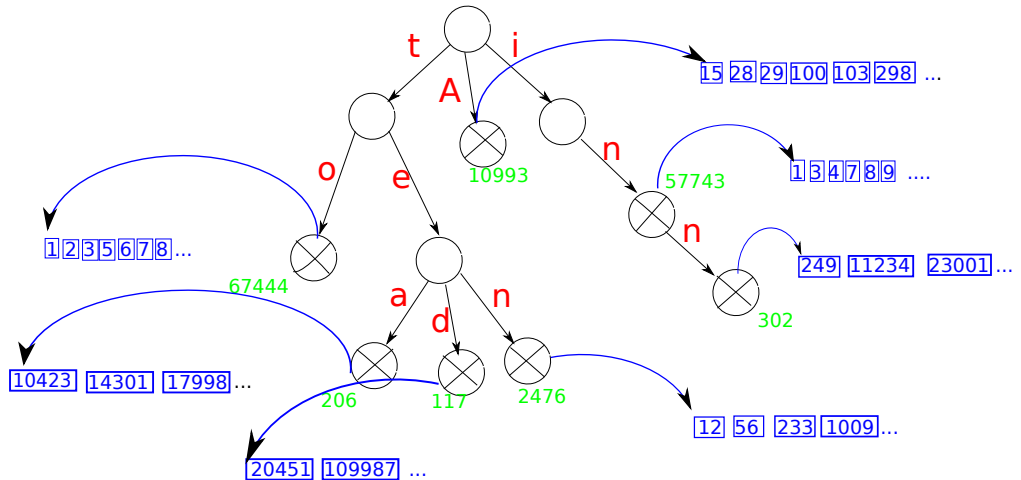
1. Trie is a search tree



2. An ordered tree data structure for strings

- A tree where the keys are strings (keys tea, ted)
- Each node is associated with a string inferred from the position of the node in the tree.

3. Tries can be searched by prefixes: all descendants of a node have a common prefix of the string associated with that node
4. Search time linear on length of term / key
5. The trie is sometimes called radix tree or prefix tree





1. Query :hel*

- Find all docs containing any term beginning with **hel**
- Easy with trie: follow letters **h-e-l** and then lookup every term you find there

2. Query : *hel

- Find all docs containing any term ending with **hel**
- Maintain an additional trie for terms backwards
- Then retrieve all terms in subtree rooted at **l-e-h**

3. In both cases:

- This procedure gives us a set of terms that are matches for the wildcard queries
- Then retrieve documents that contain any of these terms



1. Query: hel*o
2. We could look up hel* and *o in the tries as before and intersect the two term sets (expensive!).
3. Solution: permuterm index – special index for general wildcard queries

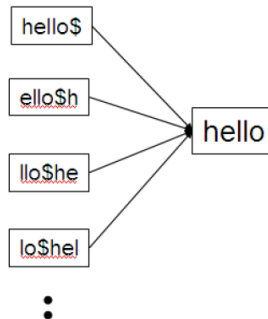
Permuterm index



1. For term `hello$` (given `$` to match the end of a term), store each of these rotations in the dictionary (trie):

`hello$, ello$h, llo$he, lo$hel, o$hell, $hello` : permuterm vocabulary

2. Rotate every wildcard query, so that the `*` occurs at the end: for `hel*$`, look up `o$hel*`



3. Problem: Permuterm more than quadruples the size of the dictionary compared to normal trie (empirical number).

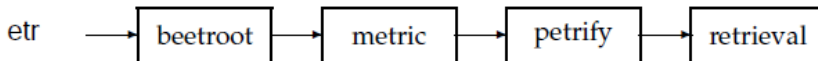
k-gram indexes

1. More space-efficient than permuterm index
2. Enumerate all character k-grams (sequence of k characters) occurring in a term and store in a dictionary

Example (Character bi-grams from April is the cruelest month)

\$a ap pr ri il l\$ \$i is s\$ \$t th he e\$ \$c cr ru ue el le es st t\$ \$m mo on nt th h\$

3. \$ special word boundary symbol
4. A postings list that points to all vocabulary terms containing a k-gram



5. Note that we have two different kinds of inverted indexes:
 - The term-document inverted index for finding documents based on a query consisting of terms
 - The k-gram index for finding terms based on a query consisting of k-grams



1. Query `hel*` can now be run as:

`$H AND HE AND EL`

2. This will show up many false positives like blueheel.
3. Post-filter, then look up surviving terms in term–document inverted index.
4. k-gram vs. permuterm index
 - k-gram index is more space-efficient
 - permuterm index does not require post-filtering.

Spelling correction



1. Query: an **asterorid** that fell **form** the sky
2. Query: britney spears
queries: britian spears, britney's spears, brandy spears, prittany spears
3. In an IR system, spelling correction is only ever run on queries.
4. Two different methods for spelling correction:
 - **Isolated word** spelling correction
Check each word on its own for misspelling
Will only attempt to catch first typo above
 - **Context-sensitive** spelling correction
Look at surrounding words
Should correct both typos above



1. There is a list of **correct** words – for instance a standard dictionary (Webster's, OED. . .)
2. Then we need a way of computing the distance between a misspelled word and a correct word
 - for instance Edit/Levenshtein distance
 - k-gram overlap
3. Return the **correct** word that has the smallest distance to the misspelled word.

informaton $\Rightarrow$ **information**



1. **Edit distance** between two strings s_1 and s_2 is defined as the minimum number of basic operations that transform s_1 into s_2 .
2. **Levenshtein distance**: Admissible operations are **insert**, **delete** and **replace**
3. Example

dog	do	1 (delete)
cat	cart	1 (insert)
cat	cut	1 (replace)
cat	act	2 (delete+insert)

```
EDITDISTANCE( $s_1, s_2$ )
1  int  $m[i, j] = 0$ 
2  for  $i \leftarrow 1$  to  $|s_1|$ 
3  do  $m[i, 0] = i$ 
4  for  $j \leftarrow 1$  to  $|s_2|$ 
5  do  $m[0, j] = j$ 
6  for  $i \leftarrow 1$  to  $|s_1|$ 
7  do for  $j \leftarrow 1$  to  $|s_2|$ 
8      do  $m[i, j] = \min\{m[i-1, j-1] + \text{if } (s_1[i] = s_2[j]) \text{ then } 0 \text{ else } 1, \\$ 
9           $m[i-1, j] + 1,$ 
10          $m[i, j-1] + 1\}$ 
11 return  $m[|s_1|, |s_2|]$ 
```



		s	n	o	w
	0	1	2	3	4
o	1	1	2	3	4
s	2	1	3	3	3
l	3	3	2	3	4
o	4	3	3	2	3

Example: Edit Distance oslo – snow



			s	n	o	w
		0	1 1	2 2	3 3	4 4
o		1 1	1 2 2 1	2 3 2 2	2 4 3 2	4 5 3 3
s		2 2	1 2 3 1	2 3 2 2	3 3 3 3	3 4 4 3
l		3 3	3 2 4 2	2 3 3 2	3 4 3 3	4 4 4 4
o		4 4	4 3 5 3	3 3 4 3	2 4 4 2	4 5 3 3

cost	operation	input	output
1	delete	o	*
0	(copy)	s	s
1	replace	l	n
0	(copy)	o	o
1	insert	*	w



Cost of getting here from my upper left neighbour (by copy or replace)	Cost of getting here from my upper neighbour (by delete)
Cost of getting here from my left neighbour (by insert)	Minimum cost out of these



		s	n	o	w
	0	1 1	2 2	3 3	4 4
o	1	1 2 2 1	2 3 2 2	2 4 3 2	4 5 3 3
s	2	1 2 3 1	2 3 2 2	3 3 3 3	3 4 4 3
l	3	3 2 4 2	2 3 3 2	3 4 3 3	4 4 4 4
o	4	4 3 5 3	3 3 4 3	2 4 4 2	4 5 3 3

Example: (2, 2):

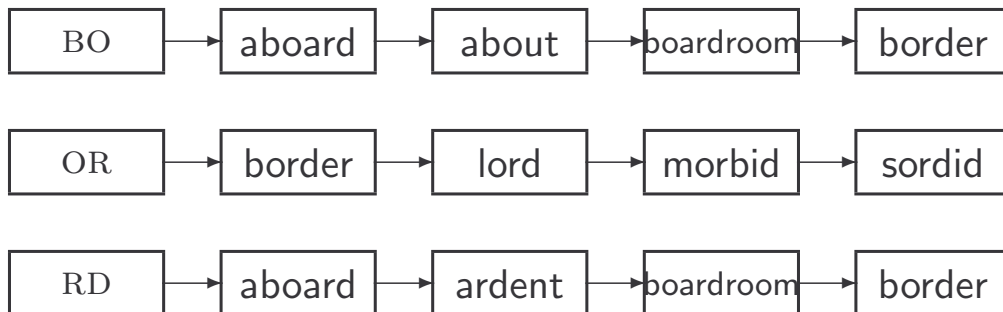
- Upper left: cost to replace "o" to "s" (cost: 0+1)
- Upper right: come from above where I have already inserted "s": all I need to do is delete "o" (cost: 1+1)
- Bottom left: come from left neighbour where I have deleted "o": all I need to do is insert "s" (cost: 1+1)
- Then choose the minimum of the three (bottom right).



1. Given a query, enumerate all character sequences within a pre-set edit distance.
2. Intersect this list with our list of **correct** words.
3. Suggest terms in the intersection to user.
4. Cons
 - Comparing query term q to all terms in the vocabulary is too expensive.
 - **Solution:** use heuristics to determine the subset.



1. Enumerate all k-grams in the query term
2. Misspelled word: **bordroom**
3. Use k-gram index to retrieve **correct** words that match query term k-grams
4. Threshold by number of matching k-grams
5. Eg. only vocabulary terms that differ by at most 3 k-grams





1. An idea: hit-based spelling correction

flew **form** munich

2. Enumerate corrections of each of the query terms

flew $\Rightarrow$ flea

form $\Rightarrow$ from

munich $\Rightarrow$ munch

3. Holding all other terms fixed, try all possible phrase queries for each replacement candidate.

4. For each phrase, the search engine runs the query and determines the number of matching results.

flea form munich $\Rightarrow$ 62 results

flew **from** munich $\Rightarrow$ 78900 results

flew form **munch** $\Rightarrow$ 66 results

5. Not efficient. Better source of information: large corpus of queries, not documents

Soundex



- Soundex is the basis for finding **phonetic** (as opposed to orthographic) alternatives.
- Example: *chebyshev* / *tchebyscheff*
- Algorithm:
 - Turn every token to be indexed into a 4-character reduced form
 - Do the same with query terms
 - Build and search an index on the reduced forms



1. Retain the first letter of the term.
2. Change all occurrences of the following letters to '0' (zero): A, E, I, O, U, H, W, Y
3. Change letters to digits as follows:
 - B, F, P, V to 1
 - C, G, J, K, Q, S, X, Z to 2
 - D, T to 3
 - L to 4
 - M, N to 5
 - R to 6
4. Repeatedly remove one out of each pair of consecutive identical digits
5. Remove all zeros from the resulting string; pad the resulting string with trailing zeros and return the first four positions, which will consist of a letter followed by three digits



- Retain H
- *ERMAN* → *ORM0N*
- *ORM0N* → *06505*
- *06505* → *655*
- Return *H655*
- Note: *HERMANN* will generate the same code



- Not very – for information retrieval
- Ok for “high recall” tasks in other applications (e.g., Interpol)
- Zobel and Dart (1996) suggest better alternatives for phonetic matching in IR.

References



1. Chapters 3 of [Information Retrieval Book](#)¹

¹Manning2008.



Questions?