Information Retrieval and Organisation

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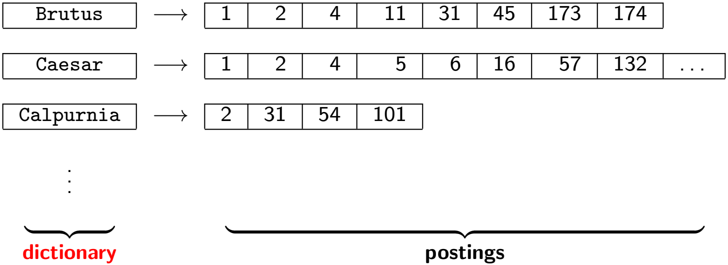
Dictionaries and Tolerant Retrieval

Dictionaries

- Dictionary: the data structure for storing the term vocabulary



Storing Dictionaries

- For each term, we need to store a couple of items:
  - document frequency
  - pointer to postings list
  - ...
- Assume for the time being that
  - we can store this information in a fixed-length entry
  - we store these entries in an array

Storing Dictionaries

term	document frequency	pointer to postings list
a	656,265	$\longrightarrow$
aachen	65	$\longrightarrow$
...	...	...
zulu	221	$\longrightarrow$
space needed: 20 bytes	4 bytes	4 bytes

- How do we look up an element in this array at query time?
- Remember: these dictionaries can be huge, scanning is not an option

Data Structures

- Two main classes of data structures:
  hash tables and trees
  - Some IR systems use hash tables, some use trees.
- Criteria for when to use hash tables vs trees:
  - Is there a fixed number of terms or will it keep growing?
  - What are the relative frequencies with which various keys will be accessed?
  - How many terms are we likely to have?

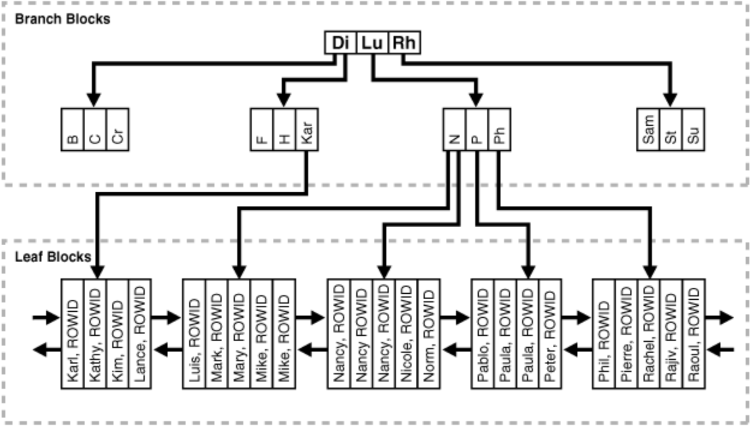
Hash Tables

- Each vocabulary term is hashed into an integer.
- Try to avoid collisions
- At query time, do the following:
  - hash query term
  - resolve collisions
  - locate entry in fixed-width array
- Pros:
  - Lookup in a hash table is faster than in a tree.
- Cons:
  - no prefix search (all terms starting with *automat*)
  - need to rehash everything periodically if vocabulary keeps growing

Trees

- Trees solve the prefix problem (find all terms starting with *automat*).
- Simplest tree: binary tree.
- However, binary trees are problematic:
  - Only balanced trees allow efficient retrieval
  - Rebalancing binary trees is expensive
- Use B-trees (the index structure that you know from database lectures)

B-Tree



Taken from documentation for Oracle 10g

Wildcard Queries

- `mon*`: find all docs containing any term beginning with *mon*
  - Easy with B-tree dictionary
  - retrieve all terms t in the range: mon $\leq t <$ moo
- `*mon`: find all docs containing any term ending with *mon*
  - Maintain an additional tree for terms *backwards*, then
  - retrieve all terms t in the range: nom $\leq t <$ non

Query Processing

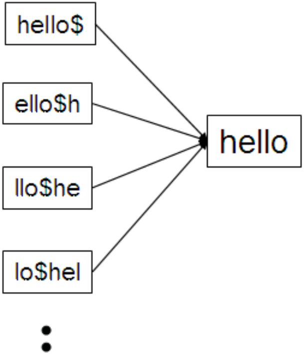
- At this point, we have an enumeration of all terms in the dictionary that match the wildcard query.
- We still have to look up the postings for each enumerated term.
  - e.g., consider the query: `gen* AND universit*`
- This may result in the execution of many Boolean `AND` queries.

Wildcards in Middle of Term

- Example: `m*nchen`
- We could look up `m*` and `*nchen` in the B-tree and intersect the two term sets.
  - Expensive (there are probably thousands and thousands of terms beginning with "m")
- Alternative: *permuterm* index
  - Basic idea: Rotate every wildcard query, so that the * occurs at the end.

Permuterm Index

- For term `hello`: add *hello\$*, *ello\$h*, *llo\$he*, *lo\$hel*, *o\$hell*, and *\$hello* to the B-tree where \$ is a special symbol



Permuterm Index

- Queries
  - For X, look up X$
  - For X*, look up $X*
  - For *X, look up X$*
  - For *X*, look up X*
  - For X*Y, look up Y$X*
- Example:
  - For hel*o, look up o$hel*
- It's really a tree and should be called permuterm tree
- But permuterm index is more common name.

Query Processing

- Once we modified the query (as shown on last slide), we can do a regular lookup on a B-tree
- This is much faster than looking up X* and *Y and combining results (for query X*Y)
- Permuterm index also handles leading wildcards: *X
- It has a disadvantage, though: quadruples the size of the dictionary compared to a regular B-tree (as every term is stored multiple times)

k-gram Index

- More space-efficient than permuterm index
- Enumerate all character k-grams (sequence of k characters) occurring in a term
  - 2-grams are also called *bigrams*
  - 3-grams are also called *trigrams*
- Example:
  - from *April is the cruelest month*
    we get the bigrams:
    $a ap pr ri il l$ $i is s$ $t th he e$ $c cr ru ue el le es st t$ $m mo on nt h$
  - $ is a special word boundary symbol.
- Maintain an inverted index from bigrams to the terms that contain the bigram

Postings List in a 3-gram Index

etr → beetroot → metric → petrify → retrieval

- Note that we now have two different types 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

Processing Wildcard Queries

- Query `mon*` can now be run as:
  `$m AND mo AND on`
- Gets us all terms with the prefix *mon* ...
- ...but also many "false positives" like `moon`
- We must post-filter these terms against query
- Surviving terms are then looked up in the term-document inverted index.
- *k*-gram indexes are fast and space efficient (compared to permuterm indexes).

Processing Wildcard Queries

- We must potentially execute a large number of Boolean queries for each enumerated, filtered term (on the term-document index)
  - Recall the query: `gen* AND universit*`
  - Most straightforward semantics: Conjunction of disjunctions
  - Very expensive
- Users hate to type
  - If abbreviated queries like `pyth* theo*` for `pythagoras' theorem` are legal, users will use them ...
  - ... a lot

Spelling Correction

- Two principal uses
  - Correcting documents being indexed
  - Correcting user queries
- Two different methods
  - *Isolated Word* Spelling Correction
    - Check each word on its own for misspelling
    - Will not catch typos resulting in correctly spelled words, e.g., *an asteroid that fell form the sky*
  - *Context-Sensitive* Spelling Correction
    - Look at surrounding words
    - Can correct the *form*/*from* error above

Correcting Documents

- We're not interested in interactive spelling correction of documents (e.g., MS Word) in this class.
- In IR, we use document correction primarily for OCR'ed documents (i.e. documents digitized via Optical Character Recognition)
- The general philosophy in IR is: don't change the documents.

Correcting Queries

- First: isolated word spelling correction
  - Fundamental premise 1: There is a list of "correct words" from which the correct spellings come.
  - Fundamental premise 2: We have a way of computing the *distance* between a misspelled word and a correct word.
- Simple spelling correction algorithm: return the "correct" word that has the *smallest* distance to the misspelled word.
  - Example: *informaton* $\rightarrow$ *information*

Correcting Queries

- Can we use the term vocabulary of the inverted index as the list of correct words?
  - It can be very biased
  - It may be missing certain terms
- Alternatives:
  - A standard dictionary
    (Webster's, Encyclopædia Britannica, etc.)
  - An industry-specific dictionary
    (for specialized IR systems)
  - The term vocabulary of the collection, appropriately weighted

Computing Distance

- How can we compute the distance between words?
- We'll look at some alternatives:
  - edit distance (Levenshtein distance)
  - weighted edit distance
  - k-gram overlap

Edit Distance

- The (minimum) edit distance between two strings s_1 and s_2 is the minimum number of basic operations to convert s_1 to s_2.
- Levenshtein distance: the admissible basic operations are: insert, delete, and replace
  - Levenshtein distance $dog \to do$: 1 (deletion)
  - Levenshtein distance $cat \to cart$: 1 (insertion)
  - Levenshtein distance $cat \to cut$: 1 (replacement)
  - Levenshtein distance $cat \to act$: 2
    (2 replacements or 1 insertion and 1 deletion)

Computing Distance

- Getting from *cats* to *fast*

	“”	f	a	s	t
“”	“” $\rightarrow$ “”	“” $\rightarrow$ f	“” $\rightarrow$ fa	“” $\rightarrow$ fas	“” $\rightarrow$ fast
c	c $\rightarrow$ “”	c $\rightarrow$ f	c $\rightarrow$ fa	c $\rightarrow$ fas	c $\rightarrow$ fast
a	ca $\rightarrow$ “”	ca $\rightarrow$ f	ca $\rightarrow$ fa	ca $\rightarrow$ fas	ca $\rightarrow$ fast
t	cat $\rightarrow$ “”	cat $\rightarrow$ f	cat $\rightarrow$ fa	cat $\rightarrow$ fas	cat $\rightarrow$ fast
s	cats $\rightarrow$ “”	cats $\rightarrow$ f	cats $\rightarrow$ fa	cats $\rightarrow$ fas	cats $\rightarrow$ fast

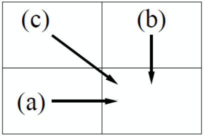
- Each cell will contain
  the (cheapest) cost of getting
  from the string on the left-hand side
  to the string on the right-hand side

Computing Distance

- We know the costs for
  the uppermost row and the leftmost column:
  - we have to get from “” to *fast* by inserting characters
  - we have to get from *cats* to “” by deleting characters

	“”	f	a	s	t
“”	0	1	2	3	4
c	1				
a	2				
t	3				
s	4				

Computing Distance



- For other cells, take the minimum of costs
  - Coming from (a):
    - add 1 to cost in (a) — insertion
  - Coming from (b):
    - add 1 to cost in (b) — deletion
  - Coming from (c):
    - if characters in row and column are equal, copy cost from (c)
    - otherwise, add 1 to cost in (c) — replacement

Resulting Matrix

- Computing the costs for all cells results in the following matrix:

	""	f	a	s	t
""	0	1	2	3	4
c	1	1	2	3	4
a	2	2	1	2	3
t	3	3	2	2	2
s	4	4	3	2	3

- So the Levenshtein distance is 3

Algorithm

EDITDISTANCE(s_1, s_2)

$int\ m[i, j] = 0$
for $i \leftarrow 1$ **to** $|s_1|$
do $m[i, 0] = i$
for $j \leftarrow 1$ **to** $|s_2|$
do $m[0, j] = j$
for $i \leftarrow 1$ **to** $|s_1|$
do for $j \leftarrow 1$ **to** $|s_2|$
    do $m[i, j] = \min\{m[i-1, j-1] + \text{if } (s_1[i] = s_2[j]) \text{ then } 0 \text{ else } 1\text{fi},$
        $m[i-1, j] + 1,$
        $m[i, j-1] + 1\}$
return $m[|s_1|, |s_2|]$

Weighted Edit Distance

- As Levenshtein distance, but weight of an operation depends on the characters involved.
- Meant to capture keyboard errors
  - e.g., m more likely to be mistyped as n than as q.
  - therefore, replacing m by n is a smaller edit distance than by q.
- We now require a weight matrix as input.
- Modify dynamic programming to handle weights.

Using Edit Distances

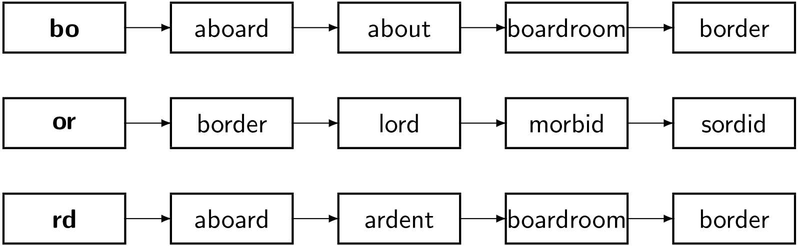
- Comparing query term q to all terms in the vocabulary is too expensive
- Solution: use heuristics to determine subset
  - Only compare to terms beginning with the same letter (doesn't work for typos at beginning)
  - Generate set of rotations for q and use a permuterm index (doesn't work well for replacements)
  - For each rotation, omit a suffix of l characters before doing lookup in permuterm index
    - Ensures that each term in query rotation shares a substring with retrieved terms
    - The value of l could be fixed to a constant length (e.g. 2), or depend on the length of q

Using a *k*-gram Index

- Enumerate all *k*-grams in the query term
- Use the *k*-gram index to retrieve "correct" words that match query term *k*-grams
- Threshold by number of matching *k*-grams
  - e.g., only vocabulary terms that differ by at most 3 *k*-grams

Example with 2-grams

- Suppose the misspelled word is "`bordroom`":
  `$b`, `bo`, `or`, `rd`, `dr`, `ro`, `oo`, `om`, `m$`



Example with 3-grams

- Suppose the correct word is "`november`":
  `$$n`, `$no`, `nov`, `ove`, `vem`, `emb`, `mbe`, `ber`, `er$`, `r$$`
- And the query term is "`december`":
  `$$d`, `$de`, `dec`, `ece`, `cem`, `emb`, `mbe`, `ber`, `er$`, `r$$`
- So 5 trigrams overlap (out of 10 in each term)
- Issue: Fixed number of k-grams that differ does not work for words of differing length.
- How can we turn this into a normalized measure of overlap?

Jaccard Coefficient

- A commonly used measure of two sets' overlap
- Let A and B be two sets
- Jaccard coefficient:

$$\frac{|A \cap B|}{|A \cup B|}$$

  - A and B don't have to be the same size.
  - Always assigns a number between 0 and 1.
- Application to spelling correction: declare a match if the coefficient is, say, > 0.8.

Context-Sensitive Correction

- Our example was:
  "`an asteroid that fell` *`form`* `the sky`"
- How can we correct *`form`* here?
- One idea: *hit-based* spelling correction
  - We'll return back to this idea when we talk about the *probabilistic* approach to spelling correction, in the second half of the module.

Context-Sensitive Correction

- Given query "`flew` *form* `munich`"
- Retrieve the correct terms close to each query term
  - `flea` for *flew*
  - `from` for *form*
  - `munch` for *munich*
- Now try all possible resulting phrases as queries, with one word fixed at a time
  - Try query "`flea form munich`"
  - Try query "`flew from munich`"
  - Try query "`flew form munch`"
- The correct query "`flew from munich`" should have the most hits.

Context-Sensitive Correction

- The *hit-based* algorithm we just outlined is not very efficient.
  - Suppose we have 7 alternatives for *flew*, 19 for *form* and 3 for *munich*
  - Then we have to test $7 \times 19 \times 3$ different variants
- More efficient alternative: look at the collection of queries, not documents
  - This assumes that we log queries

General Issues

- User interface
  - Automatic or suggested correction
    - "*Did you mean*" only works for one suggestion.
    - What about multiple possible corrections?
  - Tradeoff: simple vs powerful UI
- Cost
  - Spelling correction is potentially expensive.
  - Avoid running on every query?
  - Maybe just on queries that match few documents.

Phonetic Matching

- Soundex is the basis for finding *phonetic* (as opposed to orthographic) alternatives.
  - e.g., `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

Soundex Algorithm

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 $\Rrightarrow$ 1
   - C, G, J, K, Q, S, X, Z $\Rrightarrow$ 2
   - D,T $\Rrightarrow$ 3
   - L $\Rrightarrow$ 4
   - M, N $\Rrightarrow$ 5
   - R $\Rrightarrow$ 6
4. Repeatedly remove one out of each pair of consecutive identical digits
5. Remove all 0s from the resulting string; pad the resulting string with trailing 0s, and return the first four positions, which will consist of a letter followed by three digits

Soundex Algorithm

- Example

	difficulty	difference
steps 1 and 2	d0ff0c0lt0	d0ff0r0nc0
step 3	d011020430	d011060520
step 4	d01020430	d01060520
step 5	d124	d165

- Vowels are viewed as being interchangeable
- Consonants with similar sounds (e.g. D and T) are put in equivalence classes
- Works fairly well for European languages

Summary

- How to organize a dictionary of an inverted index
- How to do imprecise searches on this dictionary handling
  - wildcards
  - spelling mistakes