# Dictionary data structures for the Inverted Index

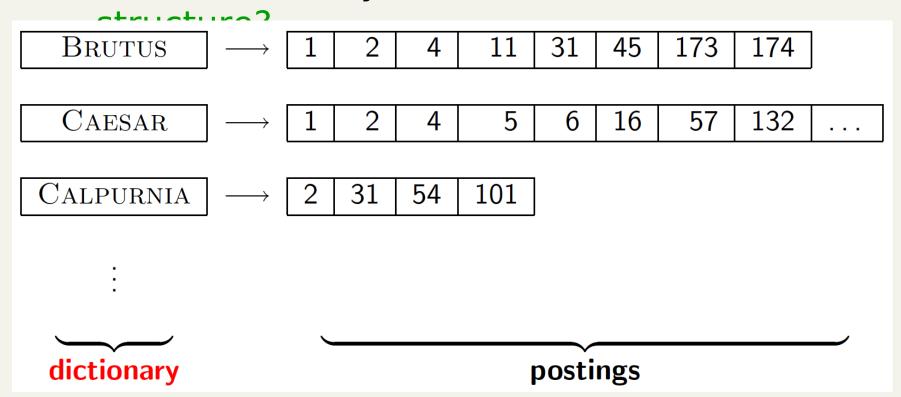
#### This lecture

- Dictionary data structures
  - Exact search
  - Prefix search

- "Tolerant" retrieval
  - Edit-distance queries
  - Wild-card queries
  - Spelling correction
  - Soundex

#### **Basics**

 The dictionary data structure stores the term vocabulary, but... in what data



# A naïve dictionary

An array of struct:

term	document	pointer to
	frequency	postings list
а	656,265	$\longrightarrow$
aachen	65	$\longrightarrow$
zulu	221	<b></b> →

char[20] int Postings \*
20 bytes 4/8 bytes 4/8 bytes

- How do we store a dictionary in memory efficiently?
- How do we quickly look up elements at query time?

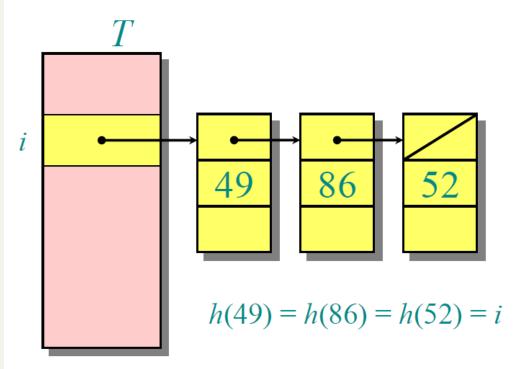
## Dictionary data structures

- Two main choices:
  - Hash table
  - Tree
  - Trie

 Some IR systems use hashes, some trees/tries

# Hashing with chaining

• Link records in the same slot into a list.



The current version is **MurmurHash** (vers 3) yields a 32-bit or 128-bit hash value.

### Prefix search

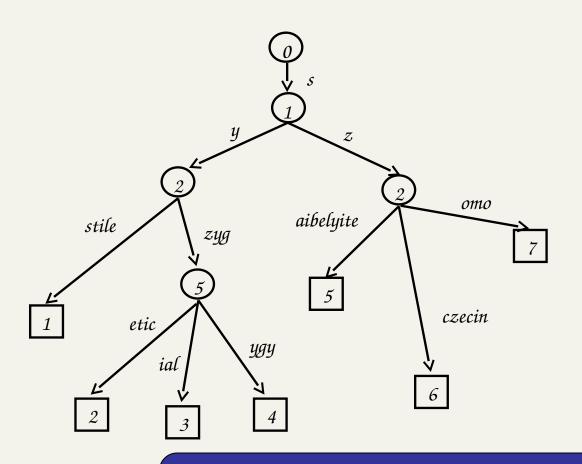
# Prefix-string Search

Given a dictionary D of K strings, of total length N, store them in a way that we can efficiently support prefix searches for a pattern P over them.

#### Ex. Pattern P is pa

Dict = {abaco, box, <u>pa</u>olo, <u>pa</u>trizio, pippo, zoo}

# Trie: speeding-up searches



Pro: O(p) search time = path scan

Cons: edge + node labels + tree structure

#### Tries

Do exist many variants and their implementations

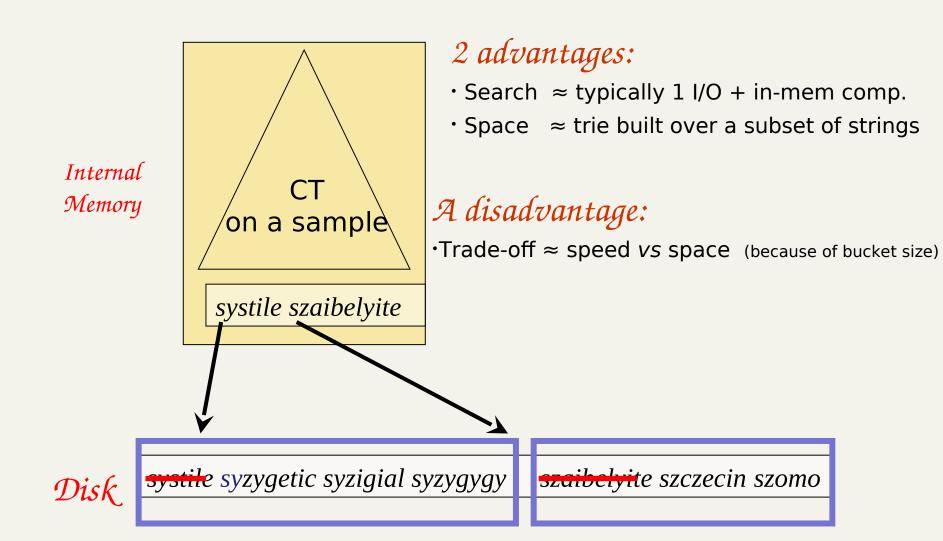
#### Pros:

Solves the prefix problem

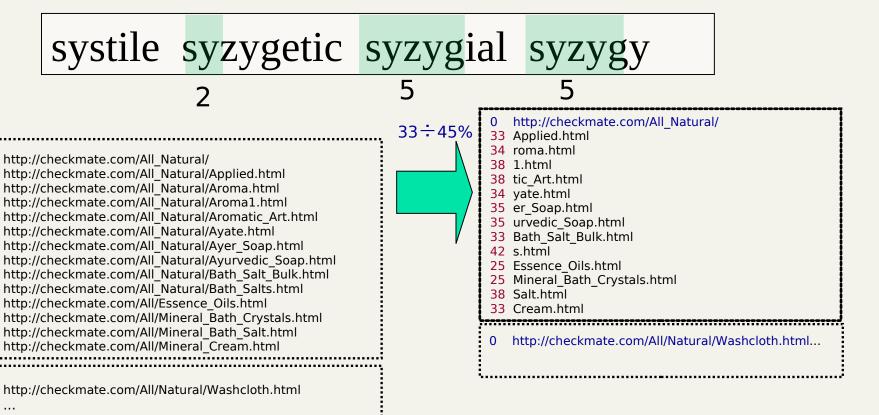
#### Cons:

- Slower: O(p) time, many cache misses
- From 10 to 60 (or, even more) bytes per node

# 2-level indexing

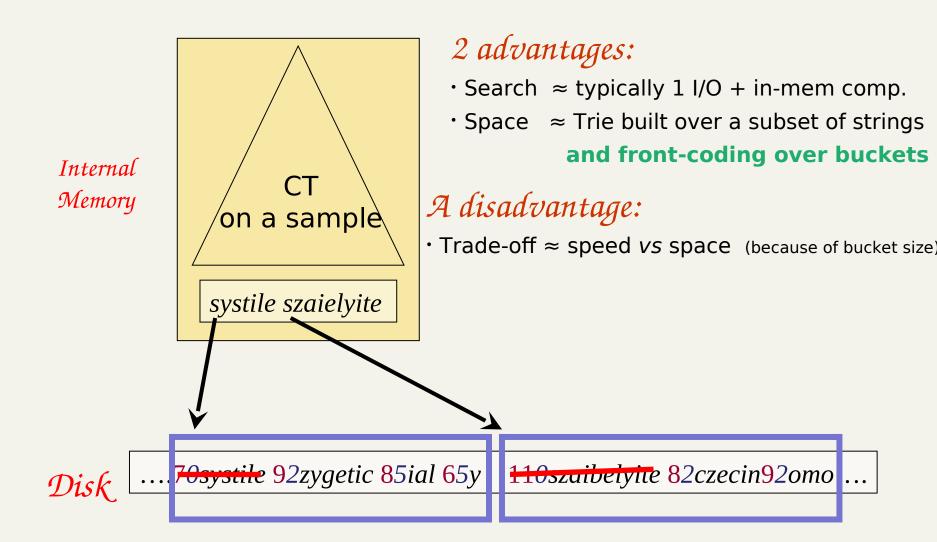


# Front-coding: squeezing dict



Gzip may be much better...

# 2-level indexing



## Spelling correction

# Spell correction

- Two principal uses
  - Correcting document(s) being indexed
  - Correcting queries to retrieve "right" answers
- Two main flavors:
  - Isolated word
    - Check each word on its own for misspelling
    - But what about: from → form
  - Context-sensitive is more effective
    - Look at surrounding words
    - e.g., I flew form Heathrow to Narita.

#### Isolated word correction

- Fundamental premise there is a lexicon from which the correct spellings come
- Two basic choices for this
  - A standard lexicon such as
    - Webster's English Dictionary
    - An "industry-specific" lexicon hand-maintained
  - The lexicon of the indexed corpus
    - E.g., all words on the web
    - All names, acronyms etc. (including the mis-spellings)
    - Mining algorithms to derive the possible corrections

#### Isolated word correction

- Given a lexicon and a character sequence
   Q, return the words in the lexicon closest
   to Q
- What's "closest"?

- We'll study several measures
  - Edit distance (Levenshtein distance)
  - Weighted edit distance
  - n-gram overlap

#### Brute-force check of ED

Given query Q,

- enumerate all character sequences within a preset (weighted) edit distance (e.g., 2)
- •Intersect this set with list of "correct" words

Show terms you found to user as suggestions

How the time complexity grows with #errors allowed and string length?

#### Edit distance

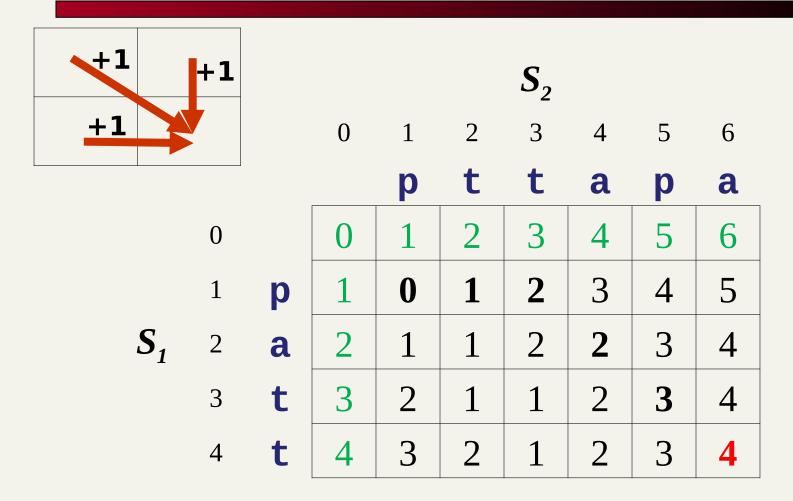
- Given two strings  $S_1$  and  $S_2$ , the minimum number of *operations* to convert one to the other
- Operations are typically character-level
  - Insert, Delete, Replace (possibly, Transposition)
- E.g., the edit distance from dof to dog is 1
  - From cat to act is 2 (Just 1 with transpose)
  - from *cat* to *dog* is 3.
- Generally found by dynamic programming.

# DynProg for Edit Distance

- Let E(i,j) = edit distance to transform  $S_1[1,i]$  in  $S_2[1,j]$
- Example: cat versus dea
- Consider the sequence of ops: ins, del, subst, match
  - Model the edit distance as an alignment problem where **insertion** in  $S_2$  correspond to a − in  $S_1$  whereas **deletion** from  $S_1$  correspond to a − in  $S_2$ .
  - If  $S_1[i] = S_2[j]$  then last op is a **match**, and thus it is not counted
  - Otherwise the last op is:  $\mathbf{subst}(S_1[i], S_2[j])$  or  $\mathbf{ins}(S_2[j])$  or  $\mathbf{del}(S_1[i])$

```
E(i,0)=i, E(0,j)=j
E(i,j)=E(i-1,j-1) \qquad \text{if } S_1[i]=S_2[j]
E(i,j)=1+\min\{E(i,j-1),
E(i-1,j),
E(i-1,j-1)\} \qquad \text{if } S_1[i]\neq S_2[j]
```

# Example



# Weighted edit distance

- As above, but the weight of an operation depends on the character(s) involved
  - Meant to capture keyboard errors, e.g. m more likely to be mis-typed as n than as q
  - Therefore, replacing m by n is a smaller cost than by q
- Requires weighted matrix as input
- Modify DP to handle weights

#### One-error correction

#### The problem

 1-error = insertion, deletion or substitution of one single character

Farragina → Ferragina (substitution)

Feragina → Ferragina (insertion)

Ferrragina → Ferragina (deletion)

- A string of length L over A chars  $\rightarrow$  #variants = L (A-1) + (L+1)A + L = A \* (2L+1)
- You could have many candidates
- You can still deploy keyb statistical information (w

Do we need to make the enumeration?

## A possible approach

at [cat], ca [cat], ct [cat]

Create two dictionaries: D1 = { strings } D2 = { strings of D1 with one deletion }  $D1 = \{cat, cast, cst, dag\}$  $D2 = {$ ■ ag [→ dag], da [dag], dg [dag], ■ ast  $[\rightarrow cast]$ , cas  $[\rightarrow cast]$ , cat  $[\rightarrow cast]$ , cst  $[\rightarrow cast]$ cs [cst], ct [cst], st [cst]}

Assume a fast string-check in a dictionary

### An example

```
D1 = {cat, cast, cst, dag}
D2 = { ag [dag], ast [cast], at [cat], ca [cat],
cas [cast], cat [cast], cs [cst], cst [cast], ct [cat; cst],
da [dag], dg [dag], st [cst] }
```

#### •Query(«cat»):

- Perfect match: Search(P) in D1, 1 query [→ cat]
- P 1-char less: Search(P) in D2, 1 query [→ cat [cast]]
- P 1-char more: Search(P -1 char) in D1, p queries [search for {at, ct, ca} in D1 → No match]
- Substitution: Search(P -1 char) in D2, p queries [e.g. {at,ct, ca} in D2 → at [cat], ct [cst], ca [cat]]

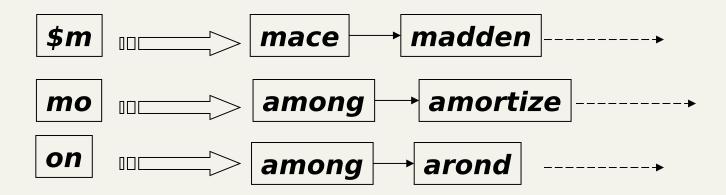
### A possible approach

- Query(P):
  - Perfect match: Search for P in D1, 1 query
  - P 1-char less: Search for P in D2 , 1 query
  - P 1-char more: Search for P -1 char in D1 , p queries
  - Substitution: Search for P -1 char in D2 , p queries
- We need 2p + 2 hash computations for P
  - Pro: CPU efficient, no cache misses for computing P's hashes; but O(p) cache misses to search in D1 and D2
  - Cons: Large space because of the many strings in D2 which must be stored to search in the hash table of D2, unless we avoid collision (perfect hash)
  - FALSE MATCHES: ctw matches cat and cst as SUBST.

# Overlap vs Edit distances

## K-gram index (useful for >1 errors)

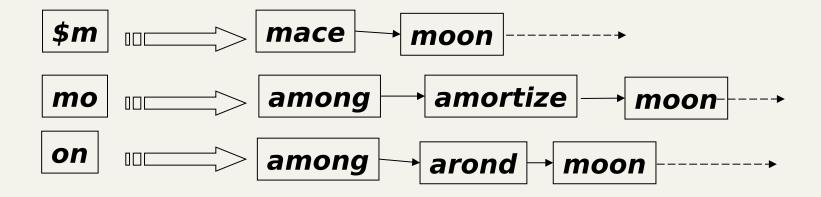
The k-gram index contains for every k-gram (here k=2) all terms including that k-gram.



Append k-1 symbol \$ at the front of each string, in order to generate a number L of k-grams for a string of length L.

### **Overlap Distance**

Enumerate all 2-grams in Q = mon (\$m, mo, on)



Use the 2-gram index to rank all lexicon terms according to the <u>number of matching</u> 2-grams (moon)

#### Overlap Distance *versus* Edit Distance

Select terms by **threshold on matching** *k*-grams

- If the term is L chars long (it consists of L k-grams)
- If E is the number of allowed errors (E\*k of the k-grams of Q might be different from term's ones because of the E errors)
- So at least L E\*k of the k-grams in Q must match a dictionary term to be a candidate answer

```
Necessary but not sufficient condition !! T=\$mom, Q=\$omo, L-E*k=3-1*2=1, T\cap Q=\{mo,om\} but EditDist = 2
```

# Example with trigrams (K=3)

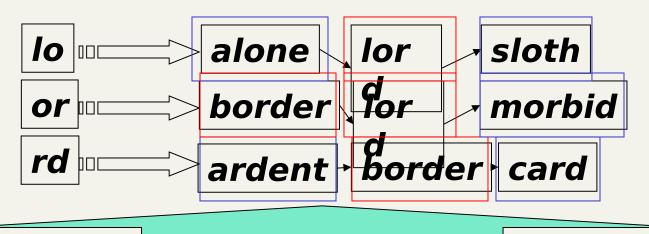
- Suppose the term to compare is \$\$november
  - Trigrams are \$\$n, \$no, nov, ove, vem, emb, mbe, ber

- The query Q = \$\$december
  - Trigrams are \$\$d, \$de, dec, ece, cem, emb, mbe, ber

- |Q|=8, K=3, if E=1  $\rightarrow$  L E\*k = 8 1\*3 = 5 NO!
- |Q|=8, K=3, if E=2  $\rightarrow$  L E\*k = 8 2\*3 = 2 Post Priter is needed to check that the distance >

# Fast searching for k-grams

Assume we wish to match the following bigrams (*lo, or, rd*) against a 2-gram index built over a dictionary of terms.



Standard postings "merge" will enumerate terms with their cardinality

Then choose terms if #occ possibly filter out < L - k\*E

# Context-sensitive spell correction

Text: I flew from Heathrow to Narita.

Consider the phrase query "flew form Heathrow"

•We'd like to respond
Did you mean "flew from Heathrow"?

because no docs matched the query phrase.

### General issues in spell correction

- We enumerate multiple alternatives and then need to figure out which to present to the user for "Did you mean?"
- Use heuristics
  - The alternative hitting most docs
  - Query log analysis + tweaking
    - For especially popular, topical queries
- Spell-correction is computationally expensive
  - Run only on queries that matched few docs

# Other sophisticated queries

# Wild-card queries: \*

- mon\*: find all docs containing words beginning with "mon".
  - Use a Prefix-search data structure
- \*mon: find words ending in "mon"
  - Maintain a prefix-search data structure for reverse terms.

How can we solve the wild-card query **pro\*cent**?

#### What about \* in the middle?

#### co\*tion

We could look up **co**\* AND \***tion** and intersect the two lists (expensive)

- se\*ate AND fil\*er
  This may result in many Boolean ANDs.
- The solution: transform wild-card queries so that the \*'s occur at the end
- This gives rise to the **Permuterm** Index.

#### Permuterm index

- For term *hello*, index under:
  - hello\$, ello\$h, llo\$he, lo\$hel, o\$hell, \$hello
  - where \$ is a special symbol.
- Queries:
  - X lookup on X\$
  - X\* lookup on \$X\*
  - \*X lookup on X\$\*
  - \*X\* lookup on X\*
  - X\*Y lookup on Y\$X\*
  - **X\*Y\*Z** ??? Exercise!

# Permuterm query processing

- Rotate query wild-card to the right
  - P\*Q → Q\$P\*
- Now use prefix-search data structure
- Permuterm problem: ≈ 4x lexicon size

Empirical observation for English.

## Soundex

#### Soundex

- Class of heuristics to expand a query into phonetic equivalents
  - Language specific mainly for names
  - E.g., chebyshev → tchebycheff
- Invented for the U.S. census in 1918

# Soundex - typical algorithm

- Turn every token to be indexed into a reduced form consisting of 4 chars
- Do the same with query terms
- Build and search an index on the reduced forms

# Soundex - typical algorithm

- 1. Retain the first letter of the word.
  - Herman → H...
- 2. Change all occurrences of the following letters to '0' (zero): 'A', E', 'I', 'O', 'U', 'H', 'W', 'Y'.
  - Herman → H0rm0n
- 3. Change letters to digits as follows:
  - B, F, P, V → 1
  - C, G, J, K, Q, S, X, Z → 2
  - D,T → 3
  - L → 4
  - M, N → 5
  - R → 6

**H0rm0n** → H06505

#### Soundex contd

- 4. Remove all pairs of consecutive equal digits. H06505 → H06505
- 5. Remove all zeros from the resulting string. H06505 → H655
- 6. Pad the resulting string with trailing zeros and return the first four positions, which will be of the form <uppercase letter> <digit> <digit>.

E.g., *Hermann* also becomes H655.

#### Soundex

- Soundex is the classic algorithm, provided by most databases (Oracle, Microsoft, ...)
- Not very useful for information retrieval
- Okay for "high recall" tasks (e.g., Interpol), though biased to names of certain nationalities
- Other algorithms for phonetic matching perform much better in the context of IR

#### Conclusion

- We have
  - Positional inverted index (with skip pointers)
  - Wild-card index
  - Spell-correction
  - Soundex
- We could solve queries such as

(SPELL(moriset) AND toron\*to) OR SOUNDEX(chaikofski)