



**BITS Pilani**  
K K Birla Goa Campus



# M3. Dictionaries and Tolerant Retrieval

Information Retrieval

# Outline

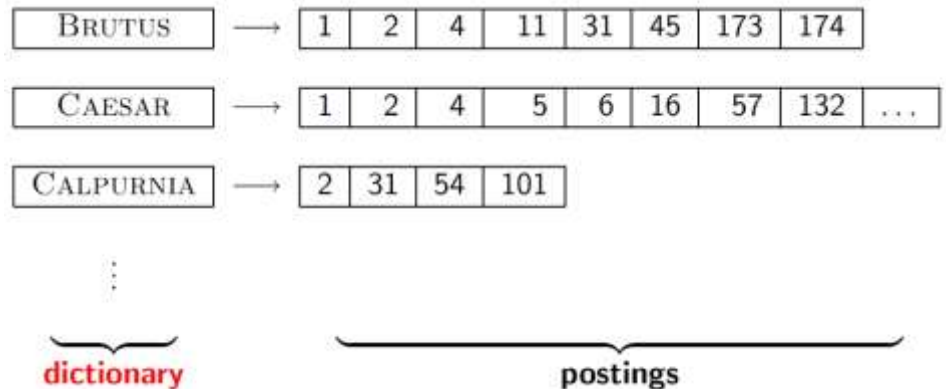


- Dictionary data structures
- “Tolerant” retrieval
  - Wild-card queries
  - Soundex
  - Spelling correction

# 1. Dictionary Data Structure

- **Vocabulary:** set of terms that are stored in the dictionary
- **Dictionary:** actual implementation of vocabulary
- The dictionary data structure stores:
  - term vocabulary
  - document frequency
  - pointers to each postings list

**Key Question: in what data structure?**



# A naïve approach

- An array of struct:

An array of lexicographically sorted terms, integer document frequency, and pointer to posting list

term	document frequency	pointer to postings list
a	656,265	→
aachen	65	→
...	...	...
zulu	221	→

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

# Dictionary Data Structure



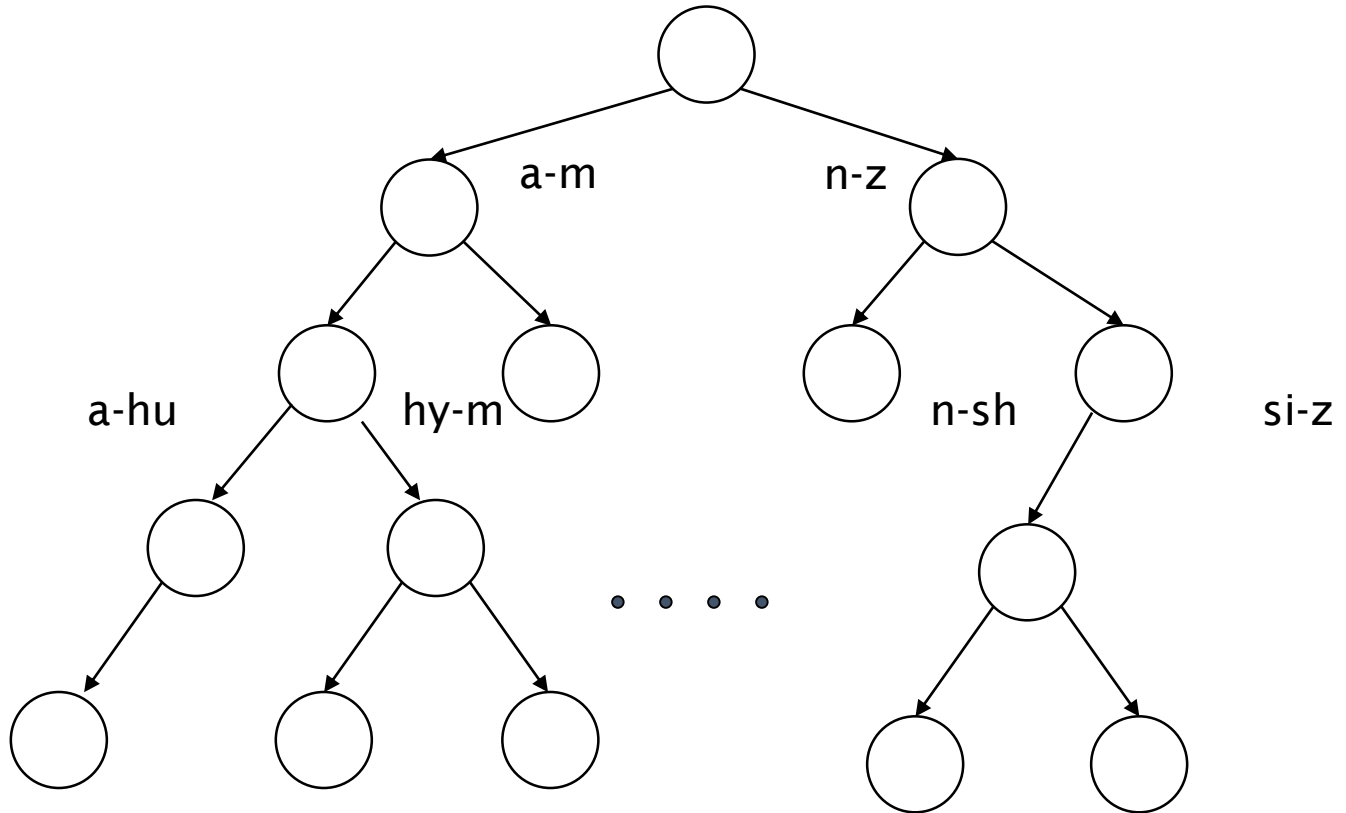
- Two main choices:
  - Hashtables
  - Search Trees
- Both techniques are in use.

# 1.1 Hashtables



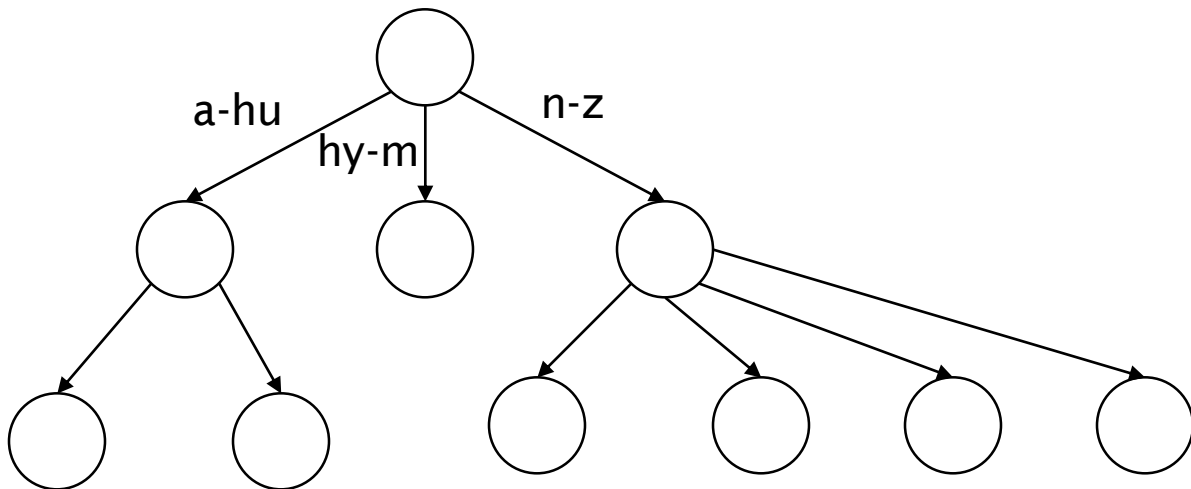
- Each vocabulary term is hashed to an integer
- Pros:
  - Lookup is faster than for a tree
  - $O(1)$
- Cons:
  - No easy way to find minor variants:
    - judgment/judgement
  - No prefix search [tolerant retrieval]
  - If vocabulary keeps growing, need to occasionally do the expensive operation of rehashing *everything*

# 1.2 Trees: BST



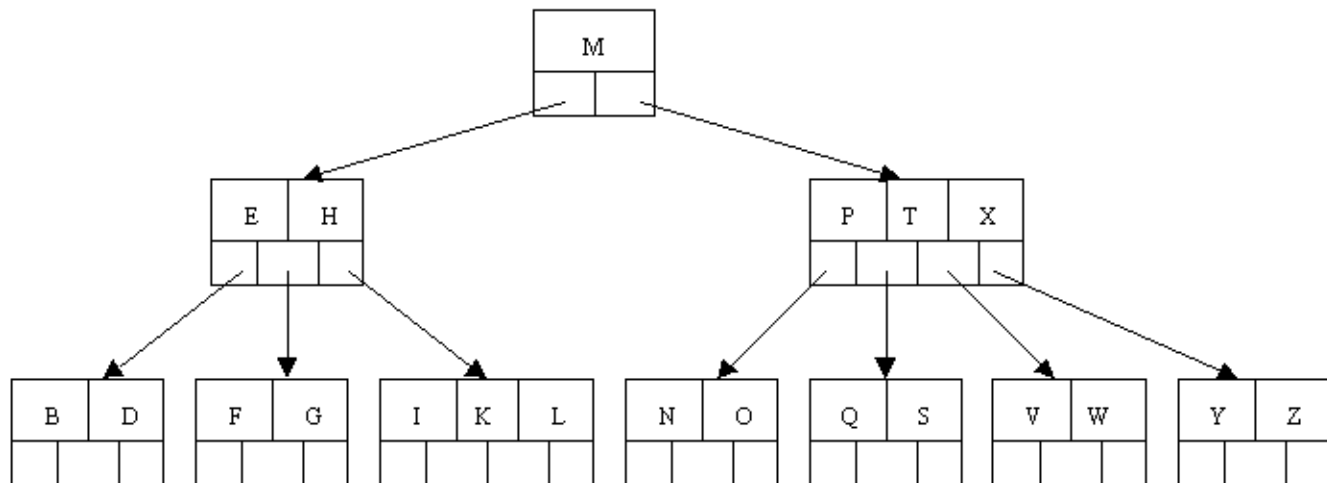
# 1.2 Trees: B-Tree

- Definition: Every internal node has a number of children in the interval  $[a, b]$  where  $a, b$  are appropriate natural numbers, e.g.,  $[2, 4]$ .
- Need of balanced tree than just Binary tree





# Example



# Trees



- Simplest: binary tree
- More usual: B-trees
- Pros:
  - Solves the prefix problem (terms starting with *hyp*)
- Cons:
  - Slower:  $O(\log M)$  [and this requires *balanced* tree]
  - Rebalancing binary trees is expensive
    - But B-trees mitigate the rebalancing problem

## 2. Wildcard Queries



# Wildcard query

---

- Returns documents that contain terms matching a wildcard pattern.
- A wildcard operator is a placeholder that matches one or more characters.
- For example, the \* wildcard operator matches zero or more characters.
- You can combine wildcard operators with other characters to create a wildcard pattern.
- Example: **mon\***: find all docs containing any word beginning with “mon”.
- Easy with binary tree (or B-tree) lexicon: retrieve all words in range: **mon ≤ w < moo**
- **\*mon**: find words ending in “mon”: harder
  - Maintain an additional B-tree for terms *backwards*.  
Can retrieve all words in range: **nom ≤ w < non**.

# Query Processing

---

- At this point, we have an enumeration of all terms in the dictionary that match the wild-card query.
- We still have to look up the postings for each enumerated term.
- E.g., consider the query:

***se\*ate AND fil\*er***

This may result in the execution of many Boolean *AND* queries.

# Wildcard operator in the middle of the query term

---

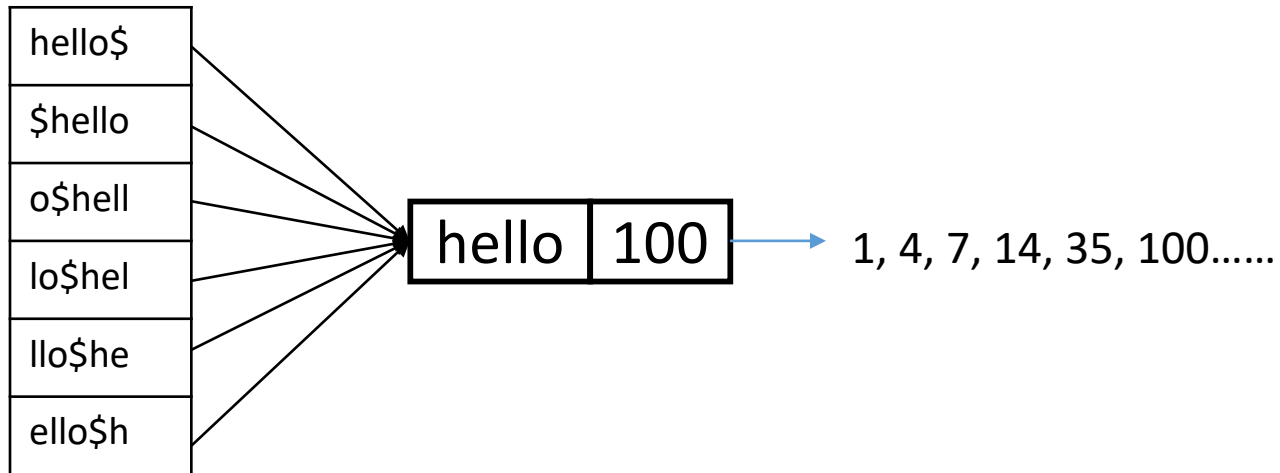
- How can we handle \* in the middle of query term?
- co\*tion
- We could look up co\* AND \*tion in a B-tree and intersect the two term sets
- Expensive
- The solution: transform wild-card queries so that the \* occur at the end
- This gives rise to the **Permuterm** Index and **k-gram** index.

# 2.1 Permuterm Index

---

- Every term that goes into standard inverted index
- Create rotations (permutations) of that term
- For term ***hello***, index under:
  - ***hello\$, ello\$h, llo\$he, lo\$hel, o\$hell, \$hello***  
where \$ is a special symbol- represents the end of the term
- Queries:
  - **X** lookup on **X\$**
  - **\*X** lookup on **X\$\***
  - **X\*Y** lookup on **Y\$X\***
  - **X\*** lookup on **\$X\***
  - **\*X\*** lookup on **X\***
  - **X\*Y\*Z** ??? Exercise!

# Permuterm Index



Examples:

Simple: hel\*

Complex: tr\*di\*on



# Multiple \* Symbols ( $X*Y*Z$ )

---

- In this case we first enumerate the terms in the dictionary that are in the permuterm index of  $Z\$X*$ .
- Not all such dictionary terms will have the string  $Y$  in the middle
  - we filter these out by exhaustive enumeration, checking each candidate to see if it contains  $Y$ .
  - For a query:  $tr*di*on$ , the term “tradition” would survive this filtering but “transportation” or “transformation” would not.
  - We then run the surviving terms through the standard inverted index for document retrieval.
- One disadvantage of the permuterm index is that its dictionary becomes quite large, including as it does all rotations of each term.

## 2.2 K-gram index

---

- Enumerate all  $k$ -grams (sequence of  $k$  chars) occurring in any term
- *e.g.*, from text “*Information Retrieval*” we get the following 2-grams (*bigrams*):

\$I, In, nf, fo, or, rm, ma, at, ti, io, on,  
n\$, \$R, Re, et, tr, ri, ie, ev, va, al, I\$

- \$ is a special word boundary symbol

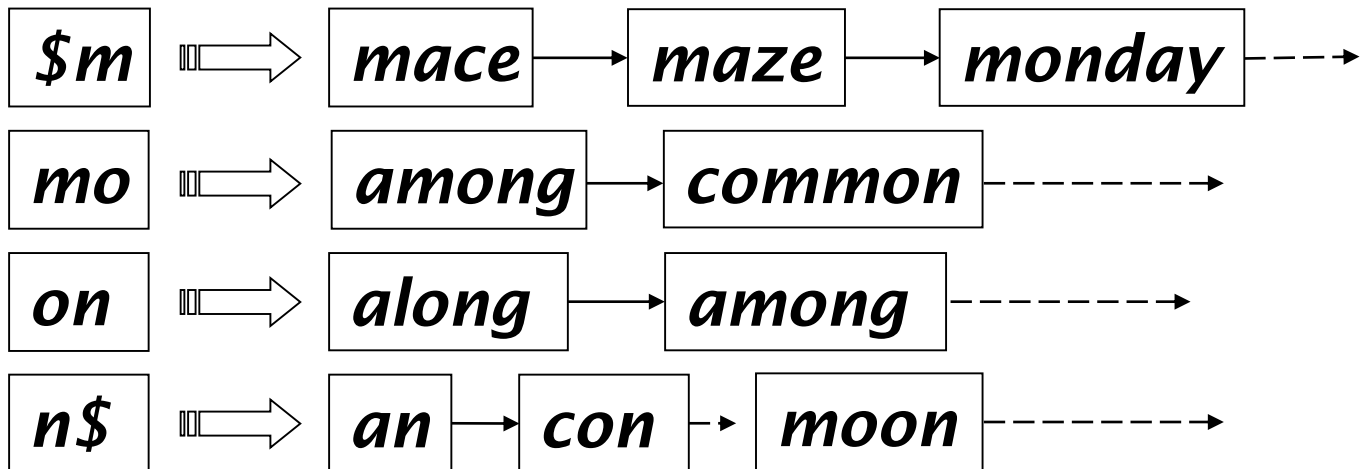
# K-gram index

---

- **Dictionary:** all possible k-grams generated from the terms (terms present in the corpus or the std. inverted index dictionary)
- **Posting lists:** all the terms containing that bigram
  - Always sorted in lexicographical order, similar to posting lists of inverted index: sorted in the ascending order of Doc IDs
- **Example:** for bi-gram “tr”, posting list will have the terms like
- **Retrieval, transform, construct, abstract, contrast.....**

# Example

- The  $k$ -gram index finds *terms* based on a query consisting of  $k$ -grams (here  $k=2$ ).



# Procedure

---

- Transform the query into k-grams (here  $k=2$ )
- Find the terms consisting of those k-grams from k-gram index
- Do an AND of all the terms found in k-gram index
- Surviving enumerated terms are then looked up in the term-document inverted index.
- **Possibility of false alarms?**
  - Reverse of the AND query to the original wild query might not be true.
- **complex than standard inverted index but efficient than permuterm**

# Examples

---

- Query **mon\*** can now be run as
  - **\$m AND mo AND on**
    - *All the terms starting with **m** AND containing **mo** AND containing **on***
  - However, all the terms after boolean AND don't have the same wildcard query pattern **mon\***
- Query **apr\***
  - **\$a AND ap AND pr**
  - Terms like **appreciate** doesn't have wildcard query pattern **apr\***

# Processing wildcard queries



- Wildcard queries are expensive
- Computational IR systems need to a lot more work than expected
- Most of the search engines hide wildcard query facility
  - Early search engines- “type wildcard queries only if needed”
  - Nowadays, hidden in form of advanced search
  - Also a constrained form of wildcard query.

# 3. Soundex





# Soundex

---

- Soundex algorithm allows you to find all the documents that contain **terms phonetically matching the query**
- Class of heuristics to expand a query into **phonetic** equivalents
  - Language specific – mainly for proper nouns (names)
  - E.g., ***chebyshev*** → ***tchebycheff***
- Invented for the U.S. census ... in 1918
  - Proposed as a way to keep a track of names of immigrants
    - Same name is spelled differently in Russian or English

# Soundex

---

- Used in linguistic model phase of inverted index construction
- Maps all terms that sound similar to the same equivalence class
- 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
  - (when the query calls for a soundex match)
- <http://www.creativyst.com/Doc/Articles/SoundEx1/SoundEx1.htm#Top>

# Typical Algorithms

1. Retain the first letter of the word.
2. Change all occurrences of the following letters to '0' (zero):
  - A', E', 'I', 'O', 'U', 'H', 'W', 'Y'. → **Consonants that sound like vowel**
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

**Consonants that sound similar**
4. Remove all pairs of consecutive digits.
5. Remove all 0s from the resulting string.
6. Pad the resulting string with trailing 0s and return the first four positions

Examples:  
Robert and Rupert  
Beijing and Peking  
Smith and Smythe

# Soundex



- Soundex is the classic algorithm, provided by not only IR systems but also by most databases (Oracle, Microsoft, ...)
- How useful is soundex?
  - Not very – for information retrieval (poor precision)
  - Okay for “high recall” tasks (e.g., Interpol), though biased to names of certain nationalities
    - E.g., different variants of names
- Zobel and Dart (1996) show that other algorithms for phonetic matching perform much better in the context of IR

# 4. Spelling Correction



# Spell Correction



- Two principal uses
  - Correcting user queries to retrieve “right” answers
    - Queries that are misspelled
    - You might not get correct results if the queries are spelled wrongly
  - Correcting document(s) being indexed
    - If the documents contain spelling mistakes, then queries on the right spelling might not retrieve those documents with error
- ^ Basic motivation of correcting spell errors in both query as well as the documents

# Two main flavors



- Isolated word
  - Check each word on its own for misspelling
  - Individual check without keeping in mind what is the context of the query
  - Will not catch **typos** resulting in correctly spelled words
  - e.g., from → form
- Context-sensitive
  - Look at surrounding words
  - Spelling correction is not sufficient to check but the words should also match the correct grammatical context
  - e.g., I flew form Delhi to Goa.
  - ^able to detect in context-sensitive method while in isolated method “form” is a meaningful word

# Query misspellings

---

- Our principal focus here
  - E.g., the query **Chrstopher Maning** instead of **Christopher Manning**
  - [click](#)
  - Before you build your spell corrector, decide which type of interface you want to provide to the user
  - We can either
    - Retrieve documents indexed by the correct spelling, OR
    - Return several suggested alternative queries with the correct spelling
      - *Did you mean ... ?*



# 4.1 Isolated word correction

---

**1. Fundamental premise** – there is a lexicon from which the correct spellings come

- Two basic choices for this
  - **A standard lexicon**
    - Oxford or Webster's English Dictionary
    - An “industry-specific” lexicon – hand-maintained (reference dictionary)
      - Healthcare, Chemistry, Law, Shopping
  - The **lexicon of the indexed corpus**
    - E.g., all words on the web
    - All names, acronyms etc. (Including the misspellings)
    - How many times a word appears in the corpus (typos will have less collection frequency **relatively rare**)

# Isolated word correction



## 2. There is a way to calculate the distance between any two words

- Given a lexicon and a character sequence  $Q$ , return the words in the lexicon closest to  $Q$
- What's "closest"? **(based on the distance)**
- We'll study several alternatives
  - Edit distance (Levenshtein distance)
  - Weighted edit distance
  - $n$ -gram overlap

# 4.1.1 Edit Distance

- **Definition:** 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.**
- There can be multiple ways to convert  $S_1$  to  $S_2$ 
  - Delete all characters of  $S_1$  and insert all characters of  $S_2$  one by one.
  - **Correct approach? (minimum #operations)**
  - From *cat* to *act* is 2
  - from *cat* to *dog* is 3.
- Generally found by dynamic programming (Insert, Delete, Replace)
  - Some variations have **Transposition (swapping of two adjacent characters)**
  - **QWERTY typos**

CAT and ACT have an edit distance of 1 with transpose

# Dynamic Programming Algorithm

LEVENSHTEINDISTANCE( $s_1, s_2$ )

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

Operations: insert (cost 1), delete (cost 1), replace (cost 1), copy (cost 0)

# Example

- S1= Hello, S2= Yellow

	Φ	Y	E	L	L	O	W
Φ	0	1	2	3	4	5	6
H	1	1	2	3	4	5	6
E	2	2	1	2	3	4	5
L	3	3	2	1	2	3	4
L	4	4	3	2	1	2	3
O	5	5	4	3	2	1	2

## 4.1.2 Weighted Edit Distance

---

- As above, but the weight depends on
  - Which operation it is
  - the character(s) involved
    - Meant to capture OCR or keyboard errors
      - Example: *m* more likely to be mis-typed as *n* than as *q*
    - Therefore, replacing *m* by *n* is a smaller edit distance than by *q*
    - This may be formulated as a probability model
  - Requires weight (or cost) matrix as input
  - Modify dynamic programming to handle weights
    - What changes???

## 4.1.3 N-gram Overlap

---

- Enumerate all the  $n$ -grams in the query string as well as in the lexicon
- Use the  $n$ -gram index (recall wild-card search) to retrieve all lexicon terms matching any of the query  $n$ -grams
- Threshold by number of matching  $n$ -grams
  - Variants – weight by keyboard layout, etc.

# Example with Trigram

---

- Suppose the text is ***november***
  - Trigrams are *nov, ove, vem, emb, mbe, ber*.
- The query is ***december***
  - Trigrams are *dec, ece, cem, emb, mbe, ber*.
- So 3 trigrams overlap (of 6 in each term)
- How can we turn this into a normalized measure of overlap?



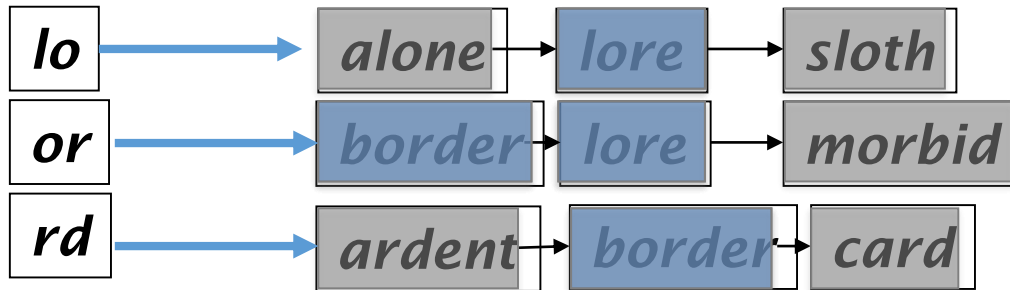
# One Option- Jaccard Coefficient



- A commonly-used measure of overlap
- Let  $X$  and  $Y$  be two sets; then the J.C. is
$$\frac{|X \cap Y|}{|X \cup Y|}$$
- Equals 1 when  $X$  and  $Y$  have the same elements and zero when they are disjoint
- $X$  and  $Y$  don't have to be of the same size
- Always assigns a number between 0 and 1
  - Now threshold to decide if you have a match
  - E.g., if J.C.  $> 0.8$ , declare a match

# Matching Trigrams

- Consider the query **lord** – we wish to identify words matching 2 of its 3 bigrams (**lo**, **or**, **rd**)



Standard postings “merge” will enumerate ...

Adapt this to using Jaccard (or another) measure.

## 4.2 Context Sensitive Spell Correction

---

- Every word is correct in isolated word form but not in the context
- Google, MS Office (after 2007, one of their new features)

- 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 (or very few) documents matched the query phrase.

# Context Sensitive Spell Correction



- Need surrounding context to catch this.
- First idea: retrieve dictionary terms close (in weighted edit distance) to each query term
- Now try all possible resulting phrases with one word “fixed” at a time
  - *flew from heathrow*
  - *fled form heathrow*
  - *flea form heathrow*

# Context Sensitive Spell Correction



- **Hit-based spelling correction:** Suggest the alternative that has lots of hits.
  - Collection frequency in document corpus
  - Query log (more suitable approach)
  - Why?
- Variants:
  - Any word can have error
  - Assume only one word has to be corrected
- Empirical Analysis for spell correction
  - Depends on the accuracy of assumption

# What queries can we process?

---

- We have
  - Positional inverted index
  - Wildcard index (n-gram, reverse b-tree, permuterm)
  - Spell correction
  - Soundex
- Queries such as
  - (SPELL(moriset) /3 toron\*to) OR SOUNDEX (chaikofski)