Outline

- Documents
- Terms
  - General + Non-English
  - English
- Skip pointers
- Phrase queries

Phrase queries

- We want to answer a query such as [stanford university] – as a phrase.
- Thus *The inventor Stanford Ovshinsky never went to university* should not be a match.
- The concept of phrase query has proven easily understood by users.
- About 10% of web queries are phrase queries.
- Consequence for inverted index: it no longer suffices to store docIDs in postings lists.
- Two ways of extending the inverted index:
  - biword index
  - positional index

Biword indexes

- Index every consecutive pair of terms in the text as a phrase.
- For example, "*Friends, Romans, Countrymen*" would generate two biwords: "*friends romans*" and "*romans countrymen*"
- Each of these biwords is now a vocabulary term.
- Two-word phrases can now easily be answered.

Longer phrase queries

- A long phrase like "*stanford university palo alto*" can be represented as the Boolean query "STANFORD UNIVERSITY" AND "UNIVERSITY PALO" AND "PALO ALTO"
- We need to do post-filtering of hits to identify subset that actually contains the 4-word phrase.

Extended biwords

- Parse each document and perform part-of-speech tagging
- Classify the terms into (say) nouns (N) and articles/prepositions (X), and others…
- Now deem any string of terms of the form NX*N to be an *extended biword* (actually a *proper noun*)
- Examples: **catcher in the rye**

  N X X N

  king of Denmark

  N X N
- Include extended biwords in the term vocabulary
- Queries are processed accordingly

Issues with biword indexes

- Why are biword indexes rarely used?
- False positives, as noted above
- Index **blowup** due to very large term vocabulary

Positional indexes

- Positional indexes are a more efficient alternative to biword indexes.
- Postings lists in a nonpositional index: each posting is just a docID
- Postings lists in a positional index: each posting is a docID and a list of positions

Positional indexes: Example

Query: *"to_1 be_2 or_3 not_4 to_5 be_6"*

TO, 993427:

‹ 1: ‹7, 18, 33, 72, 86, 231›;

2: ‹1, 17, 74, 222, 255›;

4: ‹8, 16, 190, 429, 433›;

5: ‹363, 367›;

7: ‹13, 23, 191›; . . . ›

BE, 178239:

‹ 1: ‹17, 25›;

4: ‹17, 191, 291, 430, 434›;

5: ‹14, 19, 101›; . . . ›

Document 4 is a match!

Quiz: Positional index

What is the time complexity of doing a phrasal query of length K on a positional index of D documents with max document length of L, and a dictionary of size V?

Proximity search

- We just saw how to use a positional index for phrase searches.
- We can also use it for proximity search.
- For example: employment /4 place
- Find all documents that contain EMPLOYMENT and PLACE within 4 words of each other.
- *Employment agencies that place healthcare workers are seeing growth* is a hit.
- *Employment agencies that have learned to adapt now place healthcare workers* is not a hit.

Proximity search

- Use the positional index
- Simplest algorithm: look at cross-product of positions of (i) EMPLOYMENT in document and (ii) PLACE in document
- Very inefficient for frequent words, especially stop words
- Note that we want to return the actual matching positions, not just a list of documents.
- This is important for dynamic summaries etc.

"Proximity" intersection

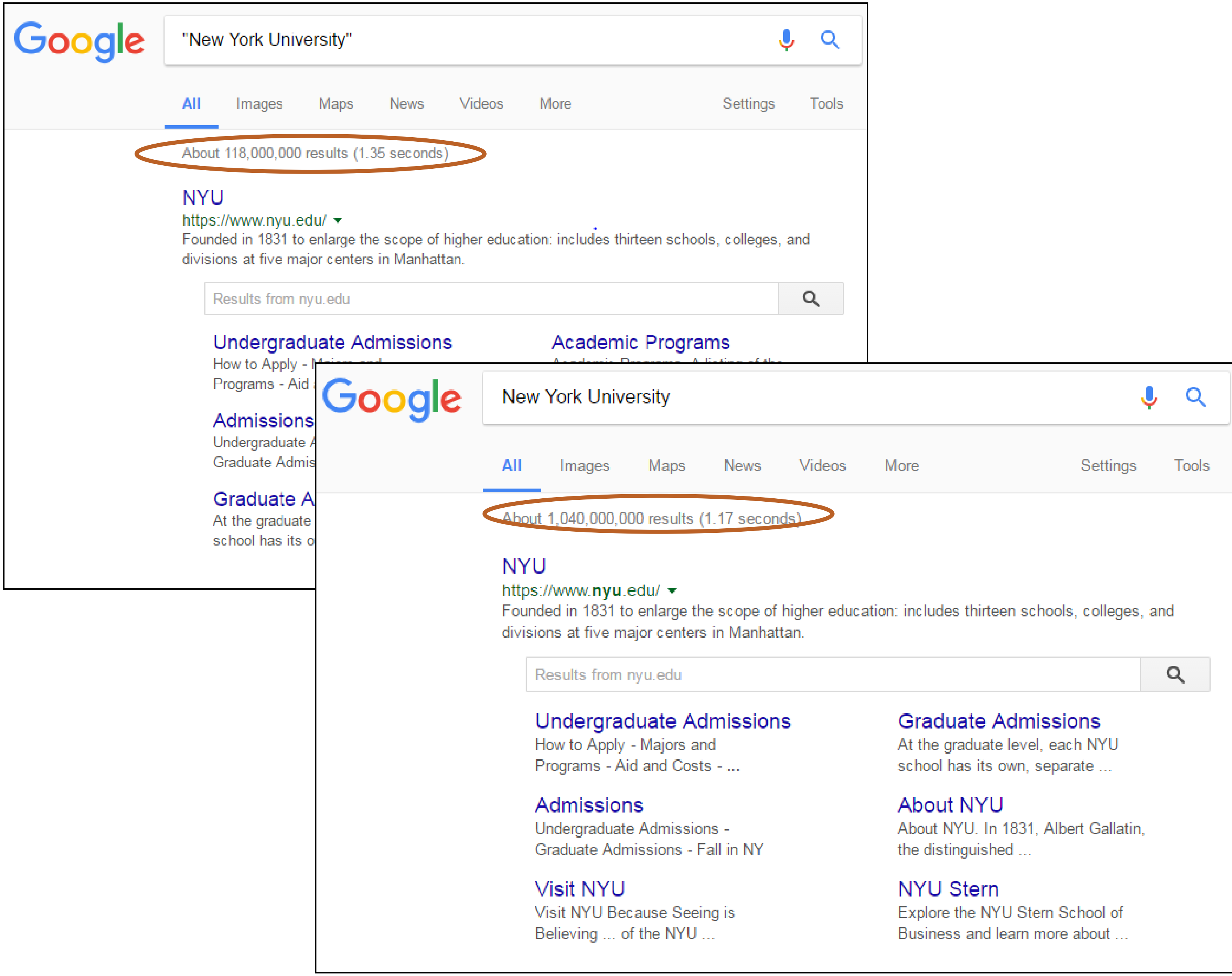
```
PositionalIntersect(p1, p2, k)
answer ← ⟨ ⟩
while p1 ≠ NIL and p2 ≠ NIL
do if docID(p1) = docID(p2)
     then l ← ⟨ ⟩
          pp1 ← positions(p1)
          pp2 ← positions(p2)
          while pp1 ≠ NIL
          do while pp2 ≠ NIL
               do if |pos(pp1) − pos(pp2)| ≤ k
                    then Add(l, pos(pp2))
                    else if pos(pp2) > pos(pp1)
                           then break
                  pp2 ← next(pp2)
               while l ≠ ⟨ ⟩ and |l[0] − pos(pp1)| > k
               do Delete(l[0])
               for each ps ∈ l
               do Add(answer, ⟨docID(p1), pos(pp1), ps⟩)
               pp1 ← next(pp1)
          p1 ← next(p1)
          p2 ← next(p2)
     else if docID(p1) < docID(p2)
            then p1 ← next(p1)
            else p2 ← next(p2)
return answer
```

Combination scheme

- Biword indexes and positional indexes can be profitably combined.
- Many biwords are extremely frequent: Michael Jackson, Britney Spears etc.
- For these biwords, increased speed compared to positional postings intersection is substantial.
- Combination scheme: Include frequent biwords as vocabulary terms in the index. Do all other phrases by positional intersection.
- Williams et al. (2004) evaluate a more sophisticated mixed indexing scheme. Faster than a positional index, at a cost of 26% more space for index.

“Positional” queries on Google

- For web search engines, positional queries are much more expensive than regular Boolean queries.
- Let’s look at some examples of phrase queries.
- Why are they more expensive than regular Boolean queries?
- Can you demonstrate on Google that phrase queries are more expensive than Boolean queries?


Google
"New York University"
All
Images
Maps
News
Videos
More
Settings
Tools
About 118,000,000 results (1.35 seconds)
NYU
https://www.nyu.edu/
Founded in 1831 to enlarge the scope of higher education: includes thirteen schools, colleges, and divisions at five major centers in Manhattan.
Results from nyu.edu
Undergraduate Admissions
Academic Programs
Google
New York University
All
Images
Maps
News
Videos
More
Settings
Tools
About 1,040,000,000 results (1.17 seconds)
NYU
https://www.nyu.edu/
Founded in 1831 to enlarge the scope of higher education: includes thirteen schools, colleges, and divisions at five major centers in Manhattan.
Results from nyu.edu
Undergraduate Admissions
How to Apply - Majors and Programs - Aid and Costs - ...
Graduate Admissions
At the graduate level, each NYU school has its own, separate ...
Admissions
Undergraduate Admissions - Graduate Admissions - Fall in NY
About NYU
About NYU. In 1831, Albert Gallatin, the distinguished ...
Visit NYU
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NYU Stern
Explore the NYU Stern School of Business and learn more about ...

Take-away

- Understanding of the basic unit of classical information retrieval systems: words and documents: What is a document, what is a term?
- Tokenization: how to get from raw text to words (or tokens)
- More complex indexes: skip pointers and phrases

Resources

- Chapter 1 and 2 of IIR
- Resources at https://tartarus.org/martin/PorterStemmer/
  - Porter stemmer

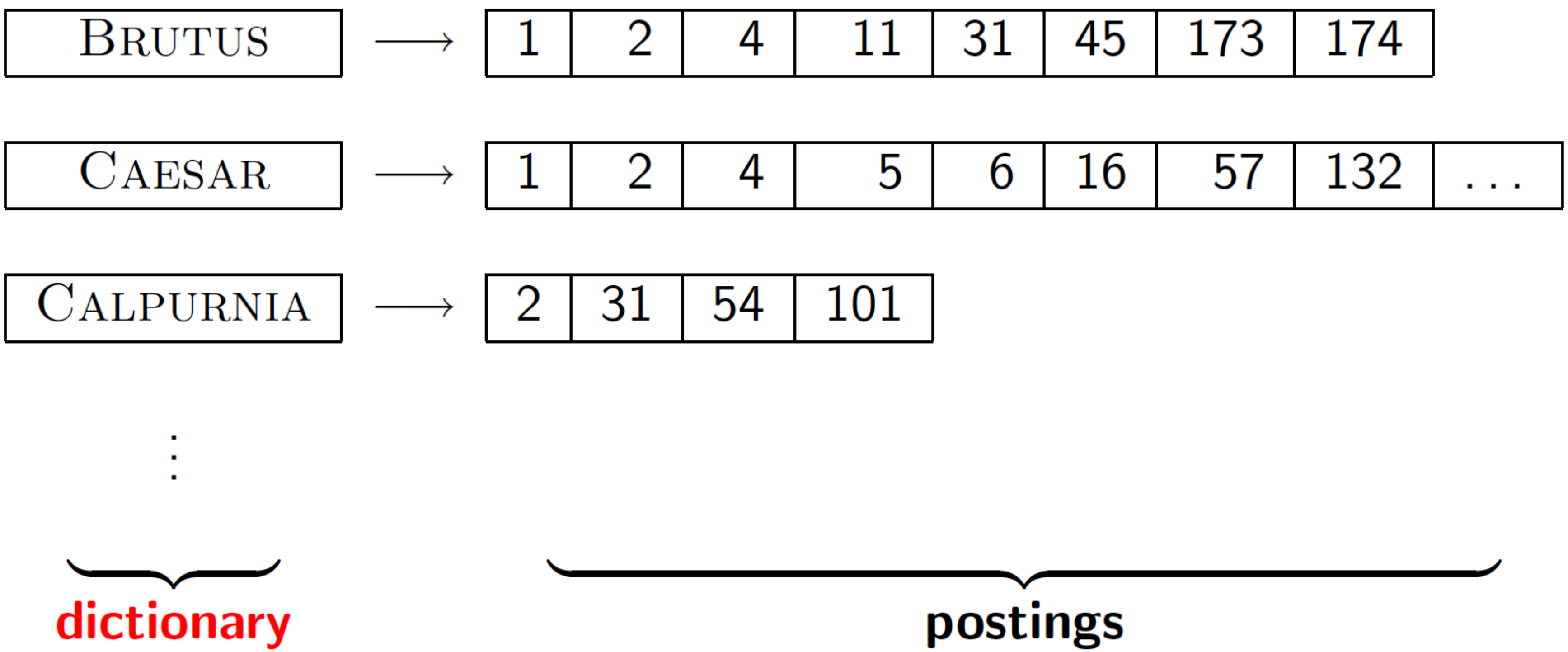
Dictionary & Tolerant Retrieval

This lecture

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

Dictionary data structures for inverted indexes

- The dictionary data structure stores the term vocabulary, document frequency, pointers to each postings list … in what data structure?



A NAÏVE DICTIONARY

- An array of struct:

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

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?

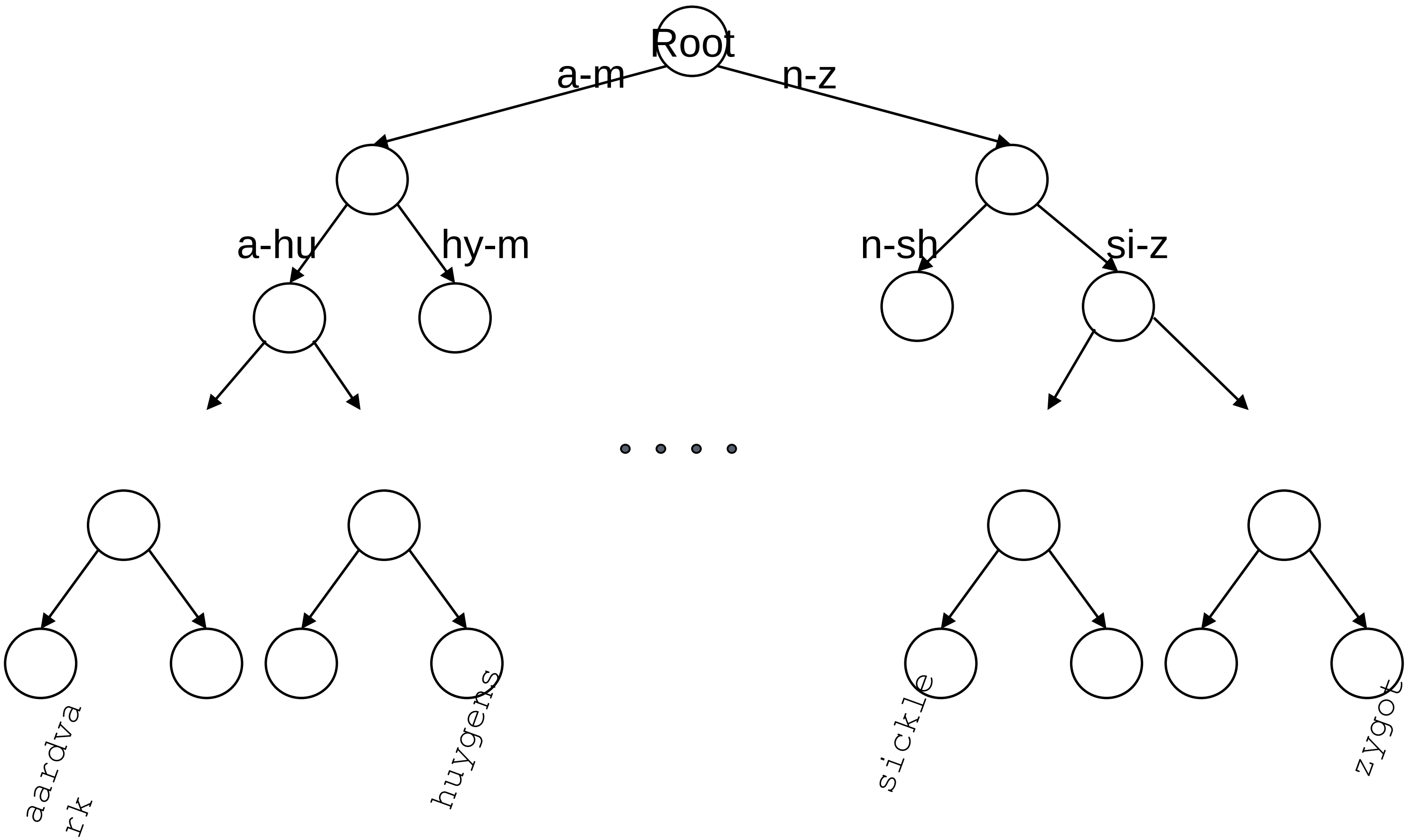
DICTIONARY DATA STRUCTURES

- Two main choices:
  - Hashtables
  - Trees
- Some IR systems use hashtables, some trees

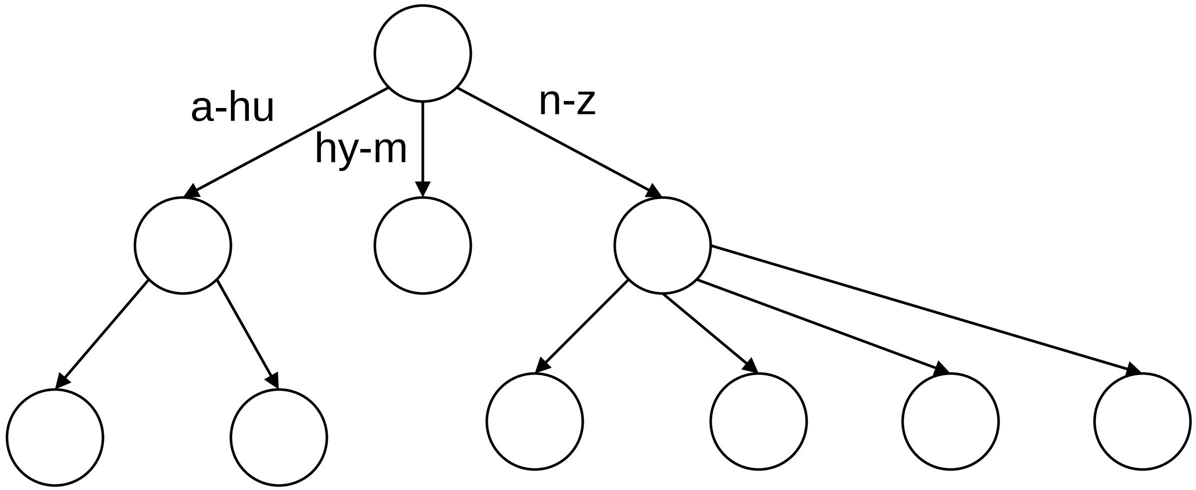
Hashtables

- Each vocabulary term is hashed to an integer
  - (We assume you've seen hashtables before)
- 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*
    - Due to bucket overflow!

TREE: BINARY TREE



TREE: 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].
- The range has to do with the size of a disk block or memory page, which stores one node

TREES

- Simplest: binary tree
- More usual: B-trees
- Trees require a standard ordering of characters and hence strings … but we typically have one
- 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

WILD-CARD QUERIES: *

- ***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***.

Quiz: Enumeration

From the last slide, how can we enumerate all terms satisfying the wild-card query

pro*nal ?

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.

B-TREES HANDLE *'S AT THE END OF A QUERY TERM

- How can we handle *'s 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 *'s occur at the end
- This gives rise to the **Permuterm** Index.

PERMUTERM INDEX

- For term ***hello***, index under:
  - ***hello$, ello$h, llohe, lohel, o$hell, $hello***

  where $ is a special symbol (end of a term).
- Queries:
  - **X** lookup on **X$**
  - **X*** lookup on $**X***
  - ***X** lookup on **X$***
  - ***X*** lookup on **X***
  - **X*Y** lookup on **Y$X***

Query = ***hel*o***
X=*hel*, Y=*o*
Lookup ***o$hel****

QUIZ: PERMUTERM

1. Using PermuTerm Index, how do we answer query “***tion***” ?

2. How do we answer query **X*Y*Z?**

Permuterm query processing

- Rotate query wild-card to the right
- Now use B-tree lookup as before.
- *Permuterm problem:* ≈ *quadruples lexicon size*

Empirical observation for English.

BIGRAM (*K*-GRAM) INDEXES

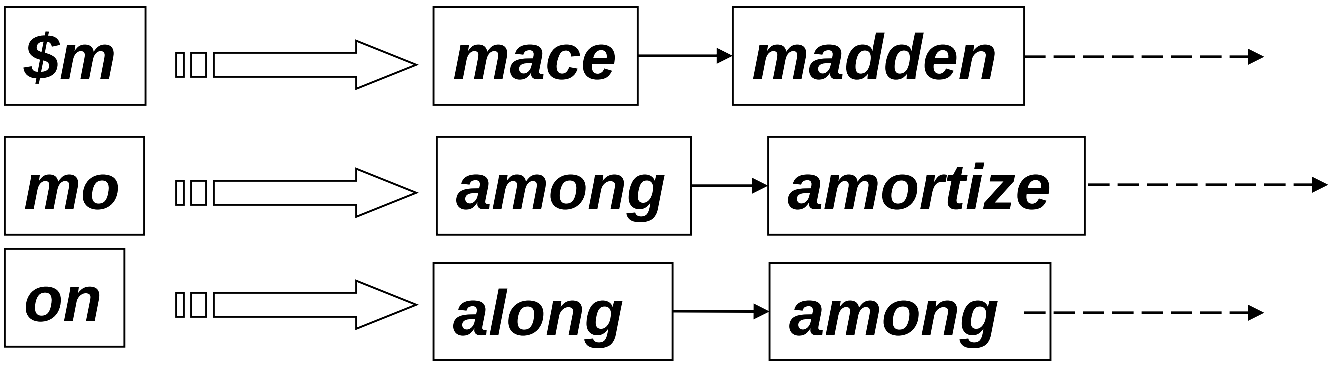
- Enumerate all *k*-grams (sequence of *k* chars) occurring in any term
- *e.g.*, from text "***April is the cruelest month***" we get the 2-grams (*bigrams*)

  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 a <u>*second*</u> inverted index <u>*from bigrams to dictionary terms*</u> that match each bigram.

Bigram index example

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

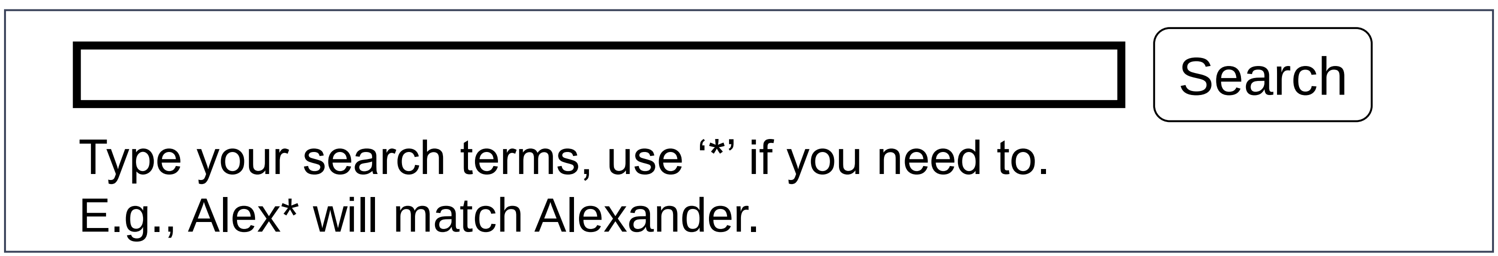


PROCESSING WILD-CARDS

- Query ***mon**** can now be run as
  - ***$m** AND **mo** AND **on***
- Gets terms that match and AND them.
- But we'd enumerate ***moon***.
- Must post-filter these terms against query.
- Surviving enumerated terms are then looked up in the term-document inverted index.
- Fast, space efficient (compared to permuterm).

PROCESSING WILD-CARD QUERIES

- As before, we must execute a Boolean query for each enumerated, filtered term.
- Wild-cards can result in expensive query execution (very large disjunctions…)
  - pyth* AND prog*
- If you encourage "laziness" people will respond!



- Which web search engines allow wildcard queries?

Spell correction

- Two principal uses
  - Correcting document(s) being indexed
  - Correcting user queries to retrieve "right" answers
- Two main flavors:
  - Isolated word
    - Check each word on its own for misspelling
    - Will not catch typos resulting in correctly spelled words
    - e.g., ***from*** $\rightarrow$ ***form***
  - Context-sensitive
    - Look at surrounding words,
    - e.g., ***I flew <u>form</u> Heathrow to Narita.***

Document correction

- Especially needed for OCR'ed documents
  - Correction algorithms are tuned for this: rn vs. m
  - Can use domain-specific knowledge
    - E.g., OCR can confuse O and D more often than it would confuse O and I (adjacent on the QWERTY keyboard, so more likely interchanged in typing).
- But also: web pages and even printed material have typos
- Goal: the dictionary contains fewer misspellings
- But often we don't change the documents and instead fix the query-document mapping

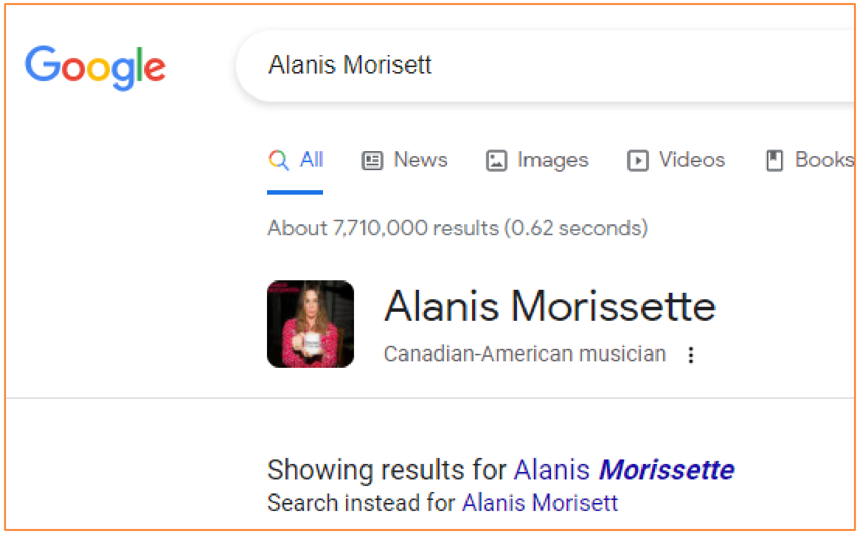
Quiz: Misspellings

- Suggest reasons for the following misspellings:

  - acwuire (acquire)
  - ornit (omit)

Query mis-spellings

- Our principal focus here
  - E.g., the query ***Alanis Morisett***
- We can either
  - Retrieve documents indexed by the correct spelling, OR
  - Return several suggested alternative queries with the correct spelling
    - *Did you mean … ?*



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)

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 alternatives
  - Edit distance (Levenshtein distance)
  - Weighted edit distance
  - *n*-gram overlap

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, (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.
- See http://www.let.rug.nl/kleiweg/lev/ for a nice example plus an applet.

Quiz: Edit distance

- Considering only insertion, deletion and replacement, what is the edit distance:

1) gap → apply

2) goat → toad

3) sonne → sony

Weighted edit distance

- As above, but the weight of an operation depends on 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 matrix as input
- Modify dynamic programming to handle weights

USING EDIT DISTANCES

- Given query, first 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
- Alternatively,
  - We can look up all possible corrections in our inverted index and return all docs … slow
  - We can run with a single most likely correction
- The second alternative disempowers the user, but saves a round of interaction with the user

EDIT DISTANCE TO ALL DICTIONARY TERMS?

- Given a (mis-spelled) query – do we compute its edit distance to every dictionary term?
  - Expensive and slow
  - Alternative?
    - generate everything up to edit distance k and then intersect.
    - Fine for distance 1; okay for distance 2.
- How do we cut the set of candidate dictionary terms?
- One possibility is to use *n*-gram overlap for this
- This can also be used by itself for spelling correction.

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 TRIGRAMS

- 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)
- The amount overlap indicates the similarity between query and the text
- How can we turn this into a normalized measure of overlap?

ONE OPTION – JACCARD COEFFICIENT

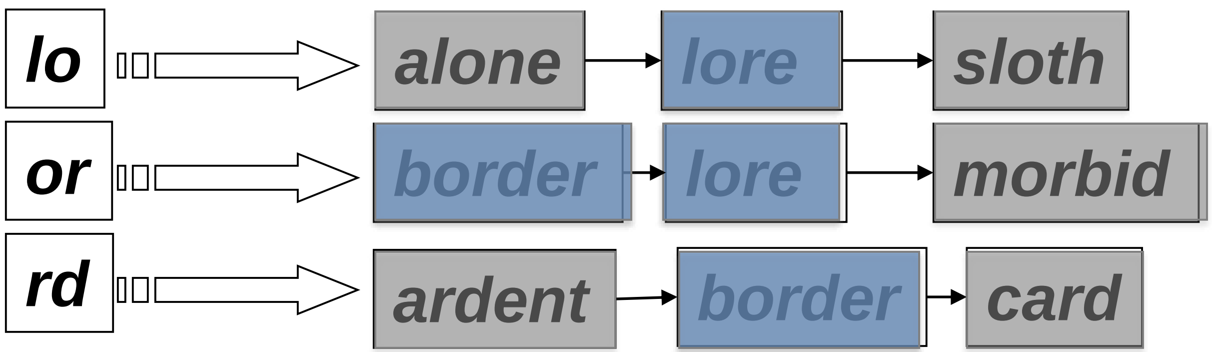
- A commonly-used measure of overlap
- Let X and Y be two sets; then the J.C. is

$$|X \cap Y| / |X \cup Y|$$

- 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.

Context-sensitive spell correction

- Text: ***I flew <u>from</u> Heathrow to Narita.***
- Consider the phrase query ***"flew <u>form</u> Heathrow"***
- We'd like to respond

Did you mean "***flew from Heathrow***"?

because no docs matched the query phrase.

Context-sensitive 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 “corrected” at a time
  - ***flew from heathrow***
  - ***fled form heathrow***
  - ***flea form heathrow***

- **Hit-based spelling correction:** Suggest the alternative that has lots of hits.

QUIZ: SPELL CORRECTION

- Suppose that for ***"flew <u>form</u> Heathrow"*** we have 7 alternatives for flew, 9 for form and 3 for heathrow.

  How many "corrected" phrases will we enumerate in this scheme?

Another approach

- Break phrase query into a conjunction of biwords (Previous lecture).
- Look for biwords that need only one term corrected.
- Enumerate only phrases containing "common" biwords.

General issues in spell correction

- We enumerate multiple alternatives for “Did you mean?”
- Need to figure out which to present to the user
  - The alternative hitting most docs
  - Query log analysis

- More generally, rank alternatives probabilistically

$$\text{argmax}_{corr}\ P(corr \mid query)$$

  - From Bayes rule, this is equivalent to

$$\text{argmax}_{corr}\ P(query \mid corr) * P(corr)$$

Noisy channel — Language model

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 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)

- Details can be found:

  http://www.creativyst.com/Doc/Articles/SoundEx1/SoundEx1.htm#Top

SOUNDEX – TYPICAL ALGORITHM

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

To be continued…

SOUNDEX (CONTINUED)

4. Retain the first digit if two identical digits are side-by-side
5. Remove all zeros from the resulting string.
6. Pad the resulting string with trailing zeros and return the first four positions, which will be of the form <uppercase letter> <digit> <digit> <digit>.

E.g., ***Herman*** → H06505 → H655.

Will ***hermann*** generate the same code?

Quiz: Soundex

- Which of the following is NOT true about soundex:

a) The first letter of the code is capitalized
b) There is no zero's in the code
c) There are exactly 4 letters in a code
d) All letter except for the first are numerical digits

SOUNDEX

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

What queries can we process?

- We have
  - Positional inverted index with skip pointers
  - Wild-card index
  - Spell-correction
  - Soundex
- Queries such as

(SPELL(moriset) /3 toron*to) OR *SOUNDEX* ***(chaikofski)***

Resources

- IIR 3, MG 4.2
- Efficient spell retrieval:
  - K. Kukich. Techniques for automatically correcting words in text. ACM Computing Surveys 24(4), Dec 1992.
  - J. Zobel and P. Dart. Finding approximate matches in large lexicons. Software - practice and experience 25(3), March 1995. http://citeseer.ist.psu.edu/zobel95finding.html
  - Mikael Tillenius: Efficient Generation and Ranking of Spelling Error Corrections. Master's thesis at Sweden's Royal Institute of Technology. http://citeseer.ist.psu.edu/179155.html
- **Nice, easy reading on spell correction:**
  - Peter Norvig: How to write a spelling corrector

  http://norvig.com/spell-correct.html