

# Information Storage and Retrieval

CSCE 670

Texas A&M University

Department of Computer Science & Engineering

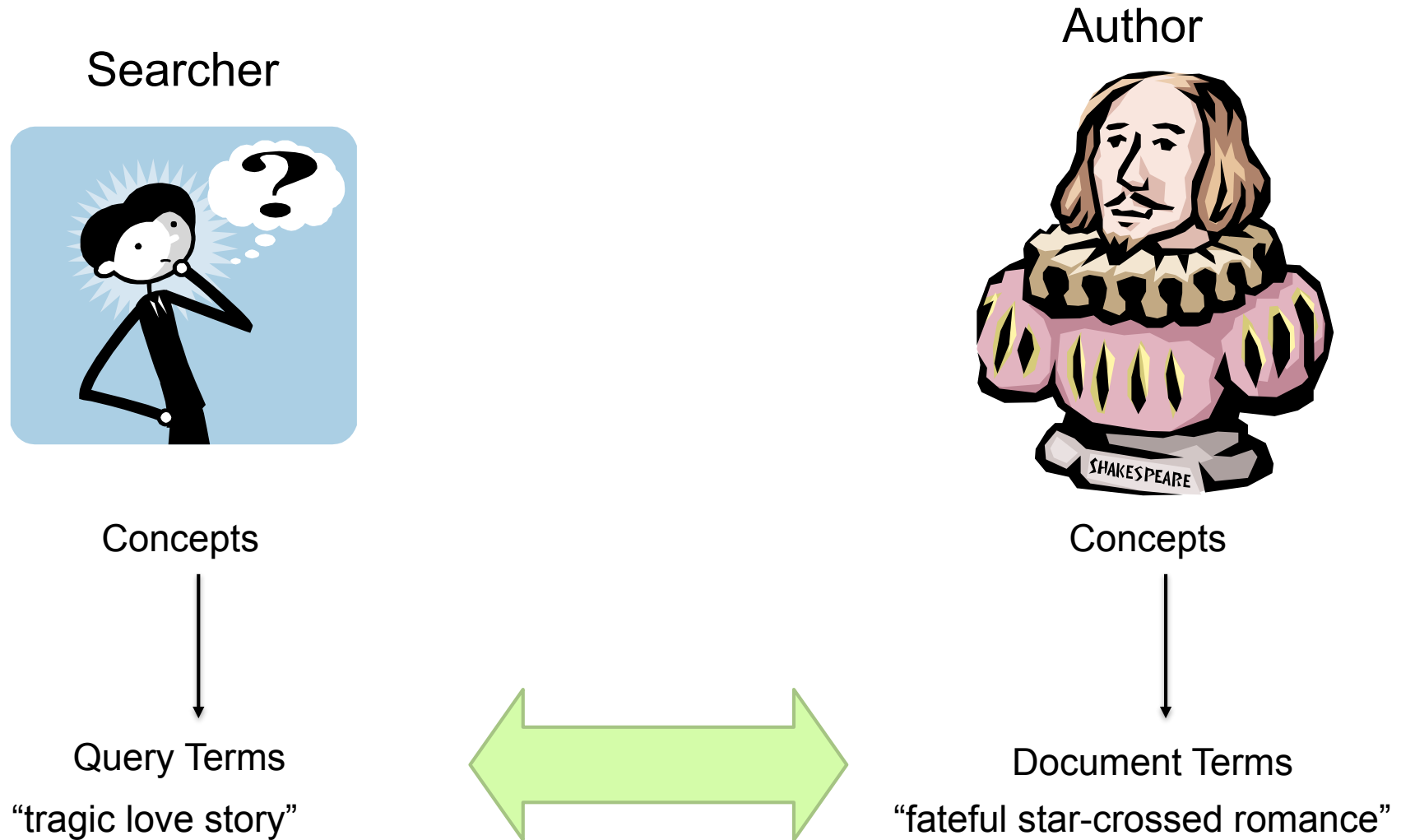
Instructor: Prof. James Caverlee

**Text Retrieval Basics**

**19 January 2017**

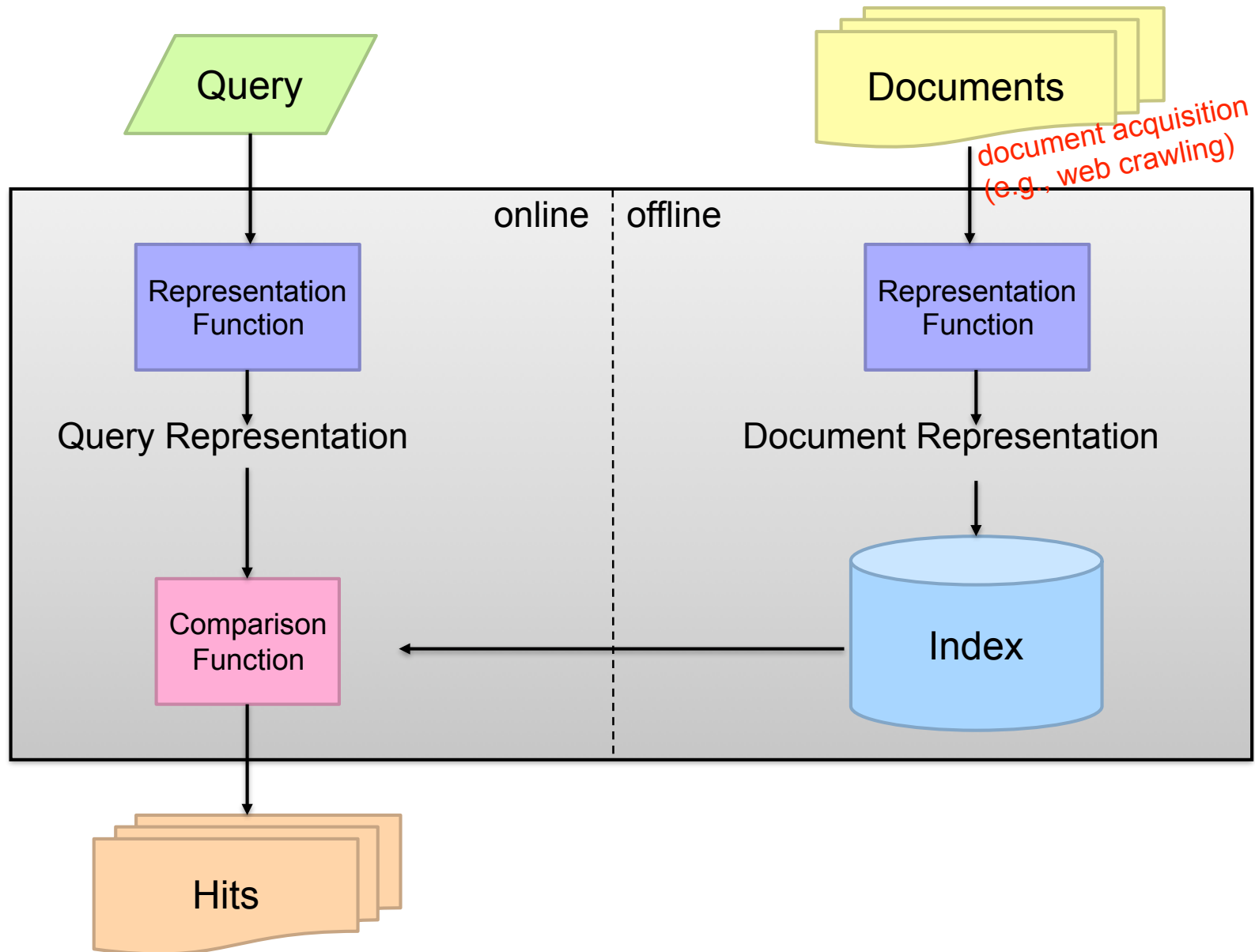
# Today: Foundations

# The Central Problem in Search



Do these represent the same concepts?

# Abstract IR Architecture



# Simplest model: Boolean Retrieval

# Term-document incidence matrix

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

*Brutus AND Caesar but NOT Calpurnia*

1 if play contains  
word, 0  
otherwise

# Incidence vectors

- So we have a 0/1 vector for each term.
- To answer query: take the vectors for Brutus, Caesar and Calpurnia (complemented)  $\Rightarrow$  bitwise AND.
- $110100 \text{ AND } 110111 \text{ AND } 101111 = 100100.$

# Answers to query

- Antony and Cleopatra, Act III, Scene ii

Agrippa [Aside to DOMITIUS ENOBARBUS]: Why, Enobarbus,  
When Antony found Julius **Caesar** dead,  
He cried almost to roaring; and he wept  
When at Philippi he found **Brutus** slain.

- Hamlet, Act III, Scene ii

Lord Polonius: I did enact Julius **Caesar** I was killed i' the  
Capitol; **Brutus** killed me.



# Bigger corpora

- Consider  $N = 1B$  documents, each with about  $1K$  terms.
- Average 6 bytes/term including spaces/punctuation
  - 6TB of data in the documents.
- Say there are  $m = 50M$  distinct terms among these.

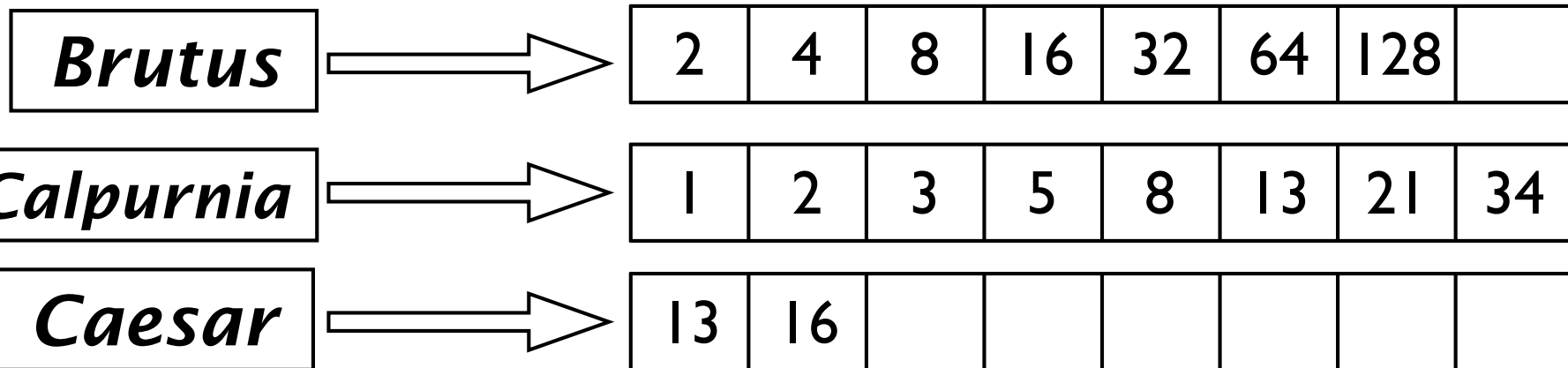
# Can't build the matrix

- 50M x 1B matrix has 50 quadrillion 0's and 1's.
  - 50,000,000,000,000,000
- But it has no more than one trillion 1's.
- Matrix is extremely sparse.
- What's a better representation?
  - We only record the 1 positions.



# Inverted index

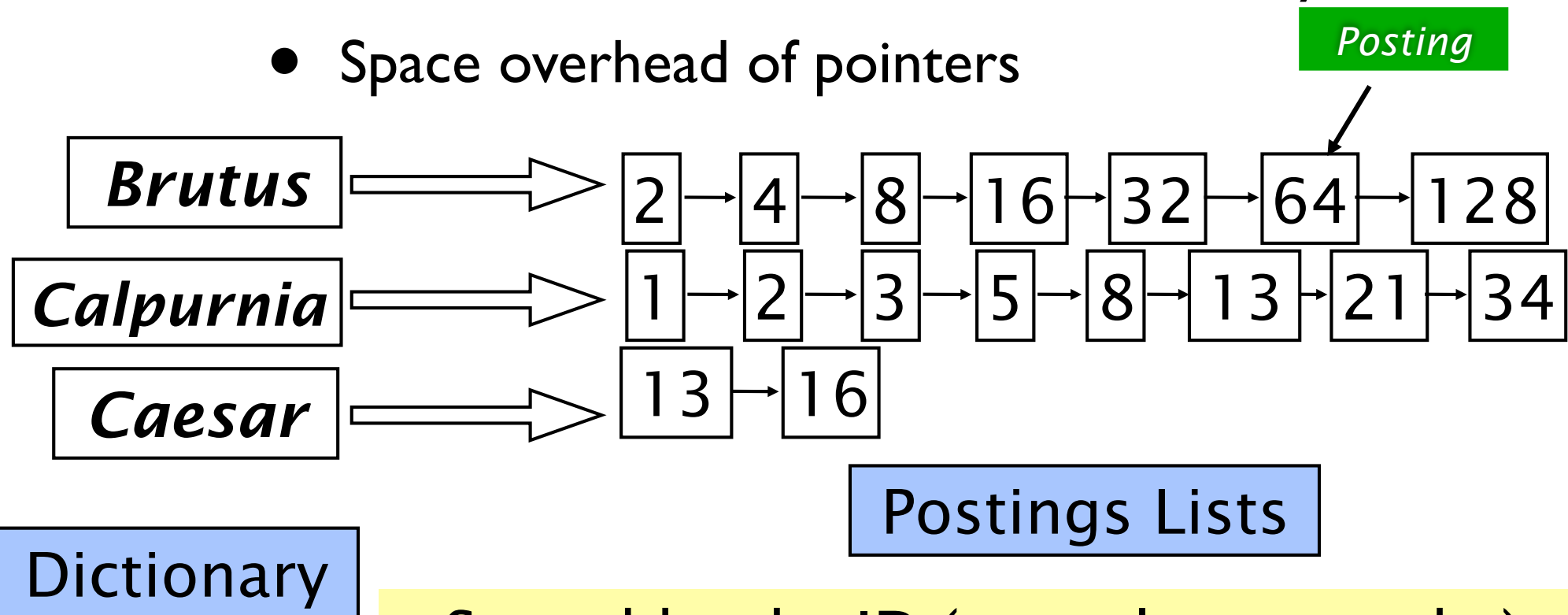
- For each term  $T$ , we must store a list of all documents that contain  $T$ .
- Do we use an array or a list for this?



What happens if the word ***Caesar*** is added to document 14?

# Inverted index

- Linked lists generally preferred to arrays
  - Dynamic space allocation
  - Insertion of terms into documents easy
  - Space overhead of pointers



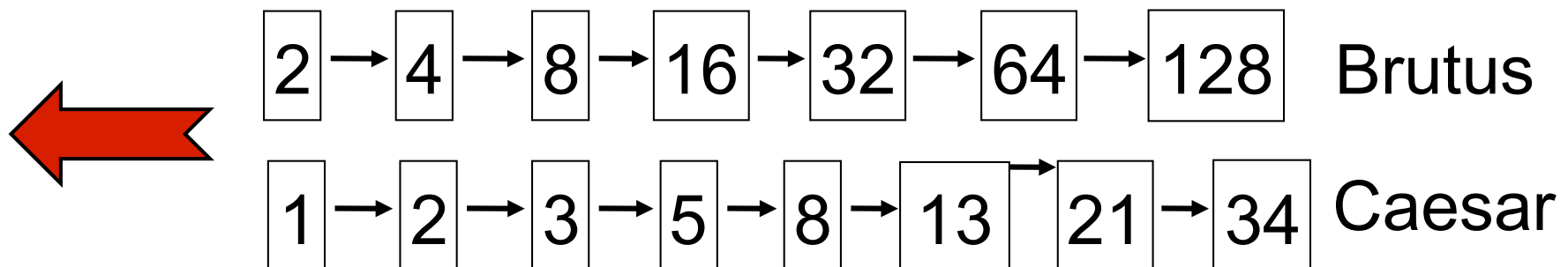
Sorted by docID (more later on why).

# Query processing: AND

- Consider processing the query:

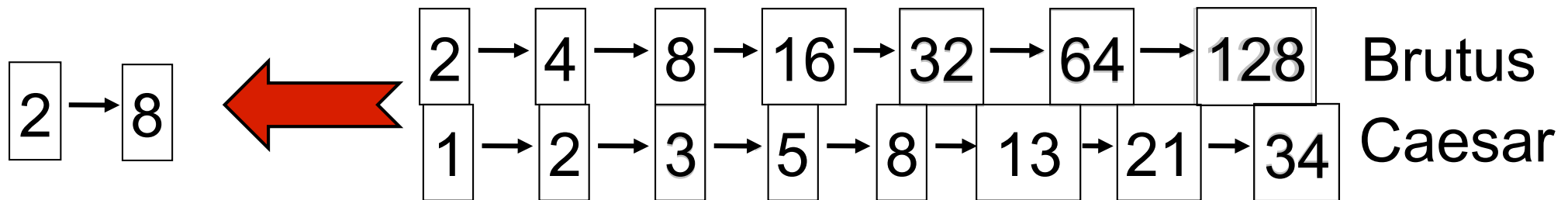
Brutus AND Caesar

- Locate Brutus in the Dictionary;
  - Retrieve its postings.
- Locate Caesar in the Dictionary;
  - Retrieve its postings.
- “Merge” the two postings:



# The merge

- Walk through the two postings simultaneously, in time linear in the total number of postings entries



If the list lengths are  $x$  and  $y$ , the merge takes  $O(x+y)$  operations.

Crucial: postings sorted by docID.

# Boolean Retrieval: Strengths and Weaknesses

## ○ Strengths

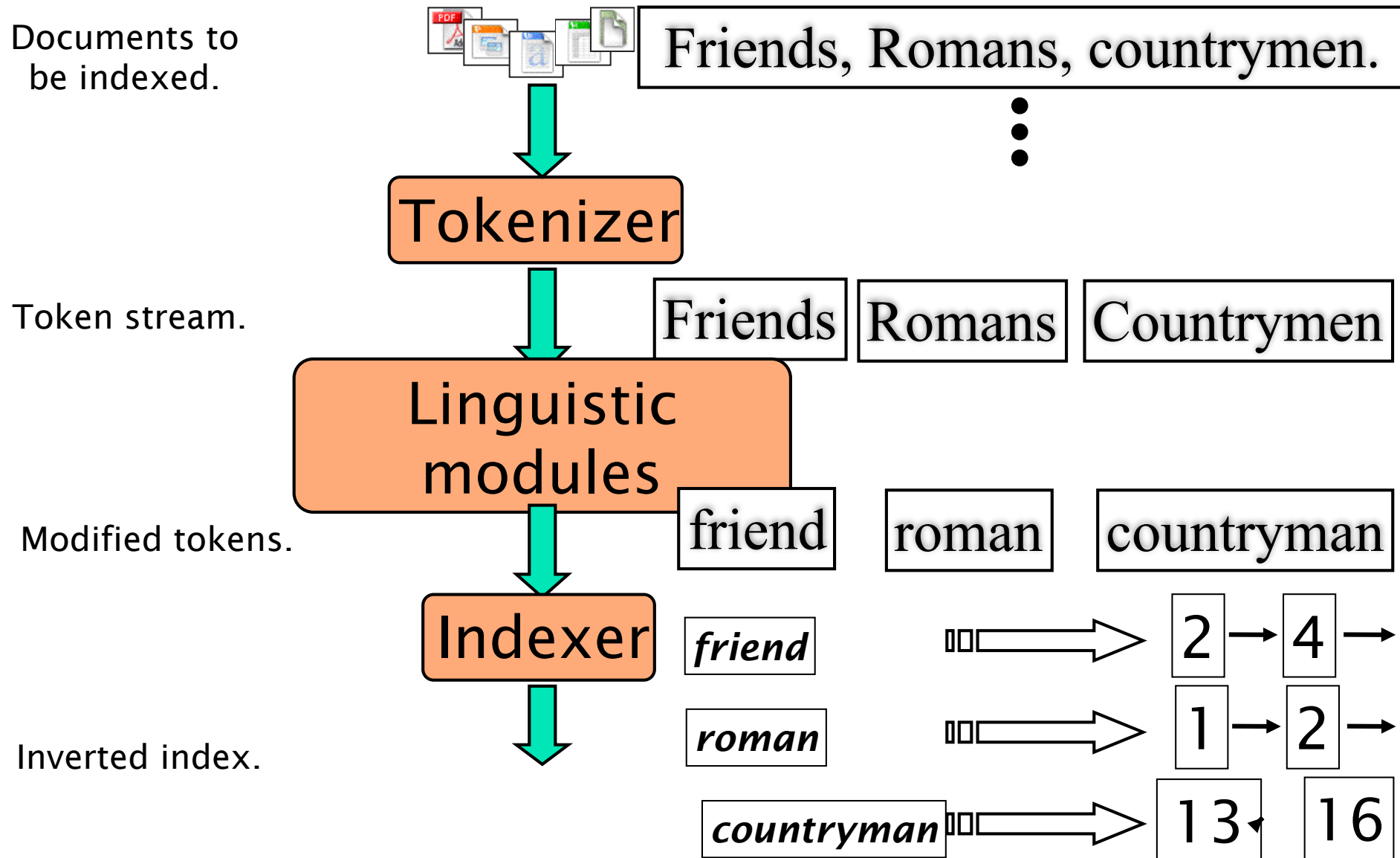
- Precise, if you know the right strategies
- Precise, if you have an idea of what you're looking for
- Implementations are fast and efficient

## ○ Weaknesses

- Users must learn Boolean logic
- Boolean logic insufficient to capture the richness of language
- No control over size of result set: either too many hits or none
- **When do you stop reading?** All documents in the result set are considered “equally good”
- **What about partial matches?** Documents that “don't quite match” the query may be useful also

**Next time, we'll talk about “ranked retrieval”  
with the vector space model**

# Inverted Index Construction





# Parsing a document

- What format is it in?
  - pdf/word/excel/html?
- What language is it in?
- What character set is in use?

Each of these is a classification problem, which we will study later in the course.

But these tasks are often done heuristically ...

# Complications: Format/language

- Documents being indexed can include docs from many different languages
  - A single index may have to contain terms of several languages.
- Sometimes a document or its components can contain multiple languages/formats
  - French email with a German pdf attachment.
- What is a unit document?
  - A file?
  - An email? (Perhaps one of many in an mbox.)
  - An email with 5 attachments?
  - A group of files (PPT or LaTeX in HTML)

# Tokenization

- Input: “*Friends, Romans and Countrymen*”
- Output: Tokens
  - *Friends*
  - *Romans*
  - *Countrymen*
- Each such token is now a candidate for an index entry, after further processing
  - Described below
- But what are valid tokens to emit?

# Pair up ... and ...

Create a set of rules to tokenize this paragraph:

The Texas A&M Aggies, buoyed by their victory over South Carolina, moved up 12 spots to No. 9 in the AP Top 25 after the opening weekend of college football. The top four in the rankings -- Florida State, Alabama, Oregon and Oklahoma -- are unchanged, but the No. 1 Seminoles and No. 2 Crimson Tide lost some support in the first poll of the regular season after close victories against heavy underdogs. Texas A&M began the post-Johnny Manziel era with a 52-28 victory at South Carolina. The loss dropped the Gamecocks from No. 9 to No. 21.

What are the tokens emitted by your approach?

# Why tokenization is difficult -- even in English

- Example: *Mr. O'Neill thinks that the boys' stories about Chile's capital aren't amusing.*
- **Tokenize this sentence**

# One word or two? (or several)

- Hewlett-Packard
- State-of-the-art
- co-education
- the hold-him-back-and-drag-him-away maneuver
- data base
- San Francisco
- Los Angeles-based company
- cheap San Francisco-Los Angeles fares
- York University vs. New York University

# Numbers

- 3/12/91
- 12/3/91
- Mar 12, 1991
- B-52
- 100.2.86.144
- (800) 234-2333
- 800.234.2333

# Chinese: No whitespace

莎拉波娃现在居住在美国东南部的佛罗里达。今年4月9日，莎拉波娃在美国第一大城市纽约度过了18岁生日。生日派对上，莎拉波娃露出了甜美的微笑。



# Ambiguous segmentation in Chinese

和尚

- Can be treated as one word meaning “monk” or as two words meaning “and” and “still”

# Tokenization: Language issues

- Chinese and Japanese have no spaces between words:
  - 莎拉波娃现在居住在美国东南部的佛罗里达。
  - Not always guaranteed a unique tokenization
- Further complicated in Japanese, with multiple alphabets intermingled
  - Dates/amounts in multiple formats



End-user can express query entirely in hiragana!

# Other cases of “no whitespace”

- Compounds in Dutch and German
- Computerlinguistik → Computer + Linguistik
- Lebensversicherungsgesellschaftsangestellter
- → leben + versicherung + gesellschaft + angestellter
- Inuit: tusaatsiarunнанngittualuujunga (I can't hear very well.)
- Swedish, Finnish, Greek, Urdu, many other languages

# Language issues in French

- *L'ensemble* → one token or two?
  - *L ? L' ? Le ?*
  - Want *l'ensemble* to match with *un ensemble*

# Bidirectionality in Arabic

- Arabic (or Hebrew) is basically written right to left, but with certain items like numbers written left to right
- Words are separated, but letter forms within a word form complex ligatures
- استقلت الجزائر في سنة 1962 بعد 132 عاما من الاحتلال الفرنسي.  
← → ← → ← start
- ‘Algeria achieved its independence in 1962 after 132 years of French occupation.’
- Bidirectionality is not a problem if text is coded in Unicode

# Normalization

- Need to “normalize” terms in indexed text as well as query terms into the same form
  - We want to match *U.S.A.* and *USA*
  - We most commonly implicitly define **equivalence classes** of terms
    - e.g., by deleting periods in a term
- Alternative is to do asymmetric expansion:
  - Enter: *window* Search: *window, windows*
  - Enter: *windows* Search: *Windows, windows*
  - Enter: *Windows* Search: *Windows*
- Potentially more powerful, but less efficient
- Why don't you want to put *window, Window, windows, and Windows* in the same equivalence class?

# Normalization: other languages

- Accents: *résumé* vs. *resume*.
- Most important criterion:
  - How are your users likely to write their queries for these words?
- Even in languages that standardly have accents, users often may not type them
- German: Tuebingen vs. Tübingen
  - Should be equivalent


# Normalization: other languages

- Need to “normalize” indexed text as well as query terms into the same form

**7月30日 vs. 7/30**

- Character-level alphabet detection and conversion
  - Tokenization not separable from this.
  - Sometimes ambiguous:

*Morgen will ich in MIT...*



Is this  
German “mit”?



# Case folding

- Reduce all letters to lower case
  - exception: upper case (in mid-sentence?)
    - e.g., *General Motors*
    - *Fed* vs. *fed*
    - *SAIL* vs. *sail*
- Often best to lower case everything, since users will use lowercase regardless of 'correct' capitalization...

# Stop words

- With a stop list, you exclude from dictionary entirely the commonest words.  
Intuition:
  - They have little semantic content: *the, a, and, to, be*
  - They take a lot of space: ~30% of postings for top 30
- But the trend is away from doing this:
  - Good compression techniques means the space for including stopwords in a system is very small
  - Good query optimization techniques mean you pay little at query time for including stop words.
  - You need them for:
    - Phrase queries: “King of Denmark”
    - Various song titles, etc.: “Let it be”, “To be or not to be”
    - “Relational” queries: “flights to London”

# More equivalence classing

- Soundex: Chapter 3
  - phonetic equivalence: Tchebyshev = Chebysheff
- Thesaurus: Chapter 9
  - semantic equivalence: car = automobile

# Lemmatization

- Reduce inflectional/variant forms to base form
- Example: am, are, is → be
- Example: car, cars, car's, cars' → car
- Example: the boy's cars are different colors → the boy car be different color
- Lemmatization implies doing “proper” reduction to dictionary headword form (the lemma).
- Inflectional morphology (cutting → cut) vs. derivational morphology (destruction → destroy)

# Stemming

- Definition of stemming: Crude heuristic process that chops off the ends of words in the hope of achieving what “principled” lemmatization attempts to do with a lot of linguistic knowledge.
- Language dependent
- Often inflectional and derivational
- Example for derivational: **automate, automatic, automation** all reduce to **automat**

# Porter algorithm

- Most common algorithm for stemming English
- Results suggest that it is at least as good as other stemming options
- Conventions + 5 phases of reductions
- Phases are applied sequentially
- Each phase consists of a set of commands.
  - Sample command: Delete final e if what remains is longer than 1 character
  - replacement → replac
  - cement → cement
- Sample convention: Of the rules in a compound command, select the one that applies to the longest suffix.

# Porter stemmer:

## A few rules

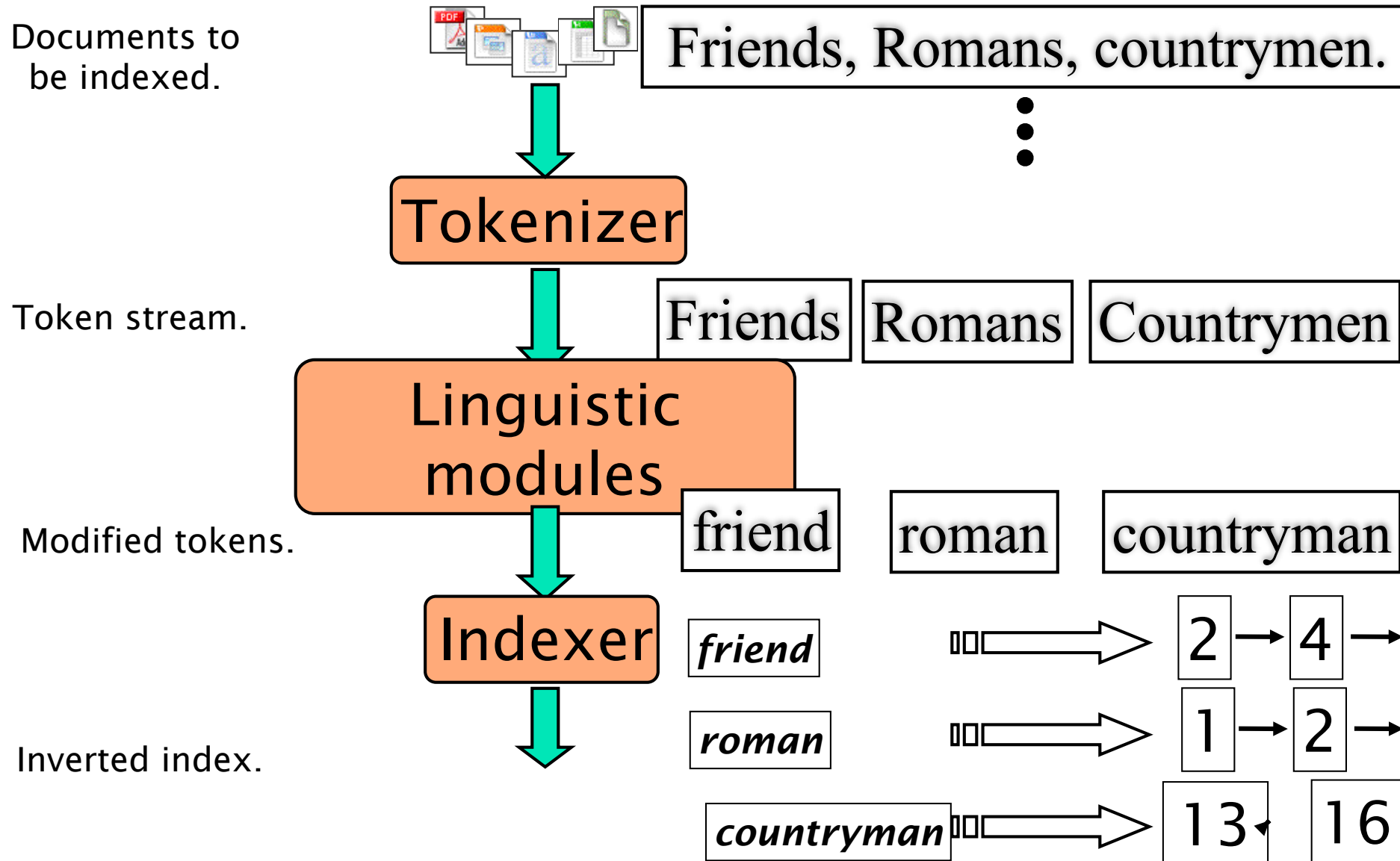
Rule			Example		
SSES	→	SS	caresses	→	caress
IES	→	I	ponies	→	poni
SS	→	SS	caress	→	caress
S	→		cats	→	cat

# Three stemmers: A comparison

- **Sample text:** Such an analysis can reveal features that are not easily visible from the variations in the individual genes and can lead to a picture of expression that is more biologically transparent and accessible to interpretation
- **Porter stemmer:** such an analysis can reveal features that are not easily visible from the variation in the individual gene and can lead to a picture of expression that is more biologically transparent and access to interpretation
- **Lovins stemmer:** such an analysis can reveal features that are not easily visible from the variation in the individual gene and can lead to a picture of expression that is more biologically transparent and access to interpretation
- **Paice stemmer:** such an analysis can reveal features that are not easily visible from the variation in the individual gene and can lead to a picture of expression that is more biologically transparent and access to interpretation



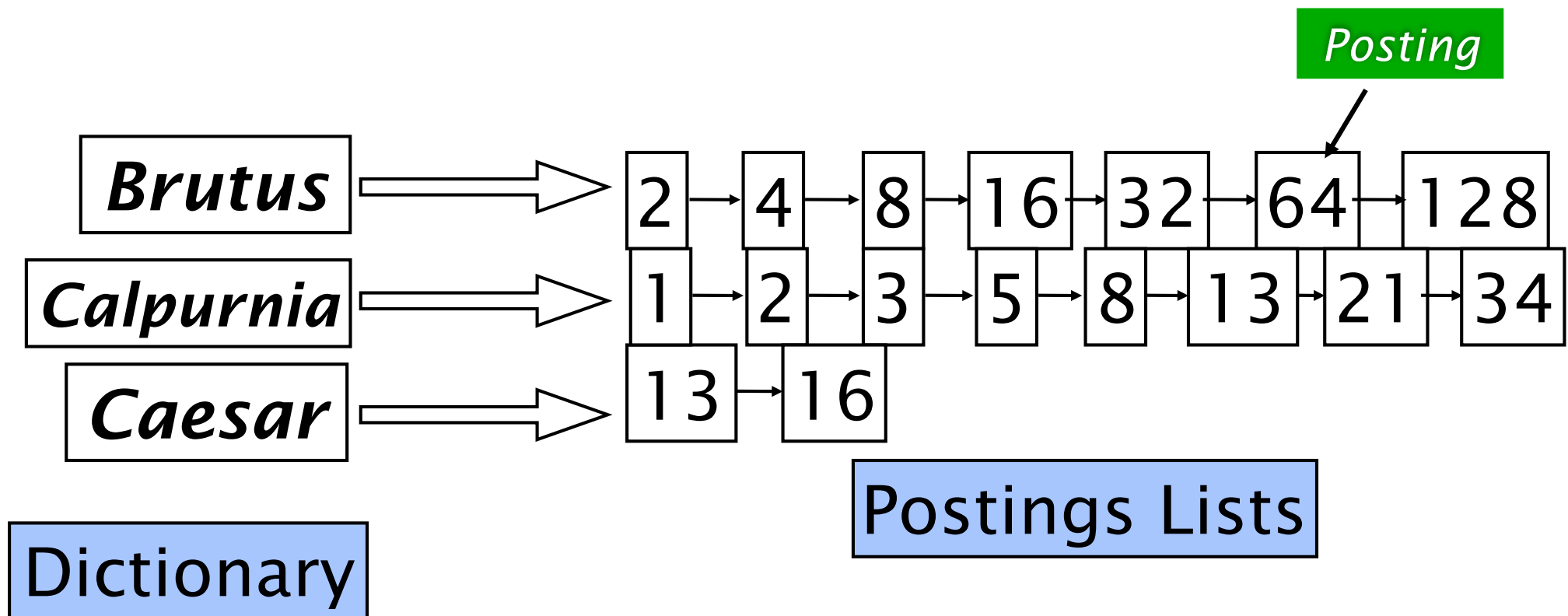
# Recall Basic Indexing Pipeline



# Dictionaries

# Inverted index

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



# Dictionaries

- The dictionary is the data structure for storing the term vocabulary
- Term vocabulary: the data

# Dictionary as array of fixed-width entries

- 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 array
- Assume that we store these entries in an array

# Dictionary as array of fixed-width entries

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

- How do we look up an element in this array at query time?

# Data structures for looking up term

- Two main classes of data structure
  - hashes and trees
- Some IR systems use hashes, some use trees
- Criteria for when to use hashes 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?

# Hashes

- Each vocabulary term is hashed to an integer
- Try to avoid collisions
- At query time, do the following: hash query term, resolve collisions, locate entry in fixed-width array
- Pros: hash lookup is faster than tree lookup
- Cons:
  - No way to find minor variants
  - No prefix search (all terms starting with “auto”)
  - Need to rehash everything periodically if vocabulary keeps growing



# Trees

- Trees solve the prefix problem
- Simplest tree: binary tree
- Search is slightly slower than in hashes:  
 $O(\log M)$ , where  $M$  = size of vocabulary
  - $O(\log M)$  holds for balanced trees only
  - Rebalancing is expensive
- One alternative: B-trees

# Alternative index structures

# How can we improve on the basic index?

- Need a better index than simple <term: docs>
  - **Skip pointers:** faster postings merges
  - **Positional index:** Phrase queries and Proximity queries
  - **Permuterm index:** Wildcard queries
  - **k-gram index:** Wildcard queries and spell correction

# Positional Indexes

# Phrase queries

- Want to answer queries such as “*stanford university*” – as a phrase
- Thus the sentence “*I went to university at Stanford*” is not a match.
- The concept of phrase queries has proven easily understood by users; about 10% of web queries are phrase queries

# A first attempt: Biword indexes

- Index every consecutive pair of terms in the text as a phrase
- For example the text “Friends, Romans, Countrymen” would generate the biwords
  - *friends romans*
  - *romans countrymen*
- Each of these biwords is now a dictionary term
- Two-word phrase query-processing is now immediate.

# Longer phrase queries

- Longer phrases are processed as we did with wild-cards:
- *stanford university palo alto* can be broken into the Boolean query on biwords:

*stanford university AND university  
palo AND palo alto*

# Longer phrase queries

- Longer phrases are processed as we did with wild-cards:
- *stanford university palo alto* can be broken into the Boolean query on biwords:

*stanford university AND university  
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Without the docs, we cannot verify that the docs matching the above Boolean query do contain the phrase.



Can have false positives!



# Solution 2:

## Positional indexes

- Store, for each *term*, entries of the form:  
    <number of docs containing *term*;  
        *doc1*: position1, position2 ... ;  
        *doc2*: position1, position2 ... ;  
    etc.>

# Positional index example

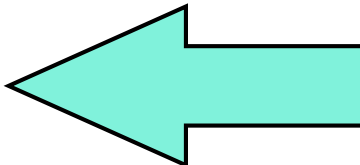
<*be*: 993427;

*1*: 7, 18, 33, 72, 86, 231;

*2*: 3, 149;

*4*: 17, 191, 291, 430, 434;

*5*: 363, 367, ...>



Which of docs *1,2,4,5*  
could contain “*to be*  
*or not to be*”?

- Can compress position values/offsets
- Nevertheless, this expands postings storage *substantially*

# Processing a phrase query

- Extract inverted index entries for each distinct term: *to, be, or, not*.
- Merge their *doc:position* lists to enumerate all positions with “*to be or not to be*”.
- *to*:
  - 2:1,17,74,222,551; 4:8,16,190,429,433; 7:13,23,191; ...
- *be*:
  - 1:17,19; 4:17,191,291,430,434; 5:14,19,101; ...
- Same general method for proximity searches

# Proximity queries

- LIMIT! /3 STATUTE /3 FEDERAL /2 TORT  
Here, / $k$  means “within  $k$  words of”.
- Clearly, positional indexes can be used for such queries; biword indexes cannot.

# Positional index size

- Need an entry for each occurrence, not just once per document
- Index size depends on average document size
  - Average web page has <1000 terms
  - SEC filings, books, even some epic poems ... easily 100,000 terms
- Consider a term with frequency 0.1%

Document size	Postings	Positional postings
1 000	1	1
1 00,000	1	1 00

# Rules of thumb

- A positional index is 2–4 as large as a non-positional index
- Positional index size 35–50% of volume of original text
- Caveat: all of this holds for “English-like” languages

# Combination schemes

- These two approaches can be profitably combined
  - For particular phrases (*“Lada Gaga”*, *“Steve Jobs”*) it is inefficient to keep on merging positional postings lists
    - Even more so for phrases like *“The Who”*
- Williams et al. (2004) evaluate a more sophisticated mixed indexing scheme
  - A typical web query mixture was executed in  $\frac{1}{4}$  of the time of using just a positional index
  - It required 26% more space than having a positional index alone

# Positional Indexes: Wrap-up

- With a positional index, we can answer
  - phrase queries
  - proximity queries