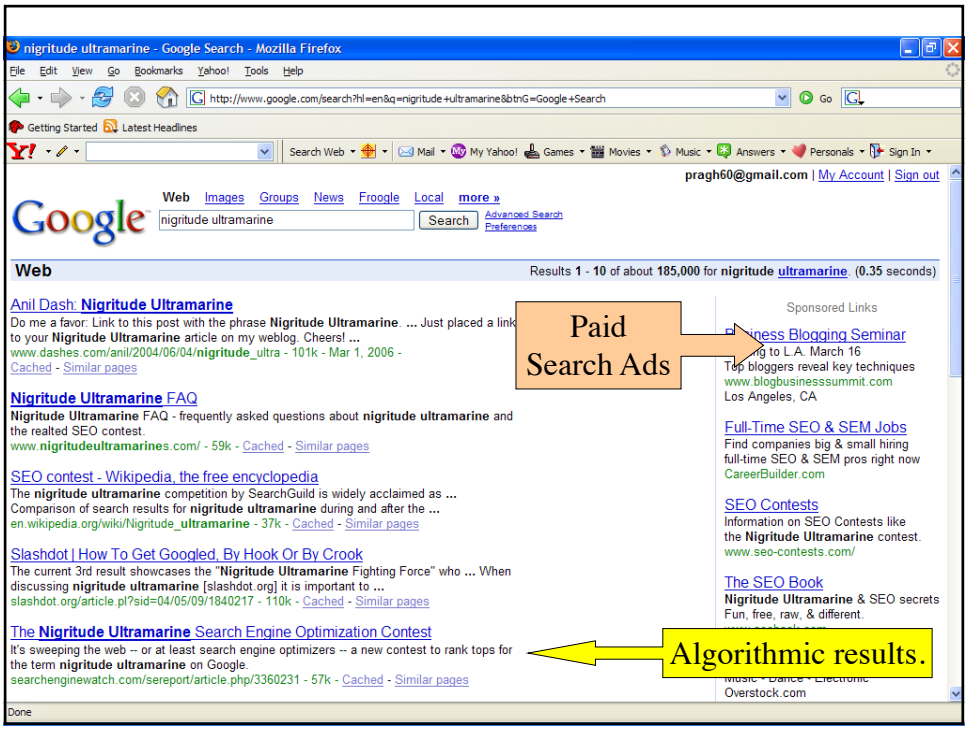
CS426 SEARCH ENGINES

Spring 2016

OUTLINE

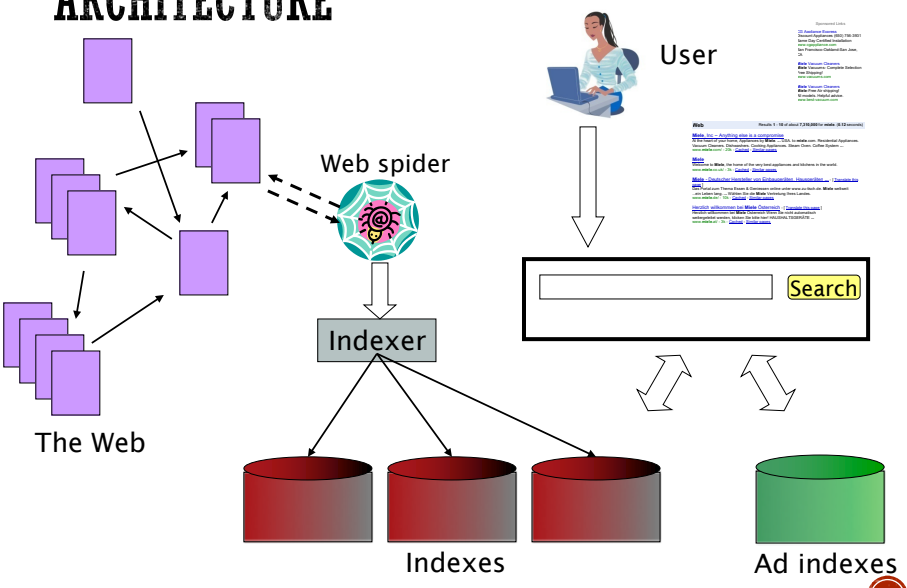
- Architecture of Search Engines
- Index Construction
- Boolean Retrieval
- Vector Space Model for Ranked Retrieval



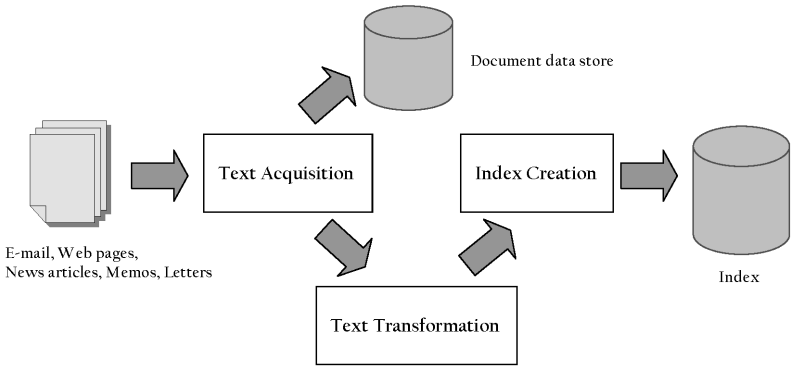
ARCHITECTURE OF SEARCH ENGINES (SE)

- How do search engines like Google work?

ARCHITECTURE



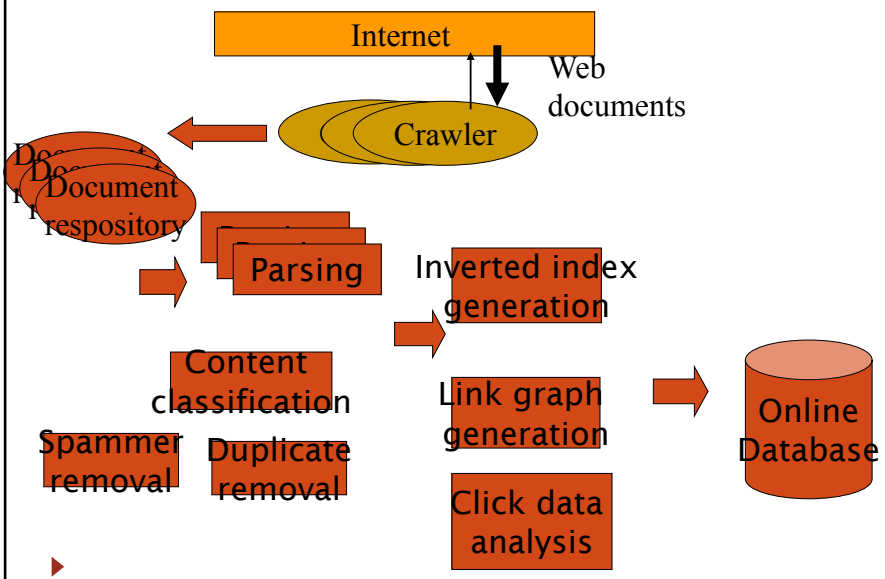
INDEXING PROCESS



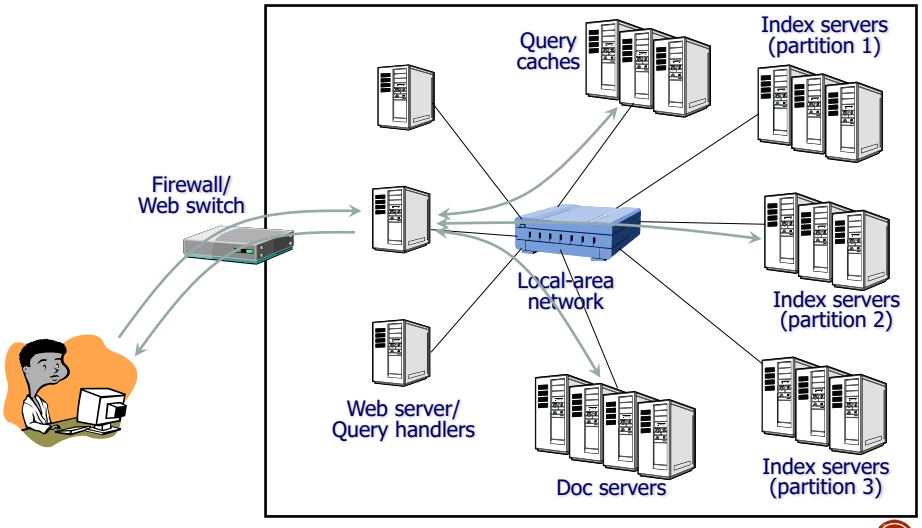
INDEXING PROCESS

- Text acquisition
  - identifies and stores documents for indexing
- Text transformation
  - transforms documents into *index terms*
- Index creation
  - takes index terms and creates data structures (*indexes*) to support fast searching

INDEXING AND MINING AT ASK.COM



DOCUMENT SEARCH ENGINE



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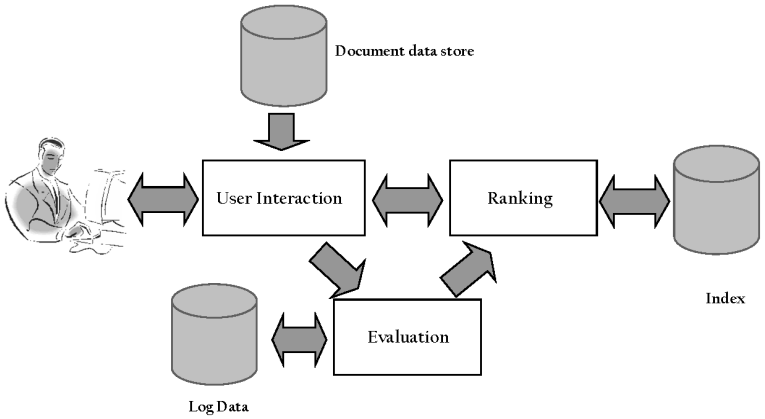
QUERY PROCESS



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QUERY PROCESS

- User interaction
  - supports creation and refinement of query, display of results
- Ranking
  - uses query and indexes to generate ranked list of documents
- Evaluation
  - monitors and measures effectiveness and efficiency (primarily offline)

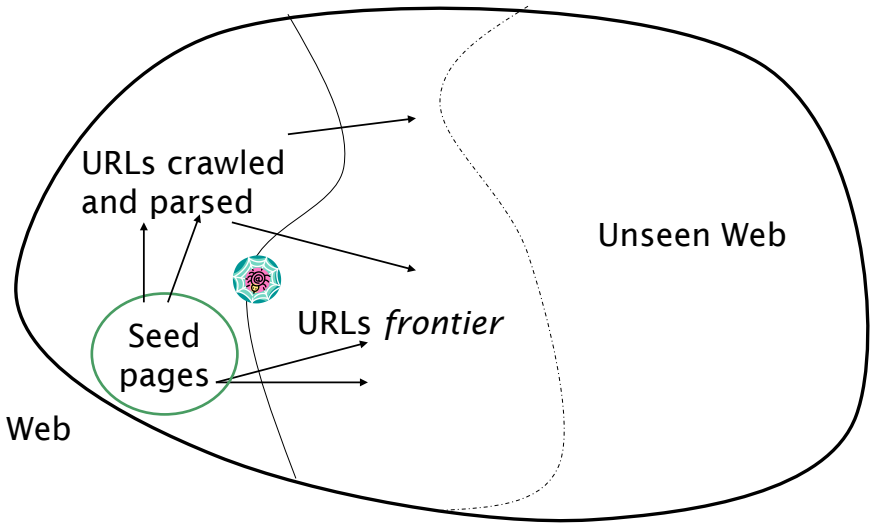
DETAILS: TEXT ACQUISITION

- Crawler
  - Identifies and acquires documents for search engine
  - Many types – web, enterprise, desktop
  - Web crawlers follow *links* to find documents
    - Must efficiently find huge numbers of web pages (*coverage*) and keep them up-to-date (*freshness*)
    - Single site crawlers for *site search*
    - *Topical* or *focused* crawlers for vertical search
  - *Document* crawlers for enterprise and desktop search
    - Follow links and scan directories

WEB CRAWLER

- Starts with a set of *seeds*, which are a set of URLs given to it as parameters
- Seeds are added to a URL request queue
- Crawler starts fetching pages from the request queue
- Downloaded pages are parsed to find link tags that might contain other useful URLs to fetch
- New URLs added to the crawler's request queue, or *frontier*
- Continue until no more new URLs or disk full

CRAWLING PICTURE



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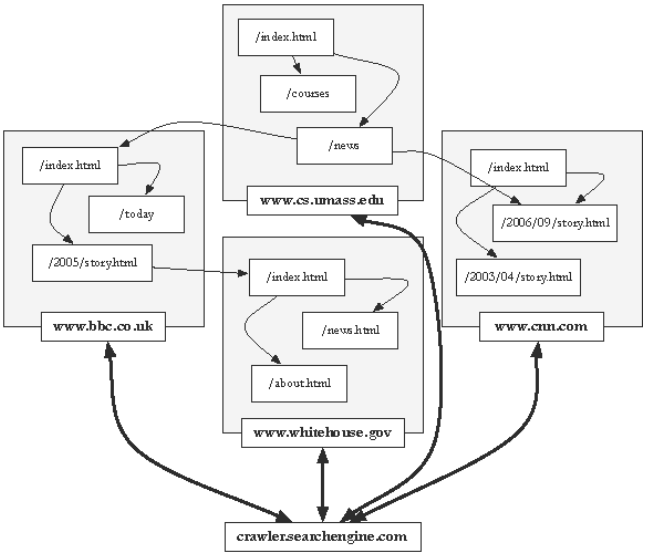
CRAWLING THE WEB



TEXT TRANSFORMATION

- Parser
  - Processing the sequence of text *tokens* in the document to recognize structural elements
    - e.g., titles, links, headings, etc.
  - *Tokenizer* recognizes "words" in the text
    - must consider issues like capitalization, hyphens, apostrophes, non-alpha characters, separators
  - *Markup languages* such as HTML, XML often used to specify structure
    - *Tags* used to specify document *elements*
      - E.g., <h2> Overview </h2>
    - Document parser uses *syntax* of markup language (or other formatting) to identify structure

TEXT TRANSFORMATION

- Stopping
  - Remove common words (*stop words*)
    - e.g., “and”, “or”, “the”, “in”
  - Some impact on efficiency and effectiveness
  - Can be a problem for some queries
- Stemming
  - Group words derived from a common *stem*
    - e.g., “computer”, “computers”, “computing”, “compute”
  - Usually effective, but not for all queries
  - Benefits vary for different languages

TEXT TRANSFORMATION

- Link Analysis
  - Makes use of *links* and *anchor text* in web pages
  - Link analysis identifies *popularity* and *community* information
    - e.g., PageRank
  - Anchor text can significantly enhance the representation of pages pointed to by links
  - Significant impact on web search
    - Less importance in other applications

TEXT TRANSFORMATION

- Information Extraction
  - Identify classes of index terms that are important for some applications
  - e.g., *named entity recognizers* identify classes such as *people*, *locations*, *companies*, *dates,* etc.
- Classifier
  - Identifies class-related metadata for documents
    - i.e., assigns labels to documents
    - e.g., topics, reading levels, sentiment, genre
  - Use depends on application

INDEX CREATION

- Document Statistics
  - Gathers counts and positions of words and other features
  - Used in ranking algorithm
- Weighting
  - Computes weights for index terms
  - Used in ranking algorithm
  - e.g., *tf.idf* weight
    - Combination of *term frequency* in document and *inverse document frequency* in the collection

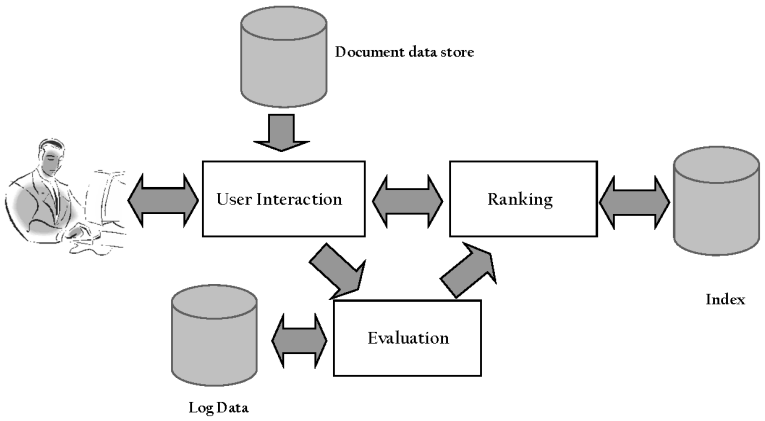
INDEX CREATION

- Inversion
  - Core of indexing process
  - Converts document-term information to term-document for indexing
    - Difficult for very large numbers of documents
  - Format of inverted file is designed for fast query processing
    - Must also handle updates
    - Compression used for efficiency

INDEX CREATION

- Index Distribution
  - Distributes indexes across multiple computers and/or multiple sites
  - Essential for fast query processing with large numbers of documents
  - Many variations
    - Document distribution, term distribution, replication
  - P2P and distributed IR involve search across multiple sites

QUERY PROCESS



USER INTERACTION

- Query input
  - Provides interface and parser for *query language*
  - Most web queries are very simple, other applications may use forms
  - Query language used to describe more complex queries and results of query transformation
    - e.g., Boolean queries, Indri and Galago query languages
    - similar to SQL language used in database applications
    - IR query languages also allow content and structure specifications, but focus on content

USER INTERACTION

- Query transformation
  - Improves initial query, both before and after initial search
  - Includes text transformation techniques used for documents
  - *Spell checking* and *query suggestion* provide alternatives to original query
  - *Query expansion* and *relevance feedback* modify the original query with additional terms

USER INTERACTION

- Results output
  - Constructs the display of ranked documents for a query
  - Generates *snippets* to show how queries match documents
  - *Highlights* important words and passages
  - Retrieves appropriate *advertising* in many applications
  - May provide *clustering* and other visualization tools

RANKING

- Scoring
  - Calculates scores for documents using a ranking algorithm
  - Core component of search engine
  - Basic form of score is $\Sigma q_i d_i$
    - q_i and d_i are query and document term weights for term i
  - Many variations of ranking algorithms and retrieval models

ONLINE SYSTEM SUPPORT

- Performance optimization
  - Designing ranking algorithms for efficient processing
    - *Term-at-a time* vs. *document-at-a-time* processing
    - *Safe* vs. *unsafe* optimizations
- Distribution
  - Processing queries in a distributed environment
  - *Query broker* distributes queries and assembles results
  - *Caching* is a form of distributed searching

EVALUATION

- Logging
  - Logging user queries and interaction is crucial for improving search effectiveness and efficiency
  - *Query logs* and *clickthrough data* used for query suggestion, spell checking, query caching, ranking, advertising search, and other components
- Ranking analysis
  - Measuring and tuning ranking effectiveness
- Performance analysis
  - Measuring and tuning system efficiency

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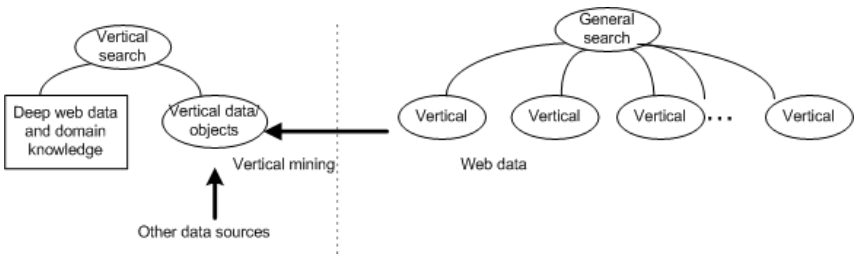
GENERAL SEARCH VS. VERTICAL SEARCH

- **General Search**: identify relevant information with a horizontal/exhaustive view of the world.
- **Vertical Search**:
  - Focus on specific segment of web content
  - Integrate domain knowledge (e.g. taxonomies /ontology), & deep web
  - Examples: travel in Expedia, products in Amazon.



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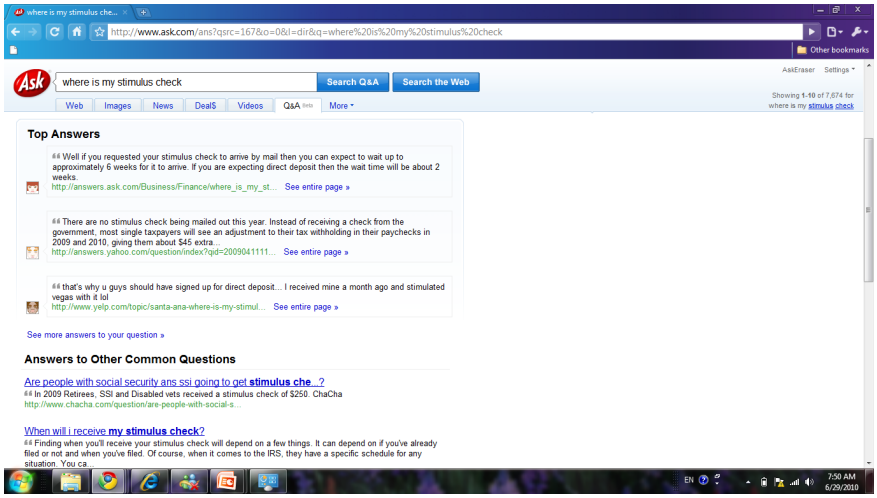
EXAMPLE OF VERTICAL SEARCH: QUESTION ANSWERING



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OUTLINE

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- Vector Space Model for Ranked Retrieval

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UNSTRUCTURED DATA IN 1680

- Which plays of Shakespeare contain the words ***Brutus*** *AND* ***Caesar*** but *NOT* ***Calpurnia***?
- One could `grep` all of Shakespeare's plays for ***Brutus*** and ***Caesar,*** then strip out lines containing ***Calpurnia***?
- Why is that not the answer?
  - Slow (for large corpora)
  - *NOT* ***Calpurnia*** is non-trivial
  - Other operations (e.g., find the word ***Romans*** near ***countrymen***) not feasible
  - Ranked retrieval (best documents to return)

TERM-DOCUMENT INCIDENCE

	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) ➔ bitwise *AND*.
- 110100 *AND* 110111 *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.

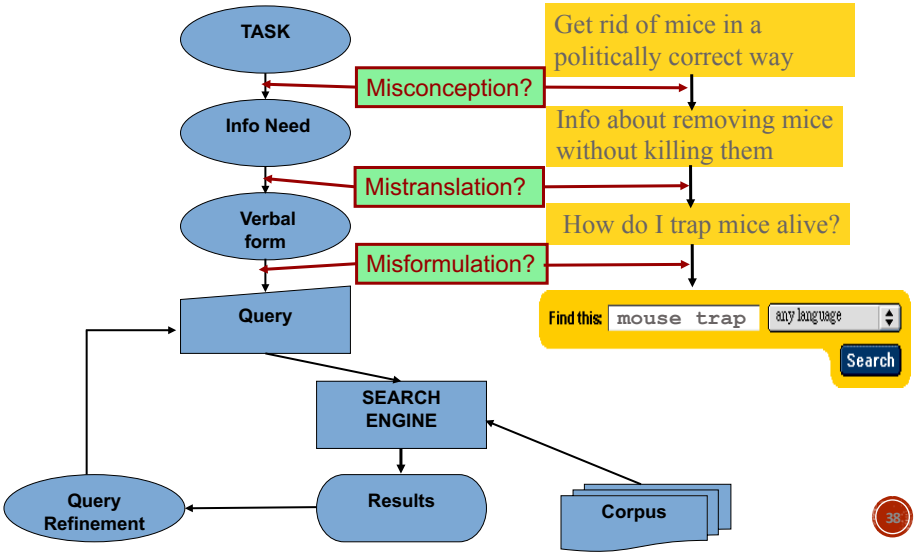
- Hamlet, Act III, Scene ii

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

BASIC ASSUMPTIONS OF INFORMATION RETRIEVAL

- Collection: Fixed set of documents
- Goal: Retrieve documents with information that is relevant to the user's information need and helps the user complete a task

THE CLASSIC SEARCH MODEL

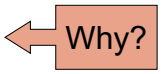


BIGGER COLLECTIONS

- Consider *N* = 1 million documents, each with about 1000 words.
- Avg 6 bytes/word including spaces/punctuation
  - 6GB of data in the documents.
- Say there are *M* = 500K *distinct* terms among these.

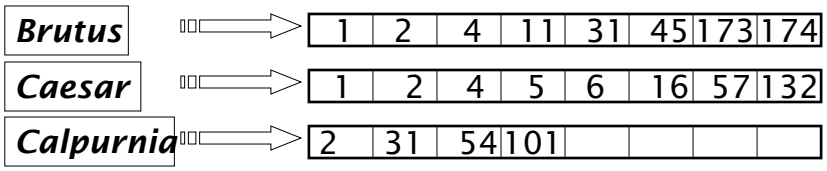
CAN'T BUILD THE MATRIX

- 500K x 1M matrix has half-a-trillion 0's and 1's.
- But it has no more than one billion 1's.
  - matrix is extremely sparse.
- What's a better representation?
  - We only record the 1 positions.



INVERTED INDEX

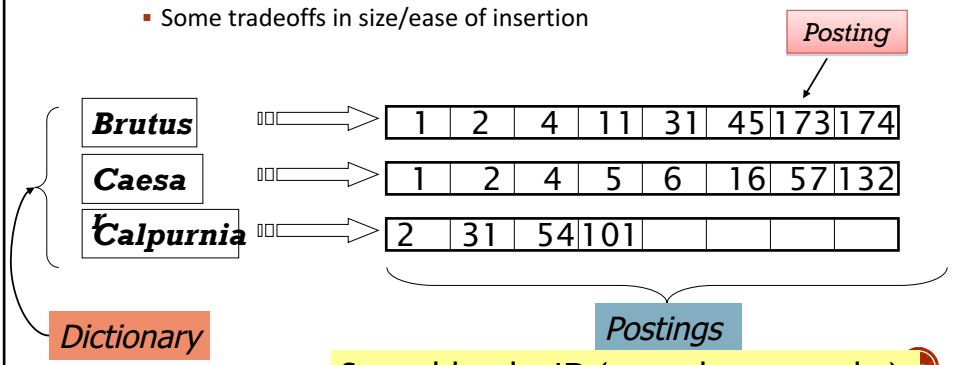
- For each term *t*, we must store a list of all documents that contain *t*.
  - Identify each by a **docID**, a document serial number
- Can we use fixed-size arrays for this?



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

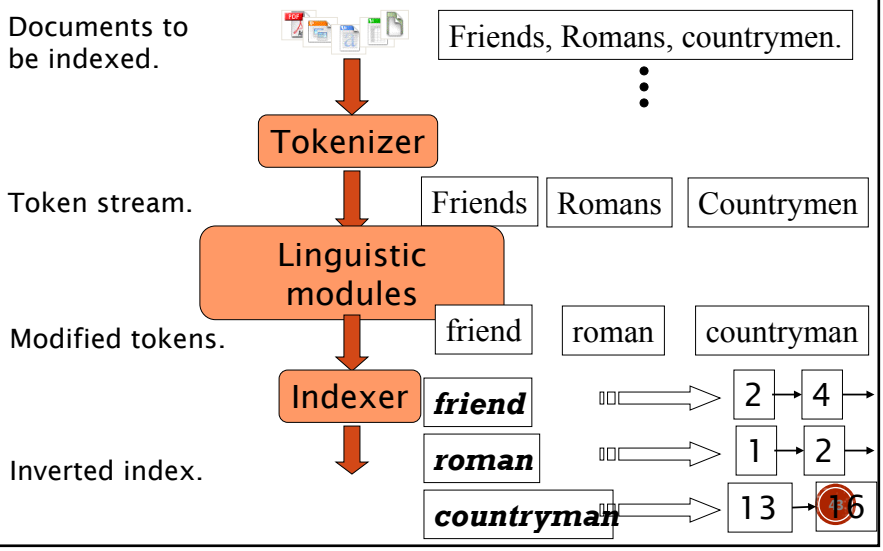
INVERTED INDEX

- We need variable-size postings lists
  - On disk, a continuous run of postings is normal and best
  - In memory, can use linked lists or variable length arrays
    - Some tradeoffs in size/ease of insertion



Sorted by docID (more later on why).

INVERTED INDEX CONSTRUCTION



INDEXER STEPS: TOKEN SEQUENCE

- Sequence of (Modified token, Document ID) pairs.

Doc 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Doc 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

INDEXER STEPS: SORT

- Sort by terms
  - And then docID

Core indexing step

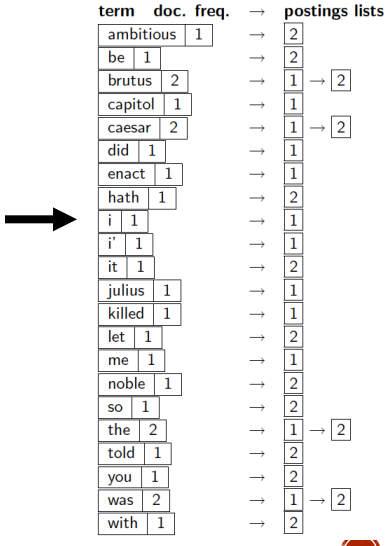
Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

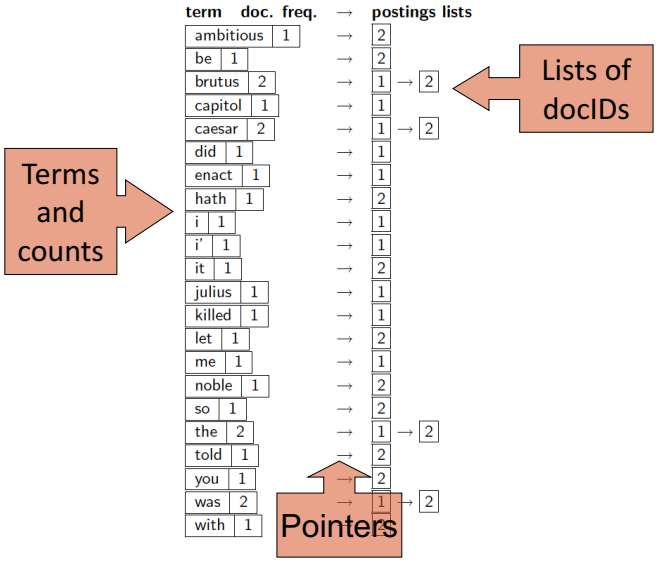
INDEXER STEPS: DICTIONARY & POSTINGS

- Multiple term entries in a single document are merged.
- Split into Dictionary and Postings
- Doc. frequency information is added.

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2



WHERE DO WE PAY IN STORAGE?



DISTRIBUTED INDEXING

- For web-scale indexing
  must use a distributed computing cluster
- Individual machines are fault-prone
  - Can unpredictably slow down or fail
- How do we exploit such a pool of machines?
  - MapReduce for indexing

PARALLEL TASKS

- We will use two sets of parallel tasks
  - Parsers
  - Inverters
- Break the input document collection into *splits*
- Each split is a subset of documents

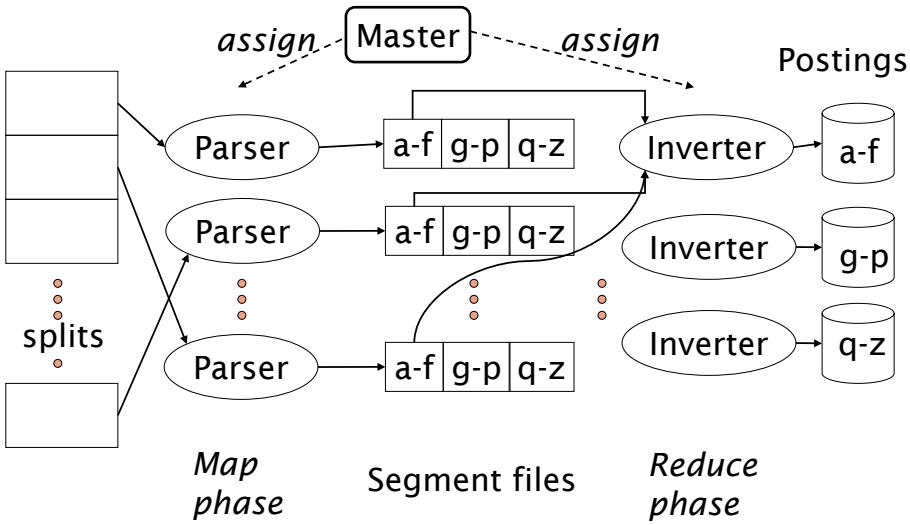
PARSERS

- Master assigns a split to an idle parser machine
- Parser reads a document at a time and emits (term, doc) pairs
- Parser writes pairs into *j* partitions
- Each partition is for a range of terms' first letters
  - (e.g., ***a-f, g-p, q-z***) – here *j* = 3.
- Now to complete the index inversion

INVERTERS

- An inverter collects all (term,doc) pairs (= postings) for one term-partition.
- Sorts and writes to postings lists

DATA FLOW



SCHEMA FOR INDEX CONSTRUCTION IN MAPREDUCE

Schema of map and reduce functions

- map: input → list(k, v) reduce: (k,list(v)) → output

Instantiation of the schema for index construction

- map: web collection → list(termID, docID)
- reduce: (<termID1, list(docID)>, <termID2, list(docID)>, …) → (postings list1, postings list2, …)

Example for index construction

- **map:** d2 : C died. d1 : C came, C c'ed. → (<C, d2>, <died,d2>, <C,d1>, <came,d1>, <C,d1>, <c'ed, d1>
- **reduce:** (<C,(d2,d1,d1)>, <died,(d2)>, <came,(d1)>, <c'ed,(d1)>) → (<C,(d1:2,d2:1)>, <died,(d2:1)>, <came,(d1:1)>, <c'ed,(d1:1)>)

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Inverted Index with counts

- supports better ranking algorithms

and	1:1			
aquarium	3:1			
are	3:1	4:1		
around	1:1			
as	2:1			
both	1:1			
bright	3:1			
coloration	3:1	4:1		
derives	4:1			
due	3:1			
environments	1:1			
fish	1:2	2:3	3:2	4:2
fishkeepers	2:1			
found	1:1			
fresh	2:1			
freshwater	1:1	4:1		
from	4:1			
generally	4:1			
in	1:1	4:1		
include	1:1			
including	1:1			
iridescence	4:1			
marine	2:1			
often	2:1	3:1		

only	2:1		
pigmented	4:1		
popular	3:1		
refer	2:1		
referred	2:1		
requiring	2:1		
salt	1:1	4:1	
saltwater	2:1		
species	1:1		
term	2:1		
the	1:1	2:1	
their	3:1		
this	4:1		
those	2:1		
to	2:2	3:1	
tropical	1:2	2:2	3:1
typically	4:1		
use	2:1		
water	1:1	2:1	4:1
while	4:1		
with	2:1		
world	1:1		

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PROXIMITY MATCHES

- Matching phrases or words within a window explicitly or implicitly.
  - e.g., "`tropical fish`", or "find tropical within 5 words of fish"
- Word positions in inverted lists make these types of query features efficient
  - e.g.,

tropical	1,1		1,7	2,6	2,17		3,1			
fish	1,2	1,4		2,7	2,18	2,23	3,2	3,6	4,3	4,13

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POSITIONAL INDEXES

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

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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***"?

- this expands postings storage *substantially*

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Inverted Index with positions

• supports proximity matches

and	1,15										marine	2,22								
aquarium	3,5										often	2,2	3,10							
are	3,3	4,14									only	2,10								
around	1,9										pigmented	4,16								
as	2,21										popular	3,4								
both	1,13										refer	2,9								
bright	3,11										referred	2,19								
coloration	3,12	4,5									requiring	2,12								
derives	4,7										salt	1,16	4,11							
due	3,7										saltwater	2,16								
environments	1,8										species	1,18								
fish	1,2	1,4	2,7	2,18	2,23						term	2,5								
			3,2	3,6	4,3						the	1,10	2,4							
			4,13								their	3,9								
fishkeepers	2,1										this	4,4								
found	1,5										those	2,11								
fresh	2,13										to	2,8	2,20	3,8						
freshwater	1,14	4,2									tropical	1,1	1,7	2,6	2,17	3,1				
from	4,8										typically	4,6								
generally	4,15										use	2,3								
in	1,6	4,1									water	1,17	2,14	4,12						
include	1,3										while	4,10								
including	1,12										with	2,15								
iridescence	4,9										world	1,11								

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FIELDS AND EXTENTS

- Document structure is useful in search
  - *field* restrictions
    - e.g., date, from:, etc.
  - some fields more important
    - e.g., title
- Options:
  - separate inverted lists for each field type
  - add information about fields to postings
  - use *extent lists to mark special areas in a document*

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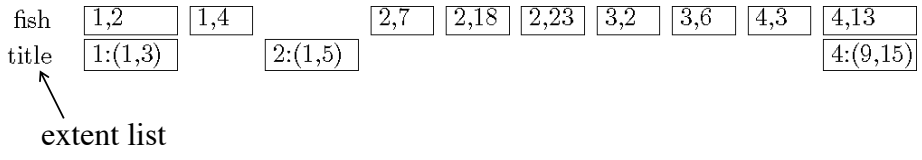
EXTENT LISTS

- An *extent* is a contiguous region of a document
  - represent extents using word positions
  - inverted list records all extents for a given field type
  - e.g.
    - 1:(1,3) → title in document 1 is from 1 to 3



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OTHER ISSUES

- Precomputed scores in inverted list
  - e.g., list for "fish" [(1:3.6), (3:2.2)], where 3.6 is total feature value for document 1
  - improves speed but reduces flexibility
- Score-ordered lists
  - query processing engine can focus only on the top part of each inverted list, where the highest-scoring documents are recorded
  - very efficient for single-word queries

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ISSUE WITH DATA SIZE: EXAMPLE

- Number of docs = n = 40M
- Number of terms = m = 1M
- Use Zipf to estimate number of postings entries:
  - $n + n/2 + n/3 + \ldots. + n/m \sim n \ln m$ = 560M entries
  - 16-byte (4+8+4) records *(term, doc, freq).*
- 9GB
- No positional info yet

Check for yourself

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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, PDF files, … easily 100,000 terms
- Consider a term with frequency 0.1% in a doc

Document size	Postings	Positional postings
1000	1	1
100,000	1	100

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COMPRESSION

- Inverted lists are very large
  - Much higher if n-grams are indexed
- Compression of indexes saves disk and/or memory space
  - Typically have to decompress lists to use them
  - Best compression techniques have good *compression ratios* and are easy to decompress
- *Lossless* compression – no information lost

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RULES OF THUMB

- Positional index size factor of 2-4 over non-positional index
- Positional index size 35-50% of volume of original text
- Caveat: all of this holds for "English-like" languages

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COMPRESSION

- *Basic idea*: Common data elements use short codes while uncommon data elements use longer codes
  - Example: coding numbers
    - number sequence: 0, 1, 0, 2,0,3,0
    - possible encoding: 00 01 00 10 00 11 00
    - encode 0 using a single 0: 0 01 0 10 0 11 0
    - only 10 bits, but...

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COMPRESSION EXAMPLE

- *Ambiguous* encoding – not clear how to decode
  - another decoding: $0\ 01\ 01\ 0\ 0\ 11\ 0$
  - which represents: $0, 1, 1, 0, 0, 3, 0$
  - use unambiguous code:

Number	Code
0	0
1	101
2	110
3	111

  - which gives:

$0\ 101\ 0\ 111\ 0\ 110\ 0$

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DELTA ENCODING

- Word count data is good candidate for compression
  - many small numbers and few larger numbers
  - encode small numbers with small codes
- Document numbers are less predictable
  - but differences between numbers in an ordered list are smaller and more predictable
- *Delta encoding*:
  - encoding differences between document numbers (*d-gaps*)

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DELTA ENCODING

- Inverted list (without counts)

$$1, 5, 9, 18, 23, 24, 30, 44, 45, 48$$

- Differences between adjacent numbers

$$1, 4, 4, 9, 5, 1, 6, 14, 1, 3$$

- Differences for a high-frequency word are easier to compress, e.g.,

$$1, 1, 2, 1, 5, 1, 4, 1, 1, 3, \ldots$$

- Differences for a low-frequency word are large, e.g.,

$$109, 3766, 453, 1867, 992, \ldots$$

BIT-ALIGNED CODES

- Breaks between encoded numbers can occur after any bit position
- *Unary* code
  - Encode *k* by *k* 1s followed by 0
  - 0 at end makes code unambiguous

Number	Code
0	0
1	10
2	110
3	1110
4	11110
5	111110

UNARY AND BINARY CODES

- Unary is very efficient for small numbers such as 0 and 1, but quickly becomes very expensive
  - 1023 can be represented in 10 binary bits, but requires 1024 bits in unary
- Binary is more efficient for large numbers, but it may be ambiguous

ELIAS-Γ CODE

- To encode a number *k*, compute
  - $k_d = \lfloor \log_2 k \rfloor$
  - $k_r = k - 2^{\lfloor \log_2 k \rfloor}$
  - k_d is number of binary digits, encoded in unary

Number (k)	k_d	k_r	Code
1	0	0	0
2	1	0	10 0
3	1	1	10 1
6	2	2	110 10
15	3	7	1110 111
16	4	0	11110 0000
255	7	127	11111110 1111111
1023	9	511	1111111110 111111111

ELIAS-Δ CODE

- Elias-γ code uses no more bits than unary, many fewer for k > 2
  - 1023 takes 19 bits instead of 1024 bits using unary
- In general, takes $2\lfloor \log_2 k \rfloor + 1$ bits
- To improve coding of large numbers, use Elias-δ code
  - Instead of encoding k_d in unary, we encode k_d + *1* using Elias-γ
  - Takes approximately $2 \log_2 \log_2 k + \log_2 k$ bits

ELIAS-Δ CODE

- Split k_d into:
  - $k_{dd} = \lfloor \log_2(k_d + 1) \rfloor$
  - $k_{dr} = k_d - 2^{\lfloor \log_2(k_d+1) \rfloor}$
- encode k_{dd} in unary, k_{dr} in binary, and k_r in binary

Number (k)	k_d	k_r	k_{dd}	k_{dr}	Code
1	0	0	0	0	0
2	1	0	1	0	10 0 0
3	1	1	1	0	10 0 1
6	2	2	1	1	10 1 10
15	3	7	2	0	110 00 111
16	4	0	2	1	110 01 0000
255	7	127	3	0	1110 000 1111111
1023	9	511	3	2	1110 010 111111111

```
#
# Generating Elias-gamma and Elias-delta codes in Python
#

import math

def unary_encode(n):
 return "1" * n + "0"

def binary_encode(n, width):
    r = ""
    for i in range(0,width):
     if ((1<<i) & n) > 0:
     r = "1" + r
     else:
     r = "0" + r
    return r

def gamma_encode(n):
    logn = int(math.log(n,2))
    return unary_encode( logn ) + " " + binary_encode(n, logn)

def delta_encode(n):
  logn = int(math.log(n,2))
if n == 1:
  return "0"
  else:
  loglog = int(math.log(logn+1,2))
  residual = logn+1 - int(math.pow(2, loglog))
        return unary_encode( loglog ) + " " + binary_encode( residual, loglog ) + " " + binary_encode(n, logn)

if __name__ == "__main__":
    for n in [1,2,3, 6, 15,16,255,1023]:
        logn = int(math.log(n,2))
        loglogn = int(math.log(logn+1,2))
        print n, "d_r", logn
        print n, "d_dd", loglogn
        print n, "d_dr", logn + 1 - int(math.pow(2,loglogn))
        print n, "delta", delta_encode(n)
        #print n, "gamma", gamma_encode(n)
        #print n, "binary", binary_encode(n)
```

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BYTE-ALIGNED CODES

- Variable-length bit encodings can be a problem on processors that process bytes
- *v-byte* is a popular byte-aligned code
  - Similar to Unicode UTF-8
- Shortest v-byte code is 1 byte
- Numbers are 1 to 4 bytes, with high bit 1 in the last byte, 0 otherwise

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V-BYTE ENCODING

k	Number of bytes
$k < 2^7$	1
$2^7 \leq k < 2^{14}$	2
$2^{14} \leq k < 2^{21}$	3
$2^{21} \leq k < 2^{28}$	4

k	Binary Code	Hexadecimal
1	1 0000001	81
6	1 0000110	86
127	1 1111111	FF
128	0 0000001 1 0000000	01 80
130	0 0000001 1 0000010	01 82
20000	0 0000001 0 0011100 1 0100000	01 1C A0

V-BYTE ENCODER

```
public void encode( int[] input, ByteBuffer output ) {
    for( int i : input ) {
        while( i >= 128 ) {
            output.put( i & 0x7F );
            i >>>= 7;
        }
        output.put( i | 0x80 );
    }
}
```

V-BYTE DECODER

```
public void decode( byte[] input, IntBuffer output ) {
    for( int i=0; i < input.length; i++ ) {
        int position = 0;
        int result = ((int)input[i] & 0x7F);

        while( (input[i] & 0x80) == 0 ) {
            i += 1;
            position += 1;
            int unsignedByte = ((int)input[i] & 0x7F);
            result |= (unsignedByte << (7*position));
        }

        output.put(result);
    }
}
```

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COMPRESSION EXAMPLE

- Consider invert list with positions:

$$(1, 2, [1, 7])(2, 3, [6, 17, 197])(3, 1, [1])$$

- Delta encode document numbers and positions:

$$(1, 2, [1, 6])(1, 3, [6, 11, 180])(1, 1, [1])$$

- Compress using v-byte:

```
81 82 81 86 81 82 86 8B 01 B4 81 81 81
```

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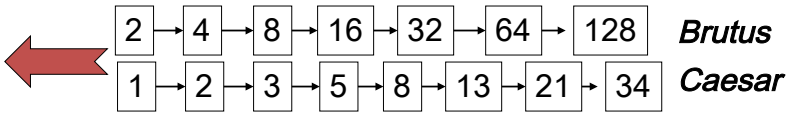
OUTLINE

- Architecture of Search Engines
- Index Construction
- Boolean Retrieval
- Vector Space Model for Ranked Retrieval

- How do we process a (Boolean) query?

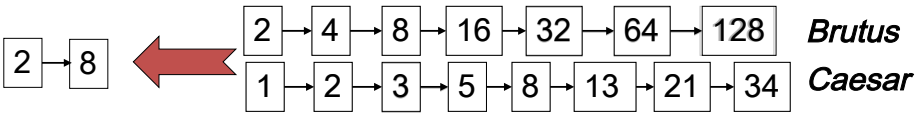
QUERY PROCESSING: AND

- 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.

INTERSECTING TWO POSTINGS LISTS (A "MERGE" ALGORITHM)

```
INTERSECT(p1, p2)
 1  answer ← ⟨ ⟩
 2  while p1 ≠ NIL and p2 ≠ NIL
 3  do if docID(p1) = docID(p2)
 4        then ADD(answer, docID(p1))
 5             p1 ← next(p1)
 6             p2 ← next(p2)
 7        else if docID(p1) < docID(p2)
 8                then p1 ← next(p1)
 9                else p2 ← next(p2)
10  return answer
```

BOOLEAN QUERIES: EXACT MATCH

- The Boolean retrieval model is being able to ask a query that is a Boolean expression:
  - Boolean Queries are queries using AND, OR and NOT to join query terms
    - Views each document as a set of words
    - Is precise: document matches condition or not.
  - Perhaps the simplest model to build an IR system on
- Primary commercial retrieval tool for 3 decades.
- Many search systems you still use are Boolean:
  - Email, library catalog, Mac OS X Spotlight

EXAMPLE: WESTLAW HTTP://WWW.WESTLAW.COM/

- Largest commercial (paying subscribers) legal search service (started 1975; ranking added 1992)
- Tens of terabytes of data; 700,000 users
- Majority of users *still* use boolean queries
- Example query:
  - What is the statute of limitations in cases involving the federal tort claims act?
  - LIMIT! /3 STATUTE ACTION /S FEDERAL /2 TORT /3 CLAIM
    - /3 = within 3 words, /S = in same sentence

EXAMPLE: WESTLAW HTTP://WWW.WESTLAW.COM/

- Another example query:
  - Requirements for disabled people to be able to access a workplace
  - disabl! /p access! /s work-site work-place (employment /3 place
- Note that SPACE is disjunction, not conjunction!
- Long, precise queries; proximity operators; incrementally developed; not like web search
- Many professional searchers still like Boolean search
  - You know exactly what you are getting
- But that doesn't mean it actually works better….

OUTLINE

- Architecture of Search Engines
- Index Construction
- Boolean Retrieval
- Vector Space Model for Ranked Retrieval

RANKED RETRIEVAL

- Thus far, our queries have all been Boolean.
  - Documents either match or don't.
- Good for expert users with precise understanding of their needs and the collection.
  - Also good for applications: Applications can easily consume 1000s of results.
- Not good for the majority of users.
  - Most users incapable of writing Boolean queries (or they are, but they think it's too much work).
  - Most users don't want to wade through 1000s of results.
    - This is particularly true of web search.

PROBLEM WITH BOOLEAN SEARCH: FEAST OR FAMINE

- Boolean queries often result in either too few (=0) or too many (1000s) results.
- Query 1: "*standard user dlink 650*" → 200,000 hits
- Query 2: "*standard user dlink 650 no card found*": 0 hits
- It takes a lot of skill to come up with a query that produces a manageable number of hits.
  - AND gives too few; OR gives too many

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RANKED RETRIEVAL MODELS

- Rather than a set of documents satisfying a query expression, in ranked retrieval models, the system returns an ordering over the (top) documents in the collection with respect to a query
- Free text queries: Rather than a query language of operators and expressions, the user's query is just one or more words in a human language
- In principle, there are two separate choices here, but in practice, ranked retrieval models have normally been associated with free text queries and vice versa

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FEAST OR FAMINE: NOT A PROBLEM IN RANKED RETRIEVAL

- When a system produces a ranked result set, large result sets are not an issue
  - Indeed, the size of the result set is not an issue
  - We just show the top k (≈ 10) results
  - We don't overwhelm the user

  - Premise: the ranking algorithm works

TERM-DOCUMENT COUNT MATRICES

- Consider the number of occurrences of a term in a document:
  - Each document is a count vector in $\mathbb{N}^{v}$: a column below

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

BAG OF WORDS MODEL

- Vector representation doesn't consider the ordering of words in a document
- *John is quicker than Mary* and *Mary is quicker than John* have the same vectors
- This is called the bag of words model.

TERM FREQUENCY TF

- The term frequency $tf_{t,d}$ of term *t* in document *d* is defined as the number of times that *t* occurs in *d*.
- We want to use tf when computing query-document match scores. But how?
- Raw term frequency is not what we want:
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence of the term.
  - But not 10 times more relevant.
- Relevance does not increase proportionally with term frequency.

NB: frequency = count in IR

LOG-FREQUENCY WEIGHTING

- The log frequency weight of term t in d is

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d}, & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

- 0 → 0, 1 → 1, 2 → 1.3, 10 → 2, 1000 → 4, etc.
- Score for a document-query pair: sum over terms *t* in both *q* and *d*
- score $= \sum_{t \in q \cap d} (1 + \log \mathrm{tf}_{t,d})$
- The score is 0 if none of the query terms is present in the document.

DOCUMENT FREQUENCY

- Rare terms are more informative than frequent terms
  - Recall stop words
- Consider a term in the query that is rare in the collection (e.g., *arachnocentric*)
- A document containing this term is very likely to be relevant to the query *arachnocentric*
- → We want a high weight for rare terms like *arachnocentric*.

DOCUMENT FREQUENCY, CONTINUED

- Frequent terms are less informative than rare terms
- Consider a query term that is frequent in the collection (e.g., *high, increase, line*)
- A document containing such a term is more likely to be relevant than a document that doesn't
- But it's not a sure indicator of relevance.
- → For frequent terms, we want high positive weights for words like *high, increase, and line*
- But lower weights than for rare terms.
- We will use document frequency (df) to capture this.

IDF WEIGHT

- df_t is the document frequency of t: the number of documents that contain t
  - df_t is an inverse measure of the informativeness of t
  - $df_t \leq N$
- We define the idf (inverse document frequency) of t by
  - We use log (N/df_t) instead of N/df_t to "dampen" the effect of idf.

$$idf_t = \log_{10}(N/df_t)$$

Will turn out the base of the log is immaterial.

IDF EXAMPLE, SUPPOSE N = 1 MILLION

term	df_t	idf_t
calpurnia	1	
animal	100	
sunday	1,000	
fly	10,000	
under	100,000	
the	1,000,000	

$$idf_t = \log_{10}(N/df_t)$$

There is one idf value for each term *t* in a collection.

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EFFECT OF IDF ON RANKING

- Does idf have an effect on ranking for one-term queries, like
  - iPhone
- idf has no effect on ranking one term queries
  - idf affects the ranking of documents for queries with at least two terms
  - For the query capricious person, idf weighting makes occurrences of capricious count for much more in the final document ranking than occurrences of person.

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TF-IDF WEIGHTING

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

$$w_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
  - Note: the "-" in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, tf x idf
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

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FINAL RANKING OF DOCUMENTS FOR A QUERY

$$\mathrm{Score}(q,d) = \sum_{t \in q \cap d} \mathrm{tf.idf}_{t,d}$$

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BINARY → COUNT → WEIGHT MATRIX

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	5.25	3.18	0	0	0	0.35
Brutus	1.21	6.1	0	1	0	0
Caesar	8.59	2.54	0	1.51	0.25	0
Calpurnia	0	1.54	0	0	0	0
Cleopatra	2.85	0	0	0	0	0
mercy	1.51	0	1.9	0.12	5.25	0.88
worser	1.37	0	0.11	4.15	0.25	1.95

Each document is now represented by a real-valued vector of tf-idf weights $\in \mathbb{R}^{|V|}$

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VECTOR SPACE MODEL ---- DOCUMENTS AS VECTORS

- So we have a |V|-dimensional vector space
- Terms are axes of the space
- Documents are points or vectors in this space
- Very high-dimensional: tens of millions of dimensions when you apply this to a web search engine
- These are very sparse vectors - most entries are zero.

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QUERIES AS VECTORS

- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors
- proximity ≈ inverse of distance
- Recall: We do this because we want to get away from the you're-either-in-or-out Boolean model.
- Instead: rank more relevant documents higher than less relevant documents

LENGTH NORMALIZATION

- A vector can be (length-) normalized by dividing each of its components by its length – for this we use the L_2 norm:

$$\|\vec{x}\|_2 = \sqrt{\sum_i x_i^2}$$

- Dividing a vector by its L_2 norm makes it a unit (length) vector (on surface of unit hypersphere)

COSINE(QUERY,DOCUMENT)

Dot product | Unit vectors

$$\cos(\vec{q},\vec{d}) = \frac{\vec{q}\bullet\vec{d}}{|\vec{q}||\vec{d}|} = \frac{\vec{q}}{|\vec{q}|}\bullet\frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2}\sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

q_i is the tf-idf weight of term i in the query
d_i is the tf-idf weight of term i in the document

$\cos(\vec{q},\vec{d})$ is the cosine similarity of $\vec{q}$ and $\vec{d}$ … or, equivalently, the cosine of the angle between $\vec{q}$ and $\vec{d}$.

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COSINE FOR LENGTH-NORMALIZED VECTORS

- For length-normalized vectors, cosine similarity is simply the dot product (or scalar product):

$$\cos(\vec{q},\vec{d}) = \vec{q}\bullet\vec{d} = \sum_{i=1}^{|V|} q_i d_i$$

for q, d length-normalized.

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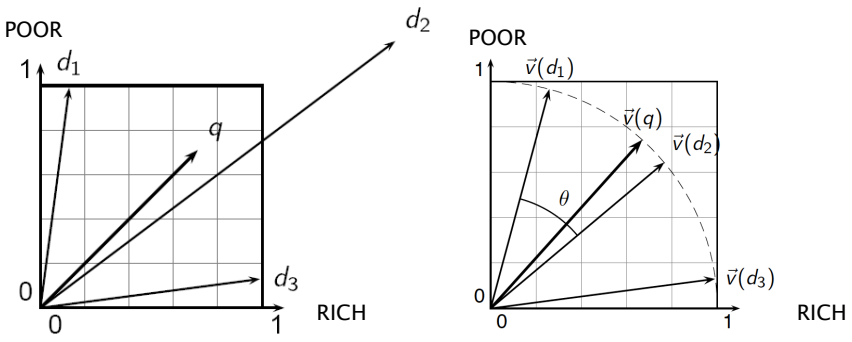
COSINE SIMILARITY ILLUSTRATED



COSINE SIMILARITY AMONGST 3 DOCUMENTS

How similar are the novels SaS: *Sense and Sensibility* PaP: *Pride and Prejudice*, and WH: *Wuthering Heights*?

term	SaS	PaP	WH
affection	115	58	20
jealous	10	7	11
gossip	2	0	6
wuthering	0	0	38

Term frequencies (counts)

Note: To simplify this example, we don't do idf weighting.

3 DOCUMENTS EXAMPLE CONTD.

Log frequency weighting

term	SaS	PaP	WH
affection	3.06	2.76	2.30
jealous	2.00	1.85	2.04
gossip	1.30	0	1.78
wuthering	0	0	2.58

After length normalization

term	SaS	PaP	WH
affection	0.789	0.832	0.524
jealous	0.515	0.555	0.465
gossip	0.335	0	0.405
wuthering	0	0	0.588

cos(SaS,PaP) ≈
0.789 × 0.832 + 0.515 × 0.555 + 0.335 × 0.0 + 0.0 × 0.0
≈ 0.94
cos(SaS,WH) ≈ 0.79
cos(PaP,WH) ≈ 0.69

COMPUTING COSINE SCORES

```
CosineScore(q)
 1  float Scores[N] = 0
 2  float Length[N]
 3  for each query term t
 4  do calculate w_{t,q} and fetch postings list for t
 5      for each pair(d, tf_{t,d}) in postings list
 6      do Scores[d]+ = w_{t,d} × w_{t,q}
 7  Read the array Length
 8  for each d
 9  do Scores[d] = Scores[d]/Length[d]
10  return Top K components of Scores[]
```

SUMMARY – VECTOR SPACE RANKING

- Represent the query as a weighted tf-idf vector
- Represent each document as a weighted tf-idf vector
- Compute the cosine similarity score for the query vector and each document vector
- Rank documents with respect to the query by score
- Return the top *K* (e.g., *K* = 10) to the user