Introduction to Information Retrieval

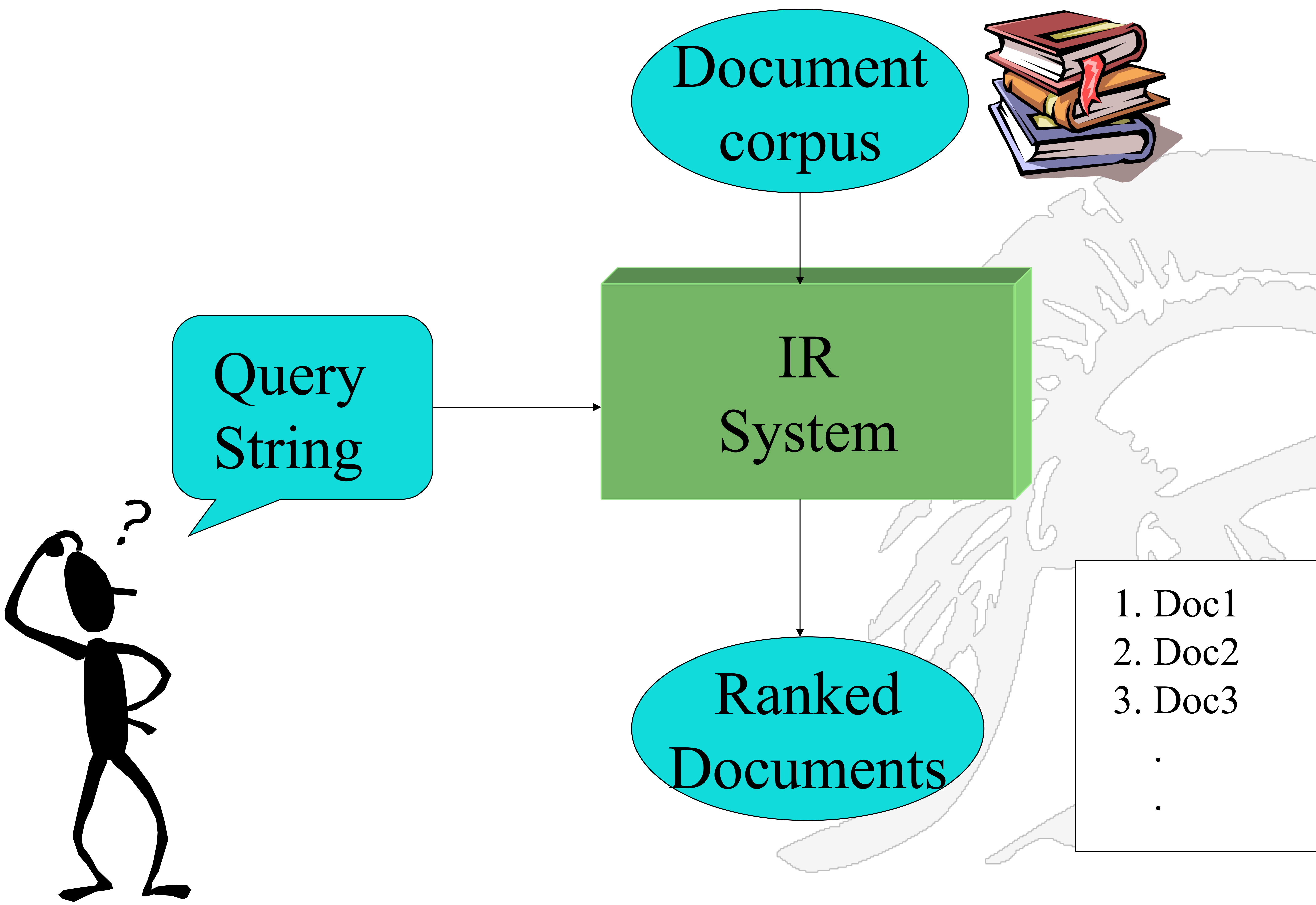
Information Retrieval

- ***Information retrieval (IR)* has been a computer science subject for many decades**
  - Traditionally it deals with the *indexing* of a given set of textual documents and the *retrieval* of relevant documents given a query
- Searching for pages on the World Wide Web has become the "killer app."

- **There has been a great deal of research on**
  - How to index a set of documents (a corpus)
  - How to efficiently retrieve relevant documents
- Jurafsky and Manning have an excellent video introducing the subject of Information Retrieval;
- http://csci572.com/movies/01_IntroIR.mp4 (9 minutes)

  then jump to slide 16

The Traditional IR System



History of IR

- **1960-70's:**
  - Initial exploration of text retrieval systems for "small" corpora of scientific abstracts, and law and business documents.
  - Development of the basic Boolean and vector-space models of retrieval.
  - Prof. Salton and his students at Cornell University were the leading researchers in the area.

IR History Continued

- **1980's:**
  - **Creation of large document database systems, many run by companies:**
    - Lexis-Nexis, http://www.lexisnexis.com/
      - information to legal, corporate, government and academic markets, and publishes legal, tax and regulatory information
    - Dialog, http://www.dialog.com/
      - data from more than 1.4 billion unique records of key information.
    - MEDLINE, http://www.medlineplus.gov/
      - National Library of Medicine health information

IR History Continued

- **1990's:**
  - **Searching FTP'able documents on the Internet**
    - Archie
    - WAIS
  - **After the World Wide Web is invented, search engines appear**
    - Lycos
    - Yahoo
    - Altavista

IR History Continued

- **1990's continued:**
  - **Organized Competitions**
    - NIST TREC (Text REtrieval Conferences, http://trec.nist.gov/)
    - Sponsored by National Institute of Standards and Technology, NIST
  - **Several New Types of IR Systems are Developed**
    1. *Recommender Systems*: computer programs which attempt to predict items (movies, music, books, news, web pages) that a user may be interested in, given some information about the user's profile.
       - **Often implemented as a collaborative filtering algorithm, examples include:**
         - » **YouTube, perhaps the largest scale such system in existence**
         - » **https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/45530.pdf**
         - » **Amazon's recommendation system, see https://stackoverflow.com/questions/2323768/how-does-the-amazon-recommendation-feature-work**
         - » **http://rejoiner.com/resources/amazon-recommendations-secret-selling-online/**
    2. *Automated Text Categorization & Clustering Systems*
       - **Useful for grouping news articles**

USC Viterbi School of Engineering

Recent IR History Moves to the Web

- 2000’s
  - Link analysis for Web Search
    - Google started this
  - Extension to retrieval of multimedia: images, music, video
    - It is much harder to index multimedia artifacts
  - Question Answering
    - Question answering systems return an actual answer rather than a ranked list of documents
    - Since 1999 TREC has had a Question/Answer track, see http://trec.nist.gov/data/qa.html

Areas Related To, But Different Than, Information Retrieval

- Database Management
- Library and Information Science
- Artificial Intelligence
- Natural Language Processing
- Machine Learning
- Data Science

Database Management is Different from IR

- Focused on *structured* data stored in relational tables rather than free-form text
- Focused on efficient processing of well-defined queries in a formal language (SQL)
- Clearer semantics for both data and queries
- Web pages are mostly unstructured, though the Document Object Model (DOM) can provide some clues

Library and Information Science

- **Focused on the human user aspects of information retrieval (human-computer interaction, user interface, visualization).**
- **Concerned with effective categorization of human knowledge.**
- **Concerned with citation analysis and *bibliometrics* (structure of information).**
- **Recent work on *digital libraries* brings it closer to Computer Science & IR.**

Artificial Intelligence

- **Focused on the representation of knowledge, reasoning, and intelligent action.**
- **Formalisms for representing knowledge and queries:**
  - ***First-order Predicate Logic* –** a formal system that uses quantified variables over a specified domain of discourse
  - ***Bayesian Networks* –** a directed acyclic graph model that represents a set of random variables and their dependencies
    - **E.g.** A Bayesian Network that represents the probabilistic relationships between diseases and symptoms
- **Recent work on web ontologies and intelligent information agents brings it closer to IR**
  - Web Ontology Language OWL is a family of knowledge representation languages for authoring ontologies
  - See https://www.w3.org/OWL/

Natural Language Processing

- Focused on the syntactic, semantic, and pragmatic analysis of natural language text and discourse.
- Ability to analyze syntax (phrase structure) and semantics allows retrieval based on *meaning* rather than keywords
- NLP now uses vast amounts of web pages as data to run statistical and machine learning models to infer meaning

Machine Learning

- **A branch of Artificial Intelligence concerned with algorithms that allow computers to evolve their behavior based on empirical data**
- **Focused on the development of computational systems that improve their performance with experience**
- **Two major subtypes of machine learning are**:
  - Automated classification of examples based on learning concepts from labeled training examples (*supervised learning*).
  - Automated methods for clustering unlabeled examples into meaningful groups (*unsupervised learning*)
- **Machine learning is distinct from *data mining*, which focuses on the discovery of previously unknown properties of the given data**
  - Data mining is akin to query analysis and ranking

USC Viterbi School of Engineering

Data Science

- "*Data science* is an inter-disciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from many structural and unstructured data. Data science is related to data mining, machine learning and big data." wikipedia
- A *data scientist* is someone who knows how to extract meaning from and interpret data, which requires both tools and methods from **statistics** and **machine learning**, as well as human review. They spend a lot of time in the process of collecting and cleaning data, because data is never clean
- For fun watch *The Beauty of Data Visualization*
- **https://www.youtube.com/watch?v=5Zg-C8AAIGg (18 min)**

Basic Information Retrieval Begins with Keyword Matching

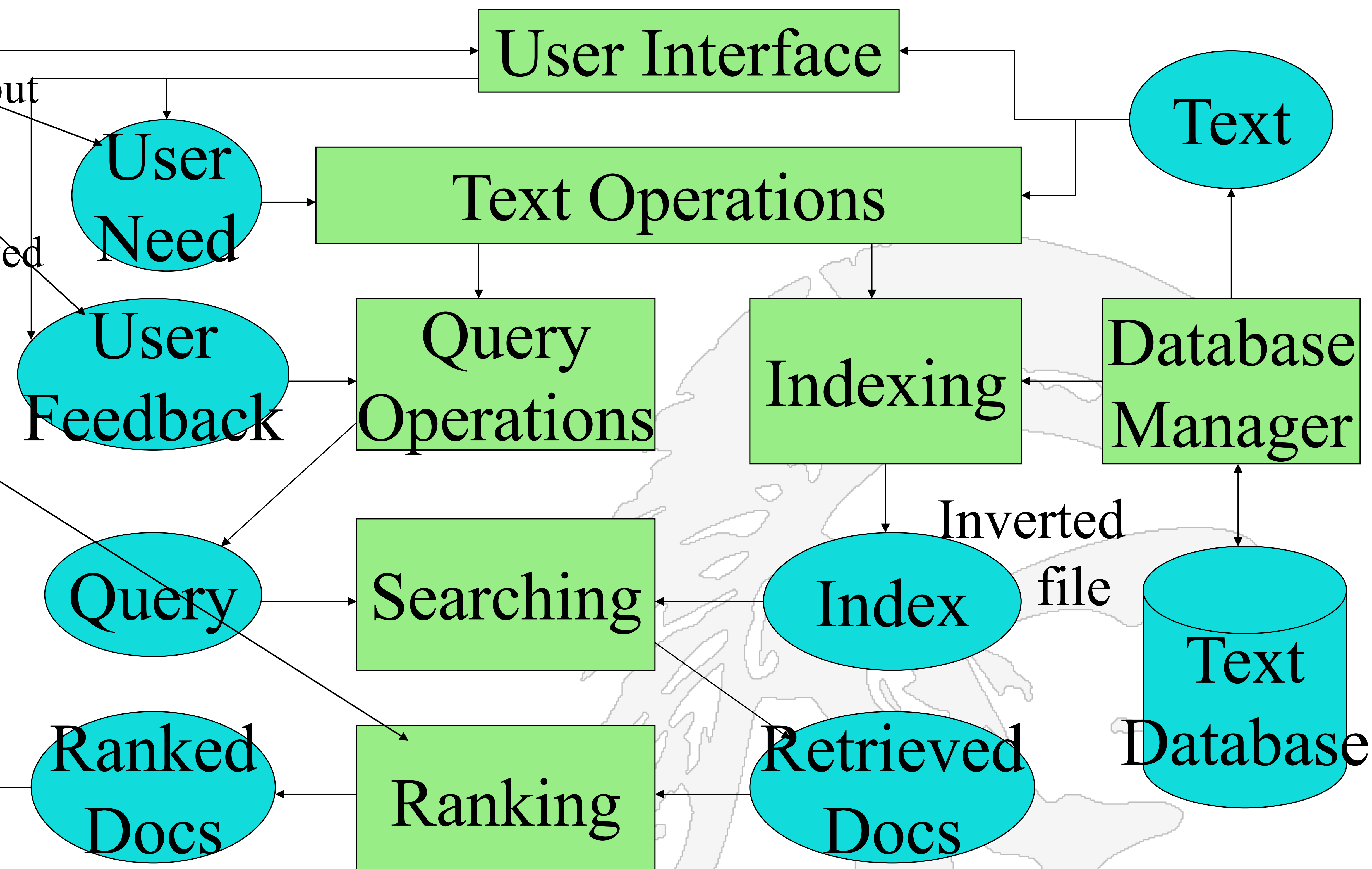
- **Simplest notion of relevance is that the query string appears verbatim in the document.**
  - Slightly less strict notion is that the words in the query appear frequently in the document, in any order (this is like viewing the document as a *bag of words*).
- **But that may not retrieve relevant documents that include synonymous terms.**
  - "restaurant" vs. "café"
  - "PRC" vs. "China"
- **And it may retrieve irrelevant documents that include ambiguous terms.**
  - "bat" (baseball vs. mammal)
  - "Apple" (company vs. fruit)
  - "bit" (unit of data vs. act of eating)

- **Goes beyond using just keyword matching, instead it**
  - Takes into account the *meaning* of the words used
  - Takes into account the *order* of words in the query
  - Adapts to the user based on direct or indirect feedback
  - Takes into account the *authority* of the source

A More Detailed IR Architecture

Logical View

- User needs are part of the input
- User feedback is provided
- Queries initiate a search of the index and docs are retrieved
- A ranking function orders the results



Start with a text database; it is indexed; a user interface permits query operations which cause a search on the Index; matched documents are retrieved and ranked

Defining Terms

- **Parsing forms index words (tokens) and includes:**
  - *Stopword* removal
    - See http://www.ranks.nl/stopwords for google stopwords
  - *Stemming*: reducing a word to its root
    - More about this later
- ***Indexing* constructs an *inverted index* of word to document pointers.**
- ***Searching* retrieves documents that contain a given query token from the inverted index.**
- ***Ranking* scores all retrieved documents according to a relevance metric.**

Boolean and Vector Space Retrieval Models

***Primary goal*: to formalize the processes that underlie a person making the decision that a piece of text is relevant to his information need**

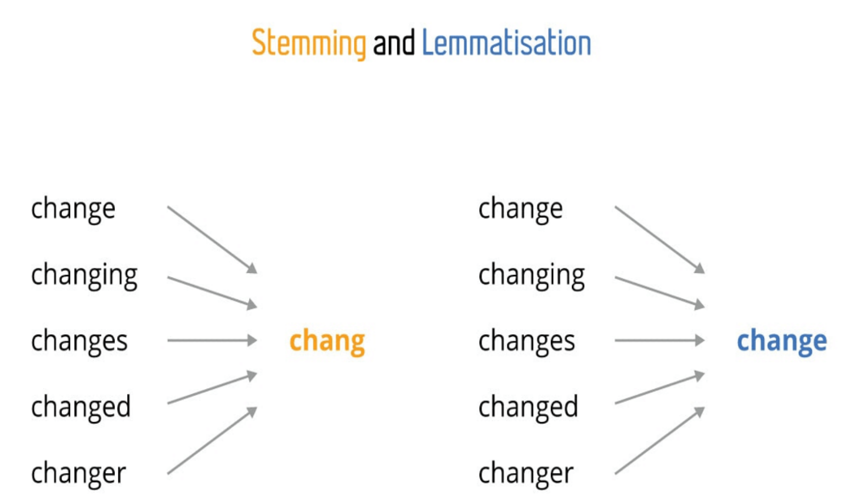
Retrieval Models

- **A retrieval model specifies the details of:**
  - Document representation
  - Query representation
  - Retrieval function
- **Determines a notion of relevance.**
- **Notion of relevance can be binary or continuous (i.e. *ranked retrieval*)**
- **Three major Information Retrieval Models are:**

1. Boolean models (set theoretic) (*Chapter 1 in Manning et al*)
2. Vector space models (statistical/algebraic) (*Chapter 2 in Manning et al*)
3. Probabilistic models (*Chapter 11 in Manning et al*)

Common Pre-Processing Steps

1. Strip unwanted characters/markup (e.g. HTML tags, punctuation, page numbers, etc.).
2. Break into tokens (keywords) separating out whitespace.
3. Stem tokens to “root” words

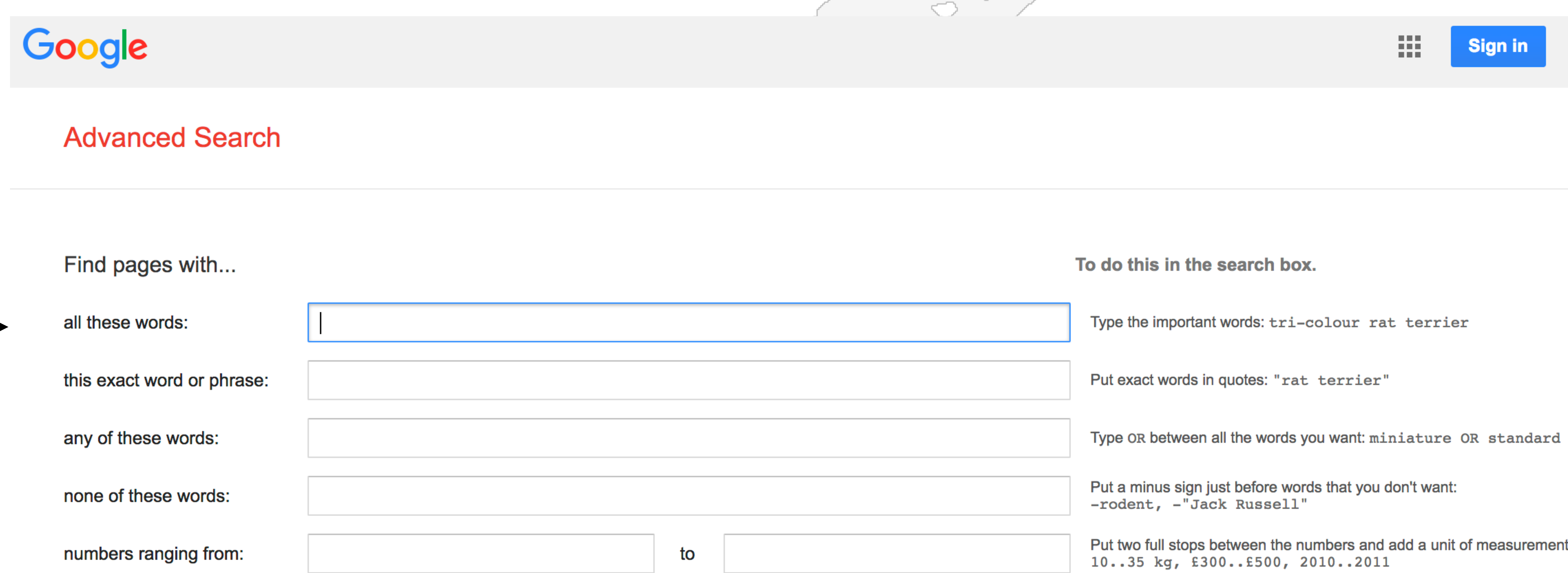


4. Remove common stopwords (e.g. a, the, it, etc.).
5. Detect common phrases (possibly using a domain specific dictionary).
6. Build inverted index (keyword → list of docs containing it).

Boolean Model

- **A document is represented as a set of keywords.**
- **Queries are Boolean expressions of keywords, connected by AND, OR, and NOT, including the use of brackets to indicate scope**
- **Here is a sample Boolean query with explicit AND, OR, NOT operators**
  - [[Rio & Brazil] | [Hilo & Hawaii]] & hotel & !Hilton]

Google Advanced Search;
Note inclusion of AND, OR, NOT operators



Boolean Retrieval Model

- **Popular retrieval model because:**
  - Easy to understand for simple queries.
  - Clean formalism.
- **Boolean models can be extended to include ranking**
- **Reasonably efficient implementations possible for normal queries.**

Boolean Models – Problems

- **Very rigid: AND means all; OR means any**
- **Difficult to express complex user requests**
- **Difficult to control the number of documents retrieved**
  - *All* matched documents will be returned
- **Difficult to rank output**
  - *All* matched documents logically satisfy the query
- **Difficult to perform relevance feedback**
  - If a document is identified by the user as relevant or irrelevant, how should the query be modified?

Problem Example For the Boolean Model

- **The simple query "Lincoln"**
  - Too many matches including Lincoln cars and places named Lincoln as well as Abraham Lincoln
- **More detailed query "President AND Lincoln"**
  - Returns documents that discuss the President of Ford Motor company that makes the Lincoln car
- **Even more detailed query "president AND Lincoln AND NOT (automobile OR car)"**
  - Better, but the use of NOT will remove a document about President Lincoln that says "Lincoln's body departs Washington in a nine car funeral train"
- **Perhaps try**
  - President AND lincoln AND biography AND life AND birthplace AND gettysburg AND NOT (automobile OR car), but too many ANDs can lead to nothing, so
  - President AND lincoln AND (biography OR life OR birthplace OR gettysburg) AND NOT (automobile OR car)

USC Viterbi School of Engineering

The Vector-Space Model

- **Assume *t* distinct terms remain after preprocessing; call them index terms or the vocabulary**
- **These "orthogonal" terms form a vector space**

  size of the vocabulary = Dimension = t = |vocabulary|
- **A document D_i is represented by a vector of index terms**

  $$D_i = (d_{i1}, d_{i2}, \ldots, d_{it})$$
- **Where d_{ij} represents the weight of the *j*-th term in the i^{th} doc**
  - *but how is the weight computed?*
- **Both documents and queries are expressed as *t*-dimensional vectors**

Graphic Representation Example

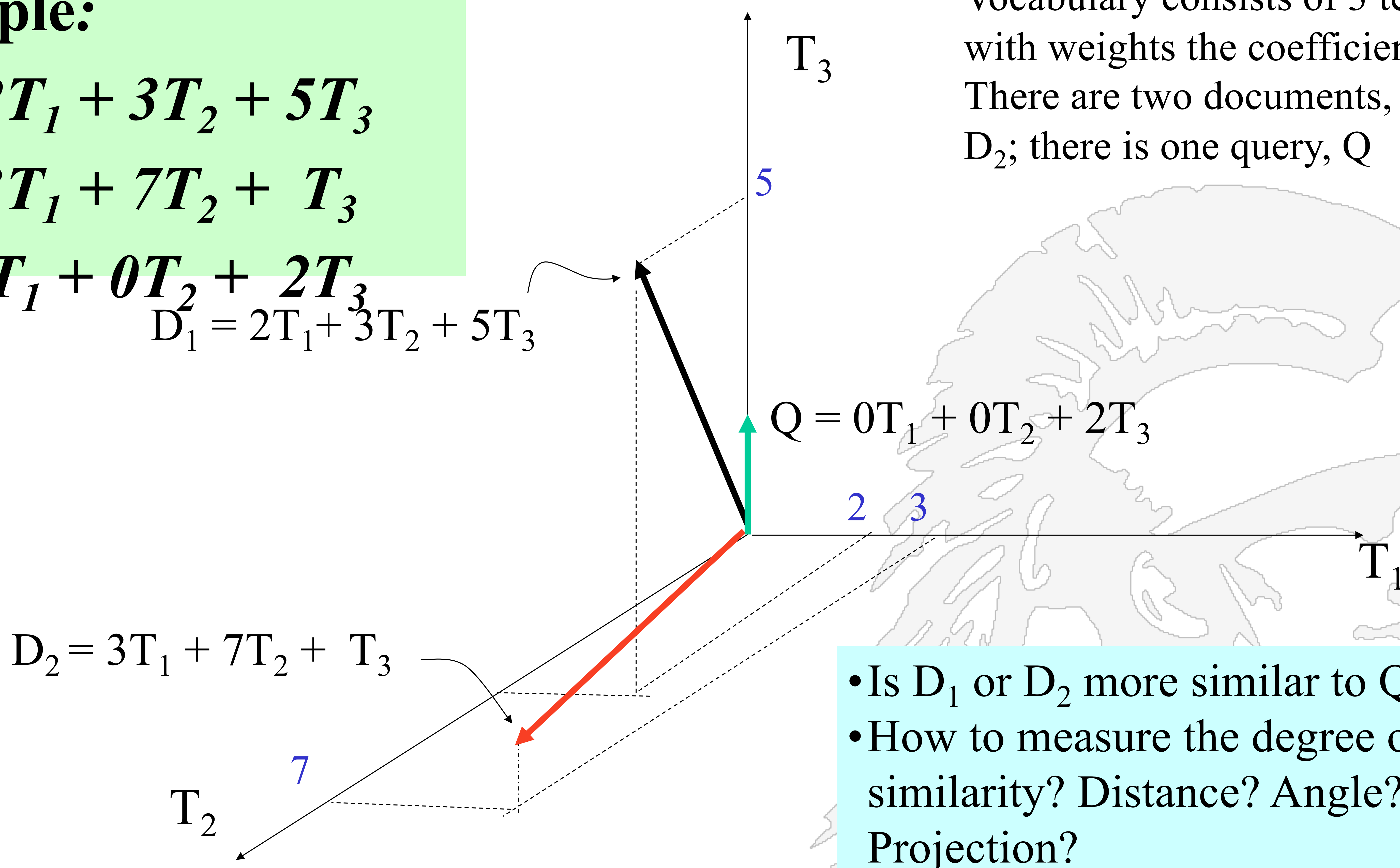
Example:

$$D_1 = 2T_1 + 3T_2 + 5T_3$$

$$D_2 = 3T_1 + 7T_2 + T_3$$

$$Q = 0T_1 + 0T_2 + 2T_3$$

Vocabulary consists of 3 terms with weights the coefficients There are two documents, D_1 and D_2; there is one query, Q



- Is D_1 or D_2 more similar to Q?
- How to measure the degree of similarity? Distance? Angle? Projection?

Representing a Collection of Documents

- A collection of *n* documents can be represented in the vector space model by a term-document matrix.
- An entry in the matrix corresponds to the "weight" of a term in the document; zero means the term has no significance in the document or it simply doesn't exist in the document; but we still need a way to compute the weight

$$
\begin{array}{ccccc}
 & T_1 & T_2 & \cdots & T_t \\
D_1 & w_{11} & w_{21} & \cdots & w_{t1} \\
D_2 & w_{12} & w_{22} & \cdots & w_{t2} \\
\vdots & \vdots & \vdots & & \vdots \\
\vdots & \vdots & \vdots & & \vdots \\
D_n & w_{1n} & w_{2n} & \cdots & w_{tn}
\end{array}
$$

USC Viterbi School of Engineering

Term Weights: Term Frequency

- **One way to compute the weight is to use the term's frequency in the document**
- **Assumption: the more frequent terms in a document are more important, i.e. more indicative of the topic.**

  f_{ij} = frequency of term i in document j
- **May want to normalize *term frequency* (*tf*) across the entire corpus:**

  $$tf_{ij} = f_{ij} \;/\; max\{f_{ij}\}$$

Term Weights: Inverse Document Frequency

- **Terms that appear in many *different* documents are *less* indicative of overall topic**

  df_i = document frequency of term i

  = number of documents containing term i

of course df_i is always <= N (total number of documents)

  idf_i = inverse document frequency of term i,

  $= \log_2 (N/df_i)$

  (N: total number of documents)

- **An indication of a term's *discrimination* power**
- **Log is used to dampen the effect relative to *tf***

An Example of Inverse Document Frequency

term	df_i	idf_i
Calpurnia	1	log(1,000,000/1)=6
animal	100	4
Sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

- $idf_i = \log_{10}(N/df_i)$, $N = 1{,}000{,}000$
- **there is one *idf* value for each term *t* in a collection**

TF.IDF Weighting

- **A typical combined term importance indicator is *tf-idf weighting* (*note: it is often written with a hyphen, but the hyphen is NOT a minus sign; some people replace the hyphen with a dot*):**

$$w_{ij} = tf_{ij} . idf_i = (1 + \log tf_{ij})^* \log_2 (N/ df_i)$$

- **A term occurring frequently in the document but rarely in the rest of the collection is given high weight.**
- **Many other ways of determining term weights have been proposed.**
- **Experimentally, *tf.idf* has been found to work well**

- **Given a query *q*, then we score the query against a document *d* using the formula**

- $Score\ (q, d) = \sum(tf.idf_{t,d})$ **where *t* is in $q \cap d$**

Computing TF.IDF -- An Example

Given a document containing 3 terms with given frequencies:

A(3), B(2), C(1)

Assume collection contains 10,000 documents and document frequencies of these 3 terms are:

A(50), B(1300), C(250)

Then:

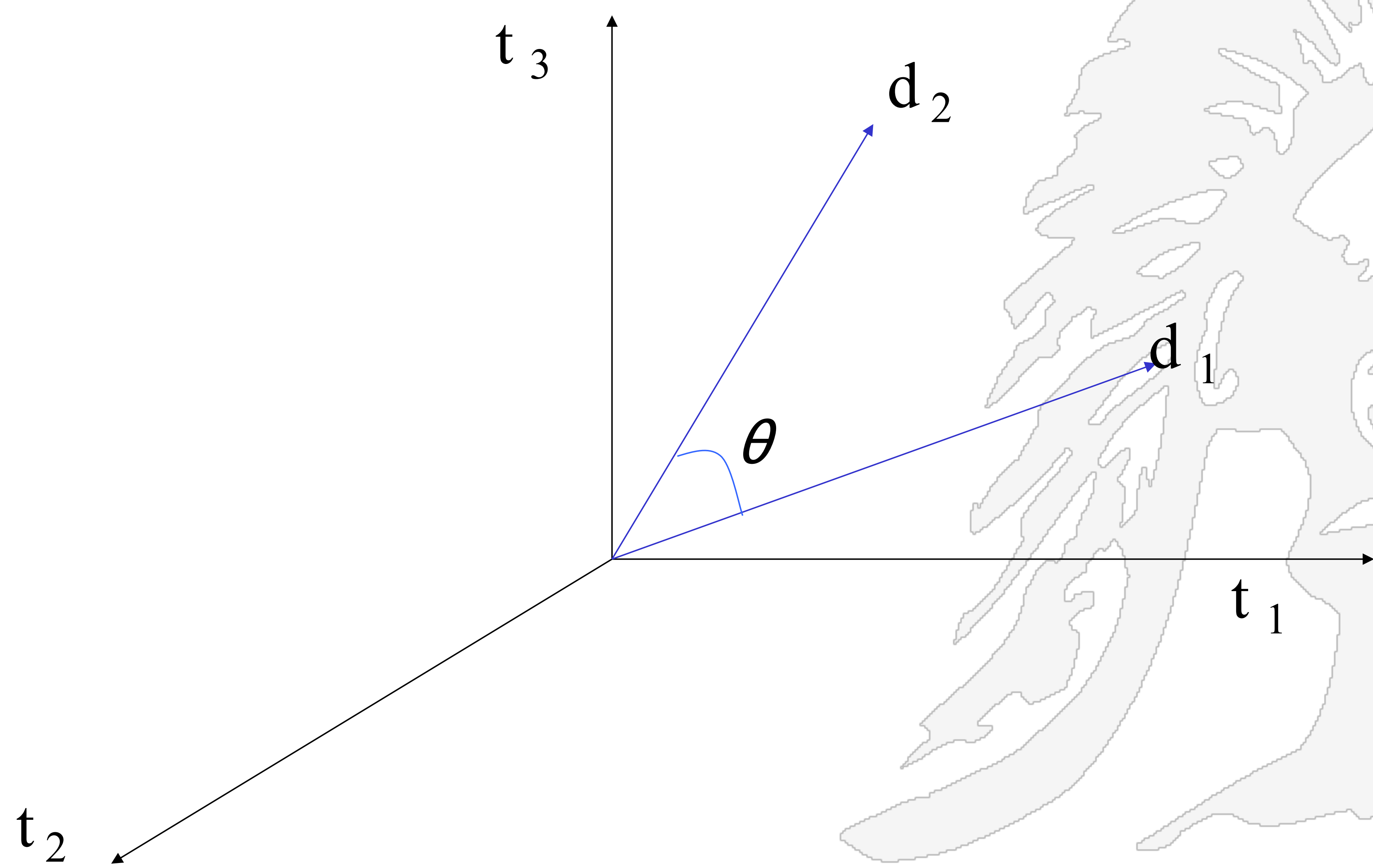
A: tf = 3/3; idf = log(10000/50) = 5.3; tf.idf = 5.3

B: tf = 2/3; idf = log(10000/1300) = 2.0; tf.idf = 1.3

C: tf = 1/3; idf = log(10000/250) = 3.7; tf.idf = 1.2

Cosine Similarity

- **Distance between vectors d_1 and d_2 is *captured* by the cosine of the angle x between them.**
- **Note – this is a *similarity* measure, not a distance measure**



Similarity Measure

- **A similarity measure is a function that computes the *degree of similarity* between two vectors**
  - **Look back at the previous lecture slides for the definition of similarity**
- **Using a similarity measure between the query and each document has positive aspects:**
  - It is possible to rank the retrieved documents in the order of presumed relevance.
  - It is possible to enforce a certain threshold so that the size of the retrieved set can be controlled.

Normalized Vectors

- A vector can be normalized (given a length of 1) by dividing each of its components by the vector's length
- This maps vectors onto the unit circle:
- Then, $\left|\vec{d}_j\right| = \sqrt{\sum_{i=1}^{n} w_{i,j}^{2}} = 1$
- Longer documents don't get more weight
- For normalized vectors, the cosine is simply the dot product:

$$\cos(\vec{d}_j, \vec{d}_k) = \vec{d}_j \cdot \vec{d}_k$$

Similarity Measure for Document and Query

- **Similarity between vectors for the document d_j and query q can be computed as the vector inner product:**

$$sim(d_j,q) = d_j \bullet q = \sum_{i=1}^{t} w_{ij} \cdot w_{iq}$$

where w_{ij} is the weight of term i in document j and w_{iq} is the weight of term i in the query

- **For binary vectors, the inner product is the number of matched query terms in the document (size of intersection) (Hamming distance)**
- **For weighted term vectors, it is the sum of the products of the weights of the matched terms.**

Limitations of the Inner Product

- **Favors long documents with a large number of unique terms.**
- **Measures how many terms matched but not how many terms are *not* matched.**

USC Viterbi School of Engineering

Cosine Similarity Using Inner Product -- Examples

Binary:

	retrieval	database	architecture	computer	text	management	information
– **D** =	**1,**	**1,**	**1,**	**0,**	**1,**	**1,**	**0**
– **Q** =	**1,**	**0 ,**	**1,**	**0,**	**0,**	**1,**	**1**

Size of vector = size of vocabulary = 7

0 means corresponding term not found in document or query

similarity(D, Q) = 3 **(the inner product)**

Weighted:

$D_1 = 2T_1 + 3T_2 + 5T_3$ $\quad D_2 = 3T_1 + 7T_2 + 1T_3$

$Q = 0T_1 + 0T_2 + 2T_3$

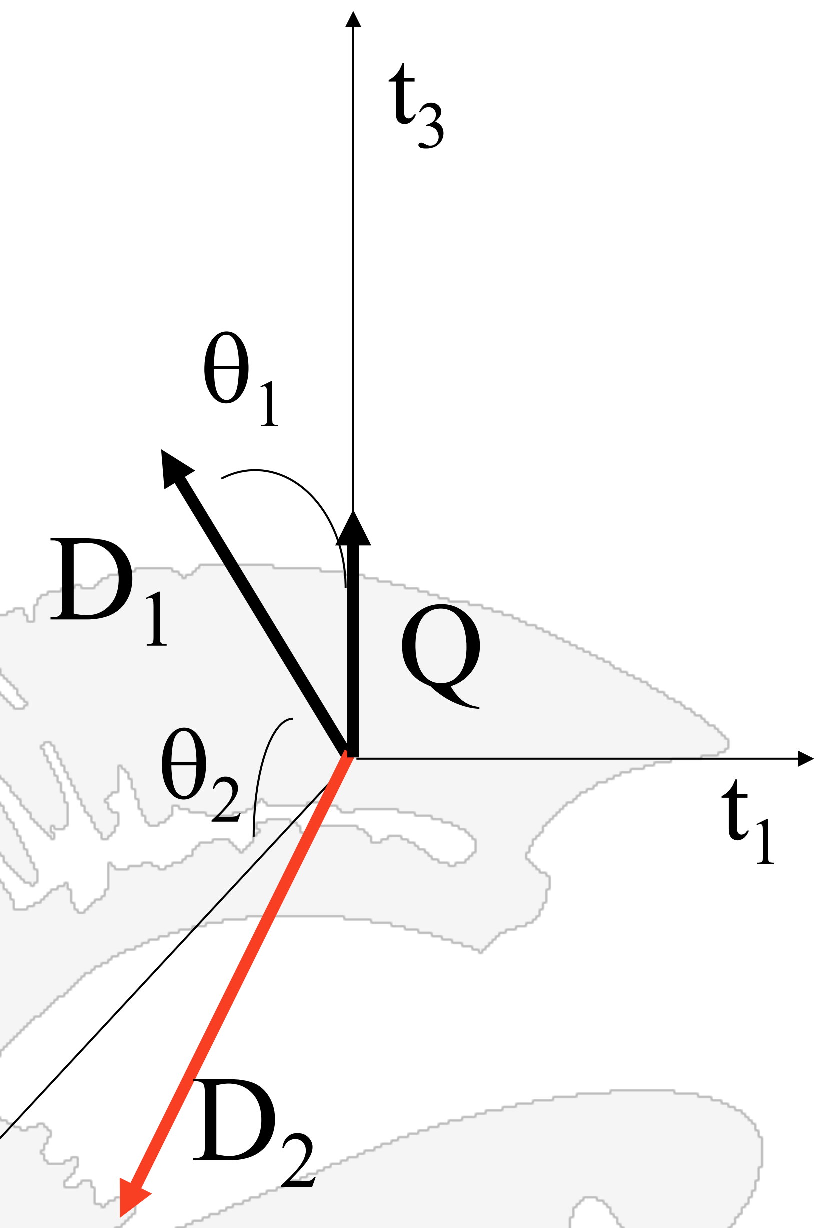
$\text{sim}(D_1, Q) = 2*0 + 3*0 + 5*2 = 10$

$\text{sim}(D_2, Q) = 3*0 + 7*0 + 1*2 = 2$

Cosine Similarity Measure Normalized

- **Cosine similarity measures the cosine of the angle between two vectors**
- **We compute the inner product normalized by the vector lengths**

$$CosSim(\mathbf{d}_j, \mathbf{q}) = \frac{\vec{d_j} \bullet \vec{q}}{\left|\vec{d_j}\right| \cdot \left|\vec{q}\right|} = \frac{\sum_{i=1}^{t}(w_{ij} \cdot w_{iq})}{\sqrt{\sum_{i=1}^{t} w_{ij}^{2} \cdot \sum_{i=1}^{t} w_{iq}^{2}}}$$



$D_1 = 2T_1 + 3T_2 + 5T_3$ CosSim(D_1 , Q) = $10 / \sqrt{(4+9+25)(0+0+4)} = 0.81$
$D_2 = 3T_1 + 7T_2 + 1T_3$ CosSim(D_2 , Q) = $2 / \sqrt{(9+49+1)(0+0+4)} = 0.13$
$Q = 0T_1 + 0T_2 + 2T_3$

D_1 is 6 times better than D_2 using cosine similarity but only 5 times better using inner product.

Naïve Implementation

1. **Convert all documents in collection D to *tf.idf* weighted vectors, the j^{th} document denoted by d_j, for keywords in vocabulary V**
2. **Convert each query to a *tf.idf* weighted vector q**
3. **For each d_j in D do**

   Compute score $s_j = cosSim(d_j, q)$
4. **Sort documents by decreasing score**
5. **Present top ranked documents to the user**

Time complexity: O(|V|·|D|) Bad for large V & D !

|V| = 10,000; |D| = 100,000; |V|·|D| = 1,000,000,000

USC Viterbi School of Engineering

Efficient Cosine Ranking

- Ranking consists of computing the *k* docs in the corpus "nearest" to the query $\Rightarrow$ *k* largest query-doc cosines.
- To do efficient ranking one must:
  - Compute a single cosine efficiently.
  - Choose the *k* largest cosine values efficiently.

Computing Cosine Scores

cosineScore(q)

1. **float** ***Scores[N] = 0;*** ***//Scores array for all documents***
2. **float** ***Length[N]*** ***//lengths of all documents***
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** $Scores[d] += w_{t,d} \times w_{t,q}$
7. **Read the array Length**
8. **for each** ***d do***
9. $Scores[d] = Scores[d]/Length[d]$
10. **return Top** ***K*** **components of** ***Scores[]***

weight of query term is *1*; then, for each document in the postings list, the term *t* occurs *tf* times; then we take the dot product of weight of term *t* in document times weight of term *t* in query;

divide scores by length of each document

ranking

in practice we only work with a subset of the documents

Summary of Algorithm for 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 that contains the query term**
- **Rank documents with respect to the query by score**
- **Return the top *k* (e.g. *k=10*) to the user**

Use Heap for Selecting Top *k*

- **Binary tree in which each node's value > values of children**
- **Takes *2n* operations to construct, then each of *k* log *n* "winners" read off in 2log *n* steps.**
- **For *n=1M*, *k=100*, this is about 10% of the cost of sorting.**

Bottleneck

- Still need to first compute cosines from query to each of *n* docs → several seconds for *n* = 1M
- Can select from only non-zero cosines
  - Need union of postings lists accumulators (<<1M)
- Can further limit to documents with non-zero cosines on rare (high idf) words
- Enforce conjunctive search (a la Google): non-zero cosines on *all* words in query
  - Need min of postings lists sizes accumulators
- But still potentially expensive

A Pre-Processing Strategy

- **Preprocess: Pre-compute, for each term, its *k* nearest docs.**
  - **(Treat each term as a 1-term query)**
  - **lots of preprocessing.**
  - **Result: “preferred list” for each term.**
- **Search:**
  - **For a *t*-term query, take the union of their *t* preferred lists – call this set *S*.**
  - **Compute cosines from the query to only the docs in *S*, and choose top *k*.**

Comments on Vector Space Model

- Simple, mathematically based approach.
- Considers both local (*tf*) and global (*idf*) word occurrence frequencies.
- Provides partial matching and ranked results.
- Tends to work quite well in practice despite obvious weaknesses.
- Allows efficient implementation for large document collections.

Problems with Vector Space Model

- **Missing semantic information (e.g. word sense).**
- **Missing syntactic information (e.g. phrase structure, word order, proximity information).**
- **Assumption of term independence**
- **Lacks the control of a Boolean model (e.g., *requiring* a term to appear in a document).**
  - Given a two-term query “A B”, may prefer a document containing A frequently but not B, over a document that contains both A and B, but both less frequently.