Boolean and Vector Space Retrieval Models

- CS 293S, 2020

Outline

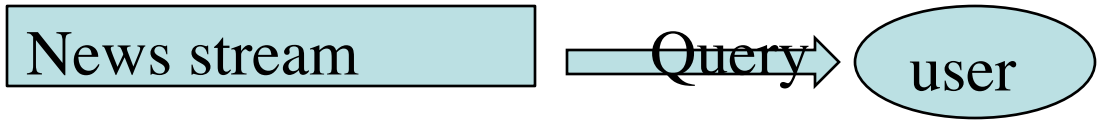
- **Which results satisfy the query constraint?**
  - Boolean model
    - Document processing steps
    - Query processing
  - Statistical vector space model
  - Neural representations with word embeddings

Retrieval Models

- **A retrieval model specifies the details of:**
  - 1) Document representation
  - 2) Query representation
  - 3) Retrieval function: how to find relevant results
  - Determines a notion of relevance.
- **Classical models**
  - Boolean models (set theoretic)
    - Extended Boolean
  - Vector space models
  - Probabilistic models

Retrieval Tasks

- **Ad hoc retrieval: Fixed document corpus, varied queries.**
- **Filtering: Fixed query, continuous document stream.**
  - User Profile: A model of relative static preferences.
  - Binary decision of relevant/not-relevant.



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.
  - Rio & Brazil | Hilo & Hawaii, hotel & !Hilton
- Output: Document is relevant or not. No partial matches
  - Can be extended to include ranking.

Incident vector representation for Shakespeare plays

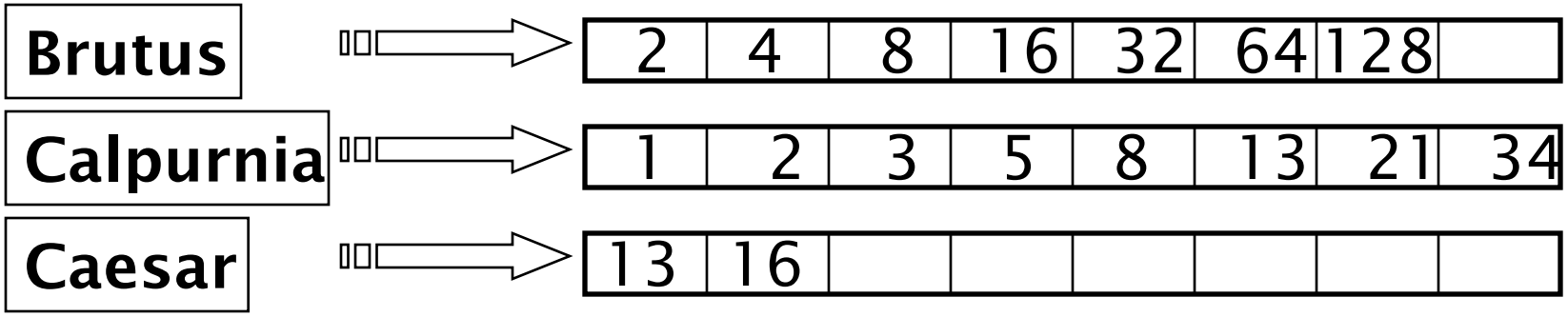
1 if play contains word, 0 otherwise

	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

- Query answer with bitwise operations (AND, negation, OR):
  - Which plays of Shakespeare contain the words *Brutus AND Caesar* but *NOT Calpurnia*?
  - 110100 *AND* 110111 *AND* 101111 = 100100.

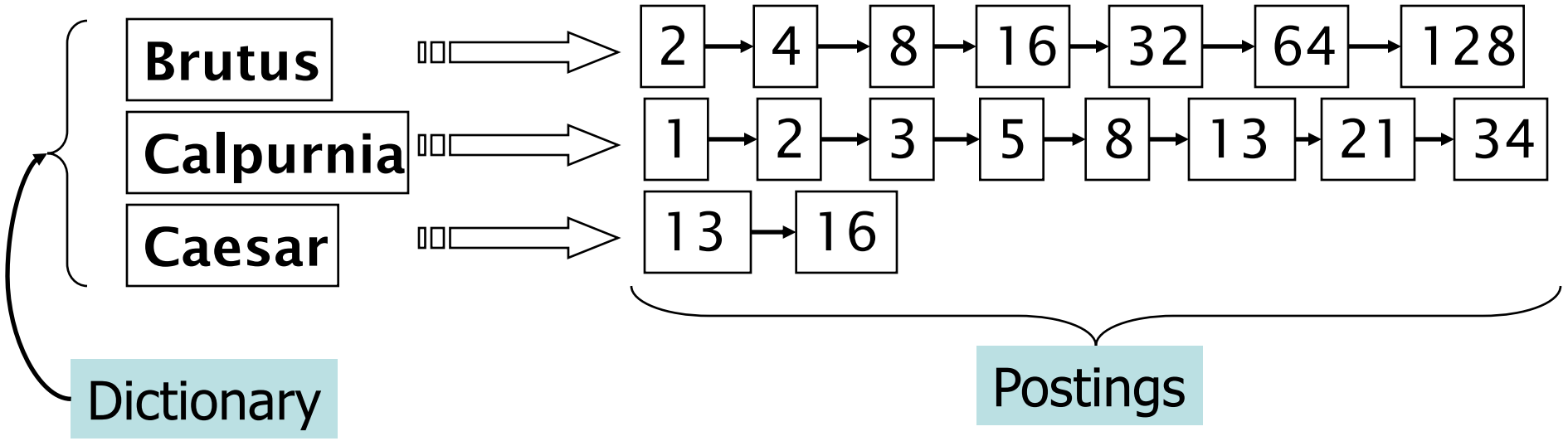
Inverted index

- **Incident vectors are sparse → sparse matrix**
  - Compact representation needed to save storage
- **Inverted index**
  - For each term *T*, must store a list of all documents that contain *T*.



Inverted index

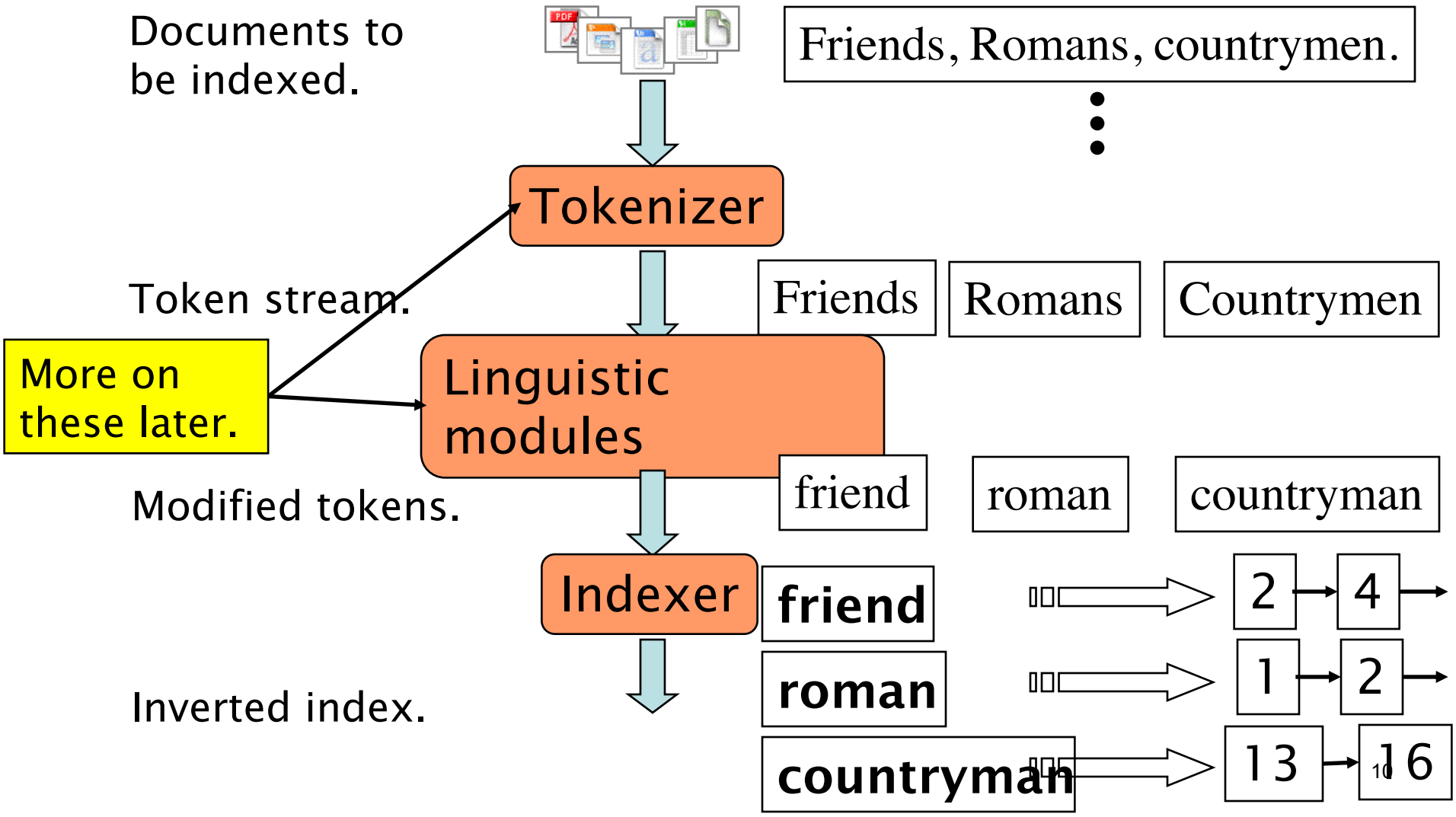
- **Linked lists generally preferred to arrays**
  - Dynamic space allocation
  - Insertion of terms into documents easy
  - Space overhead of pointers



Document Preprocessing Steps

- **Strip unwanted characters/markup** (e.g. HTML tags, punctuation, numbers, etc.).
- **Break into tokens (keywords) on whitespace.**
- **Possible linguistic processing** (used in some applications, but dangerous for general web search)
  - Stemming (cards ->card)
  - Remove common stopwords (e.g. a, the, it, etc.).
  - Used sometime, but dangerous
- **Build inverted index**
  - keyword → list of docs containing it.
  - Common phrases may be detected first using a domain specific dictionary.

Inverted index construction



Discussions

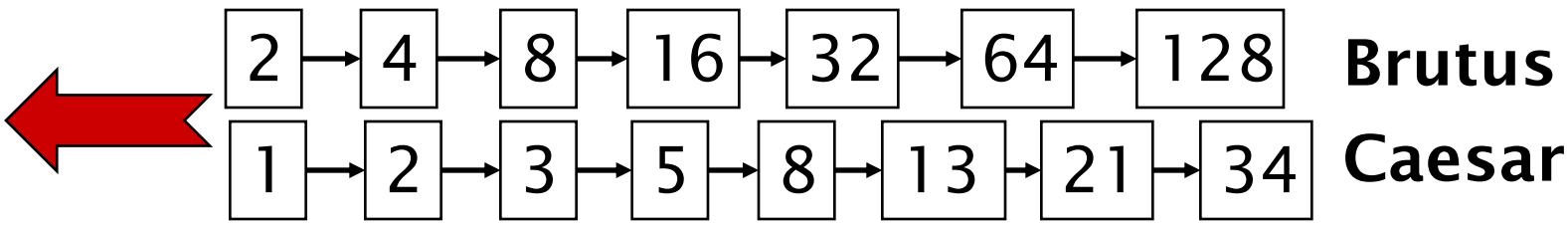
- **Which terms in a doc do we index?**
  - All words or only “important” ones?
- **Stopword list: terms that are so common**
  - they MAY BE ignored for indexing.
  - *e.g.*, ***the, a, an, of, to*** …
  - language-specific.
- **How do we process a query?**
  - What kinds of queries can we process?

Query processing

- **Consider processing the query:**

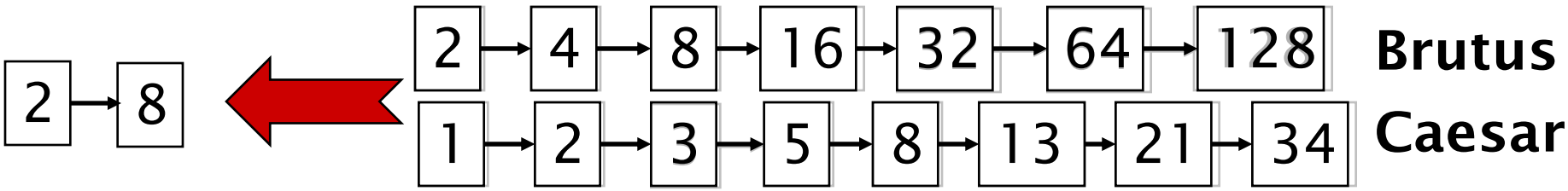
  Brutus *AND* ***Caesar***

  - 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 m and n, the merge for sorted lists takes O(m+n) operations.

Crucial: postings sorted by docID.

More general merges

- **Exercise: How to handle NOT, OR?**

  Brutus AND NOT Caesar

  Brutus OR NOT Caesar

Can we still run through the merge in time O(*m*+*n*)?

Boolean Models – Problems

- **Very rigid: AND means all; OR means any.**
  - Easy to understand. Clean formalism.
- **Difficult to express complex user requests.**
  - Still too complex for general web users
- **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?

Example Application: WestLaw

http://www.westlaw.com/

- **Largest commercial (paying subscribers) legal search service (started 1975; ranking added 1992)**
  - Long, precise queries; proximity operators; incrementally developed; not like web search
  - Professional searchers (e.g., Lawyers) still like Boolean queries: You know exactly what you're getting.
- **Example query with proximity operators:**
  - What is the statute of limitations in cases involving the federal tort claims act?
  - LIMIT! /3 STATUTE ACTION /S FEDERAL /2 TORT /3 CLAIM

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    - Query processing
  - Statistical vector space model
  - Neural representations

Statistical Retrieval Models

- A document is typically represented by a *bag of words* (unordered words with frequencies).
- Bag = set that allows multiple occurrences of the same element.
- User specifies a set of desired terms with optional weights:
  - Weighted query terms:

    Q = < database 0.5; text 0.8; information 0.2 >
  - Unweighted query terms:

    Q = < database; text; information >
  - No Boolean conditions specified in the query.
- Retrieval based on *similarity* between query and documents.
  - Output documents are ranked by similarity to query.
- Weights in vectors
  - Similarity based on occurrence *frequencies* of keywords in query and document.

The Vector-Space Representation

- Assume *t* distinct terms remain after preprocessing; call them index terms or the vocabulary.
- Each term, *i*, in a document or query, *j*, is given a real-valued weight, w_{ij}.
- Both documents and queries are expressed as t-dimensional vectors:

$$d_j = (w_{1j}, w_{2j}, \ldots, w_{tj})$$

	T_1	T_2	....	T_t
D_1	w_{11}	w_{21}	...	w_{t1}
D_2	w_{12}	w_{22}	...	w_{t2}
:	:	:		:
:	:	:		:
D_n	w_{1n}	w_{2n}	...	w_{tn}

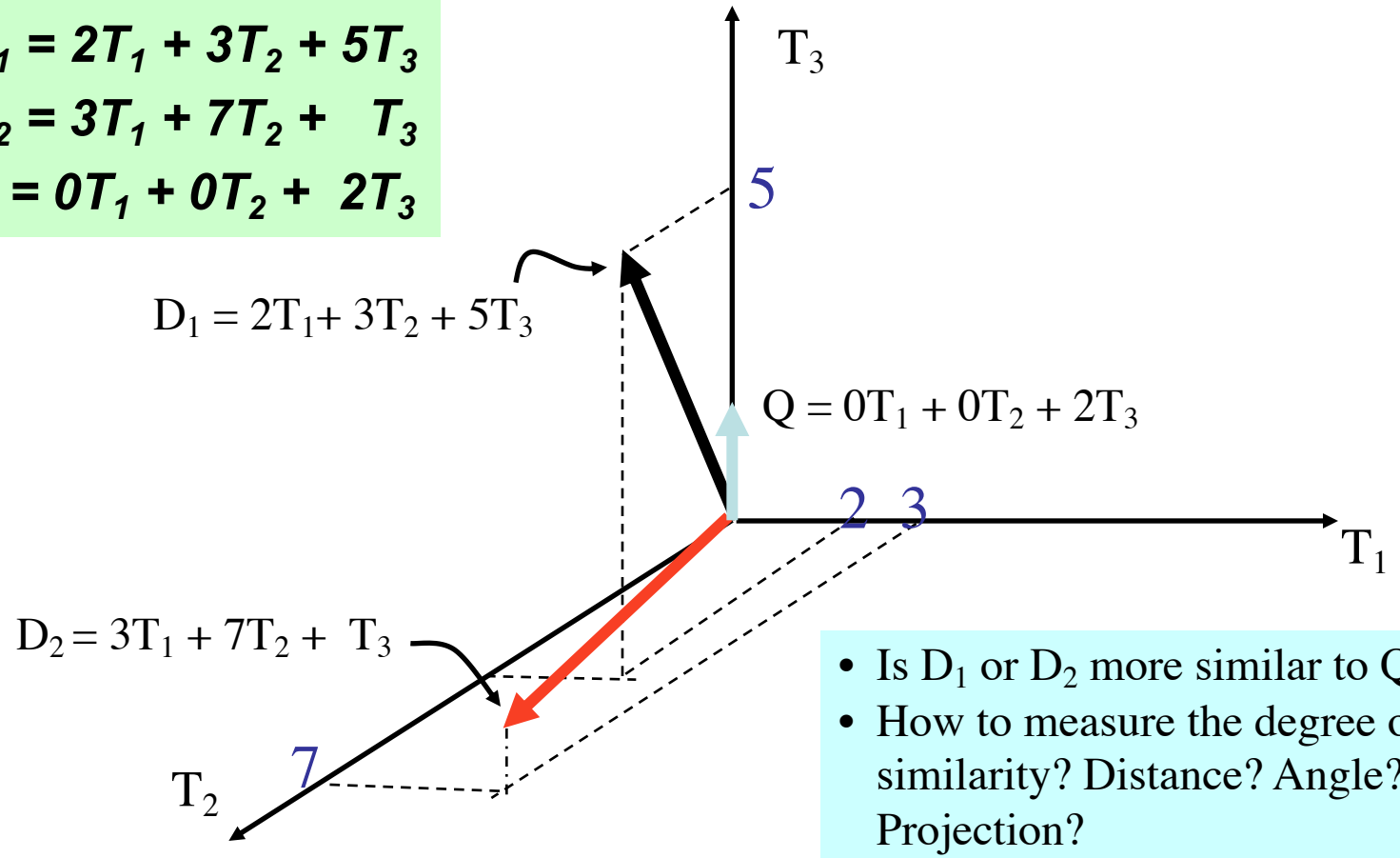
Example: Graphic representation

Example:

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

$D_2 = 3T_1 + 7T_2 + T_3$

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



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

Issues for Vector Space Model

- How to determine important words in a document?
  - Word n-grams (and phrases, idioms,…) → terms
- How to determine the degree of importance of a term within a document and within the entire collection?
- How to determine the degree of similarity between a document and the query?
- In the case of the web, what is a collection and what are the effects of links, formatting information, etc.?

Term Weights: Term Frequency

- 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:

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

- Terms that appear in many *different* documents are *less* indicative of overall topic. *Less discrimination* power.

  df_i = document frequency of term *i*

  = number of documents containing term *i*

  idf_i = **inverse document frequency** of term *i,*

  $= \log_2 (N/ df_i)$ N: total number of documents

- Log used to dampen the effect relative to *tf*.

TF-IDF Weighting

- A typical combined term importance indicator is *tf-idf weighting*:

$$w_{ij} = tf_{ij}\, idf_i = tf_{ij} \log_2 (N/ df_i)$$

- A term occurring frequently in the document but rarely in the rest of the collection is given high weight.

Example: A document has term frequencies: A(3), B(2), C(1)

Assume collection contains 10,000 documents and

document frequencies of these 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

Similarity Measure

- A similarity measure is a function that computes the *degree of similarity* between two vectors.
- Using a similarity measure between the query and each document:
- Similarity between vectors for the document d_i and query q can be computed as the vector inner product:

$$\text{sim}(d_j, q) = d_j \bullet q = \text{sum} \quad w_{ij} \cdot w_{iq}$$

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

Example:

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

sim(D, Q) = 3

Example & Properties of Inner Product

Another example with weighted vectors:

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

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

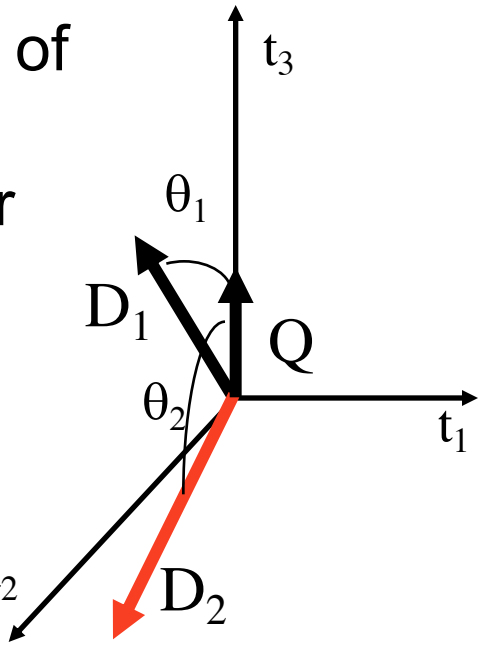
$\text{sim}(D_1, Q) = 2*0 + 3*0 + 5*2 = 10$

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

- **Properties of Inner Product**
  - The inner product is unbounded.
  - Favors long documents with a large number of unique terms.
  - Measures how many terms matched but not how many terms are *not* matched.

Cosine Similarity Measure

- Cosine similarity measures the cosine of the angle between two vectors.
- Inner product normalized by the vector lengths.



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

$D_1 = 2T_1 + 3T_2 + 5T_3$ $\quad \text{CosSim}(D_1, Q) = 10 / \sqrt{(4+9+25)(0+0+4)} = 0.81$

$D_2 = 3T_1 + 7T_2 + 1T_3$ $\quad \text{CosSim}(D_2, Q) = 2 / \sqrt{(9+49+1)(0+0+4)} = 0.13$

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

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

Improvement: BM25

- Rank or feature score with an extension of TF-IDF
- Given document d for query q

$$\sum_{w \in q \cap d} \ln \frac{N - df(w) + 0.5}{df(w) + 0.5} \cdot \frac{(k_1 + 1) \times c(w,d)}{k_1((1-b) + b\frac{|d|}{avdl}) + c(w,d)} \cdot \frac{(k_3 + 1) \times c(w,q)}{k_3 + c(w,q)}$$

- df: nuber of documents containing this word
- |d|: document length
- avdl: average document length
- c(w,d): term frequency in this document
- c(w,q): term frequency in this query
- Constants k_1 in [1,2], b=0.75, k_3 in [0, 3000]

Comments on Vector Space Models

- **Simple, practical, and mathematically based approach**
- **Provides partial matching and ranked results.**
- **Problems**
  - Missing syntactic information (e.g. phrase structure, word order, proximity information).
  - Missing semantic information
    - word sense: multiple meanings of a word
    - Assumption of term independence. ignores synonymy.
  - 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.

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  - Neural representations
    - Word embeddings

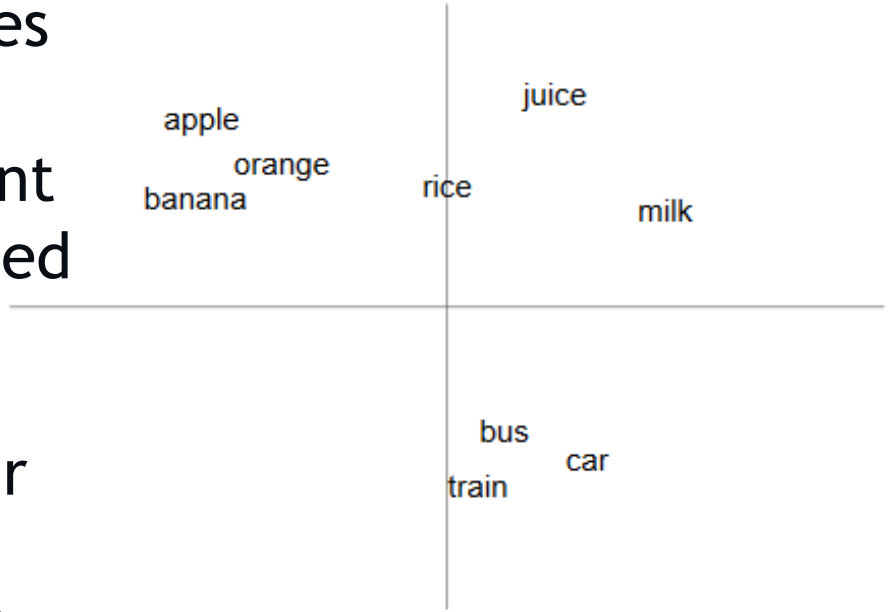
Word Representations

Traditional Method - Bag of Words Model	Word Embeddings
• Uses one hot encoding • Each word in the vocabulary is represented by one bit position in a HUGE vector. • For example, if we have a vocabulary of 10000 words, and "Hello" is the 4th word in the dictionary, it would be represented by: 0 0 0 1 0 0 . . . . . 0 0 0 0 • Context information is not utilized	• Stores each word in as a point in space, where it is represented by a vector of fixed number of dimensions (generally 300) • Unsupervised, built just by reading huge corpus • For example, "Hello" might be represented as : [0.4, -0.11, 0.55, 0.3 . . . 0.1, 0.02]

Word embedding: Motivation for a new word representation

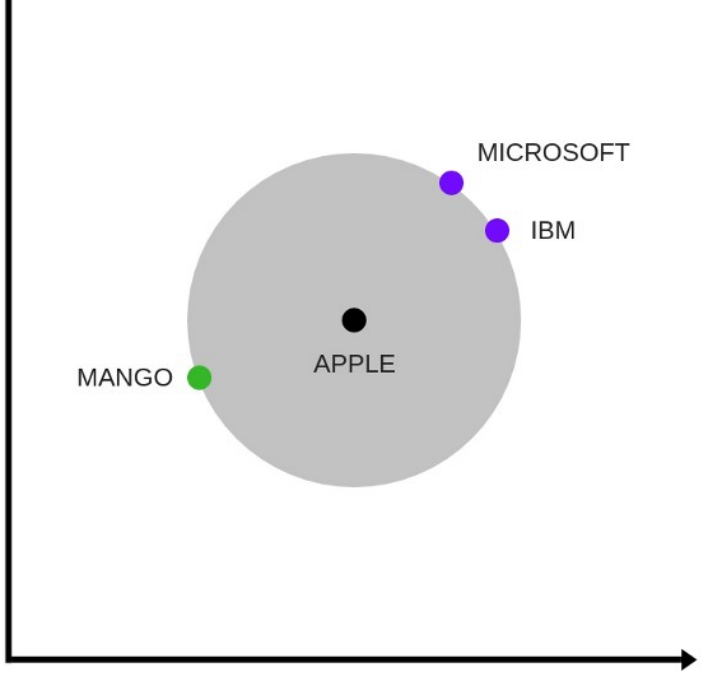
A Word Embedding format generally tries to map a word to a numerical vector.

- A representation that captures words' *meanings*, *semantic relationships* and the different types of contexts they are used in
- Similar words tend to occur together and will have similar context– Orange is a fruit. Banana is a fruit. They have a similar context i.e fruit.
- A context may be a single word or a group of words.



Usage of Word Embeddings

- Similarity distance of mango, apple, Microsoft, IBM



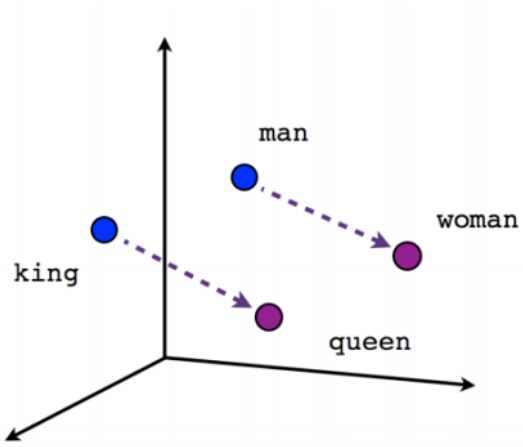
- Finding the degree of similarity between two words.
similarity('woman','man')= 0.73723527

- Finding odd one out.
doesnt_match('breakfast cereal dinner lunch’) = 'cereal’

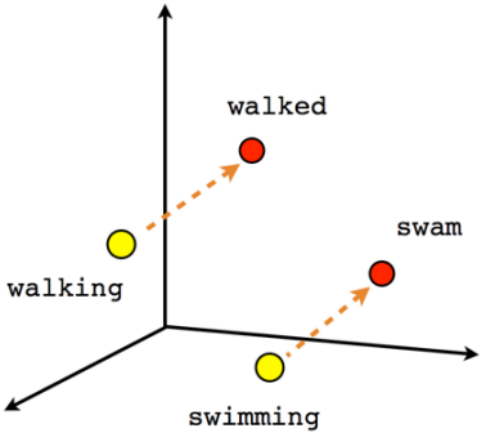
- Compute woman+king-man =queen
most_similar(positive=['woman','king'],negative=['man'])
queen: 0.508

Examples on Characteristics of Word Embeddings

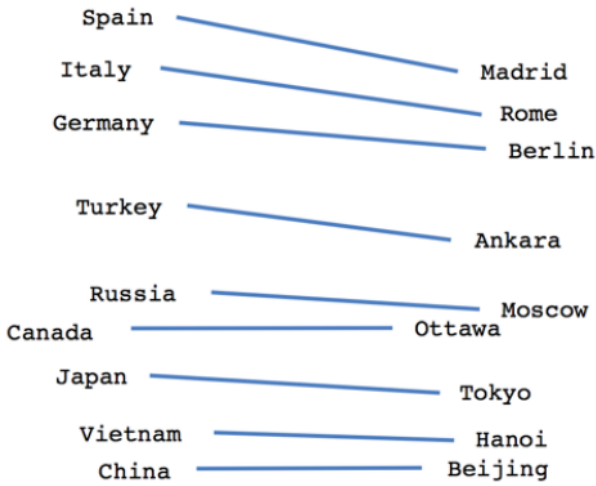
Numerical representations of contextual similarities between words



Male-Female



Verb tense



Country-Capital

vector[Queen] = vector[King] - vector[Man] + vector[Woman]

Data and Software for word2vec

- Easiest way to use it is via the Gensim libarary for Python (tends to be slowish, even though it tries to use C optimizations like Cython, NumPy)

https://radimrehurek.com/gensim/models/word2vec.html

- Original word2vec C code by Google

https://code.google.com/archive/p/word2vec/

Use of word embedding in document matching: Representation-based neural ranking

Match(query,doc)=F(Φ(query),Φ(doc))

F: scoring function

Φ: map to a document representation vector with a sequence of word embeddings