University of Southampton

COMP6237 Data Mining
Lecture 5: Search and Rank

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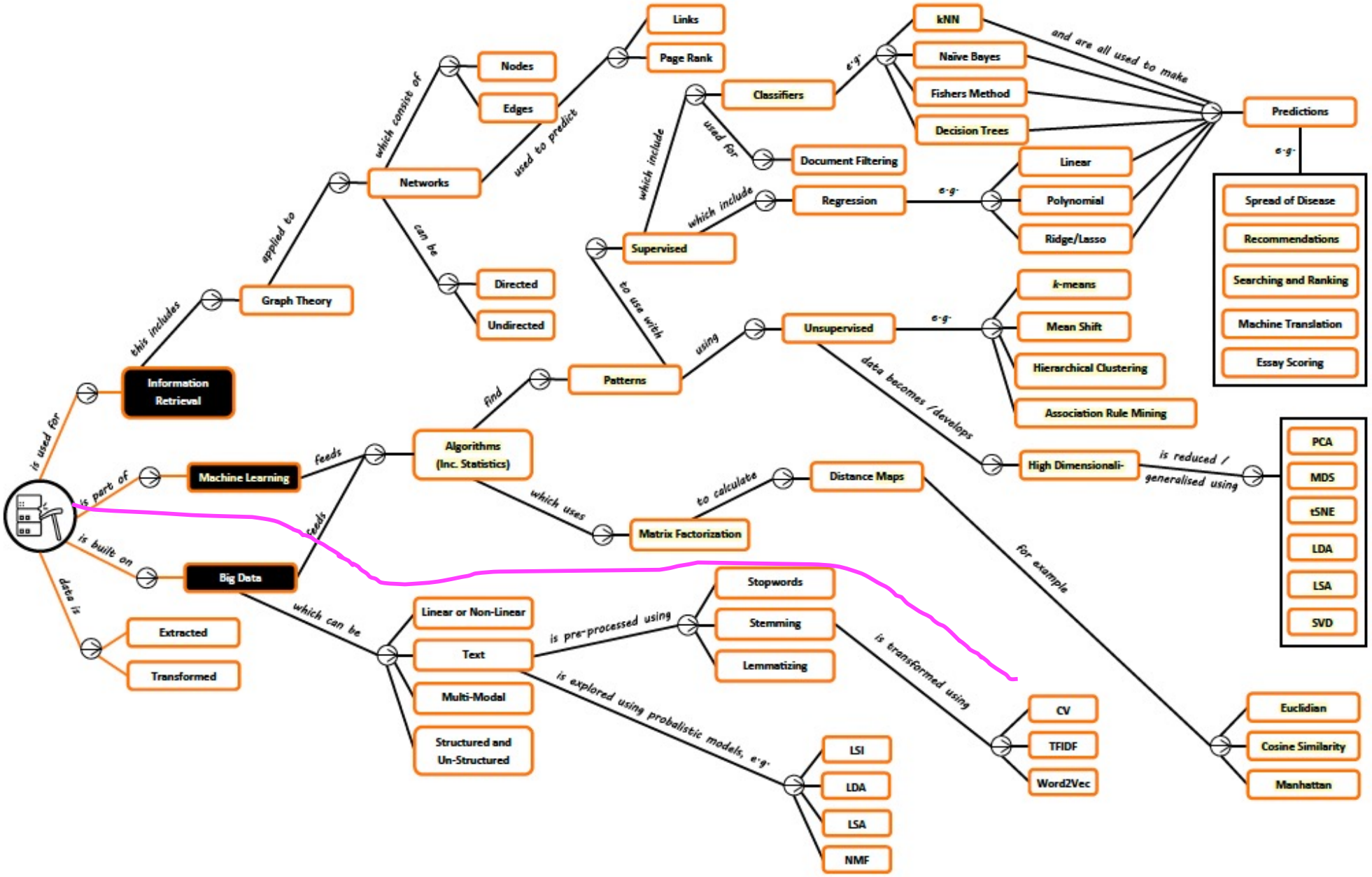
Lecture slides available here:

http://comp6237.ecs.soton.ac.uk/zh.html

(Thanks to Prof. Jonathon Hare and Dr. Jo Grundy for providing the lecture materials used to develop the slides.)

Search and Rank – **Roadmap**



Search and Rank – **Textbook**

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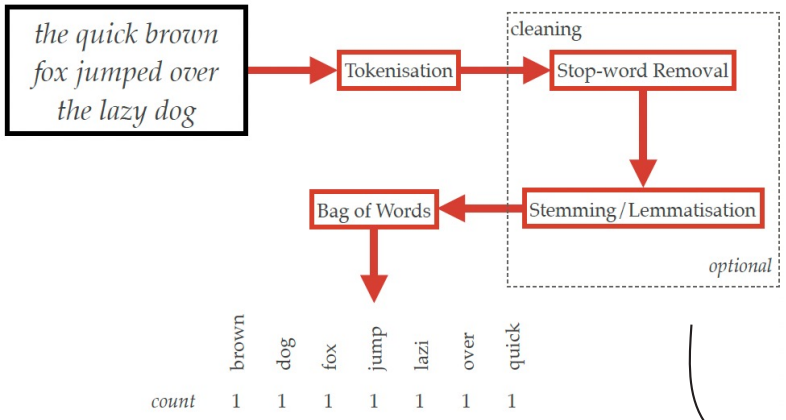
Chapter 3

Finding Similar Items

A fundamental data-mining problem is to examine data for "similar" items. We shall take up applications in Section 3.1, but an example would be looking at a collection of Web pages and finding near-duplicate pages. These pages could be plagiarisms, for example, or they could be mirrors that have almost the same content but differ in information about the host and about other mirrors.

- Mining of Massive Datasets J. Leskovec *et al*
  https://www.cambridge.org/core/books/mining-of-massive-datasets/C1B37BA2CBB8361B94FDD1C6F4E47922

Search and Rank – **Overview**



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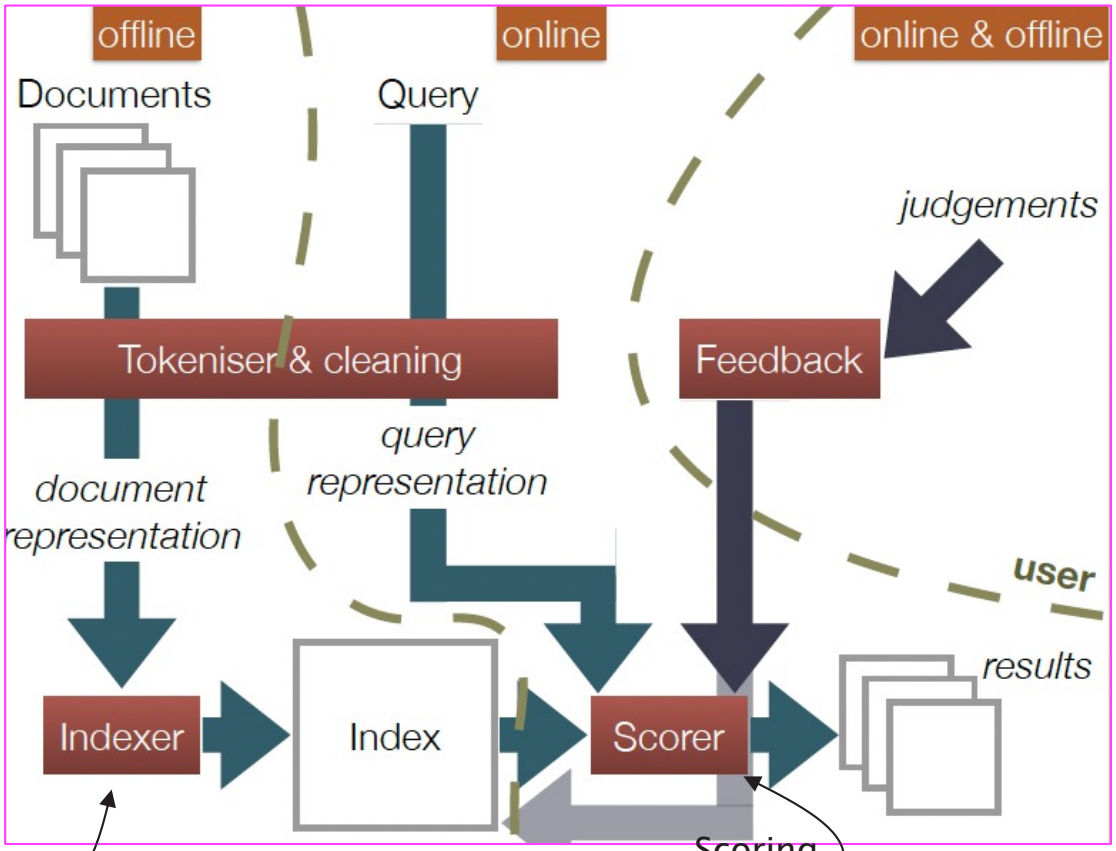
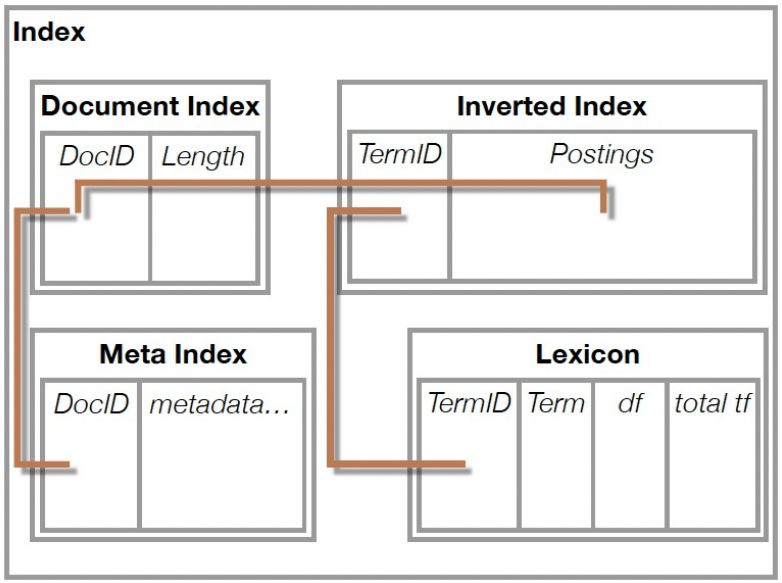


Indexing (sorting)

Scoring (matching)



Number of times *w* appears in *d*

Total #docs in collection

$$f(\mathbf{q},\mathbf{d}) = \sum_{i=1}^{N} q_i y_i = \sum_{w \in q \cap d} c(w,q)c(w,d)log\frac{M+1}{df(w)}$$

Number of times *w* appears in *q*

document frequency (number of docs containing *w*)

Credit: Jon Hare

Search and Rank – **Learning Outcomes**

- **LO1**: Demonstrate an understanding of the fundamental concepts and approaches for search and ranking, such as: (exam)
  - ❖ Understanding the basic pipeline of searching and raking
  - ❖ Encoding document/query using the vector space modeling methods?
  - ❖ Making index for search?
- **LO2**: Implement the learned algorithms for searching and ranking (coursework)

Assessment hints: Multi-choice Questions (single answer: concepts, calculation etc)

- *Textbook Exercises: textbooks (Programming + Mining)*
- *Other Exercises: https://www-users.cse.umn.edu/~kumar001/dmbook/sol.pdf*
- *ChatGPT or other AI-based techs*

Search and Rank – Introduction

Searching the web has become the default way to find information. However, there is so much information on the web, how can we find what we are actually looking for?

This is **information retrieval**

"the activity of obtaining information resources relative to an information need from a collection of information resources"

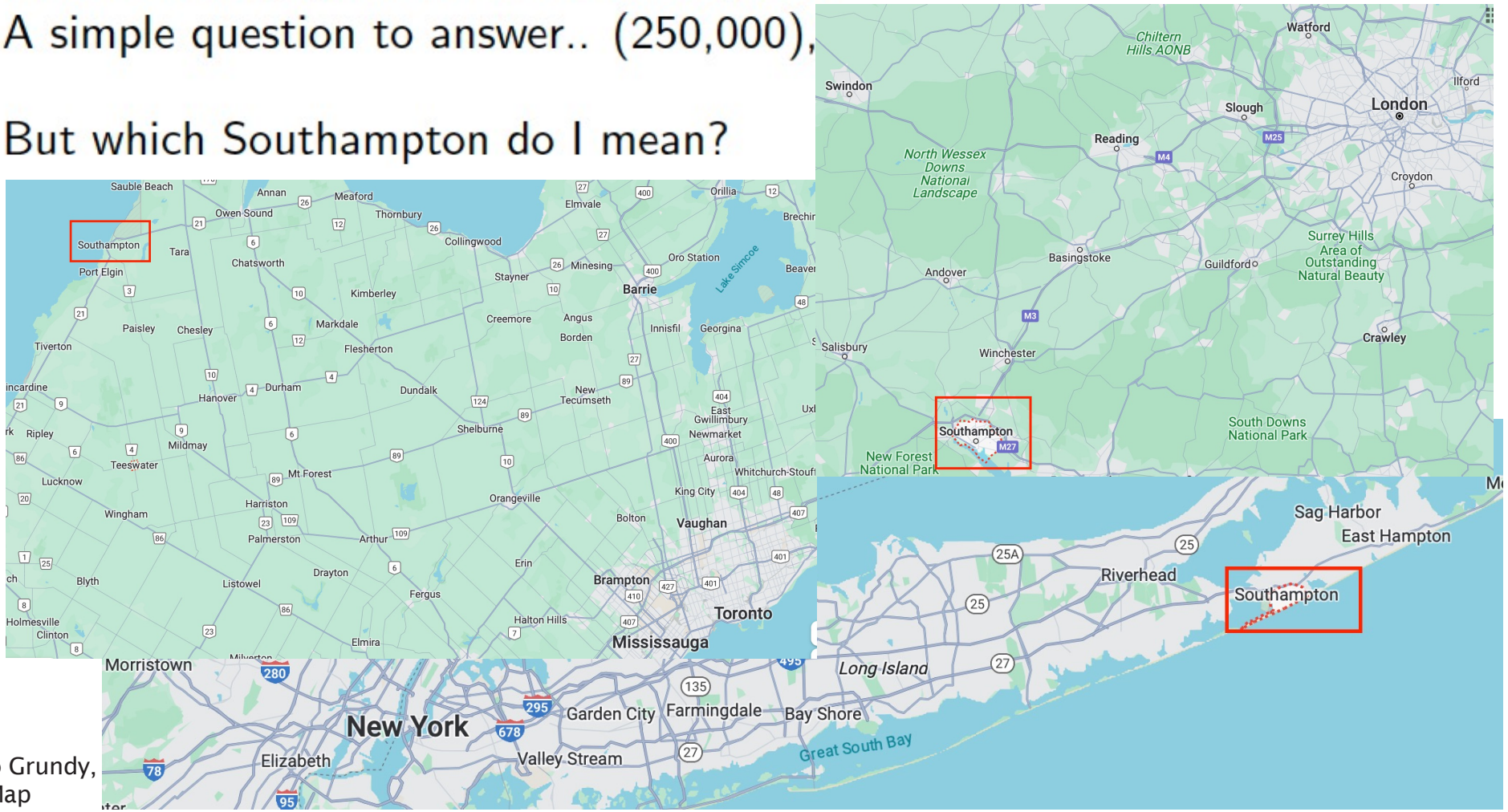
Credit: Jo Grundy

Search and Rank – Problem

It's all about the user.

'What is the population of Southampton?'
A simple question to answer.. (250,000),

But which Southampton do I mean?



Credit: Jo Grundy, Google Map

Search and Rank – Problem

Information retrieval exercise

'Where is the best Chinese food? I'm hungry!'

If I am searching for the best Chinese food, I need somewhere near me, that isn't too expensive, that will deliver to my house, and will not take too long.

A good information retrieval system should be aware of the implicit preferences I have.

ChatGPT

Finding the "best" Chinese food can be subjective and depends on personal preferences. However, some cities are known for their excellent Chinese cuisine. Here are a few places around the world that are renowned for their delicious Chinese food:

1. **Hong Kong, China:** Known for its diverse culinary scene, Hong Kong offers a wide range of authentic Chinese dishes, from Cantonese to Sichuan.
2. **New York City, USA:** With a large Chinese population, New York City has many neighborhoods like Chinatown and Flushing, where you can find authentic and diverse Chinese cuisine.
3. **San Francisco, USA:** San Francisco's Chinatown is one of the oldest and largest in North America, offering a variety of Chinese regional cuisines. ...

Credit: Jo Grundy, ChatGPT

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Search and Rank – History

Information retrieval was originally aided by a catalogue.

For the ancient library of Alexandria, ca. 300BC, Greek poet and scholar Callimachus made the 'Pinakes' (tables)

This was a list of all the works sorted by genre, but only small fragments survive. The idea survived, and as soon as books could be printed, they had printed indexes (1460 CE)

In 1842, a Paris bookseller Jean Claude Brunet had developed a simple classification system for his books.

Most modern libraries use the Dewey Decimal system (1876) which introduced idea of location based on subject.

Credit: Jo Grundy

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Search and Rank – History

With computers,

- 1960s, databases were indexed
- 1970s, larger boolean systems on the computer
- 1980s, expert systems, natural language processing
- 1990s, the **internet**.. ranking
- 2000 - now, much better search and ranking, big data, language modelling

Credit: Jo Grundy

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Search and Rank – Text Retrieval

Text retrieval:

- For a collection of text documents - text corpus
- User provides query - expresses information need
- Search engine returns relevant documents

This is **search technology** in industry

Credit: Jo Grundy

University of Southampton

Search and Rank – Text Retrieval

	Database	Text
Information	Well-defined structure and semantics	Unstructured, ambiguous semantics
Query	Well defined semantics, complete specification (eg SQL)	Ambiguous, incomplete specification
Answers	Matched records	Relevant documents

You cannot prove mathematically what the best ways to retrieve a text item is. It is *empirically defined*, noone knows what the user wants until the user finds it.

Credit: Jo Grundy

University of Southampton

Search and Rank – Text Retrieval

- Boolean Model: get every document that satisfies a Boolean Expression result selection
- Vector Space Model: how similar is document to query vector? ranked results
- Probabilistic Model: what is the probability that the document is generated by the query? ranked results

Selecting results is hard: if query is *over-constrained*, you may get nothing. If query is *under-constrained*, you may get way too many unsorted results.

Ranking is preferred, allows prioritisation.

Credit: Jo Grundy

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Search and Rank – Text Retrieval

Robertson 1977:
Using Decision Theory, the optimal strategy for finding the most relevant document is:
To give a ranked list of documents in descending order of probability that a document is relevant to the query.
This assumes:

- utility of document is independent of utility of any other document
- user browses results sequentially

Do these assumptions hold?

Credit: Jo Grundy

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Quick Recap – One Hot Encoding

We use a 'Bag of Words', where each word is a vector:

- a $\rightarrow [1, 0, 0, 0, 0, 0, 0, 0, \ldots, 0]$
- aa $\rightarrow [0, 1, 0, 0, 0, 0, 0, 0, \ldots, 0]$
- aardvark $\rightarrow [0, 0, 1, 0, 0, 0, 0, 0, \ldots, 0]$
- aardwolf $\rightarrow [0, 0, 0, 1, 0, 0, 0, 0, \ldots, 0]$

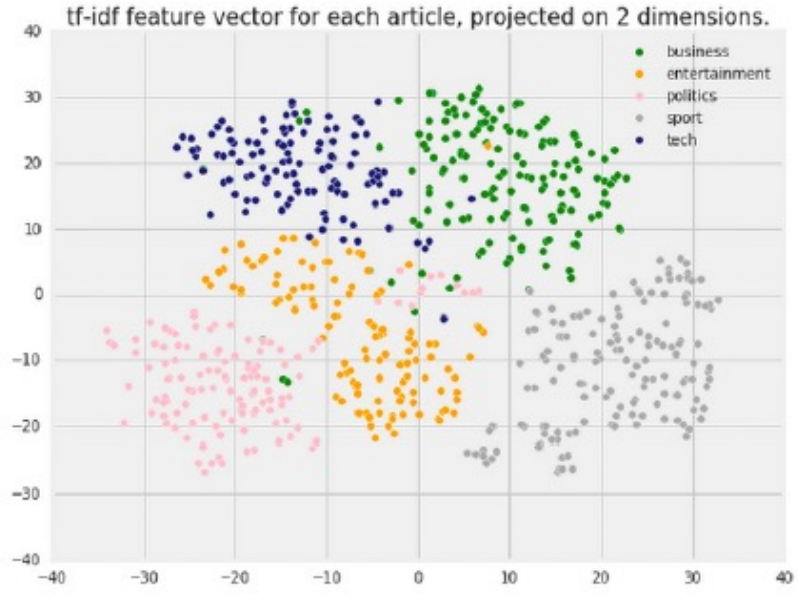
This is called *One Hot Encoding*

Credit: Jo Grundy

Search and Rank – Vector Space Model

Vector Space Model is quite simple.

- Each document is a vector
- Each query is a vector
- Assume that if close together in space they are similar
- Rank each document by similarity



https://cloud.google.com/blog/products/gcp/problem-solving-with-ml-automatic-document-classification

Credit: Jo Grundy

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Search and Rank – Vector Space Model

Each document is represented by a **term vector**
A **Term** is a basic concept, e.g. word or phrase
This gives an N-dimensional space for N **terms**

- Query Vector $q = (x_1, x_2, \ldots, x_N)$, $x_i \in \Re$ is query term weight
- Document Vector $d = (y_1, y_2, \ldots, y_N)$, $y_i \in \Re$ is document term weight

$$\text{relevance}(\boldsymbol{q}, \boldsymbol{d}) \propto \text{similarity}(\boldsymbol{q}, \boldsymbol{d}) = f(\boldsymbol{q}, \boldsymbol{d})$$

Credit: Jo Grundy

University of Southampton

Search and Rank – Vector Space Model

As seen before, each **term** is assumed to be orthogonal
We still don't know:

- Which basic concepts to select for the **terms**
- How to assign weights $(x_1, x_2, \ldots, x_N)$ and $(y_1, y_2, \ldots, y_N)$
- How to define the similarity measure $(f(\boldsymbol{q}, \boldsymbol{d}))$

Credit: Jo Grundy

Quick Recap - Documents

e.g. "The quick brown fox jumped over the lazy dog."
becomes:

Tokenisation
'The': 1, 'quick': 1, 'brown': 1, 'fox': 1, 'jumped': 1, 'over': 1, 'the': 1, 'lazy': 1, 'dog.': 1

After further tokenising and sorting, you could get:
'brown': 1, 'dog': 1, 'fox': 1, 'jumped': 1, 'lazy': 1,'over': 1, 'quick': 1, 'the': 2

Further stemming and removal of stop words could give:
'brown': 1, 'dog': 1, 'fox': 1, 'jump': 1, 'lazi': 1,'over': 1, 'quick': 1

Credit: Jo Grundy

Quick Recap - Documents

The bag of words vector for a document will be very sparse

The vocabulary or lexicon will be the *set* of all (processed) words across all documents known to the system.

For a document, the vector contains the number of occurrences of each **term**, like a histogram

Vectors will have very high number of dimensions, but are very sparse

Alice ipynb demo

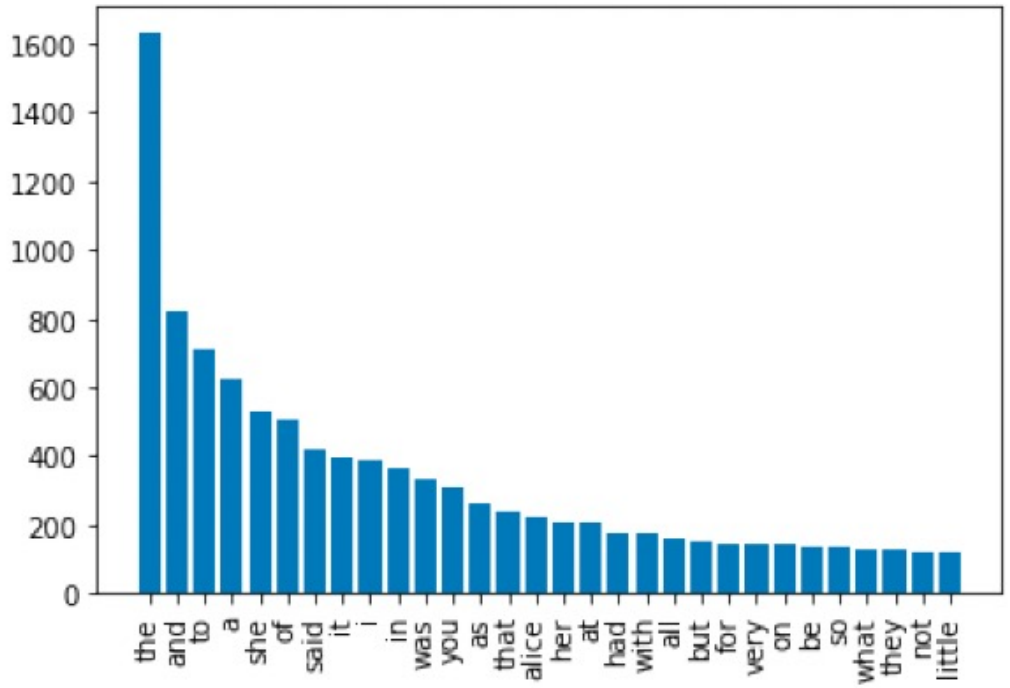
https://github.com/zhiwu-huang/Data-Mining-Demo-Code-18-19

Credit: Jo Grundy

Search and Rank – Vector Space Model

Zipf's law

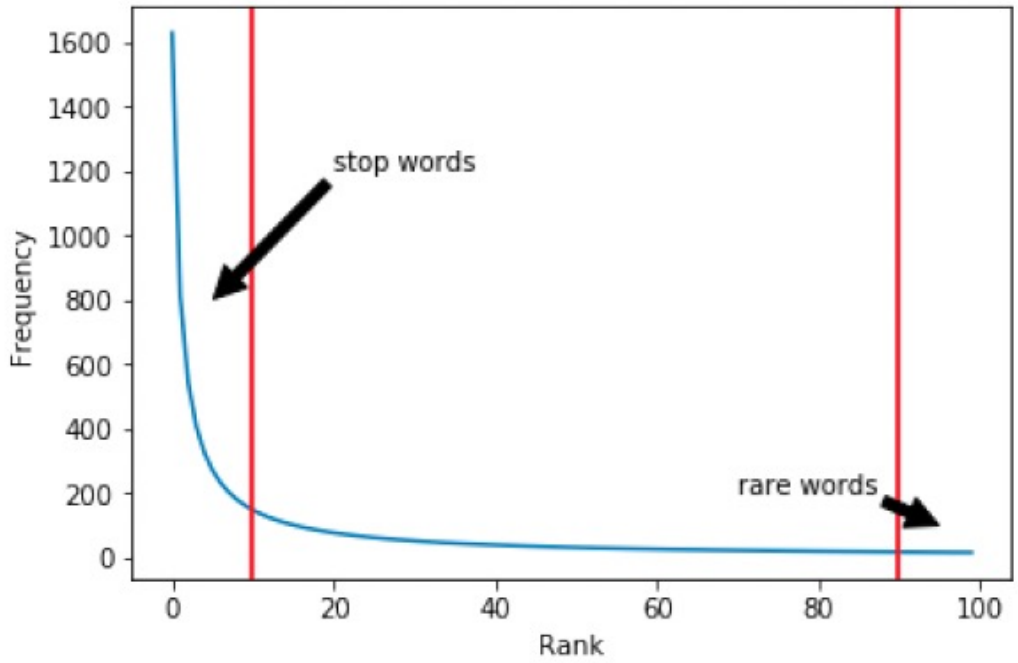
States that the frequency of a word is proportional to the inverse of its rank, i.e. the second most common word will be half the frequency of the first, the third will be a third the frequency of the first, e.t.c.



Credit: Jo Grundy

Search and Rank – Vector Space Model

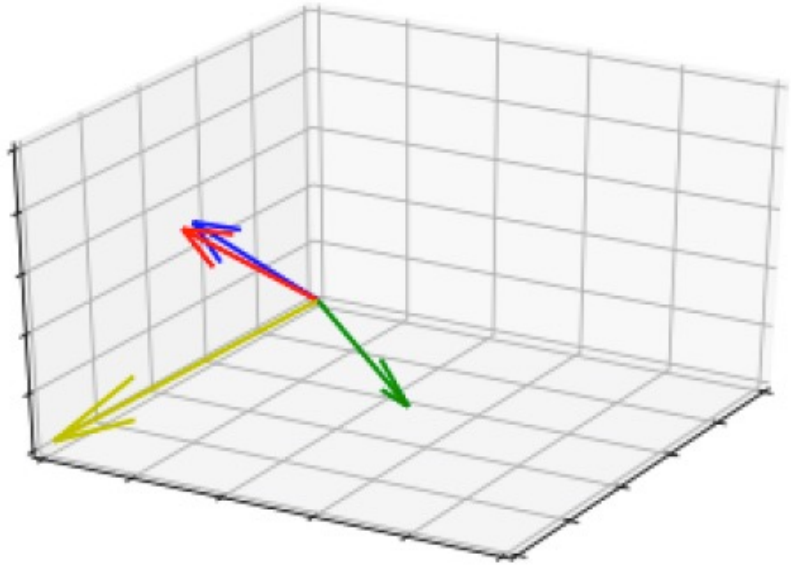
We should remove the most common and the least common, as they hold little information, and may skew any vector to look similar.
We should also remove the very rare words, as they would make the document vector unnecessarily sparse without gaining much information.



Credit: Jo Grundy

Search and Rank – Vector Space Model

How to search the Vector Space Model?

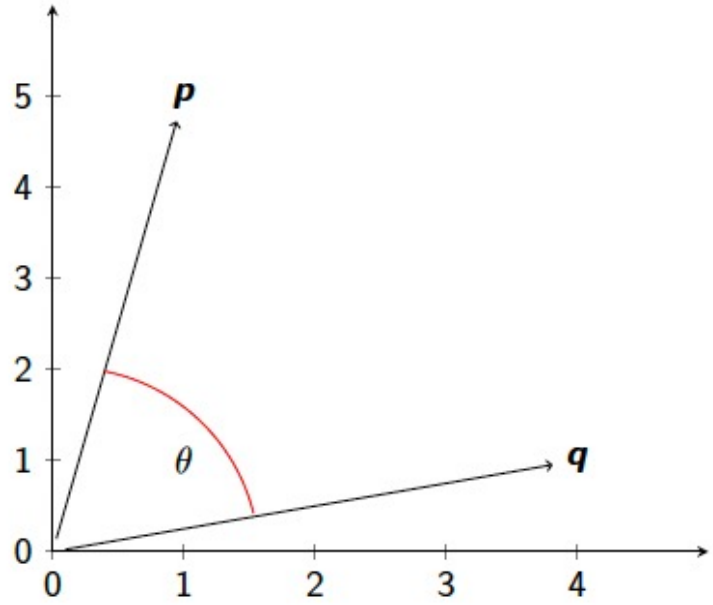


If my query vector is red, which of the three document vectors is it closest to?

Credit: Jo Grundy

Quick Recap – Cosine Similarity

- Cosine Similarity



Only measures direction, not magnitude of vector.

$\boldsymbol{p}$ and $\boldsymbol{q}$ are N-dim vectors,
$\boldsymbol{p} = [p_1, p_2, ..., p_N]$,
$\boldsymbol{q} = [q_1, q_2, ..., q_N]$

Cosine Similarity:

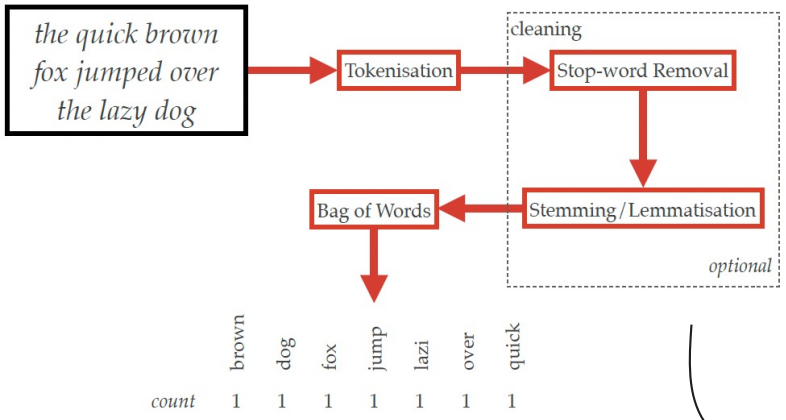
$$cos(\theta) = \frac{\boldsymbol{p}.\boldsymbol{q}}{|\boldsymbol{p}||\boldsymbol{q}|}$$

$$= \frac{\sum_{i=1}^{N} p_i q_i}{\sqrt{\sum_{i=1}^{N} p_i^2}\sqrt{\sum_{i=1}^{N} q_i^2}}$$

$\sum p_i^2$ and q_i^2 can be precomputed and stored

Credit: Jo Grundy

Search and Rank – **Overview**



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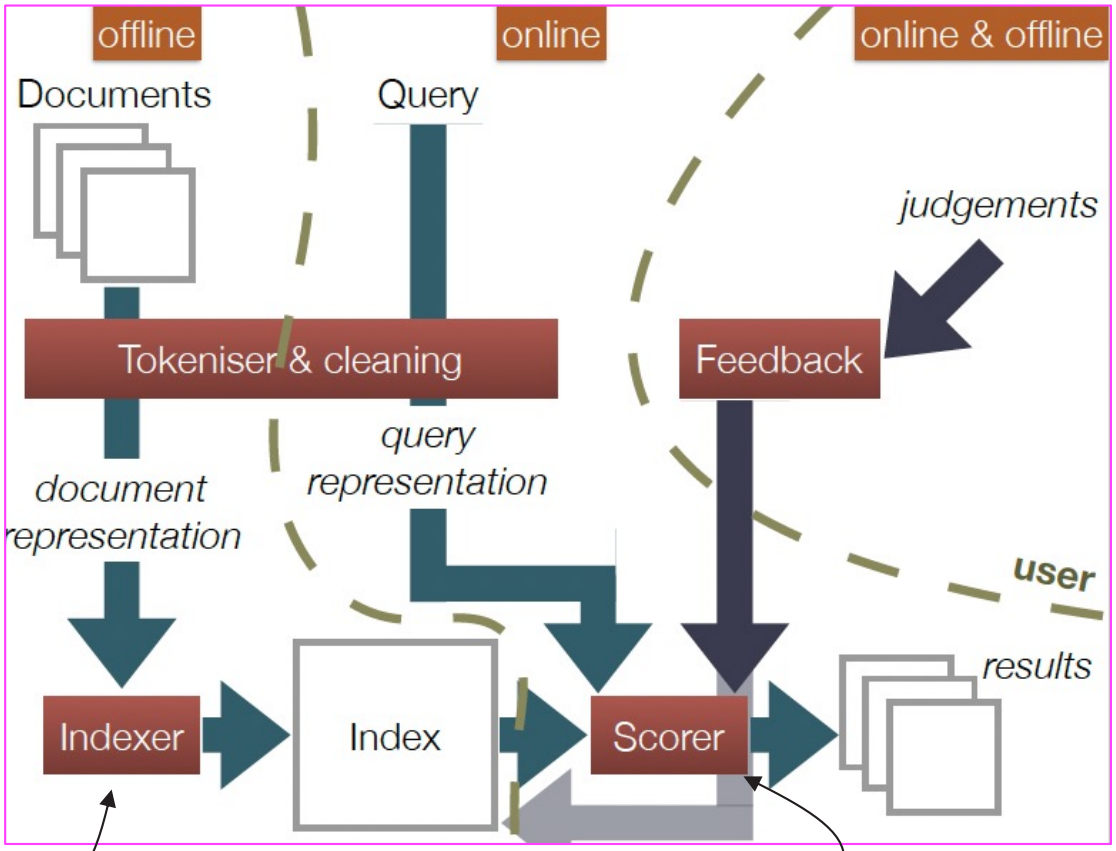
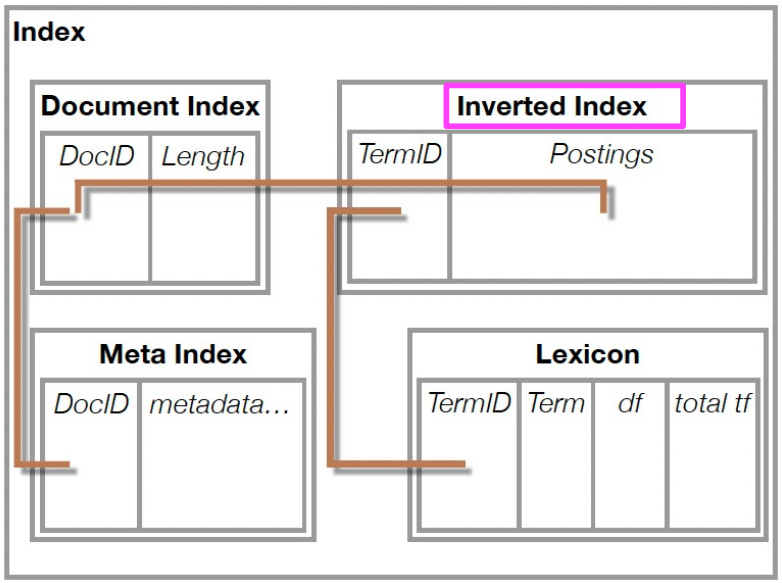


Matching (searching)



Number of times *w* appears in *d*

Total #docs in collection

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Number of times *w* appears in *q*

document frequency (number of docs containing *w*)

Credit: Jon Hare

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Search and Rank – Vector Space Model

Inverted Index:

A mapping from content to location, e.g. in a set of documents.

Inverted index ipynb demo

alic	(0, 399), (1, 207), (2, 232)
said	(0, 462), (1, 11), (2, 0)
cooper	(0, 0), (1, 398), (2, 0)
spring	(0, 0), (1, 2), (2, 218)
not	(0, 145), (1, 21), (2, 5)
retriev	(0, 0), (1, 111), (2, 47)
littl	(0, 128), (1, 4), (2, 3)
one	(0, 105), (1, 21), (2, 5)

A posting is a pair formed by a document ID and the number of times the specific word appeared in that document.

Credit: Jo Grundy

Search and Rank – Vector Space Model

To efficiently compute the cosine similarity, look up the relevant postings list and accumulate similarities only for the documents in those lists.

alic	(0, 399), (1, 207), (2, 232)
said	(0, 462), (1, 11), (2, 0)
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For example: "Alice Cooper"

Accumulation table:

Doc ID	Frequency
0	399
1	207
2	232

Credit: Jo Grundy

Search and Rank – Vector Space Model

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For example: "Alice Cooper"

Accumulation table:

Doc ID	Frequency
0	399
1	207 + 398
2	232

cosine similarity ipynb demo

Credit: Jo Grundy

University of Southampton

Search and Rank – Vector Space Model

Using frequency of a word in a document is not always a good idea

How can we weight these vectors better?

- Binary weights
  record only if a word is present or absent in the vector
- Raw Frequency
  record frequency of occurrence of a term in the vector
- TF-IDF - Term Frequency - Inverse Document Frequency
  - Term Frequency - the raw frequency of a word in a document usually normalised by the number of words in the document
  - Inverse Document Frequency - 1/number of occurrences of word in all documents

  A high weight in TF-IDF is reached by a high frequency in a given document, but low frequency in the whole collection of documents, this would filter out the more common terms.

Credit: Jo Grundy

Search and Rank – Vector Space Model

There are many variants of TF-IDF
For the TF (term frequency term:

- term frequency $\mathrm{tf}(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$
- log normalisation $\log(1 + f_{t,d})$
- double normalisation K $K + (1-K)\frac{f_{t,d}}{\max_{t' \in d} f'_{t,d}}$

For the inverse document frequency term:

- Inverse document frequency $\mathrm{idf}(t,D) = \log \frac{N}{n_t}$
- Inverse document frequency smooth $\log \frac{N}{1+n_t}$
- Inverse document frequency max $\log \frac{\max_{t' \in d} n_{t'}}{i+n_t}$
- Probabilistic inverse document frequency $\log \frac{N-n_t}{n_t}$

where N is total number of documents in the corpus $N = |D|$

$n_t = |\{d \in D : t \in d\}|$: number of documents where the term t appears (i.e., $\mathrm{tf}(t,d) \neq 0$).

Credit: Jo Grundy

Search and Rank – Vector Space Model

Then TF-IDF is calculated as TF $\times$ IDF

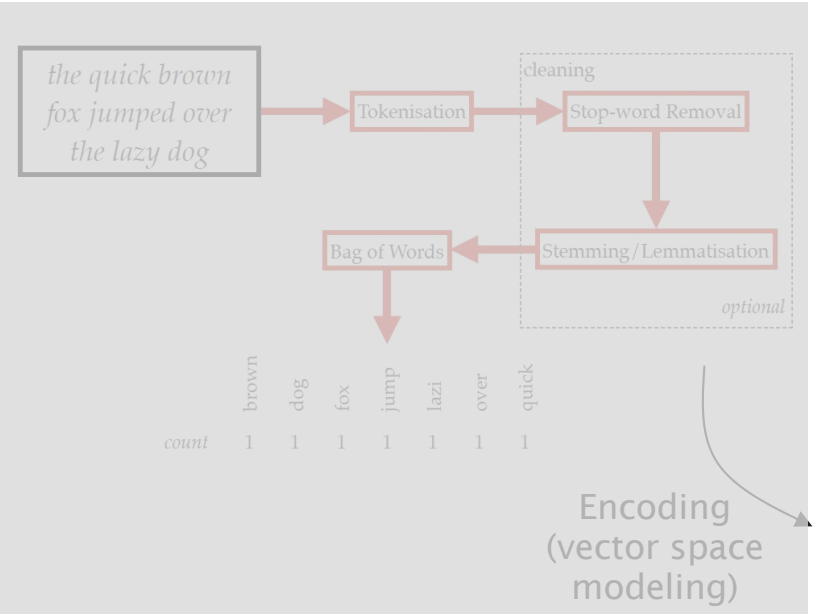
TF-IDF ipynb demo

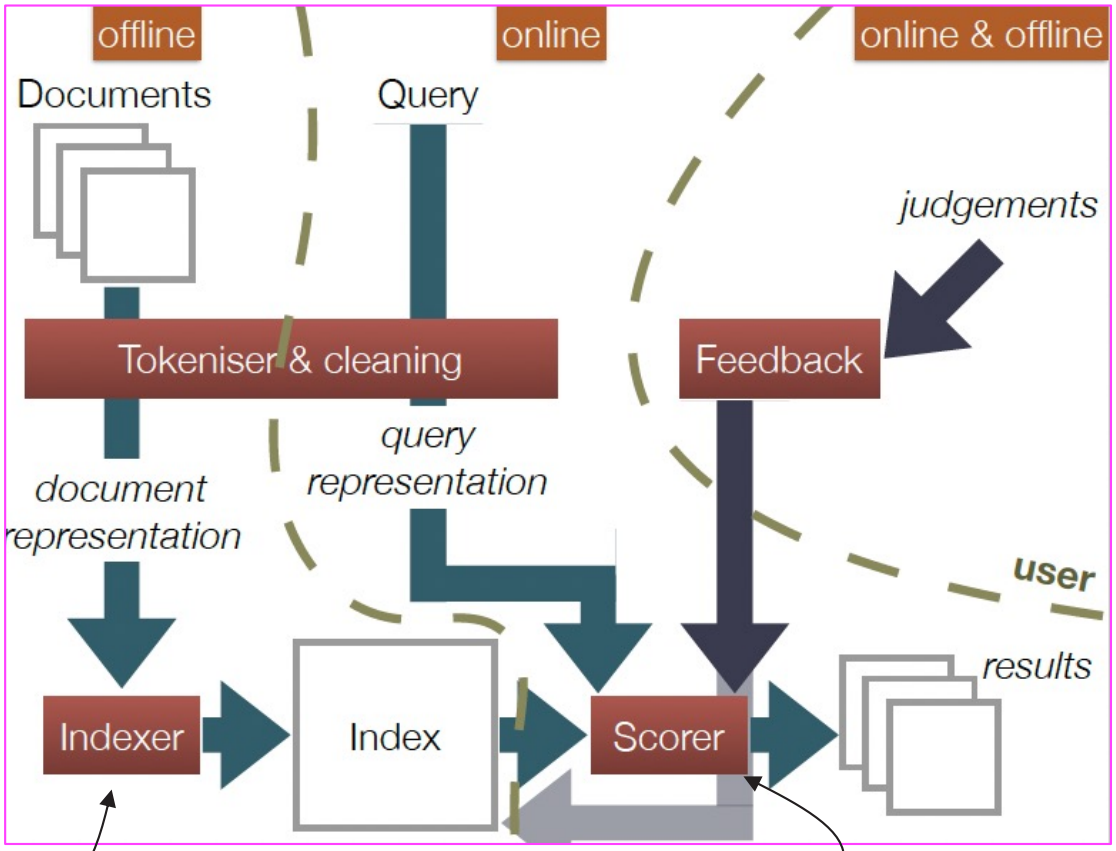
Some possible schemes for TF-IDF:

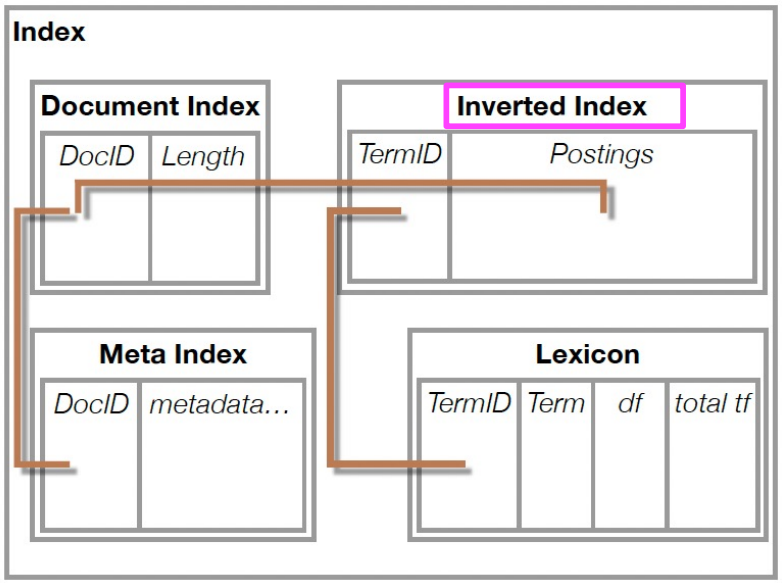
Document	*Query*	
$f_{t,d} \log \frac{N}{n_t}$	$(K + K \frac{f_{t,q}}{\max_t f_{t,q}}) \log \frac{N}{n_t}$	$K = 0.5$
$1 + \log f_{t,d}$	$\log(1 + \frac{N}{n_t})$	
$(1 + \log f_{t,d}) \log \frac{N}{n_t}$	$(1 + \log f_{t,q}) \log \frac{N}{n_t}$	

Credit: Jo Grundy

Search and Rank – **Overview**







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Number of times *w* appears in *q*

document frequency (number of docs containing *w*)

Credit: Jon Hare

University of Southampton

Search and Rank – Vector Space Model

Building the index is difficult with big data:
Can't just use memory

Can use sort based methods:

- collect local <term, doc, freq> tuples in a run
- sort tuples within the run and write to disk
- merge runs on disk
- output inverted index

Credit: Jo Grundy

Search and Rank – Retrieval System

Go through a few documents..

<"alic", 0, 399>
<"said", 0, 462>
<"not", 0, 145>
..
<"alic", 1, 207>
<"said", 1, 11>
<"cooper", 1, 398>
...
<"alic", 2, 232>
<"spring", 2, 218>
<"not", 2, 5>

Sort by term

<"alic", 0, 399>
<"alic", 1, 207>
<"alic", 2, 232>
..
<"cooper", 1, 398>
<"not", 0, 145>
<"not", 2, 5>
...
<"said", 0, 462>
<"said", 1, 11>
<"spring", 2, 218>

This is one run.

Then run a merge sort with other runs, and build the inverted index with the sorted data

In an inverted index, the index is organized by terms (words), and each term points to a list of documents or web pages that contain that term.

Credit: Jo Grundy

University of Southampton

Search and Rank – Retrieval System

Improving Information retrieval:
Can use Location weighting:

- More relevant if closer to start of document
- Exact phrase or proximity of terms in query

Requires term position of every instance in the document to be indexed
i.e. "alic" = [Doc0, 399, < 3, 11, 29, ..>]

Increases size of index dramatically, need to use compression

Credit: Jo Grundy

Search and Rank – Web Search

For web pages, we can use the number of links to a document as a way of scoring them

However this is prone to manipulation, as you can make lots of pages that all point to each other lots of times.

Page and Brin: PageRank Markus will cover this in May

In brief: Calculates the importance of a page from the importance of all the other pages that link to it and the number of links each of those other pages have.

Credit: Jo Grundy

Search and Rank – User Feedback

What user feedback do we get with a web search?

Use what they actually click on. Documents that are more clicked on could be more important.
Can also learn associations between queries and documents, and if this query is met again, use this to increase the rank of the document that was clicked on before for this query.

Credit: Jo Grundy

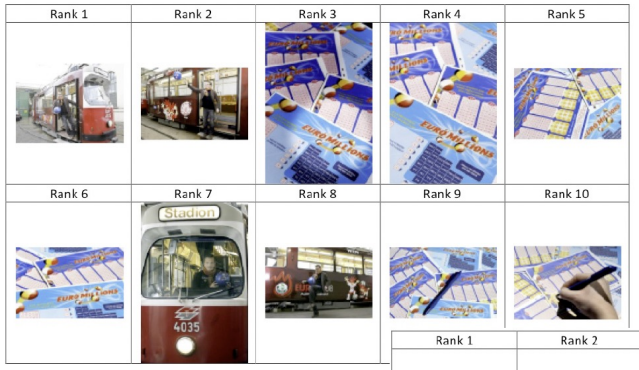
Search and Rank – Result Diversification

Is a ranked list always the right thing?

e.g. If I search for "University"
Do I want..

- Lots of links to Southampton University..?
  or
- Links to a range of universities

A diverse range of results has a better chance of finding what the search was actually looking for.



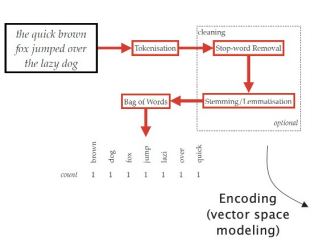
Original Ranking

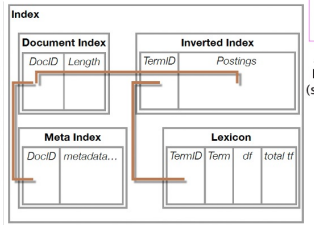
Credit: Jon Hare

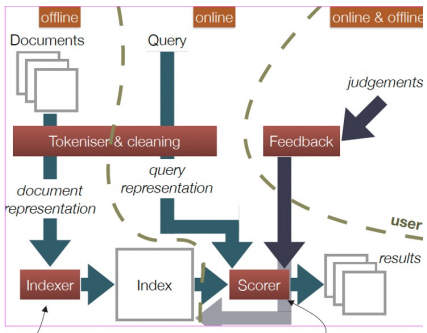
Diversified Ranking

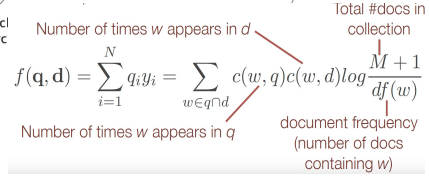
Credit: Jo Grundy

Search and Rank – Summary









Search engines are a key tool in Data Mining

Important Points:

- Feature extraction
- Scalable and efficient indexing and search

Information Retrieval Process:

- Encode Documents
  - stemming, lemmatization, stop word removal
  - Make feature vector (e.g. Bag of words, TF-IDF..)
- Make index (inverted index aids search)
- Encode query
- Search index using encoded query

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