### Information Retrieval

Natural Language Processing

Master in Business Analytics and Big Data

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#### What is IR?

Information Retrieval (IR) is **finding material** (usually documents) of an **unstructured nature** (usually text) that satisfies an **information need** from within **large collections** (usually stored on computers).

Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze
Introduction to Information Retrieval

#### What is IR?





**Buscar con Google** 

Voy a tener suerte

Ofrecido por Google en: English català galego euskara

# IR beyond Google

- Finding items (documents, webpages, images) of an unstructured nature (usually text) from within large collections.
  - E-mail search
  - Searching your laptop
  - Corporate knowledge bases
  - Legal information retrieval
  - Image Search

person
http://es.dbpedia.org/resource/José_Antonio_Pavón_y_Jiménez
http://es.dbpedia.org/resource/Carmen_Vela
http://es.dbpedia.org/resource/Fernando_Baquero_Mochales
http://es.dbpedia.org/resource/Juana_Álvarez-Prida_y_Vega
http://es.dbpedia.org/resource/Montserrat_Gomendio
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http://es.dbpedia.org/resource/Agustín_Escardino
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http://es.dbpedia.org/resource/Ricardo_Carmona_(físico)



#### spanish scientists





#### Category: Spanish scientists - Wikipedia

https://en.wikipedia.org/wiki/Category:Spanish\_scientists ▼ Traducir esta página Pages in category "Spanish scientists". The following 41 pages are in this category, out of 41 total. This list may not reflect recent changes (learn more). A. José de Acosta · José María Albareda · María de los Ángeles Alvariño González · Antonio Arnaiz-Villena · Félix de Azara. B. Ferran Sunyer i Balaguer · Xavier Barcons ...

#### List of Spanish inventors and discoverers - Wikipedia

https://en.wikipedia.org/.../List of Spanish inventors and disco... ▼ Traducir esta página This is a list of Spanish inventors and discoverers. Santiago Ramón y Cajal, father of Neuroscience, Nobel prize Laureate. Contents. [hide]. 1 A; 2 B; 3 C; 4 D; 5 E; 6 F; 7 G; 8 H; 9 J; 10 L; 11 M; 12 O; 13 P; 14 R; 15 S; 16 T; 17 U; 18 V; 19 See also; 20 References. A[edit]. José de Acosta (1540-1600), one of the first naturalists ... C · G · M · R

#### Famous Scientists from Spain | List of Top Spanish Scientists - Ranker https://www.ranker.com/list/famous-scientists...spain/reference ▼ Traducir esta página

List of notable or famous scientists from Spain, with bios and photos, including the top scientists born in Spain and even some popular scientists who immigrated to Spain. If you're trying to find out the names of famous Spanish scientists then this list is the perfect resource for you. These scientists are among the most ...

#### 10 Hispanic Scientists You Should Know | HowStuffWorks

https://science.howstuffworks.com > ... > Physicists ▼ Traducir esta página Over the centuries, many remarkable scientists have emerged from Spanish-speaking lands, cultures and ancestors. Though grouping such a diverse collection of people under a single rubric -- particularly the politically expedient but dubious term Hispanic - isn't ideal, it does make room to explore their wideranging array ...

#### Top H-Index For Scientists in Spain - Guide 2 Research

www.guide2research.com/scientists/ES ▼ Traducir esta página

Top H-Index For Scientists in Spain: We list only scientists having H-Index>=40. If you or other scholars are not listed, we appreciate if you can contact us ... 12,538. 58. 996. 7. Mario Piattini · University of Castile-La Mancha · Spain, 15,694, 56, 1034, 8, Carles Sierra · Spanish National Research Council · Spain. 17.292. 55 ...

#### Científicos > Idioma español









Severo Ochoa

1905-1993





Aureliano Maestre de ...

1828-1890

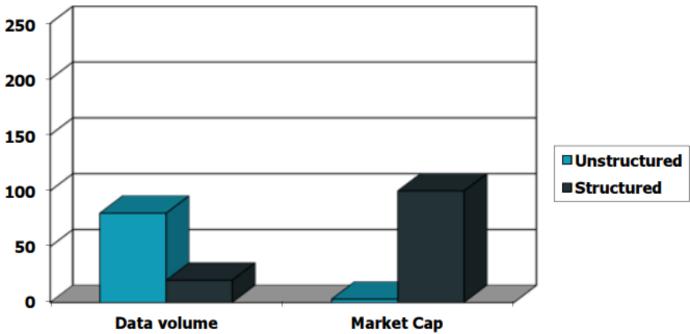
Ramón y Cajal 1852-1934

Andrés Manuel del Río 1764-1849

Margarita Salas

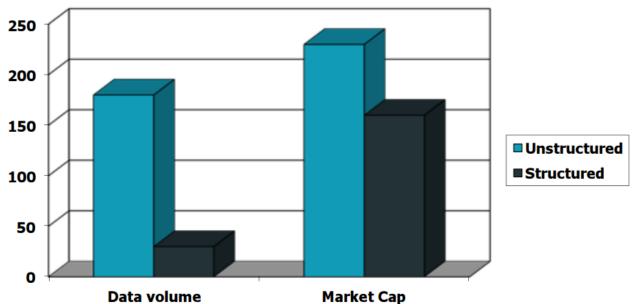
Miguel Servet -1553

 Unstructured (text) vs. structured (database) data in the midnineties.



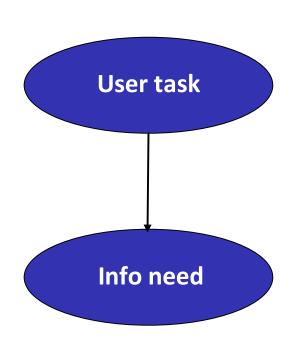
Source: Stanford NLP

Unstructured (text) vs. structured (database) data today.



Source: Stanford NLP

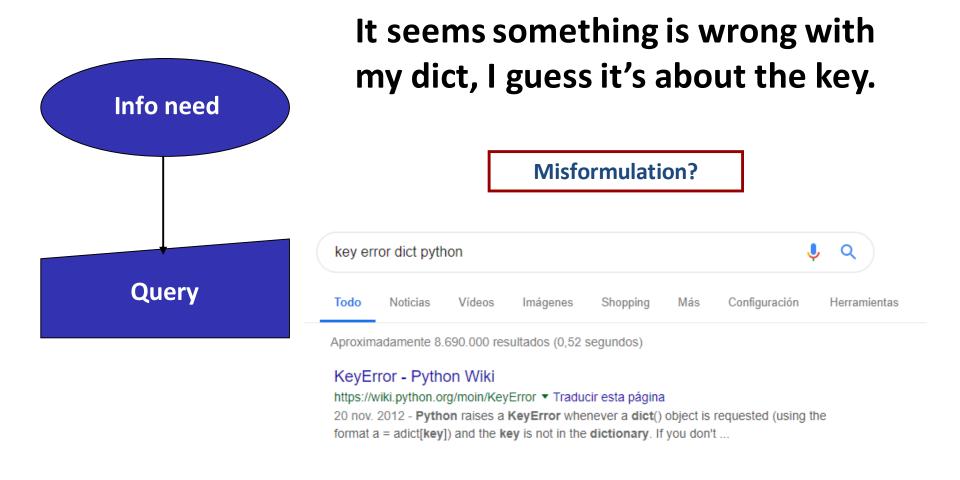
#### Classical Model



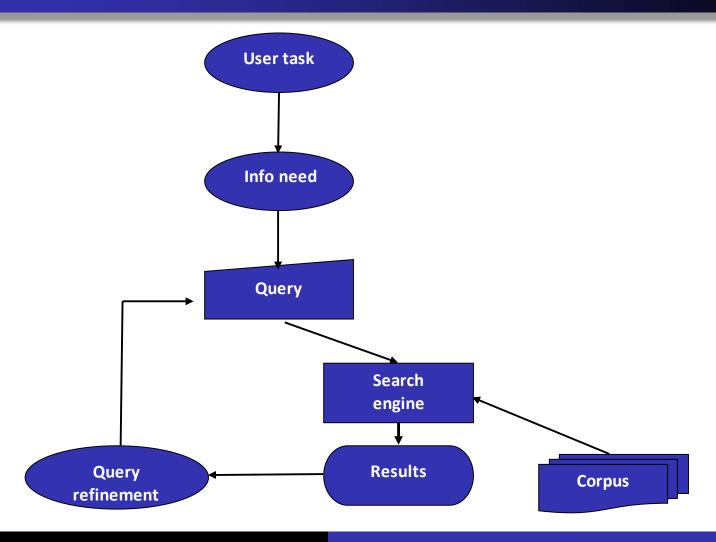
Misconception?

It seems something is wrong with my dict, I guess it's about the key.

### Classical Model



## Classical Model



# Why is it hard?

#### From user task → Query

- Misconception: But users don't often know what they want
- Misformulation: Verbalizing information needs

#### Query

- Semantics
  - banks in Madrid
  - second-hand jaguar
- Context
  - funny images about...
  - cheap hotels
- Weak signals
  - Only a few words to express a need

# **Preliminary Approach**

 Which plays of Shakespeare contain the words Brutus AND Caesar but NOT Calpurnia?

```
grep (Shakespeare's plays, (Brutus and Caesar) | strip out (Calpurnia)
```

- Problems:
  - Slow: you have to go over all documents
  - NOT Calpurnia is non-trivial
  - Other operations not feasible:
    - find the word *Romans* near *countrymen*
  - Ranked retrieval (best documents to return)

### Term-document incidence matrices

	<b>Antony and Cleopatra</b>	<b>Julius Caesar</b>	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	4	0	. 1	4	1	0

**Brutus** AND **Caesar** BUT NOT **Calpurnia** 

1 if play contains word,0 otherwise

#### Incidence vectors

- We have a 0/1 vector for each term.
- Answer query:
  - take the vectors for Brutus, Caesar and Calpurnia (complemented) → bitwise AND.

	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

110100 AND 110111 AND 101111 = **100100** 

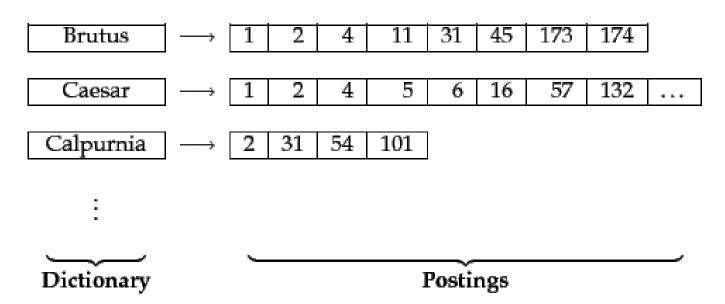
# Bigger collections

N = 1 million documents, document = 1000 words.

- avg. 6 bytes/word including spaces/punctuation
  - 6GB of data in the documents.
- M = 500K distinct terms among these.
  - 500K x 1M matrix has half-a-trillion 0's and 1's.
    - It is extremely sparse
    - We only record the 1 positions.

#### Inverted index

 For each term t, we must store a list of all documents that contain t.



https://nlp.stanford.edu/IR-book/html/htmledition/an-example-information-retrieval-problem-1.html

# 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

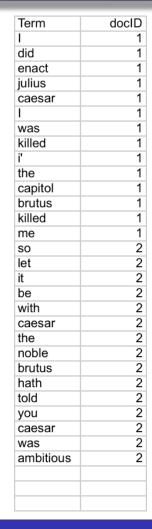
So let it be with
Caesar. The noble
Brutus hath told you
Caesar was ambitious

ierm	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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
was	2
ambitious	2

docID

# Indexer steps: Sort

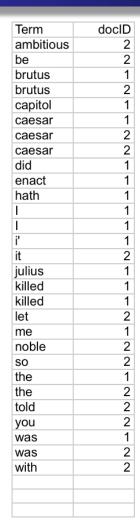
Sort by terms and docID

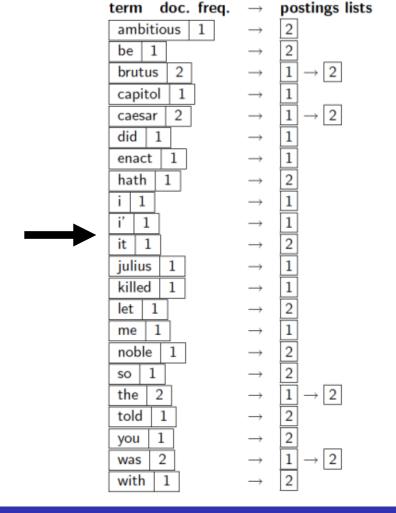




# Indexer steps: Dictionary & Postings

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





# 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 (intersect the document sets):

Brutus 
$$\longrightarrow$$
 1  $\longrightarrow$  2  $\longrightarrow$  4  $\longrightarrow$  11  $\longrightarrow$  31  $\longrightarrow$  45  $\longrightarrow$  173  $\longrightarrow$  174

Calpurnia  $\longrightarrow$  2  $\longrightarrow$  31  $\longrightarrow$  54  $\longrightarrow$  101

Intersection  $\Longrightarrow$  2  $\longrightarrow$  31

https://nlp.stanford.edu/IR-book/html/htmledition/processing-boolean-queries-1.html

# Phrase queries

• "IE university" – as a phrase

```
"I went to university at Madrid"

"I went to the IE university at Madrid"
```

Our inverted index is not sufficient

We need to also store the position in the document

# A first attempt: Biword indexes

- Index every consecutive pair of terms as a phrase
- ""IE university Madrid" would generate the bi-words
  - IE university
  - University Madrid
- Each of these bi-words is now a dictionary term

```
<(term1, term2) : docs>
```

- Longer phrases can be processed by breaking them down
  - "IE university Madrid": IE university AND university Madrid
- Problems?

### Issues for biword indexes

#### False positives

verify that the matches of the previous Boolean query:
 (IE university AND university Madrid)
 do contain the phrase

#### Index blowup due to bigger dictionary

- Huge for bi-words
- Infeasible for more larger n-grams

#### Solution 2: Positional indexes

Store the position(s) of the term

```
<term, number of docs containing term;
  doc1: position1, position2 ...;
  doc2: position1, position2 ...;
  ...
>
```

# Processing a phrase query

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

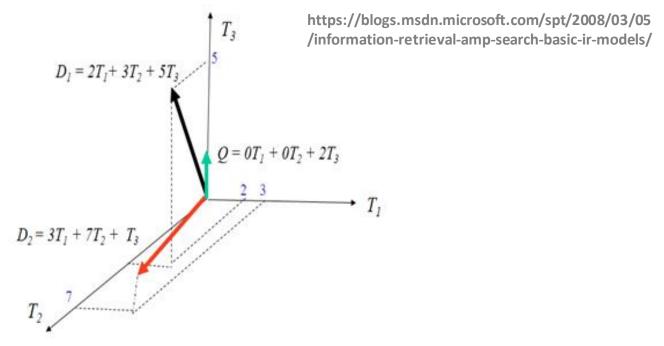
#### Positional index size

- Positional index substantially larger
  - A positional index is 2–4 as large as a non-positional index
  - Positional index size 35–50% of volume of original text

 We assume that because of the power and usefulness of phrase and proximity queries.

- Bigrams and positional indexes can be combined
  - Use bigrams for particular phrases ("Michael Jackson", "Britney Spears")

# Solution 3: Vector Space model

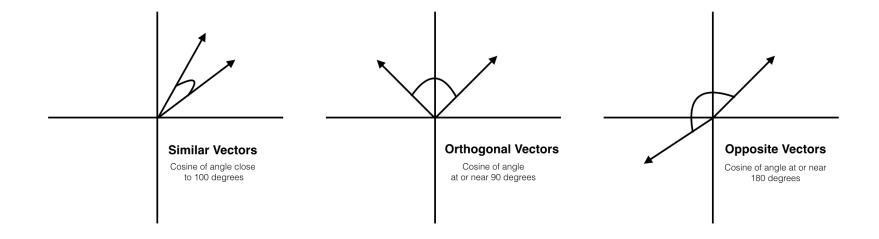


**Assumption**: Documents close in this space talk about the same things.

Retrieve the documents close to the query in this space

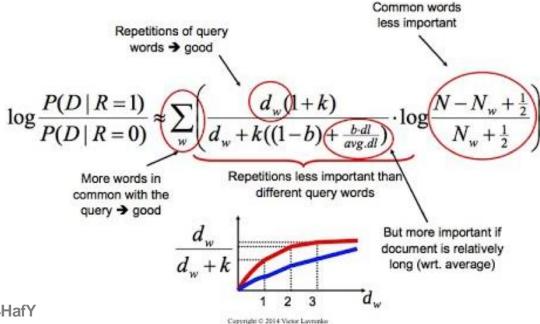
# **VSM Similarity**

- Measure how close two vectors are
  - Cosine Distance



# **VSM Similarity**

- Measure how close two vectors are
  - Cosine Distance
  - Okapi BM25



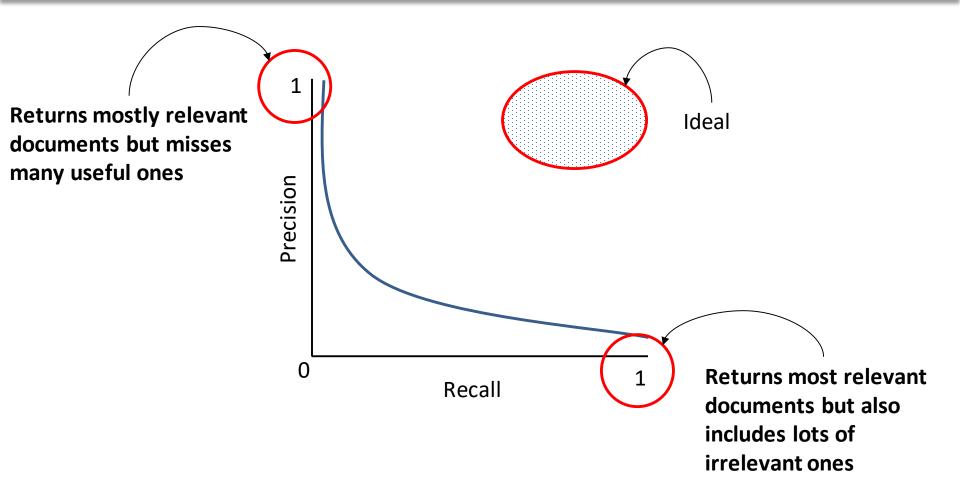
https://www.youtube.com/watch?v=XFIKE34HafY

## How good are the retrieved docs?

- Precision: Fraction of retrieved docs that are relevant to the user's information need
  - From what you gave, what is what I actually wanted
- Recall: Fraction of relevant docs in collection that are retrieved
  - From what I actually wanted, how much have you given me
- F-measure of both

Why not accuracy?

### Precision-Recall Trade-off



# How good are the retrieved docs?

#### Precision/Recall @N

- Focus on the N-first results
- Why?

#### MAP (Mean Average Precision):

 Average of the precision for the top k documents, each time a relevant doc is retrieved

avg(P@k / iff k is relevant)

- Avoids use of fixed recall levels
- NDCG (Normalized Cumulative Discounted Gain)
  - Take into account the ranking of the relevant documents
  - Reward you more for getting rank 1 right than for getting rank 10 right

## More practical measures

- Users finds what they want
  - eCommerce: searching --> buying
  - Search Engine: user returns to the engine
  - Enterprise search: time spent by employees when looking for information
- Indexing speed
- Search speed
- A/B testing

- Integrate User in the process (Relevant Feedback)
  - User annotates query results

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  - User annotates query results
  - User cooperation is rare --> Pseudo RF
    - Use the top-ranked documents as user annotation (as if they are relevant)
    - ~ 10% Improvement

- Integrate User in the process (Relevant Feedback)
- Query expansion
  - Add terms related to the query terms
    - Thesaurus-based (e.g. Wordnet)
    - Corpus-based
      - Mutual information find terms that co-occur frequently
      - Word2vec
  - Global vs. Local context
    - Subset of retrieved documents to find term relationships

- Integrate User in the process (Relevant Feedback)
- Query expansion
- Importance of the Retrieved Results
  - Google's Page Rank
    - More and more-quality input links = Important the website
    - More important websites are likely to receive more links from other websites

#### Standard benchmarks

- TREC National Institute of Standards and Technology (NIST) has run a large IR test bed for many years
  - https://trec.nist.gov/
- Reuters collections
  - https://archive.ics.uci.edu/ml/datasets/reuters-21578+text+categorization+collection
- CLEF datasets
  - European languages and cross-language IR.
  - http://www.clef-initiat:ve.eu/dataset/test-collection