

Course Outline

- Question Answering systems (Q.A.) +lab (Q.A. finetune BERT model)
- Multilingual and Multimodal Q.A. +lab (Q.A. test BERT models)
- Information Retrieval (I.R.) +lab (I.R. train and test BM25 model)
- Open Domain Q.A. +assignment (Open Domain Q.A)

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- **Question Answering systems (Q.A.)** +lab
 - **Multilingual and Multimodal Q.A.** +lab
 - Information Retrieval (I.R.) +lab
 - Open Domain Q.A. +assignment
- } **summary!**

What is question answering?



The goal of question answering is to build systems that automatically answer questions posed by humans in a natural language

Q.A. is a Reading Comprehension problem

Reading comprehension = comprehend a passage of text and answer questions about its content (P, Q) → A

Tesla was the fourth of five children. He had an older brother named Dane and three sisters, Milka, Angelina and Marica. Dane was killed in a horse-riding accident when Nikola was five. In 1861, Tesla attended the "Lower" or "Primary" School in Smiljan where he studied German, arithmetic, and religion. In 1862, the Tesla family moved to Gospić, Austrian Empire, where Tesla's father worked as a pastor. Nikola completed "Lower" or "Primary" School, followed by the "Lower Real Gymnasium" or "Normal School."

Q: What language did Tesla study while in school?

A: German

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A: German

Extractive Q.A.

Models for reading comprehension

- **How can we build a model to solve SQuAD?**

- Problem formulation (extractive Q.A.)

- Input:

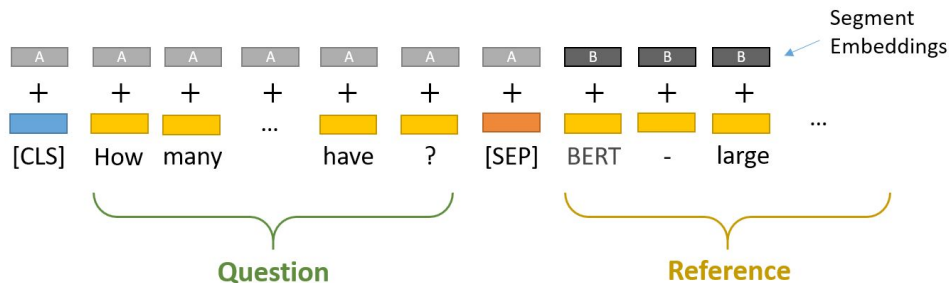
$$C = (c_1, c_2, \dots, c_N), Q = (q_1, q_2, \dots, q_M), c_i, q_i \in V$$

- c: passage or document
 - q: question or query

- Output: $1 \leq \text{start} \leq \text{end} \leq N$ (answer is a span in the passage)

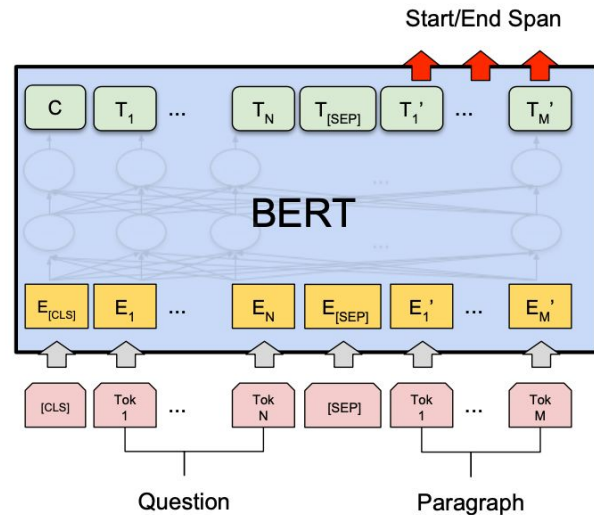
- **From pipelined models ~ LSTM based ~ BERT like models**

BERT based Neural Models for reading comprehension



Question: How many parameters does BERT-large have?

Reference Text: BERT-large is really big... it has 24 layers and an embedding size of 1,024, for a total of 340M parameters! Altogether it is 1.34GB, so expect it to take a couple minutes to download to your Colab instance.

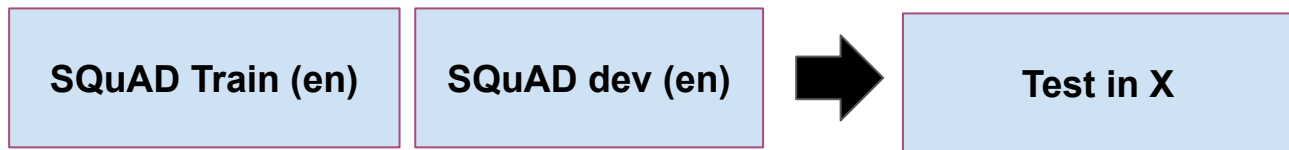


- **Input:**
 - tokenization (BPE)
 - segment ids
 - CLS & SEP
- **Output:**
 - Argmax start & end idx.
 - Recover answer (BPE)
 - Get score

Multilingual Neural Models for reading comprehension

Problem: most of the datasets in NLP are in English... SQuAD, QuAC....

- Translate Train (MT + alignment)
- Translate Test (MT + alignment)
- **Zero-Shot** (CrossLingual pretrained L.M.)



We don't need M.T. and alignment!

Is reading comprehension solved?



- **Of course not!**
- Super human performance on SQuAD
- Out of domain Q.A. is still a problem
- Extractive models -> **We assume always a given passage**

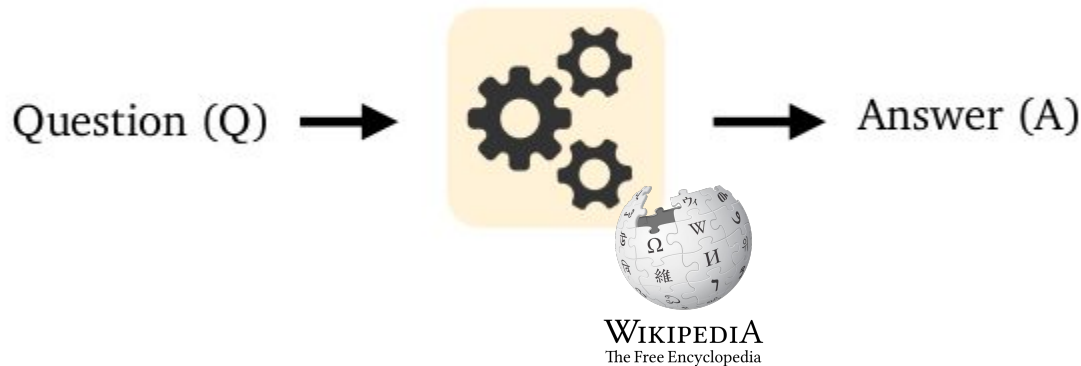
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Open Domain Q.A.

Open Domain Q.A.



- Different from reading comprehension, we don't assume a given passage.
- Instead, we only have access to a large collection of documents (e.g., Wikipedia). We don't know where the answer is located, and the goal is to return the answer for any open-domain questions.
- Much more challenging but **a more practical problem!**

Open Domain Q.A.

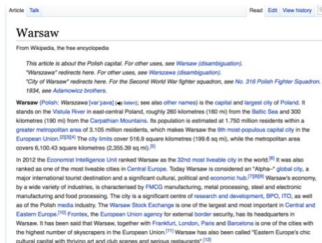
Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

Q: How many of Warsaw's inhabitants spoke Polish in 1933?

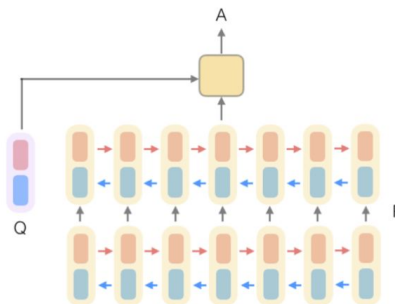


Document
Retriever



Document
Reader

833,500

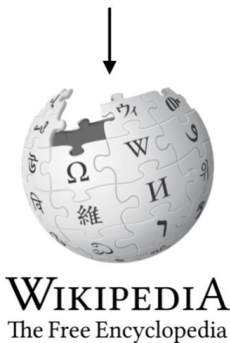


Open Domain Q.A.

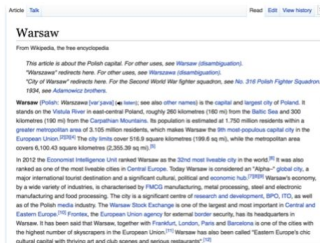
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**Document
Retriever**

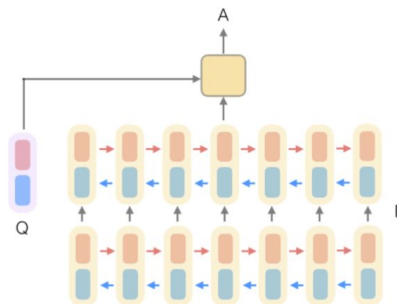


**Document
Reader**

833,500



**Information
Retrieval
Model (I.R.)**



BERT
fine-tuned for
Q.A.

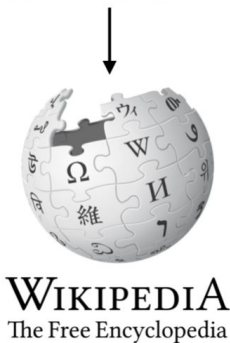
Open Domain Q.A.

Open-domain QA

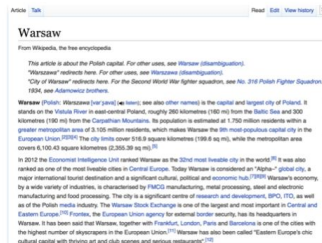
SQuAD, TREC, WebQuestions, WikiMovies

This is your assignment :D

Q: How many of Warsaw's inhabitants spoke Polish in 1933?



Document
Retriever

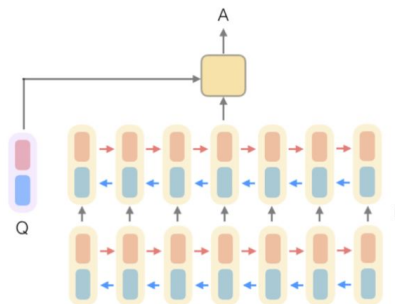


Document
Reader

833,500



Information
Retrieval
Model (I.R.)



BERT
fine-tuned for
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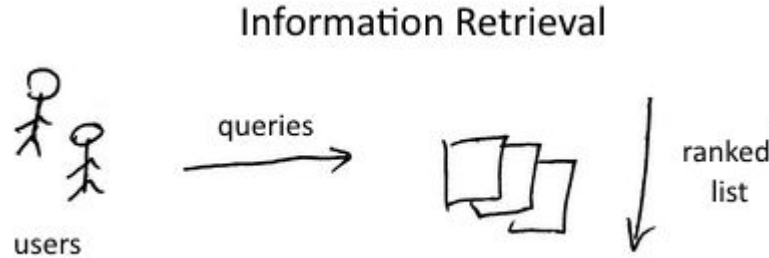
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- **Information Retrieval (I.R.)** +lab
- Open Domain Q.A. +assignment

Course Outline

- **Information retrieval**
 - **Introduction**
 - I.R. practical applications
 - I.R. for text retrieval

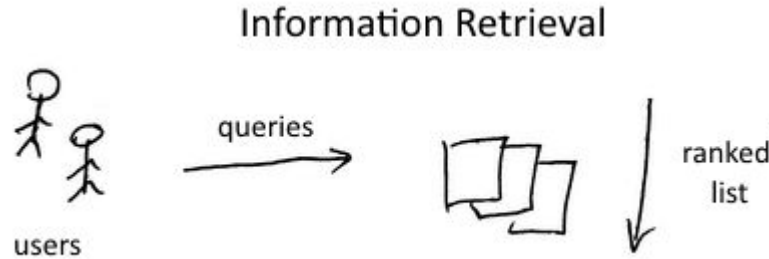
What is information retrieval?



Information retrieval (**IR**) is the process of obtaining information system resources that are relevant to an information need from a collection of those **resources**.

- Full-text
- Books
- Passages
- Music
- ...

What is information retrieval?



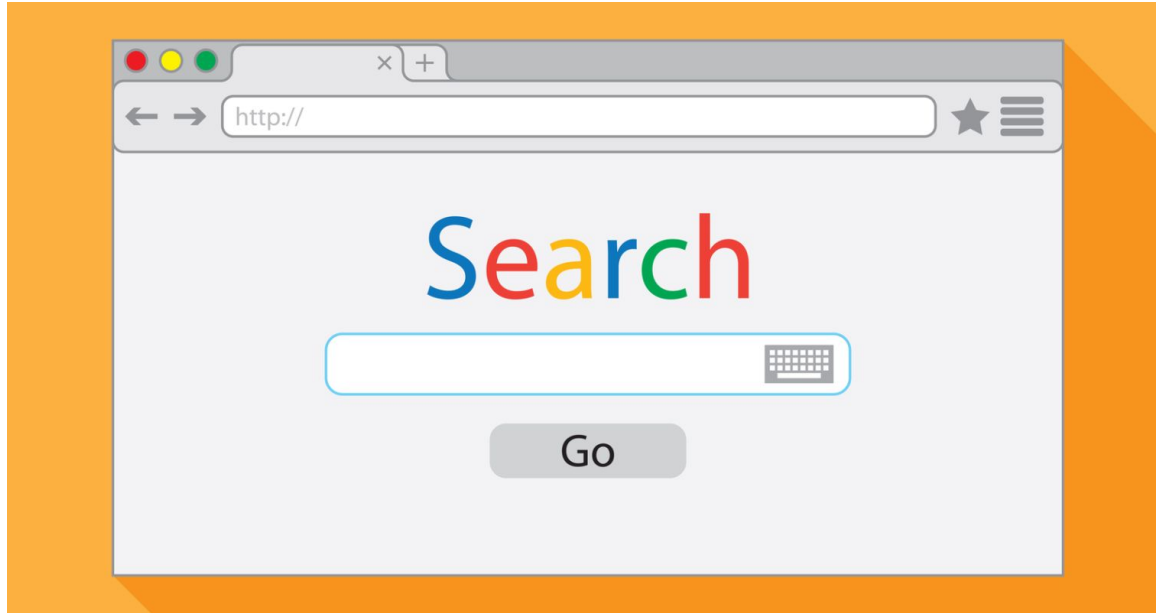
Automated information retrieval systems are used to reduce what has been called information overload (**Infoxication**).

- **Information overload:** is the difficulty in understanding an issue and effectively making decisions when one has too much information about that issue

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I.R.: Lots of practical application



<https://www.searchenginejournal.com/alternative-search-engines/271409/>



Search engines
Web Search

I.R.: Lots of practical application



<https://www.mentionlytics.com/blog/10-best-social-search-engines/>

Search engines
Desktop search
Social media search
...

I.R.: Lots of practical application



Also called an **online library**, an **internet library**, a **digital repository**, or a **digital collection** is an online database of digital objects that can include text, still images, audio, video, digital documents, or other digital media formats or a library accessible through the internet.

Digital Libraries

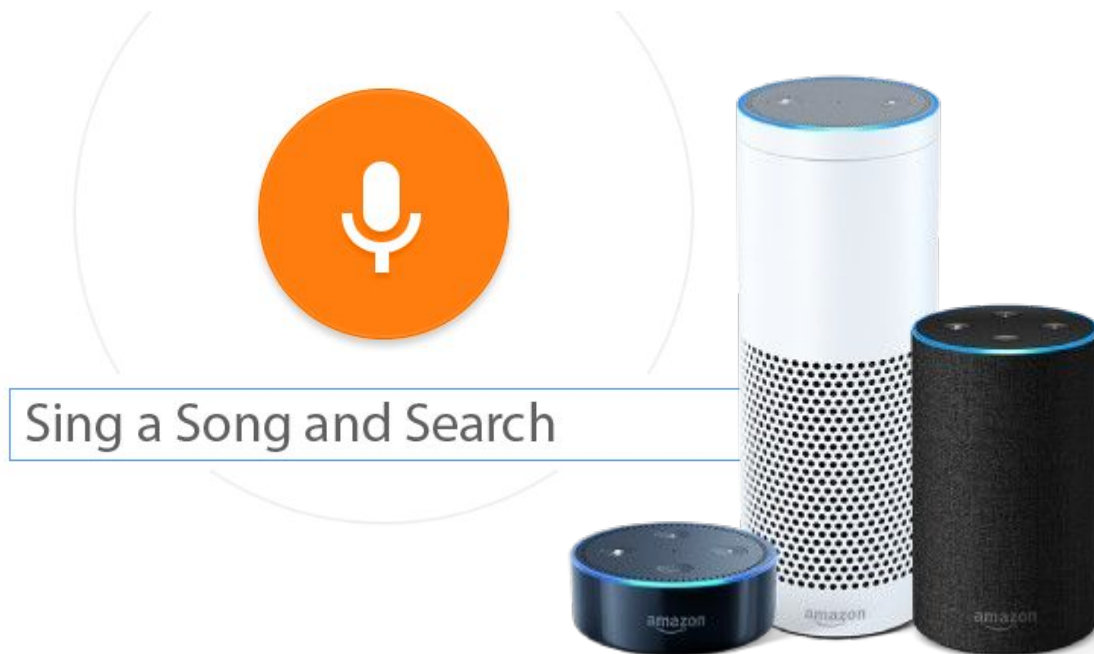
I.R.: Lots of practical application

A recommender system, or a recommendation system (sometimes replacing 'system' with a synonym such as platform or engine), is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user would give to an item.



Information Filtering
&
**Recomender
Systems**

I.R.: Lots of practical application



Media search

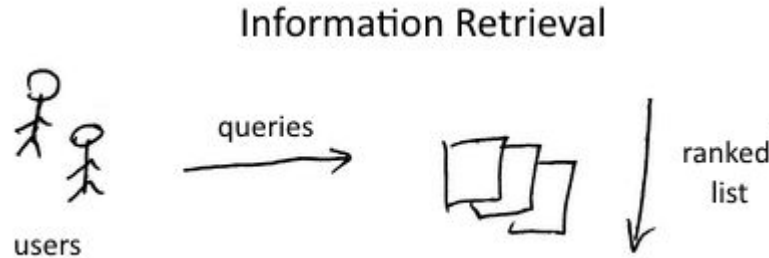
blogs
images
music
news
speech
video

...

Course Outline

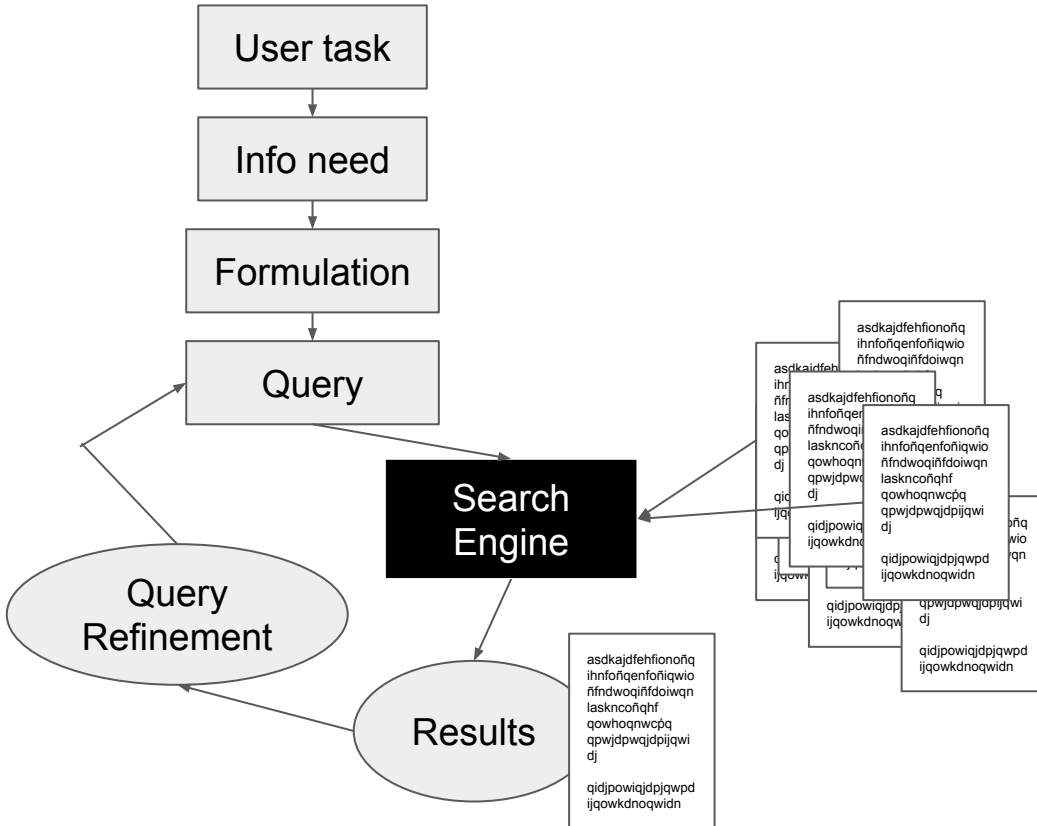
- **Information retrieval**
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Basic assumption of I.R.



- Collection: A set of documents
 - A static set of unstructured or semistructured 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



Get ride of mice in a politically correct way

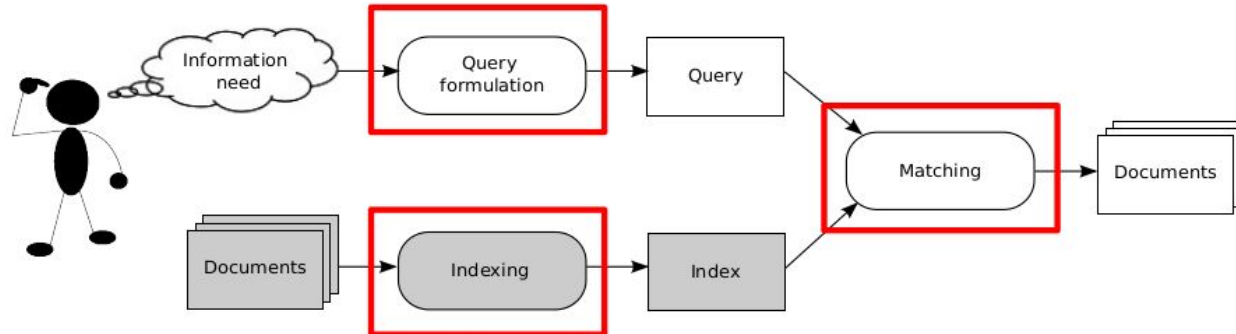
Info about removing mice without killing them

Whats the best way to trap mice alive?

Trap mice alive

The classic search model

- Collecting documents
- **Indexing** documents (representation)
- **Query** formulation: the user formulates a query according to his information need
- **Matching**: the query representation is compared against the document representation (index) to select relevant documents

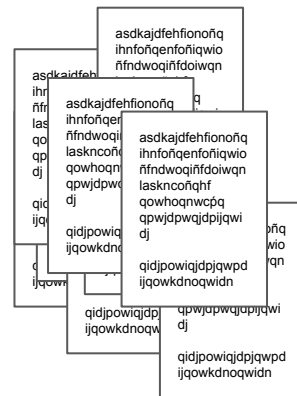


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 - **I.R. for text retrieval**
 - **Boolean retrieval**
 - Ranked retrieval
 - I.R. models

Boolean retrieval

- Term-document incidence matrix
- Inverted index
- Query processing
- The Merge
- Boolean queries



Doc collection: Works of William Shakespeare
Query: Which plays of Shakespeare contain the words Brutus and Caesar, but not Calpurnia?

Boolean retrieval

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- **Term-document incidence matrix**
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- Boolean queries

	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

1 if doc contains
word, 0 otherwise

Boolean retrieval

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- **Term-document incidence matrix**
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- So we have a 0/1 vector for each term
 - **To answer the query:** Brutus AND Caesar BUT NOT Calpurnia
 - Take the vectors for Brutus, Caesar and Calpurnia
 - Bitwise AND

110100 **AND** 110111 **AND** 101111 = **100100**

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Boolean retrieval

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110100 **AND** 110111 **AND** 101111 = **100100**

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.

Boolean retrieval

Doc collection: Works of William Shakespeare

Query: Which plays of Shakespeare contain the words Brutus and Caesar, but not Calpurnia?

- **Term-document incidence matrix**
 - Inverted index
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 - Boolean queries
- Consider 1 million documents, each with about 1000 words
 - Avg 6 bytes/word including spaces/punctuation
 - 6GB of data in the documents
 - Say there are 500K distinct terms among these
 - 500K x 1M matrix has half-a-trillion 0's and 1's
 - **Too big!!**
 - But it has no more than one billion 1's
 - Matrix is extremely sparse
 - A minimum of 99.8% of the cells are 0
 - What's a better representation?
 - **We only record the 1 positions**

Boolean retrieval

Doc collection: Works of William Shakespeare

Query: Which plays of Shakespeare contain the words Brutus and Caesar, but not Calpurnia?

- **Term-document incidence matrix**
 - **Inverted index**
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 - Boolean queries
- For each term t , we must store a list of all documents that contain t
 - Identify each document by a docID
 - Can we use fixed-size arrays for this?
 - We need variable-size posting lists
 - On disk, a continuous run of postings is normal and best
 - In memory, can use linked list or variable length arrays

Brutus	1 2 4 11 31 45 173 174
Caesar	1 2 4 5 6 16 57 132
Calpurnia	2 31 54 101

Boolean retrieval

Doc collection: Works of William Shakespeare

Query: Which plays of Shakespeare contain the words Brutus and Caesar, but not Calpurnia?

- **Term-document incidence matrix**
- **Inverted index**
- **Query processing**
 - Consider processing the query: **Brutus AND Caesar**
- **The Merge**
 - Locate Brutus in the dictionary
 - Locate Caesar in the dictionary
 - “Merge” **intersect the document sets**
- **Boolean queries**
 - Retrieve the documents

Brutus	1 2 4 11 31 45 173 174
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Boolean retrieval

Doc collection: Works of William Shakespeare

Query: Which plays of Shakespeare contain the words Brutus and Caesar, but not Calpurnia?

- **Term-document incidence matrix**
- **Inverted index**
- **Query processing**
- **The Merge**
- **Boolean queries**
- 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
 - Perhaps the simplest model to build an IR system on
- Primary commercial retrieval tool for 3 decades
- Many search system you still use are boolean
 - Email, library catalog

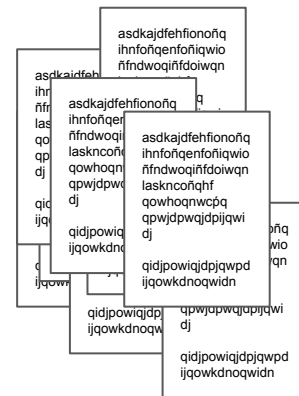
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 - **I.R. for text retrieval**
 - Boolean retrieval
 - **Ranked retrieval**
 - I.R. models

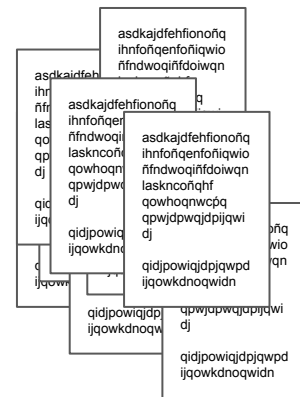
Ranked retrieval Motivation

- Thus far, our queries have been **Boolean**
 - Documents either match or don't
- Good for expert users with precise understanding of their needs and of 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



Ranked retrieval Motivation

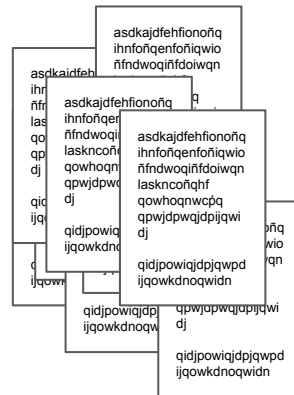
- Rather than a set of documents satisfying a query expression, the system returns and **ordering** over the documents in the collection for a query
- **Too few or too many:** is not a problem in ranked retrieval
- With ranking, large result sets are not an issue
 - Just show the top k (≈ 10) results
 - Doesn't overwhelm the user
- **The ranking algorithm works:** More relevant results are ranked higher than less relevant results



Ranked retrieval

Ranked retrieval

- Bag of words model
- Term-document count matrix
- Term frequency
- Document frequency
- IDF
- TF-IDF



	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

Course Outline

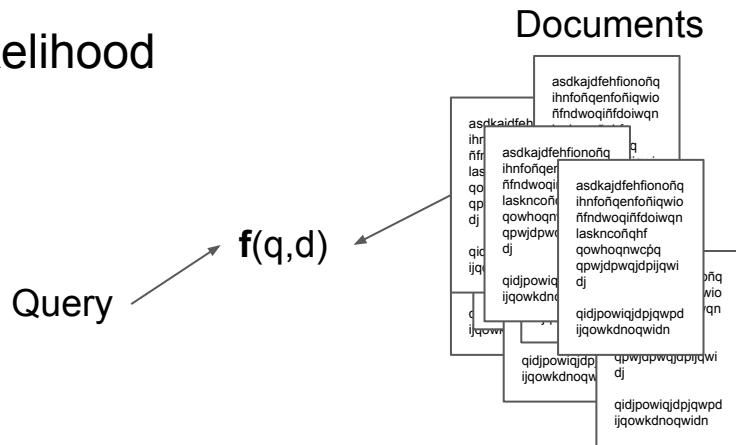
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 - **I.R. models (Okapi BM25)**

I.R. models

Key challenge: how to measure the likelihood that document d is relevant to query q

Ranking function: $f(q,d)$

- Similarity-based
- Probabilistic models
 - **Okapi BM25**

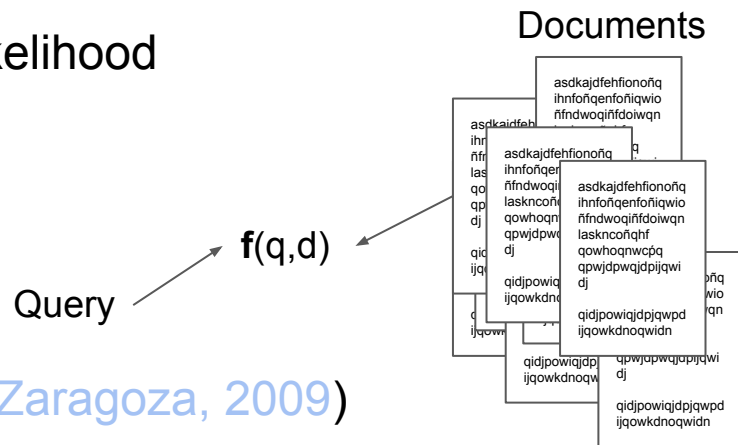


I.R. models **Okapi BM25** (BM = best matching)

Key challenge: how to measure the likelihood that document d is relevant to query q

Ranking function: $f(q,d)$

- Similarity-based
- Probabilistic models
 - **Okapi BM25** (Robertson and Zaragoza, 2009)



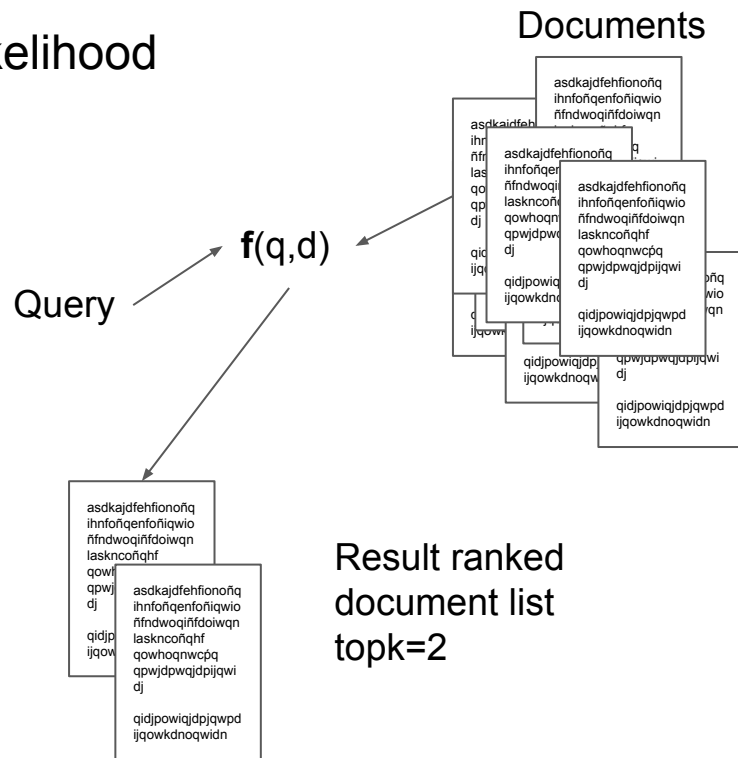
$$w_{tD} = \frac{(k_1 + 1) tf_{tD}}{k_1((1 - b) + b \frac{l_D}{avl}) + tf_{tD}} idf_t$$

term frequency of t in D
Documents length
Average document length
 K, B Tuning parameters

I.R. models **Okapi BM25** (BM = best matching)

Key challenge: how to measure the likelihood that document d is relevant to query q

This is still the most used algorithm to I.R. task!!!!



I.R. models **Okapi BM25** (BM = best matching)

Key challenge: how to measure the likelihood that document d is relevant to query q

Documents

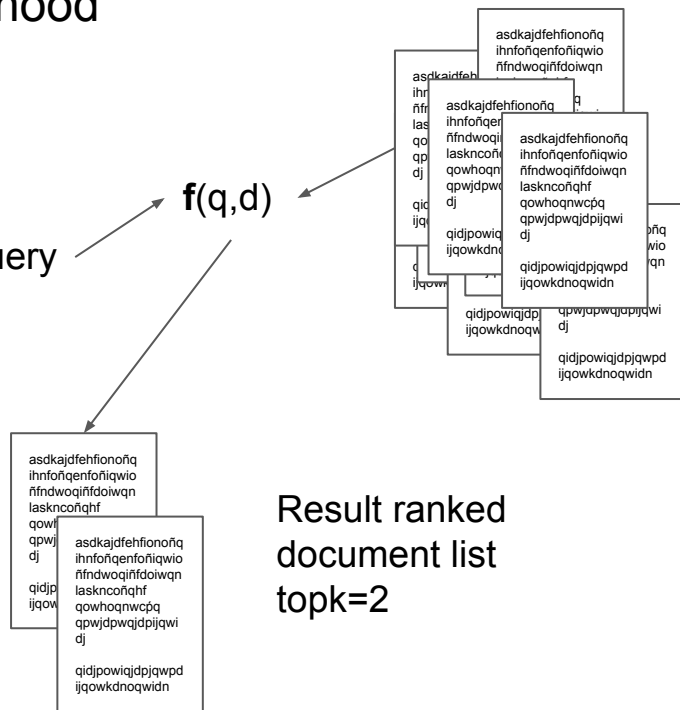
Query $\rightarrow f(q,d)$

This is still the most used algorithm to I.R. task!!!!

CrossLingual I.R.???

Use Case???

Result ranked document list
topk=2



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 - Boolean retrieval
 - Ranked retrieval
 - I.R. models (Okapi BM25)
- **Open domain Q.A. (I.R. + Q.A.)**

Open Domain Q.A.

This is your assignment :D
(Using Covid19 research papers)

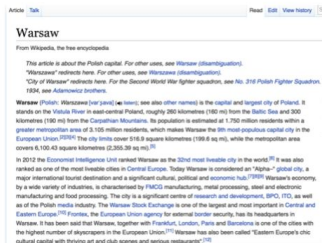
Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

Q: How many of Warsaw's inhabitants spoke Polish in 1933?



**Document
Retriever**

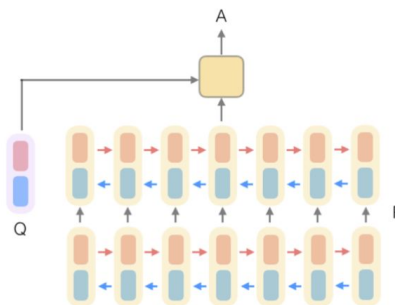


**Document
Reader**

833,500



**Information
Retrieval
Model (I.R.)**



BERT
fine-tuned for
Q.A.

Thanks!

ander.barrena@ehu.eus
@4nderB

Lab Time! <http://ixa2.si.ehu.eus/~jibblleo/nlpapp2>

- [8.IR_for_covid19]

- Edited from <https://www.kaggle.com/aotegi/neural-question-answering-for-cord19-task8>
 - Jon Ander Campos and Arantxa Otegi (winners of the task :D)
- Index a set of covid related passages (from scientific papers)
- Perform I.R. task and retrieve the **n** most relevant documents given a query
- Test if retrieved documents are relevant
 - Persistence of virus on surfaces of different materials
 - Range of incubation periods for the disease in humans
- **Optional:** change “domain” and use your own data, for example SQuAD passages, Wikipedia abstracts...
- Complete the assignment using lab. code
- Download the data in /labs/data/**passages** (176M)