Advanced Topics in Information Retrieval

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Agenda

- Organization
- Course overview
- What is IR?
- Retrieval Models
- Link Analysis
- Indexing and Query Processing
- Tools for IR - Elasticsearch

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- **Organization**
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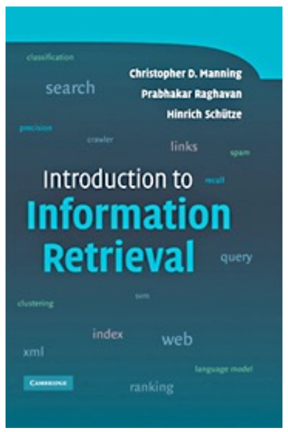
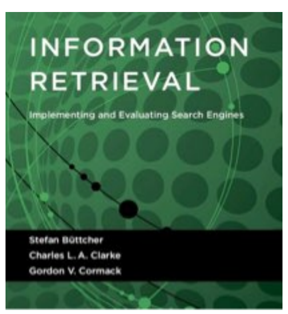
Organization

- **Lectures**: Thursdays, 14:15 - 15:45, Weekly, room 023, E14, MPI-INF
  - Except for lectures on 16th and 23rd June, they will be held in room 0.01 in building E 1.7 (MMCI)
- **Tutorials**: Mondays 14:15 - 15:45, Biweekly, Room 023, E14, MPI-INF
  - Except for tutorial on13th of June room 0.01in building E 1.7 (MMCI)
- Lecturers:
  - Vinay Setty (vsetty@mpi-inf.mpg.de) Appointments only by email (no fixed office hours)
  - Jannik Strötgen (jtroetge@mpi-inf.mpg.de) Appointments only by email (no fixed office hours)
- Tutor: We are the tutors!

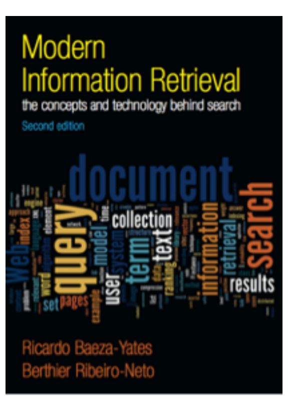
Background Literature



- C. D. Manning, P. Raghavan, H. Schütze,
  Introduction to Information Retrieval,
  Cambridge University Press, 2008
  http://www.informationretrieval.org



- S. Büttcher, C. L. A. Clarke, G.V. Cormack,
  Information Retrieval,
  MIT Press, 2010



- R. Baeza-Yates and R. Ribeiro-Neto,
  Modern Information Retrieval,
  Addison-Wesley, 2011

Required Background Knowledge

- Preferably passed IRDM lecture
- Basic programming skills (any language of your choice)
- Latex basics

Exercise Sheets

- **Biweekly (almost) exercise sheets**
  - six exercise sheets each with up to six problems
  - handed out during the lecture on Thursday (almost biweekly)
    - **Refer to the course page for exact dates!**
  - due by Thursday 11:59 PM of the following week
  - submit electronically as
    - PDF to atir16@mpi-inf.mpg.de
      (best: typeset using LaTeX, worst: scans of your handwriting)
    - If programming questions are given, also include the zip/tar of the source code

Tutorials

- **Biweekly (almost) tutorials**
  - on Mondays after due dates
  - **Refer to the course page for exact dates!**
  - we'll grade your solutions as (P)resentable, (S)erious, (F)ail
  - no example solutions

Requirements for 6 ECTS

- Submit **serious or better** solutions to **at least 50%** of problems
- Present solutions in tutorial
  - **at least once** during the semester
  - additional presentations score you **bonus points** (one grade per bonus point, at most three, at most one per session)
- Pass **oral exam** at the end of the semester

Registration & Password

- You'll have to register for this course and the exam in **HISPOS**
- Please **register** by email to atir16@mpi-inf.mpg.de
  - Full name
  - Student number
  - Preferred e-mail address
- Some materials (e.g. papers and data) will be made available in a password-protected area on the course website
  - Username: atir16 / Password: you should know it from the first lecture, if not send an email to atir16@mpi-inf.mpg.de

Questions/Suggestions?

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What is this Course About?

- **IR Basics recap (today)**
  - Different retrieval models
  - Indexing and Query processing
  - Link analysis
  - IR Tools
- **NLP for IR (April 28)**
  - Tokenization, stop word removal, lemmatization
  - Part-of-speech tagging, dependency parsing, named entity recognition
  - Information extraction
  - IR evaluation measures

What is this Course About?

- **Efficiency and Scalability issues in IR (May 12)**
  - Index construction and maintenance
  - Index pruning
  - Query Processing
  - Web archives (versioned documents)
- **Mining and Organizing (May 19)**
  - Clustering
  - Classification
  - Temporal mining
  - Event mining and timelines

What is this Course About?

- **Diversity and Novelty (Jun 2)**
  - Diversification techniques: implicit and explicit
  - Diversification measures
- **Semantic search (Jun 9)**
  - Semantic web
  - Knowledge graphs
  - Entity linking and disambiguation
  - Semantic search, geographic IR

What is this Course About?

- **Temporal Information Extraction (Jun 16)**
  - Temporal expressions
  - Temporal tagging
  - Temporal scopes, document creation time
  - Temporal reasoning
  - Temporal information extraction
  - Demo: HeidelTime and SUTime
- **Temporal Information Retrieval 1 (Jun 23)**
  - Searching with temporal constraints
  - Temporal question answering
  - Temporal document and query profiles
  - Language models for temporal expressions
  - Historical document retrieval, Language evolution - Cultoronomics

What is this Course About?

- **Temporal Information Retrieval 2 (tentative) (Jun 30)**
  - ?
- **Social Media (Jul 7)**
  - Blogosphere mining TREC TSIT
  - Opinion retrieval
  - Spam/hoax detection
  - TDT and Event mining
  - Feed Distillation
- **Learning to rank (Jul 14)**
- **Q&A (Jul 21)**
- **Oral Exam (Jul 28)**

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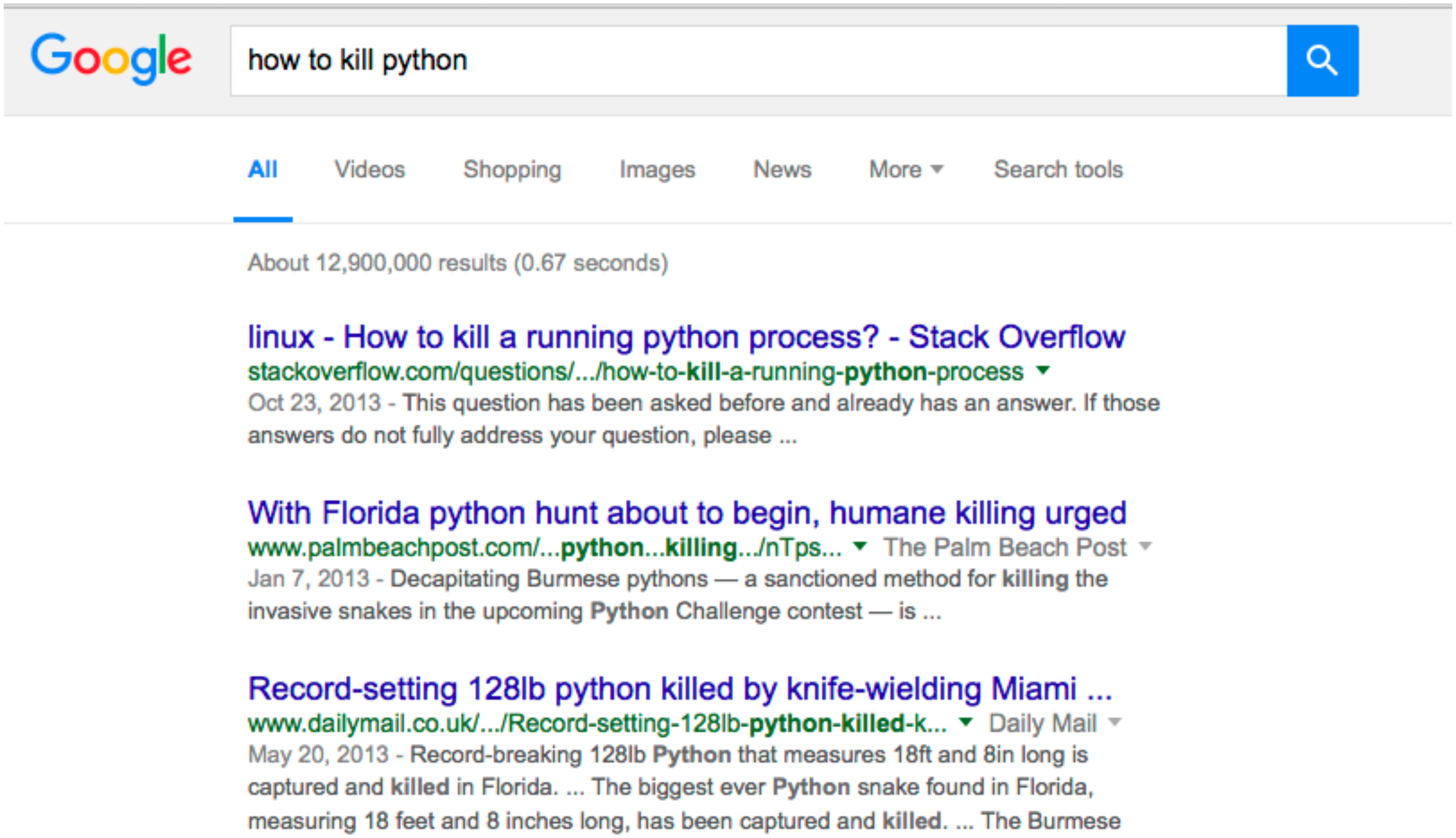

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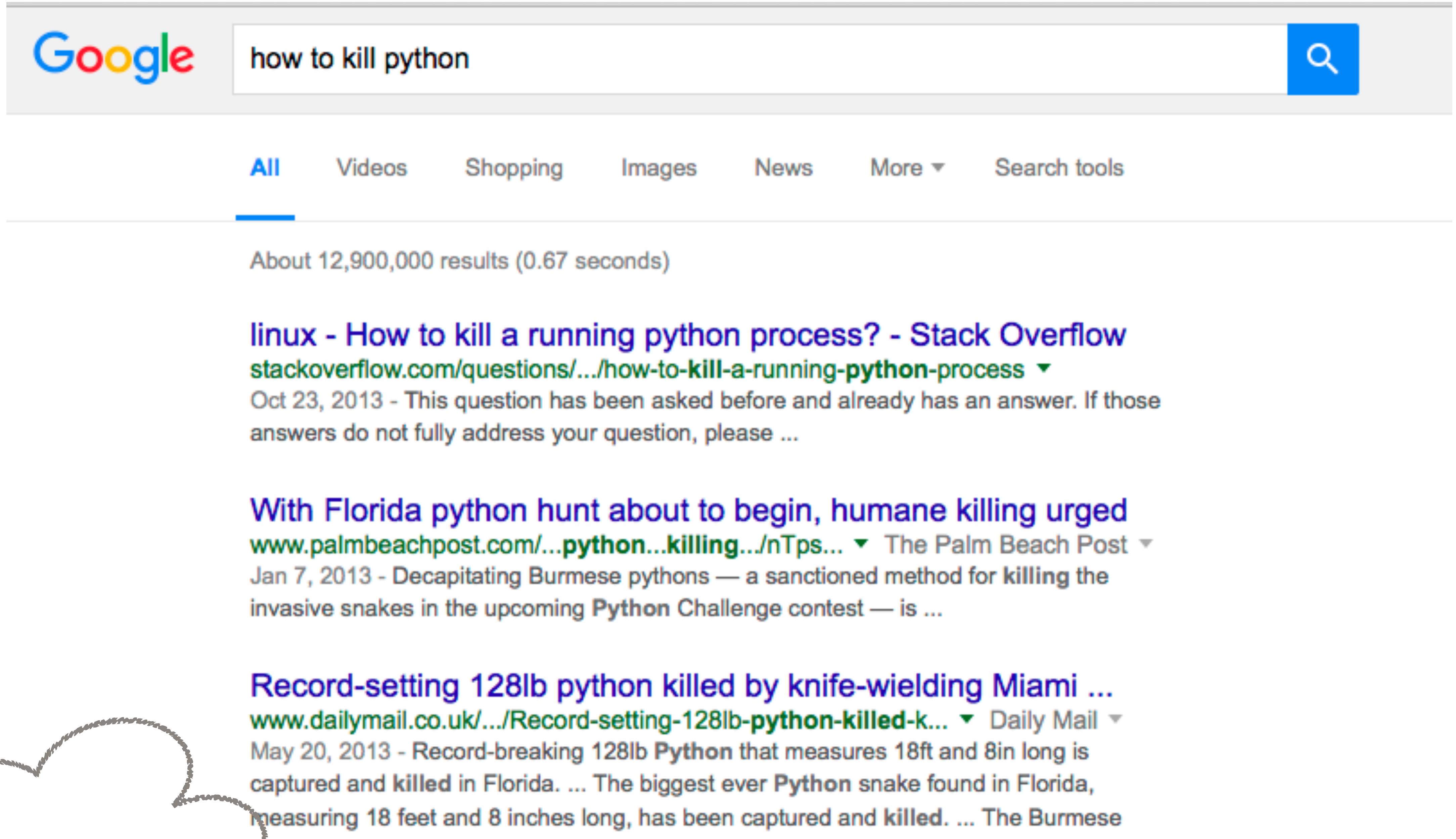

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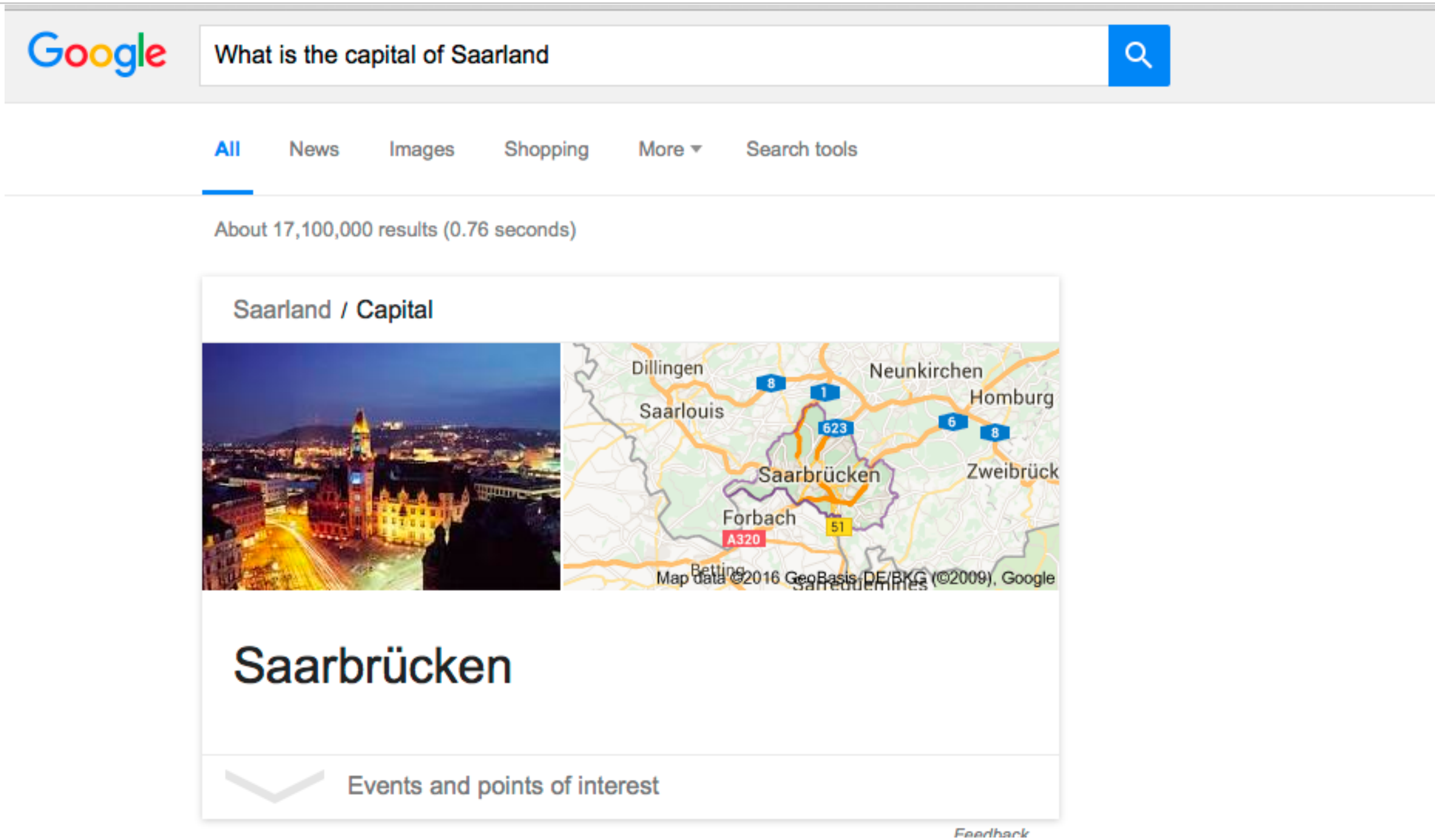

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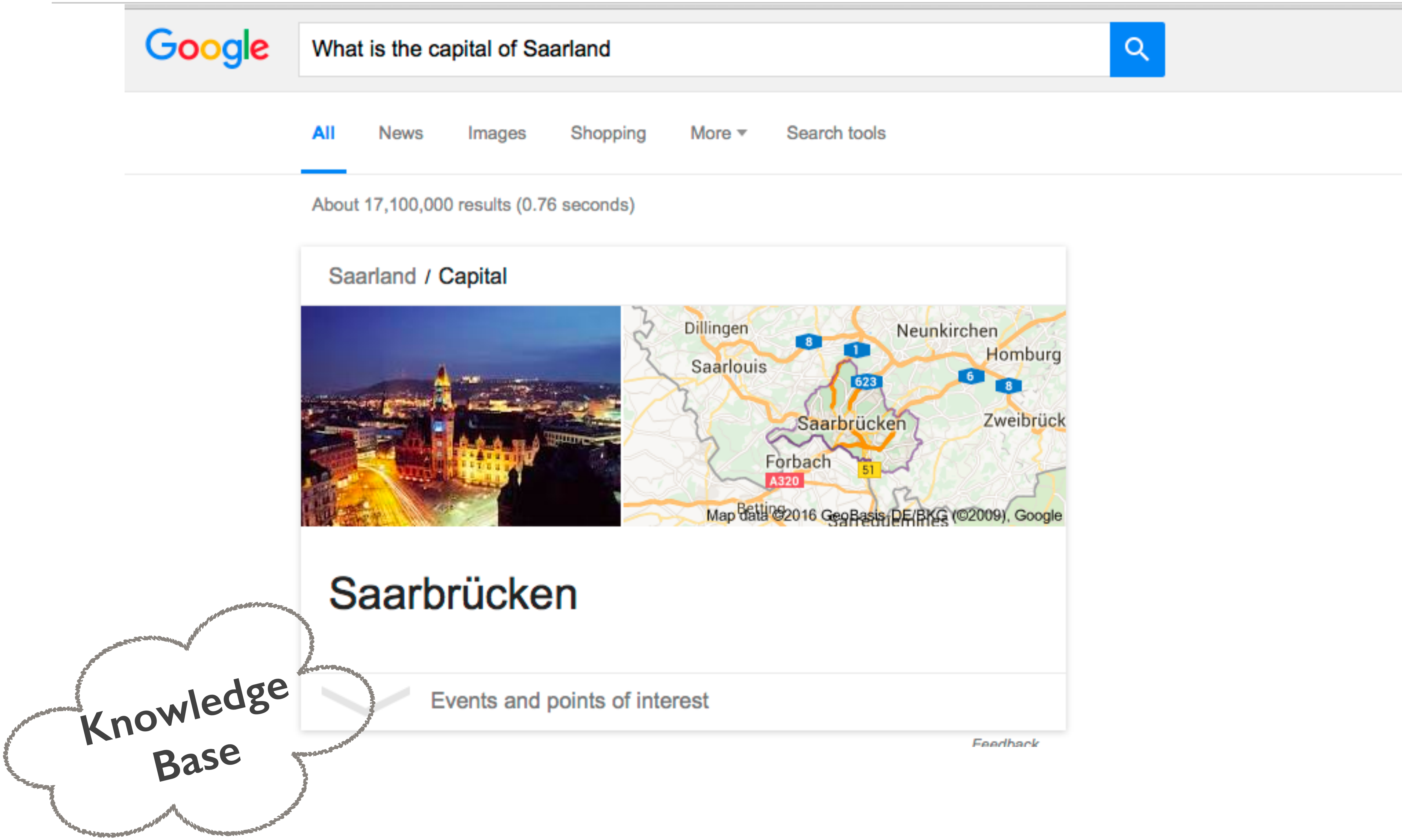

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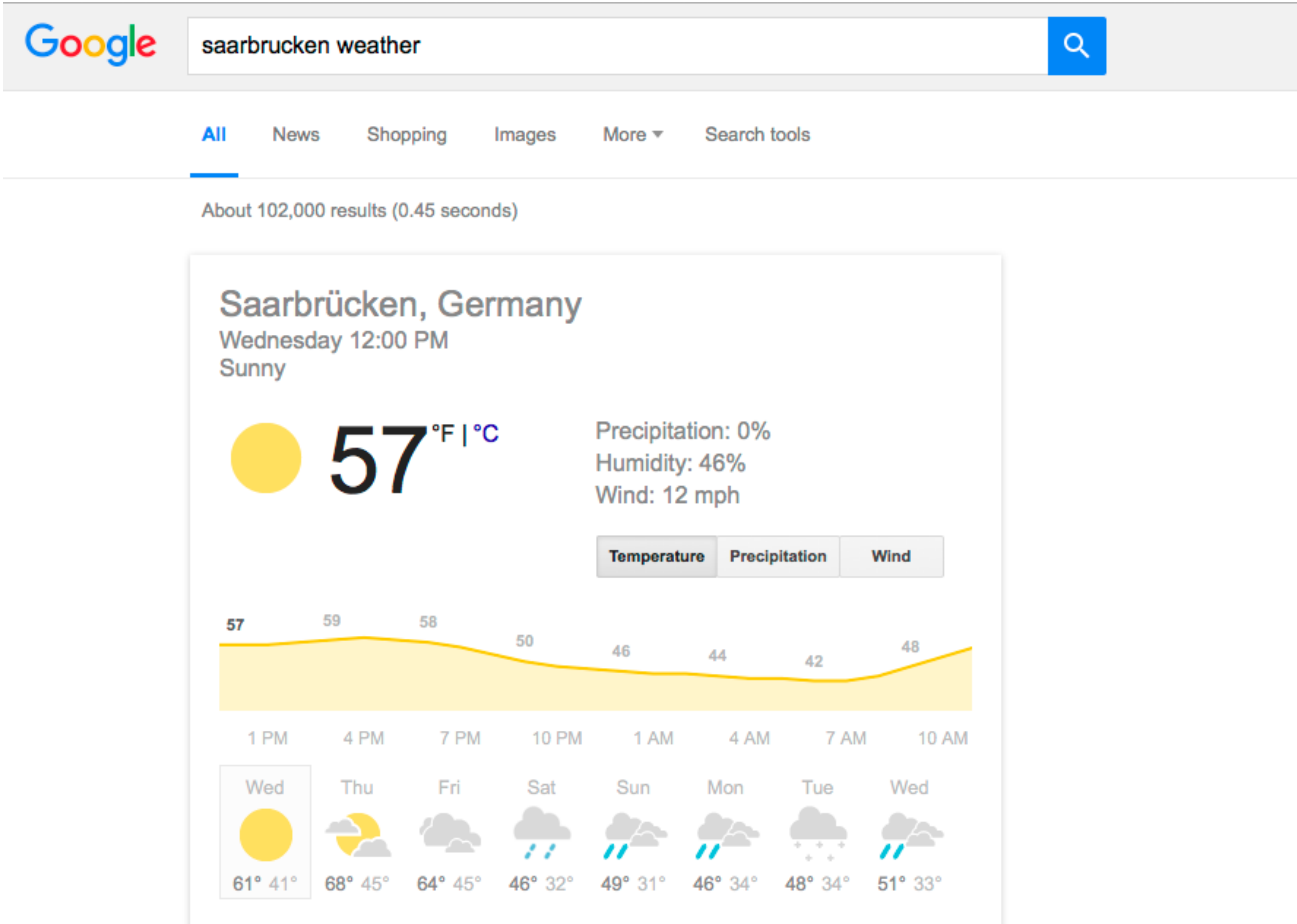

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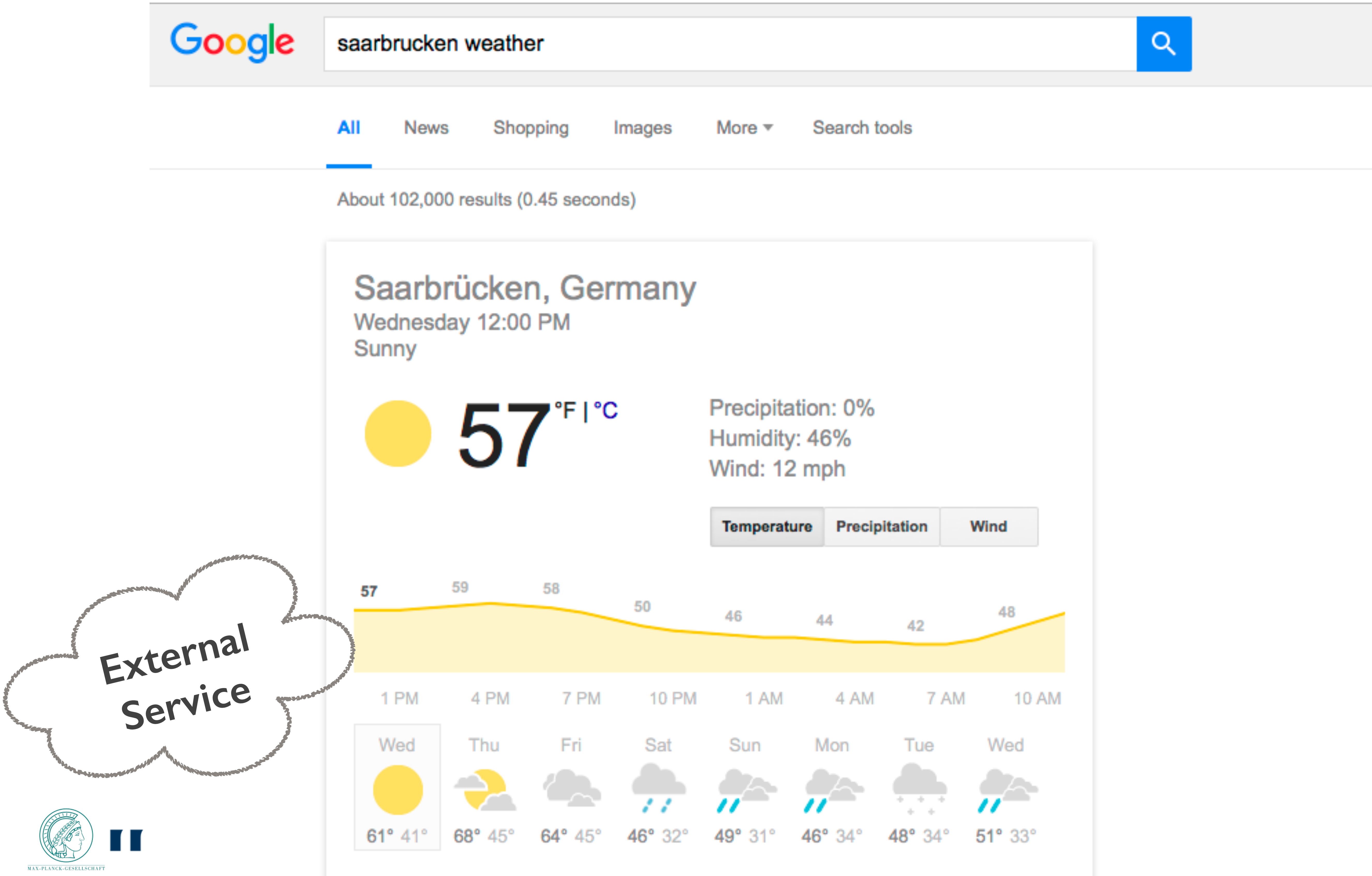

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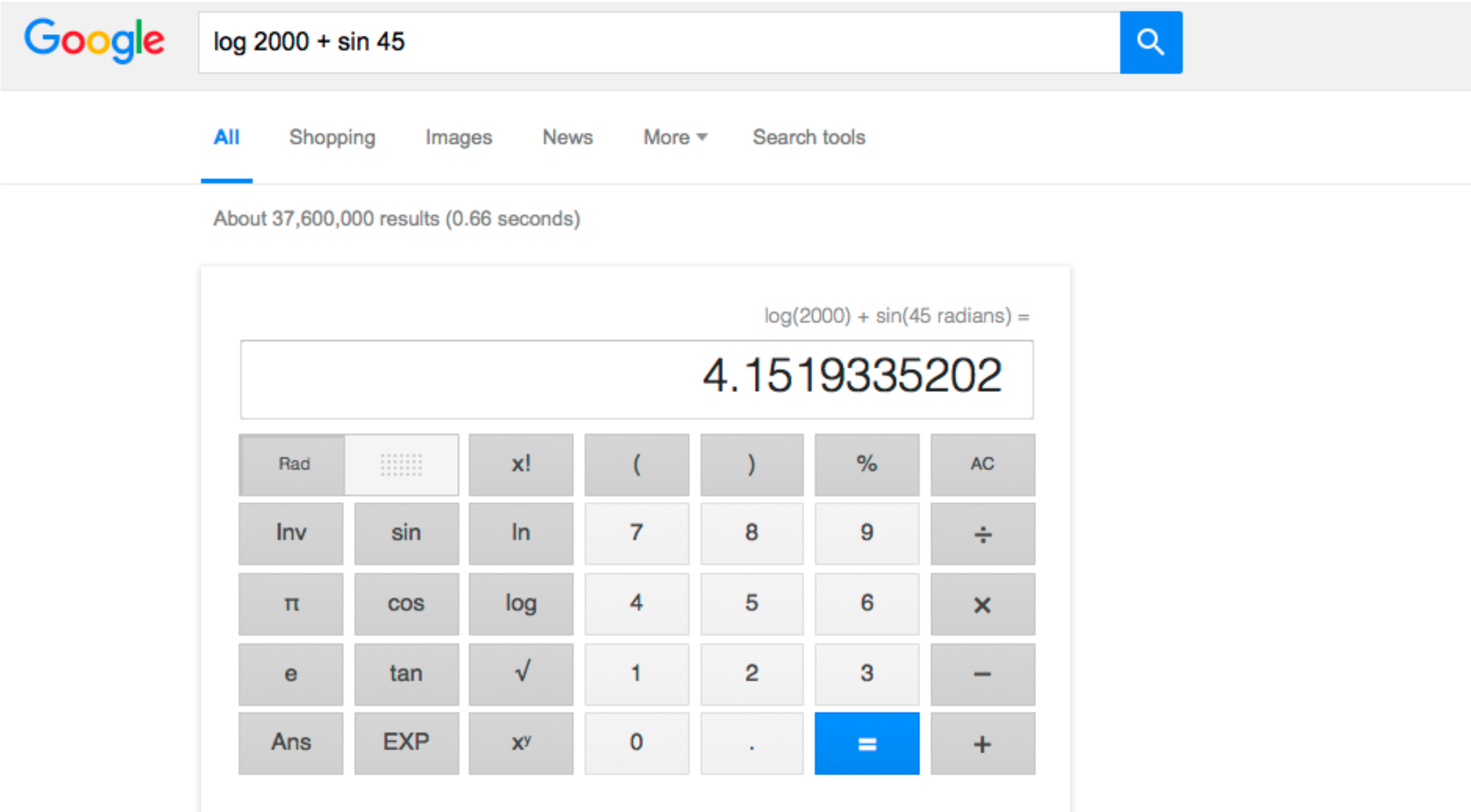

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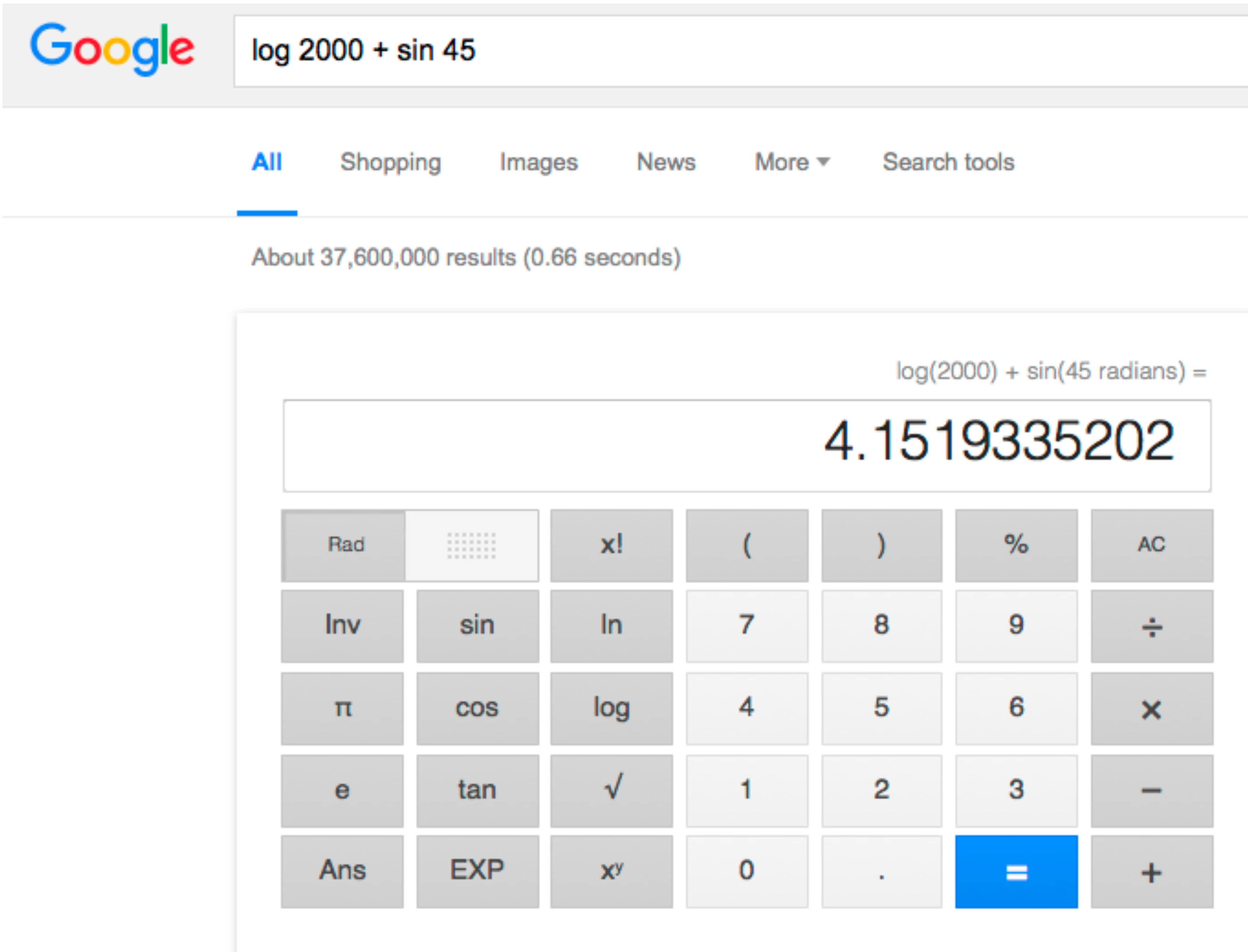

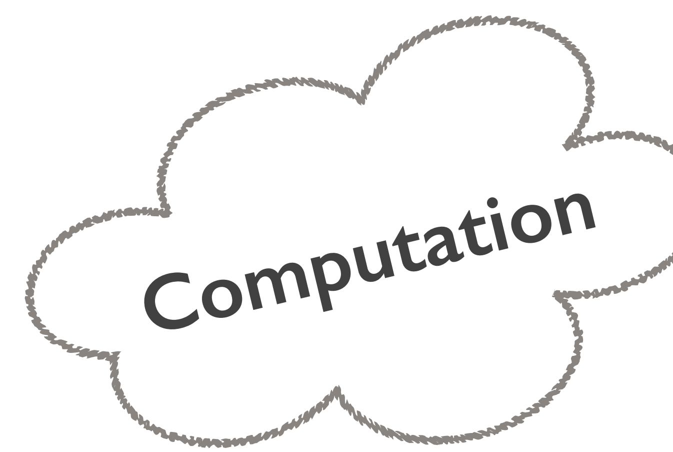

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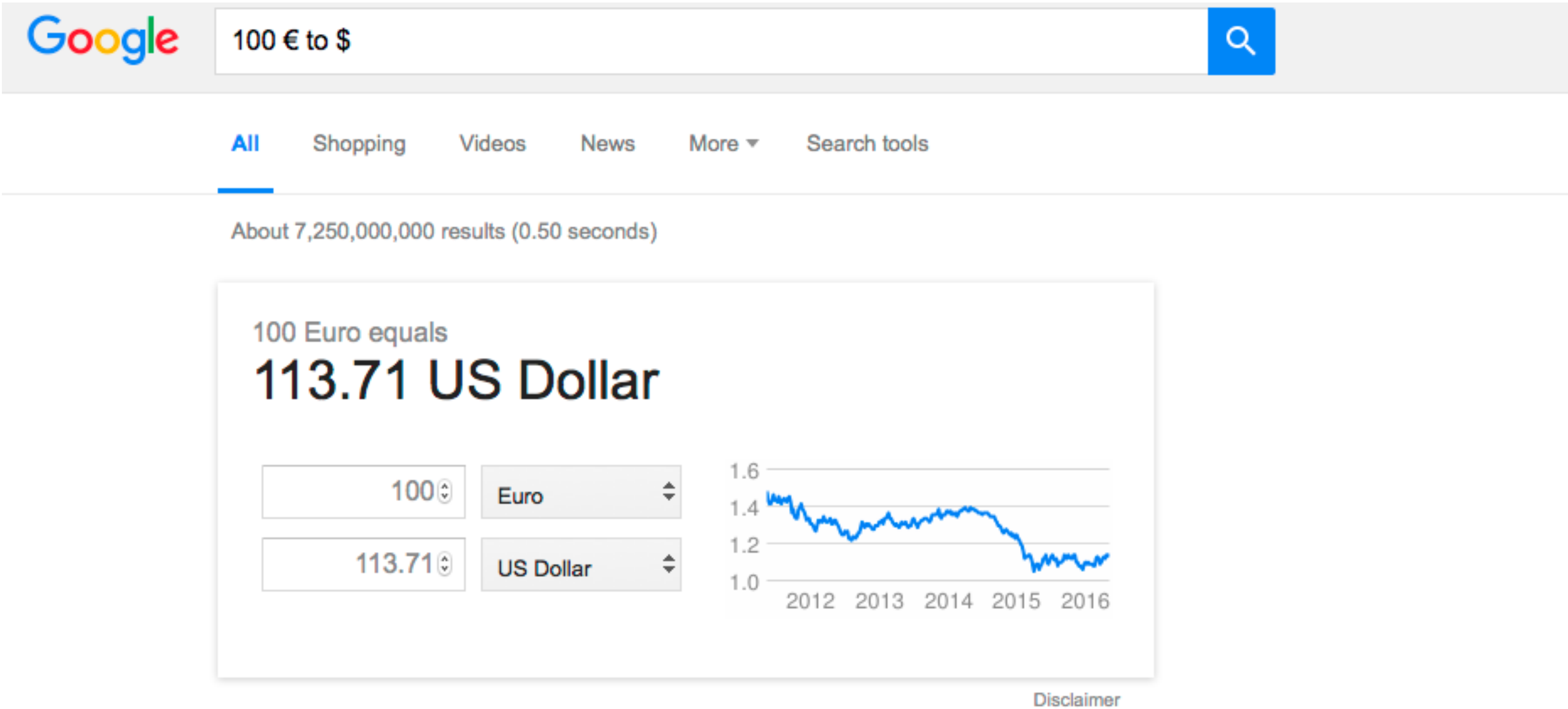

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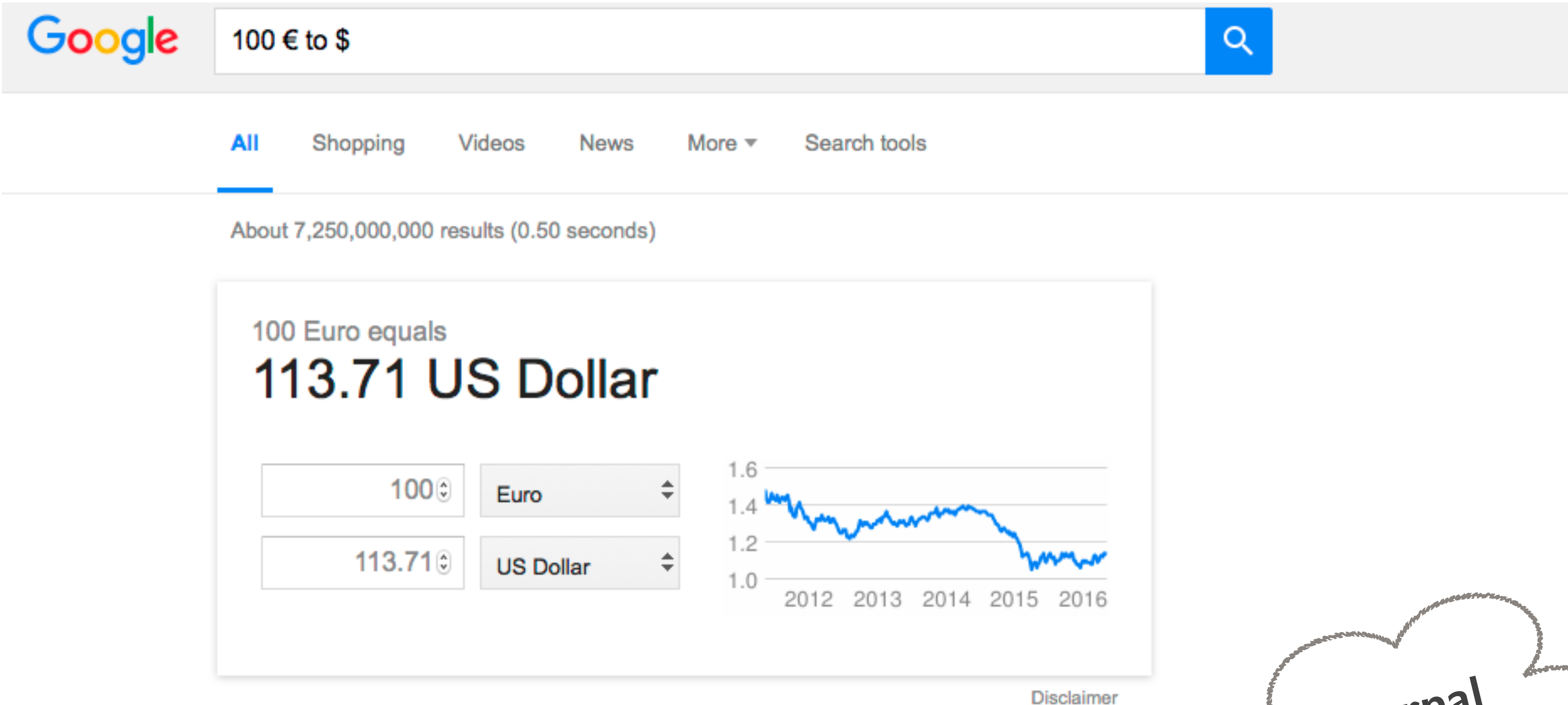

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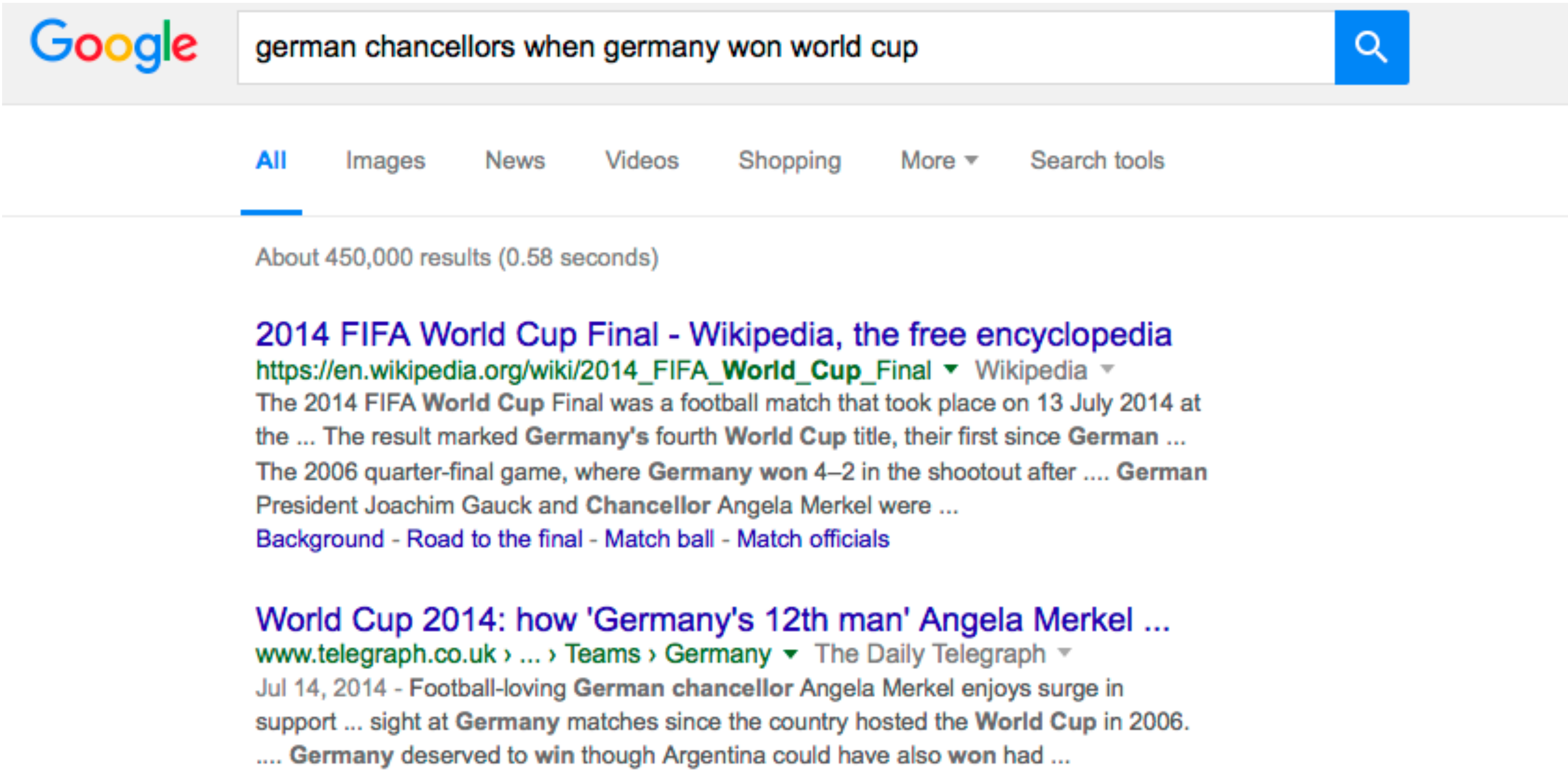

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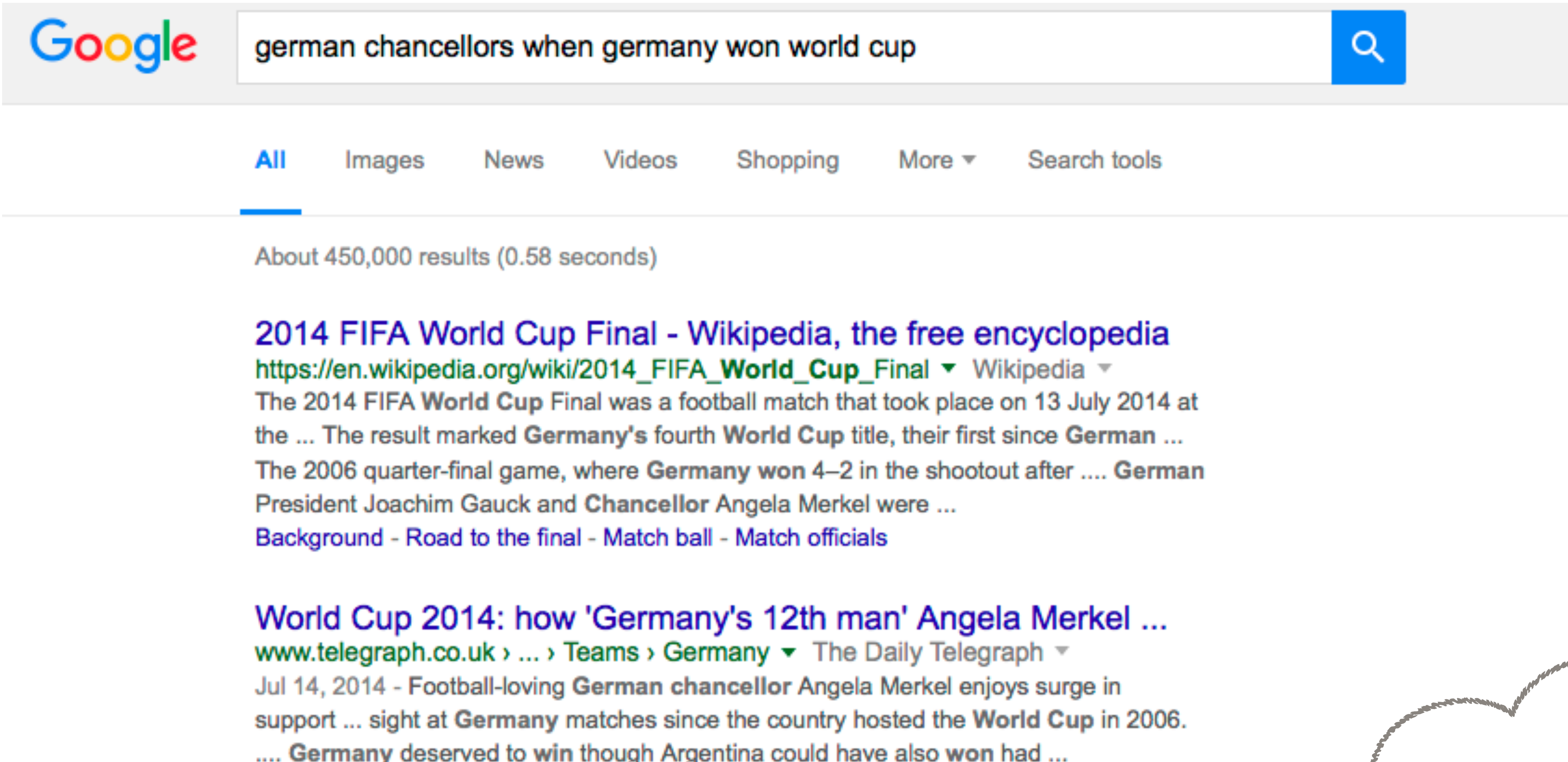

Google

german chancellors when germany won world cup

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About 450,000 results (0.58 seconds)

2014 FIFA World Cup Final - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/2014_FIFA_**World_Cup**_Final ▾ Wikipedia ▾
The 2014 FIFA **World Cup** Final was a football match that took place on 13 July 2014 at the ... The result marked **Germany's** fourth **World Cup** title, their first since **German** ... The 2006 quarter-final game, where **Germany won** 4–2 in the shootout after .... **German** President Joachim Gauck and **Chancellor** Angela Merkel were ...
Background - Road to the final - Match ball - Match officials

World Cup 2014: how 'Germany's 12th man' Angela Merkel ...
www.telegraph.co.uk › ... › Teams › Germany ▾ The Daily Telegraph ▾
Jul 14, 2014 - Football-loving **German chancellor** Angela Merkel enjoys surge in support ... sight at **Germany** matches since the country hosted the **World Cup** in 2006. .... **Germany** deserved to **win** though Argentina could have also **won** had ...

Temporal QA?

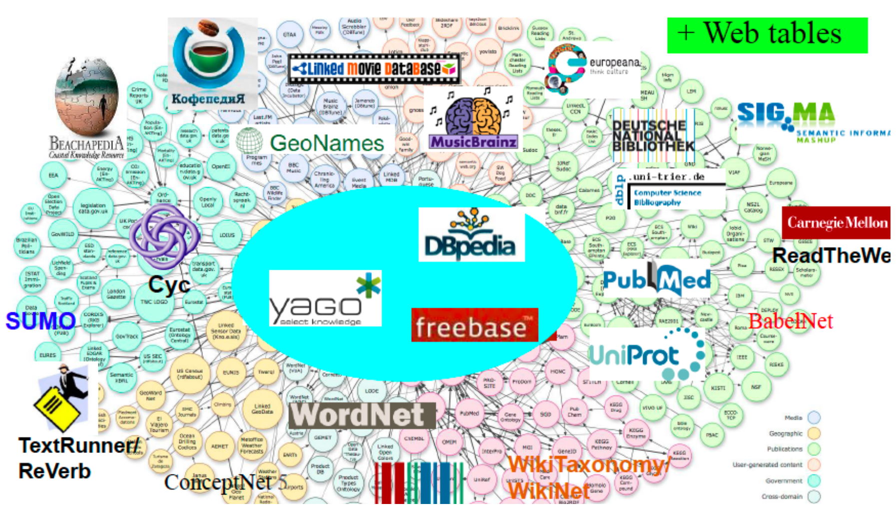
Documents

Webpages, news articles etc

Social media tweets, forums, Facebook status etc.

Files/data on your personal computer

Books, Journals, scholars article etc



Knowledge Graphs

Apps/data on your smartphones

What is Information Retrieval?

What is Information Retrieval?

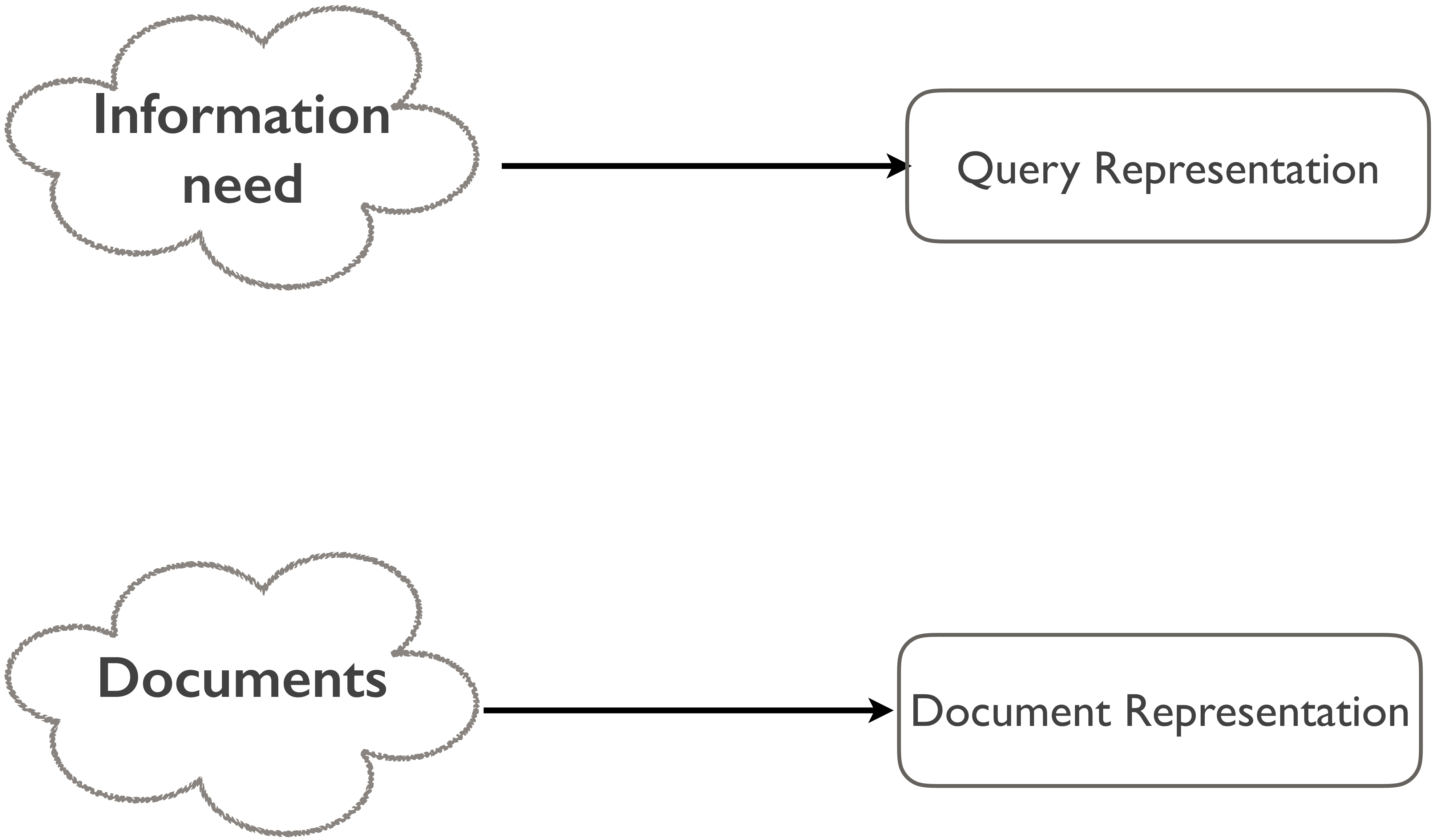
- **Information Retrieval** (IR) is finding material (usually **documents**) of an unstructured nature (usually **text**) that satisfies an **information need** (usually a **query**) from within large collections (usually stored on computers). - Manning et. al.

Information Retrieval

Information need

Documents

Information Retrieval



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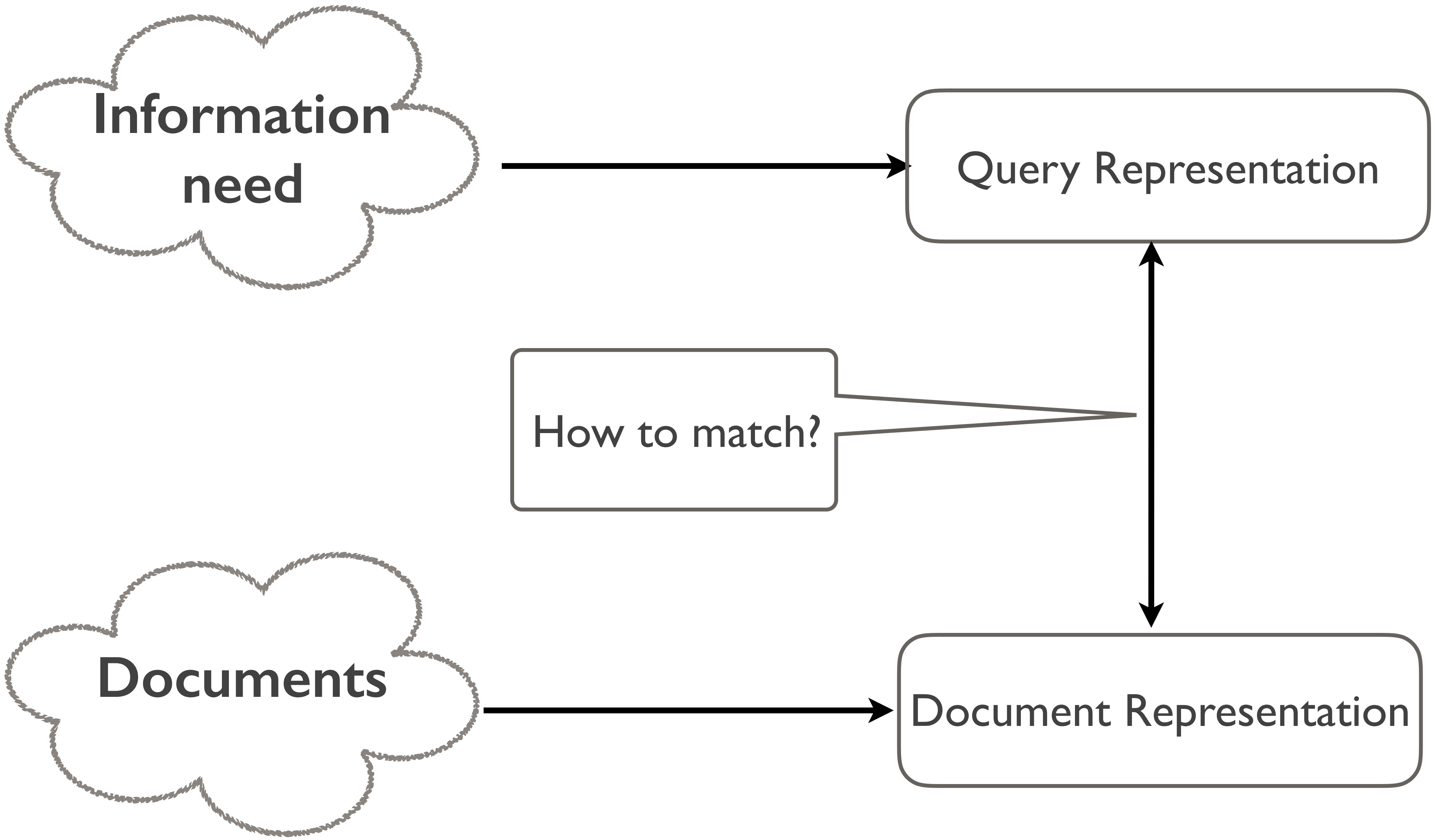
Information Retrieval



Information Retrieval in a Nutshell

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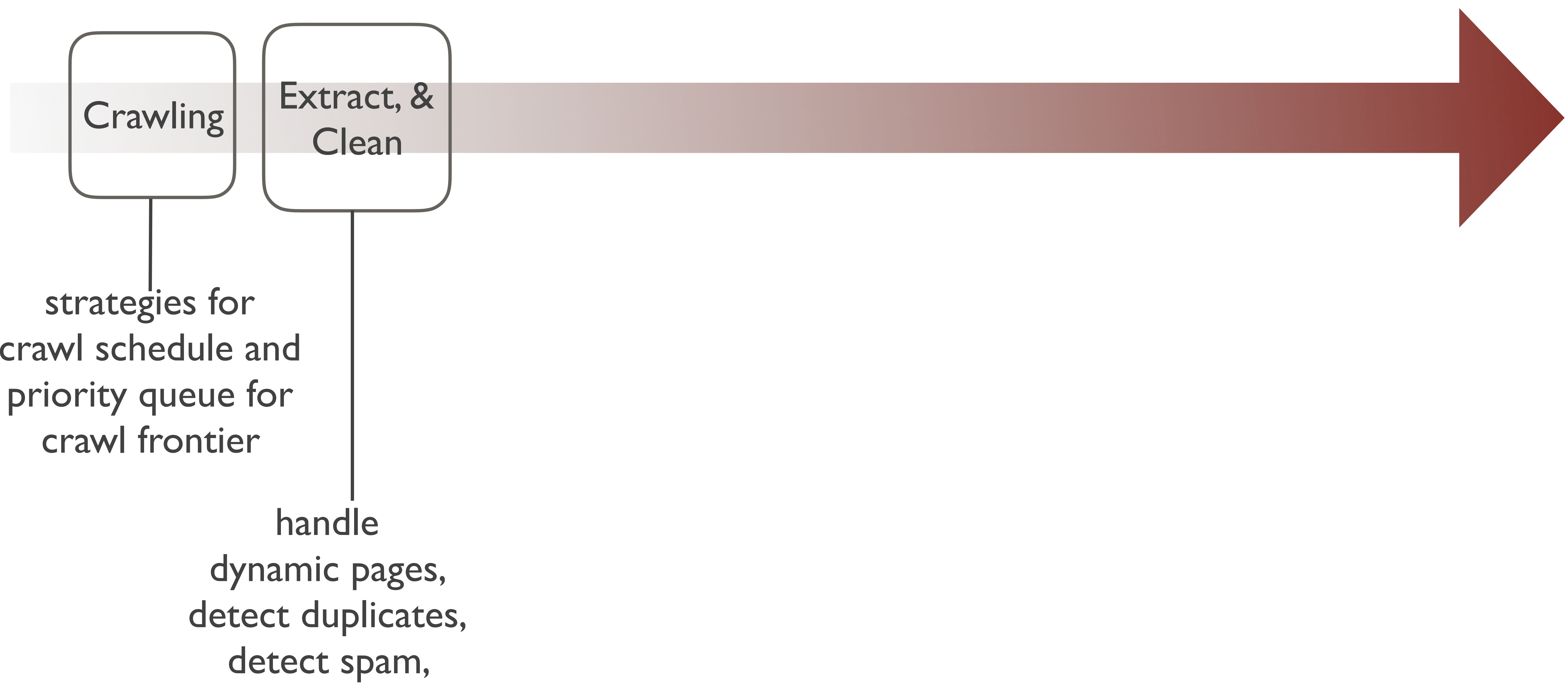

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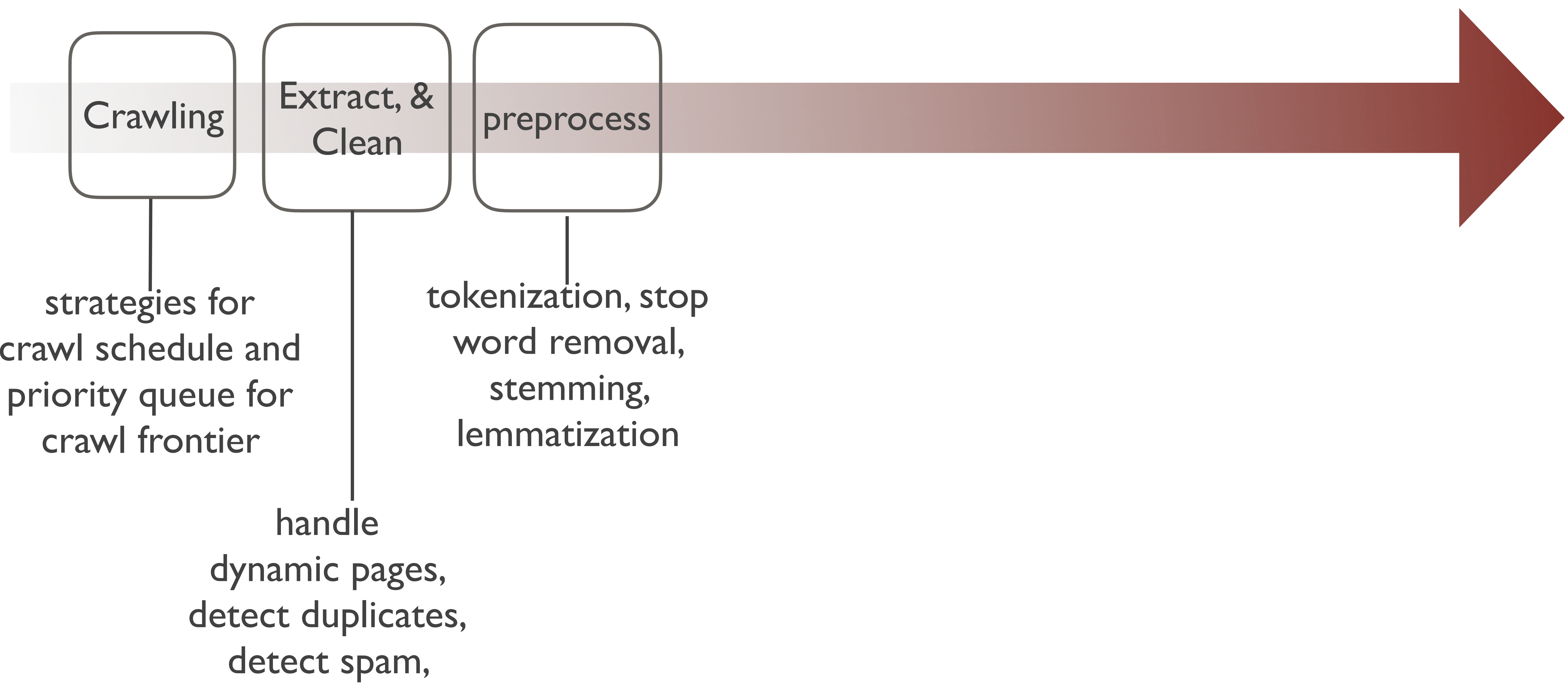

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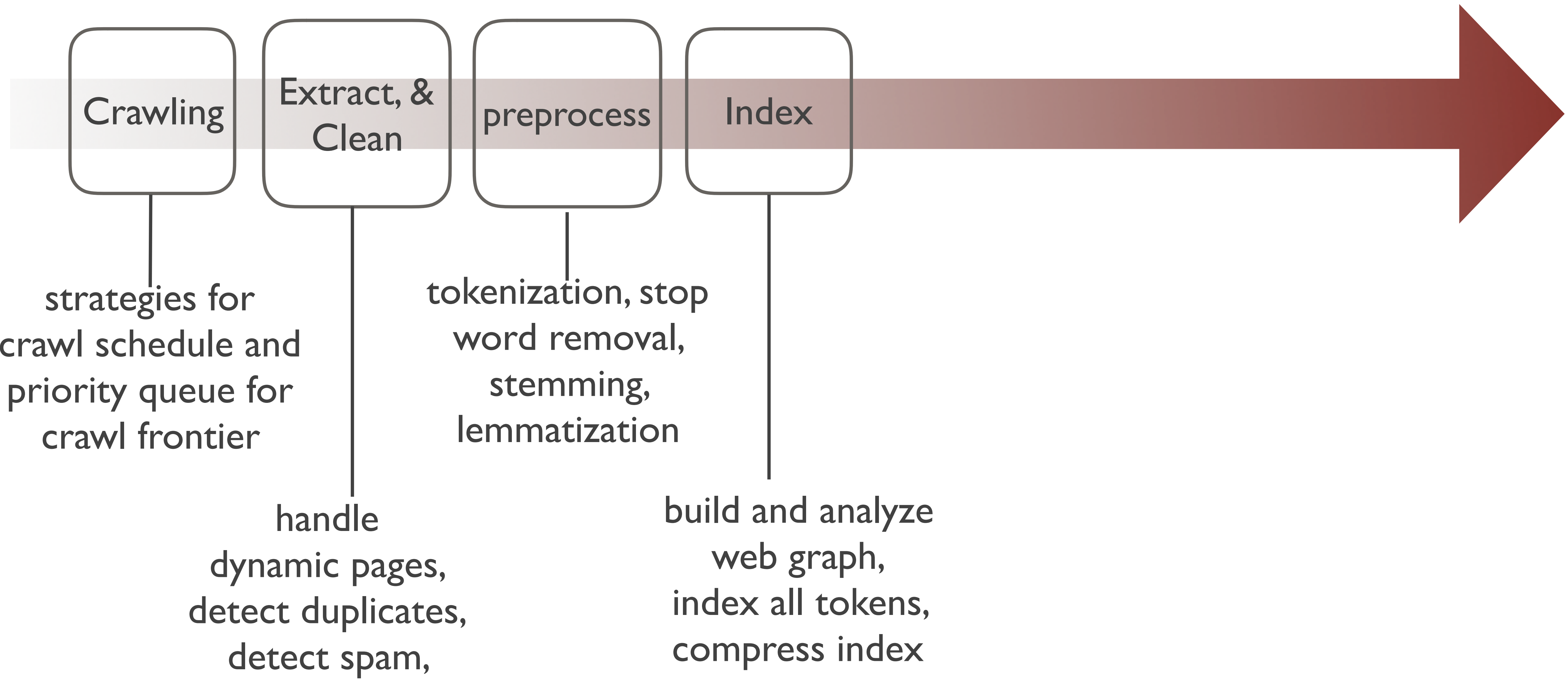

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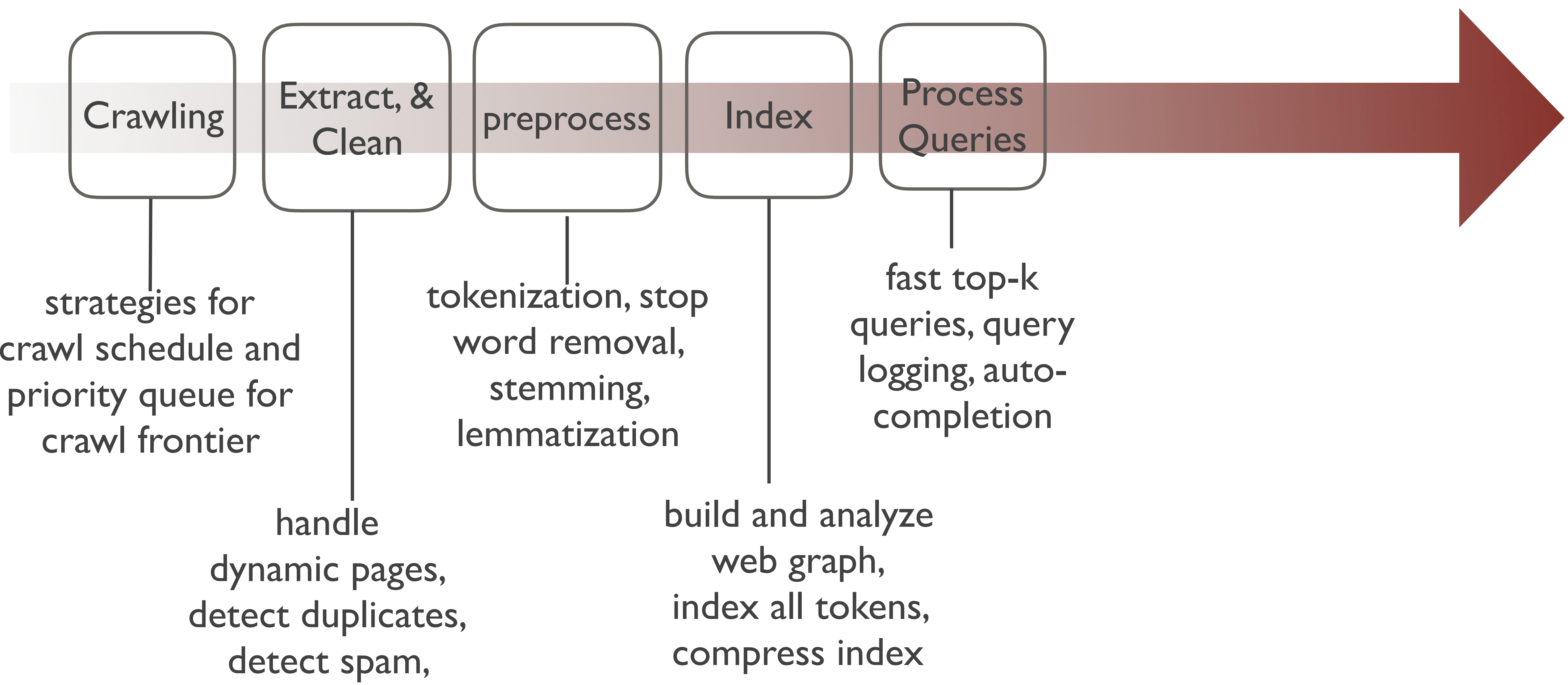

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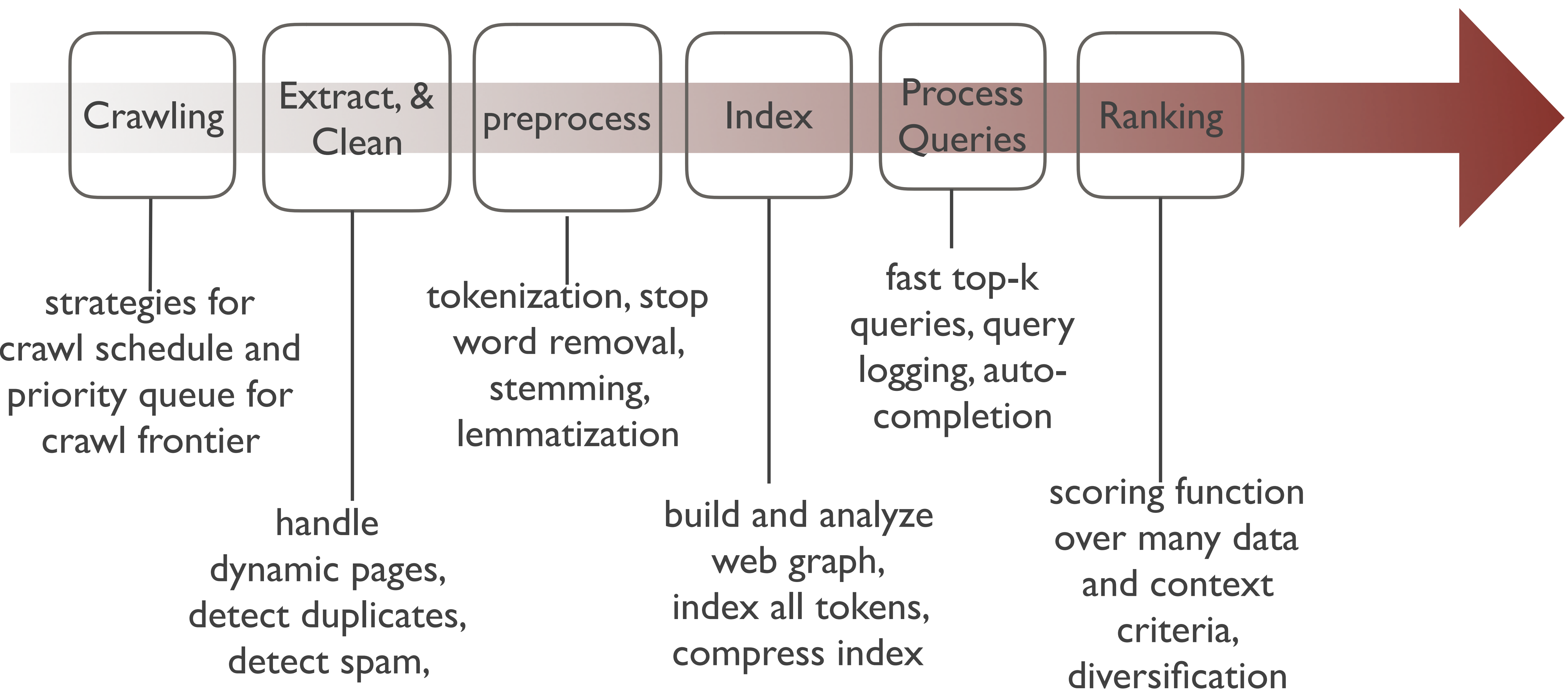

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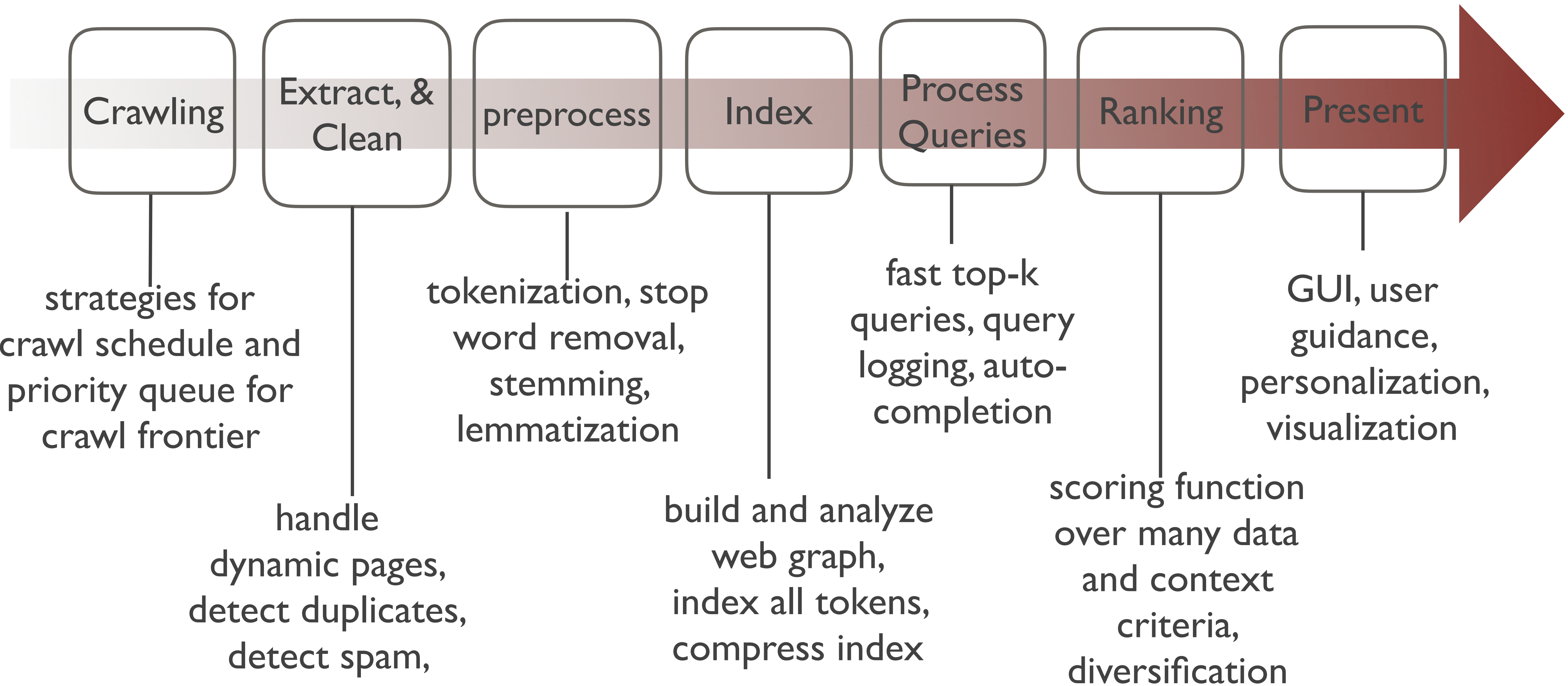

Documents & Queries

- Pre-processing of documents and queries typically includes
  - **tokenization** (e.g., splitting them up at white spaces and hyphens)
  - **stemming** or **lemmatization** (to group variants of the same word)
  - **stopword removal** (to get rid of words that bear little information)
- This results in a **bag (or sequence) of indexable terms**

Investigators entered the company's HQ located in Boston MA on Thursday.

{ investig enter compani hq locat boston ma thursdai }

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More in next lecture

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Retrieval Models

- Retrieval model defines for a given **document collection** D and a **query** q which documents to return and in which order
  - **Boolean retrieval**
  - Probabilistic retrieval models (e.g., binary independence model)
  - **Vector space model** with **tf.idf** term weighting
  - **Language models**
  - Latent topic models (e.g., LSI, pLSI, LDA)

Boolean Retrieval

- **Boolean variables** indicate presence/absence of query terms
- **Boolean operators** AND, OR, and NOT
- Boolean queries are **arbitrary compositions** of those, e.g.:
    - Frodo AND Sam AND NOT Gollum
    - NOT ((Saruman AND Sauron) OR (Smaug AND Shelob))
- **Extensions of Boolean retrieval** (e.g., proximity, wildcards, fields) with **rudimentary ranking** (e.g., weighted matches) exist

Processing Boolean Queries

	d1	d2	d3	d4	d5	d6
Frodo	1	1	0	1	0	0
Sam	1	1	0	1	1	1
Gollum	0	1	0	0	0	0
Saruman	1	0	0	0	0	0
Gandalf	1	0	1	1	1	1
Sauron	1	0	1	1	1	0

How to Process the query:

Frodo AND Sam AND NOT Gollum

Processing Boolean Queries

- Take the term vectors (Frodo, Sam, and Gollum)
- Flip the bits for terms with NOT (e.g. Gollum)
- bitwise AND the vectors finally the documents which return 1 are relevant

	d1	d2	d3	d4	d5	d6
Frodo	1	1	0	1	0	0
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	1	0	0	1	0	0

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Sam	1	1	0	1	1	1
Gollum	1	0	1	1	1	1
	1	0	0	1	0	0

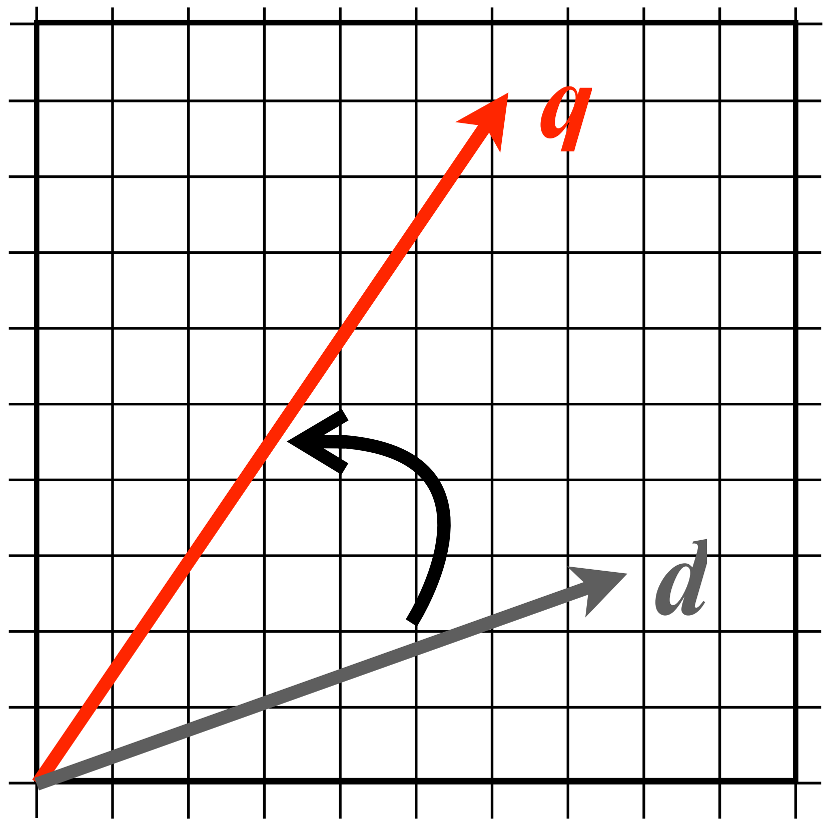
d1 and d4 are the relevant documents for
Frodo AND Sam AND NOT Gollum

Vector Space Model

- Vector space model considers **queries and documents** as vectors in a common **high-dimensional vector space**
- Cosine similarity between two vectors q and d is the **cosine of the angle between them**

$$sim(q,d) = \frac{q \cdot d}{\|q\| \, \|d\|}$$

$$= \frac{\sum_v q_v \, d_v}{\sqrt{\sum_v q_v^2} \sqrt{\sum_v d_v^2}}$$



tf.idf

- How to set the **components** of query and document vectors?
- Intuitions behind **tf.idf term weighting**:
  - documents should profit if they **contain a query term more often**
  - terms that are common in the collection should be assigned a lower weight
- **Term frequency** tf(v,d) – # occurrences of term v in document d
- **Document frequency** df(v) – # documents containing term v
- Components of **document vectors** set as

$$d_v = tf(v,d) \log \frac{|D|}{df(v)}$$

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Statistical Language Models

- Models to describe language generation
- Traditional NLP applications: Assigns a probability value to a sentence
  - Machine Translation — P(**high** snowfall) > P(**large** snowfall)
  - Spelling Correction — P(in the **vineyard**) > P(in the **vinyard**)
  - Speech Recognition — P(It's hard to **recognize speech**) > P(It's hard to **wreck a nice beach**)
  - Question Answering
- Goal: compute the probability of a sentence or sequence of words:
  - P(S) = P(w1,w2,w3,w4,w5...wn)

Language Model of a Document

- Language model describes the **probabilistic generation** of elements from a **formal language** (e.g., sequences of words)
- Documents and queries can be seen as **samples from a language model** and be used to **estimate its parameters**
- **Maximum Likelihood Estimate (MLE) for each word is the most natural estimate**

$$P[\, v \mid \theta_d \,] = \frac{tf(v, d)}{\sum_w tf(w, d)}$$

a b a c a
a a c a b
b b b a a
c b a a a
a a a a a

$$P[\, a \mid \theta_d \,] = \frac{16}{25}$$

$$P[\, b \mid \theta_d \,] = \frac{6}{25}$$

$$P[\, c \mid \theta_d \,] = \frac{3}{25}$$

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Unigram Language Models

- Unigram Language Model provides a probabilistic model for representing text
- With unigram we can also assume terms are independent

Words	M1	M2
the	0.2	0.15
a	0.1	0.12
Frodo	0.01	0.0002
Sam	0.01	0.0001
said	0.03	0.03
likes	0.02	0.04
that	0.04	0.04
Rosie	0.005	0.01
Gandalf	0.003	0.015
Saruman	0.001	0.002
…	…	…

P(Frodo said that Sam likes Rosie)

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P(Frodo said that Sam likes Rosie)

= P(Frodo) * P(said) * P(that) * P(Sam) * P(likes) * P(Rosie)

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s	Frodo	said	that	Sam	likes	Rosie
M1	0.01	0.03	0.04	0.01	0.02	0.005
M2	0.0002	0.03	0.04	0.0001	0.04	0.01

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= P(Frodo) * P(said) * P(that) * P(Sam) * P(likes) * P(Rosie)

s	Frodo	said	that	Sam	likes	Rosie
M1	0.01	0.03	0.04	0.01	0.02	0.005
M2	0.0002	0.03	0.04	0.0001	0.04	0.01

P(s|M1) = 0.000000000012
P(s|M2) = 0.0000000000000096

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Zero Probability Problem

- what if some of the queried terms are absent in the document ?
- frequency based estimation results in a zero probability for query generation

Words	M1	M2
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Frodo	0.01	0.0002
Sam	0.01	0.0001
said	0.03	0.03
likes	0.02	0.04
that	0.04	0.04
Rosie	0.005	0.01
Gandalf	0.003	0.015
Saruman	0.001	0.002

$P(\text{"Frodo"}, \text{"Gollum"}|M1) = 0.01 * 0$
$P(\text{"Frodo"}, \text{"Gollum"}|M2) = 0.0002 * 0$

Smoothing

- Need to smooth the probability estimates for terms to avoid zero probabilities
- Smoothing introduces a **relative term weighting** (idf-like effect) since more common terms now have higher probability for all documents
- Parameter estimation from a **single document or query** bears the **risk of overfitting** to this very limited sample
- Smoothing methods estimate parameters considering the **entire document collection as a background model**

Jelinek-Mercer smoothing

- Linear combination of document and corpus statistics to estimate term probabilities

$$P[\, v \mid \theta_d \,] = \alpha \cdot \frac{tf(v,d)}{\sum_w tf(w,d)} + (1-\alpha) \cdot \frac{tf(v,D)}{\sum_w tf(w,D)}$$

- Collection frequency: fraction of occurrence of term in the document d
- Document frequency: fraction of document occurrence of term in the entire collection D

Jelinek-Mercer smoothing

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doc. contrib.

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collection freq. or
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param. regulates contribution

collection freq. or document fréquency

- Collection frequency: fraction of occurrence of term in the document d

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Dirichlet Smoothing

- Smoothing with Dirichlet Prior:

$$P[\, v \mid \theta_d \,] = \frac{tf(v,d) + \mu \, \frac{tf(v,D)}{\sum_w tf(w,D)}}{\sum_w tf(w,d) + \mu}$$

  - Takes the corpus distribution as a prior to estimating the prob. for terms

Dirichlet Smoothing

- Smoothing with Dirichlet Prior:

term freq of
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dirichlet prior

  - Takes the corpus distribution as a prior to estimating the prob. for terms

Query Likelihood vs. Divergence

- **Query-likelihood approaches** rank documents according to the probability that their language model generates the query

$$P[\, q \mid \theta_d \,] \propto \prod_{v \in q} P[\, v \mid \theta_d \,]$$

- **Divergence-based approaches** rank according to the **Kullback-Leibler divergence** between the query language model and language models estimate from documents

$$KL(\, \theta_q \,\|\, \theta_d) = \sum_{v} P[\, v \mid \theta_q \,] \, \log \frac{P[\, v \mid \theta_q \,]}{P[\, v \mid \theta_d \,]}$$

Agenda

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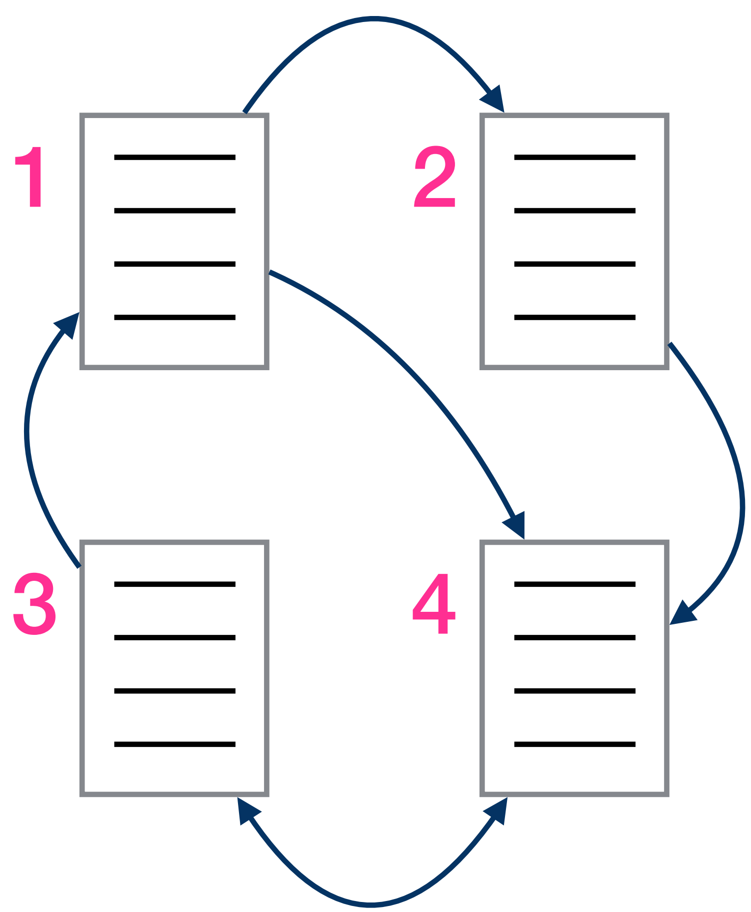
- Tools for IR - Elasticsearch

Link Analysis

- Link analysis methods consider the Web's **hyperlink graph** to determine **characteristics** of individual **web pages**



$$A = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

PageRank

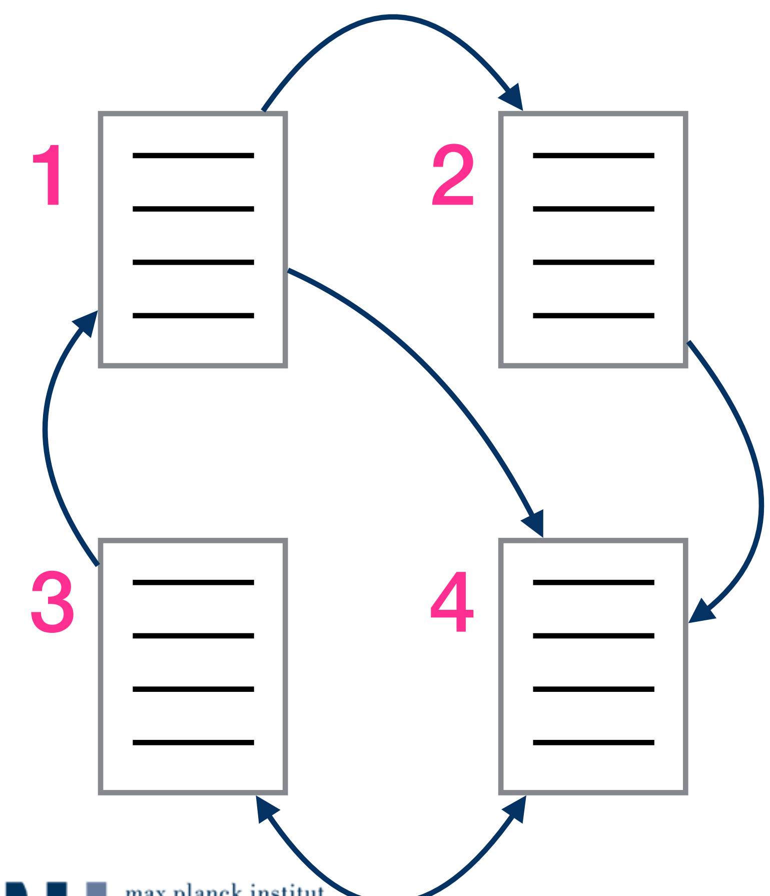
- PageRank (by Google) is based on the following **random walk**
  - jump to a random vertex (1 / |V|) in the graph with probability ε
  - follow a random outgoing edge (1 / out(v)) with probability (1-ε)

$$p(v) = (1-\epsilon) \cdot \sum_{(u,v) \in E} \frac{p(u)}{out(u)} + \frac{\epsilon}{|V|}$$

- PageRank score p(v) of vertex v is a **measure of popularity** and corresponds to its **stationary visiting probability**

PageRank

- PageRank scores correspond to components of the **dominant Eigenvector π** of the **transition probability matrix** P which can be computed using the **power-iteration method**



$\epsilon = 0.2$

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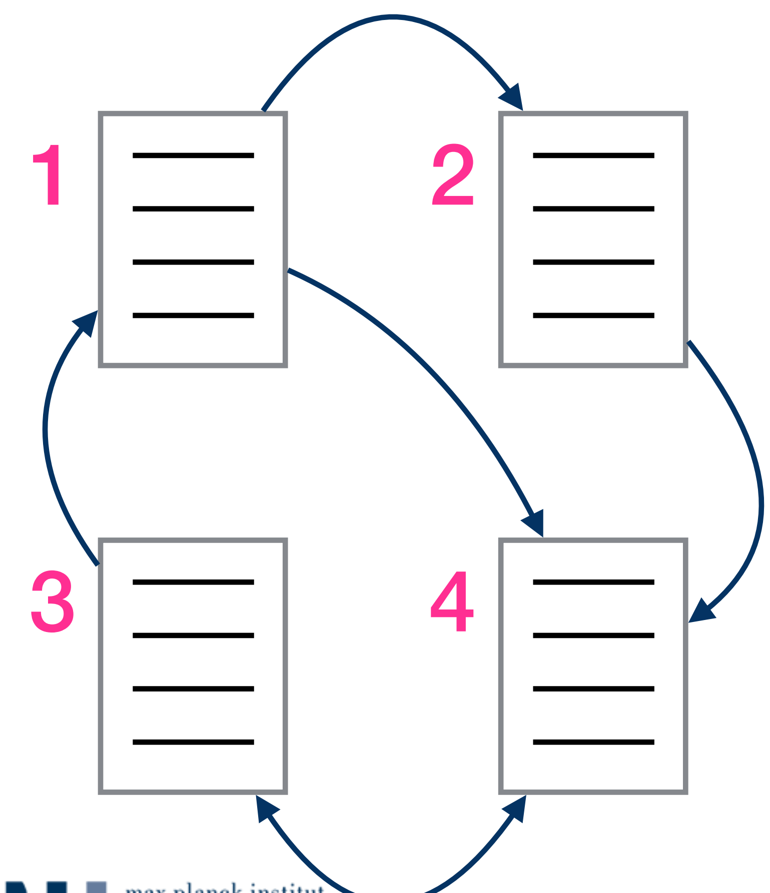

$\epsilon = 0.2$

$$P = \begin{bmatrix} 0.05 & 0.45 & 0.05 & 0.45 \\ 0.05 & 0.05 & 0.05 & 0.85 \\ 0.45 & 0.05 & 0.05 & 0.45 \\ 0.05 & 0.05 & 0.85 & 0.05 \end{bmatrix}$$

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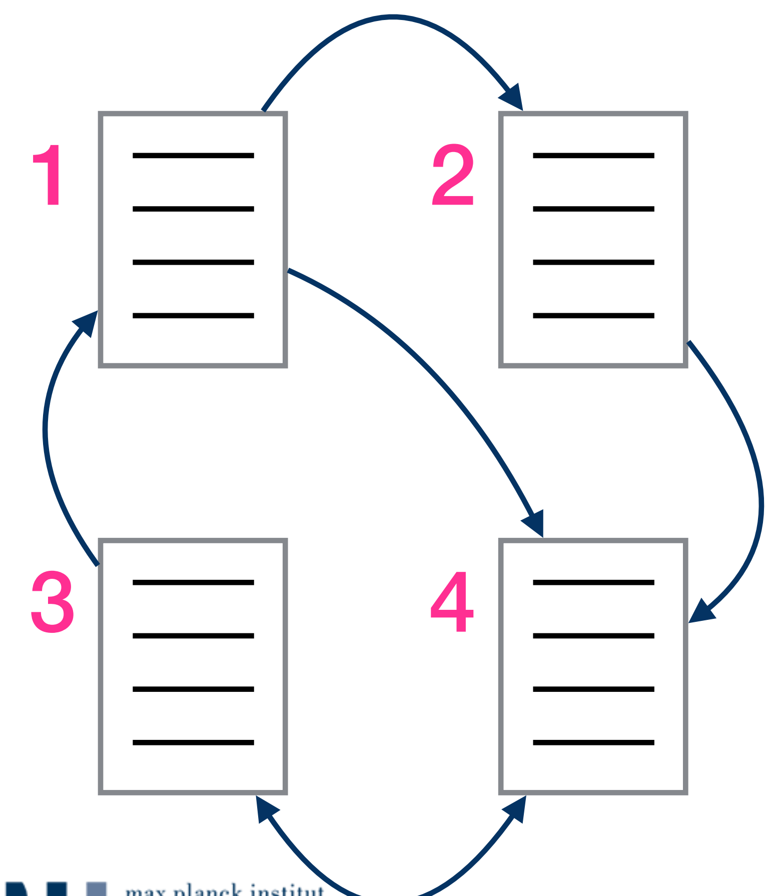

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$$\pi^{(0)} = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \end{bmatrix}$$

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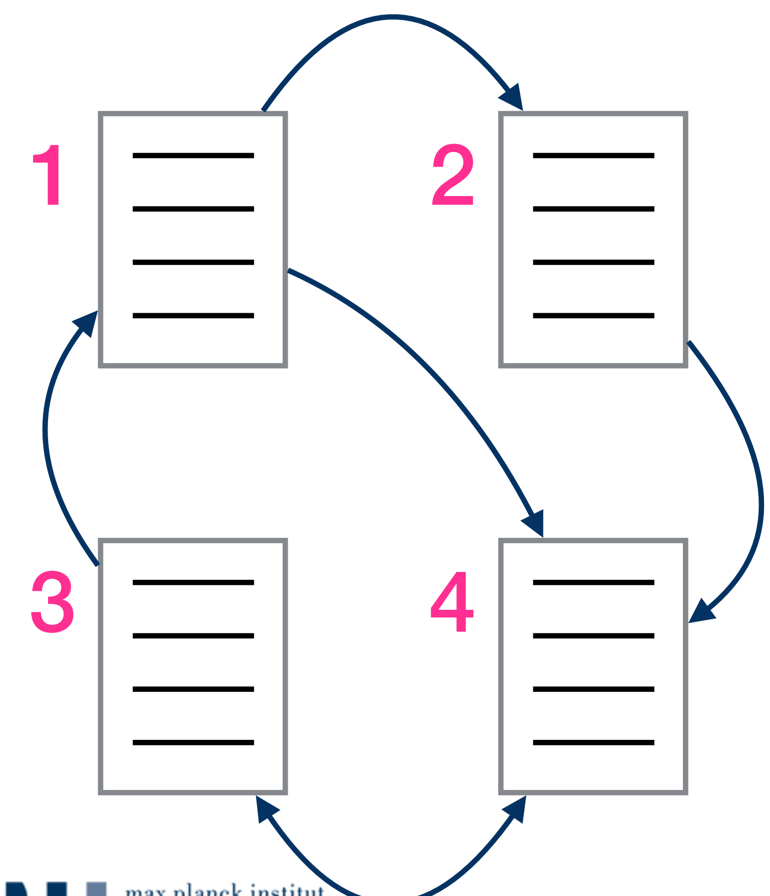

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$$\pi^{(0)} = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \end{bmatrix}$$
$$\pi^{(1)} = \begin{bmatrix} 0.15 & 0.15 & 0.25 & 0.45 \end{bmatrix}$$

PageRank

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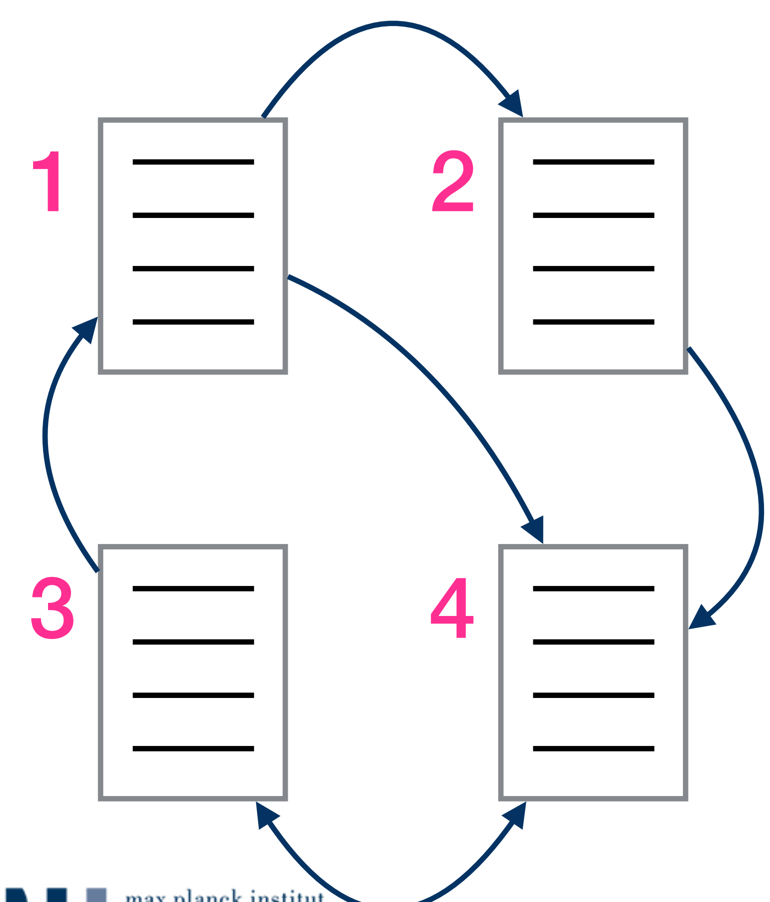

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$$\pi^{(0)} = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \end{bmatrix}$$
$$\pi^{(1)} = \begin{bmatrix} 0.15 & 0.15 & 0.25 & 0.45 \end{bmatrix}$$
$$\pi^{(2)} = \begin{bmatrix} 0.15 & 0.11 & 0.41 & 0.33 \end{bmatrix}$$
$$\vdots$$
$$\pi^{(10)} = \begin{bmatrix} 0.18 & 0.12 & 0.34 & 0.36 \end{bmatrix}$$

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HITS

- HITS operates on a **subgraph of the Web** induced by a keyword query and considers
  - **hubs** as vertices **pointing to good authorities**
  - **authorities** as vertices **pointed to by good hubs**
- **Hub score** h(u) and **authority score** a(v) defined as

$$h(u) \propto \sum_{(u,v) \in E} a(v) \qquad a(v) \propto \sum_{(u,v) \in E} h(u)$$

- Hub vector h and authority vector a are **Eigenvectors** of the **co-citation matrix** AA^T and **co-reference matrix** A^TA

$$h = \alpha \, \beta A A^T h \qquad a = \alpha \, \beta A^T A \, a$$

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Agenda

- Organization
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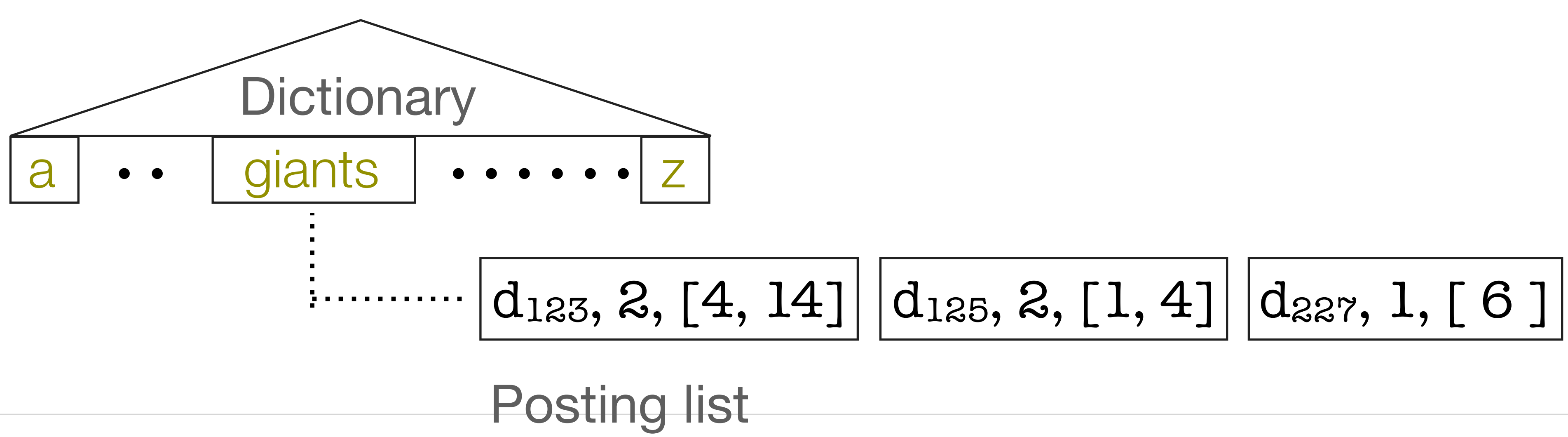
- **Indexing and Query Processing**
- Tools for IR - Elasticsearch

Indexing & Query Processing

- Retrieval models define which documents to return for a query but **not how they can be identified efficiently**
- **Index structures** are an essential building block for IR systems; variants of the inverted index are by far most common
- **Query processing methods** operate on these index structures
  - **holistic** query processing methods determine **all query results** (e.g., term-at-a-time, document-at-a-time)

Inverted Index

- Inverted index as widely used index structure in IR consists of
  - **dictionary** mapping terms to term identifiers and statistics (e.g., df)
  - **posting list** for every term recording details about its occurrences
- Posting lists can be **document- or score-ordered** and be equipped with additional structure (e.g., to support **skipping**)
- Postings contain a **document identifier** plus additional **payloads** (e.g., term frequency, tf.idf score contribution, term offsets)



Term-at-a-Time

- Processes posting lists for query terms $\langle\, q_1,\ldots,q_m \,\rangle$ **one at a time**
- Maintains an **accumulator for each document** seen; after processing the first k query terms this corresponds to

$$acc(d) = \sum_{i=1}^{k} score(q_i, d)$$

$\boxed{a}$ $\cdots\cdots$ $\boxed{d_1, 0.2}$ $\boxed{d_3, 0.1}$ $\boxed{d_5, 0.5}$

$\boxed{b}$ $\cdots\cdots$ $\boxed{d_5, 0.3}$ $\boxed{d_7, 0.2}$

- **Main memory** proportional to number of accumulators
- Top-k result determined at the end by sorting accumulators

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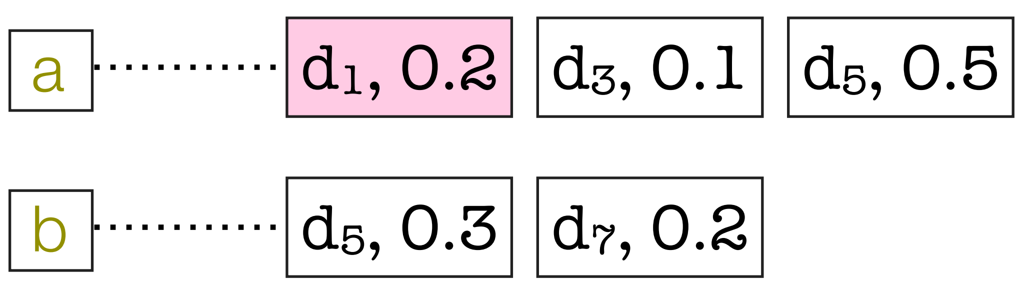

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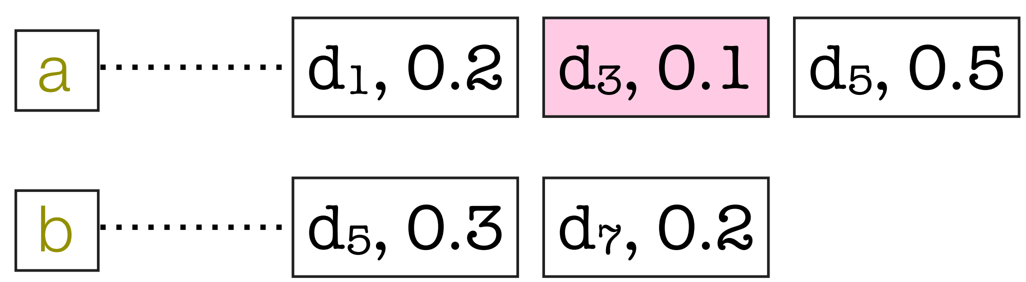

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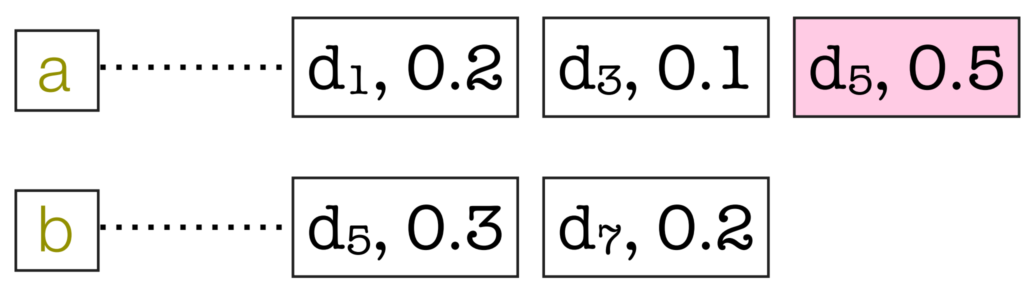

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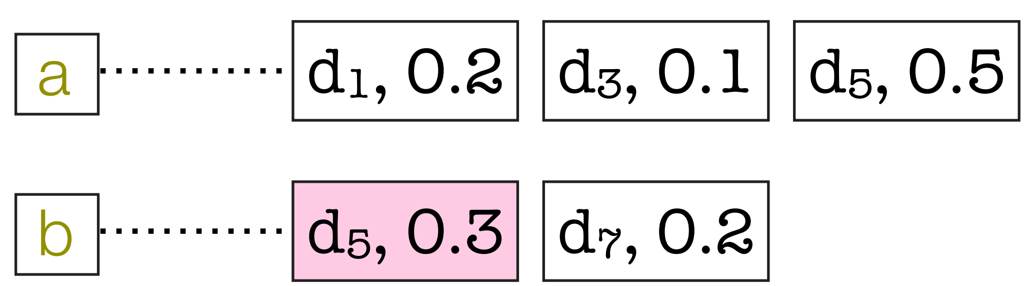

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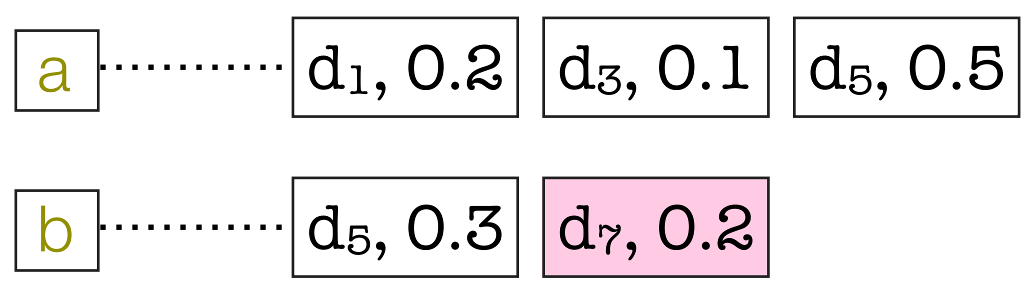

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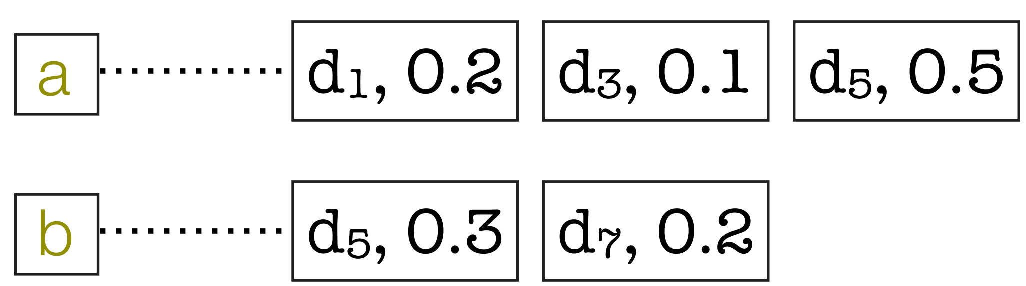

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Document-at-a-Time

- Processes posting lists for query terms $\langle q_1,\ldots,q_m \rangle$ **all at once**

- Sees **the same document in all posting lists at the same time**, determines score, and decides whether it belongs into top-k

a	d_1, 0.2	d_3, 0.1	d_5, 0.5
b	d_5, 0.3	d_7, 0.2	

- **Main memory** proportional to k or number of results

- **Skipping** aids conjunctive queries (all query terms required)

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Elasticsearch

- Flexible and powerful open source, distributed real-time search and analytics engine
- Features:
  - real time data, real time analytics,
  - distributed, high availability,
  - full text search, document oriented,
  - conflict management, schema free (json)
  - restful api, per-operation persistence,
  - apache 2 open source license, build on top of apache lucene.

Elasticsearch Installation

- curl -L -O https://download.elastic.co/elasticsearch/release/org/elasticsearch/distribution/tar/elasticsearch/2.3.1/elasticsearch-2.3.1.tar.gz
- tar -xvf elasticsearch-2.3.1.tar.gz
- cd elasticsearch-2.3.1/bin
- ./elasticsearch

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Elasticsearch - Indexing

- Create Index

```
$ curl -XPUT 'http://localhost:9200/atirtest'
```

- Add records to index

```
$ curl -XPUT 'http://localhost:9200/atirtest/doc/1' -d '{
    "title" : "Ecuador earthquake: Aid agencies step up efforts",
    "pub_date" : 1461230434627,
    "content" : "Aid agencies are stepping up help following Saturdays devastating
earthquake in Ecuador, amid concerns over the conditions faced by survivors."
}'
```

```
$ curl -XPUT 'http://localhost:9200/atirtest/doc/2' -d '{
    "title" : "Syria conflict: Air strikes on Idlib markets kill dozens",
    "pub_date" : 1461230434457,
    "content" : "At least 44 people have been killed and dozens hurt in Syrian
government air strikes on markets in two rebel-held towns in Idlib province, activists
say."
}'
```

Elasticsearch - Boolean Queries

```
curl -XGET 'localhost:9200/atirtest/_search?pretty' -d ' {
 "query":{
   "query_string" : {
          "default_field" : "content",
           "query": "earthquake AND Ecuador AND NOT Syrian"
   }
   }
 }'
```

Language Analyzers

- Elasticsearch has builtin language tools for
  - tokenization
  - stop word removal
  - stemming
  - For arabic, armenian, basque, brazilian, bulgarian, catalan, cjk, czech, danish, dutch, **english**, finnish, french, galician, **german**, greek, **hindi**, hungarian, indonesian, irish, italian, latvian, lithuanian, **norwegian**, persian, portuguese, romanian, russian, sorani, spanish, swedish, turkish, thai.

English Analyzer Example

```
"settings": {
  "analysis": {
   "filter": {
   "stop_filter": {
         "type": "stop",
         "stopwords": ["_english_"]
     },
     "custom_english_stemmer": {
       "type": "stemmer",
       "name": "minimal_english"
     }
   },
   "analyzer": {
     "custom_lowercase_stemmed": {
       "tokenizer": "standard",
       "filter": [
       "stop_filter",
        "custom_english_stemmer",
        "lowercase"        ]
     }
   }
  }
}
```

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Elasticsearch - TF-IDF

- Query with TF-IDF score

```
curl -XGET 'localhost:9200/atirtest/_search?pretty' -d '
 {

   "query": {
       "match": {
           "content": "Earthquake in Ecuador"
       }
   }
 }'
```

Okapi BM25 in Elasticsearch

```
curl -XPUT 'localhost:9200/atirtest/' -d'
{
  "mappings": {
    "doc": {
      "properties": {
        "title": {
          "type":       "string",
          "similarity": "BM25"
      },
      "pub_date": {
          "type":       "date"
        },

        "content": {
          "type":       "string",
          "similarity": "BM25"
        },
      }
    }
}'
```

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Caveats

- For debugging: Most errors can be because of a comma missing or a bracket not closed
- Use Marvel sense UI to compose your elasticsearch code
  - https://www.elastic.co/guide/en/marvel/current/introduction.html
  - It compiles the code and points the error for you

Credits

Thanks to **Prof. Klaus Berberich** and **Dr. Avishek Anand** for allowing us to use their slides!