Information Retrieval

Ranking

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Boolean model limits

- Thus far, our queries have all been boolean.
  - Documents **either match or don't**.
- Good for **expert users** with precise understanding of their needs and knowledge of the collection.
  - Also good for applications: applications can easily make use of 1000s of results for further processing.
- 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.

Boolean model limits: example

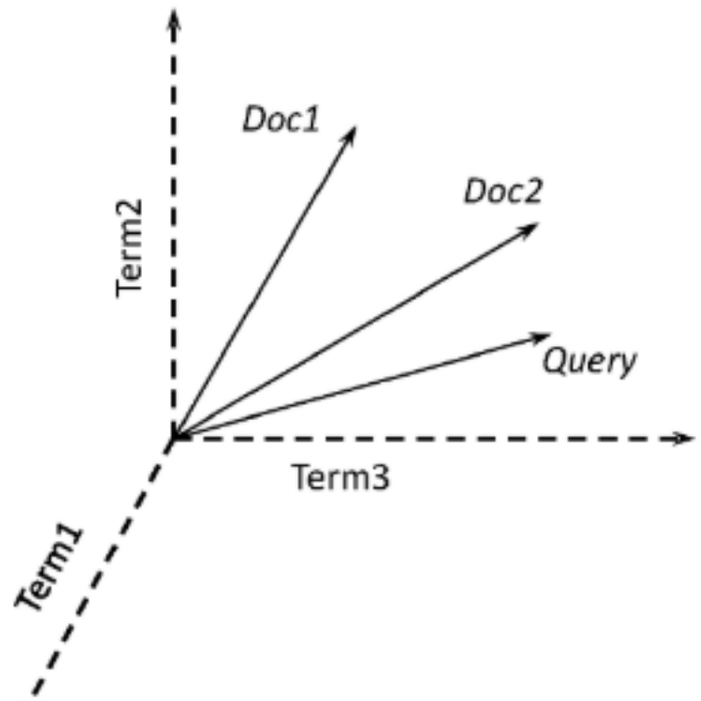
- Boolean queries often result in either **too few** (=0) or **too many** (1000s) results.
- Example: suppose a user is having troubles with his network card:
  - Query 1: "*standard user dlink 650*" → 200,000 hits
  - Query 2: "*standard user dlink 650 no card found*": 0 hits
- It takes a lot of skill to come up with a query that produces a manageable number of hits.
  - **AND gives too few**
  - **OR gives too many**

Ranked retrieval

- Rather than a set of documents satisfying a query expression, in ranked retrieval, the system returns an ordering over the (**top**) documents in the collection for a query
- When a system produces a ranked result set, large result sets are not an issue
  - Indeed, the size of the result set is not an issue
  - We just show the **top *k*** (≈ 10) results
  - We don't overwhelm the user
  - Premise: the ranking model works
- Most known ranking model is Vector Space Model (G. Salton, 1975)

Vector Space Model (VSM)

- Like in the bag-of-word model, documents are **represented by a vector** of "term weights":



- Collection represented by a matrix of **term weights**

- d_{ij} is the weight of Doc_i for $Term_j$

$$D_i = (d_{i1}, d_{i2}, \ldots, d_{it}) \qquad Q = (q_1, q_2, \ldots, q_t)$$

	$Term_1$	$Term_2$	$\ldots$	$Term_t$
Doc_1	d_{11}	d_{12}	$\ldots$	d_{1t}
Doc_2	d_{21}	d_{22}	$\ldots$	d_{2t}
$\vdots$	$\vdots$			
Doc_n	d_{n1}	d_{n2}	$\ldots$	d_{nt}

VSM: vector representation

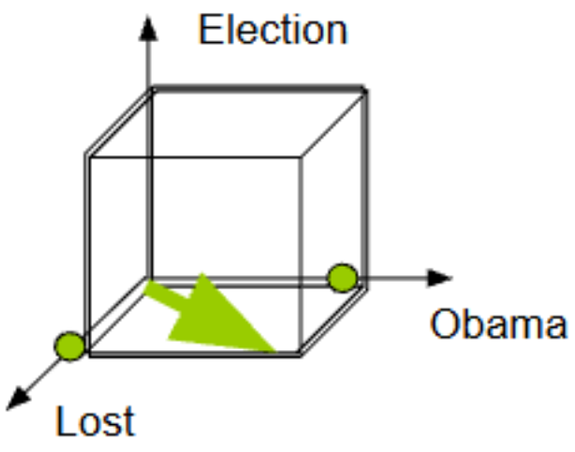
- An example with 3 terms (3-dimensional vector space) and 3 documents.

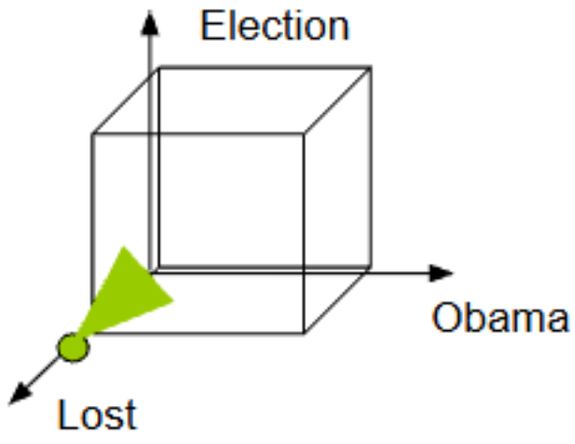
D1 In last year election, Romney **lost election** against **Obama**

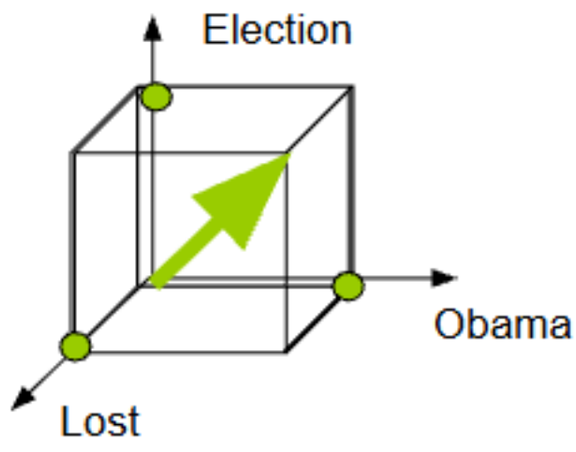
D2 I **lost** my faith in Clinton's ability to win

D3 **Obama** has **lost** control on Senate

We consider only the terms in figure

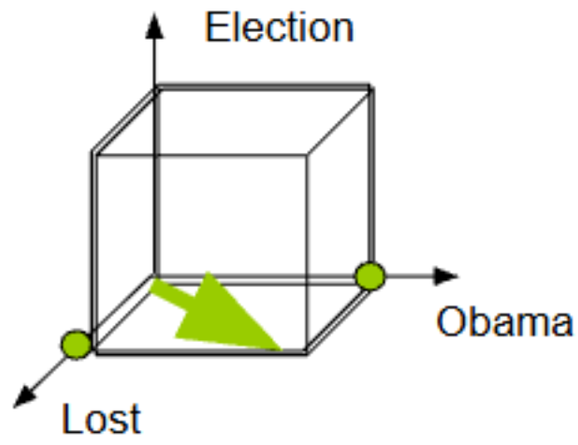






Documents as vectors

- So we have a |V|-dimensional vector space
- Terms are axes of the space
- Documents are points or vectors in this space
- Very high-dimensional: tens of millions of dimensions when you apply this to a web search engine
- These are very sparse vectors - most entries are zero.



Queries as vectors

- **Key idea 1:** Do the same for queries: represent them as vectors in the space
- **Key idea 2:** Rank documents according to their proximity to the query in this space
- proximity = **similarity of vectors**
- proximity ≈ inverse of distance
- **Reminder**: We do this because we want to get away from the in-or-out Boolean model.
- Instead: **rank more relevant documents** higher than less relevant documents

Recap

- In the boolean model, a document is either relevant or non-relevant.
- Representing document and queries as vectors, we can compute the **similarity between the vector** of the document and the vector of the query:
  - This is an estimation of the relevance of the document with respect to the query.

- We need to define the similarity between vectors but...
  - Before going on we must introduce the **term frequency**.

TF: Term Frequencies

- So far, vectors were binary, representing the **presence or absence** of terms in a document.
- We would like to assign a **weight** for each term in a vector space:
  - The term frequency $tf_{t,d}$ of term *t* in document *d* is defined as the number of times that *t* occurs in *d*.
  - We want to use term frequency (**tf**) when computing query-document match scores.

Example: TF as term weight

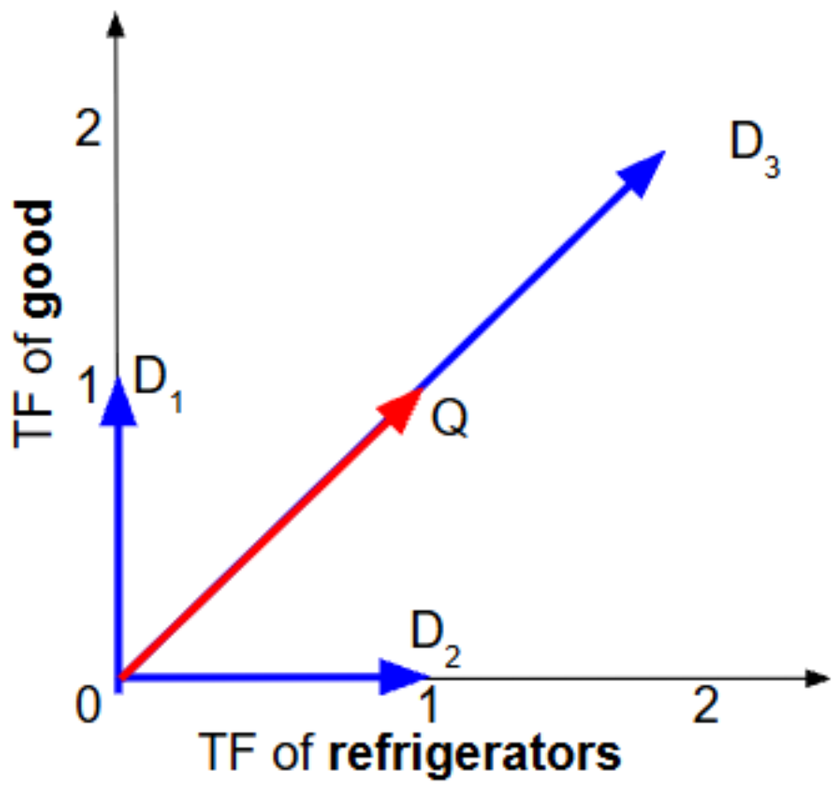
Three dimensional pictures are useful, but can be misleading for high-dimensional space (more than 3 terms considered):

D_1 Tropical Freshwater Aquarium Fish.
D_2 Tropical Fish, Aquarium Care, Tank Setup.
D_3 Keeping Tropical Fish and Goldfish in Aquariums, and Fish Bowls.
D_4 The Tropical Tank Homepage - Tropical Fish and Aquariums.

	Documents			
Terms	**D_1**	**D_2**	**D_3**	**D_4**
Aquarium	1	1	1	1
Bowl	0	0	1	0
Care	0	1	0	0
Fish	1	1	2	1
Freshwater	1	0	0	0
Goldfish	0	0	1	0
Homepage	0	0	0	1
Keep	0	0	1	0
Setup	0	1	0	0
Tank	0	1	0	1
Tropical	1	1	1	2

Vector Space Distance

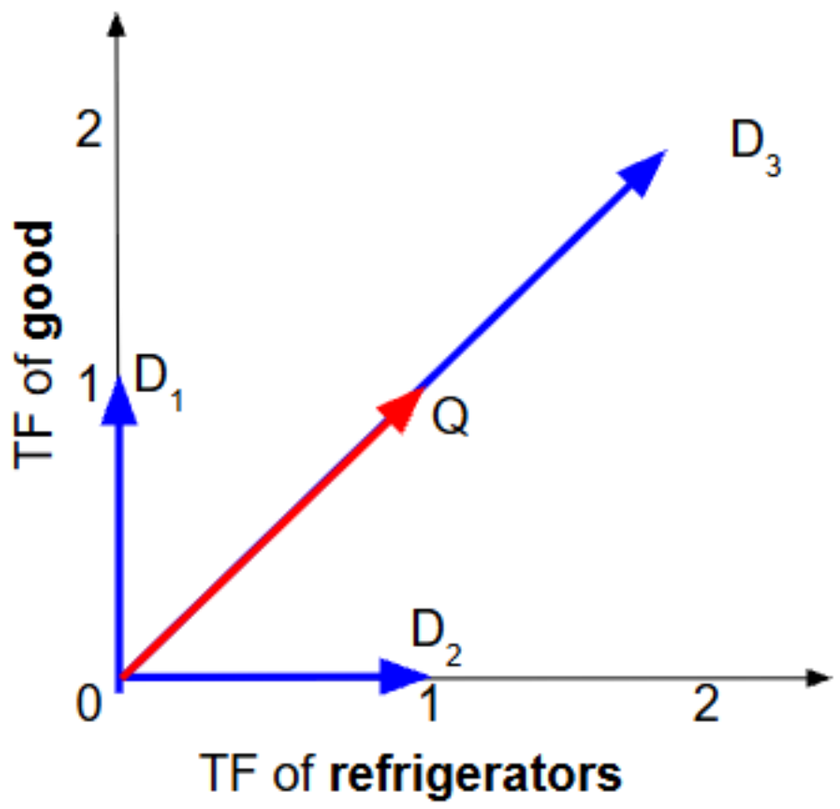
- How to formalize the proximity between two vectors when we have term frequencies?
- Example query Q: “Good refrigerators”
  - D_1: “Good morning to all of you.”
  - D_2: “Don’t put pizza in refrigerators”
  - D_3: “Good refrigerators review: top five good refrigerators.”



Note: we are showing only the two interesting dimensions, “good” and “refrigerators”.
There is a dimension for each indexed term (e.g. for pizza, morning, review…)

First cut: euclidean distance?

- We could consider the straight line distance between the end points, i.e. the euclidean distance
  - Distance between Q and D_1 is 1
  - Distance between Q and D_2 is 1
  - Distance between Q and D_3 is $\sqrt{2} \cong 1.414$
- D_3 is the least similar, this doesn't seems right!



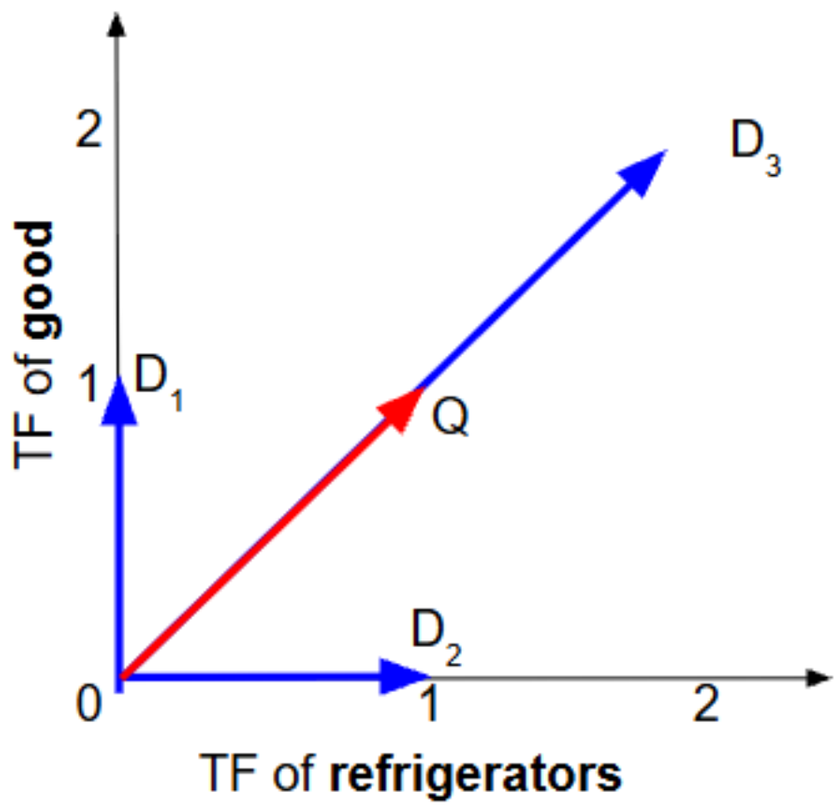
- Remember Q: "Good refrigerators"
  - D_1: "Good morning to all of you."
  - D_2: "Don't put pizza in refrigerators"
  - D_3: "Good refrigerators review: top five good refrigerators."

Angle instead of distance

- Thought experiment: take a document *d* and append it to itself many times. Call this longer document *d′*.
- “Semantically” d and d′ have the same content
- The Euclidean distance between the two documents can be quite large
- The angle between the two documents is 0, corresponding to maximal similarity.
- **Key idea:** Rank documents according to angle with query.

Example: Using angles

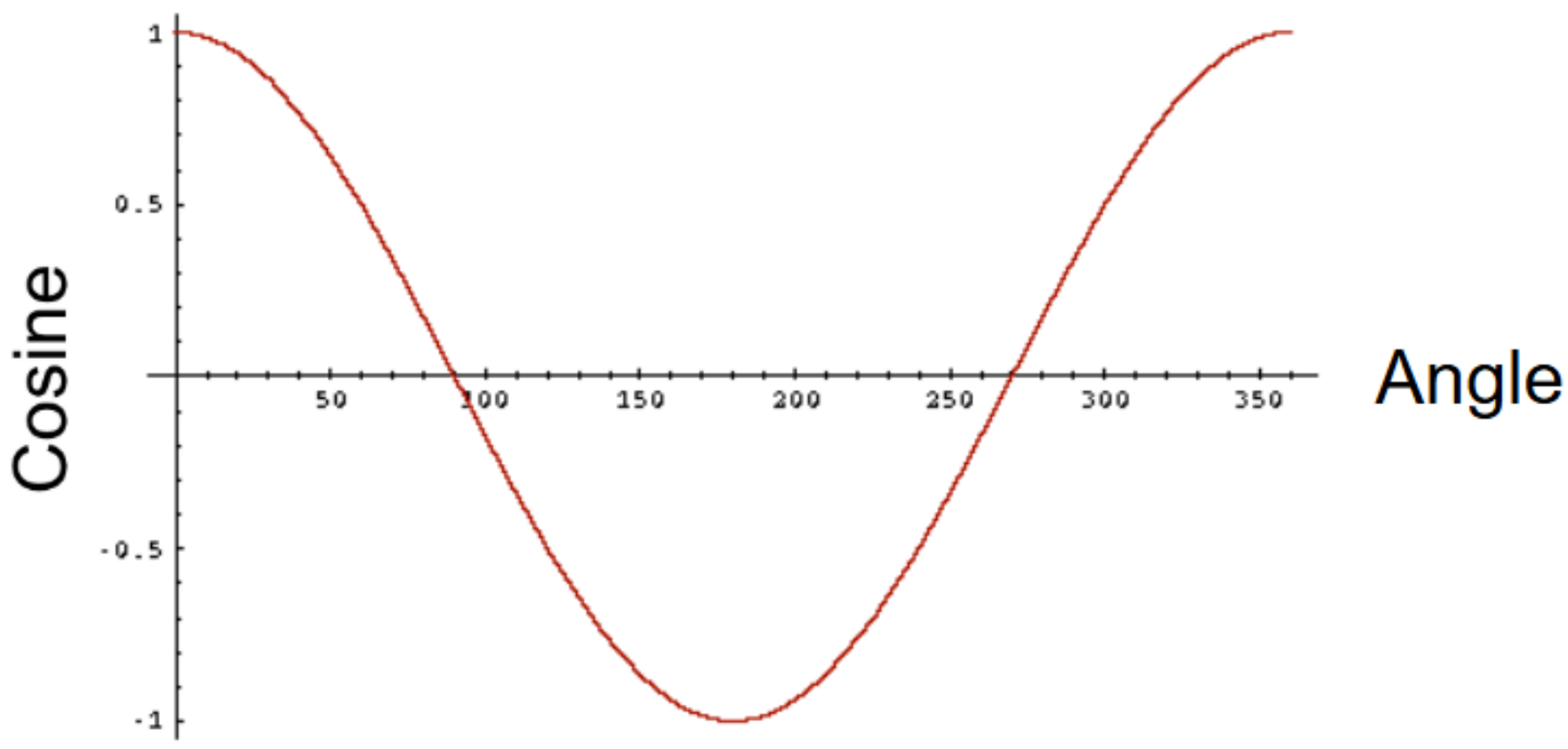
- We now consider the angle between vectors
  - Angle between Q and D_1 is 45°
  - Angle between Q and D_2 is 45°
  - Angle between Q and D_3 is 0°
- D_3 is the most similar, this is what we need!



- Remember Q: “Good refrigerators”
  - D_1: “Good morning to all of you.”
  - D_2: “Don’t put pizza in refrigerators”
  - D_3: “Good refrigerators review: top five good refrigerators.”

From angles to cosines

- The following two notions are equivalent.
  - Rank documents in decreasing order of the angle between query and document
  - Rank documents in increasing order of cosine(query, document)
- Cosine is a monotonically **decreasing** function for the interval [0°, 180°], meaning that it's inversely proportional of the angle



Cosine similarity

Dot product

Unit vectors

$$\cos(\vec{q},\vec{d}) = \frac{\vec{q} \bullet \vec{d}}{|\vec{q}||\vec{d}|} = \frac{\vec{q}}{|\vec{q}|} \bullet \frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2} \sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

- q_i is the tf weight of term i in the query
- d_i is the tf weight of term i in the document

$\cos(\vec{q},\vec{d})$ is the cosine similarity of $\vec{q}$ and $\vec{d}$ … or, equivalently, the cosine of the angle between $\vec{q}$ and $\vec{d}$.

Example: Formula

	Election	Lost	Obama
D1	1	1	1
D2	0	1	0
D3	0	1	1
Q	**0**	**0**	**1**

$$\text{Sim(Q,D1)} = \frac{\sum_{i=1}^{3} Q_i * D1_i}{\sqrt{\sum_{i=1}^{3} Q_i^2} * \sqrt{\sum_{i=1}^{3} D1_i^2}}$$

$$\text{Sim(Q,D2)} = \frac{\sum_{i=1}^{3} Q_i * D2_i}{\sqrt{\sum_{i=1}^{3} Q_i^2} * \sqrt{\sum_{i=1}^{3} D2_i^2}}$$

$$\text{Sim(Q,D3)} = \frac{\sum_{i=1}^{3} Q_i * D3_i}{\sqrt{\sum_{i=1}^{3} Q_i^2} * \sqrt{\sum_{i=1}^{3} D3_i^2}}$$

Example: Instantiation

	Election	Lost	Obama
D1	1	1	1
D2	0	1	0
D3	0	1	1
Q	**0**	**0**	**1**

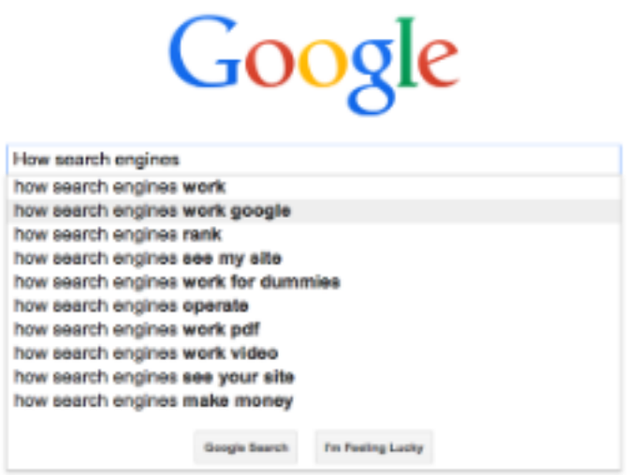
$$\text{Sim}(Q,D1) = \frac{0*1 + 0*1 + 1*1}{\sqrt{1} * \sqrt{3}} = 0.577$$

$$\text{Sim}(Q,D2) = \frac{0*0 + 0*1 + 1*0}{\sqrt{1} * \sqrt{1}} = 0.000$$

$$\text{Sim}(Q,D3) = \frac{0*0 + 0*1 + 1*1}{\sqrt{1} * \sqrt{2}} = 0.707$$

How Search Engines Work

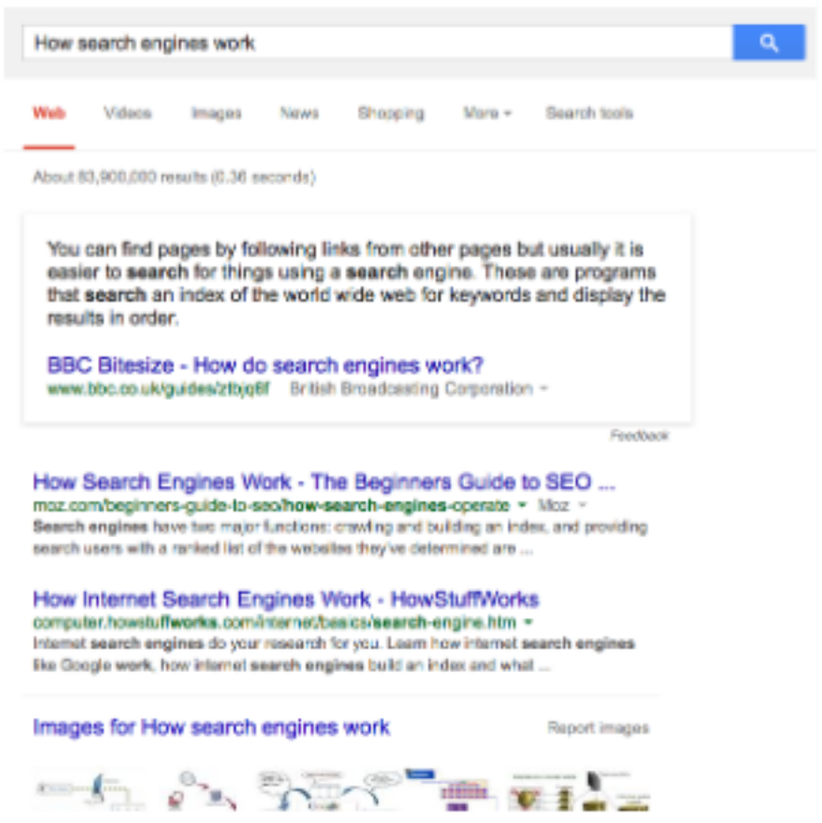
The user inputs a query



The search engine search the query terms in its very large **index**

About 83,900,000 results (0.36 seconds)

Millions of results found are **ranked** accordingly to a notion of **relevance** and are shown as a sorted list

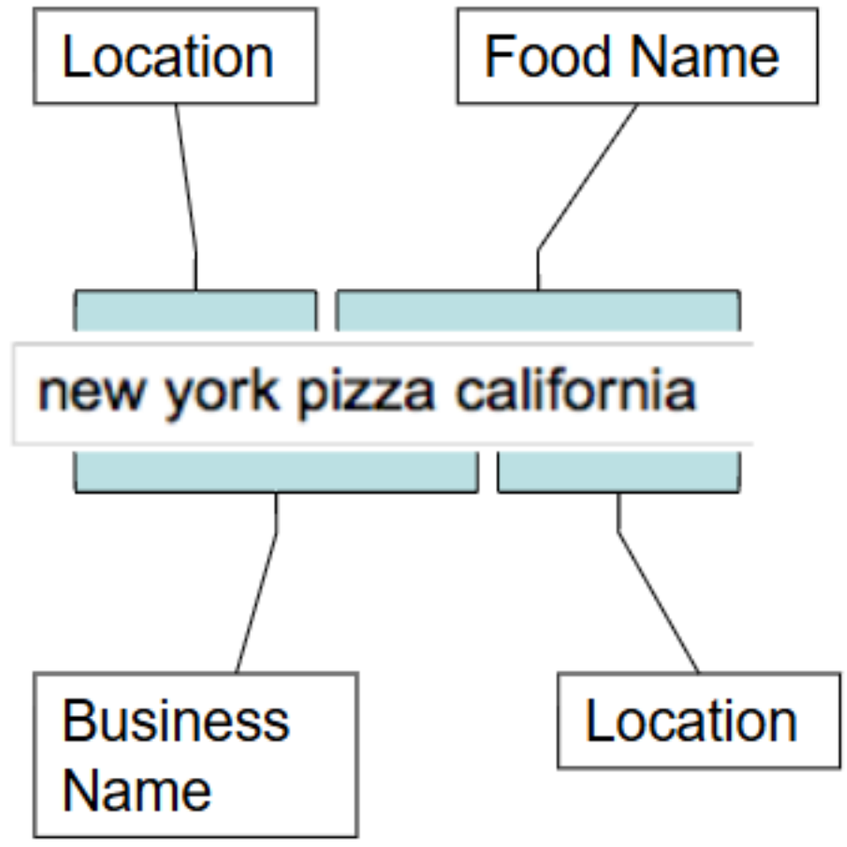


Automated programs (a.k.a. spiders or **crawlers**) scan all pages in the web to build an index

What is Relevant?

- How can a search engine know what the user is looking for?
  - **Information need:** *a desire to locate and obtain information to satisfy a conscious or unconscious need* (Wikipedia)
  - **User query:** the set of consecutive terms formulated by a user to express his information need
  - **Query intent:** the task, goal or intent of a user, expressed by a query. The same query formulated by different users may be the result of different intents

Query intent can be ambiguous:

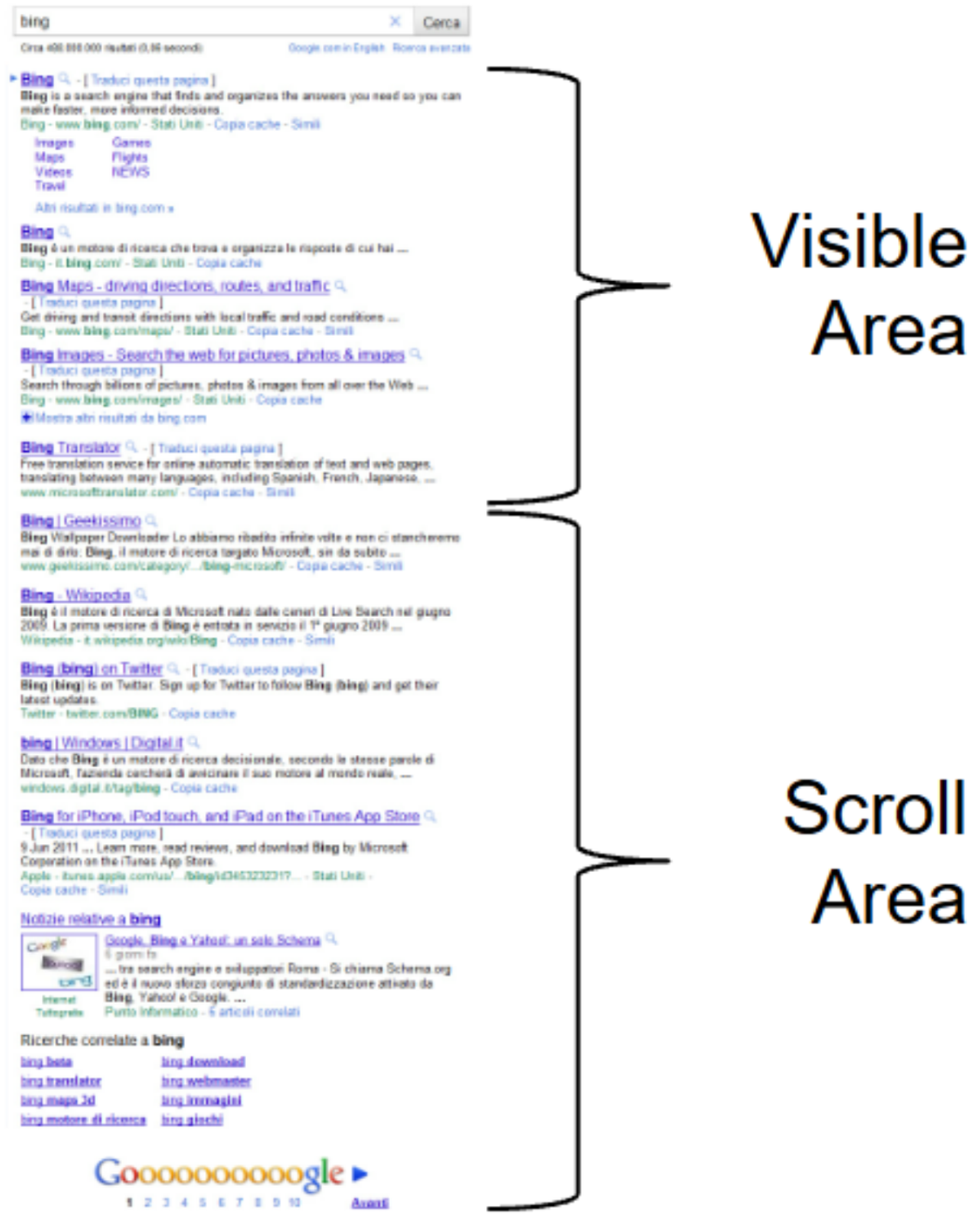


Ranking: Google PageRank

- A relevance notion based solely on term frequencies is not enough to rank billions of documents
- Complex measures are applied to evaluate the quality, reliability and authority of web pages:
  - Measures based **on topological network properties** (such as Google PageRank)
  - Measures based **on different field boosting** (Title, subtitle, body have different weight)
  - Measures based **on semantics and time-space properties** (freshness of a page)
- PageRank set up a **rich-get-richer loop**, whereby few sites dominate the top ranks

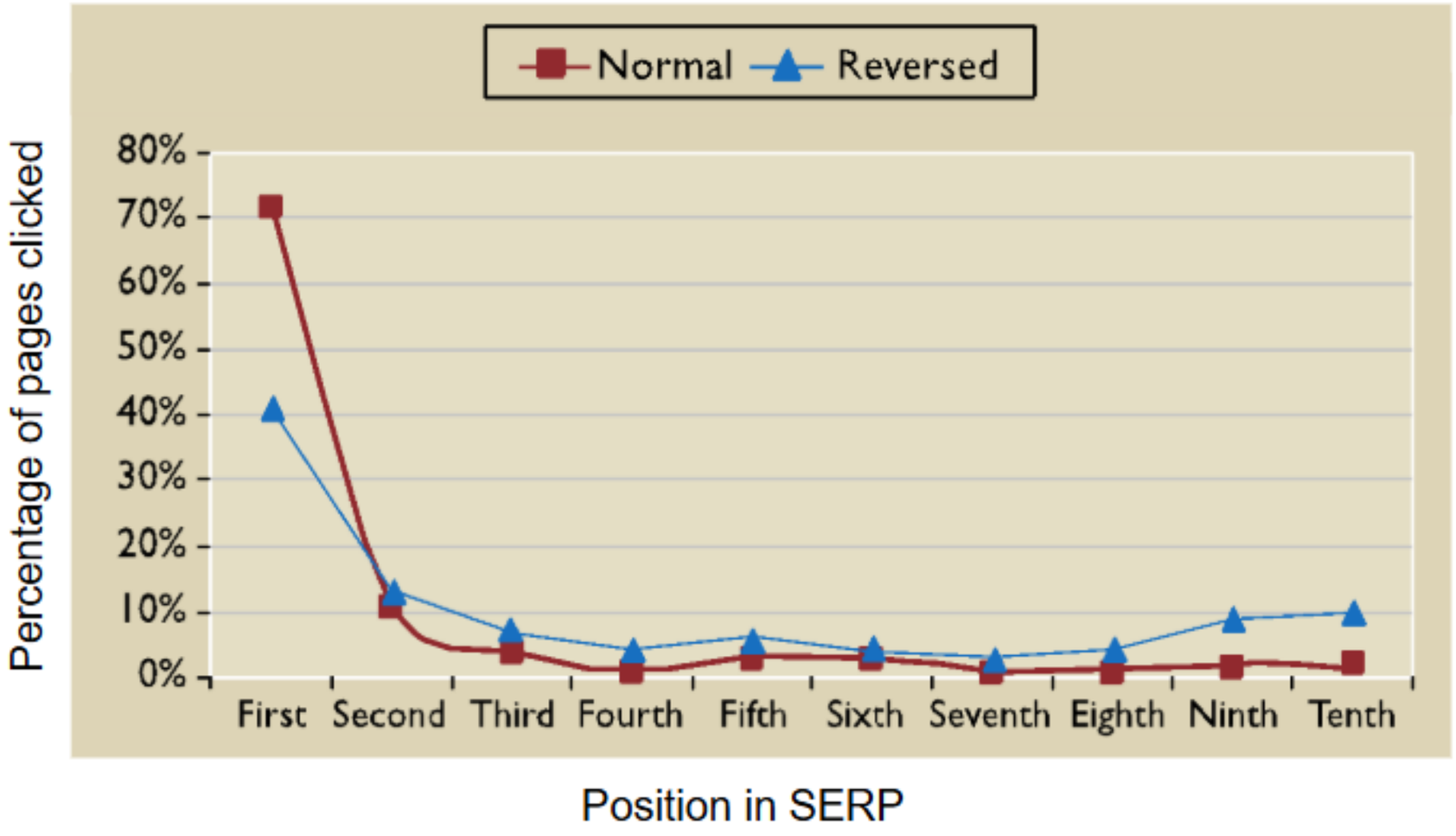
Search Engine Results Page

- A Search Engine Results Page (SERP) shows by default **10 results**
- Of these results, on average, the first **5 are visible** without scrolling down
- We will take in consideration the **user behavior on the first SERP** of search engines (the first 10 results)

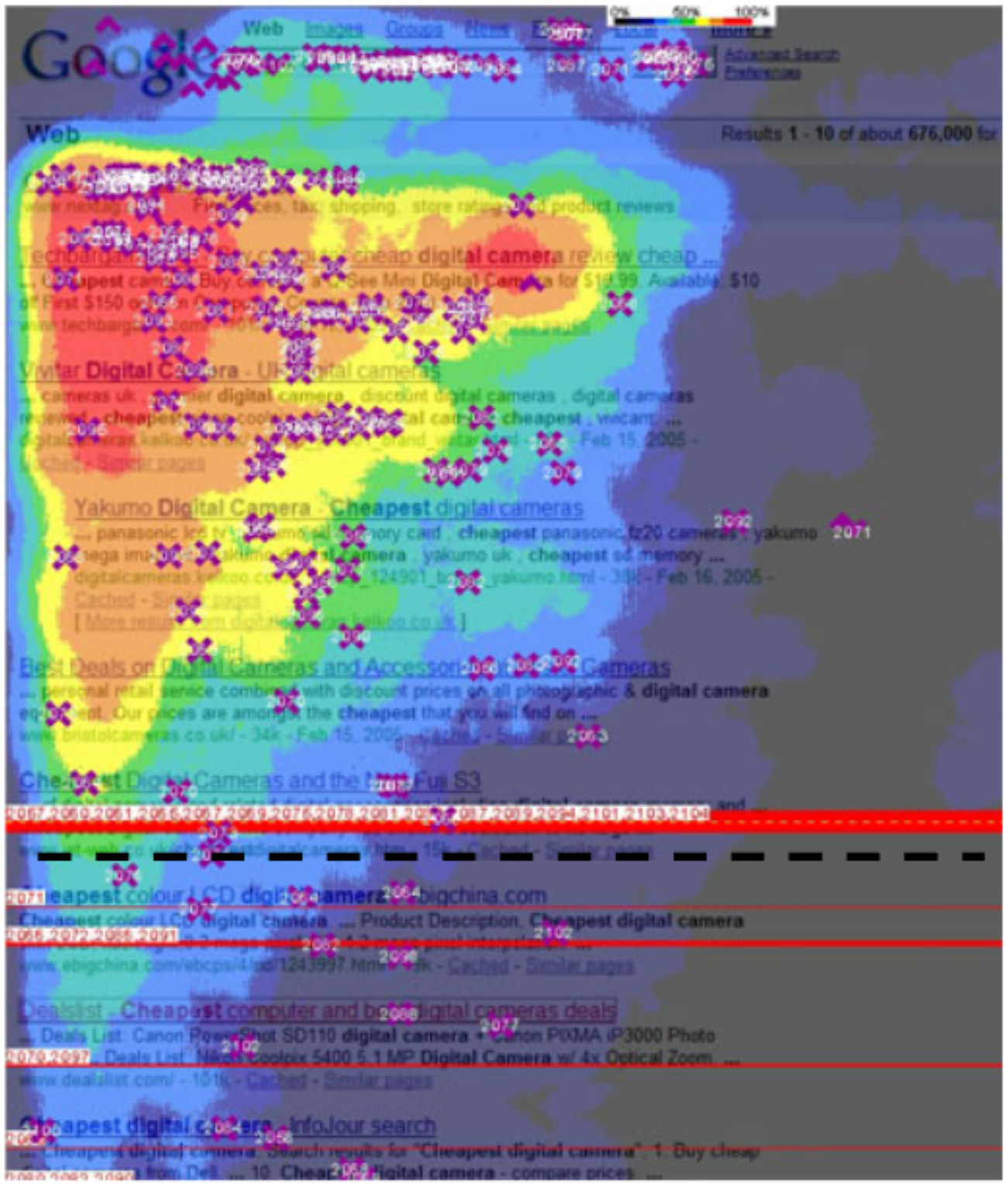


Result positioning bias

- When searching for information, the average searchers do not judge systematically all the results, instead they **simply click on top results**
- Studies have been conducted comparing the users' responses when they received results lists in **normal ordering versus a reversed order**



Eye-tracking: Golden Triangle

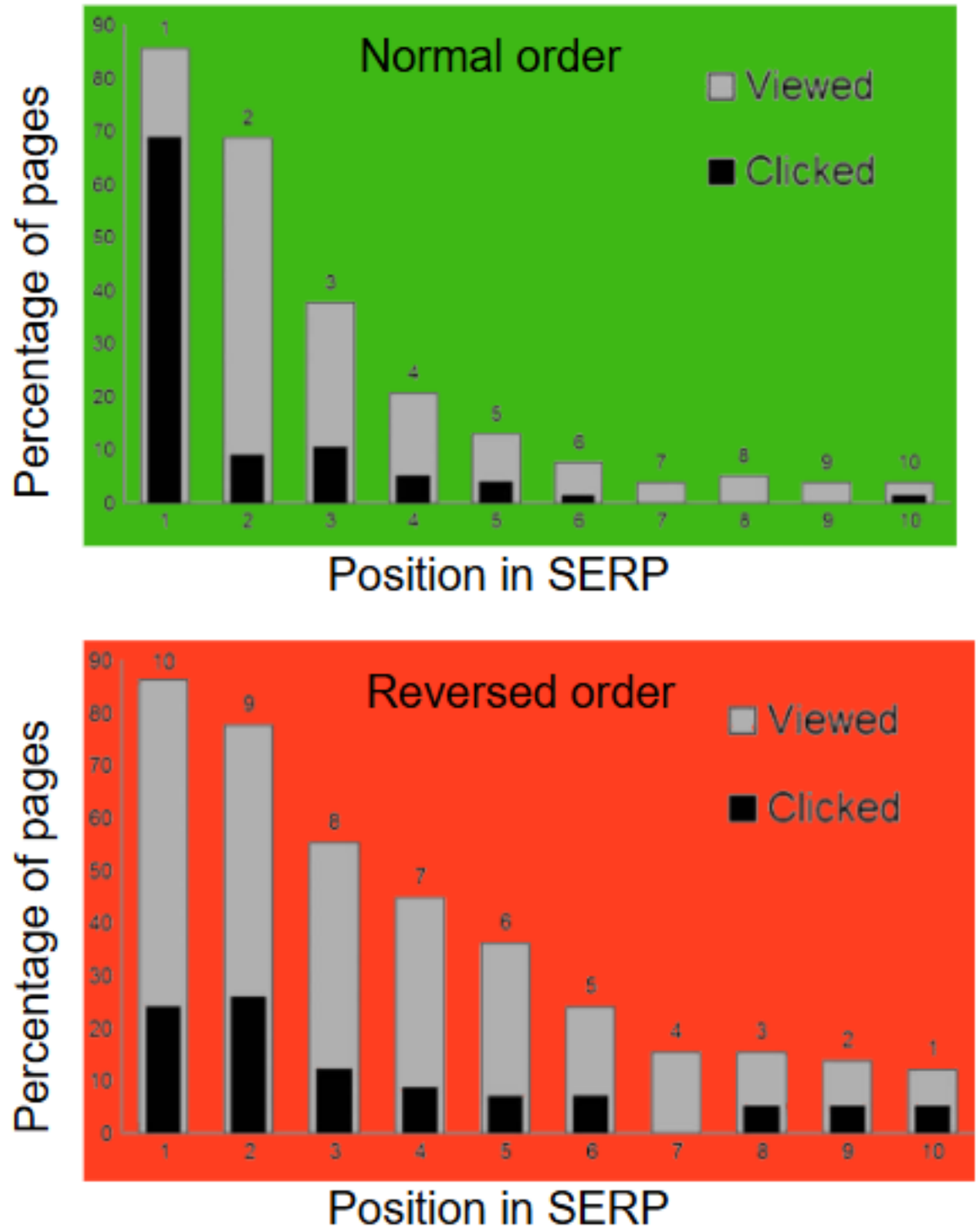


- Color  represents percentage of time spent looking the area.
- Purple **X** represents a mouse click on the page.
- Dotted line **- - -** represents where the page breaks on the computer screen (Visible area/Scroll area).
- Red lines ▬ indicate how far down the page scrolled before leaving the page.

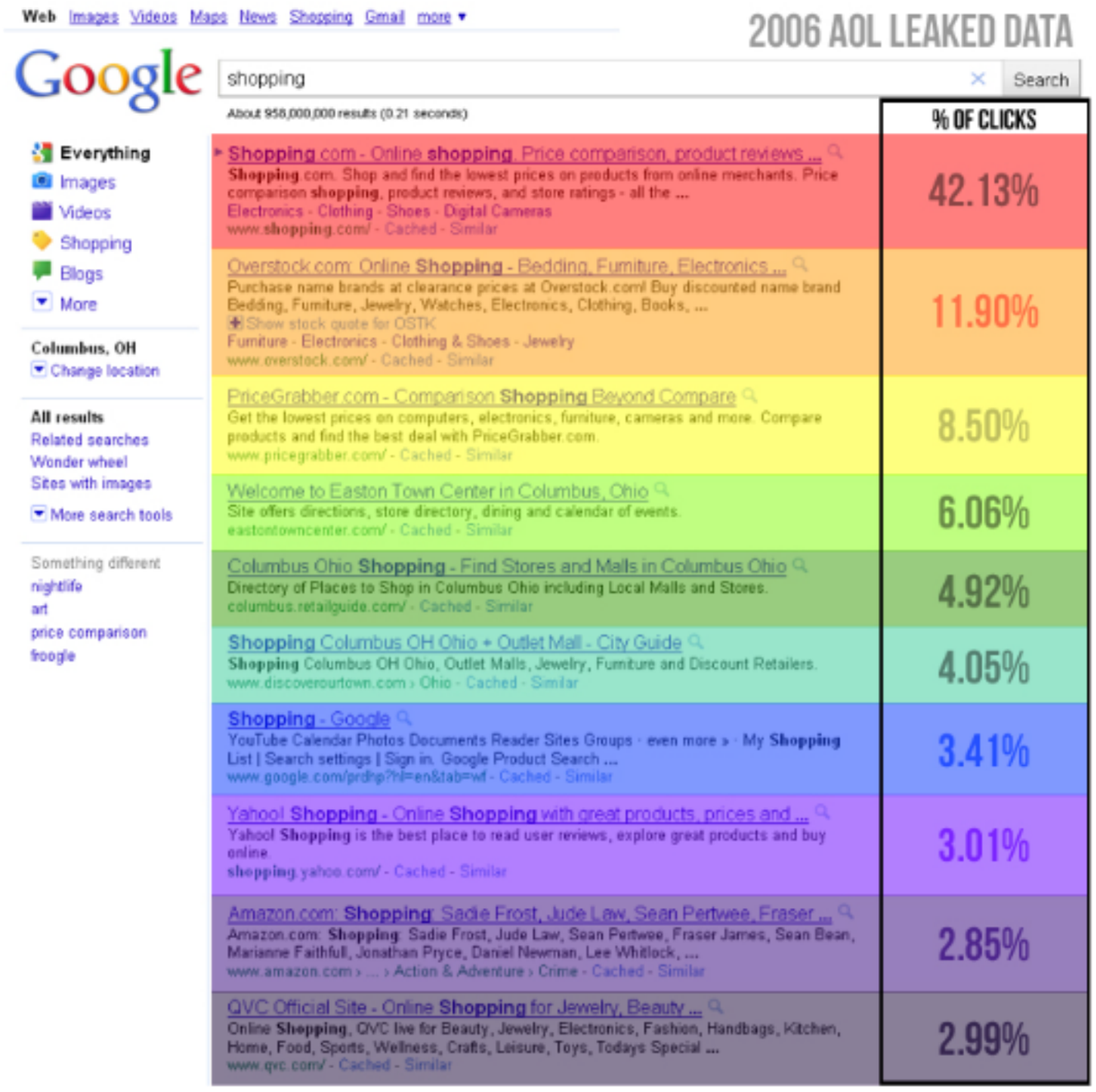
Results in 1st position are clicked more than 10 times results on 6th position

Click and Eye-tracking biasy

- View percentage and mouse clicks are compared in normal vs. reversed order of the first 10 results
- Even though results show some user awareness, **excessive trust in ranking** algorithms may negatively affect smaller positioned websites

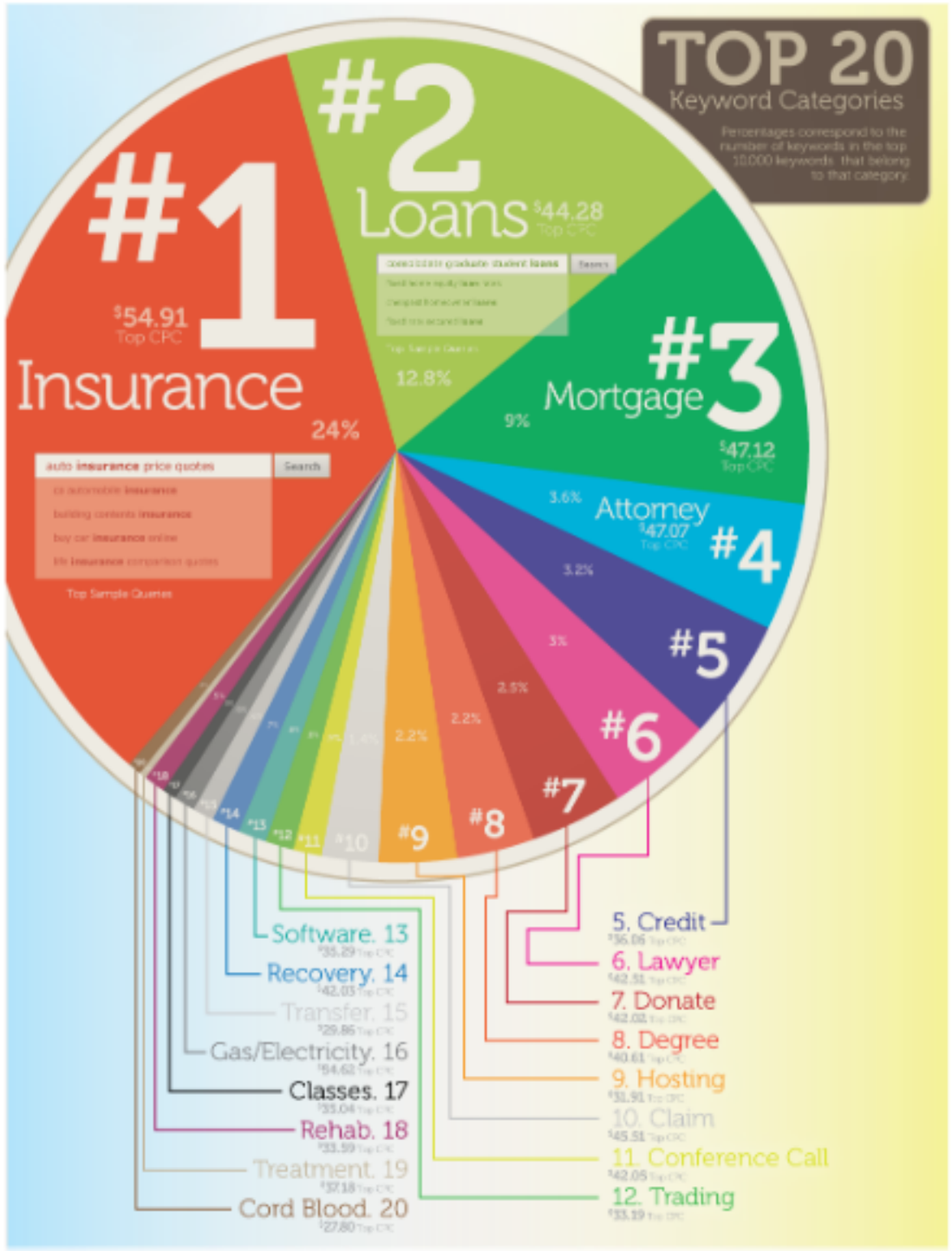


Position impact on business



- Results in 1st position are clicked **more than 10 times** results on 6th position
- Suppose company A and company B are respectively on the 1st and 6th position for a valuable business keyword
- B should buy 10 times the clicks that A gets to obtain the same traffic!
- **How much does a click cost?**

Click economic value



- In web advertising, the cost of a single click, also known as Cost-Per-Click (CPC), is **1$ on average**. However...
- On Google some keywords can be really expensive (Google most expensive keywords 2011):
  - **Insurance: 54.91$**
  - Mortgage: 47.12$
  - Attorney: 47.07
  - Claim: 45.51$
  - Loans: 44.28$
  - Lawyer: 42.51$
- Bing is even more expensive (Bing most expensive keywords 2015):
  - **Lawyers: 109.21$**
  - Attorney: 101.77$
  - Structured settlements: 78.39$

Terms rarity

- Common terms are less informative than rare terms.
- Consider a query like "*good refrigerators*".
  - With TF (term frequency) we consider the words frequency in each document
  - However, *good* is a very common word, that can be found in most documents, while *refrigerators* is less common and thus more informative for relevance
    - We **should weight more the rare words** than the common words
- We will use inverse document frequency (**idf**) to capture this, which in turn is based on document frequency (**df**)

DF: Document Frequency

- df_t is the document frequency of *t*: the number of documents that contain *t*
  - Note: despite its name is *document* frequency, it involves the **whole collection of documents!**
  - It measures **how common a term is in the whole collection of documents**.
- df_t is an **inverse** measure of the informativeness of *t*
  - The **more common** is a word, the **less informative** will be for relevance (extreme case: stop words).
  - We use the **df** to formulate the **inverse** concept, in order to express the **rarity** of a word.

IDF: Inverse Document Frequency

- We define the inverse document frequency (**idf**) of term *t* by

$$\text{idf}_t = \log_{10}(N/\text{df}_t)$$

- *N* is the number of documents in the collection.
- We use **log** (N/df_t) instead of N/df_t to smooth the effect of idf.
  - E.g. a common word like *"home"* can have a frequency **1 million bigger** than a rare word such as *"fenestration"*
  - We apply the logarithm to flatten this **exponential** phenomenon of linguistics (Zipf's law), otherwise very common words would have an idf of zero

Effect of IDF on ranking

- Does idf have an effect on ranking for one-term queries, like
  - iPhone ?
- idf has no effect on ranking one term queries
  - idf affects the ranking of documents for queries with at least two terms
    - For the query capricious person, idf weighting makes occurrences of capricious count for much more in the final document ranking than occurrences of person
- IDF is never used alone, instead is used together with the TF for a better estimation of document relevance

TF-IDF 1/2

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

$$w_{t,d} = \mathrm{tf}_{t,d} \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
  - Note: the “-” in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, **tf x idf**

TF-IDF 2/2

$$w_{t,d} = tf_{t,d} \times \log_{10}(N / df_t)$$

- The tf-idf weight of a term:
  - Increases with the number of occurrences within a document (**tf**)
  - Increases with the rarity of the term in the collection (**idf**)

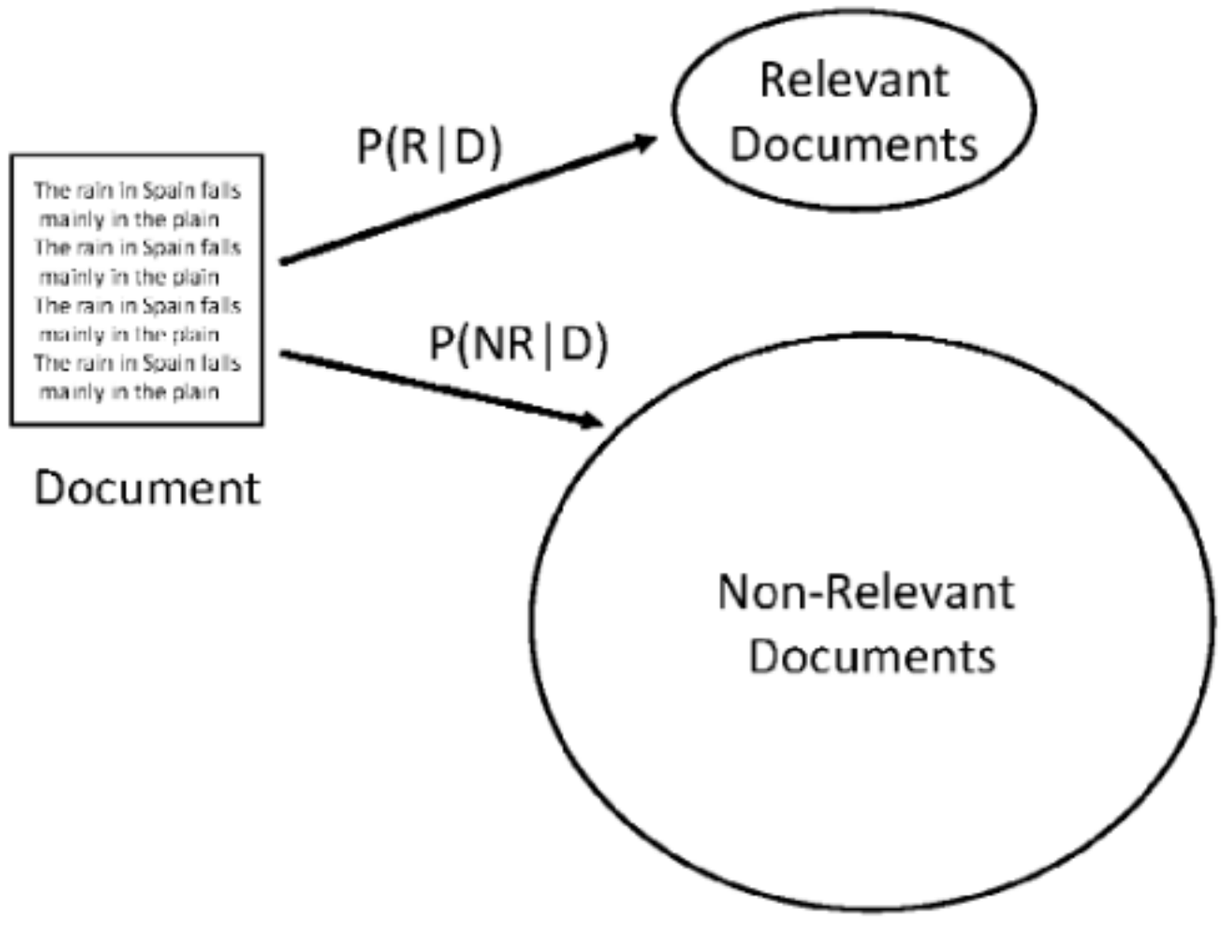
Retrieval Models

- **Classic models**
  - Boolean retrieval
  - Vector Space model
- **Probabilistic Models**
  - BM25
  - Language models
- Progress in retrieval models has corresponded with improvements in effectiveness

Probabilistic Models

- Probability Ranking Principle, Robertson (1977)
- The ranking is given by a probability of relevance
- Probability is estimated as accurately as possible using the available data → best effectiveness

"[...] If the **ranking of the documents** is **in order of decreasing probability of relevance** (where the probabilities are estimated as accurately as possible from the available data) **the overall effectiveness will be the best** that is obtainable on the basis of those data."

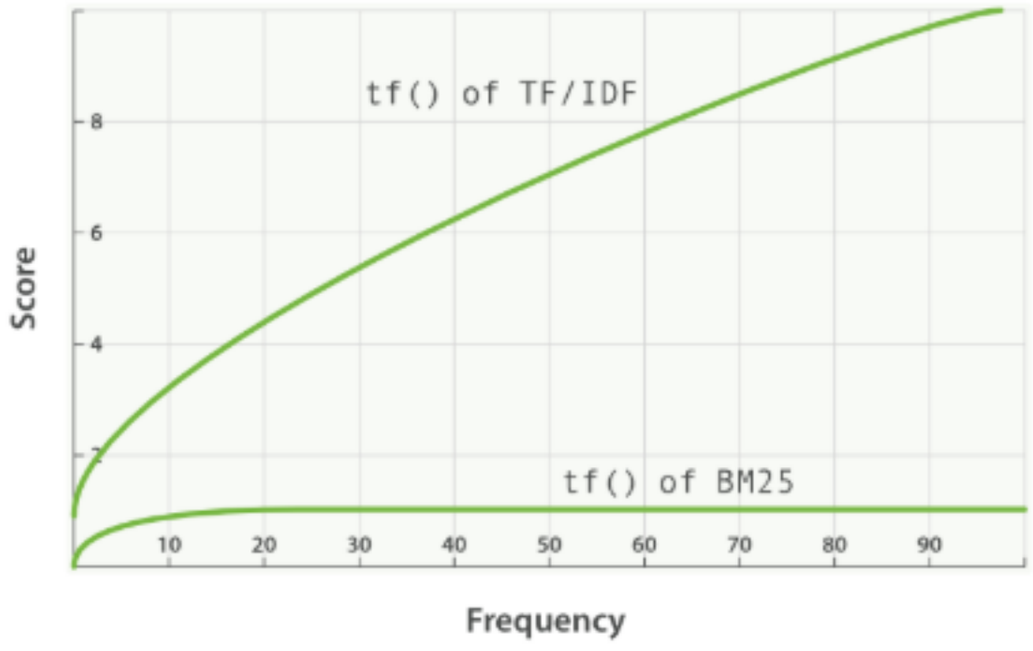


Okapi BM25

- The *BM25 weighting scheme*, often called *Okapi weighting*, after the system in which it was first implemented, was developed as a way of building a probabilistic model sensitive to
  - **term frequency**
  - **term rareness** in corpus (similarly to IDF)
  - **document length**.
- BM25 became a popular and effective ranking algorithm while relying on probabilistic foundations.
- The BM25 term weighting formulas have been used quite widely and quite successfully across a range of collections and search tasks.

Okapi BM25: TF saturation

- In TF-IDF, a document similarity score could reach very high values if the term frequency of the query term is very high
- In Okapi BM25, the similarity score is always comprised between 0 and 1
  - At a certain point, highest values of term frequency do not affects the score



Okapi BM25: parameters

- Okapi BM25 has two parameters:
  - **k1**: this parameter controls how quickly an increase in term frequency results in term-frequency saturation. The default value is 1.2. Lower values result in quicker saturation, and higher values in slower saturation
  - **b**: this parameter controls how much effect document length normalization should have. A value of 0.0 disables normalization completely, and a value of 1.0 normalizes fully. The default is 0.75

Language Model

- A statistical language model assigns a probability to a sequence of m words $P(w_1,\ldots,w_m)$ by means of a probability distribution.
- A separate language model is associated with each document in a collection. Documents are ranked based on the probability of the query Q in the document's language model $P(Q \mid M_d)$.

- Unigram language model
  - probability distribution over the words in a language
  - generation of text consists of pulling words out of a “bucket” according to the probability distribution and replacing them
- N-gram language model
  - some applications use bigram and trigram language models where probabilities depend on previous words

Efficiency aspects of ranking

- Computing the relevance score using non boolean models can be quite computationally-intensive:
  - Document is retrieved (has a relevance score) even if not all the query terms are found in it
  - Complex relevance formulas requires additional computations to compute score
- Strategies to control the efficiency:
  - The way we access documents affects computation time (one document at a time or one term at a time?)
  - Most of the time we are not interested in the least relevant documents

Efficient scoring

- A large fraction of the CPU work for each search query is devoted just to **compute the score** of relevance
  - Generally, we have a tight budget on latency (say, 250ms) to answer the query, otherwise the user will not be happy
  - CPU provisioning doesn't permit exhaustively scoring every document for every query
- Basic idea: avoid scoring docs that won't make it into the top K

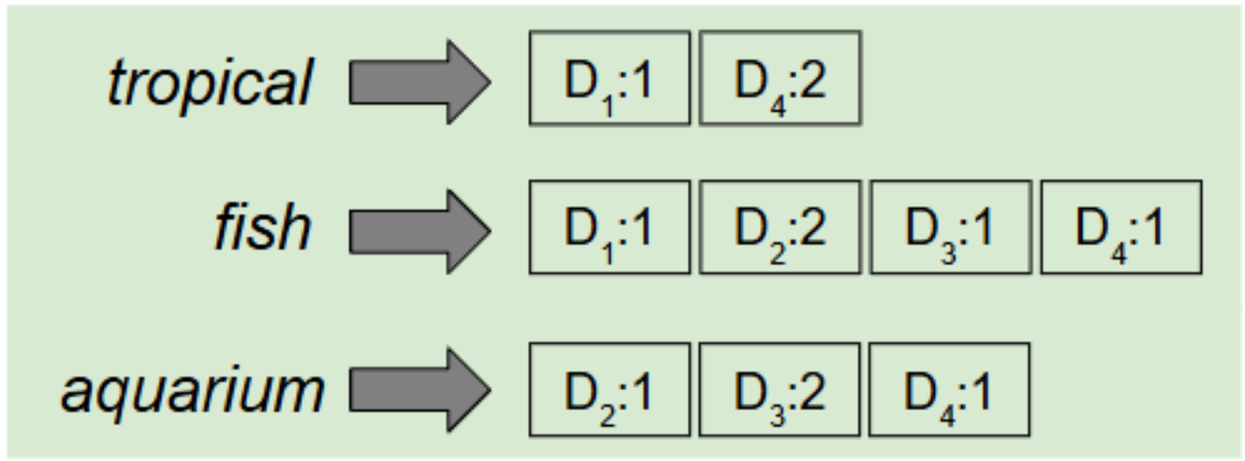
TAAT vs DAAT techniques

- **TAAT** : “Term At A Time”
  - Scores for all docs computed concurrently, one query term at a time
- **DAAT** : “Document At A Time”
  - Total score for each doc (including all query terms) computed, before proceeding to the next
- Each has implications for how the retrieval **index** is structured and stored

TAAT: Example

Query: *tropical fish aquarium*

Inverted index:



Term frequency for each document:

$D_1 = 1 + 1 = 2$

$D_2 = 2 + 1 = 3$

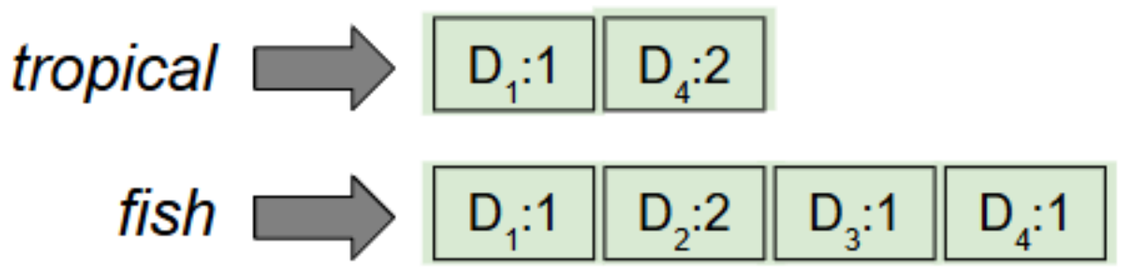
$D_3 = 1 + 2 = 3$

$D_4 = 2 + 1 + 1 = 4$

DAAT: Example

Query: *tropical fish aquarium*

Inverted index:



Term frequency for each document:

$D_1 = 1 + 1 = 2$

$D_2 = 2 + 1 = 3$

$D_3 = 1 + 2 = 3$

$D_4 = 2 + 1 + 1 = 4$

Safe ranking

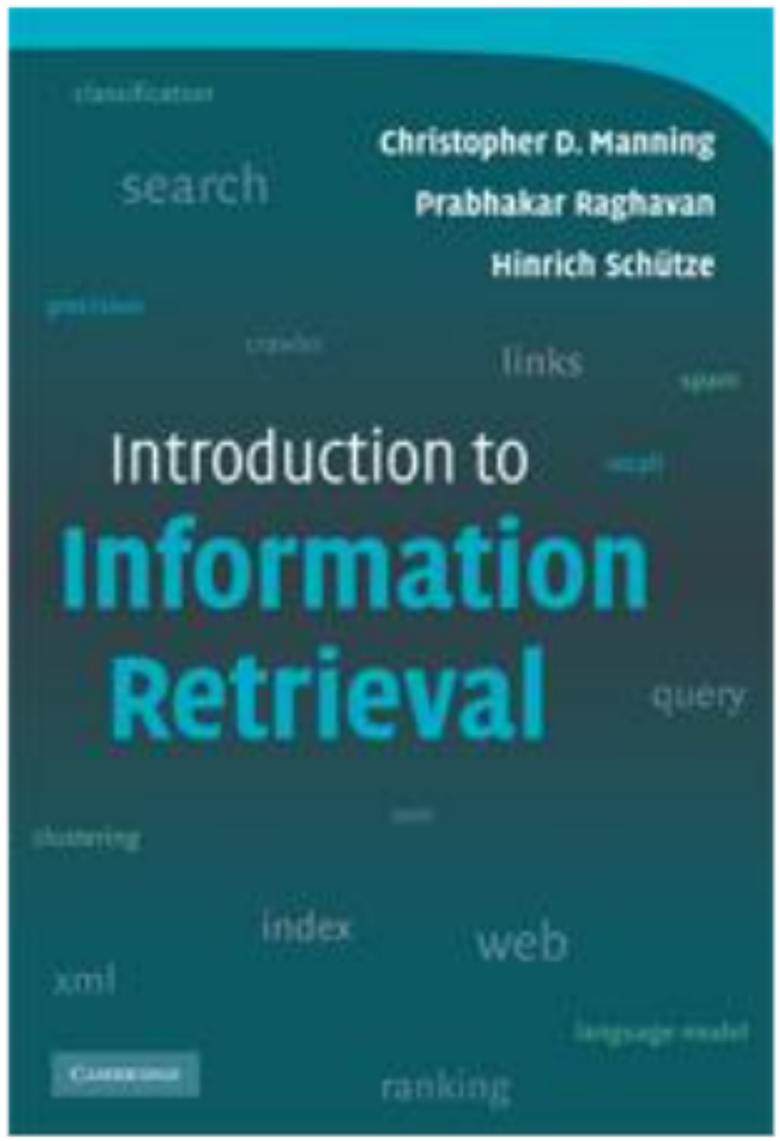
- The terminology “safe ranking” is used for methods that guarantee that the K docs returned are the **K absolute highest scoring** documents
  - (Not necessarily just under cosine similarity)
- Is it ok to be non-safe? Yes, the results would be approximated but good enough to satisfy the user.
- The goal is to run less computations while giving good results.

Non-safe ranking

- Non-safe ranking may be okay
  - Ranking function is only a proxy for user happiness
  - Documents close to top K may be just fine
- Non-safe: Index “elimination”
  - Only consider **high-idf (rare) query terms**, discard the common ones
  - Only consider **documents containing many query terms**, discard the ones with only few query terms.
- Non-safe: Champion lists
  - For each term, the scores of top relevant documents are pre-computed (before any query is issued)

References

Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze
Introduction to Information Retrieval
Cambridge University Press.
2008



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