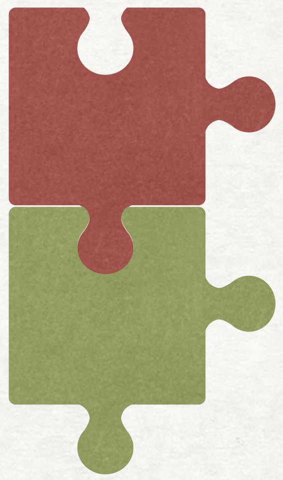
# INFORMATION RETRIEVAL

Laura Nenzi
lnenzi@units.it

Lecture 7

# LECTURE OUTLINE

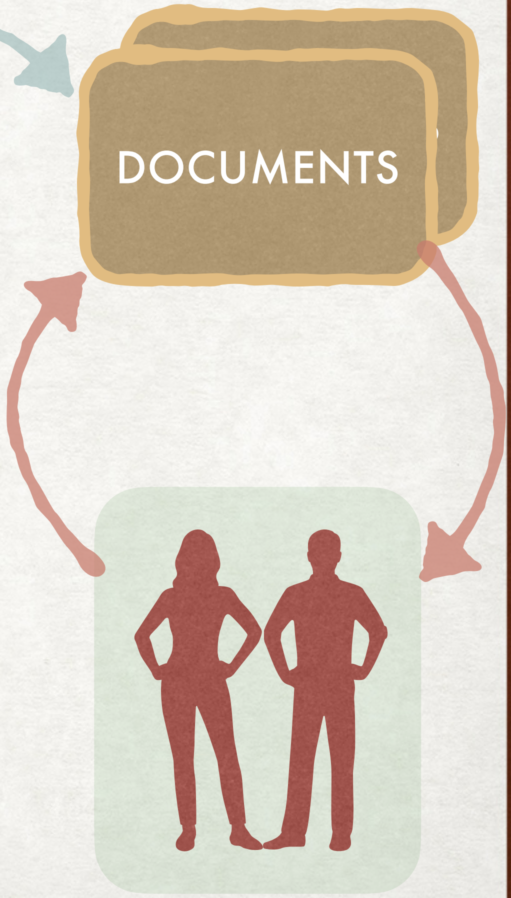
Putting Everything Together



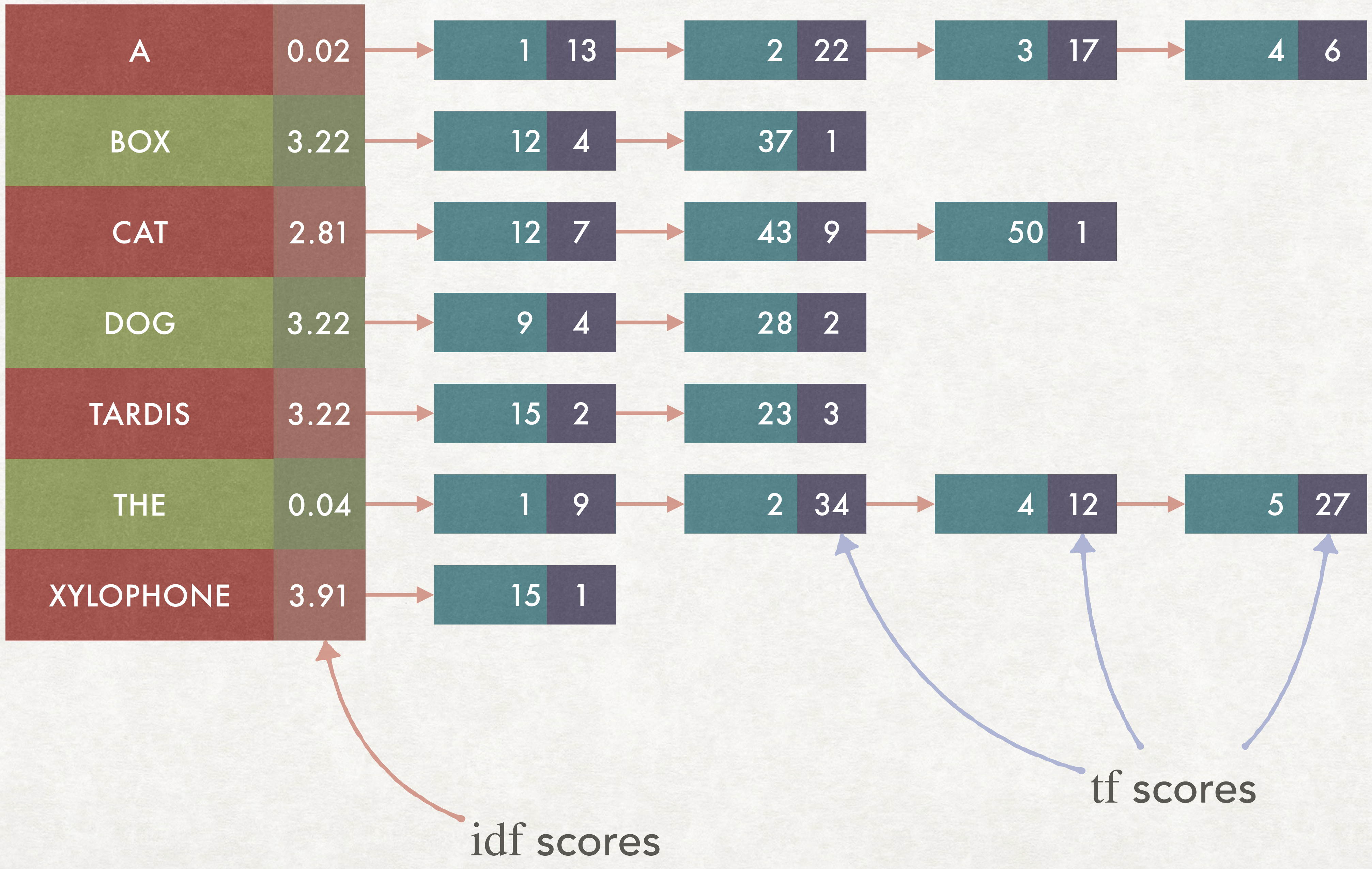
PRACTICAL PART
A PYTHON IMPLEMENTATION OF A VECTOR SPACE MODEL

Evaluation of IR systems

Relevance Feedback



# COMPUTING TF-IDF



A 0.02 → 1 13 → 2 22 → 3 17 → 4 6
BOX 3.22 → 12 4 → 37 1
CAT 2.81 → 12 7 → 43 9 → 50 1
DOG 3.22 → 9 4 → 28 2
TARDIS 3.22 → 15 2 → 23 3
THE 0.04 → 1 9 → 2 34 → 4 12 → 5 27
XYLOPHONE 3.91 → 15 1
idf scores
tf scores

## DOCUMENTS AS VECTORS

### THE START OF THE VECTOR SPACE REPRESENTATION

A document is a point in this $n$-dimensional space:

$$\overrightarrow{V}(d) = (0.6, 0.5, \underset{\uparrow}{0.1}, 0, 0.9)$$

$\text{tf-idf}_{\text{cat},d}$

The normalized *vector* $\vec{v}(d)$ is:

$$\vec{v}(d) = \frac{\overrightarrow{V}(d)}{|\overrightarrow{V}(d)|}$$

## COMPUTING SIMILARITY EFFICIENTLY

## A FEW INITIAL CONSIDERATIONS

### THE LOW-HANGING FRUITS

- We can have an inverted index in which each term has an associated $\mathrm{idf}_t$ value (since it depends only on the term).
- Each posting will have the term frequency $\mathrm{tf}_{t,d}$ associated to it (since it depends on both the term and the document).
- We can then compute the score of each document while traversing the posting lists.
- If a DocID does not appear in the posting list of any query term its score is zero.
- To retrieve the K highest scoring documents we can use a *heap* data structure, which is more efficient than sorting all documents.

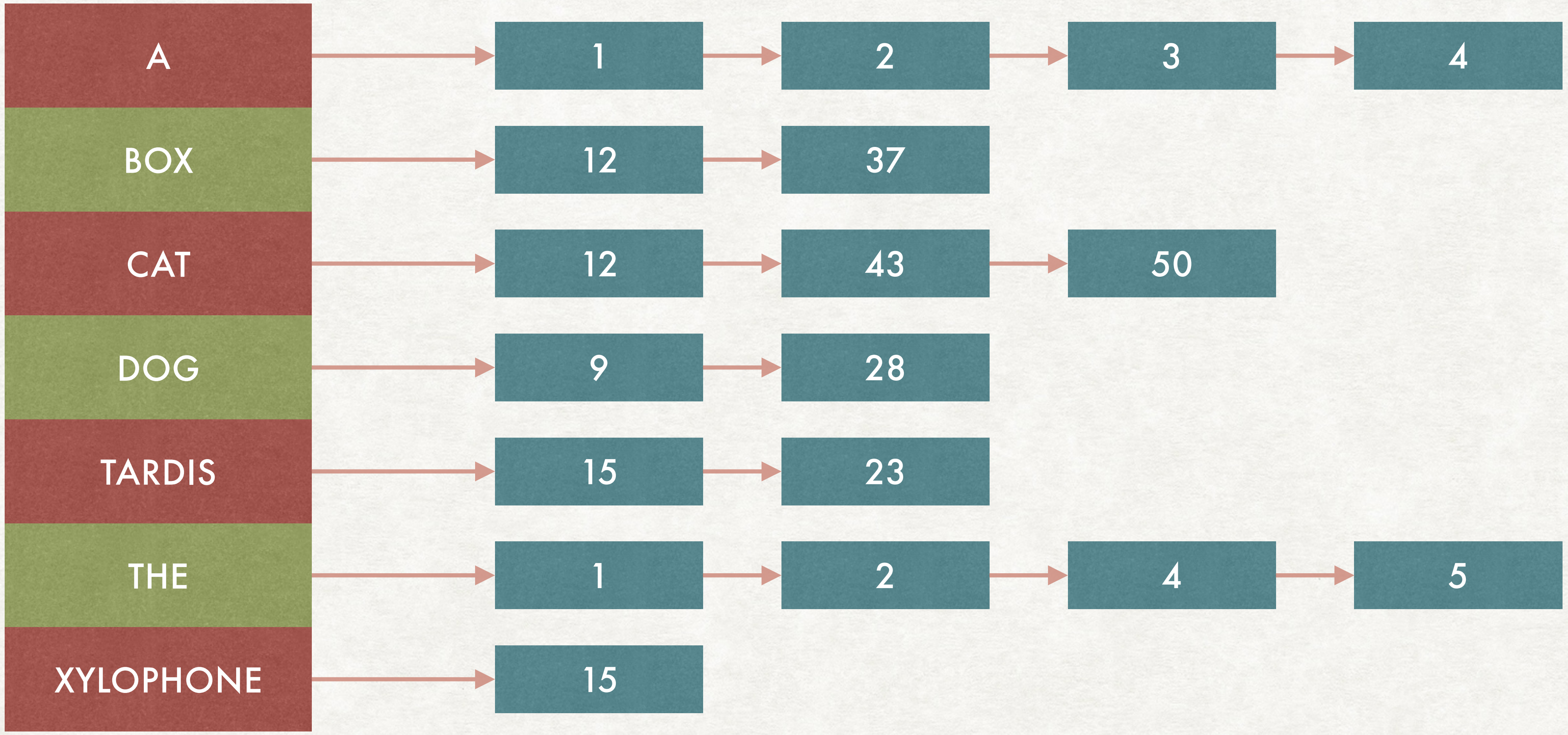
## INEXACT TOP K DOCUMENT RETRIEVAL

### BEING FAST AND “WRONG”

- Sometimes it is more important to be efficient than to retrieve exactly the K highest scoring documents.
- We want to retrieve K documents that are *likely* to be among the K highest scored.
- Notice that the similarity score is a proxy of the relevance of a document to a query, so we already have some “approximation”.
- The main idea to perform an inexact retrieval is:
  - Find a subset $A$ of the documents that is both small and likely to contain documents with scores near to the K highest ranking.
  - Return the K highest ranked documents in $A$.

# INDEX ELIMINATION

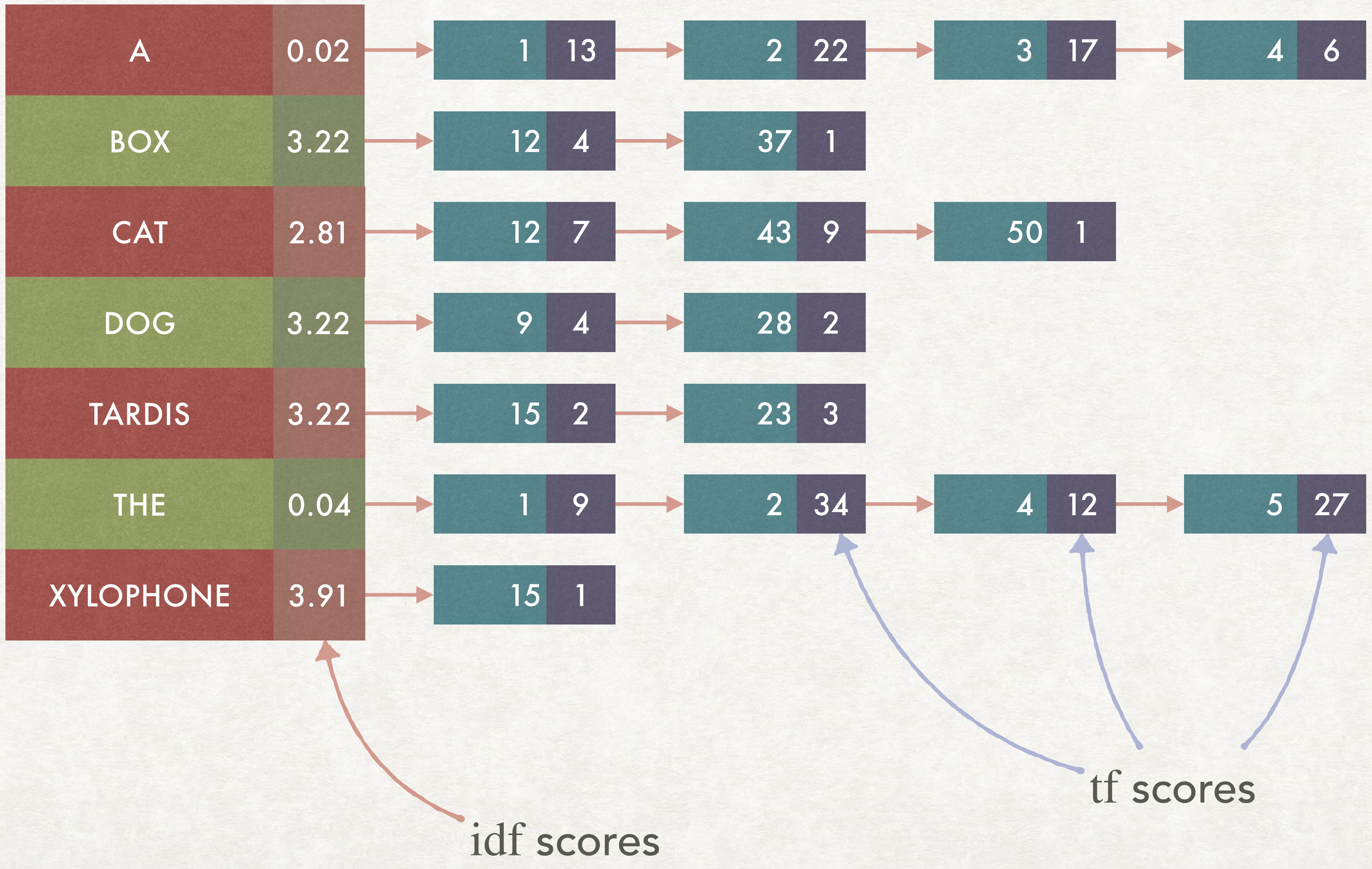
## HOW TO IGNORE SOME TERMS



standard inverted index

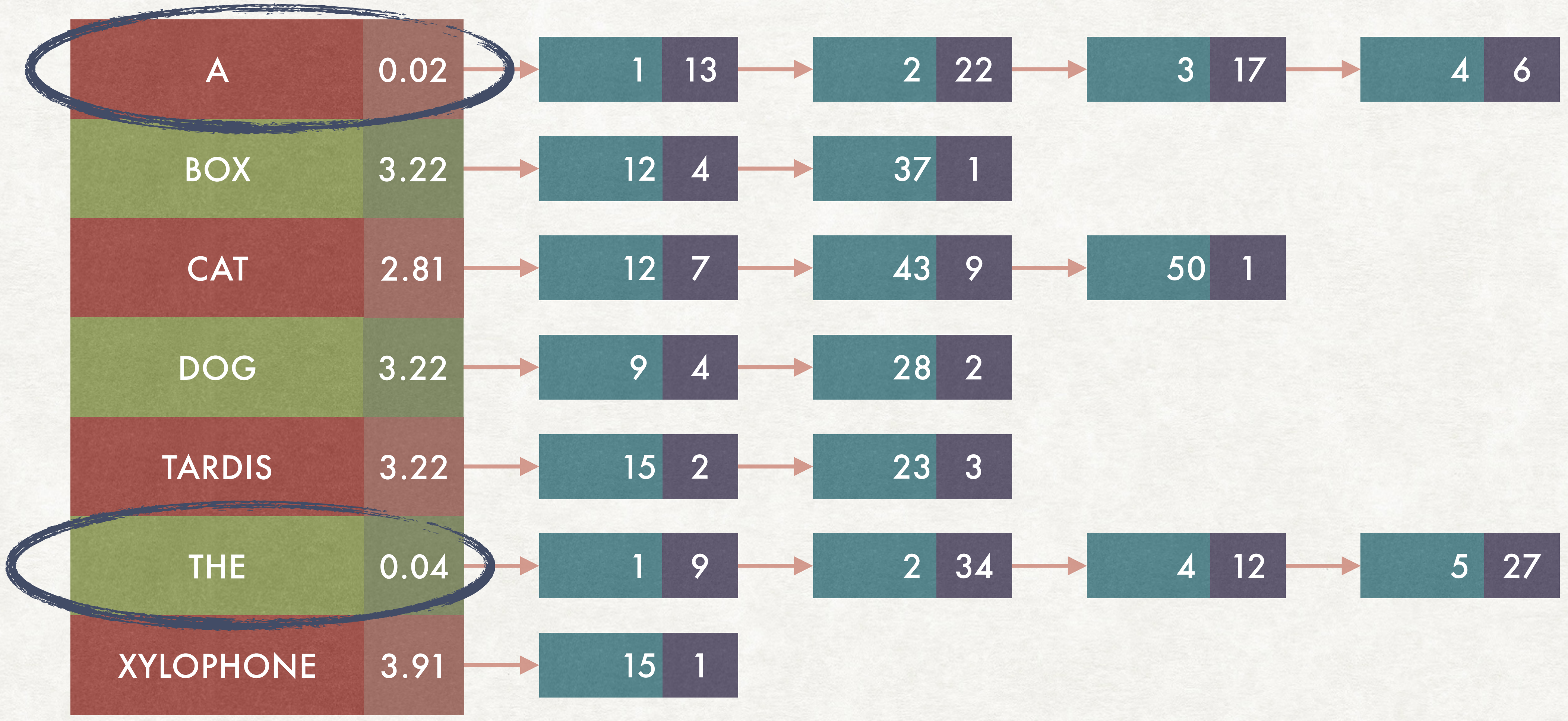
# INDEX ELIMINATION

## HOW TO IGNORE SOME TERMS


A 0.02 → 1 13 → 2 22 → 3 17 → 4 6
BOX 3.22 → 12 4 → 37 1
CAT 2.81 → 12 7 → 43 9 → 50 1
DOG 3.22 → 9 4 → 28 2
TARDIS 3.22 → 15 2 → 23 3
THE 0.04 → 1 9 → 2 34 → 4 12 → 5 27
XYLOPHONE 3.91 → 15 1
idf scores
tf scores

# INDEX ELIMINATION

## HOW TO IGNORE SOME TERMS



A 0.02 → 1 13 → 2 22 → 3 17 → 4 6
BOX 3.22 → 12 4 → 37 1
CAT 2.81 → 12 7 → 43 9 → 50 1
DOG 3.22 → 9 4 → 28 2
TARDIS 3.22 → 15 2 → 23 3
THE 0.04 → 1 9 → 2 34 → 4 12 → 5 27
XYLOPHONE 3.91 → 15 1

We can remove terms with very low idf score from the search: they are like "stop words" with very long postings list

# INDEX ELIMINATION

## HOW TO IGNORE SOME TERMS

- By removing terms with low $\mathrm{idf}$ value we can only work with relatively shorter lists.
- The cutoff value can be adapted according to the other terms present in the query.
- We can also only consider documents in which most or all the query terms appears…
- …but a problem might be that we do not have at least K documents matching all query terms.

## CHAMPION LISTS

### OR "TOP DOCS"

- Keep an additional pre-computed list for each term containing only the $r$ highest-scoring documents (usually $r > K$).
- These additional lists are known as *champion lists*, *fancy lists*, or *top docs*.
- We compute the union of the champion lists of all terms in the query, obtaining a set $A$ of documents.
- We find the K highest ranked documents in $A$ (computing cosine similarity).
- Problem: we might have too few documents if K is not known until the query is performed.

## STATIC QUALITY SCORES

### ADDING A PRE-COMPUTABLE SCORE TO DOCUMENTS

- In some cases we might want to add a score to a document that is independent from the query: a **static quality score**, denoted by $g(d) \in [0,1]$.

- Example: good reviews by users might "push" a document higher in the scoring.

- We need to combine $g(d)$ with the scoring given by the query, a simple possibility is a linear combination: $\text{score}(q, d) = g(d) + \vec{v}(d) \cdot \vec{v}(q)$.

- We can also sort posting list by $g(d) + \text{idf}_{t,d}$, to process documents more likely to have high scores first.

## IMPACT ORDERING

### SORTING POSTING LISTS NOT BY DOCID

- We only want to compute scores for docs for which $\mathrm{tf}_{t,d}$ is high enough

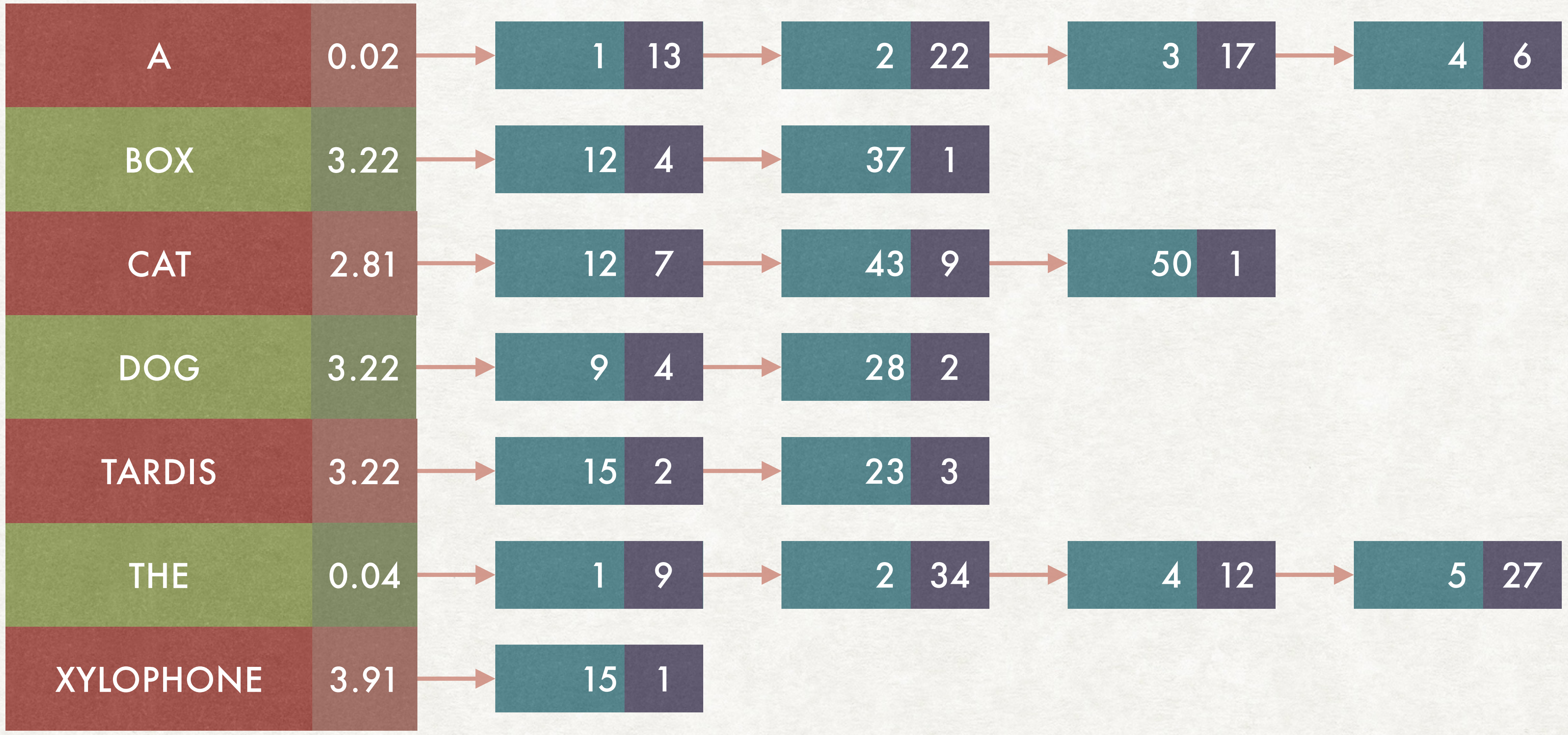
- Idea: Order the documents by decreasing $\mathrm{tf}_{t,d}$. In this way the documents which will obtain the highest scoring will be processed first.

- If the $\mathrm{tf}_{t,d}$ value drops below a threshold, then we can stop.

# IMPACT ORDERING

## SORTING POSTING LISTS NOT BY DOCID

From this…

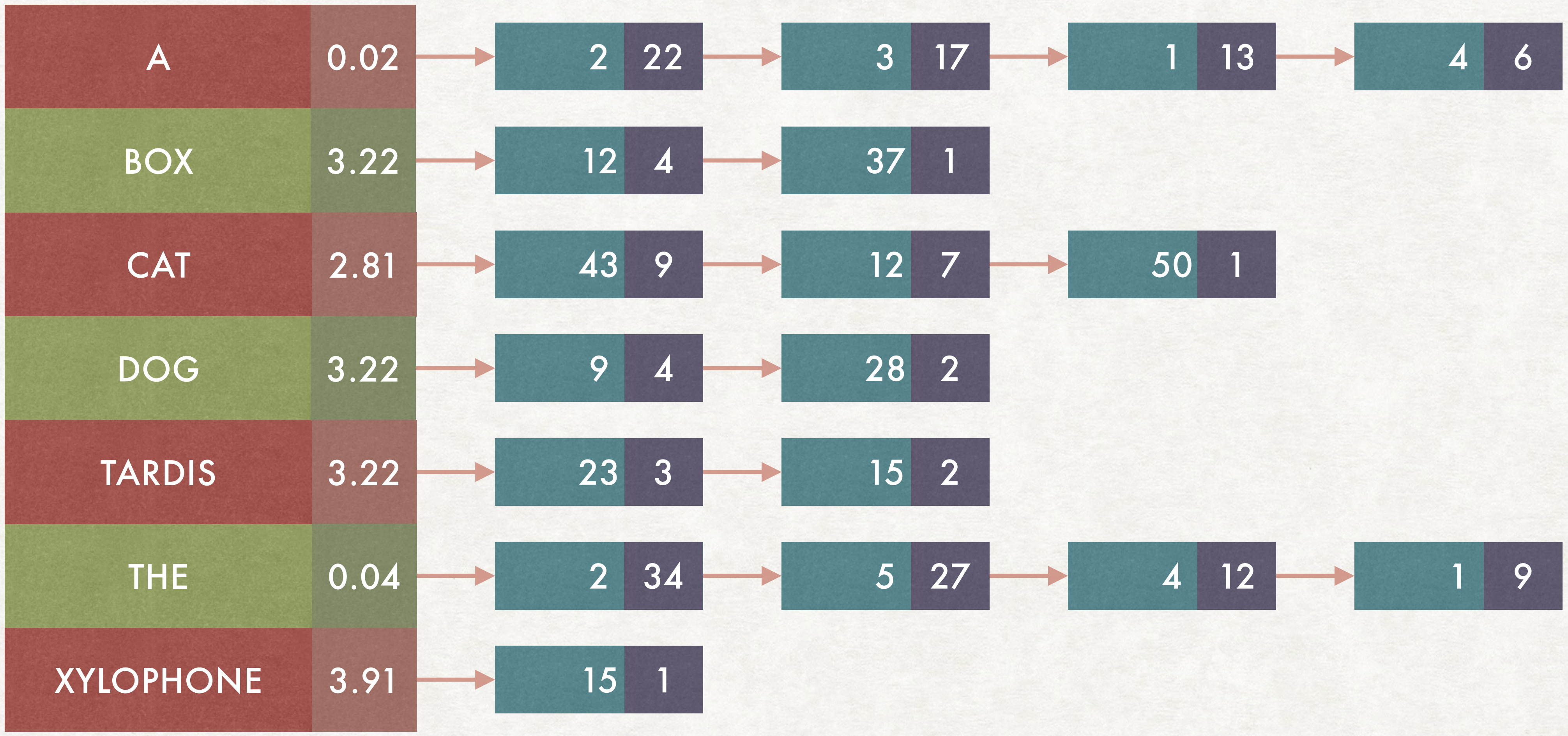


A 0.02 → 1 13 → 2 22 → 3 17 → 4 6
BOX 3.22 → 12 4 → 37 1
CAT 2.81 → 12 7 → 43 9 → 50 1
DOG 3.22 → 9 4 → 28 2
TARDIS 3.22 → 15 2 → 23 3
THE 0.04 → 1 9 → 2 34 → 4 12 → 5 27
XYLOPHONE 3.91 → 15 1

# IMPACT ORDERING

## SORTING POSTING LISTS NOT BY DOCID

…to this


A 0.02 → 2 22 → 3 17 → 1 13 → 4 6
BOX 3.22 → 12 4 → 37 1
CAT 2.81 → 43 9 → 12 7 → 50 1
DOG 3.22 → 9 4 → 28 2
TARDIS 3.22 → 23 3 → 15 2
THE 0.04 → 2 34 → 5 27 → 4 12 → 1 9
XYLOPHONE 3.91 → 15 1

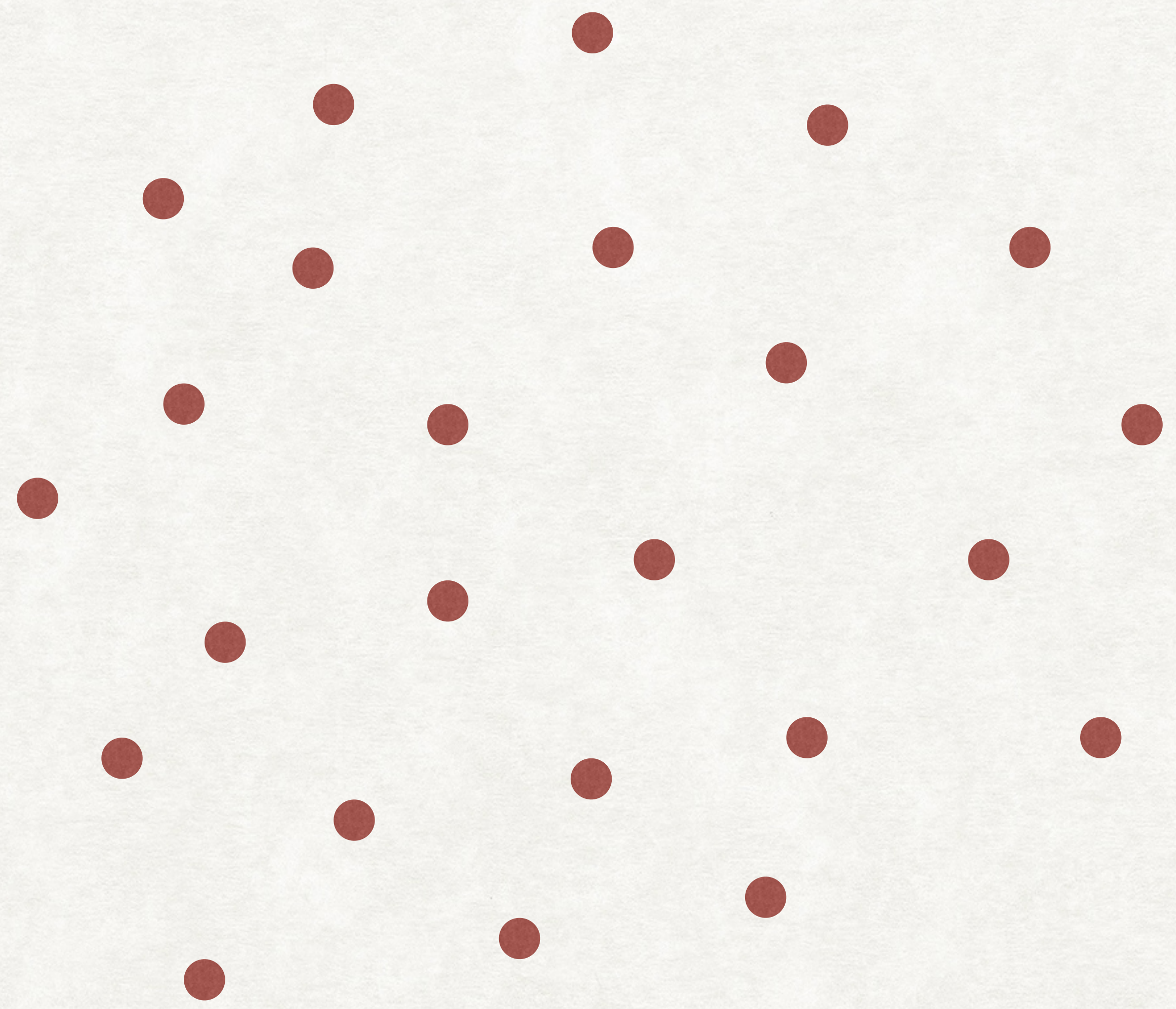
## CLUSTER PRUNING

### SEARCHING ONLY INSIDE A CLUSTER

- With $N$ document, $M = \sqrt{N}$ are randomly selected as *leaders*. Each leader identifies a cluster of documents.
- For each of the remaining documents (*followers*), we find the most similar among the $M$ documents selected and we add it to the corresponding cluster.
- For a query $q$ we find the document among the $M$ leaders that is most similar to it.
- The K highest ranked documents are selected among the ones in the cluster of the selected leader.

## CLUSTER PRUNING

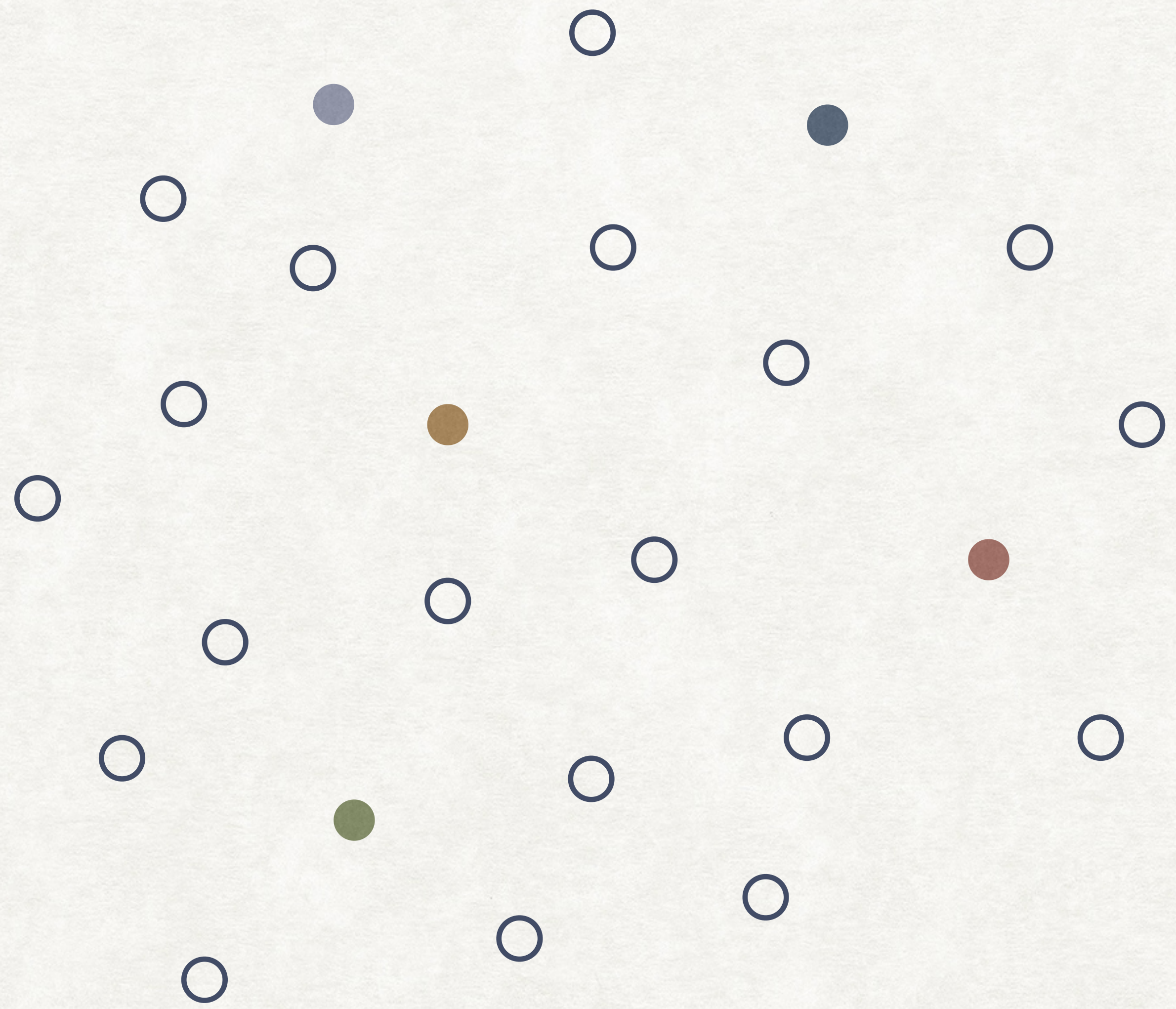
### AN EXAMPLE



Documents represented as points in space

# CLUSTER PRUNING

## AN EXAMPLE

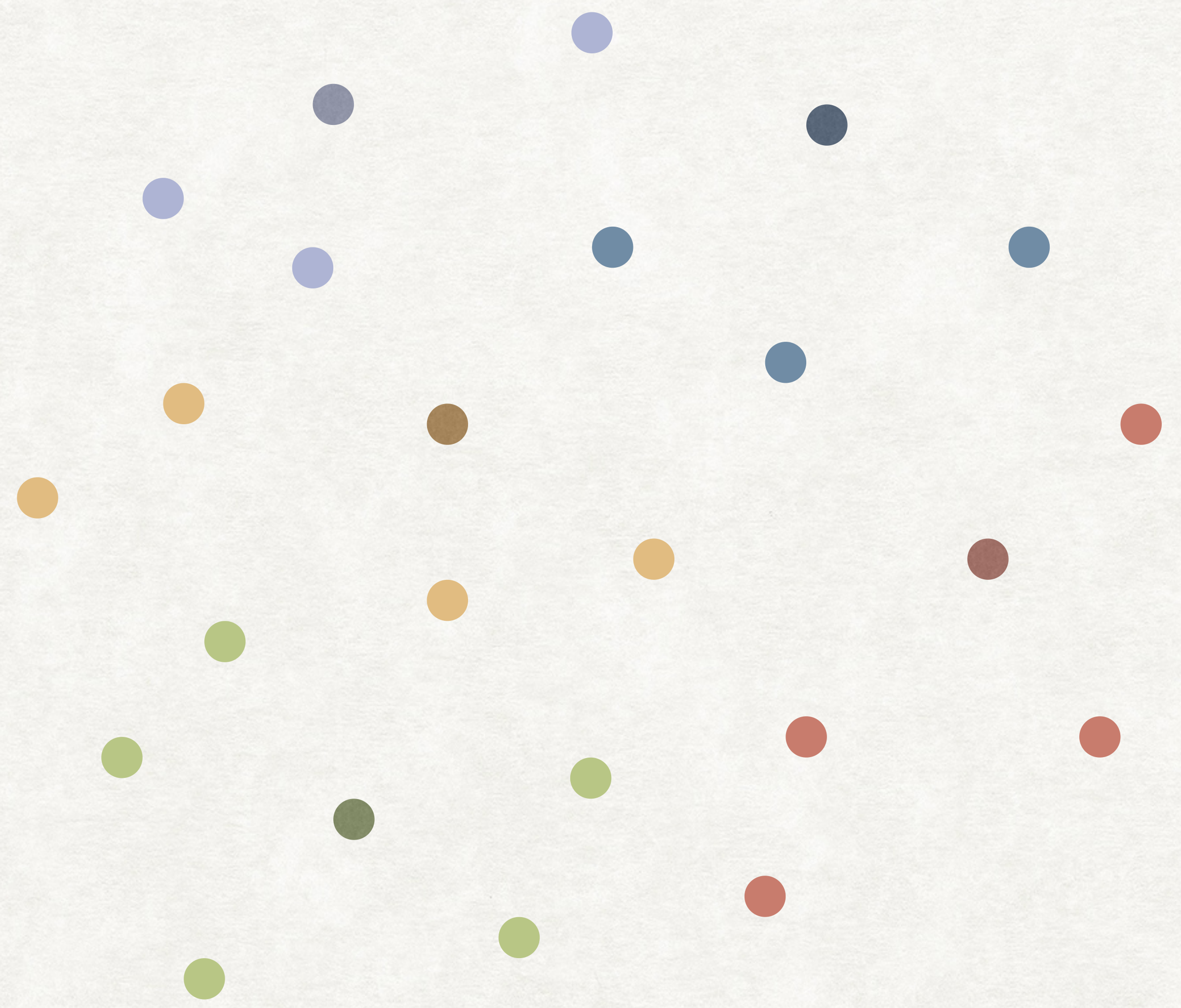


Documents represented as points in space

Selection of the leaders

## CLUSTER PRUNING

### AN EXAMPLE



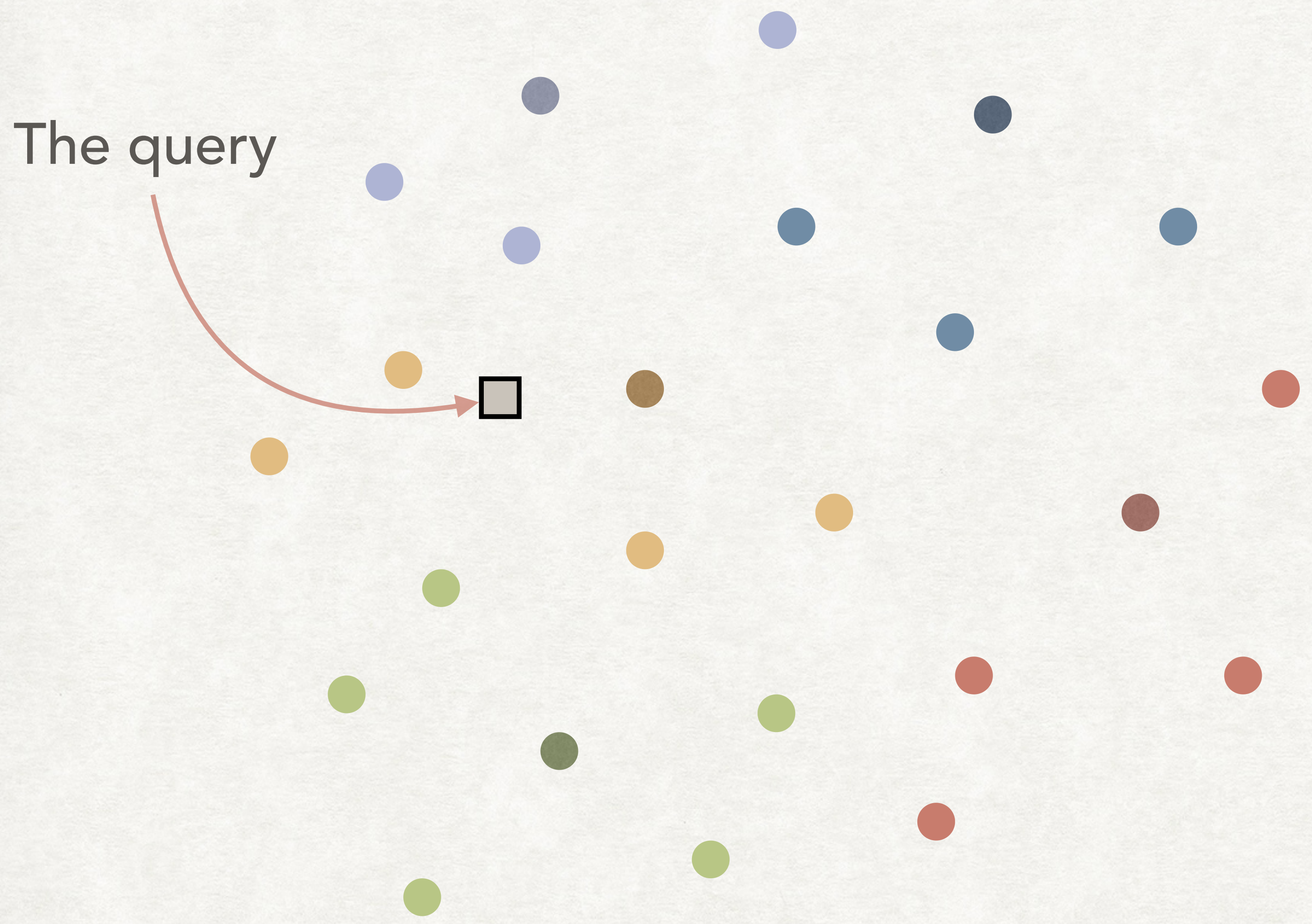
Documents represented as points in space

Selection of the leaders

Assigning documents to clusters

## CLUSTER PRUNING

### AN EXAMPLE



Documents represented as points in space

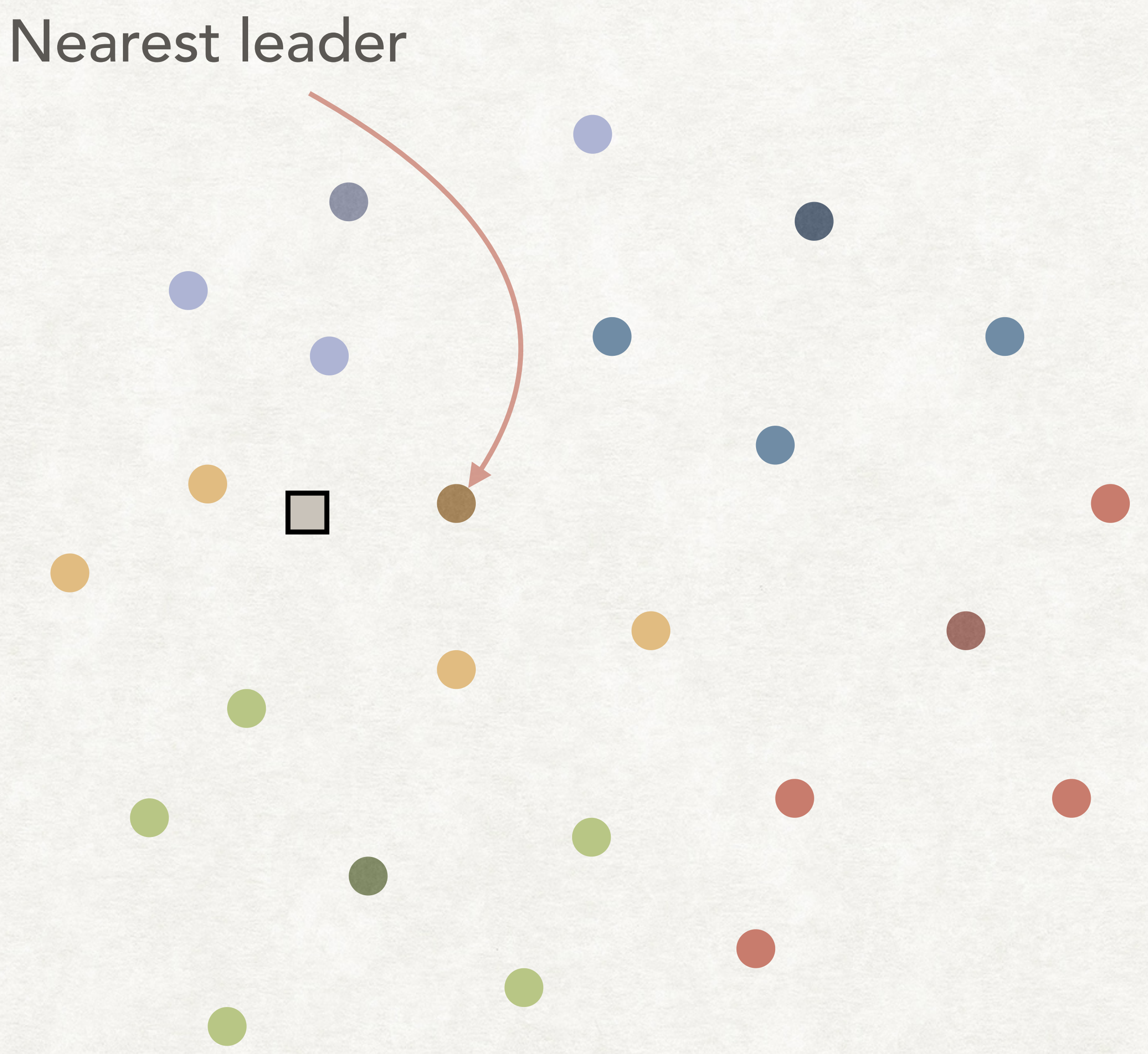
Selection of the leaders

Assigning documents to clusters

A query arrives

# CLUSTER PRUNING

## AN EXAMPLE



Documents represented as points in space

Selection of the leaders

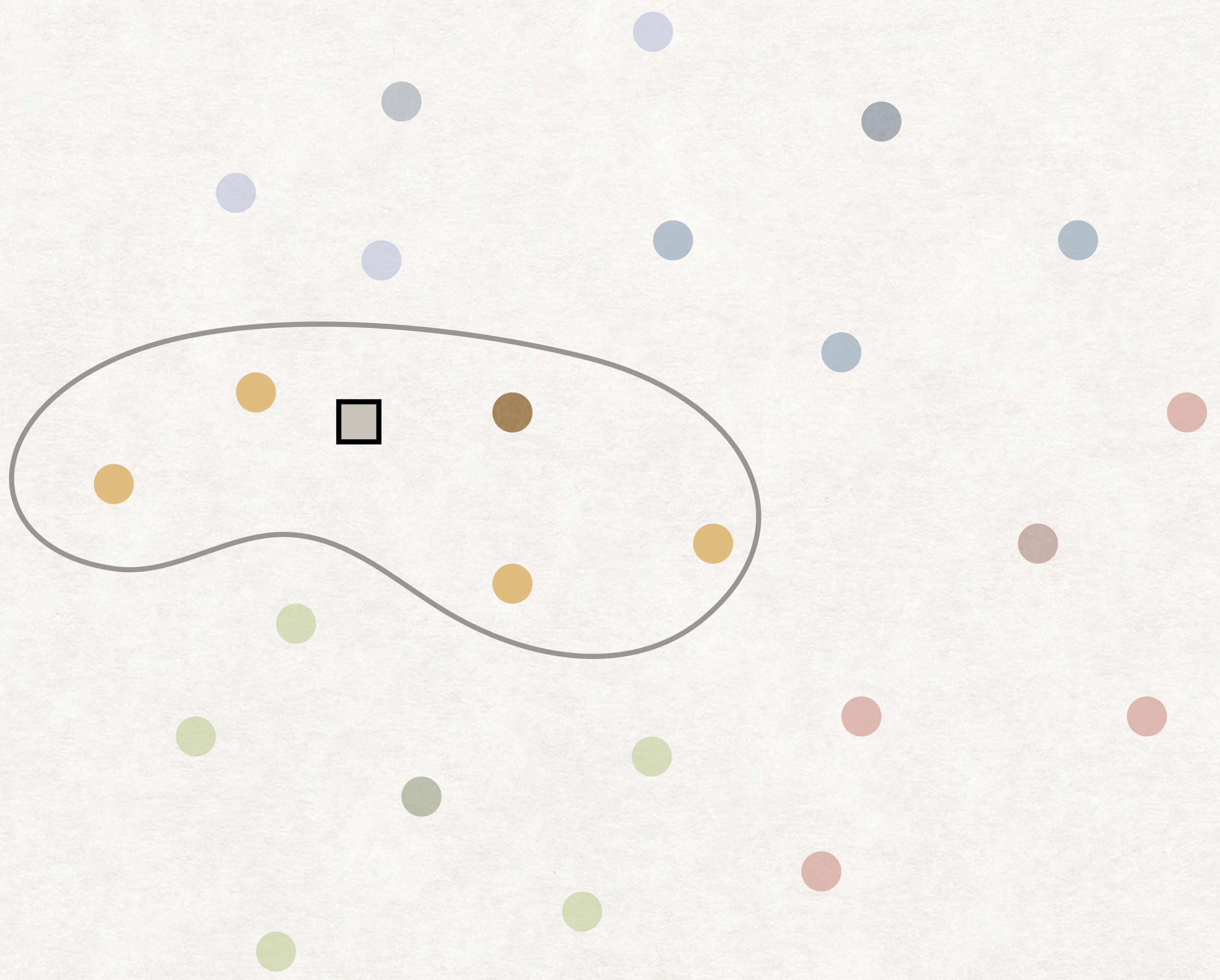
Assigning documents to clusters

A query arrives

The nearest leader is found

# CLUSTER PRUNING

## AN EXAMPLE



Documents represented as points in space

Selection of the leaders

Assigning documents to clusters

A query arrives

The nearest leader is found

The similarity is computed only in one cluster

## CLUSTER PRUNING

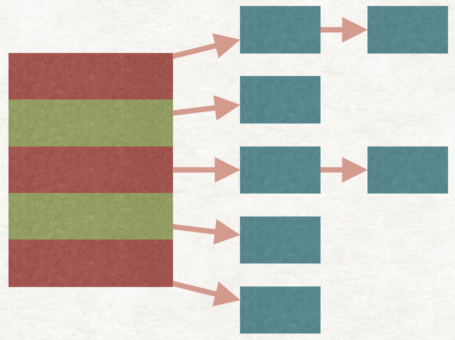
### ADDITIONAL CONSIDERATIONS

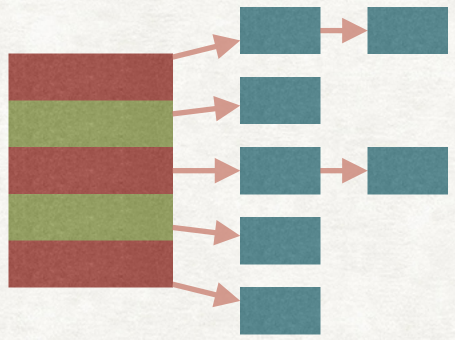
- The selection of $\sqrt{N}$ leaders randomly likely reflects the distribution of documents in the vector space: the most crowded regions will have more leaders.
- A variant more likely to return the “real” K highest ranked document is the following:
    - When creating clusters, each document is associated to $b_1$ leaders (i.e., it is part of more than one cluster).
    - When a query is received the clusters of the $b_2$ nearest leaders are considered.

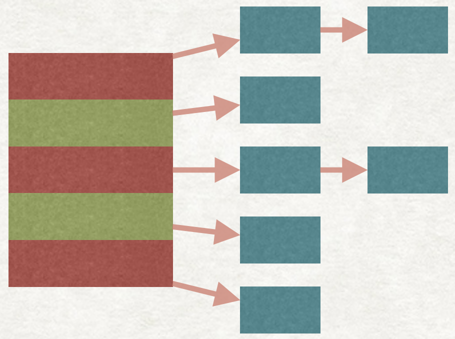
## INTEGRATING EVERYTHING

# TIERED INDEXES

## GENERALISATION OF CHAMPION LISTS

Rank 1  Index for documents with tf over 20

Rank 2  Index for documents with tf between 10 and 20

Rank 3  Index for documents with tf below 10

We search for K documents in the rank 1 index,
if we have less than K we continue in the rank 2 index, and so on

## QUERY TERM PROXIMITY

### TOWARDS A “SOFT CONJUNCTIVE” SEMANTICS

- If we have a query $q = t_1\ t_2\ \ldots, t_k$ we might want to give a higher score to documents in which the three terms appears close to each other.

- This is not a phrase query, but if the terms appears in close proximity the documents might be an indication that the document is more relevant.

- Let $\omega$ the length of the window (in term of number of words) in which $t_1, t_2, \ldots, t_k$ all appear.

## QUERY TERM PROXIMITY

### TOWARDS A “SOFT CONJUNCTIVE” SEMANTICS

Query: CAT XYLOPHONE

$\omega = 5$

Document 1: THE CAT JUMPED ON THE XYLOPHONE

$\omega =$ a lot more than $5$

Document 2: CAT: NOUN, A FELINE […] XYLOPHONE: NOUN, AN […]

How can we use $\omega$ in out scoring function?

- Hand-coding a scoring function using $\omega$
- As an additional linear term whose weight we can learn from training samples

## BOOLEAN RETRIEVAL

### HOW TO PERFORM IT IN THE VECTOR SPACE MODEL

- We can use the vector space representation to perform Boolean retrieval:
- A document $d$ is inside the set of documents denoted by $t$ iff $\vec{v}(d)_t > 0$ (i.e., if the entry $t$ of the vector of $d$ is positive).
- The reverse is not true: the Boolean model does not keep trace of frequencies.
- The two models are different in a more fundamental way: in the Boolean model the queries are written to *select documents*, in the vector space model queries are a form of *evidence accumulation*.

## WILDCARD QUERIES

### CAN WE IMPLEMENT IT IN THE VECTOR SPACE MODEL?

- In most cases wildcard queries need an additional (and separate) index.
- We can return, from that index, the set of terms that satisfy the wildcards present in the query.
- Suppose that we have CAT* as a query. We obtain the terms “CAT”, “CATASTROPHE”, and “CATERPILLAR”.
- How can we score a document?
- We simply consider the three terms as “normal” query terms: if a document contains all three of them then it will probably be more relevant.

## PHRASE QUERIES

### PHRASES IN A "BAG OF WORDS" MODEL

- In the vector space model our documents are "bags of words", without any ordering, while in phrase queries the ordering is important.
- The two models are, in some sense, incompatible: a bag of words model cannot be directly used for phrase queries.
- They can still be combined in some meaningful way:
    - Perform the phrase query and rank only the documents returned by the query.
    - If less than K documents are present then "reduce" the share query and start again.

## EVALUATION OF IR SYSTEMS

## STANDARD TEST COLLECTIONS

### STANDARD BENCHMARKS

CRANFIELD COLLECTION

ONE OF THE OLDEST, NOW TOO SMALL.
1398 ABSTRACTS OF AERODYNAMICS JOURNAL ARTICLES AND 225 QUERIES.

TREC
(TEXT RETRIEVAL CONFERENCE)

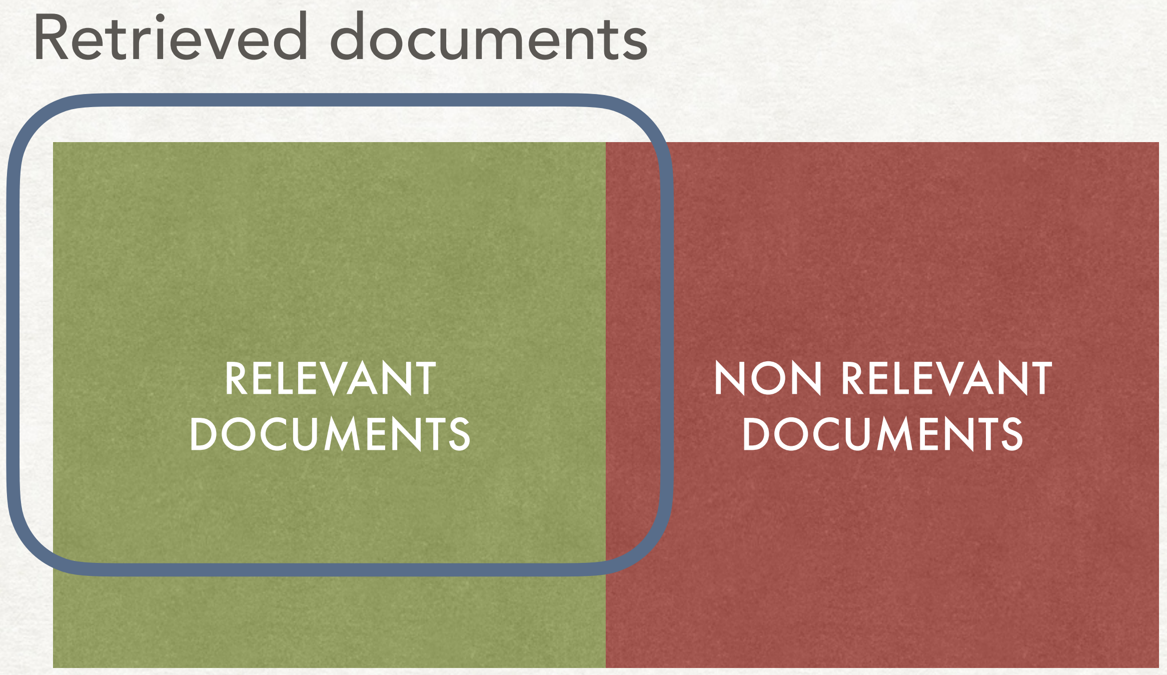
NOT A SINGLE COLLECTION. THERE IS A RANGE OF TEXT COLLECTIONS ON DIFFERENT TOPICS.
SEE : HTTPS://TREC.NIST.GOV

REUTERS

REUTERS-21578 (21578 DOCUMENTS) AND REUTERS-RCV1 (806791 DOCUMENTS) COLLECT A LARGE NUMBER OF NEWSWIRE ARTICLES

Also see: http://ir.dcs.gla.ac.uk/resources/test_collections/

## MEASURING EFFECTIVENESS



$$\text{precision} = \frac{\text{relevant} \cap \text{retrieved}}{\text{retrieved}}$$

Which fraction of the retrieved documents is relevant

$$\text{recall} = \frac{\text{relevant} \cap \text{retrieved}}{\text{relevant}}$$

Which fraction of the relevant documents has been retrieved

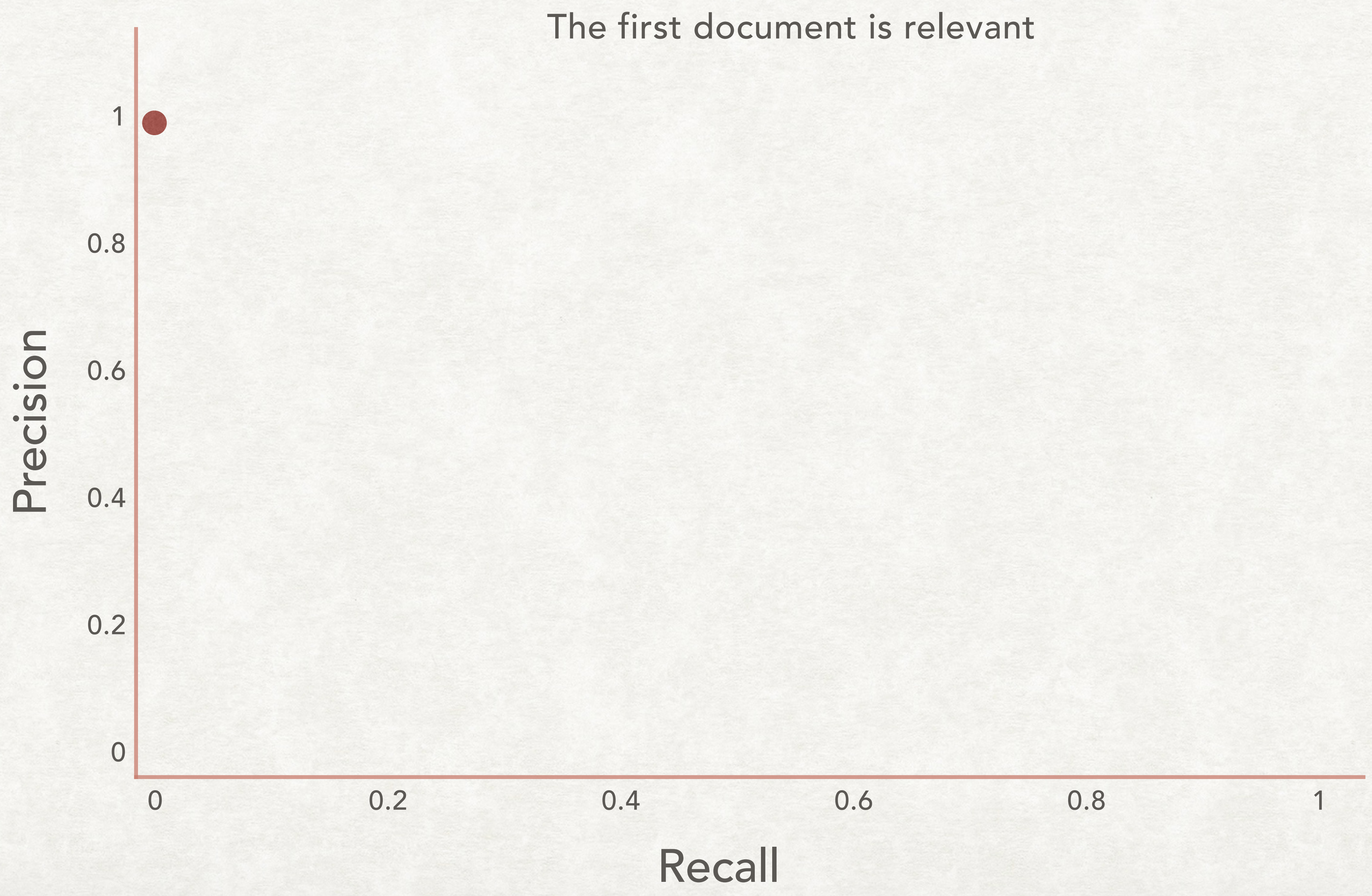
## RANKED RETRIEVAL

### HOW TO COMPUTE PRECISION AND RECALL?

- We usually evaluate the effectiveness of a IR system with precision and recall (other measures are also possible)…
- …and this works well with *unranked* results.
- How can we extend it to *ranked* results, where position is important?
    - Precision-recall curve and interpolated precision
    - Eleven-point interpolated average precision
    - Mean average precision (MAP)
    - Precision at $k$ and $R$-precision

## PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:

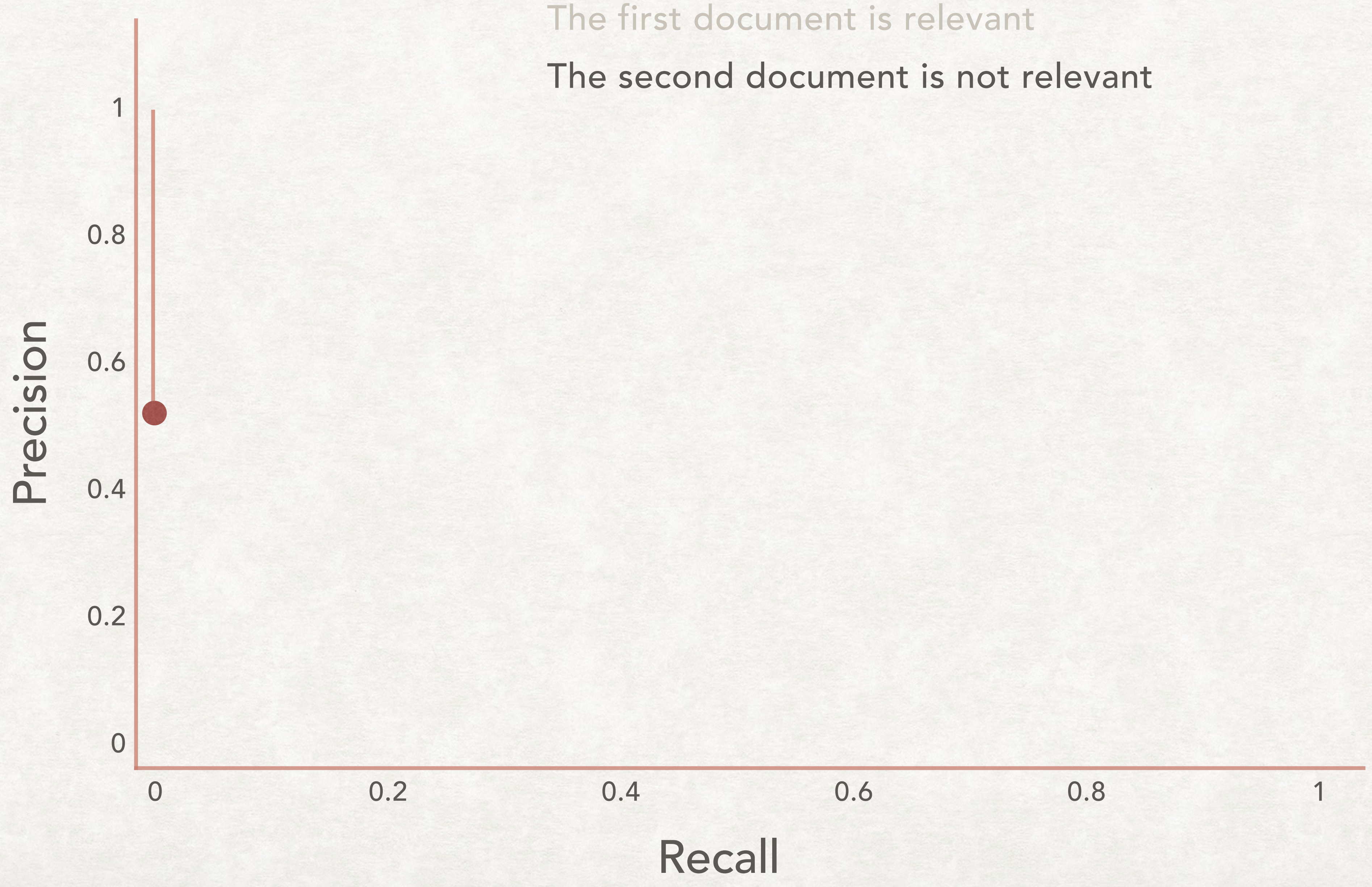


# PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:

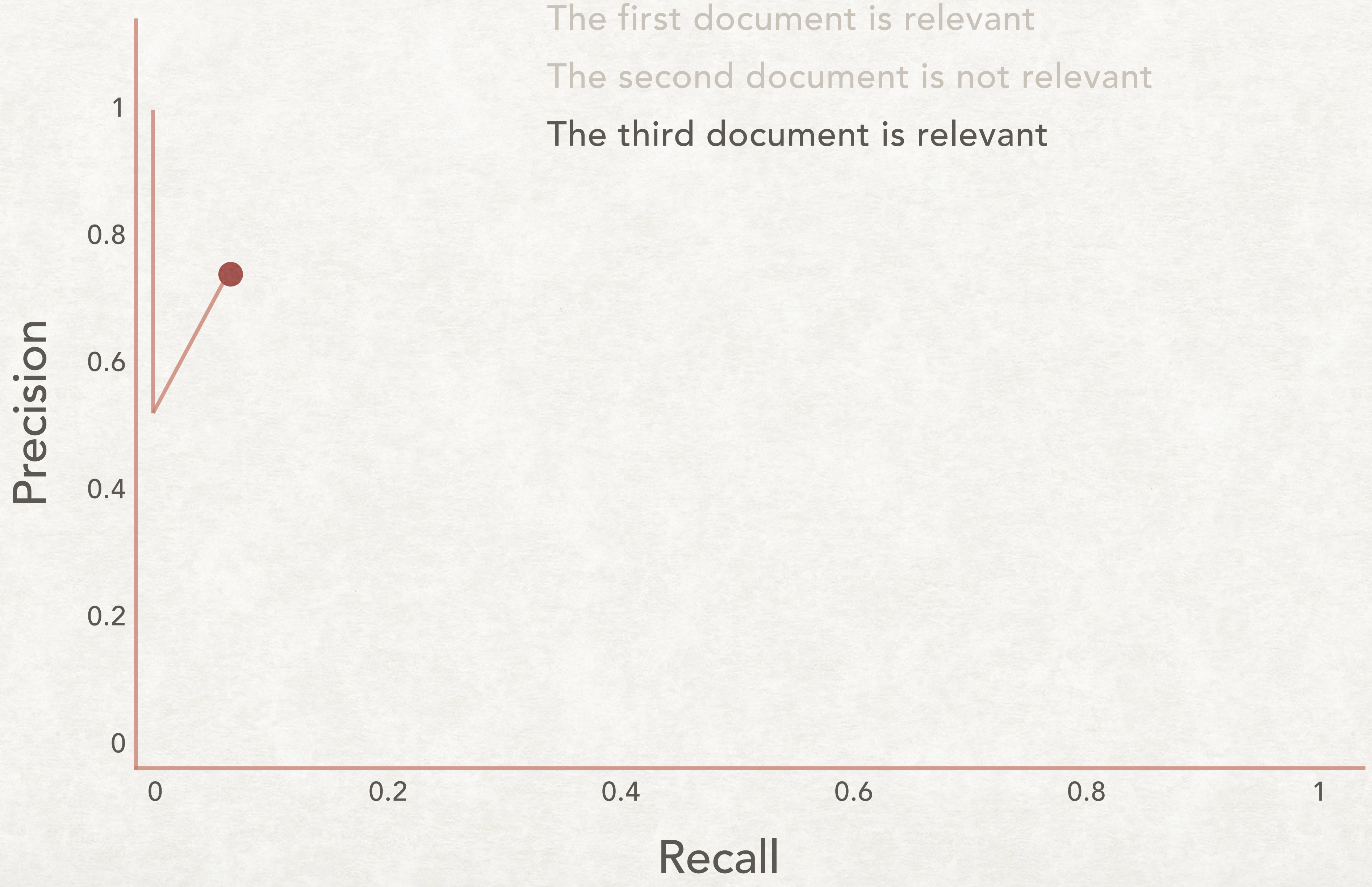
The first document is relevant

The second document is not relevant



# PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:



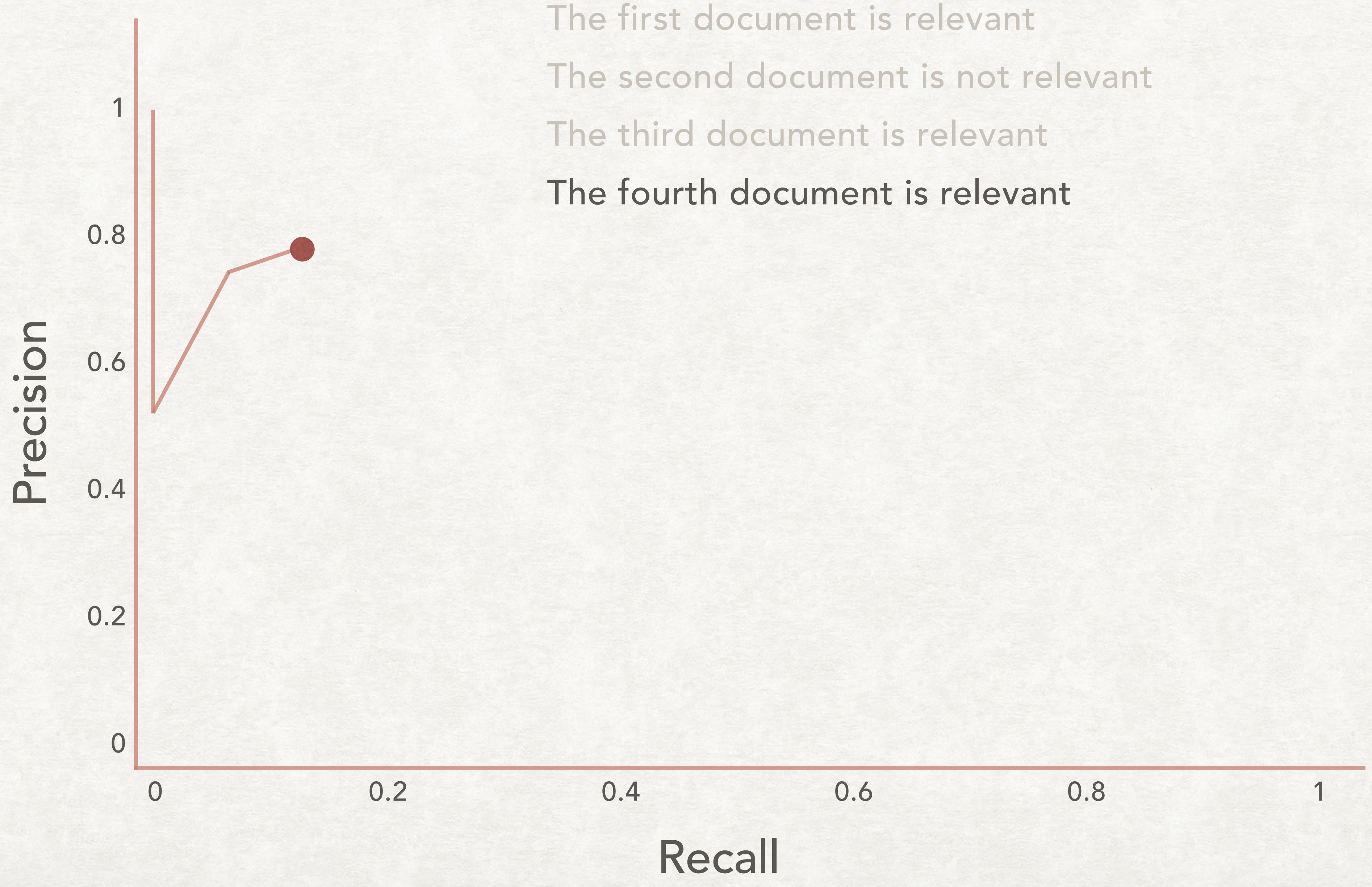
The first document is relevant

The second document is not relevant

The third document is relevant

## PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:



The first document is relevant

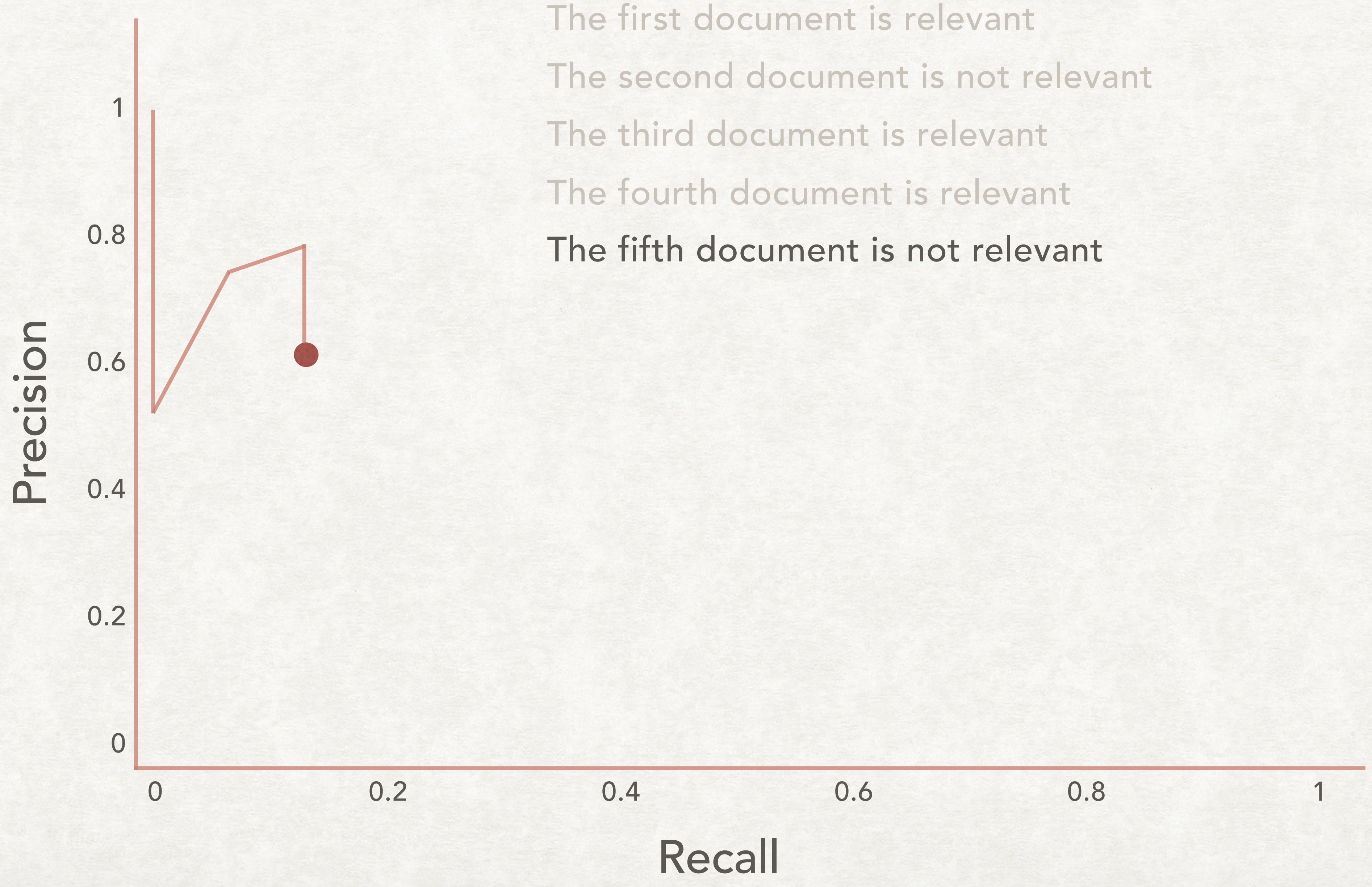
The second document is not relevant

The third document is relevant

The fourth document is relevant

## PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:



The first document is relevant

The second document is not relevant

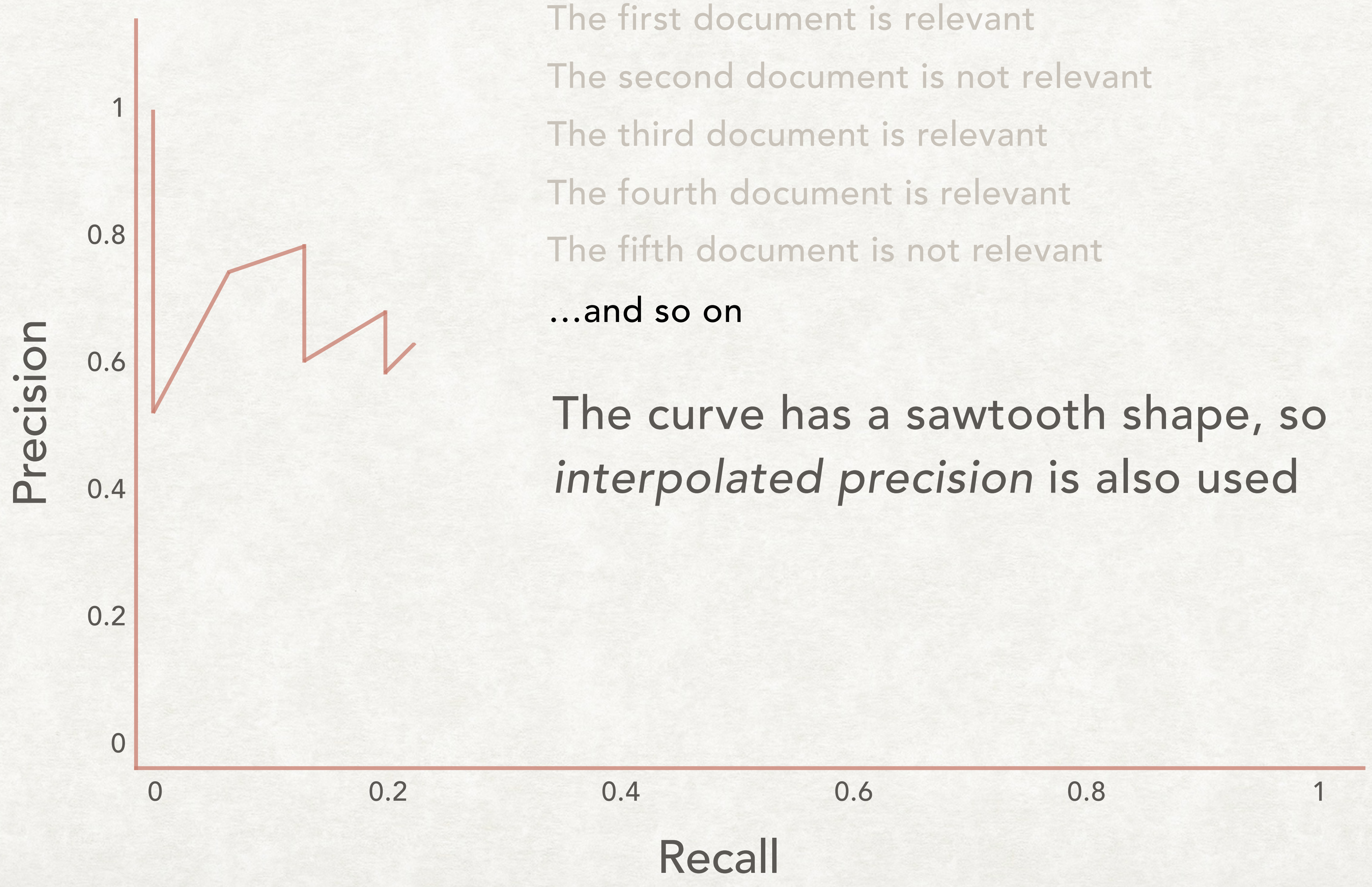
The third document is relevant

The fourth document is relevant

The fifth document is not relevant

# PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:



The first document is relevant

The second document is not relevant

The third document is relevant

The fourth document is relevant

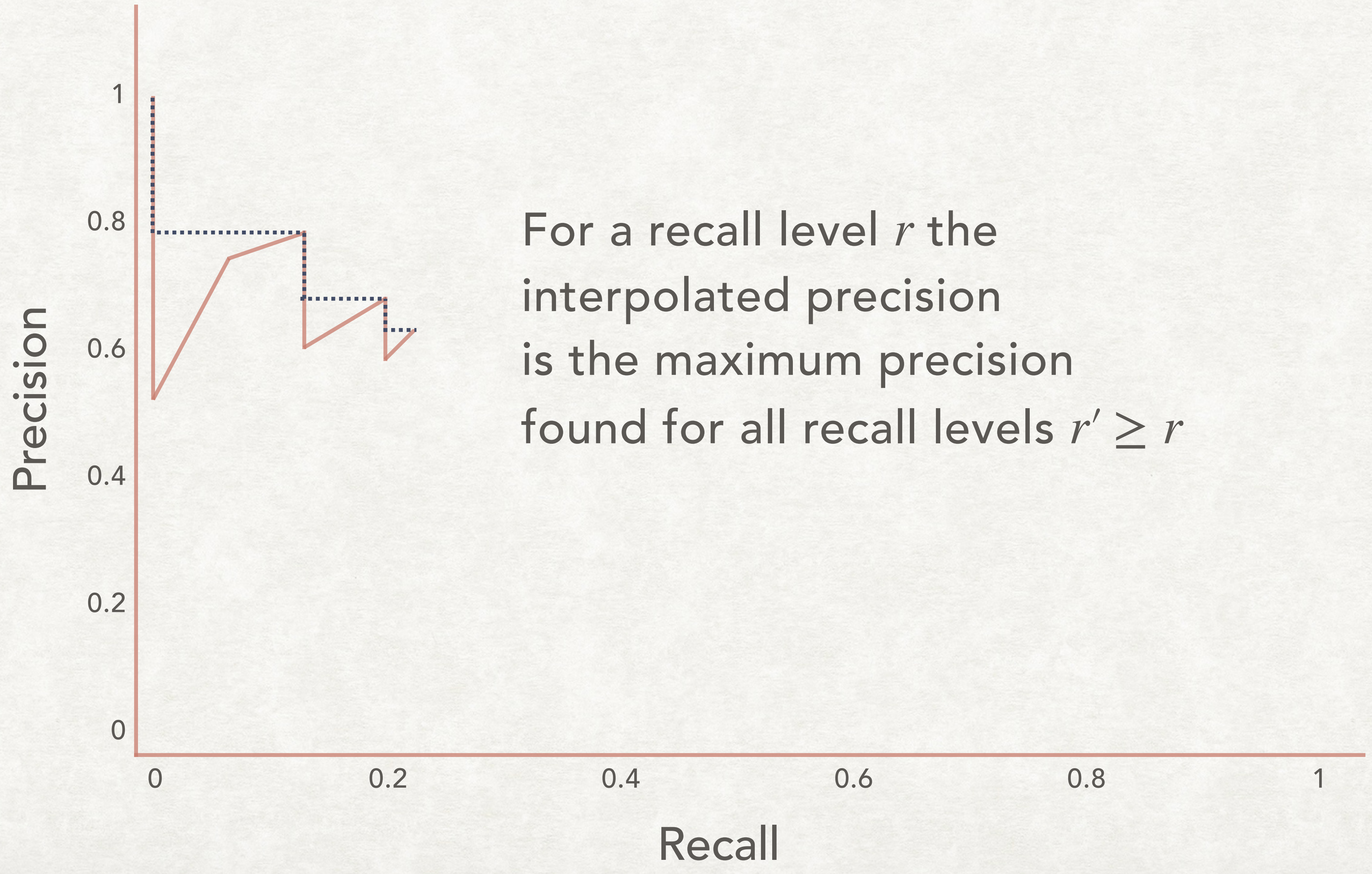
The fifth document is not relevant

…and so on

The curve has a sawtooth shape, so *interpolated precision* is also used

## PRECISION-RECALL CURVE

We compute precision and recall for the first 1, 2, 3, 4, etc. retrieved documents:



For a recall level $r$ the interpolated precision is the maximum precision found for all recall levels $r' \geq r$

## ELEVEN POINT INTERPOLATED PRECISION

### PRECISION AT ELEVEN RECALL LEVELS

| Recall | Precision |
|---|---|
| 0,0 | 1,0 |
| 0,1 | 0,73 |
| 0,2 | 0,64 |
| 0,3 | 0,58 |
| 0,4 | 0,51 |
| 0,5 | 0,45 |
| 0,6 | 0,38 |
| 0,7 | 0,27 |
| 0,8 | 0,21 |
| 0,9 | 0,13 |
| 1,0 | 0,09 |

The recall levels are fixed and for each recall level the corresponding precision is recorded.

## MEAN AVERAGE PRECISION (MAP)

### A SINGLE FIGURE

We have a set of queries $Q = \{q_1, \ldots, q_n\}$

For each $q_j$ we know the set of documents $\{d_1, \ldots, d_{m_j}\}$ that are relevant

Let $R_{jk}$ the set of ranked documents retrieved for the $j$th query that we get to obtain $k$ relevant documents

Then the mean average precision $\mathrm{MAP}(Q)$ is:

$$\frac{1}{n}\sum_{j=1}^{n}\left(\underbrace{\frac{1}{m_j}\sum_{k=1}^{m_j}\mathrm{Precision}(R_{jk})}_{\text{Average precision of the } j^{\text{th}} \text{ query}}\right)$$

## PRECISION AT K AND R-PRECISION

### OTHER SINGLE FIGURES

- Precision at $k$ simply means that we record the precision of the first $k$ retrieved documents. Like “precision at 10”.
- If there are less than $k$ relevant documents then the value cannot be one. Its value is highly dependant on the number of relevant documents that exists.
- A solution to this is the $R$-precision. If there are $R$ relevant documents for a query, the $R$-precision is the precision of the top $R$ ranked documents returned by the query.
- $R$-precision can be averaged across queries.

## RELEVANCE FEEDBACK

## WHAT IS RELEVANCE FEEDBACK

### RECEIVING FEEDBACK FROM THE USER

- The main idea is to involve the user in giving feedback on the initial set of results:
- The user issues a query.
- The system returns an initial set of results.
- The user decides which results are relevant and which are not.
- The system computes a new set of results based on the feedback received by the user.
- If necessary, repeat.

## WHAT RELEVANCE FEEDBACK CAN SOLVE

### AND WHAT IT CANNOT SOLVE

- Relevance feedback can help the user in refining the query without having him/her reformulate it manually.
- It is a *local method*, where the initial query is modified, in contrast to *global methods* that change the wording of the query (like spelling correction).
- Relevance feedback can be ineffective when in the case of
    - Misspelling (but we have seen spelling correction techniques).
    - Searching documents in another language.
    - Vocabulary mismatch between the user and the collection.

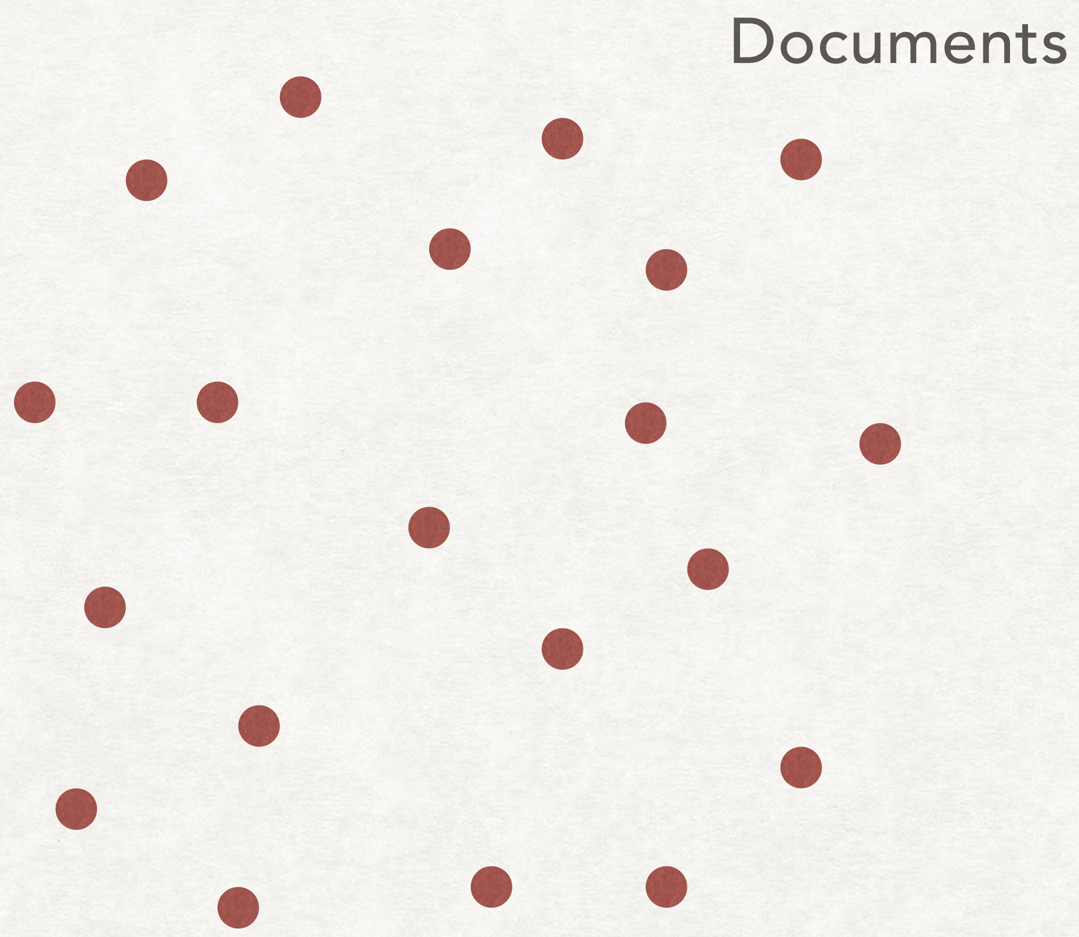
## THE ROCCHIO ALGORITHM

### FEEDBACK FOR THE VECTOR SPACE MODEL

- It is possible to introduce relevance feedback in the vector space model
- We will see the Rocchio Algorithm (1971)
- It was introduced in the SMART (*System for the Mechanical Analysis and Retrieval of Text*) information retrieval system…
- …which is also where the vector space model was firstly developed

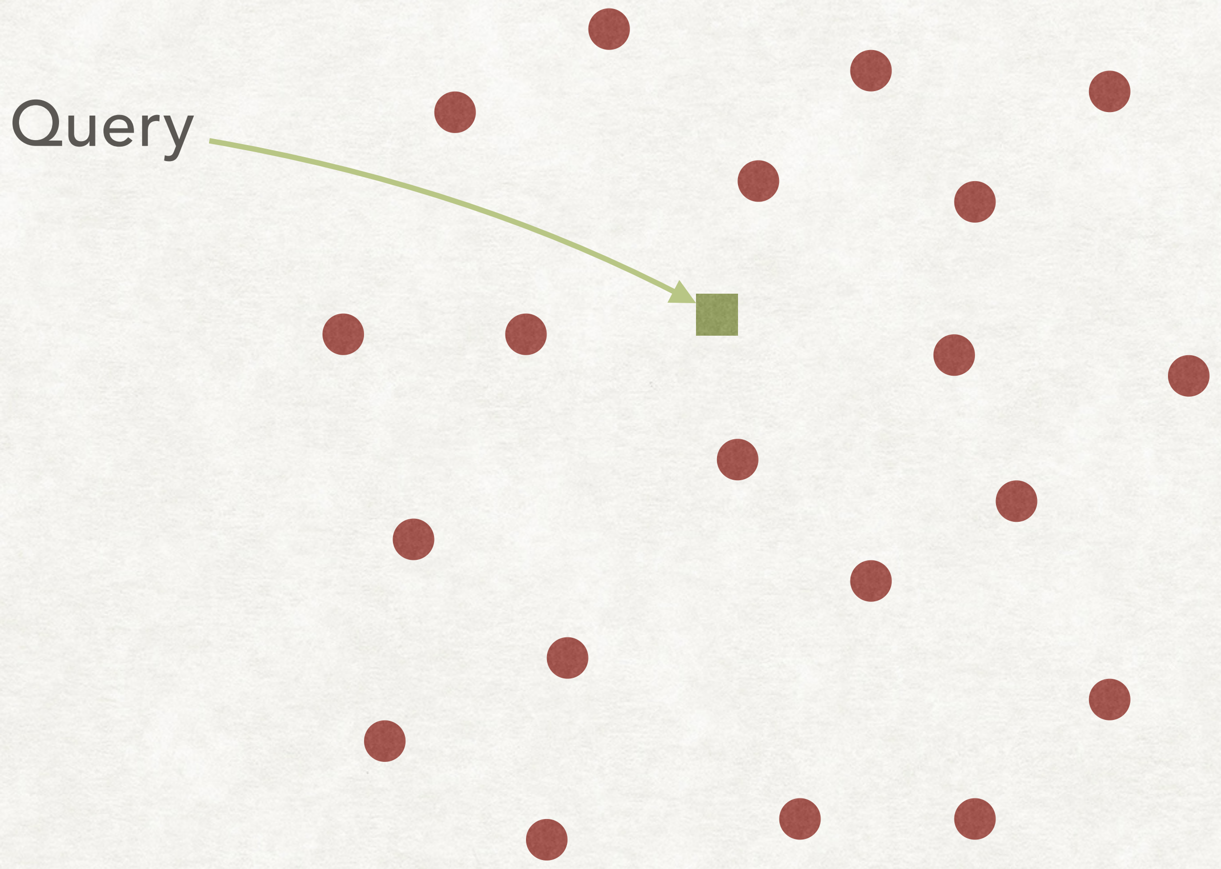
## ROCCHIO ALGORITHM: MAIN IDEA

### MOVING THE QUERY VECTOR



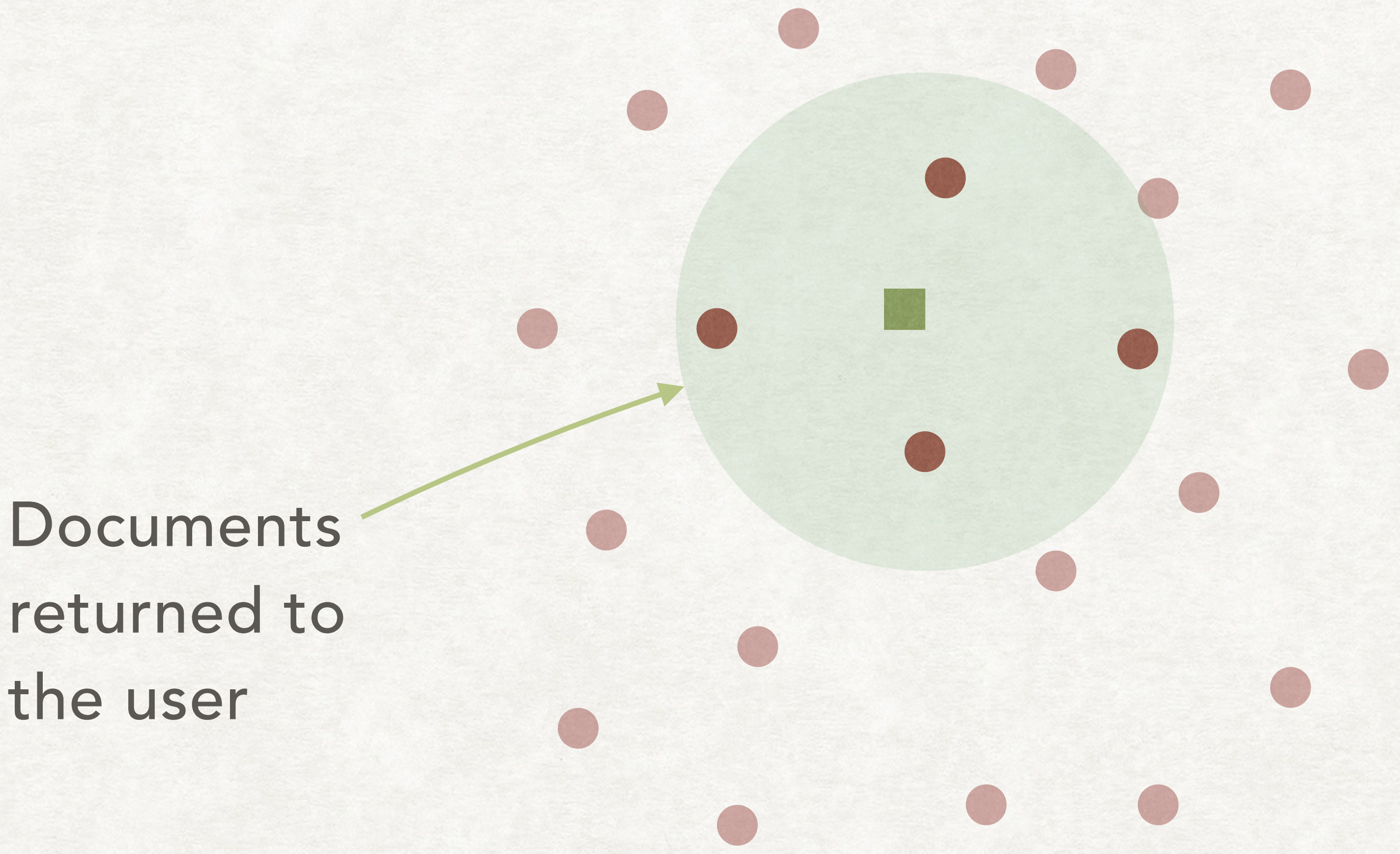
## ROCCHIO ALGORITHM: MAIN IDEA

### MOVING THE QUERY VECTOR



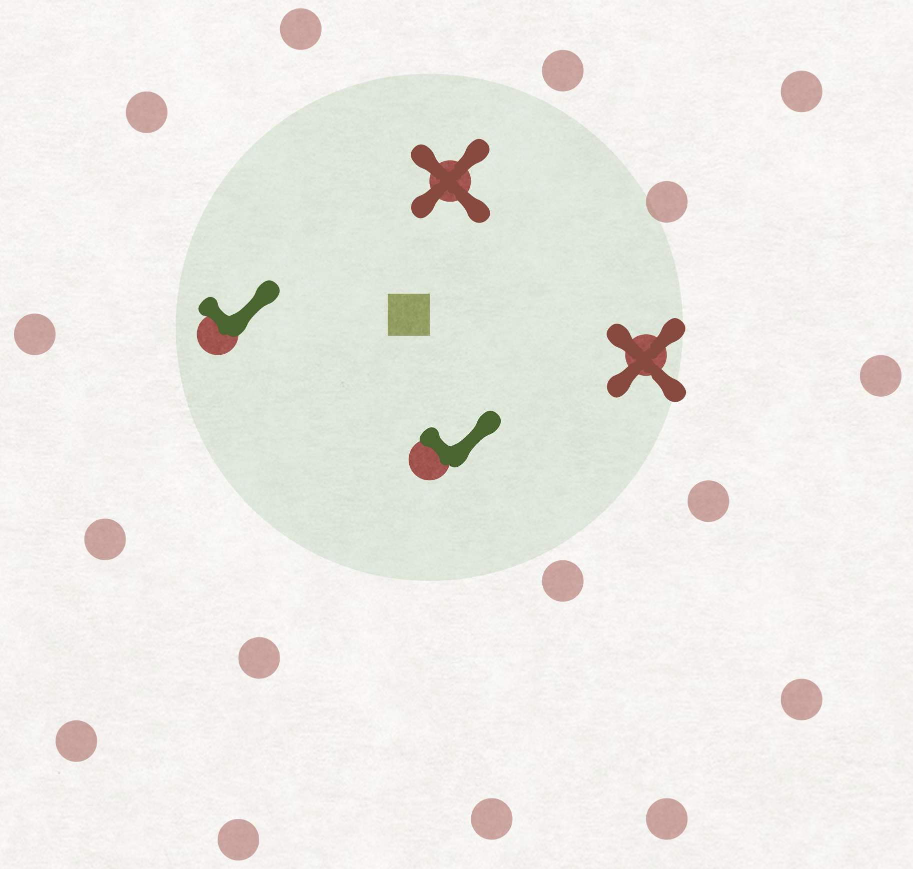
# ROCCHIO ALGORITHM: MAIN IDEA

## MOVING THE QUERY VECTOR



# ROCCHIO ALGORITHM: MAIN IDEA

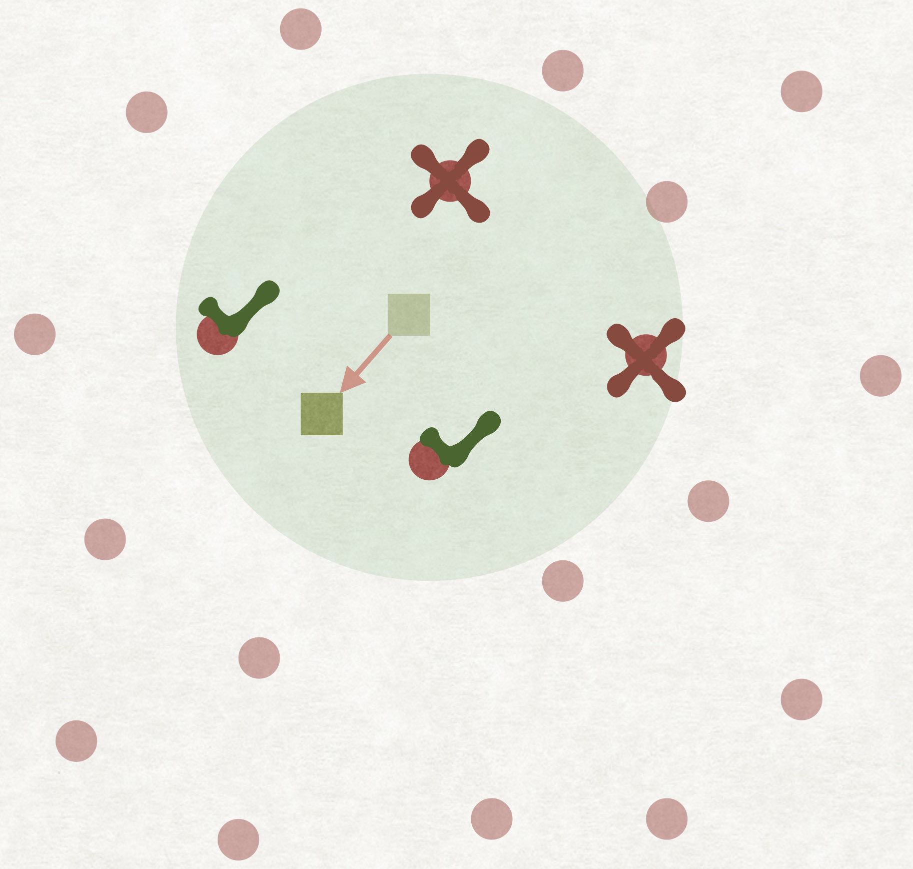
## MOVING THE QUERY VECTOR



Feedback from the user

# ROCCHIO ALGORITHM: MAIN IDEA

## MOVING THE QUERY VECTOR



Revised query

## ROCCHIO ALGORITHM: THEORY

- The user gives us two sets of documents:
  - The relevant documents $C_r$
  - The non-relevant documents $C_{nr}$
- We want to maximise the similarity of the query with the set of relevant documents…
- …while minimising it with respect to the set of non-relevant documents.

# ROCCHIO ALGORITHM: THEORY

This can be formalised as defining the *optimal* query $\vec{q}_{opt}$ as:

$$\vec{q}_{opt} = \arg\max_{\vec{q}} [\mathrm{sim}(\vec{q}, C_r) - \mathrm{sim}(\vec{q}, C_{nr})]$$

If we use cosine similarity, we can reformulate the definition as:

$$\vec{q}_{opt} = \underbrace{\frac{1}{|C_r|} \sum_{\vec{d} \in C_r} \vec{d}}_{\text{Centroid of relevant documents}} - \underbrace{\frac{1}{|C_{nr}|} \sum_{\vec{d} \in C_{nr}} \vec{d}}_{\text{Centroid of non-relevant documents}}$$

## ROCCHIO ALGORITHM

However, we usually do not have knowledge of the relevance of *all* documents in the system. Instead we have:

- a set $D_r$ of *known relevant* documents
- a set $D_{nr}$ of *known non-relevant* documents

We also have the original query $\vec{q}_0$ performed by the user.

We can perform a linear combination of:

- The centroid of $D_r$
- The centroid of $D_{nr}$
- The original query $\vec{q}_0$

## ROCCHIO ALGORITHM

In the Rocchio algorithm the query is updated as follows:

$$\vec{q}_m = \alpha \underbrace{\vec{q}_0}_{\text{Original query}} + \beta \underbrace{\frac{1}{|D_r|} \sum_{\vec{d} \in C_r} \vec{d}}_{\text{Centroid of the known relevant documents}} - \gamma \underbrace{\frac{1}{|D_{nr}|} \sum_{\vec{d} \in C_{nr}} \vec{d}}_{\text{Centroid of the known non-relevant documents}}$$

If one of the components of $\vec{q}_m$ is less than $0$, we set it to $0$ (all documents have non-negative coordinates)

## ROCCHIO ALGORITHM

### SELECTING THE WEIGHTS

- We need to select reasonable weights $\alpha$, $\beta$, and $\gamma$:
- Positive feedback is more valuable than negative feedback, so usually $\gamma < \beta$.
- Reasonable values might be $\alpha = 1$, $\beta = 0.75$, and $\gamma = 0.15$.
- It is also possible to also have only positive feedback with $\gamma = 0$.

## PSEUDO-RELEVANCE FEEDBACK

### NOW WITHOUT THE USER

- It is possible to perform a relevance feedback without the user…
- …even before he/she receives the results of the first query.
- Perform the query $\vec{q}$ as usual.
- Consider the first $k$ retrieved documents in the ranking as relevant.
- Perform relevance feedback using this assumption.
- Might provide better results, but the retrieved documents might drift the query in an unwanted direction.