Natural Language Processing and Information Retrieval

VSM and Optmization

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Summary: weighting

- Term Weighting

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d}, & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

- The idf (inverse document frequency) of *t* by

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

Summary: tf-idf weighting

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

$$w_{t,d} = (1 + \log_{10} \mathrm{tf}_{t,d}) \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

Recap: 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

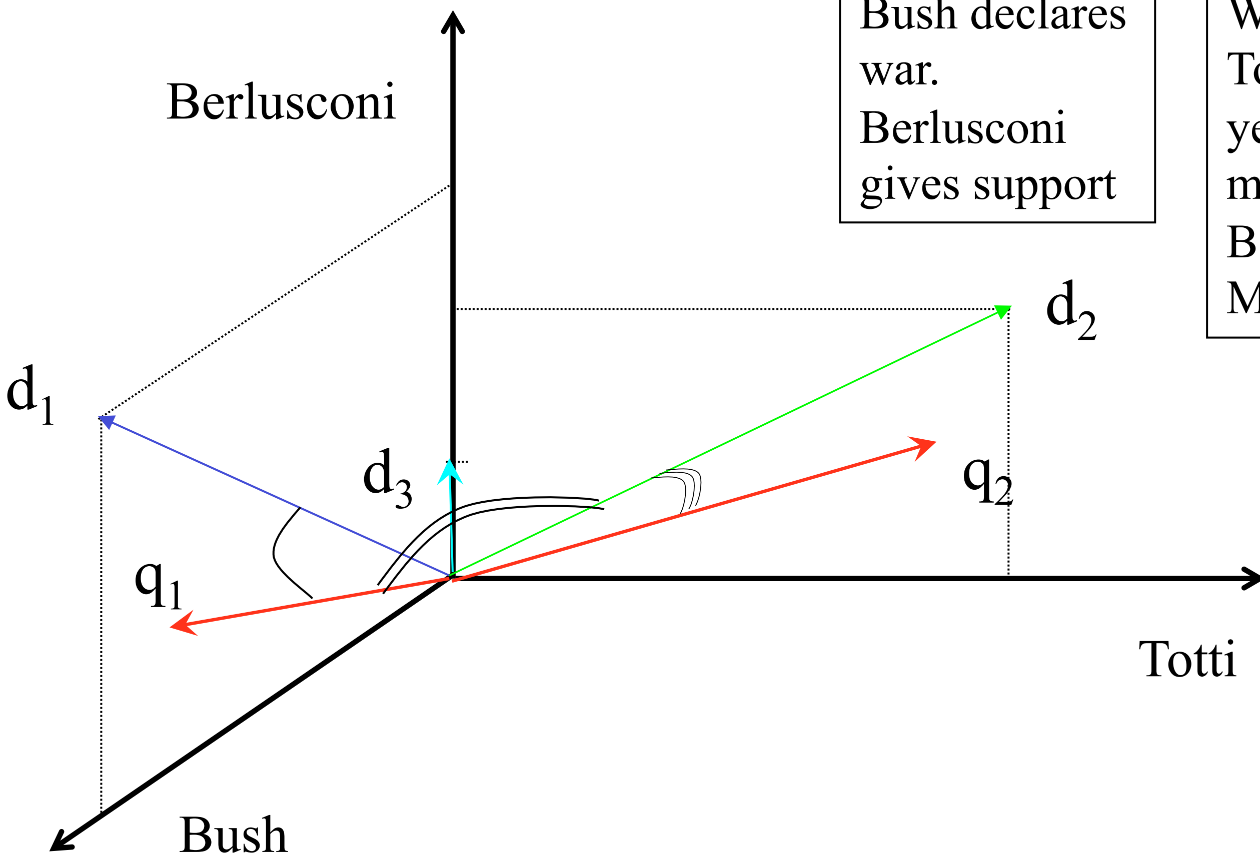
Summary – vector space ranking

- Represent the query as a weighted tf-idf vector
- Represent each document as a weighted tf-idf vector
- Compute the cosine similarity score for the query vector and each document vector
- Rank documents with respect to the query by score
- Return the top K (e.g., $K = 10$) to the user

VSM: formal definition (see Salton 89’)

- Features are dimensions of a Vector Space
- Documents and Queries are vectors of feature weights
- A set of documents is retrieved based on $\vec{d} \cdot \vec{q}$,
- where $\vec{d}, \vec{q}$ are the vectors representing documents and query

The Vector Space Model



d_1: Politic

Bush declares war. Berlusconi gives support

d_2: Sport

Wonderful Totti in the yesterday match against Berlusconi's Milan

d_3:Economic

Berlusconi acquires Inzaghi before elections

$\mathbf{q_1}$: **Berlusconi** visited **Bush**

$\mathbf{q_2}$: **Totti** will not play against **Berlusconi's** milan

tf-idf weighting has many variants

Term frequency		Document frequency		Normalization	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(\mathrm{tf}_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{df}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2+w_2^2+\ldots+w_M^2}}$
a (augmented)	$0.5 + \frac{0.5\times\mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N-\mathrm{df}_t}{\mathrm{df}_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases} 1 & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/CharLength^{\alpha}$, $\alpha < 1$
L (log ave)	$\frac{1+\log(\mathrm{tf}_{t,d})}{1+\log(\mathrm{ave}_{t\in d}(\mathrm{tf}_{t,d}))}$				

Columns headed 'n' are acronyms for weight schemes.

Why is the base of the log in idf immaterial?

Weighting may differ in queries vs documents

- Many search engines allow for different weightings for queries vs. documents
- SMART Notation: denotes the combination in use in an engine, with the notation *ddd.qqq,* using the acronyms from the previous table
- A very standard weighting scheme is: lnc.ltc
- Document: logarithmic tf (l as first character), no idf and cosine normalization

A bad idea?

- Query: logarithmic tf (l in leftmost column), idf (t in second column), no normalization …

tf-idf example: lnc.ltc

Document: *car insurance auto insurance*
Query: *best car insurance*

Term	Query						Document				Prod
	tf-raw	tf-wt	df	idf	wt	n'lize	tf-raw	tf-wt	wt	n'lize	
auto	0	0	5000	2.3	0	0	1	1	1	0.52	0
best	1	1	50000	1.3	1.3	0.34	0	0	0	0	0
car	1	1	10000	2.0	2.0	0.52	1	1	1	0.52	0.27
insurance	1	1	1000	3.0	3.0	0.78	2	1.3	1.3	0.68	0.53

$$\text{Doc length} = \sqrt{1^2 + 0^2 + 1^2 + 1.3^2} \approx 1.92$$

Score = 0+0+0.27+0.53 = 0.8

Computing cosine scores

$\textsc{CosineScore}(q)$

$\mathit{float}\ \mathit{Scores}[N] = 0$
$\mathit{float}\ \mathit{Length}[N]$
for each query term t
do calculate $\mathrm{w}_{t,q}$ and fetch postings list for t
    for each pair$(d, \mathrm{tf}_{t,d})$ in postings list
    do $\mathit{Scores}[d] += \mathrm{w}_{t,d} \times \mathrm{w}_{t,q}$
Read the array Length
for each d
do $\mathit{Scores}[d] = \mathit{Scores}[d]/\mathit{Length}[d]$
return Top K components of $\mathit{Scores}[]$

Efficient cosine ranking

- Find the K docs in the collection "nearest" to the query $\Rightarrow$ K largest query-doc cosines.
- Efficient ranking:
  - Computing a single cosine efficiently.
  - Choosing the K largest cosine values efficiently.
    - Can we do this without computing all N cosines?

Efficient cosine ranking

- What we're doing in effect: solving the *K*-nearest neighbor problem for a query vector
- In general, we do not know how to do this efficiently for high-dimensional spaces
- But it is solvable for short queries, and standard indexes support this well

Special case – unweighted queries

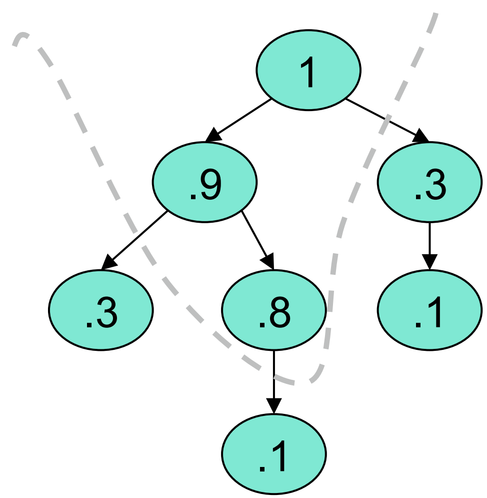
- No weighting on query terms
  - Assume each query term occurs only once
- Then for ranking, don't need to normalize query vector
  - Slight simplification of algorithm

Computing the *K* largest cosines: selection vs. sorting

- Typically we want to retrieve the top *K* docs (in the cosine ranking for the query)
  - not to totally order all docs in the collection
- Can we pick off docs with *K* highest cosines?
- Let *J* = number of docs with nonzero cosines
  - We seek the *K* best of these *J*

Use heap for selecting top *K*

- Binary tree in which each node's value > the values of children
- Takes 2*J* operations to construct, then each of *K* "winners" read off in 2log *J* steps.
- For *J*=1M, *K*=100, this is about 10% of the cost of sorting.



Bottlenecks

- Primary computational bottleneck in scoring: <u>cosine computation</u>
- Can we avoid all this computation?
- Yes, but may sometimes get it wrong
  - a doc *not* in the top *K* may creep into the list of *K* output docs
  - Is this such a bad thing?

Cosine similarity is only a proxy

- User has a task and a query formulation
- Cosine matches docs to query
- Thus cosine is anyway a proxy for user happiness
- If we get a list of *K* docs "close" to the top *K* by cosine measure, should be ok

Generic approach

- Find a set *A* of *contenders*, with $K < |A| << N$
  - *A* does not necessarily contain the top *K*, but has many docs from among the top *K*
  - Return the top *K* docs in *A*
- Think of *A* as <u>pruning</u> non-contenders
- The same approach is also used for other (non-cosine) scoring functions
- Will look at several schemes following this approach

Index elimination

- Basic algorithm cosine computation algorithm only considers docs containing at least one query term
- Take this further:
  - Only consider high-idf query terms
  - Only consider docs containing many query terms

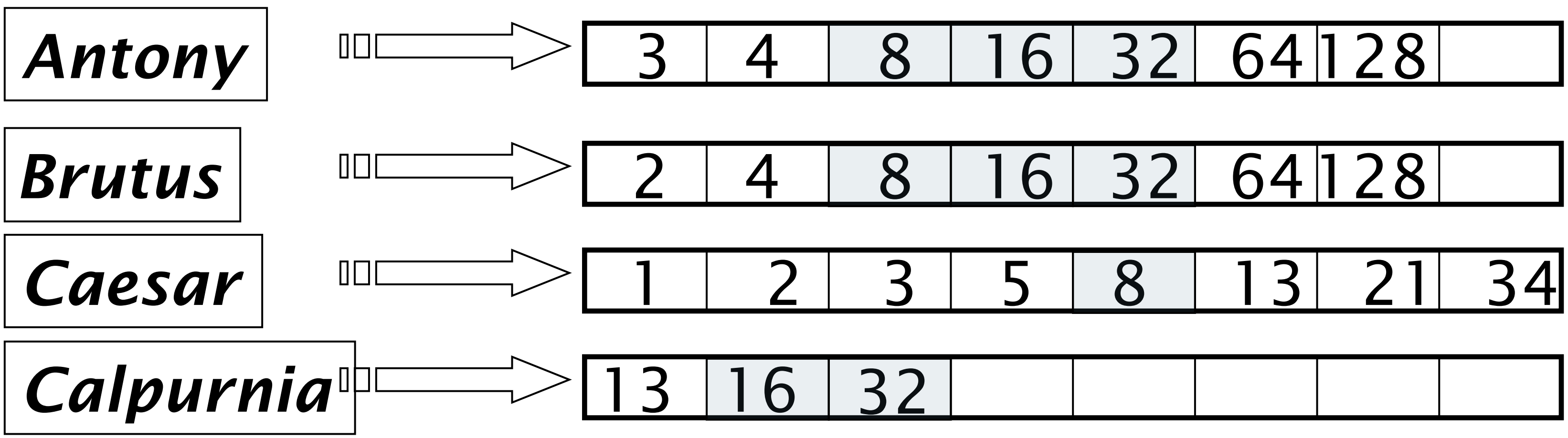
High-idf query terms only

- For a query such as *catcher in the rye*
- Only accumulate scores from *catcher* and *rye*
- Intuition: ***in*** and ***the*** contribute little to the scores and so don't alter rank-ordering much
- Benefit:
  - Postings of low-idf terms have many docs → these (many) docs get eliminated from set *A* of contenders

Docs containing many query terms

- Any doc with at least one query term is a candidate for the top *K* output list
- For multi-term queries, only compute scores for docs containing several of the query terms
  - Say, at least 3 out of 4
  - Imposes a "soft conjunction" on queries seen on web search engines (early Google)
- Easy to implement in postings traversal

3 of 4 query terms



Scores only computed for docs 8, 16 and 32.

Champion lists

- Precompute for each dictionary term *t*, the *r* docs of highest weight in *t*'s postings
  - Call this the <u>champion list</u> for *t*
  - (aka <u>fancy list</u> or <u>top docs</u> for *t*)
- Note that *r* has to be chosen at index build time
  - Thus, it's possible that $r < K$
- At query time, only compute scores for docs in the champion list of some query term
  - Pick the *K* top-scoring docs from amongst these

Exercises

- How do Champion Lists relate to Index Elimination? Can they be used together?
- How can Champion Lists be implemented in an inverted index?
  - Note that the champion list has nothing to do with small docIDs

Static quality scores

- We want top-ranking documents to be both *relevant* and *authoritative*
- *Relevance* is being modeled by cosine scores
- *Authority* is typically a query-independent property of a document
- Examples of authority signals
  - Wikipedia among websites
  - Articles in certain newspapers
  - A paper with many citations
  - Account from website, e.g. delicious.com
  - Pagerank

Quantitative

Modeling authority

- Assign to each document a *query-independent* quality score in [0,1] to each document *d*
  - Denote this by *g(d)*
- Thus, a quantity like the number of citations is scaled into [0,1]
  - Exercise: suggest a formula for this.

Net score

- Consider a simple total score combining cosine relevance and authority
- net-score(q,d) = $g(d)$ + cosine(q,d)
  - Can use some other linear combination
  - Indeed, any function of the two "signals" of user happiness – more later
- Now we seek the top *K* docs by net score

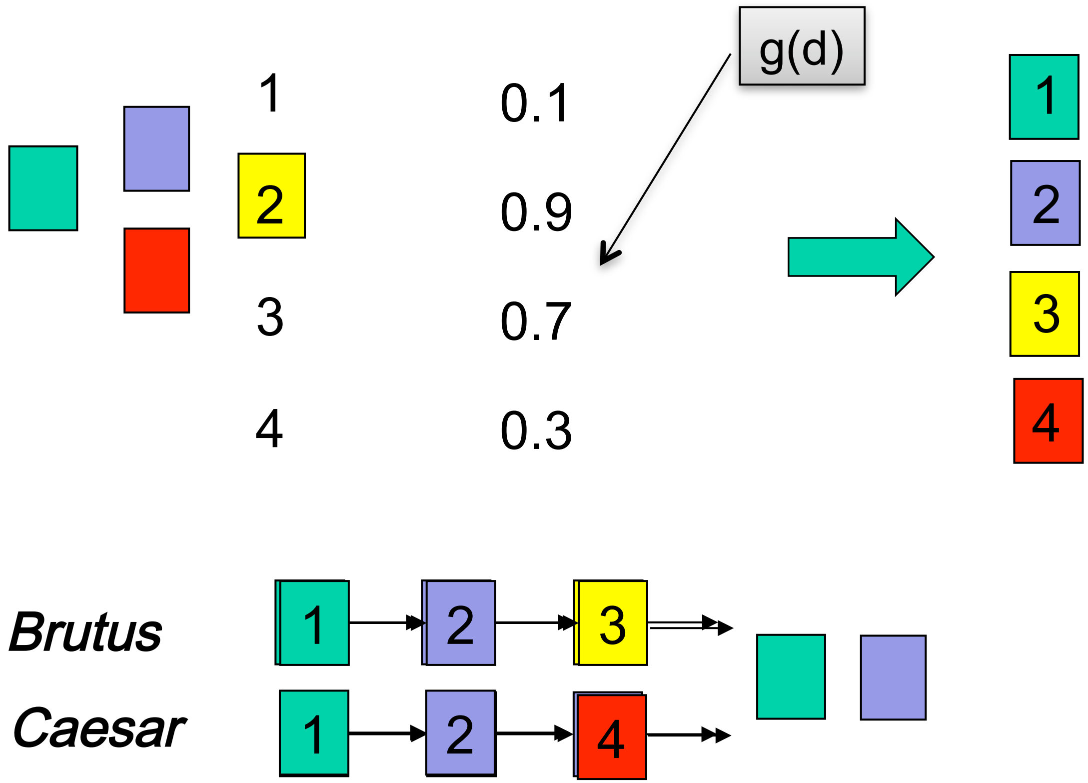
Top *K* by net score – fast methods

- First idea: Order all postings by *g(d)*
- Key: this is a common ordering for all postings
- Thus, can concurrently traverse query terms' postings for
  - Postings intersection
  - Cosine score computation
- Exercise: write pseudocode for cosine score computation if postings are ordered by *g(d)*

Why order postings by *g(d)*?

- Under *g(d)*-ordering, top-scoring docs likely to appear early in postings traversal
- In time-bound applications (say, we have to return whatever search results we can in 50 ms), this allows us to stop postings traversal early
    - Short of computing scores for all docs in postings

Re-ordering with respect to g(d)



Champion lists in *g(d)*-ordering

- Can combine champion lists with *g(d)*-ordering
- Maintain for each term a champion list of the *r* docs with highest $g(d)$ + tf-idf$_{td}$
- Seek top-*K* results from only the docs in these champion lists

High and low lists

- For each term, we maintain two postings lists called *high* and *low*
  - Think of *high* as the champion list
- When traversing postings on a query, only traverse *high* lists first
  - If we get more than *K* docs, select the top *K* and stop
  - Else proceed to get docs from the *low* lists
- Can be used even for simple cosine scores, without global quality *g(d)*
- A means for segmenting index into two tiers

Impact-ordered postings

- We only want to compute scores for docs for which $wf_{t,d}$ is high enough
- We sort each postings list by $wf_{t,d}$
- Now: not all postings in a common order!
- How do we compute scores in order to pick off top *K*?
  - Two ideas follow

1. Early termination

- When traversing t's postings, stop early after either
  - a fixed number of r docs
  - $wf_{t,d}$ drops below some threshold
- Take the union of the resulting sets of docs
  - One from the postings of each query term
- Compute only the scores for docs in this union

2. idf-ordered terms

- When considering the postings of query terms
- Look at them in order of decreasing idf
  - High idf terms likely to contribute most to score
- As we update score contribution from each query term
  - Stop if doc scores relatively unchanged
- Can apply to cosine or some other net scores

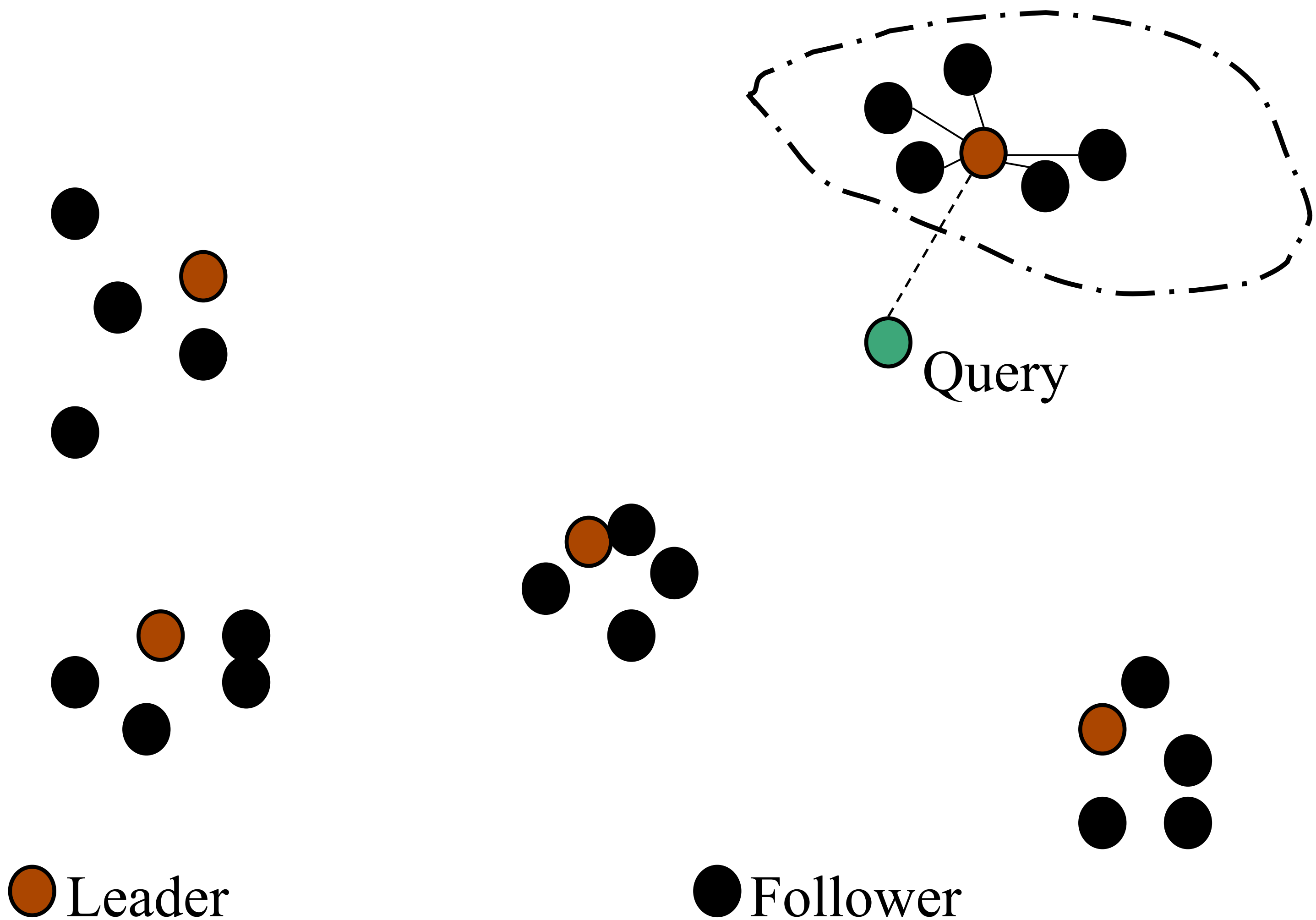
Cluster pruning: preprocessing

- Pick √N *docs* at random: call these *leaders*
- For every other doc, pre-compute nearest leader
  - Docs attached to a leader: its *followers;*
  - <u>Likely</u>: each leader has ~ √*N* followers.

Cluster pruning: query processing

- Process a query as follows:
  - Given query *Q*, find its nearest *leader L.*
  - Seek *K* nearest docs from among *L*'s followers.

Visualization



Why use random sampling

- Fast
- Leaders reflect data distribution

General variants

- Have each follower attached to $b1$=3 (say) nearest leaders.
- From query, find $b2$=4 (say) nearest leaders and their followers.
- Can recurse on leader/follower construction.

Exercises

- To find the nearest leader in step 1, how many cosine computations do we do?
  - Why did we have √N in the first place?
- What is the effect of the constants *b1, b2* on the previous slide?
- Devise an example where this is *likely to* fail – i.e., we miss one of the *K* nearest docs.
  - *Likely* under random sampling.

Parametric and zone indexes

- Thus far, a doc has been a sequence of terms
- In fact documents have multiple parts, some with special semantics:
  - Author
  - Title
  - Date of publication
  - Language
  - Format
  - etc.
- These constitute the metadata about a document

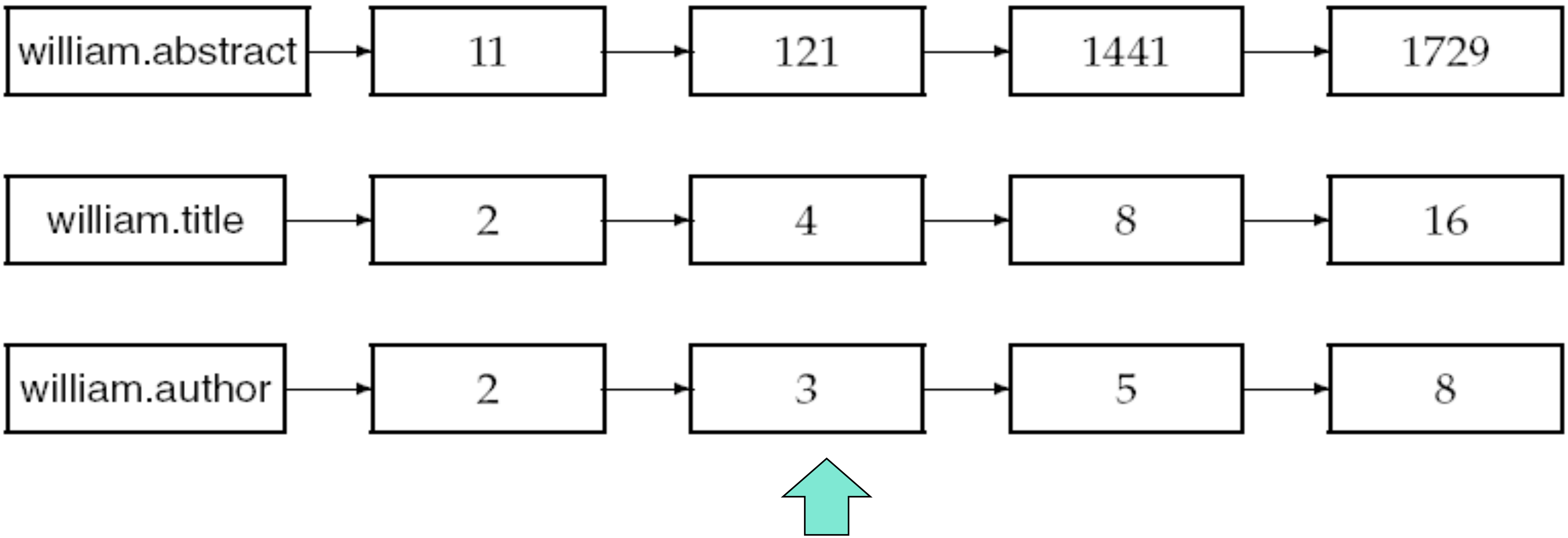
Fields

- We sometimes wish to search by these metadata
  - E.g., find docs authored by William Shakespeare in the year 1601, containing *alas poor Yorick*
- Year = 1601 is an example of a <u>field</u>
- Also, author last name = shakespeare, etc.
- Field or parametric index: postings for each field value
  - Sometimes build range trees (e.g., for dates)
- Field query typically treated as conjunction
  - (doc *must* be authored by shakespeare)

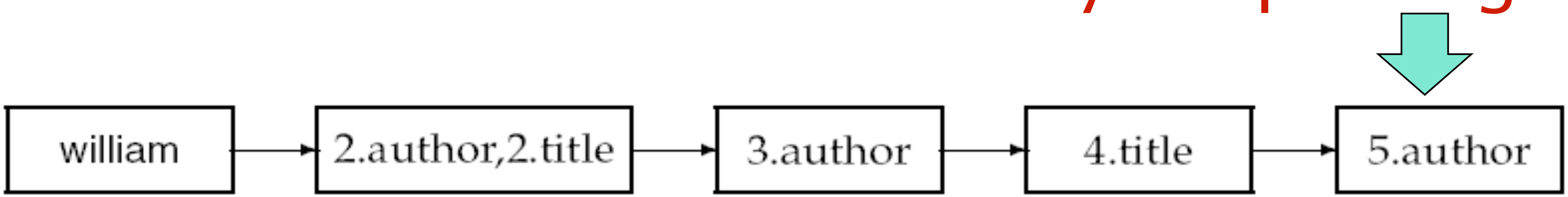
Zone

- A zone is a region of the doc that can contain an arbitrary amount of text, e.g.,
  - Title
  - Abstract
  - References …
- Build inverted indexes on zones as well to permit querying
- E.g., "find docs with *merchant* in the title zone and matching the query *gentle rain*"

Example zone indexes



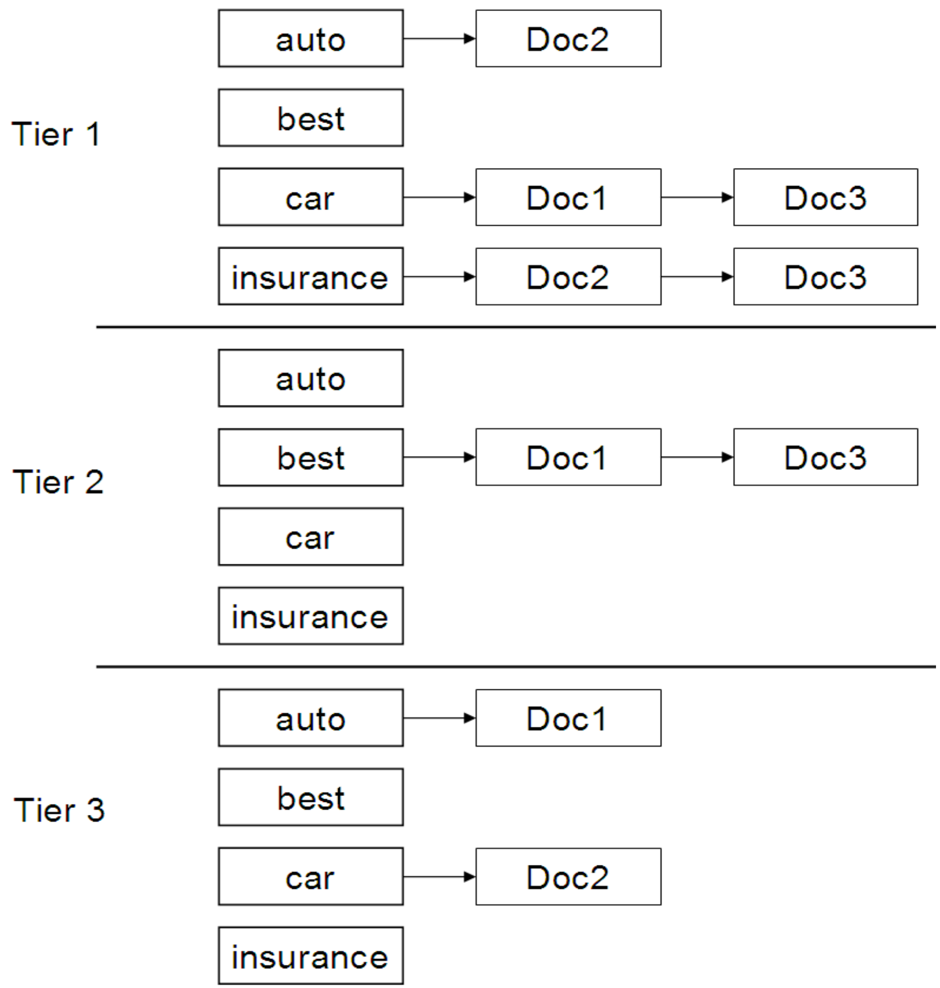
Encode zones in dictionary vs. postings.



Tiered indexes

- Break postings up into a hierarchy of lists
  - Most important
  - …
  - Least important
- Can be done by *g(d)* or another measure
- Inverted index thus broken up into tiers of decreasing importance
- At query time use top tier unless it fails to yield *K* docs
  - If so drop to lower tiers

Example tiered index



Query term proximity

- Free text queries: just a set of terms typed into the query box – common on the web
- Users prefer docs in which query terms occur within close proximity of each other
- Let *w* be the smallest window in a doc containing all query terms, e.g.,
  - For the query *strained mercy* the smallest window in the doc *The quality of mercy is not strained* is 4 (words)
- Would like scoring function to take this into account – how?

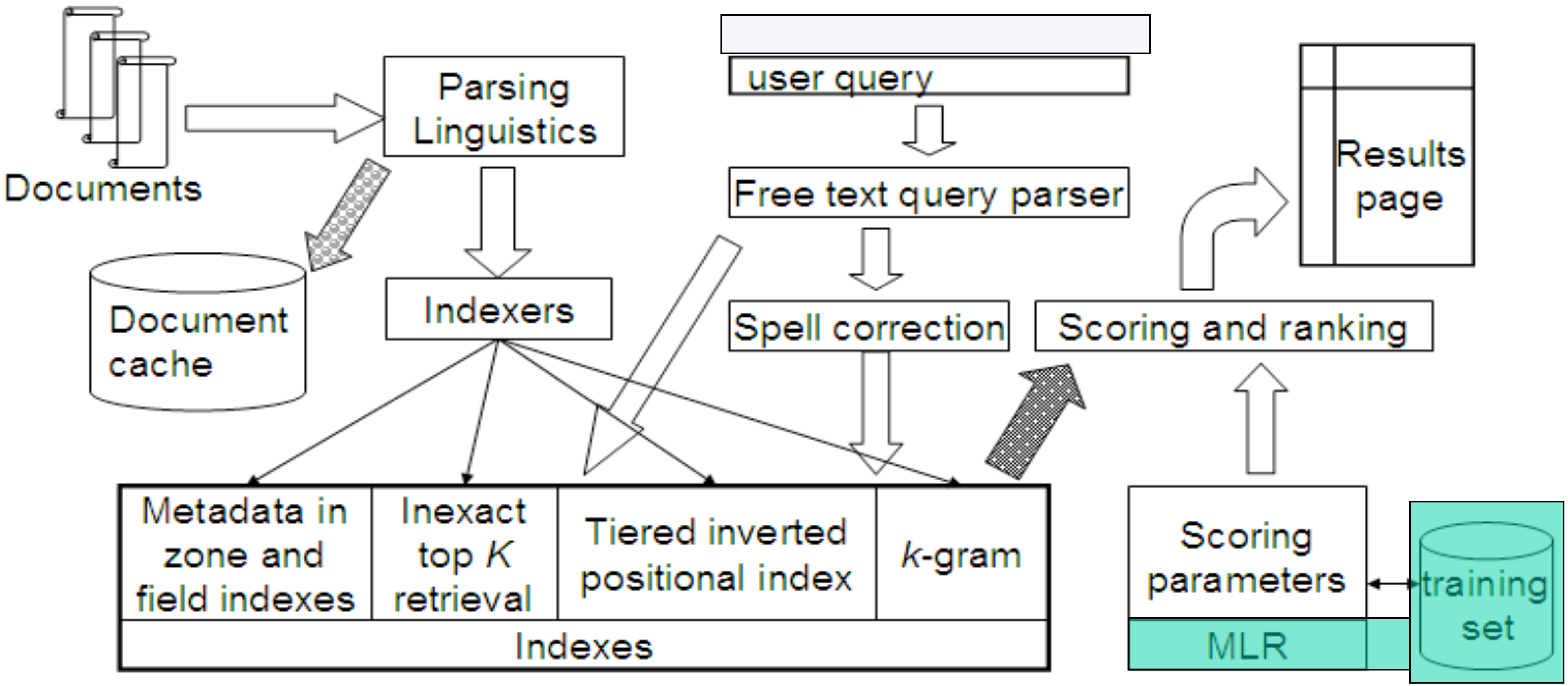
Query parsers

- Free text query from user may in fact spawn one or more queries to the indexes, e.g., query *rising interest rates*
  - Run the query as a phrase query
  - If <*K* docs contain the phrase *rising interest rates*, run the two phrase queries *rising interest* and *interest rates*
  - If we still have <*K* docs, run the vector space query *rising interest rates*
  - Rank matching docs by vector space scoring
- This sequence is issued by a <u>query parser</u>

Aggregate scores

- We've seen that score functions can combine cosine, static quality, proximity, etc.
- How do we know the best combination?
- Some applications – expert-tuned
- Increasingly common: machine-learned

Putting it all together



End Lecture

- Next time
  - Performance Measures for Retrieval Systems
  - Connected with Machine Learning and Natural Language Processing
- Introduction to ML if time allows

Query Expansion

- N, the overall number of documents,
- N_f, the number of documents that contain the feature *f*
- o_f^d the occurrences of the features *f* in the document *d*
- The weight *f* in a document is:

$$\omega_f^d = \left(\log \frac{N}{N_f}\right) \times o_f^d = IDF(f) \times o_f^d$$

- The weight can be normalized:

$$\omega'^d_f = \frac{\omega_f^d}{\sqrt{\sum_{t \in d} (\omega_t^d)^2}}$$

Relevance Feeback and query expansion: the Rocchio's formula

- ω_f^d, the weight of *f* in *d*
  - Several weighting schemes (e.g. TF * IDF, Salton 91')

- $\vec{q}_f$, the profile weights of *f* in C_i:

$$\vec{q}_f = \max\left\{0,\ \frac{\beta}{|T|}\sum_{d\in T}\omega_f^d \ - \ \frac{\gamma}{|\overline{T}|}\sum_{d\in \overline{T}}\omega_f^d\right\}$$

- T_i, the training documents in *q*

Similarity estimation between query and documents

- Given the document and the category representation

$$\vec{d} = \left\langle \omega_{f_1}^{d}, \ldots, \omega_{f_n}^{d} \right\rangle, \quad \vec{q} = \left\langle \Omega_{f_1}, \ldots, \Omega_{f_n} \right\rangle$$

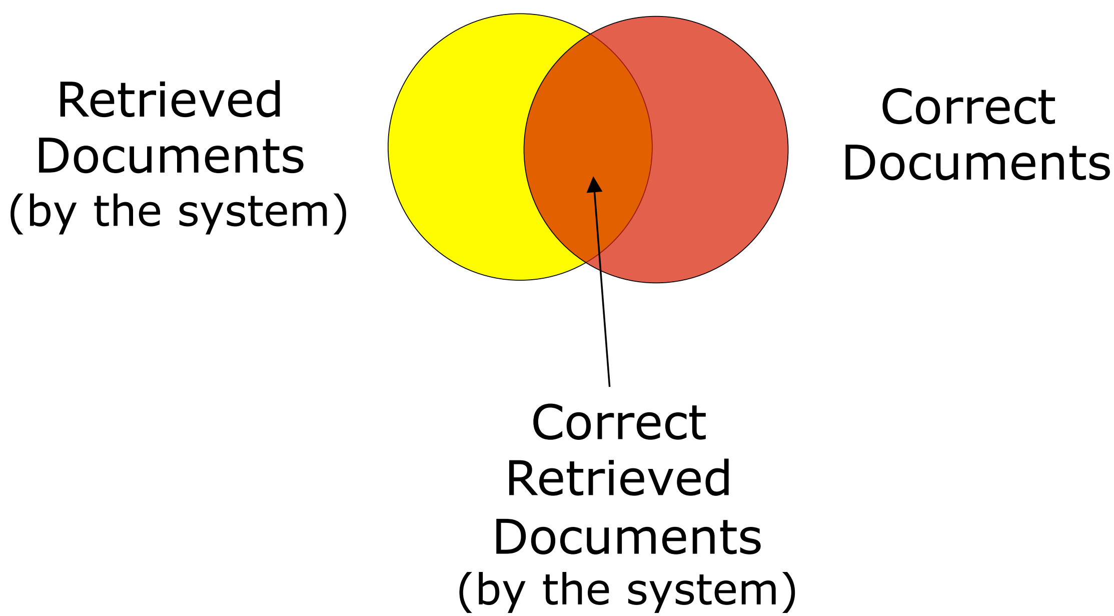
- It can be defined the following similarity function (cosine measure

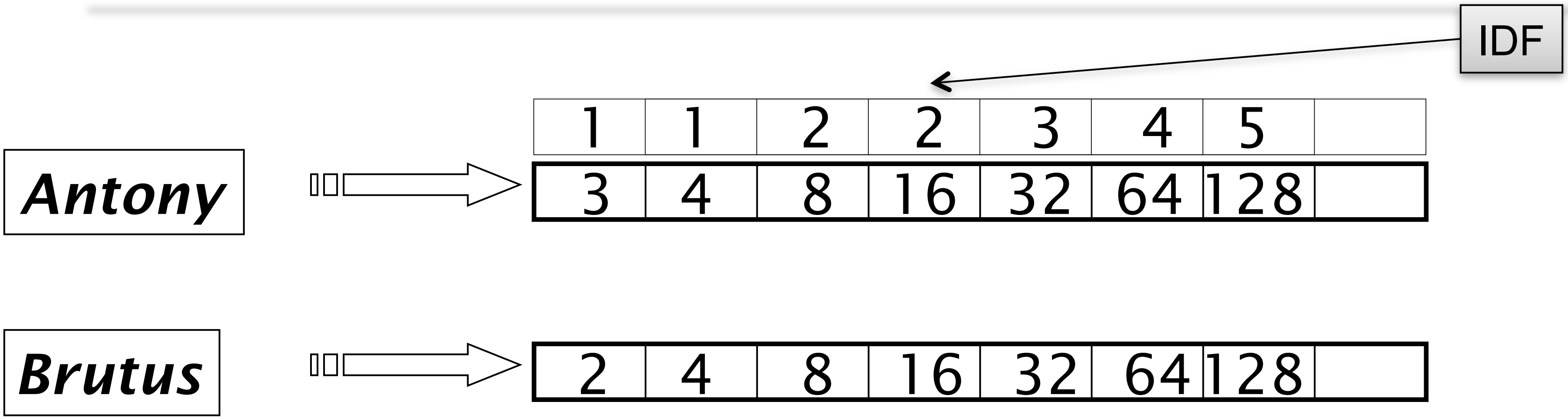
$$s_{d,i} = \cos(\vec{d}, \vec{q}) = \frac{\vec{d} \cdot \vec{q}}{\left\| \vec{d} \right\| \times \left\| \vec{q} \right\|} = \frac{\sum_{f} \omega_{f}^{d} \times \Omega_{f}^{i}}{\left\| \vec{d} \right\| \times \left\| \vec{q} \right\|}$$

- *d* is assigned to $\vec{q}$ if $\vec{d} \cdot \vec{q} > \sigma$

Performance Measurements

- Given a set of document *T*
- Precision = # Correct Retrieved Document / # Retrieved Documents
- Recall = # Correct Retrieved Document/ # Correct Documents




IDF
1 1 2 2 3 4 5
Antony
3 4 8 16 32 64 128
Brutus
2 4 8 16 32 64 128