# Εύρεση & Διαχείριση Πληροφορίας στον Παγκόσμιο Ιστό

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**Διάλεξη 10η: 31/03/2014**

## Problem with Boolean search: feast or famine

- Boolean queries often result in either too few (=0) or too many (1000s) results.
- 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 models

- Rather than a set of documents satisfying a query expression, in ranked retrieval models, the system returns an ordering over the (top) documents in the collection with respect to a query
- Free text queries: Rather than a query language of operators and expressions, the user's query is just one or more words in a human language
- In principle, there are two separate choices here, but in practice, ranked retrieval models have normally been associated with free text queries and vice versa

## Scoring as the basis of ranked retrieval

- We wish to return in order the documents most likely to be useful to the searcher
- How can we rank-order the documents in the collection with respect to a query?
- Assign a score – say in [0, 1] – to each document
- This score measures how well document and query "match".

## Query-document matching scores

- We need a way of assigning a score to a query/document pair
- Let’s start with a one-term query
- If the query term does not occur in the document: score should be 0
- The more frequent the query term in the document, the higher the score (should be)
- We will look at a number of alternatives for this.

## Take 1: Jaccard coefficient

- Recall from Lecture 3: A commonly used measure of overlap of two sets *A* and *B*
- jaccard(*A*,*B*) = |*A* ∩ *B*| / |*A* □ *B*|
- jaccard(*A*,*A*) = 1
- jaccard(*A*,*B*) = 0 if *A* ∩ *B* = 0
- *A* and *B* don’t have to be the same size.
- Always assigns a number between 0 and 1.

## Term frequency tf

- The term frequency $\mathrm{tf}_{t,d}$ of term $t$ in document $d$ is defined as the number of times that $t$ occurs in $d$.
- We want to use tf when computing query-document match scores. But how?
- Raw term frequency is not what we want:
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence of the term.
  - But not 10 times more relevant.
- Relevance does not increase proportionally with term frequency.

NB: frequency = count in IR

## Log-frequency weighting

- The log frequency weight of term t in d is

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

- $0 \rightarrow 0$, $1 \rightarrow 1$, $2 \rightarrow 1.3$, $10 \rightarrow 2$, $1000 \rightarrow 4$, etc.
- Score for a document-query pair: sum over terms *t* in both *q* and *d*:
- score

$$= \sum\nolimits_{t \in q \cap d} (1 + \log \mathrm{tf}_{t,d})$$

- The score is 0 if none of the query terms is present in the document.

## Document frequency

- Rare terms are more informative than frequent terms
  - Recall stop words
- Consider a term in the query that is rare in the collection (e.g., *arachnocentric*)
- A document containing this term is very likely to be relevant to the query *arachnocentric*
- → We want a high weight for rare terms like *arachnocentric*.

## Document frequency, continued

- Frequent terms are less informative than rare terms
- Consider a query term that is frequent in the collection (e.g., *high, increase, line*)
- A document containing such a term is more likely to be relevant than a document that doesn’t
- But it’s not a sure indicator of relevance.
- → For frequent terms, we want high positive weights for words like *high, increase, and line*
- But lower weights than for rare terms.
- We will use document frequency (df) to capture this.

## idf weight

- $\text{df}_t$ is the document frequency of $t$: the number of documents that contain $t$
  - $\text{df}_t$ is an inverse measure of the informativeness of $t$
  - $\text{df}_t \leq N$
- We define the idf (inverse document frequency) of $t$ by

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

  - We use $\log (N/\text{df}_t)$ instead of $N/\text{df}_t$ to "dampen" the effect of idf.

Will turn out the base of the log is immaterial.

## idf example, suppose $N = 1$ million

| term | $\text{df}_t$ | $\text{idf}_t$ |
|---|---:|---|
| calpurnia | 1 | |
| animal | 100 | |
| sunday | 1,000 | |
| fly | 10,000 | |
| under | 100,000 | |
| the | 1,000,000 | |

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

There is one idf value for each term *t* in a collection.

## 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.

## Collection vs. Document frequency

- The collection frequency of *t* is the number of occurrences of *t* in the collection, counting multiple occurrences.
- Example:

| Word | Collection frequency | Document frequency |
|---|---:|---:|
| *insurance* | 10440 | 3997 |
| *try* | 10422 | 8760 |

- Which word is a better search term (and should get a higher weight)?

## tf-idf weighting

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

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

- 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
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

## Final ranking of documents for a query

$$\text{Score}(q,d) = \sum_{t \in q \cap d} \text{tf.idf}_{t,d}$$

## Binary → count → weight matrix

| | Antony and Cleopatra | Julius Caesar | The Tempest | Hamlet | Othello | Macbeth |
|---|---|---|---|---|---|---|
| Antony | 5.25 | 3.18 | 0 | 0 | 0 | 0.35 |
| Brutus | 1.21 | 6.1 | 0 | 1 | 0 | 0 |
| Caesar | 8.59 | 2.54 | 0 | 1.51 | 0.25 | 0 |
| Calpurnia | 0 | 1.54 | 0 | 0 | 0 | 0 |
| Cleopatra | 2.85 | 0 | 0 | 0 | 0 | 0 |
| mercy | 1.51 | 0 | 1.9 | 0.12 | 5.25 | 0.88 |
| worser | 1.37 | 0 | 0.11 | 4.15 | 0.25 | 1.95 |

Each document is now represented by a real-valued vector of tf-idf weights □ $R^{|V|}$

## 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
- Recall: We do this because we want to get away from the you’re-either-in-or-out Boolean model.
- Instead: rank more relevant documents higher than less relevant documents

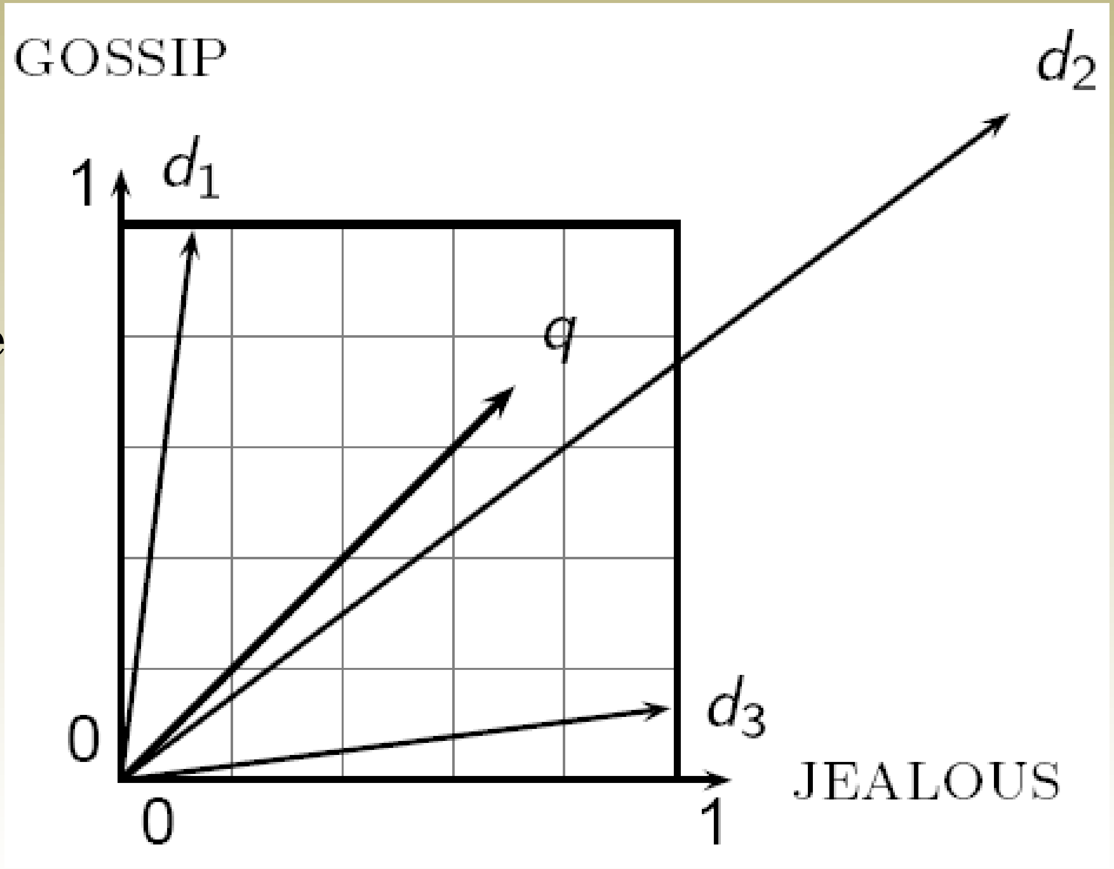
## Formalizing vector space proximity

- First cut: distance between two points
  - ( = distance between the end points of the two vectors)
- Euclidean distance?
- Euclidean distance is a bad idea . . .
- . . . because Euclidean distance is large for vectors of different lengths.

## Why distance is a bad idea

The Euclidean distance between $q$ and $\vec{d_2}$ is large even though the distribution of terms in the query $q$ and the distribution of terms in the document $d_2$ are very similar.

$\rightarrow$



## Use angle instead of distance

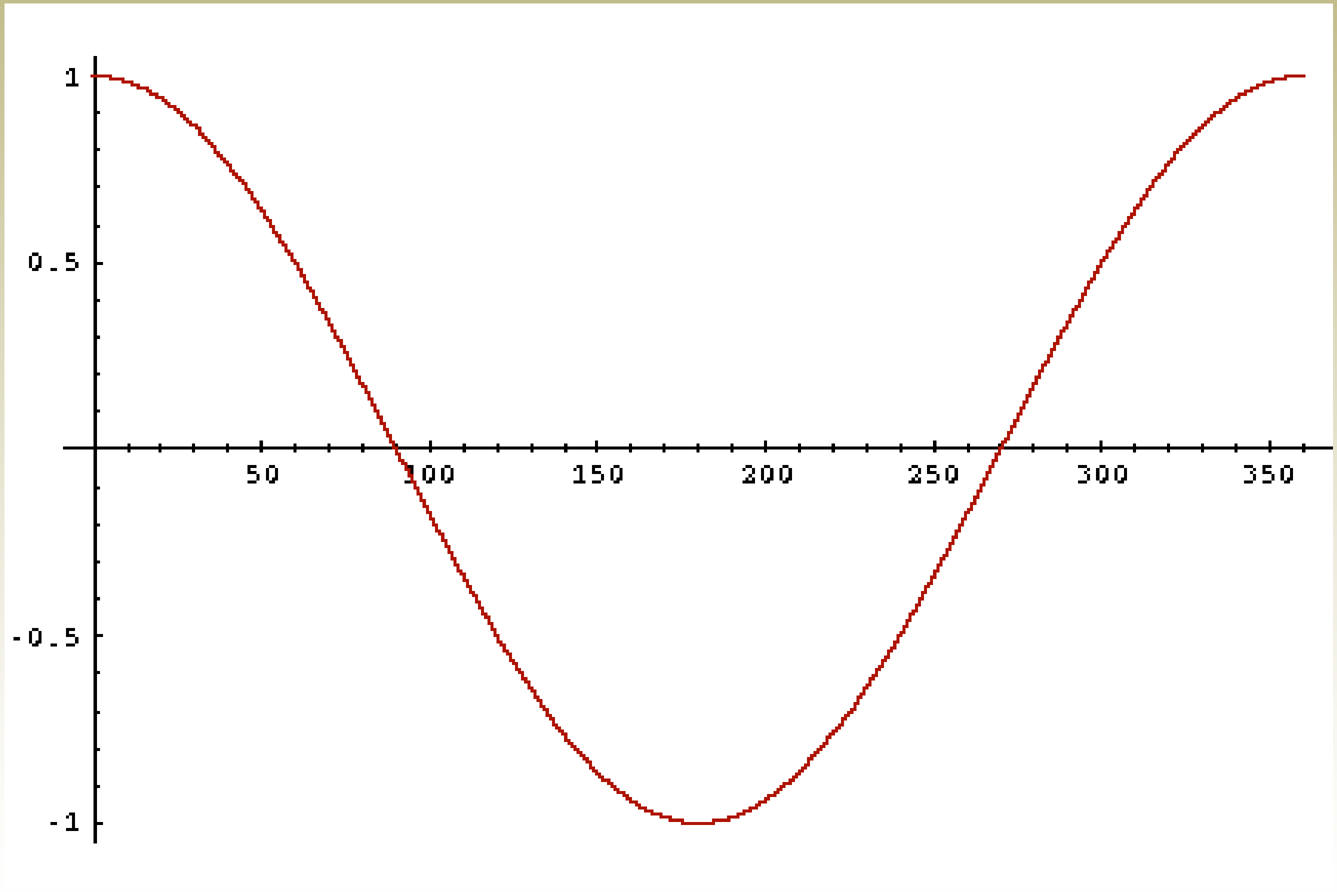
- Thought experiment: take a document *d* and append it to itself. Call this document *d*′.
- "Semantically" d and d′ have the same content
- The Euclidean distance between the two documents can be quite large
- The angle between the two documents is 0, corresponding to maximal similarity.

- Key idea: Rank documents according to angle with query.

## From angles to cosines

- The following two notions are equivalent.
  - Rank documents in <u>decreasing</u> order of the angle between query and document
  - Rank documents in <u>increasing</u> order of cosine(query,document)
- Cosine is a monotonically decreasing function for the interval [$0^o$, $180^o$]

## From angles to cosines



- But how – *and why* – should we be computing cosines?

## Length normalization

- A vector can be (length-) normalized by dividing each of its components by its length – for this we use the $L_2$ norm:

$$\left\|\vec{x}\right\|_2 = \sqrt{\sum_i x_i^2}$$

- Dividing a vector by its $L_2$ norm makes it a unit (length) vector (on surface of unit hypersphere)
- Effect on the two documents d and d′ (d appended to itself) from earlier slide: they have identical vectors after length-normalization.
  - Long and short documents now have comparable weights

## cosine(query,document)

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-idf weight of term *i* in the query
$d_i$ is the tf-idf 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 $\vec{d}$.

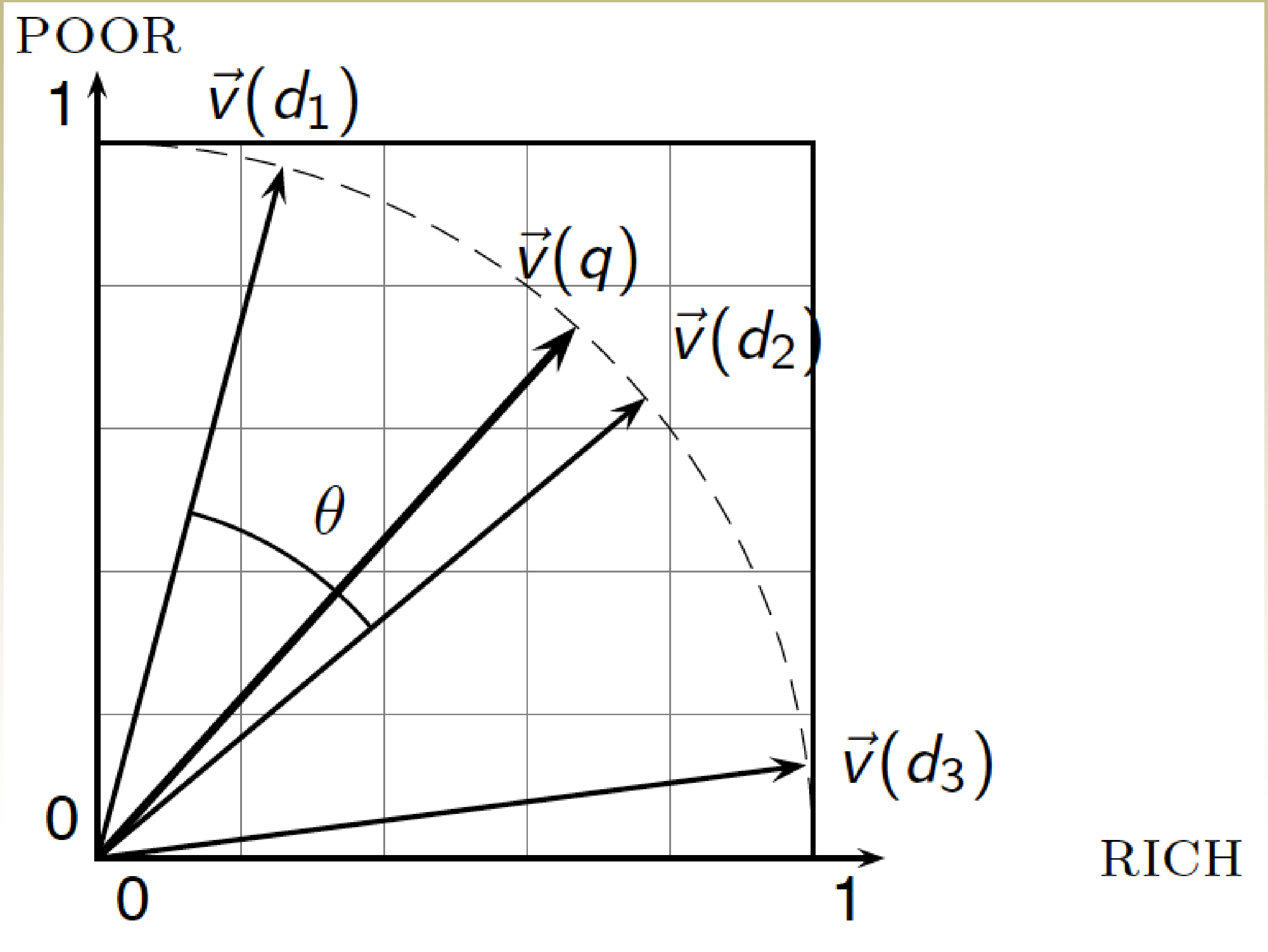
## Cosine for length-normalized vectors

- For length-normalized vectors, cosine similarity is simply the dot product (or scalar product):

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

for q, d length-normalized.

## Cosine similarity illustrated



## Cosine similarity amongst 3 documents

How similar are the novels SaS: *Sense and Sensibility* PaP: *Pride and Prejudice*, and WH: *Wuthering Heights*?

| term | SaS | PaP | WH |
|---|---|---|---|
| affection | 115 | 58 | 20 |
| jealous | 10 | 7 | 11 |
| gossip | 2 | 0 | 6 |
| wuthering | 0 | 0 | 38 |

Term frequencies (counts)

Note: To simplify this example, we don’t do idf weighting.

## 3 documents example contd.

**Log frequency weighting**

| term | SaS | PaP | WH |
|---|---|---|---|
| affection | 3.06 | 2.76 | 2.30 |
| jealous | 2.00 | 1.85 | 2.04 |
| gossip | 1.30 | 0 | 1.78 |
| wuthering | 0 | 0 | 2.58 |

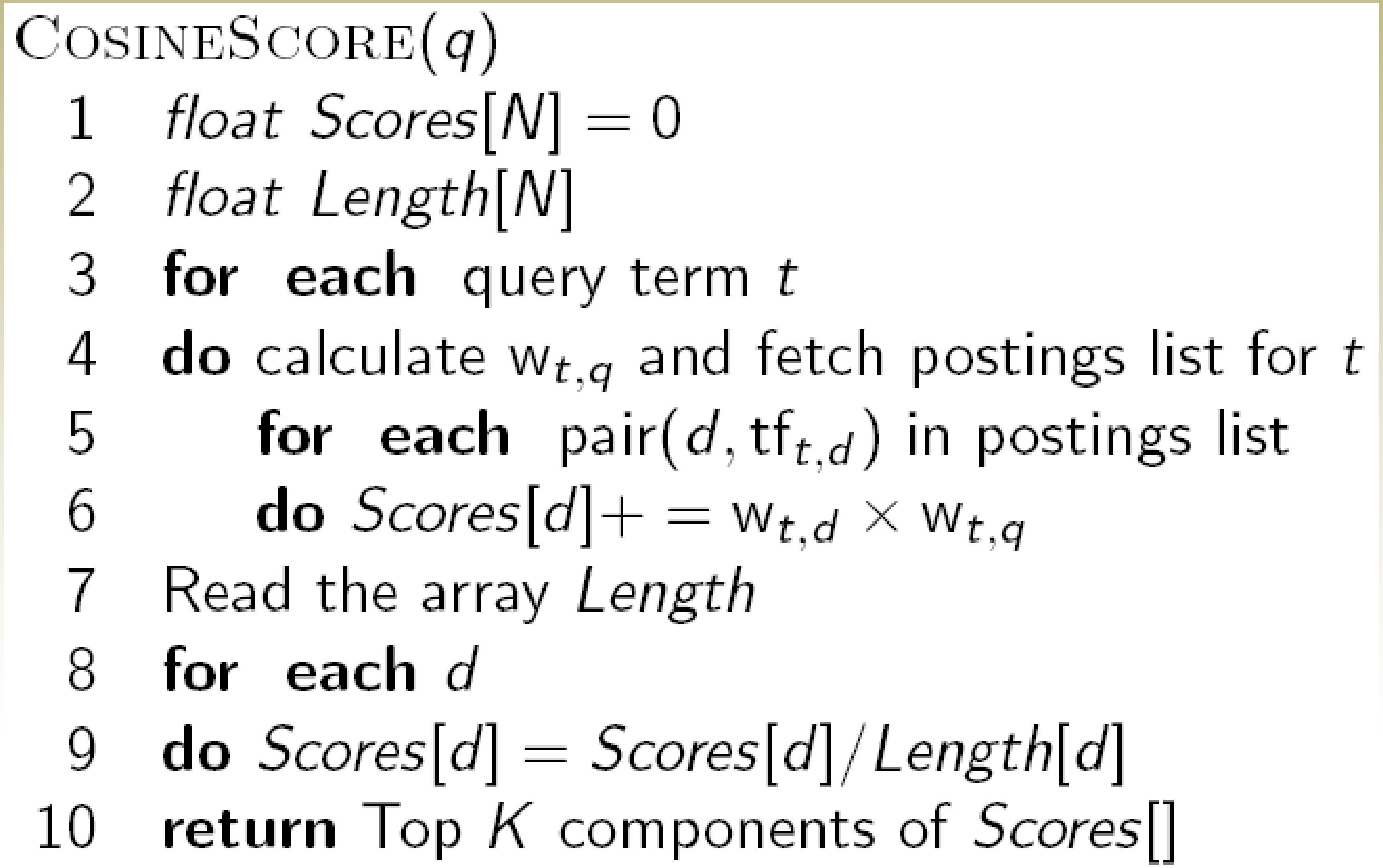
**After length normalization**

| term | SaS | PaP | WH |
|---|---|---|---|
| affection | 0.789 | 0.832 | 0.524 |
| jealous | 0.515 | 0.555 | 0.465 |
| gossip | 0.335 | 0 | 0.405 |
| wuthering | 0 | 0 | 0.588 |

cos(SaS,PaP) ≈
$0.789 \times 0.832 + 0.515 \times 0.555 + 0.335 \times 0.0 + 0.0 \times 0.0$
≈ 0.94
cos(SaS,WH) ≈ 0.79
cos(PaP,WH) ≈ 0.69

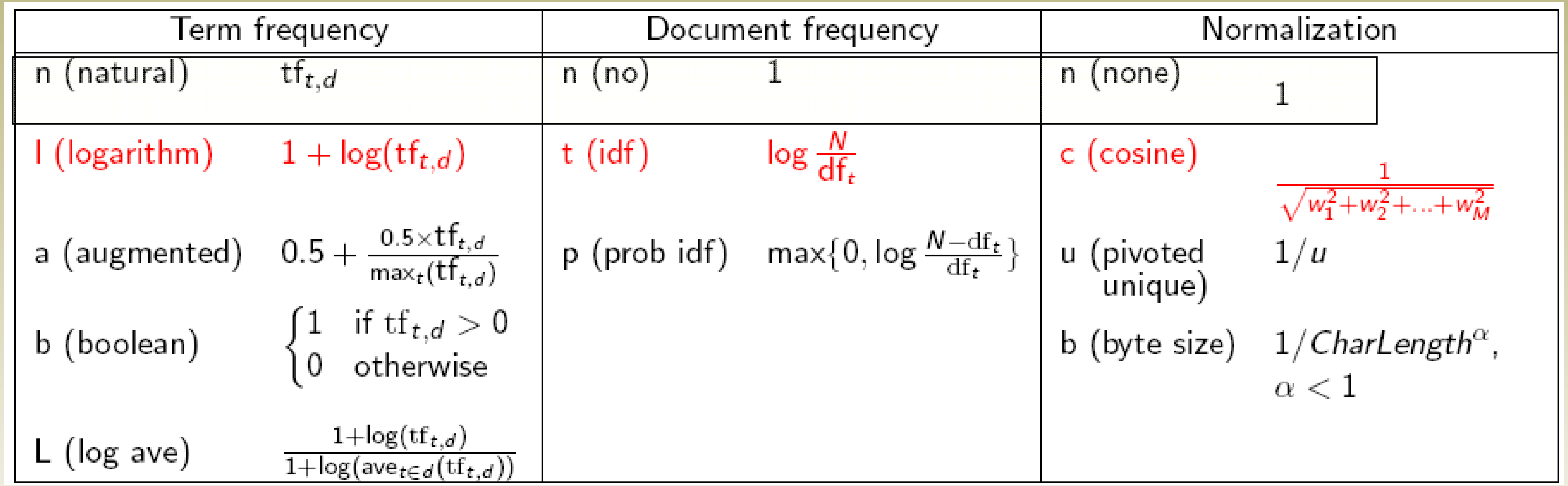
Why do we have cos(SaS,PaP) > cos(SAS,WH)?

## Computing cosine scores



```
COSINESCORE($q$)
 1  float $Scores[N] = 0$
 2  float $Length[N]$
 3  for each query term $t$
 4  do calculate $w_{t,q}$ and fetch postings list for $t$
 5      for each pair($d$, $\mathrm{tf}_{t,d}$) in postings list
 6      do $Scores[d] += w_{t,d} \times w_{t,q}$
 7  Read the array $Length$
 8  for each $d$
 9  do $Scores[d] = Scores[d]/Length[d]$
10  return Top $K$ components of $Scores[]$
```

## 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) | $1/\mathit{CharLength}^{\alpha}$, $\alpha < 1$ |
| 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
- 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 |

Exercise: what is *N*, the number of docs?

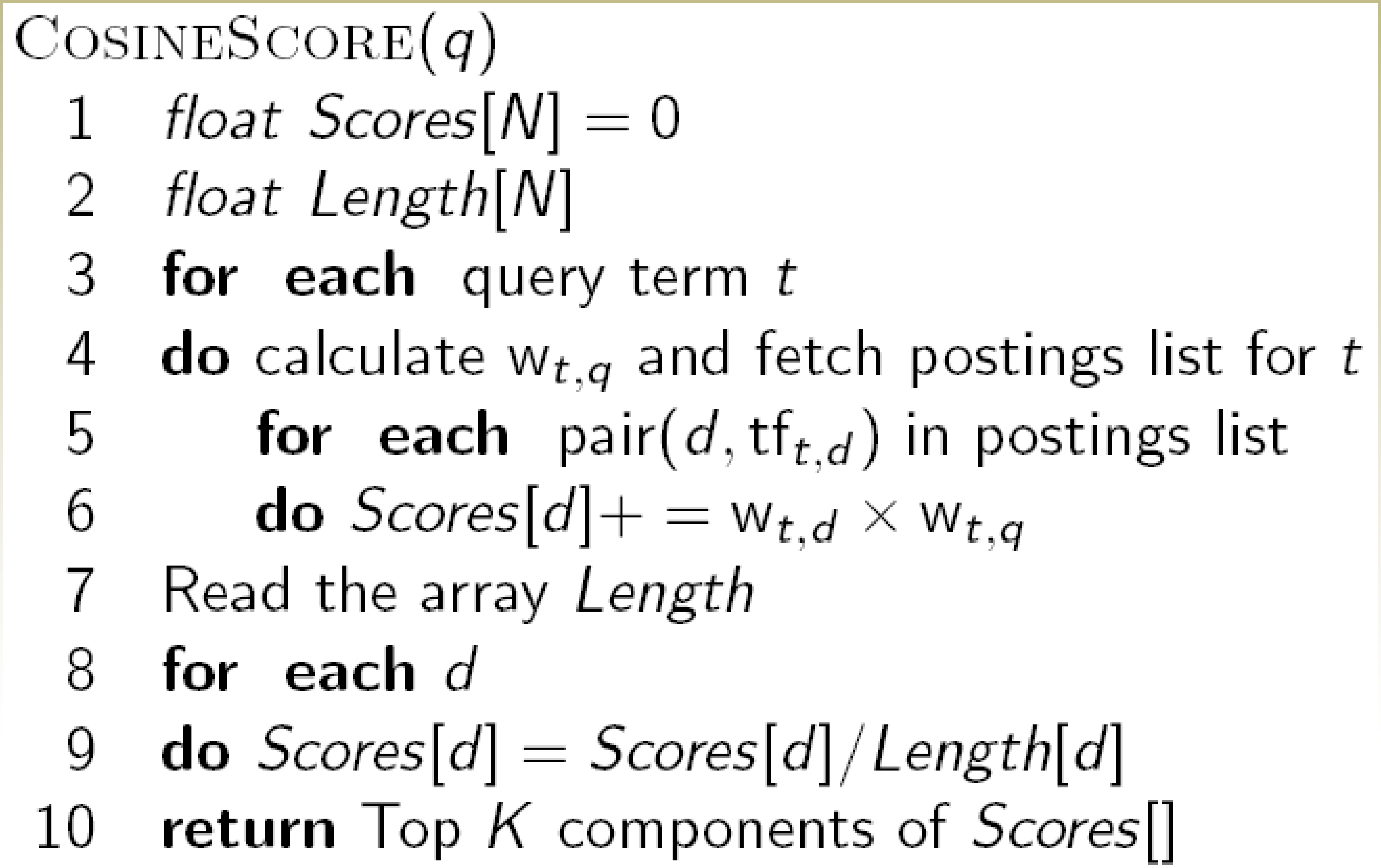
Doc length $=\sqrt{1^2+0^2+1^2+1.3^2}\approx 1.92$

Score = 0+0+0.27+0.53 = 0.8

## 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

## Computing cosine scores



```
CosineScore($q$)
 1  float $Scores[N] = 0$
 2  float $Length[N]$
 3  for each query term $t$
 4  do calculate $w_{t,q}$ and fetch postings list for $t$
 5      for each pair($d$, $tf_{t,d}$) in postings list
 6      do $Scores[d] += w_{t,d} \times w_{t,q}$
 7  Read the array $Length$
 8  for each $d$
 9  do $Scores[d] = Scores[d] / Length[d]$
10  return Top $K$ components of $Scores[]$
```

## 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?

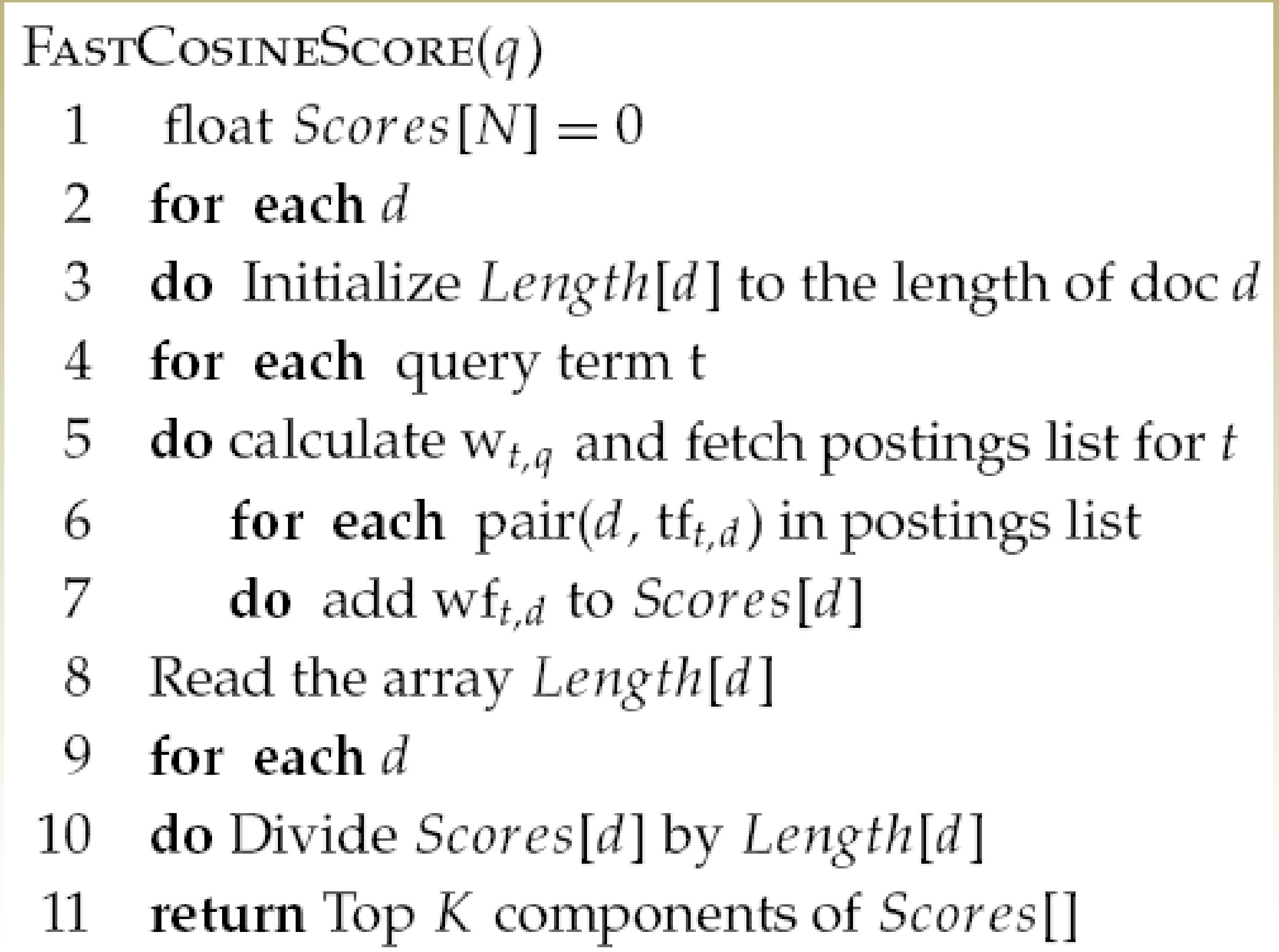
## Efficient cosine ranking

- 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 from Lecture 6

## Faster cosine: unweighted query



```
FastCosineScore($q$)
float $Scores[N] = 0$
for each $d$
do Initialize $Length[d]$ to the length of doc $d$
for each query term t
do calculate $w_{t,q}$ and fetch postings list for $t$
    for each pair($d$, $tf_{t,d}$) in postings list
    do add $wf_{t,d}$ to $Scores[d]$
Read the array $Length[d]$
for each $d$
do Divide $Scores[d]$ by $Length[d]$
return Top $K$ components of $Scores[]$
```

**Figure 7.1** A faster algorithm for vector space scores.

## Bottlenecks

- Primary computational bottleneck in scoring: cosine computation
- 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 $K < |A| \ll N$
  - $A$ 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 pruning 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 FastCosineScore of Fig 7.1 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

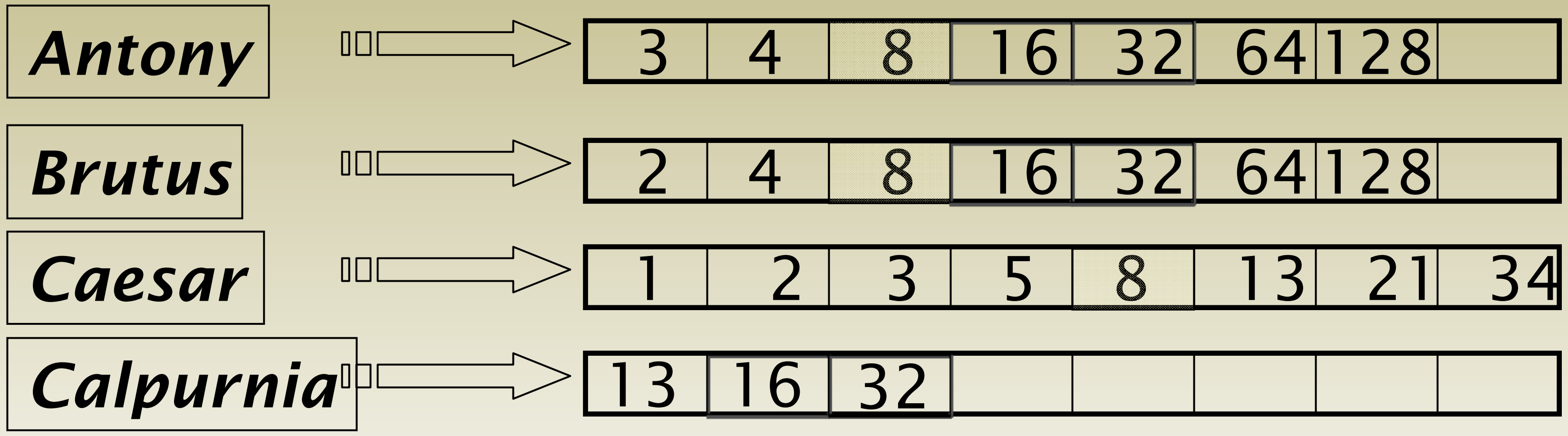
## High-idf query terms only

- 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 $\rightarrow$ 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 champion list for *t*
  - (aka fancy list or top docs 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

## 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
  - Many diggs, Y!buzzes or del.icio.us marks
  - (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 than an equal weighting
  - 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

## 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)* + $\text{tf-idf}_{td}$
- 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

## 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 field
- 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 <u>zone</u> 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

$$\begin{tikzcd}
\boxed{\text{william.abstract}} \arrow[r] & \boxed{11} \arrow[r] & \boxed{121} \arrow[r] & \boxed{1441} \arrow[r] & \boxed{1729} \\
\boxed{\text{william.title}} \arrow[r] & \boxed{2} \arrow[r] & \boxed{4} \arrow[r] & \boxed{8} \arrow[r] & \boxed{16} \\
\boxed{\text{william.author}} \arrow[r] & \boxed{2} \arrow[r] & \boxed{3} \arrow[r] & \boxed{5} \arrow[r] & \boxed{8}
\end{tikzcd}$$

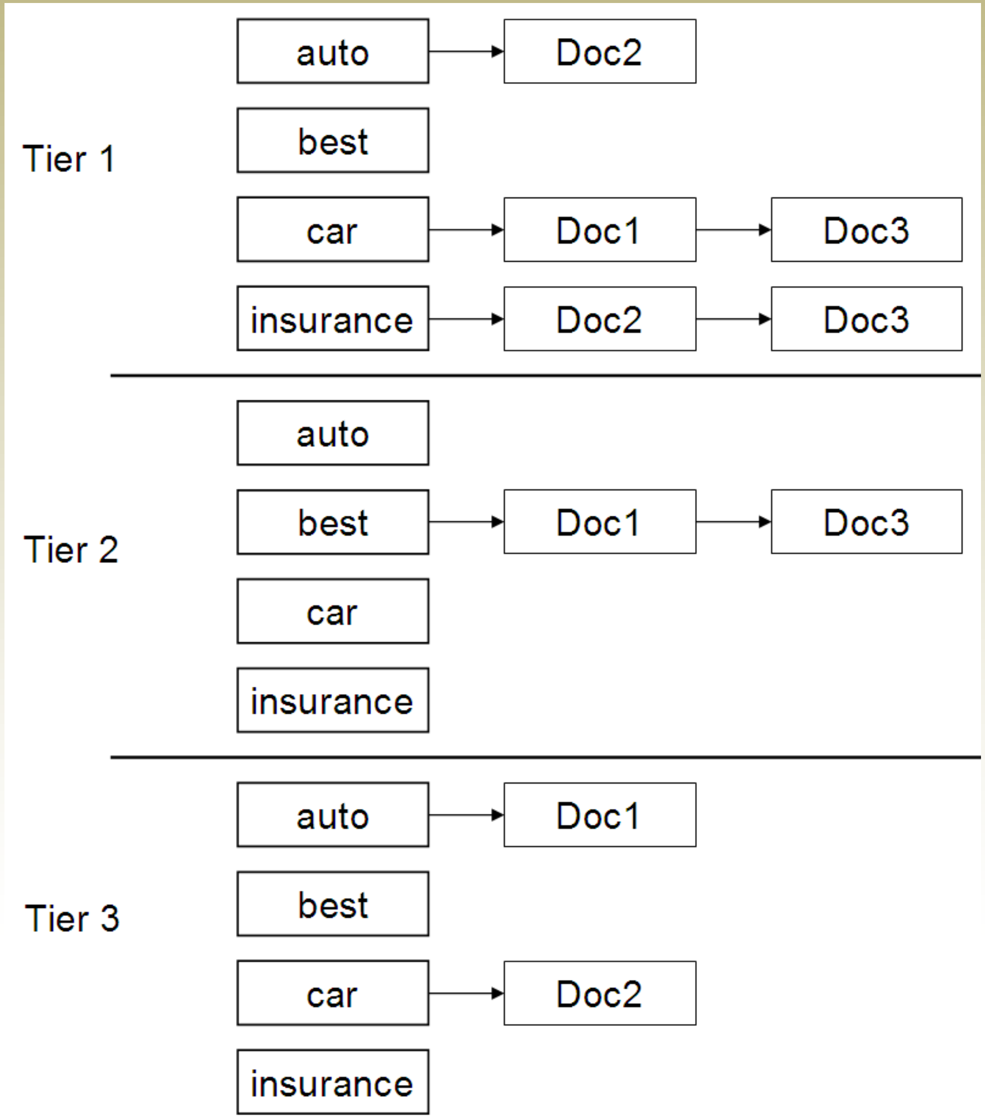
Encode zones in dictionary vs. postings.

$$\begin{tikzcd}
\boxed{\text{william}} \arrow[r] & \boxed{\text{2.author,2.title}} \arrow[r] & \boxed{\text{3.author}} \arrow[r] & \boxed{\text{4.title}} \arrow[r] & \boxed{\text{5.author}}
\end{tikzcd}$$

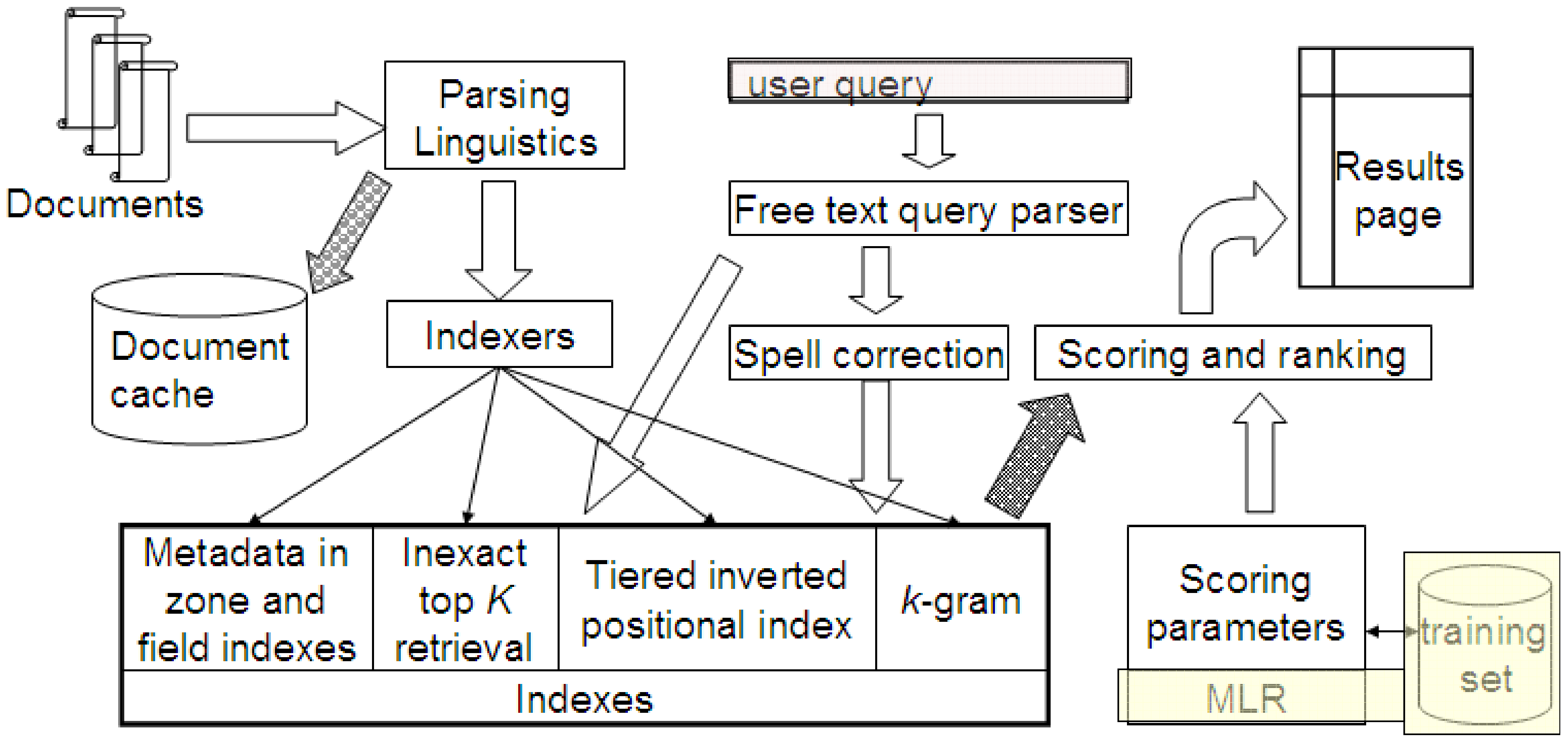
# Tiered indexes

- 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



## Putting it all together


Documents
Parsing Linguistics
Document cache
Indexers
user query
Free text query parser
Spell correction
Scoring and ranking
Results page
Metadata in zone and field indexes
Inexact top K retrieval
Tiered inverted positional index
k-gram
Indexes
Scoring parameters
MLR
training set