Introduction to

Information Retrieval

Lecture 7: Scoring and results assembly

Recap: tf-idf weighting

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

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

- 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

Recap: cosine(query,document)

Dot product Unit vectors

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

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

This lecture

- Speeding up vector space ranking
- Putting together a complete search system
  - Will require learning about a number of miscellaneous topics and heuristics

Question: Why don't we just use the query processing methods for Boolean queries?

Term-at-a-time

Computing cosine scores

CosineScore(q)

float $Scores[N] = 0$

float $Length[N]$

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 $Scores[d] += \mathrm{w}_{t,d} \times \mathrm{w}_{t,q}$

Read the array *Length*

for each d

do $Scores[d] = Scores[d] / Length[d]$

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.

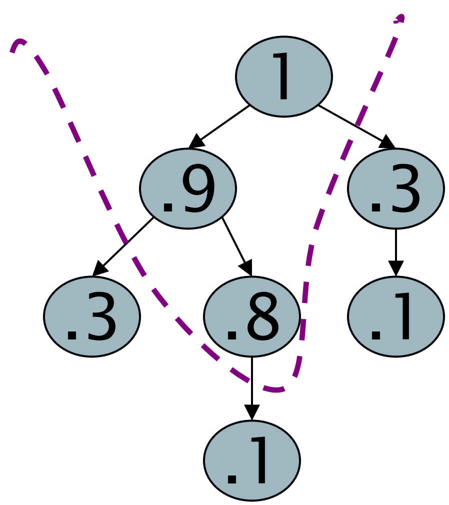
Computing the *K* largest cosines: selection vs. sorting

- 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 *n* of docs with nonzero cosines
  - We seek the *K* best of these *n*

http://en.wikipedia.org/wiki/Binary_heap

Use heap for selecting top *K* /1

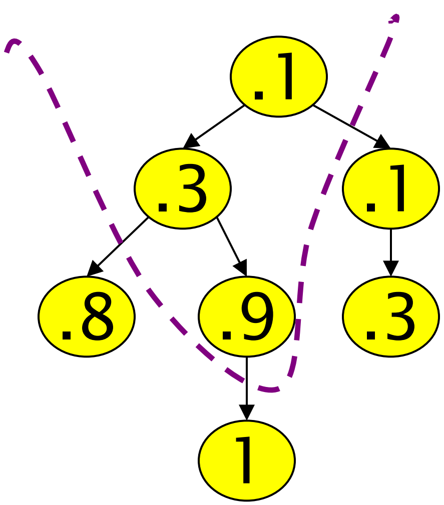
- Max-heap:
  - Binary tree in which each node's value > the values of children
- Takes 2*n* operations to construct, then each of *K* "winners" read off in 2log *n* steps
- Total time is O(n + K*log(n)); space complexityis O(n)
- For *n*=1M, *K*=100, this is about 10% of the cost of sorting.



http://en.wikipedia.org/wiki/Binary_heap

Use heap for selecting top *K* /2

- What about using a min-heap?
- Use the min-heap to maintain the top k scores so far.
- For each new score, s, scanned:
  - H.push (s)
  - H.pop()
- Total time is O(n*log(k) + k*log(k)); space complexityis O(k)



http://en.wikipedia.org/wiki/Quickselect

Quick Select

- QuickSelect is similar to QuickSort to find the top-K elements from an array
  - Takes O(n) time (in expectation)
- Sorting the top-K items takes O(K*log(K)) time
- Total time is O(n + K*log(K))

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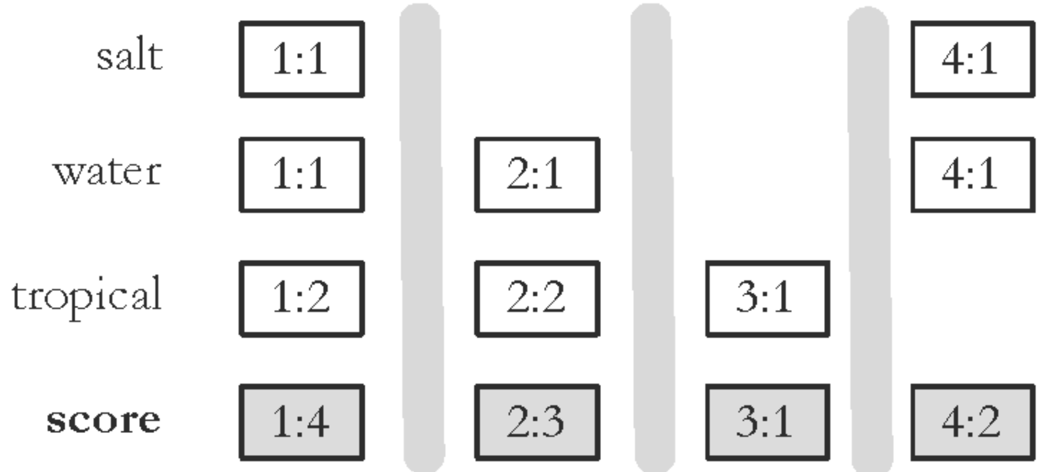
Query Processing

- Document-at-a-time
  - Calculates complete scores for documents by processing all term lists, one document at a time
- Term-at-a-time
  - Accumulates scores for documents by processing term lists one at a time
- Both approaches have optimization techniques that significantly reduce time required to generate scores
  - Distinguish between safe and heuristic optimizations

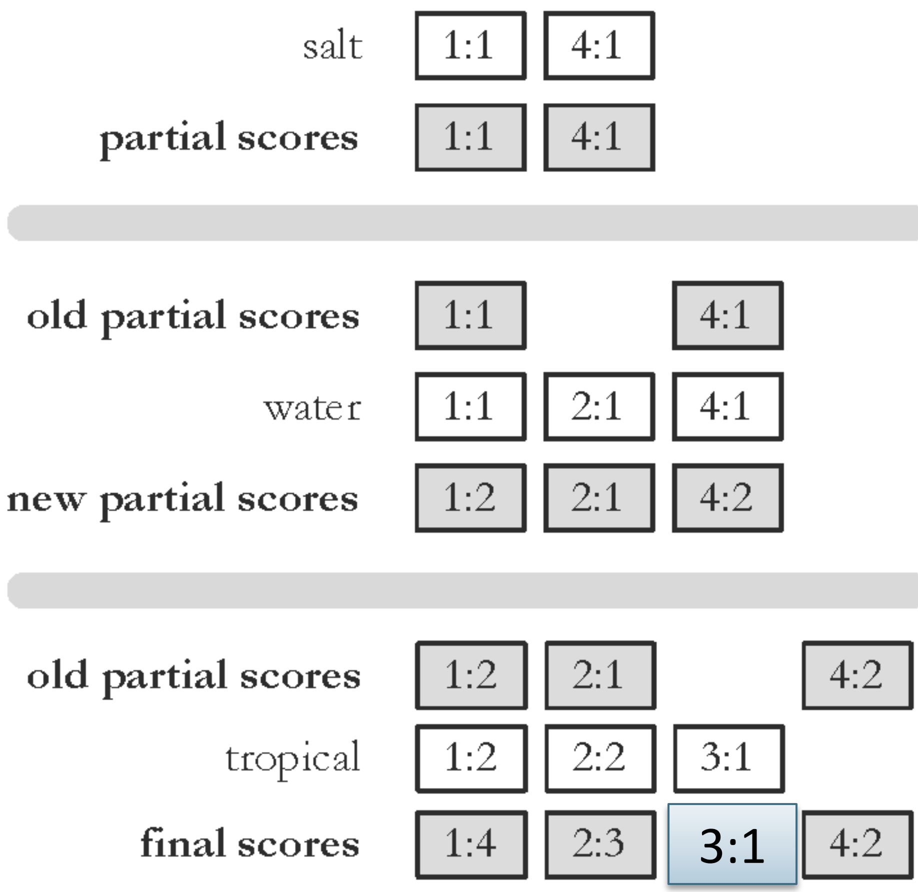
Document-At-A-Time



Document-At-A-Time

```
procedure DocumentAtATimeRetrieval(Q, I, f, g, k)
    L ← Array()
    R ← PriorityQueue(k)
    for all terms w_i in Q do
        l_i ← InvertedList(w_i, I)
        L.add( l_i )
    end for
    for all documents d ∈ I do
        for all inverted lists l_i in L do
            if l_i points to d then
                s_D ← s_D + g_i(Q)f_i(l_i)          ▷ Update the document score
                l_i.movePastDocument( d )
            end if
        end for
        R.add( s_D, D )
    end for
    return the top k results from R
end procedure
```

Term-At-A-Time



Term-At-A-Time

```
procedure TermAtATimeRetrieval(Q, I, f, g k)
    A ← HashTable()
    L ← Array()
    R ← PriorityQueue(k)
    for all terms w_i in Q do
        l_i ← InvertedList(w_i, I)
        L.add( l_i )
    end for
    for all lists l_i ∈ L do
        while l_i is not finished do
            d ← l_i.getCurrentDocument()
            A_d ← A_d + g_i(Q) f(l_i)
            l_i.moveToNextDocument()
        end while
    end for
    for all accumulators A_d in A do
        s_D ← A_d                  ▷ Accumulator contains the document score
        R.add( s_D, D )
    end for
    return the top k results from R
end procedure
```

// accumulators

// A_d contains partial score

Optimization Techniques

- Term-at-a-time uses more memory for accumulators, but accesses disk more efficiently
- Two classes of optimization
  - Read less data from inverted lists
    - e.g., skip lists
    - better for simple feature functions
  - Calculate scores for fewer documents
    - e.g., conjunctive processing
    - better for complex feature functions

Conjunctive Processing

- Requires the result document containing all the query terms (i.e., conjunctive Boolean queries)
  - More efficient
  - Can also be more effective for short queries
  - Default for many search engines
- Can be combined with both DAAT and TAAT (see pseudocodes next)

Conjunctive Term-at-a-Time

```
procedure TermAtATimeRetrieval(Q, I, f, g, k)
    A ← Map()
    L ← Array()
    R ← PriorityQueue(k)
    for all terms w_i in Q do
        l_i ← InvertedList(w_i, I)
        L.add( l_i )
    end for
    for all lists l_i ∈ L do
        d_0 ← −1
        while l_i is not finished do
            if i = 0 then
                d ← l_i.getCurrentDocument()
                A_d ← A_d + g_i(Q)f(l_i)
                l_i.moveToNextDocument()
            else
                d ← l_i.getCurrentDocument()
                d′ ← A.getNextAccumulator(d)
                A.removeAccumulatorsBetween(d_0,d′)
                if d = d′ then
                    A_d ← A_d + g_i(Q)f(l_i)
                    l_i.moveToNextDocument()
                else
                    l_iskipForwardToDocument(d′)
                end if
                d_0 ← d′
            end if
        end while
    end for
    for all accumulators A_d in A do
        s_d ← A_d                    ▷ Accumulator contains the document scor
        R.add( s_d, d )
    end for
    return the top k results from R
end procedure
```

Fig. 5.20. A term-at-a-time retrieval algorithm with conjunctive processing

Conjunctive Document-at-a-Time

```
procedure DocumentAtATimeRetrieval(Q, I, f, g, k)
    L ← Array()
    R ← PriorityQueue(k)
    for all terms w_i in Q do
        l_i ← InvertedList(w_i, I)
        L.add( l_i )
    end for
    d ← −1
    while all lists in L are not finished do
        s_d ← 0
        for all inverted lists l_i in L do
            if l_i.getCurrentDocument() > d then
                d ← l_i.getCurrentDocument()
            end if
        end for
        for all inverted lists l_i in L do
            l_i.skipForwardToDocument(d)
            if l_i.getCurrentDocument() = d then
                s_d ← s_d + g_i(Q) f_i(l_i)          ▷ Update the document score
                l_i.movePastDocument( d )
            else
                d ← −1
                break
            end if
        end for
        if d > −1 then R.add( s_d, d )
        end if
    end while
    return the top k results from R
end procedure
```

Fig. 5.21. A document-at-a-time retrieval algorithm with conjunctive processing

Threshold Methods

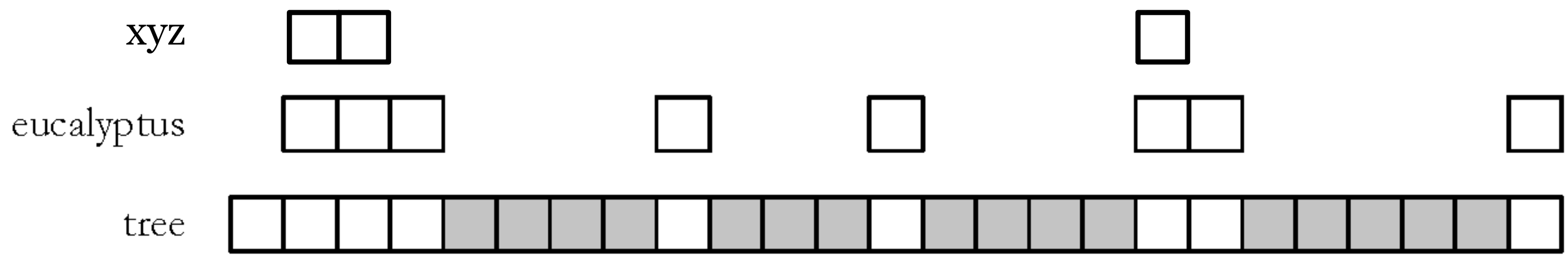
- Threshold methods use number of top-ranked documents needed (k) to optimize query processing
  - for most applications, k is small
- For any query, there is a *minimum score* that each document needs to reach before it can be shown to the user
  - score of the kth-highest scoring document
  - gives *threshold* τ
  - optimization methods estimate τ' to ignore documents

Threshold Methods

- For document-at-a-time processing, use score of lowest-ranked document so far for τ'
  - for term-at-a-time, have to use k_{th}-largest score in the accumulator table
- *MaxScore* method compares the maximum score that remaining documents could have to τ'
  - *safe* optimization in that ranking will be the same without optimization

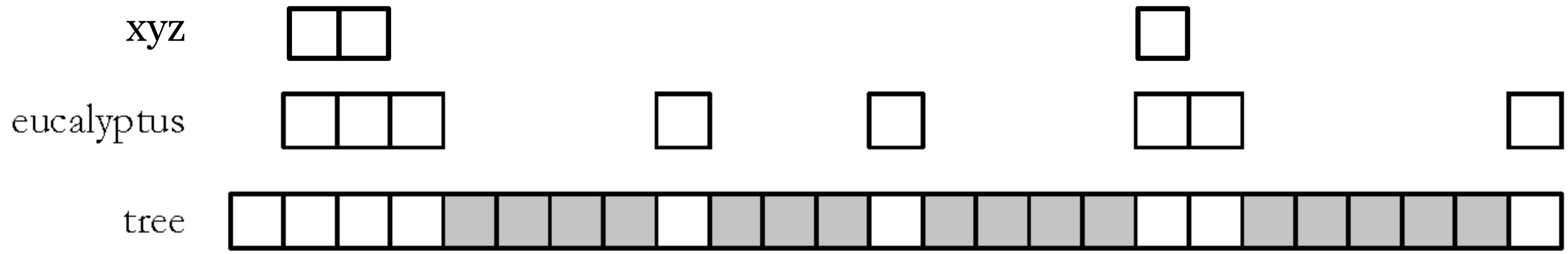
Better than the example in the textbook. See my Note 2 too.

MaxScore Example



- Compute max term scores, μ_t, of each list and sort them in decreasing order (fixed during query processing)
- Assume k =3, τ' is lowest score of the current top-k documents
- If $\mu_{tree} < \tau'$ ➔ any doc that scores higher than τ' must contains *at least one of* the first two keywords (aka *required term set*)
  - Use postings lists of required term set to "drive" the query processing
  - Will only check **some of** the white postings in the list of "tree" to compute score ➔ at least all gray postings are skipped.

MaxScore



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Other Approaches

- Early termination of query processing
  - ignore high-frequency word lists in term-at-a-time
  - ignore documents at end of lists in doc-at-a-time
  - *unsafe* optimization
- List ordering
  - order inverted lists by quality metric (e.g., PageRank) or by partial score
  - makes unsafe (and fast) optimizations more likely to produce good documents

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

- Justifications
  - User has a task and a query formulation
  - Cosine matches docs to query
  - Thus cosine is anyway a proxy for user happiness
- Approximate query processing
  - 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 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

Can generalize to WAND method (safe)

3 of 4 query terms

Antony	3	4	8	16	32	64	128	
Brutus	2	4	8	16	32	64	128	
Caesar	1	2	3	5	8	13	21	34
Calpurnia	13	16	32					

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 A = $\cup_{t \in Q}$ ChampionList(t)
  - Pick the *K* top-scoring docs from amongst these

Inspired by "fancy lists" of Google:
http://infolab.stanford.edu/~backrub/google.html

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
  - 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 $g(d)$ + 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 all the *high* lists first
  - If we get more than *K* docs, select the top *K* and stop
    - Only union the high lists
  - 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

Why $N^{1/2}$ learder?

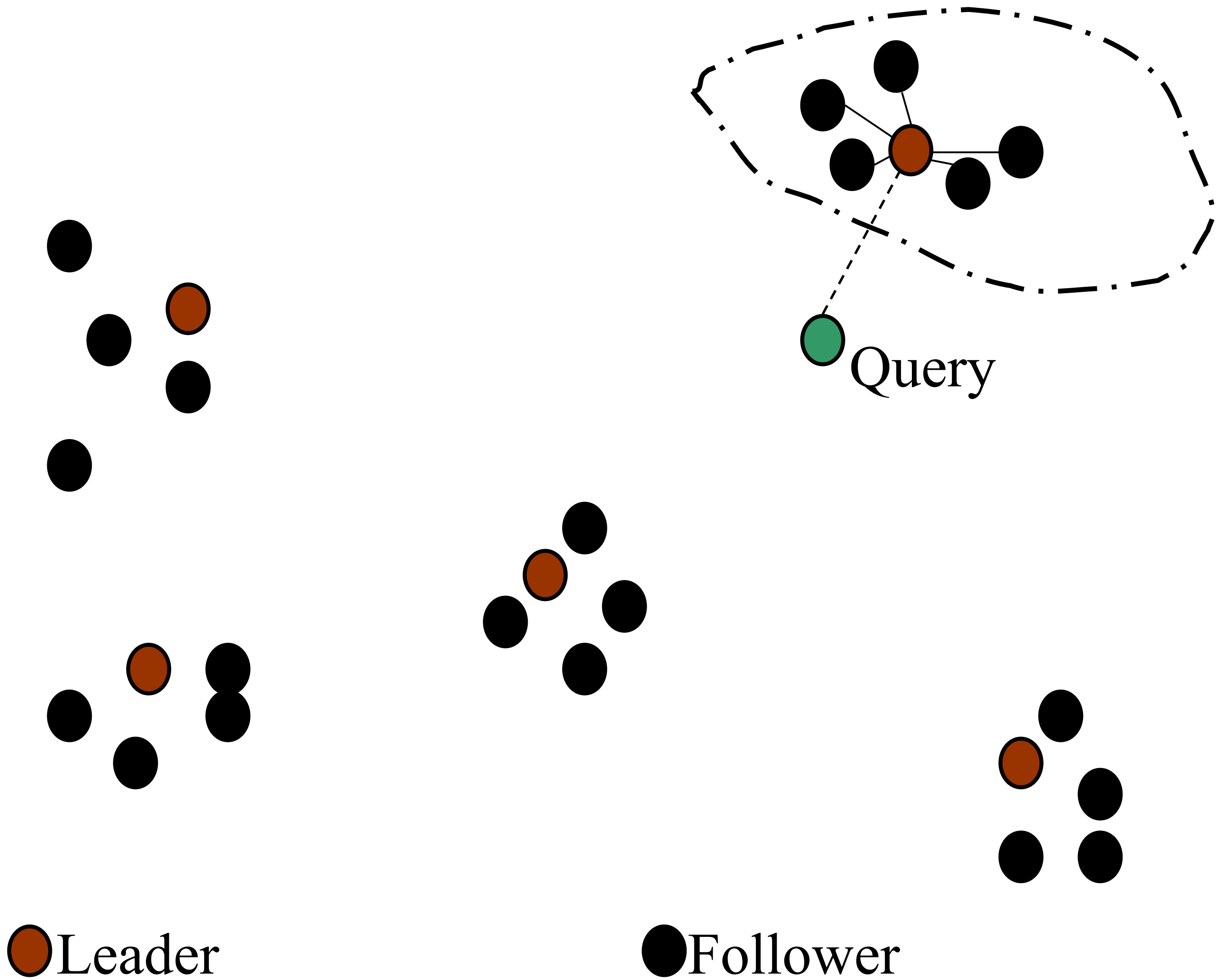
Cluster pruning: preprocessing

- Pick $\sqrt{N}$ *docs* at random: call these *leaders*
- For every other doc, pre-compute nearest leader
  - Docs attached to a leader: its *followers;*
  - Likely: each leader has ~ $\sqrt{N}$ 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 recur on leader/follower construction.

Exercises

- To find the nearest leader in step 1, how many cosine computations do we do?
  - Why did we have $\sqrt{N}$ in the first place?
  - Hint: write down the algorithm, model its cost, and minimize the cost.
- 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

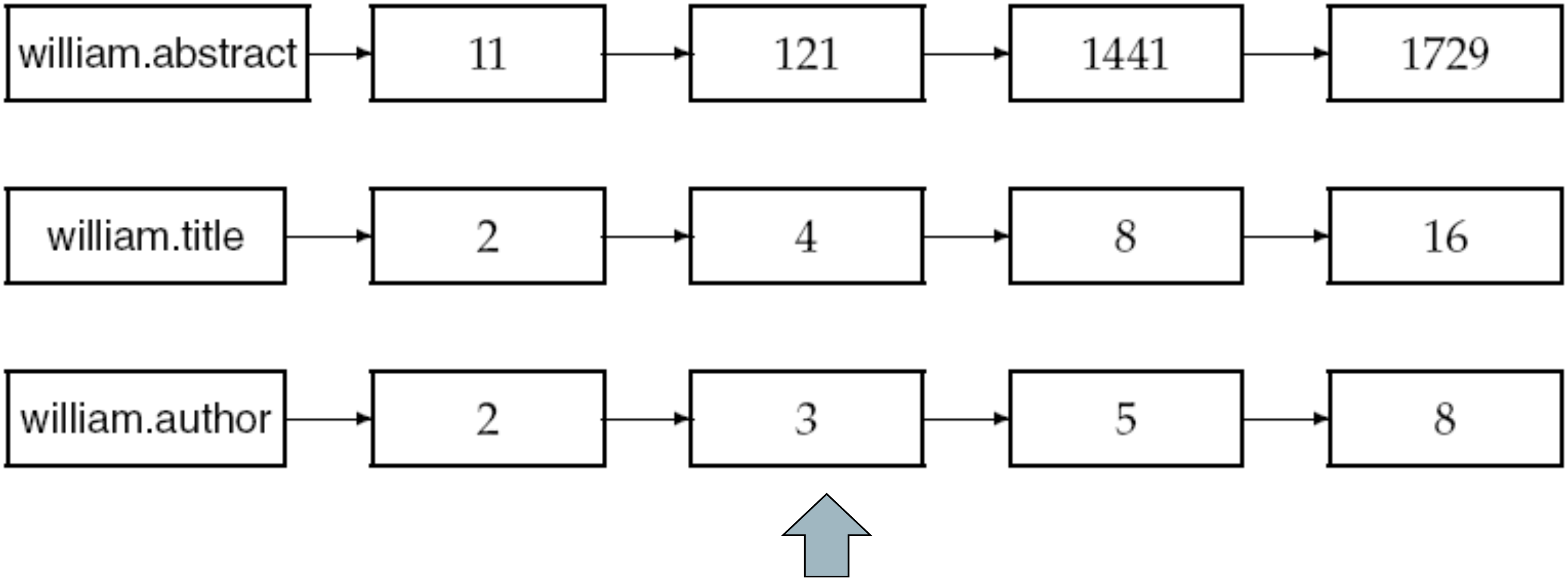
Fields

- 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 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)

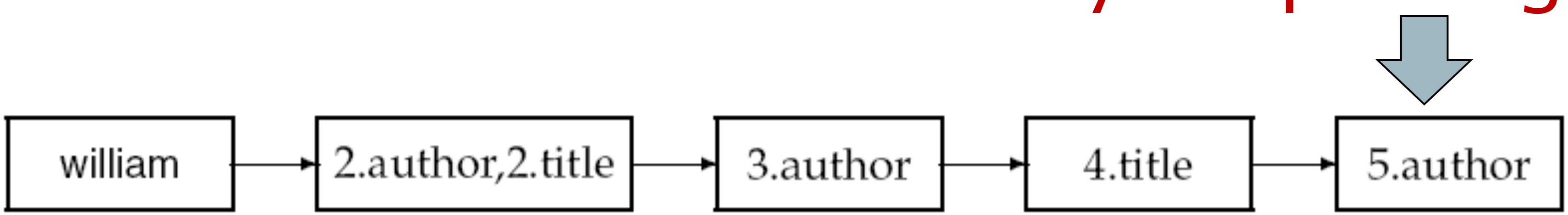
Zone

- A 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



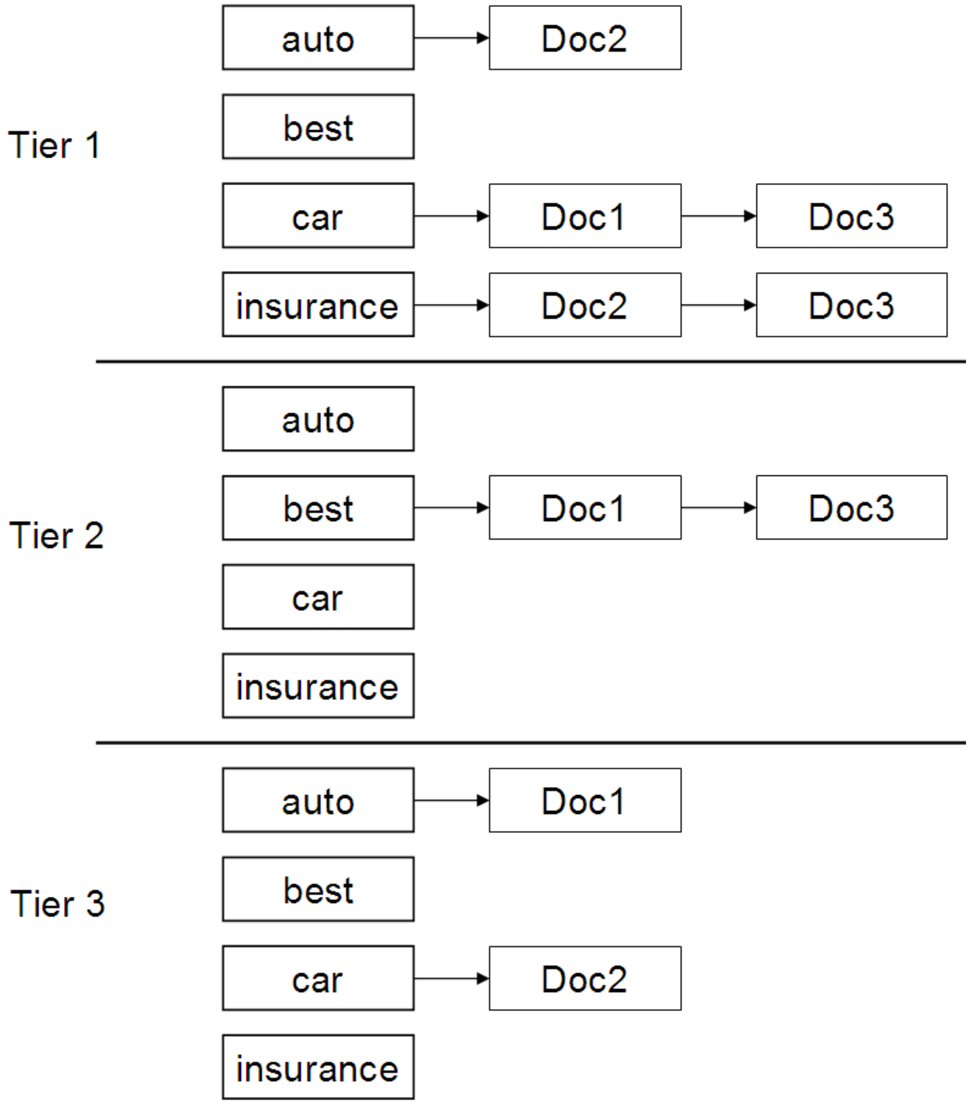
Encode zones in dictionary vs. postings.



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?

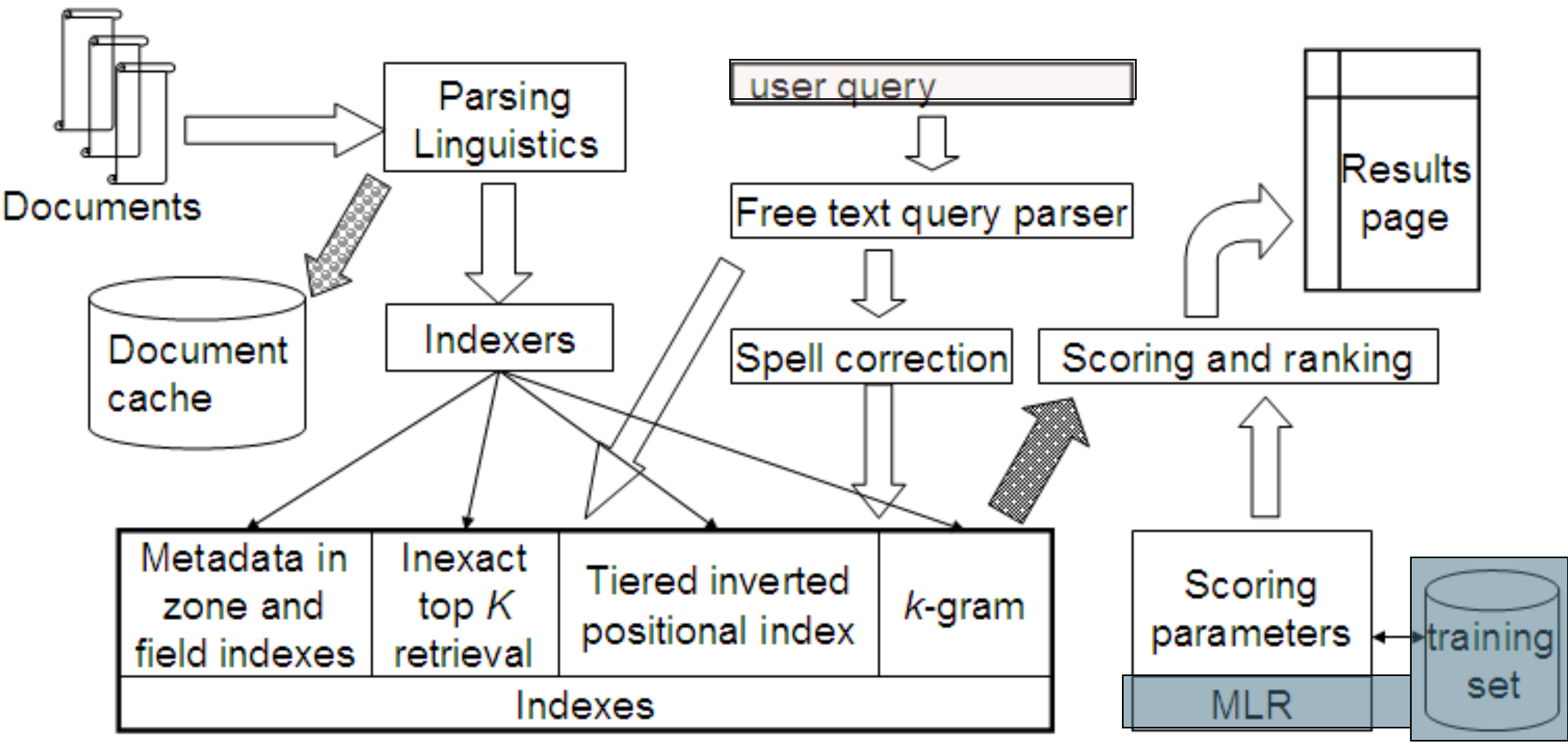
Query parsers

- 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 query parser

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



Resources

- IIR 7, 6.1