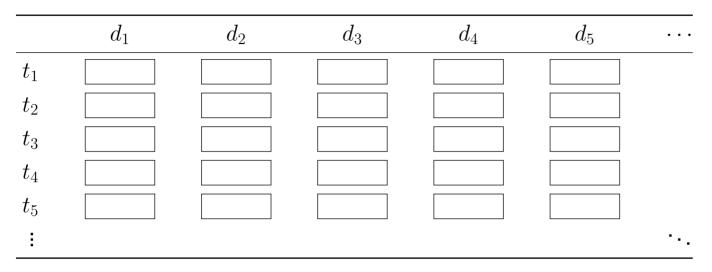
Chapter IR:II

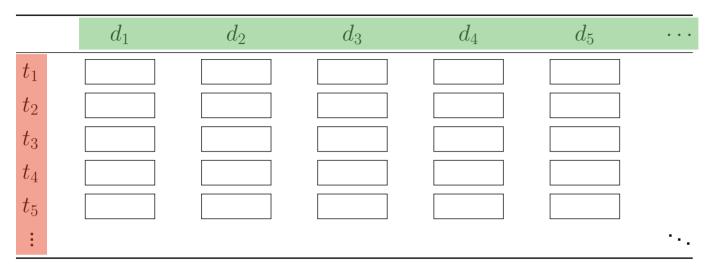
II. Indexing

- □ Indexing Basics
- □ Inverted Index
- Query Processing I
- Query Processing II
- Index Construction
- □ Index Compression
- □ Size Estimation

Term–Document Matrix



Term–Document Matrix

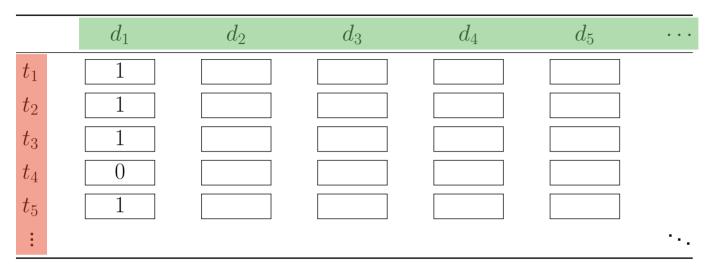


Documents D

- *d*₁ Antony and Cleopatra
- d₂ Julius Caesar
- *d*₃ The Tempest
- d_4 Hamlet
- d_5 Othello

- t_1 Antony
- t_2 Brutus
- t_3 Caesar
- t_4 Calpurnia
- t_5 Cleopatra

Term–Document Matrix

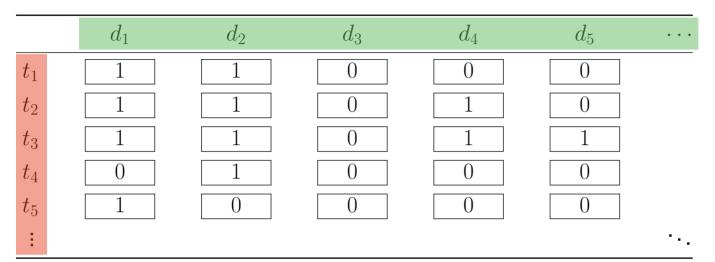


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- t₅ Cleopatra

Term–Document Matrix

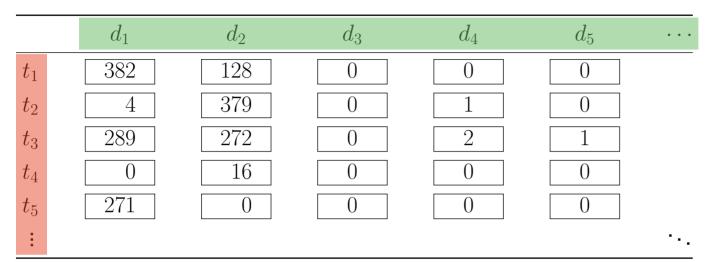


Documents *D*

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Term–Document Matrix

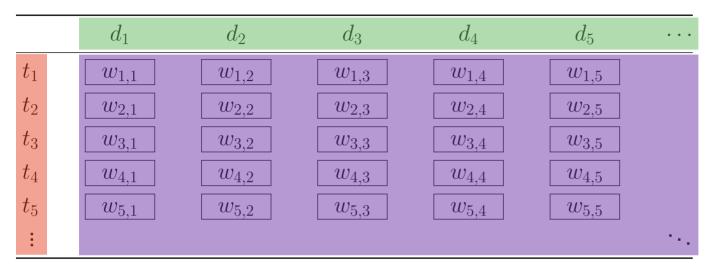
	d_1	d_2	d_3	d_4	d_5	• • •
t_1	$w_{1,1}$	$w_{1,2}$	$w_{1,3}$	$w_{1,4}$	$w_{1,5}$	
t_2	$w_{2,1}$	$w_{2,2}$	$w_{2,3}$	$w_{2,4}$	$w_{2,5}$	
t_3	$w_{3,1}$	$w_{3,2}$	$w_{3,3}$	$w_{3,4}$	$w_{3,5}$	
t_4	$w_{4,1}$	$w_{4,2}$	$w_{4,3}$	$w_{4,4}$	$w_{4,5}$	
t_5	$w_{5,1}$	$w_{5,2}$	$w_{5,3}$	$w_{5,4}$	$w_{5,5}$	
÷						·

Documents D

- d₁ Antony and Cleopatra
- d₂ Julius Caesar
- *d*₃ The Tempest
- d_4 Hamlet
- d_5 Othello

- t_1 Antony
- t_2 Brutus
- t_3 Caesar
- t_4 Calpurnia
- t_5 Cleopatra

Term–Document Matrix



Documents *D*

- *d*₁ Antony and Cleopatra
- d₂ Julius Caesar
- *d*₃ The Tempest
- d_4 Hamlet
- d_5 Othello

\Box Index terms T

- t_1 Antony
- t_2 Brutus
- t_3 Caesar
- t_4 Calpurnia
- t₅ Cleopatra

Term Weights

- Boolean
- Term frequency
- ...

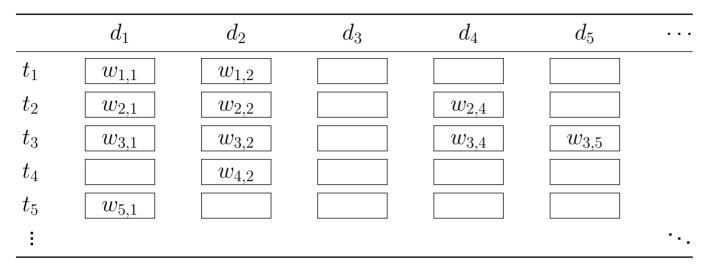
Term–Document Matrix

	d_1	d_2	d_3	d_4	d_5	•••
t_1	$w_{1,1}$	$w_{1,2}$	$w_{1,3}$	$w_{1,4}$	$w_{1,5}$	
t_2	$w_{2,1}$	$w_{2,2}$	$w_{2,3}$	$w_{2,4}$	$w_{2,5}$	
t_3	$w_{3,1}$	$w_{3,2}$	$w_{3,3}$	$w_{3,4}$	$w_{3,5}$	
t_4	$w_{4,1}$	$w_{4,2}$	$w_{4,3}$	$w_{4,4}$	$w_{4,5}$	
t_5	$w_{5,1}$	$w_{5,2}$	$w_{5,3}$	$w_{5,4}$	$w_{5,5}$	
÷						•••

Observations:

- □ Most retrieval models induce a term–document matrix by computing term weights $w_{i,j}$ for each pair of term $t_i \in T$ and document $d_j \in D$.
- \Box Query-independent computations that depend only on *D* are done offline.
- Online, for a query q, the required term weights are looked up to score documents.

Term–Document Matrix



Observations:

- The size of the term–document matrix is $|T| \cdot |D|$.
- □ The term–document matrix is sparse: the vast majority of term weights are 0.
- □ Therefore, most of the storage space required for the full matrix is wasted.
- □ Using a sparse-matrix representation yields significant space savings.
- ➔ An inverted index efficiently encodes a sparse term-document matrix.

Data Structure

Т	\rightarrow	Postings (Posting Lists, Postlists)
t_1	\rightarrow	$\overline{d_1,w_{1,1}}$ $\overline{d_2,w_{1,2}}$
t_2	\rightarrow	$egin{array}{cccccccccccccccccccccccccccccccccccc$
t_3	\rightarrow	$egin{array}{cccccccccccccccccccccccccccccccccccc$
t_4	\rightarrow	$\overline{d_2,w_{4,2}}$
t_5	\rightarrow	$\overline{d_1,w_{5,1}}$
:		

An index is implemented as a multimap (i.e., a hash table with multiple values).

Components of an externalized implementation:

□ Term vocabulary file

Lookup table which maps terms $t_i \in T$ to the start of their posting list in the postings file.

D Postings file(s)

File(s) that store posting lists on disk.

\Box Index entries d_i , [...], so-called postings

Data Structure

Т	\rightarrow	Postings (Posting Lists, Postlists)
t_1	\rightarrow	$egin{array}{cccccccccccccccccccccccccccccccccccc$
t_2	\rightarrow	$egin{array}{cccccccccccccccccccccccccccccccccccc$
t_3	\rightarrow	$egin{array}{cccccccccccccccccccccccccccccccccccc$
t_4	\rightarrow	$\overline{d_2,w_{4,2}}$
t_5	\rightarrow	$\overline{d_1,w_{5,1}}$
:		

An index is implemented as a multimap (i.e., a hash table with multiple values).

Design choices:

- □ Information stored in a posting d_i , [...].
- Ordering of each term's posting list.
- □ Encoding and compression techniques for further space savings.
- Physical implementation details, such as external memory and distribution.

Inverted Index Posting

Given term t and document d, their posting may include the following:

```
<document> [<weights>] [<positions>] ...
```

<document>:

 \Box Reference to the document *d* in which term *t* occurs (or to which it applies).

<weights>:

- \Box Term weight *w* for term *t* in document *d*.
- □ Often, only basic term weights are stored (e.g., term frequency tf(t, d)). Storing model-specific weights saves runtime at the expense of flexibility.

<positions>:

- □ Term positions within the document, e.g., term, sentence, page, chapter, etc.
- □ Field information, e.g., title, author, introduction, etc.

Inverted Index Posting

Two special-purpose entries are distinguished:

... [<list length>]

... [<skip pointer>]

<list length>:

- \Box Added to the first entry of the posting list of a term *t*.
- □ Stores the length of the posting list.
- What does the length of a posting list indicate?

<skip pointer>:

- □ Used to implement a skip list in a term's posting list, when ordered by ID.
- □ Allows for random access to postings in $O(\log df(t, D))$.
- □ An effective amount of skip entries has been found to be $\sqrt{df(t, D)}$. First entry of a posting list, and then at random (or regular) intervals.

Inverted Index Posting

Two special-purpose entries are distinguished:

... [<list length>]

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<list length>:

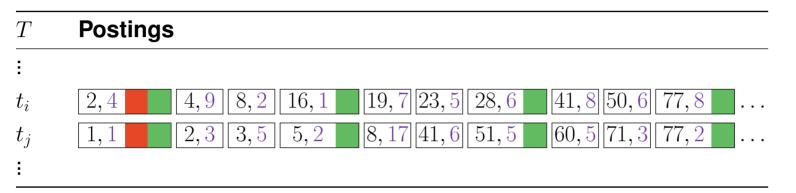
- \Box Added to the first entry of the posting list of a term *t*.
- □ Stores the length of the posting list.
- **□** Equals the number of documents containing t (document frequency df(t, D)).

<skip pointer>:

- □ Used to implement a skip list in a term's posting list, when ordered by ID.
- □ Allows for random access to postings in $O(\log df(t, D))$.
- □ An effective amount of skip entries has been found to be $\sqrt{df(t, D)}$. First entry of a posting list, and then at random (or regular) intervals.

Inverted Index Posting List, Postlist

Example for two posting lists, where for term t_i postings $k, tf(t_i, d_k)$ are stored:



Ordering:

- □ by document identifier. Problem: "good" documents randomly distributed.
- □ by document quality. Problem: index updates more complicated.
- □ by term weight. Problem: no canonical order across rows; skip lists useless.

Compression:

- □ The size of an index is in O(|D|), where |D| denotes the disk size of D.
- Posting lists can be effectively compressed with tailored techniques.

Remarks:

- The term "inverted index" is redundant: "index" already denotes the structure in which terms are assigned to the (parts of) documents in which they occur. Better suited, but less frequently used, is "inverted file", which expresses that a (document) file is "inverted" to form an index. So instead of assigning terms to documents, an index assigns documents to terms.
- □ A trade-off must be made between the amount of information stored in a posting and the time required to process a post list. The more information stored in a posting, the more has to be loaded into memory and decoded as the posting list is traversed.
- □ A skip entry can contain more than one pointer, so skip steps of different lengths are possible.
- Depending on the search domain, it may be beneficial to create more than one index with different properties.

Chapter IR:II

II. Indexing

- □ Indexing Basics
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Query Processing I Retrieval Types

Query processing can be based on two basic approaches:

Set retrieval

A query induces a subset of the indexed documents which is considered relevant. Important applications: e-discovery, patent search, systematic reviews.

Ranked retrieval

A query induces a ranking among all indexed documents in descending order of relevance.

Ranked retrieval is the norm in virtually all modern search engines.

Query Semantics for Set Retrieval

Keyword queries have Boolean semantics that is either implicitly specified by user behavior and expectations or explicitly specified.

We distinguish four types:

Single-term queries

Disjunctive multi-term queries

Only Boolean OR connectives. Example: Antony \lor Brutus \lor Calpurnia.

Conjunctive multi-term queries

Only Boolean AND connectives. Example: Antony \wedge Brutus \wedge Calpurnia.

+ Constraint: Proximity

Example: Antony /5 Caesar

+ Constraint: Phrase

Example: "Antony and Caesar"

Complex" Boolean multi-term queries

Remainder of Boolean formulas. Example: (Antony \vee Caesar) $\wedge \neg$ Calpurnia. Normalized to disjunctive or conjunctive normal form.

Remarks:

□ Which index configuration applies to which type of query?

Query types:

- Single-term queries
- Disjunctive multi-term queries
- Conjunctive multi-term queries
 - Boolean AND queries
 - Proximity queries
 - Phrase queries

Index configurations:

- Postlists ordered by document ID
- Postlists ordered by document quality
- Postlists ordered by term weight
- Positional indexing
 Postings also store term positions.

Remarks:

□ Which index configuration applies to which type of query?

Query types:

- Single-term queries
- Disjunctive multi-term queries
- Conjunctive multi-term queries
 - Boolean AND queries
 - Proximity queries
 - Phrase queries

Index configurations:

- Postlists ordered by document ID
- Postlists ordered by document quality
- Postlists ordered by term weight
- Positional indexing
 Postings also store term positions.
- □ Single-term queries are directly answered with a term weight ordering.
- Disjunctive multi-term queries can be processed with any postlist ordering.
- □ Conjunctive multi-term queries benefit from a canonical postlist order.
- □ Proximity and phrase queries require positional indexing.

Conjunctive Multi-Term Queries

Given an index with postings $k, tf(t, d_k)$ and a query $q = t_1 \land \ldots \land t_n$, compute the collection $R \subseteq D$ of documents relevant to q.

\overline{T}	Postings
:	
t_i	2,4 $4,9$ $8,2$ $16,1$ $19,7$ $23,5$ $28,6$ $41,8$ $50,6$ $77,8$
t_{j}	$1,1 \qquad 2,3 \ 3,5 \ 5,2 \qquad 8,17 \ 41,6 \ 51,5 \qquad 60,5 \ 71,3 \ 77,2 \qquad \dots$
÷	

What is the underlying problem to which processing query q can be reduced?

Conjunctive Multi-Term Queries

Given an index with postings $k, tf(t, d_k)$ and a query $q = t_1 \land \ldots \land t_n$, compute the collection $R \subseteq D$ of documents relevant to q.

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t_i	2, 4 $4, 9$ $8, 2$ $16, 1$ $19, 7$ $23, 5$ $28, 6$ $41, 8$ $50, 6$ $77, 8$
t_{j}	$1,1 \qquad 2,3 \ 3,5 \ 5,2 \qquad 8,17 \ 41,6 \ 51,5 \qquad 60,5 \ 71,3 \ 77,2 \qquad \dots$
:	

Problem: List Intersection.

- Instance: L_1, \ldots, L_n . $n \ge 2$ skip lists of numbers.
- Solution: A sorted list R of numbers, so that each number occurs in all n lists.
- Idea: (1) Intersection of the two shortest lists L_i and L_j to obtain $R' \supseteq R$.
 - (2) Iterative intersection of R' with the remaining lists in ascending order of length.

List Intersection

- Algorithm: Intersection of Two Lists.
- Input: L_1, L_2 . Skip lists of numbers implemented as singly linked lists.
- Output: Sorted list of numbers occurring in both L_1 and L_2 .

IntersectTwo (L_1, L_2)

- 1. Initialization of result list R and one iterator variable x_1 and x_2 per list.
- 2. While the iterators point to list entries, process them as follows.
- 3. If the list entries' keys match, append a merged entry to the result list R.
- 4. While the key of x_1 is smaller than that of x_2 advance x_1 .
- 5. While the key of x_2 is smaller than that of x_1 advance x_2 .
- 6. Return R, once an iterator reaches the end of its list.

List Intersection

- Algorithm: Intersection of Two Lists.
- Input: L_1, L_2 . Skip lists of numbers implemented as singly linked lists.
- Output: Sorted list of numbers occurring in both L_1 and L_2 .

```
IntersectTwo(L_1, L_2)
  1. R = list(); x_1 = L_1.head; x_2 = L_2.head
  2. WHILE x_1 \neq NIL and x_2 \neq NIL do
  3. IF x_1.key == x_2.key THEN
  4. R = Insert(R, merge(x_1, x_2))
  5.
       x_1 = x_1.next; x_2 = x_2.next
  6.
       ENDIF
  7. WHILE x_1 \neq NIL and x_2 \neq NIL and x_1.key < x_2.key do
          IF CanSkip(x_1, x_2.key) THEN
  8.
       x_1 = Skip(x_1, x_2.key)
  9.
 10.
     ELSE
11.
     x_1 = x_1.next
12.
     ENDIF
13. ENDDO
 :
       Like lines 7-13 with x_1 and x_2 exchanged.
21.
      ENDDO
```

22. return(R)

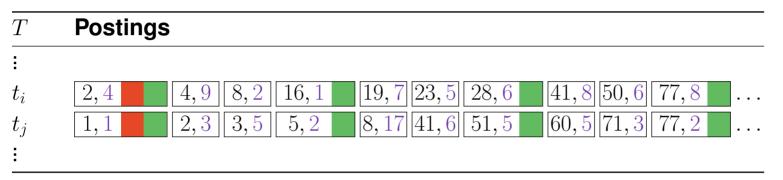
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IntersectTwo(L_1, L_2)
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  2. WHILE x_1 \neq NIL and x_2 \neq NIL do
  3. IF x_1.key == x_2.key THEN
  4. R = Insert(R, merge(x_1, x_2))
  5. x_1 = x_1.next; x_2 = x_2.next
  6.
       ENDIF
  :
     Like lines 14-20 with x_1 and x_2 exchanged.
14. WHILE x_1 \neq NIL and x_2 \neq NIL and x_2.key < x_1.key do
15. IF CanSkip(x_2, x_1.key) THEN
16. x_2 = Skip(x_2, x_1, key)
17. ELSE
18. x_2 = x_2.next
19.
         ENDIF
20.
     ENDDO
21. ENDDO
22. return(R)
```

List Intersection: Example

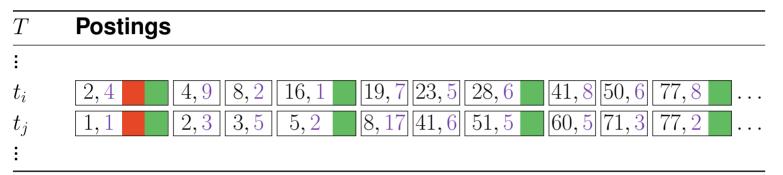
Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:



Execute *IntersectTwo* (L_i, L_j) .

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

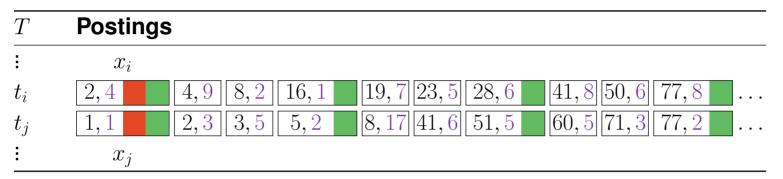


Execute *IntersectTwo* (L_i, L_j) .

Result R = ()

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

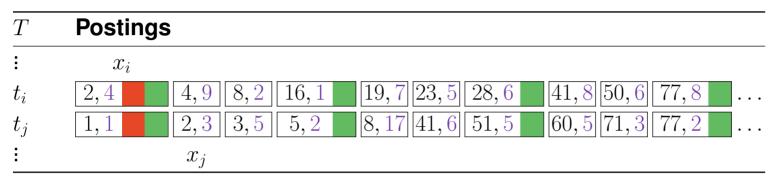


Execute *IntersectTwo* (L_i, L_j) .

Result R = ()

List Intersection: Example

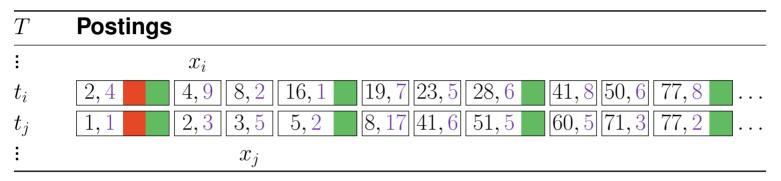
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Execute *IntersectTwo* (L_i, L_j) .

List Intersection: Example

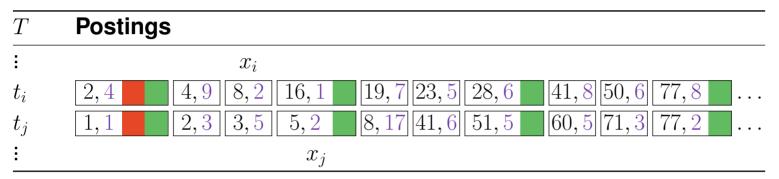
Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

T**Postings** x_i 77, 816, 1|19,7||23,5||28,6||41, 8||50, 6|2, 44, 98,2 t_i . . . 2, 33, 55, 28,17 41,6 51,5 |60, 5||71, 3||77, 2|1, 1 t_{j} . . . x_j

Execute *IntersectTwo* (L_i, L_j) .

List Intersection: Example

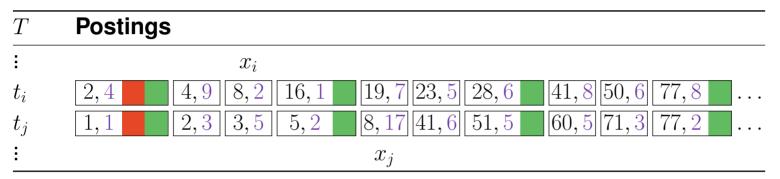
Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:



Execute *IntersectTwo* (L_i, L_j) .

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:



Execute *IntersectTwo* (L_i, L_j) .

Result $R = 2, \dots 8, \dots$

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

TPostings x_i 2, 416, 1|19,7||23,5||28,6||41, 8||50, 6|77, 88,2 t_i 4, 9. . . [60, 5] [71, 3] [77, 2]2, 33, 55, 28,17 41,6 51,5 1, 1 t_{j} . . . x_j

Execute *IntersectTwo* (L_i, L_j) .

Result $R = 2, \dots 8, \dots$

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

TPostings x_i 2, 48,2 16, 1|19, 7||23, 5|28, 6|41, 8||50, 6|4, 977,8 t_i . . . 2, 33, 55, 28,17 41,6 51,5 |60, 5||71, 3||77, 21, 1 t_{j} . . . x_j

Execute *IntersectTwo* (L_i, L_j) .

Result $R = 2, \dots 8, \dots$

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

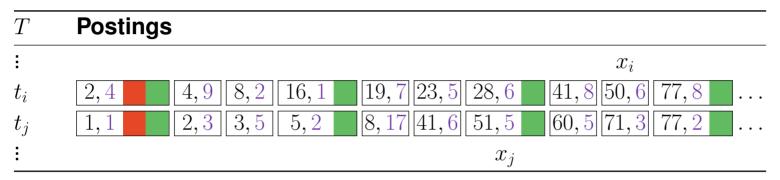
TPostings x_i |41,8||50,6|2, 48,2 16, 1|19, 7||23, 5|28, 6|77,8| t_i 4, 9. . . 2, 33, 55, 28,17 41,6 51,5 |60, 5||71, 3||77, 21, 1 t_{j} . . . x_j

Execute *IntersectTwo* (L_i, L_j) .

Result R = 2, ..., 8, ..., 41, ...

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

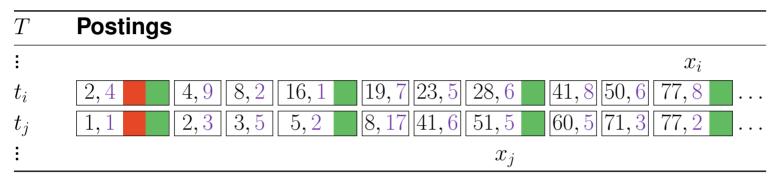


Execute *IntersectTwo* (L_i, L_j) .

Result R = 2, ..., 8, ..., 41, ...

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

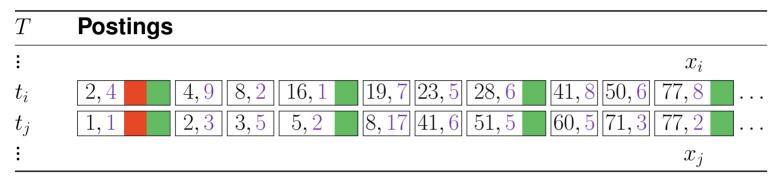


Execute *IntersectTwo* (L_i, L_j) .

Result R = 2, ..., 8, ..., 41, ...

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:

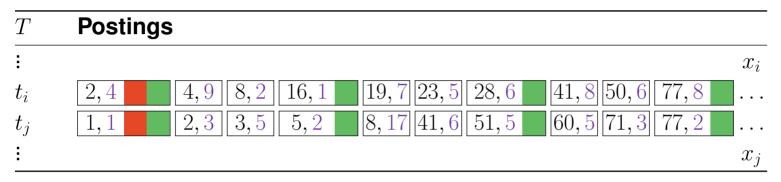


Execute *IntersectTwo* (L_i, L_j) .

Result R = 2, ..., 8, ..., 41, ..., 77, ...

List Intersection: Example

Given an index with postings k, $tf(t, d_k)$, two postlists L_i, L_j for terms t_i, t_j , and the query $q = t_i \wedge t_j$:



Execute *IntersectTwo* (L_i, L_j) .

Result R = 2, ..., 8, ..., 41, ..., 77, ...

Remarks:

- Postlists are usually too large to fit in main memory, so iterating them brings performance benefits.
- □ The *key* attribute stores the document identifier of a posting.
- □ The *merge* function returns a posting merged from the two postings passed in. It merges the potentially stored term weights and other information stored in them.
- □ The *next* attribute stores the successive posting.
- □ The *CanSkip* function checks whether the current posting contains skip information and whether a target with a document identifier less than or equal to the *key* value passed is available.
- □ The *Skip* function returns the posting that is closest to but less than or equal to the *key* value passed.

List Intersection

- Algorithm: Intersect Many Lists.
- Input: L_1, \ldots, L_n . Skip lists of numbers implemented as singly linked lists.
- Output: Sorted list of numbers occurring in all L_1, \ldots, L_n .

```
IntersectMany(L_1, \ldots, L_n)
```

- // Sort by list length.
- 1. $H = BuildMinHeap(L_1, \ldots, L_n);$
- 2. R = ExtractMin(H)
- 3. WHILE |H| > 0 do
- 4. $L_{\min} = ExtractMin(H)$
- 5. $R = IntersectTwo(R, L_{min})$
- 6. **ENDDO**
- 7. return(R)

Why are lists intersected in ascending order of list length?

List Intersection

Algorithm: Intersect Many Lists.

Input: L_1, \ldots, L_n . Skip lists of numbers implemented as singly linked lists.

Output: Sorted list of numbers occurring in all L_1, \ldots, L_n .

IntersectMany (L_1, \ldots, L_n)

- // Sort by list length.
- 1. $H = BuildMinHeap(L_1, ..., L_n);$
- 2. R = ExtractMin(H)
- 3. WHILE |H| > 0 do
- 4. $L_{\min} = ExtractMin(H)$
- 5. $R = IntersectTwo(R, L_{min})$
- 6. **ENDDO**
- 7. return(R)

Observations:

- □ The amount of memory required to store the result list *R* is bounded by the shortest list from L_1, \ldots, L_n .
- Hard disk seeking is minimized since every list is read sequentially.

Proximity Queries

Given a query $q = t_i / \epsilon t_j$, retrieve documents in which t_i and t_j are in close proximity, i.e., within an ϵ -environment of one another, where $\epsilon \ge 1$ terms.

Proximity Queries

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Processing proximity queries requires term positions in postings:

<document> [<weights>] [<positions>] [...]

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Processing proximity queries requires term positions in postings:

Example:

d = "You cannot end a sentence with because because because is a conjunction." $d = \frac{1}{2} \sum_{1}^{2} \frac{1}{10} \sum_{1}^{2} \frac{1$

Posting for "because" and d:Posting for "sentence" and d:d, 3, (7,8,9)d, 1, (5)

In d, "because" is in a 2-environment of {"sentence", "with", "because", "is", "a"}.

Proximity Queries

- Algorithm: Position List Intersection.
- Input: A_1, A_2 . Sorted arrays of positions of two terms t_1, t_2 in a document d. ϵ . Maximal term distance.

Output: For each position in A_1 , the positions from A_2 within an ϵ -environment.

```
IntersectPositions(A_1, A_2, \epsilon)
```

- 1. R = map()
- 2. For i=1 to $A_1.length$ do
- 3. R' = list()
- 4. For j=1 to A_2 .length do
- 5. IF $|A_1[i] A_2[j]| \le \epsilon$ THEN 6. insert $(R', A_2[j])$
- $[IISEII(n, A_2[J])]$
- 7. ELSE IF $A_2[j] > A_1[i]$ Then
- 8. break
- 9. **ENDIF**
- 10. **ENDDO**
- 11. $insert(R, A_1[i], R')$
- 12. **ENDDO**
- 13. return(R)

Remarks:

Pruning unnecessary comparisons

Lines 7–9: Stop comparing once the *j*-th position in A_2 exceeds the *i*-th position in A_1 by more than ϵ . The difference can never get smaller than ϵ again.

Integration into postlist intersection

The if-statement of Line 3 of *IntersectTwo* then additionally checks whether *IntersectPositions* returns a non-empty result.

Phrase Queries

Given a phrase query $q = t_1 \ldots t_m$, retrieve documents in which the terms t_1, \ldots, t_m occur in the same order as in the query q.

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Processing phrase queries requires term positions in postings.

Example:

T	Postings
to	$\dots [4, 250, (\dots, 133, 137, \dots)] \dots$
be	\dots 4, 125, $(\dots, 134, 138, \dots)$ \dots
or	\dots 4, 40, $(\dots, 135, \dots)$ \dots
not	\dots 4, 15, (, 136,) \dots

What phrase does document 4 contain?

Phrase Queries

Given a phrase query $q = t_1 \ldots t_m$, retrieve documents in which the terms t_1, \ldots, t_m occur in the same order as in the query q.

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to	\dots 4, 250, $(\dots, 133, 137, \dots)$
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not	\dots 4, 15, (, 136,) \dots

Document 4 contains the phrase to be or not to be at term positions 133–138.

Observations:

- Processing phrase queries can be reduced to the list intersection problem.
 Algorithms IntersectMany and IntersectTwo can be adjusted to process phrase queries.
- □ The additional run time for phrase processing is in $O(\sum_{d \in IntersectMany(L_t:t \in q)} |d|)$.

Phrase Queries

Given a phrase query $q = t_1 \ldots t_m$, retrieve documents in which the terms t_1, \ldots, t_m occur in the same order as in the query q.

To speed up phrase search, *n*-grams can be used as index terms.

Example:

\overline{T}	Postings	
to be	\dots 4, 80, $(\dots, 133, 137, \dots)$]
be or	\dots 4, 55, $(\dots, 134, \dots)$]
or not	\dots 4, 20, $(\dots, 135, \dots)$]
not to	\dots 4,7, (, 136,)]

Document 4 contains the phrase to be or not to be at term positions 133–138.

How much faster can phrase queries be processed?

Phrase Queries

Given a phrase query $q = t_1 \ldots t_m$, retrieve documents in which the terms t_1, \ldots, t_m occur in the same order as in the query q.

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\overline{T}	Postings	
to be	\dots 4, 80, $(\dots, 133, 137, \dots)$]
be or	\dots 4, 55, $(\dots, 134, \dots)$]
or not	\dots 4, 20, $(\dots, \frac{135}{5}, \dots)$]
not to	\dots 4,7, (, 136,)]

Document 4 contains the phrase to be or not to be at term positions 133–138.

Observations:

- The time to process phrase queries of length at least n is divided by n.
 Only non-overlapping n-grams need to be intersected.
- Maintaining an index with *n*-grams and/or common phrases as index terms speeds up non-phrase queries as well.

Remarks:

- □ The space requirements of a positional index are 2–4 times that of a nonpositional index.
- Most basic retrieval models do not directly employ positional information. If keyword proximity is a desired feature in a retrieval system using a basic retrieval model, positional information usually is implemented as an additional relevance signal or as a prior probability for a document.

Chapter IR:II

II. Indexing

- □ Indexing Basics
- □ Inverted Index
- Query Processing I
- Query Processing II
- Index Construction
- □ Index Compression
- □ Size Estimation

Query Processing II Retrieval Types

Query processing can be based on two basic approaches:

Set retrieval

A query induces a subset of the indexed documents which is considered relevant. Important applications: e-discovery, patent search, systematic reviews.

Ranked retrieval

A query induces a ranking among all indexed documents in descending order of relevance.

Ranked retrieval is the norm in virtually all modern search engines.

Relevance Scoring (Recap)

Quantification of the relevance of an indexed document d to a query q.

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Let $t \in T$ denote a term t from the terminology T of index terms, and let $\omega_X : T \times X \to \mathbf{R}$ denote a term weighting function, where X may be a set of documents D or a set of queries Q. Then the most basic relevance function ρ is:

$$\rho(q,d) = \sum_{t \in T} \omega_Q(t,q) \cdot \omega_D(t,d),$$

where $\omega_Q(t,q)$ and $\omega_D(t,d)$ are term weights indicating the importance of t for the query $q \in Q$ and the document $d \in D$, respectively.

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Observations:

- □ A term *t* may have importance, and hence non-zero weights, for a query *q* or document *d* despite not occurring in them. Example: synonyms.
- \Box The majority of terms from *T* will have insignificant importance to both.
- □ The term weights $\omega_D(t, d)$ can be pre-computed and indexed.
- □ The term weights $\omega_Q(t,q)$ must be computed on the fly.

Query Semantics for Ranked Retrieval

Keyword queries have Boolean semantics that is either implicitly specified by user behavior and expectations or explicitly specified.

We distinguish four types:

Single-term queries

Disjunctive multi-term queries Only Boolean OR connectives. Example: Antony V Brutus V Calpurnia.

Conjunctive multi-term queries

Only Boolean AND connectives. Example: Antony \wedge Brutus \wedge Calpurnia.

- + Constraint: Proximity Example: Antony / Caesar
- + Constraint: Phrase Example: "Antony and Caesar"

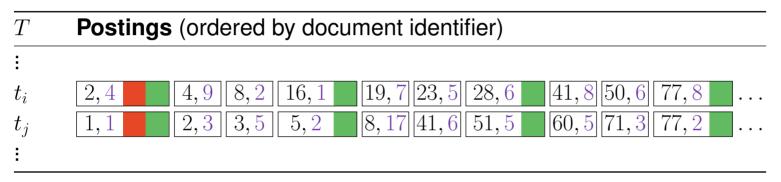
Complex" Boolean multi-term queries

Remainder of Boolean formulas. Example: (Antony \lor Caesar) $\land \neg$ Calpurnia. Can be normalized to disjunctive or conjunctive normal form.

Single-Term Queries

Given a single-term query q = t, the optimal postlist ordering is by term weight.

Example:

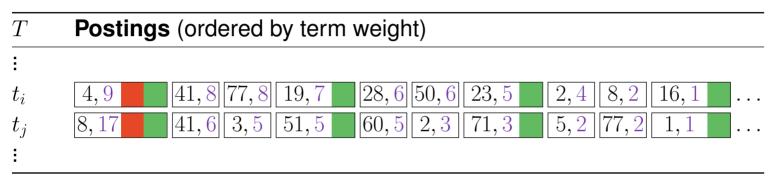


Worst case: The last document of the postlist is the most relevant one. The whole postlist must be examined.

Single-Term Queries

Given a single-term query q = t, the optimal postlist ordering is by term weight.

Example:



Best case: The document whose content is best represented by the term t is the one with the highest term weight. A partial examination of the postlist suffices.

Including a skip list in a postlist ordered by term weights may not be useful.

Disjunctive Queries

In general, a query q is processed as a disjunctive query, where each term $t_i \in q$ may or may not occur in a relevant document d, as long as at least one t_i occurs.

Document-at-a-time scoring

- Precondition: a total order of documents in the index's postlists is enforced
 Ordering criterion: document ID or document quality
- □ Parallel traversal of query term postlists, document ID by document ID.
- □ Each document's score is instantly complete, but the ranking only at the end.
- □ Concurrent disk IO overhead increases with query length.

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- □ Concurrent disk IO overhead increases with query length.

Term-at-a-time scoring

- □ Iterative traversal of query term postlists (e.g., in order of term frequency).
- □ Temporary query postlist contains candidate documents.
- □ As document scores accumulate, an approximate ranking becomes available.
- □ More main memory required for maintaining temporary postlist.

Safe and unsafe optimizations exist (e.g., to stop the search early).

Remarks:

Web search engines often return results without some of a query's terms for very specific queries, indicating a disjunctive interpretation. Nevertheless, many retrieval models assign higher scores to documents matching more of a query's terms, leaning toward a "conjunctive" interpretation at least for the (visible) top results.

Disjunctive Queries

Algorithm: Document-at-a-time Scoring.

Input: L_1, \ldots, L_m . The postlists of the terms t_1, \ldots, t_m of query q. q. Representation of query q, e.g., as array of m term weights.

Output: A list of documents in *D*, sorted in descending order of relevance to *q*.

 $DAATScoring(L_1, \ldots, L_m, \mathbf{q})$

- 1. Initialization of result list R as priority queue, and postlist iterator variables.
- 2. While not all postlists have been processed, repeat the following steps.
- 3. Determine the smallest document identifier d to which the iterators point.
- 4. Collect all term weights of d in an array d.
- 5. Calculate the relevance score $\rho(\mathbf{q}, \mathbf{d})$ and insert it in R.
- 6. Advance all iterators pointing to d.
- 7. Return the list of scored documents R.

Disjunctive Queries

$DAATScoring(L_1, \ldots, L_m, \mathbf{q})$ R = PriorityQueue()1. 2. $x_1 = L_1$.head; ...; $x_m = L_m$.head 3. continue = TRUEWHILE continue DO 4. 5. $d = \min_{i \in [1,m]}(x_i.key)$ $\mathbf{d} = Array(|q|)$ 6. For $i \in [1,m]$ do 7. IF $x_i \neq NIL$ and $x_i.key = d$ then 8. 9. $\mathbf{d}[i] = x_i$. weight 10. ENDIF 11. **ENDDO** 12. $r = \rho(\mathbf{q}, \mathbf{d})$ 13. lnsert(R, record(d, r))continue = FALSE 14. FOR $i \in [1, m]$ do 15. 16. IF $x_i \neq NIL$ and x_i . key = d then 17. $x_i = x_i$.next 18. ENDIF IF $x_i \neq NIL$ THEN 19. 20. continue = TRUE 21. ENDIF 22. **ENDDO** 23. **ENDDO**

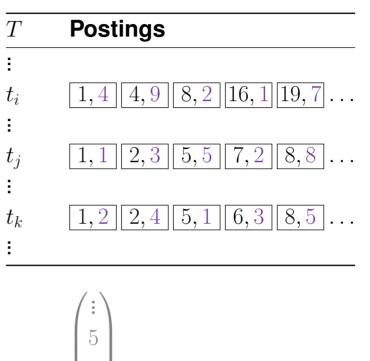
Example:

q

8

i

3



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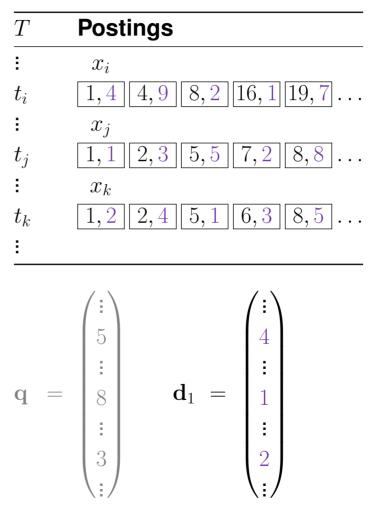
24.

return(R)

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Example:

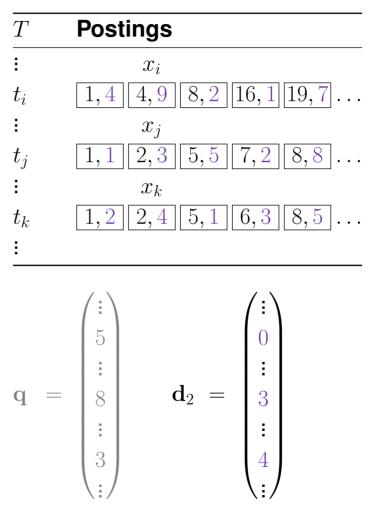


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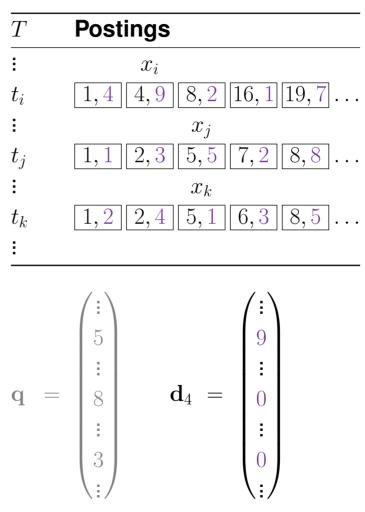


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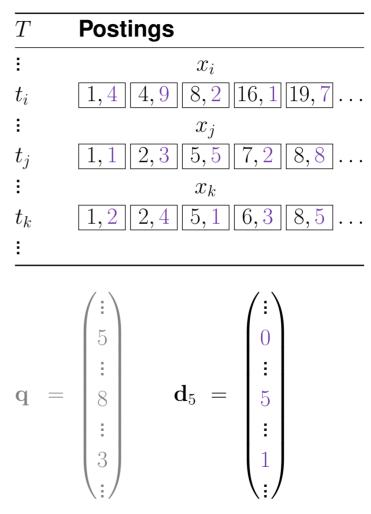


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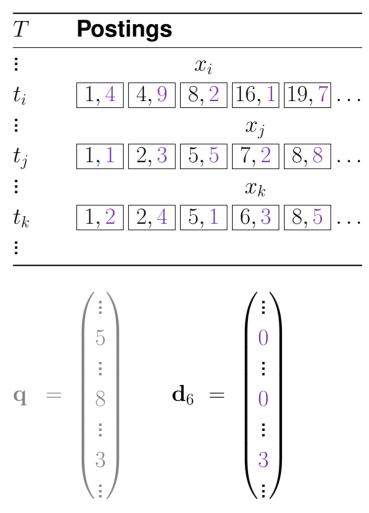


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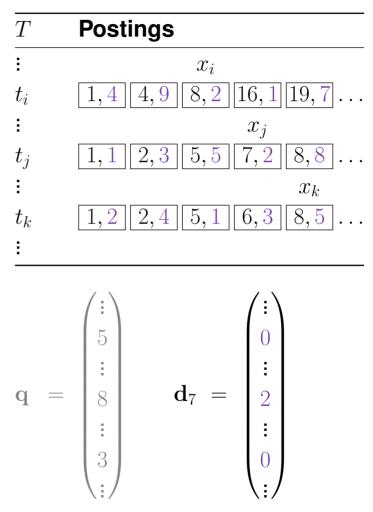


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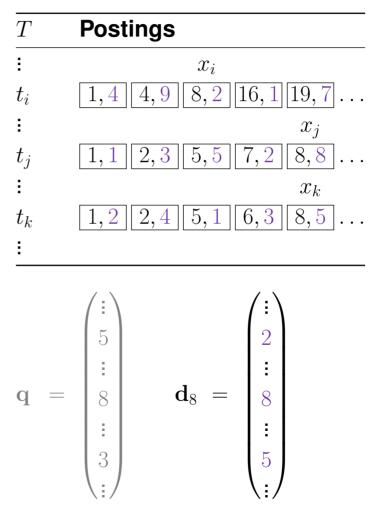


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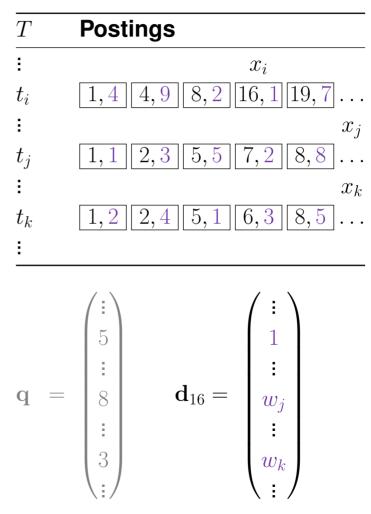


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Example:



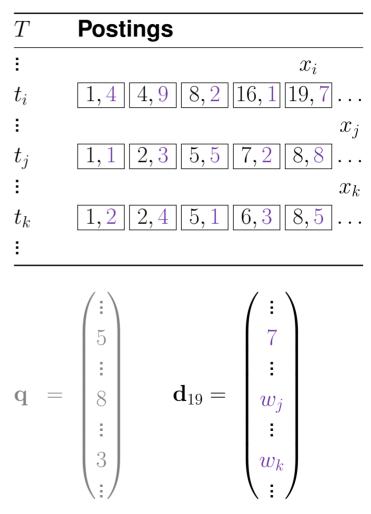
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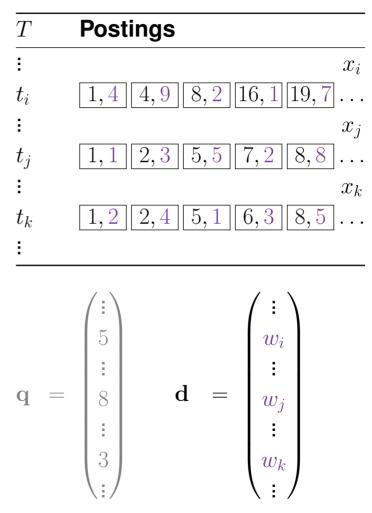


return(R)

Disjunctive Queries

$DAATScoring(L_1, \ldots, L_m, \mathbf{q})$ R = PriorityQueue()1. $x_1 = L_1$.head; ...; $x_m = L_m$.head 2. continue = TRUE 3. WHILE continue DO 4. 5. $d = \min_{i \in [1,m]}(x_i.key)$ $\mathbf{d} = Array(|q|)$ 6. For $i \in [1,m]$ do 7. IF $x_i \neq NIL$ and $x_i.key = d$ then 8. 9. $\mathbf{d}[i] = x_i$. weight 10. ENDIF 11. **ENDDO** 12. $r = \rho(\mathbf{q}, \mathbf{d})$ 13. lnsert(R, record(d, r))continue = FALSE 14. For $i \in [1,m]$ do 15. 16. IF $x_i \neq NIL$ and x_i . key = d then 17. $x_i = x_i$.next 18. ENDIF IF $x_i \neq NIL$ THEN 19. continue = TRUE 20. 21. ENDIF 22. **ENDDO** 23. **ENDDO**

Example:



24.

return(R)

Remarks:

- \Box DAAT = Document at a time
- \Box We distinguish between a real-world query q and its computer representation \mathbf{q} . Likewise, document (identifier) *d*'s representation is d. More complex representations can be imagined than the array-of-weights representations exemplified.
- □ Relevance function $\rho(\mathbf{q}, \mathbf{d})$ maps pairs of document and query representations to a real-valued score indicating document *d*'s relevance to query *q*.
- Document-at-a-time scoring makes heavy use of disk seeks. With increasing query length |q|, dependent on the type of disks used, and the distribution of the index across disks, the practical run time of this approach can be poor (albeit, theoretically, exactly the same postings are processed as for term-at-a-time scoring).
- Document-at-a-time scoring has a rather small memory footprint on the order of the number of documents to return. This footprint can easily be bounded within top-k retrieval by limiting the size of the results priority queue to the k entries with the currently highest scores.
- Document-at-a-time scoring presumes a global postlist ordering by document identifier or document quality.

Disjunctive Queries

Algorithm: Term-at-a-time Scoring.

Input: L_1, \ldots, L_m . The postlists of the terms t_1, \ldots, t_m of query q.

q. Representation of query q, e.g., as array of m term weights.

Output: A list of documents in *D*, sorted in descending order of relevance to *q*.

 $TAATS coring(L_1, \ldots, L_m, \mathbf{q})$

- 1. R = map()
- 2. For $i\in[1,m]$ do
- 3. $x_i = L_i$.head
- 4. While $x_i \neq \textit{NIL}$ do
- 5. $d = x_i.key$
- 6. $w = x_i$. weight
- 7. $R[d] = R[d] + \mathbf{q}[i] \cdot w$
- 8. $x_i = x_i$.next
- 9. **ENDDO**
- 10. **ENDDO**
- 11. return(PriorityQueue(R))

- 1. Initialization of result list R as map.
- 2. Process postlists interatively.
- 3. Initialization of postlist iterator for the *i*-th postlist.
- 4. For each document *d*'s posting in the postlist:
- 5. Get d's ID.
- 6. Get *t*'s term weight for d.
- 7. Update *d*'s partial document score.
- 8. Advance the iterator.

11. Return the result list, ordered by document scores.

Remarks:

- \Box TAAT = Term at a time
- □ Term-at-a-time scoring has a comparably high main memory load, since the last "intermediate" $|R| = |\bigcup_{i=1}^{m} L_i|$ before an actual ordering is performed. Otherwise, postlists are read consecutively, which suits rotating hard disks. Massive parallelization is possible.
- \Box The order in which terms are processed (Line 2) affects how quick the intermediate scores in R approach the final document scores.
- \Box The relevance function ρ must be additive (Line 7), or otherwise incrementally computable.
- Term-at-a-time scoring makes no a priori assumptions about postlist ordering; in case of conjunctive interpretation some ordering by document identifier is still very helpful since then skip lists can be exploited. However, to speed up retrieval and allow for (unsafe) early termination, ordering by term weight is required.

Top-k Retrieval

Search engine users are often interested only in the top ranked k documents. Lower-ranked documents will likely never be viewed.

Query processing optimization approaches:

Term weight threshold

TAAT-scoring: skip query terms whose inverse document frequency is lower than that of other query terms. Exception: stop word-heavy queries (e.g., to be or not to be).

Relevance score threshold

DAAT-scoring: once >k documents have been found, determine co-occurring query terms in the top k ones; skip remaining documents not containing co-occurring query terms.

Early termination

Postlists ordered by term weight: stop postlist traversal early, disregarding the rest of the postlist that cannot contribute enough to a document's relevance score.

Tiered indexes

Divide documents into index tiers by quality or term frequency. If an insufficient amount of documents is found in the top tier, resort to the next one.

Index Distribution

The larger the size of the document collection D to be indexed, the more query processing time can be improved by scaling up and scaling out.

Term distribution

- Distribution of postlists across local disks.
- □ Speeds up processing on spinning hard drives.

Document distribution (also: sharding)

- Random division of the document collection into subsets (so-called shards) and indexing of each shard on a different server for parallel query processing.
- □ Benefit: Smaller indexes return (more) results faster due to shorter postlists.
- □ Overhead: Query broker to dispatch queries and fuse each server's results.

Tiered indexes

- □ Sharding of the document collection into tiers (e.g., by document importance)
- For instance: Tier 1 shards are kept in RAM, Tier 2 shards are kept in flash memory, and Tier 3 shards on spinning hard disks.

Query Processing II Caching

Queries obey Zipf's law: roughly half the queries a day are unique on that day. Moreover, about 15% of the queries per day have never occurred before [Gomes 2017].

Consequently, the majority of queries have been seen before, enabling the use of caching to speed up query processing.

Caching can be applied at various points:

- Result caching
- Caching of postlist intersections
- Postlist caching

Individual cache refresh strategies must be employed to avoid stale data. Cache hierarchies of hardware and operating system should be exploited.

Chapter IR:II

II. Indexing

- □ Indexing Basics
- □ Inverted Index
- Query Processing I
- Query Processing II
- Index Construction
- □ Index Compression
- □ Size Estimation

In-Memory Index Construction

Algorithm: Index Construction.

Input: $D = \{d_1, \ldots, d_n\}$. Set of documents $d_i = (t_1, \ldots, t_m)$ as lists of terms.

Output: Inverted index of D; postlist of term t_j contains postings $i, tf(t_j, d_i)$.

In Memory Index(D)

- 1. I = map()2. FOR $i \in [1, n]$ DO
- 3. $d_i = D[i]; T = set(); TF = map()$
- 4. For $t \in d_i$ do
- 5. lnsert(T, t)
- 6. TF[t] = TF[t] + 1
- 7. **ENDDO**
- 8. For $t \in T$ do
- 9. If $t \notin I$ then I[t] = list() endif
- 10. L = I[t]
- 11. posting = record(i, TF[t])
- 12. InsertEnd(L, posting)
- 13. **ENDDO**
- 14. **ENDDO**
- 15. return(I)

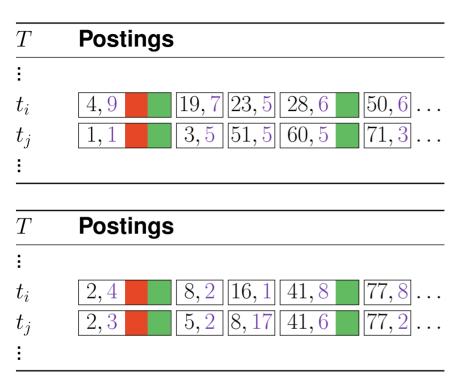
- 1. Initialization of an empty map as index I.
- 2. For each document d in D:
- 3. Collect d's terminology in T.
- 4. Accumulate *d*'s term frequencies.
- 5. For each term t in d's terminology T:

- 6. Insert new posting $i, tf(t_j, d_i)$ for d in I.
- 7. Return index of *D*.

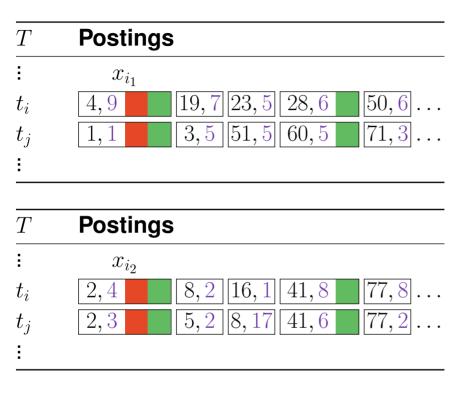
Index Merging

If the document collection *D* does not fit into main memory, indexing is done iteratively, sharding the document collection and merging the shard indexes similar to an <u>external merge sort</u>:

- 1. The *InMemoryIndex* procedure runs until main memory is full.
- 2. The postlists are written to disk in alphabetical order of terms.
- 3. Steps 1 and 2 are repeated until *D* is processed.
- 4. All k postlist files created are read concurrently, performing a k-way merge.

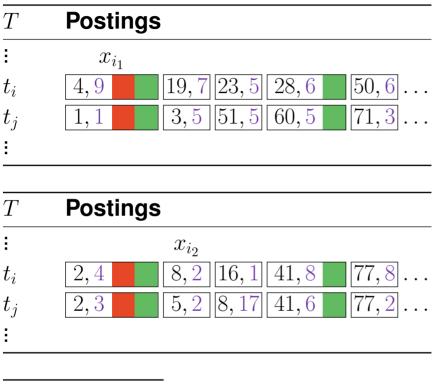


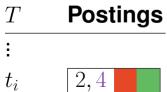
Index Merging

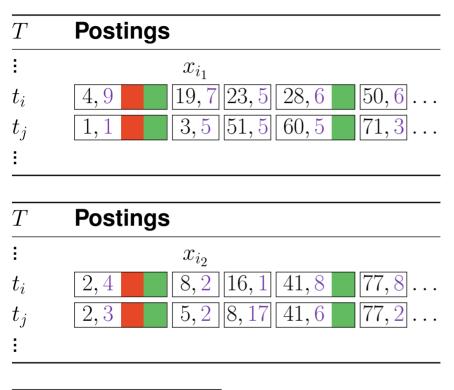


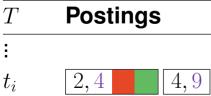
T Postings

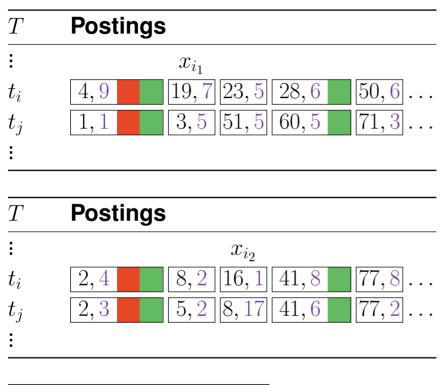
- :
- t_i

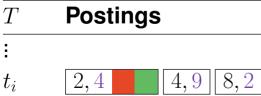


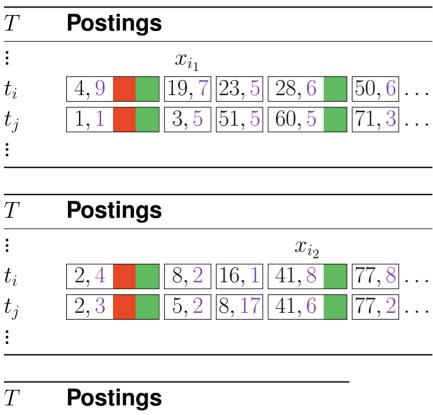


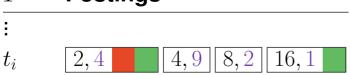


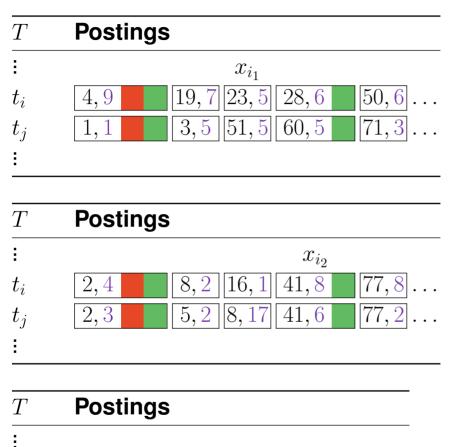


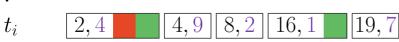


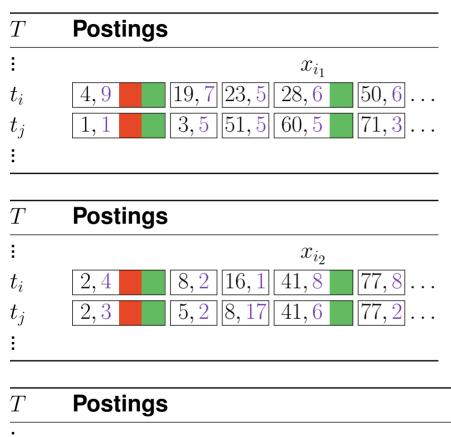


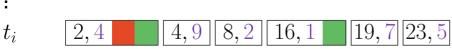


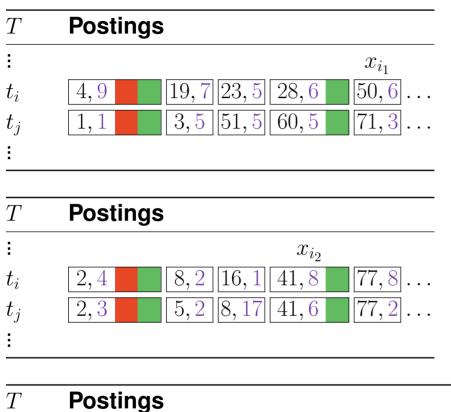


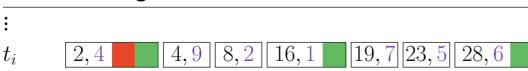


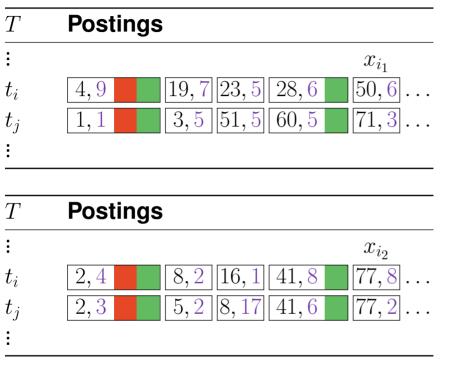


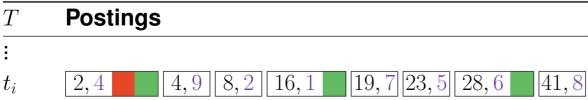




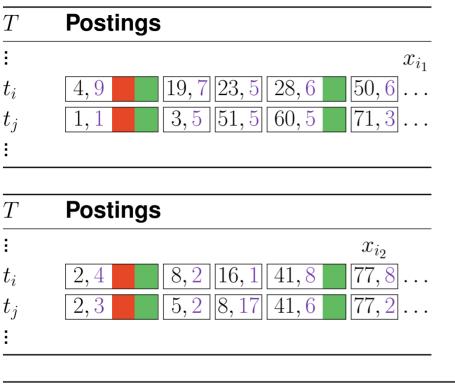


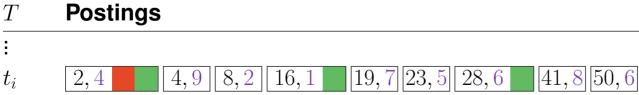




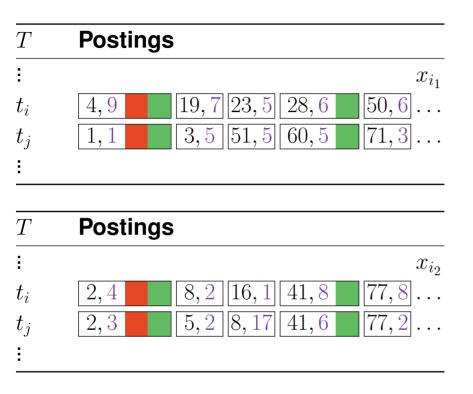


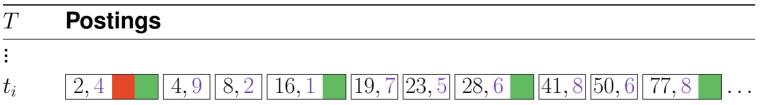
Index Merging

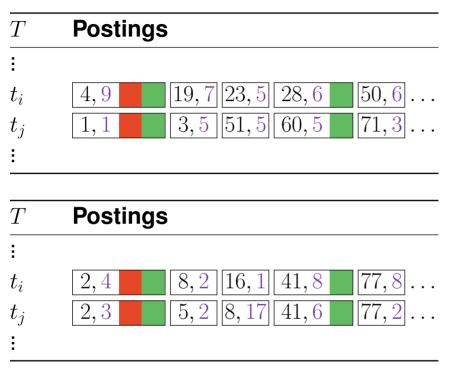


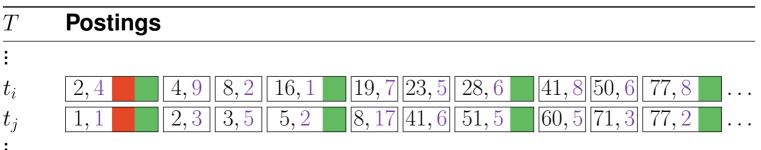


IR:II-119 Indexing









Remarks:

- □ Alphabetical ordering of intermediary postlist files ensures that the index can be read sequentially, albeit concurrently, during merging. Compare to document-at-a-time scoring.
- □ If a term appears in only one of the indexes, its postlist is directly added to the merged index.
- Postings with skip pointers can be pre-determined before merging a postlist so that appropriate space can be allocated immediately, but the actual skip pointers need to be recomputed after the postlist is merged.
- □ The number k of intermediary postlist files that can be read concurrently without causing too much seeking overhead depends on the underlying hardware (e.g., k is smaller for spinning hard disks than for solid state disks). In case k is too large, the intermediary postlist files are merged in multiple passes, k' < k at a time, until all are merged.

Distributed Indexing

If neither the document collection *D*, nor its index can be stored on a single machine, indexing must be performed distributed across a computer cluster.

Many cluster computing frameworks exist nowadays; the <u>NoSQL movement</u>, and ultimately the Big Data hype, was kicked off by Google's MapReduce [Dean 2004].

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From a developer perspective, data processing with MapReduce boils down to implementing two procedures:

- □ Map: Given a key–value pair as input, it outputs a list of key–value pairs.
- Reduce: Given a key and the list of values output by map under that key, it outputs a key-value pair.

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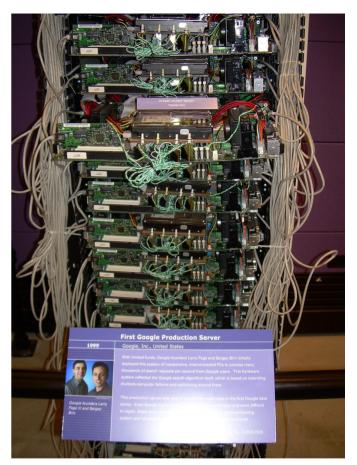
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- Reduce: Given a key and the list of values output by map under that key, it outputs a key-value pair.
- Example:
 - □ IndexingMapper: Given a pair (i, d_i) , where *i* is the document identifier of document d_i as input, output a pair (t, i) for every unique $t \in d_i$.
 - **DFReducer:** Given (t, [..., i, ...]) as input, output (t, |[..., i, ...]|) = (t, df(t, D)).

Remarks:

 Computer clusters are often built from inexpensive commodity hardware. In the early days, desktop computers were used as <u>Beowulf clusters</u>, or dismantled and stacked. Google 1997 and 1999:





- The key contributions of the MapReduce framework are not the actual map and reduce functions, but the scalability and fault-tolerance achieved for a variety of applications by optimizing the execution engine [Wikipedia].
- □ This framework is best-suited for problems that are <u>embarrassingly parallel</u>.
- □ The most widespread open-source implementation is found in <u>Apache Hadoop</u>.

Distributed Indexing

Presuming the document collection is stored in a distributed document storage across the cluster, the execution of a MapReduce job divides into three basic phases:

□ Map phase

The map function is called in parallel on all cluster nodes and fed chunks of the data. Its output is recorded locally on each cluster node.

□ Shuffle phase

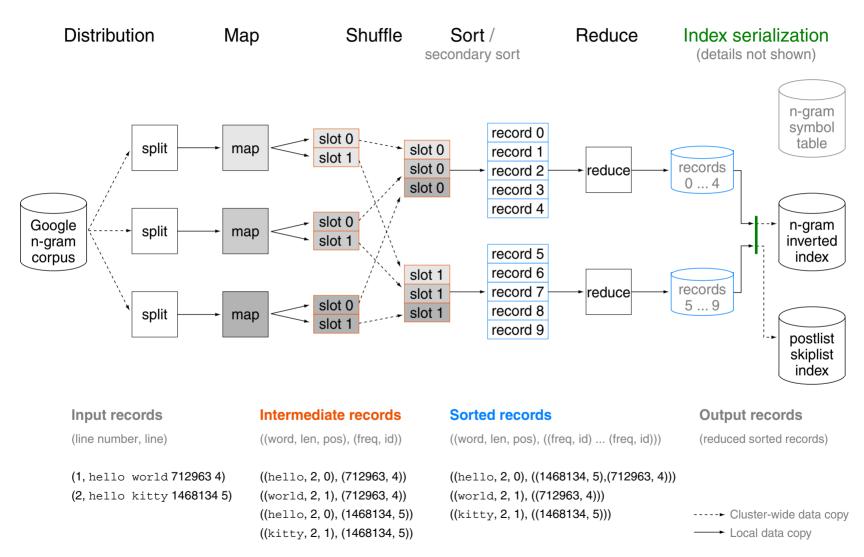
The output is transferred to a random cluster node chosen using a hash function, so that the same key is always transferred to the same cluster node. Once all data belonging to a key are on the same node, the values are sorted.

□ Reduce phase

The reduce function is called in parallel on all cluster nodes and fed the sorted lists, recording their output.

The map and reduce functions are idempotent: they are reexecuted in case of failures. To make optimal use of available resources, the framework may execute the same task more than once on different machines, retaining the first output that emerges (so-called speculative execution).

Distributed Indexing: Example Netspeak [www.netspeak.org]



Index Updates

Document collections grow and change. Therefore, the index must be updated. The following strategies are applied:

□ Index merging

When new documents arrive in large numbers at a time, they are indexed and then the existing index is merged with the new one.

Result merging

When new documents arrive in small numbers at a time, a separate, small index is maintained and updated. Queries are processed against both the existing index and the small one containing the new arrivals, fusing the results.

Deletions list

Deletions are recorded in a deletions list, and deleted documents are removed from search results before results are shown.

Modifications are done by inserting a new document, and deleting the previous version.

Chapter IR:II

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Query Result Set Size

tropical fish aquarium

Search

Web results Page 1 of 3,880,000 results

The total number of results is estimated, since web search engines typically do not explore the entire indexed document collection to compute the first page of results returned, but only a subset.

Approaches:

- Joint probability estimation
- Conditional probability estimation
- Initial result set-based estimation

Remarks:

\Box Example data from the GOV2 collection (collection size |D| is 25,205,179):

Query	Document frequency
aquarium	26,480
breeding	81,885
fish	1,131,855
lincoln	771,326
tropical	120,990
aquarium breeding	1,848
fish aquarium	9,722
fish breeding	36,427
tropical aquarium	1,921
tropical breeding	5,510
tropical fish	18,472
tropical fish aqua	.rium 1,529
tropical fish bree	eding 3,629

Query Result Set Size: Joint Probability

Let $P_{df}(t)$ denote the probability of t occurring at least once in a document:

$$P_{df}(t) = \frac{df(t)}{|D|},$$

where *D* denotes the document collection of size |D| and df(t) the number of documents in *D* containing *t*, called document frequency.

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The result set size df(q) of a query q of length |q| terms can be estimated with

$$df(q) = |D| \cdot \prod_{i=1}^{|q|} P_{df}(t_i) = \frac{\prod_{i=1}^{|q|} df(t_i)}{|D|^{|q|-1}},$$

where t_i denotes the *i*-th term in *q*. This estimation presumes term independence.

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Examples:

- \Box *df*(tropical fish aquarium) = 5.71
- \Box *df*(tropical fish breeding) = 17.65

actual: 1,529 documents actual: 3,629 documents

Query Result Set Size: Conditional Probability

By exploiting term co-occurrence information, we can obtain better estimates with

$$P_{\rm df}(q) \ = \ P_{\rm df}(t_1, t_2, t_3) \ = \ P_{\rm df}(t_1, t_2) \cdot P_{\rm df}(t_3 \mid t_1, t_2),$$

where $P_{df}(t_3 | t_1, t_2) \approx P_{df}(t_3 | t_x) = \max\{P_{df}(t_3 | t_1), P_{df}(t_3 | t_2)\}$ and |q| = 3. Recall that P(A | B) = P(A, B)/P(B). Hence

$$df(q) = |D| \cdot P_{df}(q) = \frac{df(t_1, t_2) \cdot df(t_x, t_3)}{df(t_x)}.$$

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$$df(q) = |D| \cdot P_{df}(q) = \frac{df(t_1, t_2) \cdot df(t_x, t_3)}{df(t_x)}.$$

- \Box Queries of length |q| = 2 need not be estimated, anymore.
- □ Queries of length |q| = 3 are typically underestimated.
- □ Queries of length |q| > 3 still require estimations based on term independence, or storing higher-order co-occurrence information.

Examples:

- \Box *df*(tropical fish aquarium) = 293
- \Box *df*(tropical fish breeding) = 841

actual: 1,529 documents actual: 3,629 documents

Query Result Set Size: Initial Result Set-based Estimation

Let $D' \subset D$ denote the documents initially scored for a query q (e.g., in tiered index). Then the size of the total result set in D can be estimated with

$$df(q) = |D_t| \cdot \frac{|D'_q|}{|D'|} = df(t) \cdot \frac{|\{d \mid d \in D' \land q \in d\}|}{|D'|},$$

where *t* is the query term with the smallest subset $D_t \subset D$ of documents that contain *t*, and $D'_q \subset D'$ is the subset of the initially scored documents D' that contain all terms of *q*.

Query Result Set Size: Initial Result Set-based Estimation

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where *t* is the query term with the smallest subset $D_t \subset D$ of documents that contain *t*, and $D'_q \subset D'$ is the subset of the initially scored documents D' that contain all terms of *q*.

This estimation presumes relevant documents are uniformly distributed across all documents in D_t . Why does it usually overestimate the result set size?

Examples:

- **D** With $D_{\text{aquarium}} = 26,480$, let |D'| = 3,000, and $|D'_q| = 258$:
- \Box *df*(tropical fish aquarium) = 2,277

actual: 1,529 documents

- **D** With $D_{\text{breeding}} = 81, 885$, let |D'| = 3,000, and $|D'_q| = 150$:
- \Box *df*(tropical fish breeding) = 4,094

actual: 3,629 documents

Query Result Set Size: Initial Result Set-based Estimation

Let $D' \subset D$ denote the documents initially scored for a query q (e.g., in tiered index). Then the size of the total result set in D can be estimated with

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This estimation presumes relevant documents are uniformly distributed across all documents in D_t . Overestimations result from D' containing the most "important" documents indexed. As |D'| approaches $|D_w|$, estimations approach the true value.

Examples:

- **D** With $D_{\text{aquarium}} = 26,480$, let |D'| = 6,000, and $|D'_q| = 402$:
- \Box **df**(tropical fish aquarium) = 1,774

actual: 1,529 documents

- **D** With $D_{\text{breeding}} = 81,885$, let |D'| = 6,000, and $|D'_q| = 276$:
- \Box *df*(tropical fish breeding) = 3,767

actual: 3,629 documents

Indexed Collection Size: Joint Probability-based

Most search engines are black boxes to outsiders, and many do not share the size of the document collection they index.

Indexed Collection Size: Joint Probability-based

Most search engines are black boxes to outsiders, and many do not share the size of the document collection they index.

Given a web search engine, the size |D| of the document collection D indexed can be estimated using two independently occurring terms t_1 and t_2 :

$$P_{df}(t_1, t_2) = P_{df}(t_1) \cdot P_{df}(t_2) \quad \rightsquigarrow \quad |D| = \frac{df(t_1) \cdot df(t_2)}{df(t_1, t_2)}.$$

Averaging over many term pairs improves the estimate.

Example for GOV2:

- df(tropical) = 120,990,
 df(lincoln) = 771,326, and
 df(tropical, lincoln) = 3018.
- **□** Then |D| = 30,922,045

actual: 25,205,179 documents

Indexed Collection Size: Proportionality [van den Bosch 2016] [worldwidewebsize.com]

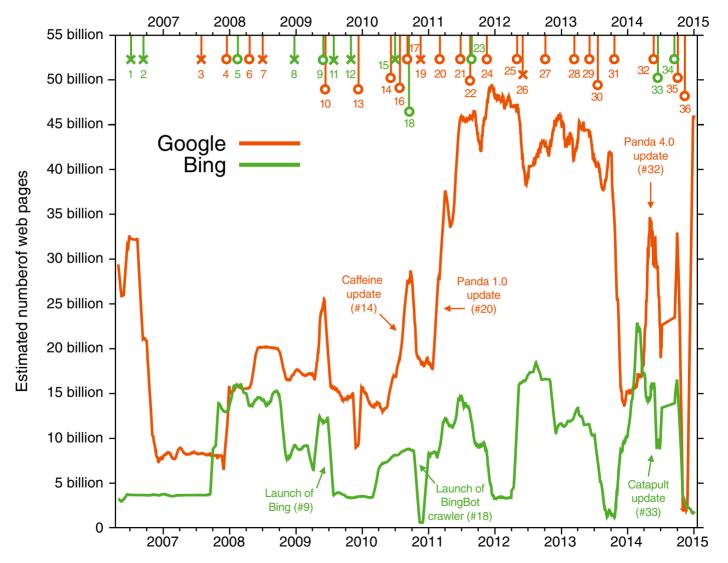
Given a web search engine, the size |D| of the document collection D indexed can be estimated when presuming proportionality to a different reference collection D':

$$P_{\mathrm{df}}^{(D)}(t) = P_{\mathrm{df}}^{(D')}(t) \quad \rightsquigarrow \quad |D| = \frac{\mathrm{d} \mathbf{f}_D(t) \cdot |D'|}{\mathrm{d} \mathbf{f}_{D'}(t)},$$

where *t* is a term occurring in both *D* and *D'*, and $df_D(df_{D'})$ computes the document frequency for *D* (*D'*).

Averaging over terms of varying frequencies improves the estimate.

Indexed Collection Size: Proportionality [van den Bosch 2016] [worldwidewebsize.com]



IR:II-144 Indexing

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Remarks:

- 1. [2006-07-04] MSN Search outage
- 2. [2006-09-11] Launch of (improvements to) Live Search
- 3. [2007-07-31] Update to supplemental results indexing
- 4. [2007-12-18] No more supplemental index; whole index is searched for every query
- 5. [2008-02-12] Crawler improvements for Live Search
- 6. [2008-04-11] Improved crawling of HTML forms
- 7. [2008-06-30] Improved Flash indexing
- 8. [2008-12-11] First experiments with MSNBot 2.0
- 9. [2009-05-28] Launch of Bing
- 10. [2009-06-18] Improved Flash indexing
- 11. [2009-07-31] Bing and Yahoo! team up on search
- 12. [2009-11-04] MSNBot 2.0
- 13. [2009-12-07] Updates to real-time search
- 14. [2010-06-08] Launch of new web indexing system Caffeine
- 15. [2010-06-28] Experiments with BingBot crawler
- 16. [2010-07-29] Improved Flash & AJAX indexing
- 17. [2010-08-31] Google indexes SVG
- 18. [2010-09-03] Launch of BingBot crawler
- 19. [2010-11-11] Improved Flash indexing
- 20. [2011-02-24] Panda Refresh (update to promote (English) high-quality sites more)

Remarks: (continued)

- 21. [2011-06-21] Panda 2.2
- 22. [2011-08-12] Panda (rolled out to all languages)
- 23. [2011-08-15] Gradual roll-out of Tiger indexing architecture
- 24. [2011-11-03] Panda (update, affects 35% of queries)
- 25. [2012-04-24] Penguin update (targeting Web spam, impacting around 3.1% of queries)
- 26. [2012-05-26] Penguin 2 update (impacting less than 0.1% of queries)
- 27. [2012-10-05] Penguin 3 update (impacting around 0.3% of queries)
- 28. [2013-03-12] Panda update
- 29. [2013-05-22] Penguin 4 (v2.0, impacting 2.3% of queries)
- 30. [2013-07-18] Panda update
- 31. [2013-10-04] Penguin 5 (v2.1, impacting around 1% of queries)
- 32. [2014-05-21] Panda 4.0
- 33. [2014-06-18] Launch of Bing Catapult
- 34. [2014-09-09] Improved spam filtering
- 35. [2014-09-26] Panda 4.1 (3-5% of queries affected)
- 36. [2014-10-17] Penguin 6 (v3.0, impacting less than 1% English queries)