UNIVERSITY OF WATERLOO

Data-Intensive Distributed Computing

CS 431/631 451/651 (Fall 2019)

Part 3: Analyzing Text (2/2)

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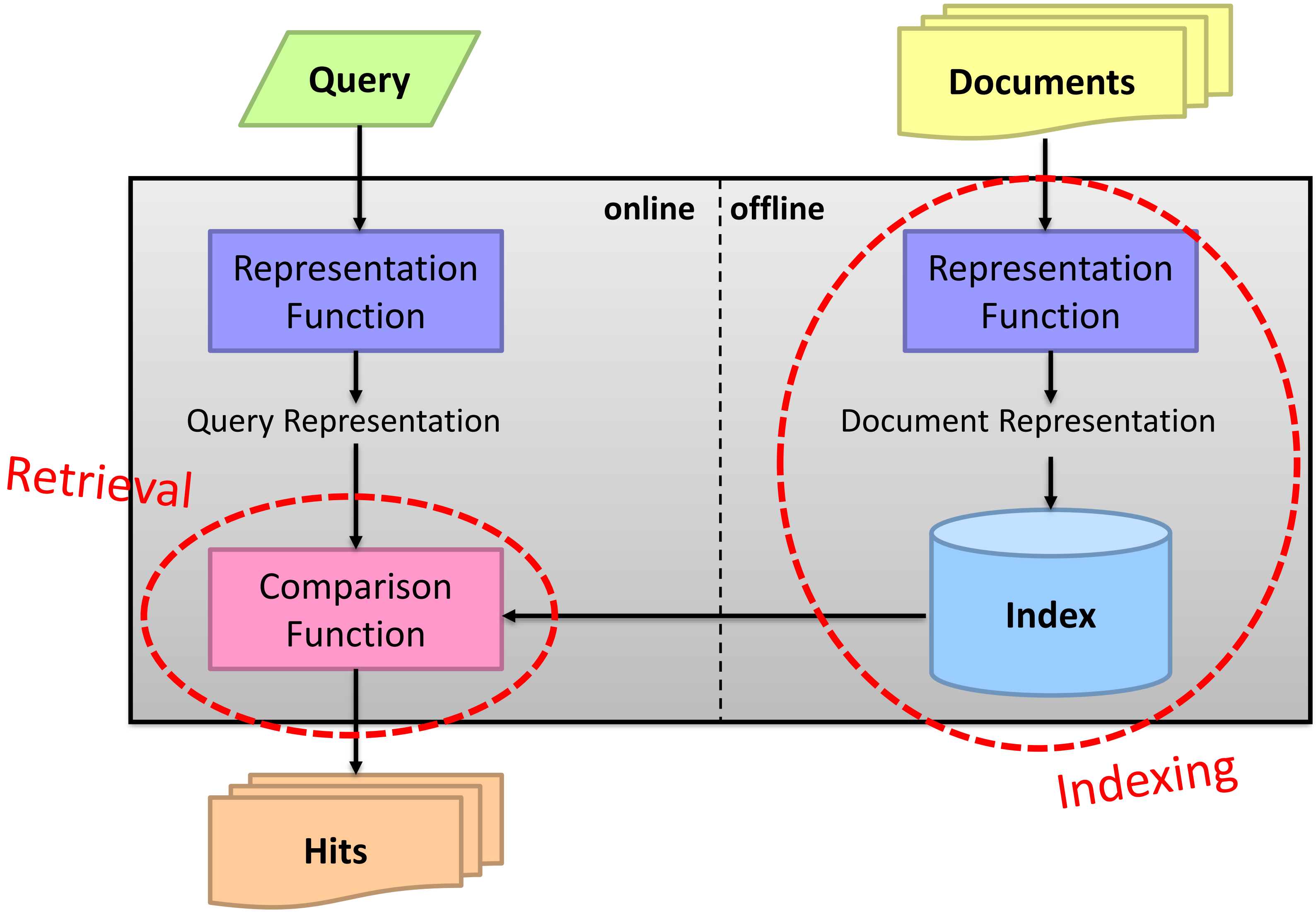
These slides are available at https://www.student.cs.uwaterloo.ca/~cs451

Source: http://www.flickr.com/photos/guvnah/7861418602/

Abstract IR Architecture



Doc 1
one fish, two fish

Doc 2
red fish, blue fish

Doc 3
cat in the hat

Doc 4
green eggs and ham

	1	2	3	4
blue		1		
cat			1	
egg				1
fish	1	1		
green				1
ham				1
hat			1	
one	1			
red		1		
two	1			

What goes in each cell?

boolean
count
positions

Doc 1
one fish, two fish

Doc 2
red fish, blue fish

Doc 3
cat in the hat

Doc 4
green eggs and ham

	1	2	3	4
blue		1		
cat			1	
egg				1
fish	1	1		
green				1
ham				1
hat			1	
one	1			
red		1		
two	1			

Indexing: building this structure

Retrieval: manipulating this structure

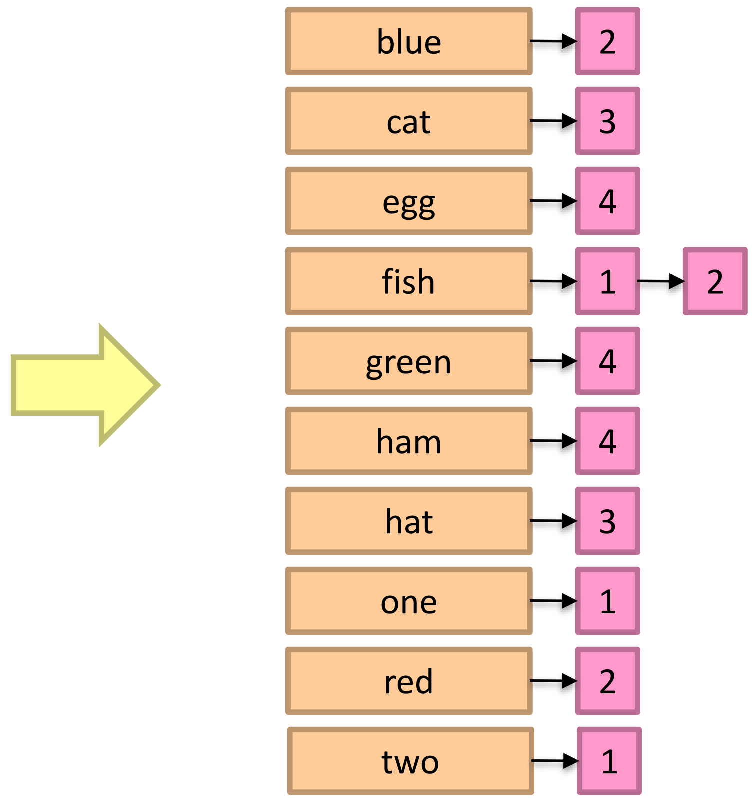
Doc 1
one fish, two fish

Doc 2
red fish, blue fish

Doc 3
cat in the hat

Doc 4
green eggs and ham

	1	2	3	4
blue		1		
cat			1	
egg				1
fish	1	1		
green				1
ham				1
hat			1	
one	1			
red		1		
two	1			



postings lists
(always in sorted order)

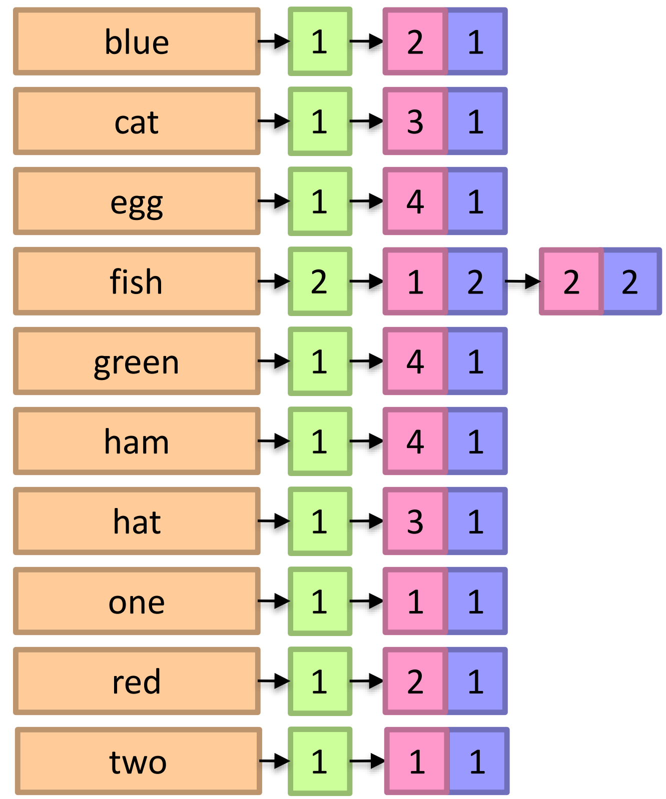
Doc 1
one fish, two fish

Doc 2
red fish, blue fish

Doc 3
cat in the hat

Doc 4
green eggs and ham

	tf				
	1	2	3	4	*df*
blue		1			1
cat			1		1
egg				1	1
fish	2	2			2
green				1	1
ham				1	1
hat			1		1
one	1				1
red		1			1
two	1				1



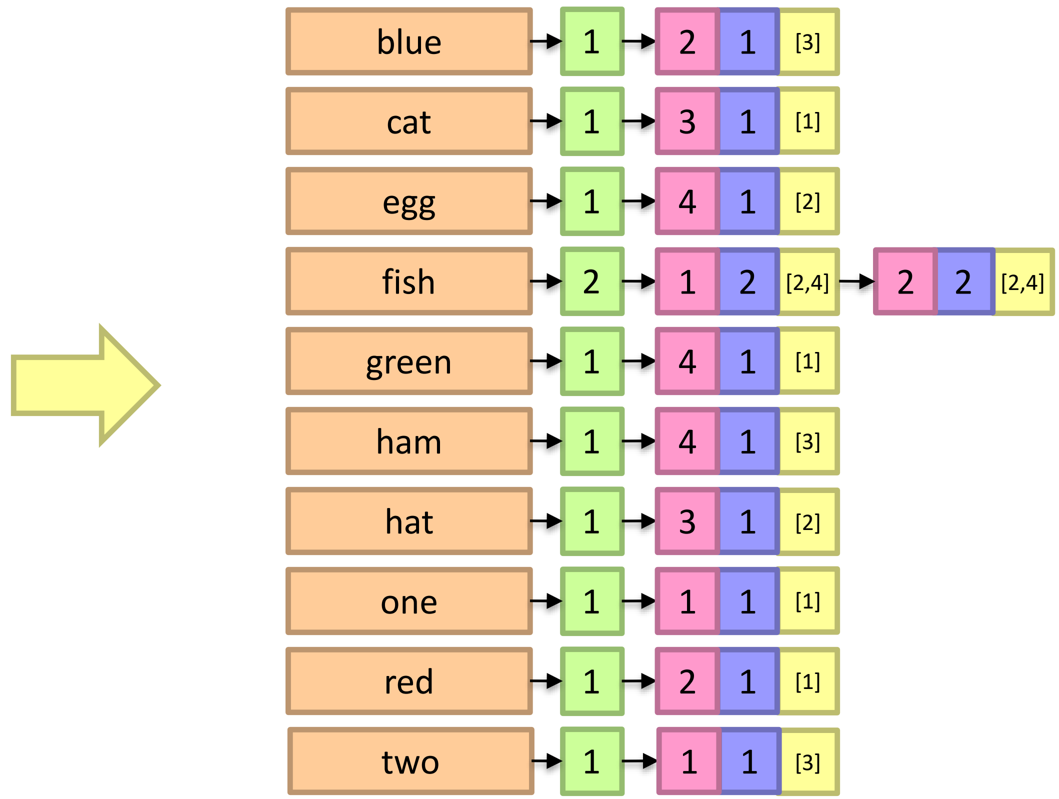
Doc 1
one fish, two fish

Doc 2
red fish, blue fish

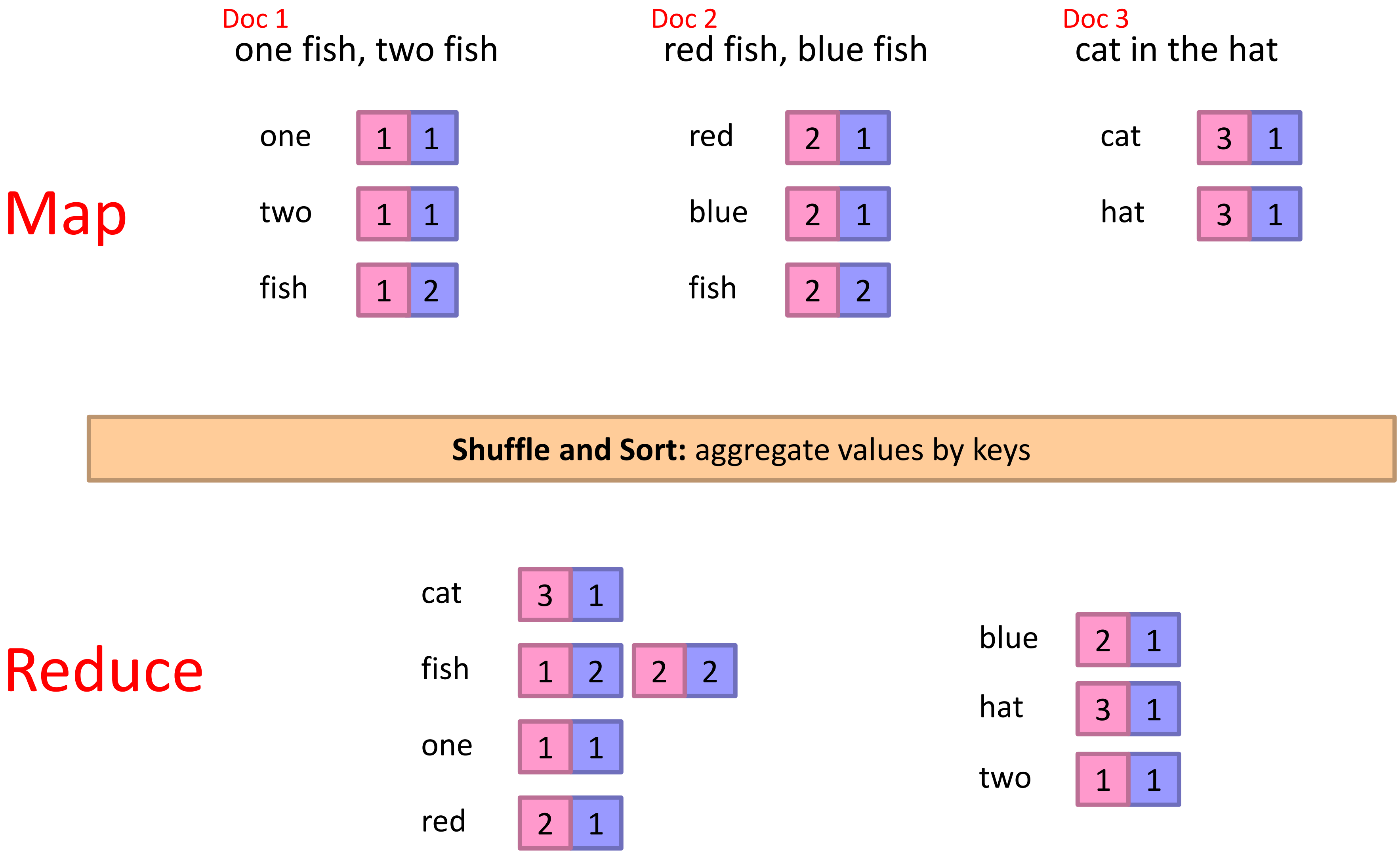
Doc 3
cat in the hat

Doc 4
green eggs and ham

	tf 1	2	3	4	*df*
blue		1			1
cat			1		1
egg				1	1
fish	2	2			2
green				1	1
ham				1	1
hat			1		1
one	1				1
red		1			1
two	1				1



Inverted Indexing with MapReduce



Inverted Indexing: Pseudo-Code

```
class Mapper {
  def map(docid: Long, doc: String) = {
    val counts = new Map()
    for (term <- tokenize(doc)) {
      counts(term) += 1
    }
    for ((term, tf) <- counts) {
      emit(term, (docid, tf))
    }
  }
}

class Reducer {
  def reduce(term: String, postings: Iterable[(docid, tf)]) = {
    val p = new List()
    for ((docid, tf) <- postings) {
      p.append((docid, tf))
    }
    p.sort()
    emit(term, p)
  }
}
```

Positional Indexes

Map

Doc 1: one fish, two fish			
one	1	1	[1]
two	1	1	[3]
fish	1	2	[2,4]

Doc 2: red fish, blue fish			
red	2	1	[1]
blue	2	1	[3]
fish	2	2	[2,4]

Doc 3: cat in the hat			
cat	3	1	[1]
hat	3	1	[2]

Shuffle and Sort: aggregate values by keys

Reduce

cat	3	1	[1]			
fish	1	2	[2,4]	2	2	[2,4]
one	1	1	[1]			
red	2	1	[1]			

blue	2	1	[3]
hat	3	1	[2]
two	1	1	[3]

Inverted Indexing: Pseudo-Code

```
class Mapper {
  def map(docid: Long, doc: String) = {
    val counts = new Map()
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      p.append((docid, tf))
    }
    p.sort()
    emit(term, p)
  }
}
```

What’s the problem?

Another Try…

(key)	(values)	
fish	1	2
	34	1
	21	3
	35	2
	80	3
	9	1

(keys)		(values)
fish	1	2
fish	9	1
fish	21	3
fish	34	2
fish	35	3
fish	80	1

How is this different?

Let the framework do the sorting!

Where have we seen this before?

Inverted Indexing: Pseudo-Code

```
class Mapper {
  def map(docid: Long, doc: String) = {
    val counts = new Map()
    for (term <- tokenize(doc)) {
      counts(term) += 1
    }
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      emit((term, docid), tf)
    }
  }
}

class Reducer {
  var prev = null
  val postings = new PostingsList()

  def reduce(key: Pair, tf: Iterable[Int]) = {
    if key.term != prev and prev != null {
      emit(prev, postings)
      postings.reset()
    }
    postings.append(key.docid, tf.first)
    prev = key.term
  }

 def cleanup() = {
   emit(prev, postings)
 }
}
```

Wait, how's this any better?

What else do we need to do?

Postings Encoding

Conceptually:

fish	1	2	9	1	21	3	34	1	35	2	80	3	…

In Practice:

Don’t encode docids, encode gaps (or *d*-gaps)
But it’s not obvious that this save space…

fish	1	2	8	1	12	3	13	1	1	2	45	3	…

= delta encoding, delta compression, gap compression

Overview of Integer Compression

Byte-aligned technique

VarInt (Vbyte)

Group VarInt

Word-aligned

Simple family

Bit packing family (PForDelta, etc.)

Bit-aligned

Unary codes

γ/δ codes

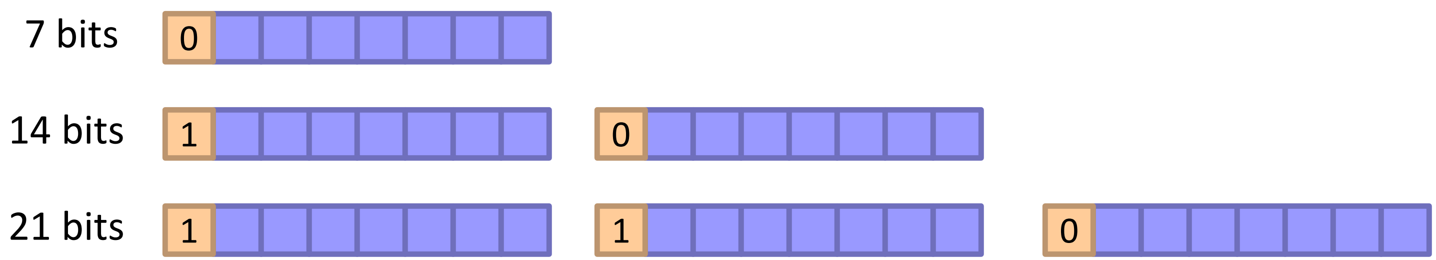
Golomb codes (local Bernoulli model)

VarInt (Vbyte)

Simple idea: use only as many bytes as needed

Need to reserve one bit per byte as the “continuation bit”

Use remaining bits for encoding value



Works okay, easy to implement…

Beware of branch mispredicts!

Group VarInt

Designed by Google

Pack integers in blocks of four

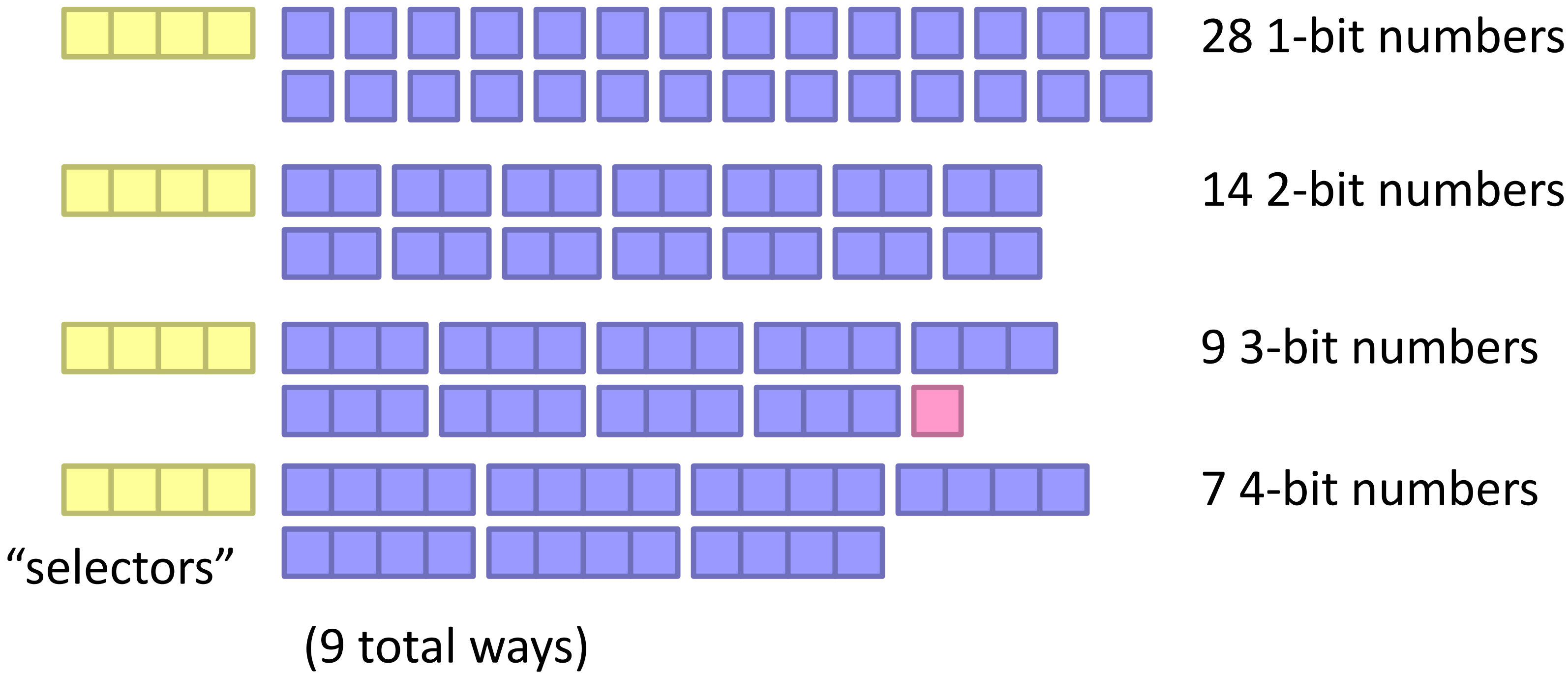
80, 320, 31, 255

VarInt: 01010000 11000000 00000010 00011111 11111111 00000001

Group VarInt: 00010000 0101000 01000000 00000001 00011111 11111111

Simple-9

How many different ways can we divide up 28 bits?



Efficient decompression with hard-coded decoders

Simple Family – general idea applies to 64-bit words, etc.

Beware of branch mispredicts?

Golomb Codes

$x \geq 1$, parameter b:

- $q + 1$ in unary, where $q = \lfloor (x - 1) / b \rfloor$
- r in binary, where $r = x - qb - 1$, in $\lfloor \log b \rfloor$ or $\lceil \log b \rceil$ bits

Example:

- $b = 3$, $r = 0, 1, 2$ (0, 10, 11)
- $b = 6$, $r = 0, 1, 2, 3, 4, 5$ (00, 01, 100, 101, 110, 111)
- $x = 9$, $b = 3$: $q = 2$, $r = 2$, code = 110:11
- $x = 9$, $b = 6$: $q = 1$, $r = 2$, code = 10:100

Punch line: optimal $b \sim 0.69$ (N/df)

Different b for every term!

Inverted Indexing: Pseudo-Code

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class Mapper {
  def map(docid: Long, doc: String) = {
    val counts = new Map()
    for (term <- tokenize(doc)) {
      counts(term) += 1
    }
    for ((term, tf) <- counts) {
      emit((term, docid), tf)
    }
  }
}

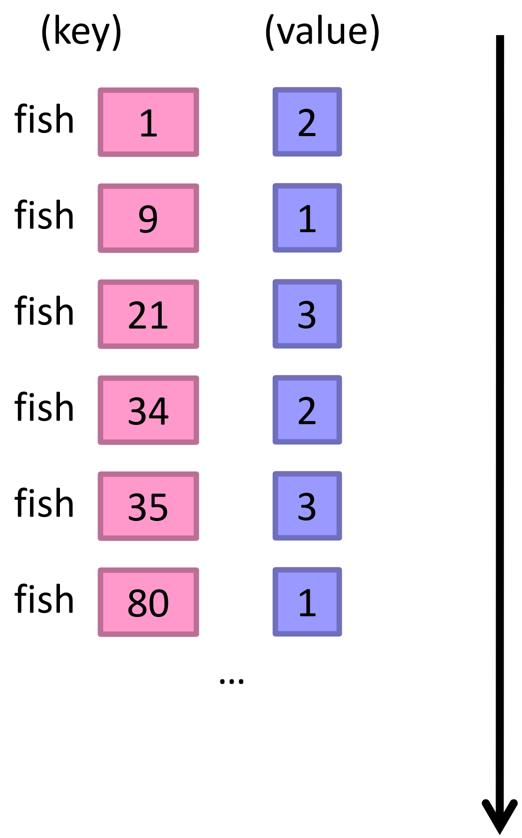
class Reducer {
  var prev = null
  val postings = new PostingsList()

  def reduce(key: Pair, tf: Iterable[Int]) = {
    if key.term != prev and prev != null {
      emit(prev, postings)
      postings.reset()
    }
    postings.append(key.docid, tf.first)
    prev = key.term
  }

 def cleanup() = {
   emit(prev, postings)
 }
}
```

Ah, now we know why this is different!

Chicken and Egg?



Write postings *compressed*

But wait! How do we set the Golomb parameter *b*?

Recall: optimal *b* ~ 0.69 (*N/df*)

We need the *df* to set *b*…

But we don't know the *df* until we've seen all postings!

Sound familiar?

Getting the *df*

In the mapper:

Emit "special" key-value pairs to keep track of *df*

In the reducer:

Make sure "special" key-value pairs come first: process them to determine *df*

Remember: proper partitioning!

Getting the *df*: Modified Mapper

Doc 1

one fish, two fish

Input document…

	(key)	(value)
fish	1	2
one	1	1
two	1	1

Emit normal key-value pairs…

fish	★	1
one	★	1
two	★	1

Emit “special” key-value pairs to keep track of *df*…

Getting the *df*: Modified Reducer

	(key)	(value)
fish	★	1 1 1 …
fish	1	2
fish	9	1
fish	21	3
fish	34	2
fish	35	3
fish	80	1
	…	

First, compute the *df* by summing contributions from all "special" key-value pair…

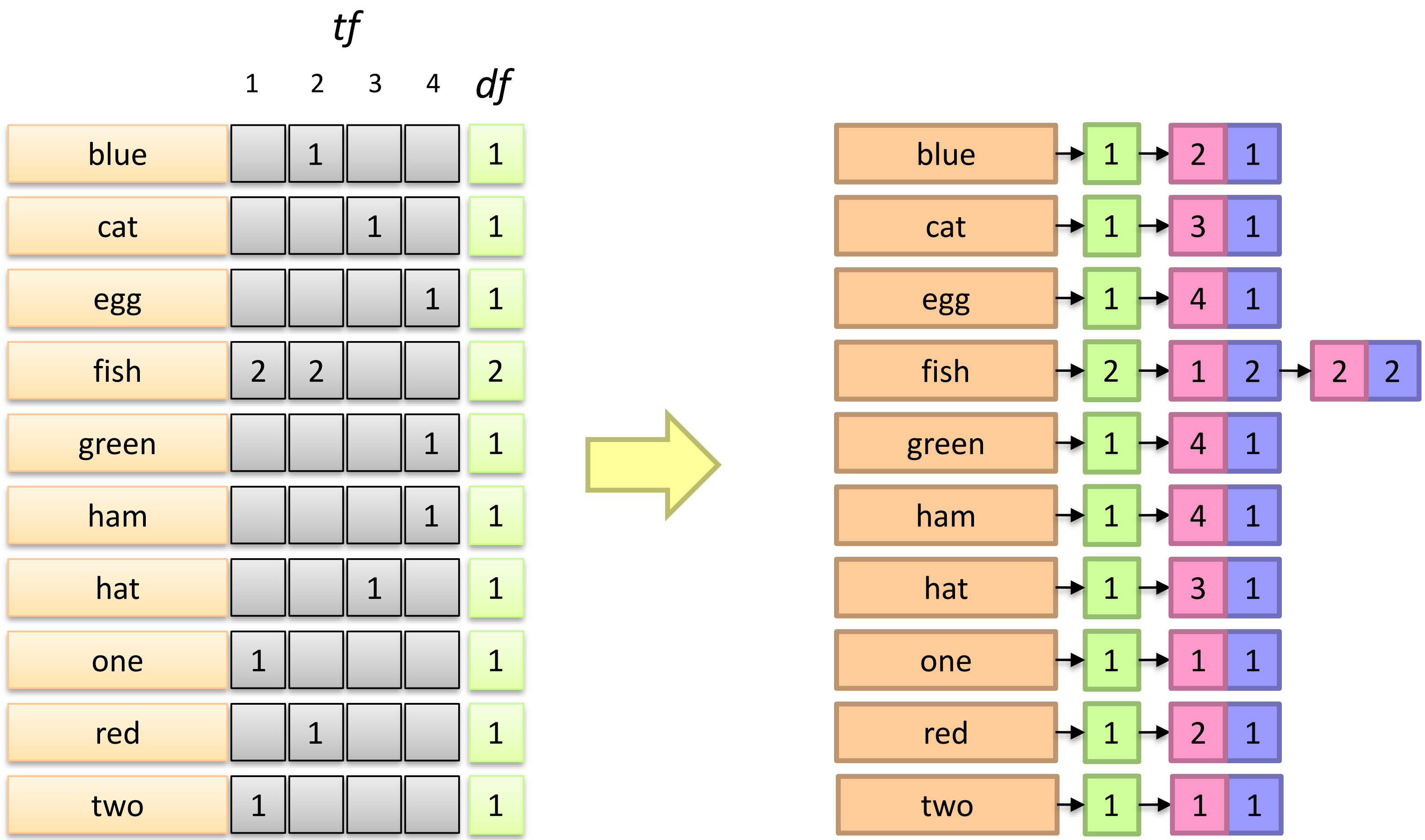
Compute *b* from *df*

Important: properly define sort order to make sure "special" key-value pairs come first!

Write postings compressed

Where have we seen this before?

But I don't care about Golomb Codes!



Inverted Indexing (~Pairs)

```
class Mapper {
  def map(docid: Long, doc: String) = {
    val counts = new Map()
    for (term <- tokenize(doc)) {
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    }
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    postings.append(key.docid, tf.first)
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 def cleanup() = {
   emit(prev, postings)
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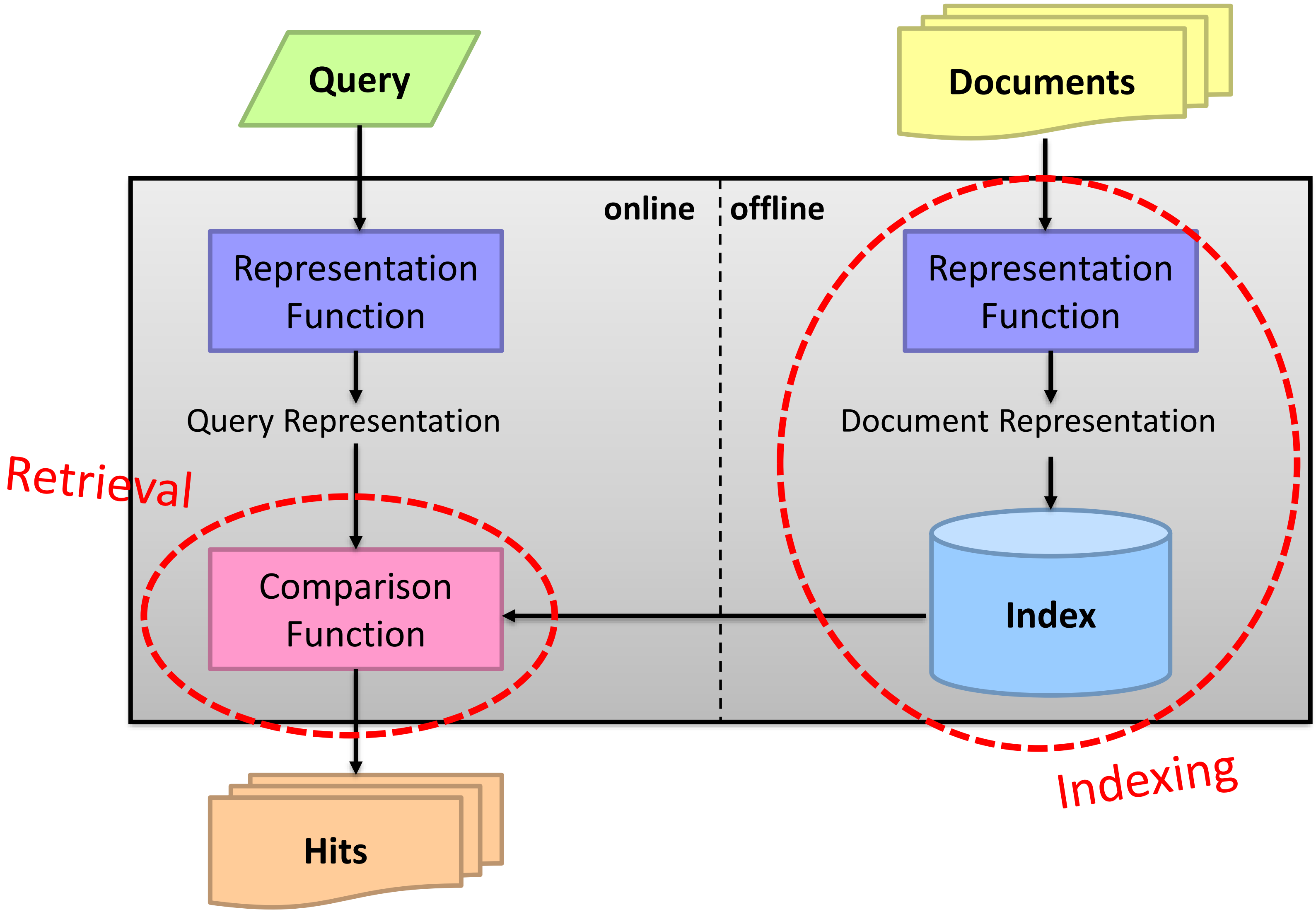
}
```

What's the assumption?
Is it okay?

Abstract IR Architecture



MapReduce it?

Perfect for MapReduce!

The indexing problem

Scalability is critical

Must be relatively fast, but need not be real time

Fundamentally a batch operation

Incremental updates may or may not be important

For the web, crawling is a challenge in itself

The retrieval problem

Must have sub-second response time

For the web, only need relatively few results

Uh… not so good…

Assume everything fits in memory on a single machine…

(For now)

Boolean Retrieval

Users express queries as a Boolean expression

AND, OR, NOT

Can be arbitrarily nested

Retrieval is based on the notion of sets

Any query divides the collection into two sets: retrieved, not-retrieved

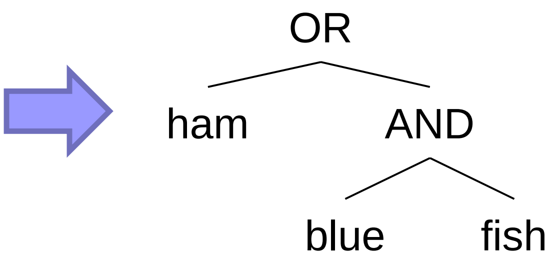
Pure Boolean systems do not define an ordering of the results

Boolean Retrieval

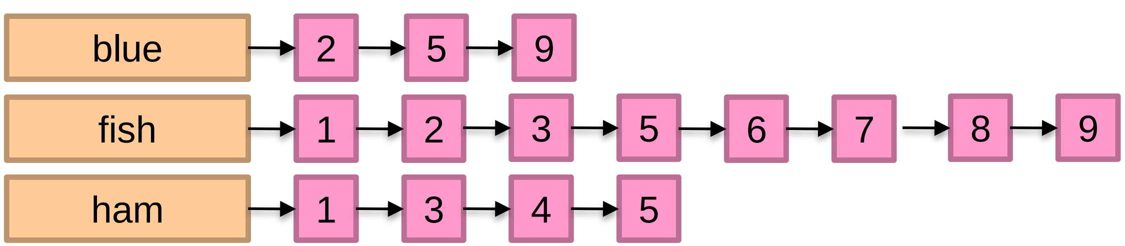
To execute a Boolean query:

Build query syntax tree

(blue AND fish) OR ham

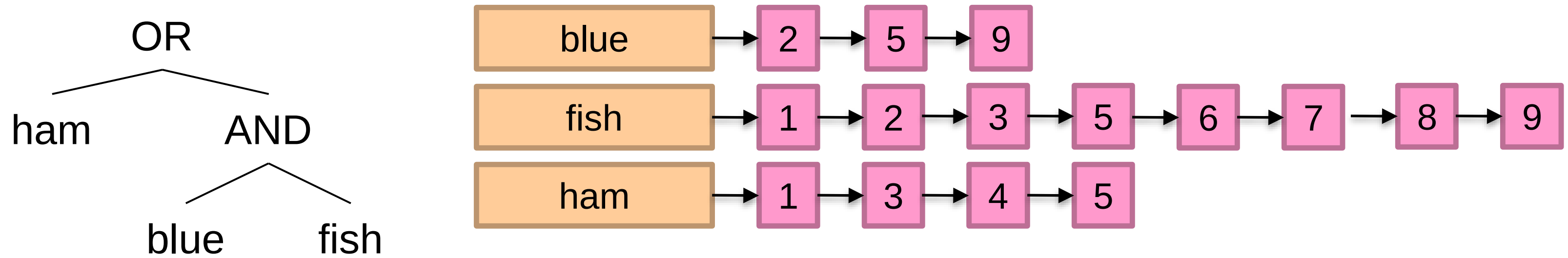


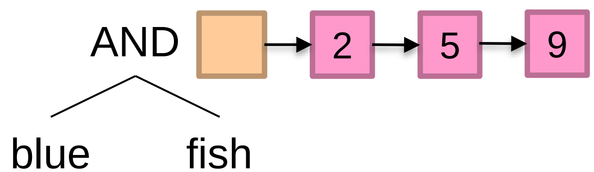
For each clause, look up postings



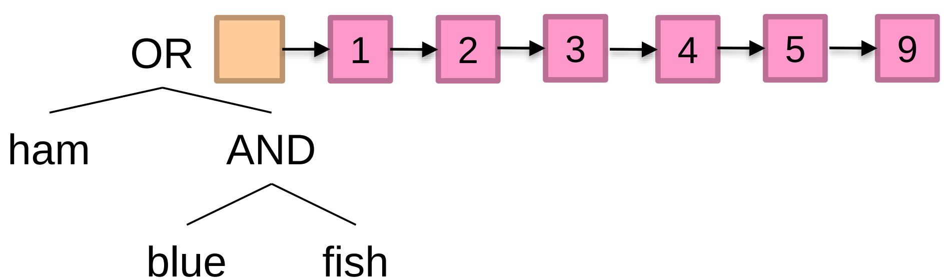
Traverse postings and apply Boolean operator

Term-at-a-Time

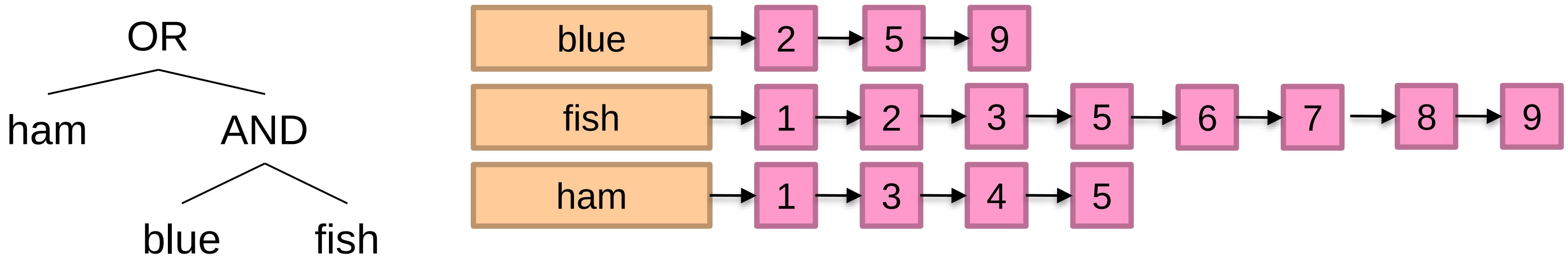


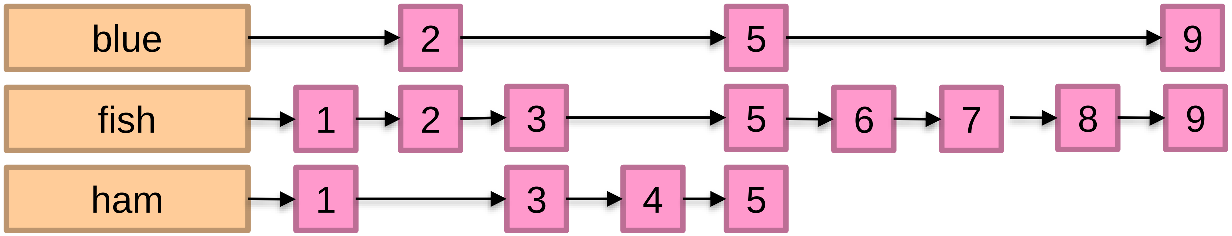


Efficiency analysis?



Document-at-a-Time





Tradeoffs?

Efficiency analysis?

Boolean Retrieval

Users express queries as a Boolean expression

AND, OR, NOT

Can be arbitrarily nested

Retrieval is based on the notion of sets

Any query divides the collection into two sets: retrieved, not-retrieved

Pure Boolean systems do not define an ordering of the results

What's the issue?

Ranked Retrieval

Order documents by how likely they are to be relevant

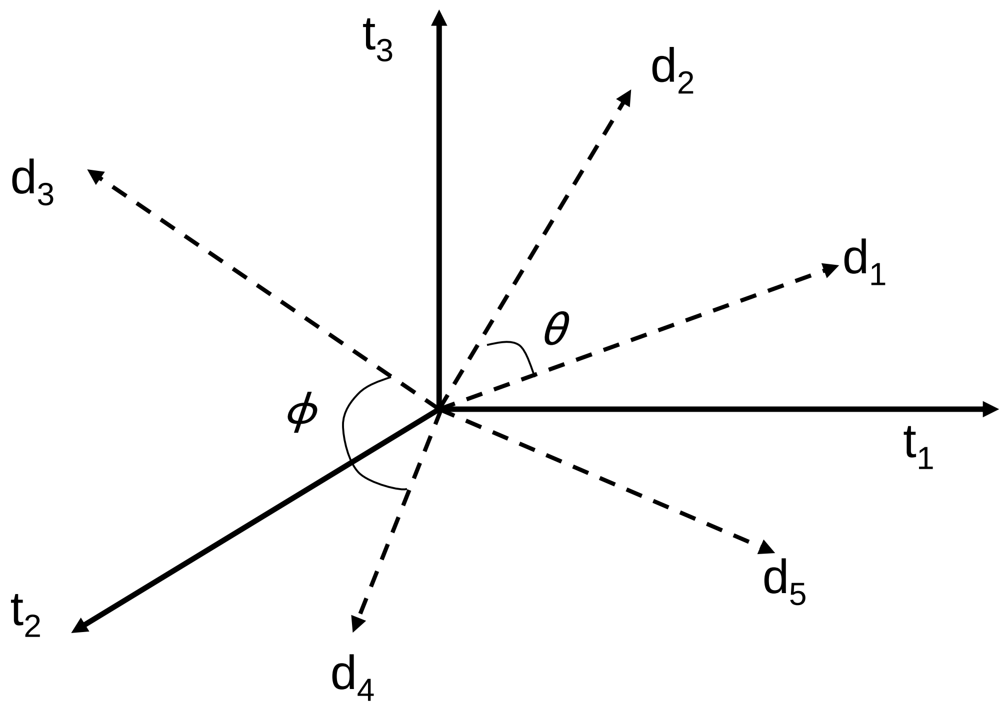
Estimate relevance(q, d_i)

Sort documents by relevance

How do we estimate relevance?

Take "similarity" as a proxy for relevance

Vector Space Model



Assumption: Documents that are “close together” in vector space “talk about” the same things

Therefore, retrieve documents based on how close the document is to the query (i.e., similarity ~ “closeness”)

Similarity Metric

Use "angle" between the vectors:

$$d_j = [w_{j,1}, w_{j,2}, w_{j,3}, \ldots w_{j,n}]$$
$$d_k = [w_{k,1}, w_{k,2}, w_{k,3}, \ldots w_{k,n}]$$

$$\cos\theta = \frac{d_j \cdot d_k}{|d_j||d_k|}$$

$$\mathrm{sim}(d_j, d_k) = \frac{d_j \cdot d_k}{|d_j||d_k|} = \frac{\sum_{i=0}^{n} w_{j,i} w_{k,i}}{\sqrt{\sum_{i=0}^{n} w_{j,i}^2}\sqrt{\sum_{i=0}^{n} w_{k,i}^2}}$$

Or, more generally, inner products:

$$\mathrm{sim}(d_j, d_k) = d_j \cdot d_k = \sum_{i=0}^{n} w_{j,i} w_{k,i}$$

Term Weighting

Term weights consist of two components

Local: how important is the term in this document?

Global: how important is the term in the collection?

Here's the intuition:

Terms that appear often in a document should get high weights

Terms that appear in many documents should get low weights

How do we capture this mathematically?

Term frequency (local)

Inverse document frequency (global)

TF-IDF* Term Weighting

$$w_{i,j} = \mathrm{tf}_{i,j} \cdot \log \frac{N}{n_i}$$

$w_{i,j}$ weight assigned to term *i* in document *j*

$\mathrm{tf}_{i,j}$ number of occurrence of term *i* in document *j*

N number of documents in entire collection

n_i number of documents with term *i*

*Term Frequency-Inverse Document Frequency

Retrieval in a Nutshell

Look up postings lists corresponding to query terms

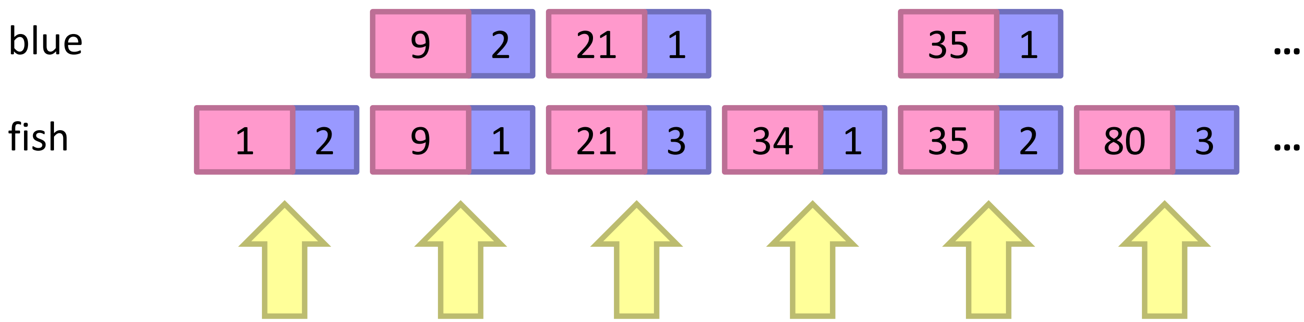
Traverse postings for each query term

Store partial query-document scores in accumulators

Select top *k* results to return

Retrieval: Document-at-a-Time

Evaluate documents one at a time (score all query terms)



Accumulators
(e.g. min heap)

Document score in top k?

Yes: Insert document score, extract-min if heap too large
No: Do nothing

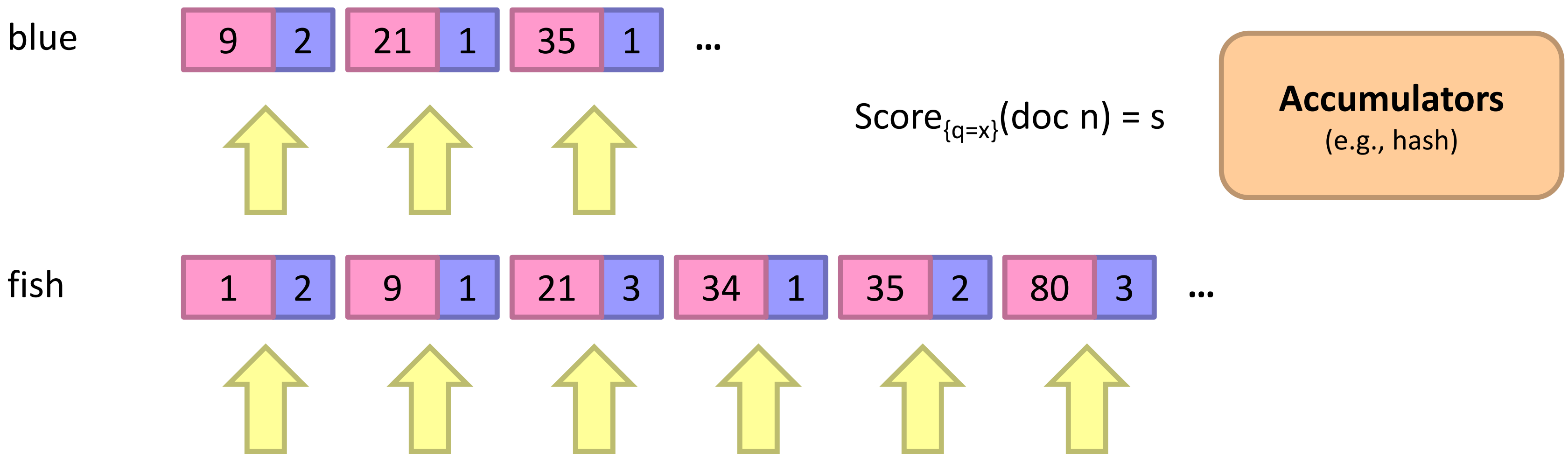
Tradeoffs:

Small memory footprint (good)
Skipping possible to avoid reading all postings (good)
More seeks and irregular data accesses (bad)

Retrieval: Term-At-A-Time

Evaluate documents one query term at a time

Usually, starting from most rare term (often with *tf*-sorted postings)



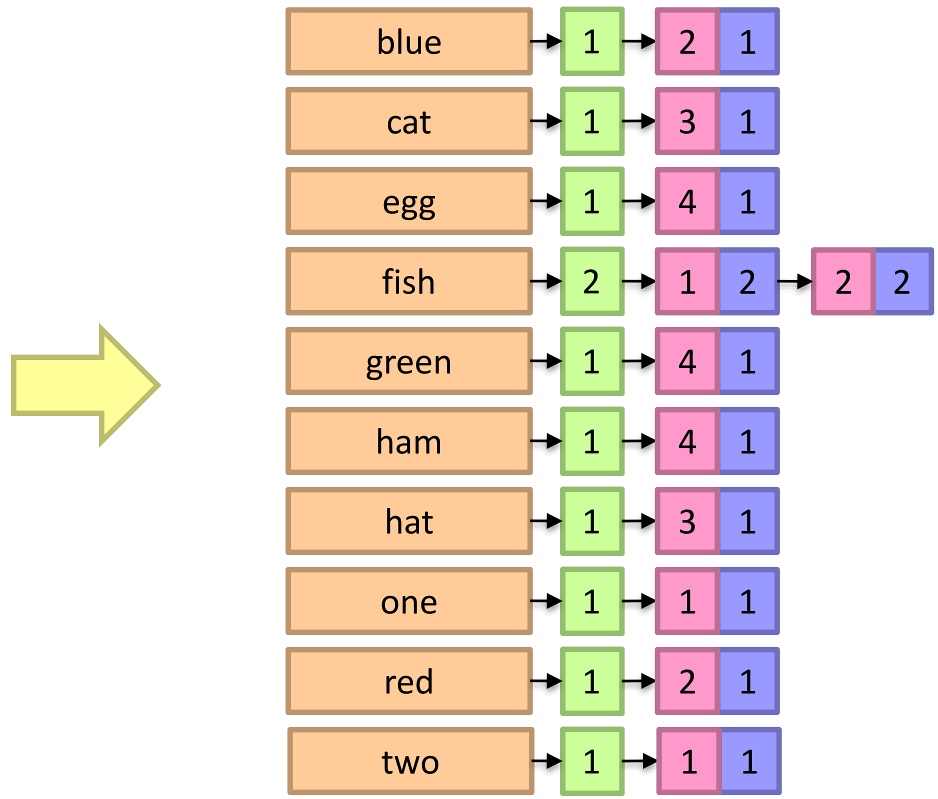
Tradeoffs:

Early termination heuristics (good)

Large memory footprint (bad), but filtering heuristics possible

Why store *df* as part of postings?

	tf				
	1	2	3	4	*df*
blue		1			1
cat			1		1
egg				1	1
fish	2	2			2
green				1	1
ham				1	1
hat			1		1
one	1				1
red		1			1
two	1				1



Assume everything fits in memory on a single machine…

Okay, let's relax this assumption now

Important Ideas

Partitioning (for scalability)

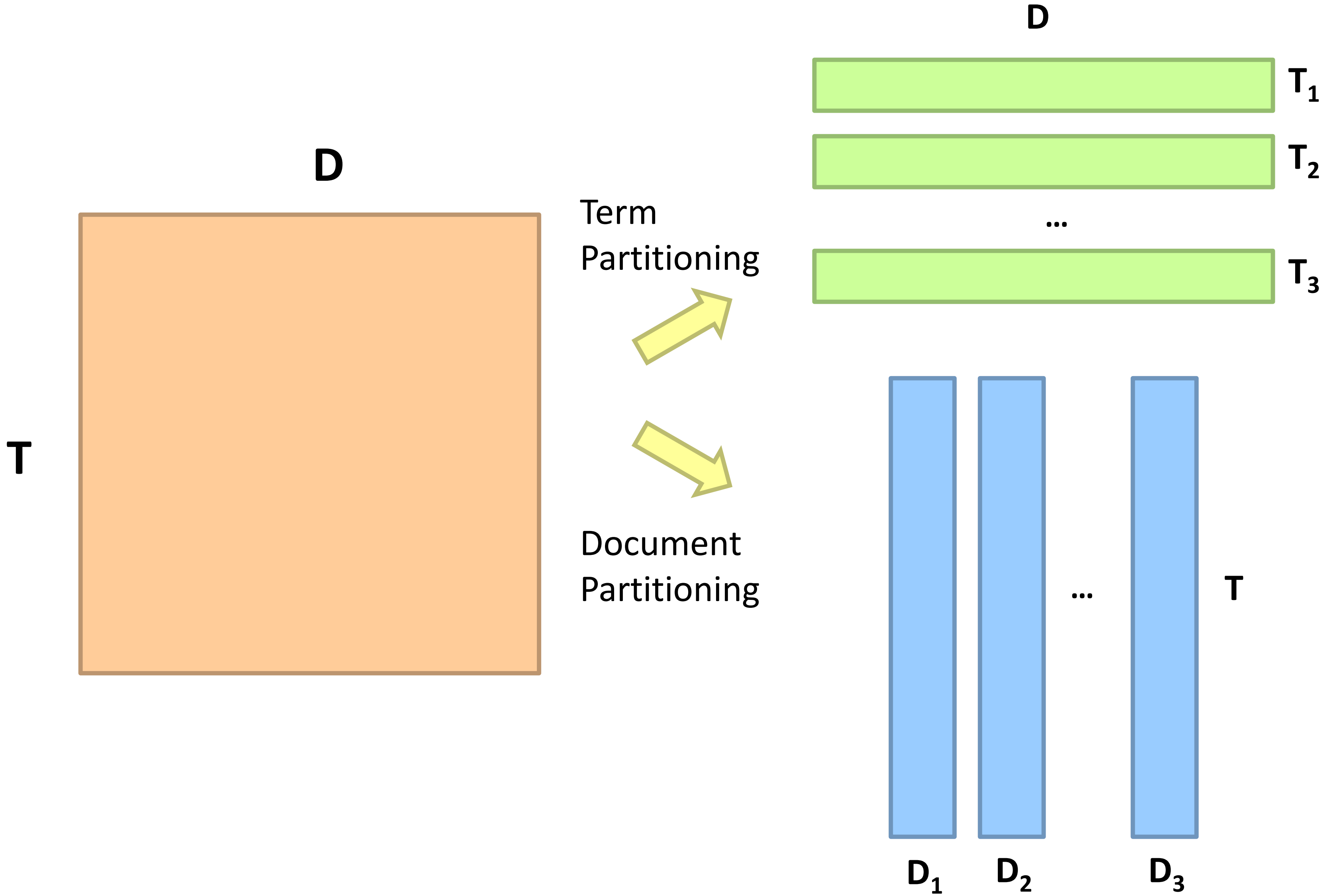
Replication (for redundancy)

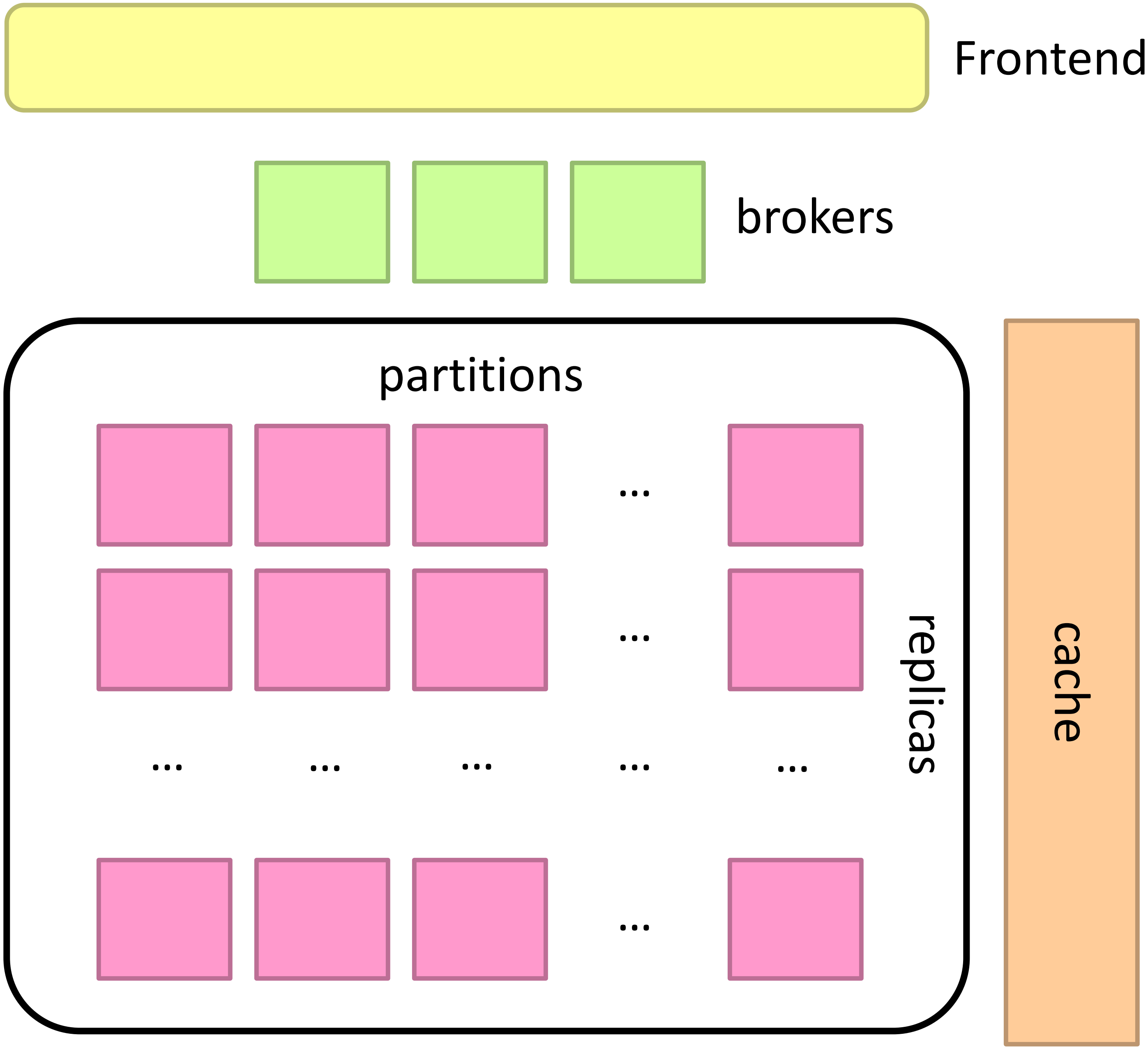
Caching (for speed)

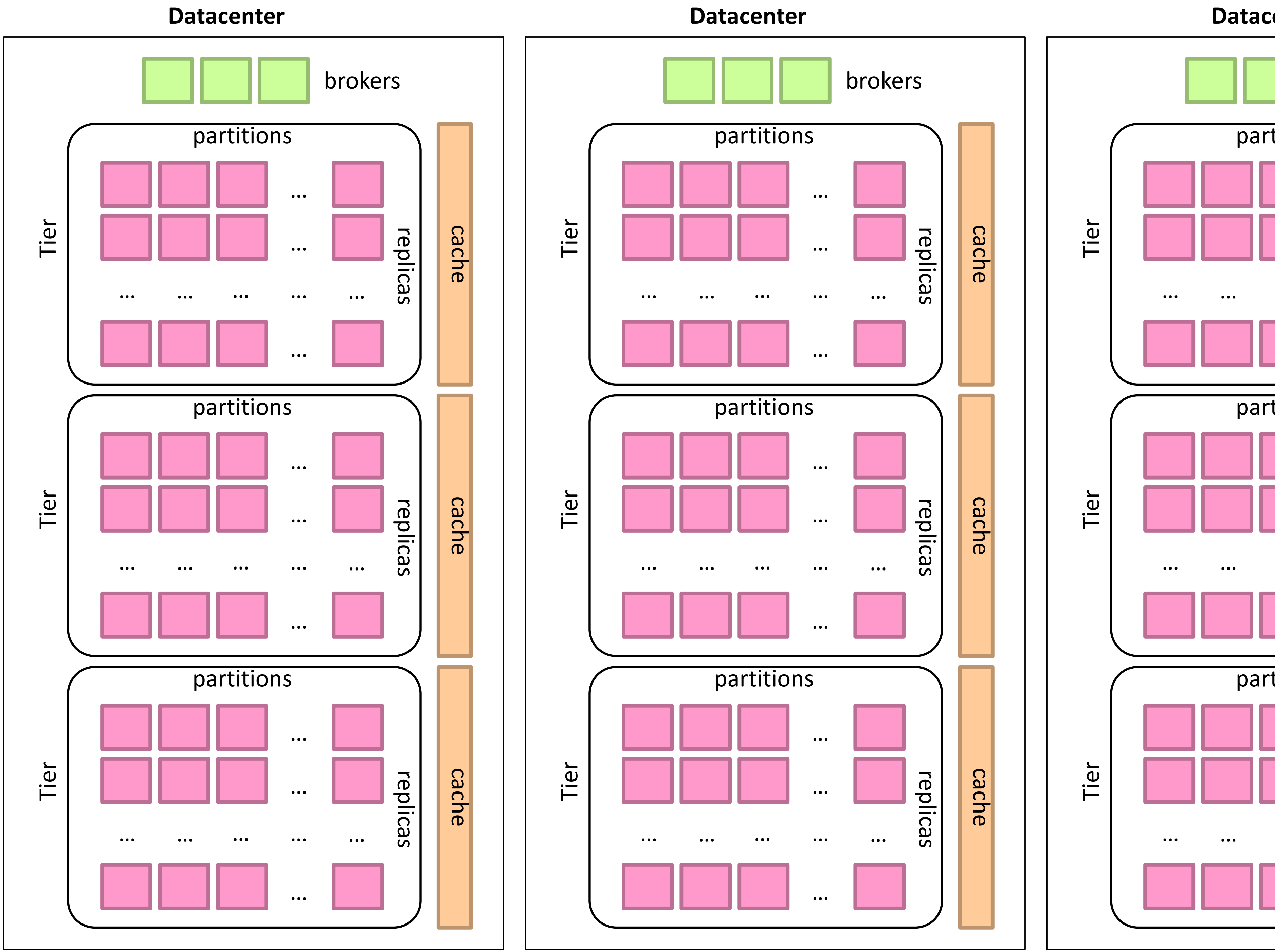
Routing (for load balancing)

The rest is just details!

Term vs. Document Partitioning




Frontend
brokers
partitions
replicas
cache



Datacenter
brokers
partitions
Tier
replicas
cache
...
Datacenter
brokers
partitions
Tier
replicas
cache
...