

Data-Intensive Distributed Computing

CS 451/651 431/631 (Winter 2018)

Part 3: Analyzing Text (2/2)

January 30, 2018

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These slides are available at <http://lintool.github.io/bigdata-2018w/>

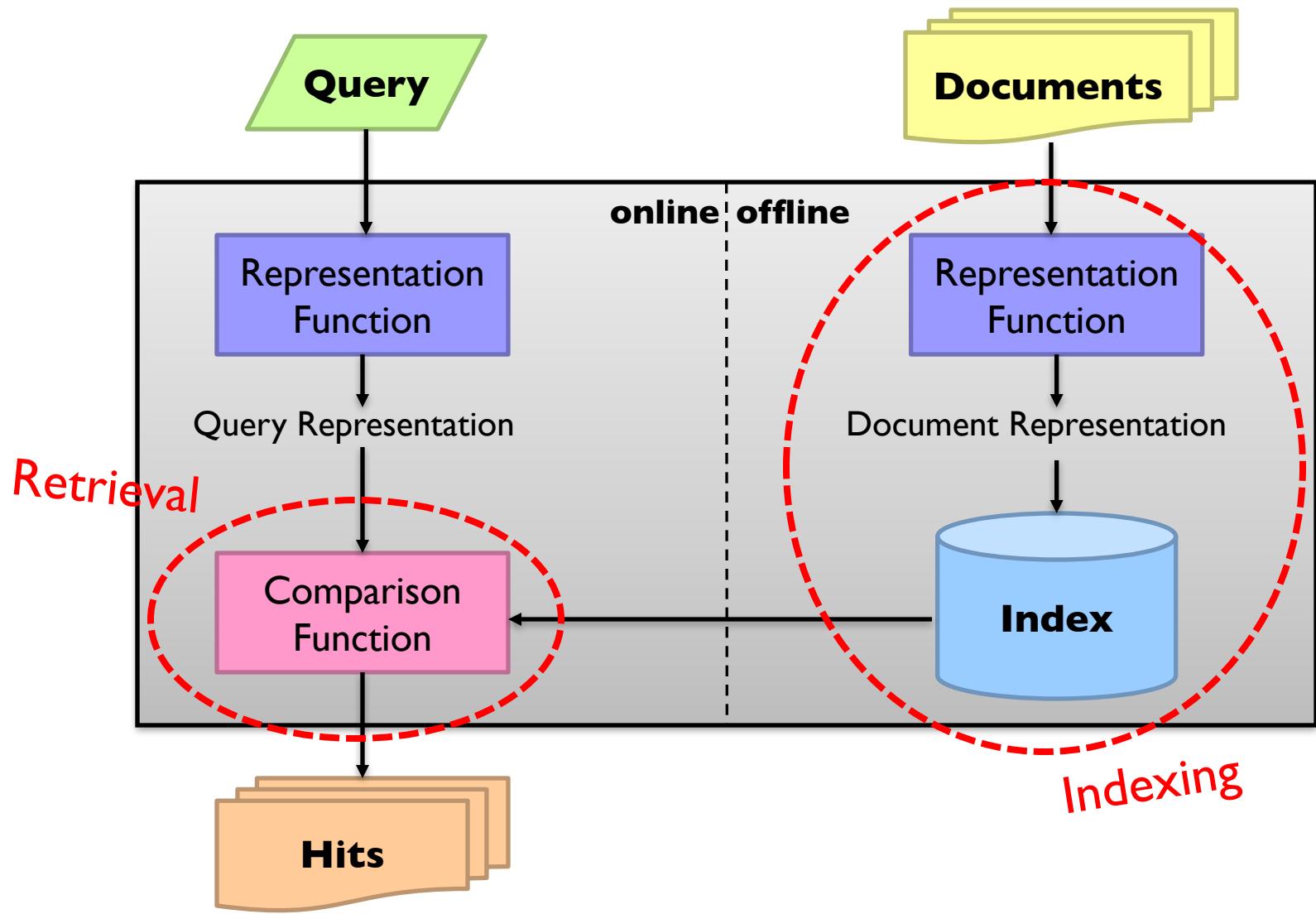


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Search!

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		I		
cat			I	
egg				I
fish	I	I		
green				I
ham				I
hat			I	
one	I			
red		I		
two	I			

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		I		
cat			I	
egg				I
fish	I	I		
green				I
ham				I
hat			I	
one	I			
red		I		
two	I			

Indexing: building this structure

Retrieval: manipulating this structure

Doc 1

one fish, two fish

Doc 2

red fish, blue fish

Doc 3

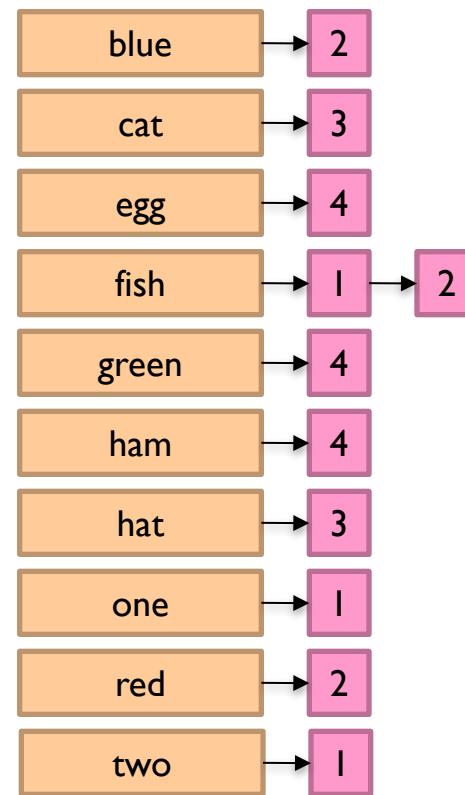
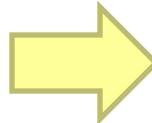
cat in the hat

Doc 4

green eggs and ham

1 2 3 4

blue				
cat				
egg				
fish				
green				
ham				
hat				
one				
red				
two				



postings lists
(always in sorted order)

Doc 1

one fish, two fish

Doc 2

red fish, blue fish

Doc 3

cat in the hat

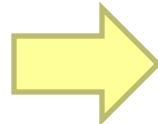
Doc 4

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



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

Doc 1

one fish, two fish

Doc 2

red fish, blue fish

Doc 3

cat in the hat

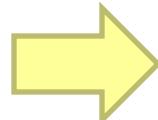
Doc 4

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



blue	→	1	→	2	1	[3]
cat	→	1	→	3	1	[1]
egg	→	1	→	4	1	[2]
fish	→	2	→	1	2	[2,4]
green	→	1	→	4	1	[1]
ham	→	1	→	4	1	[3]
hat	→	1	→	3	1	[2]
one	→	1	→	1	1	[1]
red	→	1	→	2	1	[1]
two	→	1	→	1	1	[3]

Inverted Indexing with MapReduce

Doc 1
one fish, two fish

one	
two	
fish	

Doc 2
red fish, blue fish

red	
blue	
fish	

Doc 3
cat in the hat

cat	
hat	

Map

Shuffle and Sort: aggregate values by keys

Reduce

cat	
fish	
one	
red	

blue	
hat	
two	

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

Doc 1

one fish, two fish

one



two



fish



Doc 2

red fish, blue fish

red



blue



fish



Doc 3

cat in the hat

cat



hat



Map

Shuffle and Sort: aggregate values by keys

Reduce

cat



fish



one



red



blue



hat



two



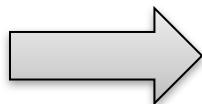
Inverted Indexing: Pseudo-Code

```
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)  
    }  
}
```

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  
        }  
        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(key.term, 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

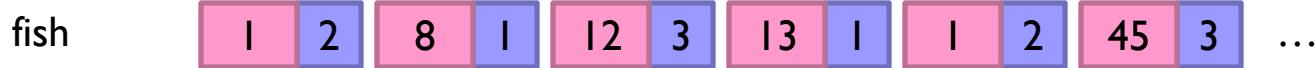
Conceptually:



In Practice:

Don't encode docids, encode gaps (or d -gaps)

But it's not obvious that this save space...



= delta encoding, delta compression, gap compression

Overview of Integer Compression

Byte-aligned technique
VByte

Bit-aligned
Unary codes
 γ/δ codes
Golomb codes (local Bernoulli model)

Word-aligned
Simple family
Bit packing family (PForDelta, etc.)

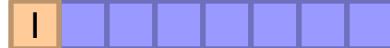
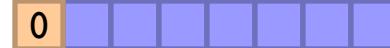
VByte

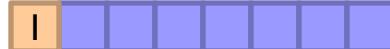
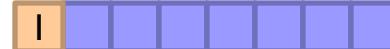
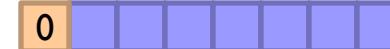
Simple idea: use only as many bytes as needed

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

Use remaining bits for encoding value

7 bits 0 

14 bits 1  0 

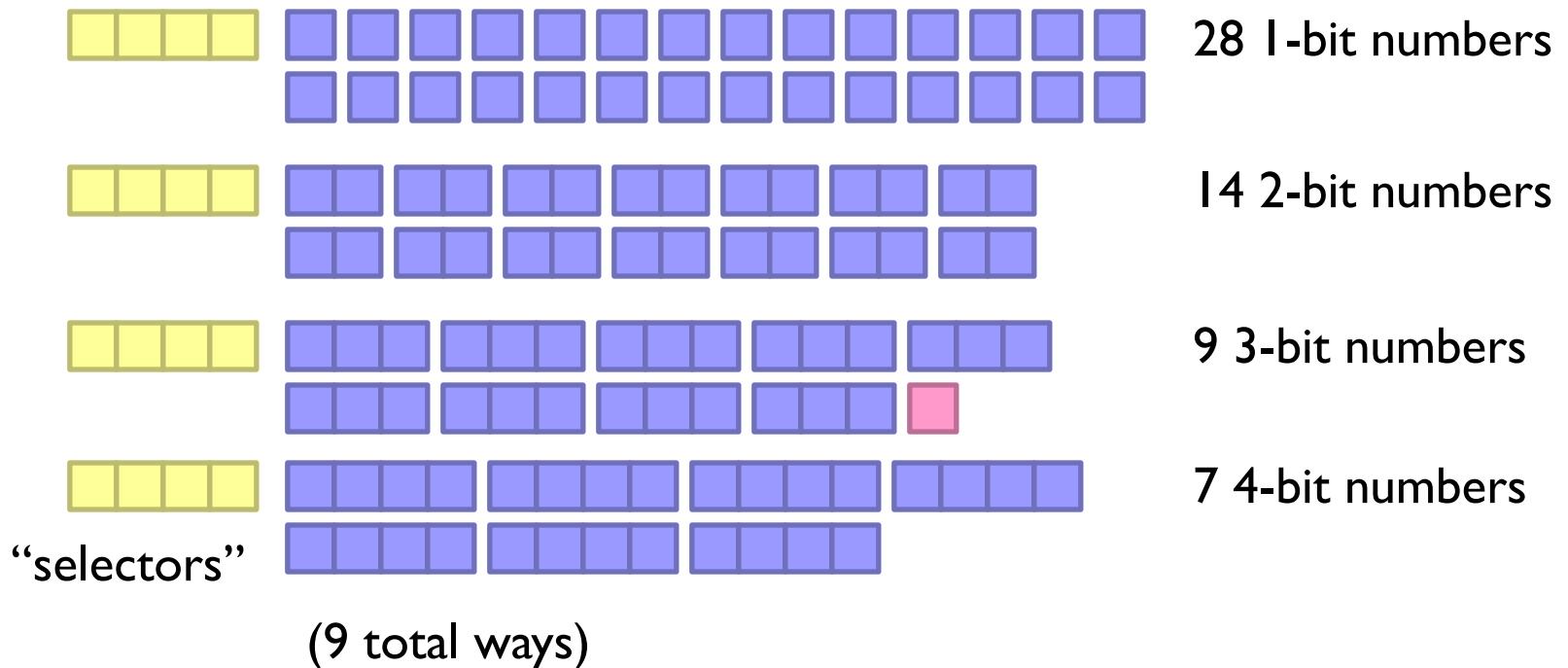
21 bits 1  1  0 

Works okay, easy to implement...

Beware of branch mispredicts!

Simple-9

How many different ways can we divide up 28 bits?

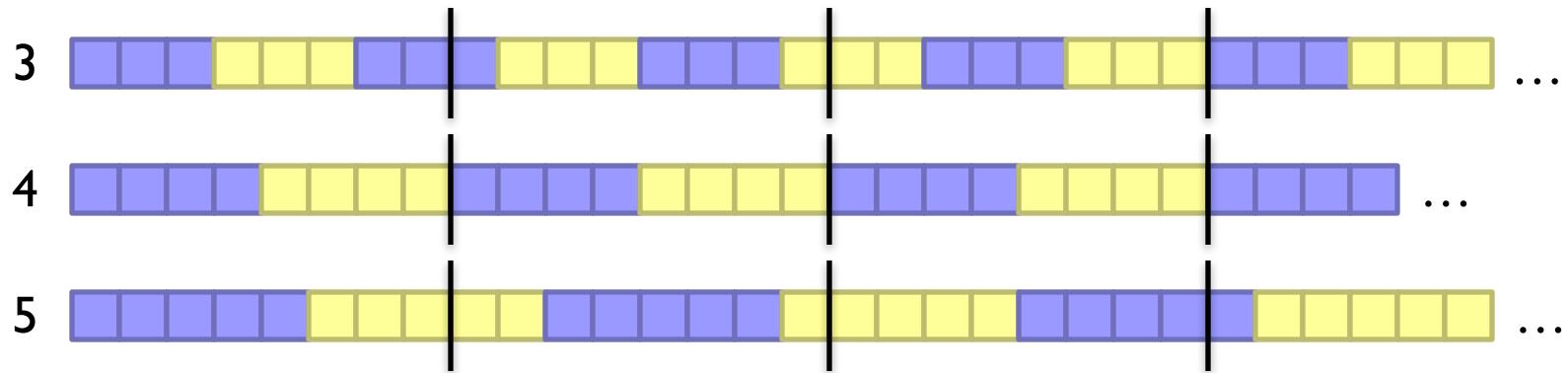


Efficient decompression with hard-coded decoders
Simple Family – general idea applies to 64-bit words, etc.

Beware of branch mispredicts?

Bit Packing

What's the smallest number of bits we need
to code a block (=128) of integers?



Efficient decompression with hard-coded decoders
PForDelta – bit packing + separate storage of “overflow” bits

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

```
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(key.term, 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?

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

...

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

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

We need the df to set b ...

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

Write postings compressed

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   Emit normal key-value pairs...

one  

two  

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

one  

two  

Getting the df : Modified Reducer

(key)	(value)
fish	★ ...

First, compute the df by summing contributions from all “special” key-value pair...

Compute b from df

fish		2
fish	9	
fish	21	
fish	34	
fish	35	
fish	80	
...		

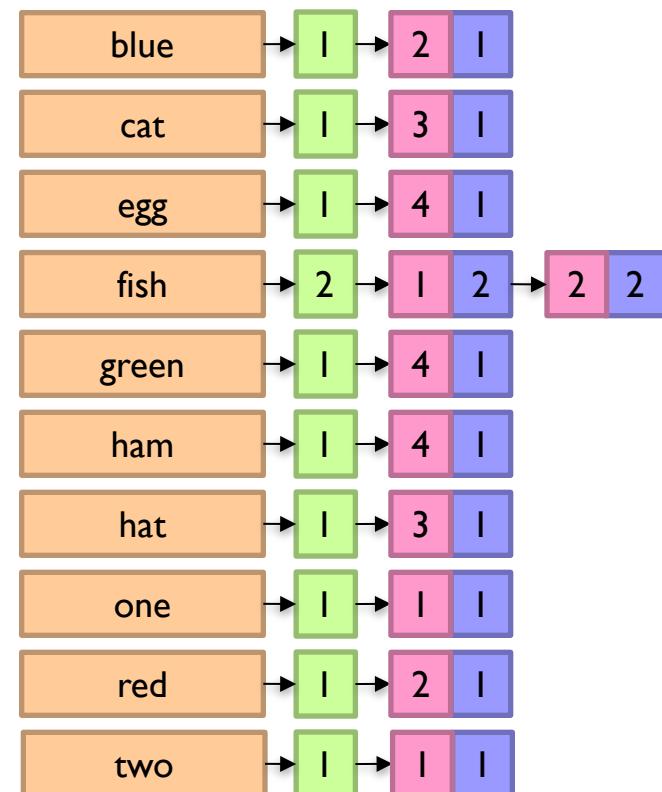
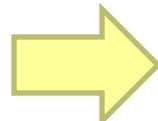
Important: properly define sort order to make sure “special” key-value pairs come first!

↓ Write postings compressed

Where have we seen this before?

But I don't care about Golomb Codes!

	tf				df
	1	2	3	4	
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



Basic Inverted Indexer: Reducer

(key)	(value)
fish	 [] [] [] ...

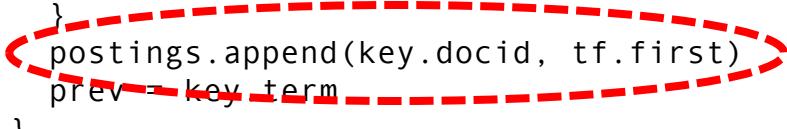
Compute the df by summing contributions from all “special” key-value pair...

Write the *df*

fish	1	2
fish	9	1
fish	21	3
fish	34	2
fish	35	3
fish	80	1

Write postings compressed

Inverted Indexing: IP (~Pairs)

```
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(key.term, postings)  
            postings.reset()  
        }  
          
        postings.append(key.docid, tf.first)  
        prev = key.term  
    }  
  
    def cleanup() = {  
        emit(prev, postings)  
    }  
}
```

What's the assumption?
Is it okay?

Merging Postings

Let's define an operation \oplus on postings lists P :

$$\begin{aligned}\text{Postings}(1, 15, 22, 39, 54) \oplus \text{Postings}(2, 46) \\ = \text{Postings}(1, 2, 15, 22, 39, 46, 54)\end{aligned}$$

What exactly is this operation?
What have we created?

Then we can rewrite our indexing algorithm!

flatMap: emit singleton postings
reduceByKey: \oplus

What's the issue?

$\text{Postings}_1 \oplus \text{Postings}_2 = \text{Postings}_M$

Solution: apply compression as needed!

Inverted Indexing: LP (~Stripes)

Slightly less elegant implementation... but uses same idea

```
class Mapper {  
    val m = new Map()  
  
    def map(docid: Long, doc: String) = {  
        val counts = new Map()  
        for (term <- tokenize(doc)) {  
            counts(term) += 1  
        }  
        for ((term, tf) <- counts) {  
            m(term).append((docid, tf))  
        }  
        if memoryFull()  
            flush()  
    }  
  
    def cleanup() = {  
        flush()  
    }  
  
    def flush() = {  
        for (term <- m.keys) {  
            emit(term, new PostingsList(m(term)))  
        }  
        m.clear()  
    }  
}
```

What's happening here?

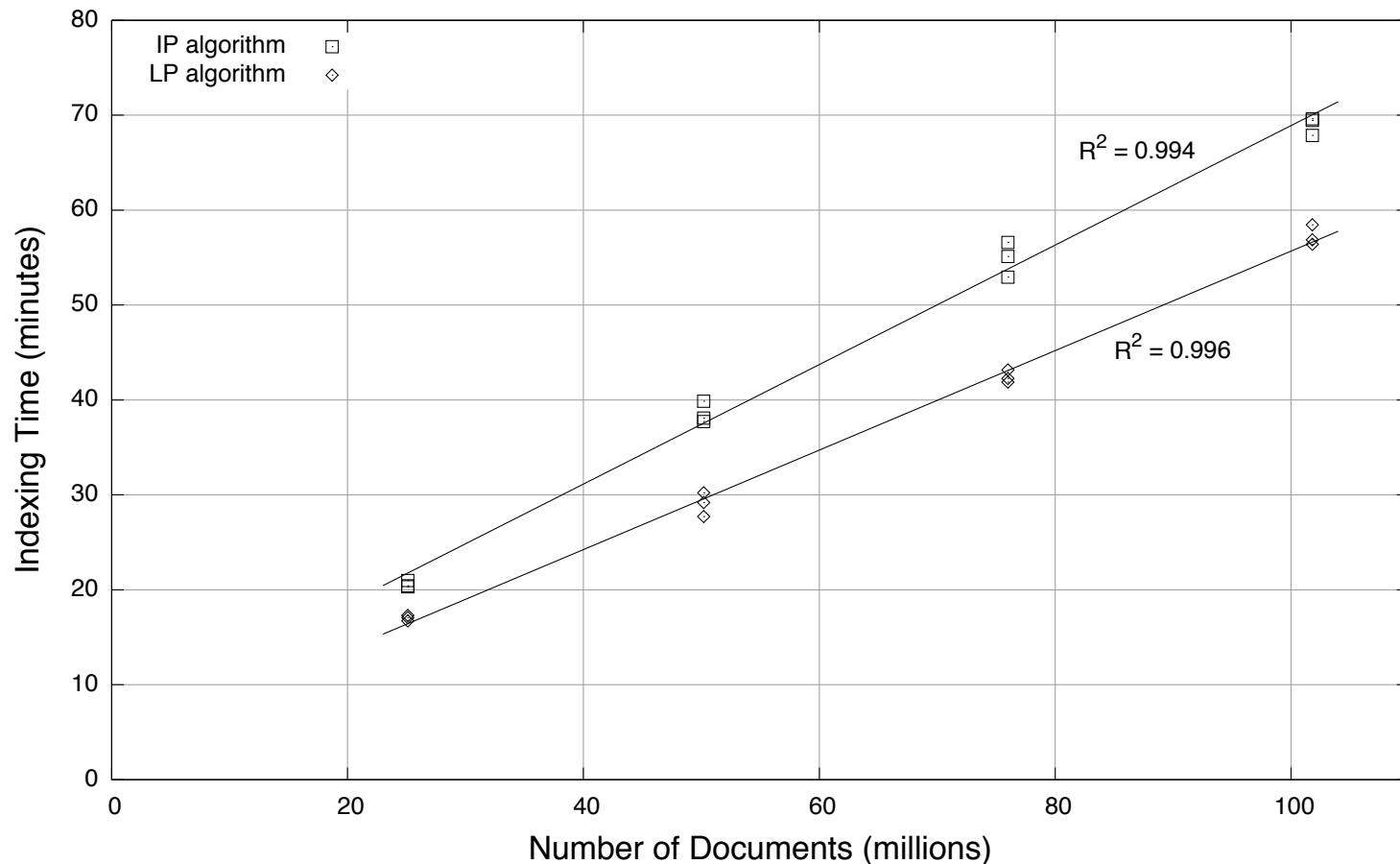
Inverted Indexing: LP (~Stripes)

```
class Reducer {  
    def reduce(term: String, lists: Iterable[PostingsList]) = {  
        var f = new PostingsList()  
  
        for (list <- lists) {  
            f = f + list  
        }  
        emit(term, f)  
    }  
}
```

What's happening here?

LP vs. IP?

Experiments on ClueWeb09 collection: segments 1 + 2
101.8m documents (472 GB compressed, 2.97 TB uncompressed)



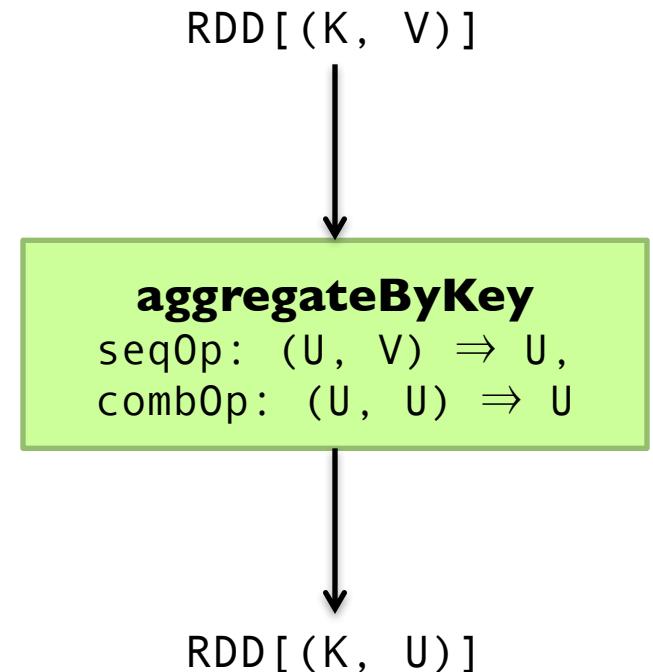
Alg.	Time	Intermediate Pairs	Intermediate Size
IP	38.5 min	13×10^9	306×10^9 bytes
LP	29.6 min	614×10^6	85×10^9 bytes

Another Look at LP

```
class Mapper {  
    val m = new Map()  
  
    def map(docid: Long, doc: String) = {  
        val counts = new Map()  
        for (term <- tokenize(doc)) {  
            counts(term) += 1  
        }  
        for ((term, tf) <- counts) {  
            m(term).append((docid, tf))  
        }  
        if memoryFull()  
            flush()  
    }  
  
    def cleanup() = {  
        flush()  
    }  
  
    def flush() = {  
        for (term <- m.keys) {  
            emit(term, new PostingsList(m(term)))  
        }  
        m.clear()  
    }  
  
    class Reducer {  
        def reduce(term: String, lists: Iterable[PostingsList]) = {  
            val f = new PostingsList()  
            for (list <- lists) {  
                f = f + list  
            }  
            emit(term, f)  
        }  
    }  
}
```

flatMap: emit singleton postings
reduceByKey: \oplus

Remind you of anything in Spark?



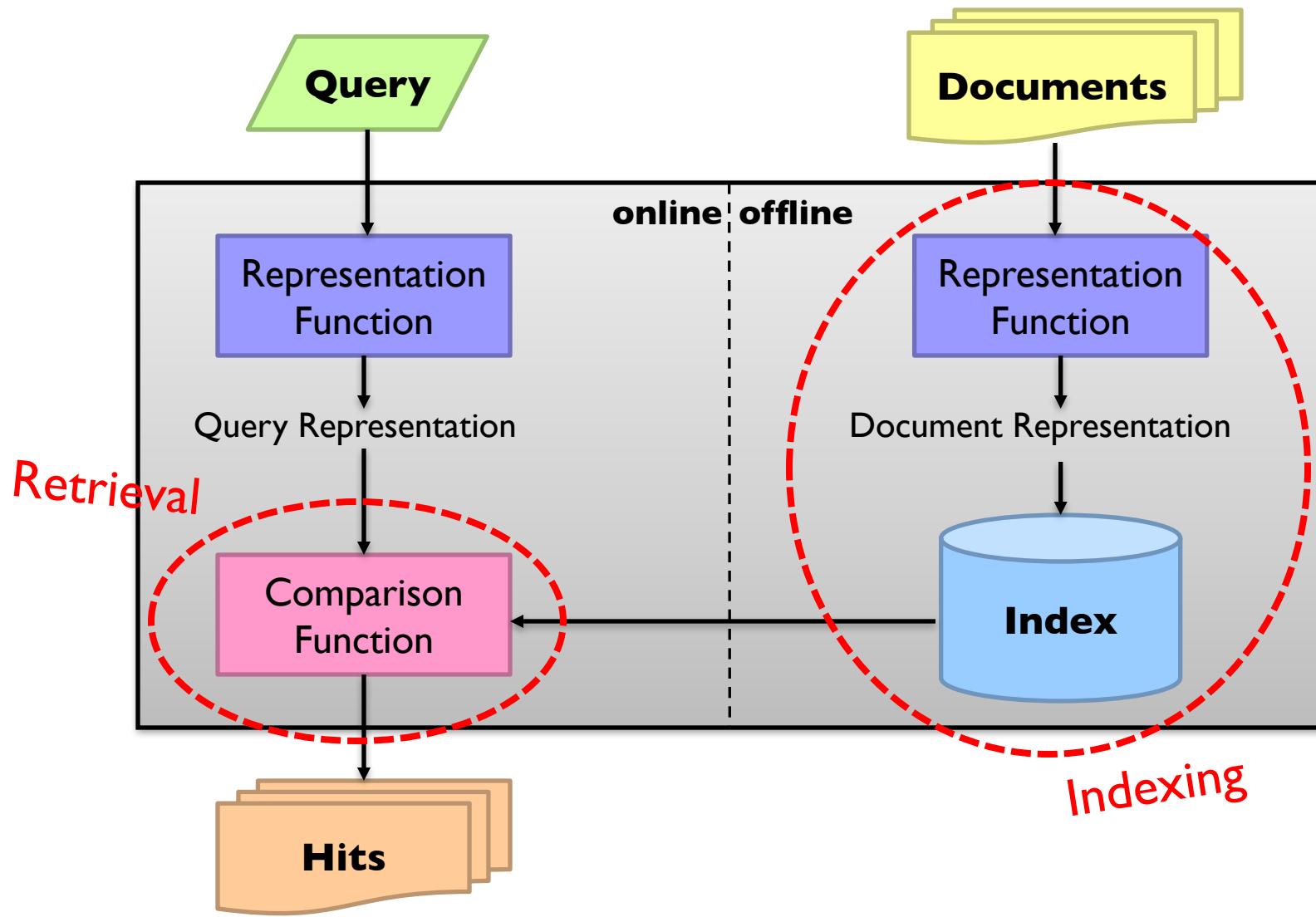
Algorithm design in a nutshell...



Exploit associativity and commutativity
via commutative monoids (if you can)

Exploit framework-based sorting to
sequence computations (if you can't)

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

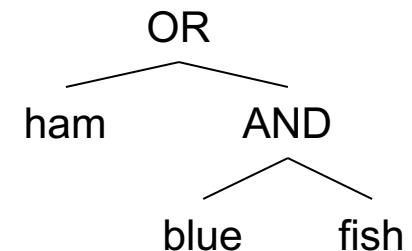
Pure Boolean systems do not define an ordering of the results

Boolean Retrieval

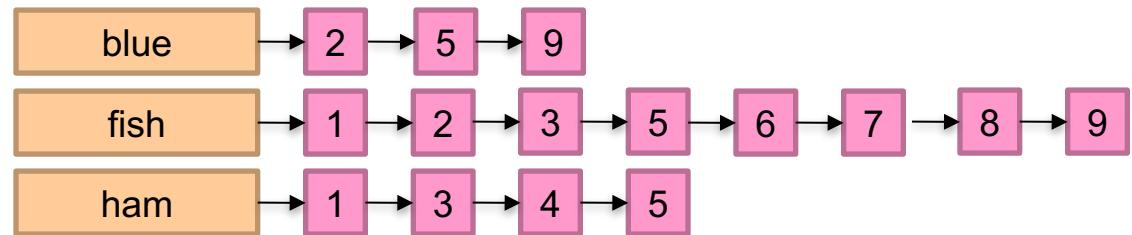
To execute a Boolean query:

Build query syntax tree

(blue AND fish) OR ham

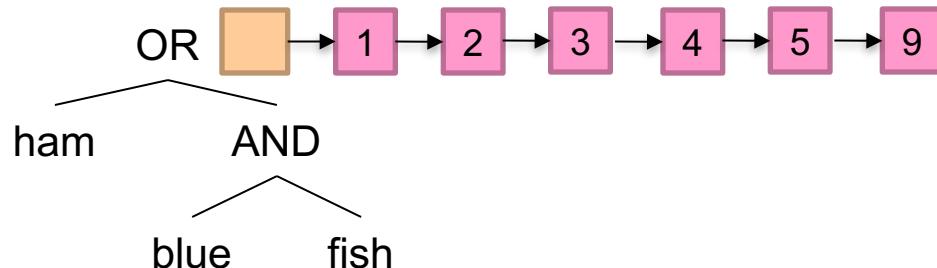
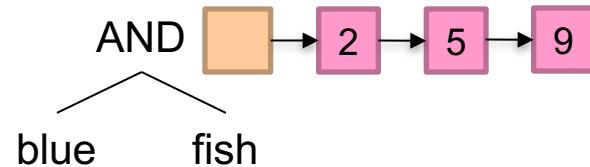
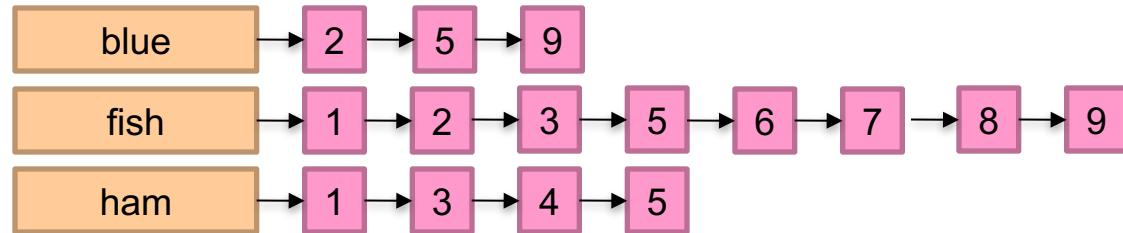
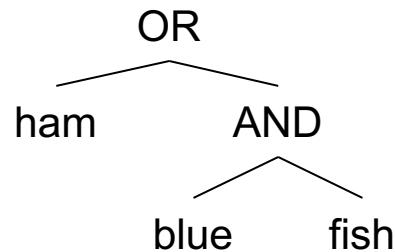


For each clause, look
up postings



Traverse postings and apply Boolean operator

Term-at-a-Time

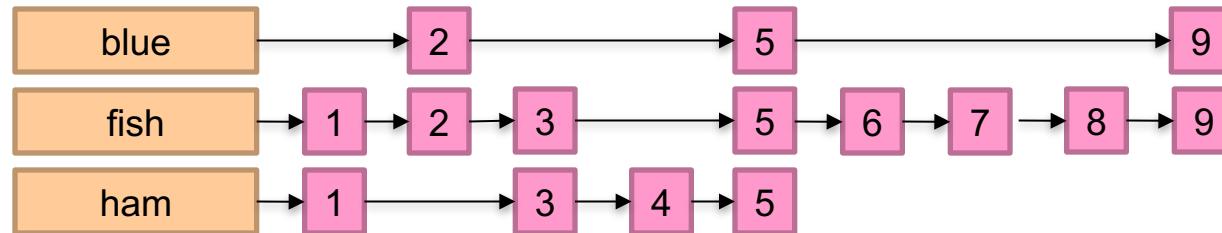
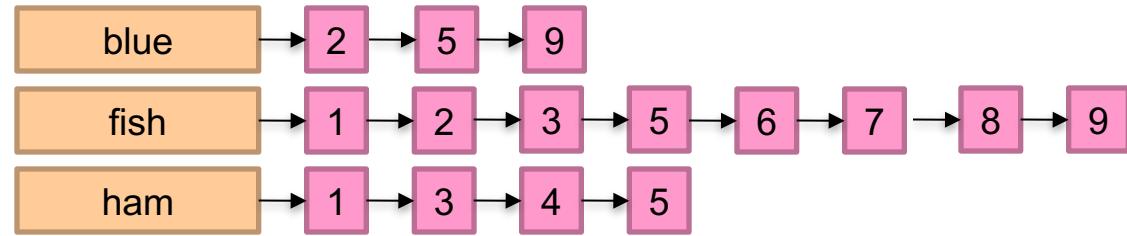


Efficiency analysis?

What's RPN?

Document-at-a-Time

ham AND
 / \
 blue fish
 OR
 / \
 ham blue



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

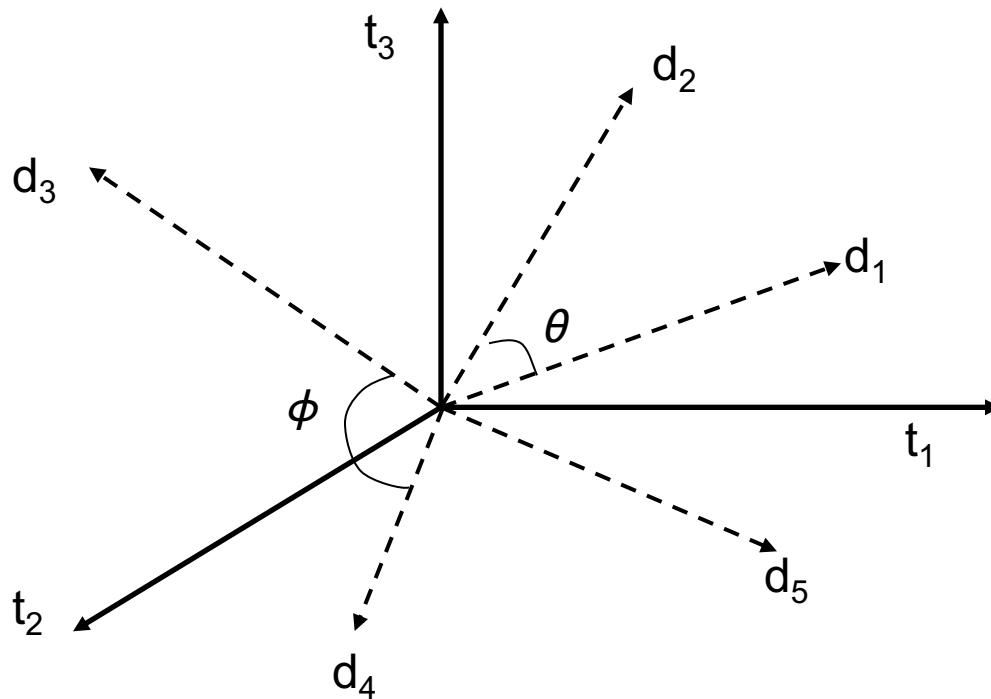
Estimate relevance(q, d_i)

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 \sim “closeness”)

Similarity Metric

Use “angle” between the vectors:

$$\begin{aligned}d_j &= [w_{j,1}, w_{j,2}, w_{j,3}, \dots, w_{j,n}] \\d_k &= [w_{k,1}, w_{k,2}, w_{k,3}, \dots, w_{k,n}]\end{aligned}$$

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

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

Or, more generally, inner products:

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

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

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

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

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

N number of documents in entire collection

n_i number of documents with term i

Retrieval in a Nutshell

Look up postings lists corresponding to query terms

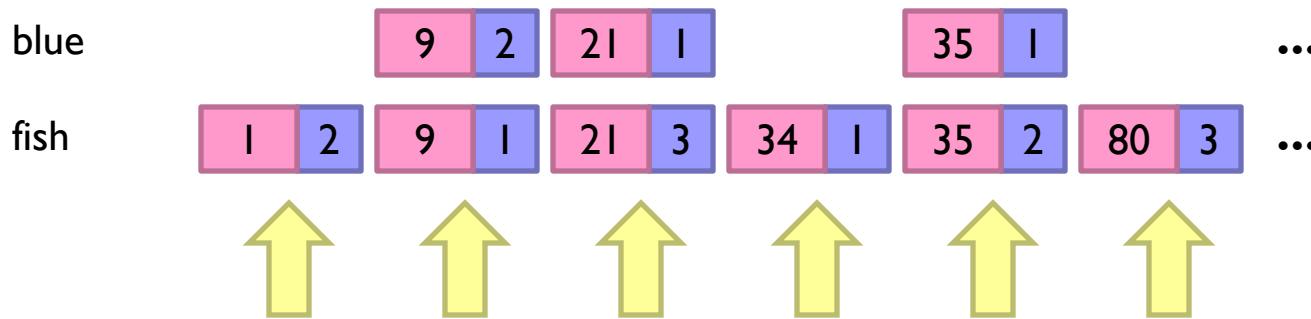
Traverse postings for each query term

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)

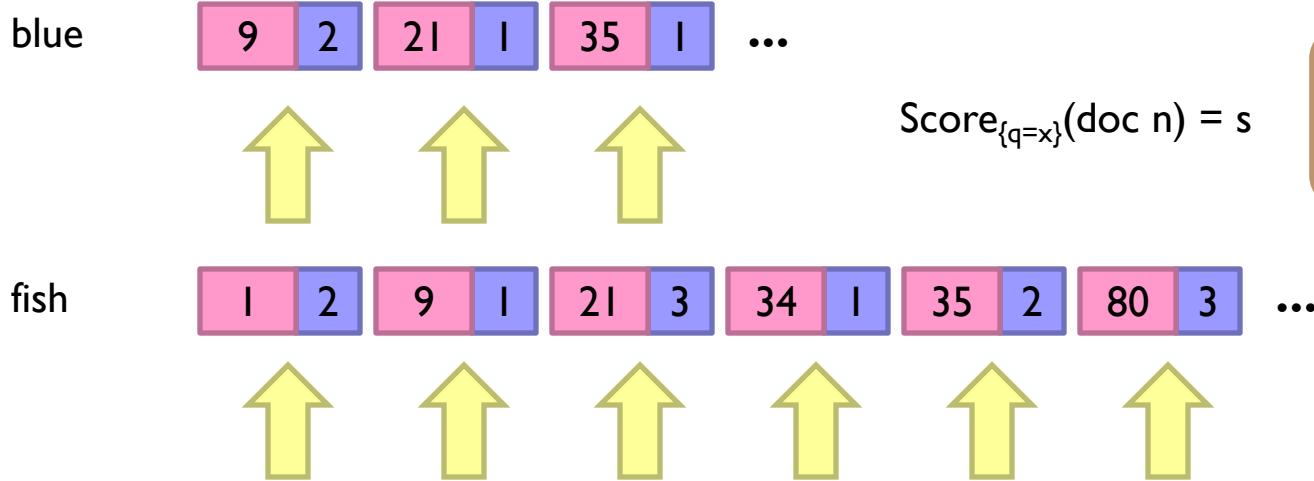
Skipping possible to avoid reading all postings (good)

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)

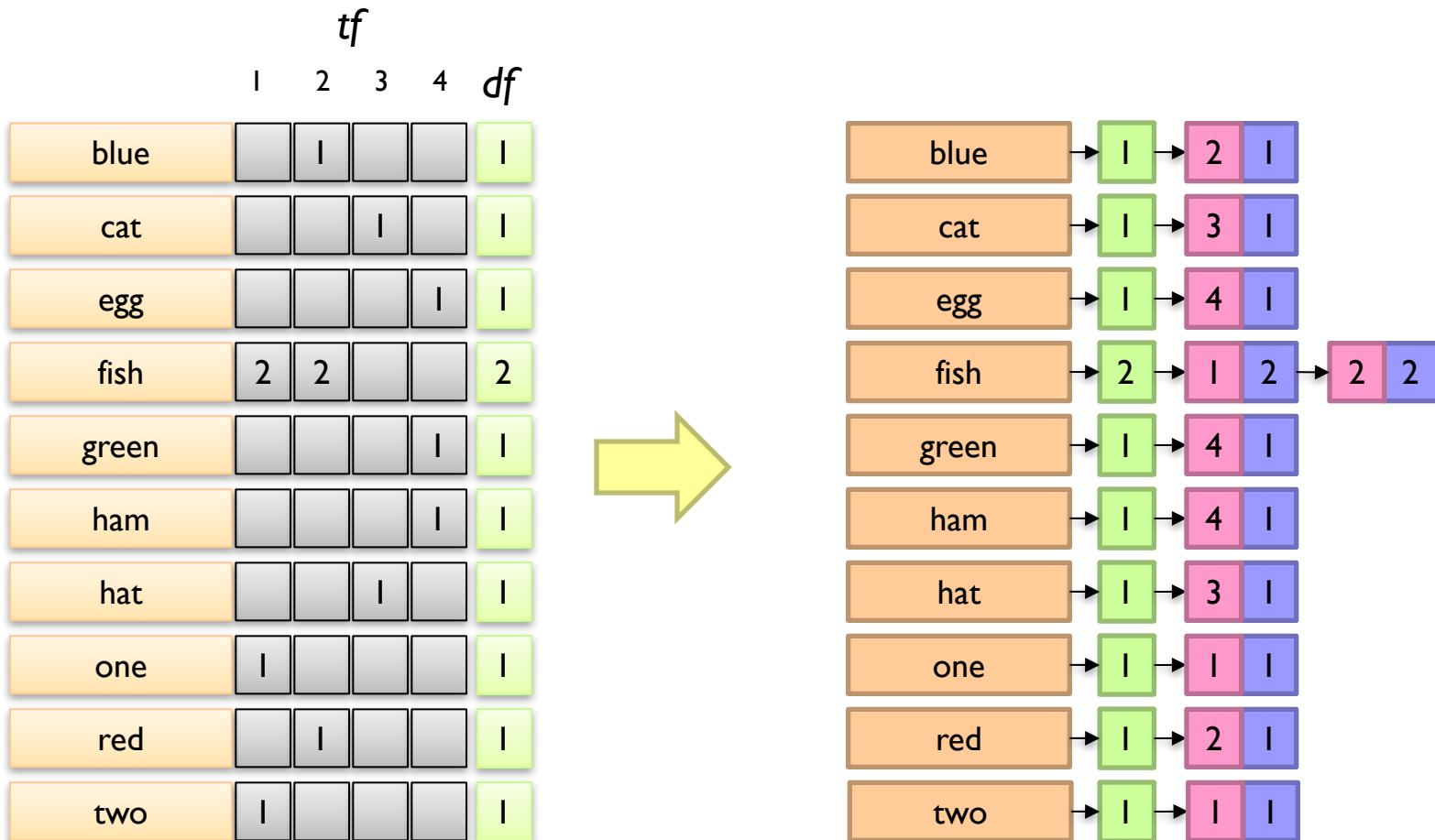


Tradeoffs:

Early termination heuristics (good)

Large memory footprint (bad), but filtering heuristics possible

Why store df as part of postings?



Assume everything fits in memory on a single machine...

Okay, let's relax this assumption now

Important Ideas

Partitioning (for scalability)

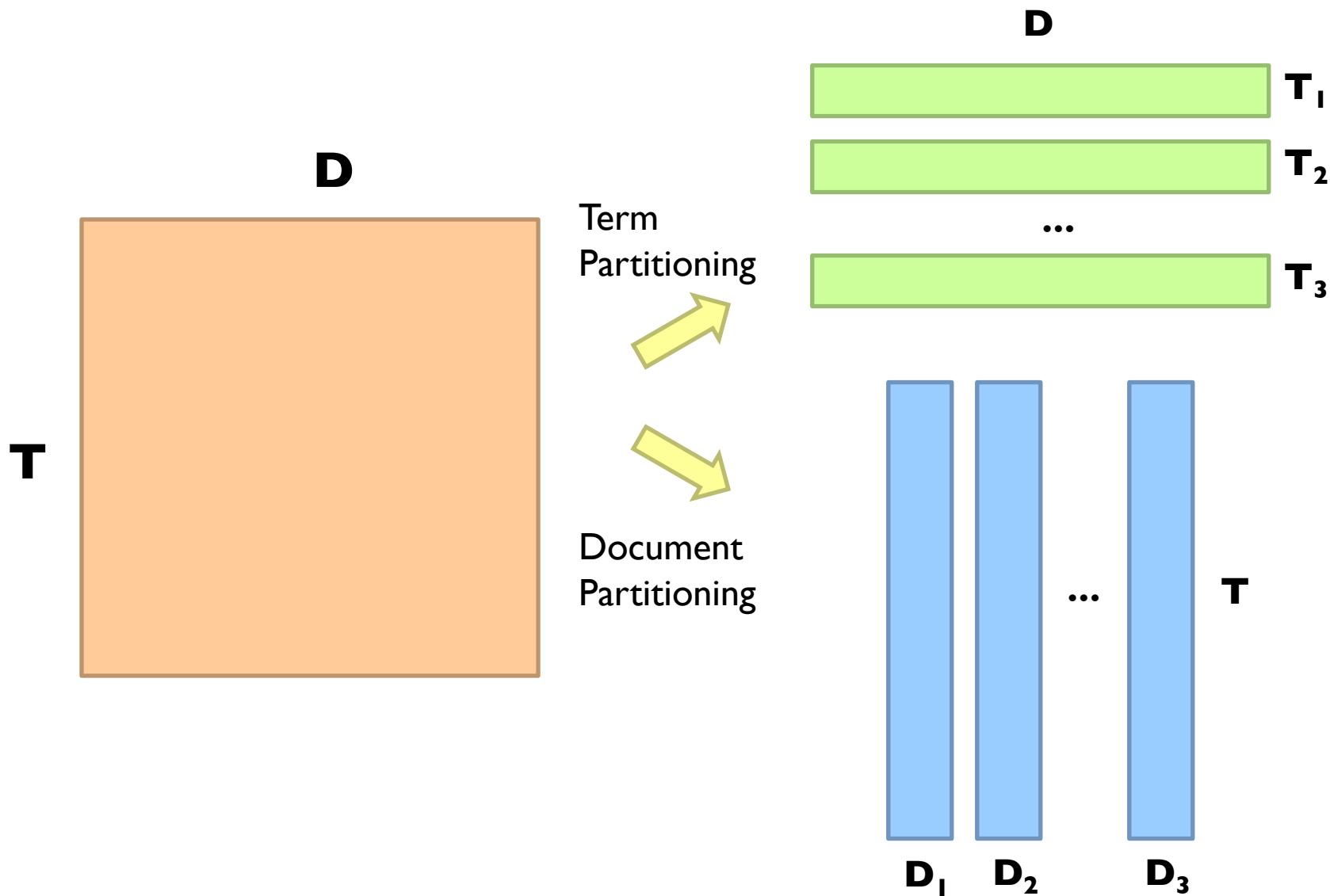
Replication (for redundancy)

Caching (for speed)

Routing (for load balancing)

The rest is just details!

Term vs. Document Partitioning



FE



brokers

partitions



...



...



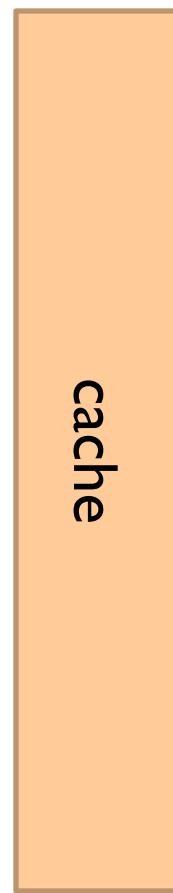
...



...

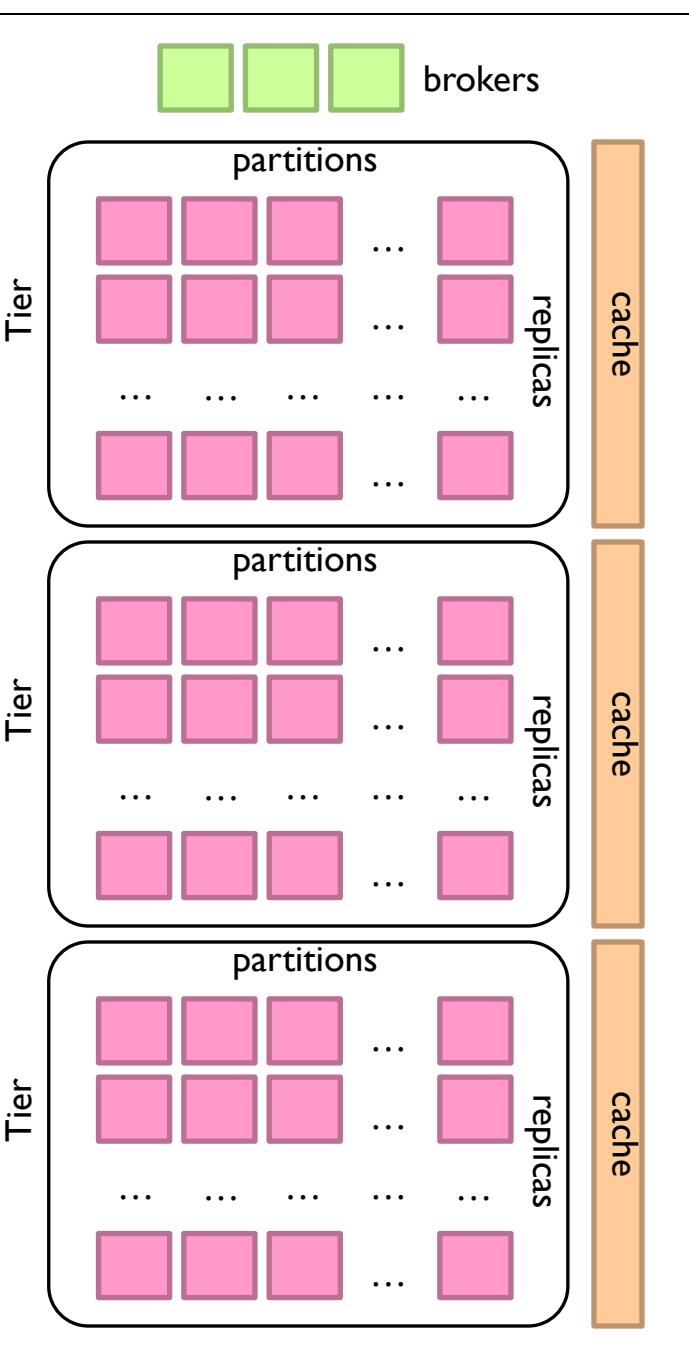


replicas

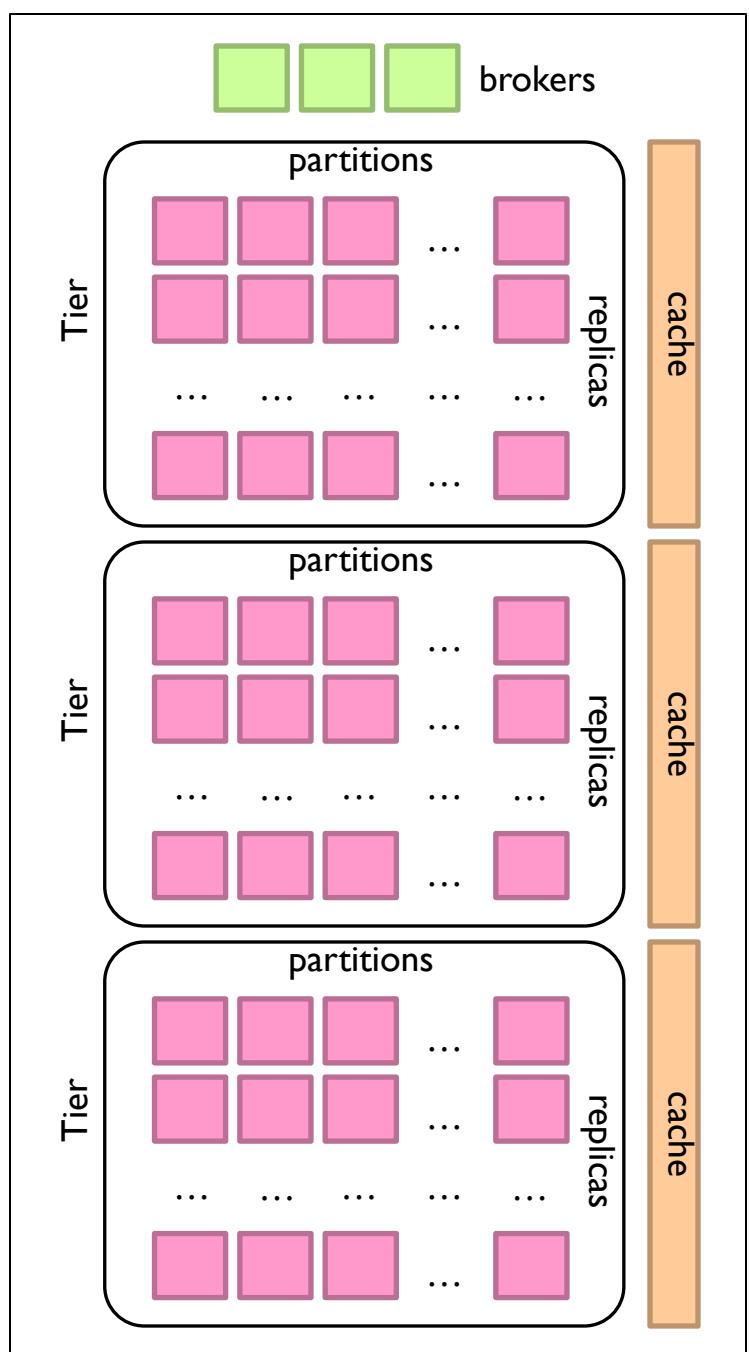


cache

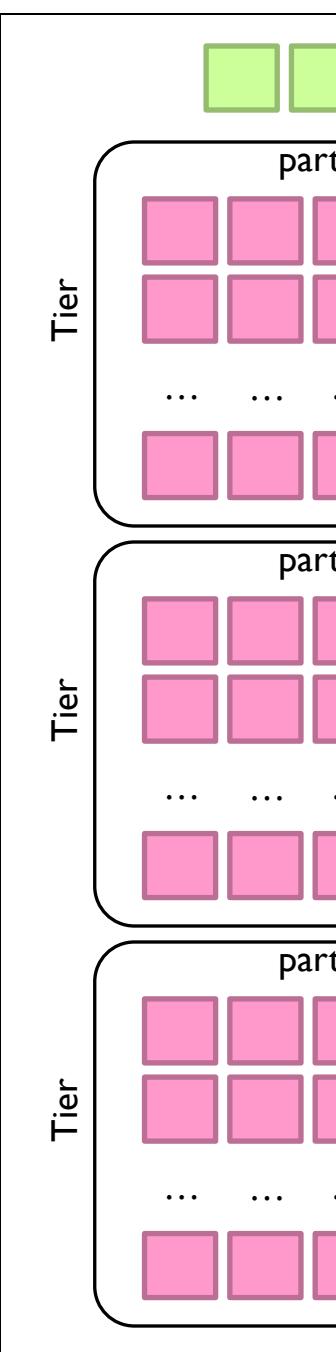
Datacenter



Datacenter



Datacenter



Important Ideas

Partitioning (for scalability)

Replication (for redundancy)

Caching (for speed)

Routing (for load balancing)

A photograph of a traditional Japanese rock garden. In the foreground, a gravel path is raked into fine, parallel lines. Several large, dark, irregular stones are scattered across the garden. A small, shallow pond is visible in the middle ground, surrounded by more stones and some low-lying green plants. In the background, there are more stones, some small trees, and the wooden buildings of a residence with tiled roofs.

Questions?