UNIVERSITY OF WATERLOO

Data-Intensive Distributed Computing

CS 431/631 451/651 (Winter 2019)

Part 5: Analyzing Relational Data (3/3)

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These slides are available at http://roegiest.com/bigdata-2019w/

MapReduce: A Major Step Backwards?

MapReduce is a step backward in database access

Schemas are good

Separation of the schema from the application is good

High-level access languages are good

MapReduce is poor implementation

Brute force and only brute force (no indexes, for example)

MapReduce is not novel

MapReduce is missing features

Bulk loader, indexing, updates, transactions…

MapReduce is incompatible with DBMS tools

Source: Blog post by DeWitt and Stonebraker

Hadoop vs. Databases: Grep

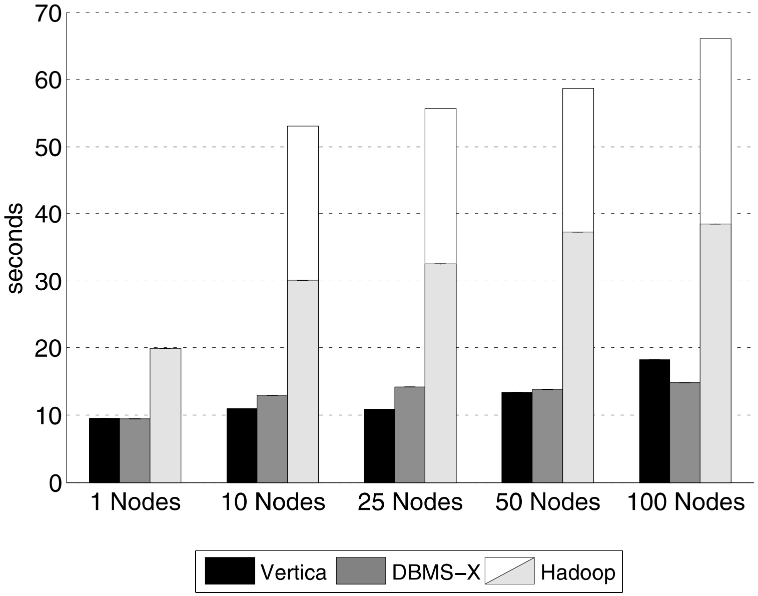


Figure 4: Grep Task Results – 535MB/node Data Set

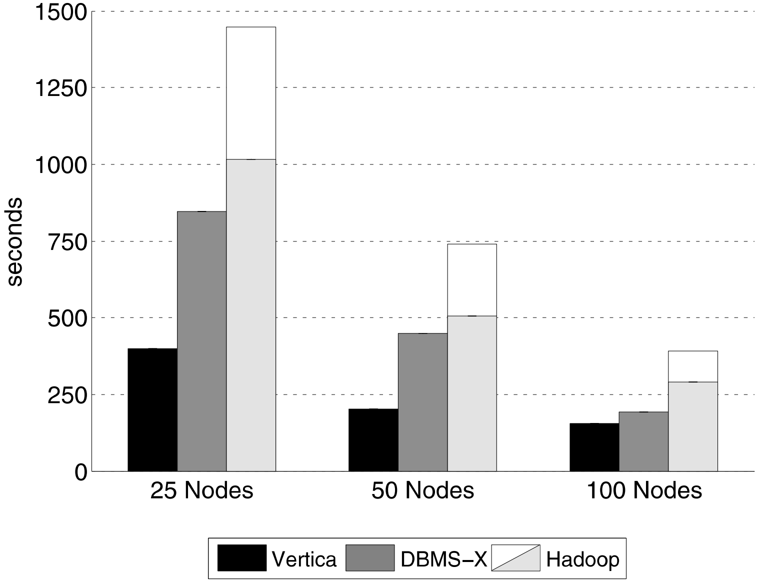


Figure 5: Grep Task Results – 1TB/cluster Data Set

SELECT * FROM Data WHERE field LIKE ‘%XYZ%’;

Source: Pavlo et al. (2009) A Comparison of Approaches to Large-Scale Data Analysis. SIGMOD.

Hadoop vs. Databases: Select

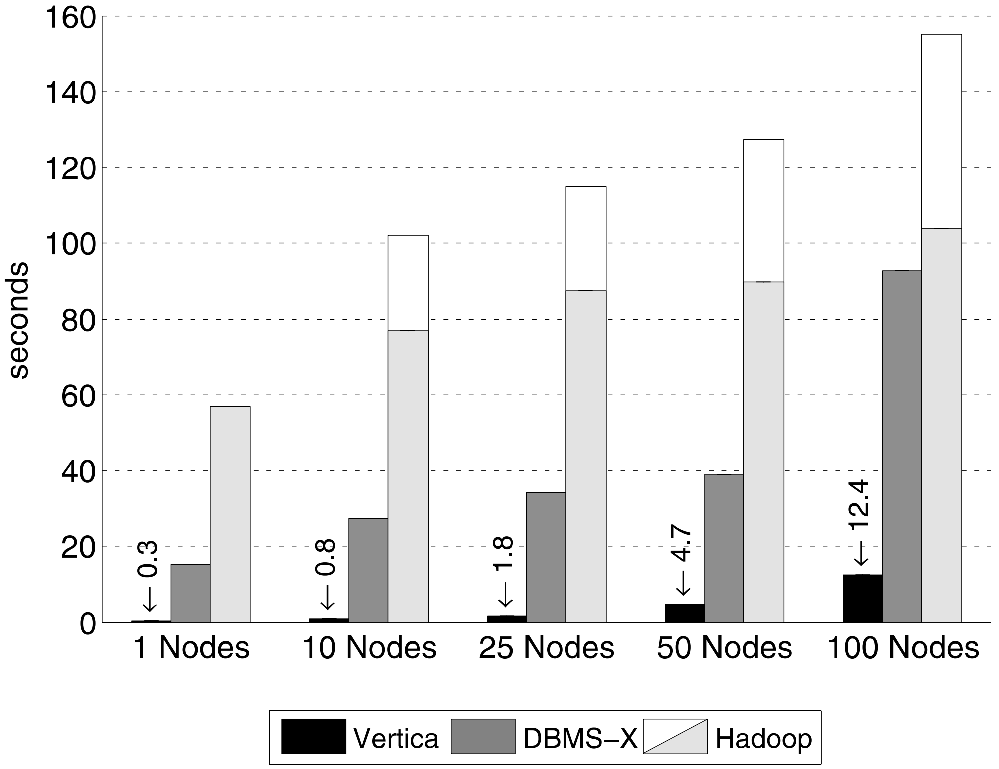


Figure 6: Selection Task Results

```
SELECT pageURL, pageRank
FROM Rankings WHERE pageRank > X;
```

Source: Pavlo et al. (2009) A Comparison of Approaches to Large-Scale Data Analysis. SIGMOD.

Hadoop vs. Databases: Aggregation

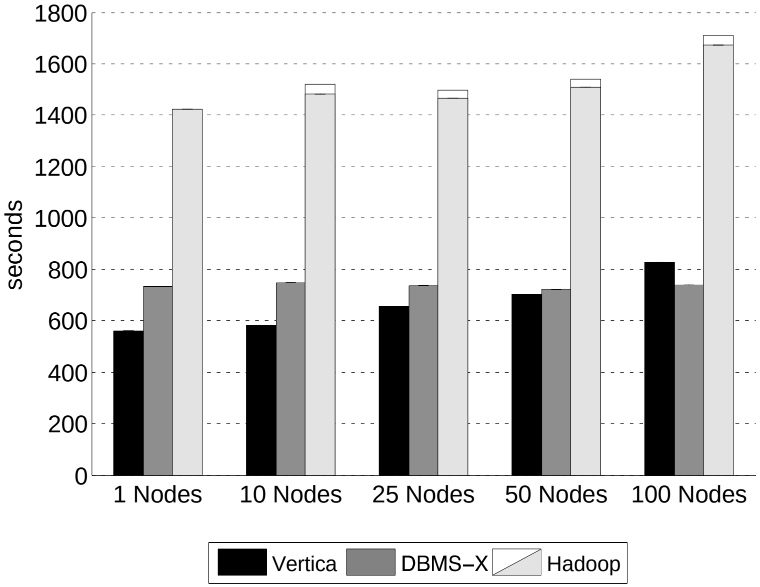


Figure 7: Aggregation Task Results (2.5 million Groups)

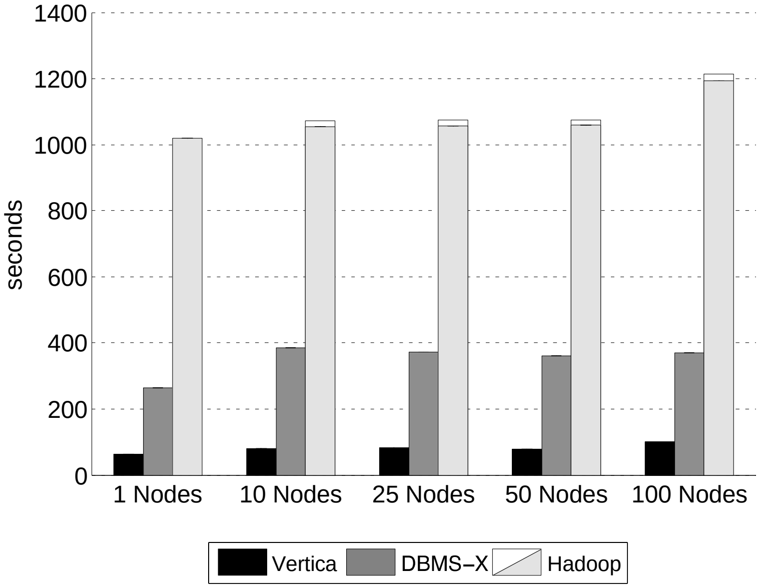


Figure 8: Aggregation Task Results (2,000 Groups)

```
SELECT sourceIP, SUM(adRevenue)
FROM UserVisits GROUP BY sourceIP;
```

Source: Pavlo et al. (2009) A Comparison of Approaches to Large-Scale Data Analysis. SIGMOD.

Hadoop vs. Databases: Join

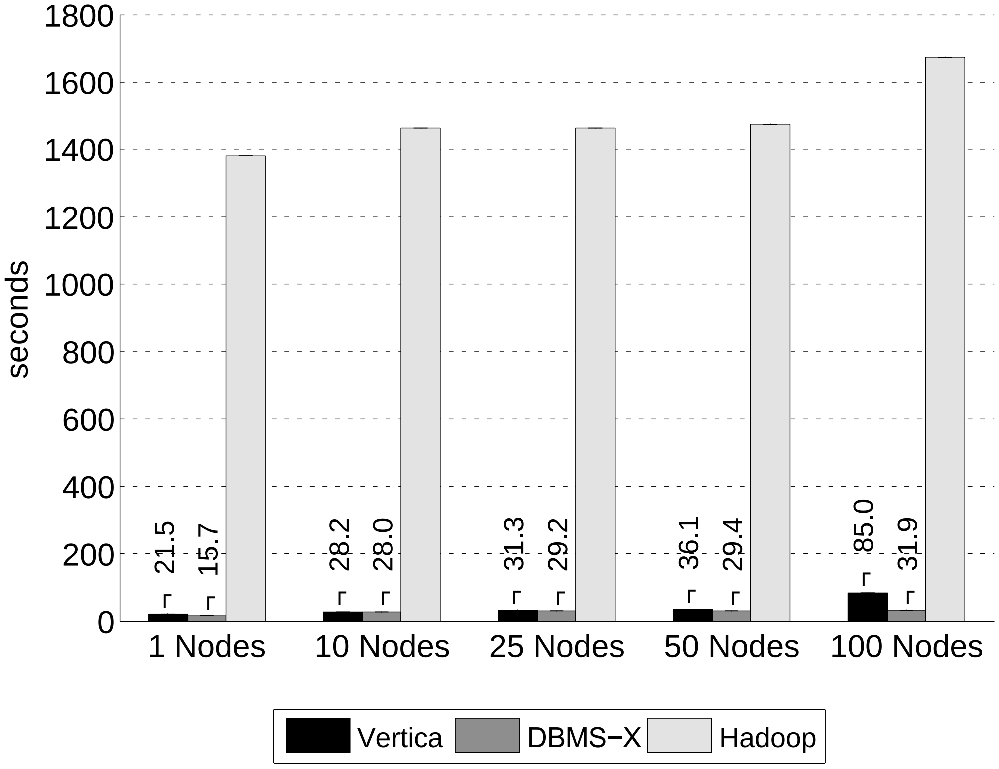


Figure 9: Join Task Results

```
SELECT INTO Temp sourceIP, AVG(pageRank) as avgPageRank, SUM(adRevenue) as totalRevenue
FROM Rankings AS R, UserVisits AS UV
WHERE R.pageURL = UV.destURL AND UV.visitDate BETWEEN Date('2000-01-15') AND Date('2000-01-22') GROUP BY UV.sourceIP;

SELECT sourceIP, totalRevenue, avgPageRank FROM Temp ORDER BY totalRevenue DESC LIMIT 1;
```

Source: Pavlo et al. (2009) A Comparison of Approaches to Large-Scale Data Analysis. SIGMOD.

Hadoop is slow...

Source: Wikipedia (Tortoise)

Something seems fishy…

Source: Wikipedia (Fish)

Why was Hadoop slow?

Integer.parseInt

String.substring

String.split

Hadoop slow because string manipulation is slow?

Key Ideas

Binary representations are good

Binary representations need schemas

Schemas allow logical/physical separation

Logical/physical separation allows you to do cool things

Thrift

Originally developed by Facebook, now an Apache project

Provides a DDL with numerous language bindings

Compact binary encoding of typed structs

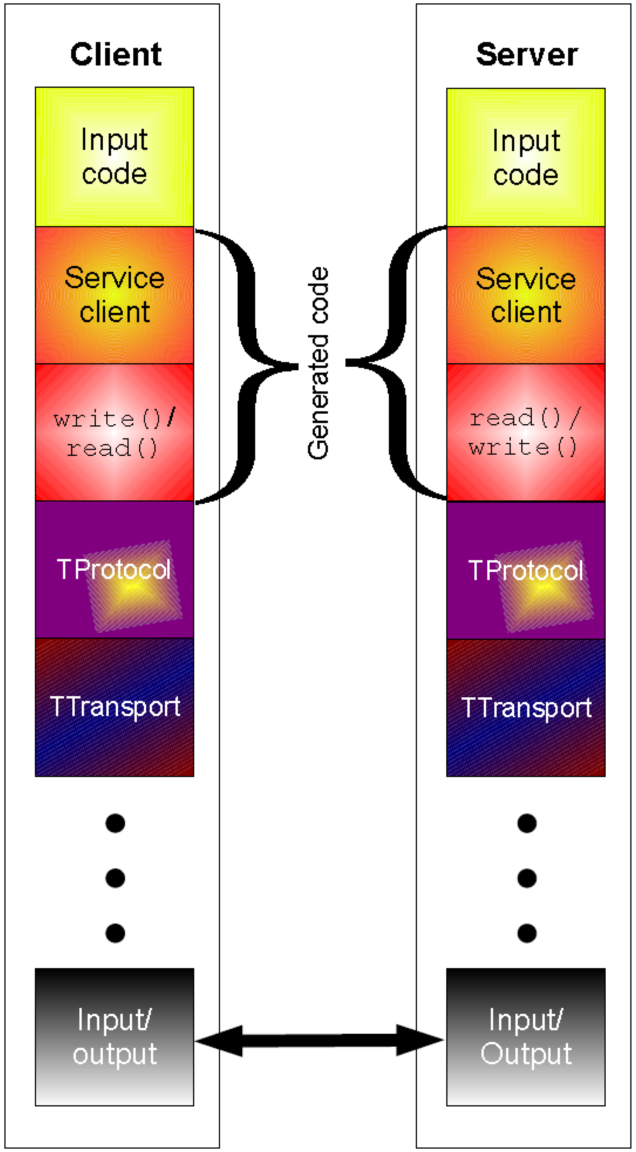
Fields can be marked as optional or required

Compiler automatically generates code for manipulating messages

Provides RPC mechanisms for service definitions

Don’t like Thrift? Alternatives include protobufs and Avro

Thrift



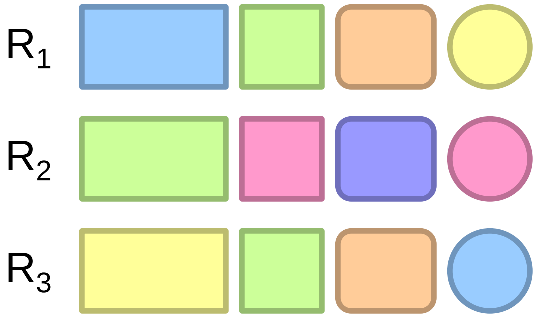
```
struct Tweet {
 1: required i32 userId;
 2: required string userName;
 3: required string text;
 4: optional Location loc;
}

struct Location {
 1: required double latitude;
 2: required double longitude;
}
```

Why not…

XML or JSON?

REST?

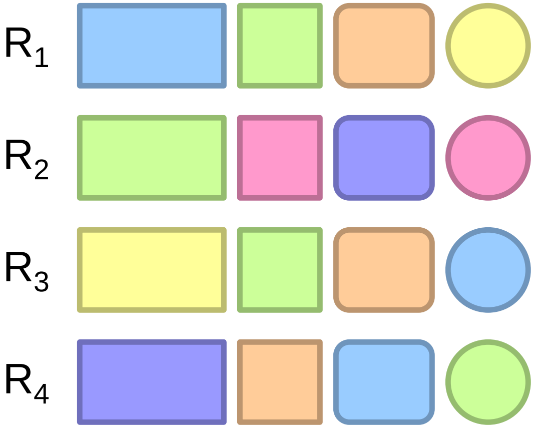
Logical



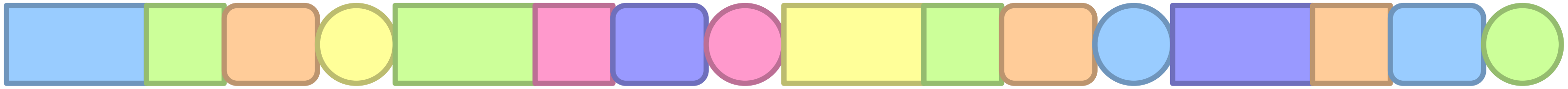
Physical

How bytes are actually represented in storage…

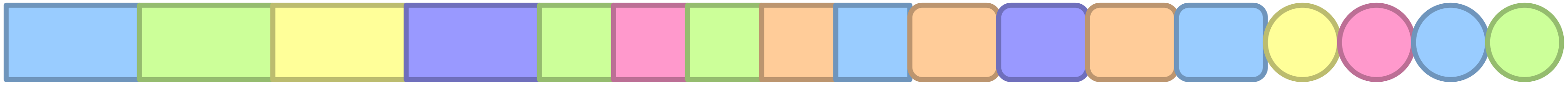
Row vs. Column Stores



Row store



Column store



Row vs. Column Stores

Row stores

Easier to modify a record: in-place updates

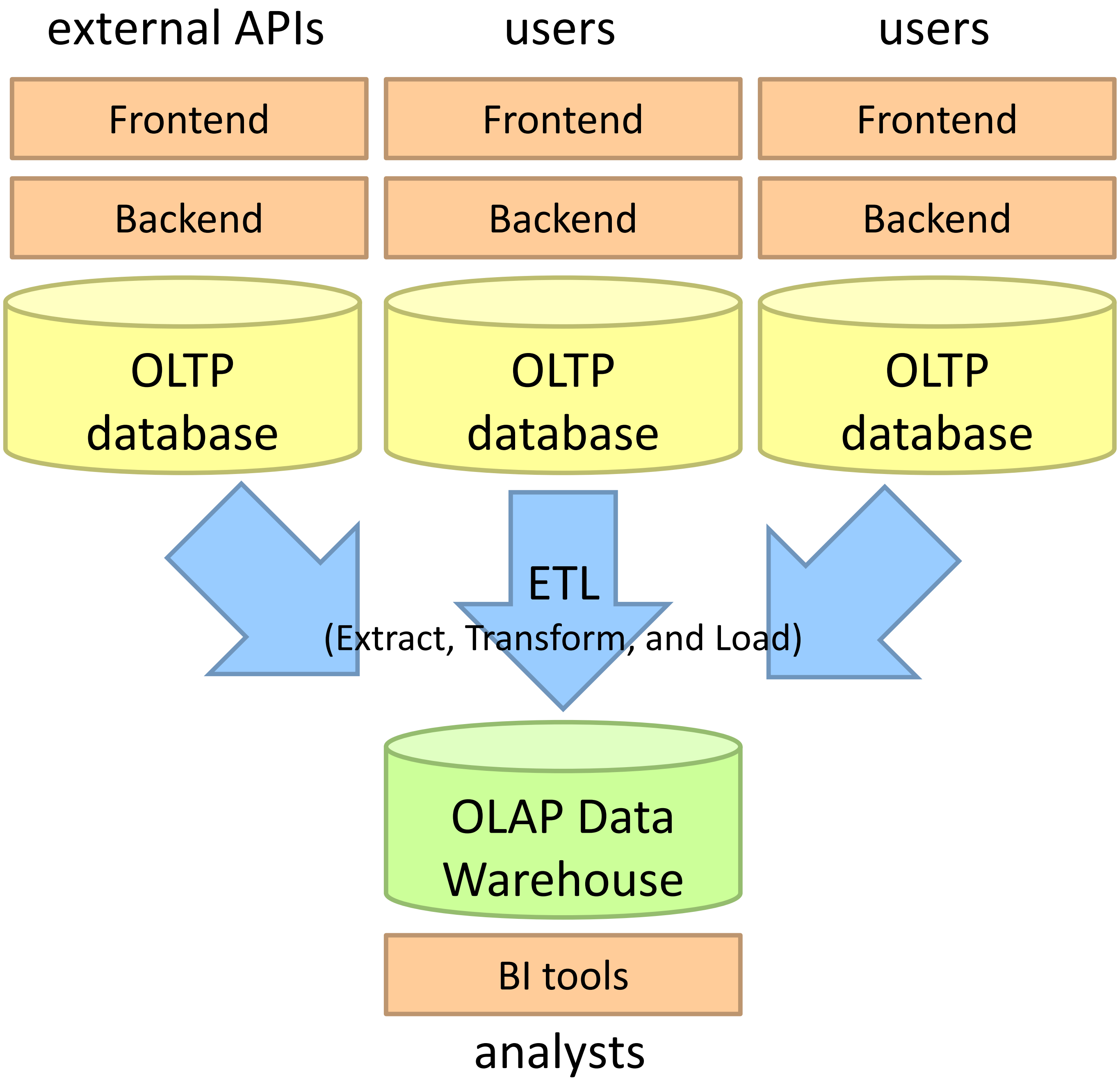
Might read unnecessary data when processing

Column stores

Only read necessary data when processing

Tuple writes require multiple operations

Tuple updates are complex



external APIs

users

users

Frontend

Frontend

Frontend

Backend

Backend

Backend

OLTP database

OLTP database

OLTP database

ETL

(Extract, Transform, and Load)

OLAP Data Warehouse

BI tools

analysts

Advantages of Column Stores

Inherent advantages:

Better compression

Read efficiency

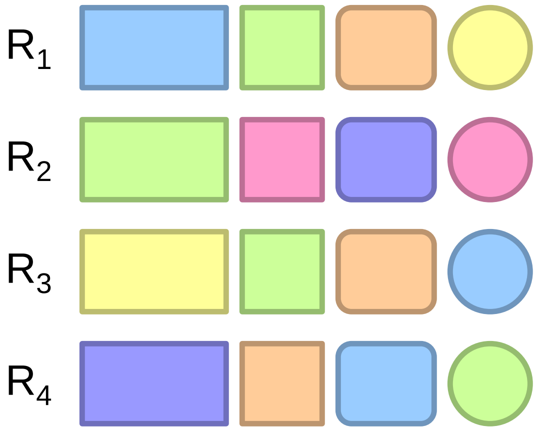
Works well with:

Vectorized Execution

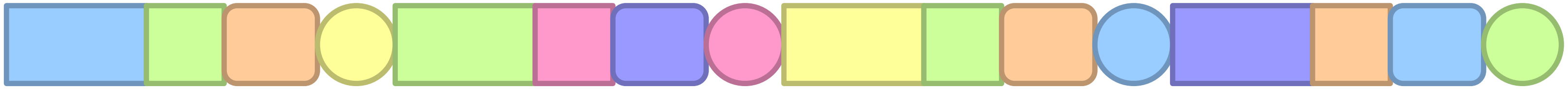
Compiled Queries

These are well-known in traditional databases…

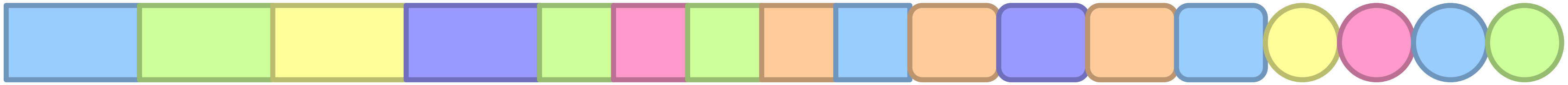
Row vs. Column Stores: Compression



Row store



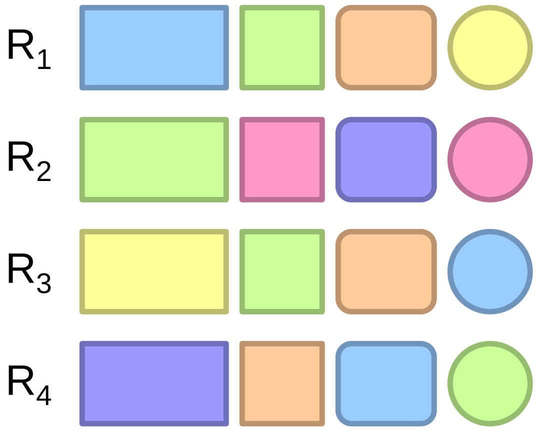
Column store



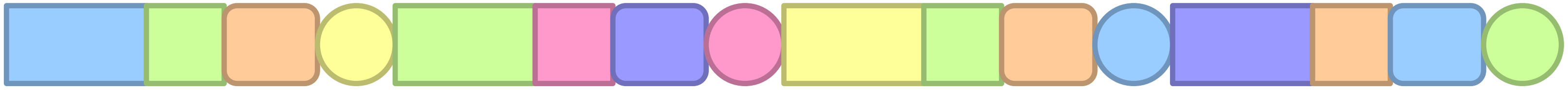
This compresses better with off-the-shelf tools, e.g., gzip.

Why?

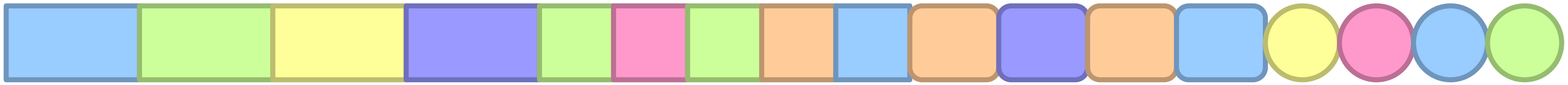
Row vs. Column Stores: Compression



Row store



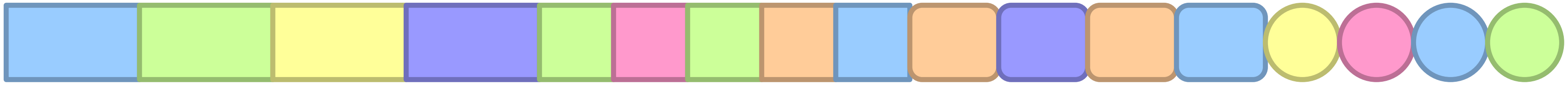
Column store



Additional opportunities for smarter compression…

Columns Stores: RLE

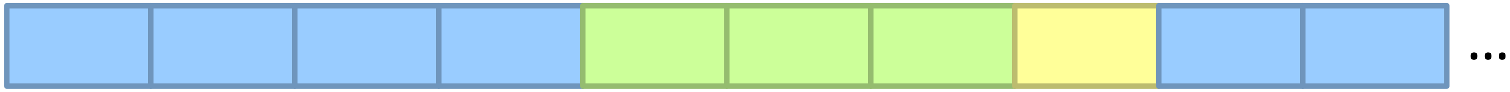
Column store



Run-length encoding example:

🟦 is a foreign key, relatively small cardinality
(even better, boolean)

In reality:

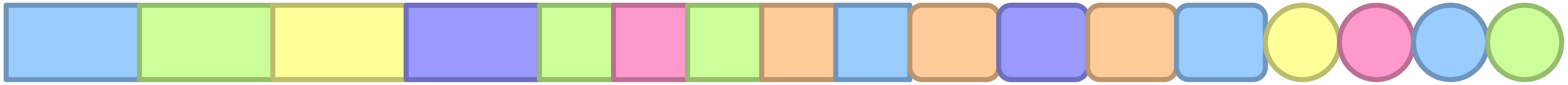


Encode:

🟦 3 🟩 2 🟨🟦 1 …

Columns Stores: Integer Coding

Column store



Say you’re coding a bunch of integers…

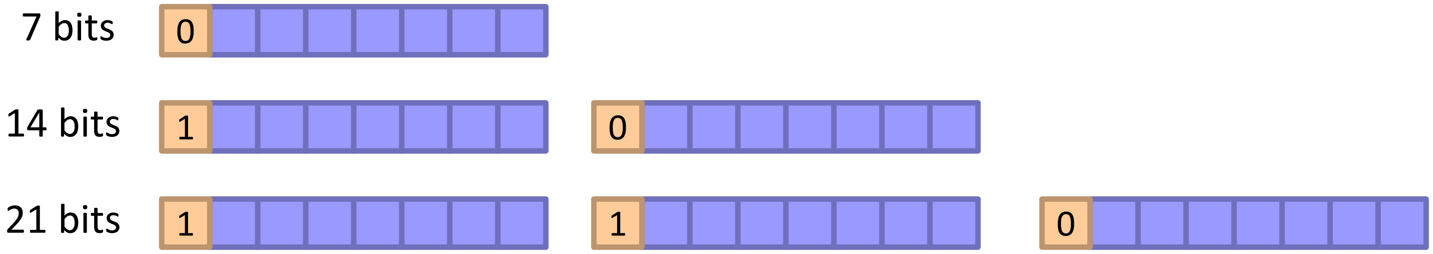
Remember this?
(Part 3)

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



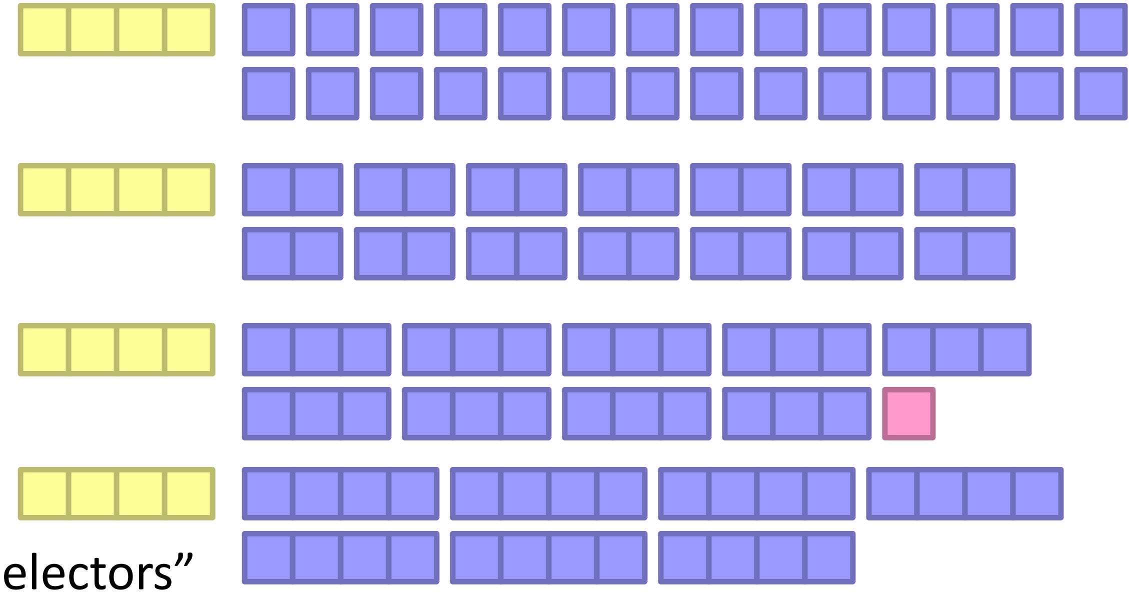
Works okay, easy to implement…

Beware of branch mispredicts!

Remember this?
(Part 3)

Simple-9

How many different ways can we divide up 28 bits?



28 1-bit numbers

14 2-bit numbers

9 3-bit numbers

7 4-bit numbers

“selectors”

(9 total ways)

Efficient decompression with hard-coded decoders

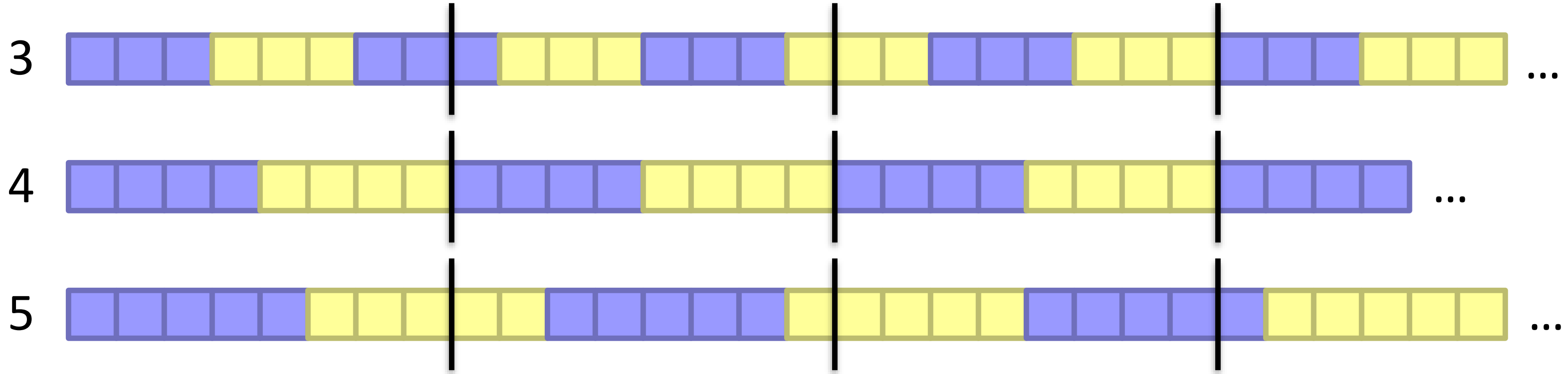
Simple Family – general idea applies to 64-bit words, etc.

Beware of branch mispredicts?

Remember this?
(Part 3)

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?

Advantages of Column Stores

Inherent advantages:

Better compression

Read efficiency

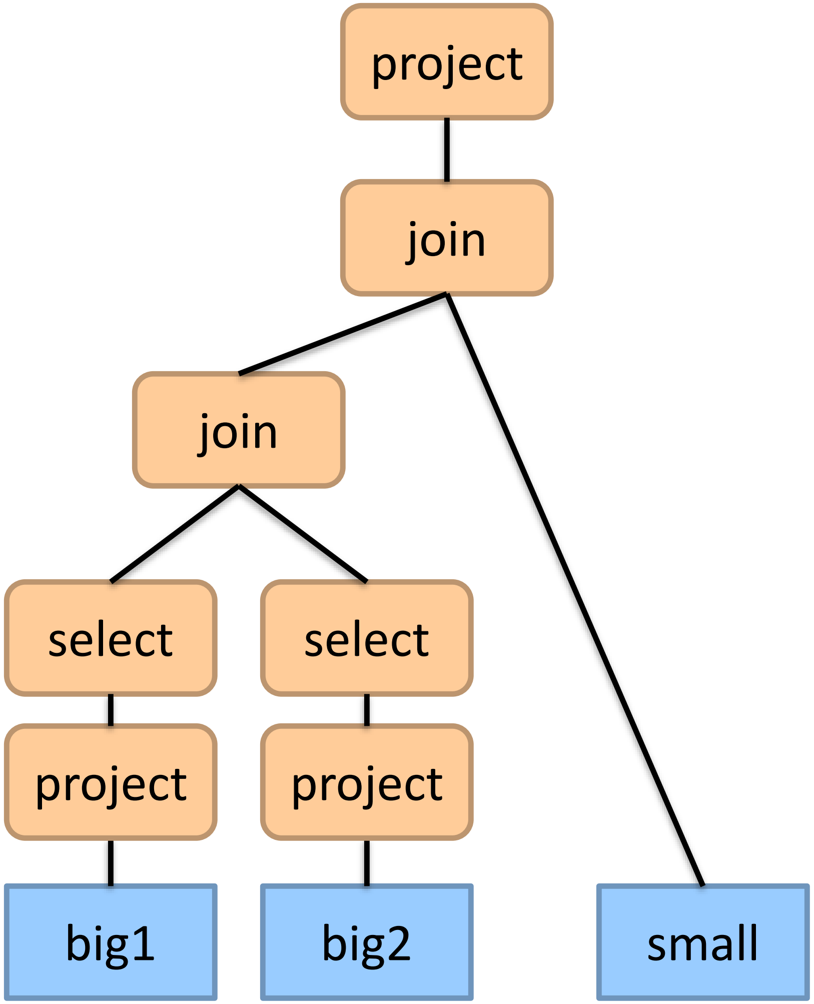
Works well with:

Vectorized Execution

Compiled Queries

Putting Everything Together

```
SELECT big1.fx, big2.fy, small.fz
FROM big1
JOIN big2 ON big1.id1 = big2.id1
JOIN small ON big1.id2 = small.id2
WHERE big1.fx = 2015 AND
      big2.f1 < 40 AND
      big2.f2 > 2;
```



Build logical plan

Optimize logical plan

Select physical plan

```
  val size = 100000000

  var col = new Array[Int](size)          // List of random ints
  var selected = new Array[Boolean](size)  // Matches a predicate?
```

```
for (i <- 0 until size) {
  selected(i) = col(i) > 0
}
```

```
for (i <- 0 until size by 8) {
  selected(i) = col(i) > 0
  selected(i+1) = col(i+1) > 0
  selected(i+2) = col(i+2) > 0
  selected(i+3) = col(i+3) > 0
  selected(i+4) = col(i+4) > 0
  selected(i+5) = col(i+5) > 0
  selected(i+6) = col(i+6) > 0
  selected(i+7) = col(i+7) > 0
}
```

Which is faster?
Why?

On my laptop: 409ms
(avg over 10 trials)

On my laptop: 174ms
(avg over 10 trials)

```
 val size = 100000000

 var col = new Array[Int](size)          // List of random ints
 var selected = new Array[Boolean](size)  // Matches a predicate?
```

```
for (i <- 0 until size) {
  selected(i) = col(i) > 0
}
```

```
for (i <- 0 until size by 8) {
  selected(i) = col(i) > 0
  selected(i+1) = col(i+1) > 0
  selected(i+2) = col(i+2) > 0
  selected(i+3) = col(i+3) > 0
  selected(i+4) = col(i+4) > 0
  selected(i+5) = col(i+5) > 0
  selected(i+6) = col(i+6) > 0
  selected(i+7) = col(i+7) > 0
}
```

Why does it matter?

```
SELECT pageURL, pageRank
FROM Rankings WHERE pageRank > X;
```

On my laptop: 409ms
(avg over 10 trials)

On my laptop: 174ms
(avg over 10 trials)

Actually, it’s worse than that!

Each operator implements a common interface

open() Initialize, reset internal state, etc.

next() Advance and deliver next tuple

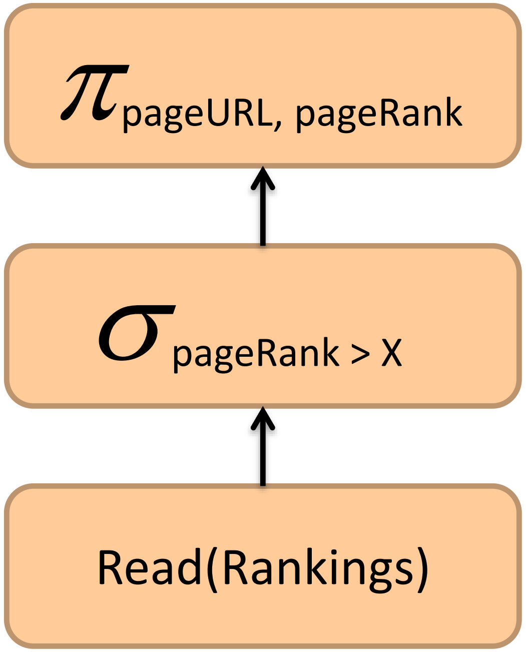
close() Clean up, free resources, etc.

Execution driven by repeated calls
to top of operator tree

open() next() next()...
close()

open() next() next()...
close()

open() next() next()...
close()



$\pi_{\text{pageURL, pageRank}}$

$\sigma_{\text{pageRank > X}}$

Read(Rankings)

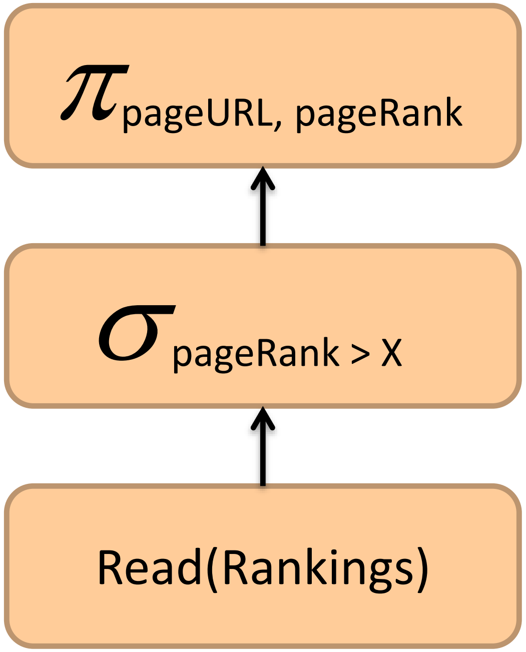
```
SELECT pageURL, pageRank
FROM Rankings WHERE pageRank > X;
```

Very little actual computation is being done!

open() next() next()...
close()

open() next() next()...
close()

open() next() next()...
close()



$\pi_{\text{pageURL, pageRank}}$

$\sigma_{\text{pageRank > X}}$

Read(Rankings)

SELECT pageURL, pageRank
FROM Rankings WHERE pageRank > X;

Solution?

```
val size = 100000000

var col = new Array[Int](size)          // List of random ints
var selected = new Array[Boolean](size)  // Matches a predicate?
```

✗

```
for (i <- 0 until size) {
  selected(i) = col(i) > 0
```

✓

```
for (i <- 0 until size by 8) {
  selected(i) = col(i) > 0
  selected(i+1) = col(i+1) > 0
  selected(i+2) = col(i+2) > 0
  selected(i+3) = col(i+3) > 0
  selected(i+4) = col(i+4) > 0
  selected(i+5) = col(i+5) > 0
  selected(i+6) = col(i+6) > 0
  selected(i+7) = col(i+7) > 0
}
```

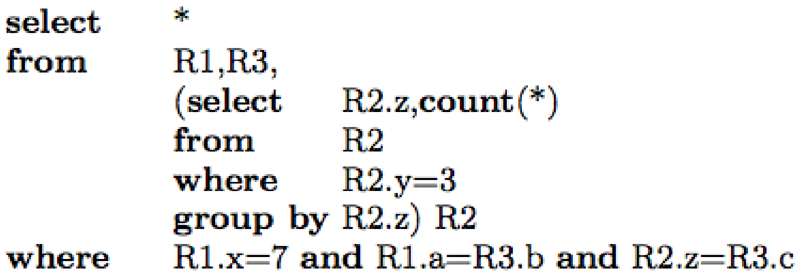
Vectorized Execution

next() returns a vector of tuples

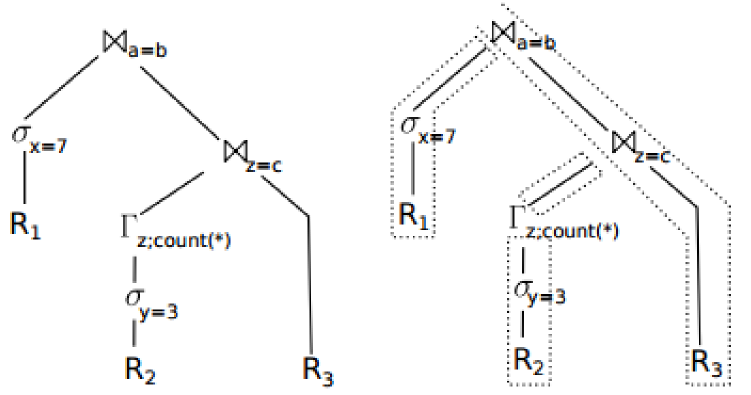
All operators rewritten to work on vectors of tuples

Can we do even better?

Compiled Queries

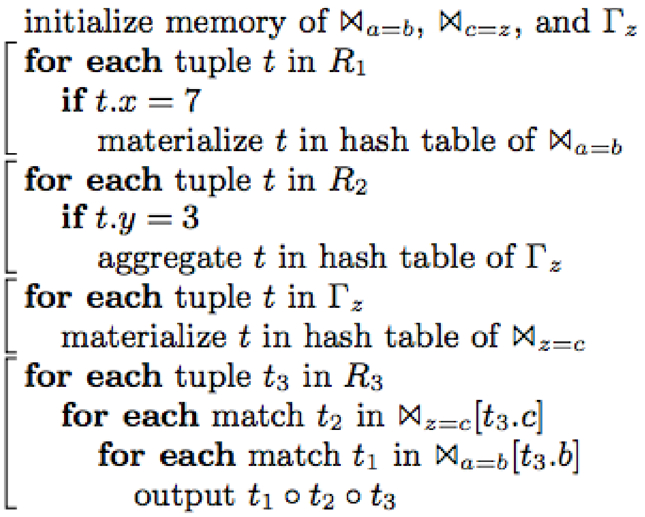


```
select    *
from      R1,R3,
          (select   R2.z,count(*)
          from      R2
          where     R2.y=3
          group by R2.z) R2
where     R1.x=7 and R1.a=R3.b and R2.z=R3.c
```



original

with pipeline boundaries

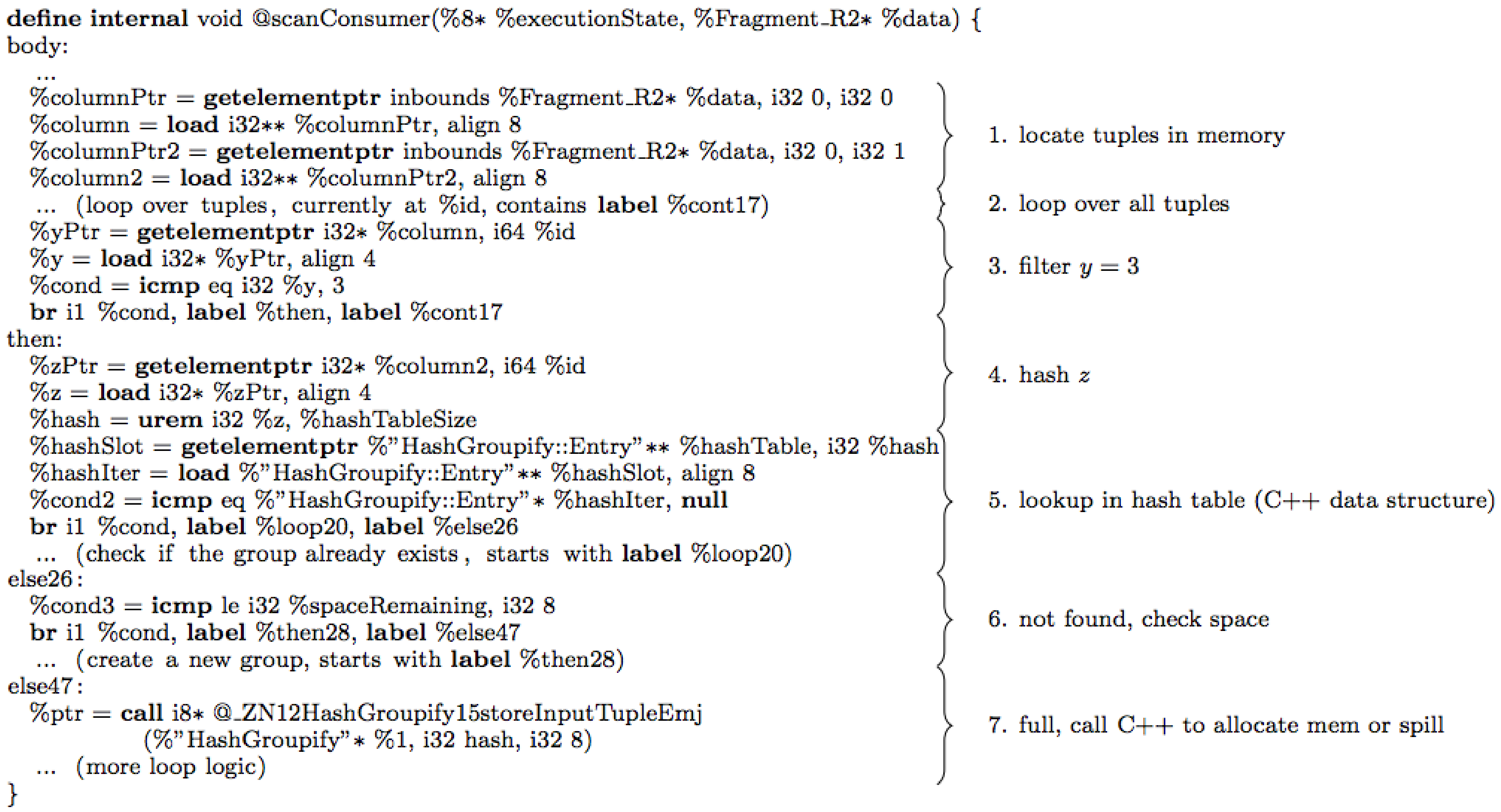


```
initialize memory of $\bowtie_{a=b}$, $\bowtie_{c=z}$, and $\Gamma_z$
for each tuple $t$ in $R_1$
  if $t.x = 7$
    materialize $t$ in hash table of $\bowtie_{a=b}$
for each tuple $t$ in $R_2$
  if $t.y = 3$
    aggregate $t$ in hash table of $\Gamma_z$
for each tuple $t$ in $\Gamma_z$
  materialize $t$ in hash table of $\bowtie_{z=c}$
for each tuple $t_3$ in $R_3$
  for each match $t_2$ in $\bowtie_{z=c}[t_3.c]$
    for each match $t_1$ in $\bowtie_{a=b}[t_3.b]$
      output $t_1 \circ t_2 \circ t_3$
```

Source: Neumann (2011) Efficiently Compiling Efficient Query Plans for Modern Hardware. VLDB.

Compiled Queries

Example LLVM query template



```
define internal void @scanConsumer(%8* %executionState, %Fragment_R2* %data) {
body:
  ...
  %columnPtr = getelementptr inbounds %Fragment_R2* %data, i32 0, i32 0
  %column = load i32** %columnPtr, align 8
  %columnPtr2 = getelementptr inbounds %Fragment_R2* %data, i32 0, i32 1
  %column2 = load i32** %columnPtr2, align 8
  ... (loop over tuples, currently at %id, contains label %cont17)
  %yPtr = getelementptr i32* %column, i64 %id
  %y = load i32* %yPtr, align 4
  %cond = icmp eq i32 %y, 3
  br i1 %cond, label %then, label %cont17
then:
  %zPtr = getelementptr i32* %column2, i64 %id
  %z = load i32* %zPtr, align 4
  %hash = urem i32 %z, %hashTableSize
  %hashSlot = getelementptr %"HashGroupify::Entry"** %hashTable, i32 %hash
  %hashIter = load %"HashGroupify::Entry"** %hashSlot, align 8
  %cond2 = icmp eq %"HashGroupify::Entry"* %hashIter, null
  br i1 %cond, label %loop20, label %else26
  ... (check if the group already exists, starts with label %loop20)
else26:
  %cond3 = icmp le i32 %spaceRemaining, i32 8
  br i1 %cond, label %then28, label %else47
  ... (create a new group, starts with label %then28)
else47:
  %ptr = call i8* @_ZN12HashGroupify15storeInputTupleEmj
              (%"HashGroupify"* %1, i32 hash, i32 8)
  ... (more loop logic)
}
```

1. locate tuples in memory
2. loop over all tuples
3. filter $y = 3$
4. hash z
5. lookup in hash table (C++ data structure)
6. not found, check space
7. full, call C++ to allocate mem or spill

Source: Neumann (2011) Efficiently Compiling Efficient Query Plans for Modern Hardware. VLDB.

Advantages of Column Stores

Inherent advantages:

Better compression

Read efficiency

Works well with:

Vectorized Execution

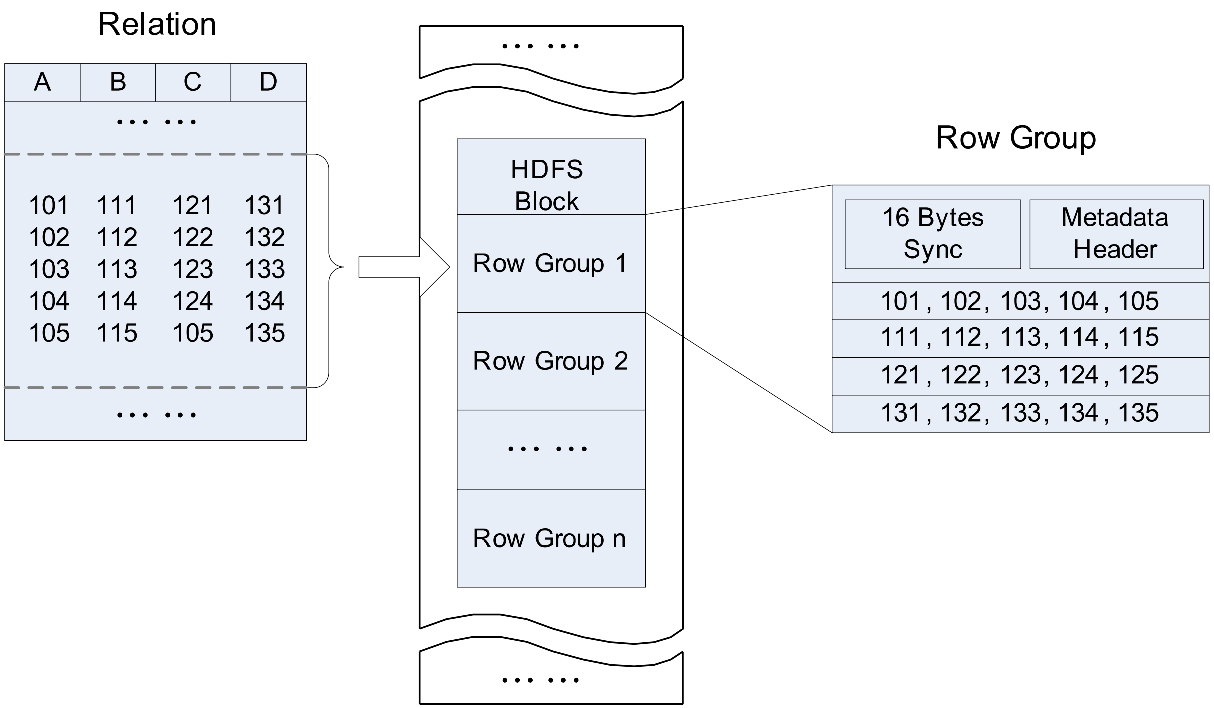
Compiled Queries

These are well-known in traditional databases…

Why not in Hadoop?

Why not in Hadoop?
No reason why not!

RCFile



Relation

A	B	C	D
… …			
101	111	121	131
102	112	122	132
103	113	123	133
104	114	124	134
105	115	105	135
… …			

Row Group

16 Bytes Sync	Metadata Header

101 , 102, 103, 104 , 105
111 , 112, 113, 114 , 115
121 , 122, 123, 124 , 125
131 , 132, 133, 134 , 135

Source: He et al. (2011) RCFile: A Fast and Space-Efficient Data Placement Structure in MapReduce-based Warehouse Systems. ICDE.

✓Vectorized Execution?

```
set hive.vectorized.execution.enabled = true;
```

Batch of rows, organized as columns:

```
class VectorizedRowBatch {
  boolean selectedInUse;
  int[] selected;
  int size;
  ColumnVector[] columns;
}

class LongColumnVector extends ColumnVector {
  long[] vector
}
```

✓Vectorized Execution?

```
class LongColumnAddLongScalarExpression {
 int inputColumn;
 int outputColumn;
 long scalar;

 void evaluate(VectorizedRowBatch batch) {
  long [] inVector = ((LongColumnVector)
  batch.columns[inputColumn]).vector;
  long [] outVector = ((LongColumnVector)
  batch.columns[outputColumn]).vector;
  if (batch.selectedInUse) {
   for (int j = 0; j < batch.size; j++) {
    int i = batch.selected[j];
    outVector[i] = inVector[i] + scalar;
   }
  } else {
   for (int i = 0; i < batch.size; i++) {
    outVector[i] = inVector[i] + scalar;
   }
  }
 }
}
```

Vectorized operator example

✓Compiled Queries?

```
SELECT x, y
FROM z WHERE x * (1 – y)/100 < 434;
```

Predicate is “interpreted” as

```
LessThan(
  Multiply(Attribute("x"),
    Divide(Minus(Literal("1"), Attribute("y")), 100)),
  434)
```

Slow!

Dynamic code generation
(feed AST into Scala compiler to generate bytecode):

```
row.get("x") * (1 – row.get("y"))/100 < 434
```

Much faster!

Advantages of Column Stores

Inherent advantages:

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Read efficiency

Works well with:

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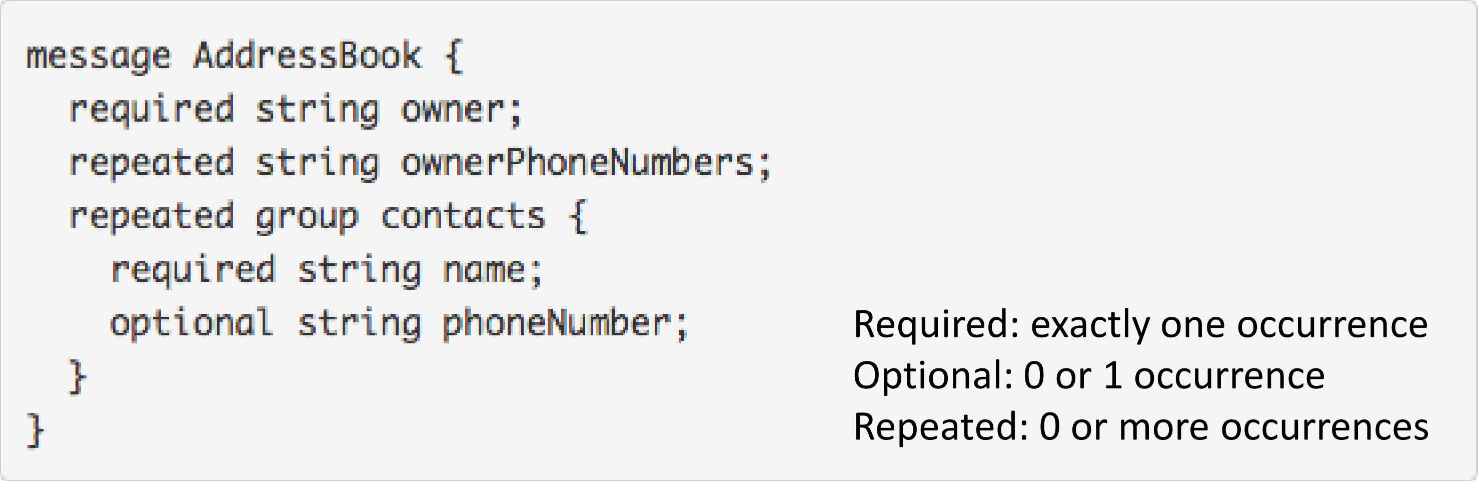
Hadoop can adopt all of these optimizations!

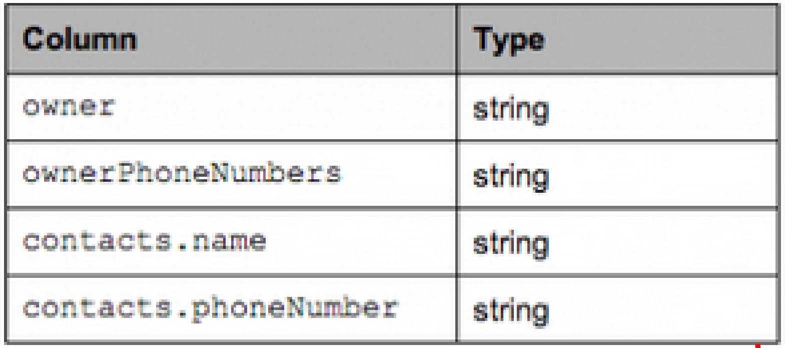
What about semi-structured data?



```
message AddressBook {
  required string owner;
  repeated string ownerPhoneNumbers;
  repeated group contacts {
    required string name;
    optional string phoneNumber;
  }
}
```

Required: exactly one occurrence
Optional: 0 or 1 occurrence
Repeated: 0 or more occurrences

Columnar Decomposition



Column	Type
owner	string
ownerPhoneNumbers	string
contacts.name	string
contacts.phoneNumber	string

What's the issue?

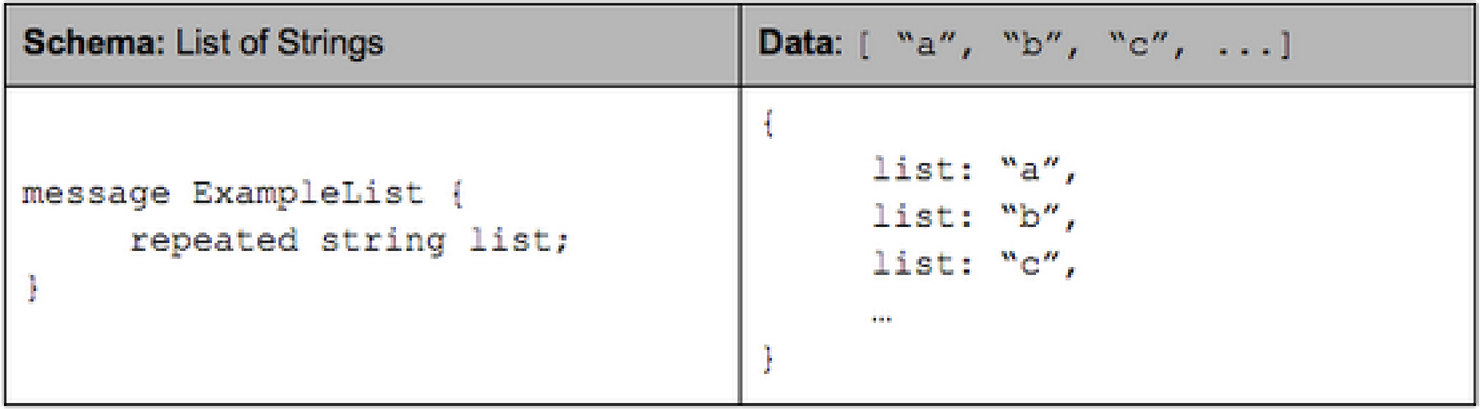
What’s the solution?

Google’s Dremel storage model

Open-source implementation in Parquet

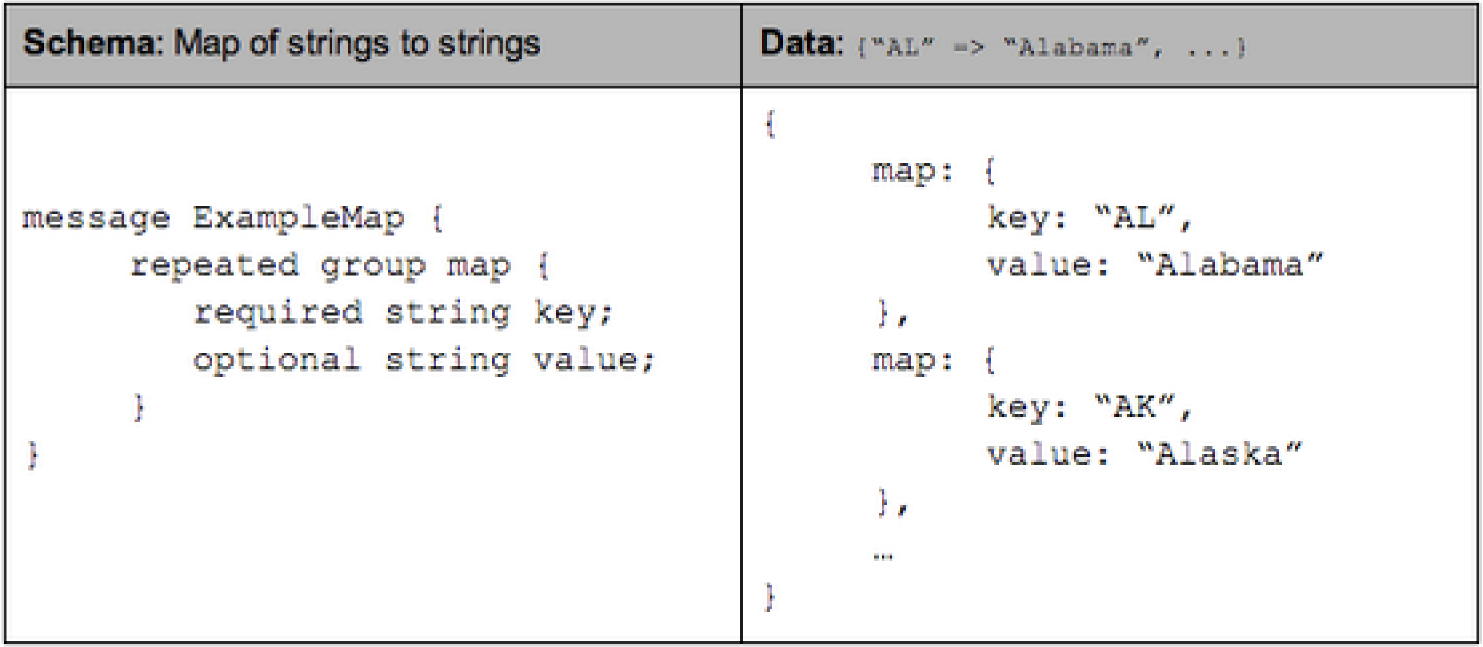
Source: https://blog.twitter.com/2013/dremel-made-simple-with-parquet

Optional and Repeated Elements



Schema: List of Strings	**Data:** [“a”, “b”, “c”, ...]

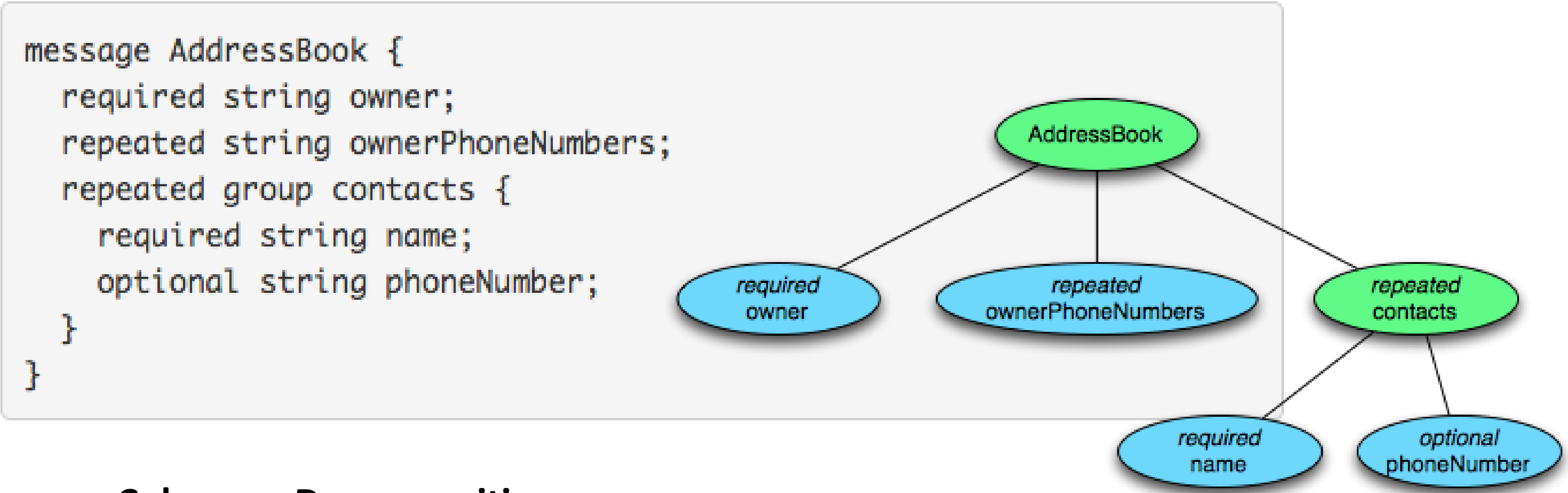
message ExampleList {
        repeated string list;
}
	{
	        list: “a”,
	        list: “b”,
	        list: “c”,
	        …
	}



Schema: Map of strings to strings	**Data:** {“AL” => “Alabama”, ...}

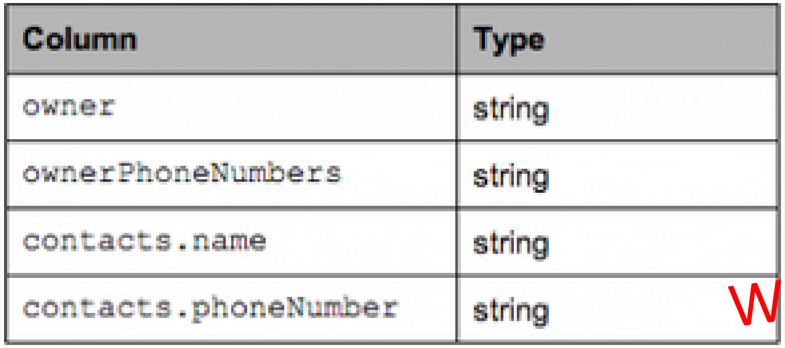
message ExampleMap {
        repeated group map {
            required string key;
            optional string value;
        }
}
	{
	        map: {
	                key: “AL”,
	                value: “Alabama”
	        },
	        map: {
	                key: “AK”,
	                value: “Alaska”
	        },
	        …
	}

Tree Decomposition



```
message AddressBook {
  required string owner;
  repeated string ownerPhoneNumbers;
  repeated group contacts {
    required string name;
    optional string phoneNumber;
  }
}
```

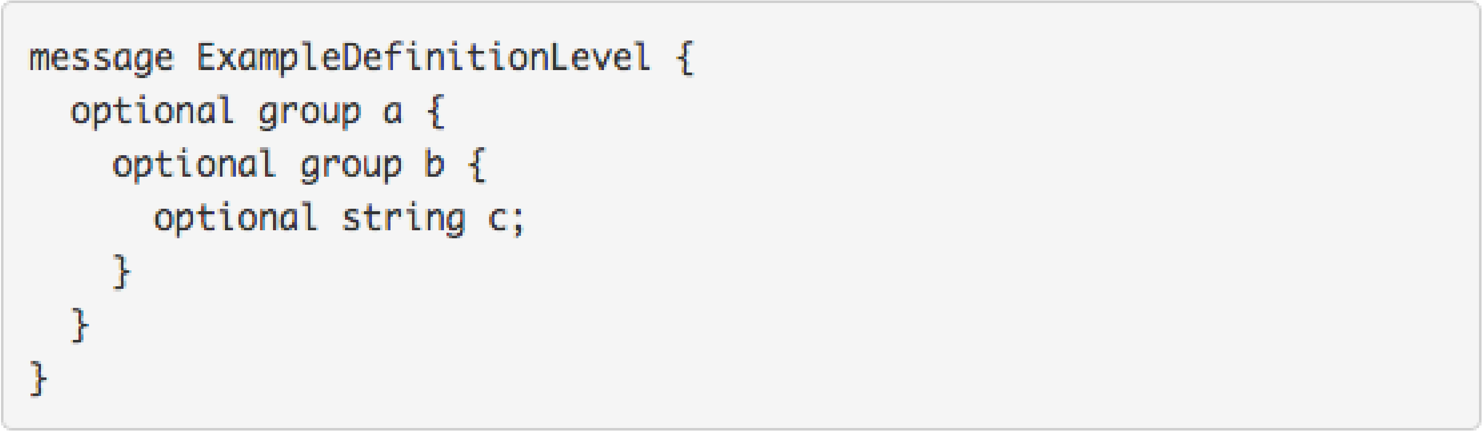
Columnar Decomposition



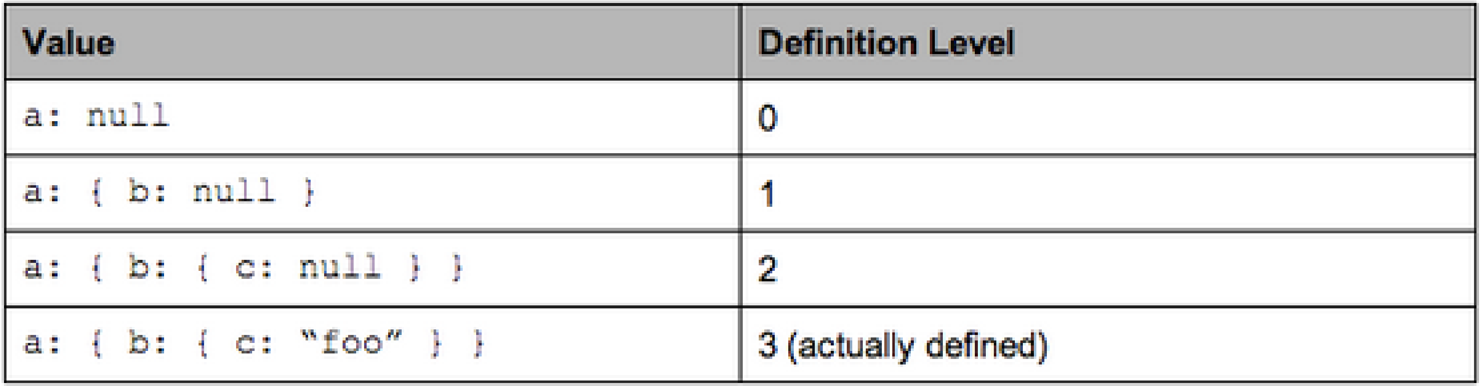
Column	Type
owner	string
ownerPhoneNumbers	string
contacts.name	string
contacts.phoneNumber	string

What other information do we need to store?

Definition Level

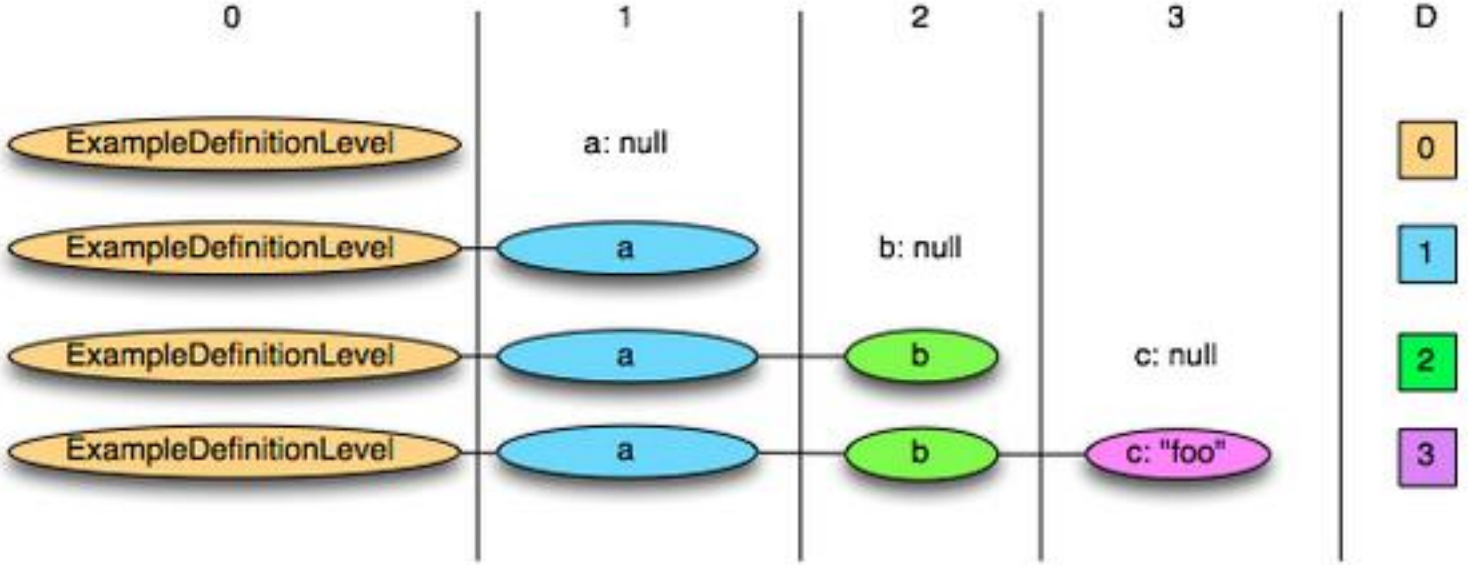


```
message ExampleDefinitionLevel {
  optional group a {
    optional group b {
      optional string c;
    }
  }
}
```

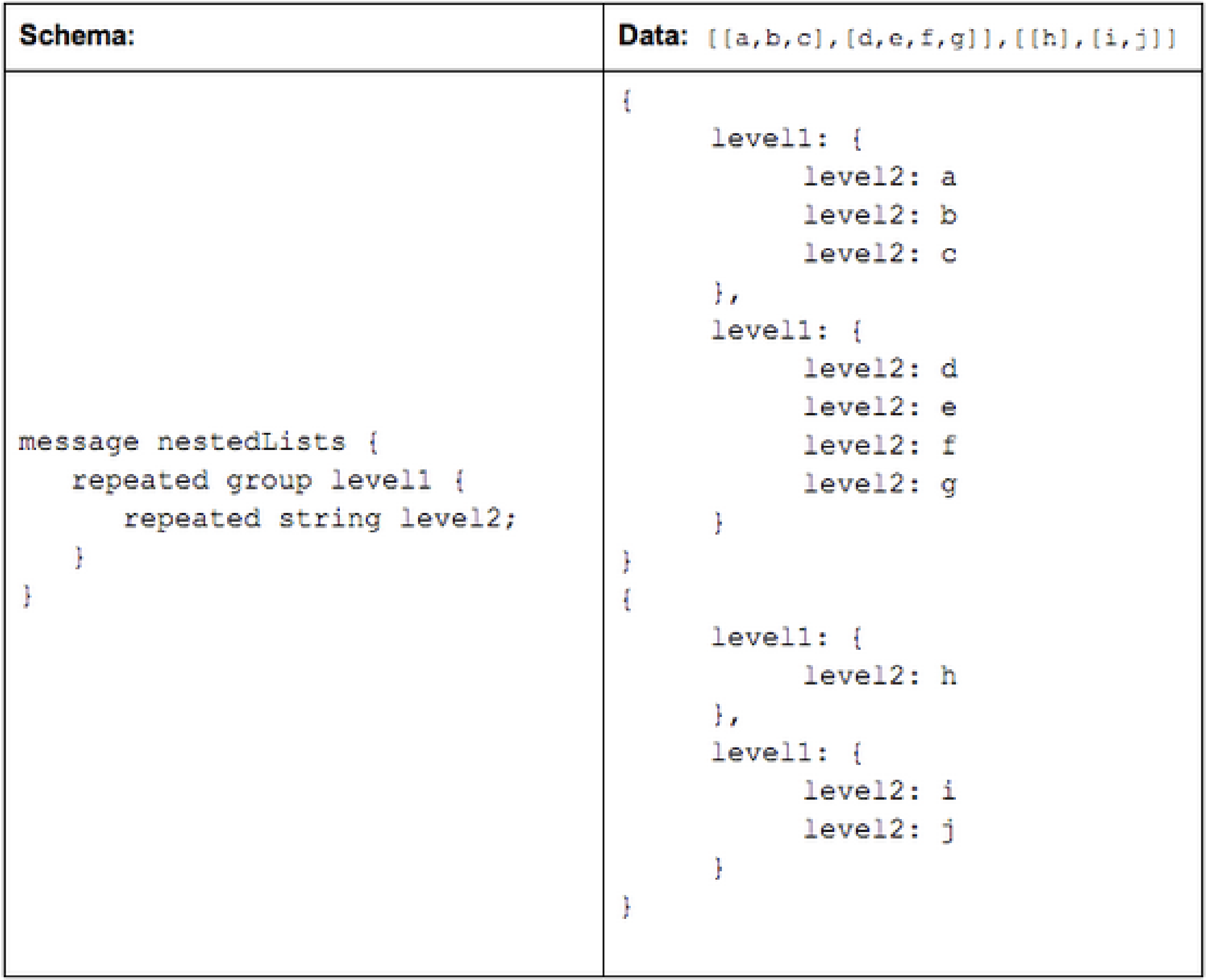


Value	Definition Level
a: null	0
a: { b: null }	1
a: { b: { c: null } }	2
a: { b: { c: "foo" } }	3 (actually defined)

Definition Level: Illustration



Repetition Level



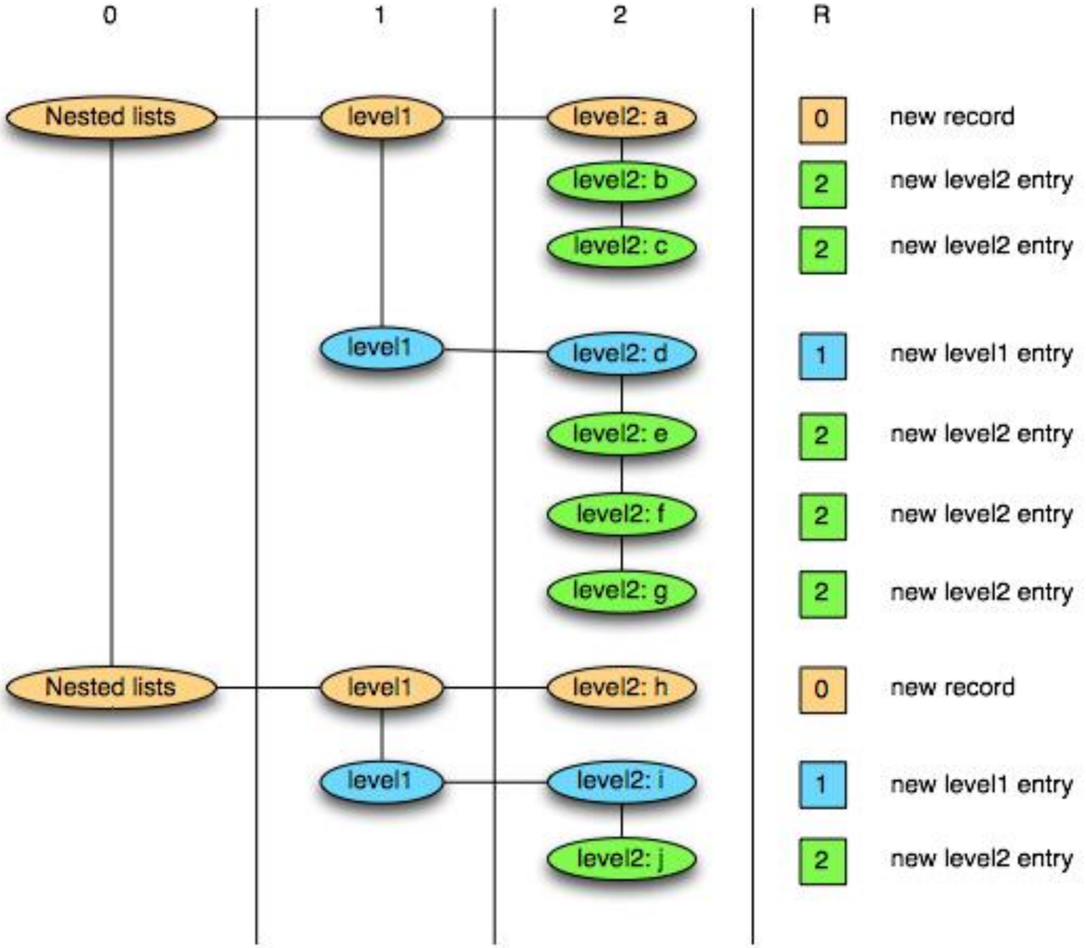
Schema:

```
message nestedLists {
   repeated group level1 {
      repeated string level2;
   }
}
```

Data: `[[a,b,c],[d,e,f,g]],[[h],[i,j]]`

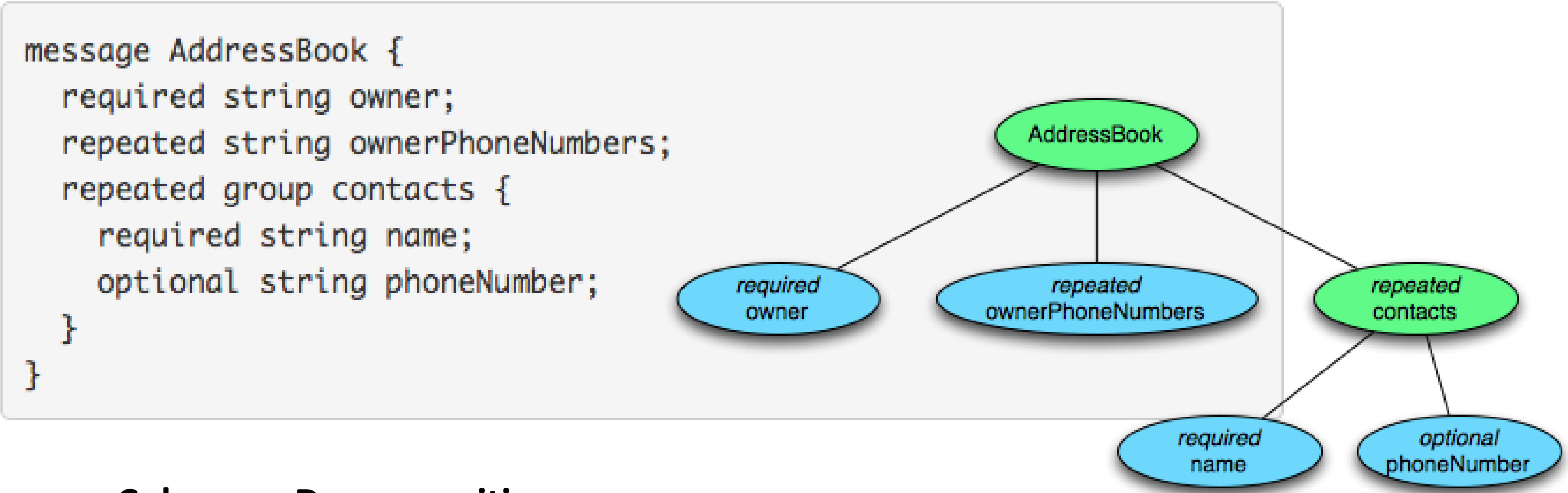
```
{
     level1: {
          level2: a
          level2: b
          level2: c
     },
     level1: {
          level2: d
          level2: e
          level2: f
          level2: g
     }
}
{
     level1: {
          level2: h
     },
     level1: {
          level2: i
          level2: j
     }
}
```

Repetition Level: Illustration



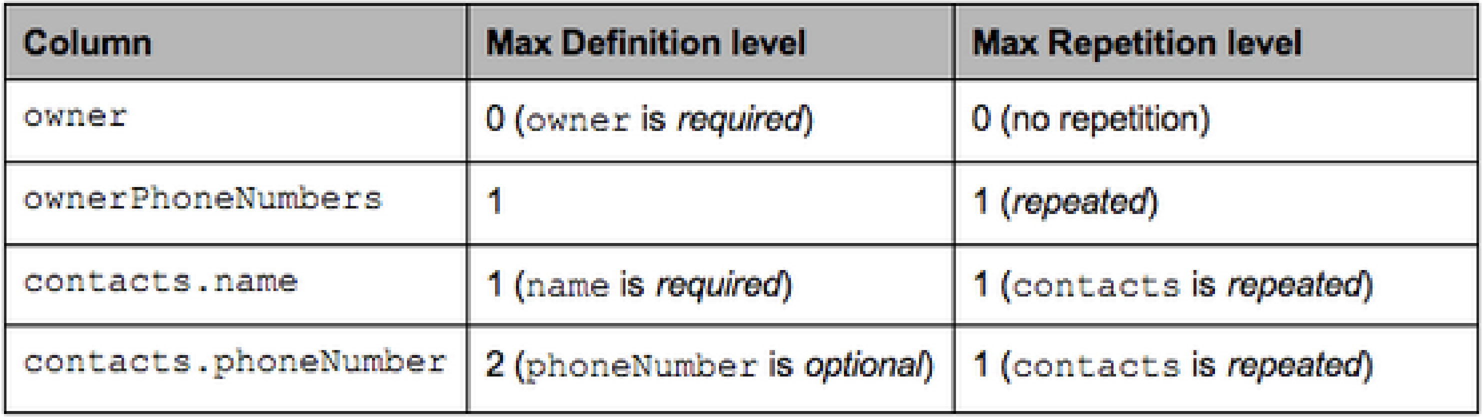
0 marks new record and implies creating a new level1 and level2 list
1 marks new level1 list and implies creating a new level2 list as well.
2 marks every new element in a level2 list.

Putting It Together



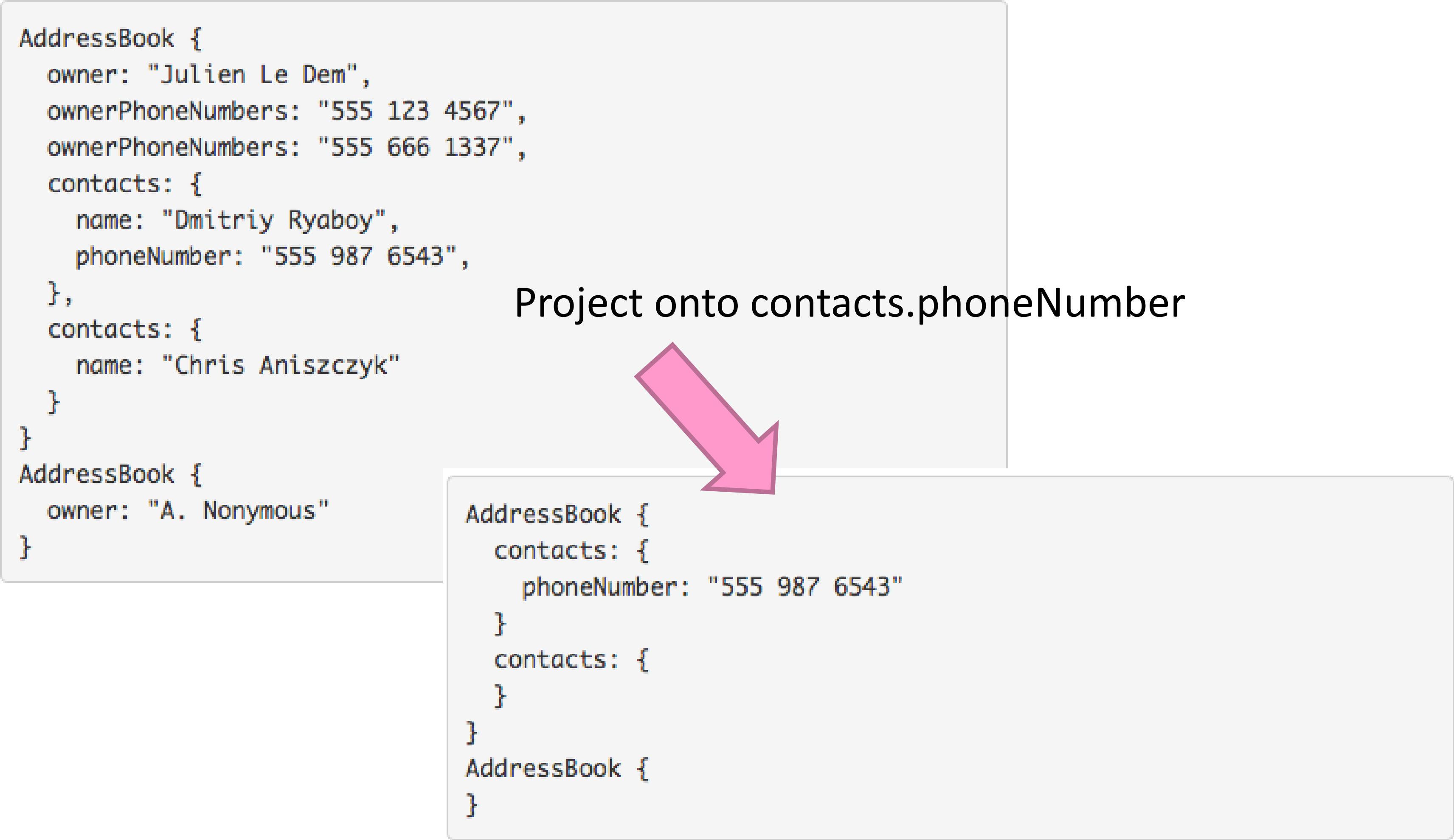
```
message AddressBook {
  required string owner;
  repeated string ownerPhoneNumbers;
  repeated group contacts {
    required string name;
    optional string phoneNumber;
  }
}
```

Columnar Decomposition



Column	Max Definition level	Max Repetition level
`owner`	0 (`owner` is *required*)	0 (no repetition)
`ownerPhoneNumbers`	1	1 (*repeated*)
`contacts.name`	1 (`name` is *required*)	1 (`contacts` is *repeated*)
`contacts.phoneNumber`	2 (`phoneNumber` is *optional*)	1 (`contacts` is *repeated*)

Sample Projection



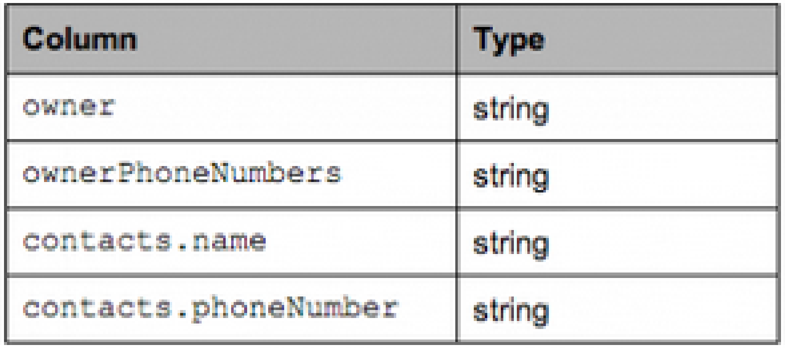
```
AddressBook {
  owner: "Julien Le Dem",
  ownerPhoneNumbers: "555 123 4567",
  ownerPhoneNumbers: "555 666 1337",
  contacts: {
    name: "Dmitriy Ryaboy",
    phoneNumber: "555 987 6543",
  },
  contacts: {
    name: "Chris Aniszczyk"
  }
}
AddressBook {
  owner: "A. Nonymous"
}
```

Project onto contacts.phoneNumber

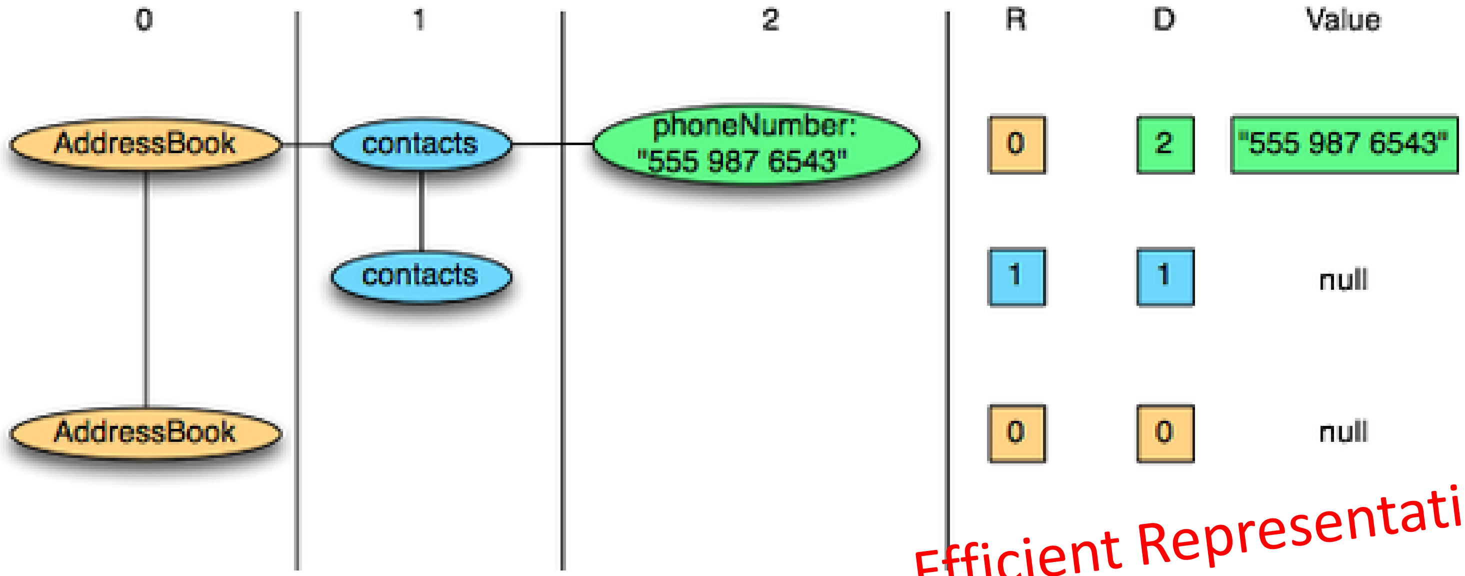
```
AddressBook {
  contacts: {
    phoneNumber: "555 987 6543"
  }
  contacts: {
  }
}
AddressBook {
}
```

Physical Layout

Columnar Decomposition



Column	Type
owner	string
ownerPhoneNumbers	string
contacts.name	string
contacts.phoneNumber	string



R	D	Value
0	2	"555 987 6543"
1	1	null
0	0	null

Efficient Representations?

Key Ideas

Binary representations are good

Binary representations need schemas

Schemas allow logical/physical separation

Logical/physical separation allows you to do cool things

MapReduce: A Major Step Backwards?

MapReduce is a step backward in database access

Schemas are good

Separation of the schema from the application is good

High-level access languages are good

MapReduce is poor implementation

Brute force and only brute force (no indexes, for example)

MapReduce is not novel

MapReduce is missing features

Bulk loader, indexing, updates, transactions…

MapReduce is incompatible with DMBS tools

Source: Blog post by DeWitt and Stonebraker

Indexes are a good thing!

Source: Wikipedia (Card Catalog)

Hadoop + Full-Text Indexes

```
status = load ’/tables/statuses/2011/03/01’
    using StatusProtobufPigLoader()
    as (id: long, user_id: long, text: chararray, ...);

filtered = filter status by text matches ’.*\\bhadoop\\b.*’;
…
```

Pig performs a brute force scan

Then promptly chucks out most of the data

Stupid.

Source: Lin et al. (2011) Full-Text Indexing for Optimizing Selection Operations in Large-Scale Data Analytics. MAPREDUCE Workshop.

“Trying to find a needle in a haystack… with a snowplow”
@squarecog

Hadoop + Full-Text Indexes

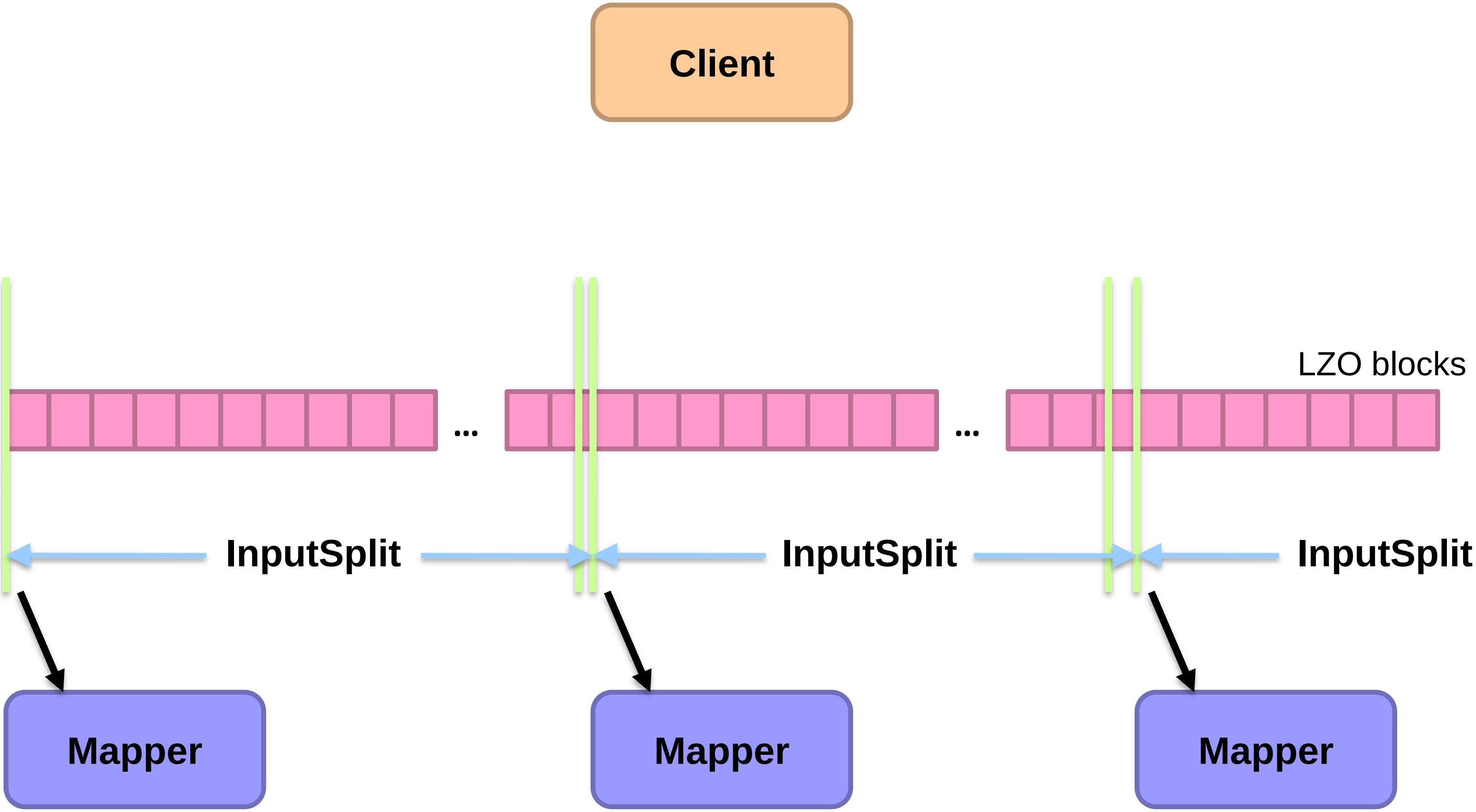
```
status = load ’/tables/statuses/2011/03/01’
    using StatusProtobufPigLoader()
    as (id: long, user_id: long, text: chararray, ...);

filtered = filter status by text matches ’.*\\bhadoop\\b.*’;
…
```

Pig performs a brute force scan

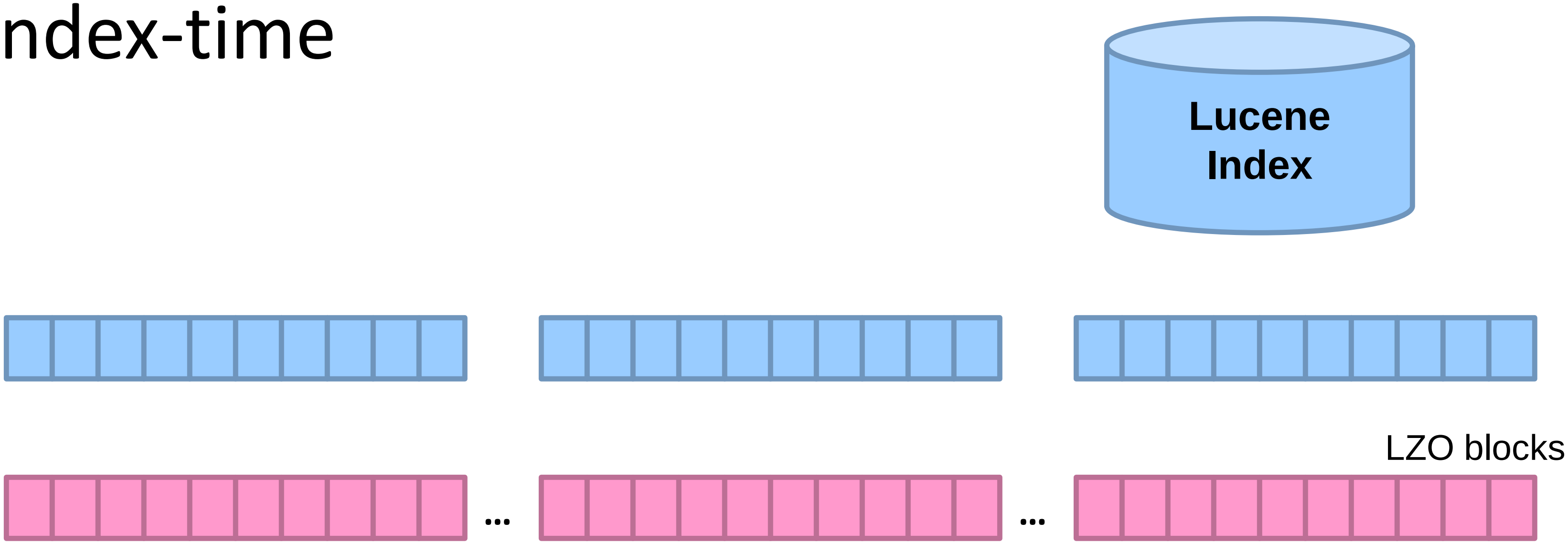
Then promptly chucks out most of the data Stupid.

Uhhh… how about an index?

Use Lucene full-text index


Client
LZO blocks
...
...
InputSplit
InputSplit
InputSplit
Mapper
Mapper
Mapper

Index-time

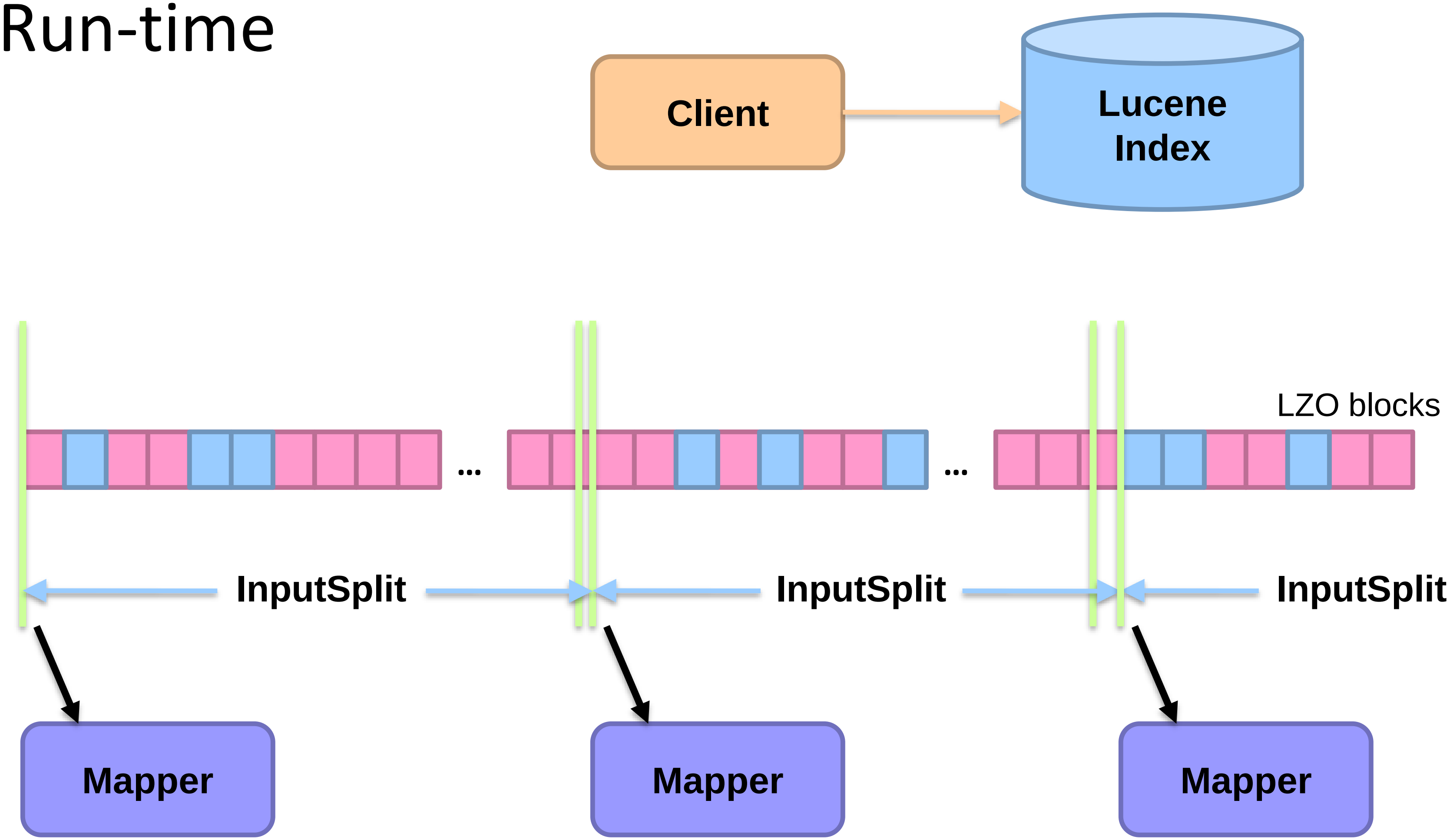


Index for selection on tweet content

Build "pseudo-document" for each Lzo block

Index pseudo-documents with Lucene

Run-time



Only process blocks known to satisfy selection criteria

Hadoop Integration

Everything encapsulated in the InputFormat

RecordReaders know what blocks to process and skip

Completely transparent to mappers

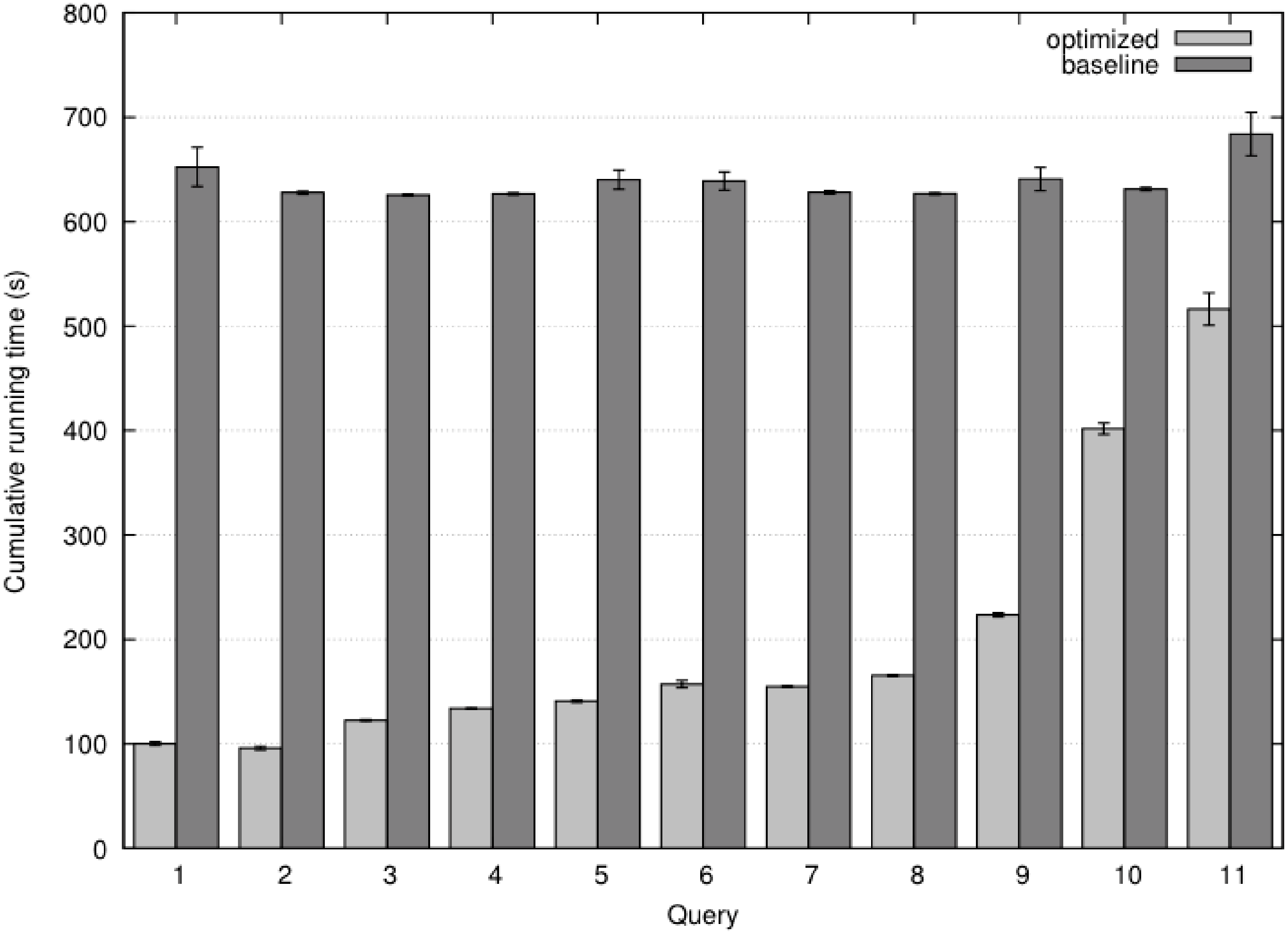
Experiments

Selection on tweet content

Varied selectivity range

One day sample data (70m tweets, 8/1/2010)

	Query	**Blocks**	**Records**	**Selectivity**
1	hadoop	97	105	1.517×10^{-6}
2	replication	140	151	2.182×10^{-6}
3	buffer	500	559	8.076×10^{-6}
4	transactions	819	867	1.253×10^{-5}
5	parallel	999	1159	1.674×10^{-5}
6	ibm	1437	1569	2.267×10^{-5}
7	mysql	1511	1664	2.404×10^{-5}
8	oracle	1822	1911	2.761×10^{-5}
9	database	3759	3981	5.752×10^{-5}
10	microsoft	13089	17408	2.515×10^{-4}
11	data	20087	30145	4.355×10^{-4}


optimized
baseline
Cumulative running time (s)
800
700
600
500
400
300
200
100
0
1
2
3
4
5
6
7
8
9
10
11
Query

Analytical model

Task: prediction LZO blocks scanned by selectivity

Poisson model: P(observing k occurrences in a block)

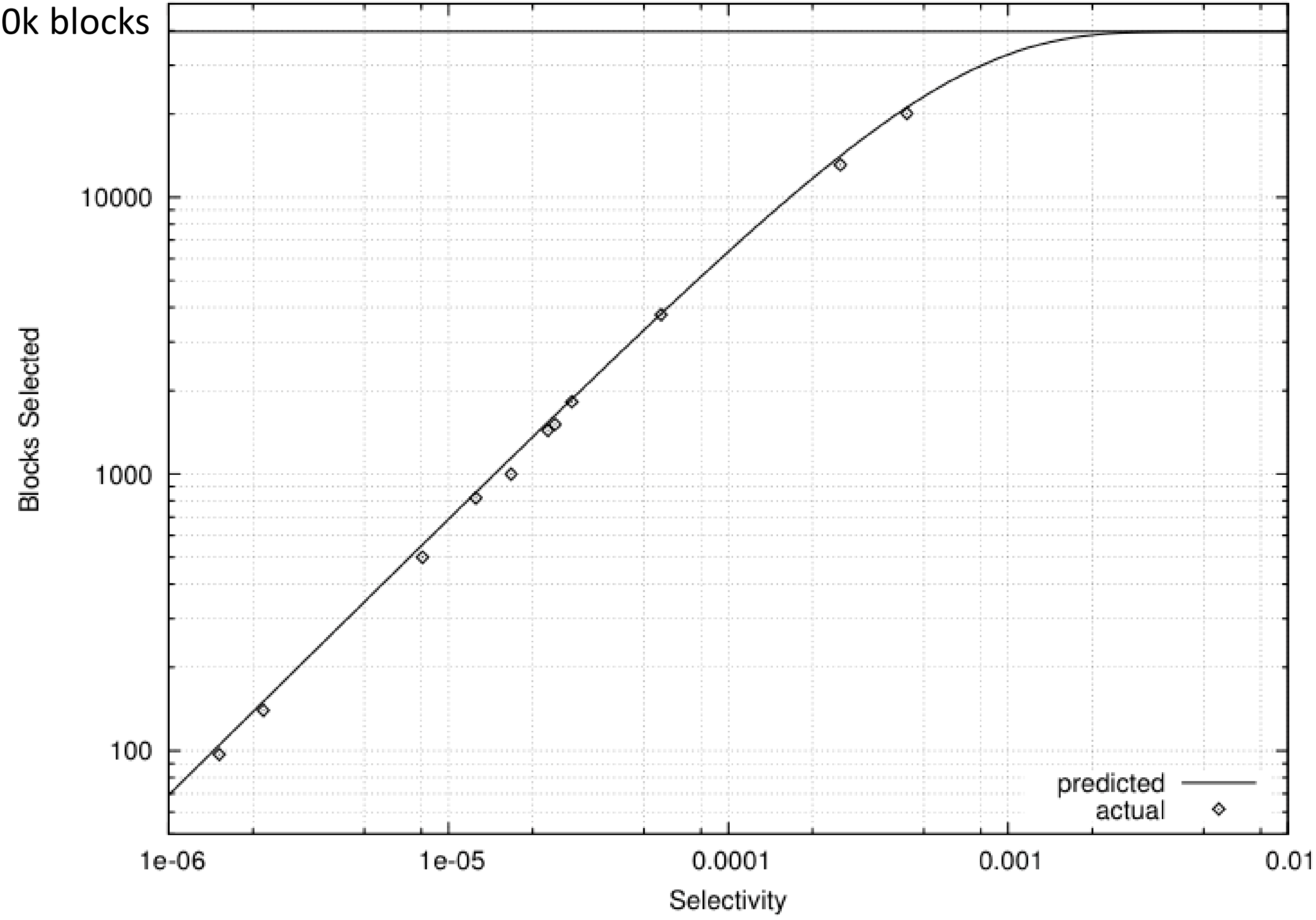
$$f(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

E(fraction of blocks scanned)

$$1 - f(k = 0;\lambda)$$

Selectivity 0.001 → 82% of all blocks
Selectivity 0.002 → 97% of all blocks

Total: ~40k blocks



But: can predic*t a priori*!

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Source: Blog post by DeWitt and Stonebraker

Source: Wikipedia (Japanese rock garden)