wibi!data

developed by odiago

wibidata: Large-Scale User-Centric Data Analysis

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About me

- M.S. from CSE ’08
  - Officially: I studied PL with Dan Grossman
  - Unofficially: Spent most of my time tinkering with Hadoop
- Left to join Cloudera as the first engineer
- Started Odiago in 2010 with Christophe Bisciglia

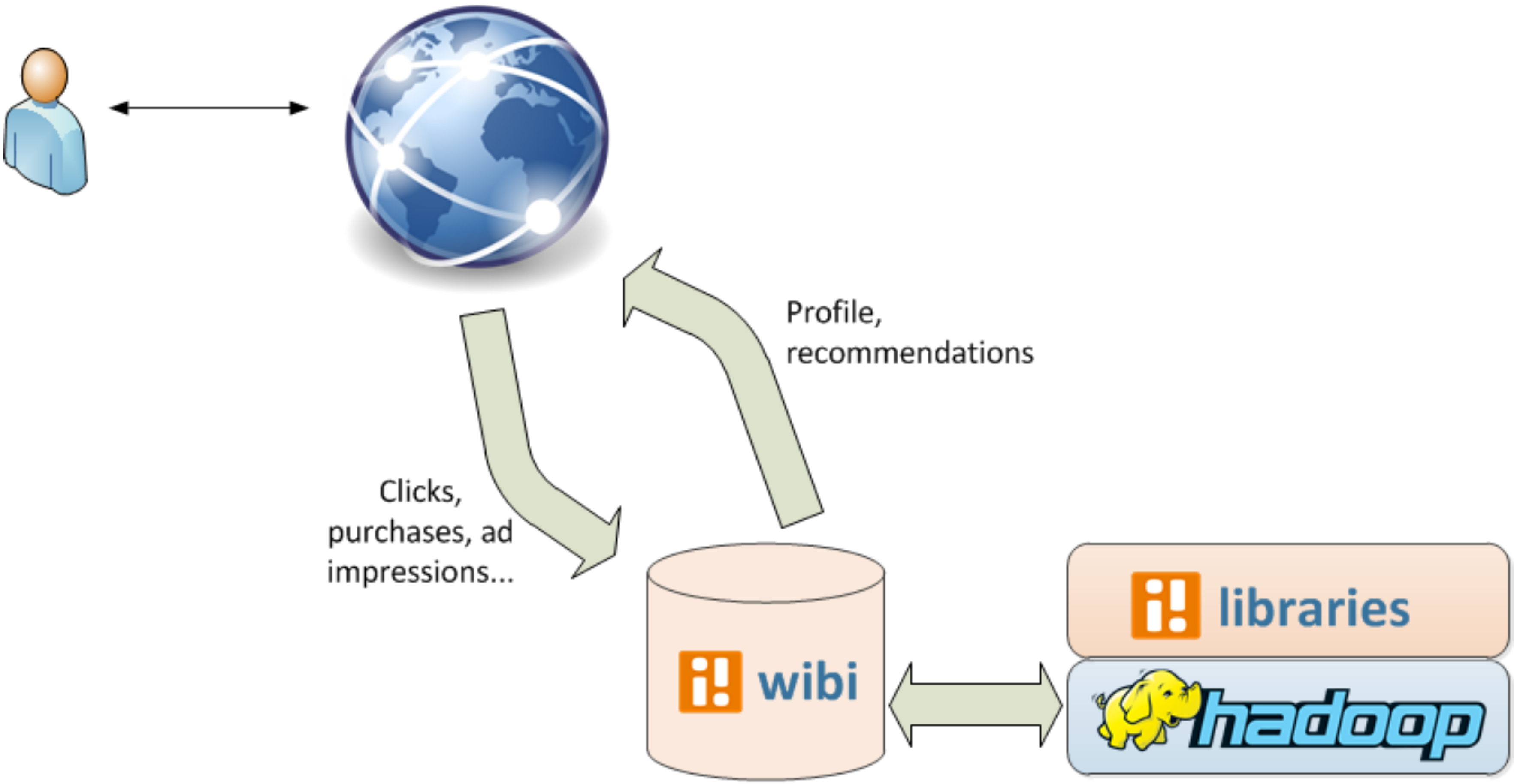
wibidata is…

- A large-scale storage, serving, and analysis platform
- For user- or other entity-centric data

wibidata use cases

- Have a large number of users
- Want to store (large) transaction data as well as derived data (e.g., recommendations)
- Need to serve recommendations interactively
- Require a combination of offline and on-the-fly computation

A typical workflow



- Investigative analytics
- Batch processing

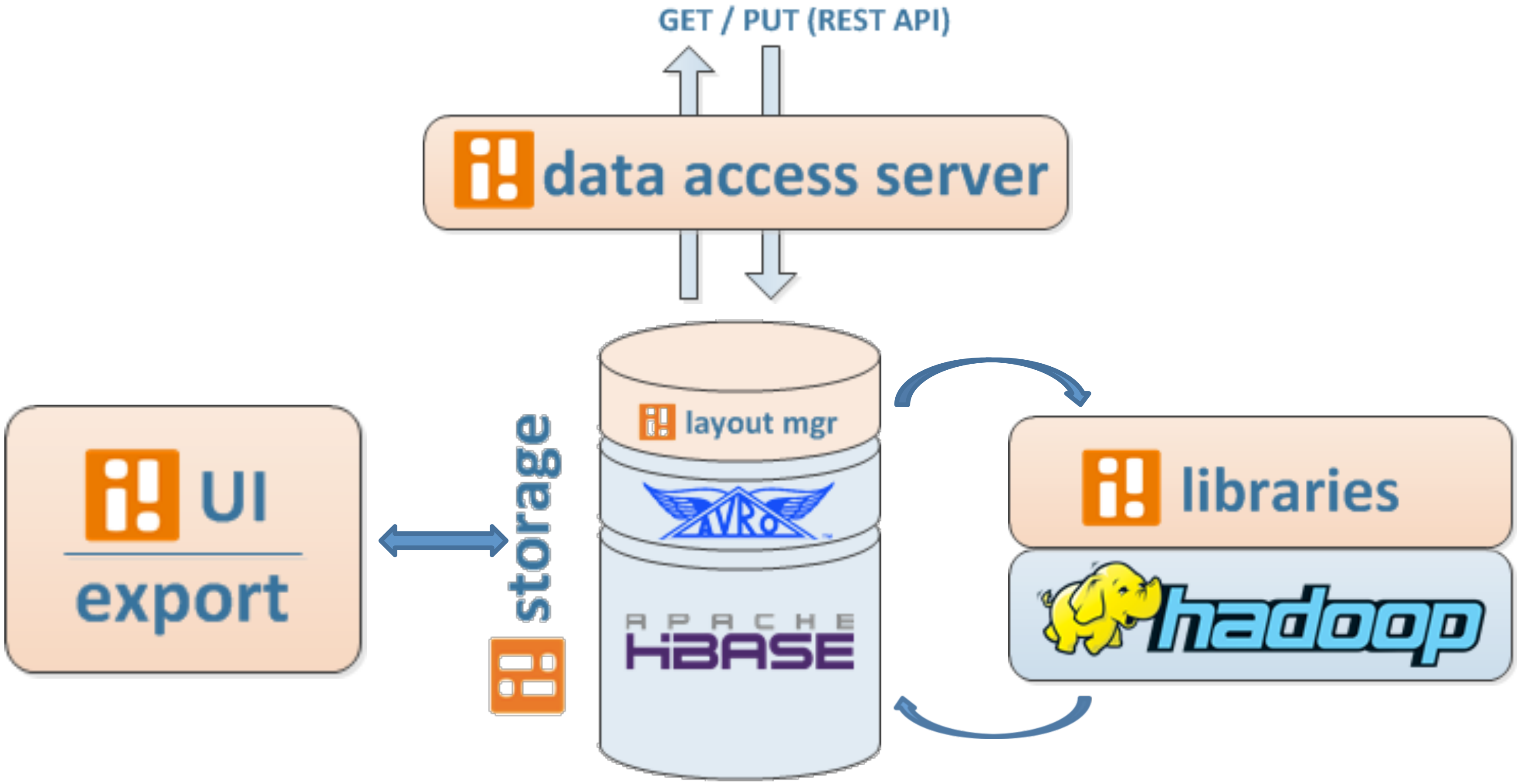
Challenges

- Support real-time retrieval of profile data
- Store a long transactional data history
- Keep related data logically and physically close
- Update data in a timely fashion without wasting computation

This talk…

- Wibi Architecture
- Background: Hadoop & HBase
- Modeling Data: schemas & layouts
- Analysis: producers and gatherers
- Fresheners: on-the-fly recomputation
- Conclusions

wibidata architecture



cloudera Certified Technology product

hadoop

- A distributed, fault-tolerant file system (HDFS)
- … and computation platform (MapReduce)

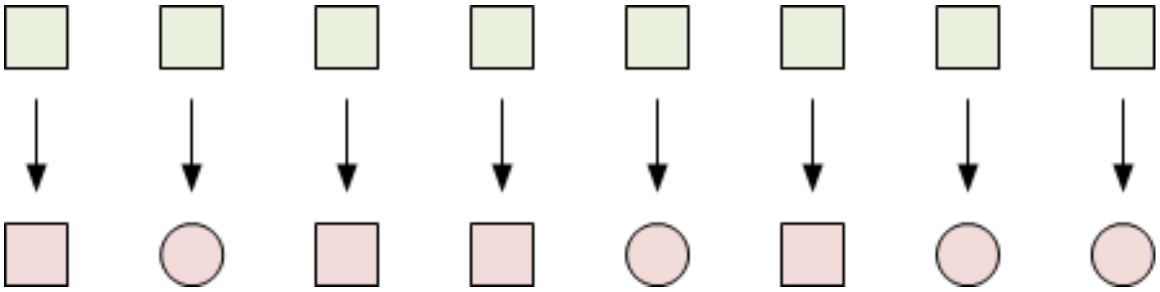
- Open source (Apache Software Foundation)
- Several commercial vendors, distributions…

Hadoop design principles

- At scale, failure is common
- Shared-nothing architecture
- Data durability through replication
- Bring computation to the data

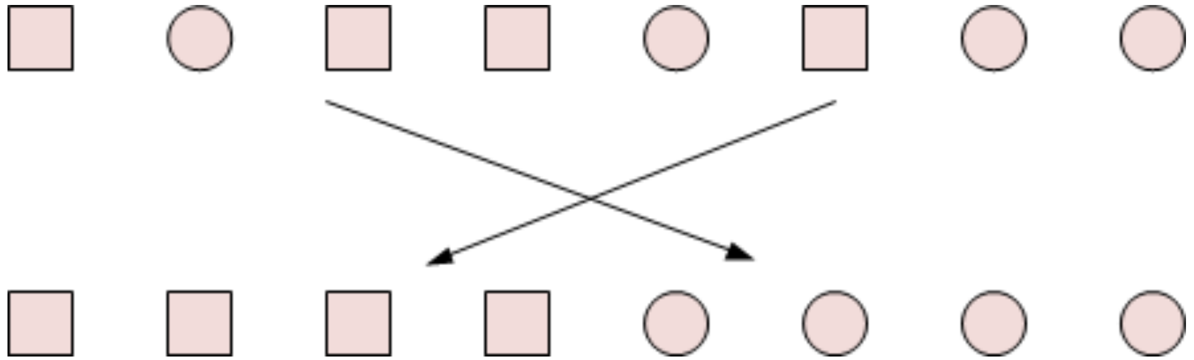
MapReduce: Map phase

- Mapper converts input (key, value) pairs into intermediate (k, v) pairs



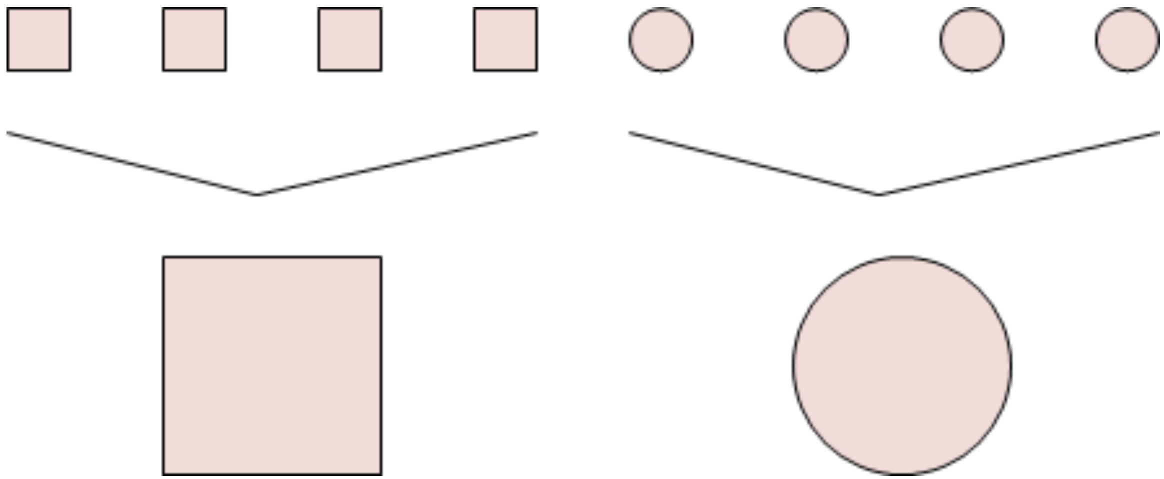
MapReduce: Shuffle phase

- Arranges data so values with the same intermediate key are on the same node
- Performed automatically by the framework



MapReduce: Reduce phase

- Applies an aggregate function to each set of values with a common intermediate key



Difficulties of working with Hadoop

- (key, value)-pairs are a cumbersome format
- Data is stored across a filesystem
  - Hard to discover all data about a user
  - Hard to process multiple data sets together
- Serialization of complex data is user-defined
- Cannot access individual users/records easily

Files: A log-oriented data model

- HDFS-backed records are usually log-oriented

```
At T1 Alice clicked...
At T2 Bob viewed...
At T3 Alice...
```

APACHE HBASE : NoSQL storage

- Cousin-project to Hadoop
- 3-d storage: Data organized in rows, columns, and timestamped “cells”
- HBase servers allow fast get/put access to individual rows or cells
- Data physically stored in underlying HDFS
- “Schema free”

HBase data model

- Data in cells, addressed by four “coordinates”
  - Row Id (primary key)
  - Column family
  - Column “qualifier”
  - Timestamp

HBase data model

- Column families are units of physical storage
- Data is stored in sparse files
- Data sorted by row id, qualifier, timestamp
- Cells hold uninterpreted byte arrays

Schema free: not what you want

- HBase may not impose a schema, but your data still has one
- Up to the application to determine how to organize & interpret data
- You still need to pick a serialization system

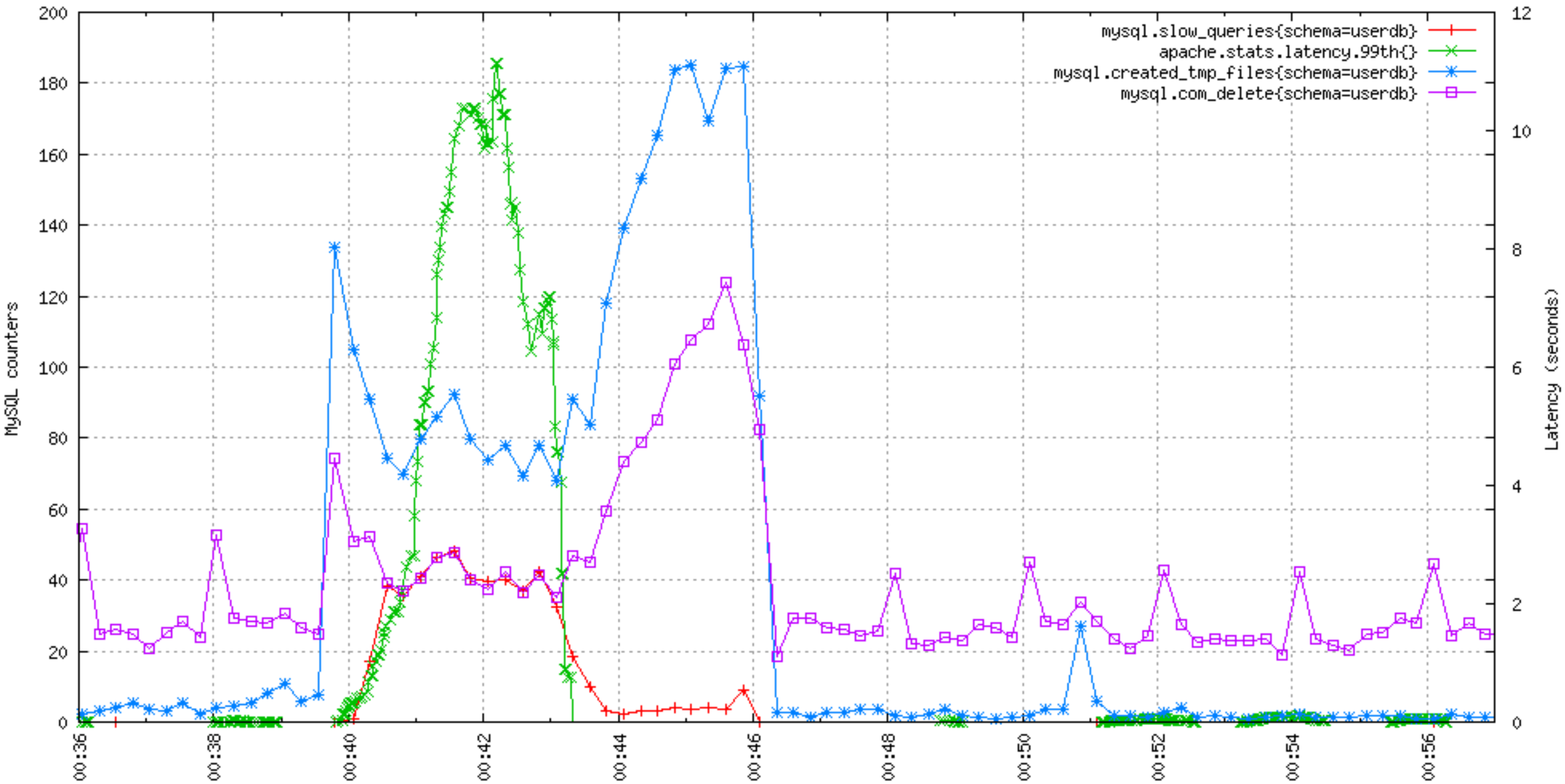
Schemas = trade-offs

- Different schemas enable efficient storage/retrieval/analysis of different types of data
- Physical organization of data still makes a big difference
  - Especially with respect to read/write patterns

Example: OpenTSDB

- Goal: Capture time-series metrics from a large number of machines
- High write bandwidth from many input nodes
- Reads: aggregates for graph visualizations
- Supports drill-down on pre-specified axes

OpenTSDB


mysql.slow_queries{schema=userdb}
apache.stats.latency.99th{}
mysql.created_tmp_files{schema=userdb}
mysql.com_delete{schema=userdb}
MySQL counters
Latency (seconds)
200
180
160
140
120
100
80
60
40
20
0
12
10
8
6
4
2
0
00:36
00:38
00:40
00:42
00:44
00:46
00:48
00:50
00:52
00:54
00:56

WibiData workloads

- Large number of fat rows (one per user)
- Each row updated relatively few times/day
  - Though updates may involve large records
- Raw data written to one set of columns
- Processed results read from another
  - Often with an interactive latency requirement
- Needs to support complex data types

Serialization with AVRO™

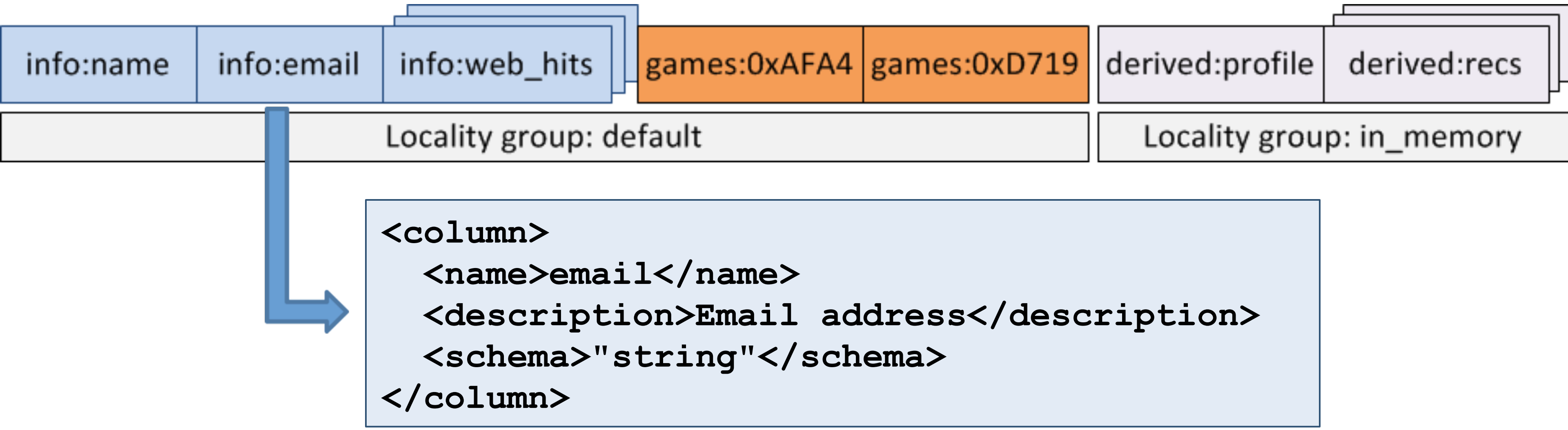
- Apache Avro provides flexible serialization
- All data written along with its “writer schema”
- Reader schema may differ from the writer’s

```
{
  "type": "record",
  "name": "LongList",
  "fields" : [
    {"name": "value", "type": "long"},
    {"name": "next", "type": ["LongList", "null"]}
  ]
}
```

Serialization with AVRO™

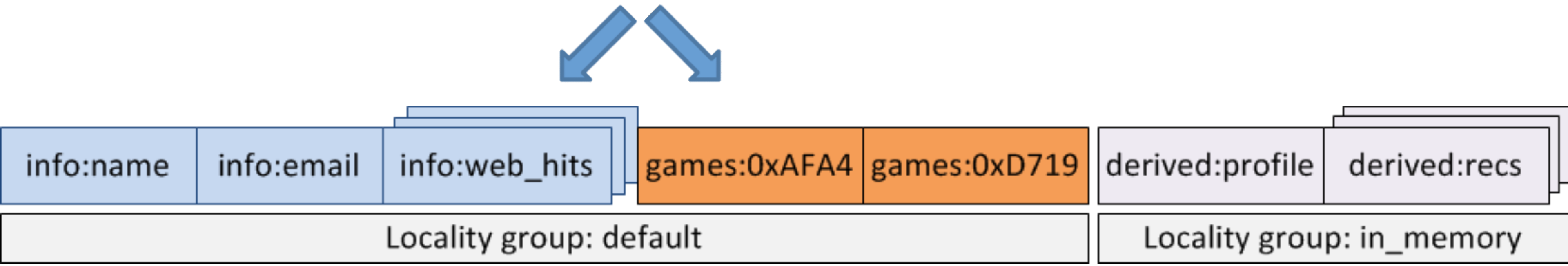
- No code generation required
- Producers and consumers of data can migrate independently
- Data format migrations do not require structural changes to underlying data

WibiData: An extended data model



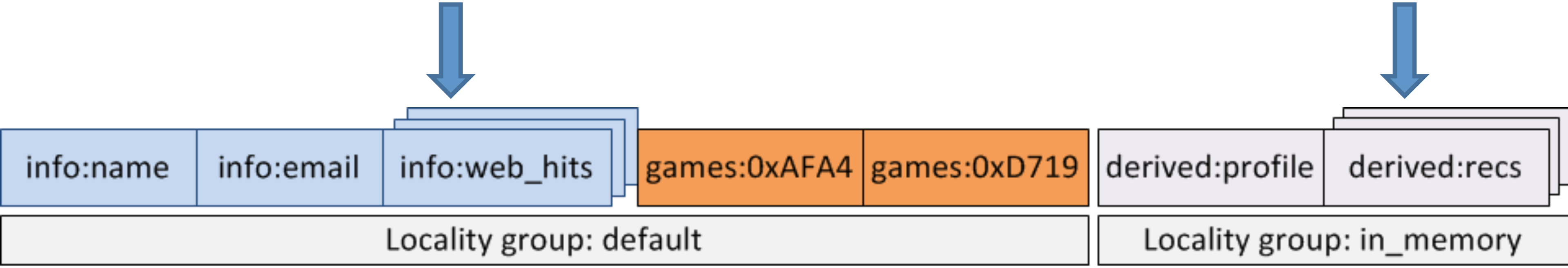
- Columns or whole families have common Avro schemas for evolvable storage and retrieval

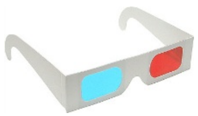
WibiData: An extended data model



- Column families are a logical concept
- Data is physically arranged in *locality groups*
- Row ids are hashed for uniform write pressure

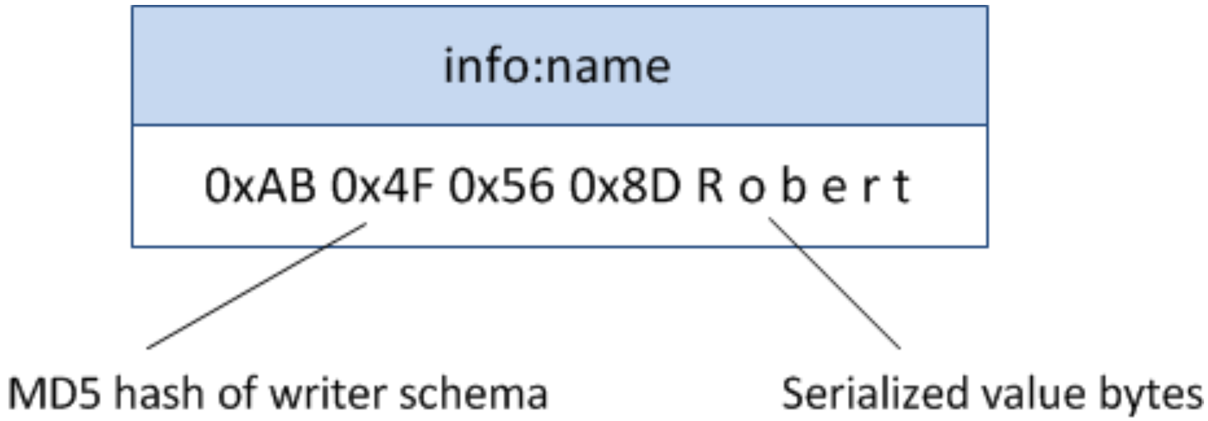
WibiData: An extended data model



- Wibi uses 3-d storage 
- Data is often sorted by timestamp

Storing Avro-serialized data

- Need to store writer schema with each independently-serialized datum



- Wibi: Store MD5 of schema inside cell

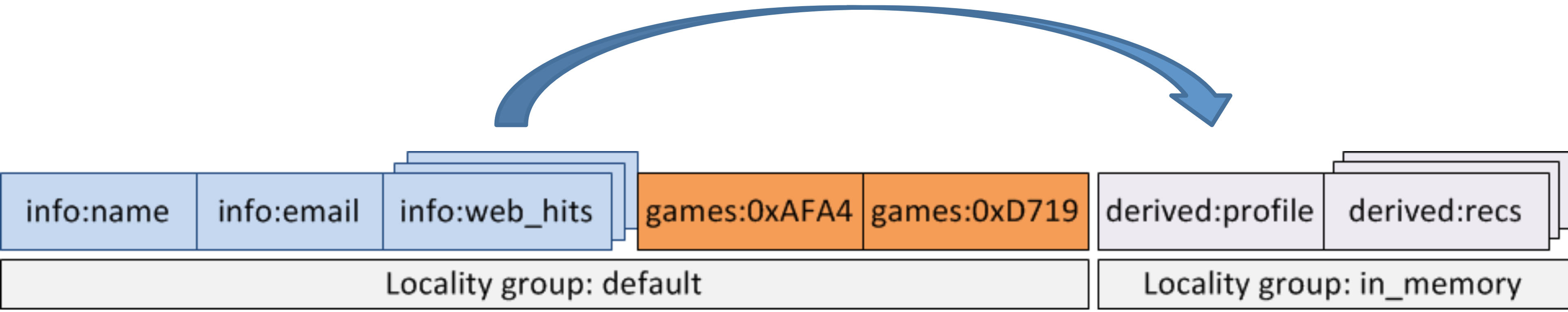
Reading data: the schema table

- MD5 hash of schema is used as the row id in the “schema table”

	info:schema
0xAB 0x4F 0x56 0x8D	“string”

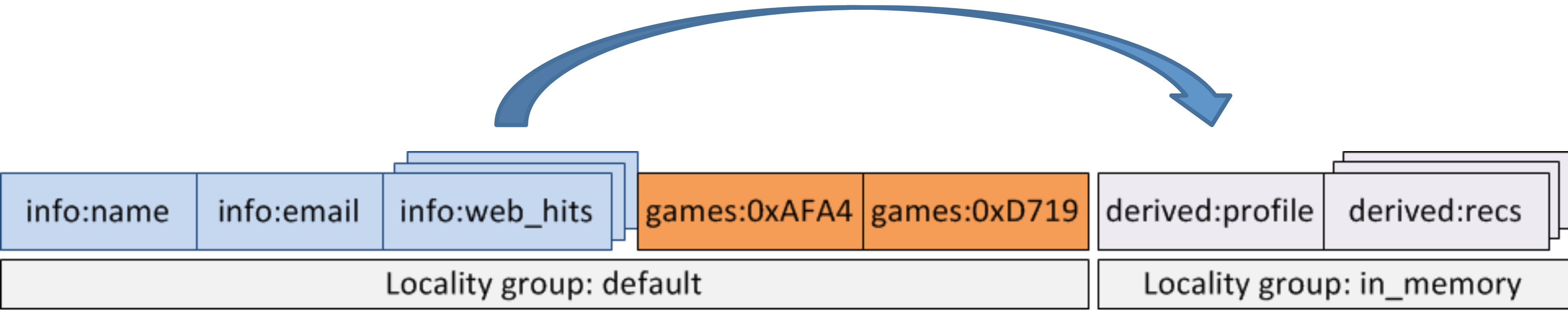
- Schema table is small; fully cached by clients
- Write races are ok

Analyzing data: Producers



- *Producers* create derived column values
- Produce operator works on one row at a time
  - Can be run in MapReduce, or on a one-off basis

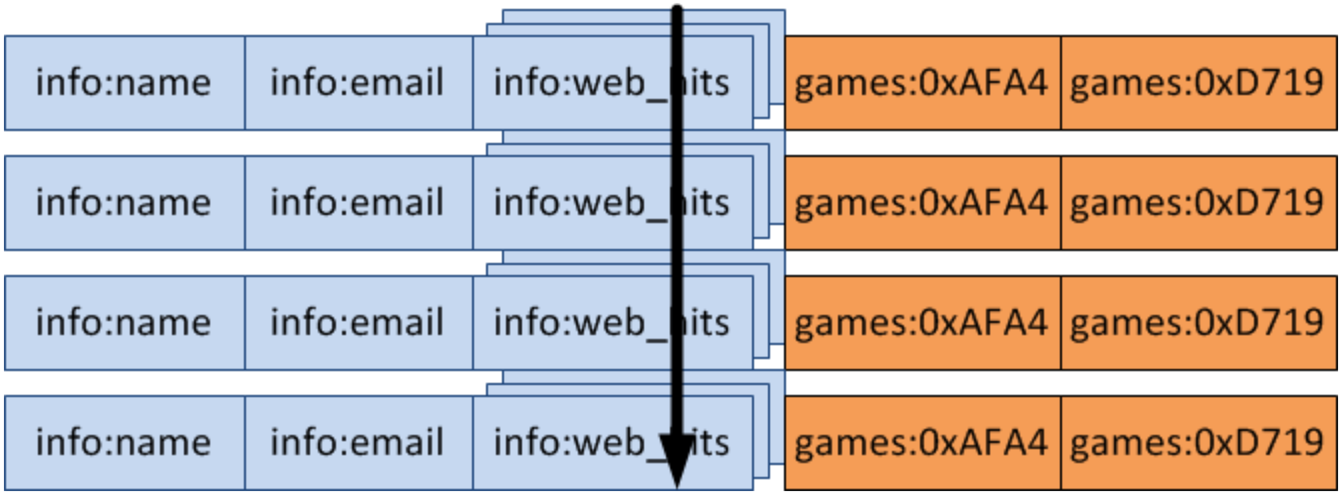
Analyzing data: Producers



`produce: (ref Row → unit) → Row list → unit`

Decouples row mutations from MapReduce execution model, (key, value)-pair data model

Analyzing data: Gatherers



- *Gatherers* aggregate data across all rows
- Always run within MapReduce

```
gather: (Row → ('a, 'b)) → Row list
     → ('a, 'b) list
```

Example: TF-IDF

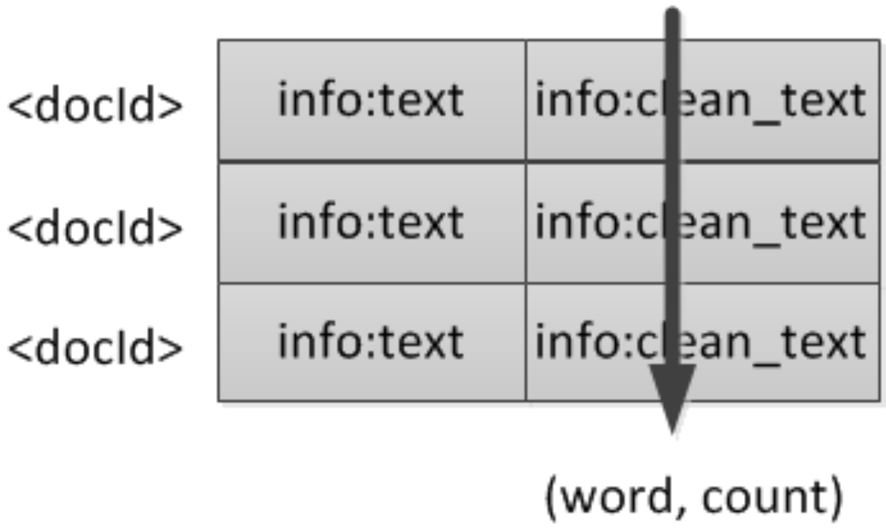
- Producers and gatherers can be chained to analyze data for online use
- For example, ranking search results from Wikipedia
- …Assuming you have a separate text index (e.g., Lucene)

TF-IDF: Clean up inputs

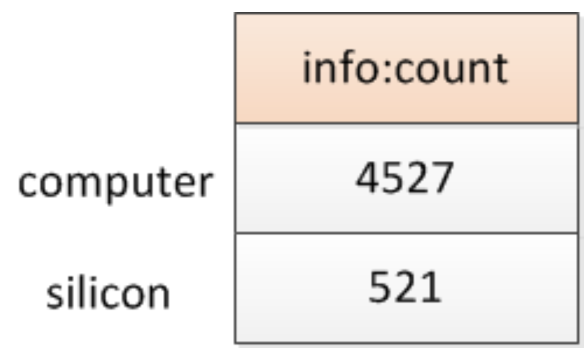
	info:text	info:clean_text
<docId>	Computers have a silicon …	computer silicon …

- First producer: remove stop words and stem input

TF-IDF: Global term frequency



- Gatherer: Get word counts across all documents, loads this into a new IDF table



TF-IDF: Per-document term frequency

<docId>	info:text	info:clean_text	word:computer	word:silicon
	Computers have a silicon ...	computer silicon ...	4	2

- Producer: Create a *map-type* column family containing per-document word counts

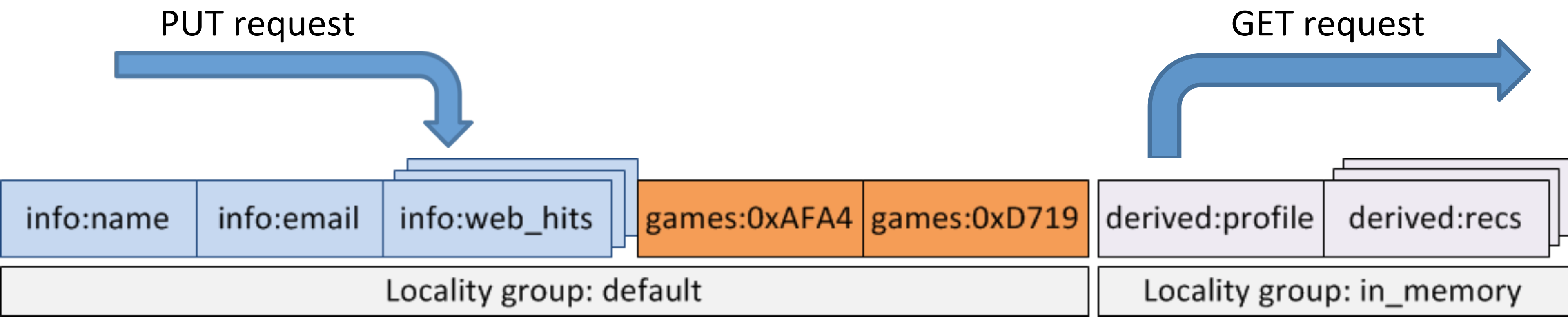
TF-IDF: Search ranker

	word:computer	word:silicon
<docId>	4	2

	info:count
computer	4527
silicon	521

- Ranking program looks up docId's returned by Lucene, getting TF for each search term
- Calculates relevance score using global IDF table entries for each search term

Interactive access: REST API



- REST API provides interactive access
- Producers can be triggered "on demand" to create fresh recommendations

Conclusions

- Hadoop, HBase, Avro form the core of a large-scale machine learning/analysis platform
- How you set up your schema matters
- Producer/gatherer programming model allows computations over tables to be expressed naturally; works with MapReduce

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