Schema Design Patterns for a Peta-Scale World

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About me


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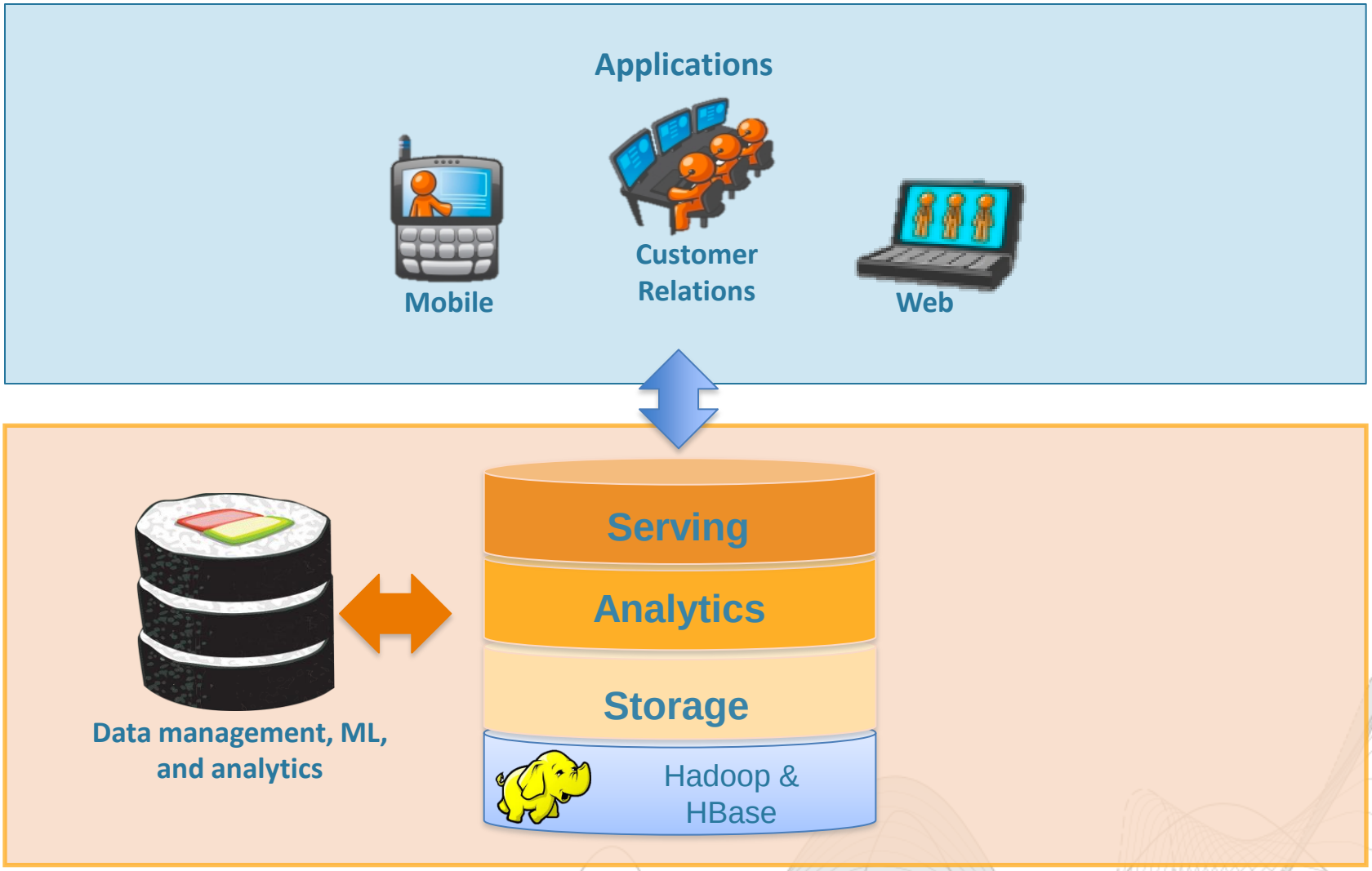
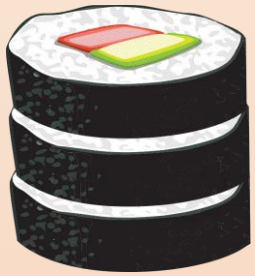
Big Data Applications



Major application targets

Real Time Models



SQL Analytics

Batch Processing

MapReduce,
Cascading,
Crunch,
Pig…

Big Data Apps are hard to build

- Schemas, serialization & versioning
- Distributed deployment
- Communication between teams
- Batch + real-time capacity planning

kiji

Kiji is designed to help you build real-time Big Data Applications on Apache HBase

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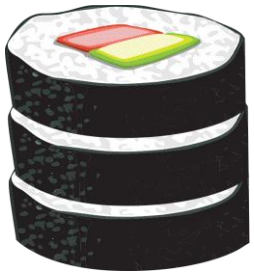

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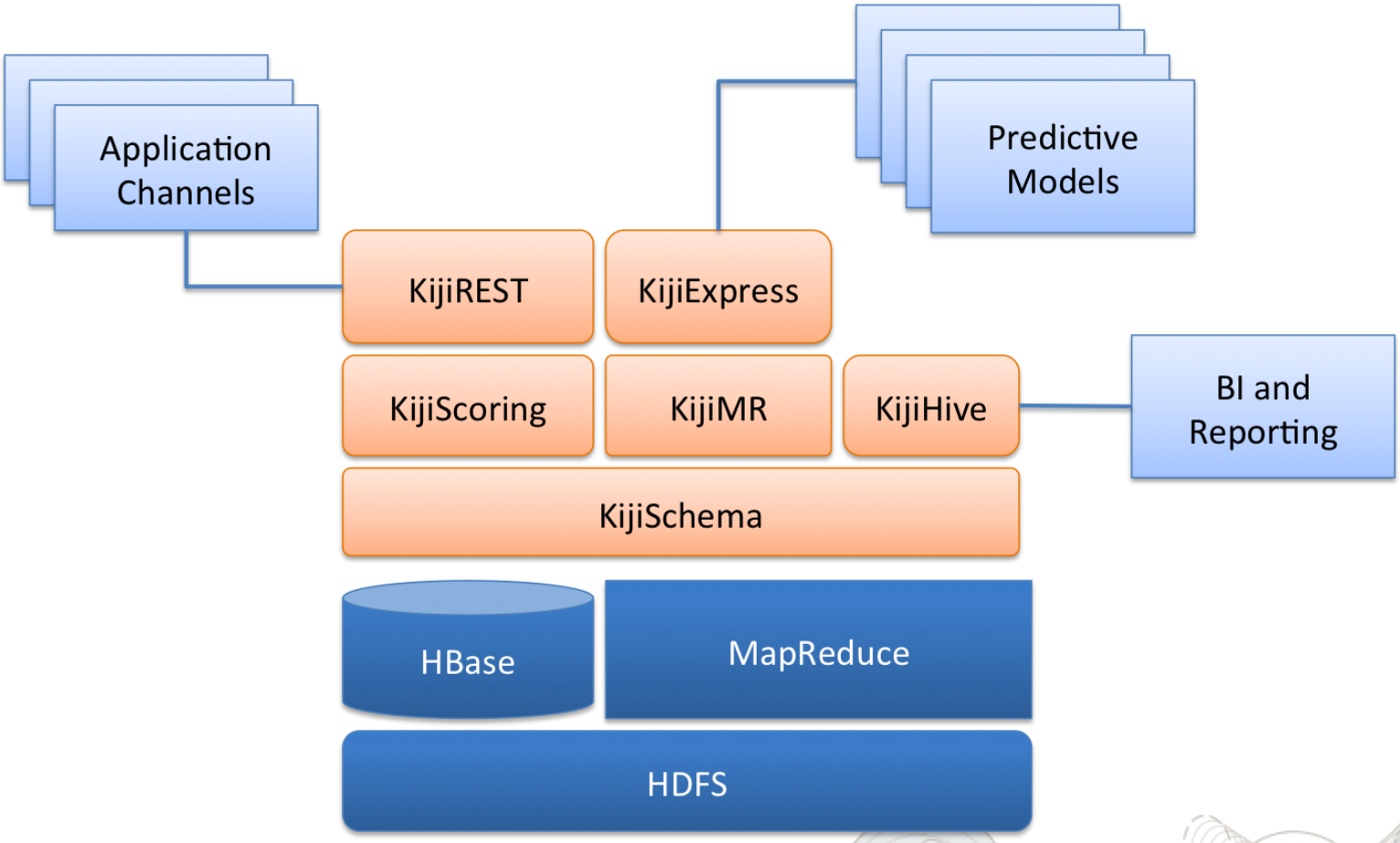
Kiji architecture



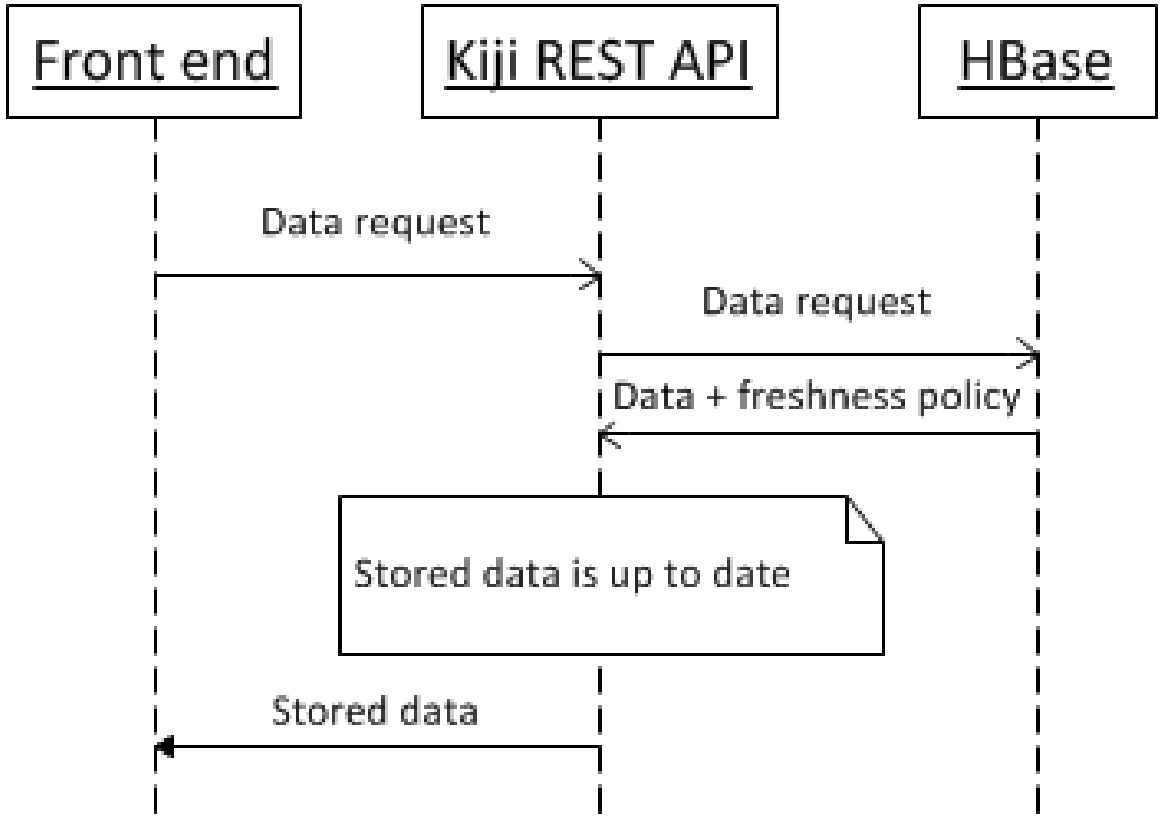
Leading design decisions

- Store your data in HBase
- Encode it using Avro
- An *entity-centric* table design
- Manage a data dictionary around tables
- Distribute writes across the cluster

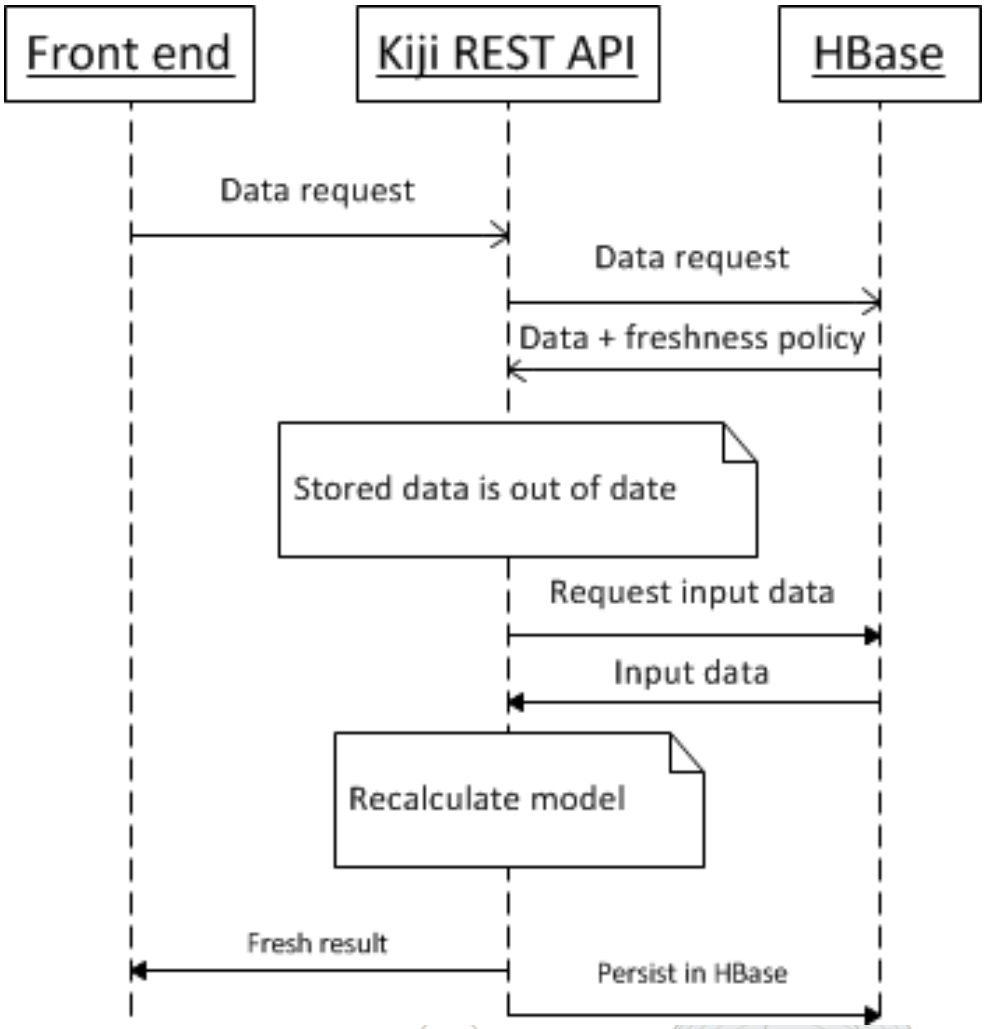
Key features

- Work with big data in rich types with schema evolution
- Guides users to successful schema design
- Deployment of real-time model scoring

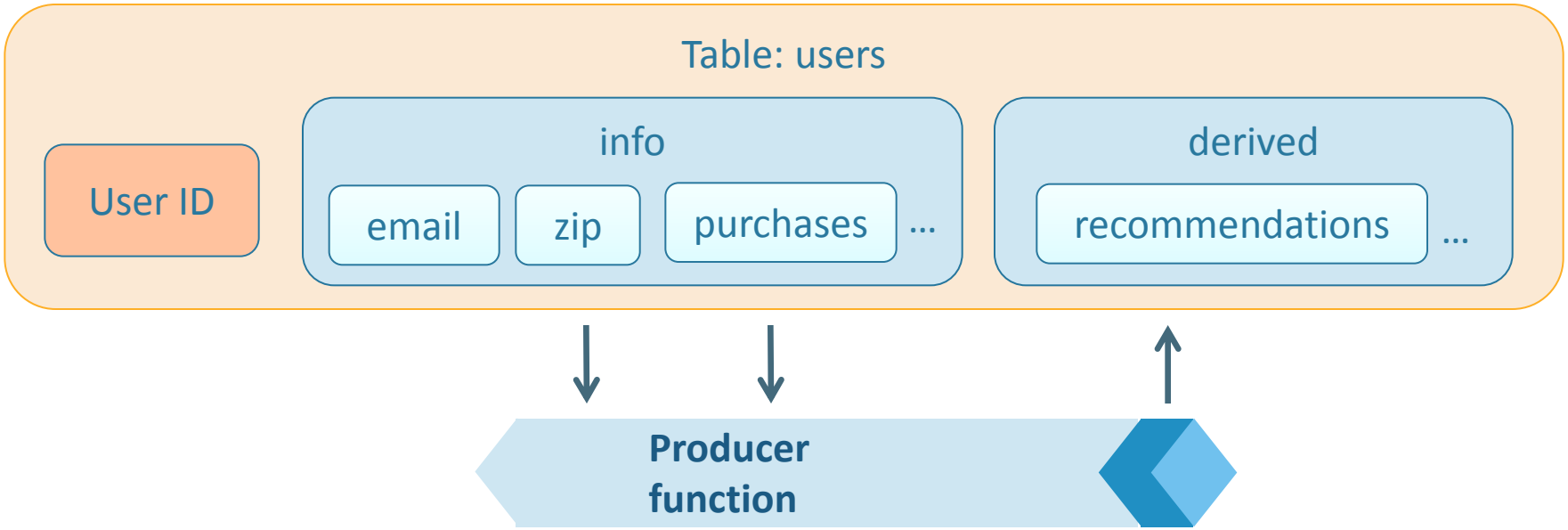
Processing big data in real time



Real time “freshening”



Producer functions

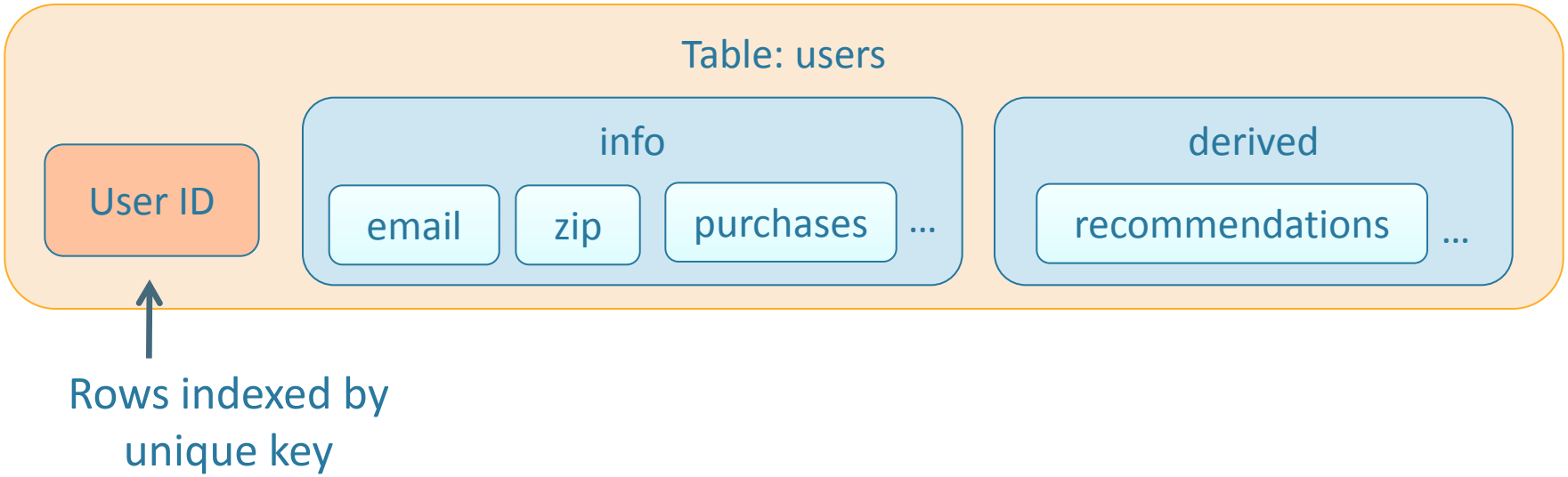


Producers provide custom per-entity analytics operating on fine-grained data

The Kiji data model

- Kiji tables have a *layout* (schema) describing their columns and data types
- Each column can hold integers or strings as well as complex Avro records

The Kiji data model

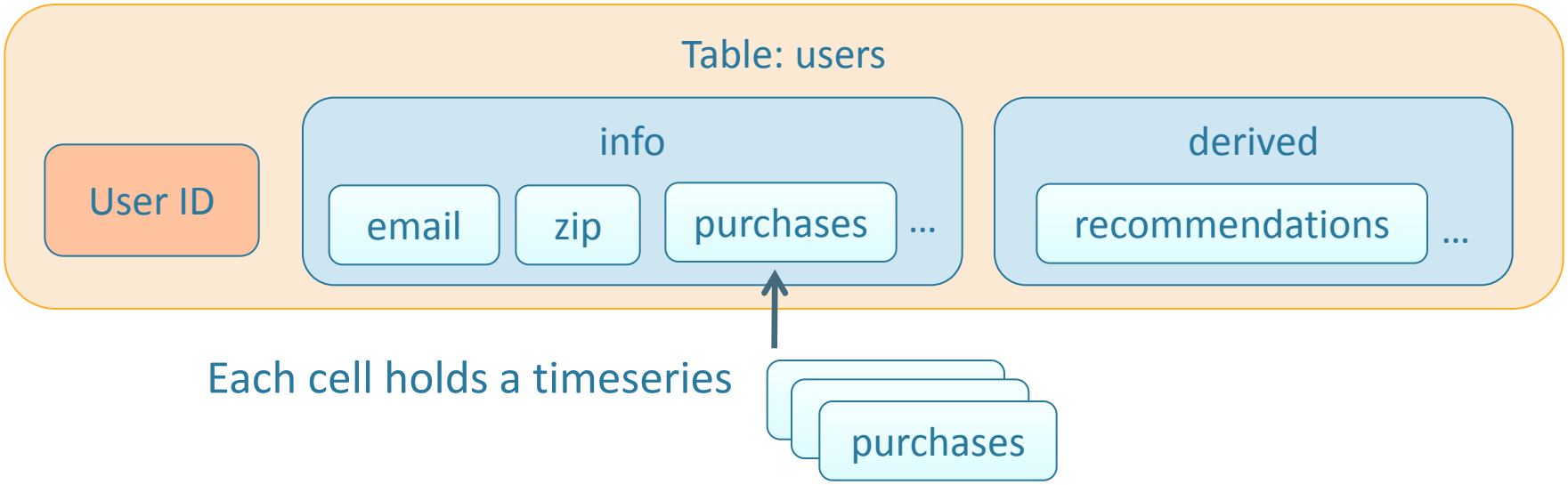


In this *entity-centric* model, all data for one entity (e.g., user) sits in one row

The Kiji data model

Data is grouped together logically in *column families*

The Kiji data model



Historical values for a given (row, column) can be easily aggregated, iterated, or filtered

Why  ?

- Schema evolution
- Compact representation
- Rich set of types
- Generic API is attractive for framework level
- Plays nicely with Hadoop ecosystem (Input/OutputFormats, etc.)

Schema evolution

Initial schema for info:location

```
record Point {
    float x;
    float y;
}
```

Later schema adds a field

```
record Point {
    float x;
    float y;
    float z = 0.0;
}
```

Applications expecting either the old or new data structure can read all records from disk, regardless of which was used when writing the data.

Efficient I/O with Avro

- Each row (entity) stores many complex-valued cells
- Data logically read and written together is physically stored in the same cell
- Sparse column storage allows fine-grained access to disparate elements of an entity for complex model building

Schema upgrade concerns

- Big data repositories are accessed by many versions of different apps concurrently
- Apps each evolve local schema definitions at different rates
- “Flag day” approaches to using new schemas do not work in practice
- Avro admits incompatible schema migrations

Incompatible migration example

- #1 `record R { int x; string y; }`
- #2 `record R { int x; }`
- #3 `record R { int x; int y = 0; }`

Incompatibility detection requires a history of all schemas previously used

Poly-schema key-value storage

- Each column records lists of all current and prior schemas
  - Separate lists for reader and writer schemas
- DDL for registering and unregistering them

```
ALTER TABLE t ADD READER SCHEMA s...
ALTER TABLE t DROP READER SCHEMA s2...
```

- Zookeeper used to check active clients

Conclusions

- Store data in an entity-centric fashion
- Hash-prefix row keys to avoid hot spots
- Use complex records in each column
  - Granularity of records is app-specific tradeoff
- Each column is *poly-schema*: several potential views at a time!

Try Kiji today!

- Go to kiji.org and download the BentoBox
  - Zero-config Hadoop + HBase + Kiji instance
  - “Batteries included”
- 15-minute quickstart guide and a tutorial with full source code

EXPERIENCE

DATA-DRIVEN

APPLICATIONS

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