UMD DATA605 - Big Data Systems

Issues with Relational DBs
NoSQL Taxonomy
(Apache) HBase

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with thanks to Prof.
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Oliver Kennedy (U. Buffalo)
Doug Thain (U. Notre Dame)

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Jupyter Tutorial

- Let's start with a tutorial of Jupyter notebooks
- Jupyter tutorial dir
- Readme
  - Explains how to run the tutorial
- Notebook to execute / study

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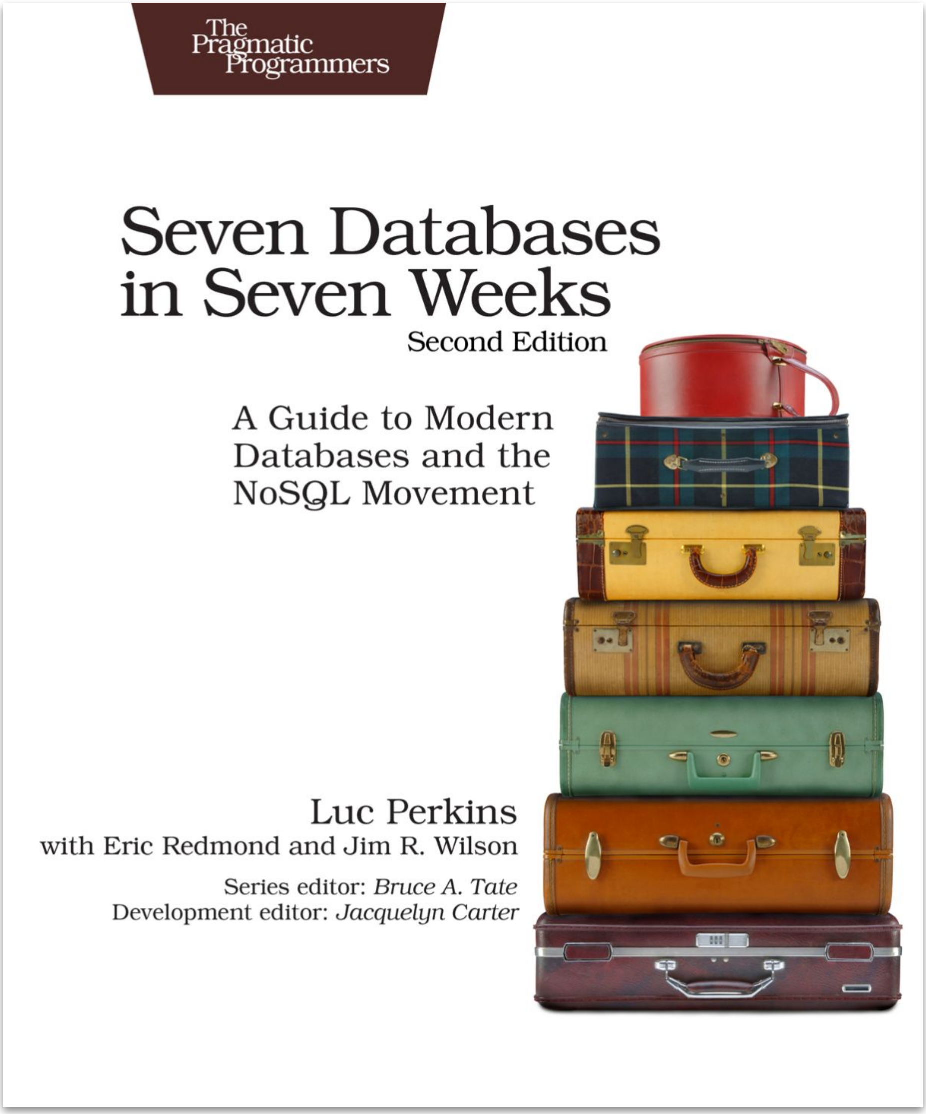
Issues with Relational DBs

NoSQL Taxonomy

(Apache) HBase

Resources

- Concepts in the slides
- Tutorial on MongoDB next lesson
- Tons of tutorials on line
- Silbershatz Chap 10.2
- Nice high-level view:
  - Seven Databases in Seven Weeks, 2e



From SQL to NoSQL

- **DBs are central tools to big data**
  - New applications, new constraints to data / storage
  - Around 2000s NoSQL “movement” started
    - Initially it meant “No SQL” -> “Not Only SQL”
- **DBs (e.g., SQL vs NoSQL) make different trade-offs**
  - Different worldviews
  - Schema vs schema-less
  - Rich vs fast ability of query
  - Strong consistency (ACID), weak, eventual consistency
  - APIs (SQL, JS, REST)
  - Horizontal vs vertical scaling, sharding, replication schemes
  - Indexing (for rapid lookup) vs no indexing
  - Tuned for reads or writes, how much control over tuning
- **The user base / applications have expanded**
  - IMO Postgres + Mongo cover 99% of use cases
  - Any data scientist / engineer needs to be familiar with both
  - “Which DB solves my problem best?”
- **Polyglot model**
  - Use more than one DB in each project
  - Relational DBs are not going to disappear any time soon

Issues with Relational DBs

- **Relational DBs have drawbacks**
  - 1) Application-DB impedance mismatch
  - 2) Schema flexibility
  - 3) Consistency in distributed set-up
  - 4) Limited scalability
- In the next slides for each drawback we will discuss:
  - **What is the problem**
  - **Possible solutions**
    - Within relational SQL paradigm
    - With NoSQL approach

1) App-DB Impedance Mismatch: Problem

- **Mismatch between how data is represented in the code and in a relational DB**
  - Code thinks in terms of:
    - Data structures (e.g., lists, dictionaries, sets)
    - Objects
  - Relational DB thinks in terms of:
    - Tables (entities)
    - Rows (actual instances of entities)
    - Relationships between tables (relationships between entities)
- **Example of the app-DB mismatch**:
  - Application stores a simple Python map like:

```
# Store a dictionary from name (string) to tags (list of strings).
tag_dict: Dict[str, List[str]]
```

  - A relational DB needs 3 tables:
    - `Names(nameId, name)` to store the keys
    - `Tags(tagId, tag)` to store the values
    - `Names_To_Tags(nameId, tagId)` to map the keys to the values
  - One could denormalize the tables using a single table
    - `Names(name, tag)`

1) App-DB Impedance Mismatch: Solutions

- **Ad-hoc mapping layer**
  - Translate objects and data structures into DB data model
    - E.g., you implement a layer that handles storing into the DB “Name to Tags” transparently
    - The code thinks in terms of a map, but there are 3 tables in the DB
  - Cons
    - You need to write / maintain code
- **Object-relational mapping (ORM)**
  - Pros
    - Convert automatically data between object code and relational DB
    - E.g., implement a `Person` object (e.g., name, phone number, addresses) using DB
    - E.g., SQLAlchemy for Python and SQL
  - Cons
    - Complex types (e.g., struct), polymorphism, inheritance
- **NoSQL approach**
  - No schema
    - Every object can be flat or complex (e.g., nested JSON)
    - Stored objects (aka documents) can be different

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2) Schema Flexibility

- **Problem**
  - Not all applications have data that fits neatly into a schema
  - E.g., data can be nested and / or dishomogeneous (e.g., `List[Obj]`)
- **Within relational DB**
  - Use a schema general enough to accommodate all the possible cases
  - Cons
    - Super-complicated schema with implicit relations
    - DB tables are sparse
    - It is a violation of the basic relational DB assumption
- **NoSQL approach**
  - E.g., MongoDB does not enforce any schema
  - Pros
    - Application does not worry about schema when writing data
  - Cons
    - Application needs to deal with variety of schemas when it processes the data
    - Related to ETL vs ELT data pipelines

3) Consistency in Relational DBs

- **All systems in the real-world fail**
  - Application error (e.g., corner case, internal error)
  - Application crash (e.g., OS issue)
  - Hardware failure (e.g., RAM ECC error, disk)
  - Power failure
- **Relational DBs enforce <u>ACID</u> properties**
  - Need to be guaranteed for any system failure
- **Atomicity**
  - = transactions are "*all or nothing*"
  - Either a transaction (which can be composed of multiple statements) succeeds completely or fails
- **Consistency**
  - = any transaction brings the DB *from a valid state to another*
  - The "invariants" of the DB (e.g., primary, foreign key constraints) must be maintained
- **Isolation**
  - = if transactions are executed *concurrently*, the result is the same as if the transactions were executed *sequentially*
- **Durability**
  - = once a transaction has been committed, the *content is preserved for any system failure*
  - Just record the data in non-volatile memory

Application error

Hardware failure

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3) Consistency in Distributed DB

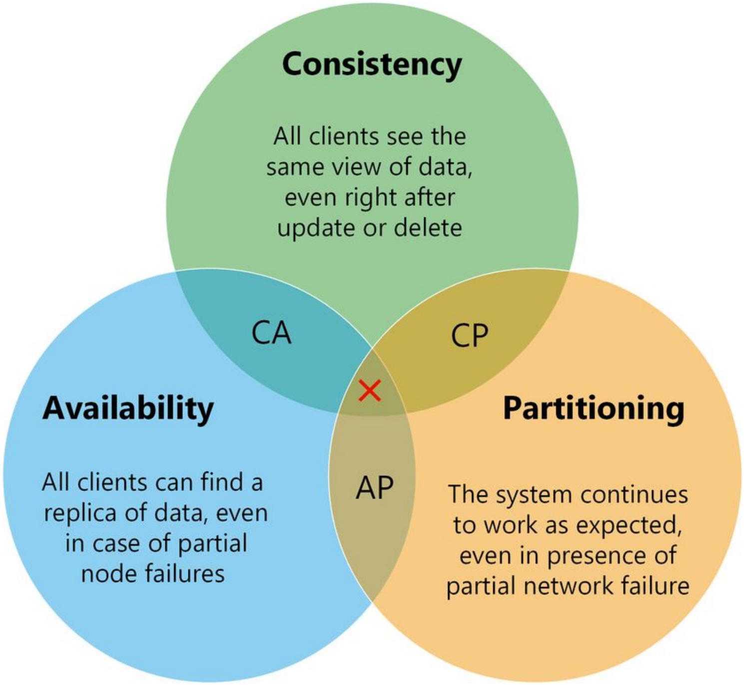
- When data scales up or number of clients increases → **distributed setup**
- Goals to achieve:
  - Performance (e.g., transaction per seconds)
  - Availability (guarantee of a certain up-time)
  - Fault-tolerance (can recover from faults)

- **Achieving ACID consistency is:**
  - *Not easy* in a single DB setup
    - E.g., Postgres guarantees ACID
    - E.g., MongoDB doesn't guarantee ACID
  - *Impossible* in a distributed DB setup
    - Due to CAP theorem
    - Even weak consistency is difficult to achieve

A = **Atomicity**
C = **Consistency**
I = **Isolation**
D = **Durability**

CAP Theorem

- **CAP theorem**: Any *distributed* DB can have *at most two* of the following *three* properties
  - **Consistent**:
    - All clients see the same data
    - Writes are atomic and subsequent reads retrieve the new value
  - **Available**: a value is returned as long as a single server is running
  - **Partition tolerant**: the system still works even if communication is temporary lost (i.e., the network is partitioned)
- Originally a conjecture (Eric Brewer)
- Made formal later (Gilbert, Lynch, 2002)



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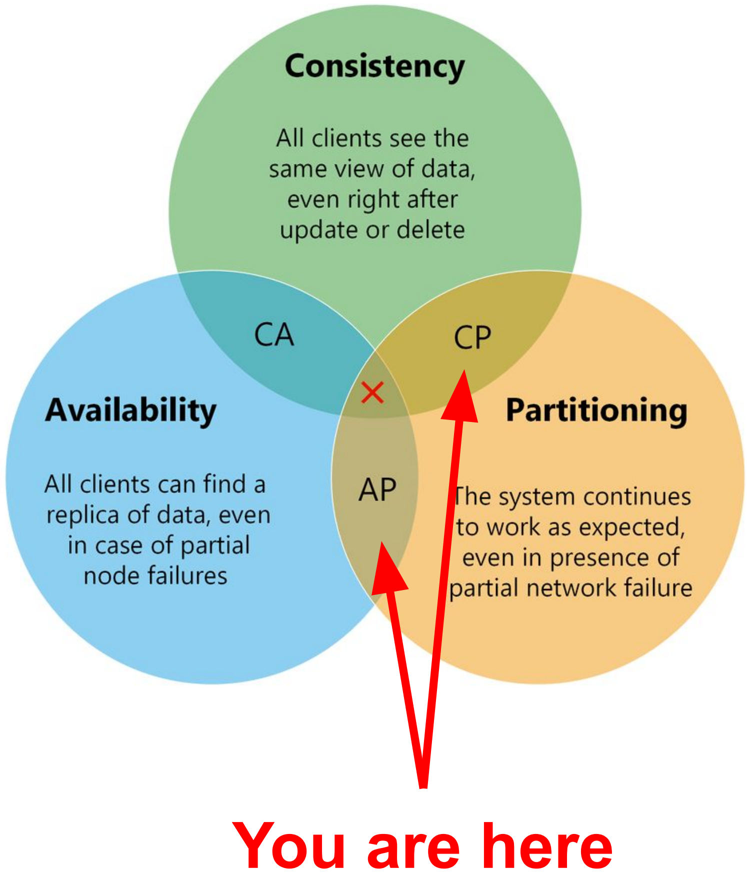
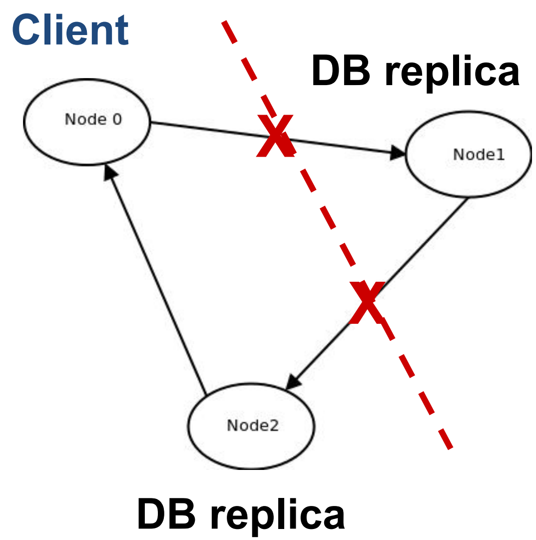
CAP Corollary

- **CAP Theorem**: pick 2 among consistency, availability, partition tolerance
- *Network partitions* cannot be prevented in large-scale distributed system
  - Minimize probability of failures using redundancy and fault-tolerance
- Need to either sacrifice:
  - *Availability* (i.e., allow system to go down)
    - E.g., banking system
  - *Consistency* (i.e., allow different views of the system)
    - E.g., social network



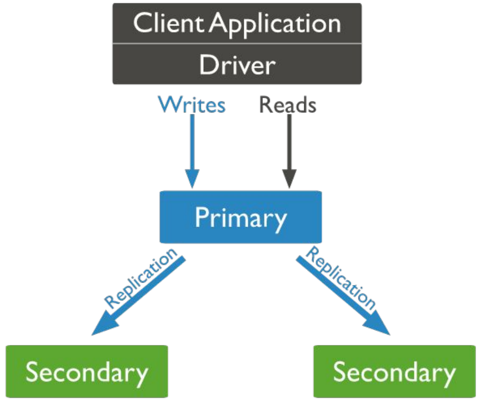
CAP Theorem: Intuition

- Imagine there are
  - a client (*Node0*)
  - two DB replicas (*Node1*, *Node2*)
- **A network partition happens**
  - DB servers (*Node1*, *Node2*) can't communicate with each other
  - Users (*Node0*) can access only one of them (*Node2*)
  - **Reads**: the user can access the data of the server in the same partition
  - **Writes**: data can't be updated since multiple users might be updating the data on different replicas, leading to inconsistency
- **CAP theorem:** one needs to sacrifice consistency or availability
- **Available, but not consistent**
  - Let updates happen on the accessible replica at cost of inconsistency
  - Sometimes inconsistency is fine (e.g., social networking)
- **Consistent, but not available**
  - Stop the service (no availability) to avoid inconsistency
  - Sometimes inconsistency is not acceptable (e.g., a banking system)

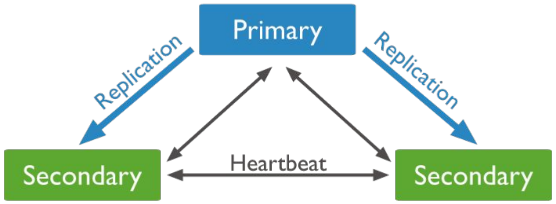


Replication Schemes

- **Replication schemes**: how to organize multiple servers implementing a distributed DB
- **Primary-secondary replication**
  - Application only communicates with primary
  - Replicas cannot update local data, but require primary node to perform update
  - Single-point of failure
- **Update-anywhere replication**
  - Aka “multi-master replication”
  - Every replica can update a data item, which is then propagated (synchronously or asynchronously) to the other replicas
- **Quorum**
  - Let N be the total number of replicas
  - When writing, we make sure to write to W replicas
  - When reading, we read from R replicas and pick the latest update (using timestamps)



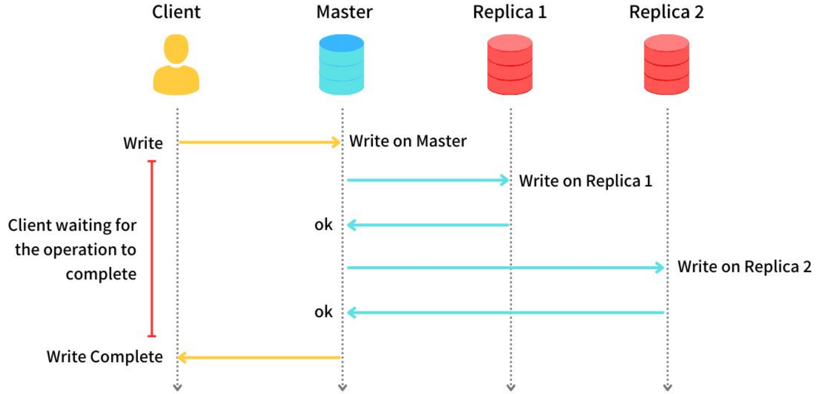
Primary-secondary replication



Update-anywhere replication

Synchronous Replication

- **Synchronous replication**: updates are propagated to other replicas as part of a single transaction
- Implementations
  - **2-Phase Commit (2PC)**: original proposal for doing this
    - Single point of failure
    - Can't handle primary server failure
  - **Paxos**: more widely used today
    - Doesn't require a primary
    - More fault tolerant
  - Both solutions are complex / expensive
- **CAP theorem**: still only one among Consistency, Availability, in case of Network partition
  - Many systems use relaxed / loose consistency models



Synchronous Replication

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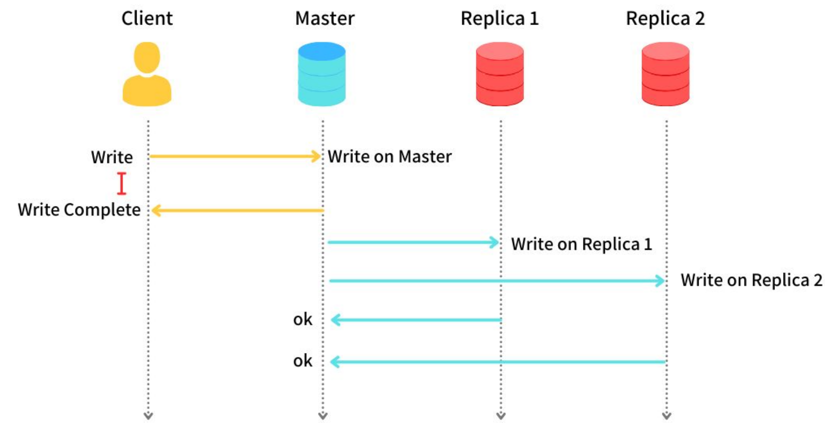
Asynchronous Replication

- **Asynchronous replication**
  - The primary node propagates updates to replicas
  - The transaction is completed before replicas are updated (even if there are failures)
  - Commits are quick at cost of consistency
- **Eventual consistency**
  - Popularized by AWS DynamoDB
  - Consistency guaranteed only on the eventual outcome
  - "*Eventual*" can mean after the server or network is fixed
- **"Freshness" property**
  - Under asynchronous updates, a read from a replica may not get the latest version of a data item
  - User can request a version with a certain "freshness"
    - E.g., "data from not more than 10 minutes ago"
    - E.g., it's ok to show price for an airplane ticket that is few minutes old
  - Replicas version their data with timestamps
  - If local replica has fresh data, uses it, otherwise send request to primary node



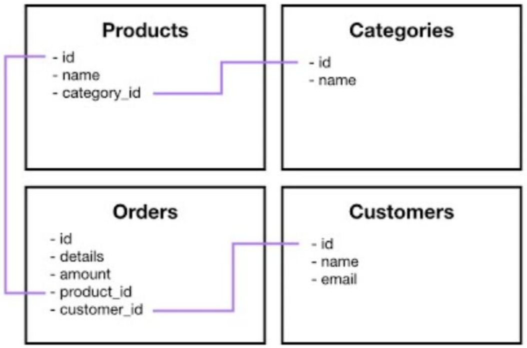
Asynchronous Replication

4) Scalability Issues with RDMS

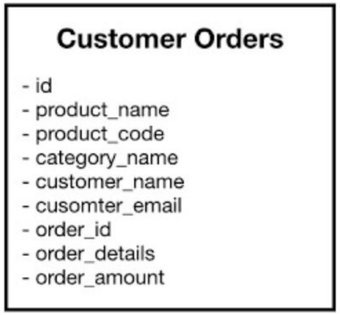
- The sources of relational SQL DB scalability issues are:
- **Locking data**
  - The DB engine needs to lock rows and tables to ensure ACID properties
  - When DB locked:
    - Higher latency → Fewer updates per second → Slower application
- **Even worse in distributed set-up**
  - Requires replicating data over multiple servers (scaling out)
  - Application becomes even slower
    - Network delays
    - To enforce DB consistency, locks are applied across networks
    - Overhead of replica consistency (2PC, Paxos)

Scalability Issues with RDMS: Solutions

- **Table denormalization**
  - = approach used to increase relational DB performance by adding redundant data
  - Pros
    - Reads become faster
      - Lock only one table, instead of multiple ones, reducing resource contention
      - No need for joins
  - Cons
    - Writes become slower
      - There is more data to update
      - E.g., to update a *category name*, need to do a scan
    - If we join the tables, we lose relations between tables (this is the main reason of using a relational DB!)
- **Relax consistency**
  - Give up on part of ACID
  - Make definition of consistency weaker
    - E.g., eventual consistency
- **NoSQL**



Normalized data



Denormalized data

NoSQL Stores

- **Use cases of large-scale web applications**
  - Applications need real-time access with a few ms latencies
    - E.g., Facebook: 4ms for reads to get snappy UI
  - Applications don't need ACID properties
  - In fact, MongoDB started at DoubleClick (AdTech), acquired by Google
- **Solve previous problems with relational databases**
  - 1) Application-DB impedance mismatch
  - 2) Schema flexibility
  - 3) Consistency in distributed set-up
  - 4) Scalability
- **If you want to really scale out, you must give up something**
  - Give up consistency
  - Give up joins
    - Most NoSQL stores don't allow server-side joins
    - Instead require data to be denormalized and duplicated
  - Only allow restricted transactions
    - Most NoSQL stores will only allow one object transactions
    - E.g., one document / key

Relational DB vs MongoDB

How MongoDB solves the four RDBM problems

1) **Application-DB impedance mismatch**
   - Store data as nested objects
2) **Schema flexibility**
   - No schema, no tables, no rows, no columns, no relationships between tables
3) **Consistency in replicated set-up**
   - Application decides consistency level
     - *Synchronous*: wait until primary and secondary servers are updated
     - *Quorum synchronous*: wait until the majority of secondary servers are updated
     - *Asynchronous*, *eventual*: wait until only the primary is updated
     - *"Fire and forget"*: not even wait until the primary persisted the data
4) **Scalability**
   - Updating data means locking only one document, and not entire collection
   - Sharding: use more machines to do collectively do more work

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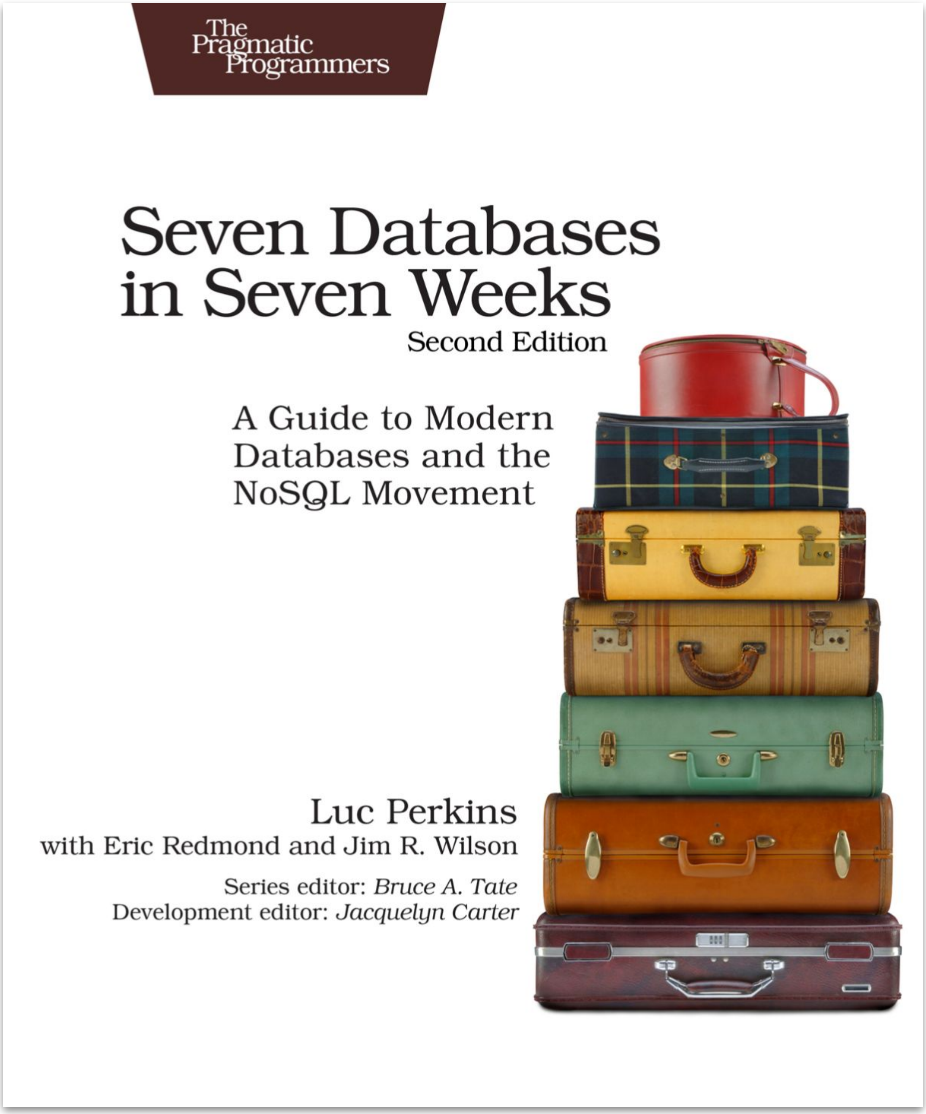
Issues with Relational DBs

NoSQL Taxonomy

(Apache) HBase

Resources

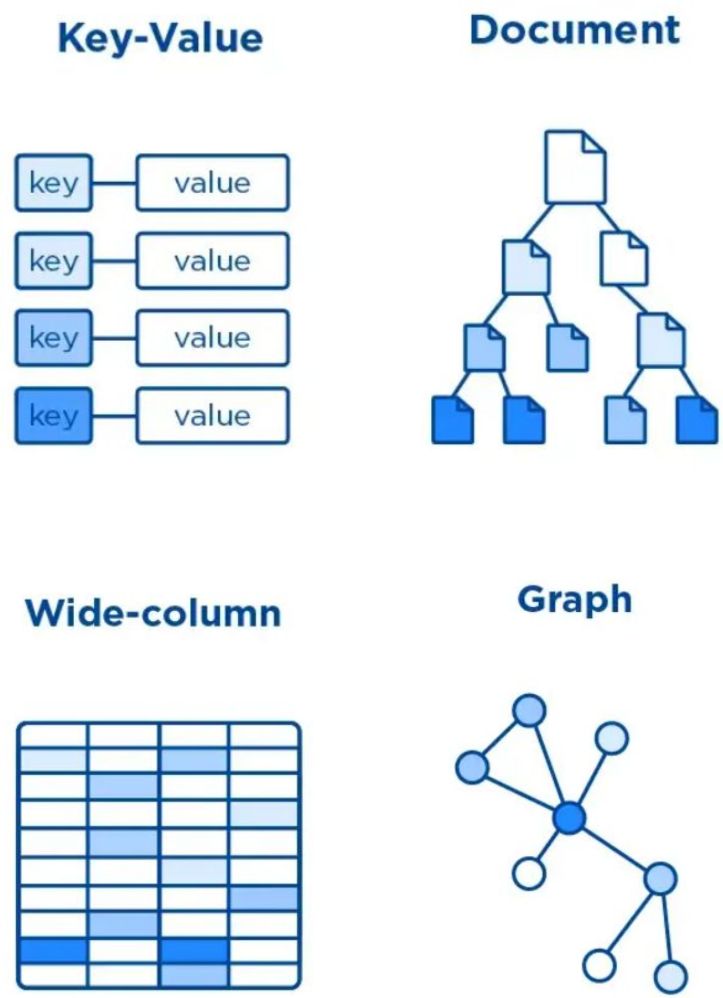
- Concepts in the slides
- Silberschatz Chapter 23.6
- Mastery:
  - Seven Databases in Seven Weeks, 2e



DB Taxonomy

- **At least five DB genres**
  - *Relational* (e.g., Postgres)
  - *Key-value* (e.g., Redis)
  - *Document* (e.g.,. MongoDB)
  - *Columnar* (e.g., Parquet)
  - *Graph* (e.g., Neo4j)

- **Criteria to differentiate DBs**
  - Data model
  - Trade-off with respect to CAP theorem
  - Querying capability
  - Replication scheme



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Relational DB

- E.g., *Postgres*, MySQL, Oracle, SQLite
- **Data model**
  - Based on set-theory and relational algebra
  - Data as two dimensional tables with rows and columns
  - Many attribute types (e.g., numeric, strings, dates, arrays, blobs)
  - Attribute types are strictly enforced
  - SQL query language
  - ACID consistency
- **Application**
  - Any relational tabular data
- **Good for**
  - When layout of data is known, but not the data access pattern
  - Complexity upfront for schema to achieve query flexibility
  - Used when data is regular
- **Not so good for**
  - When data is hierarchical (not a nice row in one or more tables)
  - When data structure is variable/dishomogeneous (record-to-record variation)

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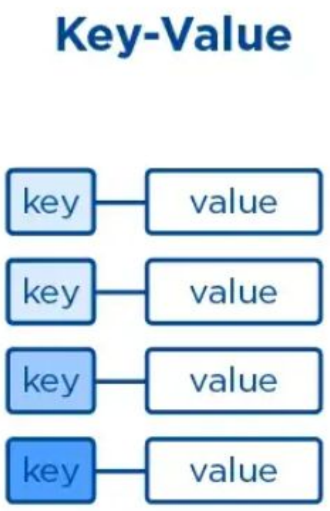
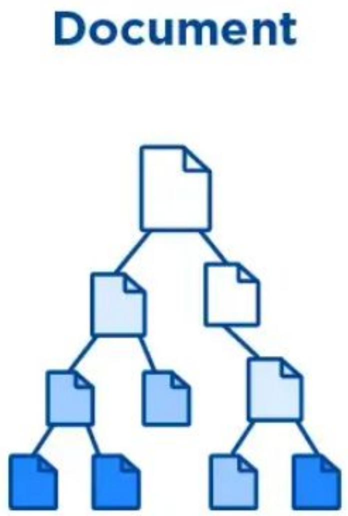
Key-Value Store

- E.g., Redis, DynamoDB, *Git*, *AWS S3*, *filesystem*
- **Data model**
  - Map simple keys (e.g., strings) to more complex values (e.g., it can be anything, binary blob)
  - Support get, put, and delete operations on a primary key
- **Application**
  - Caching data
  - E.g., store users' session data in a web application
  - E.g., store the shopping cart in an e-commerce application
- **Good for**
  - Useful when data is not "related" (e.g., no joins)
  - Lookups are fast
  - Easy to scale horizontally using partitioning scheme
- **Not so good for**
  - Not great if data queries are needed
  - Lacking secondary indexes and scanning capabilities



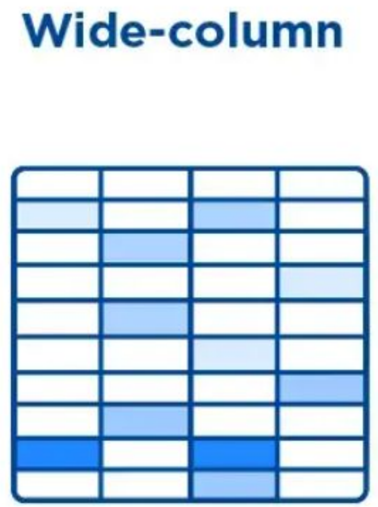
Document Store

- E.g., *MongoDB*, CouchDB
- **Data model**
  - Like key-value but value is a document (i.e., a nested dict)
  - Each document has a unique ID (e.g., hash)
  - Any number of fields per document, even nested
    - E.g., JSON, XML, dict data
- **Application**
  - Any semi-structured data
- **Good for**
  - When you don't know how your data will look like
  - Map well to OOP models (less impedance mismatch between application and DB)
  - Since documents are not related, it's easy to shard and replicate over distributed servers
- **Not so good for**
  - Complex join queries
  - Denormalized form is the norm



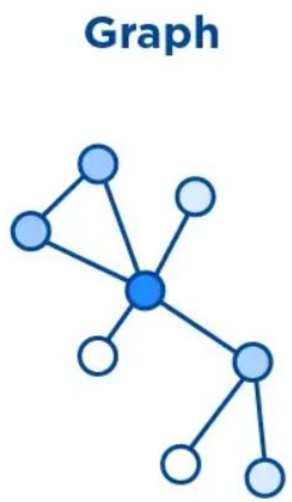
Columnar Store

- E.g., *HBase*, Cassandra, *Parquet*
- **Data model**
  - Data is stored by columns, instead of rows like in relational DBs
  - Share similarities with both key-value and relational DBs
    - Keys are used to query values (like key-value stores)
    - Values are groups of zero or more columns (like relational stores)
- **Application**
  - Storing web-pages
  - Storing time series data
  - OLAP workloads
- **Good for**
  - Horizontal scalability
  - Enable compression and versioning
  - Tables can be sparse without extra storage cost
  - Columns are inexpensive to add
- **Not so good for**
  - Need to design the schema based on how you plan to query the data
  - No native joins, applications need to handle join

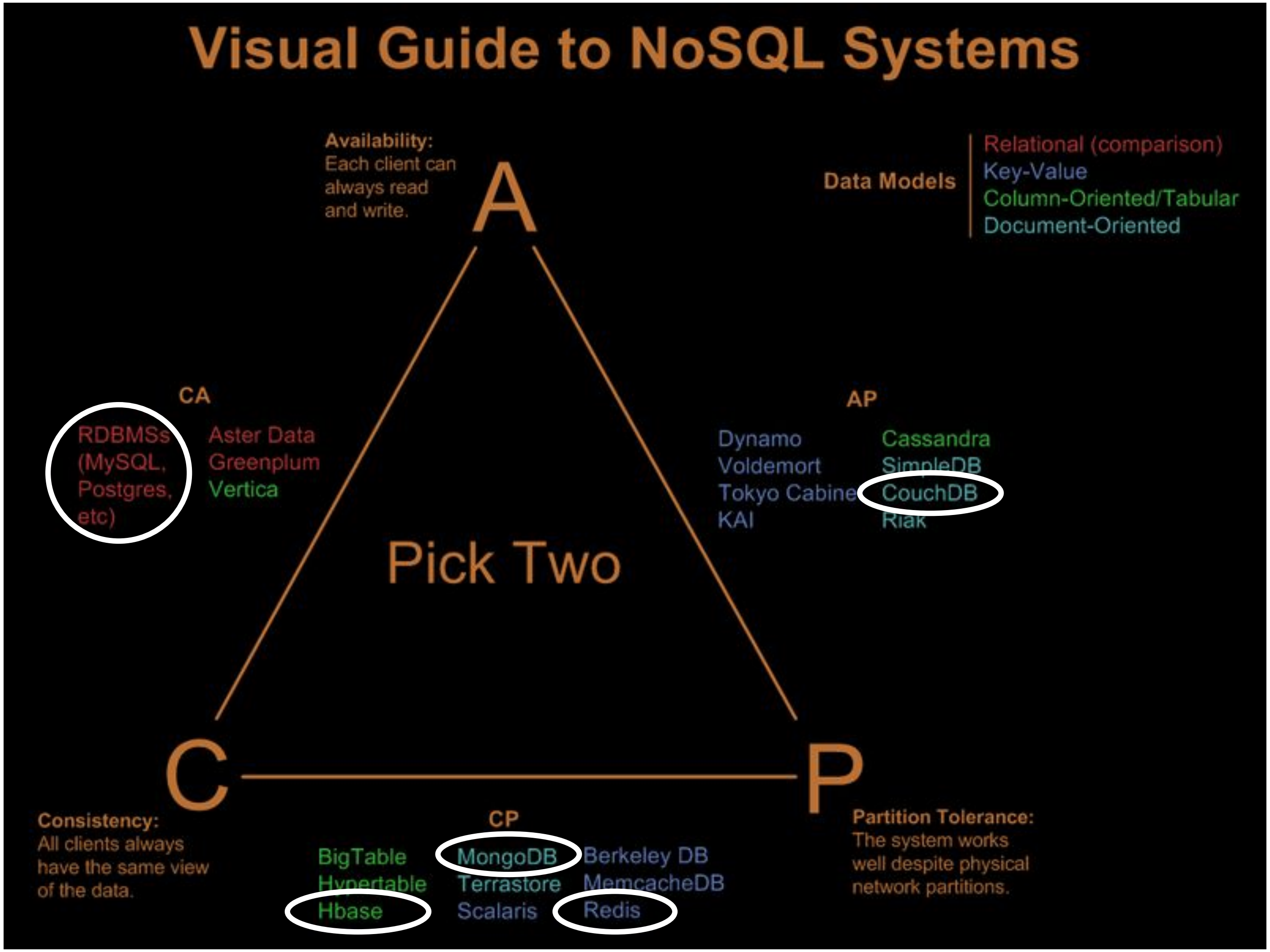


Graph DB

- E.g., *Neo4J*, GraphX
- **Data model**
  - Highly interconnected data, storing nodes and relationships between nodes
  - Both nodes and edges have properties (i.e,. key-value pairs)
  - Queries involve traversing nodes and relationships to find relevant data
- **Applications**
  - Social data
  - Recommendation engines
  - Geographical data
- **Good for**
  - Perfect for "networked data", which is difficult to model with relational model
  - Good match for OO systems
- **Not so good for**
  - Don't scale well, since it's difficult to partition graph on different nodes
    - Store the graph in the graph DB and the relations in a key-value store



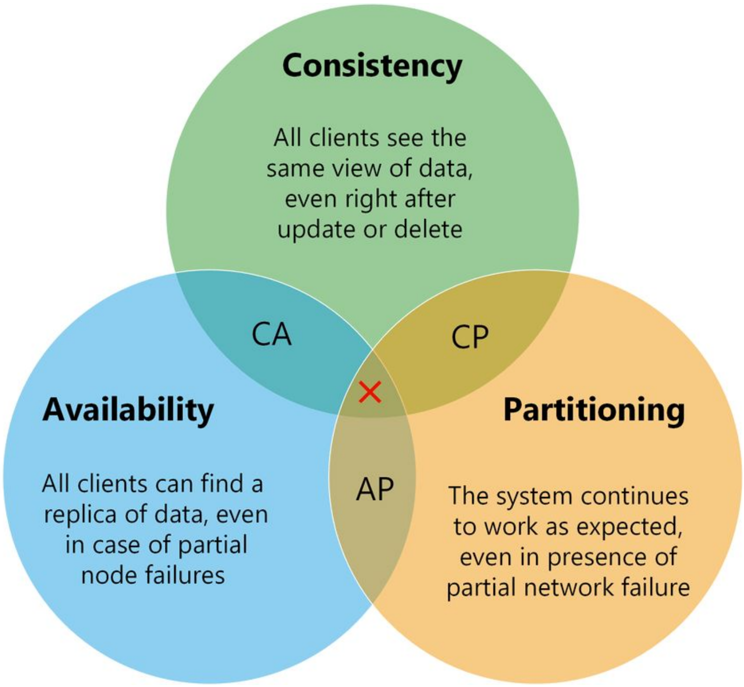
Taxonomy by CAP



From http://blog.nahurst.com/visual-guide-to-nosql-systems

Taxonomy by CAP

- **CA (Consistent, Available) systems**
  - Have trouble with partitions and typically deal with it with replication
  - Traditional RDBMSs (e.g., PostgreSQL, MySQL)
- **CP (Consistent, Partition-Tolerant) systems**
  - Have trouble with availability while keeping data consistent across partitioned nodes
  - BigTable (column-oriented/tabular)
  - HBase (column-oriented/tabular)
  - MongoDB (document-oriented)
  - Redis (key-value)
  - MemcacheDB (key-value)
  - Berkeley DB (key-value)
- **AP (Available, Partition-Tolerant) systems**
  - Achieve "eventual consistency" through replication and verification
  - Dynamo (key-value)
  - Cassandra (column-oriented/tabular)
  - CouchDB (document-oriented)



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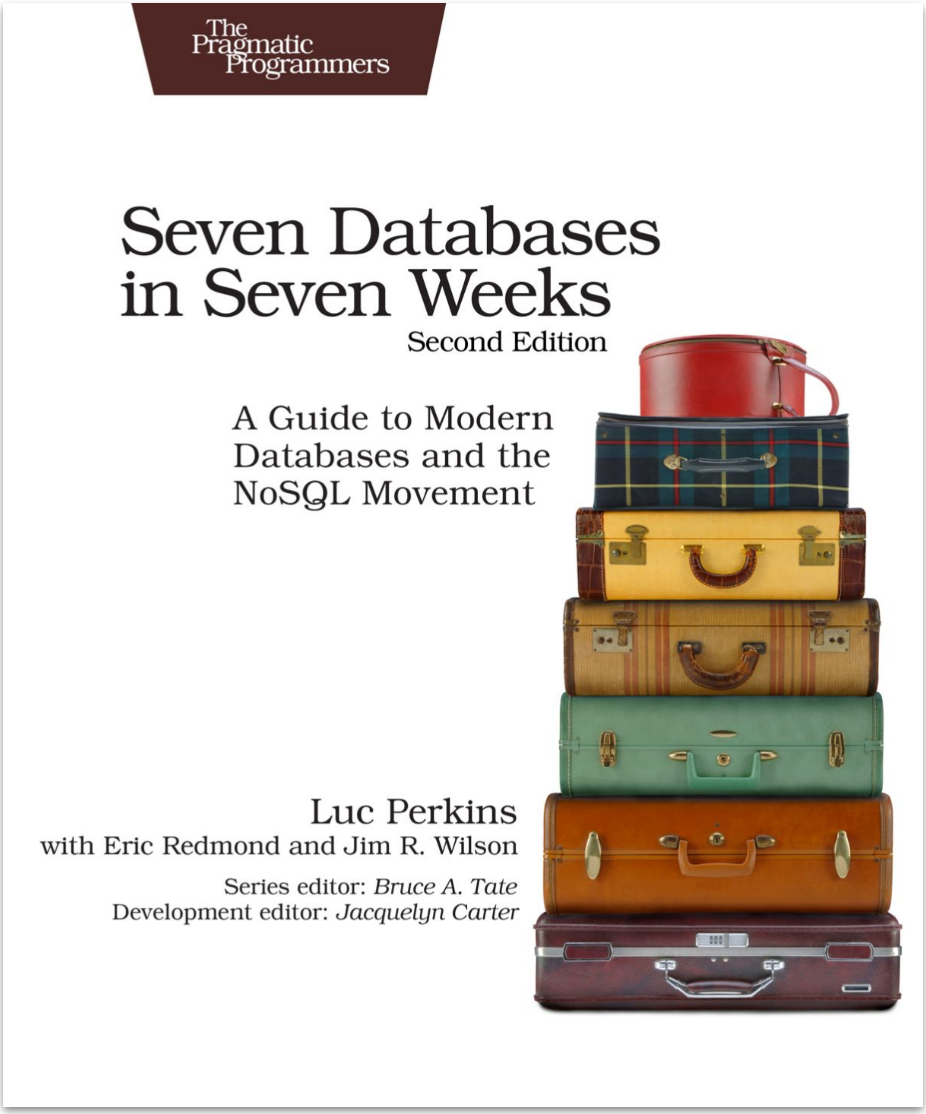
NoSQL Stores

NoSQL Taxonomy

(Apache) HBase

Resources

- Content in slides
- Web
  - [2006, BigTable paper]
  - https://hbase.apache.org/
  - https://github.com/apache/hbase
- Good overview:
  - Seven Databases in Seven Weeks, 2e



(Apache) HBase

- HBase = **H**adoop Data**Base**
  - Support very large tables on clusters of commodity hardware
  - Column oriented DB
  - Part of Apache Hadoop ecosystem
  - Use Hadoop filesystem (HDFS)
    - HDFS modeled after Google File System (GFS)
    - HBase based on Google BigTable
    - Google BigTable runs on GFS, HBase runs on HDFS
  - Used at Google, Airbnb, eBay
- **When to use HBase**
  - For large DBs (e.g., at least many 100 GBs or TBs)
  - When having at least 5 nodes in production
- **Applications**
  - Large-scale online analytics
  - Heavy-duty logging
  - Search systems (e.g., Internet search)
  - Facebook Messages (based on Cassandra)
  - Twitter metrics monitoring

HBase: Features

- Data versioning
  - Store versions of data
- Data compression
  - Compress and decompress on-the-fly
  - Makes the system much more complicated
  - Difficult to do random access
- Garbage collection (for expired data)
- In-memory tables
- Atomicity, but only at row level
  - Relational DBs have flexible atomicity `begin ... end transaction`
- Strong consistency guarantees
- Fault tolerant (for machines and network)
  - Write-ahead logging
    - Write data to an in-memory log before it's written to disk
  - Distributed configuration
    - Nodes can rely on each other rather than on a centralized source

From HDFS to HBase

- **Different types of workloads for DB backends**
  - **OLTP** (**O**n-**L**ine **T**ransactional **P**rocessing)
    - Read and write individual data items in a large table
    - E.g., update inventory and price as orders come in
  - **OLAP** (**O**n-**L**ine **A**nalytical **P**rocessing)
    - Read large amount of data and process it
    - E.g., analyze item purchases over time
- **Hadoop FileSystem (HDFS) supports OLAP workloads**
  - Provide a filesystem consisting of arbitrarily large files
  - Data should be read sequentially, end-to-end
  - Rarely updated
- **HBase supports OLTP interactions**
  - Built on top of HDFS
  - Use additional storage and memory to organize the tables
  - Write tables back to HDFS as needed

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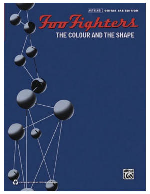
HBase Data Model

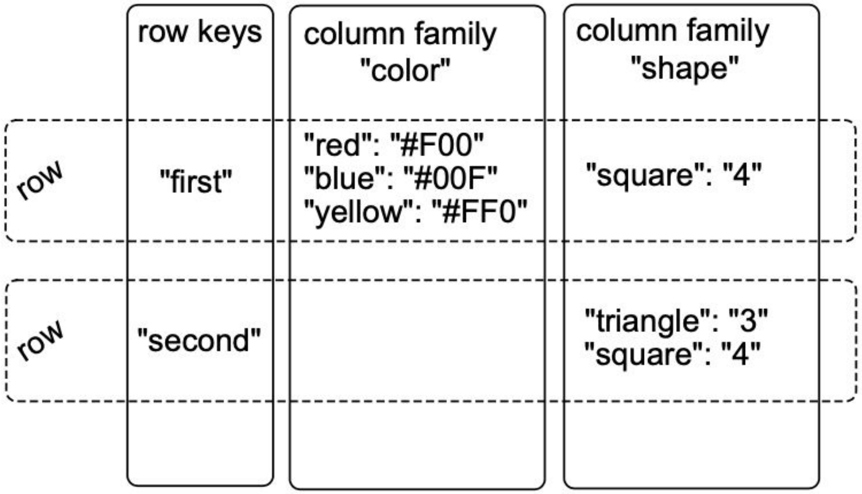
- **Warning**: HBase uses names similar to relational DB concepts, but with different meanings
- A **database** consists of multiple tables
- Each **table** consists of multiple rows, sorted by row key
- Each row contains a **row key** and one or more column families
- Each **column family**
  - Can contain multiple **columns** (family:column)
  - Is defined when the table is created
- A **cell**
  - Is uniquely identified by (table, row, family:column)
  - Contains **metadata** (e.g., timestamp) and an uninterpreted array of bytes (blob)
- Versioning
  - New values don't overwrite the old ones
  - \`put()\` and \`get()\` allow to specify a timestamp (otherwise uses current time)

```
# HBase Database: from table name to Table.
Database = Dict[str, Table]

# HBase Table.
table: Table = {
  # Row key
  'row1': {
    # (column family:column) → value
    'cf1:col1': 'value1',
    'cf1:col2': 'value2',
    'cf2:col1': 'value3'
  },
  'row2': {
    ... # More row data
  }
}

database = {'table1': table}

# Querying data.
(value, metadata) = \
     table['row1']['cf1:col1']
```

Example 1: Colors and Shape



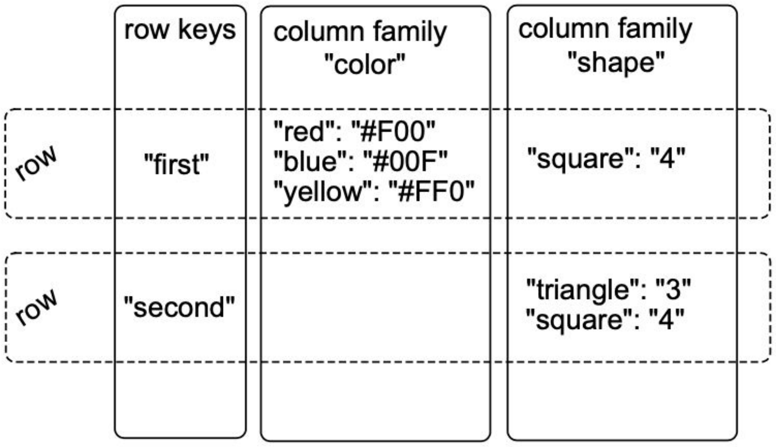
- Table with:
  - 2 column families
    - “color” and “shape”
  - 2 rows
    - “first” and “second”)
- The row “first” has:
  - 3 columns in the column family “color”
    - “red”, “blue”, “yellow”
  - 1 column in the column family “shape”
    - shape = 4
- The row “second” has:
  - no columns in “color”
  - 2 columns in the column family “shape”
- Data is accessed using a row key and column (family:qualifier)




```
table = {
  'first': {
    # (column family, column) →
value
    'color': {'red': '#F00',
              'blue': '#00F',
              'yellow': '#FF0'}
    'shape': {'square': '4'}
  },
  'second': {
    'shape': {'triangle': '3',
              'square': '4'}
  }
}
```

Why all this convoluted stuff?

- A row in HBase is almost like a mini-database
  - A cell has many different values associated with it
  - Data is stored in a sparse format
- Rows in HBase are "deeper" than in relational DBs
  - In relational DBs rows contain a lot of column values (fixed array with types)
  - In HBase rows contain something like a two-level nested dictionary and metadata (e.g., timestamp)
- Applications
  - Store versioned web-site data
  - Store a wiki



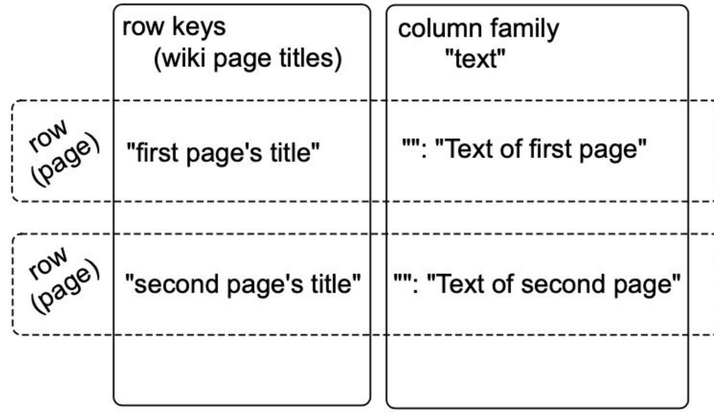
Example 2: Storing a Wiki

Wiki (e.g., Wikipedia)

- Contains pages
- Each page has a title, an article text varying over time

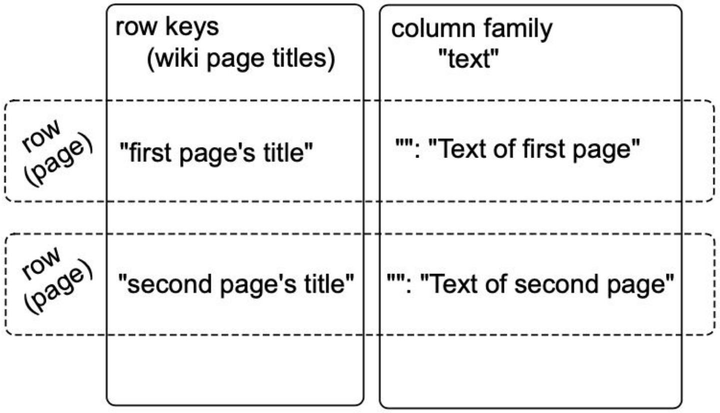
HBase data model

- Table name → `wikipedia`
- Row → entire wiki page
- Row keys → wiki identifier (e.g., title or URL)
- Column family → `text`
- Column → ‘’ (empty)
- Cell value → article text




```
wikipedia_table = {
  # wiki id.
  'Home': {
    # Column family:column → value
    ':text': 'Welcome to the wiki!',
  },
  'Welcome page': {
    … # More row data
  }
}

Database = Dict[str, Table]
database: Database = {'wikipedia':
wiki_table}


(article, metadata) = \
     wiki_table['Home']['text']
```

Example 2: Storing a Wiki



Add data

- Columns don't need to be predefined when creating a table
- The column is defined as `text`

  ```
  > put 'wikipedia', 'Home', 'text',
  'Welcome!'
  ```

Query data

- Specify the table name, the row key, and optionally a list of columns

  ```
  > get 'wikipedia', 'Home', 'text'
  text: timestamp=1295774833226,
  value=Welcome!
  ```

- HBase returns the timestamp (ms since the epoch 01-01-1970 UTC)

```
wikipedia_table = {
  # wiki id.
  'Home': {
    # Column family, column → value
    'text': 'Welcome to the wiki!',
  },
  'Welcome page': {
    … # More row data
  }
}

Database = Dict[str, Table]
database: Database = {'wikipedia':
wiki_table}


(queried_value, metadata) = \
     wiki_table['Home']['text']
```

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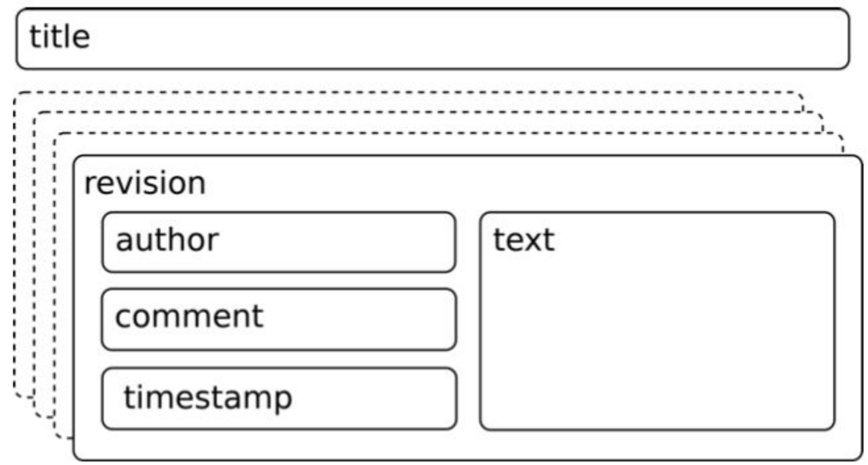
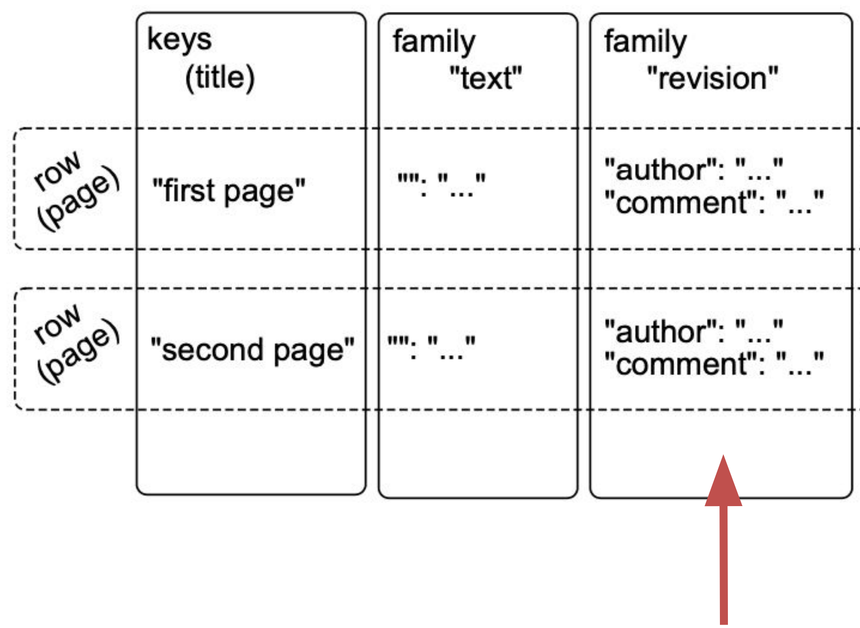
Example 2: Improved Wiki

- **Improved wiki using versioning**
- A page
  - Is uniquely identified by its title
  - Can have multiple revisions
- A revision
  - Is made by an author
  - Contains optionally a commit comment
  - Is identified by its timestamp
  - Contains text
- **HBase data model**
- Add a family column “revision” with multiple columns
  - E.g., author, comment, ...
- Timestamp is automatic and binds article text and metadata
- The title is not part of the revision
  - It's fixed and identified uniquely the page (like a primary key)
  - If you want to change the title you need to re-write all the row





Data in Tabular Form

	Name		Home		Office	
Key	First	Last	Phone	Email	Phone	Email
101	Florian	Krepsbach	555-1212	florian@wobegon.org	666-1212	fk@phc.com
102	Marilyn	Tollerud	555-1213		666-1213	
103	Pastor	Inqvist			555-1214	inqvist@wel.org

- Fundamental operations
  - `CREATE table, families`
  - `PUT table, rowid, family:column, value`
  - `PUT table, rowid, whole-row`
  - `GET table, rowid`
  - `SCAN table` *`(WITH filters)`*
  - `DROP table`

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Data in Tabular Form

	Name			Home		Office		Social
Key	**First**		**Last**	**Phone**	**Email**	**Phone**	**Email**	**FacebookID**
101	Florian	Garfield	Krepsbach	555-1212	florian@wobegon.org	666-1212	fk@phc.com	
102	Marilyn		Tollerud	555-1213		666-1213		
103	Pastor		Inqvist			555-1214	inqvist@wel.org	

New columns can be added at runtime

Column families cannot be added at runtime

```
Table People(Name, Home, Office)
{
     101: {
          Timestamp: T403;
          Name: {First="Florian", Middle="Garfield", Last="Krepsbach"},
          Home: {Phone="555-1212", Email="florian@wobegon.org"},
          Office: {Phone="666-1212", Email="fk@phc.com"}
     },
     102: {
          Timestamp: T593;
          Name: {First="Marilyn", Last="Tollerud"},
          Home: {Phone="555-1213"},
          Office: {Phone="666-1213"}
     },
     …
}
```

Nested Data Representation

	Name		Home		Office	
Key	First	Last	Phone	Email	Phone	Email
101	Florian	Krepsbach	555-1212	florian@wobegon.org	666-1212	fk@phc.com
102	Marilyn	Tollerud	555-1213		666-1213	
103	Pastor	Inqvist			555-1214	inqvist@wel.org

```
GET People:101
    {
        Timestamp: T403;
        Name: {First="Florian", Last="Krepsbach"},
        Home: {Phone="555-1212", Email="florian@wobegon.org"},
        Office: {Phone="666-1212", Email="fk@phc.com"}
    }

GET People:101:Name
    {First="Florian", Last="Krepsbach"}

GET People:101:Name:First
    "Florian"
```

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Column Family vs Column

- **Adding a column**
  - Is cheap
  - Can be done at run-time
- **Adding a column family**
  - Can't be done at run-time
  - Need a copy operation of the table (expensive)
  - This tells you something about how the data is stored
    - Easy to add is a map
    - Hard to add is some sort of static array
    - E.g., MongoDB document vs Relational DB column

- **Why differentiating column families vs columns?**
  - Why not storing all the row data in a single column family?
  - Each column family can be configured independently, e.g.,
    - Compression
    - Performance tuning
    - Stored together in files
  - Everything is designed to accommodate a special kind of data
    - E.g., timestamped web data for search engine

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Consistency Model

- **Atomicity**
  - Entire rows are updated atomically or not at all
  - Independently of how many columns are affected
- **Consistency**
  - A GET is guaranteed to return a complete row that existed at some point in the table's history
    - Weak / eventual consistency
    - Check the timestamp to be sure!
  - A SCAN
    - Must include all data written prior to the scan
    - May include updates since it started
- **Isolation**
  - Concurrent vs sequential semantics
  - Not guaranteed outside a single row
  - The atom of information is a row
- **Durability**
  - All successful writes have been made durable on disk

Checking for Row or Column Existence

- HBase supports Bloom filters to check whether a row or column exists
  - It's like a cache for `key in keys`, instead of `keys[key]`
  - E.g., instead of querying one can keep track of what's present
- **Hashset complexity**
  - Space needed to store data is unbounded
  - No false positives
  - O(1) in average / amortized (because of reallocations, re-balancing)
- **Bloom filter implementation**
  - Bloom filter is like a probabilistic hash set
  - Array of bits initially all equal to 0
  - When a new blob of data is presented, turning the blob into a hash, and then use hash to set some bits to 1
  - To test if we have seen a blob, compute the hash, check the bits
    - If all bits are 0s, then for sure we didn't see it
    - If all bits are 1s, then it’s likely but not sure you have seen that blob (false positive)
- **Bloom filter complexity**
  - Use a constant amount of space
  - Has false positives (no false negatives)
  - O(1)

Write-Ahead Log (WAL)

- Write-Ahead Log is a general technique used by DBs
  - Provide atomicity and durability
  - Protect against node failures
  - Equivalent to journaling in file system
- HBase and Postgres uses WAL

- **WAL mechanics**
- For performance reasons, the updated state of tables are:
  - Not written to disk immediately
  - Buffered in memory
  - Written to disk as checkpoints periodically
- **Problem**
  - If the server crashes during this limbo period, the state is lost
- **Solution**
  - Use append-only disk-resident data structure
  - Log of operations performed since last table checkpoint are appended to the WAL (it's like storing deltas)
  - When tables are stored to disk, the WAL is cleared
  - If the server crashes during the limbo period, use WAL to recover the state that was not written yet
- When running a big import job, disable the WAL to improve performance
  - Trade off disaster recovery protection for speed

Storing variable-length data in DBs

SQL Table

`People(ID: Integer, FirstName: CHAR[20], LastName: CHAR[20], Phone: CHAR[8])`

`UPDATE People SET Phone="555-3434" WHERE ID=403;`

ID	FirstName	LastName	Phone
101	Florian	Krepsbach	555-3434
102	Marilyn	Tollerud	555-1213
103	Pastor	Ingvist	555-1214

- Each row is exactly 4 + 20 + 20 + 8 = 52 bytes long
- To move to the next row: `fseek(file,+52)`
- To get to Row 401 `fseek(file, 401*52);`
- Overwrite the data in place

HBase Table

`People(ID, Name, Home, Office)`

`PUT People, 403, Home:Phone, 555-3434`

```
{
     101: {
          Timestamp: T403;
          Name: {First="Florian", Middle="Garfield", Last="Krepsbach"},
          Home: {Phone="555-1212", Email="florian@wobegon.org"},
          Office: {Phone="666-1212", Email="fk@phc.com"}
     },
...
```

Need to use pointers

HBase Implementation

- **How to store the web on disk?**
- **HBase is backed by HDFS**
  - Store each table (e.g., Wikipedia) in one file
  - "One file" means one gigantic file stored in HDFS
    - HDFS splits/replicate file into blocks on different servers
- Here is the idea in several steps:
  - **Idea 1: Put an entire table in one file**
    - Need to overwrite the file every time there is a change in any cell
    - Too slow
  - **Idea 2: One file + WAL**
    - Better, but doesn't scale to large data
  - **Idea 3: One file per column family + WAL**
    - Getting better!
  - **Idea 4: Partition table into regions by key**
    - Region = a chunk of rows [a, b)
    - Regions never overlap

Idea 1: Put the Table in a Single File

File "People"

```
Table People(Name, Home, Office)
{
     101: {
          Timestamp: T403;
          Name: {First="Florian", Middle="Garfield", Last="Krepsbach"},
          Home: {Phone="555-1212", Email="florian@wobegon.org"},
          Office: {Phone="666-1212", Email="fk@phc.com"}
     },
     102: {
          Timestamp: T593;
          Name: {First="Marilyn", Last="Tollerud"},
          Home: {Phone="555-1213"},
          Office: {Phone="666-1213"}
     },
     …
}
```

- How do we do the following operations?
  - `CREATE, DELETE` (easy / fast)
  - `SCAN` (easy / fast)
  - `GET, PUT` (difficult / slow)

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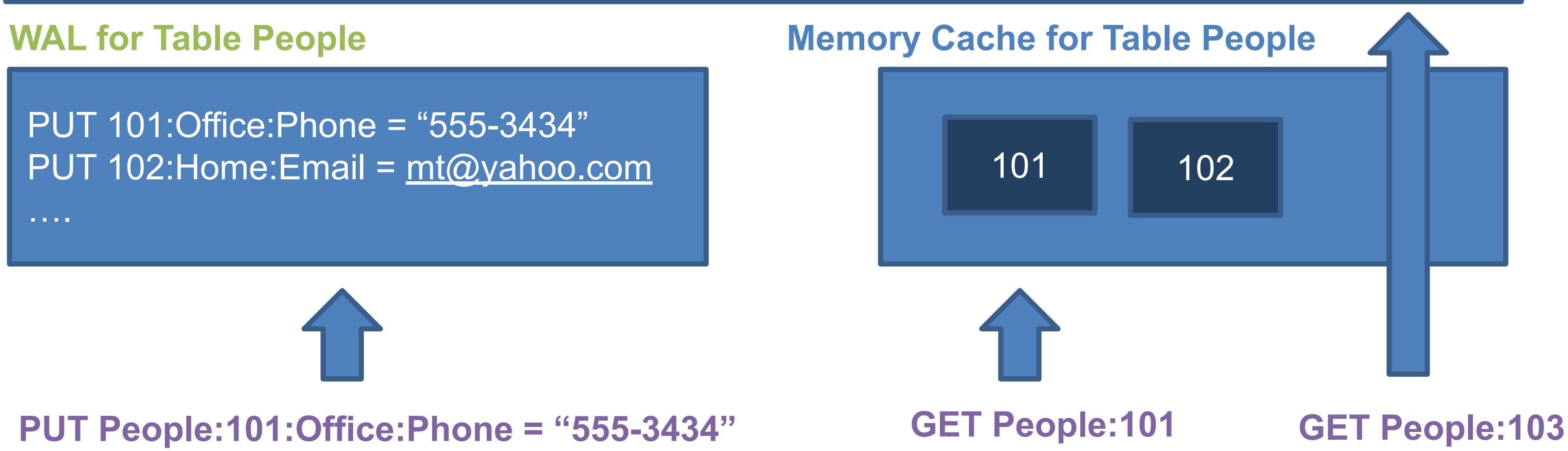
Idea 2: One file + WAL

Table People(Name, Home, Office)

```
101: {
     Timestamp: T403;
     Name: {First="Florian", Middle="Garfield", Last="Krepsbach"},
     Home: {Phone="555-1212", Email="florian@wobegon.org"},
     Office: {Phone="666-1212", Email="fk@phc.com"}
},
102: {
     Timestamp: T593;
     Name: {First="Marilyn", Last="Tollerud"},
     Home: {Phone="555-1213"},
     Office: {Phone="666-1213"}
},
```



- Changes are applied only to the log file
- The resulting record is cached in memory
- Reads must consult both memory and disk

Idea 2 Requires Periodic Table Update

Table for People on Disk (Old)

101: {Timestamp: T403;Name: {First="Florian", Middle="Garfield", Last="Krepsbach"},Home: {Phone="555-1212", Email="florian@wobegon.org"},Office: {Phone="666-1212", Email="fk@phc.com"}},
102: {Timestamp: T593;Name: { First="Marilyn", Last="Tollerud"},Home: { Phone="555-1213" },Office: { Phone="666-1213" }}, . . .

WAL for Table People:

PUT 101:Office:Phone = "555-3434"
PUT 102:Home:Email = mt@yahoo.com
….

- Write out a new copy of the table, with all of the changes applied
- Delete the log and memory cache
- Start over

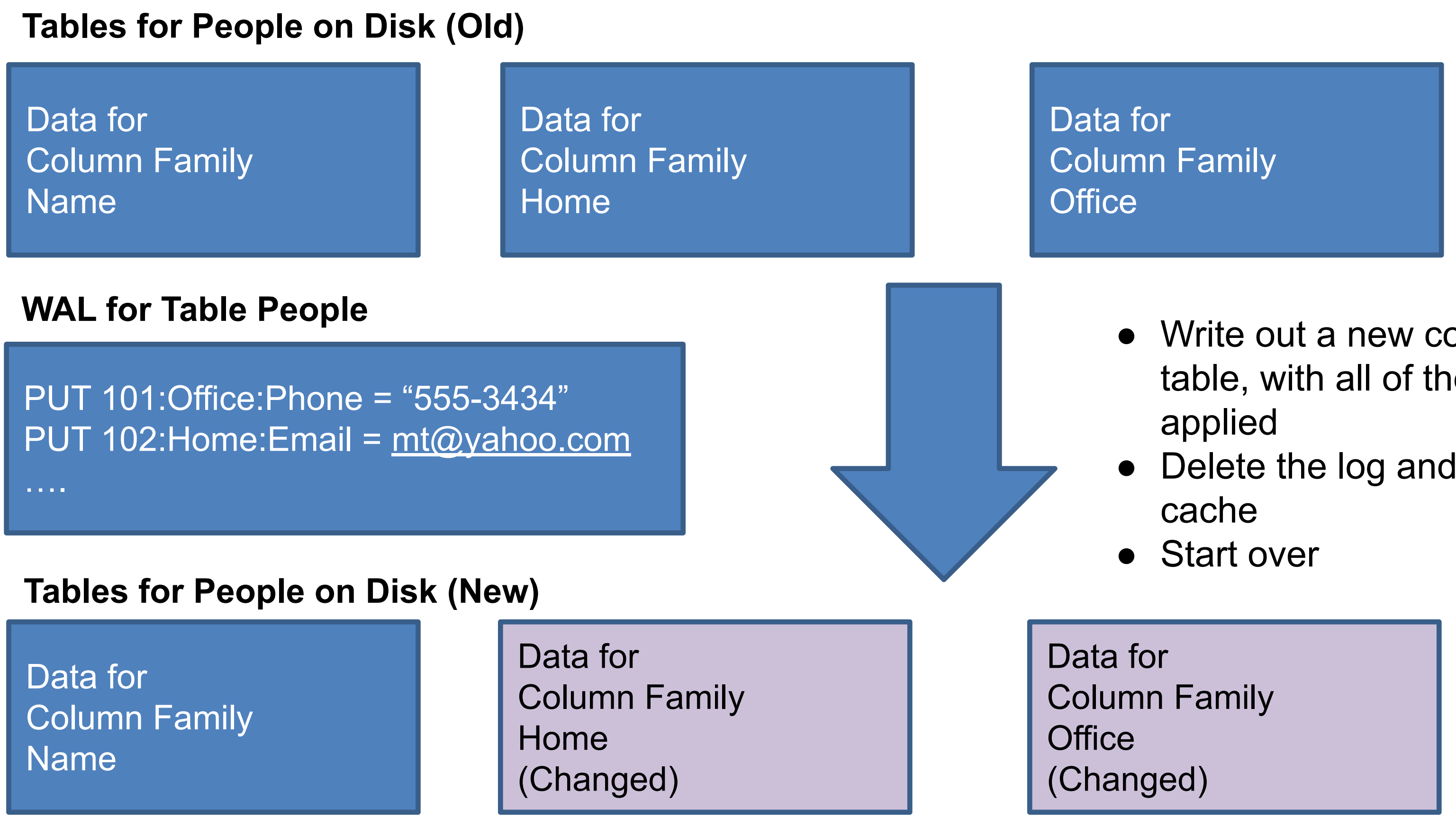
Table for People on Disk (New)

101: {Timestamp: T403;Name: {First="Florian", Middle="Garfield", Last="Krepsbach"},Home: {Phone="555-1212", Email="florian@wobegon.org"},Office: {Phone="**555-3434**", Email="fk@phc.com"}},102: {Timestamp: T593;Name: { First="Marilyn", Last="Tollerud"},Home: { Phone="555-1213", **Email="my@yahoo.com"** }, . . .

- Similar to caching in memory hierarchy

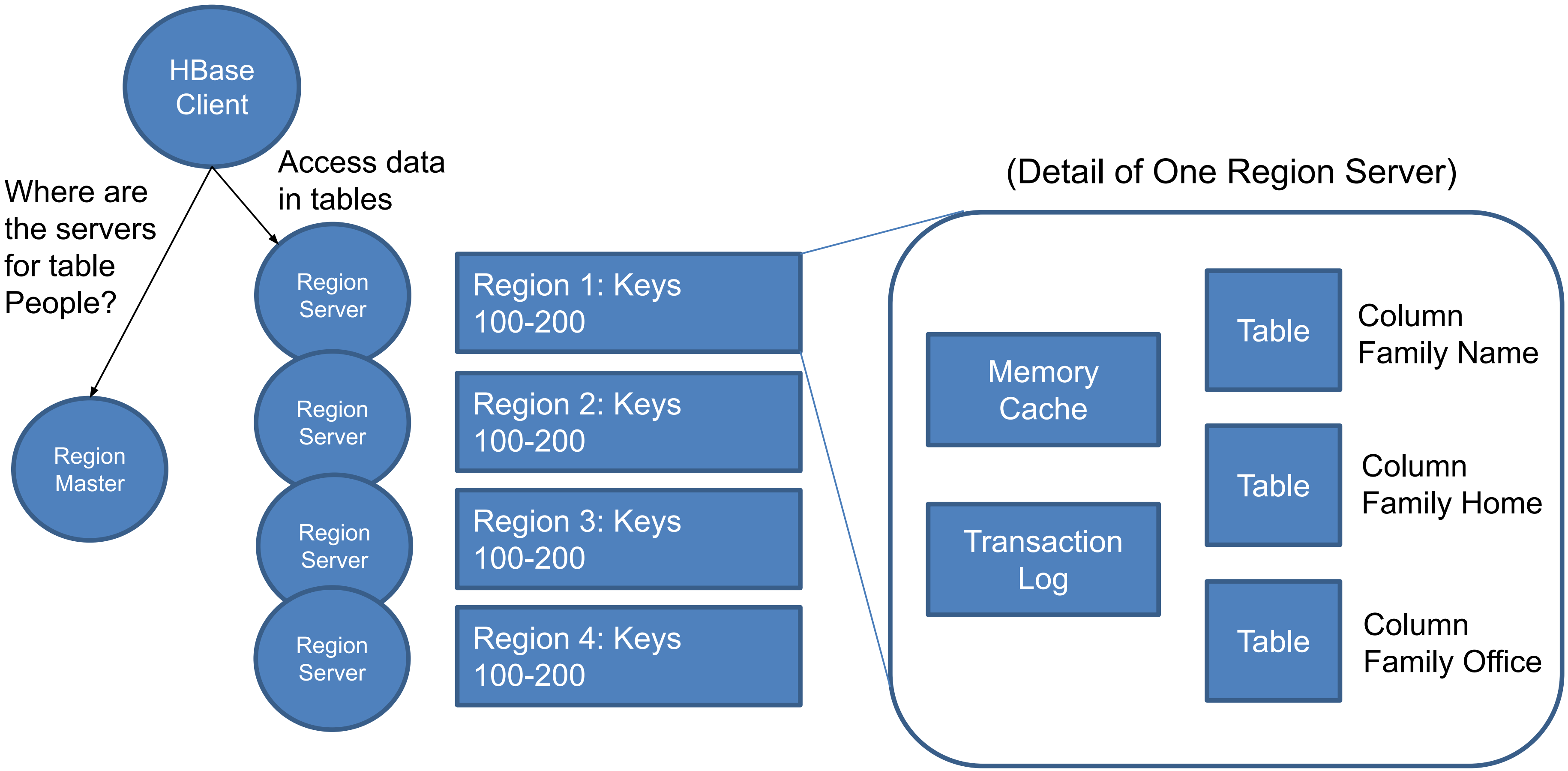
Idea 3: Partition by Column Family

- Same scheme as before but split by column family
- Now it's clear why column family vs columns



- Write out a new copy of the table, with all of the changes applied
- Delete the log and memory cache
- Start over

Idea 4: Split Into Regions



Final HBase Data Layout