# Large-Scale and Multi-Structured Databases Key-value Databases Insights

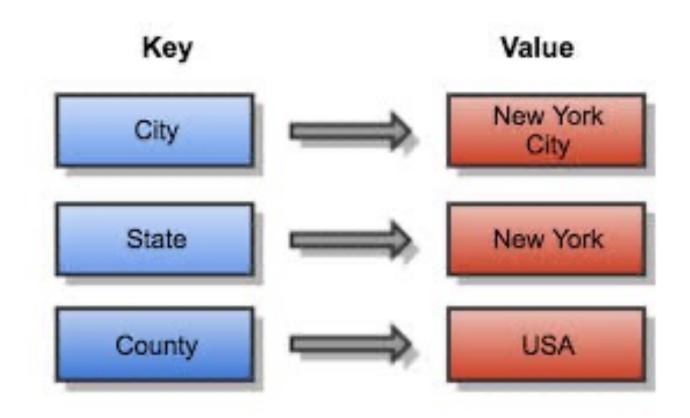
Prof. Pietro Ducange







### **Key-Value Databases**









#### From Key to Values

In general, *values* may be *strings*, *numbers*, *list* or other *complex structures*.

In order to *identify a value* in the database, we actually need the "address" of the specific location in which this value is stored.

Hash functions as usually used to obtain the address, namely a number, from an arbitrary key.

Usually, hash functions returns values that **seem** to be **random** values.

Values returned by hash functions may be not unique (*collision problems*!!)







#### **About Keys**

At a minimum, a key is specified as a *string* of characters

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Strings representing keys should not be *too long*.

Long keys will use more memory and key-value databases tend to be *memory-intensiv*e systems already.

At the same time, avoid keys that are **too short**. Short keys are more likely to lead to **conflicts** in key names







#### **About Values**

A value is an *object*, typically a set of bytes, that has been associated with a key.

Values can be integers, floating-point numbers, strings of characters and even *complex objects* such as picture, video, and JSON files.

Key-value implementations will vary in the *types* of *operations* supported on values.

*Limits* on the dimension of a single value may be fixed by the different *frameworks* for Key-Value databases.







#### Namespace

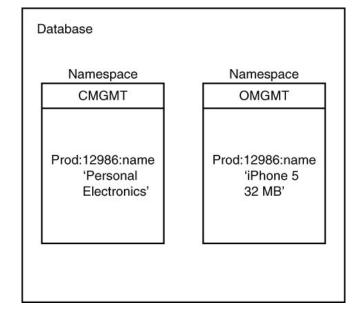
A name space is a *collection* of key-value pairs that has *no duplicate keys*.

It is allowed to have *duplicate values* in a namespace.

Namespaces enable duplicate keys to exist without causing conflicts by maintaining separate collections of keys.

Namespaces are helpful when *multiple* applications use the same key-value database.

Namespaces allows to organize data into *subunits*.

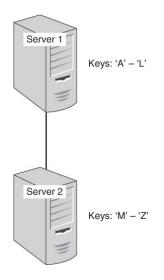


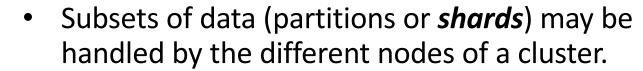




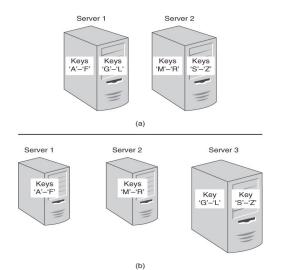


#### **Data Partitioning**





- A cluster may contain more than one partition.
- Several strategies exists for data partitioning.
- The main objective of partitioning data would be to *evenly balance*, both write and read loads, among servers.
- If needed, *additional* nodes would be *easily* added to the cluster and data appropriately *relocated*.









#### **Partition Keys**

- A partition key identifies the specific partition in which the value has been stored.
- Any key in a key-value database is used as a partition key.
- In the previous example, the first letter of a key (string) acts as the value of partition key.
- Usually, hashing functions are adopted for actually identifying the specific cluster or partition.







#### Schema-less

We are **not** required to **define** all the **keys** and **types of values** we will use prior to adding them to the database.

We may decide to *change* how storing the attributes of a specific entity.

Regarding the example in the table, we might decide that storing a customer's full name in a single value is a bad idea, thus we will separate first and last names.

We need to *update* the application *code* to handle both ways of representing customer names or convert all instances of one form into the other.

| Key-Value<br>Database |                 |  |
|-----------------------|-----------------|--|
| Keys Values           |                 |  |
| cust:8983:firstName   | 'Jane'          |  |
| cust:8983:lastName    | 'Anderson'      |  |
| cust:8983:fullName    | 'Jane Anderson' |  |







#### **About Clusters**

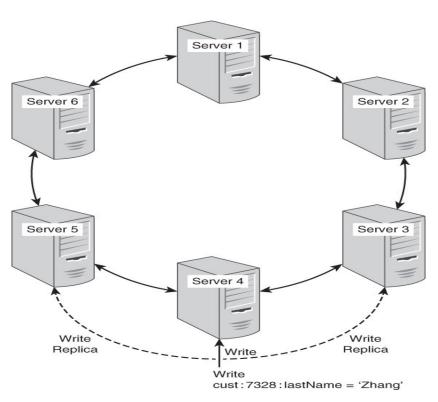
- In Key-Value databases, clusters tend to be *loosely* coupled.
- This means that the server are fairly independent and complete many functions on their own with minimal coordination with other servers in the cluster.
- Each server is *responsible* for the operations on *its own partitions* and routinely *send messages* to each other to indicate they are still functioning.
- When a node fails, the other nodes in the cluster can respond by taking over the work of that node.







# Rings: logical structures for organizing partitions



- Let consider a *hashing function* that generates a number from a key and calculates the modulo.
- Whenever a piece of data is written to a server, it is also written to the two servers linked to the original server (high availability).
- If Server 4 fails, both Server 3 and Server 5 could respond to read/write requests for the data on Server 4.
- When Server 4 is back online, Servers 3 and 5 can update it







#### Replication

**High availability** is ensured by using **replication**, namely saving **multiple copies** of the data in the nodes of a cluster.

The *number* of data *replicas* is often a *parameter* to set.

The *higher* number of *replicas*, the *less* likely we will *loose* data, the *lower* the *performance* of the systems (in terms of response time).

The *lower* the number of *replicas*, the *better* the *performance* of the systems, the *higher* the probability of *loosing data*.

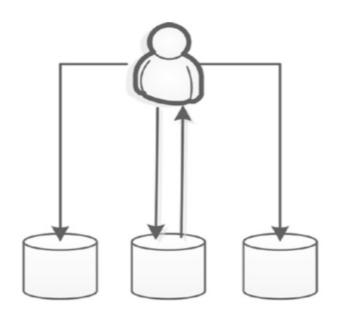
A *low* number of replicas may be used whenever *data* is easily *regenerated* and *reloaded*.



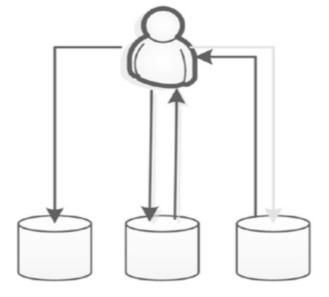




### Write/Read operations with Replicas



N=3 W=3 R=1
Slow writes, fast reads, consistent
There will be 3 copies of the data.
A write request only returns when all 3
have written to disk.
A read request only needs to read one
version.



N=3 W=2 R=2
Faster writes, still consistent (quorum assembly)
There will be 3 copies of the data.
A write request returns when 2 copies

A read request reads 2 copies make sure it has the latest version.

are written - the other can happen

later.

N = # of replicas

W = # of copies to be written before the write can complete

R = # of copies to be read for reading a data record

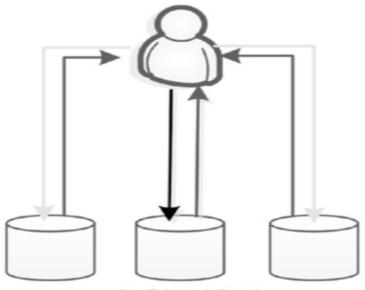
Image extracted from "Guy Harrison, Next Generation Databases, Apress, 2015"







#### Write/Read operations with Replicas



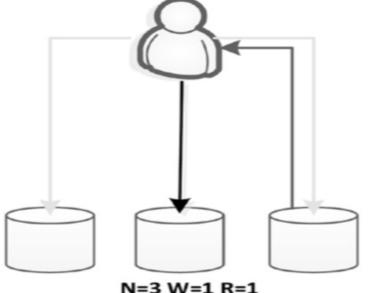
N=3 W=1 R=N
Fastest write, slow but consistent reads

There will be 3 copies of the data.

A write request returns once the first copy is written – the other 2 can happen later.

A read request reads all copies to make sure it gets the latest version.

Data might be lost if a node fails before the second write.



Fast, but not consistent

There will be 3 copies of the data.

A write request returns once the first copy is written – the other 2 can happen later.

A read request reads a single version only: it might not get the latest copy. Data might be lost if a node fails before the second write.

Image extracted from "Guy Harrison, Next Generation Databases, Apress, 2015"







## Hash Mapping

| Key                                  | Hash Value                               |  |  |
|--------------------------------------|--|--|--|
| customer:1982737:<br>firstName       | e135e850b892348a4e516cfcb385eba3bfb6d209 |  |  |
| customer:1982737:<br>lastName        | f584667c5938571996379f256b8c82d2f5e0f62f |  |  |
| customer:1982737:<br>shippingAddress | d891f26dcdb3136ea76092b1a70bc324c424ae1e |  |  |
| customer:1982737:<br>shippingCity    | 33522192da50ea66bfc05b74d1315778b6369ec5 |  |  |
| customer:1982737:<br>shippingState   | 239ba0b4c437368ef2b16ecf58c62b5e6409722f |  |  |
| customer:1982737:<br>shippingZip     | 814f3b2281e49941e1e7a03b223da28a8e0762ff |  |  |

In the example above, the Hash Value is a number in hexadecimal format.







#### Hash Function Properties

One of the important characteristics of hash algorithms is that *even small changes* in the input can lead to *large changes* in the output.

Hash functions are generally designed to *distribute* inputs *evenly* over the set of all possible outputs. The output space can be quite large

This is especially useful when *hashing keys*.

**No matter how similar** your keys are, they are evenly distributed across the range of possible output values.







## Hash Function: An Example of Load Distribution

Assume we have a cluster of **16** nodes and each node is responsible for one partition.

The key 'cust:8983:firstName' has a hash value of

4b2cf78c7ed41fe19625d5f4e5e3eab20b064c24

and would be assigned to partition 4.

The key 'cust:8983:lastName' has a hash value of

c0017bec2624f736b774efdc61c97f79446fc74f

would be assigned to node 12 (c is the hexadecimal digit for the base-10 number 12).



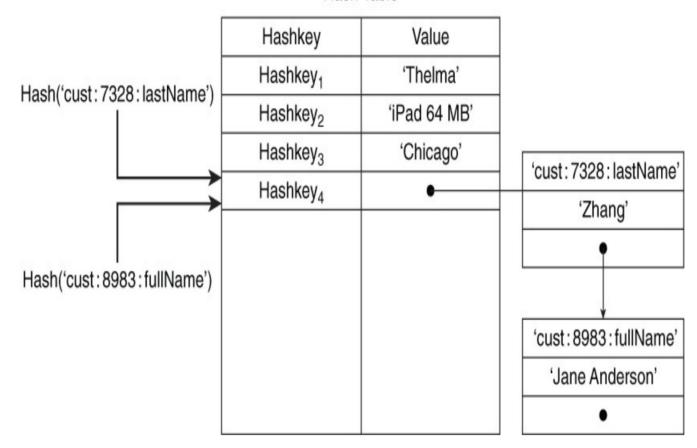




#### **Collision Resolution Strategy**

From a logical point of view, the table that projects a hashed key to the corresponding value may include a list of values. In each block of the list, also the original key must be present.

Hash Table









#### Consistent Hashing (I)

*Use Case*: adding or removing a node, even for a short time period.

**Problem:** we need to change the *hashing function* and to re-locate all the data among the servers of the cluster.

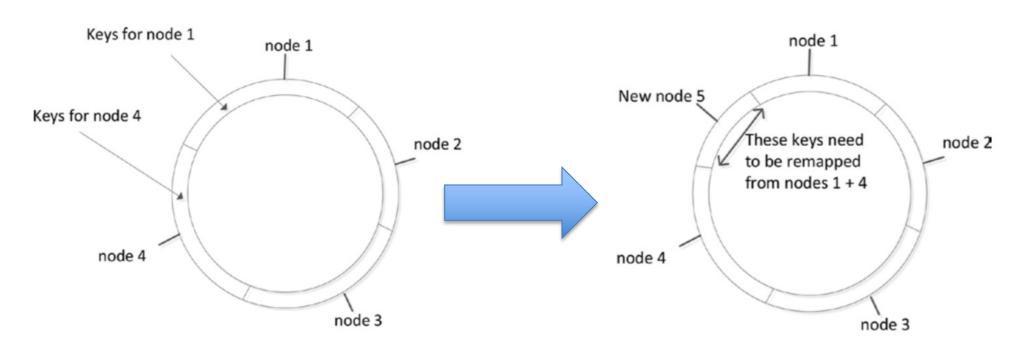
**Solution:** to exploit the ring structure and a consistent **hashing function** that allows us to remap only the keys mapped to the neighbors of the new node.







#### Consistent Hashing (II)



Split of keys in 4-node cluster

Adding a new node to the cluster

#### Consistent hashing ensures a good load balance among servers



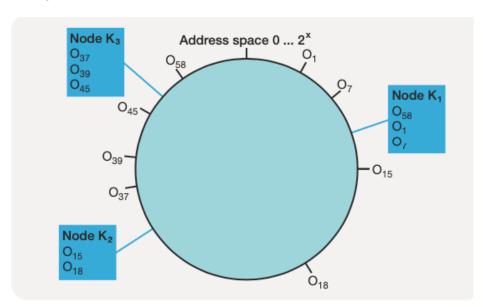


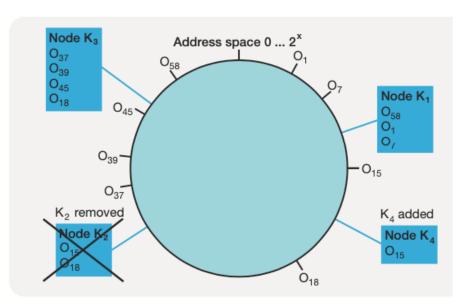


#### Consistent Hashing (III)

The same *hashing* function is applied to both the *keys* and the *server/partition ID/Address/Name*.

The hash values must be in the *same range*, for example hexadecimal on 32 bit representation





The actual server (Node)  $k_j$  associated to a specific key (object)  $o_i$  is its **successor** in the hashing/address space.

Images extracted from "Andreas Meier, Michael Kaufmann , SQL & NoSQL databases : models, languages, consistency options and architectures for big data management, 2019"





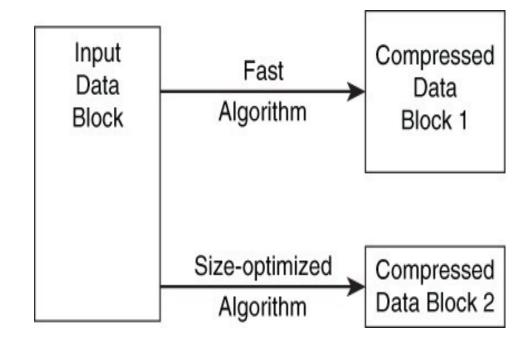
#### Data Compression for KV Databases

Key-value databases are *memory intensive*.

Operating systems can exploit *virtual memory* management, but that entails writing data to disk or flash storage.

Reading from and writing to *disk* is significantly *slower* than reading from RAM memory.

One way to optimize memory and persistent storage is to use data *compression techniques*.



Look for compression algorithms that ensure a *trade-off* between the *speed* of compression/decompression and the *size* of the compressed data.







#### Using Key-Value Databases

If *data organization* and *management* is more important than the performances, classical relational databases are more suitable rather than key-value databases.

However, if we are more interested to the *performances* (high availability, short response time, etc.) and/or the data model is not *too much complicated* (no hierarchical organization, limited number of relationships) we may use key-values databases.

Indeed, key-value stores are really *simple* and *easy* to handle, data can be modeled in a less complicated manner than in RDBMS







#### From RBDMS to Key-Value Store (I)

Let consider the following data structures:

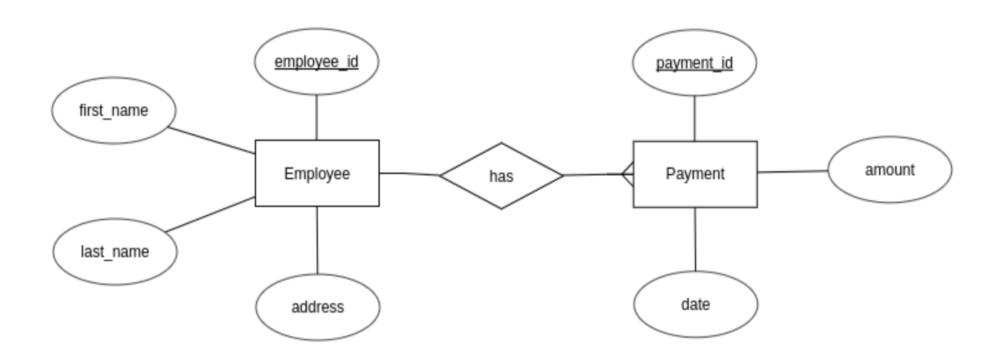


Image extracted from: https://medium.com/@wishmithasmendis/from-rdbms-to-key-value-store-data-modeling-techniques-a2874906bc46







#### From RBDMS to Key-Value Store (II)

In a relational model we can define the following tables. The one-to-many relationship is handled by using a *foreign key*.

| employee_id | first_name | last_name | address  |
|-------------|------------|-----------|----------|
| 1           | John       | Doe       | New York |
| 2           | Benjamin   | Button    | Chicago  |
| 3           | Mycroft    | Holmes    | London   |

#### FOREIGN KEY

| payment_id | employee_id | amount | date       |
|------------|-------------|--------|------------|
| 1          | 1           | 50,000 | 01/12/2017 |
| 2          | 1           | 20,000 | 01/13/2017 |
| 3          | 2           | 75,000 | 01/14/2017 |
| 4          | 3           | 40,000 | 01/15/2017 |
| 5          | 3           | 20,000 | 01/17/2017 |
| 6          | 3           | 25,000 | 01/18/2017 |

Image extracted from: https://medium.com/@wishmithasmendis/from-rdbms-to-key-value-store-data-modeling-techniques-a2874906bc46







#### From RBDMS to Key-Value Store (II)

Now, we want to *translate* the data modelling from a relational model to a key-value model.

Take in mind that keys *embed* information regarding *Entity Name*, *Entity Identifie*r and *Entity Attributes*.

Thus, we can translate the *Employees table* as follows:

| employee_id | first_name | last_name | address  |
|-------------|------------|-----------|----------|
| 1           | John       | Doe       | New York |
| 2           | Benjamin   | Button    | Chicago  |
| 3           | Mycroft    | Holmes    | London   |



```
employee:$employee_id:$attribute_name = $value

employee:1:first_name = "John"
  employee:1:last_name = "Doe"
  employee:1:address = "New York"

employee:2:first_name = "Benjamin"
  employee:2:last_name = "Button"
  employee:2:address = "Chicago"

employee:3:first_name = "Mycroft"
  employee:3:last_name = "Holmes"
  employee:3:address = "London"
```







#### From RBDMS to Key-Value Store (III)

As further step, we have to translate the *Payment table* and to manage the one-to-many relationship.

In this case, we can define the following key-value configuration:

payment:\$payment\_id:\$employee\_id:\$attribute\_name = \$value

The Payment table con be translated as follows:

| payment_id | employee_id | amount | date       |
|------------|-------------|--------|------------|
| 1          | 1           | 50,000 | 01/12/2017 |
| 2          | 1           | 20,000 | 01/13/2017 |
| 3          | 2           | 75,000 | 01/14/2017 |
| 4          | 3           | 40,000 | 01/15/2017 |
| 5          | 3           | 20,000 | 01/17/2017 |
| 6          | 3           | 25,000 | 01/18/2017 |











#### From RBDMS to Key-Value Store (IV)

At the end of the translation process, data will be organized in a *unique* bucket as follows:

```
employee:1:first name = "John"
employee:1:last name = "Doe"
employee:1:address = "New York"
employee:2:first_name = "Benjamin"
employee:2:last_name = "Button"
employee:2:address = "Chicago"
employee:3:first_name = "Mycroft"
employee:3:last_name = "Holmes"
employee:3:address = "London"
payment:1:1:amount = "50000"
payment:1:1:date = "01/12/2017"
payment:2:1:amount = "20000"
payment:2:1:date = "01/13/2017"
payment:3:2:amount = "75000"
payment:3:2:date = "01/14/2017"
payment:4:3:amount = "40000"
payment:4:3:date = "01/15/2017"
payment:5:3:amount = "20000"
payment:5:3:date = "01/17/2017"
payment:6:3:amount = "25000"
payment:6:3:date = "01/18/2017"
```

Image extracted from: https://medium.com/@wishmithasmendis/from-rdbms-to-key-value-store-data-modeling-techniques-a2874906bc46







#### Suggested Readings

Chapter 4 of the book "Dan Sullivan, NoSQL For Mere Mortals, Addison-Wesley, 2015"

Chapter 3 of the book "Guy Harrison, Next Generation Databases, Apress, 2015"

Chapter 5.2.2 of the book "Andreas Meier, Michael Kaufmann, SQL & NoSQL databases: models, languages, consistency options and architectures for big data management, 2019"

Web pages accessible with the links spread along the slides.







#### **Images**

If not specified, the images shown in this lecture have been extracted from:

"Dan Sullivan, NoSQL For Mere Mortals, Addison-Wesley, 2015"





