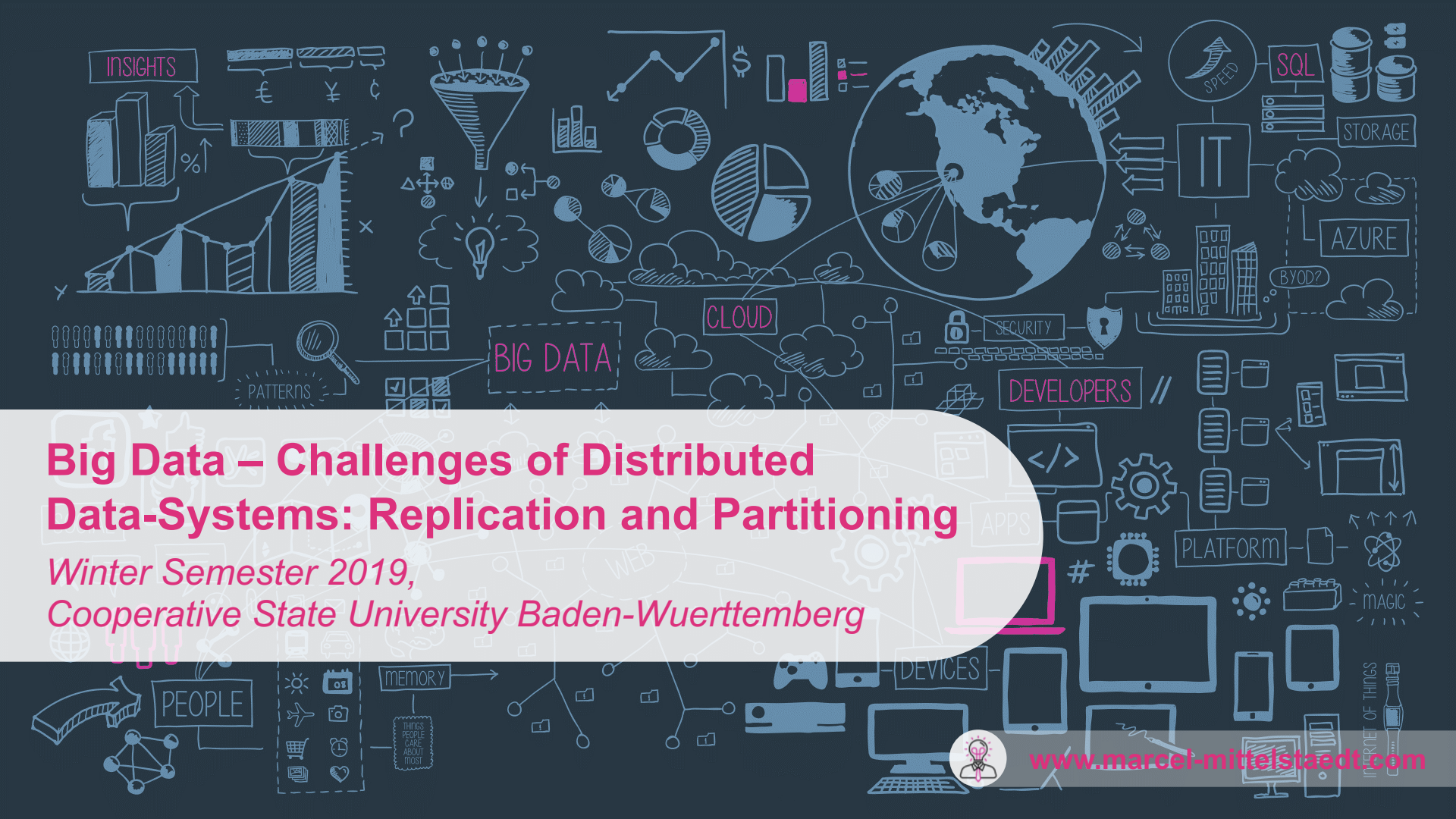

Big Data – Challenges of Distributed Data-Systems: Replication and Partitioning

Winter Semester 2019,
Cooperative State University Baden-Wuerttemberg

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Agenda – 28.10.2019

01

Presentation and Discussion: Exercise Of Last Lecture

HiveQL, HDFS/Hive Partitioning, HiveServer2

02

Introduction To The Challenges Of Distributed Data-Systems: Replication

Basics of Replication, Master-based, Multi-Master-based and Masterless replication, Consistency Issues and Quorums

03

Introduction To The Challenges Of Distributed Data-Systems: Partitioning

Basics of Partitioning, Key-Range and Hash Partitioning, Partitioning of Secondary Indices, Rebalancing and Lookup of Partitions

04

HandsOn – Spark, PySpark and Jupyter. Working on IMDb Dataset.

Quick Introduction To Apache Spark, especially Spark-Shell, PySpark Shell and Jupyter Notebooks. Use PySpark Shell and/or Jupyter to solve certain problems.

Schedule

	Lecture Topic	*HandsOn*
14.10.2019 13:15-18:00 Ro. 1.18	About This Lecture, Introduction to Big Data, Setup Cloud Environment (Google Cloud)	HandsOn Hadoop, Hive and Hive-QL
21.10.2019 13:15-18:00 Ro. 1.18	(Non-)Functional Requirements Of Distributed Data-Systems, Data Models and Access	Partitioning with HDFS/Hive, HiveServer2
28.10.2019 13:15-18:00 Ro. 1.18	**Challenges Of Distributed Data Systems: Replication and Partitioning**	Spark, Scala and PySpark/Jupyter
04.11.2019 13:15-18:00 Ro. 1.18	ETL Workflow and Automation, Batch Processing	Pentaho Data Integration & Airflow
11.11.2019 13:15-18:00 Ro. 1.18	Practical Exam	Work On Practical Exam
18.11.2019 13:15-18:00 Ro. 1.18	Practical Exam Presentation	

Solution – Exercise IV

HiveQL, HDFS/Hive Partitioning, HiveServer2

Solution

Prerequisites:

- Start Gcloud instance
- Pull and start Docker image (`marcelmittelstaedt/hiveserver_base:latest`)
- Start Hadoop Cluster
- Start HiveServer2
- Download, Install and Configure JDBC Rich-client:
    - e.g. DBeaver,
    - SquirrelSQL,
    - …
- Execute all preparation and example tasks of previous HandsOn slides of last lecture

Solution

Exercise IV:

2.1 Create table `name_basics_partitioned` partitioned by column `partition_is_alive`:

```
CREATE EXTERNAL TABLE IF NOT EXISTS name_basics_partitioned (
          nconst STRING,
          primary_name STRING,
          birth_year INT,
          death_year STRING,
          primary_profession STRING,
          known_for_titles STRING
) PARTITIONED BY (partition_is_alive STRING)
STORED AS ORCFILE LOCATION '/user/hadoop/imdb/actors_partitioned';
```


Solution

Exercise IV:

2.2 Use static partitioning to create and fill partition ‘alive‘

```
INSERT OVERWRITE TABLE name_basics_partitioned
partition(partition_is_alive='alive')
SELECT
          a.nconst,
          a.primary_name,
          a.birth_year,
          a.death_year,
          a.primary_profession,
          a.known_for_titles
FROM name_basics a WHERE a.death_year IS NULL
```


Solution

Exercise IV:

2.3 Use static partitioning to create and fill partition ‘dead‘

```
INSERT OVERWRITE TABLE name_basics_partitioned
partition(partition_is_alive='dead')
SELECT
          a.nconst,
          a.primary_name,
          a.birth_year,
          a.death_year,
          a.primary_profession,
          a.known_for_titles
FROM name_basics a WHERE a.death_year IS NOT NULL
```


Solution

Exercise IV:

2.4 Check Results:

```
hadoop fs -ls /user/hadoop/imdb/actors_partitioned
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:18 /user/hadoop/imdb/actors_partitioned/partition_is_alive=alive
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:18 /user/hadoop/imdb/actors_partitioned/partition_is_alive=dead
```


Solution

Exercise IV:

2.4 Check Results:

```
SELECT * FROM name_basics_partitioned WHERE partition_is_alive = 'dead' LIMIT 100
```

Result

SELECT * FROM name_basics_partitioned WHERE p | *Geben Sie einen SQL-Ausdruck ein, um die Ergebnisse zu filtern (verwenden Sie Strg+ Leertaste).*

	nconst	primary_name	birth_year	death_year	primary_profession	known_for_titles	partition_is_alive
1	nm0000001	Fred Astaire	1.899	1987	soundtrack,actor,miscellaneous	tt0072308,tt0043044,tt0050419,tt0053137	dead
2	nm0000002	Lauren Bacall	1.924	2014	actress,soundtrack	tt0117057,tt0037382,tt0038355,tt0071877	dead
3	nm0000004	John Belushi	1.949	1982	actor,writer,soundtrack	tt0072562,tt0077975,tt0078723,tt0080455	dead
4	nm0000005	Ingmar Bergman	1.918	2007	writer,director,actor	tt0083922,tt0050986,tt0050976,tt0069467	dead
5	nm0000006	Ingrid Bergman	1.915	1982	actress,soundtrack,producer	tt0036855,tt0071877,tt0038787,tt0038109	dead
6	nm0000007	Humphrey Bogart	1.899	1957	actor,soundtrack,producer	tt0033870,tt0037382,tt0034583,tt0043265	dead
7	nm0000008	Marlon Brando	1.924	2004	actor,soundtrack,director	tt0047296,tt0068646,tt0070849,tt0078788	dead
8	nm0000009	Richard Burton	1.925	1984	actor,producer,soundtrack	tt0087803,tt0057877,tt0059749,tt0061184	dead
9	nm0000010	James Cagney	1.899	1986	actor,soundtrack,director	tt0031867,tt0035575,tt0029870,tt0042041	dead
10	nm0000011	Gary Cooper	1.901	1961	actor,soundtrack,producer	tt0035896,tt0034167,tt0044706,tt0027996	dead
11	nm0000012	Bette Davis	1.908	1989	actress,soundtrack,make_up_department	tt0056687,tt0035140,tt0031210,tt0042192	dead

Solution

Exercise IV:

3.1 Create table `imdb_movies_and_ratings_partitioned` partitioned by column `partition_year` using fields of table `title_basics` and `title_ratings`:

```
CREATE TABLE IF NOT EXISTS imdb_movies_and_ratings_partitioned (
            tconst STRING,
            title_type STRING,
            primary_title STRING,
            original_title STRING,
            is_adult DECIMAL(1,0),
            start_year DECIMAL(4,0),
            end_year STRING,
            runtime_minutes INT,
            genres STRING,
            average_rating DECIMAL(2,1),
            num_votes BIGINT
) PARTITIONED BY (partition_year int) STORED AS ORCFILE LOCATION '/user/hadoop/imdb/
movies_and_ratings_partitioned';
```

Solution

Exercise IV:

3.2 Use dynamic partitioning to create and fill partition `partition_year`:

```
SET hive.exec.dynamic.partition.mode=nonstrict;
INSERT OVERWRITE TABLE imdb_movies_and_ratings_partitioned partition(partition_year)
SELECT
            tb.tconst,
            tb.title_type,
            tb.primary_title,
            tb.original_title,
            tb.is_adult,
            tb.start_year,
            tb.end_year,
            tb.runtime_minutes,
            tb.genres,
            tr.average_rating,
            tr.num_votes,
            tb.start_year
FROM title_basics tb JOIN title_ratings tr ON (tb.tconst = tr.tconst)
```


Solution

Exercise IV:

3.3 Check Results:

```
hadoop fs -ls /user/hadoop/imdb/movies_and_ratings_partitioned

[…]
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1874
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1878
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1881
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1883
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1885
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1887
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1888
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1889
drwxr-xr-x   - hadoop supergroup          0 2019-10-20 18:27 /user/hadoop/imdb/movies_and_ratings_partitioned/partition_year=1890
[…]
```

Solution

Exercise IV:

3.3 Check Results:

```
select * from imdb_movies_and_ratings_partitioned where partition_year = 2019 LIMIT 100
```

Result

select * from imdb_movies_and_ratings_partitioned | *Geben Sie einen SQL-Ausdruck ein, um die Ergebnisse zu filtern (verwenden Sie Strg+ Leertaste).*

	tconst	title_type	primary_title	original_title	is_adult	start_year	en	runtime_minutes	genres	average_rating	num_votes	partition_year
1	tt0091490	short	Martina's Playhouse	Martina's Playhouse	0	2.019	[NULL]	20	Drama,Short	5,8	27	2.019
2	tt0172112	short	Ambulans	Ambulans	0	2.019	[NULL]	11	Short	7,6	41	2.019
3	tt0172817	tvShort	Monolog trebacza	Monolog trebacza	0	2.019	[NULL]	22	Short	7,2	11	2.019
4	tt0255841	short	Bird in a Window	Bird in a Window	0	2.019	[NULL]	10	Animation,Short	7,4	23	2.019
5	tt0269235	short	Flying Nansen	Flying Nansen	0	2.019	[NULL]	11	Animation,Short	7,9	21	2.019
6	tt0302617	tvMovie	Great Bear Rainforest	Great Bear Rainforest	0	2.019	[NULL]	[NULL]	Documentary	8,2	25	2.019
7	tt0345776	tvMovie	The Patchwork Girl of Oz	The Patchwork Girl of Oz	0	2.019	[NULL]	[NULL]	Adventure,Animatior	4,8	15	2.019
8	tt0385887	movie	Motherless Brooklyn	Motherless Brooklyn	0	2.019	[NULL]	144	Crime,Drama	7,8	1.135	2.019
9	tt0437086	movie	Alita: Battle Angel	Alita: Battle Angel	0	2.019	[NULL]	122	Action,Adventure,Sc	7,4	165.972	2.019
10	tt0441881	movie	Danger Close	Danger Close: The Battle of Long	0	2.019	[NULL]	118	Action,Drama,War	8,0	882	2.019
11	tt0446792	movie	Surviving in L.A.	Surviving in L.A.	0	2.019	[NULL]	[NULL]	Comedy,Drama,Rom	8,1	13	2.019
12	tt0448115	movie	Shazam!	Shazam!	0	2.019	[NULL]	132	Action,Adventure,Co	7,1	185.949	2.019
13	tt0489974	tvSeries	Carnival Row	Carnival Row	0	2.019	[NULL]	[NULL]	Crime,Drama,Fantas	8,0	22.760	2.019
14	tt0800325	movie	The Dirt	The Dirt	0	2.019	[NULL]	107	Biography,Comedy,D	7,0	31.148	2.019
15	tt0810836	movie	Dirt Music	Dirt Music	0	2.019	[NULL]	105	Crime,Drama,Roman	7,1	28	2.019

Introduction To The Challenges Of Distributed Data-Systems: Replication

Basics of Replication, Master-based, Multi-Master-based and Masterless replication, Consistency Issues and Quorums

Why Replication (and Partitioning)?

Availability and Redundancy: Even if some parts or nodes fail the whole data-system is able to continue working, as it can make of another replica.

Scalability and Performance: Using multiple replicas, for instance increases read performance and throughput as read queries can be distributed to any node of a replica set or even be handled concurrently by multiple nodes of the same replica set.

Reliability: Using multiple replicas stored in different data centers and locations, the data-system even continues to run during a catastrophe like an earthquake, typhoon or just a construction worker, having a bad day and cutting of the power link of one of your data-centers.

Low Latency: Keeping replicas of a data-system geographically close to users or consuming applications reduces latency (e.g. in case of a multi- national webshop, having a replica in every country).

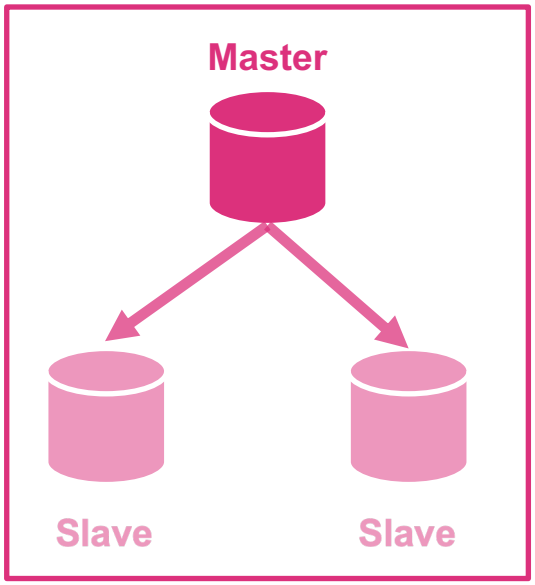
Replication vs Partitioning

	Replication	Partitioning
stores:	**copies** of the **same data** on **multiple nodes**	**subsets** (*partitions*) on **multiple nodes**
introduces:	**redundancy**	**distribution**
scalability:	**parallel IO**	**memory consumption**, certain parallel IO
availability:	**nodes** can **take** load of **failed nodes**	node **failures affect only parts** of the data

Different purposes, but usually used together

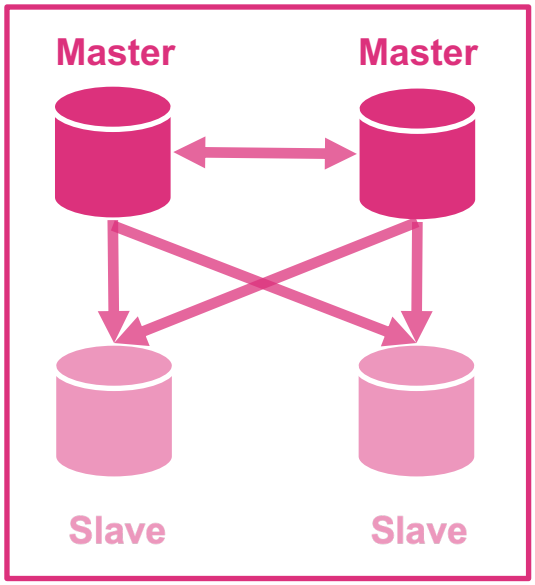
Approaches For Replication

Master-based



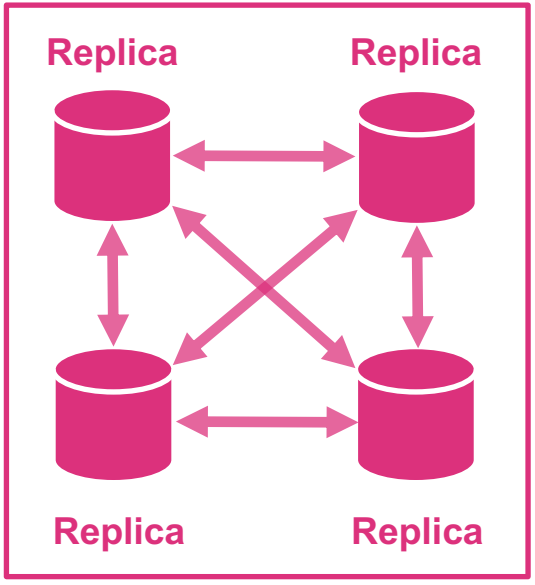
e.g. **Oracle, PostgreSQL, MySQL…**

Multi-Master-based



e.g. **CouchDB, PostgreSQL, MySQL…**

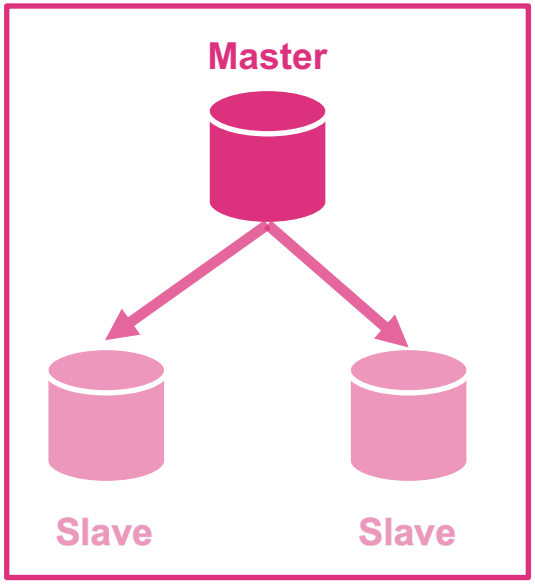
Masterless



e.g. **Cassandra, Riak, Vol demortDB, DynamoDB…**

Master Replication

Master-based



e.g. **Oracle, PostgreSQL, MySQL…**

Multi-Master-based

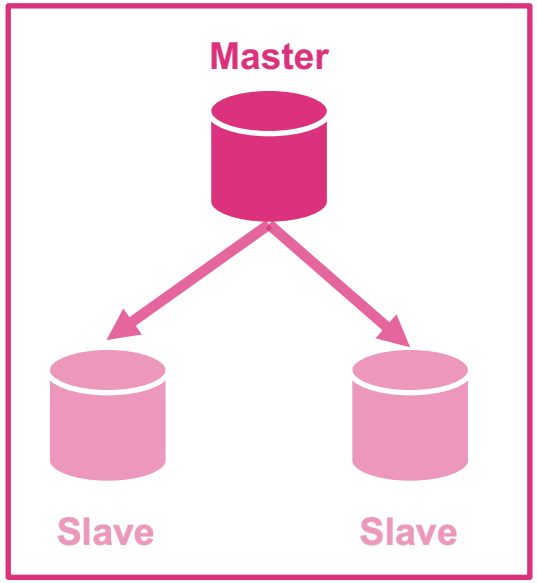
e.g. **CouchDB, PostgreSQL, MySQL…**

Masterless

e.g. **Cassandra, Riak, Vol demortDB, DynamoDB…**

Master Replication

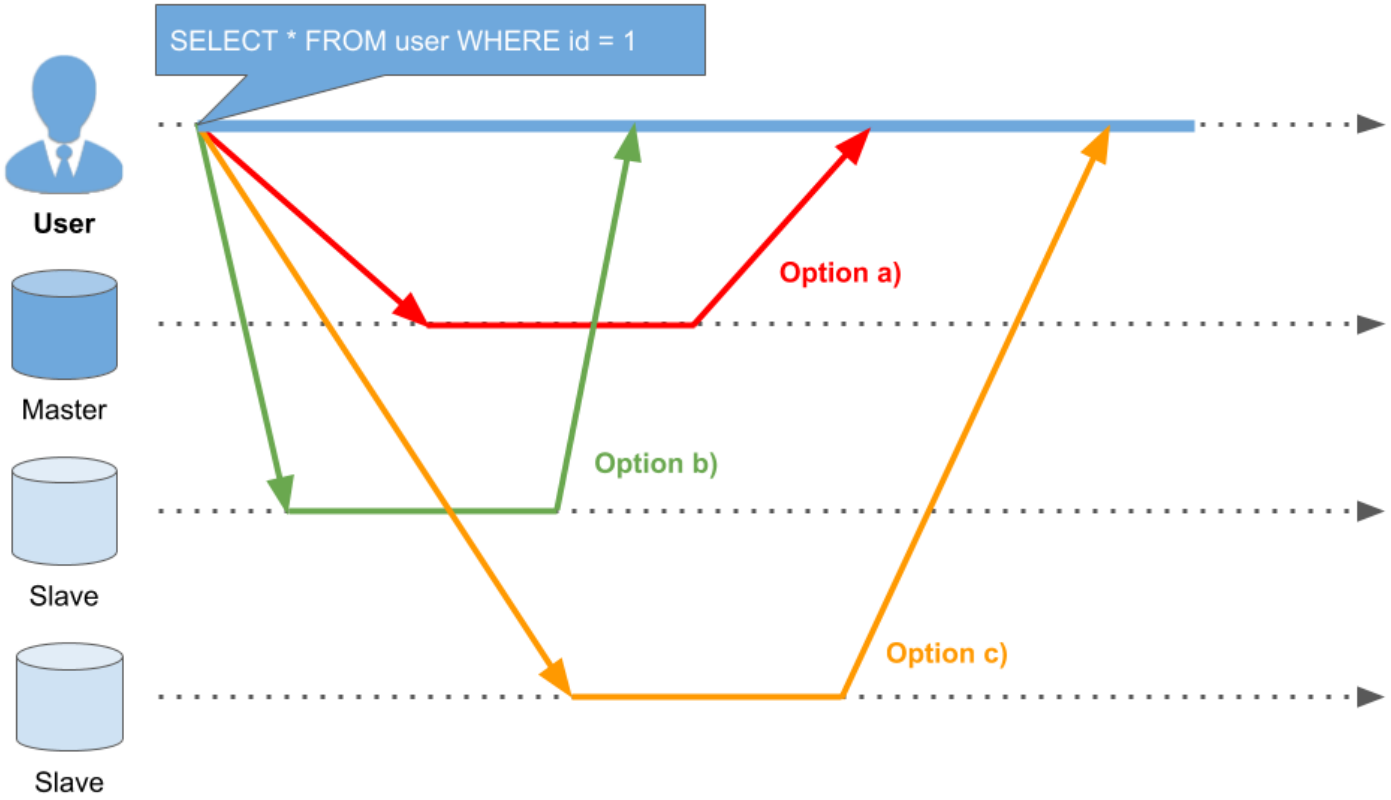
Also known as: *Primary/Secondary, Master/Slave or Single-Leader Replication*



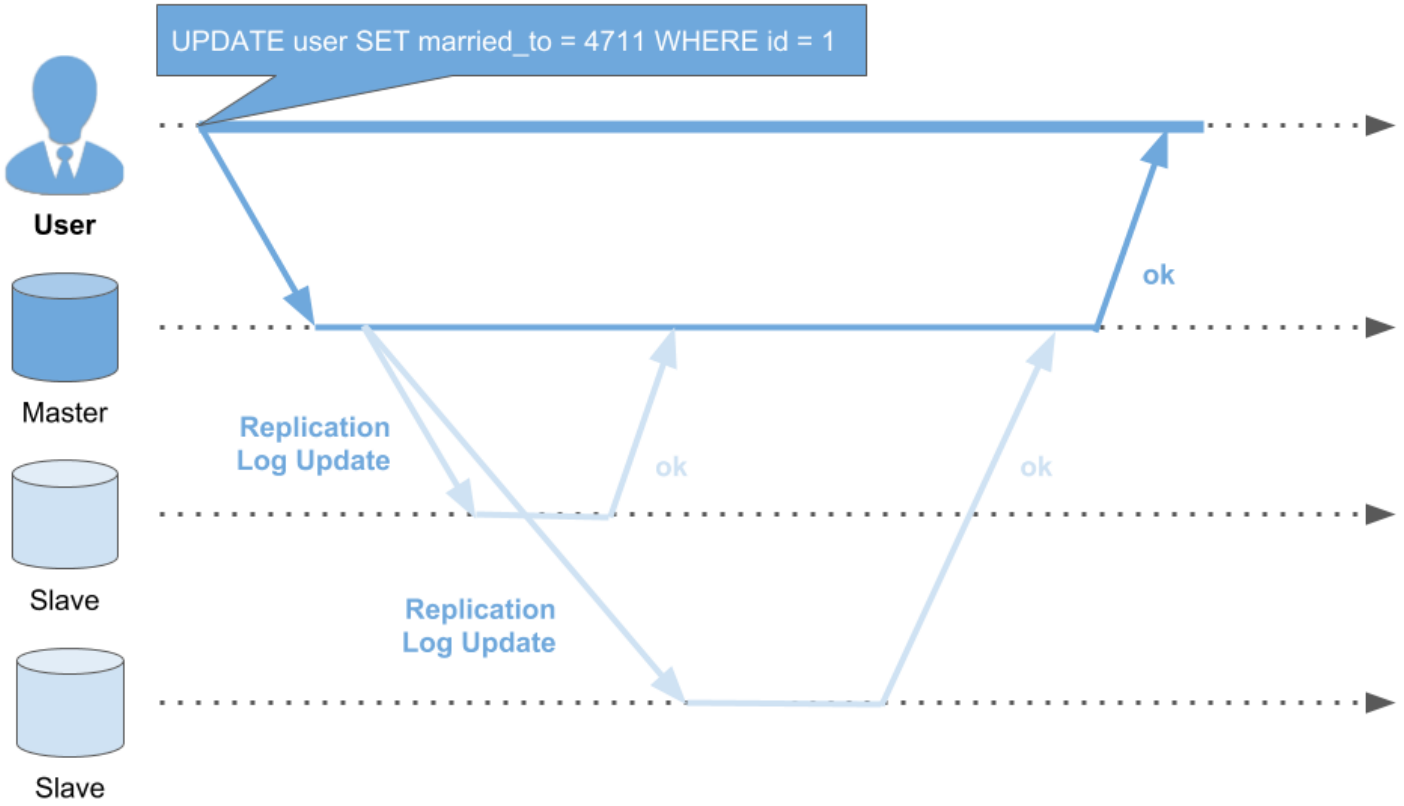
Master: (also known as *leader* or *primary*) dedicated processing node, usually also a replica and also known as primary or leader. The master node serves read as well as write queries, is responsible for persisting changes locally and propagates changes (e.g. by using replication logs or change streams) to slave nodes.

Slave: (also known as *secondary*, *follower* or *hot-standby*) are d edicated for serving read queries only. They receive changes from the master node and update their local replica accordingly to and in the same order as the replication log provided by the master.

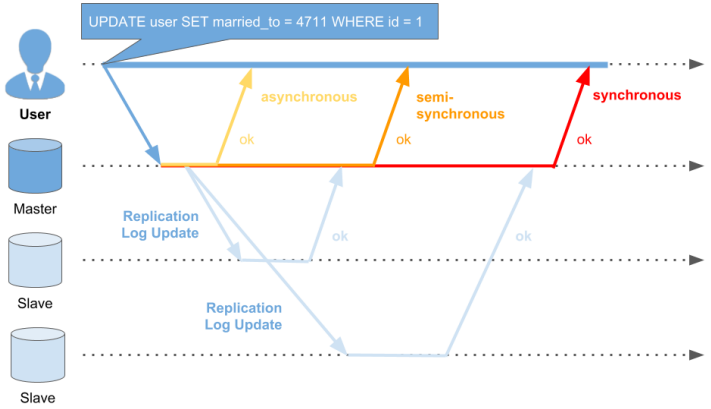
Master Replication - **Read**



Master Replication - **Write**



Master Replication – Write Synchrony



1. Synchronous:

- master waits for **all slaves** to succeed before reporting success to the user

→ all *slaves* have up-to-date copy of *master*
→ any *slave* can take over, if *master* crashes
→ Latency (like network) will directly effect write performance of the data-system, as the master waits for all slaves
- even if everything is running fine, it's slow, as slaves add additonal processing time to write queries

2. Semi-Synchronous:

- the **master waits** for **one slave** to report success before reporting success to the user

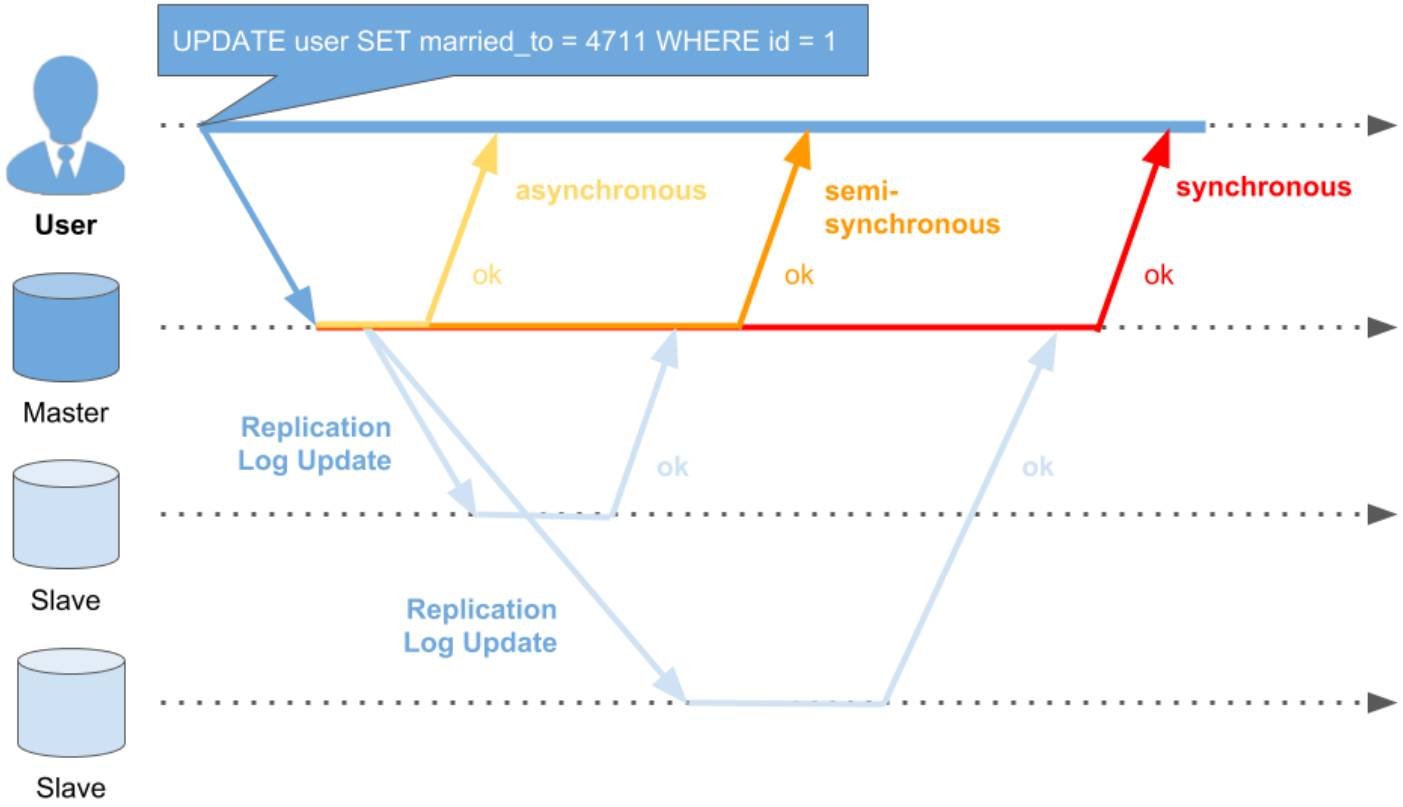
→ one slave runs synchronous to master, all other slaves asynchronous
→ If synchronous slave gets slow or crashes, another slave becomes synchronous
→ it is guaranteed, that at least two nodes store a replica which is up-to-date

3. Asynchronous:

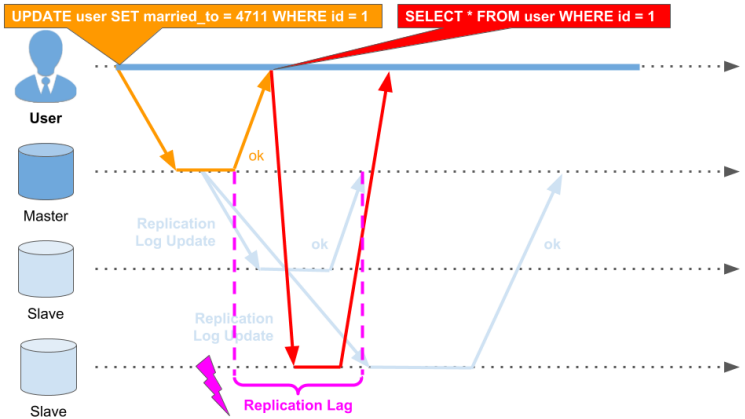
- the **master does not wait for any slaves** to report success, before reporting success to a user

→ not guaranteed to ensure durability
→ If the master crashs and cannot be re- covered, any write requests processed but not replicated to slaves, are lost
→ write-performance is incredibly fast

Master Replication - Synchrony



Master Replication – Replication Lag



Asynchronous and **semi-synchronous replication** are great for scalability of read-intensive data-systems/applications

→ Distribute and scale read requests by „just“ adding more slaves

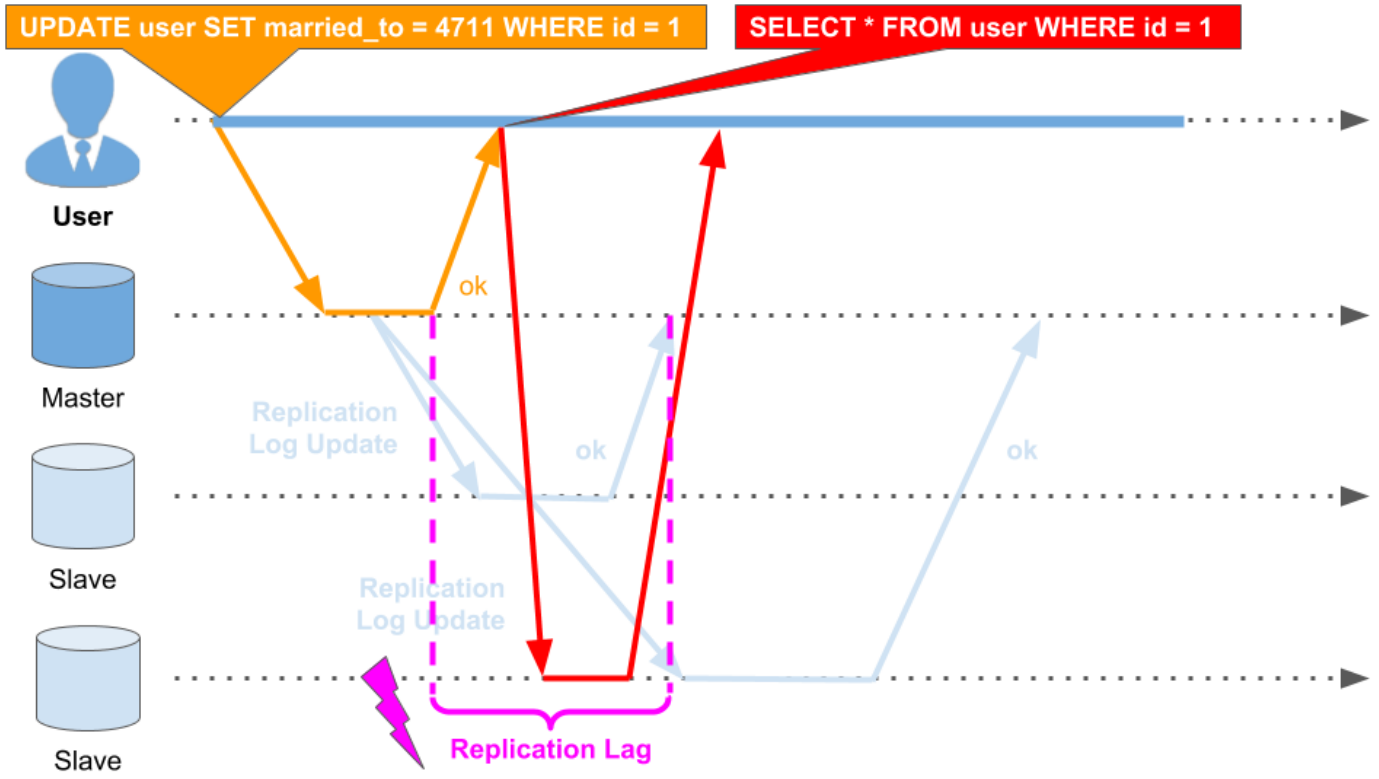
→ Data locality = put slaves geographically close to user/client-applications

→ But: **vulerable to replication lag** (timeframe when master a nd slaves ar inconsistent, as the slaves have not yet process ed the most recent write requests)

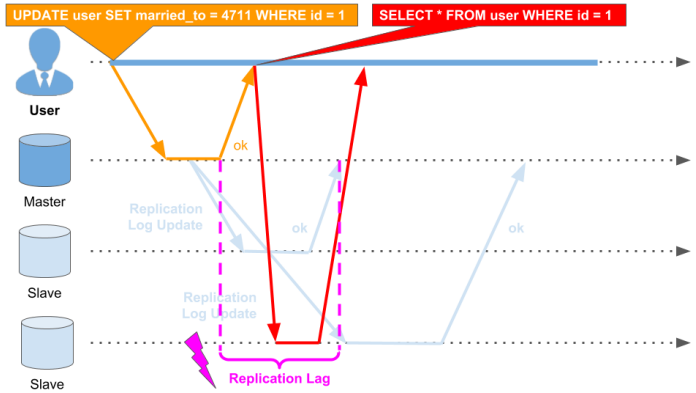
→ **replication lag** = **temporary incosistency** (usually just fractions of seconds)

- Examples of replication lag causing a data-system to be inconsistent:
  - ***Reading Your Own Writes***
  - **Monotonic Reads**

Master Replication – Replication Lag



Master Replication – Read-Your-Own-Writes

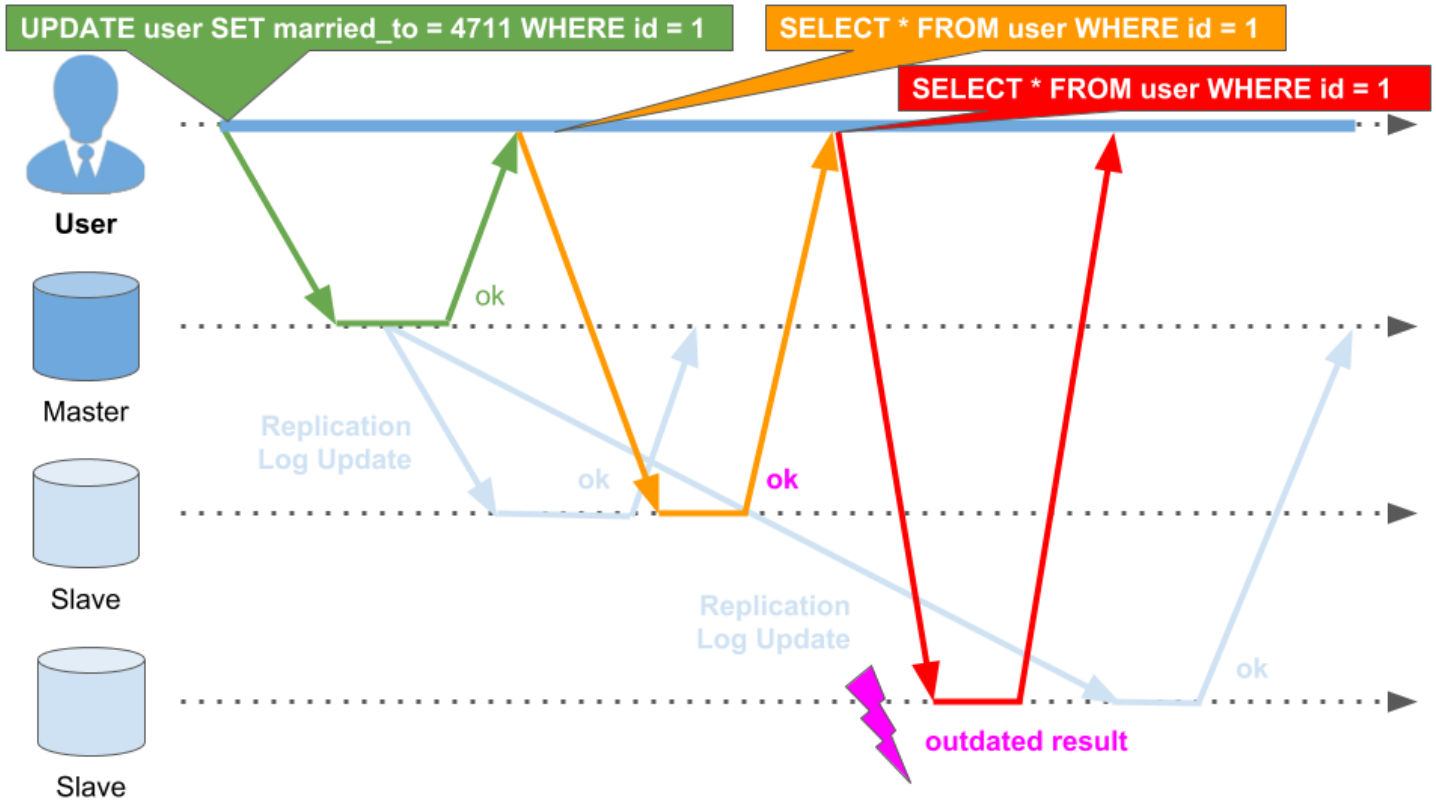


Read-Your-Writes Consistency:
ensures that any write requests submitted by a user will directly be seen on any further read requests (by the same user, guaranteeing a user his write request has been processed successfully.

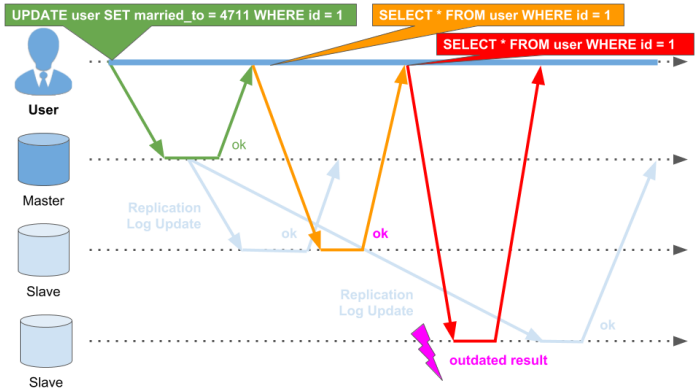
Approaches for achieving Read-Your-Writes consistency:

- **Read data**, a **user may have modified**, **from the master**, otherwise make use of a slave. E.g. Xin g/LinkedIn/Facebook Profile profiles → those profiles can only be edited by the user itself.
- The previous approach does not work very well for data-systems where a user is able to edit almost anything of a data-system, as this would cause any read request to end up oon the master.
  Time or replication state could be a valuable criteria to decide wether use of he master or a slave is appropriate, e.g. if an update request is newer than X seconds or less than the replication lag**, read from master** node **otherwise** make use of a **slave node**.

Master Replication – **Monotonic Reads**



Master Replication – **Monotonic Reads**



Monotonic Reads Consistency:

A user is reading from 2 different slaves, one with less and one with more replication lag, whereas the last one is still missing a replication update. Monotonic Reads Consistency ensures that this kind of divergence does not happen - a user will not read less recent data after reading new data .

Approaches for achieving Monotonic Reads consistency:

- a user needs to always read from same replica (master or slave) within a session
- (different user can read from different replica nodes)
- E.g. determine replica by *user id* `modulo` the *number of replica nodes*

Master Replication – **Adding New Slave Nodes**

1. Create Snapshot

- take a snapshot of a master or slave node
- usually achieved by tools of a data system (e.g. *Ops Manager* in case of *MongoDB*) or Ops storage system tool like *LVM* or *Amazon EBS* in case of *EC2* instances

→ last one requires stop of data-system

→ plain snapshots require a lot of space as they contain indices, storage padding and fragmentation

2. Copy Snapshot

- copy Snapshot to new replica slave node
- for instance automatically by using tools of the data-system or in a lot of cases even rsync or cp is used and recommended (e.g. MySQL).

Master Replication – Adding New Slave Nodes

3. Process Replication Log

- the new slave node connects to the master node and processes all dataset changes happened since the snapshot used, was created.
→ this is usually done by using a *replication log* of the *master node*
→ oldest entry within the *replication log* needs to be less recent than or equal to the creation time of the snapshot
→ a *slave* which is too far behind the replication log (*stale slave*) would lead to data loss

4. Go-Live

- as soon as the new slave successfully processed the replication log and is up-to-date, it can start working again like any slave node
- serve read requests and processing changes from the master as they happen

Master Replication – Outages Of Nodes

Slave Outage:

- slave nodes make use of **repliation logs** to stay in-sync with the master
- Those replication logs and processing state (usually
  - timestamp,
  - number or
  - position of event within replication log)

stored on the slave, e.g as

- ***OpLog*** collection *local.oplog.rs* in case of MongoDB)
- **relay logs** in case of MySQL relay logs

- If a slave node crashes and gets back up again or recovers from an network issue, it:
  - can just start right away using the **replication log** where it stopped
  - **connect to the master** and **request all dataset changes** that have happened during the time of outage
- As soon as the new slave successfully processed all missing data changes and is up-to-date, it works like before

Master Replication – Outages Of Nodes

Master Outage:

1. Determining Master Failure

- e.g. done by defining and using timeouts (*heartbeat*)

→ if a node does not respon within a defined timeframe, it is supposed to be dead

2. Evaluating New Master

- several approaches, most common: choose new master by the majority of the remaining nodes or a controller node (e.g. an *Arbiter* node in case of MongoDB)
- best candidate: node containing most-recent updates of old master node
- vulnerable to *split-brain scenario* (if node failure was caused by network outage)

3. Reconfiguration

- as soon as *new master* node is elected, all clients need to send their write requests to the *new master*
- all *slave nodes* need to receive the replication log from the new master as well

Master Replication – Replication Logs

Statement Based:

- most-simple approach
- master node processes each query and afterwards adds them to the replication log (e.g. `INSERT`, `UPDATE`, `DELETE`…)
- statements are later executed by slave nodes
- Pitfalls:
  - How to handle **non-deterministic** functions within a write request (like `RAND()`, `USER()` or `NOW()` used in an SQL query) or external functions like StoredProcedures, Triggers or user-defined functions?
    → The master node would need to **replace** those **non-deterministic functions** with deterministic values (like the return value of the called function).
  - What if statements depend on other data, like in an `UPDATE` ... `WHERE` ... statement.
    → This requires all statements to be executed **within the exact same order**, oth- erwise they will end up in different results.

- For instance previously used by MySQL and still supported in a mixed-approach (with row-based replication)

Master Replication – Replication Logs

WAL *(Write-Ahead-Log)*:

- the master logs all IO data changes to a **WAL** (e.g. (re-)writes of disk blocks, appends t o files, etc.), writes the WAL to disk and sends it to all slaves
  → when a slave processes this log file, it builds an exact same copy of the data structures as found at the master.
- **significantly reduces IO** (disk writes) → only the log file needs to be flushed to disk to guarantee that a transaction is committed, rather than every state-ment or data file changed by the transaction
- Highly dependent on storage engine (which byte has changed within which disk block)
  - → different versions of a data-system or storage engine on master and slave nodes i mpossible
  - → increases complexity of maintenance tasks, especially rolling-upgrades of single n odes within a data-system are not possible any more
  - → makes downtimes inevitable

- For instance used by ArangoDB or PostgreSQL

Master Replication – Replication Logs

Logical Log Replication

- logical row-based replication (decoupled from storage engine)
- Replication log contains records describing changes of a dataset in a row-based way, e.g.:
  - **`INSERT`**: The log contains one record with all values for each inserted row.
  - **`UPDATE`**: The log contains one record for each updated row as well as all new values and an information to uniquely identify the updated row (e.g. primary key).
  - **`DELETE`**: The log contains one record for each row to be deleted as well as inform ation to uniquely identify the row to be deleted (e.g. primary key).
- For instance used by MongoDB

Master Replication – Replication Logs

Update on MongoDB collection

```
$ use test
 switched to db test
$ db.user.insert({user_id:1})
$ db.user.update({user_id:1}, {$set : {married_to:4711}})
```

Resulting Replication Log

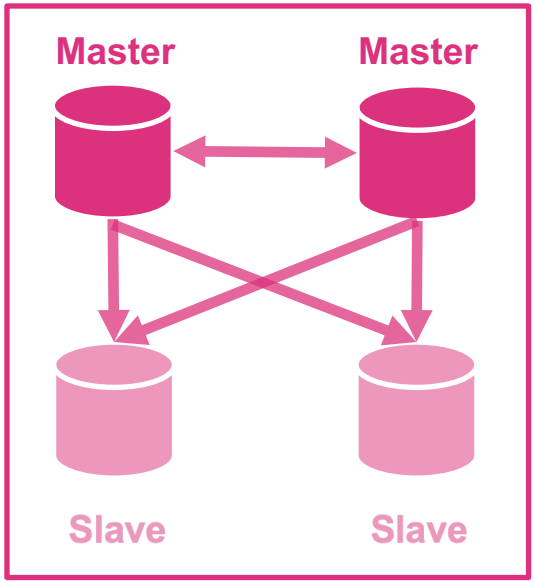
```
$ use local
switched to db local
$ db.oplog.rs.find()
{
  "ts" : { "t" : 1534616696000, "i" : 1 },
  "h" : NumberLong("1342870845645633201"),
  "op" : "i",
  "ns" : "test.user",
  "o" : {
    "_id" : ObjectId("4cb35859543cc1f4f9f7f85d"),
    "user_id" : 1
  }
}
{
  "ts" : { "t" : 1534616699000, "i" : 1 },
  "h" : NumberLong("1233487572903545434"),
  "op" : "u",
  "ns" : "test.user",
  "o2" : {
    "_id" : ObjectId("4cb35859543cc1f4f9f7f85d")
  },
    "o" : {
      "$set" : { "married_to" : 4711 }
    }
}
```

Multi-Master Replication

Master-based

e.g. **Oracle, PostgreSQL, MySQL…**

Multi-Master-based



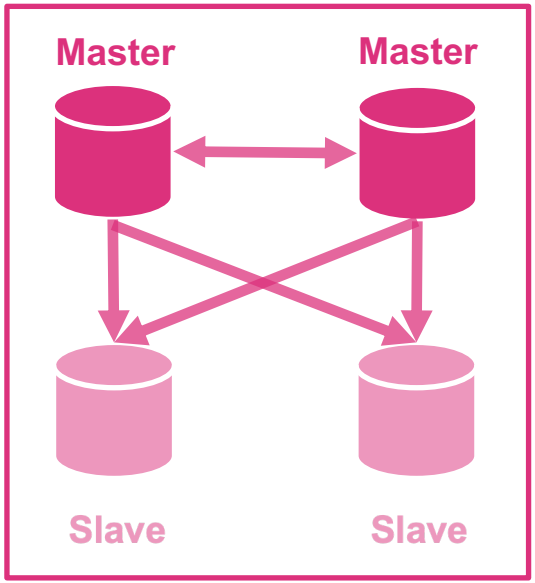
e.g. **CouchDB, PostgreSQL, MySQL…**

Masterless

e.g. **Cassandra, Riak, Vol demortDB, DynamoDB…**

Multi-Master Replication

Also known as: *Multi-Leader, Active/Active or Master/Master Replication*

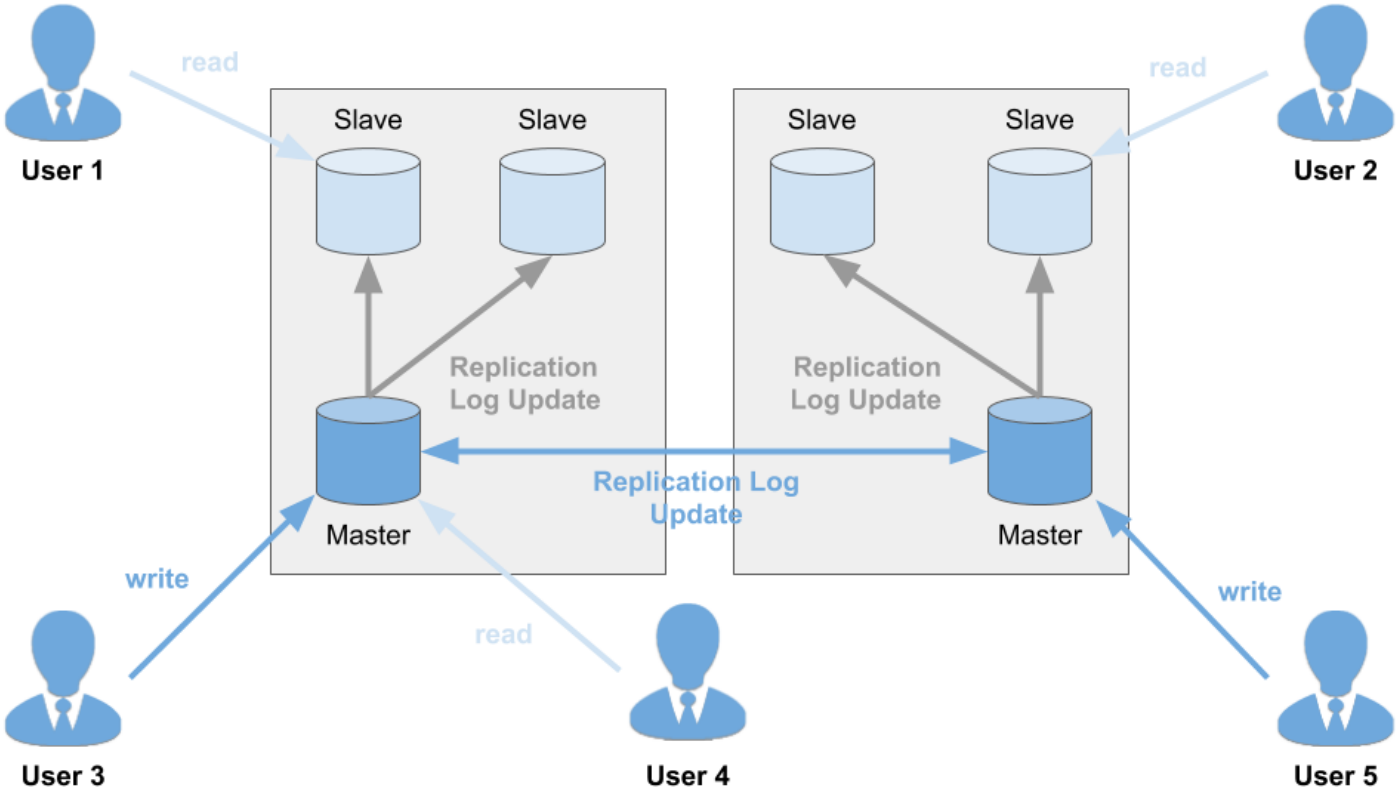


Setup:
- **multiple master** nodes (which accept write requests)
- query and replication processing similar to master-based replication

Advantages:
- **fault tolerance** (ability to mitigate faults of master nodes)
- **write performance** and horiz. scalability (parallel writes)
- able to run on **multiple datacenters** (e.g. one master in each of them)

Disadvantages:
- **write conflicts** possible (requires conflict resolution)
- complexity

Multi-Master Replication – **Example**



Multi-Master Replication - **Conflicts**

- **same record/dataset** is being **edited in parallel** using **multiple master nodes**

→ e.g. editing the same line of a document within Google Docs simultanously (user 1 on a master node based in Frankfurt and user 2 on a master node in Berlin)
→ Later asynchronous replication between the two master nodes will conflict (this won't happen if you are using a master replication).
→ **Possible solution:** application needs to ensure both users are pushing their write request to the same master.

But what if the application is not able to prevent those confict? **Approaches:**

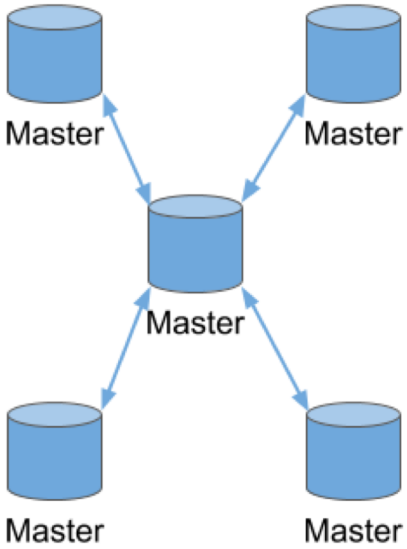
LWW: only accept the most recent operation by e.g. unique operation ID, timestamp or both (*Last-Write-Wins*). It is important to notice that this approach is highly vulnerable to data loss.

Merge: merge values of multiple updates together (e.g. alphabetically or in order of appearance).

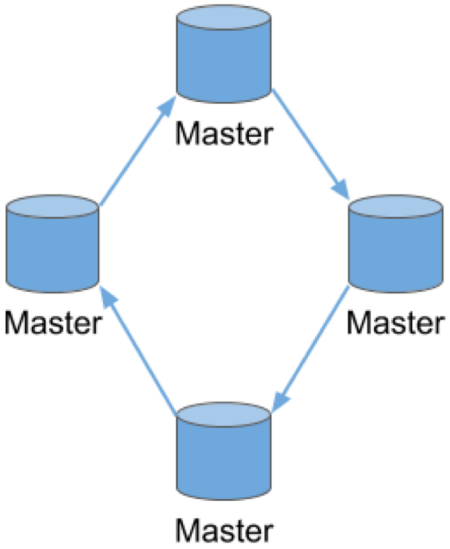
Application Managed: persist the conflict in a way, that it preserves all information without loss and let the application, using the data-system, or rather the user of the application take care about it later on (e.g. implemented by SVN or Git)

Multi-Master Replication - **Topologies**

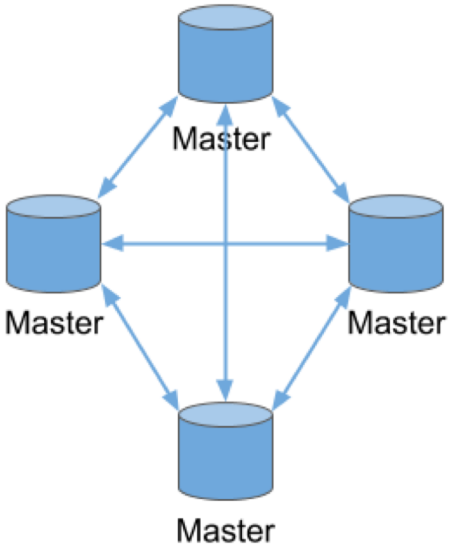
Star Topology



Circle Topology



All-To-All Topology



Masterless Replication

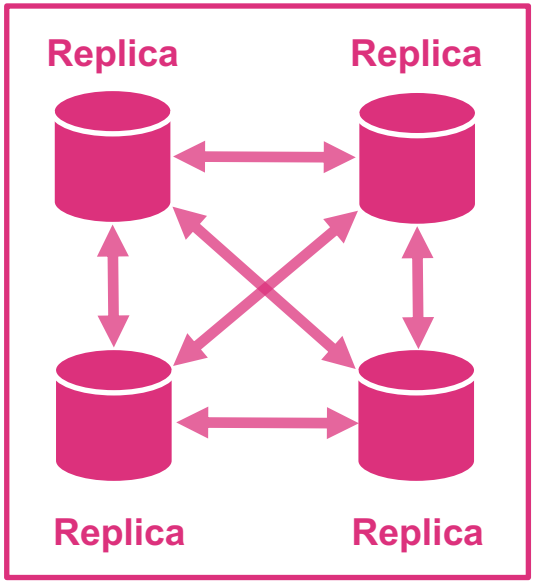
Master-based

e.g. **Oracle, PostgreSQL, MySQL…**

Multi-Master-based

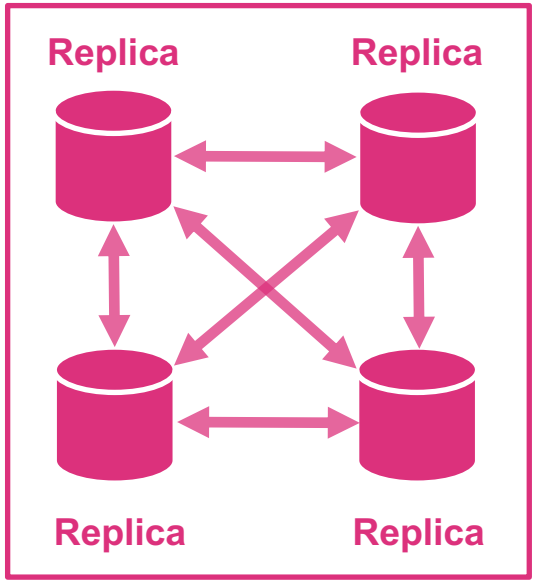
e.g. **CouchDB, PostgreSQL, MySQL…**

Masterless



e.g. **Cassandra, Riak, Voldemort, DynamoDB…**

Masterless Replication



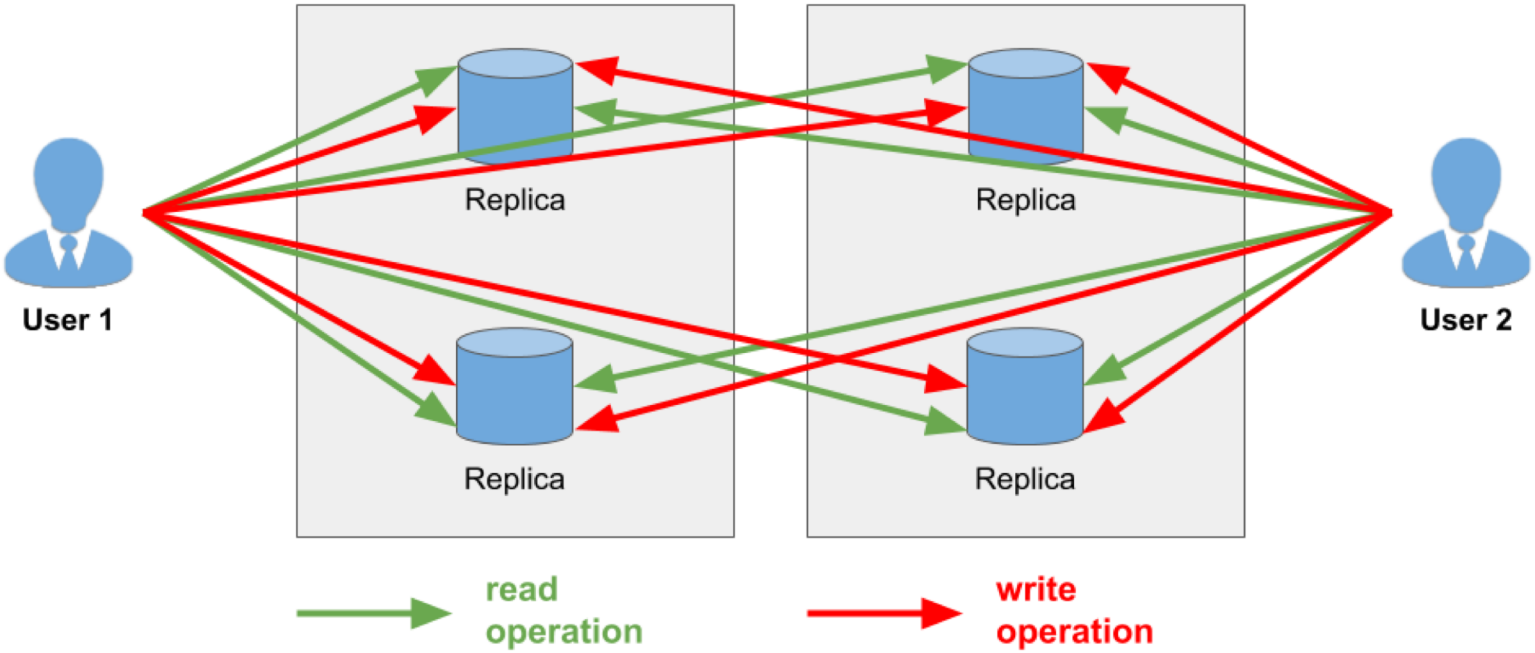
Also known as:
Leaderless Replication

Setup:
- **no leader** (all nodes/replicas accept write requests)
- makes use of **gossip protocol** (all replica nodes run local processes which periodically match their states)
- queries are sent to multiple nodes of data-system
  → if a certain number of nodes succeeded, the query is considered successful

Advantages:
- **fault tolerance** (tolerates multiple failed or slow nodes)
- **write performance** and horiz. scalability (parallel writes)
- able to run on **multiple datacenters** (with respect to *quorum*)

Disadvantages:
- **consistency, complexity** and additional **tasks** clients need to handle (e.g. quorum, conflict resolution, consistency)
- most data-system are key/value stores

Masterless Replication – Example



Masterless Replication- **Quorums**

Quorum:

- a *quorum* is the minimum number of votes that a read/write request to a distributed data-system has to obtain in order to be sure the requests is successful (and the result consistent)

Reasonable quorum:

- every read and write request must be processed and confirmed by at least **r nodes** (read) or acknowledged by at least **w nodes** (write):

$$r + w > n$$

→ sure to get an up-to-date resul, as at least one of the replica will have the most-recent value

- able to run on **multiple datacenters** (with respect to *quorum*)

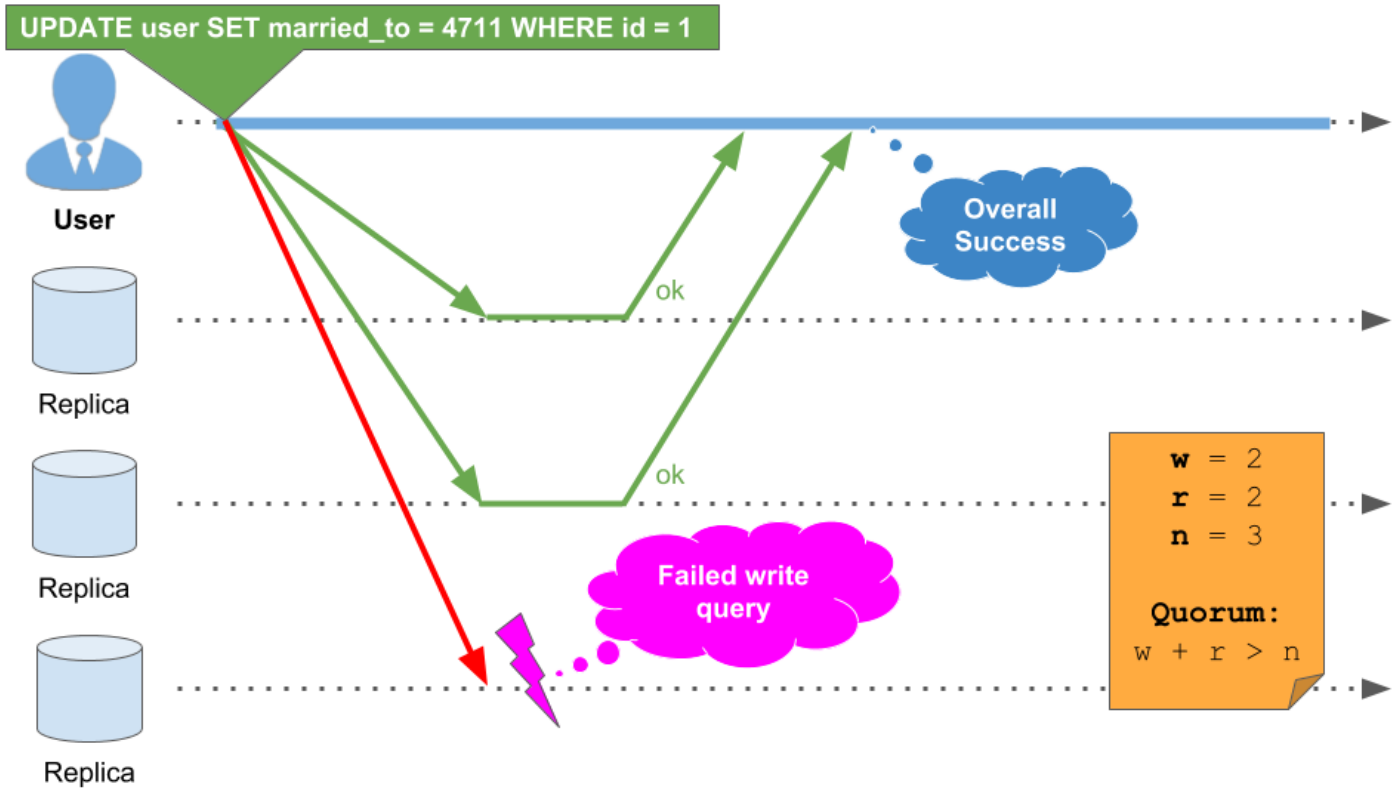
Masterless Replication- **Quorums**

- **r** and **w** are configurable depending on *read/write performance* and *fault-tolerance* you wa nt to achieve
  - → smaller **r** = faster reads, slower writes
  - → smaller **w** = faster writes, slower reads

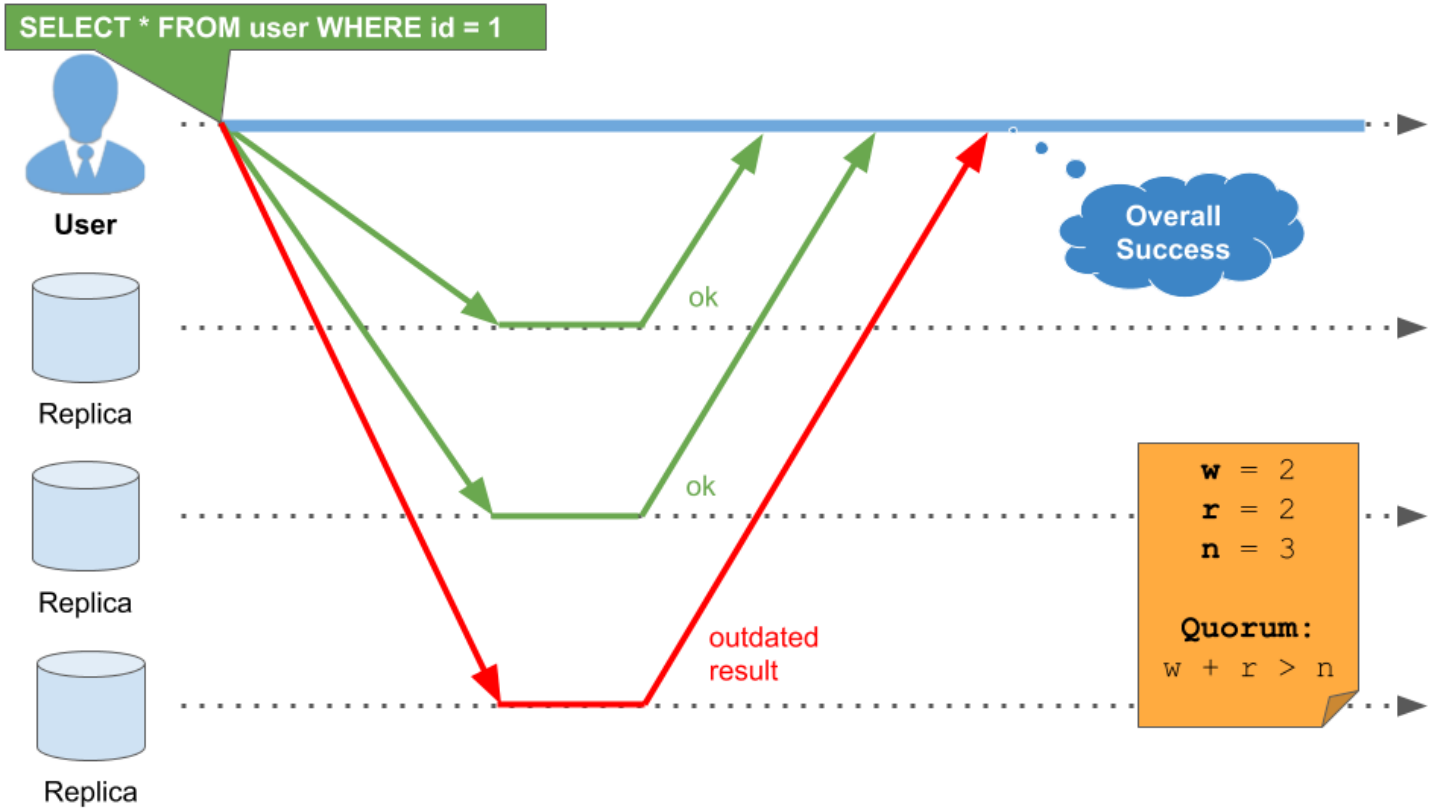
- Number of node failures a data-system can handle, is calculated by:
  - → **n - r = number** of nodes tolerated to be unavailable for read requests
  - → **n - w = number** of nodes tolerated to be unavailable for write requests

- For instance, a data-system of **5 nodes** (n = 5, r = 3 and w = 3) is able to tolerate 2 unavailable nodes.

Masterless Replication- **Quorum Write**



Masterless Replication- **Quorum Read**



Masterless Replication – **Eventual Consistency**

Read Repair: If a user application or controller node executes a read requests and recognizes a replica node with a *stale* value, the user application or controller sends it the most recent value afterwards.
For instance used by *Cassandra*, *Riak* and *VoldemortDB*.

Anti-Entropy Repair: Some data-systems are running background processes or provide tools (e.g. *nodetool repair* in case of *Casssandra*) which run in background constantly looking for differences between different replica nodes and copying data from one node to another to keep everything up-to- date.
For instance used by *Cassandra* and *Riak* but not supported by *VoldemortDB*.

Hinted Handoff: If a node is unable to process a particular write request, the user application or coordinator node (which executed the write request) preserves the data to be written as a set of hints. As soon as the faulty node comes back online, the user application or coordinator triggers a repair process by handing off hints to the faulty node to catch up with the missed writes.
For instance used by Cassandra and Riak but not supported by VoldemortDB.

Masterless Replication- Limitations of Quorums

Concurrent Writes: If two write requests are executed concurrently, it is **not clear which one happened first**, as both are executed from different controller nodes or applications. Both requests need to be merged, for instance based on a timestamp (*last-write-wins*), which is highly vulnerable to *clock skew*, causing **older values to overwrite more recent ones**.
For instance *Cassandra* is based on *last-write-wins* whereas *Riak* requires the admin to choose whether to make use of *last-write-wins* or *handle write conflicts within the application* using the data-system.

Concurrent Reads And Writes: If **read and write requests** (regarding the same value) happen at the **same time** it is unclear whether the read request returns the **stale or the new value**. As the write request may succeeded only on some nodes during execution of the read query, the new value might be under-represented, causing the old value to win the quorum.

Node Failure: If a node previously processed a new value, crashed and comes back online and is **restored** from a node with the **old value**, the **quorum might be violated** as the number of nodes storing the new value might be < w.

Masterless Replication- **Limitations of Quorums**

Sloppy Quorum and Hinted Handoff: There are cases like network or datacenter outages causing some user or consumer applications being cut off from some nodes of a data-system (while the unreachable nodes are still online). In this case it is possible that some user or consumer applications won't be able to achieve a quorum. If the data-systems contains more than n nodes, it needs to make a crucial decision here, whether to ignore all requests that cannot achieve a quorum or still accept write requests and just write them to some nodes outside of n to ensure write availability and durability. A sloppy quorum still requires r and w nodes, but those do not need to be one of the original n nodes. As soon as the network or datacenter outage is fixed, all writes processed by nodes outside of n are sent to the appropriate nodes inside of n (*Hinted Handoff*).
Using this approach it is no longer guaranteed a data-system will provide the most recent value as read and write requests may not overlap on r and w nodes. This could also be mitigated by using versioning of values, like *vector clocks* (e.g. used by *DynamoDB*).
For instance *sloppy quorums* are enabled by default within *Riak* and disabled by default within *Cassandra*.

Introduction To The Challenges Of Distributed Data-Systems: Partitioning

Basics of Partitioning, Key-Range and Hash Partitioning, Partitioning of Secondary Indices, Rebalancing and Lookup of Partitions

Why Partitioning (and Replication)?

Partitioning is the process of continuously dividing data into subsets and distributing it to several nodes within a data-system. Usually each record or document within a partitioned data-system is distributed and directly assigned to certain partition. Partitioning serves the pur pose of, e.g.:

Scalability and Performance: Distributing data to multiple nodes, for instance increases read/write performance and throughput as read/write queries can be distributed to multiple nodes and handled concurrently. In this way it is possible parallelize IO (disk), computing power (CPU) as well as scale the memory usage needed to run a certain operation on a part of the dataset.

Low Latency: Using partitioning it is possible to place data close to where it is used (user or consumer applications).

Availability: Even if some nodes fail, only parts of the data are offline.

Replication vs Partitioning

	Replication	Partitioning
stores:	**copies** of the **same data** on **multiple nodes**	**subsets** (*partitions*) on **multiple nodes**
introduces:	**redundancy**	**distribution**
scalability:	**parallel IO**	**memory consumption**, certain parallel IO
availability:	**nodes** can **take** load of **failed nodes**	node **failures affect only parts** of the data

Different purposes, but usually used together

Partitioning – **Avoid Confusion On Terms**

To avoid confusion on the term partition or partitioning, let's list some other terms, you might have heard and which are frequently used synonymously:

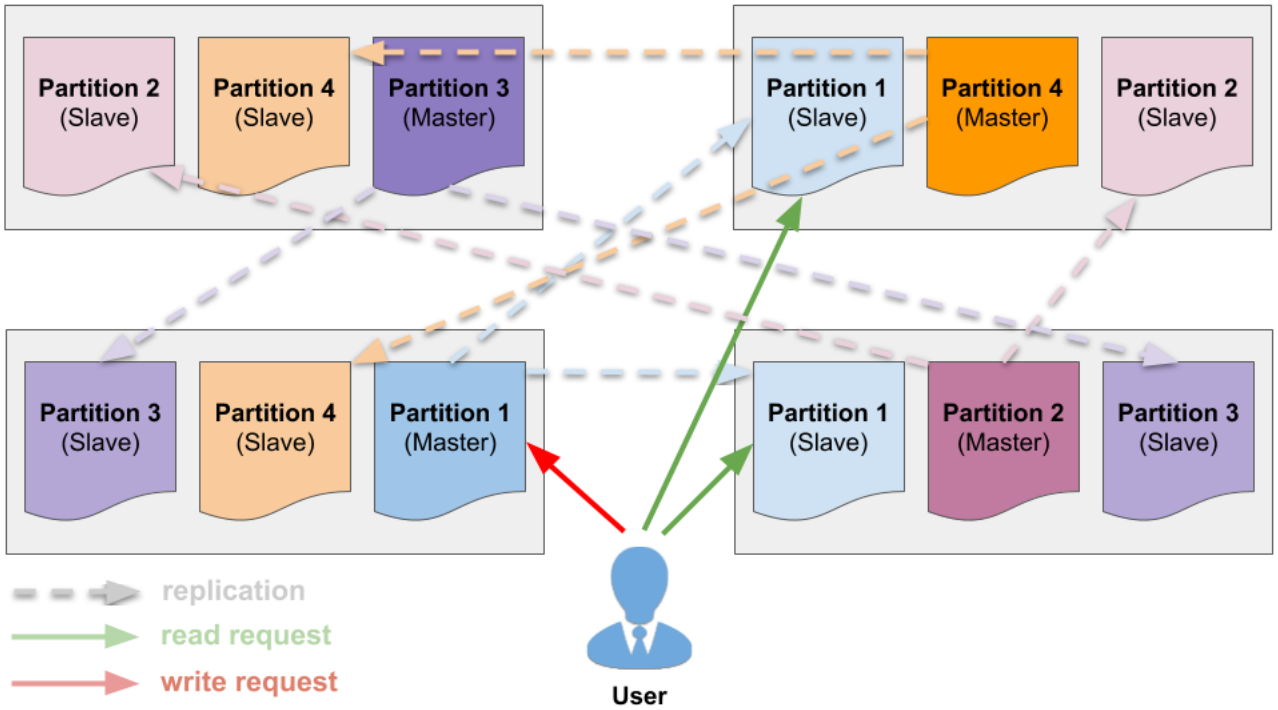
- ***shards/sharding*** - (e.g. *MongoDB*, *ElasticSearch* or *RethinkDB*)
- ***Vnodes/Virtual Nodes*** - (e.g. *Riak* or *Cassandra*)
- ***region*** - (e.g. *HBase*)
- ***tablet*** - (e.g. *BigTable*)
- ***vBucket*** - (e.g. *Couchbase*)

Partitioning and **Replication** are usually used together, especially when building data-intensive applications, as datasets are too big to be stored on a single server or replica, and benefits of replication are required (e.g. redundancy, fault-tolerance or high read/write through put). This can be achieved by storing partitions of a data set on multiple replica nodes.

Partitioning – **Avoid Confusion On Terms**

As **horizontal** *and* **vertical** *partitioning are mixed up sometimes, it is important to notice: when we speak about* ***partitioning*** *within this lecture, we mean* ***horizontal partioning****.* ***Vertical partitioning*** *is an* ***approach of traditional relational databases****, usually done by splitting datasets into multiple entities (e.g. tables or databases) and using references (e.g. to achieve normalization).*

Partitioning – An Example



- Partitioning and Replication
- Using Master-based Replication
- Each node is master for a certain partition
- Each partition has 2 slave nodes

→ **Ensure HA**

Partitioning – **Key-Value Data**

2 Purposes of Partitioning:

- **distributing a dataset**,
- more important: **distribute related load** (read/write queries) evenly among several nodes of a data-system

This requires:

- a **wise way of determining the partition** of a certain row or document → as it **directly affects the performance of a data-system**
- an **improper choosen distribution key** may cause:
  - **some nodes** to be **idle and/or empty** and
  - a **single node** to be the **processing bottleneck** and hitting its space limitations as all read/write requests end up on that single node
- an **appropriate distribution key** will **distribute the data evenly** and enable the data-system to (theoretically) scale linearily in terms of space utilization and request throug hput.

Partitioning – Key-Value Data (Approaches)

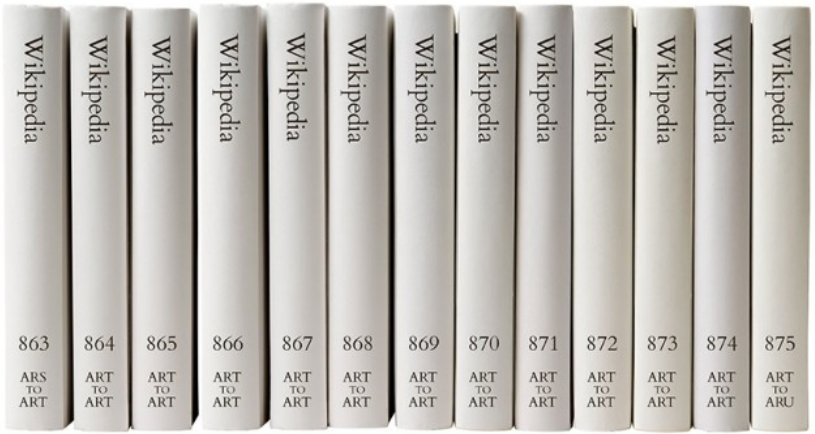
Key Range Partitioning: Derive a partition by determining whether a key is inside a certain value range.
→ *More details on next slides.*

Partitioning By Hash Value Of A Key: Derive a partition by a certain hash of a given key to achieve a mor e even data distribution. → *More details on next slides.*

Partitioning By List: Every partition to be used has an assigned list of values. A related partition is derived from the input dataset by checking whether it contains one of those values. For instance all rows containing iPhone, Samsung Galaxy and HTC One within a column `device_type` are assigned to partition Smart-phone. → *As no data-intensive system makes use of partitioning by list (as it is very improper to provide even data distributio n), we wont discuss this approach in detail.*

Round-Robin Partitioning: A very simple approach, which ensures even data distribution. For instance assignment to a partition can be achieved by **n** modulo **p** (*n = number of inccoming data records, p = number of partitions*). → *As no data-intensive system makes use of round-robin partitioning (as for instance the direct access to an individual data record or subset usually requires accessing the whole dataset), we wont discuss this approach in detail.*

Partitioning – Key-Range Partitioning



Key Range partitioning is done by:

- **defining continues ranges of keys**
- **assigning each range to a certain partition**

→ If you are aware of the boundaries of each key range, you can easily derive a partition belonging to a certain data record (and in this way node of a dat a-system) just by using the key of the record.

→ This approach can be compared with an encyclopedia, which is partitioned into books, of which every-one stores a certain range of articles partitioned by the first letters of the name of the article.

→ For instance the article "*Arsenal F.C.*" will be found in partition 863 "*ARS*" - "*ART*".

→ For instance used by: **RethinkDB** (called *ranged sharding*)

Partitioning – Key-Range Partitioning

Strengths:
- **Simple**
- **Range Lookups**

Weaknesses:
- **Datasets Are Changing:** A *key range* partitioning which was suitable in the past might not be appropriat e in the future. Expensive rebalancing or even repartitioning might be needed somewhen.
  For instance web server log files partitioned per ranges of the URL (`/products/[A-B]`, `/products/[C-D ]`... `/products/[Y-Z]`) maybe improper in the future, as some products will have heavier traffic than other products over time (***load skew***).

- **Hotspots:** Keys that seem very appropriate in terms of even distribution at first sight, e.g. partitioning of webserver logfiles over time (by using timestamp of data record), create hotspots as all write requests end up on the same partition (e.g. *today*), a single partition (and node(-s)) will underly heavy load whereas other partitions or rather nodes are idle (***load skew***).

- **Query Performance:** As you do not know the size of a partition beforehand, query performance is impredictable as well as partition pruning and partitionwise joins are more complex and less efficient.

Partitioning – Hash Partitioning

Hash partitioning is used to spread data efficiently and evenly among several certain partitions. This is achieved by:

→ splitting data in a randomized way
→ rather than by using information provided within the dataset (e.g. IDs) or
→ derived by arbitrary factors (e.g. time of data receival)

- The hash value itself is derived by a hash function (on a certain key of a data record) and is used to determine the partition a data records should be saved on.

Hash Function *is a function which takes input data of arbitrary size and usua lly provides an output of fixed size. The output of a hash function is called has h, hash value or digest. A hash function needs to be deterministic and unifor m. Common use cases for hash functions are cryptography, checksums and partitioning.*

Partitioning – **Hash Partitioning** (Hash Functions)

Hash functions are commonly used for partitioning, as they are:

→ **deterministic** - as we need to be able to find records to be saved later on and
→ **uniform** - as we want to distribute the data as evenly as possible among the set of available partitions and nodes, even if the inputs of the hash function (e.g. data record key) are very similar.

Unlike cryptography, **partitioning makes use of hash functions** that are **not cryptographilly strong** (as this is not needed) but fast and less CPU consuming.
Examples of commonly used hash function for distributed data-systems are:

- **MD5** - For instance used and supported by *MySQL* and *Cassandra.*
- **MurmurHash** - For instance supported by *Cassandra*.
- **SHA1** - For instance used and supported by *Riak*.
- **CRC32** - For instance used and supported by *Couchbase*.

Partitioning – **Hash Partitioning** (Hash Functions)

As an example for **determinism** and **uniformity** let's take a quick look at **MD5** and how the hash value changes:

- when **a** single **character is added** to the input value,
- when just **a** single **character** of the input value is **changed** or
- the **same input** value is **hashed twice**

```
1  marcel$ md5 -s abc
2  MD5 ("abc") = 900150983cd24fb0d6963f7d28e17f72
3  // add a single character ("d")
4  marcel$ md5 -s abcd
5  MD5 ("abcd") = e2fc714c4727ee9395f324cd2e7f331f
6  // change a single character ("d" to "e")
7  marcel$ md5 -s abce
8  MD5 ("abce") = b9c4fe92c2a30ef69833ac8f53eebcec
9  // hash again with same input value
10 marcel$ md5 -s abce
11 MD5 ("abce") = b9c4fe92c2a30ef69833ac8f53eebcec
```

Code Snippet 2.7: Bash Output - *MD5 Hash For Several Input Values*

Partitioning – Hash Partitioning (Hash Modulo)

Hash Modulo Partitioning = take the calculated *hash value* **V** and calculate **`V modulo N`** (*number of partitions*).

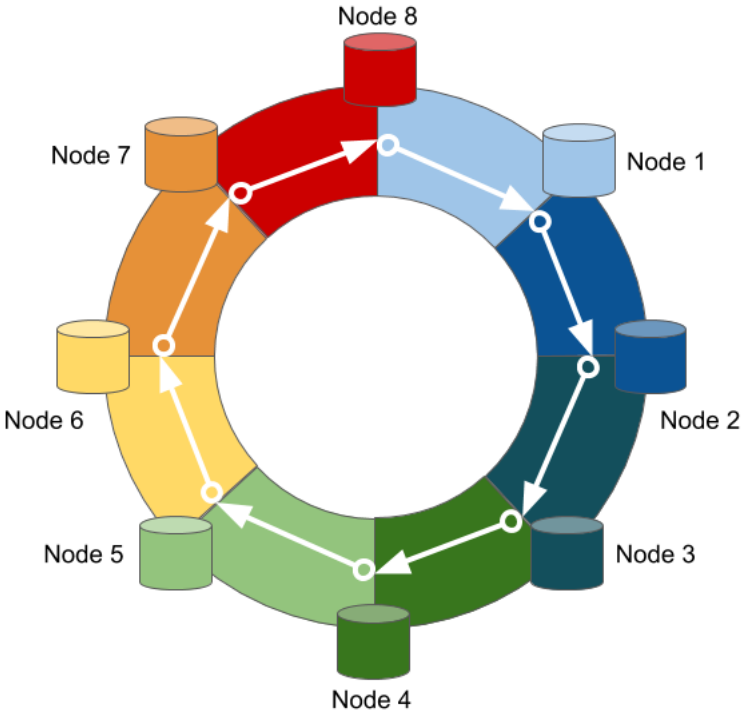
→ This allows the the data-system to easily distribute and receive records to and from a given number of partitions.
→ Major disadvantage in terms of **scalability** and **operability**.
→ Adding nodes results in different partition assignments for a lot of records (depending on size of N), which will require to **shuffle and reassign already saved data again** among all partitions.

- Nevertheless for instance **elasticsearch** makes use of it, a partition (called shard) is derived by: ***`shard = hash(routing) % number_of_primary_shards`***
- The number of shards for an *index* can increased (by ***`_split`***) or decreased (by ***`_shrink`***) some time after creation but this is not a trivial task and will usually require recreating the same or even creating a new index.

Partitioning – **Hash Partitioning (Consistent Hashing)**

- assign a *range of hashes* to every partition (and in this way node)
- every record will be stored and read from the partition in charge for a given *range of hash values*.
- imagine **consistent hashing** as a *ring of keys*
- each node (***Ni***) is in charge for serving all hash values ***v*** in between:
  - ***i*** and
  - the position ***j*** of its clockwise pre-decessor ***Nj***

`J < v < i`

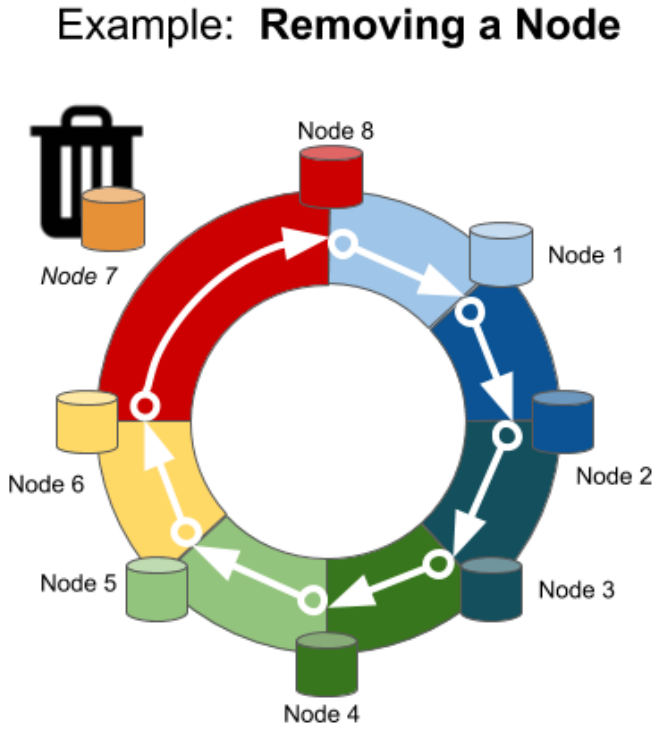


Partitioning – **Hash Partitioning (Consistent Hashing)**

Strenghts:
- Adding/Removing a node → only *c/N* keys need to be re-distributed
  - *c* is the **count of hash values** and
  - *N* is the **number of nodes** within the data-system

Weaknesses:
- Range Queries (as keys are randomly distributed amon data system)
- e.g. MongoDB provides *key-range partitioning* as well as *hash partitioning* to efficiently serve both use cases

Used by e.g.:
- Cassandra
- Riak
- VoldemortDB
- DynamoDB



Partitioning – **Partitioning Of Secondary Indices**

Secondary Index = Index in addition to primary index, which:

- is used to accelerates queries
- may not identify records uniquely
- used to lookup records with a certain value/attribute
- **needs to be partitioned as well**

→ Remember previous Facebook Profile example (Primary Key = User ID)
→ What if you want to acclerate the lookup of `cities` and `comanies`? Add a seco ndary index!

Partitioning – **Local Secondary Indices**

- **LSI** = *Local Secondary Index*
- every partition manages ist own index
- all pointers reference only to local data items

Strenths:

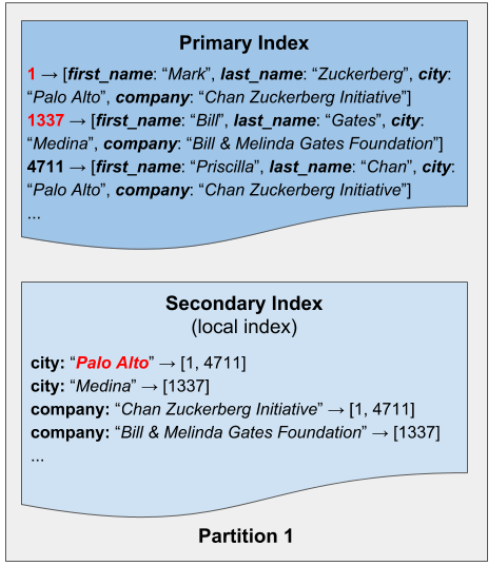
→ maintaining *local index* requires less over-head than *global index*

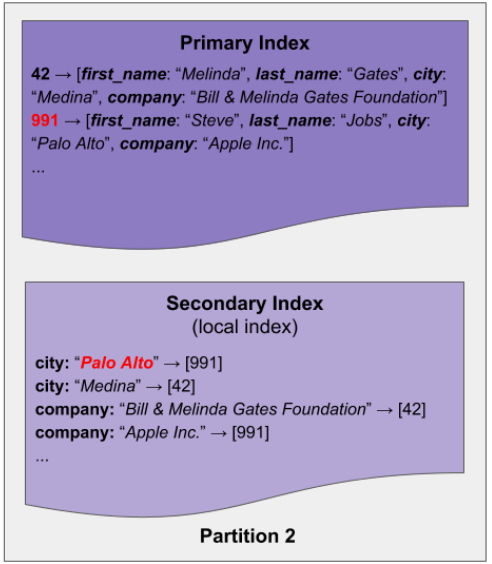
→ `INSERT`/`DELETE`/`UPDATE` performed locally

Weaknesses:

→ maintaining *local index* will compete with *local workload* niand affect throughput

→ expensive `SELECT`: *scattering and gathering as well as related* overhead will probably affect read request performance





E.g. provided by:

- Riak
- Cassandra
- DynamoDB

Partitioning – **Global Secondary Indices**

- **GSI** = *Global Secondary Index*
- Index is partitioned, distributed and stored among several nodes independently of local data records
- pointers reference to local but also remote data records

Strenths:

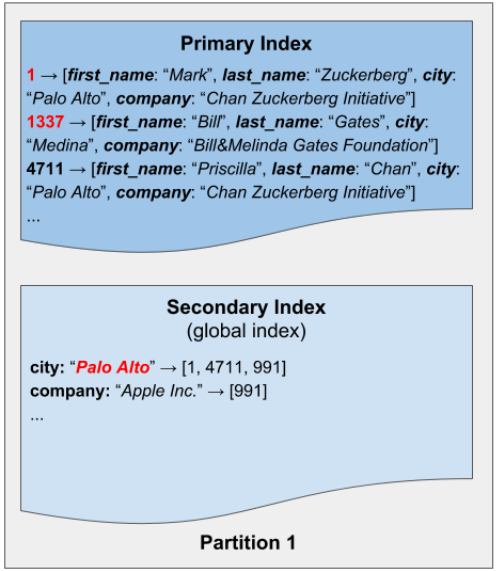
→ `SELECT` statements need to query only one index partition

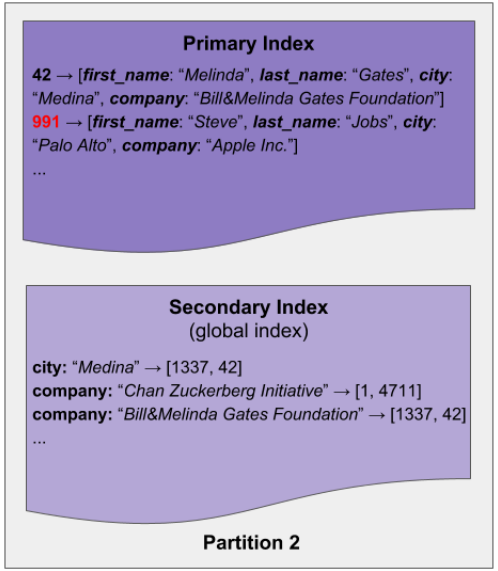
→ No *scattering and gathering (like using LSI)*

Weaknesses:

→ maintaining *global index* requires more overhead than a *local index* → `INSERT/DELETE/UPDATE` statements require remote updates

→ usually weakens read-consistency as indices updates take more time → DynamoDB ***eventual consistency***





E.g. provided by:

- Oracle
- MS SQL Server
- Couchbase
- DynamoDB

Partitioning – **Rebalancing Partitions**

Why?

- Node Failure → other nodes need to take over
- Query load increases → more CPUs and RAM required
- Data Size increases → more RAM and disk space required

Goals:

- Minimal Data Shuffle: Move as less data as possible around nodes during rebalancing
- Evenly Distribution: Data distribution should be even after rebalacning.
- No Availability Impact: Rebalancing should have as less impact as possible on a running data-system, requiring no downtime.

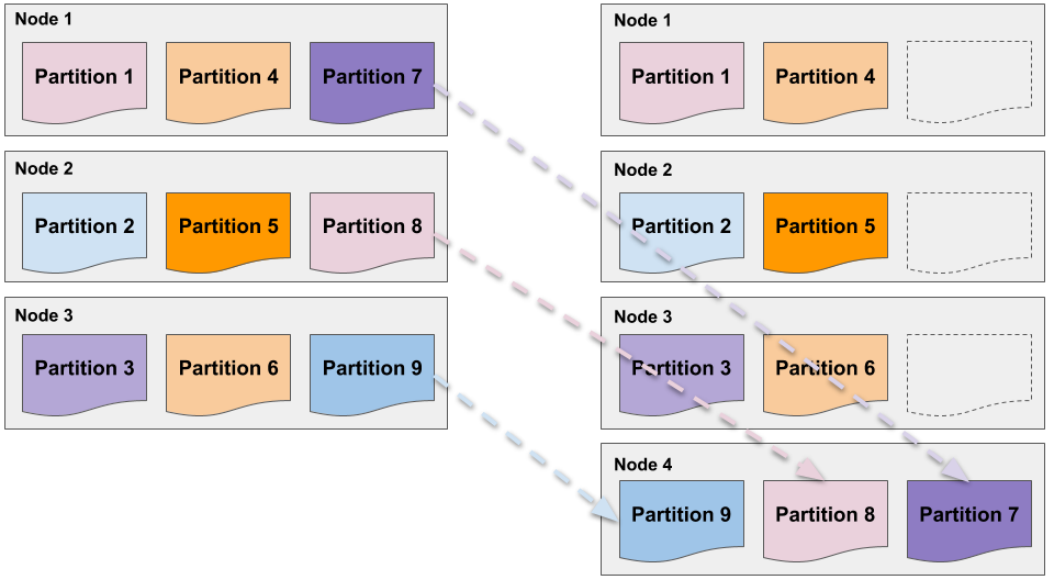
Partitioning – **Rebalancing Partitions (Hash Modulo)**

Approach:
- hash % n

Contra:
- stupid
- requires shuffling a lot of data, as assignment of partitions to nodes changes significantly

Used by e.g.:
- shouldn't be used

Partitioning – **Rebalancing Partitions (Fixed Number of Partitions)**



Approach:

- Create more partitions than there are nodes on initial setup
- new nodes „steal“ partitions from old ones

Pro/Contra:

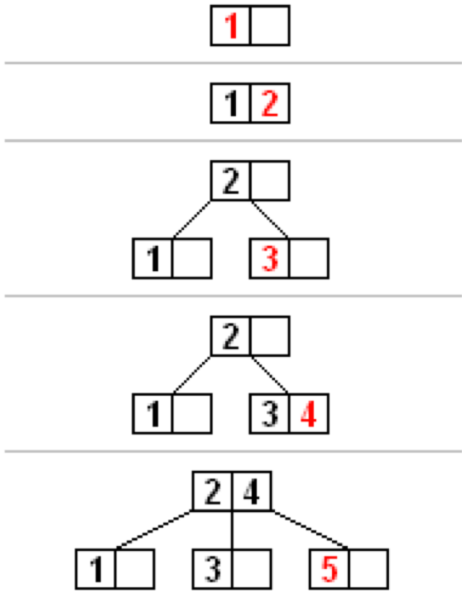
- partition/node mappings change
- but for less partitions

→ only partial rewrite of partitions

Used by e.g.:

- Voldemort
- Riak
- ElasticSearch
- Couchbase

Partitioning – **Rebalancing Partitions (Dynamic No. Of Partitions)**

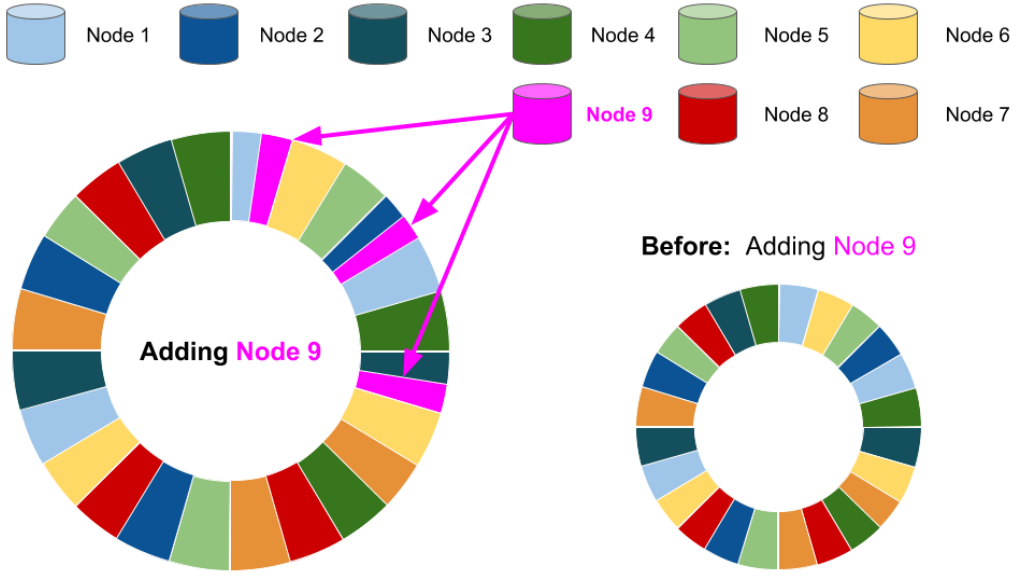


Approach:
- Create certain number of initial partitions
- Idea similar to B-Trees
→ If a partition exceeds a threshold in size, it gets split
→ If a partition falls below a threshold in size, merge it with another
- new nodes „steal“ partitions from old ones

Pro/Contra:
- evenly distribution
- continues overhead during runtime

Used by e.g.:
- MongoDB
- RethinkDB

Partitioning – **Rebalancing Partitions (Fixed Partition No. Per Node)**



Approach:

- create fixed number of partitions at initial setup
- new nodes randomly split partitions of old nodes

→ steal half of partitions of old nodes

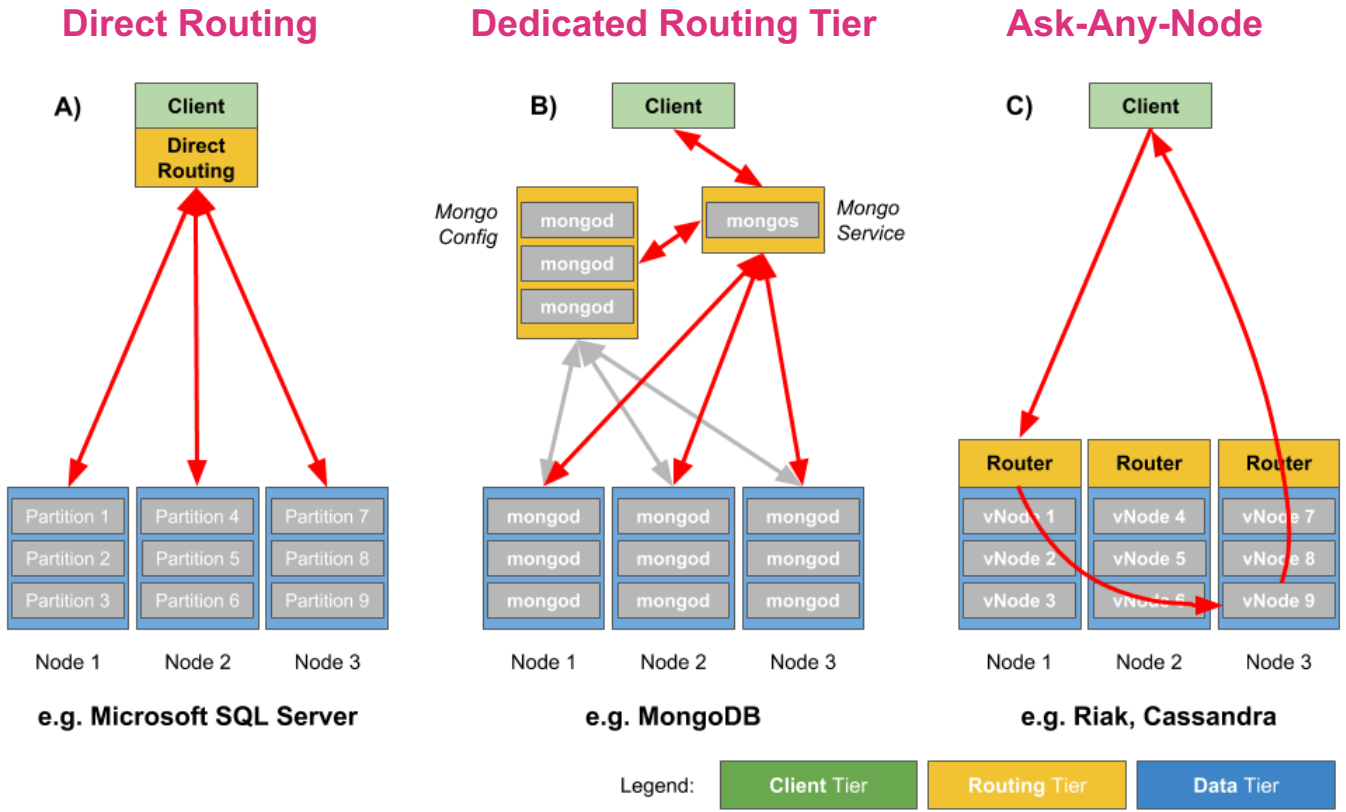
Pro/Contra:

- works well for range partitioning (hash or keys)
- load may be temprorarily unbalanced but will be even again over time

Used by e.g.:

- Cassandra

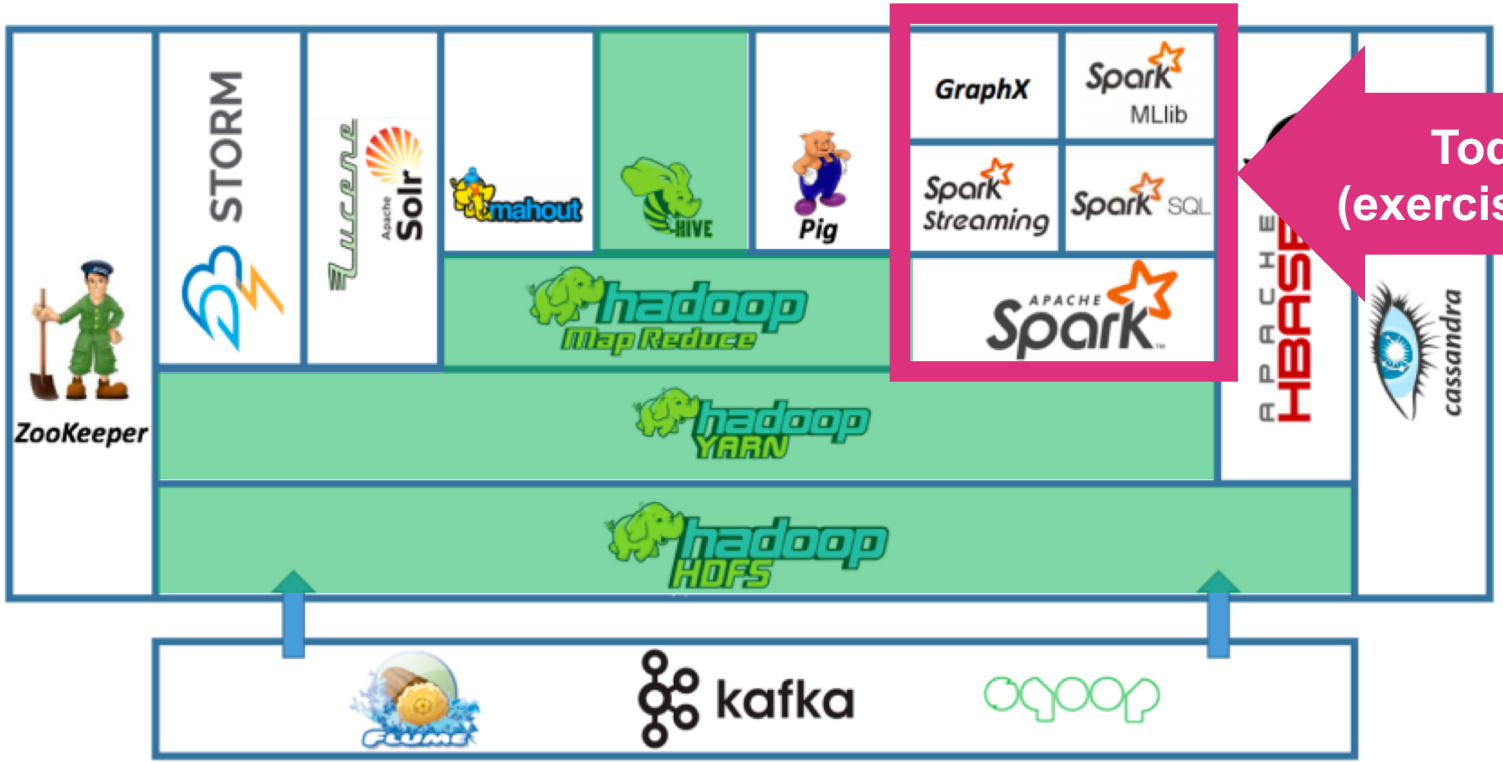
Partitioning – **Partition Lookup**



HandsOn – **Spark, Scala, PySpark and Jupyter**

A quick Introduction to Spark, Scala, PySpark and Jupyter

The Hadoop Ecosystem



Spark

API Languages: Java Scala Python R

APIs and Libraries: Spark SQL | Spark Streaming | Mlib | GraphX

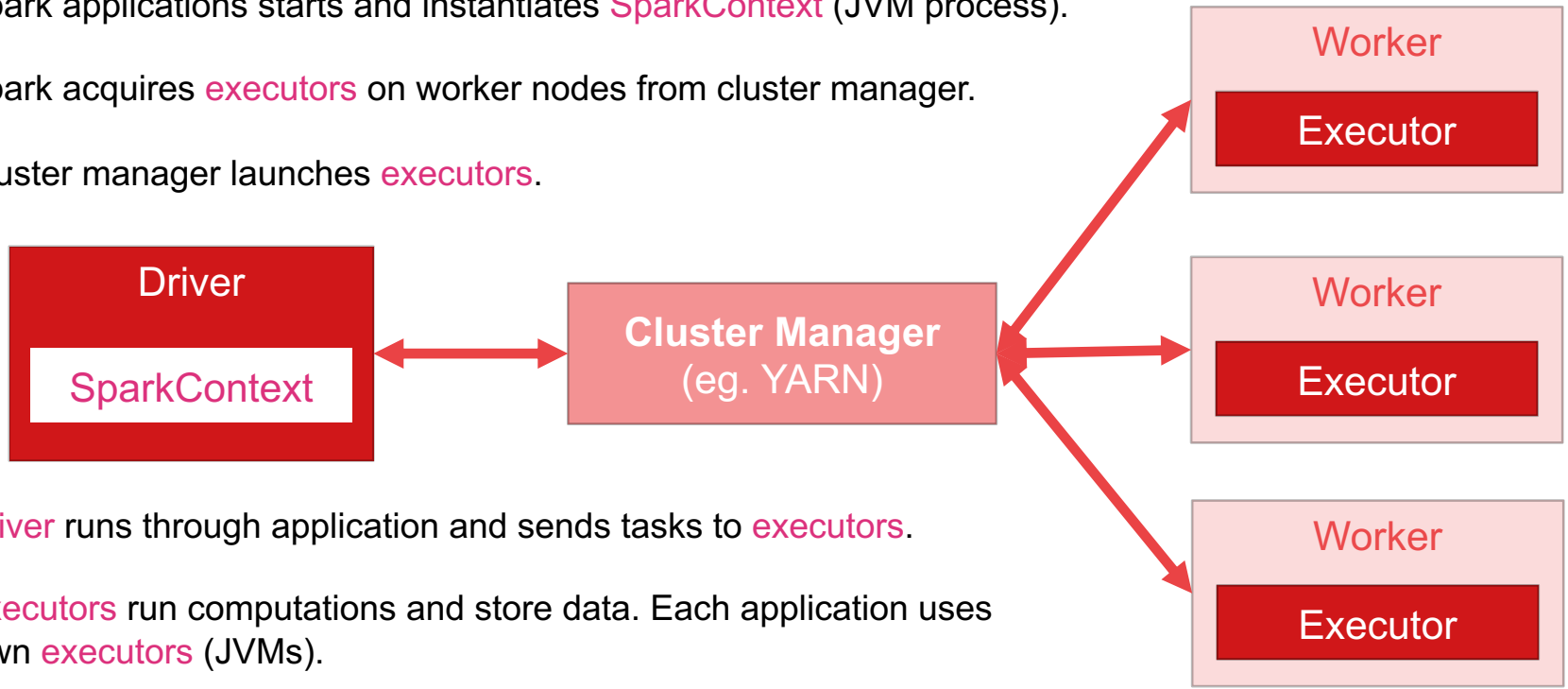
Spark Core

Ressource/ Cluster Manager: Standalone | YARN | Mesos | Kubernetes

Data Source APIs: HDFS, ElasticSearch, Amazon S3, Azure, Redis, Riak, Couchbase, MongoDB, SQL(Hive, Avro, CSV, Parquet, JDBC DB…)

Spark – Execution Process

1. Spark applications starts and instantiates SparkContext (JVM process).
2. Spark acquires executors on worker nodes from cluster manager.
3. Cluster manager launches executors.



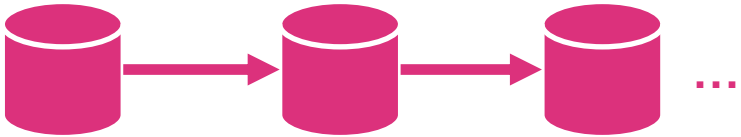
4. Driver runs through application and sends tasks to executors.
5. Executors run computations and store data. Each application uses its own executors (JVMs).
6. If any worker crashes, ist taks will be send to another executor.

Spark – RDDs, DataFrame and DataSet

	RDD (2011)	DataFrame (2013)	DataSet (2015)
Supported by:	Scala, Java, Python	Scala, Java, Python	Scala, Java
Idea:	- RDD = immutable distributed collection of data - partitioned across nodes of cluster - can be operated in parallel with a low-level API	- based on RDD - immutable distributed collection of data - but organized into columns - higher level abstraction	- based on DataFrame API, but type-safe - immutable distributed collection of data - high-level API - converted into optimized RDD
Typed:	typed, no schema	untyped, schema	typed, schema
Use for:	unstructured data	semi-structured and structured data	structured data

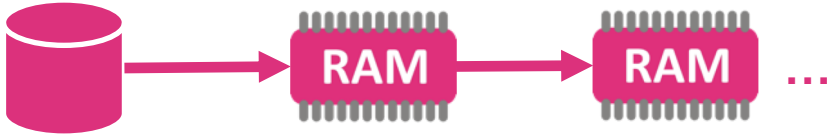
Hadoop MapReduce vs Spark

Hadoop MapReduce



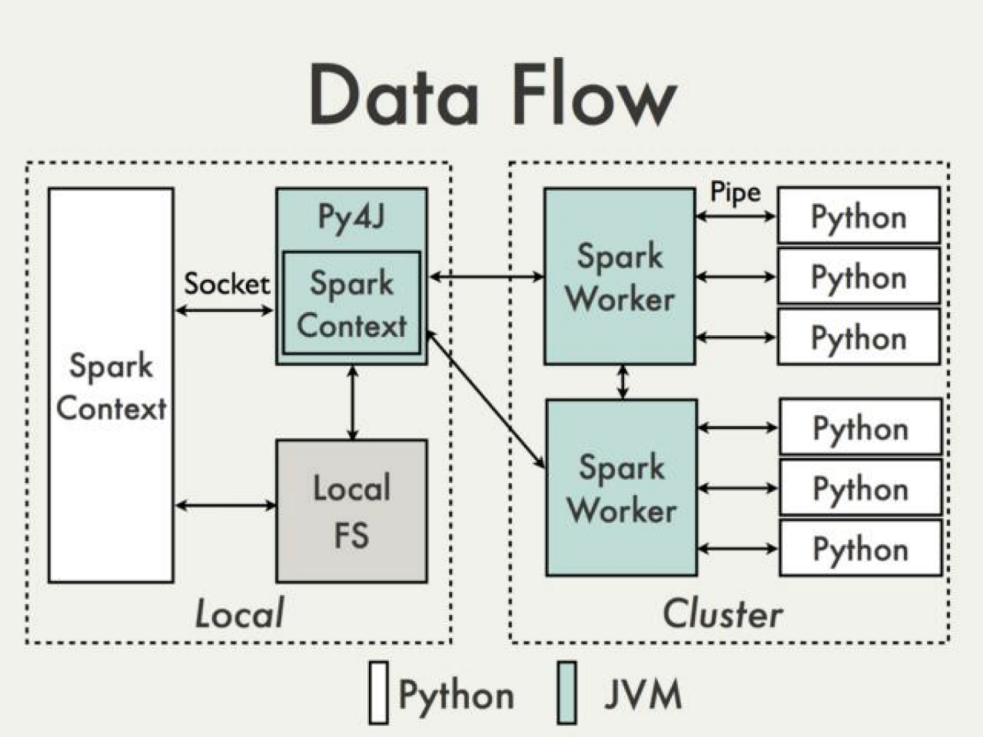
- performs read from HDFS (HDD) before every computation
- performs write on HDFS (HDD) after every computation
- using distributed disk space

Spark



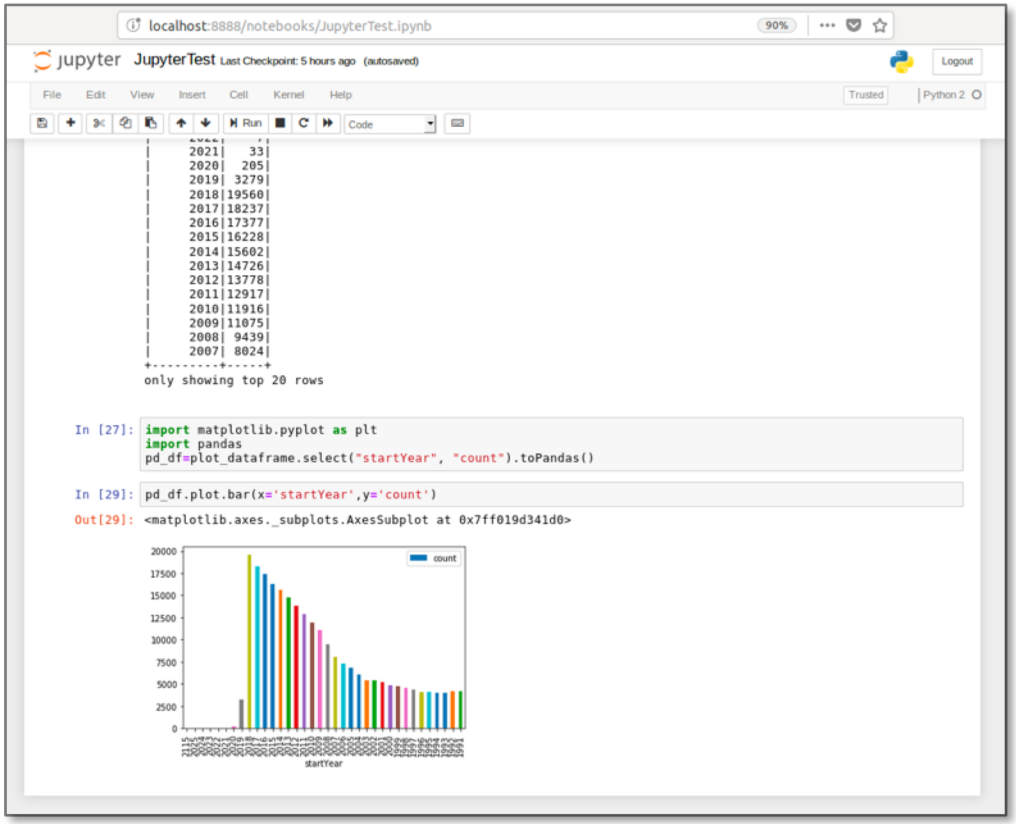
- performs read from RAM before e very computation (except first)
- performs write on RAM after every computation
- using distributed **memory**

PySpark



- built on-top of Sparks Java API
- data is processed in Python and cached/ shuffled within the JVM
- Spark executors on the cluster start Python interpreter to execute user code
- A Python RDD corrresponds to an RDD in
- the local JVM
- e.g. **sc.textFile()** in Python will call JavaSparkContext **textFile()**

Jupyter (Notebooks)



- Interactive Web IDE
- Kernel-based Notebooks
- Open-source
- Create and share:
  - code,
  - visualizations and
  - narrative text like documentation
- Supports:
  - Python
  - R
  - Scala
  - …
- Works well with Spark

Exercises Preparation I

Start Hadoop Cluster and Test Spark Shell
(Word Count Example)

Start Gcloud VM and Connect

1. Start Gcloud Instance:

```
gcloud compute instances start big-data
```

2. Connect to Gcloud instance via SSH (on Windows using Putty):

```
ssh hans.wurst@XXX.XXX.XXX.XXX
```


Pull and Start Docker Container

1. Pull Docker Image:

```
docker pull marcelmittelstaedt/spark_base:latest
```

2. Start Docker Image:

```
docker network create --driver bridge bigdatanet
docker run -dit --name hadoop \
          -p 8088:8088 -p 9870:9870 -p 9864:9864 -p 10000:10000 \
          -p 8032:8032 -p 8030:8030 -p 8031:8031 -p 9000:9000 \
          -p 8888:8888 --net bigdatanet \
          marcelmittelstaedt/spark_base:latest
```

3. Wait till first Container Initialization finished:

```
docker logs hadoop

[…]
Stopping nodemanagers
Stopping resourcemanager
Container Startup finished.
```


Start Hadoop Cluster

1. Get into Docker container:

```
docker exec -it hadoop bash
```

2. Switch to hadoop user:

```
sudo su hadoop
```

```
cd
```

3. Start Hadoop Cluster:

```
start-all.sh
```


Add Test text file to HDFS (Faust 1)

1. Download test Text File (Faust_1.txt):

```
wget https://raw.githubusercontent.com/marcelmittelstaedt/BigData/master/exercises/winter_semester_2019-2020/01_hadoop/sample_data/Faust_1.txt
```

2. Upload file to HDFS:

```
hadoop fs -put Faust_1.txt /user/hadoop/Faust_1.txt
```


Start Spark (on Yarn)

1. Start Spark Shell:

```
spark-shell --master yarn
```

```
Spark context Web UI available at http://localhost:4040
Spark context available as 'sc' (master = yarn, app id = application_1572177196643_0001).
Spark session available as 'spark'.
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 2.3.4
      /_/

Using Scala version 2.11.8 (OpenJDK 64-Bit Server VM, Java 1.8.0_222)
Type in expressions to have them evaluated.
Type :help for more information.

scala>
```


Start Spark – WordCount Example (Scala)

1. Execute Word Count Example in Scala:

```
scala> val text_file = sc.textFile("/user/hadoop/Faust_1.txt")
scala> val words = text_file.flatMap(line => line.split(" "))
scala> val counts = words.map(word => (word, 1))
scala> val reduced_counts = counts.reduceByKey((count1, count2) => count1 + count2)
scala> val sorted_counts = reduced_counts.sortBy(- _._2)
```

```
scala> sorted_counts.take(10)

res0: Array[(String, Int)] = Array(("",1603), (und,509), (die,463), (der,440), (ich,435), (Und,
400), (nicht,346), (zu,319), (ist,291), (ein,284))
```

2. Save results to HDFS:

```
scala> sorted_counts.saveAsTextFile("/user/hadoop/Faust_1_WordCounts_Scala.txt")
```


Start Spark – WordCount Example (Scala)

3. Get results from HDFS to local filesystem:

```
hadoop fs -get /user/hadoop/Faust_1_WordCounts_Scala.txt/part-00000 Faust_1_WordCounts_Scala.txt
```

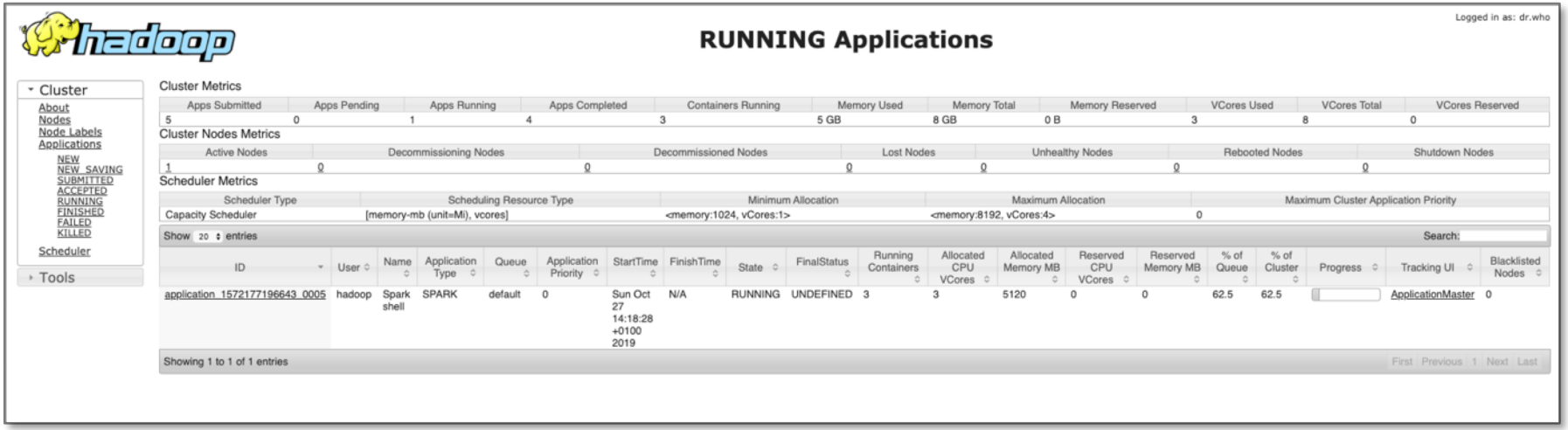
4. Check Result:

```
head -10 Faust_1_WordCounts_Scala.txt

(,1603)
(und,509)
(die,463)
(der,440)
(ich,435)
(Und,400)
(nicht,346)
(zu,319)
(ist,291)
(ein,284)
```


Start Spark (on Yarn) – WordCount Example

5. See Spark Shell Container Running on Yarn http://xxx.xxx.xxx.xxx:8088/cluster :



Exercises Preparation II

Test PySpark Shell (Word Count Example)

Start PySpark (on Yarn) – Test Install

1. As PySpark is already installed, start PySpark Shell and execute previous example as Python code:

```
pyspark --master yarn
```

```
Python 3.6.8 (default, Oct  7 2019, 12:59:55)
[GCC 8.3.0] on linux
Type "help", "copyright", "credits" or "license" for more information.
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 2.3.4
      /_/

Using Python version 3.6.8 (default, Oct  7 2019 12:59:55)
SparkSession available as 'spark'.
>>>
```

PySpark – WordCount Example (Python)

1. Execute Word Count Example in Python:

```
>>> text_file = spark.read.text("/user/hadoop/Faust_1.txt").rdd.map(lambda r: r[0])
>>> words = text_file.flatMap(lambda line: line.split(" "))
>>> counts = words.map(lambda word: (word, 1)).reduceByKey(lambda a,b:a +b)
>>> output = counts.collect()
>>> sorted_output = sorted(output,key=lambda x:(-x[1],x[0]))
```

```
>>> c

[('', 1603), ('und', 509), ('die', 463), ('der', 440), ('ich', 435), ('Und', 400), ('nicht', 34
6), ('zu', 319), ('ist', 291), ('ein', 284)]
```

2. Save results to HDFS:

```
>>> counts.saveAsTextFile("/user/hadoop/Faust_1_WordCounts_Python.txt")
```


PySpark – WordCount Example (Python)

3. Get results from HDFS to local filesystem:

```
hadoop fs -get /user/hadoop/Faust_1_WordCounts_Python.txt/part-00000 Faust_1_WordCounts_Python.txt
```

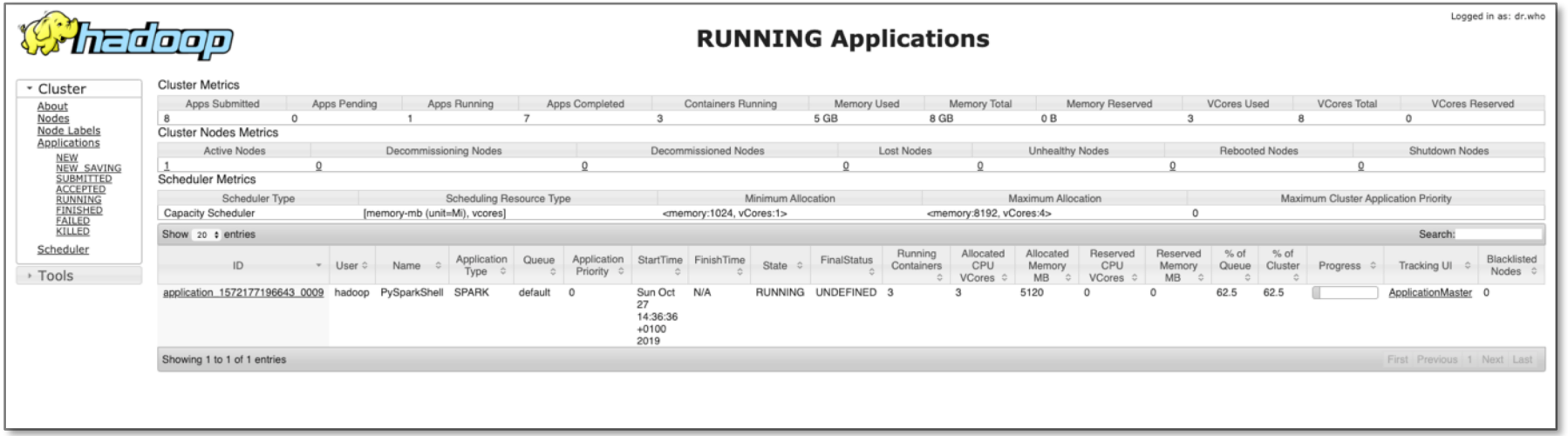
4. Check Result:

```
head -10 Faust_1_WordCounts_Python.txt

('Johann', 1)
('Wolfgang', 1)
('von', 133)
('Goethe:', 1)
('Faust,', 8)
('Der', 130)
('Tragödie', 1)
('erster', 2)
('Teil', 6)
('', 1603)
```

PySpark (on Yarn) – WordCount Example

5. See PySpark Shell Container Running on Yarn http://xxx.xxx.xxx.xxx:8088/cluster :



Exercises Preparation III

Start and work with Jupyter Notebooks
(on PySpark)

Start Jupyter

1. Start Jupyter Notebook

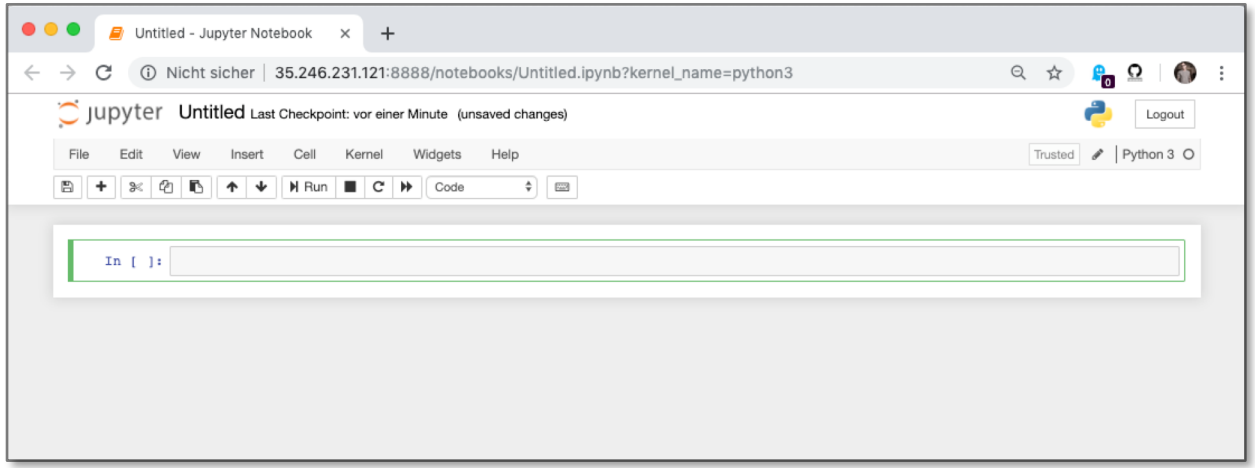
```
jupyter notebook

[I 14:02:39.790 NotebookApp] Writing notebook server cookie secret to /home/hadoop/.local/share/jupyter/runtime/notebook_cookie_secret
[I 14:02:40.957 NotebookApp] Serving notebooks from local directory: /home/hadoop
[I 14:02:40.957 NotebookApp] The Jupyter Notebook is running at:
[I 14:02:40.957 NotebookApp] http://e0f4472dcb12:8888/?token=76b68a3c700b415790b019e07a3dd46a0d068c153a732d27
[I 14:02:40.957 NotebookApp]  or http://127.0.0.1:8888/?token=76b68a3c700b415790b019e07a3dd46a0d068c153a732d27
[I 14:02:40.957 NotebookApp] Use Control-C to stop this server and shut down all kernels (twice to skip confirmation).
[W 14:02:40.979 NotebookApp] No web browser found: could not locate runnable browser.
[C 14:02:40.980 NotebookApp]

    To access the notebook, open this file in a browser:
        file:///home/hadoop/.local/share/jupyter/runtime/nbserver-8624-open.html
    Or copy and paste one of these URLs:
        http://e0f4472dcb12:8888/?token=76b68a3c700b415790b019e07a3dd46a0d068c153a732d27
     or http://127.0.0.1:8888/?token=76b68a3c700b415790b019e07a3dd46a0d068c153a732d27
```

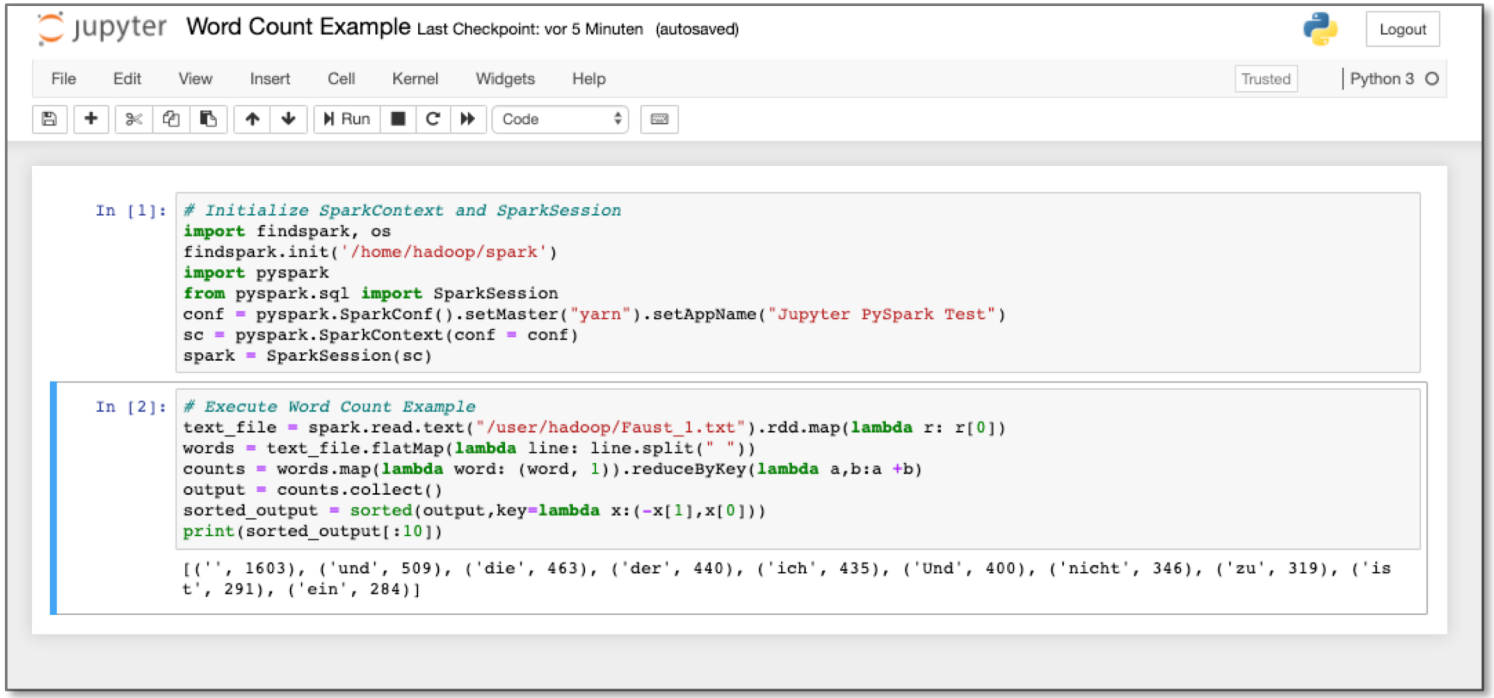

Start Jupyter

2. Open Notebook in Browser: http://XXX.XXX.XXX.XXX:8888/?token=[XYZXYZXYZ]



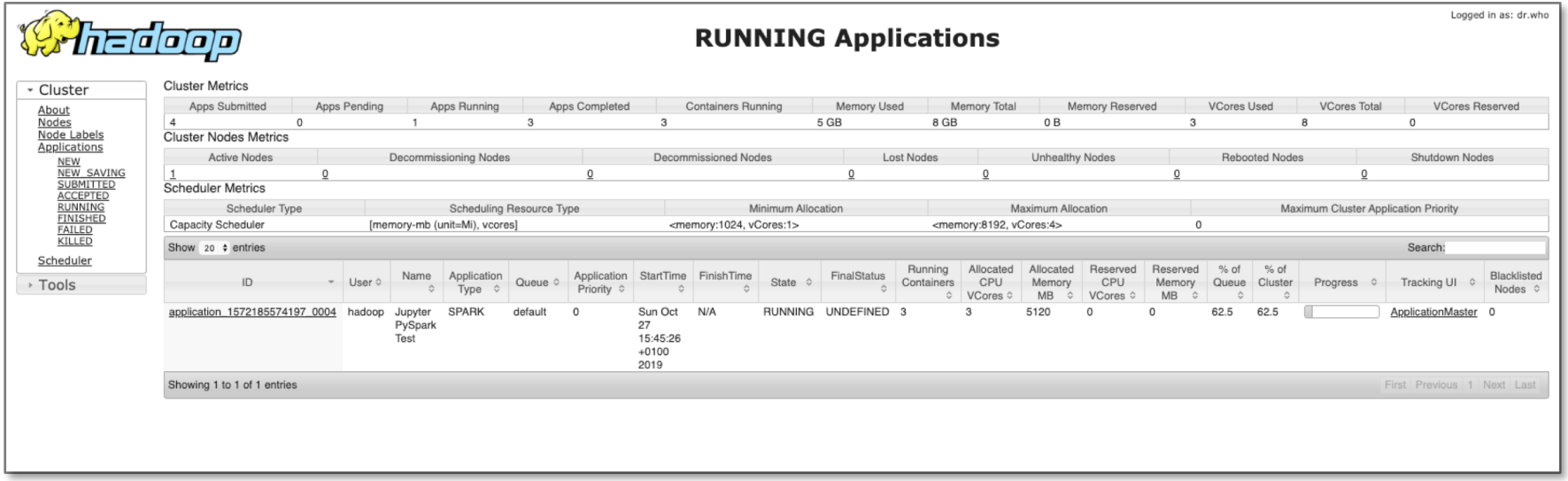
Use Jupyter (Word Count Example)

1. Execute previous Word Count example



Use Jupyter (Word Count Example)

2. See **Jupyter** PySpark Container Running on Yarn http://xxx.xxx.xxx.xxx:8088/cluster :



Get some data…

1. Get some IMDb data:

```
wget https://datasets.imdbws.com/title.basics.tsv.gz && gunzip title.basics.tsv.gz
wget https://datasets.imdbws.com/title.ratings.tsv.gz && gunzip title.ratings.tsv.gz
```

2. Put them into HDFS:

```
hadoop fs -mkdir /user/hadoop/imdb
```

```
hadoop fs -mkdir /user/hadoop/imdb/title_basics
hadoop fs -mkdir /user/hadoop/imdb/title_ratings
```

```
hadoop fs -put title.basics.tsv /user/hadoop/imdb/title_basics/title.basics.tsv
hadoop fs -put title.ratings.tsv /user/hadoop/imdb/title_ratings/title.ratings.tsv
```


PySpark Operations

1. Basic PySpark operations: Read Files from HDFS into DataFrames:

```
In [5]: # Read title.basics.tsv into Spark dataframe
imdb_title_basics_dataframe = spark.read.format('csv').options(\
    header='true', delimiter='\t', nullValue='null', inferschema='true')\
    .load('/user/hadoop/imdb/title_basics/title.basics.tsv')

In [6]: imdb_title_basics_dataframe.printSchema() # Print Schema of title_basics dataframe

root
 |-- tconst: string (nullable = true)
 |-- titleType: string (nullable = true)
 |-- primaryTitle: string (nullable = true)
 |-- originalTitle: string (nullable = true)
 |-- isAdult: integer (nullable = true)
 |-- startYear: string (nullable = true)
 |-- endYear: string (nullable = true)
 |-- runtimeMinutes: string (nullable = true)
 |-- genres: string (nullable = true)

In [7]: imdb_title_basics_dataframe.show(5) # Show first 5 rows of title_basics dataframe

+---------+---------+--------------------+--------------------+-------+---------+-------+--------------+--------------
-------+
|   tconst|titleType|        primaryTitle|       originalTitle|isAdult|startYear|endYear|runtimeMinutes|
genres|
+---------+---------+--------------------+--------------------+-------+---------+-------+--------------+--------------
-------+
|tt0000001|    short|           Carmencita|           Carmencita|      0|     1894|     \N|             1|   Documentar
y,Short|
|tt0000002|    short|Le clown et ses c...|Le clown et ses c...|      0|     1892|     \N|             5|     Animatio
n,Short|
|tt0000003|    short|      Pauvre Pierrot|      Pauvre Pierrot|      0|     1892|     \N|             4|Animation,Com
edy,...|
|tt0000004|    short|         Un bon bock|         Un bon bock|      0|     1892|     \N|            \N|     Animatio
n,Short|
|tt0000005|    short|    Blacksmith Scene|    Blacksmith Scene|      0|     1893|     \N|             1|       Comed
y,Short|
+---------+---------+--------------------+--------------------+-------+---------+-------+--------------+--------------
-------+
only showing top 5 rows
```

https://github.com/marcelmittelstaedt/BigData/tree/master/exercises/ winter_semester_2019-2020/04_spark_pyspark_jupyter/PySparkExamples.html

www.marcel-mittelstaedt.com

PySpark Operations

2. Basic PySpark: Operations on DataFrames (filter, aggregate, sort…):

```
In [5]: imdb_title_basics_dataframe.count() # show number of rows within title_basics dataframe
Out[5]: 6262637
```

```
In [11]: # Get column titleTypes values with counts and ordered descending
from pyspark.sql.functions import desc
imdb_title_basics_dataframe.groupBy("titleType").count().orderBy(desc("count")).show()
```

```
+------------+-------+
|   titleType|  count|
+------------+-------+
|   tvEpisode|4392190|
|       short| 707983|
|       movie| 533869|
|       video| 245253|
|    tvSeries| 173337|
|     tvMovie| 120824|
|tvMiniSeries|  28114|
|   tvSpecial|  25479|
|   videoGame|  24322|
|     tvShort|  11266|
+------------+-------+
```

```
In [28]: # Calculate average Movie length in minutes
from pyspark.sql.functions import avg
imdb_title_basics_dataframe.filter(imdb_title_basics_dataframe['titleType']=='movie')\
    .agg(avg('runtimeMinutes')).show()
```

```
+------------------+
|avg(runtimeMinutes)|
+------------------+
|  88.34293031750659|
+------------------+
```

https://github.com/marcelmittelstaedt/BigData/tree/master/exercises/ winter_semester_2019-2020/04_spark_pyspark_jupyter/PySparkExamples.html

PySpark Operations

3. PySpark SQL: Join DataFrames:

In [12]:
```
# Read title.ratings.tsv into Spark dataframe
imdb_title_ratings_dataframe = spark.read.format('csv').options(\
    header='true', delimiter='\t', nullValue='null', inferschema='true')\
    .load('/user/hadoop/imdb/title_ratings/title.ratings.tsv')
```

In [13]:
```
imdb_title_ratings_dataframe.printSchema() # Print Schema of title_ratings dataframe
```

```
root
 |-- tconst: string (nullable = true)
 |-- averageRating: double (nullable = true)
 |-- numVotes: integer (nullable = true)
```

In [14]:
```
imdb_title_ratings_dataframe.show(5) # Show first 5 rows of title_ratings dataframe
```

```
+---------+-------------+--------+
|   tconst|averageRating|numVotes|
+---------+-------------+--------+
|tt0000001|          5.6|    1543|
|tt0000002|          6.1|     186|
|tt0000003|          6.5|    1201|
|tt0000004|          6.2|     114|
|tt0000005|          6.1|    1921|
+---------+-------------+--------+
only showing top 5 rows
```

In [15]:
```
# JOIN Data Frames
title_basics_and_ratings_df = imdb_title_basics_dataframe.join(imdb_title_ratings_dataframe, \
                              imdb_title_basics_dataframe.tconst == imdb_title_ratings_dataframe.tconst)
```

In [25]:
```
top_tvseries=title_basics_and_ratings_df.filter(title_basics_and_ratings_df['titleType']=='tvSeries')\
                              .filter(title_basics_and_ratings_df['numVotes'] > 200000)\
                              .orderBy(desc('averageRating'))\
                              .select('originalTitle', 'startYear', 'endYear', 'averageRating', 'numVotes')
top_tvseries.show(5)
```

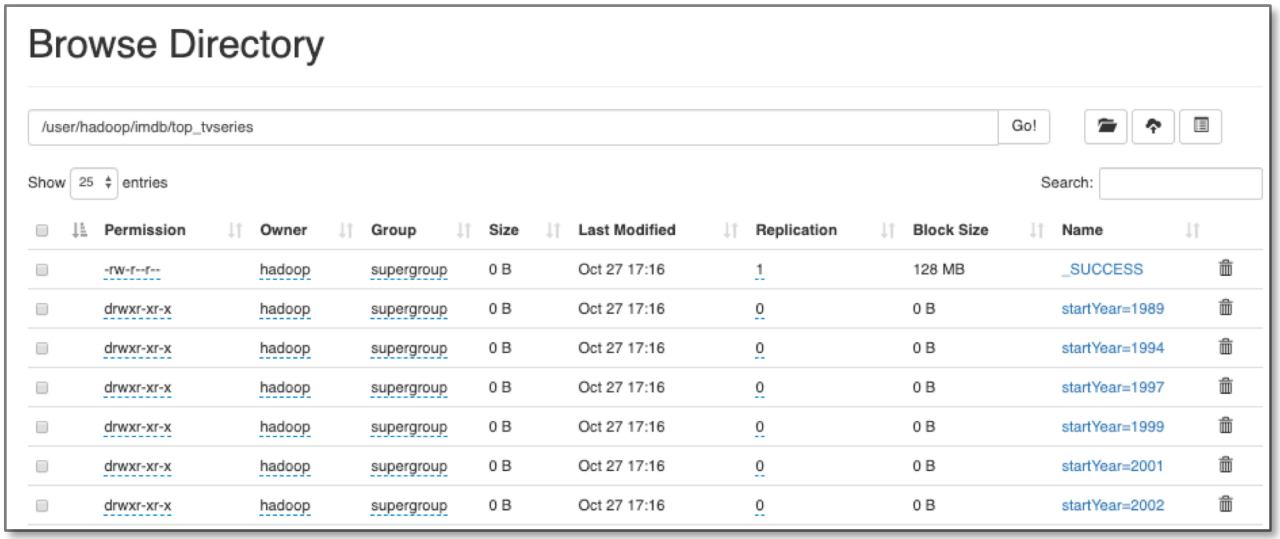
```
+--------------------+---------+-------+-------------+--------+
|       originalTitle|startYear|endYear|averageRating|numVotes|
+--------------------+---------+-------+-------------+--------+
|        Breaking Bad|     2008|   2013|          9.5| 1271805|
|     Game of Thrones|     2011|   2019|          9.4| 1598911|
|      Rick and Morty|     2013|     \N|          9.3|  296206|
|            The Wire|     2002|   2008|          9.3|  254371|
|Avatar: The Last ...|     2005|   2008|          9.2|  200077|
+--------------------+---------+-------+-------------+--------+
only showing top 5 rows
```

https://github.com/marcelmittelstaedt/BigData/tree/master/exercises/ winter_semester_2019-2020/04_spark_pyspark_jupyter/PySparkExamples.html

PySpark Operations

4. Basic PySpark: Save DataFrames as File to HDFS:

```
In [27]: top_tvseries.write.format('parquet')\ # Could also be CSV, but parquet requires less space
                           .partitionBy('startYear')\ # partition data by startYear (not mandatory but useful)
                           .mode('overwrite')\ # overwrite existing data
                           .save('/user/hadoop/imdb/top_tvseries') # where to save
```



PySpark Operations

5. PySpark SQL: Save DataFrames as (temporary Hive) Table:

```
In [17]: title_basics_and_ratings_df.select('originalTitle', 'titleType', 'startYear', \
                                            'endYear', 'numVotes', 'averageRating')\
                                    .write.saveAsTable('movies_and_ratings')
```

6. PySpark SQL : Read from (temporary Hive) Table:

```
In [18]: result_df = spark.sql("""SELECT originalTitle, averageRating FROM movies_and_ratings WHERE
                                  numVotes > 200000 AND titleType= 'movie' AND averageRating > 8.5 AND startYear > 2010
                                  ORDER BY averageRating DESC LIMIT 10""")
                                ).show(10)
+-------------+-------------+
|originalTitle|averageRating|
+-------------+-------------+
|       Joker|          8.9|
| Interstellar|          8.6|
+-------------+-------------+
```

PySpark Operations

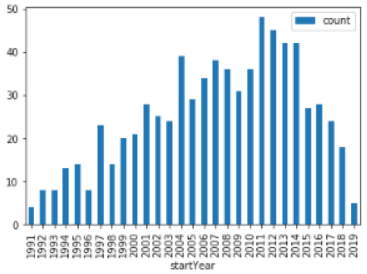
7. Basic Python: Plot results:

In [6]:
```
good_movies_df = title_basics_and_ratings_df.filter(title_basics_and_ratings_df['titleType']=='movie')\
                            .filter(title_basics_and_ratings_df['numVotes'] > 200000)\
                            .filter(title_basics_and_ratings_df['startYear'] > 1990)\
                            .groupBy('startYear')\
                            .count()\
                            .orderBy('startYear')
good_movies_df.show(5)
```

```
+---------+-----+
|startYear|count|
+---------+-----+
|     1991|    4|
|     1992|    8|
|     1993|    8|
|     1994|   13|
|     1995|   14|
+---------+-----+
only showing top 5 rows
```

In [11]:
```
import matplotlib.pyplot as plt
import pandas
pandas_dataframe = good_movies_df.select('startYear', 'count').toPandas()
pandas_dataframe.plot.bar(x='startYear', y='count')
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd4e21a2240>
```



Exercises

Use PySpark Shell or Jupyter Notebooks on PySpark to solve exercises

PySpark Exercises - **IMDB**

1. Execute Tasks of previous HandsOn Slides

2. Use PySpark or Jupyter on PySpark to answer following questions:

    a) How many **tv series** are within the IMDB dataset?

    b) Who is the **youngest** actor/writer/… within the dataset?

    c) Create a list (`tconst, original_title, start_year, average_rating, num_votes`) of movies which are:
    - equal or newer than year 2010
    - have an average rating better than 8
    - have been voted more than 100.000 times

    save result (DataFrame) back to HDFS as CSV File.

PySpark Exercises - IMDB

2. Use PySpark or Jupyter on PySpark to answer following questions:

d) How many movies are in list of c)?

e) create following plot with result of c) (plot visualizes the amount of good movies per year since 2001)