

Agenda – 13.10.2025

Presentation and Discussion: Exercise Of Last Lecture

Write, compile and run Java MapReduce, Hive, HiveQL and external tables

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

HandsOn – Hive, HiveQL, Hive/HDFS Partitioning and HiveServer2

Quick Introduction To Hive, HiveQL, Hive/HDFS Partitioning and HiveQL via JDBC (HiveServer2)

Exercise – HDFS/Hive work with Partitions on IMDb dataset.

HiveServer2, HiveQL via JDBC, Partitioning with HDFS and Hive



01

02

03

04

Schedule

	Lecture Topic	HandsOn
29.09.2025 13:15-15:45 Ro. N/A	About This Lecture, Introduction to Big Data	Setup Google Cloud, Create Own Hadoop Cluster and Run MapReduce
06.10.2025 13:15-15:45 Ro. N/A	(Non-)Functional Requirements Of Distributed Data-Systems, Data Models and Access	Hive and HiveQL
13.10.2025 13:15-15:45 Ro. N/A	Challenges Of Distributed Data Systems: Partitioning	HiveQL via JDBC, Data Partitioning (with HDFS and Hive)
20.10.2025 13:15-15:45 Ro. N/A	Challenges Of Distributed Data Systems: Replication	Spark and Scala
27.10.2025 13:15-15:45 Ro. N/A	ETL Workflow and Automation	PySpark and Notebooks (Jupyter)
03.11.2025 13:15-15:45 Ro. N/A	Batch and Stream Processing	Airflow
10.11.2025 13:15-15:45 Ro. N/A	Practical Exam	Work On Practical Exam
17.11.2025 13:15-15:45 Ro. N/A	Practical Exam	Work On Practical Exam
24.11.2025 13:15-15:45 Ro. N/A	Practical Exam Presentation	
01.12.2025 13:15-15:45 Ro. N/A	Practical Exam Presentation	





Prerequisites:

- Setup Google Cloud SDK
- Start VM instance
- Pull docker container marcelmittelstaedt/hive base:latest
- Start docker container: docker run -dit --name hive_base_container -p 8088:8088 -p 9870:9870 -p 9864:9864 marcelmittelst aedt/hive base:latest
- Get into docker container
- Start Hadoop and Hive Shell:
 - start-all.sh
 - hive



Exercise 1-4:

1. Download and unzip https://datasets.imdbws.com/name.basics.tsv.gz

```
wget https://datasets.imdbws.com/name.basics.tsv.gz
gunzip name.basics.tsv.gz
```

2. Create HDFS directory /user/hadoop/imdb/name_basics/ for file name.basics.tsv

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

3. Put TSV file to HDFS:

hadoop fs -put name.basics.tsv /user/hadoop/imdb/name_basics/name.basics.tsv



Exercise 1-4:

4. Create Hive Table name basics:



Exercise 5:

a) How many movies and how many TV series are within the IMDB dataset?

```
hive > SELECT m.title_type, count(*)
    FROM title_basics m GROUP BY m.title_type;

tvMovie 152520
movie 727439
tvEpisode 9200239
tvSeries 288488
[...]

Time taken: 32.908 seconds, Fetched: 11 row(s)
```

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

```
hive > SELECT * FROM name_basics n

WHERE n.birth_year = ( SELECT MAX(birth_year) FROM name_basics);
```



Exercise 5:

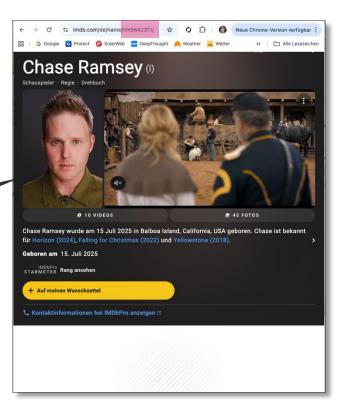
b) Who is the youngest actor/writer/... within the dataset?

```
hive > SELECT * FROM name_basics n
WHERE n.birth_year = ( SELECT MAX(birth_year)
FROM name_basics);

And it's Chase Ramsey, who is way older, so this one is
actually shitty data in IMDB:D

rmm5642311 Chase Ramsey 2025 NULL actor, director, writer tt17505010, tt14715170, t
t4236770, tt17062324

Time taken: 65.166 seconds, Fetched: 1 row(s)
```





Exercise 5:

- c) Create a list (m.tconst, m.original_title, m.start_year, r.average rating, r.num votes) of movies which are:
 - equal or newer than year 2010
 - have an average rating equal or better than 8,1
 - have been voted more than 100.000 times



Exercise 5:

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

```
hive > SELECT count(*)
    FROM title_basics m JOIN title_ratings r on (m.tconst = r.tconst)
    WHERE r.average_rating >= 8.1 and m.start_year >= 2010 and m.title_type = 'movie'
    and r.num_votes > 100000;
```



Exercise 5:

e) We want to know which years have been great for cinema.

Create a list with one row per year and a related count of movies which:

- have an average rating better than 8
- have been voted more than 100.000 times ordered descending by count of movies.

```
hive > SELECT m.start_year, count(*)
FROM title_basics m JOIN title_ratings r on (m.tconst = r.tconst)
WHERE r.average_rating > 8 AND m.title_type = 'movie'
AND r.num_votes > 100000
GROUP BY m.start_year
ORDER BY count(*) DESC;

1995 8
2004 7
2018 6
2016 6
2015 6
[...]
```



Exercise 5:

So 1995 seems to be a really good year for cinema, 8 really good movies have been releases, but which

are they?

```
hive > SELECT
            m.tconst, m.original title, m.start year, r.average rating,
            r.num votes
       FROM title basics m JOIN title ratings r ON (m.tconst = r.tconst)
       WHERE
            r.average rating > 8 AND m.title type = 'movie'
            AND r.num votes > 100000 AND m.start year = 1995
       ORDER BY r.average rating DESC;
```





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)

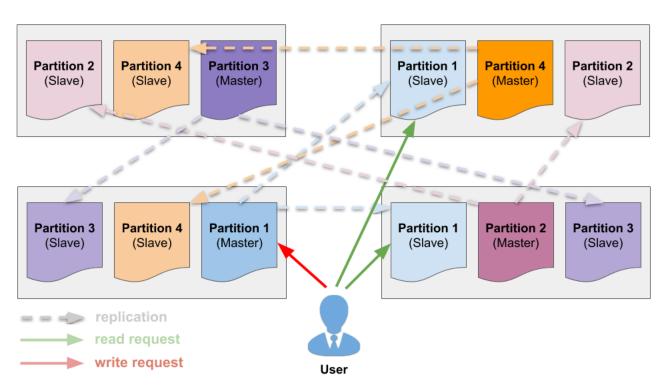
Partitioning and Replication are usually used together, especially when building dataintensive applications, as datasets are too big to be stored on a single server or replica, and benefits of replication are required (e.g. redundancy, fault-tolerance or high read/write through put). This can be achieved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

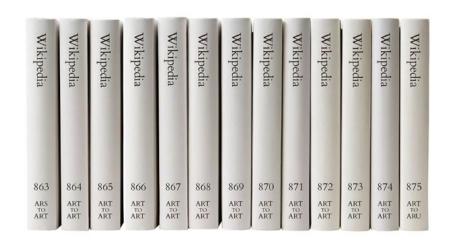
Partitioning By Hash Value Of A Key: Derive a partition by a certain hash of a given key to achieve a mor e even data distribution. → More details on next slides.

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 Smartphone. → As no data-intensive system makes use of partitioning by list (as it is very improper to provide even data distribution), 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 \mathbf{n} modulo \mathbf{p} (n = number of incoming data records, p = number of partitions). \rightarrow 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 everyone 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 *Ily provides an output of fixed size. The output of a hash function is called hash, hash value or digest. A hash function needs to be deterministic and uniform. 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

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

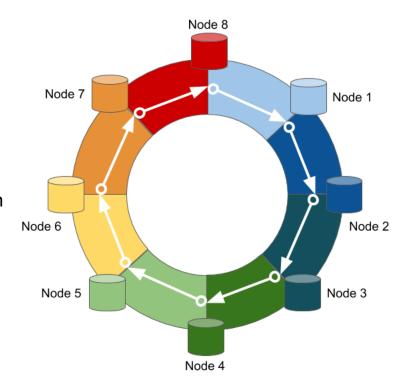
- → This allows the the data-system to easily distribute and receive records to and from a given number of partitions.
- → Major disadvantage in terms of **scalability** and **operability**.
 - → Adding nodes results in different partition assignments for a lot of records (depending on size of N), which 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 predecessor Nj

J < v < i





Partitioning – Hash Partitioning (Consistent Hashing)

Strenghts:

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

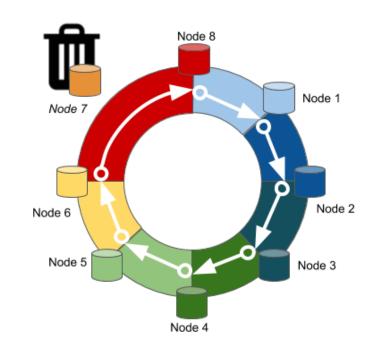
Weaknesses:

- 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

Example: Removing a Node





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 secondary index!



Partitioning – Local Secondary Indices

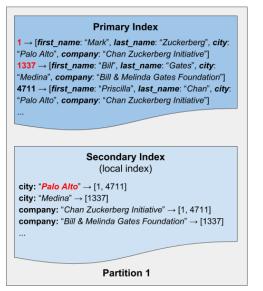
- LSI = Local Secondary Index
- every partition manages ist own index
- all pointers reference only to local data items

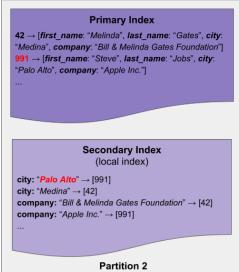
Strenths:

- → maintaining local index requires less overhead than global index
- → INSERT/DELETE/UPDATE performed locally

Weaknesses:

- → maintaining local index will compete with local workload and 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 amo ng several nodes independently of local data r ecords
- pointers reference to local but also remote data records

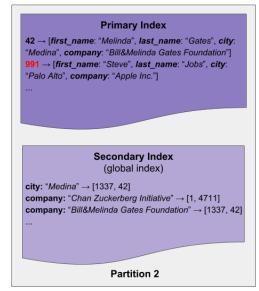
Strenths:

- → 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/DELET E/UPDATE statements require remote updates
- → usually weakens read-consistency as indices u pdates take more time → DynamoDB eventual consistency

Primary Index 1 → [first_name: "Mark", last_name: "Zuckerberg", city: "Palo Alto", company: "Chan Zuckerberg Initiative"] 1337 → [first_name: "Bill", last_name: "Gates", city: "Medina", company: "Bill&Melinda Gates Foundation"] 4711 → [first name: "Priscilla", last name: "Chan", city: "Palo Alto", company: "Chan Zuckerberg Initiative"] Secondary Index (global index) city: "Palo Alto" → [1, 4711, 991] company: "Apple Inc." → [991] Partition 1



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:

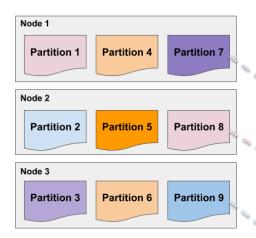
- stupid
- requires shuffling a lot of data, as assignment of partitions to nodes changes significantly

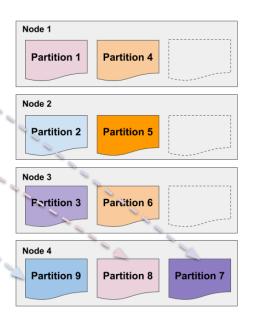
Used by e.g.:

- 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:

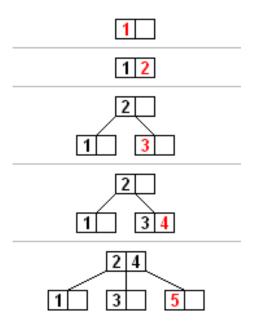
- partition/node mappings change
- but for less partitions
- → only partial rewrite of partitions

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:

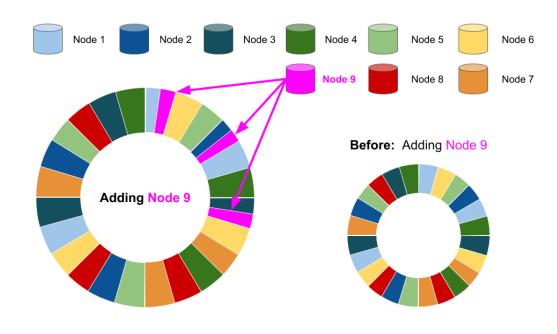
- evenly distribution
- continues overhead during runtime

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:

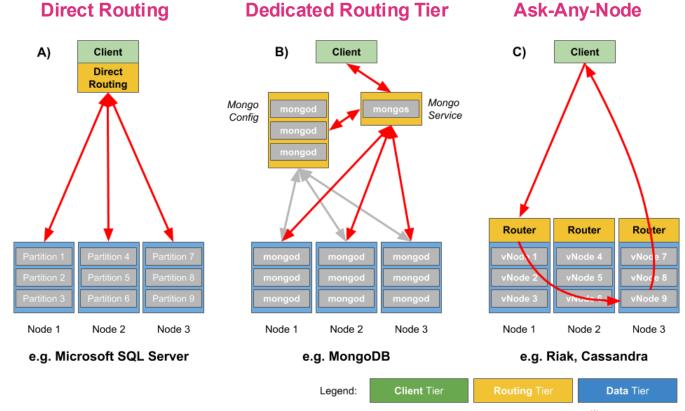
- works well for range partitioning (hash or keys)
- load may be temprorarily unbalanced but will be even again over time

Used by e.g.:

Cassandra



Partitioning – Partition Lookup



Break





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



Pull and Start Docker Container

1. Pull Docker Image:

```
docker pull marcelmittelstaedt/hiveserver_base:latest
```

2. Start Docker Image:

```
docker run -dit --name hiveserver_base_container \
   -p 8088:8088 -p 9870:9870 -p 9864:9864 \
   -p 10000:10000 -p 9000:9000 \
   marcelmittelstaedt/hiveserver_base:latest
```

3. Wait till first Container Initialization finished:

```
docker logs hiveserver_base_container

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



Start Hadoop Cluster

1. Get into Docker container:

```
docker exec -it hiveserver_base_container bash
```

2. Switch to hadoop user:

sudo su hadoop

cd

3. Start Hadoop Cluster:

start-all.sh



Start HiveServer2

1. Start HiveServer2 (takes some time!), wait till you see:

```
hive/bin/hiveserver2

2021-02-21 16:43:55: Starting HiveServer2

SLF4J: Class path contains multiple SLF4J bindings.

SLF4J: Found binding in [jar:file:/home/hadoop/hive/lib/log4j-slf4j-impl-2.10.0.jar!/org/slf4
j/impl/StaticLoggerBinder.class]

SLF4J: Found binding in [jar:file:/home/hadoop/hadoop/share/hadoop/common/lib/slf4j-log4j12-1
.7.25.jar!/org/slf4j/impl/StaticLoggerBinder.class]

SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.

SLF4J: Actual binding is of type [org.apache.logging.slf4j.Log4jLoggerFactory]

Hive Session ID = ae41ac72-4dbd-4115-9863-59c3859c3db6

Hive Session ID = 17f9f63b-4018-4976-bb7d-15fbf1bc8042

Hive Session ID = 83b2ad76-c248-46a1-91d4-f2ad289614ee

Hive Session ID = b9ff1fd3-ccb1-4254-abc7-4c696d8ff8a1
[...]
```



Connect To HiveServer2 via JDBC

1. Download JDBC SQL Client, e.g. *DBeaver*:

Mac OSX: wget https://dbeaver.io/files/dbeaver-ce-latest-macos.dmg

Linux (Debian): wget https://dbeaver.io/files/dbeaver-ce latest amd64.deb

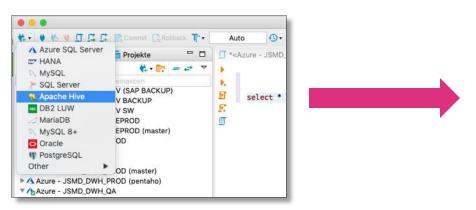
Linux (RPM): wget https://dbeaver.io/files/dbeaver-ce-latest-stable.x86_64.rpm

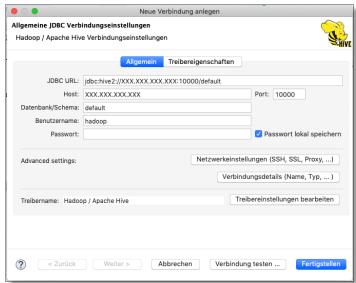
Windows: wget https://dbeaver.io/files/dbeaver-ce-latest-x86_64-setup.exe



Connect To HiveServer2 via JDBC

2. Configure Connection To Hive Server:







Let's 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 wget https://datasets.imdbws.com/name.basics.tsv.gz && gunzip name.basics.tsv.gz
```

2. Put it into HDFS:

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

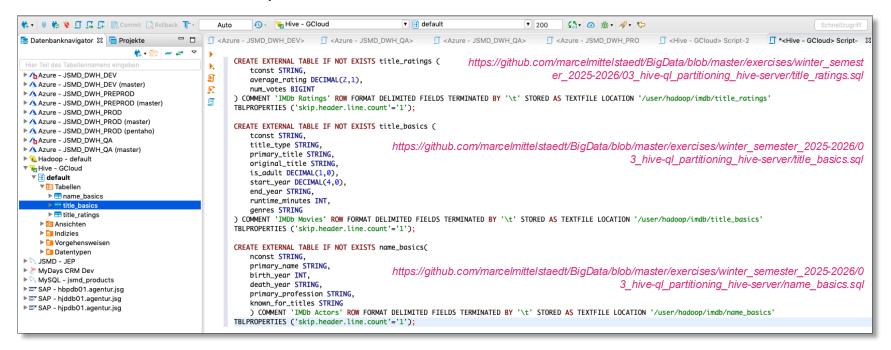
hadoop fs -mkdir /user/hadoop/imdb/title_basics && hadoop fs -mkdir /user/hadoop/imdb/title_ratings && hadoop fs -mkdir /user/hadoop/imdb/name basics

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 && hadoop fs -put na me.basics.tsv /user/hadoop/imdb/name basics/name.basics.tsv



Create some external tables...

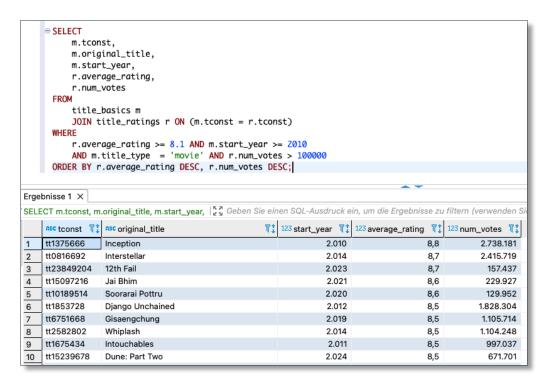
1. Create some tables on top of files:





Query some data...

1. Query some data:





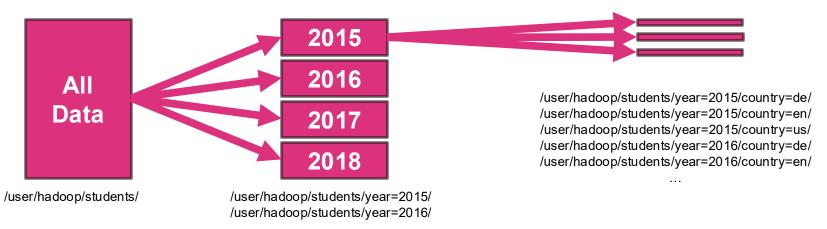
Break





HDFS/Hive - Partitioning

- Partitioning of data distributes load and speeds up data processing
- A table can have one or more partition columns, defined by the time of creating a table (CREATE TABLE student(id Int, name STRING) PARTITIONED BY (year STRING)... STORED AS TEXTFILE LOCATION '/user/hadoop/students')
- partitioning can be done either static or dynamic
- each distinct value of a partition column is represented by a HDFS directory



Static Partitioning – Create Partitioned Table

1. Create partitioned version of table imdb_ratings: imdb_ratings_partitioned:

```
CREATE TABLE IF NOT EXISTS title_ratings_partitioned(
    tconst STRING,
    average_rating DECIMAL(2,1),
    num_votes BIGINT
) PARTITIONED BY (partition_quality STRING)
STORED AS PARQUET LOCATION '/user/hadoop/imdb/ratings_partitioned';
```

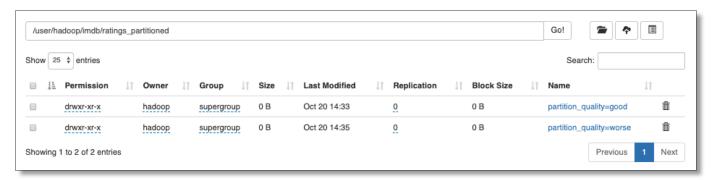


Static Partitioning – **INSERT Into Table via Hive**

1. Migrate and partition data of table title_ratings to table title_ratings_partitioned:

```
INSERT OVERWRITE TABLE title_ratings_partitioned PARTITION(partition_quality='good')
SELECT r.tconst, r.average_rating, r.num_votes FROM title_ratings r WHERE r.average_rating >= 7;
INSERT OVERWRITE TABLE title_ratings_partitioned PARTITION(partition_quality='worse')
SELECT r.tconst, r.average_rating, r.num_votes FROM title_ratings r WHERE r.average_rating < 7;</pre>
```

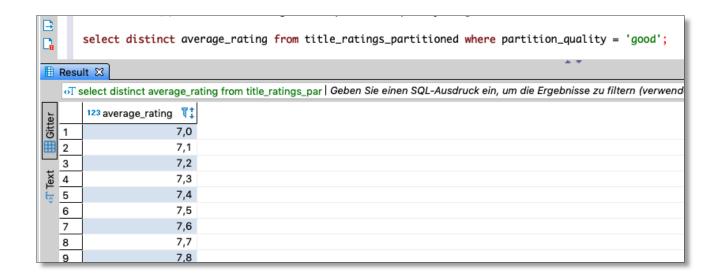
2. Check Success on HDFS:





Static Partitioning – **INSERT Into Table via Hive**

3. Check Success via Hive:





Dynamic Partitioning – Create Partitioned Table

1. Create partitioned version of table title_basics: title_basics_partitioned:

```
CREATE TABLE IF NOT EXISTS title_basics_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
) PARTITIONED BY (partition_year DECIMAL(4,0)) STORED AS PARQUET L
OCATION '/user/hadoop/imdb/title_basics_partitioned';
```



Dynamic Partitioning – **INSERT Into Table via Hive**

1. Migrate and partition data of table title_basics to table title_basics_partitioned:

```
set hive.exec.dynamic.partition.mode=nonstrict; -- enable dynamic partitioning

INSERT OVERWRITE TABLE title_basics_partitioned partition(partition_year)

SELECT t.tconst, t.title_type, t.primary_title, t.original_title, t.is_adult,
t.start_year, t.end_year, t.runtime_minutes, t.genres,
t.start_year -- last column = partition column
FROM title_basics t;
```

2. Check Success via Hive:

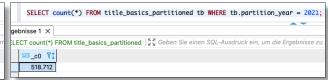
Runtime: 28 seconds



Runtime: 28 seconds



Runtime: <1 second





Dynamic Partitioning – **INSERT Into Table via Hive**

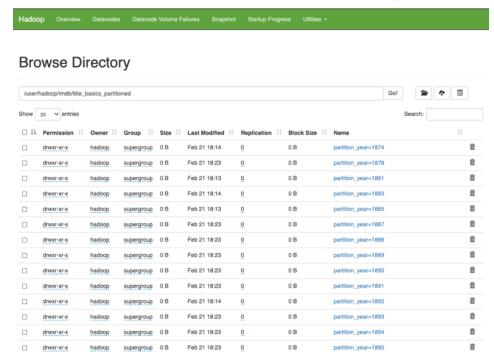
3. Check Success on HDFS:

```
hadoop fs -ls /user/hadoop/imdb/title basics partitioned
Found 149 items
                                          0 2021-02-21 17:14 /user/hadoop/imdb/title basics partitioned/partition year=1874
drwxr-xr-x
             - hadoop supergroup
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1878
drwxr-xr-x
                                          0 2021-02-21 17:13 /user/hadoop/imdb/title basics partitioned/partition year=1881
             - hadoop supergroup
drwxr-xr-x
                                          0 2021-02-21 17:14 /user/hadoop/imdb/title basics partitioned/partition year=1883
drwxr-xr-x
             - hadoop supergroup
             - hadoop supergroup
                                          0 2021-02-21 17:13 /user/hadoop/imdb/title basics partitioned/partition year=1885
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1887
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1888
             - hadoop supergroup
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1889
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1890,
             - hadoop supergroup
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1891
drwxr-xr-x
             - hadoop supergroup
                                          0 2021-02-21 17:14 /user/hadoop/imdb/title basics partitioned/partition year=1892
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1893
             - hadoop supergroup
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1894
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1895
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1896
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1897
             - hadoop supergroup
                                          0 2021-02-21 17:23 /user/hadoop/imdb/title basics partitioned/partition year=1898
             - hadoop supergroup
             - hadoop supergroup
                                          0 2021-02-21 17:22 /user/hadoop/imdb/title basics partitioned/partition year=1899
             - hadoop supergroup
                                          0 2021-02-21 17:22 /user/hadoop/imdb/title basics partitioned/partition year=1900
                                          0 2021-02-21 17:22 /user/hadoop/imdb/title basics partitioned/partition year=1901
             - hadoop supergroup
[...]
```



Dynamic Partitioning – **INSERT Into Table via Hive**

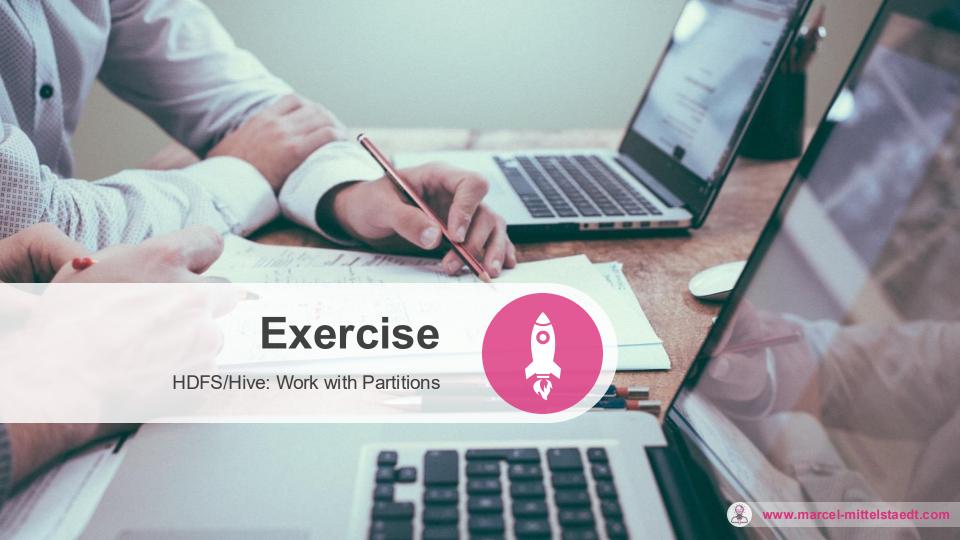
4. Check Success via HDFS Web Browser (http://X.X.X.X:9870/)





Break





HDFS/Hive Partitioning Exercises - IMDB

- 1. Execute Tasks of previous HandsOn Slides
- 2. Create a (statically) partitioned table name_basics_partitioned, which:
 - contains all columns of table name basics
 - is statically partitioned by partition_is_alive, containing:
 - "alive" in case actor is still alive
 - "dead" in case actor is already dead

Load all data from name_basics into table name_basics_partitioned

- 3. Create a (dynamically) partitioned table imdb_movies_and_ratings_partitioned, which:
 - contains all columns of the two tables title_basics and title_ratings and
 - is partitioned by start year of movie (create and add column partition_year).

Load all data of title_basics and title_ratings into table:

imdb_movies_and_ratings_partitioned



Well Done



Stop Your VM Instances

DON'T FORGET TO STOPYOURW

gcloud compute instances stop big-data

