

<http://arnaud-nauwynck.github.io>

Big Data – Part 4

Hadoop Ecosystem
HiveMetaStore, Parquet, IO Optimis

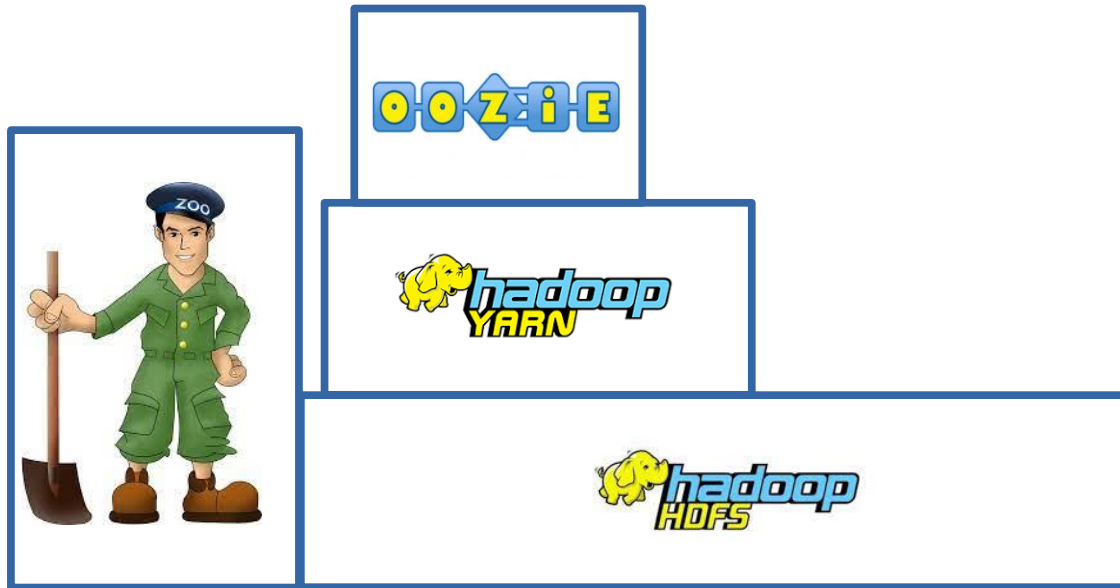
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Outline

- Prev Part3: Low-Level Hadoop components
 - ZooKeeper, Hdfs, Yarn, Oozie
- Hive MetaStore
- Parquet
- IO Optimis
 - Schema, Splittable blocks format, Partitions Pruning, Columns Pruning, PPD

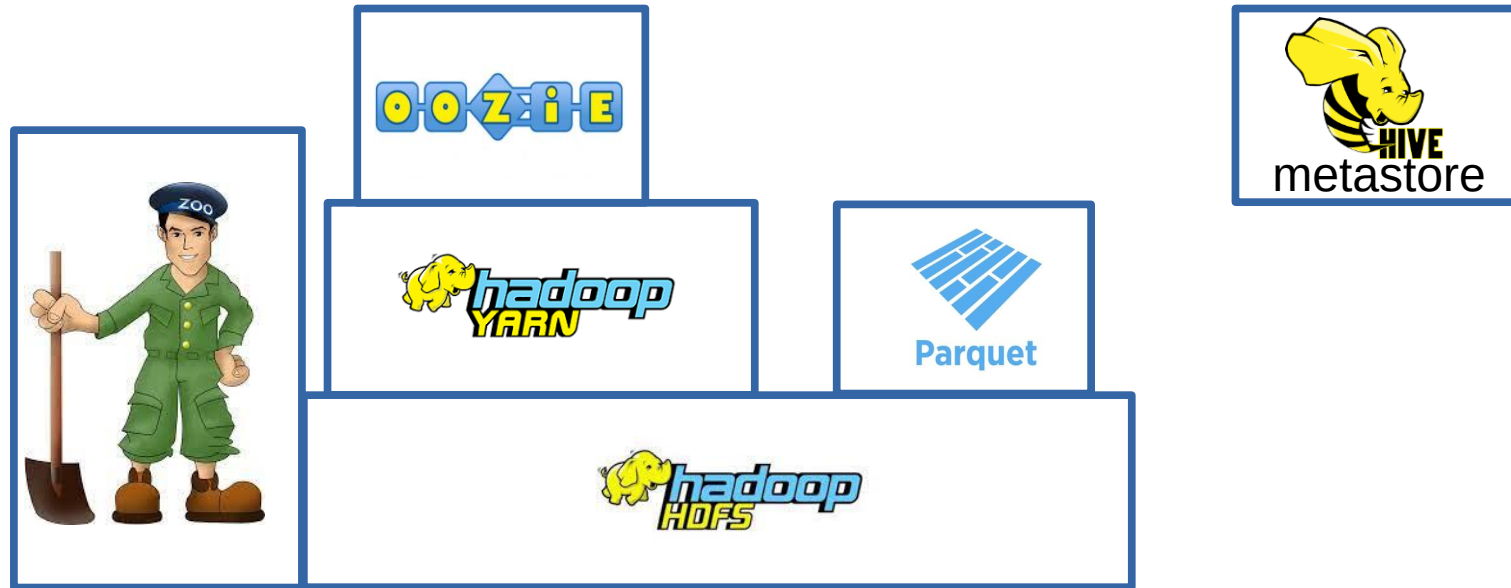
Prev Part3: Low-Level Focus

ZooKeeper, HDFS, Yarn, Oozie



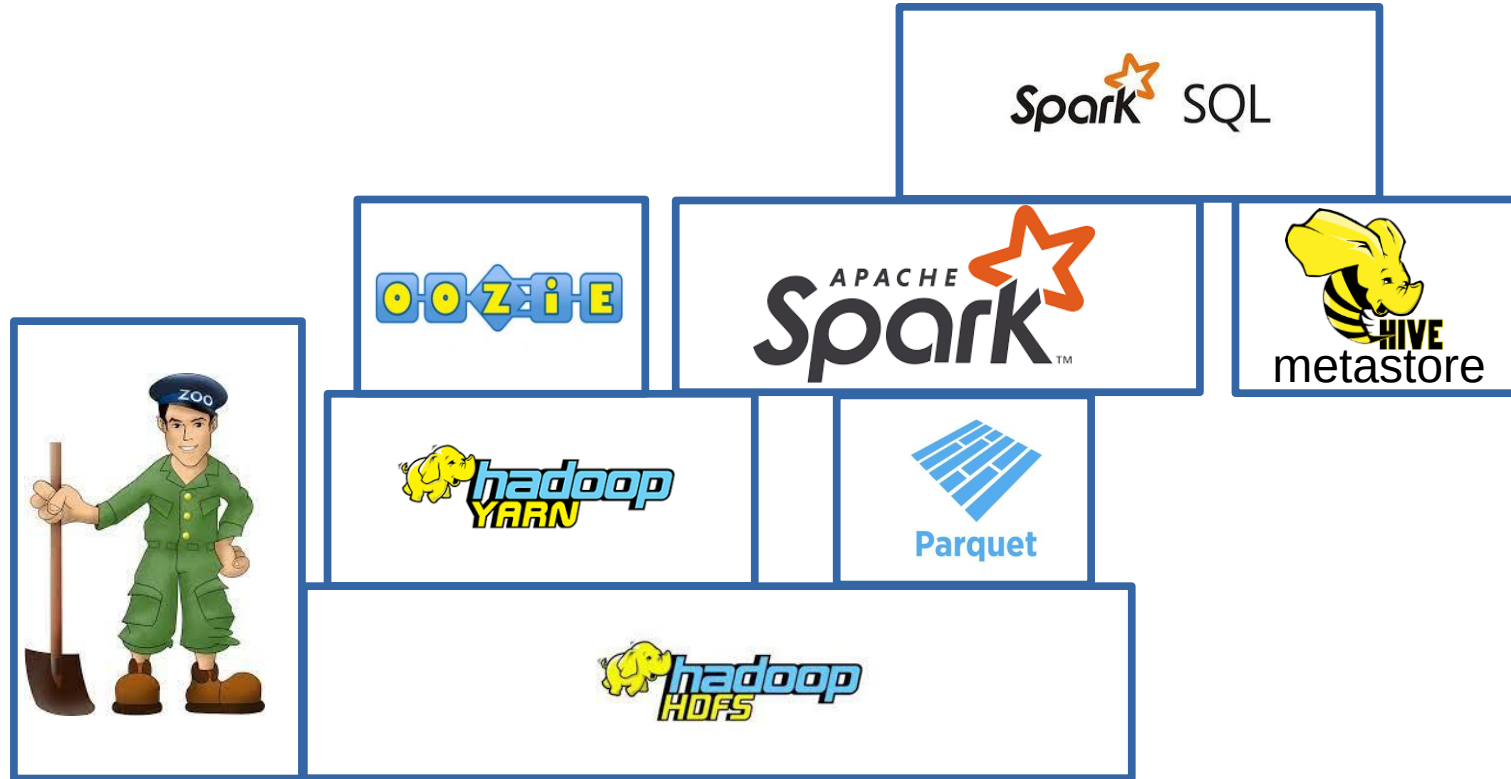
This Part: 4... Technical Focus

MetaStore, Parquet, IO Optimis



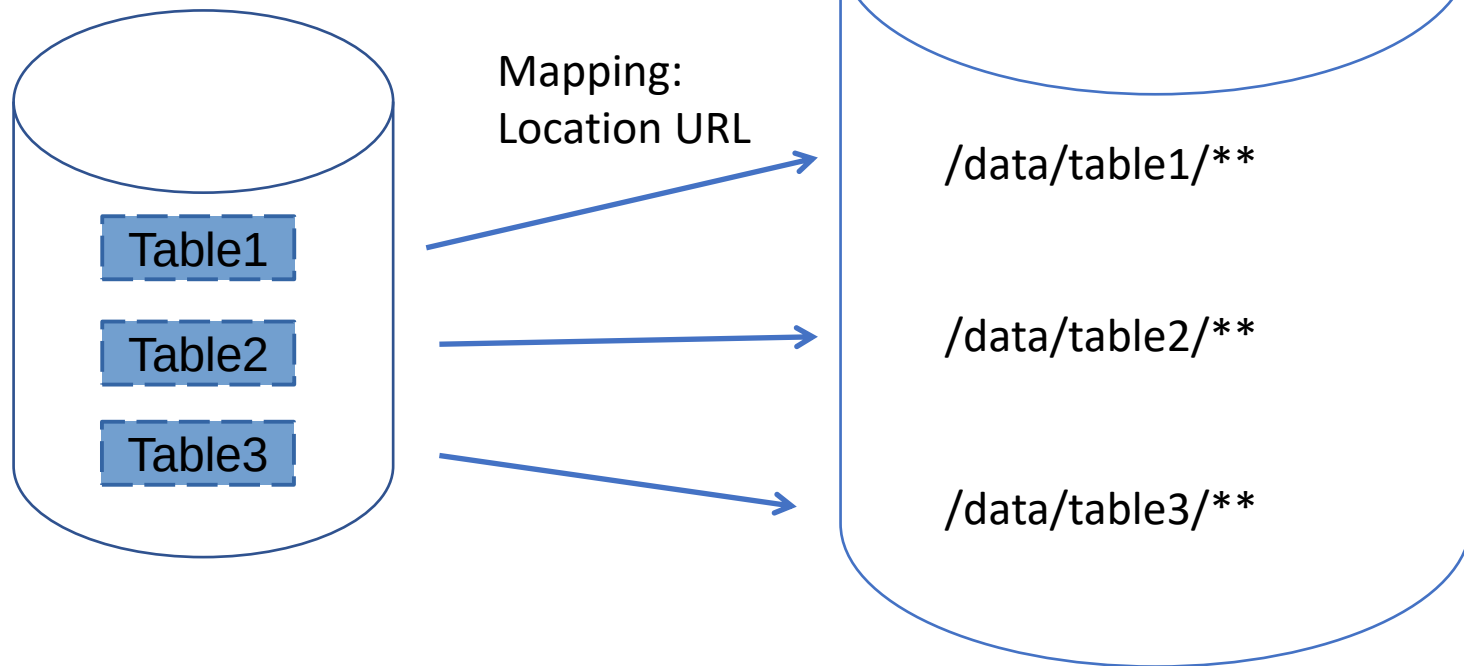
Next Part 5 ... High-Level Focus

Spark, Spark SQL



(Hive) MetaStore

MetaStore DB
(ex: postgresql)



MetaStore

Contains only **DDL** (Data Definition Language)
metadata (no HDFS data)

Logical view mapping : **name in SQL** \Leftrightarrow **location in HDFS**

File format encoding: parquet, orc, avro, csv, json, ...

Schema : **column types**

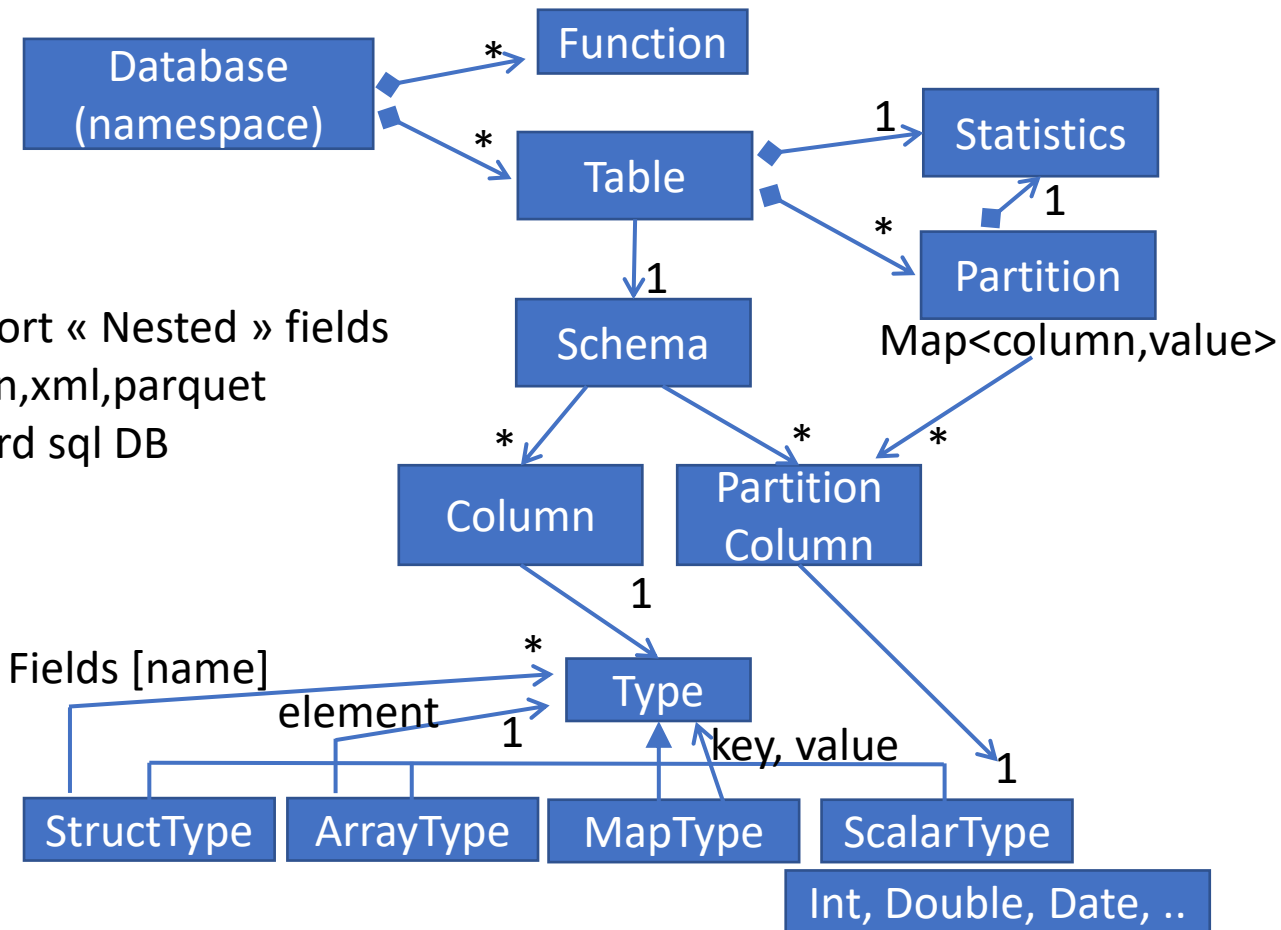
Sample CREATE EXTERNAL TABLE

```
CREATE EXTERNAL TABLE db.student (  
    id int,  
    firstName string,  
    lastName string  
)  
PARTITIONED BY (  
    promo int  
)  
STORED AS parquet  
LOCATION '/data/student'
```


Advanced CREATE EXTERNAL TABLE

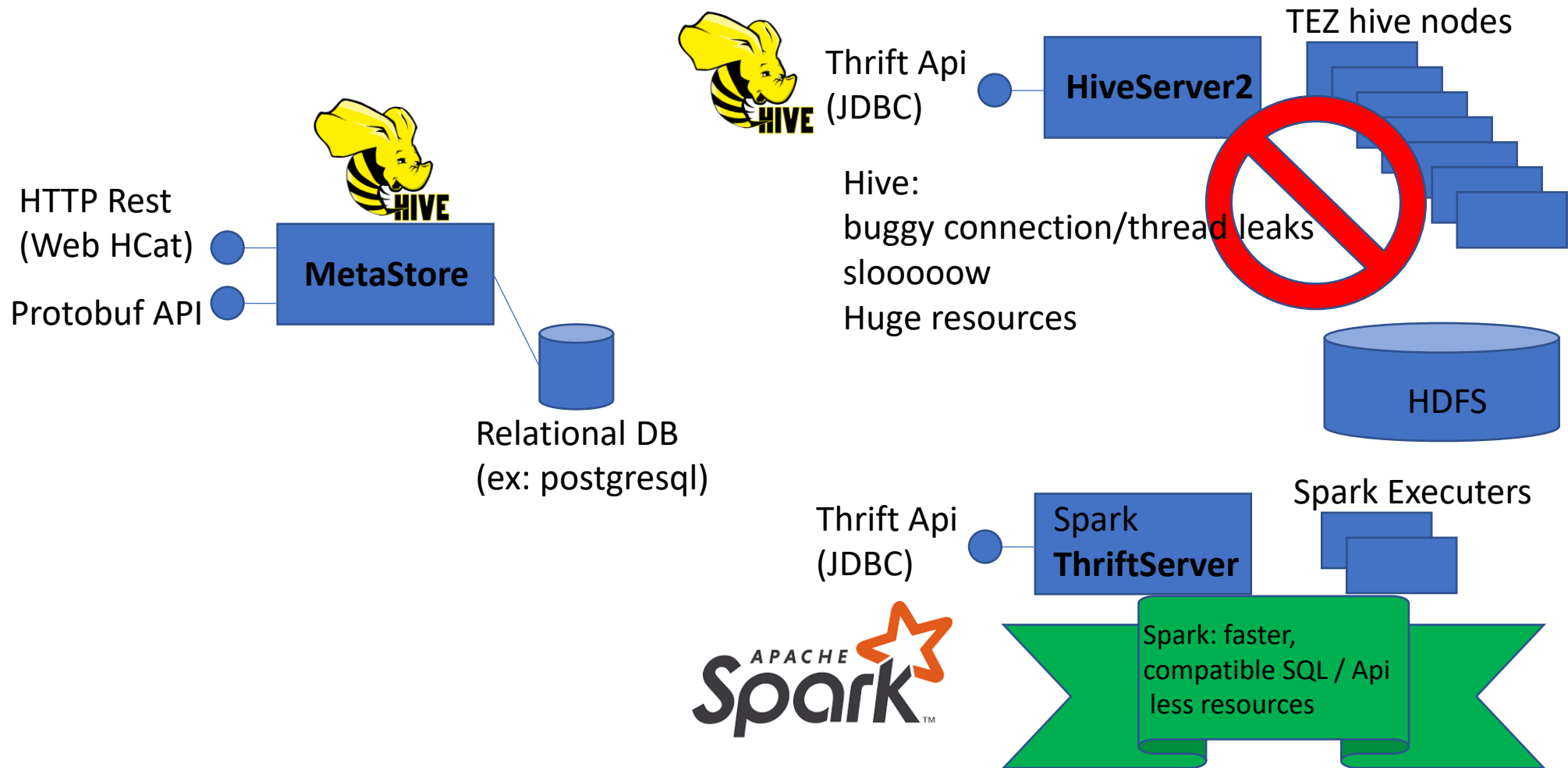
```
CREATE EXTERNAL TABLE db.student (  
  id int, firstName string, lastName string,  
  address struct< street string,number int,zipcode int >,  
  graduations array< struct< name string, obtentionDate date > >,  
  extraData map< string,string >  
)  
PARTITIONED BY ( promo int )  
CLUSTERED BY ( id, ...) SORTED BY (lastName, firstName )  
STORED AS parquet  
LOCATION '/data/student'
```

MetaStore Model

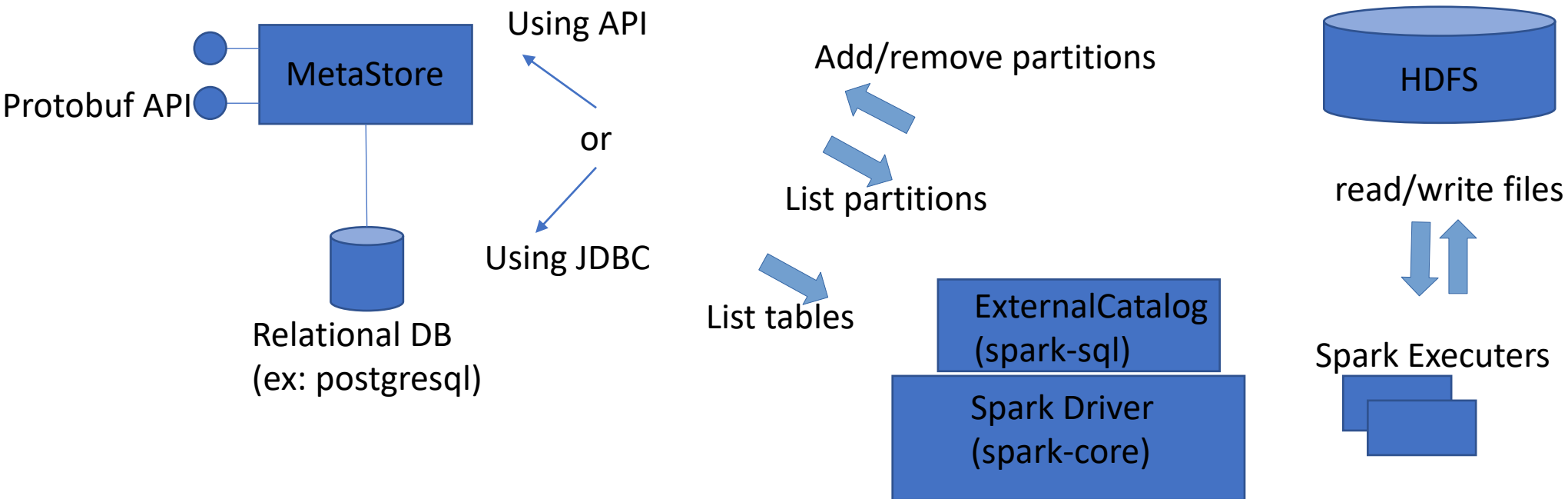


Schema support « Nested » fields
like typed json,xml,parquet
unlike standard sql DB

Hive MetaStore Architecture



Spark supports Hive MetaStore



Sql> DDL

Sql>

show databases;

use 'db';

show tables in 'db';

show tables in 'db' like 's*';

describe table db.student;

show create table db.student;

alter table db.student set location '/data/student2';

drop table db.student;

DDL.. EXTERNAL table

« EXTERNAL TABLE » : data exists independently of metastore

when creating table ... Schema must be compatible with existing files

Non-sense to « alter table » for column

When dropping ... files are not deleted

Do not use opposite « MANAGED TABLE »

When creating => create empty dir, location= « {db.location}/{table} »

When dropping => delete all files !

Sql> DML

Sql>

INSERT INTO table values(..)

=> save to new file(s) !!

preserve existing ones

(also preserve partially uncommitted ones..)

INSERT OVERWRITE / DELETE

=> reload all files

+ save all to new files

+ delete old files

Sql> Update? DML

by default Spark 3.x does NOT support UPDATE
(nor UPSERT, MERGE)

Only with extensions of « DeltaLake », « Iceberg », ..



Spark> Update?

`read().map().write()`

spark

```
.read().format(« PARQUET »).load(« /data/table1 »)
```

Full Scan ALL files
Load ALL
in-memory

```
.map( x -> { ...transform row to 'update' values; return newRow } )
```

Process ALL
In-memory

```
.write().format(« PARQUET »).mode(SaveMode.Overwrite).save(« /data/table2 »)
```

Delete ALL files
+ save ALL
in-memory

Sql> ... NO « ACID »




A tomic

onsistent

solated

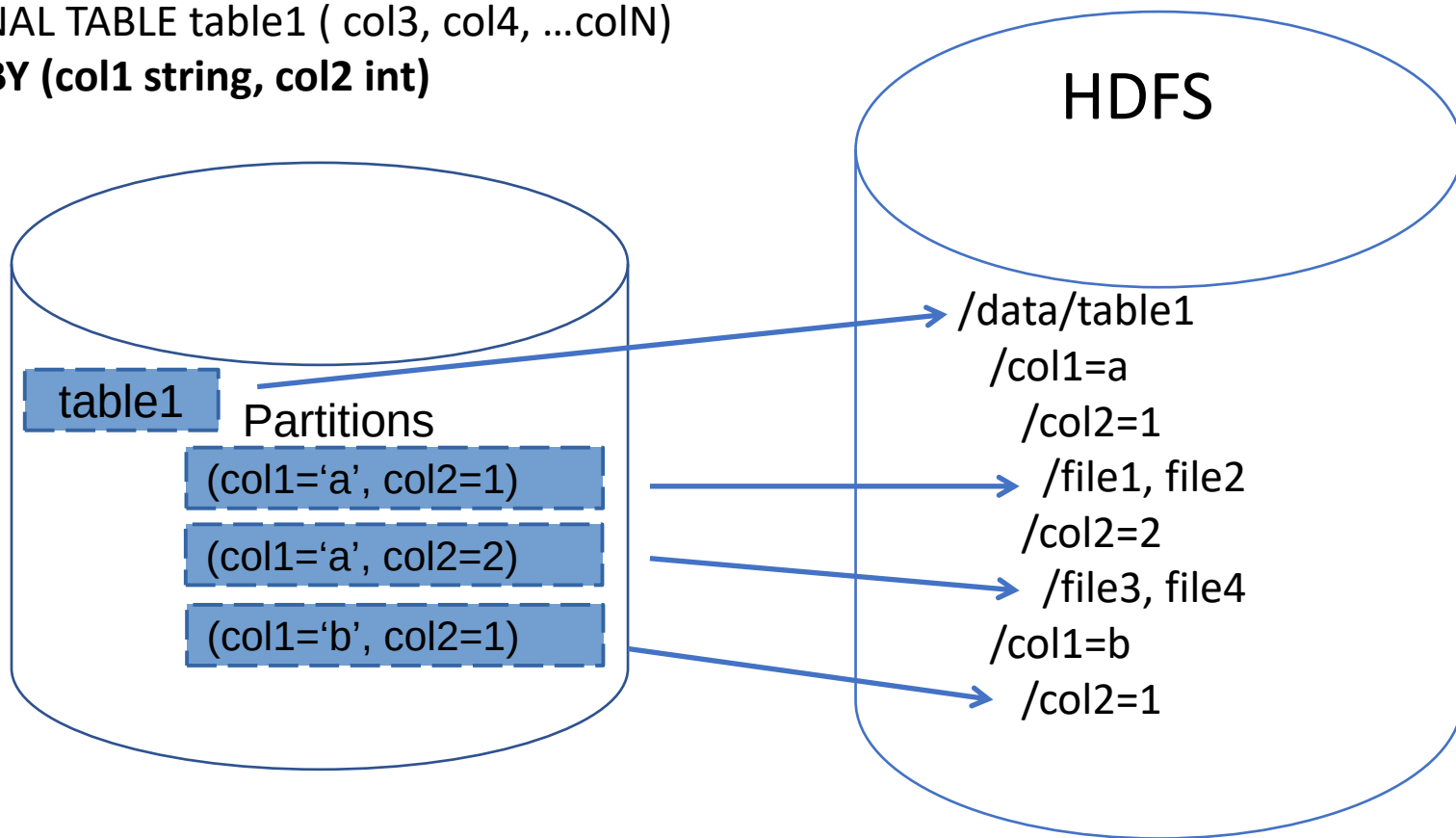
D urable

Granularity of insert (append / overwrite)

- Write a single ROW  in 1 new **File**
- HDFS hates Small Files
(Too many files) !!
- Write from shuffled RDD
(several executors)  in 200 **Files**
- by default
`spark.sql.shuffle.partitions=200` !!
- Overwrite some files,
and no touch others  Possible only by **partition**

PARTITIONED BY (col1, col2)

```
CREATE EXTERNAL TABLE table1 ( col3, col4, ...colN)  
PARTITIONED BY (col1 string, col2 int)
```



Alter table ADD PARTITION / MSCK REPAIR TABLE

Need EXPLICIT add !!

Otherwise dir/files not scanned => 0 result

Sql>

```
ALTER TABLE .. ADD PARTITION (col1='a', col2=1);
```

... Or

```
MSCK REPAIR TABLE ..; -- (inefficient rescan all)
```

Discover.partitions ??

... False good idea

```
ALTER TABLE ... SET TBLPROPERTIES ('discover.partitions' = 'true')
```

hive-site.xml

```
metastore.partition.management.task.frequency=600
```

... => INNEFICIENT : Polling metastore thread every 10mn to scan HDFS, and alter
+ Spark still using explicit partitions

What if you have Peta bytes, with millions of dirs?

Optim: Partitions Pruning

Sql> select ... from db.student where promo=2020 and ...


Condition on partitioned column



Scan only files in

/data/student/promo=2020/**

Skip others

/data/student/promo=2019/

/data/student/promo=2018/

...

Partition: what for ?

NOT (Not-only) for searching faster !!!

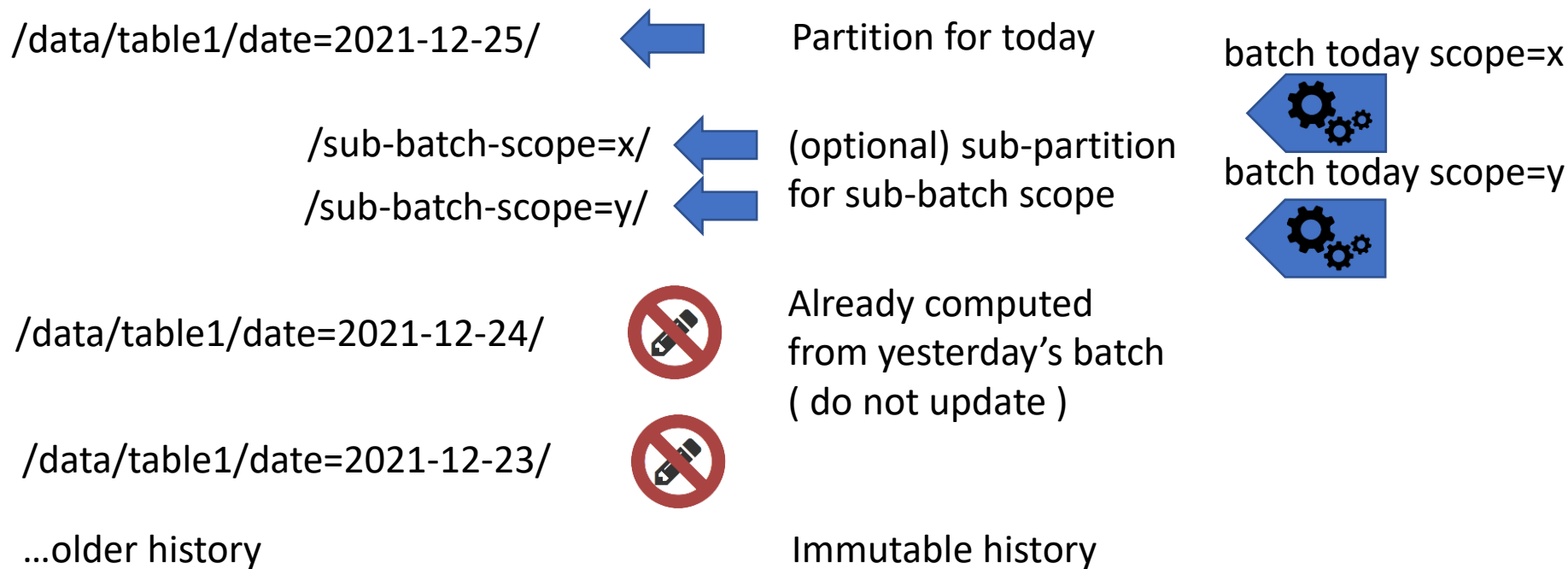
(worst than parquet Predicate-Push-Down)

Granularity of Save mode Overwrite

... adapt to your batch scope

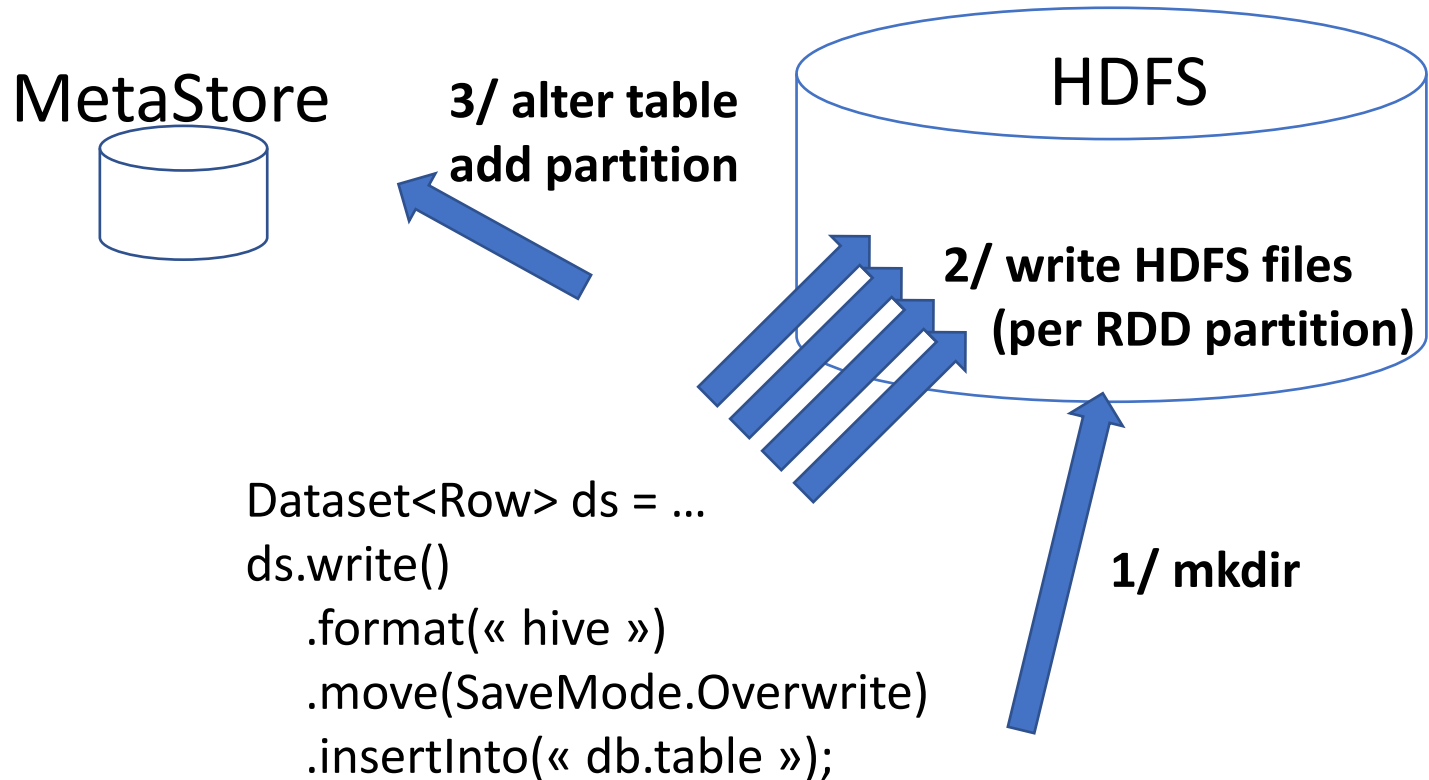
DO NOT define too (>2) many partition levels

Example Batch – Partitioned save

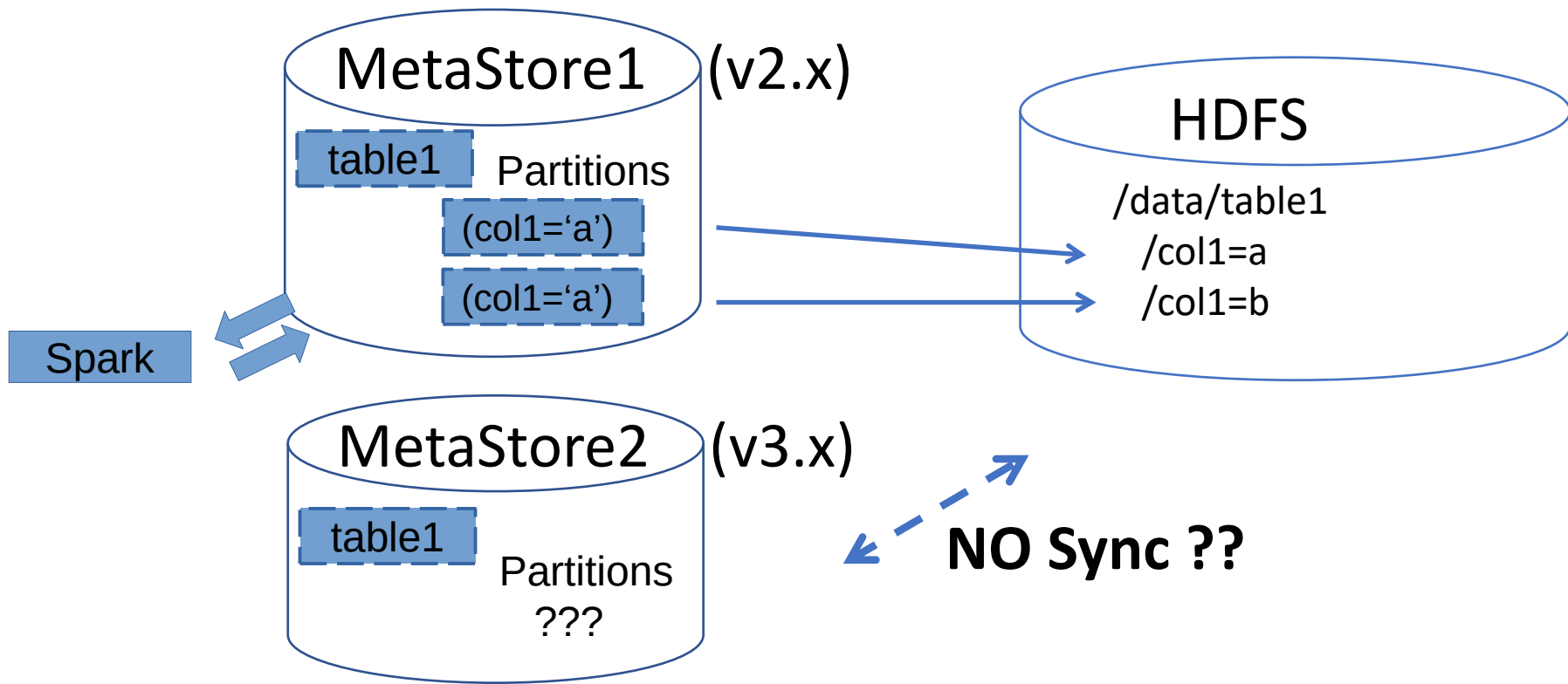


Spark .save()

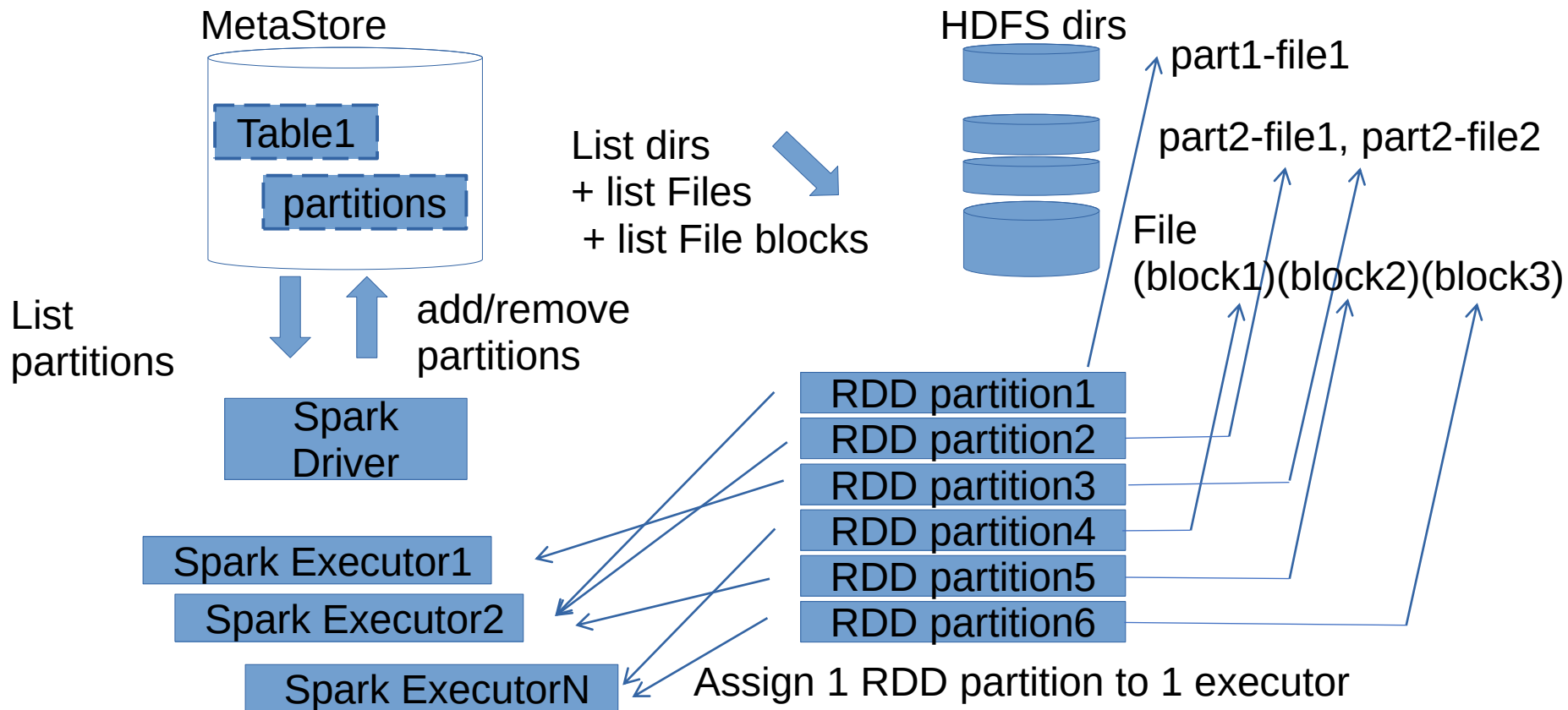
=> mkdir + write Files + add partition



Synchronize HDFS with several MetaStores?

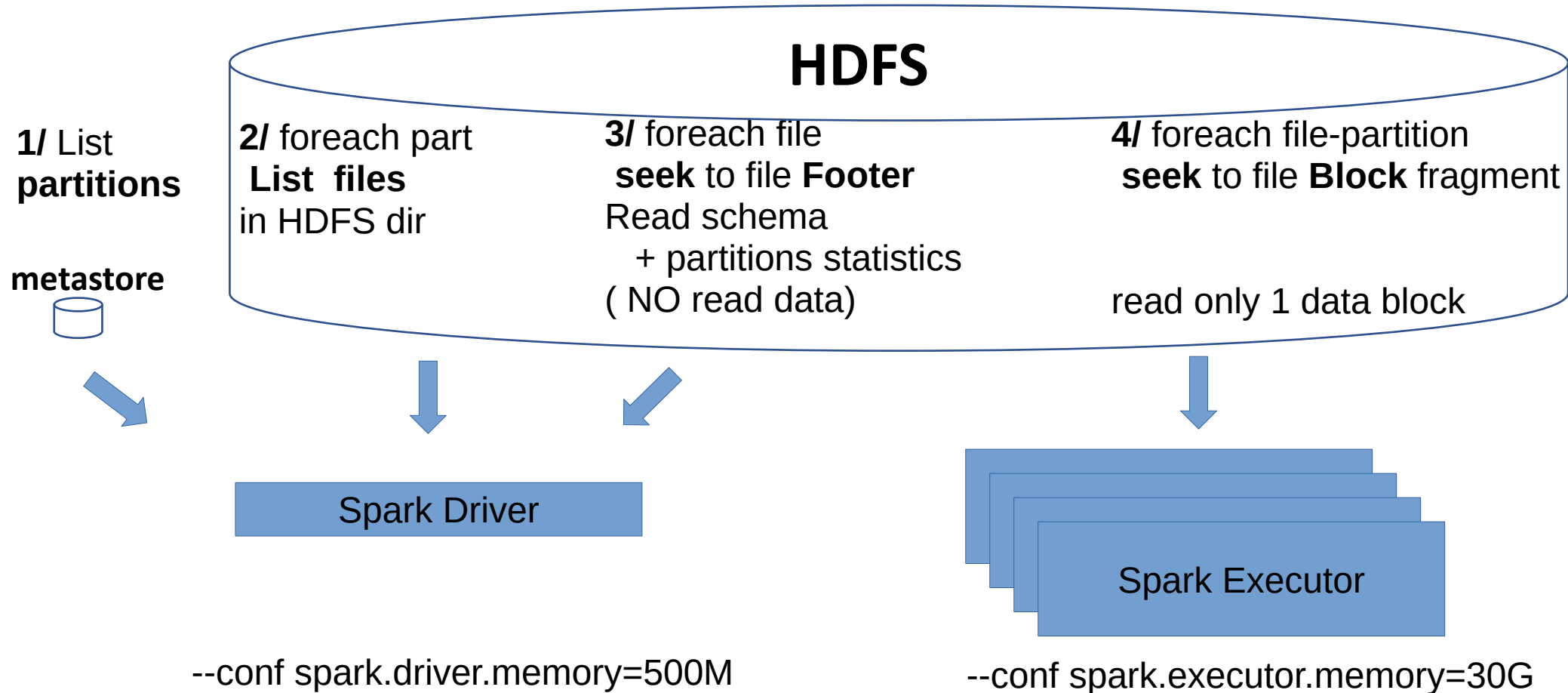


Spark RDD Partitions >> MetaStore Partitions



Spark RDD Partitions

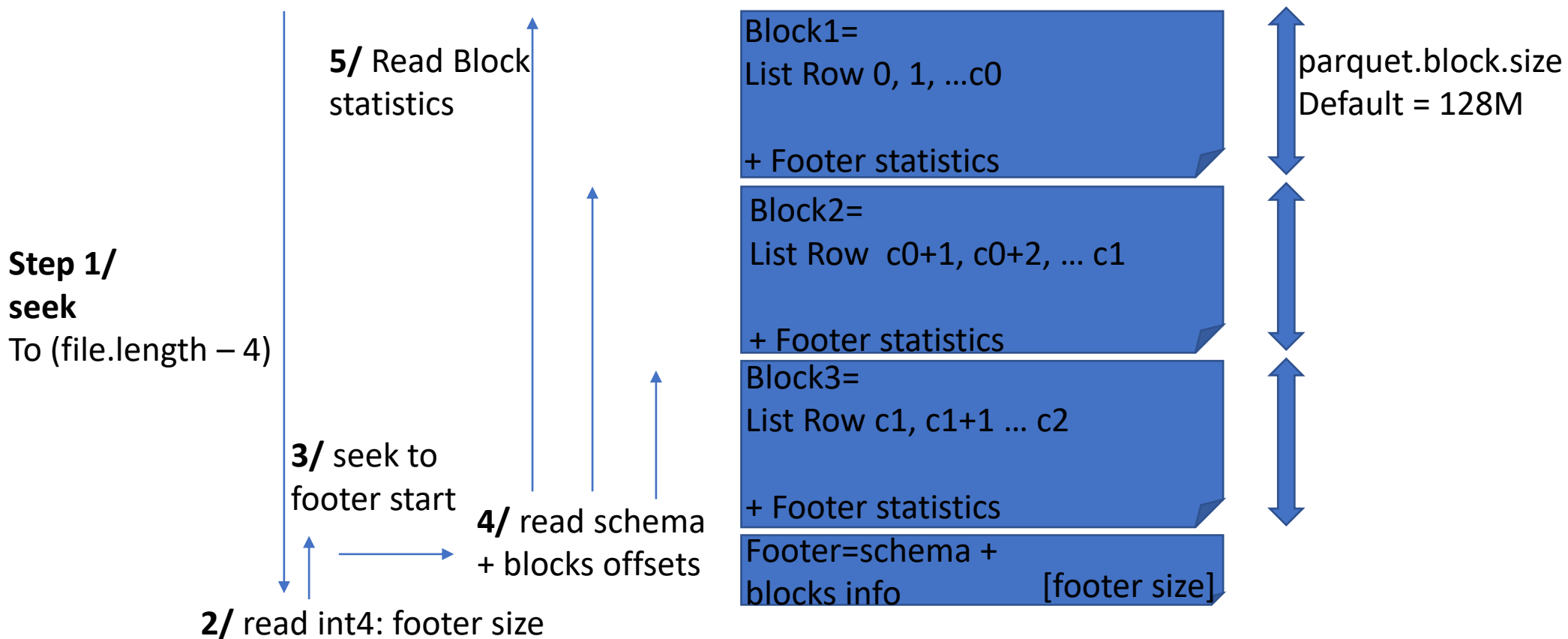
= MetaStore Partition * Files * Blocks



PARQUET File Format



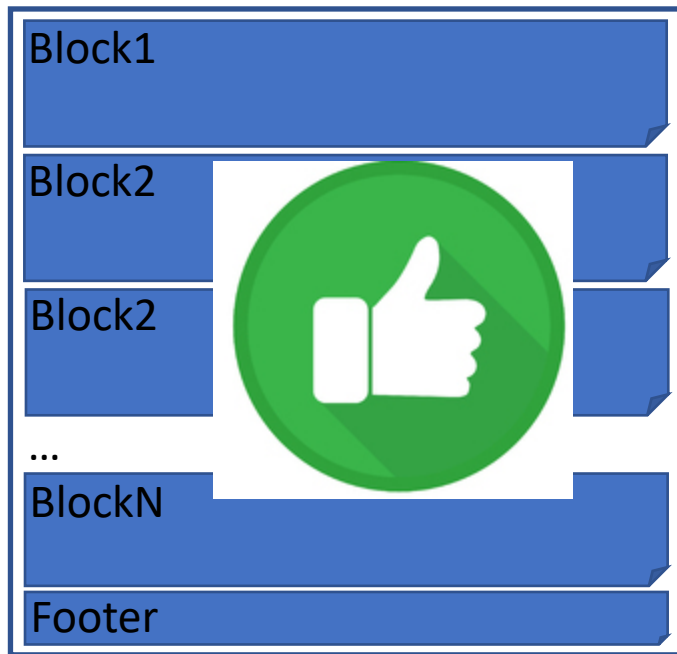
Splitteable File Format



Performances

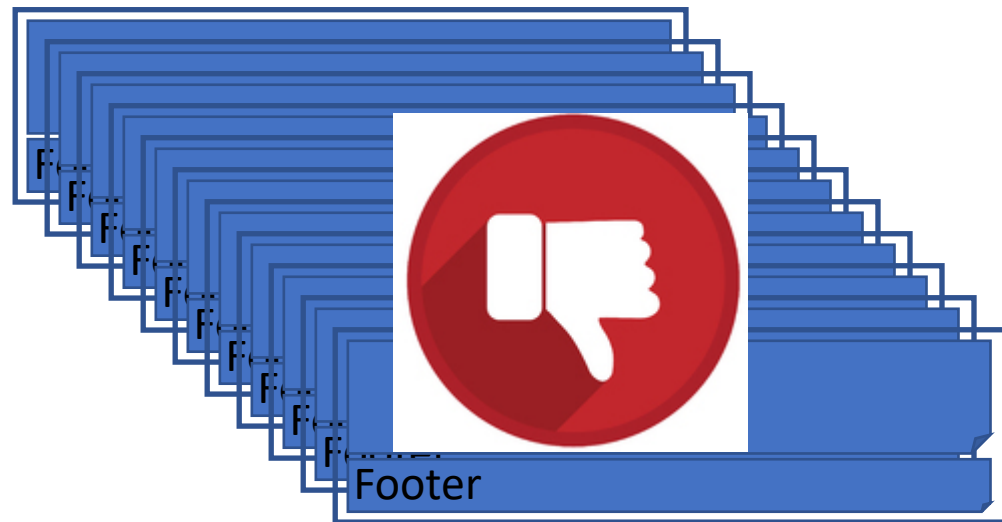
File Blocks >> MetaStore + HDFS Dir + Files

Better to
have 1 Huge HDFS file
(several Go)



than

Too MANY
Too Small files
(few 128+1 Mo)



Typical Partition / Files Volumes

For daily batch

1 partition per day ... 5 year of data = ~1500 partitions OK

1 file per partition ... OK, even if strange to have 1 file per directory

(maybe 2,3 files per partition ... if no fit in spark executor mem)

File may be >= several Giga bytes OK great

File parquet.block.size = 16M, 32M (? overwrite default 128M)

compromise:

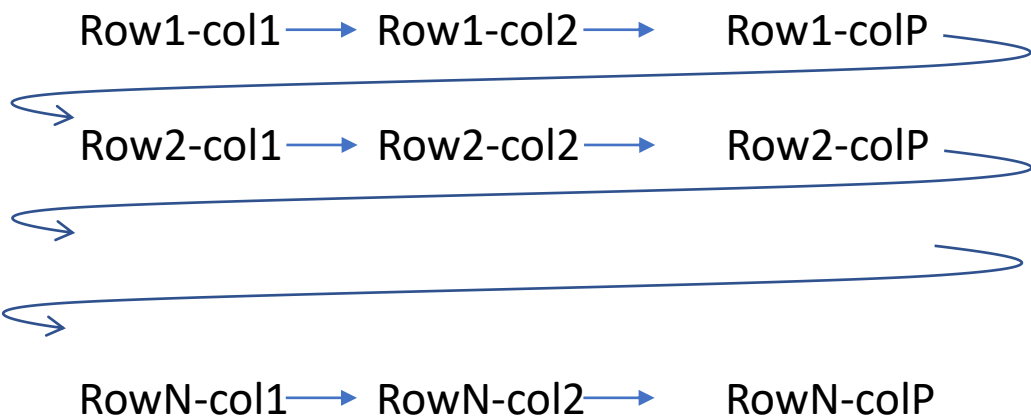
Smaller => more dictionary encoding,
better PPD, maybe less compression

Bigger => less partitions

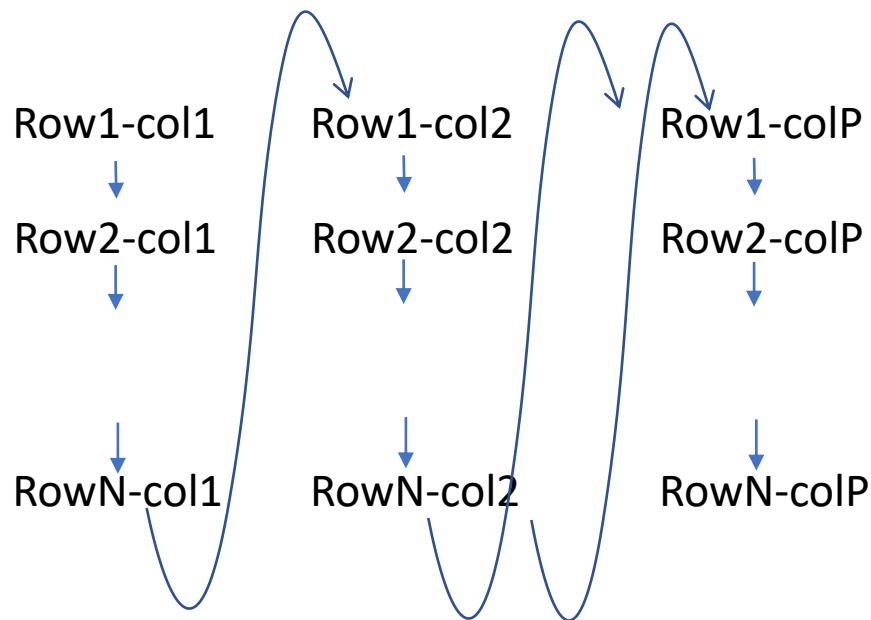
« Columnar » Storage File

Content = List<Row> = row1, row2, .. rowN * Row=col1, col2, ... colP

Classic (row-storage) file



Columnar-storage file



Why columnar ?

Read only needed columns data

Seek to skip unneeded ones

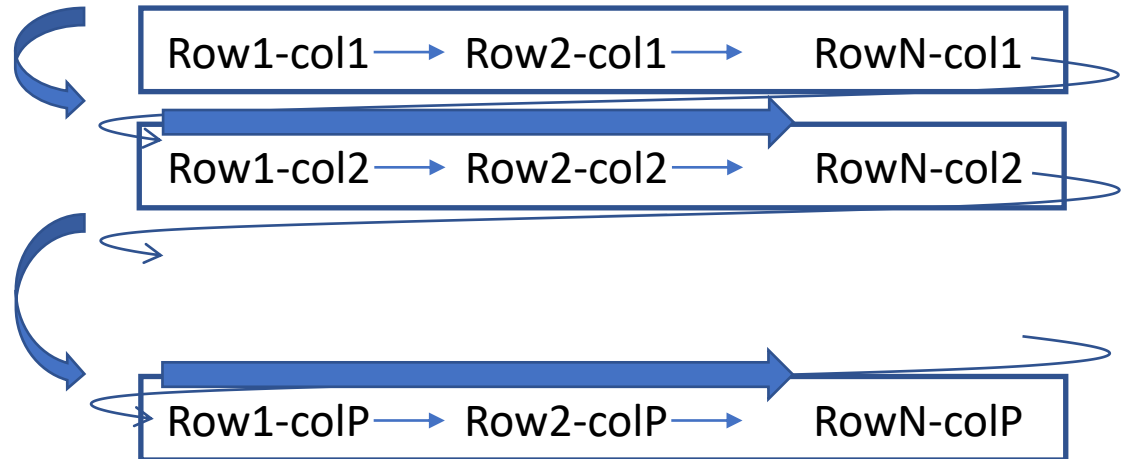
Example: SELECT col2, colP from ...

1/ seek() to col2 offset
(Skip sequential bytes for col1)

2/ Full read col2

3/ seek to colP offset
(Skip bytes for col3, col4, ... colP-1)

4/ Full read colP

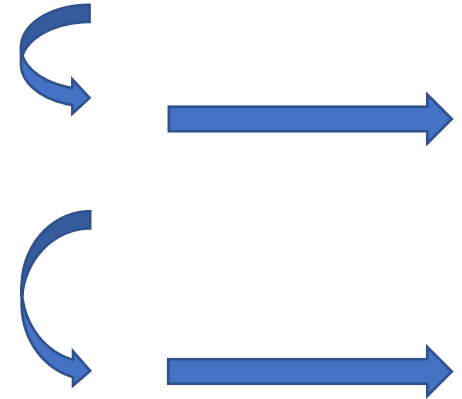
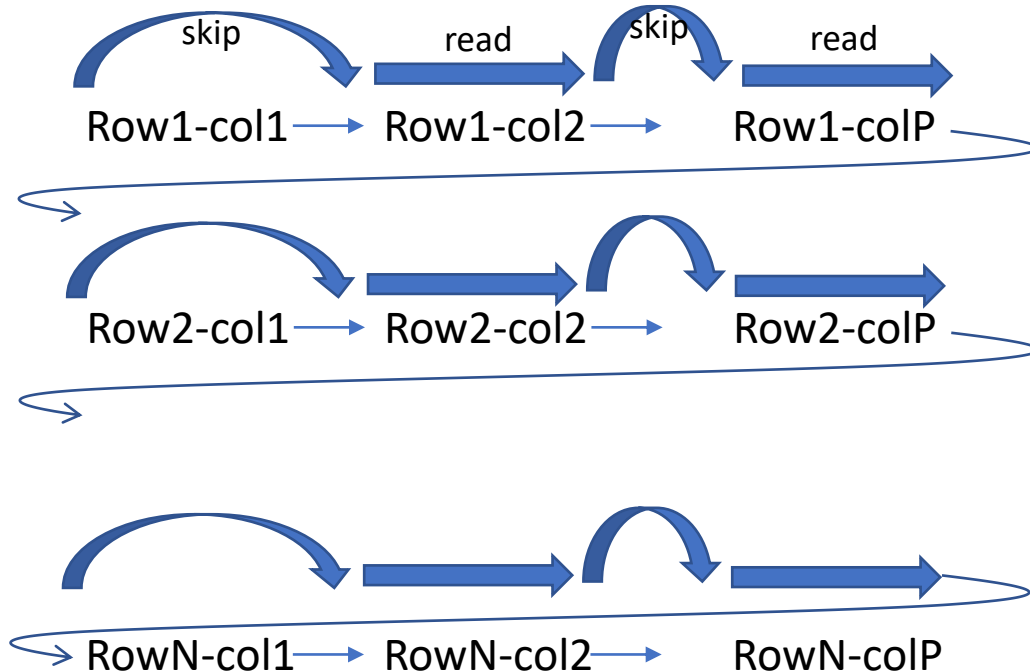


Comparison .. Full Read & Garbage

$2*N$ skips
+ $2*N$ small unitary reads

vs

2 skips
+ 2 array reads



Much faster
Fewer data IO / fewer ops

Optim: « Column Pruning »

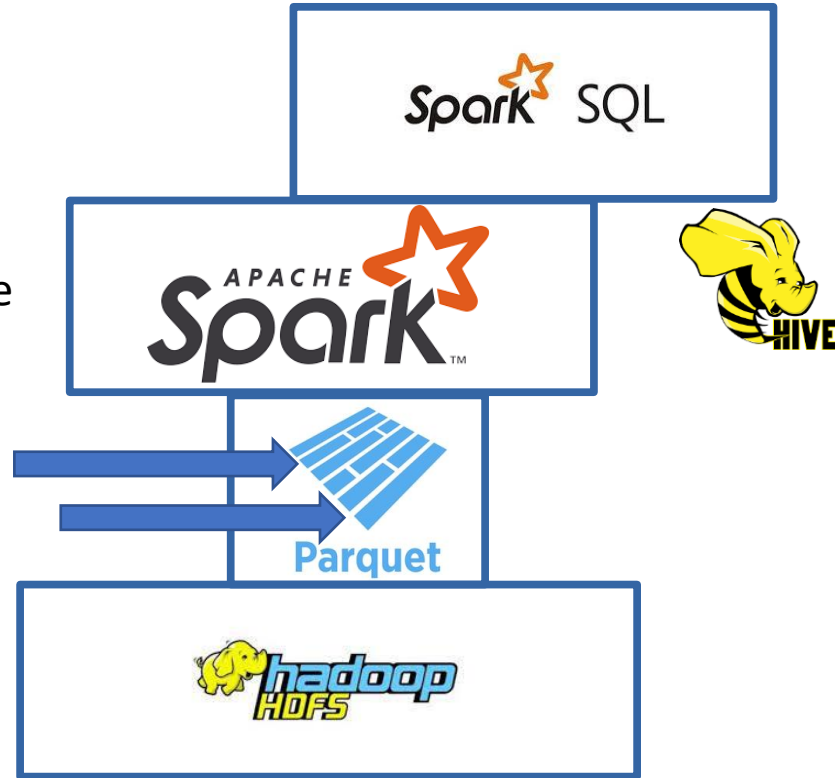
From SQL to Parquet IO .. Hadoop IO

Select col2, colP from table...
(prune all other columns)

DataSet / RDD on Parquet file

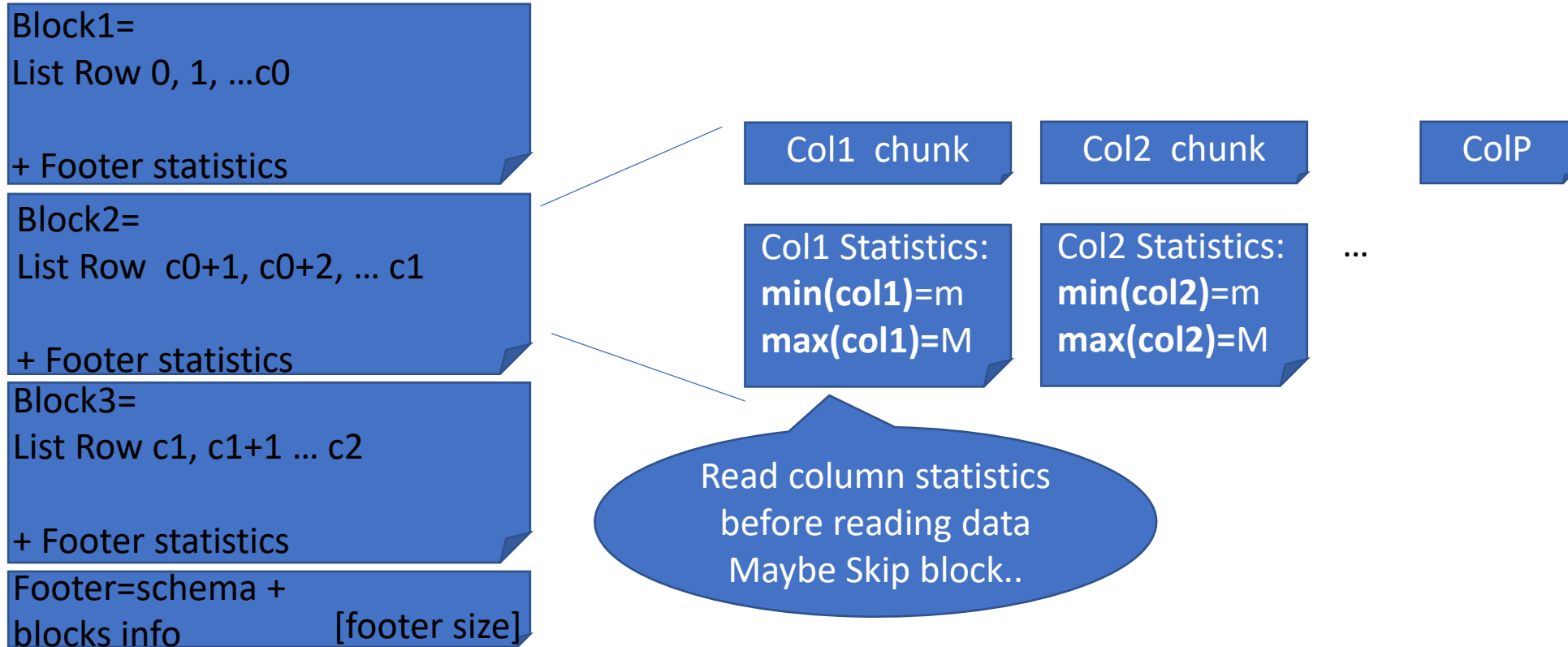
Parquet API
to read columns chunks

Fewer IO



Last but not Least Optim

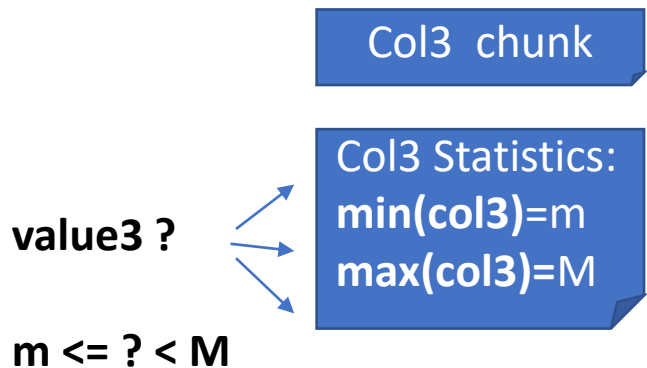
Using page-column statistics



Predicate... skip with statistics (maybe False Positive)

Example:

```
SELECT col2, colP FROM ... WHERE col3 = value3
```



If (**(value3 < m) OR (value3 > M)**)

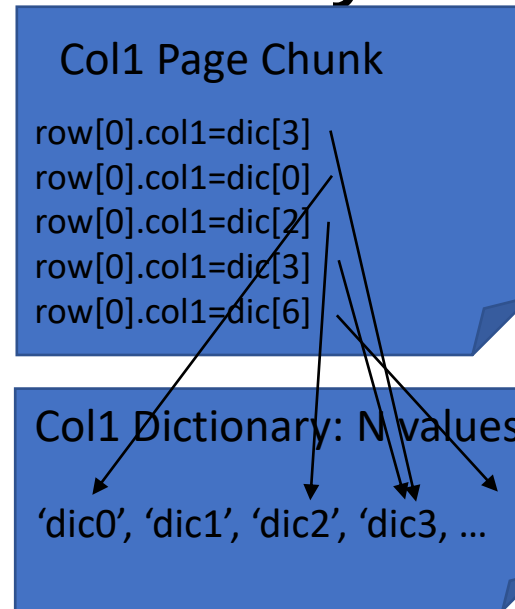
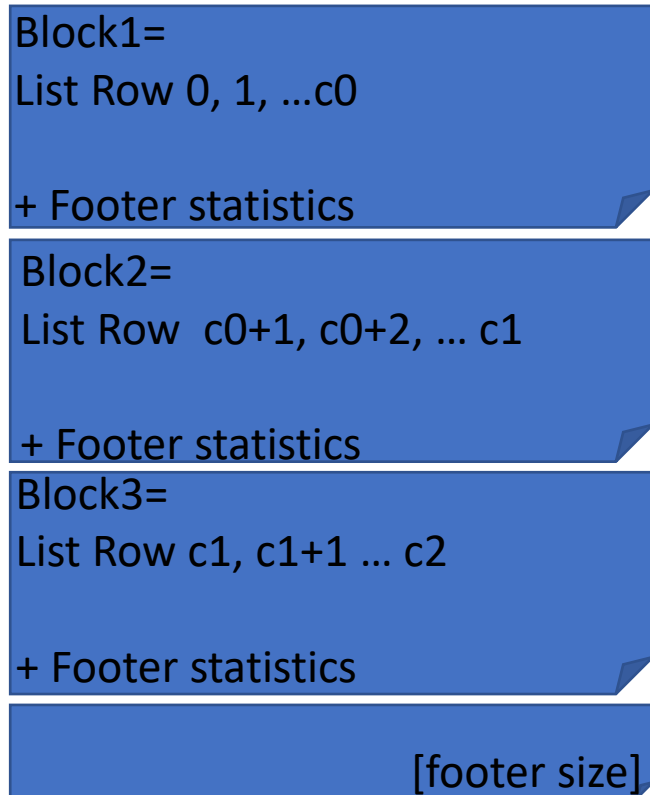
... AND check for null to please SQL semantic ?!

⇒ Impossible to find row in this block

⇒ Skip block!

Column with small number of distinct values

... Stored using Dictionary encoding



Example:
~100 000 rows
(... to fit in 128Mo
= parquet block size)

...

Example:
~10 distinct values

Spark choose encode
with Dictionary if
compressed size $\leq 2\text{Mo}$

Predicate Push-Down for « col='value' » or « col in ['value1', .. 'valueN'] »

Example:

SELECT col2, colP FROM ...

WHERE **col3 = 'value3'** and **col4 in ['value1', 'value2', value3']**



For each page chunk of col3

If encoded as Dictionary

=> read dictionary

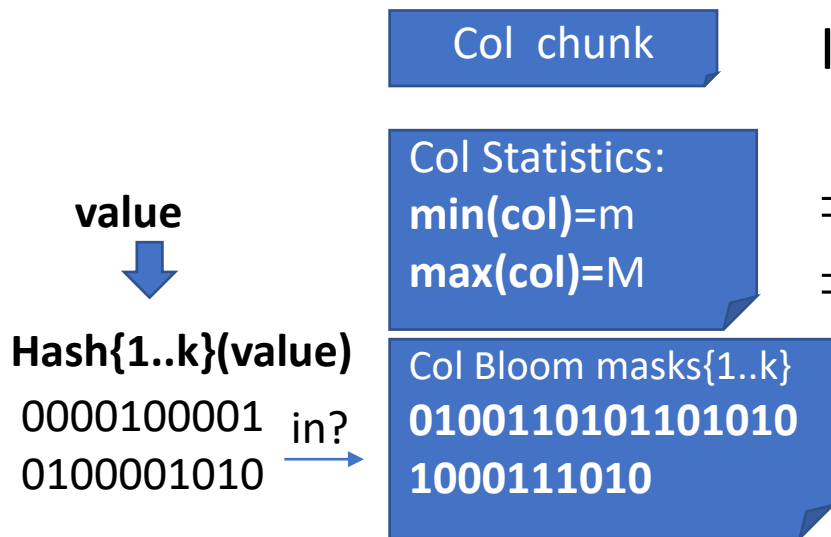
then if 'value3' not in dictionary

=> SKIP Row Group !!!

Bloom Filter: mask=Union(hash(..))

New in Parquet ... (older in ORC)

statistics can also contain Bloom Filter masks



Bitmask $h = \text{hash}(\text{value})$

If (**$h \ \& \ \text{bloom}$**) == **h**)

... AND check for null to please SQL semantic ?!

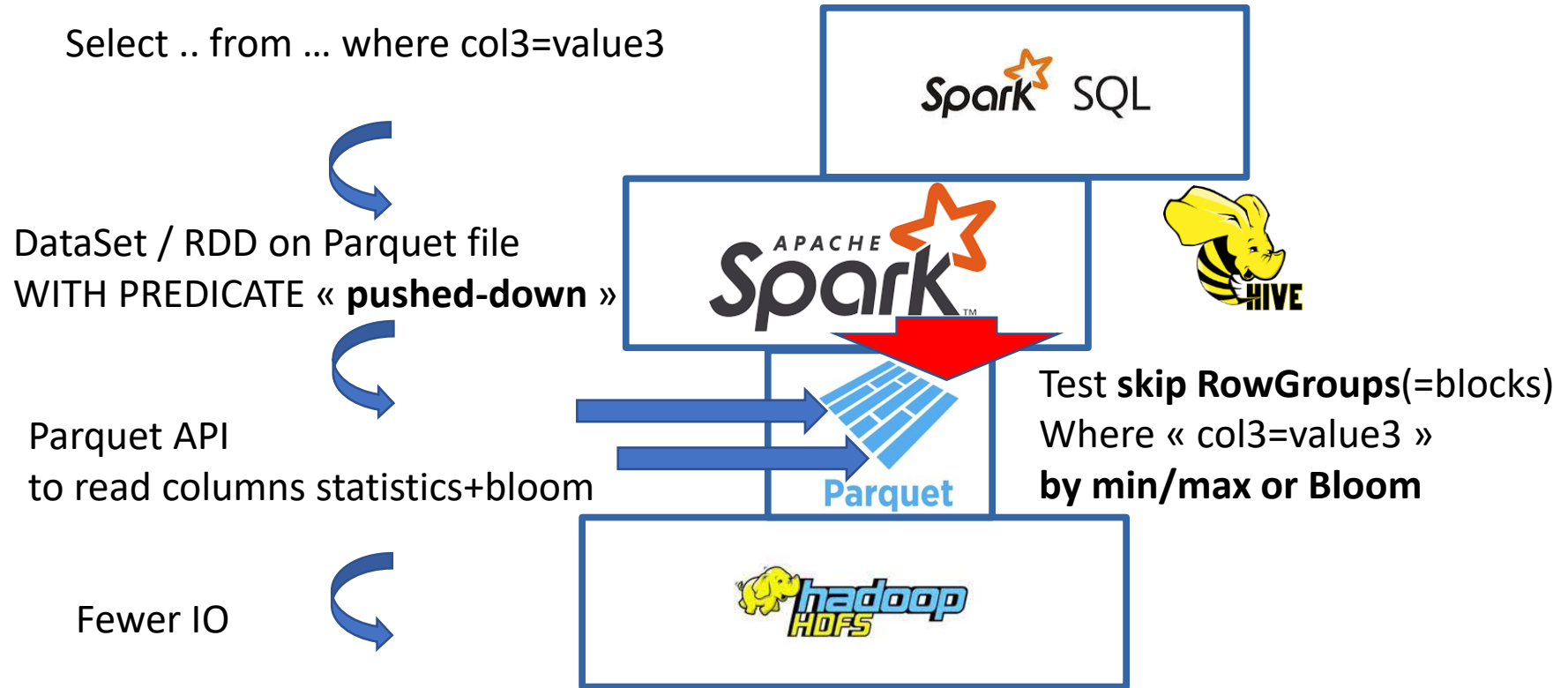
⇒ Impossible to find row in this block

⇒ Skip block!

k hashes, m bits, n elements

⇒ False positive rate $\sim (1 - e^{-kn/m})^k$

« PPD » : Predicate-Push-Down

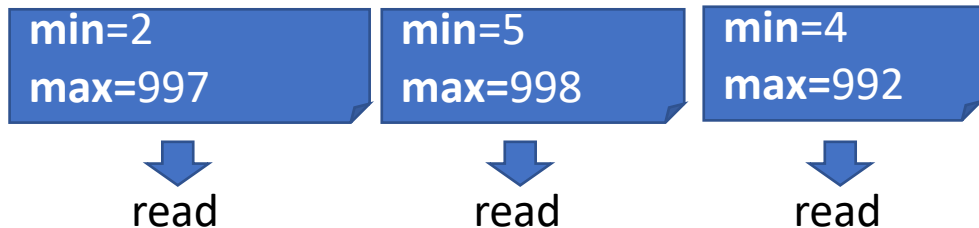


Sort + parquet.block.size for better Predicate-Push-Down

When writting PARQUET files
... think to optimize reads later (PPD)

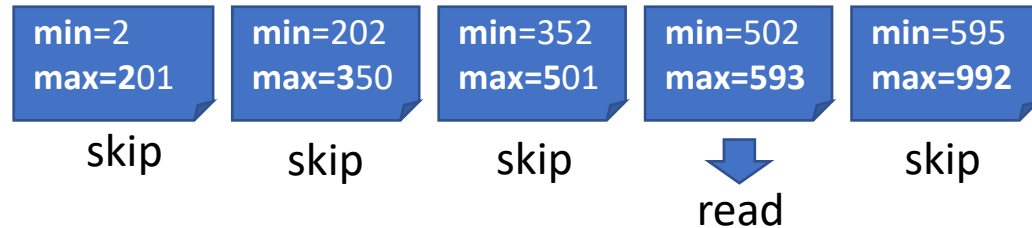
Example: id in range 1..1000 predicate id=542

Unsorted, Big block 128M



... value within min/Max of all blocks
=> **NO skipped block** ... only False positives

Sorted + Small blocks 16M



How to « Write » parquet files : Adapt for best « Reads » later

```
Dataset<Row> ds = spark.sql(« ... » );  
// ds contains probably 200 partitions (default value after a SHUFFLE)  
  
ds = ds.repartition(1); // equivalent to « .coalesce(1) »  
    // or ds.repartition(2) // or 3 ... if RDD does not fit in spark.executor.memory !!  
  
ds = ds.sortWithinPartition(« colA », « colB », ... « colID »)  
    // sort by general columns first « colA » (example portfolio, region, productType...  
    // last by « id » column  
  
ds.write().format(« hive »).mode(SaveMode.overwrite).insertInto(« db.table_name »);
```

Recap 5 Optimizations

1/ typed schema, binary encoding, dictionary + compression

2/ **splittable** file (blocks) = distributed

3/ Hive Metastore **Partition Pruning** = skip/scan dirs

4/ **Column Pruning** (Columnar storage format) = seek + array read

5/ **Predicate-Push-Down** = skip using statistics, bloom filter

Recap Optimizations 1/5

Schema, Binary Encoding, Dictionary

CSV, Xml, ND-JSON

Schema-less file formats !

... inefficient text encoding

Redundant <xml> value</xml> or « json »: « value»

PARQUET, ORC

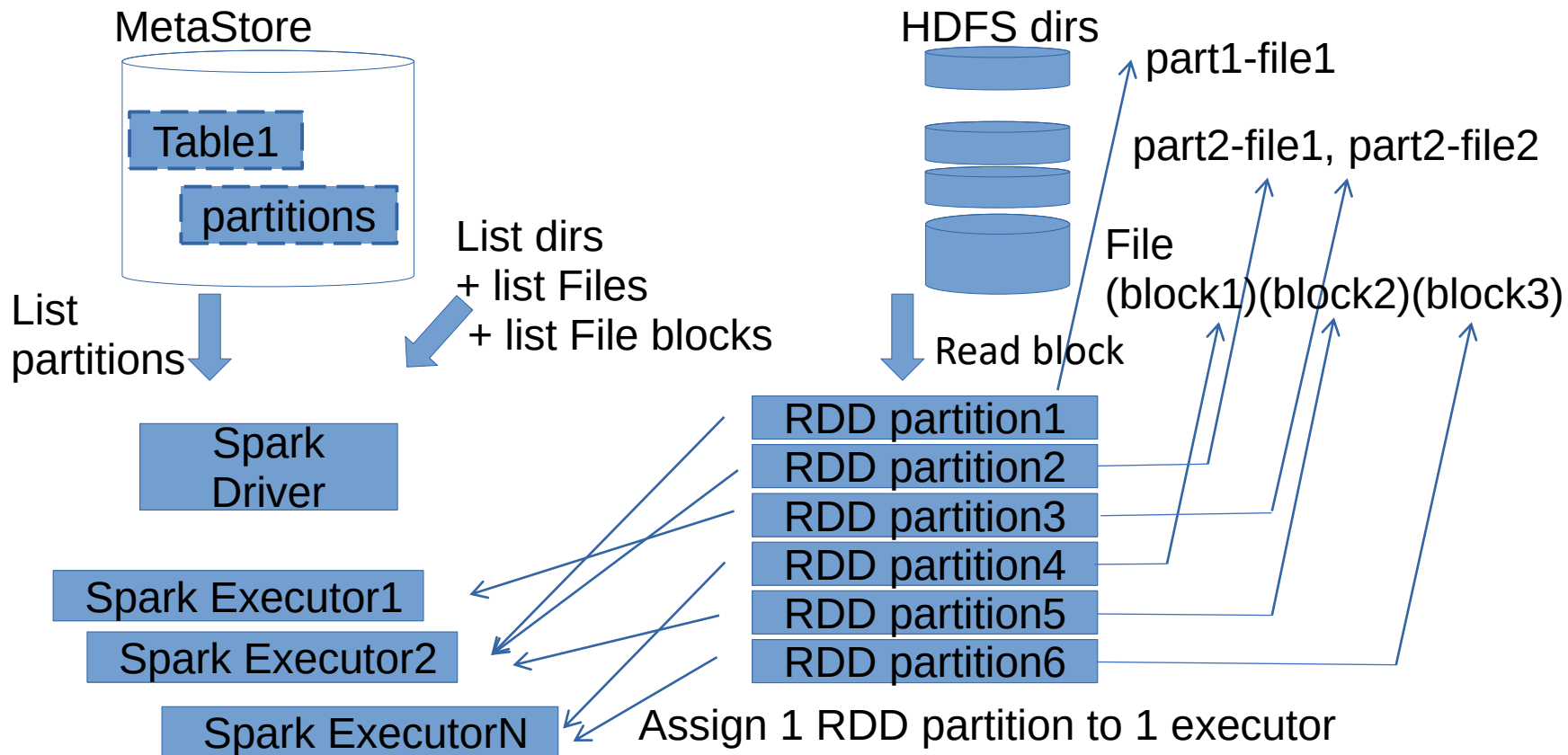
Strongly typed Schema embedded in file

... efficient binary encoding

Efficient incremental encoding, or Dictionary

Recap Optimizations 2/5

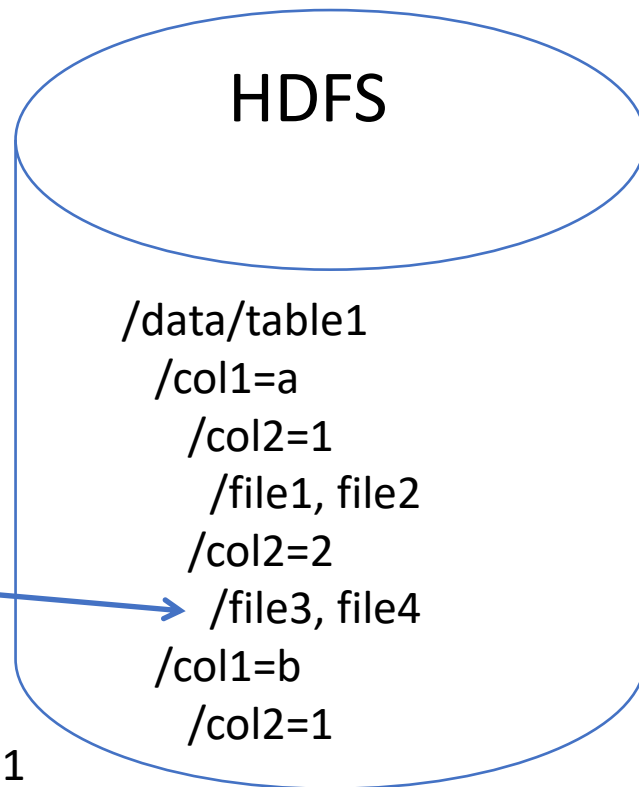
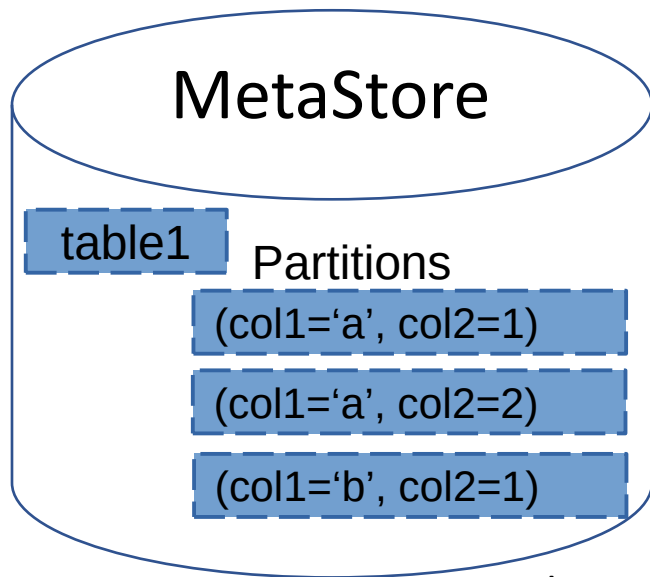
Distributed RDD: Splittable File Blocks



Recap Optimizations 3/5

Hive Metastore Partitions Pruning

```
CREATE EXTERNAL TABLE table1 ( col3, col4, ...colN)  
PARTITIONED BY (col1 string, col2 int)
```



Select .. From table1
Where col1=a and col2=2
-- partitioned columns

Recap Optimizations 4/5

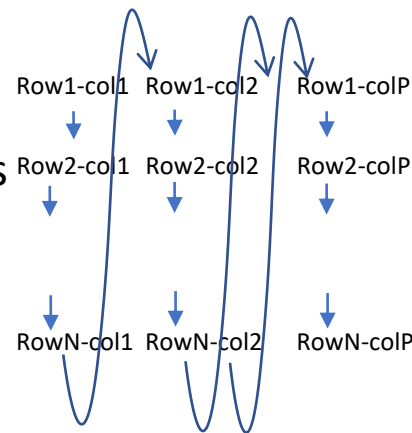
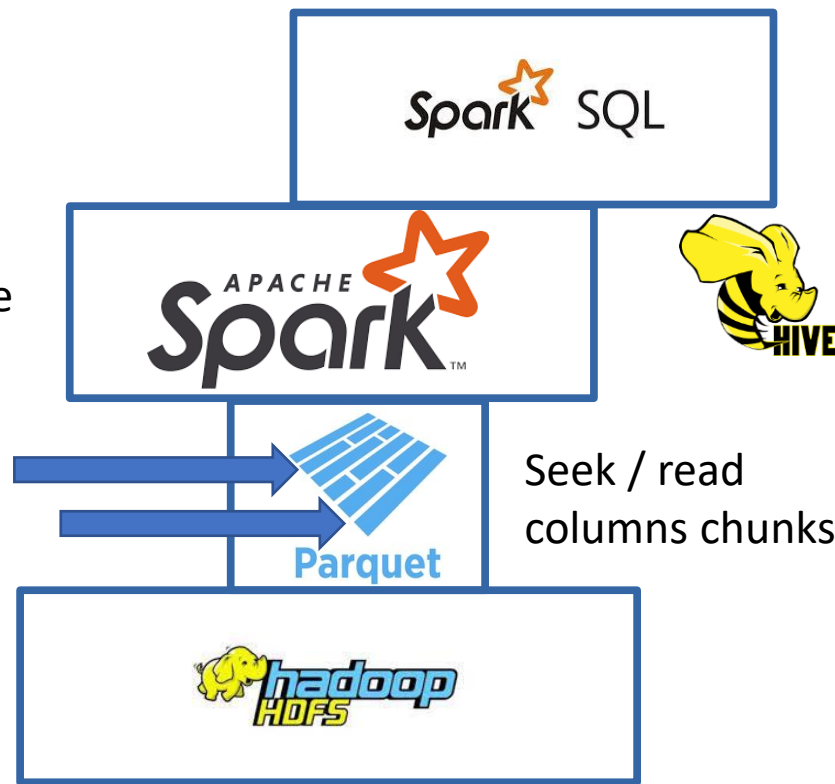
Columns Pruning (seek in Columnar Format)

Select col2, colP from table...
(prune all other columns)

DataSet / RDD on Parquet file

Parquet API
to read columns chunks

Fewer IO



Recap Optimizations 5/5

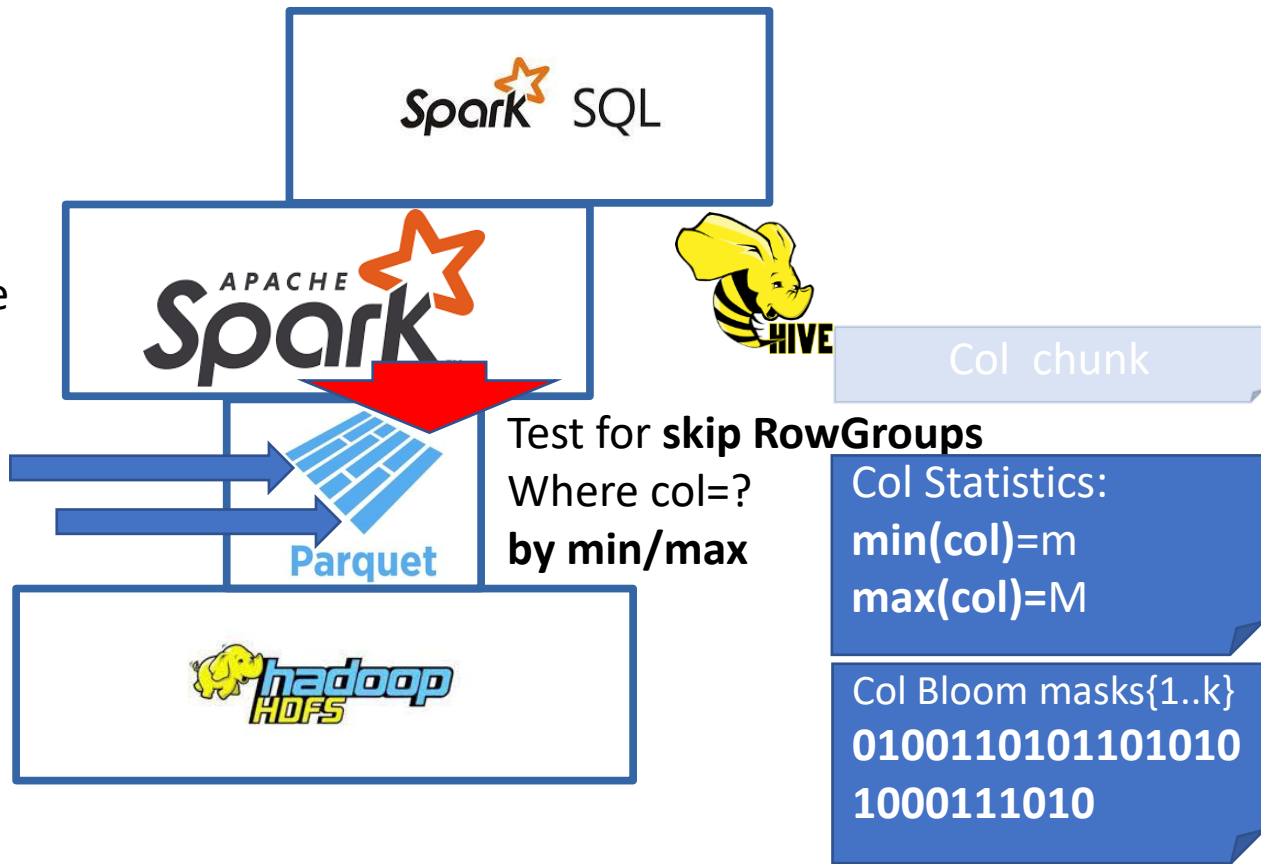
PredicatePushDown (min-max statistics/Bloom)

Select col2, colP from table...
(prune all other columns)

DataSet / RDD on Parquet file

Parquet API
to read columns chunks

Fewer IO



Next... part 5
Spark