Why you should care about data layout in the file system

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databricks

About Databricks

TEAM

Started Spark project (now Apache Spark) at UC Berkeley in 2009

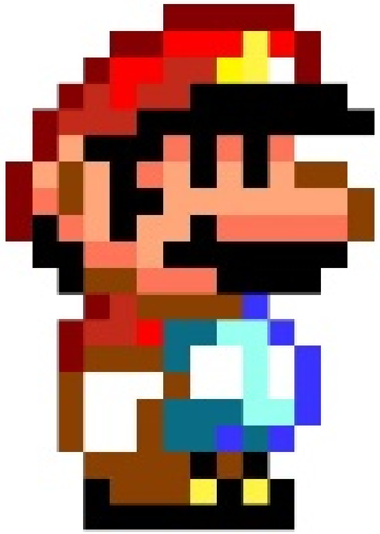
MISSION

Making Big Data Simple

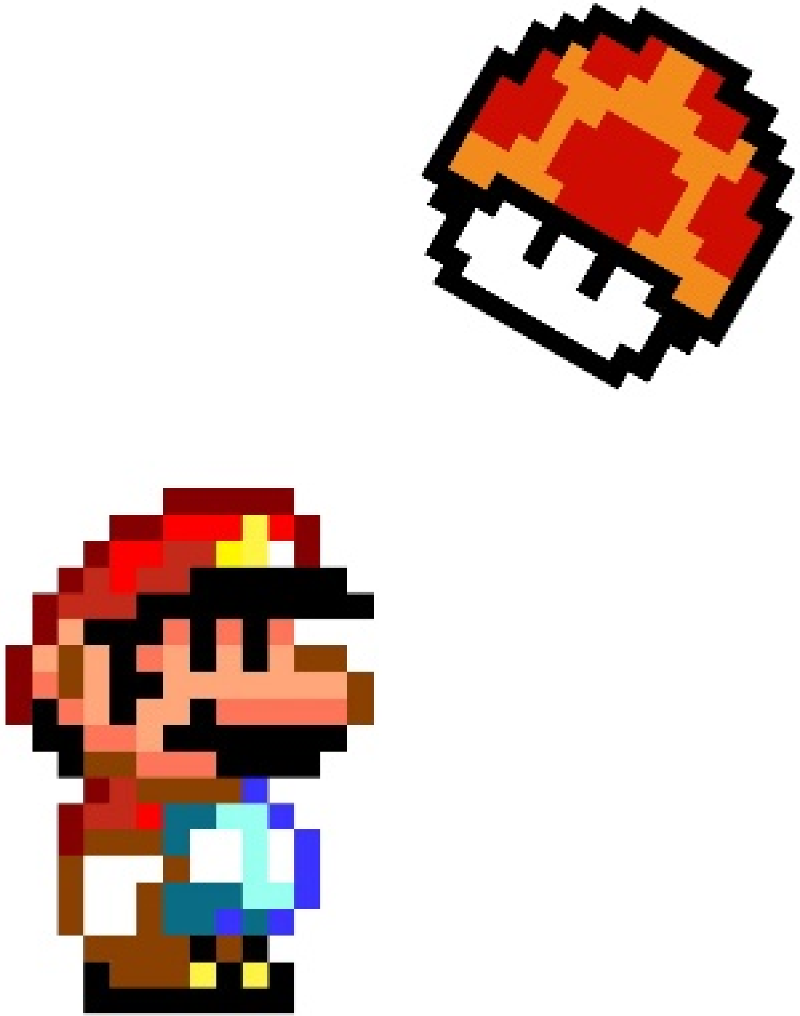
PRODUCT

Unified Analytics Platform

Apache Spark is a powerful framework with some temper



Just like
super mario



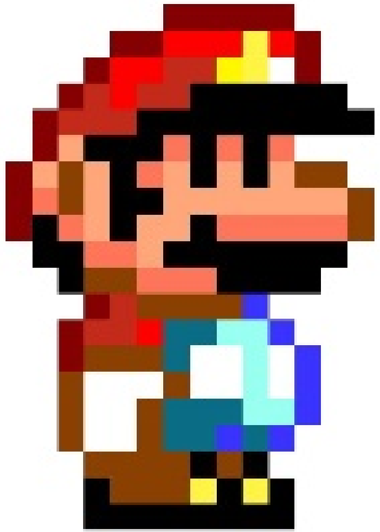
Serve him the
right ingredients

Powers up and
gets more efficient

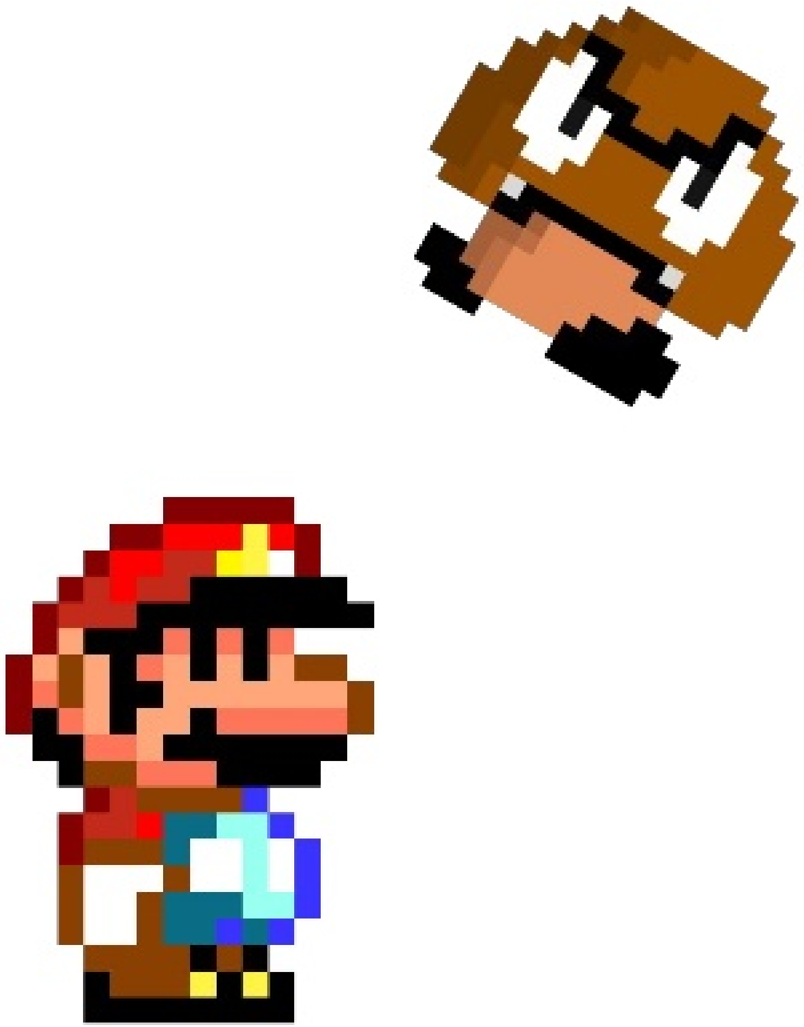
Keep serving

He even knows how to *Spark*!

However,
once served
a wrong dish...



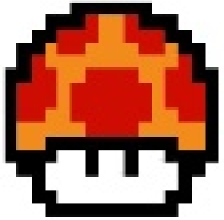
Meh...



And sometimes...

It can be messy...

Secret sauces
we feed APACHE Spark



File Formats

Choosing a compression scheme

The obvious

- Compression ratio: the higher the better
- De/compression speed: the faster the better

Choosing a compression scheme

Splittable v.s. non-splittable

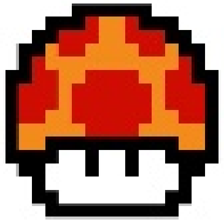
- Affects parallelism, crucial for big data
- Common splittable compression schemes
  - LZ4, Snappy, BZip2, LZO, and etc.
- *GZip is non-splittable*
  - Still common if file sizes are << 1GB
  - Still applicable for Parquet

Columnar formats

Smart, analytics friendly, optimized for big data

- Support for nested data types
- Efficient data skipping
  - Column pruning
  - Min/max statistics based predicate push-down
- Nice interoperability
- Examples:
  - Spark SQL built-in support: Apache Parquet and Apache ORC
  - Newly emerging: Apache CarbonData and Spinach

Columnar formats



Parquet

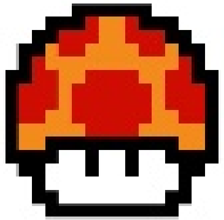
- Apache Spark default output format
- Usually the best practice for Spark SQL
- Relatively heavy write path
  - Worth the time to encode for repeated analytics scenario
- Does not support fine grained appending
  - Not ideal for, e.g., collecting logs
- Check out Parquet [presentations] for more details

Semi-structured text formats

Sort of structured but not self-describing

- Excellent write path performance but slow on the read path
  - Good candidates for collecting raw data (e.g., logs)
- Subject to inconsistent and/or malformed records
- Schema inference provided by Spark (for JSON and CSV)
  - Sampling-based
  - Handy for exploratory scenario but can be inaccurate
  - Always specify an accurate schema in production

Semi-structured text formats



JSON

- Supported by Apache Spark out of the box
- One JSON object per line for fast file splitting
- JSON object: map or struct?
  - Spark schema inference always treats JSON objects as structs
  - Watch out for arbitrary number of keys (may OOM executors)
  - Specify an accurate schema if you decide to stick with maps

Semi-structured text formats

JSON

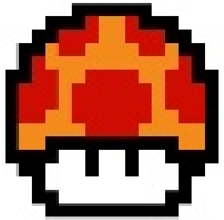
- Malformed records
  - Bad records are collected into column `_corrupted_record`
  - All other columns are set to null

Semi-structured text formats

CSV

- Supported by Spark 2.x out of the box
  - Check out the spark-csv package for Spark 1.x
- Often used for handling legacy data providers & consumers
  - Lacks of a standard file specification
    - Separator, escaping, quoting, and etc.
  - Lacks of support for nested data types

Raw text files

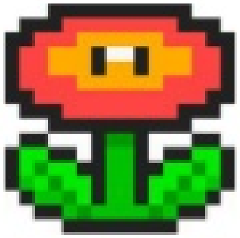


Arbitrary line-based text files

- Splitting files into lines using `spark.read.text()`
  - Keep your lines a reasonable size
- Keep file size < 1GB if compressed with a non-splittable compression scheme (e.g., GZip)
- Handing inevitable malformed data
  - Use a `filter()` transformation to drop bad lines, or
  - Use a `map()` transformation to fix bad line

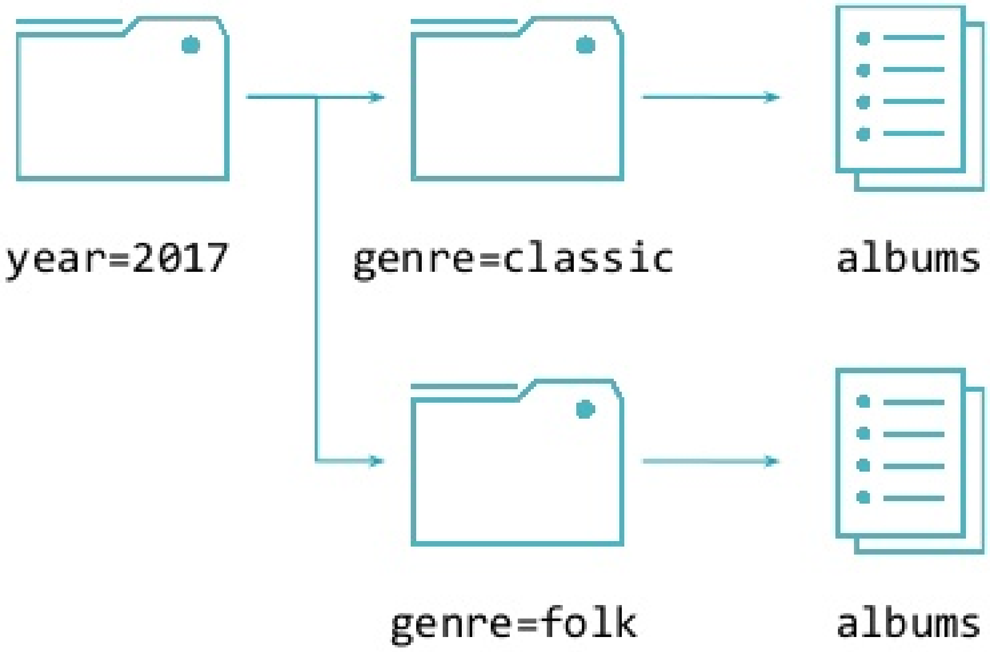
Directory layout

Partitioning

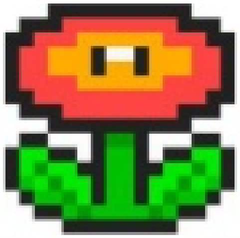


Overview

- Coarse-grained data skipping
- Available for both persisted tables and raw directories
- Automatically discovers Hive style partitioned directories



Partitioning



SQL

```
CREATE TABLE ratings
USING PARQUET
PARTITIONED BY (year, genre)
AS SELECT artist, rating, year, genre
FROM music
```

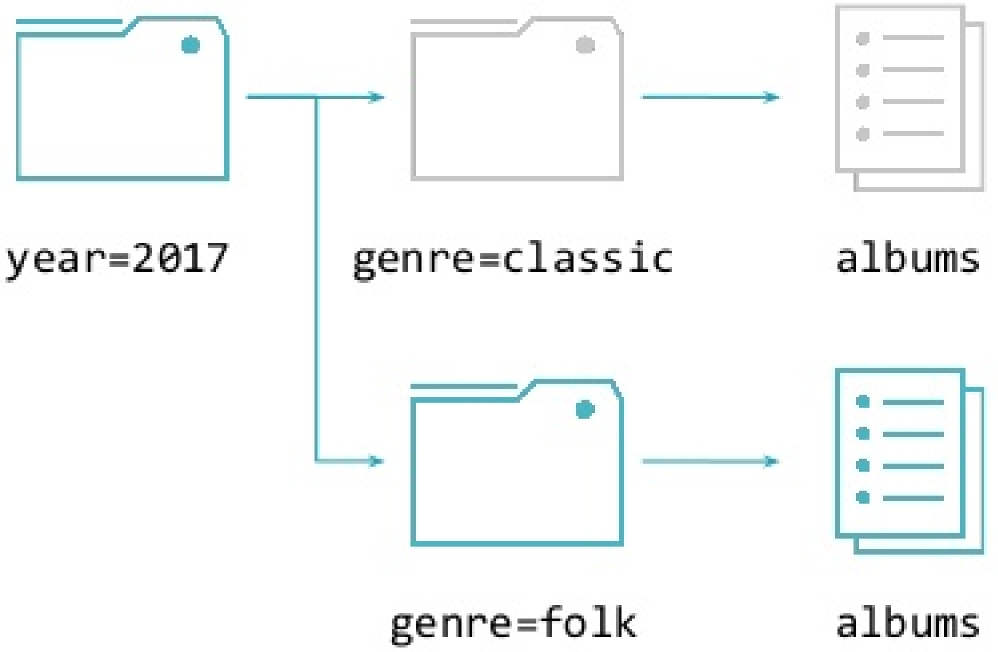
DataFrame API

```
spark
  .table("music")
  .select('artist, 'rating, 'year, 'genre)
  .write
  .format("parquet")
  .partitionBy('year, 'genre)
  .saveAsTable("ratings")
```

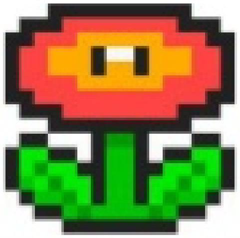
Partitioning

Filter predicates

Use simple filter predicates containing partition columns to leverage partition pruning



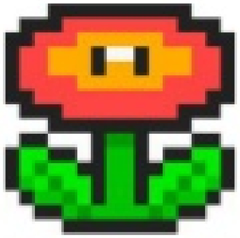
Partitioning



Filter predicates

- `year = 2000 AND genre = ‘folk’`
- `year > 2000 AND rating > 3`
- `year > 2000 OR genre <> ‘rock’`

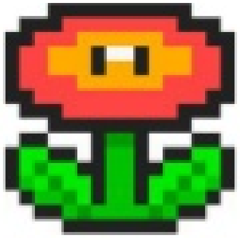
Partitioning



Filter predicates

- `year > 2000 OR rating = 5`
- `year > rating`

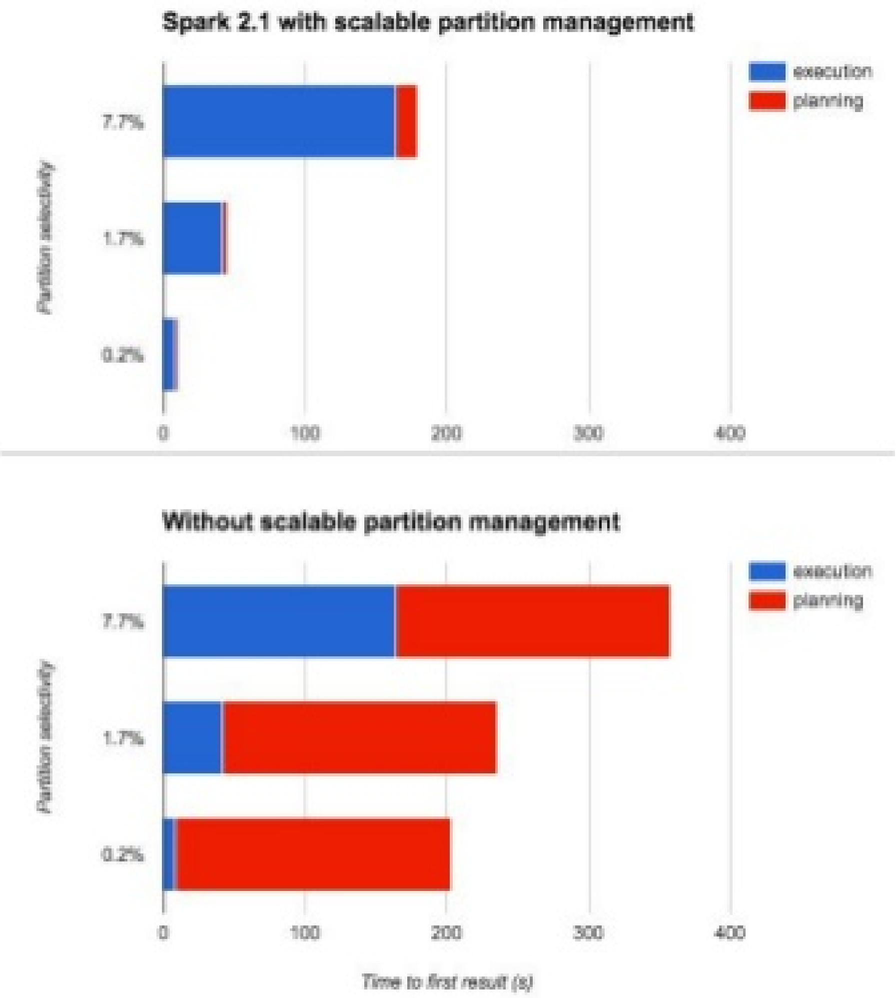
Partitioning



Avoid excessive partitions

- Stress metastore for persisted tables
- Stress file system when reading directly from the file system
- Suggestions
  - Avoid using too many partition columns
  - Avoid using partition columns with too many distinct values
    - Try hashing the values
    - E.g., partition by first letter of first name rather than first name

Partitioning



Scalable partition handling

Using persisted partitioned tables with Spark 2.1+

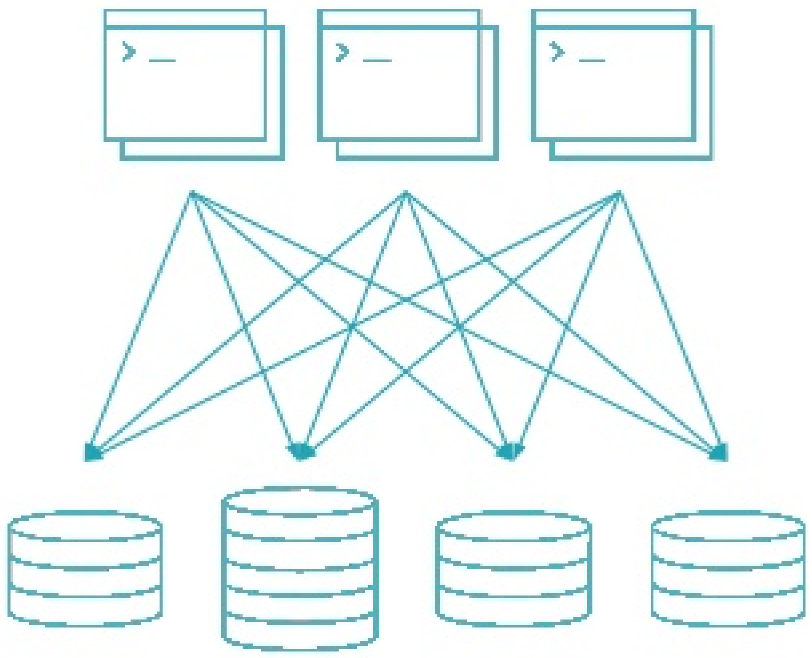
- Per-partition metadata gets persisted into the metastore
- Avoids unnecessary partition discovery (esp. valuable for S3)

Check our blog post for more details

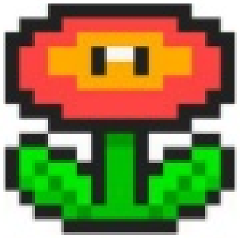
Bucketing

Overview

- *Pre-shuffles* and optionally *pre-sorts* the data while writing
- Layout information gets persisted in the metastore
- Avoids shuffling and sorting when joining large datasets
- Only available for persisted tables



Bucketing



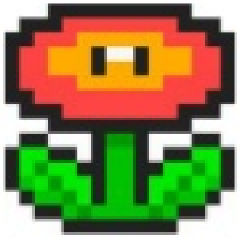
SQL

```
CREATE TABLE ratings
USING PARQUET
PARTITIONED BY (year, genre)
CLUSTERED BY (rating) INTO 5 BUCKETS
SORTED BY (rating)
AS SELECT artist, rating, year, genre
FROM music
```

DataFrame

```
ratings
  .select(’artist, ’rating, ’year, ’genre)
  .write
  .format(“parquet”)
  .partitionBy(“year”, “genre”)
  .bucketBy(5, “rating”)
  .sortBy(“rating”)
  .saveAsTable(“ratings”)
```

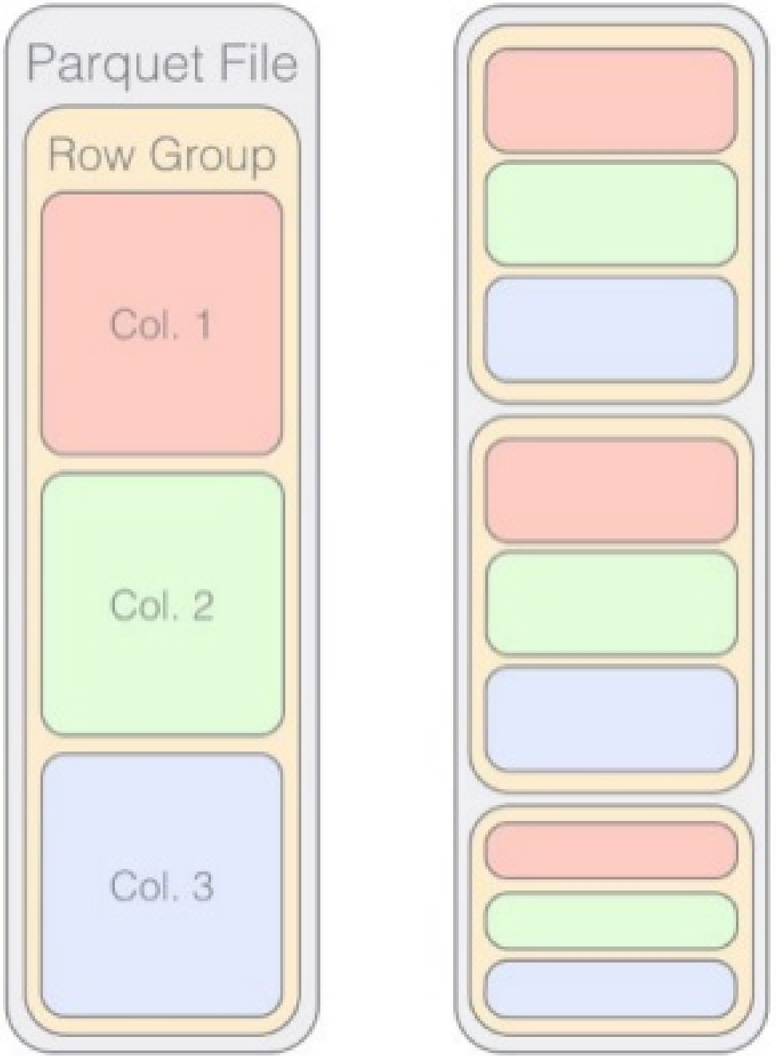
Bucketing



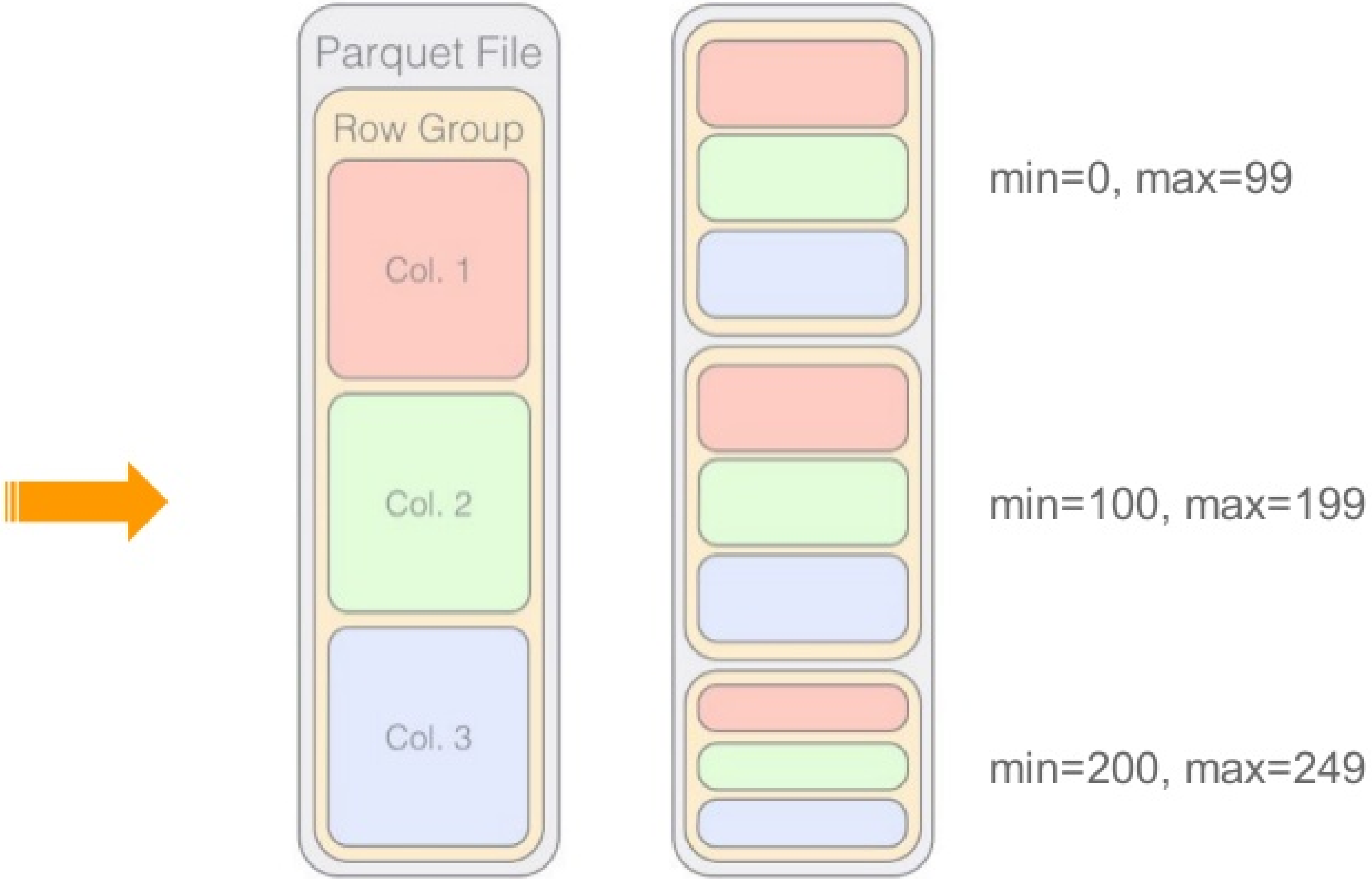
In combo with columnar formats

- Bucketing
  - Per-bucket sorting
- Columnar formats
  - Efficient *data skipping* based on min/max statistics
  - Works best when the searched columns are *sorted*

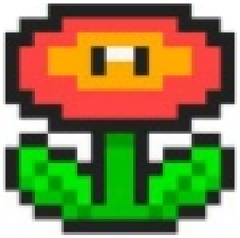
Bucketing



Bucketing


Parquet File
Row Group
Col. 1
Col. 2
Col. 3
min=0, max=99
min=100, max=199
min=200, max=249

Bucketing

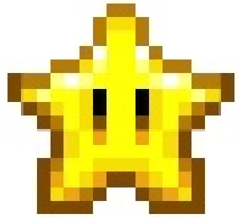


In combo with columnar formats

Perfect combination, makes your Spark jobs FLY!

⭐ More tips

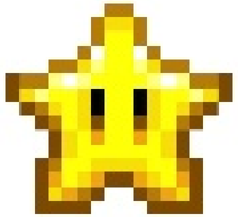
File size and compaction



Avoid small files

- Cause excessive parallelism
  - Spark 2.x improves this by packing small files
- Cause extra file metadata operations
  - Particularly bad when hosted on S3

File size and compaction



How to control output file sizes

- In general, one task in the output stage writes one file
  - Tune parallelism of the output stage
- `coalesce(N)`, for
  - Reduces parallelism for small jobs
- `repartition(N)`, for
  - Increasing parallelism for all jobs, or
  - Reducing parallelism of final output stage for large jobs
  - Still preserves high parallelism for previous stages

True story

Customer

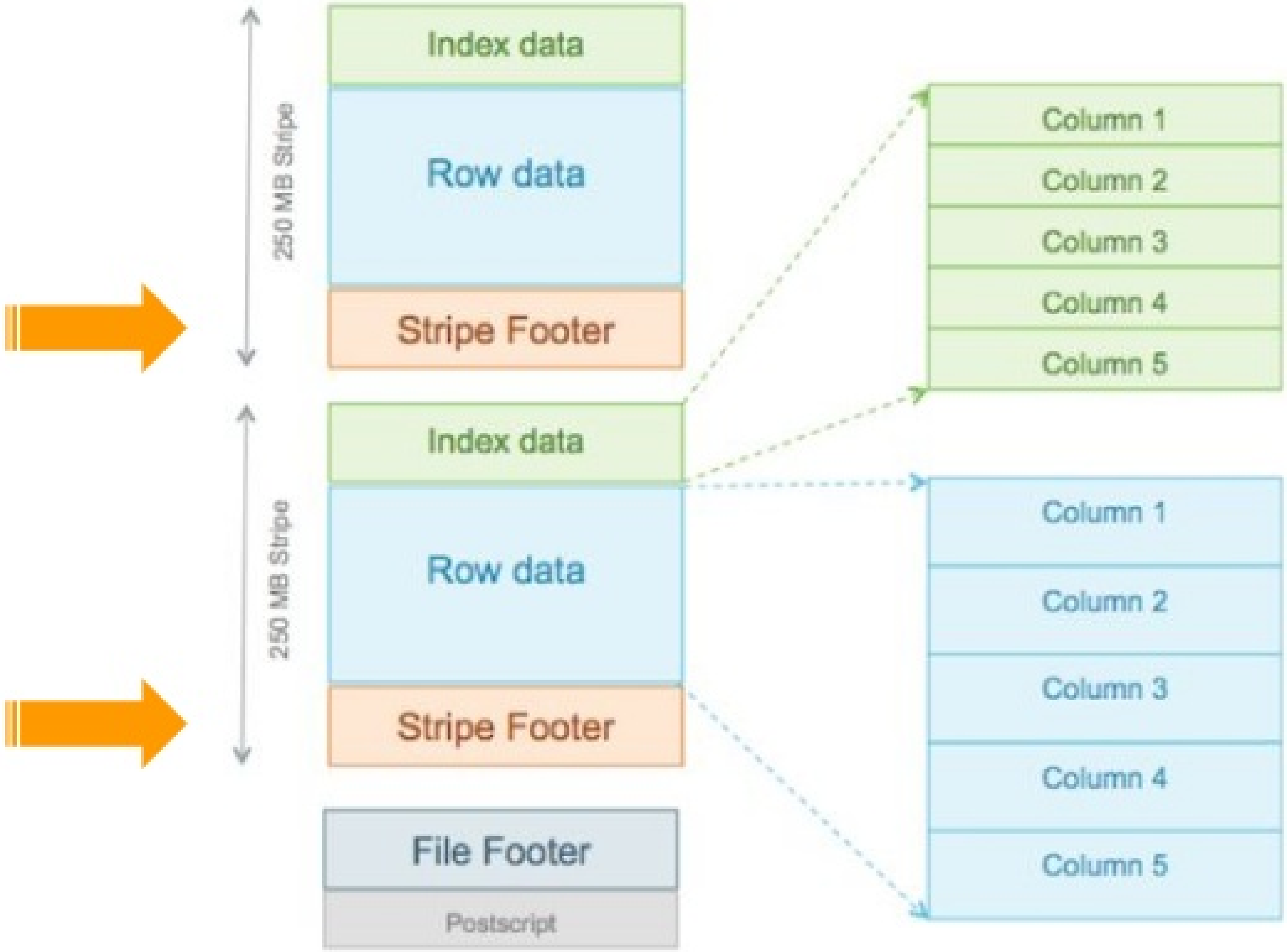
- Spark ORC Read Performance is much slower than Parquet
- The same query took
  - 3 seconds on a Parquet dataset
  - 4 minutes on an equivalent ORC dataset

True story

Me

- Ran a `simple count(*)`, which took
  - Seconds on the Parquet dataset with a handful IO requests
  - 35 minutes on the ORC dataset with 10,000s of IO requests
- Most task execution threads are *reading ORC stripe footers*

True story



250 MB Stripe
Index data
Row data
Stripe Footer
250 MB Stripe
Index data
Row data
Stripe Footer
File Footer
Postscript
Column 1
Column 2
Column 3
Column 4
Column 5
Column 1
Column 2
Column 3
Column 4
Column 5

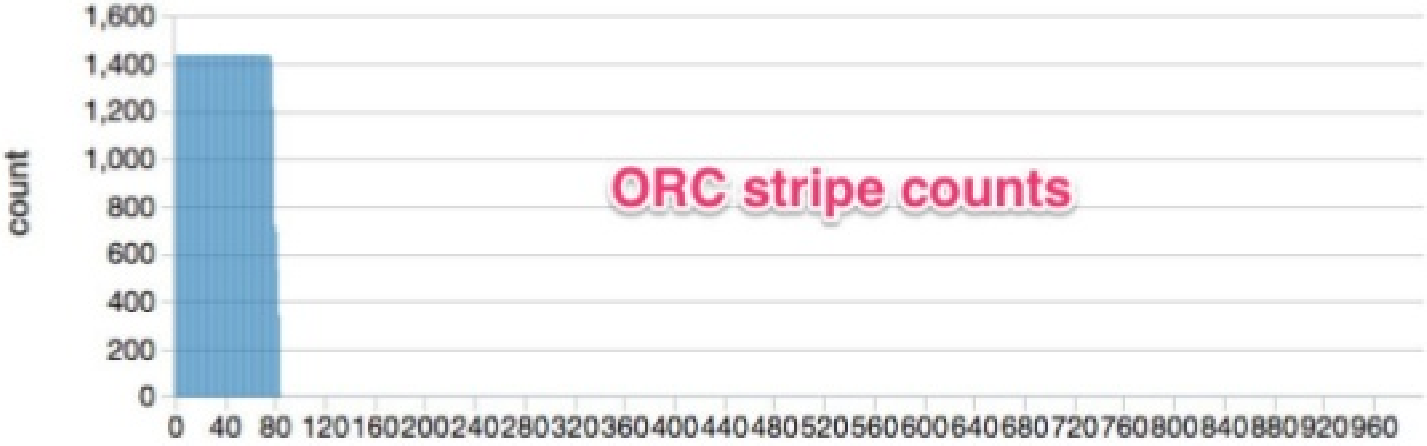
True story

```
import org.apache.hadoop.hive.ql.io.orc._
import org.apache.hadoop.conf.Configuration
import org.apache.hadoop.fs.Path

val conf = new Configuration

def countStripes(file: String): Int = {
  val path = new Path(file)
  val reader = OrcFile.createReader(path, OrcFile.readerOptions(conf))
  val metadata = reader.getMetadata
  metadata.getStripeStatistics.size
}
```

True story

Maximum file size: ~15 MB

Maximum ORC stripe counts: ~1,400



True story

Root cause

Malformed (but not corrupted) ORC dataset

- ORC readers read the footer first before consuming a strip
- ~1,400 stripes within a single file as small as 15 MB
- ~1,400 x 2 read requests issued to S3 for merely 15 MB of data

True story

Root cause

Malformed (but not corrupted) ORC dataset

- ORC readers read the footer first before consuming a strip
- ~1,400 stripes within a single file as small as 15 MB
- ~1,400 x 2 read requests issued to S3 for merely 15 MB of data

Much worse than even CSV, not mention Parquet

True story

Why?

- Tiny ORC files (~10 KB) generated by Streaming jobs
    - Resulting one tiny ORC stripe inside each ORC file
    - The footers might take even more space than the actual data!

True story

Why?

Tiny files got compacted into larger ones using

```
ALTER TABLE ... PARTITION (...) CONCATENATE;
```

The CONCATENATE command just, well, *concatenated* those tiny stripes and produced larger (~15 MB) files with a huge number of tiny stripes.

True story

Lessons learned

Again, avoid writing small files in *columnar formats*

- Output files using CSV or JSON for Streaming jobs
  - For better write path performance
- Compact small files into large chunks of columnar files later
  - For better read path performance

True story

The cure

Simply read the ORC dataset and write it back using

```
spark.read.orc(input).write.orc(output)
```

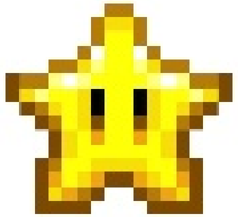
So that stripes are adjusted into more reasonable sizes.

Schema evolution

Columns come and go

- Never ever change the data type of a published column
- Columns with the same name should have the same data type
- If you really dislike the data type of some column
  - Add a new column with a new name and the right data type
  - Deprecate the old one
  - Optionally, drop it after updating all downstream consumers

Schema evolution

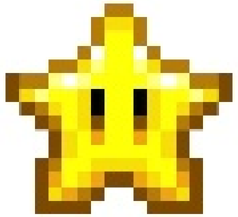


Columns come and go

Spark built-in data sources that support schema evolution

- JSON
- Parquet
- ORC

Schema evolution



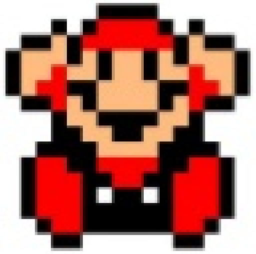
Common columnar formats are less tolerant of data type mismatch. E.g.:

- `INT` cannot be promoted to `LONG`
- `FLOAT` cannot be promoted to `DOUBLE`

JSON is more tolerating, though

- `LONG` → `DOUBLE` → `STRING`

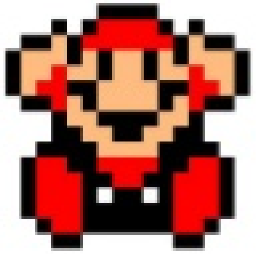
True story



Customer

Parquet dataset corrupted!!! HALP!!!

True story



What happened?

Original schema

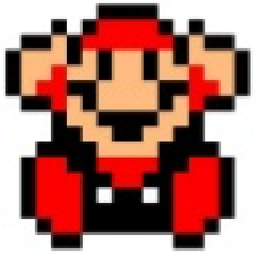
- `{col1: DECIMAL(19, 4), col2: INT}`

Accidentally appended data with schema

- `{col1: DOUBLE, col2: DOUBLE}`

All files written into the same directory

True story



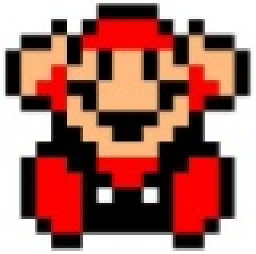
What happened?

Common columnar formats are less tolerant of data type mismatch. E.g.:

- `INT` cannot be promoted to `LONG`
- `FLOAT` cannot be promoted to `DOUBLE`

Parquet considered these schemas as incompatible ones and refused to merge them.

True story



BTW

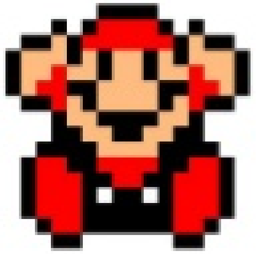
JSON schema inference is more tolerating

- `LONG` → `DOUBLE` → `STRING`

However

- JSON is NOT suitable for analytics scenario
- Schema inference is unreliable, not suitable for production

True story



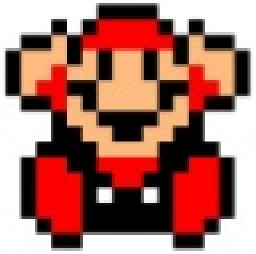
The cure

Correct the schema

- Filter out all the files with the wrong schema
- Rewrite those files using the correct schema

Exhausting because all files are appended into a single directory

True story



Lessons learned

- Be very careful on the write path
- Consider partitioning when possible
    - Better read path performance
    - Easier to fix the data when something went wrong

Recap

File formats

- Compression schemes
- Columnar (Parquet, ORC)
- Semi-structured (JSON, CSV)
- Raw text format

Directory layout

- Partitioning
- Bucketing

Other tips

- File sizes and compaction
- Schema evolution

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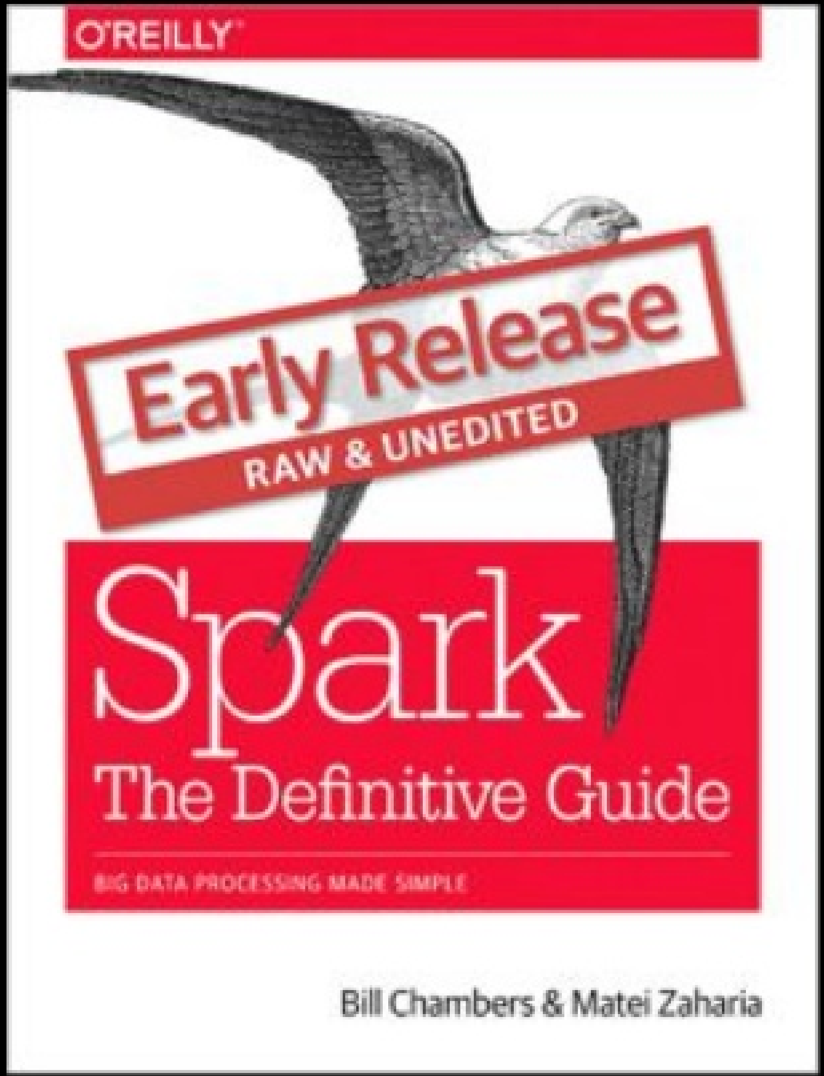

Thank you

Q & A