Top 5 Mistakes when writing Spark applications

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tiny.cloudera.com/spark-mistakes

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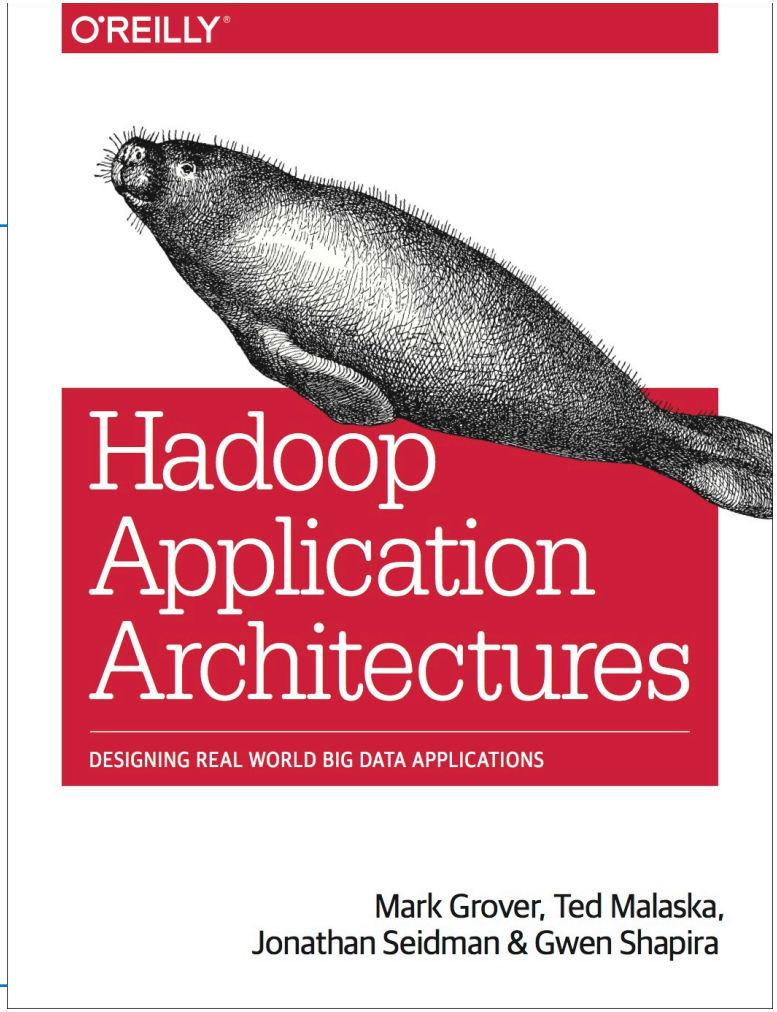
About the book

- @hadooparchbook
- hadooparchitecturebook.com
- github.com/hadooparchitecturebook
- slideshare.com/hadooparchbook



Mistakes people make

when using Spark

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Mistakes ~~people~~ we made

when using Spark

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Mistake # 1

Executors, cores, memory !?!

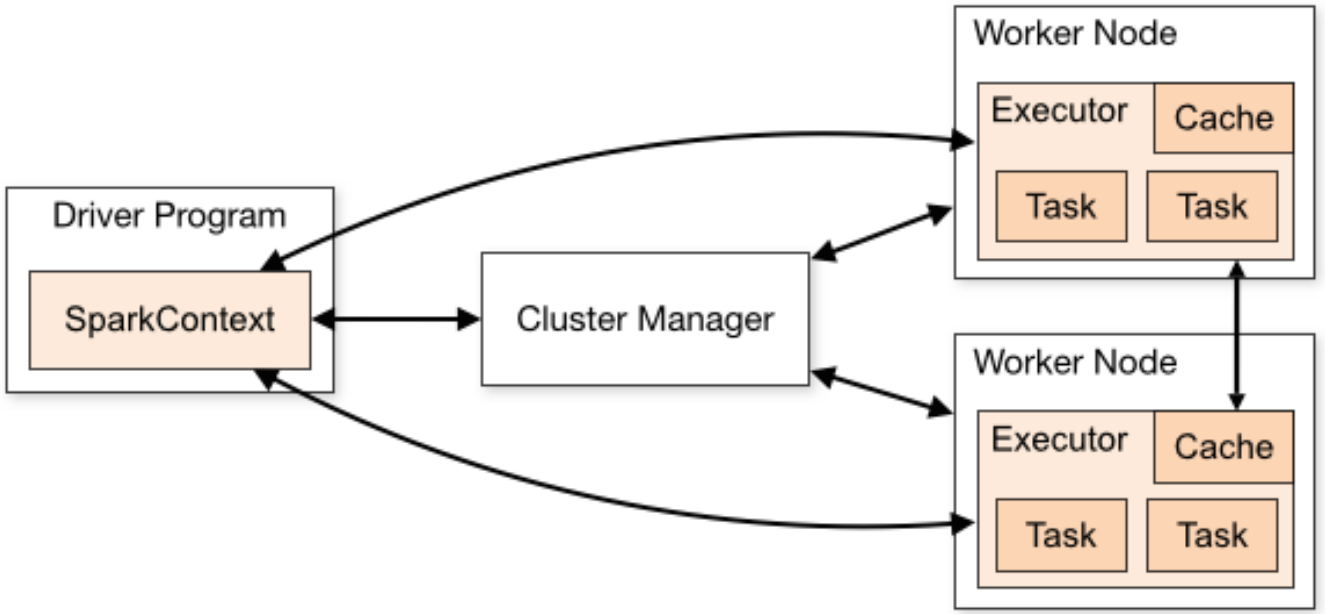
- 6 Nodes
- 16 cores each
- 64 GB of RAM each

Decisions, decisions, decisions

- 6 nodes
- 16 cores each
- 64 GB of RAM

- Number of executors (--num-executors)
- Cores for each executor (--executor-cores)
- Memory for each executor (--executor-memory)

Spark Architecture recap



Answer #1 – Most granular

- Have smallest sized executors as possible
- 1 core each
- Total of 16 x 6 = 96 cores
- 96 executors
- 64/16 = 4 GB per executor (per node)

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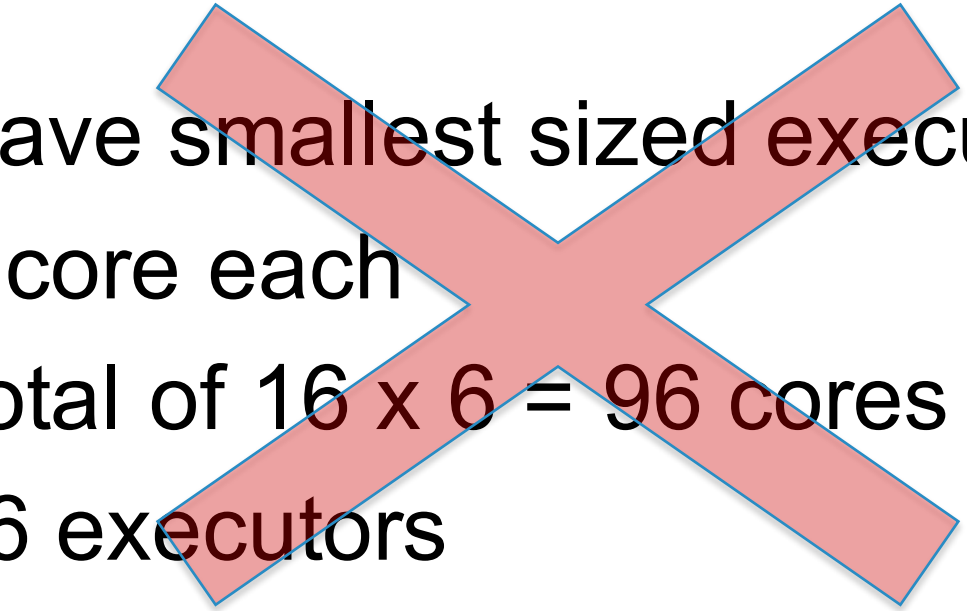

Why?

- Not using benefits of running multiple tasks in same JVM

Answer #2 – Least granular

- 6 executors
- 64 GB memory each
- 16 cores each

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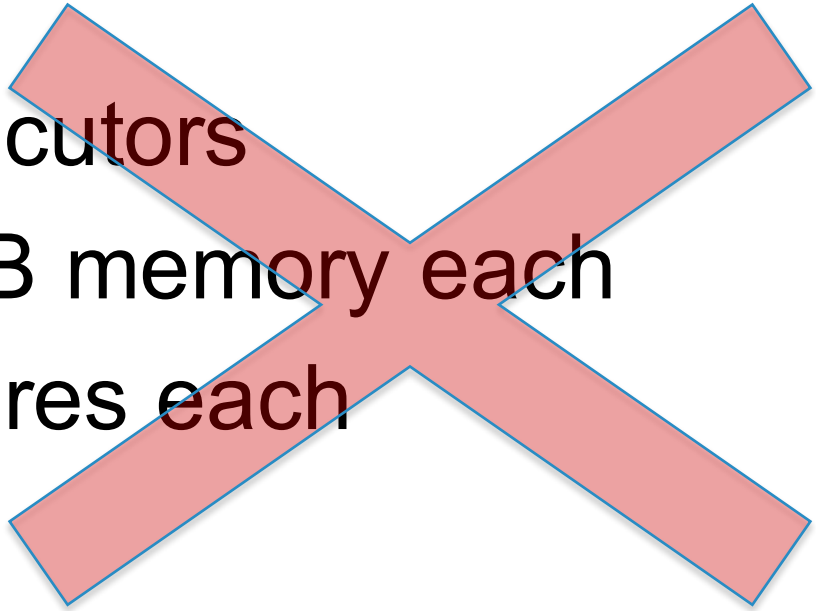

Why?

- Need to leave some memory overhead for OS/Hadoop daemons

Answer #3 – with overhead

- 6 executors
- 63 GB memory each
- 15 cores each

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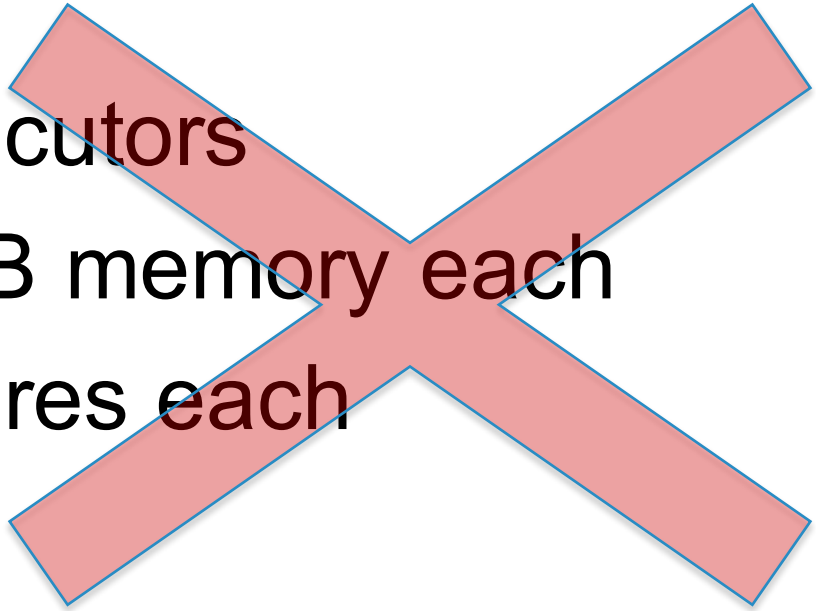
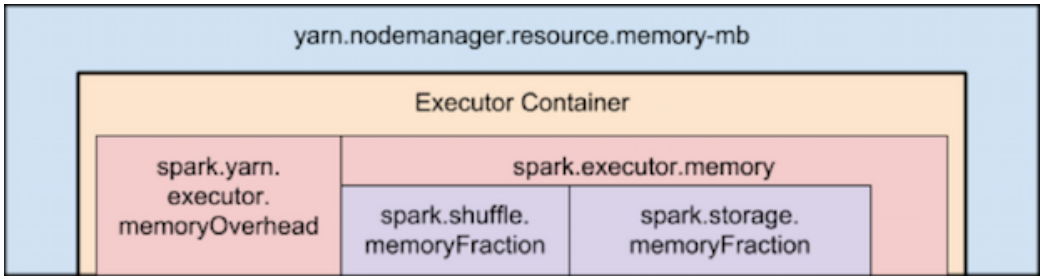
- 6 executors
- 63 GB memory each
- 15 cores each

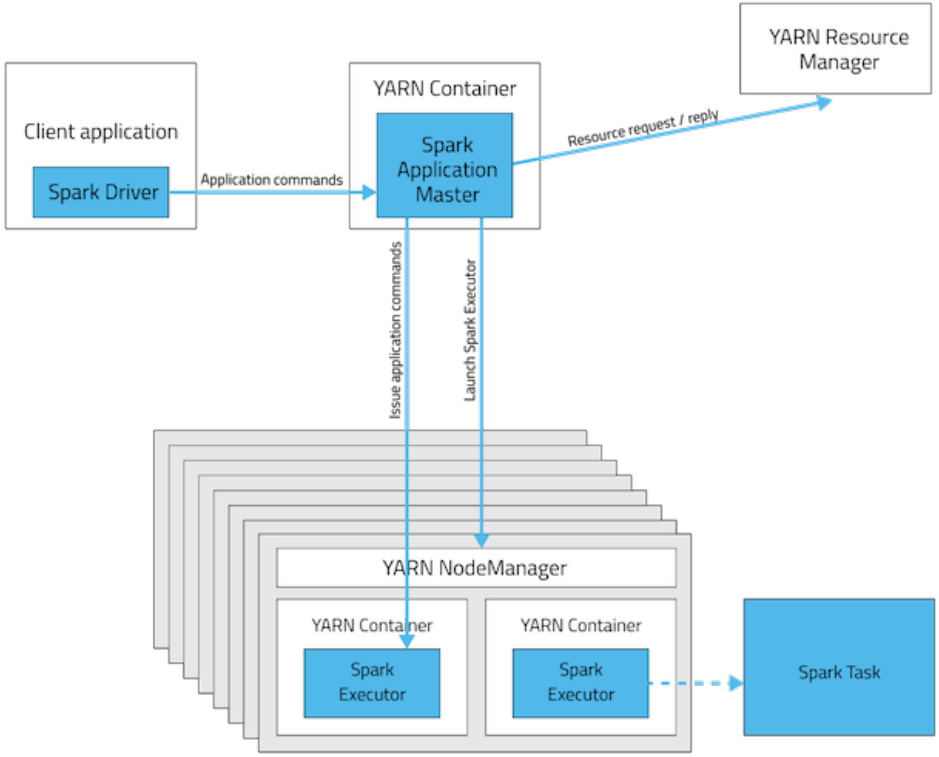


Spark on YARN – Memory usage

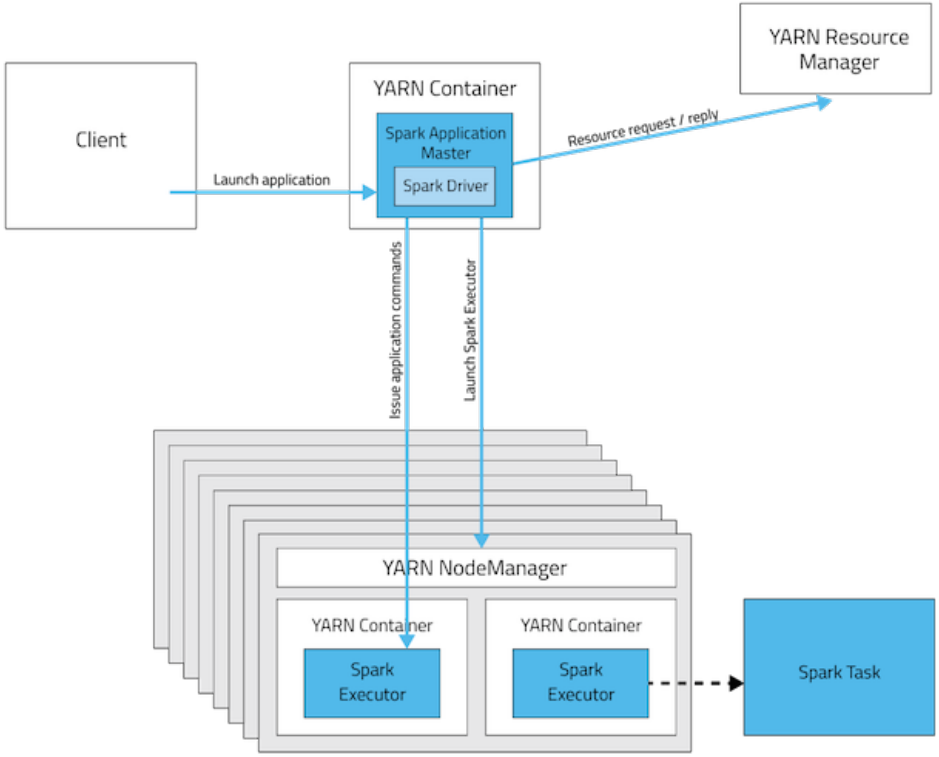


- --executor-memory controls the heap size
- Need some overhead (controlled by spark.yarn.executor.memory.overhead) for off heap memory
  - Default is max(384MB, .07 * spark.executor.memory)

YARN AM needs a core: Client mode



YARN AM needs a core: Cluster mode



HDFS Throughput

- 15 cores per executor can lead to bad HDFS I/O throughput.
- Best is to keep under 5 cores per executor

Calculations

- 5 cores per executor
  - For max HDFS throughput
- Cluster has 6 * 15 = 90 cores in total (after taking out Hadoop/Yarn daemon cores)
- 90 cores / 5 cores/executor = 18 executors
- 1 executor for AM => 17 executors
- Each node has 3 executors
- 63 GB/3 = 21 GB, 21 x (1-0.07) ~ 19 GB (counting off heap overhead)

Correct answer

- 17 executors
- 19 GB memory each
- 5 cores each

** Not etched in stone*

Read more

- From a great blog post on this topic by Sandy Ryza:

http://blog.cloudera.com/blog/2015/03/how-to-tune-your-apache-spark-jobs-part-2/

Mistake # 2

Application failure

```
15/04/16 14:13:03 WARN scheduler.TaskSetManager: Lost task 19.0 in
stage 6.0 (TID 120, 10.215.149.47):
java.lang.IllegalArgumentException: Size exceeds Integer.MAX_VALUE
at sun.nio.ch.FileChannelImpl.map(FileChannelImpl.java:828) at
org.apache.spark.storage.DiskStore.getBytes(DiskStore.scala:123) at
org.apache.spark.storage.DiskStore.getBytes(DiskStore.scala:132) at
org.apache.spark.storage.BlockManager.doGetLocal(BlockManager.scala:51
7) at
org.apache.spark.storage.BlockManager.getLocal(BlockManager.scala:432)
at org.apache.spark.storage.BlockManager.get(BlockManager.scala:618)
at
org.apache.spark.CacheManager.putInBlockManager(CacheManager.scala:146
) at org.apache.spark.CacheManager.getOrCompute(CacheManager.scala:70)
```

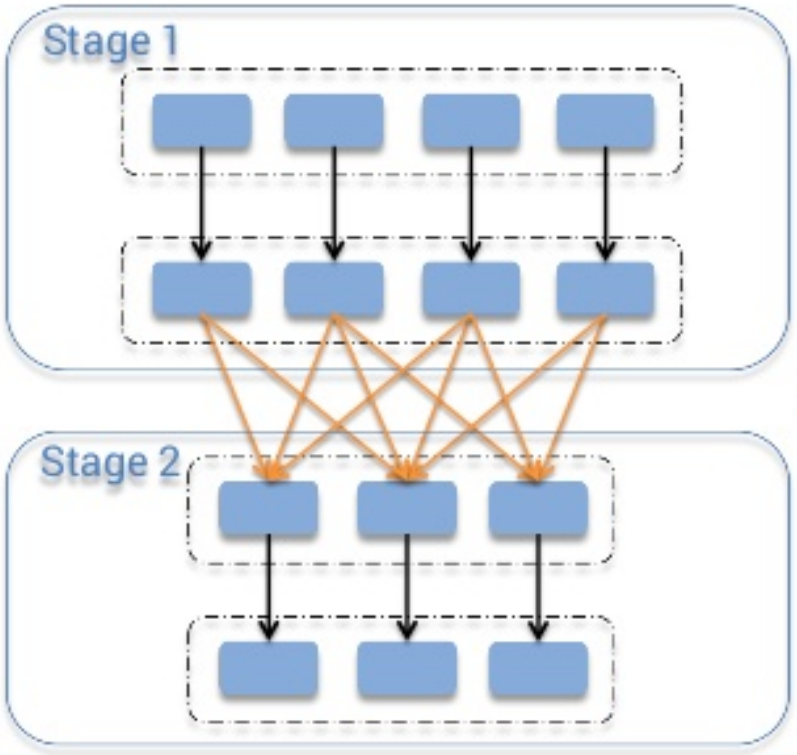
Why?

- No Spark shuffle block can be greater than 2 GB

Ok, what's a shuffle block again?

- In MapReduce terminology, a Mapper-Reducer pair – the file from local disk that the reducers read from local disk in MapReduce.

In other words



Each yellow arrow in this diagram represents a shuffle block.

Wait! What!?! This is Big Data stuff, no?

- Yeah! Nope!
- Spark uses `ByteBuffer` as abstraction for storing blocks

```
val buf = ByteBuffer.allocate(length.toInt)
```

- `ByteBuffer` is limited by `Integer.MAX_SIZE` (2 GB)!

Once again

- No Spark shuffle block can be greater than 2 GB

Spark SQL

- Especially problematic for Spark SQL
- Default number of partitions to use when doing shuffles is 200
  - This low number of partitions leads to high shuffle block size

Umm, ok, so what can I do?

1. Increase the number of partitions
   – Thereby, reducing the average partition size
2. Get rid of skew in your data
   – More on that later

Umm, how exactly?

- In Spark SQL, increase the value of `spark.sql.shuffle.partitions`
- In regular Spark applications, use `rdd.repartition()` or `rdd.coalesce()`

But, how many partitions should I have?

- Rule of thumb is around 128 MB per partition

But!

- Spark uses a different data structure for bookkeeping during shuffles, when the number of partitions is less than 2000, vs. more than 2000.

Don’t believe me?

- In `MapStatus.scala`

```
def apply(loc: BlockManagerId, uncompressedSizes:
Array[Long]): MapStatus = {
  if (uncompressedSizes.length > 2000) {
    HighlyCompressedMapStatus(loc,
uncompressedSizes)
  } else {
    new CompressedMapStatus(loc, uncompressedSizes)
  }
}
```

Ok, so what are you saying?

- If your number of partitions is less than 2000, but close enough to it, bump that number up to be slightly higher than 2000.

Can you summarize, please?

- Don’t have too big partitions
  - Your job will fail due to 2 GB limit
- Don’t have too few partitions
  - Your job will be slow, not making using of parallelism
- Rule of thumb: ~128 MB per partition
- If #partitions < 2000, but close, bump to just > 2000

Mistake # 3

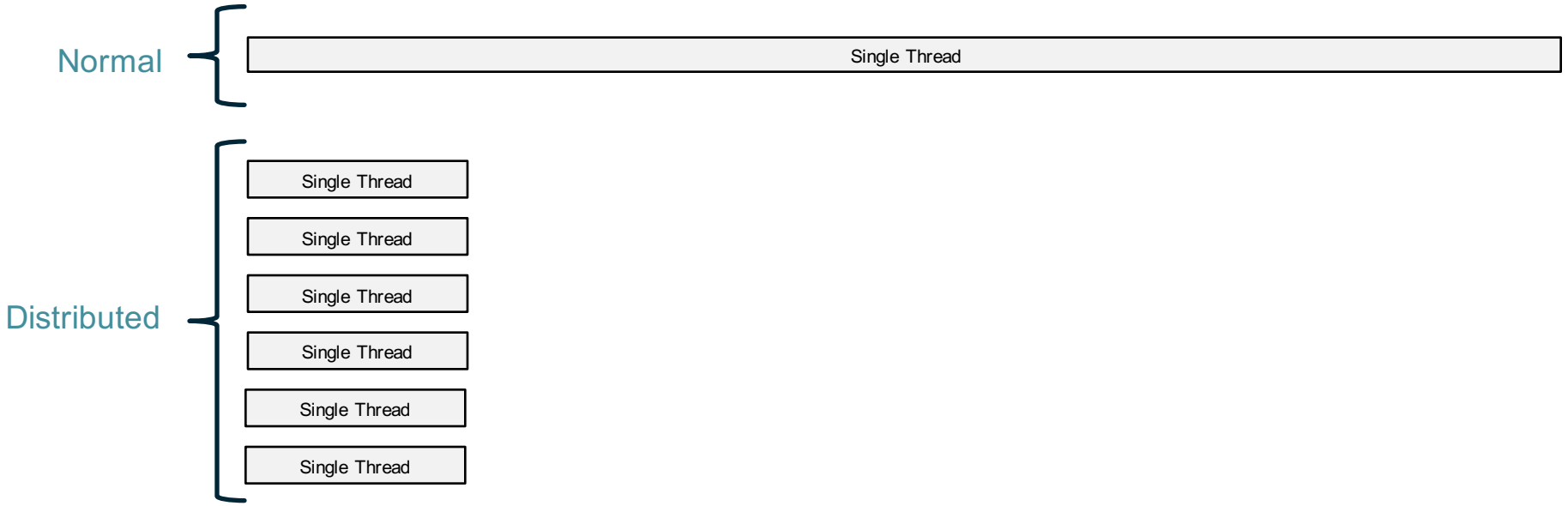
Slow jobs on Join/Shuffle

- Your dataset takes 20 seconds to run over with a map job, but take 4 hours when joined or shuffled. What wrong?

Skew and Cartesian

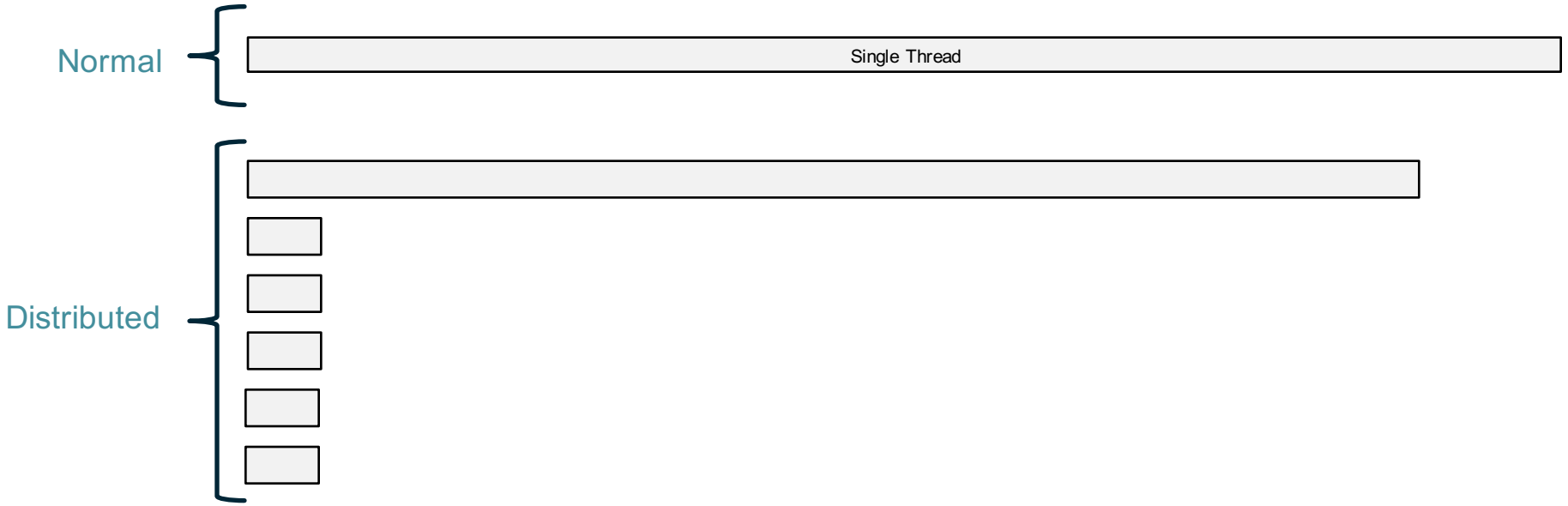
Mistake - Skew

The Holy Grail of Distributed Systems



Mistake - Skew

What about Skew, because that is a thing



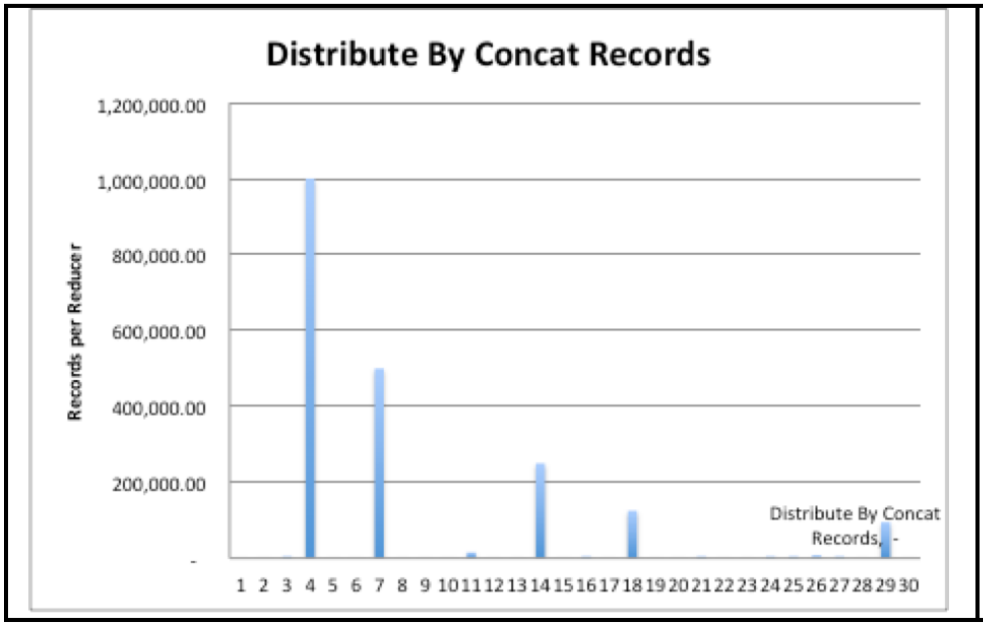
Mistake – Skew : Answers

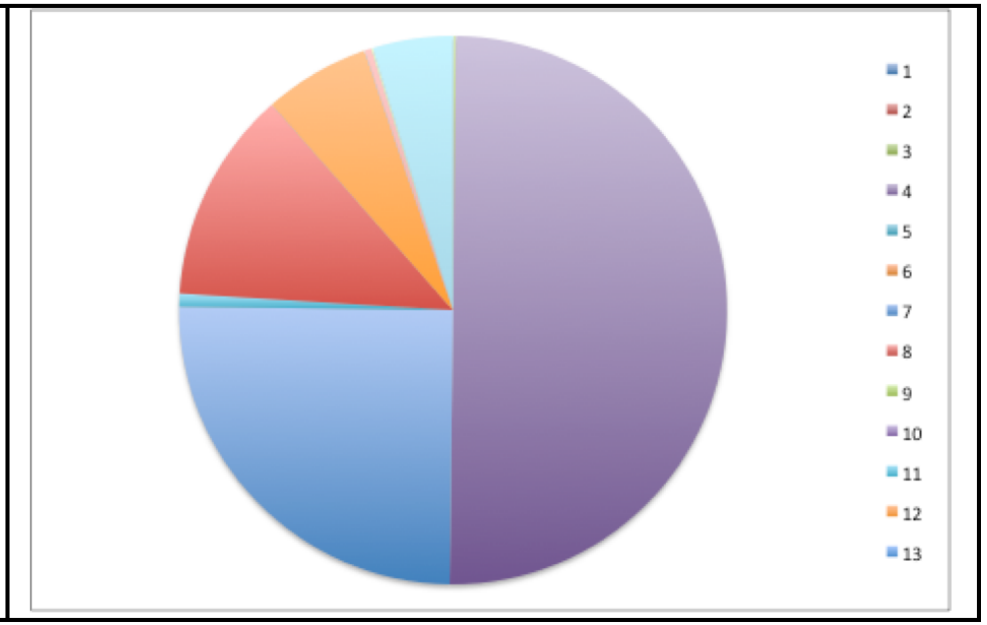
- Salting
- Isolation Salting
- Isolation Map Joins

Mistake – Skew : Salting

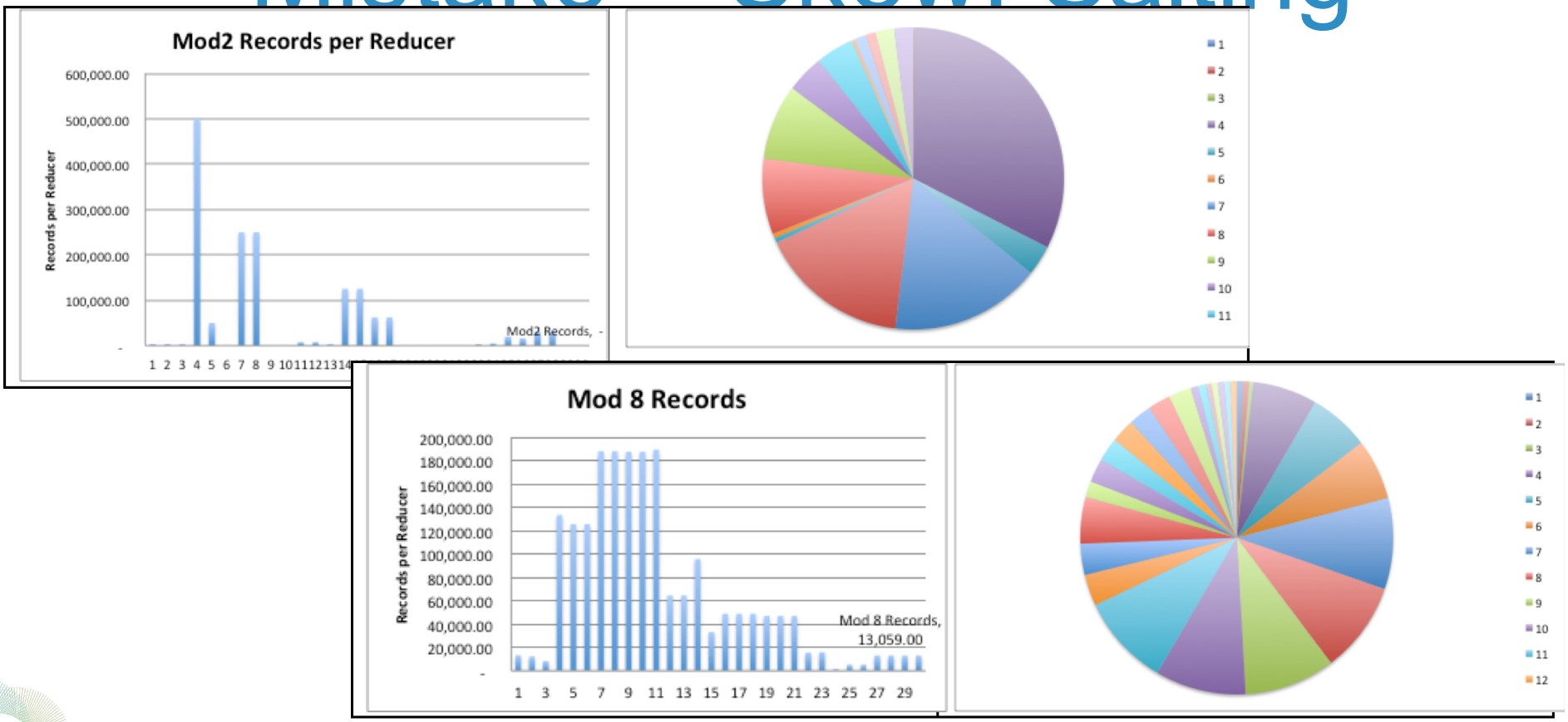
- Normal Key: “Foo”
- Salted Key: “Foo” + random.nextInt(saltFactor)

Managing Parallelism





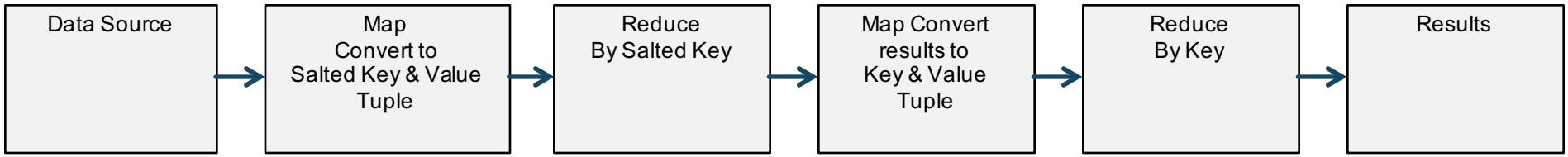
Mistake – Skew: Salting



Add Example Slide

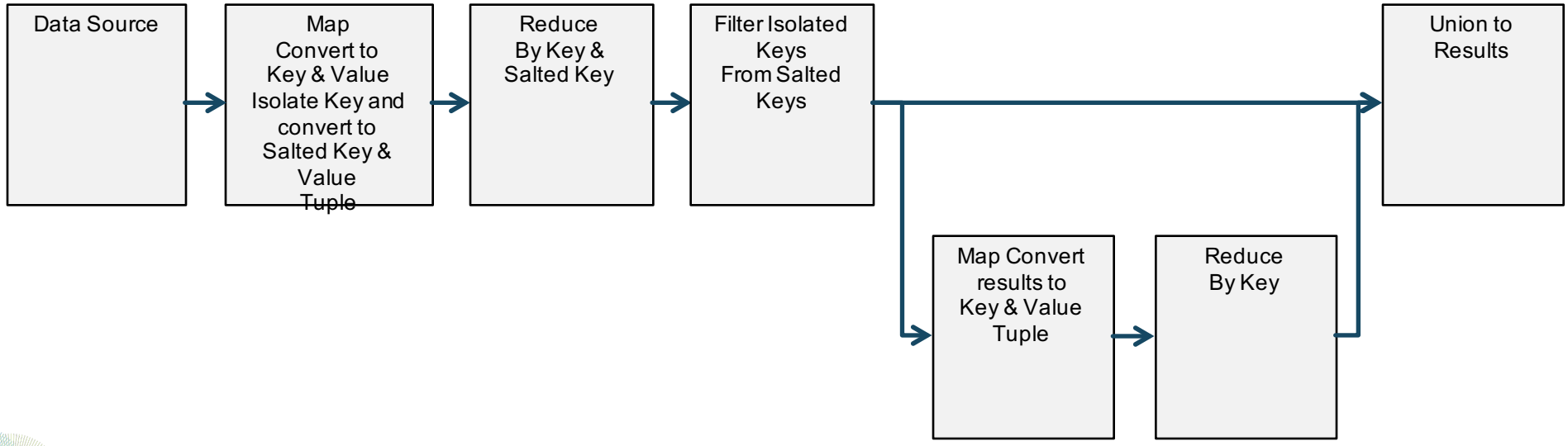
Mistake – Skew : Salting

- Two Stage Aggregation
  - Stage one to do operations on the salted keys
  - Stage two to do operation access unsalted key results



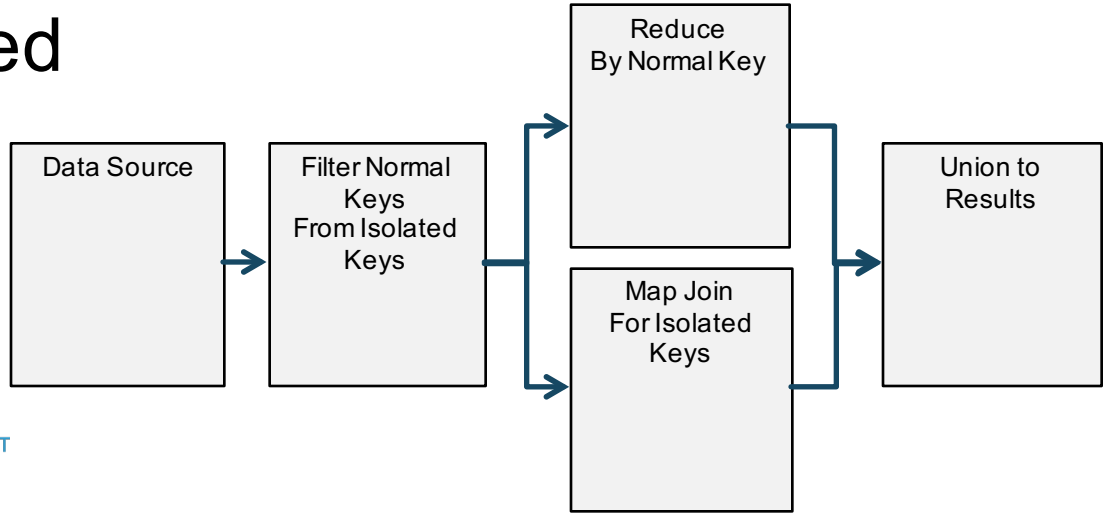
Mistake – Skew : Isolated Salting

- Second Stage only required for Isolated Keys



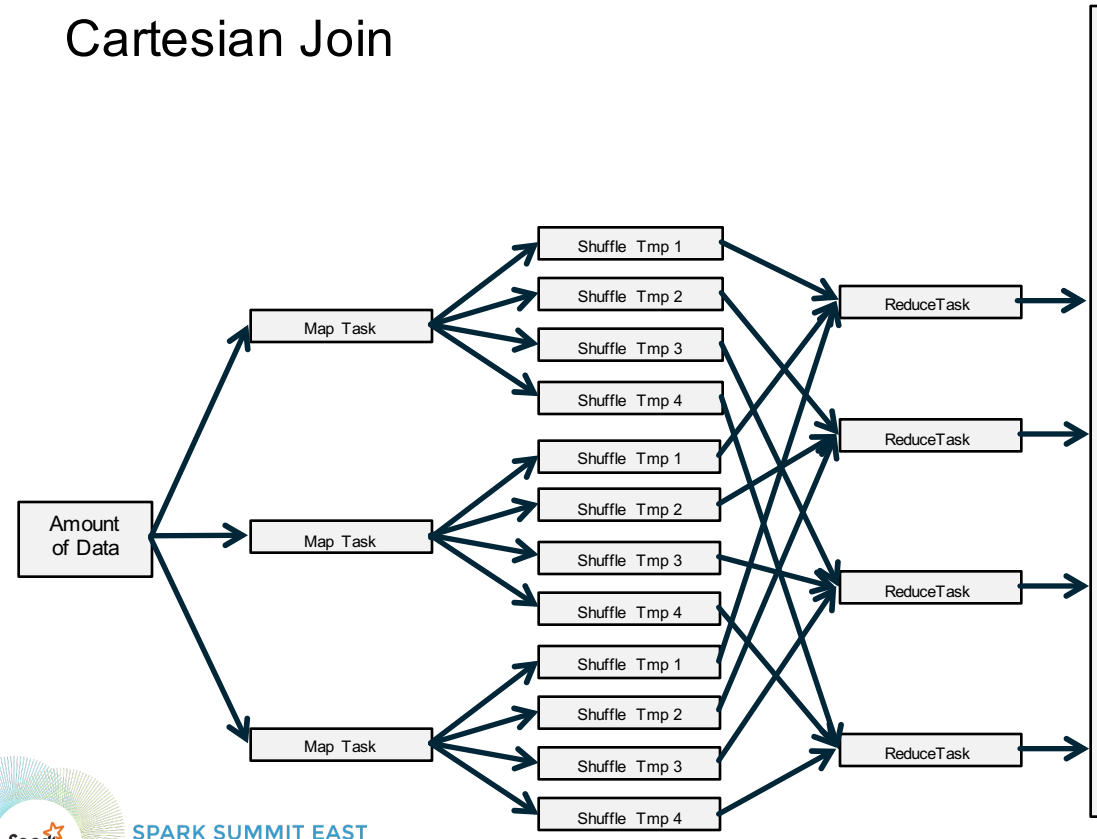
Mistake – Skew : Isolated Map Join

- Filter Out Isolated Keys and use Map Join/Aggregate on those
- And normal reduce on the rest of the data
- This can remove a large amount of data being shuffled



Managing Parallelism

Cartesian Join



Amount of Data

10x
100x
1000x
10000x
100000x
1000000x
Or more

Managing Parallelism

- To fight Cartesian Join
  - Nested Structures
  - Windowing
  - Skip Steps

Mistake # 4

Out of luck?

- Do you every run out of memory?
- Do you every have more then 20 stages?
- Is your driver doing a lot of work?

Mistake – DAG Management

- Shuffles are to be avoided
- ReduceByKey over GroupByKey
- TreeReduce over Reduce
- Use Complex Types

Mistake – DAG Management: Shuffles

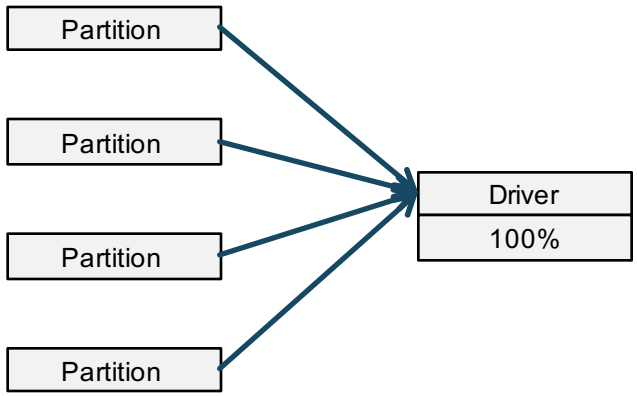
- Map Side Reducing if possible
- Think about partitioning/bucketing ahead of time
- Do as much as possible with a single Shuffle
- Only send what you have to send
- Avoid Skew and Cartesians

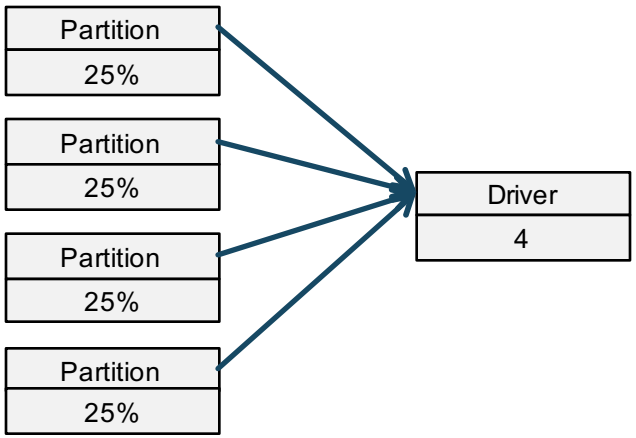
ReduceByKey over GroupByKey

- ReduceByKey can do almost anything that GroupByKey can do
  - Aggregations
  - Windowing
  - Use memory
  - But you have more control
- ReduceByKey has a fixed limit of Memory requirements
- GroupByKey is unbound and dependent of the data

TreeReduce over Reduce

- TreeReduce & Reduce returns a result to the driver
- TreeReduce does more work on the executors
- Where Reduce bring everything back to the driver





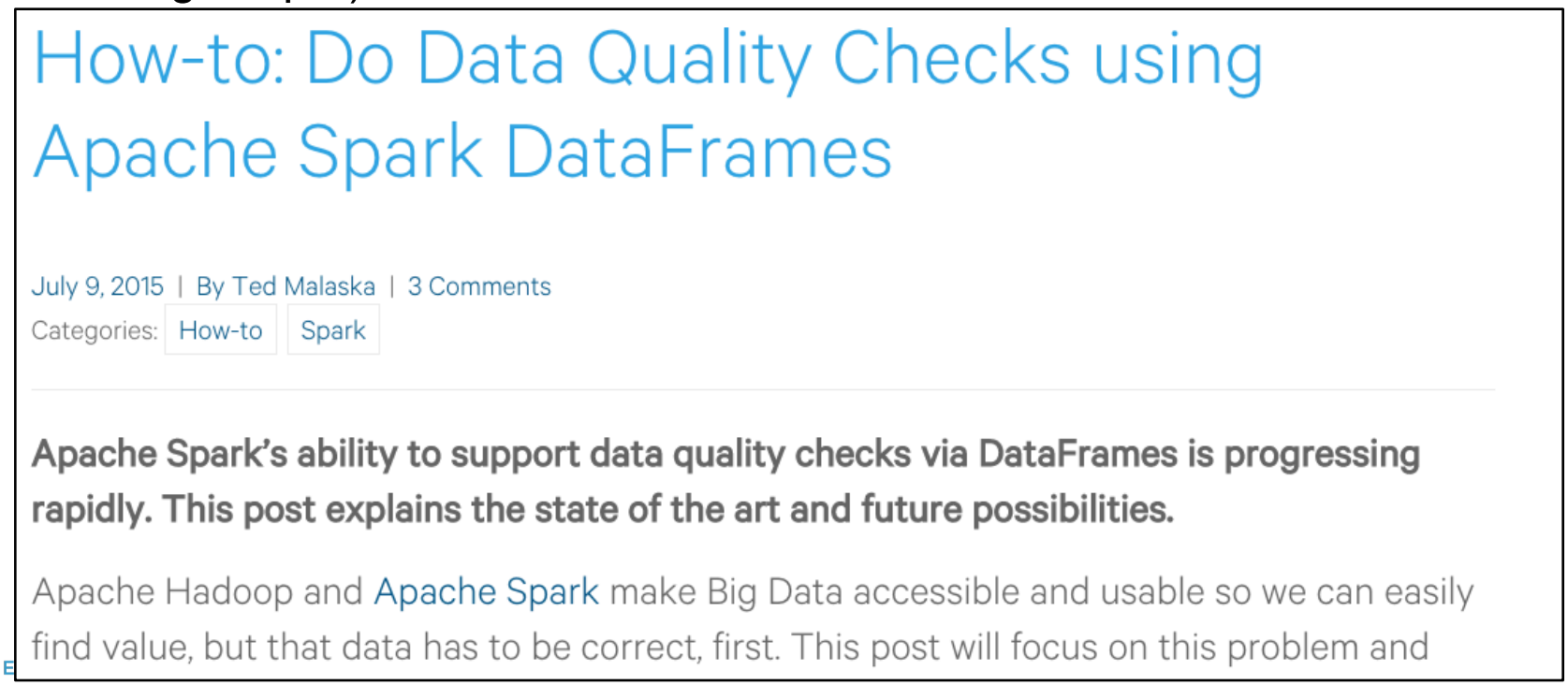
Complex Types

- Top N List
- Multiple types of Aggregations
- Windowing operations

- All in one pass

Complex Types

- Think outside of the box use objects to reduce by
- (Make something simple)



How-to: Do Data Quality Checks using Apache Spark DataFrames

July 9, 2015 | By Ted Malaska | 3 Comments

Categories: How-to Spark

Apache Spark's ability to support data quality checks via DataFrames is progressing rapidly. This post explains the state of the art and future possibilities.

Apache Hadoop and Apache Spark make Big Data accessible and usable so we can easily find value, but that data has to be correct, first. This post will focus on this problem and

Mistake # 5

Ever seen this?

```
Exception in thread "main" java.lang.NoSuchMethodError:
com.google.common.hash.HashFunction.hashInt(I)Lcom/google/common/hash/HashCode;
    at org.apache.spark.util.collection.OpenHashSet.org
$apache$spark$util$collection$OpenHashSet$$hashcode(OpenHashSet.scala:261)
    at
org.apache.spark.util.collection.OpenHashSet$mcI$sp.getPos$mcI$sp(OpenHashSet.scala:165)
    at
org.apache.spark.util.collection.OpenHashSet$mcI$sp.contains$mcI$sp(OpenHashSet.scala:102)
    at
org.apache.spark.util.SizeEstimator$$anonfun$visitArray$2.apply$mcVI$sp(SizeEstimator.scala:214)
    at scala.collection.immutable.Range.foreach$mVc$sp(Range.scala:141)
    at
org.apache.spark.util.SizeEstimator$.visitArray(SizeEstimator.scala:210)
    at…....
```

But!

- I already included guava in my app's maven dependencies?

Ah!

- My guava version doesn't match with Spark's guava version!

Shading

```
<plugin>
  <groupId>org.apache.maven.plugins</groupId>
  <artifactId>maven-shade-plugin</artifactId>
  <version>2.2</version>
...
  <relocations>
    <relocation>
    <pattern>com.google.protobuf</pattern>
    <shadedPattern>com.company.my.protobuf</shadedPattern>
  </relocation>
</relocations>
```

Summary

5 Mistakes

- Size up your executors right
- 2 GB limit on Spark shuffle blocks
- Evil thing about skew and cartesians
- Learn to manage your DAG, yo!
- Do shady stuff, don’t let classpath leaks mess you up

THANK YOU.

tiny.cloudera.com/spark-mistakes

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