Memory Management & Optimisation for Spark

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Quick Facts about Spark

- Runs on **JVM**.
- Has **Garbage Collection**.
- Uses **Tungsten** for representing objects.
- **Lazy evaluation**, and highly optimisable.
- Spark is slower on small data.

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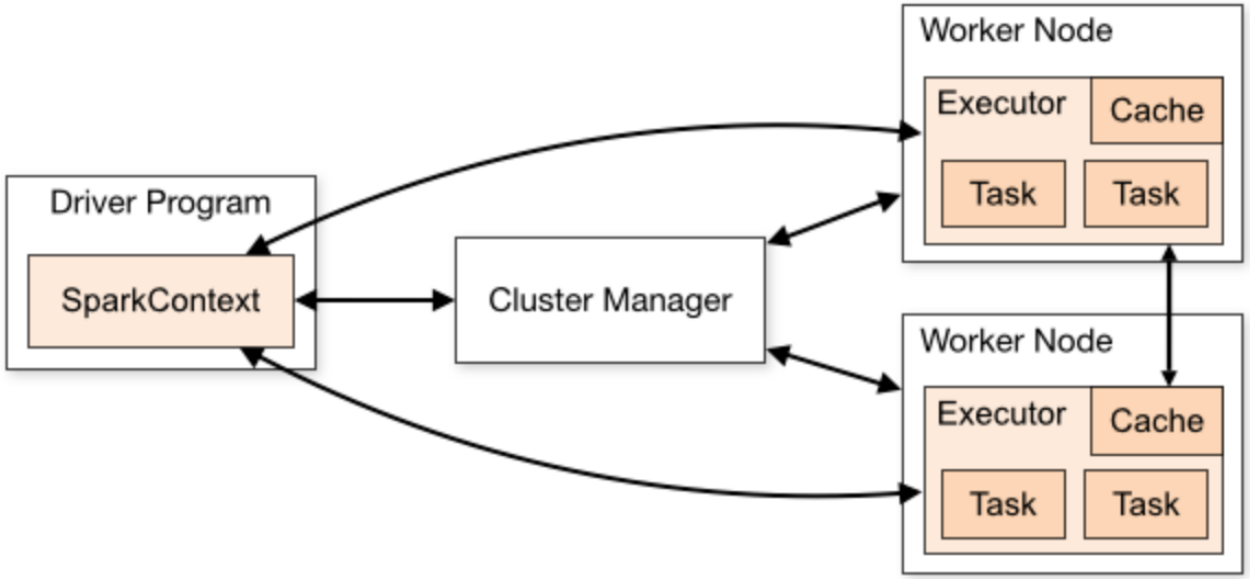
How does Spark Architecture look like?



1 Driver process per Application

Multiple worker processes

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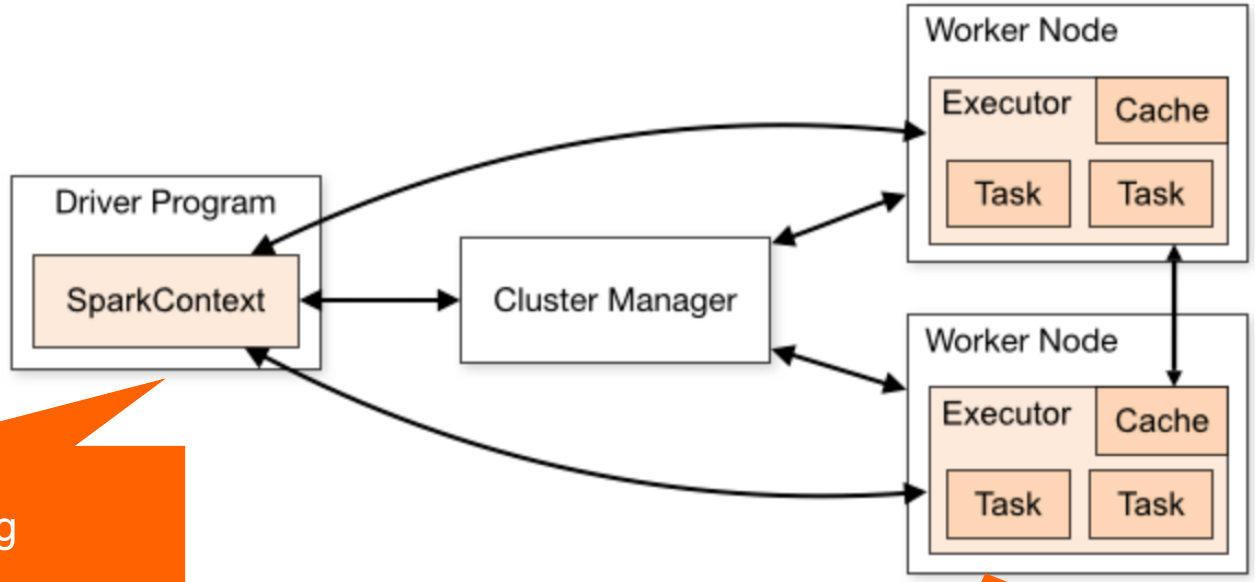
Configurable resources



spark.driver.memory = 1g
spark.driver.cores = 1
spark.driver.maxResultSize = 1g

spark.executor.memory = 1g
spark.executor.cores = 1
spark.dynamicAllocation.enabled = false

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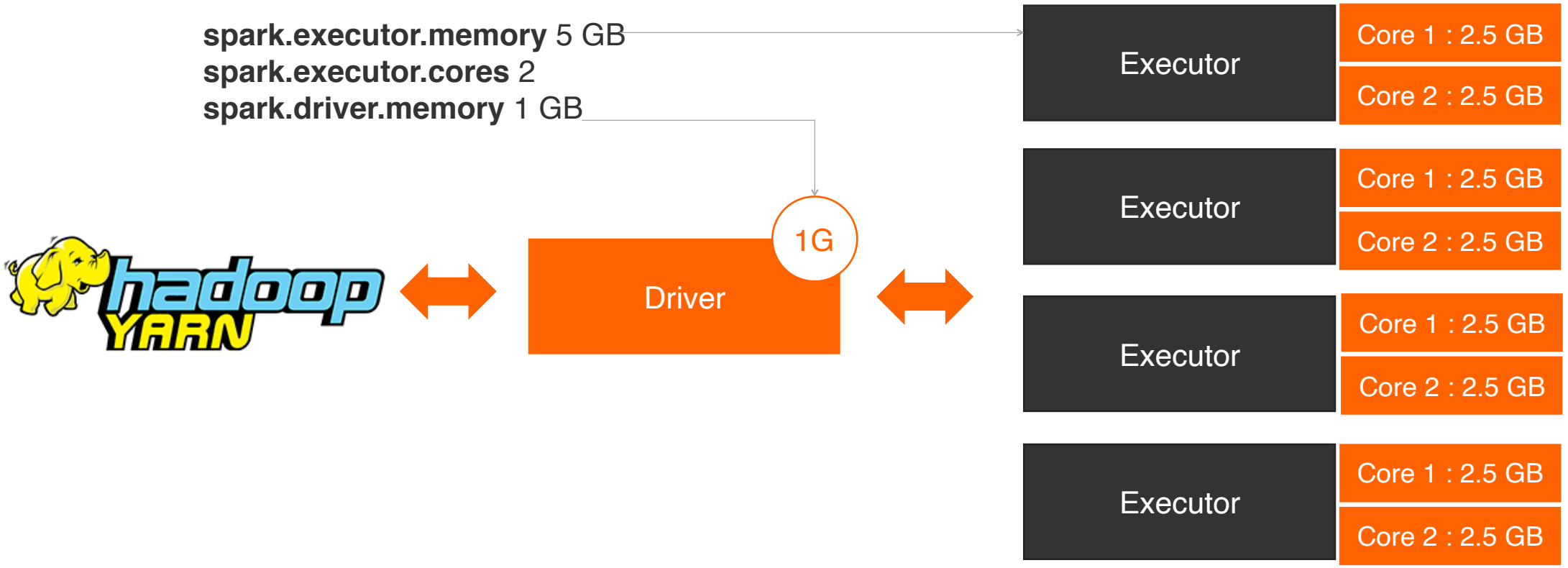
How memory is allocated on Spark



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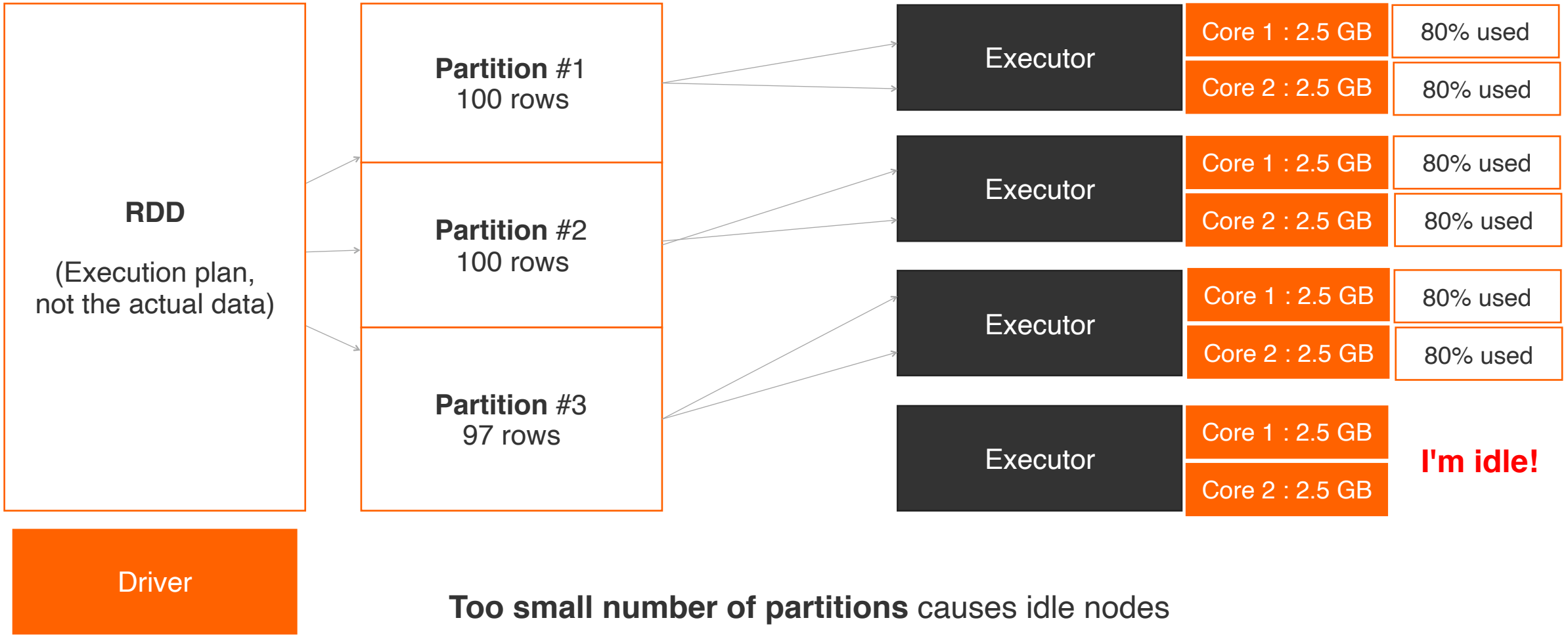
How RDD is stored on each executor



Too small number of partitions causes idle nodes

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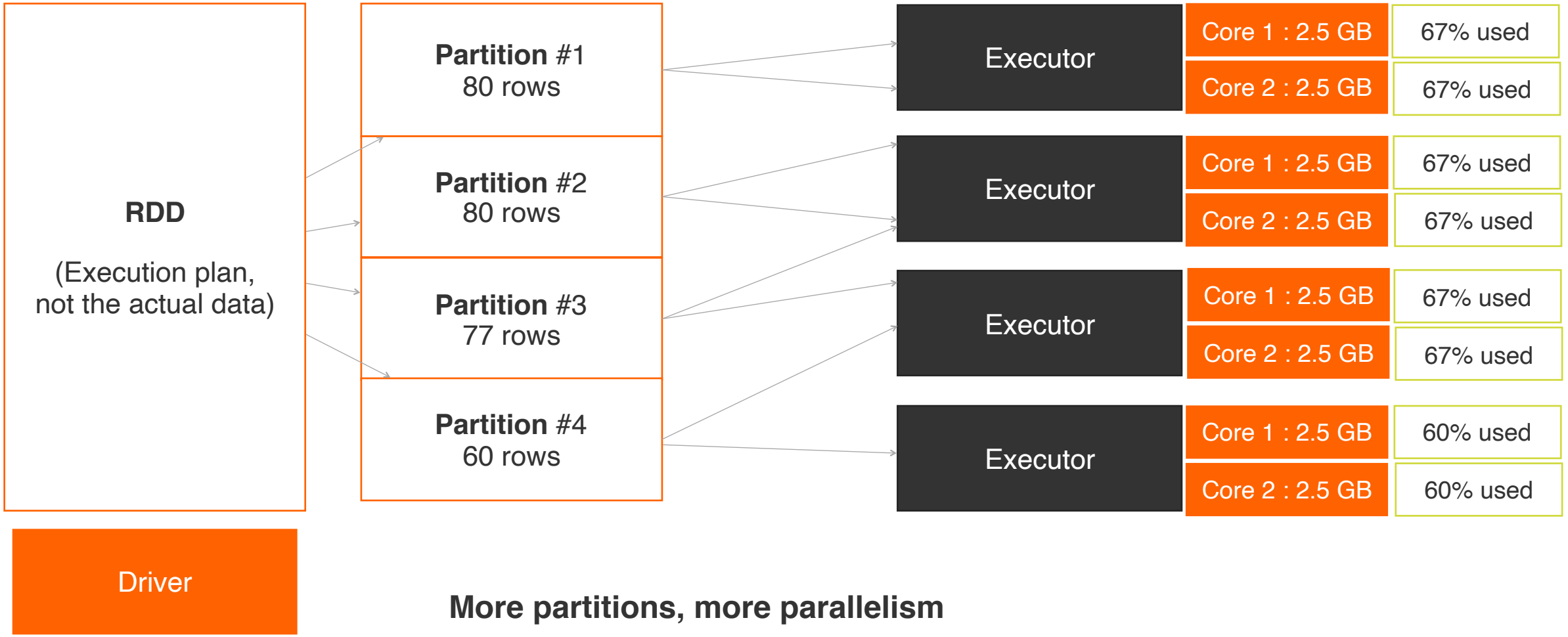
Find the right number of partitions



More partitions, more parallelism

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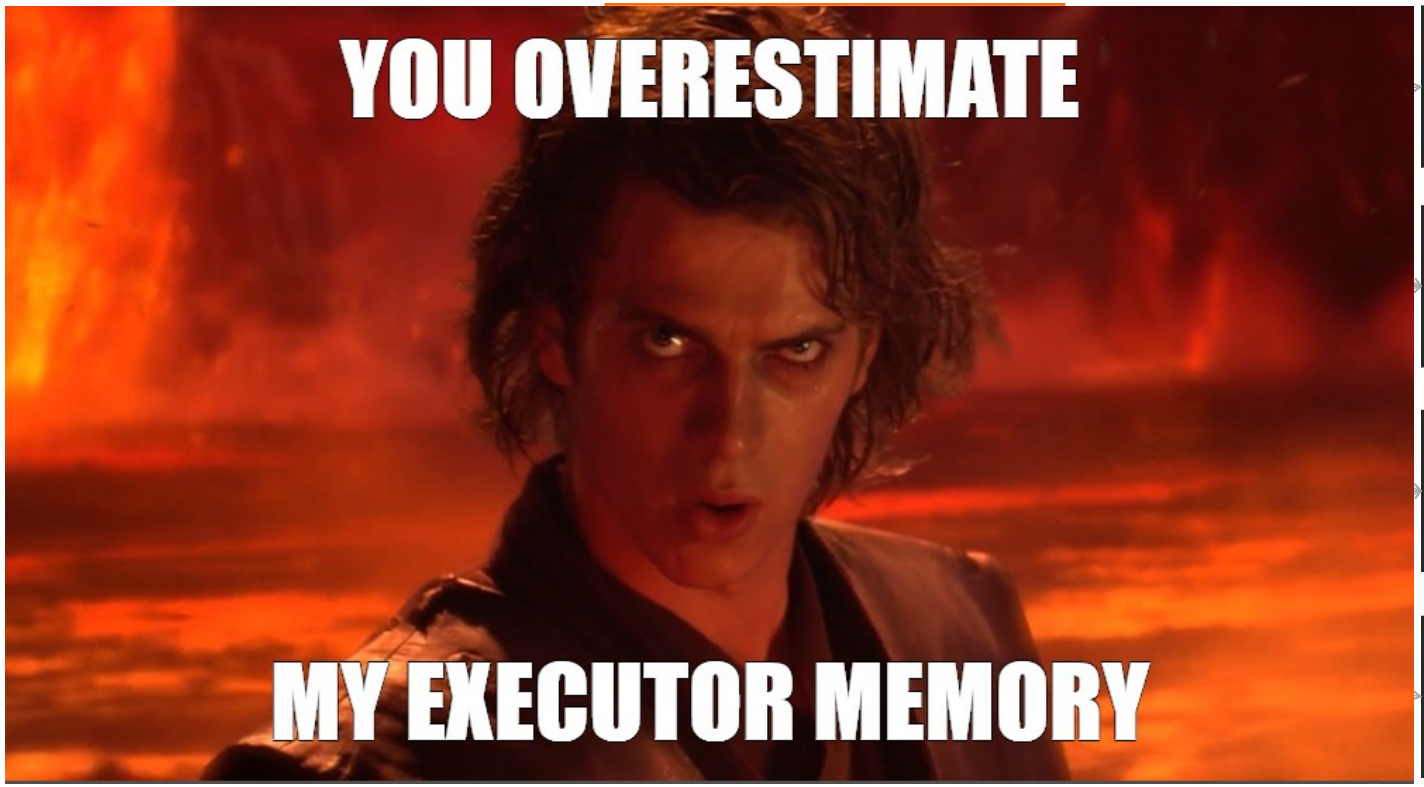
What if an executor is memory overloaded?



Executor	Core 1 : 2.5 GB	70% used
	Core 2 : 2.5 GB	80% used
Executor	Core 1 : 2.5 GB	75% used
	Core 2 : 2.5 GB	80% used
Executor	Core 1 : 2.5 GB	70% used
	Core 2 : 2.5 GB	75% used
Executor	Core 1 : 2.5 GB	150% used
	Core 2 : 2.5 GB	140% used

Overloading excessive memory on an executor can bring it down.

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Root causes of executor memory overload

1 Scenario : Skewed Join

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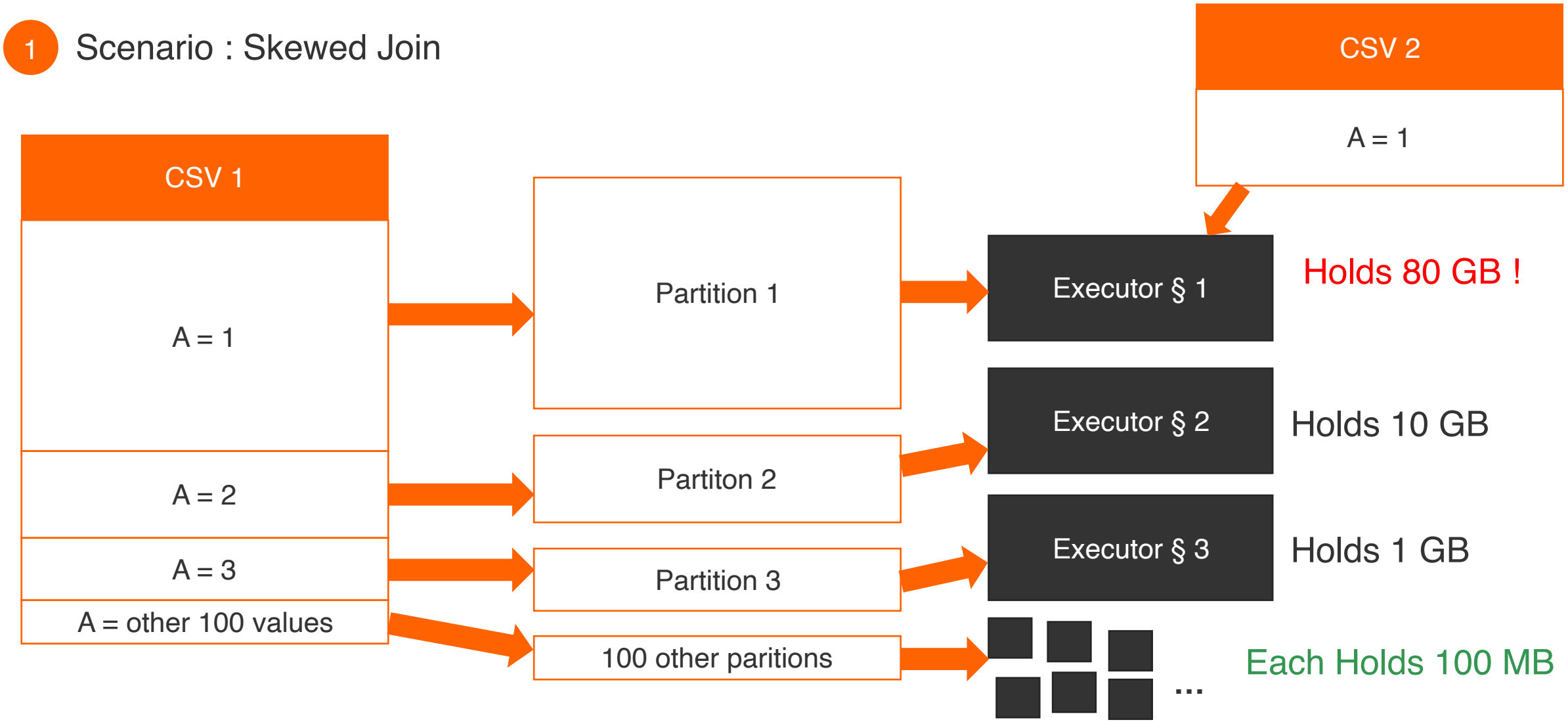

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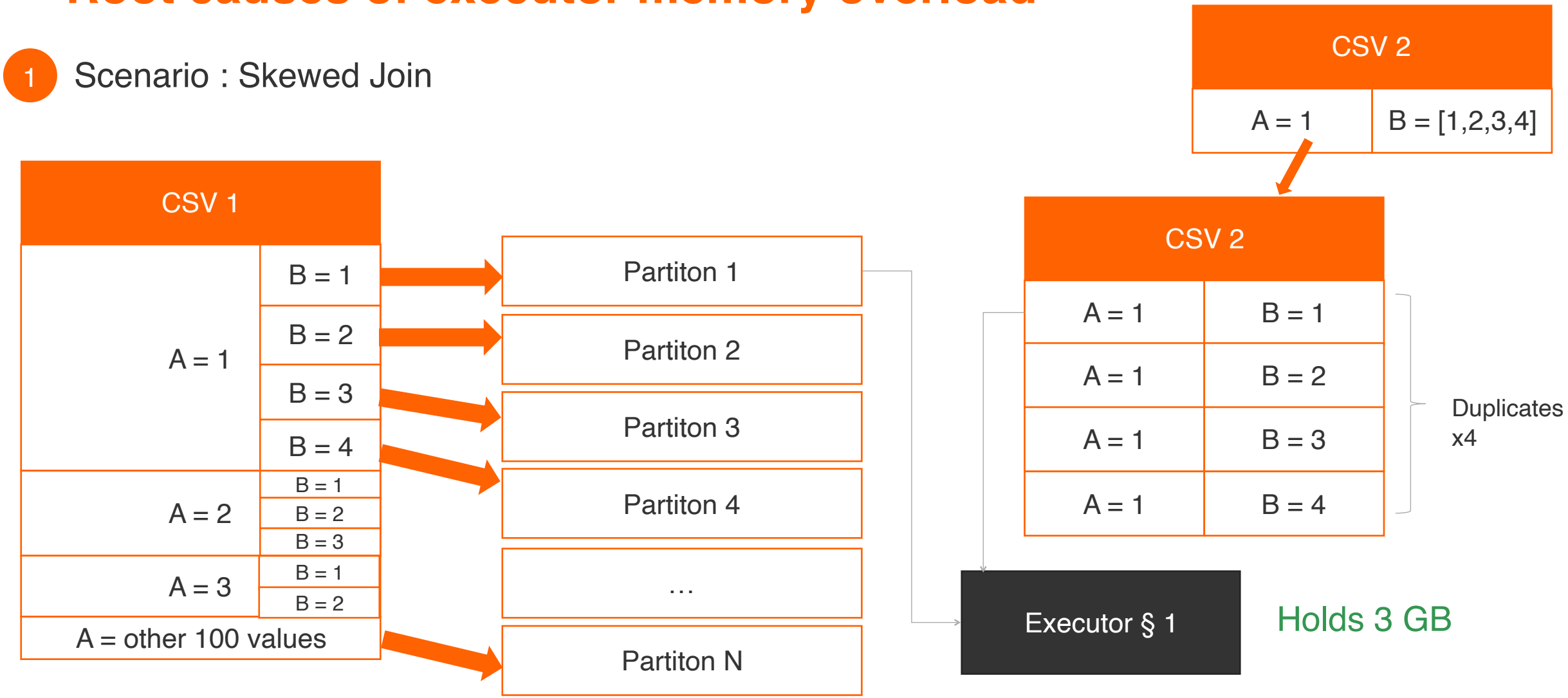
Root causes of executor memory overload

1 Scenario : Skewed Join



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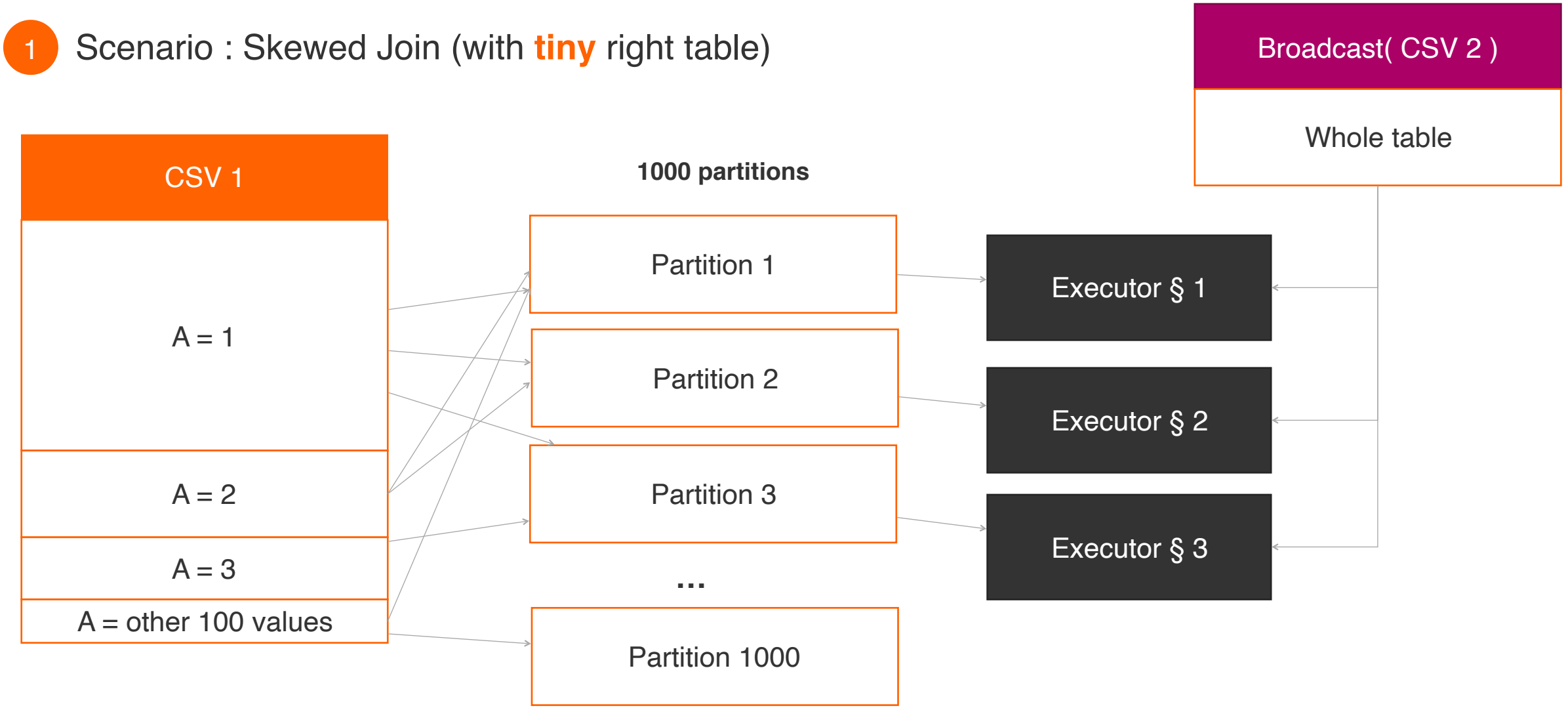
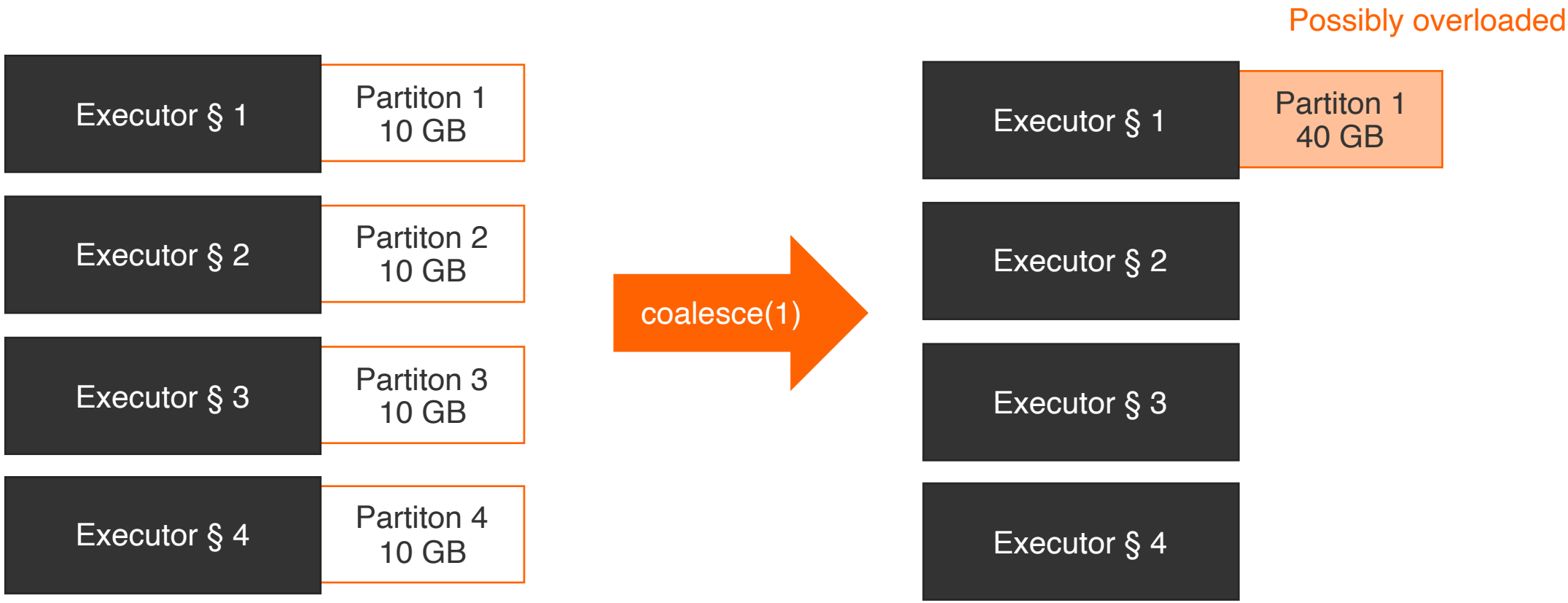
Root causes of executor memory overload

1 Scenario : Skewed Join (with **tiny** right table)



Root causes of executor memory overload

2 Scenario : Coalesce large data



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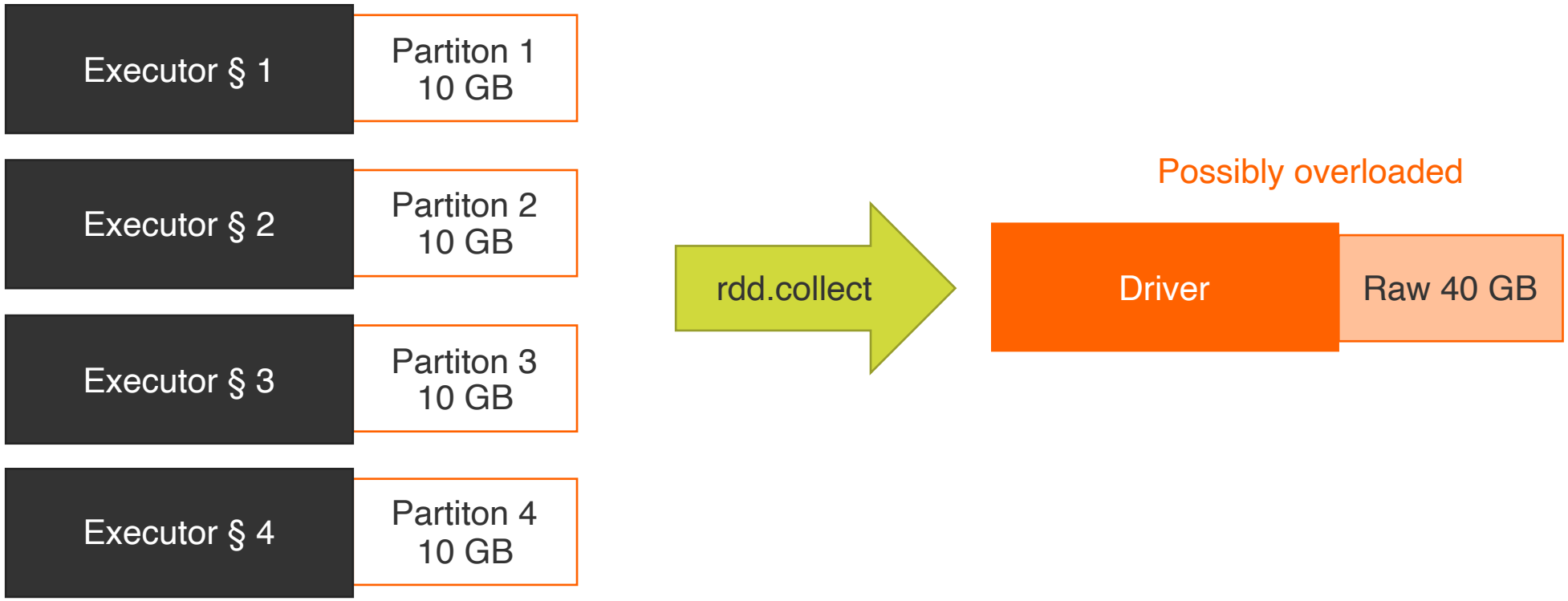
Root causes of driver memory overload

3 Scenario : Collect large data



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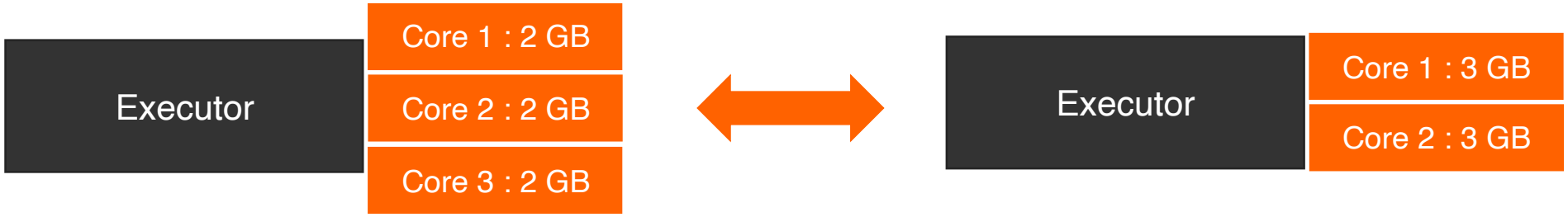
Trade-offs : cores & memory



spark.executor.memory = 6 GB
spark.executor.cores = 3

spark.executor.memory = 6 GB
spark.executor.cores = 2

More parallelsim

Less parallelsim

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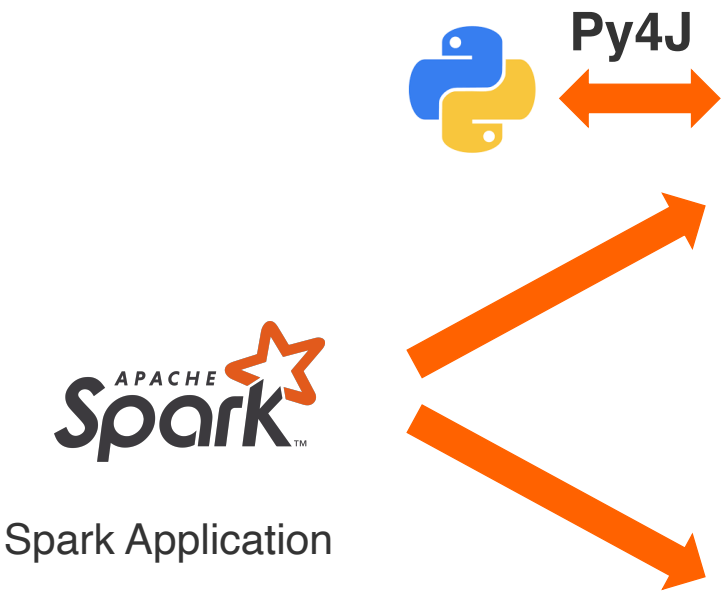
Spark RDD, Dataset API

	What's in each row	Memory usage	Serialiser	Compatibility
RDD[object]	Java Object	Larger (JVM)	Java (Kryo)	Scala, Java
DataFrame	"Row" object	Smaller (Off-JVM)	Tungsten	Scala, Java, Python, R
Dataset[Object]	Binary object	Smaller (Off-JVM)	Java & Tungsten	Scala, Java

JVM v Off-JVM ?



JVM

- Execution code
- Functions, UDF
- Classes
- Cache
- RDD

KryoSerializer

- Optimised for **Storage**
- **JVM** specific
- **Garbage Collected**

Off-Heap

- Rows as Binary
- Non-executable data
- DataFrame
- SQL

Tunsten Serializer

- Optimised for **Memory**
- **Universal**
- **Optimised for CPU**

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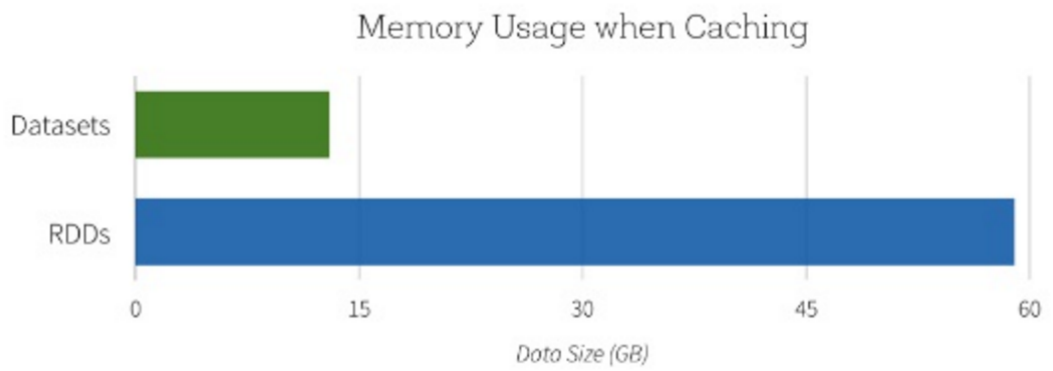
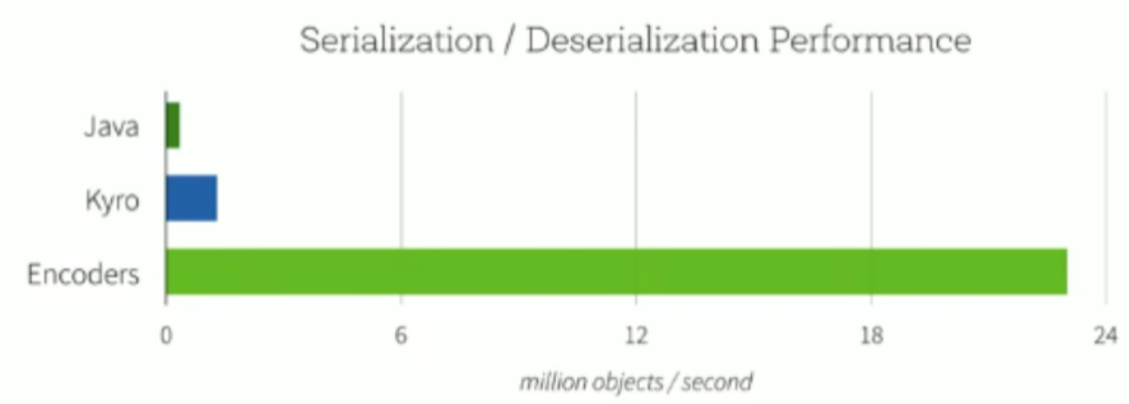
Tungstens as an object encoder

Space Efficiency





More info: https://databricks.com/blog/2016/07/14/a-tale-of-three-apache-spark-apis-rdds-dataframes-and-datasets.html
And https://github.com/spoddutur/spark-notes/blob/master/deep_dive_into_storage_formats.md

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Tungsten binary format – vs - Python

Row Schema

Key	Name	Feature
Int	String	Array[Double]

Tungsten Row (DF)

Memory block representing a row

Python Memory Map

Key	Name	Feature
24 bytes	49 bytes overhead + **X bytes** per character	64 bytes overhead + **Y bytes** per element

Memory alignment in Python, always larger than original

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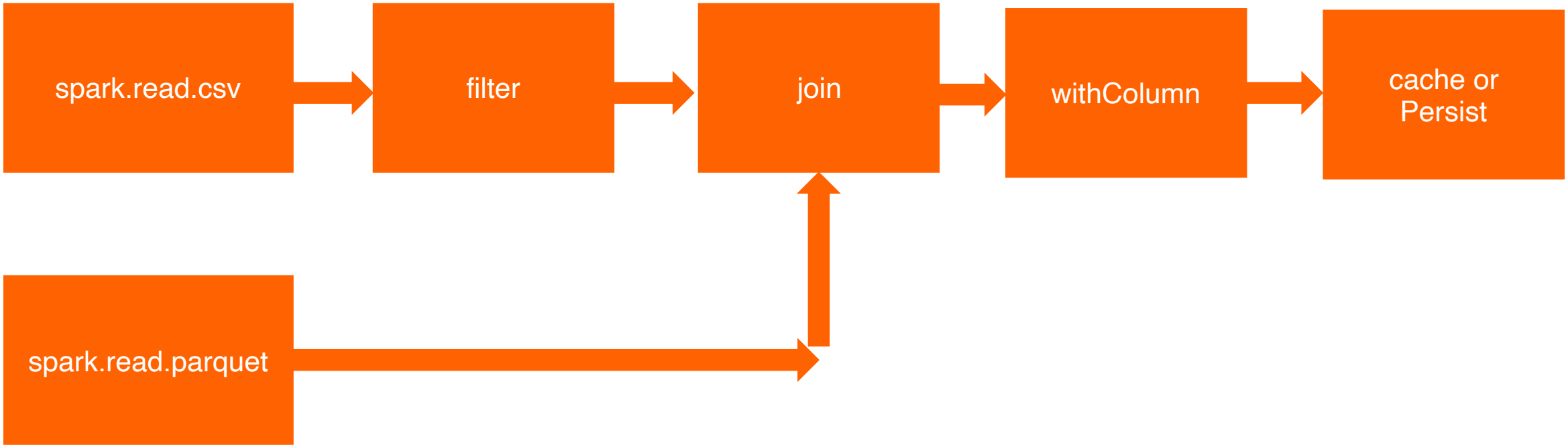
Note that Spark is lazy evaluated

Following DAG **will not be executed rightway** after declaration.



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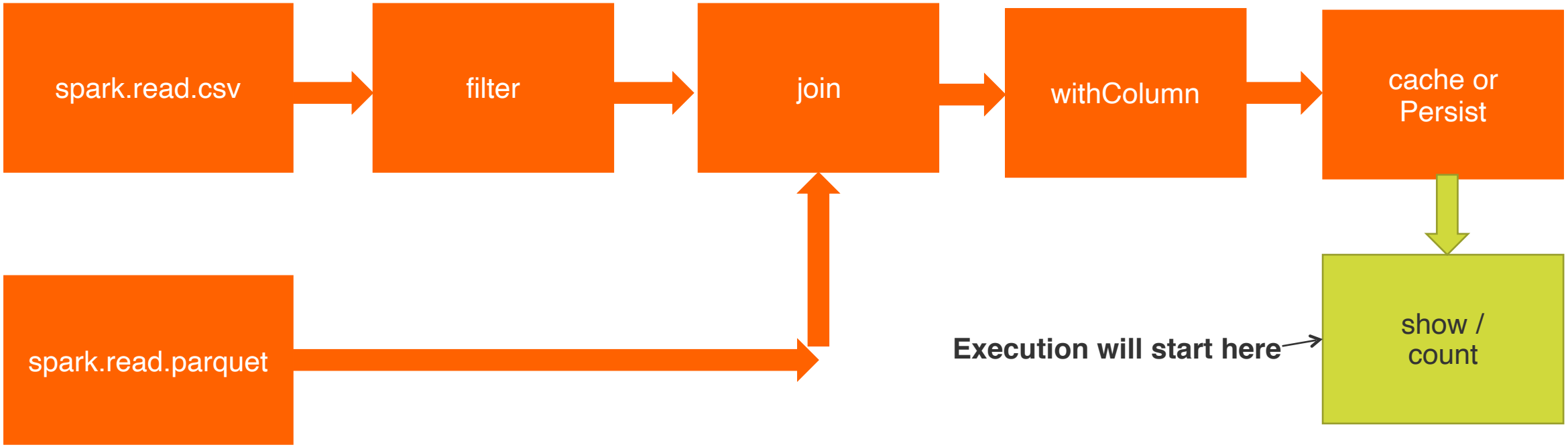
Note that Spark is lazy evaluated

Materialisation happens when the result is **needed**.



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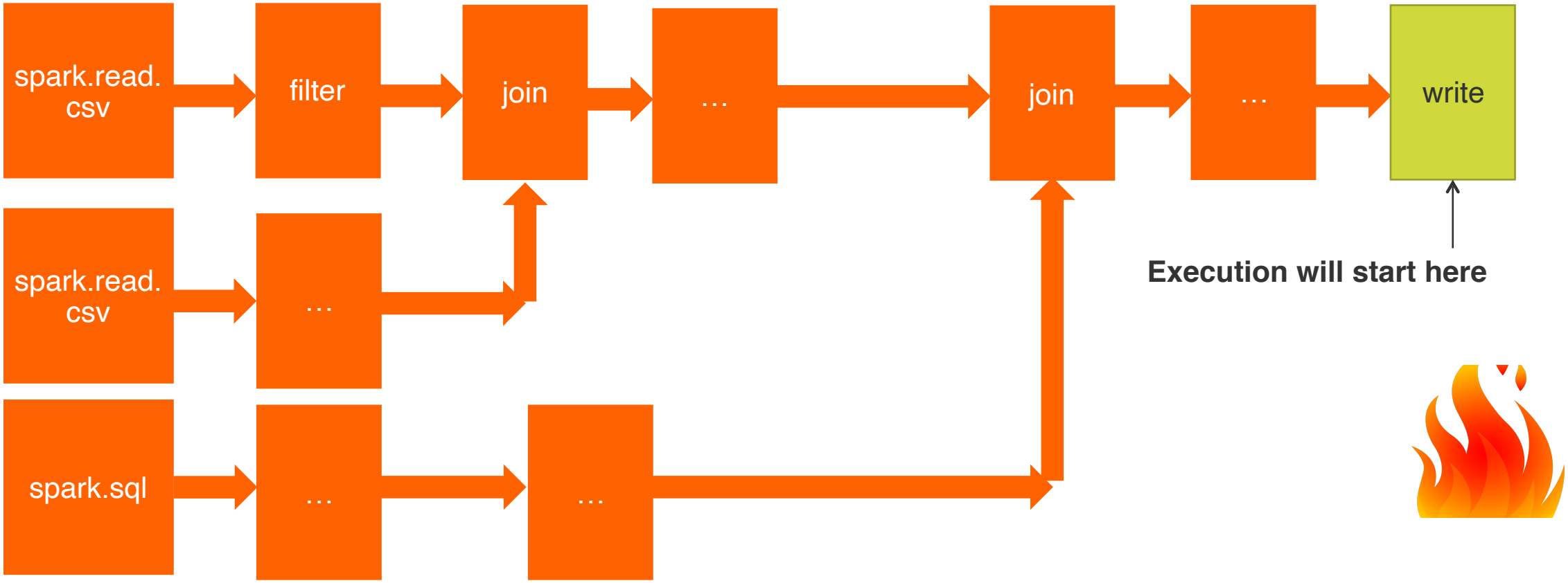
Note that Spark is lazy evaluated

WARNING: Large DAG causes high overhead and less reliablity



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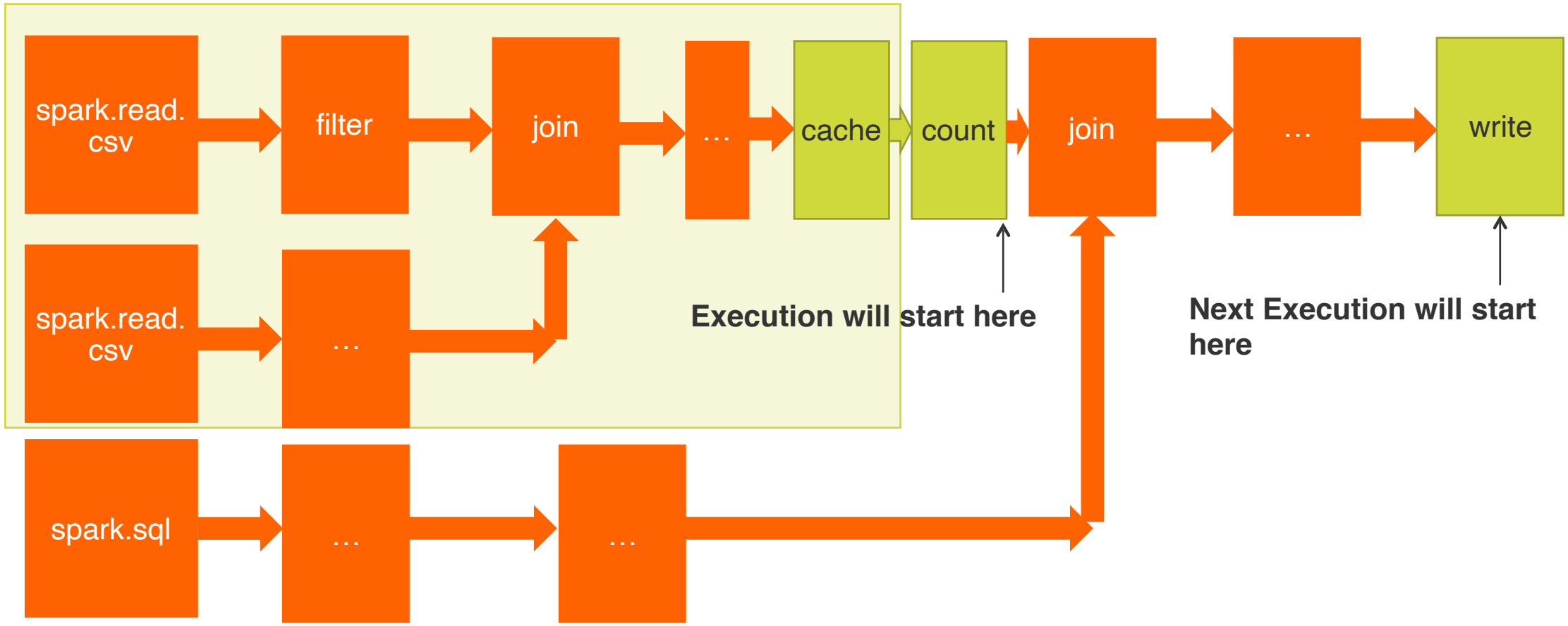
TIPS: Split DAG for more efficiency, by adding materiasliation enforcement



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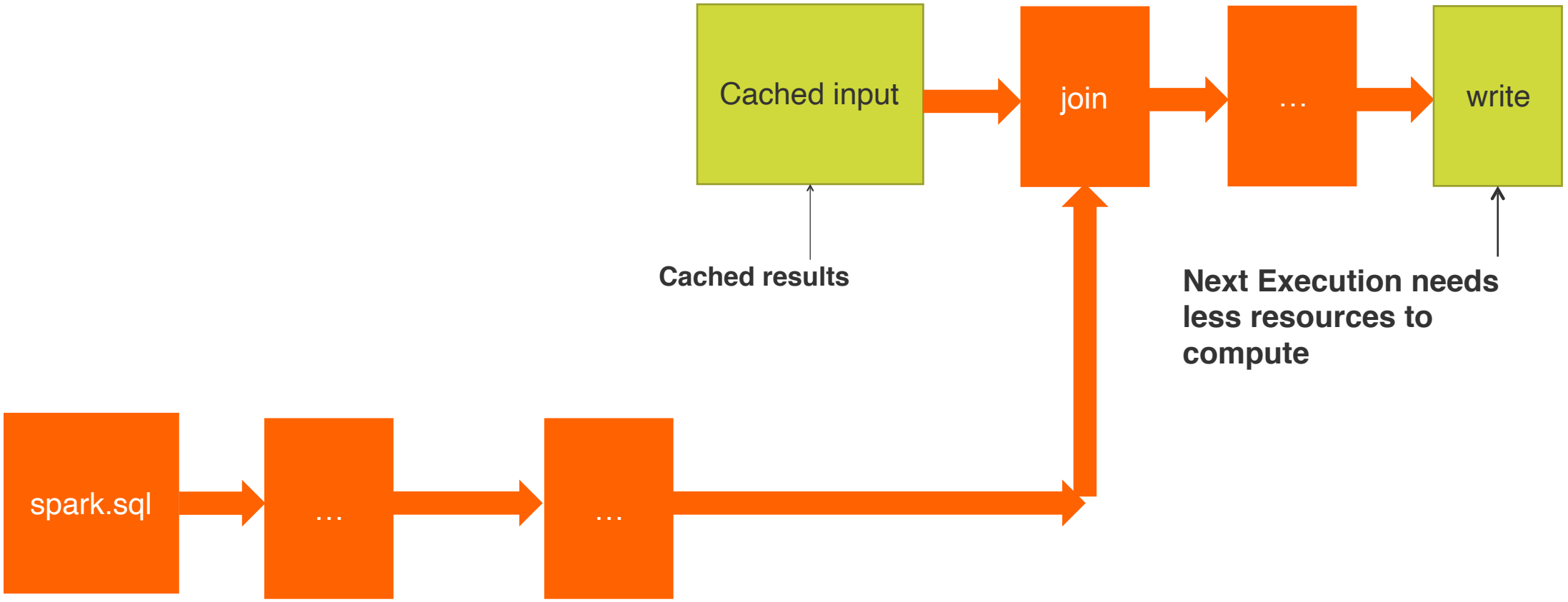

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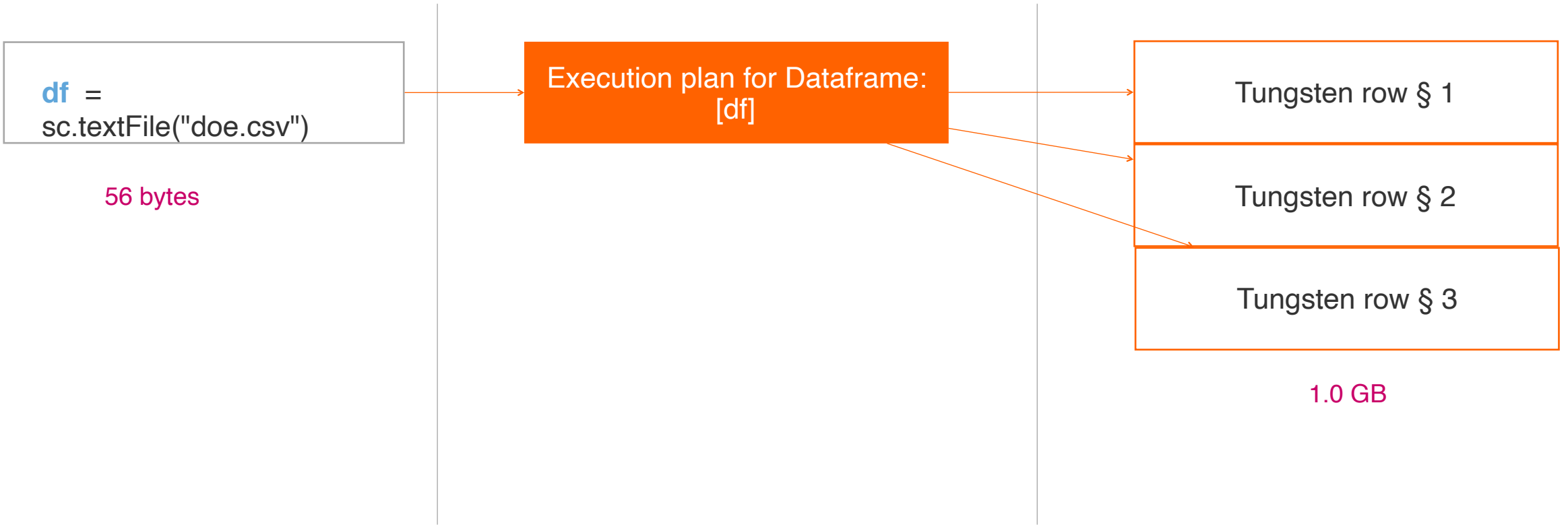
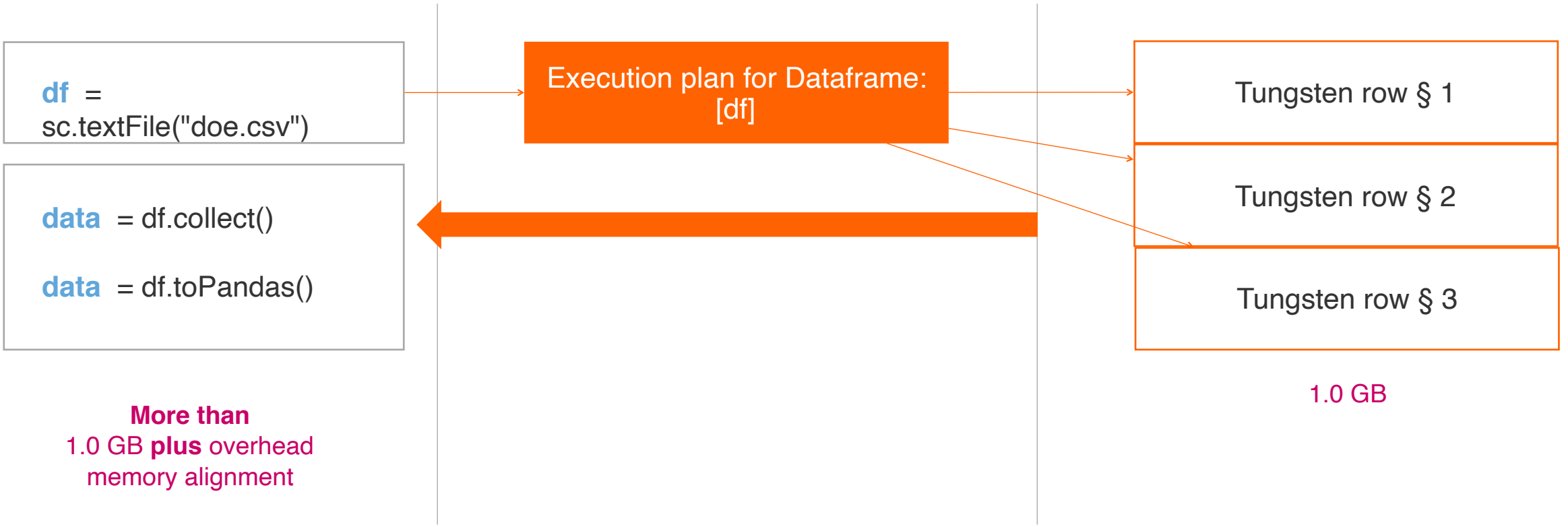
PySpark : Where the memory is stored?



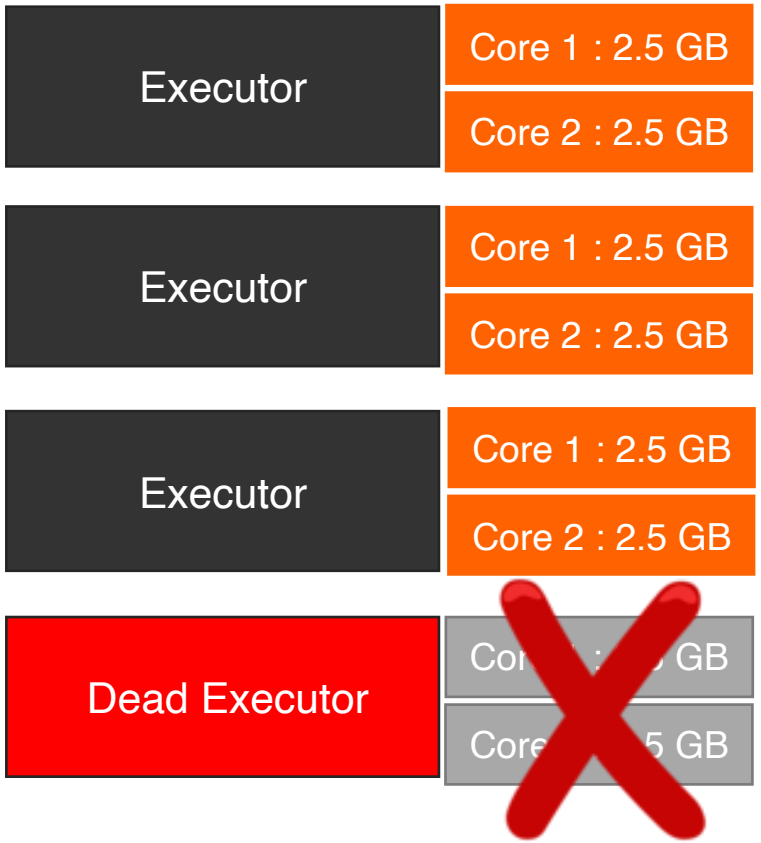
Collecting data from Spark to Python



Common Spark Failures due to memory

Case: Executor dies of Out of memory
- Unable to connect to executor machine
- Executor raising OOM
- Timeout while waiting for a task to finish

Possible cause:
- Low number of partition
- Too many cores
- Skewness of joining data (Big DF vs Tiny DF)
- Too large DAG
- Unstable cluster



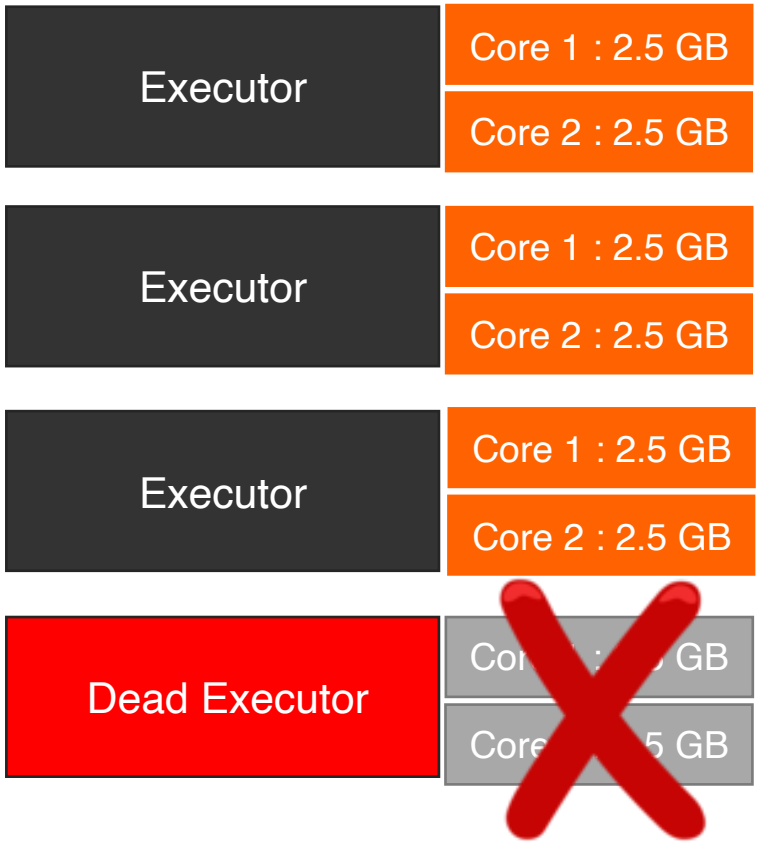
Common Spark Failures due to memory

Case: Executor dies of Out of memory

- Unable to connect to executor machine
- Executor raising OOM
- Timeout while waiting for a task to finish

Possible cause:

- Low number of partition : Increase number of partitions
- Too many cores : Decrease number of core per executor
- Skewness of joining data (Big DF vs Tiny DF) : Broadcast
- Too large DAG : Cut by forcing materialisation after cache
- Unstable cluster : Infrastructure solution



More useful resources

Spark Partitioning	https://medium.com/@adrianchang/apache-spark-partitioning-e9faab369d14
Spark Cluster overview	https://spark.apache.org/docs/latest/cluster-overview.html
Spark Configurations	https://spark.apache.org/docs/latest/configuration.html
Tungsten overview	https://jaceklaskowski.gitbooks.io/mastering-spark-sql/spark-sql-tungsten.html
RDD v DataFrame v Dataset	https://databricks.com/blog/2016/07/14/a-tale-of-three-apache-spark-apis-rdds-dataframes-and-datasets.html
RDD v DataFrame v Dataset (more advanced)	https://data-flair.training/blogs/apache-spark-rdd-vs-dataframe-vs-dataset/
KryoSerialiser Github	https://github.com/EsotericSoftware/kryo
Spark Memory Management (v.2.x)	https://databricks.com/session/deep-dive-apache-spark-memory-management

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