Optimizing Spark Job

Dano Lee

Apache Spark Optimization

- computation efficiency
- the communication between nodes.

Optimizing Spark Job

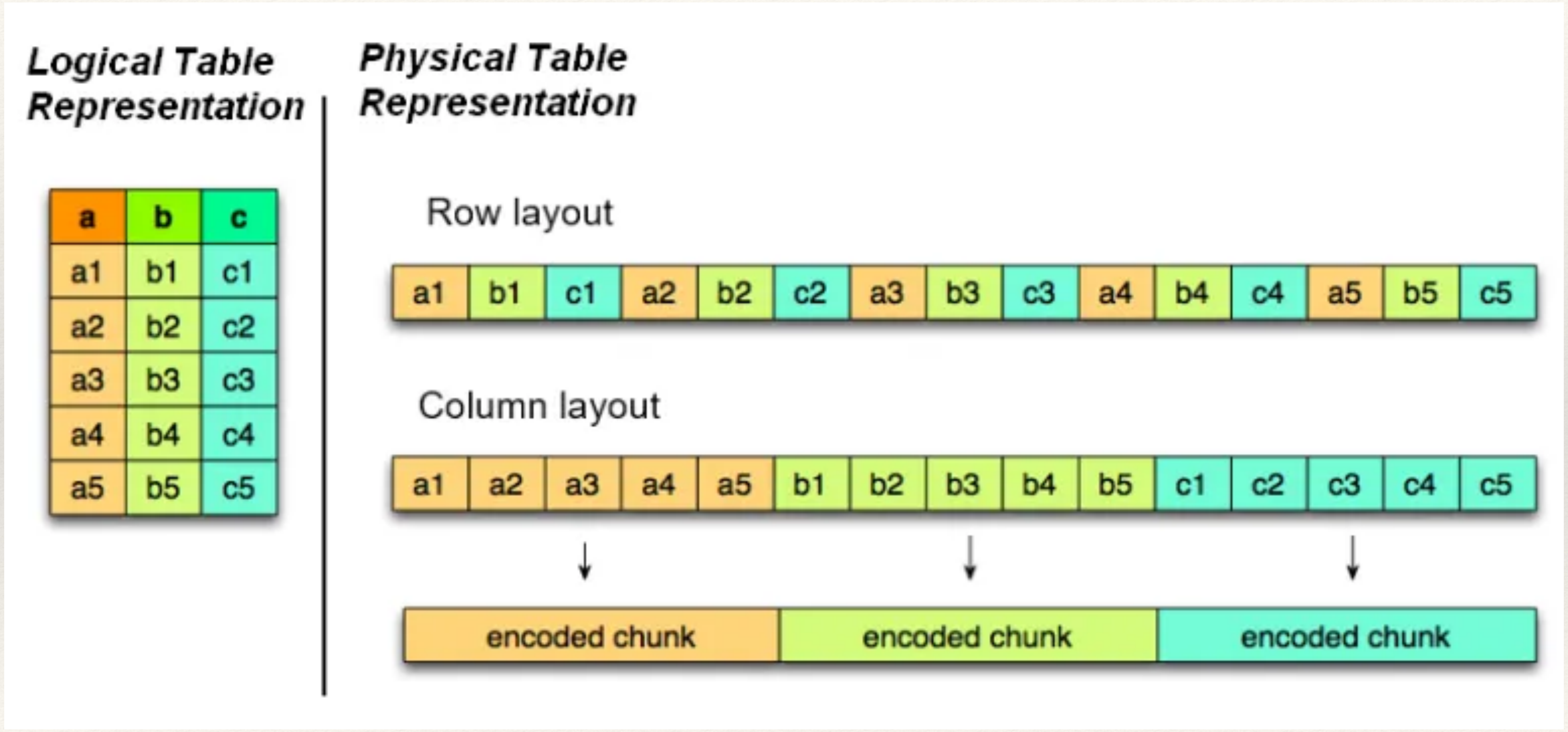
RDD over DataFrames?

- Because of their higher-level API and optimizations, DataFrames are typically easier to use and offer better performance;
- however, due to their lower-level nature, RDDs can still be useful for defining custom operations, as well as debugging complex data processing tasks.
- RDDs offer more granular control over partitioning and memory usage.
- **When dealing with raw, unstructured data, such as text streams, binary files, or custom formats**, RDDs can be more flexible, allowing for custom parsing and manipulation in the absence of a predefined structure.

Use an efficient file format and compression type

- The file format and compression type that you use can have a significant impact on the performance of shuffling.
  - Using a file format that is optimized for Spark, such as **Apache Parquet** or Apache ORC, and a compression type that is efficient for shuffling, such as Snappy or LZ4 helps to minimize shuffling and improve the performance of your Spark applications.

Row vs Column


Logical Table Representation
Physical Table Representation
a
b
c
a1
b1
c1
a2
b2
c2
a3
b3
c3
a4
b4
c4
a5
b5
c5
Row layout
a1 b1 c1 a2 b2 c2 a3 b3 c3 a4 b4 c4 a5 b5 c5
Column layout
a1 a2 a3 a4 a5 b1 b2 b3 b4 b5 c1 c2 c3 c4 c5
encoded chunk
encoded chunk
encoded chunk

source

Advantages of Columnar Storage Over Row-Based Storage:

- **Compression Efficiency**: Columnar storage allows for better compression techniques. Since column values are often of the same type, compression algorithms can be tailored to that type, resulting in higher compression ratios. This reduces storage requirements and speeds up data transfers.
- **Column Pruning**: When executing queries, columnar databases can skip irrelevant columns, reducing I/O and improving query performance. In row-based storage, entire rows must be read, even if only a few columns are needed.
- **Aggregation Performance**: Columnar storage is highly efficient for aggregate queries, as aggregations involve operations on single columns. This leads to faster query performance for analytics tasks.
- **Predicate Pushdown**: Columnar databases can apply filters early in the query execution process by analyzing metadata, minimizing the amount of data read from storage. This feature significantly speeds up query processing.
- **Analytics and Data Warehousing**: Columnar storage is well-suited for analytical workloads, reporting, and data warehousing. It allows for rapid analysis and reporting on large datasets.
- **Schema Evolution**: Columnar storage formats like Parquet support schema evolution, enabling the addition of new columns or changes to existing columns without disrupting existing data.

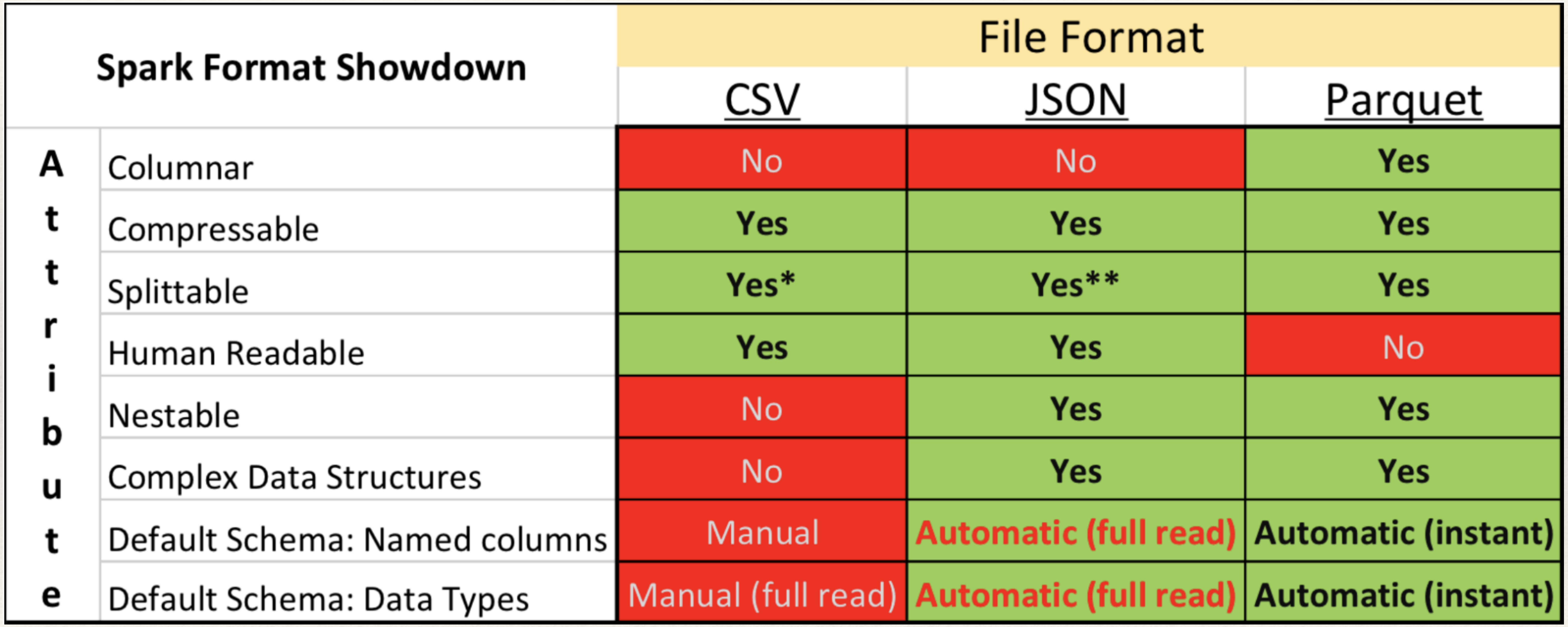
Relational DB vs Dataware House

	Amazon RDS	Amazon Redshift
Purpose	OLTP (Transactional)	OLAP (Analytics)
Data Structure	Row-based storage	Columnar storage
Query Performance	Fast for small transactions	Optimized for large-scale analytics
Scaling	Vertical + Read Replicas	Horizontal (MPP architecture)
Use Case	Applications, websites, CRM, ERP	Business intelligence, data analysis, reporting
Database Engines	MySQL, PostgreSQL, Oracle, SQL Server, Aurora	Redshift (based on PostgreSQL)
Optimized For	Real-time transactions	Batch processing and analytics
Data Size	Gigabytes to terabytes	Terabytes to petabytes

Apache Parquet vs Other Formats

- Parquet is optimized for the Write Once Read Many (WORM) paradigm. It's slow to write, but incredibly fast to read, **especially when you're only accessing a subset of the total columns**.
- For use cases requiring operating on **entire rows of data**, a format like CSV, JSON or even AVRO should be used.

Apache Parquet vs Other Formats



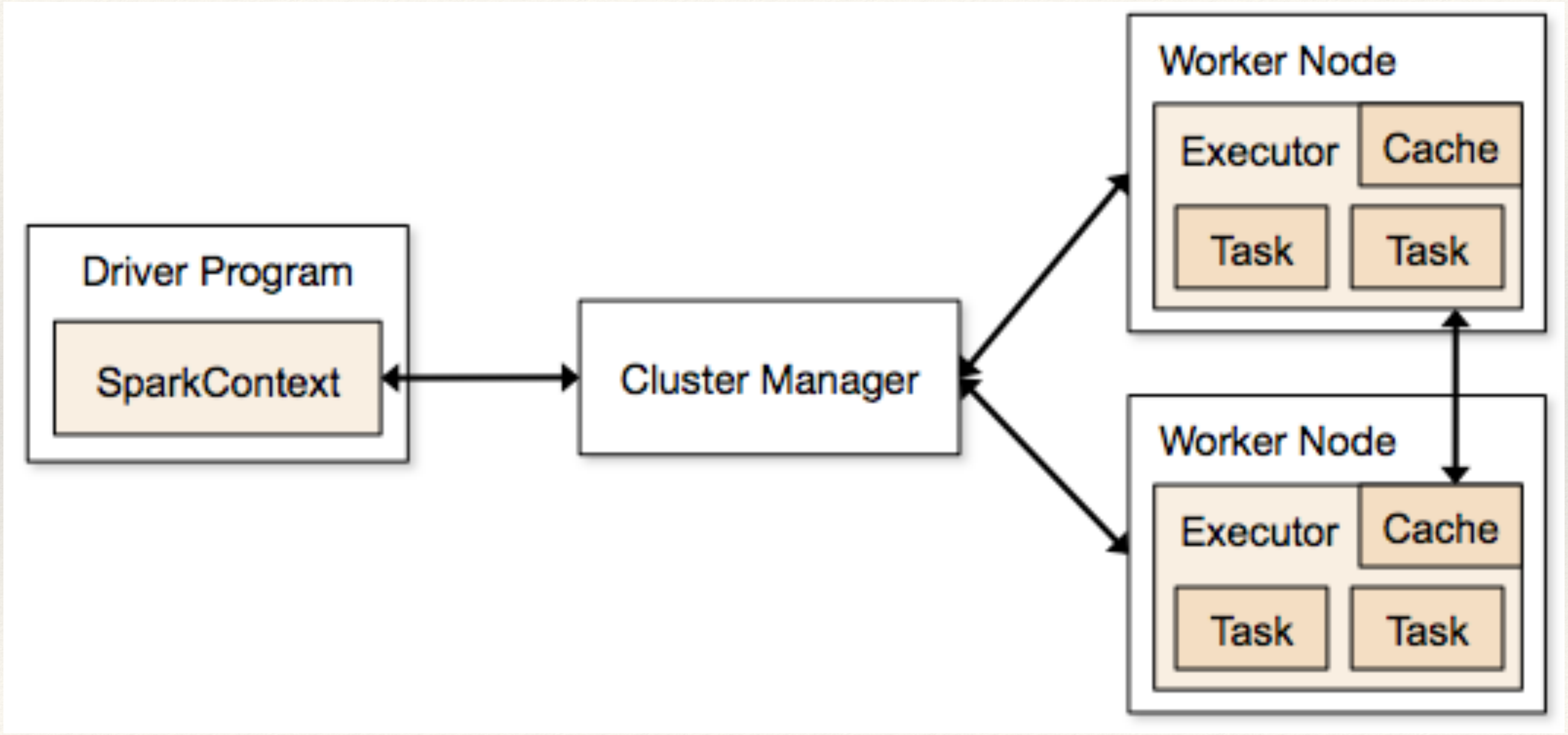
Spark Format Showdown		File Format		
		CSV	JSON	Parquet
Attribute	Columnar	No	No	Yes
	Compressable	Yes	Yes	Yes
	Splittable	Yes*	Yes**	Yes
	Human Readable	Yes	Yes	No
	Nestable	No	Yes	Yes
	Complex Data Structures	No	Yes	Yes
	Default Schema: Named columns	Manual	Automatic (full read)	Automatic (instant)
	Default Schema: Data Types	Manual (full read)	Automatic (full read)	Automatic (instant)

source

Apache Spark and JVM

- Spark is predominantly in Scala and runs on **Java virtual machines** (JVMs)

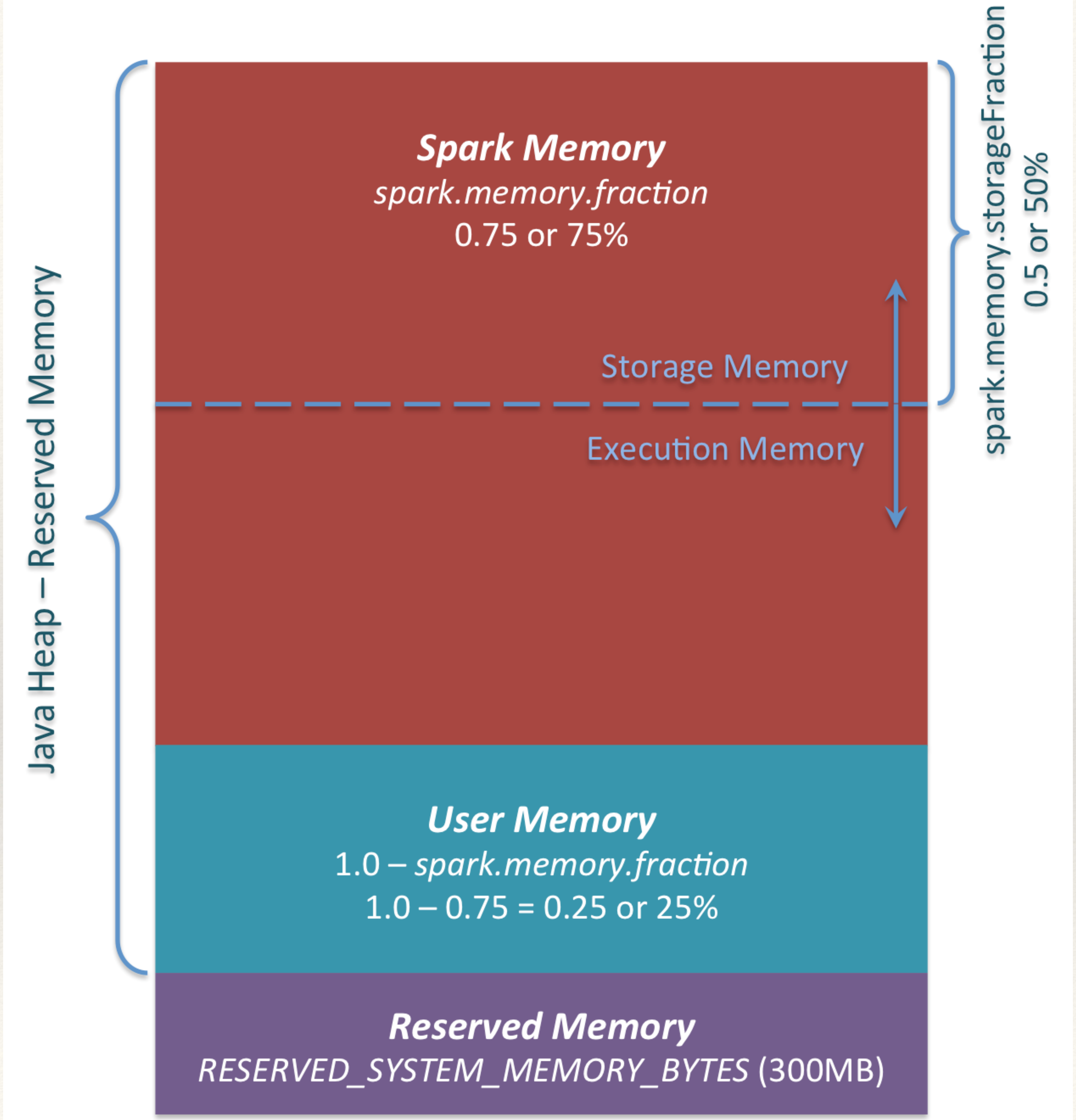
Spark is not really in-memory tool, it just utilizes the memory for its LRU cache



source: apache.org

LRU Cache

- **Least Recently Used Cache**
  - Picks the data that is least recently used and removes it in order to make space for the new data.
  - The priority of the data in the cache changes according to the need of that data


Spark Memory
spark.memory.fraction
0.75 or 75%
Storage Memory
Execution Memory
spark.memory.storageFraction
0.5 or 50%
Java Heap – Reserved Memory
User Memory
1.0 – spark.memory.fraction
1.0 – 0.75 = 0.25 or 25%
Reserved Memory
RESERVED_SYSTEM_MEMORY_BYTES (300MB)

source

On Heap Memory

- **Storage Memory**: mainly used to store Spark cache data, such as RDD cache, Unroll data, and so on.
- **Execution Memory**: mainly used to store temporary data in the calculation process of Shuffle, Join, Sort, Aggregation, etc.
- **User Memory**: mainly used to store the data needed for RDD conversion operations, such as the information for RDD dependency.
- **Reserved Memory**: reserved for the system and is used to store Spark's internal object

Yarn.nodemanager.resource.memory-mb
Executor container
spark.executor.memory (heap space)
spark.yarn.executor.MemoryOverhead
Max(384MB, 10% of spark.executor.memory)
Reserved memory
(RESERVED_SYSTEM_MEMORY_BYTES)
spark.memory.fraction
spark.memory.storageFraction
User memory
• User data structures
300MB
Default: 0.6
Default: 0.5
1 – spark.memory.fraction

source

If your executor memory is 5 GB,

- spark.executor.memory = 5 GB
- memory overhead = max(10% of spark.executor.memory, 384 MB)
  - max(5 GB * 1024 MB * 0.1, 384 MB) = max(512 MB, 384 MB) = 512 MB.
- heap space = 5 GB - 512 MB = 4608 MB
  - **reserved memory = 300 MB**
  - heap space - reserved memory = 4308 MB
  - **spark.memory.fraction = 0.6 (default)**
    - 4308 MB * 0.6 = 2585 MB
  - **spark.memory.storageFaction = 0.5 (default)**
    - 2585 MB * 0.5 = 1293 MB
  - **user memory** = (1- spark.memory.fraction) * 4308 MB = 1723 MB

Use SparkSQL

- Use SparkSQL to express your queries more effectively if you need to filter, group, or aggregate data. Most of the time, SparkSQL can reduce shuffling and improve the execution of these queries.
- Spark SQL provides support for both reading and writing Parquet files that automatically preserves the schema of the original data.

Shuffle in Spark

- **In order that spark ensures that all the records with the same key are on the same node**, Spark needs to shuffle the data if performing operations like groupBy and joins on a large dataset.
    - This makes it possible to process all the records at once and combine the results.
- The shuffle operation must be finished before the next stage of processing can start, which can also delay the processing of the data.

Data shuffling is a performance killer

- costly process as it leads to network data transfer by data travel between nodes, High disk I/O and Rearranging files operations.
- The performance of Spark applications can then be enhanced by being aware of these elements and avoiding shuffling whenever possible.

Causes of Shuffle

- **Data skew**
  - Spark shuffling may take place when some keys in a dataset are significantly more heavily populated with data than others. Data skew is the term used to describe this.
  - Operations like groupByKey, reduceByKey or same sort of joins which call for the grouping or aggregation of data by key, can also cause data shuffling. But not only, the shuffling can be caused by different other factors like :
- **Partitioning**:
  - Spark divides data among nodes through a procedure known as partitioning. The possibility of shuffling exists if the data is not distributed among partitions equally.
- **Spark operations**:
  - Grouping, aggregating the data by key or when joining two datasets, some operations, such as groupByKey and reduceByKey, will cause shuffling.
- **Caching** :
  - Shuffling may occur if a dataset is cached in memory and the amount of data in the cache exceeds the amount of memory on a single node.
- **Data locality**:
  - Spark tries to minimize shuffling by putting data on the same node as the computation that will be run on it. It must be moved to the node where the computation is being done if the data is not already stored there.

Transformation Optimization (1)

- Using efficient transformations and avoiding unnecessary shuffles can improve performance.
    - Use the **sortWithinPartitions** transformation: If you need to sort the data within each partition, you can **use the sortWithinPartitions transformation instead of sort**. This will minimize shuffling by sorting the data within each partition rather than across all the partitions.
    - Use the **repartitionByRange** transformation: If you need to sort the data and you are using a range-based partitioner, such as the RangePartitioner, you can use the **repartitionByRange transformation instead of sort**. This will minimize shuffling by sorting the data within each partition and ensuring that data with the same key is placed in the same partition.

Transformation Optimization (2)

- Using efficient transformations and avoiding unnecessary shuffles can improve performance.
    - Use the **window** function: If you need to **perform windowed aggregations**, using window functions can be helpful to specify the window and the aggregation function. The window function does not trigger shuffling, as it operates on the data within each partition.
    - Use **filtering** and **aggregation** instead of groupBy: If you only need to filter the data or perform simple aggregations, you can use
the filter and agg transformations instead of groupBy. These transformations do not trigger shuffling.

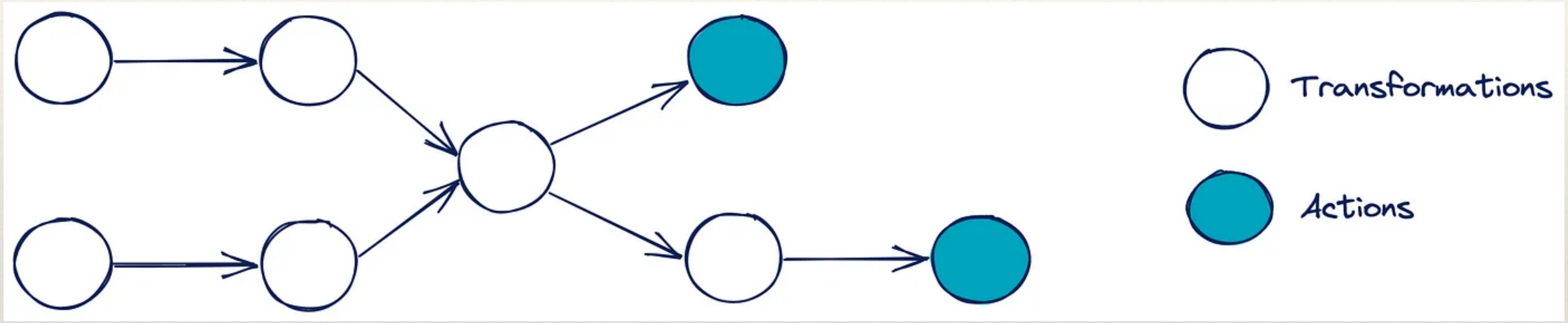
Caching in Spark

```
df.cache()
```

Caching in Spark

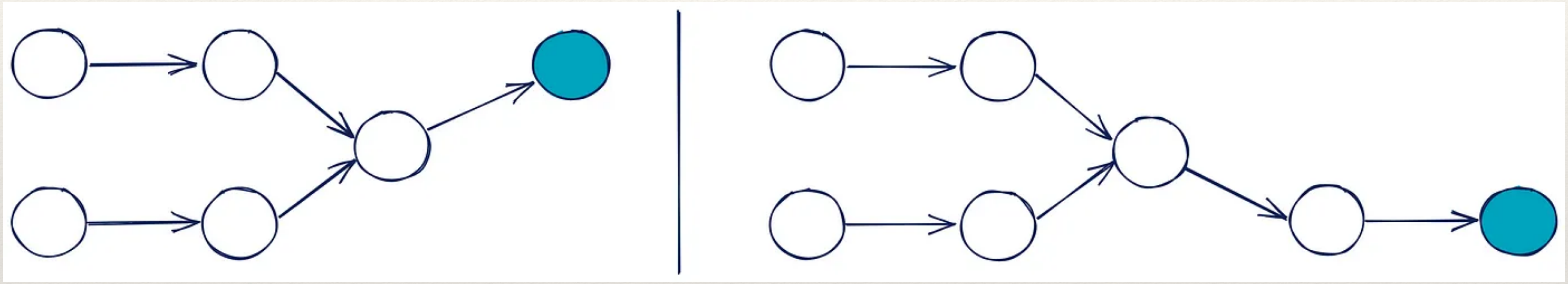
- It is important to keep in mind that caching requires careful planning, because it utilizes the memory resources of Spark’s worker nodes, which perform such tasks as executing computations and storing data.
- If the data set is significantly larger than the available memory, or you’re caching RDDs or DataFrames without reusing them in subsequent steps, the potential overflow and other memory management issues could introduce bottlenecks in performance.

Caching in Spark



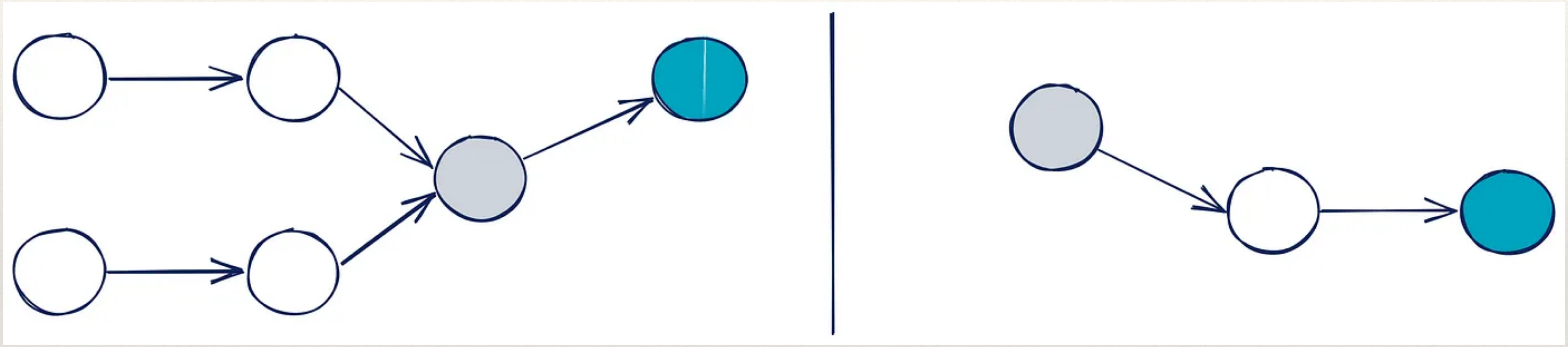
source

Caching in Spark



source

Caching in Spark



source

Persist in Spark

- Persist is similar to Cache the only difference is it can take argument and that too is optional. If no argument is given which by default saves it to MEMORY_AND_DISK storage level and the second signature which takes StorageLevel as an argument to store it to different storage levels.

Persist in Spark

```scala
val rdd = sc.textFile("hdfs://...")
val processedRdd = rdd.map(...).filter(...)

// Persist the processed RDD in memory
processedRdd.persist()

// Perform multiple actions on the persisted RDD
processedRdd.count()
processedRdd.collect()
```

RDD Persistence

Storage Level	Description	Not available in Python
MEMORY_ONLY	This storage level stores the RDD or DataFrame as deserialized Java objects in the JVM heap. This provides fast access to the data but consumes more memory	
MEMORY_ONLY_ SER	This is the same as MEMORY_ONLY but the difference being it stores RDD as serialized objects to JVM memory. This reduces memory usage but requires	X
MEMORY_AND_ DISK	It stores partitions that do not fit in memory on disk and keeps the rest in memory. This can be useful when working with datasets that are larger than the	
MEMORY_AND_ DISK_SER	Similar to MEMORY_AND_DISK, but stores serialized Java objects on disk.	X
DISK_ONLY	Data is stored only on disk, and it is read into memory on-demand when accessed. This storage level has the least memory usage but may result in slower	
OFF_HEAP	The data is stored off the JVM heap in serialized form. This can be useful for large data sets that do not fit into the heap	

When to use Persist

- Use persist when you have a job that involves repeated operations on the same dataset. Without persist, each action in Spark recomputes the RDD from scratch, which can be inefficient if the RDD is large and the computation is complex. By persisting the RDD, you save the computational cost of re-evaluation.

Checkpoint in Spark

- The checkpoint method is used to truncate the lineage of an RDD, which means that Spark will save the RDD to a reliable storage (HDFS, S3, etc.), and from that point onwards, Spark will read the RDD from the checkpointed file rather than recomputing it from the original source.
- This is useful for long-running jobs where there is a risk of failure and recomputing the RDD from the beginning would be costly.

Checkpoint in Spark

```scala
val rdd = sc.textFile("hdfs://...")
val processedRdd = rdd.map(...).filter(...)

// Checkpoint the processed RDD
sc.setCheckpointDir("/path/to/checkpoint/dir")
processedRdd.checkpoint()

// Action to trigger the checkpoint
processedRdd.count()
```

When to use Checkpoint

- Use checkpoint when you have a job where intermediate stages of the computation are costly to recompute and there is a risk of node failures or other issues that could cause the job to restart. Checkpointing helps ensure fault tolerance by breaking the lineage of RDD transformations.

Cache vs Checkpoint

- Cache materializes the RDD and keeps it in memory (and/or disk). But the lineage (computing chain) of RDD (that is, seq of operations that generated the RDD) will be remembered, so that if there are node failures and parts of the cached RDDs are lost, they can be regenerated.
- However, checkpoint saves the RDD to an HDFS file and **actually forgets the lineage completely**. This allows long lineages to be truncated and the data to be saved reliably in HDFS, which is naturally fault tolerant by replication.

Combining Persist and Checkpoint

```scala
val rdd = sc.textFile("hdfs://...")
val processedRdd = rdd.map(...).filter(...)

// Persist the processed RDD in memory
processedRdd.persist()

// Checkpoint the processed RDD
sc.setCheckpointDir("/path/to/checkpoint/dir")
processedRdd.checkpoint()

// Action to trigger the persist and checkpoint
processedRdd.count()
```

Data Partitioning in Spark

- While Spark provides a default partitioning strategy typically based on the number of available CPU cores, it also provides options for custom partitioning. Users might instead specify a custom partitioning function, such as dividing data on a certain key.
- One of the most important factors affecting the efficiency of parallel processing is the number of partitions.
  - If there aren't enough partitions, the available memory and resources may be underutilized.
  - On the other hand, too many partitions can lead to increased performance overhead due to task scheduling and coordination.
  - The optimal number of partitions is **usually set as a factor of the total number of cores available in the cluster.**

repartition() and coalesce()

```
df = df.repartition(200)    # repartition method
df = df.coalesce(200)       # coalesce method
```

repartition() and coalesce()

- The repartition() method increases or decreases the number of partitions in an RDD or DataFrame and **performs a full shuffle of the data across the cluster**, which can be costly in terms of processing and network latency.
- The coalesce() method decreases the number of partitions in an RDD or DataFrame and, unlike repartition(), **does not perform a full shuffle**, instead combining adjacent partitions to reduce the overall number.

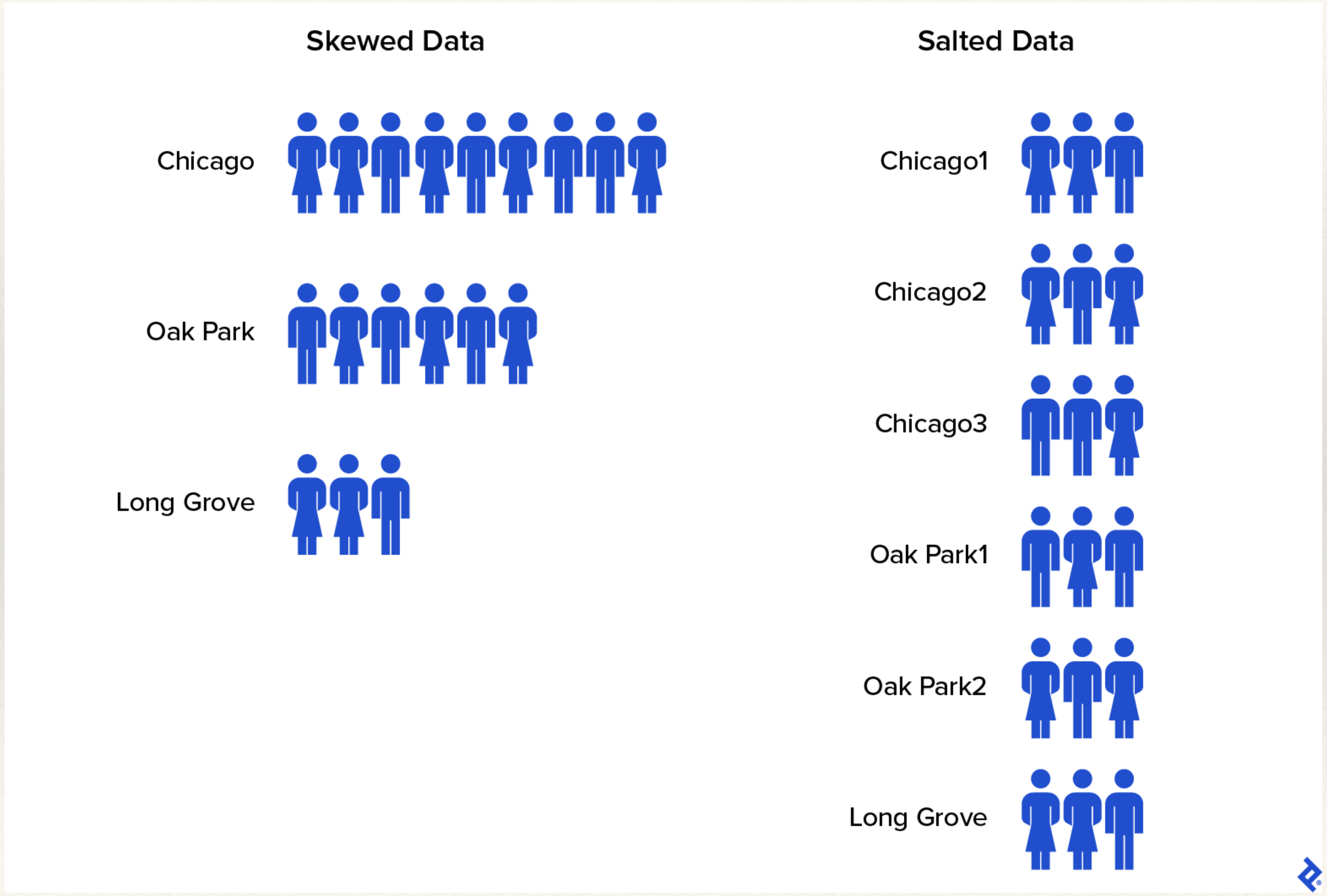
Handling Data Skews

- Partitioning
  - Properly partitioning data can help distribute the workload evenly across nodes.
- Sampling
  - Using sampling techniques to identify skewed keys and apply custom partitioning or filtering strategies.
- Aggregation
  - Using alternative aggregation strategies, such as pre-aggregation or partial aggregation, to reduce the impact of data skew.

Splitting

```python
from pyspark.sql.functions import rand

# Split the DataFrame into two DataFrames based on the skewed key.
df_skew = df.filter(df['id'] == 12345)  # contains all rows where id = 12345
df_non_skew = df.filter(df['id'] != 12345) # contains all other rows

# Repartition the skewed DataFrame into more partitions.
df_skew = df_skew.repartition(10)

# Now operations can be performed on both DataFrames separately.
df_result_skew = df_skew.groupBy('id').count()  # just an example operation
df_result_non_skew = df_non_skew.groupBy('id').count()

# Combine the results of the operations together using union().
df_result = df_result_skew.union(df_result_non_skew)
```

Salting



source

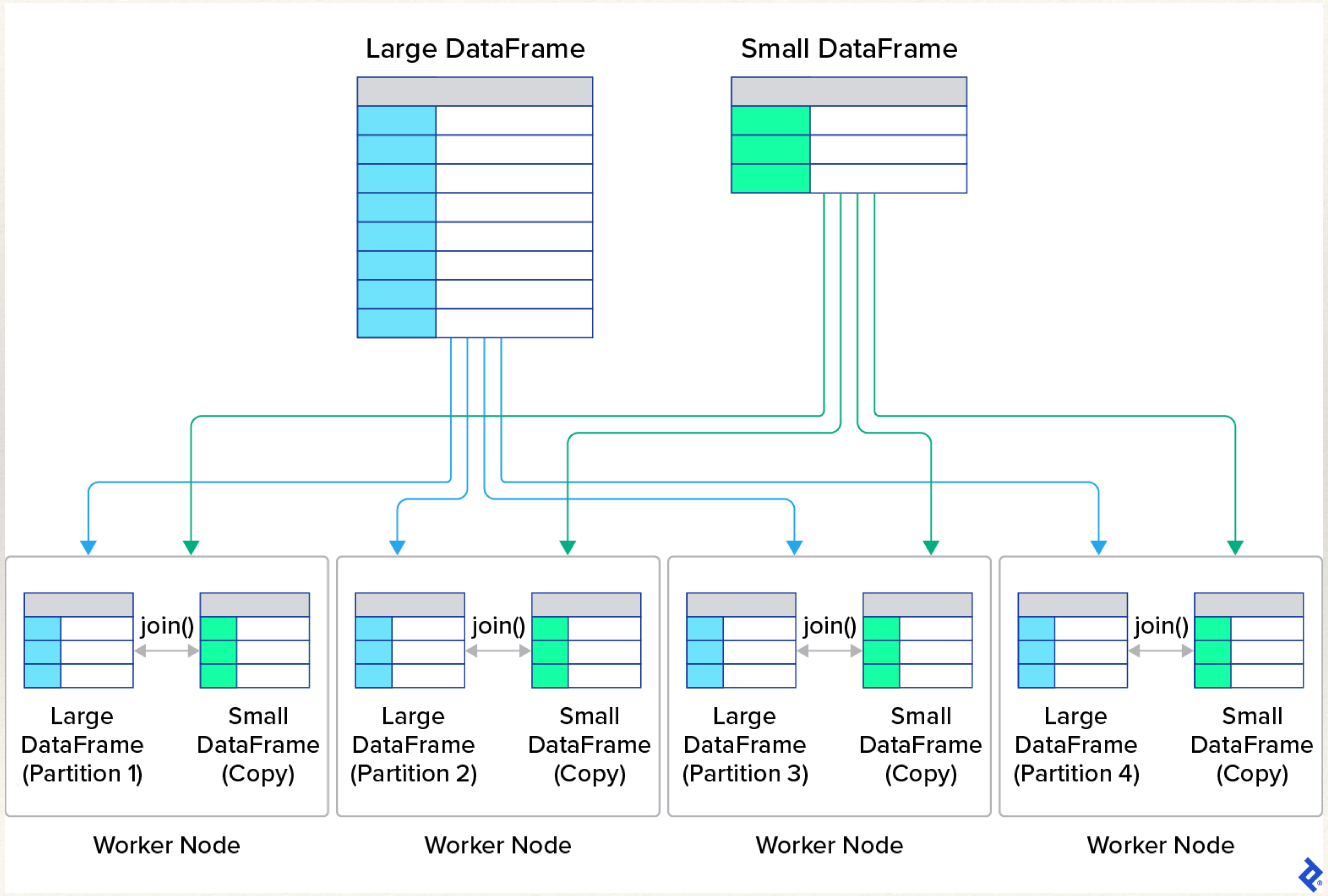
Salting

```
# In this example, the DataFrame 'df' has a skewed column 'city'.
skewed_column = 'city'

# Create a new column 'salted_city'.
# 'salted_id' consists of the original 'id' with a random integer
between 0-10 added behind it
df = df.withColumn('salted_city', (df[skewed_column].cast("string") +
(rand()*10).cast("int").cast("string")))

# Now operations can be performed on 'salted_city' instead of 'city'.
# Let’s say we are doing a groupBy operation.
df_grouped = df.groupby('salted_city').count()

# After the transformation, the salt can be removed.
df_grouped = df_grouped.withColumn('original_city',
df_grouped['salted_city'].substr(0, len(df_grouped['salted_city'])-1))
```

Broadcasting

- A join() is a common operation in which two data sets are combined based on one or more common keys. Rows from two different data sets can be merged into a single data set by matching values in the specified columns. Because data shuffling across multiple nodes is required, a join() can be a costly operation in terms of network latency.
- In scenarios in which **a small data set is being joined with a larger data set**, Spark offers an optimization technique called broadcasting.
- **If one of the data sets is small enough to fit into the memory of each worker node, it can be sent to all nodes, reducing the need for costly shuffle operations.** The join() operation simply happens locally on each node.

Broadcasting



source

Broadcasting

```
from pyspark.sql.functions import broadcast
df1.join(broadcast(df2), 'id')
# must be small enough to fit into the memory of each worker node;
a DataFrame that is too large will cause out-of-memory errors.
```

Filtering Unused Data

- When working with high-dimensional data, minimizing computational overhead is essential. Any rows or columns that are not absolutely required should be removed. Two key techniques that reduce computational complexity and memory usage are early filtering and column pruning:
  - **Early filtering**: Filtering operations should be applied as early as possible in the data processing pipeline. This **cuts down on the number of rows** that need to be processed in subsequent transformations, reducing the overall computational load and memory resources.
  - **Column pruning**: Many computations involve only a subset of columns in a data set. **Columns that are not necessary for data processing should be removed.** Column pruning can significantly decrease the amount of data that needs to be processed and stored.

Filtering

```
df = df.select('name', 'age').filter(df['age'] > 21)
```