Explanation

Manually persisting RDDs in Spark prevents them from being garbage collected.
This statement is incorrect, and thus the correct answer to the question.
Spark's garbage collector will remove even persisted objects, albeit in an "LRU" fashion. LRU stands for least recently used. So, during a garbage collection run, the objects that were used the longest time ago will be garbage collected first.
See the linked StackOverflow post below for more information.

Serialized caching is a strategy to increase the performance of garbage collection.
This statement is correct. The more Java objects Spark needs to collect during garbage collection, the longer it takes. Storing a collection of many Java objects, such as a DataFrame with a complex schema, through serialization as a single byte array thus increases performance. This means that garbage collection takes less time on a serialized DataFrame than an unserialized DataFrame.

Optimizing garbage collection performance in Spark may limit caching ability.
This statement is correct. A full garbage collection run slows down a Spark application. When taking about "tuning" garbage collection, we mean reducing the amount or duration of these slowdowns.
A full garbage collection run is triggered when the Old generation of the Java heap space is almost full. (If you are unfamiliar with this concept, check out the link to the Garbage Collection Tuning docs below.) Thus, one measure to avoid triggering a garbage collection run is to prevent the Old generation share of the heap space to be almost full.
To achieve this, one may decrease its size. Objects with sizes greater than the Old generation space will then be discarded instead of cached (stored) in the space and helping it to be "almost full" . This will decrease the number of full garbage collection runs, increasing overall performance.
Inevitably, however, objects will need to be recomputed when they are needed. So, this mechanism only works when a Spark application needs to reuse cached data as little as possible.
Garbage collection information can be accessed in the Spark UI's stage detail view.
This statement is correct. The task table in the Spark UI's stage detail view has a "GC Time" column, indicating the garbage collection time needed per task.

In Spark, using the G1 garbage collector is an alternative to using the

default Parallel garbage collector.
This statement is correct. The G1 garbage collector, also known as garbage first garbage collector, is an alternative to the default Parallel garbage collector. While the default Parallel garbage collector divides the heap into a few static regions, the G1 garbage collector divides the heap into many small regions that are created dynamically. The G1 garbage collector has certain advantages over the Parallel garbage collector which improve performance particularly for Spark workloads that require high throughput and low latency.
The G1 garbage collector is not enabled by default, and you need to explicitly pass an argument to Spark to enable it. For more information about the two garbage collectors, check out the Databricks article linked below.

Hierarchy

Stages with narrow dependencies can be grouped into one task.
Wrong, tasks with narrow dependencies can be grouped into one stage.

Tasks with wide dependencies can be grouped into one stage.
Wrong, since a wide transformation causes a shuffle which always marks the boundary of a stage. So, you cannot bundle multiple tasks that have wide dependencies into a stage.

Deploy Mode

cluster	In **cluster** mode, the driver runs on one of the worker nodes, and this node shows as a driver on the Spark Web UI of your application. cluster mode is used to run production jobs.
client	In **client** mode, the driver runs locally from where you are submitting your application using spark-submit command. client mode is majorly used for interactive and debugging purposes. Note that in client mode only the driver runs locally and all tasks run on cluster worker nodes.

In client mode, the cluster manager runs on the same host as the driver, while in cluster mode, the cluster manager runs on a separate node.
No. In both modes, the cluster manager is typically on a separate node – not on the same host as the driver. It only runs on the same host as the driver in local execution mode.

Deployment Modes

There are only 3 valid execution modes in Spark: Client, cluster, and local execution modes. Execution modes do not refer to specific frameworks, but to where infrastructure is located with respect to each other.
In client mode, the driver sits on a machine outside the cluster. In cluster mode, the driver sits on a machine inside the cluster. Finally, in local mode, all Spark infrastructure is started in a single JVM (Java Virtual Machine) in a single computer which then also includes the driver.
Deployment modes often refer to ways that Spark can be deployed in cluster mode and how it uses specific frameworks outside Spark. Valid deployment modes are standalone, Apache YARN, Apache Mesos and Kubernetes.

Modes

The differences between the roles of the cluster manager in cluster and in client execution mode:

In **cluster mode**, the cluster manager is responsible for launching both Spark driver and executors across the cluster.
In **client mode**, the cluster manager is only responsible for taking care of the executors. The Spark driver is maintained by the client machine.

Dynamic partition pruning

Ref - https://dzone.com/articles/dynamic-partition-pruning-in-spark-30

is intended to skip over the data you do not need in the results of a query.
Correct - Dynamic partition pruning provides an efficient way to selectively read data from files by skipping data that is irrelevant for the query. For example, if a query asks to consider only rows which have numbers >12 in column purchases via a filter, Spark would only read the rows that match this criteria from the underlying files. This method works in an optimal way if the purchases data is in a nonpartitioned table and the data to be filtered is partitioned.

Dynamic partition pruning reoptimizes query plans based on runtime statistics collected during query execution.
No – this is what adaptive query execution does, but not dynamic partition pruning.

Dynamic partition pruning reoptimizes physical plans based on data types and broadcast variables.

It is true that dynamic partition pruning works in joins using broadcast variables. This actually happens in both the logical optimization and the physical planning stage. However, data types do not play a role for the reoptimization.

Modes

In client mode, the cluster manager runs on the same host as the driver, while in cluster mode, the cluster manager runs on a separate node.
No. In both modes, the cluster manager is typically on a separate node – not on the same host as the driver. It only runs on the same host as the driver in local execution mode.

Difference of Dataset and DataFRame

DataFrames
DataFrames gives a schema view of data basically, it is an abstraction. In dataframes, view of data is organized as columns with column name and types info. In addition, we can say data in dataframe is as same as the table in relational database.
As similar as RDD, execution in dataframe too is lazy triggered. Moreover, to allow efficient processing datasets is structure as a distributed collection of data. Spark also uses catalyst optimizer along with dataframes.
DataSets
In Spark, datasets are an extension of dataframes. Basically, it earns two different APIs characteristics, such as strongly typed and untyped. Datasets are by default a collection of strongly typed JVM objects, unlike dataframes. Moreover, it uses Spark's Catalyst optimizer. For exposing expressions & data field to a query planner.
Now we will see the difference in both based on certain features:

Spark Release
DataFrame- In Spark 1.3 Release, dataframes are introduced.
whereas,
DataSets- In Spark 1.6 Release, datasets are introduced.
Data Formats
DataFrame- Dataframes organizes the data in the named column. Basically, dataframes can efficiently process unstructured and structured data. Also, allows the Spark to manage schema.
whereas,
DataSets- As similar as dataframes, it also efficiently processes unstructured and structured data. Also, represents data in the form of a collection of row object or JVM objects of row. Through encoders, is represented in tabular forms.

Data Representation

DataFrame- In dataframe data is organized into named columns. Basically, it is as same as a table in a relational database.
whereas,
DataSets- As we know, it is an extension of dataframe API, which provides the functionality of type-safe, object-oriented programming interface of the RDD API. Also, performance benefits of the Catalyst query optimizer.

Compile-time type safety
DataFrame- There is a case if we try to access the column which is not on the table. Then, dataframe APIs does not support compile-time error.
whereas,
DataSets- Datasets offers compile-time type safety.

Data Sources API
DataFrame- It allows data processing in different formats, for example, AVRO, CSV, JSON, and storage system HDFS, HIVE tables, MySQL.
whereas,
DataSets- It also supports data from different sources.

Immutability and Interoperability
DataFrame- Once transforming into dataframe, we cannot regenerate a domain object.
whereas,
DataSets- Datasets overcomes this drawback of dataframe to regenerate the RDD from dataframe. It also allows us to convert our existing RDD and dataframes into datasets.
Both dataframe and dataset are immutable .

Memory Management Overview

Memory usage in Spark largely falls under one of two categories: execution and storage. Execution memory refers to that used for computation in shuffles, joins, sorts and aggregations, while storage memory refers to that used for caching and propagating internal data across the cluster. In Spark, execution and storage share a unified region (M). When no execution memory is used, storage can acquire all the available memory and vice versa. Execution may evict storage if necessary, but only until total storage memory usage falls under a certain threshold (R). In other words, R describes a subregion within M where cached blocks are never evicted. Storage may not evict execution due to complexities in implementation.
This design ensures several desirable properties. First, applications that do not use caching can use the entire space for execution, obviating unnecessary disk spills. Second, applications that do use caching can reserve a minimum storage space (R) where their data blocks are immune to being evicted. Lastly, this approach provides reasonable out-of-the-box performance for a variety of workloads without requiring user expertise of how memory is divided internally.

Although there are two relevant configurations, the typical user should not need to adjust them as the default values are applicable to most workloads:

- spark.memory.fraction expresses the size of M as a fraction of the (JVM heap space - 300MiB) (default 0.6). The rest of the space (40%) is reserved for user data structures, internal metadata in Spark, and safeguarding against OOM errors in the case of sparse and unusually large records.
- spark.memory.storageFraction expresses the size of R as a fraction of M (default 0.5). R is the storage space within M where cached blocks immune to being evicted by execution.

The value of spark.memory.fraction should be set in order to fit this amount of heap space comfortably within the JVM's old or "tenured" generation. See the discussion of advanced GC tuning below for details.

spark Config

Increase values for the properties spark.dynamicAllocation.maxExecutors, spark.default.parallelism, and spark.sql.shuffle.partitions
The property spark.dynamicAllocation.maxExecutors is only in effect if dynamic allocation is enabled, using the spark.dynamicAllocation.enabled property. It is disabled by default. Dynamic allocation can be useful when running multiple applications on the same cluster in parallel. However, in this case there is only a single application running on the cluster, so enabling dynamic allocation would not yield a performance benefit.

Adaptive Query Execution

Adaptive Query Execution is enabled in Spark by default.
No, Adaptive Query Execution is disabled in Spark needs to be enabled through the spark.sql.adaptive.enabled property.

Dynamically injecting scan filters, are part of Adaptive Query Execution. Dynamically injecting scan filters for join operations to limit the amount of data to be considered in a query is part of Dynamic Partition Pruning and not of Adaptive Query Execution.

Spark will only perform the broadcast operation if this behavior has been enabled on the Spark cluster.
No, it is enabled by default, since the spark.sql.autoBroadcastJoinThreshold property is set to 10 MB by default. If that property would be set to -1, then broadcast joining would be disabled.

Shuffle

A shuffle is a process that compares data between partitions.
This is correct. During a shuffle, data is compared between partitions because

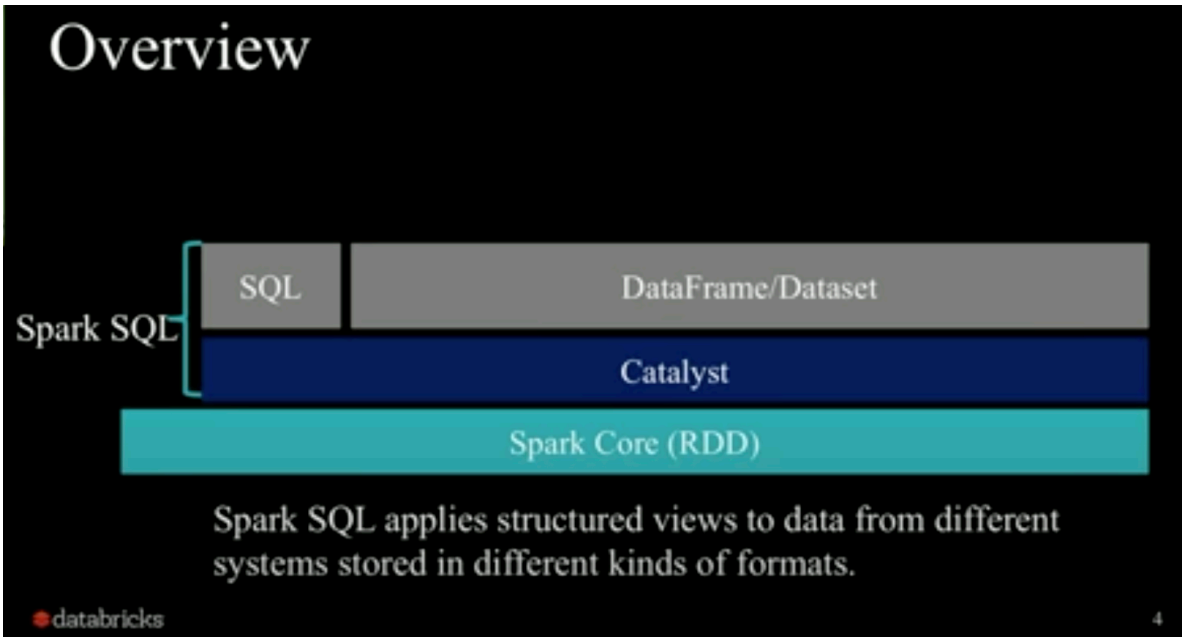
shuffling includes the process of sorting. For sorting, data need to be compared. Since per definition, more than one partition is involved in a shuffle, it can be said that data is compared across partitions. You can read more about the technical details of sorting in the blog post linked below.

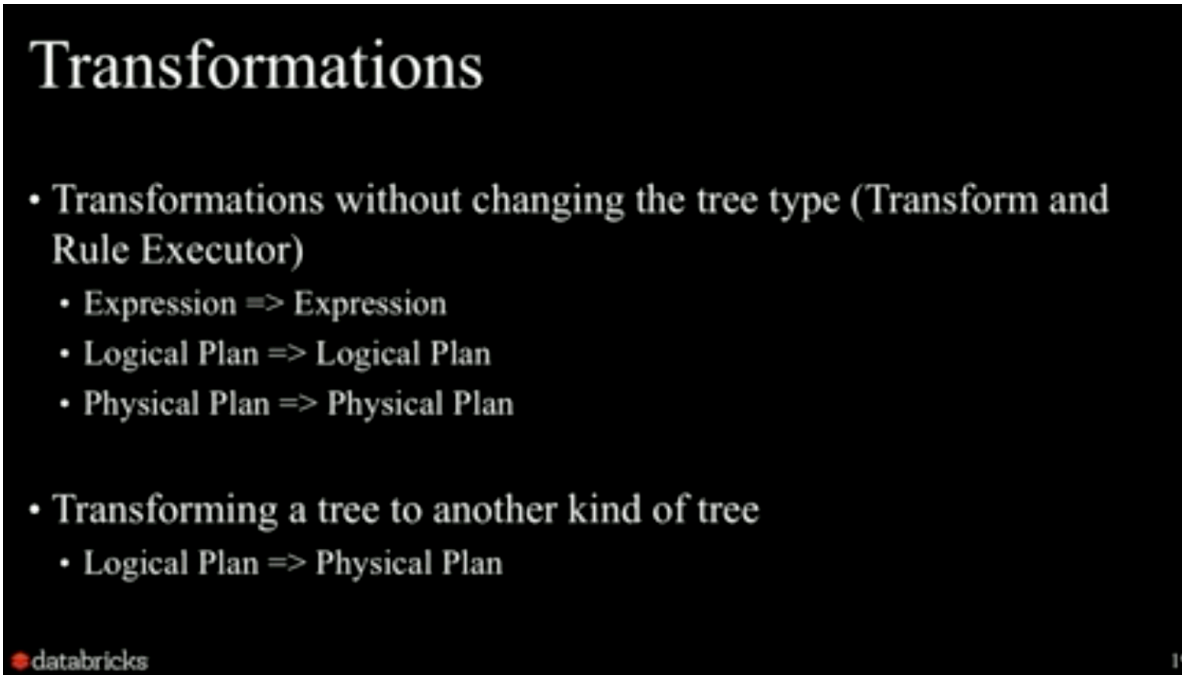
A shuffle is a Spark operation that results from DataFrame.coalesce().
No. DataFrame.coalesce() does not result in a shuffle.

A shuffle is a process that allocates partitions to executors.
This is incorrect. A shuffle is not allocating partitions to executors, this happens in a different process in Spark.

A shuffle is a process that is executed during a broadcast hash join.
No, broadcast hash joins avoid shuffles and yield performance benefits if at least one of the two tables is small in size (<= 10 MB by default). Broadcast hash joins can avoid shuffles because instead of exchanging partitions between executors, they broadcast a small table to all executors that then perform the rest of the join operation locally.

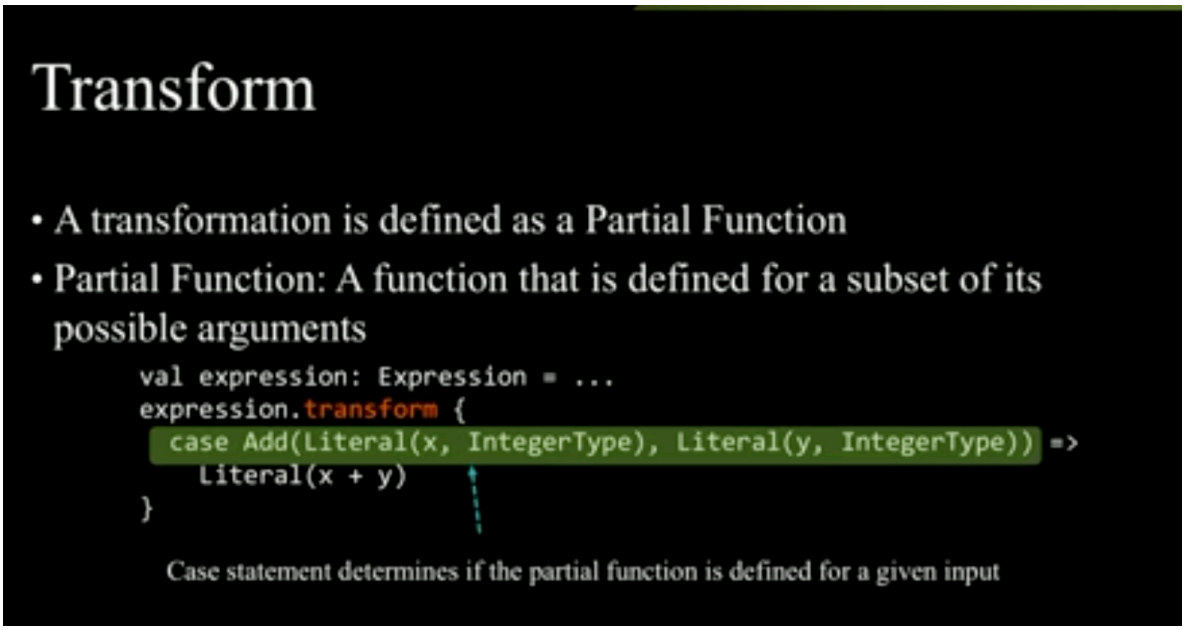
A shuffle is a process that compares data across executors.
No, in a shuffle, data is compared across partitions, and not executors.

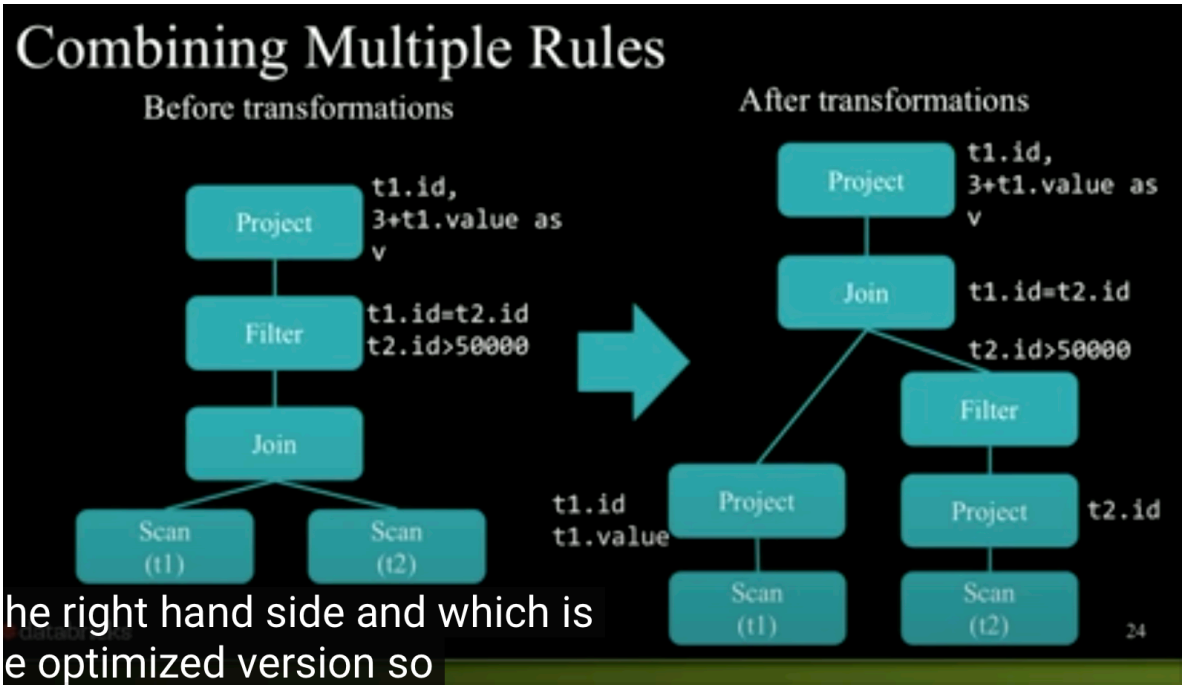




Transformations in pyspark like select,groupBy, orderBy,forEach etc are lazily evaluated and return DataFrame, Dataset, or RDD only when it is triggered by an action.

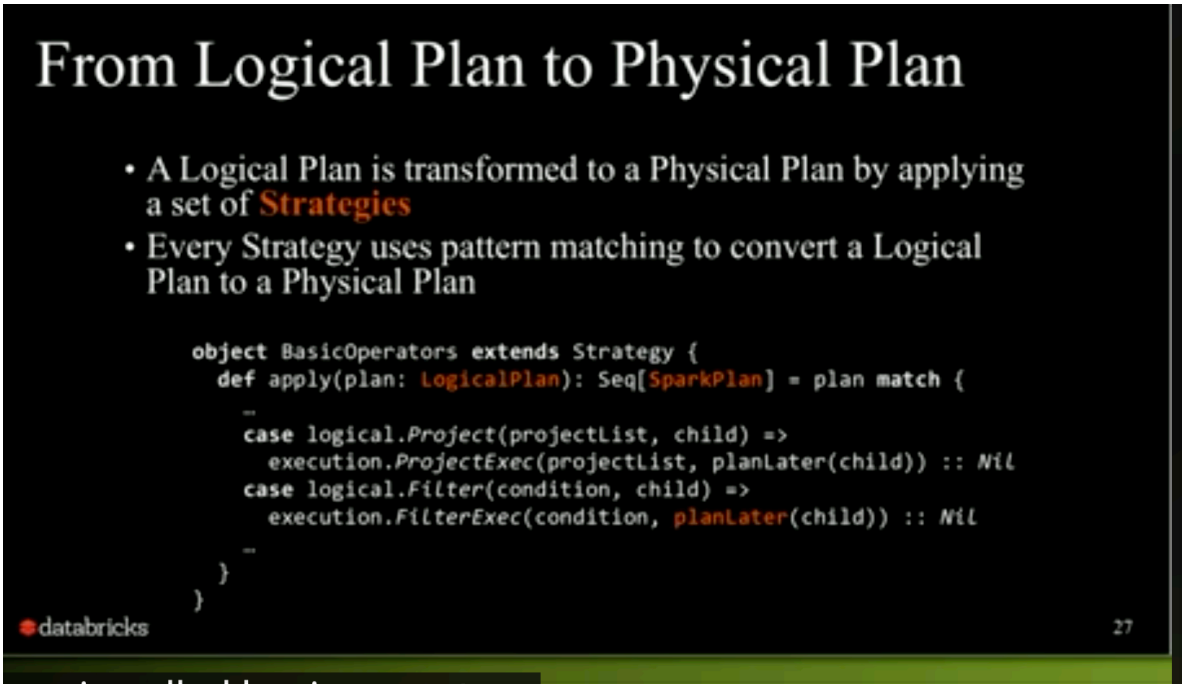
where actions are computed at the same moment of time.

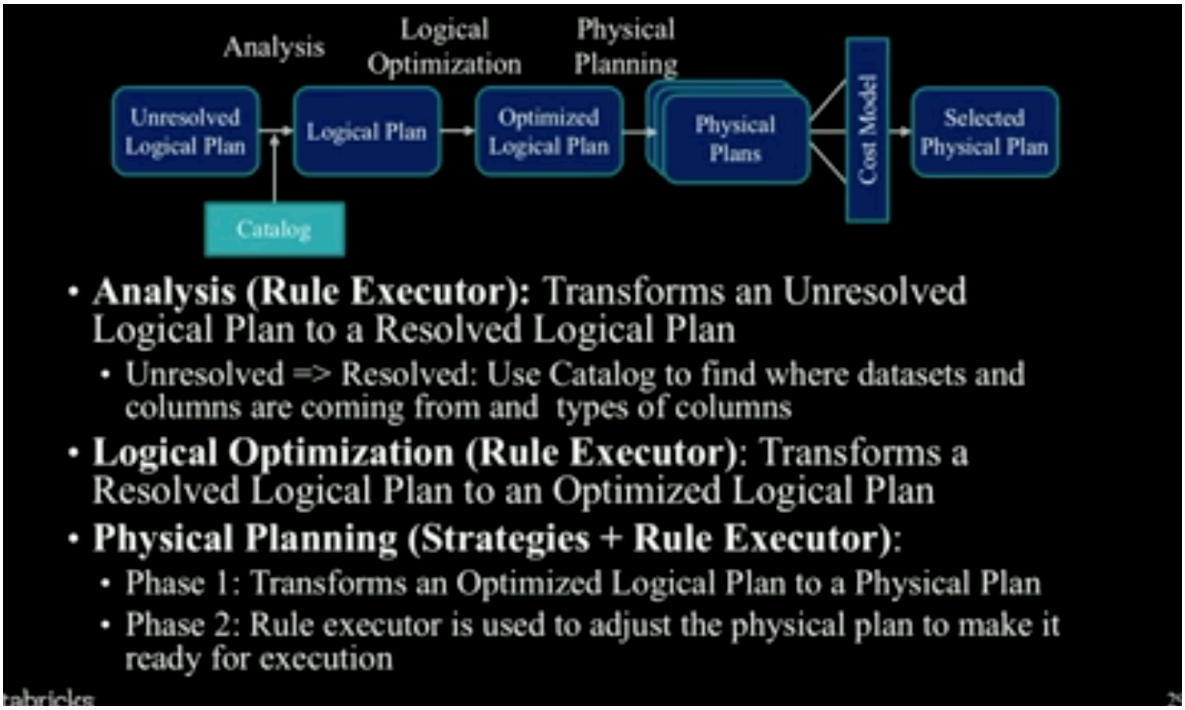




he right hand side and which is
e optimized version so

in above, **Predicate pushdown is a feature which leverages lazy evaluation.**





From many physical model, the cost analysis is done. The final physical paln is then selected with minimum cost.

Explanation
The executed physical plan depends on a cost optimization from a previous stage.
Correct! Spark considers multiple physical plans on which it performs a cost analysis and selects the final physical plan in accordance with the lowest-cost outcome of that analysis. That final physical plan is then executed by Spark.

Spark uses the catalog to resolve the optimized logical plan.
No. Spark uses the catalog to resolve the unresolved logical plan, but not the optimized logical plan. Once the unresolved logical plan is resolved, it is then optimized using the Catalyst Optimizer. The optimized logical plan is the input for physical planning.

The catalog assigns specific resources to the physical plan.
No. The catalog stores metadata, such as a list of names of columns, data types, functions, and databases. Spark consults the catalog for resolving the references in a logical plan at the beginning of the conversion of the query into an execution plan. The result is then an optimized logical plan.

Depending on whether DataFrame API or SQL API are used, the physical plan may differ.
Wrong – the physical plan is independent of which API was used. And this is one of the great strengths of Spark!

The catalog assigns specific resources to the optimized memory plan.
There is no specific "memory plan" on the journey of a Spark computation.

Catalyst optimiser

Spark uses a rule-based optimized in logical optimization of the query plan. This is part of what is known as "Catalyst Optimizer". An addition the the rule-based optimizer, there is also a cost-based optimizer in the Catalyst Optimizer. This cost-based optimizer is primarily used for optimizing joins. As a Spark user, you have the opportunity to tune the cost-based optimizer.

Accumulators

Accumulators - https://sparkbyexamples.com/pyspark/pyspark-accumulator-with-example/#:~:text=What%20is%20PySpark%20Accumulator%3F,automatically%20to%20the%20driver%20program.

A shared variable that can be accumulated, i.e., has a commutative and associative “add” operation. Worker tasks on a Spark cluster can add values to an Accumulator with the *+=* operator, but only the driver program is allowed to access its value, using *value*. Updates from the workers get propagated automatically to the driver program.

While **SparkContext** supports accumulators for primitive data types like **int** and **float**, users can also define accumulators for custom types by providing a custom **AccumulatorParam** object.

Datetime functions related to convert StringType to/from DateType or TimestampType. For example, unix_timestamp, date_format, to_unix_timestamp, from_unixtime, to_date, to_timestamp, from_utc_timestamp, to_utc_timestamp.

We can convert Unix Timestamp to regular date or timestamp and vice versa.

We can use unix_timestamp to convert regular date or timestamp to a unix timestamp value.
For example unix_timestamp(lit("2019-11-19 00:00:00"))

We can use from_unixtime to convert unix timestamp to regular date or timestamp.
For example from_unixtime(lit(1574101800))

Null Values

Here, it says that "a condition expression is a boolean expression and can return True, False or Unknown (NULL). They are 'satisfied' if the result of the condition is True.". So, in case a result is "null", it does not evaluate as true, but as "null". For this reason, the null value is not included in the result.

– ——>

order_items.grouped.\

agg(sum(col("order_item_quantity")),round(sum("order_item_subtotal"),2)).show() - works

tranDf.groupBy("StoreId").avg(**"value"**) - Correct
tranDf.groupBy("StoreId").avg(**col("value")**) - wrong as per syntax

Cache/Persist

Hi Abhishek,
You are correct in assuming that DataFrame.cache() is a transformation. It is only executed when followed by an action. However, DataFrame.cache() already marks a DataFrame for caching, so when it is involved in an action this caching will be executed.
In the case of the storage level MEMORY_AND_DISK, Spark will first fill up as much memory as it has available for caching and then spill to disk.
You can also observe this behavior yourself when you go into the Storage part of the Spark UI. You will only see cached DataFrames once an action has been called after DataFrame.cache() or DataFrame.persist().
Different from the aforementioned commands, DataFrame.unpersist() is an action and executed immediately

Question : I have a question regarding Jobs that are being triggered by Spark Driver. I used a notebook in Databricks Community Free Edition and ran the following simple code snippet :
spark.createDataFrame([("John",)], ["Name"]).show()

I believe that there is only one Action, namely **show** happening. But my Spark UI shows that there has been 3 Jobs launched. I want to understand why a single action is triggering multiple Jobs, when it should be triggering a single Job comprising of multiple Stages.

Answer. : The reason that 3 jobs are launched is buried deep within the Spark code base.

DEFAULT NUMBER OF PARTITIONS

spark.default.parallelism - no of partitions to be created

Fundamentally, the reason that there is more than one job is the default parallelism of Spark. This means the default number of partitions which a DataFrame is split into. The Spark configuration property to look out for here is spark.default.parallelism which is set to 8 in the Spark instance you are running on Databricks Community edition.
You can find out about this value by running sc.defaultParallelism in your notebook. And you can change the value to 40, for example, by adding spark.default.parallelism 40 in the Spark configuration in your Databricks cluster configuration. Note that after changing this value you will have to restart your cluster.
Note that if you count all tasks which are running in the 3 jobs you observe, they sum up to 8 - exactly the number of partitions set as default. Have you tried investigating the number of partitions of the created DataFrame via spark.createDataFrame([("John",)], ["Name"]).rdd.getNumPartitions() ? Spark creates 8 partitions! So, here is one part of the answer: You are seeing 8 tasks because Spark runs one task per partition.
If you set spark.default.parallelism to 1, you would just see a single task.

UNDERSTANDING THE NUMBER OF JOBS

You are not the only person puzzled by how the simple DataFrame.show() command results in multiple jobs. There are already some answers on StackOverflow (see here and here) which I will summarize for you here.
At its core, Spark attempts to iteratively estimate the number of partitions which it needs to run. For the result of each iteration, it creates a new job. The first iteration, so the first job, has one task - Spark starts scanning the very first partition. Then, the second iteration, so the second job, has 4 tasks. In the example where spark.default.parallelism is 8, there would only be 3 partitions left to reach a total of 1+4+3=8 partitions – so Spark would fill the next job with 3 tasks.
However, I ran an experiment for you where I set spark.default.parallelism to 200 and ran your DataFrame create command. Here, we can observe a 1/4/20/100/75 split of tasks.
You can see at this location in the Spark code base that Spark will estimate the number of partitions (tasks) by quadrupling the number of partitions it has already checked. So, for the example with the 200 partitions, here is what this would look like:
Job 0: 1 task
Job 1: 1*4=4 tasks
Job 2: (1+4)*4=20 tasks
Job 3: (1+4+20)*4=100 tasks
Job 4: (1+4+20+100)*4=500 tasks – but only 200-(100+20+4+1)=75 partitions are left, so ony 75 tasks can be run
At this point in the code in the take() method, the actual jobs are launched. The

take() method is called via this chain of calls: "show() method will call showString(), and showString() -> getRows() -> take(n) -> head(n). And finally, it will lead to RDD's take(n)." (see StackOverflow)

Adaptive Quer Execution (AQE)

The Databricks exam is about Apache Spark version 3.0. In version 3.0, Adaptive Query Execution is disabled by default. You can also find this information in the Apache Spark 3.0 documentation. Here, look for the configuration property spark.sql.adaptive.enabled. It is set to false by default.

IsNull()

In the documentation, it says that we can use Column.isNull() or isnull(col) ?

In fact, both of your answers are correct:
- There is an isnull method in pyspark.sql.functions – this is the one we are using in the correct answer (see documentation).

Standalone

Spark Standalone (*Standalone Cluster*) is Spark's own built-in cluster environment. Since Spark Standalone is available in the default distribution of Apache Spark it is the easiest way to run your Spark applications in a clustered environment in many cases.

Standalone Master (*standalone Master*) is the resource manager for the Spark Standalone cluster.
Standalone Worker is a worker in a Spark Standalone cluster. There can be one or many workers in a standalone cluster.

In Standalone cluster mode Spark allocates resources based on cores. By default, an application will grab all the cores in the cluster.
Standalone cluster mode is subject to the constraint that only one executor can be allocated on each worker per application.

Accumulators

Which of the following code blocks prints out in how many rows the expression Inc. appears in the string-type column supplier of DataFrame itemsDf?

```
counter = 0

for index, row in itemsDf.iterrows():
  if 'Inc.' in row['supplier']:
    counter = counter + 1

print(counter)
```

```
counter = 0

def count(x):
  if 'Inc.' in x['supplier']:
    counter = counter + 1

itemsDf.foreach(count)
print(counter)
```

```
print(itemsDf.foreach(lambda x: 'Inc.' in x))
```

```
print(itemsDf.foreach(lambda x: 'Inc.' in x).sum())
```

(Incorrect)

```
accum=sc.accumulator(0)

def check_if_inc_in_supplier(row):
  if 'Inc.' in row['supplier']:
    accum.add(1)

itemsDf.foreach(check_if_inc_in_supplier)
print(accum.value)
```

(Correct)

Explanation

Correct code block:

- accum=sc.accumulator(0)
-
- def check_if_inc_in_supplier(row):
- if 'Inc.' in row['supplier']:
- accum.add(1)
-
- itemsDf.foreach(check_if_inc_in_supplier)
- print(accum.value)

To answer this question correctly, you need to know both about the DataFrame.foreach() method and accumulators.

When Spark runs the code, it executes it on the executors. The executors do not have any information about variables outside of their scope. This is whhy simply using a Python variable counter, like in the two examples that start with counter = 0, will not work. You need to tell the executors explicitly that counter is a special shared variable, an Accumulator, which is managed by the driver and can be accessed by all executors for the purpose of adding to it.

If you have used Pandas in the past, you might be familiar with the iterrows() command. Notice that there is no such command in PySpark.

The two examples that start with print do not work, since DataFrame.foreach() does not have a return value.