SPARK INTERVIEW Q&A

200 PAGES

1. **Why Spark, even Hadoop exists?**

   Ans: Below are few reasons.

   - **Iterative Algorithm:** Generally MapReduce is not good to process iterative algorithms like Machine Learning and Graph processing**.** Graph and Machine Learning algorithms are iterative by nature and less saves to disk, this type of algorithm needs data in memory to run algorithm steps again and again or less transfers over network means better performance.
   - **In Memory Processing:** MapReduce uses disk storage for storing processed intermediate data and also read from disks which is not good for fast processing**. .** Because Spark keeps data in Memory (Configurable), which saves lot of time, by not reading and writing data to disk as it happens in case of Hadoop.
   - **Near real-time data processing:** Spark also supports near real-time streaming workloads via Spark Streaming application framework.

2. **Why both Spark and Hadoop needed?**

   Ans: Spark is often called cluster computing engine or simply execution engine. Spark uses many concepts from Hadoop MapReduce. Both Spark and Hadoop work together well. Spark with HDFS and YARN gives better performance and also simplifies the work distribution on cluster. As HDFS is storage engine for storing huge volume of data and Spark as a processing engine (In memory as well as more efficient data processing).

   HDFS: It is used as a Storage engine for Spark as well as Hadoop.

   YARN: It is a framework to manage Cluster using pluggable scedular.

   Run other than MapReduce: With Spark you can run MapReduce algorithm as well as other higher level of operators for instance **map(), filter(), reduceByKey(), groupByKey() etc.**

3. **How can you use Machine Learning library "SciKit library" which is written in Python, with Spark engine?**

   Ans: Machine learning tool written in Python, e.g. SciKit library, can be used as a Pipeline API in Spark MLlib or calling pipe().

4. **Why Spark is good at low-latency iterative workloads e.g. Graphs and Machine Learning?**

   Ans: Machine Learning algorithms for instance logistic regression require many iterations before creating optimal resulting model. And similarly in graph algorithms which traverse all the nodes and edges. Any algorithm which needs many iteration before creating results can increase their performance when the intermediate partial results are stored in memory or at very fast solid state drives.

   Spark can cache/store intermediate data in memory for faster model building and training.

   Also, when graph algorithms are processed then it traverses graphs one connection per iteration with the partial result in memory. **Less disk access and network traffic can make a huge difference when you need to process lots of data**.

5. **Which all kind of data processing supported by Spark?**

   Ans: Spark offers three kinds of data processing using **batch**, **interactive** (Spark Shell), and **stream processing** with the unified API and data structures.

6. **How do you define SparkContext?**

   Ans: It's an entry point for a Spark Job. Each Spark application starts by instantiating a Spark context. A Spark application is an instance of SparkContext. Or you can say, a Spark context constitutes a Spark application.

   SparkContext represents the connection to a Spark execution environment (deployment mode).

   A Spark context can be used to create RDDs, accumulators and broadcast variables, access Spark services and run jobs.

   A Spark context is essentially a client of Spark's execution environment and it acts as the master of your Spark.

7. **How can you define SparkConf?**

   Ans: Spark properties control most application settings and are configured separately for each application. These properties can be set directly on a SparkConf passed to your SparkContext. SparkConf allows you to configure some of the common properties (e.g. master URL and application name), as well as arbitrary key-value pairs through the set() method. For example, we could initialize an application with two threads as follows:
   Note that we run with local[2], meaning two threads - which represents "minimal" parallelism, which can help detect bugs that only exist when we run in a distributed context.

```
val conf = new SparkConf()
             .setMaster("local[2]")
             .setAppName("CountingSheep")
val sc = new SparkContext(conf)
```

8. **Which all are the, ways to configure Spark Properties and order them least important to the most important.**

   Ans: There are the following ways to set up properties for Spark and user programs (in the order of importance from the least important to the most important):

   - conf/spark-defaults.conf - the default
   - --conf - the command line option used by spark-shell and spark-submit
   - SparkConf

9. **What is the Default level of parallelism in Spark?**

   Ans: Default level of parallelism is the number of partitions when not specified explicitly by a user.

10. **Is it possible to have multiple SparkContext in single JVM?**

    Ans: Yes, **spark.driver.allowMultipleContexts** is true (**default: false**). If true Spark logs warnings instead of throwing exceptions when multiple SparkContexts are active, i.e. multiple SparkContext are running in this JVM. When creating an instance of SparkContex.

11. **Can RDD be shared between SparkContexts?**

    Ans: No, When an RDD is created; it belongs to and is completely owned by the Spark context it originated from. RDDs can't be shared between SparkContexts.

12. **In Spark-Shell, which all contexts are available by default?**

    Ans: SparkContext and SQLContext

13. **Give few examples , how RDD can be created using SparkContext**

    Ans: SparkContext allows you to create many different RDDs from input sources like:

    - **Scala's collections**: i.e. sc.parallelize(0 to 100)
    - **Local or remote filesystems** : sc.textFile("README.md")
    - **Any Hadoop InputSource** : using sc.newAPIHadoopFile

14. **How would you brodcast, collection of values over the Sperk executors?**

    Ans: sc.broadcast("hello")

15. **What is the advantage of broadcasting values across Spark Cluster?**

    Ans: Spark transfers the value to Spark executors once, and tasks can share it without incurring repetitive network transmissions when requested multiple times.

16. **Can we broadcast an RDD?**

    Ans: Yes, you should not broadcast a RDD to use in tasks and Spark will warn you. It will not stop you, though.

17. **How can we distribute JARs to workers?**

    Ans: The jar you specify with SparkContext.addJar will be copied to all the worker nodes.

18. **How can you stop SparkContext and what is the impact if stopped?**

    Ans: You can stop a Spark context using SparkContext.stop() method. Stopping a Spark context stops the Spark Runtime Environment and effectively shuts down the entire Spark application.

19. **Which scheduler is used by SparkContext by default?**

Ans: By default, SparkContext uses DAGScheduler , but you can develop your own custom DAGScheduler implementation.

20. How would you the amount of memory to allocate to each executor?

Ans: SPARK_EXECUTOR_MEMORY sets the amount of memory to allocate to each executor.

21. How do you define RDD?

Ans: A Resilient Distributed Dataset (RDD), the basic abstraction in Spark. It represents an immutable, partitioned collection of elements that can be operated on in parallel. Resilient Distributed Datasets (RDDs) are a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a fault-tolerant manner.

- **Resilient**: Fault-tolerant and so able to recomputed missing or damaged partitions on node failures with the help of RDD lineage graph.
- **Distributed**: across clusters.
- **Dataset**: is a collection of partitioned data.

22. What is Lazy evaluated RDD mean?

Ans: Lazy evaluated, i.e. the data inside RDD is not available or transformed until an action is executed that triggers the execution.

23. How would you control the number of partitions of a RDD?

Ans You can control the number of partitions of a RDD using **repartition** or **coalesce** operations.

24. What are the possible operations on RDD

Ans: RDDs support two kinds of operations:

- **transformations** - lazy operations that return another RDD.
- **actions** - operations that trigger computation and return values.

25. How RDD helps parallel job processing?

Ans: Spark does jobs in parallel, and RDDs are split into partitions to be processed and written in parallel. Inside a partition, data is processed sequentially.

26. What is the transformation?

Ans: A transformation is a lazy operation on a RDD that returns another RDD, like map , flatMap , filter , reduceByKey , join , cogroup , etc. Transformations are lazy and are not executed immediately, but only after an action have been executed.

27. **How do you define actions?**

Ans: An action is an operation that triggers execution of RDD transformations and returns a value (to a Spark driver - the user program). They trigger execution of RDD transformations to return values. Simply put, an action evaluates the RDD lineage graph.

You can think of actions as a valve and until no action is fired, the data to be processed is not even in the pipes, i.e. transformations. Only actions can materialize the entire processing pipeline with real data.

28. **How can you create an RDD for a text file?**

Ans: SparkContext.textFile

29. **What is Preferred Locations**

Ans: A preferred location (aka locality preferences or placement preferences) is a block location for an HDFS file where to compute each partition on.
def getPreferredLocations(split: Partition): Seq[String] specifies placement preferences for a partition in an RDD.

30. **What is a RDD Lineage Graph**

Ans: A RDD Lineage Graph (aka RDD operator graph) is a graph of the parent RDD of a RDD. It is built as a result of applying transformations to the RDD. A RDD lineage graph is hence a graph of what transformations need to be executed after an action has been called.

31. **Please tell me , how execution starts and end on RDD or Spark Job**

Ans: Execution Plan starts with the earliest RDDs (those with no dependencies on other RDDs or reference cached data) and ends with the RDD that produces the result of the action that has been called to execute.

32. Give example of transformations that do trigger jobs

Ans: There are a couple of transformations that do trigger jobs, e.g. sortBy , zipWithIndex , etc.

33. How many type of transformations exist?

Ans: There are two kinds of transformations:

- narrow transformations
- wide transformations

34. What is Narrow Transformations?

Ans: Narrow transformations are the result of map, filter and such that is from the data from a single partition only, i.e. it is self-sustained.

An output RDD has partitions with records that originate from a single partition in the parent RDD. Only a limited subset of partitions used to calculate the result. Spark groups narrow transformations as a stage.

35. What is wide Transformations?

Ans: Wide transformations are the result of groupByKey and reduceByKey . The data required to compute the records in a single partition may reside in many partitions of the parent RDD.

All of the tuples with the same key must end up in the same partition, processed by the same task. To satisfy these operations, Spark must execute RDD shuffle, which transfers data across cluster and results in a new stage with a new set of partitions. (54)

36. Data is spread in all the nodes of cluster, how spark tries to process this data?

Ans: By default, Spark tries to read data into an RDD from the nodes that are close to it. Since Spark usually accesses distributed partitioned data, to optimize transformation operations it creates partitions to hold the data chunks

37. **How would you hint, minimum number of partitions while transformation ?**

Ans: You can request for the minimum number of partitions, using the second input parameter to many transformations.

scala> sc.parallelize(1 to 100, 2).count

Preferred way to set up the number of partitions for an RDD is to directly pass it as the second input parameter in the call like rdd = sc.textFile("hdfs://… /file.txt", 400) , where400 is the number of partitions. In this case, the partitioning makes for 400 splits that would be done by the Hadoop's TextInputFormat , not Spark and it would work much faster. It'salso that the code spawns 400 concurrent tasks to try to load file.txt directly into 400 partitions.

38. **How many concurrent task Spark can run for an RDD partition?**

Ans: Spark can only run 1 concurrent task for every partition of an RDD, up to the number of cores in your cluster. So if you have a cluster with 50 cores, you want your RDDs to at least have 50 partitions (and probably 2-3x times that).

As far as choosing a "good" number of partitions, you generally want at least as many as the number of executors for parallelism. You can get this computed value by calling sc.defaultParallelism .

39. **Which limits the maximum size of a partition?**

Ans: The maximum size of a partition is ultimately limited by the available memory of an executor.

40. **When Spark works with file.txt.gz, how many partitions can be created?**

Ans: When using textFile with compressed files (file.txt.gz not file.txt or similar), Spark disables splitting that makes for an RDD with only 1 partition (as reads against gzipped files cannot be parallelized). In this case, to change the number of partitions you should do repartitioning.

Please note that Spark disables splitting for compressed files and creates RDDs with only 1 partition. In such cases, it's helpful to use sc.textFile('demo.gz') and do repartitioning using rdd.repartition(100) as follows:

```
rdd = sc.textFile('demo.gz')
rdd = rdd.repartition(100)
```

With the lines, you end up with rdd to be exactly 100 partitions of roughly equal in size.

41. **What is coalesce transformation?**

Ans: The coalesce transformation is used to change the number of partitions. It can trigger RDD shuffling depending on the second shuffle boolean input parameter (defaults to false).

42. **What is the difference between cache() and persist() method of RDD**

Ans: RDDs can be cached (using RDD's cache() operation) or persisted (using RDD's persist(newLevel: StorageLevel) operation). The cache() operation is a synonym of persist() that uses the default storage level MEMORY_ONLY .

43. **You have RDD storage level defined as MEMORY_ONLY_2 , what does _2 means ?**
    Ans: number _2 in the name denotes 2 replicas

44. **What is Shuffling?**
    Ans: Shuffling is a process of repartitioning (redistributing) data across partitions and may cause moving it across JVMs or even network when it is redistributed among executors.
    Avoid shuffling at all cost. Think about ways to leverage existing partitions. Leverage partial aggregation to reduce data transfer.

45. **Does shuffling change the number of partitions?**
    Ans: No, By default, shuffling doesn't change the number of partitions, but their content

46. **What is the difference between groupByKey and use reduceByKey ?**
    Ans : Avoid groupByKey and use reduceByKey or combineByKey instead.
    groupByKey shuffles all the data, which is slow.
    reduceByKey shuffles only the results of sub-aggregations in each partition of the data.

47. **When you call join operation on two pair RDDs e.g. (K, V) and (K, W), what is the result?**
    Ans: When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key [68]

48. **What is checkpointing?**
    Ans: Checkpointing is a process of truncating RDD lineage graph and saving it to a reliable distributed (HDFS) or local file system. RDD checkpointing that saves the actual intermediate RDD data to a reliable distributed file system.

    You mark an RDD for checkpointing by calling **RDD.checkpoint()** . The RDD will be saved to a file inside the checkpoint directory and all references to its parent RDDs will be removed. This function has to be called before any job has been executed on this RDD.

49. What do you mean by Dependencies in RDD lineage graph?

Ans: Dependency is a connection between RDDs after applying a transformation.

50. Which script will you use Spark Application, using spark-shell ?

Ans: You use spark-submit script to launch a Spark application, i.e. submit the application to a Spark deployment environment.

51. Define Spark architecture

Ans: Spark uses a master/worker architecture. There is a driver that talks to a single coordinator called master that manages workers in which executors run. The driver and the executors run in their own Java processes.

52. What is the purpose of Driver in Spark Architecture?

Ans: A Spark driver is the process that creates and owns an instance of SparkContext. It is your Spark application that launches the main method in which the instance of SparkContext is created.

- Drive splits a Spark application into tasks and schedules them to run on executors.
- A driver is where the task scheduler lives and spawns tasks across workers.
- A driver coordinates workers and overall execution of tasks.

53. Can you define the purpose of master in Spark architecture?

Ans: A master is a running Spark instance that connects to a cluster manager for resources. The master acquires cluster nodes to run executors.

54. What are the workers?

Ans: Workers or slaves are running Spark instances where executors live to execute tasks. They are the compute nodes in Spark. A worker receives serialized/marshalled tasks that it runs in a thread pool.

55. **Please explain, how worker's work, when a new Job submitted to them?**

    Ans: When SparkContext is created, each worker starts one executor. This is a separate java process or you can say new JVM, and it loads application jar in this JVM. Now executors connect back to your driver program and driver send them commands, like, foreach, filter, map etc. As soon as the driver quits, the executors shut down

56. **Please define executors in detail?**

    Ans: Executors are distributed agents responsible for executing tasks. Executors provide in-memory storage for RDDs that are cached in Spark applications. When executors are started they register themselves with the driver and communicate directly to execute tasks. [112]

57. **What is DAGSchedular and how it performs?**

    Ans: DAGScheduler is the scheduling layer of Apache Spark that implements stage-oriented scheduling, i.e. after an RDD action has been called it becomes a job that is then transformed into a set of stages that are submitted as TaskSets for execution.

    DAGScheduler uses an event queue architecture in which a thread can post DAGSchedulerEvent events, e.g. a new job or stage being submitted, that DAGScheduler reads and executes sequentially.

58. **What is stage, with regards to Spark Job execution?**

    Ans: A stage is a set of parallel tasks, one per partition of an RDD, that compute partial results of a function executed as part of a Spark job.

59. What is Task, with regards to Spark Job execution?

Ans: Task is an individual unit of work for executors to run. It is an individual unit of physical execution (computation) that runs on a single machine for parts of your Spark application on a data. All tasks in a stage should be completed before moving on to another stage.

- A task can also be considered a computation in a stage on a partition in a given job attempt.
- A Task belongs to a single stage and operates on a single partition (a part of an RDD).
- Tasks are spawned one by one for each stage and data partition.

60. What is Speculative Execution of a tasks?

Ans: Speculative tasks or task strugglers are tasks that run slower than most of the all tasks in a job.

Speculative execution of tasks is a health-check procedure that checks for tasks to be speculated, i.e. running slower in a stage than the median of all successfully completed tasks in a taskset . Such slow tasks will be re-launched in another worker. It will not stop the slow tasks, but run a new copy in parallel.

61. Which all cluster manager can be used with Spark?

Ans:

Apache Mesos, Hadoop YARN, Spark standalone and

Spark local: Local node or on single JVM. Drivers and executor runs in same JVM. In this case same node will be used for execution.

62. What is a BlockManager?

Ans: Block Manager is a key-value store for blocks that acts as a cache. It runs on every node, i.e. a driver and executors, in a Spark runtime environment. It provides interfaces for putting and retrieving blocks both locally and remotely into various stores, i.e. memory, disk, and offheap.

A BlockManager manages the storage for most of the data in Spark, i.e. block that represent a cached RDD partition, intermediate shuffle data, and broadcast data.

63. What is Data locality / placement?

Ans: Spark relies on data locality or data placement or proximity to data source, that makes Spark jobs sensitive to where the data is located. It is therefore important to have Spark running on Hadoop YARN cluster if the data comes from HDFS.

With HDFS the Spark driver contacts NameNode about the DataNodes (ideally local) containing the various blocks of a file or directory as well as their locations (represented as InputSplits), and then schedules the work to the SparkWorkers. Spark's compute nodes / workers should be running on storage nodes.

64. What is master URL in local mode?

Ans: You can run Spark in local mode using local , local[n] or the most general local[*].
The URL says how many threads can be used in total:

- local uses 1 thread only.
- local[n] uses n threads.
- local[*] uses as many threads as the number of processors available to the Java virtual machine (it uses Runtime.getRuntime.availableProcessors() to know the number).

65. Define components of YARN?

Ans: YARN components are below
ResourceManager: runs as a master daemon and manages ApplicationMasters and NodeManagers.
ApplicationMaster: is a lightweight process that coordinates the execution of tasks of an application and asks the ResourceManager for resource containers for tasks. It monitors tasks, restarts failed ones, etc. It can run any type of tasks, be them MapReduce tasks or Giraph tasks, or Spark tasks.
NodeManager offers resources (memory and CPU) as resource containers.
NameNode
Container: can run tasks, including ApplicationMasters.

66. What is a Broadcast Variable?

Ans: Broadcast variables allow the programmer to keep a read-only variable cached on each machine rather than shipping a copy of it with tasks.

67. How can you define Spark Accumulators?

Ans: This are similar to counters in Hadoop MapReduce framework, which gives information regarding completion of tasks, or how much data is processed etc.

68. What all are the data sources Spark can process?

Ans:

- Hadoop File System (HDFS)
- Cassandra (NoSQL databases)
- HBase (NoSQL database)
- S3 (Amazon WebService Storage : AWS Cloud)

69. What is Apache Parquet format?

Ans: Apache Parquet is a columnar storage format

70. What is Apache Spark Streaming?

Ans: Spark Streaming helps to process live stream data. Data can be ingested from many sources like Kafka, Flume, Twitter, ZeroMQ, Kinesis, or TCP sockets, and can be processed using complex algorithms expressed with high-level functions like map, reduce, join and window.

1. How is Apache Spark different from MapReduce?

Ans:

Apache Spark	MapReduce
Spark processes data in batches as well as in real-time	MapReduce processes data in batches only
Spark runs almost 100 times faster than Hadoop Map Reduce	Hadoop MapReduce is slower when it comes to large sc processing
Spark stores data in the RAM i.e. in-memory. So, it is easier to retrieve it	Hadoop MapReduce data is stored in HDFS and henc longer time to retrieve the data
Spark provides caching and in-memory data storage	Hadoop is highly disk-dependent

2. What are the important components of the Spark ecosystem?

Ans:

Apache Spark has 3 main categories that comprise its ecosystem. Those are:

- Language support: Spark can integrate with different languages to applications and perform analytics. These languages are Java, Python, Scala, and R.
- Core Components: Spark supports 5 main core components. There are Spark Core, Spark SQL, Spark Streaming, Spark MLlib, and GraphX.
- Cluster Management: Spark can be run in 3 environments. Those are the Standalone cluster, Apache Mesos, and YARN.

3. What are the different cluster managers available in Apache Spark?

Ans:

- Standalone Mode: By default, applications submitted to the standalone mode cluster will run in FIFO order, and each application will try to use all available nodes. You can launch a standalone cluster either manually, by starting a master and workers by hand or use our provided launch scripts. It is also possible to run these daemons on a single machine for testing.
- Apache Mesos: Apache Mesos is an open-source project to manage computer clusters, and can also run Hadoop applications. The advantages of deploying Spark with Mesos include dynamic partitioning between Spark and other frameworks as well as scalable partitioning between multiple instances of Spark.
- Hadoop YARN: Apache YARN is the cluster resource manager of Hadoop 2. Spark can be run on YARN as well.
- Kubernetes: Kubernetes is an open-source system for automating deployment, scaling, and management of containerized applications.

4. What is a lazy evaluation in Spark?

Ans:

When Spark operates on any dataset, it remembers the instructions.When a transformation such as a map() is called on an RDD, the operation is not performed instantly. Transformations in Spark are not evaluated until you perform an action, which aids in optimizing the overall data processing workflow, known as lazy evaluation.

5. What makes Spark good at low latency workloads like graph processing and Machine Learning?

Ans:

Apache Spark stores data in-memory for faster processing and building machine learning models. Machine Learning algorithms require multiple iterations and different conceptual steps to create an optimal model. Graph algorithms traverse through all the nodes and edges to generate a graph. These low latency workloads that need multiple iterations can lead to increased performance.

6. How can you connect Spark to Apache Mesos?

Ans:

There are a total of 4 steps that can help you connect Spark to Apache Mesos.

- Configure the Spark Driver program to connect with Apache Mesos
- Put the Spark binary package in a location accessible by Mesos
- Install Spark in the same location as that of the Apache Mesos
- Configure the spark.mesos.executor.home property for pointing to the location where Spark is installed

7. What is a Parquet file and what are its advantages?

Ans:

Parquet is a columnar format that is supported by several data processing systems. With the Parquet file, Spark can perform both read and write operations.

Some of the advantages of having a Parquet file are:

- It enables you to fetch specific columns for access.
- It consumes less space
- It follows the type-specific encoding
- It supports limited I/O operations

8. What is shuffling in Spark? When does it occur?

Ans:

- Shuffling is the process of redistributing data across partitions that may lead to data movement across the executors. The shuffle operation is implemented differently in Spark compared to Hadoop.

  Shuffling has 2 important compression parameters:

- spark.shuffle.compress – checks whether the engine would compress shuffle outputs or not spark.shuffle.spill.compress – decides whether to compress intermediate shuffle spill files or not
- It occurs while joining two tables or while performing byKey operations such as GroupByKey or ReduceByKey

9. What are the various functionalities supported by Spark Core?

Ans:

Spark Core is the engine for parallel and distributed processing of large data sets. The various functionalities supported by Spark Core include:

- Scheduling and monitoring jobs
- Memory management
- Fault recovery
- Task dispatching
- eDataFrame

10. Explain the types of operations supported by RDDs.

Ans:

RDDs support 2 types of operation:

- **Transformations:** Transformations are operations that are performed on an RDD to create a new RDD containing the results (Example: map, filter, join, union)
- **Actions:** Actions are operations that return a value after running a computation on an RDD (Example: reduce, first, count)

11. How to programmatically specify a schema for DataFrame?

Ans:

DataFrame can be created programmatically with three steps:

- Create an RDD of Rows from the original RDD;
- Create the schema represented by a StructType matching the structure of Rows in the RDD created in Step 1.
- Apply the schema to the RDD of Rows via createDataFrame method provided by SparkSession.

12. What is a Lineage Graph?

Ans:

- A Lineage Graph is a dependencies graph between the existing RDD and the new RDD. It means that all the dependencies between the RDD will be recorded in a graph, rather than the original data.
- The need for an RDD lineage graph happens when we want to compute new RDD or if we want to recover the lost data from the lost persisted RDD.Spark does not support data replication in memory. So, if any data is lost, it can be rebuilt using RDD lineage. It is also called an RDD operator graph or RDD dependency graph.

13. Which transformation returns a new DStream by selecting only those records of the source DStream for which the function returns true?

1. map(func)

2. transform(func)

3. filter(func)

4. count()

Ans:

3) filter(func).

14. Does Apache Spark provide checkpoints?

Ans:

- Yes, Apache Spark provides an API for adding and managing checkpoints. Checkpointing is the process of making streaming applications resilient to failures. It allows you to save the data and metadata into a checkpointing directory. In case of a failure, the spark can recover this data and start from wherever it has stopped.
- There are 2 types of data for which we can use checkpointing in Spark.
- **Metadata Checkpointing:** Metadata means the data about data. It refers to saving the metadata to fault-tolerant storage like HDFS. Metadata includes configurations, DStream operations, and incomplete batches.
- **Data Checkpointing:** Here, we save the RDD to reliable storage because its need arises in some of the stateful transformations. In this case, the upcoming RDD depends on the RDDs of previous batches.

15. What are the different levels of persistence in Spark?

Ans:

- DISK_ONLY – Stores the RDD partitions only on the disk
- MEMORY_ONLY_SER – Stores the RDD as serialized Java objects with one-byte array per partition
- MEMORY_ONLY – Stores the RDD as deserialized Java objects in the JVM. If the RDD is not able to fit in the memory available, some partitions won't be cached
- OFF_HEAP – Works like MEMORY_ONLY_SER but stores the data in off-heap memory
- MEMORY_AND_DISK – Stores RDD as deserialized Java objects in the JVM. In case the RDD is not able to fit in the memory, additional partitions are stored on the disk
- MEMORY_AND_DISK_SER – Identical to MEMORY_ONLY_SER with the exception of storing partitions not able to fit in the memory to the disk

16. What is the difference between map and flatMap transformation in Spark Streaming?

Ans:

map()	flar map();
A map function returns a new DStream by passing each element of the source DStream through a function function	It is similar to map function and applies to each e RDD and it returns the result as new RDD
Spark Map function takes one element as input process it according to custom code (specified by the developer) and returns one element at a time	FlatMap allows returning 0, 1 or more elements fro function.In the FlatMap operation

17. How would you compute the total count of unique words in Spark?

Ans:

1. **Load the text file as RDD:**

- sc.textFile("hdfs://Hadoop/user/test_file.txt");

2. Function that breaks each line into words:

- def toWords(line):
- return line.split();

3. Run the toWords function on each element of RDD in Spark as flatMap transformation:

- words = line.flatMap(toWords);

4. Convert each word into (key,value) pair:

- def toTuple(word):
- return (word, 1);
- wordTuple = words.map(toTuple);

5. Perform reduceByKey() action:

- def sum(x, y):
- return x+y:
- counts = wordsTuple.reduceByKey(sum)

6. Print:

- counts.collect()

18. What are the different MLlib tools available in Spark?

Ans:

- ML Algorithms: Classification, Regression, Clustering, and Collaborative filtering
- Featurization: Feature extraction, Transformation, Dimensionality reduction, and Selection
- Pipelines: Tools for constructing, evaluating, and tuning ML pipelines
- Persistence: Saving and loading algorithms, models and pipelines
- Utilities: Linear algebra, statistics, data handling

19. What is a Sparse Vector?

Ans:

A Sparse vector is a type of local vector which is represented by an index array and a value array.

- public class SparseVector
- extends Object
- implements Vector

1. *Example: sparse1 = SparseVector(4, [1, 3], [3.0, 4.0])*
2. *where:*
3. *4 is the size of the vector*

4. *[1,3] are the ordered indices of the vector*
5. *[3,4] are the value*

20. What are the functions of Spark SQL?

Ans:

- Spark SQL is Apache Spark's module for working with structured data.
- Spark SQL loads the data from a variety of structured data sources.
- It queries data using SQL statements, both inside a Spark program and from external tools that connect to Spark SQL through standard database connectors (JDBC/ODBC).
- It provides a rich integration between SQL and regular Python/Java/Scala code, including the ability to join RDDs and SQL tables and expose custom functions in SQL.

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21. What are the different types of operators provided by the Apache GraphX library?

Ans:

- **Property Operator:** Property operators modify the vertex or edge properties using a user-defined map function and produce a new graph.
- **Structural Operator:** Structure operators operate on the structure of an input graph and produce a new graph.
- **Join Operator:** Join operators add data to graphs and generate new graphs.

22. What are the analytic algorithms provided in Apache Spark GraphX?

Ans:

GraphX is Apache Spark's API for graphs and graph-parallel computation. GraphX includes a set of graph algorithms to simplify analytics tasks. The algorithms are contained in the

org.apache.spark.graphx.lib package and can be accessed directly as methods on Graph via GraphOps.

- **PageRank:** PageRank is a graph parallel computation that measures the importance of each vertex in a graph. Example: You can run PageRank to evaluate what the most important pages in Wikipedia are.
- **Connected Components:** The connected components algorithm labels each connected component of the graph with the ID of its lowest-numbered vertex. For example, in a social network, connected components can approximate clusters.
- **Triangle Counting:** A vertex is part of a triangle when it has two adjacent vertices with an edge between them. GraphX implements a triangle counting algorithm in the TriangleCount object that determines the number of triangles passing through each vertex, providing a measure of clustering.

23. Which Profilers do we use in PySpark?

Ans:

Custom profilers are PySpark supported in PySpark to allow for different Profilers to be used and for outputting to different formats than what is offered in the BasicProfiler.

We need to define or inherit the following methods, with a custom profiler:

- profile – Basically, it produces a system profile of some sort.
- stats – Well, it returns the collected stats.
- dump – Whereas, it dumps the profiles to a path.
- add – Moreover, this method helps to add a profile to the existing accumulated profile

Generally, when we create a SparkContext, we choose the profiler class.

24. Explain Basic Profiler.

Ans:

It is a default profiler, which we implement on the basis of cProfile and Accumulator.

25. Do we have a machine learning API in Python?

Ans:

As Spark provides a Machine Learning API, MLlib. Similarly, in Python as well, PySpark has this machine learning API.

26. Name algorithms supported in PySpark?

Ans:

There are several algorithms in PySpark:

- mllib.classification
- mllib.clustering
- mllib.fpm
- mllib.linalg
- mllib.recommendation
- spark.mllib
- Mllib.regression

27. Name parameter of SparkContext?

Ans:

The parameters of a SparkContext are:

- Master − URL of the cluster from which it connects.
- appName − Name of our job.
- sparkHome − Spark installation directory.
- pyFiles − It is the .zip or .py files, in order to send to the cluster and also to add to the PYTHONPATH.
- Environment − Worker nodes environment variables.
- Serializer − RDD serializer.
- Conf − to set all the Spark properties, an object of L{SparkConf}.
- JSC − It is the JavaSparkContext instance.

28. Which of the parameters of SparkContext we mostly use?

Ans:

Master and app name.

29. What Makes Apache Spark Good At Low-latency Workloads Like Graph Processing And Machine Learning?

Ans:

Apache Spark stores data in-memory for faster model building and training. Machine learning algorithms require multiple iterations to generate a resulting optimal model and similarly graph algorithms traverse all the nodes and edges.These low latency workloads that need multiple iterations can lead to increased performance. Less disk access and controlled network traffic make a huge difference when there is lots of data to be processed.

30. Is It Necessary To Start Hadoop To Run Any Apache Spark Application ?

Ans:

Starting hadoop is not mandatory to run any spark application. As there is no separate storage in Apache Spark, it uses Hadoop HDFS but it is not mandatory. The data can be stored in the local file system, can be loaded from the local file system and processed.

31. What Is The Default Level Of Parallelism In Apache Spark?

Ans:

If the user does not explicitly specify then the number of partitions are considered as default level of parallelism in Apache Spark.

32. Explain About The Common Workflow Of A Spark Program

Ans:

- The foremost step in a Spark program involves creating input RDD's from external data.
- Use various RDD transformations like filter() to create new transformed RDD's based on the business logic.
- persist() any intermediate RDD's which might have to be reused in future.
- Launch various RDD actions() like first(), count() to begin parallel computation , which will then be optimized and executed by Spark.

33. Name A Few Commonly Used Spark Ecosystems.

Ans:

- Spark SQL (Shark)
- Spark Streaming
- GraphX
- MLlib
- SparkR

34. What is Spark Streaming?

Ans:

At whatever point there is information streaming constantly and you need to process the information as right on time as could reasonably be expected, all things considered you can exploit Spark Streaming.

35. Can We Do Real-time Processing Using Spark Sql?

Ans:

Not directly but we can register an existing RDD as a SQL table and trigger SQL queries on top of that.

36. What Is Spark Sql?

Ans:

SQL Spark, better known as Shark is a novel module introduced in Spark to work with structured data and perform structured data processing. Through this module, Spark executes relational SQL queries on the data. The core of the component supports an altogether different RDD called SchemaRDD, composed of rows objects and schema objects defining data type of each column in the row. It is similar to a table in a relational database.

37. What Is A Parquet File?

Ans:

Parquet is a columnar format file supported by many other data processing systems. Spark SQL performs both read and write operations with Parquet files and considers it to be one of the best big data analytics formats so far.

38. List The Functions Of Spark Sql.

Ans:

Spark SQL is capable of:

- Loading data from a variety of structured sources
- Querying data using SQL statements, both inside a Spark program and from external tools that connect to Spark SQL through standard database connectors (JDBC/ODBC). For instance, using business intelligence tools like Tableau
- Providing rich integration between SQL and regular Python/Java/Scala code, including the ability to join RDDs and SQL tables, expose custom functions in SQL, and more

39. What Is Spark?

Ans:

Spark is a parallel data processing framework. It allows developers to develop fast, unified big data applications that combine batch, streaming and interactive analytics.

40. What Is Hive On Spark?

Ans:

- Hive is a component of Hortonworks' Data Platform (HDP). Hive provides an SQL-like interface to data stored in the HDP. Spark users will automatically get the complete set of Hive's rich features, including any new features that Hive might introduce in the future.
- The main task around implementing the Spark execution engine for Hive lies in query planning, where Hive operator plans from the semantic analyzer which is translated to a task plan that Spark can execute. It also includes query execution, where the generated Spark plan gets actually executed in the Spark cluster.

41. What Is A "Parquet" In Spark?

Ans:

"Parquet" is a columnar format file supported by many data processing systems. Spark SQL performs both read and write operations with the "Parquet" file.

42. What Are Benefits Of Spark Over Mapreduce?

Ans:

Due to the availability of in-memory processing, Spark implements the processing around 10-100x faster than Hadoop MapReduce. MapReduce makes use of persistence storage for any of the data processing tasks.

- Unlike Hadoop, Spark provides in-built libraries to perform multiple tasks form the same core like batch processing, Steaming, Machine learning, Interactive SQL queries. However, Hadoop only supports batch processing.
- Hadoop is highly disk-dependent whereas Spark promotes caching and in-memory data storage
- Spark is capable of performing computations multiple times on the same dataset. This is called iterative computation while there is no iterative computing implemented by Hadoop.

43. How Spark Sql Is Different From Hql And Sql?

Ans:

SparkSQL is a special component on the spark Core engine that supports SQL and Hive Query Language without changing any syntax. It's possible to join SQL table and HQL table.

44. What do you understand about SchemaRDD in Apache Spark RDD?

Ans:

- *SchemaRDD* is an RDD that consists of row objects (wrappers around the basic string or integer arrays) with schema information about the type of data in each column.
- SchemaRDD was designed as an attempt to make life easier for developers in their daily routines of code debugging and unit testing on SparkSQL core module. The idea can boil down to describing the data structures inside RDD using a formal description similar to the relational database schema. On top of all basic functions provided by common RDD APIs, SchemaRDD also provides some straightforward relational query interface functions that are realized through SparkSQL.
- Now, it is officially renamed to *DataFrame API* on Spark's latest trunk.

45. How is Spark SQL different from HQL and SQL?

Ans:

Spark SQL is a special component on the Spark Core engine that supports SQL and Hive Query Language without changing any syntax. It is possible to join SQL table and HQL table to Spark SQL.

46. What is a DStream in Apache Spark?

Ans:

- *Discretized Stream* (DStream) is the basic abstraction provided by Spark Streaming. It is a continuous stream of data. It is received from a data source or from a processed data stream generated by transforming the input stream. Internally, a DStream is represented by a continuous

series of RDDs and each RDD contains data from a certain interval. Any operation applied on a DStream translates to operations on the underlying RDDs.

DStreams can be created from various sources like Apache Kafka, HDFS, and Apache Flume.

DStreams have two operations:

- Transformations that produce a new DStream.
- Output operations that write data to an external system.

There are many DStream transformations possible in Spark Streaming. Let us look at filter(*func*). filter(*func*) returns a new DStream by selecting only the records of the source DStream on which *func* returns true.

47. When running Spark applications, is it necessary to install Spark on all the nodes of the YARN cluster?

Ans:

Spark need not be installed when running a job under YARN or Mesos because Spark can execute on top of YARN or Mesos clusters without affecting any change to the cluster.

48. What are the various data sources available in Spark SQL?

Ans:

Parquet file, JSON datasets and Hive tables are the data sources available in Spark SQL.

49. What are the various levels of persistence in Apache Spark?

Ans:

Apache Spark automatically persists the intermediary data from various shuffle operations, however, it is often suggested that users call persist () method on the RDD in case they plan to reuse it. Spark has various persistence levels to store the RDDs on disk or in memory or as a combination of both with different replication levels.

The various storage/persistence levels in Spark are:

- **MEMORY_ONLY:** Store RDD as deserialized Java objects in the JVM. If the RDD does not fit in memory, some partitions will not be cached and will be recomputed on the fly each time they're needed. This is the default level.
- **MEMORY_AND_DISK:** Store RDD as deserialized Java objects in the JVM. If the RDD does not fit in memory, store the partitions that don't fit on disk, and read them from there when they're needed.
- **MEMORY_ONLY_SER:** Store RDD as *serialized* Java objects (one byte array per partition).
- **MEMORY_AND_DISK_SER:** Similar to MEMORY_ONLY_SER, but spill partitions that don't fit in memory to disk instead of recomputing them on the fly each time they're needed.
- **DISK_ONLY:** Store the RDD partitions only on disk.
- **OFF_HEAP:** Similar to MEMORY_ONLY_SER, but store the data in off-heap memory.

50. How Spark uses Akka?

Ans:

Spark uses Akka basically for scheduling. All the workers request for a task to master after registering. The master just assigns the task. Here Spark uses Akka for messaging between the workers and masters.

51. What do you understand by Lazy Evaluation?

Spark is intellectual in the manner in which it operates on data. When you tell Spark to operate on a given dataset, it heeds the instructions and makes a note of it, so that it does not forget – but it does nothing, unless asked for the final result. When a transformation like map*()* is called on an RDD, the operation is not performed immediately. Transformations in Spark are not evaluated till you perform an action. This helps optimize the overall data processing workflow.

52. How is AI executed in Spark?

Ans:

MLlib is an adaptable AI library given by Spark. It goes for making AI simple and adaptable with normal learning calculations and use cases like bunching, relapse separating, dimensional decrease, and alike.

53. What is Spark Executor?

Ans:

At the point when SparkContext associates with a group chief, it obtains an Executor on hubs in the bunch. Representatives are Spark forms that run controls and store the information on the laborer hub. The last assignments by SparkContext are moved to agents for their execution.

54. Name kinds of Cluster Managers in Spark.

Ans:

The Spark system underpins three noteworthy sorts of Cluster Managers:

- **Standalone:** An essential administrator to set up a group.
- **Apache Mesos:** Generalized/regularly utilized group administrator, additionally runs Hadoop MapReduce and different applications.
- **YARN:** Responsible for asset the board in Hadoop.

55. Show some utilization situations where Spark beats Hadoop in preparing.

Ans:

- Sensor Data Processing: Apache Spark's "In-memory" figuring works best here, as information is recovered and joined from various sources.
- Real Time Processing: Spark is favored over Hadoop for constant questioning of information. for example Securities exchange Analysis, Banking, Healthcare, Telecommunications, and so on.
- Stream Processing: For preparing logs and identifying cheats in live streams for cautions, Apache Spark is the best arrangement.
- Big Data Processing: Spark runs upto multiple times quicker than Hadoop with regards to preparing medium and enormous estimated datasets.

56. By what method can Spark be associated with Apache Mesos?

Ans:

To associate Spark with Mesos:

- Configure the sparkle driver program to associate with Mesos.

- Spark paired bundle ought to be in an area open by Mesos.
- Install Apache Spark in a similar area as that of Apache Mesos and design the property ‘spark.mesos.executor.home’ to point to the area where it is introduced.

57. How is Spark SQL not the same as HQL and SQL?

Ans:

Flash SQL is a unique segment on the Spark Core motor that supports SQL and Hive Query Language without changing any sentence structure. It is conceivable to join SQL table and HQL table to Spark SQL.

58. What is ancestry in Spark? How adaptation to internal failure is accomplished in Spark utilizing Lineage Graph?

Ans:

- At whatever point a progression of changes are performed on a RDD, they are not assessed promptly, however languidly.
- At the point when another RDD has been made from a current RDD every one of the conditions between the RDDs will be signed in a diagram.
- This chart is known as the ancestry diagram.
- Consider the underneath situation

Ancestry chart of every one of these activities resembles:

- First RDD
- Second RDD (applying map)
- Third RDD (applying channel)
- Fourth RDD (applying check)

This heredity diagram will be helpful on the off chance that if any of the segments of information is lost.

- Need to set spark.logLineage to be consistent with empowering the Rdd.toDebugString() gets empowered to print the chart logs.

59. What is the contrast between RDD , DataFrame and DataSets?

Ans:

RDD :

- It is the structure square of Spark. All Dataframes or Dataset is inside RDDs.
- It is lethargically assessed permanent gathering objects
- RDDS can be effectively reserved if a similar arrangement of information should be recomputed.

DataFrame :

- Gives the construction see (lines and segments). It tends to be thought of as a table in a database.
- Like RDD even the dataframe is sluggishly assessed.
- It offers colossal execution due to a.) Custom Memory Management – Data is put away in off load memory in twofold arrangement .No refuse accumulation because of this.
- **Optimized Execution Plan –** Query plans are made utilizing Catalyst analyzer.
- **DataFrame Limitations :** Compile Time wellbeing , i.e no control of information is conceivable when the structure isn't known.
- **DataSet :** Expansion of DataFrame
- DataSet Features – Provides best encoding component and not at all like information edges supports arrange time security.

60. What is DStream?

Ans:

- Discretized Stream (DStream)
- Apache Spark Discretized Stream is a gathering of RDDS in grouping .
- Essentially, it speaks to a flood of information or gathering of Rdds separated into little clusters. In addition, DStreams are based on Spark RDDs, Spark's center information reflection. It likewise enables Streaming to flawlessly coordinate with some other Apache Spark segments. For example, Spark MLlib and Spark SQL.

61. What is the connection between Job, Task, Stage ?

Ans:

- **Errand**

  An errand is a unit of work that is sent to the agent. Each stage has some assignment, one undertaking for every segment. The Same assignment is done over various segments of RDD.

- **Occupation**

  The activity is a parallel calculation consisting of numerous undertakings that get produced in light of activities in Apache Spark.

- **Stage**

  Each activity gets isolated into littler arrangements of assignments considered stages that rely upon one another. Stages are named computational limits. All calculation is impossible in a single stage. It is accomplished over numerous stages.

62. Clarify quickly about the parts of Spark Architecture?

Ans:

Flash Driver: The Spark driver is the procedure running the sparkle setting . This driver is in charge of changing over the application to a guided diagram of individual strides to execute on the bunch. There is one driver for each application.

63. How might you limit information moves when working with Spark?

Ans:

- The different manners by which information moves can be limited when working with Apache Spark are:
- Communicate and Accumulator factors

64. When running Spark applications, is it important to introduce Spark on every one of the hubs of YARN group?

Ans:

Flash need not be introduced when running a vocation under YARN or Mesos in light of the fact that Spark can execute over YARN or Mesos bunches without influencing any change to the group.

65. Which one will you decide for an undertaking – Hadoop MapReduce or Apache Spark?

Ans:

The response to this inquiry relies upon the given undertaking situation – as it is realized that Spark utilizes memory rather than system and plate I/O. In any case, Spark utilizes enormous measure of RAM and requires devoted machines to create viable outcomes. So the choice to utilize Hadoop or Spark changes powerfully with the necessities of the venture and spending plan of the association.

66. What is the distinction among continue() and store()

Ans:

endure () enables the client to determine the capacity level while reserve () utilizes the default stockpiling level.

67. What are the different dimensions of constancy in Apache Spark?

Ans:

Apache Spark naturally endures the mediator information from different mix tasks, anyway it is regularly proposed that clients call persevere () technique on the RDD on the off chance that they intend to reuse it. Sparkle has different tirelessness levels to store the RDDs on circle or in memory or as a mix of both with various replication levels.

68. What are the disservices of utilizing Apache Spark over Hadoop MapReduce?

Ans:

Apache Spark's in-memory ability now and again comes a noteworthy barrier for cost effective preparing of huge information. Likewise, Spark has its own record the board framework and consequently should be incorporated with other cloud based information stages or apache hadoop.

69. What is the upside of Spark apathetic assessment?

Ans:

Apache Spark utilizes sluggish assessment all together the advantages:

- Applying Transformations tasks on RDD or "stacking information into RDD" isn't executed quickly until it sees an activity. Changes on RDDs and putting away information in RDD are languidly assessed. Assets will be used in a superior manner if Spark utilizes sluggish assessment.

- Lazy assessment advances the plate and memory utilization in Spark.
- The activities are activated just when the information is required. It diminishes overhead.

70. What are the advantages of Spark over MapReduce?

Ans:

- Because of the accessibility of in-memory handling, Spark executes the preparing around 10 to multiple times quicker than Hadoop MapReduce while MapReduce utilizes diligence stockpiling for any of the information handling errands.
- Dissimilar to Hadoop, Spark gives inbuilt libraries to play out numerous errands from a similar center like cluster preparing, Steaming, Machine learning, Interactive SQL inquiries. Be that as it may, Hadoop just backings cluster handling.
- Hadoop is very plate subordinate while Spark advances reserving and in-memory information stockpiling.

71. How DAG functions in Spark?

Ans:

- At the point when an Action is approached Spark RDD at an abnormal state, Spark presents the heredity chart to the DAG Scheduler.
- Activities are separated into phases of the errand in the DAG Scheduler. A phase contains errands dependent on the parcel of the info information. The DAG scheduler pipelines administrators together. It dispatches tasks through the group chief. The conditions of stages are obscure to the errand scheduler.The Workers execute the undertaking on the slave.

72. What is the hugeness of the Sliding Window task?

Ans:

Sliding Window controls transmission of information bundles between different PC systems. Sparkle Streaming library gives windowed calculations where the changes on RDDs are connected over a sliding window of information. At whatever point the window slides, the RDDs that fall inside the specific window are consolidated and worked upon to create new RDDs of the windowed DStream.

73. What are communicated and Accumulators?

Ans:

- **Communicate variable:**

  On the off chance that we have an enormous dataset, rather than moving a duplicate of informational collection for each assignment, we can utilize a communication variable which can be replicated to every hub at one time and share similar information for each errand in that hub. Communicate variable assistance to give a huge informational collection to every hub.

- **Collector:**

  Flash capacities utilized factors characterized in the driver program and nearby replicated factors will be produced. Aggregators are shared factors which help to refresh factors in parallel during execution and offer the outcomes from specialists to the driver.

74. What are activities ?

Ans:

An activity helps in bringing back the information from RDD to the nearby machine. An activity's execution is the aftereffect of all recently made changes. lessen() is an activity that executes the capacity passed over and over until one esteem assuming left. take() move makes every one of the qualities from RDD to nearby hub.

75. What is YARN?

Ans:

Like Hadoop, YARN is one of the key highlights in Spark, giving a focal and asset the executives stage to convey adaptable activities over the bunch. YARN is a conveyed holder chief, as Mesos for instance, while Spark is an information preparing instrument. Sparkle can keep running on YARN, a similar way Hadoop Map Reduce can keep running on YARN. Running Spark on YARN requires a double dispersion of Spark as based on YARN support.

76. Clarify the key highlights of Apache Spark.

Ans:

Coming up next are the key highlights of Apache Spark:

- Polyglot
- Speed
- Multiple Format Support
- Lazy Evaluation
- Hadoop Integration
- Machine Learning

77. How is Streaming executed in Spark? Clarify with precedents.

Ans:

Sparkle Streaming is utilized for handling constant gushing information. Along these lines it is a helpful expansion into the Spark API. It empowers high-throughput and shortcoming tolerant stream handling of live information streams. The crucial stream unit is DStream which is fundamentally a progression of RDDs (Resilient Distributed Datasets) to process the constant information. The information from various sources like Flume, HDFS is spilled lastly to document frameworks, live

dashboards and databases. It is like a bunch preparing as the information is partitioned into streams like clusters.

78. What are the enhancements that engineers can make while working with flash?

Ans:

- Flash is memory serious, whatever you do it does in memory.
- Initially, you can alter to what extent flash will hold up before it times out on every one of the periods of information region information neighborhood process nearby hub nearby rack neighborhood Any.
- Channel out information as ahead of schedule as could be allowed. For reserving, pick carefully from different capacity levels.
- Tune the quantity of parcels in sparkle.

79. List some use cases where Spark outperforms Hadoop in processing.

Ans:

- Sensor Data Processing: Apache Spark's "In-memory" computing works best here, as data is retrieved and combined from different sources.
- Real Time Processing: Spark is preferred over Hadoop for real-time querying of data. e.g. Stock Market Analysis, Banking, Healthcare, Telecommunications, etc.
- Stream Processing: For processing logs and detecting frauds in live streams for alerts, Apache Spark is the best solution.
- Big Data Processing: Spark runs upto 100 times faster than Hadoop when it comes to processing medium and large-sized datasets.

80. What is a Data Frame?

Ans:

An information casing resembles a table, it got some named sections which are composed into segments. You can make an information outline from a document or from tables in hive, outside databases SQL or NoSQL or existing RDD's. It is practically equivalent to a table.

81. How might you associate Hive to Spark SQL?

Ans:

- The principal significant thing is that you need to place the hive-site.xml record in the conf index of Spark.
- At that point with the assistance of Spark session object we can develop an information outline as,

82. What is GraphX?

Ans:

- Ordinarily you need to process the information as charts, since you need to do some examination on it. It endeavors to perform Graph calculation in Spark in which information is available in documents or in RDD's.
- GraphX is based on the highest point of Spark center, so it has got every one of the abilities of Apache Spark like adaptation to internal failure, scaling and there are numerous inbuilt chart calculations too. GraphX binds together ETL, exploratory investigation and iterative diagram calculation inside a solitary framework.
- You can see indistinguishable information from the two charts and accumulations, change and unite diagrams with RDD effectively and compose custom iterative calculations utilizing the pregel API.
- GraphX contends on execution with the quickest diagram frameworks while holding Spark's adaptability, adaptation to internal failure and convenience.

1) What are the advantages of using Apache Spark over Hadoop MapReduce for big data processing?

Simplicity, Flexibility and Performance are the major advantages of using Spark over Hadoop.

- Spark is 100 times faster than Hadoop for big data processing as it stores the data in-memory, by placing it in Resilient Distributed Databases (RDD).
- Spark is easier to program as it comes with an interactive mode.
- It provides complete recovery using lineage graph whenever something goes wrong.

2) What is Shark?

Most of the data users know only SQL and are not good at programming. Shark is a tool, developed for people who are from a database background - to access Scala MLib capabilities through Hive like SQL interface. Shark tool helps data users run Hive on Spark - offering compatibility with Hive metastore, queries and data.

3) List some use cases where Spark outperforms Hadoop in processing.

i. Sensor Data Processing –Apache Spark's 'In-memory computing' works best here, as data is retrieved and combined from different sources.

ii. Spark is preferred over Hadoop for real time querying of data

iii. Stream Processing – For processing logs and detecting frauds in live streams for alerts, Apache Spark is the best solution.

4) What is a Sparse Vector?

A sparse vector has two parallel arrays –one for indices and the other for values. These vectors are used for storing non-zero entries to save space.

5) What is RDD?

RDDs (Resilient Distributed Datasets) are basic abstraction in Apache Spark that represent the data coming into the system in object format. RDDs are used for in-memory computations on large clusters, in a fault tolerant manner. RDDs are read-only portioned, collection of records, that are –

- Immutable – RDDs cannot be altered.
- Resilient – If a node holding the partition fails the other node takes the data.

6) Explain about transformations and actions in the context of RDDs.

Transformations are functions executed on demand, to produce a new RDD. All transformations are followed by actions. Some examples of transformations include map, filter and reduceByKey.

Actions are the results of RDD computations or transformations. After an action is performed, the data from RDD moves back to the local machine. Some examples of actions include reduce, collect, first, and take.

7) What are the languages supported by Apache Spark for developing big data applications?

Scala, Java, Python, R and Clojure

8) Can you use Spark to access and analyse data stored in Cassandra databases?

Yes, it is possible if you use Spark Cassandra Connector.

9) Is it possible to run Apache Spark on Apache Mesos?
Yes, Apache Spark can be run on the hardware clusters managed by Mesos.

10) Explain about the different cluster managers in Apache Spark
The 3 different clusters managers supported in Apache Spark are:

- YARN
- Apache Mesos -Has rich resource scheduling capabilities and is well suited to run Spark along with other applications. It is advantageous when several users run interactive shells because it scales down the CPU allocation between commands.
- Standalone deployments – Well suited for new deployments which only run and are easy to set up.

11) How can Spark be connected to Apache Mesos?
To connect Spark with Mesos-

- Configure the spark driver program to connect to Mesos. Spark binary package should be in a location accessible by Mesos. (or)
- Install Apache Spark in the same location as that of Apache Mesos and configure the property 'spark.mesos.executor.home' to point to the location where it is installed.

12) How can you minimize data transfers when working with Spark?
Minimizing data transfers and avoiding shuffling helps write spark programs that run in a fast and reliable manner. The various ways in which data transfers can be minimized when working with Apache Spark are:

1. Using Broadcast Variable- Broadcast variable enhances the efficiency of joins between small and large RDDs.
2. Using Accumulators – Accumulators help update the values of variables in parallel while executing.
3. The most common way is to avoid operations ByKey, repartition or any other operations which trigger shuffles.

13) Why is there a need for broadcast variables when working with Apache Spark?
These are read only variables, present in-memory cache on every machine. When working with Spark, usage of broadcast variables eliminates the necessity to ship copies of a variable for every task, so data can be processed faster. Broadcast variables help in storing a lookup table inside the memory which enhances the retrieval efficiency when compared to an RDD lookup ().

14) Is it possible to run Spark and Mesos along with Hadoop?
Yes, it is possible to run Spark and Mesos with Hadoop by launching each of these as a separate service on the machines. Mesos acts as a unified scheduler that assigns tasks to either Spark or Hadoop.

15) What is lineage graph?
The RDDs in Spark, depend on one or more other RDDs. The representation of dependencies in between RDDs is known as the lineage graph. Lineage graph information is used to compute each RDD on demand, so that whenever a part of persistent RDD is lost, the data that is lost can be recovered using the lineage graph information.

16) How can you trigger automatic clean-ups in Spark to handle accumulated metadata?
You can trigger the clean-ups by setting the parameter 'spark.cleaner.ttl' or by dividing the long running jobs into different batches and writing the intermediary results to the disk.

17) Explain about the major libraries that constitute the Spark Ecosystem

- **Spark MLib**- Machine learning library in Spark for commonly used learning algorithms like clustering, regression, classification, etc.
- **Spark Streaming** – This library is used to process real time streaming data.
- **Spark GraphX** – Spark API for graph parallel computations with basic operators like joinVertices, subgraph, aggregateMessages, etc.
- **Spark SQL** – Helps execute SQL like queries on Spark data using standard visualization or BI tools.

18) What are the benefits of using Spark with Apache Mesos?
It renders scalable partitioning among various Spark instances and dynamic partitioning between Spark and other big data frameworks.

19) What is the significance of Sliding Window operation?
Sliding Window controls transmission of data packets between various computer networks. Spark Streaming library provides windowed computations where the transformations on RDDs are applied over a sliding window of data. Whenever the window slides, the RDDs that fall within the particular window are combined and operated upon to produce new RDDs of the windowed DStream.

20) What is a DStream?
Discretized Stream is a sequence of Resilient Distributed Databases that represent a stream of data. DStreams can be created from various sources like Apache Kafka, HDFS, and Apache Flume. DStreams have two operations –

- Transformations that produce a new DStream.
- Output operations that write data to an external system.

21) When running Spark applications, is it necessary to install Spark on all the nodes of YARN cluster?
Spark need not be installed when running a job under YARN or Mesos because Spark can execute on top of YARN or Mesos clusters without affecting any change to the cluster.

22) What is Catalyst framework?
Catalyst framework is a new optimization framework present in Spark SQL. It allows Spark to automatically transform SQL queries by adding new optimizations to build a faster processing system.

23) Name a few companies that use Apache Spark in production.
Pinterest, Conviva, Shopify, Open Table

24) Which spark library allows reliable file sharing at memory speed across different cluster frameworks?
Tachyon

25) Why is BlinkDB used?
BlinkDB is a query engine for executing interactive SQL queries on huge volumes of data and renders query results marked with meaningful error bars. BlinkDB helps users balance 'query accuracy' with response time.

26) How can you compare Hadoop and Spark in terms of ease of use?

Hadoop MapReduce requires programming in Java which is difficult, though Pig and Hive make it considerably easier. Learning Pig and Hive syntax takes time. Spark has interactive APIs for different languages like Java, Python or Scala and also includes Shark i.e. Spark SQL for SQL lovers - making it comparatively easier to use than Hadoop.

27) What are the common mistakes developers make when running Spark applications?
Developers often make the mistake of-

- Hitting the web service several times by using multiple clusters.
- Run everything on the local node instead of distributing it.

Developers need to be careful with this, as Spark makes use of memory for processing.

28) What is the advantage of a Parquet file?
Parquet file is a columnar format file that helps –

- Limit I/O operations
- Consumes less space
- Fetches only required columns.

29) What are the various data sources available in SparkSQL?

- Parquet file
- JSON Datasets
- Hive tables

30) How Spark uses Hadoop?
Spark has its own cluster management computation and mainly uses Hadoop for storage.

For the complete list of big data companies and their salaries-

31) What are the key features of Apache Spark that you like?

- Spark provides advanced analytic options like graph algorithms, machine learning, streaming data, etc
- It has built-in APIs in multiple languages like Java, Scala, Python and R
- It has good performance gains, as it helps run an application in the Hadoop cluster ten times faster on disk and 100 times faster in memory.

32) What do you understand by Pair RDD?
Special operations can be performed on RDDs in Spark using key/value pairs and such RDDs are referred to as Pair RDDs. Pair RDDs allow users to access each key in parallel. They have a reduceByKey () method that collects data based on each key and a join () method that combines different RDDs together, based on the elements having the same key.

33) Which one will you choose for a project –Hadoop MapReduce or Apache Spark?
The answer to this question depends on the given project scenario - as it is known that Spark makes use of memory instead of network and disk I/O. However, Spark uses large amount of RAM and requires dedicated machine to produce effective results. So the decision to use Hadoop or Spark varies dynamically with the requirements of the project and budget of the organization.

34) Explain about the different types of transformations on DStreams?

- Stateless Transformations- Processing of the batch does not depend on the output of the previous batch. Examples – map (), reduceByKey (), filter ().
- Stateful Transformations- Processing of the batch depends on the intermediary results of the previous batch. Examples –Transformations that depend on sliding windows.

35) Explain about the popular use cases of Apache Spark

Apache Spark is mainly used for

- Iterative machine learning.
- Interactive data analytics and processing.
- Stream processing
- Sensor data processing

36) Is Apache Spark a good fit for Reinforcement learning?

No. Apache Spark works well only for simple machine learning algorithms like clustering, regression, classification.

37) What is Spark Core?

It has all the basic functionalities of Spark, like - memory management, fault recovery, interacting with storage systems, scheduling tasks, etc.

38) How can you remove the elements with a key present in any other RDD?

Use the subtractByKey () function

39) What is the difference between persist() and cache()

persist () allows the user to specify the storage level whereas cache () uses the default storage level.

40) What are the various levels of persistence in Apache Spark?

Apache Spark automatically persists the intermediary data from various shuffle operations, however it is often suggested that users call persist () method on the RDD in case they plan to reuse it. Spark has various persistence levels to store the RDDs on disk or in memory or as a combination of both with different replication levels.

The various storage/persistence levels in Spark are -

- MEMORY_ONLY
- MEMORY_ONLY_SER
- MEMORY_AND_DISK
- MEMORY_AND_DISK_SER, DISK_ONLY
- OFF_HEAP

41) How Spark handles monitoring and logging in Standalone mode?

Spark has a web based user interface for monitoring the cluster in standalone mode that shows the cluster and job statistics. The log output for each job is written to the work directory of the slave nodes.

42) Does Apache Spark provide check pointing?

Lineage graphs are always useful to recover RDDs from a failure but this is generally time consuming if the RDDs have long lineage chains. Spark has an API for check pointing i.e. a REPLICATE flag to persist. However, the decision on which data to checkpoint - is decided by the user. Checkpoints are useful when the lineage graphs are long and have wide dependencies.

43) How can you launch Spark jobs inside Hadoop MapReduce?

Using SIMR (Spark in MapReduce) users can run any spark job inside MapReduce without requiring any admin rights.

44) How Spark uses Akka?

Spark uses Akka basically for scheduling. All the workers request for a task to master after registering. The master just assigns the task. Here Spark uses Akka for messaging between the workers and masters.

45) How can you achieve high availability in Apache Spark?

- Implementing single node recovery with local file system
- Using StandBy Masters with Apache ZooKeeper.

46) Hadoop uses replication to achieve fault tolerance. How is this achieved in Apache Spark?

Data storage model in Apache Spark is based on RDDs. RDDs help achieve fault tolerance through lineage. RDD always has the information on how to build from other datasets. If any partition of a RDD is lost due to failure, lineage helps build only that particular lost partition.

47) Explain about the core components of a distributed Spark application.

- Driver- The process that runs the main () method of the program to create RDDs and perform transformations and actions on them.
- Executor –The worker processes that run the individual tasks of a Spark job.
- Cluster Manager-A pluggable component in Spark, to launch Executors and Drivers. The cluster manager allows Spark to run on top of other external managers like Apache Mesos or YARN.

48) What do you understand by Lazy Evaluation?

Spark is intellectual in the manner in which it operates on data. When you tell Spark to operate on a given dataset, it heeds the instructions and makes a note of it, so that it does not forget - but it does nothing, unless asked for the final result. When a transformation like map () is called on a RDD-the operation is not performed immediately. Transformations in Spark are not evaluated till you perform an action. This helps optimize the overall data processing workflow.

49) Define a worker node.

A node that can run the Spark application code in a cluster can be called as a worker node. A worker node can have more than one worker which is configured by setting the SPARK_ WORKER_INSTANCES property in the spark-env.sh file. Only one worker is started if the SPARK_ WORKER_INSTANCES property is not defined.

50) What do you understand by SchemaRDD?

An RDD that consists of row objects (wrappers around basic string or integer arrays) with schema information about the type of data in each column.

We invite the big data community to share the most frequently asked Apache Spark Interview questions and answers, in the comments below - to ease big data job interviews for all prospective analytics professionals.

Top Answers to Spark Interview Questions

Get Ready to Nail Your Spark Interview

1.What is Apache Spark?

Spark is a fast, easy-to-use and flexible data processing framework. It has an advanced execution engine supporting cyclic data flow and in-memory computing. Spark can run on Hadoop, standalone or in the cloud and is capable of accessing diverse data sources including HDFS, HBase, Cassandra and others. Learn more in this Apache Spark Tutorial .

2.Explain key features of Spark.

• Allows Integration with Hadoop and files included in HDFS.
• Spark has an interactive language shell as it has an independent Scala (the language in which Spark is written) interpreter
• Spark consists of RDD's (Resilient Distributed Datasets), which can be cached across computing nodes in a cluster.
• Spark supports multiple analytic tools that are used for interactive query analysis , real-time analysis and graph processing

3.Define RDD.

RDD is the acronym for Resilient Distribution Datasets – a fault-tolerant collection of operational elements that run parallel. The partitioned data in RDD is immutable and distributed. There are primarily two types of RDD:
• Parallelized Collections : The existing RDD's running parallel with one another
• Hadoop datasets: perform function on each file record in HDFS or other storage system

4.What does a Spark Engine do?

Spark Engine is responsible for scheduling, distributing and monitoring the data application across the cluster.

5.Define Partitions?

As the name suggests, partition is a smaller and logical division of data similar to 'split' in MapReduce. Partitioning is the process to derive logical units of data to speed up the processing process. Everything in Spark is a partitioned RDD.

Are you interested in learning Apache Spark? Well, find out more in this comprehensive Apache Spark Course to give your career a head start.

6.What operations RDD support?

• Transformations
• Actions

7.What do you understand by Transformations in Spark?

Transformations are functions applied on RDD, resulting into another RDD. It does not execute until an action occurs. map() and filer() are examples of transformations, where the former applies the function passed to it on each element of RDD and results into another RDD. The filter() creates a new RDD by selecting elements form current RDD that pass function argument.

8. Define Actions.

An action helps in bringing back the data from RDD to the local machine. An action's execution is the result of all previously created transformations. reduce() is an action that implements the function passed again and again until one value if left. take() action takes all the values from RDD to local node.

9.Define functions of SparkCore.

Serving as the base engine, SparkCore performs various important functions like memory management, monitoring jobs, fault-tolerance, job scheduling and interaction with storage systems.

10.What is RDD Lineage?

Spark does not support data replication in the memory and thus, if any data is lost, it is rebuild using RDD lineage. RDD lineage is a process that reconstructs lost data partitions. The best is that RDD always remembers how to build from other datasets.

11.What is Spark Driver?

Spark Driver is the program that runs on the master node of the machine and declares transformations and actions on data RDDs. In simple terms, driver in Spark creates SparkContext, connected to a given Spark Master.
The driver also delivers the RDD graphs to Master, where the standalone cluster manager runs.

Are you interested in the comprehensive Apache Spark and Scala Videos to take your career to the next level?

12.What is Hive on Spark?

Hive contains significant support for Apache Spark, wherein Hive execution is configured to Spark:

```
hive> set spark.home=/location/to/sparkHome;
hive> set hive.execution.engine=spark;
```

Hive on Spark supports Spark on yarn mode by default.

13.Name commonly-used Spark Ecosystems.

- Spark SQL (Shark)- for developers
- Spark Streaming for processing live data streams
- GraphX for generating and computing graphs
- MLlib (Machine Learning Algorithms)
- SparkR to promote R Programming in Spark engine.

14.Define Spark Streaming.

Spark supports stream processing – an extension to the Spark API , allowing stream processing of live data streams. The data from different sources like Flume, HDFS is streamed and finally processed to file systems, live dashboards and databases. It is similar to batch processing as the input data is divided into streams like batches.

Learn about the Top Four Apache Spark use cases in this blog post.

15.What is GraphX?

Spark uses GraphX for graph processing to build and transform interactive graphs. The GraphX component enables programmers to reason about structured data at scale.

16.What does MLlib do?

MLlib is scalable machine learning library provided by Spark. It aims at making machine learning easy and scalable with common learning algorithms and use cases like clustering, regression filtering, dimensional reduction, and alike.

Our in-depth Scala Certification Course can give your career a big boost!

17.What is Spark SQL?

SQL Spark, better known as Shark is a novel module introduced in Spark to work with structured data and perform structured data processing. Through this module, Spark executes relational SQL queries on the data. The core of the component supports an altogether different RDD called SchemaRDD, composed of rows objects and schema objects defining data type of each column in the row. It is similar to a table in relational database.

18.What is a Parquet file?

Parquet is a columnar format file supported by many other data processing systems. Spark SQL performs both read and write operations with Parquet file and consider it be one of the best big data analytics format so far.

19.What file systems Spark support?

• Hadoop Distributed File System (HDFS). Learn more about HDFS in these Top Interview questions.
• Local File system
• S3

20.What is Yarn?

Similar to Hadoop, Yarn is one of the key features in Spark, providing a central and resource management platform to deliver scalable operations across the cluster . Running Spark on Yarn necessitates a binary distribution of Spar as built on Yarn support.

21.List the functions of Spark SQL.

Spark SQL is capable of:
• Loading data from a variety of structured sources
• Querying data using SQL statements, both inside a Spark program and from external tools that connect to Spark SQL through standard database connectors (JDBC/ODBC). For instance, using business intelligence tools like Tableau. Get to know more about Tableau in this Tableau Tutorial.
• Providing rich integration between SQL and regular Python/Java/Scala code, including the ability to join RDDs and SQL tables, expose custom functions in SQL, and more.

22.What are benefits of Spark over MapReduce?

• Due to the availability of in-memory processing, Spark implements the processing around 10-100x faster than Hadoop MapReduce. MapReduce makes use of persistence storage for any of the data processing tasks.
• Unlike Hadoop, Spark provides in-built libraries to perform multiple tasks form the same core like batch processing, Steaming, Machine learning, Interactive SQL queries. However, Hadoop only supports batch processing.
• Hadoop is highly disk-dependent whereas Spark promotes caching and in-memory data storage
• Spark is capable of performing computations multiple times on the same dataset. This is called iterative computation while there is no iterative computing implemented by Hadoop.
Read more in this blog about the comparison of Spark and MapReduce.

23.Is there any benefit of learning MapReduce, then?

Yes, MapReduce is a paradigm used by many big data tools including Spark as well. It is extremely relevant to use MapReduce when the data grows bigger and bigger. Most tools like Pig and Hive convert their queries into MapReduce phases to optimize them better. Learn more in this MapReduce Tutorial.

24.What is Spark Executor?

When SparkContext connect to a cluster manager, it acquires an Executor on nodes in the cluster. Executors are Spark processes that run computations and store the data on the worker node. The final tasks by SparkContext are transferred to executors for their execution.

25.Name types of Cluster Managers in Spark.

The Spark framework supports three major types of Cluster Managers:
• Standalone: a basic manager to set up a cluster
• Apache Mesos: generalized/commonly-used cluster manager, also runs Hadoop

MapReduce and other applications

• Yarn: responsible for resource management in Hadoop

26.What do you understand by worker node?

Worker node refers to any node that can run the application code in a cluster.

27.What is PageRank?

A unique feature and algorithm in graph, PageRank is the measure of each vertex in the graph. For instance, an edge from u to v represents endorsement of v's importance by u. In simple terms, if a user at Instagram is followed massively, it will rank high on that platform.

28.Do you need to install Spark on all nodes of Yarn cluster while running Spark on Yarn?

No because Spark runs on top of Yarn.

29.Illustrate some demerits of using Spark.

Since Spark utilizes more storage space compared to Hadoop and MapReduce, there may arise certain problems. Developers need to be careful while running their applications in Spark. Instead of running everything on a single node, the work must be distributed over multiple clusters.

30.How to create RDD?

Spark provides two methods to create RDD:• By parallelizing a collection in your Driver program. This makes use of SparkContext's 'parallelize' methodval IntellipaatData = Array(2,4,6,8,10)
val distIntellipaatData = sc.parallelize(IntellipaatData)• By loading an external dataset from external storage like HDFS, HBase, shared file system.

1. What is Apache Spark?

Wikipedia defines Apache Spark "an open source cluster computing framework originally developed in the AMPLab at University of California, Berkeley but was later donated to the Apache Software Foundation where it remains today. In contrast to Hadoop's two-stage disk-based MapReduce paradigm, Spark's multi-stage in-memory primitives provides performance up to 100 times faster for certain applications. By allowing user programs to load data into a cluster's memory and query it repeatedly, Spark is well-suited to machine learning algorithms."

Spark is essentially a fast and flexible data processing framework. It has an advanced execution engine supporting cyclic data flow with in-memory computing functionalities. Apache Spark can run on Hadoop, as a standalone system or on the cloud. Spark is capable of accessing diverse data sources including HDFS, HBase, Cassandra among others

2. Explain the key features of Spark.

• Spark allows Integration with Hadoop and files included in HDFS.

• It has an independent language (Scala) interpreter and hence comes with an interactive language shell.

• It consists of RDD's (Resilient Distributed Datasets), that can be cached across computing nodes in a cluster.

• It supports multiple analytic tools that are used for interactive query analysis, real-time analysis and graph processing. Additionally, some of the salient features of Spark include:

Lighting fast processing: When it comes to Big Data processing, speed always matters, and Spark runs Hadoop clusters way faster than others. Spark makes this possible by reducing the number of read/write operations to the disc. It stores this intermediate processing data in memory.

Support for sophisticated analytics: In addition to simple "map" and "reduce" operations, Spark supports SQL queries, streaming data, and complex analytics such as machine learning and graph algorithms. This allows users to combine all these capabilities in a single workflow.

Real-time stream processing: Spark can handle real-time streaming. MapReduce primarily handles and processes previously stored data even though there are other frameworks to obtain real-time streaming. Spark does this in the best way possible.

3. What is "RDD"?

RDD stands for Resilient Distribution Datasets: a collection of fault-tolerant operational elements that run in parallel. The partitioned data in RDD is immutable and is distributed in nature.

4. How does one create RDDs in Spark?

In Spark, parallelized collections are created by calling the SparkContext "parallelize" method on an existing collection in your driver program.

```
val data = Array(4,6,7,8)
val distData = sc.parallelize(data)
```

Text file RDDs can be created using SparkContext's "textFile" method. Spark has the ability to create distributed datasets from any storage source supported by Hadoop, including your local file system, HDFS, Cassandra, HBase, Amazon S3, among others. Spark supports text files, "SequenceFiles", and any other Hadoop "InputFormat" components.

```
val inputfile = sc.textFile("input.txt")
```

5. What does the Spark Engine do?

Spark Engine is responsible for scheduling, distributing and monitoring the data application across the cluster.

6. Define "Partitions".

A "Partition" is a smaller and logical division of data, that is similar to the "split" in Map Reduce. Partitioning is the process that helps derive logical units of data in order to speed up data processing.

Here's an example: `val someRDD = sc.parallelize( 1 to 100, 4)`

Here an RDD of 100 elements is created in four partitions, which then distributes a dummy map task before collecting the elements back to the driver program.

7. What operations does the "RDD" support?

- Transformations
- Actions

8. Define "Transformations" in Spark.

"Transformations" are functions applied on RDD, resulting in a new RDD. It does not execute until an action occurs. *map*() and *filer*() are examples of "transformations", where the former applies the function assigned to it on each element of the RDD and results in another RDD. The *filter*() creates a new RDD by selecting elements from the current RDD.

9. Define "Action" in Spark.

An "action" helps in bringing back the data from the RDD to the local machine. Execution of "action" is the result of all transformations created previously. *reduce*() is an action that implements the function passed again and again

until only one value is left. On the other hand, the *take*() action takes all the values from the RDD to the local node.

10. What are the functions of "Spark Core"?

The "SparkCore" performs an array of critical functions like memory management, monitoring jobs, fault tolerance, job scheduling and interaction with storage systems.

It is the foundation of the overall project. It provides distributed task dispatching, scheduling, and basic input and output functionalities. RDD in Spark Core makes it fault tolerance. RDD is a collection of items distributed across many nodes that can be manipulated in parallel. Spark Core provides many APIs for building and manipulating these collections.

11. What is an "RDD Lineage"?

Spark does not support data replication in the memory. In the event of any data loss, it is rebuilt using the "RDD Lineage". It is a process that reconstructs lost data partitions.

12. What is a "Spark Driver"?

"Spark Driver" is the program that runs on the master node of the machine and declares transformations and actions on data RDDs. The driver also delivers RDD graphs to the "Master", where the standalone cluster manager runs.

13. What is SparkContext?

"SparkContext" is the main entry point for Spark functionality. A "SparkContext" represents the connection to a Spark cluster, and can be used to create RDDs, accumulators and broadcast variables on that cluster.

14. What is Hive on Spark?

Hive is a component of Hortonworks' Data Platform (HDP). Hive provides an SQL-like interface to data stored in the HDP. Spark users will automatically get the complete set of Hive's rich features, including any new features that Hive might introduce in the future.

The main task around implementing the Spark execution engine for Hive lies in query planning, where Hive operator plans from the semantic analyzer which is translated to a task plan that Spark can execute. It also includes query execution, where the generated Spark plan gets actually executed in the Spark cluster.

15. Name a few commonly used Spark Ecosystems.

- Spark SQL (Shark)
- Spark Streaming
- GraphX
- MLlib
- SparkR

16. What is "Spark Streaming"?

Spark supports stream processing, essentially an extension to the Spark API. This allows stream processing of live data streams. The data from different sources like Flume and HDFS is streamed and processed to file systems, live dashboards and databases. It is similar to batch processing as the input data is divided into streams like batches.

Business use cases for Spark streaming: Each Spark component has its own use case. Whenever you want to analyze data with the latency of less than 15 minutes and greater than 2 minutes i.e. near real time is when you use Spark streaming

17. What is “GraphX” in Spark?

“GraphX” is a component in Spark which is used for graph processing. It helps to build and transform interactive graphs.

18. What is the function of “MLlib”?

“MLlib” is Spark’s machine learning library. It aims at making machine learning easy and scalable with common learning algorithms and real-life use cases including clustering, regression filtering, and dimensional reduction among others.

19. What is “Spark SQL”?

Spark SQL is a Spark interface to work with structured as well as semi-structured data. It has the capability to load data from multiple structured sources like “textfiles”, JSON files, Parquet files, among others. Spark SQL provides a special type of RDD called SchemaRDD. These are row objects, where each object represents a record.

Here’s how you can create an SQL context in Spark SQL:

```
SQL context: scala> var sqlContext=new SqlContext
HiveContext: scala> var hc = new HIVEContext(sc)
```

20. What is a “Parquet” in Spark?

“Parquet” is a columnar format file supported by many data processing systems. Spark SQL performs both read and write operations with the “Parquet” file.

21. What is an “Accumulator”?

“Accumulators” are Spark’s offline debuggers. Similar to “Hadoop Counters”, “Accumulators” provide the number of “events” in a program.

Accumulators are the variables that can be added through associative operations. Spark natively supports accumulators of numeric value types and standard mutable collections. “AggregrateByKey()” and “combineByKey()” uses accumulators.

22. Which file systems does Spark support?

- Hadoop Distributed File System (HDFS)
- Local File system
- S3

23. What is “YARN”?

“YARN” is a large-scale, distributed operating system for big data applications. It is one of the key features of Spark, providing a central and resource management platform to deliver scalable operations across the cluster.

24. List the benefits of Spark over MapReduce.

- Due to the availability of in-memory processing, Spark implements the processing around 10-100x faster than Hadoop MapReduce.
- Unlike MapReduce, Spark provides in-built libraries to perform multiple tasks form the same core; like batch processing, steaming, machine learning, interactive SQL queries among others.
- MapReduce is highly disk-dependent whereas Spark promotes caching and in-memory data storage
- Spark is capable of iterative computation while MapReduce is not.

Additionally, Spark stores data in-memory whereas Hadoop stores data on the disk. Hadoop uses replication to achieve fault tolerance while Spark uses a different data storage model, resilient distributed datasets (RDD). It also uses a clever way of guaranteeing fault tolerance that minimizes network input and output.

25. What is a "Spark Executor"?

When "SparkContext" connects to a cluster manager, it acquires an "Executor" on the cluster nodes. "Executors" are Spark processes that run computations and store the data on the worker node. The final tasks by "SparkContext" are transferred to executors.

26. List the various types of "Cluster Managers" in Spark.

The Spark framework supports three kinds of Cluster Managers:

- Standalone
- Apache Mesos
- YARN

27. What is a "worker node"?

"Worker node" refers to any node that can run the application code in a cluster.

28. Define "PageRank".

"PageRank" is the measure of each vertex in a graph.

29. Can we do real-time processing using Spark SQL?

Not directly but we can register an existing RDD as a SQL table and trigger SQL queries on top of that.

30. What is the biggest shortcoming of Spark?

Spark utilizes more storage space compared to Hadoop and MapReduce.

Also, Spark streaming is not actually streaming, in the sense that some of the window functions cannot properly work on top of micro batching.

Got a question for us? Please mention it in the comments section and we will get back to you.

1) What is Apache Spark ?

It is a cluster computing platform designed for general and fast purposes.Spark is essentially a fast and flexible data processing framework. It has a capable of getting data from hdfs,hbase,cassandra and others.It has an advanced execution engine supporting cyclic data flow with in-memory computing functionalities

2) What are the features of Apache Spark?

- In-Memory Computation
- RDD (Resilient Distributed Dataset)
- Supports many languages
- Integration with Hadoop
- fast processing
- Real time stream processing

3) What is RDD ?

RDD (Resilient Distrubution Datasets) : Collection of objects that runs in parallel.Partitions data in RDD is immutable and is distributed in nature.

4) What operations does the Apache Spark RDD support ?

- Transformations
- Actions

Transformations are two types

1. Narrow Transformation
2. Wide transformation

5) Define Transformations in Apache Spark ?

"Transformations" are functions applied on RDD, gives a new RDD. Transformations does not execute until an action occurs.

map() and ***filer***() are examples of "transformations".The ***filter***() creates a new RDD by selecting elements from the current RDD.

Apache Spark interview questions

6) Define Actions in Apache Spark ?

"Action" take back the data from the RDD to the local machine. Execution of "action" is the result of all transformations created previously. ***fold***() is an action that implements the function passed again and again until only one value is left.

Apache Spark interview questions

Apache Spark interview questions and answers for Experienced and Freshers

7) What are the commonly used Ecosystems in Apache Spark ?

- *Spark Streaming*
- ***Spark Sql***
- *Spark Mllib*
- *Spark graphx*

8) What is Spark Core ?

SparkCore performs memory management, monitoring jobs, fault tolerance, job scheduling and interaction with storage systems.

RDD in Spark Core makes it fault tolerance. RDD is a collection of items distributed across many nodes that can be manipulated in parallel.

Apache Spark interview questions

9) What is Spark SQL ?

Spark SQL is a Spark module for structured data processing.Spark SQL is almost similar to SQL and it supports also Hive Query Language.There are several ways to interact with Spark SQL including SQL, the DataFrames API and the Datasets API.

10) What is Spark Streaming ?

Spark Streaming allows stream processing of live data streams.Data can be ingested from many sources like Kafka, Flume, Twitter, ZeroMQ, Kinesis, or TCP sockets, and can be processed using complex algorithms expressed with high-level functions like `map`,`reduce`, `join` and `window`. Finally, processed data can be pushed out to filesystems, databases, and live dashboards.

Apache Spark interview questions

11) What is Spark Graphx ?

Spark GraphX is a component in Spark which is used for graph processing (Social Media Friends Recommendation).

12) What is Spark MLlib ?

Spark MLlib is supporting for Machine Learning Algorithms before Spark MLlib hadoop using Apache Mahout for Machine Leaning Algorithms.It consists of common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, as well as lower-level optimization primitives and higher-level pipeline APIs.Machine Learning Algorithms are mainly used for predictions,Recommendations and other purposes.

13) Which File System does Apache Spark support ?

Spark can create distributed datasets from any storage source supported by**Hadoop**, including your local file system, **HDFS**, Cassandra, HBase, Amazon S3, etc.

14) What are the cluster modes in Apache Spark ?

The Spark framework supports three kinds of Cluster Managers:

- *Standalone*
- *Apache Mesos*
- *YARN*

15) What is Hadoop Yarn ?

Yarn means yet another resource negotiator.Yarn is a cluster Management technology.It introduced from Hadoop 2.X version.Yarn mainly used for reduce the burden on Mapreduce.

Apache Spark interview questions

16)What is Apache Mesos ?

Apache Mesos is one of the cluster Management technology like Yarn.It “provides efficient resource isolation and sharing across distributed applications, or frameworks”.

17) What is Standalone Mode ?

Spark Cluster can also be run with out support of Yarn and Apache Mesos or any other cluster Manager.Spark can run itself called Standalone Mode.

18) What is a Apache Spark Executor ?

When “SparkContext” connects to a cluster manager, it acquires an “Executor” on the cluster nodes. “Executors” are Spark processes that run computations and store the data on the worker node. The final tasks by “SparkContext” are transferred to executors.

19) What is a Apache Spark Work Node ?

Spark Work Node is a slave node.“Worker node” refers to any node that can run the application code in a cluster.

20) How does create a spark RDD ?

We can create a RDD in 2 ways

i) parallelize

ii) textFile

val a= Array(4,6,7,8)

val b= sc.parallelize(a)

val input = sc.textFile(“input.txt”);

Apache Spark interview questions

21) What does the Spark Engine Do ?

Spark Engine is responsible for scheduling, distributing and monitoring the data application across the cluster.

22) What is RDD Partitions ?

A “Partition” is a smaller and logical division of data, that is similar to the “split” in Map Reduce. Partitioning is the process that helps derive logical units of data in order to speed up data processing.

Here’s an example: val someRDD = sc.parallelize(1 to 100, 4)

In the above example 4 Mention the number of Partitions in RDD

23) Apache Spark Supported File Formates ?

What is Spark?

Spark is a parallel data processing framework. It allows to develop fast, unified big data application combine batch, streaming and interactive analytics.

Why Spark?

Spark is third generation distributed data processing platform. It's unified bigdata solution for all bigdata processing problems such as batch , interacting, streaming processing.So it can ease many bigdata problems.

What is RDD?
Spark's primary core abstraction is called Resilient Distributed Datasets. RDD is a collection of partitioned data that satisfies these properties. Immutable, distributed, lazily evaluated, catchable are common RDD properties.

What is Immutable?
Once created and assign a value, it's not possible to change, this property is called Immutability. Spark is by default immutable, it's not allows updates and modifications. Please note data collection is not immutable, but data value is immutable.

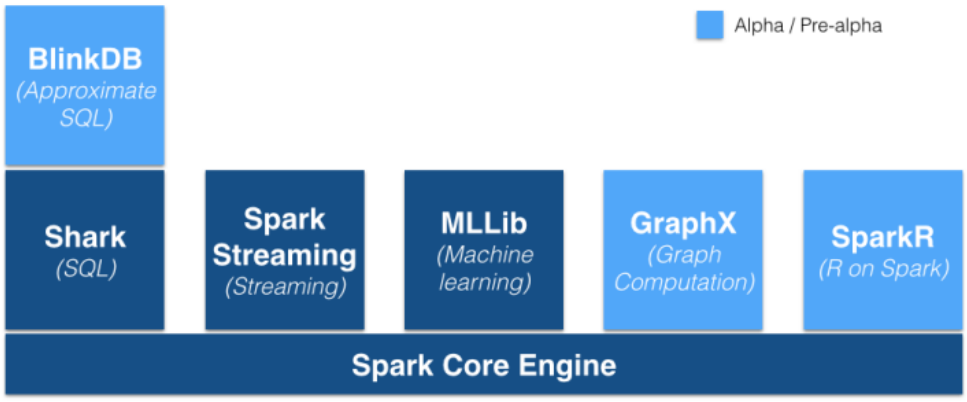
What is Distributed?
RDD can automatically the data is distributed across different parallel computing nodes.

What is Lazy evaluated?
If you execute a bunch of program, it's not mandatory to evaluate immediately. Especially in Transformations, this Laziness is trigger.

What is Catchable?
keep all the data in-memory for computation, rather than going to the disk. So Spark can catch the data 100 times faster than Hadoop.

What is Spark engine responsibility?
Spark responsible for scheduling, distributing, and monitoring the application across the cluster.

What are common Spark Ecosystems?
Spark SQL(Shark) for SQL developers,
Spark Streaming for streaming data,
MLLib for machine learning algorithms,
GraphX for Graph computation,
SparkR to run R on Spark engine,
BlinkDB enabling interactive queries over massive data are common Spark ecosystems.
GraphX, SparkR and BlinkDB are in incubation stage.



What is Partitions?
partition is a logical division of the data, this idea derived from Map-reduce (split). Logical data specifically derived to process the data. Small chunks of data also it can support scalability and speed up the process. Input data, intermediate data and output data everything is Partitioned RDD.

How spark partition the data?

Spark use map-reduce API to do the partition the data. In Input format we can create number of partitions. By default HDFS block size is partition size (for best performance), but its' possible to change partition size like Split.

How Spark store the data?
Spark is a processing engine, there is no storage engine. It can retrieve data from any storage engine like HDFS, S3 and other data resources.

Is it mandatory to start Hadoop to run spark application?
No not mandatory, but there is no separate storage in Spark, so it use local file system to store the data. You can load data from local system and process it, Hadoop or HDFS is not mandatory to run spark application.

What is SparkContext?
When a programmer creates a RDDs, SparkContext connect to the Spark cluster to create a new SparkContext object. SparkContext tell spark how to access the cluster. SparkConf is key factor to create programmer application.

What is SparkCore functionalities?
SparkCore is a base engine of apache spark framework. Memory management, fault tolarance, scheduling and monitoring jobs, interacting with store systems are primary functionalities of Spark.

How SparkSQL is different from HQL and SQL?
SparkSQL is a special component on the sparkCore engine that support SQL and HiveQueryLanguage without changing any syntax. It's possible to join SQL table and HQL table.

When did we use Spark Streaming?
Spark Streaming is a real time processing of streaming data API. Spark streaming gather streaming data from different resources like web server log files, social media data, stock market data or Hadoop ecosystems like Flume, and Kafka.

How Spark Streaming API works?
Programmer set a specific time in the configuration, with in this time how much data gets into the Spark, that data separates as a batch. The input stream (DStream) goes into spark streaming. Framework breaks up into small chunks called batches, then feeds into the spark engine for processing. Spark Streaming API passes that batches to the core engine. Core engine can generate the final results in the form of streaming batches. The output also in the form of batches. It can allows streaming data and batch data for processing.

What is Spark MLlib?

Mahout is a machine learning library for Hadoop, similarly MLlib is a Spark library. MetLib provides different algorithms, that algorithms scale out on the cluster for data processing. Most of the data scientists use this MLlib library.

What is GraphX?

GraphX is a Spark API for manipulating Graphs and collections. It unifies ETL, other analysis, and iterative graph computation. It's fastest graph system, provides fault tolerance and ease of use without special skills.

What is File System API?
FS API can read data from different storage devices like HDFS, S3 or local FileSystem. Spark uses FS API to read data from different storage engines.

Why Partitions are immutable?
Every transformation generate new partition. Partitions uses HDFS API so that partition is immutable, distributed and fault tolerance. Partition also aware of data locality.

What is Transformation in spark?

Spark provides two special operations on RDDs called transformations and Actions. Transformation follow lazy operation and temporary hold the data until unless called the Action. Each transformation generate/return new RDD. Example of transformations: Map, flatMap, groupByKey, reduceByKey, filter, co-group, join, sortByKey, Union, distinct, sample are common spark transformations.

What is Action in Spark?

Actions is RDD's operation, that value return back to the spar driver programs, which kick off a job to execute on a cluster. Transformation's output is input of Actions. reduce, collect, takeSample, take, first, saveAsTextfile, saveAsSequenceFile, countByKey, foreach are common actions in Apache spark.

What is RDD Lineage?
Lineage is a RDD process to reconstruct lost partitions. Spark not replicate the data in memory, if data lost, Rdd use linege to rebuild lost data.Each RDD remembers how the RDD build from other datasets.

What is Map and flatMap in Spark?

Map is a specific line or row to process that data. In FlatMap each input item can be mapped to multiple output items (so function should return a Seq rather than a single item). So most frequently used to return Array elements.

What are broadcast variables?
Broadcast variables let programmer keep a read-only variable cached on each machine, rather than shipping a copy of it with tasks. Spark supports 2 types of shared variables called broadcast variables (like Hadoop distributed cache) and accumulators (like Hadoop counters). Broadcast variables stored as Array Buffers, which sends read-only values to work nodes.

What are Accumulators in Spark?
Spark of-line debuggers called accumulators. Spark accumulators are similar to Hadoop counters, to count the number of events and what's happening during job you can use accumulators. Only the driver program can read an accumulator value, not the tasks.

How RDD persist the data?
There are two methods to persist the data, such as persist() to persist permanently and cache() to persist temporarily in the memory. Different storage level options there such as MEMORY_ONLY, MEMORY_AND_DISK, DISK_ONLY and many more. Both persist() and cache() uses different options depends on the task.

1) What is Apache Spark?

Apache Spark is easy to use and flexible data processing framework. Spark can round on Hadoop, standalone, or in the cloud. It is capable of assessing diverse data source, which includes HDFS, Cassandra, and others.

2) Explain Dsstream with reference to Apache Spark

Dstream is a sequence of resilient distributed database which represent a stream of data. You can create Dstream from various source like HDFS, Apache Flume, Apache Kafka, etc.

3) Name three data source available in SparkSQL

There data source available in SparkSQL are:

- JSON Datasets
- Hive tables
- Parquet file

4) Name some internal daemons used in spark?

Important daemon used in spark are Blockmanager, Memestore, DAGscheduler, Driver, Worker, Executor, Tasks,etc.

5) Define the term 'Sparse Vector.'

Sparse vector is a vector which has two parallel arrays, one for indices, one for values, use for

6) Name the language supported by Apache Spark for developing big data applications

Important language use for developing big data application are:

- Java
- Python
- R
- Clojure
- Scala

7) What is the method to create a Data frame?

In Apache Spark, a Data frame can be created using Tables in Hive and Structured data files.

8) Explain SchemaRDD

An RDD which consists of row object with schema information about the type of data in each column is called SchemaRDD.

9) What are accumulators?

Accumulators are the write-only variables. They are initialized once and sent to the workers. These workers will update based on the logic written, which will send back to the driver.

10) What are the components of Spark Ecosystem?

An important component of Spark are:

- Spark Core: It is a base engine for large-scale parallel and distributed data processing
- Spark Streaming: This component used for real-time data streaming.
- Spark SQL: Integrates relational processing by using Spark’s functional programming API
- GraphX: Allows graphs and graph-parallel computation
- MLlib: Allows you to perform machine learning in Apache Spark

11) Name three features of using Apache Spark

Three most important feature of using Apache Spark are:

1. Support for Sophisticated Analytics
2. Helps you to Integrate with Hadoop and Existing Hadoop Data
3. It allows you to run an application in Hadoop cluster, up to 100 times faster in memory, and ten times faster on disk.

12) Explain the default level of parallelism in Apache Spark

If the user isn't able to specify, then the number of partitions are considered as default level of parallelism in Apache Spark.

13) Name three companies which is used Spark Streaming services

Three known companies using Spark Streaming services are:

- Uber
- Netflix
- Pinterest

14) What is Spark SQL?

Spark SQL is a module for structured data processing where we take advantage of SQL queries running on that database.

15) Explain Parquet file

Paraquet is a columnar format file support by many other data processing systems. Spark SQL allows you to performs both read and write operations with Parquet file.

16) Explain Spark Driver?

Spark Driver is the program which runs on the master node of the machine and declares transformations and actions on data RDDs.

17) How can you store the data in spark?

Spark is a processing engine which doesn't have any storage engine. It can retrieve data from another storage engine like HDFS, S3.

18) Explain the use of File system API in Apache Spark

File system API allows you to read data from various storage devices like HDFS, S3 or local Fileyste.

19) What is the task of Spark Engine

Spark Engine is helpful for scheduling, distributing and monitoring the data application across the cluster.

20) What is the user of sparkContext?
SparkContent is the entry point to spark. SparkContext allows you to create RDDs which provided various way of churning data.

21) How can you implement machine learning in Spark?

MLif is a versatile machine learning library given by Spark.

22) Can you do real-time processing with Spark SQL?

Real-time data processing is not possible directly. However, it is possible by registering existing RDD as a SQL table and trigger the SQL queries on priority.

23) What are the important differences between Apache and Hadoop

Parameter	**Apache Spark**	**Hadoop**
Speed	100 times faster compares to Hadoop.	It has moderate speed.
Processing	Real-time batch processing functionality.	It offers batch processing only.
Learning curve	Easy	Hard
Interactivity	It has interactive modes	Apart from Pig and Hive, it has not an interactive way.

24) can you run Apache Spark On Apache Mesos?

Yes, you can run Apache Spark on the hardware clusters managed by Mesos.

25) Explain partitions

Partition is a smaller and logical division of data. It is the method for deriving logical units of data to speed up the processing process.

26) Define the term ‘Lazy Evolution’ with reference to Apache Spark

Apache Spark delays its evaluation until it is needed. For the transformations, Spark adds them to a DAG of computation and only when derive request some data.

27) Explain the use of broadcast variables

The most common use of broadcast variables are:

- Broadcast variables help programmer to keep a read-only variable cached on each machine instead of shipping a copy of it with tasks.
- You can also use them to give every node a copy of a large input dataset in an efficient manner.
- Broadcast algorithms also help you to reduce communication cost

28) How you can use Akka with Spark?

Spark uses Akka use for scheduling. It also uses Akka for messaging between the workers and masters.

29) Which the fundamental data structure of Spark

Data frame is fundamental is the fundamental data structure of Spark.

30) Can you use Spark for ETL process?

Yes, you can use spark for the ETL process.

31) What is the use of map transformation?

Map transformation on an RDD produces another RDD by translating each element. It helps you to translates every element by executing the function provided by the user.

32) What are the disadvantages of using Spark?

The following are some of the disadvantages of using Spark:

- Spark consume a huge amount of data compared with Hadoop.
- You can’t run everything on a single node as work must be distrusted over multiple clusters.
- Developers needs extra care while running their application in Spark.
- Spark streaming does not provide support for record-based window criteria.

33) What are common uses of Apache Spark?

- Apache Spark is used for:

- Interactive machine learning
- Stream processing
- Data analytics and processing
- Sensor data processing

34) State the difference between persist() and cache() functions.

Persist() function allows the user to specify the storage level whereas cache() use the default storage level.

35) Name the Spark Library which allows reliable file sharing at memory speed across different cluster frameworks.

Tachyon is a spark library which allows reliable file sharing at memory speed across various cluster frameworks.

36) Apache Spark is a good fit for which type of machine learning techniques?

Apache Spark is ideal for simple machine learning algorithms like clustering, regression, and classification.

37) How you can remove the element with a critical present in any other Rdd is Apache spark?

In order to remove the elements with a key present in any other rdd, you need to use substractkey() function.

38) What is the use of checkpoints in spark?

Checkpoints allow the program to run all around the clock. Moreover, it helps to make it resilient towards failure irrespective to application logic.

39) Explain lineage graph

Lineage graph information computer each RDD on demand. Therefore, whenever a part of persistent RDD is lost. In that situation, you can recover this data using lineage graph information.

40) What are the file formats supported by spark?

Spark supports file format json, tsv, snappy, orc, rc, etc.

41) What are Actions?

Action helps you to bring back the data from RDD to the local machine. Its execution is the result of all previously created transformations.

42) What is Yarn?

Yarn is one of the most important features of Apache Spark. Running spark on Yarn makes binary distribution of spark as it is built on Yarn support.

43) Explain Spark Executor

An executor is a Spark process which runs computations and stores the data on the worker node. The final tasks by SparkContent are transferred to the executor for their execution.

44) is it necessary to install Spark on all nodes while running Spark application on Yarn?

No, you don't necessarily need to install spark on all nodes as spark runs on top of Yarn.

45) What is a worker node in Apache Spark?

A worker node is any node which can run the application code in a cluster.

46) How can you launch Spark jobs inside Hadoop MapReduce?

Spark in MapReduce allows users to run all kind of spark job inside MapReduce without need to obtain admin rights of that application.

47) Explain the process to trigger automatic clean-up in Spark to manage accumulated metadata.

You can trigger automatic clean-ups by seeing the parameter 'spark.cleaner.ttf or by separating the long-running jobs into various batches and writing the intermediate results to the disk.

48) Explain the use of Blinkdb

BlinkDB is a query engine tool which allows you to execute SQL queries on huge volumes of data and renders query results in the meaningful error bars.

49) Does Hoe Spark handle monitoring and logging in Standalone mode?

Yes, a spark can handle monitoring and logging in standalone mode as it has a web-based user interface.

50) How can you identify whether a given operation is Transformation or Action?

You can identify the operation based on the return type. If the return type is not RDD, then the operation is an action. However, if the return type is the same as the RDD, then the operation is transformation.

51) Can You Use Apache Spark To Analyze and Access Data Stored In Cassandra

Databases?

Yes, you can use Spark Cassandra Connector which allows you to access and analyze data stored in Cassandra Database.

52) State the difference between Spark SQL and Hql

SparkSQL is an essential component on the spark Core engine. It supports SQL and Hive Query Language without altering its syntax.

Q. What is PySpark?

This is almost always the first PySpark interview question you will face.

PySpark is the Python API for Spark. It is used to provide collaboration between Spark and Python. PySpark focuses on processing structured and semi-structured data sets and also provides the facility to read data from multiple sources which have different data formats. Along with these features, we can also interface with RDDs (Resilient Distributed Datasets) using PySpark. All these features are implemented using the py4j library.

Q. List the advantages and disadvantages of PySpark? (Frequently asked PySpark Interview Question)

The advantages of using PySpark are:

- Using the PySpark, we can write a parallelized code in a very simple way.
- All the nodes and networks are abstracted.
- PySpark handles all the errors as well as synchronization errors.
- PySpark contains many useful in-built algorithms.

The disadvantages of using PySpark are:

- PySpark can often make it difficult to express problems in MapReduce fashion.
- When compared with other programming languages, PySpark is not efficient.

Q. What are the various algorithms supported in PySpark?

The different algorithms supported by PySpark are:

1. spark.mllib
2. mllib.clustering
3. mllib.classification
4. mllib.regression
5. mllib.recommendation
6. mllib.linalg
7. mllib.fpm

Q. What is PySpark SparkContext?

PySpark SparkContext can be seen as the initial point for entering and using any Spark functionality. The SparkContext uses py4j library to launch the JVM, and then create the JavaSparkContext. By default, the SparkContext is available as ‘sc’.

Q. What is PySpark SparkFiles?

One of the most common PySpark interview questions. PySpark SparkFiles is used to load our files on the Apache Spark application. It is one of the functions under SparkContext and can be called using sc.addFile to load the files on the Apache Spark. SparkFIles can also be used to get the path using SparkFile.get or resolve the paths to files that were added from sc.addFile. The class methods present in the SparkFiles directory are getrootdirectory() and get(filename).

Q. What is PySpark SparkConf?

PySpark SparkConf is mainly used to set the configurations and the parameters when we want to run the application on the local or the cluster.

We run the following code whenever we want to run SparkConf:

class pyspark.Sparkconf(

localdefaults = True,

_jvm = None,

_jconf = None

)

Q. What is PySpark StorageLevel?

PySpark StorageLevel is used to control how the RDD is stored, take decisions on where the RDD will be stored (on memory or over the disk or both), and whether we need to replicate the RDD partitions or to serialize the RDD. The code for StorageLevel is as follows:

class pyspark.StorageLevel(useDisk, useMemory, useOfHeap, deserialized, replication = 1)

Q. What is PySpark SparkJobinfo?

One of the most common questions in any PySpark interview. PySpark SparkJobinfo is used to gain information about the SparkJobs that are in execution. The code for using the SparkJobInfo is as follows:

class SparkJobInfo(namedtuple(“SparkJobInfo”, “jobId stageIds status ”)):

Q. What is PySpark SparkStageinfo?

One of the most common questions in any PySpark interview question and answers guide. PySpark SparkStageInfo is used to gain information about the SparkStages that are present at that time. The code used fo SparkStageInfo is as follows:

class SparkStageInfo(namedtuple(“SparkStageInfo”, “stageId currentAttemptId name numTasks unumActiveTasks” “numCompletedTasks numFailedTasks”)):

Q. What's the difference between an RDD, a DataFrame, and a DataSet?

RDD-

- It is Spark's structural square. RDDs contain all datasets and dataframes.
- If a similar arrangement of data needs to be calculated again, RDDs can be efficiently reserved.
- It's useful when you need to do low-level transformations, operations, and control on a dataset.
- It's more commonly used to alter data with functional programming structures than with domain-specific expressions.

DataFrame-

- It allows the structure, i.e., lines and segments, to be seen. You can think of it as a database table.
- Optimized Execution Plan- The catalyst analyzer is used to create query plans.
- One of the limitations of dataframes is Compile Time Wellbeing, i.e., when the structure of information is unknown, no control of information is possible.
- Also, if you're working on Python, start with DataFrames and then switch to RDDs if you need more flexibility.

DataSet (A subset of DataFrames)-

- It has the best encoding component and, unlike information edges, it enables time security in an organized manner.
- If you want a greater level of type safety at compile-time, or if you want typed JVM objects, Dataset is the way to go.

- Also, you can leverage datasets in situations where you are looking for a chance to take advantage of Catalyst optimization or even when you are trying to benefit from Tungsten's fast code generation.

Q. How can you create a DataFrame a) using existing RDD, and b) from a CSV file?

Here's how we can create DataFrame using existing RDDs-

The toDF() function of PySpark RDD is used to construct a DataFrame from an existing RDD. The DataFrame is constructed with the default column names "_1" and "_2" to represent the two columns because RDD lacks columns.

dfFromRDD1 = rdd.toDF()

dfFromRDD1.printSchema()

Here, the printSchema() method gives you a database schema without column names-

root

|-- _1: string (nullable = true)

|-- _2: string (nullable = true)

Use the toDF() function with column names as parameters to pass column names to the DataFrame, as shown below.-

columns = ["language","users_count"]

dfFromRDD1 = rdd.toDF(columns)

dfFromRDD1.printSchema()

The above code snippet gives you the database schema with the column names-

root

|-- language: string (nullable = true)

|-- users: string (nullable = true)

Q. Explain the use of StructType and StructField classes in PySpark with examples.

The StructType and StructField classes in PySpark are used to define the schema to the DataFrame and create complex columns such as nested struct, array, and map columns. StructType is a collection of StructField objects that determines column name, column data type, field nullability, and metadata.

- PySpark imports the StructType class from pyspark.sql.types to describe the DataFrame's structure. The DataFrame's printSchema() function displays StructType columns as "struct."
- To define the columns, PySpark offers the pyspark.sql.types import StructField class, which has the column name (String), column type (DataType), nullable column (Boolean), and metadata (MetaData).

Example showing the use of StructType and StructField classes in PySpark-

import pyspark

from pyspark.sql import SparkSession

```
from pyspark.sql.types import StructType,StructField, StringType, IntegerType

spark = SparkSession.builder.master("local[1]") \

                    .appName('ProjectPro') \

                    .getOrCreate()

data = [("James","","William","36636","M",3000),

   ("Michael","Smith","","40288","M",4000),

   ("Robert","","Dawson","42114","M",4000),

   ("Maria","Jones","39192","F",4000)

 ]

schema = StructType([ \

   StructField("firstname",StringType(),True), \

   StructField("middlename",StringType(),True), \

   StructField("lastname",StringType(),True), \

   StructField("id", StringType(), True), \

   StructField("gender", StringType(), True), \

   StructField("salary", IntegerType(), True) \

 ])

df = spark.createDataFrame(data=data,schema=schema)
```

```
df.printSchema()

df.show(truncate=False)
```

Q. What are the different ways to handle row duplication in a PySpark DataFrame?

There are two ways to handle row duplication in PySpark dataframes. The distinct() function in PySpark is used to drop/remove duplicate rows (all columns) from a DataFrame, while dropDuplicates() is used to drop rows based on one or more columns.

Here's an example showing how to utilize the distinct() and dropDuplicates() methods-

First, we need to create a sample dataframe.

```
import pyspark

from pyspark.sql import SparkSession

from pyspark.sql.functions import expr

spark = SparkSession.builder.appName('ProjectPro).getOrCreate()

data = [("James", "Sales", 3000), \

    ("Michael", "Sales", 4600), \

    ("Robert", "Sales", 4100), \

    ("Maria", "Finance", 3000), \

    ("James", "Sales", 3000), \
```

```
    ("Scott", "Finance", 3300), \
    ("Jen", "Finance", 3900), \
    ("Jeff", "Marketing", 3000), \
    ("Kumar", "Marketing", 2000), \
    ("Saif", "Sales", 4100) \
  ]
column= ["employee_name", "department", "salary"]
df = spark.createDataFrame(data = data, schema = column)
df.printSchema()
df.show(truncate=False)
```

Output-

```
+-------------+----------+------+
|employee_name|department|salary|
+-------------+----------+------+
|James        |Sales     |3000  |
|Michael      |Sales     |4600  |
|Robert       |Sales     |4100  |
|Maria        |Finance   |3000  |
|James        |Sales     |3000  |
|Scott        |Finance   |3300  |
|Jen          |Finance   |3900  |
|Jeff         |Marketing |3000  |
|Kumar        |Marketing |2000  |
|Saif         |Sales     |4100  |
+-------------+----------+------+
```

The record with the employer name Robert contains duplicate rows in the table above. As we can see, there are two rows with duplicate values in all fields and four rows with duplicate values in the department and salary columns.

Below is the entire code for removing duplicate rows-

```
import pyspark

from pyspark.sql import SparkSession

from pyspark.sql.functions import expr

spark = SparkSession.builder.appName('ProjectPro').getOrCreate()

data = [("James", "Sales", 3000), \

   ("Michael", "Sales", 4600), \

   ("Robert", "Sales", 4100), \

   ("Maria", "Finance", 3000), \

   ("James", "Sales", 3000), \

   ("Scott", "Finance", 3300), \

   ("Jen", "Finance", 3900), \

   ("Jeff", "Marketing", 3000), \

   ("Kumar", "Marketing", 2000), \

   ("Saif", "Sales", 4100) \

 ]
```

```
column= ["employee_name", "department", "salary"]

df = spark.createDataFrame(data = data, schema = column)

df.printSchema()

df.show(truncate=False)



#Distinct

distinctDF = df.distinct()

print("Distinct count: "+str(distinctDF.count()))

distinctDF.show(truncate=False)

#Drop duplicates

df2 = df.dropDuplicates()

print("Distinct count: "+str(df2.count()))

df2.show(truncate=False)

#Drop duplicates on selected columns

dropDisDF = df.dropDuplicates(["department","salary"])

print("Distinct count of department salary : "+str(dropDisDF.count()))

dropDisDF.show(truncate=False)

}
```

Q. Explain PySpark UDF with the help of an example.

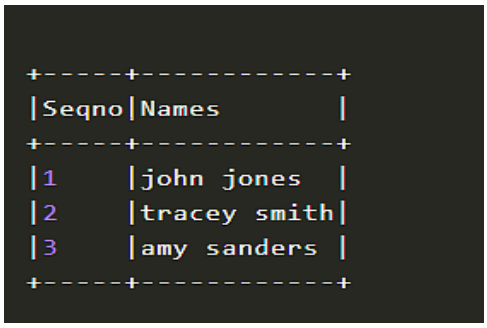
The most important aspect of Spark SQL & DataFrame is PySpark UDF (i.e., User Defined Function), which is used to expand PySpark's built-in capabilities. UDFs in PySpark work similarly to UDFs in conventional databases. We write a Python function and wrap it in PySpark SQL udf() or register it as udf and use it on DataFrame and SQL, respectively, in the case of PySpark.

Example of how we can create a UDF-

1. First, we need to create a sample dataframe.

```
spark = SparkSession.builder.appName('ProjectPro').getOrCreate()

column = ["Seqno","Name"]

data = [("1", "john jones"),

   ("2", "tracey smith"),

   ("3", "amy sanders")]

df = spark.createDataFrame(data=data,schema=column)

df.show(truncate=False)
```

Output-



2. The next step is creating a Python function. The code below generates the convertCase() method, which accepts a string parameter and turns every word's initial letter to a capital letter.

```
def convertCase(str):
    resStr=""
    arr = str.split(" ")
    for x in arr:
      resStr= resStr + x[0:1].upper() + x[1:len(x)] + " "
    return resStr
```

3. The final step is converting a Python function to a PySpark UDF.

By passing the function to PySpark SQL udf(), we can convert the convertCase() function to UDF(). The org.apache.spark.sql.functions.udf package contains this function. Before we use this package, we must first import it.

The org.apache.spark.sql.expressions.UserDefinedFunction class object is returned by the PySpark SQL udf() function.

```
""" Converting function to UDF """
```

convertUDF = udf(lambda z: convertCase(z),StringType())

Q. Discuss the map() transformation in PySpark DataFrame with the help of an example.

PySpark map or the map() function is an RDD transformation that generates a new RDD by applying 'lambda', which is the transformation function, to each RDD/DataFrame element. RDD map() transformations are used to perform complex operations such as adding a column, changing a column, converting data, and so on. Map transformations always produce the same number of records as the input.

Example of map() transformation in PySpark-

- First, we must create an RDD using the list of records.

spark = SparkSession.builder.appName("Map transformation PySpark").getOrCreate()

records = ["Project","Gutenberg's","Alice's","Adventures",

"in","Wonderland","Project","Gutenberg's","Adventures",

"in","Wonderland","Project","Gutenberg's"]

rdd=spark.sparkContext.parallelize(records)

- The map() syntax is-

map(f, preservesPartitioning=False)

- We are adding a new element having value 1 for each element in this PySpark map() example, and the output of the RDD is PairRDDFunctions, which has key-value pairs, where we have a word (String type) as Key and 1 (Int type) as Value.

rdd2=rdd.map(lambda x: (x,1))

for element in rdd2.collect():

print(element)

Output-

```
('Project', 1)
('Gutenberg's', 1)
('Alice's', 1)
('Adventures', 1)
('in', 1)
('Wonderland', 1)
('Project', 1)
('Gutenberg's', 1)
('Adventures', 1)
('in', 1)
('Wonderland', 1)
('Project', 1)
('Gutenberg's', 1)
```

Q. What do you mean by 'joins' in PySpark DataFrame? What are the different types of joins?

Joins in PySpark are used to join two DataFrames together, and by linking them together, one may join several DataFrames. INNER Join, LEFT OUTER Join, RIGHT OUTER Join, LEFT ANTI Join, LEFT SEMI Join, CROSS Join, and SELF Join are among the SQL join types it supports.

PySpark Join syntax is-

join(self, other, on=None, how=None)

The join() procedure accepts the following parameters and returns a DataFrame-

'other': The join's right side;

'on': the join column's name;

'how': default inner (Options are inner, cross, outer, full, full outer, left, left outer, right, right outer, left semi, and left anti.)

Types of Join in PySpark DataFrame-

Join String	Equivalent SQL Join
inner	INNER JOIN
outer, full, fullouter, full_outer	FULL OUTER JOIN
left, leftouter, left_outer	LEFT JOIN
right, rightouter, right_outer	RIGHT JOIN
cross	
anti, leftanti, left_anti	
semi, leftsemi, left_semi	

Q. What is PySpark ArrayType? Explain with an example.

PySpark ArrayType is a collection data type that extends PySpark's DataType class, which is the superclass for all kinds. The types of items in all ArrayType elements should be the same. The ArraType() method may be used to construct an instance of an ArrayType. It accepts two arguments: valueType and one optional argument valueContainsNull, which

specifies whether a value can accept null and is set to True by default. valueType should extend the DataType class in PySpark.

from pyspark.sql.types import StringType, ArrayType

arrayCol = ArrayType(StringType(),False)

Q. What do you understand by PySpark Partition?

Using one or more partition keys, PySpark partitions a large dataset into smaller parts. When we build a DataFrame from a file or table, PySpark creates the DataFrame in memory with a specific number of divisions based on specified criteria. Transformations on partitioned data run quicker since each partition's transformations are executed in parallel. Partitioning in memory (DataFrame) and partitioning on disc (File system) are both supported by PySpark.

Q. What is meant by PySpark MapType? How can you create a MapType using StructType?

PySpark MapType accepts two mandatory parameters- keyType and valueType, and one optional boolean argument valueContainsNull.

Here's how to create a MapType with PySpark StructType and StructField. The StructType() accepts a list of StructFields, each of which takes a fieldname and a value type.

from pyspark.sql.types import StructField, StructType, StringType, MapType

schema = StructType([

StructField('name', StringType(), True),

```
    StructField('properties', MapType(StringType(),StringType()),True)
])
```

Now, using the preceding StructType structure, let's construct a DataFrame-

```
spark= SparkSession.builder.appName('PySpark StructType StructField').getOrCreate()
dataDictionary = [
        ('James',{'hair':'black','eye':'brown'}),
        ('Michael',{'hair':'brown','eye':None}),
        ('Robert',{'hair':'red','eye':'black'}),
        ('Washington',{'hair':'grey','eye':'grey'}),
        ('Jefferson',{'hair':'brown','eye':''})
        ]
df = spark.createDataFrame(data=dataDictionary, schema = schema)
df.printSchema()
df.show(truncate=False)
```

Output-

```
root
 |-- Name: string (nullable = true)
 |-- properties: map (nullable = true)
 |    |-- key: string
 |    |-- value: string (valueContainsNull = true)

+----------+-----------------------------+
|Name      |properties                   |
+----------+-----------------------------+
|James     |[eye -> brown, hair -> black]|
|Michael   |[eye ->, hair -> brown]      |
|Robert    |[eye -> black, hair -> red]  |
|Washington|[eye -> grey, hair -> grey]  |
|Jefferson |[eye -> , hair -> brown]     |
+----------+-----------------------------+
```

Q. How can PySpark DataFrame be converted to Pandas DataFrame?

First, you need to learn the difference between the PySpark and Pandas. The key difference between Pandas and PySpark is that PySpark's operations are quicker than Pandas' because of its distributed nature and parallel execution over several cores and computers.

In other words, pandas use a single node to do operations, whereas PySpark uses several computers.

You'll need to transfer the data back to Pandas DataFrame after processing it in PySpark so that you can use it in Machine Learning apps or other Python programs.

Below are the steps to convert PySpark DataFrame into Pandas DataFrame-

1. You have to start by creating a PySpark DataFrame first.

```
spark = SparkSession.builder.appName('Spark Dataframe to Pandas PySpark').getOrCreate()

SampleData = [("Ravi","","Gupta","36636","M",70000),
        ("Ram","Aggarwal","","40288","M",80000),
        ("Shyam","","Shinde","42114","",500000),
        ("Sarla","Priya","Gupta","39192","F",600000),
        ("Monica","Garg","Brown","","F",0)]

DataColumns = ["first_name","middle_name","last_name","dob","gender","salary"]

PysparkDF = spark.createDataFrame(data = SampleData, schema = DataColumns)
PysparkDF.printSchema()
PysparkDF.show(truncate=False)
```

Output-

```
root
 |-- first_name: string (nullable = true)
 |-- middle_name: string (nullable = true)
 |-- last_name: string (nullable = true)
 |-- dob: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- salary: long (nullable = true)

+----------+-----------+---------+-----+------+------+
|first_name|middle_name|last_name|dob  |gender|salary|
+----------+-----------+---------+-----+------+------+
|Ravi      |           |Gupta    |36636|M     |70000 |
|Ram       |Aggarwal   |         |40288|M     |80000 |
|Shyam     |           |Shinde   |42114|      |500000|
|Sarla     |Priya      |Gupta    |39192|F     |600000|
|Monica    |Garg       |Brown    |     |F     |0     |
+----------+-----------+---------+-----+------+------+
```

2. The next step is to convert this PySpark dataframe into Pandas dataframe.

To convert a PySpark DataFrame to a Python Pandas DataFrame, use the toPandas() function. toPandas() gathers all records in a PySpark DataFrame and delivers them to the driver software; it should only be used on a short percentage of the data. When using a bigger dataset, the application fails due to a memory error.

```
# Converting dataframe to pandas
PandasDF = PysparkDF.toPandas()
print(PandasDF)
```

Output-

```
first_name middle_name last_name    dob gender  salary
      Ravi                 Gupta  36636      M   70000
       Ram    Aggarwal           40288      M   80000
     Shyam                Shinde  42114          500000
     Sarla       Priya     Gupta  39192      F  600000
    Monica        Garg     Brown              F       0
```

Q. With the help of an example, show how to employ PySpark ArrayType.

PySpark ArrayType is a data type for collections that extends PySpark's DataType class. The types of items in all ArrayType elements should be the same.

The ArraType() method may be used to construct an instance of an ArrayType. It accepts two arguments: valueType and one optional argument valueContainsNull, which specifies whether a value can accept null and is set to True by default. valueType should extend the DataType class in PySpark.

from pyspark.sql.types import StringType, ArrayType

arrayCol = ArrayType(StringType(),False)

The above example generates a string array that does not allow null values.

Q. What is the function of PySpark's pivot() method?

The pivot() method in PySpark is used to rotate/transpose data from one column into many Dataframe columns and back using the unpivot() function (). Pivot() is an aggregation in which the values of one of the grouping columns are transposed into separate columns containing different data.

To get started, let's make a PySpark DataFrame.

```
import pyspark

from pyspark.sql import SparkSession

from pyspark.sql.functions import expr

#Create spark session

data = [("Banana",1000,"USA"), ("Carrots",1500,"USA"), ("Beans",1600,"USA"), \

    ("Orange",2000,"USA"),("Orange",2000,"USA"),("Banana",400,"China"), \

    ("Carrots",1200,"China"),("Beans",1500,"China"),("Orange",4000,"China"), \

    ("Banana",2000,"Canada"),("Carrots",2000,"Canada"),("Beans",2000,"Mexico")]

columns= ["Product","Amount","Country"]

df = spark.createDataFrame(data = data, schema = columns)

df.printSchema()

df.show(truncate=False)
```

Output-

```
root
 |-- Product: string (nullable = true)
 |-- Amount: long (nullable = true)
 |-- Country: string (nullable = true)

+-------+------+-------+
|Product|Amount|Country|
+-------+------+-------+
|Banana |1000  |USA    |
|Carrots|1500  |USA    |
|Beans  |1600  |USA    |
|Orange |2000  |USA    |
|Orange |2000  |USA    |
|Banana |400   |China  |
|Carrots|1200  |China  |
|Beans  |1500  |China  |
|Orange |4000  |China  |
|Banana |2000  |Canada |
|Carrots|2000  |Canada |
|Beans  |2000  |Mexico |
+-------+------+-------+
```

To determine the entire amount of each product's exports to each nation, we'll group by Product, pivot by Country, and sum by Amount.

pivotDF = df.groupBy("Product").pivot("Country").sum("Amount")

pivotDF.printSchema()

pivotDF.show(truncate=False)

This will convert the nations from DataFrame rows to columns, resulting in the output seen below. Wherever data is missing, it is assumed to be null by default.

```
root
 |-- Product: string (nullable = true)
 |-- Canada: long (nullable = true)
 |-- China: long (nullable = true)
 |-- Mexico: long (nullable = true)
 |-- USA: long (nullable = true)

+-------+------+-----+------+----+
|Product|Canada|China|Mexico|USA |
+-------+------+-----+------+----+
|Orange |null  |4000 |null  |4000|
|Beans  |null  |1500 |2000  |1600|
|Banana |2000  |400  |null  |1000|
|Carrots|2000  |1200 |null  |1500|
+-------+------+-----+------+----+
```

Q. In PySpark, how do you generate broadcast variables? Give an example.

Broadcast variables in PySpark are read-only shared variables that are stored and accessible on all nodes in a cluster so that processes may access or use them. Instead of sending this information with each job, PySpark uses efficient broadcast algorithms to distribute broadcast variables among workers, lowering communication costs.

The broadcast(v) function of the SparkContext class is used to generate a PySpark Broadcast. This method accepts the broadcast parameter v.

Generating broadcast in PySpark Shell:

broadcastVariable = sc.broadcast(Array(0, 1, 2, 3))

broadcastVariable.value

PySpark RDD Broadcast variable example

```
spark=SparkSession.builder.appName('SparkByExample.com').getOrCreate()

states = {"NY":"New York", "CA":"California", "FL":"Florida"}

broadcastStates = spark.sparkContext.broadcast(states)

data = [("James","Smith","USA","CA"),

    ("Michael","Rose","USA","NY"),

    ("Robert","Williams","USA","CA"),

    ("Maria","Jones","USA","FL")

  ]

rdd = spark.sparkContext.parallelize(data)

def state_convert(code):

    return broadcastState.value[code]

res = rdd.map(lambda a: (a[0],a[1],a[2],state_convert(a{3]))).collect()

print(res)
```

PySpark DataFrame Broadcast variable example

```
spark=SparkSession.builder.appName('PySpark broadcast variable').getOrCreate()

states = {"NY":"New York", "CA":"California", "FL":"Florida"}

broadcastStates = spark.sparkContext.broadcast(states)

data = [("James","Smith","USA","CA"),
```

```
    ("Michael","Rose","USA","NY"),
    ("Robert","William","USA","CA"),
    ("Maria","Jones","USA","FL")
  ]
columns = ["firstname","lastname","country","state"]
df = spark.createDataFrame(data = data, schema = columns)
df.printSchema()
df.show(truncate=False)
def state_convert(code):
    return broadcastState.value[code]
res = df.rdd.map(lambda a: (a[0],a[1],a[2],state_convert(a[3]))).toDF(column)
res.show(truncate=False)
```

Q. You have a cluster of ten nodes with each node having 24 CPU cores. The following code works, but it may crash on huge data sets, or at the very least, it may not take advantage of the

cluster's full processing capabilities. Which aspect is the most difficult to alter, and how would you go about doing so?

```
def cal(sparkSession: SparkSession): Unit = { val NumNode = 10 val userActivityRdd: RDD[UserActivity] = readUserActivityData(sparkSession) . repartition(NumNode) val result = userActivityRdd .map(e => (e.userId, 1L)) . reduceByKey(_ + _) result .take(1000) }
```

The repartition command creates ten partitions regardless of how many of them were loaded. On large datasets, they might get fairly huge, and they'll almost certainly outgrow the RAM allotted to a single executor.

In addition, each executor can only have one partition. This means that just ten of the 240 executors are engaged (10 nodes with 24 cores, each running one executor).

If the number is set exceptionally high, the scheduler's cost in handling the partition grows, lowering performance. It may even exceed the execution time in some circumstances, especially for extremely tiny partitions.

The optimal number of partitions is between two and three times the number of executors. In the given scenario, 600 = 10 × 24 x 2.5 divisions would be appropriate.

Q. Explain the following code and what output it will yield- case class User(uId: Long, uName: String) case class UserActivity(uId: Long, activityTypeId: Int, timestampEpochSec: Long) val LoginActivityTypeId = 0 val LogoutActivityTypeId = 1 private def readUserData(sparkSession: SparkSession): RDD[User] = { sparkSession.sparkContext.parallelize(Array(User(1, "Doe, John"), User(2, "Doe, Jane"), User(3, "X, Mr."))) } private def readUserActivityData(sparkSession: SparkSession): RDD[UserActivity] = { sparkSession.sparkContext.parallelize(Array(UserActivity(1, LoginActivityTypeId, 1514764800L), UserActivity(2, LoginActivityTypeId, 1514808000L), UserActivity(1, LogoutActivityTypeId, 1514829600L), UserActivity(1, LoginActivityTypeId, 1514894400L))) } def calculate(sparkSession: SparkSession): Unit = { val userRdd: RDD[(Long, User)] = readUserData(sparkSession).map(e =>

(e.userId, e)) val userActivityRdd: RDD[(Long, UserActivity)] = readUserActivityData(sparkSession).map(e => (e.userId, e)) val result = userRdd .leftOuterJoin(userActivityRdd) .filter(e => e._2._2.isDefined && e._2._2.get.activityTypeId == LoginActivityTypeId) .map(e => (e._2._1.uName, e._2._2.get.timestampEpochSec)) .reduceByKey((a, b) => if (a < b) a else b) result .foreach(e => println(s"${e._1}: ${e._2}")) }

The primary function, calculate, reads two pieces of data. (They are given in this case from a constant inline data structure that is transformed to a distributed dataset using parallelize.) Each of them is transformed into a tuple by the map, which consists of a userId and the item itself. To combine the two datasets, the userId is utilised.

All users' login actions are filtered out of the combined dataset. The uName and the event timestamp are then combined to make a tuple.

This is eventually reduced down to merely the initial login record per user, which is then sent to the console.

The following will be the yielded output-

Doe, John: 1514764800

Doe, Jane: 1514808000

Q. The code below generates two dataframes with the following structure: DF1: uId, uName DF2: uId, pageId, timestamp, eventType. Join the two dataframes using code and count the number of events per uName. It should only output for users who have events in the format uName; totalEventCount.

def calculate(sparkSession: SparkSession): Unit = { val UIdColName = "uId" val UNameColName = "uName" val CountColName = "totalEventCount" val userRdd: DataFrame = readUserData(sparkSession) val userActivityRdd: DataFrame = readUserActivityData(sparkSession) val res = userRdd .repartition(col(UIdColName)) // ??????????????? . select(col(UNameColName))// ??????????????? result.show() }

This is how the code looks:

def calculate(sparkSession: SparkSession): Unit = {

val UIdColName = "uId"

```
val UNameColName = "uName"

val CountColName = "totalEventCount"

val userRdd: DataFrame = readUserData(sparkSession)

val userActivityRdd: DataFrame = readUserActivityData(sparkSession)

val result = userRdd

  .repartition(col(UIdColName))

  .join(userActivityRdd, UIdColName)

  .select(col(UNameColName))

  .groupBy(UNameColName)

  .count()

  .withColumnRenamed("count", CountColName)

 result.show()

}
```

Q. Please indicate which parts of the following code will run on the master and which parts will run on each worker node.

val formatter: DateTimeFormatter = DateTimeFormatter.ofPattern("yyyy/MM") def

getEventCountOnWeekdaysPerMonth(data:

RDD[(LocalDateTime, Long)]): Array[(String, Long)] = { val res =

data .filter(e => e._1.getDayOfWeek.getValue <

DayOfWeek.SATURDAY.getValue) . map(mapDateTime2Date)

. reduceByKey(_ + _) . collect() result . map(e =>

(e._1.format(formatter), e._2)) } private def

mapDateTime2Date(v: (LocalDateTime, Long)): (LocalDate,

Long) = { (v._1.toLocalDate.withDayOfMonth(1), v._2) }

The driver application is responsible for calling this function. The DAG is defined by the assignment to the result value, as well as its execution, which is initiated by the collect() operation. The worker nodes handle all of this (including the logic of the method mapDateTime2Date). Because the result value that is gathered on the master is an array, the map performed on this value is also performed on the master.

Q. What are the elements used by the GraphX library, and how are they generated from an RDD? To determine page rankings, fill in the following code-

def calculate(sparkSession: SparkSession): Unit = { val pageRdd: RDD[(???, Page)] = readPageData(sparkSession) . map(e => (e.pageId, e)) . cache() val pageReferenceRdd: RDD[???[PageReference]] = readPageReferenceData(sparkSession) val graph = Graph(pageRdd, pageReferenceRdd) val PageRankTolerance = 0.005 val ranks = graph.??? ranks.take(1000).foreach(print) }

The output yielded will be a list of tuples:

(1,1.4537951595091907) (2,0.7731024202454048) (3,0.7731024202454048)

Vertex, and Edge objects are supplied to the Graph object as RDDs of type RDD[VertexId, VT] and RDD[Edge[ET]] respectively (where VT and ET are any user-defined types associated with a given Vertex or Edge). For Edge type, the constructor is Edge[ET](srcId: VertexId, dstId: VertexId, attr: ET). VertexId is just an alias for Long.

Q. Under what scenarios are Client and Cluster modes used for deployment?

- Cluster mode should be utilized for deployment if the client computers are not near the cluster. This is done to prevent the network delay that would occur in Client mode while communicating between executors. In case of Client mode, if the machine goes offline, the entire operation is lost.
- Client mode can be utilized for deployment if the client computer is located within the cluster. There will be no network latency concerns because the computer is part of the cluster, and the cluster's maintenance is already taken care of, so there is no need to be concerned in the event of a failure.

Q.How is Apache Spark different from MapReduce?

MapReduce	Apache Spark
Only batch-wise data processing is done using MapReduce.	Apache Spark can handle data in both real-time and batch mode.
The data is stored in HDFS (Hadoop Distributed File System), which takes a long time to retrieve.	Spark saves data in memory (RAM), making data retrieval quicker and faster when needed.
MapReduce is a high-latency framework since it is heavily reliant on disc.	Spark is a low-latency computation platform because it offers in-memory data storage and caching.

Q. Write a spark program to check whether a given keyword exists in a huge text file or not?

```
def keywordExists(line):
  if (line.find(“my_keyword”) > -1):
     return 1
  return 0
lines = sparkContext.textFile(“sample_file.txt”);
isExist = lines.map(keywordExists);
sum=isExist.reduce(sum);
print(“Found” if sum>0 else “Not Found”)
```

Q. What is meant by Executor Memory in PySpark?

Spark executors have the same fixed core count and heap size as the applications created in Spark. The heap size relates to the memory used by the Spark executor, which is controlled by the *-executor-memory* flag's property *spark.executor.memory*. On each worker node where Spark operates, one executor is assigned to it. The executor memory is a measurement of the memory utilized by the application's worker node.

Q. List some of the functions of SparkCore.

The core engine for large-scale distributed and parallel data processing is SparkCore. The distributed execution engine in the Spark core provides APIs in Java, Python, and Scala for constructing distributed ETL applications.

Memory management, task monitoring, fault tolerance, storage system interactions, work scheduling, and support for all fundamental I/O activities are all performed by Spark Core. Additional libraries on top of Spark Core enable a variety of SQL, streaming, and machine learning applications.

They are in charge of:

- Fault Recovery
- Interactions between memory management and storage systems
- Monitoring, scheduling, and distributing jobs
- Fundamental I/O functions

Q. What are some of the drawbacks of incorporating Spark into applications?

Despite the fact that Spark is a strong data processing engine, there are certain drawbacks to utilizing it in applications.

- When compared to MapReduce or Hadoop, Spark consumes greater storage space, which may cause memory-related issues.
- Spark can be a constraint for cost-effective large data processing since it uses "in-memory" calculations.
- When working in cluster mode, files on the path of the local filesystem must be available at the same place on all worker nodes, as the task execution shuffles across different worker nodes based on resource availability. All worker nodes must copy the files, or a separate network-mounted file-sharing system must be installed.

Q. How can data transfers be kept to a minimum while using PySpark?

The process of shuffling corresponds to data transfers. Spark applications run quicker and more reliably when these transfers are minimized. There are quite a number of approaches that may be used to reduce them. They are as follows:

- Using broadcast variables improves the efficiency of joining big and small RDDs.
- Accumulators are used to update variable values in a parallel manner during execution.
- Another popular method is to prevent operations that cause these reshuffles.

Q. What are Sparse Vectors? What distinguishes them from dense vectors?

Sparse vectors are made up of two parallel arrays, one for indexing and the other for storing values. These vectors are used to save space by storing non-zero values. E.g.- *val sparseVec: Vector = Vectors.sparse(5, Array(0, 4), Array(1.0, 2.0))*

The vector in the above example is of size 5, but the non-zero values are only found at indices 0 and 4.

When there are just a few non-zero values, sparse vectors come in handy. If there are just a few zero values, dense vectors should be used instead of sparse vectors, as sparse vectors would create indexing overhead, which might affect performance.

The following is an example of a dense vector:

val denseVec = Vectors.dense(4405d,260100d,400d,5.0,4.0,198.0,9070d,1.0,1.0,2.0,0.0)

The usage of sparse or dense vectors has no effect on the outcomes of calculations, but when they are used incorrectly, they have an influence on the amount of memory needed and the calculation time.

Q. What role does Caching play in Spark Streaming?

The partition of a data stream's contents into batches of X seconds, known as DStreams, is the basis of Spark Streaming. These DStreams allow developers to cache data in memory, which may be particularly handy if the data from a DStream is utilized several times. The cache() function or the persist() method with proper persistence settings can be used to cache data. For input streams receiving data through networks such as Kafka, Flume, and others, the default persistence level setting is configured to achieve data replication on two nodes to achieve fault tolerance.

- Cache method-

val cacheDf = dframe.cache()

- Persist method-

val persistDf = dframe.persist(StorageLevel.MEMORY_ONLY)

The following are the key benefits of caching:

- Cost-effectiveness: Because Spark calculations are costly, caching aids in data reuse, which leads to reuse computations, lowering the cost of operations.
- Time-saving: By reusing computations, we may save a lot of time.

- More Jobs Achieved: Worker nodes may perform/execute more jobs by reducing computation execution time.

Q. What API does PySpark utilize to implement graphs?

Spark RDD is extended with a robust API called GraphX, which supports graphs and graph-based calculations. The Resilient Distributed Property Graph is an enhanced property of Spark RDD that is a directed multi-graph with many parallel edges. User-defined characteristics are associated with each edge and vertex. Multiple connections between the same set of vertices are shown by the existence of parallel edges. GraphX offers a collection of operators that can allow graph computing, such as subgraph, mapReduceTriplets, joinVertices, and so on. It also offers a wide number of graph builders and algorithms for making graph analytics chores easier.

Q. What is meant by Piping in PySpark?

According to the UNIX Standard Streams, Apache Spark supports the pipe() function on RDDs, which allows you to assemble distinct portions of jobs that can use any language. The RDD transformation may be created using the pipe() function, and it can be used to read each element of the RDD as a String. These may be altered as needed, and the results can be presented as Strings.

Q. What are the various levels of persistence that exist in PySpark?

Spark automatically saves intermediate data from various shuffle processes. However, it is advised to use the RDD's persist() function. There are many levels of persistence for storing RDDs on memory, disc, or both, with varying levels of replication. The following are the persistence levels available in Spark:

- MEMORY ONLY: This is the default persistence level, and it's used to save RDDs on the JVM as deserialized Java objects. In the event that the RDDs are too large to fit in memory, the partitions are not cached and must be recomputed as needed.
- MEMORY AND DISK: On the JVM, the RDDs are saved as deserialized Java objects. In the event that memory is inadequate, partitions that do not fit in memory will be kept on disc, and data will be retrieved from the drive as needed.

- MEMORY ONLY SER: The RDD is stored as One Byte per partition serialized Java Objects.
- DISK ONLY: RDD partitions are only saved on disc.
- OFF HEAP: This level is similar to MEMORY ONLY SER, except that the data is saved in off-heap memory.

The persist() function has the following syntax for employing persistence levels:

df.persist(StorageLevel.)

Q. What steps are involved in calculating the executor memory?

Suppose you have the following details regarding the cluster:

No. of nodes = 10

No. of cores in each node = 15 cores

RAM of each node = 61GB

We use the following method to determine the number of cores:

No. of cores = How many concurrent tasks the executor can handle.

As a rule of thumb, 5 is the best value.

Hence, we use the following method to determine the number of executors:

No. of executors = No. of cores/Concurrent Task

= 15/5

= 3

No. of executors = No. of nodes * No. of executors in each node

= 10 * 3

= 30 executors per Spark job

Q. Do we have a checkpoint feature in Apache Spark?

Yes, there is an API for checkpoints in Spark. The practice of checkpointing makes streaming apps more immune to errors. We can store the data and metadata in a checkpointing directory. If there's a failure, the spark may retrieve this data and resume where it left off.

In Spark, checkpointing may be used for the following data categories-

1. Metadata checkpointing: Metadata rmeans information about information. It refers to storing metadata in a fault-tolerant storage system such as HDFS. You can consider configurations, DStream actions, and unfinished batches as types of metadata.
2. Data checkpointing: Because some of the stateful operations demand it, we save the RDD to secure storage. The RDD for the next batch is defined by the RDDs from previous batches in this case.

Q. In Spark, how would you calculate the total number of unique words?

1. Open the text file in RDD mode:

sc.textFile("hdfs://Hadoop/user/sample_file.txt");

2. A function that converts each line into words:

def toWords(line):

return line.split();

3. As a flatMap transformation, run the toWords function on each item of the RDD in Spark:

words = line.flatMap(toWords);

4. Create a (key,value) pair for each word:

def toTuple(word):

return (word, 1);

wordTuple = words.map(toTuple);

5. Run the reduceByKey() command:

def sum(x, y):

return x+y:

counts = wordsTuple.reduceByKey(sum)

6. Print:

counts.collect()

Q. List some of the benefits of using PySpark.

PySpark is a specialized in-memory distributed processing engine that enables you to handle data in a distributed fashion effectively.

- PySpark-based programs are 100 times quicker than traditional apps.
- You can learn a lot by utilizing PySpark for data intake processes. PySpark can handle data from Hadoop HDFS, Amazon S3, and a variety of other file systems.
- Through the use of Streaming and Kafka, PySpark is also utilized to process real-time data.
- You can use PySpark streaming to swap data between the file system and the socket.
- PySpark contains machine learning and graph libraries by chance.

Q. What distinguishes Apache Spark from other programming languages?

- High Data Processing Speed: By decreasing read-write operations to disc, Apache Spark aids in achieving a very high data processing speed. When doing in-memory computations, the speed is about 100 times quicker, and when performing disc computations, the speed is 10 times faster.
- Dynamic in nature: Spark's dynamic nature comes from 80 high-level operators, making developing parallel applications a breeze.
- In-memory Computing Ability: Spark's in-memory computing capability, which is enabled by its DAG execution engine, boosts data processing speed. This also allows for data caching, which reduces the time it takes to retrieve data from the disc.

- Fault Tolerance: RDD is used by Spark to support fault tolerance. Spark RDDs are abstractions that are meant to accommodate worker node failures while ensuring that no data is lost.
- Stream Processing: Spark offers real-time stream processing. The difficulty with the previous MapReduce architecture was that it could only handle data that had already been created.

Q. Explain RDDs in detail.

Resilient Distribution Datasets (RDD) are a collection of fault-tolerant functional units that may run simultaneously. RDDs are data fragments that are maintained in memory and spread across several nodes. In an RDD, all partitioned data is distributed and consistent.

There are two types of RDDs available:

1. Hadoop datasets- Those datasets that apply a function to each file record in the Hadoop Distributed File System (HDFS) or another file storage system.
2. Parallelized Collections- Existing RDDs that operate in parallel with each other.

Q. Mention some of the major advantages and disadvantages of PySpark.

Some of the major advantages of using PySpark are-

- Writing parallelized code is effortless.
- Keeps track of synchronization points and errors.
- Has a lot of useful built-in algorithms.

Some of the disadvantages of using PySpark are-

- Managing an issue with MapReduce may be difficult at times.
- It is inefficient when compared to alternative programming paradigms.

Q. Explain the profilers which we use in PySpark.

PySpark allows you to create custom profiles that may be used to build predictive models. In general, profilers are calculated using the minimum and maximum values of each

column. It is utilized as a valuable data review tool to ensure that the data is accurate and appropriate for future usage.

The following methods should be defined or inherited for a custom profiler-

- profile- this is identical to the system profile.
- add- this is a command that allows us to add a profile to an existing accumulated profile.
- dump- saves all of the profiles to a path.
- stats- returns the stats that have been gathered.

Q. List some recommended practices for making your PySpark data science workflows better.

- Avoid dictionaries: If you use Python data types like dictionaries, your code might not be able to run in a distributed manner. Consider adding another column to a dataframe that may be used as a filter instead of utilizing keys to index entries in a dictionary. This proposal also applies to Python types that aren't distributable in PySpark, such as lists.
- Limit the use of Pandas: using toPandas causes all data to be loaded into memory on the driver node, preventing operations from being run in a distributed manner. When data has previously been aggregated, and you wish to utilize conventional Python plotting tools, this method is appropriate, but it should not be used for larger dataframes.
- Minimize eager operations: It's best to avoid eager operations that draw whole dataframes into memory if you want your pipeline to be as scalable as possible. Reading in CSVs, for example, is an eager activity, thus I stage the dataframe to S3 as Parquet before utilizing it in further pipeline steps.

Q. What are SparkFiles in Pyspark?

PySpark provides the reliability needed to upload our files to Apache Spark. This is accomplished by using sc.addFile, where 'sc' stands for SparkContext. We use SparkFiles.net to acquire the directory path.

We use the following methods in SparkFiles to resolve the path to the files added using SparkContext.addFile():

- get(filename),

- getrootdirectory()

Q. What is SparkConf in PySpark? List a few attributes of SparkConf.

SparkConf aids in the setup and settings needed to execute a spark application locally or in a cluster. To put it another way, it offers settings for running a Spark application. The following are some of SparkConf's most important features:

- set(key, value): This attribute aids in the configuration property setting.
- setSparkHome(value): This feature allows you to specify the directory where Spark will be installed on worker nodes.
- setAppName(value): This element is used to specify the name of the application.
- setMaster(value): The master URL may be set using this property.
- get(key, defaultValue=None): This attribute aids in the retrieval of a key's configuration value.

Q. What is the key difference between list and tuple?

The primary difference between lists and tuples is that lists are mutable, but tuples are immutable.

When a Python object may be edited, it is considered to be a mutable data type. Immutable data types, on the other hand, cannot be changed.

Here’s an example of how to change an item list into a tuple-

list_num[3] = 7

print(list_num)

tup_num[3] = 7

Output:

[1,2,5,7]

Traceback (most recent call last):

File "python", line 6, in

TypeError: 'tuple' object doesnot support item assignment

We assigned 7 to list_num at index 3 in this code, and 7 is found at index 3 in the output. However, we set 7 to tup_num at index 3, but the result returned a type error. Because of their immutable nature, we can't change tuples.

Q. What do you understand by errors and exceptions in Python?

There are two types of errors in Python: syntax errors and exceptions.

Syntax errors are frequently referred to as parsing errors. Errors are flaws in a program that might cause it to crash or terminate unexpectedly. When a parser detects an error, it repeats the offending line and then shows an arrow pointing to the line's beginning.

Exceptions arise in a program when the usual flow of the program is disrupted by an external event. Even if the program's syntax is accurate, there is a potential that an error will be detected during execution; nevertheless, this error is an exception. ZeroDivisionError, TypeError, and NameError are some instances of exceptions.

Q. What are the most significant changes between the Python API (PySpark) and Apache Spark?

PySpark is a Python API created and distributed by the Apache Spark organization to make working with Spark easier for Python programmers. Scala is the programming language used by Apache Spark. It can communicate with other languages like Java, R, and Python.

Also, because Scala is a compile-time, type-safe language, Apache Spark has several capabilities that PySpark does not, one of which includes Datasets. Datasets are a highly typed collection of domain-specific objects that may be used to execute concurrent calculations.

Q. Define SparkSession in PySpark. Write code to create SparkSession in PySpark

Spark 2.0 includes a new class called SparkSession (pyspark.sql import SparkSession). Prior to the 2.0 release, SparkSession was a unified class for all of the many contexts we had (SQLContext and HiveContext, etc). Since version 2.0, SparkSession may replace SQLContext, HiveContext, and other contexts specified before version 2.0. It's a way to get into the core PySpark technology and construct PySpark RDDs and DataFrames programmatically. Spark is the default object in pyspark-shell, and it may be generated programmatically with SparkSession.

In PySpark, we must use the builder pattern function builder() to construct SparkSession programmatically (in a.py file), as detailed below. The getOrCreate() function retrieves an already existing SparkSession or creates a new SparkSession if none exists.

```
spark=SparkSession.builder.master("local[1]") \
        .appName('ProjectPro') \
        .getOrCreate()
```

Q. Suppose you encounter the following error message while running PySpark commands on Linux-

ImportError: No module named py4j.java_gateway

How will you resolve it?

Py4J is a Java library integrated into PySpark that allows Python to actively communicate with JVM instances. Py4J is a necessary module for the PySpark application to execute, and it may be found in the $SPARK_HOME/python/lib/py4j-*-src.zip directory.

To execute the PySpark application after installing Spark, set the Py4j module to the PYTHONPATH environment variable. We'll get an ImportError: No module named py4j.java_gateway error if we don't set this module to env.

So, here's how this error can be resolved-

```
export SPARK_HOME=/Users/abc/apps/spark-3.0.0-bin-hadoop2.7
```

export PYTHONPATH=$SPARK_HOME/python:$SPARK_HOME/python/build:$SPARK_HOME/python/lib/py4j-0.10.9-src.zip:$PYTHONPATH

Put these in *.bashrc* file and re-load it using *source ~/.bashrc*

The py4j module version changes depending on the PySpark version we're using; to configure this version correctly, follow the steps below:

export PYTHONPATH=${SPARK_HOME}/python/:$(echo ${SPARK_HOME}/python/lib/py4j-*-src.zip):${PYTHONPATH}

Use the pip show command to see the PySpark location's path- *pip show pyspark*

Use the environment variables listed below to fix the problem on Windows-

set SPARK_HOME=C:\apps\opt\spark-3.0.0-bin-hadoop2.7

set HADOOP_HOME=%SPARK_HOME%

set PYTHONPATH=%SPARK_HOME%/python;%SPARK_HOME%/python/lib/py4j-0.10.9-src.zip;%PYTHONPATH%

Q. Suppose you get an error- NameError: Name 'Spark' is not Defined while using spark. createDataFrame(), but there are no errors while using the same in Spark or PySpark shell. Why?

Spark shell, PySpark shell, and Databricks all have the SparkSession object 'spark' by default. However, if we are creating a Spark/PySpark application in a.py file, we must manually create a SparkSession object by using builder to resolve NameError: Name 'Spark' is not Defined.

 # Import PySpark

import pyspark

from pyspark.sql import SparkSession

#Create SparkSession

```
spark = SparkSession.builder
        .master("local[1]")
        .appName("SparkByExamples.com")
        .getOrCreate()
```

If you get the error message 'No module named pyspark', try using findspark instead-

```
#Install findspark
pip install findspark
# Import findspark
import findspark
findspark.init()
#import pyspark
import pyspark
from pyspark.sql import SparkSession
```

Q. What are the various types of Cluster Managers in PySpark?

Spark supports the following cluster managers:

- Standalone- a simple cluster manager that comes with Spark and makes setting up a cluster easier.
- Apache Mesos- Mesos is a cluster manager that can also run Hadoop MapReduce and PySpark applications.
- Hadoop YARN- It is the Hadoop 2 resource management.
- Kubernetes- an open-source framework for automating containerized application deployment, scaling, and administration.
- local – not exactly a cluster manager, but it's worth mentioning because we use "local" for master() to run Spark on our laptop/computer.

Q. Explain how Apache Spark Streaming works with receivers.

Receivers are unique objects in Apache Spark Streaming whose sole purpose is to consume data from various data sources and then move it to Spark. By streaming contexts as long-running tasks on various executors, we can generate receiver objects.

There are two different kinds of receivers which are as follows:

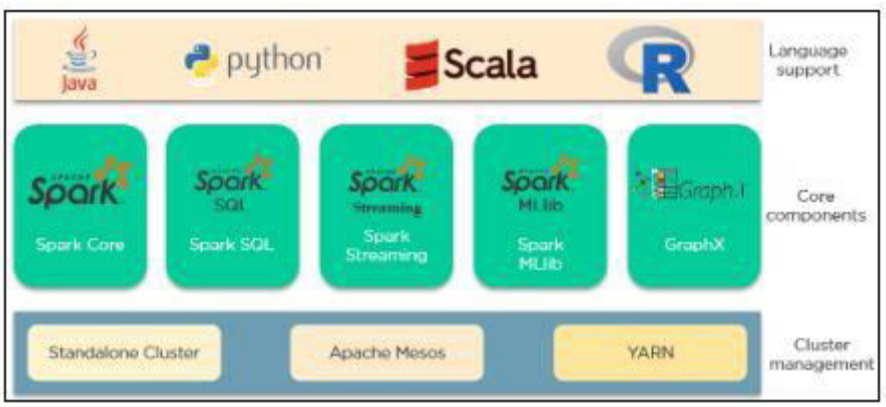
- Reliable receiver: When data is received and copied properly in Apache Spark Storage, this receiver validates data sources.
- Unreliable receiver: When receiving or replicating data in Apache Spark Storage, these receivers do not recognize data sources.

How is Apache Spark different from MapReduce?

Apache Spark	MapReduce
Spark processes data in batches as well as in real-time	MapReduce processes data in batches only
Spark runs almost 100 times faster than Hadoop MapReduce	Hadoop MapReduce is slower when it comes to large scale data processing
Spark stores data in the RAM i.e. in-memory. So, it is easier to retrieve it	Hadoop MapReduce data is stored in HDFS and hence takes a long time to retrieve the data

Spark provides caching and in-memory data storage	Hadoop is highly disk-dependent

Q. What are the important components of the Spark ecosystem?

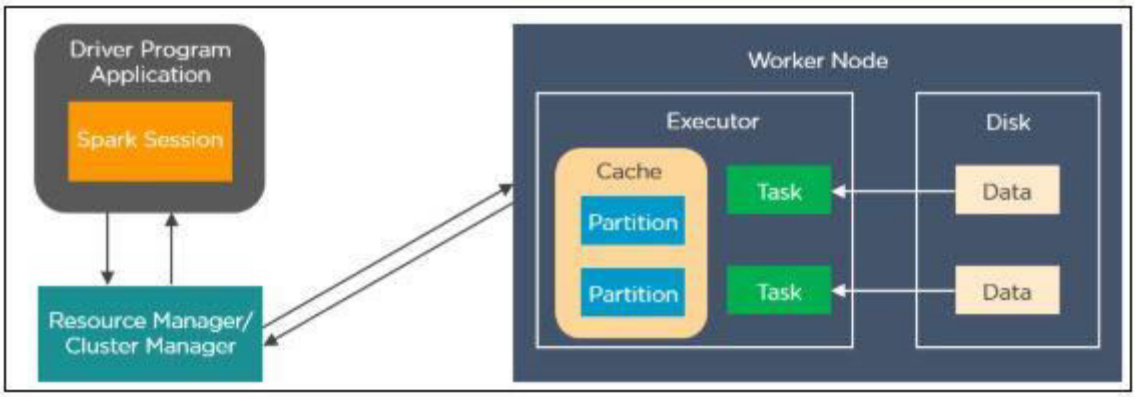


Apache Spark has 3 main categories that comprise its ecosystem. Those are:

- Language support: Spark can integrate with different languages to applications and perform analytics. These languages are Java, Python, Scala, and R.
- Core Components: Spark supports 5 main core components. There are Spark Core, Spark SQL, Spark Streaming, Spark MLlib, and GraphX.
- Cluster Management: Spark can be run in 3 environments. Those are the Standalone cluster, Apache Mesos, and YARN.

Q. Explain how Spark runs applications with the help of its architecture.

This is one of the most frequently asked spark interview questions, and the interviewer will expect you to give a thorough answer to it.



Spark applications run as independent processes that are coordinated by the SparkSession object in the driver program. The resource manager or cluster manager assigns tasks to the worker nodes with one task per partition. Iterative algorithms apply operations repeatedly to the data so they can benefit from caching datasets across iterations. A task applies its unit of work to the dataset in its partition and outputs a new partition dataset. Finally, the results are sent back to the driver application or can be saved to the disk.

Q. What are the different cluster managers available in Apache Spark?

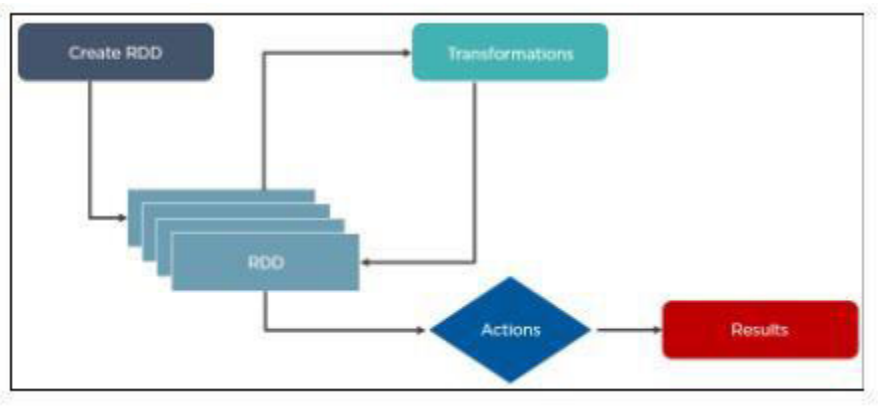
- Standalone Mode: By default, applications submitted to the standalone mode cluster will run in FIFO order, and each application will try to use all available nodes. You can launch a standalone cluster either manually, by starting a master and workers by hand, or use our provided launch scripts. It is also possible to run these daemons on a single machine for testing.
- Apache Mesos: Apache Mesos is an open-source project to manage computer clusters, and can also run Hadoop applications. The advantages of deploying Spark with Mesos include dynamic partitioning between Spark and other frameworks as well as scalable partitioning between multiple instances of Spark.
- Hadoop YARN: Apache YARN is the cluster resource manager of Hadoop 2. Spark can be run on YARN as well.
- Kubernetes: Kubernetes is an open-source system for automating deployment, scaling, and management of containerized applications.

Q. What is the significance of Resilient Distributed Datasets in Spark?

Resilient Distributed Datasets are the fundamental data structure of Apache Spark. It is embedded in Spark Core. RDDs are immutable, fault-tolerant, distributed collections of objects that can be operated on in parallel.RDD's are split into partitions and can be executed on different nodes of a cluster.

RDDs are created by either transformation of existing RDDs or by loading an external dataset from stable storage like HDFS or HBase.

Here is how the architecture of RDD looks like:



So far, if you have any doubts regarding the apache spark interview questions and answers, please comment below.

Q. What is a lazy evaluation in Spark?

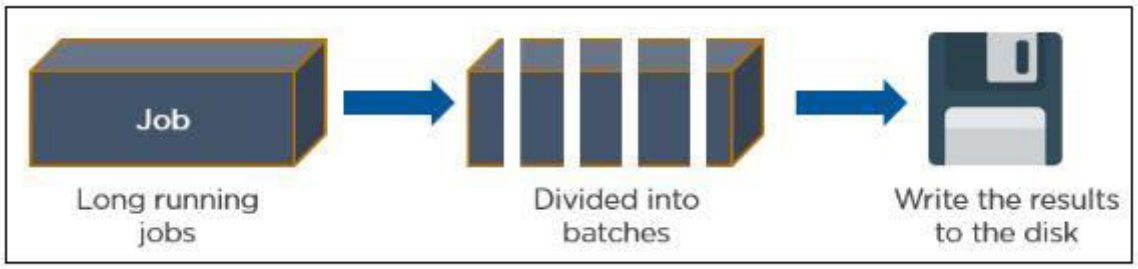
When Spark operates on any dataset, it remembers the instructions. When a transformation such as a map() is called on an RDD, the operation is not performed instantly. Transformations in Spark are not evaluated until you perform an action, which aids in optimizing the overall data processing workflow, known as lazy evaluation.

Q. What makes Spark good at low latency workloads like graph processing and Machine Learning?

Apache Spark stores data in-memory for faster processing and building machine learning models. Machine Learning algorithms require multiple iterations and different conceptual steps to create an optimal model. Graph algorithms traverse through all the nodes and edges to generate a graph. These low latency workloads that need multiple iterations can lead to increased performance.

How can you trigger automatic clean-ups in Spark to handle accumulated metadata?

To trigger the clean-ups, you need to set the parameter spark.cleaner.ttlx.



Q. How can you connect Spark to Apache Mesos?

There are a total of 4 steps that can help you connect Spark to Apache Mesos.

- Configure the Spark Driver program to connect with Apache Mesos
- Put the Spark binary package in a location accessible by Mesos
- Install Spark in the same location as that of the Apache Mesos
- Configure the spark.mesos.executor.home property for pointing to the location where Spark is installed

Q. What is a Parquet file and what are its advantages?

Parquet is a columnar format that is supported by several data processing systems. With the Parquet file, Spark can perform both read and write operations.

Some of the advantages of having a Parquet file are:

- It enables you to fetch specific columns for access.
- It consumes less space
- It follows the type-specific encoding
- It supports limited I/O operations

Q. What is shuffling in Spark? When does it occur?

Shuffling is the process of redistributing data across partitions that may lead to data movement across the executors. The shuffle operation is implemented differently in Spark compared to Hadoop.

Shuffling has 2 important compression parameters:

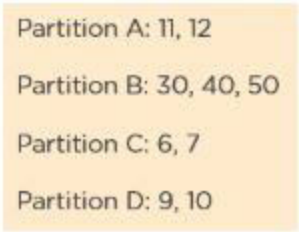
spark.shuffle.compress – checks whether the engine would compress shuffle outputs or not spark.shuffle.spill.compress – decides whether to compress intermediate shuffle spill files or not

It occurs while joining two tables or while performing byKey operations such as GroupByKey or ReduceByKey

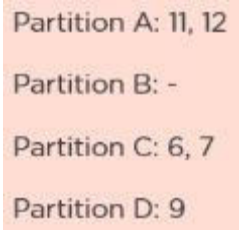
Q. What is the use of coalesce in Spark?

Spark uses a coalesce method to reduce the number of partitions in a DataFrame.

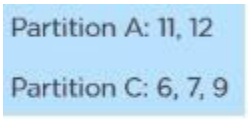
Suppose you want to read data from a CSV file into an RDD having four partitions.



This is how a filter operation is performed to remove all the multiple of 10 from the data.



The RDD has some empty partitions. It makes sense to reduce the number of partitions, which can be achieved by using coalesce.

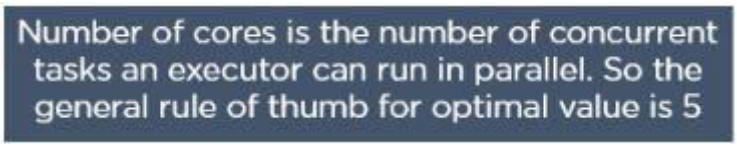


This is how the resultant RDD would look like after applying to coalesce.

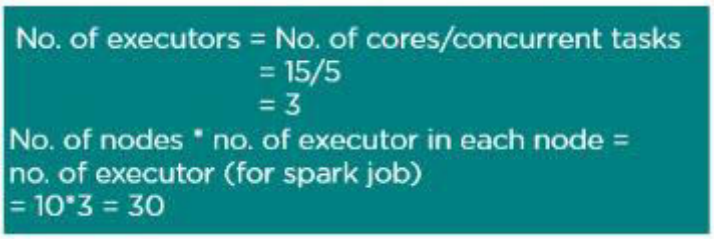
Q. How can you calculate the executor memory?

Consider the following cluster information:

Here is the number of core identification:



To calculate the number of executor identification:



Q. What are the various functionalities supported by Spark Core?

Spark Core is the engine for parallel and distributed processing of large data sets. The various functionalities supported by Spark Core include:

- Scheduling and monitoring jobs
- Memory management
- Fault recovery
- Task dispatching

Q. How do you convert a Spark RDD into a DataFrame?

There are 2 ways to convert a Spark RDD into a DataFrame:

- Using the helper function - toDF

import com.mapr.db.spark.sql._

val df = sc.loadFromMapRDB(<table-name>)

.where(field("first_name") === "Peter")

.select("_id", "first_name").toDF()

- Using SparkSession.createDataFrame

You can convert an RDD[Row] to a DataFrame by

calling createDataFrame on a SparkSession object

def createDataFrame(RDD, schema:StructType)

Q. Explain the types of operations supported by RDDs.

RDDs support 2 types of operation:

Transformations: Transformations are operations that are performed on an RDD to create a new RDD containing the results (Example: map, filter, join, union)

Actions: Actions are operations that return a value after running a computation on an RDD (Example: reduce, first, count)

Q.What is a Lineage Graph?

This is another frequently asked spark interview question. A Lineage Graph is a dependencies graph between the existing RDD and the new RDD. It means that all the dependencies between the RDD will be recorded in a graph, rather than the original data.

The need for an RDD lineage graph happens when we want to compute a new RDD or if we want to recover the lost data from the lost persisted RDD. Spark does not support data replication in memory. So, if any data is lost, it can be rebuilt using RDD lineage. It is also called an RDD operator graph or RDD dependency graph.

Q. What do you understand about DStreams in Spark?

Discretized Streams is the basic abstraction provided by Spark Streaming.

It represents a continuous stream of data that is either in the form of an input source or processed data stream generated by transforming the input stream.

dstream.

Q. Explain Caching in Spark Streaming.

Caching also known as Persistence is an optimization technique for Spark computations. Similar to RDDs, DStreams also allow developers to persist the stream’s data in memory. That is, using the persist() method on a DStream will automatically

persist every RDD of that DStream in memory. It helps to save interim partial results so they can be reused in subsequent stages.

The default persistence level is set to replicate the data to two nodes for fault-tolerance, and for input streams that receive data over the network.

kafka

Q. What is the need for broadcast variables in Spark?

Broadcast variables allow the programmer to keep a read-only variable cached on each machine rather than shipping a copy of it with tasks. They can be used to give every node a copy of a large input dataset in an efficient manner. Spark distributes broadcast variables using efficient broadcast algorithms to reduce communication costs.

scala

scala> val broadcastVar = sc.broadcast(Array(1, 2, 3))

broadcastVar: org.apache.spark.broadcast.Broadcast[Array[Int]] = Broadcast(0)

scala> broadcastVar.value

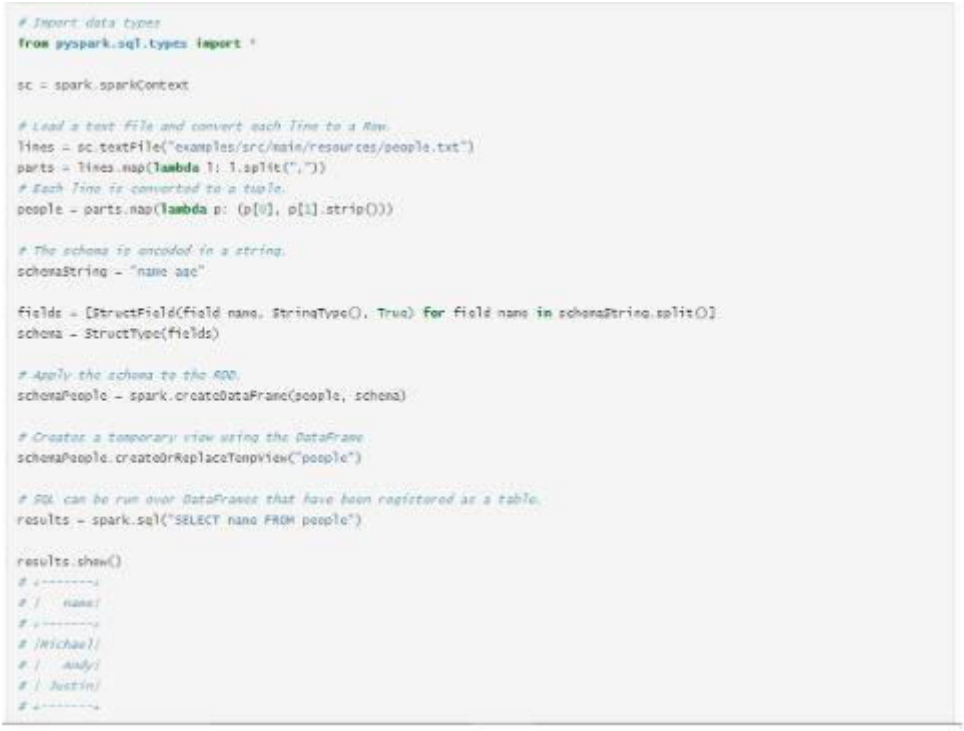
res0: Array[Int] = Array(1, 2, 3)

So far, if you have any doubts regarding the spark interview questions for beginners, please ask in the comment section below.

How to programmatically specify a schema for DataFrame?

DataFrame can be created programmatically with three steps:

- Create an RDD of Rows from the original RDD;
- Create the schema represented by a StructType matching the structure of Rows in the RDD created in Step 1.
- Apply the schema to the RDD of Rows via createDataFrame method provided by SparkSession.



```
# Import data types
from pyspark.sql.types import *

sc = spark.sparkContext

# Load a text file and convert each line to a Row.
lines = sc.textFile("examples/src/main/resources/people.txt")
parts = lines.map(lambda l: l.split(","))
# Each line is converted to a tuple.
people = parts.map(lambda p: (p[0], p[1].strip()))

# The schema is encoded in a string.
schemaString = "name age"

fields = [StructField(field_name, StringType(), True) for field_name in schemaString.split()]
schema = StructType(fields)

# Apply the schema to the RDD.
schemaPeople = spark.createDataFrame(people, schema)

# Creates a temporary view using the DataFrame
schemaPeople.createOrReplaceTempView("people")

# SQL can be run over DataFrames that have been registered as a table.
results = spark.sql("SELECT name FROM people")

results.show()
# +-------+
# |   name|
# +-------+
# |Michael|
# |   Andy|
# | Justin|
# +-------+
```

Q. Which transformation returns a new DStream by selecting only those records of the source DStream for which the function returns true?

1. map(func)

2. transform(func)

3. filter(func)

4. count()

The correct answer is c) filter(func).

Q. Does Apache Spark provide checkpoints?

This is one of the most frequently asked spark interview questions where the interviewer expects a detailed answer (and not just a yes or no!). Give as detailed an answer as possible here.

Yes, Apache Spark provides an API for adding and managing checkpoints. Checkpointing is the process of making streaming applications resilient to failures. It allows you to save the data and metadata into a checkpointing directory. In case of a failure, the spark can recover this data and start from wherever it has stopped.

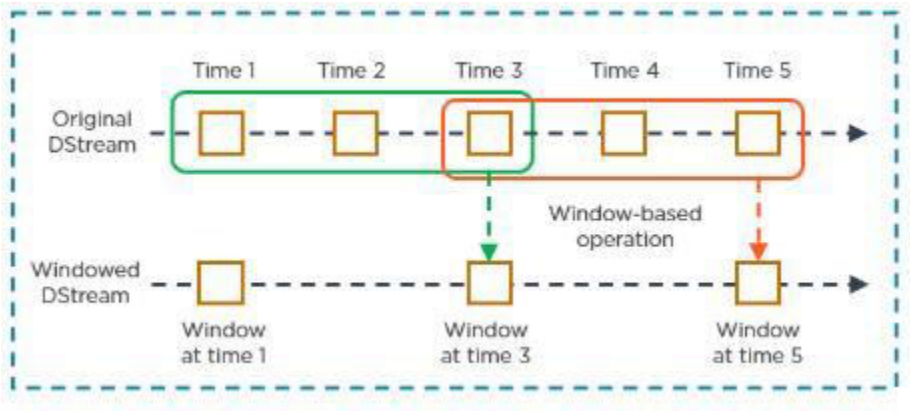
There are 2 types of data for which we can use checkpointing in Spark.

Metadata Checkpointing: Metadata means the data about data. It refers to saving the metadata to fault-tolerant storage like HDFS. Metadata includes configurations, DStream operations, and incomplete batches.

Data Checkpointing: Here, we save the RDD to reliable storage because its need arises in some of the stateful transformations. In this case, the upcoming RDD depends on the RDDs of previous batches.

Q. What do you mean by sliding window operation?

Controlling the transmission of data packets between multiple computer networks is done by the sliding window. Spark Streaming library provides windowed computations where the transformations on RDDs are applied over a sliding window of data.



Q. What are the different levels of persistence in Spark?

DISK_ONLY - Stores the RDD partitions only on the disk

MEMORY_ONLY_SER - Stores the RDD as serialized Java objects with a one-byte array per partition

MEMORY_ONLY - Stores the RDD as deserialized Java objects in the JVM. If the RDD is not able to fit in the memory available, some partitions won't be cached

OFF_HEAP - Works like MEMORY_ONLY_SER but stores the data in off-heap memory

MEMORY_AND_DISK - Stores RDD as deserialized Java objects in the JVM. In case the RDD is not able to fit in the memory, additional partitions are stored on the disk

MEMORY_AND_DISK_SER - Identical to MEMORY_ONLY_SER with the exception of storing partitions not able to fit in the memory to the disk

Q. What is the difference between map and flatMap transformation in Spark Streaming?

map()	flatMap()
A map function returns a new DStream by passing each element of the source DStream through a function func	It is similar to the map function and applies to each element of RDD and it returns the result as a new RDD
Spark Map function takes one element as an input process it according to custom code (specified by the developer) and returns one element at a time	FlatMap allows returning 0, 1, or more elements from the map function. In the FlatMap operation

Q. How would you compute the total count of unique words in Spark?

1. Load the text file as RDD:

sc.textFile(“hdfs://Hadoop/user/test_file.txt”);

2. Function that breaks each line into words:

def toWords(line):

return line.split();

3. Run the toWords function on each element of RDD in Spark as flatMap transformation:

words = line.flatMap(toWords);

4. Convert each word into (key,value) pair:

def toTuple(word):

return (word, 1);

wordTuple = words.map(toTuple);

5. Perform reduceByKey() action:

def sum(x, y):

return x+y:

counts = wordsTuple.reduceByKey(sum)

6. Print:

counts.collect()

Suppose you have a huge text file. How will you check if a particular keyword exists using Spark?

lines = sc.textFile(“hdfs://Hadoop/user/test_file.txt”);

def isFound(line):

if line.find(“my_keyword”) > -1

return 1

return 0

foundBits = lines.map(isFound);

sum = foundBits.reduce(sum);

if sum > 0:

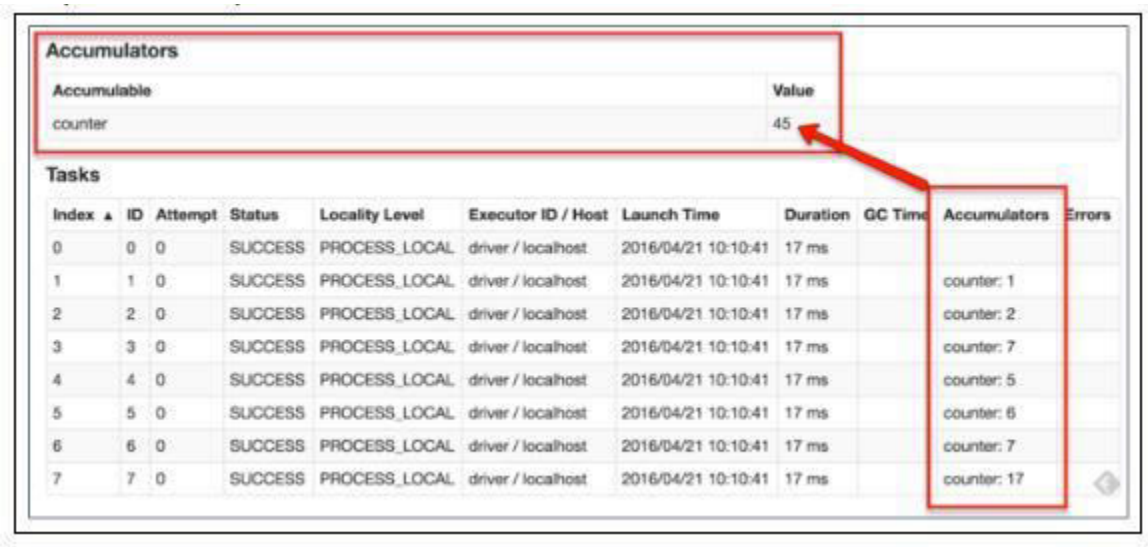
print “Found”

else:

print “Not Found”;

Q. What is the role of accumulators in Spark?

Accumulators are variables used for aggregating information across the executors. This information can be about the data or API diagnosis like how many records are corrupted or how many times a library API was called.



30. What are the different MLlib tools available in Spark?

- ML Algorithms: Classification, Regression, Clustering, and Collaborative filtering
- Featurization: Feature extraction, Transformation, Dimensionality reduction,

and Selection

- Pipelines: Tools for constructing, evaluating, and tuning ML pipelines
- Persistence: Saving and loading algorithms, models, and pipelines
- Utilities: Linear algebra, statistics, data handling

Hope it is clear so far. Let us know what were the apache spark interview questions ask'd by/to you during the interview process.

Q. What are the different data types supported by Spark MLlib?

Spark MLlib supports local vectors and matrices stored on a single machine, as well as distributed matrices.

Local Vector: MLlib supports two types of local vectors - dense and sparse

Example: vector(1.0, 0.0, 3.0)

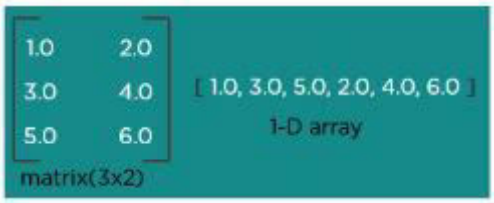
dense format: [1.0, 0.0, 3.0]

sparse format: (3, [0, 2]. [1.0, 3.0])

Labeled point: A labeled point is a local vector, either dense or sparse that is associated with a label/response.

Example: In binary classification, a label should be either 0 (negative) or 1 (positive)

Local Matrix: A local matrix has integer type row and column indices, and double type values that are stored in a single machine.



Distributed Matrix: A distributed matrix has long-type row and column indices and double-type values, and is stored in a distributed manner in one or more RDDs.

Types of the distributed matrix:

- RowMatrix
- IndexedRowMatrix
- CoordinatedMatrix

Q. What is a Sparse Vector?

A Sparse vector is a type of local vector which is represented by an index array and a value array.

public class SparseVector

extends Object

implements Vector

Example: sparse1 = SparseVector(4, [1, 3], [3.0, 4.0])

where:

4 is the size of the vector

[1,3] are the ordered indices of the vector

[3,4] are the value

Do you have a better example for this spark interview question? If yes, let us know.

Q. Describe how model creation works with MLlib and how the model is applied.

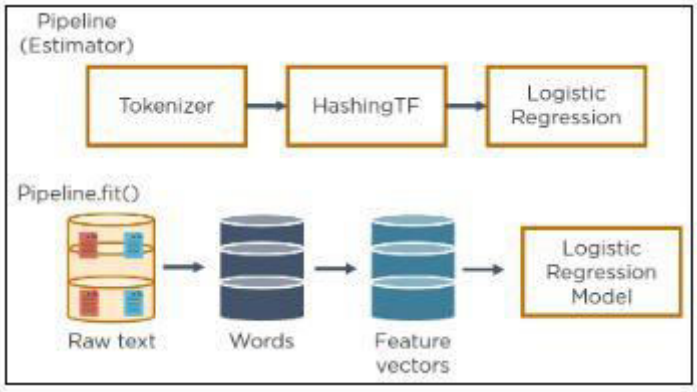
MLlib has 2 components:

Transformer: A transformer reads a DataFrame and returns a new DataFrame with a specific transformation applied.

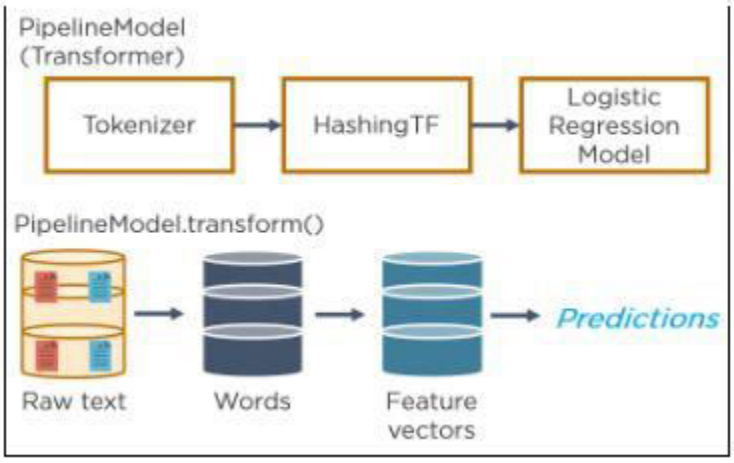
Estimator: An estimator is a machine learning algorithm that takes a DataFrame to train a model and returns the model as a transformer.

Spark MLlib lets you combine multiple transformations into a pipeline to apply complex data transformations.

The following image shows such a pipeline for training a model:



The model produced can then be applied to live data:



Q. What are the functions of Spark SQL?

Spark SQL is Apache Spark's module for working with structured data.

Spark SQL loads the data from a variety of structured data sources.

It queries data using SQL statements, both inside a Spark program and from external tools that connect to Spark SQL through standard database connectors (JDBC/ODBC).

It provides a rich integration between SQL and regular Python/Java/Scala code, including the ability to join RDDs and SQL tables and expose custom functions in SQL.

How can you connect Hive to Spark SQL?

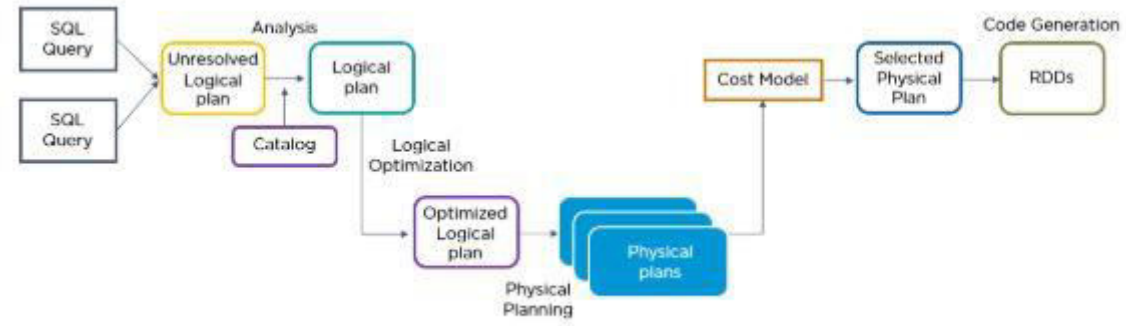
To connect Hive to Spark SQL, place the hive-site.xml file in the conf directory of Spark.

Using the Spark Session object, you can construct a DataFrame.

result=spark.sql("select * from <hive_table>")

Q. What is the role of Catalyst Optimizer in Spark SQL?

Catalyst optimizer leverages advanced programming language features (such as Scala's pattern matching and quasi quotes) in a novel way to build an extensible query optimizer.



Q. How can you manipulate structured data using domain-specific language in Spark SQL?

Structured data can be manipulated using domain-Specific language as follows:

Suppose there is a DataFrame with the following information:

val df = spark.read.json("examples/src/main/resources/people.json")

// Displays the content of the DataFrame to stdout

df.show()

// +----+-------+

// | age| name|

// +----+-------+

// |null|Michael|

// | 30| Andy|

// | 19| Justin|

// +----+-------+

```
// Select only the "name" column

df.select("name").show()

// +-------+

// |   name|

// +-------+

// |Michael|

// |   Andy|

// | Justin|

// +-------+

// Select everybody, but increment the age by 1

df.select($"name", $"age" + 1).show()

// +-------+---------+

// |   name|(age + 1)|

// +-------+---------+

// |Michael|     null|

// |   Andy|       31|

// | Justin|       20|

// +-------+---------+
```

```
// Select people older than 21

df.filter($"age" > 21).show()

// +---+----+

// |age|name|

// +---+----+

// | 30|Andy|

// +---+----+

// Count people by age

df.groupBy("age").count().show()

// +----+-----+

// | age|count|

// +----+-----+

// |  19|    1|

// |null|    1|

// |  30|    1|

// +----+-----+
```

Q. What are the different types of operators provided by the Apache GraphX library?

In such spark interview questions, try giving an explanation too (not just the name of the operators).

Property Operator: Property operators modify the vertex or edge properties using a user-defined map function and produce a new graph.

Structural Operator: Structure operators operate on the structure of an input graph and produce a new graph.

Join Operator: Join operators add data to graphs and generate new graphs.

Q. What are the analytic algorithms provided in Apache Spark GraphX?

GraphX is Apache Spark's API for graphs and graph-parallel computation. GraphX includes a set of graph algorithms to simplify analytics tasks. The algorithms are contained in the org.apache.spark.graphx.lib package and can be accessed directly as methods on Graph via GraphOps.

PageRank: PageRank is a graph parallel computation that measures the importance of each vertex in a graph. Example: You can run PageRank to evaluate what the most important pages in Wikipedia are.

Connected Components: The connected components algorithm labels each connected component of the graph with the ID of its lowest-numbered vertex. For example, in a social network, connected components can approximate clusters.

Triangle Counting: A vertex is part of a triangle when it has two adjacent vertices with an edge between them. GraphX implements a triangle counting algorithm in the TriangleCount object that determines the number of triangles passing through each vertex, providing a measure of clustering.

Qq. What is the PageRank algorithm in Apache Spark GraphX?

It is a plus point if you are able to explain this spark interview question thoroughly, along with an example! PageRank measures the importance of each vertex in a graph, assuming an edge from u to v represents an endorsement of v's importance by u.

If a Twitter user is followed by many other users, that handle will be ranked high.

PageRank algorithm was originally developed by Larry Page and Sergey Brin to rank websites for Google. It can be applied to measure the influence of vertices in any network graph. PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The assumption is that more important websites are likely to receive more links from other websites.

A typical example of using Scala's functional programming with Apache Spark RDDs to iteratively compute Page Ranks is shown below:

```
object SparkPageRank {
  def main(args: Array[String]) {
    val spark = SparkSession
      .builder
      .appName("SparkPageRank")
      .getOrCreate()

    val iters = if (args.length > 1) args(1).toInt else 10
    val lines = spark.read.textFile(args(0)).rdd
    val links = lines.map{ s =>
      val parts = s.split("\\s+")
      (parts(0), parts(1))
    }.distinct().groupByKey().cache()

    var ranks = links.mapValues(v => 1.0)

    for (i <- 1 to iters) {
      val contribs = links.join(ranks).values.flatMap{ case (urls, rank) =
        val size = urls.size
        urls.map(url => (url, rank / size))
      }
      ranks = contribs.reduceByKey(_ + _).mapValues(0.15 + 0.85 * _)
    }

    val output = ranks.collect()
    output.foreach(tup => println(tup._1 + " has rank: " + tup._2 + "."))

    spark.stop()
  }
}
```

Q. Explain how an object is implemented in python?

Ans: An object is an instantiation of a class. A class can be instantiated by calling the class using the class name.

Syntax:

```
 = ()
```

Example:

```
class Student:

    id = 25;

    name = "HKR Trainings"

   estb = 10

    def display (self):
```

```
        print("ID: %d \n Name: %s \n Estb: %d "%(self.id,self.name,self.estb))


stud = Student()


stud.display()
```

Output:

ID: 25

Name: HKR Trainings

Estb: 10

Q. Explain Methods in Python

Ans: In Python, a method is a function that is associated with an object. Any object type can have methods.

Example:

```
class Student:

    roll = 17;

    name = "gopal"

   age = 25

    def display (self):

        print(self.roll,self.name,self.age)
```

In the above example, a class named Student is created which contains three fields as Student's roll, name, age and a function "display()" which is used to display the information of the Student.

Q. What is encapsulation in Python?

Ans: Encapsulation is used to restrict access to methods and variables. Here, the methods and data/variables are wrapped together within a single unit so as to prevent data from direct modification.

Below is the example of encapsulation whereby the max price of the product cannot be modified as it is set to 75 .

Example:

```
class Product:


  def __init__(self):

    self.__maxprice = 75


  def sell(self):
```

```
        print("Selling Price: {}".format(self.__maxprice))



    def setMaxPrice(self, price):

        self.__maxprice = price



p = Product()

p.sell()



# change the price

p.__maxprice = 100

p.sell()
```

Output:

Selling Price: 75

Selling Price: 75

Q. Explain the concept of Python Inheritance

Ans: Inheritance refers to a concept where one class inherits the properties of another. It helps to reuse the code and establish a relationship between different classes.

Amongst following two types of classes, inheritance is performed:

Parent class (Super or Base class): A class whose properties are inherited.

Child class (Subclass or Derived class): A class which inherits the properties.

In python, a derived class can inherit base class by just mentioning the base in the bracket after the derived class name.

The syntax to inherit a base class into the derived class is shown below:

Syntax:

class derived-class(base class):

The syntax to inherit multiple classes is shown below by specifying all of them inside the bracket.

Syntax:

class derive-class(, , ...):

Q. What is a python for loop?

Ans: A for loop in Python requires at least two variables to work. The first is the iterable object such as a list, tuple or a string and second is the variable to store the successive values from the sequence in the loop.

Syntax:

```
for iter in sequence:
    statements(iter)
```

The “iter” represents the iteration variable. It gets assigned with the successive values from the input sequence.

The “sequence” may refer to any of the following Python objects such as a list, a tuple or a string.

Q. What is a for-else in python?

Ans: Python allows us to handle loops in an interesting manner by providing a function to write else blocks for cases when the loop does not satisfy a certain condition.

Example :

```
x = [ ]

 for i in x:
```

```
    print "in for loop"

else:

    print "in else block"
```

Output:

```
in else block
```

Q. What are errors and exceptions in python programming?

Ans: In Python, there are two types of errors - syntax error and exceptions.

Syntax Error: It is also known as parsing errors. Errors are issues in a program which may cause it to exit abnormally. When an error is detected, the parser repeats the offending line and then displays an arrow which points at the earliest point in the line.

Exceptions: Exceptions take place in a program when the normal flow of the program is interrupted due to the occurrence of an external event. Even if the syntax of the program is correct, there are chances of detecting an error during execution, this error is nothing

but an exception. Some of the examples of exceptions are - ZeroDivisionError, TypeError and NameError.

Q. What is the key difference between list and tuple?

Ans:

The key difference between lists and tuples is the fact that lists have mutable nature and tuples have immutable nature.

It is said to be a mutable data type when a python object can be modified. On the other hand, immutable data types cannot be modified. Let us see an example to modify an item list vs tuple.

Example:

```
list_num[3] = 7

print(list_num)

tup_num[3] = 7
```

Output:

[1,2,5,7]

Traceback (most recent call last):

File "python", line 6, in

TypeError: 'tuple' object does not support item assignment

In this code, we had assigned 7 to list_num at index 3 and in the output, we can see 7 is found in index 3 . However, we had assigned 7 to tup_num at index 3 but we got type error on the output. This is because we cannot modify tuples due to its immutable nature.

Q. How to convert a string to a number in python?

Ans: The method provided by Python, is a standard built-in function which converts a string into an integer value.

It can be called with a string containing a number as the argument, and it will return the number converted to an actual integer.

Example:

```
print int("1") + 2
```

The above prints 3 .

Q. What is data cleaning?

Ans: Data cleaning is the process of preparing data for analysis by removing or modifying data that is incorrect, incomplete, irrelevant, duplicated, or improperly formatted.

Q. What is data visualization and why is it important?

Ans: Data visualization is the representation of data or information in a graph, chart, or other visual format. It communicates relationships of the data with images. The data visualizations are important because it allows trends and patterns to be more easily seen.

Q. What is Pyspark and explain its characteristics?

Ans: To support Python with Spark, the Spark community has released a tool called PySpark. It is primarily used to process structured and semi-structured datasets and also supports an optimized API to read data from the multiple data sources containing different file formats. Using PySpark, you can also work with RDDs in the Python programming language using its library name Py4j.

The main characteristics of PySpark are listed below:

Nodes are Abstracted.

Based on MapReduce.

API for Spark.

The network is abstracted.

Q. Explain RDD and also state how you can create RDDs in Apache Spark.

Ans: RDD stands for Resilient Distribution Datasets, a fault-tolerant set of operational elements that are capable of running in parallel. These RDDs, in general, are the portions of data, which are stored in the memory and distributed over many nodes.

All partitioned data in an RDD is distributed and immutable.

There are primarily two types of RDDs are available:

Hadoop datasets: Those who perform a function on each file record in Hadoop Distributed File System (HDFS) or any other storage system.

Parallelized collections: Those existing RDDs which run in parallel with one another.

Q. How do we create RDDs in Spark?

Ans: Spark provides two methods to create RDD:

By parallelizing a collection in your Driver program.

This makes use of SparkContext's 'parallelize'.

method val DataArray = Array(2,4,6,8,10)

val DataRDD = sc.parallelize(DataArray)

By loading an external dataset from external storage like HDFS, HBase, shared file system.

Q. Name the components of Apache Spark?

Ans: The following are the components of Apache Spark.

Spark Core: Base engine for large-scale parallel and distributed data processing.

Spark Streaming: Used for processing real-time streaming data.

Spark SQL: Integrates relational processing with Spark's functional programming API.

GraphX: Graphs and graph-parallel computation.

MLlib: Performs machine learning in Apache Spark.

Q. How DAG functions in Spark?

Ans: When an Action is approached at a certain point, Spark RDD at an abnormal state, Spark presents the heredity chart to the DAG Scheduler.

Activities are separated into phases of the errand in the DAG Scheduler. A phase contains errands dependent on the parcel of the info information. The DAG scheduler pipelines administrators together. It dispatches tasks through the group chief. The conditions of stages are obscure to the errand scheduler. The Workers execute the undertaking on the slave.

Q. What do you mean by Spark Streaming?

Ans: Stream processing is an extension to the Spark API that lets stream processing of live data streams. Data from multiple sources such as Flume, Kafka, Kinesis, etc., is processed and then pushed to live dashboards, file systems, and databases. Compared to the terms of input data, it is just similar to batch processing, and data is segregated into streams like batches in processing.

Q. What does MLlib do?

Ans: MLlib is a scalable Machine Learning library offered by Spark. It supports making Machine Learning secure and scalable with standard learning algorithms and use cases such as regression filtering, clustering, dimensional reduction.

Q. What are the different MLlib tools available in Spark?

Ans:

ML Algorithms: Classification, Regression, Clustering, and Collaborative filtering.

Featurization: Feature extraction, Transformation, Dimensionality reduction, and Selection.

Pipelines: Tools for constructing, evaluating, and tuning ML pipelines

Persistence: Saving and loading algorithms, models and pipelines.

Utilities: Linear algebra, statistics, data handling.

Q. Explain the functions of SparkCore.

Ans: SparkCore implements several key functions such as

Memory management.

Fault-tolerance.

Monitoring jobs.

Job scheduling.

Interaction with storage systems.

Moreover, additional libraries, built atop the core, let diverse workloads for streaming, machine learning, and SQL. This is useful for:

Memory management.

fault recovery.

Interacting with storage systems.

Scheduling and monitoring jobs on a cluster.

Q. What is the module used to implement SQL in Spark? How does it work?

Ans: The module used is Spark SQL, which integrates relational processing with Spark's functional programming API. It helps to query data either through Hive Query Language or SQL. These are the four libraries of Spark SQL.

Data Source API.

Interpreter & Optimizer.

DataFrame API.

SQL Service.

Q. List the functions of Spark SQL.

Ans: Spark SQL is capable of:

Loading data from a variety of structured sources.

Querying data using SQL statements, both inside a Spark program and from external tools that connect to Spark SQL through standard database connectors (JDBC/ODBC). For instance, using business intelligence tools like Tableau.

Providing rich integration between SQL and regular Python/Java/Scala code, including the ability to join RDDs and SQL tables, expose custom functions in SQL, and more.

Q. What are the various algorithms supported in PySpark?

Ans: The different algorithms supported by PySpark are:

Spark.mllib.

mllib.clustering.

mllib.classification.

mllib.regression.

mllib.recommendation.

mllib.linalg.

mllib.fpm.

Q. Explain the purpose of serializations in PySpark?

Ans: For improving performance, PySpark supports custom serializers to transfer data. They are:

MarshalSerializer: It supports only fewer data types, but compared to PickleSerializer, it is faster.

PickleSerializer: It is by default used for serializing objects. Supports any Python object but at a slow speed.

Q. What is PySpark StorageLevel?25 . What is PySpark StorageLevel?

Ans: PySpark Storage Level controls storage of an RDD. It also manages how to store RDD in the memory or over the disk, or sometimes both. Moreover, it even controls the replicate or serializes RDD partitions. The code for StorageLevel is as follows

class pyspark.StorageLevel(useDisk, useMemory, useOfHeap, deserialized, replication = 1)

Q. What is PySpark SparkContext?

Ans: PySpark SparkContext is treated as an initial point for entering and using any Spark functionality. The SparkContext uses py4j library to launch the JVM, and then create the JavaSparkContext. By default, the SparkContext is available as ‘sc’.

Q. What is PySpark SparkFiles?

Ans: PySpark SparkFiles is used to load our files on the Apache Spark application. It is one of the functions under SparkContext and can be called using sc.addFile to load the

files on the Apache Spark. SparkFIles can also be used to get the path using SparkFile.get or resolve the paths to files that were added from sc.addFile. The class methods present in the SparkFiles directory are getrootdirectory() and get(filename).

Q. Explain Spark Execution Engine?

Ans: Apache Spark is a graph execution engine that enables users to analyze massive data sets with high performance. For this, Spark first needs to be held in memory to improve performance drastically, if data needs to be manipulated with multiple stages of processing.

Q. What do you mean by SparkConf in PySpark?

Ans: SparkConf helps in setting a few configurations and parameters to run a Spark application on the local/cluster. In simple terms, it provides configurations to run a Spark application.

Q. Name a few attributes of SparkConf.

Ans: Few main attributes of SparkConf are listed below:

set(key, value): This attribute helps in setting the configuration property.

setSparkHome(value): This attribute enables in setting Spark installation path on worker nodes.

setAppName(value): This attribute helps in setting the application name.

setMaster(value): This attribute helps in setting the master URL.

get(key, defaultValue=None): This attribute supports in getting a configuration value of a key.

Q. What is PySpark?

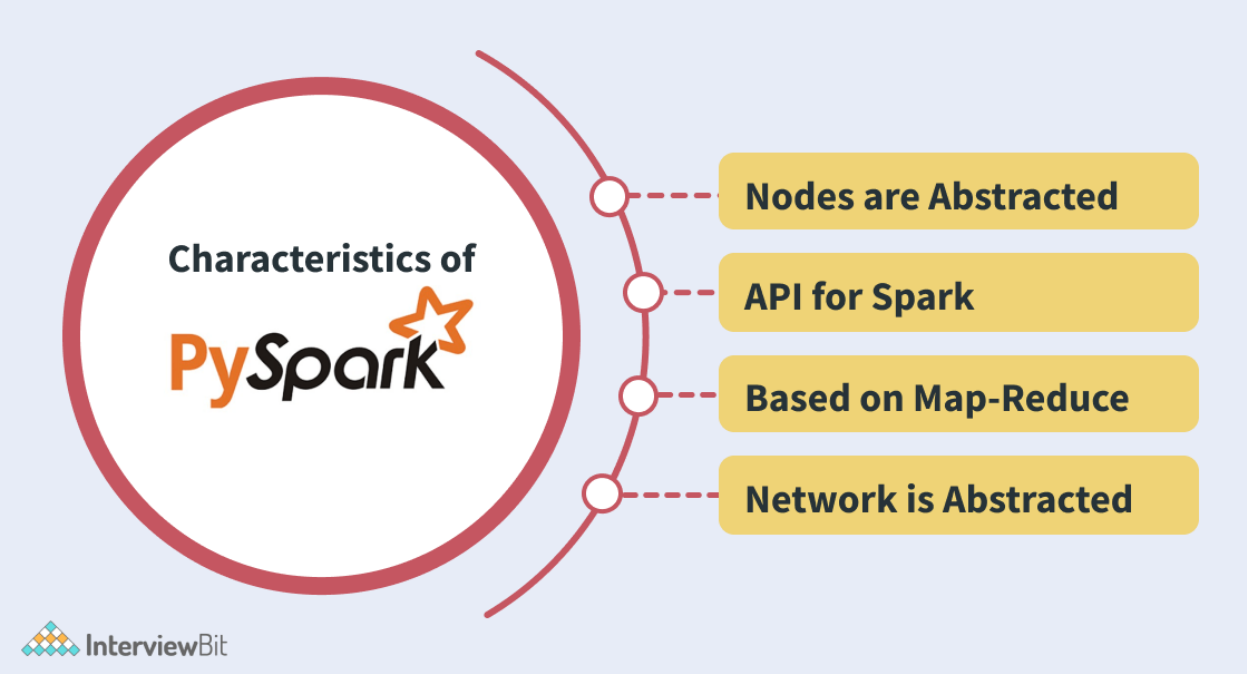
PySpark is an Apache Spark interface in Python. It is used for collaborating with Spark using APIs written in Python. It also supports Spark's features like Spark DataFrame, Spark SQL, Spark Streaming, Spark MLlib and Spark Core. It provides an interactive PySpark shell to analyze structured and semi-structured data in a distributed environment. PySpark supports reading data from multiple sources and different formats. It also facilitates the use of RDDs (Resilient Distributed Datasets). PySpark features are implemented in the py4j library in python.

PySpark can be installed using PyPi by using the command:

```
pip install pyspark
```

Q. What are the characteristics of PySpark?

There are 4 characteristics of PySpark:



- Abstracted Nodes: This means that the individual worker nodes can not be addressed.
- Spark API: PySpark provides APIs for utilizing Spark features.
- Map-Reduce Model: PySpark is based on Hadoop's Map-Reduce model this means that the programmer provides the map and the reduce functions.
- Abstracted Network: Networks are abstracted in PySpark which means that the only possible communication is implicit communication.

Q. What are the advantages and disadvantages of PySpark?

Advantages of PySpark:

- Simple to use: Parallelized code can be written in a simpler manner.
- Error Handling: PySpark framework easily handles errors.
- Inbuilt Algorithms: PySpark provides many of the useful algorithms in Machine Learning or Graphs.
- Library Support: Compared to Scala, Python has a huge library collection for working in the field of data science and data visualization.
- Easy to Learn: PySpark is an easy to learn language.

Disadvantages of PySpark:

- Sometimes, it becomes difficult to express problems using the MapReduce model.
- Since Spark was originally developed in Scala, while using PySpark in Python programs they are relatively less efficient and approximately 10x times slower than the Scala programs. This would impact the performance of heavy data processing applications.
- The Spark Streaming API in PySpark is not mature when compared to Scala. It still requires improvements.
- PySpark cannot be used for modifying the internal function of the Spark due to the abstractions provided. In such cases, Scala is preferred.

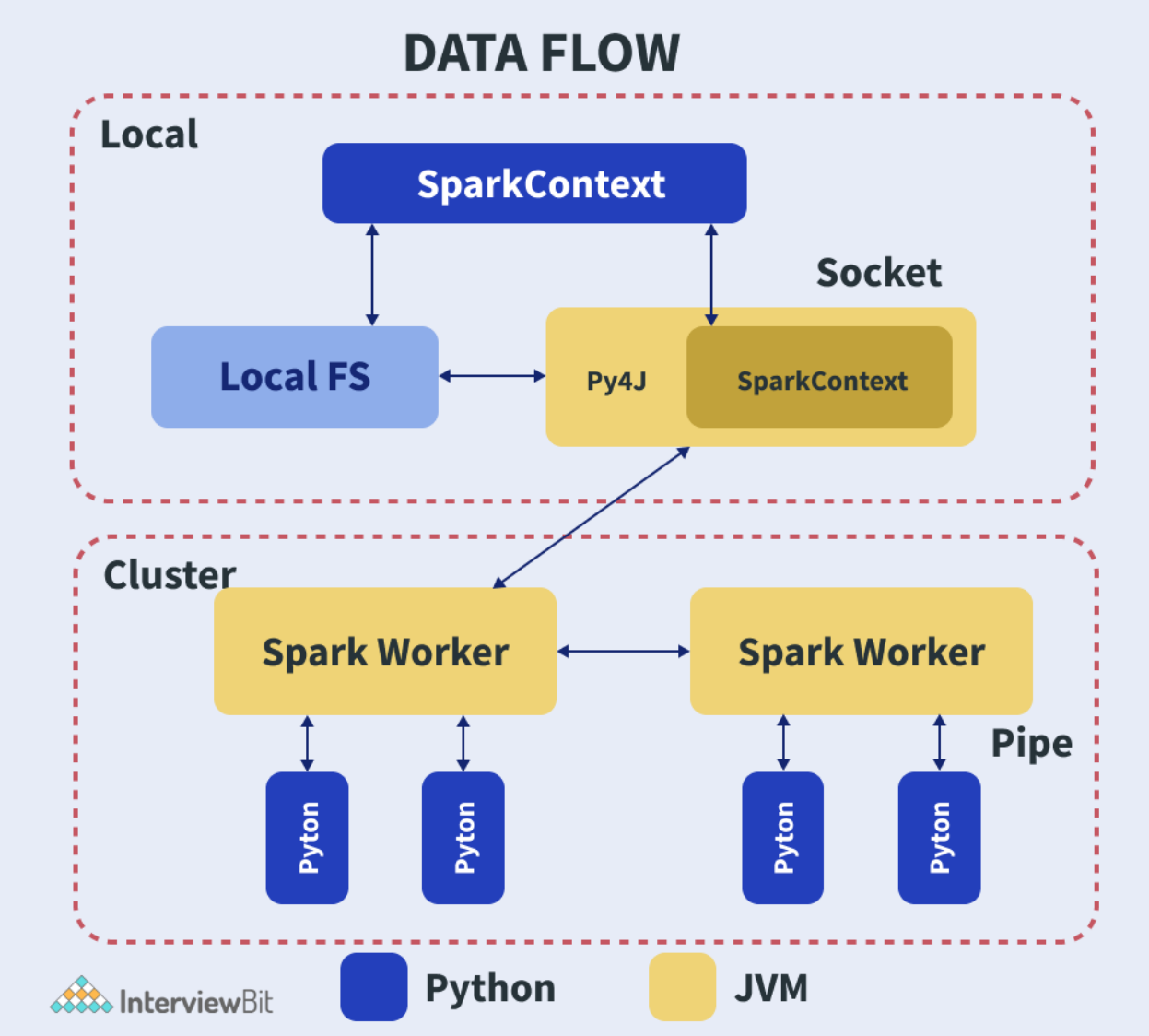
You can download a PDF version of Pyspark Interview Questions.

Download PDF

Q. What is PySpark SparkContext?

PySpark SparkContext is an initial entry point of the spark functionality. It also represents Spark Cluster Connection and can be used for creating the Spark RDDs (Resilient Distributed Datasets) and broadcasting the variables on the cluster.

The following diagram represents the architectural diagram of PySpark's SparkContext:



When we want to run the Spark application, a driver program that has the main function will be started. From this point, the SparkContext that we defined gets initiated. Later on, the driver program performs operations inside the executors of the worker nodes. Additionally, JVM will be launched using Py4J which in turn creates JavaSparkContext. Since PySpark has default SparkContext available as “sc”, there will not be a creation of a new SparkContext.

Q. Why do we use PySpark SparkFiles?

PySpark's SparkFiles are used for loading the files onto the Spark application. This functionality is present under SparkContext and can be called using the `sc.addFile()` method for loading files on Spark. SparkFiles can also be used for getting the path using the `SparkFiles.get()` method. It can also be used to resolve paths to files added using the `sc.addFile()` method.

Q. What are PySpark serializers?

The serialization process is used to conduct performance tuning on Spark. The data sent or received over the network to the disk or memory should be persisted. PySpark supports serializers for this purpose. It supports two types of serializers, they are:

- PickleSerializer: This serializes objects using Python's PickleSerializer (`class pyspark.PickleSerializer`). This supports almost every Python object.
- MarshalSerializer: This performs serialization of objects. We can use it by using `class pyspark.MarshalSerializer`. This serializer is faster than the PickleSerializer but it supports only limited types.

Consider an example of serialization which makes use of MarshalSerializer:

```
# --serializing.py----
from pyspark.context import SparkContext
from pyspark.serializers import MarshalSerializer
sc = SparkContext("local", "Marshal Serialization", serializer =
MarshalSerializer())    #Initialize spark context and serializer
print(sc.parallelize(list(range(1000))).map(lambda x: 3 *
x).take(5))
sc.stop()
```

When we run the file using the command:

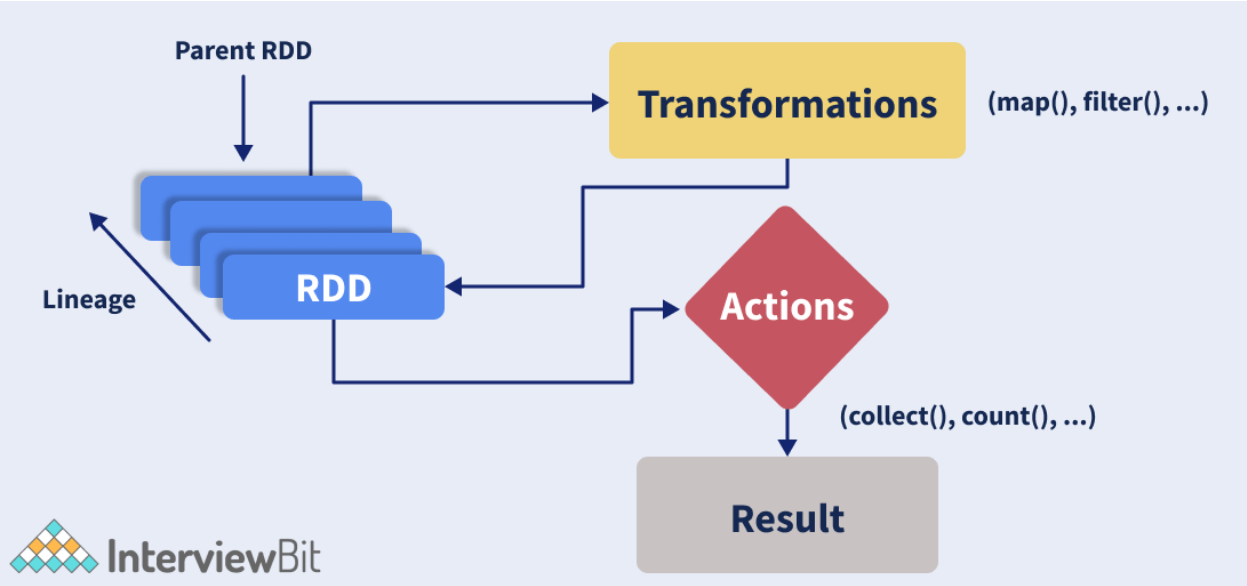
```
$SPARK_HOME/bin/spark-submit serializing.py
```

The output of the code would be the list of size 5 of numbers multiplied by 3:

```
[0, 3, 6, 9, 12]
```

Q. What are RDDs in PySpark?

RDDs expand to Resilient Distributed Datasets. These are the elements that are used for running and operating on multiple nodes to perform parallel processing on a cluster. Since RDDs are suited for parallel processing, they are immutable elements. This means that once we create RDD, we cannot modify it. RDDs are also fault-tolerant which means that whenever failure happens, they can be recovered automatically. Multiple operations can be performed on RDDs to perform a certain task. The operations can be of 2 types:



- Transformation: These operations when applied on RDDs result in the creation of a new RDD. Some of the examples of transformation operations are filter, groupBy, map.

  Let us take an example to demonstrate transformation operation by considering filter() operation:

```
from pyspark import SparkContext
sc = SparkContext("local", "Transdormation Demo")
words_list = sc.parallelize (
  ["pyspark",
  "interview",
  "questions",
```

```
  "at",
  "interviewbit"]
)
filtered_words = words_list.filter(lambda x: 'interview' in x)
filtered = filtered_words.collect()
print(filtered)
```

The above code filters all the elements in the list that has ‘interview’ in the element. The output of the above code would be:

```
[
  "interview",
  "interviewbit"
]
```

- Action: These operations instruct Spark to perform some computations on the RDD and return the result to the driver. It sends data from the Executer to the driver. count(), collect(), take() are some of the examples.
  Let us consider an example to demonstrate action operation by making use of the count() function.

```
from pyspark import SparkContext
sc = SparkContext("local", "Action Demo")
words = sc.parallelize (
  ["pyspark",
  "interview",
  "questions",
  "at",
  "interviewbit"]
)
counts = words.count()
print("Count of elements in RDD -> ",  counts)
```

In this class, we count the number of elements in the spark RDDs. The output of this code is

```
Count of elements in RDD -> 5
```

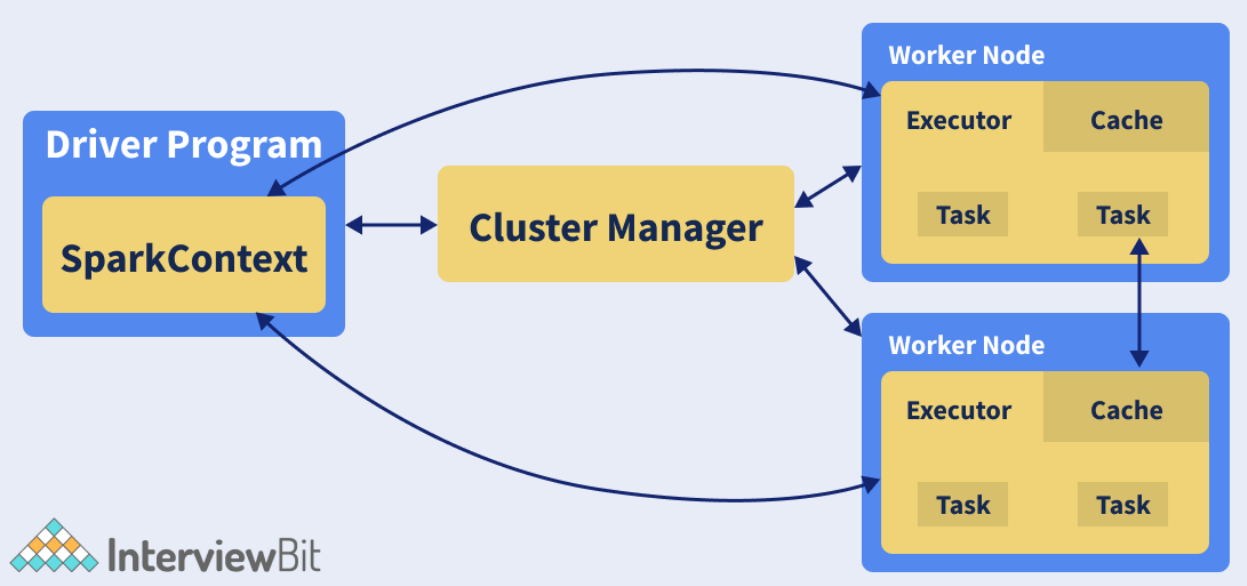
Q. Does PySpark provide a machine learning API?

Similar to Spark, PySpark provides a machine learning API which is known as MLlib that supports various ML algorithms like:

- `mllib.classification` - This supports different methods for binary or multiclass classification and regression analysis like Random Forest, Decision Tree, Naive Bayes etc.
- `mllib.clustering` - This is used for solving clustering problems that aim in grouping entities subsets with one another depending on similarity.
- `mllib.fpm` - FPM stands for Frequent Pattern Matching. This library is used to mine frequent items, subsequences or other structures that are used for analyzing large datasets.
- `mllib.linalg` - This is used for solving problems on linear algebra.
- `mllib.recommendation` - This is used for collaborative filtering and in recommender systems.
- `spark.mllib` - This is used for supporting model-based collaborative filtering where small latent factors are identified using the Alternating Least Squares (ALS) algorithm which is used for predicting missing entries.
- `mllib.regression` - This is used for solving problems using regression algorithms that find relationships and variable dependencies.

Q. What are the different cluster manager types supported by PySpark?

A cluster manager is a cluster mode platform that helps to run Spark by providing all resources to worker nodes based on the requirements.



The above figure shows the position of cluster manager in the Spark ecosystem. Consider a master node and multiple worker nodes present in the cluster. The master nodes provide the worker nodes with the resources like memory, processor allocation etc depending on the nodes requirements with the help of the cluster manager.

PySpark supports the following cluster manager types:

- Standalone – This is a simple cluster manager that is included with Spark.
- Apache Mesos – This manager can run Hadoop MapReduce and PySpark apps.
- Hadoop YARN – This manager is used in Hadoop2.
- Kubernetes – This is an open-source cluster manager that helps in automated deployment, scaling and automatic management of containerized apps.
- local – This is simply a mode for running Spark applications on laptops/desktops.

Q. What are the advantages of PySpark RDD?

PySpark RDDs have the following advantages:

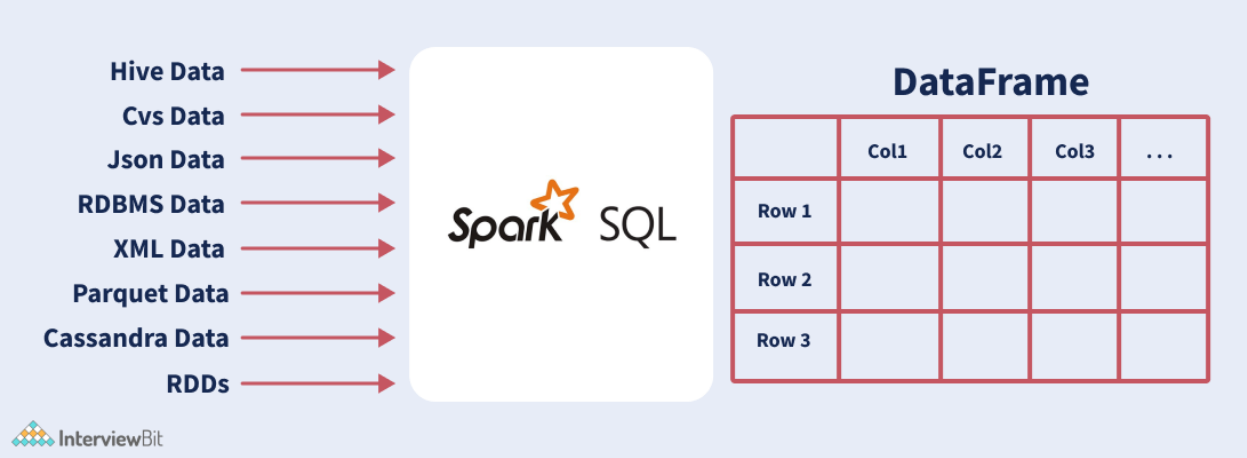
- In-Memory Processing: PySpark's RDD helps in loading data from the disk to the memory. The RDDs can even be persisted in the memory for reusing the computations.
- Immutability: The RDDs are immutable which means that once created, they cannot be modified. While applying any transformation operations on the RDDs, a new RDD would be created.
- Fault Tolerance: The RDDs are fault-tolerant. This means that whenever an operation fails, the data gets automatically reloaded from other available partitions. This results in seamless execution of the PySpark applications.
- Lazy Evolution: The PySpark transformation operations are not performed as soon as they are encountered. The operations would be stored in the DAG and are evaluated once it finds the first RDD action.
- Partitioning: Whenever RDD is created from any data, the elements in the RDD are partitioned to the cores available by default.

Q. Is PySpark faster than pandas?

PySpark supports parallel execution of statements in a distributed environment, i.e on different cores and different machines which are not present in Pandas. This is why PySpark is faster than pandas.

Q. What do you understand about PySpark DataFrames?

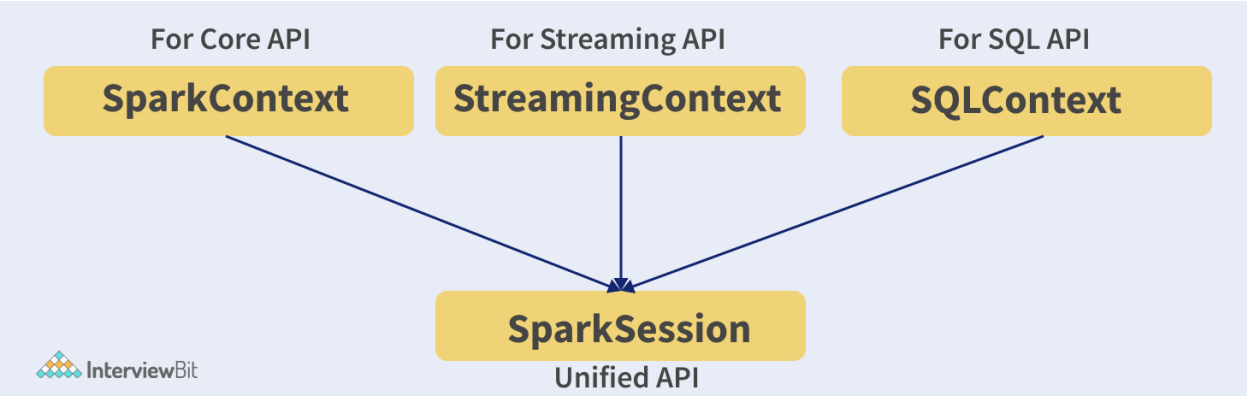
PySpark DataFrame is a distributed collection of well-organized data that is equivalent to tables of the relational databases and are placed into named columns. PySpark DataFrame has better optimisation when compared to R or python. These can be created from different sources like Hive Tables, Structured Data Files, existing RDDs, external databases etc as shown in the image below:



The data in the PySpark DataFrame is distributed across different machines in the cluster and the operations performed on this would be run parallelly on all the machines. These can handle a large collection of structured or semi-structured data of a range of petabytes.

Q. What is SparkSession in Pyspark?

SparkSession is the entry point to PySpark and is the replacement of SparkContext since PySpark version 2.0. This acts as a starting point to access all of the PySpark functionalities related to RDDs, DataFrame, Datasets etc. It is also a Unified API that is used in replacing the SQLContext, StreamingContext, HiveContext and all other contexts.



The SparkSession internally creates SparkContext and SparkConfig based on the details provided in SparkSession. SparkSession can be created by making use of builder patterns.

Q. What are the types of PySpark's shared variables and why are they useful?

Whenever PySpark performs the transformation operation using filter(), map() or reduce(), they are run on a remote node that uses the variables shipped with tasks. These variables are not reusable and cannot be shared across different tasks because they are not returned to the Driver. To solve the issue of reusability and sharing, we have shared variables in PySpark. There are two types of shared variables, they are:

Broadcast variables: These are also known as read-only shared variables and are used in cases of data lookup requirements. These variables are cached and are made available on all the cluster nodes so that the tasks can make use of them. The variables are not sent with every task. They are rather distributed to the nodes using efficient algorithms for reducing the cost of communication. When we run an RDD job operation that makes use of Broadcast variables, the following things are done by PySpark:

- The job is broken into different stages having distributed shuffling. The actions are executed in those stages.
- The stages are then broken into tasks.
- The broadcast variables are broadcasted to the tasks if the tasks need to use it.

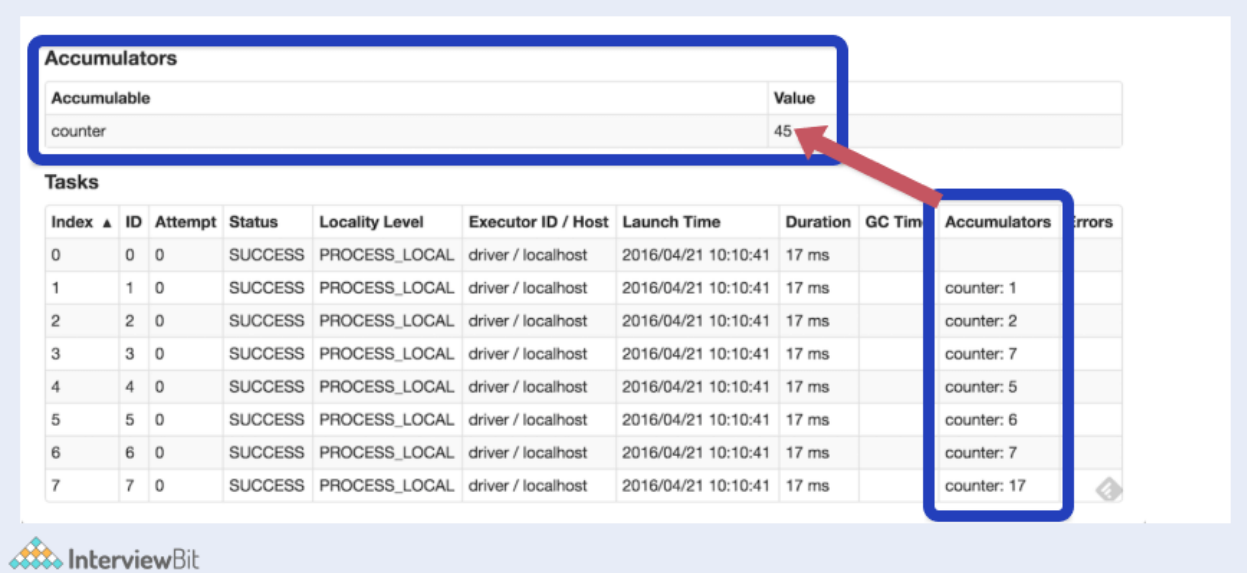
Broadcast variables are created in PySpark by making use of the broadcast(variable) method from the SparkContext class. The syntax for this goes as follows:

```
broadcastVar = sc.broadcast([10, 11, 22, 31])
broadcastVar.value    # access broadcast variable
```

An important point of using broadcast variables is that the variables are not sent to the tasks when the broadcast function is called. They will be sent when the variables are first required by the executors.

Accumulator variables: These variables are called updatable shared variables. They are added through associative and commutative operations and are used for performing counter or sum operations. PySpark supports the creation of numeric type accumulators by default. It also has the ability to add custom accumulator types. The custom types can be of two types:

- Named Accumulators: These accumulators are visible under the “Accumulator” tab in the PySpark web UI as shown in the image below:



Here, we will see the Accumulable section that has the sum of the Accumulator values of the variables modified by the tasks listed in the Accumulator column present in the Tasks table.

- Unnamed Accumulators: These accumulators are not shown on the PySpark Web UI page. It is always recommended to make use of named accumulators.

Accumulator variables can be created by using SparkContext.longAccumulator(variable) as shown in the example below:

```
ac = sc.longAccumulator("sumaccumulator")
sc.parallelize([2, 23, 1]).foreach(lambda x: ac.add(x))
```

Depending on the type of accumulator variable data - double, long and collection, PySpark provide DoubleAccumulator, LongAccumulator and CollectionAccumulator respectively.

Q. What is PySpark UDF?

UDF stands for User Defined Functions. In PySpark, UDF can be created by creating a python function and wrapping it with PySpark SQL's udf() method and using it on the DataFrame or SQL. These are generally created when we do not have the functionalities supported in PySpark's library and we have to use our own logic on the data. UDFs can be reused on any number of SQL expressions or DataFrames.

Q. What are the industrial benefits of PySpark?

These days, almost every industry makes use of big data to evaluate where they stand and grow. When you hear the term big data, Apache Spark comes to mind. Following are the industry benefits of using PySpark that supports Spark:

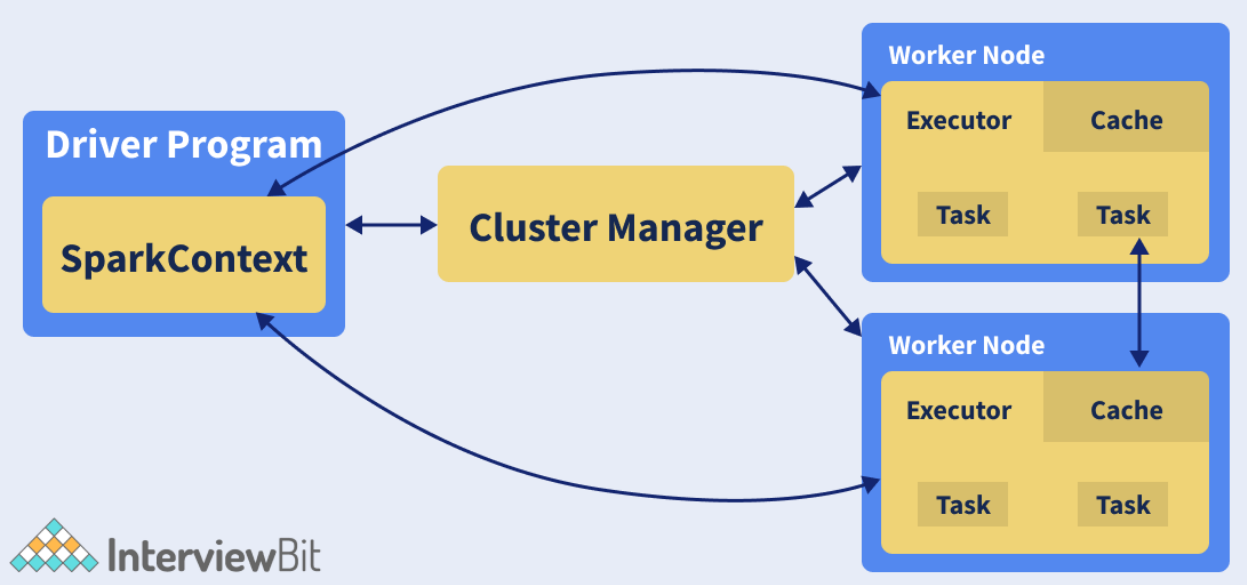
- Media streaming: Spark can be used to achieve real-time streaming to provide personalized recommendations to subscribers. Netflix is one such example that uses Apache Spark. It processes around 450 billion events every day to flow to its server-side apps.
- Finance: Banks use Spark for accessing and analyzing the social media profiles and in turn get insights on what strategies would help them to make the right decisions regarding customer segmentation, credit risk assessments, early fraud detection etc.

- Healthcare: Providers use Spark for analyzing the past records of the patients to identify what health issues the patients might face posting their discharge. Spark is also used to perform genome sequencing for reducing the time required for processing genome data.
- Travel Industry: Companies like TripAdvisor uses Spark to help users plan the perfect trip and provide personalized recommendations to the travel enthusiasts by comparing data and review from hundreds of websites regarding the place, hotels, etc.
- Retail and e-commerce: This is one important industry domain that requires big data analysis for targeted advertising. Companies like Alibaba run Spark jobs for analyzing petabytes of data for enhancing customer experience, providing targetted offers, sales and optimizing the overall performance.

Pyspark Interview Questions for Experienced

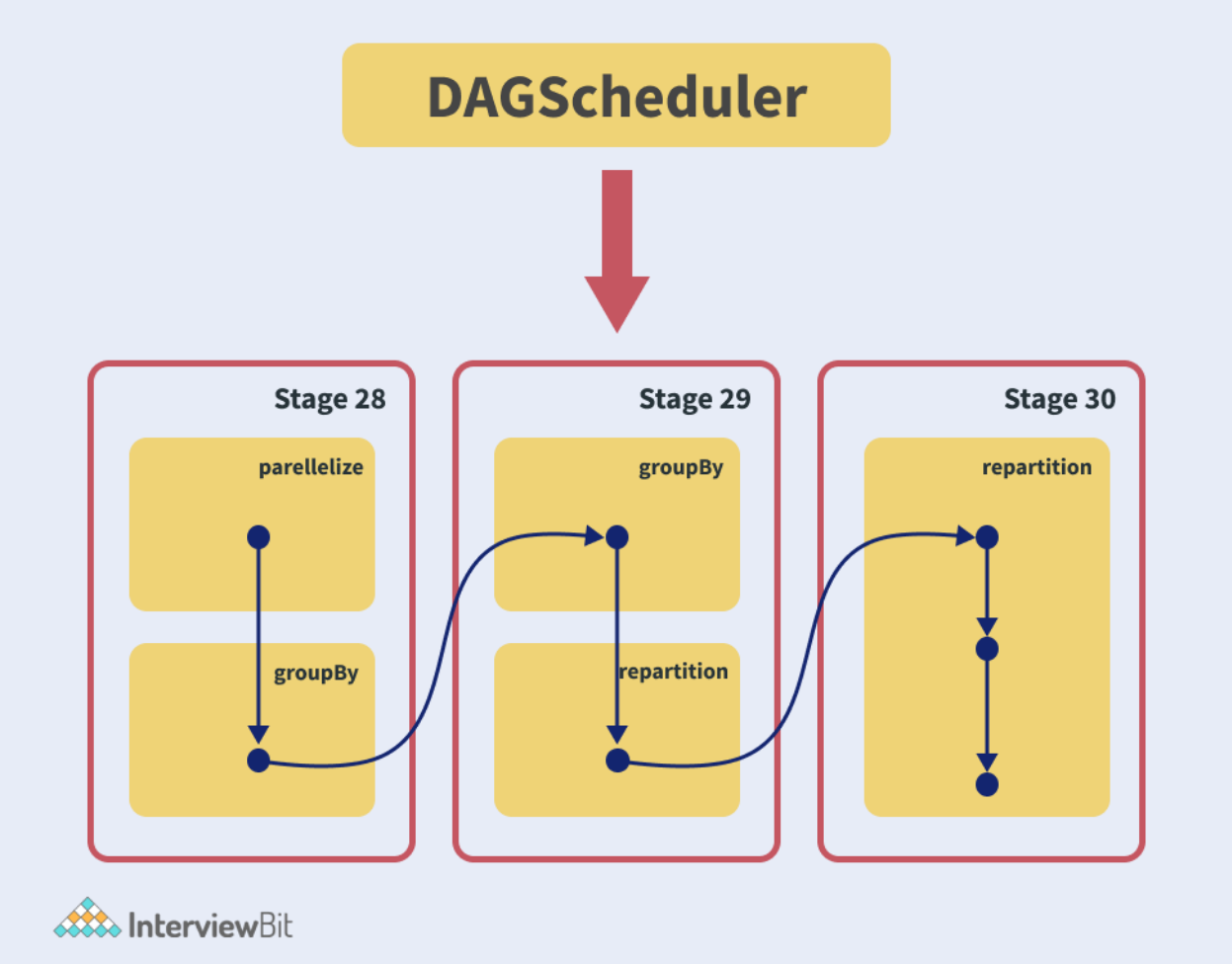
Q. What is PySpark Architecture?

PySpark similar to Apache Spark works in master-slave architecture pattern. Here, the master node is called the Driver and the slave nodes are called the workers. When a Spark application is run, the Spark Driver creates SparkContext which acts as an entry point to the spark application. All the operations are executed on the worker nodes. The resources required for executing the operations on the worker nodes are managed by the Cluster Managers. The following diagram illustrates the architecture described:



Q. What PySpark DAGScheduler?

DAG stands for Direct Acyclic Graph. DAGScheduler constitutes the scheduling layer of Spark which implements scheduling of tasks in a stage-oriented manner using jobs and stages. The logical execution plan (Dependencies lineage of transformation actions upon RDDs) is transformed into a physical execution plan consisting of stages. It computes a DAG of stages needed for each job and keeps track of what stages are RDDs are materialized and finds a minimal schedule for running the jobs. These stages are then submitted to TaskScheduler for running the stages. This is represented in the image flow below:



DAGScheduler performs the following three things in Spark:

- Compute DAG execution for the job.
- Determine preferred locations for running each task
- Failure Handling due to output files lost during shuffling.

PySpark's DAGScheduler follows event-queue architecture. Here a thread posts events of type DAGSchedulerEvent such as new stage or job. The DAGScheduler then reads the stages and sequentially executes them in topological order.

Q. What is the common workflow of a spark program?

The most common workflow followed by the spark program is:

- The first step is to create input RDDs depending on the external data. Data can be obtained from different data sources.
- Post RDD creation, the RDD transformation operations like filter() or map() are run for creating new RDDs depending on the business logic.
- If any intermediate RDDs are required to be reused for later purposes, we can persist those RDDs.
- Lastly, if any action operations like first(), count() etc are present then spark launches it to initiate parallel computation.

Q. Why is PySpark SparkConf used?

PySpark SparkConf is used for setting the configurations and parameters required to run applications on a cluster or local system. The following class can be executed to run the SparkConf:

```
class pyspark.Sparkconf(
localdefaults = True,
_jvm = None,
_jconf = None
)
```

where:

- `loadDefaults` - is of type boolean and indicates whether we require loading values from Java System Properties. It is True by default.
- `_jvm` - This belongs to the class `py4j.java_gateway.JVMView` and is an internal parameter that is used for passing the handle to JVM. This need not be set by the users.
- `_jconf` - This belongs to the class `py4j.java_gateway.JavaObject`. This parameter is an option and can be used for passing existing SparkConf handles for using the parameters.

Q. How will you create PySpark UDF?

Consider an example where we want to capitalize the first letter of every word in a string. This feature is not supported in PySpark. We can however achieve this by creating a UDF `capitalizeWord(str)` and using it on the DataFrames. The following steps demonstrate this:

- Create Python function `capitalizeWord` that takes a string as input and capitalizes the first character of every word.

```
def capitalizeWord(str):
   result=""
   words = str.split(" ")
   for word in words:
      result= result + word[0:1].upper() + word[1:len(x)] + " "
   return result
```

- Register the function as a PySpark UDF by using the udf() method of `org.apache.spark.sql.functions.udf` package which needs to be imported. This method returns the object of class `org.apache.spark.sql.expressions.UserDefinedFunction`.

```
""" Converting function to UDF """
capitalizeWordUDF = udf(lambda z:
capitalizeWord(z),StringType())
```

- Use UDF with DataFrame: The UDF can be applied on a Python DataFrame as that acts as the built-in function of DataFrame.
  Consider we have a DataFrame of stored in variable df as below:

```
+----------+-----------------+
|ID_COLUMN |NAME_COLUMN      |
+----------+-----------------+
|1         |harry potter     |
|2         |ronald weasley   |
|3         |hermoine granger |
+----------+-----------------+
```

To capitalize every first character of the word, we can use:

```
df.select(col("ID_COLUMN"), convertUDF(col("NAME_COLUMN"))
```

```
 .alias("NAME_COLUMN") )
 .show(truncate=False)
```

The output of the above code would be:

```
+----------+-----------------+
|ID_COLUMN |NAME_COLUMN      |
+----------+-----------------+
|1         |Harry Potter     |
|2         |Ronald Weasley   |
|3         |Hermoine Granger |
+----------+-----------------+
```

UDFs have to be designed in a way that the algorithms are efficient and take less time and space complexity. If care is not taken, the performance of the DataFrame operations would be impacted.

Q. What are the profilers in PySpark?

Custom profilers are supported in PySpark. These are useful for building predictive models. Profilers are useful for data review to ensure that it is valid and can be used for consumption. When we require a custom profiler, it has to define some of the following methods:

- profile: This produces a system profile of some sort.
- stats: This returns collected stats of profiling.
- dump: This dumps the profiles to a specified path.
- add: This helps to add profile to existing accumulated profile. The profile class has to be selected at the time of SparkContext creation.
- dump(id, path): This dumps a specific RDD id to the path given.

Q. How to create SparkSession?

To create SparkSession, we use the builder pattern. The SparkSession class from the `pyspark.sql` library has the getOrCreate() method which creates a new SparkSession

if there is none or else it returns the existing SparkSession object. The following code is an example for creating SparkSession:

```
import pyspark
from pyspark.sql import SparkSession
spark = SparkSession.builder.master("local[1]")
                    .appName('InterviewBitSparkSession')
                    .getOrCreate()
```

Here,

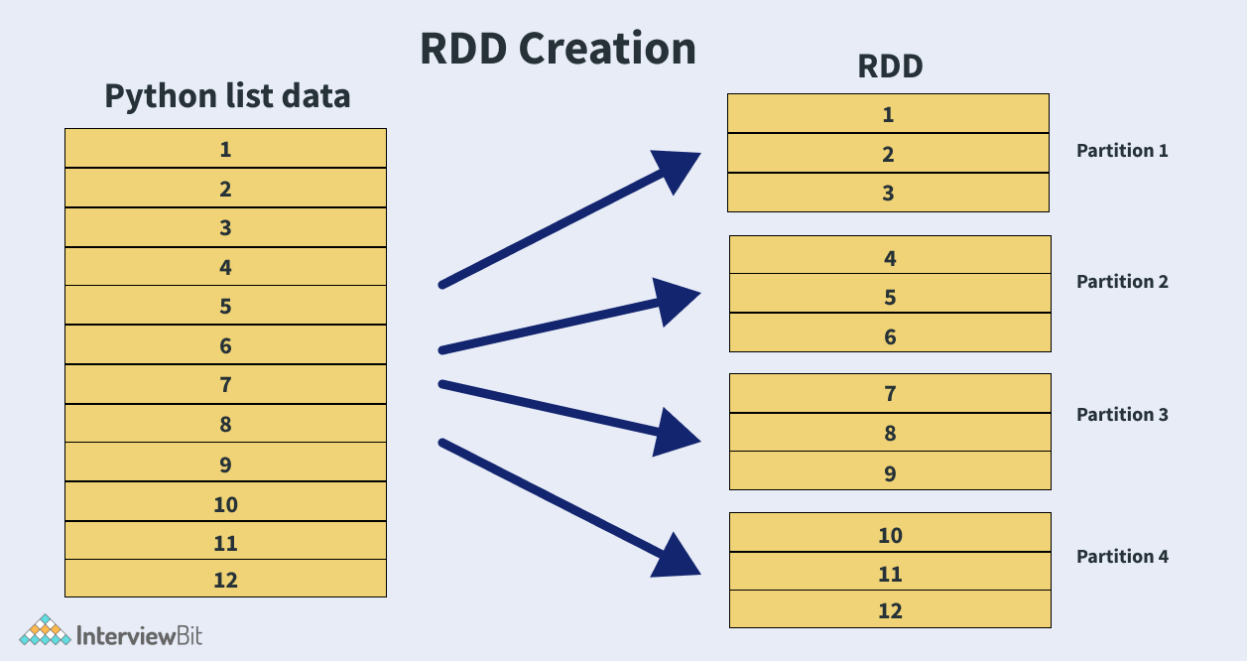
- master() – This is used for setting up the mode in which the application has to run - cluster mode (use the master name) or standalone mode. For Standalone mode, we use the `local[x]` value to the function, where x represents partition count to be created in RDD, DataFrame and DataSet. The value of x is ideally the number of CPU cores available.
- appName() - Used for setting the application name
- getOrCreate() – For returning SparkSession object. This creates a new object if it does not exist. If an object is there, it simply returns that.

If we want to create a new SparkSession object every time, we can use the newSession method as shown below:

```
import pyspark
from pyspark.sql import SparkSession
spark_session = SparkSession.newSession
```

Q. What are the different approaches for creating RDD in PySpark?

The following image represents how we can visualize RDD creation in PySpark:



In the image, we see that the data we have is the list form and post converting to RDDs, we have it stored in different partitions.

We have the following approaches for creating PySpark RDD:

- Using `sparkContext.parallelize()`: The parallelize() method of the SparkContext can be used for creating RDDs. This method loads existing collection from the driver and parallelizes it. This is a basic approach to create RDD and is used when we have data already present in the memory. This also requires the presence of all data on the Driver before creating RDD. Code to create RDD using the parallelize method for the python list shown in the image above:

```
list = [1,2,3,4,5,6,7,8,9,10,11,12]
rdd=spark.sparkContext.parallelize(list)
```

- Using `sparkContext.textFile()`: Using this method, we can read .txt file and convert them into RDD. Syntax:

```
rdd_txt = spark.sparkContext.textFile("/path/to/textFile.txt")
```

- Using `sparkContext.wholeTextFiles()`: This function returns PairRDD (RDD containing key-value pairs) with file path being the key and the file content is the value.

```
#Reads entire file into a RDD as single record.
rdd_whole_text =
spark.sparkContext.wholeTextFiles("/path/to/textFile.txt")
```

We can also read csv, json, parquet and various other formats and create the RDDs.

- Empty RDD with no partition using `sparkContext.emptyRDD`: RDD with no data is called empty RDD. We can create such RDDs having no partitions by using emptyRDD() method as shown in the code piece below:

```
empty_rdd = spark.sparkContext.emptyRDD
# to create empty rdd of string type
empty_rdd_string = spark.sparkContext.emptyRDD[String]
```

- Empty RDD with partitions using `sparkContext.parallelize`: When we do not require data but we require partition, then we create empty RDD by using the parallelize method as shown below:

```
#Create empty RDD with 20 partitions
empty_partitioned_rdd = spark.sparkContext.parallelize([],20)
```

Q. How can we create DataFrames in PySpark?

We can do it by making use of the `createDataFrame()` method of the SparkSession.

```
data = [('Harry', 20),
        ('Ron', 20),
        ('Hermoine', 20)]
columns = ["Name","Age"]
df = spark.createDataFrame(data=data, schema = columns)
```

This creates the dataframe as shown below:

```
+-----------+----------+
| Name      | Age      |
```

```
+-----------+----------+
| Harry     | 20       |
| Ron       | 20       |
| Hermoine  | 20       |
+-----------+----------+
```

We can get the schema of the dataframe by using `df.printSchema()`

```
>> df.printSchema()
root
|-- Name: string (nullable = true)
|-- Age: integer (nullable = true)
```

Q. Is it possible to create PySpark DataFrame from external data sources?

Yes, it is! Realtime applications make use of external file systems like local, HDFS, HBase, MySQL table, S3 Azure etc. Following example shows how we can create DataFrame by reading data from a csv file present in the local system:

```
df = spark.read.csv("/path/to/file.csv")
```

PySpark supports csv, text, avro, parquet, tsv and many other file extensions.

Q. What do you understand by Pyspark's startsWith() and endsWith() methods?

These methods belong to the Column class and are used for searching DataFrame rows by checking if the column value starts with some value or ends with some value. They are used for filtering data in applications.

- startsWith() – returns boolean Boolean value. It is true when the value of the column starts with the specified string and False when the match is not satisfied in that column value.

- endsWith() – returns boolean Boolean value. It is true when the value of the column ends with the specified string and False when the match is not satisfied in that column value.

Both the methods are case-sensitive.

Consider an example of the startsWith() method here. We have created a DataFrame with 3 rows:

```
data = [('Harry', 20),
        ('Ron', 20),
        ('Hermoine', 20)]
columns = ["Name","Age"]
df = spark.createDataFrame(data=data, schema = columns)
```

If we have the below code that checks for returning the rows where all the names in the Name column start with “H”,

```
import org.apache.spark.sql.functions.col
df.filter(col("Name").startsWith("H")).show()
```

The output of the code would be:

```
+-----------+----------+
| Name      | Age      |
+-----------+----------+
| Harry     | 20       |
| Hermoine  | 20       |
+-----------+----------+
```

Notice how the record with the Name “Ron” is filtered out because it does not start with “H”.

Q. What is PySpark SQL?

PySpark SQL is the most popular PySpark module that is used to process structured columnar data. Once a DataFrame is created, we can interact with data using the SQL

syntax. Spark SQL is used for bringing native raw SQL queries on Spark by using select, where, group by, join, union etc. For using PySpark SQL, the first step is to create a temporary table on DataFrame by using `createOrReplaceTempView()` function. Post creation, the table is accessible throughout SparkSession by using sql() method. When the SparkSession gets terminated, the temporary table will be dropped.

For example, consider we have the following DataFrame assigned to a variable `df`:

```
+-----------+----------+----------+
| Name      | Age      | Gender   |
+-----------+----------+----------+
| Harry     | 20       |    M     |
| Ron       | 20       |    M     |
| Hermoine  | 20       |    F     |
+-----------+----------+----------+
```

In the below piece of code, we will be creating a temporary table of the DataFrame that gets accessible in the SparkSession using the sql() method. The SQL queries can be run within the method.

```
df.createOrReplaceTempView("STUDENTS")
df_new = spark.sql("SELECT * from STUDENTS")
df_new.printSchema()
```

The schema will be displayed as shown below:

```
>> df.printSchema()
root
|-- Name: string (nullable = true)
|-- Age: integer (nullable = true)
|-- Gender: string (nullable = true)
```

For the above example, let's try running group by on the Gender column:

```
groupByGender = spark.sql("SELECT Gender, count(*) as
Gender_Count from STUDENTS group by Gender")
```

```
groupByGender.show()
```

The above statements results in:

```
+------+------------+
|Gender|Gender_Count|
+------+------------+
|     F|           1|
|     M|           2|
+------+------------+
```

Q. How can you inner join two DataFrames?

We can make use of the join() method present in PySpark SQL. The syntax for the function is:

```
join(self, other, on=None, how=None)
```

where,

other - Right side of the join

on - column name string used for joining

how - type of join, by default it is inner. The values can be inner, left, right, cross, full, outer, left_outer, right_outer, left_anti, left_semi.

The join expression can be appended with where() and filter() methods for filtering rows. We can have multiple join too by means of the chaining join() method.

Consider we have two dataframes - employee and department as shown below:

```
-- Employee DataFrame --
+------+--------+-----------+
```

```
|emp_id|emp_name|empdept_id |
+------+--------+-----------+
|     1|   Harry|          5|
|     2|    Ron |          5|
|     3| Neville|         10|
|     4|  Malfoy|         20|
+------+--------+-----------+
```

```
-- Department DataFrame --
+-------+--------------------------+
|dept_id| dept_name                |
+-------+--------------------------+
|     5 |   Information Technology |
|     10|   Engineering            |
|     20|   Marketting             |
+-------+--------------------------+
```

We can inner join the Employee DataFrame with Department DataFrame to get the department information along with employee information as:

```
emp_dept_df = empDF.join(deptDF,empDF.empdept_id ==
deptDF.dept_id,"inner").show(truncate=False)
```

The result of this becomes:

```
+------+--------+-----------+-------+--------------------------+
|emp_id|emp_name|empdept_id |dept_id| dept_name                |
+------+--------+-----------+-------+--------------------------+
|     1|   Harry|          5|      5 |   Information Technology |
|     2|    Ron |          5|     5  |   Information Technology |
|     3| Neville|         10|     10 |   Engineering            |
|     4|  Malfoy|         20|     20 |   Marketting             |
+------+--------+-----------+-------+--------------------------+
```

We can also perform joins by chaining join() method by following the syntax:

```
dfQ.join(df2,["column_name"]).join(df3,df1["column_name"] ==
df3["column_name"]).show()
```

Consider we have a third dataframe called Address DataFrame having columns emp_id, city and state where emp_id acts as the foreign key equivalent of SQL to the Employee DataFrame as shown below:

```
-- Address DataFrame --
+------+--------------+------+
|emp_id| city         |state |
+------+--------------+------+
|1     | Bangalore    |   KA |
|2     | Pune         |   MH |
|3     | Mumbai       |   MH |
|4     | Chennai      |   TN |
+------+--------------+------+
```

If we want to get address details of the address along with the Employee and the Department Dataframe, then we can run,

```
resultDf = empDF.join(addressDF,["emp_id"])
                .join(deptDF,empDF["empdept_id"] ==
deptDF["dept_id"])
                .show()
```

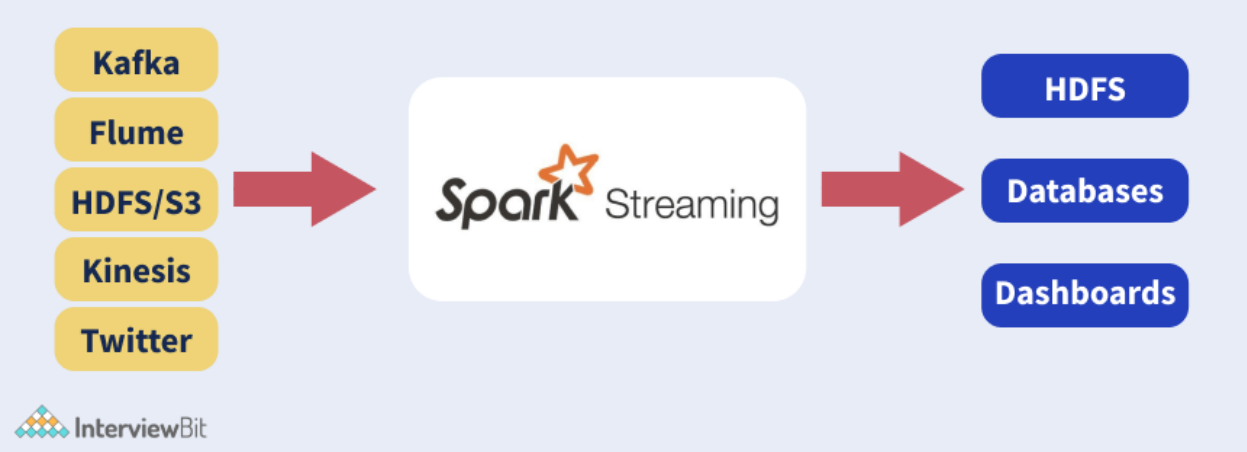
The resultDf would be:

```
+------+--------+-----------+--------------+------+-------+-----
---------------------+
|emp_id|emp_name|empdept_id | city         |state |dept_id|
dept_name                |
+------+--------+-----------+--------------+------+-------+-----
---------------------+
|     1|   Harry|          5| Bangalore    |   KA |      5 |
Information Technology |
|     2|    Ron |          5| Pune         |   MH |      5 |
Information Technology |
|     3| Neville|         10| Mumbai       |   MH |     10 |
Engineering            |
|     4|  Malfoy|         20| Chennai      |   TN |     20 |
Marketting             |
```

```
+------+--------+----------+-------------+------+-------+-----
--------------------+
```

Q. What do you understand by Pyspark Streaming? How do you stream data using TCP/IP Protocol?

PySpark Streaming is scalable, fault-tolerant, high throughput based processing streaming system that supports streaming as well as batch loads for supporting real-time data from data sources like TCP Socket, S3, Kafka, Twitter, file system folders etc. The processed data can be sent to live dashboards, Kafka, databases, HDFS etc.



To perform Streaming from the TCP socket, we can use the readStream.format("socket") method of Spark session object for reading data from TCP socket and providing the streaming source host and port as options as shown in the code below:

```
from pyspark import SparkContext
from pyspark.streaming import StreamingContext
from pyspark.sql import SQLContext
from pyspark.sql.functions import desc
sc = SparkContext()
ssc = StreamingContext(sc, 10)
sqlContext = SQLContext(sc)
socket_stream = ssc.socketTextStream("127.0.0.1", 5555)
lines = socket_stream.window(20)
```

```
df.printSchema()
```

Spark loads the data from the socket and represents it in the value column of the DataFrame object. The `df.printSchema()` prints

```
root
|-- value: string (nullable = true)
```

Post data processing, the DataFrame can be streamed to the console or any other destinations based on the requirements like Kafka, dashboards, database etc.

Q. What would happen if we lose RDD partitions due to the failure of the worker node?

If any RDD partition is lost, then that partition can be recomputed using operations lineage from the original fault-tolerant dataset.