

Nagarro Data Engineer Interview Guide – Experienced 3+

Round 1 & 2 – Technical

1. Introduce Yourself

Begin with a concise summary of your professional background, emphasizing key experiences, tools, and projects related to data engineering. Highlight your expertise in big data frameworks, cloud platforms, and programming languages.

Example:

"I am a Data Engineer with over 5 years of experience designing and implementing scalable data pipelines using Spark, Python, and Azure. I've worked extensively with batch and streaming data solutions, focusing on performance optimization and cost-efficiency for large-scale enterprise data platforms."

2. Explain Your Project Architecture

Describe the high-level architecture, data flow, and key components. Example for a cloud-based data pipeline:

- Data Ingestion: Using Kafka and Azure Data Factory.
- Data Processing: Utilizing Spark on Databricks.
- Storage: Data lakes on Azure Blob Storage and structured data in Delta Lake.
- Reporting: Power BI for dashboards. Explain key design choices, challenges faced, and optimizations implemented.

3. How to Upsert Your Data Daily Using Spark

Upsert (update + insert) in Spark can be achieved using merge statements with Delta Lake or manually combining dataframes:

```
from delta.tables import DeltaTable
```

```
delta_table = DeltaTable.forPath(spark, "/path/to/delta")
```

```
delta_table.alias("target").merge(
```

```
    updates.alias("source"),
```

```
    "target.id = source.id"
```

```
).whenMatchedUpdate(set={"name": "source.name", "age": "source.age"})
```

```
.whenNotMatchedInsert(values={"id": "source.id", "name": "source.name", "age":  
"source.age"})
```

```
.execute()
```

4. How to Perform SCD Type 3 Using Spark

Type 3 SCD tracks only the current and previous values.

```
from pyspark.sql import functions as F
```

```
df = df.withColumn("previous_value", F.col("current_value"))
```

```
df = df.withColumn("current_value", F.when(condition,  
new_value).otherwise(F.col("current_value")))
```

5. What is Shuffle and How to Handle It in Spark

Shuffle refers to redistributing data across partitions, causing costly operations involving disk I/O and network transfers. Occurs during wide transformations (e.g., groupByKey, join).

Optimizations:

- Use reduceByKey instead of groupByKey.
- Apply salting for skewed keys.
- Enable Adaptive Query Execution (AQE) to dynamically optimize shuffle partitions.

6. What is Broadcast Join and Why is It Required?

A broadcast join sends a small dataset to all worker nodes to avoid shuffle. It improves performance for joins between a large and small table.

```
small_df = spark.read.parquet("small_table").broadcast()
```

```
large_df = spark.read.parquet("large_table")
```

```
result = large_df.join(small_df, "key_column")
```

7. What is Predicate Pushdown and AQE with Example

Predicate pushdown reduces data read by applying filters at the data source level.

```
df = spark.read.option("pushDownPredicate", True).parquet("/data").filter("col > 100")
```

AQE dynamically adjusts partitions and joins at runtime to optimize performance.

8. PySpark Code for Broadcast Join and Conditional Aggregation by Location

```
from pyspark.sql import functions as F  
  
result = df.join(broadcast(dim_table), "key")  
result.groupBy("location").agg(F.max(F.avg("salary"))).show()
```

9. SQL Query for Best of 3 Marks and Average in a Student Table

```
SELECT student_id, AVG(mark)
FROM (
    SELECT student_id, mark
    FROM student_marks
    ORDER BY mark DESC
    LIMIT 3
) AS top3
GROUP BY student_id;
```

10. How to Handle Null in Spark Use fill, drop, or replace functions:

`df.fillna({"column_name": 0}).dropna().replace("null_value", "replacement")`

11. SCD Implementation in ETL

Use **merge** for Delta tables or a combination of union and filter for traditional tables.

12. Converting SCD0 to SCD3 Add columns for current and previous values, updating only the most recent records.

13. Facts and Dimension Tables Properties

- **Fact Table:** Contains measurements, often with numeric values (e.g., sales, revenue).
- **Dimension Table:** Contains descriptive attributes (e.g., product, date).

14. Handling Large-Scale Data Ingestion in AWS Pipelines Use S3 triggers with Lambda or Glue jobs. Automate with Step Functions for scheduling and retries.

15. Challenges with Spark Jobs and Resolutions

- **Memory errors:** Use correct partitioning.
- **Shuffle issues:** Apply salting and broadcast joins.

16. Data Shuffling Causes and Techniques Causes: Wide transformations and data skew. Techniques: Repartition, salting, and AQE.

17. Narrow vs. Wide Transformations

- **Narrow:** Data from one partition (e.g., map).
- **Wide:** Data from multiple partitions (e.g., groupBy).

18. **ReduceByKey vs. GroupByKey**

- reduceByKey aggregates data in each partition first, reducing shuffle.
- groupByKey sends all data to a single key, causing higher shuffle costs.

19. **Data Volume in Pipelines and Scalability Solutions** Use partitioning, caching, and efficient file formats (like Parquet) for large datasets.

20. **Monitoring and Orchestrating Spark Jobs** Tools: **Airflow, Oozie, or Azure Data Factory**. Use Spark UI to track stages and task execution.

21. **Features of NoSQL Databases**

- Schema flexibility, scalability, and high availability.
- Types: Key-value stores, document stores, column-family stores.

22. **Graph Databases** Designed for handling relationships. Example: Neo4j for social network analysis.

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<https://www.glassdoor.co.in/Reviews/Nagarro-Reviews-E240077.htm>

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