

Exploratory Data Analysis (EDA)











1. Data Loading

- Read CSV File: df = spark.read.csv('filename.csv', header=True, inferSchema=True)
- Read Parquet File: df = spark.read.parquet('filename.parquet')
- Read from JDBC (Databases): df =
 spark.read.format("jdbc").options(url="jdbc_url",
 dbtable="table_name").load()

2. Basic Data Inspection

- Display Top Rows: df.show()
- Print Schema: df.printSchema()
- Summary Statistics: df.describe().show()
- Count Rows: df.count()
- Display Columns: df.columns

3. Data Cleaning

- Drop Missing df.na.drop()
- Values: Fill df.na.fill(value)
- DispigglVmhuesf.drop('column_name')
- Rename Column: df.withColumnRenamed('old_name', 'new_name')

4. Data Transformation

- Select Columns: df.select('column1', 'column2')
- Add New or Transform Column: df.withColumn('new_column', expression)
- Filter Rows: df.filter(df['column'] > value)
- Group By and Aggregate: df.groupby('column').agg({'column': 'sum'})
- Sort Rows: df.sort(df['column'].desc())

5. SQL Queries on DataFrames

Create Temporary View:

• **SQL Query**: spark.sql('SELECT * FROM view_name WHERE condition')

6. Statistical Analysis

- Correlation Matrix: from pyspark.ml.stat import Correlation;
 Correlation.corr(df, 'column') Covariance:
- o df.stat.cov('column1', 'column2')
- Frequency Items: df.stat.freqItems(['column1', 'column2'])
- Sample By: df.sampleBy('column', fractions={'class1': 0.1,
 'class2': 0.2})

7. Handling Missing and Duplicated Data

- Fill Missing Values in Column: df.fillna({'column': value})
- Drop Duplicates: df.dropDuplicates()
- Replace Value: df.na.replace(['old_value'], ['new_value'], 'column')

8. Data Conversion and Export

- Convert to Pandas DataFrame: pandas_df = df.toPandas()
- Write DataFrame to CSV: df.write.csv('path_to_save.csv')
- Write DataFrame to Parquet: df.write.parquet('path_to_save.parquet')

9. Column Operations

- Change Column Type: df.withColumn('column', df['column'].cast('new_type'))
- Split Column into Multiple Columns: df.withColumn('new_col1', split(df['column'], 'delimiter')[0])
- Concatenate Columns: df.withColumn('new_column', concat_ws(' ', df['col1'], df['col2']))

10. Date and Time Operations

 Current Date and Time: df.withColumn('current_date', current_date())

- Date Formatting: df.withColumn('formatted_date', date_format('dateColumn', 'yyyyMMdd'))
- Date Arithmetic: df.withColumn('date_plus_days', date_add(df['date'], 5))

11. Advanced Data Processing

- Window Functions: from pyspark.sql.window import Window; df.withColumn('rank', rank().over(Window.partitionBy('column').orderBy('other_column')))
- Pivot Table:

```
df.groupBy('column').pivot('pivot_column').sum('sum_column')
```

UDF (User Defined Functions): from pyspark.sql.functions import udf; my_udf = udf(my_python_function); df.withColumn('new_col', my_udf(df['col']))

12. Performance Optimization

- Caching DataFrame: df.cache()
- Repartitioning: df.repartition(10)
- Broadcast Join Hint: df.join(broadcast(df2), 'key', 'inner')

13. Exploratory Data Analysis Specifics

- Column Value Counts: df.groupBy('column').count().show()
- Distinct Values in a Column: df.select('column').distinct().show()
- Aggregations (sum, max, min, avg):
 df.groupBy().sum('column').show()

14. Working with Complex Data Types

- Exploding Arrays: df.withColumn('exploded', explode(df['array_column']))
- Working with Structs: df.select(df['struct_column']['field'])
- Handling Maps: df.select(map_keys(df['map_column']))

15. Joins

• Inner Join: df1.join(df2, df1['id'] == df2['id'])

- Left Outer Join: df1.join(df2, df1['id'] == df2['id'],
 'left_outer')
- Right Outer Join: df1.join(df2, df1['id'] == df2['id'],
 'right_outer')

16. Saving and Loading Models

- Saving ML Model: model.save('model_path')
- Loading ML Model: from pyspark.ml.classification import
 LogisticRegressionModel; LogisticRegressionModel.load('model_path')

17. Handling JSON and Complex Files

- Read JSON: df = spark.read.json('path_to_file.json')
- Explode JSON Object: df.selectExpr('json_column.*')

18. Custom Aggregations

Custom Aggregate Function: from pyspark.sql import functions as F;
 df.groupBy('group_column').agg(F.sum('sum_column'))

19. Working with Null Values

• Counting Nulls in Each Column:

```
df.select([F.count(F.when(F.isnull(c), c)).alias(c) for c in df.columns])
```

• Drop Rows with Null Values: df.na.drop()

20. Data Import/Export Tips

- Read Text Files: df = spark.read.text('path_to_file.txt')
- Write Data to JDBC: df.write.format("jdbc").options(url="jdbc_url", dbtable="table_name").save()

21. Advanced SQL Operations

Register DataFrame as Table:

```
df.createOrReplaceTempView('temp_table')
```

Perform SQL Queries: spark.sql('SELECT * FROM temp_table WHERE condition')

22. Dealing with Large Datasets

- Sampling Data: sampled_df = df.sample(False, 0.1)
- Approximate Count Distinct: df.select(approx_count_distinct('column')).show()

23. Data Quality Checks

- Checking Data Integrity: df.checkpoint()
- Asserting Conditions: df.filter(df['column'] > 0).count()

24. Advanced File Handling

- Specify Schema While Reading: schema = StructType([...]); df =
 spark.read.csv('file.csv', schema=schema)
- Writing in Overwrite Mode: df.write.mode('overwrite').csv('path_to_file.csv')

25. Debugging and Error Handling

- Collecting Data Locally for Debugging: local_data = df.take(5)
- Handling Exceptions in UDFs: def safe_udf(my_udf): def wrapper(*args, **kwargs): try: return my_udf(*args, **kwargs) except: return None; return wrapper

26. Machine Learning Integration

• Creating Feature Vector: from pyspark.ml.feature import
VectorAssembler; assembler = VectorAssembler(inputCols=['col1',
 'col2'], outputCol='features'); feature_df =
 assembler.transform(df)

27. Advanced Joins and Set Operations

• Cross Join: df1.crossJoin(df2)

• Set Operations (Union, Intersect, Minus): df1.union(df2); df1.intersect(df2); df1.subtract(df2)

28. Dealing with Network Data

• Reading Data from HTTP Source:

```
spark.read.format("csv").option("url",
"http://example.com/data.csv").load()
```

29. Integration with Visualization Libraries

• Convert to Pandas for Visualization: pandas_df = df.toPandas(); pandas_df.plot(kind='bar')

30. Spark Streaming for Real-Time EDA

- Reading from a Stream: df = spark.readStream.format('source').load()
- Writing to a Stream: df.writeStream.format('console').start()

31. Advanced Window Functions

- Cumulative Sum: from pyspark.sql.window import Window;
 df.withColumn('cum_sum',
 F.sum('column').over(Window.partitionBy('group_column').orderBy('order_column')))
- Row Number: df.withColumn('row_num',
 F.row_number().over(Window.orderBy('column')))

32. Handling Complex Analytics

- Rollup: df.rollup('column1', 'column2').agg(F.sum('column3'))
- Cube for Multi-Dimensional Aggregation: df.cube('column1', 'column2').agg(F.sum('column3'))

33. Dealing with Geospatial Data

• Using GeoSpark for Geospatial Data: from geospark.register import GeoSparkRegistrator; GeoSparkRegistrator.registerAll(spark)

34. Advanced File Formats

- Reading ORC Files: df = spark.read.orc('filename.orc')
- Writing Data to ORC: df.write.orc('path_to_file.orc')

35. Dealing with Sparse Data

• Using Sparse Vectors: from pyspark.ml.linalg import SparseVector; sparse_vec = SparseVector(size, {index: value})

36. Handling Binary Data

• Reading Binary Files: df =
 spark.read.format('binaryFile').load('path_to_binary_file')

37. Efficient Data Transformation

Using mapPartitions for Transformation: rdd =
 df.rdd.mapPartitions(lambda partition: [transform(row) for row in partition])

38. Advanced Machine Learning Operations

- Using ML Pipelines: from pyspark.ml import Pipeline; pipeline =
 Pipeline(stages=[stage1, stage2]); model = pipeline.fit(df)
- Model Evaluation: from pyspark.ml.evaluation import
 BinaryClassificationEvaluator; evaluator =
 BinaryClassificationEvaluator(); evaluator.evaluate(predictions)

39. Optimization Techniques

- Broadcast Variables for Efficiency: from pyspark.sql.functions import broadcast; df.join(broadcast(df2), 'key')
- Using Accumulators for Global Aggregates: accumulator = spark.sparkContext.accumulator(0); rdd.foreach(lambda x: accumulator.add(x))

40. Advanced Data Import/Export

- Reading Data from Multiple Sources: df =
 spark.read.format('format').option('option',
 'value').load(['path1', 'path2'])
- Writing Data to Multiple Formats: df.write.format('format').save('path', mode='overwrite')

41. Utilizing External Data Sources

Connecting to External Data Sources (e.g., Kafka, S3): df = spark.read.format('kafka').option('kafka.bootstrap.servers', 'host1:port1').load()

42. Efficient Use of SQL Functions

 Using Built-in SQL Functions: from pyspark.sql.functions import col, lit; df.withColumn('new_column', col('existing_column') + lit(1))

43. Exploring Data with GraphFrames

 Using GraphFrames for Graph Analysis: from graphframes import GraphFrame; g = GraphFrame(vertices_df, edges_df)

44. Working with Nested Data

- Exploding Nested Arrays: df.selectExpr('id', 'explode(nestedArray) as element')
- Handling Nested Structs: df.select('struct_column.*')

45. Advanced Statistical Analysis

- Hypothesis Testing: from pyspark.ml.stat import ChiSquareTest; r = ChiSquareTest.test(df, 'features', 'label')
- Statistical Functions (e.g., mean, stddev): from pyspark.sql.functions import mean, stddev; df.select(mean('column'), stddev('column'))

46. Customizing Spark Session

Configuring SparkSession: spark =
SparkSession.builder.appName('app').config('spark.some.config.optio
n', 'value').getOrCreate()