Databricks PySpark

Introduction to Databricks & PySpark

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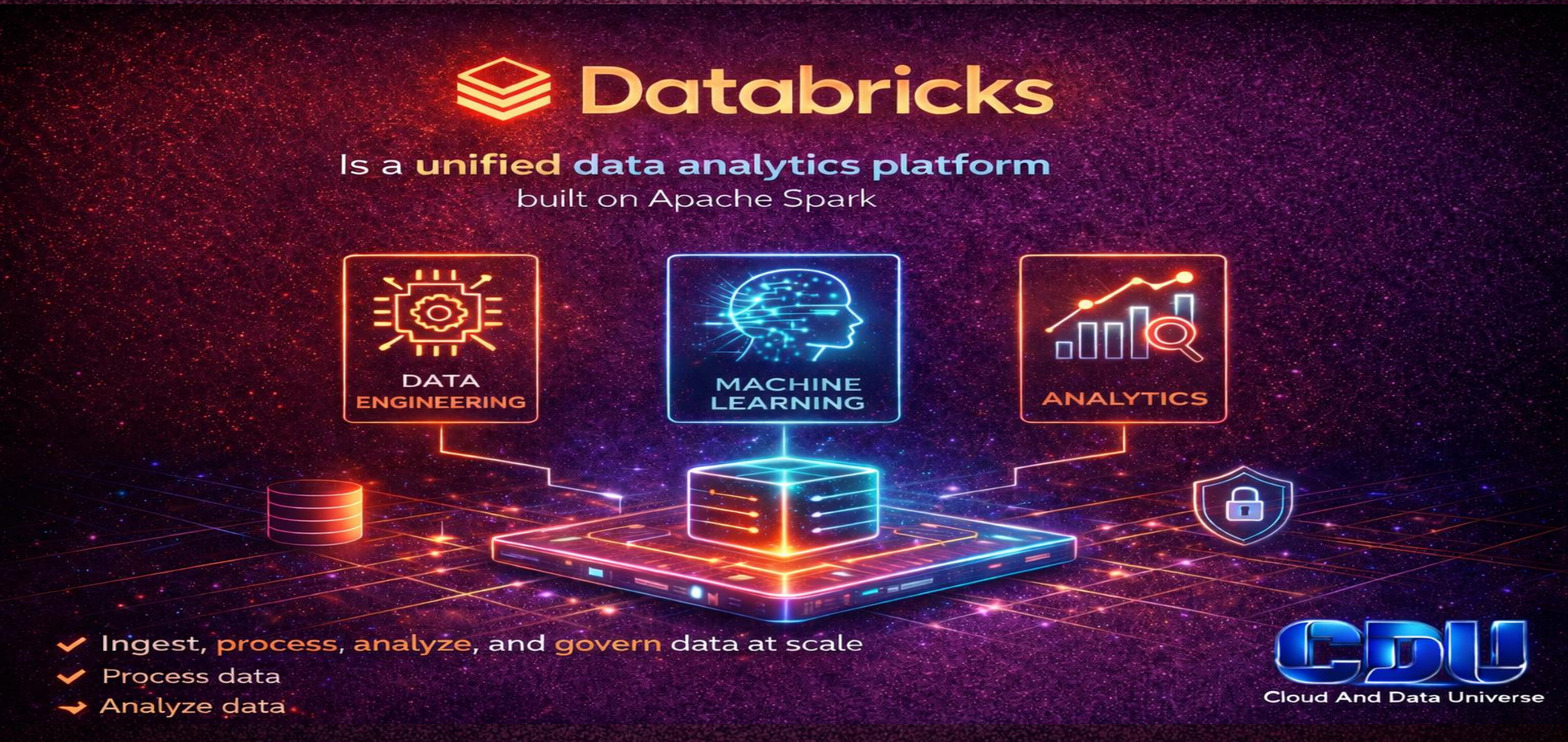
Cloud And Data Universe

databricks

PySpark

Introduction to Databricks & PySpark



databricks

PySpark

Databricks Features

Databricks

Databricks – Core Platform Features

Unified Analytics Platform

- Single platform for DE, DS, ML & Analytics
- Eliminates silos

Apache Spark Engine

- Optimized runtime
- Batch & Streaming

Lakehouse Architecture

- Data Lake + – Data Warehouse
- Structured & unstructured data
- Built on Delta Lake

Delta Lake

DELTA LAKE

- ACID transactions
- Schema enforcement
- Time travel

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Databricks Features

Databricks

Databricks – Enterprise & AI Capabilities

Data Engineering

- ETL / ELT pipelines
- Job scheduling
- Cloud storage integration

Machine Learning & AI

- MLflow
- Model lifecycle
- Python, Scala, R

Databricks SQL & BI

- Serverless SQL
- Dashboards
- Power BI & Tableau

Governance & Security

- Unity Catalog
- Fine-grained access
- Lineage & auditing

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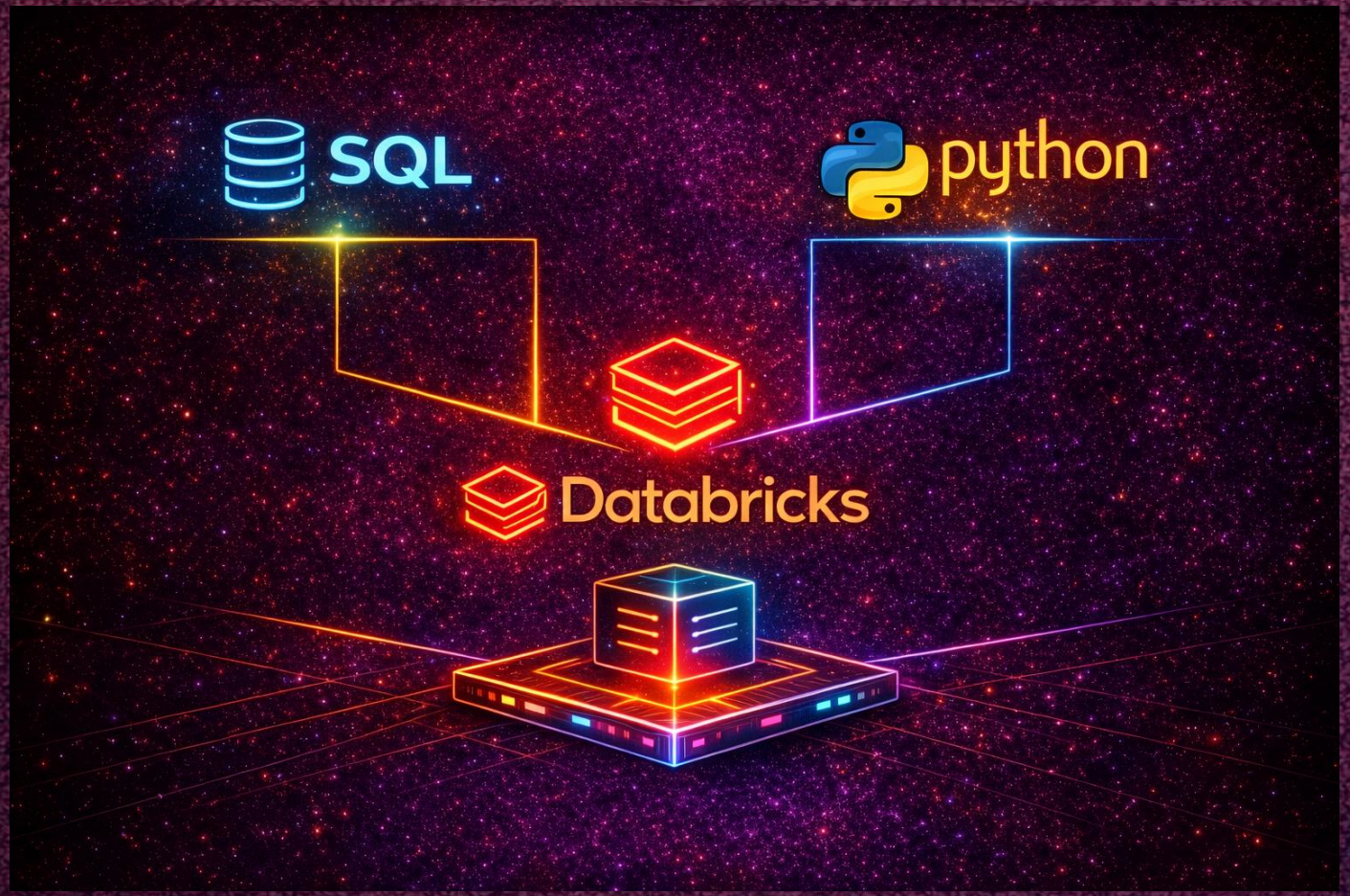
Pre-Requisites



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Let's begin a great journey!

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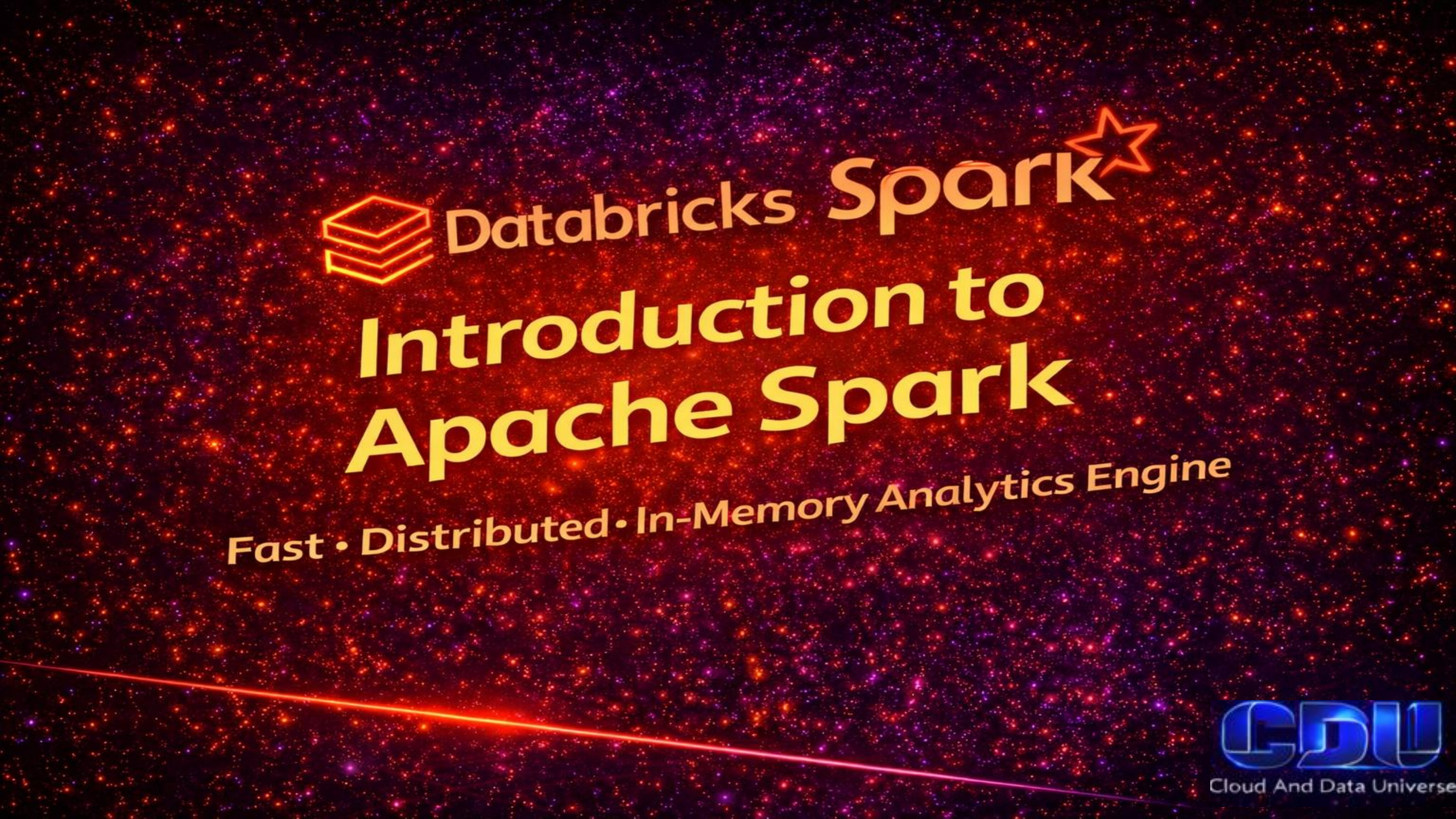
Databricks Spark
Introduction to Apache Spark
Fast • Distributed • In-Memory Analytics Engine
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Why Apache Spark?

- In-memory processing
- Faster than MapReduce
- Scales to big data
- Batch & Streaming support

⚠ MapReduce Challenges

Slow processing

Disk I/O bottleneck

Complex programming

Difficult to scale

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The Evolution of APACHE SPARK

2009 — BIRTH OF SPARK

UC Berkeley | AMPLab

Faster than Hadoop MapReduce

Written in Scala

2010 — OPEN SOURCE RELEASE

Spark released as open source

Early academic & Startup adoption

- RDD (Resilient Distributed Dataset)

2013 — APACHE INCUBATION

Donated to Apache Software Foundation

- Community-driven development begins

2014 — APACHE SPARK 1.0

Top-level Apache project

- Spark Core
- Streaming, MLLib.
- GrapX
- Early Spark SQL

2015 — DATAFRAMES & SPARK SQL

DataFrame API introduced

- Catalyst Optimizer added
- SQL becomes first-class API

2016 — SPARK 2.0 (MAJOR MILESTONE)

Unified APIs: RDD, DataFrame-Dataset

- Dataset API introduced
- Structured Streaming introduced

RDDs → DataFrames → Datasets

STRUCTURED STREAMING

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The Evolution of APACHE SPARK

2017–2018 — STREAMING & PERFORMANCE

- Structured Streaming becomes stable
- Event-time processing
- Windowing & watermarking
- Cloud adoption increases

2020 — SPARK 3.0

- Adaptive Query Execution (AQE)
- ANSI SQL complance
- Dynamic partition pruning

2020 — SPARK 3.0

- ANSI SQL compliance
- Dynamic partition pruning
- Faster joins & queries

2021–2022 — LAKEHOUSE ERA

- Deep cloud storage integration
- ADLS • S3 • GCS
- Delta Lake, Iceberg, Hudi
- Foundation of Lakehouse architecture

2023 — SPARK 3.4+

- Faster Python execution
- Pandas API on Spark
- Better observability

2024–2025 — MODERN SPARK

- SQL, Streaming & ML engine
- Cloud-native analytics
- AI feature pipelines
- Industry standard for big data

2017-2018 STREAMING & PERFORMANCE 2020 SPARK 3.4+ MODERN SPARK

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Apache Spark

Core Components

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Apache Spark

Core Components

SPARK CORE

SPARK SQL

STRUCTURED STREAMING

MLLIB

GRAPHX

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Apache Spark
Core Components

SPARK CORE

- The foundation of Spark
- Distributed task scheduling
- Memory management
- Fault tolerance
- RDD abstraction
- Interaction with storage systems (HDFS, S3, ADLS, etc.)

SPARK SQL

- For structured & semi-structured data
- SQL queries
- DataFrame & Dataset APIs
- Catalyst Optimizer
- ANSI SQL support
- Integration with Hive Metastore
- Analytics, BI workloads, ETL transformations

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Apache Spark
Core Components

STRUCTURED STREAMING

- Modern streaming engine
- Event-time processing
- Windowing & watermarking
- Exactly-once guarantees
- Same API as batch (DataFrames)

GRAPHX

- Graph processing framework
- Graph algorithims
- PageRank
- Connected components
- Social network analysis

MLLIB

- Classification
- Regression
- Clustering
- Recommendation systems
- Feature engineering

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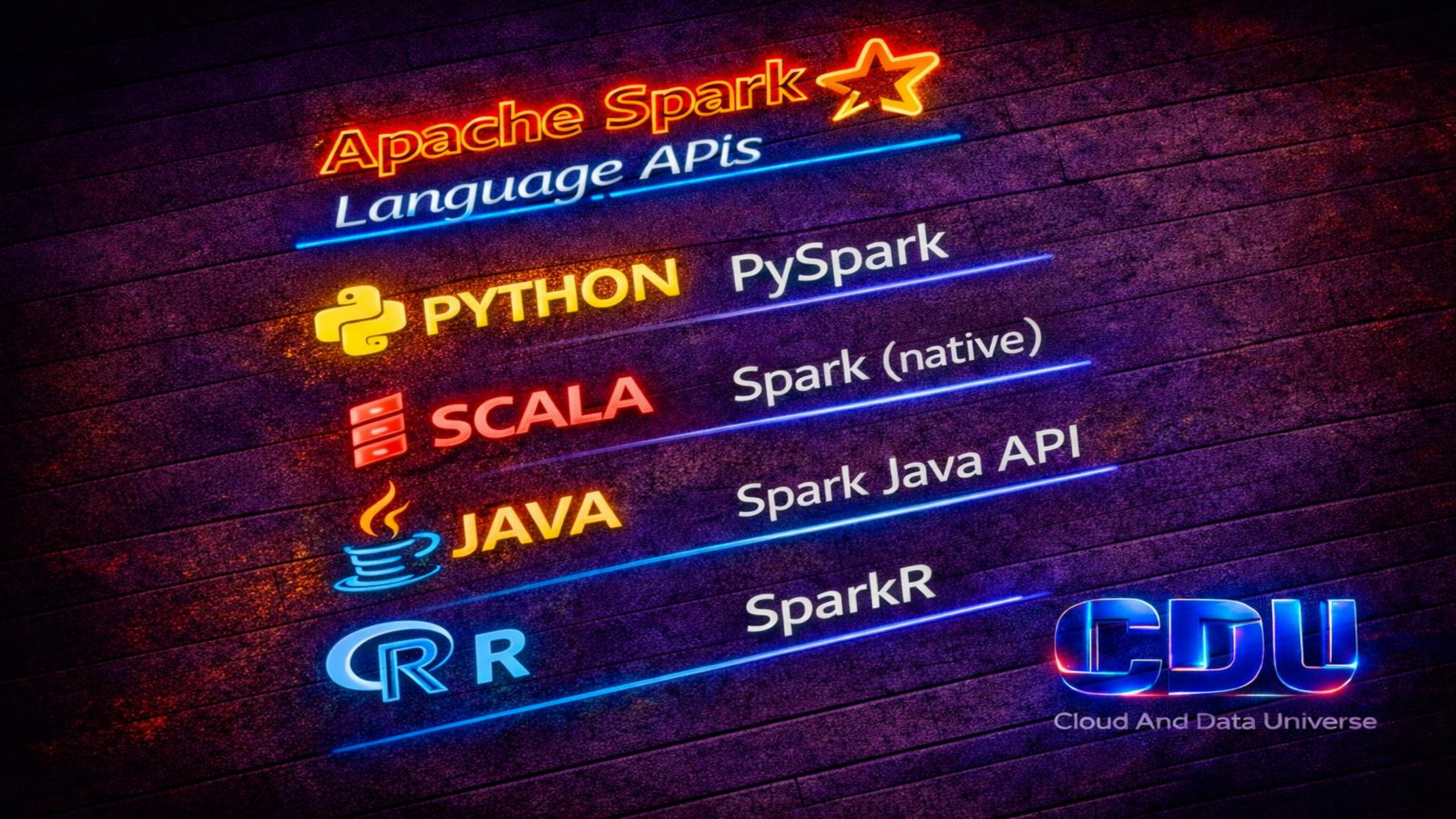
Apache Spark
Language APIs
PYTHON
PySpark
SCALA
Spark (native)
JAVA
Spark Java API
R
SparkR
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Spark Architecture

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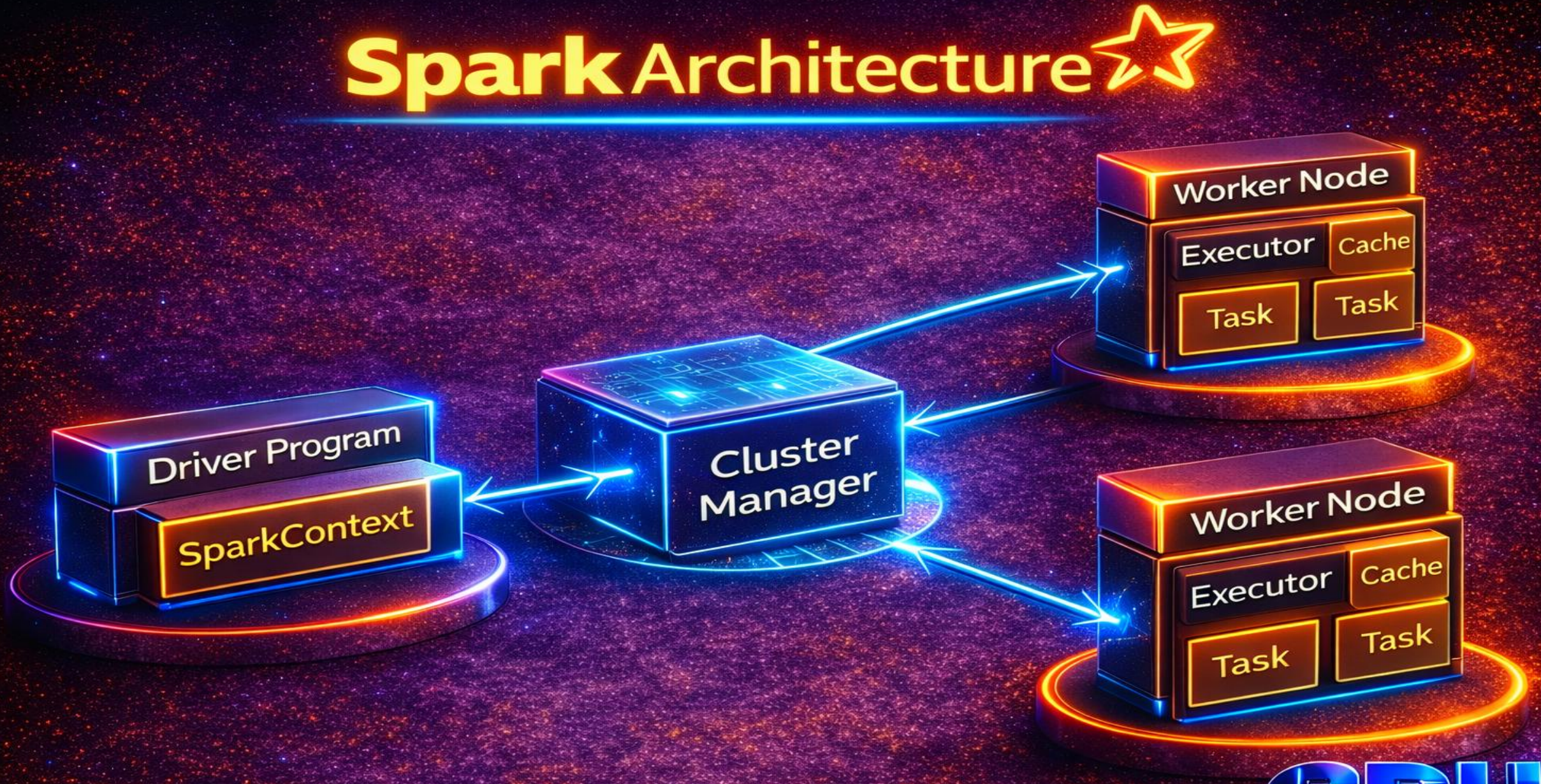
Spark Architecture



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What is a Spark Application?

A **Spark Application** is a single, complete program that runs on on Apache Spark to process data.

In simple words: = your code + **Spark engine** + **cluster resources** working to complete a task.

Formal Definition (Interview-Ready)

- A **Spark application** is a **user program** that runs on Apache Spark,
- Consisting of **one driver program** and **one or more executor processes**,
- Used to perform **distributed data processing.**

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Driver Program

(Brain of Spark)

The **Driver** is where your Spark application starts.

Responsibilities:

- ✔ Creates **SparkSession / SparkContext**
- ✔ Converts your code into a logical plan
- ✔ Splits jobs into **stages** & tasks
- ✔ Sends **tasks** to **executors**
- ✔ Collects **results**

📌 **Only ONE driver** per Spark application

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SparkContext / SparkSession

Entry point to Spark

Talks to:

- ✔ Cluster Manager
- ✔ Executors

Tracks:

- ✔ RDDs
- ✔ DataFrames
- ✔ Jobs

In modern Spark, you mainly use **SparkSession.**

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Cluster Manager

The Middle Layer in Spark

Role of Cluster Manager

The Cluster Manager acts as the mediator between the **Driver** and the **Executors**.

- ✗ It does **NOT process data.**
- ✓ It manages **resources.**

What the Cluster Manager Actually Does

1 Driver requests resources

- ✓ CPU cores
- ✓ Memory

2 Cluster Manager allocates executors

- ✓ Decides where executors run
- ✓ Decides how many executors are created

3 Executors are launched on worker nodes

- ✓ Cluster Manager starts them
- ✓ Executors then register back with the Driver

📌 After this, Driver talks directly to Executors
Cluster Manager steps aside.

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Executors

Executors

- JVM processes running on worker nodes
- Execute tasks
- Store data in memory or disk
- Send results back to the driver

📌 Executors live only as long as the application runs

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Spark Tasks

What is a Task?

- A task is the smallest unit of work in Spark
- Runs on a single data partition
- Executed by an executor

Key Characteristics

- One task = one partition
- Tasks run in parallel across executors
- Tasks are stateless
- Tasks cannot be shared across executors

How Tasks Are Created

- Triggered by a Spark action (count(), collect(), save())
- A job is divided into stages
- Each stage contains multiple tasks

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What is a Job in Spark?

A Spark Job is a unit of execution that is triggered when an action is called on a Spark DataFrame, Dataset, or RDD.

In simple words:
A job is the work Spark decides to execute when you ask for a result.

Formal Definition (Interview-Ready)

- A Spark job is a computation triggered by an **action**, which Spark executes by dividing the work into **multiple stages** and tasks.

How a Spark Job is Created

1. You write Spark transformations
2. Spark builds a logical plan (lazy execution)
3. You call an action

   `count()` → `collect()` → `save().`
4. Spark creates a job
5. Job is split into stages
6. Stages are split into tasks
7. Tasks run on executors

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Spark Application Execution Flow

1. **You submit a Spark program**
   - Code is sent to the cluster

2. **Driver starts**
   - Creates SparkSession / SparkContext
   - Builds the logical plan

3. **Driver requests resources**
   - CPU cores
   - Memory

4. **Cluster Manager allocates executors**
   - Launches executors on worker nodes
   - Executors register back with the driver
   - This is where data distribution begins

5. **Data is read from source**
   - HDFS / ADLS / S3 / Database
   - Data is split into partitions

6. **Partitions are distributed across executors**
   - Each executor receives multiple partitions
   - One task is created per partition

7. **Driver creates jobs, stages, and tasks**
   - Job → triggered by action
   - Stage → split at shuffle boundaries
   - Task → one per partition

8. **Driver sends tasks to executors**
   - Tasks are scheduled close to data when possible

9. **Executors process data in parallel**
   - Transformations applied
   - Shuffles happen if required
   - Data cached if needed

10. **Results are returned to the driver**
    - Or written to storage

11. **Application finishes**
    - Executors are terminated
    - Resources released back to cluster manager

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Time for Practical Execution


Databricks
Assistant
Your AI Copilot
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Databricks

What Databricks Assistant does

Understands Your Workspace

It has context of:

Provides Context-Aware Answers...

...Not Generic AI Replies

Databricks

Data & analytics assistance

- Generate Databricks SQL queries
- Explain query execution plans
- Help with window functions, joins, aggregations
- Suggest performance improvements (AQE, caching, partitioning)

Example:

- Optimize this Pyspark join"
- Convert this SQL query to PySpark DataFrame API"

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Databricks

Databricks
Assistant
Your AI Copilot

Code Help
(Core Strength)

You can ask it to:

- ✓ Write PySpark / Spark SQL / Python code
- ✓ Convert SQL ⟷ PySpark
- ✓ Optimize slow Spark jobs
- ✓ Explain existing notebook code
- ✓ Fix errors and exceptions

Example:

- “Optimize this PySpark join”
- “Convert this SQL query to PySpark DataFrame API”

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Databricks

Databricks
Assistant
Your AI Copilot

Platform & governance help

- Explain Unity Catalog
- Help with permissions & access control
- Answer questions on Delta Lake, time travel, schema enforcement

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Databricks

Databricks
Assistant
Your AI Copilot

ML & AI support

- Help with MLflow
- Feature engineering in Spark
- Model training & tracking examples.
- Explain notebooks used.
  in ML pipelines

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Creating RDD from list

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Understanding RDD Partitions

Parallelism

- Allows many tasks to be executed in parallel

Optimization

- Number of partitions impacts performance

Fault Tolerance

- Individual partitions can be recomputed if lost

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Managing PARTITIONS

Parallel Processing

- Optimizes resource usage

Load Balancing

- Handles skewed data distribution

Repartition/Coalesce

- Scale partitions up or down using: *repartition| | coalese*

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Unity Catalog

We're at a transition point in Databricks.

As DBFS is no longer the recommended approach,
we need to adopt

Unity Catalog

as the industry standard
to manage files and tables.

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❌ Why DBFS Is No Longer the Best Option

- DBFS is workspace-scoped, not account-scoped

- Limited governance & access control

- Not designed for enterprise-grade data security

- Difficult to manage permissions across teams

- Not aligned with modern lakehouse governance

⚠ DBFS = legacy convenience, not enterprise standard

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Why Unity Catalog Is the Industry Standard

- Centralized data & file governance
- Fine-grained access control (catalog → schema → table)
- Works across all Databricks workspaces
- Integrated with cloud storage (ADLS / S3 / GCS)
- Built for security, compliance, and scalability

Unity Catalog = governance-first architecture

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How We Should Manage Files & Tables Now

Storage Layer

- ✔ Use external locations (ADLS / S3 / GCS)
- Controlled via Unity Catalog

Data Objects

- ✔ Managed Tables

- ✔ External Tables

- ✔ Volumes (for files)

Access Control

- ✔ Centralized permissions
- ✔ Identity-based access

- ✔ Audit-ready

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“Unity Catalog is not optional anymore — it’s the foundation of modern Databricks.

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Over the next few videos you will learn basics on metastore, its objects and setting up Unity Catalog.

This is important before we move ahead in Databricks & PySpark.

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Introduction to DataFrames

DataFrame

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What are DataFrames in Spark?

A DataFrame is a distributed collection of data organized into named collumns, similar to table in a database or a DataFrame in Pandas, built to work at big-data scale.

DataFrame

👉 Internally, DataFrames are optimized and distributed across a Spark cluster.

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Key Characteristics of DataFrames

1 Schema-Based

- Data has column names and data types
- Enables validation and optimization

2 Distributed

- Data is split into **partitions**
- Processed in **parallel** across executors

3 Immutable

- Any transformation creates a new DataFrame

4 Optimized (Very Important)

- **Catalyst Optimizer** → query optimization
- **Tungsten Engine** → memory & CPU optimization
- 👉 This makes DataFrames **much faster than RDDs.**

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DataFrame vs RDD
(Interview Favorite)

Feature	DataFrame	RDD
Schema	Yes	No
Optimization	Automatic	Manual
Performance	Faster	Slower
API level	High-level	Low-level
SQL support	Yes	No

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Different Ways to Create a DataFrame in Spark

Broadly, DataFrames can be created from:

1. **Files**
   (csv, json, parquet, delta)

2. **Tables**

ID	Name	Salary

3. **RDDs**

4. **Databases** (using jdbc)

Databases (using jdbc)

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RDD vs DataFrame vs Dataset — Which to Use When?

Scenario	Best Choice
Unstructured data	RDD
Structured data	DataFrame
SQL / analytics	DataFrame
Maximum performance	DataFrame
Type safety	Dataset
Python users	DataFrame
Fine-grained control	RDD

Conclusion on DataFrames

DataFrames are the **most powerful** and **production-ready abstraction** in **Spark** — **optimized, scalable,** and **built for real-world data workloads.**

Optimized
Leverage Catalyst & Tungsten for peak performance

Scalable
Handle massive datasets with ease

Production-Ready
Industry-proven and widely adopted

Built for Real Workloads
Ideal for ETL, analytics, and reports

RDDs give control, **DataFrames** give **power,** and **optimization** makes the **difference.**

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Create DataFrame from RDD

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Create DataFrame from CSV

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