Programming for Big Data

Large Scale Data Processing

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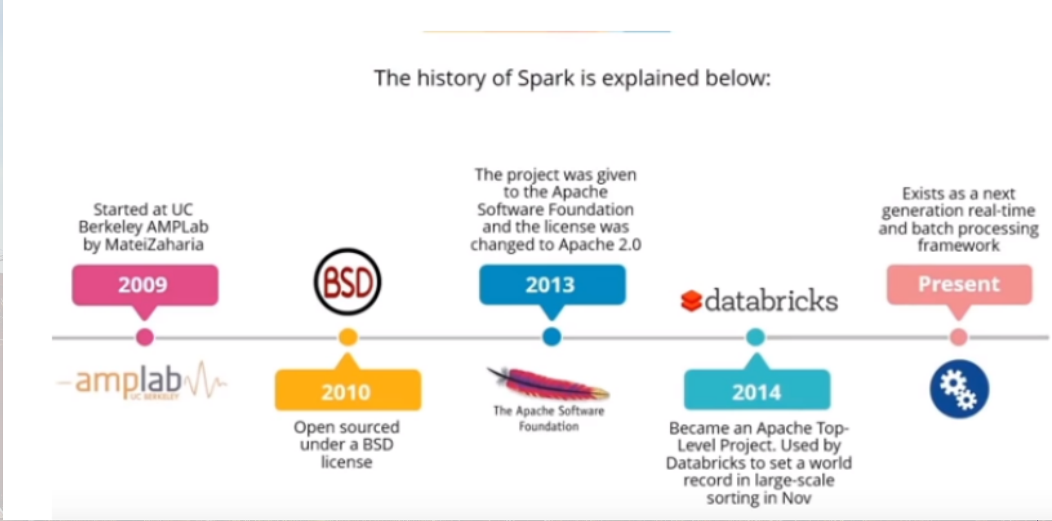
Outline

- History of Spark
- What is Spark
- Hadoop vs Spark
- Components of Apache Spark
- Spark Architecture
- Application of Spark
- Spark Use Cases

Assignment 4

[**Assignment 4** – Download Hadoop `hadoop.apache.org/`, install, Configure and run test program (word count)]



- Spark was first open sourced in March 2010, and was transferred to the Apache Software Foundation in June 2013, where it is now a top-level project.

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- Provides development APIs in Java, Scala, Python and R.
- Internet powerhouses such as Netflix, Yelp, Zillow, and eBay have deployed Spark at massive scale, collectively processing multiple petabytes of data on clusters of over 8,000 nodes.

Why Spark Matters

Apache Hadoop vs Spark

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Spark: It has adopted micro-batching. Micro-batches are an essentially "collect and then process".

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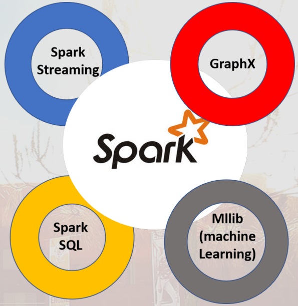
Spark: The security bonus that Spark can enjoy is that if you run Spark on HDFS.

Components of Spark

There are five main components of Apache Spark:

1. **Apache Spark Core:** Responsible for necessary functions such as Scheduling, task dispatching, input and output operations, fault recovery, etc.



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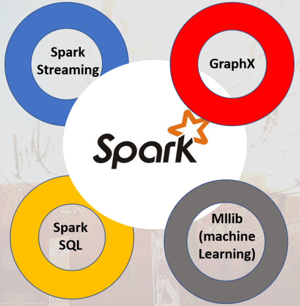

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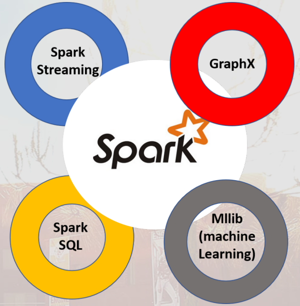

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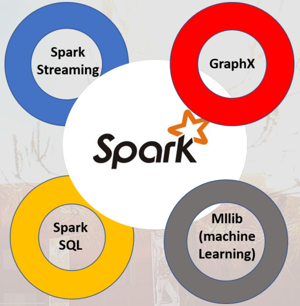

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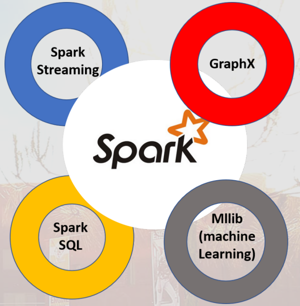

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5. **GraphX:** Facilitating graph analytics tasks and graph-parallel computation.

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- **Slave:** The machine on which the Executor program runs.

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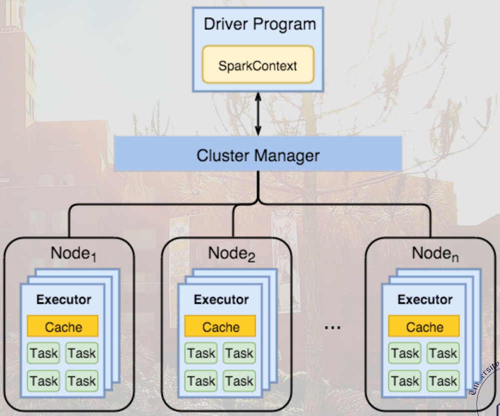
   - Creates SparkContext to schedule jobs execution and negotiate with cluster manager.



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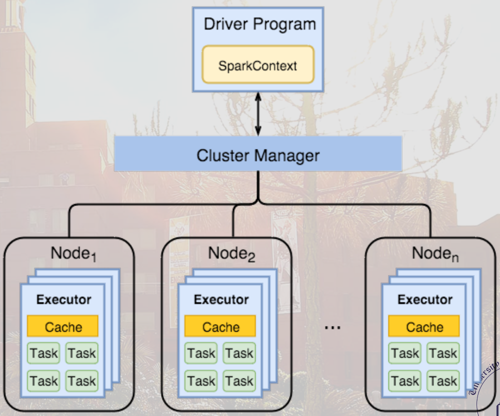

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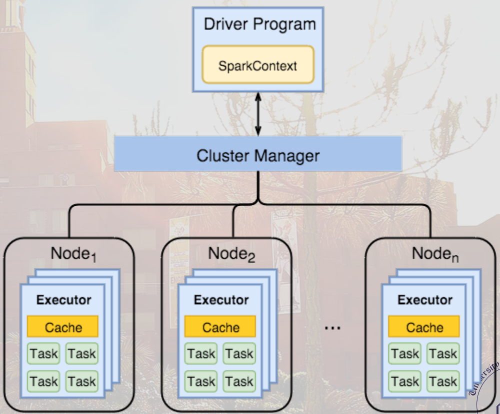

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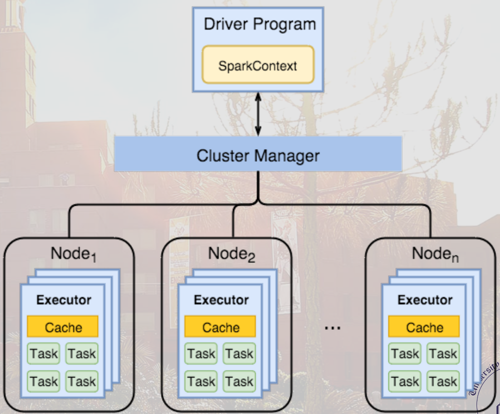

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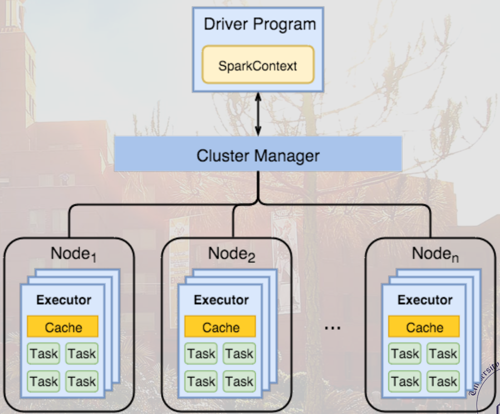
3. **Cluster Manager:**
   - YARN or Spark Standalone or Mesos



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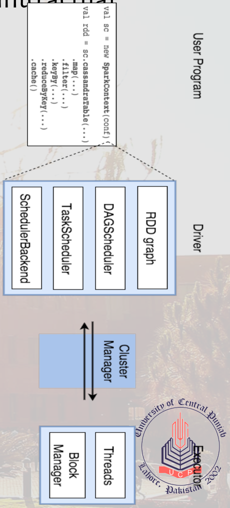

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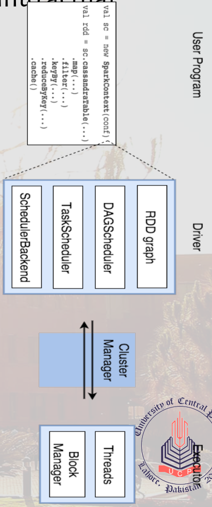

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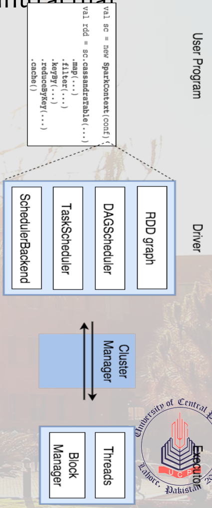

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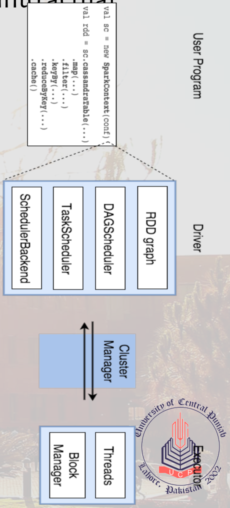

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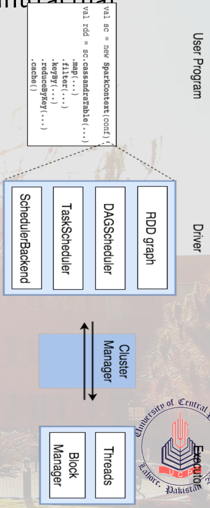
5. **BlockManager:** Provides interfaces for putting and retrieving blocks both locally and remotely into various stores (memory, disk, and off-heap).



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- **Transformations:**
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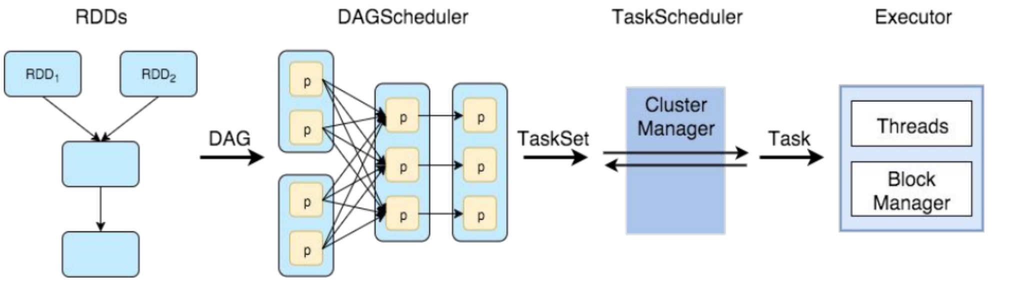
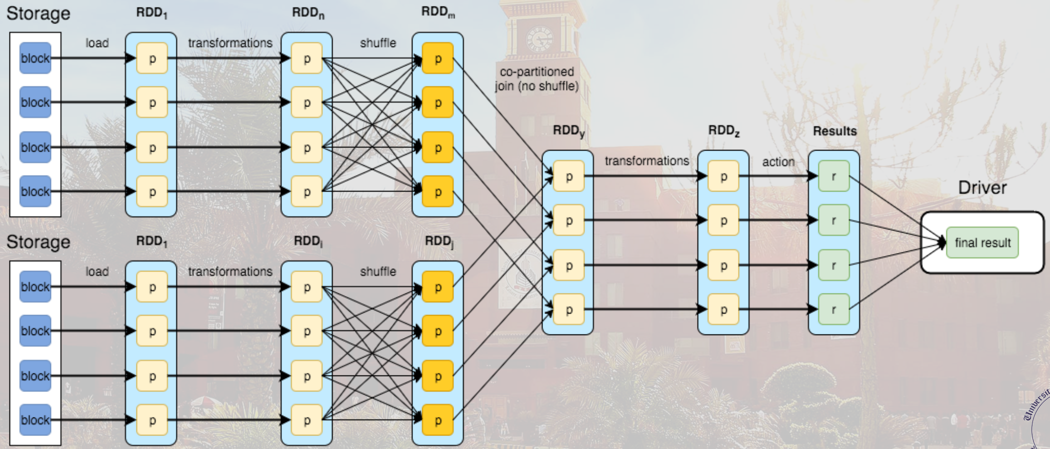
Execution Flow



RDDs	DAGScheduler	TaskScheduler	Executor
rdd1.**join**(rdd2) .**groupBy**(...) .**filter**(...)	splits graph into *stages* of tasks	launches tasks via cluster manager	executes tasks
	submits each stage as ready	retries failed or struggling tasks	stores and serves blocks

Direct Acyclic Graph (DAG)



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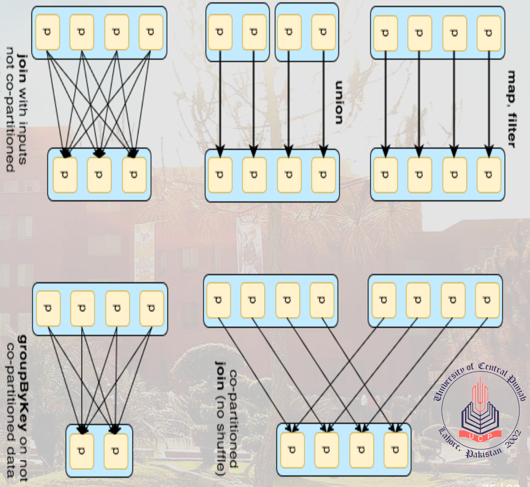

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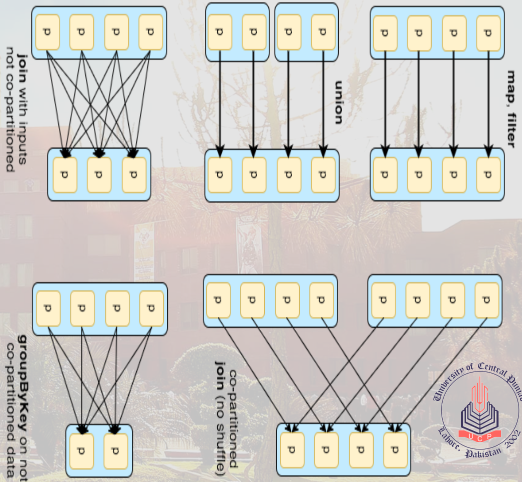

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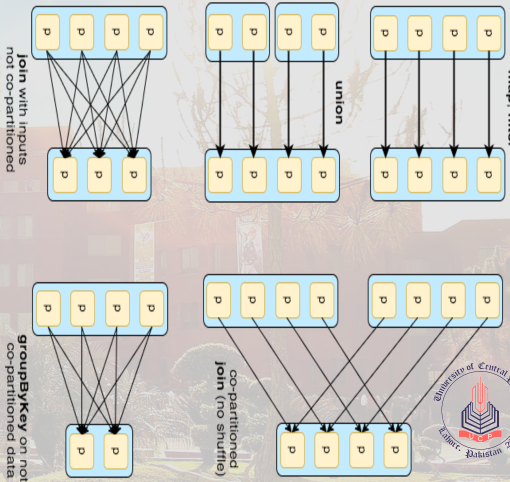

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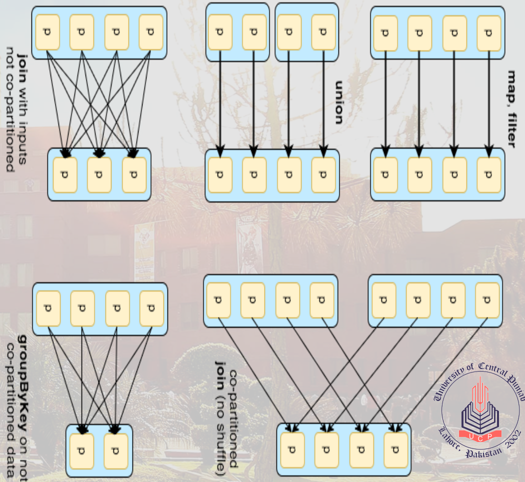

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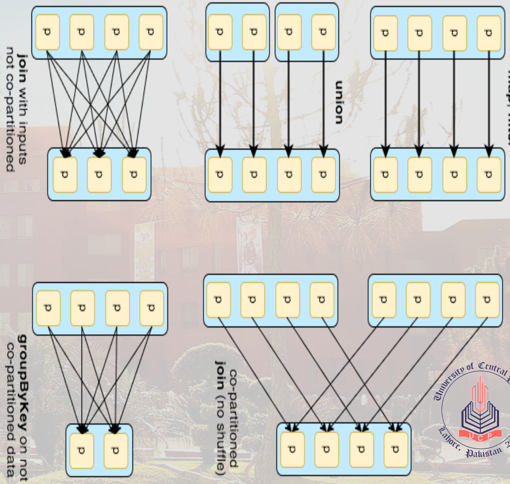

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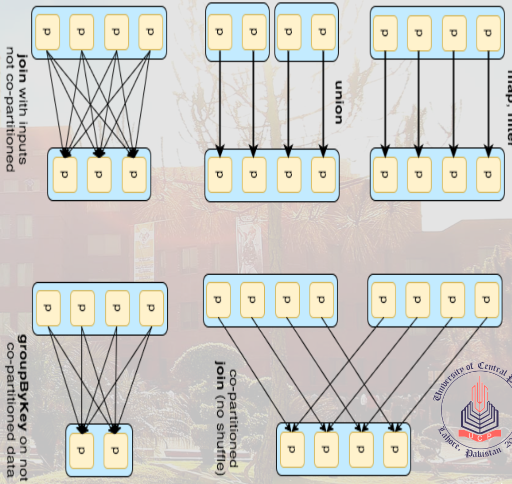
6. If some partition is lost from all the ancestors a complete recomputation is needed.



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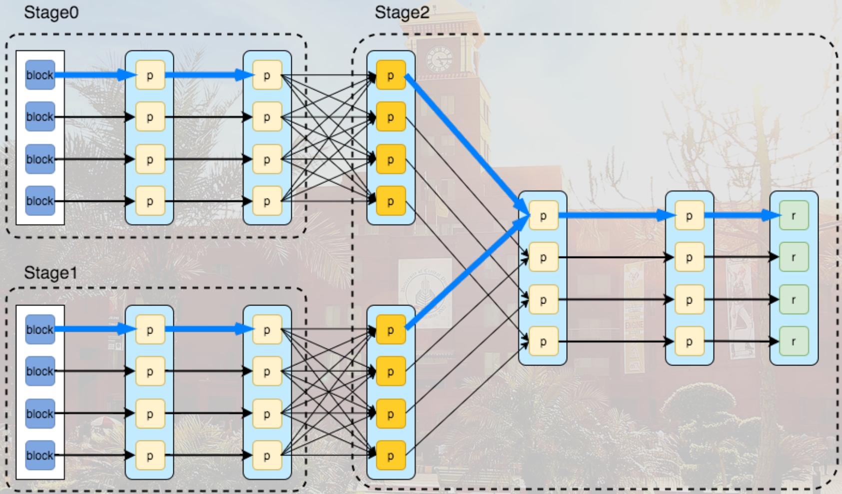

Thank You