Big Data Computing

Master's Degree in Computer Science

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Recap from Last Lecture

- MapReduce → new distributed computing framework suitable for woriking with large scale datasets
- Useful in all those situations where data need to be accessed sequentially
- May be hard to program and does not support well multiple map-reduce rounds

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- Generalized Data-Flow Systems abstract from this in two ways:
  - Allow any number of "ranks"/tasks
  - Allow functions other than just map and reduce
- As long as data goes in one direction only, recovery at intermediate rank is possible

Spark: Most Popular Data-Flow System

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  - General execution graphs (DAGs)
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- In addition to MapReduce, Spark provides:
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  - General execution graphs (DAGs)
  - Richer functions than just map and reduce
- Compatible with Hadoop

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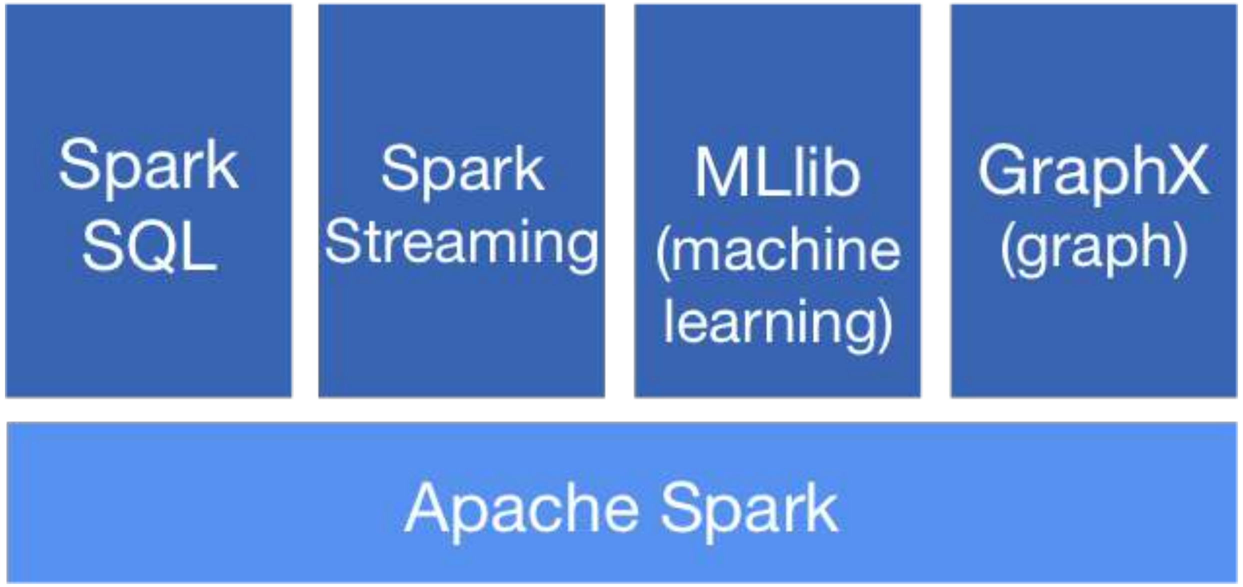
- Unified computing engine (Spark Core)
- Set of high-level APIs for data analysis:
  - Spark SQL (structured data), MLlib (machine learning), GraphX (graph analytics), Spark Streaming (stream data processing)

Spark: Overview



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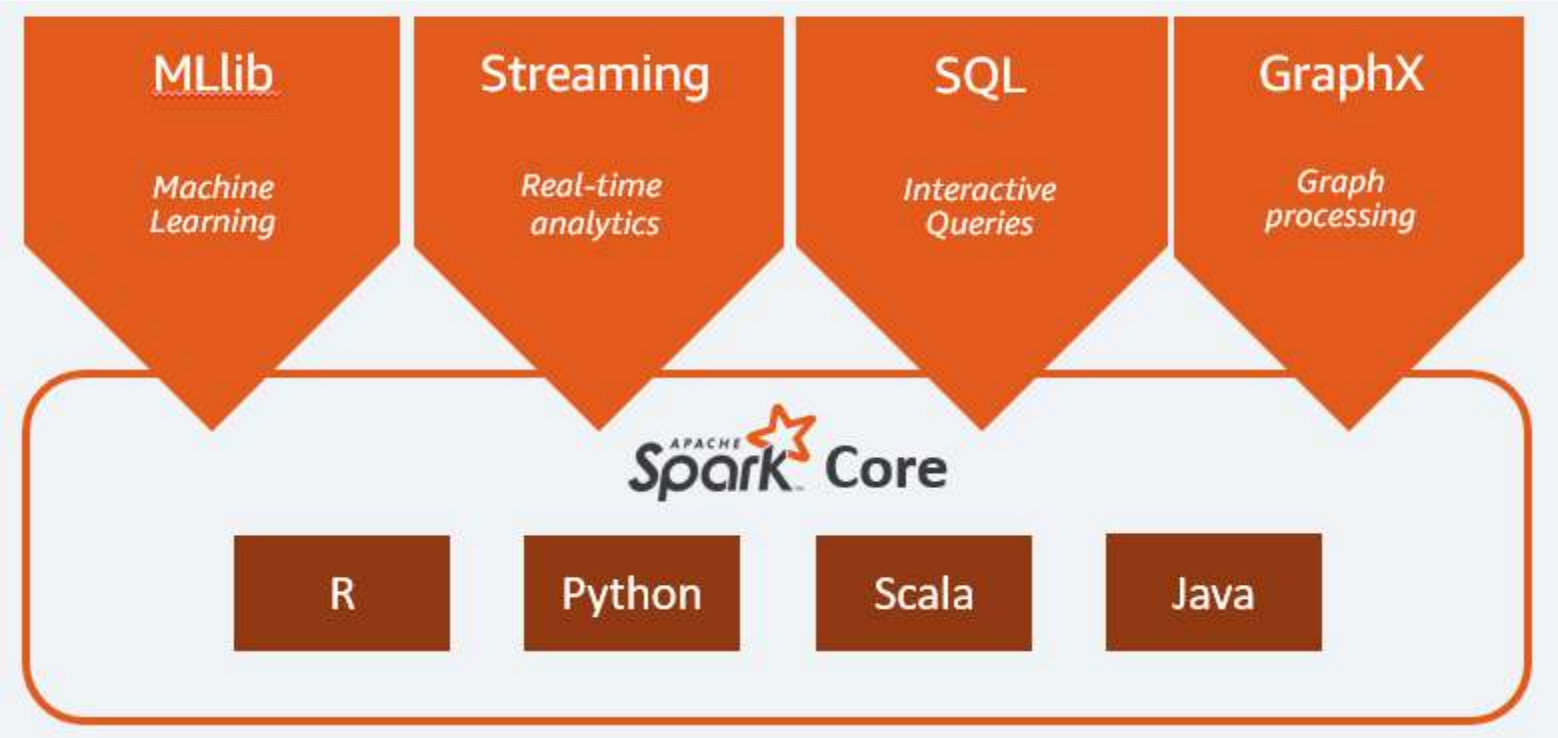
- Additionally, Spark's APIs are available for many programming languages: Scala, Java, Python, and R
- This flexibility is the key of its success in the Big Data landscape

Spark: More Detailed Overview



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- Spark can run:
  - on a single machine → local mode
  - on a cluster managed by a cluster manager (e.g., Spark Standalone, YARN, Mesos)

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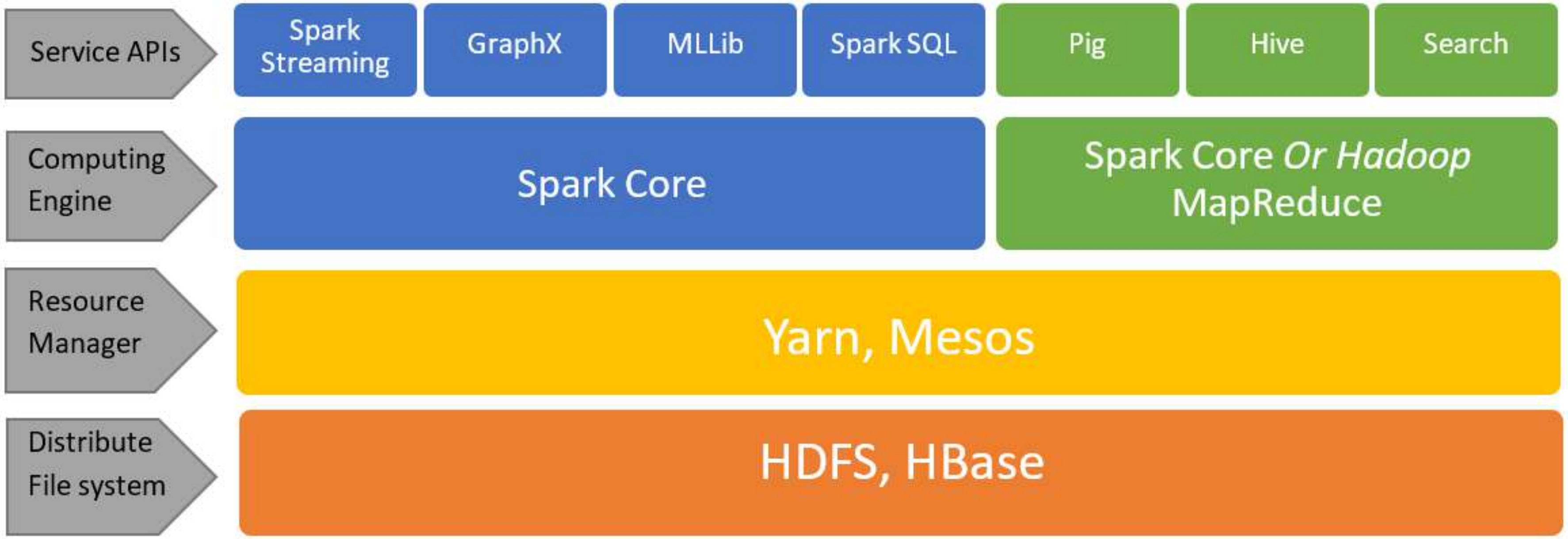

Figure 1 - Spark Context

Spark Application: Driver

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- The driver is represented by an object called Spark Context

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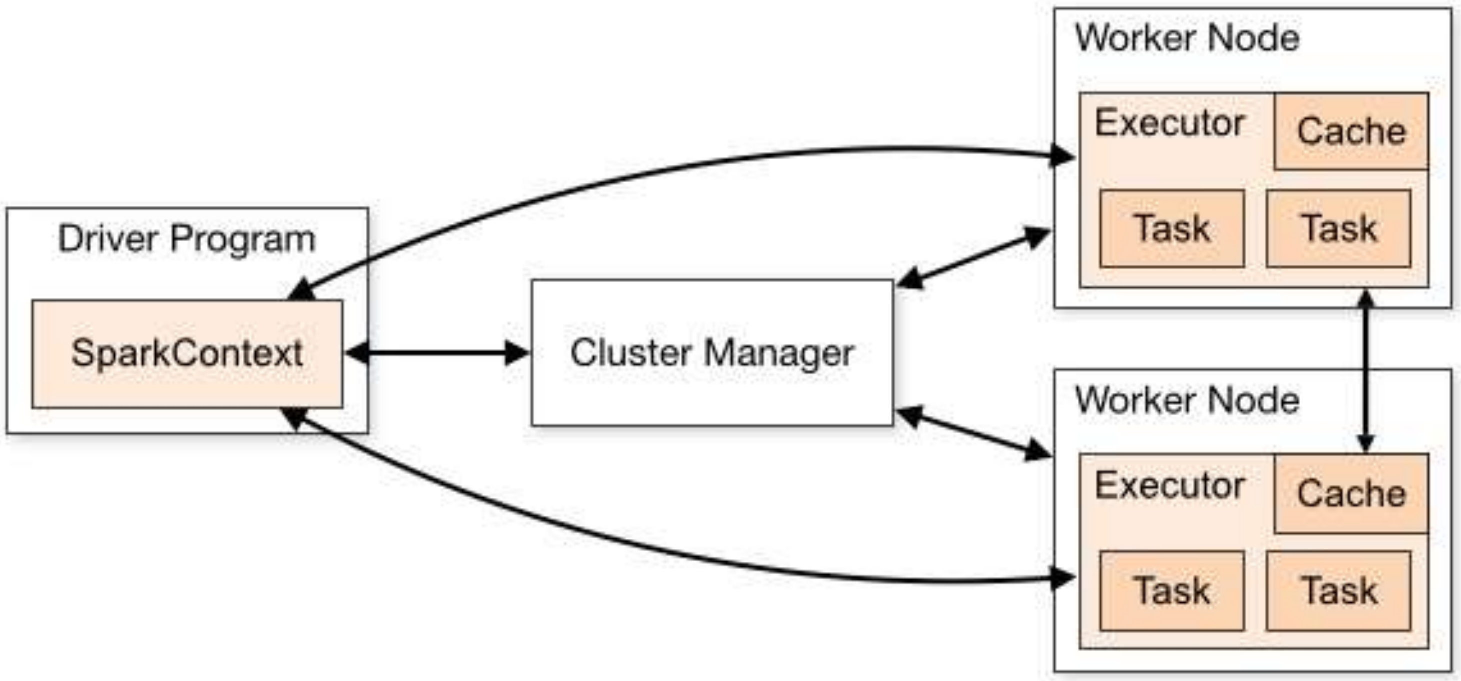
- The cluster manager controls physical machines and allocates resources to applications

Spark Application



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- Executors mostly run Scala code
- Driver can be governed by different languages using Spark's APIs

Resilient Distributed Dataset (RDD)

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Resilient Distributed Dataset (RDD)

- Fundamental abstraction of Spark to indicate a collection of elements of the same type
  - Generalization of MapReduce's key-value pairs
- RDDs are partitioned and possibly spread across multiple nodes of the cluster
- Best suited for applications that apply the same operation across all the elements of the dataset

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- A typical number of partitions is 2 or 3 times the number of cores

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  - Parallelism → Some data transformations are applied independently to each partition thereby avoiding expensive data transfers

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- Can be created either from data stored on distributed file system (e.g., HDFS) or as a result of transformations of other RDDs
- RDDs do not need to be always materialized
  - Each RDD maintains a sort of "trace" of transformations (lineage) that led to the current status
  - This way, RDD can always be re-created even upon a failure

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  - Actions → launch a computation on the data in A, which returns a value to the application
  - Persistence → save the RDD in memory for later actions

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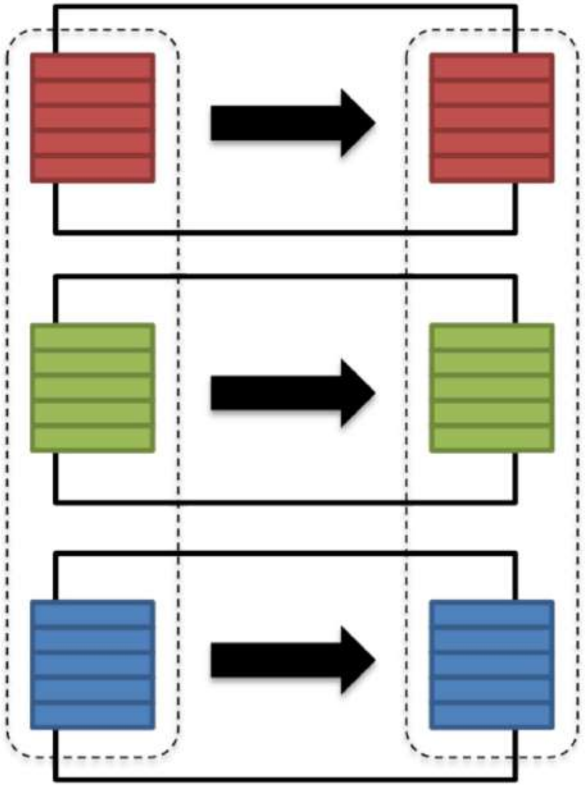
- Wide: each partition of A may contribute to multiple partitions of B (e.g., **`groupBy`**)
  - Possible need to transfer data across nodes
- Lazy evaluation: nothing is computed unless required by an action

Narrow vs. Wide Transformations

Narrow

Input and output stay on the same partition



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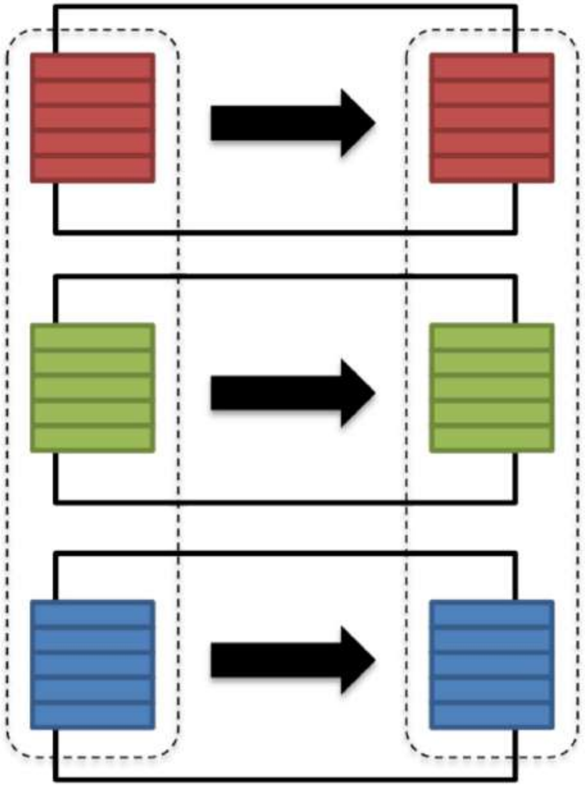

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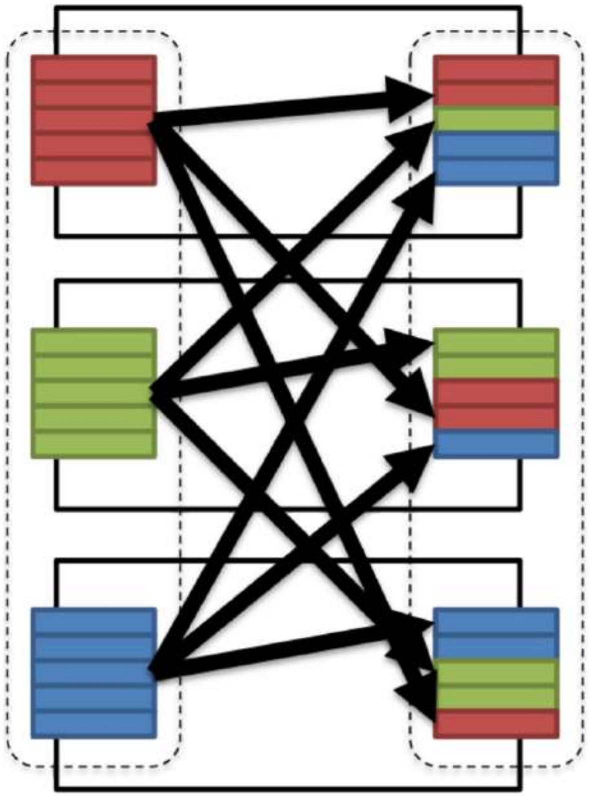

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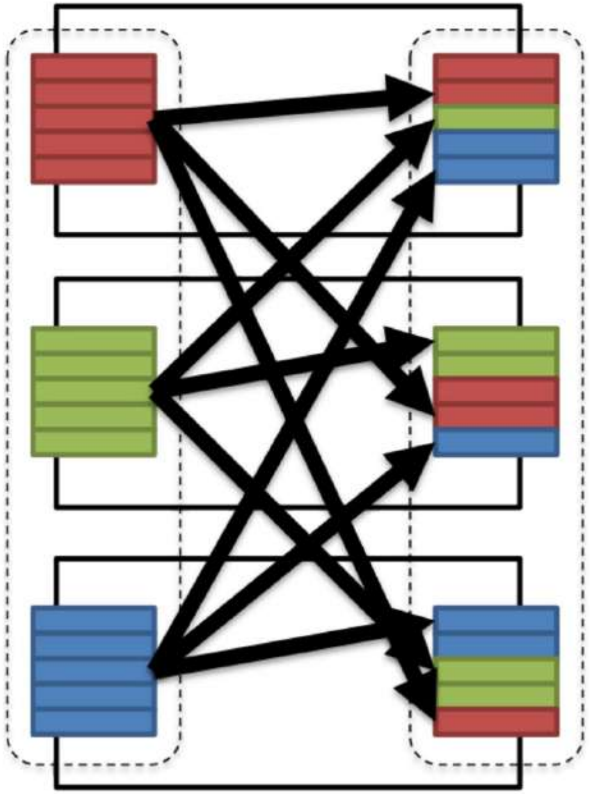

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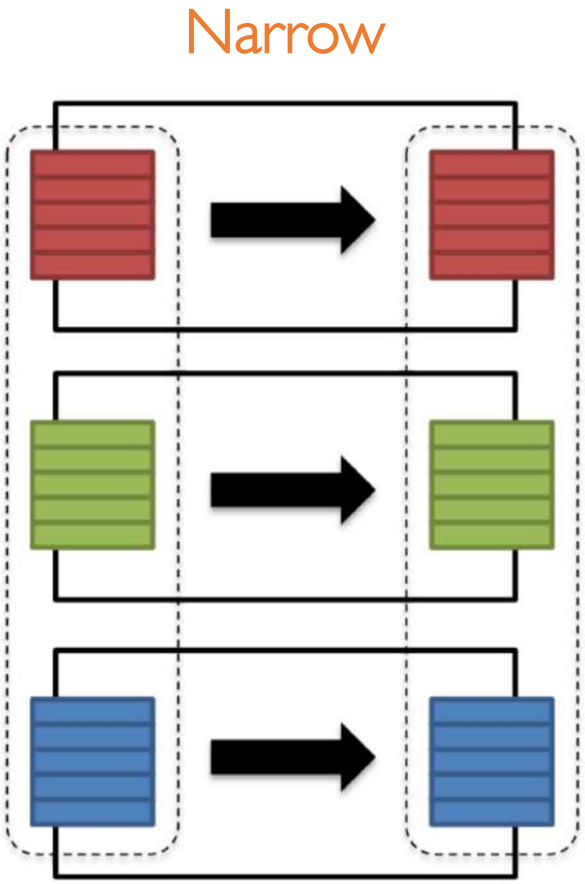

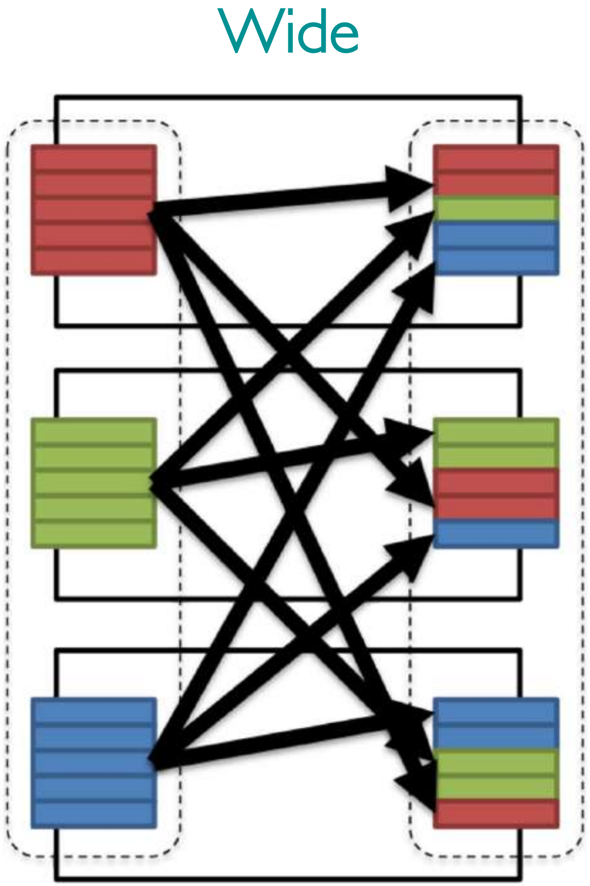

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RDD Operations: Actions

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- When the action is called the RDD is actually materialized (lazy evaluation)

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Spark DataFrame and Dataset APIs

- RDDs are the most basic data model used by Spark
  - low-level and schema-less
- On top of RDD API, Spark SQL module provides 2 interfaces to operate on structured data like tables in relational databases:
  - DataFrame API
  - Dataset API

Spark: DataFrame

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- Similar to Pandas DataFrame unless few differences

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- DataFrame (and Dataset as well) can be turned back to RDD

Spark vs. Hadoop MapReduce

- **Performance:** Spark is usually faster
  - In-memory data processing vs. data persistencing to disk after any map/reduce step
  - Spark requires lots of memory to run fast, otherwise its performance deteriorates
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- **Data processing:** Spark is more flexible and general

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- Spark provides a rich ecosystem of services to work on (big) data through APIs accessible via multiple programming languages
- Lazy execution avoids frequent and costly disk operations
- Spark's DataFrame as the main abstraction for playing with data