MA-INF 4223- Lab Distributed Big Data Analytics

Smart Data Analytics

Spark Fundamentals II

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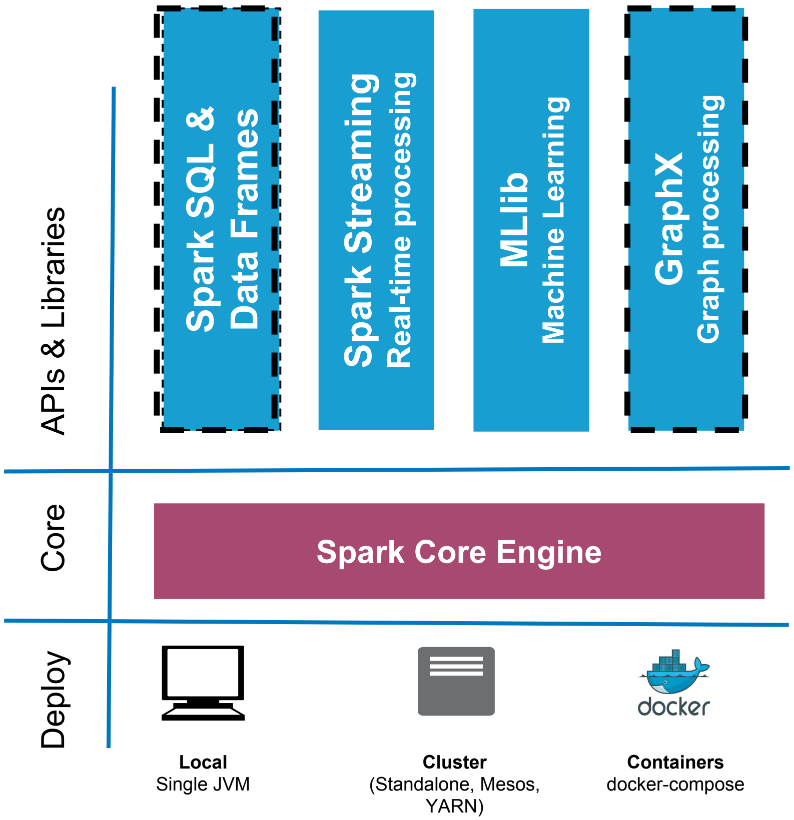
Lesson objectives

- After completing this lesson, you should be able to:
  - Understand and use various Spark Libraries
    - Spark SQL
    - Spark GraphX - graph processing

Spark Libraries

- A unified analytics stack



Overview

- Spark SQL: Relational Data Processing in Spark
- GraphX: A Resilient Distributed Graph System on Spark

Motivation

- Support relational processing both within Spark programs
- Provide high performance with established DBMS techniques
- Easily support new data sources, including semi-structured data and external databases amenable to query federation
- Enable extension with advanced analytics algorithms such as graph processing and machine learning

Motivation

- Users:
  - Want to perform ETL-relational
    - data Frames
  - Analytics - procedural tasks
    - UDFs

Spark SQL

- A module that integrates relational processing with Spark's Functional programming API
- SQL allows relational processing
- Perform complex analytics
  - Integration between relational and procedural processing through declarative Data Frame
  - Optimizer (catalyst)
    - Composable rules
    - Control code generation
    - Extension points
    - Schema inference for json
    - ML types
    - Query federation

Data Frame

- DataFrames are collections of structured records that can be manipulated using Spark's procedural API,
- Supports relational APIs that allow richer optimizations.
- Created directly from Spark's built-in distributed collections of Java/Python objects,
- Enables relational processing in existing Spark Programs
- DataFrame operations in SparkSQL go through a relational optimizer, Catalyst

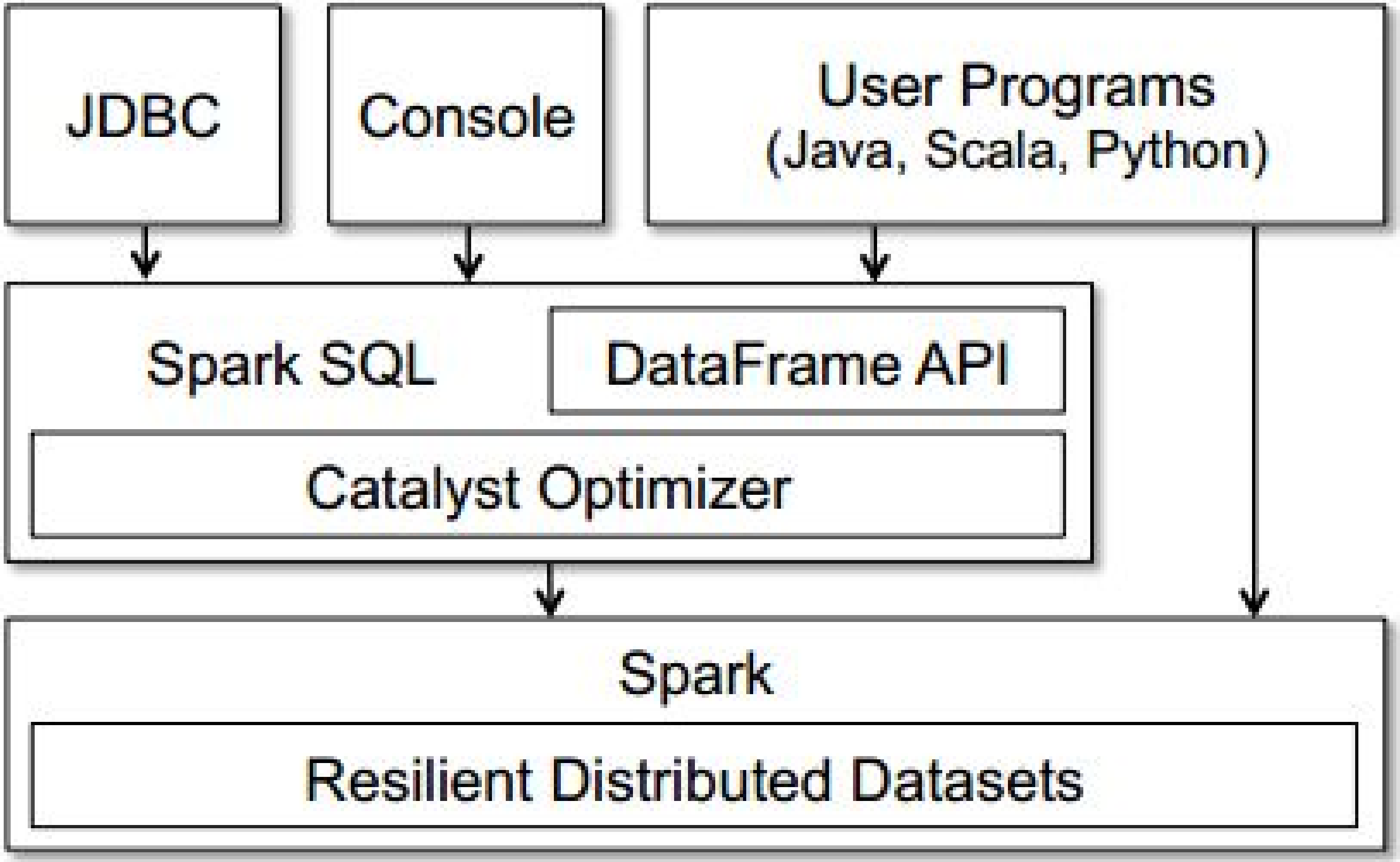
Catalyst

- Catalyst is the first production quality query optimizer built on such functional language.
- It contains an extensible query optimizer
- Catalyst uses features of the Scala programming language,
  - Pattern-matching,
  - Express composable rules
  - Turing complete language

Catalyst

- Catalyst can also be
  - extended with new data sources,
  - semi-structured data
    - such as JSON
    - "smart" data stores to use push filters
    - e.g., HBase
    - user-defined functions;
    - User-defined types for domains e.g. machine learning.
- Spark SQL simultaneously makes Spark accessible to more users and improves optimizations

Spark SQL


JDBC
Console
User Programs
(Java, Scala, Python)
Spark SQL
DataFrame API
Catalyst Optimizer
Spark
Resilient Distributed Datasets

DataFrame

- DataFrame is a distributed collection of rows with the same schema like table in a relational database.
- Each DataFrame can also be viewed as an RDD of Row objects, allowing users to call procedural Spark APIs such as map.
- Spark DataFrames are lazy, in that each DataFrame object represents a logical plan to compute a dataset, but no execution occurs until the user calls a special “output operation” such as save

Example


```
ctx = new HiveContext()
users = ctx.table("users")
young = users.where(users("age") < 21)
println(young.count())
```

Data Model

- DataFrames support all common relational operators, including
  - projection (select),
  - filter (where),
  - join, and
  - aggregations (groupBy).
- Users can break up their code into Scala, Java or Python functions that pass DataFrames between them to build a logical plan, and will still benefit from optimizations across the whole plan when they run an output operation.

Optimization

- The API analyze logical plans eagerly
  - identify whether the column names used in expressions exist in the underlying tables,
  - whether the data types are appropriate
- Spark SQL allows users to construct DataFrames directly against RDDs of objects native to the programming language.
- Spark SQL can automatically infer the schema of these objects using reflection

Optimization

- Uses <u>columnar cache</u>
  - reduce memory footprint by an order of magnitude because it applies columnar
  - compression schemes such as dictionary encoding and run-length encoding.
- In Spark SQL, UDFs can be registered inline by passing Scala, Java or Python functions, which may use the full Spark API internally.
-

Catalyst - Extension

- Easy to add new optimization techniques and features to Spark SQL
- Enable external developers to extend the optimizer
  - E.g. adding data source specific rules that can push filtering or aggregation into external storage systems,
  - support for new data types.
- Catalyst supports both rule-based and cost-based optimizations

Catalyst

- Catalyst contains a general library for representing trees(Abstract Syntax Tree) and applying rules to manipulate them
- Catalyst offers several public extension points, including external data sources and user-defined types.

Trees

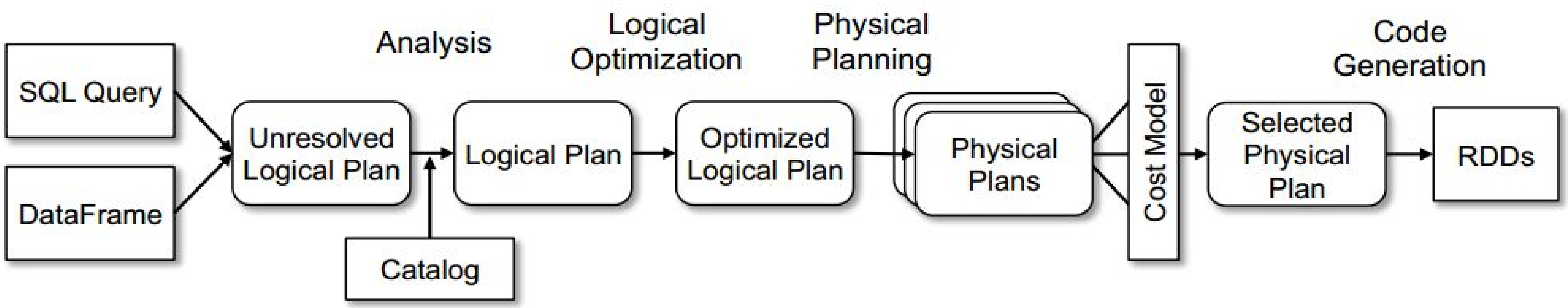
- The main data type in Catalyst is a tree composed of node objects.
- Each node has a node type and zero or more children.
- New node types are defined in Scala as subclasses of the TreeNode class.
- These objects are immutable and can be manipulated using functional transformations,

Rules

- Trees can be manipulated using rules, which are functions from a tree to another tree.
- While a rule can run arbitrary code on its input tree (given that this tree is just a Scala object),
- the most common approach is to use a set of pattern matching functions that find and replace subtrees with a specific structure.

Tree Transformation

- Catalyst's general tree transformation framework works in four phases
  - analyzing a logical plan to resolve references
  - logical plan optimization
  - physical planning
  - code generation to compile parts of the query to Java bytecode.



Spark GraphX

- Graph computation system which runs in the Spark data-parallel framework.
- GraphX extends Spark's Resilient Distributed Dataset (RDD) abstraction to introduce the Resilient Distributed Graph (RDG)

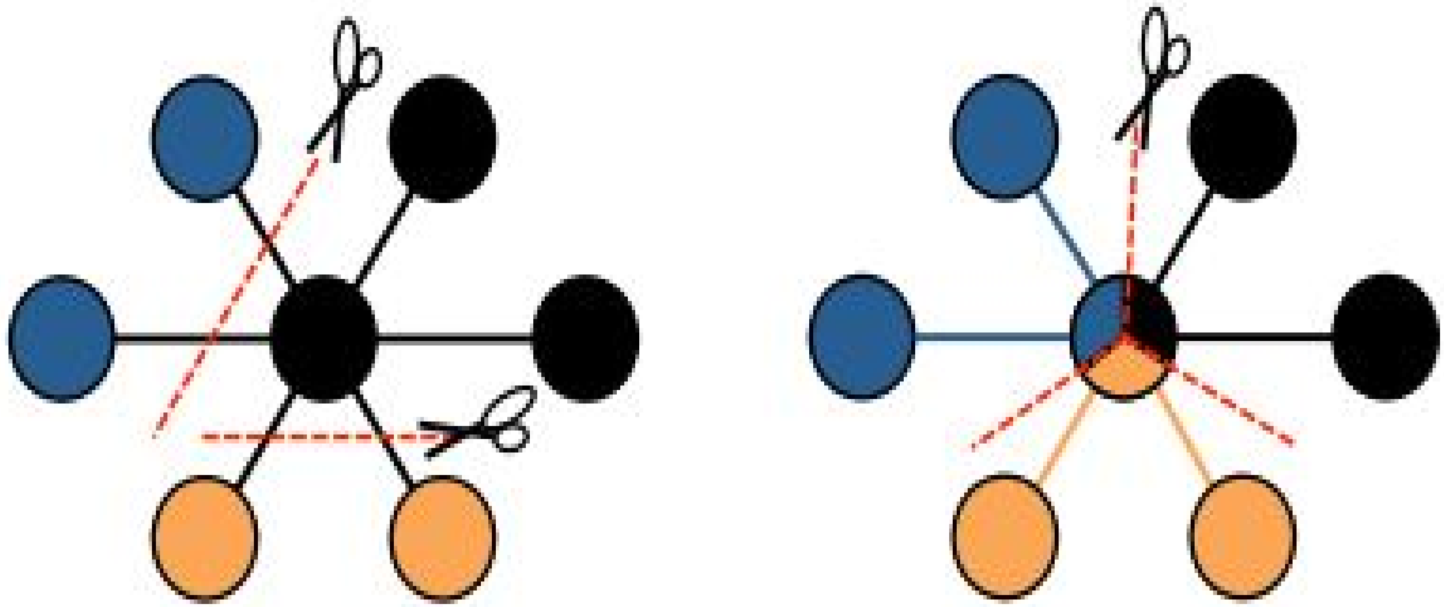
Resilient Distribute Graph (RDG)

- A tabular representation of the efficient vertex-cut partitioning and data-parallel partitioning heuristics.
- Supports implementations of the
  - PowerGraph and
  - Pregel graph-parallel
- preliminary performance comparisons between a popular dataparallel and graph-parallel frameworks running PageRank on a large real-world graph

Graph Parallel

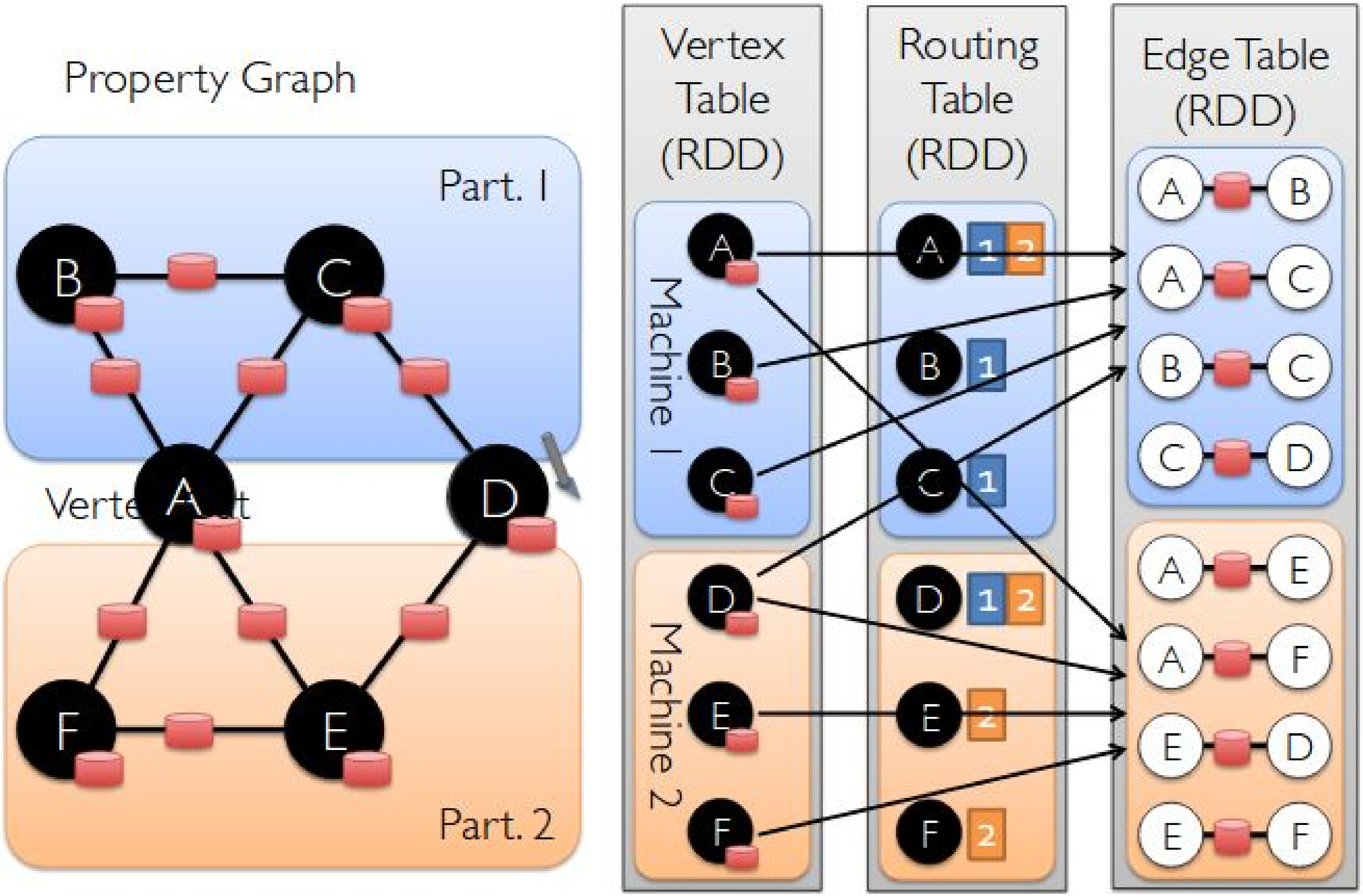
- Graph-parallel computation typically adopts a vertex (and occasionally edge) centric view of computation
- Retaining the **data-parallel metaphor,** program logic in the GraphX system defines transformations on graphs with each operation yielding a new graph.
- The core data-structure in the GraphX systems is an <u>immutable graph.</u>

```
class Graph[V, E] {
 def vertices(): RDD[(Id, V)]

 def edges(): RDD[(Id, Id, E)]

 def filterVertices(f: (Id, V)=>Bool): Graph[V, E]

 def filterEdges(f: Edge[V, E]=>Bool): Graph[V, E]

 def mapVertices(f: (Id,V)=>(Id,V2)): Graph[V2, E]

 def mapEdges(
   f: (Id, Id, E)=>(Id, Id, E2)): Graph[V, E2]
```



(a) Edge-Cut (b) Vertex-Cut

Encoding Property Graphs as RDDs



Edge Table

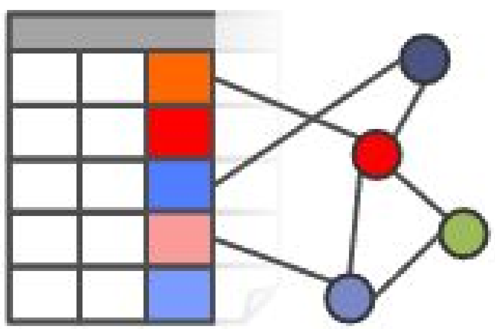
- EdgeTable(pid, src, dst, data): stores the adjacency structure and edge data.
- Each edge is represented as a tuple consisting of the
  - source vertex id,
  - destination vertex id,
  - user-defined data
  - virtual partition identifier (pid).

Vertex Data Table

- VertexDataTable(id, data): stores the vertex data, in the form of a vertex (id, data) pairs.
- VertexMap(id, pid): provides a mapping from the id of a vertex to the ids of the virtual partitions that contain adjacent edges

New API

Blurs the distinction between Tables and Graphs



New Library

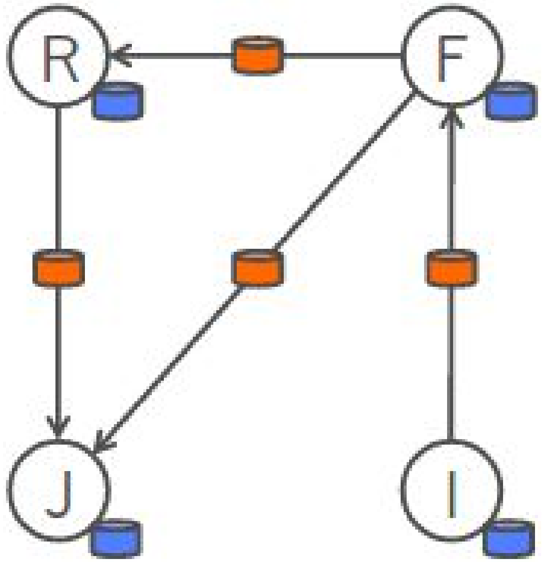
Embeds Graph-Parallel model in Spark

APACHE GIRAPH

Spark

GraphLab

Property Graph



Vertex Table

Id	Attribute (V)
Rxin	(Stu., Berk.)
Jegonzal	(PstDoc, Berk.)
Franklin	(Prof., Berk)
Istoica	(Prof., Berk)

Edge Table

SrcId	DstId	Attribute (E)
rxin	jegonzal	Friend
franklin	rxin	Advisor
istoica	franklin	Coworker
franklin	jegonzal	PI

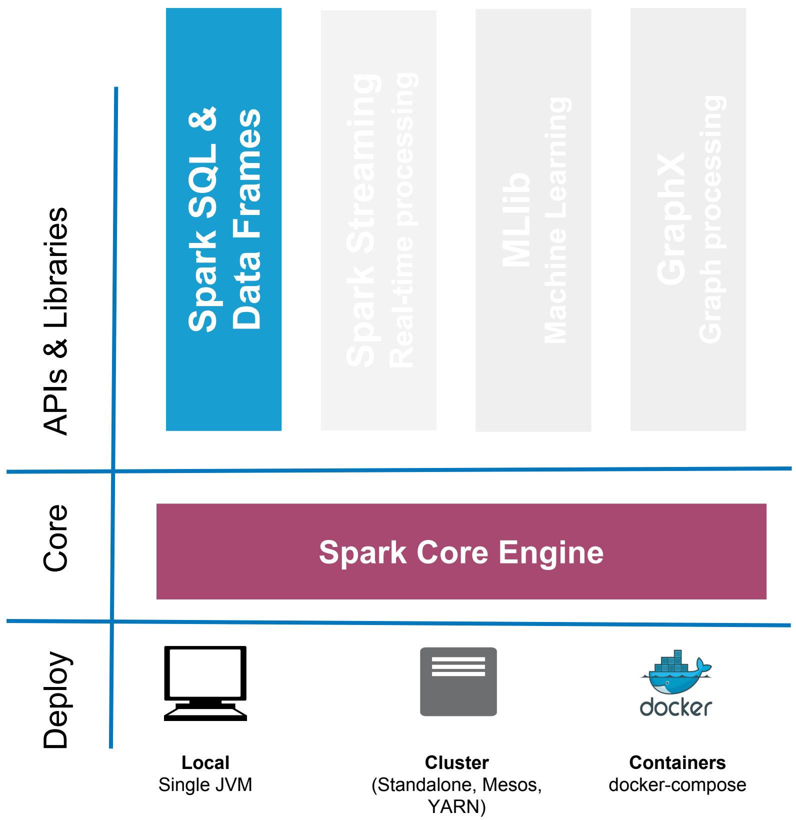
GraphX Optimizations

- Mirror Caches
- Incremental Updates to Mirror Caches
- Join Elimination
- Index Scanning for Active Sets
- Local Vertex and Edge Indices
- Index and Routing Table Reuse

Spark Libraries

- They are extensions of the Spark core API (RDDs).
- Transformations among these data representations

Spark SQL


APIs & Libraries
Core
Deploy
Spark SQL &
Data Frames
Spark Streaming
Real-time processing
MLlib
Machine Learning
GraphX
Graph processing
Spark Core Engine
docker
Local
Single JVM
Cluster
(Standalone, Mesos,
YARN)
Containers
docker-compose

Spark SQL

- Spark SQL lets you query structured data inside Spark programs, using either SQL or a familiar DataFrame API.
- It has it own RDD called SchemaRDD consisting of
  - Row objects
  - Schema - describe the type of the data in each column in the row
  - SchemaRDD can be created via :
    - Existing RDD, Parquet file, JSON dataset, HiveQL, Cassandra or other JDBC connectors.

- Is available in Scala, Java, Python, and R.

Spark SQL - Getting Started

- Starting point: SparkSession
  - Created from SparkSession.builder()
  - Existing contexts: SQLContext/HiveContext
    - Entry point for all SQL functionality
- For implicit conversions like converting RDDs to DataFrames we have to use:

```
import spark.implicits._
```

- Create an RDD of `Triple` objects from a nt file, convert it to a Dataframe

```
val tripleDF = spark.sparkContext
        .textFile("src/main/resources/rdf.nt")
        .map(parsTriples)
        .toDF()
```

Spark SQL - Getting Started

- Register the DataFrame as a temporary view

```
tripleDF.createOrReplaceTempView("triple")
```

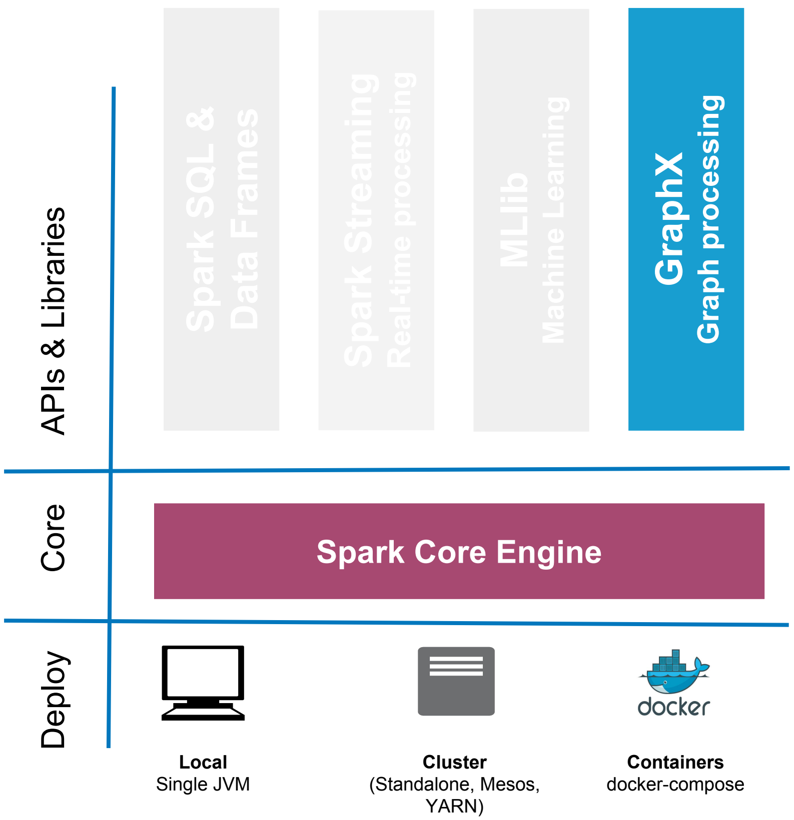
- SQL statements can be run by using the sql methods provided by Spark

```
val authorDF = spark.sql("SELECT subject, object FROM triple
WHERE
predicate='http://commons.dbpedia.org/property/author'")
```

- The columns of a row in the result can be accessed by field index

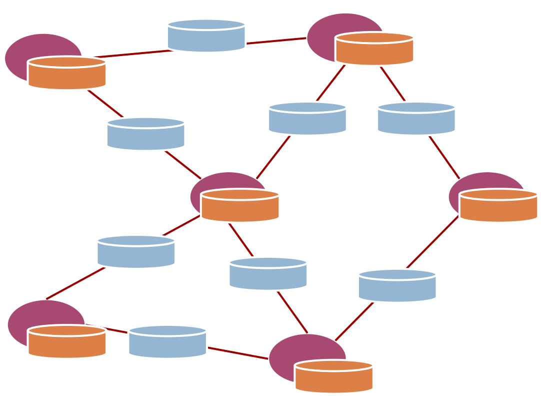
```
authorDF.map( author => "Author: " + author(0))
.collect().foreach(println(_))
```

Spark GraphX



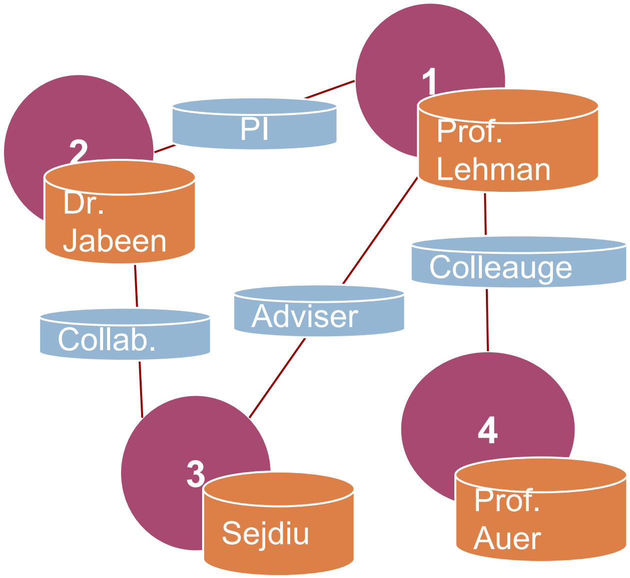
Spark GraphX

- Spark GraphX - stands for graph processing
  - For graph and graph-parallel computation
- At a high level, GraphX extends the Spark RDD by introducing a new Graph abstraction:
  - a directed multigraph with properties attached to each vertex and edge.
- It is based on Property Graph model → **G(V, E)**
  - Vertex Property
    - Triple details
  - Edge Property
    - Relations
    - Weights



Spark GraphX - Getting Started

Creating a Graph




```
type VertexId = Long

// Create an RDD for the vertices
val users: RDD[(VertexId, (String, String))]=
spark.sparkContext.parallelize(
                Array((3L, ("sejdiu", "phd_student")),
                       (2L, ("jabeen", "postdoc")),
                       (1L, ("lehmann", "prof")),
                       (4L, ("auer", "prof"))))
// Create an RDD for edges
val relationships: RDD[Edge[String]] =
spark.sparkContext.parallelize(
                Array(Edge(3L, 2L, "collab"),
                       Edge(1L, 3L, "advisor"),
                       Edge(1L, 4L, "colleague"),
                       Edge(2L, 1L, "pi")))

// Build the initial Graph
val graph = Graph(users, relationships)
```

Vertex RDD	
vID	**Property(V)**
1L	(lehmann, prof)
2L	(jabenn, postdoc)
3L	(sejdiu, phd_student)
4L	(auer, prof)

Edge RDD		
sID	**dID**	**Property(E)**
1L	3L	advisor
1L	4L	colleague
2L	1L	pi
3L	2L	collab

Spark GraphX

Graph Operators

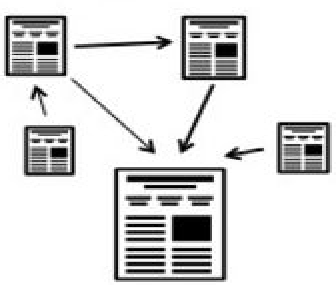
```
/** Summary of the functionality in the property graph */
class Graph[VD, ED] {
// Information about the Graph
===============================================================
val numEdges: Long
val numVertices: Long
val inDegrees: VertexRDD[Int]
val outDegrees: VertexRDD[Int]
val degrees: VertexRDD[Int]
// Views of the graph as collections
===============================================================
val vertices: VertexRDD[VD]
val edges: EdgeRDD[ED]
val triplets: RDD[EdgeTriplet[VD, ED]]
// Functions for caching graphs
===============================================================
def persist(newLevel: StorageLevel = StorageLevel.MEMORY_ONLY): Graph[VD, ED]
def cache(): Graph[VD, ED]
def unpersistVertices(blocking: Boolean = true): Graph[VD, ED]
// Change the partitioning heuristic
===============================================================
def partitionBy(partitionStrategy: PartitionStrategy): Graph[VD, ED]
// Transform vertex and edge attributes
===============================================================
def mapVertices[VD2](map: (VertexId, VD) => VD2): Graph[VD2, ED]
def mapEdges[ED2](map: Edge[ED] => ED2): Graph[VD, ED2]
    ----
```

Spark GraphX

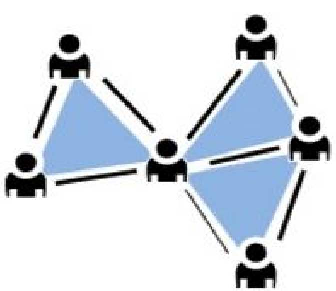
Build-in Graph Algorithms

```
// Basic graph algorithms
==============================================================================
def pageRank(tol: Double, resetProb: Double = 0.15): Graph[Double, Double]
def connectedComponents(): Graph[VertexId, ED]
def triangleCount(): Graph[Int, ED]
def stronglyConnectedComponents(numIter: Int): Graph[VertexId, ED]
```

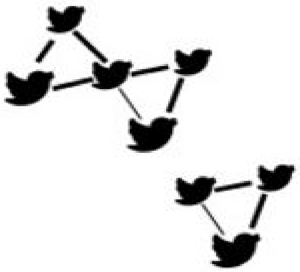
PageRank



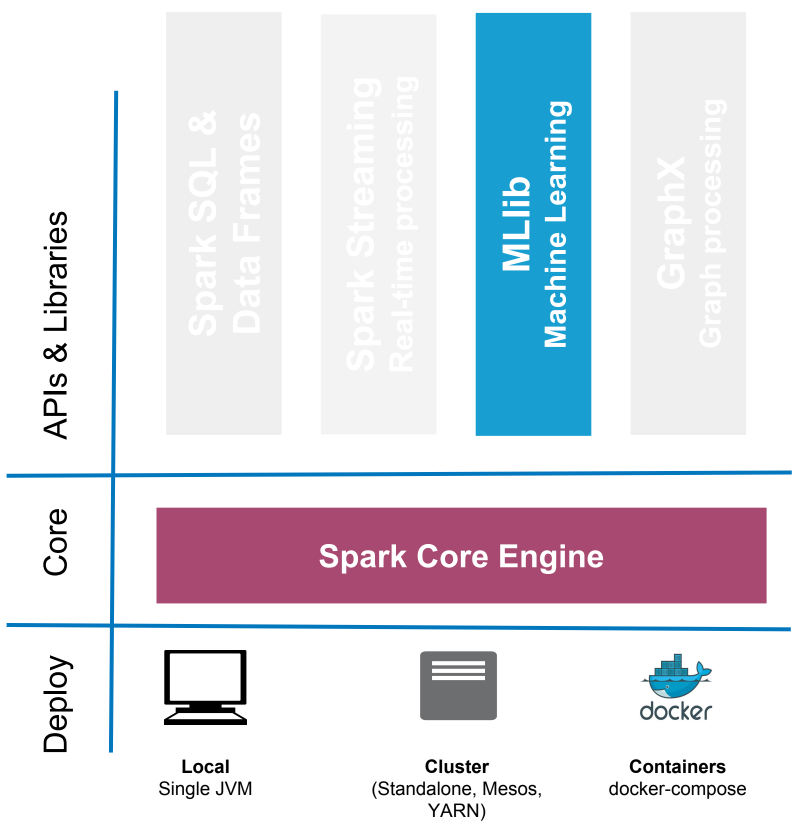
Triangle Count



Connected Components



Spark ML


APIs & Libraries
Spark SQL & Data Frames
Spark Streaming Real-time processing
MLlib Machine Learning
GraphX Graph processing
Core
Spark Core Engine
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docker
Local
Single JVM
Cluster
(Standalone, Mesos, YARN)
Containers
docker-compose

Spark ML

- Spark ML

Spark ML - Getting Started

- Spark ML

References

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[2]. GraphX: Graph Processing in a Distributed Dataflow Framework by Gonzalez, Joseph, Reynold Xin, Ankur Dave, Daniel Crankshaw, Michael J. Franklin and Ion Stoica *in OSDI,* 2014.

[3]. MLlib: Machine Learning in Apache Spark by Meng, Xiangrui, Joseph K. Bradley, Burak Yavuz, Evan R. Sparks, Shivaram Venkataraman, Davies Liu, Jeremy Freeman, D. B. Tsai, Manish Amde, Sean Owen, Doris Xin, Reynold Xin, Michael J. Franklin, Reza Bosagh Zadeh, Matei Zaharia and Ameet Talwalkar *in Journal of Machine Learning Research 17*, 2016.

[4]. "Spark SQL, DataFrames and Datasets Guide" - http://spark.apache.org/docs/latest/sql-programming-guide.html

[5]. "GraphX Programming Guide" - http://spark.apache.org/docs/latest/graphx-programming-guide.html

[6]. "Machine Learning Library (MLlib) Guide" - http://spark.apache.org/docs/latest/ml-guide.html