MA-INF 4223 - Lab Distributed Big 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

Pair RDDs

- A common form of data processing
- Main intuition behind the mapreduce
- Often beneficial to project down the complex data types to Key-value pairs

Distributed key-value pairs

- Additional specialised methods for working with data associated with Keys
- groupByKey(),reduceByKey(),join

Pair RDDs

Creation: Mostly from existing non-pair RDDs

E.g.

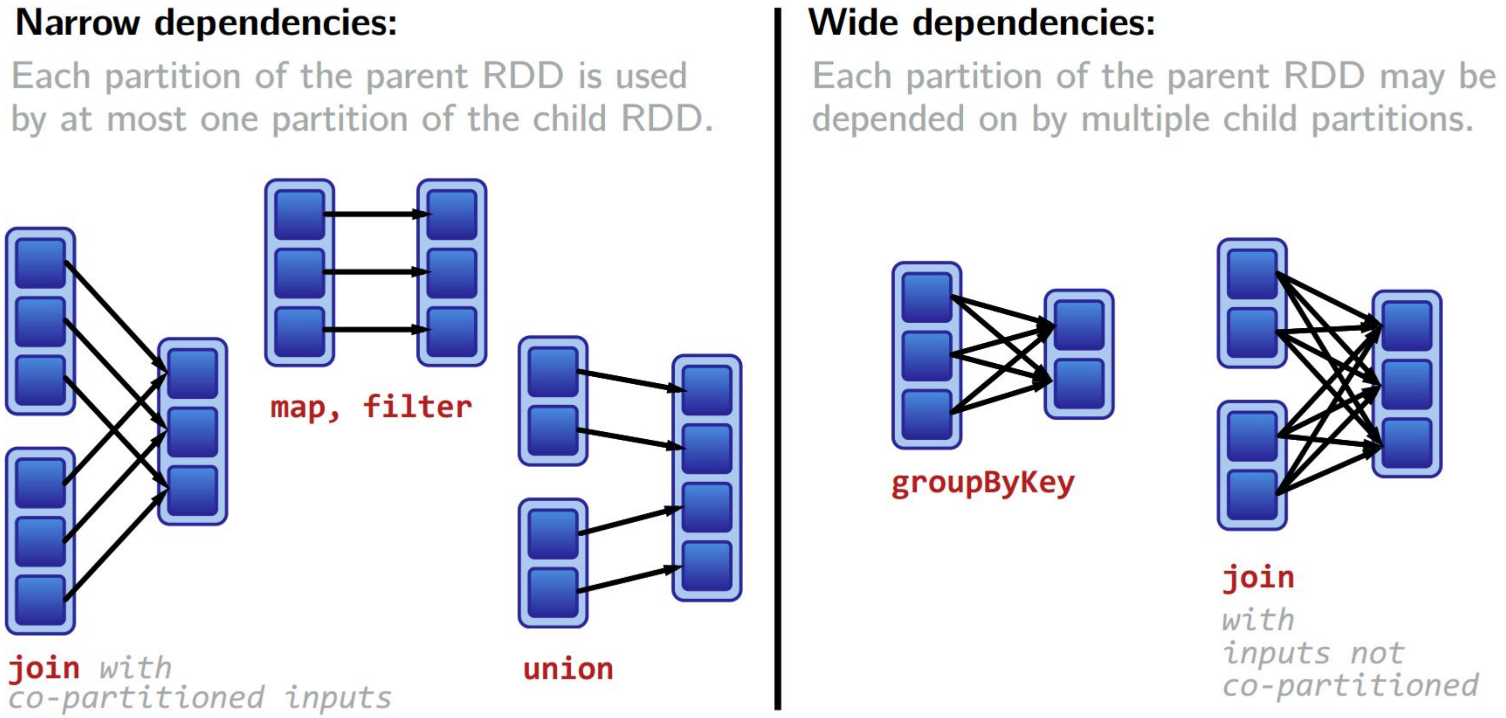
```
val pairRdd = rdd.map(page => (page.title, page.text))
```

- groupByKey
- reduceByKey
- mapValues
- keys
- Join
- leftOuterJoin/rightOuterJoin
- countByKey

Shuffling

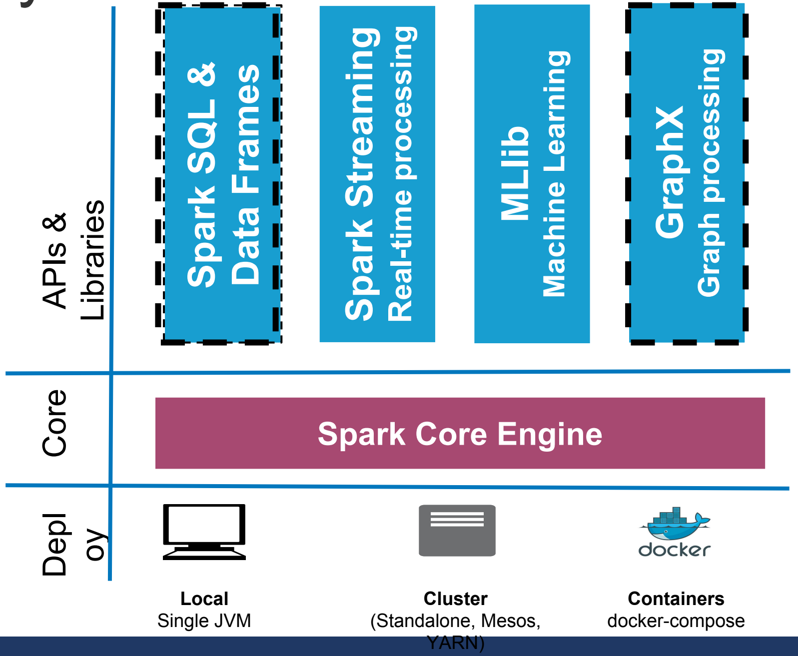
- groupByKey()
  - Shuffles all the keys across network to combine all the keys
- reduceByKey(func: (V, V) => V): RDD[(K, V)J)
  - Conceptually, reduceByKey can be thought of as a combination of first doing groupByKey and then reducing on all the values grouped per key.
  - Reduces on the mapper side first
  - Reduce again after shuffling
  - Less data needs to be sent over the network
  - Non trivial gains in performance

Dependencies / Shuffling



Spark Libraries

- A unified analytics stack



Overview

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

Spark SQL

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 processing
    - data Frames
  - Analytics - procedural tasks
    - UDFs

Spark SQL

- A module that integrates relational processing with Spark's Functional programming API
- Spark 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

Spark SQL

Three main APIs

- SQL Syntax
- DataFrames
- Datasets

Two specialised backend components

- Catalyst
- Tungsten

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

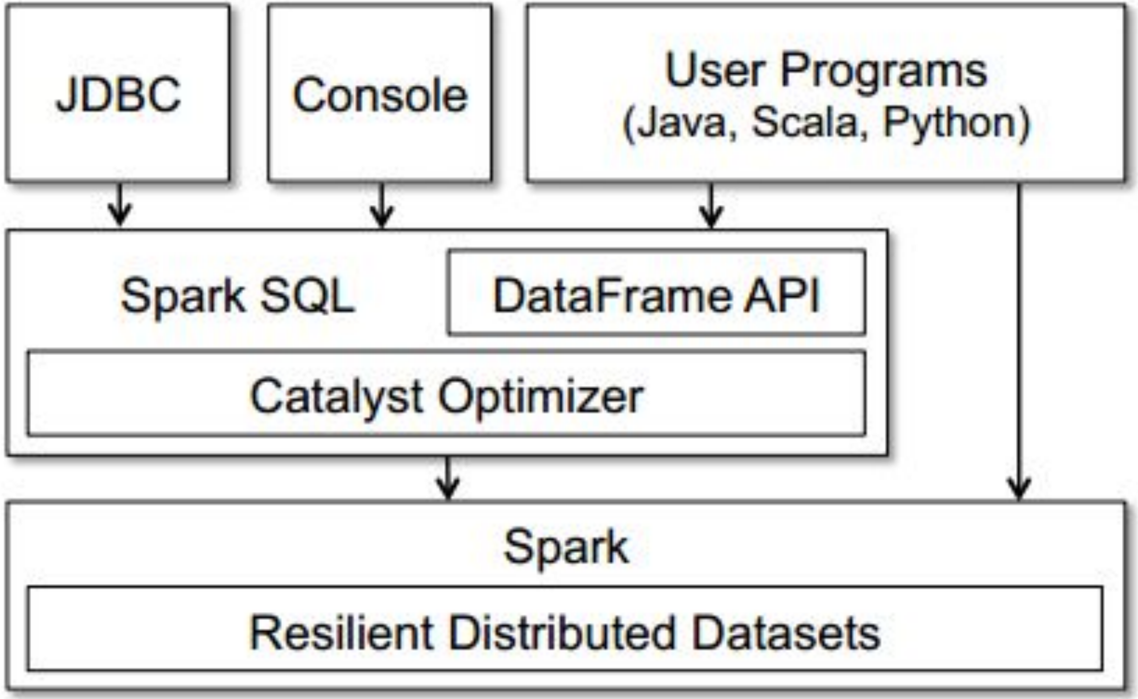
Catalyst

- 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 "Known" 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

DataFrame

- Created from an RDD using .toDF()
- Reading from a file ()

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 columnar cache
  - 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

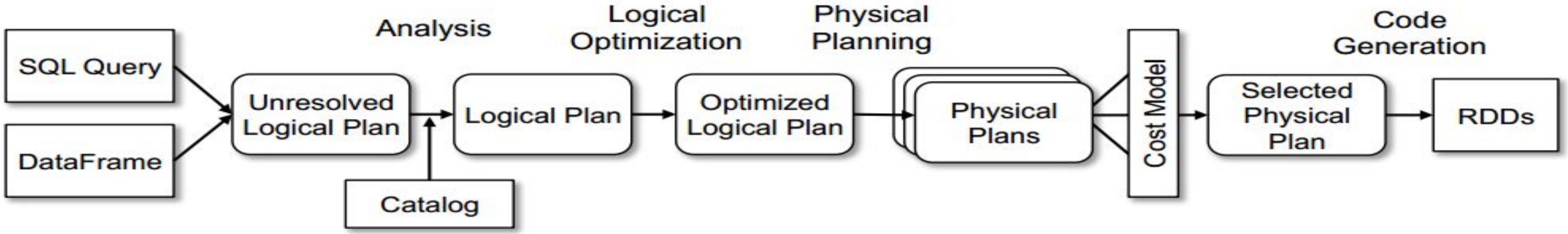
- The main data type in Catalyst is a tree composed of node objects.
- Each node has a node type and zero or more children.
- New node types are defined in Scala as subclasses of the TreeNode class.
- These objects are immutable and can be manipulated using functional transformations

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.



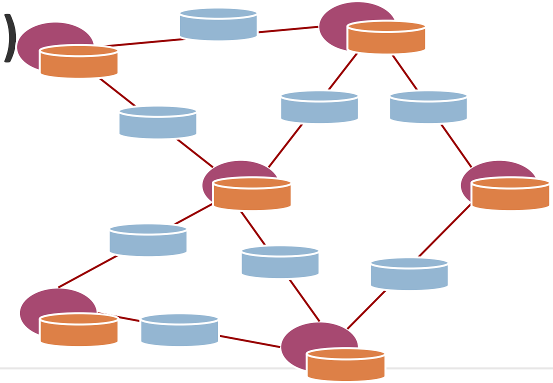
Spark GraphX

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)

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



Resilient Distributed 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

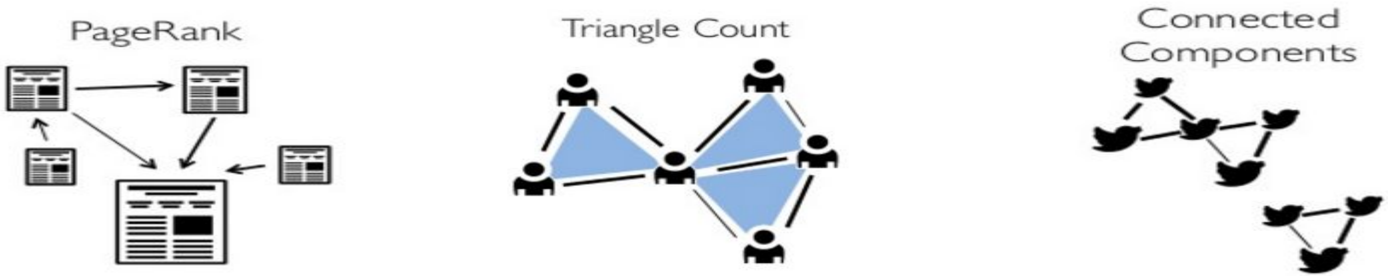
- Graph-parallel computation typically adopts a vertex (and occasionally edge) centric view of computation
- Retaining the **data-parallel metaphor,** program logic in the GraphX system defines transformations on graphs with each operation yielding a new graph
- The core data-structure in the GraphX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

GraphX operations

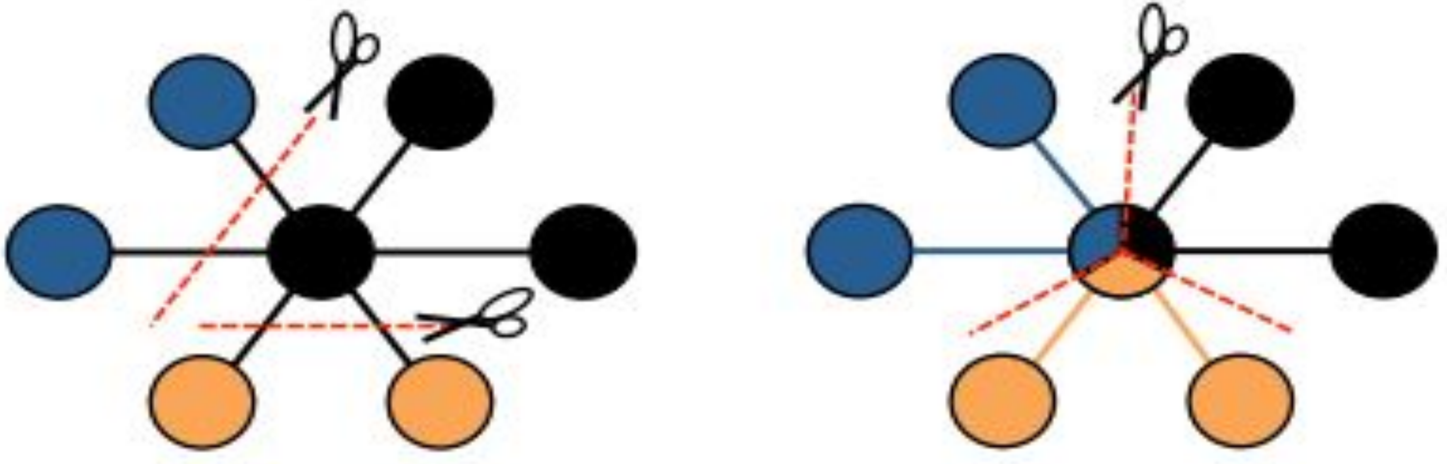
```
class Graph[VD, ED] {
// Information about the Graph
val numEdges: Long
val numVertices: Long
val inDegrees: VertexRDD[Int]
val outDegrees: VertexRDD[Int]
val degrees: VertexRDD[Int]

// 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]
        ----
```

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]
```

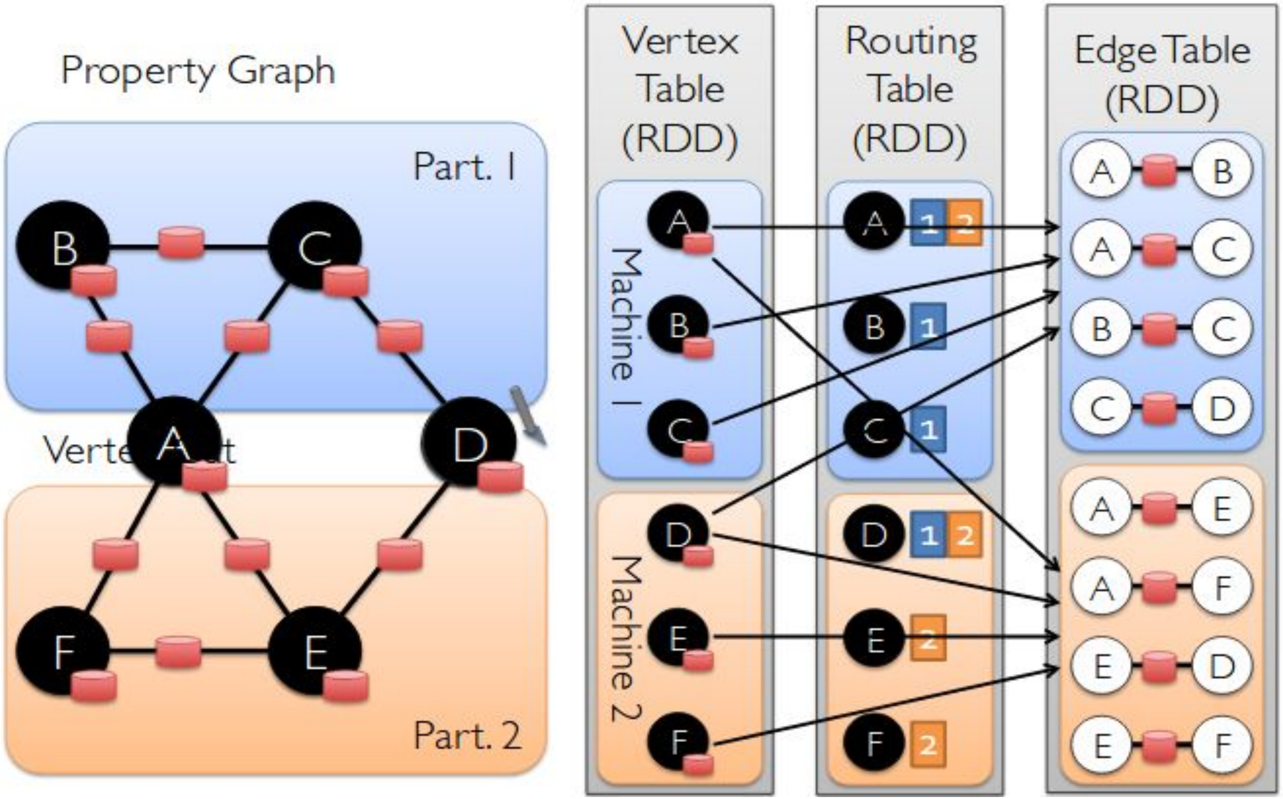


Edge-Cut vs Vertex-Cut



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

Encoding Property Graphs as RDDs



Edge Table

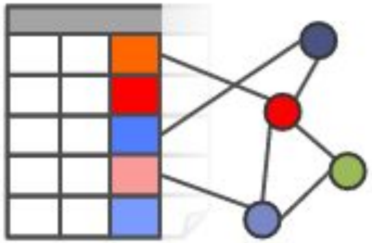
- EdgeTable(pid, src, dst, data): stores the adjacency structure and edge data
- Each edge is represented as a tuple consisting of the
  - source vertex id,
  - destination vertex id,
  - user-defined data
  - virtual partition identifier (pid).

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

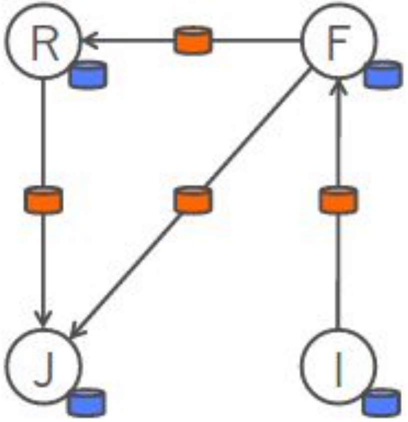
Blurs the distinction between Tables and Graphs



New Library

Embeds Graph-Parallel model in Spark

Property Graph



Vertex Table

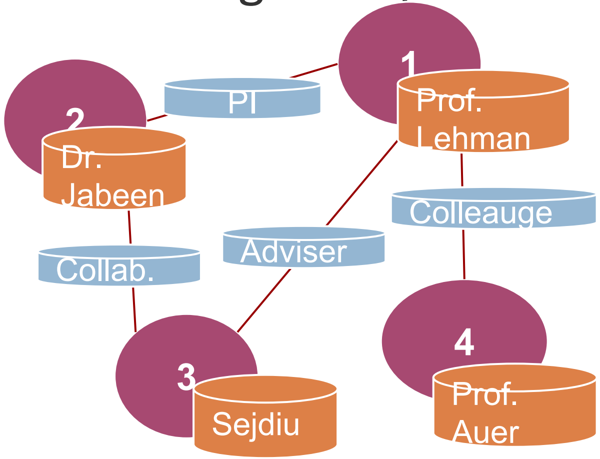
Id	Attribute (V)
Rxin	(Stu., Berk.)
Jegonzal	(PstDoc, Berk.)
Franklin	(Prof., Berk)
Istoica	(Prof., Berk)

Edge Table

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

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

GraphX Optimizations

- Mirror Vertices
- Partial materialization
- Incremental view
- Index Scanning for Active Sets
- Local Vertex and Edge Indices
- Index and Routing Table Reuse

References

[1]. Spark SQL: Relational Data Processing in Spark by Armbrust, Michael, Reynold Xin, Cheng Lian, Yin Huai, Davies Liu, Joseph K. Bradley, Xiangrui Meng, Tomer Kaftan, Michael J. Franklin, Ali Ghodsi and Matei Zaharia *in SIGMOD Conference,* 2015.

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

[3]. 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.

[4]. “GraphX Programming Guide” - http://spark.apache.org/docs/latest/graphx-programming-guide.html

THANK YOU !

http://sda.cs.uni-bonn.de/teaching/dbda/

- http://sda.cs.uni-bonn.de/
- https://github.com/SANSA-Stack
- https://github.com/big-data-europe
- https://github.com/SmartDataAnalytics

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