Introduction to Spark and GeoSpark

Yijun Lin

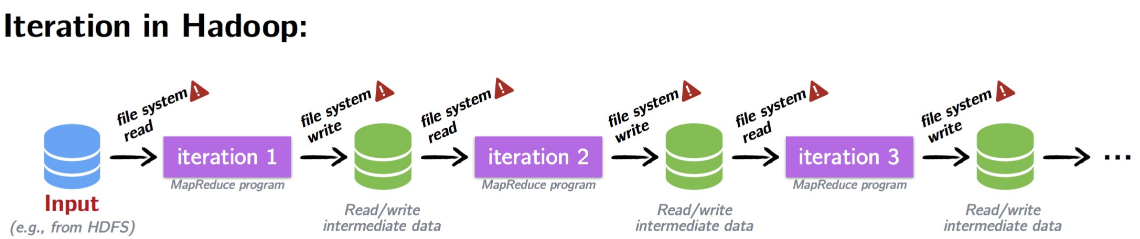
Department of Computer Science & Engineering

University of Minnesota, Twin Cities

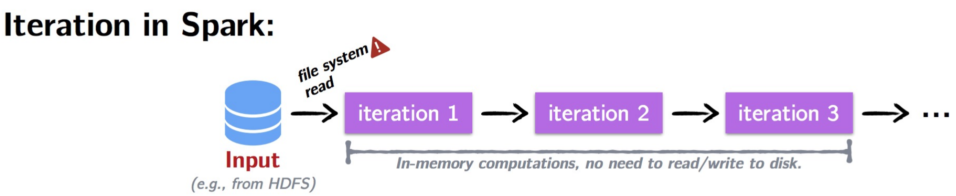
lin00786@umn.edu

Hadoop MapReduce VS. Apache Spark

- Hadoop MapReduce
  - Typically, data are read from disk, processed, and written back to disk
  - MapReduce is inefficient for multi-pass applications that read data more than once



- Apache Spark
  - When the output of an operation needs to be fed into another operation, Spark passes the data directly without writing to persistent storage

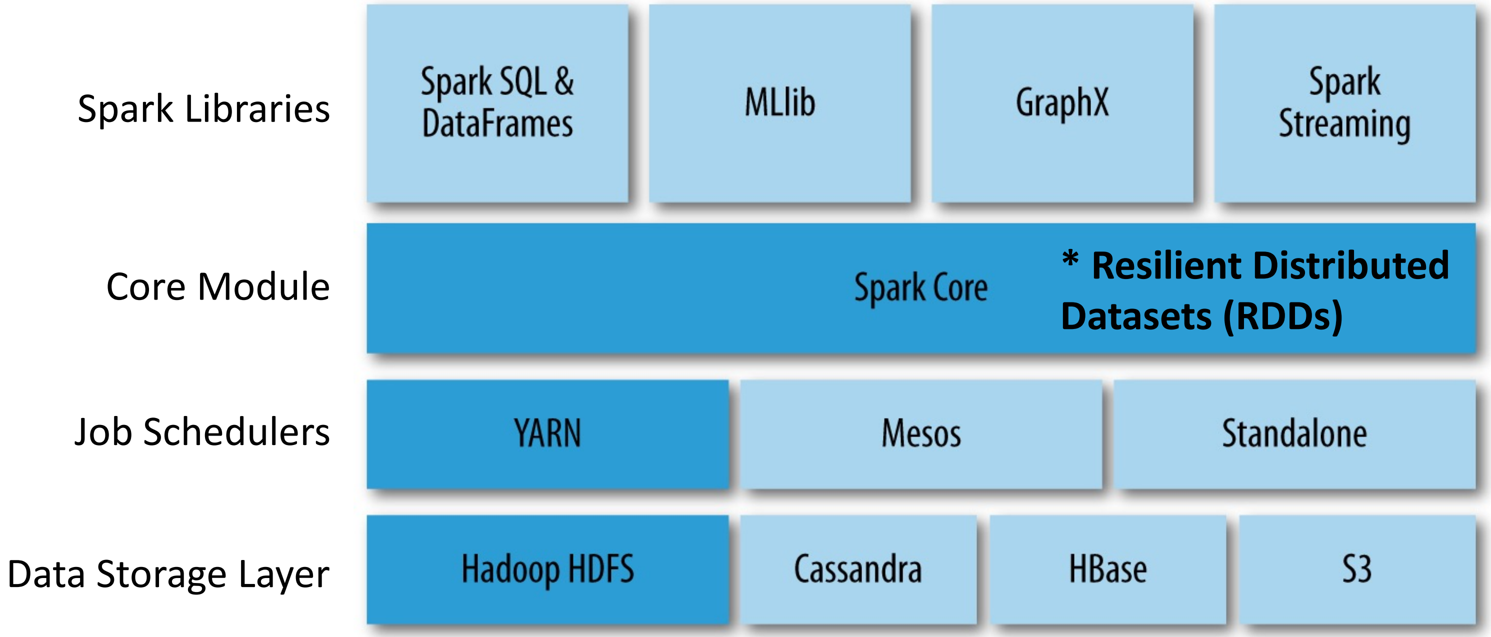


What is Spark

- Apache Spark is an open-source cluster computing framework

- Application areas
    - Iterative Algorithms
    - Interactive Data Mining
    - Streaming Applications

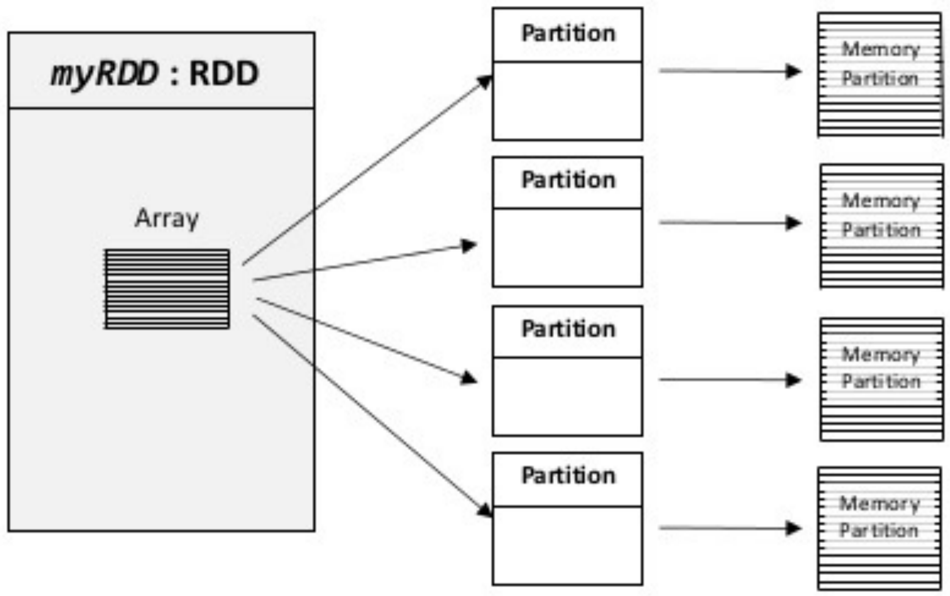
Spark Stack



Resilient Distributed Datasets (RDDs)

- An RDD is an **immutable**, **in-memory** collection of objects.
- Each RDD can be split into multiple partitions, which in turn are computed on different nodes of the cluster, so that users can
  - Explicitly persist intermediate results in memory
  - Control the partitioning to optimize data operations
  - Manipulate data using a rich set of operators

- RDDs seem a lot like Scala collections
  - RDD[T] and List[T]



Partitioning Strategy of RDDs

- Spark partitioning
  - Dividing the data into chunks that consider the number of partitions (cluster size) and how data is distributed across partitions.

- Number of partitions? Cannot be too large or too small

- How are data distributed across partitions?
  - HashPartitioner will distribute data, e.g., (key, value) pairs, across the partitions using

    partitionId = hash(Key) % n_partitions
  - RangePartitioner will distribute data across partitions based on a specific range
  - Customized Partitioner

```
def partition_func(x):     #  x: (word, 1)         1)
    return ord(x[0][0])    # ord("a") => 97 % n_partitions
                           # ord("P") => 80 % n_partitions
                           # ord("Z") => 90 % n_partitions

word_rdd = word_rdd.partitionBy(n_partitions, partition_func)
```

RDD Operations - Transformation VS. Action

- Transformation
  - Return new RDDs as results
  - They are **lazy**, the result RDD is not immediately computed

```
# call a map operation on an RDD
length_rdd = word_rdd.map(lambda x: len(x))  # RDD[Int]
```

map[T](f: A=>B): RDD[T]
Apply function to each element in the RDD and return an RDD of the result

- Action
  - Compute a result based on an RDD, and returned
  - They are **eager**, the result is immediately computed

```
a_coll = a_rdd.collect()  # RDD -> collection
print(a_coll)  # ['you', 'jump', 'I', 'jump', '']
```

collect: Array[T]
Return all elements from RDD.

Example

- Consider the following example:

```
a_list = ['you', 'jump', 'I', 'jump', '']
# create an RDD from a list
a_rdd = sc.parallelize(a_list)  # RDD[String]
# call a map operation RDD
a_len_rdd = a_rdd.map(lambda x: len(x))  # RDD[Int]
```

sc - a SparkContext (or SparkSession) object
The SparkContext object can be thought as your handle to the Spark cluster. It represents the connection between the Spark cluster and your running application. Initializing a SparkContext or SparkSession object is the first step of a Spark program.

```
ss = SparkSession. \
    builder. \
    appName("hw1"). \
    getOrCreate()
```

What has happened on the cluster at this point?

Example

- Consider the following example:

```
a_list = ['you', 'jump', 'I', 'jump', '']
# create an RDD from a list
a_rdd = sc.parallelize(a_list)  # RDD[String]
# call a map operation RDD
a_len_rdd = a_rdd.map(lambda x: len(x))  # RDD[Int]
```

What has happened on the cluster at this point?

Nothing. Execution of map (a transformation) is deferred.

Example (Cont.)

- Consider the following example:

```
a_list = ['you', 'jump', 'I', 'jump', '']
# create an RDD from a list
a_rdd = sc.parallelize(a_list)  # RDD[String]
# call a map operation RDD
a_len_rdd = a_rdd.map(lambda x: len(x))  # RDD[Int]

total_len = a_len_rdd.reduce(lambda a, b: a + b)  # 12
```

reduce(op: (A, A) => A): A
Combine the elements in the RDD together using op function and return result

add an action, *reduce*

Spark starts the execution when an action is called

Return the total number of characters in the entire RDD of strings

Benefits of Laziness

- Another example:

```
input_file = 'work-count-sample-doc.txt'
text_rdd = sc.textFile(input_file)
word_rdd = text_rdd.flatMap(lambda x: x.split(' ')).take(10)
```

- The execution of *flatMap* is **deferred** until *take* action happens
  - As soon as the first 10 elements of have been computed, word_rdd is done
- Spark analyzes and optimizes the **chain of operations** before executing it
  - Spark saves time and space by avoiding unnecessary computation

Common Transformations

map

map[T](f: A=>B): RDD[T]
Apply function to each element in the RDD and return an RDD of the result.

flatmap

flatmap[T](f: A=>B): RDD[T]
Apply function to each element in the RDD and return an RDD of the result, but output is flattened.

filter

filter[T](pred: A=>Boolean): RDD[T]
Apply predicate function, pred, to each element in the RDD and return an RDD of elements that passed the condition.

distinct

distinct():RDD[T]
Return an RDD with duplicates removed

Common Transformations

flatmap **flatmap[T](f: A=>B): RDD[T]**

Apply function to each element in the RDD and return an RDD of the result, but output is flattened.

```
val text: List[String] = List("you and me", "jump and run", "I love you", "jump forward", "")
val textRDD = sc.parallelize(text)

val splitText = textRDD.flatMap(phase => phase.split(" ")) // Flatten the output

val splitTextColl = splitText.collect()
splitTextColl.foreach(println) // "you", "me", "jump", "and", "run", "I", "love", "you", "jump", "forward"
```

Common Transformations

distinct **distinct():RDD[T]**

Return an RDD with duplicates removed

```
val text: List[String] = List("you and me", "jump and run", "I love you", "jump forward", "")
val textRDD = sc.parallelize(text)

val splitText = textRDD.flatMap(phase => phase.split(" ")) // Flatten the output
val textDist = splitText.distinct() // Get the distinct words

val textDistColl = textDist.collect()
textDistColl.foreach(println) // "me", "I", "love", "run", "forward", "jump", "you", "and"
```

Common Actions

collect **collect: Array[T]**
Return all elements from RDD.

count **count(): Long**
Return the number of elements in the RDD.

take **take(num: Int): Array[T]**
Return the first num elements of the RDD.

reduce **reduce(op: (A, A) => A): A**
Combine the elements in the RDD together using op function and return result.

foreach **foreach(f: A => Unit): Unit**
Apply function to each element in the RDD, and return Unit.

Common Actions

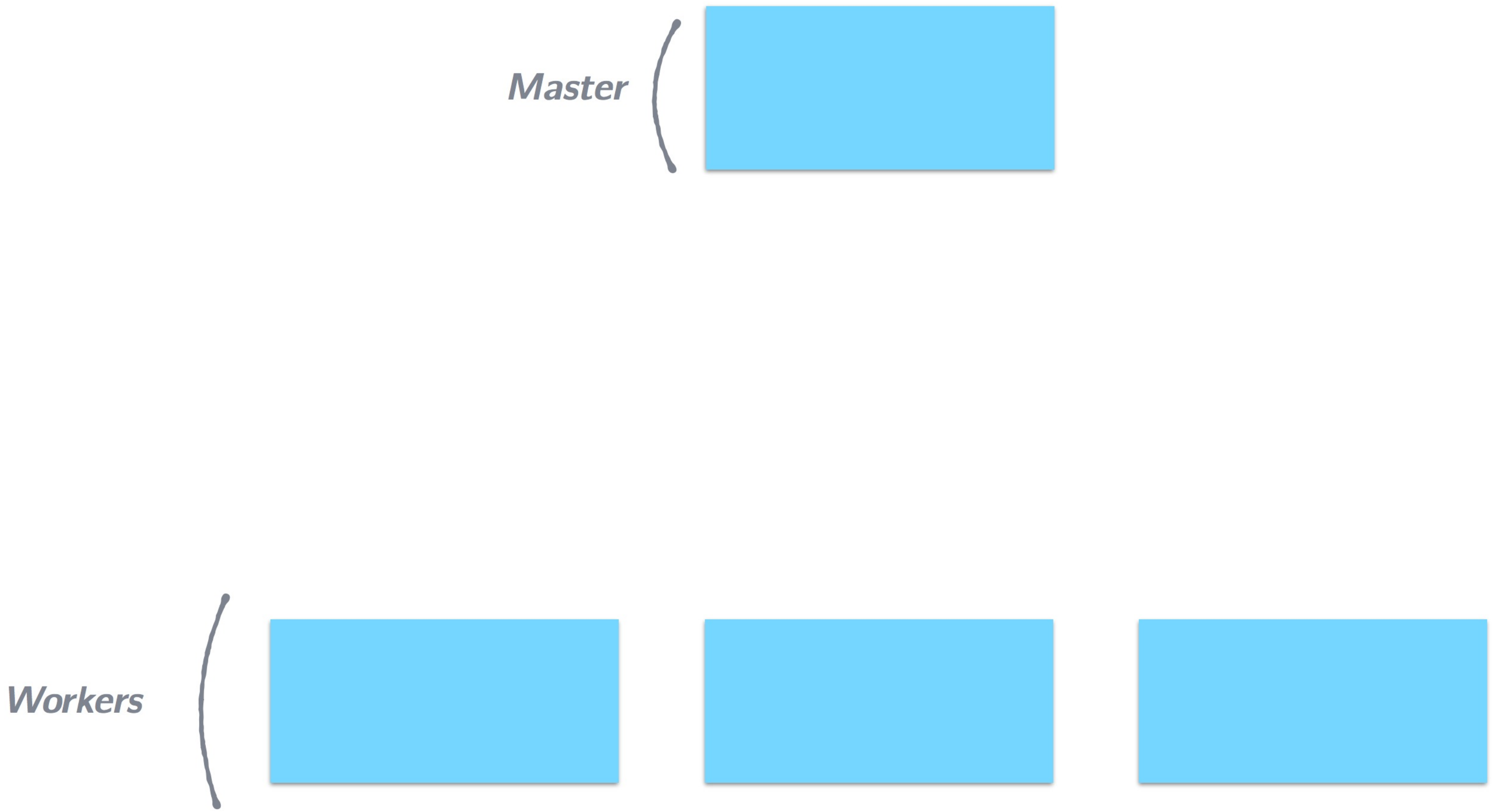
count **count(): Long**

Return the number of elements in the RDD.

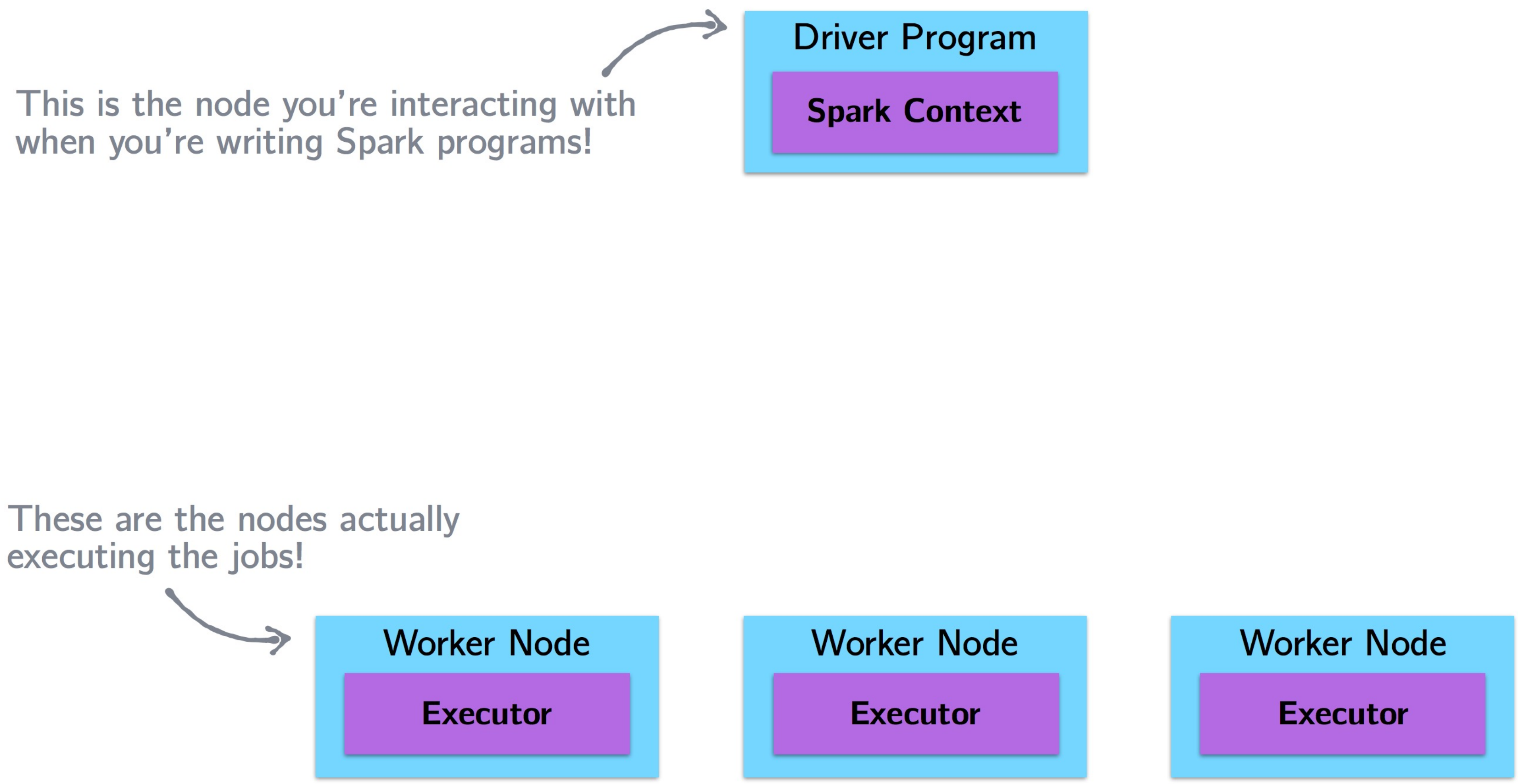
```scala
val text: List[String] = List("you and me", "jump and run", "I love you", "jump forward", "")
val textRDD = sc.parallelize(text)

val splitText = textRDD.flatMap(phase => phase.split(" ")) // Flatten the output
val textDist = splitText.distinct() // Get the distinct words
val counts = textDist.count() // return 8
```

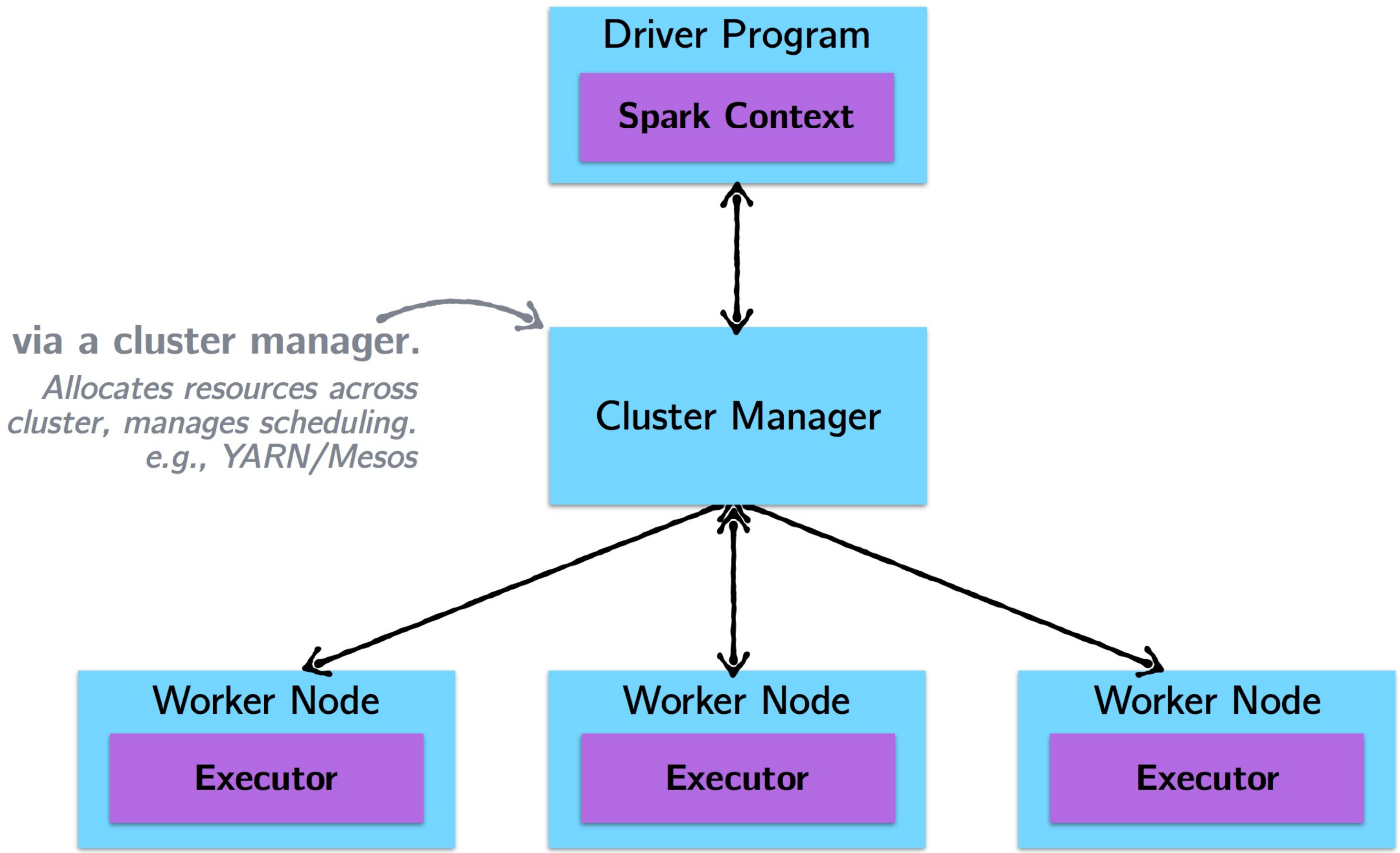
How Spark Jobs are Executed



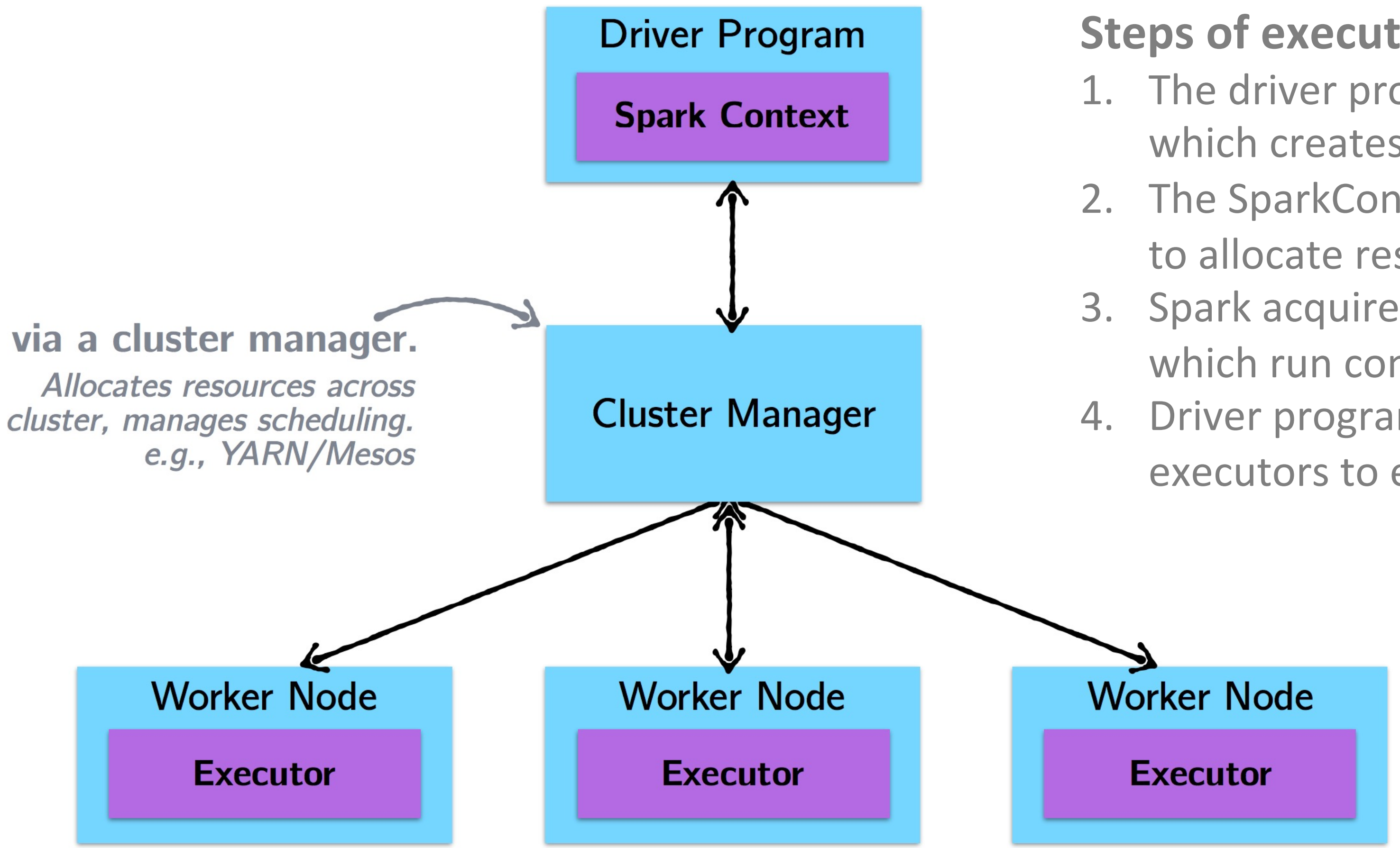
How Spark Jobs are Executed



How Spark Jobs are Executed



How Spark Jobs are Executed



Steps of executing a Spark program:

1. The driver program runs the Spark application, which creates a SparkContext
2. The SparkContext connects to a cluster manager to allocate resources
3. Spark acquires executors on nodes in the cluster, which run computations for your application.
4. Driver program sends your application code to executors to execute.

Example

- A simple example with *println* (Scala code)

```scala
case class Person(name: String, age: Int)

val people: RDD[Person]
people.foreach(println)
```

foreach(f: A => Unit): Unit
Apply function to each element in the RDD and return Unit

What will you see?

Example

- A simple example with *println* (Scala code)

```scala
case class Person(name: String, age: Int)

val people: RDD[Person]
people.foreach(println)
```

foreach(f: A => Unit): Unit
Apply function to each element in the RDD and return Unit

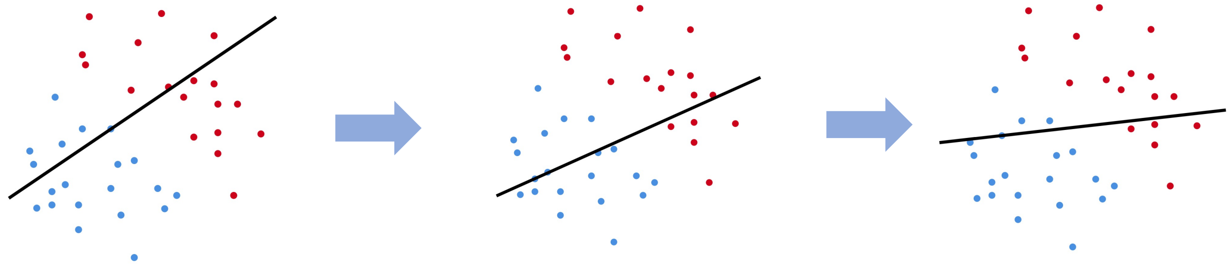
On the driver: Nothing.

The operation foreach is an action, with return type Unit.

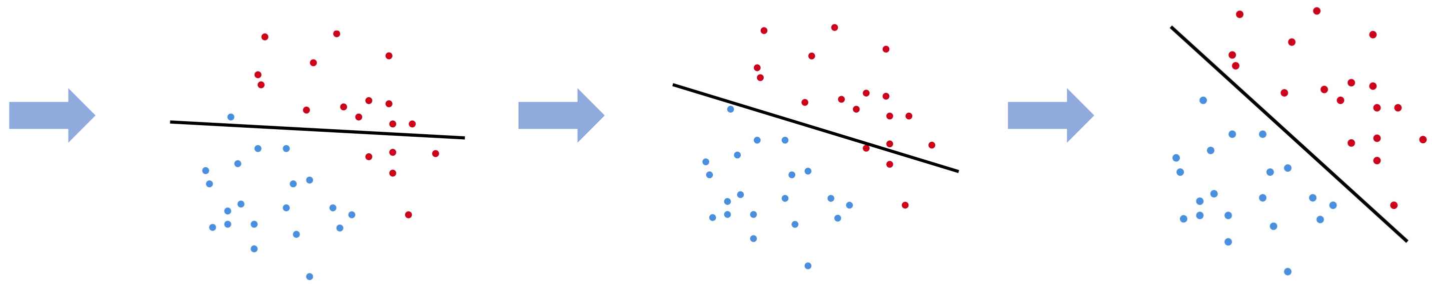
Therefore, it is eagerly executed on the executors, not the driver. Thus, *println* are happening on the worker nodes and return nothing to the driver node.

Programming with Spark

- Example: Logistic Regression
  - Logistic regression is an iterative algorithm typically used for classification. Like most classification algorithms, it updates weights iteratively based on the training data.



$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$



Programming with Spark

- Example: Logistic Regression
  - Logistic regression is an iterative algorithm typically used for classification. Like most classification algorithms, it updates weights iteratively based on the training data.

```
val points = sc.textFile(...).map(parsePoint) // case class Point(x: Double, y: Double)
var w = Vector.zero(d)
for(i <- 1 to numIterations) {
  val gradient = points.map {p =>
    g(p) // Apply the function of logistic regression
  }.reduce(_+_)
  w -= alpha * gradient
}
```

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

Programming with Spark

- Example: Logistic Regression
  - Logistic regression is an iterative algorithm typically used for classification. Like most classification algorithms, it updates weights iteratively based on the training data.

```
val points = sc.textFile(...).map(parsePoint) // case class Point(x: Double, y: Double)
var w = Vector.zero(d)
for(i <- 1 to numIterations) {
  val gradient = points.map {p =>
    g(p) // Apply the function of logistic regression
  }.reduce(_+_)
  w -= alpha * gradient
}
```

Spark starts the execution when the action *reduce* is applied

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

Programming with Spark

- Example: Logistic Regression
  - Logistic regression is an iterative algorithm typically used for classification. Like most classification algorithms, it updates weights iteratively based on the training data.

```
val points = sc.textFile(...).map(parsePoint) // case class Point(x: Double, y: Double)
var w = Vector.zero(d)
for(i <- 1 to numIterations) {
  val gradient = points.map {p =>
    g(p) // Apply the function of logistic regression
  }.reduce(_+_)
  w -= alpha * gradient
}
```

***points* is being re-loaded upon every iteration!**
Unnecessary!

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

Caching and Persistence

- By default, RDDs are recomputed each time you run an action on them. This can be expensive (time-consuming) if you need to use a dataset more than once.

- **Spark allows you to control what is cached in memory**
  - ***persist()* or *cache()***

```
val points = sc.textFile(...).map(parsePoint).persist() // case class Point(x: Double, y: Double)
var w = Vector.zero(d)
for(i <- 1 to numIterations) {
  val gradient = points.map {p =>
    g(p) // Apply the function of logistic regression
  }.reduce(_+_)
  w -= alpha * gradient
}
```

***points* is loaded once and is cached in memory.**
It can be re-used on each iteration.

Word Count Example Using Spark RDD

```
import pyspark


if __name__ == '__main__':

    sc_conf = pyspark.SparkConf() \
        .setAppName('task1') \
        .setMaster('local[*]') \
        .set('spark.driver.memory', '8g') \
        .set('spark.executor.memory', '4g')

    sc = pyspark.SparkContext(conf=sc_conf)
    sc.setLogLevel("OFF")

    input_path = './work-count-sample-doc.txt'
    data = sc.textFile(input_path)
    first10 = data.map(lambda line: line.split(' ')).take(10)

    count = data.flatMap(lambda line:line.split(' ')) \
        .map(lambda word: (word, 1)).reduceByKey(lambda a, b: a + b).collect()
```

Spark SQL

- Spark SQL is a component of Spark Stack
  - A Spark module for structured data processing
  - Implemented as a library on top of Spark

- Advantages
  - Support relational processing in spark
  - High performance
  - Easily support new data sources such as semi-structured data

Spark SQL - DataFrame

order_id	account	date
1	aaa	2017/01/01
2	bbb	2017/01/02
3	ccc	2017/01/02
4	ddd	2017/01/03
5	eee	2017/01/03

- DataFrame is the core abstraction of Spark SQL
  - Conceptually, RDDs are full of records with some known schema
  - DataFrame is like a table in relational database

  - Once you have a DataFrame to operate on, you can freely write familiar SQL syntax to operate on your dataset!

```
// Register the DataFrame as a SQL temporary view
testDF.createOrRepllaceTempView("order")
// This gives the name to the DataFrame in SQL,
// so we can refer it in an SQL FROM statement

val testDF1 = spark.sql("select * from order where date == '2017/01/03'")
```

Managing Spatial Data in Spark

- Classic - single machine DBMS or GIS tools
  - ArcGIS/QGIS
  - PostgreSQL + PostGIS
- Managing spatial data is not easy in Spark
  - No spatial data type support
  - No spatial index
  - No spatial query

Managing Spatial Data in Spark

- Classic - single machine DBMS or GIS tools
  - ArcGIS/QGIS
  - PostgreSQL + PostGIS
- Managing spatial data is not easy in Spark
  - No spatial data type support
  - No spatial index
  - No spatial query

+

APACHE Spark

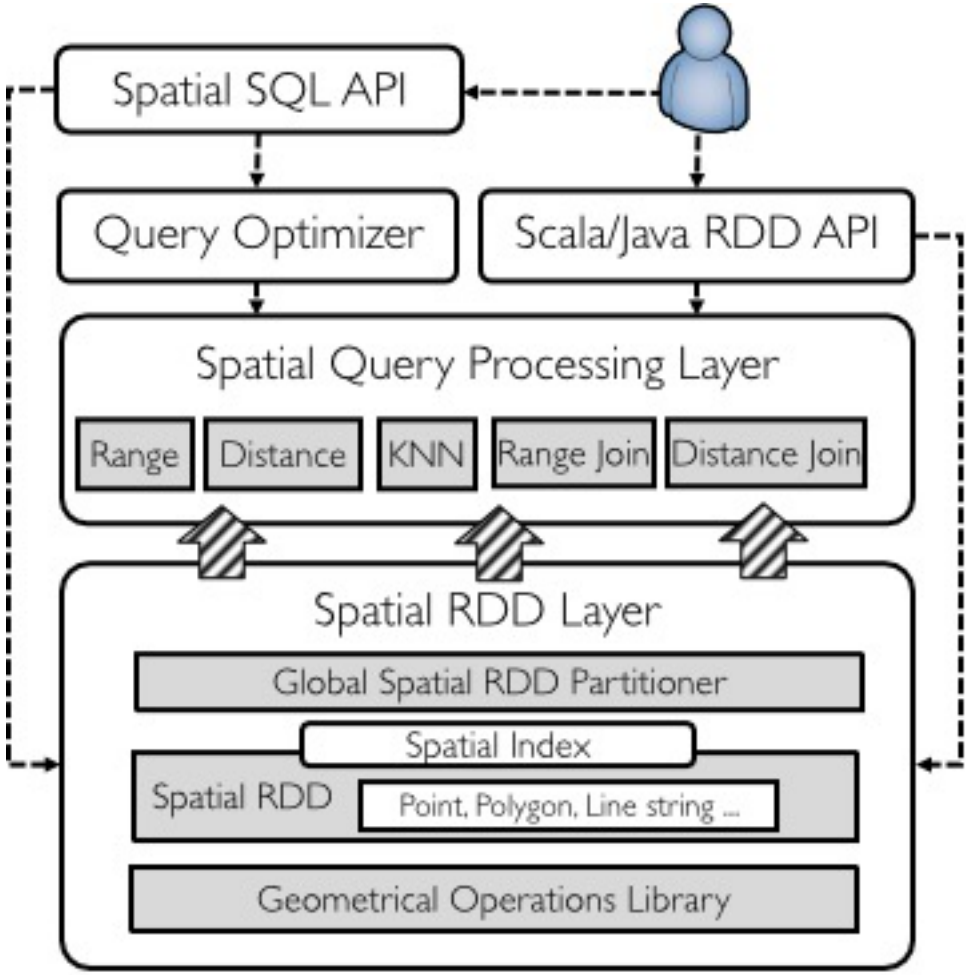
GeoSpark

Apache Sedona (GeoSpark)

- GeoSpark is a cluster computing system for processing large-scale spatial data

- GeoSpark extends RDDs to Spatial Resilient Distributed Datasets (SRDDs) that efficiently load, process, and analyze large-scale spatial data across machines

- Spark SQL => Spatial SQL



Examples: https://jiayuasu.github.io/files/talk/jia-sigspatial19-teaser.pdf

Spatial RDD (SRDD) Layer

- SRDD supports heterogeneous data sources
  - E.g., CSV, WKT, GeoJSON, NetCDF/HDF, and Shapefile

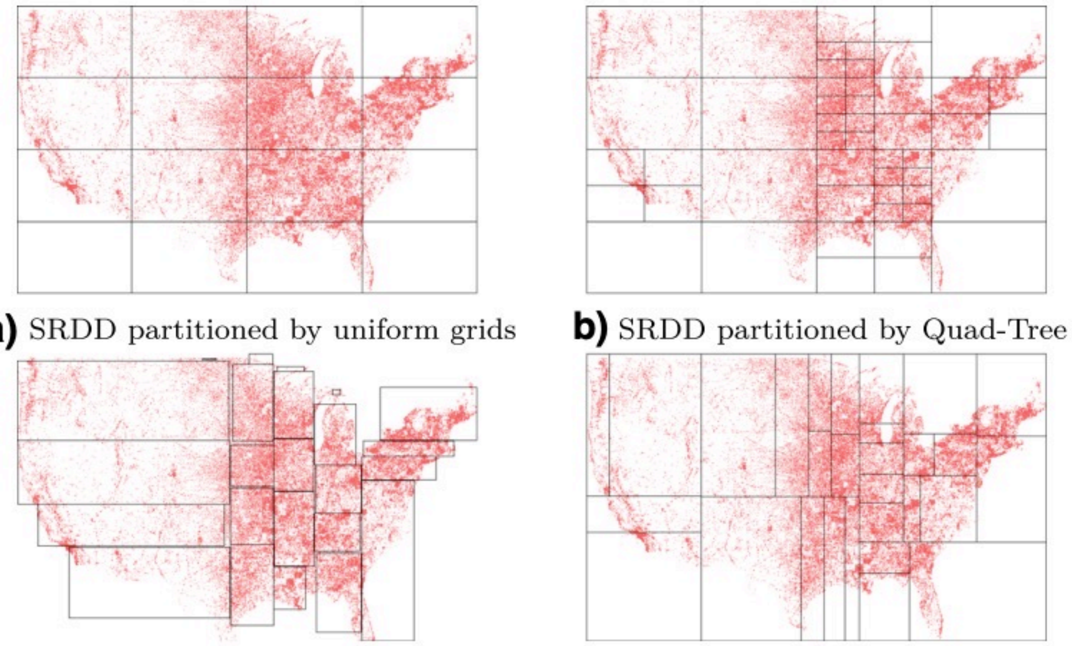
- SRDD partitioning
  - GeoSpark automatically repartitions a loaded Spatial RDD according to its internal spatial data distribution
  - The intuition is to group spatial objects into the same partition based on the spatial proximity, so that reducing the data shuffles across cluster

Yu et al. Spatial data management in apache spark: the GeoSpark perspective and beyond, 2018

SRDD Partitioning

Algorithm 1 SRDD spatial partitioning

```
Data: An original SRDD
Result: A repartitioned SRDD
/* Step 1: Build a global grid file at master node
Take samples from the original SRDD A partitions in parallel;
Construct the selected spatial structure on the collected sample at master node;
Retrieve the grids from built spatial structures;
/* Step 2: Assign grid ID to each object in parallel
foreach spatial object in SRDD A do
    foreach grid do
        if the grid intersects the object then
            Add (grid ID, object) pair into SRDD B;
    // Only needed for R-Tree partitioning
    if no grid intersects the object then
        Add (overflow grid ID, object) pair into SRDD B;
/* Step 3: Repartition SRDD across the cluster
Partition SRDD B by ID and get SRDD C;
Cache the new SRDD C in memory and return it;
```



a) SRDD partitioned by uniform grids

b) SRDD partitioned by Quad-Tree

c) SRDD partitioned by R-Tree

d) SRDD partitioned by KDB-Tree

Yu et al. Spatial data management in apache spark: the GeoSpark perspective and beyond, 2018

Building Local Indexes

- Building a spatial index for the entire dataset is not possible because a tree-like spatial index yields additional 15% storage overhead

- If the user wants to use a spatial index, GeoSpark will build a set of local spatial indexes rather than a single global index
  - Create a spatial index (R-Tree or Quad-Tree) per RDD partition
  - Local indexes can be persisted in memory or disk

Spatial SQL Example

```
schema_point = StructType() \
    .add("tid", IntegerType(), False) \
    .add("x", DoubleType(), False) \
    .add("y", DoubleType(), False)

def distance_join():
  # 1. self join
  df_all_point = spark.read.option("header", True).schema(schema_point).csv(all_point_file_path)
  df_all_point.createOrReplaceTempView("all_point_import")
  df_all_point1 = spark.sql("SELECT tid, ST_Point(x, y) as point from all_point_import")
  df_all_point1.createOrReplaceTempView("all_point")

  df_join = spark.sql(f"""
    SELECT/*+ BROADCAST(t2) */
        t1.tid AS tid_1,
        t2.tid AS tid_2,
    FROM all_point t1, all_point t2
    WHERE ST_Distance(t1.point, t2.point) < {prec_distance}
      AND t1.tid != t2.tid
    ORDER BY t1.tid, t2.tid;
  """)
  df_join.createOrReplaceTempView("distance_join")
```

Other examples: https://sedona.apache.org/tutorial/sql-python/

Assignment 1

2. Programming Requirements and Environment Settings

a. You must use **SQL** and **Python** to implement all tasks.

b. Programming Environment:

- JAVA version 1.8, Python 3.7, Pyspark 3.0.0, Sedona 1.1.1
- [Optional] You can use Conda to manage your programming environment.

  $conda create --name [ENV] -y python=3.7

  $conda activate [ENV]

  $conda install -c conda-forge gdal==3.4.0

  $conda install -c conda-forge pyspark==3.0.0

  $pip install apache-sedona

Sedona Python requires two additional jar packages, **sedona-python-adapter** and **geotools-wrapper,** to work properly.[1] Specifically, you need to put two jar packages[2] under [YOUR PYTHON PATH]/site-packages/pyspark/jar/.