Resilient Distributed Datasets

Big Data Management

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DTIM
www.essi.upc.edu/dtim

Knowledge objectives

1. Define RDD
2. Name the main Spark contributions and characteristics
3. Compare MapReduce and Spark
4. Distinguish between Base RDD and Pair RDD
5. Distinguish between transformations and actions
6. Explain available transformations
7. Explain available actions
8. Name the main Spark runtime components
9. Explain how to manage parallelism in Spark
10. Explain how recoverability works in Spark
11. Distinguish between narrow and wide dependencies
12. Name the two mechanisms to share variables
13. Enumerate some abstraction on top of Spark

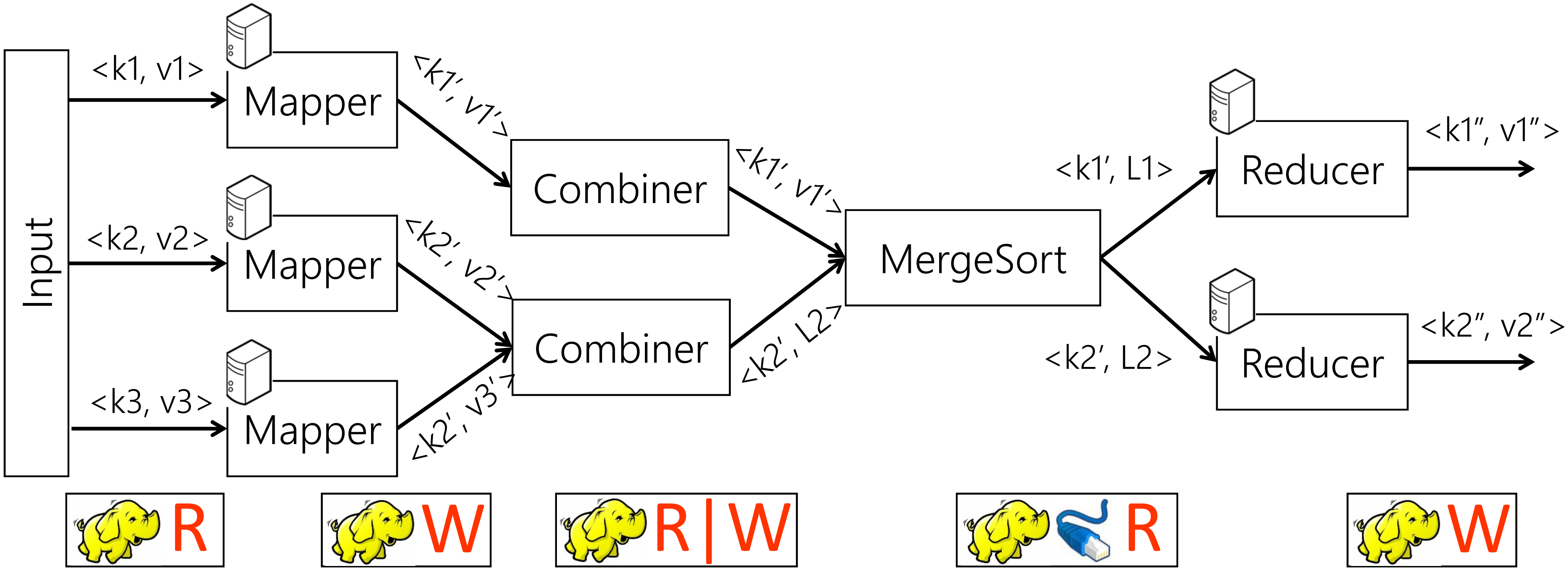
Application Objectives

- Provide the Spark pseudo-code for a simple problem

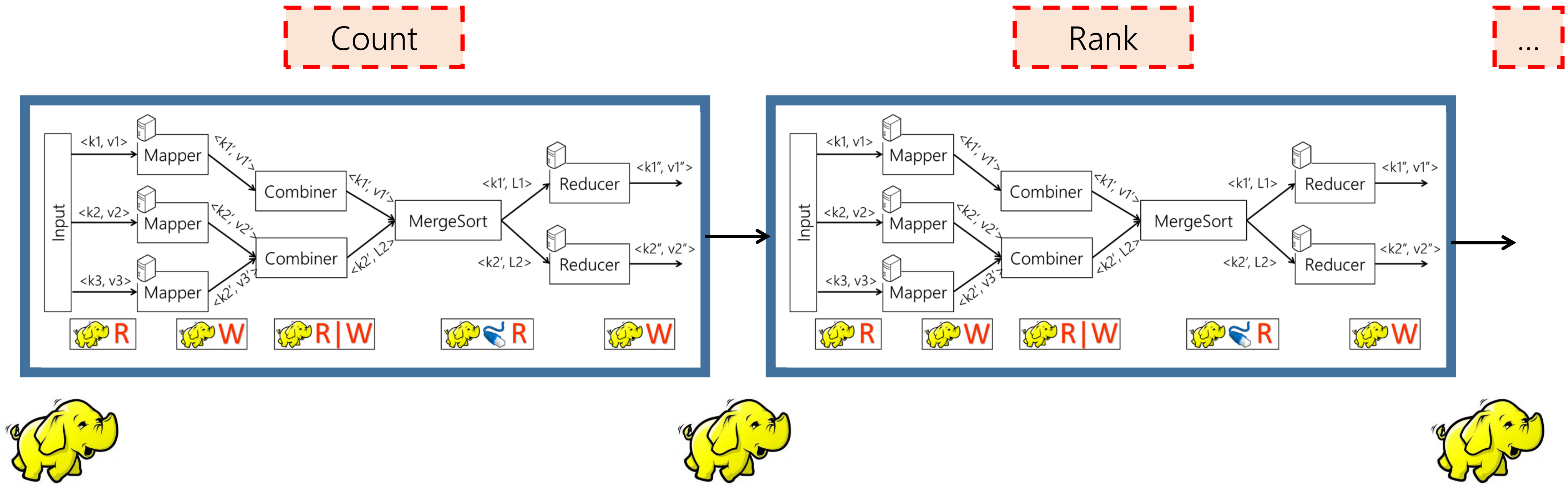
Background

MapReduce limitations

MapReduce intra-job coordination

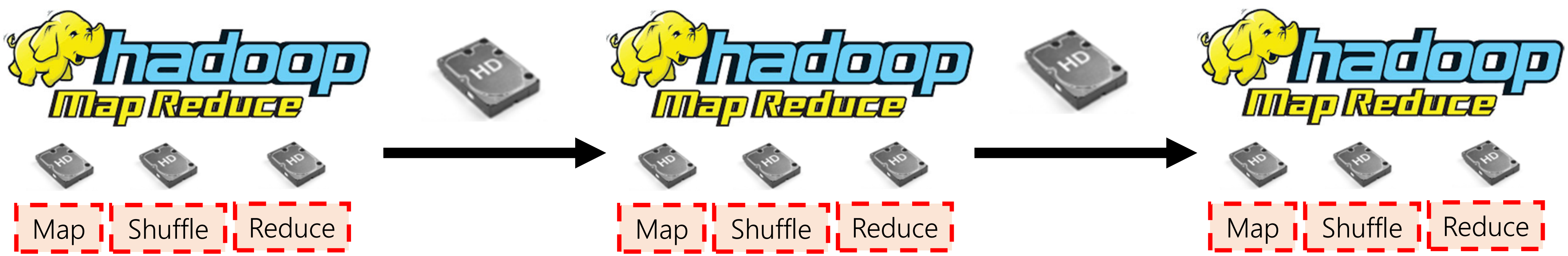


MapReduce inter-job coordination



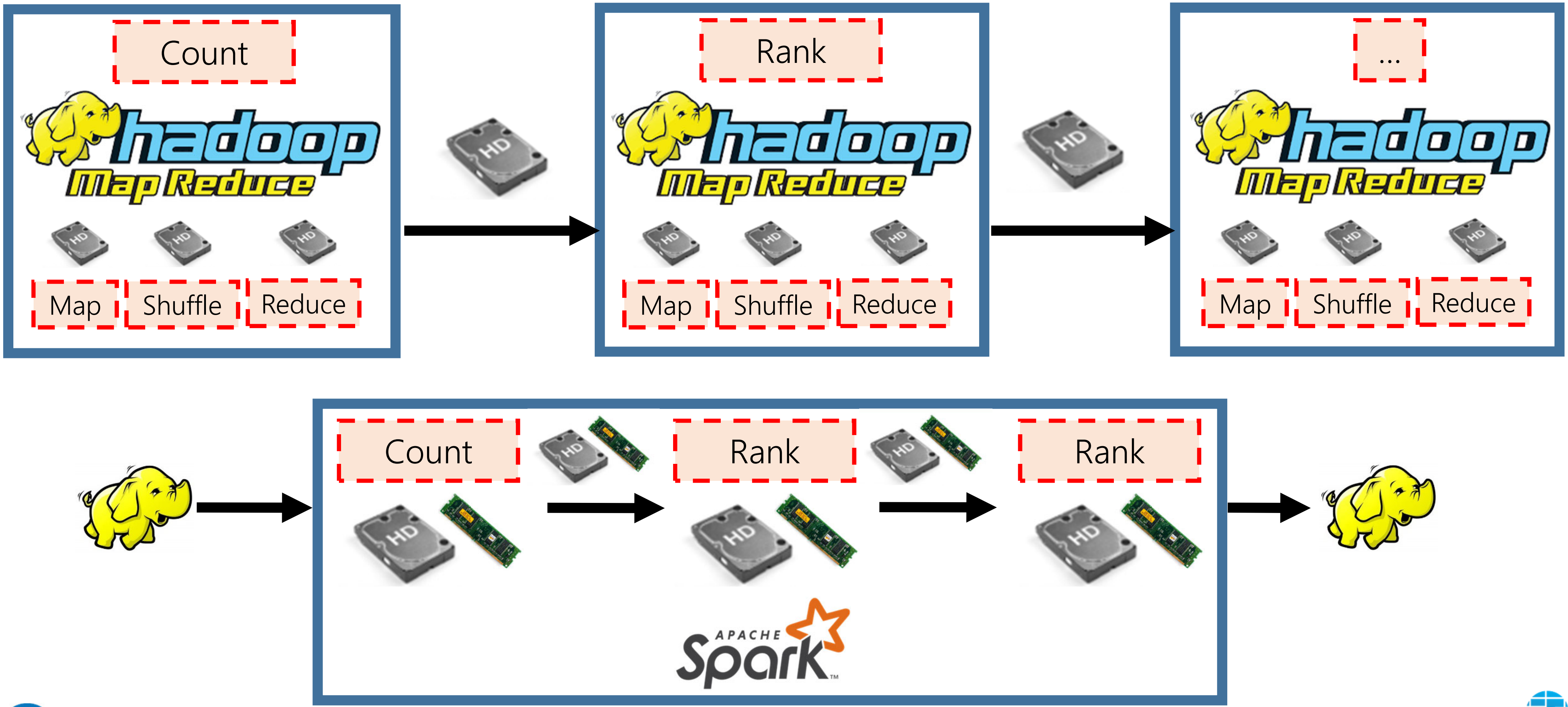
MapReduce limitations

- Coordination between phases using DFS
  - Map, Shuffle, Reduce
- Coordination between jobs using DFS
  - Count, rank, aggregate, …



Apache Spark

Main memory coordination



Resilient Distributed Datasets

- RDD
  - Resilient: Fault-tolerant
  - Distributed: Partitioned
  - Dataset: ….. a set of data

*"Unified **abstraction** for cluster computing, consisting in a **read-only**, partitioned collection of records. Can only be created through deterministic operations on either (1) data in stable storage or (2) other RDDs."*

rdd := spark.textFile("hdfs://…")

M. Zaharia

Types of RDDs in Spark

- Base RDD
  - `RDD<T>`
- Pair RDDs
  - `RDD<K,V>`
    - Particularly important for MapReduce-style operations
- Other specific types
  - `VertexRDD`
  - `EdgeRDD`
  - …

Characteristics

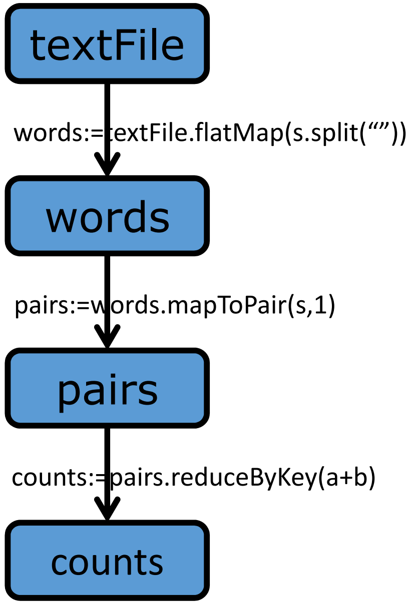
- Statically typed
- Parallel data structures
  - Disk
  - Memory
- User controls ...
  - Data sharing
  - Partitioning (fixed number per RDD)
    - Repartition (shuffles data through disk)
    - Coalesce (reduces partitions in the same worker)
- Rich set of coarse-grained operators
  - Simple and efficient programming interface
- Fault tolerant
- Baseline for more abstract applications

MapReduce vs Spark

	MapReduce	Spark
Records	Key-Value pairs	Arbitrary
Storage	Results always in disk	Results can simply stay in memory
Functions	Only two	Rich palette
Partitioning	Statically	Dynamically

Example: Word count (Java)

```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaRDD<String> words = textFile.flatMap(s -> {
    return Arrays.asList(s.split(" "))
});
JavaPairRDD<String, Integer> pairs = words.mapToPair(s -> {
    return new Tuple2<String, Integer>(s, 1);
});
JavaPairRDD<String, Integer> counts = pairs.reduceByKey(a,b -> {
    return a + b;
});
counts.saveAsTextFile("hdfs://...");
```



Transformations and Actions

Apache Spark

Transformations vs. Actions

- Transformations
  - Applied to RDDs and generate new RDDs
  - They are run lazily
    - Only run when required to complete an action
- Actions
  - Trigger the execution of a pipeline of transformations
  - The result is …
    a) … a primitive data type (not an RDD)
    b) … data written to an external storage system

Transformations on base RDDs

map(f:T→U): RDD[T]→RDD[U]

filter(f:T→bool): RDD[T]→RDD[T]

sample(fraction: Float): RDD[T]→RDD[T] (deterministic)

flatMap(f:T→seq[U]): RDD[T]→RDD[U]

union/intersection/substract(): (RDD[T],RDD[T])→RDD[T]

cartesian(): (RDD[T1],RDD[T2])→RDD[(T1,T2)]

partitionBy(p:partitioner[T]): RDD[T]→RDD[T]

sort(c:comparator[T]): RDD[T]→RDD[T]

distinct(T): RDD[T]→RDD[T]

persist(): RDD[T]→RDD[T]

mapToPair(f:T→(K,V)): RDD[T]→RDD[(K,V)] (can be implicit)

https://spark.apache.org/docs/latest/api/java/index.html?org/apache/spark/api/java/RDD.html

Added transformations on pair RDDs

mapValues(f:V→W): RDD[(K,V)]→RDD[(K,W)] !

reduceByKey(f:(V,V)→V): RDD[(K,V)]→RDD[(K,V)]

groupByKey(): RDD[(K,V)]→RDD[(K,seq(V))]

join(): (RDD[(K,V)],RDD[(K,W)])→RDD[(K,(V,W))]

cogroup(): (RDD[(K,V)],RDD[(K,W)])→RDD[(K,(seq[V],seq[W])]

partitionBy(p:partitioner[K]): RDD[(K,V)]→RDD[(K,V)]

keys(): RDD[(K,V)] → RDD[K] (can be implicit)

values(): RDD[(K,V)] → RDD[V] (can be implicit)

https://spark.apache.org/docs/latest/api/java/index.html?org/apache/spark/api/java/JavaPairRDD.html

Actions on base RDDs

save(path: String): Writes the RDD to external storage (e.g., HDFS)

collect(): RDD[T]→seq[T] ☠

take(k): RDD[T]→seq[T]

first(): RDD[T]→T

count(): RDD[T]→Long

countByValue(): RDD[T]→seq[(T,Long)]

reduce(f:(T,T)→T): RDD[T]→T

foreach(f:T->U): RDD[T]→ - (executes in the workers)

https://spark.apache.org/docs/latest/api/java/index.html?org/apache/spark/api/java/RDD.html

Added actions on pair RDDs

countByKey(): RDD[(K,V)]→seq[(K,Long)]

lookup(k: K): RDD[(K,V)]→seq[V]

https://spark.apache.org/docs/latest/api/java/index.html?org/apache/spark/api/java/JavaPairRDD.html

Example

Analyzing HR data with Spark

Average satisfaction level

- Does the number of projects an employee works on affect their satisfaction level?
- CSV Dataset (HR_comma_sep.csv)
  - Satisfaction Level
  - Last evaluation
  - Number of projects
  - Salary
  - Time spent at the company (in months)

Sample data

0.38,0.53,2,3,low
0.8,0.86,5,6,medium
0.11,0.88,7,4,medium
0.72,0.87,5,5,low
0.37,0.52,2,3,low
0.41,0.5,2,3,low
0.1,0.77,6,4,low
0.92,0.85,5,5,high
...

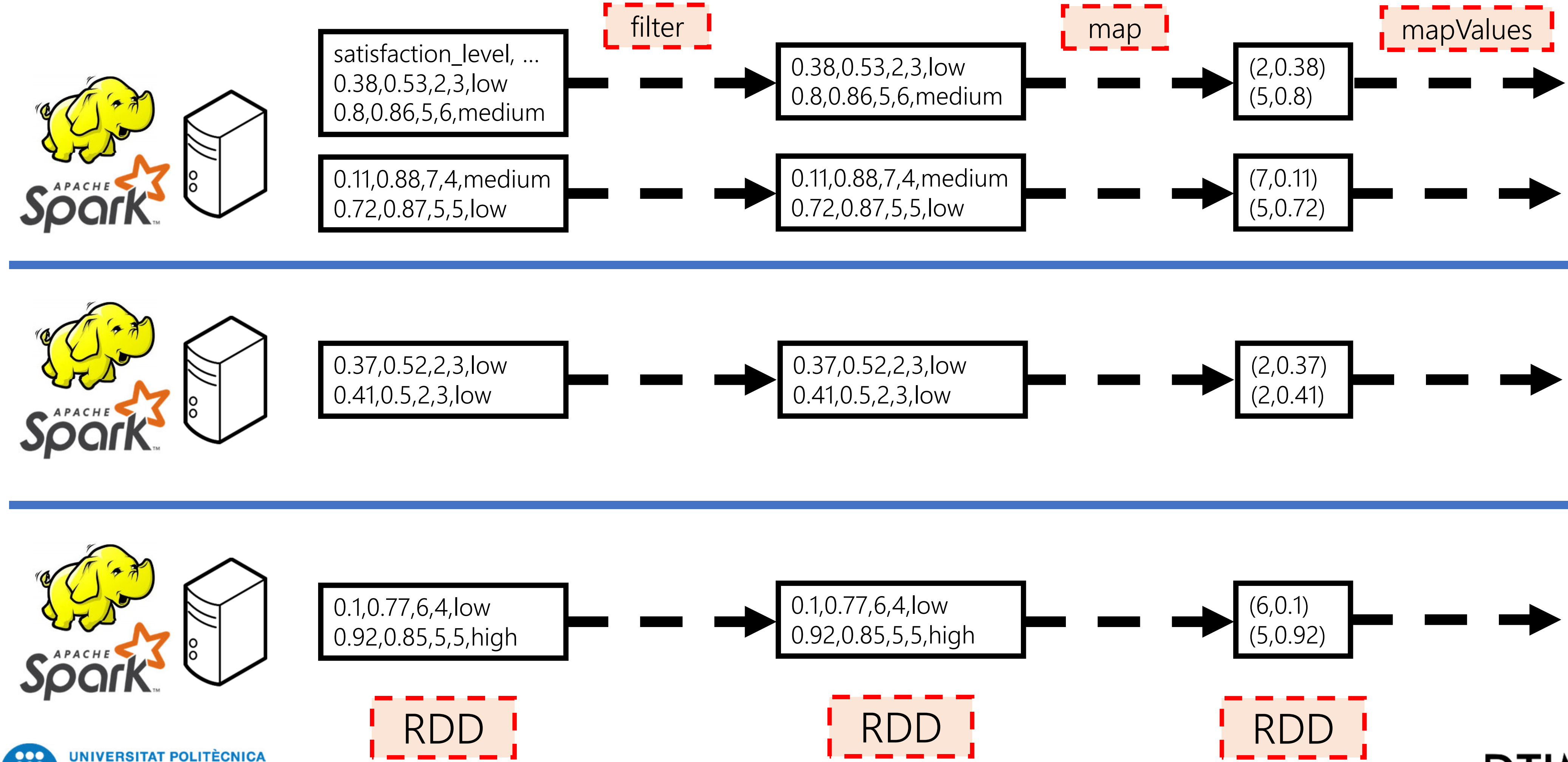
https://www.kaggle.com/liujiaqi/hr-comma-sepcsv

Implementation (Python)

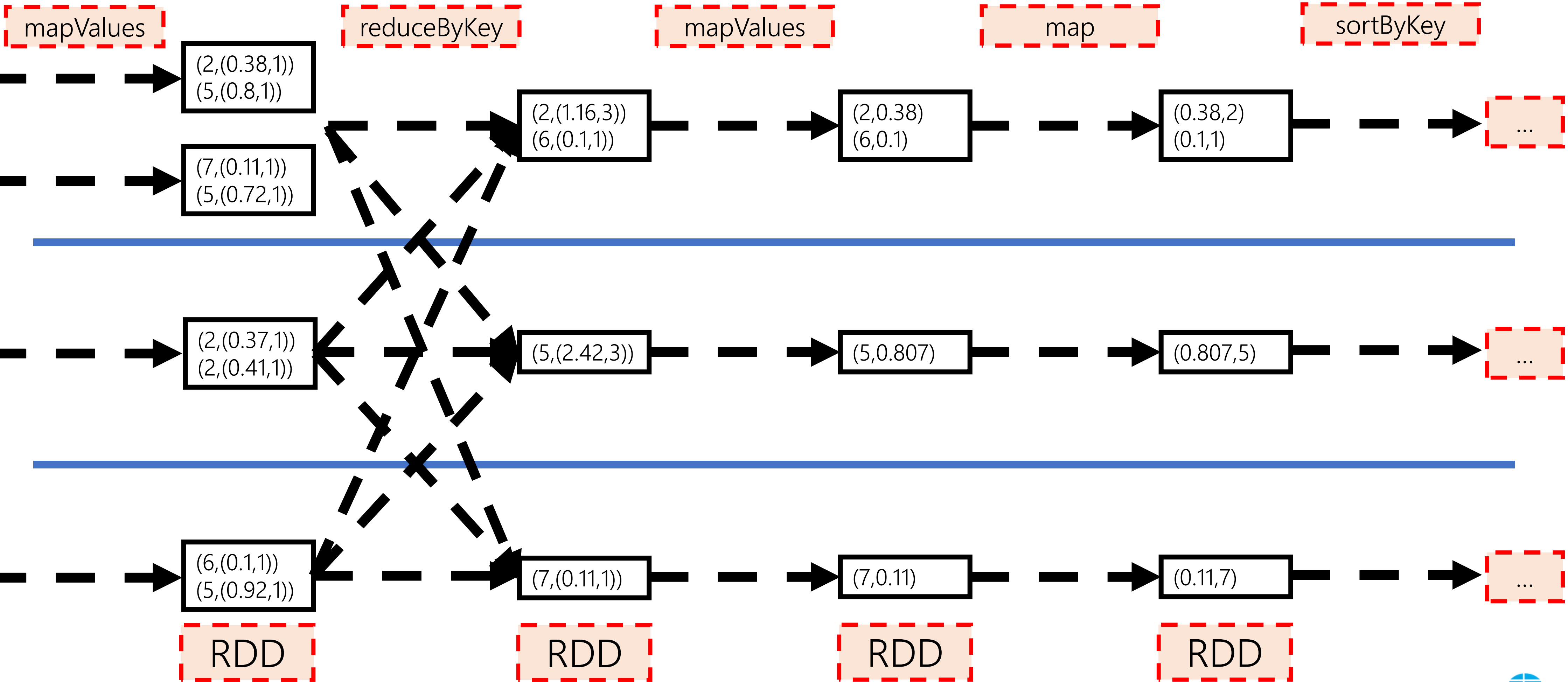
Average satisfaction level per number of projects, ordered from lowest to highest.

```python
sc = pyspark.SparkContext.getOrCreate()

out = sc.textFile("HR_comma_sep.csv") \
    .filter(lambda t: "satisfaction_level" not in t) \
    .map(lambda t: (int(t.split(",")[2]), float(t.split(",")[0]))) \
    .mapValues(lambda t: (t,1)) \
    .reduceByKey(lambda a,b: (a[0]+b[0],a[1]+b[1])) \
    .mapValues(lambda t: t[0]/t[1]) \
    .map(lambda t: (t[1],t[0])) \
    .sortByKey()

for x in out.collect():
    print(x)
```

Runtime execution (I)



Runtime execution (II)

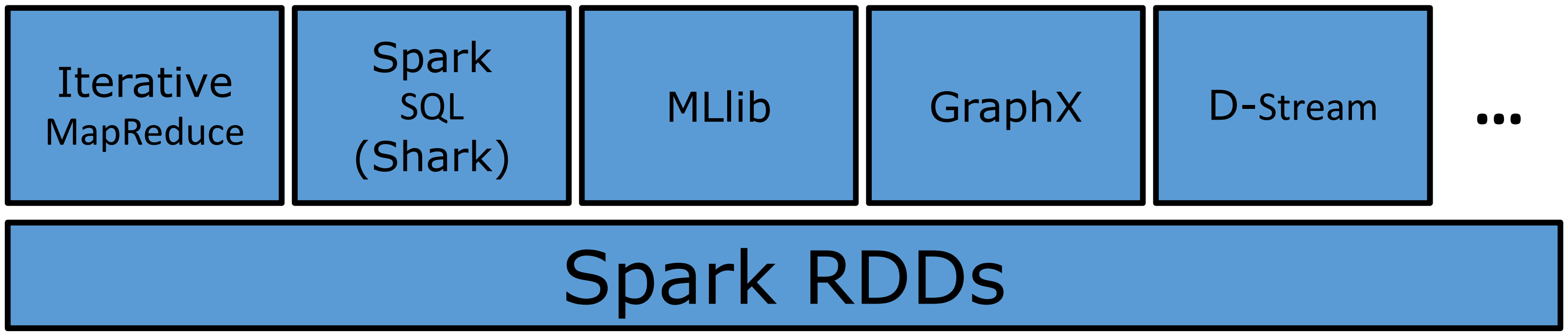


Closing

Summary

- Resilient Distributed Datasets
    - Operations
        - Transformations
        - Actions
- Abstractions

Abstractions



References

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- M. Zaharia. *An Architecture for Fast and General Data Processing on Large Clusters*. ACM Books, 2016
- A. Hogan. *Procesado de Datos Masivos* (Universidad de Chile). http://aidanhogan.com/teaching/cc5212-1-2020