Experiments with Docker and Spark

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Outline

VizieR & Docker

Apache Spark (& Docker)

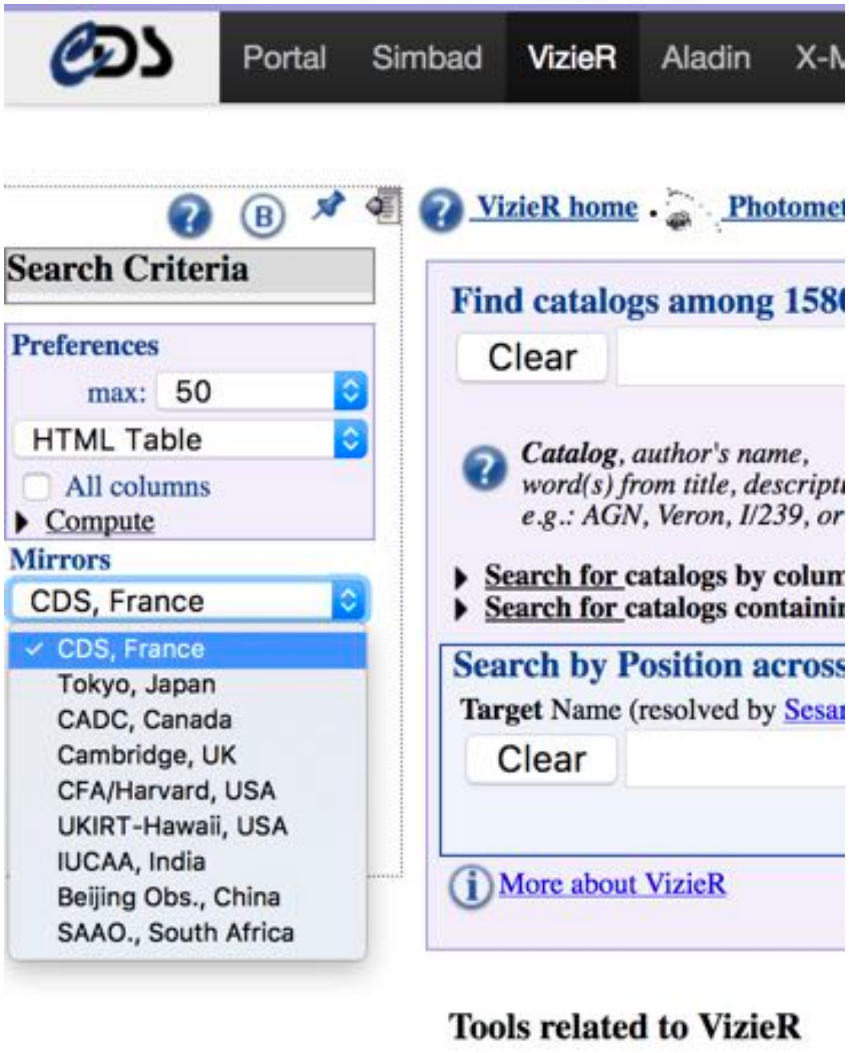
Use case & data

Test beds, experiments and what we learned

Perspectives

VizieR & Docker

- VizieR is deployed on several mirrors
- Hosts with different Linux distributions, kernels, etc.
- Docker as a solution to deploy “quick and easy” ?



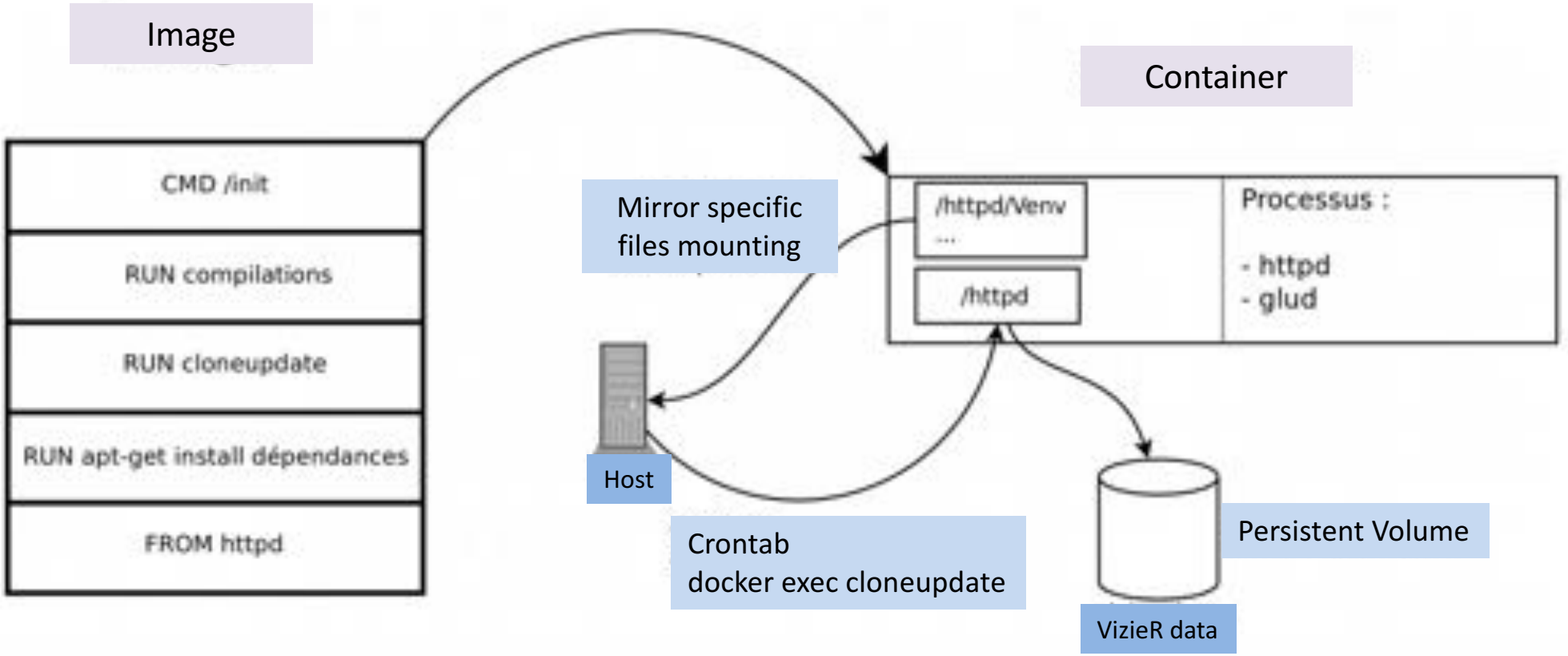
VizieR mirror update process

- Typical installation of VizieR
  - Dependencies and CGI scripts transfer through Rsync and scp
  - Dependencies installation with the package manager
  - Compilation of the dependencies only available as sources (developed at CDS)
  - CGI files copy and Apache configuration
  - Apache start

To a VizieR Docker image…

- Prototyping following the previous process
  - Resolution of missing packages (like gcc, make, rsync, .., not present in the Apache image)
- To an optimized version
  - Sources directly from CVS
  - CGI scripts and static files in a Docker volume (between the host and the container), these files will be updated through scripts (executed at each container start and via a cronjob service (on the host)
  - Path corrections
  - Also use of Portainer (Simple management UI)

VizieR & Docker at the End



And now

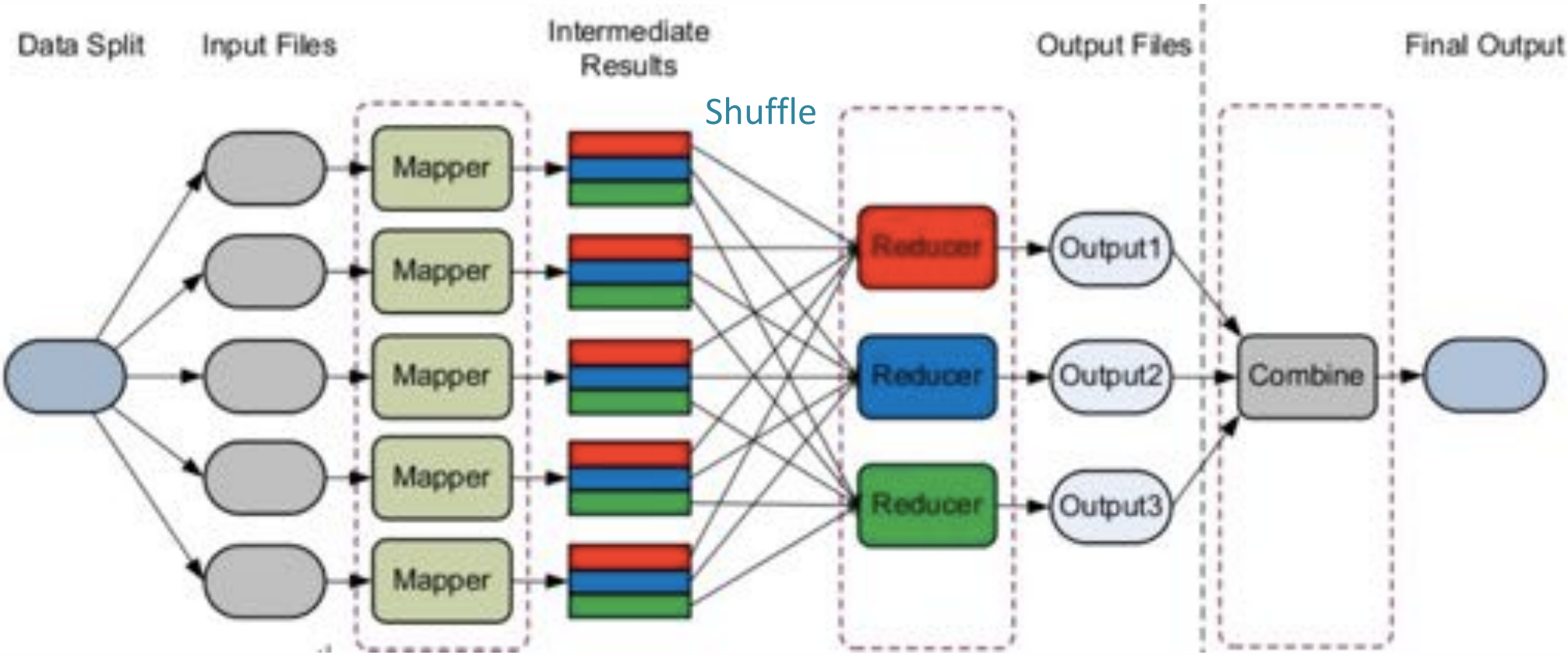
- Will be used in a first step inside CDS
  - To test Docker use on a mid-term basis
  - To install local “VizieR” to test it before update
- Needs discussion and agreement with at least one host (in a first step) to start to use it “in production” all over the world !

Apache Spark

- "Apache Spark is a cluster computing platform designed to be fast and general purpose."

- It extends the MapReduce model to support more types of computations (interactive queries, stream processing, etc.) and it offers APIs for Scala, Java, Python, R,...

MapReduce



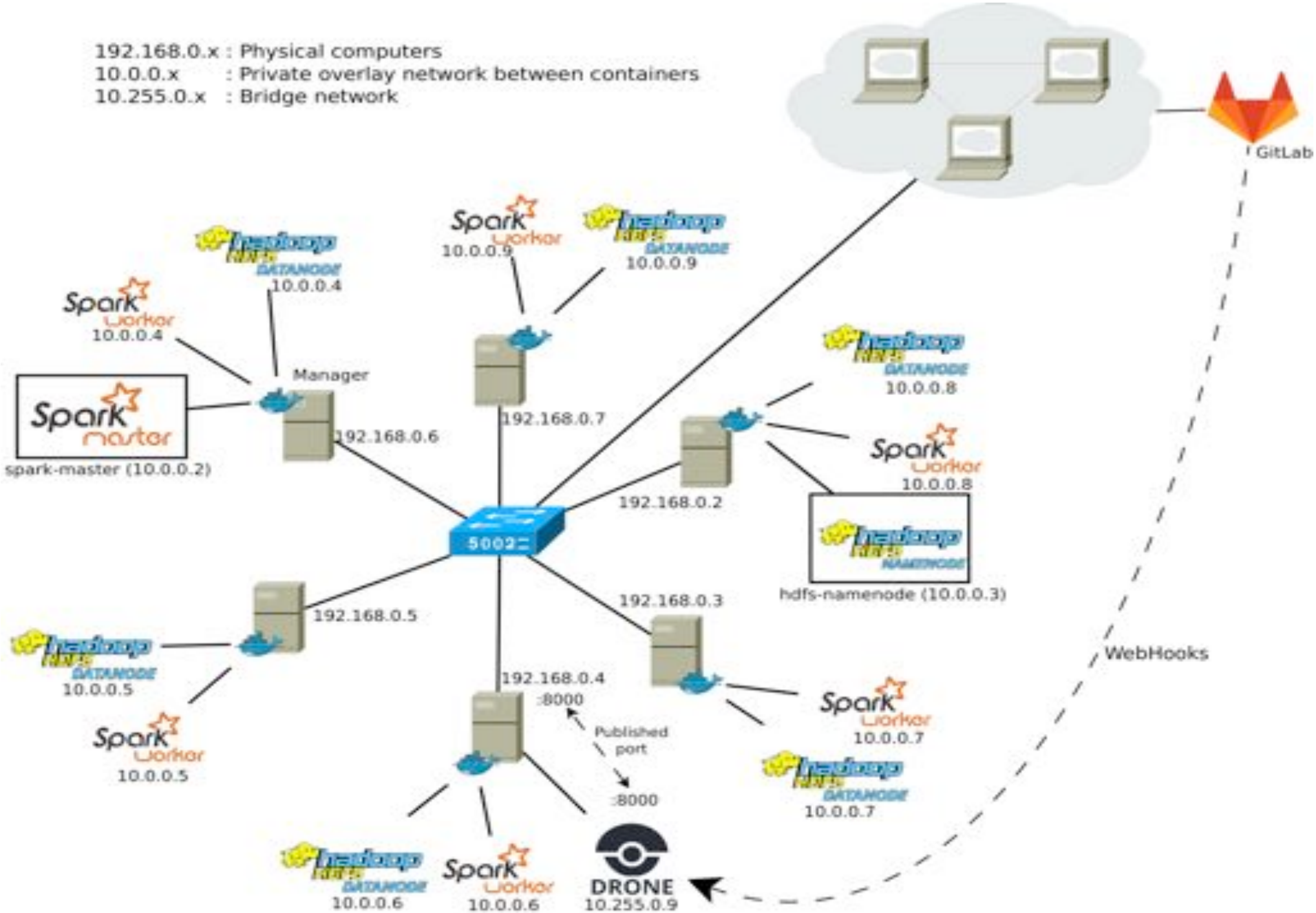
Credit: G. Fedak, INRIA

Apache Spark, so quick ?

- Computations in memory (as much as possible, otherwise pilling to the disks)
- Introduction of data models
  - RDD (Resilient Distributed Datasets)
    - Immutable distributed collection of elements
    - Operations: Transformations (map, filter, etc.), Actions (reduce, count, etc.)
  - Datasets to represent tabular data, queryiable via SQL
- It uses mainly Hadoop Distributed File System (HDFS).

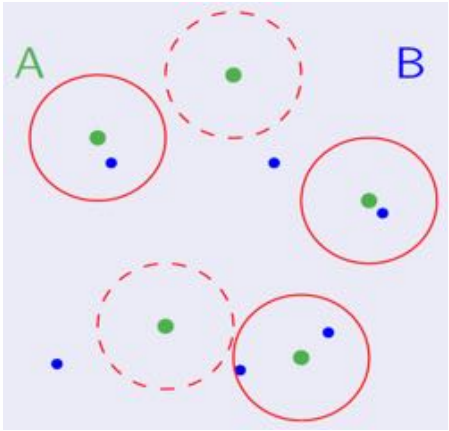
Other **technical aspects**

- Introduction of Docker (components) and Drone (continuous integration) to “automate” the deployment process and to focus mainly on the development side. It is becoming easy to migrate to external resources when needed.
- Use of Scala which is native in Spark (a part of the Java API is “experimental”).

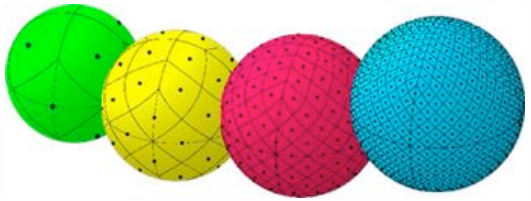

192.168.0.x : Physical computers
10.0.0.x : Private overlay network between containers
10.255.0.x : Bridge network
GitLab
Spark Worker
10.0.0.9
10.0.0.9
10.0.0.4
Spark Worker
10.0.0.4
Manager
Spark master
spark-master (10.0.0.2)
192.168.0.6
192.168.0.7
10.0.0.8
Spark Worker
10.0.0.8
192.168.0.2
hdfs-namenode (10.0.0.3)
192.168.0.5
192.168.0.3
10.0.0.5
Spark Worker
10.0.0.5
192.168.0.4
:8000
Published port
:8000
Spark Worker
10.0.0.7
10.0.0.7
10.0.0.6
Spark Worker
10.0.0.6
DRONE
10.255.0.9
WebHooks

Use case & data

- The "cross-match" of (large) source catalogues.
- Examples:
  - 2MASS[1], 470,992,970
  - SDSS[2] DR9, 469,053,874

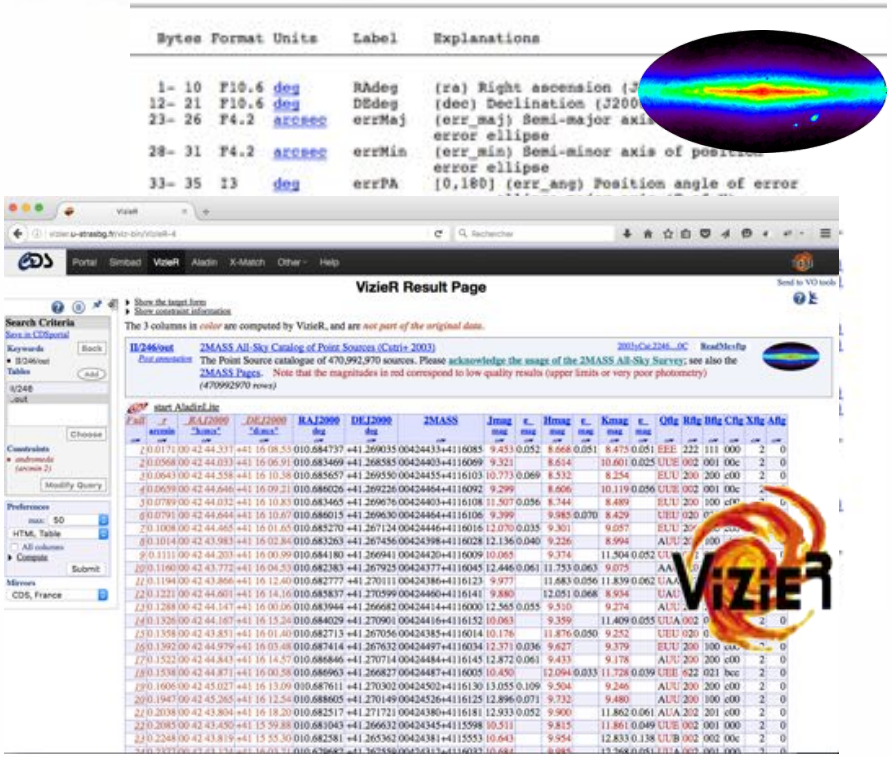


Full sky: all the sources
A cone: only the sources which are at a certain angular distance from a given position
A HEALPix cell



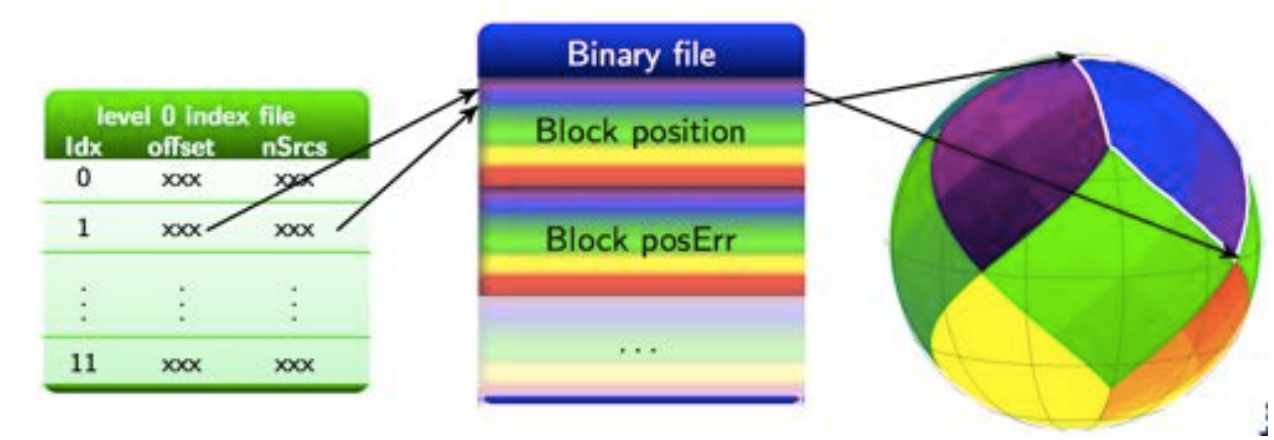
Credits: http://healpix.jpl.nasa.gov/

Fuzzy join between 2 tables (A and B) of several hundred millions of data



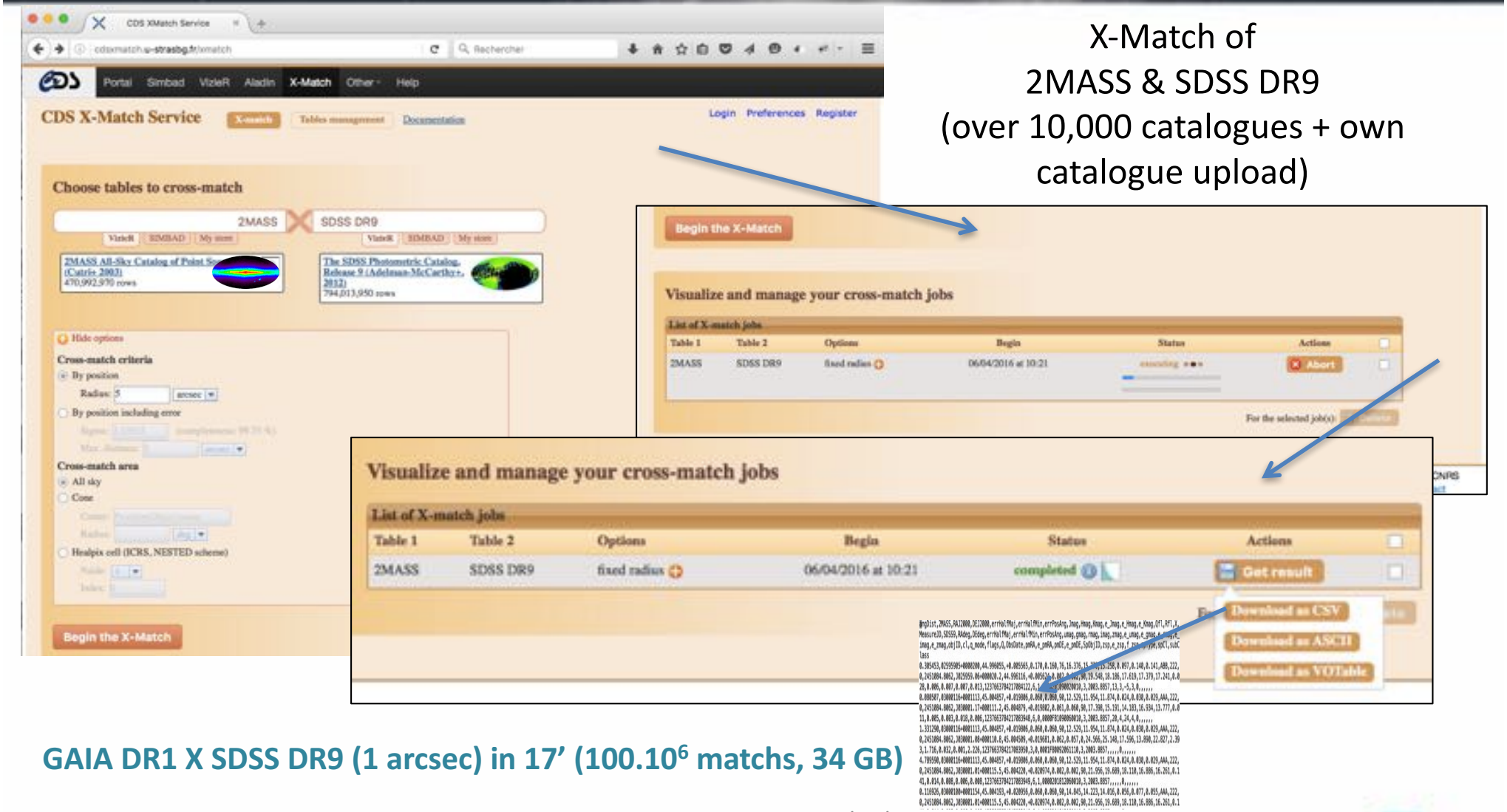
Not distributed but…

- organised and stored on one server (2x10 cores, 64GB, 12TB (15k tours))



The sky is cut into diamonds of the same size, pixels, each source or sky object is a numbered pixel.

Illustration: X-Match frontend

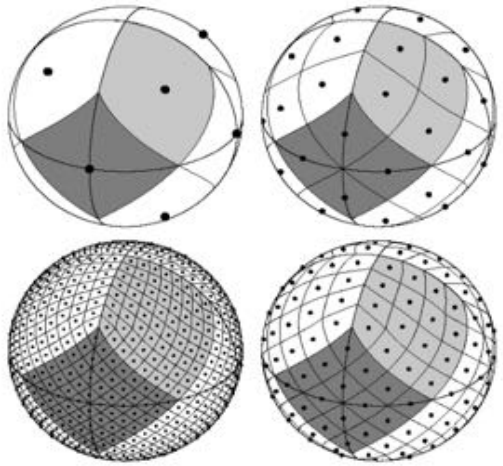


X-Match of
2MASS & SDSS DR9
(over 10,000 catalogues + own catalogue upload)

GAIA DR1 X SDSS DR9 (1 arcsec) in 17' (100.10^6 matchs, 34 GB)

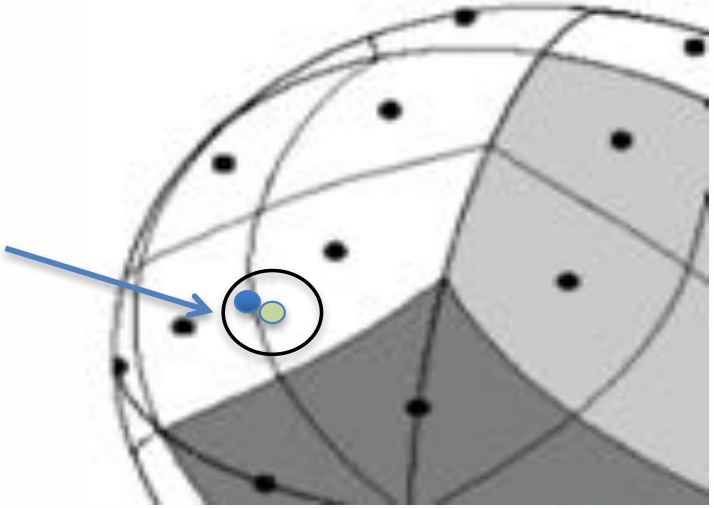
Illustration

- A X-Match implementation in MapReduce, couples (Key = pixel number, Value)



HEALPix sky cutting

- Side effects
  - Fuzzy join
  - Source duplication in the neighbour cells if needed



Credits: HEALPix – arXiv:astro-ph/0409513

Test beds: hardware & software

- Internal resources to learn / prototype
  - 6 nodes (4 cores, 16GB, 1 TB), Ubuntu
- External resources renting (Experiment 1)
  - 12 nodes, 4 cores, 32GB, Raid 2*2TB, Ubuntu (8000€ / year)
  - Configuration was defined “ad hoc” and low cost
- Collaboration with IN2P3 (Experiment 2)
  - 9 nodes (only one VM per physical server, CentOS), 24 threads (-> 216 threads), 64GB (-> 576 GB) -> possible X-Match of billion sources

Test beds: hardware & software

- Software side:
  - Apache distributions of Spark (1.5.0 to 2.0.2) and Hadoop (2.6 to 2.7.3)
  - Java, Scala
  - Docker, Drone, …

Experiment 1 (12 nodes)

- Input data (SDSS DR7 (primary sources) and 2MASS): 54GB and 58GB file size; 357 175 411 and 470 992 970 elements
- Output data: 49 208 820 elements

X-Match service reference time was: 10 minutes

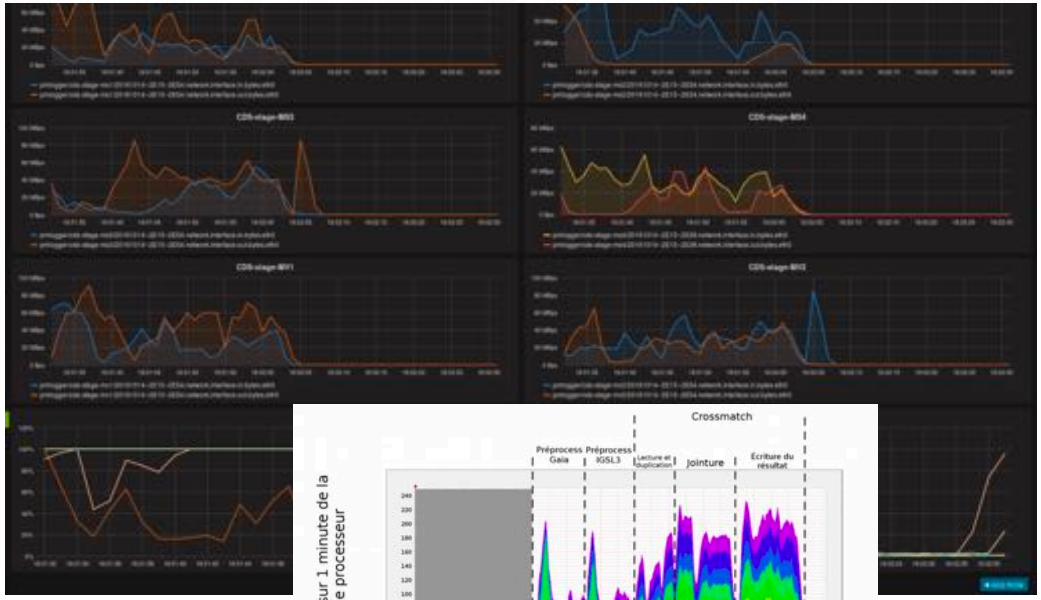
Cross-Match (source duplication done in phase 2 with all the data as output)					
HDFS block size= 128MB for the input files ; sdss7.csv and t 2mass.csv replicated 2 times					
HashPartitioner	60 partitions				
HDFS output files size	32MB				
Number of nodes Spark/HDFS	5	7	9	10	11
Phase 1: prepare	**23,0**	**16,0**	**14,0**	**14,0**	**13,0**
mapToPair (sdss7.csv)	5,1	4,9	4,9	4,8	4,7
saveAsHadoopFile (sdss7.bin)	5,7	2,7	2,0	2,3	1,5
mapToPair (2mass.csv)	5,7	5,2	5,2	5,1	5,0
saveAsHadoopFile (2mass.bin)	6,5	3,6	1,9	1,6	[illegible]
Phase 2: join	**31,0**	**21,0**	**13,0**	**11,0**	**9,9**
mapToPair (sdss7.bin)	7,2	4,7	3,5	3,0	[illegible]
flatMapToPair (2mass.bin)	11,8	8,3	5,5	4,9	4,3
saveAsTextFile (crossMatch_D.txt)	12,0	7,6	3,4	2,4	2,3
TOTAL	**54,0**	**37,0**	**27,0**	**25,0**	**22,9**

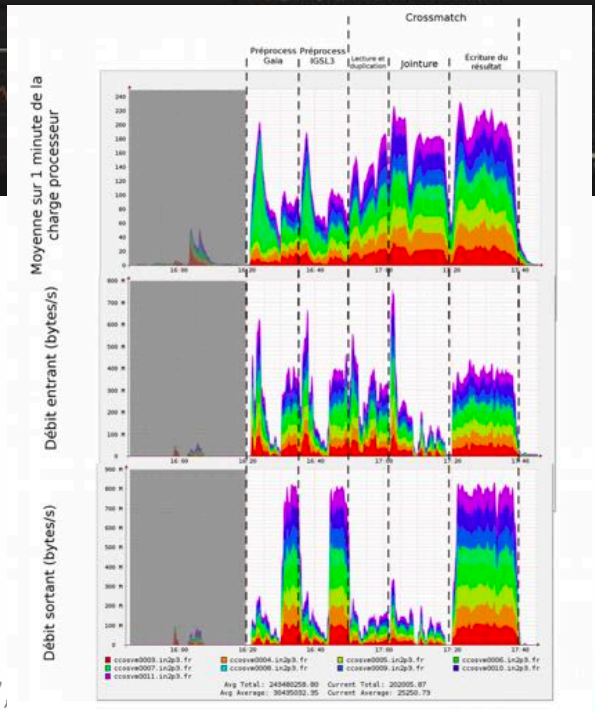
What we have learned

- Time was similar to the X-Match service from 11 nodes
- Keys common to 2 RDDs are not necessarily on the same node
  - It implies a transfer overhead between the nodes during the join => impact on the performances
  - We had clearly a bottleneck in the join phase ("shuffle")
  - "block affinity groups" is an on-going work at Apache.
- We spent time on the "data co-location"
- We found a solution to do it "manually" via Python scripts.

Experiment 2: IN2P3 cluster

- Gaia X IGSL3 (> 1 billion sources each)
- Time divided by 2 compared to the production X-Match Server
- Analyzing and debriefing are on going





Perspective and conclusion

- Apache Spark quick to install, easy to use for common tasks
- But not easy to understand what happens, how it works when you have particular use cases
- Real interest in several communities
- Docker use will continue with an application to the X-Match service

Links

- Apache Spark, http://spark.apache.org/
- Apache Hadoop, http://hadoop.apache.org/
- Spark : Cluster Computing with Working Sets, Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, Ion Stoica, University of California, Berkeley, http://static.usenix.org/legacy/events/hotcloud10/tech/full_papers/Zaharia.pdf
- Optimizing Shuffle Performance in Spark, Aaron Davidson, Andrew Or, UC Berkeley, http://www.cs.berkeley.edu/~kubitron/courses/cs262a-F13/projects/reports/project16_report.pdf
- Resilient Distributed Datasets : A Fault-Tolerant Abstraction for In-Memory Cluster Computing, Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, Ion Stoica, University of California, Berkeley, https://www.cs.berkeley.edu/~matei/papers/2012/nsdi_spark.pdf
- JavaSpark Api, http://spark.apache.org/docs/latest/api/java/
- HEALPix, http://healpix.jpl.nasa.gov/

Additional slides

- Data preparation and Join
  - The process
  - Its translation in Java

First experiment (SDSS DR7 X 2MASS)

Data preparation phase

Input files to HDFS and loading into 2 RDDs (information about an object in the Sky)

Each RDD is transformed in a pairRDD (key = “source pixel number”, value = “all the information whose the source (ra, dec) ”)

PairRDD distribution over the nodes (hashpartionning => grouping elements having the same key (same pixel number) in the same partition)

Elements with the same key are on the same node, distribution is essential to the join phase

PairRDDs are stored into HDFS as binary files preserving the structure (Key, Value)

Example, Java API

Data preparation phase of our use case

```
private void parsePartitionSave(final JavaSparkContext jsc,
        final String hdfUrlIn, final int nPartitions, final String hdfUrlOut) {
    // Create the partitioner
    final HashPartitioner hp = new HashPartitioner(nPartitions);
    // Load HDFS CSV file into JavaRDD
    final JavaRDD<String> csvRDD = jsc.textFile(hdfUrlIn);
    // Parse, compute index and put result in PairRDD,
    // partitioning according to the key
    final JavaPairRDD<LongWritable, RowWritable> pairRDD =
            csvRDD.mapToPair(this.parseFunction).partitionBy(hp);
    // Save the PairRDD in HDFS
    pairRDD.saveAsHadoopFile(hdfUrlOut,
            LongWritable.class, RowWritable.class,
            SequenceFileOutputFormat.class);
}
```

First experiment (2)

Join phase

Loading in two PairRDDs + duplication* of some sources in the neighbour pixels in one of it

PairRDDs joined following the Key into a new PairRDD where the elements are (Key, Value1, Value2) triples

Join done following the Key (cell number), 2 near sources can be in the different cells and are not joined (=> duplication* of sources in the neighbour cells to avoid the side effects)
*a circle with a fixed radius is drawn around the source, If neighbour pixels are partially in this circle, the source is then duplicated in the neighbour cells

The joined elements are then filtered (distance between the 2 sources < a given threshold)

Final result stored in HDFS (in a text format for a later visualization and use)

Example, Java API (2)

Join phase of our use case

```
private void performXmatch(final JavaSparkContext jsc,
        final String rdd1URL, final String rdd2URL, final String txtResultURL) {
    // Load HDFS file 1 into JavaPairRDDs
    final JavaPairRDD<LongWritable, RowWritable> pairRDD1 =
            jsc.sequenceFile(rdd1URL, LongWritable.class, RowWritable.class)
            .mapToPair(READ_FUNCTION);
    // Load HDFS file 2 into JavaPairRDDs and duplicate
    JavaPairRDD<LongWritable, RowWritable> pairRDD2 =
            jsc.sequenceFile(rdd2URL, LongWritable.class, RowWritable.class)
            .mapToPair(READ_FUNCTION).flatMapToPair(this.duplicateFunction);
    // Perform the xmatch: join operation + filtering
    JavaPairRDD<LongWritable, Tuple2<RowWritable, RowWritable>> joinRes =
            pairRDD1.join(pairRDD2).filter(this.filterFunction);
    // Save the resul in HDFS
    joinRes.saveAsTextFile(txtResultURL);
}
```

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