UMD DATA605 - Big Data Systems

(Apache) Spark

Instructor: Dr. GP Saggese - gsaggese@umd.edu**
TAs: Krishna Pratardan Taduri, kptaduri@umd.edu Prahar Kaushikbhai Modi, pmodi08@umd.edu
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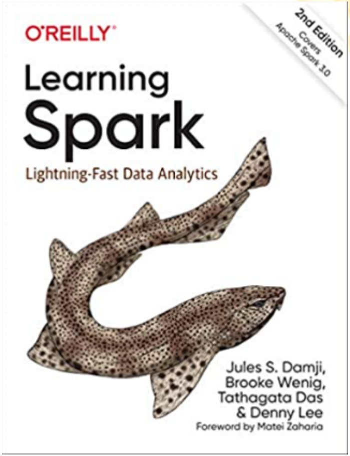
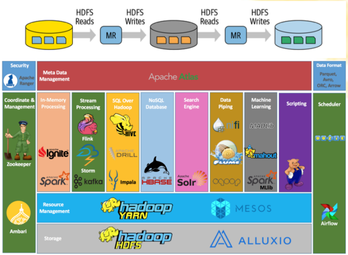
Apache Spark - Resources

- Concepts in the slides
- Academic paper
  - "Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing", 2012
- Web resources
  - Spark programming guide
  - Coursera Spark in Python tutorial
- Mastery
  - "Learning Spark: Lightning-Fast Data Analytics" (2nd Edition)
  - Not my favorite, but free here



Hadoop MapReduce: Shortcomings

- Hadoop is hard to administer
  - Lots of layers (HDFS, Yarn, Hadoop, ...)
  - Lots of configuration
- Hadoop is hard to use
  - API is verbose (example later)
  - Not great binding for multiple languages (e.g., Java is native)
  - MapReduce jobs interact by writing data on disk
- Large but fragmented ecosystem
  - No native support in Hadoop for
    - Machine learning
    - SQL, streaming
    - Interactive computing
    - ...
  - To handle new workloads new systems developed on top of Hadoop
  - E.g., Apache Hive, Storm, Impala, Giraph, Drill



(Apache) Spark

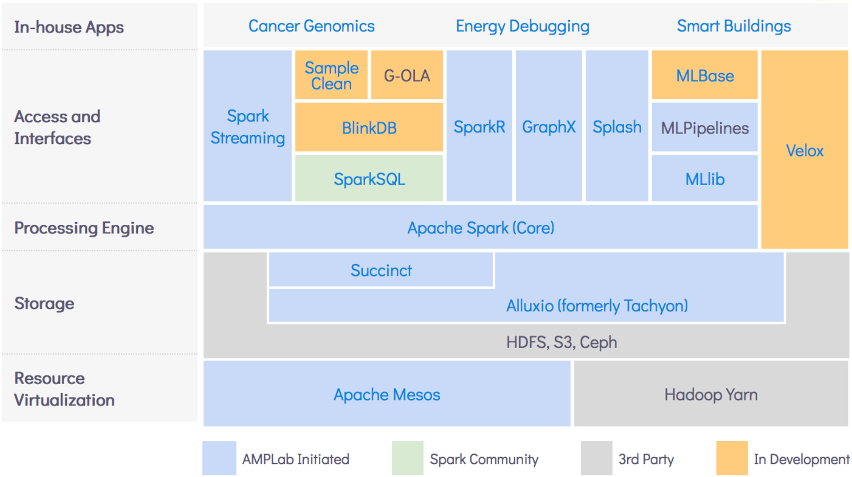
- **Open-source**
  - DataBrick monetizes it (40B startup)
- **General processing engine**
  - Large set of operations instead of just **Map()** and **Reduce()**
  - Operations can be arbitrarily combined in any order
  - Transformations vs Actions
  - Computation is organized as a DAG
  - DAGs are decomposed into tasks that can run in parallel
  - Scheduler / optimizer on parallel workers
- **Supports several languages**
  - Java, Scala (preferred)
  - Python good support through bindings, but not the main language
- **Data abstraction**
  - Resilient Distributed Dataset (RDD)
  - Other data structures (e.g., DataFrames, Datasets) built on top of RDDs
- **Fault tolerance through RDD lineage**

Berkeley: From Research to Companies

- Amplab
  - Projects
- Rise lab
- Projects
- DataBricks
  - Private company worth 40B
  - Accidental Billionaires: How Seven Academics Who Didn't Want To Make A Cent Are Now Worth Billions, 2023

Berkeley AMPLab Data Analytics Stack

- So many tools that they have their own big data stack!

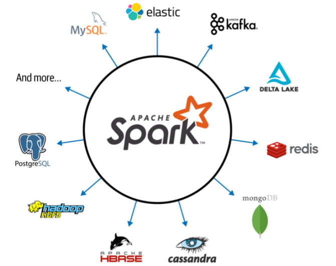


https://amplab.cs.berkeley.edu/software/

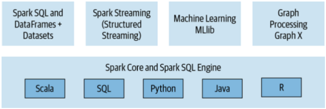
Apache Spark

- Unified stack
  - Different computation models in a single framework
- Spark SQL
  - ANSI SQL compliant
  - Work with structured relational data
- Spark MLlib
  - Build ML pipelines
  - Support popular ML algorithms
  - Built on top of Spark DataFrame
- Spark Streaming
  - Handle continually growing tables
  - Tables are treated as static table
- GraphX
  - Manipulate graphs
  - Perform graph-parallel computation
- Extensibility
  - Read from a many sources
  - Write to many backends

One computation engine

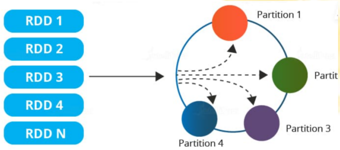


General purpose applications



Resilient Distributed Dataset (RDD)

- **A Resilient Distributed Dataset (RDD)**
  - Collection of data elements
  - Partitioned across nodes
  - Can be operated on in parallel
  - Fault-tolerant
  - In-memory / serializable
- **Applications**
  - Best suited for applications that apply the same operation to all elements of a dataset (vectorized)
  - Less suitable for applications that make asynchronous fine-grained updates to shared state
    - E.g., updating one value in a dataframe
- **Ways to create RDDs**
  - *Reference* data in an external storage system
    - E.g., a file-system, HDFS, HBase
  - *Parallelize* an existing collection in your driver program
  - *Transform* RDDs into other RDDs



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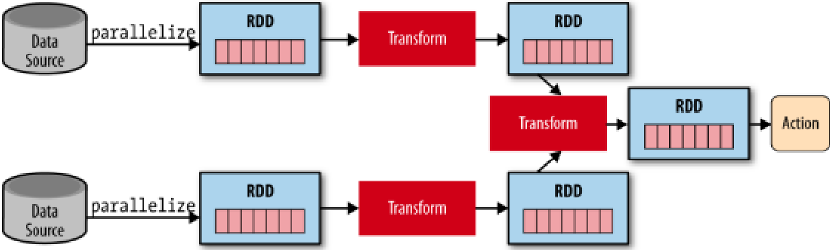
Transformations vs Actions

- **Transformations**
  - Lazy evaluation
  - Nothing computed until an Action requires it
  - Build a graph of transformations
- **Actions**
  - When applied to RDDs force calculations and return values
  - Aka Materialize



Spark Example: Estimate Pi

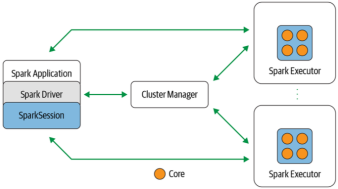
```python
# Estimate π (compute-intensive task).
# Pick random points in the unit square [(0,0)-(1,1)].
# See how many fall in the unit circle center=(0, 0), radius=1.
# The fraction should be π / 4.

import random
random.seed(314)

def sample(p):
    x, y = random.random(), random.random()
    in_unit_circle = 1 if x*x + y*y < 1 else 0
    return in_unit_circle

# "parallelize" method creates an RDD.
NUM_SAMPLES = int(1e6)
count = sc.parallelize(range(0, NUM_SAMPLES)) \
          .map(sample) \
          .reduce(lambda a, b: a + b)
approx_pi = 4.0 * count / NUM_SAMPLES
print("pi is roughly %f" % approx_pi)
```

executed in 386ms, finished 04:27:53 2022-11-23

```
pi is roughly 3.141400
```

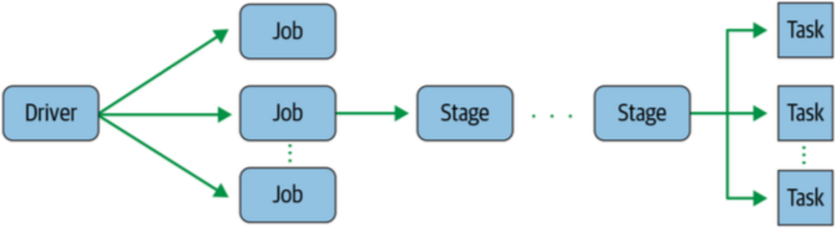
Spark: Architecture

- **Architecture** = who does what, what are the responsibilities of each piece
- **Spark Application**
  - Code that the user writes to describe the computation
  - E.g., Python code calling into Spark
- **Spark Driver**
  - Instantiate a *SparkSession*
  - Communicate with *Cluster Manager* to request resources
  - Transform operations into DAG computations
  - Distribute execution of tasks across *Executors*
- **Spark Session**



Spark: Computation Model

- Architecture = who does what, what are the responsibilities of each piece
- Computational model = how are things done



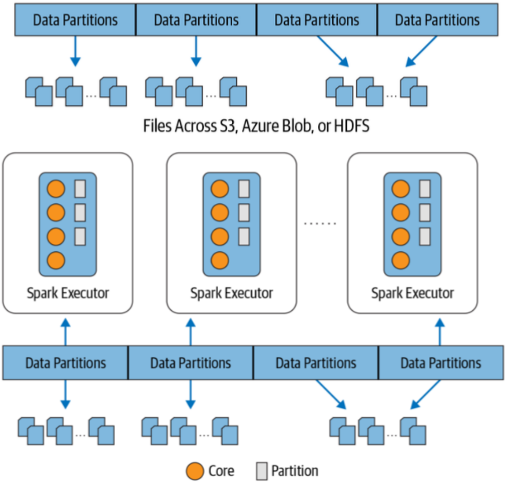
- **Spark Driver**
  - The driver converts the Spark application into one or more Spark *Jobs*
  - Computation is described by *Transformations* and triggered by *Actions*
- **Spark Job**
  - A parallel computation that runs in response to a Spark *Action*
    - E.g., **save(), collect()**
  - Each *Job* is a DAG containing one or more *Stages* depending on each other
- **Spark Stage**
  - Each *Job* is a smaller operation

Deployment Modes

- Spark can run on several different configurations
  - **Local**
    - E.g., run on your laptop
    - Driver, Cluster Manager, Executors all run in a single JVM on the same node
  - **Standalone**
    - Driver, Cluster Manager, Executors run in different JVMs on different nodes
  - **YARN**
  - **Kubernetes**
    - Driver, Cluster Manager, Executors run on different pods (i.e., containers)

Distributed Data and Partitions

- **Data is distributed as partitions across different physical nodes**
  - Each partition is typically stored in memory
  - Partitions allow efficient parallelism
- **Spark Executors process data that is "close" to them**
  - Minimize network bandwidth
  - Data locality
  - Same approach as Hadoop



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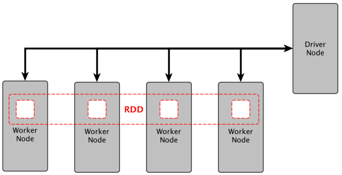
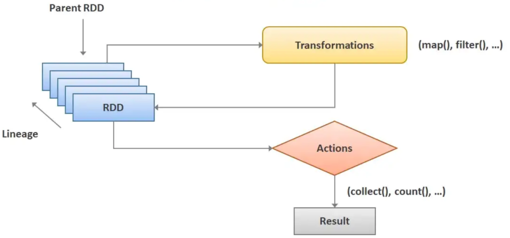
Parallelized Collections

- Parallelized collections are created by calling *SparkContext* **parallelize()** method on an existing collection
- Data is spread across nodes
- Number of *partitions* to cut the dataset into
  - Spark will run one *Task* for each partition of the cluster
  - Typically you want 2-4 partitions for each CPU in your cluster
  - Spark tries to set the number of partitions automatically based on your cluster
  - You can also set it manually by passing it



Transformations vs Actions

- **Transformations**
- Transform a Spark RDD into a new RDD without modifying the input data
  - Immutability like in functional programming
  - E.g., **select(), filter(), join(), orderBy()**
- Transformations are evaluated lazily
  - Inspect computation and decide how to optimize it
  - E.g., joining, pipeline operations, breaking into stages
- Results are recorded as "lineage"
  - A sequence of stages that can be rearranged,



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Spark Example: MapReduce in 1 (or 4) Line

- MapReduce in 4 lines

```
!more data.txt
```

executed in 1.77s, finished 04:37:35 2022-11-23

```
One a penny, two a penny, hot cross buns
```

```
lines = sc.textFile("data.txt").flatMap(lambda line: line.split(" "))
pairs = lines.map(lambda s: (s, 1))
counts = pairs.reduceByKey(lambda a, b: a + b)
result = counts.collect()
print(result)
```

executed in 428ms, finished 04:36:24 2022-11-23

```
[('One', 1), ('two', 1), ('hot', 1), ('cross', 1), ('a', 2), ('penny,', 2), ('buns', 1)]
```

```
result = sc.textFile("data.txt").flatMap(lambda line: line.split(" ")).map(
    lambda s: (s, 1)).reduceByKey(lambda a, b: a + b).collect()
print(result)
```

executed in 591ms, finished 05:06:00 2022-11-23

```
[('One', 1), ('two', 1), ('hot', 1), ('cross', 1), ('a', 2), ('penny,', 2), ('buns', 1)]
```

- MapReduce in 1 line (show-off version)

Same Code in Java Hadoop

```java
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

public class WordCount {

  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }
```

```java
public static class IntSumReducer
     extends Reducer<Text,IntWritable,Text,IntWritable> {
  private IntWritable result = new IntWritable();

  public void reduce(Text key, Iterable<IntWritable> values,
                     Context context
                     ) throws IOException, InterruptedException {
    int sum = 0;
    for (IntWritable val : values) {
      sum += val.get();
    }
    result.set(sum);
    context.write(key, result);
  }
}

public static void main(String[] args) throws Exception {
  Configuration conf = new Configuration();
  Job job = Job.getInstance(conf, "word count");
  job.setJarByClass(WordCount.class);
  job.setMapperClass(TokenizerMapper.class);
  job.setCombinerClass(IntSumReducer.class);
  job.setReducerClass(IntSumReducer.class);
  job.setOutputKeyClass(Text.class);
  job.setOutputValueClass(IntWritable.class);
  FileInputFormat.addInputPath(job, new Path(args[0]));
  FileOutputFormat.setOutputPath(job, new Path(args[1]));
  System.exit(job.waitForCompletion(true) ? 0 : 1);
}
}
```

Spark Example: Logistic Regression in MapReduce

Logistic Regression

####
- _**\textcolor{red}{Load points}**_
- Initial separating plane
- Until convergence
- Use `broadcast_var.value` instead of `
- Here, accum is still 0 because no acti
- of nodes

```
points= spark.textFile(...).map(parsePoi
```

Repeat {

$$\theta_j := \theta_j - \frac{\alpha}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

}

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)^2$$

Repeat until convergence {

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}

####
- Load points
- _**\textcolor{red}{Initial separating plane}**_
- Until convergence
- Use `broadcast_var.value` instead of `var`.
- Here, accum is still 0 because no actions have caused the `map` t
- of nodes

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Spark Transformations: 1 / 3

- **map**(func)
  - Return a new RDD passing each element through a function *func()*
- **flatmap(**func**)**
  - Similar to map, but each input item can be mapped to 0 or more output items
  - *func()* returns a sequence rather than a single item
- **filter(**func**)**
  - Return a new RDD selecting elements on which *func()* returns true
- **union(**otherDataset**)**
  - Return a new RDD with the union of the elements in the source dataset and the argument
- **intersection(**otherDataset**)**
  - Return a new RDD with the intersection of elements in the source dataset and the argument

https://spark.apache.org/docs/latest/rdd-programming-guide.html

Spark Transformations: 2 / 3

- **distinct**(*[numTasks]*)
  - Return a new RDD that contains the distinct elements of the source dataset
- **join**(otherDataset, *[numTasks]*)
  - When called on RDDs (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key
  - Outer joins are supported through leftOuterJoin, rightOuterJoin, and fullOuterJoin
- **cogroup**(otherDataset, *[numPartitions]*)
  - Aka **groupWith()**
  - Same as join but returning a dataset of (K, (Iterable, Iterable)) tuples

Spark Transformations: 3 / 3

- **groupByKey**(*[numPartitions]*)
  - When called on a RDD of (K, V) pairs, return a dataset of (K, Iterable) pairs
  - If you are grouping in order to perform an aggregation (e.g., a sum or average) over each key, **reduceByKey** yields better performance
    - Gathering data and processing in place is better than iterators
  - By default, the level of parallelism in the output depends on the number of partitions of the parent RDD
    - Pass an optional numPartitions argument to set a different number of tasks
- **reduceByKey(**func, *[numPartitions]***)**
  - When called on a RDD of (K, V) pairs, return a dataset of (K, f(V_1, . . . , V_n)) pairs where the values for each key are aggregated using the given reduce function *func()*
  - func(): (V, V) $\to$ V
  - This is Shuffle + Reduce from MapReduce
  - Number of reduce tasks is configurable through *numPartitions*
- **sortByKey(**[ascending], *[numPartitions]***)**
  - Return a dataset of (K, V) pairs sorted by keys in ascending or descending order

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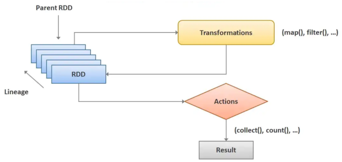
Spark Actions

- **reduce**(func)
  - Aggregate the elements of the dataset using a function *func()*
  - *func()* takes two arguments and returns one
  - *func()* should be commutative and associative so that it can be computed correctly in parallel
- **collect()**
  - Return all the elements of the dataset as an array
  - This is usually useful after operation that returns a small subset of the data (e.g., **filter()**)
- **count()**
  - Return the number of elements in the dataset
- **take(**n**)**
  - Return an array with the first *n* elements of the dataset
  - Note that **.collect()[:n]** is not the same as **.take(n)**

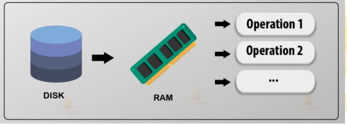
https://spark.apache.org/docs/latest/rdd-programming-guide.html

Spark: Fault-tolerance

- Spark uses *immutability* and *lineage* to provide fault tolerance
- In case of failure:
  - A RDD can be reproduced by simply replaying the recorded lineage
  - No need to store checkpoints
  - Data can be kept in memory to increase performance
- Fault-tolerance comes for free!



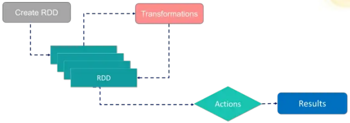
Spark: RDD Persistence



- **User explicitly persists (aka cache) an RDD**
  - User can call **persist(), unpersist()** on RDD
  - Cache only if RDD is expensive to compute
    - E.g., filtering large amount of data
  - When you persist an RDD, each node:
    - Stores (in memory or disk) partitions of the RDD
    - Reuses cached partitions on datasets derived from it
- **Cache**
  - Allows future actions to be much faster (often $>$10x)
  - Managed by Spark with an LRU policy $+$ garbage collector
- **User can choose storage level**
  - MEMORY_ONLY (default level)
  - DISK_ONLY (e.g., Python Pickle)
  - MEMORY_AND_DISK
    - If RDD doesn't fit in memory, store partitions on disk

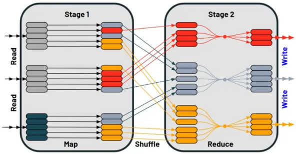
Spark: RDD Persistence and Fault-tolerance

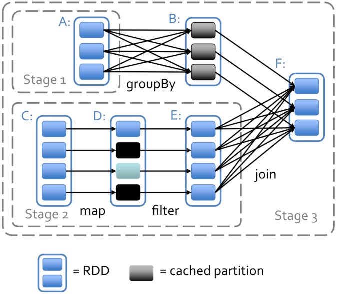
- Spark handles persistence and fault-tolerance in a similar way
- **Caching/Persistence**
  - Cache RDD (in memory or on disk) instead of recomputing it
- **Fault-tolerance**
  - If any partition of an RDD is lost
    - RDD is automatically recomputed (when needed) using the transformations that generated it
    - Based on immutability and lineage
- **Caching is fault-tolerant!**



Spark Shuffle

- E.g., **reduceByKey()**
  - **Definition**: all values [v1, . . . , vn] for a single key *k* are combined into a tuple *(k, v)* where $v = \text{reduce}(v1, \ldots, vn)$
  - **Problem**: all the values for a single key need to reside on the same partition / machine
  - **Solution**: data shuffle moving the data across machines
- Certain Spark operations trigger a data shuffle
  - E.g., **reduceByKey()**, **groupByKey()**, join, repartition, transpose
- **Data shuffle** = re-distribute data grouped differently across partitions / machines
- **Data shuffle is expensive** since it involves:
  - Data serialization (pickle)
  - Disk I/O (save to disk)
  - Network I/O (copy across Executors)
  - Deserialization and memory allocation





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Broadcast Variables

- **Problem**
  - Common variables are shipped to the nodes together with the code
  - Broadcasting means serializing, sending over the network, de-serializing
  - If the data is constant and large, sending the data every time is expensive
- **Solution**
  - Keep read-only variables cached on each node, instead of shipping a copy with the tasks

```
- `var` is large variable.
var = list(range(1, int(1e6)))
- Create a broadcast variable.
broadcast_var = sc.broadcast(var)
- Do not modify `var`.
####
- Load points
- Initial separating plane
- Until convergence
- _**\textcolor{red}{Use `broadcast_var.value` instead of `var`.}*
- Here, accum is still 0 because no actions have caused the `map`
- of nodes
```

Accumulators

- **Accumulator** = variable that can be "added to" through associative and commutative operations
  - They can be efficiently supported in parallel execution (e.g., MapReduce)
- Spark supports Accumulators with numerical types by default (e.g., integers)
  - User can define Accumulators for different types

```
>>> accum = sc.accumulator(0)
>>> accum
Accumulator<id=0, value=0>
>>> sc.parallelize([1, 2, 3, 4]).foreach(lambda x: accum.add(x
>>> accum.value
10
```

- Each node computes the value to add to the Accumulator and then the value added
- Usual semantic:
  - Accumulators work with the same logic of transformations (lazy evaluation) and actions "‘ accum = sc.accumulator(0) def g(x): accum.add(x) return f(x) data.map(g) ####
- Load points
- Initial separating plane

Gray Sort Competition

	Hadoop MR Record	Spark Record (2014)
Data Size	102.5 TB	100 TB
Elapsed Time	72 mins	23 mins
# Nodes	2100	206
# Cores	50400 physical	6592 virtualized
Cluster disk throughput	3150 GB/s	618 GB/s
Network	dedicated data center, 10Gbps	virtualized (EC2) 10Gbps network
Sort rate	1.42 TB/min	4.27 TB/min
Sort rate/node	0.67 GB/min	20.7 GB/min

http://databricks.com/blog/2014/11/05/spark-officially-sets-a-new-record-in-large-scale-sorting.html

Sort benchmark, Daytona Gray: sort of 100 TB of data (1 trillion records)

Spark-based System 3x faster with 1/10 #### Load points Initial

Spark vs Hadoop MapReduce

- **Performance**: Spark normally faster but with caveats
  - Spark can process data in-memory
  - Spark generally outperforms MapReduce, but it often needs lots of memory to do well
  - Hadoop MapReduce persists back to the disk after a map or reduce action
- **Ease of use**: Spark is easier to program
- **Data processing**: Spark more general

"Spark vs. Hadoop MapReduce", Saggi Neumann, 2014
https://www.xplenty.com/blog/2014/11/apache-spark-vs-hadoop-mapreduce/