UMD DATA605 - Big Data Systems

(Apache) Spark

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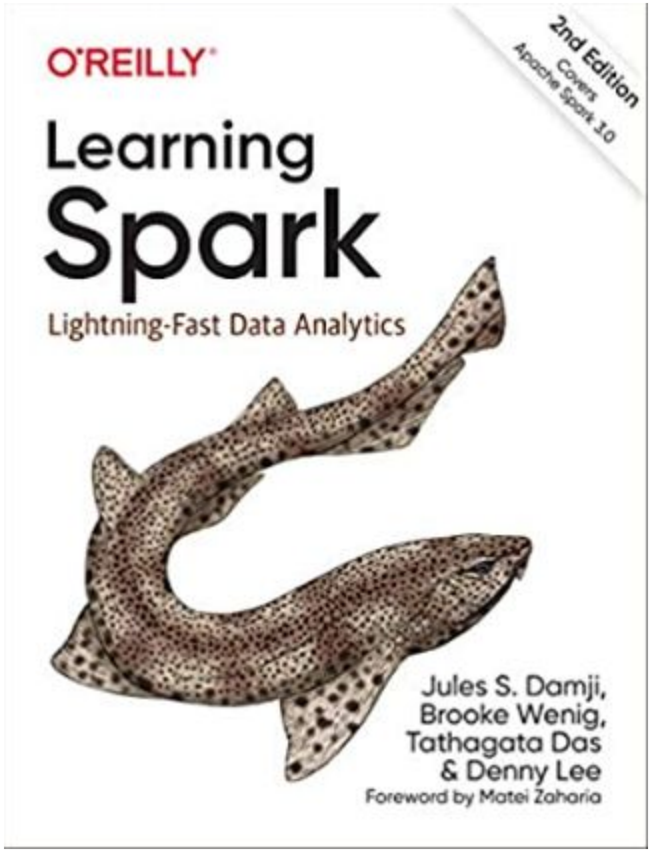
with thanks to Alan Sussman, Amol Deshpande,
David Wheeler (GMU), T. Yang (UCSB)
and Apache documentation

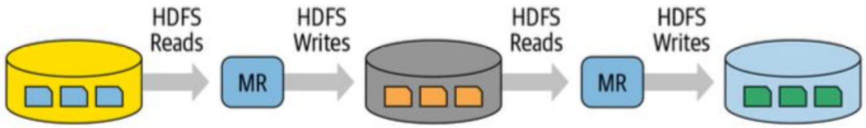
Apache Spark - Resources

- 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

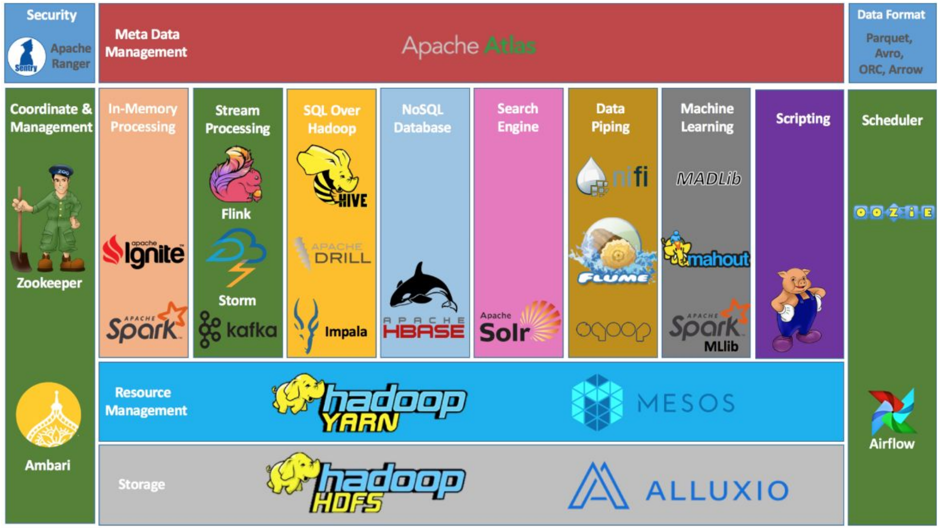


Hadoop MapReduce: Shortcomings

- **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

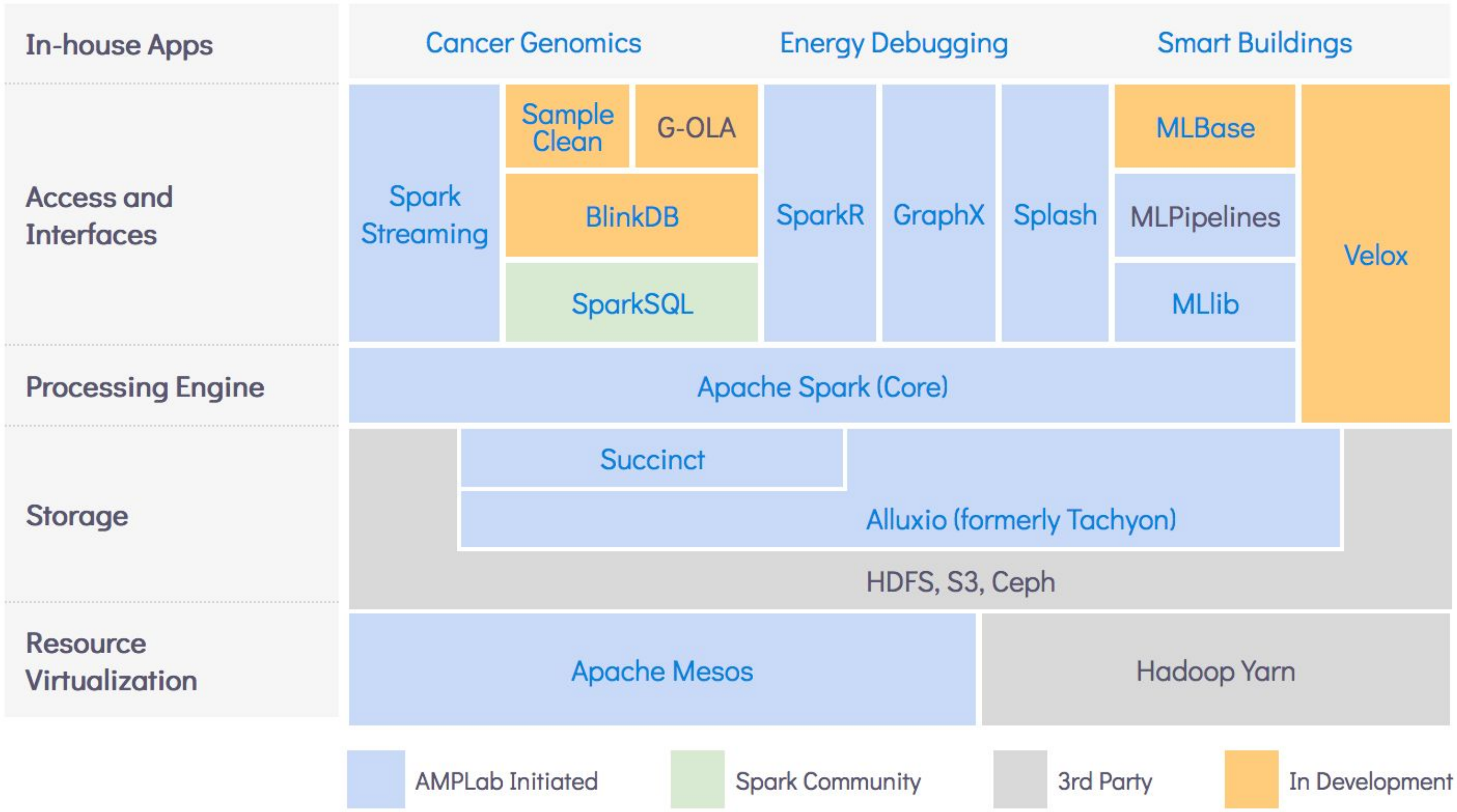
- **Open-source (DataBrick monetizing it)**
- **General processing engine**
  - Large set of operations instead of just `Map()` and `Reduce()`
  - Operations can be arbitrarily combined in any order
  - Transformations vs Actions
  - Computation is organized as DAG
  - DAGs are decomposed into tasks that can run in parallel
  - Scheduler / optimizer on parallel workers
- **Supports several languages**
  - Java, Scala (preferred)
  - Python good support, not the main language (through bindings)
- **Data abstraction**
  - Resilient Distributed Dataset (RDD)
  - Other data structures (e.g., DataFrames, Datasets) built on top of RDDs
- **Fault tolerance through RDD lineage**
- **In-memory computation**
  - All intermediate results are kept in memory instead of disk
  - Persist data on disk or in memory, if needed -> speed
  - Initial winning advantage

Berkeley: From Research to Companies

- Amplab
  - Projects
- Rise lab
  - Projects
- DataBricks
  - Private company worth $26b
  - 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!

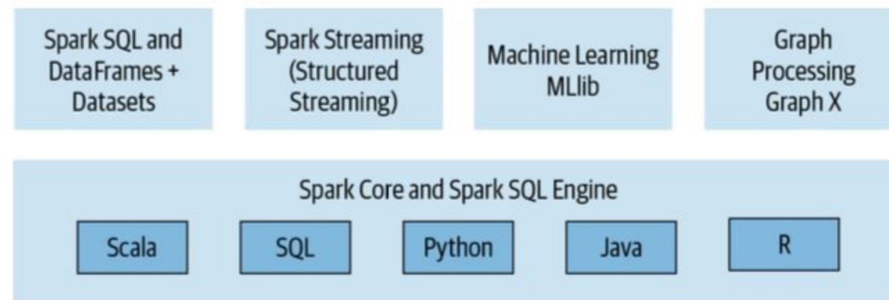


https://amplab.cs.berkeley.edu/software/

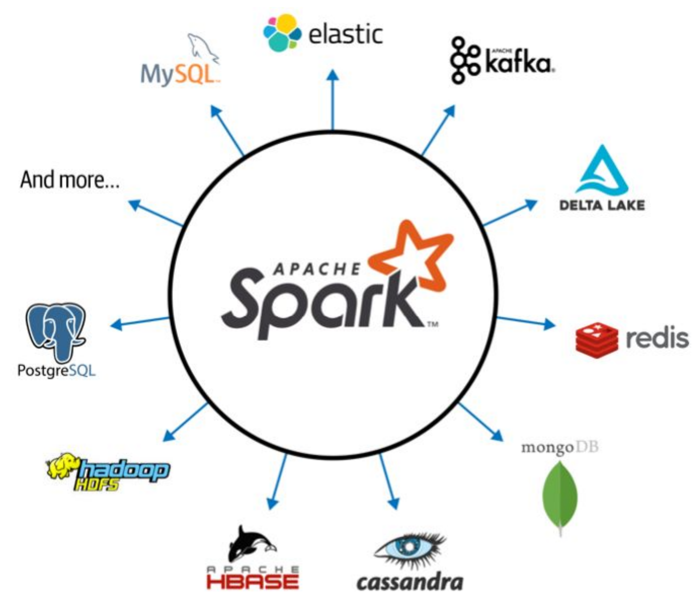
Apache Spark

- **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

General purpose applications

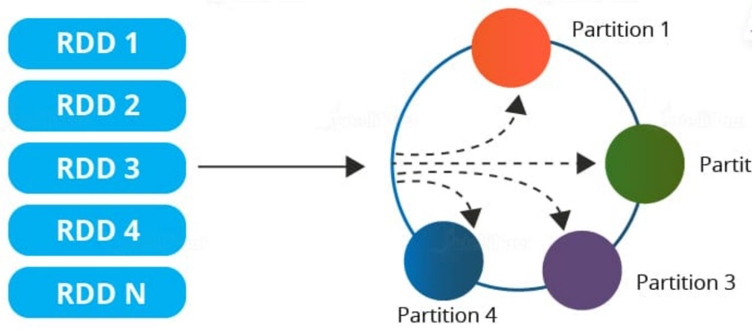


One computation engine



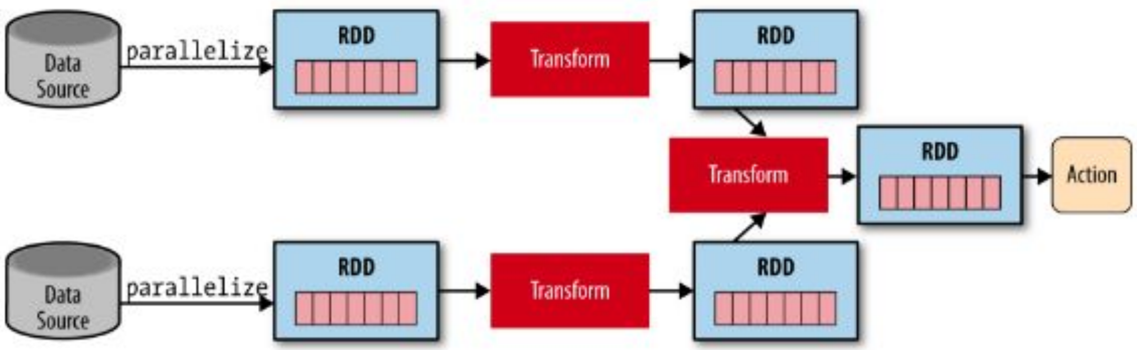
Resilient Distributed Dataset (RDD)

- **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 values 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



Transformation 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

- Estimate Pi with MapReduce in Spark

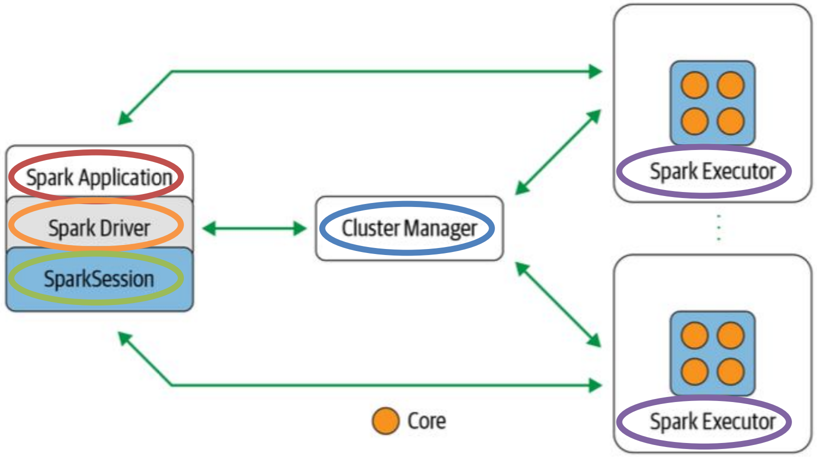
```
# Estimate π (compute-intensive task).
# Pick random points in the unit square [(0,0)-(1,1)].
# See how many fall in the unit circle center=(0, 0), radius=1.
# The fraction should be π / 4.

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
```

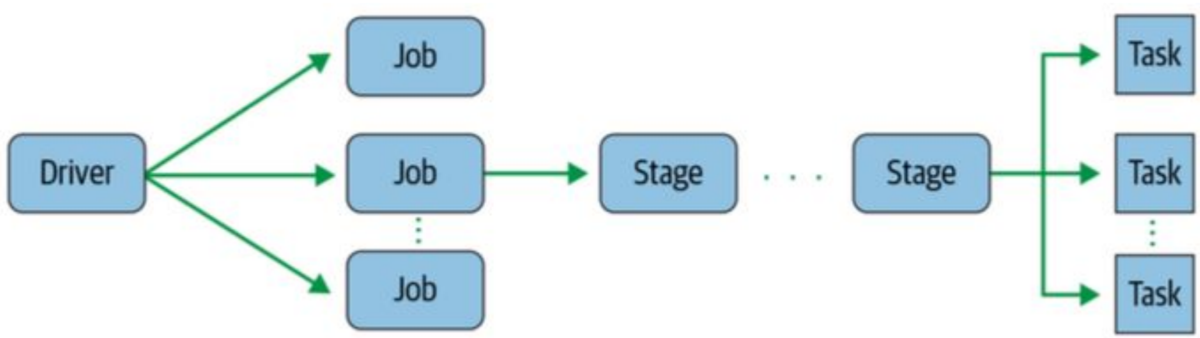
Spark: Architecture

- **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 Spark executors
- Spark Session
  - Represent the interface to Spark system
- Cluster Manager
  - Manage and allocate resources
  - Support Hadoop, YARN, Mesos, Kubernetes
- Spark Executor
  - Run a worker node to execute tasks
  - Typically one executor per node
  - JVM



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
  - Spark Transformations vs Actions
    - 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 becomes a DAG containing one or more Stages
- **Spark Stage**
  - Each Job is divided in smaller tasks called Stages that depend on each other
  - Stages can be performed serially or in parallel
- **Spark Task**
  - Each Stage is comprised of multiple Tasks
  - A single unit of work sent to a Spark Executor
  - Each Task maps to a single core and works on a single partition of data

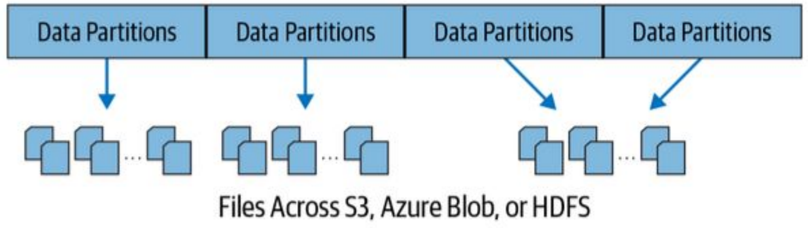


Deployment Modes

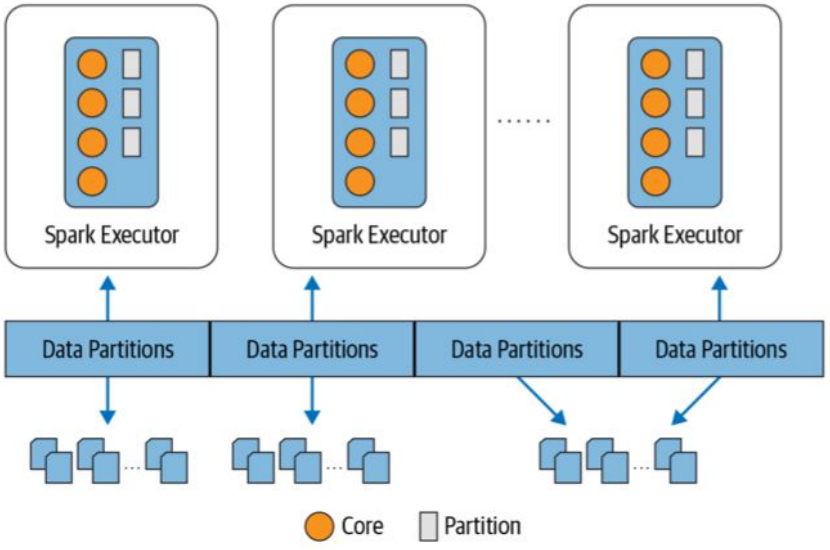
- Spark can run on several different configurations
  - **Local**
    - E.g., run on your laptop
    - Driver, Cluster Manager, Executors all run in a single JVM on the same node
  - **Standalone**
    - Driver, Cluster Manager, Executors run in different JVMs on different nodes
  - **YARN**
  - **Kubernetes**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

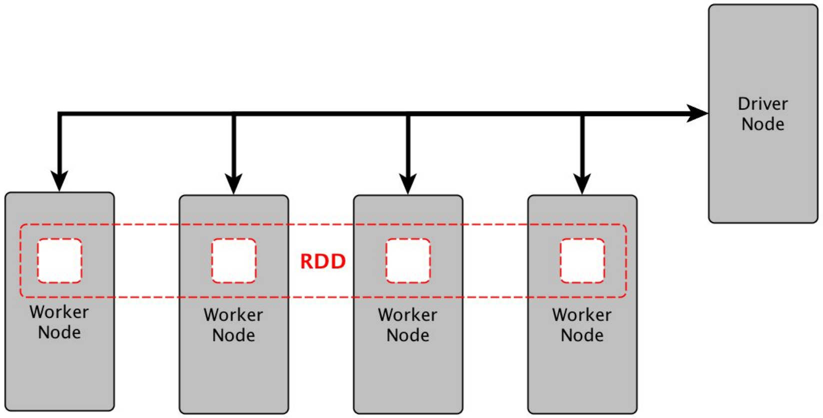


- **Spark Executors process data that is "close" to them**
  - Minimize network bandwidth
  - Data locality
  - Same approach as Hadoop



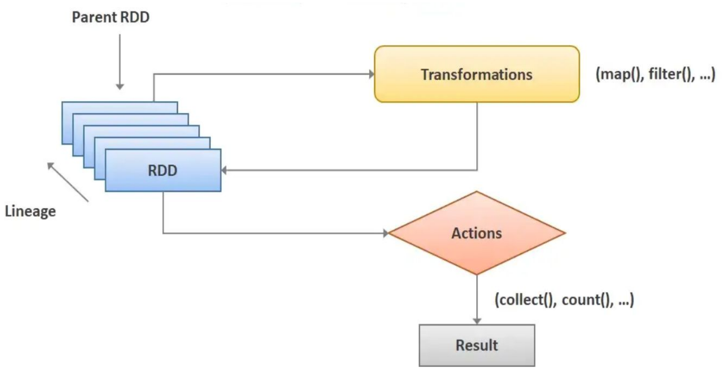
Parallelized Collections

- Parallelized collections are created by calling SparkContext's `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 as a second parameter to `parallelize()`



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
    - Lazy execution allows to 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, optimized without changing results
- **Actions**
  - An action triggers the evaluation of a computation
    - E.g., `show(), take(), count(), collect(), save()`



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)]
```

- MapReduce in 1 line (show-off version)

```
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)]
```

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

```python
# Logistic Regression
# - iterative machine learning algorithm
# - find best hyperplane that separates two sets
#   of points in a multi-dimensional feature space
#
# Apply MapReduce operation repeatedly to the same
# dataset, so it benefits greatly from caching the
# input in RAM.

points = spark.textFile(...).map(parsePoint).cache()
# Initial separating plane.
w = numpy.random.ranf(size = D)
# Until convergence.
for i in range(ITERATIONS):
   # Parallel loop over the samples i=1...m
   gradient = points.map(
       lambda p:
             (1 / (1 + exp(-p.y*(w.dot(p.x)))) - 1)
         * p.y * p.x
   ).reduce(lambda a, b: a + b)
   w -= alpha * gradient
print("Final separating plane: %s" % w)
```

Repeat until convergence {

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

}

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

Repeat {

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

}

https://spark.apache.org/docs/latest/quick-start.html

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]`*`)`
  - Same as join but returning a dataset of (K, (Iterable<V>, Iterable<W>)) tuples
  - This operation is also called **`groupWith()`**

Spark Transformations: 3 / 3

- `groupByKey([numPartitions])`
  - When called on a RDD of (K, V) pairs, return a dataset of (K, Iterable<V>) 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) → 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

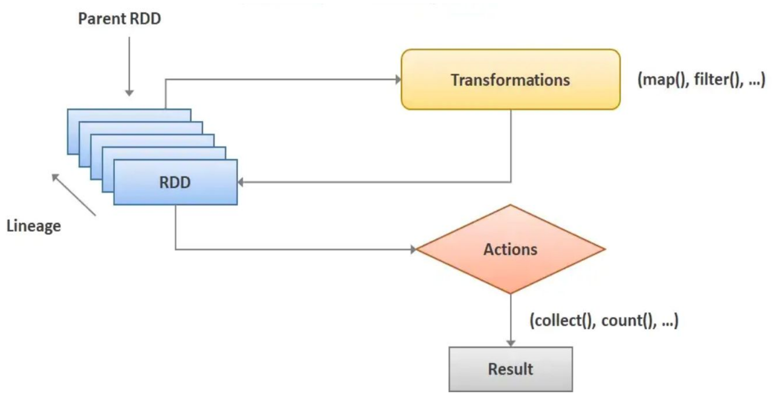
Spark Actions

- `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

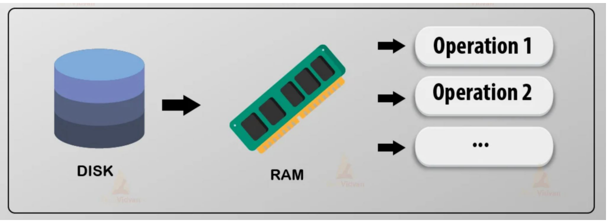
Spark: Fault-tolerance

- 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

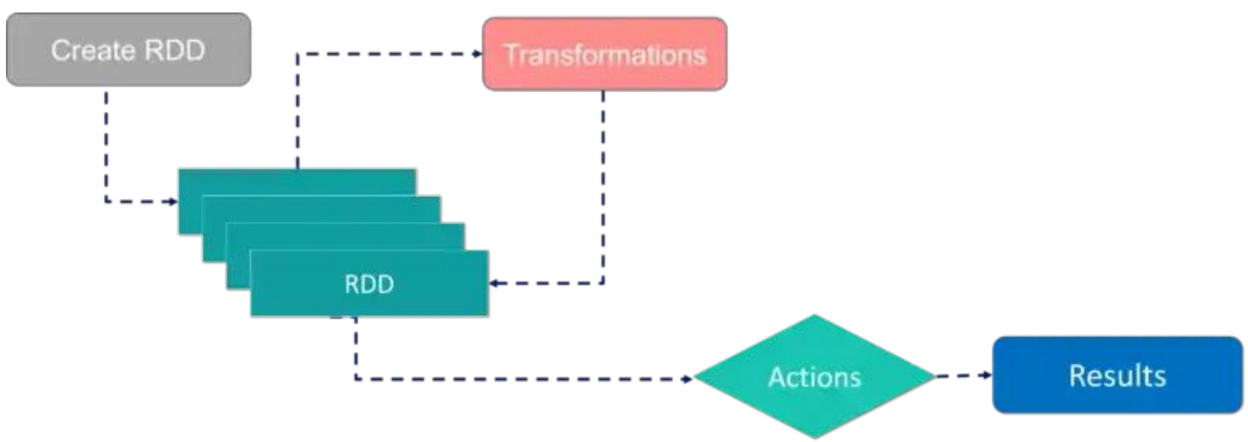
- **User explicitly persists (aka cache) an RDD**
  - User can call `persist()` on RDD
  - Cache only if RDD is expensive to compute
    - E.g., filtering large amount of data
  - When you persist an RDD, each node:
    - Stores in memory or disk partitions of the RDD
    - Reuses cached partitions on datasets derived from it



- **Cache**
  - Allows future actions to be much faster (often >10x)
  - Is managed by Spark with an LRU policy + garbage collector
  - User can manually call `unpersist()`
- **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
  - MEMORY_AND_DISK_2
    - Same as above, but replicate each partition on two nodes
  - Forcing to cache on disk can be more expensive than not caching!

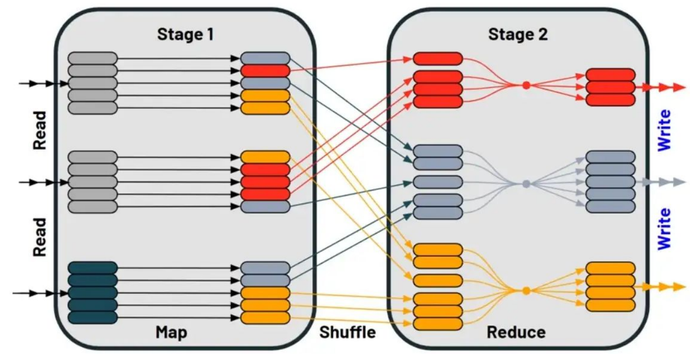
Spark: RDD Persistence and Fault-tolerance

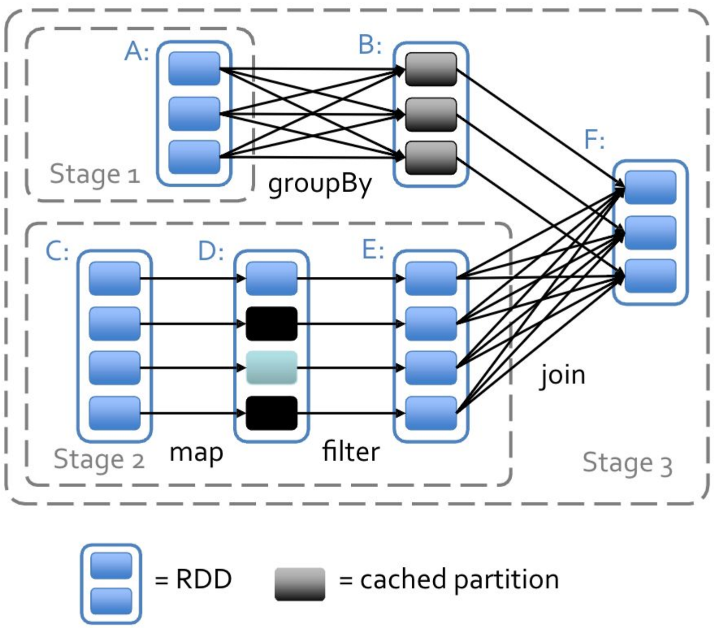
- Spark handles persistence and fault-tolerance in a similar way
- **Persistence**
  - Cache RDD (in memory or on disk) instead of recomputing it
- **Fault-tolerance**
  - If any partition of an RDD is lost
    - RDD is automatically recomputed (when needed) using the transformations that generated it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



Spark Shuffle

- Certain Spark operations trigger a data shuffle
  - E.g., `reduceByKey()`, `groupByKey()`, join, repartition, transpose
- **Data shuffle** = re-distribute data grouped differently across partitions / machines
- E.g., `reduceByKey()`
  - **Definition**: all values [v_1, ..., v_n] for a single key *k* are combined into a tuple *(k, v)* where *v* = reduce(v_1, ..., v_n)
  - **Problem**: all the values for a single key need to reside on the same partition / machine
  - **Solution**: data shuffle moving the data across 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
- **Spark schedules general task graphs**
  - Automatically pipelining of functions
  - Data locality aware
  - Partitioning aware to avoid shuffles





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

```python
# `var` is large variable.
var = list(range(1, int(1e6)))
# Create a broadcast variable.
broadcast_var = sc.broadcast(var)
# Do not modify `var`.
# Use `broadcast_var.value` instead of `var`.
```

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)
# Here, accum is still 0 because no actions have caused the `map` to be computed.
```

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**

Spark-based System 3x faster with 1/10 # of nodes

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

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

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/