

CIML Summer Institute Scalable Machine Learning



Scalable Machine Learning Agenda

8:00 - 8:30 -- Machine Learning Overview

8:30 - 9:15 -- R on HPC

9:15 - 9:30 -- Break

9:30 - 10:45 -- Spark

10:45 - 11:45 -- Lunch

11:45 - 12:30 -- Intro to Neural Networks / CNNs

12:30 - 12:45 -- Break

12:45 - 1:30 -- Deep Learning Layers & Models

1:30 - 2:00 -- Deep Learning Tutorial

Spark

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SPARK



- **Computing platform for distributed computing**
 - Built-in parallelism & fault-tolerance on commodity cluster
 - Provides interactive querying, iterative analytics, streaming processing
 - Goals: speed, ease of use, generality, unified platform
- **History**
 - Research project began in 2009 at UC Berkeley's AMPLab
 - Paper published in 2010
 - Contributed to Apache Software Foundation in 2013
 - Commercial version by Databricks

SPARK

- Goals: **speed**, ease of use, generality, unified platform
- In-memory processing
 - Exploits distributed memory to cache data
 - Intermediate results written to memory whenever possible
- How does Spark manage data in distributed system?

RESILIENT DISTRIBUTED DATASETS (RDDs)

- Spark central concept
 - Abstraction of data as distributed collection of objects
- Resilient Distributed Datasets (RDDs)
 - Data abstraction
 - Programming construct for storing data
 - Spark uses RDDs to distribute data and computations across nodes in cluster

RDD

- Resilient Distributed **Dataset**
 - Collection of data
 - From files in local filesystem (text, JSON, etc.)
 - From data store (HDFS, RDBMS, NoSQL, etc.)
 - Created from another RDD
- Resilient **Distributed** Dataset
 - Data is divided into partitions
 - Partitions are distributed across nodes in cluster
- **Resilient** Distributed Dataset
 - Provides resilience (e.g., fault tolerance) to failures
 - History of operations performed on each partition is tracked to provide lineage-based fault tolerance
- All provided automatically by Spark engine

SPARK CONTEXT

- Spark Context
 - Entry point to Spark engine
 - Provides way to create RDDs

```
from pyspark import SparkContext, SparkConf

conf = SparkConf() \
    .setAppName("RDD Example") \
    .config("config.option", "config.value")
sc = SparkContext(conf=conf)
```

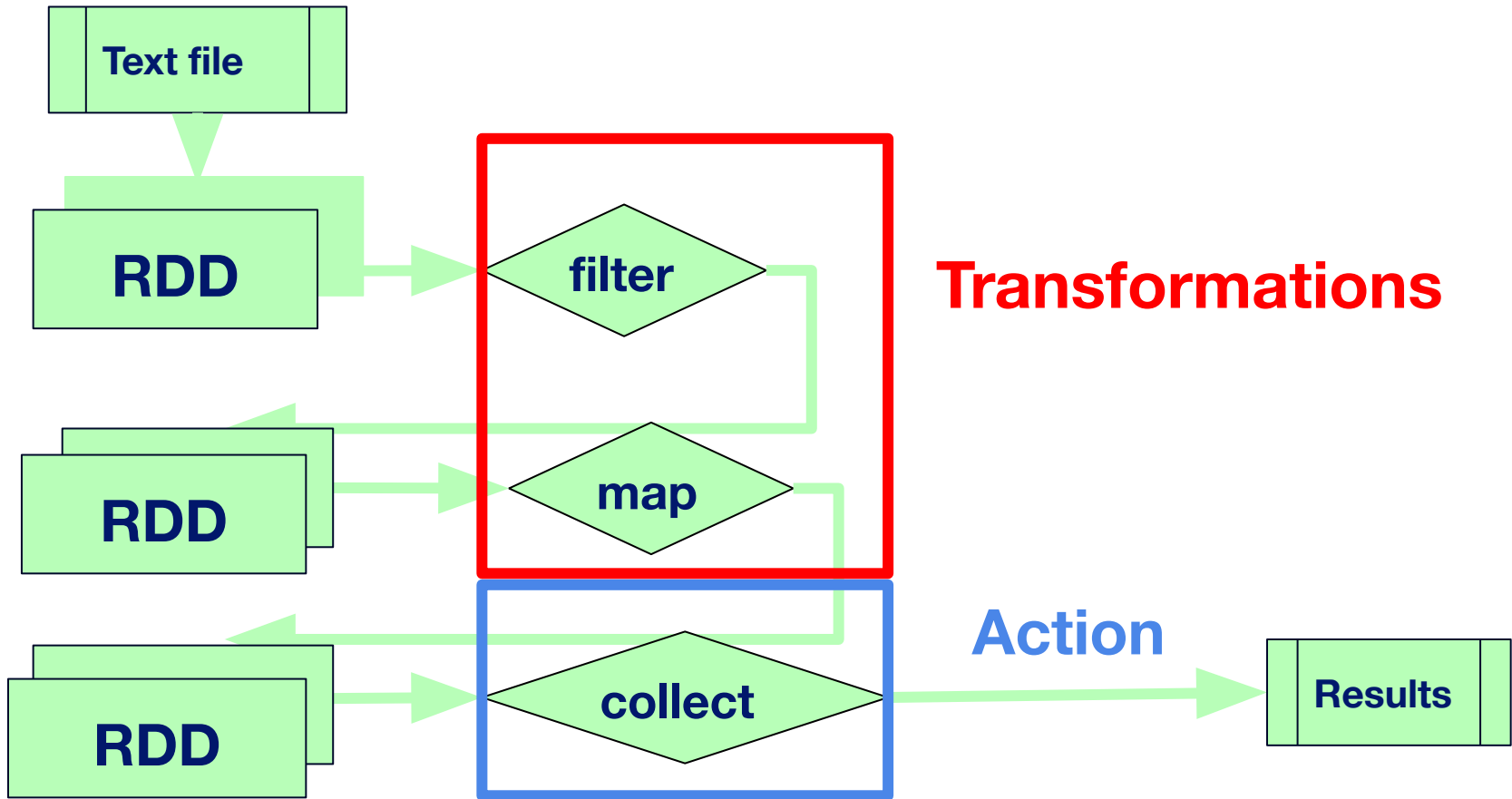
- SparkContext: connection to Spark engine
- SparkConf: configuration parameters for application

CREATING RDDs

- Read data from files in local filesystem (text, JSON, etc.)
 - `lines = sc.textFile("inputfile.txt")`
- Data read in from data store (HDFS, RDBMS, NoSQL, etc.)
 - `lines = sc.textFile("hdfs://<path>/inputfile.txt")`
- Generate data
 - `numbers = sc.parallelize(range(100),3)`
 - Divide data into 3 partitions
- Created by transforming another RDD
 - `newLines = lines.filter(lambda s: "Spark" in s)`
- Note: RDDs are **immutable**
 - To “change” RDD, create another RDD to hold changed data

PROCESSING RDDs

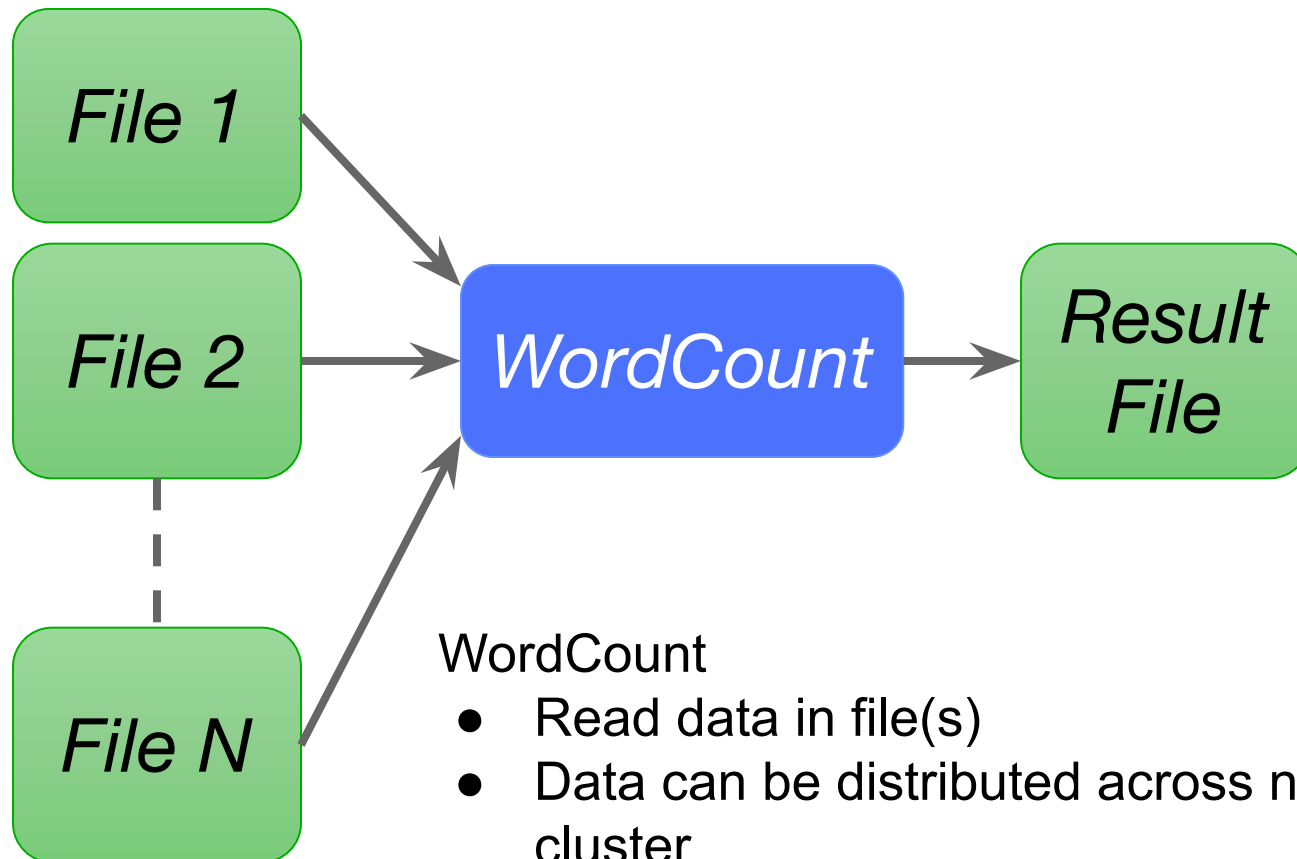
- RDDs can be processed using 2 types of operations
 - **Transformation:** Creates new RDD from existing RDD
 - **Action:** Runs computation(s) on RDD and returns value



LAZY EVALUATION

- Transformations on RDDs have **lazy evaluation**
 - Transformations are not immediately processed
 - Plan of operations is built
- Operations executed when **action** is performed
 - i.e., actions force computation
- Allows for optimizations in generating physical plan
- Example:
 - `filtered = strings.filter(strings.value.contains("Spark"))`
 - Nothing is returned
 - `filtered.count()`
 - 'filter' is performed, and count is returned

WordCount

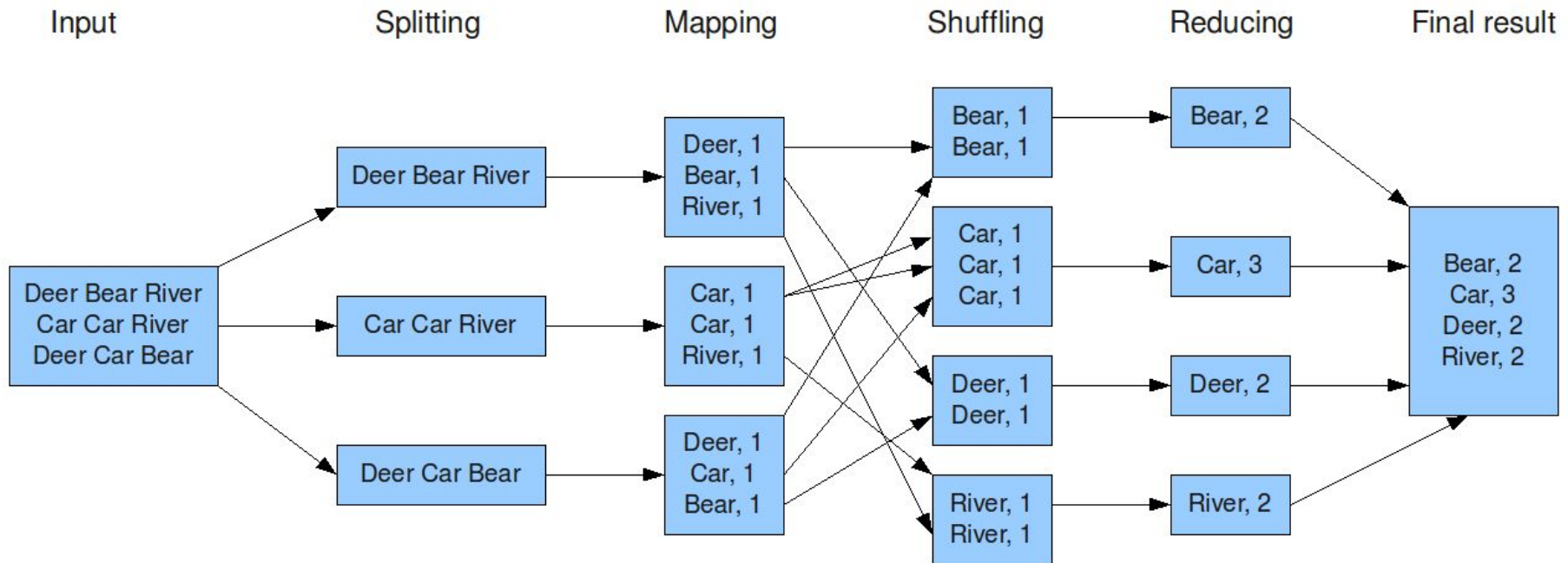


WordCount

- Read data in file(s)
- Data can be distributed across nodes in cluster
- Count number of occurrences of each word

WordCount

The overall MapReduce word count process



<https://www.todaysoftmag.com/article/1358/hadoop-mapreduce-deep-diving-and-tuning>

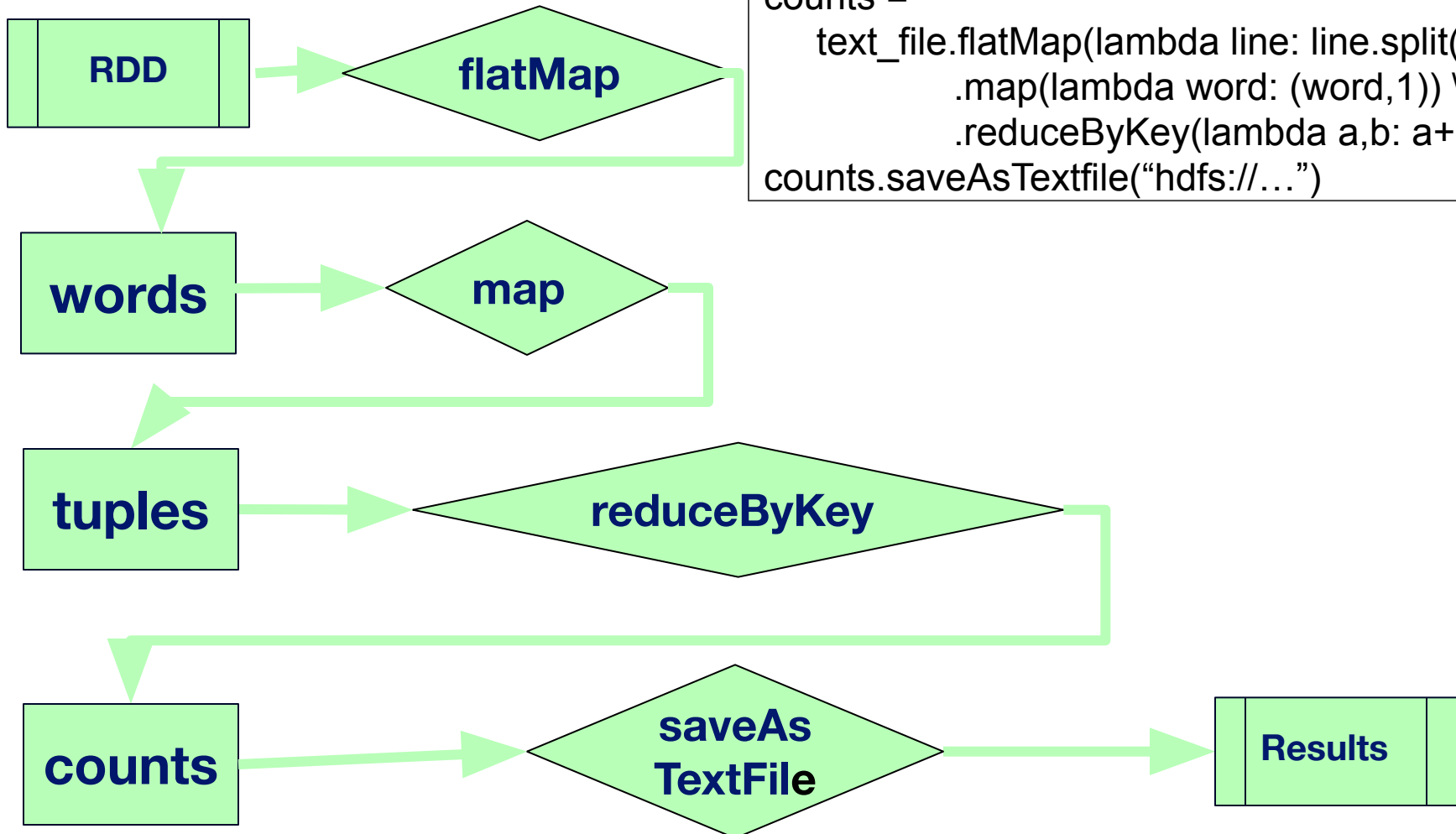
Data is partitioned
across nodes

Map generates
key-value pairs

Pairs with same
key moved to
same node

Reduce sums
values for each key

WordCount (RDD)



```
text_file = sc.textFile("hdfs://..")
counts =
    text_file.flatMap(lambda line: line.split(" ")) \
                .map(lambda word: (word,1)) \
                .reduceByKey(lambda a,b: a+b)
counts.saveAsTextfile("hdfs://...")
```

DATAFRAMES & DATASETS

- **Extensions to RDDs**
 - Higher-level abstractions
 - Improved performance
 - Better scalability
- **Can convert to/from RDDs and use with RDDs**

DATAFRAMES & DATASETS

DataFrame

- Lazy evaluation
- Data organized as collection of Rows
- No static type checking
- APIs in Java, Scala, Python, R

DataSet

- Lazy evaluation
- Data organized as collection of Rows
- Provides static type checking
- APIs in Java and Scala

USING DATAFRAMES

- Spark Session
 - Entry point to Spark engine
 - Note that SparkContext is now **SparkSession**

```
from pyspark import SparkSession

conf = SparkSession \
    .builder \
    .appName("DataFrame Example") \
    .config("config.option", "config.value")

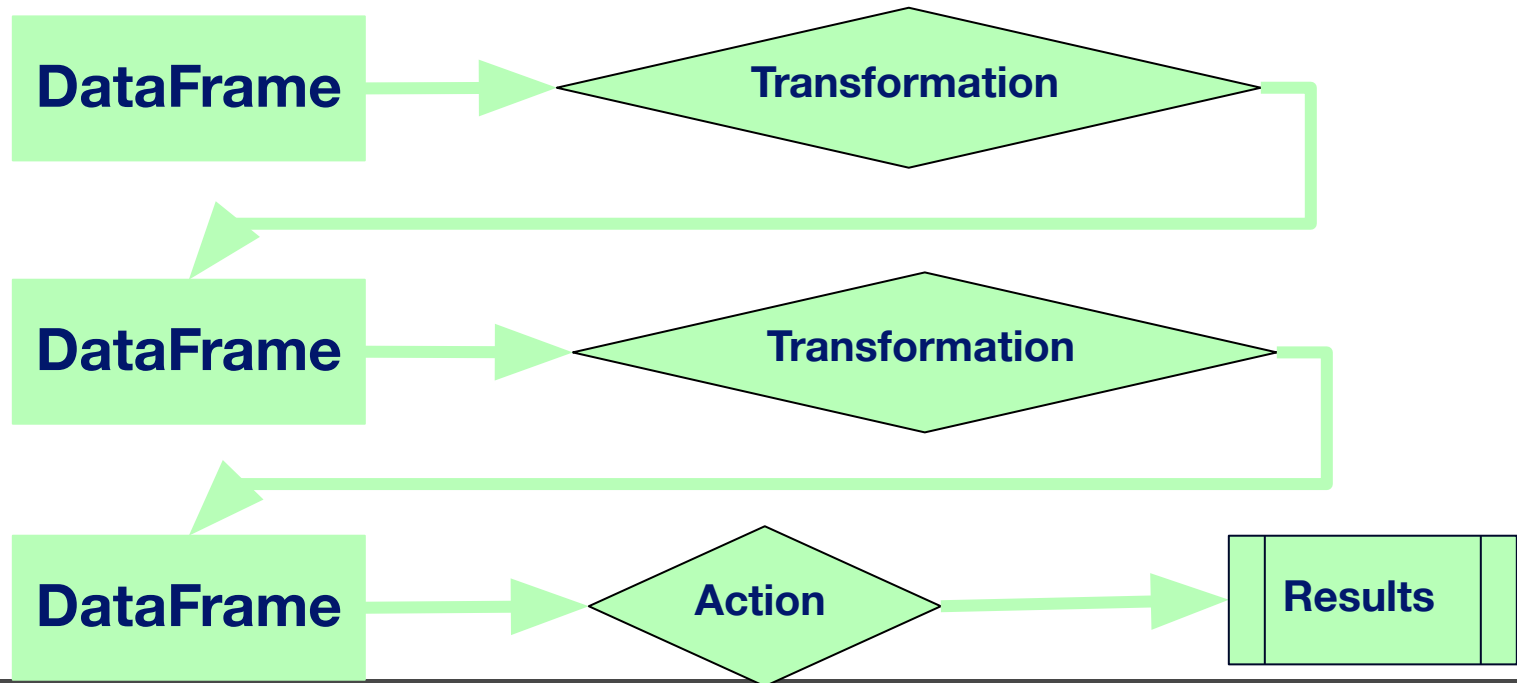
spark =
    SparkSession.builder.config(conf=conf) \
        .getOrCreate()
```

CREATING DATAFRAMES

- Read data from files in local filesystem (text, JSON, etc.)
 - `df = spark.read.csv("data.csv", header="True")`
- Data read in from data store (HDFS, RDBMS, NoSQL, etc.)
 - `df = spark.read.csv("hdfs:///<path>/data.csv")`
- Generate data
 - `empl_0 = Row(id="123", name="John")`
 - `empl_1 = Row(id="456", name="Mary")`
 - `employees = [empl_0, empl_1]`
 - `df = spark.createDataFrame(employees)`
- Created by transforming another DataFrame
 - `filter_df = df.filter(col("name")== "Mary")`

DATAFRAME TRANSFORMATIONS & ACTIONS

- Similar to RDDs, DataFrames can be processed using transformations and actions
- Transformations on DataFrames also have lazy evaluation
- Operations executed when action is performed



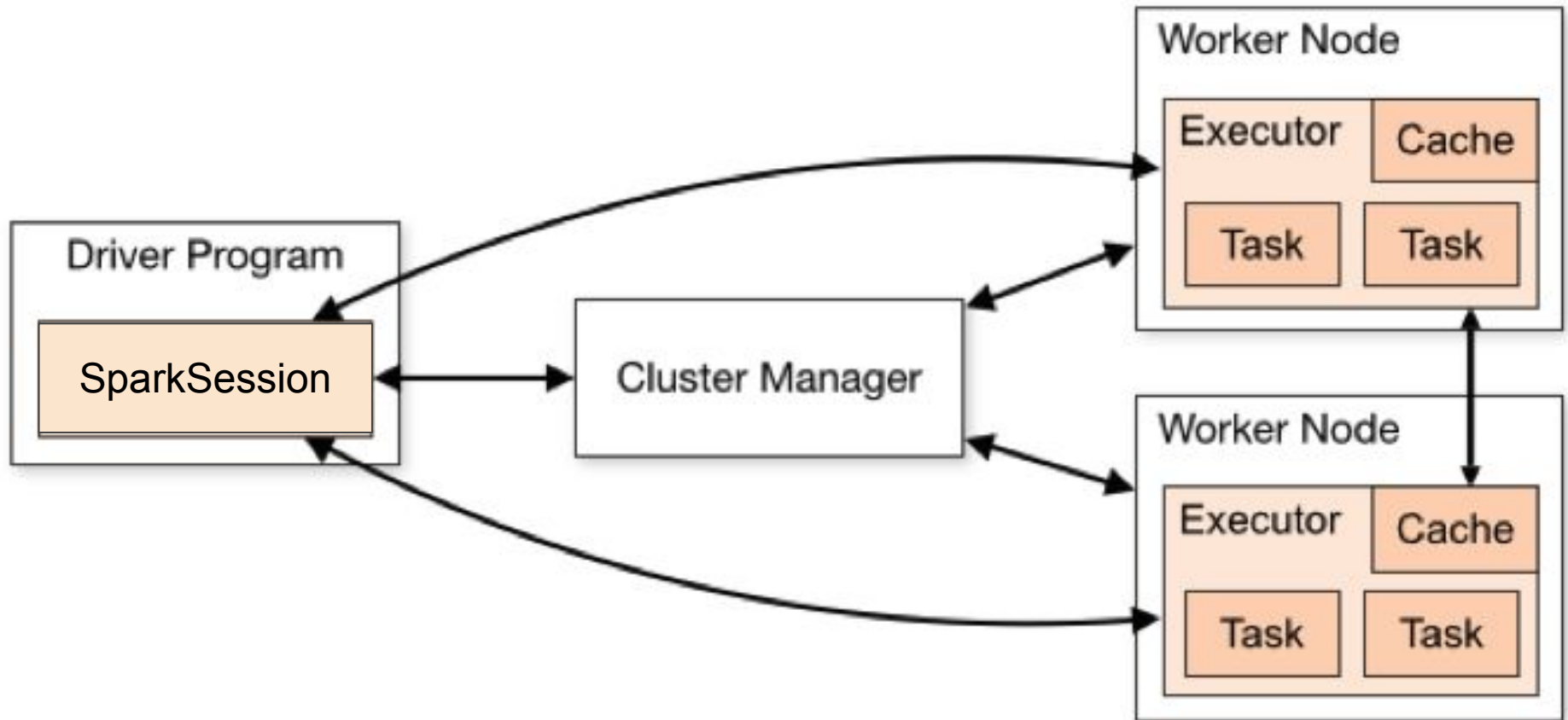
DATA PERSISTENCE

- Persist data through caching
 - Data is stored in memory to avoid re-computing
- Can specify different storage levels
 - In memory, on disk, serialized in memory, etc.
- Examples
 - `df.cache()` – MEMORY_ONLY
 - `df.persist(MEMORY_ONLY_SER)` – Serialized in memory
 - `df.unpersist()` – Remove from cache

SPARK PROGRAM STRUCTURE

- **Start Spark session**
 - `spark = SparkSession.builder.config(conf=conf).getOrCreate()`
- **Create distributed dataset**
 - `df = spark.read.csv("data.csv",header="True")`
- **Apply transformations**
 - `new_df = df.filter(col("dept") == "Sales")`
- **Perform actions**
 - `df.collect()`
- **Stop Spark session**
 - `spark.stop()`

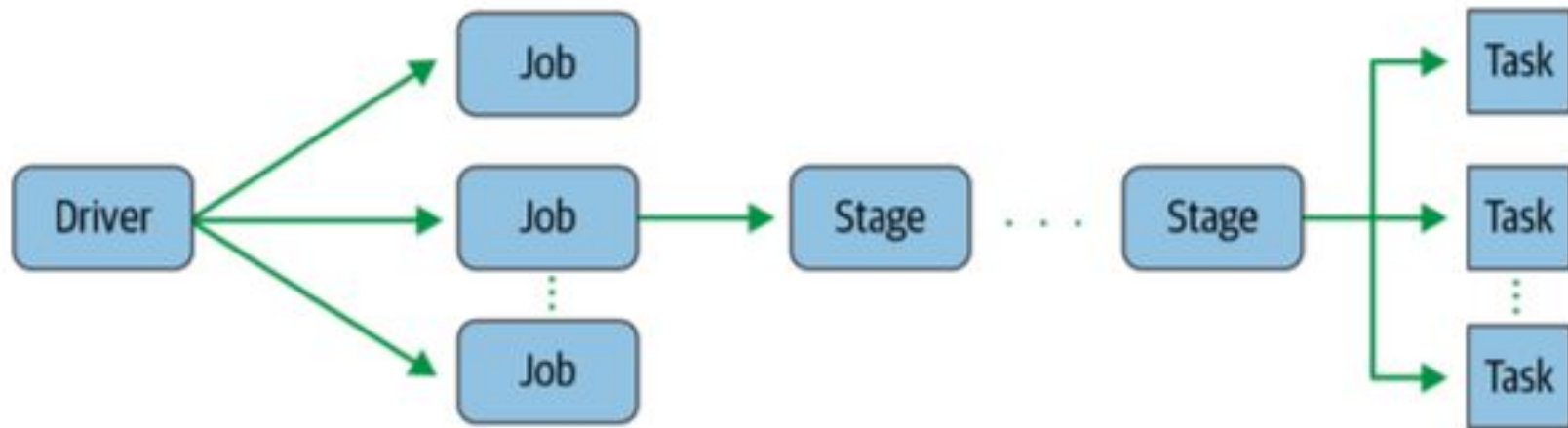
SPARK ARCHITECTURE



SPARK PROCESS CONCEPTS

- **Application**
 - User program consists of driver program and executors on cluster
- **SparkSession**
 - Object that provides point of entry to interact with underlying Spark functionality using Spark APIs
- **Job**
 - Parallel computation consisting of multiple operations that are executed in response to Spark actions
- **Stage**
 - Each job gets divided into smaller units called stages
- **Task**
 - Single unit of work or execution sent to executor

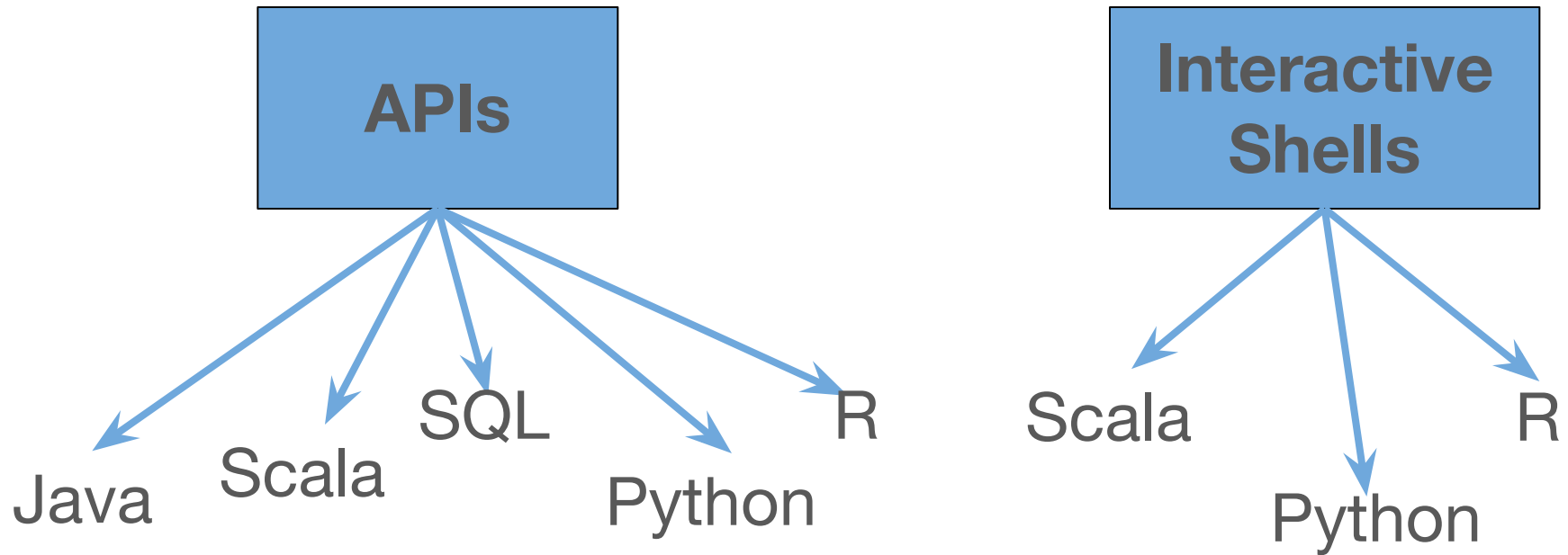
SPARK APPLICATION



- Driver creates SparkSession object
- Driver converts Spark application into one or more jobs
- An action creates a job
- DAG (directed acyclic graph) of instructions built for each job
- Each node in DAG is single or multiple Spark stages
- Each stage is broken down into tasks
- Tasks are distributed to executors

SPARK INTERFACE

Goals: speed, **ease of use**, generality, unified platform



RDD WORDCOUNT EXAMPLE IN SPARK

Spark RDD API available in Python, Scala, Java, and R

```
text_file = sc.textFile("hdfs://...")
counts = text_file.flatMap(lambda line: line.split(" ")) \
    .map(lambda word: (word, 1)) \
    .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs://...")
```

```
val textFile = sc.textFile("hdfs://...")
val counts = textFile.flatMap(line => line.split(" "))
    .map(word => (word, 1))
    .reduceByKey(_ + _)
counts.saveAsTextFile("hdfs://...")
```

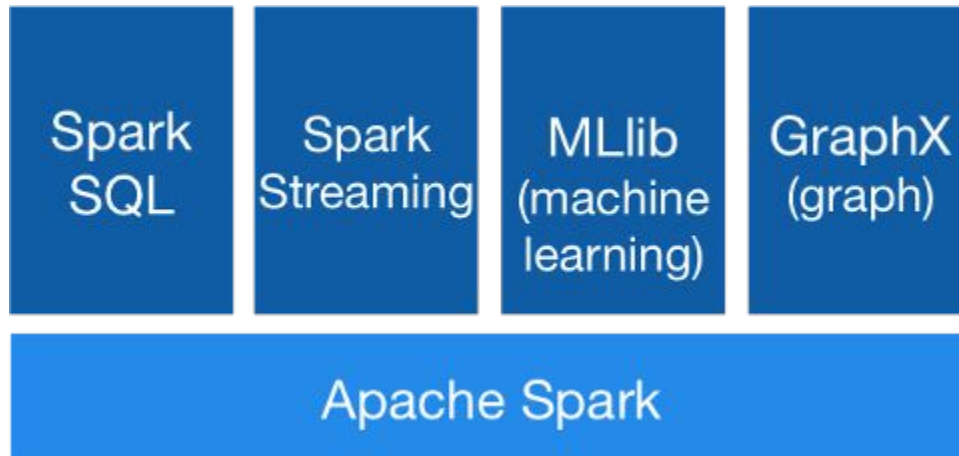
```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" ")).iterator())
    .mapToPair(word -> new Tuple2<>(word, 1))
    .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```

SPARK - GENERALITY

- Goals: speed, ease of use, **generality**, unified platform
- Support for several data sources
 - Local file systems, HDFS, RDBMSs, MongoDB, Kafka, AWS S3, etc.
- Can run on various platforms
 - Hadoop, Kubernetes, cloud, standalone
- Support for multiple workloads
 - batch, streaming
 - machine learning, SQL, graph processing

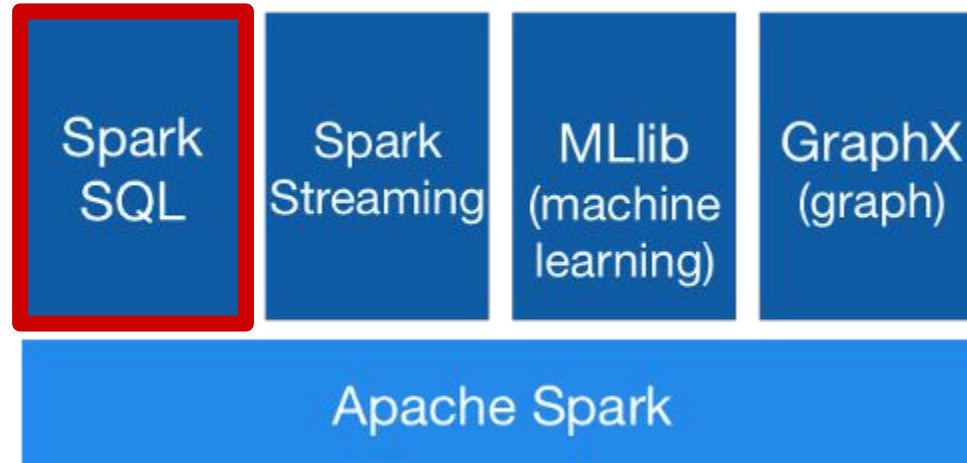
SPARK - UNIFIED PLATFORM

- Goals: speed, ease of use, generality, **unified platform**



- Provides unified platform for various analytics processing
- **Spark engine** provides core capabilities for distributed processing
- **Spark libraries** provide additional higher-level functionality for diverse workloads

SPARK SQL



- **Structured Data Processing**

- Provides support for SQL and query processing
- Structure of data and computations allow for efficient query plan can be constructed
- Has APIs for SQL, Scala, Java, Python, and R
- Generated underlying code is identical

SPARK SQL

- Execute SQL queries

- SQL

```
spark.sql("SELECT max(count)  
FROM flight_data").take(1)
```

- PySpark

```
from pyspark.sql.functions import max  
flight_data.select(max("count")).take(1)
```

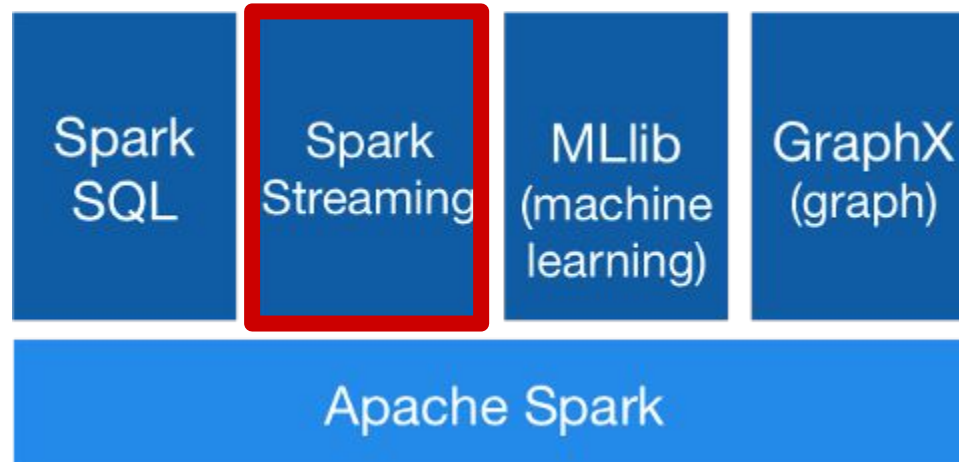
SPARK SQL

- Integrate SQL queries with Spark commands

```
df = spark.sql ("SELECT * FROM Employees")  
df.show(100)
```

```
num_employees =  
    df.select("Age","Dept","Salary")  
        .groupBy("Dept")  
        .where(df.Salary > 80000)  
        .count()
```

SPARK STREAMING



- **Streaming Data Processing**
 - Scalable processing for real-time analytics
 - Structured streaming
 - Data stream is divided into micro-batches of data
 - Same operations for static data can be used
 - Has APIs for Scala, Java, and Python

REAL-TIME ANALYTICS

- (Near) Real-Time Analytics
 - Analysis and use of data as it enters system
- Examples
 - Identifying fraudulent credit card transaction at point-of-sale
 - Viewing orders as they happen for up-to-date inventory tracking and trend analysis
 - Understanding trending topics of tweets/news articles/etc.

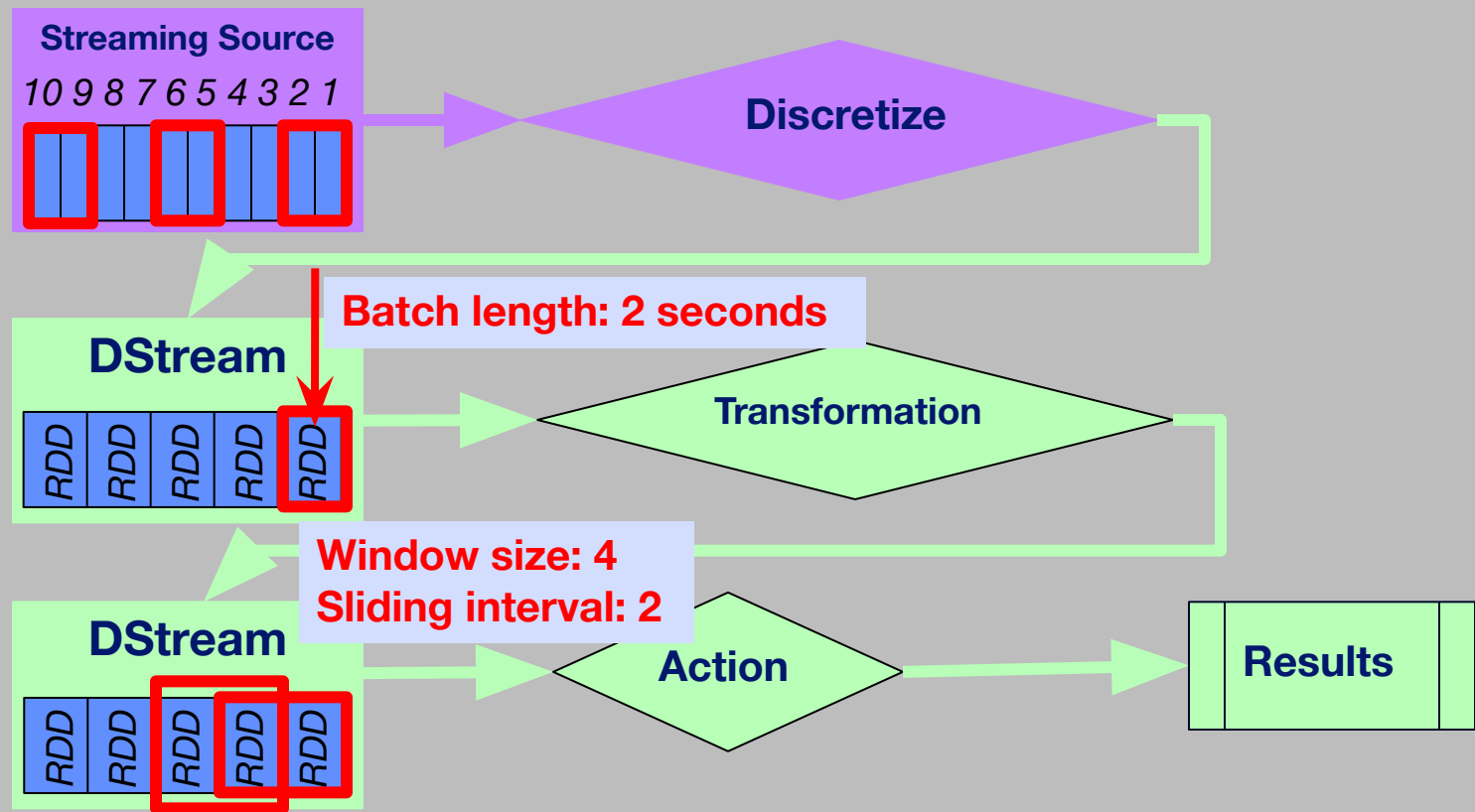
SPARK STREAMING

- Input data stream is divided into batches of data that are processed by Spark engine
- DStream: high-level abstraction
 - Implemented as sequence of RDDs
- Any Spark operation can be applied to DStreams

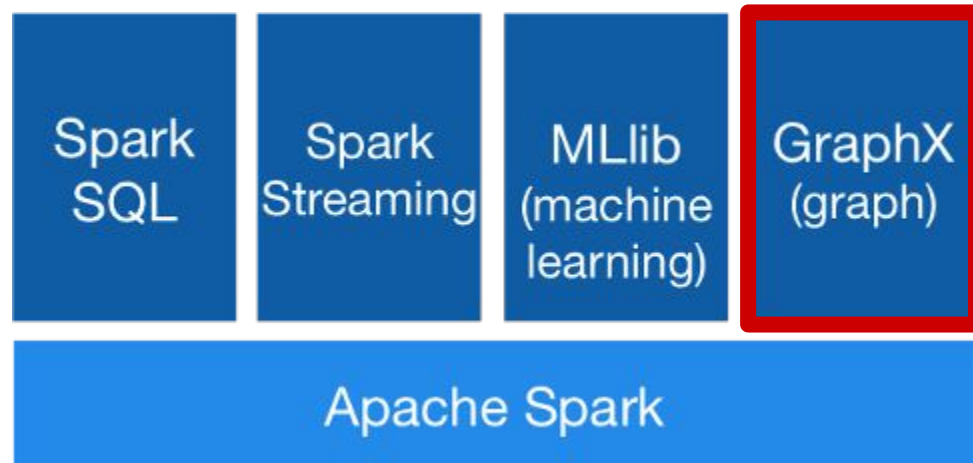


<https://spark.apache.org/docs/latest/streaming-programming-guide.html>

SPARK STREAMING



SPARK GRAPHX / GRAPHFRAMES

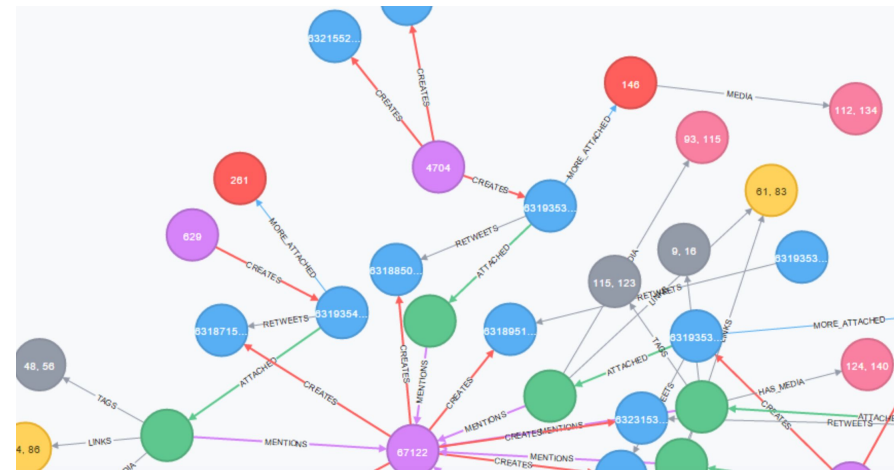


- **Graph Computation**

- Distributed graph processing
- Special structures for storing vertex and edge information & operations for manipulating graphs
- GraphX (RDD-based) & GraphFrames (DF-based)
- Has APIs in Scala, Java, Python (GraphFrames)

SPARK GRAPHX / GRAPHFRAMES

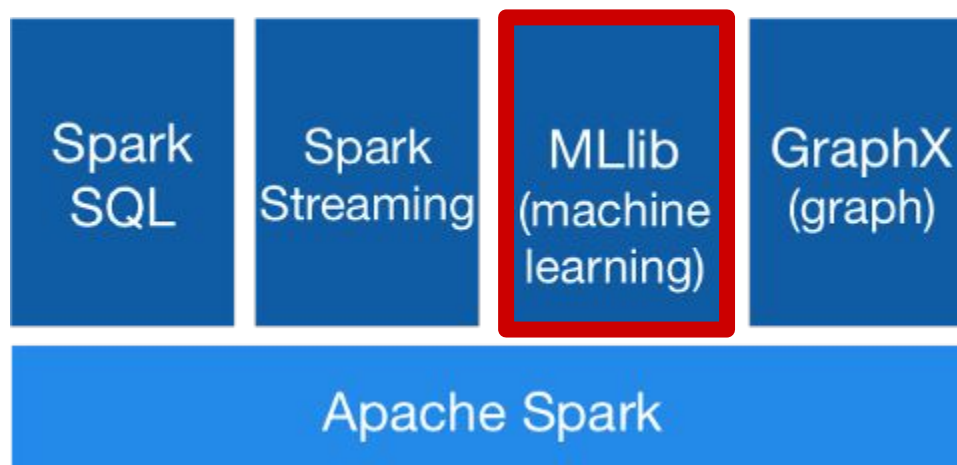
- **Graph analytics**
 - Analysis of relations among entities
- **Data represented as graph**
 - Entities are vertices
 - Relationships are edges
- **Example: Analyzing tweets**
 - Extract conversation threads
 - Find interacting groups
 - Find influencers in community



SPARK GRAPHX / GRAPHFRAMES

- Graph operators & algorithms
 - Connected Components
 - PageRank
 - Triangle Counting
 - Label Propagation Algorithm
 - Shortest Paths

SPARK MLLIB



- **Machine Learning**

- Scalable machine learning library
- Distributed implementations of machine learning algorithms and utilities
- Has APIs for Scala, Java, Python, and R

SPARK MLLIB ALGORITHMS

- **Machine Learning**
 - Classification, regression, clustering, etc.
 - Evaluation metrics
- **Statistics**
 - Summary statistics, sampling, etc.
- **Utilities**
 - Dimensionality reduction, transformation, etc.
- **ML Pipelines**
 - Similar to scikit-learn

MLLIB EXAMPLE: STATISTICS

```
from pyspark.sql.functions import rand
```

```
# Generate random numbers
```

```
df = sqlContext.range(0,10)  
    .withColumn("rand1", rand(seed=10))  
    .withColumn("rand2", rand(seed=27))
```

```
# Show summary statistics
```

```
df.describe().show()
```

```
# Compute correlation
```

```
df.stat.corr("rand1", "rand2")
```

MLLIB EXAMPLE: CLUSTER ANALYSIS

```
from pyspark.ml.clustering import KMeans
```

```
# Read and parse data
```

```
data = spark.read.csv("data.csv", header="true")
```

```
# k-means model for clustering
```

```
kmeans = Kmeans().setK(3).setSeed(123)
```

```
model = kmeans.fit (data)
```

```
for center in model.clusterCenters()  
    print (center)
```

MLLIB EXAMPLE: CLASSIFICATION

```
from pyspark.ml.classification import DecisionTreeClassifier
```

```
# Split data into train & test sets
```

```
trainDF, testDF = data.randomSplit([0.7, 0.3], seed=123)
```

```
# Build model
```

```
dt = DecisionTreeClassifier(  
    featuresCol='features',  
    labelCol='label',  
    predictionCol='prediction')  
model = dt.fit(trainDF)
```

```
# Test model
```

```
predictions = model.transform(testDF)
```

MLLIB LIBRARIES

ml

(DataFrame-based)

mllib

(RDD-based)

The screenshot shows the Apache Spark MLib Guide page. A red arrow points from the 'ml' label to the 'MLlib: Main Guide' link in the sidebar. A green arrow points from the 'mllib' label to the 'MLlib: RDD-based API Guide' link in the sidebar. The main content area displays the 'Machine Learning Library (MLlib) Guide' and an announcement about the DataFrame-based API.

MLlib: Main Guide

- Basic statistics
- Data sources
- Pipelines
- Extracting, transforming and selecting features
- Classification and Regression
- Clustering
- Collaborative filtering
- Frequent Pattern Mining
- Model selection and tuning
- Advanced topics

MLlib: RDD-based API Guide

- Data types
- Basic statistics
- Classification and regression
- Collaborative filtering
- Clustering
- Dimensionality reduction
- Feature extraction and transformation
- Frequent pattern mining
- Evaluation metrics
- PMML model export
- Optimization (developer)

Machine Learning Library (MLlib) Guide

MLlib is Spark's machine learning (ML) library. Its goal is to make practical machine learning scalable and easy. At a high level, it provides tools such as:

- ML Algorithms: common learning algorithms such as classification, regression, clustering, and collaborative filtering
- Featurization: feature extraction, transformation, dimensionality reduction, and selection
- Pipelines: tools for constructing, evaluating, and tuning ML Pipelines
- Persistence: saving and load algorithms, models, and Pipelines
- Utilities: linear algebra, statistics, data handling, etc.

Announcement: DataFrame-based API is primary API

The MLlib RDD-based API is now in maintenance mode.

As of Spark 2.0, the [RDD](#)-based APIs in the `spark.mllib` package have entered maintenance mode. The primary Machine Learning API for Spark is now the [DataFrame](#)-based API in the `spark.ml` package.

What are the implications?

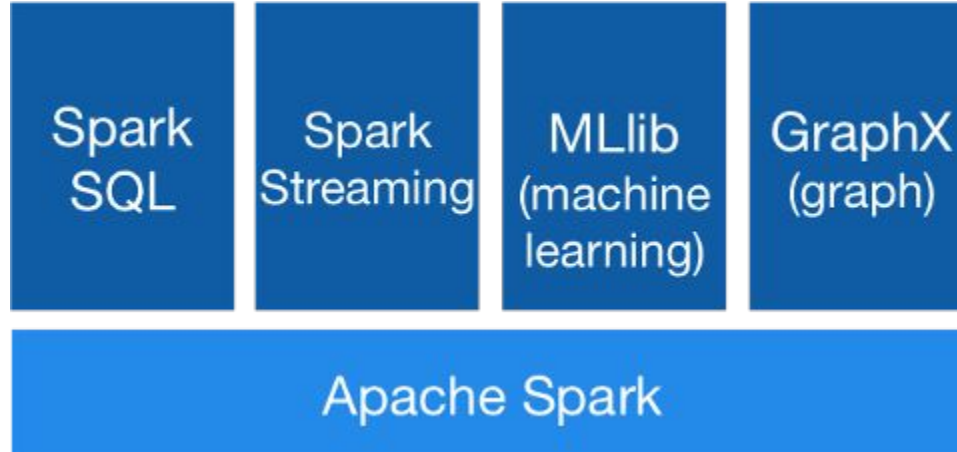
- MLlib will still support the RDD-based API in `spark.mllib` with bug fixes.
- MLlib will not add new features to the RDD-based API.
- In the Spark 2.x releases, MLlib will add features to the DataFrames-based API to reach feature parity with the RDD-based API.
- After reaching feature parity (roughly estimated for Spark 2.3), the RDD-based API will be deprecated.
- The RDD-based API is expected to be removed in Spark 3.0.

Why is MLlib switching to the DataFrame-based API?

- DataFrames provide a more user-friendly API than RDDs. The many benefits of DataFrames include Spark Datasources, SQL/DataFrame queries, Tungsten and Catalyst optimizations, and uniform APIs across languages.
- The DataFrame-based API for MLlib provides a uniform API across ML algorithms and across multiple languages.
- DataFrames facilitate practical ML Pipelines, particularly feature transformations. See the [Pipelines guide](#) for details.

What is "Spark ML"?

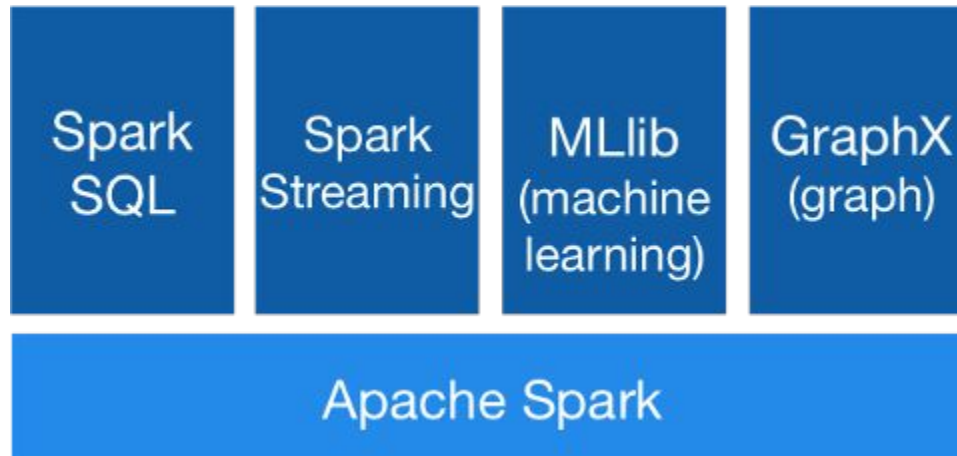
SPARK LIBRARIES



- **Spark Libraries**

- Use Spark engine as core
- Extend functionality to particular applications
- Third-party packages: <https://spark-packages.org>

SPARK



Goals: speed, ease of use, generality, unified platform

Spark

- Goals: speed, ease of use, generality, unified platform
- RDDs
 - Transformations & actions
 - Lazy evaluation
- DataFrames & DataSets
- Spark program structure
- Spark architecture
- Spark process concepts
- Spark APIs & interactive shells
- Support for different platforms & workloads
- Spark libraries

Spark Demo

- **Demo**
 - PySpark
 - To show common DataFrame operations
- **Code**
 - `3.3_spark/pyspark-intro/pyspark-dataframe.ipynb`