



2110446 - Data Science and Data Engineering

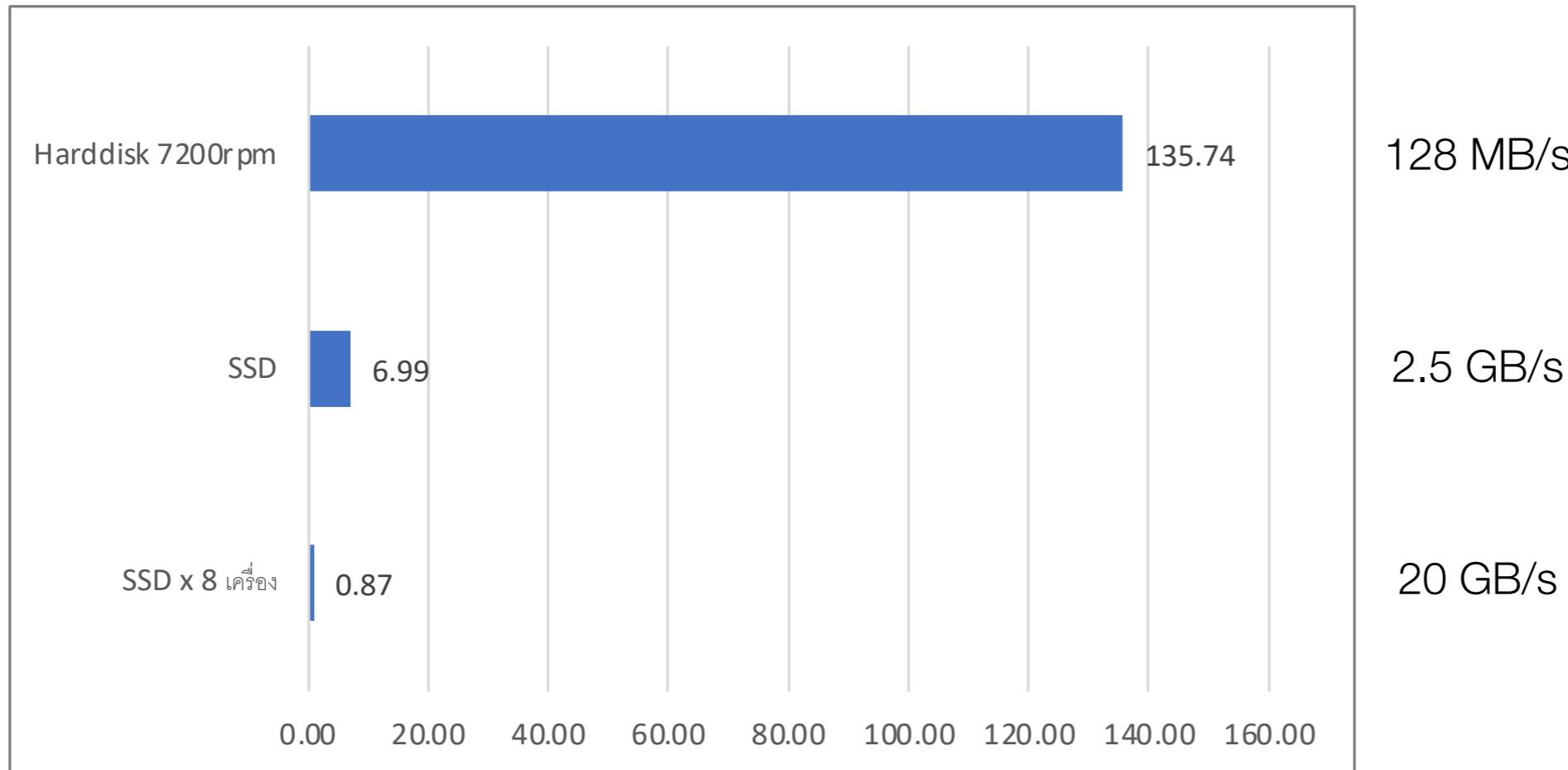
## **Big Data Processing with Spark**

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Chulalongkorn University  
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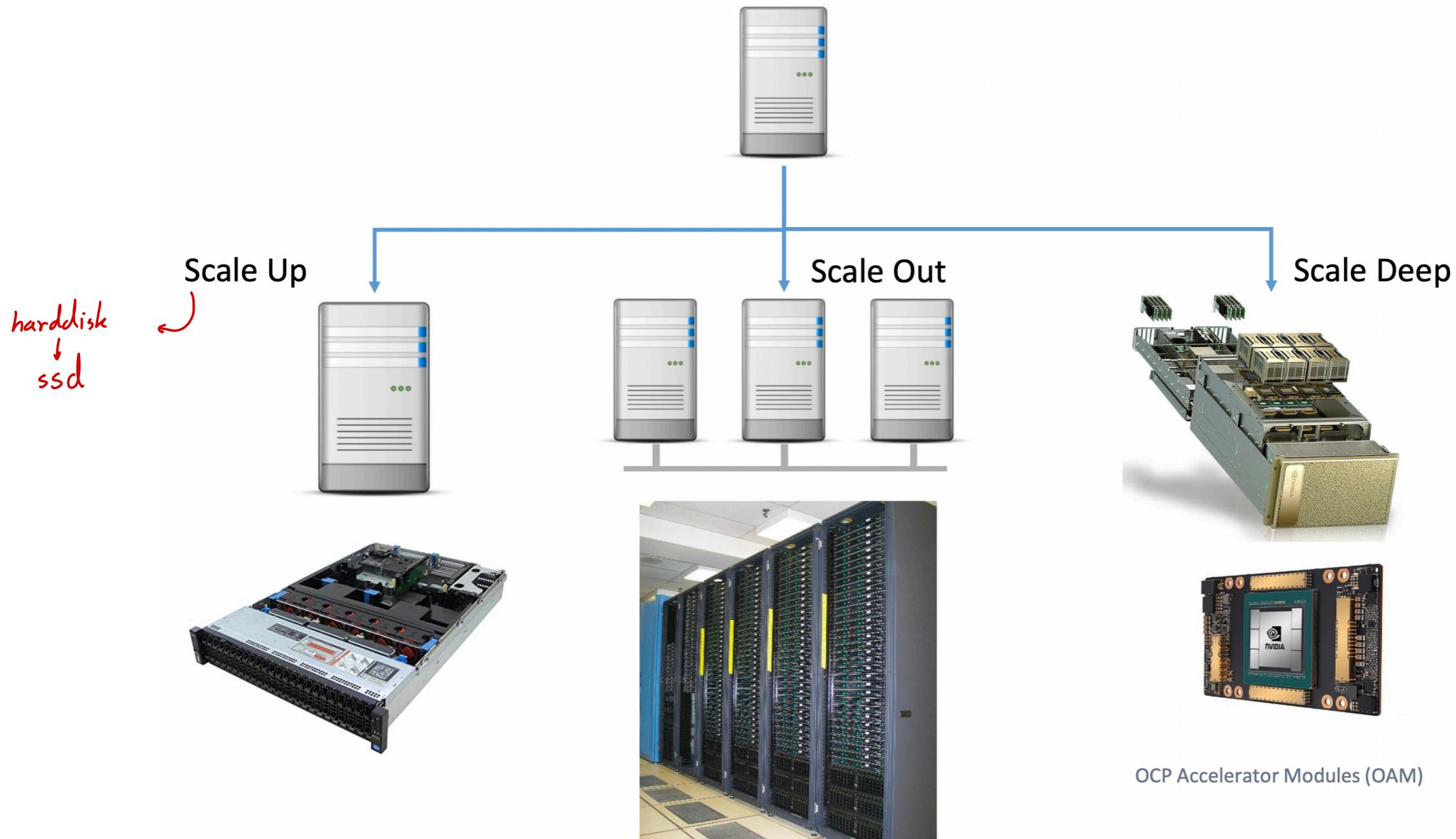
# Limitations of Disk Data Transfer Bandwidth

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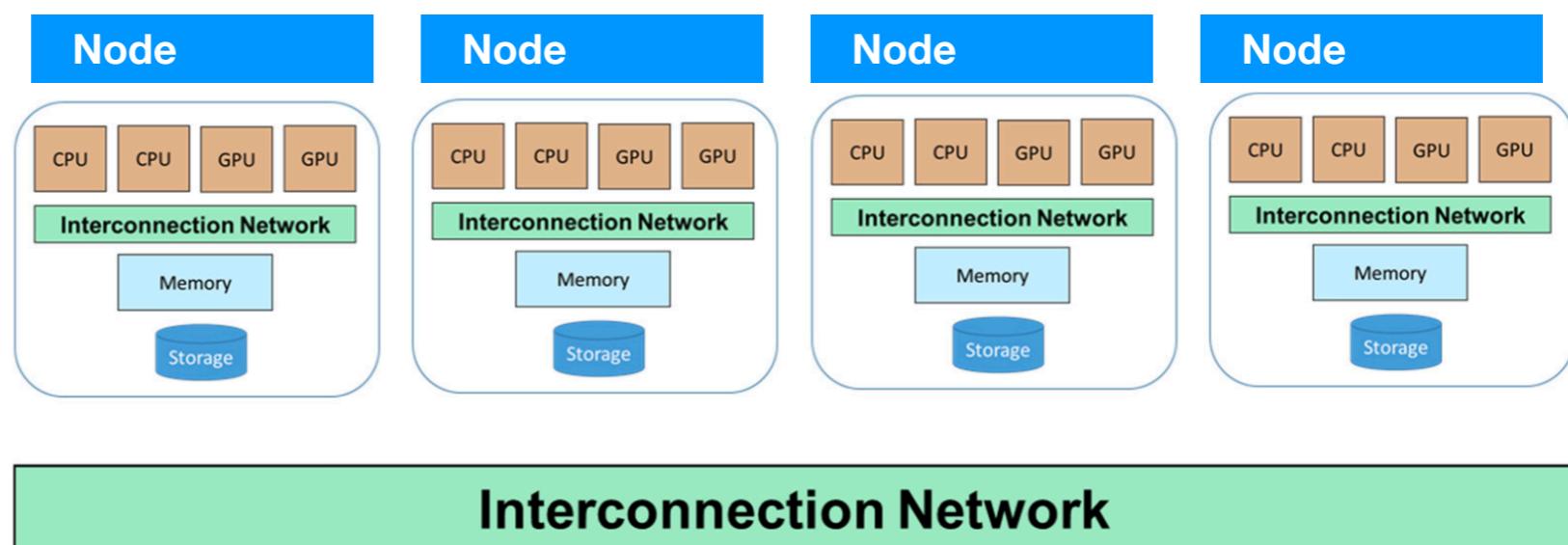
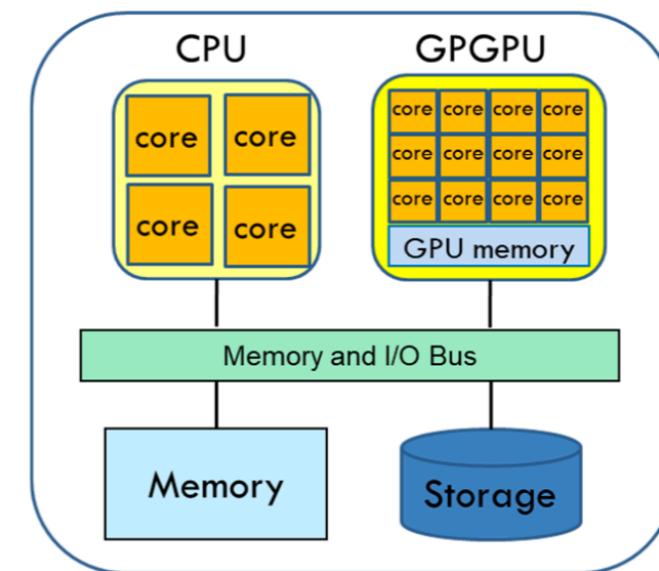
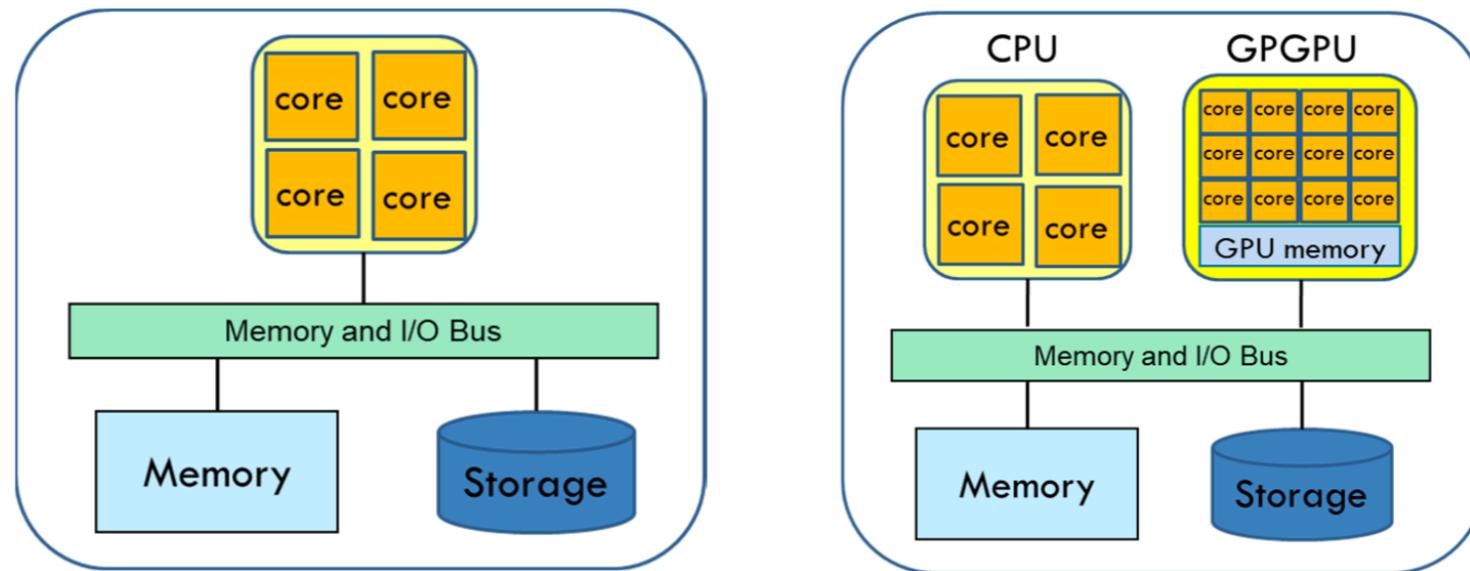


Theoretical time (in minutes) to read 1-TB data from disks

# Scale Up / Scale Out / Scale Deep



# Cluster Computing

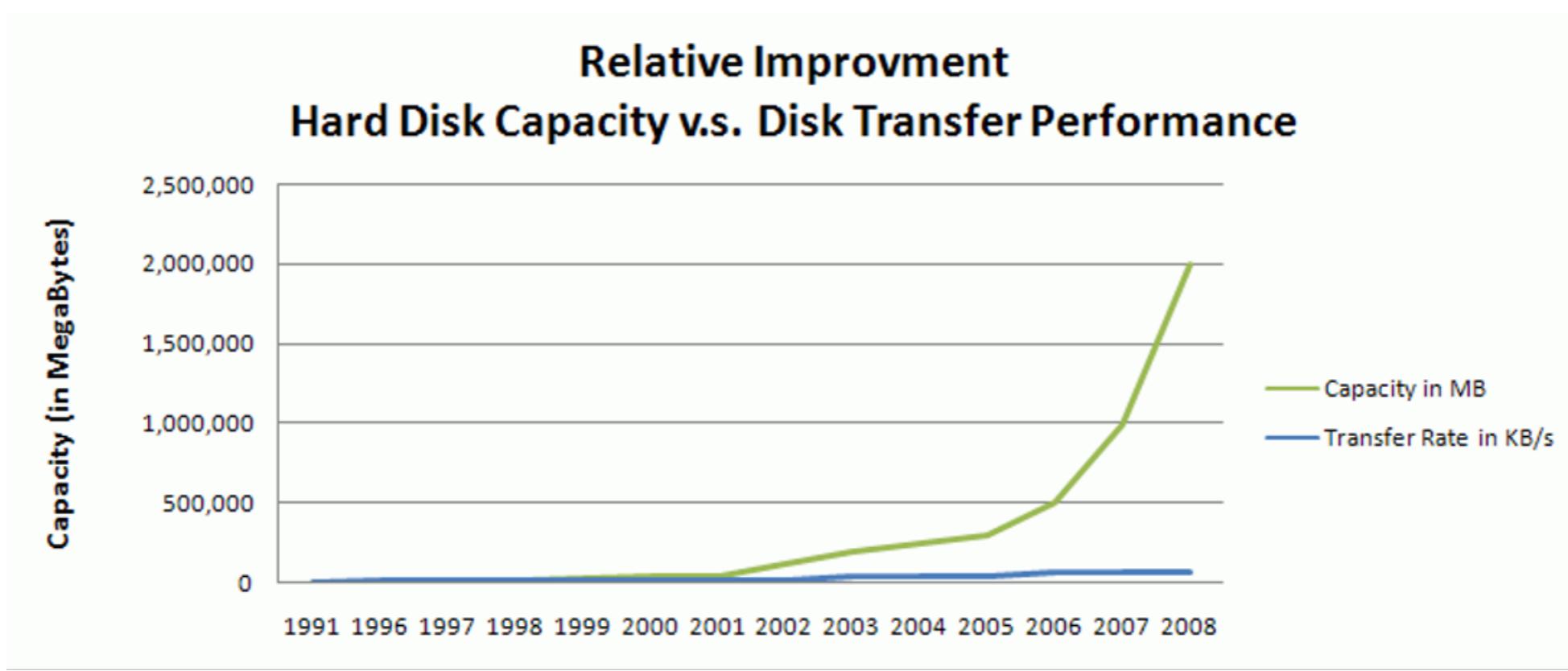


# Early Days of Big Data - Apache Hadoop

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- Opensource software framework inspired by Google Search Engine Architecture
  - Provide easy-to-program scale-out foundation for data-intensive applications on large clusters of commodity hardware
    - Three key components: cheap cluster, MapReduce, HDFS
      - Hadoop File System (HDFS) has been widely used
      - Users: Yahoo!, Facebook, Amazon, eBay, American Airline, Apple, Google, HP, IBM, Microsoft, Netflix, New York Times, etc.
- parallel system 1000*
- Map Reduce 1000*
- replace spark*

# Understand Hadoop in Principles



Source: <http://wiki.r1soft.com/pages/viewpage.action?pageId=3016608>

- Disk data transfer improves very slowly → මෙයින්ම disk හේතුවෙන්
- Solution: scale-out with cluster – processing data on multiple disks in parallel

# Understand Hadoop in Principles

---

- Hadoop relies on processing data from multiple disks
  - High throughput
  - Parallel programming is required
  - MapReduce simplifies parallel programming on multiple-disk cluster
- Cheap cluster can suffer from failure very frequently
- Failure recovery and data replication mechanisms

# Hadoop Limitations

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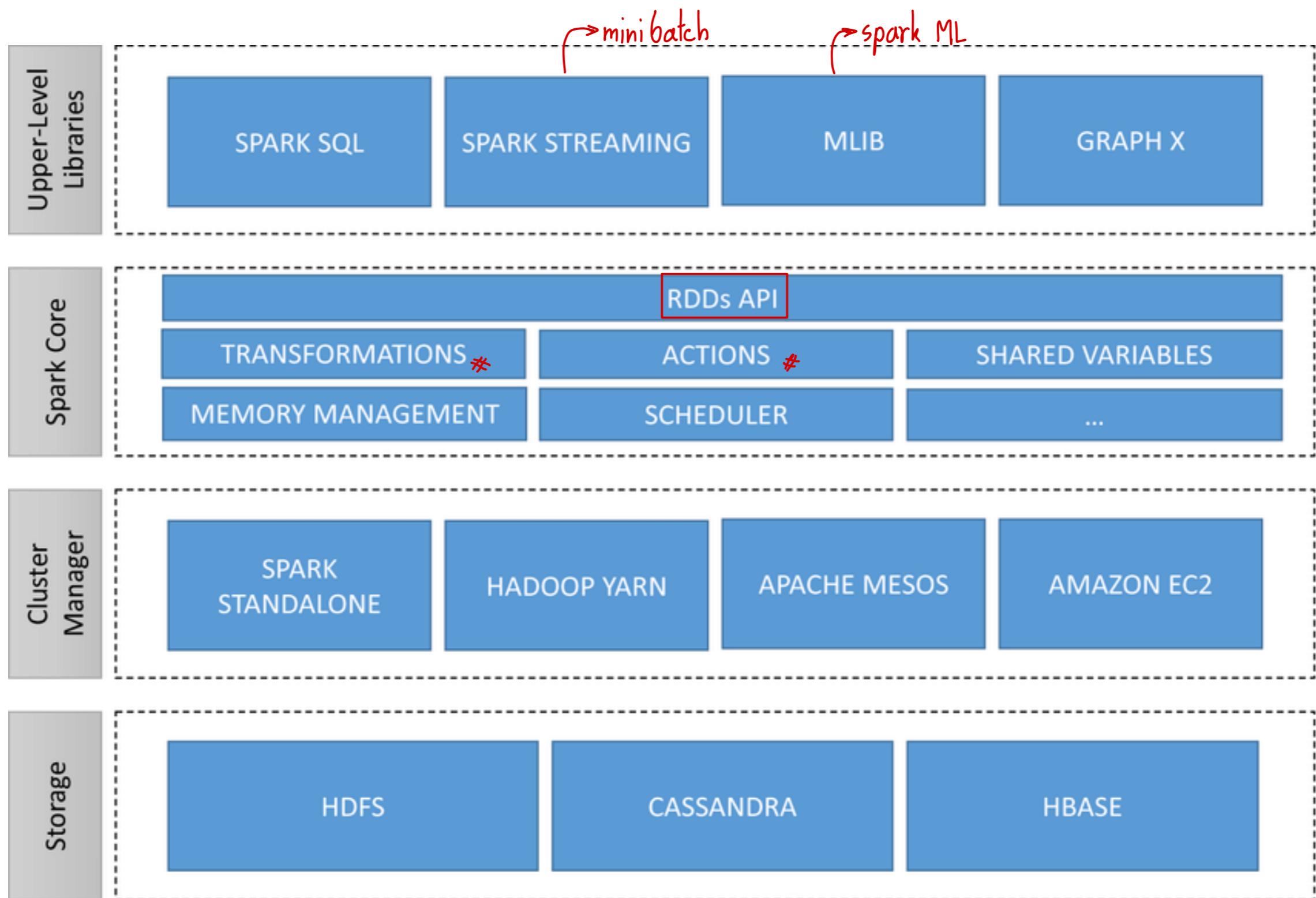
- Hadoop is disk-oriented
- Suitable for Batch System; No real-time, repetitive queries
- Data Scientist = Analyze, Discover, Investigate

↳ இந்துகள் Interactive → Hadoop பிள்ளை

# Apache Spark

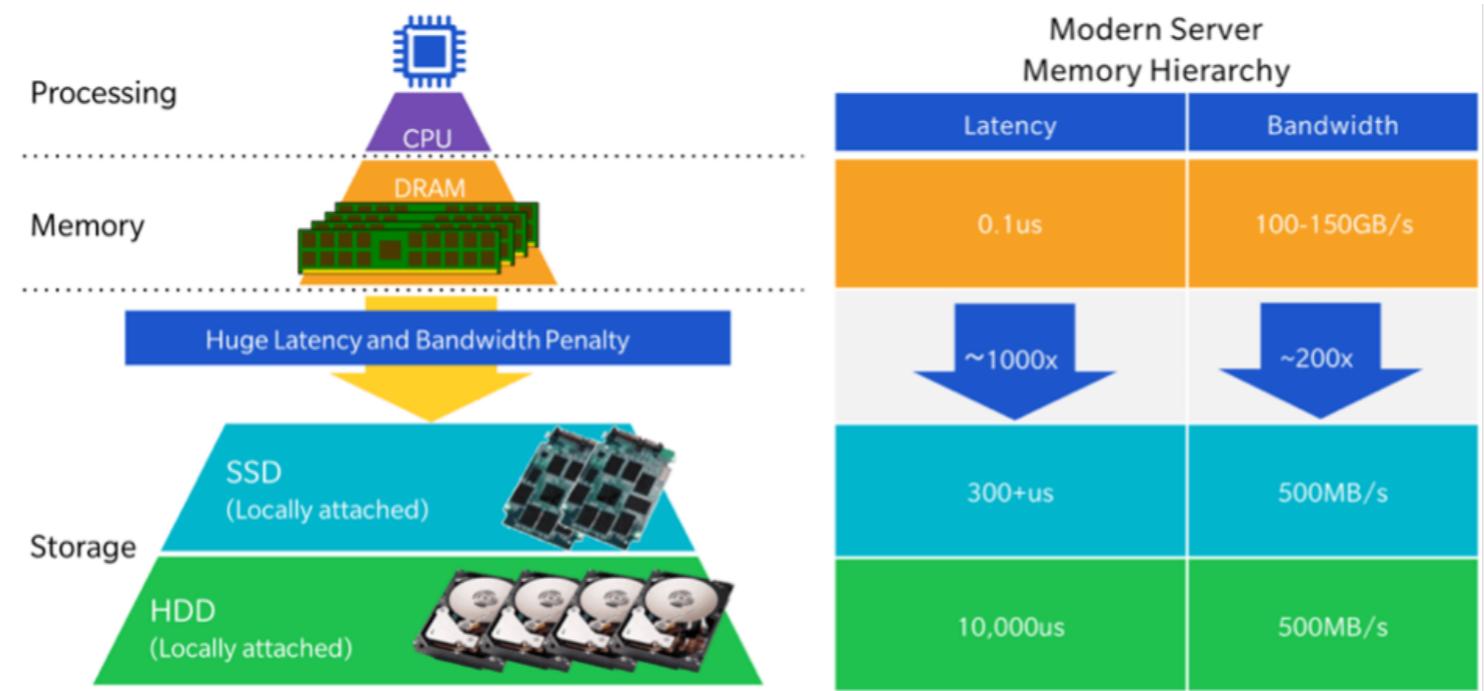
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- **Spark = In-Memory Data Processing**
  - Extend MapReduce model to support interactive queries and stream processing
  - Keep data in memory as long as possible
  - Spark supports interactive queries with Spark Shell (Scala, Python, and R)
- Data Scientist Friendly
  - Low latency (interactive) queries on historical data
  - Low latency queries on live data (streaming)
  - Compatibility with popular systems (Hadoop) → *spark on top HDFS*



# Spark's Principles

- Aggressive use of memory
- Memory transfer rates  $\gg$  disk or even SSDs
- Many datasets already fit into memory
  - E.g., 1TB = 1 billion records @ 1 KB each
- Memory density (still) grows with Moore's law - RAM/SSD hybrid memories at horizon



# Spark Ecosystems

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## Data science and Machine learning



## SQL analytics and BI



## Storage and Infrastructure



# Use Cases

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- Automatic – Data Processing for IoT
- Baidu – Business insights data analytics
- Cisco – Entity resolution for Whois clean-up
- Cloudera – Financial risk estimation
- eBay – Log Transaction Analytics
- ESRI – Geospatial and temporal analysis
- Goldman Sachs – Data curation processing
- NBC Universal – Multimedia data distribution prediction
- Novartis – Genomic data analytic
- Salesforce – Recommendation engine
- Shopify – E-commerce transaction data analytics
- SK Telecom – Mobile usage pattern analytics
- Tresata – Anti-Money Laundering real-time graph analytic
- Uber – Data analytic
- Yahoo – Real-time personalization engine

# Spark Performance

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	Hadoop MR Record	Spark Record	Spark 1PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins → ×10 =	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk throughput	3150 GB/s (est.)	618 GB/s	570 GB/s
Sort Benchmark Daytona Rules	Yes	Yes	No
Network	dedicated data center, 10Gbps	virtualized(EC2)10Gbps network	virtualized(EC2)10Gbps network
<b>Sort rate</b>	<b>1.42 TB/min</b>	<b>4.27 TB/min</b>	<b>4.27 TB/min</b>
<b>Sort rate/node</b>	<b>0.67 GB/min</b>	<b>20.7 GB/min</b>	<b>22.5 GB/min</b>

# Running pyspark

---

- Install anaconda
- Download latest apache spark from [spark.apache.org](http://spark.apache.org)
- Setup proper environment variables

```
# spark environment
export SPARK_HOME=/Users/natawut/spark
export PATH="$HOME/bin:$SPARK_HOME/bin:$PATH"
export PYTHONPATH="$SPARK_HOME/python:$PYTHONPATH"

# jupyter and pyspark integration
export ANACONDA_HOME="/Users/natawut/anaconda3"
export PYSPARK_PYTHON=$ANACONDA_HOME/bin/python
export PYSPARK_DRIVER_PYTHON=$ANACONDA_HOME/bin/jupyter
export PYSPARK_DRIVER_PYTHON_OPTS="notebook"
```

# Running pyspark: direct from command line

---

- Running pyspark  
**pyspark**
- This method starts Spark standalone and connect Jupiter notebook (or spark shell) to Spark
- References
  - Linux and mac
    - <https://medium.com/@GalarnykMichael/install-spark-on-ubuntu-pyspark-231c45677de0>
  - Windows
    - <https://medium.com/@GalarnykMichael/install-spark-on-windows-pyspark-4498a5d8d66c>
  - Using pip (Linux, mac, and windows)
    - <http://sigdelta.com/blog/how-to-install-pyspark-locally/>

# Running pyspark: import packages

- Start spark cluster separately

**start-master.sh**

- Import packages at the beginning and get spark context
- This is suitable for environment with existing spark cluster e.g. production

Apache Spark 3.2.1

Spark Master at spark://192.168.68.106:7077

URL: spark://192.168.68.106:7077

Alive Workers: 0

Cores in use: 0 Total, 0 Used

Memory in use: 0.0 B Total, 0.0 B Used

Resources in use:

Applications: 0 Running, 0 Completed

Drivers: 0 Running, 0 Completed

Status: ALIVE

Workers (0)

Worker Id	Address	State	Cores	Memory	Resources

Running Applications (0)

Application ID	Name	Cores	Memory per Executor	Resources Per Executor	Submitted Time	User	State	Duration

Completed Applications (0)

Application ID	Name	Cores	Memory per Executor	Resources Per Executor	Submitted Time	User	State	Duration

<http://localhost:8080>

```
In [1]: import os
import pyspark
from pyspark.sql import SQLContext, SparkSession
```

```
In [2]: spark = SparkSession \
    .builder \
    .master('spark://192.168.68.106:7077') \
    .appName("sparkFromJupyter") \
    .getOrCreate()

sc = spark.sparkContext
sqlContext = SQLContext(sparkContext=sc, sparkSession=spark)

WARNING: An illegal reflective access operation has occurred
WARNING: Illegal reflective access by org.apache.spark.unsafe.Platform (file:/opt/spark/jars/spark-unsafe_2.12-3.2.1.jar) to constructor java.nio.DirectByteBuffer(long,int)
WARNING: Please consider reporting this to the maintainers of org.apache.spark.unsafe.Platform
WARNING: Use --illegal-access=warn to enable warnings of further illegal reflective access operations
WARNING: All illegal access operations will be denied in a future release
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
22/02/02 11:46:38 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-jav
va classes where applicable
```

```
In [3]: sc
```

```
Out[3]: SparkContext
```

[Spark UI](#)  
**Version**  
v3.2.1  
**Master**  
spark://192.168.68.106:7077  
**AppName**  
sparkFromJupyter

```
In [4]: sqlContext
```

```
Out[4]: <pyspark.sql.context.SQLContext at 0x7f87b0aebdf0>
```

```
In [5]: spark.stop()
```

```
In [ ]:
```

# Using findspark to start a Spark local cluster in Google Colab

The screenshot shows a Google Colab notebook interface. The title bar indicates the file is named '2\_Spark\_SQL.ipynb'. The notebook content is organized into sections:

- Spark Preparation**:
  - We check if we are in Google Colab. If this is the case, install all necessary packages.
  - To run spark in Colab, we need to first install all the dependencies in Colab environment i.e. Apache Spark 3.3.2 with hadoop 3.2, Java 8 and Findspark to locate the spark in the system. The tools installation can be carried out inside the Jupyter Notebook of the Colab. Learn more from [A Must-Read Guide on How to Work with PySpark on Google Colab for Data Scientists!](https://www.analyticsvidhya.com/blog/2020/11/a-must-read-guide-on-how-to-work-with-pyspark-on-google-colab-for-data-scientists/)
- Code Cells**:
  - [1] 

```
1s [1] try:  
     import google.colab  
     IN_COLAB = True  
except:  
    IN_COLAB = False
```
  - [2] 

```
31s [2] if IN_COLAB:  
    !apt-get install openjdk-8-jdk-headless -qq > /dev/null  
    !wget -q https://dlcdn.apache.org/spark/spark-3.3.2/spark-3.3.2-bin-hadoop3.tgz  
    !tar xf spark-3.3.2-bin-hadoop3.tgz  
    !mv spark-3.3.2-bin-hadoop3 spark  
    !pip install -q findspark  
    import os  
    os.environ["JAVA_HOME"] = "/usr/lib/jvm/java-8-openjdk-amd64"  
    os.environ["SPARK_HOME"] = "/content/spark"
```
- Start a Local Cluster**:
  - Use `findspark.init()` to start a local cluster. If you plan to use remote cluster, skip the `findspark.init()` and change the `cluster_url` according.

The status bar at the bottom shows '0s completed at 19:37'.

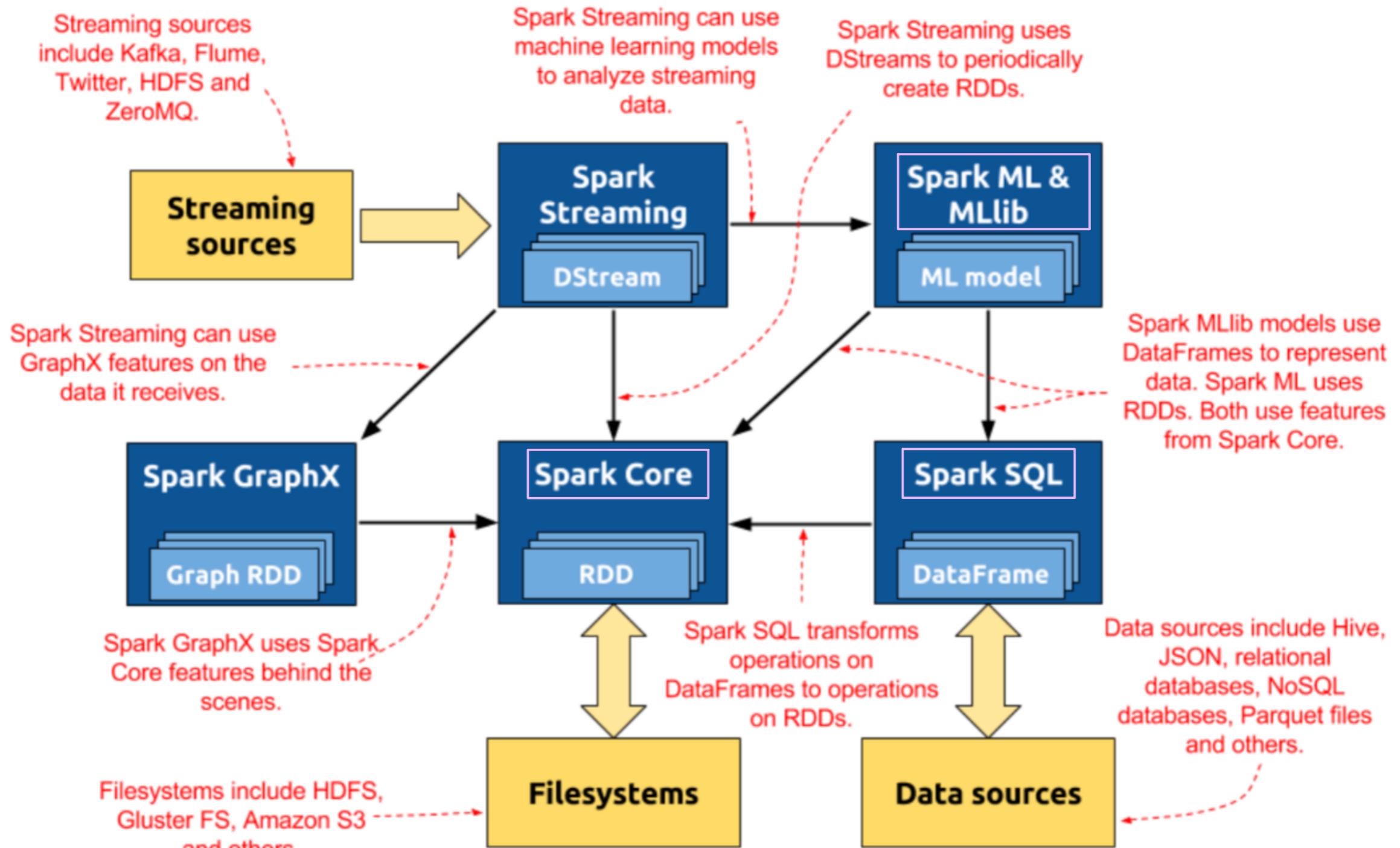


Figure 1.1: Main Spark components and various runtime environments and storage options

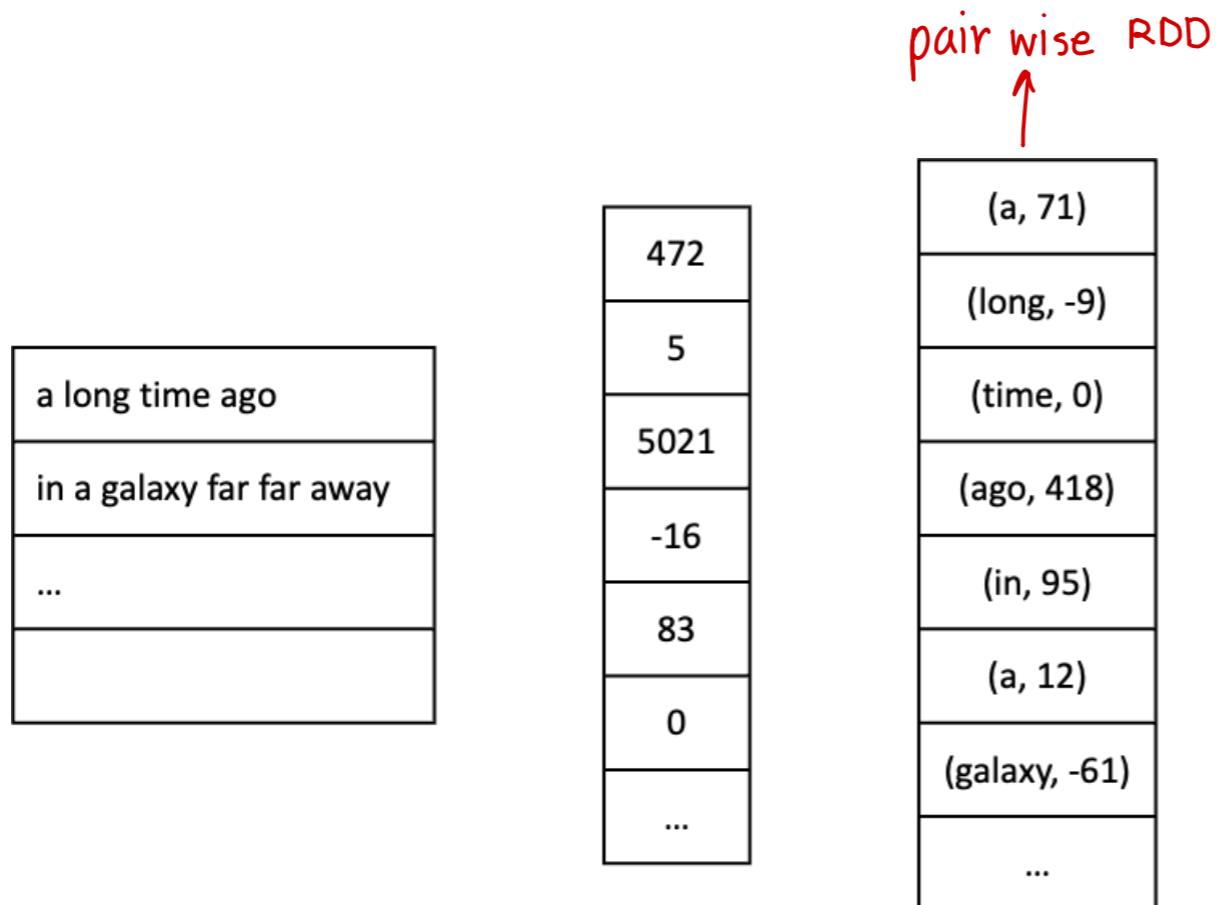
# SparkSession / SparkContext / SqlContext

---

- Spark provides ‘SparkSession’ which is an entry point to SparkContext and SqlContext
  - SparkContext tells Spark how and where to access a cluster (for client and cluster mode)
  - Spark shell automatically create the sc variable
  - Spark Submit and other programs must use a constructor to create a new SparkContext
  - Use SparkContext to create RDDs
  - SqlContext is similar to SparkContext, but for Spark SQL

read only array ↪

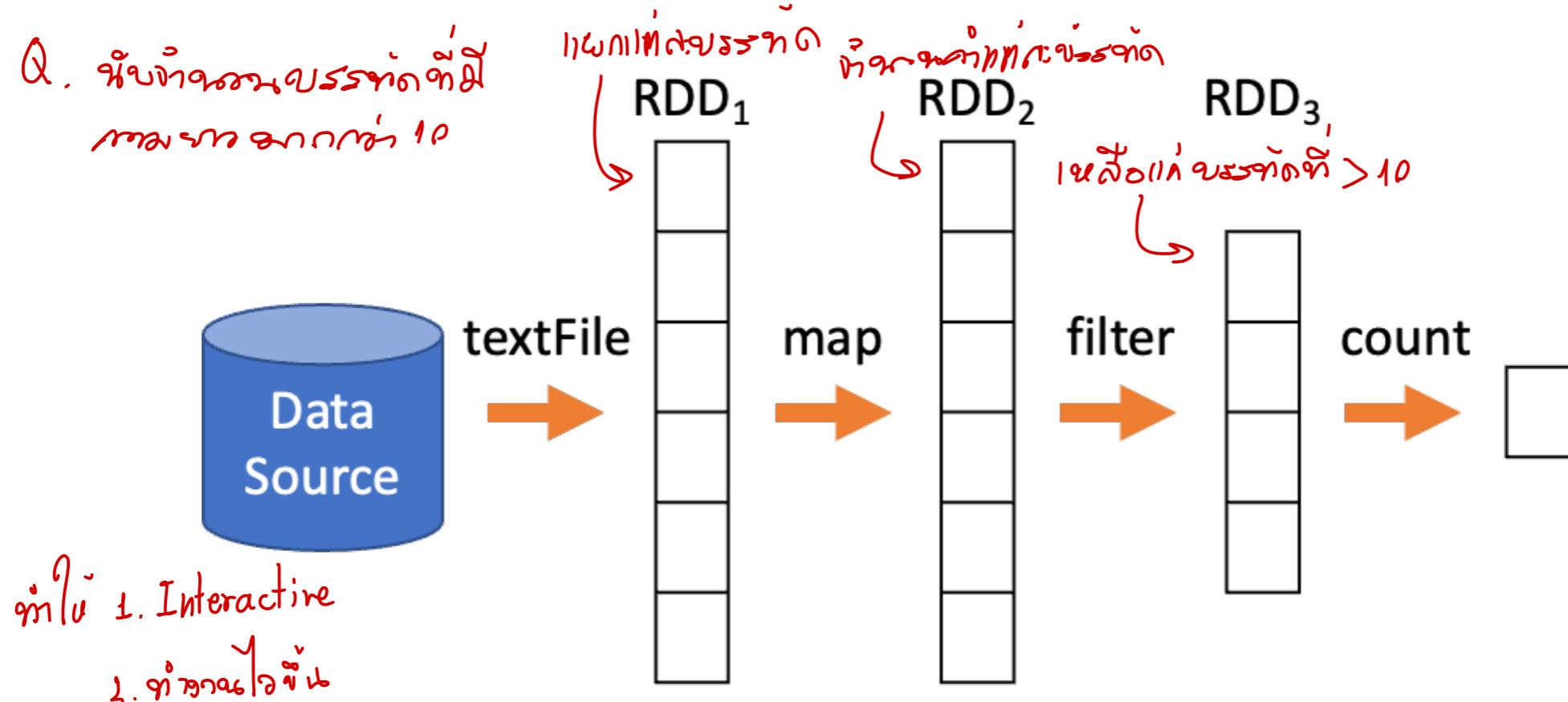
# Key Concept: RDD



- **Immutable** Distributed Collection of Objects
- Can contain any type of Python, Java, or Scala objects
- **Two types of operations: transformations and actions**  
↳ 0: မြန်မာစာတမ်း 1: ငောက်ပွဲမှုအကြောင်း ၁၁၀ တိတော် actions
- Transformations are **lazy** (not computed immediately)
- Transformed RDD is executed when action runs on it

# Typical Spark Program

- Created from external dataset (e.g. file from HDFS) or existing collection of objects (List, Set)
- Transformation (Create a new RDD from existing RDDs)
- Action (Compute result from an RDD)  $\rightarrow$  ผลลัพธ์ที่เป็น object มากกว่า RDD
- (Maybe) persist (cache) RDDs to disk or memory



# Simple RDD Operations

- `sc.parallelize(data)` — transform  
create an RDD from data
- `rdd.count()` — action  
count number of elements in an odd
- `rdd.filter(func)` — transform  
create a new rdd from existing rdd and  
keep only those elements that func is true
- `rdd.first()` — action  
get the first element in the rdd
- `rdd.collect()` — action  
gather all elements in the rdd into a  
python list
- `rdd.take(n)` — action  
gather first n-th elements in the rdd into a  
python list

```
data = [1, 2, 3, 4, 5]
rdd = sc.parallelize(data)
n = rdd.count()
print('count = {}'.format(n))
l = rdd.collect()
print(l)

count = 5
[1, 2, 3, 4, 5]
```

```
l = rdd.take(3)
print(l)

[1, 2, 3]
```

```
f_rdd = rdd.filter(lambda d: d > 2)
for d in f_rdd.collect():
    print(d)
print('filter count = {}'.format(f_rdd.count()))

3
4
5
filter count = 3
```

# RDD Operations

## map and reduce

- `rdd.map(func)`  
create a new rdd by performing function func on each element in an rdd

→ action: applied func ເປັນຄູ່ງ

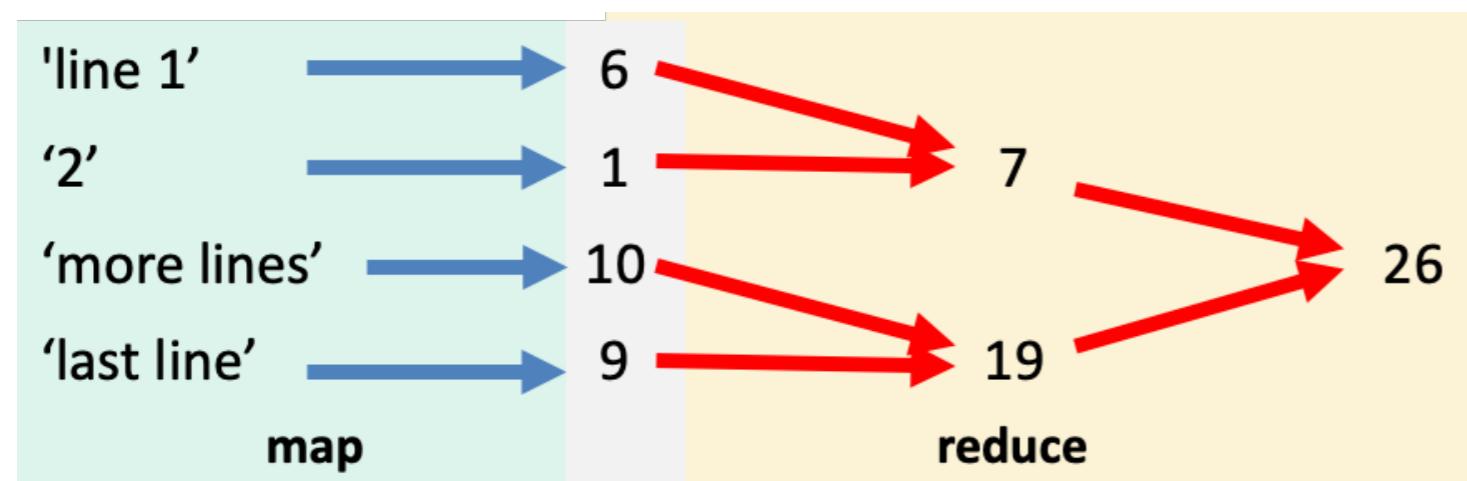
- `rdd.reduce(func)`  
aggregate all elements in an rdd using function func

→ ໄກສະກຳຕີວ່າລຳດັບ ຮະກາຕາມອາງື່ອຍຸຕິດກຳ  
ກຳໄດ້ແນ່ງຮັບຮັບ ຢຸ່ມເປັນ 2"

```
data = ['line 1', '2', 'more lines', 'last line']
lines = sc.parallelize(data)
print(lines.collect())
['line 1', '2', 'more lines', 'last line']

lineLengths = lines.map(lambda line: len(line))
print(lineLengths.collect())
[6, 1, 10, 9]

totalLength = lineLengths.reduce(lambda a, b: a + b)
print(totalLength)
26
```



# RDD Operations: more map and reduce

---

```
data = (1,2,3,4)
rdd = sc.parallelize(data)
rdd2 = rdd.map(lambda x: x**2)
print(rdd2.collect())
sum_val= rdd2.reduce(lambda a, b: a + b)
print('sum = {}'.format(sum_val))
mul_val = rdd2.reduce(lambda a, b: a * b)
print('mul = {}'.format(mul_val))
```

```
[2, 4, 6, 8]
sum = 20
mul = 384
```

---

# RDD Aggregation

- Aggregate is an action operation
  - performs *seqOp* to *zeroValue* and all RDD elements (this basically transforms all elements in RDD into the type of output value)
  - and then aggregates the transformed RDD elements using *combOp*
- Note that reduce is a simple form of aggregate operation.

→ នឹង reduce តាម action នៃពីរអង្គភាព

```
rdd.collect()
```

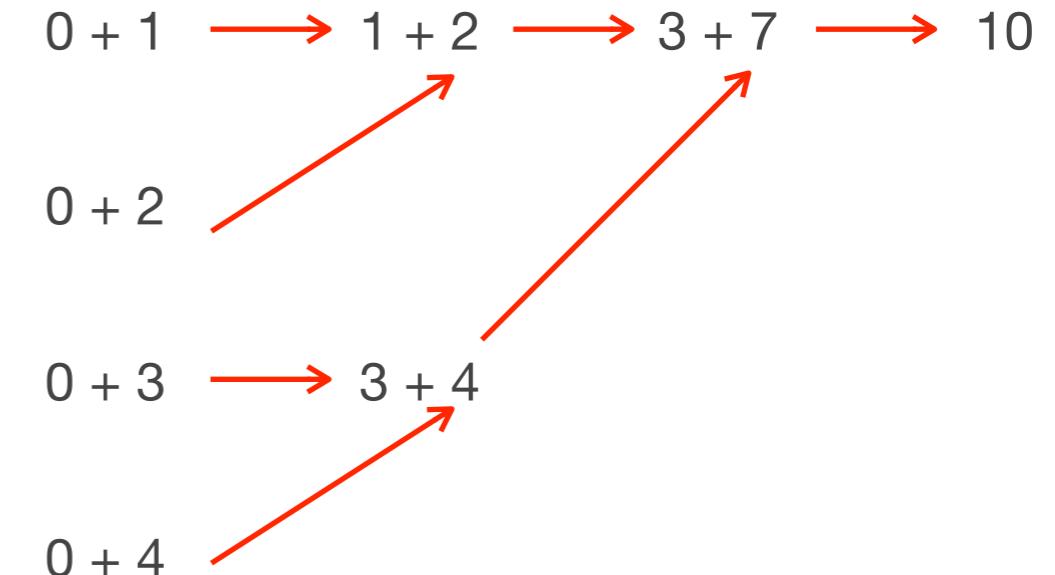
```
[1, 2, 3, 4]
```

The following aggregate operation is basically a `rdd.reduce(lambda a, b: a+b)` as the type output value is an integer which is the same as the RDD elements

```
rdd.aggregate(0,  
lambda zero, e: zero+e,  
lambda a, b: a+b)
```

10

seqOp      combOp      combOp



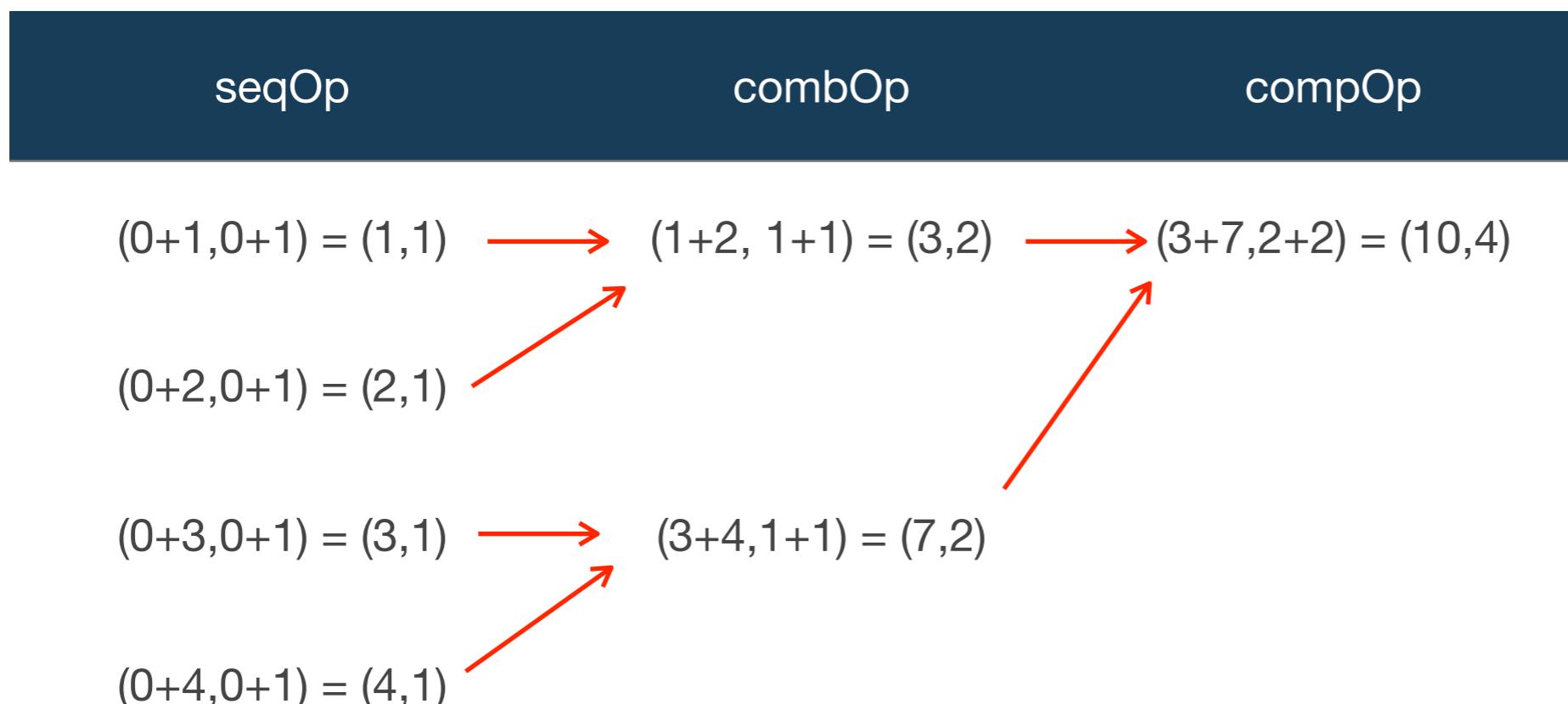
# RDD Aggregation of Pairwise RDD

The following aggregate operation returns an order pairs of (x, y) where

- x is the sum of all elements in RDD
- y is the count of all elements in RDD

```
rdd.aggregate((0, 0),  
               lambda zero, e: (zero[0]+e, zero[1]+1),  
               lambda a, b: (a[0]+b[0], a[1]+b[1]))
```

(10, 4)



# RDD Aggregation of Pairwise RDD

```
lines.collect()  
['line 1', '2', 'more lines', 'last line']
```

The following aggregate operation returns an order pairs of (x, y) where

- x is the concatenation of all elements in RDD
- y is the sum of the length of all elements in RDD

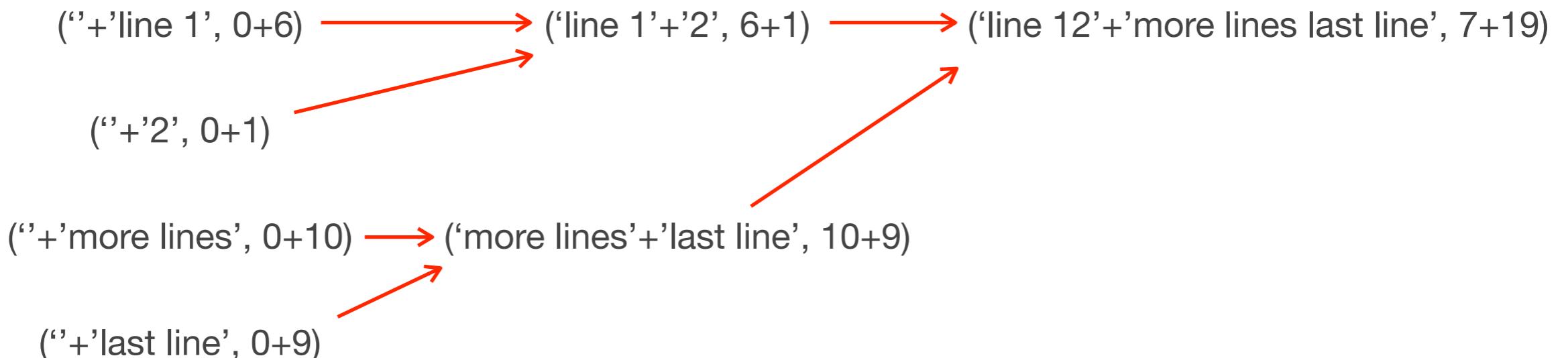
```
lines.aggregate("", 0,  
    lambda zero, e: (zero[0]+e, zero[1]+len(e)),  
    lambda a, b: (a[0]+b[0], a[1]+b[1]))
```

```
('line 12more lineslast line', 26)
```

seqOp

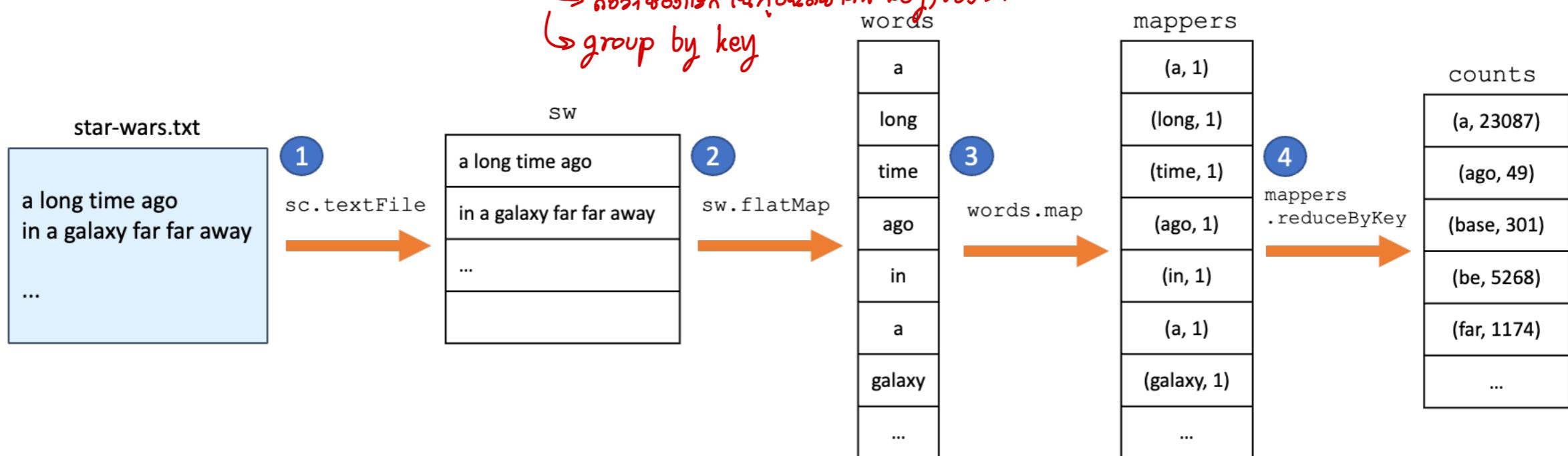
combOp

compOp



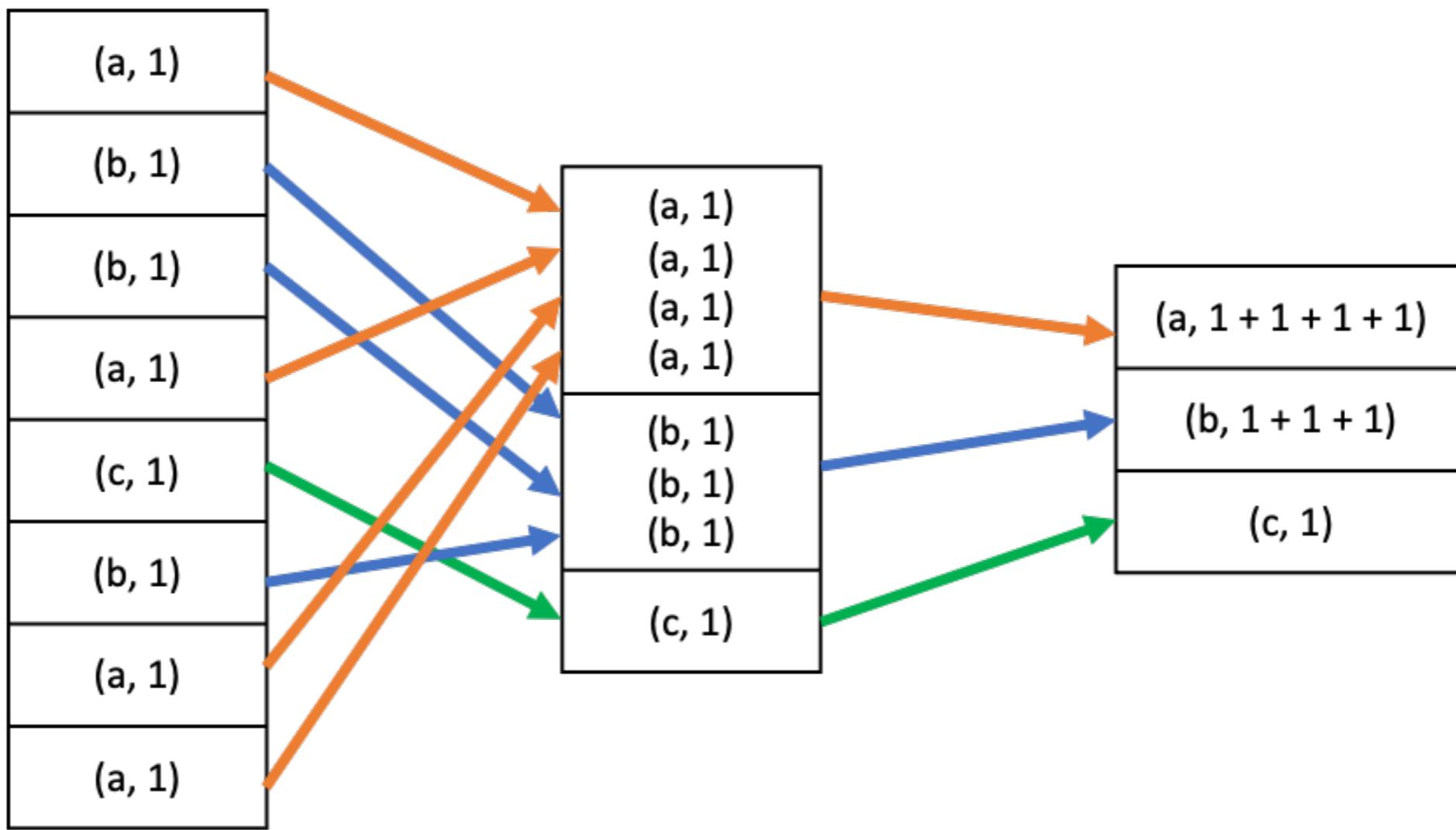
# Example: Word Count

```
sw = sc.textFile('star-wars.txt')      ↗ ['a', 'b', 'c']
words = sw.flatMap(lambda line: line.split())
mappers = words.map(lambda word: (word, 1))
counts = mappers.reduceByKey(lambda x, y: x+y)
```



# ReduceByKey

---



```
In [1]: import os
import pyspark
from pyspark.sql import SQLContext, SparkSession
```

```
In [2]: spark = SparkSession \
    .builder \
    .master('spark://192.168.68.106:7077') \
    .appName("sparkFromJupyter") \
    .getOrCreate()

sc = spark.sparkContext
sqlContext = SQLContext(sparkContext=sc, sparkSession=spark)
```

```
WARNING: An illegal reflective access operation has occurred
WARNING: Illegal reflective access by org.apache.spark.unsafe.Platform (file:/opt/spark/jars/spark-unsafe_2.12-3.2.1.jar) to constructor java.nio.DirectByteBuffer(long,int)
WARNING: Please consider reporting this to the maintainers of org.apache.spark.unsafe.Platform
WARNING: Use --illegal-access=warn to enable warnings of further illegal reflective access operations
WARNING: All illegal access operations will be denied in a future release
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
22/02/02 11:58:57 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
```

```
In [3]: sw = sc.textFile('star-wars.txt')
words = sw.flatMap(lambda line: line.split())
mappers = words.map(lambda word: (word, 1))
counts = mappers.reduceByKey(lambda x, y: x+y)
```

```
In [4]: results = counts.collect()
for row in results:
    print(row[0] + "," + str(row[1]))
```

```
STAR,150
!!,2
PUBLIC,1
VERSION,1
@A,1
long,31
ago,,1
in,379
far,,1
far,18
sea,2
of,579
as,211
drums,1
echo,1
heavens,2
crawls,1
into,147
```

```
In [5]: spark.stop()
```

# Spark Jobs (localhost:4040)

The screenshot shows the Apache Spark 3.2.1 UI interface for managing jobs. The top navigation bar includes links for Jobs, Stages, Storage, Environment, Executors, and SQL. The title bar indicates the application is "sparkFromJupyter application UI".

**Spark Jobs (?)**

User: natawut  
Total Uptime: 50 s  
Scheduling Mode: FIFO  
Completed Jobs: 1

► Event Timeline

▼ Completed Jobs (1)

Page: 1      1 Pages. Jump to  . Show  items in a page.

Job Id	Description	Submitted	Duration	Stages: Succeeded/Total	Tasks (for all stages): Succeeded/Total
0	collect at /var/folders/dh/9ktgczfj6631qmxyyc65h0x00000gn/T/ipykernel_3130/3133219802.py:1	2022/02/02 12:03:14	8 s	2/2	4/4

Page: 1      1 Pages. Jump to  . Show  items in a page.

Details for Stage 0 (Attempt 0)

Resource Profile Id: 0  
 Total Time Across All Tasks: 3 s  
 Locality Level Summary: Process local: 2  
 Input Size / Records: 308.7 KiB / 7518  
 Shuffle Write Size / Records: 66.5 KiB / 48  
 Associated Job Ids: 0

DAG Visualization

```

graph TD
    A["star-wars.txt [0]  
textFile at NativeMethodAccesso..."] --> B["star-wars.txt [1]  
textFile at NativeMethodAccesso..."]
    B --> C["PythonRDD [2]  
reduceByKey at /var/folders/dh/9ktgczfj6631qmxyyc65h0x0000gn/T/pykerne..."]
    C --> D["PairwiseRDD [3]  
reduceByKey at /var/folders/dh/9ktgczfj6631qmxyyc65h0x0000gn/T/pykerne..."]
  
```

Show Additional Metrics

Event Timeline

Enable zooming

Scheduler Delay   Executor Computing Time   Getting Result Time  
 Task Deserialization Time   Shuffle Write Time  
 Shuffle Read Time   Result Serialization Time

Tasks: 2. 1 Pages. Jump to 1 . Show 2 items in a page. Go

0 / 192.168.68.106   12:03:19   000 100 200 300 400 500 600 700 800 900 000 100 200 300 400 500 600 700 800 900 000 100 200 300 400 500 12:03:20   12:03:21

**Summary Metrics for 2 Completed Tasks**

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	2 s	2 s	2 s	2 s	2 s
GC Time	10.0 ms	10.0 ms	10.0 ms	10.0 ms	10.0 ms
Input Size / Records	116.7 KiB / 3428	116.7 KiB / 3428	192 KiB / 4090	192 KiB / 4090	192 KiB / 4090
Shuffle Write Size / Records	30.6 KiB / 24	30.6 KiB / 24	35.9 KiB / 24	35.9 KiB / 24	35.9 KiB / 24

# RDD Lineage

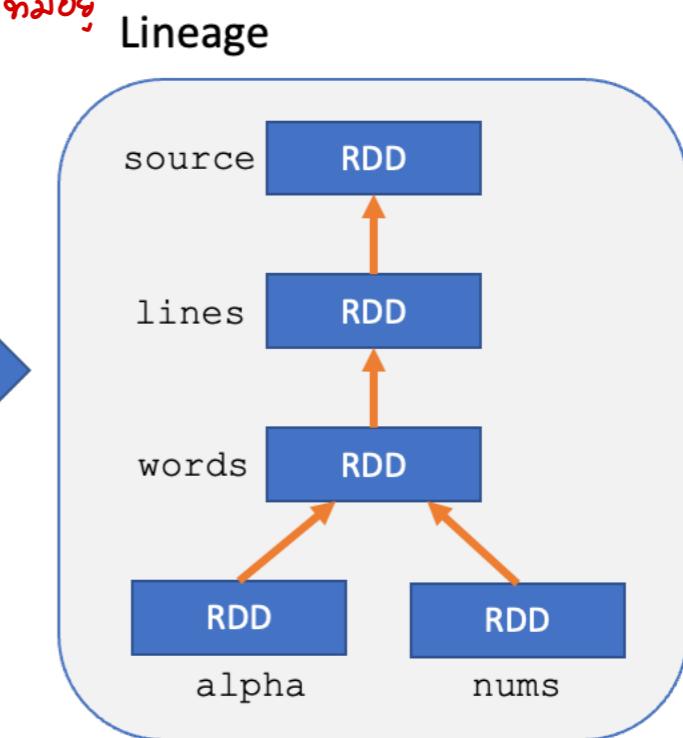
- Graph តែង dependency រវាង RDD ចងក្រ (មិនអាច read only RDD)
- ↳ ការណើនូវលទ្ធផល command (ផ្តល់ការកំណត់ និង បញ្ជាក់នៃការ Execute (lazy Execution))
- ↳ Recovery នូវការកំណត់ RDD ដើម្បី disk ការពិនិត្យនូវ RDD ដែលមួយឱ្យ inlineage

## Transformations

```
source = sc.textFile("datafile.txt")
lines = source.map(lambda line: line.lower())
words = lines.flatMap(lambda line: line.split())
alpha = words.filter(lambda word: re.match(r'[a-z]+', word))
nums = words.filter(lambda word: re.match(r'[0-9]+', word))

account = alpha.count()
ncount = nums.count()
```

## Actions



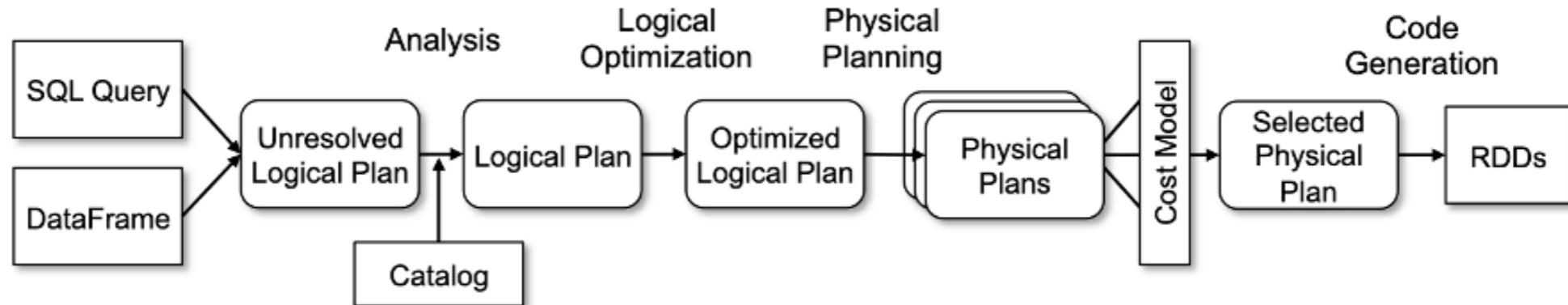
- RDD is “read-only”

និមួយៗ  
គាំសំឡុក  
កំណើនូវ

- Spark is “lazy execution” = aggregate several commands and execution in batch

# Execution Planning

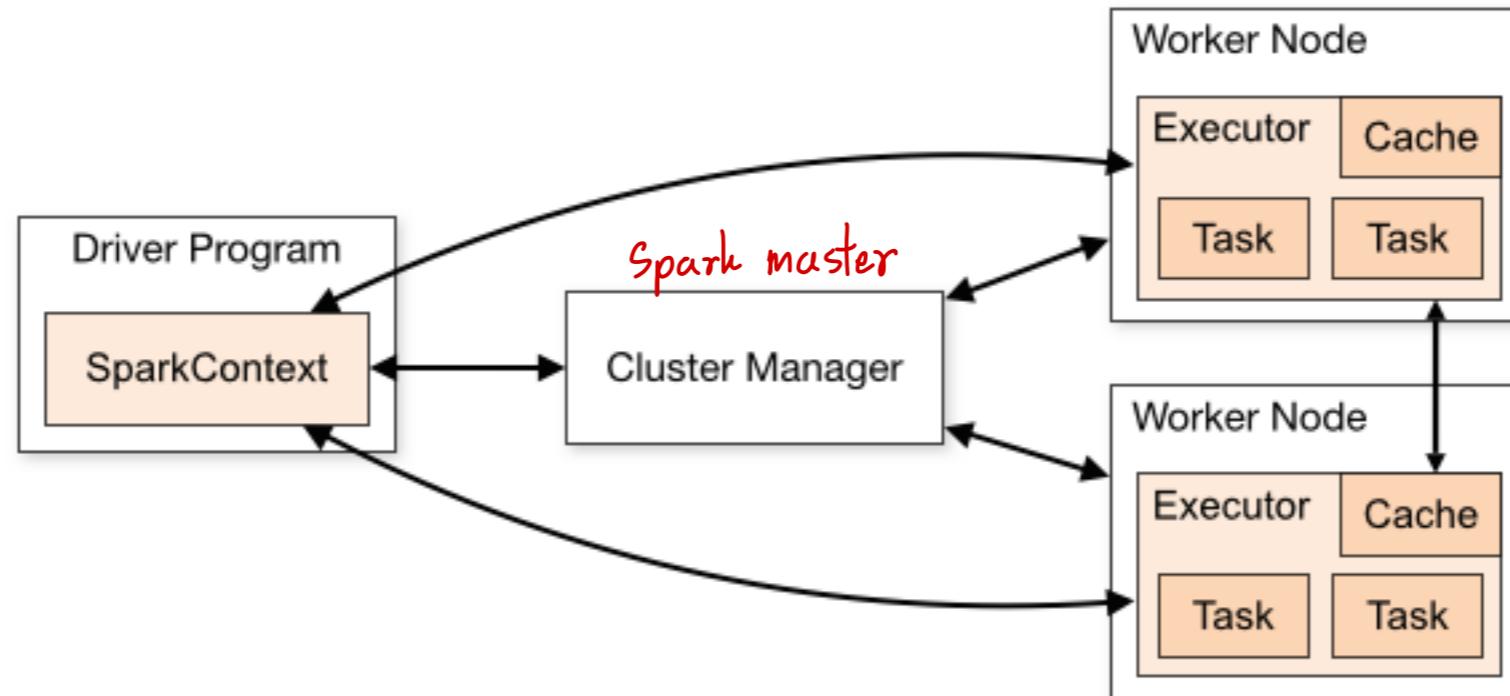
---



- Lazy execution allows Spark to perform “execution planning”
- Similar to database query execution
- Eliminate those wasteful execution e.g. no need to execute some commands for the entire data after “filter” command

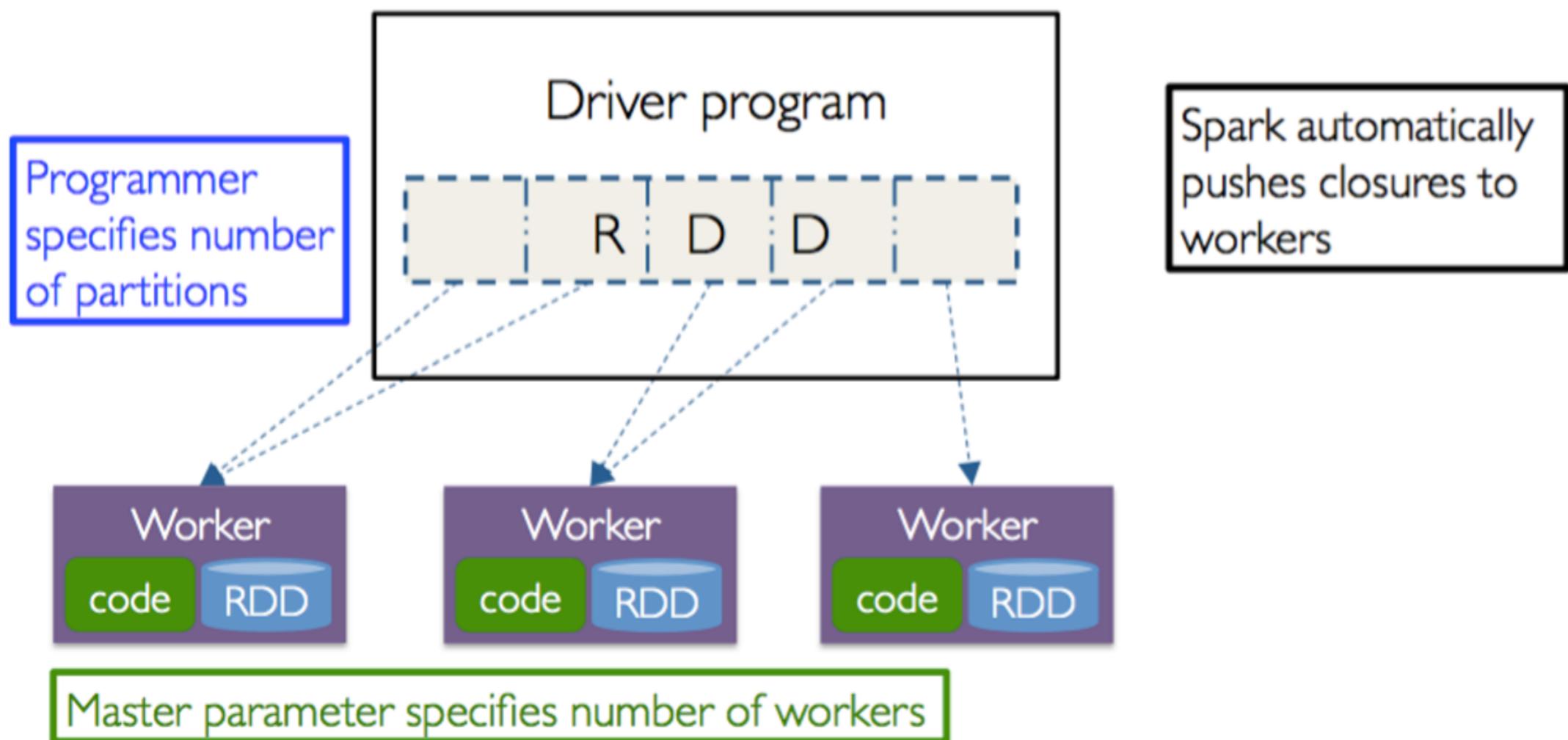
# Spark in Cluster Mode

- A Spark program is two programs
  - A **driver program** and a **workers program**
- **Worker programs run on cluster nodes or in local threads**
- **RDDs are distributed across workers**



# RDD and Workers

---



# Spark Web UI (localhost:8080)

The screenshot shows the Apache Spark 3.2.1 Web UI interface running on localhost at port 8080. The main header displays "Spark Master at spark://192.168.68.106:7077".

**Master Node Details:**

- URL: spark://192.168.68.106:7077
- Alive Workers: 1
- Cores in use: 8 Total, 0 Used
- Memory in use: 7.0 GiB Total, 0.0 B Used
- Resources in use:
- Applications: 0 Running, 2 Completed
- Drivers: 0 Running, 0 Completed
- Status: ALIVE

**Workers (1)**

Worker Id	Address	State	Cores	Memory	Resources
worker-20220202115446-192.168.68.106-49553	192.168.68.106:49553	ALIVE	8 (0 Used)	7.0 GiB (0.0 B Used)	

**Running Applications (0)**

Application ID	Name	Cores	Memory per Executor	Resources Per Executor	Submitted Time	User	State	Duration

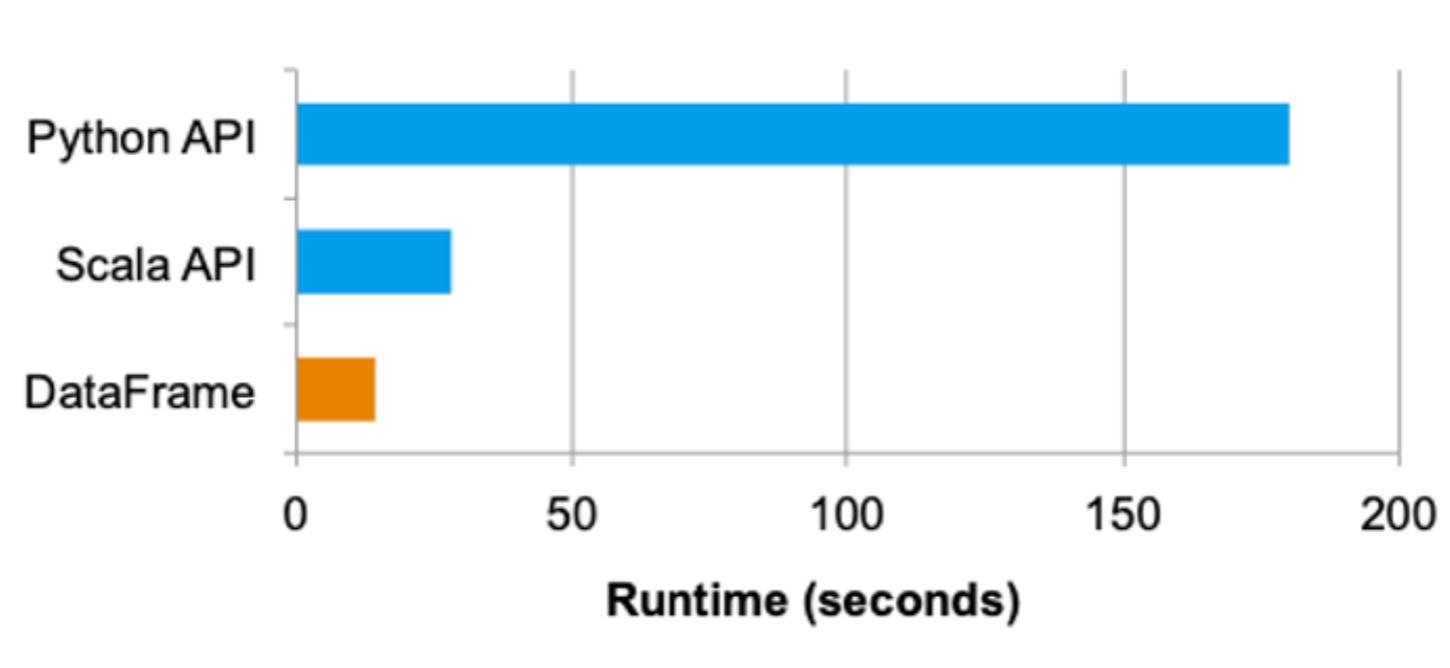
**Completed Applications (2)**

Application ID	Name	Cores	Memory per Executor	Resources Per Executor	Submitted Time	User	State	Duration
app-20220202115017-0001	sparkFromJupyter	8	1024.0 MiB		2022/02/02 11:50:17	natawut	FINISHED	8.2 min
app-20220202114640-0000	sparkFromJupyter	0	1024.0 MiB		2022/02/02 11:46:40	natawut	FINISHED	7 s

# Spark SQL

→ generates dataframe (as Type like type mentioned)

- Spark SQL provides “SQL-Like” query capability
- Provide Spark with more information about the structure of both the data and the computation being performed
- Allow better optimization, lead to better performance



# Dataframe - Schema RDD

☞ Column ഇവ Type വേണ്ടുന്നു

Title	Genre	Premiere	Runtime	IMDB Score	Language
Enter the Anime	Documentary	August 5, 2019	58	2.5	English/Japanese
Dark Forces	Thriller	August 21, 2020	81	2.6	Spanish
The App	Science fiction/Drama	December 26, 2019	79	2.6	Italian
The Open House	Horror thriller	January 19, 2018	94	3.2	English
Kaali Khuhi	Mystery	October 30, 2020	90	3.4	Hindi
Drive	Action	November 1, 2019	147	3.5	Hindi
Leyla Everlasting	Comedy	December 4, 2020	112	3.7	Turkish
The Last Days of ...	Heist film/Thriller	June 5, 2020	149	3.7	English
Paradox	Musical/Western/Fantasy	March 23, 2018	73	3.9	English
Sardar Ka Grandson	Comedy	May 18, 2021	139	4.1	Hindi

<https://www.kaggle.com/luisorter/netflix-original-films-imdb-scores>

- Two dimensional data structure
- Each row is similar to basic RDD
- Each column can have one datatype
- Spark SQL provides sql-like operations on dataframe

# Bank Marketing Dataset

---

- <https://archive.ics.uci.edu/ml/datasets/Bank+Marketing>
- The data is related with direct marketing campaigns (phone calls) of a Portuguese banking institution
- 41188 records with 20 inputs and 1 predicted variable
- The goal is to predict if the client will subscribe a term deposit (variable y) — classification problem
- In real-life, this is a “propensity to buy” which indicates the customers who we should give higher priority than others

```
df = spark.read.option("delimiter", ";").option("header", True).csv(path)
```

```
df.columns
```

```
['age',
 'job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'duration',
 'campaign',
 'pdays',
 'previous',
 'poutcome',
 'emp.var.rate',
 'cons.price.idx',
 'cons.conf.idx',
 'euribor3m',
 'nr.employed',
 'y']
```

```
cols = [c.replace('.', '_') for c in df.columns]
df = df.toDF(*cols)
```

```
df.show(5)
```

```
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|age|      job|marital| education|default|housing|loan| contact|month|day_of_week|duration|campaign|pdays|pre
vious|  poutcome|emp_var_rate|cons_price_idx|cons_conf_idx|euribor3m|nr_employed| y|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| 56|housemaid|married| basic.4y|   no|    no|telephone| may|     mon|    261|      1|  999|
0|nonexistent|       1.1|  93.994| -36.4|  4.857|      5191| no|
| 57| services|married|high.school|unknown|    no|telephone| may|     mon|    149|      1|  999|
0|nonexistent|       1.1|  93.994| -36.4|  4.857|      5191| no|
| 37| services|married|high.school|   no| yes|telephone| may|     mon|    226|      1|  999|
0|nonexistent|       1.1|  93.994| -36.4|  4.857|      5191| no|
| 40| admin.|married| basic.6y|   no|    no|telephone| may|     mon|    151|      1|  999|
0|nonexistent|       1.1|  93.994| -36.4|  4.857|      5191| no|
| 56| services|married|high.school|   no| no|yes|telephone| may|     mon|    307|      1|  999|
0|nonexistent|       1.1|  93.994| -36.4|  4.857|      5191| no|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows
```

```
df.printSchema()
```

```
root
|-- age: string (nullable = true)
|-- job: string (nullable = true)
|-- marital: string (nullable = true)
|-- education: string (nullable = true)
|-- default: string (nullable = true)
|-- housing: string (nullable = true)
|-- loan: string (nullable = true)
|-- contact: string (nullable = true)
|-- month: string (nullable = true)
|-- day_of_week: string (nullable = true)
|-- duration: string (nullable = true)
|-- campaign: string (nullable = true)
|-- pdays: string (nullable = true)
|-- previous: string (nullable = true)
|-- poutcome: string (nullable = true)
|-- emp_var_rate: string (nullable = true)
|-- cons_price_idx: string (nullable = true)
```

# Basic Spark SQL Commands

---

- When Spark reads input, it tries to guess the type of each column and uses the headers of the dataset as column names
  - To change the column name, use *withColumnRenamed* function or use *toDF* to create a new DataFrame with new column names
  - To change data type of a column, use *withColumn* and *cast*
- For data exploration, several commands can be applied e.g. select, filter, groupby, etc.

```

df = df.withColumn('age', df.age.cast('int'))

from pyspark.sql.functions import col

cols = ['age', 'duration', 'campaign', 'pdays', 'previous', 'nr_employed']
for c in cols:
    df = df.withColumn(c, col(c).cast('int'))

cols = ['emp_var_rate', 'cons_price_idx', 'cons_conf_idx', 'euribor3m']
for c in cols:
    df = df.withColumn(c, col(c).cast('double'))

```

Cast and also rename the column y to label

```
df = df.withColumn('label', df.y.cast('boolean'))
```

```
df.printSchema()
```

```

root
|-- age: integer (nullable = true)
|-- job: string (nullable = true)
|-- marital: string (nullable = true)
|-- education: string (nullable = true)
|-- default: string (nullable = true)
|-- housing: string (nullable = true)
|-- loan: string (nullable = true)
|-- contact: string (nullable = true)
|-- month: string (nullable = true)
|-- day_of_week: string (nullable = true)
|-- duration: integer (nullable = true)
|-- campaign: integer (nullable = true)
|-- pdays: integer (nullable = true)
|-- previous: integer (nullable = true)
|-- poutcome: string (nullable = true)
|-- emp_var_rate: double (nullable = true)
|-- cons_price_idx: double (nullable = true)

```

# Select and Filter Command

---

- Select is similar to SQL select command
  - select a single or multiple columns
  - select from list of column names and by column index
- Filter (or where) is very similar to SQL where condition
  - filter with column condition and multiple columns (similar to pandas)
  - filter with SQL expression
  - filter with string expression e.g. startswith, endswith, contains, etc.
- See <https://sparkbyexamples.com/pyspark/select-columns-from-pyspark-dataframe/> and <https://sparkbyexamples.com/pyspark/pyspark-where-filter/> for more details

```
df.select(df['job'], df['education'], df['housing']).show(5)
```

```
+-----+-----+
|      job| education|housing|
+-----+-----+
|housemaid| basic.4y|    no|
| services|high.school|    no|
| services|high.school|   yes|
| admin.| basic.6y|    no|
| services|high.school|    no|
+-----+-----+
only showing top 5 rows
```

```
df.select(df['age'], df['duration'], df['pdays'], df['age']*2, df['duration']+df['pdays']).show(5)
```

```
+-----+-----+-----+-----+
|age|duration|pdays|(age * 2)|(duration + pdays)|
+-----+-----+-----+-----+
| 56|     261| 999|    112|      1260|
| 57|     149| 999|    114|      1148|
| 37|     226| 999|     74|      1225|
| 40|     151| 999|     80|      1150|
| 56|     307| 999|    112|      1306|
+-----+-----+-----+-----+
only showing top 5 rows
```

```
df.filter(df.duration < 100).show(3)
```

age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	emp_var_rate	cons_price_idx	cons_conf_idx	euribor3m	nr_employed	y	label
25	services	single	high.school	no	yes	no	telephone	may	mon	50	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon	55	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
30	unemployed	married	high.school	no	no	no	telephone	may	mon	38	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
35	technician	married	university.degree	no	no	yes	telephone	may	mon	99	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
59	technician	married	unknown	no	yes	no	telephone	may	mon	93	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false

only showing top 5 rows

```
df.filter(df['job'] == 'housemaid').show(5)
```

age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	emp_var_rate	cons_price_idx	cons_conf_idx	euribor3m	nr_employed	y	label
56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
57	housemaid	divorced	basic.4y	no	yes	no	telephone	may	mon	293	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
39	housemaid	married	basic.4y	no	no	yes	telephone	may	mon	266	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
34	housemaid	married	basic.6y	no	yes	no	telephone	may	mon	300	2	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false
39	housemaid	married	basic.4y	unknown	no	no	telephone	may	mon	69	2	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no	false

only showing top 5 rows

```
df.filter((df['age'] > 60) & (df.age <= 65)).select('age', 'marital').show(5)
```

```
+---+-----+
|age| marital|
+---+-----+
| 61| married|
| 61| married|
| 61| married|
| 63| divorced|
| 62| married|
+---+-----+
only showing top 5 rows
```

```
df.filter("marital == 'married'").select('job', 'marital').show(5)
```

```
+-----+-----+
|    job|marital|
+-----+-----+
|housemaid|married|
| services|married|
| services|married|
|   admin.|married|
| services|married|
+-----+-----+
only showing top 5 rows
```

```
df.filter('age < 40 and duration > 200').select('age', 'duration', 'marital').show(5)
```

```
+---+-----+-----+
|age|duration|marital|
+---+-----+-----+
| 37|     226|married|
| 24|     380| single|
| 25|     222| single|
| 35|     312|married|
| 39|     233|married|
+---+-----+-----+
only showing top 5 rows
```

# Spark SQL Aggregate, Groupby, and User-Defined Functions

---

- Spark SQL has several built-in aggregate functions e.g. min, max, avg, std, sum, sumDistinct, count, count\_if, first, last, etc.
- Spark SQL supports groupby operation, which is similar to groupby in pandas
- User-defined function can be applied in *select* and *withColumn* commands

```
from pyspark.sql.functions import avg, min, max, countDistinct
```

```
df.select(avg('age'), min('age'), max('duration')).show()
```

[Stage 6:>

(0 + 1) / 1]

avg(age)	min(age)	max(duration)
40.02406040594348	17	4918

Groupby function allows us to work data in groups.

```
df.groupby('marital').count().show()
```

[Stage 9:>

(0 + 1) / 1]

marital	count
unknown	80
divorced	4612
married	24928
single	11568

```
df.groupby('marital', 'education').agg({'age': 'min'}).show()
```

marital	education	min(age)
divorced	high.school	24
divorced	unknown	26
unknown	university.degree	25
unknown	unknown	31
married	professional.course	22
single	basic.9y	17
married	basic.4y	20

```
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType

def agegroup_mapping(age):
    if age < 25:
        return 'young'
    if age < 55:
        return 'adult'
    return 'senior'

to_agegroup = udf(agegroup_mapping, StringType())
```

```
df.select('age', to_agegroup('age')).show(5)
```

[Stage 15:>

(0 + 1) / 1]

```
+---+-----+
|age|agegroup_mapping(age)|
+---+-----+
| 56|      senior|
| 57|      senior|
| 37|      adult|
| 40|      adult|
| 56|      senior|
+---+-----+
only showing top 5 rows
```

```
new_df = df.withColumn('agegroup', to_agegroup(df.age))
new_df.select(new_df['age'], new_df['agegroup']).show(10)
```

```
+---+-----+
|age|agegroup|
+---+-----+
| 56|  senior|
| 57|  senior|
| 37|  adult|
| 40|  adult|
| 56|  senior|
```

# Spark ML

---

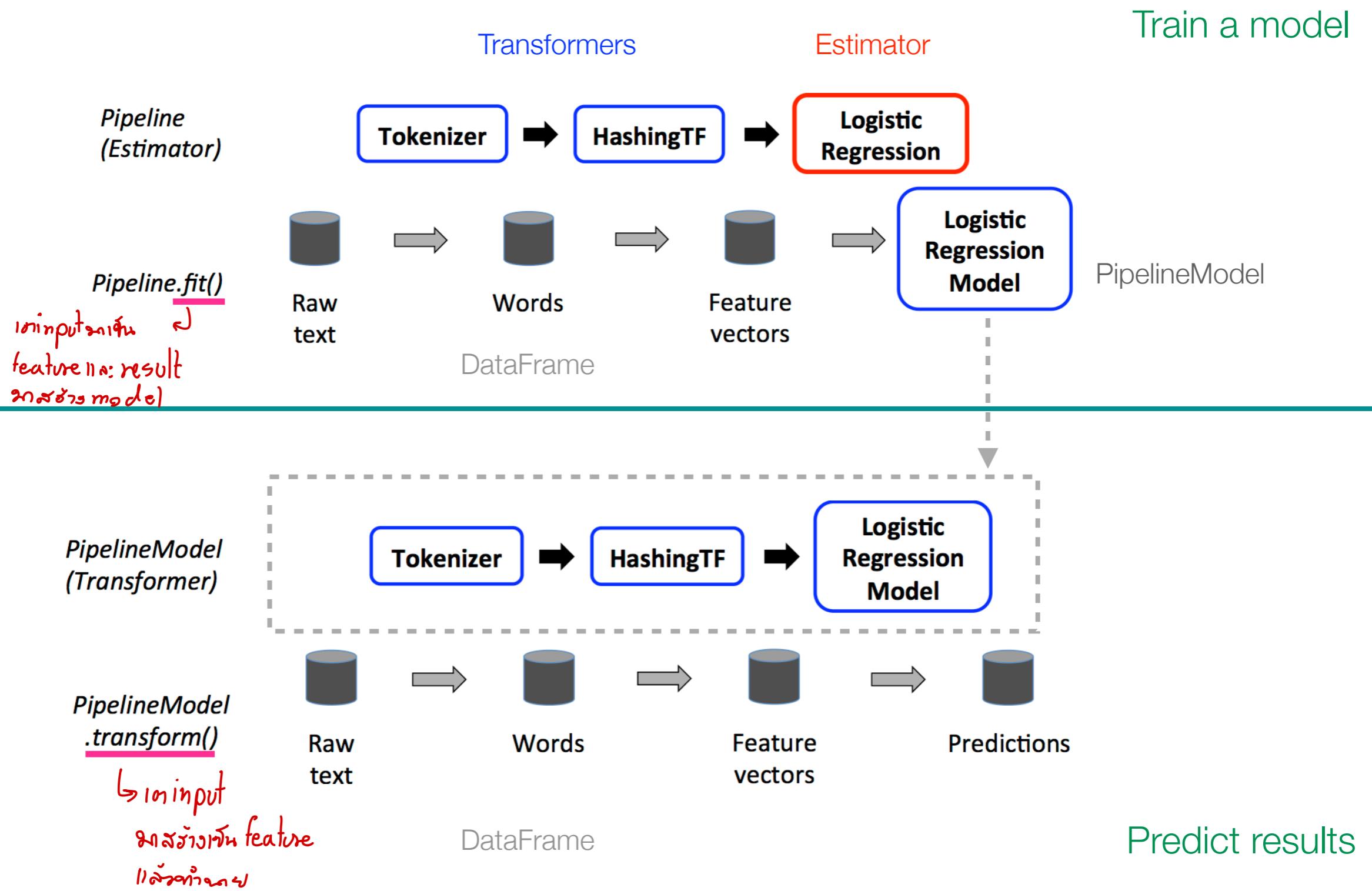
- Spark provides two machine learning packages, Spark MLlib and Spark ML
- **Spark MLlib** (spark.mllib package) is an **RDD-based** API, which is in maintenance mode
- **Spark ML** (spark.ml) is a **DataFrame-based** API, which is more user-friendly and can utilize Spark SQL capabilities

# Spark ML Pipeline Concepts

---

- DataFrame – the base of ML API to store feature vectors, true labels, and predictions  
    ↳ ගුණකාංග Estimator
- Transformer – transform DataFrame to DataFrame e.g. ML model is a Transformer – from features to predictions  
    ↳ on dataframe සඳහා නොවනු ලබන Transformer
- Estimator – fit on a DataFrame to produce a Transformer e.g. a learning algorithm is an Estimator – trains on a DataFrame to produce a model
- Pipeline – chains multiple Transformers and Estimators into stages to specify an ML workflow
- Parameter – all Transformers and Estimators share a common API for specifying parameters

# Example Pipelines



# Back to Our Bank Marketing Dataset

---

- After we prepare the data, we split data into training data (80%) and testing data (20%)
- We create 2 pipelines, feature extraction pipeline and ML prediction pipeline

- Fit `featurePipeline` with training dataset to create `featureOnlyModel` (feature extraction pipeline)
  - Transform training and testing datasets using `featureOnlyModel` to create DataFrames with features column (`trainingFeaturesDf`, `testingFeaturesDf`)
- 
- Fit `ML Pipeline` (an estimator = ML algo) with training dataset to create `PipelineModel` (ML prediction pipeline)
  - Transform `PipelineModel` with testing dataset to predict the results

```
train_df, test_df = df.randomSplit([0.8,0.2])
```

```
train_df.count()
```

```
32889
```

```
test_df.count()
```

```
8299
```

```
from pyspark.ml.feature import OneHotEncoder, StringIndexer, VectorAssembler  
from pyspark.ml import Pipeline
```

We first setup a pipeline of all data transformation.

```
stages = []
```

```
categoricalAttributes = ['job', 'marital', 'education', 'default',  
                         'housing', 'loan', 'contact',  
                         'month', 'day_of_week', 'poutcome']  
for columnName in categoricalAttributes:  
    stringIndexer = StringIndexer(inputCol=columnName, outputCol=columnName + "Index")  
    stages.append(stringIndexer)  
    oneHotEncoder = OneHotEncoder(inputCol=columnName + "Index", outputCol=columnName + "Vec")  
    stages.append(oneHotEncoder)
```

```
categoricalCols = [s + "Vec" for s in categoricalAttributes]
```

```
numericColumns = ['age', 'campaign', 'pdays', 'previous',  
                  'emp_var_rate', 'cons_price_idx', 'cons_conf_idx',  
                  'euribor3m', 'nr_employed']
```

```
# Combine all the feature columns into a single column in the dataframe
```

```
allFeatureCols = numericColumns + categoricalCols  
vectorAssembler = VectorAssembler(  
    inputCols=allFeatureCols,  
    outputCol="features")  
stages.append(vectorAssembler)
```

## Feature Extraction Pipeline

We build 2 pipelines, feature transformation pipeline and ML pipeline. This allows us to reuse the feature transformation pipeline with several ML algorithms. 'fit' method is called to create a model and we can use 'transform' to actual transform or infer data

```
# Build pipeline for feature extraction
```

```
featurePipeline = Pipeline(stages=stages)
featureOnlyModel = featurePipeline.fit(train_df) → feature extraction on input
```

```
# Apply to training and testing dataframes to create feature dataframes
```

```
trainingFeaturesDf = featureOnlyModel.transform(train_df) } Transform both train and test features
testFeaturesDf = featureOnlyModel.transform(test_df)
```

```
# Peek into training features
```

```
trainingFeaturesDf.select("features", "label").rdd.take(5)
```

```
[Row(features=SparseVector(52, {0: 17.0, 1: 2.0, 2: 999.0, 3: 1.0, 4: -2.9, 5: 92.201, 6: -31.4, 7: 0.869, 8: 5076.0, 19: 1.0, 21: 1.0, 25: 1.0, 30: 1.0, 36: 1.0, 39: 1.0, 51: 1.0}), label=1),
 Row(features=SparseVector(52, {0: 17.0, 1: 3.0, 2: 4.0, 3: 2.0, 4: -2.9, 5: 92.201, 6: -31.4, 7: 0.869, 8: 5076.0, 19: 1.0, 21: 1.0, 25: 1.0, 30: 1.0, 32: 1.0, 34: 1.0, 36: 1.0, 39: 1.0}), label=0),
 Row(features=SparseVector(52, {0: 17.0, 1: 2.0, 2: 999.0, 3: 2.0, 4: -2.9, 5: 92.201, 6: -31.4, 7: 0.869, 8: 5076.0, 19: 1.0, 21: 1.0, 25: 1.0, 30: 1.0, 32: 1.0, 34: 1.0, 36: 1.0, 39: 1.0, 51: 1.0}), label=0),
 Row(features=SparseVector(52, {0: 17.0, 1: 1.0, 2: 2.0, 3: 2.0, 4: -3.4, 5: 92.431, 6: -26.9, 7: 0.742, 8: 5077.0, 19: 1.0, 21: 1.0, 29: 1.0, 30: 1.0, 33: 1.0, 35: 1.0, 36: 1.0, 43: 1.0, 49: 1.0}), label=1),
 Row(features=SparseVector(52, {0: 17.0, 1: 3.0, 2: 4.0, 3: 2.0, 4: -2.9, 5: 92.201, 6: -31.4, 7: 0.884, 8: 5076.0, 19: 1.0, 21: 1.0, 29: 1.0, 30: 1.0, 32: 1.0, 34: 1.0, 36: 1.0, 39: 1.0, 48: 1.0}), label=0)]
```

## Logistic Regression Model

Configure an machine learning pipeline, which consists of an estimator (classification) (Logistic regression)

```
lr = LogisticRegression(maxIter=10, regParam=0.01)
lrPipeline = Pipeline(stages=[lr])
```

# Fit the pipeline to create a model from the training data

```
lrPipelineModel = lrPipeline.fit(trainingFeaturesDf) → fit 모델을 만드는 과정
```

↳ Feature + label

```
results = lrPipelineModel.transform(testFeaturesDf)
print('LogisticRegression Model test accuracy = ', calculateAccuracy(results))
```

LogisticRegression Model test accuracy = 0.896555950484128

## DecisionTree Model

```
dt = DecisionTreeClassifier(labelCol='label', featuresCol='features')
dtPipeline = Pipeline(stages=[dt])
```

```
dtPipelineModel = dtPipeline.fit(trainingFeaturesDf) → fit 모델을 만드는 과정
```

↳ Feature + label

```
results = dtPipelineModel.transform(testFeaturesDf) → 모델을 만드는 과정
print('DecisionTree Model test accuracy = ', calculateAccuracy(results))
```

DecisionTree Model test accuracy = 0.8979041549209462

# Conclusion

---

- Spark is a popular platform, especially for data science
- It enables flexible programming structure, not just “map” and “reduce”
- Spark provides in-memory processing along with lazy execution, RDD lineage, and execution planning makes Spark very efficient
- DataFrame in Spark SQL and ML pipeline in Spark ML are the mainstream features as they are more flexible and more user-friendly than RDD in Spark Core

# References

---

- A. Joseph, “Introduction to Big Data with Apache Spark”, <https://www.edx.org/course/introduction-big-data-apache-spark-uc-berkeleyx-cs100-1x>
- Spark Programming Guide, <http://spark.apache.org/docs/latest/programming-guide.html>
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