MSDS 694
Distributed Computing

DIANE WOODBRIDGE, PH.D

Announcement

Feel free to dress-up for Oct 28th class for Halloween 🎃

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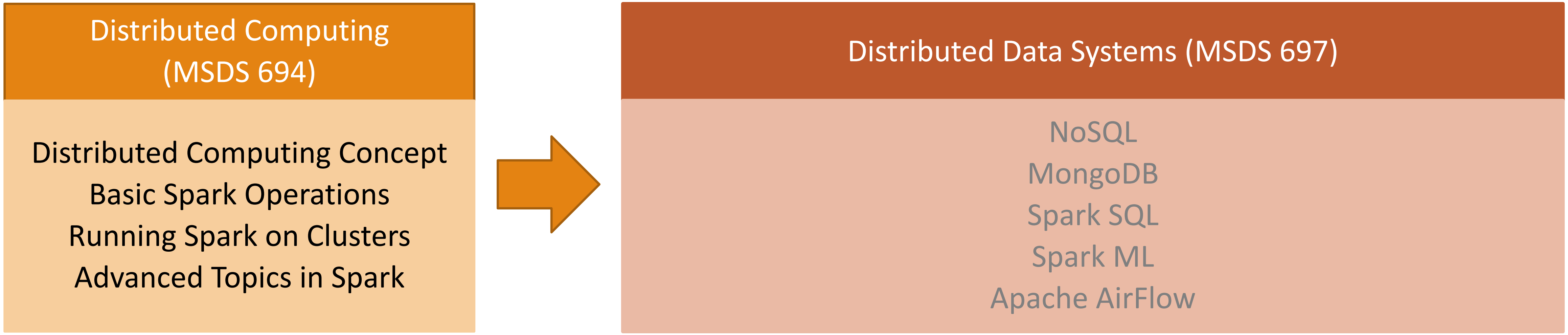
About Distributed Computing(MSDS694)



Distributed Computing (MSDS 694)

Distributed Computing Concept
Basic Spark Operations
Running Spark on Clusters
Advanced Topics in Spark

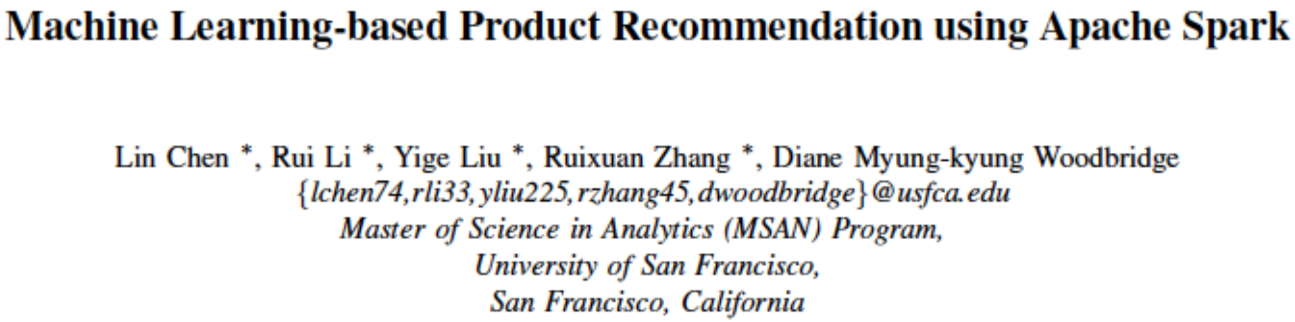
Distributed Data Systems (MSDS 697)

NoSQL
MongoDB
Spark SQL
Spark ML
Apache AirFlow

Plus, some practicum companies require Spark.

Possible Outcomes After MSDS697 (Spring)

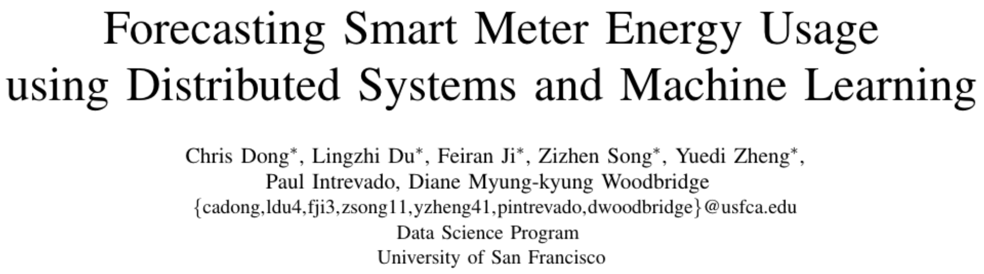
2017



Machine Learning-based Product Recommendation using Apache Spark

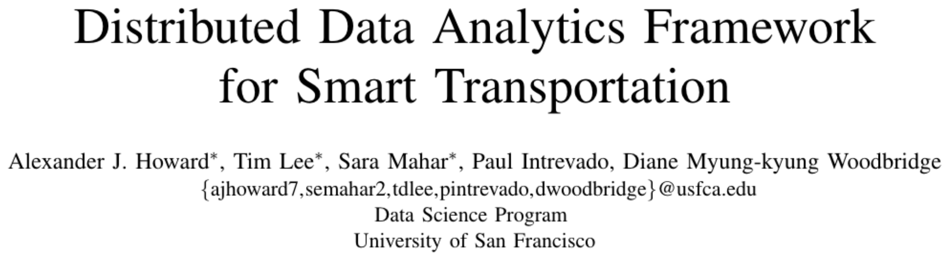
Lin Chen *, Rui Li *, Yige Liu *, Ruixuan Zhang *, Diane Myung-kyung Woodbridge
{lchen74,rli33,yliu225,rzhang45,dwoodbridge}@usfca.edu
Master of Science in Analytics (MSAN) Program,
University of San Francisco,
San Francisco, California

2018



Forecasting Smart Meter Energy Usage using Distributed Systems and Machine Learning

Chris Dong*, Lingzhi Du*, Feiran Ji*, Zizhen Song*, Yuedi Zheng*,
Paul Intrevado, Diane Myung-kyung Woodbridge
{cadong,ldu4,fji3,zsong11,yzheng41,pintrevado,dwoodbridge}@usfca.edu
Data Science Program
University of San Francisco



Distributed Data Analytics Framework for Smart Transportation

Alexander J. Howard*, Tim Lee*, Sara Mahar*, Paul Intrevado, Diane Myung-kyung Woodbridge
{ajhoward7,semahar2,tdlee,pintrevado,dwoodbridge}@usfca.edu
Data Science Program
University of San Francisco

Possible Outcomes After MSDS697 (Spring)

2019

- A Scalable Smartwatch-based Medication Adherence Monitoring System using Distributed Machine Learning. Donya Fozoonmayeh, Hai Vu Le, Ekaterina Wittfoth, Chong Geng, Natalie Ha, Jingjue Wang, Maria Vasilenko, Yewon Ahn, Diane Myung-kyung Woodbridge. Journal of Medical Systems (JOMS)
- Predicting Unethical Physician Behavior At Scale: A Distributed Computing Framework. Anastasia Quinn Keck, Miguel Romero, Robert Sandor, Diane Myung-kyung Woodbridge, Paul Intrevado. IEEE Smart World Congress. August 2019.
- A Scalable and Reliable Model for Real-time Air Quality Prediction. Liying Li, Zhi Li, Lara G. Reichmann, Diane Myung-kyung Woodbridge. IEEE Smart World Congress. August 2019.
- The Impact of Bike-Sharing Ridership on Air Quality: A Scalable Data Science Framework. Nina Hua, Victoria Suarez, Rebecca Reilly, Philip Trinh, Paul Intrevado, Diane Myung-kyung Woodbridge. IEEE International Conference on Smart City Innovations. August 2019.
- Distributed Data Analytics Framework for Cluster Analysis of Parking Violation. Nan Lin, Evan Liu, Fiorella Tenorio, Xi Yang, Diane Woodbridge. IEEE International Conference on Smart City Innovations. August 2019.
- Scalable Real-time Prediction and Analysis of San Francisco Fire Department Response Times. Xu Lian, Sarah Melancon, Jon-Ross Presta, Adam Reevesman, Brian J. Spiering, Diane Myung-kyung Woodbridge. IEEE International Conference on Ubiquitous Intelligence and Computing. August 2019.
- Scalable Motor Movement Recognition from Electroencephalography using Machine Learning. Aditi Sharma, Shivee Singh, Brian Wright, Alan Perry, Diane Myung-Kyung Woodbridge, Abbie Popa. IEEE International Workshop on Integrated Smart Healthcare (WISH). July 2019.
- A Scalable Automated Diagnostic Feature Extraction System for EEGs. Prakhar Agrawal, Divya Bhargavi, Gokul Krishna G, Xiao Han, Neha Tevathia, Abbie Popa, Nicholas Ross, Diane Myung-Kyung Woodbridge, Barbie Zimmerman-Bier and William Bosl. IEEE International Workshop on Medical Computing (MediComp). July 2019.

Possible Outcomes After MSDS697 (Spring)

2020

- A Machine Learning Approach to Detecting Low Medication State with Wearable Technologies. Andy Cheon, Stephanie Yeoju Jung, Collin Prather, Matt Sarmiento, Kevin Wong, Diane Woodbridge. International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). July 2020.
- Sensor Selection for Activity Classification at Smart Home Environments. Nithish Bolleddula, Geoffrey Hung, Daren Ma, Hoda Noorian, Diane Woodbridge. International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). July 2020.

2021

- Machine Learning-based Meal Detection Using Continuous Glucose Monitoring on Healthy Participants: An Objective Measure of Participant Compliance to Protocol. Victor Palacios, Diane Myung-kyung Woodbridge, Jean L. Fry. International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). November 2021.
- Depression Level Prediction in People with Parkinson's Disease during the COVID-19 Pandemic. Hashneet Kaur, Patrick Ka-Cheong Poon, Sophie Yuefei Wang, Diane Myung-kyung Woodbridge.International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). November 2021.

2022

- A Spotify Song and Playlist Recommendation Engine. Lucas De Oliveira, Chandrish Ambati, Anish Mukherjee. MongoDB Developer Code Example. https://www.mongodb.com/developer/code-examples/python/song-recommendations-example-app/

About Distributed Computing (MSDS694)

Learning Outcomes

- Understand needs and concepts of distributed computing.
- Understand Apache Spark programming basics.
- Gain experience with Apache Spark data processing including Spark APIs.
- Be competent to work with Spark on a distributed computing environment including Google Cloud Services (GCP) and Databricks.

About Distributed Computing (MSDS694)

Class Schedule

- Session 01 - Friday 10:00 AM - 12:00 PM (Room 527)
- Session 02 - Friday 2:00 PM - 4:00 PM (Room 529)

Office Hour

- Tuesday 9:15 - 10:00 AM (Room 606 (Or via Zoom, if you request in advance - Give me at least 12 hours.))

About Distributed Computing (MSDS694)

Class Overview

Week	Overview
Week 1 (October 21)	Class Intro, Environment Setup, What/Why Distributed Computing? Concepts of Distributed Computing
Week 2 (October 28)	Run Spark on a Single-node Environment RDD and Basic Spark Operations (1)
Week 3 (November 4)	Basic Spark Operations (2)
Week 4 (November 11)	Run Spark on a Multi-node Environment
Week 5 (November 18)	Pair RDD Operations
Week 6 (November 25)	No Class
Week 7 (December 2)	Advanced Topics - Improving Spark Performance

About Distributed Computing (MSDS694)

Spark Practice	Running Spark on a Cluster (Databricks/GCP)
Understanding and Practicing Spark	Pair RDD Operations (Transformation and Action)
	RDD Operations (Transformation and Action)
	Create Resilient Distributed Dataset (RDD)
Understanding Distributed Computing	Spark Overview
	MapReduce Concept
	Concepts of Distributed Computing
Development Basic	Environment Setup

About Distributed Computing (MSDS694)

Evaluation Criteria

- Attendance and Professionalism - 10 %
- Individual Programming Assignment - 25 %
- Group Project - 20%
- Quiz - 45% (November 11, December 2nd)

Grader : Phillip Navo (panavo@usfca.edu)

Oct 28	Spark Installation
Nov 4	Programming Assignment
Dec 3	Programming Assignment

Nov 5	Select Data Sets
Nov 28	Loading and Saving Data
Dec 14	Data Processing and Visualization on Databricks

Professionalism

Class Attendance

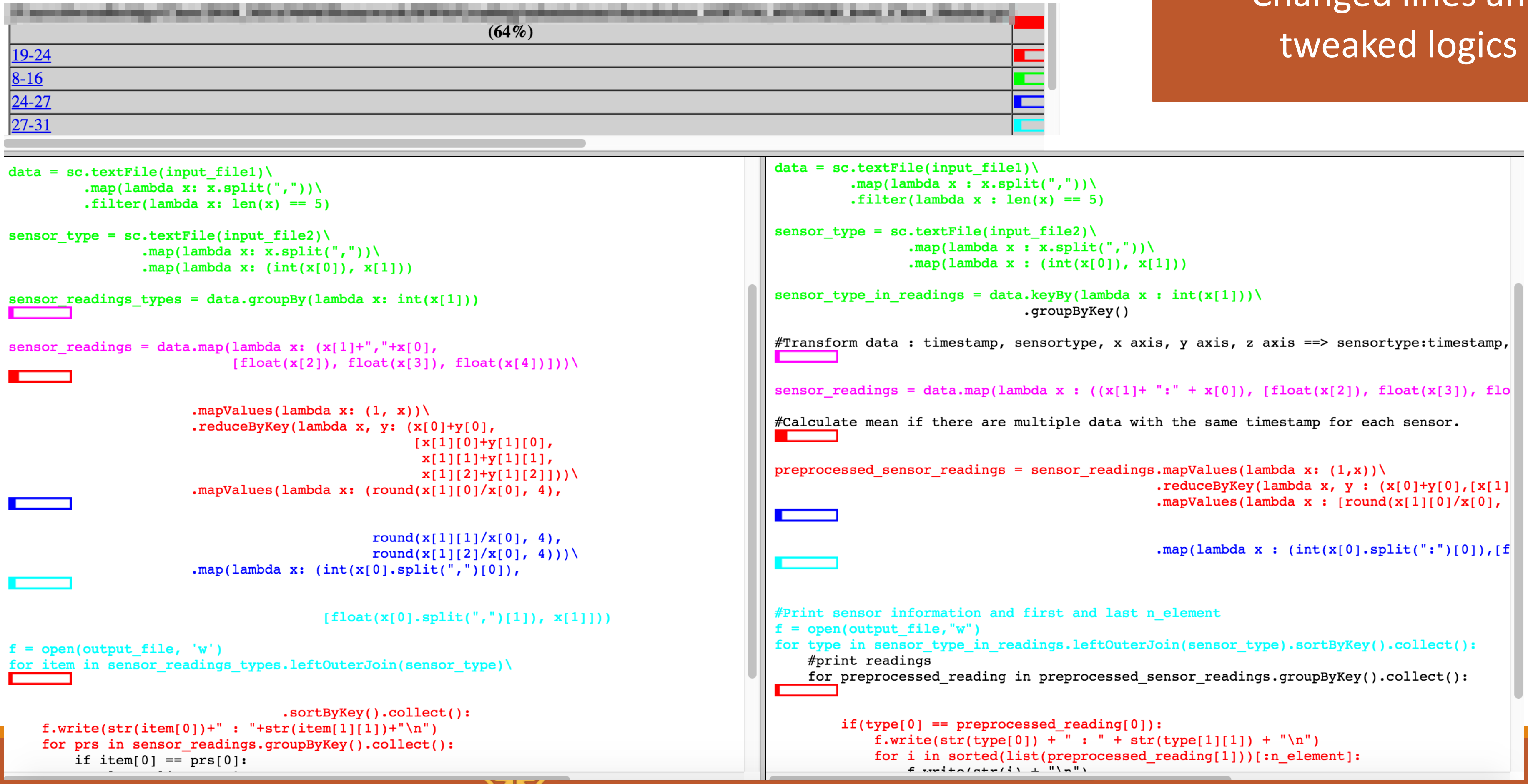
- No cellphones, social media, slack, texting during the class .

Assignment

- No late submissions are allowed.
- Do not share any homework and exam files - All the codes including the last 5 years will be tested by Moss (Measure Of Software Similarity).
- Make sure that your code runs in Python 3 and Pyspark 3.

Course Evaluation

Please no plagiarism! – Zero tolerance.



[redacted]

(64%)

19-24

8-16

24-27

27-31

```
data = sc.textFile(input_file1)\
         .map(lambda x: x.split(","))\
         .filter(lambda x: len(x) == 5)

sensor_type = sc.textFile(input_file2)\
                .map(lambda x: x.split(","))\
                .map(lambda x: (int(x[0]), x[1]))

sensor_readings_types = data.groupBy(lambda x: int(x[1]))

sensor_readings = data.map(lambda x: (x[1]+","+x[0],
                           [float(x[2]), float(x[3]), float(x[4])]))\


                      .mapValues(lambda x: (1, x))\
                      .reduceByKey(lambda x, y: (x[0]+y[0],
                                                 [x[1][0]+y[1][0],
                                                  x[1][1]+y[1][1],
                                                  x[1][2]+y[1][2]]))\
                      .mapValues(lambda x: (round(x[1][0]/x[0], 4),


                                            round(x[1][1]/x[0], 4),
                                            round(x[1][2]/x[0], 4)))\
                      .map(lambda x: (int(x[0].split(",")[0]),


                                      [float(x[0].split(",")[1]), x[1]]))

f = open(output_file, 'w')
for item in sensor_readings_types.leftOuterJoin(sensor_type)\


                                 .sortByKey().collect():
    f.write(str(item[0])+" : "+str(item[1][1])+"\n")
    for prs in sensor_readings.groupByKey().collect():
        if item[0] == prs[0]:
```

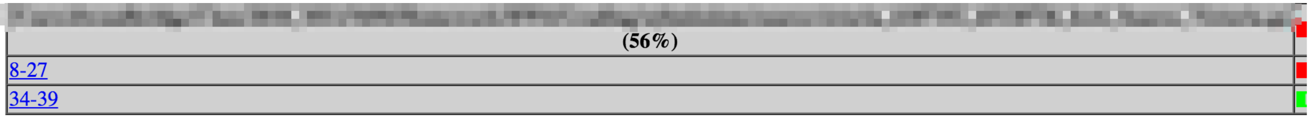
```
data = sc.textFile(input_file1)\
         .map(lambda x : x.split(","))\
         .filter(lambda x : len(x) == 5)

sensor_type = sc.textFile(input_file2)\
                .map(lambda x : x.split(","))\
                .map(lambda x : (int(x[0]), x[1]))

sensor_type_in_readings = data.keyBy(lambda x : int(x[1]))\
                                .groupByKey()

#Transform data : timestamp, sensortype, x axis, y axis, z axis ==> sensortype:timestamp,


sensor_readings = data.map(lambda x : ((x[1]+ ":" + x[0]), [float(x[2]), float(x[3]), flo

#Calculate mean if there are multiple data with the same timestamp for each sensor.


preprocessed_sensor_readings = sensor_readings.mapValues(lambda x: (1,x))\
                                             .reduceByKey(lambda x, y : (x[0]+y[0],[x[1]
                                             .mapValues(lambda x : [round(x[1][0]/x[0],


                                             .map(lambda x : (int(x[0].split(":")[0]),[f



#Print sensor information and first and last n_element
f = open(output_file,"w")
for type in sensor_type_in_readings.leftOuterJoin(sensor_type).sortByKey().collect():
    #print readings
    for preprocessed_reading in preprocessed_sensor_readings.groupByKey().collect():


        if(type[0] == preprocessed_reading[0]):
            f.write(str(type[0]) + " : " + str(type[1][1]) + "\n")
            for i in sorted(list(preprocessed_reading[1]))[:n_element]:
                f.write(str(i) + "\n")
```

Changed lines and tweaked logics

Course Evaluation

Please no plagiarism! – Zero tolerance.

Changed lines and variable names



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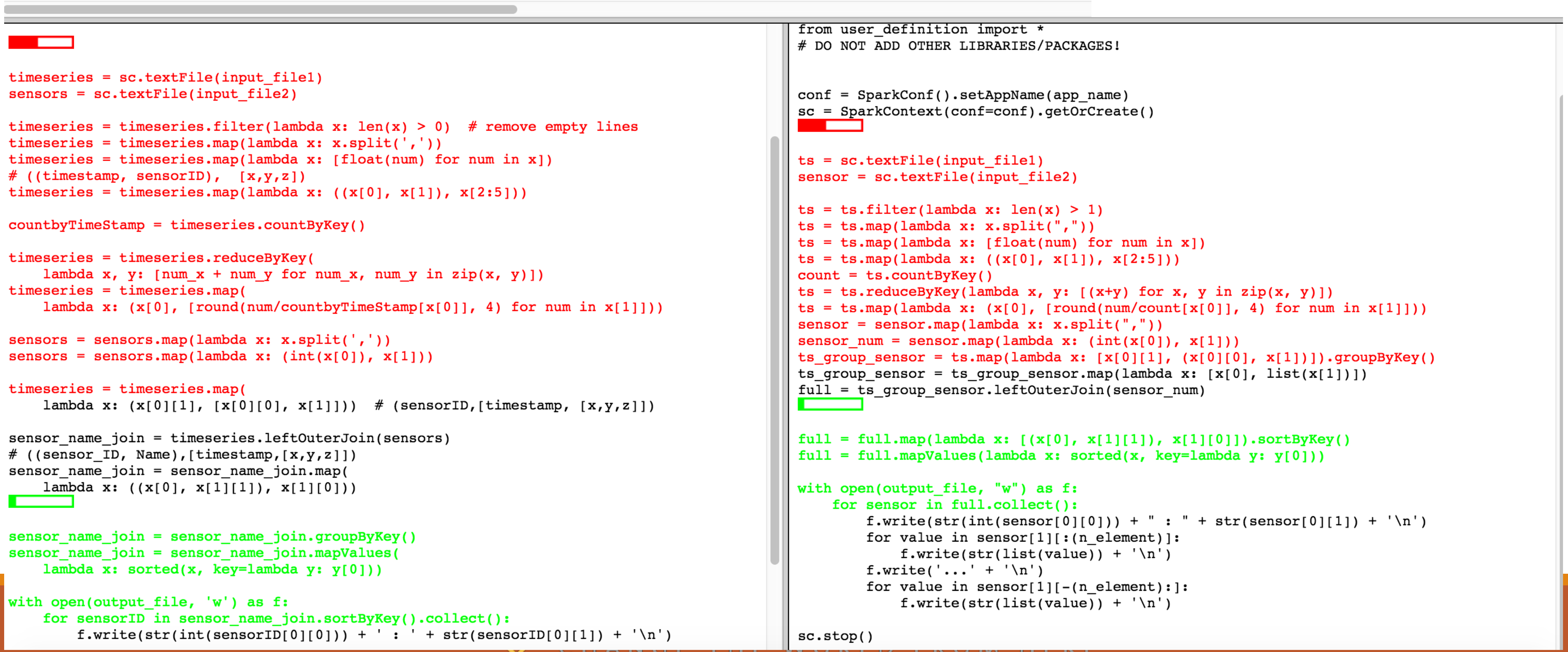
(56%)
8-27
34-39



```
timeseries = sc.textFile(input_file1)
sensors = sc.textFile(input_file2)

timeseries = timeseries.filter(lambda x: len(x) > 0)  # remove empty lines
timeseries = timeseries.map(lambda x: x.split(','))
timeseries = timeseries.map(lambda x: [float(num) for num in x])
# ((timestamp, sensorID),  [x,y,z])
timeseries = timeseries.map(lambda x: ((x[0], x[1]), x[2:5]))

countbyTimeStamp = timeseries.countByKey()

timeseries = timeseries.reduceByKey(
    lambda x, y: [num_x + num_y for num_x, num_y in zip(x, y)])
timeseries = timeseries.map(
    lambda x: (x[0], [round(num/countbyTimeStamp[x[0]], 4) for num in x[1]]))

sensors = sensors.map(lambda x: x.split(','))
sensors = sensors.map(lambda x: (int(x[0]), x[1]))

timeseries = timeseries.map(
    lambda x: (x[0][1], [x[0][0], x[1]]))  # (sensorID,[timestamp, [x,y,z]])

sensor_name_join = timeseries.leftOuterJoin(sensors)
# ((sensor_ID, Name),[timestamp,[x,y,z]])
sensor_name_join = sensor_name_join.map(
    lambda x: ((x[0], x[1][1]), x[1][0]))


sensor_name_join = sensor_name_join.groupByKey()
sensor_name_join = sensor_name_join.mapValues(
    lambda x: sorted(x, key=lambda y: y[0]))

with open(output_file, 'w') as f:
    for sensorID in sensor_name_join.sortByKey().collect():
        f.write(str(int(sensorID[0][0])) + ' : ' + str(sensorID[0][1]) + '\n')
```

```
from user_definition import *
# DO NOT ADD OTHER LIBRARIES/PACKAGES!


conf = SparkConf().setAppName(app_name)
sc = SparkContext(conf=conf).getOrCreate()


ts = sc.textFile(input_file1)
sensor = sc.textFile(input_file2)

ts = ts.filter(lambda x: len(x) > 1)
ts = ts.map(lambda x: x.split(","))
ts = ts.map(lambda x: [float(num) for num in x])
ts = ts.map(lambda x: ((x[0], x[1]), x[2:5]))
count = ts.countByKey()
ts = ts.reduceByKey(lambda x, y: [(x+y) for x, y in zip(x, y)])
ts = ts.map(lambda x: (x[0], [round(num/count[x[0]], 4) for num in x[1]]))
sensor = sensor.map(lambda x: x.split(","))
sensor_num = sensor.map(lambda x: (int(x[0]), x[1]))
ts_group_sensor = ts.map(lambda x: [x[0][1], (x[0][0], x[1])]).groupByKey()
ts_group_sensor = ts_group_sensor.map(lambda x: [x[0], list(x[1])])
full = ts_group_sensor.leftOuterJoin(sensor_num)


full = full.map(lambda x: [(x[0], x[1][1]), x[1][0]]).sortByKey()
full = full.mapValues(lambda x: sorted(x, key=lambda y: y[0]))

with open(output_file, "w") as f:
    for sensor in full.collect():
        f.write(str(int(sensor[0][0])) + " : " + str(sensor[0][1]) + '\n')
        for value in sensor[1][:(n_element)]:
            f.write(str(list(value)) + '\n')
        f.write('...' + '\n')
        for value in sensor[1][-(n_element):]:
            f.write(str(list(value)) + '\n')

sc.stop()
```

Textbook

Spark Online Documentation, http://spark.apache.org/docs/latest/

Google Cloud Online Documentation, https://cloud.google.com/docs

Databricks Online Documentation, https://docs.databricks.com/

Zecevic, Petar, et al. Spark in Action, Manning, 2016.

Student Engagement

Example Data : https://github.com/dianewoodbridge/2022-msds694-example

Poll : https://pollev.com/msds

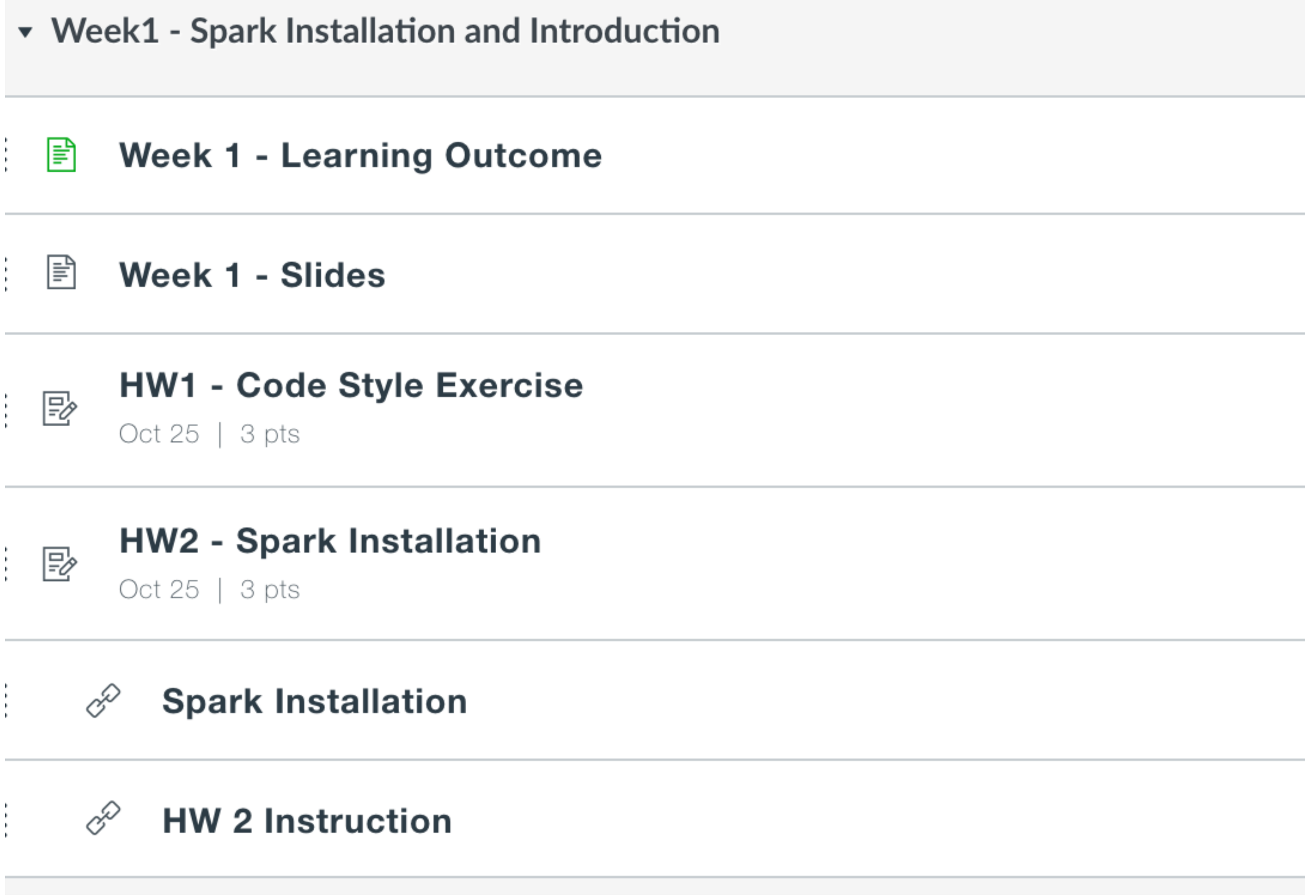
Piazza : piazza.com/usfca/fall2022/msds694

Canvas

- Under each module (week), there are learning outcome, slides, homework, example tests, tests, etc.
- For some assignment, I am going to upload video.
- For most of the lectures, I am going to publish recorded sessions – this does NOT mean that you can skip a class or not pay attention to the class.

Student Engagement

Canvas



▾ Week1 - Spark Installation and Introduction

Week 1 - Learning Outcome

Week 1 - Slides

HW1 - Code Style Exercise
Oct 25 | 3 pts

HW2 - Spark Installation
Oct 25 | 3 pts

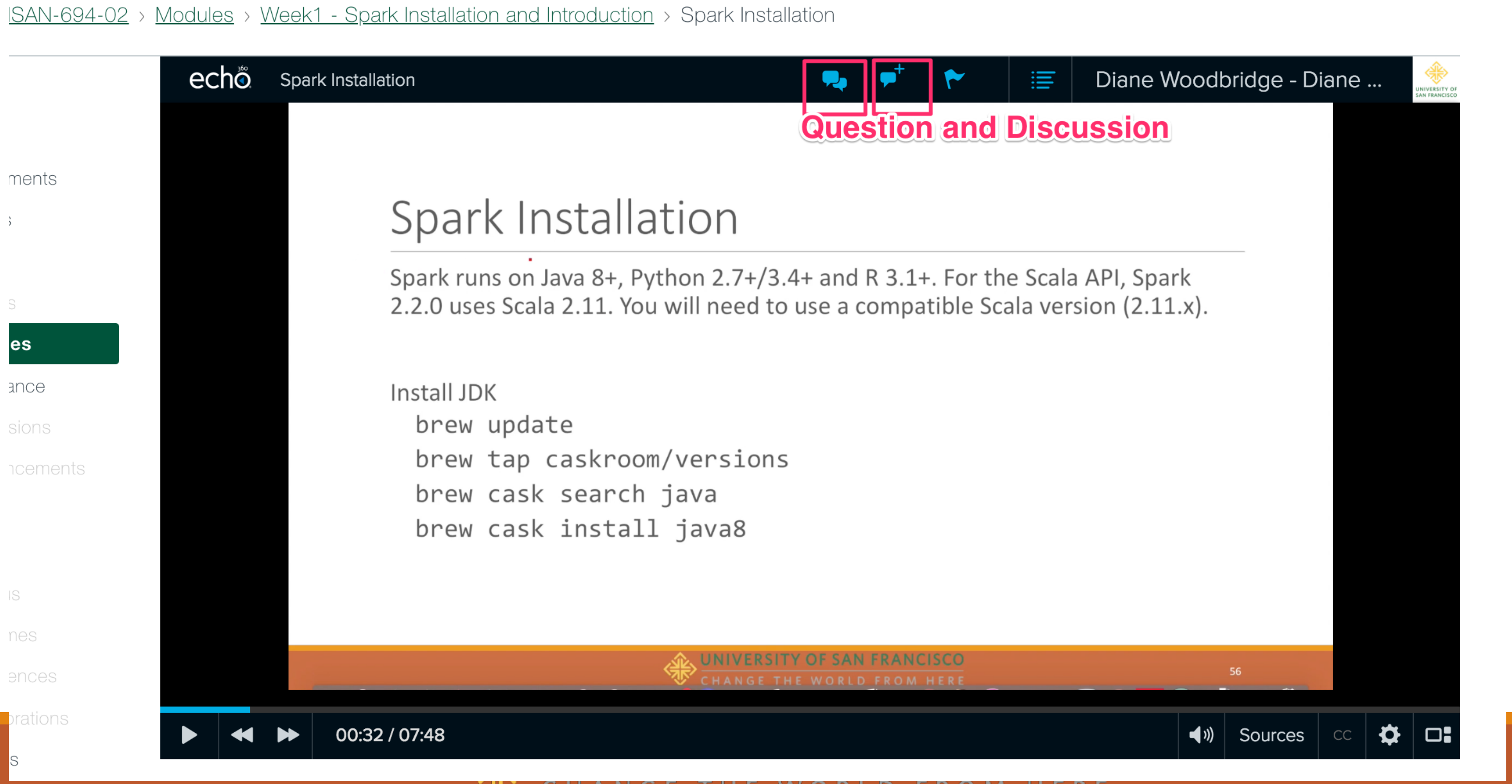
Spark Installation

HW 2 Instruction

Student Engagement

Canvas

- For some assignment, I am going to upload videos.



ISAN-694-02 › Modules › Week1 - Spark Installation and Introduction › Spark Installation
echo
Spark Installation
Diane Woodbridge - Diane ...
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Sources
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UNIVERSITY OF SAN FRANCISCO
CHANGE THE WORLD FROM HERE
56

Question and Discussion

Spark Installation

Spark runs on Java 8+, Python 2.7+/3.4+ and R 3.1+. For the Scala API, Spark 2.2.0 uses Scala 2.11. You will need to use a compatible Scala version (2.11.x).

Install JDK

```
  brew update
  brew tap caskroom/versions
  brew cask search java
  brew cask install java8
```

Any Questions?

Start the presentation to see live content. For screen share software, share the entire screen. Get help at **pollev.com/app**

Contents

Class Intro

Environment Setup

Code Standard

Big Data and Distributed Computing

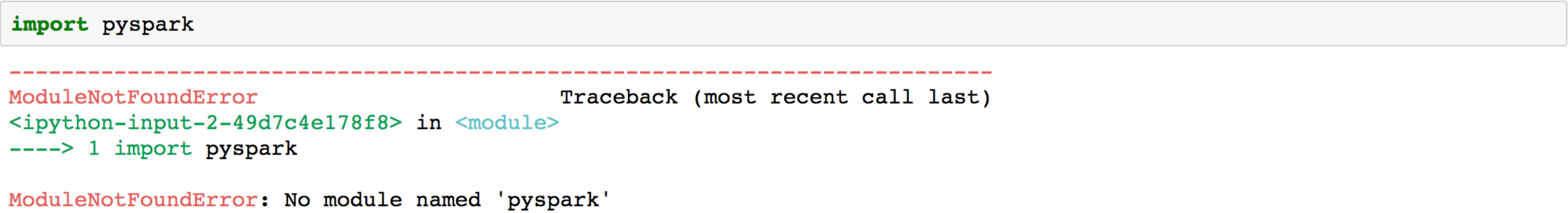
MapReduce Concept

Collaboration

This class (and many other classes) requires collaborations.

- Things to consider..
  - Environment Setup
  - Code Standard
  - Documentation
  - And many more!

Environment



```
import pyspark
```

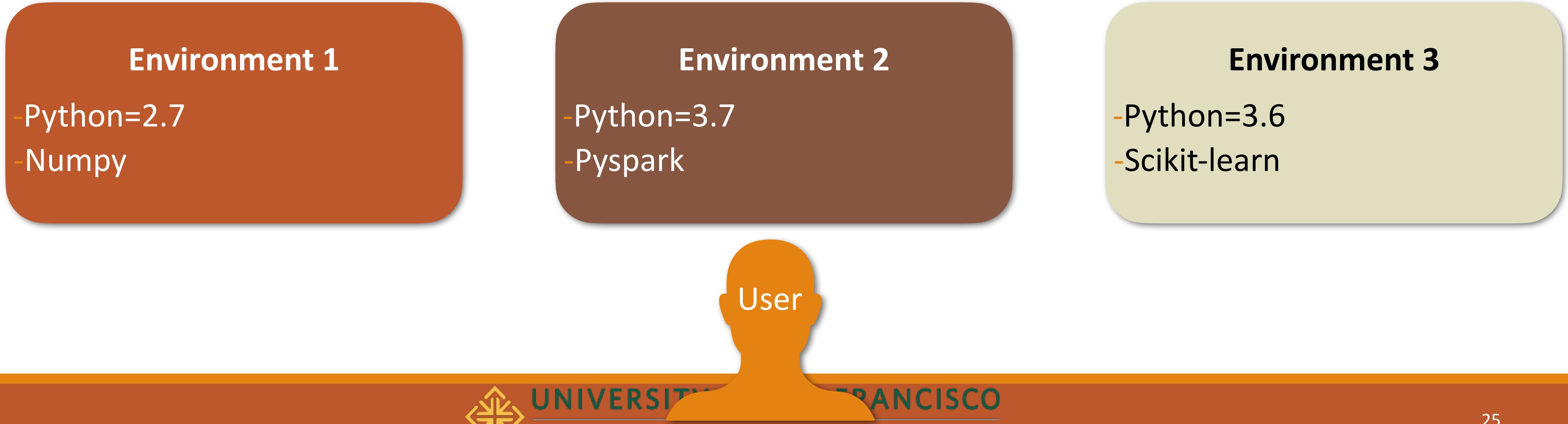
```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-2-49d7c4e178f8> in <module>
----> 1 import pyspark

ModuleNotFoundError: No module named 'pyspark'
```

Environment

A project team member might work on several projects requiring different versions of Python or other packages.

Environment

- Keep dependencies required by different project in separate places.
- Easily switch to an environment that requires different dependencies.



Environment 1

-Python=2.7
-Numpy

Environment 2

-Python=3.7
-Pyspark

Environment 3

-Python=3.6
-Scikit-learn

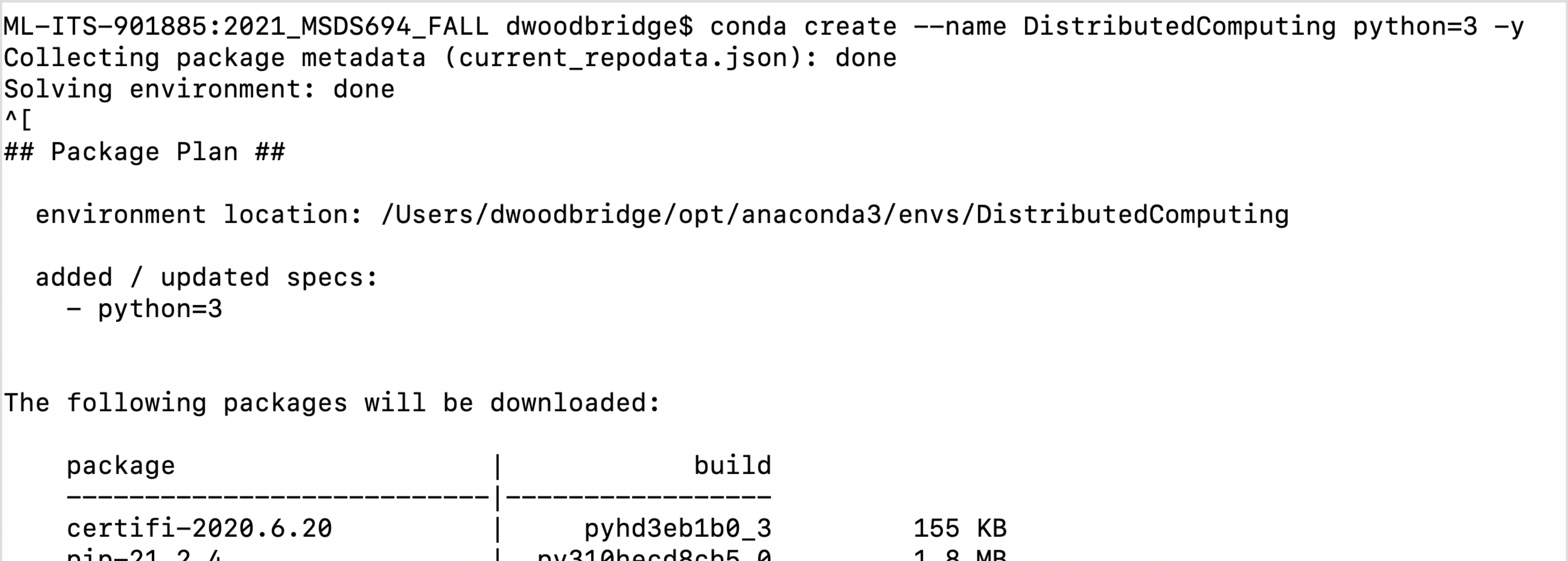
Create an Environment

Environment

- **Create** an environment

```
conda create --name DistributedComputing python=3 -y
```

- ➢ `-y` : yes to all the questions.
- ➢ It will create ”`DistributedComputing`” directory under /Users/USER_ID/opt/anaconda3/envs/



```
ML-ITS-901885:2021_MSDS694_FALL dwoodbridge$ conda create --name DistributedComputing python=3 -y
Collecting package metadata (current_repodata.json): done
Solving environment: done
^[
## Package Plan ##

  environment location: /Users/dwoodbridge/opt/anaconda3/envs/DistributedComputing

  added / updated specs:
    - python=3


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    certifi-2020.6.20          |     pyhd3eb1b0_3         155 KB
    pip-21.2.4                 |   py310hecd8cb5_0         1.8 MB
```

Create an Environment

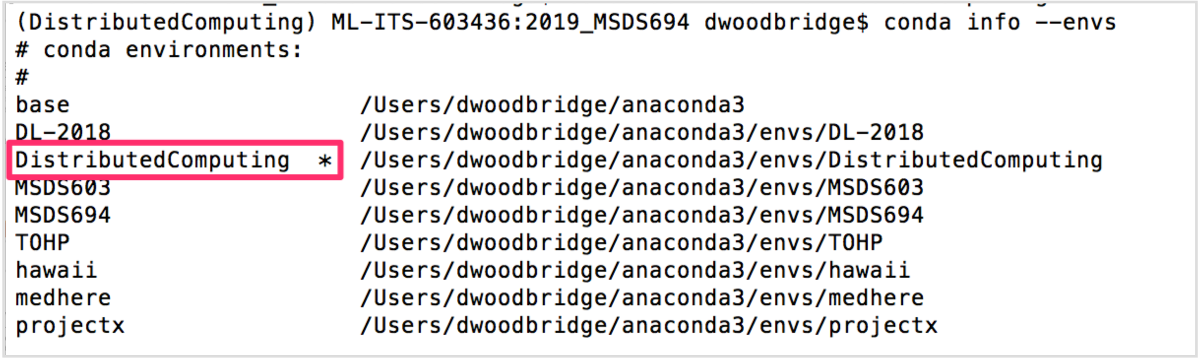
Environment

- **Activating** the environment

  ```
  conda activate DistributedComputing
  ```

- **Checking** available environments and the current environment

  ```
  conda info --envs
  ```

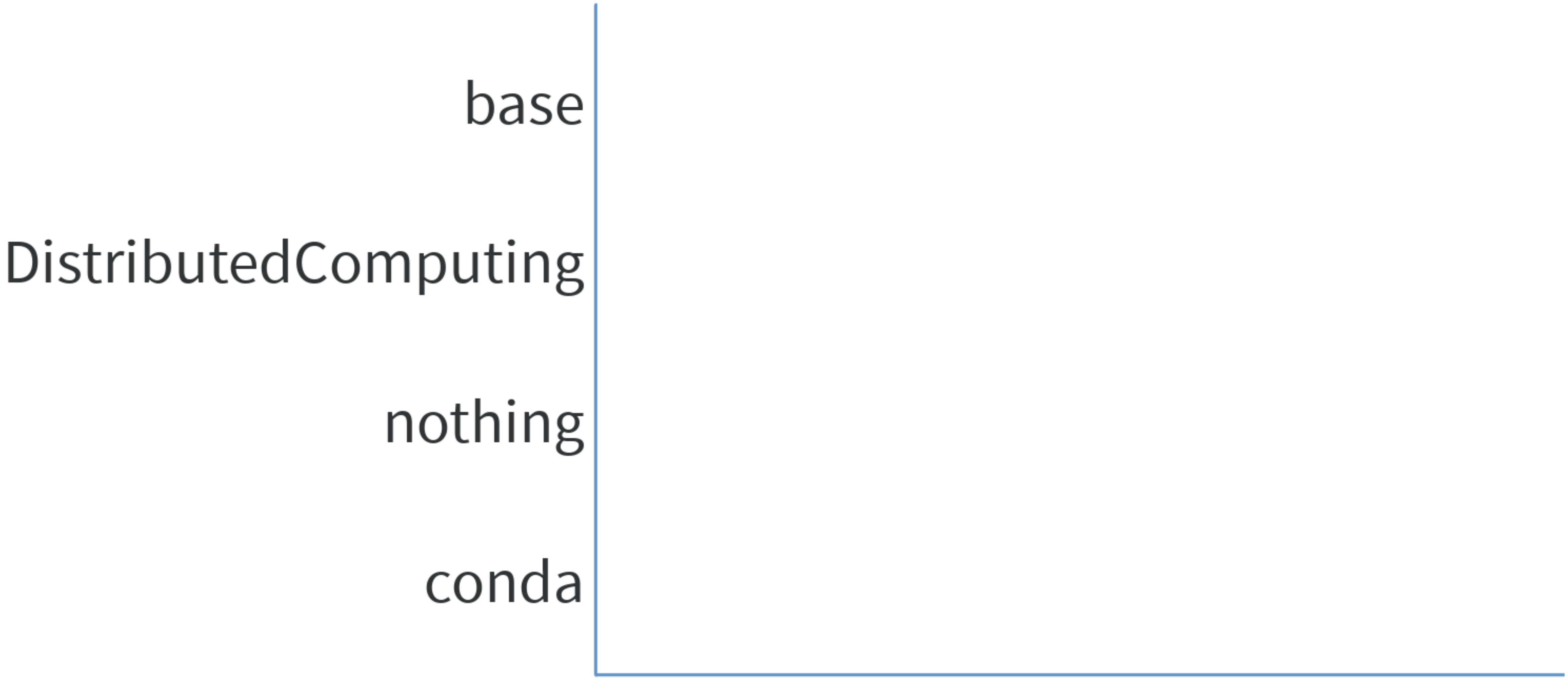


```
(DistributedComputing) ML-ITS-603436:2019_MSDS694 dwoodbridge$ conda info --envs
# conda environments:
#
base                      /Users/dwoodbridge/anaconda3
DL-2018                   /Users/dwoodbridge/anaconda3/envs/DL-2018
DistributedComputing  *   /Users/dwoodbridge/anaconda3/envs/DistributedComputing
MSDS603                   /Users/dwoodbridge/anaconda3/envs/MSDS603
MSDS694                   /Users/dwoodbridge/anaconda3/envs/MSDS694
TOHP                      /Users/dwoodbridge/anaconda3/envs/TOHP
hawaii                    /Users/dwoodbridge/anaconda3/envs/hawaii
medhere                   /Users/dwoodbridge/anaconda3/envs/medhere
projectx                  /Users/dwoodbridge/anaconda3/envs/projectx
```

- **Deactivating** the environment

  ```
  conda deactivate
  ```

What is your env after deactivating the environment?



Example 1

Let’s activate DistributedComputing again.

```
conda activate DistributedComputing
```

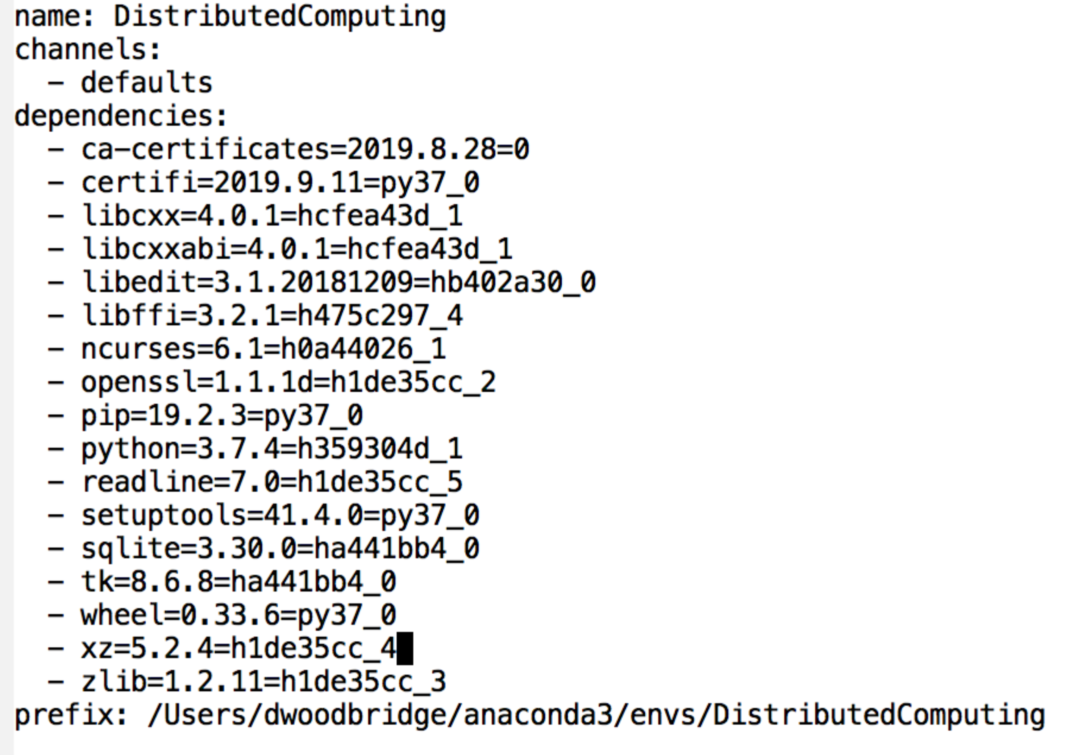
Create an Environment

When you’re pushing your code to the git, you should add the updated .yml file as well.

Environment

- **Export** the environment file to share and reproduce the current environments including all the packages with corresponding versions.

```
conda env export > DistributedComputing_environment.yml
```



```
name: DistributedComputing
channels:
  - defaults
dependencies:
  - ca-certificates=2019.8.28=0
  - certifi=2019.9.11=py37_0
  - libcxx=4.0.1=hcfea43d_1
  - libcxxabi=4.0.1=hcfea43d_1
  - libedit=3.1.20181209=hb402a30_0
  - libffi=3.2.1=h475c297_4
  - ncurses=6.1=h0a44026_1
  - openssl=1.1.1d=h1de35cc_2
  - pip=19.2.3=py37_0
  - python=3.7.4=h359304d_1
  - readline=7.0=h1de35cc_5
  - setuptools=41.4.0=py37_0
  - sqlite=3.30.0=ha441bb4_0
  - tk=8.6.8=ha441bb4_0
  - wheel=0.33.6=py37_0
  - xz=5.2.4=h1de35cc_4
  - zlib=1.2.11=h1de35cc_3
prefix: /Users/dwoodbridge/anaconda3/envs/DistributedComputing
```

.yml : Data serialization lanugage. Commonly used for configuration files.

Using Pip in a Conda Environment
https://www.anaconda.com/using-pip-in-a-conda-environment/

Create an Environment

Environment

- **Remove** the environment (after **`deactivate`**)

```
conda remove --name DistributedComputing --all
```

- **Create** or **update** an environment using .yml.

```
conda env create -f DistributedComputing_environment.yml -n DistributedComputing
conda env update -f DistributedComputing_environment.yml -n DistributedComputing
```

  - -f : file name
  - -n : environment name

Example 2

Export your environment into DistributedComputing_environment.yml.

Deactivate your environment.

Delete your environment.

Create an environment using DistributedComputing_environment.yml

Contents

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MapReduce Concept

Code Conventions

For collaborative environment, using a consistent style provides better code management, readability, understandability and maintenance.

Follow commonly used or internally agreed code conventions.

- Code Conventions : Commonly used and recommended choices as a more readable option.
- PEP (Python Enhancement Proposals)
  - PEP 8 : Style Guide for Python Code
  - PEP 20 : The Zen of Python

Contents

Class Intro

Environment Setup

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Big Data and Distributed Computing

MapReduce Concept

Big Data

Size and structure is beyond the ability of traditional data-processing application software can adequately handle.

- Example domains
  - Internet of Things (IoT) – Smart homes, Electronic toll collection, Smart grid, Wearable, etc.
  - Health Care – Electronic health records (EHR)
  - Marketing – Consumer data
  - What else?
- Size : Constantly moving target - as of 2012 ranging from terabytes (TB) to exabytes (EB).
- Structure : Mostly unstructured.

➢ Storing and **Processing** Big Data became an important issue!

https://en.wikipedia.org/wiki/Big_data

Distributed Computing

For processing large volumes of data fast,

- “Scale out” instead of scale up.
  - Cheaper : Run large data on clusters of many smaller and cheaper machines.
  - Reliable (Fault Tolerant): If one node or process fails, its workload should be assumed by other components in the system.
  - Faster : It parallelizes and distributes computations.

Contents

Class Intro

Environment Setup

Code Standard

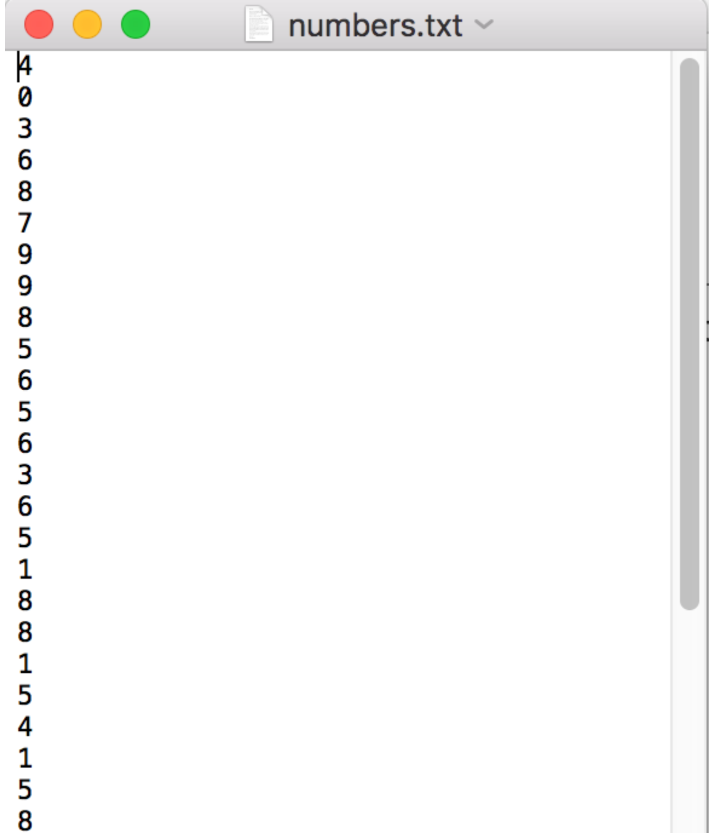
Big Data and Distributed Computing

MapReduce Concept

Discussion

In Data/numbers.txt, how to calculate the sum of numbers that are greater than or equal to 8 quickly?

- numbers.txt : 100 integers between 0 and 9.



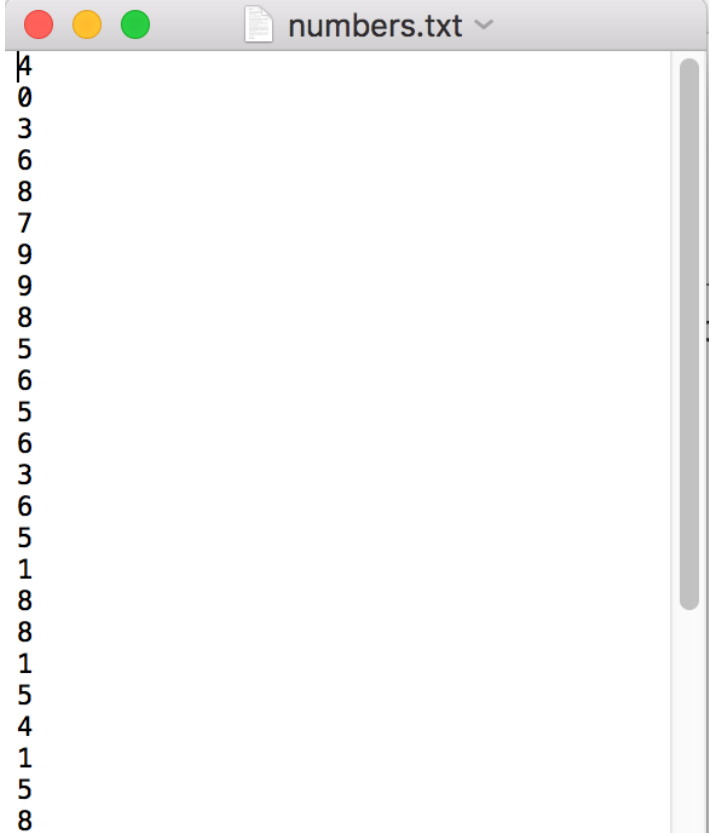
```
4
0
3
6
8
7
9
9
8
5
6
5
6
3
6
5
1
8
8
1
5
4
1
5
8
```

Discussion

In Data/numbers.txt, how to calculate the sum of numbers that are greater than or equal to 8 quickly?

- numbers.txt : 100 integers between 0 and 9.

WHAT IF WE HAVE 1 TB Of DATA?



```
4
0
3
6
8
7
9
9
8
5
6
5
6
3
6
5
1
8
8
1
5
4
1
5
8
```

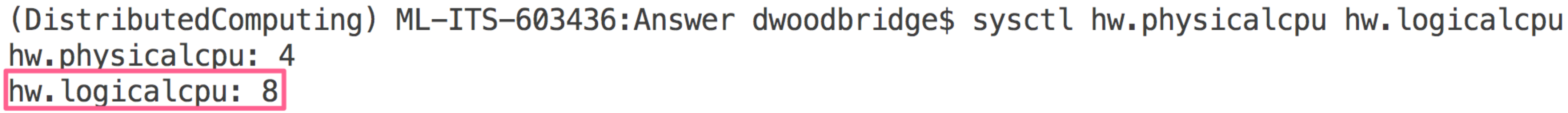
In Data/numbers.txt, how to calculate the sum of numbers that are greater than or equal to 8 quickly?

Example

My Computer

- Logical cores = (# of physical cores) x (# of threads that can run on each core)

```
sysctl hw.physicalcpu hw.logicalcpu
```



```
(DistributedComputing) ML-ITS-603436:Answer dwoodbridge$ sysctl hw.physicalcpu hw.logicalcpu
hw.physicalcpu: 4
hw.logicalcpu: 8
```

Example

My Computer

- Logical cores = (# of physical cores) x (# of threads that can run on each core)

```
sysctl hw.physicalcpu hw.logicalcpu
```

How many logical cores does your laptop have?

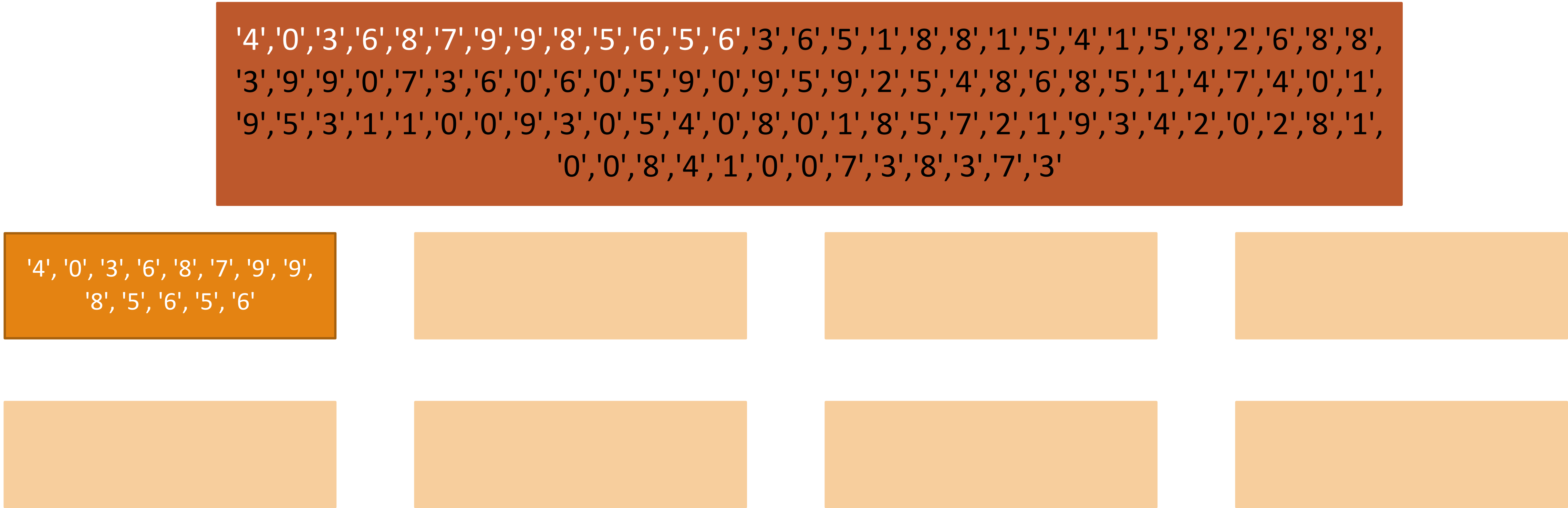
When poll is active, respond at **PollEv.com/msds**

Top

Start the presentation to see live content. Still no live content? Install the app or get help at **PollEv.com/app**

Example

Spark Way – **Utilize all the cores (or a few) !**

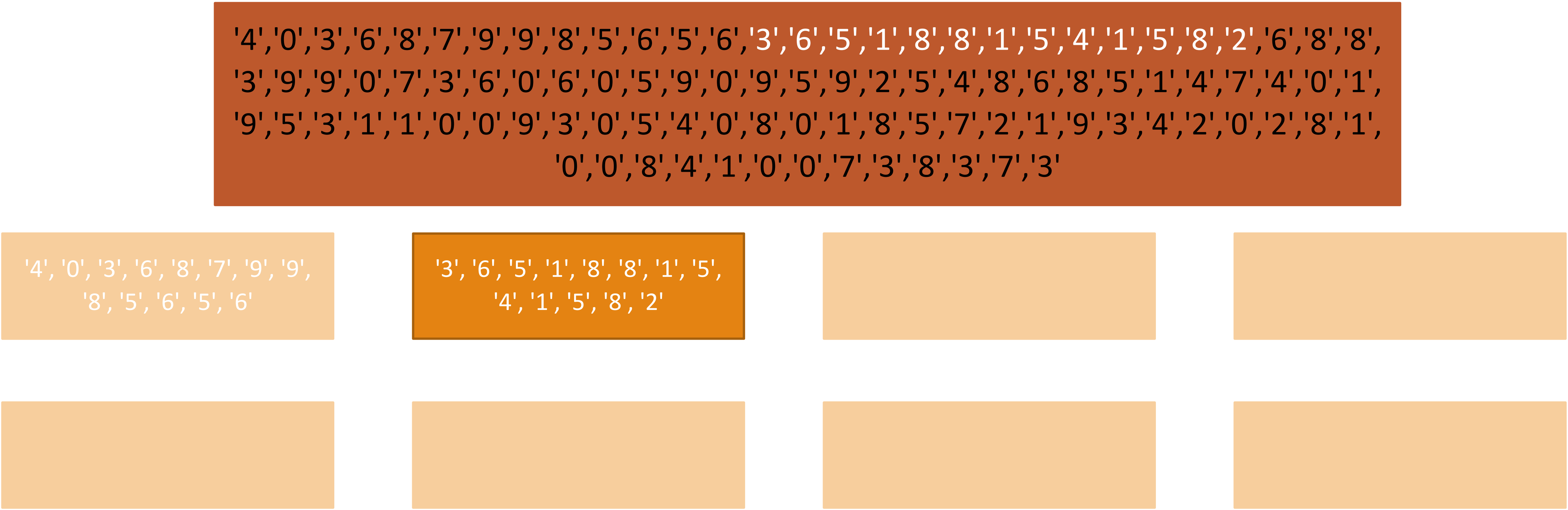


'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
'9','5','3','1','1','0','0','9','3','0','5','4','0','8','0','1','8','5','7','2','1','9','3','4','2','0','2','8','1',
'0','0','8','4','1','0','0','7','3','8','3','7','3'

'4', '0', '3', '6', '8', '7', '9', '9',
'8', '5', '6', '5', '6'

Example

Spark Way



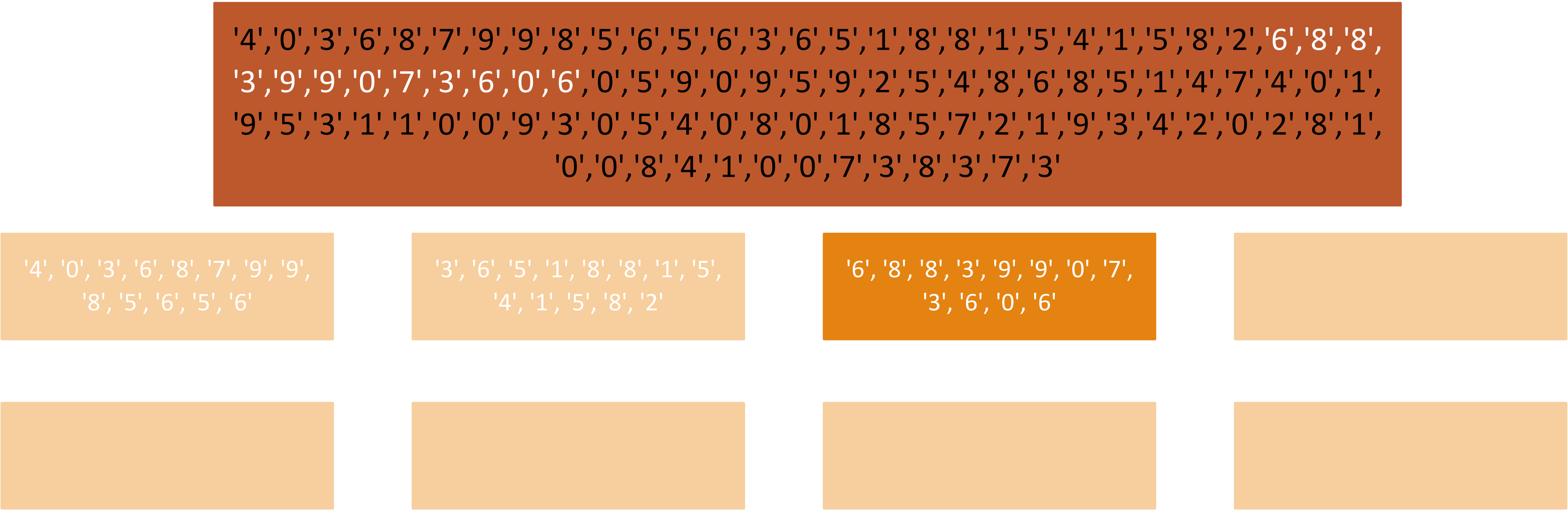
'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
'9','5','3','1','1','0','0','9','3','0','5','4','0','8','0','1','8','5','7','2','1','9','3','4','2','0','2','8','1',
'0','0','8','4','1','0','0','7','3','8','3','7','3'

'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

Example

Spark Way



'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
'9','5','3','1','1','0','0','9','3','0','5','4','0','8','0','1','8','5','7','2','1','9','3','4','2','0','2','8','1',
'0','0','8','4','1','0','0','7','3','8','3','7','3'

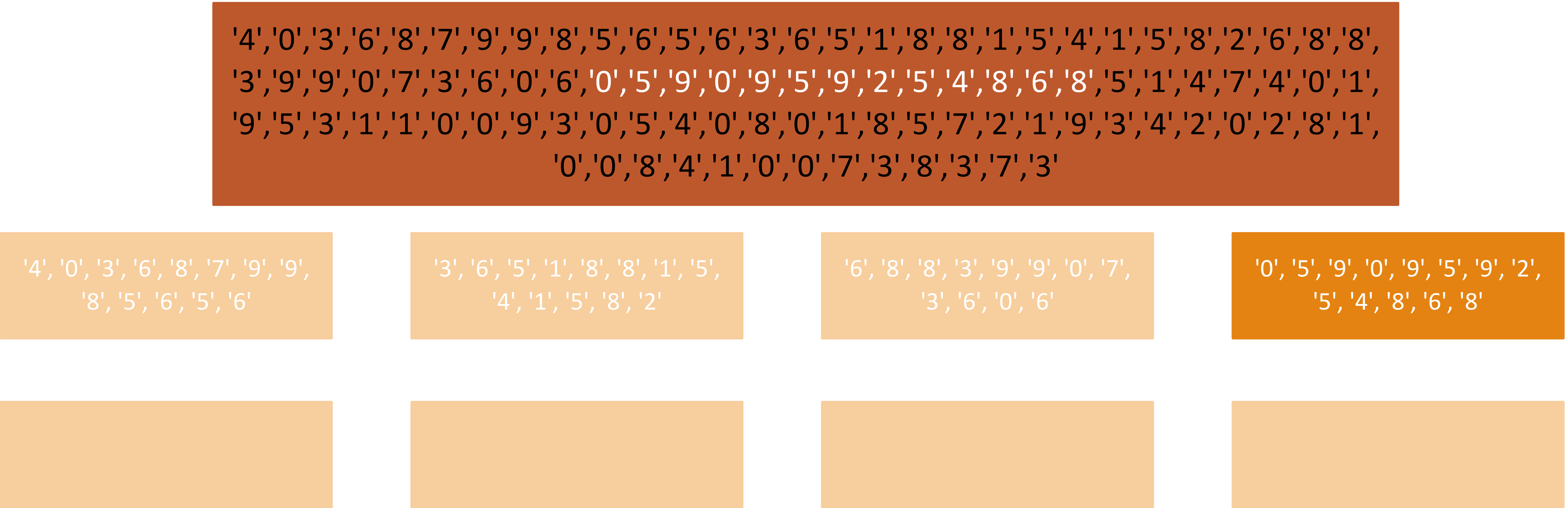
'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'

Example

Spark Way



'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
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'0','0','8','4','1','0','0','7','3','8','3','7','3'

'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

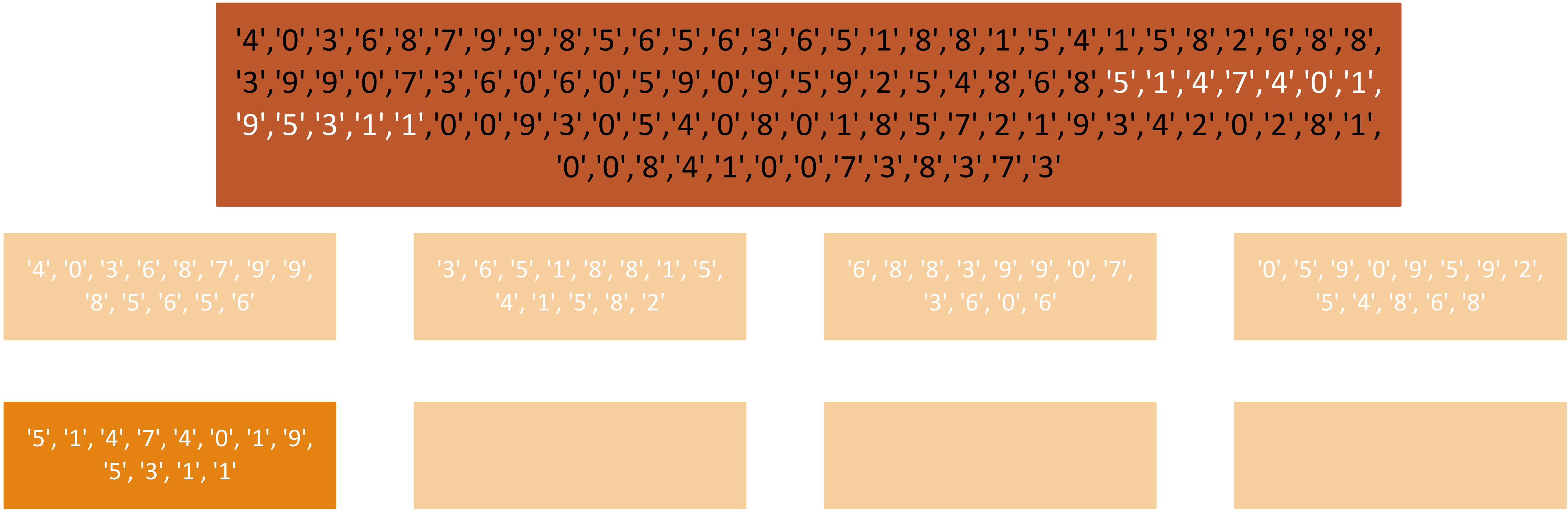
'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'

'0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'

Example

Spark Way



'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
'9','5','3','1','1','0','0','9','3','0','5','4','0','8','0','1','8','5','7','2','1','9','3','4','2','0','2','8','1',
'0','0','8','4','1','0','0','7','3','8','3','7','3'

'4', '0', '3', '6', '8', '7', '9', '9',
'8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5',
'4', '1', '5', '8', '2'

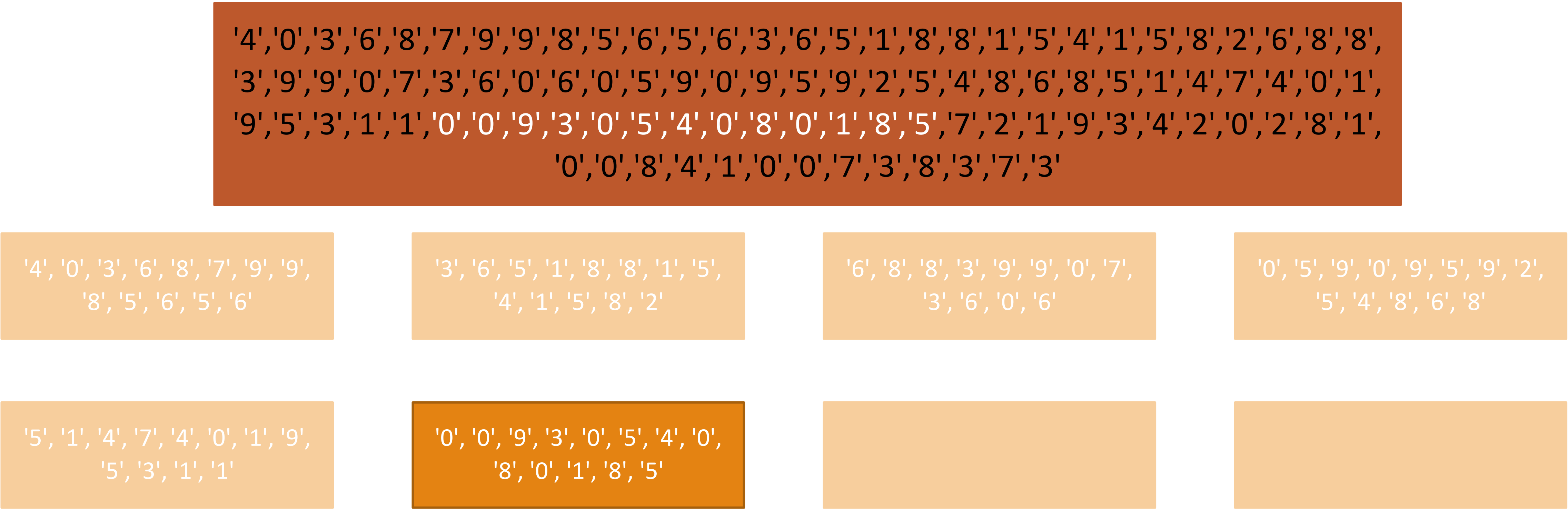
'6', '8', '8', '3', '9', '9', '0', '7',
'3', '6', '0', '6'

'0', '5', '9', '0', '9', '5', '9', '2',
'5', '4', '8', '6', '8'

'5', '1', '4', '7', '4', '0', '1', '9',
'5', '3', '1', '1'

Example

Spark Way



'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
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'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'

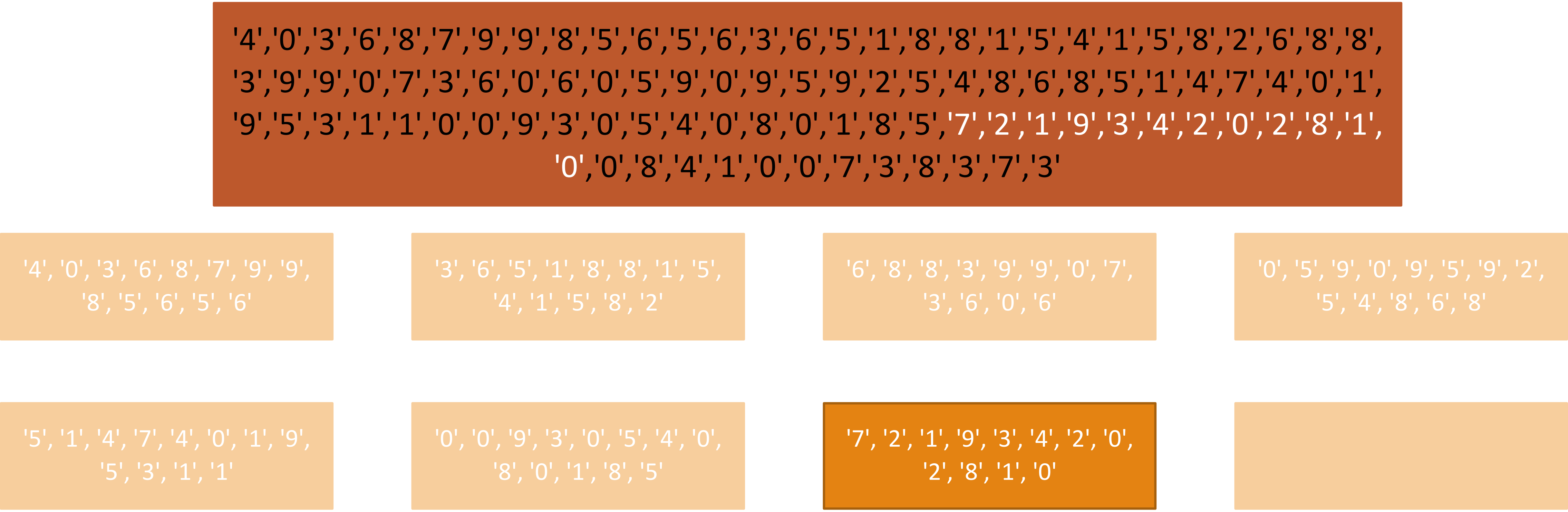
'0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'

'5', '1', '4', '7', '4', '0', '1', '9', '5', '3', '1', '1'

'0', '0', '9', '3', '0', '5', '4', '0', '8', '0', '1', '8', '5'

Example

Spark Way



'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
'9','5','3','1','1','0','0','9','3','0','5','4','0','8','0','1','8','5','7','2','1','9','3','4','2','0','2','8','1',
'0','0','8','4','1','0','0','7','3','8','3','7','3'

'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'

'0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'

'5', '1', '4', '7', '4', '0', '1', '9', '5', '3', '1', '1'

'0', '0', '9', '3', '0', '5', '4', '0', '8', '0', '1', '8', '5'

'7', '2', '1', '9', '3', '4', '2', '0', '2', '8', '1', '0'

Example

Spark Way

'4','0','3','6','8','7','9','9','8','5','6','5','6','3','6','5','1','8','8','1','5','4','1','5','8','2','6','8','8',
'3','9','9','0','7','3','6','0','6','0','5','9','0','9','5','9','2','5','4','8','6','8','5','1','4','7','4','0','1',
'9','5','3','1','1','0','0','9','3','0','5','4','0','8','0','1','8','5','7','2','1','9','3','4','2','0','2','8','1',
'0','0','8','4','1','0','0','7','3','8','3','7','3'

'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'

'0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'

'5', '1', '4', '7', '4', '0', '1', '9', '5', '3', '1', '1'

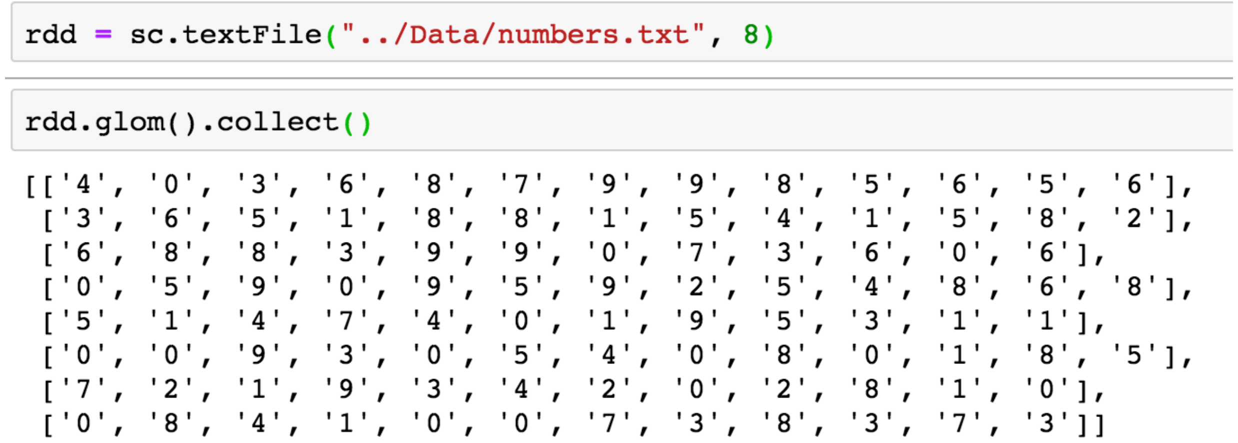
'0', '0', '9', '3', '0', '5', '4', '0', '8', '0', '1', '8', '5'

'7', '2', '1', '9', '3', '4', '2', '0', '2', '8', '1', '0'

'0', '8', '4', '1', '0', '0', '7', '3', '8', '3', '7', '3'

Example

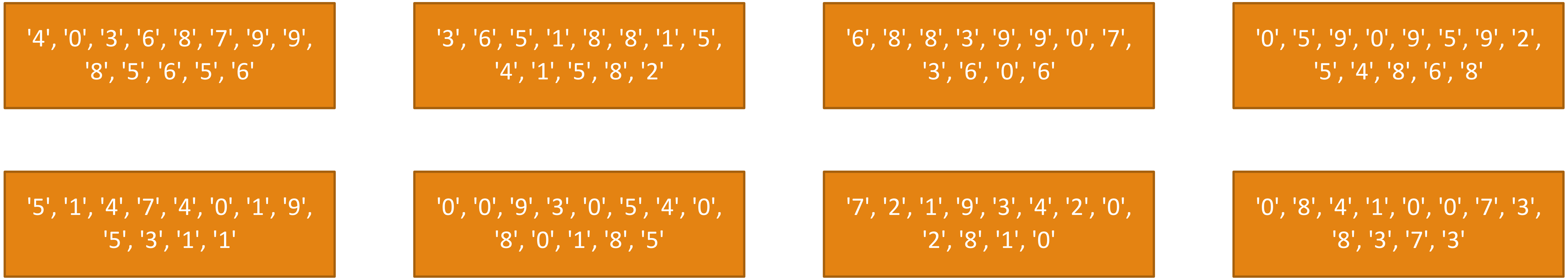
Spark Way



```
rdd = sc.textFile("../Data/numbers.txt", 8)
```

```
rdd.glom().collect()
```

```
[['4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'],
 ['3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'],
 ['6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'],
 ['0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'],
 ['5', '1', '4', '7', '4', '0', '1', '9', '5', '3', '1', '1'],
 ['0', '0', '9', '3', '0', '5', '4', '0', '8', '0', '1', '8', '5'],
 ['7', '2', '1', '9', '3', '4', '2', '0', '2', '8', '1', '0'],
 ['0', '8', '4', '1', '0', '0', '7', '3', '8', '3', '7', '3']]
```



'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'

'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'

'0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'

'5', '1', '4', '7', '4', '0', '1', '9', '5', '3', '1', '1'

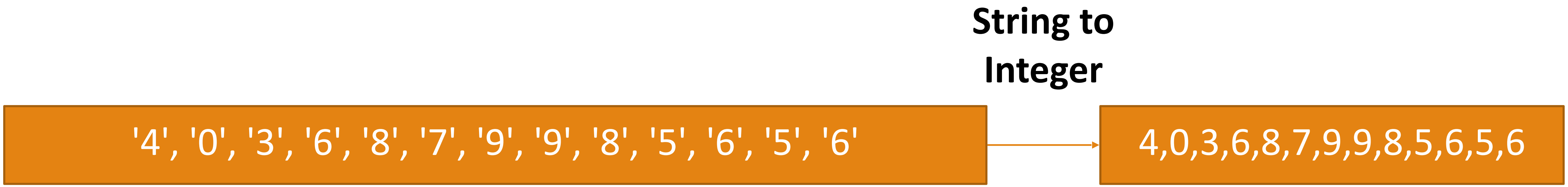
'0', '0', '9', '3', '0', '5', '4', '0', '8', '0', '1', '8', '5'

'7', '2', '1', '9', '3', '4', '2', '0', '2', '8', '1', '0'

'0', '8', '4', '1', '0', '0', '7', '3', '8', '3', '7', '3'

Example

Spark Way



String to Integer

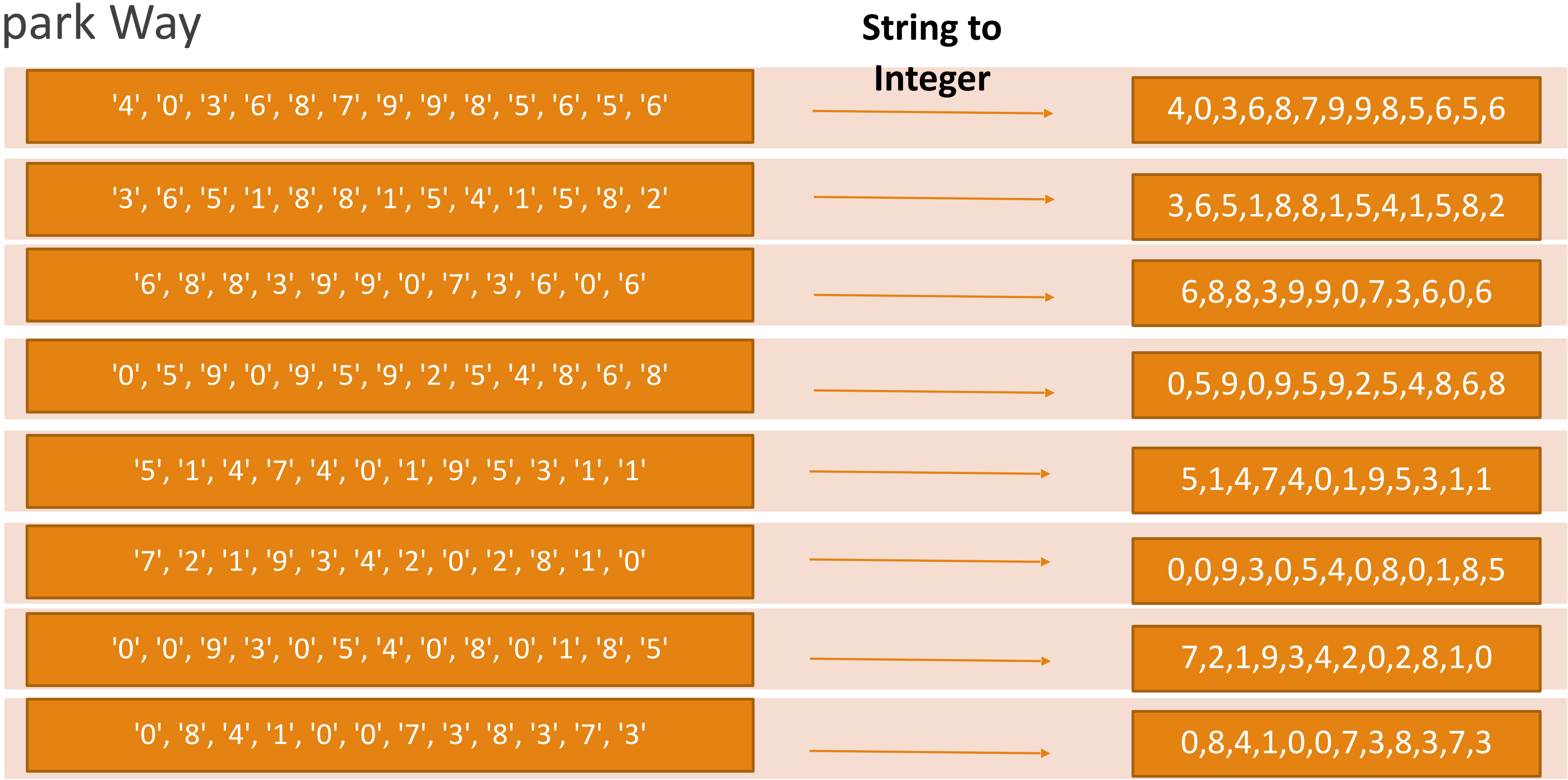
'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'

4,0,3,6,8,7,9,9,8,5,6,5,6

NOTE : This happens in parallel.

Example

Spark Way

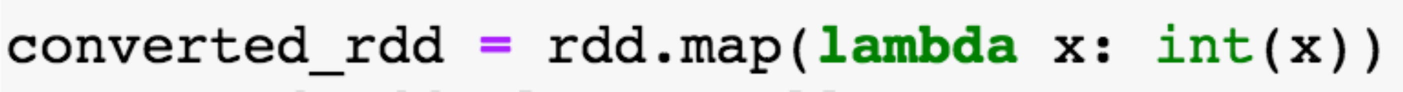


String to Integer

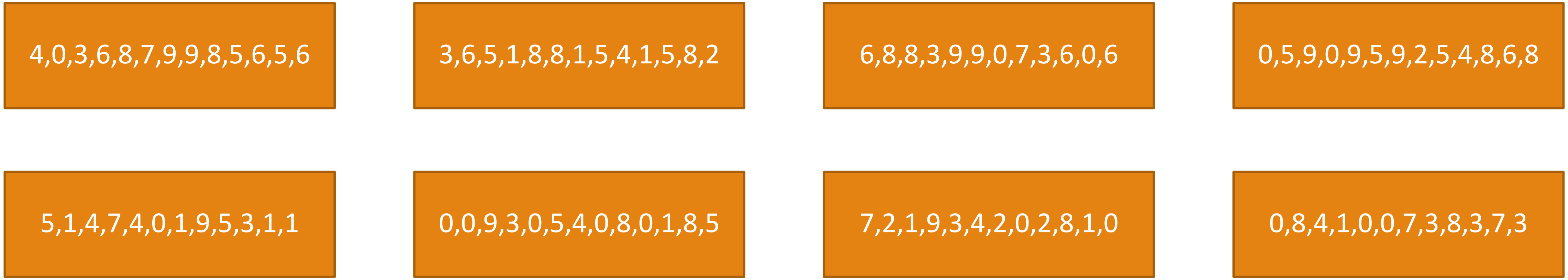
'4', '0', '3', '6', '8', '7', '9', '9', '8', '5', '6', '5', '6'	→	4,0,3,6,8,7,9,9,8,5,6,5,6
'3', '6', '5', '1', '8', '8', '1', '5', '4', '1', '5', '8', '2'	→	3,6,5,1,8,8,1,5,4,1,5,8,2
'6', '8', '8', '3', '9', '9', '0', '7', '3', '6', '0', '6'	→	6,8,8,3,9,9,0,7,3,6,0,6
'0', '5', '9', '0', '9', '5', '9', '2', '5', '4', '8', '6', '8'	→	0,5,9,0,9,5,9,2,5,4,8,6,8
'5', '1', '4', '7', '4', '0', '1', '9', '5', '3', '1', '1'	→	5,1,4,7,4,0,1,9,5,3,1,1
'7', '2', '1', '9', '3', '4', '2', '0', '2', '8', '1', '0'	→	0,0,9,3,0,5,4,0,8,0,1,8,5
'0', '0', '9', '3', '0', '5', '4', '0', '8', '0', '1', '8', '5'	→	7,2,1,9,3,4,2,0,2,8,1,0
'0', '8', '4', '1', '0', '0', '7', '3', '8', '3', '7', '3'	→	0,8,4,1,0,0,7,3,8,3,7,3

Example

Spark Way



```
converted_rdd = rdd.map(lambda x: int(x))
```



4,0,3,6,8,7,9,9,8,5,6,5,6

3,6,5,1,8,8,1,5,4,1,5,8,2

6,8,8,3,9,9,0,7,3,6,0,6

0,5,9,0,9,5,9,2,5,4,8,6,8

5,1,4,7,4,0,1,9,5,3,1,1

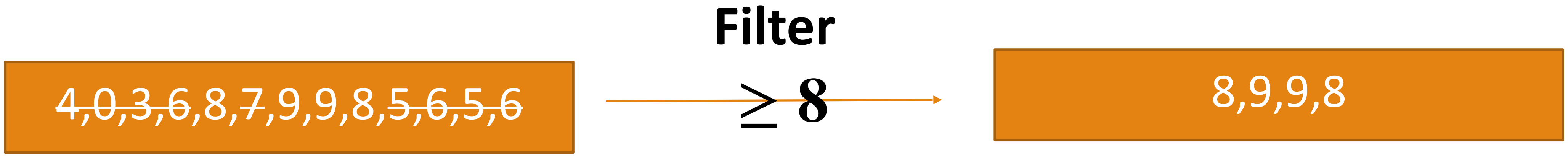
0,0,9,3,0,5,4,0,8,0,1,8,5

7,2,1,9,3,4,2,0,2,8,1,0

0,8,4,1,0,0,7,3,8,3,7,3

Example

Spark Way



~~4,0,3,6~~,8,~~7~~,9,9,8,~~5,6,5,6~~

Filter

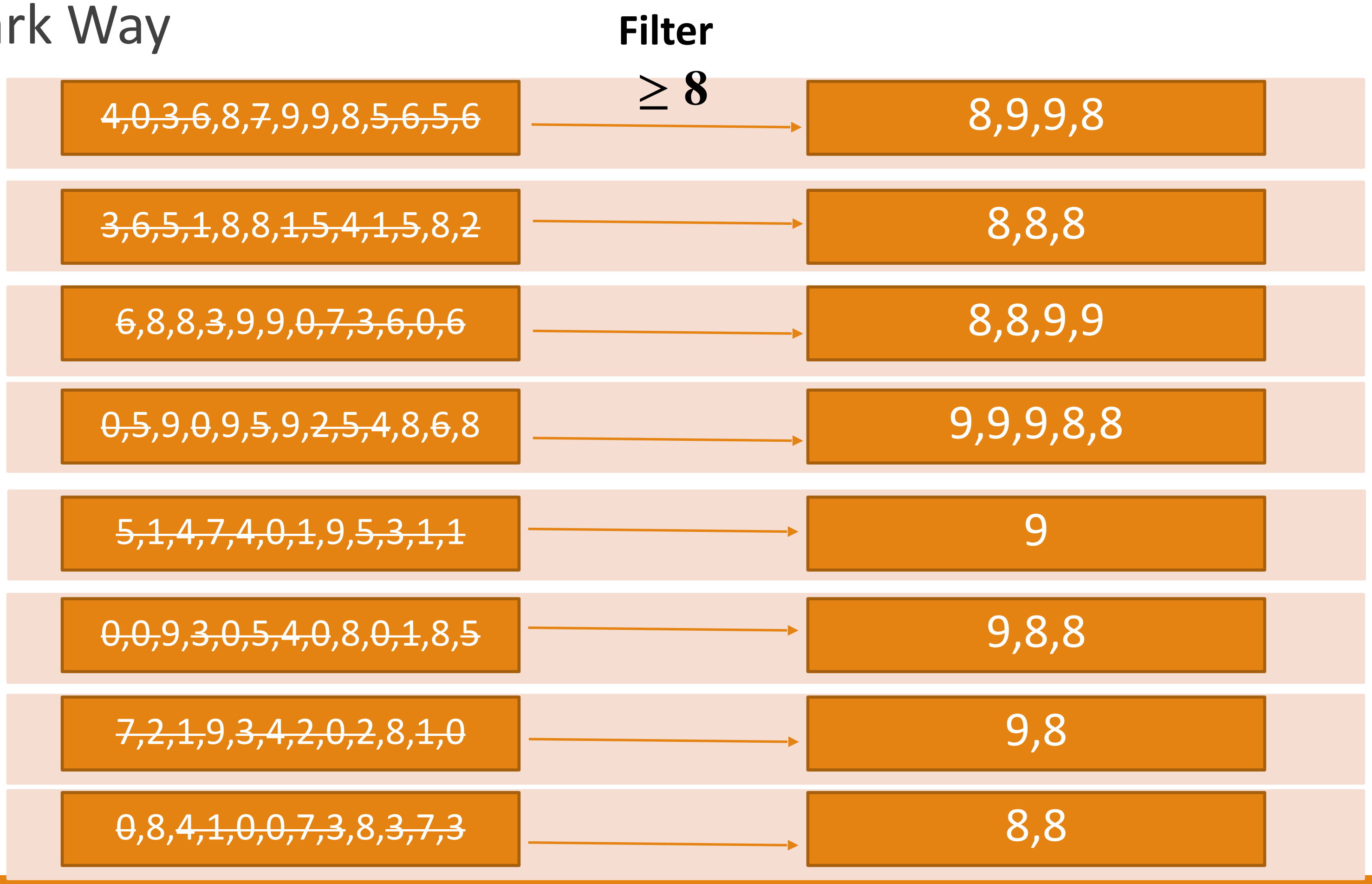
$\geq$ **8**

8,9,9,8

NOTE : This happens in parallel.

Example

Spark Way



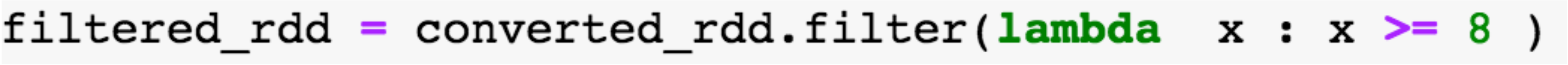
Filter

≥ 8

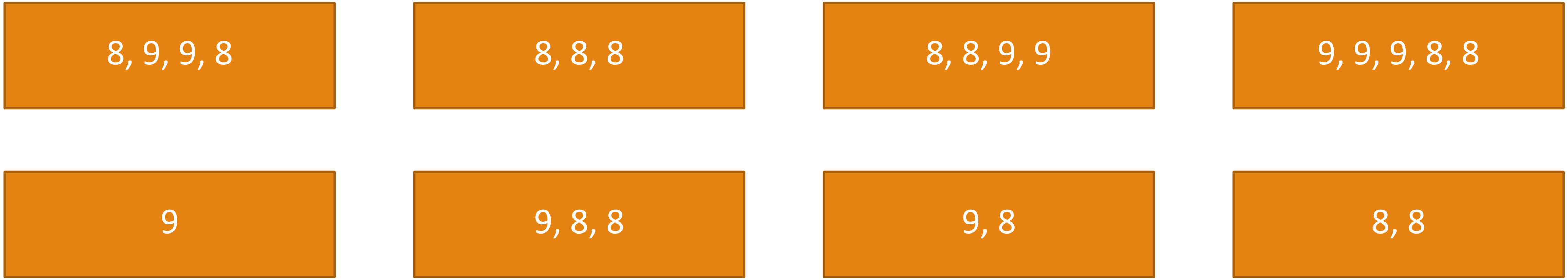
~~4,0,3,6~~,8,~~7~~,9,9,8,~~5,6,5,6~~	8,9,9,8
~~3,6,5,1~~,8,8,~~1,5,4,1,5~~,8,~~2~~	8,8,8
~~6~~,8,8,~~3~~,9,9,~~0,7,3,6,0,6~~	8,8,9,9
~~0,5~~,9,~~0~~,9,~~5~~,9,~~2,5,4~~,8,~~6~~,8	9,9,9,8,8
~~5,1,4,7,4,0,1~~,9,~~5,3,1,1~~	9
~~0,0~~,9,~~3,0,5,4,0~~,8,~~0,1~~,8,~~5~~	9,8,8
~~7,2,1~~,9,~~3,4,2,0,2~~,8,~~1,0~~	9,8
~~0~~,8,~~4,1,0,0,7,3~~,8,~~3,7,3~~	8,8

Example

Spark Way



```
filtered_rdd = converted_rdd.filter(lambda  x : x >= 8 )
```



8, 9, 9, 8

8, 8, 8

8, 8, 9, 9

9, 9, 9, 8, 8

9

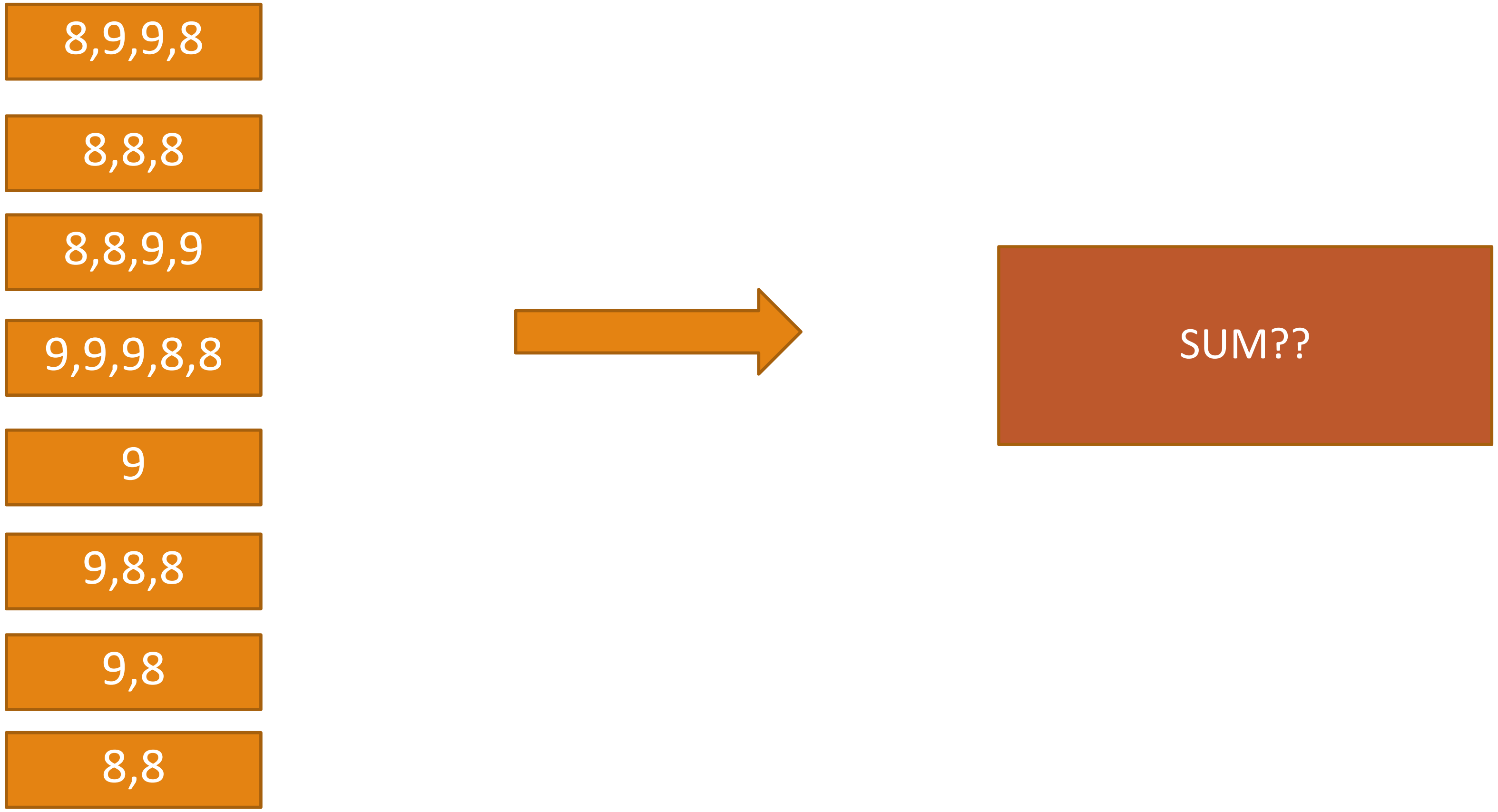
9, 8, 8

9, 8

8, 8

Example

Spark Way



8,9,9,8

8,8,8

8,8,9,9

9,9,9,8,8

9

9,8,8

9,8

8,8

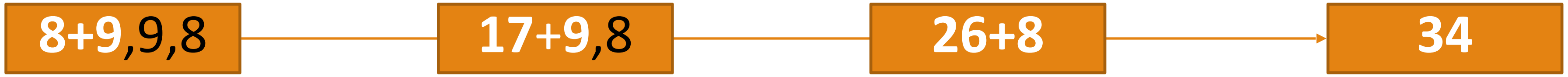
SUM??

Example

Spark Way

8, 9, 9, 8

Add two numbers in the same partition until there is only one number left.



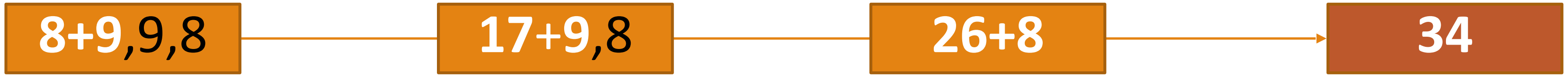
8+9,9,8 → 17+9,8 → 26+8 → 34

Example

Spark Way

8, 9, 9, 8

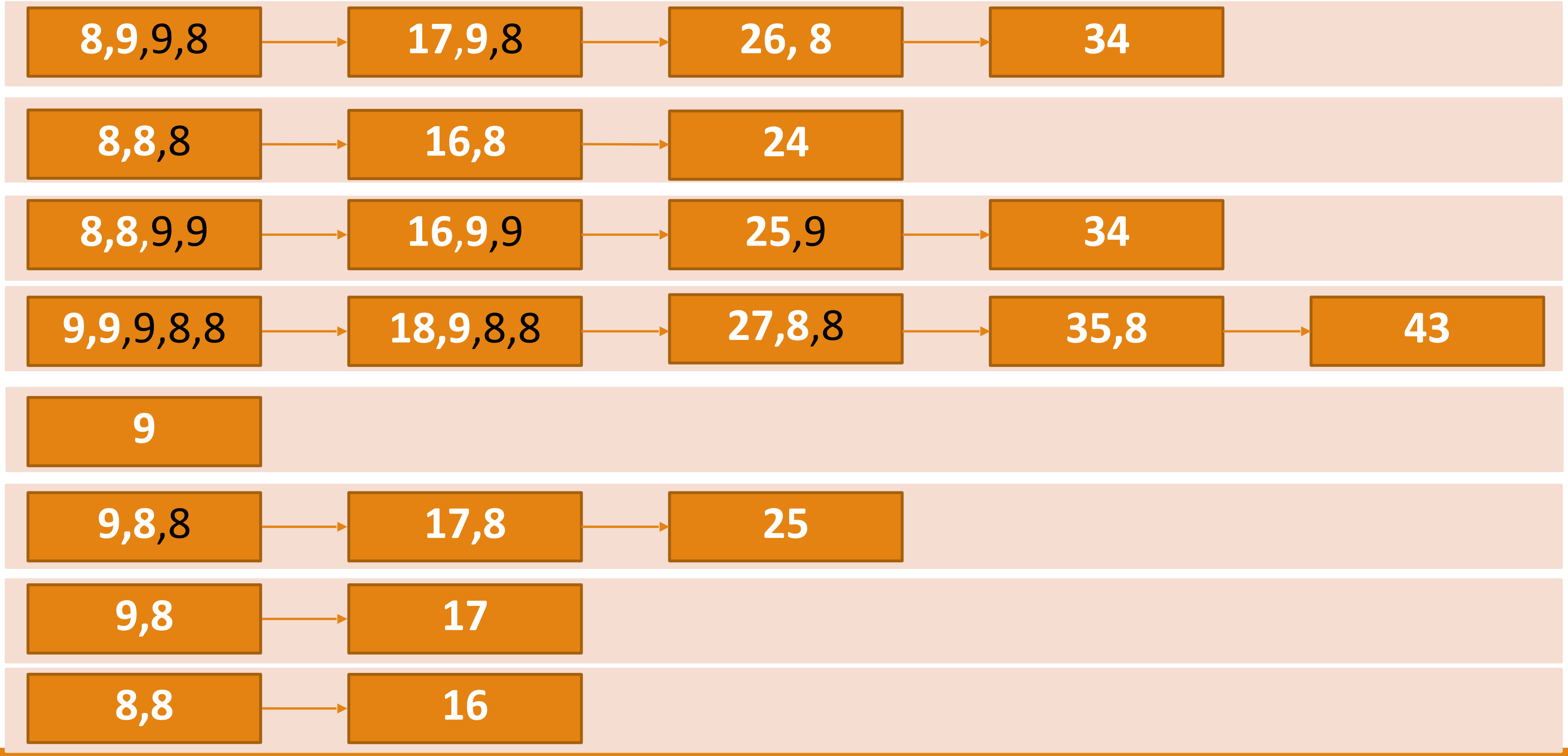
Add two numbers in the same partition until there is only one number left.



Example

NOTE : This happens in parallel.

Spark Way



8,9,9,8 → 17,9,8 → 26, 8 → 34

8,8,8 → 16,8 → 24

8,8,9,9 → 16,9,9 → 25,9 → 34

9,9,9,8,8 → 18,9,8,8 → 27,8,8 → 35,8 → 43

9

9,8,8 → 17,8 → 25

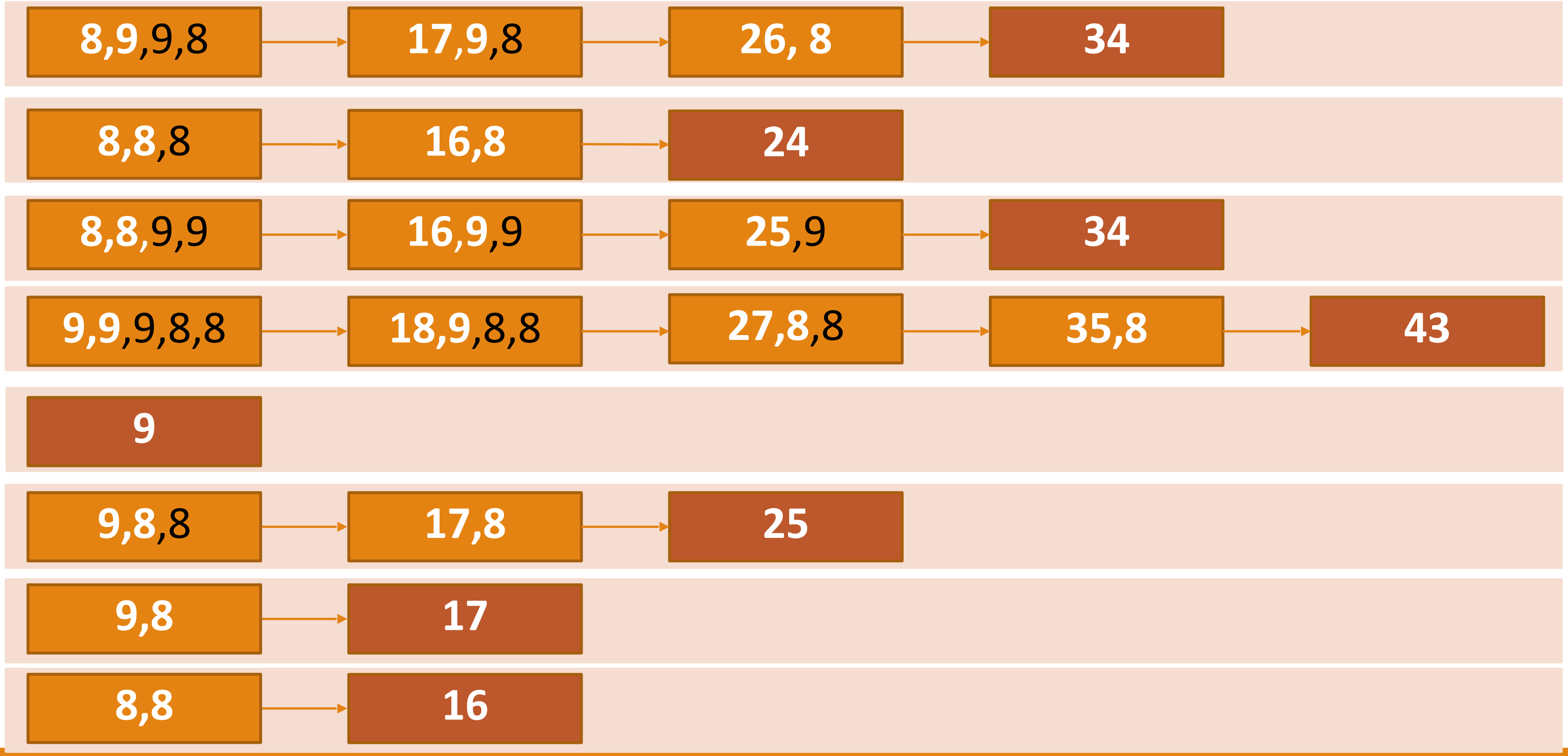
9,8 → 17

8,8 → 16

Example

NOTE : This happens in parallel.

Spark Way



8,9,9,8 → 17,9,8 → 26, 8 → 34

8,8,8 → 16,8 → 24

8,8,9,9 → 16,9,9 → 25,9 → 34

9,9,9,8,8 → 18,9,8,8 → 27,8,8 → 35,8 → 43

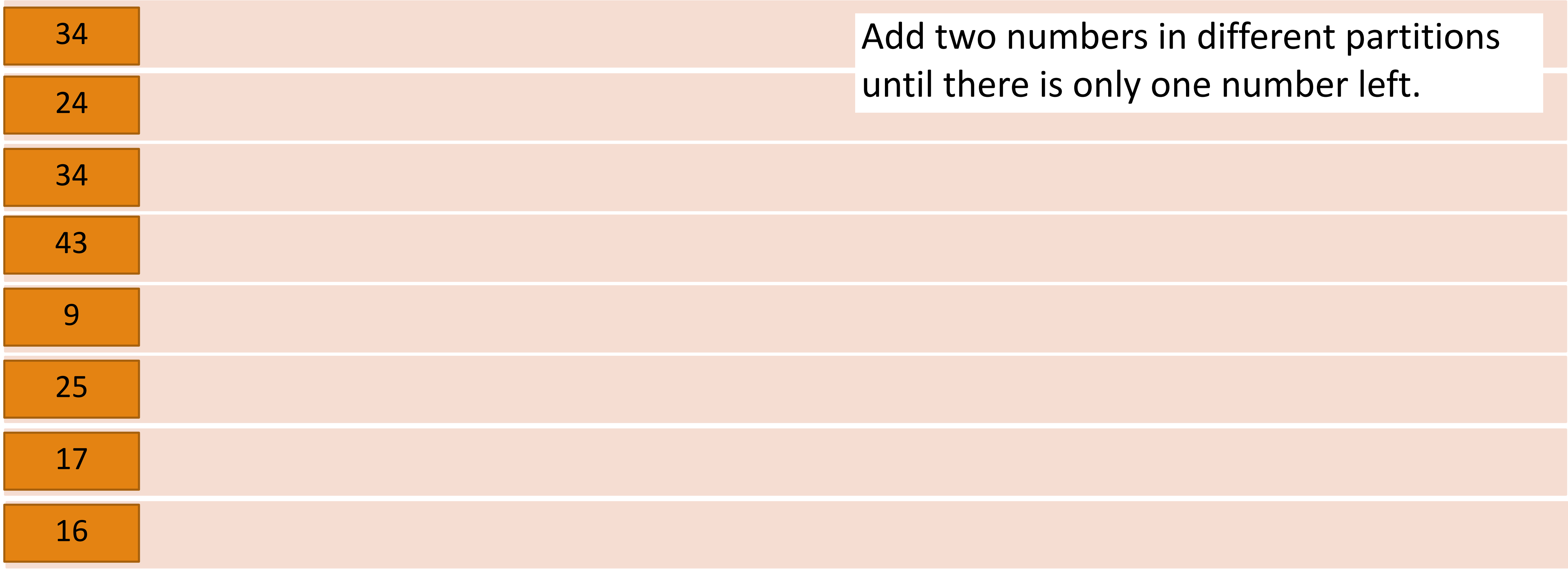
9

9,8,8 → 17,8 → 25

9,8 → 17

8,8 → 16

Example



34

24

34

43

9

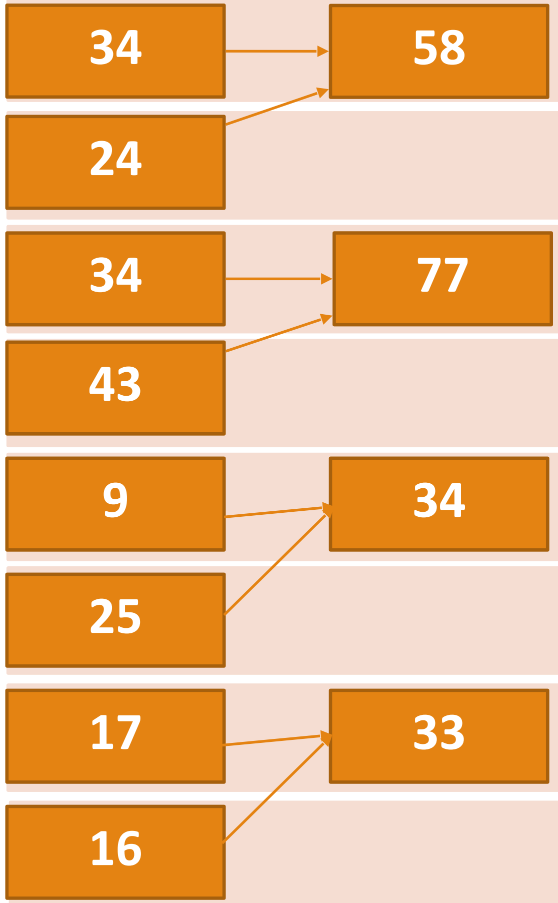
25

17

16

Add two numbers in different partitions until there is only one number left.

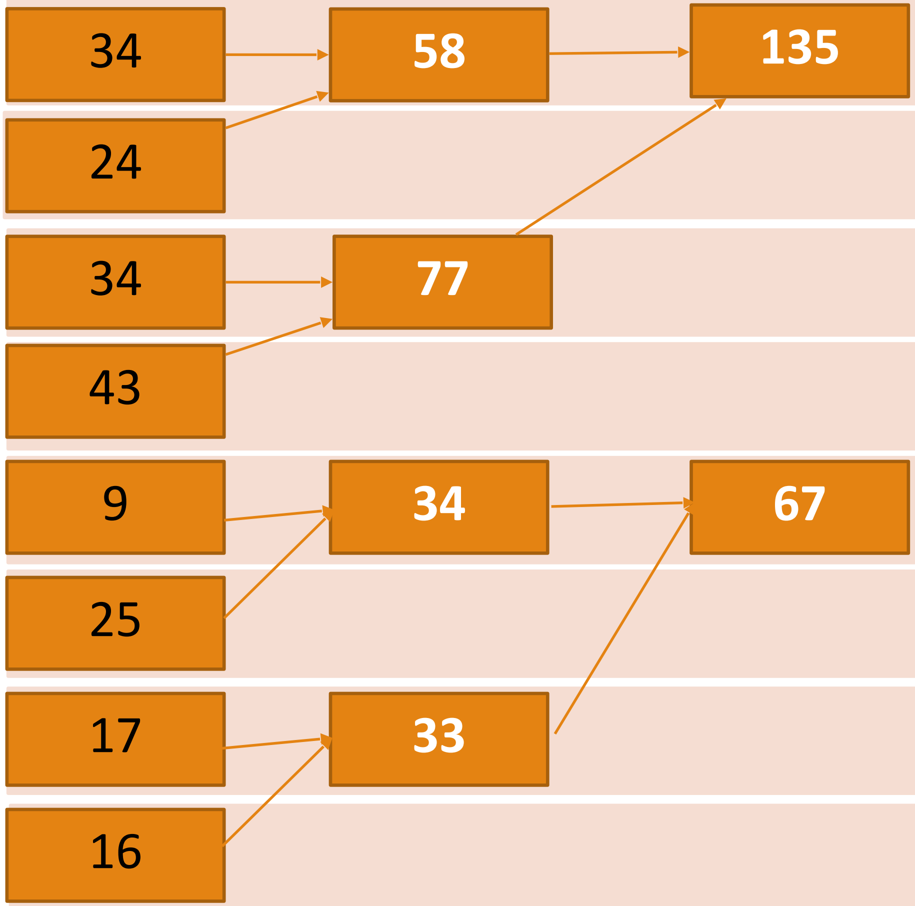
Example



Add two numbers in different partitions until there is only one number left.

- shuffling happens

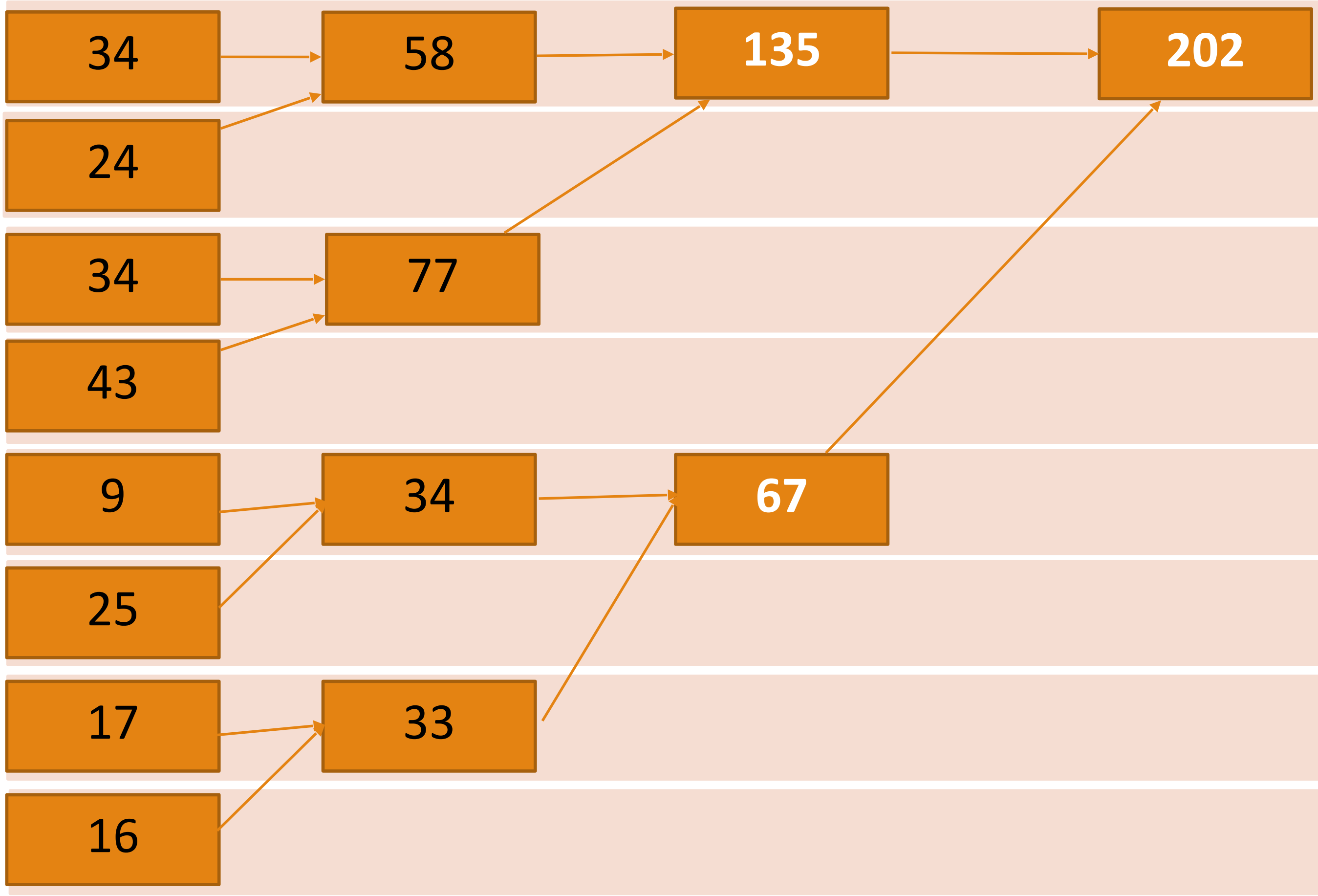
Example



Add two numbers in different partitions until there is only one number left.

- shuffling happens

Example

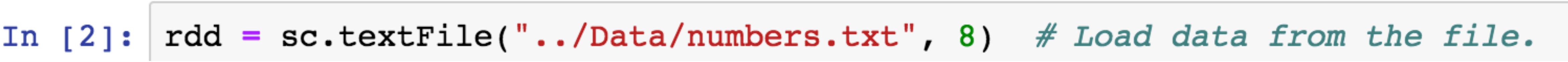


Add two numbers in different partitions until there is only one number left.
- shuffling happens

Example 3

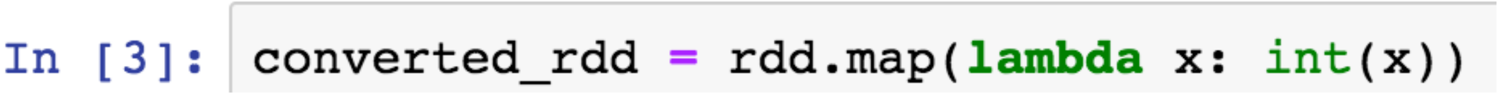
You don’t need to understand this code yet.

1. Load data to 8 partitions.



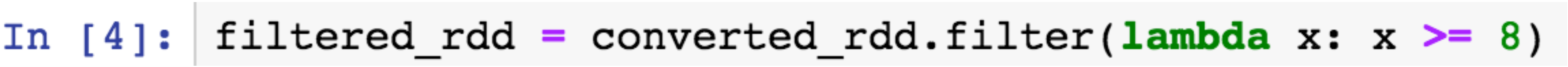
```
In [2]: rdd = sc.textFile("../Data/numbers.txt", 8)  # Load data from the file.
```

2. Convert each data to integer.



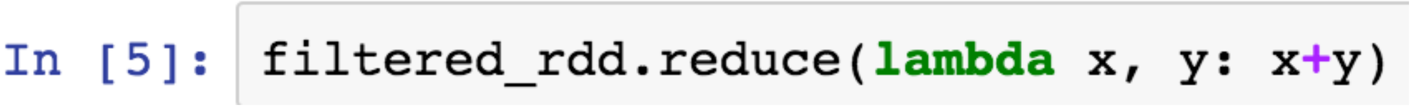
```
In [3]: converted_rdd = rdd.map(lambda x: int(x))
```

3. Filter data.



```
In [4]: filtered_rdd = converted_rdd.filter(lambda x: x >= 8)
```

4. Calculate the sum.



```
In [5]: filtered_rdd.reduce(lambda x, y: x+y)
```

MapReduce

Map-Reduce: Allow computations to be parallelized over a cluster.

- Basic Map-Reduce
  - The map-reduce framework plans map tasks to be run on the correct partitions and shuffle data for the reduce function.
  - **Map** : Apply a function to each data over a portion of data in parallel. ex. map(), filter()
  - **Reduce** : Return one value from multiple values. ex. reduce(), sum(), count()

MapReduce

Map-Reduce: Allow computations to be parallelized over a cluster.

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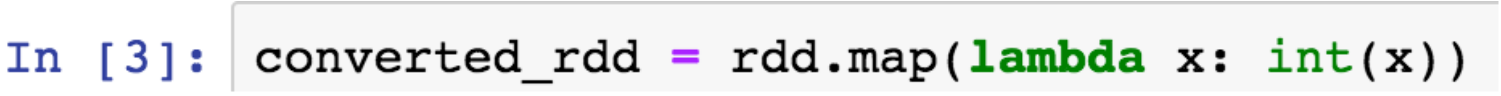
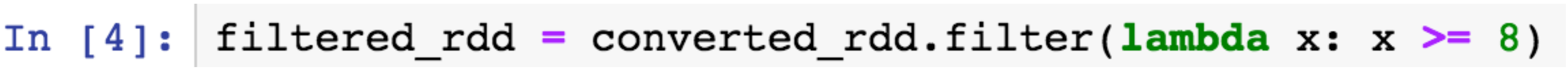
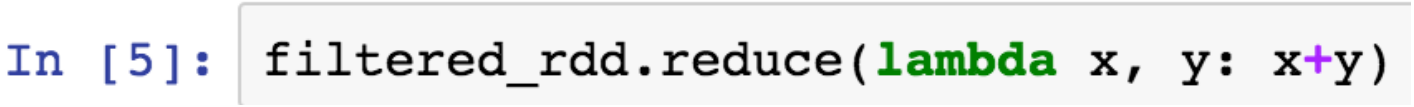


```
In [3]: converted_rdd = rdd.map(lambda x: int(x))
```



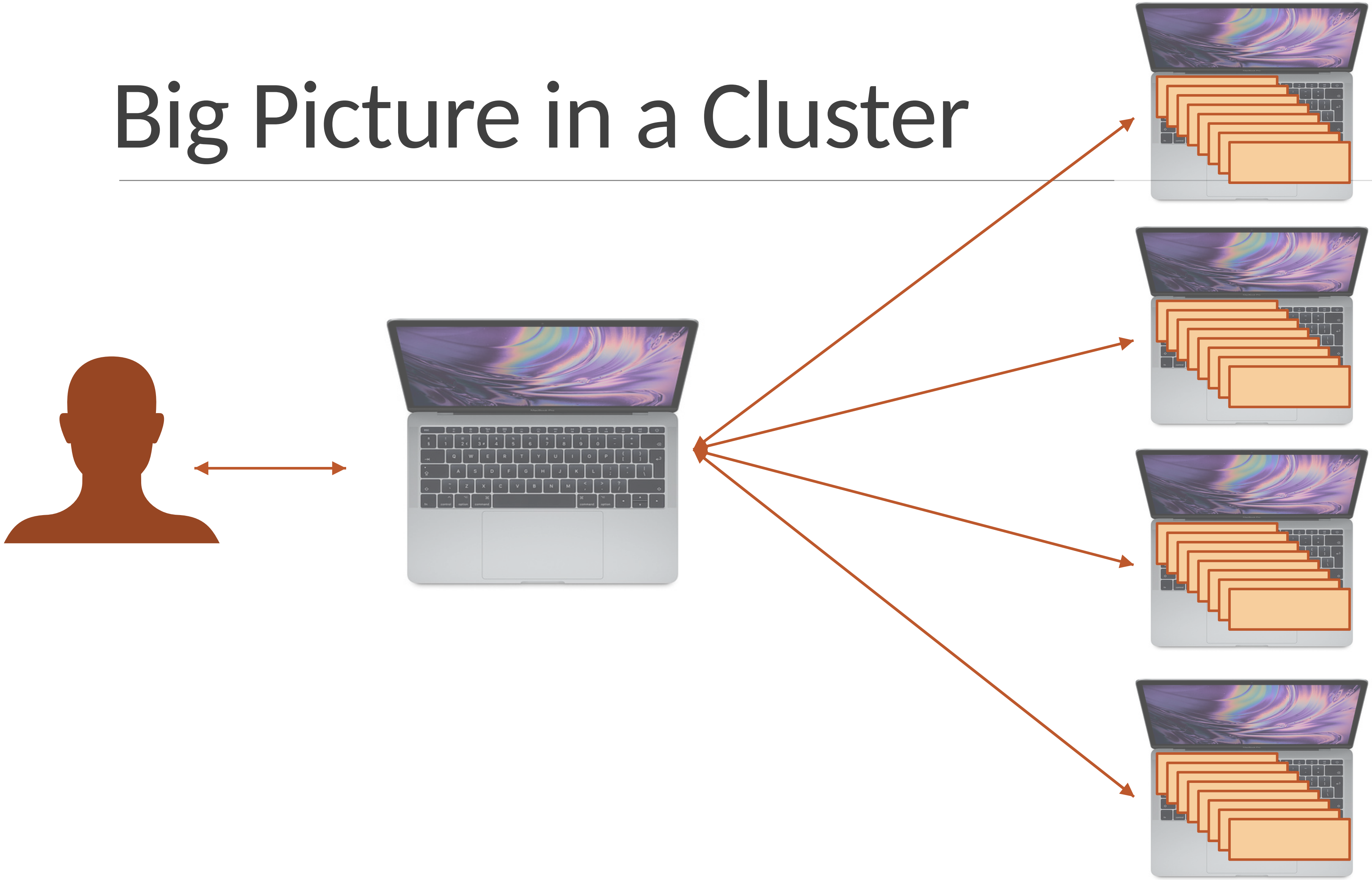
```
In [4]: filtered_rdd = converted_rdd.filter(lambda x: x >= 8)
```

  - **Reduce** : Return one value from multiple values. ex. reduce(), sum(), count()



```
In [5]: filtered_rdd.reduce(lambda x, y: x+y)
```

Big Picture in a Cluster



Contents

Class Intro

Environment Setup

Code Standard

Big Data and Distributed Computing

MapReduce Concept

Week 1 - Comments (What you liked/disliked so far? What should I do for you?)

Start the presentation to see live content. For screen share software, share the entire screen. Get help at **pollev.com/app**

Pyspark Installation

Spark Installation

Spark runs on Java 8+, Python 2.7+/3.4+ and R 3.1+. ~~For the Scala API, Spark 2.2.0 uses Scala 2.11. You will need to use a compatible Scala version (2.11.x).~~

Install JDK

```
brew update
brew tap adoptopenjdk/openjdk
brew search java
brew install --cask adoptopenjdk8
(brew install adoptopenjdk/openjdk/adoptopenjdk8 --cask)
```

```
conda
install -c
conda-forge
openjdk=11
```

https://spark.apache.org/docs/latest/

https://spark.apache.org/docs/latest/api/python/getting_started/install.html

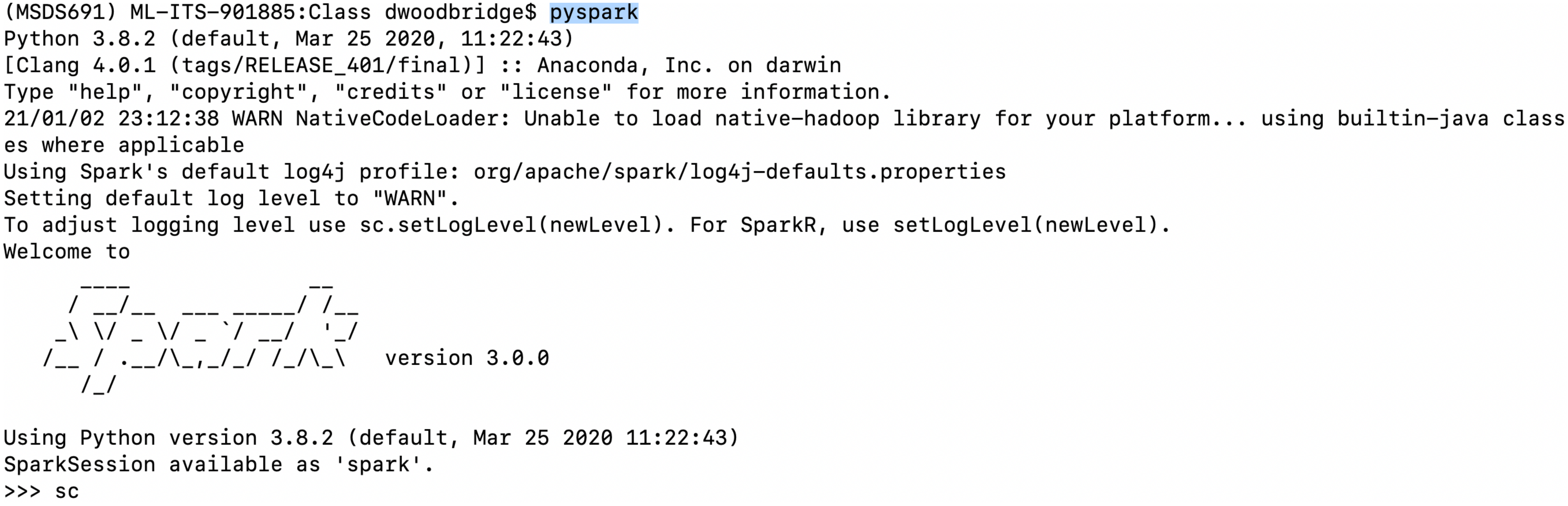
Spark Installation

Install jupyter and pyspark.

```
conda install jupyter
pip install pyspark
```

Spark Installation

Pyspark shell

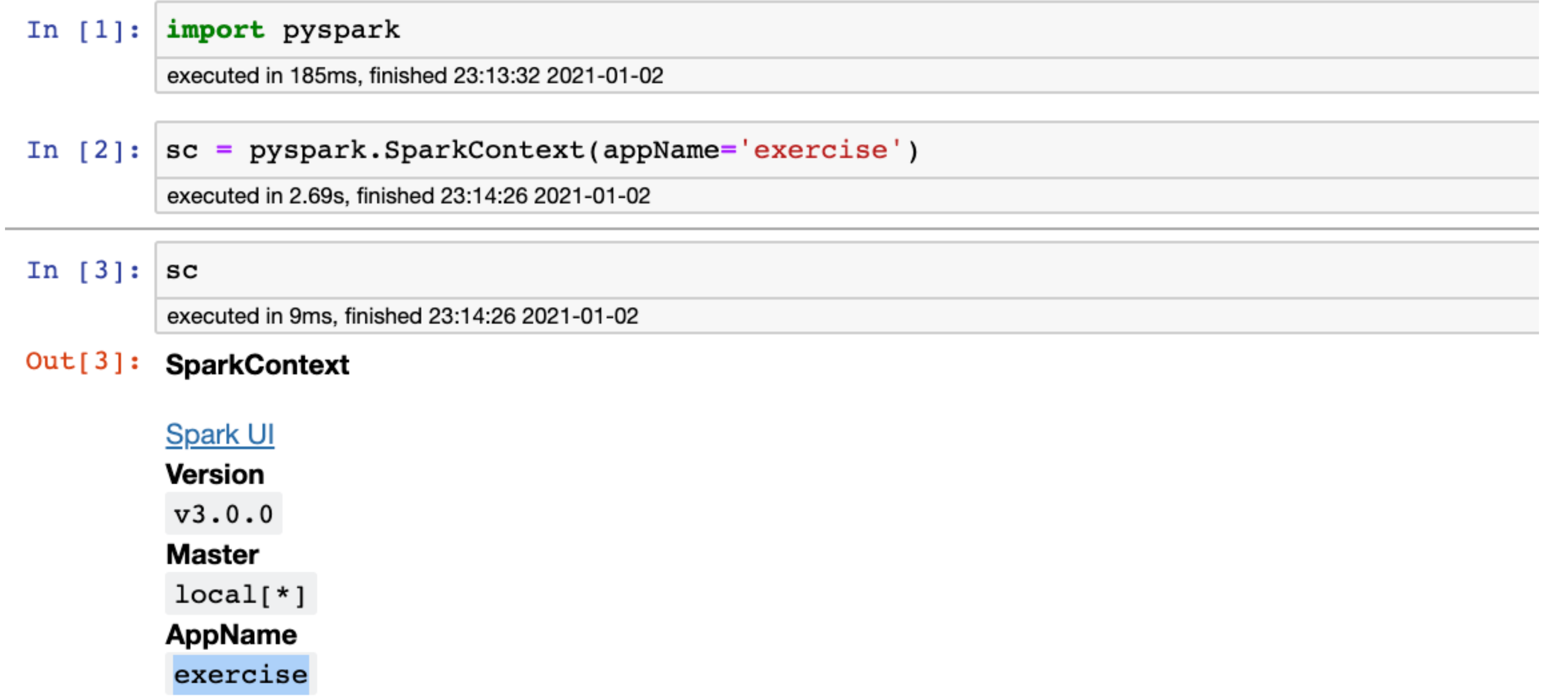


```
(MSDS691) ML-ITS-901885:Class dwoodbridge$ pyspark
Python 3.8.2 (default, Mar 25 2020, 11:22:43)
[Clang 4.0.1 (tags/RELEASE_401/final)] :: Anaconda, Inc. on darwin
Type "help", "copyright", "credits" or "license" for more information.
21/01/02 23:12:38 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java class
es where applicable
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).
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.0.0
      /_/

Using Python version 3.8.2 (default, Mar 25 2020 11:22:43)
SparkSession available as 'spark'.
>>> sc
```

Spark Installation

Jupyter notebook



```
In [1]: import pyspark
        executed in 185ms, finished 23:13:32 2021-01-02

In [2]: sc = pyspark.SparkContext(appName='exercise')
        executed in 2.69s, finished 23:14:26 2021-01-02

In [3]: sc
        executed in 9ms, finished 23:14:26 2021-01-02

Out[3]: SparkContext

        Spark UI
        Version
        v3.0.0
        Master
        local[*]
        AppName
        exercise
```

Reference

Spark Online Documentation, http://spark.apache.org/docs/latest/

Zecevic, Petar, et al. Spark in Action (Day 4), Manning, 2016.

Aven, Jeffrey. Apache Spark in 24 Hours, Sams Publishing , 2016.

Karau, Holden, et al. Learning spark: lightning-fast big data analysis. O'Reilly Media, Inc., 2015.

AWS Online Documentation, https://aws.amazon.com/documentation/