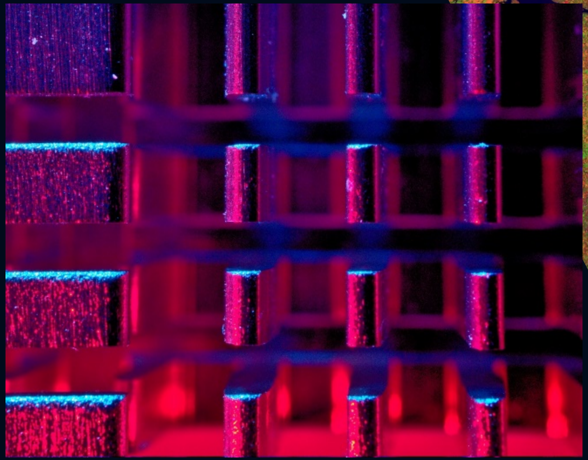
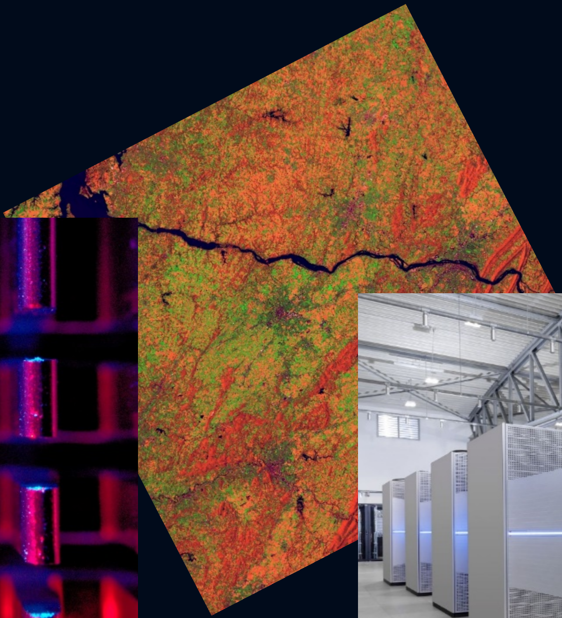


BIG DATA ANALYTICS USING APACHE SPARK

IEEE IGARSS 2021 Tutorial on Scalable Machine Learning with High Performance and Cloud Computing

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UNIVERSITY OF ICELAND

HDCRS

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GRSS

igarss BRUSSELS 2021

STRUCTURE

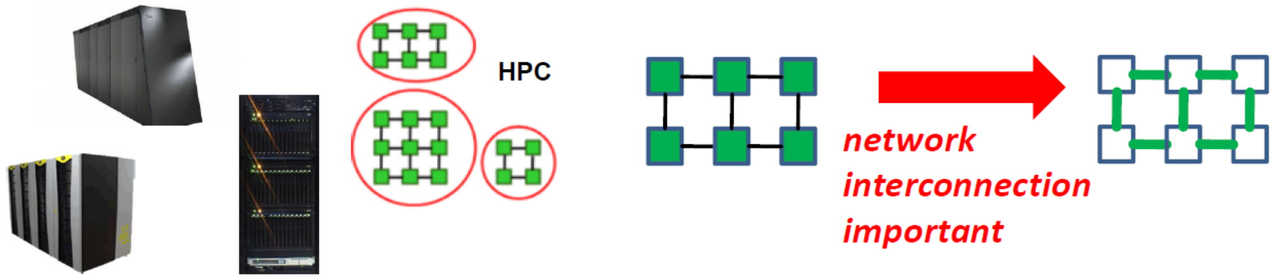
- Introduction
- Apache Spark Basics
- Developing on Spark
- Machine Learning on Spark
- Conclusions

INTRODUCTION

HPC AND HTC

Introduction

- High Performance Computing (HPC) is based on computing resources that enable the efficient use of parallel computing techniques through specific support with dedicated hardware such as high performance cpu/core interconnections. These are compute-oriented systems.

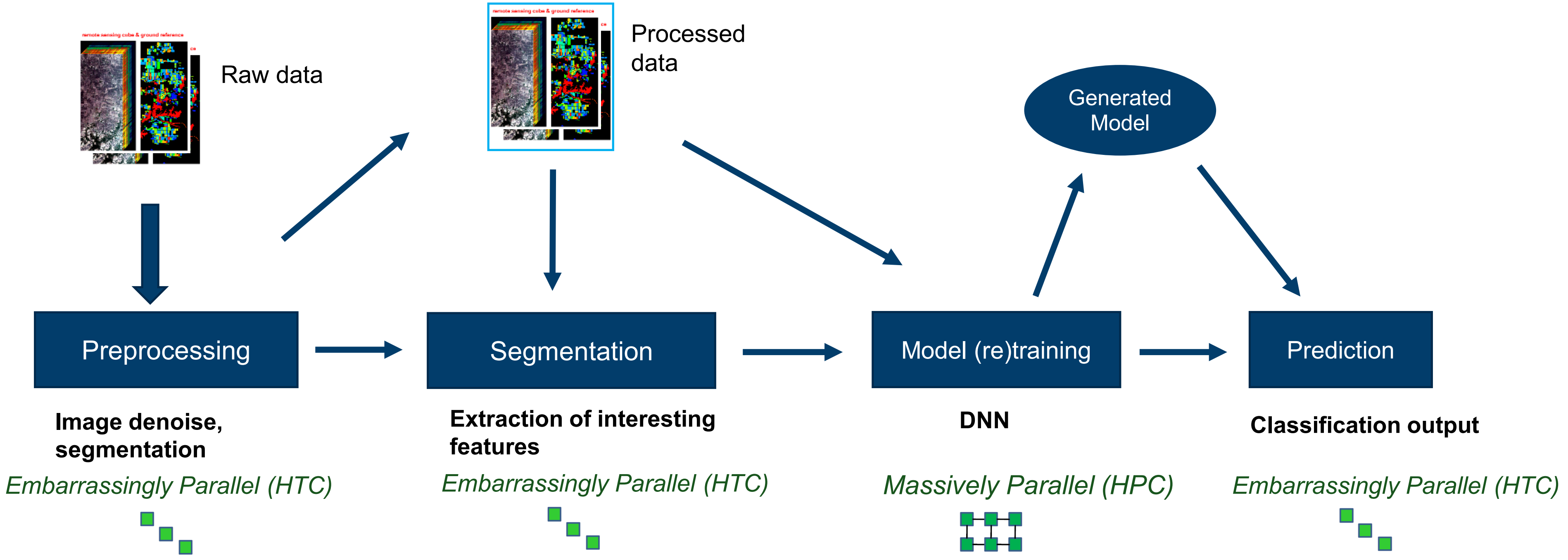


- High Throughput Computing (HTC) is based on commonly available computing resources such as commodity PCs and small clusters that enable the execution of ‘farming jobs’ without providing a high performance interconnection between the cpu/cores. These are data-oriented systems

Riedel [14]

END-TO-END IMAGE ANALYTICS

Motivational Scenario



QUESTIONS TO PONDER

- Pre- and post-processing in the scope of application, rather than on one step
- Manage all workflow tasks within one framework e.g. end-to-end Deep Learning
- Data export and import from multiple kind of storage systems
- Data-intensive rather than compute-intensive processing

BIG DATA ANALYTICS

- Support of multiple algorithms and frameworks
  - Machine Learning and Deep Learning
  - Integrated processing with HTC, HPC and ML/DL frameworks
- Abstract parallelization complexity from user
  - Parallel processing, batch systems, environmental intricacies are abstracted
- Encapsulate distributed computing and storage infrastructure details
  - Operating systems, security, networks and security interfaces

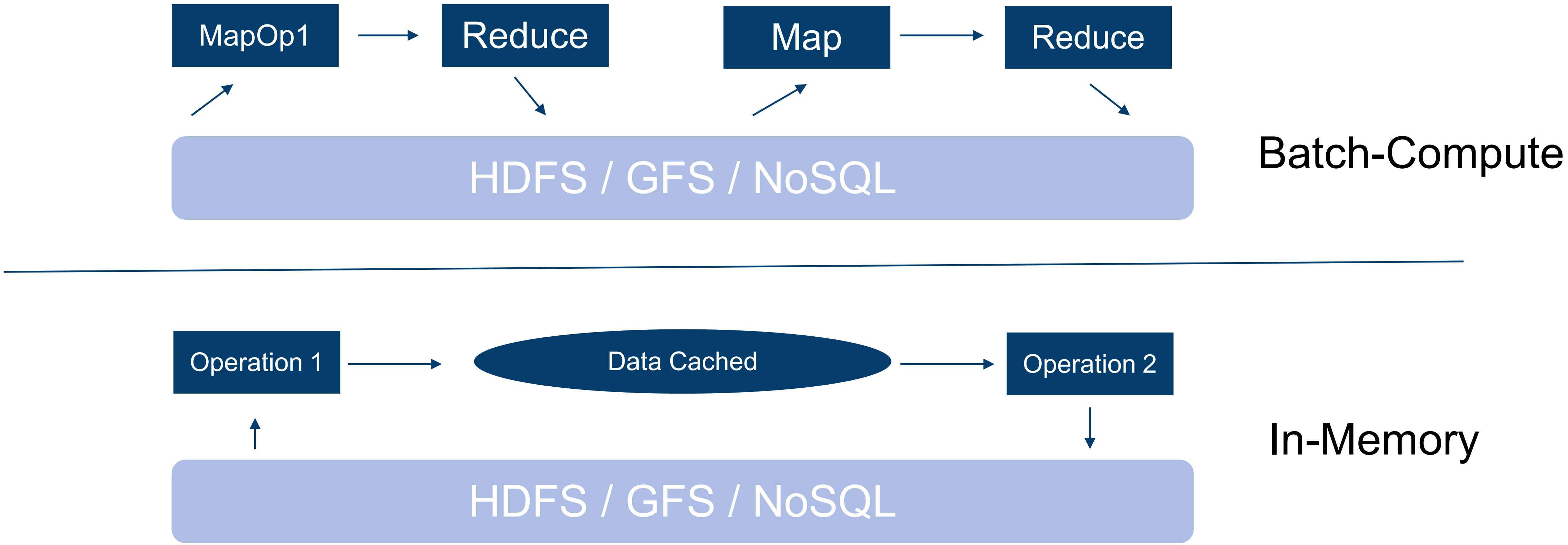
BIG DATA USE CASES

- Web mining and search (e.g Page Rank and Ad Analytics)
- Stream analytics (Twitter, Facebook and Trading)
- Graph processing
- IoT (Remote sensing, Automotive and Smart devices)
- Large scale image and video processing
- Time-series analysis

BIG DATA ANALYTIC FRAMEWORKS

- **Motto: Bring compute to data**
- Batch Processing
  - Manage job requests as batches
  - Map-reduce framework: Large problem space to many small tasks
  - E.g. Apache Hadoop
- In-Memory processing
  - Data processing in memory
  - Efficient map-reduce, filter and transform, Extract Transform and Load (ETL)
  - E.g. Apache Spark (Focus of this talk) and Apache Flink

IN-MEMORY: MORE I/O EFFICIENCY



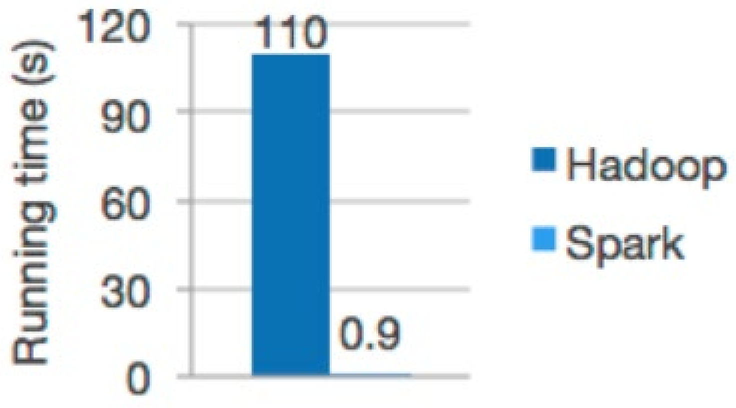
APACHE SPARK BASICS

APACHE SPARK

In-Memory Computing Framework

- Open source, unified analytics [2] engine for distributed and parallel data processing
  - Data transformations + AI and ML

- Provides a set of extensible APIs for
  - SQL for interactive queries
  - Machine learning
  - Stream processing
  - Graph processing

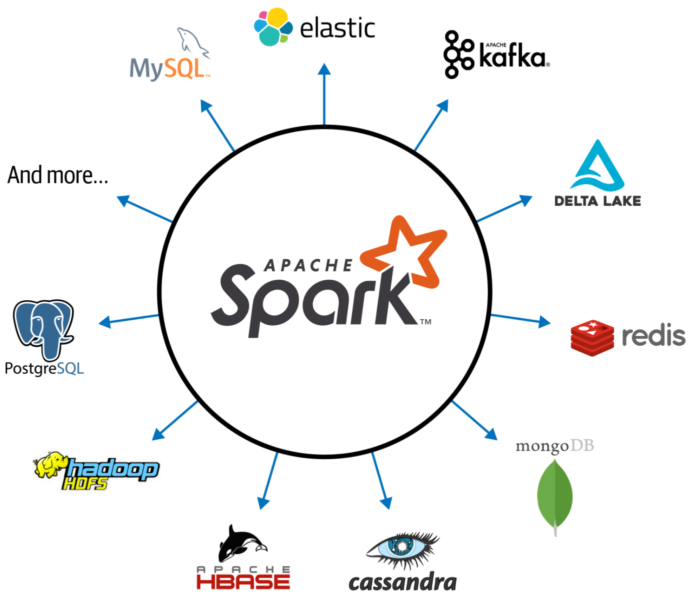


Logistic regression in Hadoop and Spark

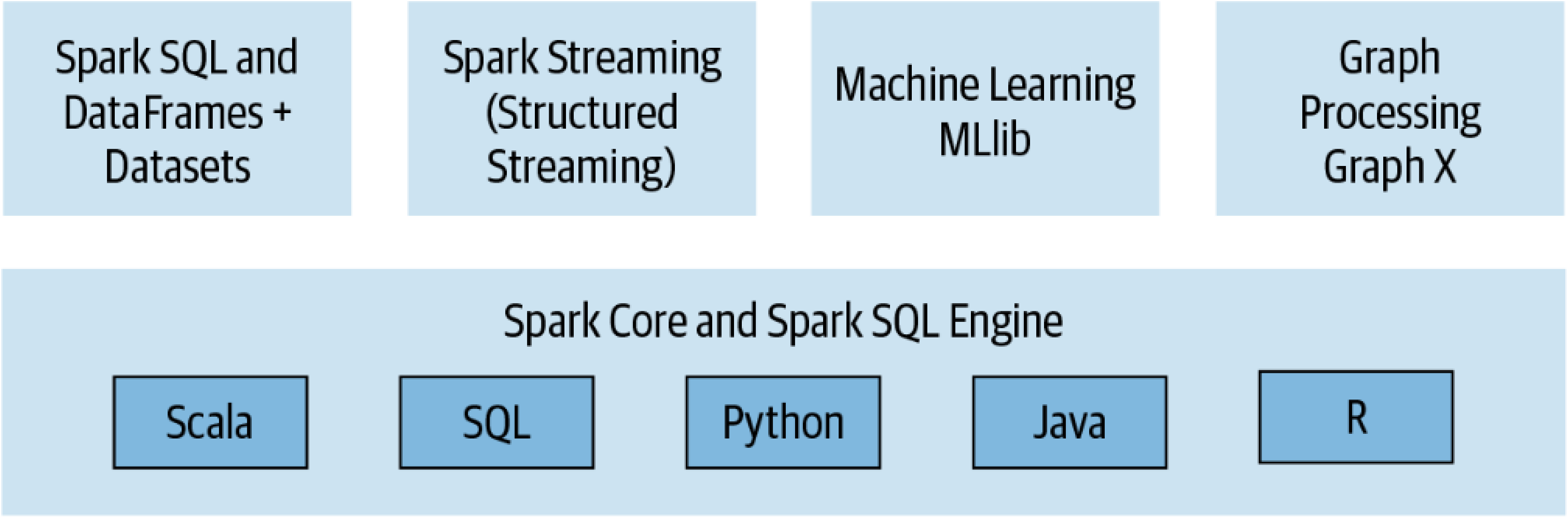
spark.apache.org [2]

ECOSYSTEM

- Apache Project and open source
- Databricks: main development driver
- Supported by major cloud computing providers
  - E.g. Amazon and Google
- Integrated with multiple schedulers, file systems, DBMS and data stores, a.k.a Connectors
- Hadoop (Batch processing) supported
  - Seamlessly complement / replace Map-Reduce layer
- HPC Supported
  - SLURM as a scheduler



APACHE SPARK COMPONENTS



Learning Spark [2]

APACHE SPARK COMPONENTS

- Spark SQL (Dataframes):
  - Standard SQL and Hive QL, but parallel execution
  - Data sources: JSON, Images, Parquet, Binary and Hive tables
- Spark Streaming (Structured Streaming)
  - High throughput and low latency scenarios
  - Log inflow, sensor data (IOT), Twitter streams
- Machine Learning (ML Lib)
  - Clustering, classification and recommender systems
  - Support Deep learning frameworks – Keras, Tensorflow and Pytorch
- Graph Processing (GraphX)
  - Iterative and parallel Graph computations
  - Social computing, semantic networks and link data

SPARK APPLICATION AREAS

Commercial and Scientific Applications

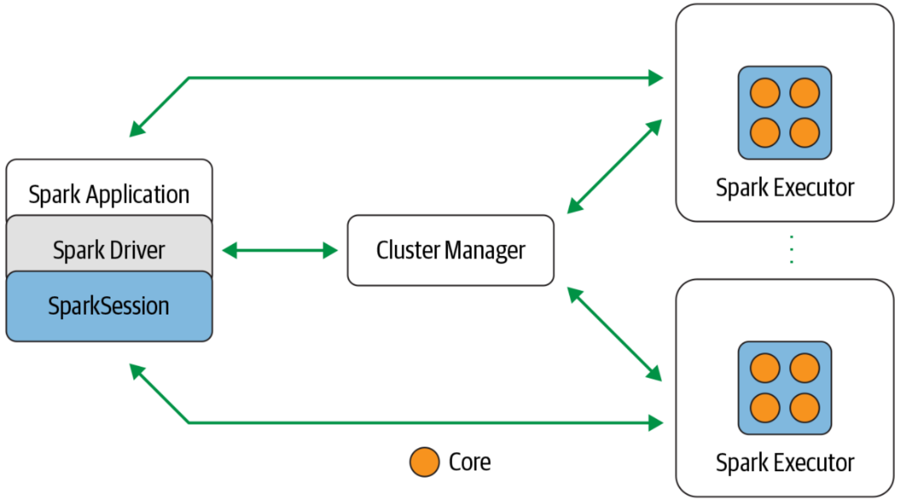
- Data processing pipeline (load, preparation and transform) include machine learning (Alibaba [7])

- Netflix recommendation ML pipeline (Netflix [8])

- Remote sensing and image analytics [5] and [6]

ARCHITECTURE

Application Concepts



Learning Spark [9]

- Jobs: A parallel computation
- Stages: A job is divided into stages
- Tasks: A single unit of execution

RESILIENT DISTRIBUTED DATASETS (RDD)

Data Structure Representation

- Basic programming abstraction (not used by every user level)
  - Dependencies: DAG structure of tasks
  - Partitions: Data locality and parallel computation on partitions
  - Iterator [T]: Handle to multiple type of collections
- Less expressive and complex
  - Computations are opaque
  - Difficult to introspect and debug
- New releases (> 3.0) prefer ***Spark DataFrames***

SPARK DATAFRAMES

Structured computing API – High level wrappers to RDDs

- Structured and the format is inspired by pandas DataFrames
- Distributed in-memory tables
  - Rows and columns, data types and schemas
  - E.g. integer, string, array and map
  - Simple and complex data types
- Scala (main implementation), Python, Java and R bindings
- Supports many formats as external data sources
  - Parquet, JSON, CSV, Images and Binary, etc

TRANSFORMATIONS AND ACTIONS

Operation Types

Transformations

- Transform Spark DataFrame into a new DataFrame without modifying the original data
- E.g. select, filter, groupBy, orderBy, join
- Lazy evaluation: not computed until action is called or any read / write occurs

Actions

- Compute operations
- E.g. show, take, count, collect, save

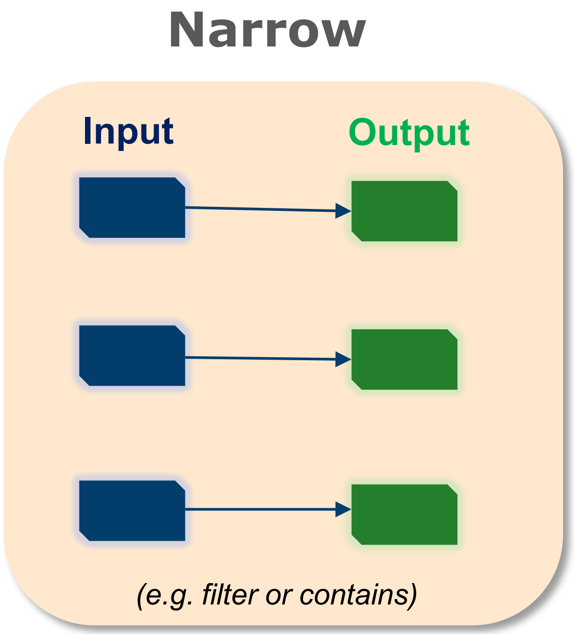
```
# In Python
>>> strings = spark.read.text("../README.md")
>>> filtered = strings.filter(strings.value.contains("Spark"))
>>> filtered.count()
20
```

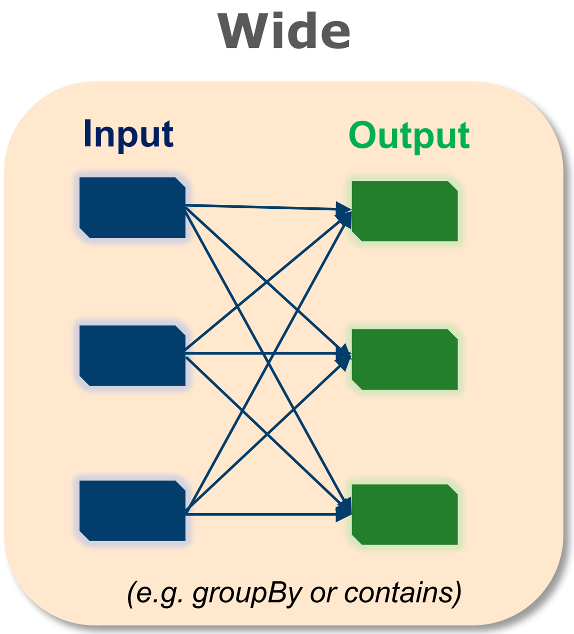
Narrow and Wide Transformations

- Wide transformations use multiple partitions

NARROW AND WIDE TRANSFORMATIONS

Transformation Types





SPARK EXECUTION WORKFLOW

1. Create or load data
   - e.g. load data set in DataFrames or RDDs

2. Apply 1-n tranformations data (narrow or wode)
   - e.g. select, filter, groupBy, orderBy

3. Perform actions that return or store data
   - E.g. reduce; count; collect

DEVELOPING ON SPARK

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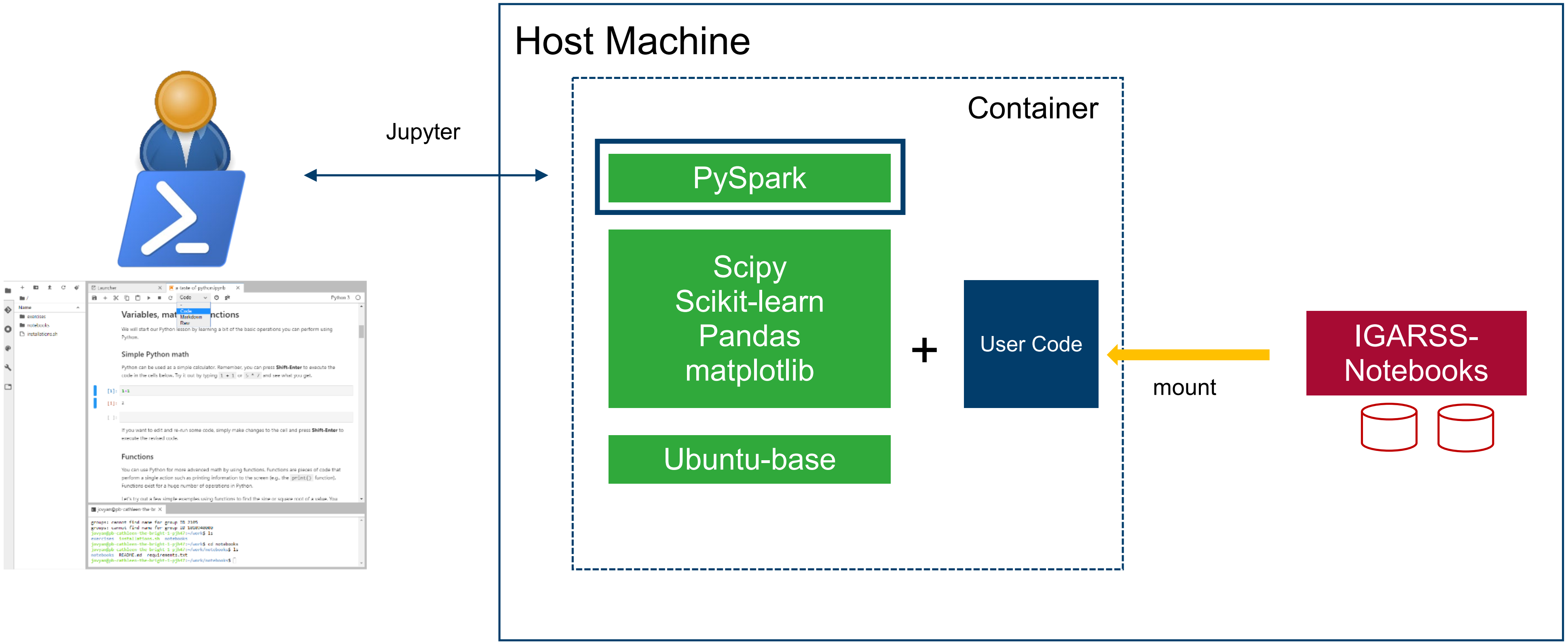
APACHE SPARK DEPLOYMENTS ON CLOUDS

- **Private Clouds:** in-premise deployments
  - E.g. OpenStack or Apache CloudStack or Containers
- **Public Clouds:** external provider, Pay-per use and Elastic scaling
  - Amazon EMR (Elastic Map-Reduce)
  - Microsoft Azure (Databricks or HDInsight)
  - Google (DataProc)

Mostly Virtualised Computing Infrastructures

JUPYTER-DOCKER STACK

User Development Environment



PYSPARK

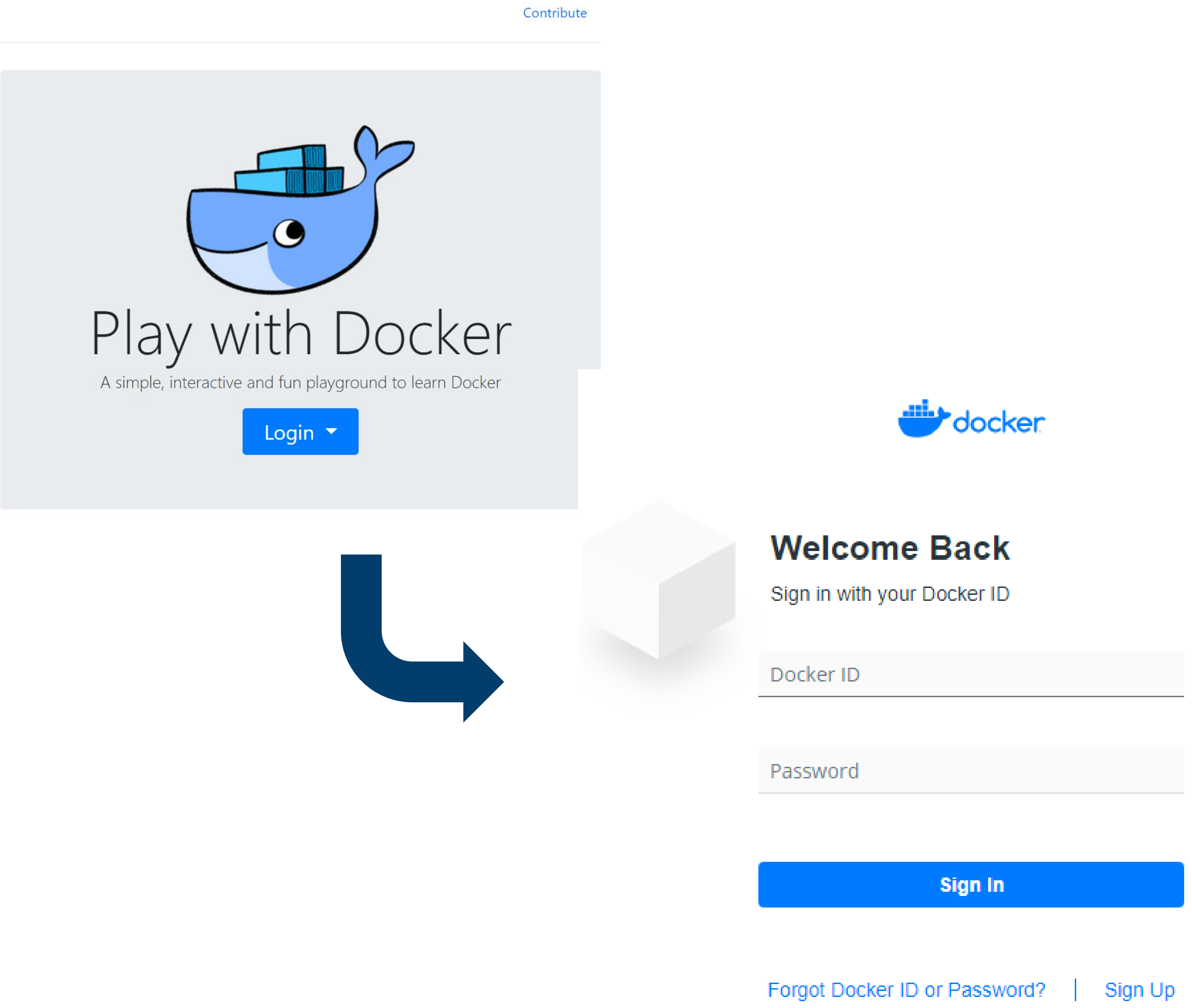
Embedded Development Environment

- Python bindings for Apache Spark (implemented in Scala)
- Mostly every functionality is available in Python
- Easily developed on Jupyter-lab instances
- PySpark Image Specifics
  - PySpark v 3.1.2
    - Includes core Spark libraries
  - PyArrow (for interoperability between Pandas and Spark Dataframes)
  - JAVA (OpenJDK) 11 and Scala 2.12.10

LAUNCHING THE PYSPARK CONTAINER

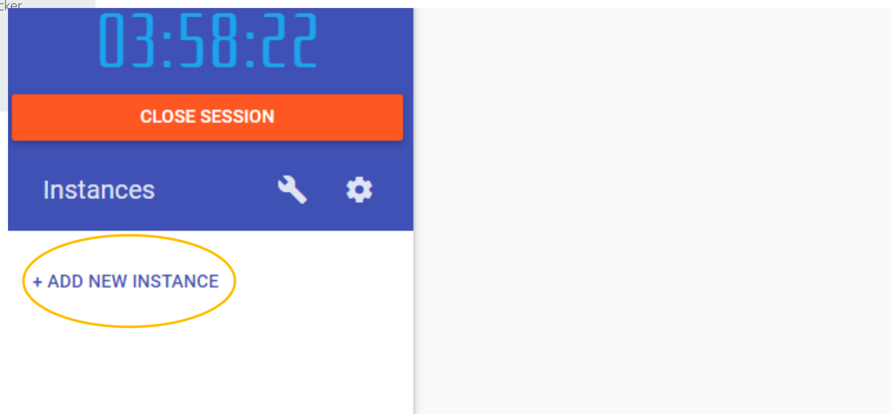
Based on Jupyter-Docker Stack

- Enter the following URL:
  - https://labs.play-with-docker.com/
- Press “Start”
- Login using your existing credentials or Sign up for a new Docker account (It is free)
- Account created

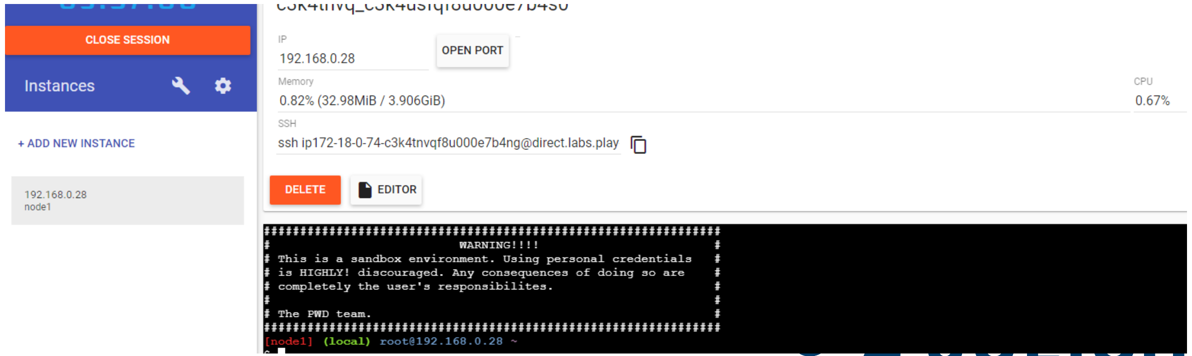


STARTING AN IMAGE

Hit “Start”



Click “Add New Instance”



Terminal is started

PREPARE THE WORKING DIRECTORY

- On the Terminal, write the following commands (step-wise)

$> mkdir igarss-nb (Press Enter)

$> chmod 777 igarss-nb (Press Enter)

$> cd igarss-nb (Press Enter)

LAUNCH THE PYSPARK IMAGE

$> docker run -p 8888:8888 -p 4040:4040 –p 4041:4041 –p 4042:4042 \

-v ~/igarss-nb:/home/jovyan/work jupyter/pyspark-notebook \

start-notebook.sh --NotebookApp.token='ig2021'

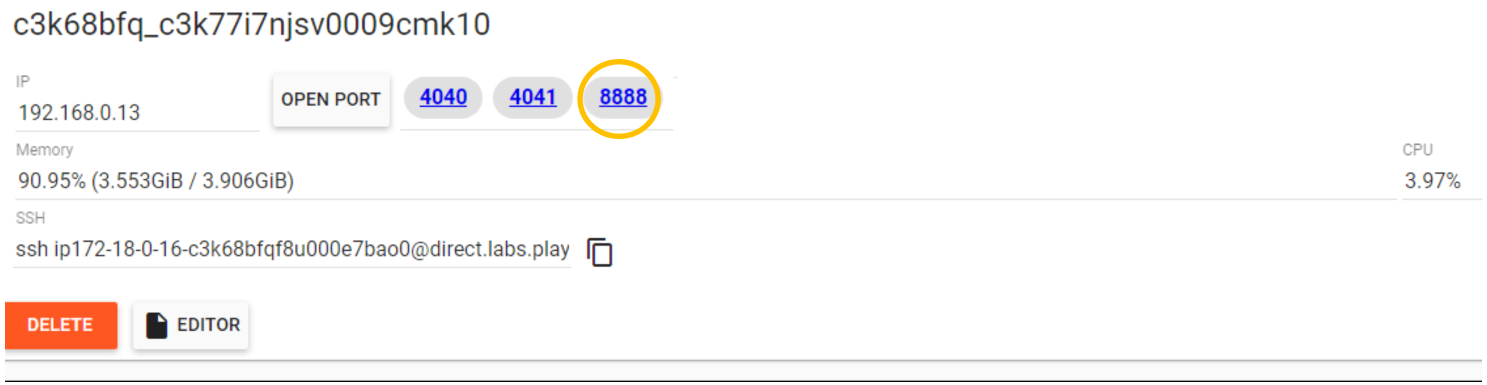
```
$ docker run -p 8888:8888 -p 4040:4040 -p 4041:4041 \
> -v ~/igarss-nb:/home/jovyan/work jupyter/pyspark-notebook \
> start-notebook.sh --NotebookApp.token='ig2021'
Unable to find image 'jupyter/pyspark-notebook:latest' locally
latest: Pulling from jupyter/pyspark-notebook
c549ccf8d472: Pull complete
6c65c50510f3: Pull complete
a89eb75169a1: Pull complete
4f4fb700ef54: Pull complete
c18636dc46c6: Pull complete
```

Server started.

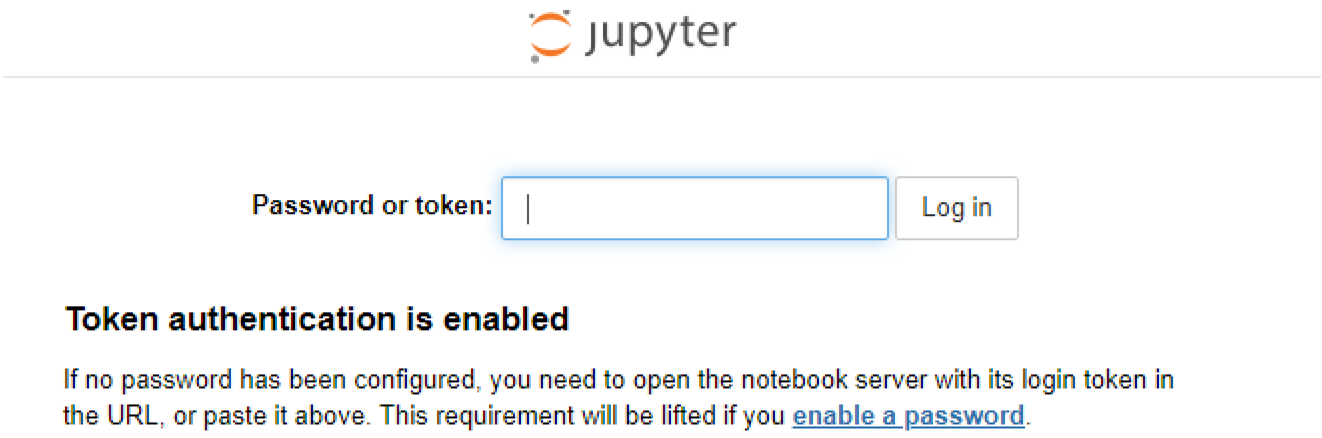
```
[I 2021-07-09 16:15:53.198 LabApp] JupyterLab application directory is /opt/conda/share/jupyter/lab
[I 16:15:53.207 NotebookApp] Serving notebooks from local directory: /home/jovyan
[I 16:15:53.207 NotebookApp] Jupyter Notebook 6.4.0 is running at:
[I 16:15:53.207 NotebookApp] http://b6679ed25797:8888/?token=...
[I 16:15:53.207 NotebookApp]  or http://127.0.0.1:8888/?token=...
[I 16:15:53.207 NotebookApp] Use Control-C to stop this server and shut down all kernels (twice to skip confirmation).
```

VIEW THE NOTEBOOK SERVER

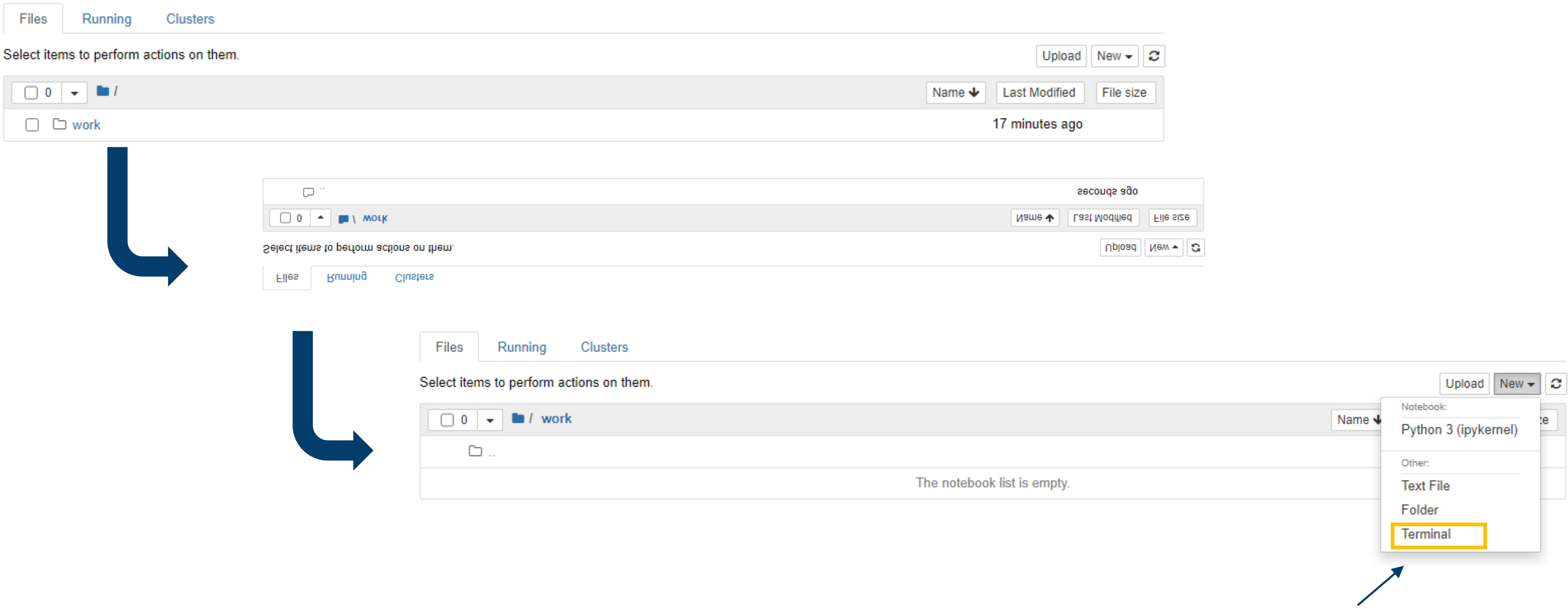
Click 8888



New tab opens and there enter **ig2021** and press Log in



OPEN THE JUPYTER TERMINAL



DOWNLOAD THE NOTEBOOKS ARCHIVE

On the shell type:
$ cd work
$ wget https://fz-juelich.sciebo.de/s/xiNXrpfOfmqLmMX/download

```
(base) jovyan@b6679ed25797:~$ cd work/
(base) jovyan@b6679ed25797:~/work$ wget https://fz-juelich.sciebo.de/s/xiNXrpfOfmqLmMX/downlo
--2021-07-09 16:37:10--  https://fz-juelich.sciebo.de/s/xiNXrpfOfmqLmMX/download
Resolving fz-juelich.sciebo.de (fz-juelich.sciebo.de)... 132.252.183.1
Connecting to fz-juelich.sciebo.de (fz-juelich.sciebo.de)|132.252.183.1|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 12029484 (11M) [application/gzip]
Saving to: 'download'
```

Untar the archive: $tar –xvf download

```
(base) jovyan@b6679ed25797:~$ tar -xvf download
IGARSS2021/
IGARSS2021/SparkUDFExample.ipynb
IGARSS2021/LogisticRegressionExample.ipynb
IGARSS2021/datasets/
```

Switch to the previous browser tab and click IGARSS2021

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BROWSER VIEW

Demonstration: Open “BasicDataFrame.ipynb”

USER DEFINED FUNCTIONS (UDF)

Explicit Customization

- Types: Simple and Pandas UDF
- Define new domain specific modules that extend the vocabulary of Spark's built-in functions
- Useful for data normalization and cleaning (e.g. handling nulls, feature scaling)
- **Simple UDF:** Row-wise operation on a data frame – sequential processing, see example notebook *(next slide)*
- **Pandas UDF:** Vectorized operations (process entire array at once)

```
import pandas as pd
from scipy import stats

@pandas_udf('double')
def cdf(v):
    return pd.Series(stats.norm.cdf(v))


df.withColumn('cumulative_probability', cdf(df.v))
```

[12] Pandas UDF

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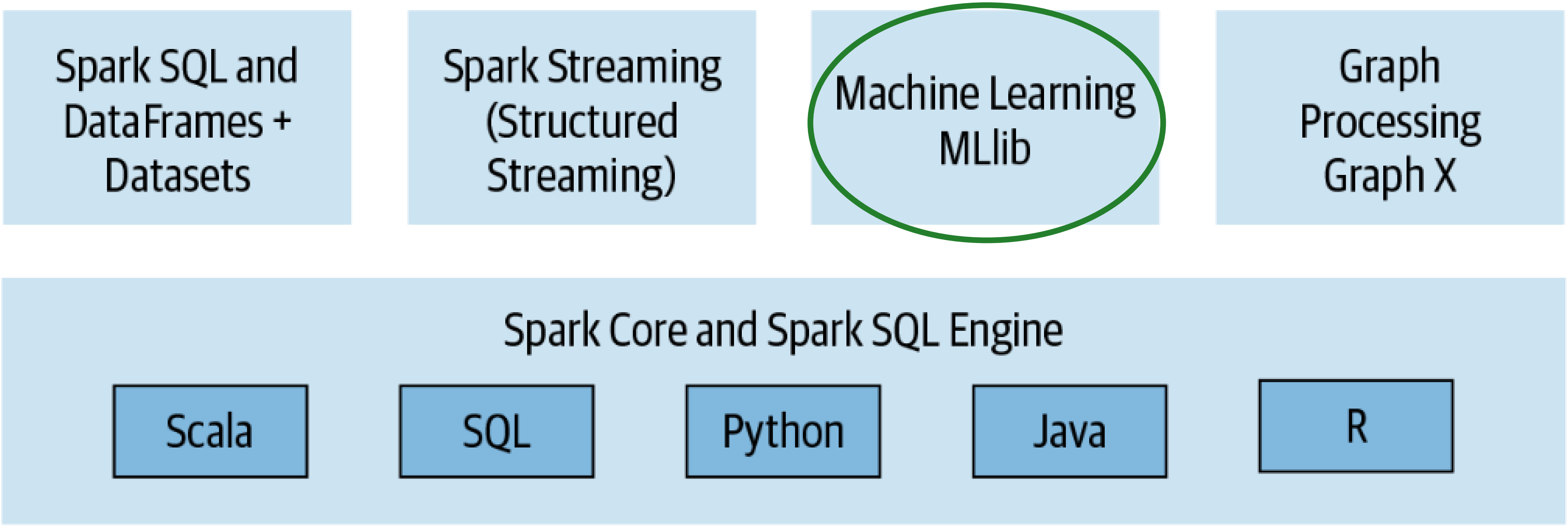
Demonstration: Open “SparkUDFExample.ipynb”

MACHINE LEARNING ON SPARK

MACHINE LEARNING WITH SPARK



Learning Spark [2]

SPARKML (MLLIB)

- Promises Machine Learning at Scale
- Parallel processing made easy
  - Develop locally (e.g. Jupyter Notebook) -> deploy on cluster
- MLLib features
  - Distributed with ML algorithms (clustering, classification..)
  - Parallel implementations
  - Processing data is cached in-memory (optimal for iterative algorithms)
  - Support of Python, Scala, Java, R

SPARK ML CONCEPTS

- **Transformer:** Data preparation and rule-based transformations. Input DataFrame and output a new DataFrame instance.

```
newDF = myDF.transform()
```

- **Estimators:** Learning or fitting parameters. Returns a Model (a transformer)

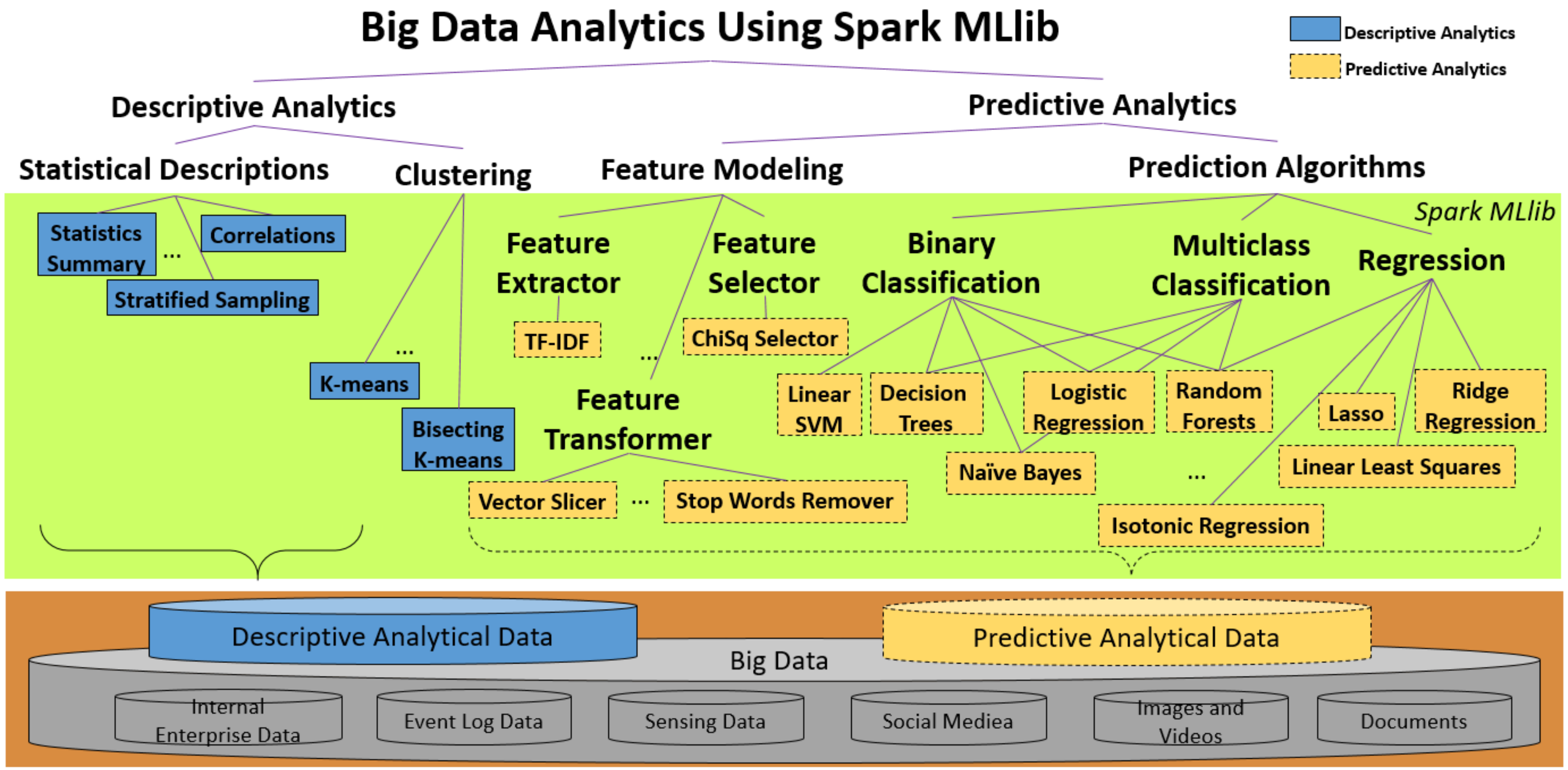
```
svmModel = svm.fit(newDF)
```

- **Pipeline:** A kind of estimator that orchestrates a series of transformers and estimators into a single model

```
pipeline = Pipeline(stages=[vec, svm]) # combine vectorization and classifier
pipelineModel = pipeline.fit(trainData) # model training
preds = pipelineModel.transform(testData) # model evaluation
```

SPARK ML IMPLEMENTATION

Taxonomy

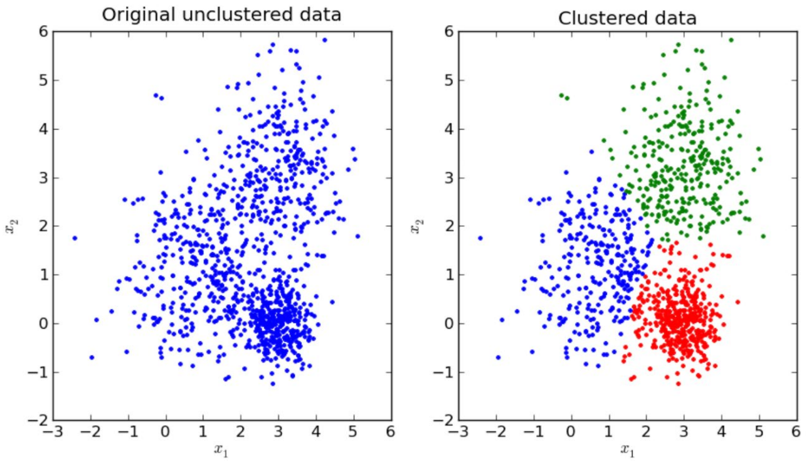


[16]

K-MEANS CLUSTERING

Clustering Example

- Partition-based clustering
- Clusters are associated with respective centroids
- Number of clusters must be known



[3] Tan et al.

Select K points as the initial centroids.
repeat
    Form K clusters by assigning all points to the closest centroid.
    Recompute the centroid of each cluster.
until The centroids don't change

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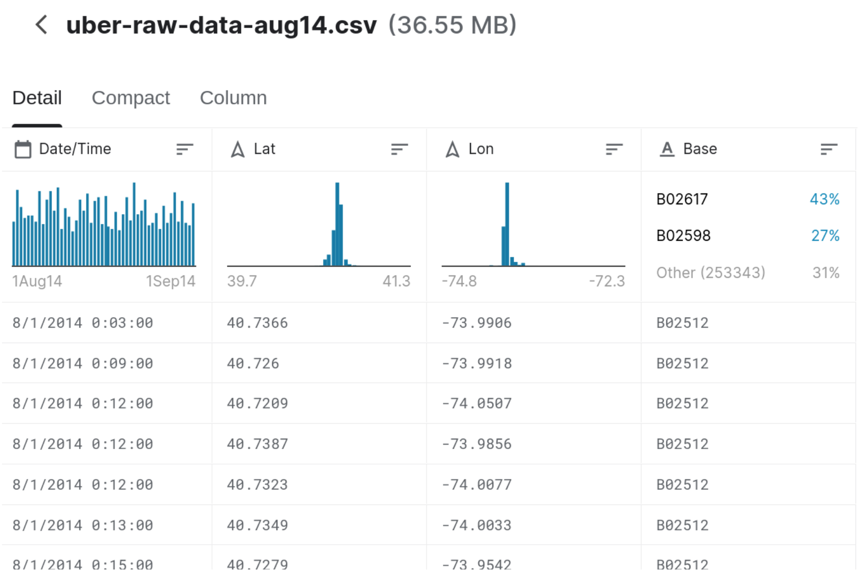
K-MEANS: UBER PICKUP DATA

Clustering Example

- Dataset: Uber Pickups in the CSV format
- Problem: Cluster the dense pickup points
- Uber trip data of August 2014
- Attributes: Lat, Lon, Date and Time, Base (TLC)



Date/Time	Lat	Lon	Base
8/1/2014 0:03:00	40.7366	-73.9906	B02512
8/1/2014 0:09:00	40.726	-73.9918	B02512
8/1/2014 0:12:00	40.7209	-74.0507	B02512
8/1/2014 0:12:00	40.7387	-73.9856	B02512
8/1/2014 0:12:00	40.7323	-74.0077	B02512
8/1/2014 0:13:00	40.7349	-74.0033	B02512
8/1/2014 0:15:00	40.7279	-73.9542	B02512

[2] Kaggle-Uber

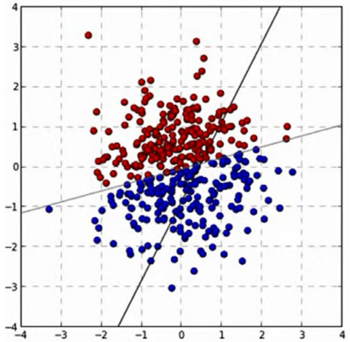
Example

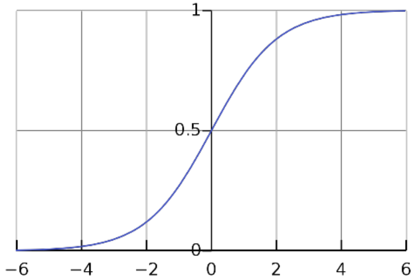
Demonstration: Switch to Notebook “KMeansExample.ipynb”

LOGISTIC REGRESSION

Classification Example

- Supervised machine learning algorithm
- Classification algorithm to deal with categorical response
- Predict binomial outcomes between 0 and 1
- Predictions are generated in the form of probabilities
- Uses Sigmoid function (a.k.a Logistic Function)





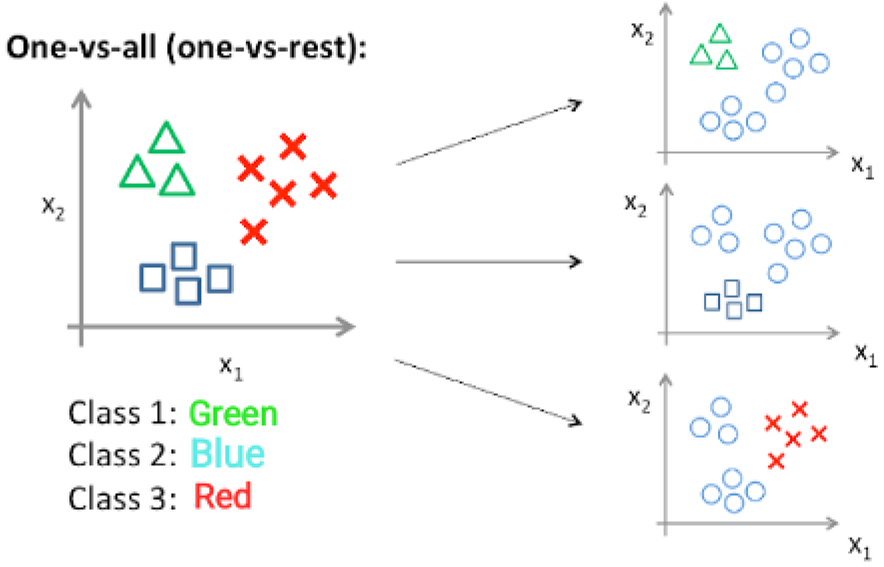
Example

Demonstration: Open “LogisticRegressionExample.ipynb”

ONEVSREST CLASSIFICATION

Multi-class classification

- Multiple class labels dataset
- Resolve multi-class as binary-class problem
- Apply N-binary classifiers for N-classes
- Example: The shape is triangle, square or cross



[1] Jatin Nanda

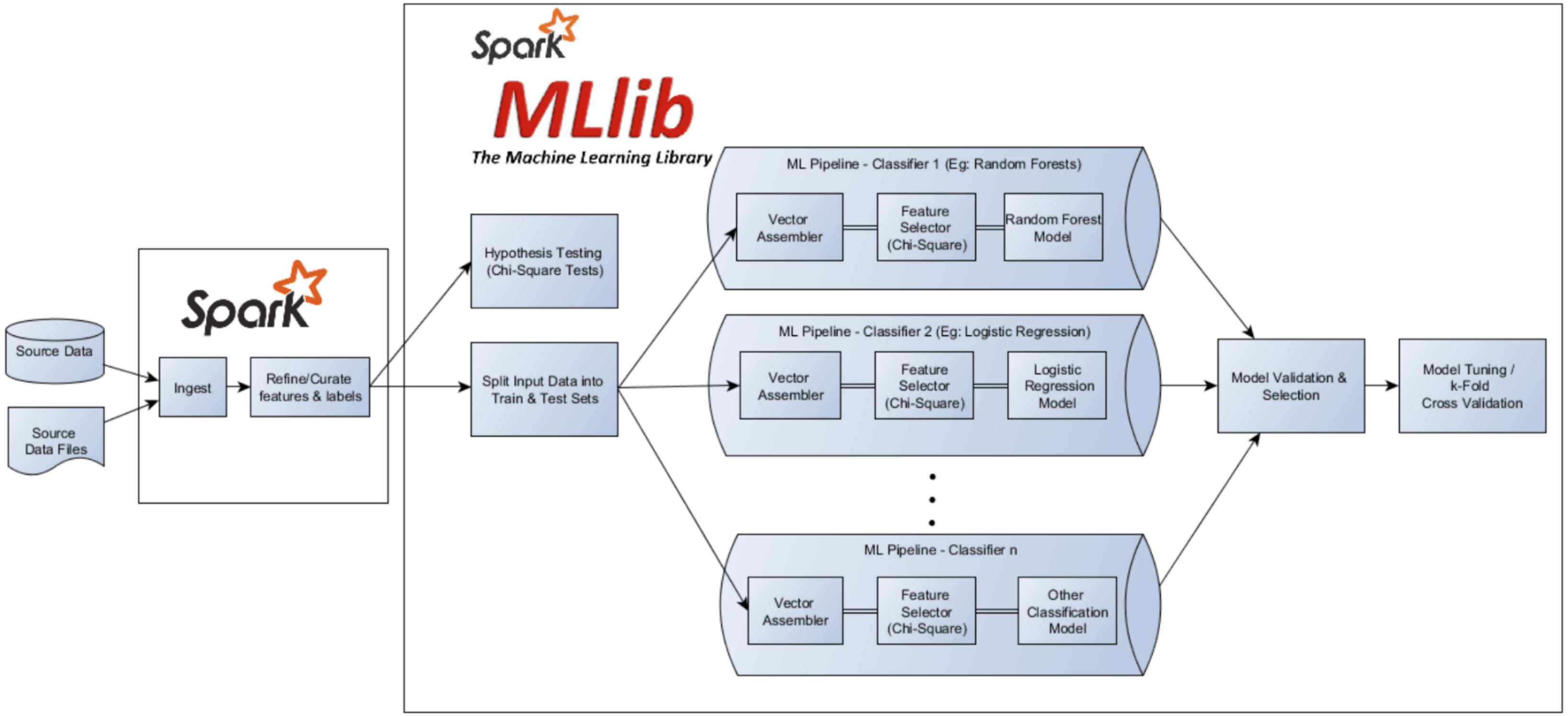
Example

Demonstration: Open "OneVsRestExample.ipynb"

ML PIPELINE – LINEAR REGRESSION EXAMPLE

Refresher

<u>Pipeline</u> is a kind of estimator that orchestrates a series of transformers and estimators into a single model



[17]

Demonstration: Open Notebook “PipelineExample.ipynb”

DOWNLOAD THE NOTEBOOKS TO THE LOCAL FILESYSTEM

- Open the Jupyter Terminal
- CD to the /home/jovyuan/work directory ($> cd ~/work)
- Create a Tar archive ($> tar –czvf igarss21.tar.gz IGARSS2021/)
- Switch to the file browser view and download the created (igarss21.tar.gz) archive

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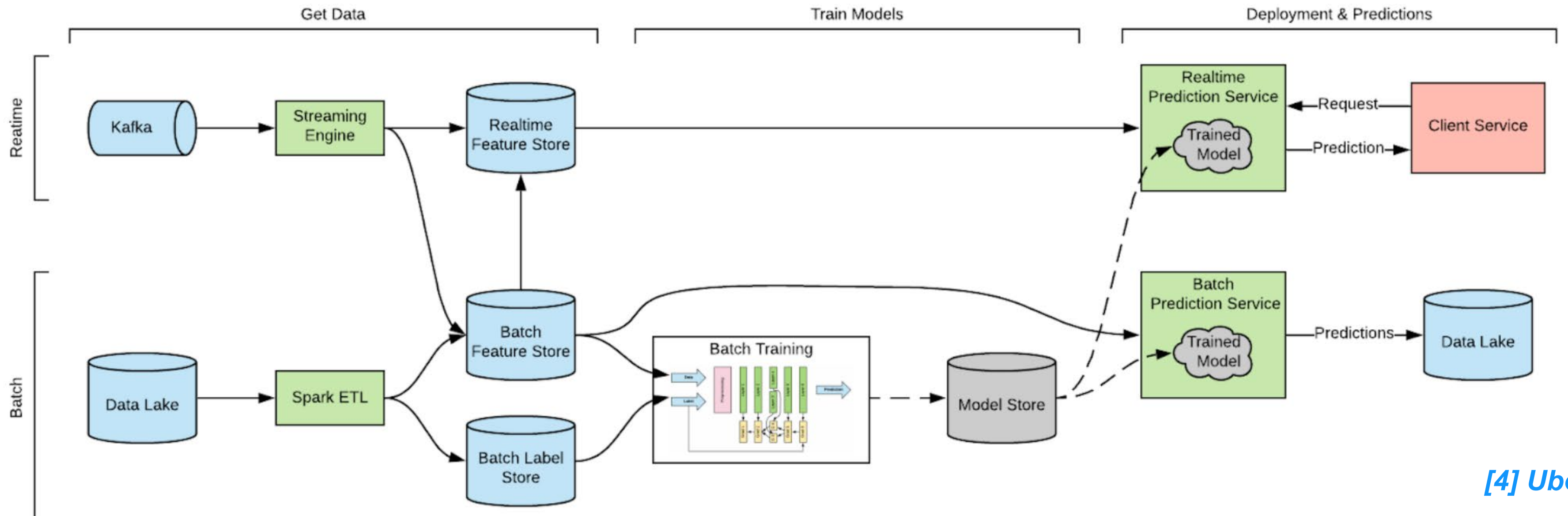
SPARK AND DEEP LEARNING

Introduction

- Combine ETL/ELT, model training and hyper-parameter tuning in one workflow
- Train TensorFlow / PyTorch models integrated with the Spark ecosystem



[4] Uber@Spark AI Summit 2020

Pre-Processing (Spark)

Distributed Training Keras/TF/PyTorch with Horovod)

Prediction DL and Spark

DISTRIBUTED DEEP LEARNING

Options

Distributed Inference

- Pandas UDF (User Defined Functions) and Apache Arrow

Distributed Training

1) Spark-TensorFlow-Distributor

```
from spark_tensorflow_distributor import MirroredStrategyRunner

runner = MirroredStrategyRunner(num_slots=1, local_mode=True, use_gpu=USE_GPU)
runner.run(train)
```

2) HorovodRunner (*only available for Databricks Runtime ML users*)

SPARK-TF-DISTRIBUTOR

Code Snapshot

```
from spark_tensorflow_distributor import MirroredStrategyRunner

# Adapted from https://www.tensorflow.org/tutorials/distribute/multi_worker_with_keras
def train():
    import tensorflow as tf
    import uuid

    BUFFER_SIZE = 10000
    BATCH_SIZE = 64

    def make_datasets():
        (mnist_images, mnist_labels), _ = \
            tf.keras.datasets.mnist.load_data(path=str(uuid.uuid4())+'mnist.npz')

        dataset = tf.data.Dataset.from_tensor_slices((
            tf.cast(mnist_images[..., tf.newaxis] / 255.0, tf.float32),
            tf.cast(mnist_labels, tf.int64))
        )
        dataset = dataset.repeat().shuffle(BUFFER_SIZE).batch(BATCH_SIZE)
        return dataset
```

```
    def build_and_compile_cnn_model():
        model = tf.keras.Sequential([
            tf.keras.layers.Conv2D(32, 3, activation='relu', input_shape=(28, 28, 1)),
            tf.keras.layers.MaxPooling2D(),
            tf.keras.layers.Flatten(),
            tf.keras.layers.Dense(64, activation='relu'),
            tf.keras.layers.Dense(10, activation='softmax'),
        ])
        model.compile(
            loss=tf.keras.losses.sparse_categorical_crossentropy,
            optimizer=tf.keras.optimizers.SGD(learning_rate=0.001),
            metrics=['accuracy'],
        )
        return model

    train_datasets = make_datasets()
    options = tf.data.Options()
    options.experimental_distribute.auto_shard_policy = tf.data.experimental.AutoShardPolicy.DATA
    train_datasets = train_datasets.with_options(options)
    multi_worker_model = build_and_compile_cnn_model()
    multi_worker_model.fit(x=train_datasets, epochs=3, steps_per_epoch=5)

MirroredStrategyRunner(num_slots=8).run(train)
```

[13] SparkTFDistributor Code Repository

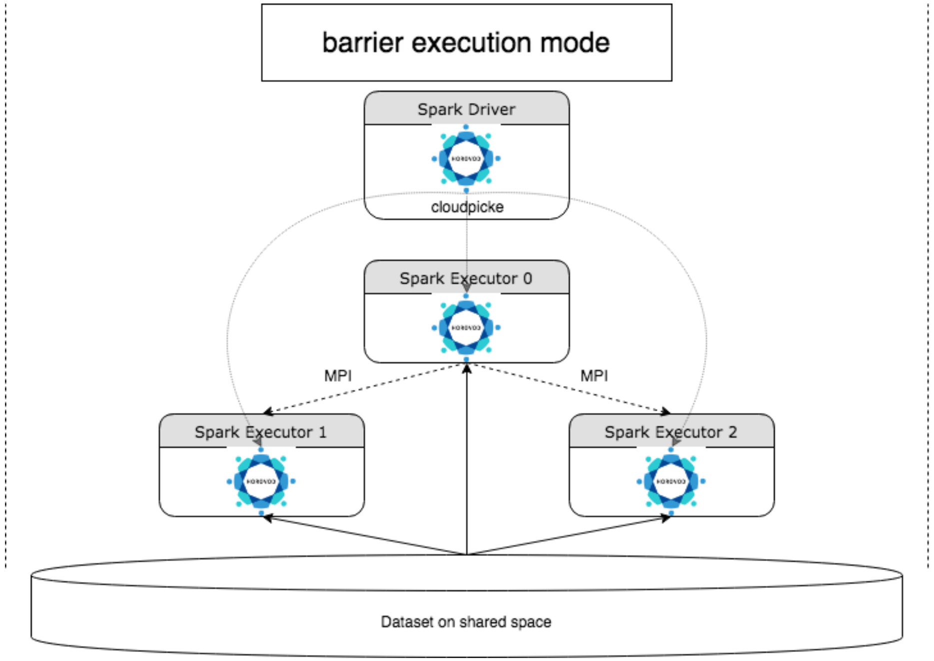
HOROVOD RUNNER

Distributed Training

- A generic API to manage distributed DL workloads
- Implemented through Spark's barrier execution mode scheduling (to support the MPI execution model)

Development workflow

1) Write single node DL code (e.g. TF/Keras)
2) Horovod-ify your code
3) Invoke HorovodRunner <hr.run(hvd_tr,..)>




```
hr = HorovodRunner(np=2)

def train():
  import tensorflow as tf
  hvd.init()

hr.run(train)
```

[10] Databricks

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CONCLUSIONS

- Big data analytics frameworks such as Apache Spark allows end-to-end ML/DL pipelines
- A viable direction for remote sensing and image analysis applications where whole processing workflow runs HPC and HTC simultaneously
- Harness public clouds (e.g. Amazon or Google) that provides stable deployments; integrated with state-of-the-art data analysis and DL frameworks (e.g. TF or PyTorch)

THANKS FOR LISTENING

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