Information Technology Department

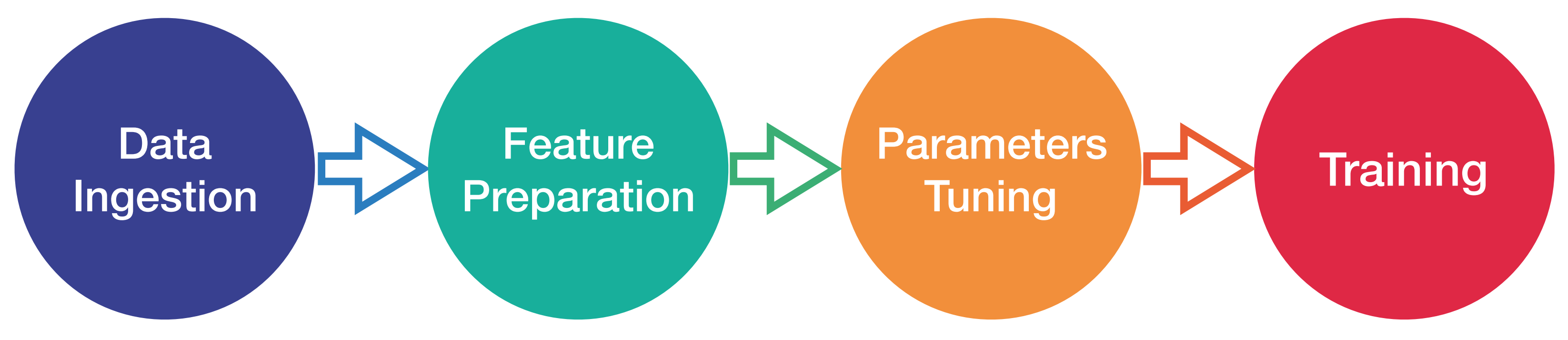
# Machine Learning Pipelines with Apache Spark and Intel BigDL

M. Migliorini[1,2], V. Khristenko[1]
M. Pierini[1], E. Motesnitsalis[1], L. Canali[1], M. Girone[1]
[1]CERN, Geneva, Switzerland; [2]University of Padova, Padova, Italy

CERN openlab

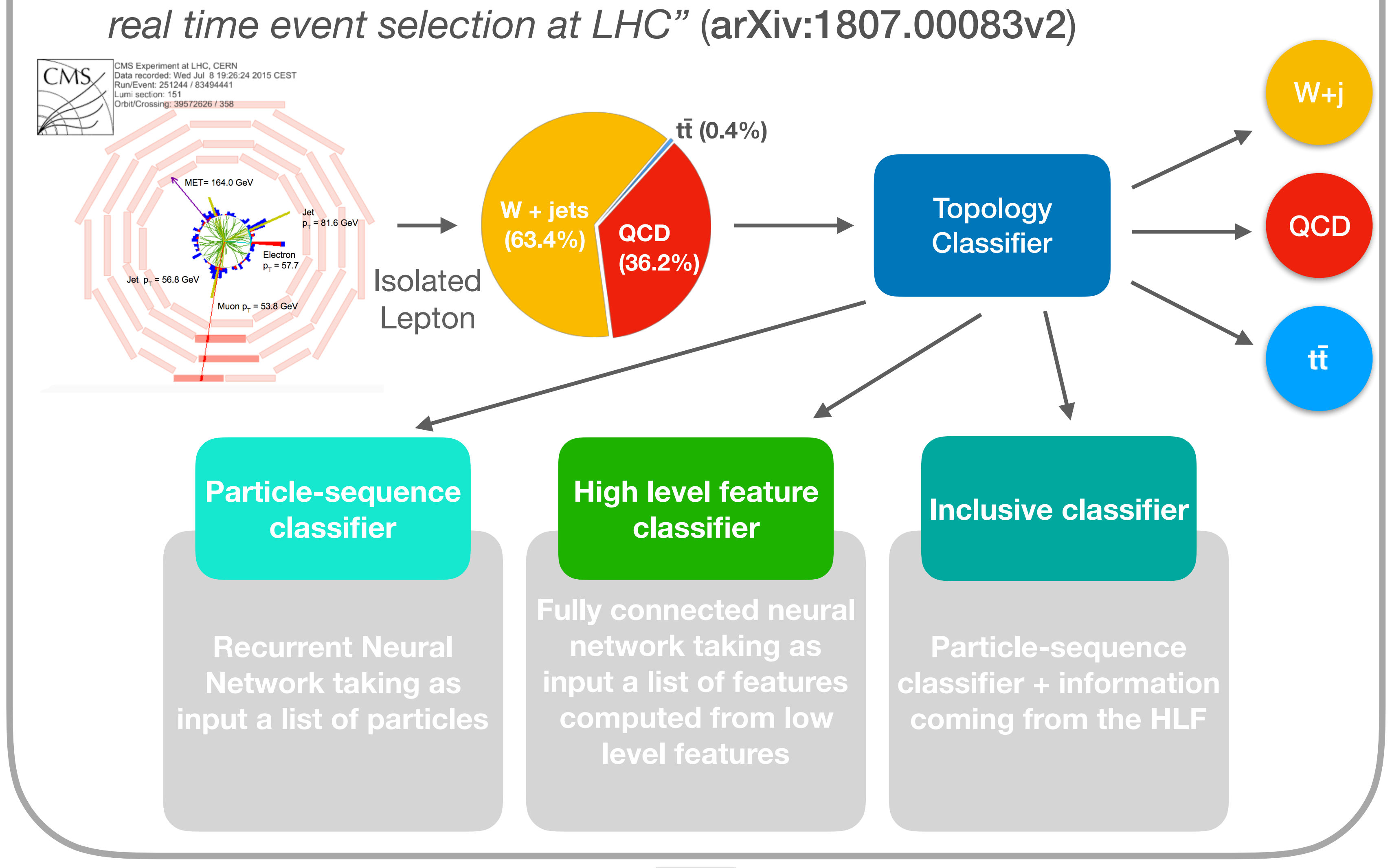
## End-to-End ML Pipeline

- The goal of this work is to produce a demonstrator of an end-to-end Machine Learning pipeline using Apache Spark
- Investigate and develop solutions integrating:
  - Data Engineering/Big Data tools
  - Machine Learning tools
  - Data analytics platform
- Use Industry standard tools:
  - Well known and widely adopted
  - Open the HEP field to a larger community
- The Pipeline is composed by the following stages:



## HEP use case

- The ability to classify events is of fundamental importance and Deep Learning proved to be able to outperform other ML methods
- See paper: “*Topology classification with deep learning to improve real time event selection at LHC*” (arXiv:1807.00083v2)


CMS Experiment at LHC, CERN
Data recorded: Wed Jul 8 19:26:24 2015 CEST
Run/Event: 251244 / 83494441
Lumi section: 151
Orbit/Crossing: 39572626 / 358
MET= 164.0 GeV
Jet p_T = 81.6 GeV
Electron p_T = 57.7
Jet p_T = 56.8 GeV
Muon p_T = 53.8 GeV
Isolated Lepton
W + jets (63.4%)
QCD (36.2%)
tt̄ (0.4%)
Topology Classifier
W+j
QCD
tt̄
Particle-sequence classifier
Recurrent Neural Network taking as input a list of particles
High level feature classifier
Fully connected neural network taking as input a list of features computed from low level features
Inclusive classifier
Particle-sequence classifier + information coming from the HLF

## Data Ingestion

**EOS storage**

Input:
- 10 TB of ROOT files
- 50M events

Spark +

- Access physics data stored in EOS using Hadoop-XRootD Connector
- Read ROOT files into a Spark DF using Spark-ROOT reader

## Feature Preparation

- Filter events: require the presence of isolated leptons
- Prepare input for the classifiers
  - Produce multiple datasets
  - Raw data (list of particles)
  - High Level features
- Store results in parquet files
  - Dev. dataset (100k events)
  - Full dataset (5M events)

Dev. dataset Parquet

Full dataset Parquet

## Parameters Tuning

Spark

Model #1 K

Model #2 K

● ● ●

Best Model K

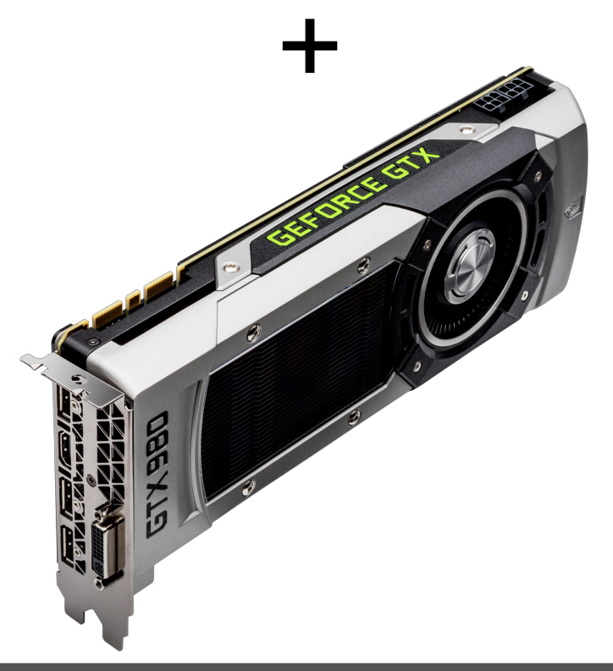
- Scan a grid of parameters to find the best model
- Train multiple models at the same time (one per executor)

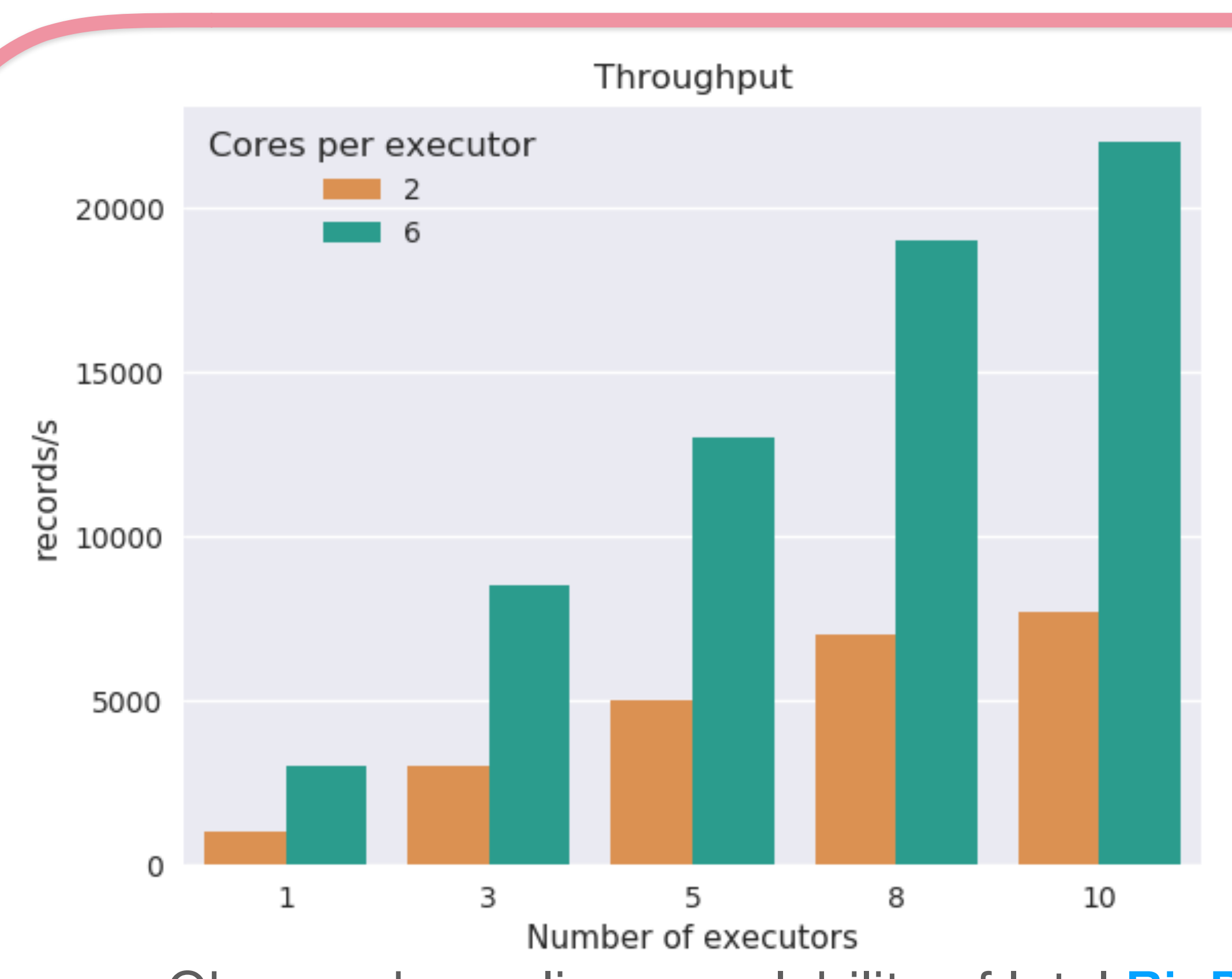
## Training

Trained the three models using various hardware and configurations

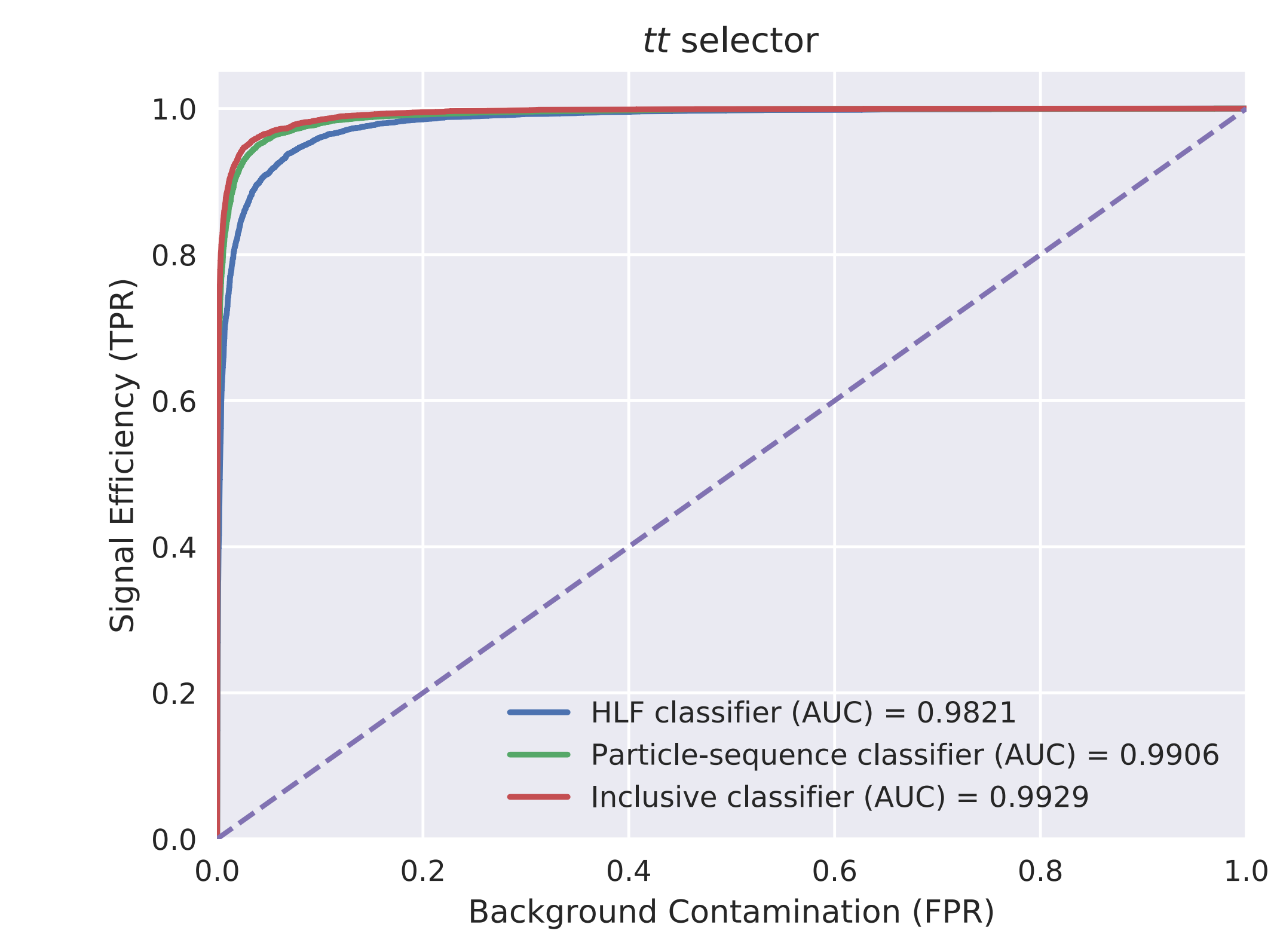
BigDL + Spark hadoop YARN

K +

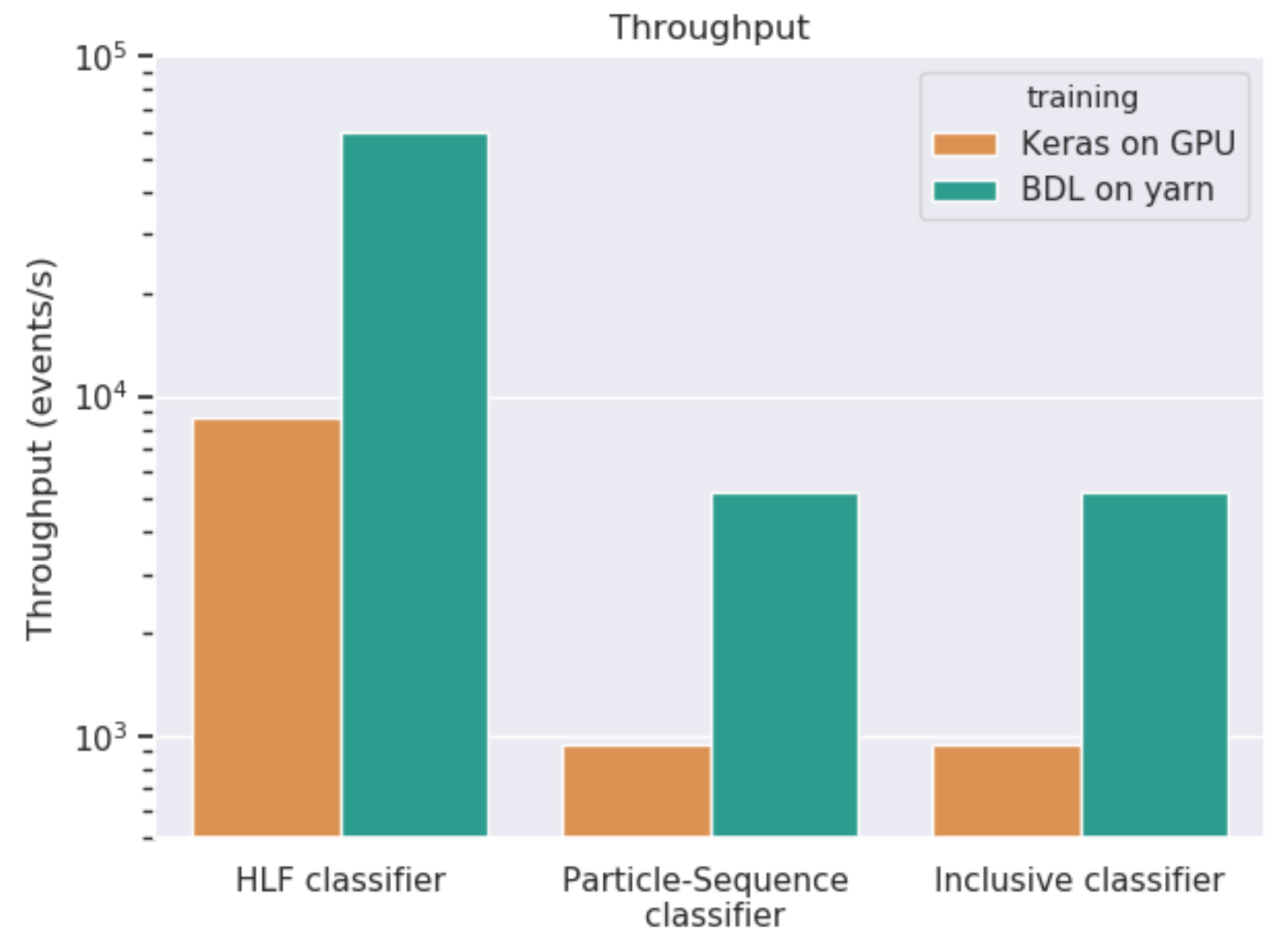




Observed near linear scalability of Intel BigDL



Reproduced the classifiers performance of the source paper



Throughput test measurements on the three different training methods and model types

## Results

- Created an end-to-end ML pipeline using Apache Spark
  - Python & Spark allow to distribute computation in a simple way
  - Intel BigDL scales well and it is easy to use because it has a similar API to Keras
  - Interactive analysis made easier by Jupiter Notebooks
- Future work
  - Test pipeline using cloud resources
  - Further performance improvements on data preparation and training
  - Model Serving: implement inference on streaming data

*https://openlab.cern/*