

Intel Big Data Analytics

openlab Technical Workshop

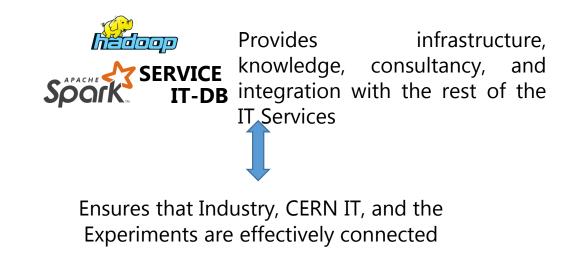
Evangelos Motesnitsalis

23 January 2019

1

openlab Big Data Analytics

in collaboration with Intel



Provides resources and consultancy on big data technologies and optimizations



openlab





Provides the relevant use cases and physics analysis



💮 diana hep



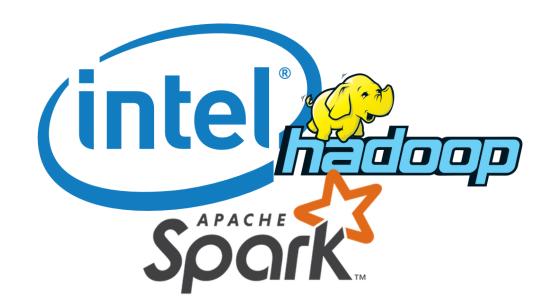
2

openlab Big Data Analytics

in collaboration with Intel

The project aims at helping and optimizing the Data Analytics Solutions at CERN in the areas of:

- Data Integration
- Data Ingestion and Transformation,
- Performance, Scalability, and Benchmarking
- Resource Management
- Data Visualization
- Hardware Utilization





Motivation and Vision

Why Big Data Analytics for High Energy Physics?



Investigate new ways to analyse physics data in preparation for the HL-LHC



Adopt new technologies widely used in the industry

- Open the HEP field to a larger community of data scientists
- Bring together engineers from industry and domain experts from academia



Use modern APIs, development environments and platforms (notebooks etc.)



Allow further development with Streaming and Machine Learning workloads



HEP Data Processing

Physics Analysis is typically done with the ROOT Framework which uses physics data that are saved in ROOT format files. At CERN these files are stored within the EOS Storage Service.

EOS Service

A disk-based, low-latency storage service with a highly-scalable hierarchical namespace, which enables data access through the XRootD protocol.



ROOT Data Analysis Framework

A modular scientific software framework which provides all the functionalities needed to deal with big data processing, statistical analysis, visualization and file storage.





CMS Data Reduction and Analysis Facility

Performing Physics Analysis and Data Reduction with Apache Spark



Investigate new ways to analyse physics data and improve resource utilization and time-tophysics



Main goal was to be able to reduce **1** PB of data in 5 hours or less



Data Reduction refers to event selection and feature preparation based on potentially complicated queries



We now have fully functioning Analysis and Reduction examples tested over CMS Open Data



The IT Hadoop and Spark Service has the capacity to run this type of jobs

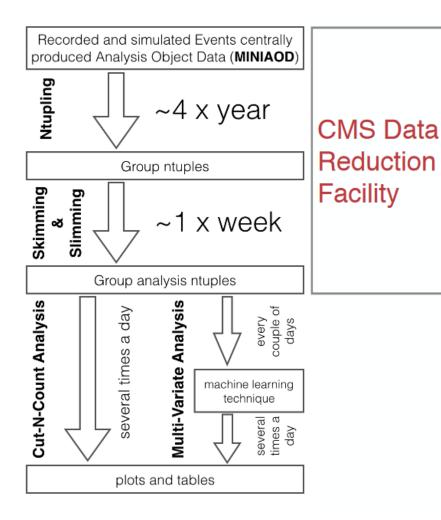


We performed extensive scaling and performance optimizations





CMS Data Reduction and Analysis Facility





It offers an alternative for 'ad-hoc' data reduction for each research group



This type of facility could be a big shift for High Energy Physics



Bridge the gap between High Energy Physics and Big Data communities



Apache Spark





Apache Spark is an open source cluster computing framework



Compatible with multiple cluster managers: Apache YARN Apache Mesos Kubernetes Standalone



Runs on: Hadoop HPC Cloud



Multiple File Formats and Filesystem Compatibility







Consists of multiple components: Spark SQL Spark Mlib Spark Graph Spark Structured Streaming



Milestones and Achievements

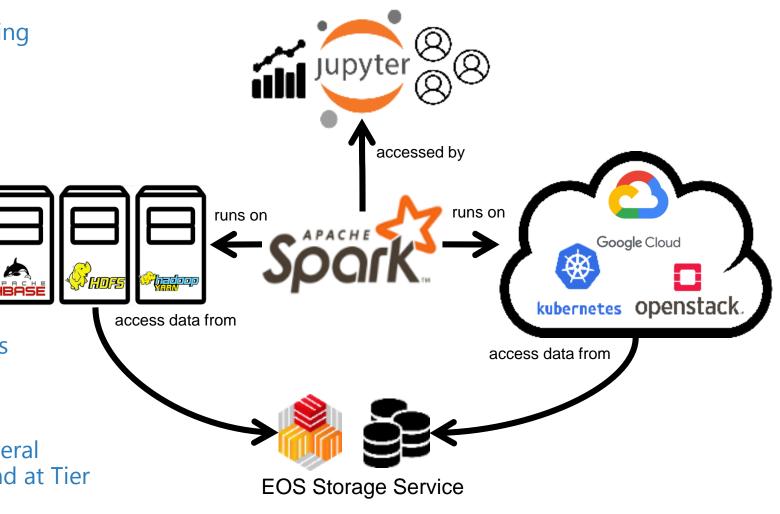


- 1. Read files in ROOT Format using Spark
- 2. Access files stored in EOS directly from Hadoop/Spark

CERN Openlab

This enabled us to produce, scale up, and optimize Physics Analysis Workloads with input up to 1 PB.

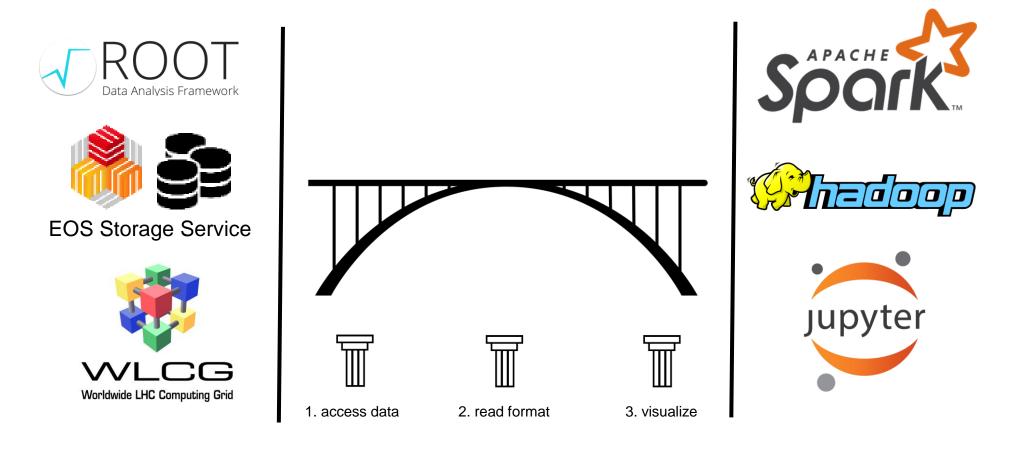
The infrastructure is actively used by several physics analysis groups both at CERN and at Tier 1s.



9

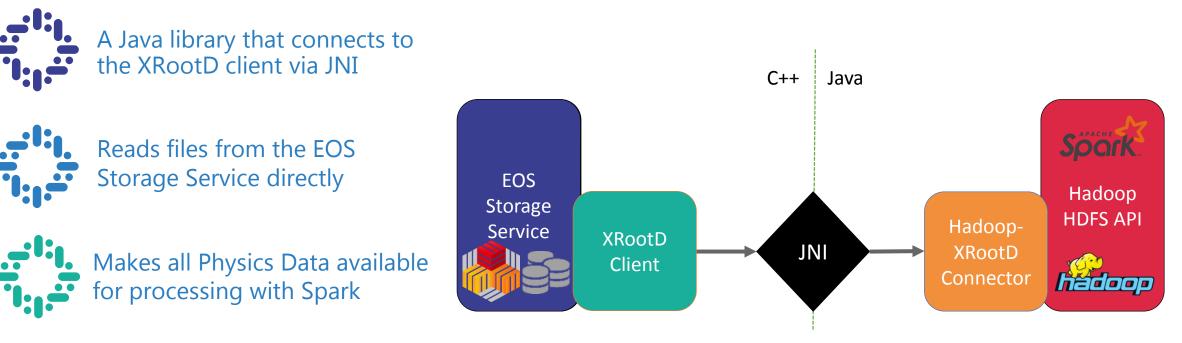
Bridging the Gap

Physics Analysis is typically done with the ROOT Framework which uses physics data that are saved in ROOT format files. At CERN these files are stored within the EOS Storage Service.



Hadoop – XRootD Connector

Connecting XRootD-based Storage Systems with Hadoop and Spark





Supports Kerberos and GRID Certificate Authentication

Open Source: https://github.com/cerndb/hadoop-xrootd











A Scala library which implements DataSource for Apache Spark



Spark can read ROOT TTrees and infer their schema



Root files are imported to Spark Dataframes/Datasets/RDDs



Open Source: https://github.com/diana-hep/spark-root/





SWAN Service and Spark Integration

Hosted Jupyter Notebooks for Data Analysis





Web-based interactive analysis using PySpark in the cloud



Collaboration between EP-SFT, IT-ST, and IT-DB



No need to install software



Combines code, equations, text and visualisations



Direct access to the EOS and HDFS



Fully Integrated with IT Spark and Hadoop Clusters

https://swan.web.cern.ch/





Scalability Tests

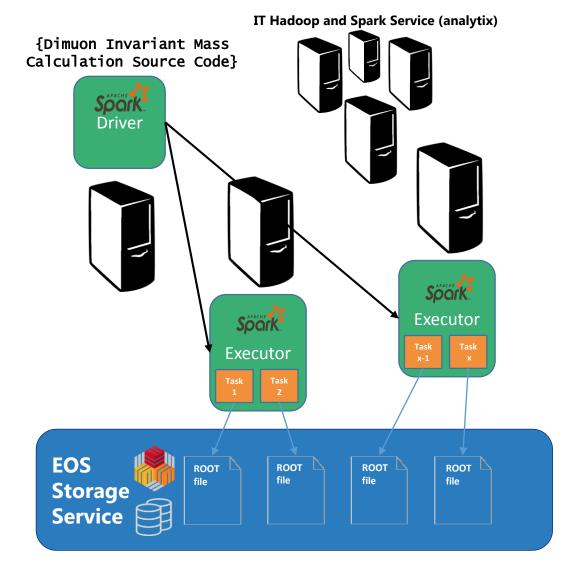
The data processing job of this project was developed in Scala by CMS members.

Its code:

- Performs event selection (i.e. Data Reduction)
- Uses the filtered events to compute the dimuon invariant mass

On a single thread/core and one single file as input, the workload reads one branch and calculates the dimuon invariant mass in approximately 10 mins for a 4GB file

Test Workload Architecture and File-Task Mapping



CERN openiab

Open Source: https://github.com/olivito/spark-root-applications

Scalability Tests



Technologies used:

- Intel CoFluent Cluster Simulation Technology
- Apache Spark
- Hadoop YARN
- Kubernetes and Openstack



CERN Openlab

Services/Tools Used:

- EOS Public, EOS UAT
- Hadoop-XRootD Connector
- spark-root
- sparkMeasure
- Spark on Kubernetes Service

Issues that we had to tackle.

- Network bottleneck •
- "readAhead" buffer configuration •
- Running tests on a shared cluster can lead to resources denial
- Performance impact on IT production services

We collaborated with:

- IT-ST and the EOS service for a • dedicated EOS instance (UAT)
- IT-DB for a dedicated queue in YARN with prereserved resources
- IT-CM and the OpenStack service for a • dedicated Kubernetes cluster on **OpenStack** 15

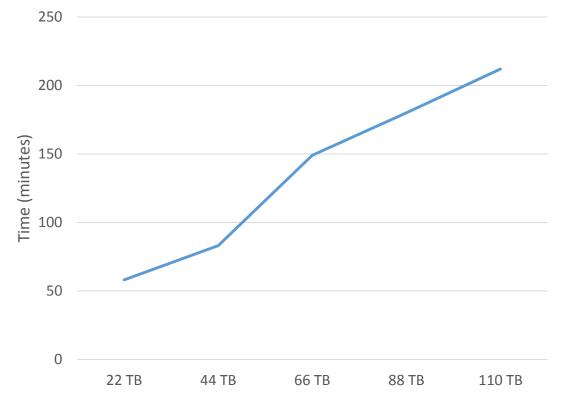


Scalability Tests – Phase I

Performance and Scalability for different input size with 32 MB "readAhead" buffer, 814 logical cores, and 2 logical cores per Spark executor

Input Data	Time for EOS Public
22 TB	58 mins
44 TB	83 mins
66 TB	149 mins
88 TB	180 mins
110 TB	212 mins

Performance for 814 cores in YARN

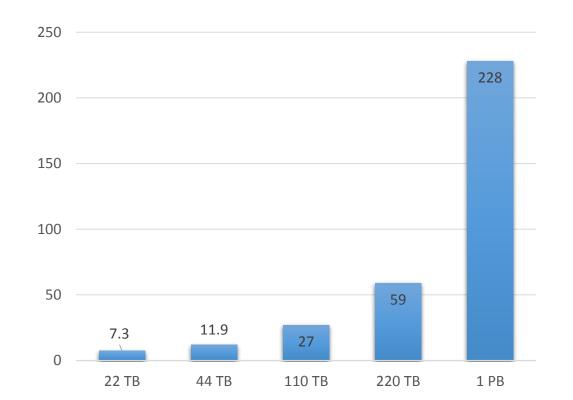


Configuration: 407 executors, 2 cores per executor, 7 GB per executor

Scalability Tests – Phase II

Performance and Scalability of the tests for different input size in minutes with 64 KB of "readAhead" buffer, 800 logical cores, and 8 logical cores per Spark executor

Input Data	Time for EOS Public
22 TB	7.3 mins
44 TB	11.9 mins
110 TB	27 mins (±2)
220 TB	59 mins (±5)
1 PB	228 mins (±10) (~3.8 hours)



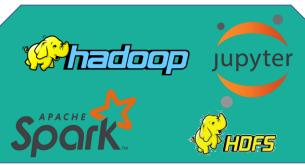
Configuration: 100 executors, 8 cores per executor, 7 GB per executor



More details in the poster "Physics Data Analysis and Data Reduction at scale with Apache Spark" 17

From Data Engineering to Machine Learning

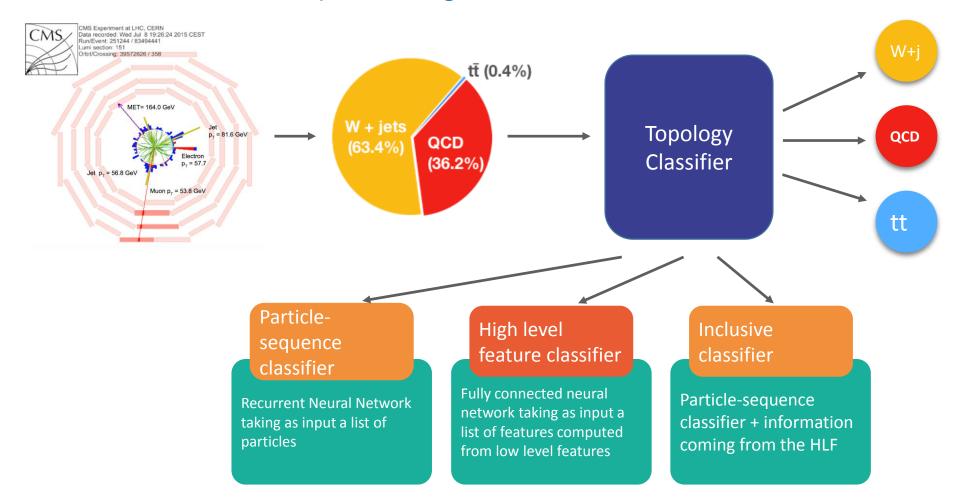






Machine Learning Workloads

Topology classification with deep learning to improve real time event selection at the LHC [https://arxiv.org/abs/1807.00083]

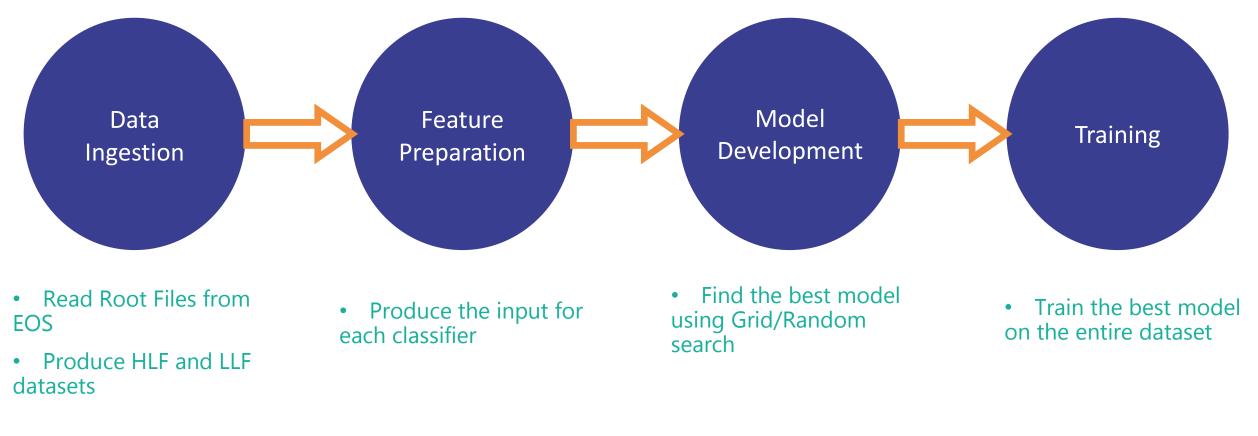


CERN Openlab

Machine Learning Workloads

The goals of this work are:

- Produce an example of a ML pipeline using Spark + EOS and ROOT format integration
- Test the performances of Spark at each stage for this use case



Machine Learning Workloads



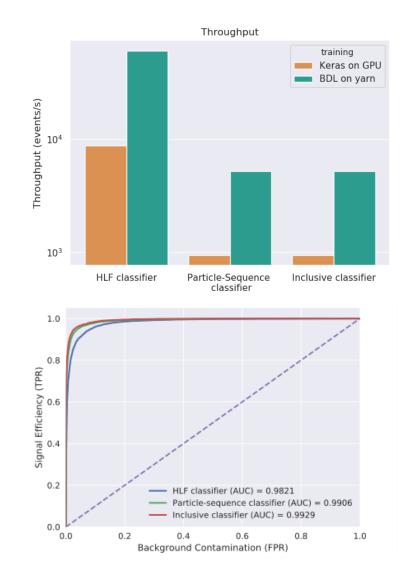
Created an End-to-End scalable machine learning pipeline using Apache Spark and industry standard tools



BigDL + Spark on CPU performs and scales well for recurrent NN and deep NN



Compatible with results presented in the paper



21



More details in the poster "Machine Learning Pipelines with Apache Spark and Intel BigDL"

Apache Spark on Cloud

Work in Progress



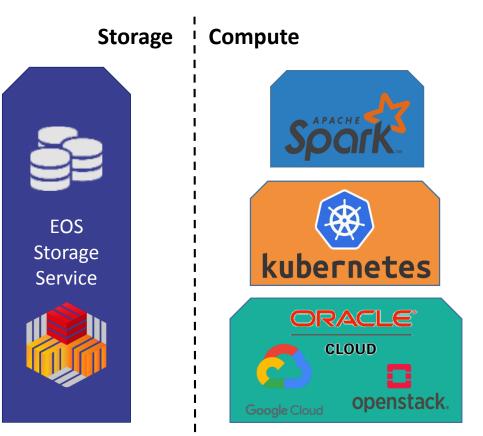
Cloud Architecture for data analysis means separating storage and computing



Allow users to access a larger environment of libraries developed by different communities



Provide an abstraction to run Spark and popular Machine Learning frameworks with Kubernetes independently from the underlying resources



, CERN 1:1: openlab More details in the poster "Physics Data Processing and Machine Learning on the Cloud"

Future Steps



Repeat the workload tests on top of virtualized/containerized infrastructure with Kubernetes in bigger infrastructure and public clouds



Extend the workloads to different and more complex use cases of Physics Analysis



Proceed with more Machine Learning and Online Data Processing (Streaming) use cases



Extend the features of the "Hadoop-XRootD Connector" library (i.e. write to EOS, better packaging, monitoring)





Conclusions



Can we reduce 1 PB in 5 hours?

• Yes, we even dropped to 4 hours in our latest tests.



- Through this project we achieved:
 - Efficient & fast processing of physics data
 - Connecting Libraries between Big Data Technologies and HEP Tools
 - Adoption of Big Data Technologies by CMS physics groups (e.g. University of Padova, Fermilab)



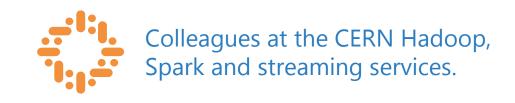
Future Plans:

- Focus on Machine Learning and Streaming workloads
- Consolidate and extend the existing libraries



Acknowledgements









CMS members of the Big Data Reduction Facility, DIANA/HEP, Fermilab as well as the authors of "Topology classification with deep learning to improve real-time event selection at the LHC" [https://arxiv.org/abs/1807.00083]





emotes@cern.ch

