Machine Learning Pipelines with Modern Big Data Tools for High Energy Physics

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Abstract

The effective utilization at scale of complex machine learning (ML) techniques to HEP use cases poses several technological challenges, most importantly on the actual implementation of dedicated end-to-end data pipelines. A solution to these challenges is presented, which allows training neural network classifiers using solutions from the Big Data ecosystems, integrated with tools, software, and platforms common in the HEP environment. In particular, Apache Spark is exploited for data preparation and feature engineering, running the corresponding (Python) code interactively on Jupyter notebooks; key integrations and libraries that make Spark capable of ingesting data stored using ROOT and its EOS/XRootD protocol is described and discussed. Training of the neural network models, defined by means of the Keras API, is performed in a distributed fashion on Spark clusters by using BigDL with Analytics Zoo and by using Tensorflow. The implementation and the results of the distributed training are described in details in this work.

Introduction

High energy physics (HEP) experiments like those at the Large Hadron Collider (LHC) are paramount examples of “big-data” endeavours: chasing extremely rare physics processes requires producing, managing and analyzing large amounts of complex data. The data processing throughput of those experiments is expected to exceed 200 TB/s in 2025 with the upgrade of the LHC (HL-LHC), which, after a tight online filtering, implies to store on permanent storage 100 PB per year. A thorough and complex data processing enables major scientific achievements, like the discovery of the Higgs boson in 2012. Data ingestion, feature engineering, data reduction and classification are complex tasks, each requiring advanced techniques to be accomplished. While, so far, custom solutions have been employed, recent developments of open source tools are making the latter compelling options for HEP specific use-cases. Furthermore, physics data analysis is profiting to a large extent from modern Machine Learning (ML) techniques, which are revolutionizing each processing step, from physics objects reconstruction (feature engineering), to parameter estimation (regression) and signal selection (classification). In this scope, \textit{Apache Spark} \cite{1} represents a very promising tool to extend the traditional HEP approach, combining in a unique system powerful means for both sophisticated data engineering and Machine Learning. Among the most popular analytics engines for big data processing, Spark allows performing an interactive analysis and data exploration by means of its mature data processing engine and API for distributed data processing, its integration with cluster systems and by featuring ML libraries giving the possibility to train in a distributed
fashion all common classifiers and regressors on large
datasets.

It has been proved (e.g. in [2]) that Deep Learning
can boost considerably the performances of physics
data analysis, yielding remarkable results from larger
sets of low-level (i.e. less "engineered") quantities.
There is thus a significant interest in integrating in
Spark external tools, like BigDL [3], allowing the dis-
tributed training of deep learning models.

The development of end-to-end machine learning
pipeline to analyze HEP data using Apache Spark is
described in this paper. After briefly recalling the
traditional data processing and analysis workflow in
HEP, the specific physics use-case addressed in work
is presented; the various steps of the pipeline are then
described in details, from data ingestion to model
training, whereas the overall results are reported in
the final section.

Traditional Analysis Workflow
and Tools

The backbone of the traditional HEP analysis work-
flow is ROOT [4], a multipurpose C++ toolkit devel-
oped at CERN implementing functionalities for I/O
operations, persistent storage, statistical analysis and
data visualization. Data gathered by LHC experi-
ments or produced by their simulation software are
provided in ROOT format, with a file-based data rep-
resentation and an event-based class structure with
branches. The latter is a feature of paramount impor-
tance, as it enables the flexibility required to preserve
the complexity of the recorded data, allowing keeping
track of intrinsic dependencies among physics objects
of each collision event.

Centralized production systems orchestrate the
data processing workflow, converting the raw infor-
mation into higher level quantities (data or feature engineering). Computing resources, organized worldwide in hierarchical tiers, are exploited by means of GRID protocols [5]. Although the centrally pro-
duced datasets may require some additional feature preparation, from this stage on, the processing is analysis-dependent and is done by the users using batch systems. Machine Learning algorithms are exe-
cuted either from within the ROOT framework (by
means of TMVA, a toolkit for multivariate data anal-
ysis) or using more common open source frameworks
(Keras/Tensorflow, PyTorch, etc.).

The Physics use case

Physicists primarily aim at distinguishing interesting
collision events from uninteresting ones, the for-
mer being those associated with specific physics sig-
als whose existence is sought or whose properties
are worth being studied. Typically, those signals are
extremely rare and correspond to a tiny fraction of
the whole dataset. Data analysis results then in a
classification problem, where in addition to the sig-
nal category, the background is often also split into
several classes.

Out of the 40 million collisions produced by the
LHC every second, only a small fraction (about 1000)
could be stored by the two omni-purposes detectors,
CMS and ATLAS. An haphazard selection of those
events would dilute the already rare signal processes,
thus efficient data classification needs to take place
already online. Experiments implement complex trig-
ger systems, designed to maximize the true-positive
rate and minimize the false-positive rate thus allow-
ing an effective utilization of computing resources
both online and offline (e.g. processing units, stor-
age, etc.).

The Machine Learning pipeline described in this
paper addresses the same physics use-case considered
in the work by Nguyen et al. [6] where event topol-
ogy classification, based on deep learning, is used to
improve the purity of data samples selected at trig-
ger level. The dataset is the result of a Monte Carlo
event generation, where three different processes (cat-
egories) have been simulated: the inclusive produc-
tion of a leptonically decaying $W^\pm$ boson, the pair
production of a top-antitop pair ($t\bar{t}$) and hadronic
production of multijet events. Variables of low and
high level are included in the dataset.

The primary goal of this work is to reproduce the
classification performance results of [6], showing that
the proposed pipeline makes a more efficient usage of
computing resources and/or provides a more productive interface for the physicists, along all the steps of the processing pipeline.

**Data Pipeline For Machine Learning**

Data pipelines are of paramount importance to make machine learning projects successful, by integrating multiple components and APIs used across the entire data processing chain. A good data pipeline implementation can accelerate and improve the productivity of the work around the core machine learning tasks. In particular, data pipelines are expected to provide solid tools for data processing, a task that ends up being one of the most time-consuming for data scientists and physicists approaching data analysis problems. Traditionally, HEP has developed custom tools for data processing, which have been successfully used for decades. Recently, a large range of solutions for data processing and machine learning have become available from open source communities. The maturity and adoption of such solutions continue to grow both in industry and academia. Using software from open source communities comes with several advantages, including lowering the cost of development and maintenance and the possibility of sharing solutions and expertise with a large user and expert base. In this work we implement the machine learning pipeline detailed in [6] using tools from the "Big Data" ecosystem. One of the key objectives for the machine learning data pipeline is to transform raw data into more valuable information used to train the ML/DL models. Apache Spark provides the backbone of the pipeline, from the task of fetching data from the storage system to feature processing and feeding training data into a DL engine (BigDL and Analytics Zoo are used in this work). The four steps of the pipeline we built are:

- **Data Ingestion**, where we read data from ROOT format and from the CERN EOS storage system, into a Spark DataFrame and save the results as a table stored in Apache Parquet files.

- **Feature Engineering and Event Selection**, where the Parquet files containing all the events details processed in Data Ingestion are filtered, and datasets with new features are produced.

- **Parameter Tuning**, where the hyperparameters for each model architecture are optimized by performing grid search.

- **Training**, where the neural network models are trained on the full dataset.

In the next sections we will describe in detail each step of this pipeline.

**Data Source**

Data used for this work have been generated using software simulators to generate events and to calculate the detector response, as previously discussed, see also [6] for details. For this exercise, the generated training data amounts to 4.5 TB, for a total of 54 million events, divided in 3 classes: "W + jet", "QCD", "tt" events. The generated training data is stored using the ROOT format, as it is a common format for HEP. Data are originally stored in the CERN EOS storage system as it is the case for the majority of HEP data at CERN at present. The authors of [6] have kindly shared the training data for the purpose of this work. Each event of the dataset consists of a list of reconstructed particles. Each particle is associated with features providing information on the particle cinematic (position and momentum) and on the type of particle.
Data Ingestion

Data ingestion is the first step of the pipeline, where we read ROOT files from the CERN EOS storage system into a Spark DataFrame. For this, we use a dedicated library able to ingest ROOT data into Spark DataFrames: spark-root, an Apache Spark data source for the ROOT file format. It is based on a Java implementation of the ROOT I/O libraries, which offers the ability to translate ROOT files into Spark DataFrames and RDDs. In order to access the files stored in the EOS storage system from Spark applications, another library was developed: the Hadoop-XRootD connector. The Hadoop-XRootD connector is a Java library, it extends the Apache Hadoop Filesystem YARN and makes its capable of accessing files stored in EOS via the XRootD protocol. This allows Spark to read directly from EOS, which is convenient for our use case as it avoids the need for copying data into HDFS or other storage compatible with Spark/Hadoop libraries. At the end of the data ingestion step the result is that data, with the same structure as the original ROOT files, are made available as a Spark DataFrame on which we can perform event selection and feature engineering.

Event Selection and Feature Engineering

In this step of the pipeline, we process the dataset by applying relevant filters, by computing derived features and by applying data normalization techniques. The first part of the processing requires domain-specific knowledge in HEP to simulate trigger selection: this is emulated by requiring all the events to include one isolated electron or muon with transverse momentum ($p_T$) above a given threshold, $p_T \geq 23$ GeV. All particle are then ranked in decreasing order of $p_T$. For each event, the isolated lepton is the first entry of the list of particles. Together with the isolated lepton, the first 450 charged particles, the first 150 photons, and the first 200 neutral hadrons have been considered, for a total of 801 particles with 19 features each. The result is, that each event passing the filter is associated with a matrix with shape 801 x 19. This defines the Low Level Features (LLF) dataset. Starting from the LLF, an additional set of 14 High Level Features (HLF) is computed. These additional features are motivated by known physics and data processing steps, and will be of great help for improving the neural network model in later steps. LLF and HLF datasets, computed as described above, are saved in Apache Parquet format: the amount of training data is reduced at this point from the original 4.5 TB of ROOT files to 950 GB of snappy-compressed Parquet files. Additional processing steps are performed and include operations frequently found when preparing training data for classifiers, notably:

- Data undersampling. This is done to work around the class imbalance in the original training data. After this step, we have the same number of events per each of the three classes, that is 1.4 million events for each of the 3 classes.

- Data shuffling. This is a standard practice, useful to improve convergence of mini-batch gradient descent-based training.

- All the features present in the datasets have been pre-processed, by scaling them take values between 0 and 1 (using MinMaxScaler) or normalized, using the StandardScaler, as needed for the different classifiers.

- The datasets, containing HLF and LLF features and labels, are split into training and test datasets (80% and 20% respectively) and saved in two separate folders, as Parquet files. Smaller datasets, samples of the full train and test datasets have also been generated for development purposes.

Data are saved in snappy-compressed Parquet format at the end of this stage and amount to about 310 GB. The decrease in total data size from the previous step is mostly due to the undersampling step and the fact that the population of the 3 topology classes in the original training data used for this work are not balanced.
Neural Network Models

We have tested three different neural network models, following [6]:

- The first and simplest model is the "HLF Classifier". It is a fully connected feed-forward deep neural network taking as input the 14 high level features. The chosen architecture consists of three hidden layers with 50, 20, 10 nodes activated by Rectified Linear Units (ReLU). The output layer consists of 3 nodes, activated by the Softmax activation function.

- The "Particle Sequence Classifier" is trained using recursive layers, taking as input the 801 particles in the Low Level Features dataset. The particles list is ordered, prior to feeding it into a recurrent neural network. Particles are ordered by decreasing $\Delta R$ distance from the isolated lepton, calculated as
  \[ \Delta R = \sqrt{\Delta \eta^2 + \Delta \phi^2} \]
  where $\eta$ is the pseudorapidity and $\phi$ the azimuthal angle of the particle. Gated Recurrent Units (GRU) have been used to aggregate the particles input sequence, using a recurrent layer of width 50. The output of the GRU layer is fed into a fully connected layer with 3 Softmax-activated nodes. Notably this model does not make use of High Level Features, but only uses "Low Level Features" from simulation data.

- The "Inclusive Classifier" is the most complex and complete of the 3 models tested. This classifier combines the "HLF classifier" with the "Particle Sequence Classifier". The model consists in concatenating the 14 High Level Features to the output of the GRU layer after a dropout layer. An additional dense layer of 25 nodes is introduced before the final output layer consisting of 3 nodes, activated by the Softmax activation function.

Parameter Tuning

Hyperparameter tuning is a common step for improving machine learning pipelines. In this work, we have used Spark to speed up this step. Spark allows training multiple models with different parameters concurrently on a cluster, with the result of speeding up the hyperparameter tuning step. We used AUC, the Area Under the ROC curve, as the performance metric to compare different classifiers. When performing a grid search each run is independent of the others, hence this process can be easily parallelized and scales very well. For example, we tested the High Level Features classifier, a feed forward neural network, taking as input the 14 High Level Features. For this model, we tested changing the number of layers and units per layer, the activation function, the optimizer, etc. As an experiment, we ran grid search on a small dataset containing 100K events sampled from the full dataset, using a grid of ~200 hyper-parameters sets (models). Hyperparameter tuning can similarly be repeated for all three classifiers described above. For the following work, we have decided to use the same models as the ones presented in [6], as they were offering the best trade-off between performances and complexity. To run grid search in parallel, we used Spark with spark-sklearn and the TensorFlow/Keras wrapper for scikit-learn [12].
Distributed Training with Spark, BigDL/Analytics Zoo and TensorFlow

There are many suitable software and platform solutions for deep learning training nowadays, however choosing among them is not straightforward, as many products are available with different characteristics and optimizations for different areas of application. For this work, we wanted to use a solution that easily integrates with the Spark service at CERN, running on Hadoop YARN [10] cluster, and more recently also running Spark on Kubernetes [13] using cloud resources. GPUs and other HW accelerators are only available in limited quantities at CERN at the time of this work, so we also wanted to explore solution that could scale on CPUs. Moreover, we wanted to use Python/PySpark and well-known APIs for neural network processing: notably Keras API [14] in this case. Those reasons combined with an ongoing collaboration between CERN openlab [15] and Intel has led us to test and develop this work using BigDL [3] and Analytics Zoo [16] for distributed model training. BigDL and Analytics Zoo are open source projects distributed under the Apache 2.0 license. They provide a distributed deep learning framework for Big Data platforms and are implemented as libraries on top of Apache Spark. Analytics Zoo, in particular, provides a unified analytics and AI platform that seamlessly unites Spark, TensorFlow, Keras and BigDL programs into an integrated pipeline. Notably, with Analytics Zoo and BigDL users can work with models defined with Keras and TensorFlow [17] APIs and run the training at scale using Spark. More information on Analytics Zoo can be found in the Analytics Zoo repository [16]. BigDL provides data-parallelism to train models in a distributed fashion across a cluster using synchronous mini-batch Stochastic Gradient Descent. Data are automatically partitioned across Spark executors as an RDD of Sample: an RDD of N-Dimensional array containing the input features and label. Distributed training is implemented as an iterative process, thus there will be multiple iterations over the same data. Reading data from disk multiple times is slow, for this reason, BigDL exploits the in-memory capabilities of Spark to cache the train RDD in the memory of each worker allowing faster access during the iterations (this also means that sufficient memory needs to be allocated for training large datasets). More information on BigDL architecture can be found in the BigDL white paper [3]. In addition we have tested distributed training using TensorFlow. TensorFlow version 1.14 and higher introduce an easy-to-use API for running distributed training. Using the package tf.distribute, bundled with TensorFlow distribution, distributed training of a Keras model can be activated by simply wrapping the code defining and compiling the model with the chosen strategy for distributed training. In this work we have used the ”Multi Worker Mirrored Strategy” to distribute training across multiple machines. Multi worker mirrored strategy is an experimental API in TensorFlow 2.0, it uses the all-reduce algorithm to keep the neural network variables in sync during training.

Models Training Results

After training the three neural network models, we evaluated the results using the test dataset. Each of the models presented in the previous section returns as output the probability that an input event is associated with a given topology: \( y_{\text{QCD}} \), \( y_{\text{W}} \) or \( y_{\bar{t}t} \). This can be used to define a classifier, for example, it suffice to apply a threshold requirement on \( y_{\bar{t}t} \) or \( y_{\text{W}} \) to define a \( W \) or a \( \bar{t}t \) classifier, respectively. A common technique to evaluate the performance of classifiers, also utilized in the reference work [6], is to compute and compare their corresponding ROC (receiver operating characteristic curve) curves and AUC (area under the ROC curve). Figure 3 shows the comparison of the ROC curves for the three classifiers for a \( \bar{t}t \) selector.

The fact that the HLF classifier performs well, despite its simplicity, can be justified by the fact that we are putting considerable physics knowledge into the the definition of the 14 high level features. This conclusion is further reinforced by additional tests, where we have built a topology classifier using a “random forest” and a “gradient boosting” (XGBoost) model, trained using the high level features dataset. In both cases we have obtained very good
Figure 3: AUC and ROC curves for the $t\bar{t}$ selector trained using BigDL. The results show that all three models perform well, with the inclusive classifier model being the best result of the three. This matches the results of Nguyen et al. \[6\]

performance of the classifiers, just close to what has been achieved with the HLF classifier model. In contrast, the fact that the particle sequence classifier performs better than the HLF classifier is remarkable, because we are not putting any \textit{a priori} knowledge into the particle sequence classifier: the model is taking just a list of reconstructed particles in the training data as input. Further improvements are seen by combining the HLF with the particle sequence classifier. In some sense, the GRU layer is identifying important features and physics quantities out of the training data, rather than using knowledge injected via feature engineering.

Another remarkable fact is that the training procedure used in this work is converging to the same results presented in the original paper \[6\] even if we are using a distributed training method in this work.

**Workload and Performance**

Multiple Spark clusters have been used to develop, run and test the data pipeline. The first group consisted of two Hadoop/YARN clusters, part the CERN Hadoop and Spark service: a development cluster, and a production cluster consisting of 52 nodes, with the following resources: 1800 vcores, 14 TB of RAM, 9 PB of storage. The production cluster is a shared general-purpose multi-tenant Hadoop YARN cluster built using commodity hardware and running Linux (CentOS 7). Only a fraction of the resources of the production cluster capacity was used when executing the pipeline (up to about 30% of the core capacity). Jobs from other and different workloads were concurrently running on the system used to develop this work, which has introduced some noise and possibly impacted performance, however, this also provided with a "real-life" scenario of what data scientists and physicists could achieve when running their data pipelines and DL training jobs on the Spark cluster at CERN. Additional work has been done using Spark clusters running on cloud resources, on premises and at a public cloud. Also in this case the resources are allocated on a multi-tenant system. The workloads for data processing and distributed training have been successfully reproduced in such environments by running Spark on Kubernetes. This has shown that cloud resources are a viable architec-
ture for this use case implementing a data pipeline for deep learning. In particular the CERN Cloud Service and Oracle Cloud Infrastructure have been tested.

Data ingestion and event filtering is a very resource-demanding step of the pipeline. Processing the original data set of 4.5 TB took approximately 3 hours, when deployed on a Hadoop/YARN cluster with 50 executors, each executor allocating 8 cores, for a total of 400 cores allocated to the Spark application. The data ingestion application workload was measured with OS tools and the Spark metrics system while running. Monitoring data showed that the majority of the application time was spent by tasks running "on CPU". CPU cycles were spent mostly executing Python code, that is outside of the Spark JVM. This can be explained by the fact that we chose to process the bulk of the training data using Python UDF functions. This a well-known behavior in current versions of Apache Spark when using Python UDF extensively. In such systems many CPU cycles are "wasted" in data serialization and deserialization operations, going back and forth from JVM and Python, in the current Spark implementation. Spark runs more efficiently when using using the DataFrame API and/or Spark SQL. To improve the performance of the event filtering we have introduced the use of Spark SQL to implement some of the filters, thus replacing part of the Python UDF code. Notably, we have made use of Spark SQL Higher Order Functions, a specialized category of SQL functions, introduced in Spark from version 2.4.0, that allow to improve processing for nested data (arrays). For our workload this has introduced the benefit of running a significant fraction of the filtering operations fully inside the JVM, optimized by the Spark code for DataFrame operations. The result is that the data ingestion step, optimized with Spark SQL and higher order functions, ran in about 2 hours, improving on previously measured job duration of 3 hours, in the implementation that uses only Python UDF. Future work on the pipeline may further address the issue of reducing the time spent in serialization and deserialization when using Python UDF, for example, we might decide to re-write the critical parts of the ingestion code in Scala. However, with the current training data size (4.5 TB), the performance of the data ingestion step, of just a couple of hours, is acceptable.

Performance of hyperparameter tuning with grid search: grid search runs multiple training jobs in parallel, therefore it is expected to scale well when run in parallel, as it was the case in our work (see also the paragraph on hyperparameter tuning). This was confirmed by measurements, as shown in Figure 2, by adding executors, and consequently the number of models trained in parallel, the time required to scan the parameters space decreased, as expected.

Performance of distributed training with BigDL and Analytics Zoo is also important for this exercise, as faster training time means improved productivity of the data scientist/physicists who will typically perform many experiments on the models’ definition and fine tuning. Figureref:scalabilityBD shows a few measurements of the training speed for the HLF classifier. The tests have been run on the development cluster, using batch size of 32 per worker, and show very good scalability behavior of the training at the scale tested. Additional measurements, using 20 executors, with 6 cores each (for a total of 120 allocated cores), using batch size of 128 per worker, showed training speed for the HLF classifier of the order of 100K rows/sec, sustained for the training of the full dataset. We were
able to train the model in less than 5 minutes, running for 12 epochs (each epoch processing 3.4 million training events). The batch size has an impact on the execution time and on the accuracy of the training. We found that a batch size of 128 for the HLF classifier is a good compromise for speed, while a batch size of 32 is slower but gives improved results. We would use the former for model development and the latter for example for producing the final training results.

An important point to keep in mind when training models with BigDL, is that the RDDs containing the features and labels datasets need to be cached in the executor’s JVM memory. This can be a significant amount of memory, of the order of 250 GB for the GRU-based models tested in this work.

The training dataset size and the model complexity of the HLF classifier are of relatively small scale, making the HLF classifier suitable for training also on desktop computers, i.e. without using distributed computing solutions. However, the Particle Sequence Classifier and the Inclusive Classifier models have a much higher complexity and require processing hundreds of GB of training data. Figure 6 shows the amount of CPU consumed during the training of the Particle Sequence classifier using BigDL/Analytics-zoo on a Spark cluster, using 70 executor and training with a batch size of 32. Notably, the neural network training in this case has lasted for 9 hours (50 epochs) and has utilized the equivalent of 200 CPU cores for the whole duration of the training job. The executor CPU measurements have been collected using Spark metrics instrumentation feeding into an InfluxDB instance, the monitoring plots have been generated using a custom Grafana dashboard custom built to visualize Spark monitoring data.

We have also measured the distributed training performance for the Inclusive Classifier model using TensorFlow and in particular tf.distribute with “multi Worker mirror strategy”, to distribute the training over multiple servers with a configurable number of nodes and CPU cores. To use TensorFlow with the data prepared in our pipeline we had to introduce an additional step, where we converted the training and test data set into TFRecord format. TFRecord is a format that TensorFlow can ingest natively using tf.data and tf.io, in essence it consists of serialized protocol buffer entries. Apache Spark has been used to convert the dataset from Parquet to TFRecord using a library and Spark datasource spark-tensorflow-connector, which is distributed as open source by the Tensorflow project. The conversion took just a few minutes, when run on a cluster, thanks to Spark’s parallel processing capabilities.

The first Tensorflow Training test used a single bare metal machine, with 24 physical cores (Broadwell) and 512 GB of RAM. Training and test data were stored locally on a SSD. After a few experiments we noticed that the system would scale up to 4 concurrent training workers before reaching saturation. Training training of the Inclusive Classifier with with 4 concurrent workers for 10 epochs, with batch size 64 (per worker) using TensorFlow 2.0-rc0 took 11.5 hours. The results for loss and AUC are comparable with what obtained in previous runs with BigDL. The seconds experiment used cloud resources to run the distributed training, both using CERN private cloud and a public cloud (OCI). We also developed a launcher script (tf-spawner) for running distributed training with tf.distribute on Kubernetes nodes. Training and test data were copied to the cloud object storage, respectively S3 and OCI object storage, and were read (over the network) using tf.data. Additional configuration of tf.data for performance included data prefetching parameters, while
Figure 7: Distributed training performance for the Inclusive classifier model using TensorFlow and tf.distribute with Multi Worker Mirror Strategy, to distribute the training over a configurable number of nodes and CPU cores on a Kubernetes cluster. Measurements show that the training time decreases as the number of allocated cores is increased. We also observe that the measured loss after 10 epochs degrades (has a higher value) as the number of training instances and cores increases.

Future work will address more thorough investigation of the performance and scalability of the different distributed training solutions tested. In particular it appears interesting to gather a deeper understanding of all the parameters influencing training performance, both in terms of training time and ability to converge to lowest loss and highest AUC for the trained models.

Conclusions and Future Outlook

This work shows an example of how a pipeline for end-to-end data preparation and deep learning for a high energy physics use case can be implemented using tools and techniques from open source projects and "big data" communities at large. In particular, this work addresses the implementation of a pipeline for data preparation and training of a particle topology classifier based on deep learning. Following the work and models developed by Nguyen et al. [6], event topology classification, based on deep learning, is used to improve the purity of data samples selected at trigger level. The application of the classifier developed in this work is intended at improving the efficiency of LHC detectors and data flow systems for data acquisition. The application of the methods developed in this paper, using open source and big data tools to implement a data pipeline, is to improve the resource utilization and scientist productivity when working on data analysis and machine learning model development.

Machine learning and deep learning on large
amounts of data are standard tools for particle physics, and their use is expected to increase in the HEP community in the coming year, both for data acquisition and data analysis workflows, given for example the challenges of High Luminosity LHC project [18]. Improvements in productivity and reduction of cost for development and deployment of machine learning pipelines on HEP data are of high interest. The authors believe that using tools and methods from the "Big Data" community at large brings important advantages in this area, in particular in terms of usability and development, with the introduction of standard APIs supported by a large community, and ease of deployment and integration with modern computing systems, notably cloud systems. We expect that many of the tools and methods used here will evolve considerably in the near future, following the directions taken by the relevant communities. This will most likely make the details of the current implementation obsolete, however we can also expect that the evolution will bring important improvements and will profit greatly from the experience of a large user and developer base.

Reference notebooks with code developed for this work and data samples are available at: https://github.com/cerndb/SparkDLTrigger

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