Reproducible Benchmarks for Data Analysis

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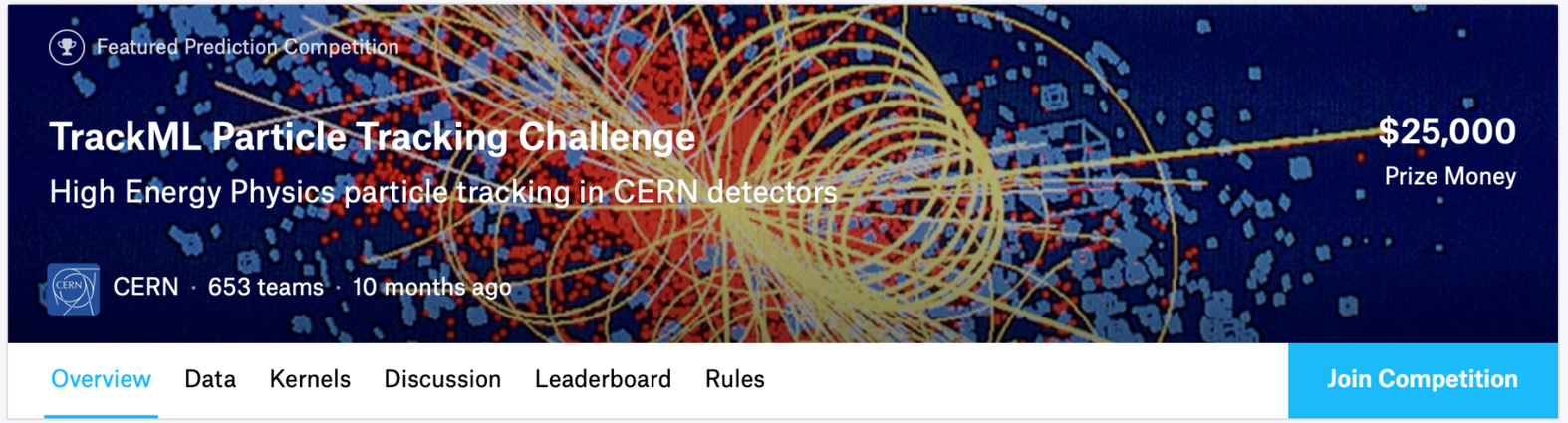
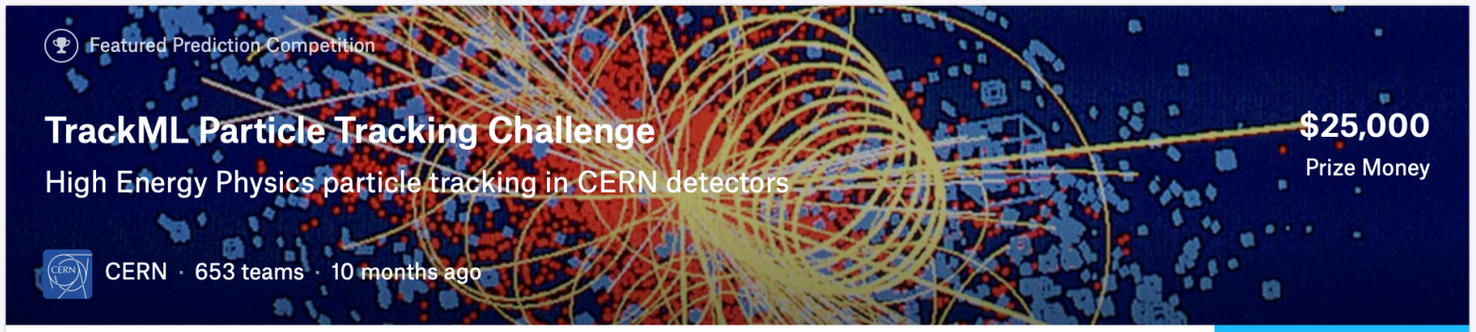
New York University

Analysis Systems Topical Workshop
19-20 June 2019

Benchmarks & Challenges:





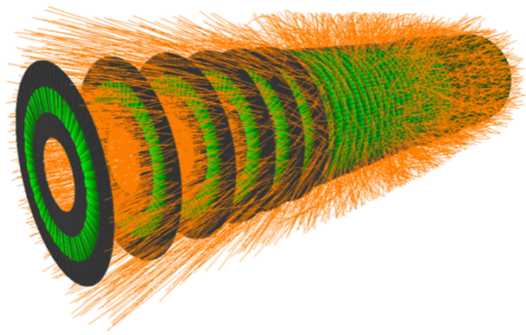
Public Leaderboard | Private Leaderboard

This leaderboard is calculated with approximately 29% of the test data.
The final results will be based on the other 71%, so the final standings may be different.

Raw Data | Refresh

In the money | Gold | Silver | Bronze

#	Team Name	Kernel	Team Members	Score	Entries	Last
1	**Top Quarks**			0.92219	10	10mo
2	**outrunner**			0.90400	9	10mo
3	**Sergey Gorbunov**			0.89416	6	10mo
4	**demelian**			0.87197	35	10mo
5	**Edwin Steiner**			0.86464	5	10mo
6	**Komaki**			0.83196	22	10mo



at our universe is made of, scientists
colliding protons, essentially
ni big bangs, and meticulously
se collisions with intricate silicon

rating the collisions and
s already a massive scientific
ent, analyzing the enormous
ata produced from the experiments
n overwhelming challenge.

ave already reached hundreds of
llisions per second, meaning physicists must sift through tens of petabytes of data per year.
solution of detectors improve, ever better software is needed for real-time pre-processing
f the most promising events, producing even more data.

ss this problem, a team of Machine Learning experts and physics scientists working at

Top-tagging benchmark example

Top Tagging Reference Dataset

File Edit View Tools Help

Contact

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Michael Russel (russell@thphys.uni-heidelberg.de)
Tilman Plehn (plehn@uni-heidelberg.de)

Idea

Provide a simple set of training/testing MC simulation for the evaluation of top tagging architectures.

This is work in progress. Please let us know about any issues you encounter and share the performance you achieve on the test sample.

Samples

v0 (2018_03_27): https://desycloud.desy.de/index.php/s/llbX3zpLhazgPJ6

1.2M training events, 400k validation events, 400k test events. Use “train” for training, “val” for validation during the training and “test” for final testing and reporting results.

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)[1], T. Plehn (ed)[2], A. Butter[2], K. Cranmer[3], D. Debnath[4], M. Fairbairn[5], W. Fedorko[6], C. Gay[6], L. Gouskos[7], P. T. Komiske[8], S. Leiss[1], A. Lister[6], S. Macaluso[3,4], E. M. Metodiev[8], L. Moore[9], B. Nachman,[10,11], K. Nordström[12,13], J. Pearkes[6], H. Qu[7], Y. Rath[14], M. Rieger[14], D. Shih[4], J. M. Thompson[2], and S. Varma[5]

	AUC	Acc	$1/\epsilon_B$ ($\epsilon_S = 0.3$) single	mean	median	#Param
CNN [16]	0.981	0.930	914±14	995±15	975±18	610k
ResNeXt [30]	0.984	0.936	1122±47	1270±28	1286±31	1.46M
TopoDNN [18]	0.972	0.916	295±5	382± 5	378 ± 8	59k
Multi-body N-subjettiness 6 [24]	0.979	0.922	792±18	798±12	808±13	57k
Multi-body N-subjettiness 8 [24]	0.981	0.929	867±15	918±20	926±18	58k
TreeNiN [43]	0.982	0.933	1025±11	1202±23	1188±24	34k
P-CNN	0.980	0.930	732±24	845±13	834±14	348k
ParticleNet [47]	0.985	0.938	1298±46	1412±45	1393±41	498k
LBN [19]	0.981	0.931	836±17	859±67	966±20	705k
LoLa [22]	0.980	0.929	722±17	768±11	765±11	127k
Energy Flow Polynomials [21]	0.980	0.932	384			1k
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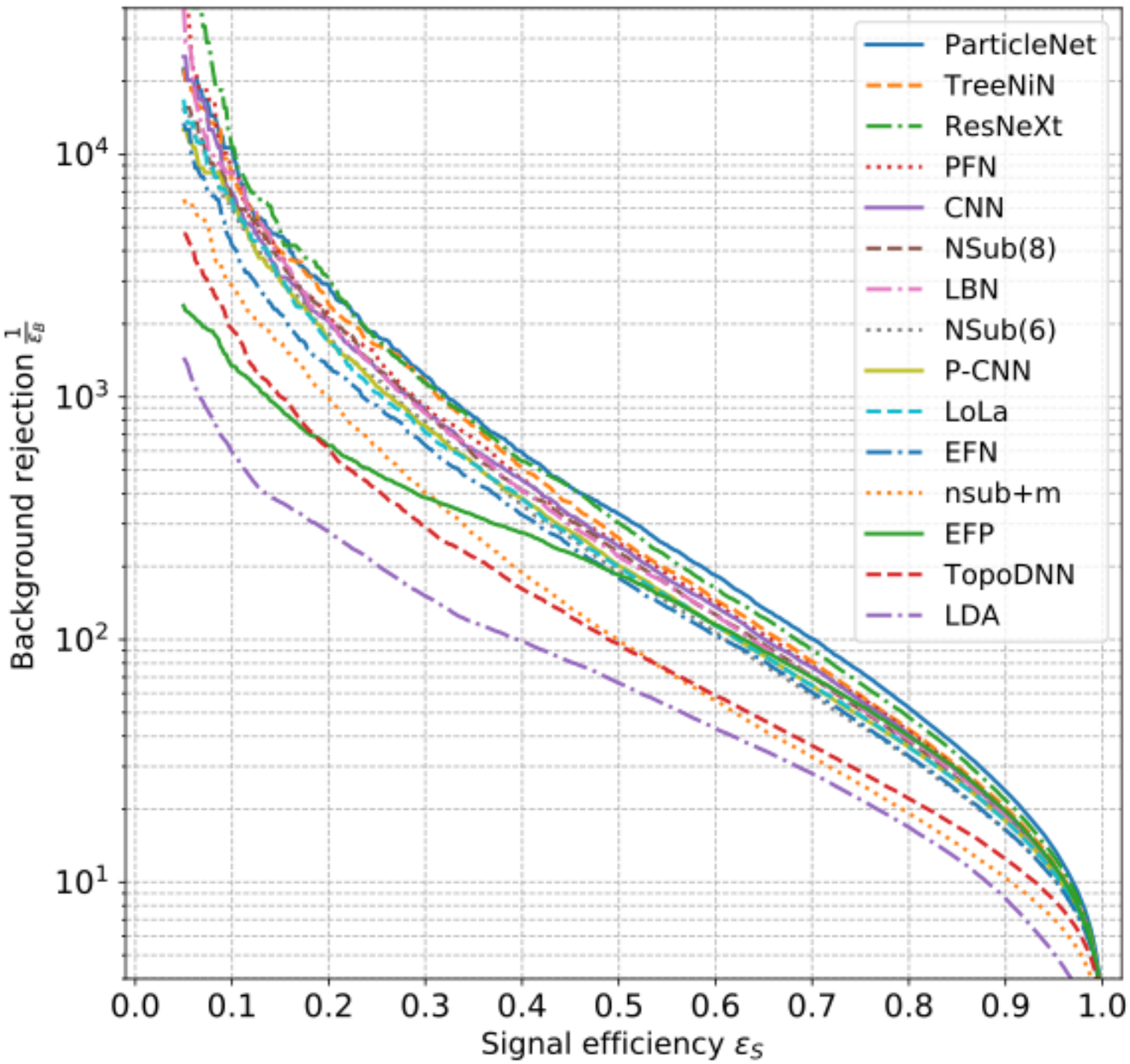
GoaT	0.985	0.939	1368±140		1549±208	35k

Algorithms ROC curves



Reproducible Open Benchmarks for Data Analysis Platform (ROB)

Exploratory work for enabling such community benchmarks.

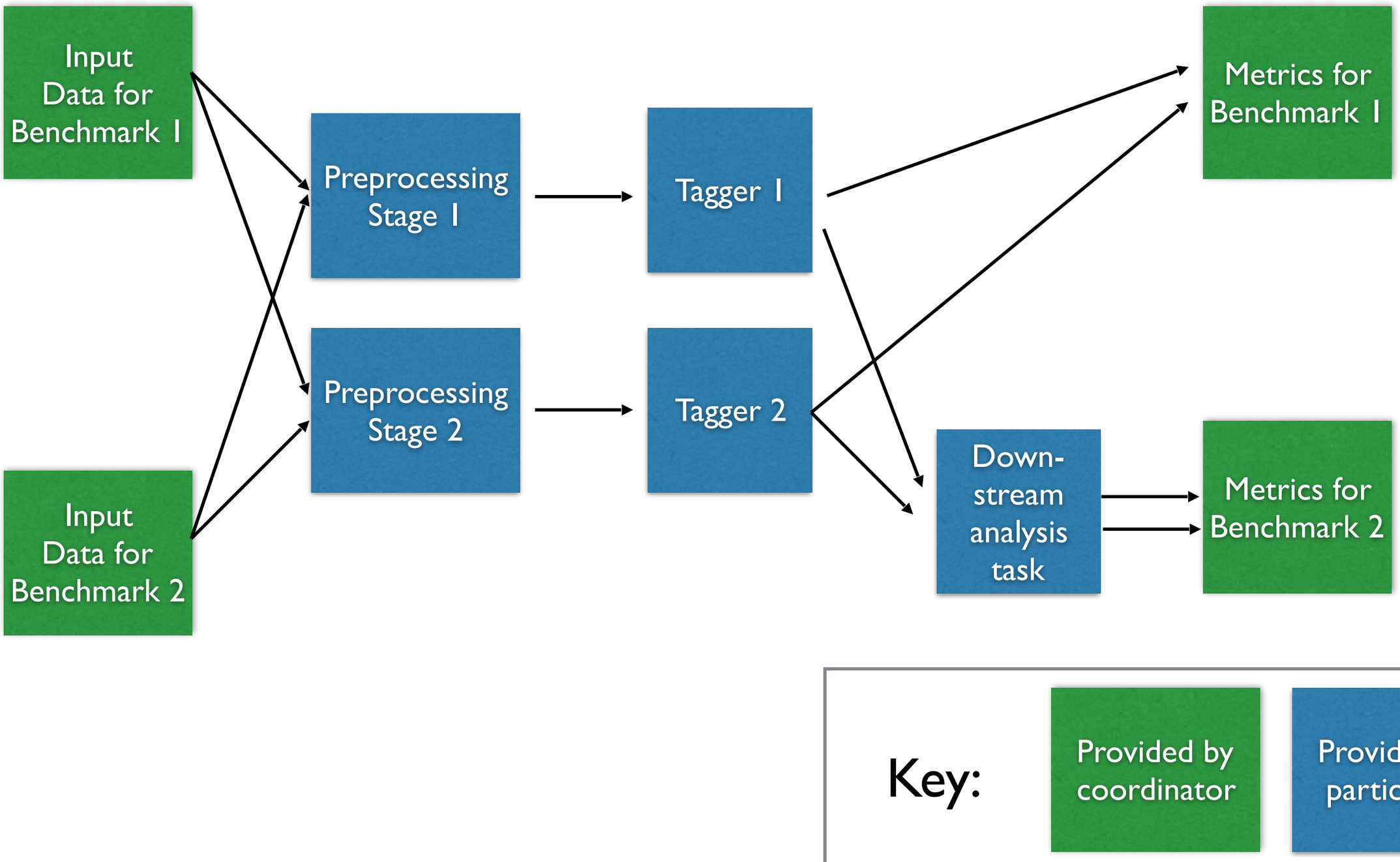
Outline of ROB usage

1. Benchmark workflow defined by **coordinator** along with input data.
2. Users provide docker containers that satisfy workflow stages
3. Back-end processes entries, evaluates metrics (powered by REANA).
4. Front-end displays results.

Benchmark Workflow Example:

1. Common input data set used for benchmarks (defined by benchmark coordinator).
2. Preprocessing stage (code provided by user).
3. Prediction stage (code provided by user).
4. Evaluate metrics, update tables & plots (defined by benchmark coordinator).

Idea: Compossible workflows support contributions used for multiple benchmarks



Reproducible Benchmark Client

About

The **Reproducible Benchmark Client** is the current user interface for the *Reproducible Open Benchmarks for Data Analysis Platform (ROB)*. The client contains a command line interface that can be used to create users and benchmarks for the Reproducible Benchmark Engine, and to execute benchmarks and show benchmark results.

Setup

The benchmark client uses the Reproducible Benchmark Engine and the Workflow Templates for Reproducible for Data Analysis Benchmarks repository.

```
# Create a new directory for the project
mkdir ~/projects/open-benchmarks
cd ~/projects/open-benchmarks

# This example uses virtualenv to install all python modules in one environment
virtualenv ~/.venv/rob
source ~/.venv/rob/bin/activate

# Clone the required benchmark repositories and install the python modules they implement
git clone https://github.com/scailfin/benchmark-templates.git
pip install -e benchmark-templates/

git clone https://github.com/scailfin/benchmark-engine.git
pip install -e benchmark-engine/

git clone https://github.com/scailfin/benchmark-client.git
pip install -e benchmark-client/
```

Reproducible Benchmarks Engine

About

The **Reproducible Benchmarks Engine** is a component of the *Reproducible Open Benchmarks for Data Analysis Platform (ROB)*. The benchmark engine is responsible for maintaining benchmark templates and benchmark runs. The results for all benchmark runs are integrated by the engine to compile a leaderboard for each benchmark.

Workflow Templates

Workflow Templates are parameterized workflow specifications for the *Reproducible Open Benchmarks for Data Analysis Platform (ROB)*. Workflow templates are motivated by the goal to allow users to run pre-defined data analytics workflows while providing their own input data, parameters, as well as their own code modules. Workflow templates are inspired by, but ot limited to, workflow specifications for the Reproducible Research Data Analysis Platform (REANA).

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Tree Network in Network (TreeNiN) for Jet Physics

Sebastian Macaluso and Kyle Cranmer

Note that this is an early development version.

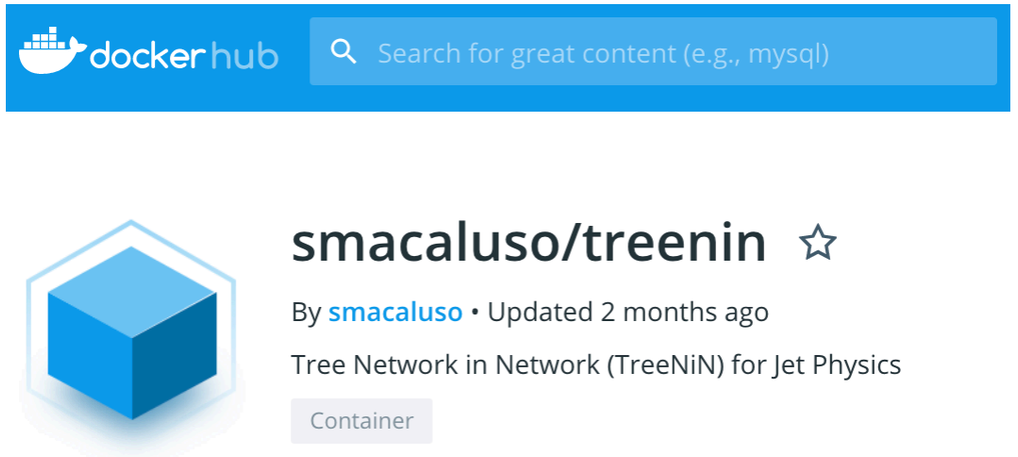
Introduction

In this method, a tree neural network (TreeNN) is trained on jet trees. The TreeNN provides a *jet embedding*, which maps a set of 4-momenta into a vector of fixed size and can be trained together with a successive network used for classification or regression (see Louppe et al. 2017, "QCD-Aware Recursive Neural Networks for Jet Physics" for more details). Jet constituents are reclustered to form binary trees, and the topology is determined by the clustering algorithm (e.g. kt, anti-kt or Cambridge/Aachen). We chose the kt clustering algorithm, and 7 features for the nodes: |p|, eta, phi, E, E/Ejet, pT and theta. We scaled each feature with the scikit-learn preprocessing method RobustScaler (this scaling is robust to outliers).

Implementing the TreeNiN on the *Top Tagging Reference Dataset*

This repository includes all the code needed to implement the TreeNiN on the *Top Tagging Reference Dataset*. A description and link to the Top Tagging Reference Dataset (provided by Gregor Kasieczka, Michael Russel and Tilman Plehn) can be found here with the link to download it here. This dataset contains about 1.2M training events, 400k validation events, 400k test events with equal numbers of top quark and qcd jets. Only 4 momentum vectors of the jet constituents.

TreeNiN implementation as a docker image



Relevant Structure:

- `Dockerfile`
- `scripts` : dir with the scripts to install specific dependencies when building the image.
- `code` : working directory for the docker container.
  - `top_reference_dataset`
    - `outProb` : dir with the output probabilities.
    - `in_data` : dir where the initial test dataset will be downloaded.
  - `dataWorkflow.py` : script with the data workflow.
  - `MLWorkflow.py` : script with the machine learning workflow.
  - `saveProb.py` : script that saves the output probabilities in `outProb/[filename.pkl]` .
  - `recnn` : dir with the code for the TreeNiN.
  - `data` : dir with the jet trees (before and after preprocessing).

Thanks for your attention!