Optimization of energy measurements at muon colliders

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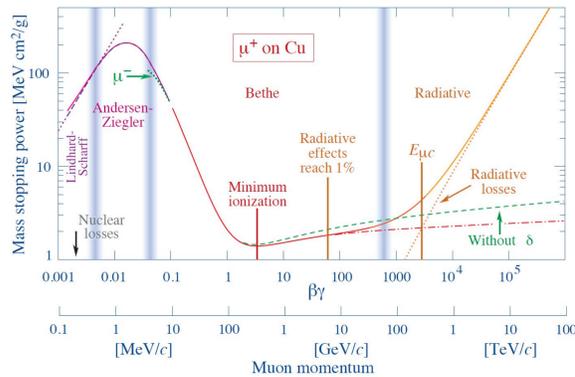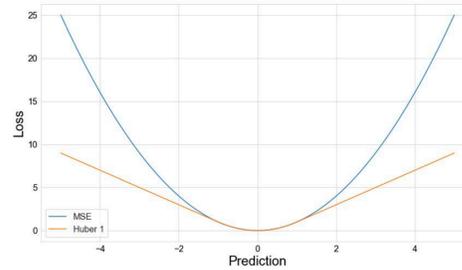
Physics Motivation

Muons are important as a **clean probe** for new physics searches & measurements. The **energy resolution** will be crucial for the search of new physics phenomena at **future high-energy colliders**. Energy estimates are determined by the **curvature** of the muon trajectory in **trackers**, which however yields a **poor resolution at high energies**.

At high energy, the **radiative energy loss** of muons **rises** [1]. Recording low-energy photons in a **granular calorimeter** can provide a complementary measurement of the muon energy.
→ **Idea: regress muon energy from energy deposits in calorimeter using modern ML techniques!**

Simulated Data

The **detector** consists of a homogeneous **lead tungstate cuboid calorimeter** simulated with **Geant4** [2]:

- Calorimeter embedded in a uniform ATLAS like 2-Tesla magnetic field
- Number of cells: 50x32x32 (z,x,y) = 51.200 cells
- Dim.: 2032x120x120 mm

The muons are unpolarized with **uniform energy** in z-direction between **50 GeV** and **8 TeV**. Around 850k muons are generated for training and validation and 430k muons are generated for testing.

Machine Learning Model

Input for Machine Learning

- **Raw-hit data** of the calorimeter cells that can be exploited with **3D Convolutional Neural Networks**
- **High-level features** built with domain knowledge by using spatial information of the energy deposits

CNN Model

- **Convolutional head**: series of 3D convolutional layers (blocks) that exploits the 3D grid of energy deposits
- **Network body**: set of fully-connected layers with single neuron output
- **Pre-computed high-level features** are passed directly to the body
- The 3D CNN architecture aims to **learn small corrections** to the reconstructed energy by **residual convolutional layers**

Loss Function

- Huberised version of the mean fractional squared error (MFSE): prevents outliers from dominating the loss
- Inspired by the physical behaviour of calorimeter showers

Training and Regression

Ensemble Training

- Train **ensemble of 5 models** with batchsize 256 with **LUMIN** [3]
- **Adam optimizer** with 1-cycle schedule with cosine annealing for 20 epochs
- **Training time**: 23×5 h on a Nvidia V100S
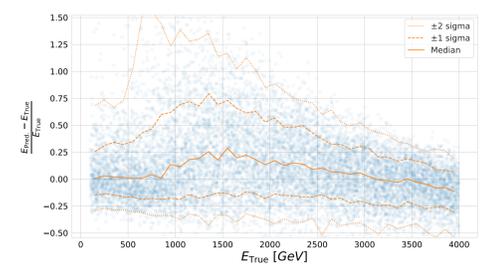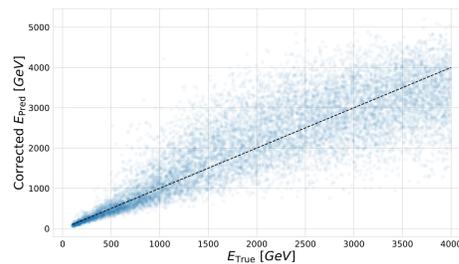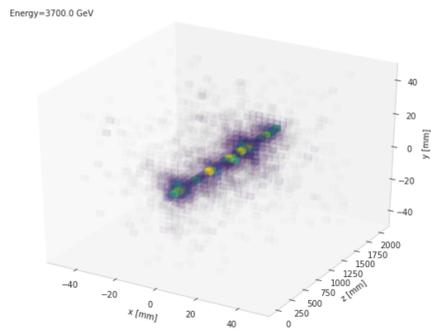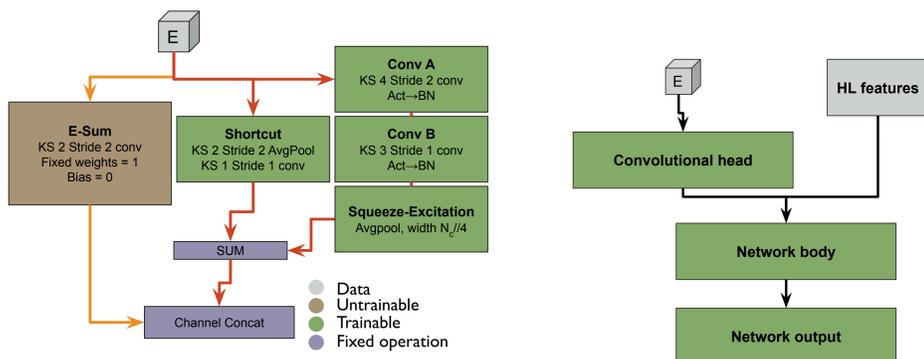

Regression Results

- **Regression predictions** scale quite **linear** with true energy
- Trend to slightly **over-predict medium energy** and **under-predict high energy** → **correction of bias** via linear fit to predictions in bins of true energy

Results

Performance Metric

- **Resolution**: RMSE quadrature of sum of variance and bias
- **Tracker** measurement **resolution** assumed to be of **20% @ 1 TeV**
- **Calorimeter** and **tracker** are complementary → best resolution is a **weighted average of both**
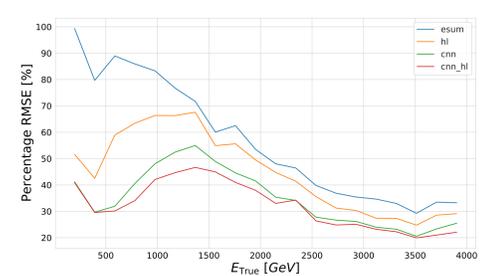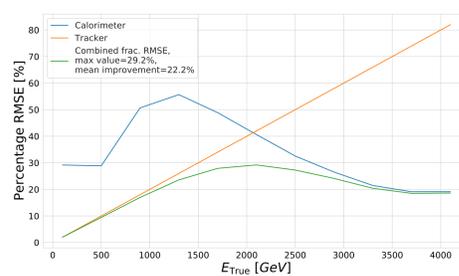
Results

- Radiative losses in calorimeters can provide muon-energy measurements in collider experiments
- Calorimetric measurements improve with energy and are complementary to existing tracker measurements → good resolution across the full muon-energy spectrum
- Performance improves with feature engineering and ML

References

[1] Particle Data Group Collaboration, Review of Particle Physics, Phys. Rev. D 98 (Aug, 2018) 030001
[2] GEANT4 Collaboration, GEANT4–a simulation toolkit, Nucl. Instrum. Meth. A 506 (2003)250–303.
[3] G. Strong, LUMIN, doi.org/10.5281/zenodo.2601857

Check out the paper!