Towards the optimization of a Muon Collider Calorimeter

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Muon Collider Optimization Workflow

- Development of a pipeline to propose an optimal configuration in terms of signal-to-background discrimination and instrumentation cost



End objective: design optimization study approached with AD techniques

- Based on **3** main lacksquarecore methods
- Provide information encoded in a **utility** function
- Minimized using automatic differentiation techniques

Muon Collider CRILIN: reference design

- Reference design chosen for our studies is CRILIN for the Electromagnetic Calorimeter (ECal)
- Array of 1x1x4.5cm³ PbF₂ voxels, arranged in a dodecahedron
- 5 layers per wedge
- Modular design, easy to modify and rearrange





Muon Collider BIB characterization

- Nozzle shields most radiation from endcaps, but area around interaction point remains unshielded
- BIB simulation at 1.5TeV center-ofmass energy. Energy deposits in ECal
- Still a considerable amount of energy deposited inside
- Non-uniform distribution alongside zaxis suggests that homogeneous voxels might be suboptimal







Muon Collider Fitting BIB distribution

- Starting from 1.5TeV BIB simulation
- Cylindrical symmetry lets us neglect transverse direction: focus on a single wedge and model component along beam axis.
- 5-parameter fit to a gaussian superimposed to a 2nd order polynomial







Muon Collider BIB simulation and checks



• Evaluate parametrization in a grid. Since we have neglected transverse direction, parametrizations will be accurate up to a normalization constant

 Constraint: parametrized deposition match layer-by-layer the Geant4 deposition

 Normalization constant can be explained by the transverse bin multiplicity (~80) times a bin width geometric factor (10mm)

Muon Collider Object Condensation for reconstruction

- To reconstruct signals in ECal we test **DeepJetCore**, a package developed for the **reconstruction of jets** in the High-Granularity Calorimeter for the CMS upgrade for the High-Luminosity LHC runs
- Core is a Graph Neural Network that clusters the data, whose dimensionality has been reduced by filter layers.
- Clustering performed through the identification of one condensation point for each object, and the subsequent minimization of a loss function

Muon Collider OC: Dataset Generation

- uniformly in [10,175]GeV
- in the transverse angle ϕ
- **BIB** parametrization superimposed
- Geometric **cuts**:
 - 2σ of total signal deposition in ϕ
 - 40cm band along z-axis

• The dataset chosen to train the algorithm is 10000 photon events, distributed

• Photons are generated with Geant4, with rapidity 0 and uniformly distributed

Muon Collider OC: Dataset Generation



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Muon Collider OC: Clustering

- Trained for 150 epochs with learning_rate=1E-3
- Jumps in loss due to too big learning step
 - Next training down 2 orders of magnitude
- Performance evaluated on 1k monochromatic photons for 8 energy points
- Decent signal (ID=0) vs background (ID=1) separation



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10

8

loss



Muon Collider OC: Energy reconstruction

- Primary energy inferred by summing the energy deposits for signal-labeled hits
- **Degrades at lower energies**, where signal and BIB deposits become comparable
- Calculate standard deviation and RMS error around each peak to evaluate resolution





Muon Collider OC: Energy reconstruction

• Fit to obtain resolution function parameters:

$$\frac{\sigma}{E} = \sqrt{\left(\frac{a}{\sqrt{E}}\right)^2 + b^2}$$

 $a = 0.14, \quad b = 0.025$

 Comparable performance with PandoraPFA and BIB preprocessing

 $a = 0.14, \quad b = 0.006$



Courtesy of L. Sestini, Muon Collider Collaboration - INFN Padova

Muon Collider Towards setting up a pipeline

- Idea: represent Crilin detector as a 3D grid of voxels, and optimizing the spacing $(\Delta x, \Delta y, \Delta z)$ between them.
- Started to work on a toy model:
 - Defining the geometry: simple 3 with custom # voxels
 - Evaluating a function on the grid: 3D gaussian with $\sigma_x \neq \sigma_y \neq \sigma_z + random$ noise





D	grid	
D	grid	

sigma_	_X	=	100.
sigma_	_У	=	120.
sigma_	_Z	=	100.

Muon Collider Towards setting up a pipeline

- Reconstruction: Use maximumlikelihood estimators to infer the gaussian parameters $\hat{\mu}, \hat{\sigma}$
- Evaluating loss: MSE for gaussian parameters + regularizer to prevent spacing to collapse towards degeneracy

$$\sum_{i=x,y,z} (\hat{\mu}_i - \mu_i)^2 + (\hat{\sigma}_i - \sigma_i)^2 + \frac{1}{\Delta x_i^2}$$

Minimization of loss and identification of ideal parameters



Final spacing: [0.47563136 0.5433373 0.44885612]



Summary

- Still work to do to come up with a design
- Differentiable blocks are however taking shape
- Tests on OC promising. Need to play with parameters, and generalize to N photons.
- Toy pipeline model to be upgraded with more realistic loss and signal generation
- If it proves successful, we are able to implement the full ECal geometry

Summary

- Still work to do to come up with a design
- Differentiable blocks are however taking shape
- Tests on OC promising. Need to play with parameters, and generalize to N photons.
- Toy pipeline model to be upgraded with more realistic loss and signal generation
- If it proves successful, we are able to implement the full ECal geometry Thank you!



Backup

DJC Architecture



Muon Collider baseline



