Evolutionary Convolutional Neural Network for High Energy Physics Detector Simulation

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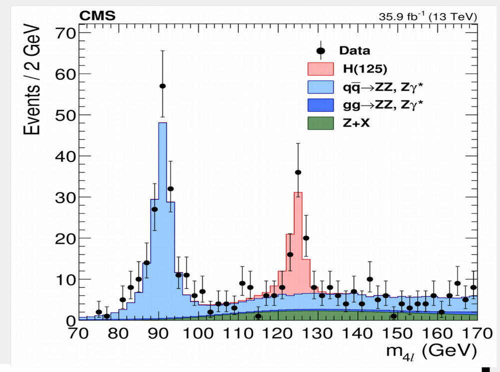
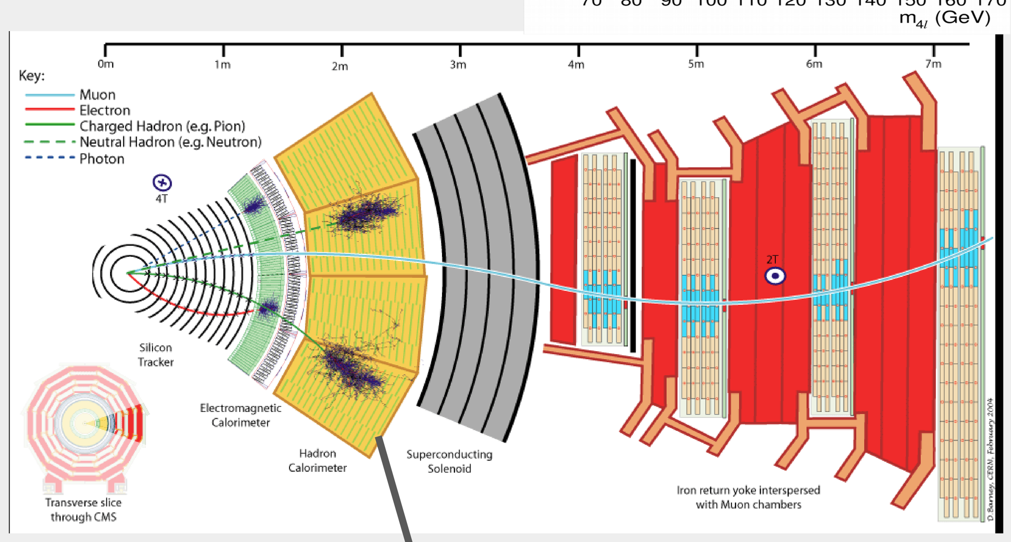
Motivation

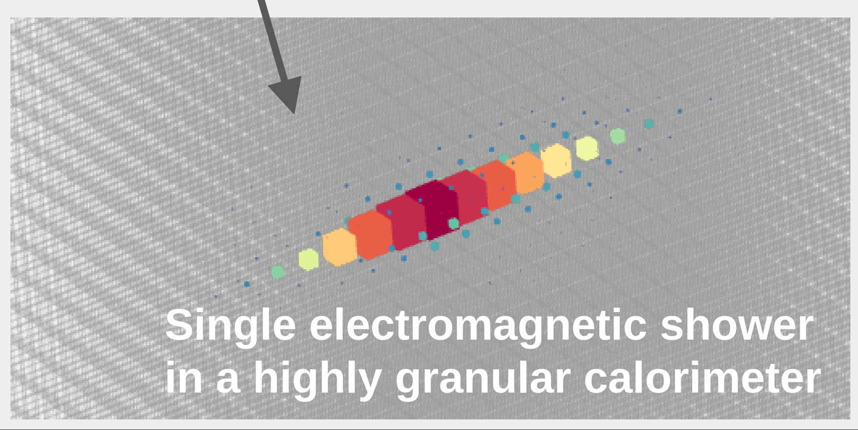
High Energy Physics relies on Monte Carlo (MC) for different aspects of data analysis. MC simulation implement **complex computations** that, today, result in **~50% of CERN Computing Grid resources**. Several alternative approaches are being investigated **trading some accuracy for speed**. Deep Learning approaches resulted in about x10^{-3} speed-up while retaining reasonable agreement (within 10%) with respect to MC [1].





CERN computing Grid :
- **170 centres** in 42 countries
- 1 exabyte of storage
- 65k cores @CERN (20% WLCG)

High Energy Physics Simulation
- Monte Carlo
  - Precise step by step modelling
- Fast Simulation
  - Classical Approach
    - Parametric, Look up tables ,…
    - 10x - 100x faster
    - ~10% accurate wrt MC
  - Deep Learning
    - Generative Models
      - x10^{-3} faster
    - ~10% accurate wrt MC



Single electromagnetic shower in a highly granular calorimeter

Main Idea: We have developed a 3-dimensional Convolutional Generative Adversarial Network (**3DGAN**) to simulate highly granular calorimeter response. **Agreement to MC simulation is remarkable**[1]. We want to **generalize 3DGAN** to different detector use-cases and use **a Genetic Algorithm** to perform **training** and **architecture optimization**.

- Create a **generic** tool that can be used to simulate **different** detectors
- Use **Evolutionary** approach for **weight and network optimization in one single step**
- Investigate structural features and patterns in Convolutional Neural Network that can be exploited for more compact coding into chromosome and efficient evolution

3DGAN — Simulation of a specific detector output interpreted as a 3D image (25x25x25 pixels).

- Convolutional Neural Networks
- Auxiliary Regression tasks and custom loss function
- 73K parameter for Discriminator, 3.5M for Generator

Generalization — Training + Optimization using Evolution ~~Gradient Descent~~

- Weight and topology optimization at same time
- Global instead of local minima
- High parallelizable
- Multi objective optimization

Timeline

Q2 2019 — Initial Prototype (Q2 19):
- Focus on **discriminator network**
- Reduced data complexity (**2-dimensional**)
- Genetic Algorithm Implementation
  - Weights as chromosome
  - Update weights by evolution

Q3 2019 — Weight and Topology Optimization (Q3 19):
- **Computing resource evaluation** and optimization
- Add more flexibility in defining network
- First comparison to standard approach

Q4 2019 — 3-Dimensional extension (Q4 19)
- Investigate performance for **3D approach**

Q1 2020 — Adversarial training and final evaluation (Q1 20):
- Incorporate **Adversarial Training** approach
- Determine merits and shortcomings

Implementation

Chromosome:
- Convolutional Layer:
  - Weights for each filter
  - Activation
- Dense Layer:
  - Weights
  - Activation

Evolutionary Strategy:
- 1 + λ strategy
  - One parent with λ offsprings
- Point Mutation
- Tournament selection

Distributed Training:
- Create workers = number of offsprings
- Evaluate each offspring in parallel

Initialization:
- Make n random individuals
- Convert genotype to phenotype
- Evaluate on batch
- Select Fittest

Per Epoch:
- Mutate parent to get offsprings
- Evaluate on next batch
- Select Fittest

Repeat for n epochs

Challenges:

- **Number of trainable parameters in millions (for combined 3DGAN Discriminator + Generator model)**
  - Deep GA [2] has been able to train successfully over four million parameters for reinforcement learning tasks taking ~ 4 hours on a desktop or ~ 1 hour on 720 cores
- **Can evolutionary approach efficiently use large data ?** size up to 40 GB in our case.
  - LEEA [3] implements genetic algorithm evaluated over batches of data
- **Adversarial Training of two networks competing with each other**

References:

[1] Gul rukh Khattak, Sofia Vallecorsa and federico Carminati. "THREE DIMENSIONAL ENERGY PARAMETRIZED GENERATIVE ADVERSARIAL NETWORKS FOR ELECTROMAGNETIC SHOWER SIMULATION", ICIP 2018.
[2] Felipe Petroski Such. et. al. "Deep Neuroevolution: Genetic Algorithms Are a Competitive Alternative for Training Deep Neural Networks for Reinforcement Learning". 2018. arXiv:1712.06567
[3] Gregory Morse, Kenneth O. Stanley. "Simple Evolutionary Optimization Can Rival Stochastic Gradient Descent in Neural Networks". GECCO 2016