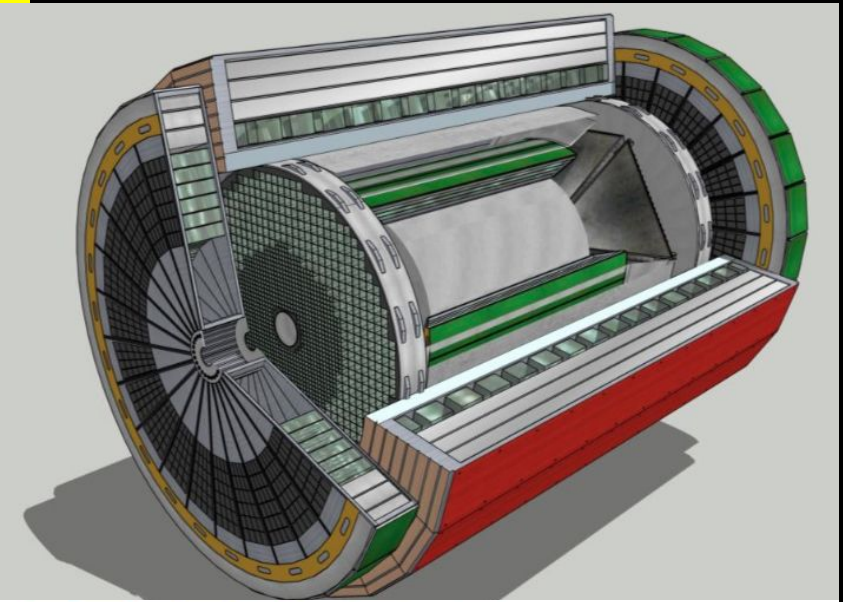
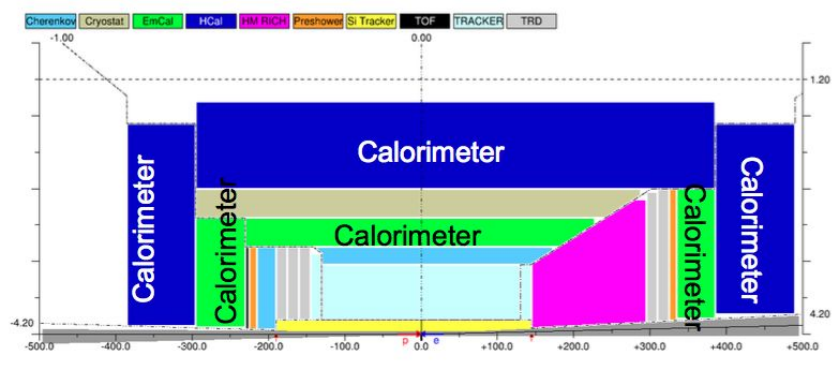
Artificial Intelligence for the EIC Calorimeter Design





"AI techniques that can optimize the design of complex, large-scale experiments have the potential to revolutionize the way experimental nuclear and particle physics is currently done"

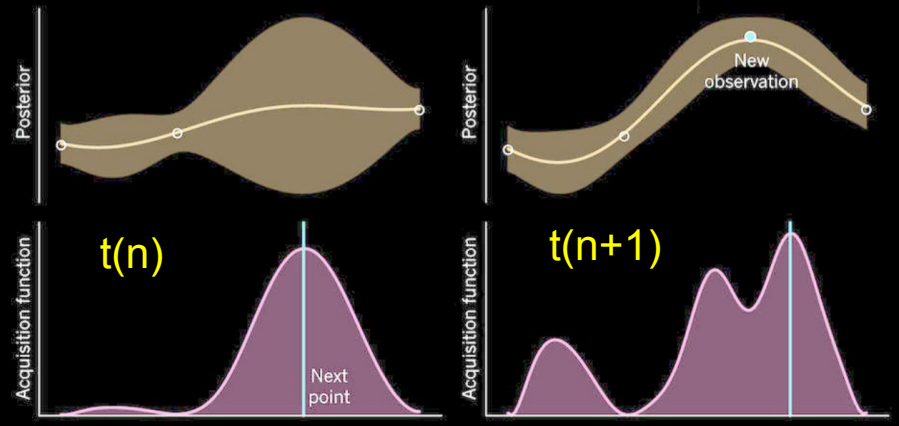
Report on the DOE Town Halls on Artificial Intelligence (AI)
Stevens, Rick, et al. *AI for Science.* No. ANL-20/17. Argonne National Lab.(ANL), Argonne, IL (United States), 2020.

Cristiano Fanelli

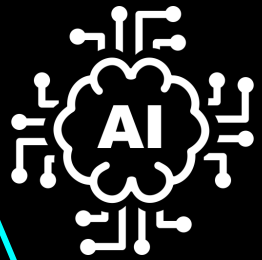
Detector Design with AI

- Designing detectors with the help of AI is a “new” area of research.
- Typically full detector designs have been studied once the subsystem prototypes are ready. In the subsystem design phase, constraints from the full detector or outer layers are taken into consideration.
- Actually many parameters (mechanics, geometry, optics) characterize the design of each sub-detector, therefore the full detector design is a large combinatorial problem. A well known phenomenon observed in optimization problems with high-dimensional spaces is the so-called “curse of dimensionality”, introduced for the first time by Bellman when considering problems in dynamic programming.
- Accurate detector simulations (e.g., with Geant4) can be computationally expensive.
- In addition to that, multiple objective functions often need to be considered at the same time in the design of each sub-detector (e.g., resolution, efficiency, cost, distinguishing power, etc).
- In this context, SOTA solutions to solve complex optimization problems in an efficient way.

Typical Workflow for Detector Optimization



A.I.
Model based on observations, decision making



Design parameters

Injection of Physics Events

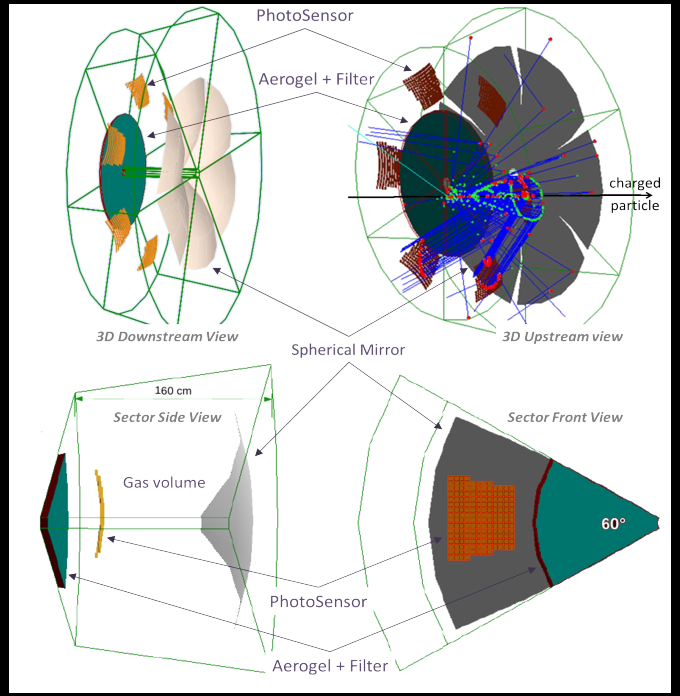
Detector Simulation

Analysis of high-level reconstruction of events

Experience of Bayesian optimization for dual-RICH

E. Cisbani, A. Del Dotto, CF*, M. Williams et al 2020 JINST 15 P05009

- First EIC paper using AI: developed an automated, highly-parallelized, self-consistent framework based on BO+ML to optimize the Geant simulation of the dual-RICH.

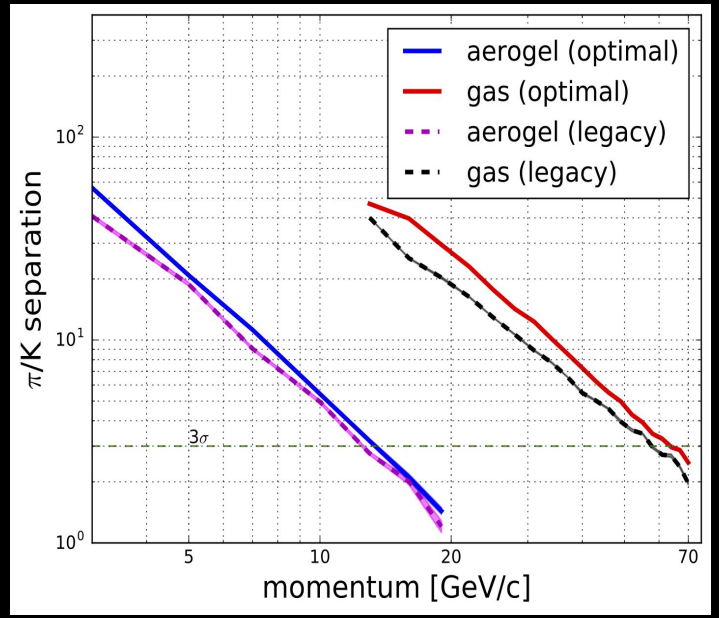


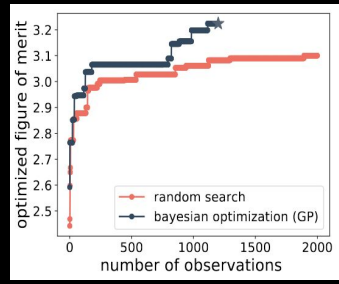
Used as a figure of merit the distinguishing power between π/K

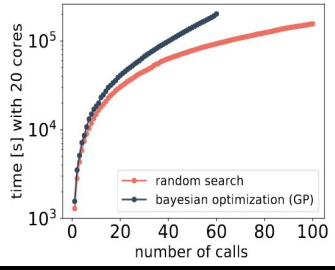
Optimized O(10) parameters (geometry + optics)

The posterior model provides insight on parameter correlations during the design phase.

Random or grid search simply hopeless.

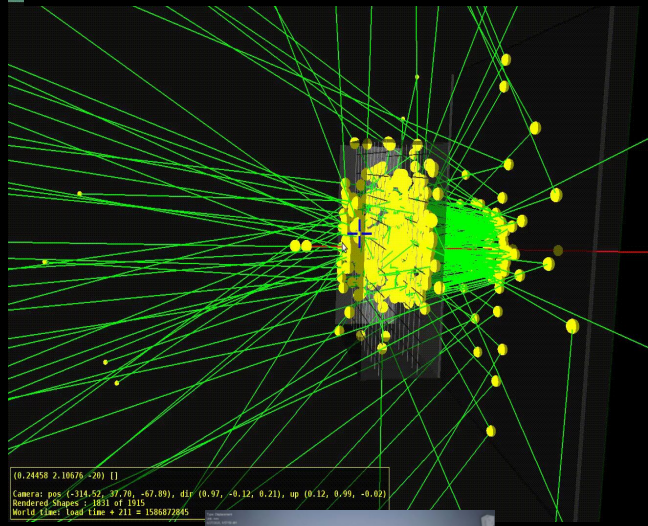






Example of Multi-objective optimization for novel aerogel material

The team: V. Berdnikov, J. Crafts, E. Cisbani, CF, T. Horn, R. Trotta

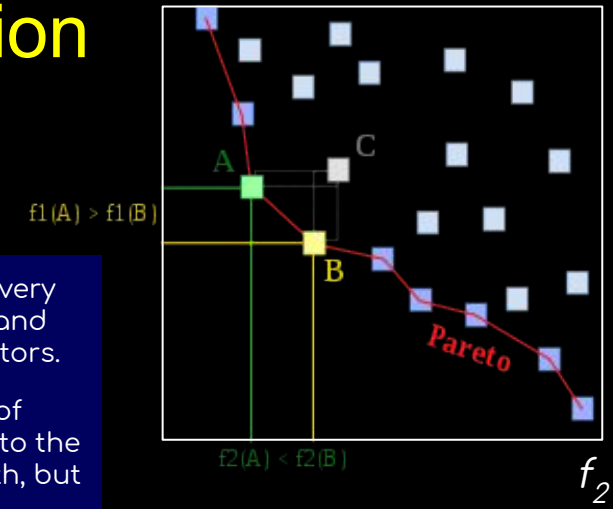


Aerogels with low refractive indices are very fragile - tiles break during production and handling, and their installation in detectors.

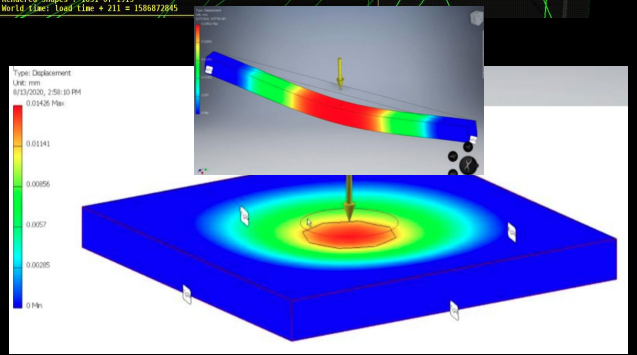
To improve the mechanical strength of aerogels, Scintilex is introducing fibers into the aerogel that increase mechanical strength, but do not affect the optical properties.

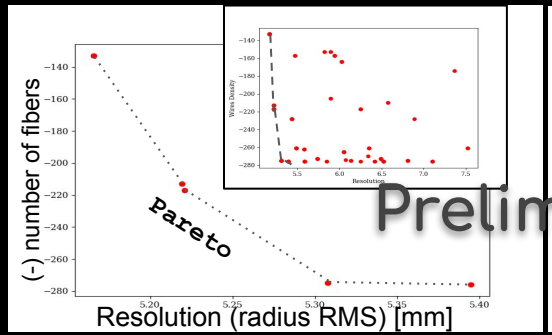
We are designing the aerogel+fibers optimizing mechanical stability and resolution.

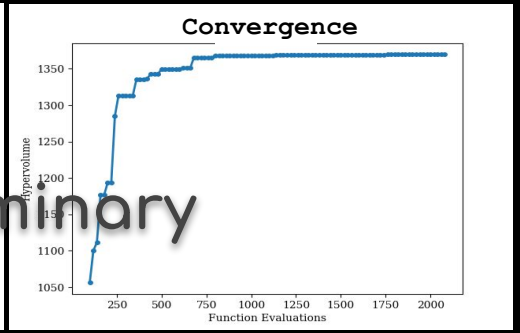
Paper in preparation.



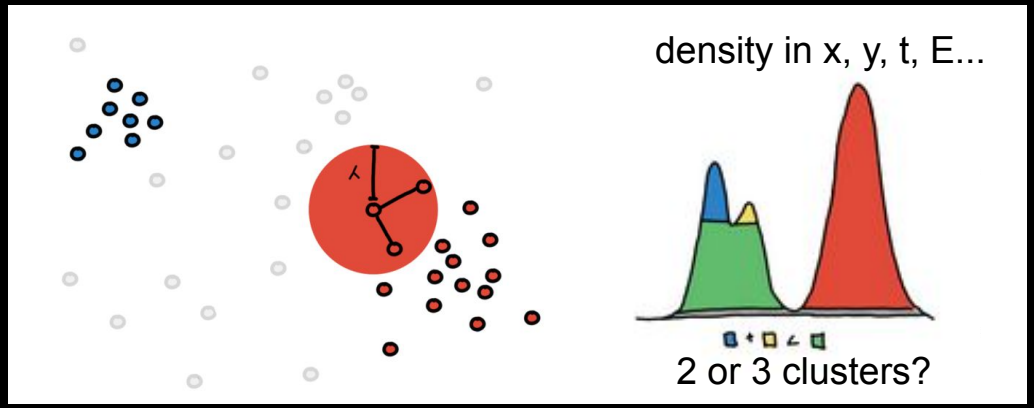
Point *C* is not on the Pareto frontier because it is dominated by both point *A* and point *B*.





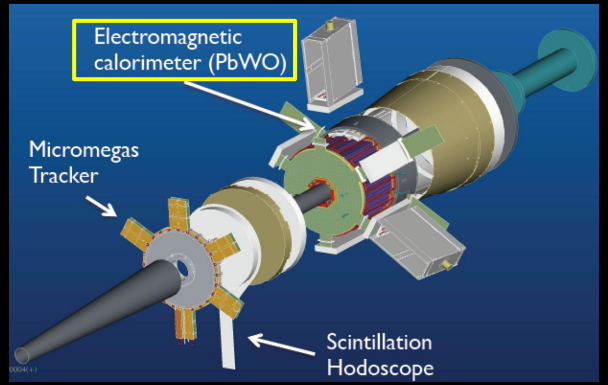


Example: Clustering and Reconstruction with ML



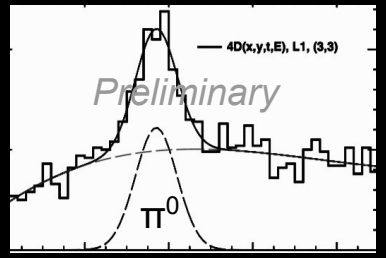
- Advantages: unsupervised clustering is not cut-based. Takes advantage of correlation among features at the hit level.
- Same algorithm can be used for different detectors. Robust against change in experimental conditions.
- First near real-time application of AI in Streaming Readout for the EM Calo of the Forward Tagger at CLAS12.

- Hierarchical clustering is an unsupervised ML technique to provide a hierarchy of clusters.
- It is based on estimate of density of points in a multi-dimensional space encoding detector information at the hit level (e.g., position, time, energy...).
- Hierarchy is defined through measurements of persistence and mutual reachability of points.



The CLAS12 Forward Tagger, JLab

Collaboration of ~20 people at JLab. I am responsible for the AI implementation.

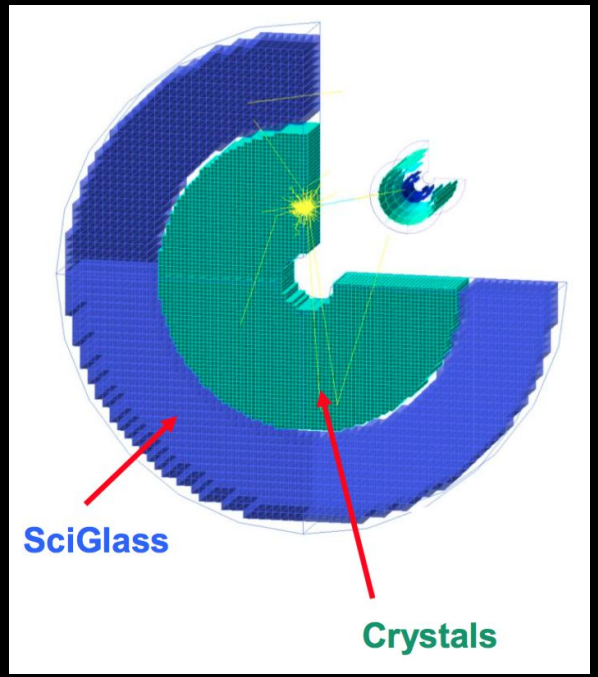


M (γγ)

EIC EMCal Electron Endcap

The team: V. Berdnikov, M. Bondi', CF, Y. Furletova, T. Horn, I. Larin, D. Romanov, R. Trotta

- Similarly to the aerogel project, we can use Multi-objective Optimization to optimize glass/crystal material selection in shared rapidity regions including mechanical constraints.
- Like in the Hall B project, we can explore implementation of AI for clustering/reconstruction.



EIC Electron Endcap require an inner part (crystal) with high resolution and an outer part (glass) with less stringent requirements

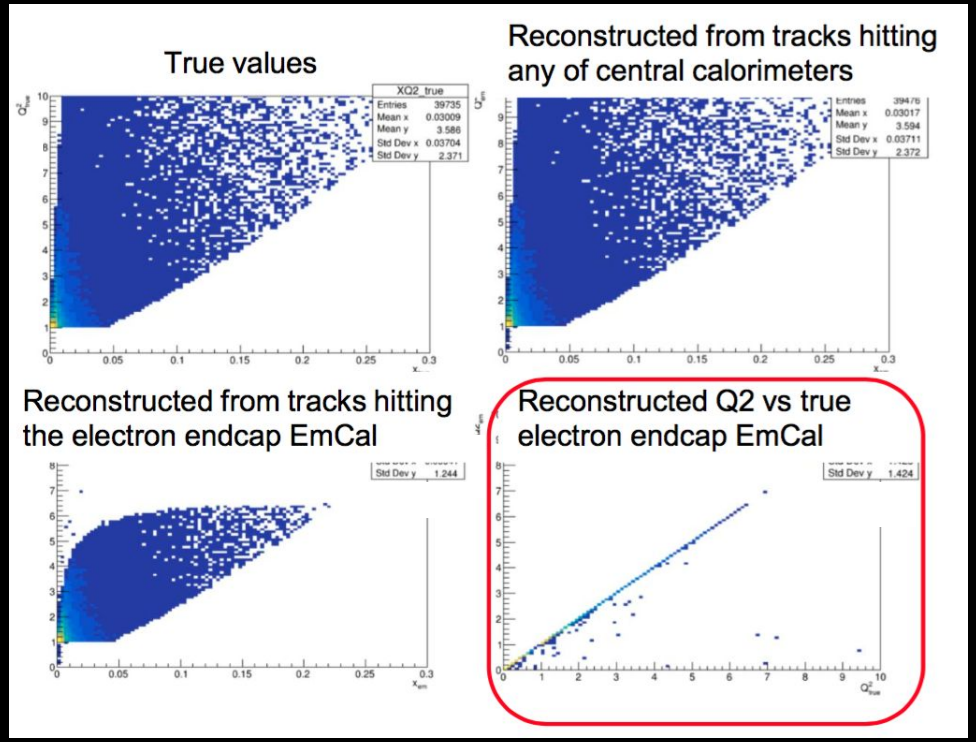
Crystals have been used in homogeneous calorimeters but their production is slow and expensive.

As an alternative Scintilex develops SciGlass that is much simpler and less expensive to produce and thus offers great potential for both cost reduction and wider application if competitive performance parameters can be achieved.

Goal: maintain the resolution needed by the physics processes while reducing the number of crystals, taking into account constraints.

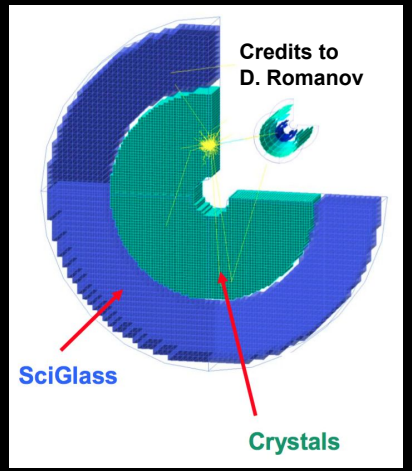
EIC EMCal Electron Endcap

Analysis of Physics Events



(For illustrative purposes)

ESCalate framework

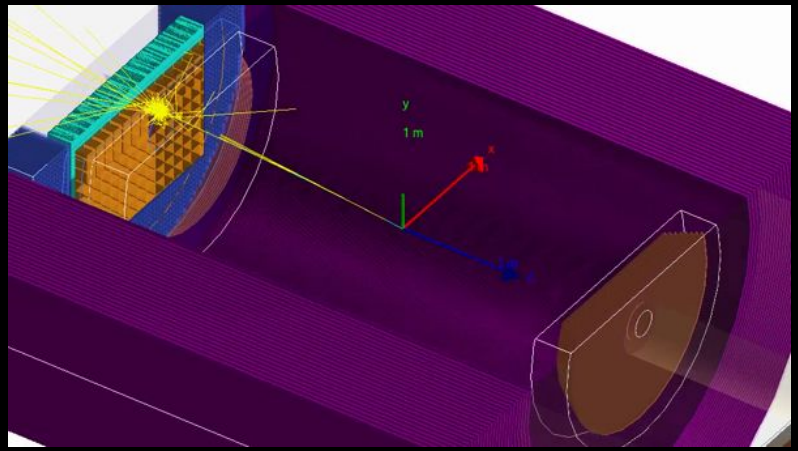


- Include FOMs based on physics processes
- Analysis of impact of EMCal resolution on reconstructed quantities
- Hybrid calorimeter reconstruction algorithm being developed. Other solutions (hierarchical clustering etc.) will be investigated for reconstruction.

Current/planned activities

- Started building a pipeline for the design optimization of the EEEmCal which can allow to determine the **design parameters** through the **objectives** both detailed below.
- The pipeline will include **construction tolerances** and **mechanical constraints** in the optimization process.

(For illustrative purposes)



Design Parameters:

- Thickness (z direction dimension) of PWO crystals [range: [20,40] cm]
- Width (and height) of each PWO crystal [range: [2,4] cm]
- Gap between PWO crystals [range: [0.1, 1.0] mm]
- Inner radius or beam hole for PWO block (baseline 15 cm)
- Outer radius of PWO block (baseline 49 cm)
- Thickness (z direction dimension) of Glass modules [range: [20,40] cm]
- Width (and height) of each Glass modules [range: [2,4] cm]
- Gap between Glass modules [range: [0.1, 1.0] mm]
- Inner radius for glass block (baseline 49 cm)
- Outer radius of glass block (baseline 133 cm)
- Density glass
- Density between cells

Figures of Merit/Objectives:

- Resolution/Residuals (flat or phase-space)
- Efficiency (“ “)
- Total Cost (crystals + glass)

AI4EIC

[1] AI4NP Wokshop, JLab, Report from the AI For Nuclear Physics Workshop, arXiv:2006.05422 (2020)
[2] Joint Machine Learning Workshop, GlueX Panda EIC, 2020.
[3] **AI4NP Winter School (11-15 January 2021)**

- Strategic moment to discuss how to fully take advantage of the new opportunities offered by AI to advance research, design, and operation of EIC.
- Growing convergence of AI, Data, and HPC provides a once in a generation opportunity to profoundly accelerate scientific discovery, create synergies across scientific areas.
- The interest of the community evidenced by the number of contributions and attendance of workshops/schools dedicated to AI in Nuclear Physics, e.g. the [1, 2, 3],
- The AI4EIC workshop will bring together the communities directly using AI technologies and provide a venue for discussion and identifying the specific needs and priorities for EIC.
- This will be a series of workshops. The first one will have a focus on experimental applications, therefore AI4EIC-exp

- Detector Design
- DAQ, SRO, near real-time decisions
- Data quality monitoring, anomaly detection, automated calibrations
- Tracking
- PID, event classification, jet physics, rare signatures
- Fast simulations