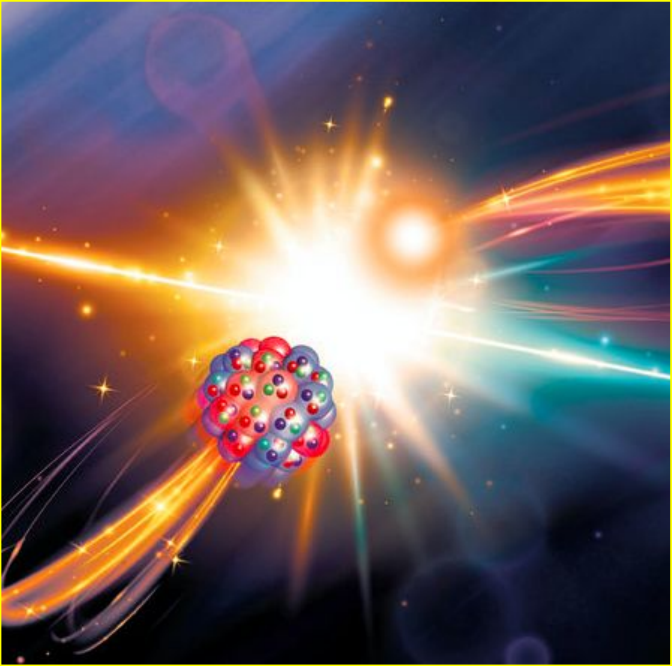
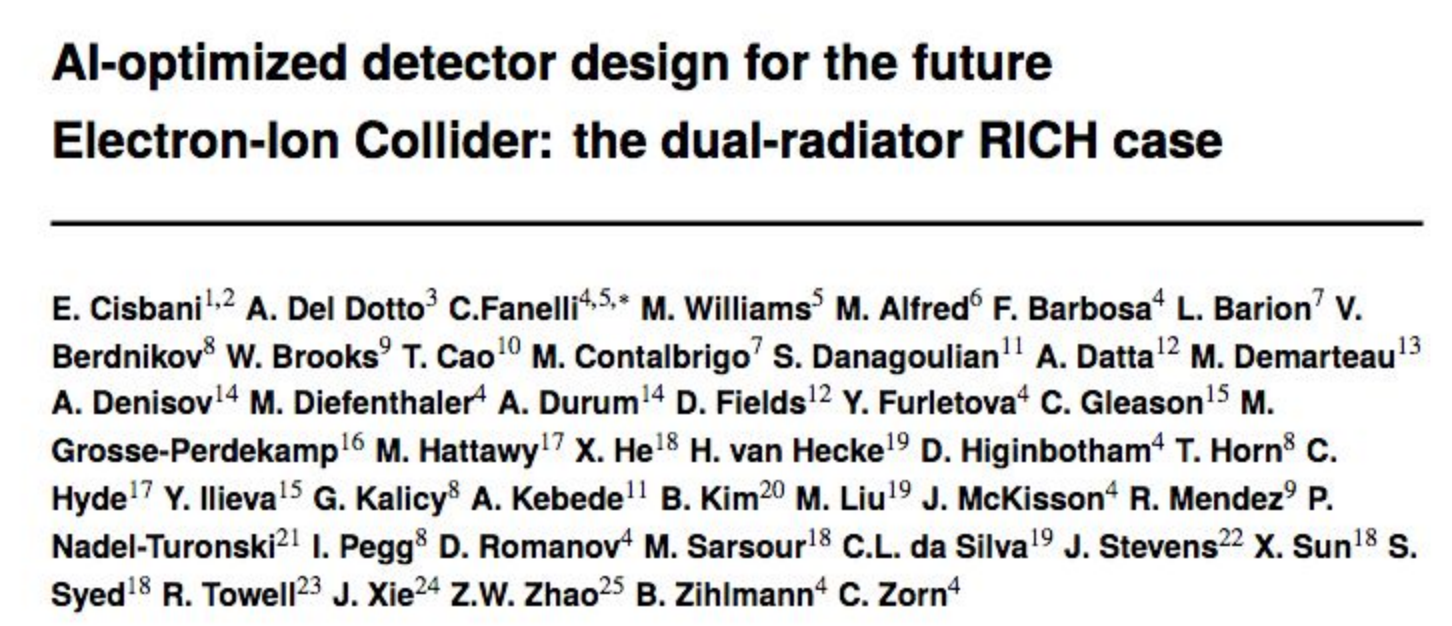
AI-optimized Detector Design



C. Fanelli

EIC Center at Jefferson Lab



AI-optimized detector design for the future Electron-Ion Collider: the dual-radiator RICH case

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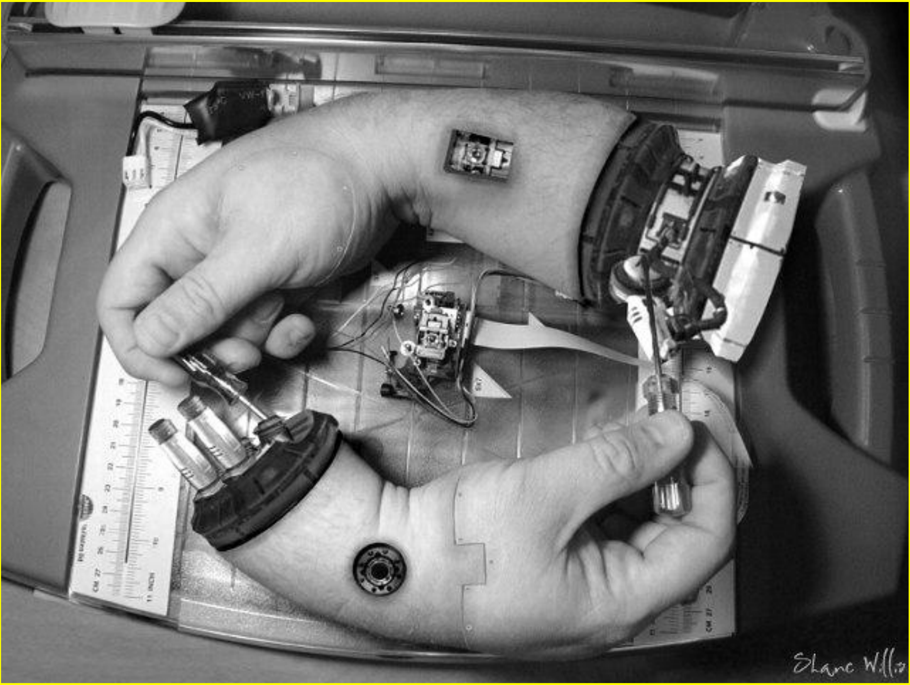
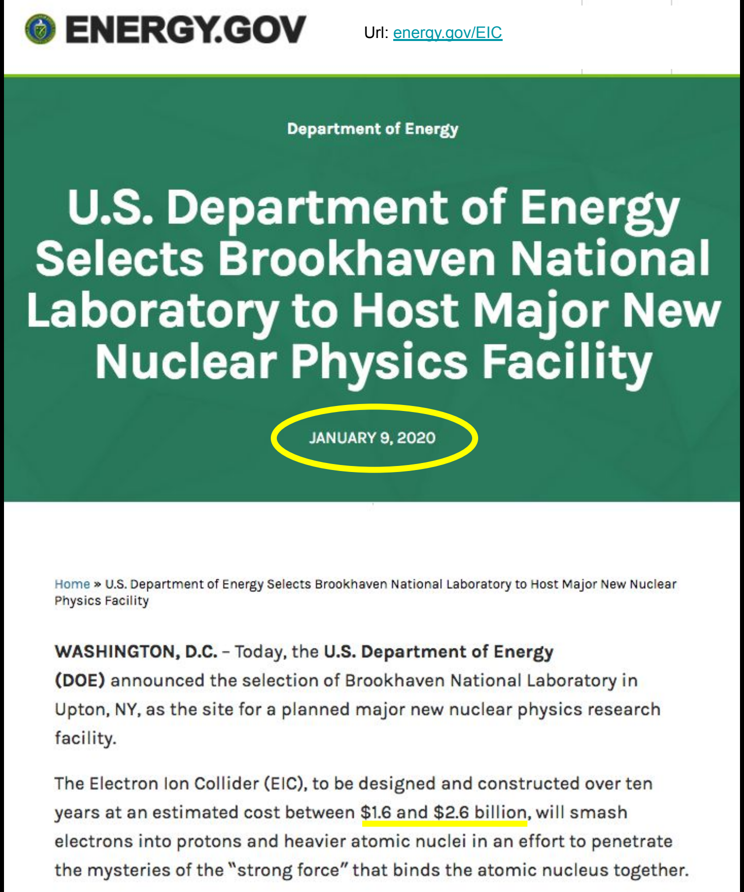
arXiv:1911.05797v1 [physics.ins-det] 13 Nov 2019

Automated Applications



AI techniques that can optimize the design of complex, large scale experiments can revolutionize the way experimental nuclear and particle physics is done

Electron Ion Collider



ENERGY.GOV Url: energy.gov/EIC

Department of Energy

U.S. Department of Energy Selects Brookhaven National Laboratory to Host Major New Nuclear Physics Facility

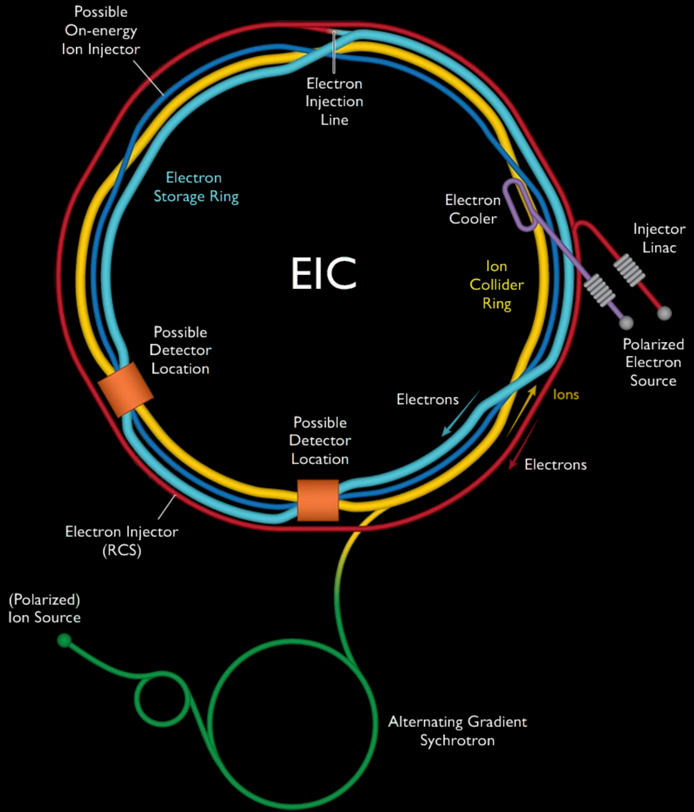
JANUARY 9, 2020

Home » U.S. Department of Energy Selects Brookhaven National Laboratory to Host Major New Nuclear Physics Facility

WASHINGTON, D.C. – Today, the **U.S. Department of Energy (DOE)** announced the selection of Brookhaven National Laboratory in Upton, NY, as the site for a planned major new nuclear physics research facility.

The Electron Ion Collider (EIC), to be designed and constructed over ten years at an estimated cost between $1.6 and $2.6 billion, will smash electrons into protons and heavier atomic nuclei in an effort to penetrate the mysteries of the "strong force" that binds the atomic nucleus together.

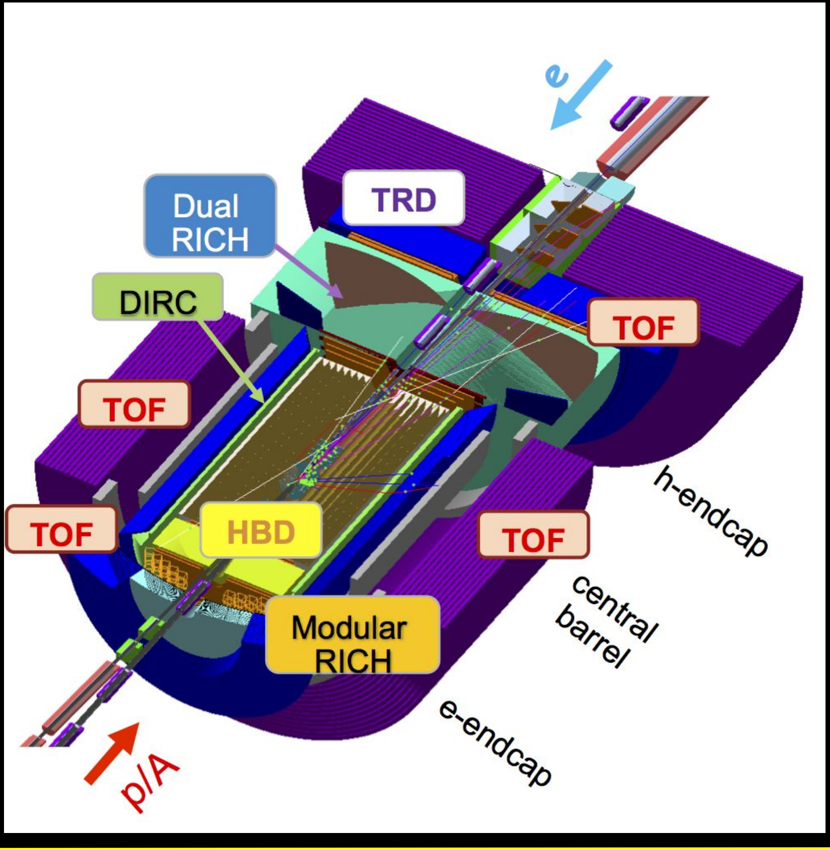
A machine for delving deeper than ever before into the building blocks of matter

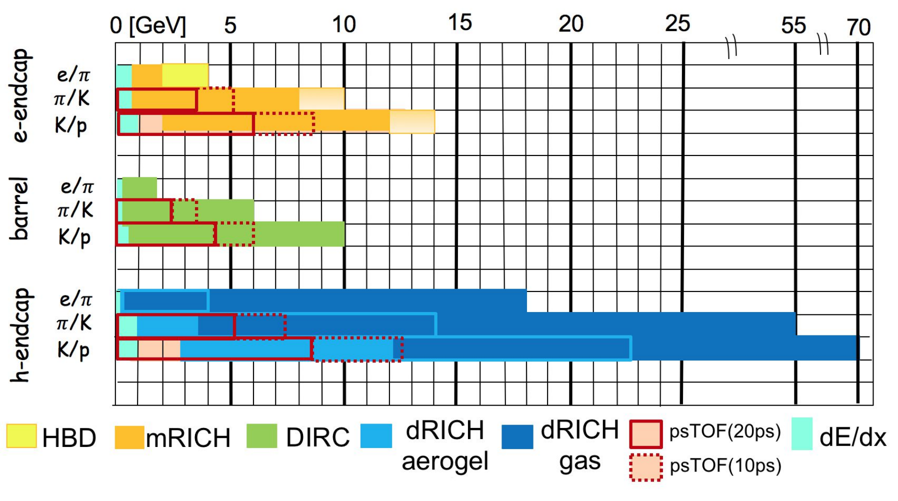


EIC will be the only electron-nucleus collider operating in the world and will be built in partnership with JLab.

It will consist of two intersecting accelerators, one producing an intense beam of electrons, the other a high-energy beam of protons or heavier atomic nuclei

Detector Concepts





Different detector concepts…

h-endcap: a dual-radiator RICH needed to cover continuously momenta up to 50 GeV/c

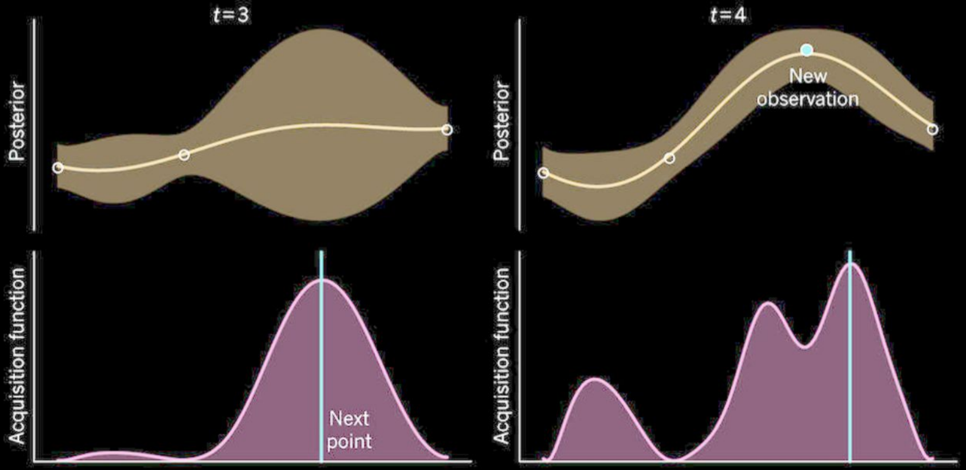
e-endcap: a small lens focused aerogel RICH for momenta up to 10 GeV/c

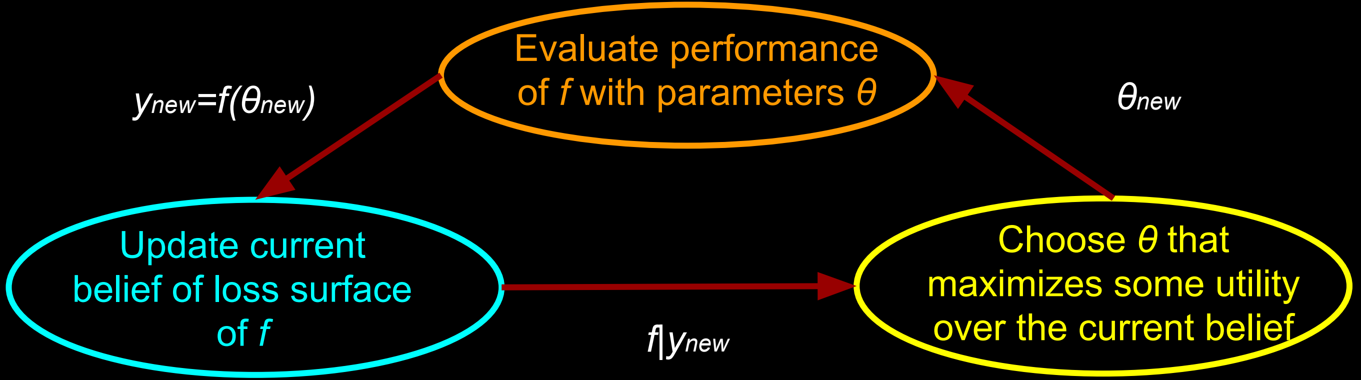
barrel: DIRC provide a compact and cost effective way to cover momenta up to 6 GeV/c

TOF (and or dE/dx in the TPC) can cover the low momenta region

Bayesian Optimization

- BO is a strategy developed for global optimization.
- After gathering evaluations BO builds a posterior distribution used to construct an **acquisition function**.
- This cheap function determines what is **next query point**.





Evaluate performance of *f* with parameters θ

$y_{new}=f(\theta_{new})$

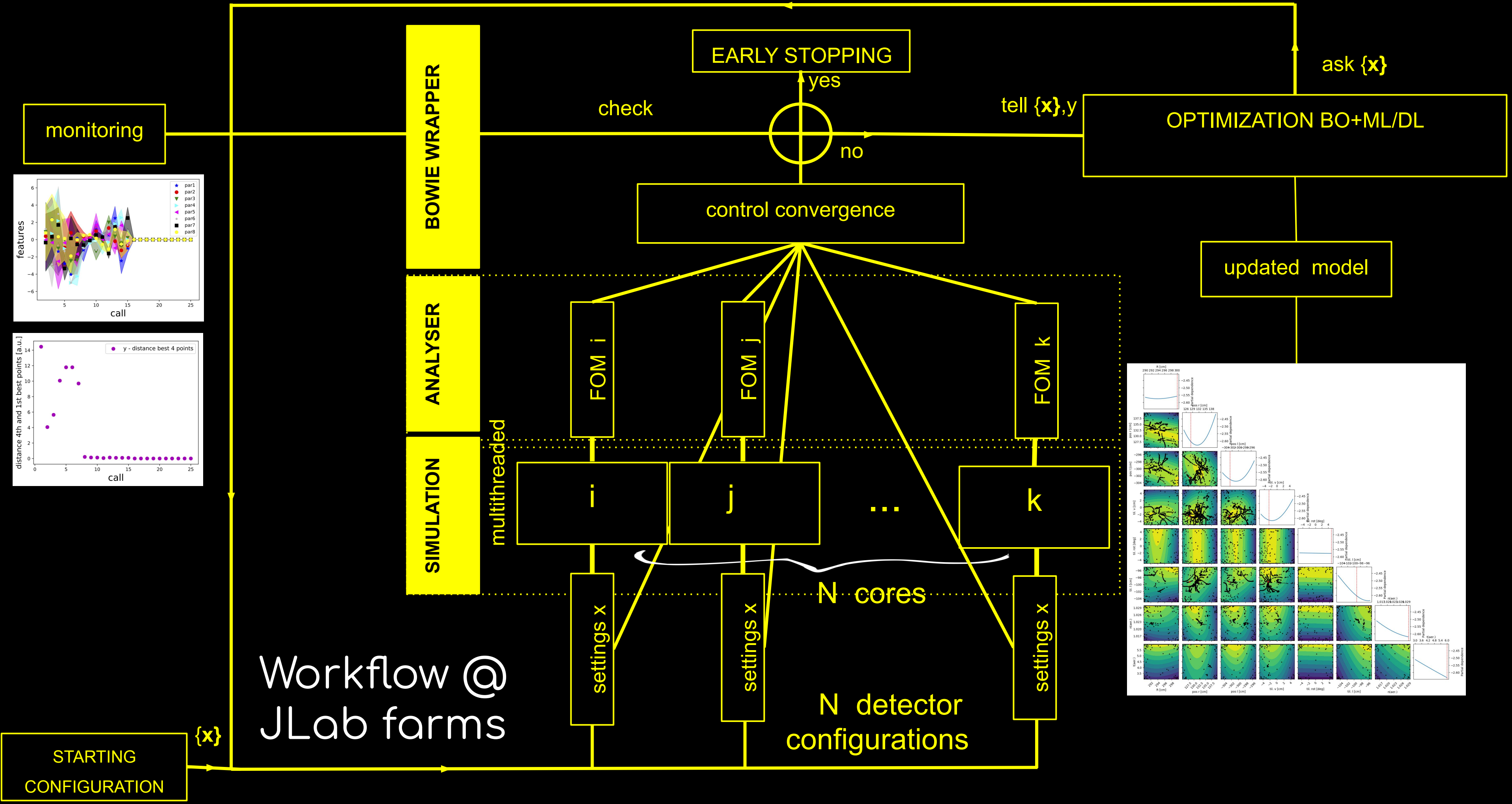
θ_{new}

Update current belief of loss surface of *f*

Choose θ that maximizes some utility over the current belief

$f|y_{new}$

Workflow @ JLab farms



STARTING CONFIGURATION

{**x**}

monitoring

BOWIE WRAPPER

ANALYSER

SIMULATION

multithreaded

check

EARLY STOPPING

yes

no

tell {**x**},y

OPTIMIZATION BO+ML/DL

ask {**x**}

updated model

control convergence

FOM i

FOM j

FOM k

i

j

...

k

N cores

settings x

settings x

settings x

N detector configurations

Case Study: dRICH

- 6 Identical open sectors (petals)
- Optical sensor elements:
  8500 cm^2/sector, 3 mm pixel
- Large focusing mirror

aerogel (4 cm, n(400 nm) 1.02)
+ 3 mm acrylic filter
+ gas (1.6 m, nC_2F_6 1.0008)

- Continuous momentum coverage.
  Simple geometry/optics,
  cost effective.
- Legacy design from EICUG2017

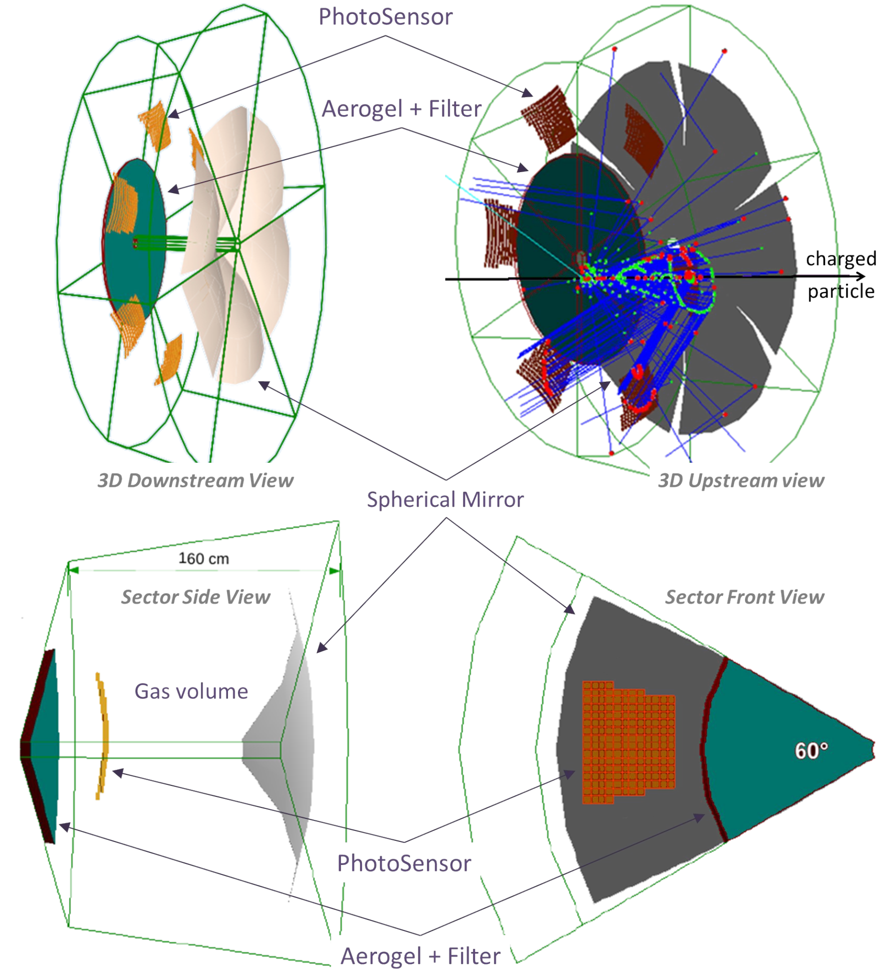


Figure of Merit

CF et al. AI-optimized detector design for the future EIC *arXiv:1911.05797* (2019)

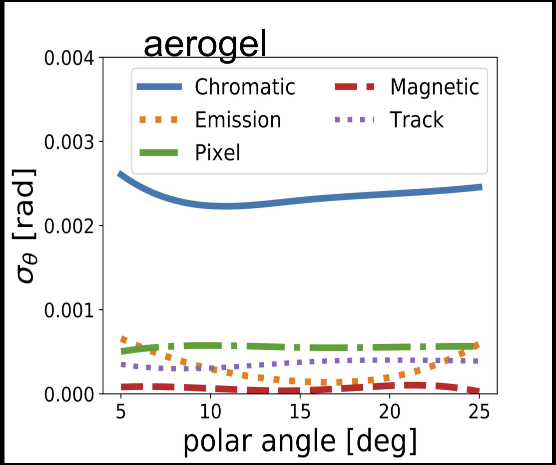
$$N\sigma = \frac{||\langle\theta_K\rangle - \langle\theta_\pi\rangle||\sqrt{N_\gamma}}{\sigma_\theta^{1p.e.}}$$

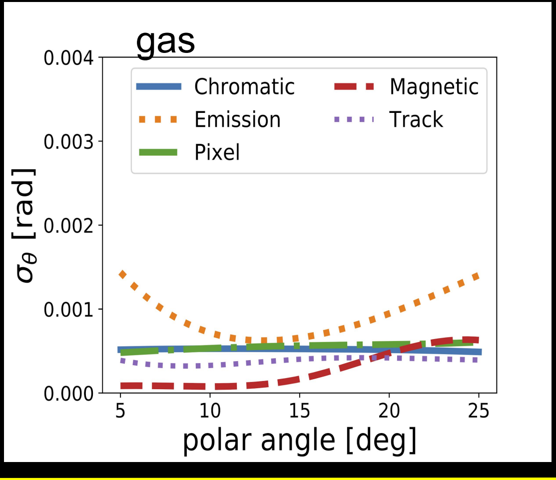
$$N_\gamma = (N_\gamma^\pi + N_\gamma^K)/2$$

$$h = 2 \cdot \left[\frac{1}{(N\sigma)|_1} + \frac{1}{(N\sigma)|_2}\right]^{-1}$$

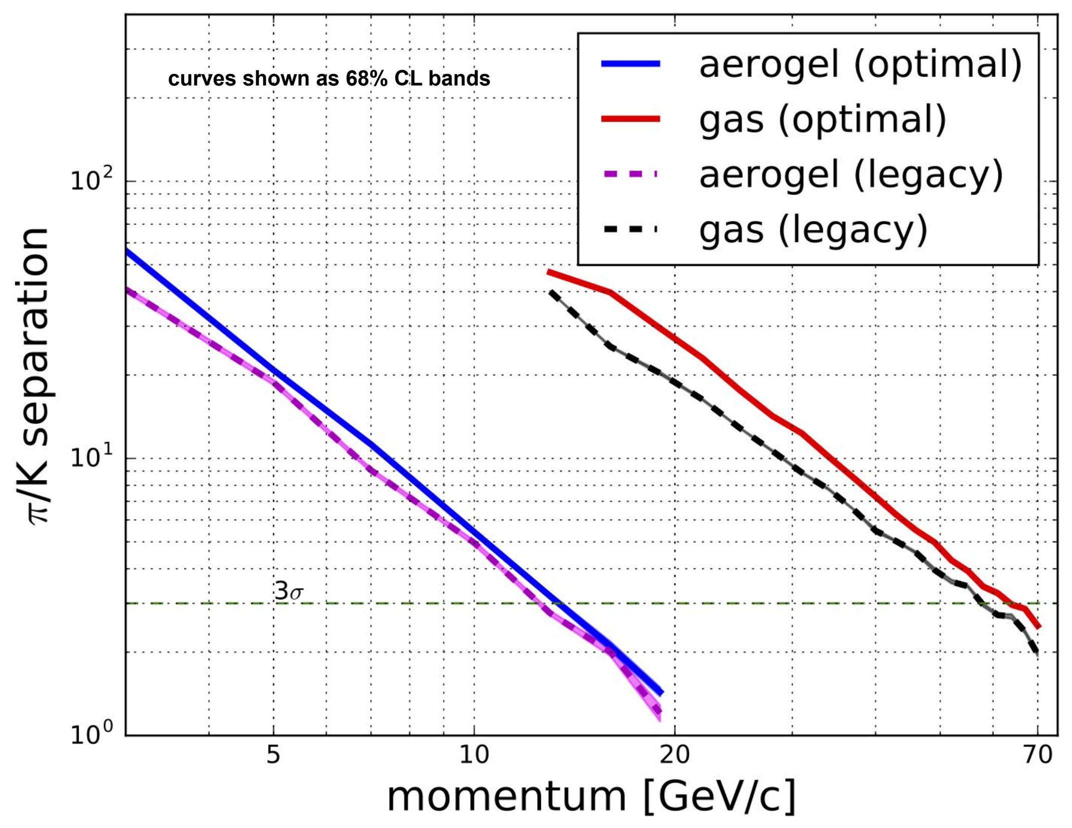
@ p_1 = 14 GeV/c (aerogel) and p_2 = 60 GeV/c (gas)

considering the two parts disentangled





dRICH Performance @ the optimal design point



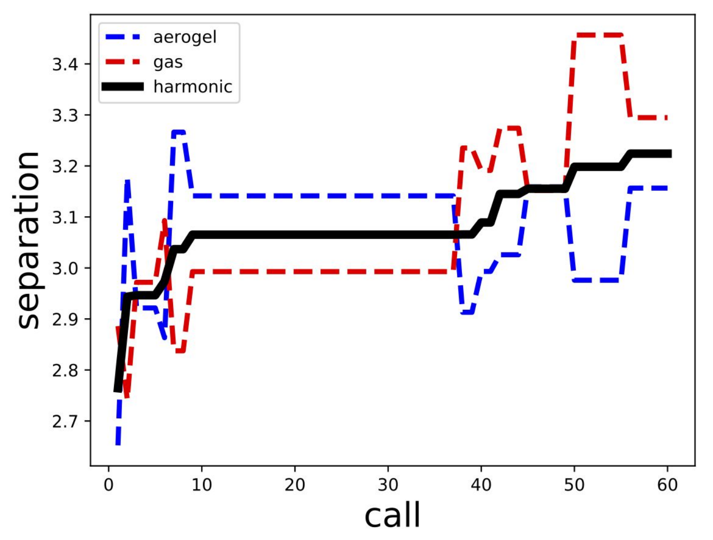
- Statistically significant Improvement in both parts.
- In particular in the gas region where the 5σ threshold shifted from 43 to 50 GeV/c and the 3σ one extended up to
- Notice that before this study we did not know “how well” the legacy design was performing.

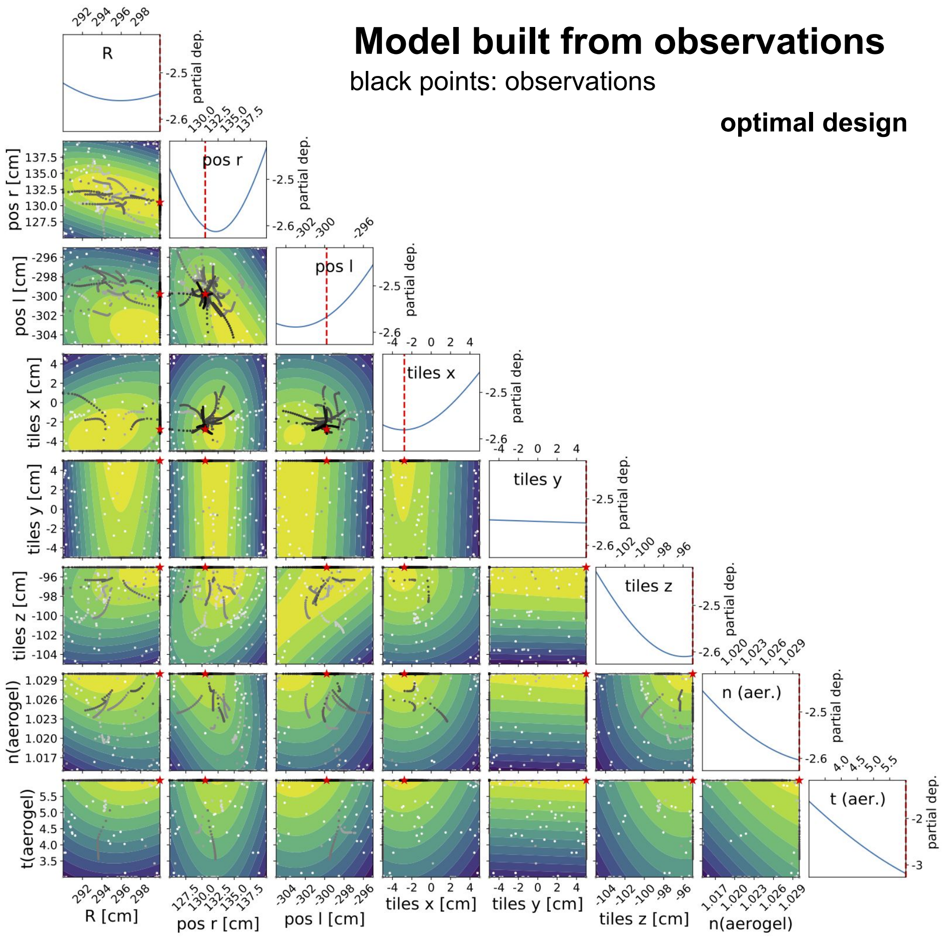
CF et al. AI-optimized detector design for the future EIC *arXiv:1911.05797* (2019)

The Model and the Optimized FoM

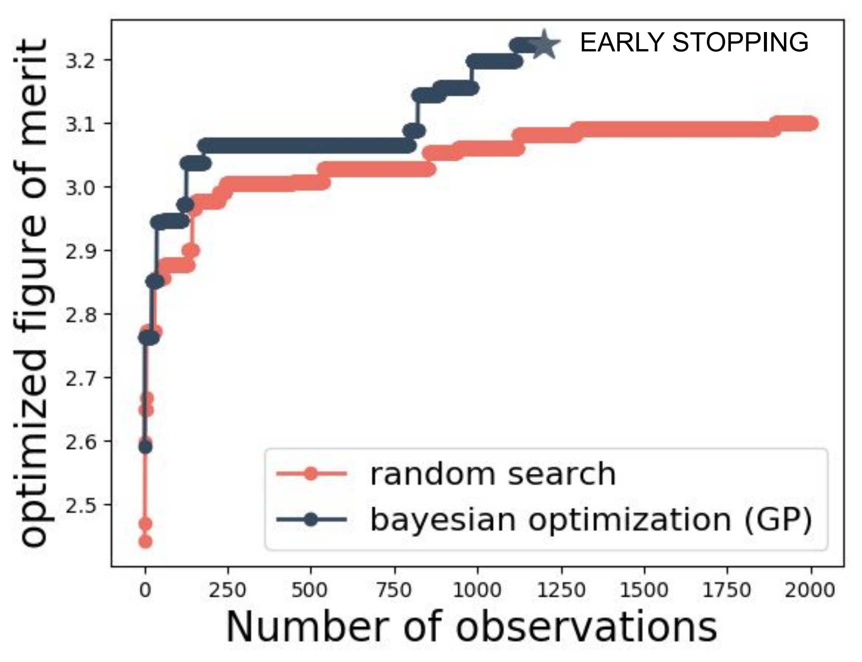
CF et al. AI-optimized detector design for the future EIC *arXiv:1911.05797* (2019)

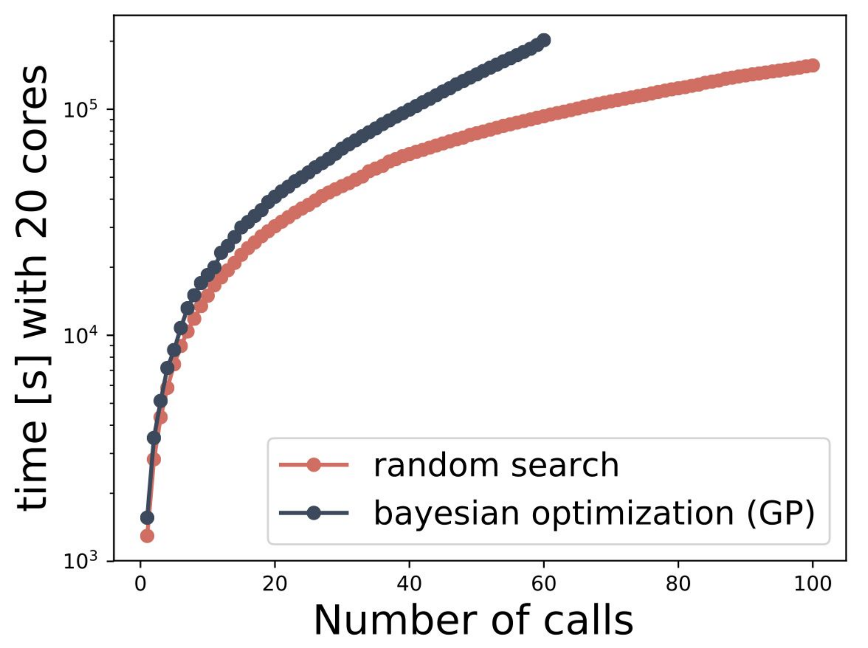
$$N\sigma = \frac{||\langle\theta_K\rangle - \langle\theta_\pi\rangle||\sqrt{N_\gamma}}{\sigma_\theta^{1p.e.}}$$





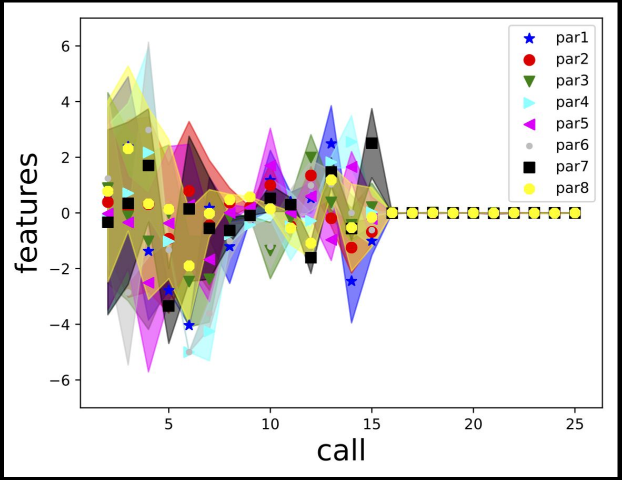
Comparison with Random Search

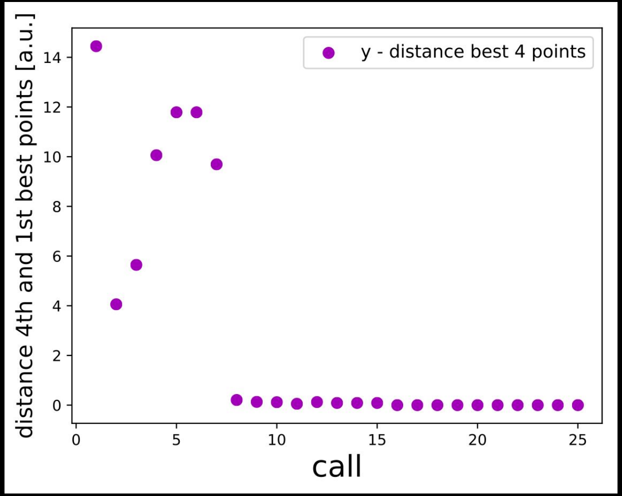




Convergence Criteria

- We defined a set of conditions to ensure convergence.
- These correspond to the logic AND of booleans on each feature and on the variation of the figure of merit.
- They are built on standardized Z and Fisher statistics.
- Pre-processing of data required to remove outliers.

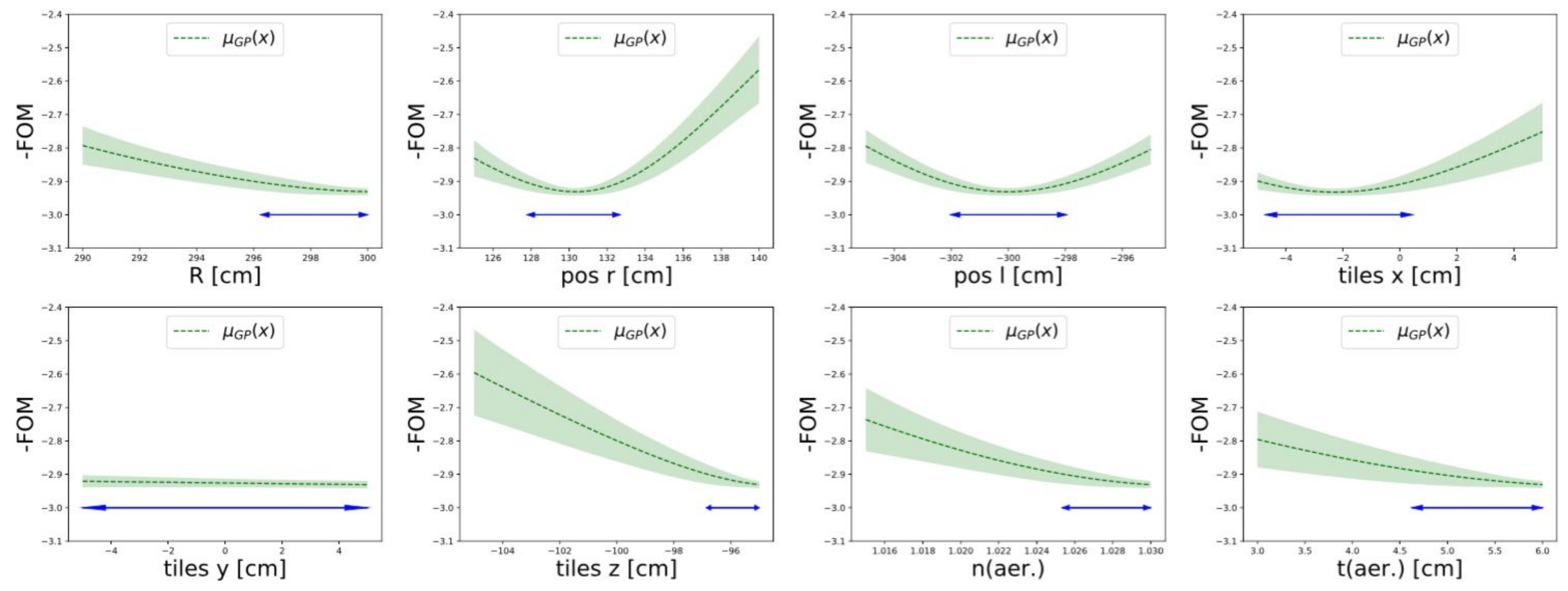




Tolerance Regions

CF et al. AI-optimized detector design for the future EIC *arXiv:1911.05797* (2019)

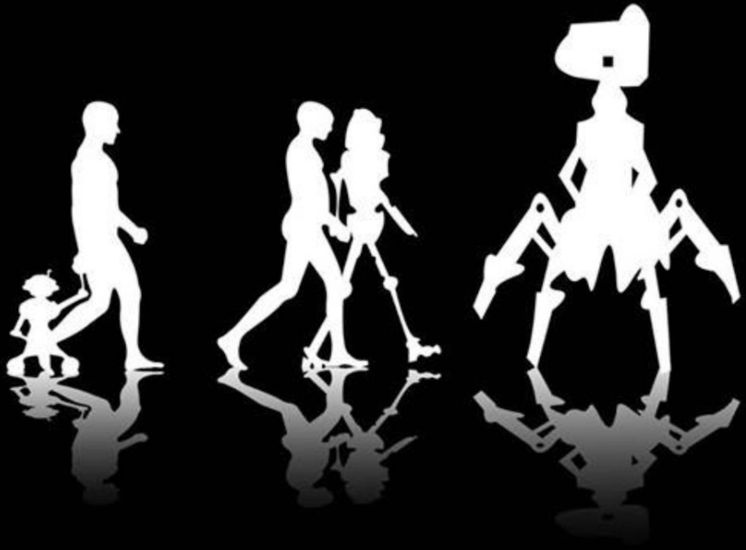
- BO provides a model of how the FoM depends on the parameters, hence it is possible to use the posterior to define a tolerance on the parameters (regions ensuring improved PID, see previous slide).



- Larger than the construction tolerances on each parameter.
  Notice a small lateral shift of the tiles has negligible impact on the PID capability.

Vision Slide

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



Bayesian Optimization

DL-boosted

Evolutionary autoML

Meta-learning

Reinforcement Learning

- AI for detector design
- Intelligent detection systems able to self-calibrate/align
- etc

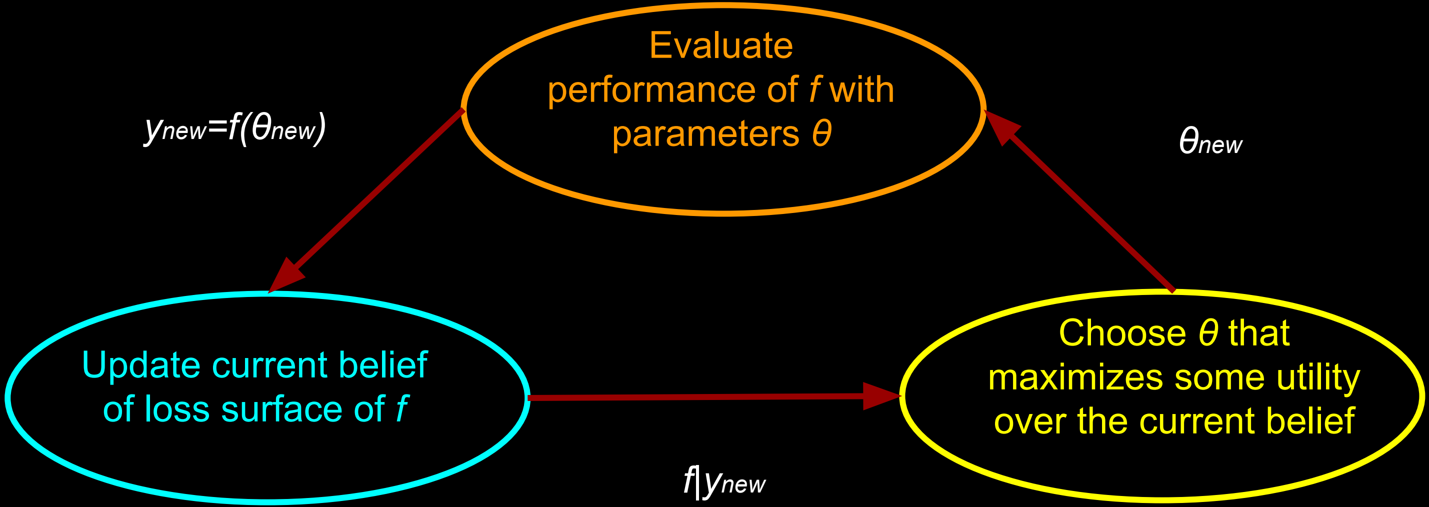
Summary

- Presented AI-driven detector design for the case of the dual-RICH in EIC.
- Key-features: automated, highly-parallelized, self-consistent.
- These same tools can be extended and applied to other detectors and possibly to the entire experiment, making the EIC R&D one of the first programs to systematically exploit AI in the detector-design phase.
- AI can help coordinate the efforts of different groups developing different sub-detectors towards the final global detector design.

BACKUP

Bayesian Optimization

It basically consists of three steps



Evaluate performance of *f* with parameters θ

$y_{new}=f(\theta_{new})$

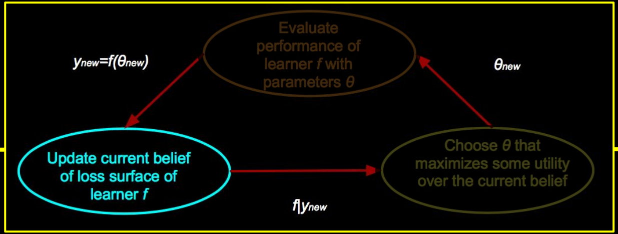
θ_{new}

Update current belief of loss surface of *f*

Choose θ that maximizes some utility over the current belief

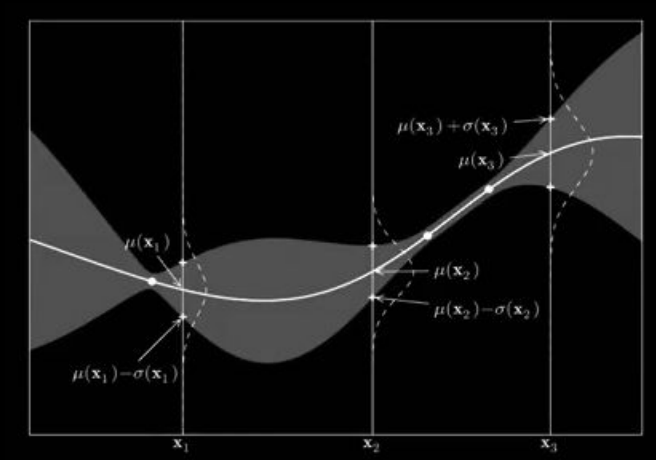
$f|y_{new}$

Update



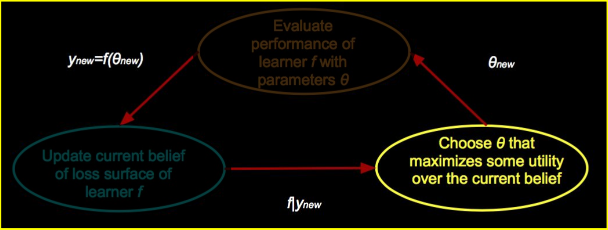
- GPs are the generalization of a Gaussian distribution to a distribution over functions, instead of random variables.

- GP is completely specified by its mean function and covariance function.



- How should I read this?
    - **Solid line**: function we are trying to min/max
    - **Shaded region:** probability model (we know the actual points already evaluated but we are more uncertain in regions where we haven't).
    - In every point a normal distribution of the potential performance function

Next points



$y_{new}=f(\theta_{new})$

Evaluate performance of learner f with parameters θ

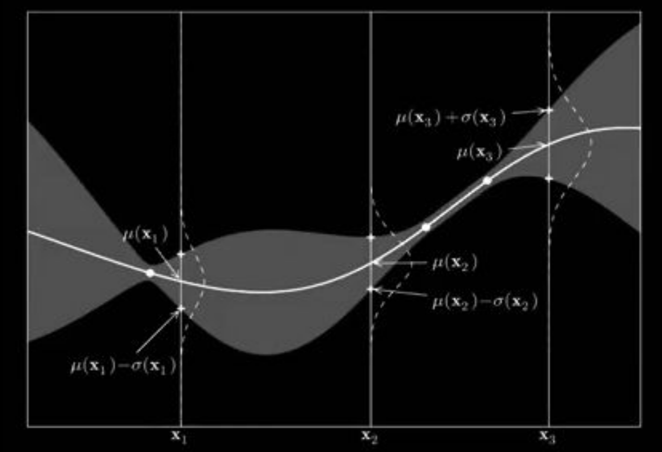
θ_{new}

Update current belief of loss surface of learner f

$f|y_{new}$

Choose θ that maximizes some utility over the current belief

- Where am I going to sample next?
- We use utility functions called acquisition functions (formalize what is the best guess)
- Expected improvements is one example: find next point that improves the performance the most.



EXPLOITATION
Sample a θ with higher value than current one

EXPLORATION
Sample a point where uncertainty is high

want to maximize

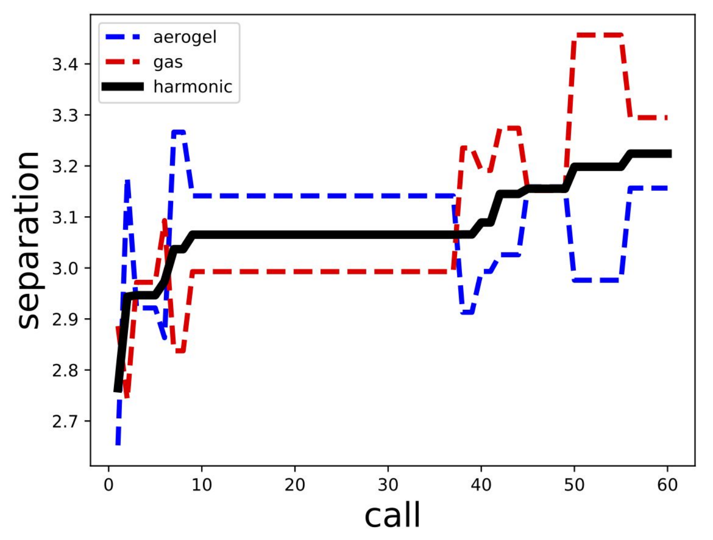
$$EI(\theta) = \begin{cases} \boxed{\left(\mu(\theta) - f(\hat{\theta})\right)}\Phi(Z) + \boxed{\sigma(\theta)}\phi(Z), & \sigma(\theta) > 0 \\ 0, & \sigma(\theta) = 0 \end{cases},$$

best value we found so far

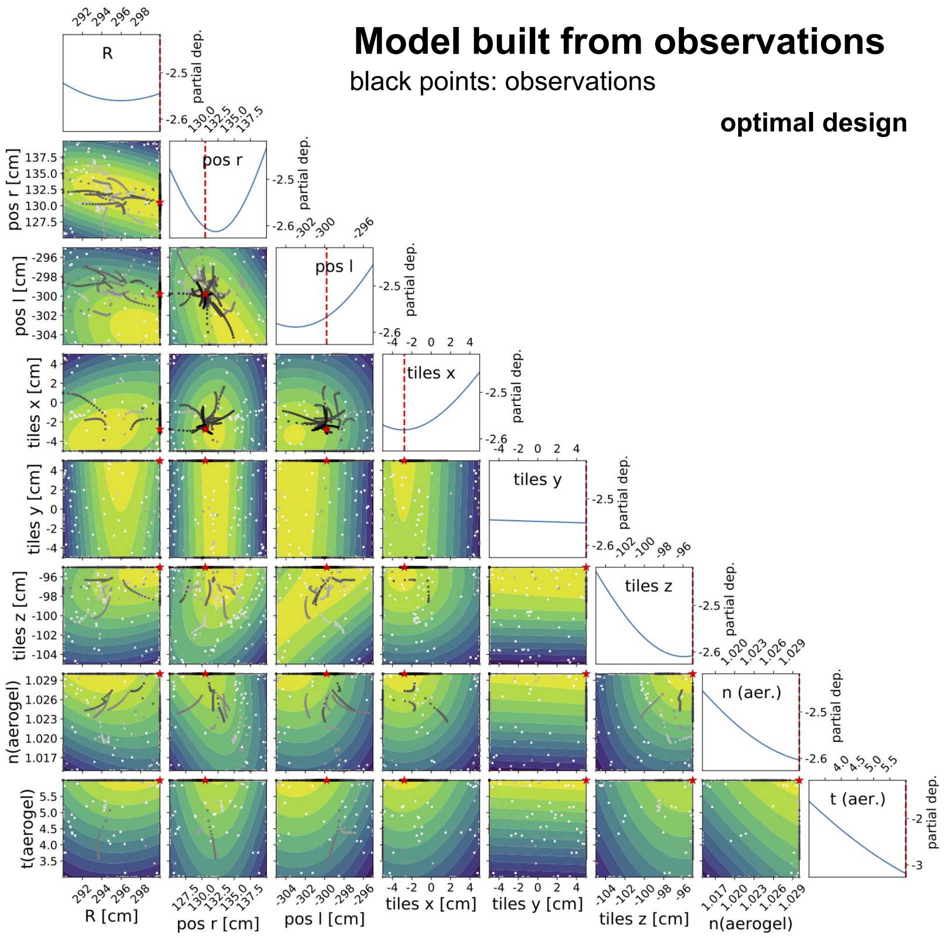
$$Z = \frac{\mu(\theta) - f(\hat{\theta})}{\sigma(\theta)}$$

The Model and the Optimized FoM

CF et al. AI-optimized detector design for the future EIC *arXiv:1911.05797* (2019)



	FoM (h)	$(N\sigma)$ @ 14 GeV/c	$(N\sigma)$ @ 60 GeV/c
BO	3.23	3.16	3.30
legacy	2.9	3.0	2.8


Model built from observations

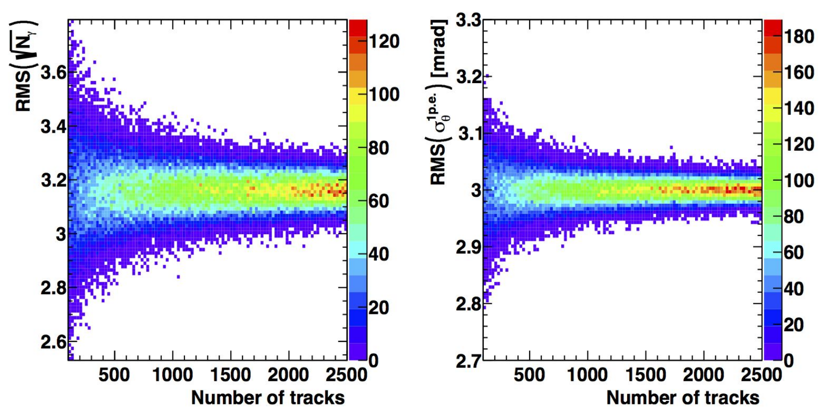
black points: observations

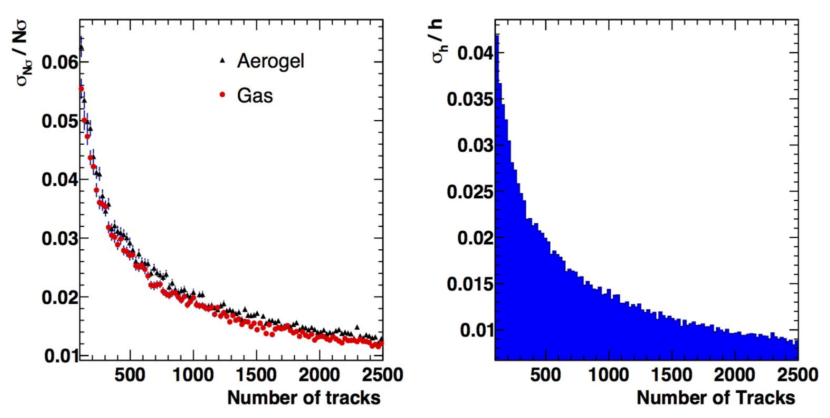
optimal design

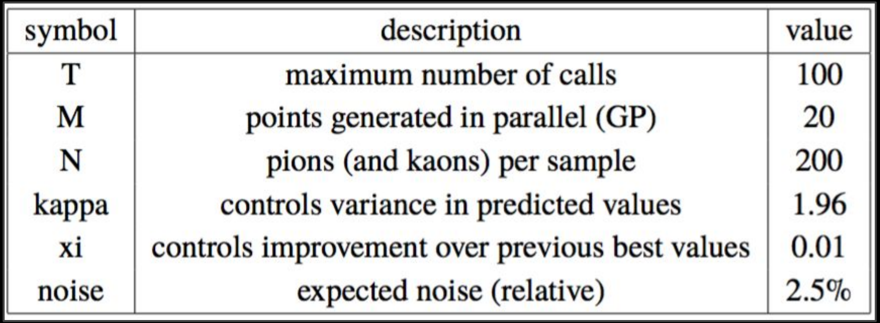
Noise Studies

CF et al. AI-optimized detector design for the future EIC *arXiv:1911.05797* (2019)

- Dedicated studies to characterize the noise as this is an optimization of a noisy function
- We choose N tracks = 400 based on the studies on noise to minimize as much as possible computing time during simulation.





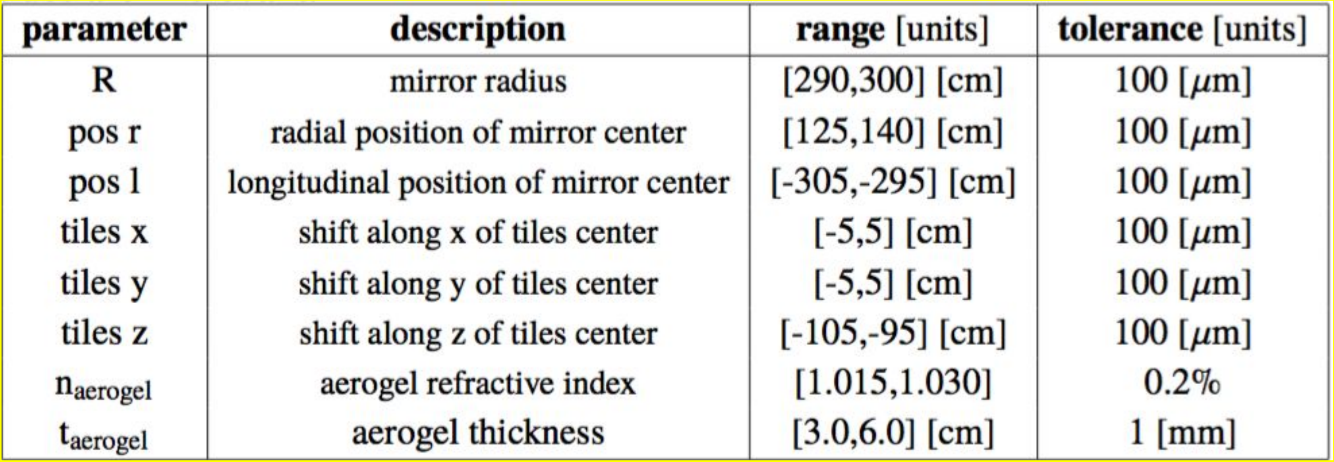


symbol	description	value
T	maximum number of calls	100
M	points generated in parallel (GP)	20
N	pions (and kaons) per sample	200
kappa	controls variance in predicted values	1.96
xi	controls improvement over previous best values	0.01
noise	expected noise (relative)	2.5%

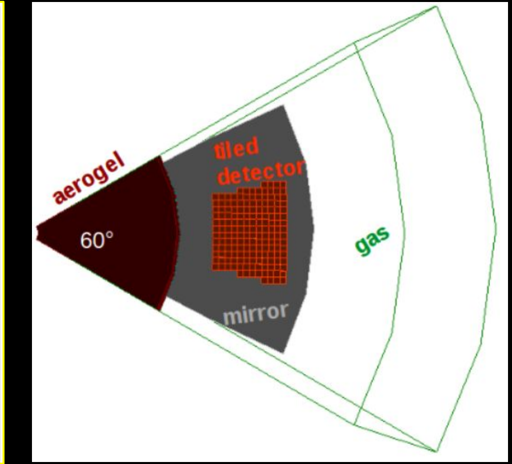
(list of hyperparameters)

Construction Constraints

The idea is that we have a bunch of parameters to optimize that characterize the detector design.
We know from previous studies their ranges and the construction tolerances.



parameter	**description**	**range** [units]	**tolerance** [units]
R	mirror radius	[290,300] [cm]	100 [μm]
pos r	radial position of mirror center	[125,140] [cm]	100 [μm]
pos l	longitudinal position of mirror center	[-305,-295] [cm]	100 [μm]
tiles x	shift along x of tiles center	[-5,5] [cm]	100 [μm]
tiles y	shift along y of tiles center	[-5,5] [cm]	100 [μm]
tiles z	shift along z of tiles center	[-105,-95] [cm]	100 [μm]
n_{aerogel}	aerogel refractive index	[1.015,1.030]	0.2%
t_{aerogel}	aerogel thickness	[3.0,6.0] [cm]	1 [mm]



Ranges depend mainly on mechanical constraints and optics requirements.
These requirements can change in the next future based on inputs from prototyping.