Tuning dRICH design with multi-objective Bayesian optimization

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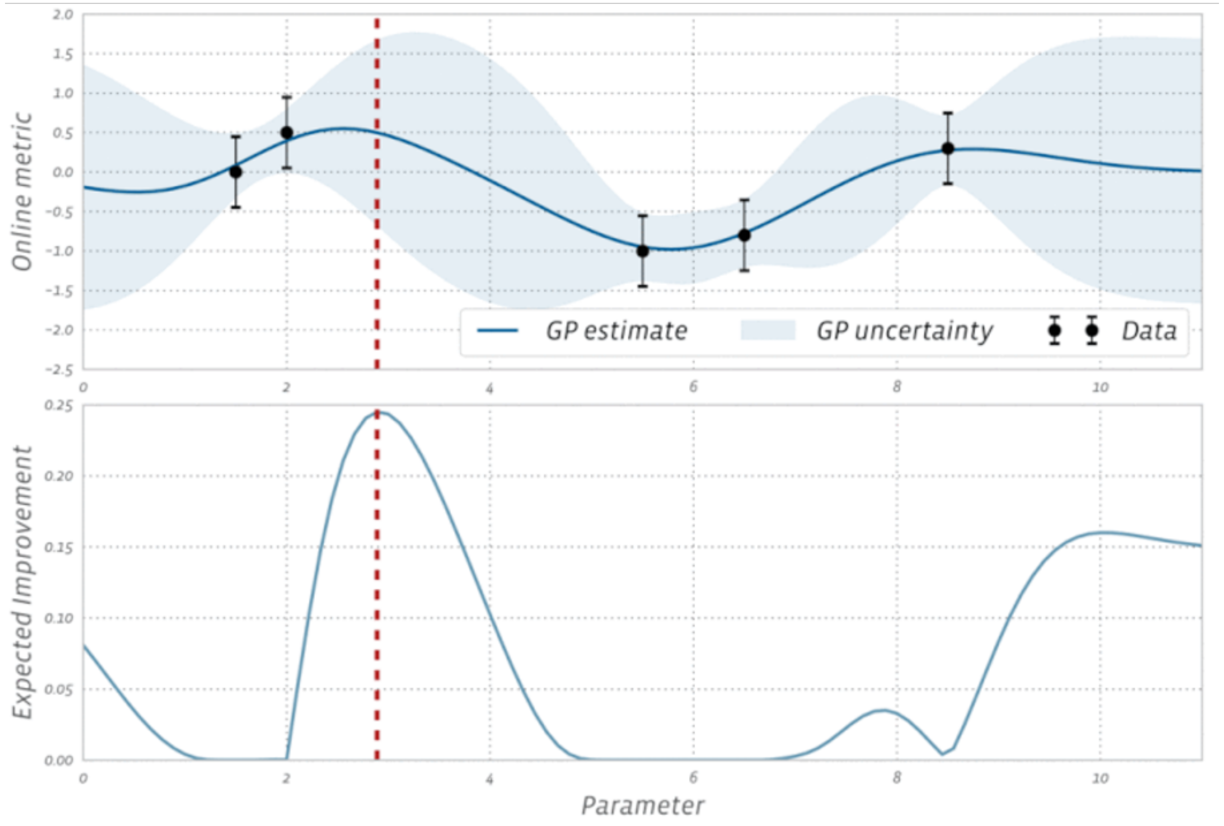
Bayesian optimization

- Optimization approach employed for hard-to-evaluate problems
- Constructs **surrogate model** (gaussian process) fit to predict objectives as a function of design parameters
- **Acquisition function** suggests new points to test based on expected improvement
  - Balance exploring new design parameter regions and looking for global optimum



From: https://ax.dev/docs/bayesopt

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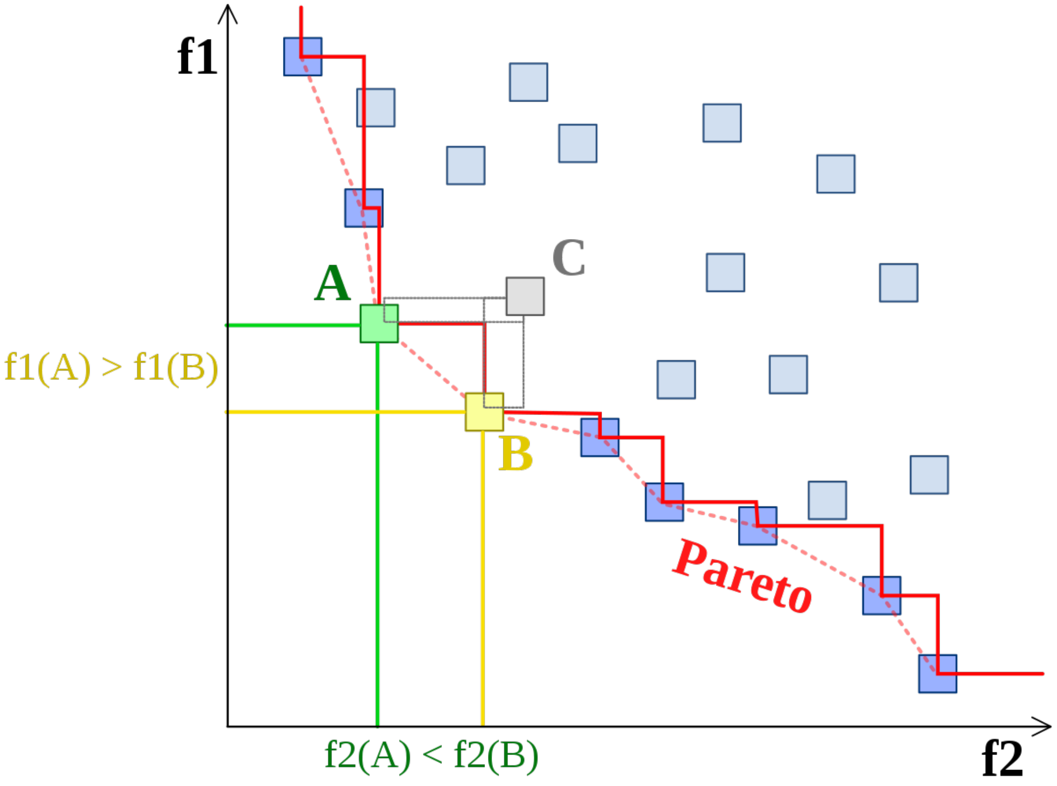
Multi-objective Bayesian optimization (MOBO)

- Can optimize a multi-objective space, with the objective of finding the set of best possible designs and tradeoffs between objectives
- Aiming to construct best possible estimate of the Pareto front
- For dRICH: performance in different p/η ranges as separate objectives



https://en.wikipedia.org/wiki/Pareto_front

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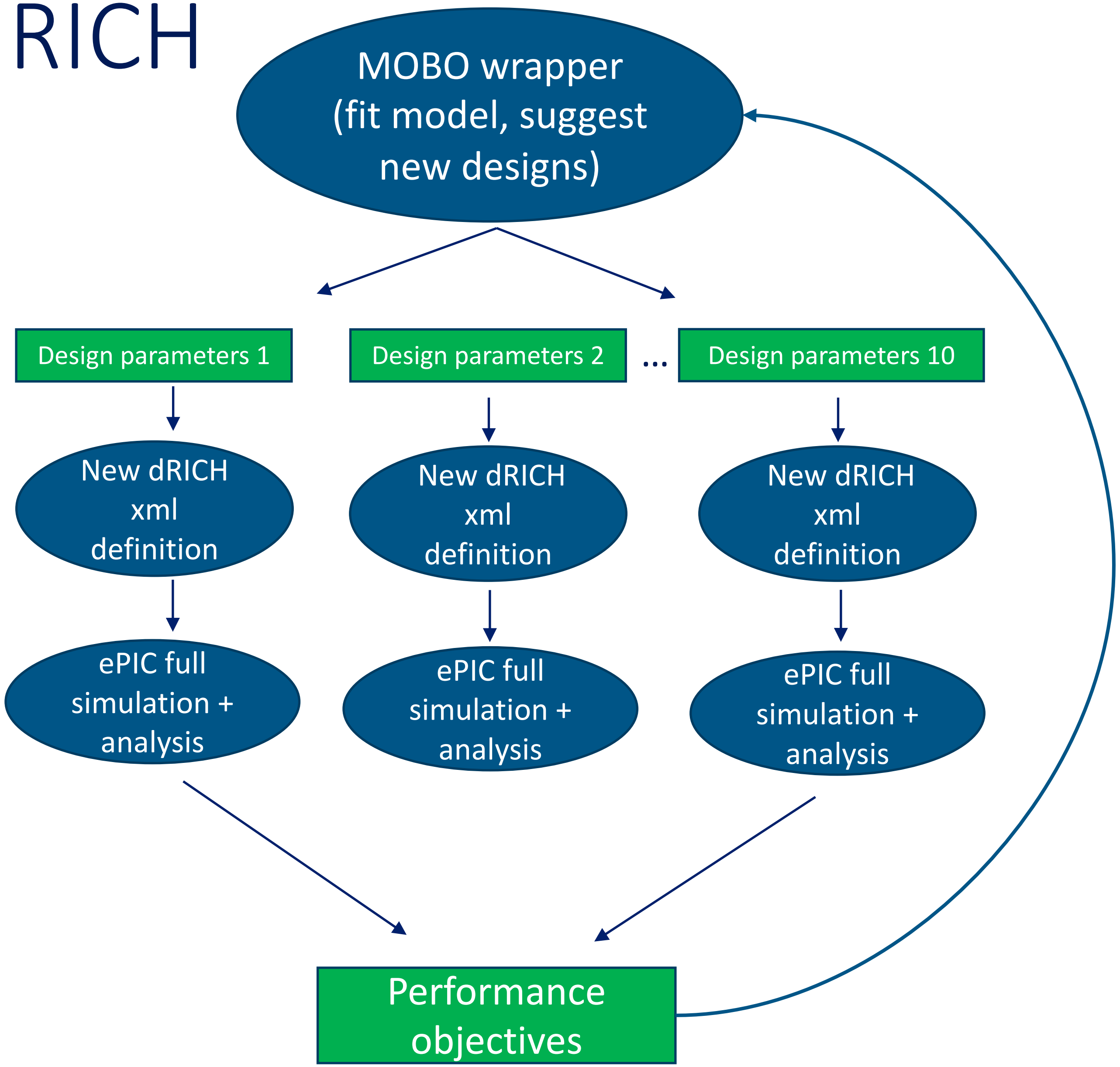
MOBO Application to dRICH

- Coupled MOBO algorithm to ePIC software stack and dRICH full simulation
  - Surrogate model, acquisition function through BoTorch
  - Trial management through Ax
- Evaluate design points in batches of 5-10



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dRICH design parameters and constraints

- As a first attempt, primarily aiming to optimize dRICH sensor/single mirror spheres
- Allowing sensor sphere to have large radius (towards flat sensor plane)
- Constraints:
  - Mirror backplane within 4cm of dRICH back wall
  - Sensors within sensor box

Parameter	Minimum	Maximum	Nominal (in dd4hep)
Aerogel radius	90 cm	100 cm	90 cm
Mirror focal radius	180 cm	260 cm	219.8 cm
Mirror sphere center x	105 cm	125 cm	114.6 cm
Mirror sphere center z	54.8 cm	174.8 cm	93.9 cm
Sensor sphere radius	80 cm	500 cm	110 cm
Sensor sphere center x	150 cm	210 cm	183.4 cm
Sensor sphere center z	-270 cm	178.4 cm	138.4 cm

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Objectives for optimization

- For each design point, simulating 1000 π^+ and 1000 K^+ each with
  - p = 15GeV/c and 40GeV/c
  - η = [1.3,2.0], [2.0, 2.5], [2.5, 3.5]
- From reconstruction output, computing $N\sigma_{\pi-K}$ and % of tracks accepted (N photons reconstructed > 0)
- > 3 objectives difficult for MOBO, so need to reduce total number of objectives (average over p or average over η)

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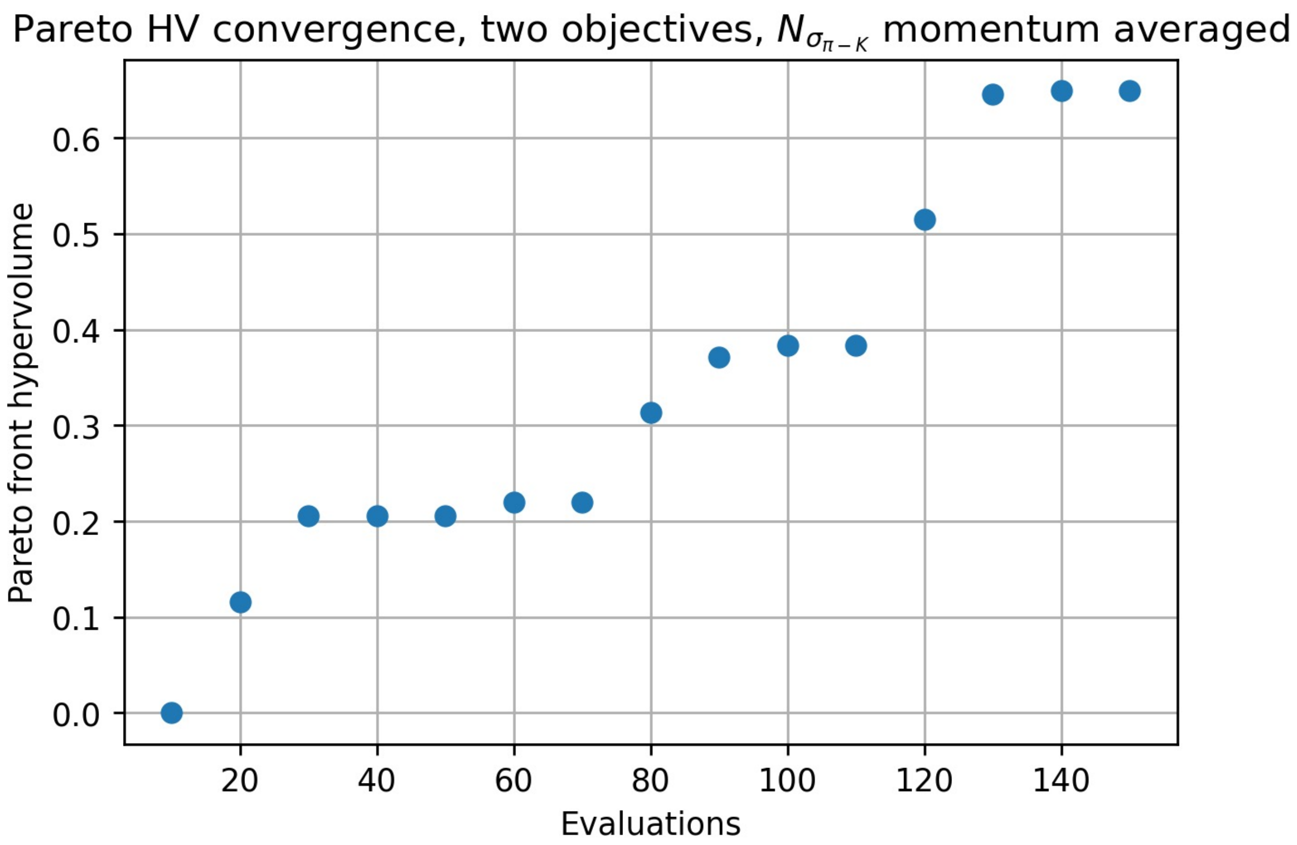
Optimizing $N\sigma_{\pi-K}$ averaged over p

- In single mirror configuration, low and high η angular resolutions are competing
- As test of framework, ran optimization with objectives as $\boldsymbol{N\sigma_{\pi-K}}$ **at low** $\boldsymbol{\eta}$ and **high** $\boldsymbol{\eta}$ (average of p=15GeV/c and 40GeV/c)
- 200 total design points sampled
  - 50 SOBOL points (pseudorandom initialization)



Hypervolume dominated by optimal points

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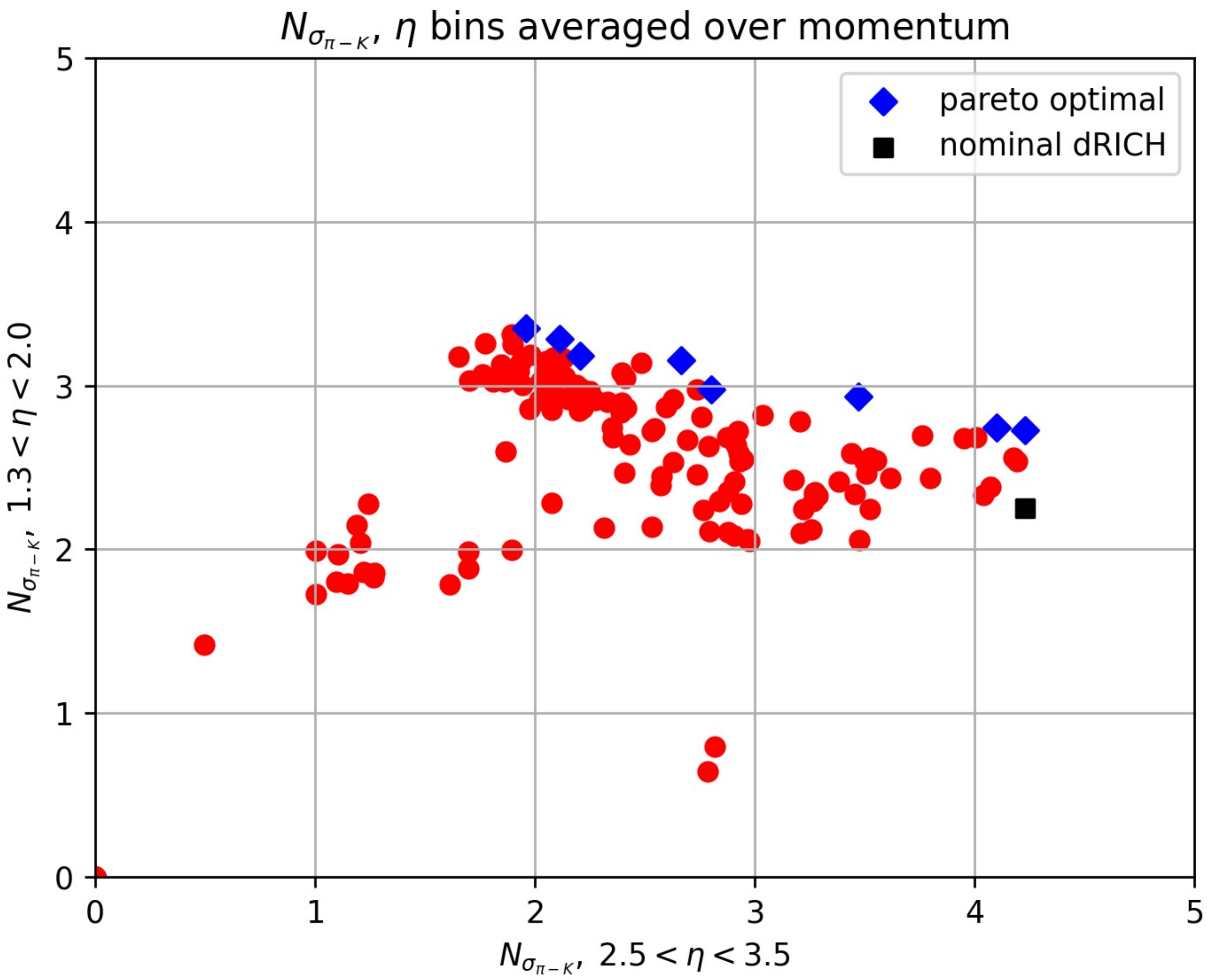
Optimizing $N\sigma_{\pi-K}$ averaged over p

- Right: $N\sigma_{\pi-K}$ results from sampled points
- Tradeoff visible between low and high η ranges
  - No design found with $N\sigma_{\pi-K}$ >= 3 for both low and high η



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Conclusion and next steps

- MOBO framework attached to the ePIC/dRICH full simulation is in place
- Need feedback on further constraints on search space
- Framework could be used to investigate more complex geometry decisions
  - Optimize a multi-mirror geometry, or determine the optimal tiling of sub-mirrors
  - Could be used to investigate the impact of the septum vs. larger bore radius

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Extra slides

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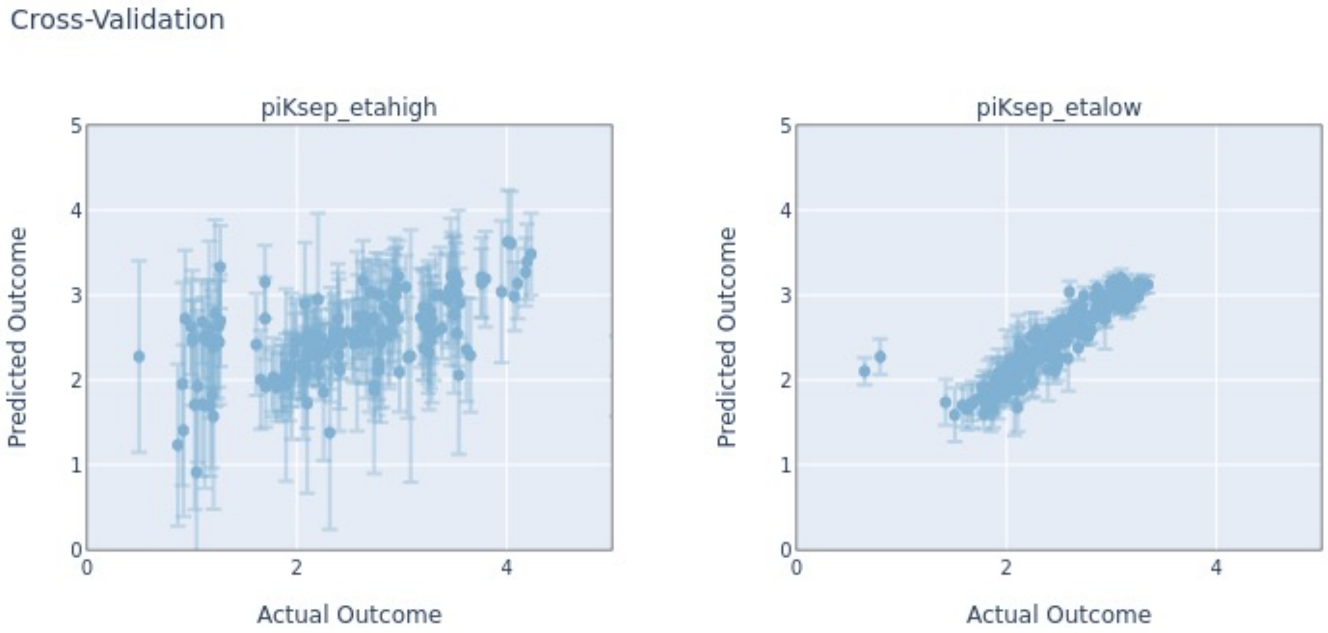
Surrogate model prediction validation

- Cross-validation of prediction from fit surrogate model with the true results of $N\sigma_{\pi-K}$



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