Calibrated Particle Identification for Belle II

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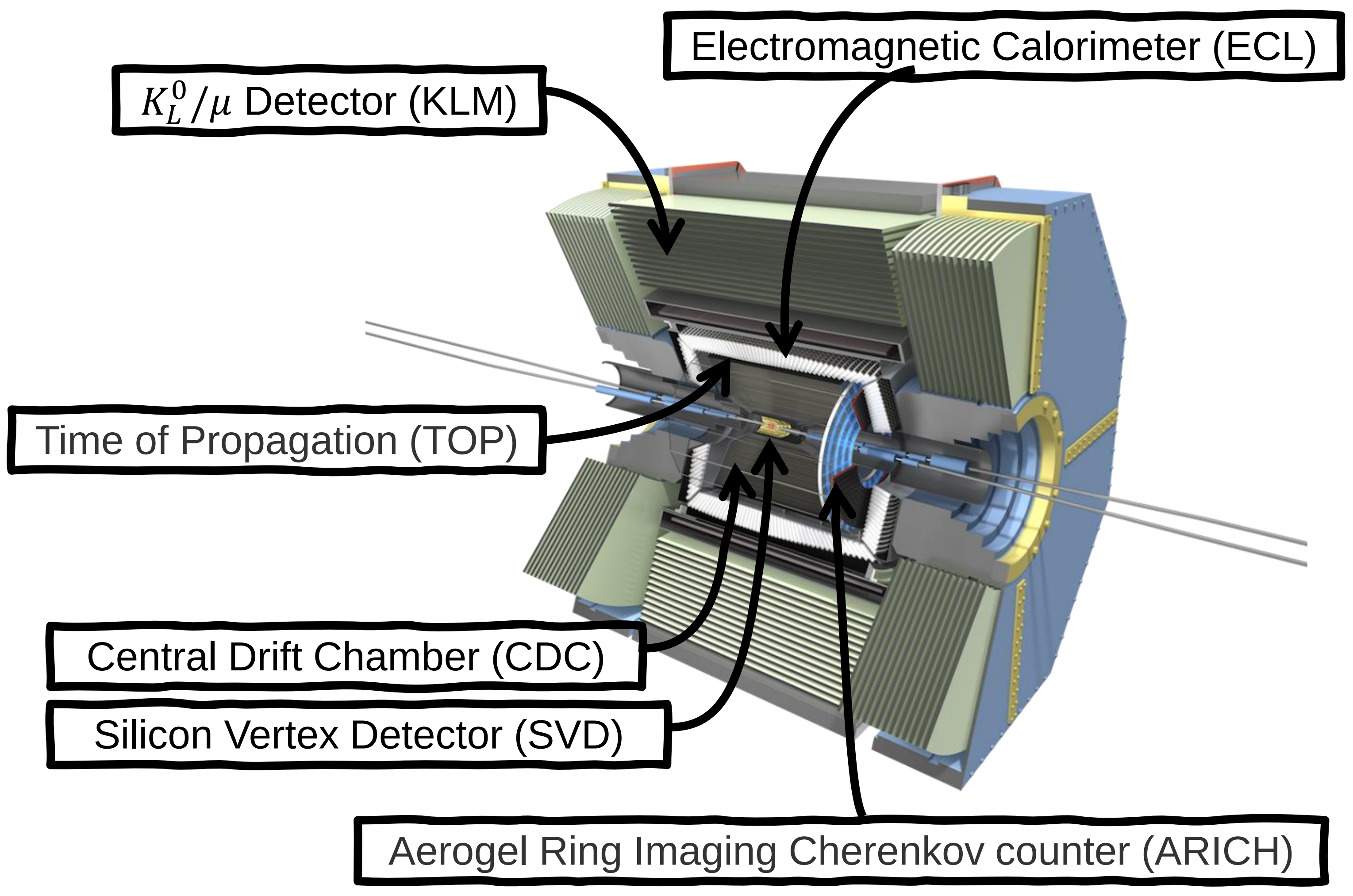
Charged Particle Identification @ Belle II

- Belle II is located at the asymmetric energy e^+e^- superKEKB collider in Tsukuba Japan, collecting data primarily at the $\Upsilon(4S)$ resonance.
- Highly performant particle identification is a key requirement for the flavor physics program.
- Six sub-detectors provide likelihoods for tracks that traverse them for each of the final state charged particle hypothesis: $h \in \{e^\pm, \mu^\pm, \pi^\pm, K^\pm, p^\pm, d^\pm\}$.



Electromagnetic Calorimeter (ECL)

K_L^0/μ Detector (KLM)

Time of Propagation (TOP)

Central Drift Chamber (CDC)

Silicon Vertex Detector (SVD)

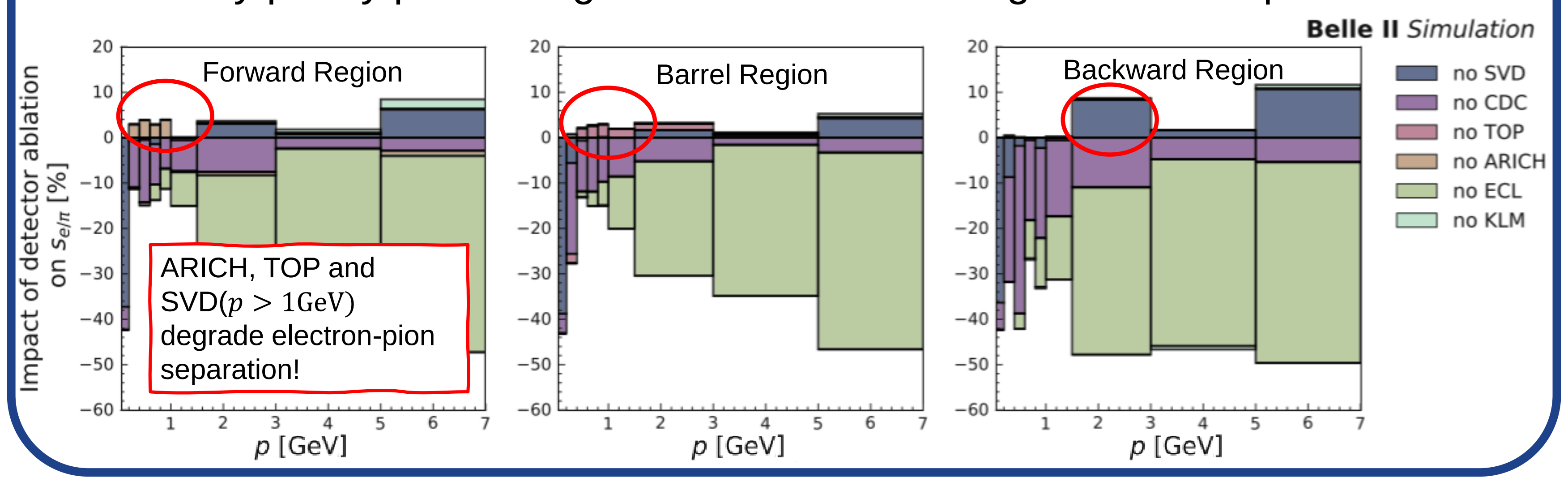
Aerogel Ring Imaging Cherenkov counter (ARICH)

- The likelihoods are combined into global particle identification scores via a likelihood ratio:

$$h\text{ID} = \frac{\exp(\log \mathcal{L}_h)}{\sum_h \exp(\log \mathcal{L}_h)},\ \log \mathcal{L}_h = \sum_{\text{Det}} \log \mathcal{L}_{h,\text{Det}}$$

The Blame Game

- To evaluate the impact of each sub-detector, consider a separation score via an ablation test.
- Calculate the difference in the overlap between the probability density function of simulated pure signal and background samples in the particle ID scores when considering all sub-detectors or all minus one sub-detectors.
- The score is bound between [-1, 1]. A negative score indicates that including the sub-detector improves the performance, a positive score that it degrades the performance.
- Identify poorly performing sub-detectors and target for development.



ARICH, TOP and SVD($p > 1\text{GeV}$) degrade electron-pion separation!

Calibration

- Over/under confident sub-detectors degrade the particle ID performance.
- Introduce per sub-detector, per hypothesis weights ($w_{h,\text{Det}}$):

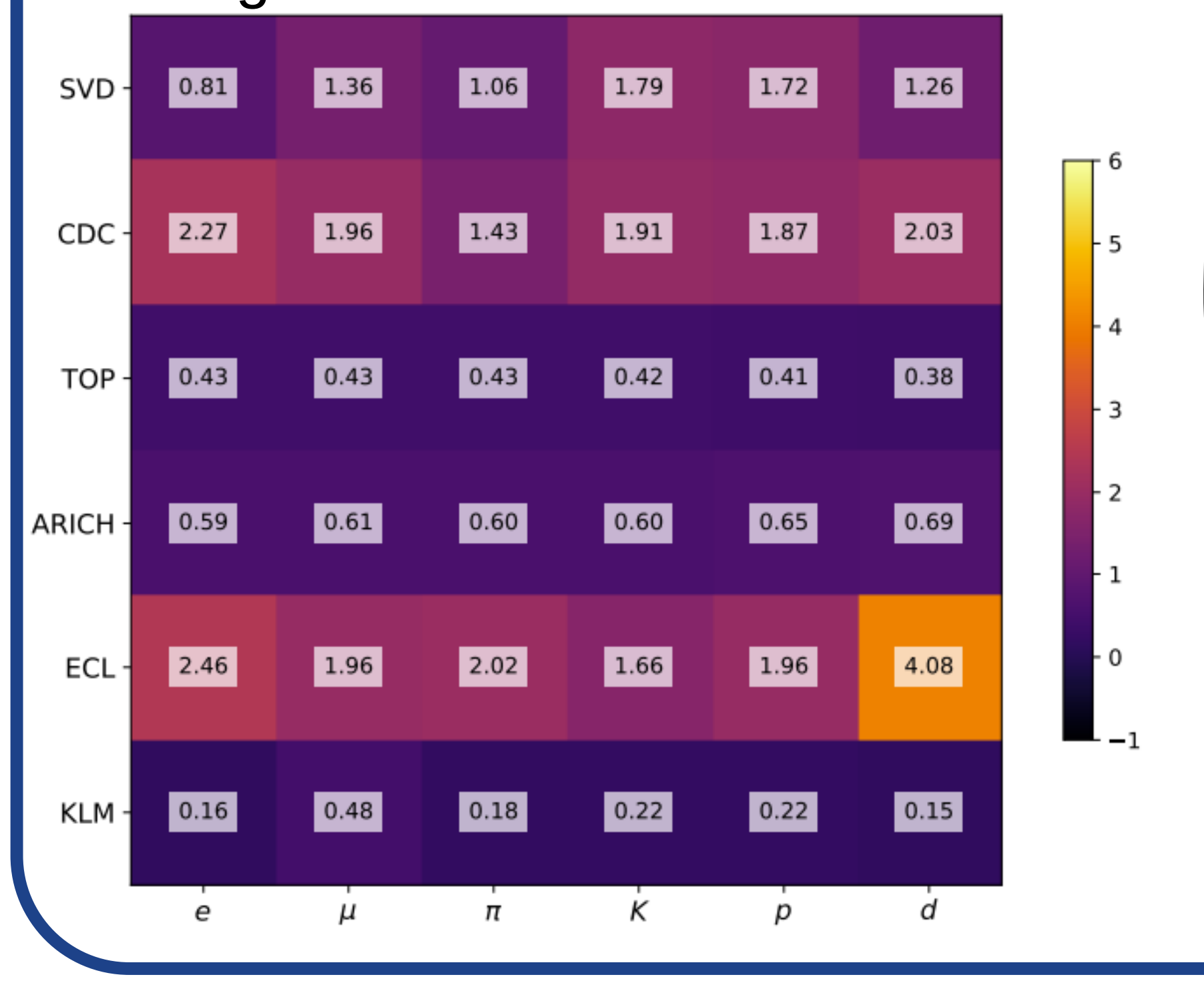
$$\log \mathcal{L}_h \rightarrow \log \tilde{\mathcal{L}}_h = \sum_{\text{Det}} w_{h,\text{Det}} \log \mathcal{L}_{h,\text{Det}}$$

- Weights are obtained with a neural network (TORCH), optimized to minimize:

True label Prediction

$$\text{Loss}(\hat{y}, y) = \text{CrossEntropy}(\hat{y}, y) + \beta \text{BinaryCrossEntropy}(\hat{y}_\pi, y_\pi)$$

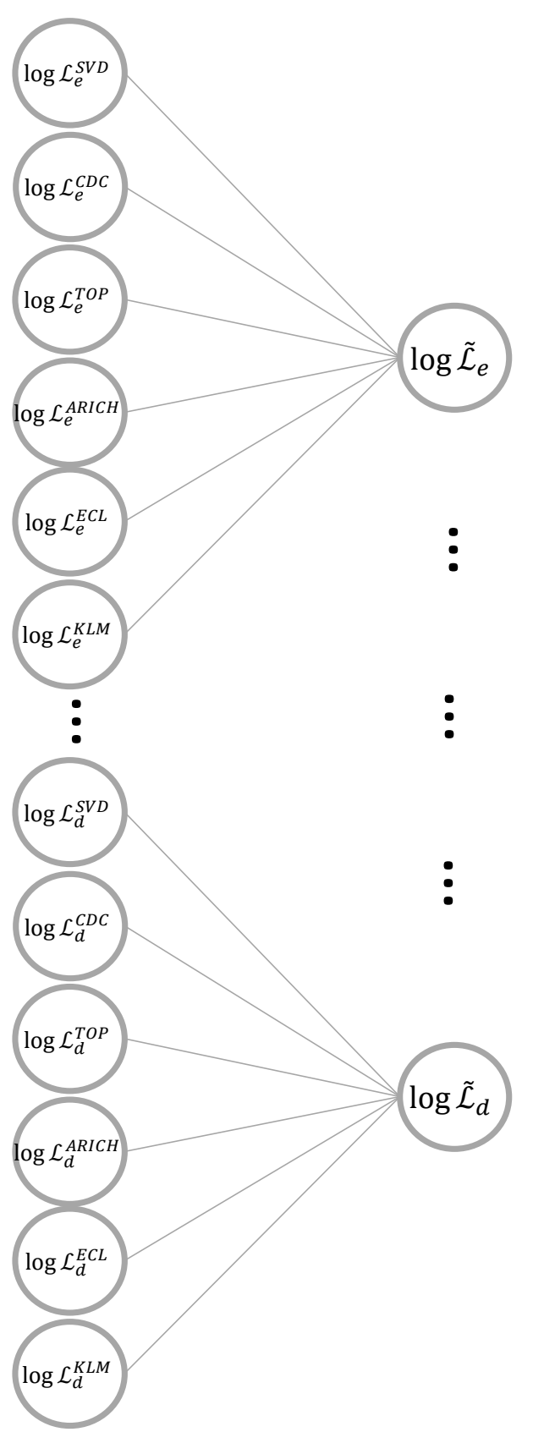
Weight Matrix



	e	μ	π	K	p	d
SVD	0.81	1.36	1.06	1.79	1.72	1.26
CDC	2.27	1.96	1.43	1.91	1.87	2.03
TOP	0.43	0.43	0.43	0.42	0.41	0.38
ARICH	0.59	0.61	0.60	0.60	0.65	0.69
ECL	2.46	1.96	2.02	1.66	1.96	4.08
KLM	0.16	0.48	0.18	0.22	0.22	0.15

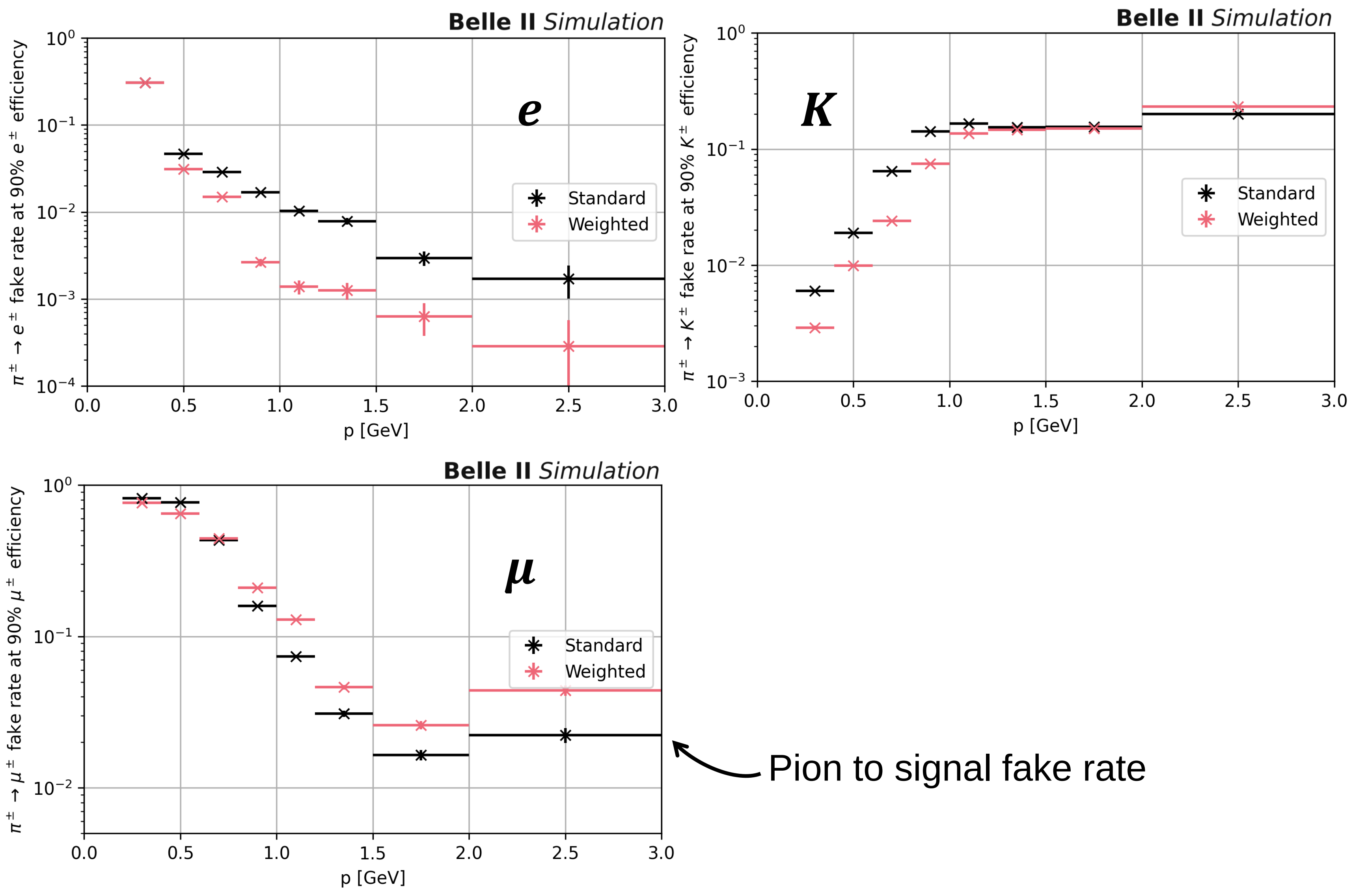
Pions are the most abundant particle species.

Add a pion specific loss to maintain low pion fake rates, $\beta = 0.1$.



Validation

- Validation studies on simulated $B\overline{B}$ decays.
- Busy environment – test performance and ability to generalize onto physics samples.

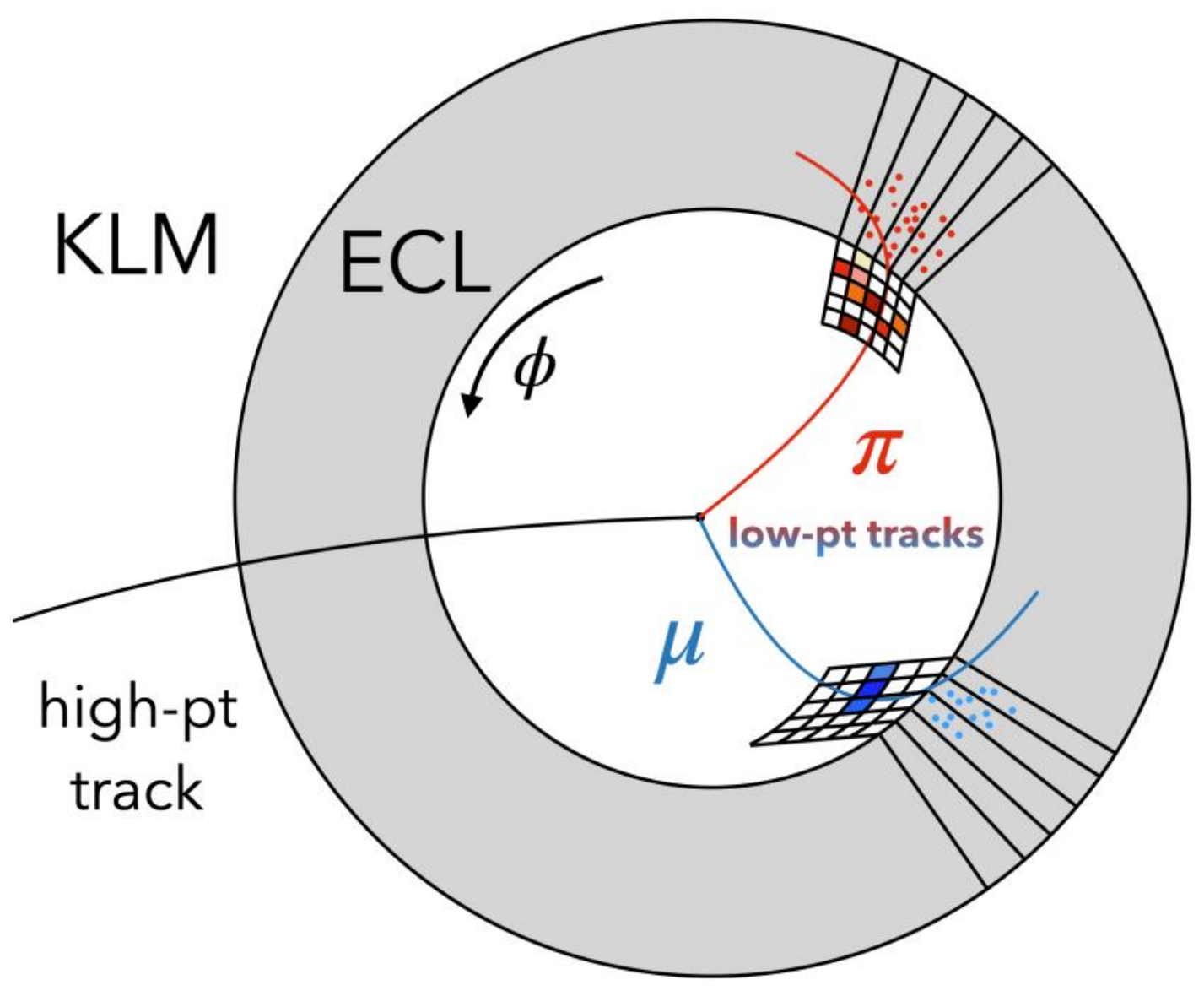


Pion to signal fake rate

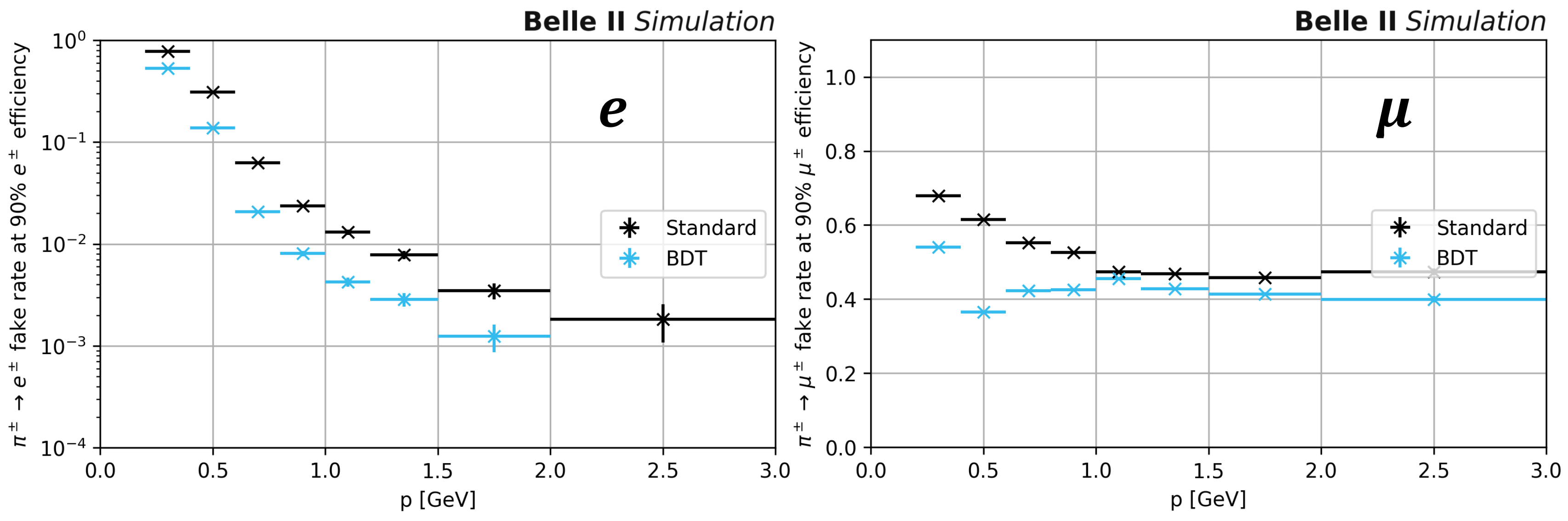
- Simple global calibration weights significantly improve $e^\pm/\pi^\pm$ and $K^\pm/\pi^\pm$ separation at a cost of degraded $\mu^\pm/\pi^\pm$ separation.

Improving the Likelihoods

- Constant development to improve likelihood definitions for both calibration and performance.
- Lepton identification relies on ECL likelihoods based on E/p distributions – powerful variable at high momentum however the separation ability degrades at low momentum.



- The shape of energy depositions differs for each particle species. This can be exploited for additional separation power.
- Expand on the scheme of [1]. Train boosted decision trees in 18 (p, θ, q) regions on simulated single particle samples considering E/p, high level shower shape variables (Zernike moments, …) and per crystal quantities. Convert BDT response to likelihood to integrate into global likelihood scheme.
- Reduces $\pi \to e$, $\pi \to \mu$ fake rates for *ECL only* identification by 55% and 31% respectively at low momentum ($< 1.0\text{GeV}$) for $B\overline{B}$ samples.



- Ongoing development to complement human engineered shower shape variables to machine learned variables via convolutional neural networks [2].

Conclusion

- Simple calibration weights improve the performance of the Belle II global likelihood scheme for charged particle identification.
- Weights trained on simulated single particle samples are generalizable to complex $B\overline{B}$ environments.
- Inclusion of shower shape describing variables into ECL likelihoods via boosted decision trees significantly improves lepton – hadron separation.

References: 1: 10.1051/epjconf/202024506023, 2: docs.belle2.org/record/2890