



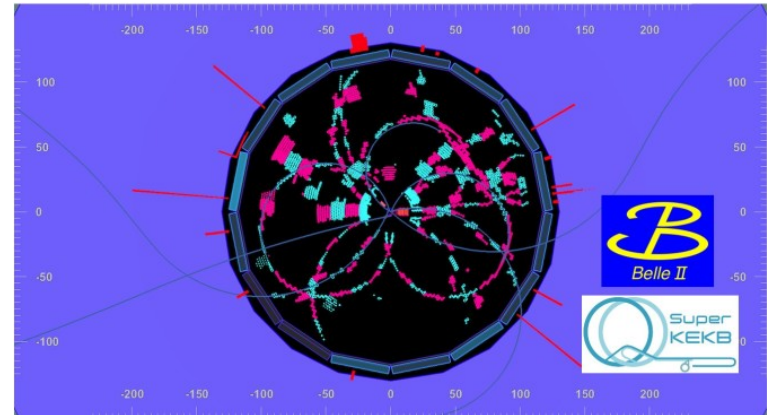
B decays reconstruction at Belle II using Graph Neural Networks

IN2P3/IRFU Machine Learning workshop - 28/09/2022

Jacopo Cerasoli
CNRS - IPHC

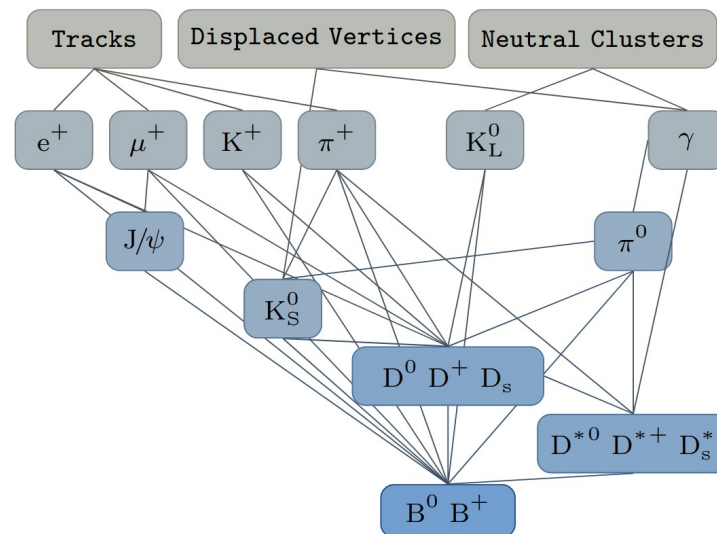
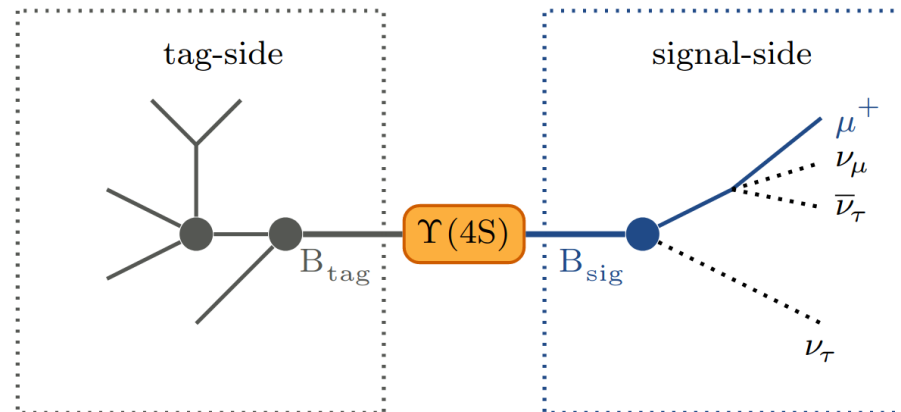
Belle II [\[arXiv:1011.0352\]](https://arxiv.org/abs/1011.0352)

- **Multi-purpose detector @ SuperKEKB** accelerator
- Collisions at center-of-mass energy of 10.58 GeV
 - $\sigma(e^+e^- \rightarrow \Upsilon(4S)) \sim 1 \text{ nb}$
 - $\mathcal{B}(\Upsilon(4S) \rightarrow B\bar{B}) \gtrsim 96\%$
- **Will collect 50 ab^{-1}** at the end of operation (now $\sim 430 \text{ fb}^{-1}$)
- Instantaneous luminosity world record: $4.7 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ (June 2022)
- **Important complementarity with LHCb**
 - Independent checks if new physics discovered



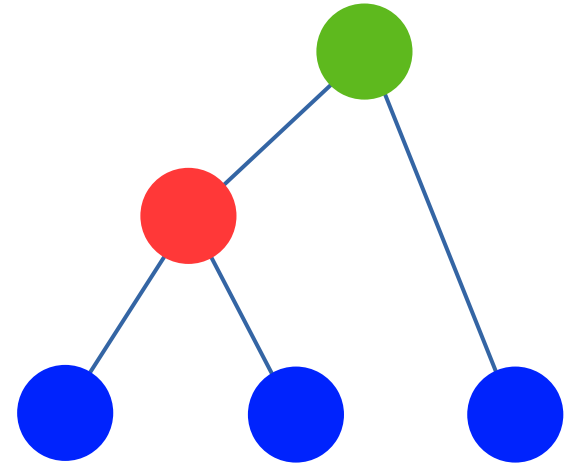
Full Event Interpretation [\[arXiv:1807.08680\]](https://arxiv.org/abs/1807.08680)

- Interested in **final states with neutrinos**
 - Reconstruct *tag-side* to constrain the kinematics
- Present solution: **Full Event Interpretation (FEI)**
 - Hierarchical approach based on BDTs
 - B reconstructed in **more than 10k modes!**
 - Overall reconstruction efficiency $\mathcal{O}(1\%)$
 - Output of final stage interpreted as “B probability”
 - **Cons:** decay modes hard-coded, $\sim 85\%$ B decays not considered



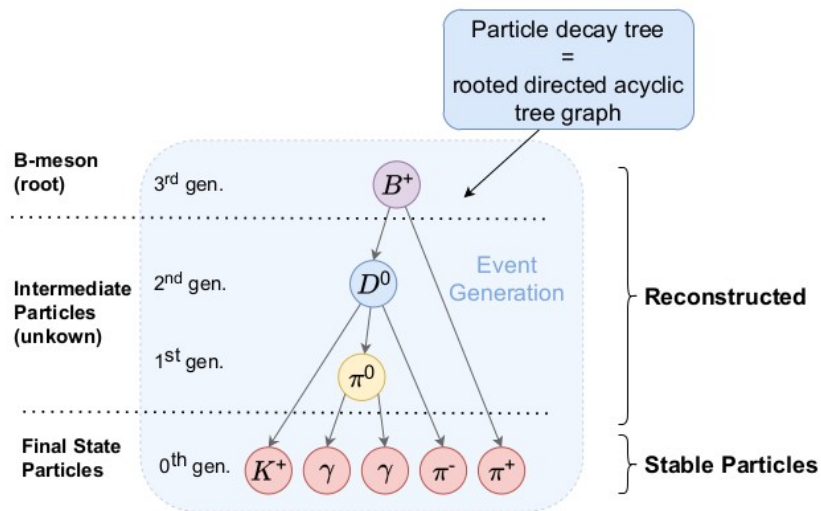
B reconstruction using Graph Neural Networks

- **Particle decays are naturally described by tree graphs**
- Goal: develop **graph-based Full Event Interpretation (graFEI)**



- Today's menu:
 - Proof of concept: *Learning tree structures from leaves for particle decay reconstruction*, James Kahn et al 2022 [[arXiv:2208.14924](https://arxiv.org/abs/2208.14924)]
(see also [Ilias Tsaklidis](#)' and [Lea Reuter](#)'s master theses)
 - First (preliminary) results on Belle II simulated dataset (see also [Arthur Thaller's talk](#))

Lowest Common Ancestor (LCA) matrix



Adjacency Matrix

	B^+	D^0	π^0	K^+	γ	γ	π^-	π^+
B^+	0	1	0	0	0	0	0	1
D^0	1	0	1	1	0	0	1	0
π^0	0	1	0	0	1	1	0	0
K^+	0	1	0	0	0	0	0	0
γ	0	0	1	0	0	0	0	0
γ	0	0	1	0	0	0	0	0
π^-	0	1	0	0	0	0	0	0
π^+	1	0	0	0	0	0	0	0

Lowest Common Ancestor (LCA) Matrix



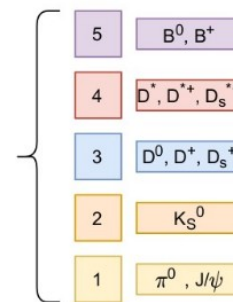
	K^+	γ	γ	π^-	π^+
K^+	K^+	D^0	D^0	D^0	B^+
γ	D^0	γ	π^0	D^0	B^+
γ	D^0	π^0	γ	D^0	B^+
π^-	D^0	D^0	D^0	π^-	B^+
π^+	B^+	B^+	B^+	B^+	π^+

LCAG

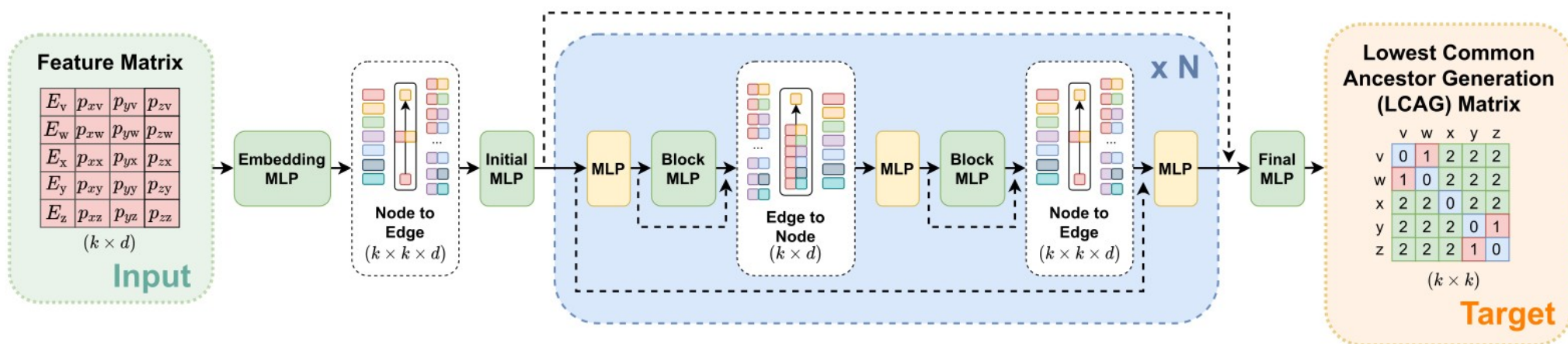
	K^+	γ	γ	π^-	π^+
K^+	0	2	2	2	3
γ	2	0	1	2	3
γ	2	1	0	2	3
π^-	2	2	2	0	3
π^+	3	3	3	3	0

LCAS

	K^+	γ	γ	π^-	π^+
K^+	0	3	3	3	5
γ	3	0	1	3	5
γ	3	1	0	3	5
π^-	3	3	3	0	5
π^+	5	5	5	5	0



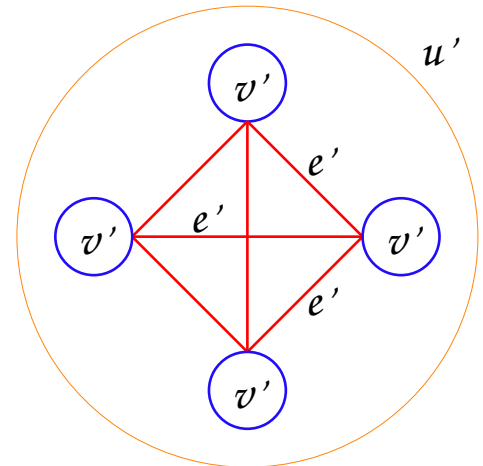
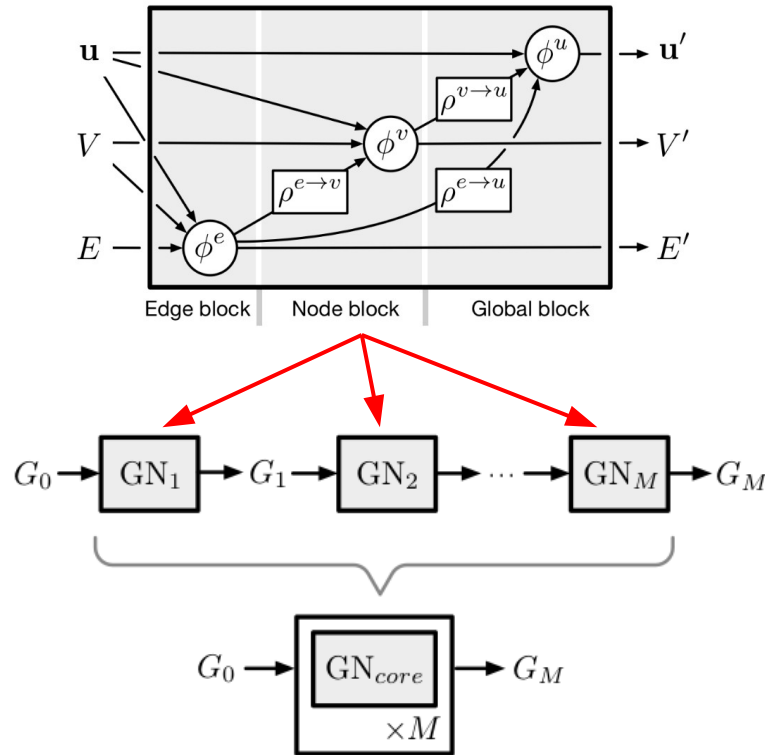
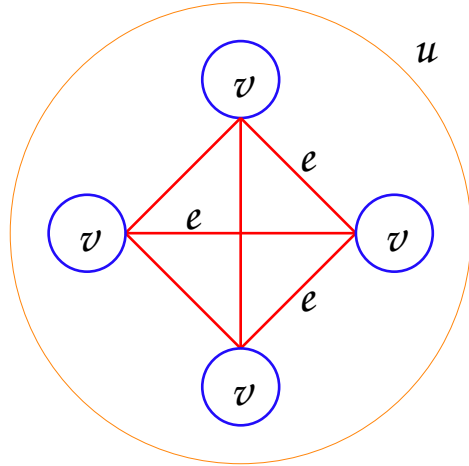
graFEI on Phasespace dataset [\[arXiv:2208.14924\]](https://arxiv.org/abs/2208.14924)



- Neural Relational Inference (NRI) model [\[arXiv:1802.04687\]](https://arxiv.org/abs/1802.04687)
- Dataset generated with Phasespace library
- 4-momentum used as input feature
- Average 47.7 % perfectly predicted LCAG on Phasespace dataset (60.9 % for decays with up to 10 leaves, 94.2 % up to 6 leaves)

GraFEI on Belle II simulated dataset – Graph network block

- “Geometric” graph neural network [[arXiv:1806.01261](https://arxiv.org/abs/1806.01261)]
- Input graph is transformed with series of GN blocks, output graph has same structure with updated values

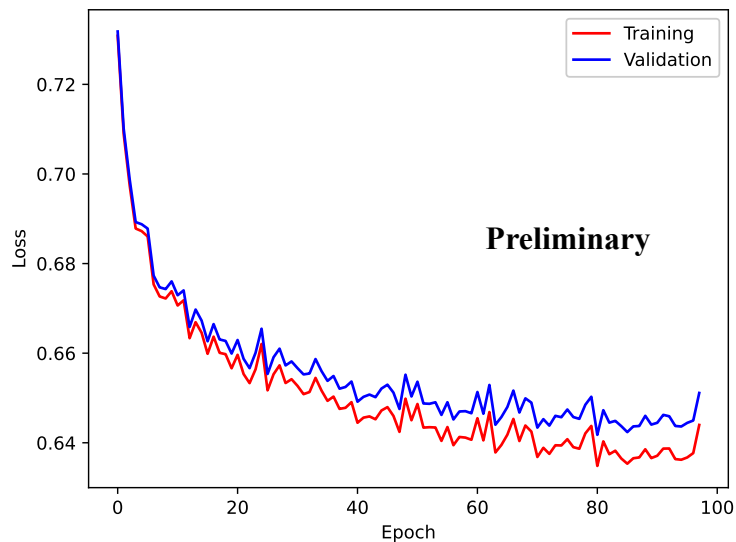


$$\begin{aligned}
 \mathbf{e}'_k &= \phi^e(\mathbf{e}_k, \mathbf{v}_{r_k}, \mathbf{v}_{s_k}, \mathbf{u}) & \bar{\mathbf{e}}'_i &= \rho^{e \rightarrow v}(E'_i) \\
 \mathbf{v}'_i &= \phi^v(\bar{\mathbf{e}}'_i, \mathbf{v}_i, \mathbf{u}) & \bar{\mathbf{e}}' &= \rho^{e \rightarrow u}(E') \\
 \mathbf{u}' &= \phi^u(\bar{\mathbf{e}}', \bar{\mathbf{v}}', \mathbf{u}) & \bar{\mathbf{v}}' &= \rho^{v \rightarrow u}(V')
 \end{aligned}$$

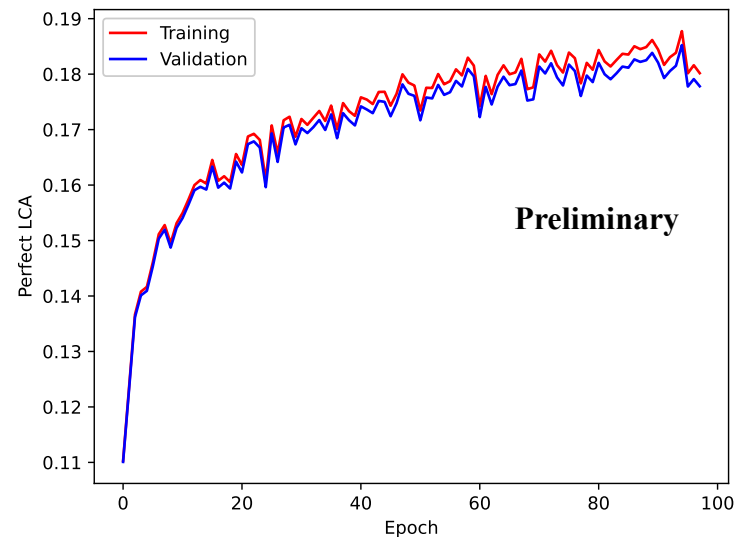
GraFEI on Belle II simulated dataset – Training

- Training done with monogeneric $\Upsilon(4S) \rightarrow B^0(\rightarrow \nu\nu)\bar{B}^0(\rightarrow X)$ simulated Belle II sample
 - Node-level features: particle IDs, 4-momentum, M, charge, impact parameter, photon cluster features
 - Edge-level feature: angle between pairs of particles' momenta
 - Global feature: number of leaves (i.e. final state particles)

$$\text{Cross-entropy} = -\frac{1}{N} \sum_i \log \frac{e^{x_{i,y_n}}}{\sum_c e^{x_{i,y_c}}}$$



$$\text{Perfect LCA} = \frac{\text{Perfectly predicted LCAs}}{\text{Total predicted LCAs}}$$

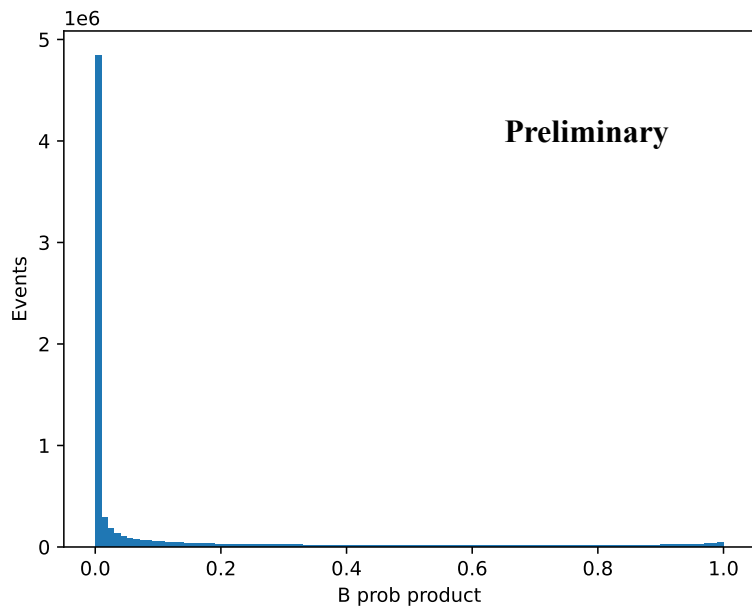


Max perfect LCA = 18.6 % (epoch 94)

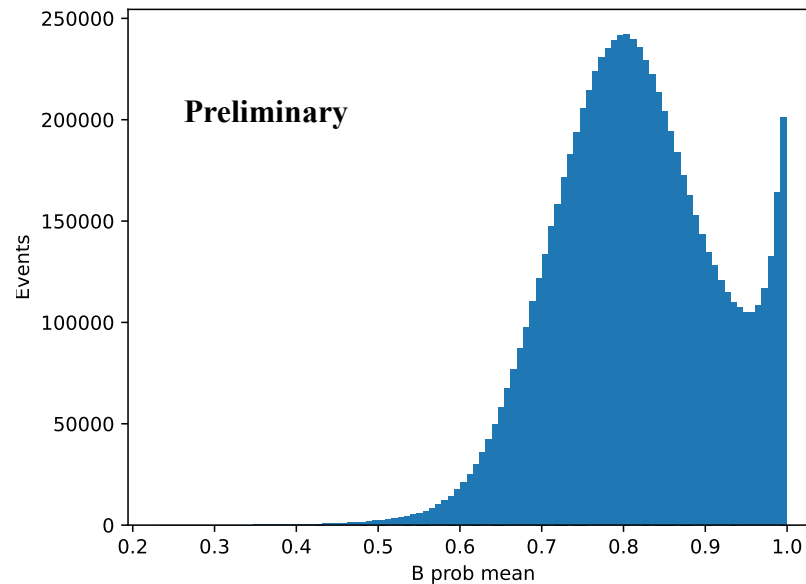
GraFEI on Belle II simulated dataset – B probability

- Having a **definition of “B probability”** analogous to FEI is desirable
 - Each LCA element has corresponding probability of belonging to the predicted class

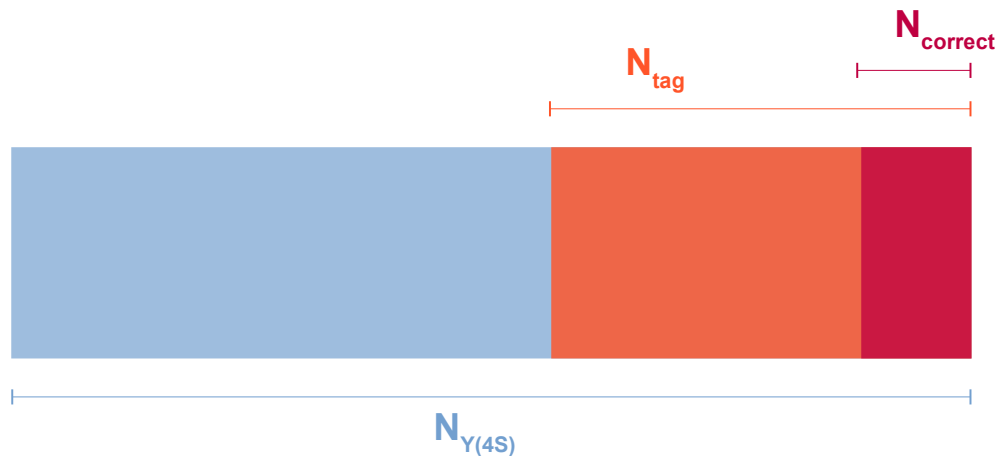
Product of class probabilities



Arithmetic mean of class probabilities



GraFEI on Belle II simulated dataset – Comparison with FEI



- **Tag-side efficiency** = $N_{correct} / N_{Y(4S)}$
- **Purity** = $N_{correct} / N_{tag}$

	FEI	graFEI
N_{tag}	# Events reconstructed	# Events with valid tree
$N_{correct}$	# Correctly reconstructed events*	# Events with perfectly predicted LCAS

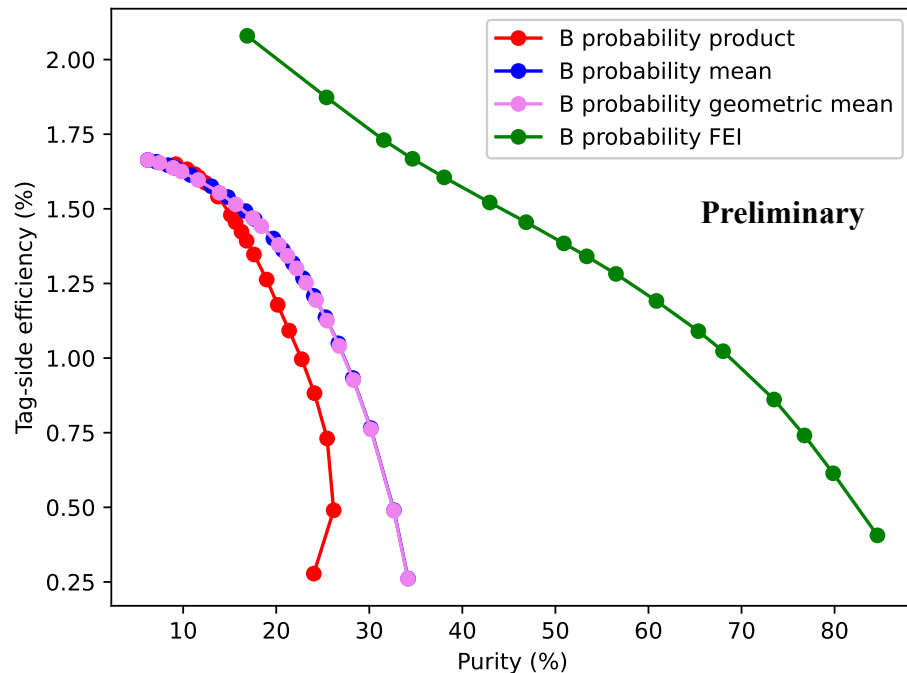
- *graFEI does not make predictions on masses of final state particles, so truth-matching criteria are relaxed accordingly

GraFEI on Belle II simulated dataset – Comparison with FEI

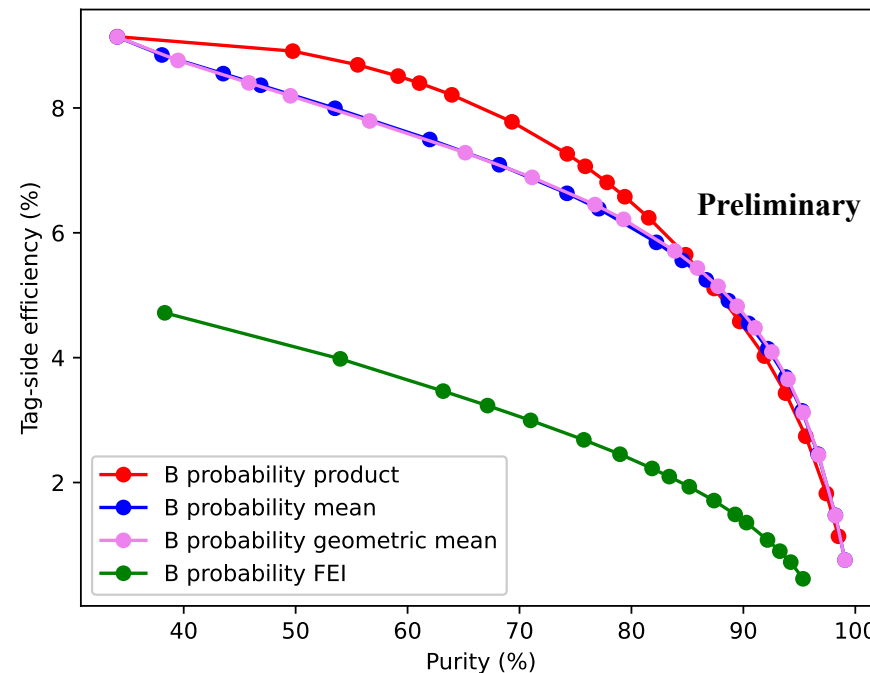
- First evaluation of the **performances on $\Upsilon(4S) \rightarrow B^0(\rightarrow \nu\nu)\bar{B}^0(\rightarrow X)$ MC signal**
- Once tag side is reconstructed, events with no extra tracks are selected

$$\text{Tag-side efficiency} = N_{\text{correct}} / N_{\Upsilon(4S)}$$

$$\text{Purity} = N_{\text{correct}} / N_{\text{tag}}$$



FEI outperforms graFEI when all the final state particles are reconstructed



graFEI outperforms FEI when some final state particles might be missing

Future prospects

- Short-term plans:

- **Investigate performances including background MC**

- **Make predictions on B momentum:** $\text{Loss} = -\frac{1}{N} \sum_i \log \frac{e^{x_{i,y_n}}}{\sum_c e^{x_{i,y_c}}} + \alpha \|\vec{p} - \vec{p}_{\text{true}}\|^2$

- **Make prediction on masses of final state particles?**

- Longer-term plans:

- Optimization of various aspects of the algorithm (input variables, hyper-parameters, architecture, ...)

- Full reconstruction of Y(4S) decay?

- ...

Stay tuned!

BACKUP

Hyper-parameters

- NRI:
 - Dropout rate = 0.3
 - Batch size = 128
 - Learning rate = 0.001
 - Feed-forward width = 2048
 - Number hidden layers = 1
 - Additional initial/final layers = 0
 - Number of blocks = 1
- graFEI:
 - Dropout rate = 0.3
 - Batch size = 128
 - Learning rate = 0.001
 - Feed-forward width = 512
 - Number hidden layers = 1
 - Number of ML = 1

GraFEI on Belle II simulated dataset – Lost particles

