Karlsruhe Institute of Technology

# Particle Decay Tree Reconstruction with Graph Neural Networks

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## Neural Network approach to Event Reconstruction

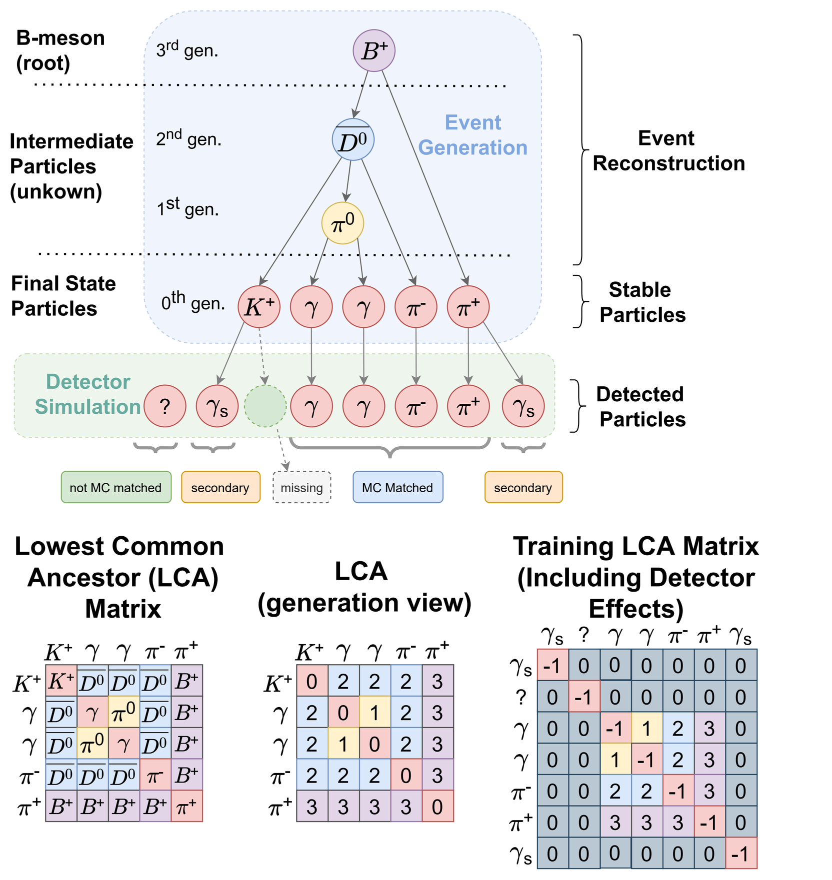
### Challenges of Event Reconstruction

Heavy particles produced in collisions decay rapidly until stable daughter particles can reach the detector

- Particles can escape the detector undetected and particle reconstruction is imperfect
  → **can only use detected particles**
- Large amount of possible decay channels leads to **unknown number of intermediate particles** and an **unknown tree structure**
- different multiplicities in event decays
  → network must handle a **variable number of particles**

**Have to predict tree structure using only detected particles**

Propose **new method** applicable for **event tagging** by reconstructing the tag side

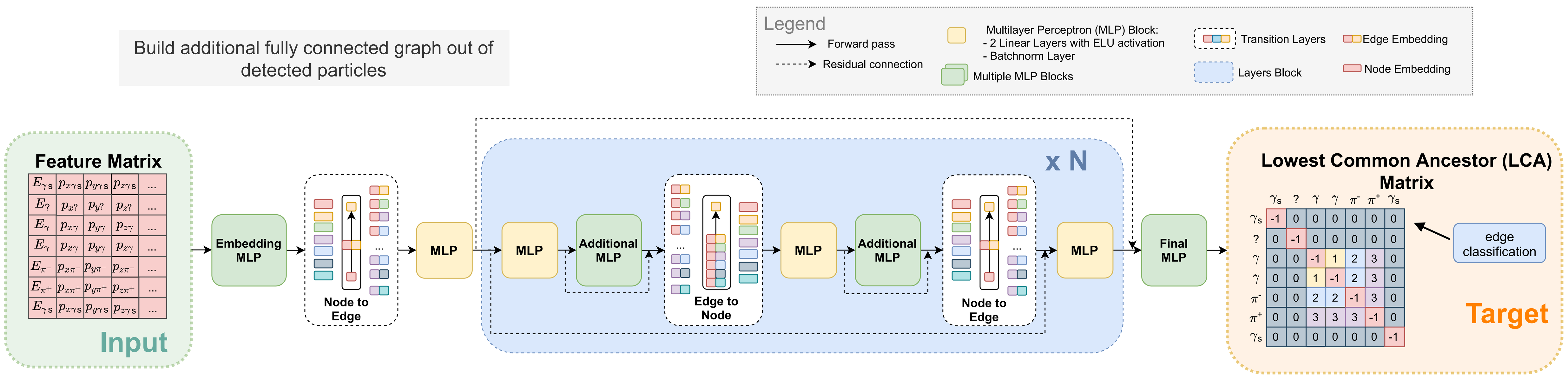



### Encoding the Particle Decay Tree

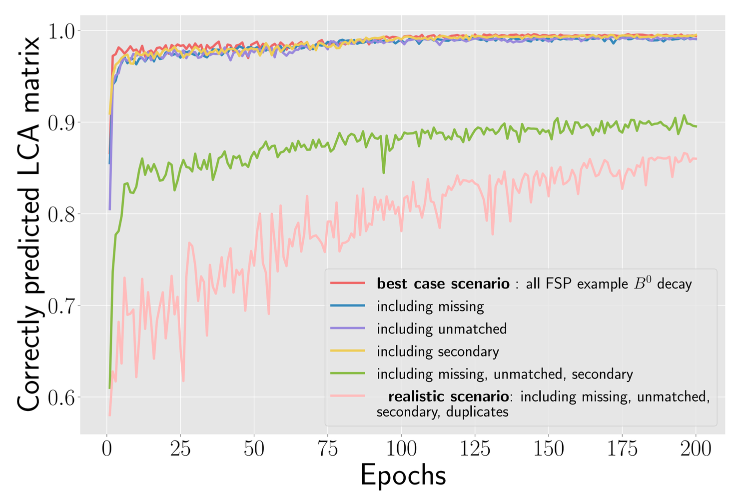
- The natural representation of a particle decay tree is a **rooted, directed, acyclic tree graph**
- Use **lowest common ancestor (LCA)** matrix representation to encode graph structure as **final state particle (FSP) relations**
  - any two detected particles connected via lowest common parent
  - intermediate particles assigned classes corresponding to generation
- LCA extracted from event generation and detector simulation, use as **single target** for training neural network
  - used **Belle II simulated datasets** [1] for benchmark studies

## Neural Relational Inference (NRI) encoder model

- Utilise Graph Neural Network based on modified encoder from the NRI [2]
- Input the kinematic features of detected particles
- Predict the LCA as edge-weights between fully connected graph of input particles



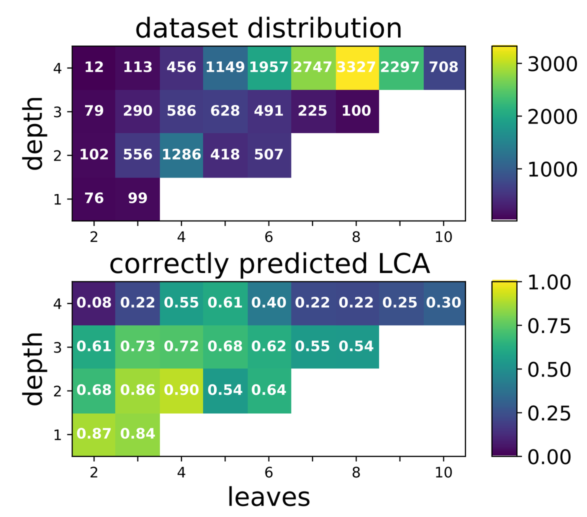

## Proof of concept on single Belle II simulated decay




Training on decay:
$B^0 \to D^{*-}(\to \overline{D}^0(\to K^+\pi^-)\pi^-)\pi^+$
with different background levels caused by detector effects

- Scaling of performance based on background levels
- Predictive capacity of 86.6% for realistic case

## Mixed Dataset of Belle II simulated decays




Trained on a mix of six decay channels (incl. missing particles)

- correctly predicted LCA matrix 43.2% compared to 31.8% on transformer model baseline [3]
- achieves high accuracy (correctly predicted LCA entries) of 85.6% for different decay topologies

## Conclusion and Outlook

We have demonstrated a **novel approach** to deal with scenarios where the **structure of the rooted tree graph representing a particle decay is unknown**. Namely, we implemented a method of **encoding the entire decay tree structure** into a **single matrix** which relies on minimal assumptions about the intermediate particles. This method allows for training on the entire decay structure as a **single training target**.
This method was tested on Belle II simulated data on

- a single decay study including various detector effects, showing that the approach is suitable for experimental realities
- a mix of different decay channels

Current work is demonstrating decay tree reconstruction on all Belle II simulated decays and comparing with the existing reconstruction algorithm.

[1] Belle II software: Kuhr, T., Pulvermacher, C., Ritter, M., Hauth, T. and Braun, N. The Belle II Core Software. In *Computing and Software for Big Science*, vol. 3 no. 1 (2018).
[2] NRI Model: Kipf, T., Fetaya, E., Wang, K.-C., Welling, M. and Zemel, R. Neural Relational Inference for Interacting Systems. In *Proceedings of the 35th International Conference on Machine Learning (ICML '18)*, vol. 80 of *Proceedings of Machine Learning Research*, 2688–2697 (PMLR, 2018).
[3] Transformer Model: Vaswani, A.et al. Attention Is All You Need. In *Advances in Neural Information Processing Systems*, vol. 30 (Curran Associates, Inc., 2017).

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