Graph Neural Network with Attention and Two-Stage Aggregation for Particle Track Reconstruction in the TPC MPD of the NICA complex

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Motivation

One of the main challenges for the TPC MPD at the NICA accelerator complex, under the extremely high interaction frequency reaching megahertz levels, which significantly increases the volume of data recorded by detectors, is the reconstruction of particle tracks. To address this issue, we developed a Graph Neural Network (GNN) with an attention mechanism and two-stage aggregation for particle track reconstruction in the TPC MPD of the NICA.

GNN model & Dataset

The architecture of the proposed GNN model has six main components (see Figure 1):

- Node and edge encoders designed as MLPs, which transform the input node and edge features into their latent representations (embeddings);
- Initial edge classifier designed as an MLP, which predicts edge labels at the beginning of event evaluation;
- Graph attentional convolution layer designed as a convolutional layer, which aggregates the embeddings of surrounding nodes and corresponding edges connecting to a certain node using the current edge labels as attentional coefficients;
- Updater of edge embeddings designed as an MLP, which utilizes new node embeddings, previous edge labels and embeddings to obtain new edge embeddings;
- Edge classifier designed as an MLP, which predicts edge labels using new node and edge embeddings.

We utilized a dataset that includes 1000 events of mean-bias Au-Au collisions obtained using MPDRoot to train and test our GNN. This dataset stores 3D points of hits produced by particles in each event and data linking hits associated with the same track. The transverse momenta p_t of particles are included to label the data by track curvature, that allows excluding particles with spiral tracks (p_t < 150 MeV) from the training process.

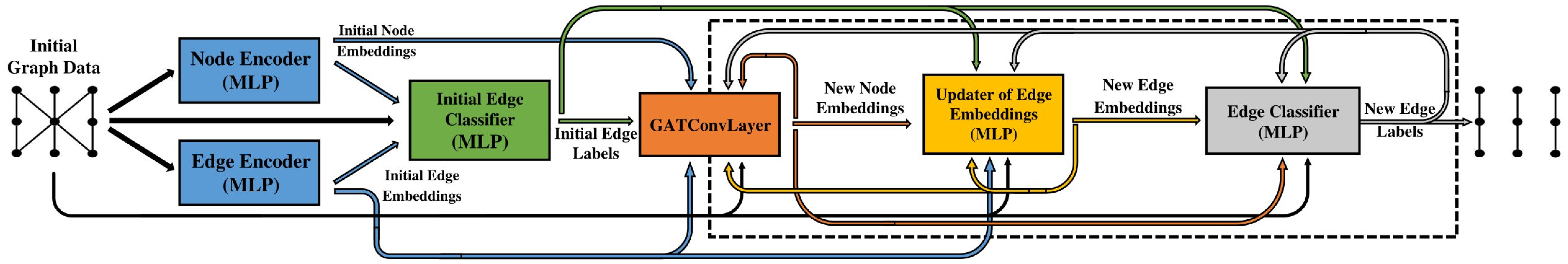

Figure 1. The Graph Neural Network architecture.

Results and discussion

We demonstrate that our GNN achieves high performance in edge classification.

- The dependencies of efficiency and purity on the model score are presented in Fig. 2a. Both the efficiency and purity metrics reach 92.6% at the parity point.
- The distributions of true and false edge scores predicted by the GNN are shown in Fig. 2b. The true edges exhibit a pronounced peak at high model scores (0.9–1.0), while the false edges dominate in the lower score range (0.0–0.1), with minimal overlap between the two distributions. A minor peak around 0.6 is attributed to the edges of tracks with p_t around 150 MeV, where the separation becomes ambiguous.
- The dependence of the track reconstruction efficiency on the integrity threshold is presented in Fig. 2c. The efficiency decreases monotonically with increasing the integrity threshold, maintaining values above 90% for integrities below 80%. For integrities above 80%, the efficiency strongly drops up to 48%.

The reconstruction result obtained using the GNN model for an event with particle tracks projected onto the *xy*-plane is illustrated in Fig. 3

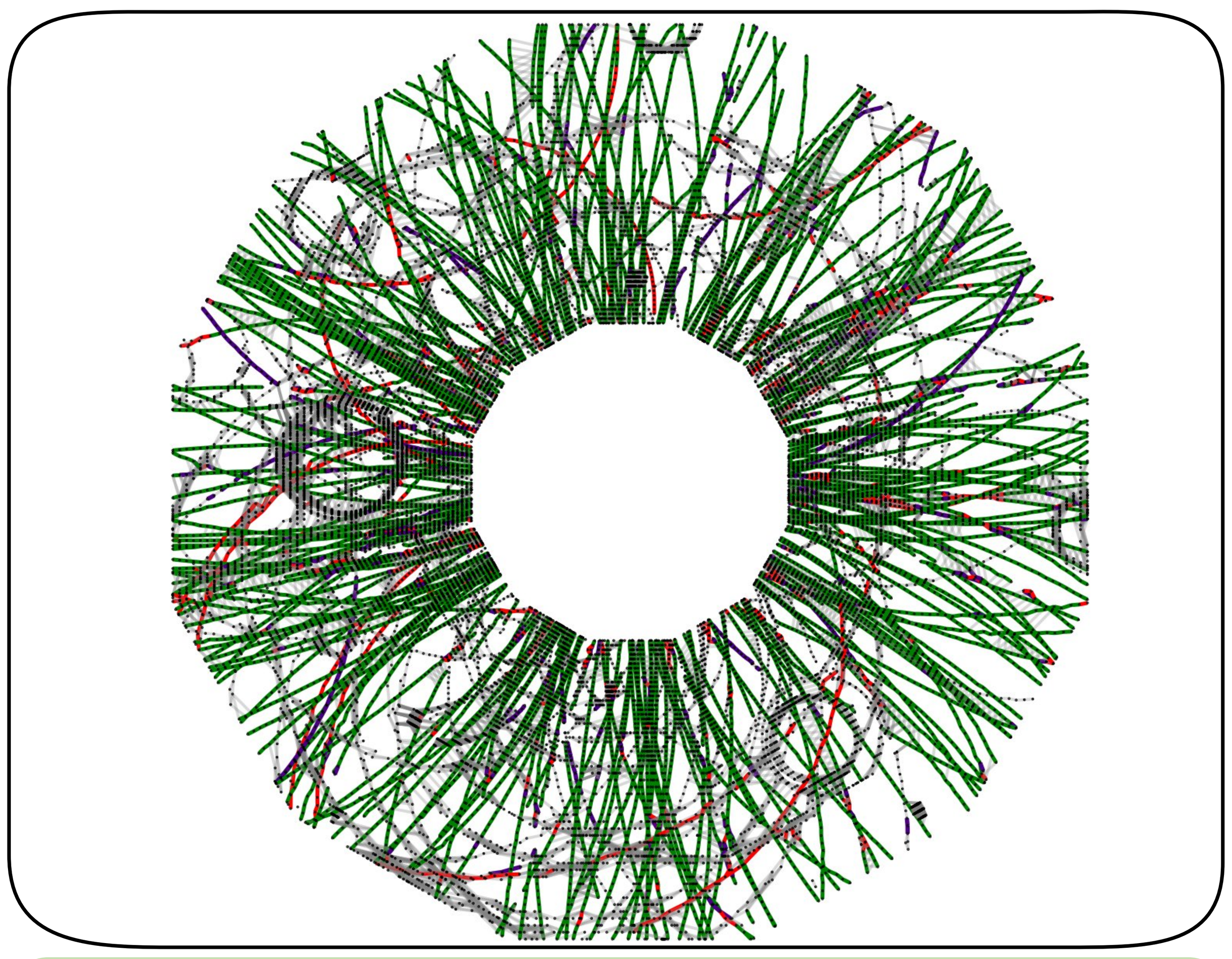

Figure 3. Example of track reconstruction results obtained using the GNN model and projected onto the *xy*-plane. The green and purple lines are true and false positive track segments, respectively; the gray and red lines are true and false negative track segments, respectively.

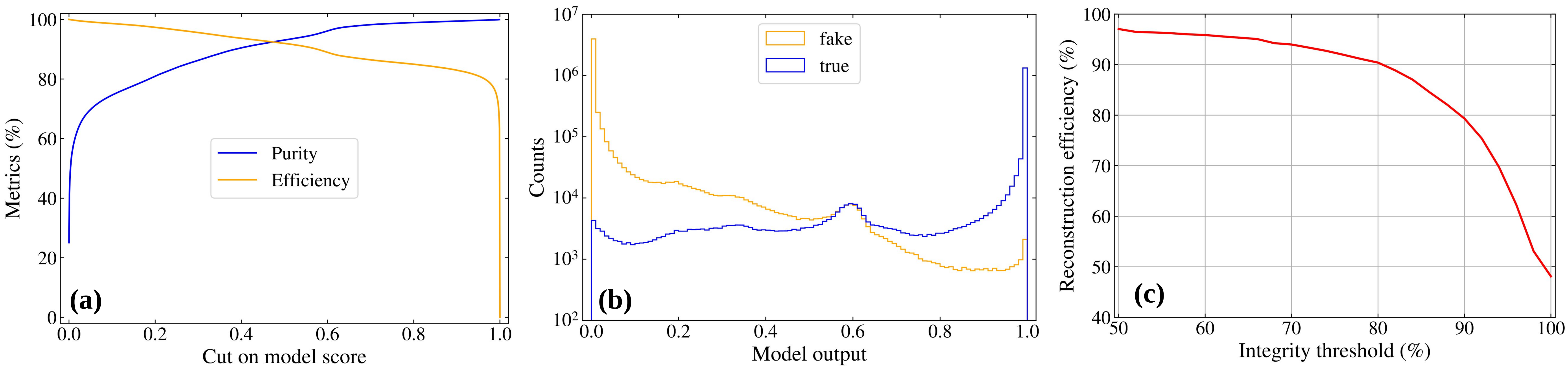

Figure 2. Training results: **(a)** Purity and efficiency of edge classification as functions of the cut value applied to the edge scores (also known as the model score). **(b)** Distributions of the edge scores predicted by the GNN for true and false edges. **(c)** Reconstruction efficiency of tracks of primary particles as a function of the integrity threshold.

Conclusions

- The model demonstrates high performance achieving an accuracy of 96.2% and an equal purity and efficiency of 92.6% in edge classification.
- The track reconstruction efficiency remains above 90% for track integrities below 80%, but decreases significantly for higher integrity requirements.
- The model achieves high efficiency in separating true and false edge labels, but exhibits minor overlap in the intermediate score range due to the ambiguous interpretation of edges from tracks with transverse momenta around 150 MeV.