HEP advanced tracking algorithms

Projects HEP.TrkX & Exa.TrkX

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HELMHOLTZ

DESY.

HEP.TrkX

pilot project to evaluate and broaden the range of computational techniques and algorithms utilized in addressing HEP tracking challenges

- https://heptrkx.github.io/

  “Novel deep learning methods for track reconstruction” S. Farrell et al. (Conneting the Dots CTD 2018 Proceedings)

- Investigation of RNNs and GNNs
- Conclusion
  - RNN method demonstrated a capability similar to today’s Kalman Filter algorithms
  - GNN methods most promising deep learning solution
- GNN
  - graph constructed by connecting plausibly-related hits using geometric constraints
    - Learn on this representation; solve tasks with predictions over graph nodes, edges or global state

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- GNN
  - Two applications:
    - Binary hit classification model: identify one track by classifying track nodes
    - Binary segment classification model: identify many tracks at once by classifying graph edges (i.e. hit pairs)
    - Input: node features (3D hit coordinates) and connectivity specification

- GNN architecture

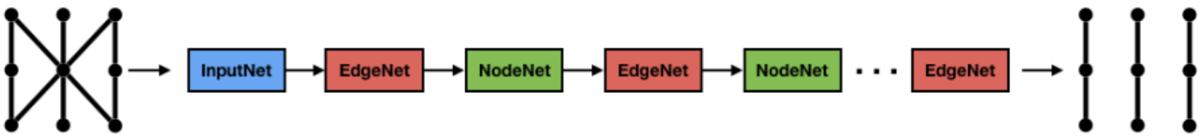

Figure 9. Diagram of the Graph Neural Network model which begins with an input transformation layer and has a number of recurrent iterations of alternating EdgeNetwork and NodeNetwork components. In this case, the final output layer is the EdgeNetwork, making this a segment classifier model.

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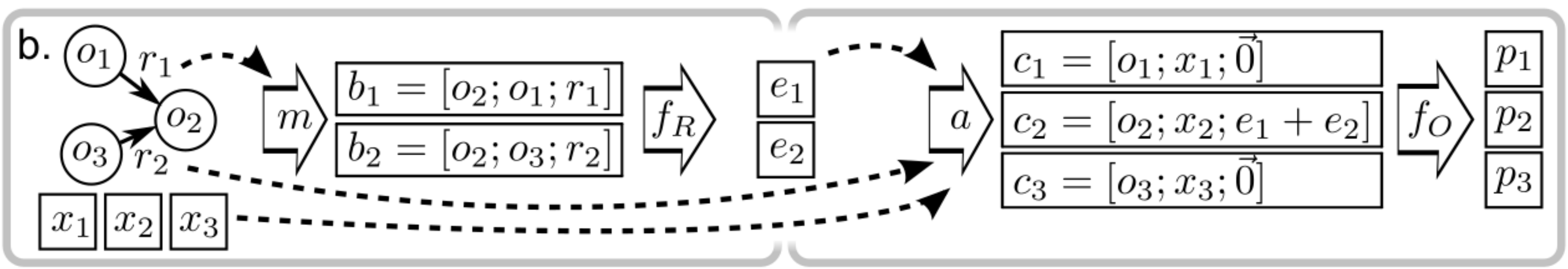
- GNN architecture
  - Both implemented as Multi-layer perceptrons with two layers each and hyperbolic tangent hidden activations
  - Similar to Interaction Networks (P. Battaglia et al. 2016 „Interaction Networks for Learning about Objects, Relations and Physics“ https://arxiv.org/abs/1612.00222)



For more complex systems, the model takes as input a graph that represents a system of objects, o_j, and relations, $\langle i, j, r_k \rangle_k$, instantiates the pairwise interaction terms, b_k, and computes their effects, e_k, via a relational model, $f_R(\cdot)$. The e_k are then aggregated and combined with the o_j and external effects, x_j, to generate input (as c_j), for an object model, $f_O(\cdot)$, which predicts how the interactions and dynamics influence the objects, p.

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- GNN methods
  - Hit classification: specify three seed hits, graphs constructed by taking four hits on each detector layer in the region around the true track location, predict whether nodes belong to the target track or not
  - Segment classification: graphs constructed with geometric constraints, produce classification scores for every edge in the graph

Choma et al. 2020 and Exa.TrkX

Track Seeding and Labeling with Embedded-space Graph Neural Networks

Proceedings of CTD 2020

- Use a learned model Ψ, parametrized by θ, to map points x (3D hit coordinates and shape of energy deposited by charged particle) into a new Euclidean space E^d: $x \in \chi \rightarrow \Psi(\Theta, x) \in R^d$
- Ψ is implemented as multi-layer perceptron (MLP) and θ are the trained parameters in the MLP
- Construct the input Graph G_{in} with a neighbor search
  - knn or ε-neighborhood
- Sparsify the set of edges using an edge refinement model Ψ'
- GNN architecture

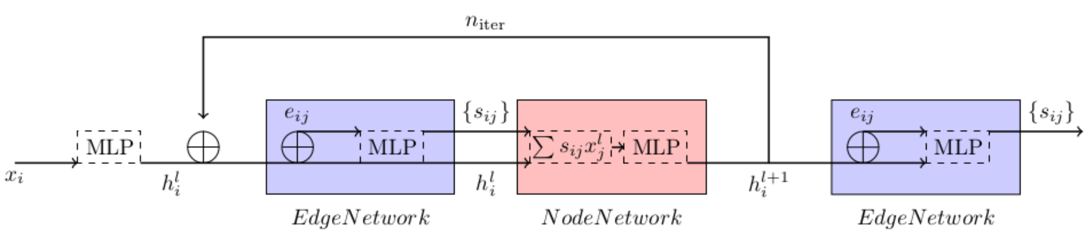

Figure 2: Recurrent Attention Message Passing Architecture

- Bayesian optimization performed over set of model hyperparameters in order to optimize both edge classification and purity

Choma et al. 2020 and Exa.TrkX

Track Seeding and Labeling with Embedded-space Graph Neural Networks

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- Classification of doublets and triplets (by identifying doublets as nodes in a new triplet graph)
- triplet GNN turned into a seeding algorithm

  → updated as fully-learned pipeline in "Performance of a geometric deep learning pipeline for HL-LHC particle tracking" Ju et al. 2021 (as part of Exa.TrkX https://exatrkx.github.io/)

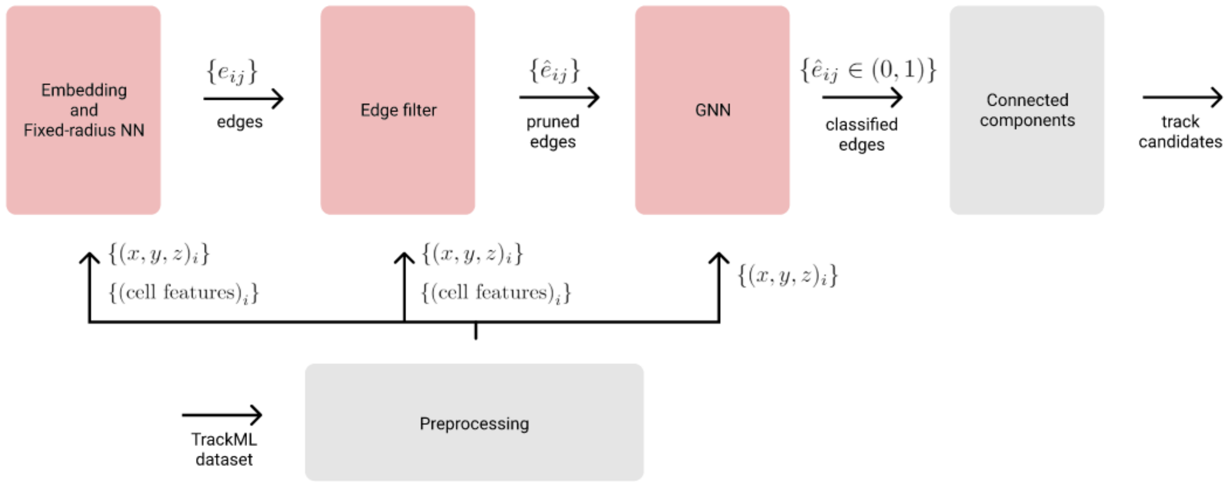

Fig. 4 Stages of the TrackML track formation inference pipeline. Light red boxes are trainable stages

- Scales linearly with number of space-points

Conclusion & future work

- Good performance on TrackML dataset
  - Collaboration with ATLAS, CMS, … to adapt the pipeline to each experiment and measure the performance and robustness
- Further studies on large scale training of GNNs
- Explore different optimization opportunities, e.g. multi-GPU training
- Measure the performance on domain-specific accelerators