ML-enabled End-to-End Tracking Reconstruction and Trigger Detection

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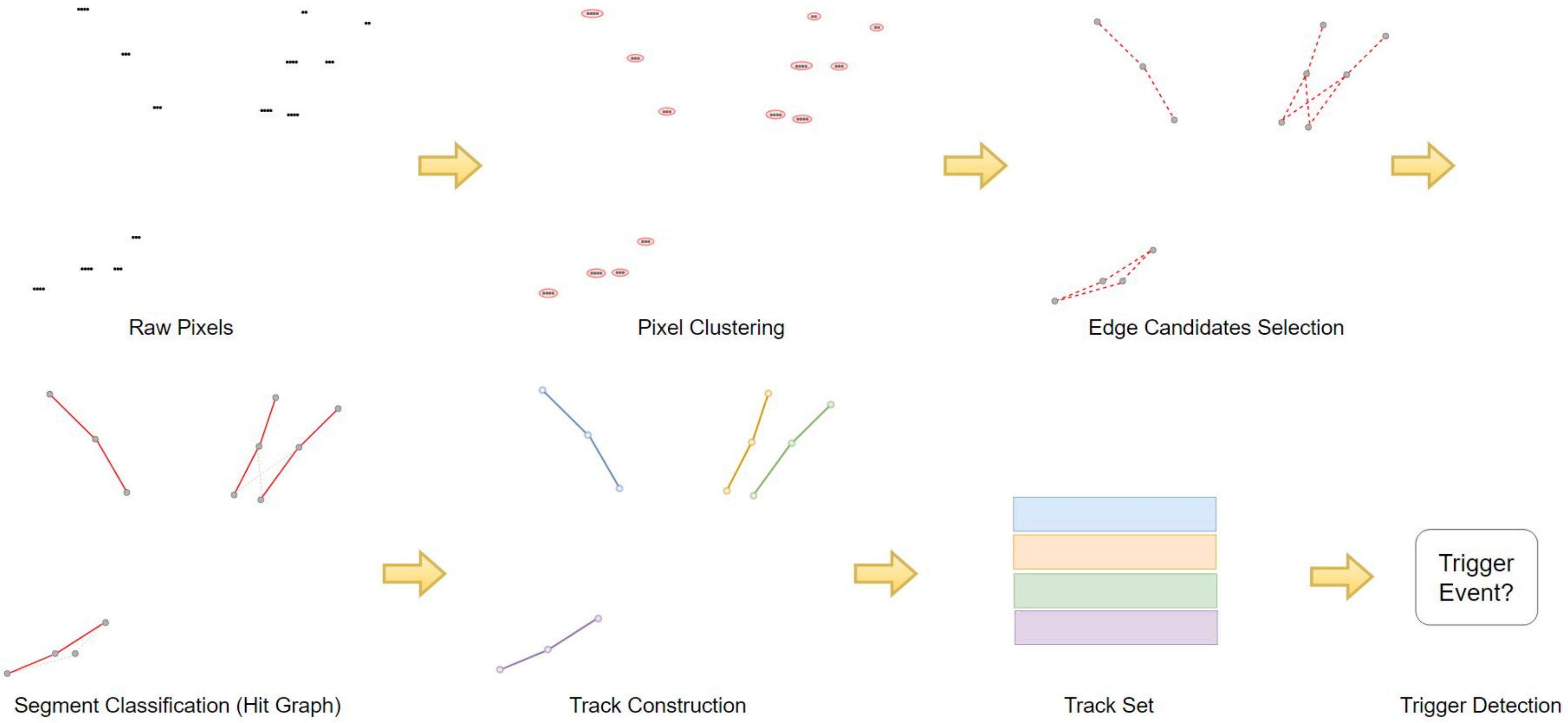
Problem Overview



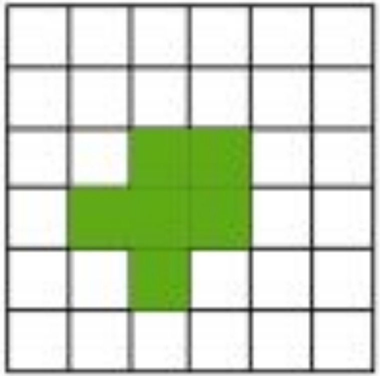
Overview

1. Problem Overview
2. Pixels ↦ Hits
3. Hits ↦ Tracks
4. Tracks ↦ Label
5. Remaining Challenges
6. Conclusion

Pixels $\mapsto$ Hits

Clustering

- Clustering is done by solving a spanning forest problem
- There is an edge between pixels that are adjacent to each other
- Mean of all pixels in a cluster is taken as the hit location
- Most time-consuming portion, we are developing a sparse CNN to perform faster clustering



Pixels on Detector

Hits $\mapsto$ Tracks

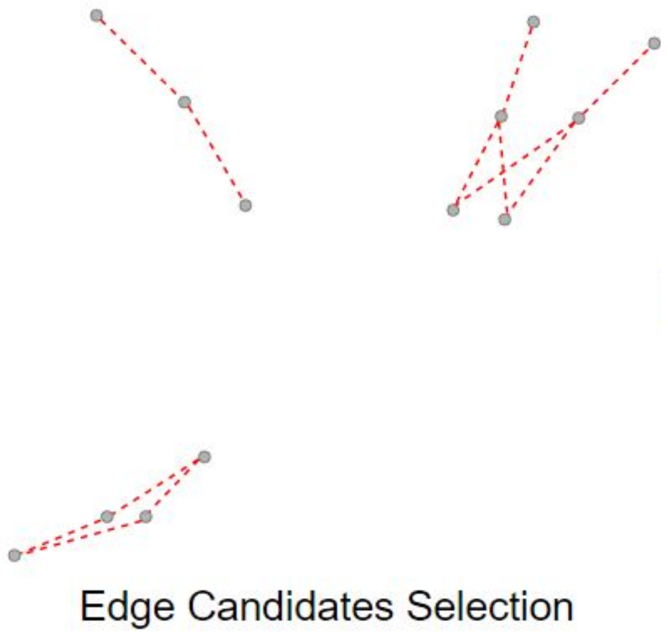
Problem Definition

- Once we have hits, we want to group hits that came from the same particle into a track
- This will be solved by treating the problem as an edge classification problem
- Out of the N^2 possible edges between the hits, we want to know the true edges.

Track Construction

Edge Candidate Selection

- Not all of the N^2 possible edges are plausible - we can eliminate a lot of edges from the get-go
- We can use some basic geometric constraints on the cylindrical coordinates of the hits
  - $|\Delta\varphi/\Delta r| <=$ PHI_SLOPE_MAX
  - $|z_0| <=$ Z_ORIGIN_MAX
  - $z_0 = z_1 - r\cdot(\Delta z/\Delta r)$
- The geometric constraints determine much of the latency and will play a vital role in further reducing the FPGA latency.



Neural Network Architecture

- Message passing architecture.
- Initialization:
  - $h_v^{(0)} = x_v \quad \forall v \in V$
  - $x_v = (r/3, \varphi, z/3, n_{\text{pixels in hit}}, \text{layer})$
- Message Creation:
  - $m_{u,v}^{(t)} = f_{\text{Message}}(h_u^{(t-1)}, h_v^{(t-1)})$
- Message Aggregation:
  - $a_v^{(t)} = (f_{\text{Agg}}(\{m_{u,v}^{(t)} : v \in N(u)\}), f_{\text{Agg}}(\{m_{v,u}^{(t)} : v \in N^{-1}(u)\}))$
- Node Update:
  - $h_v^{(t)} = f_{\text{Update}}(h_v^{(t-1)}, a_v^{(t)})$

Message Network Details (This slide is very busy)

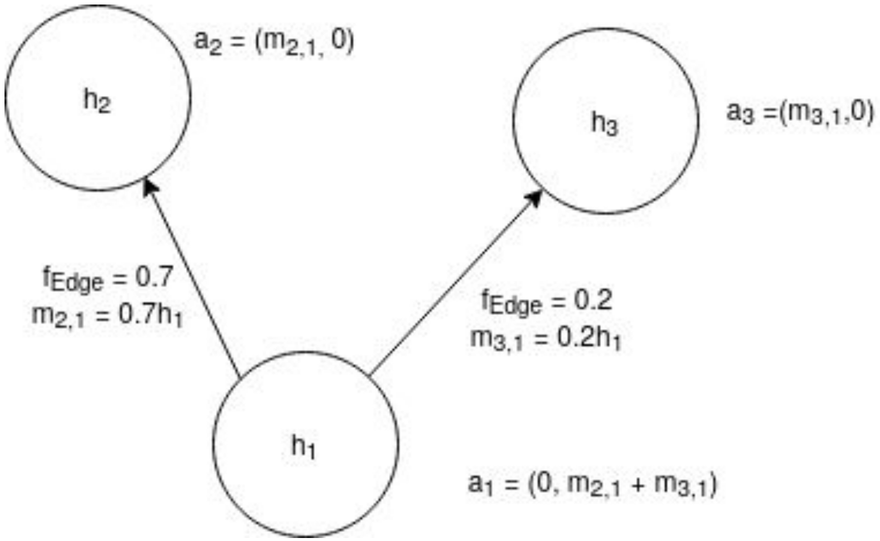
- $m_{u,v}^{(t)} = f_{Message}(h_u^{(t-1)}, h_v^{(t-1)})$

  $a_v^{(t)} = (f_{Agg}(\{m_{u,v}^{(t)} : v \in N(u)\}),$

  $f_{Agg}(\{m_{v,u}^{(t)} : v \in N^{-1}(u)\}))$
- $f_{Edge} : (\mathbb{R}^f \times \mathbb{R}^f) \mapsto [0, 1]$

  $f_{Edge}(h_u, h_v) = MLP(h_u, h_v)$
- $f_{Message} : (\mathbb{R}^f \times \mathbb{R}^f) \mapsto \mathbb{R}^{2f}$

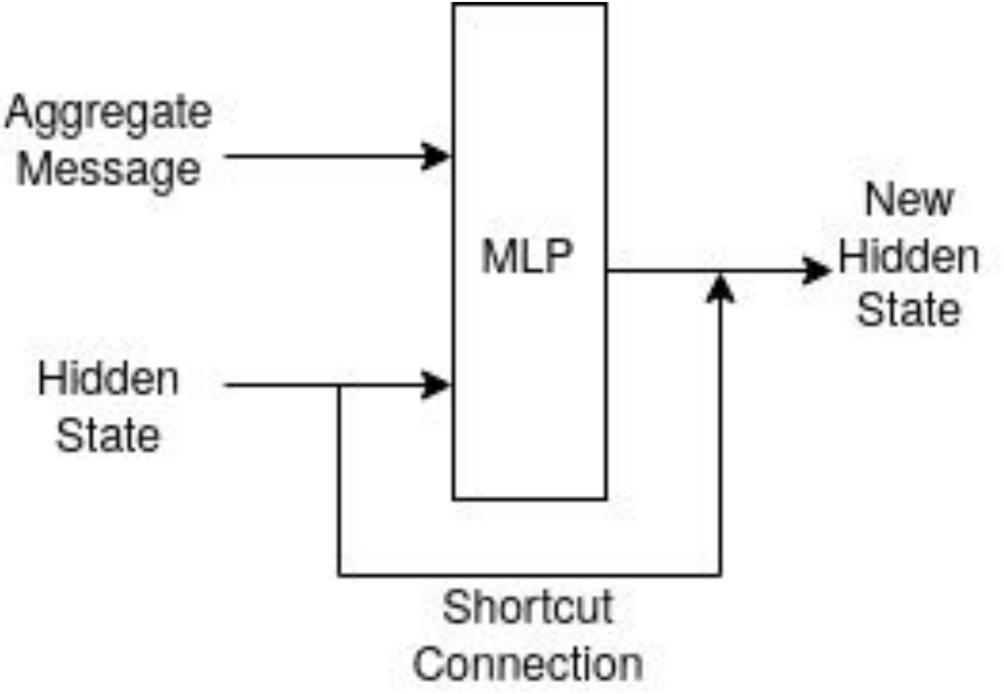
  $f_{Message}(h_u, h_v) = f_{Edge}(h_u, h_v) \cdot h_u$
- $f_{Agg}(M) = \Sigma_m m$



Node Network Details

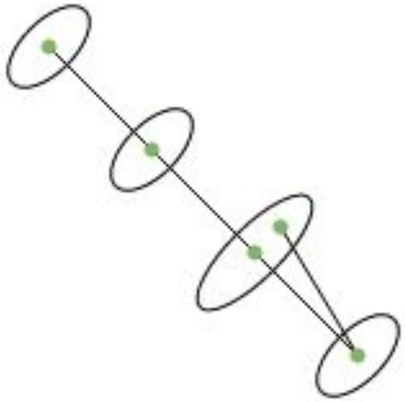
- $h_v^{(t)} = f_{Update}(h_v^{(t-1)}, a_v^{(t)})$
- $f_{Update} : (\mathbb{R}^f \times \mathbb{R}^{2f}) \mapsto \mathbb{R}^f$

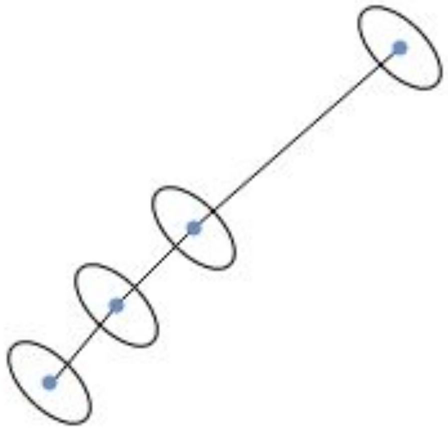
  $f_{Update}(h_u, a_u) = MLP(h_u, a_u) + h_u$



Track Construction

- Once edge classification is performed, a track is constructed by finding the connected components
- Track is constructed by finding the mean of the hits on each layer





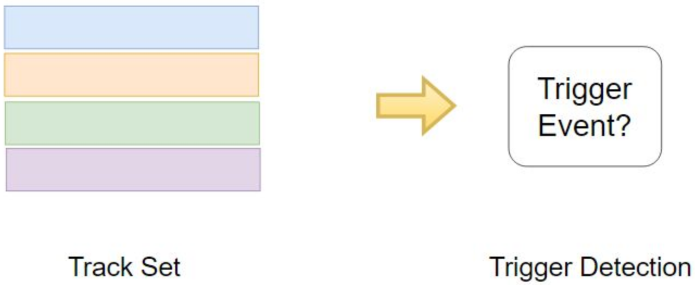
Performance

Metric	Year	Value
Accuracy	2023	92.07%
Precision	**2023**	**92.54%**
Recall	**2023**	**97.97%**
F1	**2023**	**95.18%**
Accuracy	**2022**	**96.30%**
Precision	2022	84.55%
Recall	2022	83.25%
F1	2022	83.89%

Tracks $\mapsto$ Label

Problem Definition

- After creating the tracks, we have a set of tracks
- We want to know whether the event that created these tracks was a trigger event
- A *trigger event* is an event in which we had a $D_0 \mapsto (\pi^+, K^-)$ or $D_0 \mapsto (\pi^-, K^+)$ decay

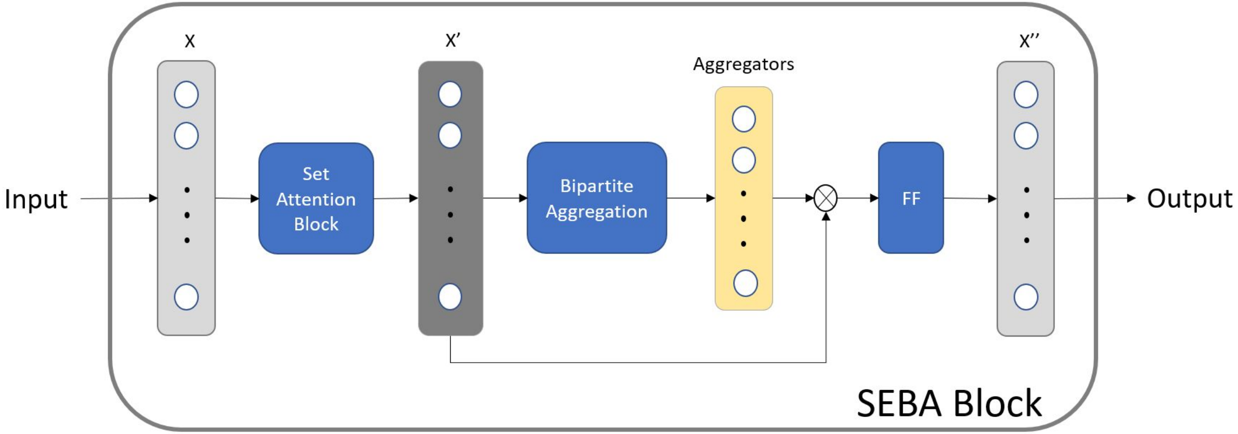


What needs to be modeled?

- $D_0 \mapsto (\pi^+, K^-)$ or $D_0 \mapsto (\pi^-, K^+)$
- Considering the problem from a high level perspective, we need to consider:
    - Track-to-track Interactions: Do these pair of tracks form a (π^+, K^-) or (π^+, K^-) pair?
    - Track-to-global Interactions: Where is the origin of this track?
    - Global-to-Track Interactions: Incorporate information about the origin of this track into the track embeddings

Architecture

- Previous considerations motivate the following block.
  - Set Encoder: Track-to-Track interactions
  - Bipartite Aggregation: Track-to-Global and Global-to-Track interactions



Set Encoder

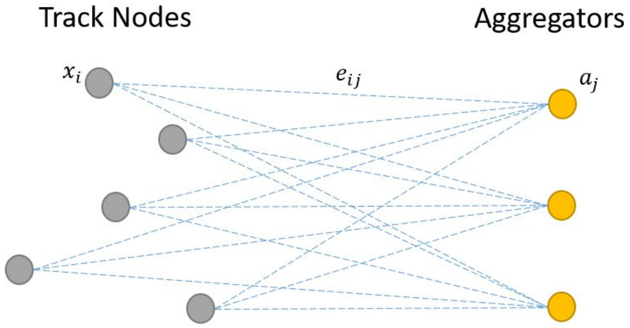
- Create Query, Key, Value embeddings from track embeddings using an MLP
- Find attention between every track i and track j by calculating $Q_i \cdot K_j$ and using the softmax to normalize the sum of attention scores to 1
- Weigh value embeddings by the attention score and aggregate to create new track embeddings

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$SAB(X) = \text{LayerNorm}(H + \text{rFF}(H)),$$
$$\text{where } H = \text{LayerNorm}(X + \text{Multihead}(X, X, X))$$

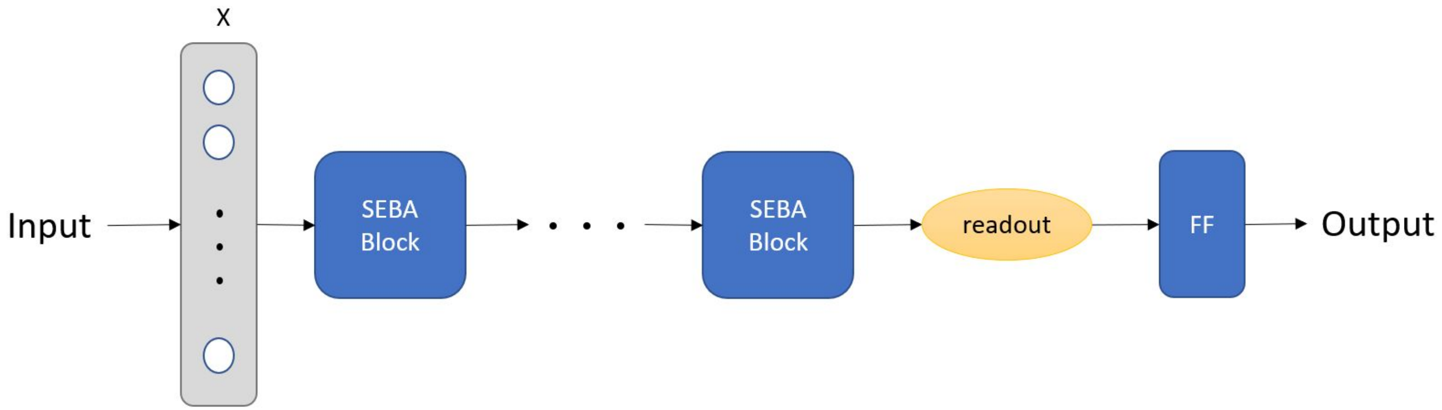
Bipartite Aggregators

- Use an MLP: $\mathbb{R}^f \mapsto \mathbb{R}^n$, followed by a softmax to determine how much each track contributes to each aggregator
  - f is size of track embedding
  - n is number of aggregators
- For each aggregator:
  - Scale each track by its contribution score to that aggregator
  - Perform max and mean pooling over scaled tracks to calculate aggregator embedding
- Concatenate aggregators to track embeddings, and use an MLP to update track embeddings



Architecture

- Stack multiple SEBA Blocks
- Use Bipartite Aggregation with single aggregator to generate event embedding
- MLP on event embedding to predict Trigger Event

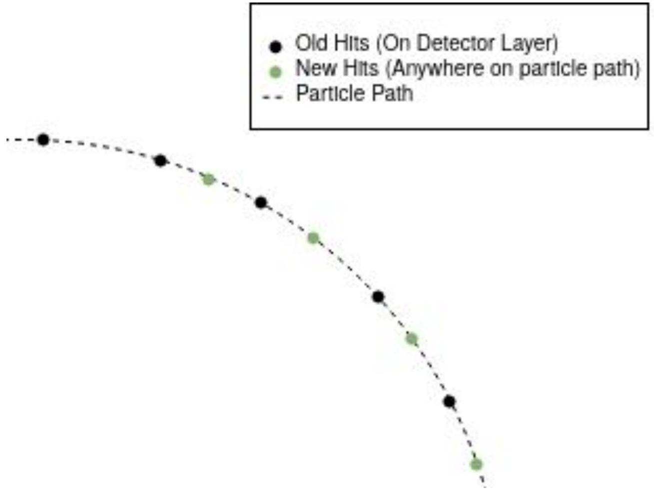


Track Features

- Track given to trigger classifier has the following features:
  - (x, y, z) location of hit on each layer
  - Length segment between each layer
  - Angle formed by segments
  - Estimated radius of circle fit to hits
  - Estimated center of circle fit to hits
  - Estimated transverse momentum of track
- Estimated radius and center provided ~10pp increase in performance

Multi-Task Learning to Improve model performance

- Several modifications to standard training process in order to improve the performance and robustness of our trigger algorithm
  - Track embeddings used predict whether two tracks come from the same parent
  - We perturb hits off the detector layers while keeping it on the particle path
- $\mathscr{L} = L_{CE}(\text{trigger}_{pred}, \text{trigger}_{true}) + L_{CE}(A_{pred}, A_{true})$



Performance

Data	Year	Metric	Result
GT Tracks	**2023**	**Accuracy**	**90.22%**
GT Tracks	2023	Precision	86.35%
GT Tracks	2023	Recall	95.41%
Predicted Tracks	**2022**	**Accuracy**	**84.01%**
GT Tracks	2022	Accuracy	87.5%

Remaining Challenges

- Modifying algorithms to deal with pile-up
- Work on simplifying algorithms and reducing data quantity to meet latency challenges
  - Initial study of latency-accuracy tradeoff showed we could reduce edge quantity at the tracking stage by 60% with minimal loss in final trigger accuracy
- Ensure trigger algorithm works in explainable and robust way
  - Initial study has shown model prefers to drop non-trigger tracks without affecting event label and prefers to perturb hits as to not affect the track radius

	$d\phi_{max}$	dz_{max}	accuracy	Maximum Edge Candidates
0	0.025005	102.000000	0.885895	1030.0
1	0.014881	16.000000	0.885360	548.0
2	0.011599	155.000000	0.884555	638.0
3	0.026555	113.000000	0.884320	1077.0
4	0.024582	178.000000	0.883860	1022.0
5	0.010320	48.000000	0.882630	556.0
6	0.012193	14.220353	0.881850	463.0
7	0.030000	200.000000	NaN	1171.0

Conclusion

- ML models have shown steady increases in performance on the triggering problem
- Incorporating physics knowledge been responsible for large gains in performance in trigger prediction
- Challenges remain in adapting the ML algorithm to the real-world latency and data availability constraints