Instance Segmentation GNNs for One-Shot Conformal Tracking at the LHC

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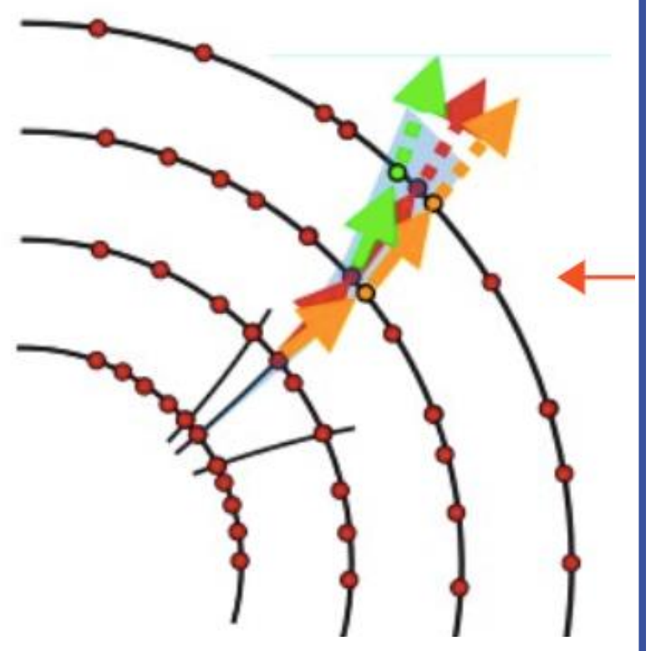
ABSTRACT

3D instance segmentation remains a challenging problem in computer vision. Particle tracking at colliders like the LHC can be framed as an instance segmentation task: beginning from a point cloud of hits in a particle detector, an algorithm must identify which hits belong to individual particle trajectories and extract track properties. Graph Neural Networks (GNNs) have shown promising performance on standard instance segmentation tasks. In this work we demonstrate the applicability of instance segmentation GNN architectures to particle tracking; moreover, we re-imagine the traditional Cartesian space approach to track-finding and instead work in a conformal geometry that allows the GNN to identify tracks and extract parameters in a single shot.

PARTICLE TRACKING

Charged Particle Tracking

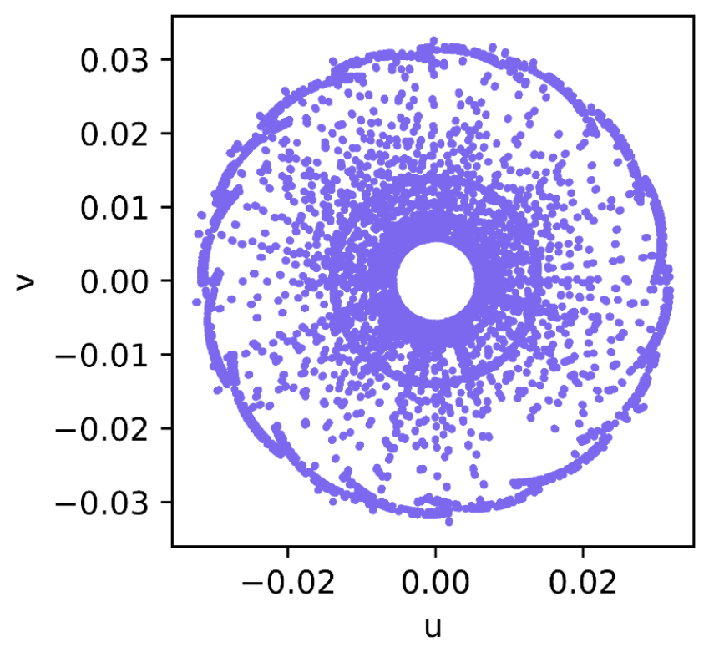
- Granular detector in magnetic field records particle interactions with material (hits)
- Charged particles follow helical path defined in transverse plane by 2 parameters: p_T, ϵ_T
- Tracking algorithms must reconstruct and fit these trajectories



Conformal Tracking

$$u = \frac{x}{x^2+y^2}$$
$$v = \frac{y}{x^2+y^2}$$

- Transformation maps prompt (displaced) tracks to lines (parabolas)
- Track parameters can be extracted from linear (parabolic) fit: $v = \frac{1}{2b} - u\frac{a}{b} - u^2\epsilon_T\left(\frac{R}{b}\right)^3$

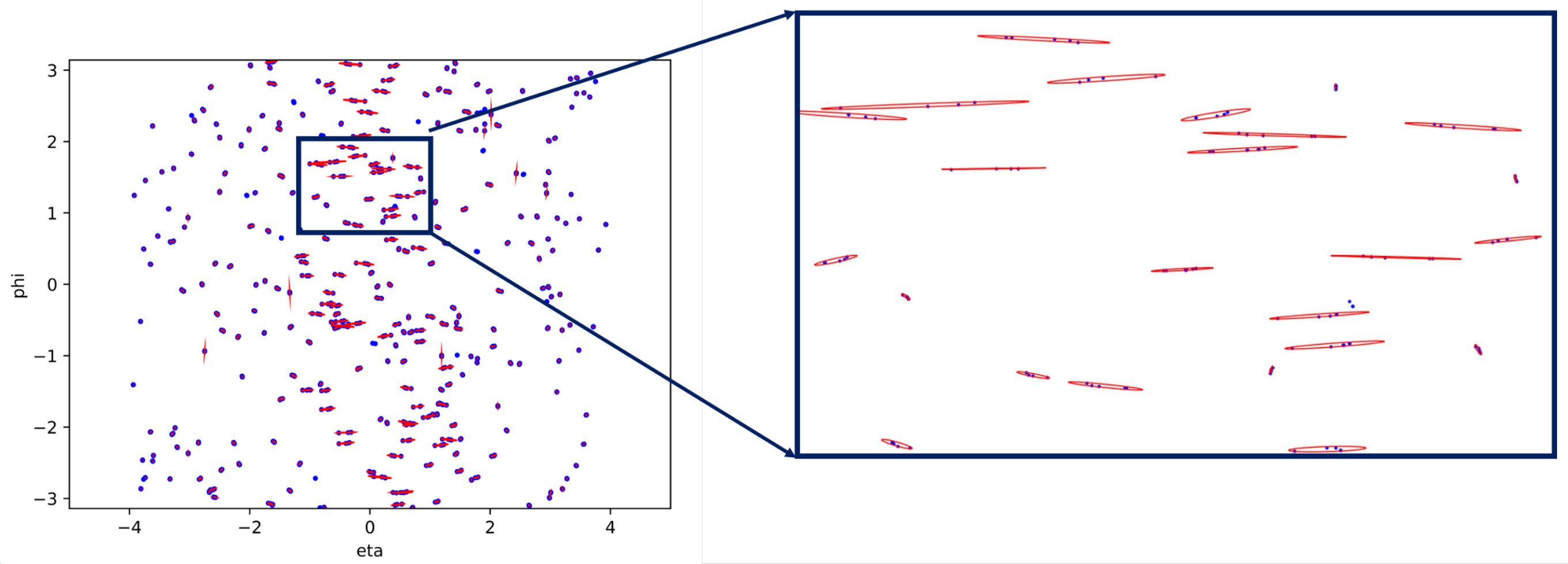


GRAPH CONSTRUCTION

Tracker Hits as Graphs

$$\phi = \arctan 2(y,x)$$
$$\eta = \operatorname{arctanh}\left(\frac{z}{\sqrt{x^2+y^2+z^2}}\right)$$

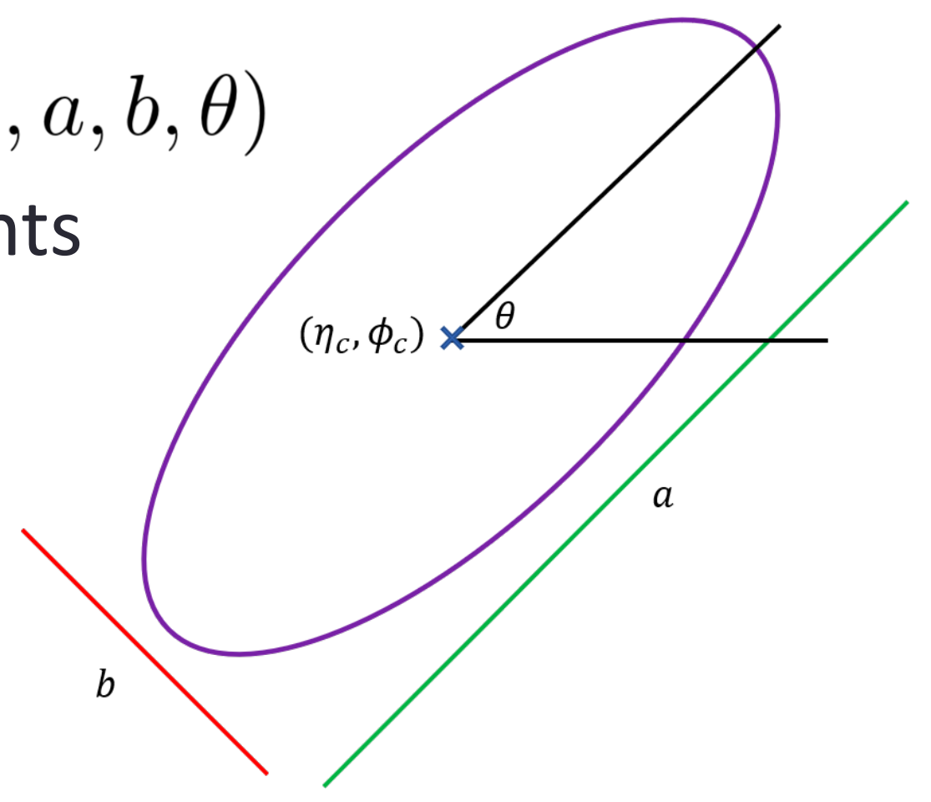
- Track hits are mapped into $\eta - \phi$ space:
- Hits are filtered based on track p_T (> 2 GeV) and the number of hits in the track they belong to (> 2 hits/track)
- Hits are clustered via DBScan, edges drawn within clusters
- Truth ellipses ("bounding boxes") fit to each track via PCA



BOUNDING ELLIPSES

Ellipse Parameterization

- 5 degrees of freedom: $B = (\eta_c, \phi_c, a, b, \theta)$
- First and second principle components of each track's hit cluster used to estimate ellipse parameters



Ellipse Encoding

- Ellipses encoded with coordinates of each node for training labels

$$\delta_\eta = \frac{(\eta_c - \eta_v)}{\eta_m},\ \delta_\phi = \frac{(\phi_c - \phi_v)}{\phi_m},\ \delta_a = log(\frac{a}{a_m}),\ \delta_b = log(\frac{b}{b_m}),\ \delta_\theta = \frac{\theta + \Delta_\theta}{\theta_m}$$

GNN ARCHITECTURE

Overview: PointGNN

- This model is based on the PointGNN, an instance segmentation network designed to localize and classify objects in a graph
- Key components: graph re-embedding, localization/classification, bounding box merging

(1) Graph Re-embedding Modules

- Nodes re-embedded with *T* separate graph modules:

$$s_i^{t+1} = g^t\underbrace{(\underbrace{\rho(\{\underbrace{f(x_j - x_i + \underbrace{\Delta x_i^t,}_{\text{auto-registration}} s_j^t)}_{\text{message passing}}\})}_{\text{aggregation}}, s_i^t)}_{\text{state update}}$$

Inputs

$s_i^0 = (z_i, layerID_i)$
$x_i = (\eta_i, \phi_i)$

(2a) Localization Branch

- MLP to predict encoded bounding ellipses for each node
- Huber Loss: $l_l = \frac{1}{n_{hits}} \sum_{i=1}^{n_{hits}} \mathbb{1}(v_i \in \{trackhits\}) l_{huber}(\delta - \delta^{gt})$

(2b) Classification

- MLP to predict the class of a hit: noise (0) or track hit (1)
- BCE Loss: $l_c = -\frac{1}{n_{hits}} \sum_{i=1}^{n_{hits}} y \log y_i + (1-y_i)\log(1-y_i)$

(3) Box Merging

- Modified NMS strategy to build hit clusters

(4) Conformal Tracking

- Predict transverse track parameters in conformal space
- MSE Loss: $l_t = \frac{1}{n_{clusters}} \sum_{i=1}^{n_{clusters}} (\frac{p_{T_i} - p_{T_i}^p}{c_{p_T}})^2 + (\frac{\epsilon_{T_i} - \epsilon_{T_i}^p}{c_{\epsilon_T}})^2$

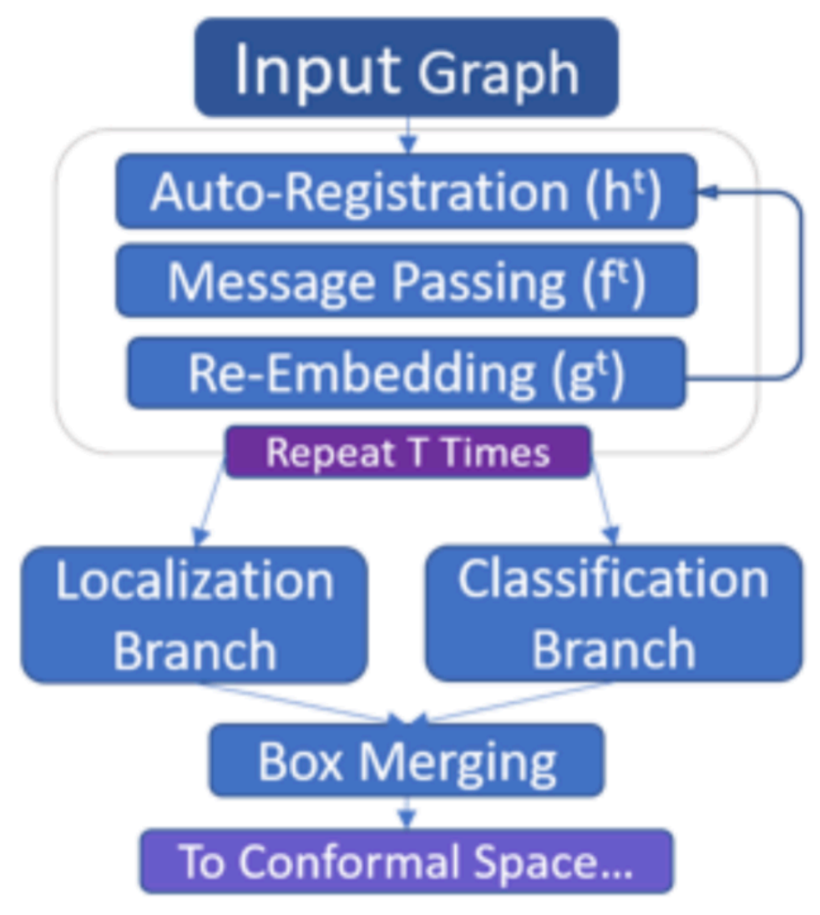
(5) Total Loss:

- Scaled to balance the terms: $l_{total} = \alpha l_c + \beta l_{loc} + \gamma l_t$

PRELIMINARY RESULTS

Experiment Design

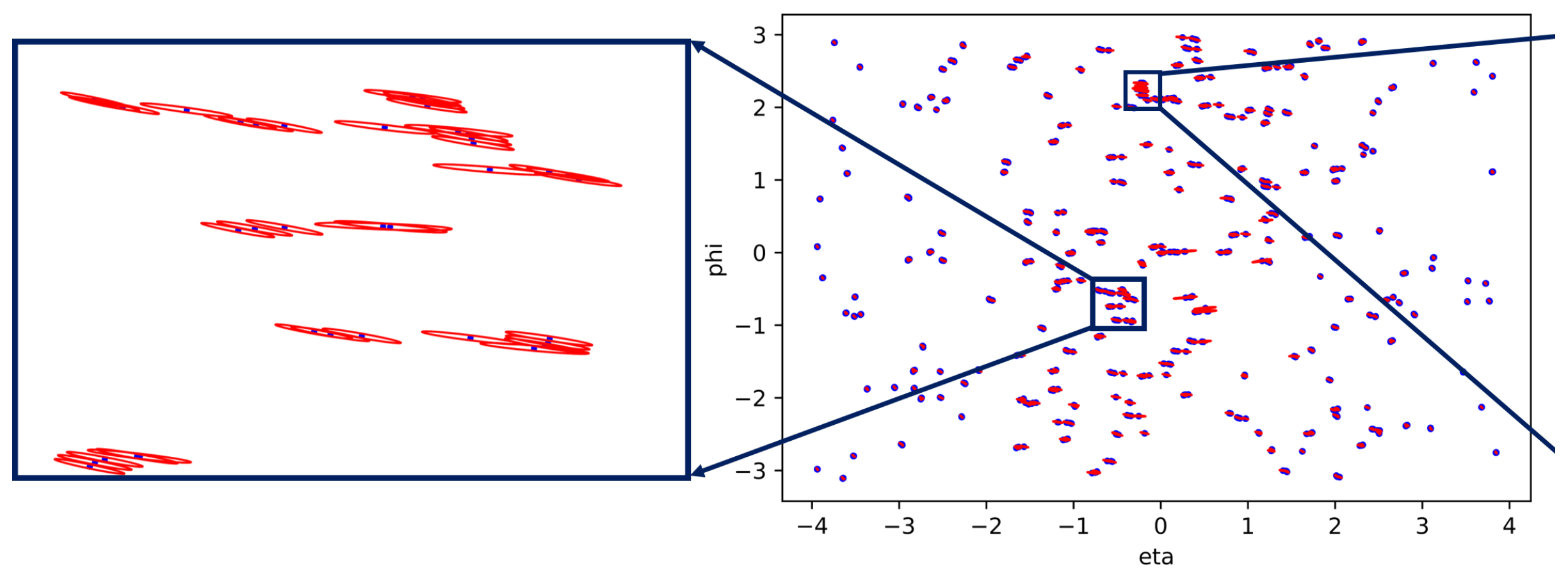
- Implemented in Pytorch Geometric
- T=4, g^t and h^t 1x64 MLPs, f^t has 2 hidden layers
- Classifier and localization branches have 3 hidden layers
- Scale parameters: $(0.01, 0.004, 0.038, 0.005, \pi/4, 0.5)$



Input Graph
Auto-Registration (h^t)
Message Passing (f^t)
Re-Embedding (g^t)
Repeat T Times
Localization Branch
Classification Branch
Box Merging
To Conformal Space...

Initial Results

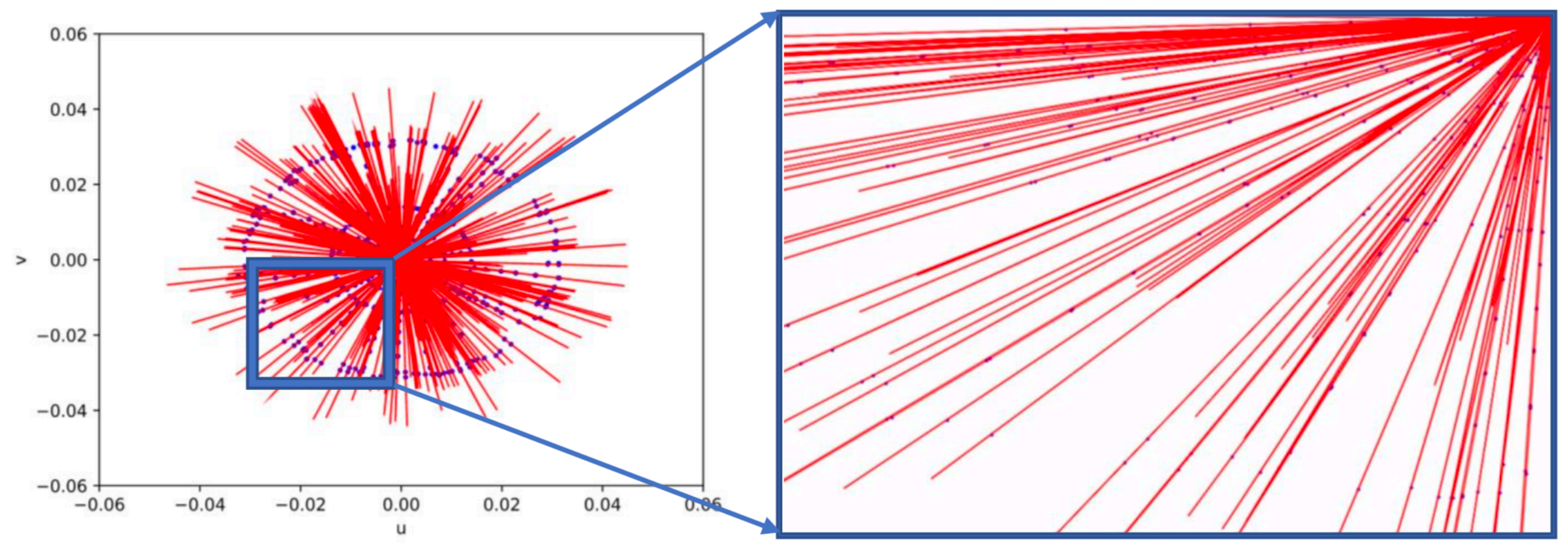
- Ellipses effectively localize tracks
- Ellipse orientation influenced by neighboring tracks



FUTURE STUDIES

On-going Work

- Increased pileup graphs (decreased p_T threshold)
- Combined NMS and IoU ellipse merging algorithm
- Implementing full architecture in conformal space
- Optimizing track parameter extraction



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