UniTrackFormer: End-to-End TrackML Particle Tracking with Transformer

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Project Overview

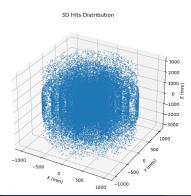
- Goal: End-to-end particle track reconstruction for the TrackML Challenge using deep learning.
- Core Idea: Use Transformer architecture to cluster detector hits into physical tracks.
- Key Contributions:
 - End-to-end modeling, no manual feature engineering
 - Multi-task loss: classification, clustering, and parameter regression
 - Rich visualization and evaluation

Data Structure

TrackML Raw Data:

- hits.csv: Each hit's spatial coordinates (x, y, z), module info, etc.
- truth.csv: True particle ID (particle_id) for each hit
- detectors.csv: Detector geometry info

Feature Example:



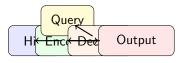
Data Table Example

hit_id	Х	У	Z	$volume_id$	module_id
1	123.4	-56.7	789.0	8	12
2	234.5	-67.8	800.1	8	13

Table: Sample fields from hits.csv

Model Architecture: UniTrackFormer

- **Input:** $N_{hits} \times D$ features
- Encoder: Multi-layer
 Transformer Encoder
- Query: Q learnable query vectors
- Decoder: Multi-layer
 Transformer Decoder
- Output:
 - Track classification
 - Hit assignment (clustering)
 - Parameter regression

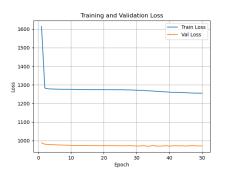


Multi-task Loss

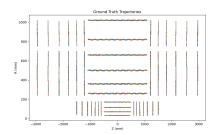
- Track classification loss (Binary Cross Entropy)
- Mask clustering loss (Dice + BCE)
- Physical parameter regression loss (MSE)
- Total loss = α classification + β mask + γ params

Training and Evaluation

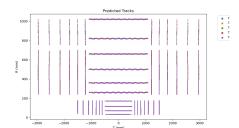
- Data loading and feature extraction
- Model training (supports K-fold cross-validation)
- Second Second
- Visualization: 3D distribution, rz projection, track clustering



Visualization Results



Ground Truth Tracks



Predicted Tracks

Summary and Outlook

- End-to-end TrackML tracking pipeline implemented
- Multi-task loss and rich visualization supported
- Future: optimize model, improve clustering, enhance physics interpretability

Thank you! Questions welcome.