Particle Flow algorithms with DEtection TRansformers for jet reconstruction in ATLAS-like detectors

PF-DETR

Maxence ALBERT – Ecole Polytechnique – France

Masahiko SAITO, Taikan SUEHARA (presenter) – ICEPP, The University of Tokyo – Japan

Introduction

In collider experiments, accurately reconstructing particles from detector information is crucial for understanding various phenomena. The limited spatial granularity of calorimeters in detectors like ATLAS presents a challenge for reconstructing particles within jets. To address this, we are developing a Machine Learning Particle Flow algorithm for an ATLAS-like detector [1]. Our model takes calorimeter cell and track information as input and outputs the features of each particle, including its class, momentum, and direction.

A key challenge is that the number of output particles is unknown in advance. The charged particle leave track so there reconstruction is facilitated. However, neutral particle reconstruction depends on the calorimeter granularity and is a harder task.

Inspired by the DEtection TRansformer (DETR) [2] architecture from object detection, we propose an end-to-end model that directly generates particle candidates from calorimeter and track data. This poster provides an overview of our model and its performance on a single-jet benchmark.

Motivation & Objective

The current state-of-the-art models in Machine Learning Particle Flow (ML-Pflow) algorithms, **HGPflow** [3], combine **GNNs** with Transformer embedder. We are transitioning to a fully **end-to-end Transformer model** for particle flow reconstruction, driven by:

- Rapid innovation & "hype" in Transformer architectures → rich new ideas.
- Compelling evidence of **scaling laws** in large Transformer models.
- Remarkable success in **object detection**, analogous to calorimeter/track data.

DETR - PFlow

✓ **End-to-end Transformer** approach.
✓ **Scalability** properties
✓ **DETR:** Active field in Object Detection

Hypergraph - Pflow

✓ **Embedder:** Transformer
✓ **Core modules:** Graph Neural Networks
✓ **Logic:** Particle Flow/Physic inspired

Proposed PF-DETR architecture

1. **Input Representation**
   - Calorimeter cells as point cloud
   - Topocluster of cells (T.C.)
   - Reconstructed tracks
2. **Backbone**
   - Embeddings modules
   - Multi-modal Cross-attention
3. **DETR Module**
   - Track queries for charged particle
   - Learnable Neutral particle queries
4. **Output Heads**
   - Classification Head
   - Momentum Predictor (p_T, η, ϕ)
   - Incidence Matrix Head (optional)

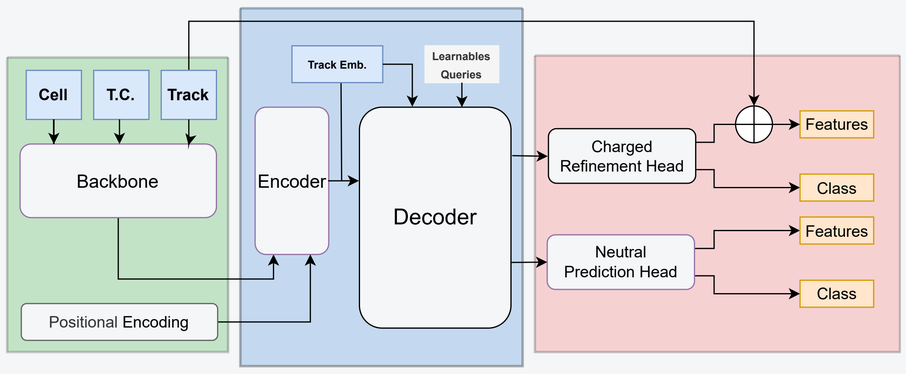

Figure 1: Illustration of the PF-DETR architecture, showing the flow from input representations to the final particle predictions.

- Our models predict a predefined number of objects, each characterized by a **class** and **kinematic properties** $\log p_T, \eta, \phi$. The possible classes are photon, muon, electron, charged hadron, neutral hadron, or a "None particle" class.
- **Hungarian matching** [4] algorithm is used to match **prediction** and **truth**. The **loss** is computed as a weighted sum of a **cross-entropy** and a **MSE** on $\log p_T, \eta, \phi$ (with matched particles).

$$\mathcal{L} = \lambda_{CE}\mathbf{L_{CE}} + \lambda_{MSE}\mathbf{L_{MSE}}$$

Data Generation - ATLAS like detector [5]

Data Generation

- PYTHIA8 + GEANT4 [6] simulation
- Single quark jet : 10-200 GeV
- Calorimeter simulation : 3 ECAL + 3 HCAL

Dataset size

- Public: 60k training / 30k test events
- Private: 900k training / 100k test events

Realistic Features

- Electronic noise simulation
- Track smearing
- Photon conversions
- Material interactions

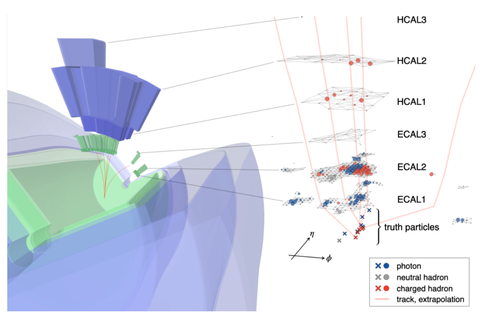

Figure 2: COCOA Jet Simulation Example [3]

Results

Scaling Law

Consistent with the scaling laws observed in neural language models [7] :

- **PF-DETR model** exhibits **scaling capacity** as dataset size increases.
- Base model, exhibits a **model size bottleneck**.

Table 1: Model Configurations and Parameters

Model	Params (M)	$N_{enc.}$	$N_{dec.}$	Hid. Dim.
Base	2.5	3	3	128
Big	9.5	3	3	256
Huge	15	6	6	256

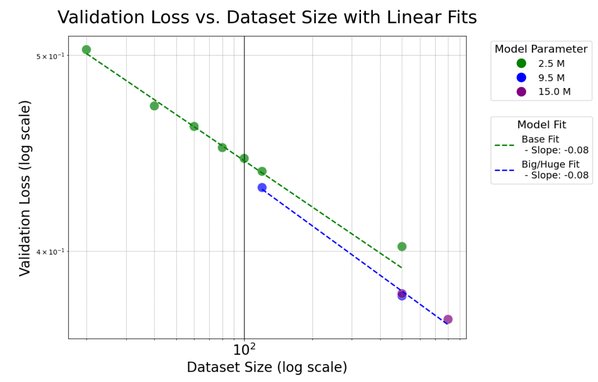

Figure 3: Test Loss Value for different model size and dataset size (Training is stop when validation loss stop improving - 300 epochs max.) .

Performance Metrics

Our PF-DETR model is evaluated across multiple metrics: particle identification accuracy, fake rate, momentum resolution, and jet-level reconstruction performance on the COCOA dataset.

Neutral Particle Classification Performance

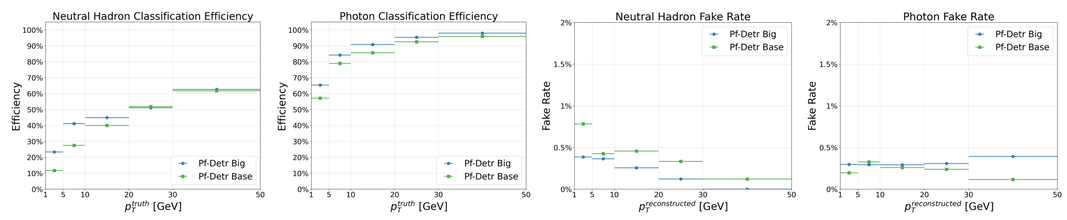

Figure 4: Efficiency and Fake rate for neutral hadrons (left) and photons (right). A confidence threshold of $\epsilon = 0.85$ is applied, if the probability associated with a predicted class is below ϵ, the class is set to None particle.

Resolution Performance

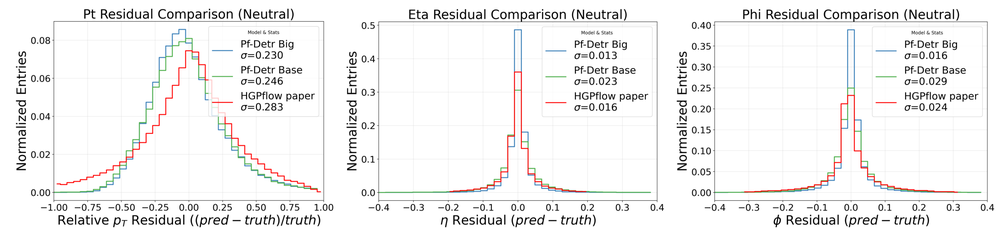

Figure 5: Momentum (p_T) relative residual and pseudorapidity (η), azimuthal angle (ϕ) residual for neutral particles.

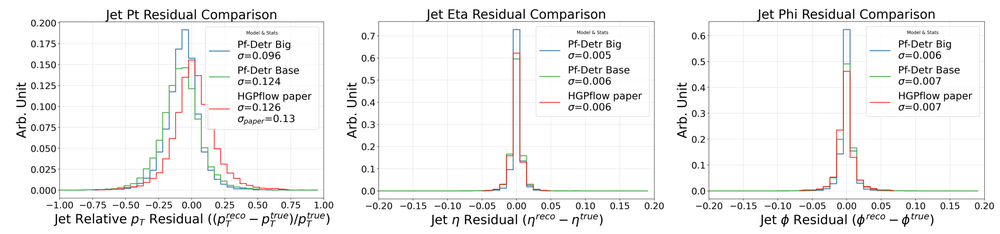

Figure 6: Jet p_T relative residual,η ϕ residual. Jet are reconstructed using the Anti-k_T algorithm [8]

Table 2: Performance Metrics Comparison. σ is calculated on the data distribution by performing Gaussian fit

Metric	PF-DETR Base	PF-DETR Big	PF-DETR Huge	HGPflow	Improvement
Nb. of params (M)	2.5	9.5	15	1.9	
Dataset Size (k)	60	500	1000	60	
Neu. Par. σ_η	0.023	**0.013**	**0.013**	0.016	**18.8%**
Jet σ_η	0.006	**0.005**	**0.005**	0.006	**16.7%**
Neu. Par. σ_ϕ	0.029	**0.016**	**0.016**	0.024	**33.3%**
Jet σ_ϕ	0.007	**0.006**	**0.006**	0.007	**14.3%**
Neu. Par. σ_{p_T}	0.246	0.233	**0.225**	0.283	**20.5%**
Jet σ_{p_T}	0.124	**0.097**	**0.097**	0.126	**23.0%**

Conclusion & Perspective

The performance comparison highlights the significant potential of End-to-End Transformer-based models for particle flow reconstruction.

- **PF-DETR (Base)** and **HGPflow** models exhibit **comparable** performance.
- **PF-DETR (Big) outperforms the HGPflow baseline (≥15% gain)** across σ_η, σ_ϕ, and σ_{p_T} jet and particle metrics.
- **Perspective/Future Direction:**
  - Our **DETR implementation** is a **basic architecture**; **advanced DETR variants** in object detection demonstrate **performance gains** (≥150%). Our model has room for improvement
  - Integrating **HGPflow's** robust feature extraction as a **backbone** for our DETR model is expected to **enhance the PF-DETR reconstruction performance**.

References

[1] M. Aaboud *et al.* [ATLAS Collaboration], *"Jet reconstruction and performance using particle flow with the ATLAS Detector"*, The European Physical Journal C **77**, 466 (2017), doi:10.1140/epjc/s10052-017-5031-2

[2] N. Carion *et al.*, *"End-to-End Object Detection with Transformers"*, In: European Conference on Computer Vision (ECCV), pp. 213–229. Springer (2020).

[3] N. Kakati *et al.*, *"HGPflow: Extending Hypergraph Particle Flow to Collider Event Reconstruction"*, (2025), arXiv:2410.23236

[4] H. W. Kuhn, *"The Hungarian method for the assignment problem"*, Naval Research Logistics Quarterly **2**, 83–97 (1955), doi:10.1002/nav.3800020109

[5] W. Blondel *et al.*, *"Configurable calorimeter simulation for AI applications"*, Journal of Instrumentation **18**, P07036 (2023)

[6] S. Agostinelli *et al.* [GEANT4 Collaboration], *"Geant4—a simulation toolkit"*, Nuclear Instruments and Methods in Physics Research A **506**, 250-303 (2003), doi:10.1016/S0168-9002(03)01368-8

[7] J. Kaplan *et al.*, *"Scaling Laws for Neural Language Models"*, (2020), arXiv:2001.08361

[8] M. Cacciari, G. P. Salam, and G. Soyez, *"FastJet user manual"*, The European Physical Journal C **72**, 1896 (2012), doi:10.1140/epjc/s10052-012-1896-2