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Foundation Model for Decay Event Classification at BESIII

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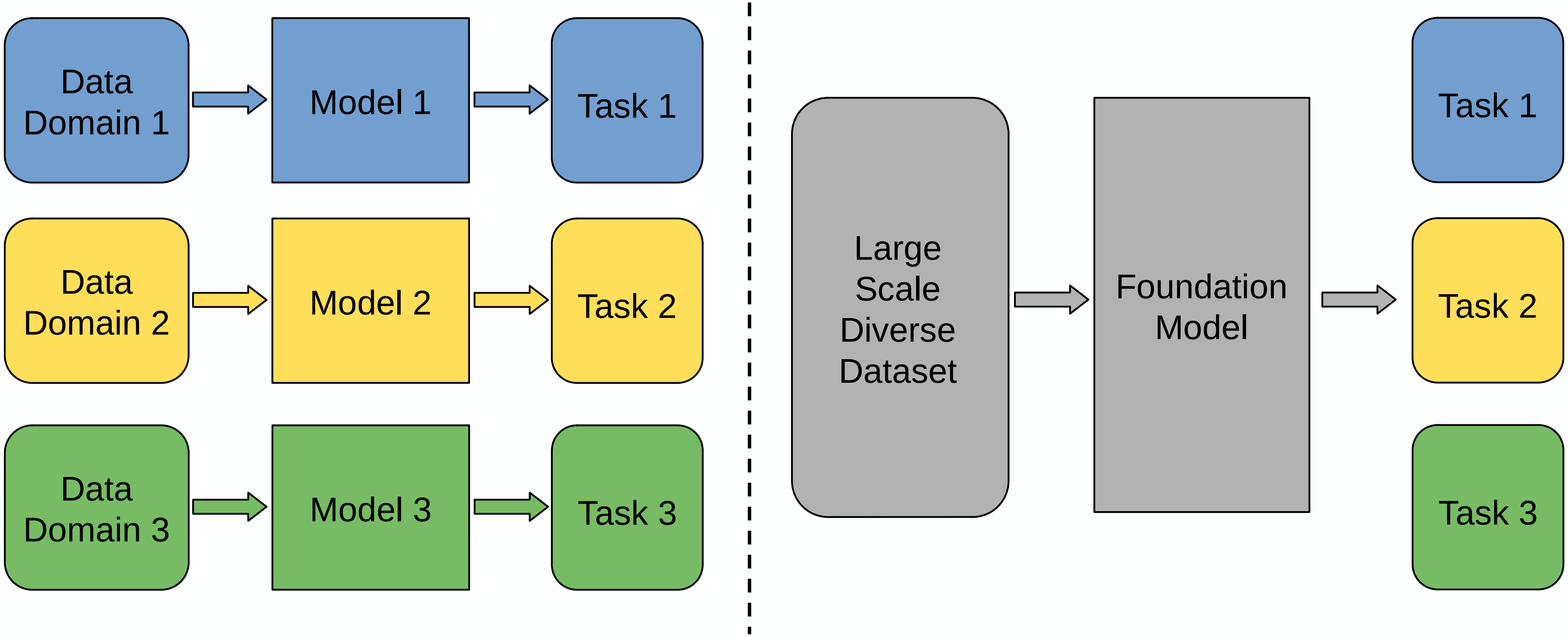
Part 1: Introduction

Introduction

What is a Foundation Model:

Any model that is trained on broad data (generally using **self-supervision** at scale) that can be adapted (e.g., **fine-tuned**) to a wide range of **downstream tasks**.



Why Foundation Model:

■ Traditionally, machine learning models are trained separately for **each specific task**.

■ A Foundation Model is pre-trained once and serves as a shared foundation for **many downstream tasks**.

Introduction

How to design Foundation Model

★ Foundation Model ≈ Pretext Tasks + Loss Functions ★

(1). Pretext Tasks: The task being solved is not of genuine interest, but is solved only for the true purpose of learning a good data representation.

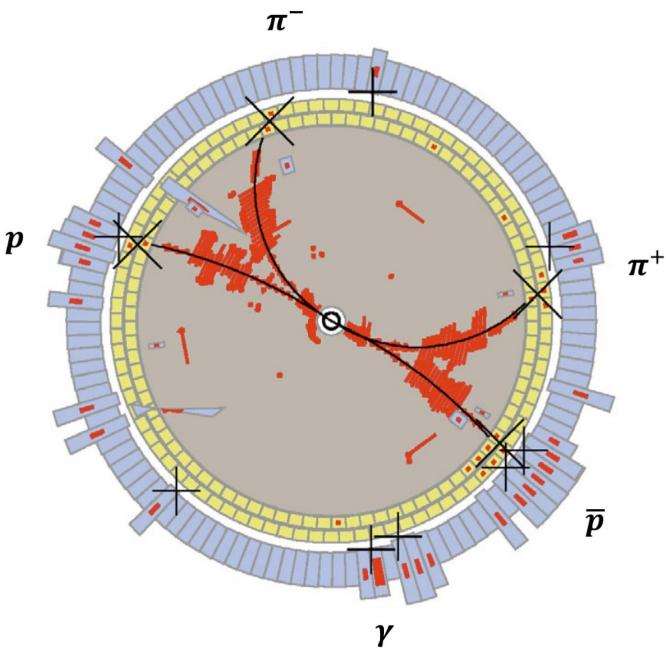
(2). Loss Functions: Loss functions can often be investigated independently of pretext tasks.

(3). Pretext tasks ≈Contrastive learning and masking learning.

Foundation Model in BESIII

■ Purpose: To cluster **all BESIII decay channels (>3,000 categories)**; our foundation model instead performs clustering at the collision-event level, potentially involving **tens to hundreds of thousands of clusters**.

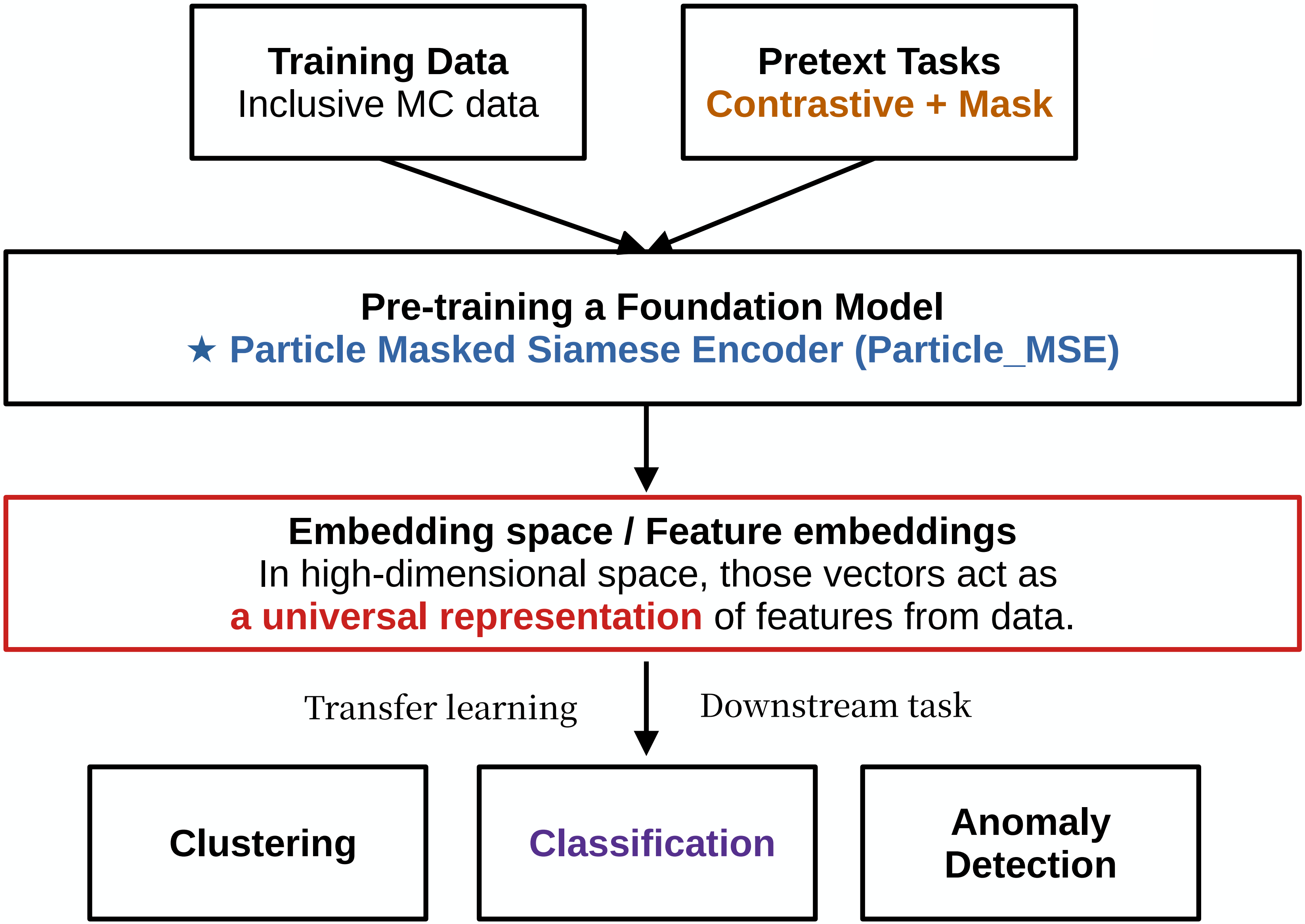
★ Research Highlight: **An extreme multi-class classification problem.**



Part 2: Research Method

Research Method

Research Procedure:



Research Method

Training Data:

◎ Decay event: **J/ψ** decay (Inclusive MC data)

◎ Event classes: **More than 1000 decay classes** in J/ψ decay. **Only the top 99** most frequent **classes** are **used for model training**.

◎ Training dataset: 99 classes of J/ψ decay events (= **3M samples**; expected to scale to over **100M in future versions**)

◎ Input features:

⇒ **Kinematic**:
['q','mdc_p3_px', 'mdc_p3_py', 'mdc_p3_pz', 'vz0', 'vr0']

⇒ **Particle identification information**:
['pid_prob_type']

⇒ **Electromagnetic calorimeter** :
['emc_numHits', 'emc_e3x3', 'emc_e5x5', 'emc_energy', 'emc_x', 'emc_y', 'emc_z', 'emc_time', 'EoP', 'emc_secmom', 'emc_latmom']

⇒ **Muon Counter** :
['muc_dpt', 'muc_numLayer', 'muc_maxHitsInlater', 'muc_chisq', 'muc_dof', 'muc_numHits']

Downstream Tasks (Excluded from Training Data):

◉ Task 1 – Clustering

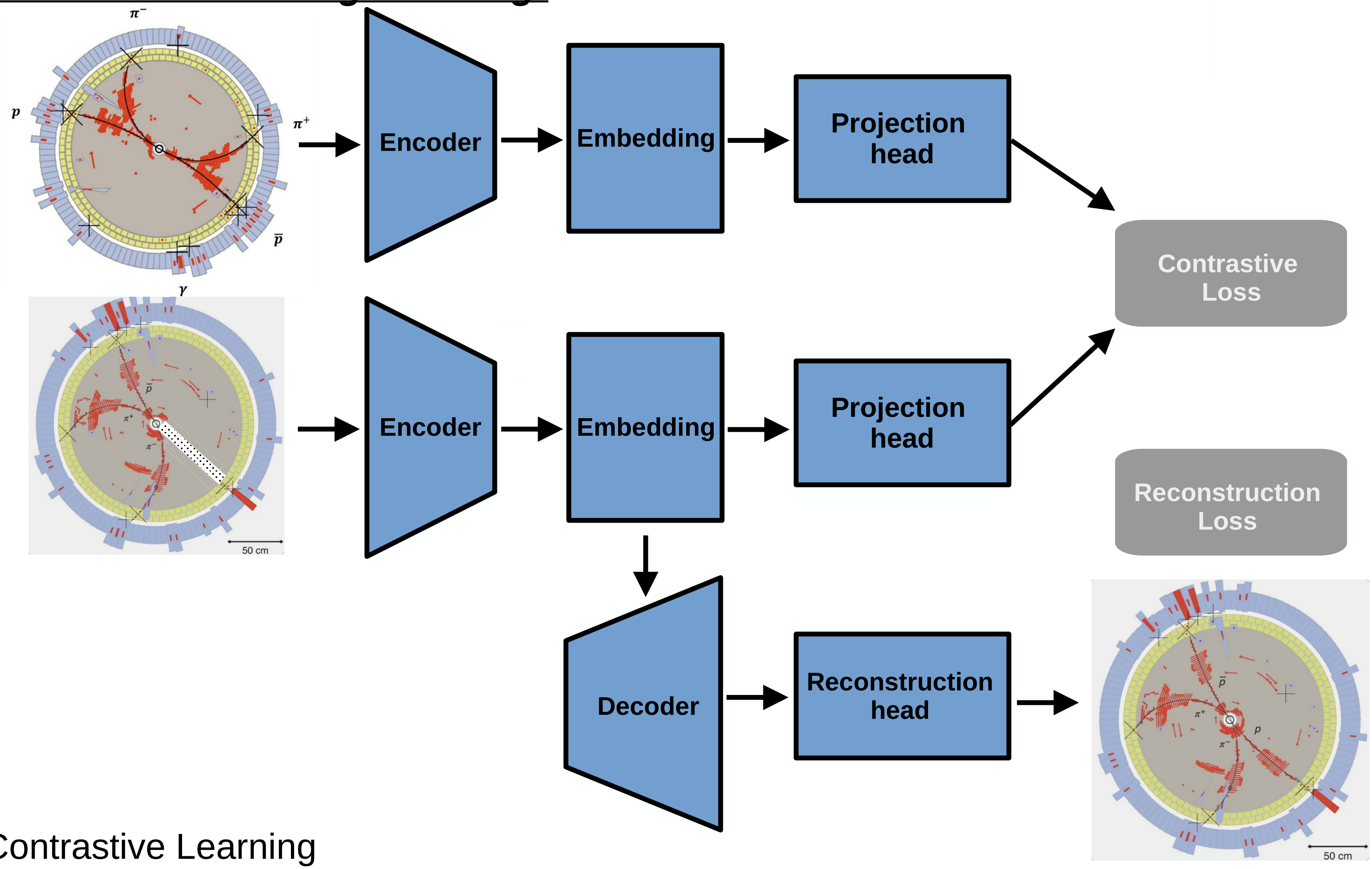
⇒ 300K samples from the top 99 classes of J/ψ decay classes.

◉ Task 2 – Classification (**99 classes classification task**)

⇒ 300K samples from the top 99 classes of J/ψ decay classes. (50% labeled, 50% unlabeled)

Research Method

Contrastive + Masking Learning:



◉ Contrastive Learning

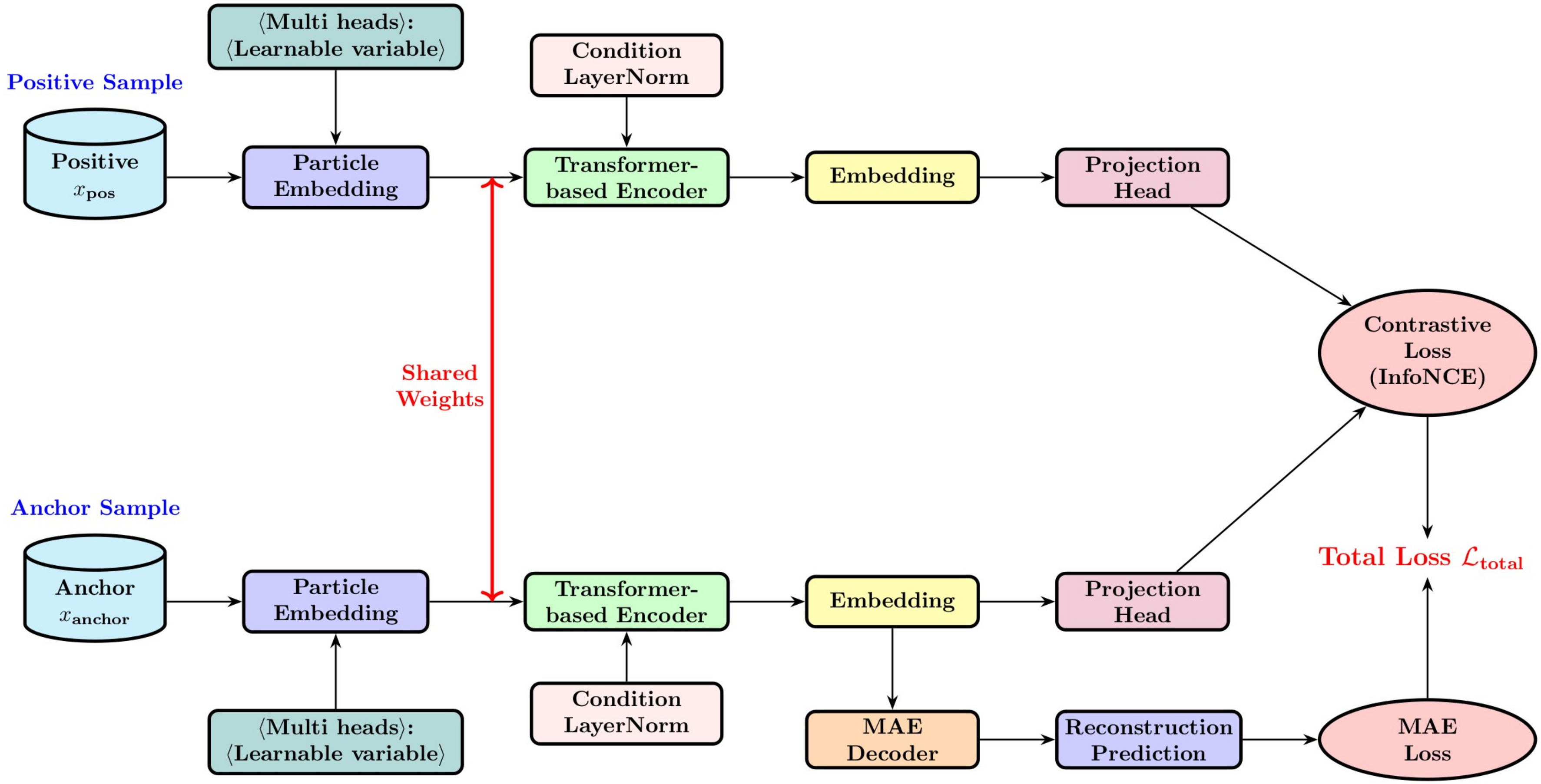
⇒ Brings representations of **same decay types closer**, and **push apart of different classes**.

◉ Masking Learning

⇒ Captures **inter-particle correlations** within decay events.

Research Method

Particle-MSE Structure:



Condition LayerNorm:

- Condition 1: Number of the total charged tracks.
- Condition 2: Number of the total neutral tracks.
- Condition 3: Number of the charged tracks with further selection.
- Condition 4: Number of the neutral tracks with further selection.

Part 3: Research Results

Research Results

Training Results:

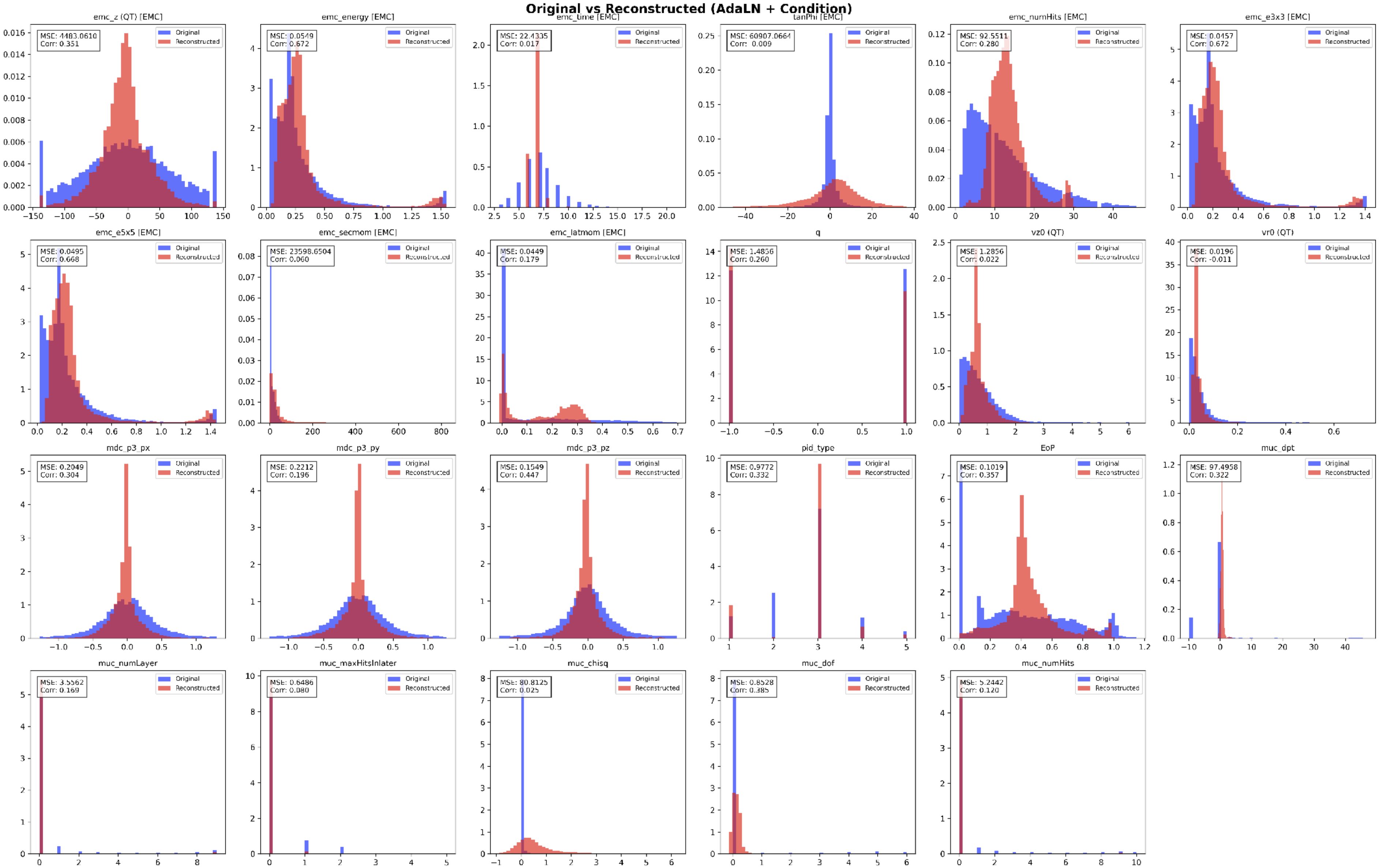
■ Total Loss: Total loss shows a steady downward trend over the first 50 epochs. however, it **does not yet appear to have converged**. Training will be extended to 100 epochs for further optimization.

■ MAE Loss (Reconstruction Loss): Reconstruction loss decreases overall but exhibits **substantial instability** during training.

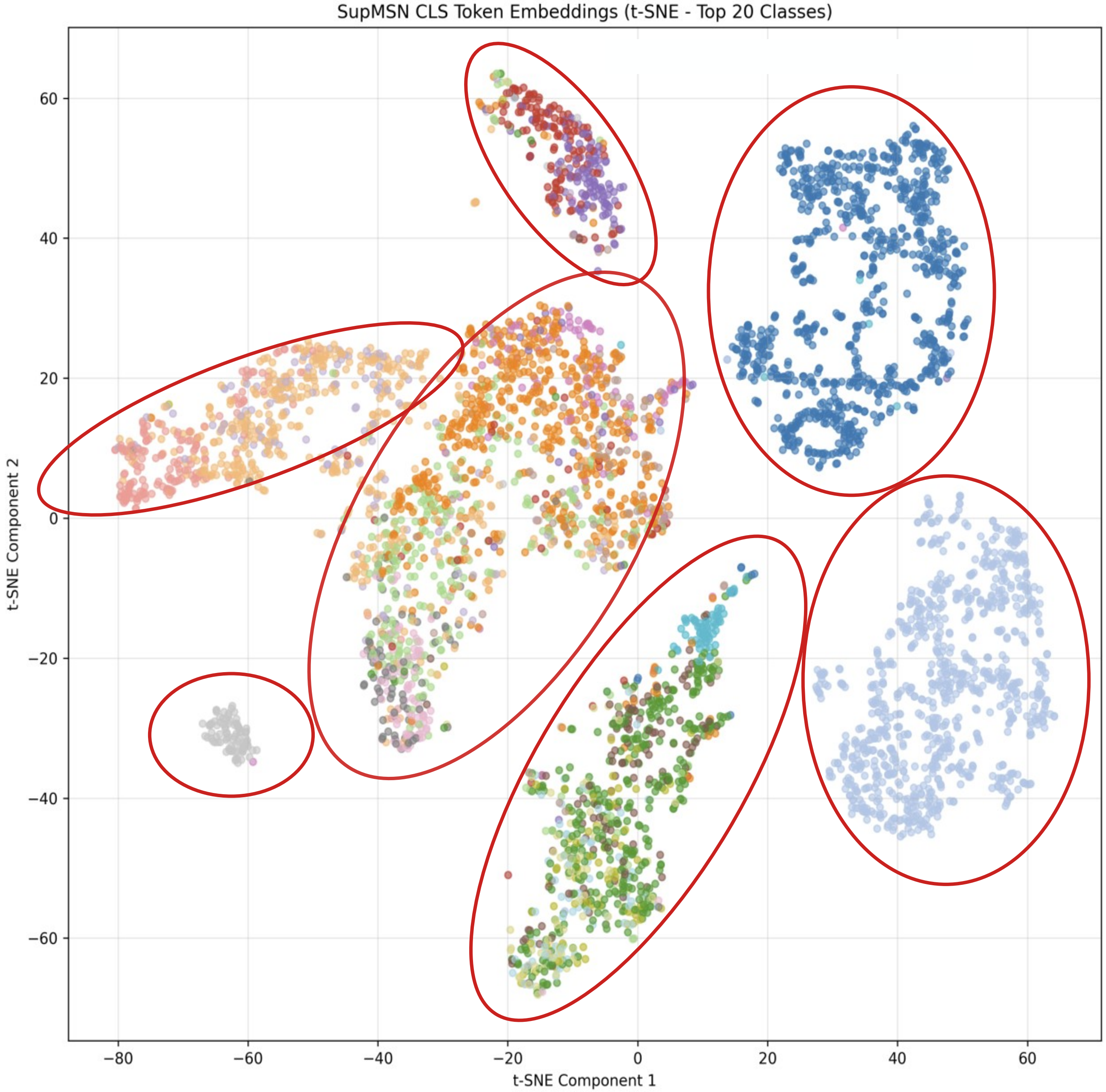
■ Contrastive Loss: Contrastive loss performs well, **benefiting from the supervised contrastive learning**. Future plans include exploring self-supervised contrastive way.

Research Results

Reconstruction Results:



Research Results



Classification results:

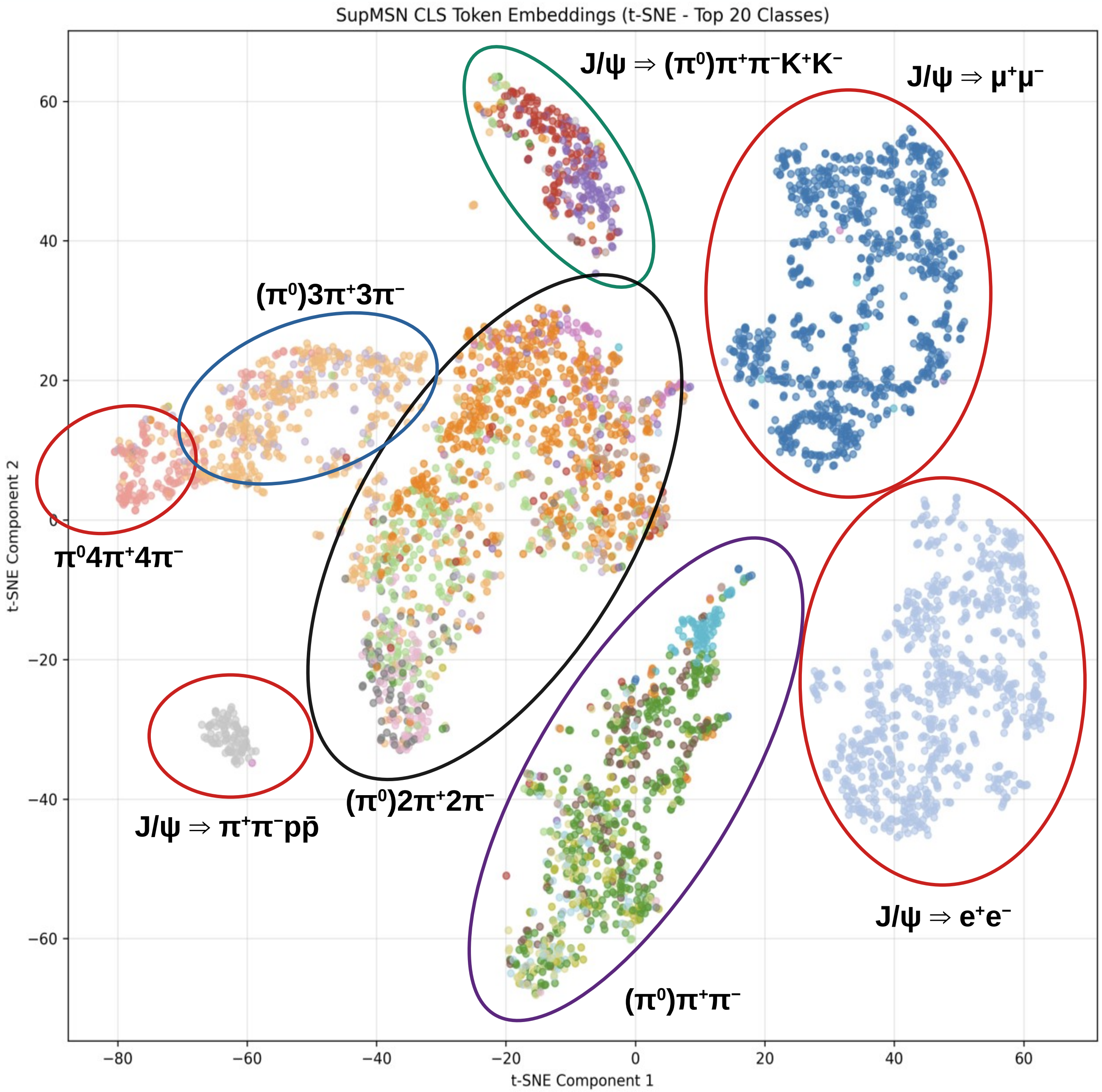
■ For the classification task, the embedding space was derived from representations of events drawn from the top 20 decay classes.

■ In the t-SNE visualization, **7 clusters emerge**.

■ Among these, **3 clusters** are composed almost of **a single type of decay event**.

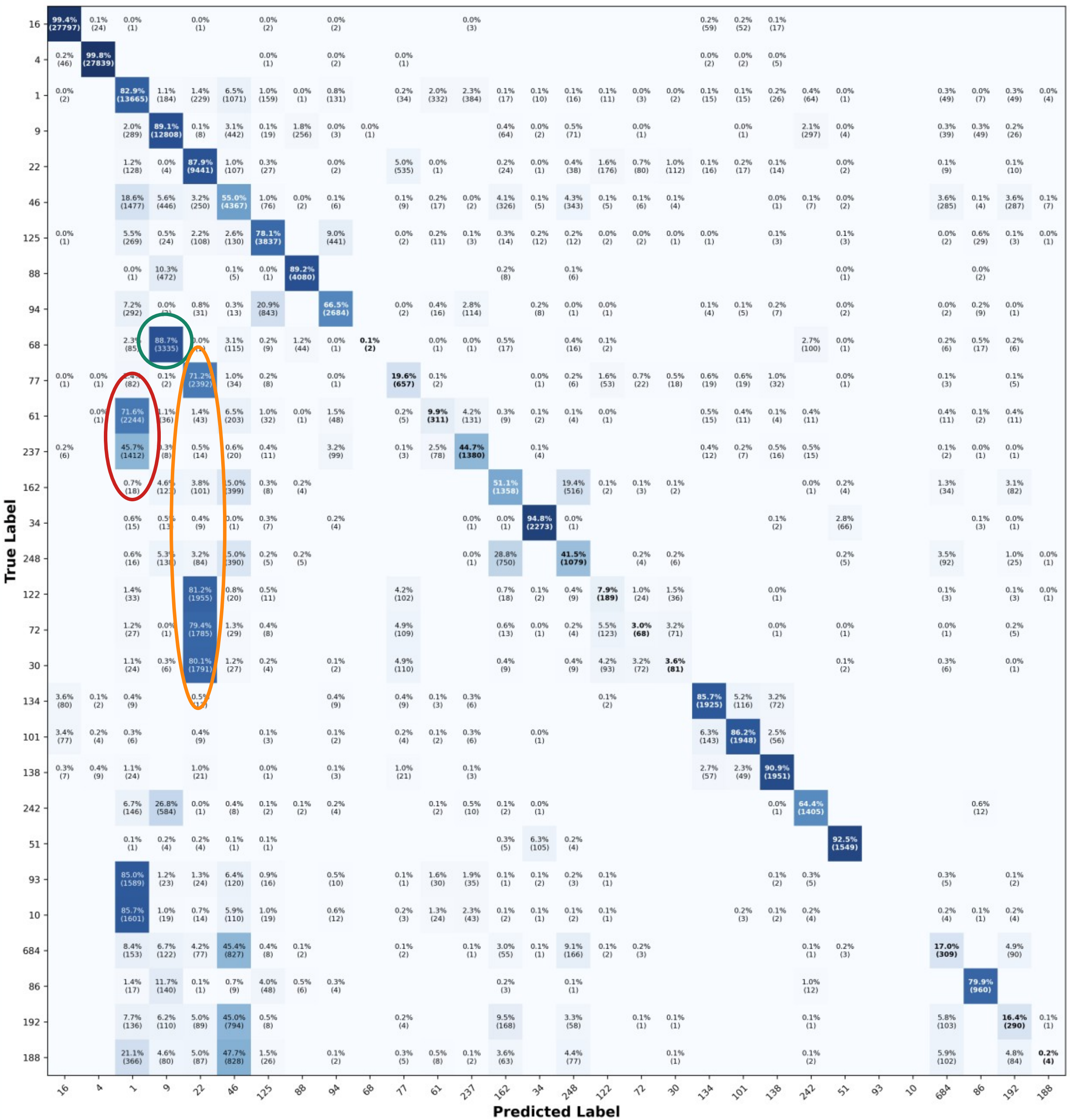
■ The remaining **4 clusters** contain events from **more than three different decay modes**.

Research Results



- Cluster 1:
  - ◎ $J/\psi \Rightarrow \pi^0\pi^+\pi^-K^+K^-$
  - ◎ $J/\psi \Rightarrow \pi^+\pi^-K^+K^-$
- Cluster 2:
  - ◎ $J/\psi \Rightarrow \pi^0\pi^+\pi^+\pi^+\pi^-\pi^-\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^+\pi^+\pi^-\pi^-\omega$, $\omega \Rightarrow \pi^0\pi^+\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^+\pi^+\pi^+\pi^+\pi^-\pi^-\pi^-\pi^-$
- Cluster 3:
  - ◎ $J/\psi \Rightarrow \pi^0\pi^+\pi^+\pi^-\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^+\pi^+\pi^-\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0\pi^+\pi^+\pi^-\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0\pi^-b^+_1$, $b^+_1 \Rightarrow \pi^+\omega$, $\omega \Rightarrow \pi^0\pi^+\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0\pi^-b^-_1$, $b^-_1 \Rightarrow \pi^+\omega$, $\omega \Rightarrow \pi^0\pi^+\pi^-$
- Cluster 4:
  - ◎ $J/\psi \Rightarrow \pi^+\rho^-$, $\rho^- \Rightarrow \pi^0\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0\pi^0\pi^+\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0\pi^+\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0h_1(1170)$, $h_1(1170) \Rightarrow \pi^0\rho^0$, $\rho^0 \Rightarrow \pi^+\pi^-$
  - ◎ $J/\psi \Rightarrow \pi^0\pi^0h_1(1170)$, $h_1(1170) \Rightarrow \pi^-\rho^+$, $\rho^+ \Rightarrow \pi^0\pi^+$

Research Results



Classification results:

■ C68 ⇒ C9: (88.7%)

C9 = $\pi^0\pi^+\pi^+\pi^+\pi^-\pi^-\pi^-$

C68 = $\pi^+\pi^+\pi^-\pi^-$**ω**, **ω** ⇒ $\pi^0\pi^+\pi^-$

■ C61 ⇒ C1: (71.6%)

■ C237 ⇒ C1: (45.7%)

C1 = $\boldsymbol{\pi^0}\pi^+\pi^+\pi^-\pi^-$

C61 = $\pi^+\pi^-$**ω**, **ω** ⇒ $\pi^0\pi^+\pi^-$

C237 = $\pi^+\pi^+\pi^-\pi^-$

■ C77 ⇒ C22: (71.2%)

■ C122 ⇒ C22: (81.2%)

■ C72 ⇒ C22: (79.4%)

■ C30 ⇒ C22: (80.1%)

C22 = $\boldsymbol{\pi^0}\pi^0\pi^0\pi^+\pi^-$

C77 = $\pi^0\pi^0\pi^+\pi^-$

C122 = $\pi^0\pi^0h_1(1170)$, **h_1 (1170)** ⇒ $\pi^0\rho^0$, $\rho^0 \Rightarrow \pi^+\pi^-$

C72 = $\pi^0\pi^0h_1(1170)$, **h_1 (1170)** ⇒ $\pi^-\rho^+$, $\rho^+ \Rightarrow \pi^0\pi^+$

C30 = $\pi^0\pi^0h_1(1170)$, **h_1 (1170)** ⇒ $\pi^+\rho^-$, $\rho^- \Rightarrow \pi^0\pi^-$

★ not sensitive to **neutral track** and **resonance state**.

Research Results

Comparison with Standard Approaches:

Table 1: Performance Comparison on Different Decay Channels

	Foundation Model			Traditional Method		
Decay Channel	**Precision**	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**
$J/\psi \to \pi^+\rho^-, \rho^- \to \pi^0\pi^-$	0.72	**0.79**	0.75	0.72	0.74	0.73
$J/\psi \to \pi^-\rho^+, \rho^+ \to \pi^0\pi^+$	0.70	**0.79**	0.74	0.71	0.74	0.72
$J/\psi \to \pi^0\rho^0, \rho^0 \to \pi^+\pi^-$	0.82	**0.87**	0.85	0.82	0.82	0.82
$J/\psi \to \pi^+\pi^-\pi^0$	0.74	**0.76**	0.74	0.74	0.70	0.71

◎ For all events that are well separated by traditional methods, our foundation model achieves comparably high classification accuracy.

◎ Compared with traditional physics-based methods, **foundation models achieve higher recall at the same precision level**.

◎ Traditional physics-based methods can **further increase precision above 99% by sacrificing recall**, which **foundation models currently cannot achieve**.

Part 4: Conclusions

Conclusions

1. We successfully developed a **foundation model** for high-energy physics collider data — the **Particle Masked Siamese Encoder (Particle MSE)** — built upon a transformer-based architecture. The model achieves promising performance across various downstream tasks, including **clustering, event-level classification and anomaly detection**.

2. There remains room for improvement for reconstruction in pretext task, particularly in **reproducing fine structures**.

3. The Particle MSE–based model shows **limited sensitivity to neural track** and **resonance states**, for event-level classification.

Future Work:

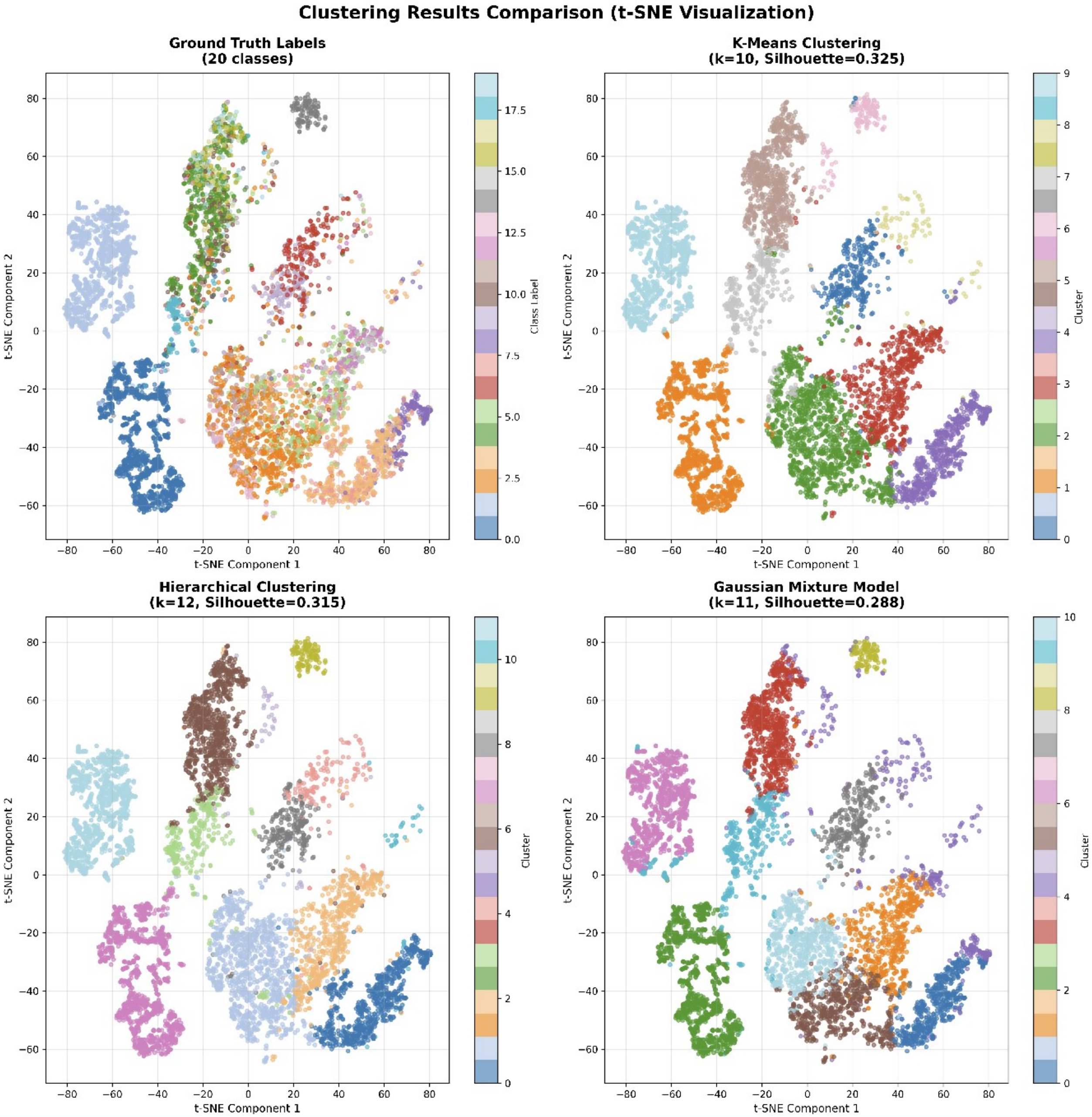
1. Address the model's insensitivity to neutral tracks and resonance states such as dynamic contrastive learning and hard mining.

2. Explore self-supervised contrastive learning approaches.

3. Explore more advance masking approaches.

Thank you for listening!
Any question?

Appendix



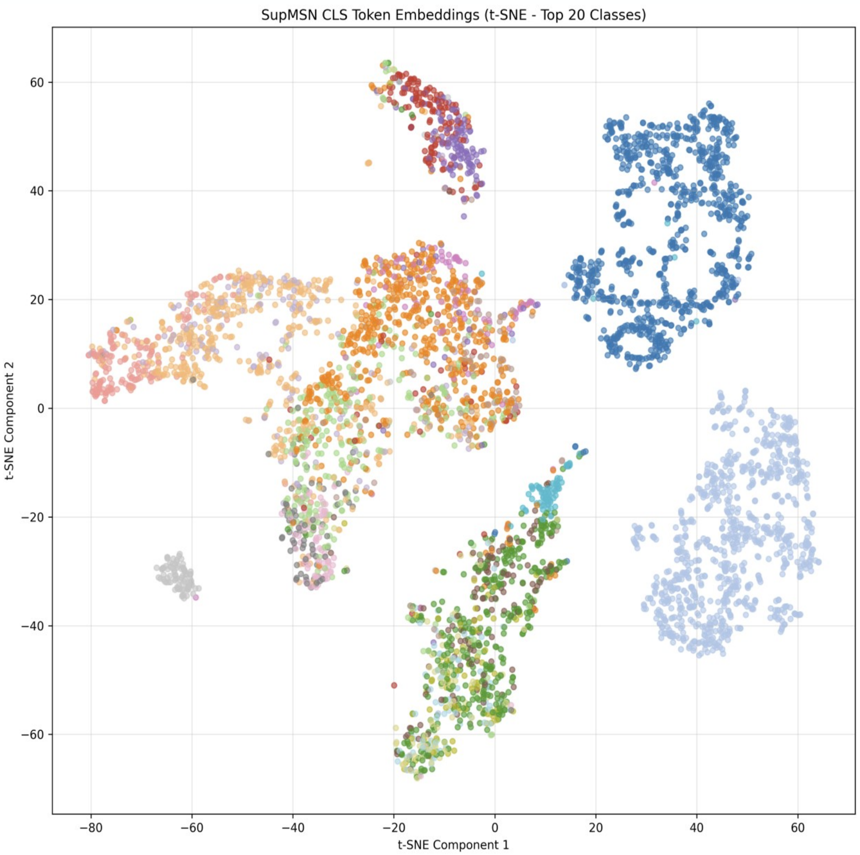
__Clustering Results:__

◉ The model can generally distinguish the decay-event timings **for the three clusters.**

✗However, **for the central four clusters**, the patterns, which have multiple decay events **remain difficult to separate**.

✗In future work, **Dynamic contrastive learning** will be incorporated to enhance clustering performance and improve class-level separability.

Appendix



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