Learning Broken Symmetries With Approximate Invariance

A Novel Dual-Subnetwork Approach to Classifying Particle Collision Events

The Problem

Scientists use machine learning models to study particle collisions. While this is necessary to learn the mysteries of the universe, it requires a lot of computing power and data. To overcome this, some models are "taught" physical symmetries beforehand, speeding up training but causing a drop in accuracy.
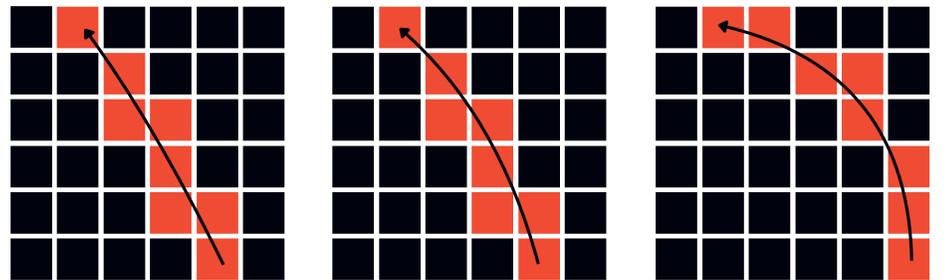
Until now, there were two main types of machine learning models used in particle physics:

Particle Flow Network (PFN)
Field-standard model when not encoding any symmetries; learns slowly but accurately (Komiske et al.)

Invariant Network
Lorentz symmetry is assumed; learns quickly but inaccurately because of symmetry breaking

I designed a new model that combines the strengths of PFNs and invariant networks, while avoiding their faults.

Even though these paths are different, the detector records them identically. This uncertainty breaks the Lorentz symmetry, confusing an invariant network.

When particles make smaller loops, they are measured more accurately.

Figure 1: Collider calorimeter and symmetry breaking. Graphics created by finalist with Canva, 2026.

Novel Model Architecture
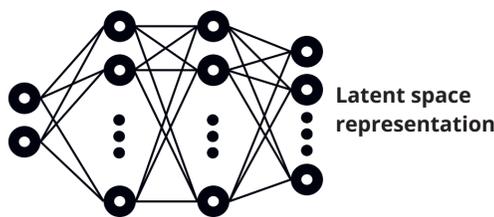

Latent space representation

Figure 2 (a). Instead of directly combining the predictions of two subnetworks, **both produce a high-dimensional representation** of the particle collision. This **preserves more information** to make a more accurate prediction later.

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_l \end{bmatrix} = w \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_l \end{bmatrix} + (1-w) \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_l \end{bmatrix}$$

Figure 2 (b). To combine the latent space representations, I used **weighted average pooling** in a new way, making it dynamic. This creates a final representation of the collision event by taking a weighted average of the two representations from each subnetwork, where the weight is *learned*.
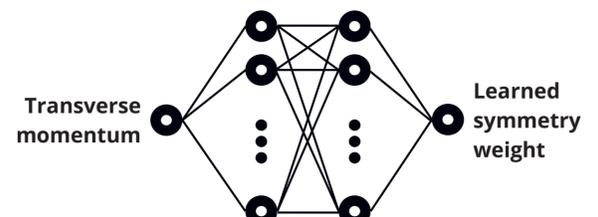
Transverse momentum — Learned symmetry weight

Figure 2 (c). I invented a novel **third subnetwork** whose job is to learn *how* and *when* the symmetry breaks. For this example, the transverse momentum is known to affect symmetry breaking. The **learned symmetry weight** allows the model to retain accuracy, even as the symmetry breaks.

Figure 2 a, c: Graphics created by finalist with Canva, 2026. **Figure 2 b:** Created by finalist with LaTeX, 2025. DOI: 10.1103/PhysRevD.111.072002.
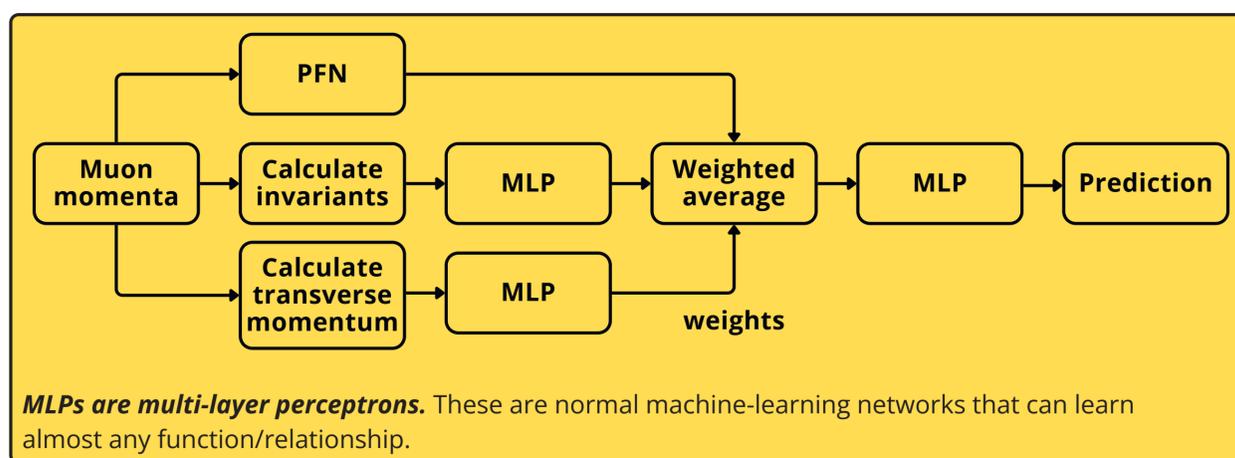
MLPs are multi-layer perceptrons. These are normal machine-learning networks that can learn almost any function/relationship.

Figure 3: Novel hybrid architecture. Diagram created by finalist with Canva, 2026. Adapted from previous diagram finalist made with LaTeX. DOI: 10.1103/PhysRevD.111.072002.
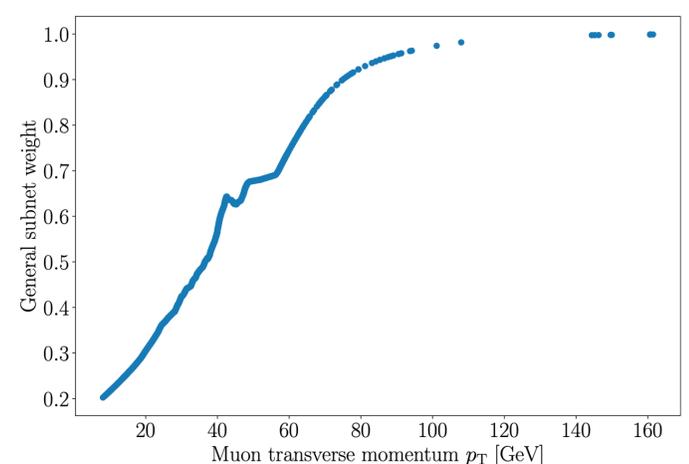

Figure 4: Learned symmetry weight versus transverse momentum. Graph created by finalist with Matplotlib, 2025. DOI: 10.1103/PhysRevD.111.072002.
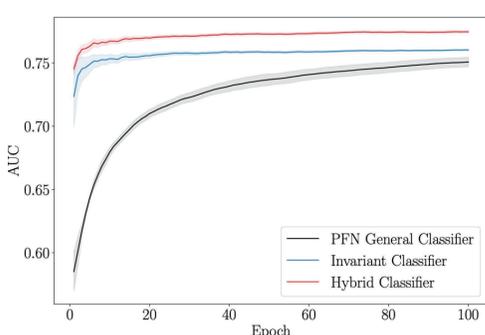
Results

Figure 5 (a): When the dataset is small, my hybrid model learns the fastest and most accurately. Many situations in particle physics have limited data, making this environment important to test in.

When resources are limited, hybrid architectures can be used to efficiently create very accurate models.
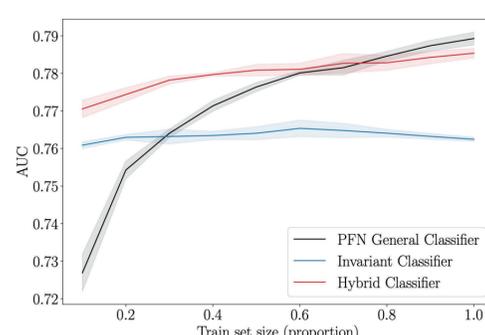

Figure 5 (b): Across different dataset sizes, the hybrid model outperforms a purely invariant classifier. It usually outperforms a PFN when training data is moderate. With ample data, the PFN still learns broken symmetries the best. Even for moderate datasets, hybrid is still best, making it a good bet for most situations.

Figure 5 a-b: Graphs created by finalist with Matplotlib, 2025. DOI: 10.1103/PhysRevD.111.072002.

References

Komiske, P. T., Metodiev, E. M., & Thaler, J. (2019). Energy flow networks: deep sets for particle jets. Journal of High Energy Physics, 1. https://doi.org/10.1007/jhep01(2019)121

Murnane, D., Thais, S., & Wong, J. (2023). Semi-Equivariant GNN Architectures for Jet Tagging. Journal of Physics: Conference Series, 1, 012121. https://doi.org/10.1088/1742-6596/2438/1/012121

Nabat, S., Ghosh, A., Witkowski, E., Kasieczka, G., & Whiteson, D. (2025). Learning broken symmetries with approximate invariance. Physical Review D, 111(7). https://doi.org/10.1103/physrevd.111.072002

Witkowski, E., & Whiteson, D. (2023). Learning Broken Symmetries with Resimulation and Encouraged Invariance. https://doi.org/10.48550/arXiv.2311.05952

Nabat, S.