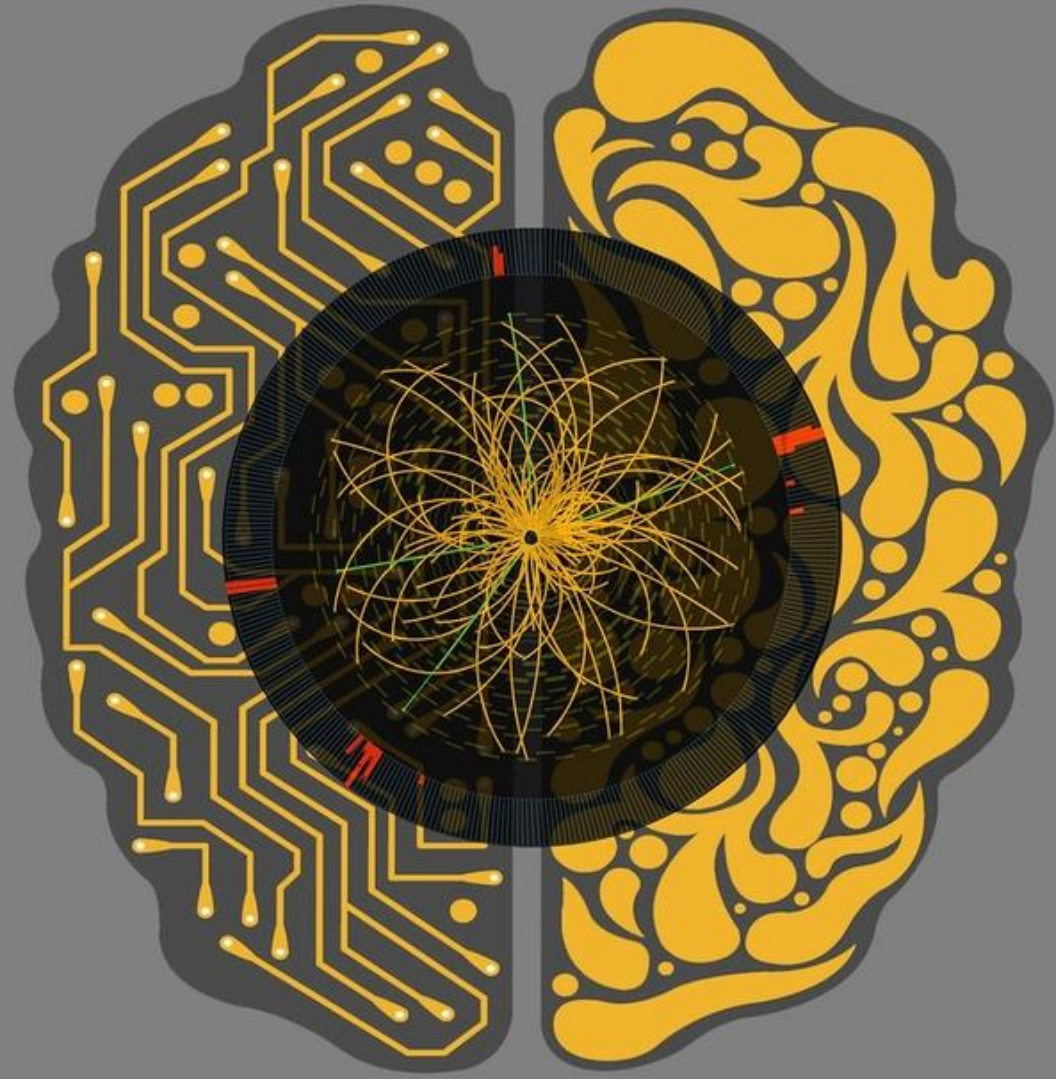




Building Foundation Models with low-level collider data

Aritra Das, Daniel Murnane, Shreya Saha

HAMLET-Physics
Copenhagen 2026

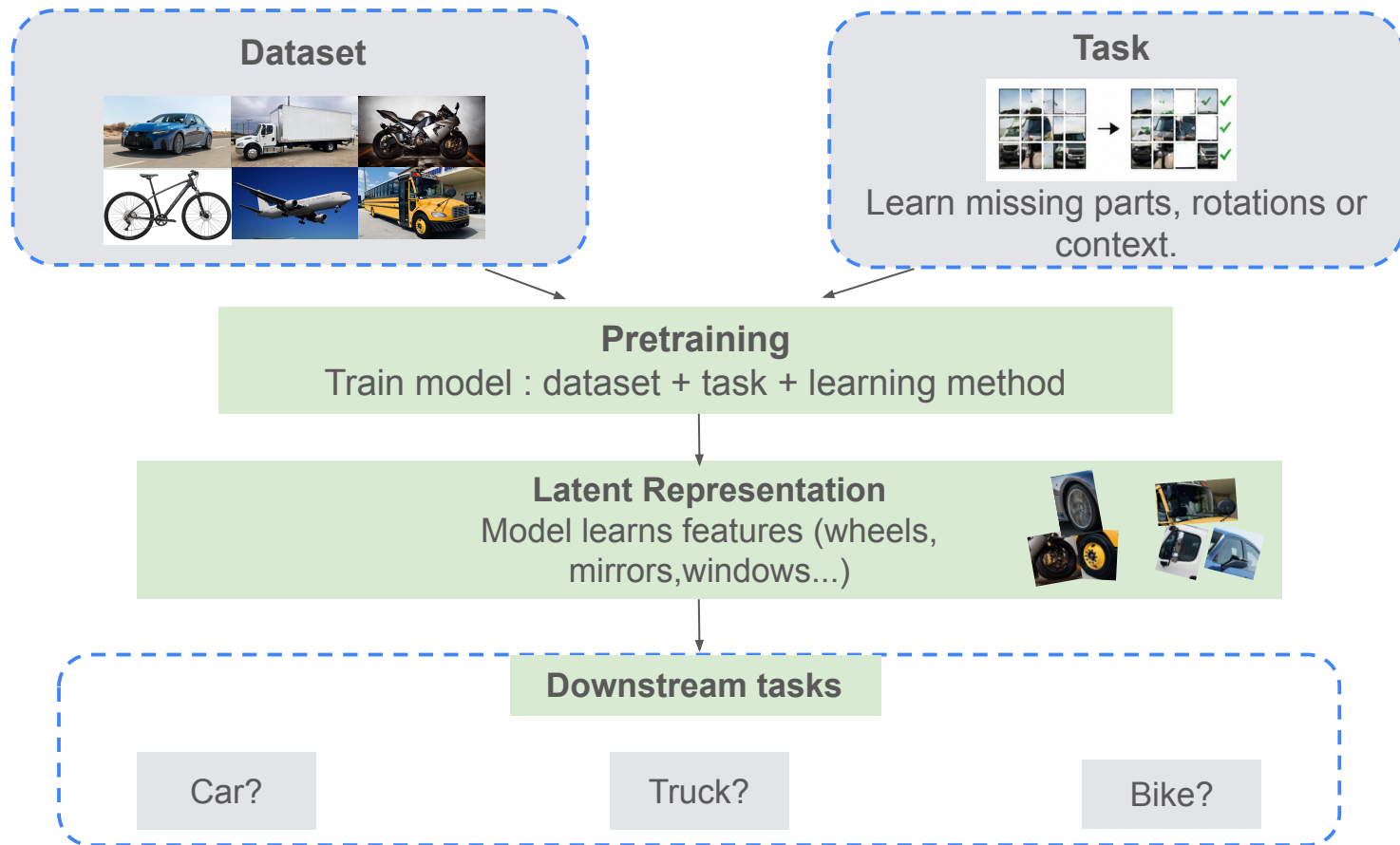


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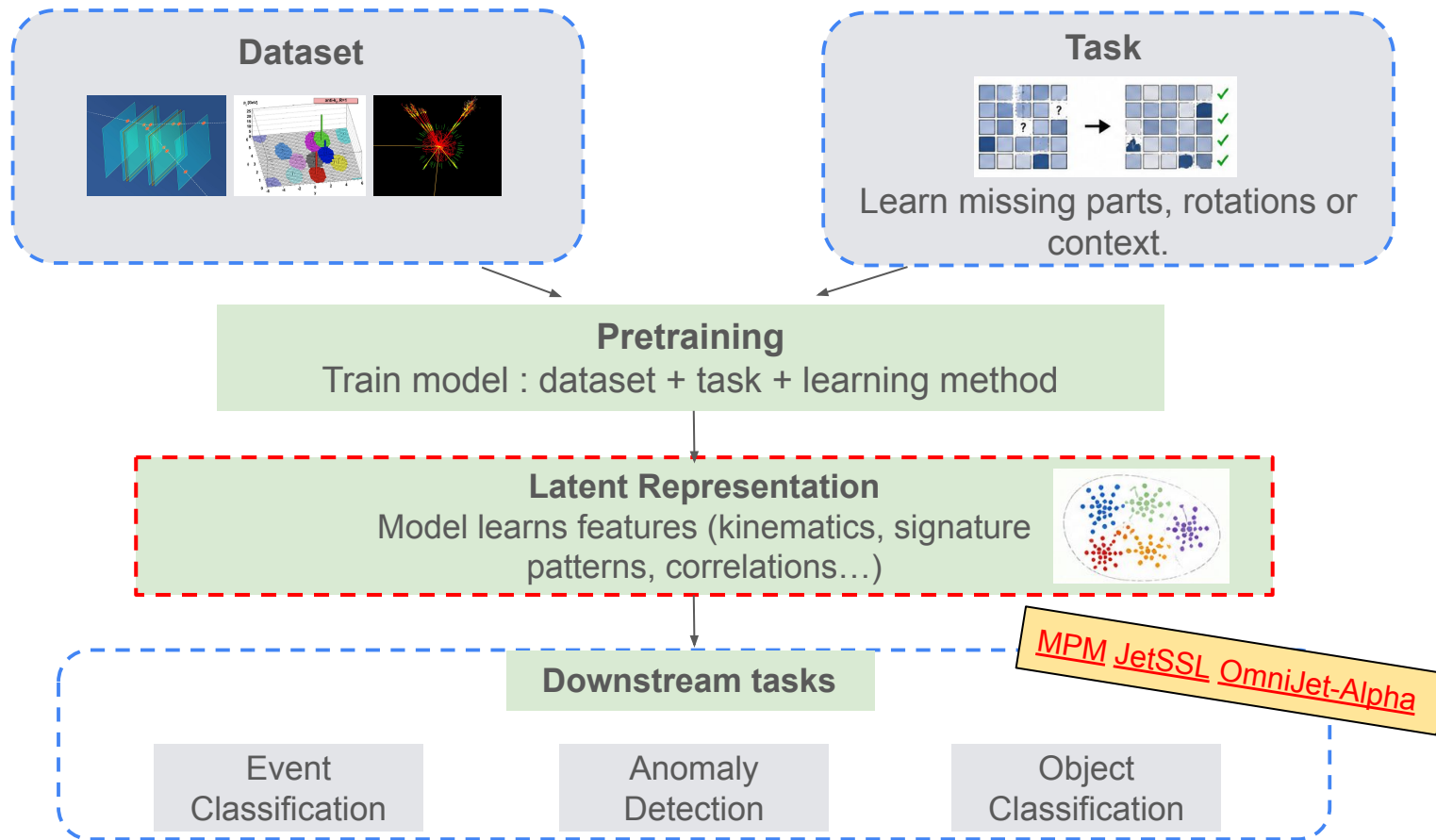


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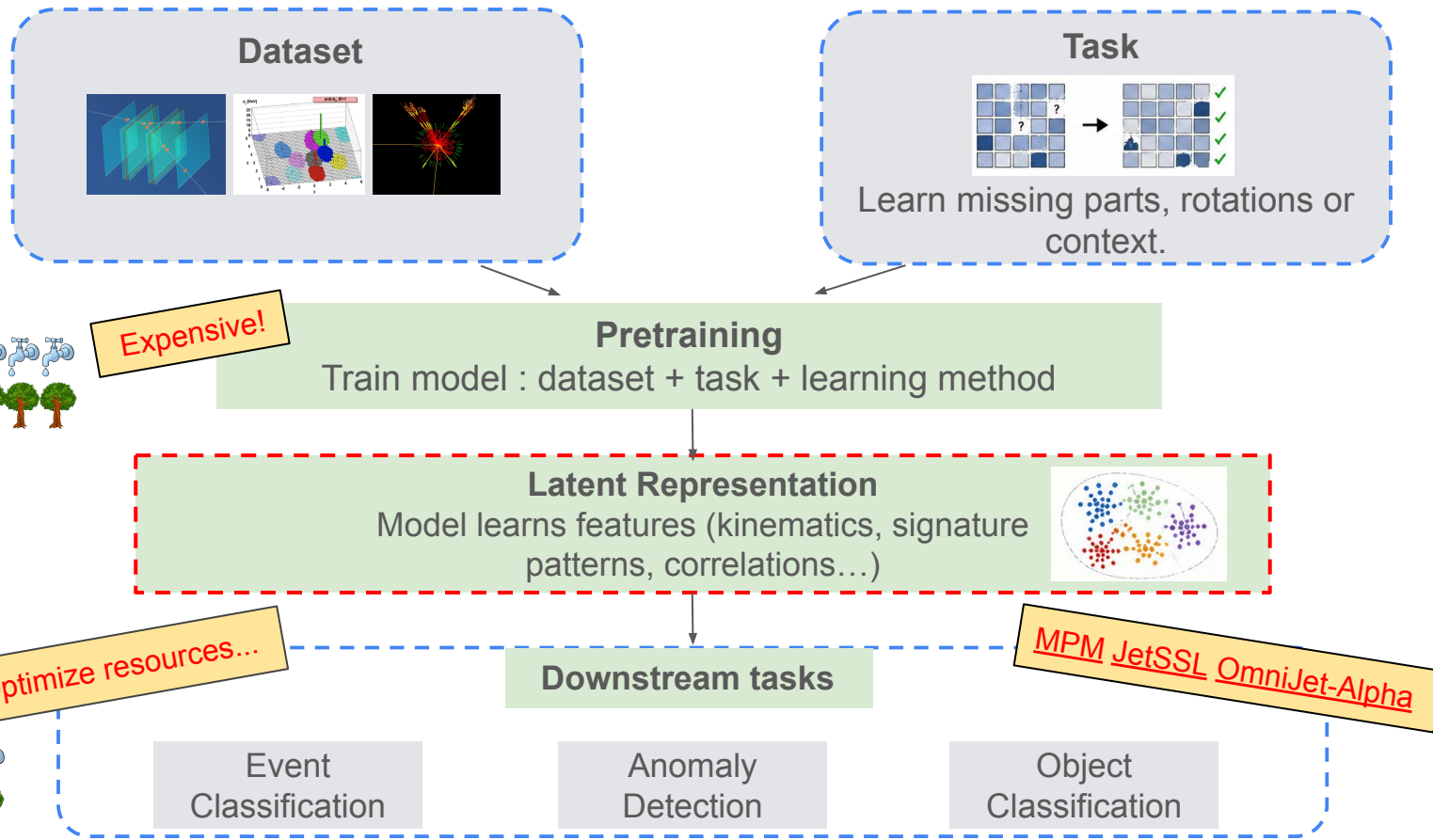
Foundation Models



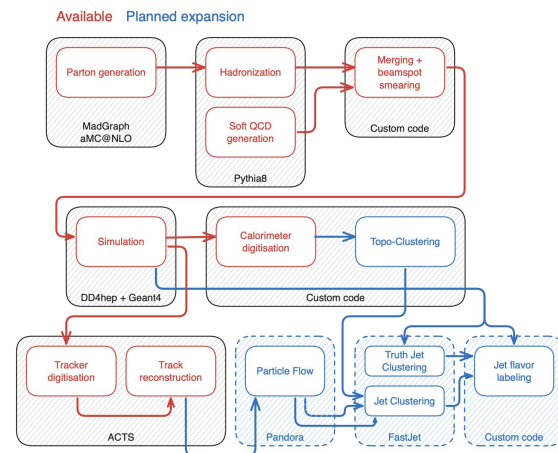
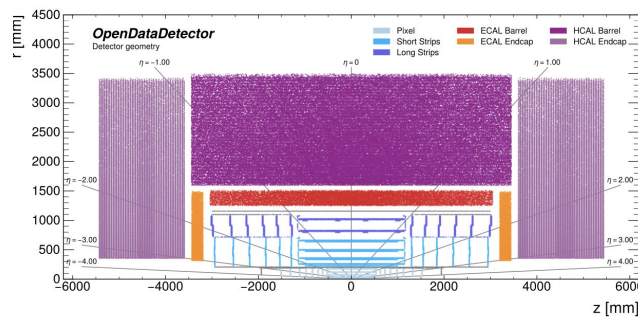
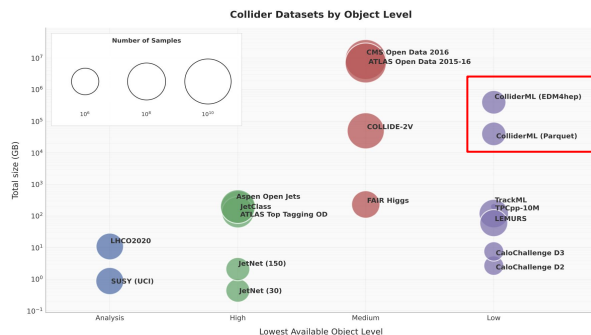
Foundation Models for Particle Physics



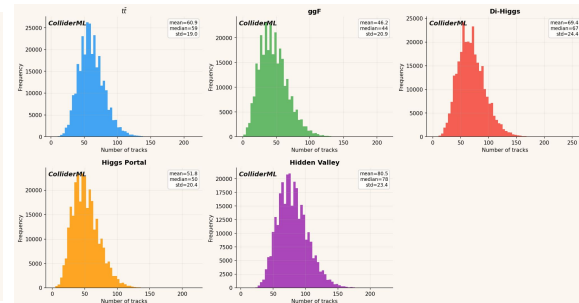
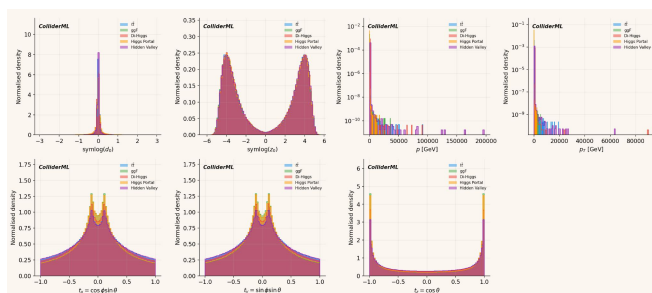
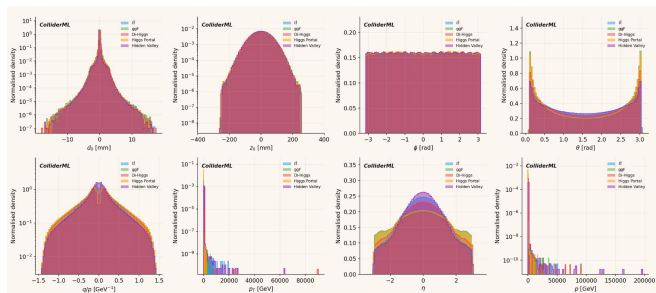
Foundation Models for Particle Physics



- Benchmark **full simulation** dataset with **low level information** (tracks, hits, calorimeter deposits) for High Luminosity LHC.
- Reconstruction based on the Open Data Detector and *A Common Tracking Software* (ACTS).
- **Standard Model processes** - Top pair production ($pp \rightarrow tt$), gluon-gluon fusion (ggF , $pp \rightarrow H$), Di-Higgs ($gg \rightarrow HH$)
- **Beyond Standard Model processes** - Higgs Portal production of a long-lived scalar ($H \rightarrow aa \rightarrow bbbb$) and Hidden Valley ($pp \rightarrow Z' \rightarrow \text{Dark QCD}$)
- Zero pileup option used for this study.



Feature distribution (tracks)



Raw track variables

Transverse impact parameter (d_0),
longitudinal impact parameter (z_0),
azimuthal angle (ϕ), polar angle (θ),
charge to momentum ratio (q/p),
transverse momentum (p_T),
pseudorapidity (η), momentum (p)

Engineered track variables (pretraining)

Log transformations for d_0 and z_0 ,
Polar to Cartesian coordinates
→ $t_x = \cos(\phi) \sin(\theta)$, $t_y = \sin(\phi) \sin(\theta)$,
 $t_z = \cos(\theta)$
 p , p_T

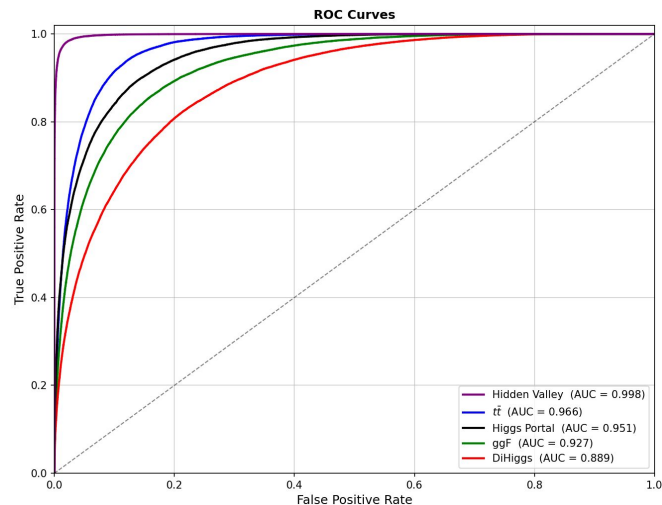
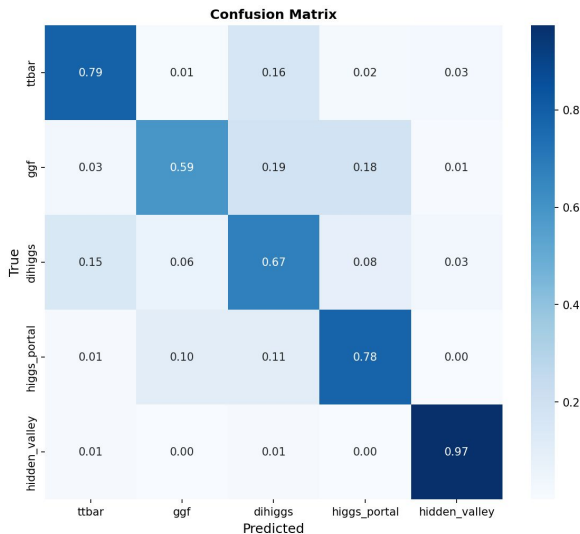
Number of tracks per event for each physics processes

Highest number of tracks - **Hidden Valley**

Lowest number of tracks - **ggF**

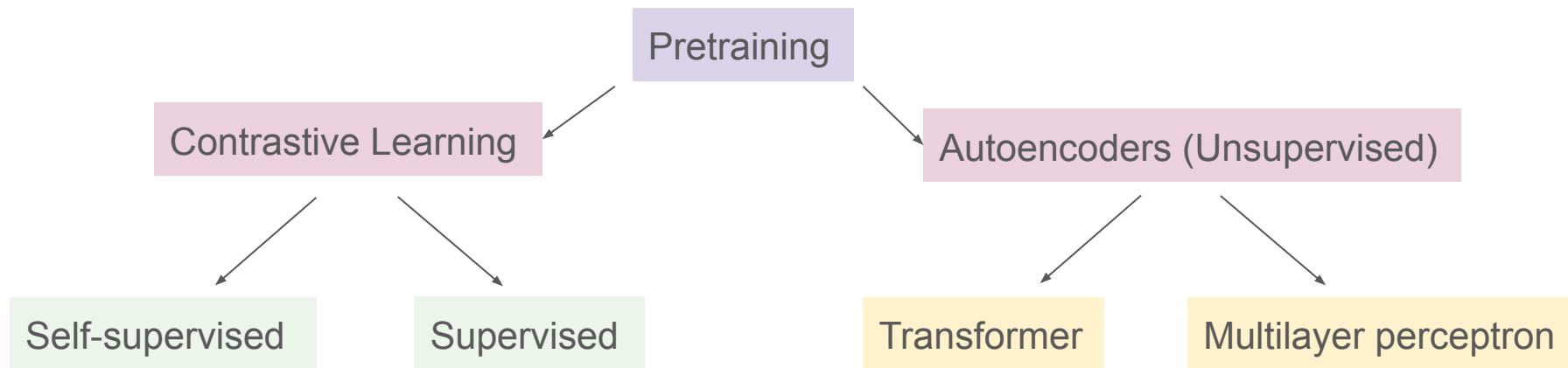
Vanilla Transformer

- **Input** - 300,000 events per process, raw track variables.
- Tracks $\rightarrow$ 128-dimensional embeddings $\rightarrow$ 8 transformer layers X 8 attention heads.
- **Classification head**: 64-dimensional multi-layer perceptron (MLP) maps the latent representation to classes.
- **Highest efficiency** - Hidden Valley
- **Lowest efficiency** – ggF
- **Largest misclassification** for ggF is with the Di-Higgs process, due to overlapping final state signatures.



Pretraining the model

The model is pretrained using **task** information, and divided into various types depending on the **learning method** (*Unsupervised*, *Self-supervised*, *Supervised*) and the **model architecture**.



Contrastive Learning

Contrastive learning (CL) learns representations of data by **contrasting** between **similar** and **dissimilar samples**.

Input - 7 engineered track variables per track.

Self Supervised CL (No labels)

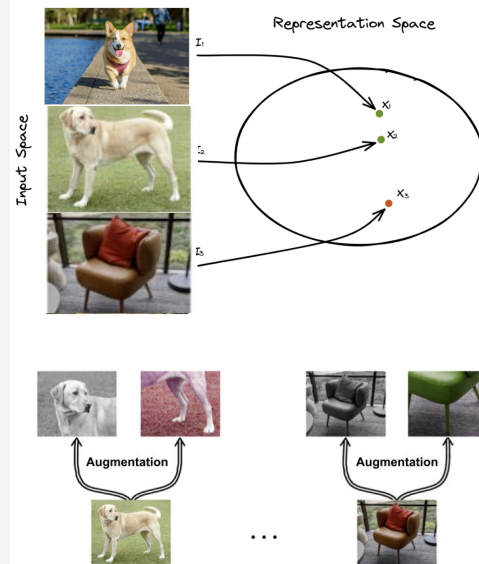
- Two independent **physics-invariant augmentations** (Random rotation and Gaussian smearing) are applied to each event.
- Augmentations from the **same event are grouped together** in the latent space.
- Loss **maximizes** the **similarity** between the **event and its positive counterpart**, and **minimizes** the **similarity** to all **other representations**.

Supervised CL (Labels)

- Similar machinery as above, but uses **physics process labels** instead of augmentations.
- Loss function is maximized to **group events** from the **same process together**.

Output - Pretrained models with $D = 8/32/64$ dimensional latent space.

[Metzger, Kyle, et al](#)



Autoencoders

The goal of the autoencoder is to compress every event (**encoder**) into a **latent representation**, to capture the most important event features, and further reconstruct the original event (**decoder**). **No labels** provided.

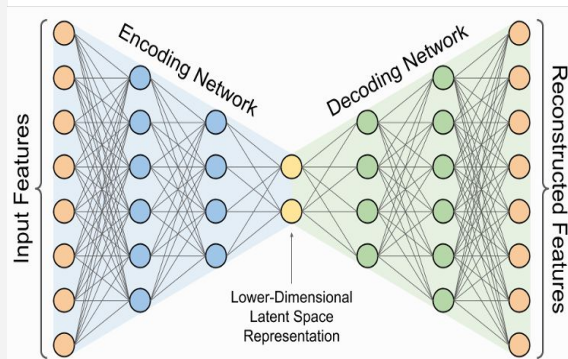
Transformer-based architecture

- **Input** - Engineered track variables.
- **Reconstruction target** - Summary statistics (mean, standard deviation, minimum and maximum value) per track variable.
- **Encoder** - 4 layers X 4 **attention heads**/ layer, **decoder** is a three-layer MLP (Dimensions: $128 \rightarrow 256 \rightarrow 28$).
- **Loss function** = Mean squared error.

Multilayer Perceptron (MLP) based architecture

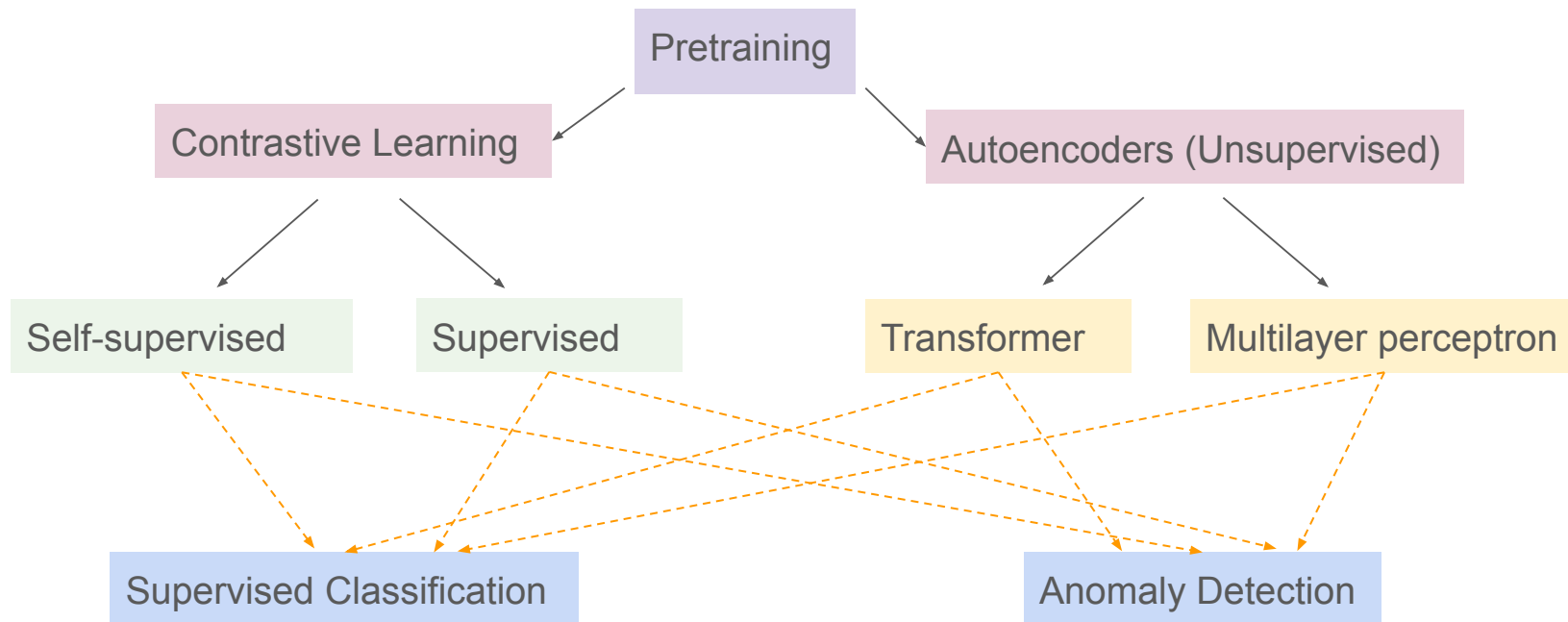
- **Input** - Summary statistics
- **Reconstruction target** - Summary statistics
- **Encoder** - Three- layer MLP ($28 \rightarrow 256 \rightarrow 128 \rightarrow D$), decoder (above).
- **Loss function** = Mean squared error.

Output - Pretrained models with $D = 8/32/64$ dimensional latent space.



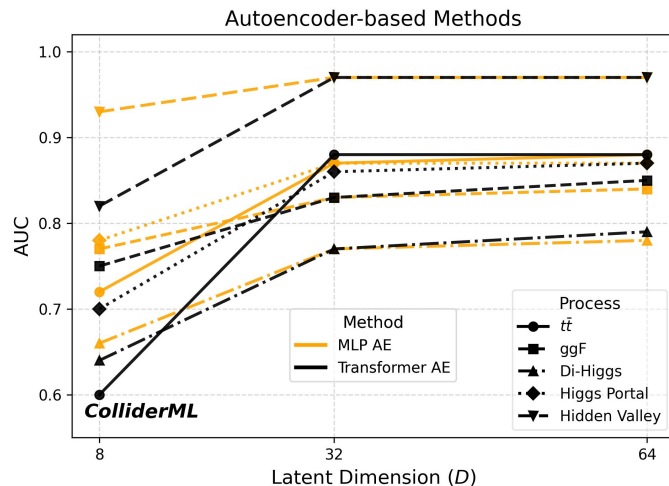
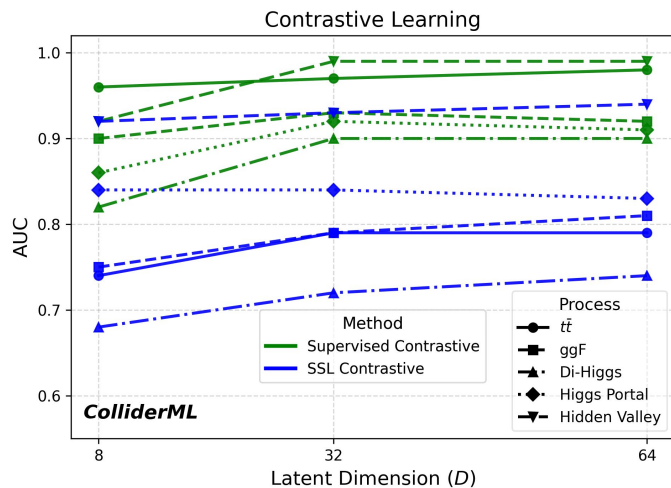
Downstream tasks

- Each pretrained model is used to produce event embeddings from the frozen encoder.
- Performance on downstream tasks → **quality of the latent representations** learned by each model.
- Supervised Classification, Anomaly Detection.

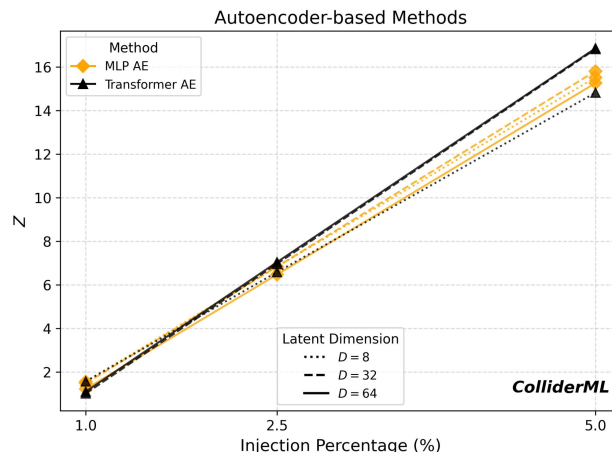
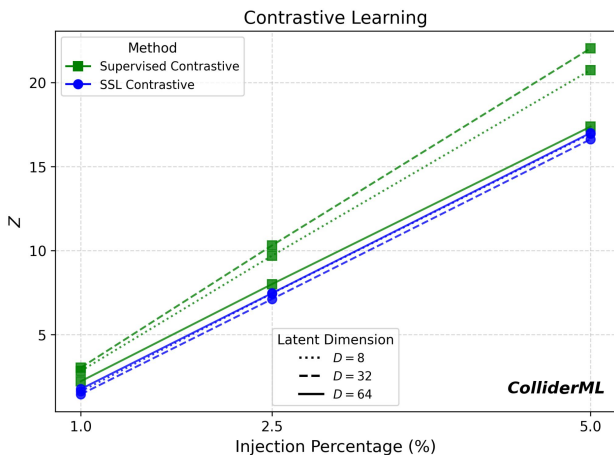
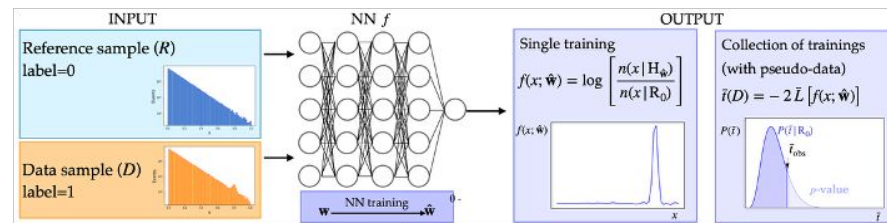


Supervised Classification

- **Frozen encoder event embeddings + labels** are used as input.
- A 5-dimensional linear probe is trained, keeping the model frozen.
- Labels during pretraining improve downstream classification, with **Supervised CL** (D= 64) achieving **highest accuracy**.
- **Transformer AE** (D = 8) gives **lowest accuracy**.
- Hidden Valley classification consistently shows the highest efficiency across models, owing to its distinct final-state features.



- **New Physics Learning Machine** : Compare the background hypothesis (R) to an unknown alternative (H_w) learnt from the data using a neural network.
- Perform 5000 pseudo-experiments and evaluate **asymptotic Z value** at varying signal injection levels.



Supervised CL shows better performance, highlighting the **benefit of label** information provided during pretraining.

Conclusion and Outlook

- Low-level collider data can be used to build robust FMs, showing promising performance in classification and anomaly detection tasks.
- Supervised Contrastive Learning performs better than other pretraining methods, due to the inclusion of labels in the training process.
- Sustainable computing practices with ML research - [SC4RC](#) [SUSHEP](#), [Green Algorithms](#)

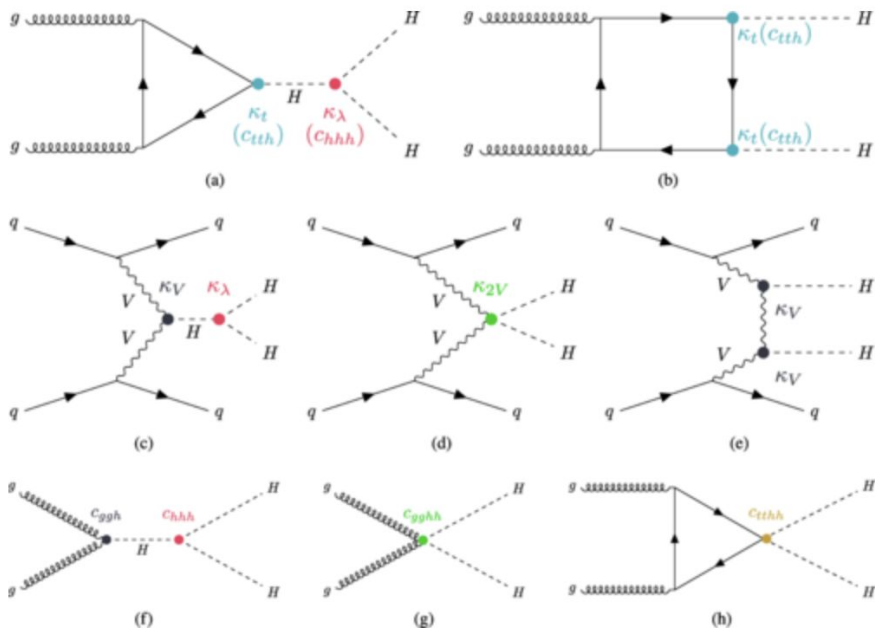
Future Work

- Compare fast vs. full simulation versions of ColliderML for more efficient models for the High-Luminosity LHC.
- Explore various downstream tasks, such as object-level anomaly classification.
- Include additional Standard Model processes (diboson and triboson events).
- Study model performance by incorporating calorimeter information alongside tracks.

Thank you!
Questions?

Backup

ColliderML dataset



ID	Process Label	Process Type	Comments
1	ttbar	$pp \rightarrow t\bar{t}$	Top quark production; important for SM tests and complex final states.
2	zee	$pp \rightarrow Z \rightarrow e^+e^-$	Drell-Yan process; detector calibration and electroweak probe.
3	zmumu	$pp \rightarrow Z \rightarrow \mu^+\mu^-$	Drell-Yan process; detector calibration and tracking probe.
4	dihiggs	$gg \rightarrow HH$	Gluon fusion di-Higgs; benchmark for high-Luminosity studies.
5	diphoton	$pp \rightarrow \gamma\gamma$	Diphoton production; loop-induced QCD/EW process.
6	multijet	$pp \rightarrow \text{jets}$	QCD production; dominant background for hadronic signatures.
7	ggf	$pp \rightarrow H$	Gluon-gluon fusion; main Higgs production channel.
8	susy	$pp \rightarrow \tilde{g}\tilde{g}$	GMSB gluino production; $\tilde{\chi}_1^0$ NLSP provides displaced vertex benchmark.
9	zprime	$pp \rightarrow Z'_{SSM}$	Heavy resonance; standard candle for bump hunting.
10	hiddenvalley	$pp \rightarrow Z' \rightarrow \text{dark}$	Dark QCD sector; semi-visible jets for anomaly detection.