Generic representations of jets at detector-level with self supervised learning

Kyle Cranmer, Etienne Dreyer, Eilam Gross, Nilotpal Kakati,
Dmitrii Kobilianskii, Patrick Rieck, Nathalie Soybelman

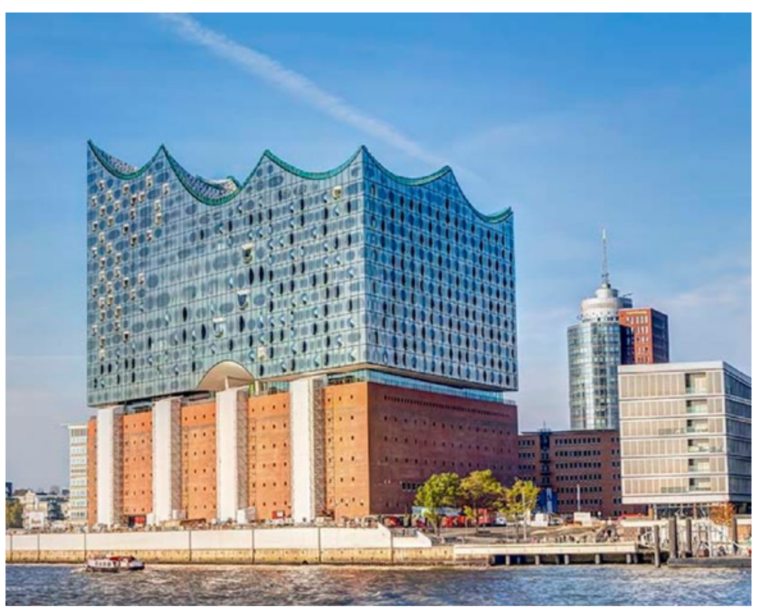
ML4Jets 2023
DESY Hamburg

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

NYU

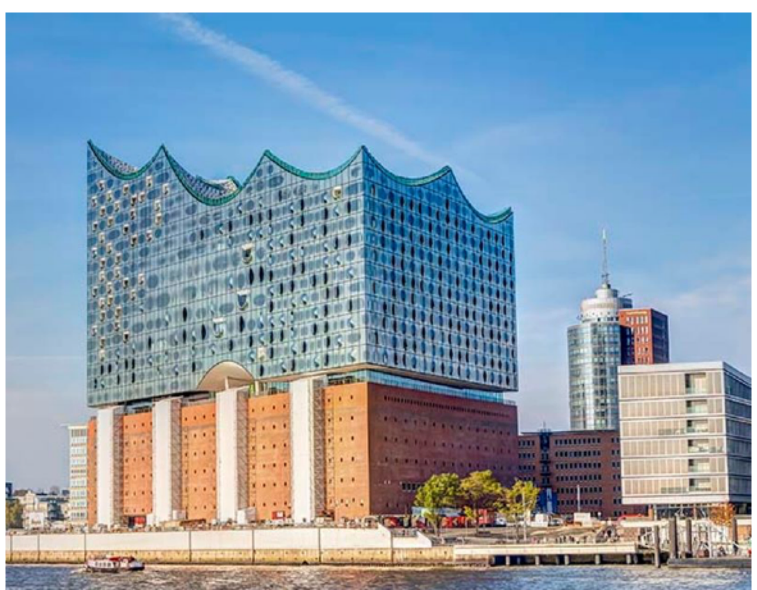
מכון ויצמן למדע
WEIZMANN INSTITUTE OF SCIENCE

representation space

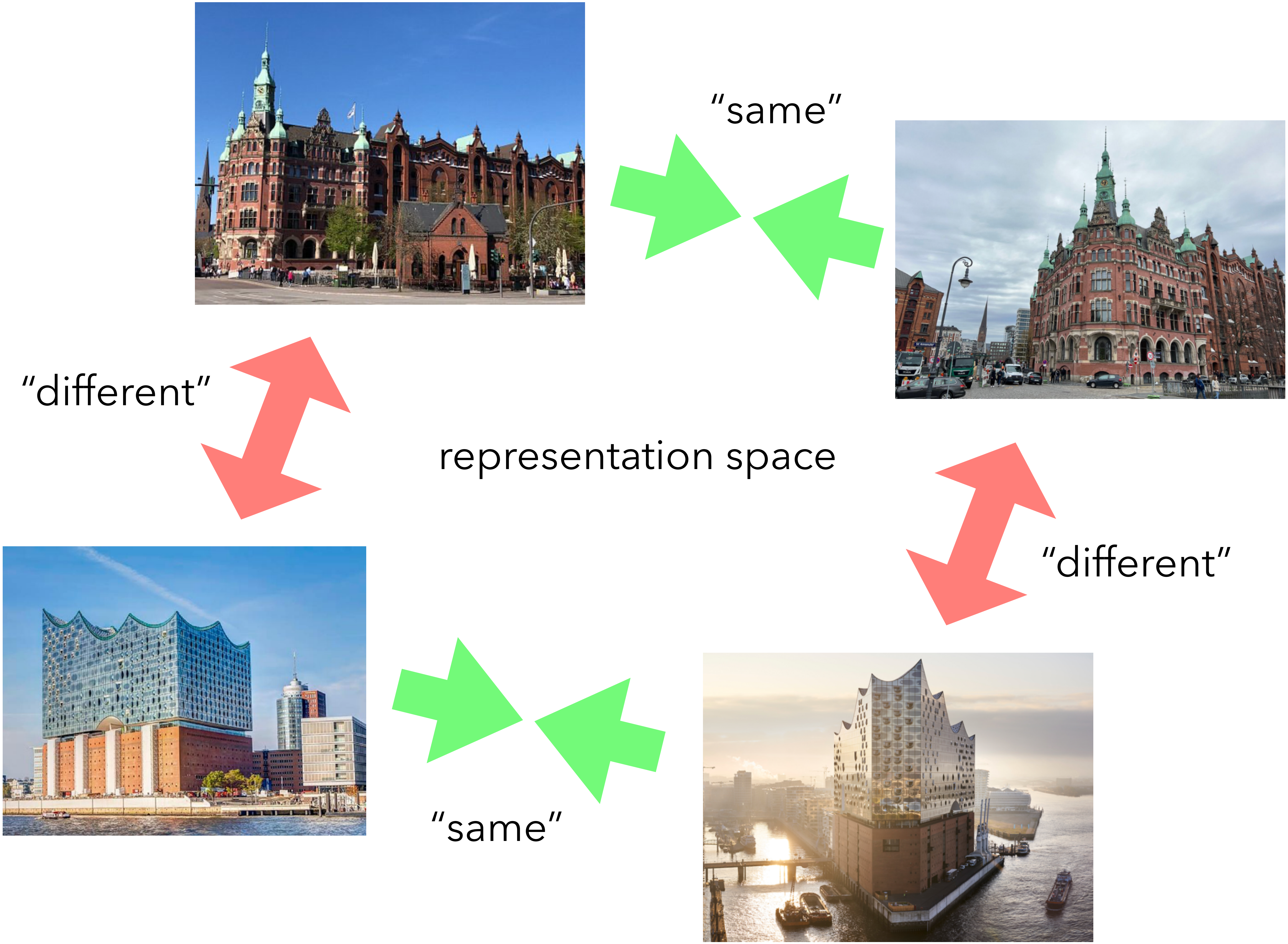


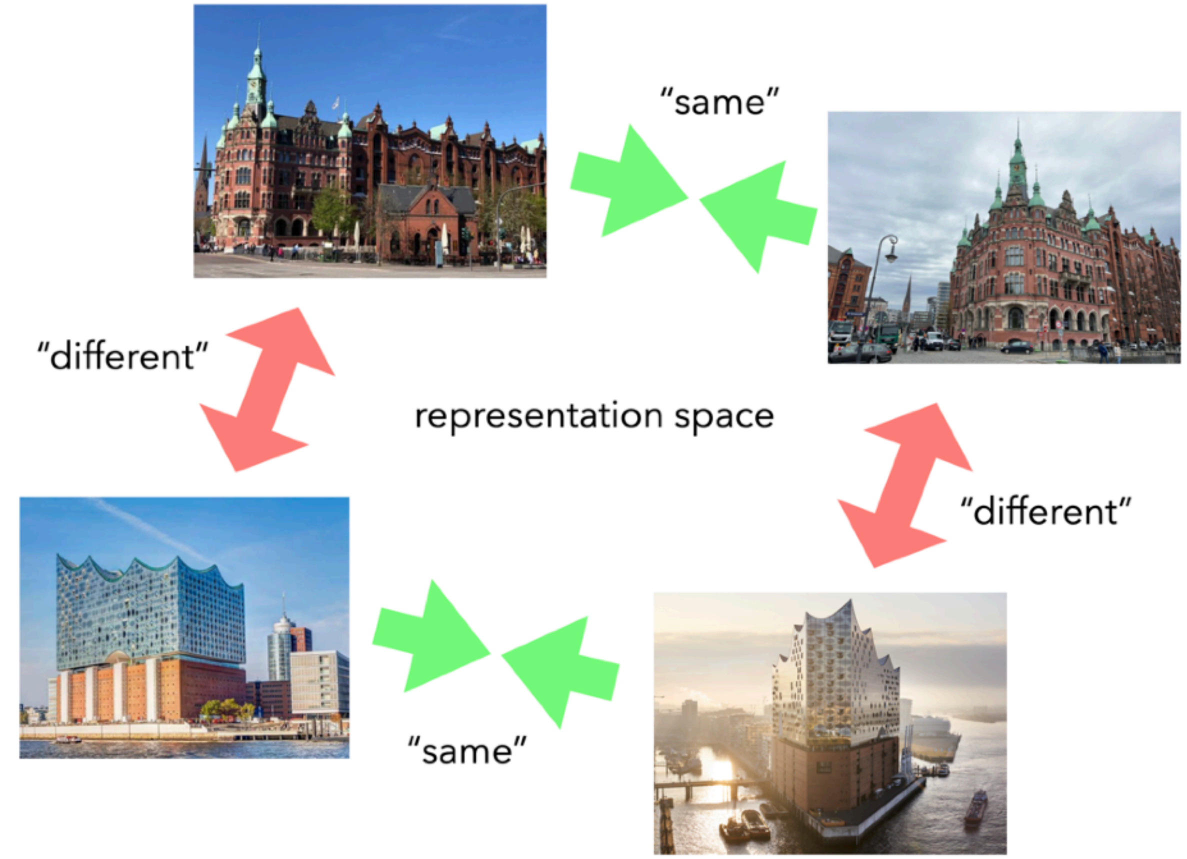
"same"

representation space



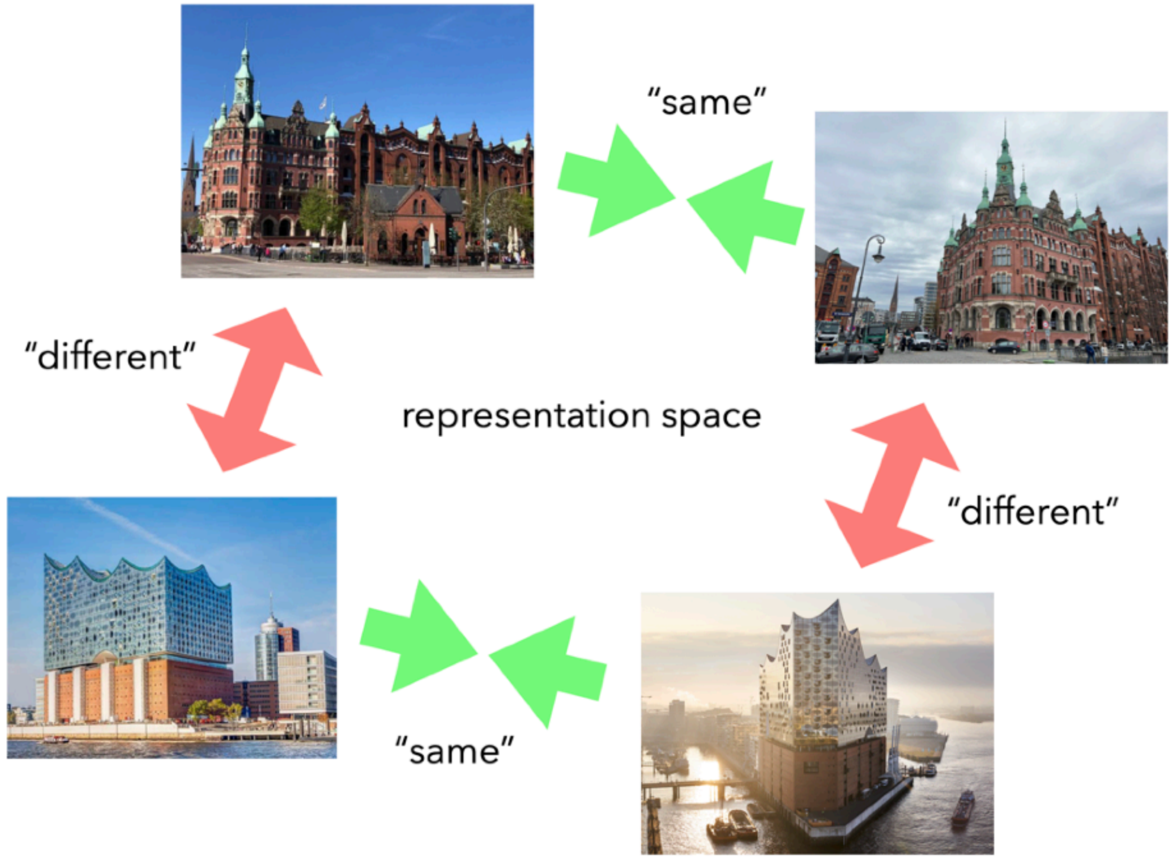
"same"


"same"
"different"
representation space
"different"
"same"



Motivation

Given an adequate method of defining "sameness" pseudo-labels, self-supervised models can be trained to extract features without relying on explicit labels



Motivation

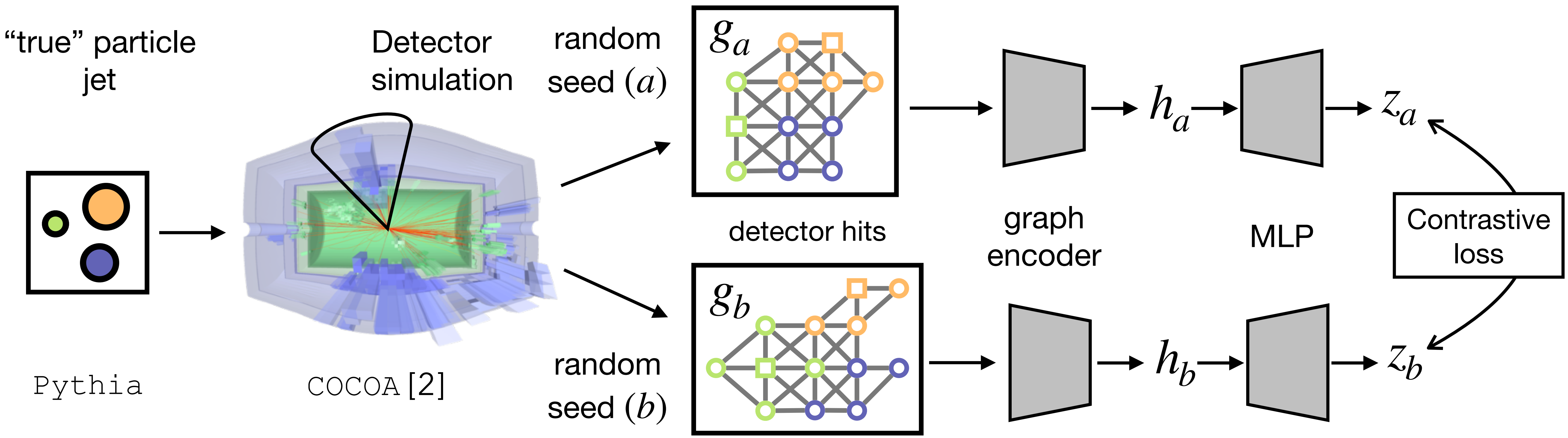
Given an adequate method of defining "sameness" pseudo-labels, self-supervised models can be trained to extract features without relying on explicit labels

Potential perks for high energy physics…

- ✓ Training (pretext task) on huge datasets from real collisions
- ✓ Mitigate dependence of models on difference between simulation and reality
- ✓ Inject notions of "sameness" (e.g. symmetries) into learned representations [1]

[1] Symmetries, Safety, and Self-Supervision. B. M. Dillon, G. Kasieczka, T. Plehn et al. (2021)

Contrastive learning of jets via detector replicas



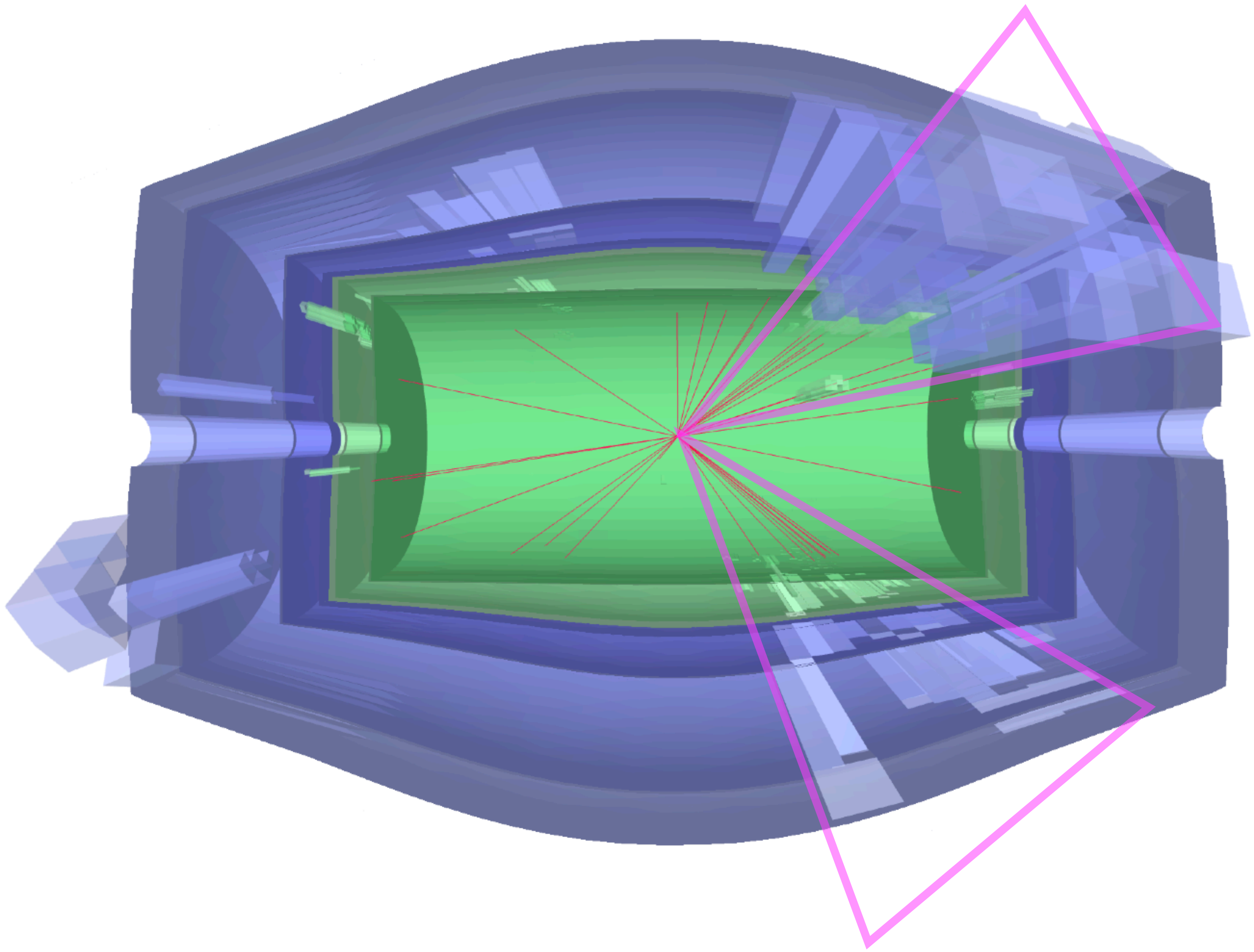
See also:

✳ Tanmoy’s talk

✳ similar effort by MIT/KIT/SLAC presented at BOOST

Dataset

* Detector response simulated with COCOA [3] (GEANT4) for 2 random seeds



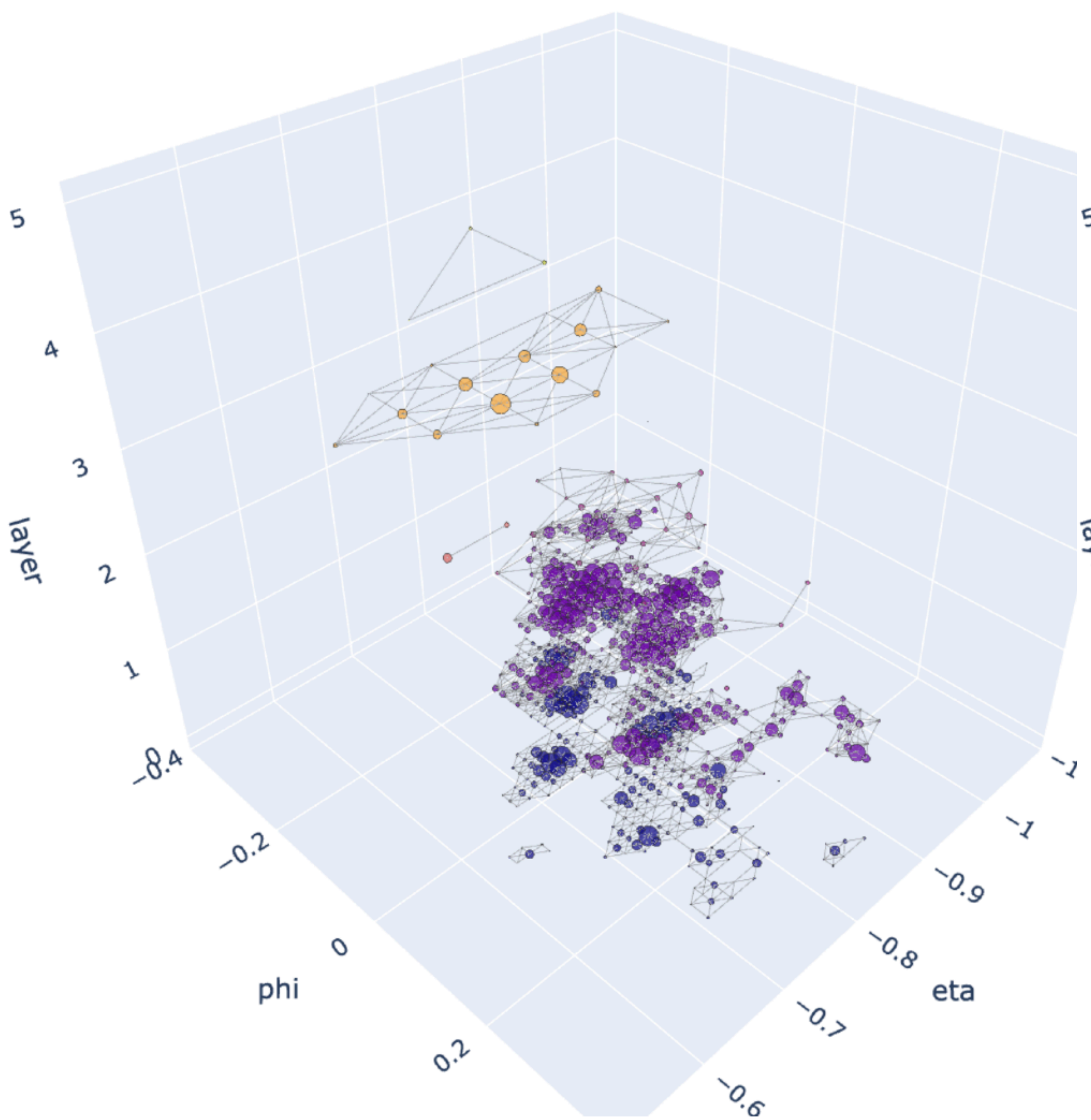
See also: Nilotpal's talk

* $p^+p^+ \to q\bar{q}, gg$ generated & showered with Pythia8 ($N_{\mathrm{train}} = 254k$)
* Select up to two $R = 0.4$ jets matched to truth jets (via ΔR)

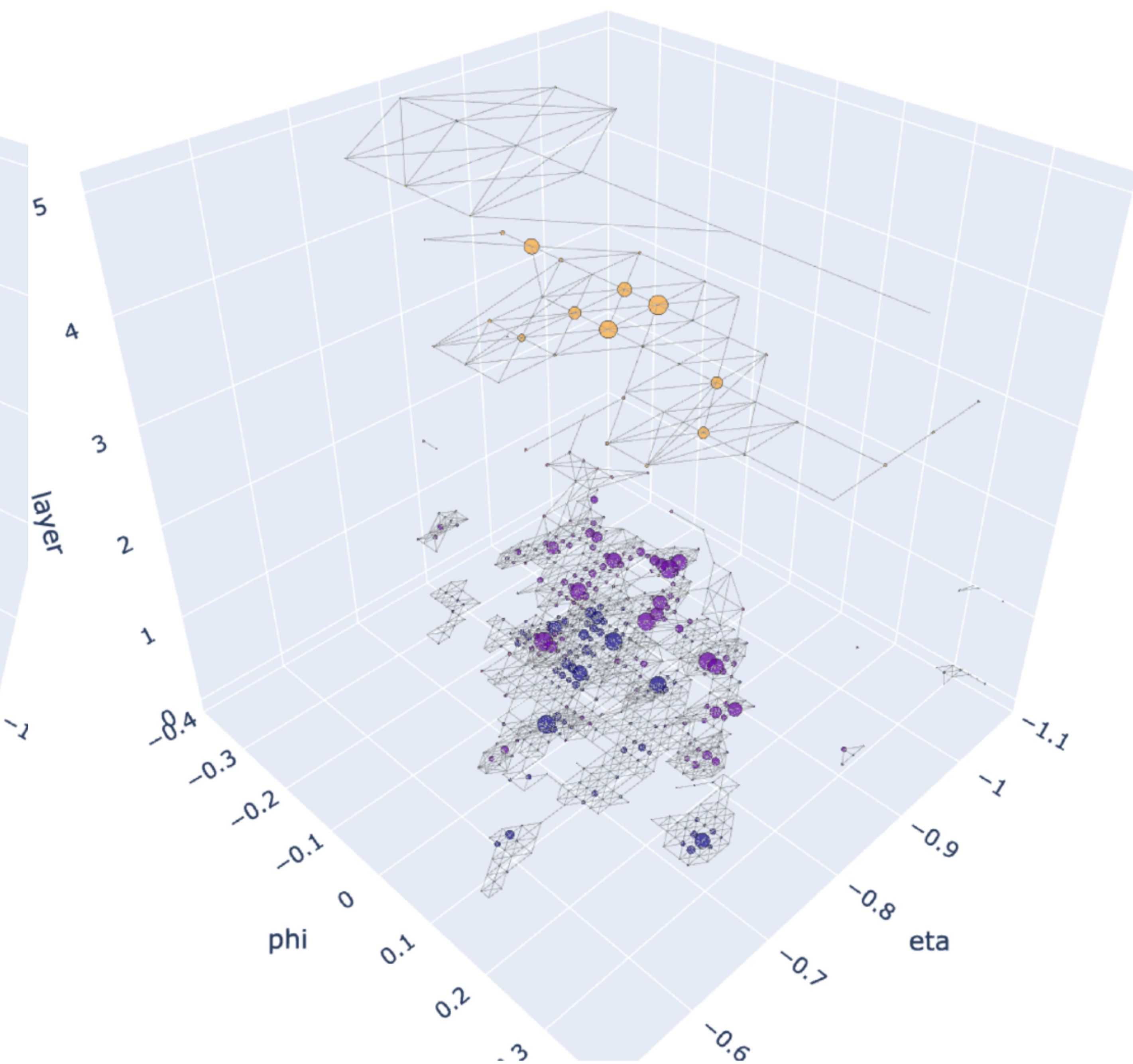
[2] Configurable calorimeter simulation for AI applications A. Charkin-Gorbulin et al, Mach. Learn.: Sci. Tech. (2023)

Example of a positive jet pair

random seed (a)

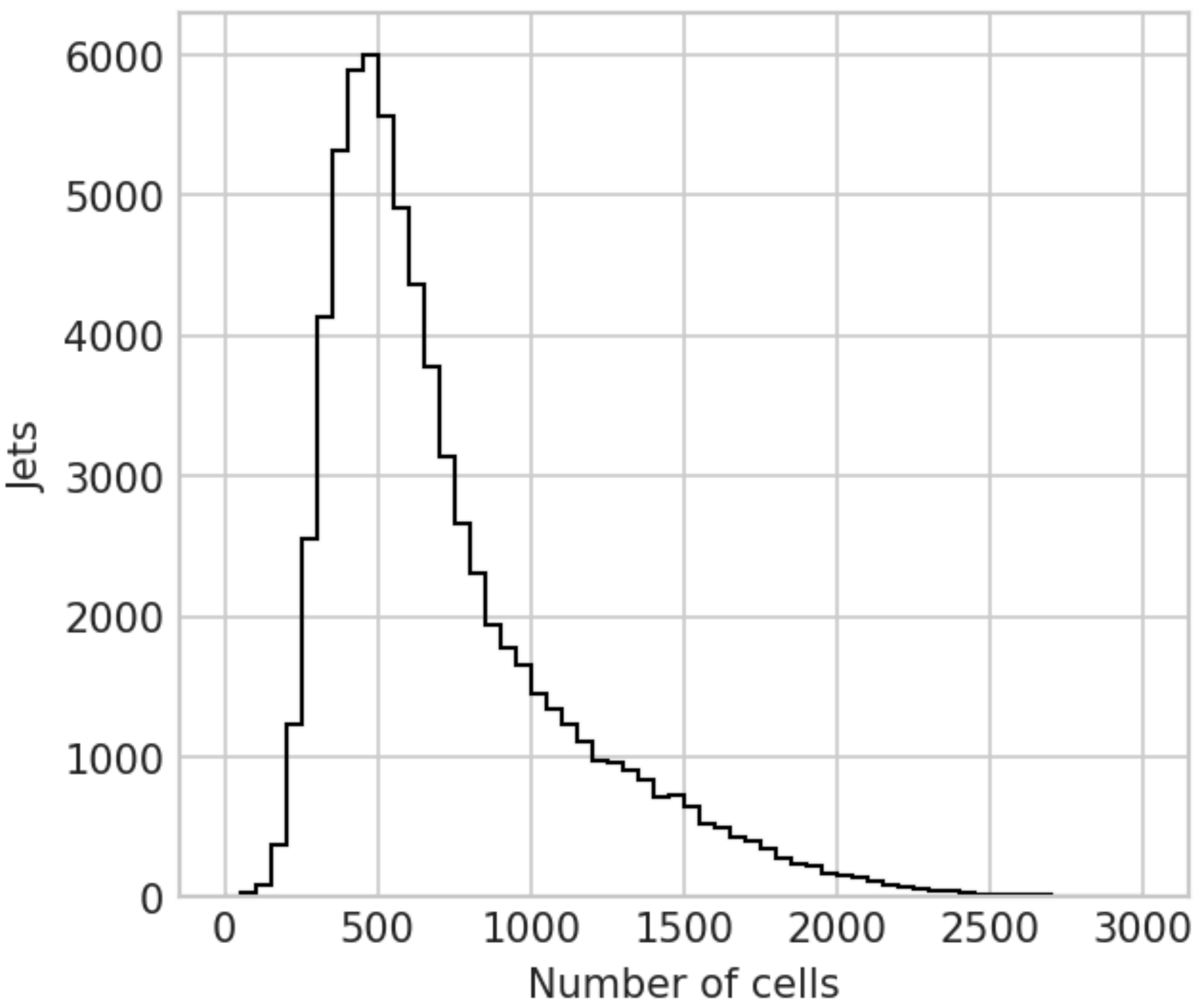


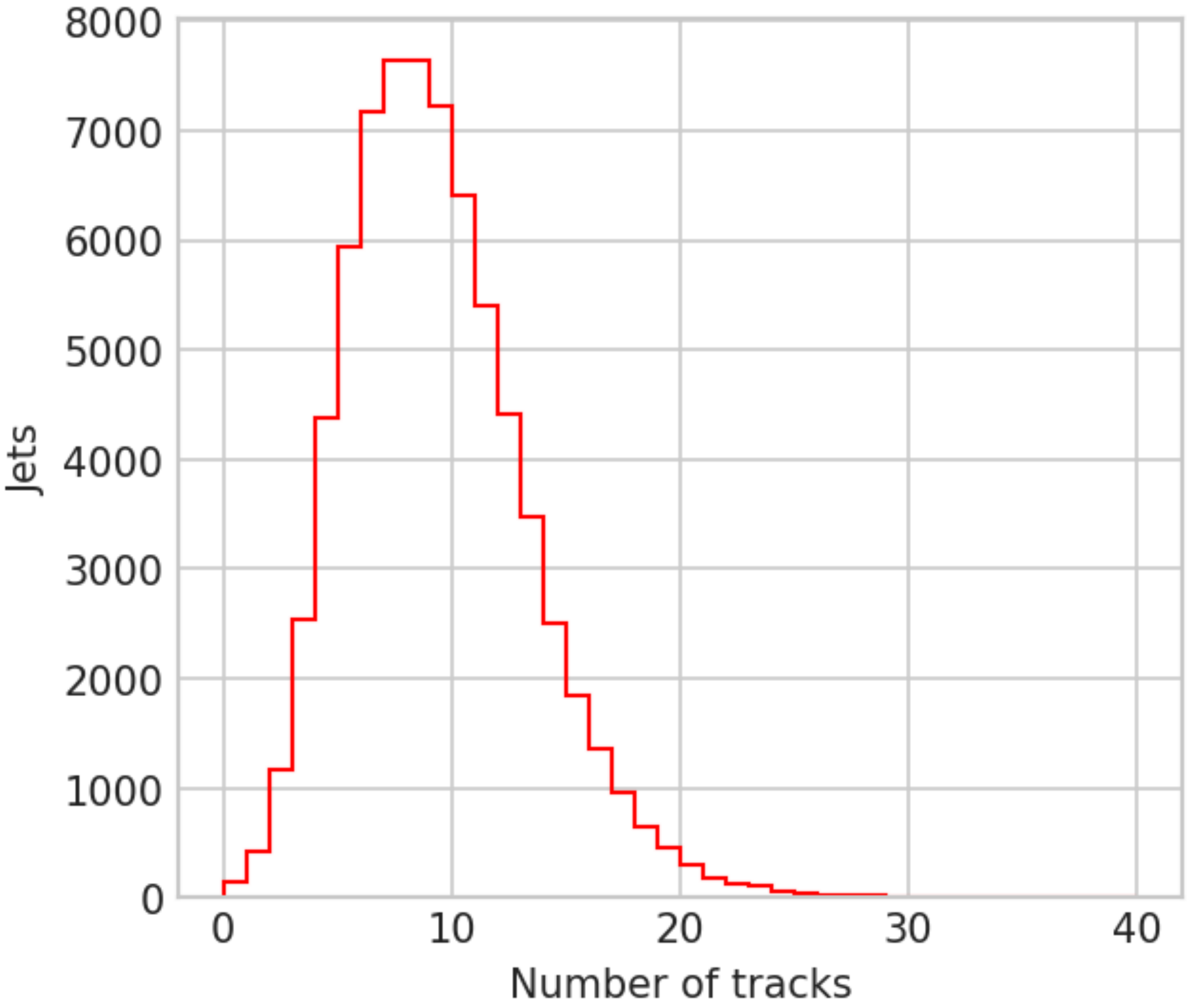
random seed (b)



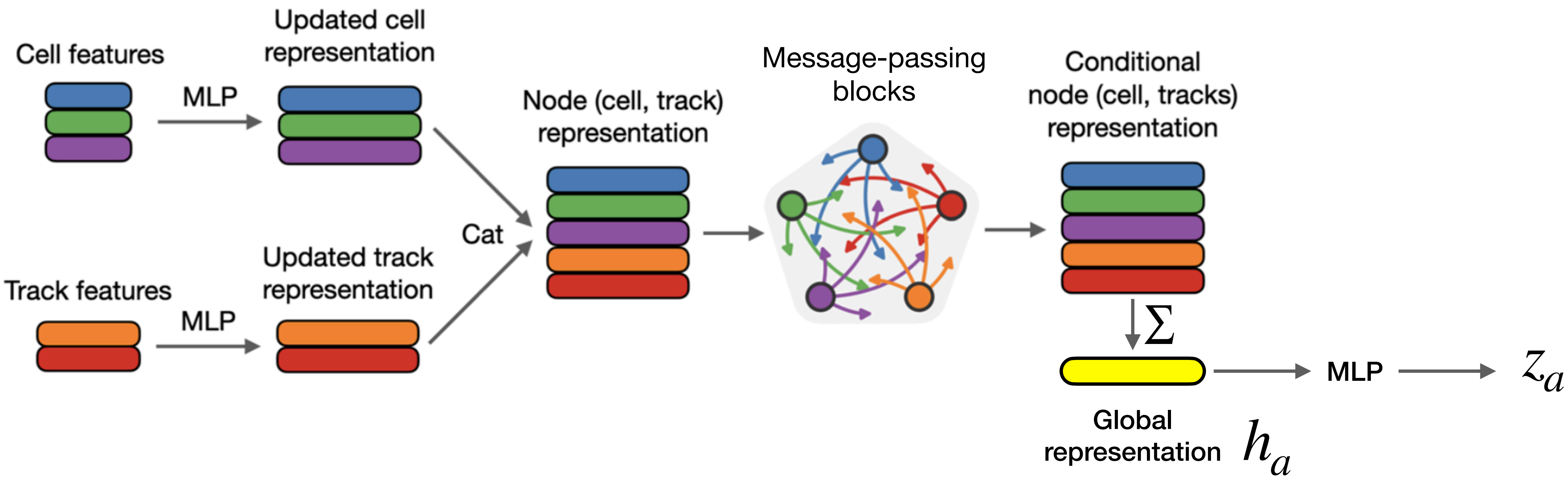
*inter-layer and track-cell edges not shown

Input dimensionality

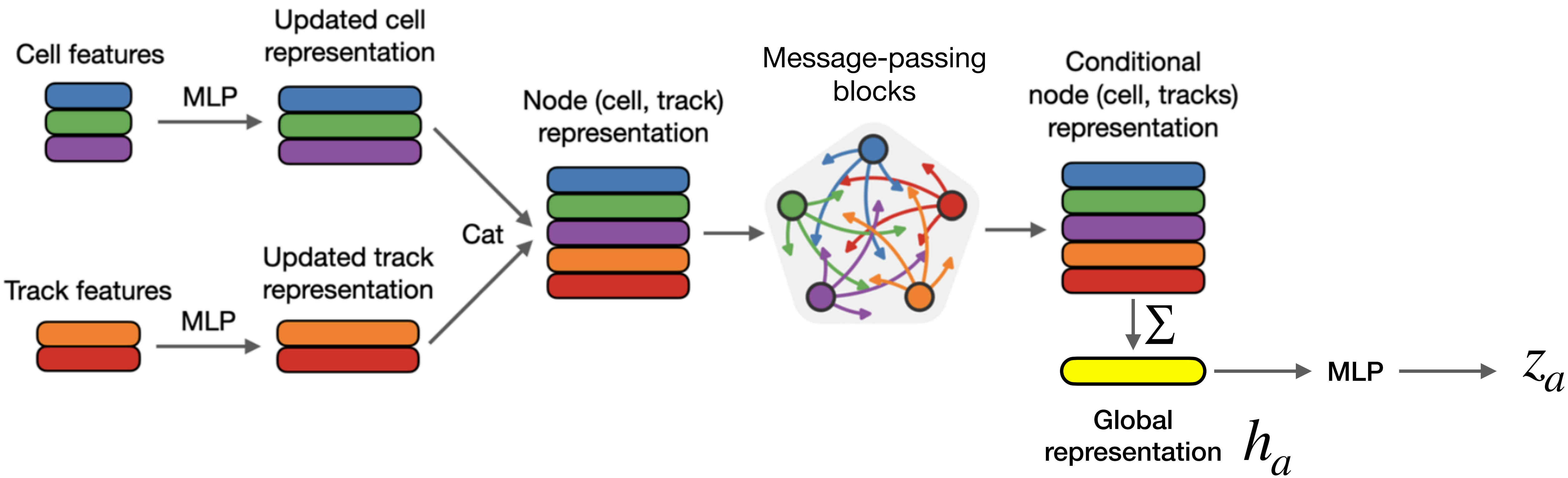




Graph encoder "backbone" model



Graph encoder "backbone" model

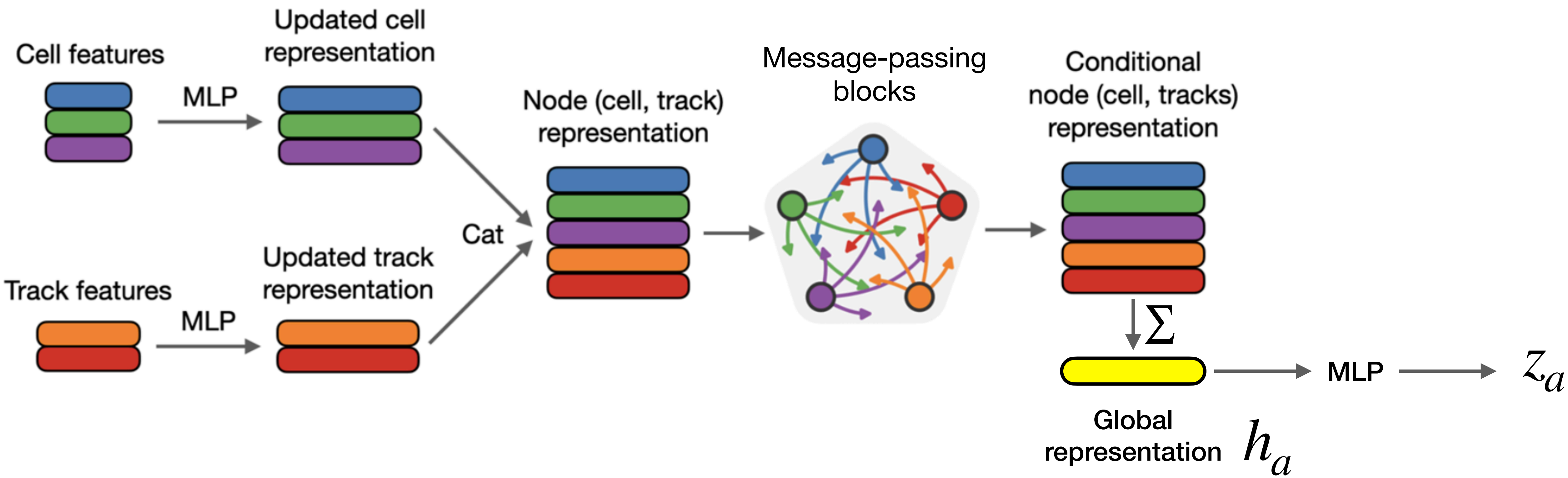


1. During SSL training, use "NT-Xent" loss [3] for each batch of $N = 300$ jet pairs:

$$L(z_a, z_b) = -\log \frac{\exp(\hat{z}_a \cdot \hat{z}_b/\tau)}{\sum_{i\neq a}^{2N} \exp(\hat{z}_a \cdot \hat{z}_i/\tau)} \qquad \text{where} \qquad \hat{z}_a := z_a/|z_a| \implies \hat{z}_a \cdot \hat{z}_b = \cos(\theta_{ab})$$

[3] A Simple Framework for Contrastive Learning of Visual Representations. T. Chen, G. Hinton. et al. (2020)

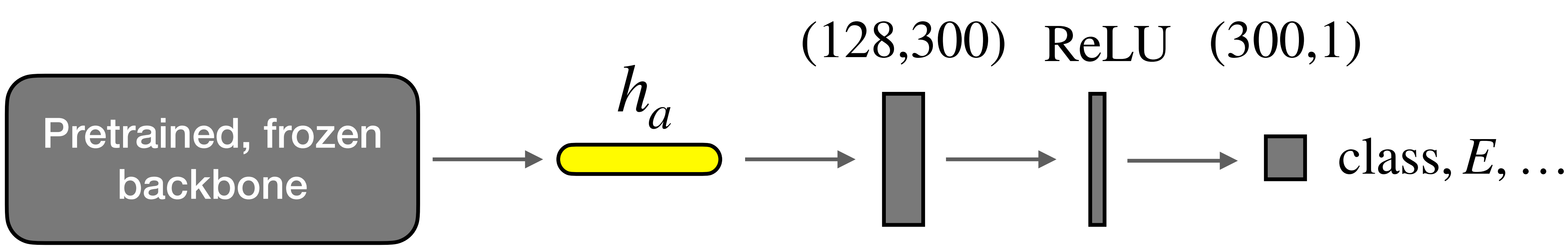
Graph encoder "backbone" model



1. During SSL training, use "NT-Xent" loss [3] for each batch of $N = 300$ jet pairs:

$$L(z_a, z_b) = -\log \frac{\exp(\hat{z}_a \cdot \hat{z}_b/\tau)}{\sum_{i\neq a}^{2N} \exp(\hat{z}_a \cdot \hat{z}_i/\tau)} \quad \text{where} \quad \hat{z}_a := z_a/|z_a| \implies \hat{z}_a \cdot \hat{z}_b = \cos(\theta_{ab})$$

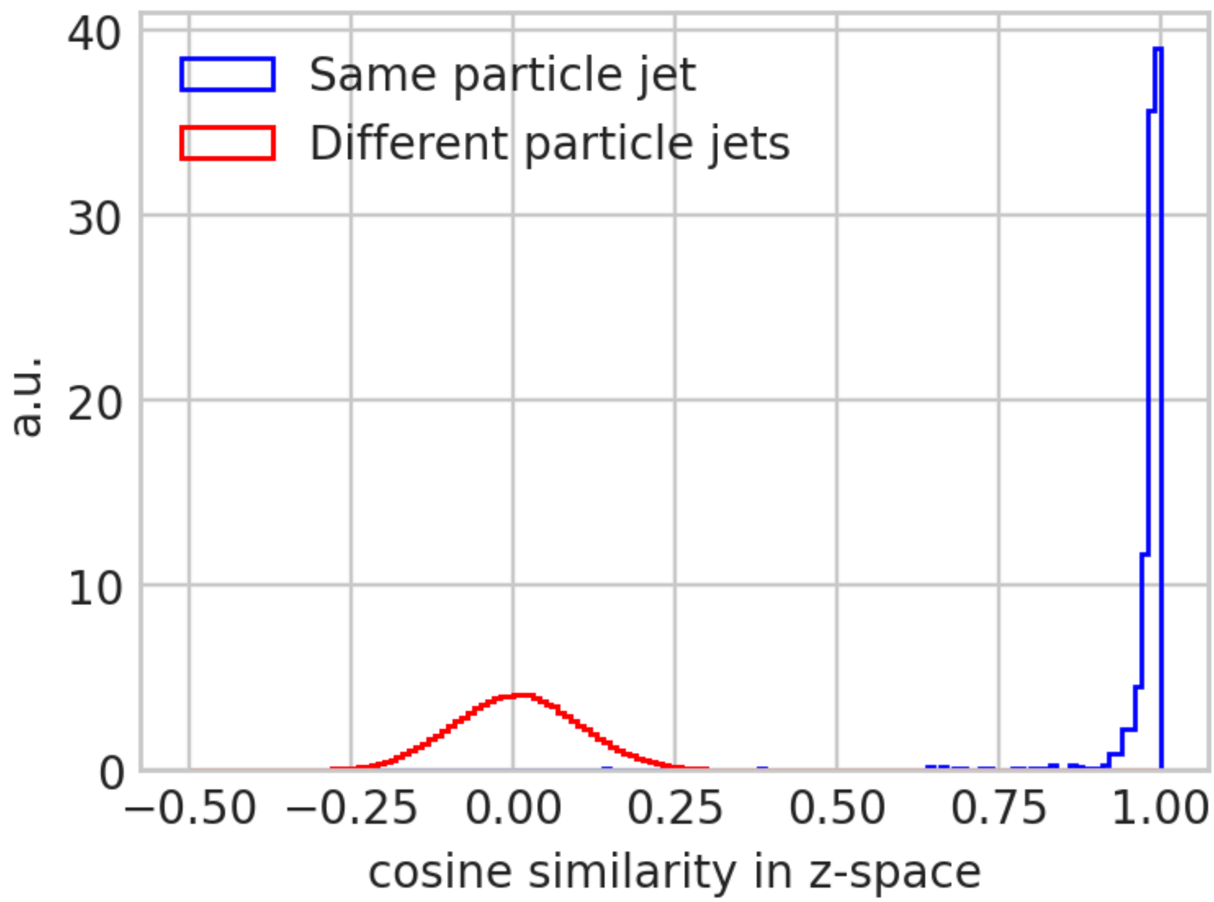
2. During downstream training, can freeze backbone and train single-layer perceptron



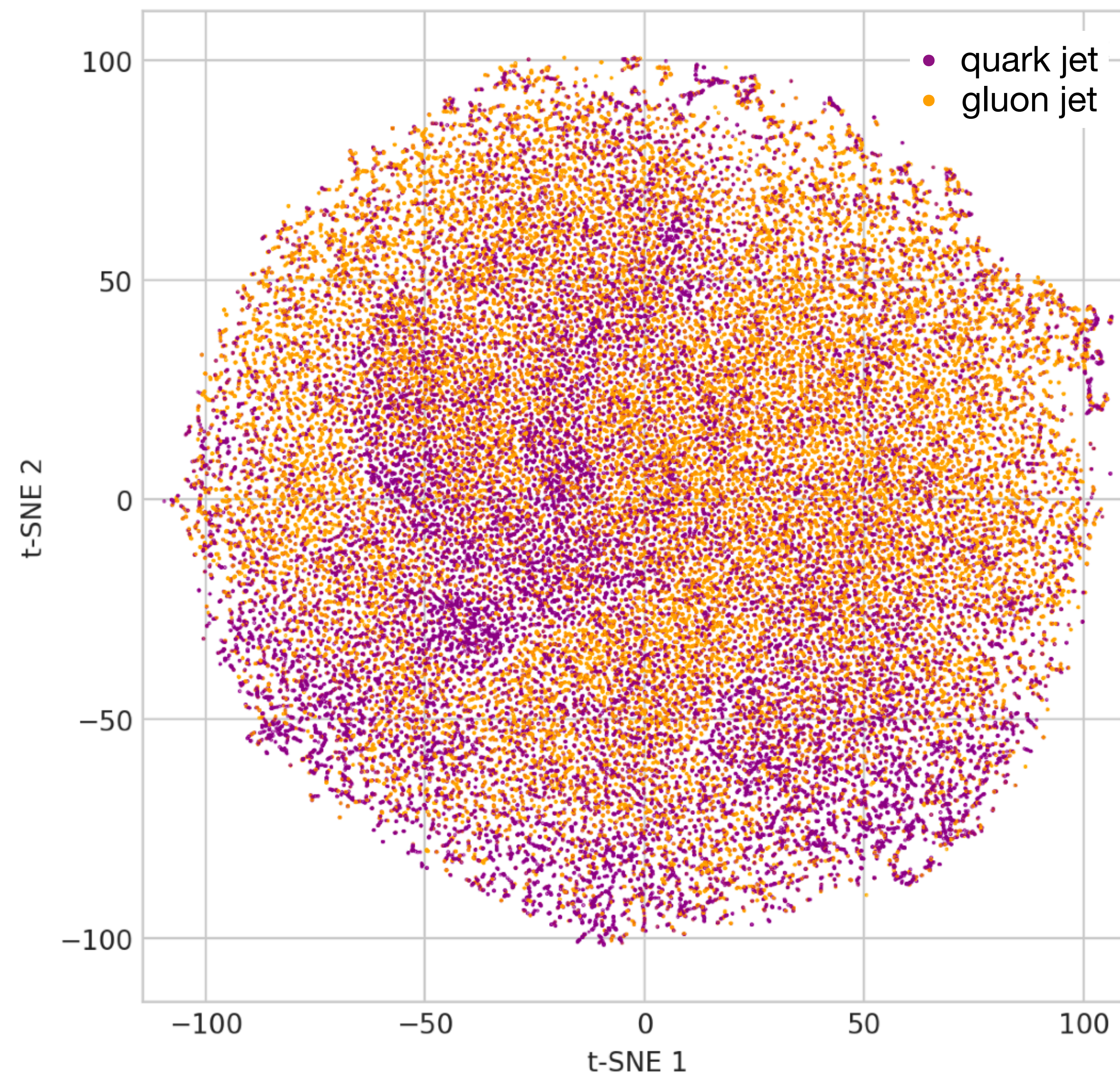
[3] A Simple Framework for Contrastive Learning of Visual Representations. T. Chen, G. Hinton. et al. (2020)

Probing the z contrastive space

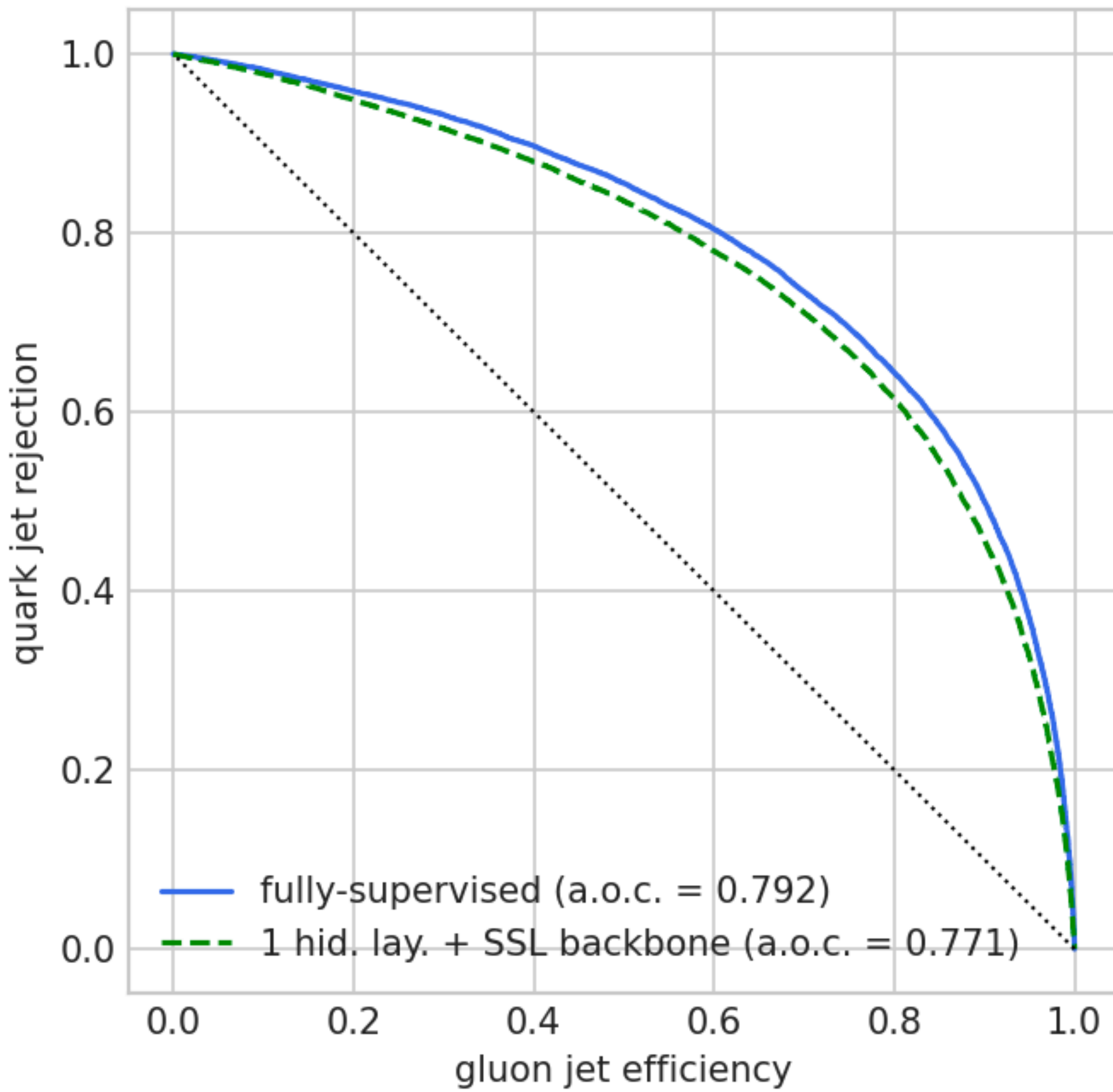
Contrast between jet pairs



t-SNE decomposition



Downstream task 1: q/g tagging

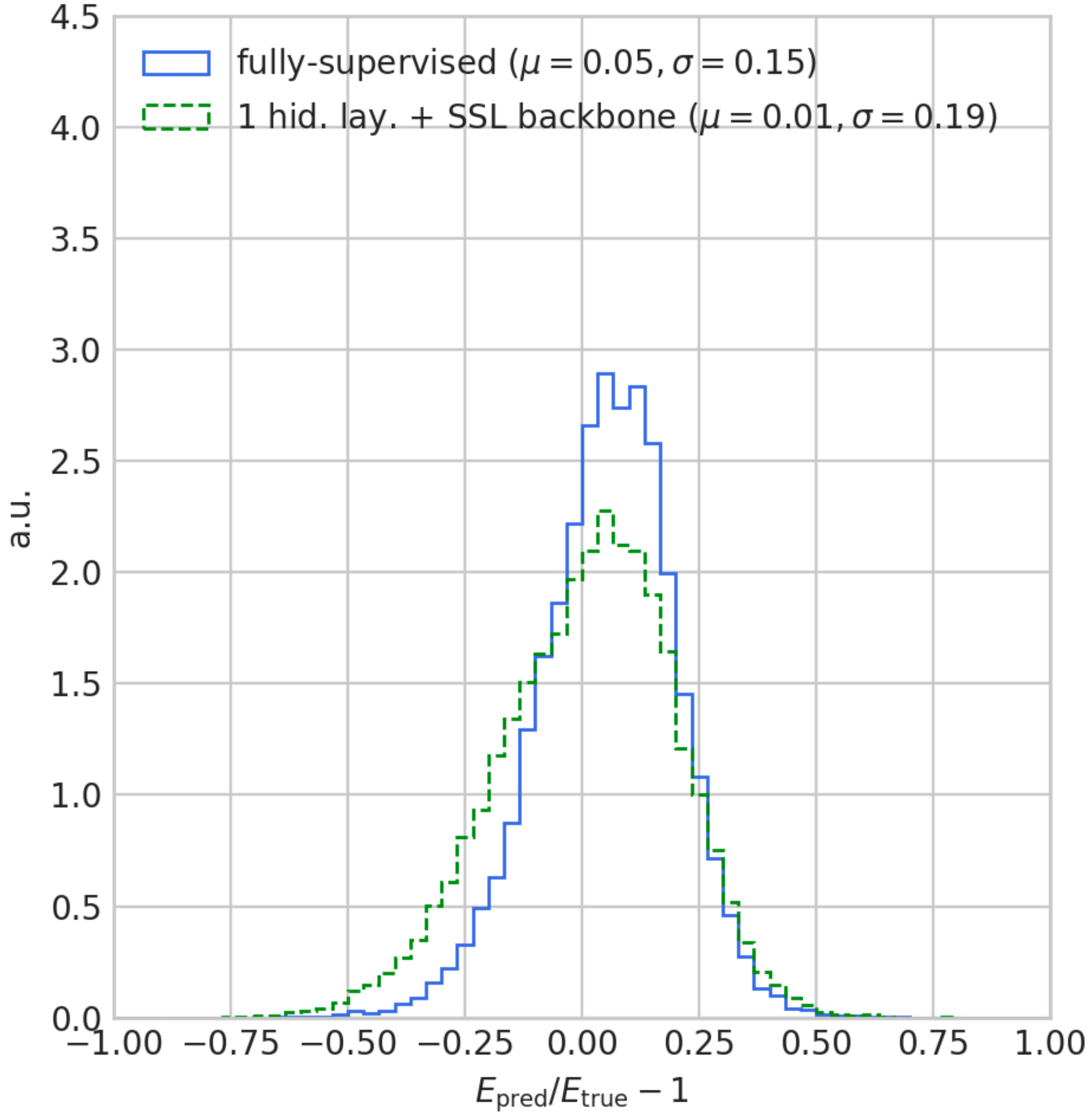


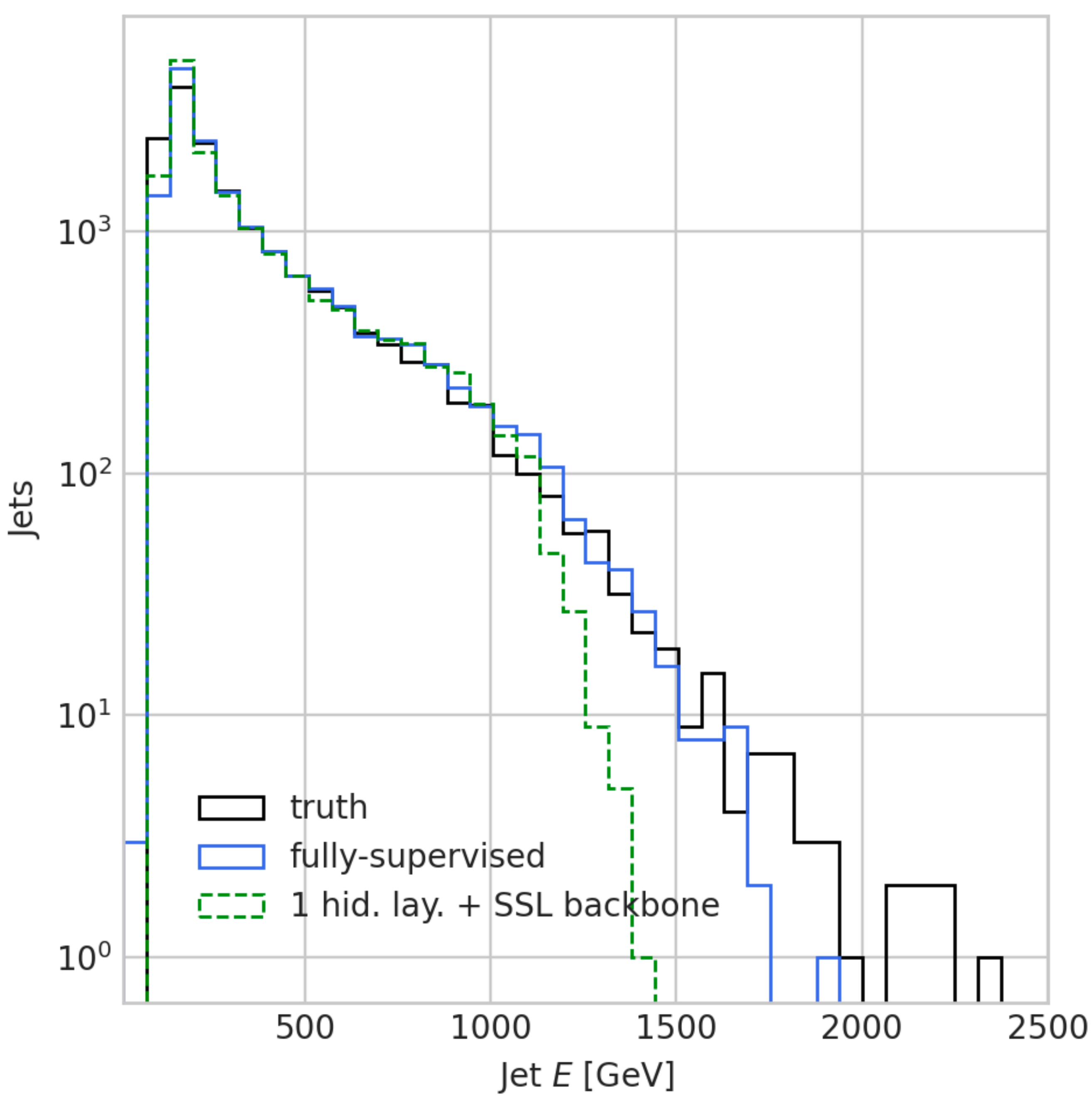
337k trainable parameters

vs.

39k *trainable* parameters

Downstream task 2: jet E reg.





Summary & Outlook

We can learn to encode high-dimensional feature space of jet detector response in a generic way using SSL

⇒ can be efficiently fine-tuned for decent performance on downstream tasks

⇒ first demonstration using low-level detection inputs

Current perf. limited by size of data used to train SSL backbone

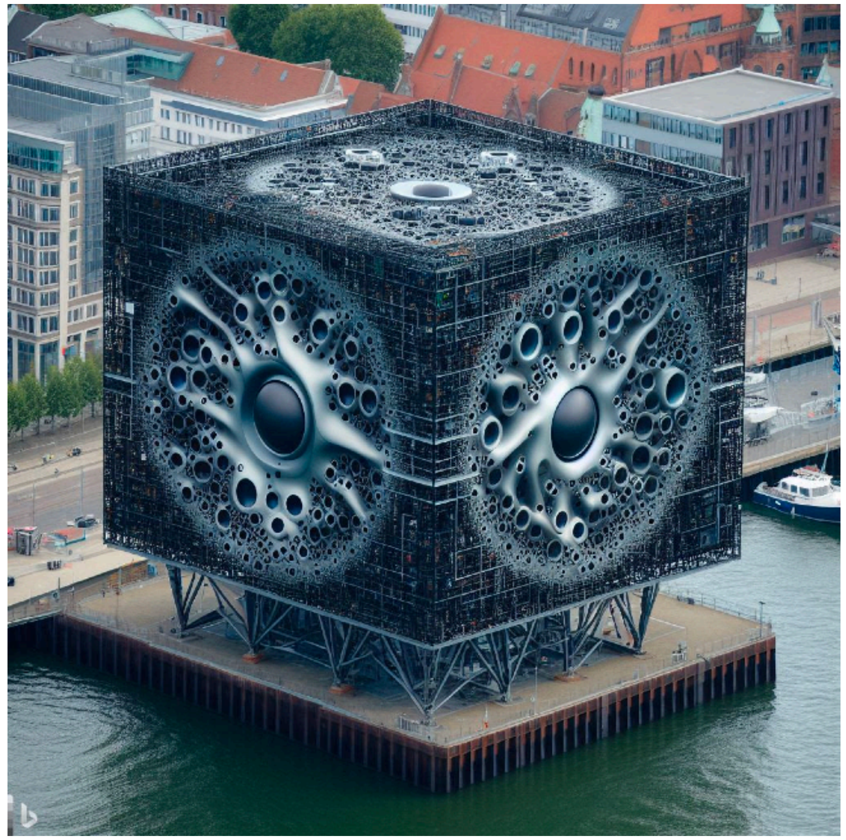
Next/future directions

- ✳ Extension to large-R jets, anomalous jet detection underway
- ✳ Can we define transformations that preserve "sameness" on *real* data?

Thank you!

"Machine learning for jets of particles in Hamburg, Germany"

AI (DALL-E)



Reality