Re-simulation-based self-supervised learning (RS3L)

6th IML Workshop
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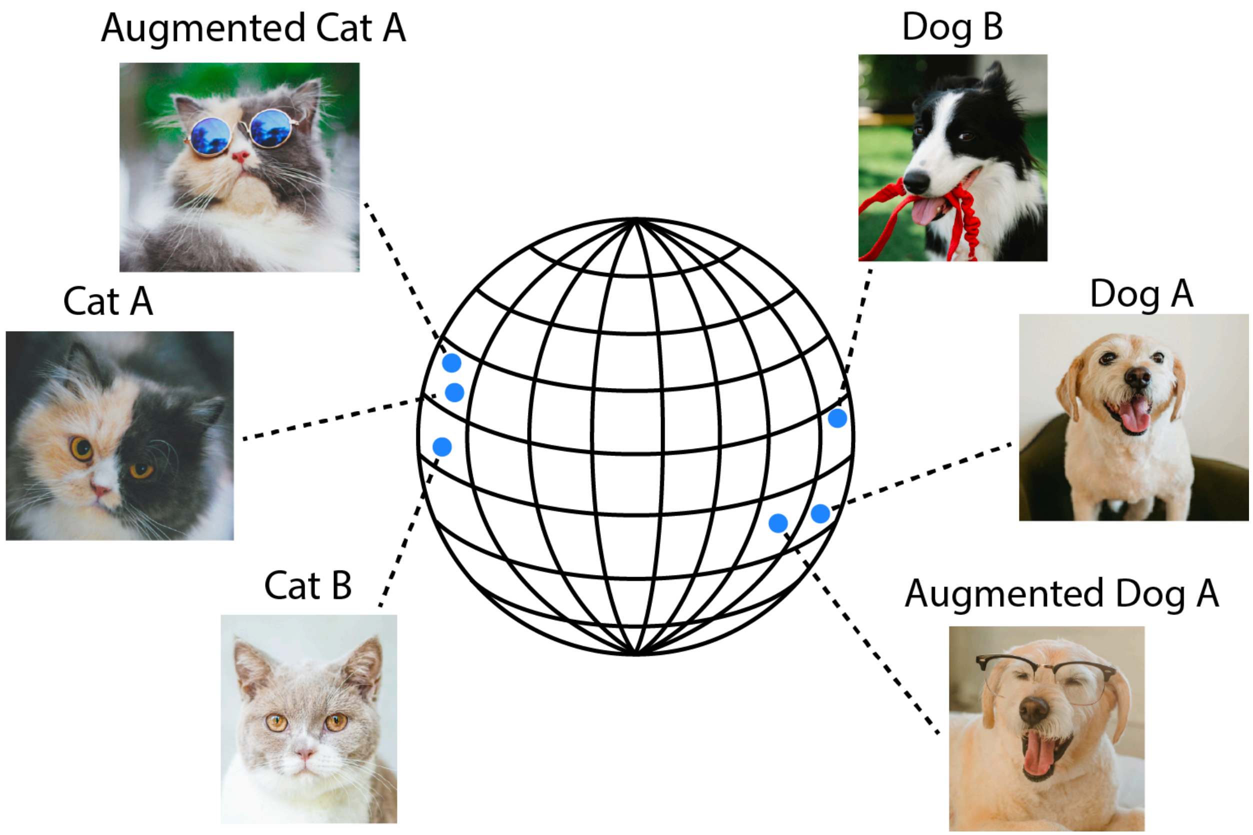
The NSF Institute for Artificial Intelligence and Fundamental Interactions

Representations

- Can we use AI to learn generic representations of jets?



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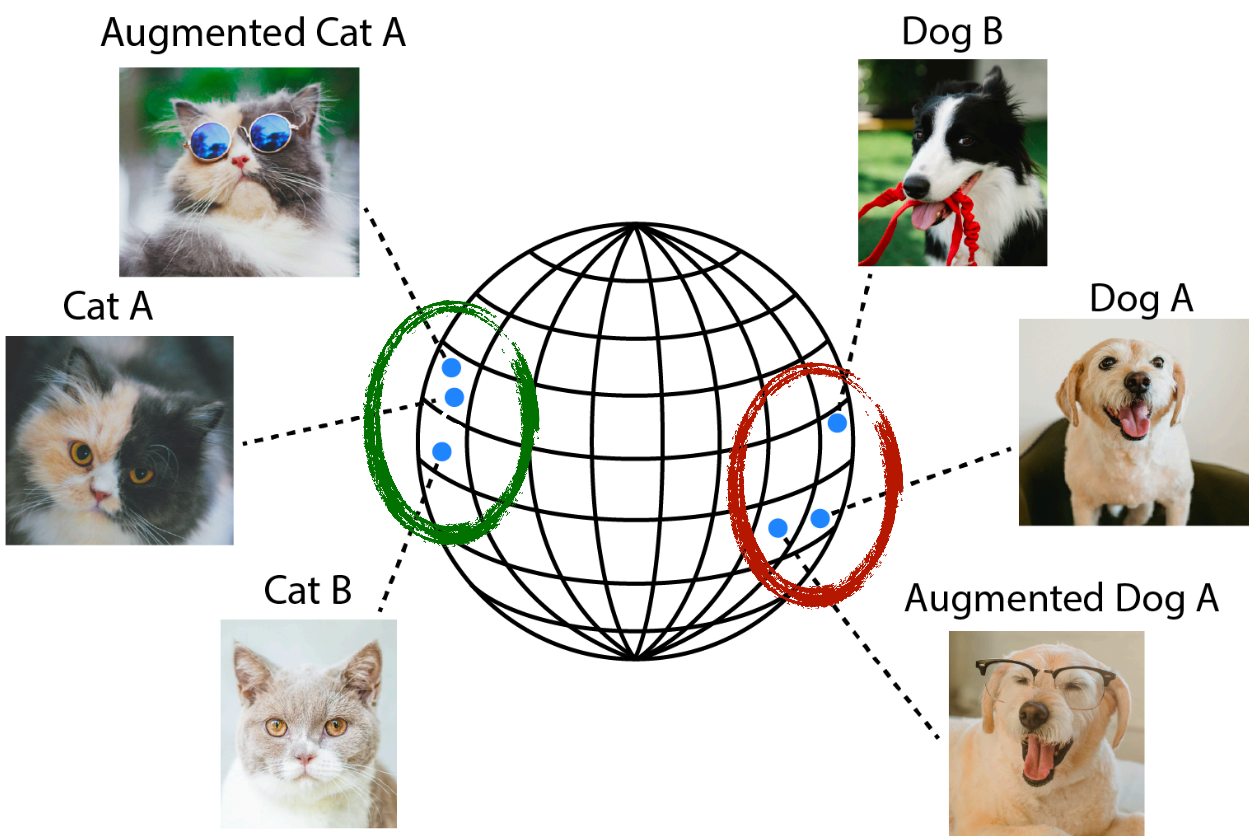

Representations

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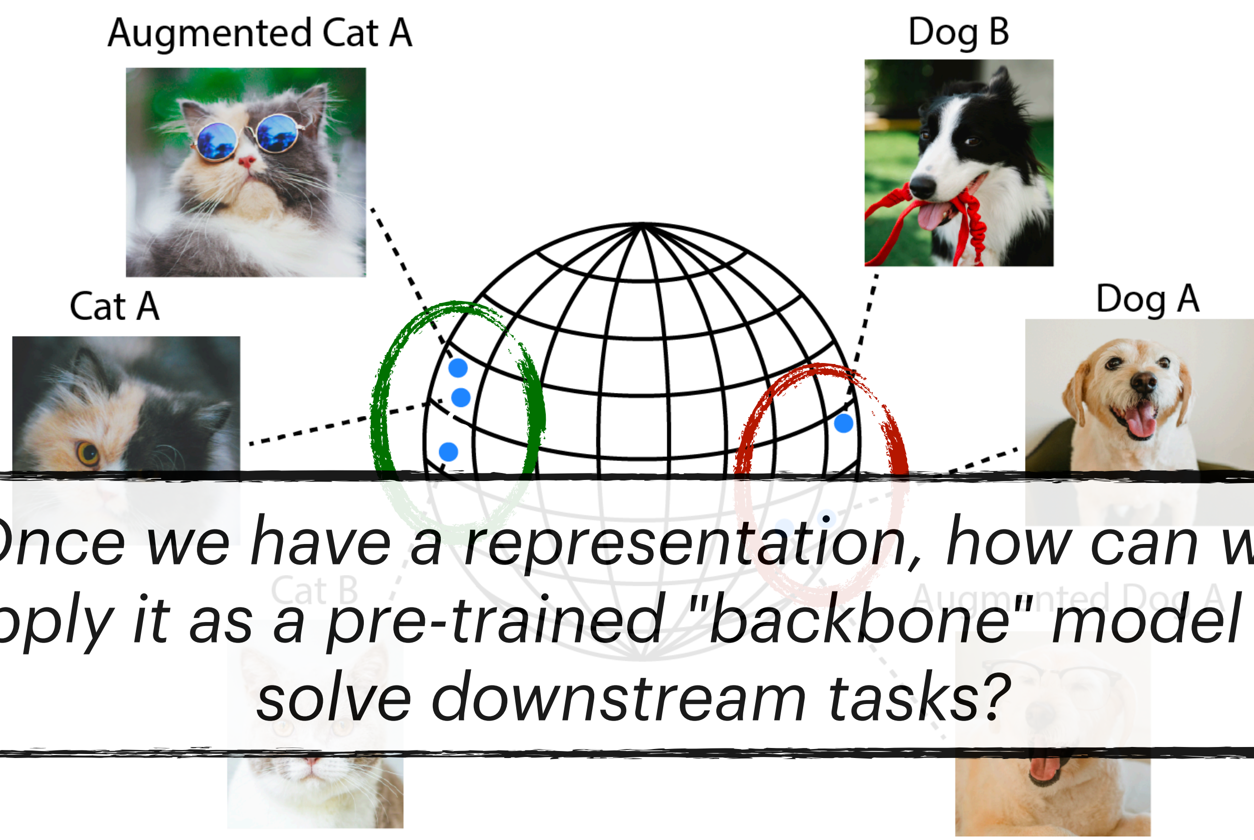
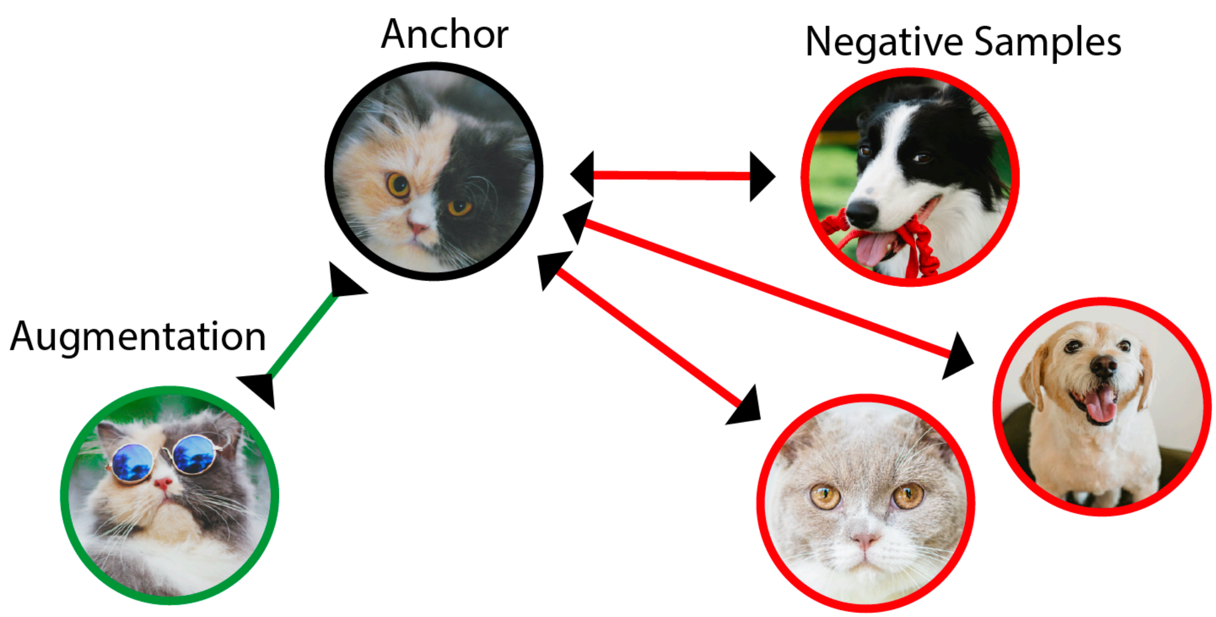


Once we have a representation, how can we apply it as a pre-trained "backbone" model to solve downstream tasks?

Self-supervised Learning (SSL)

- Learn using only relations between the **same objects from different perspectives**



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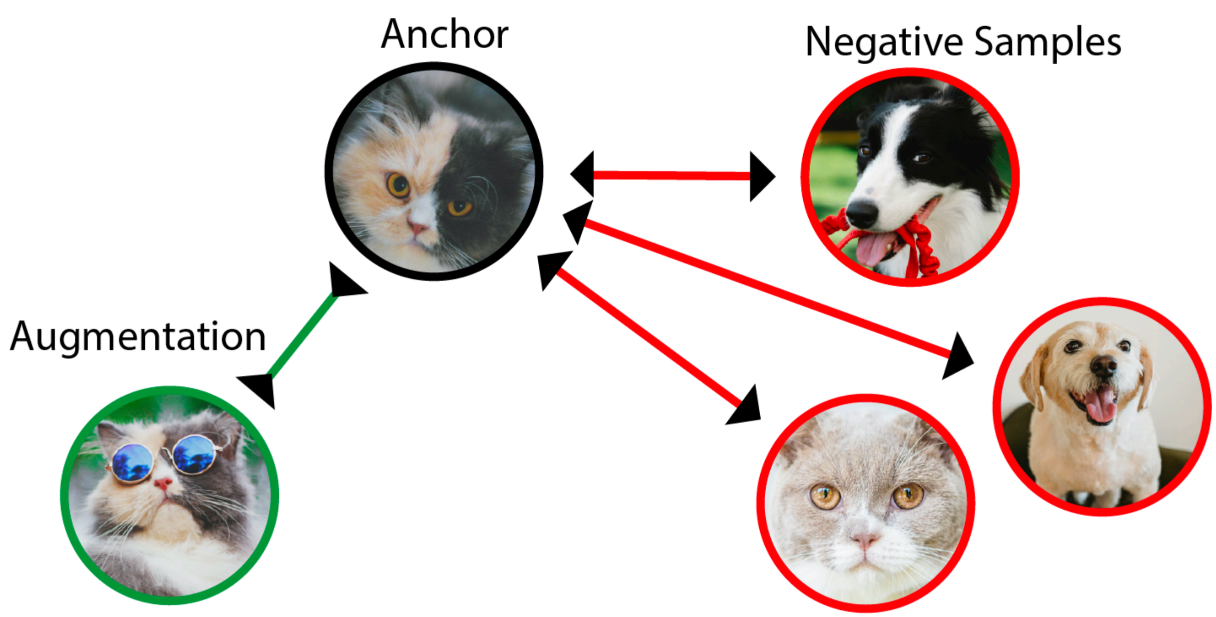
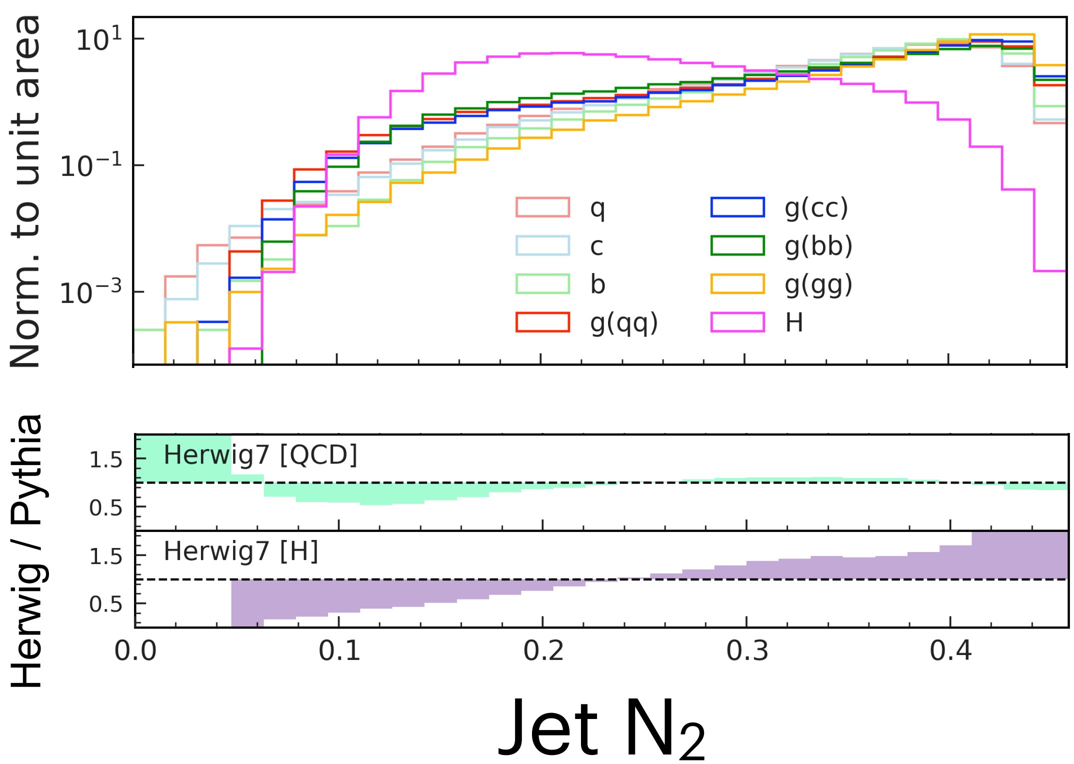


- *Classes = **Higgs and QCD***
- *Augmentations = **reshowering parton** with different simulators (pythia tunes + herwig)*

Where to start?

- We begin by investigating Higgs and QCD jets with **various parton shower models**
  - Parton shower assumptions can be leading uncertainties in physics analyses (e.g. 2208.02751)



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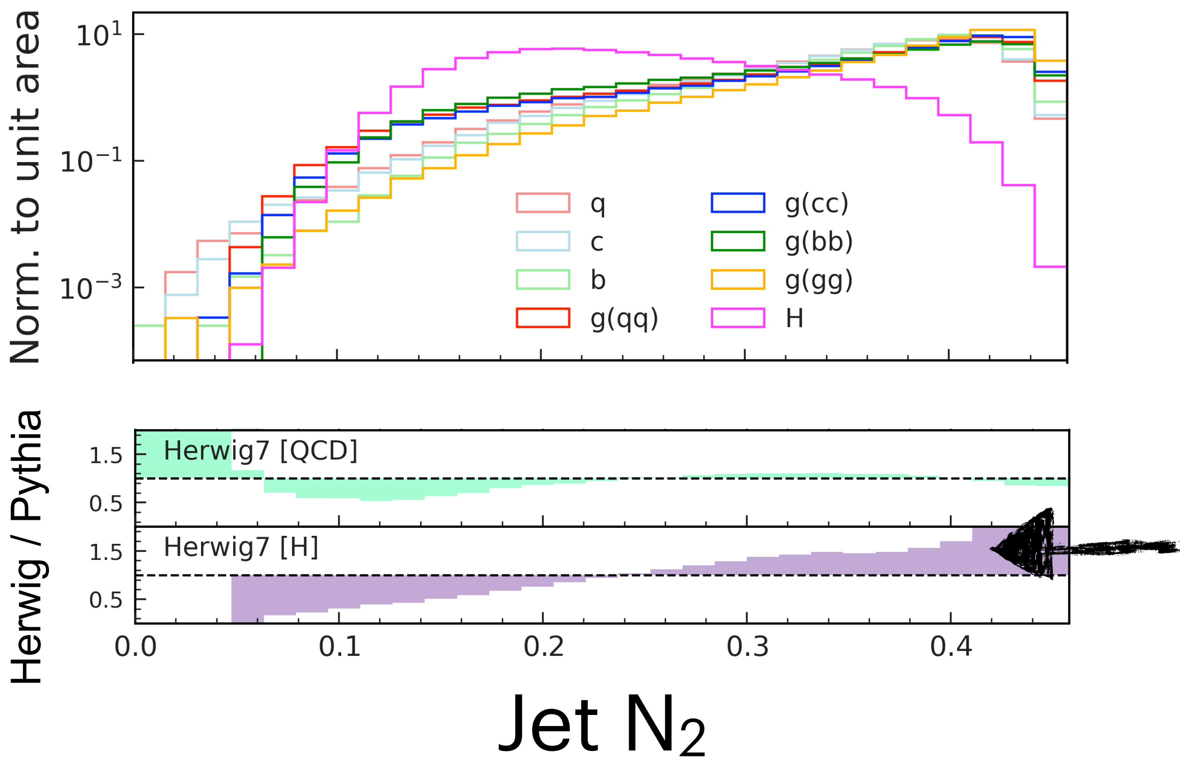
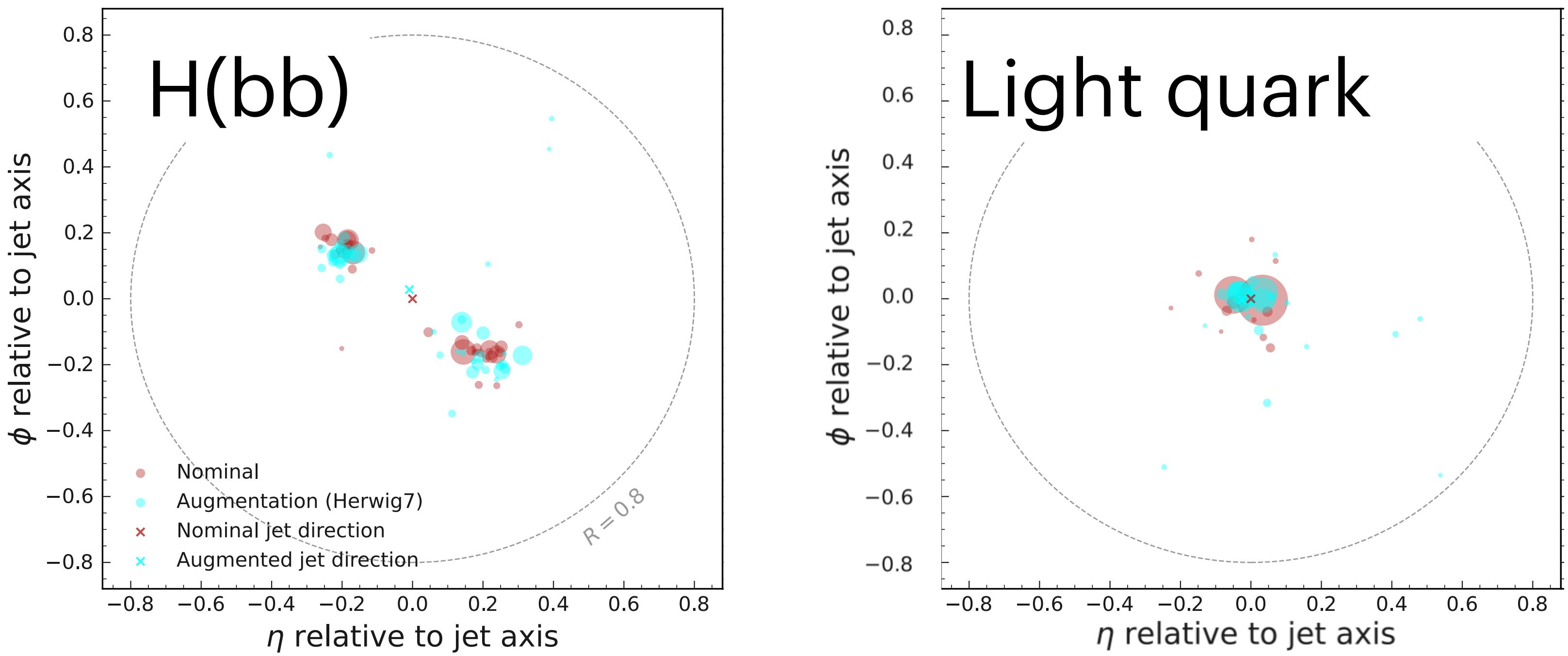


Large herwig/pythia ratio
=
Large modelling differences

The Augmentations

Parton showered with Pythia8
Same parton showered with Herwig



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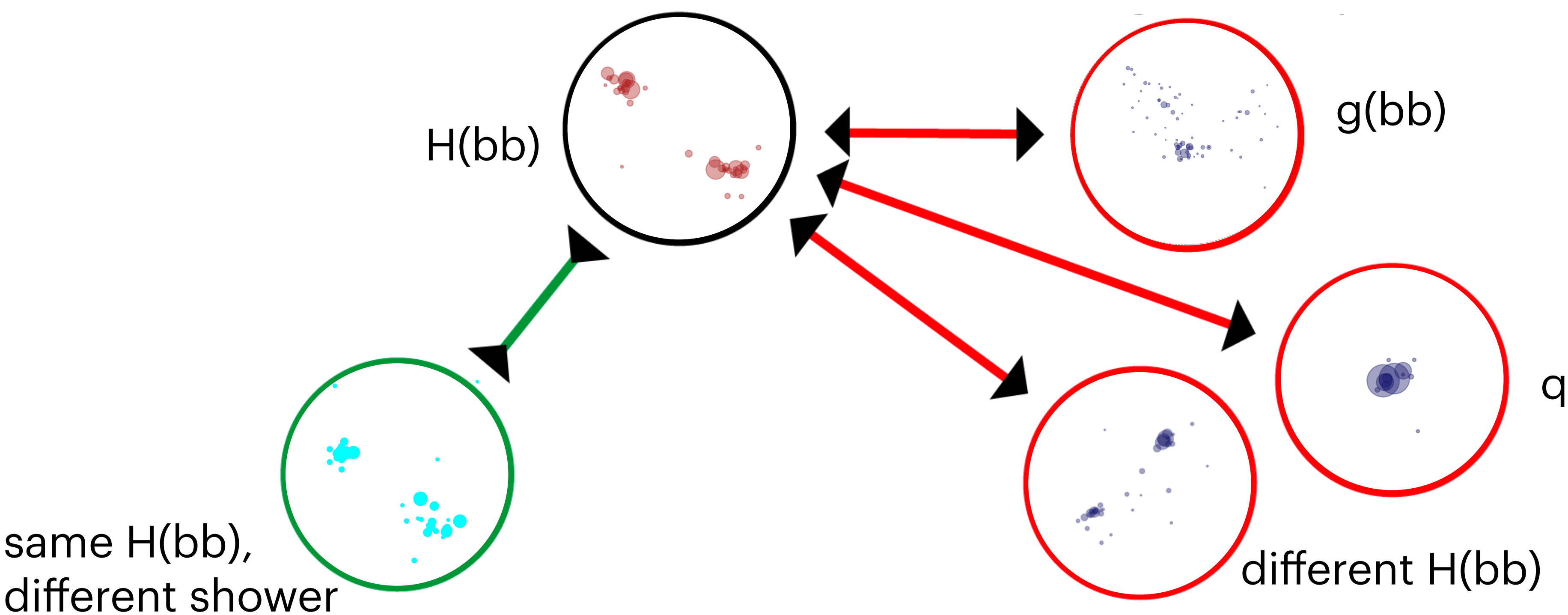

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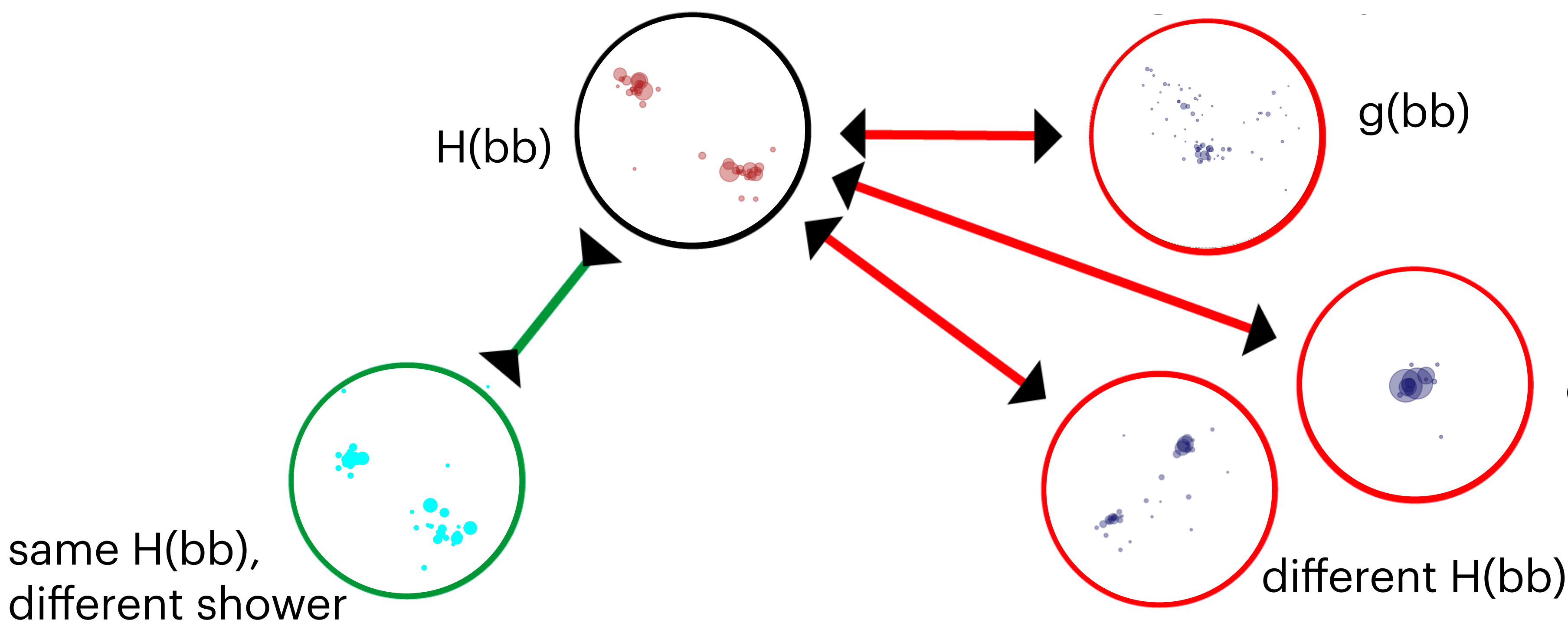
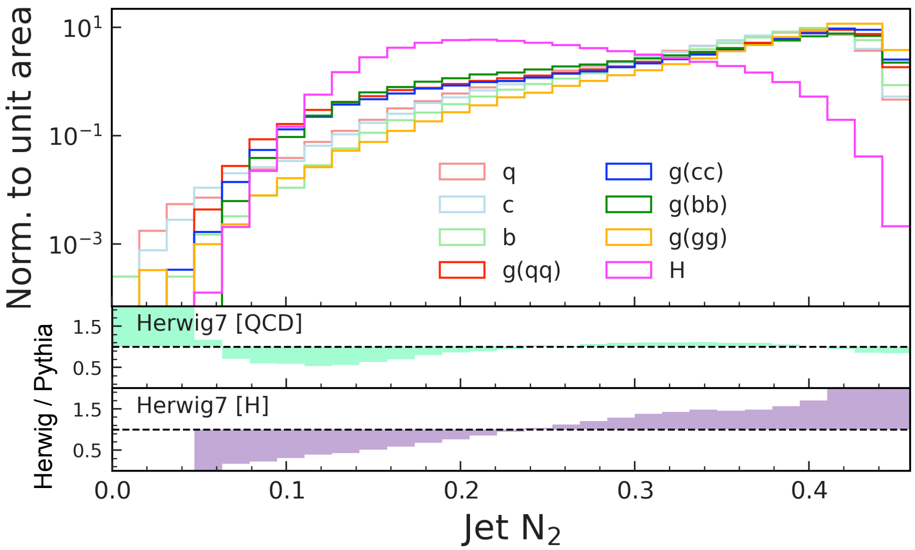


We use a self-supervised graph neural network to pull together the nominal and augmented (re-simulated) jet pair

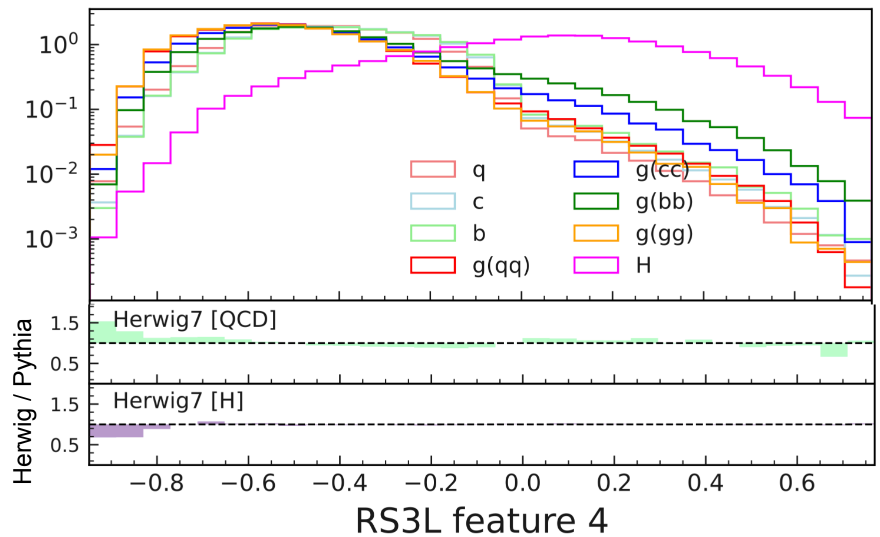
→ ***Re-simulation-based self-supervised learning (RS3L)***

The RS3L Space

Jet N_2



One RS3L feature



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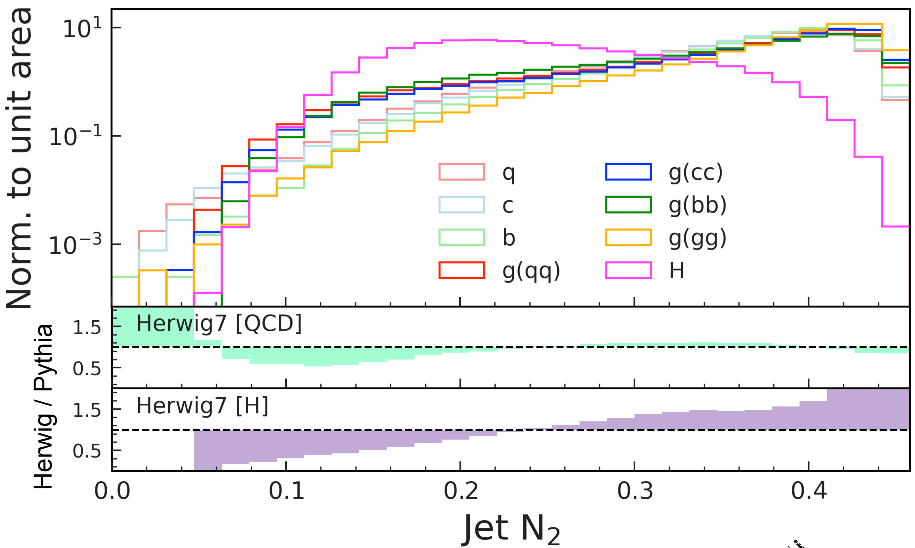

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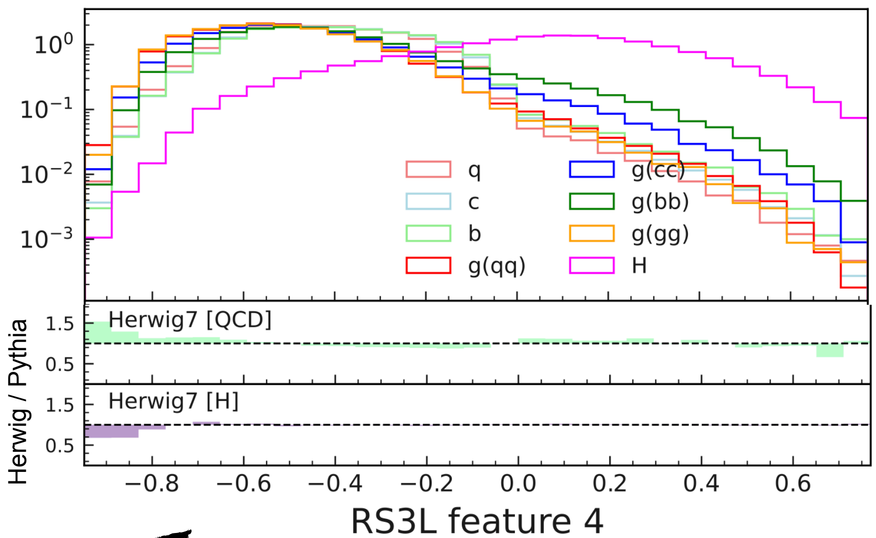
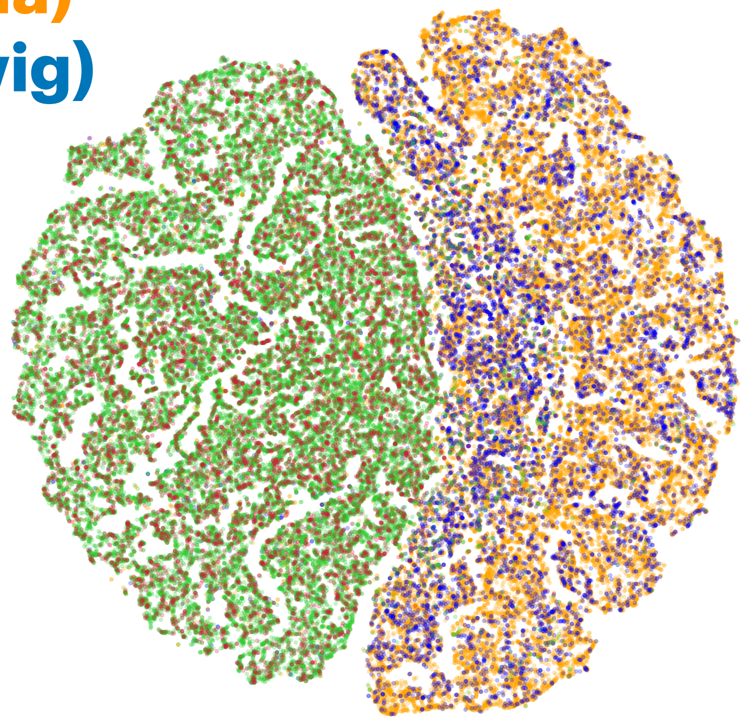


Pythia/Herwig ratio is reduced → our space learns ***features of H and QCD with less reliance on simulator***

The RS3L Space

tSNE of 8 contrastive features

QCD (pythia)
QCD (herwig)
H (pythia)
H (herwig)



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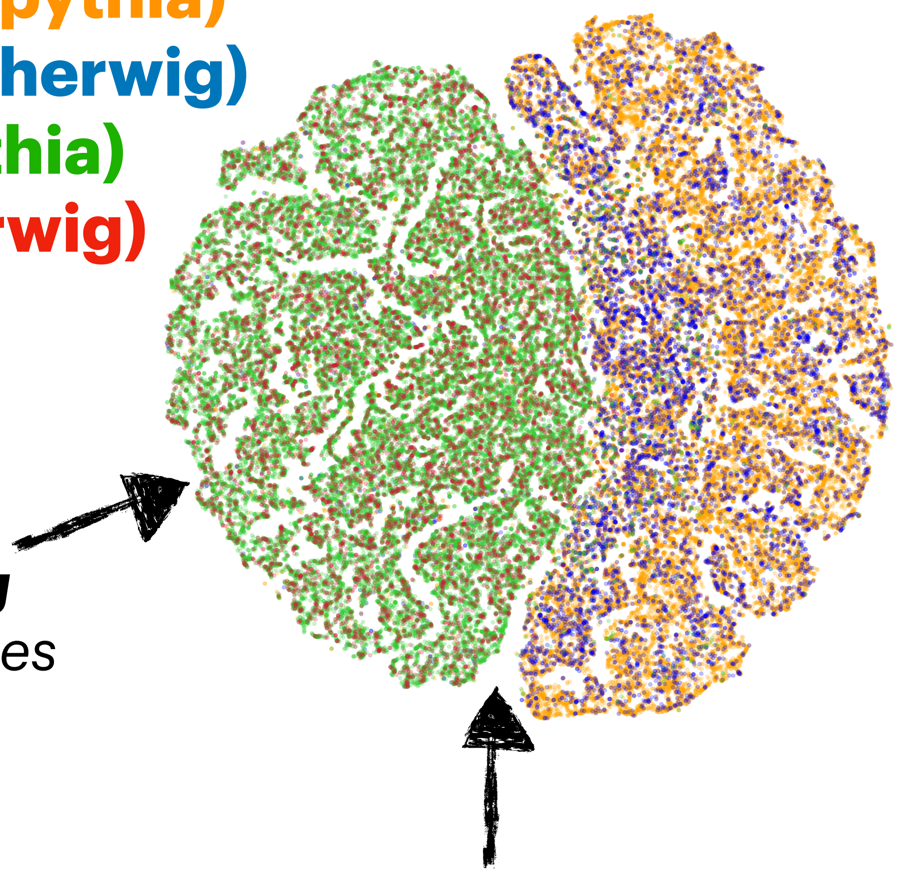
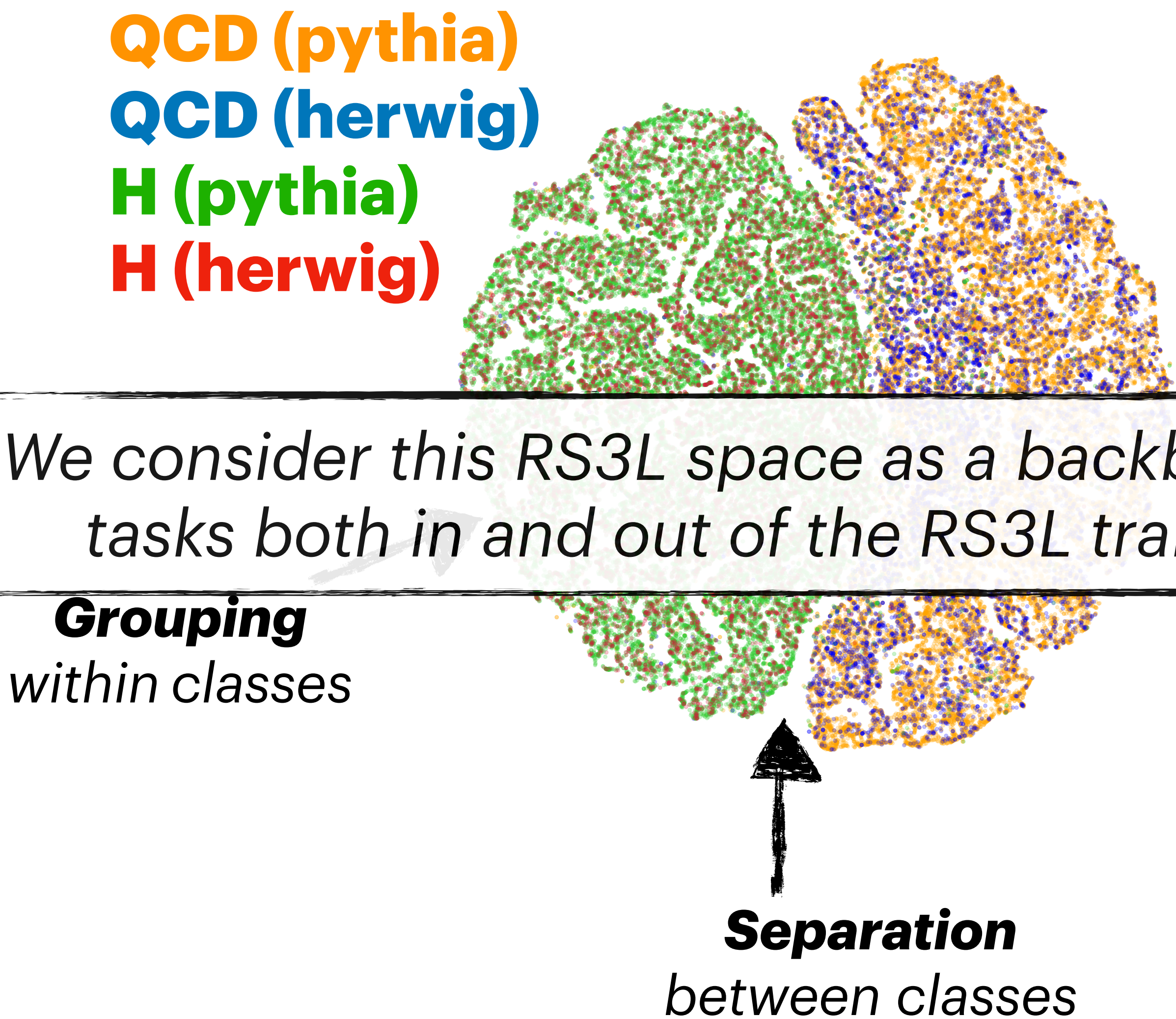


Grouping
within classes

Separation
between classes

The RS3L Space

tSNE of 8 contrastive features



We consider this RS3L space as a backbone in learning tasks both in and out of the RS3L training domain

#1: In-domain classification

QCD background rejection rates at various Higgs tagging efficiencies.

Higgs efficiency	0.3	0.5	0.7
RS3L fine-tuned (3M)	1340	379	135
Fully-supervised (8M)	1295	384	131

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RS3L gives similar performance on in-domain classification

Robustness of RS3L space

- What effect does changing simulators (pythia→Herwig) have on the output of the final classifier?
  - We use the Wasserstein distance to quantify the **difference between tagger evaluated on nominal and augmented jets**

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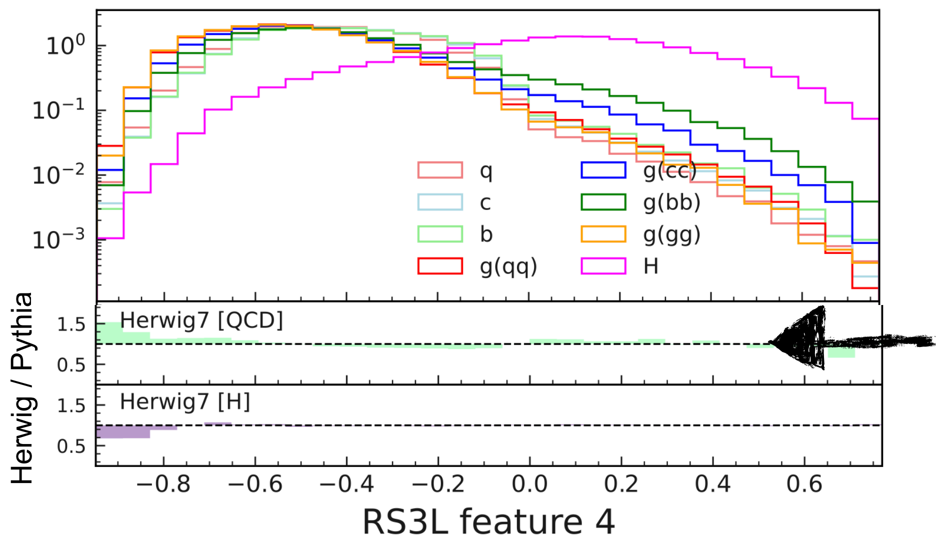

Compute Wasserstein distance between Herwig and Pythia

Robustness of RS3L space

Wasserstein distance between taggers distributions evaluated on pythia and herwig Higgs jets.

Training setup	Herwig
RS3L fine-tuned (3M)	$7.8\ \times 10^{-3}$
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Fine-tuning RS3L reduces distance

→ ***SSL can provide more robust observables***

#2: Out-of-domain classification

- Does the RS3L space (trained on Higgs and QCD) contain useful information about **other processes**
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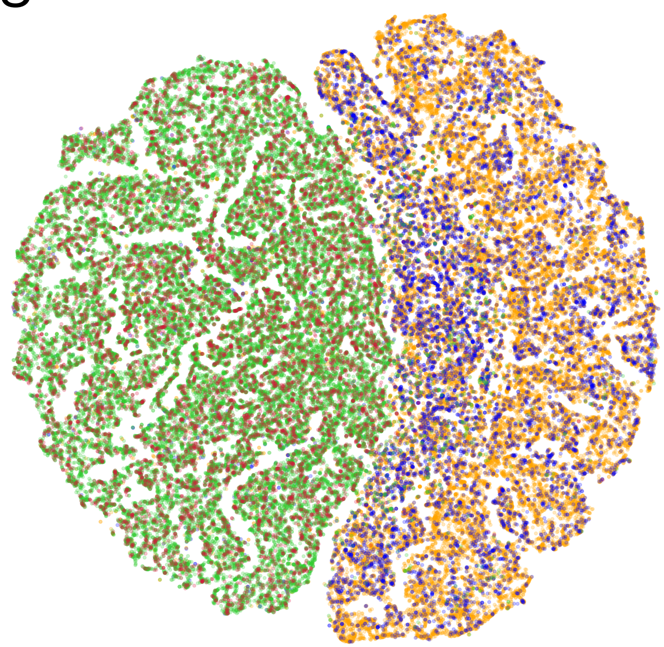
Starting from RS3L base → ***improvement in out-of-domain*** *classification*

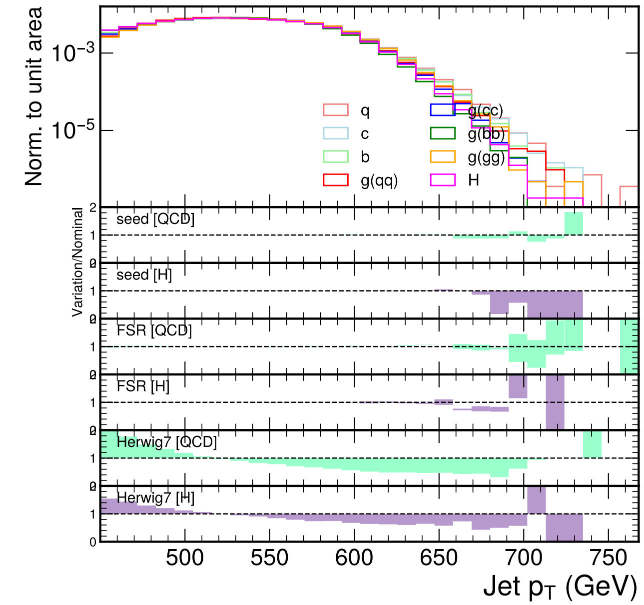
Conclusion

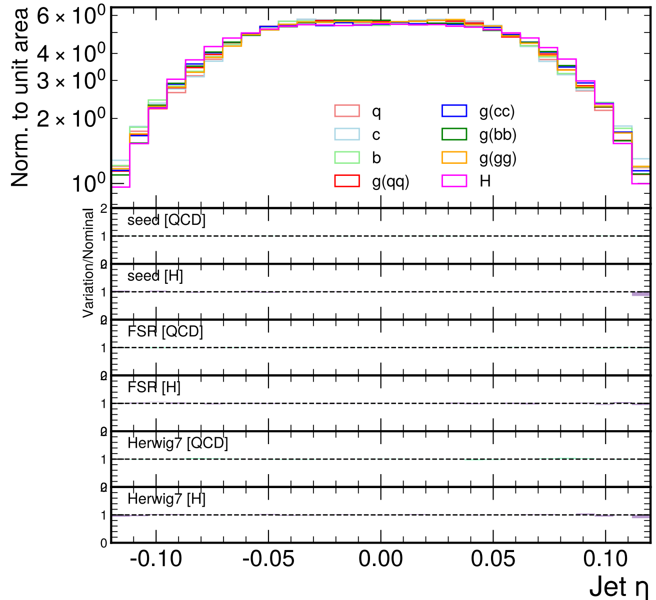
- Self-supervision helps us build a representation without labels
  - Could be a path toward a **foundation model** for HEP data
- RS3L has significant potential in downstream applications including:
  - Acting as a foundation for **discrimination tasks** (e.g. QCD/H)
  - Helping to **mitigate uncertainties** (e.g. parton showering)
  - Translating learning to out-of-domain classification tasks

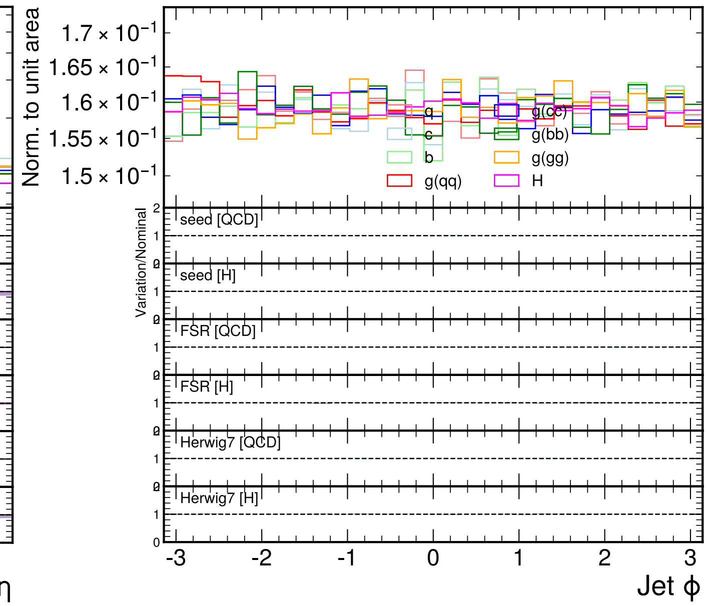


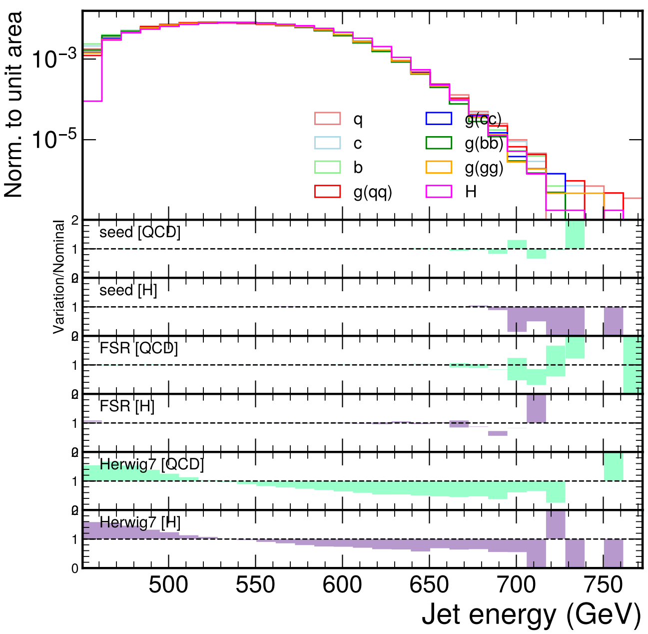
Backup

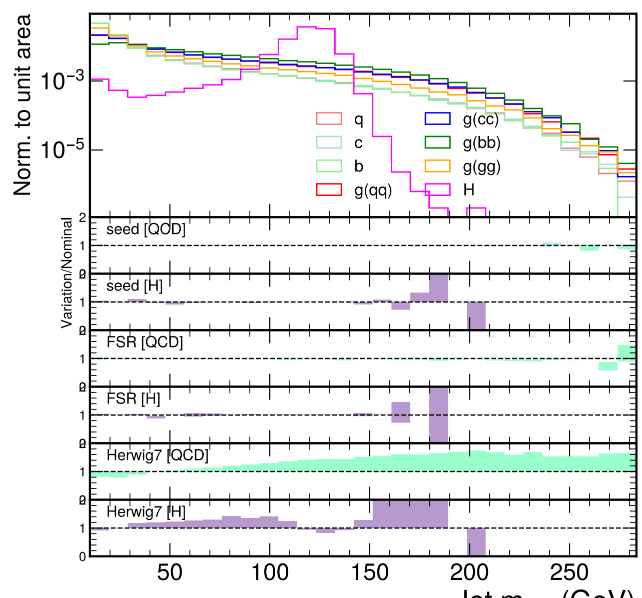
Jet kinematics

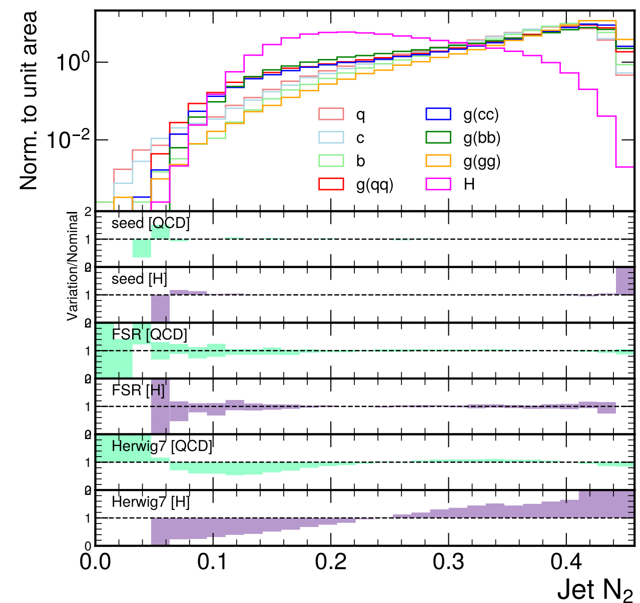








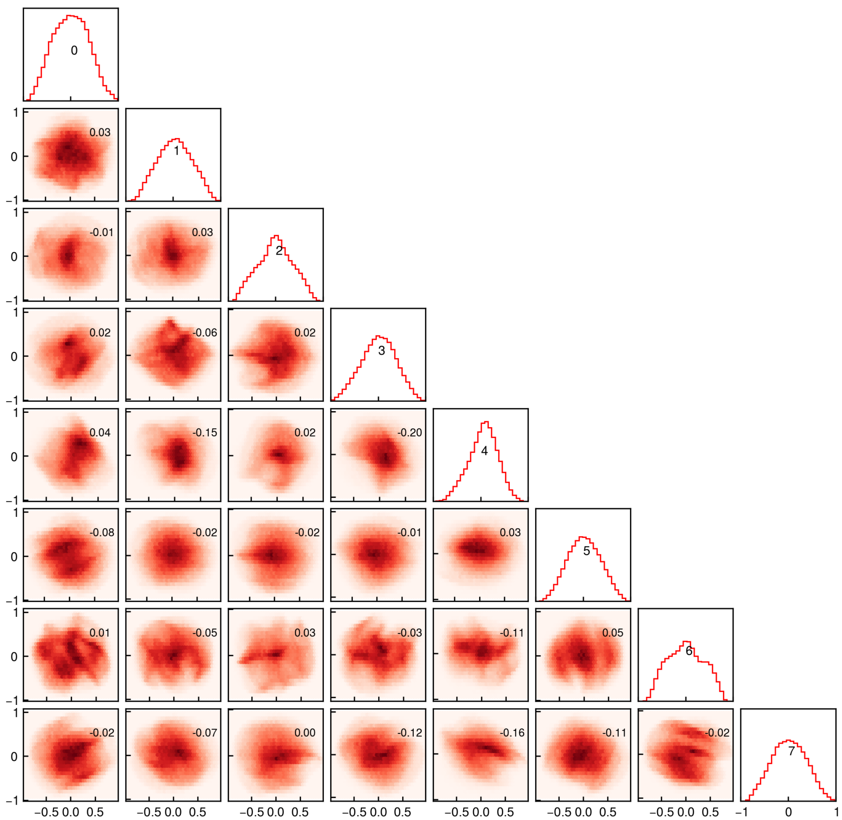




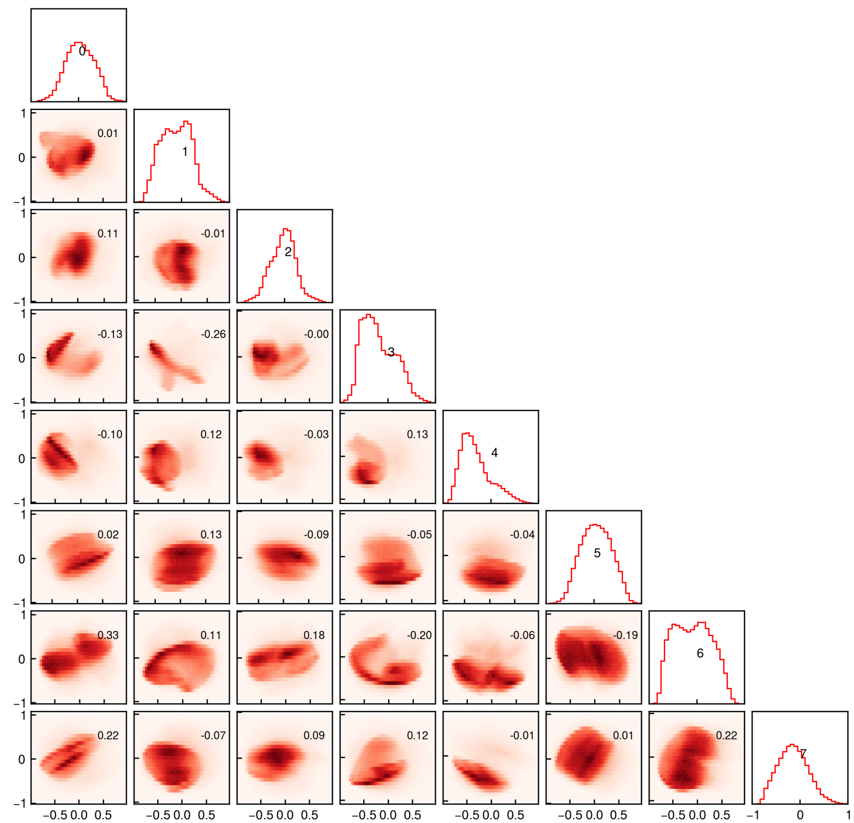
Corner Plots of contrastive features

- Higgs jets occupy a relatively larger volume of the space and tend to be distributed more uniformly

Higgs



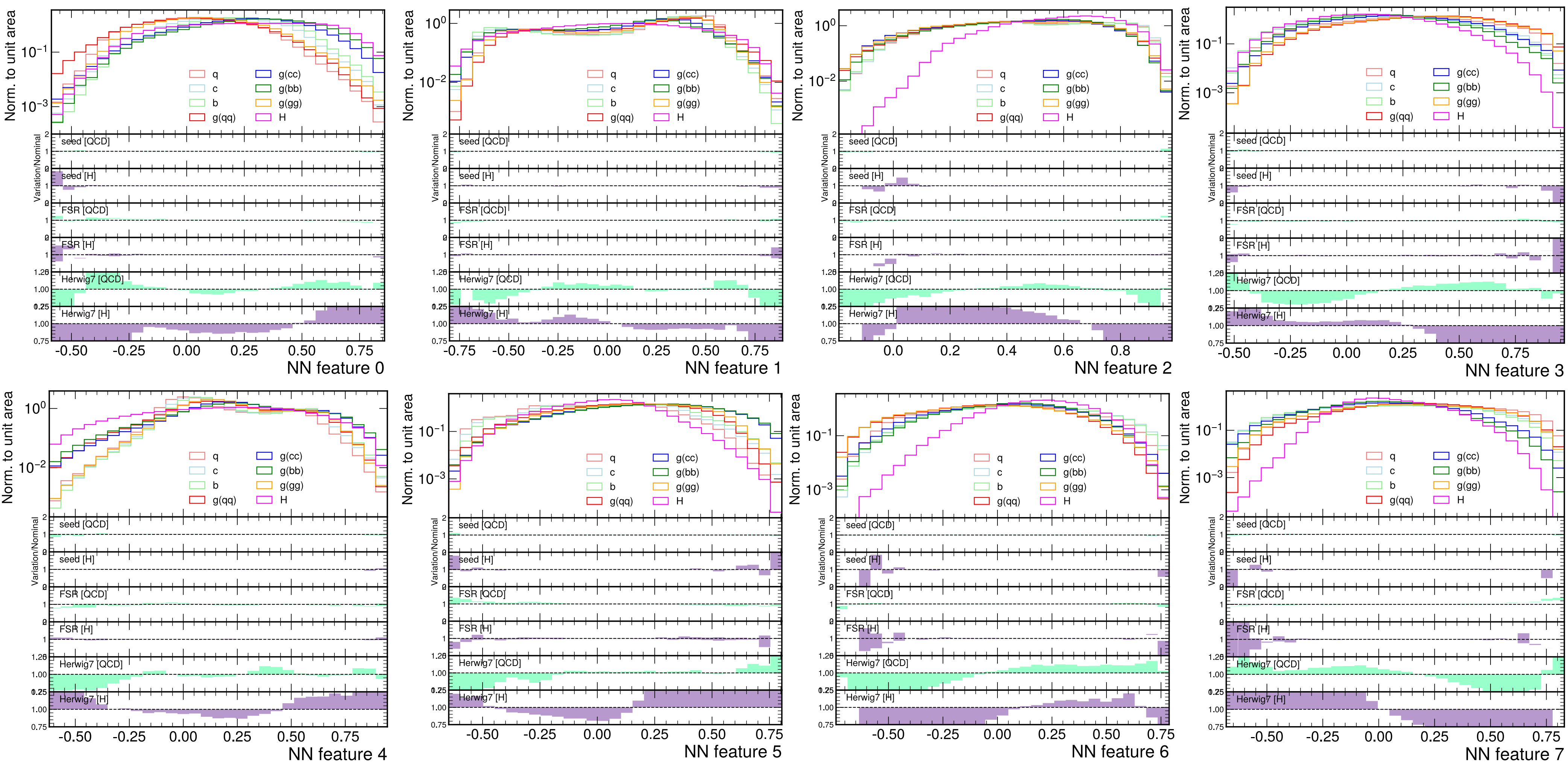
QCD



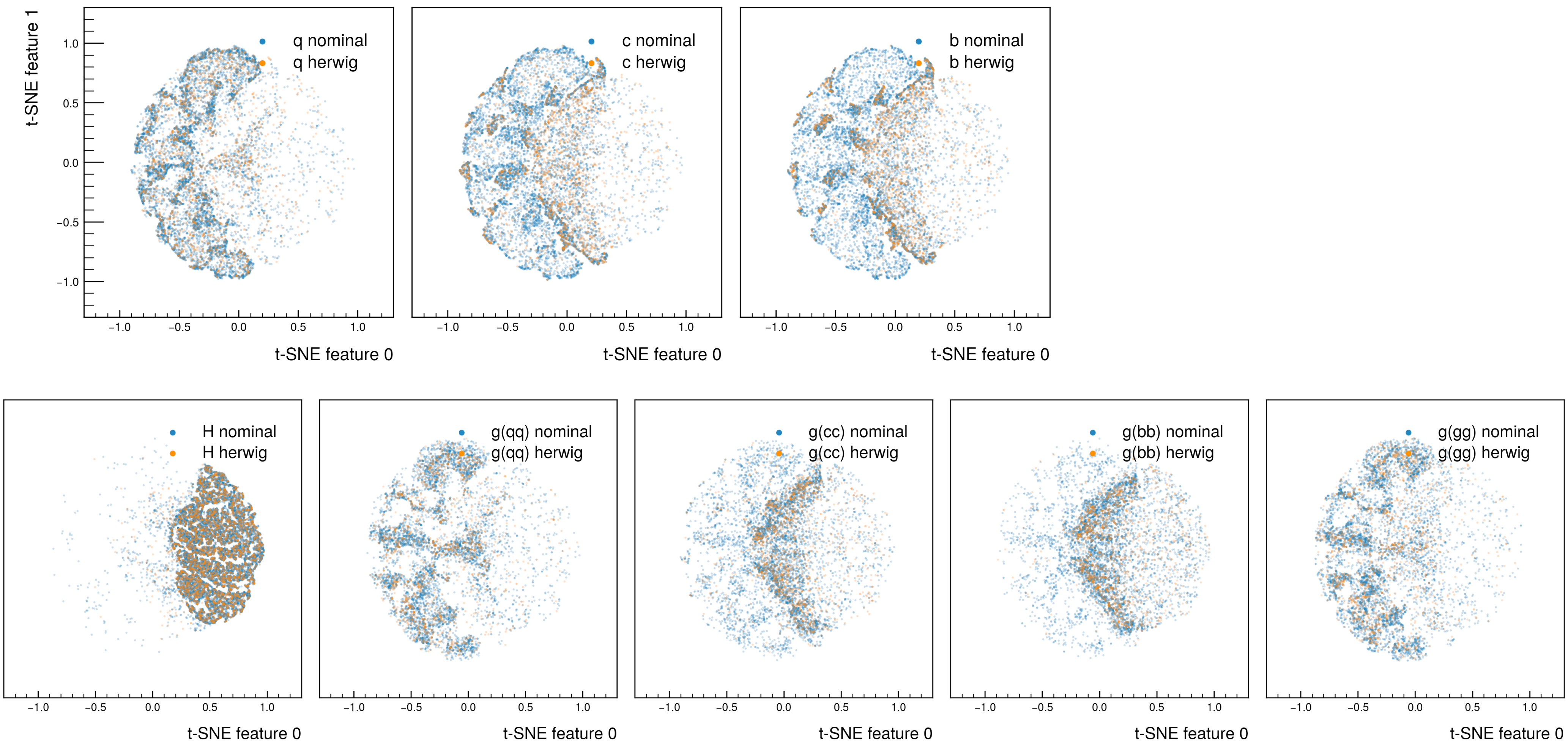
learned SSL features are largely independen
other

QCD-only training inferred on Higgs

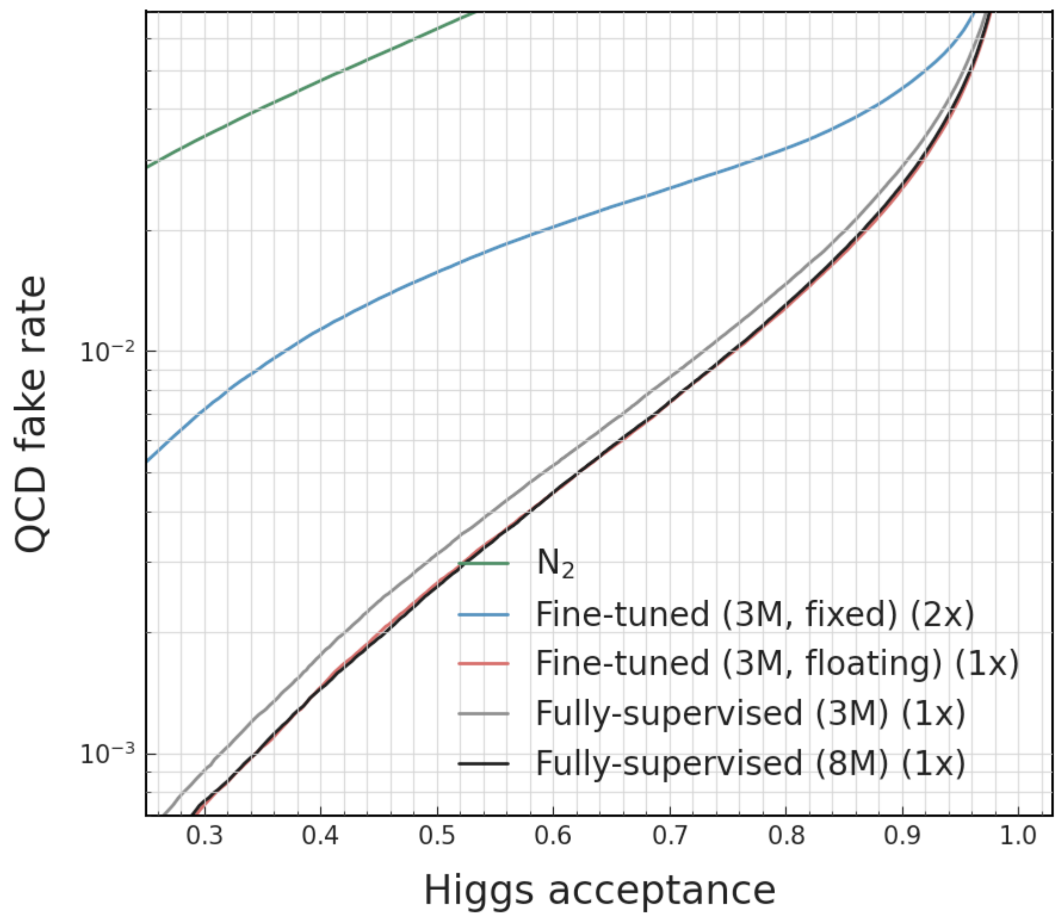
- We learn a reasonable Higgs representation despite training only on QCD



Full tSNE

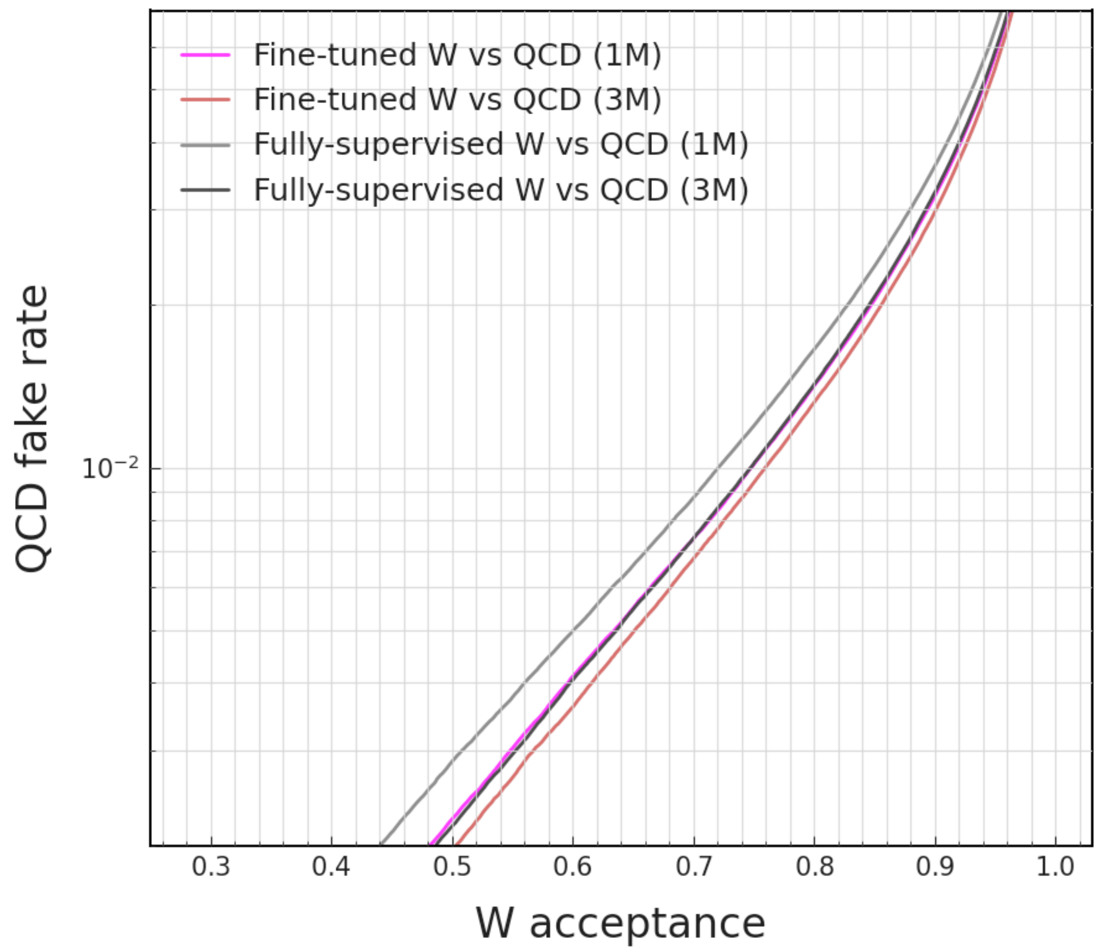

q nominal
q herwig
c nominal
c herwig
b nominal
b herwig
H nominal
H herwig
g(qq) nominal
g(qq) herwig
g(cc) nominal
g(cc) herwig
g(bb) nominal
g(bb) herwig
g(gg) nominal
g(gg) herwig
t-SNE feature 1
t-SNE feature 0

H vs QCD ROC



QCD fake rate
10^{-2}
10^{-3}
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Higgs acceptance
N_2
Fine-tuned (3M, fixed) (2x)
Fine-tuned (3M, floating) (1x)
Fully-supervised (3M) (1x)
Fully-supervised (8M) (1x)

W vs QCD ROC



Fine-tuned W vs QCD (1M)
Fine-tuned W vs QCD (3M)
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