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Anomaly detection interpretability and phenomenology

Universal new physics latent space

Based on <u>2407.20315</u>

Anna Hallin, G. Kasieczka, S. Kraml, A. Lessa, L. Moureaux, T. von Schwartz, D. Shih <u>anna.hallin@uni-hamburg.de</u>

Anomaly Detection for High Energy Physics (AD4HEP) Workshop, Columbia University, June 17, 2025



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Ппп

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... or very broad searches



Universität Hamburg

where B and C are τ leptons [9,10], b guarks [11-13], top of existing and proposed model-agnostic searches range

Interpretability

- By design, specific searches focus on small regions of model space
 - If we find something, great!
 - If we don't find anything, how can we use that result in the context of other models?
- Also by design, model-agnostic searches focuses on wide swaths of model space
 - If we find something, great!
 - ...but what is it that we have found?



Grouping models according to their phenomenology

- What if there was a way to figure out which models "belong together", phenomenologically?
 - Results of very specific searches could be easier to interpret in the context of other models
 - Further interpretation of results from model-agnostic searches could be made easier
 - Potential blind spots in our search strategies could be identified



Universal new physics latent space

- Idea: use machine learning to embed the phenomenology of different models into a universal latent space
- The distance between the models in this latent space will indicate how close they are to one another, phenomenologically







Model architecture: simple encoder



Fully connected MLP with ReLu activations



Contrastive loss function



where

Y = 0 for points from different models

Parameter for unbounded latent spaces; we set d = 1

$$L(\theta, (Y_{ij}, \vec{X}_i, \vec{X}_j)) = (1 - Y_{ij})\frac{1}{2}D_{\theta}^2 + Y_{ij}\frac{1}{2}\left(\max\left(0, d - D_{\theta}\right)\right)^2$$

The loss function is **minimized** when **points from the same model are close together** in the latent space, and **points from different models are far apart**. Since their phase spaces overlap, they cannot be collapsed to single points but must overlap in the latent space.

 $D_{\theta} \equiv D_{\theta}(\vec{X}_i, \vec{X}_j)$ Euclidian distance in latent space



Dataset 1: MSSM gluino simplified model

- Pair production of gluinos, each gluino decays to a neutralino and a quark-antiquark pair
- Signal: four hard jets and large missing energy (MET)
- Nine mass combinations: $m_{gluino} = 1.1, 1.6, 2.1 \text{ TeV}; m_{neutralino} = 0.1, 0.5, 0.9 \text{ TeV}$

• Features used for training: p_T , m, η , $\Delta \phi$ (jet, MET) of the first four jets, MET, and the invariant masses of all possible jet pairs



Observations:

- Large mass difference Δm between gluino and neutralino → harder jet and MET spectrum
- Models with similar Δm have similar spectra



Dataset 1 results

- The model has organized the models in latent space given the mass difference (labeled) between gluino and neutralino
- Agrees with observation about this correlation from the feature plots
- Orthogonal diagonal shows a slight sorting of the models according to the gluino mass, nontrivial as the signal features only depend weakly on this





Dataset 2: Dark matter simplified model

- Dark matter production at the LHC, with one jet and missing energy
 - Vector mediator
 - Pseudoscalar mediator
 - Squark mediator
- $m_{DM} = 100-900 \text{ GeV}$, in steps of 100 GeV; $M_{med} = 600-2000 \text{ GeV}$, in steps of 200 GeV
- Features used for training: p_T , η , $\Delta \phi$ (jet, MET), MET, and the mass of the leading two jets

Z'



g more t

g 2000

g unue

Observations for $m_{DM} = 100$ GeV:

- MET in vector and pseudoscalar case only weakly depends on the mediator mass
- In the squark case, the MET has a stronger correlation with the mediator mass



Dataset 2 results

- Separate embeddings
 - Not much dependence on mediator mass in vector and pseudoscalar case
 - Squark case shows dependence on mediator mass



Colorful contours: m_{DM} = 100 GeV; grey contours: all other masses



Dataset 2 results

- Separate embeddings
 - Not much dependence on mediator mass in vector and pseudoscalar case
 - Squark case shows dependence on mediator mass
- Pair embeddings
 - Vector and pseudoscalar overlap
 - Squark case has distinct arrangement
- Embedding of all three
 - Vector and pseudoscalar still overlap
 - Squark case keeps its distinct behavior



Colorful contours: m_{DM} = 100 GeV; grey contours: all other masses



Dataset 3: Dark machines subset

- A selection of models from the Dark machines anomaly challenge dataset (Dark Machines community 2020, Aarrestad et al 2022)
 - Scenarios resulting in jets + MET
 - SM background
- Features used for training: E, p_T, η, ϕ of the first four jets, MET of the event



BSM scenario	Physical process and model parameters
DM Vector Mediator	$pp \rightarrow Z' \rightarrow \chi \chi$ • $m_{Z'} = 2 \text{ TeV}, m_{\text{DM}} = 50 \text{ GeV}$
Gluino Simplified Models	$\begin{array}{l} pp \rightarrow \tilde{g}\tilde{g},\tilde{g} \rightarrow qq + \tilde{\chi}_1^0 \\ \bullet m_{\tilde{g}} = 1.4 \text{ TeV},m_{\chi^0} = 1.1 \text{ TeV} \\ \bullet m_{\tilde{g}} = 1.6 \text{ TeV},m_{\chi^0} = 0.8 \text{ TeV} \end{array}$
Stop Simplified Model	$\begin{array}{l} pp \rightarrow \tilde{t}\tilde{t}, \tilde{t} \rightarrow t + \tilde{\chi}_1^0 \\ \bullet m_{\tilde{t}} = 1 \mathrm{TeV}, m_{\chi^0} = 0.3 \mathrm{TeV} \end{array}$
Squark Simplified Model	$pp \rightarrow \tilde{q} \tilde{q}, \tilde{q} \rightarrow q + \tilde{\chi}_1^0$ • $m_{\tilde{q}} = 1.8 \text{ TeV}, m_{\chi^0} = 0.8 \text{ TeV}$

Observations:

- Squark model has the highest $\Delta m \rightarrow$ hard MET and p_T spectra
- Heavy gluino model has 4 hard jets \rightarrow high p_T of the third jet compared to other models
- Light gluino model has smallest $\Delta m \rightarrow$ soft spectra
- Z' model: jets come from ISR, not dependent on its high Δm

Dataset 3 results

- The latent space is organized along two main axes:
 - MET
 - p_T of the third jet
- Light gluino, Z' and stop models are clustered together, as expected from ISR and soft spectrum of light gluino; light gluino has softer MET, putting it higher in latent dim 2
- Heavy gluino: high p_T of the third jet, intermediate MET
- Squark: highest MET, also hard p_T spectra
- SM background: softest spectra overall





Conclusions

- We developed a machine learning model capable of clustering different BSM scenarios in a latent space according to their phenomenology
- When analyzing the arrangement in latent space, it was obvious that the model had found relevant axes
 - By analyzing such latent spaces, representative models that cover a certain area of the latent space can be selected as benchmarks for searches
 - Correlations between latent space axes and feature space can be used to identify observables suitable for distinguishing different models
 - Regions not covered in latent space could indicate gaps that need to be filled
- Future work: include cross section; explore more expressive architectures...

