

An Anomaly Detection strategy for New Physics searches at the LHC

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BICOCCA

VERSI

DEGLI STUD

Aim of the work

Probing the use of **unsupervised learning methods for anomaly detection** to identify signals of new physics at LHC → Variational AutoEncoders

- anomalous contributions modeled through **SMEFT** (**dimension-6** effects)
- physics use case: **same-sign WW scattering** in a fully leptonic final state

Why VBS for BSM searches:

Deeply connected to Higgs mechanism (probe of the SM sensitive to modifications of the EWK sector)

Tree level sensitivity to:

- triple and quartic gauge couplings
- Higgs-gauge couplings away from mass shell



SM Effective Field Theory (SMEFT)

The **SM** is seen as a **low-energy approximation** of a more complete theory:

 $\mathcal{L}_{EFT} = \mathcal{L}_{SM} + \sum_{i} \frac{c_i}{\Lambda^{d-4}} \mathcal{Q}^{(d_i)}$ i.d>4

h – new physics scale $O^{(d_i)}$ – EFT operator of dimension d_i c_i – Wilson coefficient

- BSM effects are parametrized as additional terms to the SM lagrangian, which contain **higher order operators**
- Their intensity is gauged by Wilson coefficients

The first non-zero term (after SM) is **dimension 6**

- parton-level, @LO generations of SSWW events (SMEFTsim)
- integrated luminosity of 350/fb
- backgrounds neglected
- Dim 6 operators, chosen from the Warsaw basis
- one operator at a time

Why unsupervised learning

EFT is a complex, multidimensional problem:

- o (2500) parameters to constrain
- each operator affects differently each variable
 - \circ ~ hard to define a single observable to detect all operators

→ We want to build a strategy that maximizes the observation of anything that is not Standard Model (in principle we should see all the operators):

- Variational AutoEncoders
 - Unsupervised learning is an increasingly popular choice <u>2101.08320</u>
- idea: train a model on know physics, and later use it to detect outliers (anomaly detection task)

Input distributions

The EFT operators modify the distributions of the variables, that now comprise:

- A pure SM contribution
- Additional terms with **linear** and **quadratic** dependence on the EFT operator



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Variational AutoEncoders

- The latent space is forced to be regular, namely described by a multidimensional **gaussian distribution**
 - via minimization of a regularization loss (KLD) + reconstruction loss (MSE)
- A point is sampled from the latent space and decoded



Variational AutoEncoders for Anomaly Detection

Generative model: it learns to decode samples drawn from the same probability distribution of the original dataset

→ **robust** and **variation-tolerant** Anomaly Detection strategy



Adding a supervised NN classifier to the VAE

The VAE is only trained to reconstruct a SM sample, while our goal is to isolate EFT events.

We want to **embed discrimination in the training > VAE + NN classifier**

- Trained by minimization of MSE + KLD + **Binary Crossentropy**
- Input data are divided between purely SM and SM + EFT:
 - MSE and KLD coming from **SM** events are added to the model loss
 - MSE and KLD coming from a set of **SM+EFT** events are given to the classifier
 - the binary crossentropy is added to the model loss



VAE results: shape comparison

The model collects information from various inputs → it provides a variable (**output score**) whose **shape maximizes the separation between EFT and SM**



VAE results: a proxy metric of the significance

The model is sensitive to several different operators

• We define a proxy metric for the significance *σ*, which depends on the Wilson coefficients of the operator considered during testing:

$$\sigma(c_{op}) = \frac{|n_{BSM}(c_{op}) - n_{SM}|}{\sqrt{n_{SM}}} = \frac{|n_{LIN}(c_{op}) + n_{QUAD}(c_{op}^2)|}{\sqrt{n_{SM}}}$$

• We consider the model sensitive to an operator if σ reaches the value of 3:

operator	$ c_W$	c_{qq}^1	$c_{qq}^{1,1}$	c_{qq}^3	$c_{qq}^{3,1}$	c_{Hq}^1	c_{HW}
$c_{op}:\sigma(c_{op})=2$	3 0.13	0.17	0.18	0.11	0.11	0.61	0.65

Conclusions and future perspectives

Outcome:

• The VAE allows for detecting many operators → promising!

Further steps:

- Introduce estimation of backgrounds (fake leptons)
- Test VAE on fully reconstructed events

BACKUP

fully leptonic SSWW

Scattering of two same-sign W bosons, both decaying leptonically



- Very clean signature (very low QCD background):
 - 2 forward jets
 - 2 same sign charged leptons
 - 2 neutrinos

• Main backgrounds:

- fake leptons
- WZ (QCD and EWK)

Input variables

Variables considered:

- m_{ll}, m_{jj} $\Delta \Phi_{jj}$
- $p_{t_{l1}}, p_{t_{l2}}, p_{t_{j1}}, p_{t_{j2}}$ $\eta_{j_1}, \eta_{j_2}, \eta_{l_1}, \eta_{l_2}$
- $p_{t_{ll}}$ $\Delta \eta_{jj}$

• MET

- Selections: $p_{t_{j1}}, p_{t_{j2}} > 30 GeV$
 - $m_{jj} > 200 GeV$
 - $\Delta \eta_{jj} > 2$

Loss function:



Loss function

Samples reconstruction: BSM vs SM



Why model optimization is fundamental

Our aim is to achieve a good discrimination between SM and BSM. However, **the VAE is only trained to produce a good reconstruction of the SM sample:**

- The model learns the SM distributions
 - \circ The more the model learns, the better the reconstruction of the SM
- The model extrapolates and is able to reconstruct BSM events

Example: **dimension of the latent** space. A bigger latent space allows the model to learn more features → better reconstruction of SM → better reconstruction of BSM! worse discrimination





0.2 0.4 0.6

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$\sigma_{max}(cW) = \max_k \{\sigma(k, cW)\}$

0.8 1.0

 $\Delta \eta_{ii}$ (rescaled)

Operators:

$Q_{Hl}^{(1)} = (H^{\dagger}i\overleftrightarrow{D_{\mu}}H)(\bar{l}_{p}\gamma^{\mu}l_{p})$	$Q_{Hl}^{(3)} = (H^{\dagger}i\overleftrightarrow{D_{\mu}^{i}}H)(\bar{l}_{p}\sigma^{i}\gamma^{\mu}l_{p})$
$Q_{Hq}^{(1)} = (H^{\dagger}i\overleftrightarrow{D_{\mu}}H)(\bar{q}_p\gamma^{\mu}q_p)$	$Q_{Hq}^{(3)} = (H^{\dagger} i \overleftrightarrow{D_{\mu}^{i}} H) (\bar{q}_{p} \sigma^{i} \gamma^{\mu} q_{p})$
$Q_{qq}^{(1)} = (\bar{q}_p \gamma_\mu q_p)(\bar{q}_r \gamma^\mu q_r)$	$Q_{qq}^{(1,1)} = (\bar{q}_p \gamma_\mu q_r)(\bar{q}_r \gamma^\mu q_p)$
$Q_{qq}^{(3)} = (\bar{q}_p \gamma_\mu \sigma^i q_p) (\bar{q}_r \gamma^\mu \sigma^i q_r)$	$Q_{qq}^{(3,1)} = (\bar{q}_p \gamma_\mu \sigma^i q_r) (\bar{q}_r \gamma^\mu \sigma^i q_p)$
$Q_{HD} = (H^{\dagger}D_{\mu}H)(H^{\dagger}D^{\mu}H)$	$Q_{H\square} = (H^{\dagger}H)\square(H^{\dagger}H)$
$Q_{HWB} = (H^{\dagger} \sigma^{i} H) W^{i}_{\mu\nu} B^{\mu\nu}$	$Q_{HW} = (H^{\dagger}H)W^{i}_{\mu\nu}W^{i\mu\nu}$
$Q_W = \varepsilon^{ijk} W^{i\nu}_{\mu} W^{j\rho}_{\nu} W^{k\mu}_{\rho}$	$Q_{ll}^{(1)} = (\bar{l}_p \gamma_\mu l_r) (\bar{l}_r \gamma^\mu l_p)$

- H denotes the SU(2) Higgs doublet
- Wiµv and Bµv denote the gauge fields associate with SU(2) and U(1) symmetries respectively
- l,q denote the left-handed lepton and quark doublets
- u, d, e denote the right-handed quark and <u>charged</u>-lepton fields
- i, j, k denote the SU(2) indexes and sig_i the Pauli matrices

•Enter via modifications of the EW input quantities: $(Q_{Hl}^{(3)}, Q_{ll}^{(1)}, Q_{HD}, Q_{HWB})$

•Induce modifications via:

-Vff couplings $(Q_{Hl}^{(1)}, Q_{Hl}^{(3)}, Q_{Hq}^{(1)}, Q_{Hq}^{(3)})$

-Gauge couplings (Q_W)

-HVV couplings $(Q_{HD}, Q_{HW}, Q_{HWB}, Q_{H\Box})$

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-Four-quark contact terms (Q_{qq}^{(1)},Q_{qq}^{(3)},Q_{qq}^{(1,1)},Q_{qq}^{(3,1)})
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