Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

FSP CMS
Erforschung von Universum und Materie

CMS

Explore new physics with advanced Machine Learning techniques at CMS

Manuel Sommerhalder*
on behalf of the CMS Collaboration

*University of Hamburg

ICHEP 2024, Prague

July 20, 2024

Introduction

Machine learning (ML) techniques have become standard tools

- **Tagging**: train classifier on MC, calibrate on data
- **Regression**: reconstruct analysis observables
- **Anomaly detection** (less standard): data-driven ML for model-agnostic searches

Here covering five recent analysis using ML techniques to various extents

- EXO-23-010: Search for nonresonant new physics in high-mass dilepton events in association with b-tagged jets
- EXO-22-015: Search for new physics with emerging jets in proton-proton collisions at $\sqrt{s} = 13$ TeV, *arXiv:2403.01556*
- EXO-23-013: Search for low-mass long-lived particles decaying to displaced jets in proton-proton collisions at $\sqrt{s} = 13.6$ TeV
- EXO-22-022: Search for new resonances decaying to pairs of highly merged diphotons in proton-proton collisions at $\sqrt{s} = 13$ TeV, *arXiv:2405.00834*
- EXO-22-026: Model-agnostic search for dijet resonances with anomalous jet substructure in proton-proton collisions at $\sqrt{s} = 13$ TeV

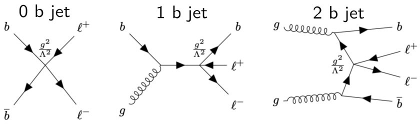
Tagging EFT contact interaction events

EXO-23-010 **NEW!**

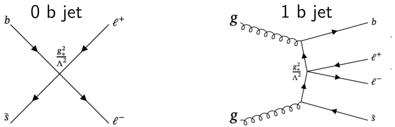
Run2 search for nonresonant dilepton events in association with b-tagged jets

2 EFT models with 4-fermion CI

$b b \ell \ell$:



$b s \ell \ell$:



Search in channels of dilepton flavors $(ee/\mu\mu)$ and number of b jets

Background rejection:

Deep neural network to reduce $t\bar{t}$ in ≥ 1 b tag channels

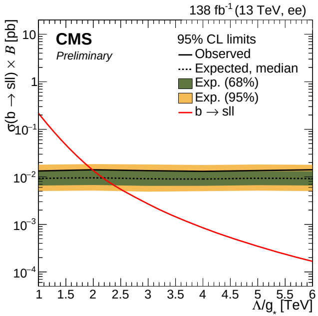
- 4-layer FCN
- High-level event features
- Working point rejecting 90% of $t\bar{t}$ and retaining 70% signal

Final fit variable:

Dilepton invariant mass $m_{\ell\ell}$

Limits:

example channel: $bsee$, 1 bjet



Most stringent *bsll* limits to date

Emergent Jet Tagging

EXO-22-015, *arXiv:2403.01556*

Searching for emergent jets (EMJ) in CMS Run2 data

Signature:

Dark mediator X_{dark} connects dark and SM sector

$X_{\text{dark}} \to qQ_{\text{dark}}$

Unstable dark pions decay to SM

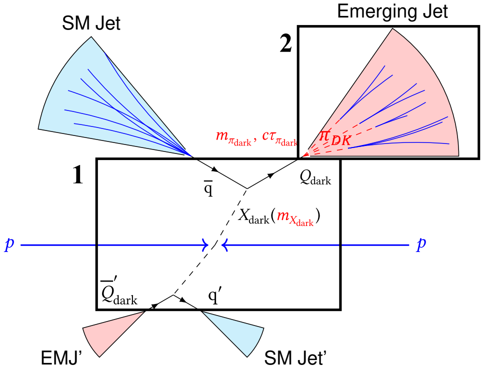
EMJ Tagging:

Model agnostic: simple cuts on

- Track displacement variables
- Track multiplicity variables

Graph neural network (GNN): ParticleNet

- Modeling tracks as point clouds
- Dynamic graph convolution

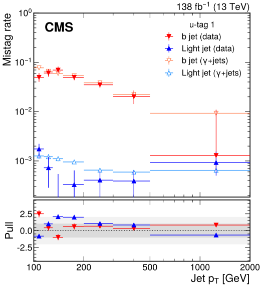


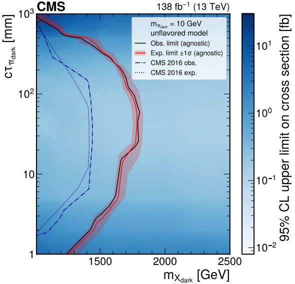
1. $pp \to 2X_{\text{dark}} \to 2(qQ_{\text{dark}})$
2. $Q_{\text{dark}} \xrightarrow{\text{hadronizes}} N\pi_{\text{dark}} \xrightarrow{\text{travel } c\tau}$ SM particles

Emergent Jet Tagging

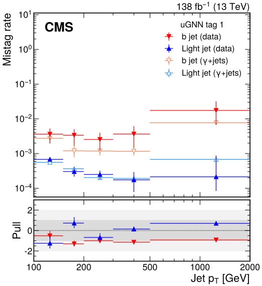
EXO-22-015, *arXiv:2403.01556*

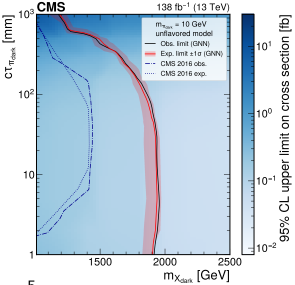
Model-agnostic →





GNN →





Lower mistag rate and more sensitive limits with GNN tagging

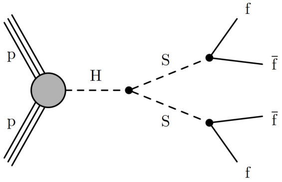
Displaced Jet Tagging

EXO-23-013

Run3 search for hadronic decays of long-lived particles (LLPs) in the inner tracker

Signature:

$H \to SS,\ S \to bb/dd/\tau\tau$
(S is LLP)



$\to$ Dijets with displaced vertices

also see Alberto's talk

2 LLP dijet taggers:

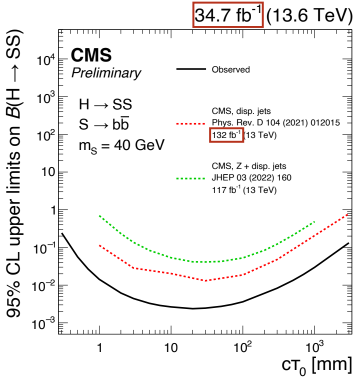
- $g_{\text{displaced}}$: displaced vertices and associated tracks as input
- g_{prompt}: only tracks with small d_{xy}

Architecture:

- Message-passing GNN
- LSTM layers

Background estimation:

ABCD method in $g_{\text{displaced}}$ and g_{prompt}



Improving over existing searches by up to 10x, despite smaller int. luminosity!

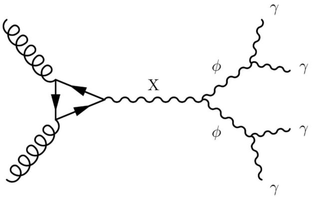
Diphoton Tagging and Mass Regression

EXO-22-022, *arXiv:2405.00834*

Run2 search for a massive resonance with two boosted diphotons in the final state

Signature:

$X \to \phi\phi \to (\gamma\gamma)(\gamma\gamma)$



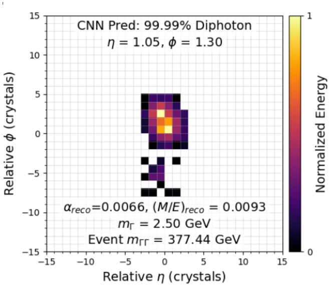
Highly boosted ϕ resulting in merged photon pairs

$\rightarrow$ Need new ML analysis techniques

also see Jyoti's talk

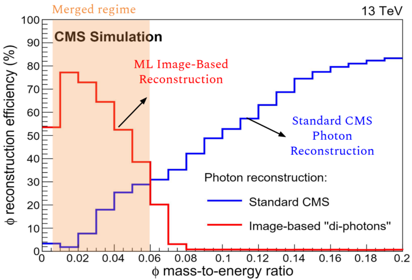
ML input:

Custom ECAL clusters



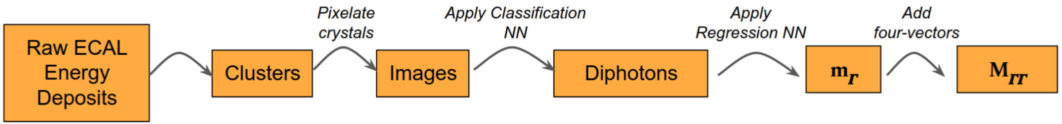
2 convolutional neural networks:

- *Classifier* selects diphotons from single photons and hadrons
- *Regressor* predicts the diphoton mass



Diphoton Tagging and Mass Regression

EXO-22-022, *arXiv:2405.00834*

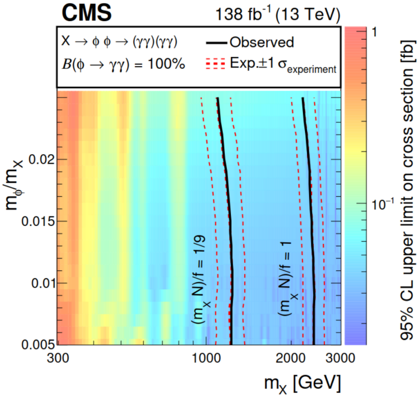


Background estimation via bump hunt in reconstructed diphoton pair mass $M_{\Gamma\Gamma}$

No significant global excess observed

Limits on Extended Higgs sector model

Most sensitive search of its kind at the LHC



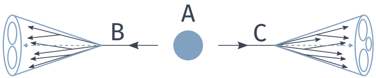
Anomaly Detection

Run2 search for heavy dijet resonances with anomalous jet substructure

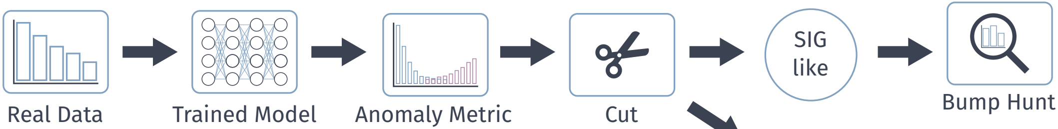
Model-agnostic search:

- Neither signal nor background models are assumed
- Data-driven selections (ML) and background estimation (bump hunt)

Target signature:



- A is heavy BSM resonance
- B and C may also be BSM particles



2 AK8 jets
$p_{\mathrm{T}} > 300$ GeV
$|\eta| < 2.5$
$|\Delta\eta| < 1.3$

Pool of different state-of-the-art anomaly detection methods

select most anomalous events

1. **Significance** vs mass
2. **Limits** on few explicit models

Anomaly Detection

EXO-22-026

Outlier detection: *VAE-QR*

- Train variational autoencoder to reconstruct control region events
- Signal region events with high loss are more anomalous

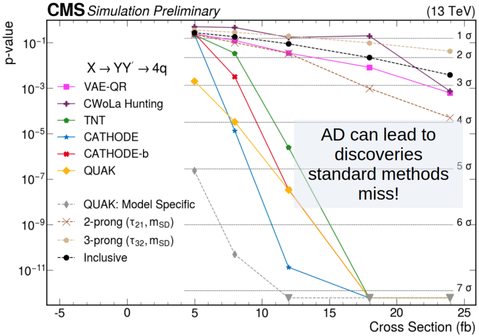
Weak supervision: *CWoLa Hunting*, *TNT*, *CATHODE*

- Train ML classifier between signal-enriched and background-enriched regions
- High output score is more signal-like

Multi-signal priors: *QUAK*

- 2 ML density estimators encoding background and mix of signal MC samples
- Select events based on 2D loss space

4/5 methods work without any MC



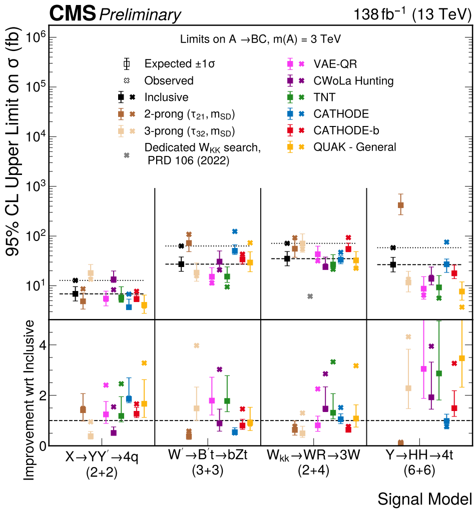
Anomaly Detection

No significant excess from any method

Novel limits on several benchmark signal models with varying substructure

Improving over standard methods by up to ~ 4x

First usage of anomaly detection in CMS!



Summary

Increasingly advanced ML methods are improving new physics searches at CMS

- **Tagging**: train on MC, calibrate on data
    - *BSM dilepton vs SM $t\bar{t}$ events*
    - *Emerging jets vs SM multijets*
    - *Displaced jets vs QCD*
    - *Diphotons vs single photons and hadrons*
- **Regression**: reconstruct analysis observables
    - *diphoton mass*
- **Anomaly detection**: data-driven ML for model agnostic searches
    - *Dijets with anomalous substructure*

$\rightarrow$ **Higher sensitivity for specific BSM processes**

$\rightarrow$ **Broader *model-unspecific* coverage**

BACKUP

ParticleNet

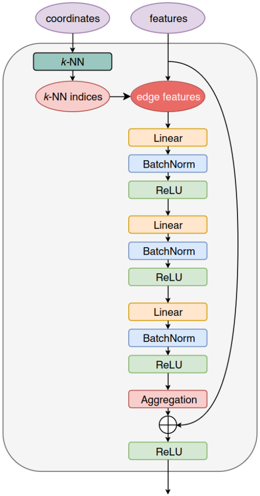
Huilin Qu and Loukas Gouskos, *Jet tagging via particle clouds*. Phys. Ref. D 101, 056019

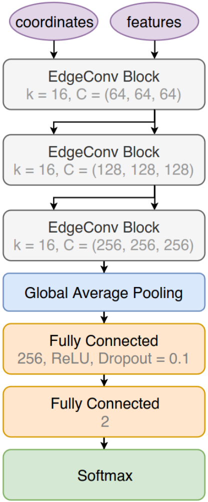
Dynamic Graph Convolutional Neural Network

Input: point (particle) clouds

EdgeConv operation:
$$x_i' = \frac{1}{k}\sum_{j=1}^{k} h_{\mathbf{\Theta}}(x_i, x_{i_j})$$

Neural network:
$$h_{\mathbf{\Theta}}(x_i, x_{i_j}) = \bar{h}_{\mathbf{\Theta}}(x_i, x_{i_j} - x_i)$$



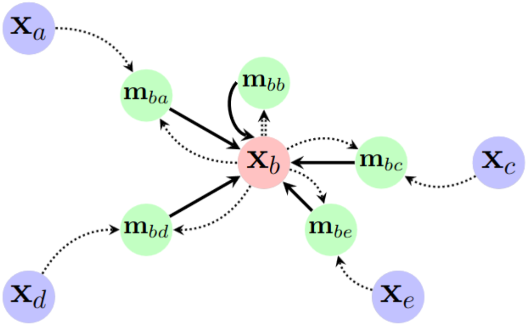


Message Passing Neural Networks

Justin Gilmer, et al, *Neural Message Passing for Quantum Chemistry*. arXiv:1704.01212

Message Passing Neural Networks (MPNNs)

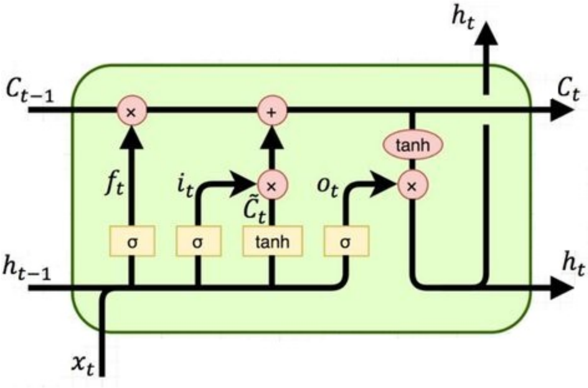
- **Message function**: $m_{t+1}^{(i)} = \sum_{j \in N(i)} M_t(h_t^{(i)}, h_t^{(j)}, e_t^{(i,j)})$
- **Update function**: $h_{t+1}^{(i)} = U_t(h_t^{(i)}, m_{t+1}^{(i)})$
- **Readout function**: $o_t = R_t(\{h_t^{(i)}\})$



Adapted from arXiv:2104.13478

LSTMs

Long Short-Term Memory (LSTM) networks



$$i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right)$$
$$f_t = \sigma\left(x_t U^f + h_{t-1} W^f\right)$$
$$o_t = \sigma\left(x_t U^o + h_{t-1} W^o\right)$$
$$\tilde{C}_t = \tanh\left(x_t U^g + h_{t-1} W^g\right)$$
$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right)$$
$$h_t = \tanh(C_t) * o_t$$

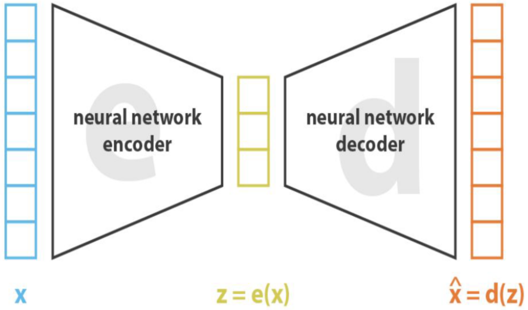
Adapted from arXiv:1811.12456

VAE-QR

Training a variational autoencoder (VAE) to reconstruct jets through a bottle neck

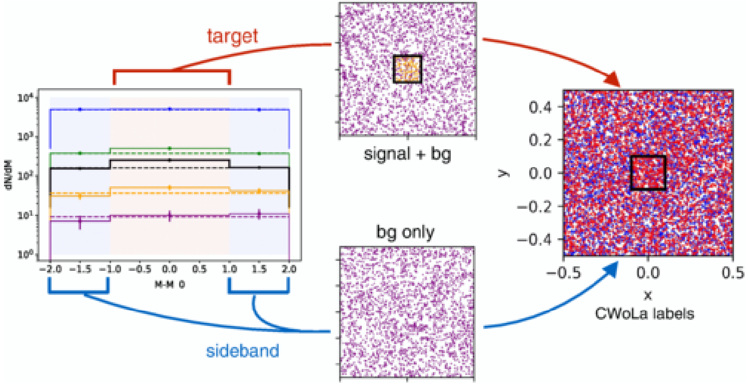
High loss indicates anomalous events

Quantile regression (QR) to decorrelate from dijet mass



CWoLa Hunting

Jack H. Collins, Kiel Howe, and Benjamin Nachman, *Extending the search for new resonances with machine learning*. Phys. Rev. D 99, 014038

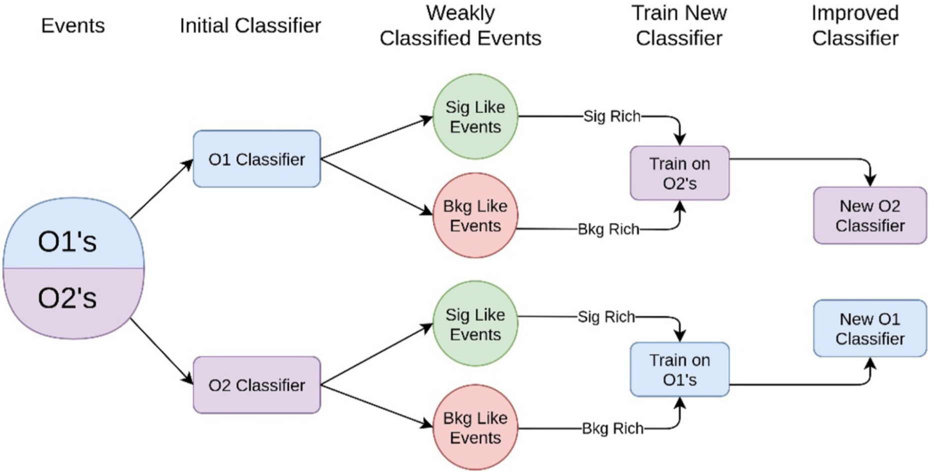


Train NN classifier to distinguish signal region from sidebands

High score indicates more signal-like/anomalous events

TNT

Oz Amram, and Cristina Mantilla Suarez, *Tag N' Train: a technique to train improved classifiers on unlabeled data*. J. High Energ. Phys. 2021, 153



CATHODE

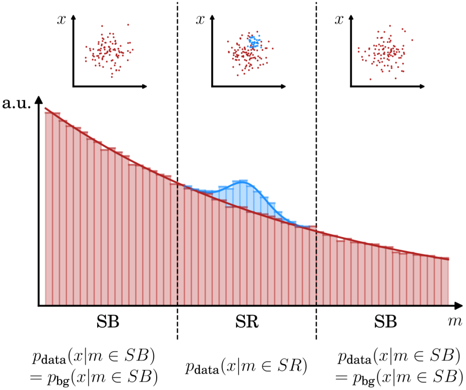
Anna Hallin, Joshua Isaacson, Gregor Kasieczka, Claudius Krause, Benjamin Nachman, Tobias Quadfasel, Matthias Schlaffer, David Shih, and Manuel Sommerhalder, *Classifying anomalies through outer density estimation*. Phys. Rev. D 106, 055006

Learn to model features in sidebands with a normalizing flow $p_{\text{bkg}}(x|m \in \text{SB})$

Sample background-like events in SR $p_{\text{bkg}}(x|m \in \text{SR})$

Train NN classifier to distinguish from real data

High score indicates more signal-like/anomalous events



QUAK

Sang Eon Park, Dylan Rankin, Silviu-Marian Udrescu, Mikaeel Yunus, and Philip Harris, *Quasi anomalous knowledge: searching for new physics with embedded knowledge*. J. High Energ. Phys. 2021, 30

Train one normalizing flow on background MC

Train one normalizing flow on mix of signal MC samples

Select events with low signal loss and high background loss