Self-supervision for data-driven anomaly detection at the LHC

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Anomaly searches

1 Introduction

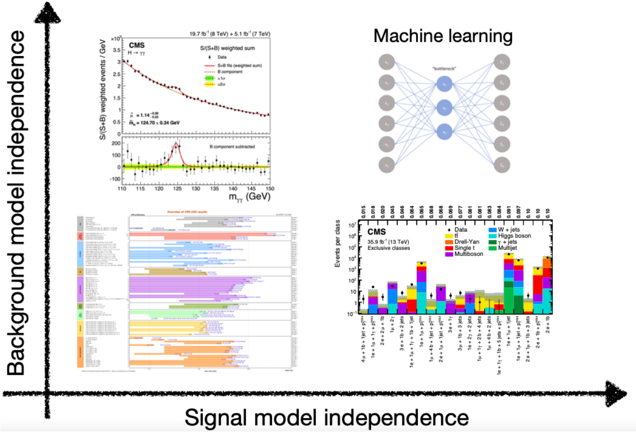
- LHC does and will generate large amount of data;
- We are still looking for BSM physics;
- No clear anomalies in the near future . . .
  $\longrightarrow$ keep exploring with direct searches is not feasible;

model agnostic searches **no loss in sensitivity**

Have we fully explored the collected data?

Anomaly searches

1 Introduction



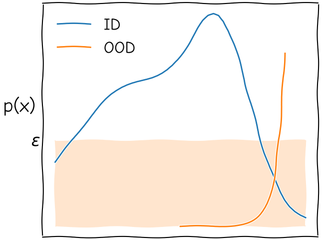
credits to M. Krämer, cf. Karagiorgi, Kasieczka, Kravitz, Nachman, Shih, arXiv:2112.03769 [hep-ph]

Density estimation

1 Introduction

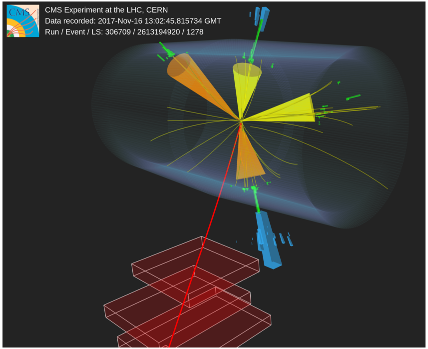
- Density estimates used as agnostic anomaly scores;
- Only focus on density estimation of background:
  - can be used directly on data;
  - sensitivity requires dealing with large input spaces;
- Improved representation of the data is key...

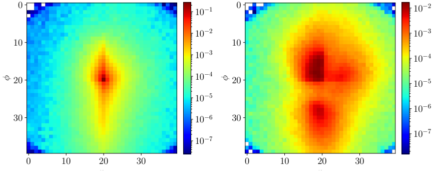
$\longrightarrow$ Physics motivated preprocessing/observables.

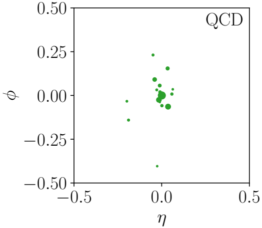


$$OOD = \{x|p(x) < \epsilon\}$$

Datasets
1 Introduction







*from CMS Open Data

Reco events

Set of objects of variable length with features (p_T, η, ϕ)

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Self-supervision

2 Contrastive Learning

*also discussed in Patrick's talk here

- Preprocessing solves many problems with neural networks;
  - NNs are not invariant to physical symmetries in data;
  - NNs like numbers of $O(1)$;
- Self-supervision: during training we use pseudo-labels, not truth labels;

  $\longrightarrow$ task used to create new representations/observables;

Key aspects of representations:

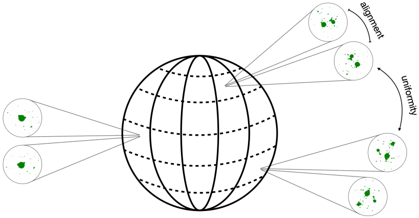
- Invariance to certain transformations of the jet/event
- Discriminative power

In CLR we construct a mapping to a new representation space

CLR training

*as in JetCLR, arXiv:210804253

- Pseudo-labels are defined from pairs:
  - $\{(x_i, x_i')\}$: positive pair
    $\rightarrow$ alignment/invariance;
  - $\{(x_i, x_j) \cup (x_i, x_j'))\}$: negative pair
    $\rightarrow$ uniformity/discriminative;
- $f : \mathcal{R} \rightarrow \mathcal{Z}$ is a transformer-encoder;
- $s(\cdot, \cdot)$ cosine distance in rep. space.

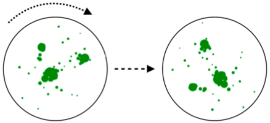


$$\mathcal{L} = -\log \frac{exp(s(z_i, z_i')/\tau)}{\sum \mathcal{I}_{i \neq j}[exp(s(z_i, z_j)/\tau) + exp(s(z_i, z_j')/\tau)]}$$

CLR for anomaly detection

Augmentation: any transformation (e.g. rotation) of the original jet

- Example:
  $\longrightarrow$ detector invariance under rotations;



- Background data does not known BSM features.

Can we train a transformer-encoder network only on background events?

- Possible, but with no guarantee to learn representations sensitive to new physics;

Introduce general BSM motivated anomalous representations z^*

*from "Anomalies, representations, and self-supervision", arXiv:2301.04660

Contrastive Learning for anomaly detection:

- anomalous pairs: $\{(x_i, x_i^*)\}$ where x_i^* comes from a different set of augmentations;
- These are motivated by BSM features, general, and signal agnostic.

$$\mathcal{L}_{aCLR} = -\log \frac{exp(s(z_i, z_i') - s(z_i, z_i^*)/\tau)}{\sum \mathcal{I}_{i\neq j}[exp(s(z_i, z_j)/\tau) + exp(s(z_i, z_j')/\tau)]}$$

$$\mathcal{L}_{aCLR+} = -\log \exp^{(s(z_i, z_i') - s(z_i, z_i*))/\tau} = \frac{s(z_i, z_i^*) - s(z_i, z_i)}{\tau}$$

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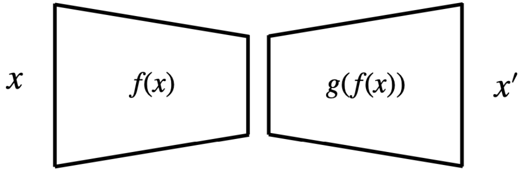
Anomaly scores

- Cut-based OOD downstream task as a benchmark;
- (Normalized)AutoEncoder based anomaly score:

$$E_\theta = MSE(x, D(E(x))) \qquad p_\theta\,(x) = \frac{e^{-E_\theta\,(x)}}{\Omega};$$

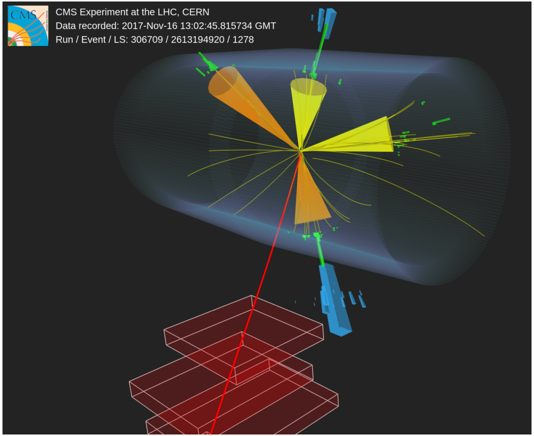
- for more details see arXiv:2206.14225;
- or posters IDs 146,95 for applications within CMS.



The corresponding anomaly score will be (approx) invariant to the augmentations

Reco events

3 Event anomalies



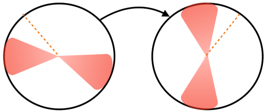
- Background data:
  - $W \to l\nu$ (59.2%);
  - $Z \to ll$ (6.7%);
  - QCD multijets (33.8%);
  - $t\bar{t}$ production (0.3%);
- Benchmark signals:
  - $A \to 4l$;
  - $h^0 \to \tau\tau$;
  - $h^+ \to \tau\nu$;
  - $LQ \to b\nu$;

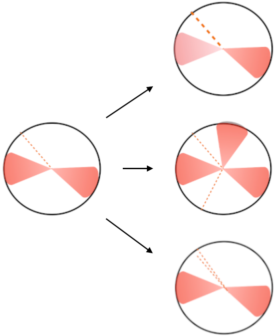
- Event-level reconstructed objects:
  - (p_T, ϕ) of missing transverse energy;
  - (p_T, η, ϕ) of e, μ, and jets;
- Selection cuts:
  - one lepton with $p_T > 23$ GeV;
  - $|\phi| \in [-\pi, \pi]$, rescaled in $[-1, 1]$;
  - $|\eta| < 3, 2.1, 4$ for e, μ, jets, rescaled in $(-1, 1)$;
- empty entries are zero-padded.

Augmentations

3 Event anomalies

- Azimuthal rotations;
- (η, ϕ) and energy smearing.

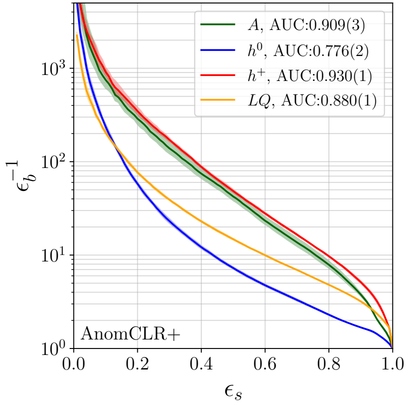


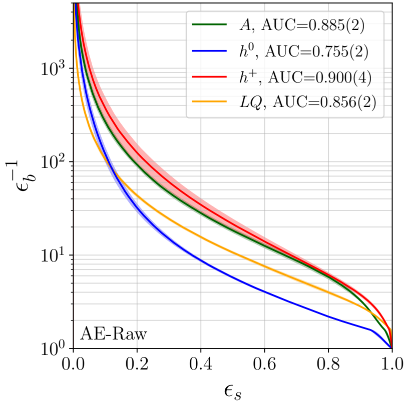


- p_T and MET shifts;
- random multiplicity shifts;
- multiplicity shifts with MET and p_T constant.

Effect of new representation

3 Event anomalies





Better performance on all the BSM signals

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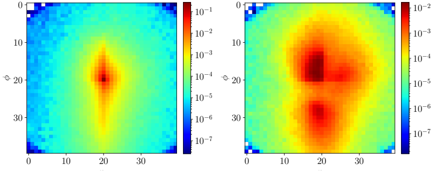
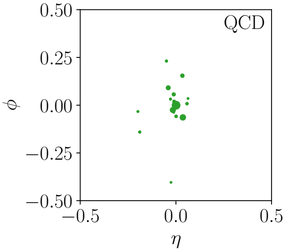
Jet substructure

4 Representing dark showers





Dark showers

4 Representing dark showers

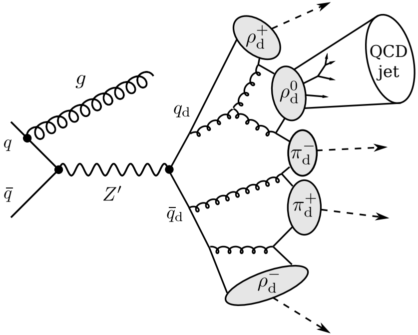
*from "Semi-visible jets, energy-based models, and self-supervision", arXiv:2312.03067

New physics hidden in jet substructure;

Benchmark signal: semi-visible jets

- $Z' = 2\text{TeV}$ dark sects mediator;
- q_d dark quarks charged under $SU(3)_d$;
- $m_{q_d} = 500\text{MeV}$;
- $\Lambda = m_{\pi_d} = m_{\rho_d} = 5\text{GeV}$;

QCD-like showers with fraction of invisible particles



*studied in arXiv:2006.08639

Dark showers

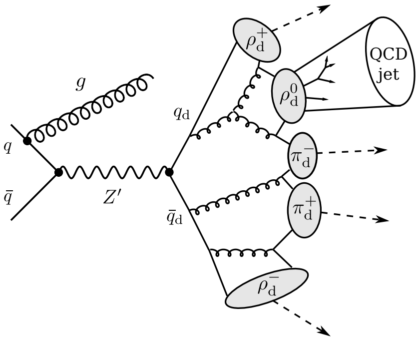
4 Representing dark showers

*from "Semi-visible jets, energy-based models, and self-supervision", arXiv:2312.03067

New physics hidden in jet substructure;

Benchmark signal: semi-visible jets

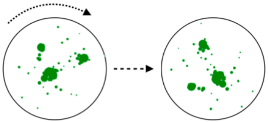
- Jet constituents:
  - (p_T, η, ϕ) of each constituent;
  - $p_T \in [150, 350]$ GeV, $|\eta_j| < 2$;
- anti-kt clustering $\Delta R = 0.8$;
- empty entries are zero-padded.



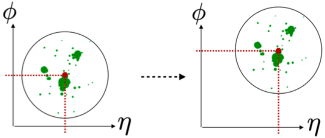
$r_{\text{inv}} = 0.75$, $m_{\text{d}} = 5\text{GeV} \longrightarrow$ referred to as "Aachen" model.

*studied in arXiv:2006.08639

rotations in $[0, 2\pi]$:



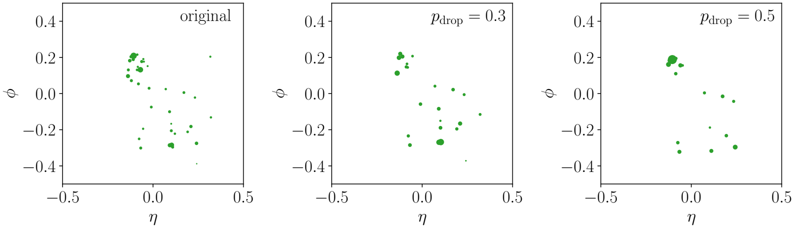
translations in $[\eta, \phi]$:



permutation invariance:

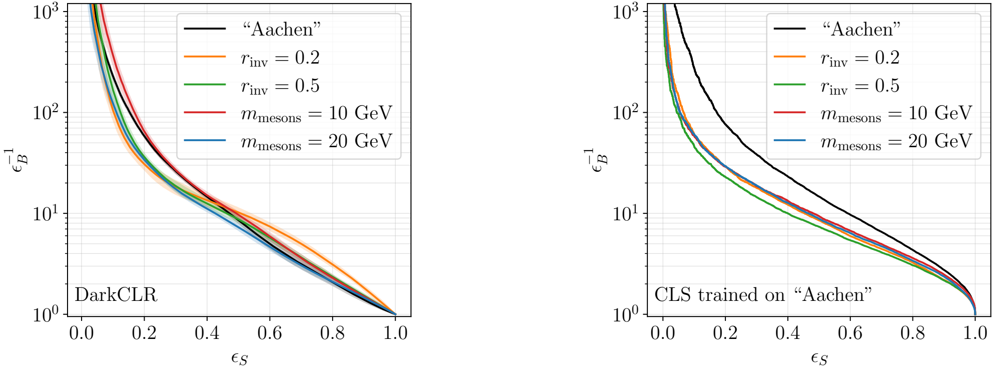
$$f(x) = f(\mathcal{S}_n(x))$$

Applying p_{drop} to a QCD jet:



Robustness of darkCLR

4 Representing dark showers



Representations generalize over different pheno parameters

Conclusions

- ML can lead the future of anomaly searches;
- We can use CLR to learn powerful representations:
  - approximately invariant under transformations;
  - sensitive to BSM effects;
- Two examples of anomaly detection with CLR:
  - Event-level reconstructed objects;
  - Semivisible jets detection;

Outlook:

- Have a more interpretable latent space;
- More detailed study of systematic uncertainties.

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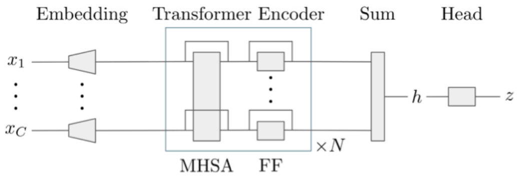
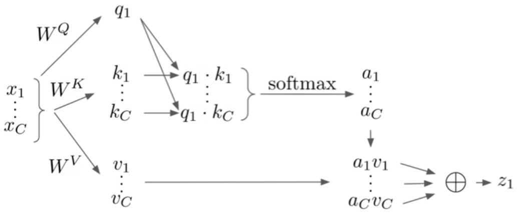
Thank you for listening!

Any questions?

Backup

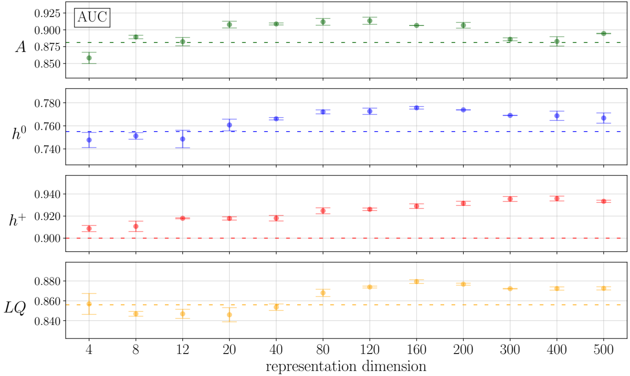
Transformer Encoder

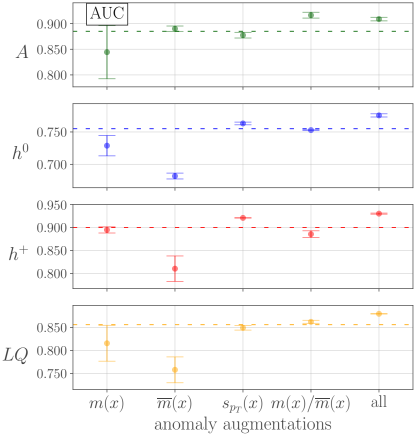




Ablation studies

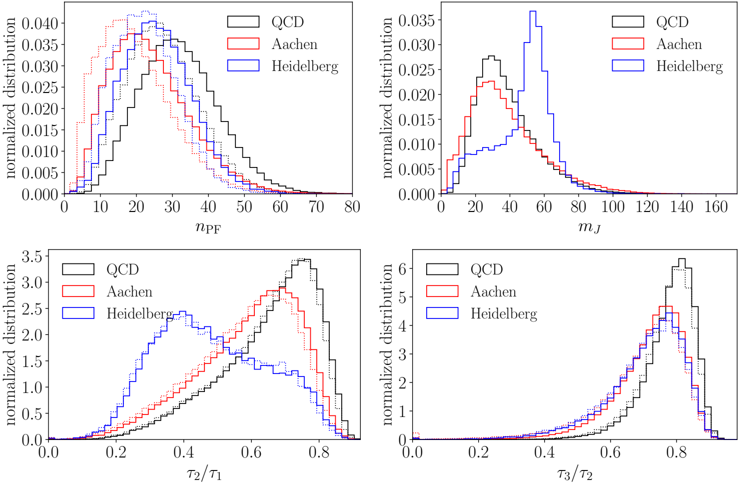
6 Backup





High-level features

6 Backup



DarkCLR LCT

6 Backup