Semi-visible jets, energy-based models, and self-supervision

BOOST 2024 - Genova

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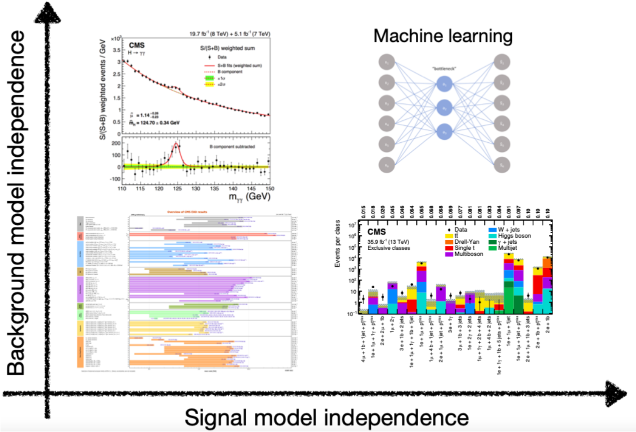
Anomaly searches

1 Introduction



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

Anomaly searches

- We are still looking for BSM physics;
- LHC does and will generate large amount of data;
- No clear anomalies in the near future . . .

  $\longrightarrow$ keep exploring with direct searches is not feasible;

  $\longrightarrow$ see recent ATLAS and CMS analysis with unsupervised methods.

Anomaly searches

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model agnostic searches

no loss in sensitivity

Have we fully explored the collected data?

Density estimation and representations

- 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.
- Different pre-trainings are pretty much in development ...

We want to learn invariances and impose them on the anomaly scores.

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Self-supervision

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

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

Self-supervision

- Preprocessing solves many problems with neural networks;
  - NNs are not invariant to physical symmetries in data;
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  - "data efficiency" and good representations?
- 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

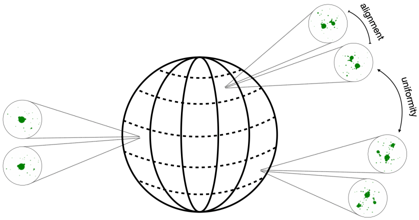
In CLR we construct a mapping to a new representation space

CLR training

2 DarkCLR

*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.

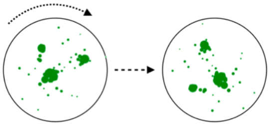


$$\mathcal{L} = -\log \frac{exp(s(z_i, z_i')/\tau)}{\sum \mathcal{I}_{i \neq j}[exp(s(z_i, z_j)/\tau) + exp(s(z_i, z_j')/\tau)]}$$

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

- Example:

  $\longrightarrow$ detector invariance under rotations;



CLR for anomaly detection

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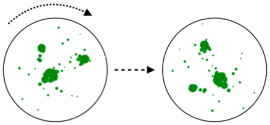

- Background data does not known BSM features.

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

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

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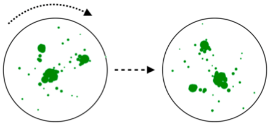

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Can we train a transformer-encoder network only on background events?

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

Introduce general BSM motivated anomalous representations z^*

CLR for anomaly detection

*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.

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

Dark showers

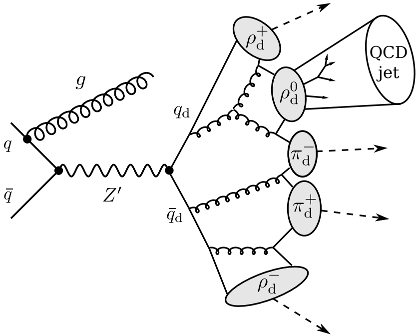
*from "Semi-visible jets, energy-based models, and self-supervision", arXiv:2312.03067

New physics hidden in jet substructure;

Benchmark signal: semi-visible jets

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

QCD-like showers with fraction of invisible particles



*studied in arXiv:2006.08639

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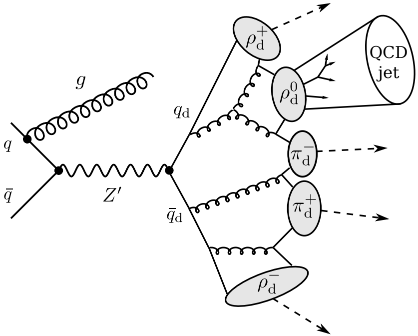
New physics hidden in jet substructure;

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.

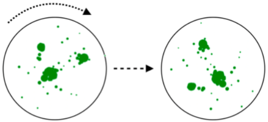


$r_{\text{inv}} = 0.75, m_{\text{d}} = 5\text{GeV} \longrightarrow$ referred to as "Aachen" model.

*studied in arXiv:2006.08639

Augmentations
2 DarkCLR

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



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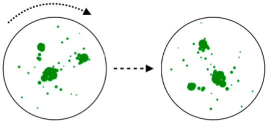

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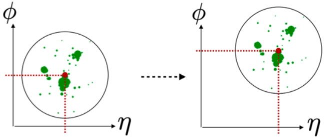

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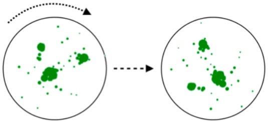

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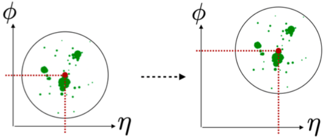

permutation invariance:

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

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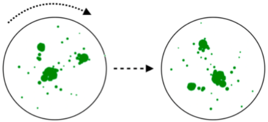

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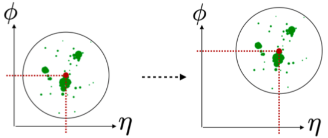

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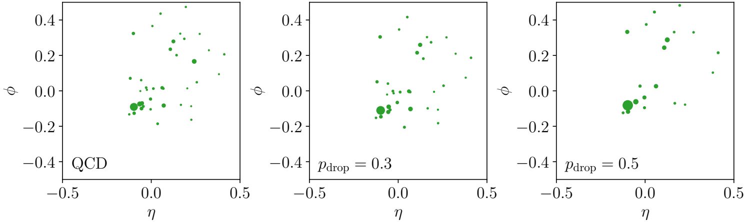
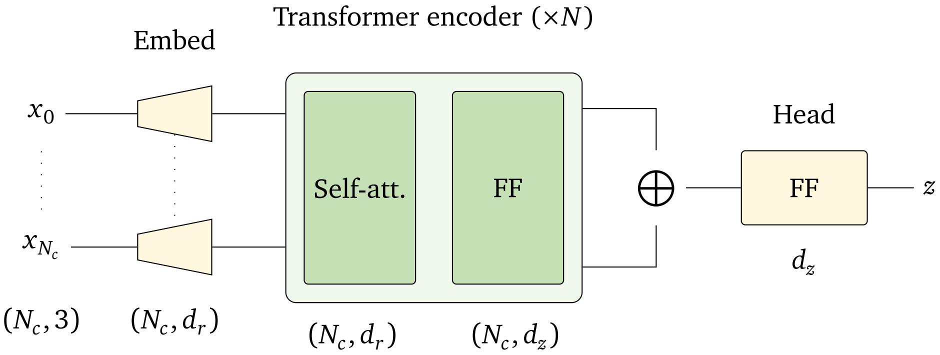
Applying p_{drop} to a QCD jet:

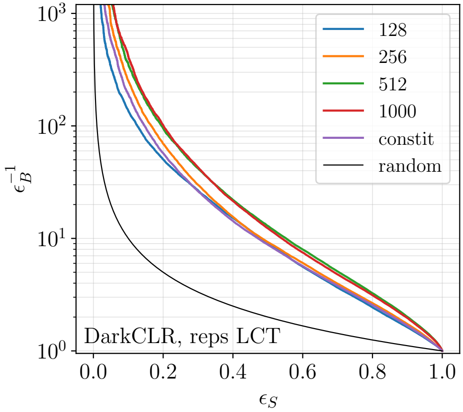


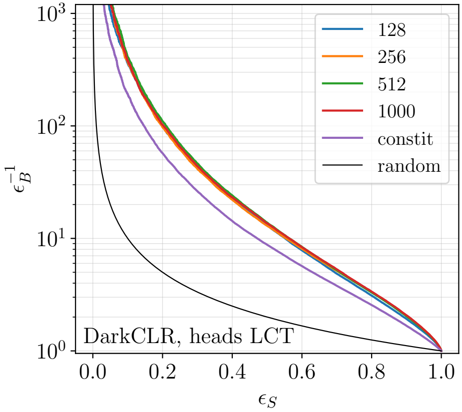
Transformer encoder

2 DarkCLR



Robustness of DarkCLR





Representations are discriminative and easier to separate with a simple linear classifier.

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Anomaly scores

- Looking at anomalous objects...
  $\longrightarrow$ events with low density.
- First look at the representation space;
- We expect information encoded in the length of the vector

$$s_{\mathrm{CLR}} = ||z||_{\mathrm{L2}}$$

- Simple and interesting anomaly score.

Anomaly scores

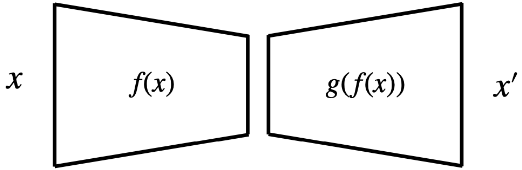
- Looking at anomalous objects…
  $\longrightarrow$ events with low density.

* from arXiv:2206.14225 and arXiv:2105.05735

- (Normalized)AutoEncoder based anomaly score:

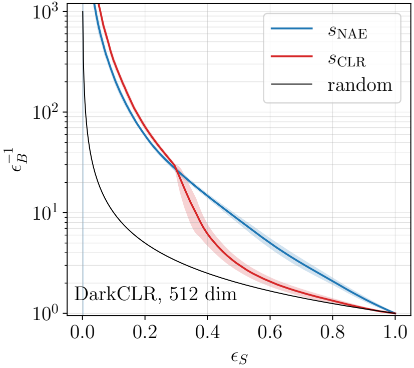
$$E_\theta = MSE(x, x') \qquad p_\theta(x) = \frac{e^{-E_\theta(x)}}{\Omega};$$

- see also Florian's talk for applications within CMS.



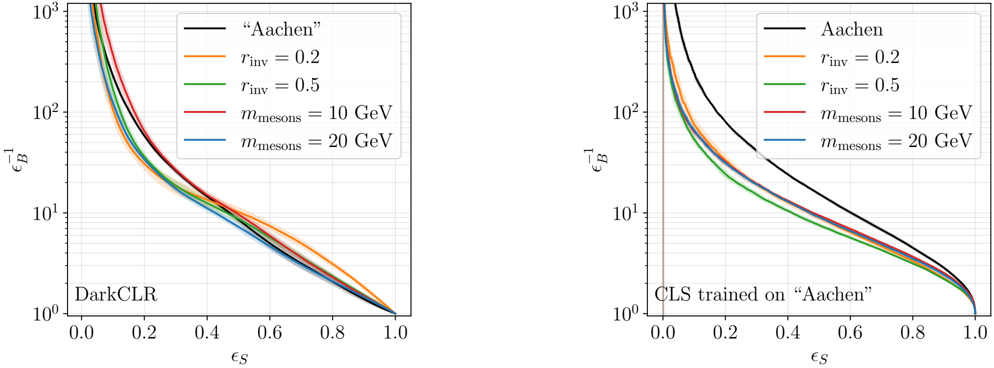
Both anomaly scores will be (approx) invariant to the augmentations

- $s_{\text{CLR}} \to$ anomalies are pushed further away in $\mathcal{Z}$ space;
- $s_{\text{NAE}} \to$ using the full information in the vector stabilizes the result.



Robustness of DarkCLR

3 Anomalies



Representations generalize over different pheno parameters

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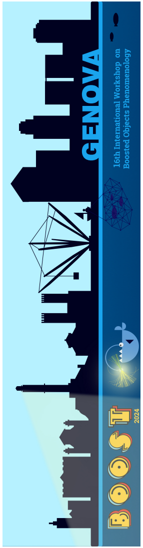
Conclusions

* data will be available on Zenodo in the next few days with DOI:10.5281/zenodo.12801842

- ML can lead the future of anomaly searches;



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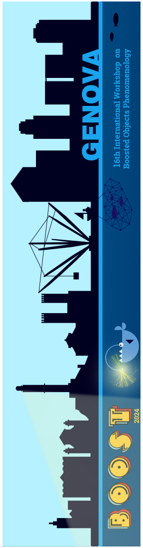

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- We studied a semi-visible jets example*:
  - representations are informative;
  - we tested the robustness to different pheno paramters.

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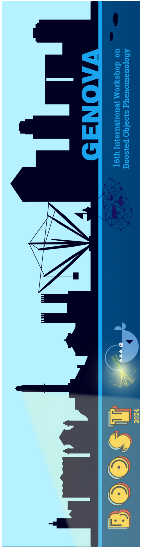
Outlook:

- Have a more interpretable latent space;
- Extend the study to other dark jet models with different signatures.



BOOS-TI-AMO!!!

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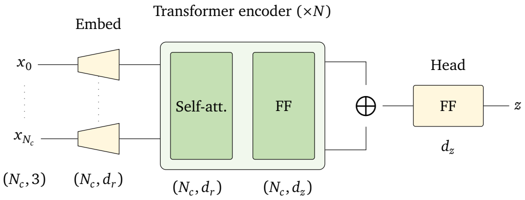
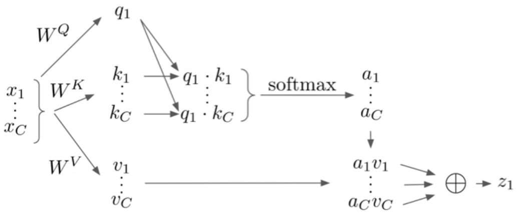
Thank you for listening! Any questions?

Backup

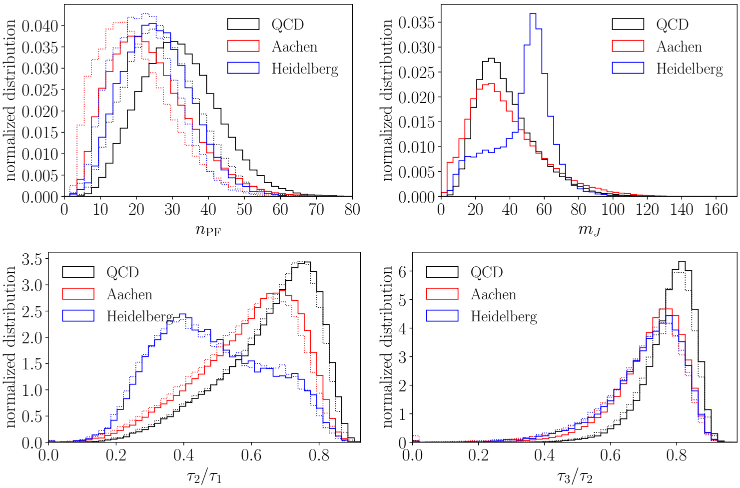
Transformer Encoder





High-level features

5 Backup



Effects of anomalous augmentations