Using unsupervised machine learning to find SUEP at the LHC

Jared Barron

University of Toronto

Based on work with David Curtin, Gregor Kasiezcka, Tilman Plehn, and Aris Spourdalakis

SUEP (Soft Unclustered Energy Patterns)

- SUEP is a particular dark shower signature that arises in hidden valley models with confinement and a large, pseudo-conformal ‘t Hooft coupling [Strassler 2008, Knapen et al. 2016].
- Shower of final-state Standard Model particles:
  - High multiplicity.
  - Democratic momentum distribution.
  - Near-isotropic emission angles in shower rest frame.
- Prompt hadronic SUEP looks very similar to QCD background (pile-up).
- Strongly coupled dynamics severely limit our theoretical modelling abilities.
- No searches currently exist. How can we look for it?
  - In particular: Look for exotic Higgs decays to SUEP.

Unsupervised Machine Learning

- Neural network classifiers are usually trained using samples of both background and signal data, with the class labels available to the network.
- Without confidence in the details of the signal model, we should avoid using it in training.
- Instead, we use an **unsupervised** approach, training only on background.
- Work towards a neural network that functions as an **anomaly detector** for SUEP.

Autoencoders

- Autoencoders train to efficiently encode their inputs.
- Practically speaking, they try to learn the identity map on their training data.
- Restricting the capacity of the network forces it to encode features of the training data in a lower-dimensional space.
- When evaluated on unfamiliar data, the autoencoder fails to reconstruct its input.
- High test loss values flag anomalous events.

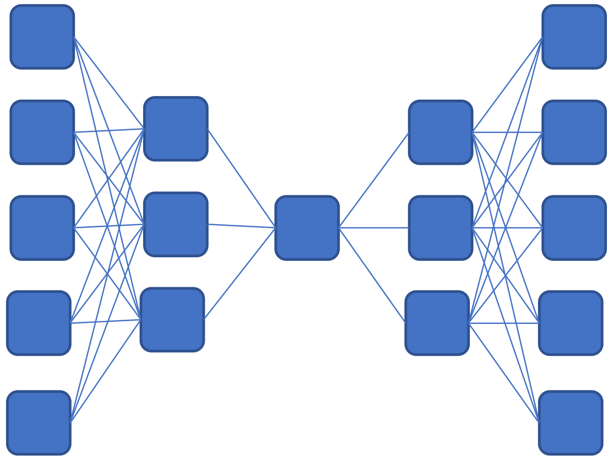


Diagram of a typical autoencoder architecture.

Two important questions

- What data representation is most effective for SUEP?
- What autoencoder architecture is most effective for SUEP?

Data representation

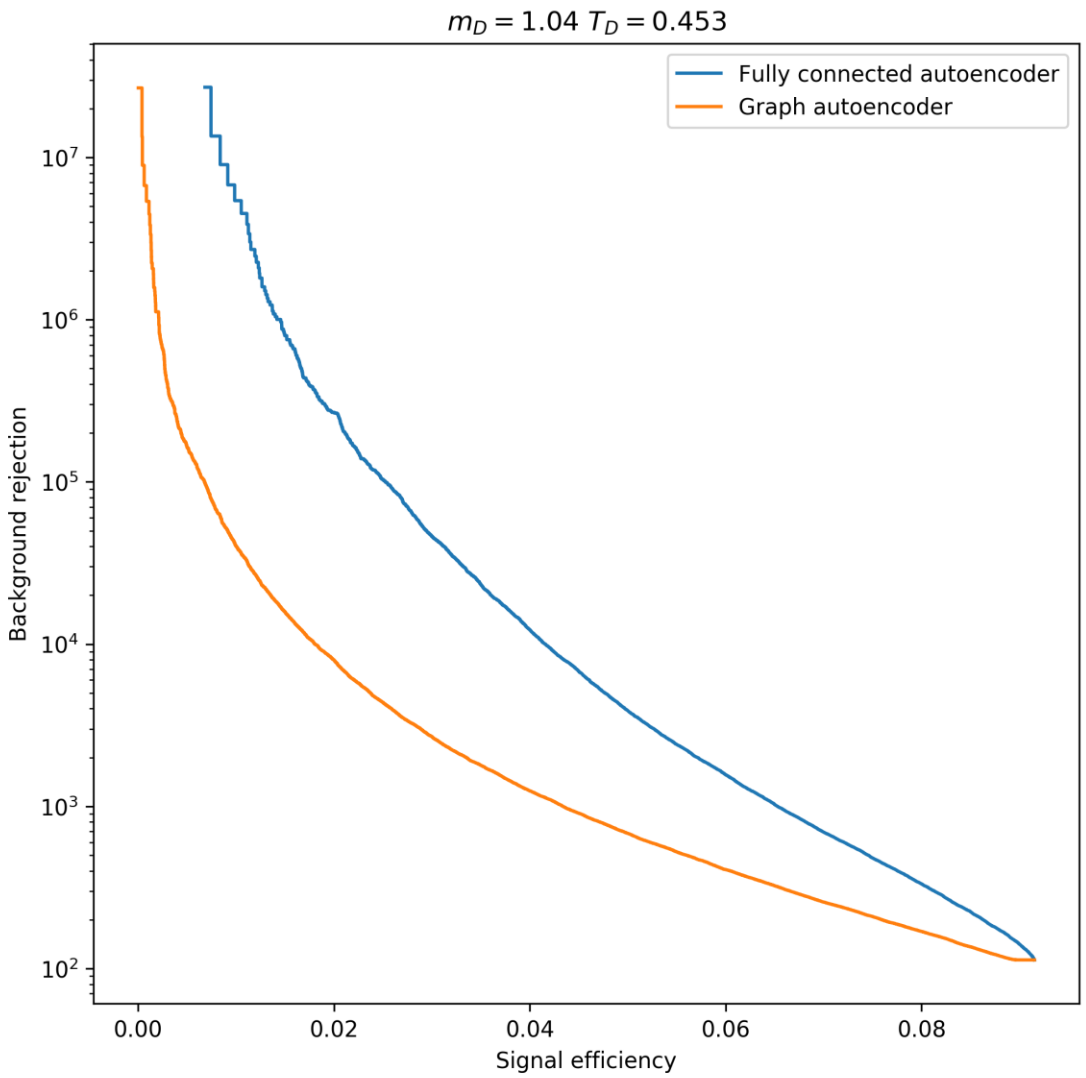
- Neural networks for jet physics often use **jet images** – discretized grids of calorimeter energy depositions, centered on the jet axis [3].
- SUEP has no jet axis, because we need to consider the entire event, not just one jet.
- Instead consider the inter-particle distance matrix

$$\Delta R_{ij} = \sqrt{(\Delta\eta_{ij})^2 + (\Delta\phi_{ij})^2}.$$

  - Invariant under rotations in ϕ.
  - Encodes information about angular correlations between particles.
  - We use it as our data representation for the autoencoder.

Autoencoder architecture

- Recently, advanced jet classifiers like ParticleNet [4] have made use of graph neural networks, using ΔR_{ij} to define a graph structure on jets.
- Following this example, we designed a graph autoencoder for SUEP.
  - Graph edges connect each particle to its k nearest neighbours in ΔR.
  - The node features are the ΔR values as well.
  - The autoencoder trains to reconstruct the node features.
- Also trained a very basic fully connected autoencoder, acting on the flattened ΔR_{ij} matrix.
- **Surprising result: Simple architecture works much better!**

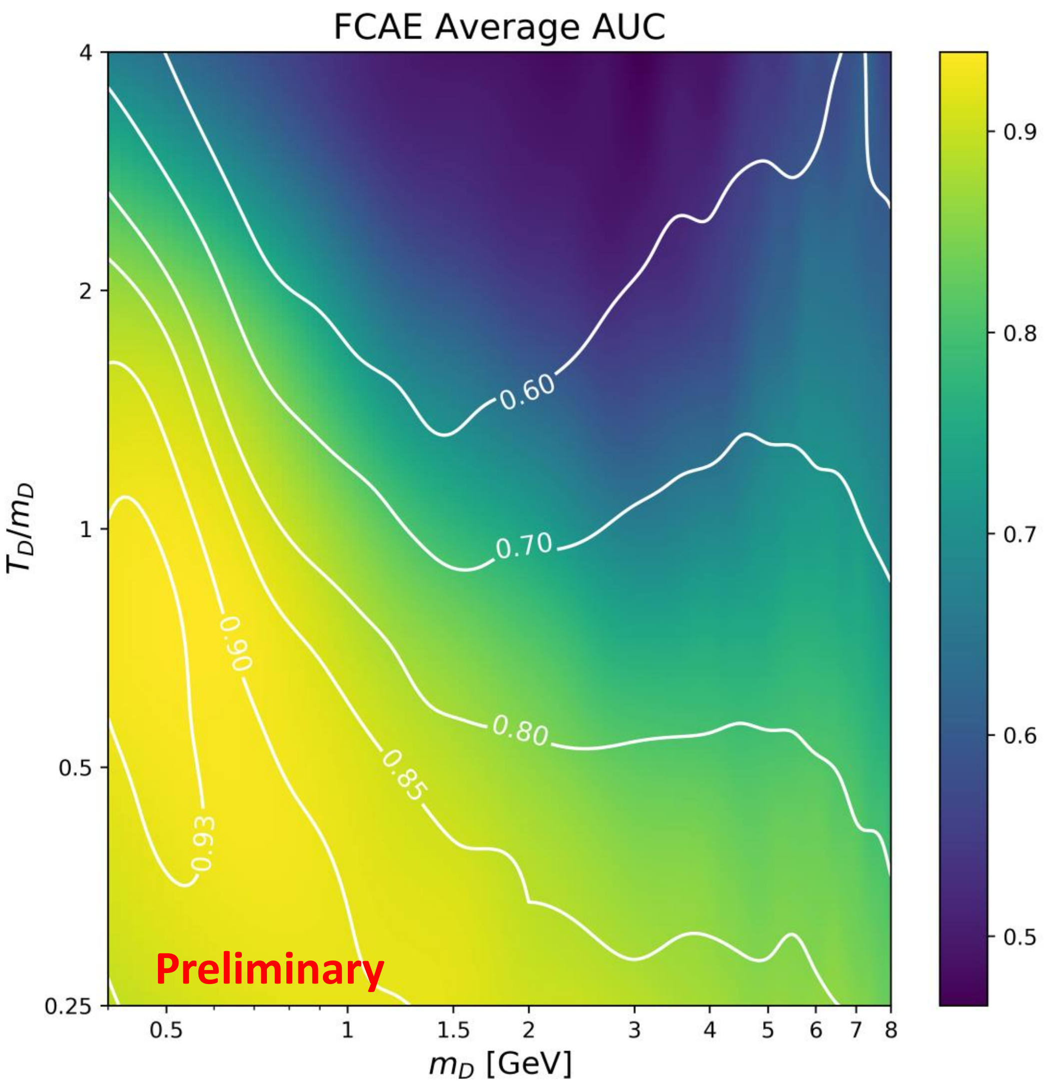


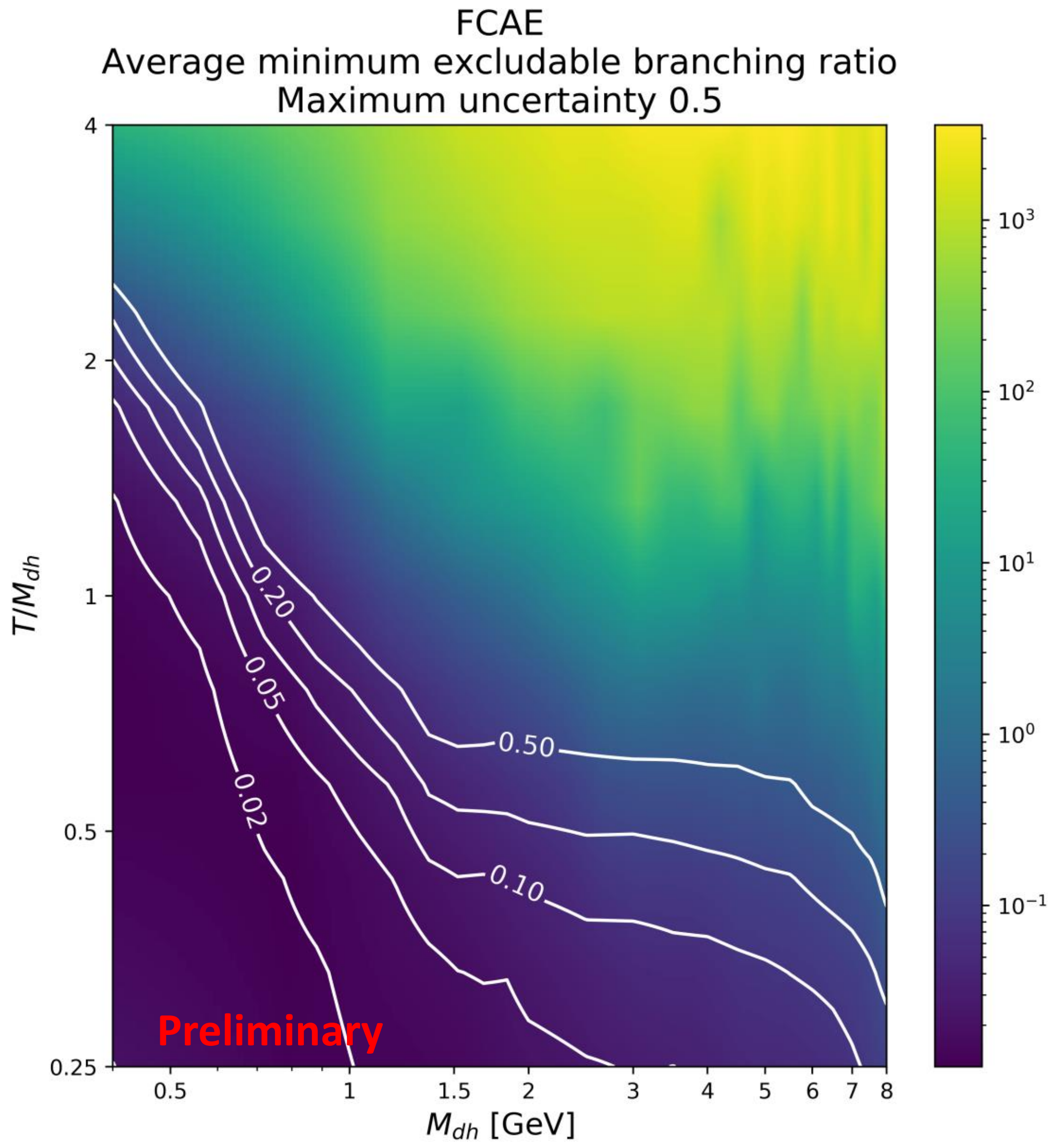
Note: Maximum signal efficiency < 1 because of trigger and pre-selection cuts.

Results

- Scenario: Exotic Higgs decay to SUEP, triggering on lepton(s) from associated vector boson production.
- We measure performance with two different metrics:
  - The Area Under Curve (AUC) of the ROC curve defined by the classifier
  - The smallest branching ratio of Higgs to SUEP we can exclude.
- Assume 1% systematic uncertainty on background rate when estimating detection significance.

Results





Autoencoder is sensitive to branching ratios of 2%!

Conclusions

- Without a reliable, detailed model of the signal, we conservatively choose to train an unsupervised model to search for SUEP at the LHC.
- The inter-particle distance matrix is an effective representation for this type of event.
- Sophisticated machine learning techniques appear to be unnecessary or even detrimental when compared to a very simple architecture.
- For dark sector hadron masses between 1 and 8 GeV, these unsupervised techniques can probe branching ratios of the Higgs boson to SUEP down to $\approx 5-10\%$, and below 1 GeV down to $\approx 2\%$.

References

- [1] M. J. Strassler, (2008), [0801.0629]
- [2] S. Knapen, S. Pagan Griso, M. Papucci and D. J. Robinson, JHEP 08 (2017) 076, [1612.00850]
- [3] T. Heimel, G. Kasieczka, T. Plehn, and J. M. Thompson, SciPost Phys. 6, 030 (2019), [1808.08979]
- [4] H. Qu and L. Gouskos, Phys. Rev. D 101, 056019 (2020), [1902.08570]