Using unsupervised machine learning to find SUEP at the LHC

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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.
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 \( \phi \).
- Encodes information about angular correlations between particles.
- We use it as our data representation for the autoencoder.
Recently, advanced jet classifiers like ParticleNet [4] have made use of graph neural networks, using $\Delta R_{ij}$ 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 $\Delta R$.
- The node features are the $\Delta R$ values as well.
- The autoencoder trains to reconstruct the node features.

Also trained a very basic fully connected autoencoder, acting on the flattened $\Delta R_{ij}$ 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


