

Promptly decaying SUEP at the LHC

Aris Spourdalakis

Physics Department University of Toronto

Based on work with Jared Barron¹, David Curtin², Gregor Kasieczka³
and Tilman Plehn⁴

Based on: arXiv:2107.12379

November 11th 2021

¹UofT

²UofT

³University of Hamburg

⁴University of Heidelberg

- Unclustered Energy Patterns (SUEP)
- VH \rightarrow SUEP
- Event representation, Observables and Analysis
- Unsupervised Machine Learning

Soft Unclustered Energy Patterns

- SUEP signatures are a subset of dark shower signatures that can arise when the gauge group of the HVMs is **confining, strong and quasi-conformal** and there is a **hierarchy between the confinement scale and the hard productions scale of the event**. [Knapen et al., 2017, Knapen et al., 2021].
- SUEP-like event: $pp \rightarrow \mathcal{S} + X$, where \mathcal{S} is a high multiplicity state of SM hadrons with an isotropic distribution of momenta and X is some other SM state associated to the SUEP production

For a given dark hadron mass, we can use a thermal distribution [Knapen et al., 2017]:

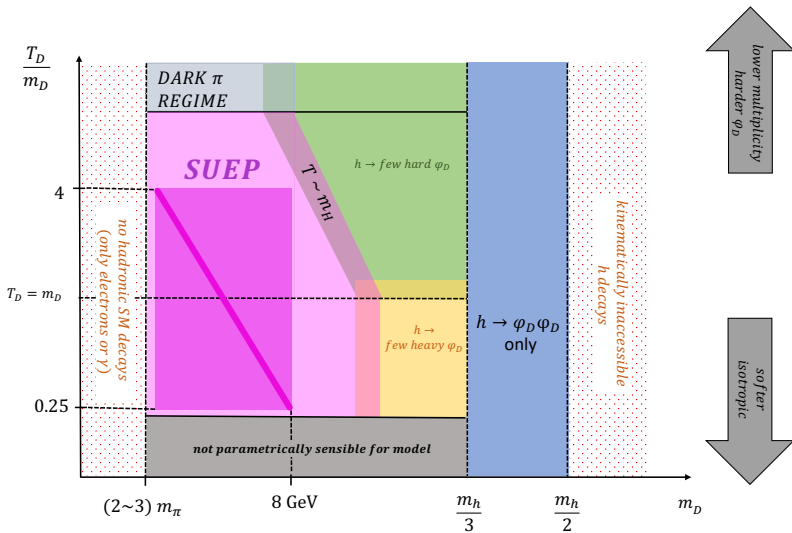
$$\frac{dN}{d^3\mathbf{p}} \sim \exp\left(-\sqrt{\mathbf{p}^2 + m_D^2}/T\right) \quad (1)$$

where $T \sim \Lambda$.

Hadronization depends more on the details of the model, but in general $m \sim T$. **Details of hadronization are large source of uncertainty.**

- Higgs production mode is highly motivated for dark showers [Knapen et al., 2021]
- Triggering for SUEP in general challenging
- Use the associated lepton(s) as a trigger

SUEP Cartoon



Long Lived SUEP?

This could be implemented either through a gluon portal or through a hadrophylic vector portal.

Naively at these masses ($m_{Dh} \lesssim \text{few GeV}$) the decay to high multiplicity states would not be prompt.

- $m_{Dh} \gtrsim 10\text{GeV}$ [Knapen et al., 2021] would generate harder jets and so could be searched for be easier to find using jet substructure techniques or other techniques.
- Non-prompt decay generates displaced vertices, and more generally can be looked for through LLP searches.

Our search's sensitivity is based on using only the charged track information. Maximally challenging scenario. **Any of the above possible features will make the signal easier to find through other means.**

Event Representation

Event representation in SUEP detection turns out to be a challenge. Most common representations don't work:

- List of jets, leptons and missing energy
- List of 4-vectors
- Pixelated jet images
- Graph structure with edges connecting "nearby particles"

This is because:

- SUEP has no jets (therefore no jet axis)
- Need a representation that respects the symmetry of SUEP
- Ordering Required
- Not obvious which metric to use with a graph network for the "distance" between particles/how many neighbors to use.

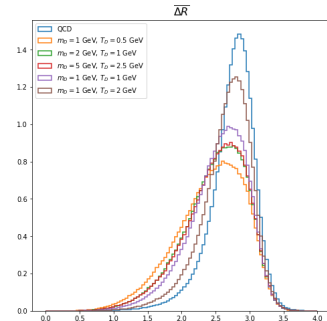
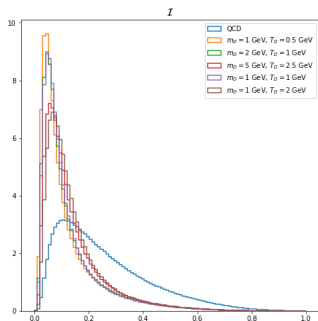
Introduce interparticle distance matrix representation for events ,

$$\Delta R_{ij} = \sqrt{\Delta\phi_{ij}^2 + \Delta\eta_{ij}^2} \text{ distance.}$$

- Rationally invariant
- Captures angular correlations and does not require any ordering of the particles
- Loses momentum information (but can be augmented with p_T along the diagonal)

Observables and conventional cuts

- Event Isotropy \mathcal{I} observable [Cesarotti and Thaler, 2020]
- Introduce the average event level $\overline{\Delta R}$ angular distance



Can do even better with an AutoEncoder!

AutoEncoder Architecture and Training

We want to make a neural net that can reproduce the identity for background, but not for signal.

- Architecture: A fully connected autoencoder with five layers. Very simple.
- Loss: $L = 1/N \sum |\sigma(x_i) - f(x_i)|^3$.

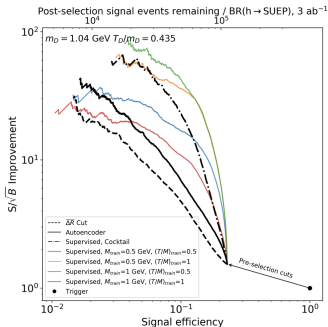
All of the above were chosen after much iteration and testing

The AutoEncoder was trained on $\sim 250,000$ background events. Tested on 600,000 background events, and $\mathcal{O}(10^4)$ signal events at each parameter point.

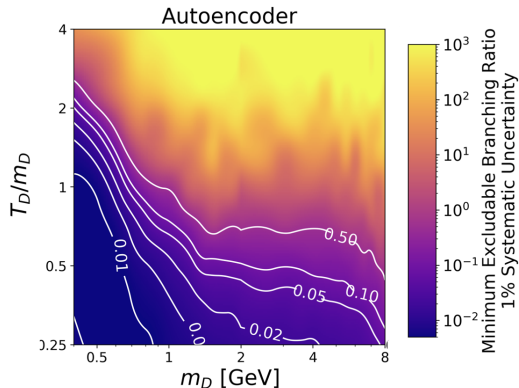
A big challenge was having signal be in some sense "simpler" than background! (Also depends on event representation).

Results

Comparing our results from different classifiers, for a single (T,m) parameter point:





- Supervised networks can perform better than unsupervised – but depend on parameter choice of signal model in training!
- A simple cut on ΔR is also useful but underperforms the unsupervised network.




- Can estimate minimum excludable $Br(h \rightarrow SUEP)$ by finding maximum $\frac{S}{\sqrt{B}}$
- Sensitive to branching ratios down to 1% at 95% CL! Estimate is limited by simulation statistics.

- Theory and simulation uncertainty make this a good candidate for an unsupervised search
- **We address the worst case SUEP signature.** Prompt, hadronic, low mass scale. **Relaxing any of these constraints will stack with our search**
- Greater Theoretical handle is always welcome and would help a lot (lots of parameter space to explore)
- AutoEncoder as an anomaly detector greatly increases sensitivity to SUEP.
- Searches could be sensitive to Higgs exotic branching ratios to SUEP down to 1% for dark hadron masses $\lesssim 1\text{GeV}$, and 10% for masses from 1 – 8 GeV.
- Realistic experimental analysis would probably be able to have greater sensitivity in a data-driven estimation of the training background.

 Cesarotti, C. and Thaler, J. (2020).
A robust measure of event isotropy at colliders.

 Knapen, S., Griso, S. P., Papucci, M., and Robinson, D. J. (2017).
Triggering soft bombs at the Lhc.
Journal of High Energy Physics, 2017(8).

 Knapen, S., Shelton, J., and Xu, D. (2021).
Perturbative benchmark models for a dark shower search program.

Dark Shower Intuition+ Gluon Portal

- Each splitting will have energy

$$Q_i \sim \frac{Q}{2^i}$$

- Splitting finishes at

$$Q_{N_{final}} \sim \frac{Q}{2^{N_{final}}} \sim \Lambda$$

- Average multiplicity is $2^{N_{final}} \sim \frac{Q}{\Lambda}$
- For large 't Hooft Coupling, the momentum fraction carried by each parton will $x \sim \frac{\Lambda}{Q}$.

Therefore, for a large enough scale separation $\frac{\Lambda}{Q} \ll 1$, we get a high multiplicity, democratic distribution of dark partons.

$$\mathcal{L} \supset -\frac{1}{2}m_a^2 a^2 - \frac{\alpha_2}{8\pi} \frac{1}{f_a} a G_{\mu\nu} \tilde{G}^{\mu\nu} - iy_{\psi_D} a \psi_D \psi_D^*$$

where a is a heavy elementary pseudo scalar.

SUEP Observable Plots

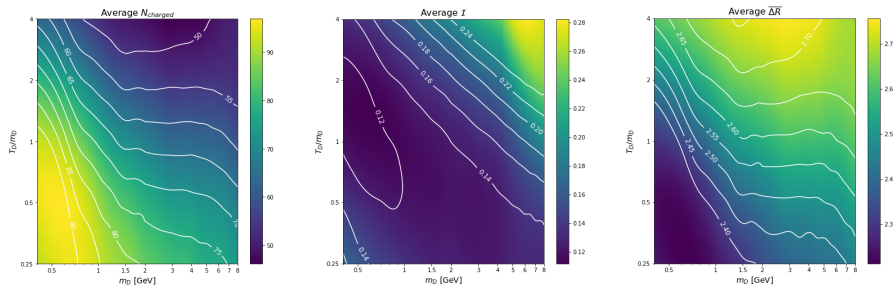


Figura: Average values of selected observables as a function of m_D and T_D for SUEP.

Signal/BG efficiency requirements + Conventional Cut numbers

- $\frac{S}{B} = \frac{\sigma_{Higgs} Br(H \rightarrow Dark) e_s}{\sigma_{BG} e_b}$
- σ_{Higgs} from W/Z+H is $\sim 300 fb$, $\sigma_{BG} \sim 3000 fb$ (2 jet sample).
- We want enough signal to beat the background systematics which are $\mathcal{O}(\text{fewpercent})$
- For $Br(H \rightarrow Dark) \sim 0.1$, we need $\frac{e_s}{e_b} \sim 1000$ background efficiency of this cut on the post-trigger sample is 2.20%, while the signal efficiency varies from 31.8% at $m_D = 0.4$ GeV, $T_D = 0.4$ GeV to 1.1% at $m_D = 5$ GeV, $T_D = 20$ GeV.

Cutting on all the above observables for the post-trigger sample, yields $\frac{e_s}{e_b} \sim 14.4$ at $m_D = 0.4$ GeV, $T_D = 0.4$ whereas it's not effective for the other end of parameter space at $m_D = 5$ GeV, $T_D = 20$ GeV

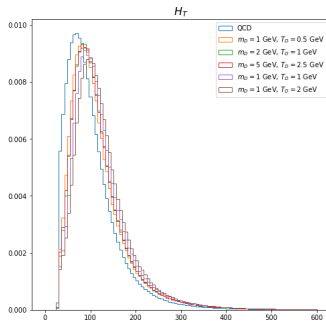
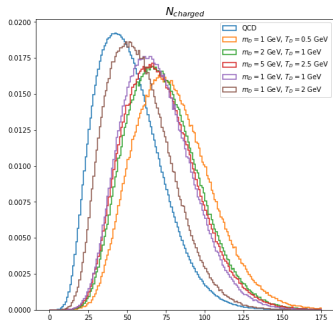
Observables and conventional cuts

Considering Higgs VH cross sections, For $Br(H \rightarrow \text{Dark}) \sim 0.1$, we need

$$\frac{e_s}{e_b} \sim 1000$$

Used some conventional event level observables:

- Start by Using N_{Charged} , H_T , Lepton momenta



Picking the right observables is important!

Production: Effective operator $O_{production} = |H|^2 \partial^{2P} \phi_D^N$ where $N \gg 1$ ϕ_D is the lightest Dark Hadron

Decay: Gluon portal (not unique) Effective decay operators:

$$O_{decay} \sim G \tilde{G} \phi_D$$

and/or

$$O_{decay} \sim GG \phi_D$$

depending on if ϕ_D is a scalar or pseudo scalar.

ϕ_D decay into gluons giving an SM rich hadron final state.