Casting a GraphNet to catch dark showers

Elias Bernreuther

RWTH Aachen University

based on arXiv:2006.xxxxx

with Thorben Finke, Felix Kahlhoefer, Michael Krämer and Alexander Mück

5 June 2020
Dark showers at the LHC

- Production of dark quarks leads to dark shower and hadronisation
  → Giovanni Grilli di Cortona’s talk
  For benchmark model and details see EB et al., 1907.04346

Large number of dark mesons in an event
Most escape the detector as $E_T$
Some decay to visible jets
⇒ Semi-visible jets

⇒ Exciting new signatures, but difficult to find
⇒ Train a neural network to distinguish dark showers from QCD
Dynamic Graph CNN

- Originally from computer vision
- Recently used as jet tagger: ParticleNet

**Jets as point clouds**
- Every constituent is a point in a high-dimensional feature space
- No ordering

**Edge convolution**
- For each point construct graph of $k$ nearest neighbours
- Carry out convolution over edges (features of pairs of neighbours)

$$x_i' = \frac{1}{k} \sum_{j=1}^{k} h_{\Theta}(x_i, x_{ij})$$

with points $x_i \in \mathbb{R}^F$ and edge function $h_{\Theta} : \mathbb{R}^F \times \mathbb{R}^F \rightarrow \mathbb{R}^{F'}$
DGCNN performance in comparison to other networks

- Signal: semi-visible jets from dark showers, background: QCD jets
- DGCNN significantly outperforms more conventional architectures (e.g. CNN operating on jet images and LoLa on 4-vectors)
- DGCNN advantage is much larger than in top tagging benchmark
Varying dark sector parameters

- Moderate effect on performance from $r_{inv}$ (average fraction of $E_T$)
- Most influential parameter: dark meson mass

![Graphs showing 1/$E_B$ vs $\varepsilon_S$ for different meson masses. Dotted line trained on $m_{meson}=5$ GeV, dashed line trained on mixed sample.]

- Network learns to reconstruct the dark meson mass
- Training on a mixed sample mitigates model dependence
Applied to monojet analysis

By how much can we improve an analysis with our dark shower tagger?

⇒ Monojet search as example ATLAS, 1711.03301
(sensitive to events with one visible and one invisible dark shower)
- Train on dark showers and dominant background ($Z\,+\text{jets}$)
- Require at least one jet tagged as dark shower after usual cuts
⇒ Sensitivity increased by factor $\sim 20$ (assuming subdominant $t\bar{t}b$ bg)

Model from EB et al., 1907.04346
Conclusions

- Strongly interacting dark sectors are a well motivated scenario predicting exciting new LHC signatures
- Difficult to identify with conventional methods: great opportunity for machine learning
- Graph nets are particularly well suited to this task
- Model dependence can be mitigated, e.g. with mixed training
- Increases the sensitivity of searches by a lot even when all other cuts remain the same
- Can reach into parameter space not covered by existing prompt or LLP searches
- So far only supervised training – still thinking about unsupervised techniques that work for dark showers and general new physics