Resonant Anomaly Detection

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MITP Virtual Workshop: Machine Learning for Particle Physics

The Plan

- 1. CWoLa Hunting: A dumb, simple strategy for finding resonant overdensities in data when backgrounds are relatively simple.
- 2. Fast run through some more complex proposals that have overlapping philosophy:
 - Simulation Assisted (SA) CWoLa
 - SALAD
 - Tag N' Train
 - ANODE
- 3. Big picture:
 - What is anomaly detection?
 - What are the strengths and weaknesses of different approaches?
 - What assumptions are we making, explicitly or implicitly, about the signal, about the background, about simulation?

1708.02949 Eric M. Metodiev, Benjamin Nachman, Jesse Thaler 1805.02664 Jack H. Collins, Kiel Howe, Benjamin Nachman 1902.02634 Jack H. Collins, Kiel Howe, Benjamin Nachman











CWoLa Hunting: Example with signal



CWoLa Hunting: Example without signal



CWoLa Hunting: Feature-space



CWoLa Hunting at ATLAS

Dijet resonance search with weak supervision using $\sqrt{s} = 13$ TeV *pp* collisions in the ATLAS detector

The ATLAS Collaboration

This Letter describes a search for resonant new physics using a machine-learning anomaly detection procedure that does not rely on a signal model hypothesis. Weakly supervised learning is used to train classifiers directly on data to enhance potential signals. The targeted topology is dijet events and the features used for machine learning are the masses of the two jets. The resulting analysis is essentially a three-dimensional search $A \rightarrow BC$, for $m_A \sim O(\text{TeV})$, $m_B, m_C \sim O(100 \text{ GeV})$ and B, C are reconstructed as large-radius jets, without paying a penalty associated with a large trials factor in the scan of the masses of the two jets. The full Run 2 $\sqrt{s} = 13$ TeV pp collision data set of 139 fb⁻¹ recorded by the ATLAS detector at the Large Hadron Collider is used for the search. There is no significant evidence of a localized excess in the dijet invariant mass spectrum between 1.8 and 8.2 TeV. Cross-section limits for narrow-width A, B, and C particles vary with m_A, m_B , and m_C . For example, when $m_A = 3$ TeV and $m_B \gtrsim 200$ GeV, a production cross section between 1 and 5 fb is excluded at 95% confidence level, depending on m_C . For certain masses, these limits are up to 10 times more sensitive than those obtained by the inclusive dijet search.

SEARCHES FOR NEW PHYSICS USING JETS WITH THE ATLAS DETECTOR

A DISSERTATION SUBMITTED TO THE DEPARTMENT OF PHYSICS AND THE COMMITTEE ON GRADUATE STUDIES OF STANFORD UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY



CWoLa Hunting at ATLAS

signal regions for the $\epsilon = 0.1$ and $\epsilon = 0.01$ NN efficiency selections are presented in Figure 2. The largest positive deviation from the fit model is 3.0σ in signal region 1, around 2500 GeV, at $\epsilon = 0.1$. Globally, the positive tail of the signal region significance distribution is consistent with a standard normal distribution at the 1.5σ level.



CWoLa Hunting at ATLAS

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CWoLa Hunting at ATLAS: Sensitivity



Simulation Assisted CWoLa

$\mathcal{L}_{\text{SA-CWola}}[f] = -\sum_{i=1}^{N} \log(f(x_i)) - \sum_{i=1}^{N} \log(1 - f(x_i))$ $i \in SR, data$ $i \in SB, data$ $+ \lambda \left(\sum_{i \in \text{SR,sim.}} \log(f(x_i)) + \sum_{i \in \text{SB,sim.}} \log(1 - f(x_i)) \right)$ 10⁶ Supervised Data vs. Sim. SALAD Optimal CWoLa CWoLa SA-CWoLa Random 10^{0} 0.0 0.2 0.4 0.6 0.8 1.0 Signal Efficiency (True Positive Rate)

arXiv:2009.02205, Kees Benkendorfer, Luc Le Pottier, Benjamin Nachman

Simulation Assisted Likelihood-free Anomaly Detection (SALAD) 2001.05001, Anders Andreassen, Benjamin Nachman, David Shih



Classify simulation vs data

Classify reweighted simulation vs data

Simulated data

SB SR SR Mres W(Mres) = (W(Mres) , interpolate SB Mres



Anomaly Detection with Density Estimation (ANODE) 2001.04990, Benjamin Nachman, David Shih

Learn probability density of bg from sideband and interpolate, and bg+signal from signal region, and explicitly form likelihood ratio





Traditional Search

Weakly Supervised

Unsupervised











Weak supervision and unsupervised: competitors or collaborators? ^{2104.02092 Jack Collins, Pablo} Martín-Ramiro, Benjamin Nachman, David Shih



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Conclusion

- We have plenty of architectures and ideas, though more are always exciting!
- More important is to organize, understand, press on with real searches. LHCO & Darkmachines competition both are good starts, but I'm not convinced that it is yet enough.
- How will recasting work?