Anomaly Detection: State-of-the-Art
Open Problem: What is dark matter?

Plausible Theory: SUSY

Verification: Confirm the theory using data

Theory was right!

Constrain the new theory
Overview of CMS EXO results

- Common New Physics Searches Workflow
- SUSY/RPC
- Higgs+Other
- W/H/H' (Higgs resonances)
- Selection of observed exclusion limits at 95% CL.

Selection of observed exclusion limits at 95% C.L. (assuming uncertainties are 10% statistical and 10% systematical.)

ArXiv:2303.15165
Open Problem: What is dark matter?

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Constrain the new theory
The Challenge

Interpretation

Look for anomalies

Constrain many theories
The Challenge

**Anomaly Detection**

- **Theoretical Physics from Machine Learning**
- **Anomaly Detection for Research Physics with Machine Learning**
- **Theoretical Physics from Machine Learning with active learning**
- **Learning from Data (Physics)**
- **Neural Networks for Deep Anomalies**
- **Unsupervised vs. Supervised Learning**
- **The Big Challenge**

**100+ anomaly detection papers so far**

https://iml-wg.github.io/HEPML-LivingReview/#anomaly-detection

- **Anomaly Detection under Coordinate Transformations**
- **Quantum probabilities in machine learning for generation, assembly, and anomaly detection**
- **Optimal Mixing Instead of Repetitive Event Cycles for Machine Learning**
- **Learning physics beyond the standard model with classical and quantum anomaly detection**
- **Nonparametric anomaly detection with decision trees for high-energy physics and real-time applications to nuclear physics**
- **The Monte Carlo: Anomaly Detection in Jet Physics**
- **CUTLASS: A Framework for Fast and Precise Construction of Unsupervised Regions with Machine-Learned Embedding**
- **High-dimensional and Nonparametric Anomaly Detection**
- **The Method of Machine Learning-based Unsupervised Anomaly Detection Methods**
- **SIFT: Anomaly detection algorithms for New Physics searches in suit data**
- **Anomaly detection searches for new physics beyond the Standard Model in a generic new particle**
- **In instrumental real stress using SPRINT**
- **A new method for new physics with unsupervised anomaly detection in jet resonant searches**
- **A novel approach for anomaly detection in online learning and anomaly detection models**
- **Black Box for Transfer Learning Algorithms for Weakly Supervised Anomaly Detection**
- **Full Phase Space Resonant Anomaly Detection**
- **Anomaly Detection in Presence of Weakly Correlated Features**
- **A probabilistic data generation framework for Machine learning based statistical anomaly detection**
- **Nonparametric Anomaly Detection with Bayesian Estimation**
- **Scattering for the global particle physics community using the advanced encoder**
- **Fast Parallelized Anomaly Detection Algorithm for Time Series Data**
- **Anomaly Detection in Collider Physics via Factorial Observations**
- **Tracking the Trackers Network for Anomaly Detection in the CMS Global Trigger**
- **Improving new physics searches with diffusion models for rare observations and jet substructures**
- **Anomaly detection with the addition of tracklet classifiers**
- **Improving Physics Searches via Time-dependent Anomaly Detection**
- **Aging Resonance Searches via Signal-space-Based Performance**
Common approaches

**Signal is rare but so is the background**
- NP at "tails" of distributions
- **Challenges:** "rarity" is not universal and the choice of features determine the sensitivity

**Signal is an over density:**
- New physics is rare, but at least one feature has a region where $\frac{p_s(x)}{p_b(x)}$ is high
- **Challenges:** Requires an estimate of $p_b(x)$ and prior knowledge of the resonant feature
Signal is rare but so is the background

- NP at “tails” of distributions
- **Challenges**: “rarity” is not universal and the choice of features determine the sensitivity
- Train **multiple autoencoders** and enforce decorrelation for background events

\[
L[f_1, f_2, g_1, g_2] = \sum_i R_1(x_i)^2 + \sum_i R_2(x_i)^2 \\
+ \lambda \text{DisCo}^2[R_1(X), R_2(X)]
\]
Anomaly detection performance

- Use the ABCD method to determine the background

No anomalies

Other colors: datasets with 0.1% anomalies and 99.9% standard physics processes

V. Mikuni, B. Nachman, and D. Shih Phys. Rev. D 105, 055006
Resonant anomaly detection

**Signal is an over density:**
- New physics is rare, but at least one feature has a region where $p_s(x)/p_b(x)$ is high
- **Challenges:** Requires an estimate of $p_b(x)$ and prior knowledge of the resonant feature

- **Bump hunts** often only use the resonant feature to achieve sensitivity
- **ML** enables the use of **multiple features** while maintaining the benefits of a resonant signal to perform background estimation
- Common benchmark for resonant AD: **LHCO R&D dataset**
- Resonant **dijet** final state: $A \rightarrow B(qq)C(qq)$ with $m_A$, $m_B$, $m_C = 3.5, 0.5, 0.1$ TeV
Learn a **4-dimensional** background using the sidebands
  - N-subjettiness
  - Jet masses

**Interpolate** the background prediction in the signal region

Train a classifier to distinguish the interpolated background from the data

**SIC** = Significance Improvement Curve (TPR/sqrt(FPR) vs TPR) “By how much can I improve the significance of a particular signal given an initial significance.”

Combining multiple methods

- Many strategies available to determine the background distribution
- Even though the performance of different methods is similar, they are not completely correlated
- Compare and investigate different combination strategies: smaller uncertainty bands!

- Current methods are limited to the 4 features
- Strong performance for new physics scenarios where jet substructure is important
- What if we estimate the complete dijet system?
  - 4 features vs up to $2 \times 279 \times 3 = 1674$ features
- Method still works and outperforms the method with 4 features for $S/B > 3\%$

E. Buhmann, C. Ewen, G. Kasieczka, V. Mikuni, B. Nachman, and D. Shih, Phys. Rev. D 109, 055015
In this very high dimensional space, performance is limited by the data. Data cannot be easily increased: requires longer data collection periods. What if we had a model that understands jets and only asked to adapt to this particular phase space? Using *OmniLearn*, a foundational model for jet physics, we are able to be sensitive to the new physics signal with as little as $S/B = 0.7\% \sim 2\sigma$.

V. Mikuni, B. Nachman, arXiv:2404.16091
Additional assumptions beyond the 2 main classes have also been proposed.

Example: **QUAK**
- Train a model using **multiple** possible NP scenarios to define “signal-like” and “background-like” regions of the phase space.

Conclusions

- **Anomaly detection** is an alternative and complementary strategy to search for new physics processes.
- **Not magic**: Different anomaly detection methods rely on a few assumptions and is important to be aware of their limitations.
- Most methods are **data-driven**: the bigger the dataset the better.
- **Foundational models** might be able to bridge the sensitivity gap and allow sensitivity even in low data regimes.
THANKS!

Any questions?
Choice of representation of inputs also affects the performance!

Differences in performance for autoencoders when using $m_1$, $m_2$ as inputs or $\log(m_1)$, $\log(m_2)$

OmniLearn

- Train a transformer model to classify and generate jets in the JetClass dataset
  - 100M jets with 10 different jet classes
- Use this pre-trained model as the starting point for multiple tasks
  - 9 additional datasets tested, including ATLAS top tagging, CMS Open data, and electron-proton collisions
  - 11 applications including standard classification, generation, anomaly detection, and unfolding
- OmniLearn improves upon all tasks investigated with faster convergence

V. Mikuni, B. Nachman, arXiv:2404.16091
Diffusion Generative Models

Forward SDE (data $\rightarrow$ noise)

$$dx = f(x, t)dt + g(t)d\bar{w}$$

Reverse SDE (noise $\rightarrow$ data)

$$dx = \left[f(x, t) - g^2(t) \nabla_x \log p_t(x) \right] dt + g(t)d\bar{w}$$

Source:
https://yang-song.net/blog/2021/score/