ML based Anomaly Detection at the LHC

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Lots of Questions

What is Dark Matter?

Why is the Higgs so light?

What is the origin of Neutrino Mass?

Baryogenesis?

Grand Unification?

And many more…

g-2?

Flavor Anomalies?

Hierarchy Problem Image from: https://physics.aps.org/articles/v13/174
No clear answers from the LHC yet
But...

DM graphic stolen from Tim Tait
What if we aren’t looking in the right places ?!
The Challenge

• How can we design searches with minimal assumptions but still have powerful sensitivity?

• New ideas in ML are enabling totally new search strategies!

Key Idea: Train directly on data!
Classification Without Labels

Mixed Sample 1

Mixed Sample 2

Classifier

Gluon Background Rejection

Quark Signal Efficiency

- Dense Net
- w. CWoLa
- Multiplicity
- Width
- Mass
- $p_T^D$
- $\sqrt{s} = 13$ TeV
- LHA

$f_1, f_2 = 0.8, 0.2$

$m_H = 500$ GeV

Metodiev, Nachman & Thaler 1708.02949
• Signal region = dijet mass window
• Train a classifier on signal region vs. others
• Select events & bump hunt
Anomaly Detection: Autoencoders

- Train a network to compress and decompress the data
- Can train directly on data, no labels needed
- Anomalous events should have a higher reconstruction loss

Heimel, Kasieczka, Plehn & Thompson 1808.08992
Farina, Nakai & Shih 1808.08979
+ Others
Drawbacks

- **CWoLa Hunting**
  - Worry about sculpting QCD dijet mass distribution
  - Apply to non-resonant signals?

- **Autoencoders**
  - Only ‘learns’ what QCD looks like
  - Room for improvement as a Sig vs. Bkg classifier
Tag N’ Train (TNT)

• A method of training improved classifiers on data

• Assumptions:
  – Signal has **2 interesting objects** in it
  – One has a **starting classifier** for each object
  – Signal-like features in background events are uncorrelated between the 2 objects

Tag with a weak classifier **N’ Train** a better one!
Tag N’ Train

Events

Initial Classifier

O1's

O2's

O1 Classifier
Tag N’ Train

Events

Initial Classifier

Weakly Classified Events

Train New Classifier

O1's

O1 Classifier

Sig Like Events

Sig Rich

Train on O2's

Bkg Like Events

Bkg Rich

O2's
Dijet Anomaly Search
Applying TNT to a Resonance Search

Events A

Events B

Events C
Applying TNT to a Resonance Search

Cross-Validate!
Classification Performance

S/B = 35%

Less Signal

- CWoLa based methods approach **supervised** case when lots of signal
- **Autoencoders** performance independent of signal
- **TNT** matches **CWoLa hunting** high/medium signal, better at low signal
In Action: LHC Olympics 2020

- A competition to test out these new anomaly detection methods
- Blackboxes with:
  - 1M events, R=1 jet pt > 1.2 TeV trigger
  - 4 vectors of all reconstructed particles
  - Mostly background + some hidden new physics (?)
• TNT found a resonance at ~3800 GeV with 4σ evidence
LHC Olympics Results

- TNT found a resonance at ~3800 GeV with 4σ evidence
- One of the few groups able to find the signal!
Many Challenges in Applying to Real Data!

Ensure no mass sculpting

Don’t “discover” a detector glitch!

Limit setting ?!
Results on Data

**ATLAS:** 2005.02983

**CMS**
Just the Beginning...

- New techniques!
  - New ideas innovations from the ML side
  - Hybrid approaches with traditional searches

- New Searches!
  - Other anomalies besides jets with substructure
  - Non-resonant searches

- Do it fast!
  - Incorporate these ideas into triggers
  - Recently announced Anomaly Detection at 40 MHz challenge!
Current LHC Analysis Group Organization

- B physics
- SM
- Top
- Higgs
- Measurement Groups
- B2G / HDBS
- Exotics / Exotica
- Search Groups
- SUSY
- Supporting organizations (Statistics forum, ML forum)
In 10 Years?

Model Agnostic?

- Unsupervised
- Weakly Supervised
- (Semi) Supervised

B2G / HDBS
Search Groups
Exotics/Exotica
SUSY

Supporting organizations

B physics
SM
Top
Higgs
Measurement Groups
Backup
Dijet Mass Sculpting

- No sculpting of dijet mass!

- Decorrelation methods also possible with TNT
  - $p_T$ reweighting tried, found no difference
TNT Technical Details

- 2 objects: heavy jet and light jet in event
- TNT Classifiers and autoencoders are CNN’s based on jet images
- Top 20% ‘sig-like’, bottom 40% ‘background-like’
  - Optional: require signal events in dijet mass window
- Combine 2 classifiers into 1
  - Require both jet’s scores be in top X% of scores
<table>
<thead>
<tr>
<th>(V)AE’s</th>
<th>CWoLa Hunting</th>
<th>TNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>+ Performance indep. of amount of signal</td>
<td>+ Great performance for large to medium signals</td>
<td>+ Great performance for medium/large signals and maintains performance for smaller signals</td>
</tr>
<tr>
<td>+ Minimal assumptions</td>
<td>+ Can do full-event classification</td>
<td>+ Mass sculpting mitigation possible</td>
</tr>
<tr>
<td>– Inherently ‘anti-QCD’ rather than a ‘pro-signal’</td>
<td>– Assumption: resonant signal</td>
<td>– Requires a starting classifier</td>
</tr>
<tr>
<td></td>
<td>– Must fully decorrelate features with $M_{jj}$</td>
<td>– Assumption: Signal has 2 interesting objects</td>
</tr>
</tbody>
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*Of course there are other interesting techniques with different trade offs too*
Assumption: Correlations

Key assumption: Anomalous features of background events are uncorrelated.

Empirically (?) seems to hold.

“Pure” CWoLa

\[ \rho_{1,2} = 0.001 \]

Tag N’ Train

\[ \rho_{1,3} = 0.005 \]