

Introduction to Anomaly **Detection at the LHC**

Dylan Rankin November 23rd, 2024

Large Hadron Collider (LHC) at CERN

SUISSE

FRANCE

=CMS

HC 27 km

CERN Prévessin



FRN Meyn

SPS_7 km

Large Hadron Collider (LHC) at CERN

SUISSE

FRANCE

25 ns 40 MHz

CERN Provessin



Large Hadron Collider (LHC) at CERN

CMS

SUISSE

FRANCE

10¹¹ proton bunch

25 ns 40 MHz

ATLAS

10¹¹ proton bunch



LHCb

CERN Prévessin



The Standard Model



 $-5\phi + h.c.$





A Toroidal LHC ApparatuS (ATLAS)





ATLAS Slice







ML in High Energy Physics (HEP)

- ML is becoming more and more popular, HEP/LHC no exception
- Better algorithms \rightarrow improved performance





The Standard Model









ATLAS Heavy Particle Searches* - 95% CL Upper Exclusion Limits ATLAS Preliminary Status: March 2023 $\sqrt{s} = 13 \text{ TeV}$ $\int \mathcal{L} dt = (3.6 - 139) \text{ fb}^{-1}$ ℓ, γ Jets $\dagger E_{-}^{\text{miss}}$ ($\mathcal{L} dt [fb^{-1}]$ Model Reference Limit ADD $G_{KK} + g/q$ $0 e, \mu, \tau, \gamma = 1 - 4 j$ Yes 139 **11.2 TeV** *n* = 2 2102 10874 36.7 139 ADD non-resonant $\gamma\gamma$ 2γ 8.6 TeV n = 3 HLZ NLO 1707.04147 ADD QBH 2 j **9.4 TeV** *n* = 6 1910.08447 ADD BH multijet 3.6 **9.55 TeV** *n* = 6, *M*_D = 3 TeV, rot BH ≥3 j -1512.02586 RS1 $G_{KK} \rightarrow \gamma \gamma$ $k/\overline{M}_{Pl} = 0.1$ 2γ 139 2102.13405 4.5 Te Bulk RS $G_{KK} \rightarrow WW/ZZ$ $k/\overline{M}_{Pl} = 1.0$ 36.1 2.3 TeV multi-channel K mass 1808 02380 $1 e, \mu \ge 1 b, \ge 1J/2j$ Yes Bulk RS $g_{KK} \rightarrow tt$ 36.1 mass $\Gamma/m = 15\%$ 1804.10823 2UED / RPP 1 e,μ ≥2 b, ≥3 j Yes 36.1 1.8 TeV Tier (1,1), $\mathcal{B}(A^{(1,1)} \to tt) = 1$ 1803.09678 SSM $Z' \rightarrow \ell \ell$ 2 e, µ 139 5.1 TeV 1903.06248 2τ 36.1 2.42 TeV 1709.07242 SSM $Z' \rightarrow \tau \tau$ mass Leptophobic $Z' \rightarrow bb$ 2 b 36.1 2.1 TeV 1805.09299 mass 0 e,μ $\Gamma/m = 1.2\%$ Leptophobic $Z' \rightarrow tt$ ≥1 b, ≥2 J Yes 139 ' mass 4.1 TeV 2005.05138 SSM $W' \rightarrow \ell v$ 1 e, µ 139 6.0 TeV 1906.05609 -Yes I' mass SSM $W' \rightarrow \tau v$ TLAS-CONF-2021-025 1τ Yes 139 5.0 TeV mass SSM $W' \rightarrow tb$ ≥1 b, ≥1 J 139 4.4 TeV ATLAS-CONF-2021-043 ' mass 0-2 e, µ $g_V = 3$ HVT $W' \rightarrow WZ$ model F 4.3 TeV 2i/1J Yes 139 mass 2004.14636 $g_V c_H = 1, g_f = 0$ HVT $W' \rightarrow WZ \rightarrow \ell \nu \ell' \ell' \text{ model } C = 3 e, \mu$ 2 j (VBF) Yes 139 mass 340 GeV 2207.03925 HVT $Z' \rightarrow WW$ model E 1 e,μ 2j/1J Yes 139 mass 3.9 TeV $g_V = 3$ 2004.14636 LRSM $W_R \rightarrow \mu N_R$ $m(N_R) = 0.5 \text{ TeV}, g_L = g_R$ 2 μ 80 5.0 TeV 1904.12679 1 J 2 j **21.8 TeV** η₁₁ 1703.09127 CI qqqq 37.0 CI llqq 2 e, µ 139 2006.12946 35.8 TeV 5 1.8 TeV CI eebs 139 2105.13847 2 e 1 b $g_* = 1$ 139 Cl µµbs 2 μ 1 b 2.0 TeV $g_* = 1$ 2105.13847 _ CI tttt ≥1 e,µ ≥1 b, ≥1 j 36.1 2.57 TeV $|C_{4t}| = 4\pi$ 1811.02305 Yes Axial-vector med. (Dirac DM) $g_q=0.25, g_{\chi}=1, m(\chi)=10 \text{ TeV}$ -PHYS-PUB-2022-036 2 i 139 3.8 Te Pseudo-scalar med. (Dirac DM) $0 e, \mu, \tau, \gamma$ 1 – 4 j 139 376 GeV $g_q=1, g_{\chi}=1, m(\chi)=1 \text{ GeV}$ 2102.10874 Yes $\tan\beta=1, g_Z=0.8, m(\chi)=100 \text{ GeV}$ Vector med. Z'-2HDM (Dirac DM) $0 e, \mu$ 139 2108,13391 2 b Yes 3 0 TeV Pseudo-scalar med. 2HDM+a multi-channel 800 GeV $\tan\beta=1, g_{\chi}=1, m(\chi)=10 \text{ GeV}$ 139 TLAS-CONF-2021-036 Scalar LQ 1st ger ≥2 j 139 1.8 TeV eta=12006.05872 Yes ≥2 j 139 1.7 TeV $\beta = 1$ 2006.05872 Scalar LQ 2nd gen 2 μ Yes 2 b $\mathcal{B}(LQ_3^u \to b\tau) = 1$ Scalar LQ 3rd gen 1τ Yes 139 1.49 TeV 2303.01294 ≥2 j, ≥2 b Yes 1.24 TeV $\mathcal{B}(LQ_3^{\tilde{u}} \to t\nu) = 1$ 0 e,μ 139 2004.14060 Scalar LQ 3rd den Scalar LQ 3rd gen $\geq 2 e, \mu, \geq 1 \tau \geq 1 j, \geq 1 b -$ 139 1.43 TeV $\mathcal{B}(\mathrm{LQ}_3^d \to t\tau) = 1$ 2101.11582 $0 e, \mu, \ge 1 \tau \ 0 - 2 j, 2 b$ Yes 139 1.26 TeV $\mathcal{B}(\mathrm{LQ}_3^d \to bv) = 1$ 2101.12527 Scalar LQ 3rd gen mass $\mathscr{B}(ilde{U}_1 o t \mu) = 1,$ Y-M coupl. Vector LQ mix gen multi-channel ≥ 1 j, ≥ 1 b Yes 139 mass 2.0 TeV LAS-CONF-2022-052 139 1.96 TeV Vector LQ 3rd gen 2 e, μ, τ ≥1 b Yes $\mathcal{B}(LQ_3^V \to b\tau) = 1$, Y-M coupl. 2303.01294 $2e/2\mu/\geq 3e,\mu \geq 1$ b, ≥ 1 j VLQ $TT \rightarrow Zt + X$ 1.46 TeV SU(2) doublet 139 2210.15413 $VLQ BB \rightarrow Wt/Zb + X$ SU(2) doublet 36.1 1.34 TeV 1808.02343 multi-channel $\mathcal{B}(T_{5/3} \rightarrow Wt) = 1, c(T_{5/3}Wt) =$ $\mathsf{VLQ}\ T_{5/3}\ T_{5/3}|\ T_{5/3}\to Wt$ 2(SS)/≥3 *e*,*µ* ≥1 b, ≥1 j Yes 36.1 a mass 1.64 TeV 1807.11883 139 VLQ $T \rightarrow Ht/Zt$ 1 *e*, μ ≥1 b, ≥3 j Yes 1.8 TeV SU(2) singlet, $\kappa_T = 0.5$ TLAS-CONF-2021-040 mass ≥1 b, ≥1 j Yes $\mathsf{VLQ}\ Y\to Wb$ 36.1 1 e,μ 1.85 TeV $\mathcal{B}(Y \to Wb) = 1, c_R(Wb) = 1$ 1812.07343 mass 139 VLQ $B \rightarrow Hb$ 0 *e*,*µ* ≥2b, ≥1j, ≥1J – SU(2) doublet, $\kappa_B = 0.3$ TLAS-CONF-2021-018 mass 2.0 TeV 139 SU(2) doublet VLL $\tau' \rightarrow Z \tau / H_2$ multi-channel ≥ 1 j Yes 898 GeV 2303.05441 Excited quark $q^* \rightarrow qg$ 2 i 139 only u^* and d^* , $\Lambda = m(q^*)$ 6.7 Te 1910.08447 Excited quark $q^* \rightarrow q\gamma$ 1γ 1 j 36.7 5.3 TeV only u^* and d^* , $\Lambda = m(q^*)$ 1709.10440 mass Excited quark $b^* \rightarrow bg$ 1 b, 1 j 139 1910.08447 _ _ mass 3.2 TeV 2τ 4.6 TeV 2303.09444 Excited lepton τ^* ≥2 j _ 139 $\Lambda = 4.6 \text{ TeV}$ Type III Seesaw 2,3,4 e, µ ≥2 j Yes 139 910 GeV 2202.02039 LRSM Majorana v3.2 TeV $m(W_R) = 4.1 \text{ TeV}, g_L = g_R$ 2μ 2 j 36.1 1809 11105 mass 2,3,4 e, μ (SS) various Higgs triplet $H^{\pm\pm} \rightarrow W^{\pm}W^{\pm}$ 139 350 GeV DY production 2101.11961 Yes ^{±±} mass Higgs triplet $H^{\pm\pm} \rightarrow \ell \ell$ 2,3,4 *e*, *µ* (SS) 139 1.08 TeV DY production 2211.07505 [±] mass Multi-charged particles 139 ulti-charged particle mass 1.59 TeV DY production, |q| = 5eLAS-CONF-2022-034 Magnetic monopoles DY production, $|g| = 1g_D$, spin 1/ 34.4 2.37 TeV 1905.10130 √s = 13 TeV $\sqrt{s} = 13 \text{ TeV}$ 10^{-1} partial data full data 10 Mass scale [TeV] Ve ν_{μ} ντ PTO 1/2 1/2 1/2 electron tau muon ш neutrino neutrino neutrino



Standard LHC Searches

 Most searches have similar basic strategy

- proton
- Search for new particle decaying to specific particles ($H \rightarrow 4\ell$)
- Select set of events that match this (eg. have 4ℓ)
- Define some variable based on this $(f(\ell_1, \ell_2, \ell_3, \ell_4) \sim E_{\ell_1} + E_{\ell_2} + E_{\ell_3} + E_{\ell_4})$
- Compare the # of events we expect to find based on Standard Model



(simulation) to the # of events we actually measure (data) ($\blacksquare + \blacksquare + \blacksquare$ vs. \bigcirc)

- What if we don't know exactly what we are looking for?
 - Select set of events that match what?
 - Define what variable?
- ML offers unique solution to this challenge (no traditional alternative)
 - Broad field of anomaly detection (AD)





Unsupervised Learning

- What if we don't have/can't use labels? \rightarrow "Unsupervised learning" or "selfsupervised learning"
- Autoencoder (AE):



• AE is just simplest form of unsupervised learning



- Train AE using known Standard Model processes
- Events with new particles may not reconstruct well

- Select set of events that don't reconstruct well
- $f(b_1, b_2, ?) \sim E_{b_1} + E_{b_2} + E_{?_1}$





arXiv:2306.03637



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- $f(\{j,b\}_1,\{j,b,e,\gamma,\mu\}_2) \sim E_{\{j,b\}_1} + E_{\{j,b,e,\gamma,\mu\}_2}$







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- Events with new particles may not reconstruct well

- Select set of events that don't reconstruct well
- $f(\{j,b\}_1,\{j,b,e,\gamma,\mu\}_2) \sim E_{\{j,b\}_1}$ -

], proton j, b, e, γ, μ

+
$$E_{\{j,b,e,\gamma,\mu\}_2}$$







- General AD can be much worse than a dedicated search
- Some methods try to use some concept of signal, still remain insensitive to details
- "Semi-supervised" techniques

• $f(j?_1, j?_2) \sim E_{j?_1} + E_{j?_2}$







Classification Without Labels (CWoLa)

- Semi-supervised method [arXiv:1708.02949]
- Requires only $f(j?_1, j?_2) \sim E_{j?_1} + E_{j?_2}$
- If ? is localized in $f(\cdot)$, can train supervised classifier based on mixed samples
 - In the limit this will approach normal supervised performance: classifier learns find whats different about sample 1 and 2 (S vs. B)







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Quasi-Anomalous Knowledge: [2011.03550]

- What if you has some general idea of what signals might look like, but you aren't sure?
- Also possible to set some criteria on roughly what signal should look like, what features it might have
 - Want to point AD in the right direction
- Ideally want method that doesn't break down if the hypothesis turns out to be wrong (like supervised classifiers typically do)

proton

- Train an AE for background
- Train an AE for hypothetical signal(s)
- Construct N-dimension QUAK space from losses

Background Loss (MSE)

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Signal Loss #1 (MSE)

Background Loss (MSE)

- QUAK can perform similarly to supervised methods when given correct signal
- QUAK greatly outperforms supervised methods when signal hypothesis is wrong

Background Loss

Conclusions

- I hope you learned a little bit about LHC research and anomaly detection Many more AD methods I didn't have time to mention
- - TNT, CATHODE, SALAD, CURTAINS, ...
- Very active area of research at the LHC!
- Recent AD sessions at ML4Jets2024 conference give a nice flavor of cutting edge ideas [1][2]

[1] <u>https://indico.cern.ch/event/1386125/timetable/?view=standard#b-587345-anomaly-detection</u> [2] https://indico.cern.ch/event/1386125/timetable/?view=standard#b-587346-anomaly-detection

ATLAS Slice

L1 Trigger AD

- Depending on anomaly, we could have none left in recorded data
- Low-latency ML is the only option! (eg. autoencoders)

ave none left in recorded data

L1 Trigger AD

- CMS has already deployed multiple AD algorithms in trigger
 - AXOL1TL [CMS DP-2023/079, CMS DP-2024/059] & CICADA [CMS DP-2023/086] (see Noah's talk later [1])
- Currently collecting interesting events that would have been missed
 - Network preferentially identifies large multiplicity events, potentially large gains in new physics acceptance
- Development ongoing in ATLAS as well

CMS Preliminary

10

20

Events

104

10³

10²

10

10⁰

[1] https://indico.cern.ch/event/1387540/timetable/?view=standard#66-realtime-anomaly-detection

30

JetHT