

The Niels Bohr Institute



Rethinking searches for new physics at the LHC

Flavia de Almeida Dias

Nordic Conference on Particle Physics - Spaatind 2020 03 January 2020

LHC Run 2 (2015 - 2018)

- Increase in energy from $8 \rightarrow 13 \text{ TeV}$
- Major new-physics sensitivity opened up, specially at high masses
- Integrated luminosity: 140 fb⁻¹



Hundreds of searches performed

A St	TLAS Exotics S atus: May 2019	Search	es* -	95%	6 CL	Upper Exclu	usion Limits		[[] dt = ('	ATLA	AS Preliminary
	Model	<i>ℓ</i> ,γ	Jets†	E ^{miss} T	∫£ dt[fb	-1]	Limit		J2 at = (5.2 - 155/10	Reference
Extra dimensions	$\begin{array}{l} \text{ADD } G_{KK} + g/q \\ \text{ADD non-resonant } \gamma \\ \text{ADD QBH } \\ \text{ADD BH high } \sum_{\mathcal{P} r} \\ \text{ADD BH multipit} \\ \text{RSI } G_{KK} \rightarrow \gamma \gamma \\ \text{Bulk RS } G_{KK} \rightarrow WW / ZZ \\ \text{Bulk RS } g_{KK} \rightarrow WW \rightarrow qqqq \\ \text{Bulk RS } g_{KK} \rightarrow tt \\ 2UED / RP \end{array}$	$\begin{array}{c} 0 \ e, \mu \\ 2 \ \gamma \\ \hline \\ - \\ 2 \ \gamma \\ \hline \\ e, \mu \\ 0 \ e, \mu \\ 1 \ e, \mu \\ 1 \ e, \mu \end{array}$	$\begin{array}{c} 1-4 \ j \\ - \\ 2 \ j \\ \geq 2 \ j \\ = 3 \ j \\ - \\ el \\ 2 \ J \\ \geq 2 \ b_i \geq 1 \ J, \\ \geq 2 \ b_i \geq 3 \ J \end{array}$	Yes - - - - 2j Yes j Yes	36.1 36.7 37.0 3.2 3.6 36.7 36.1 139 36.1 36.1	Мр Ms Ma Ma Ma Ma Ma G _{KK} mass G _{KK} mass G _{KK} mass G _{KK} mass G _{KK} mass G _{KK} mass G _{KK} mass		4.1 TeV 2.3 TeV 1.6 TeV 3.8 TeV 1.8 TeV	7.7 TeV 8.6 TeV 8.9 TeV 8.2 TeV 9.55 TeV	$\begin{array}{l} n=2 \\ n=3 \ \text{HLZ NLO} \\ n=6 \\ n=6, \ M_D=3 \ \text{TeV}, \text{rot BH} \\ n=6, \ M_D=3 \ \text{TeV}, \text{rot BH} \\ k/M_{PI}=0.1 \\ k/M_{PI}=0.1 \\ k/M_{PI}=1.0 \\ \Gamma/m=15\% \\ \text{Tref}(1.5), \ \text{S}(A^{(1.1)} \to \text{tr})=1 \end{array}$	1711.03301 1707.04147 1703.09127 1606.02255 1512.02586 1707.04147 1808.02380 ATLAS-CONF-2019-003 1804.10823 1803.09678
Gauge bosons	$\begin{array}{l} \mathrm{SSM}\ Z' \to \ell\ell \\ \mathrm{SSM}\ Z' \to \tau\tau \\ \mathrm{Leptophobic}\ Z' \to bb \\ \mathrm{Leptophobic}\ Z' \to tt \\ \mathrm{SSM}\ W' \to \ell\nu \\ \mathrm{SSM}\ W' \to \tau\nu \\ \mathrm{HVT}\ V' \to WH/ZH \ \mathrm{model}\ B \\ \mathrm{HVT}\ V' \to WH/ZH \ \mathrm{model}\ B \\ \mathrm{LRSM}\ W_R \to tb \\ \mathrm{LRSM}\ W_R \to \mu M_R \end{array}$	$\begin{array}{c} 2 \ e, \mu \\ 2 \ \tau \\ - \\ 1 \ e, \mu \\ 1 \ e, \mu \\ 1 \ \tau \\ B 0 \ e, \mu \\ multi-channe \\ 2 \ \mu \end{array}$	- 2 b $\geq 1 b, \geq 1 J/$ - 2 J el el el 1 J	- 2j Yes Yes Yes -	139 36.1 36.1 139 36.1 139 36.1 36.1 36.1 80	Z' mass Z' mass Z' mass W' mass W' mass V' mass V' mass Vg mass Wg mass		5.1 Tr 2.42 TeV 2.1 TeV 3.0 TeV 6.1 3.7 TeV 2.93 TeV 2.93 TeV 3.25 TeV 5.0 Te	3) TeV	$\label{eq:gamma} \begin{split} & \Gamma/m = 1\% \\ & g_V = 3 \\ & g_V = 3 \\ & m(N_R) = 0.5 \text{ TeV}, g_L = g_R \end{split}$	1903.06248 1709.07242 1805.08299 1804.10823 CERN-EP-2019-100 1801.06992 ATLAS-CONF-2019-003 1712.06518 1807.10473 1904.12679
C	Cl qqqq Cl llqq Cl tttt	_ 2 e,μ ≥1 e,μ	2 j _ ≥1 b, ≥1 j	– – Yes	37.0 36.1 36.1	Λ Λ Λ		2.57 TeV		21.8 TeV η_{LL}^- 40.0 TeV η_{LL}^- $ C_{tt} = 4\pi$	1703.09127 1707.02424 1811.02305
MD	Axial-vector mediator (Dirac DM Colored scalar mediator (Dirac I $VV_{\chi\chi}$ EFT (Dirac DM) Scalar reson. $\phi \rightarrow t_{\chi}$ (Dirac DM	l) 0 e, μ DM) 0 e, μ 0 e, μ 1) 0-1 e, μ	1 - 4 j 1 - 4 j $1 J, \le 1 j$ 1 b, 0-1 J	Yes Yes Yes Yes	36.1 36.1 3.2 36.1	m _{med} m _{med} M _* m _{\$}	1 700 GeV	.55 TeV 1.67 TeV 3.4 TeV		$\begin{array}{l} g_{q}{=}0.25, g_{\chi}{=}1.0, m(\chi) = 1 \; {\rm GeV} \\ g{=}1.0, m(\chi) = 1 \; {\rm GeV} \\ m(\chi) < 150 \; {\rm GeV} \\ \gamma = 0.4, \lambda = 0.2, m(\chi) = 10 \; {\rm GeV} \end{array}$	1711.03301 1711.03301 1608.02372 1812.09743
۲a	Scalar LQ 1 st gen Scalar LQ 2 nd gen Scalar LQ 3 rd gen Scalar LQ 3 rd gen	1,2 e 1,2 μ 2 τ 0-1 e,μ	≥ 2 j ≥ 2 j 2 b 2 b	Yes Yes - Yes	36.1 36.1 36.1 36.1	LQ mass LQ mass LQ ⁴ mass LQ ⁴ mass	1 1.03 TeV 970 GeV	4 TeV 56 TeV /		$\begin{split} \beta &= 1 \\ \beta &= 1 \\ \mathcal{B}(\mathrm{LQ}_3^{\nu} \to b\tau) &= 1 \\ \mathcal{B}(\mathrm{LQ}_3^{d} \to t\tau) &= 0 \end{split}$	1902.00377 1902.00377 1902.08103 1902.08103
Heavy quarks	$\begin{array}{c} VLQ\; TT \rightarrow Ht/Zt/Wb + X \\ VLQ\; BB \rightarrow Wt/Zb + X \\ VLQ\; T_{5/3}\; T_{5/3}\; T_{5/3} \rightarrow Wt + X \\ VLQ\; Y \rightarrow Wb + X \\ VLQ\; B \rightarrow Hb + X \\ VLQ\; QQ \rightarrow WqWq \end{array}$	multi-channe multi-channe $2(SS)/\geq 3 e_{,j}$ $1 e, \mu$ $0 e, \mu, 2 \gamma$ $1 e, \mu$	el el	Yes Yes Yes Yes	36.1 36.1 36.1 36.1 79.8 20.3	T mass B mass T _{5/3} mass Y mass B mass Q mass	1.3 1.3 1.21 690 GeV	7 TeV 4 TeV 1.64 TeV 1.85 TeV TeV		$\begin{array}{l} & \text{SU(2) doublet} \\ & \text{SU(2) doublet} \\ & \mathcal{B}(T_{3(3)} \rightarrow Wt) = 1, \ c(T_{5(3)}Wt) = 1 \\ & \mathcal{B}(Y \rightarrow Wb) = 1, \ c_R(Wb) = 1 \\ & \kappa_B = 0.5 \end{array}$	1808.02343 1808.02343 1807.11883 1812.07343 ATLAS-CONF-2018-024 1509.04261
Excited	Excited quark $q^* \rightarrow qg$ Excited quark $q^* \rightarrow q\gamma$ Excited quark $b^* \rightarrow bg$ Excited lepton ℓ^* Excited lepton ν^*	- 1γ - 3 e,μ 3 e,μ,τ	2j 1j 1b,1j -		139 36.7 36.1 20.3 20.3	q* mass q* mass b* mass /* mass y* mass		5.3 T 2.6 TeV 3.0 TeV 1.6 TeV	5.7 TeV eV	only u^* and d^* , $\Lambda = m(q^*)$ only u^* and d^* , $\Lambda = m(q^*)$ $\Lambda = 3.0$ TeV $\Lambda = 1.6$ TeV	ATLAS-CONF-2019-007 1709.10440 1805.09299 1411.2921 1411.2921
Other Other	Type III Seesaw LRSM Majorana γ Higgs triplet $H^{\pm\pm} \rightarrow \ell \ell$ Higgs triplet $H^{\pm\pm} \rightarrow \ell r$ Multi-charged particles Magnetic monopoles $\sqrt{s} = 8 \text{ TeV}$ \sqrt{y} <i>y</i> <i>y s</i> election of the availability	$1 e, \mu$ 2μ $2,3,4 e, \mu (SS)$ $3 e, \mu, \tau$ $-$ $-$ $s = 13 TeV$ artial data le mass lim		Yes - - - 3 TeV ata	79.8 36.1 36.1 20.3 36.1 34.4 s or pher	N [®] mass N _R mass H ^{±±} mass H ^{±±} mass monopole mass 10 ⁻¹ 10 ⁻¹ nomena is shown.	560 GeV 870 GeV 400 GeV 1.22	3.2 TeV TeV 2.37 TeV 1	1	$\begin{split} m(W_{R}) &= 4.1 \text{ TeV}, g_{L} = g_{R} \\ \text{DY production} \\ \text{DY production}, \mathcal{B}(H_{L}^{t+} \rightarrow \ell r) = 1 \\ \text{DY production}, g_{L}^{t} = 5e \\ \text{DY production}, g = 1g_{D}, \text{spin } 1/2 \\ 0 \\ \textbf{Mass scale [TeV]} \end{split}$	ATLAS-CONF-2018-020 1809.11105 1710.09748 1411.2921 1812.03673 1905.10130

ATLAS SUSY Searches* - 95% CL Lower Limits October 2019

ATLAS Preliminary $\sqrt{s} = 13 \text{ TeV}$





ts at 95% CL (theory uncertainties are not included).

Overview of CMS EXO results



mass scale [TeV]

Selection of observed exclusion limits at 95% C.L. (theory uncertainties are not included).

January 2019

UNIVERSITY OF COPENHAGEN

Many measurements to probe the SM



 The Standard Model persists being unchallenged by LHC data so far

What's next?



F. de Almeida Dias





Assume that: neutrino masses does not lead to any new physics; there is no particle composition to dark matter; ignore all b-jet anomalies; hierarchy of masses/forces just are what they are;



BSM very

F. de Almeida Dias

- Keep performing searches as we do;
- Precision measurements to look for deviations



- Development of generic, less model-dependent¹ searches
 - Algorithms aimed at detecting data departures from a given reference model
 - Ideally sensitive to any new physics, not specific BSM alternatives

discovery of something \Rightarrow falsification of the SM



D'Agnolo, Wulzer, Phys. Rev. D 99, 015014 (2019) 1: Hypothesis test unavoidably requires alternative hypothesis, or probability model, to compare with. Model-independent physically means that the alternative distribution is not selected as the one predicted by known alternative physics model

 Revolution on applications with deep learning, already in our daily lives



 Revolution on applications with deep learning, already in our daily lives

Image Recognition





 Revolution on applications with deep learning, already in our daily lives

Text Generation

Talk to Transformer

See how a modern neural network completes your text. Type a custom snippet or try one of the examples. Learn more below.

Follow @AdamDanielKing for more neat neural networks.

Custom prompt

In 2020, I wish that the Large Hadron Collider will find

Completion

In 2020, I wish that the Large Hadron Collider will find such a big particle; for then, we'll have found our opponent, our reason to exist, our final secret. The true nature of the Universe will be revealed to us! The true foundations of reality will be revealed! We will finally know what exactly this Universe is and how it came into being. Finally, we will see the cosmic picture – the structure of the entire Universe – in all its parts, and understand that the Universe was never there."



COMPLETE TEXT

https://talktotransformer.com/

 Revolution on applications with deep learning, already in our daily lives

Image and video generation



https://thispersondoesnotexist.com/



Nature 560, 41-48 (2018)

Machine Learning in HEP

- Cluster splitting identification in silicon trackers
- b quark and τ lepton identification
- Identification of substructure within hadronic showers (jets)
- Optimisation of signal-to-background ratio in physics analyses
- e and γ identification
- ➡ Fast simulation of events

Guest, Cranmer, Whiteson Annu. Rev. Nucl. Part. Sci. 2018. 68:1–22

Table 1 | Effect of machine learning on the discovery and study of the Higgs boson

Analysis	Years of data collection	Sensitivity without machine learning	Sensitivity with machine learning	Ratio of <i>P</i> values	Additional data required
$\frac{\rm CMS^{24}}{\rm H \rightarrow \gamma\gamma}$	2011–2012	2.2 <i>σ</i> , <i>P</i> = 0.014	2.7 <i>σ</i> , <i>P</i> = 0.0035	4.0	51%
$\begin{array}{l} {\rm ATLAS^{43}} \\ {\rm H} \rightarrow \tau^+ \tau^- \end{array}$	2011–2012	2.5 σ , $P = 0.0062$	3.4 <i>σ</i> , <i>P</i> = 0.00034	18	85%
ATLAS ⁹⁹ VH → bb	2011–2012	1.9σ , $P = 0.029$	2.5 <i>σ</i> , <i>P</i> = 0.0062	4.7	73%
$ATLAS^{41}$ VH \rightarrow bb	2015–2016	2.8 σ , $P = 0.0026$	3.0 <i>σ</i> , <i>P</i> = 0.00135	1.9	15%
CMS^{100} $VH \rightarrow bb$	2011–2012	1.4σ , $P = 0.081$	2.1 <i>σ</i> , <i>P</i> = 0.018	4.5	125%

Five key measurements of three decay modes of the Higgs boson *H* for which machine learning greatly increased the sensitivity of the LHC experiments, where *V* denotes a *W* or *Z* boson, γ denotes a photon and *b* a beauty quark. For each analysis, the sensitivity without and with machine learning is given, in terms of both the *P* values and the equivalent number of Gaussian standard deviations σ . (We present only analyses that provided both machine-learning-based and non-machine-learning-based results; the more recent analyses report only the machine-learning-based results.) The increase in sensitivity achieved by using machine learning, as measured by the ratio of *P* values, ranges roughly from 2 to 20. An alternative figure of merit is the minimal amount of additional data that would need to be collected to reach the machine-learning-based sensitivity without using machine learning, which varies from 15% to 125%.



https://www.weizmann.ac.il/conferences/SRitp/Aug2019/



Learning Supervision

- Supervised:
 - Given two test hypothesis
 (e.g. signal vs background), best discrimination
 - Very effective for *specific* signal
 - Most applications in HEP to date
- Unsupervised:



https://www.immuniweb.com/

- Draw inference from input datasets *without labels*, find previously unknown patterns (ex. anomaly search)
 - Learns what is normal, detect unusual instances
- Ex: credit card fraud detection, data security against hacking



Classification Without Labels (CWoLa)

- Look into di-jet (large-R jets) resonance searches
 - Regular search looks for $X \rightarrow W/Z \rightarrow JJ$
 - $\bullet \quad \text{CWoLa: } X \rightarrow Y \rightarrow J J$





Collins, Howe, Nachman Phys. Rev. Lett. 121, 241803 (2018)

F. de Almeida Dias

Classification Without Labels (CWoLa)



- Independent of model (limited to a specific signature)
- Limited application for very weak signals
- There can be complications decorrelating y features from final discriminant variable

Collins, Howe, Nachman Phys. Rev. Lett. 121, 241803 (2018)

Farina, Nakai, Shih

arXiv: 1808.08992

Anti-QCD Taggers

• Autoencoders (AE)



- Map "normal" events back to themselves, but fails to reconstruct "anomalous" events that it has never encountered before.
- $\bullet \quad \text{Reconstruction error} \Rightarrow \text{anomaly threshold}$





Anti-QCD Taggers

• Autoencoders (AE)



- Map "normal" events back to themselves, but fails to reconstruct "anomalous" events that it has never encountered before.
- Reconstruction error \Rightarrow anomaly threshold
- Train on MC background only (weakly supervised) and in data with ~small amounts of signal (typical control region - unsupervised)
- Test on Monte Carlo with top/BSM signals
- Look into correlation effects with the jet mass (control with choice of architecture [1] or with adversarial network [2])

[1] Farina, Nakai, Shih arXiv: 1808.08992



Anti-QCD Taggers



Anti-QCD Taggers

- ✓ Independent of model (limited to a specific signature)
- Can be trained in MC or data, reasonably robust for contamination in the training samples
- It is not clear if it would work if the anomaly would yield events which are less complicated than the SM (for example, training on top quark samples to find QCD)
- The full statistical treatment in a LHC-like analysis has not been shown yet

- VAE¹ trained in SM events to flag anomalies
 - Save as a separate trigger stream for further scrutiny (~1000 SM events/month)
 - Could also be used to flag detector malfunctions
 - Inspire future supervised searches on data collected afterwards
- Test case on lepton trigger:
 - Use of 21 event variables (related to isolation, p_T, charge, lepton and jet multiplicity)
 - Features not tailored to specific BSM models, but might be more suitable for certain models than for others
- Investigation on training on data
 - Using contaminated samples to train does not significantly decrease VAE performance unless signal is very strong (100x larger than method sensitivity)

Cerri, Nguyen, Pierini, Spiropulu, Vlimant J. High Energ. Phys. (2019) 2019: 36

1: Variational Autoencoder: similar to AE but allows a stochastic modelling of late space



Reconstruction loss function for SM and signal benchmarks

Dashed line indicates the threshold to have 1k SM events/month

Cerri, Nguyen, Pierini, Spiropulu, Vlimant J. High Energ. Phys. (2019) 2019: 36



- ✓ Identify anomalies that would escape detection due to trigger selection
- ✓ High purity sample of potentially interesting events
- Small signal efficiency
- Strong bias in dataset definition (not possible to perform traditional data-driven and supervised search)
- Repeated patterns to motivate new BSM scenarios and inspire new searches with future data



Summary and Outlook

- Current scenario at the LHC motivates searches other than supervised testing of specific BSM models
- Deep learning can provide tools to look for generic new physics looking into specific final states objects or full events
 - Possibility to find not yet thought of scenarios
 - Still poses challenges regarding systematic uncertainties evaluation, complicated pre-processing of input variables, etc
- It will be exciting to extract as much as possible from all the data the LHC can provide

Backup Slides



LHC and ATLAS









F. de Almeida Dias

The Large Hadron Collider Schedule



LHC Data



Effective Field Theories

- Tool to interpret possible deviations
 - Description of a problem in a given scale

