Search for New Physics Inside Jets at the ATLAS Detector using Machine Learning

Jacinthe Pilette

WNPPC 2021

Search for New Physics at ATLAS

- All we know about particle physics is in the Standard Model.

- We also know it has some limits :
  - Gravity
  - Dark matter
  - Hierarchy problem for the Higgs mass
  - Free parameters

- A lot of new physics model were conceived :
  - Supersymmetry
  - Axions
  - Composite Higgs
  - Leptoquarks
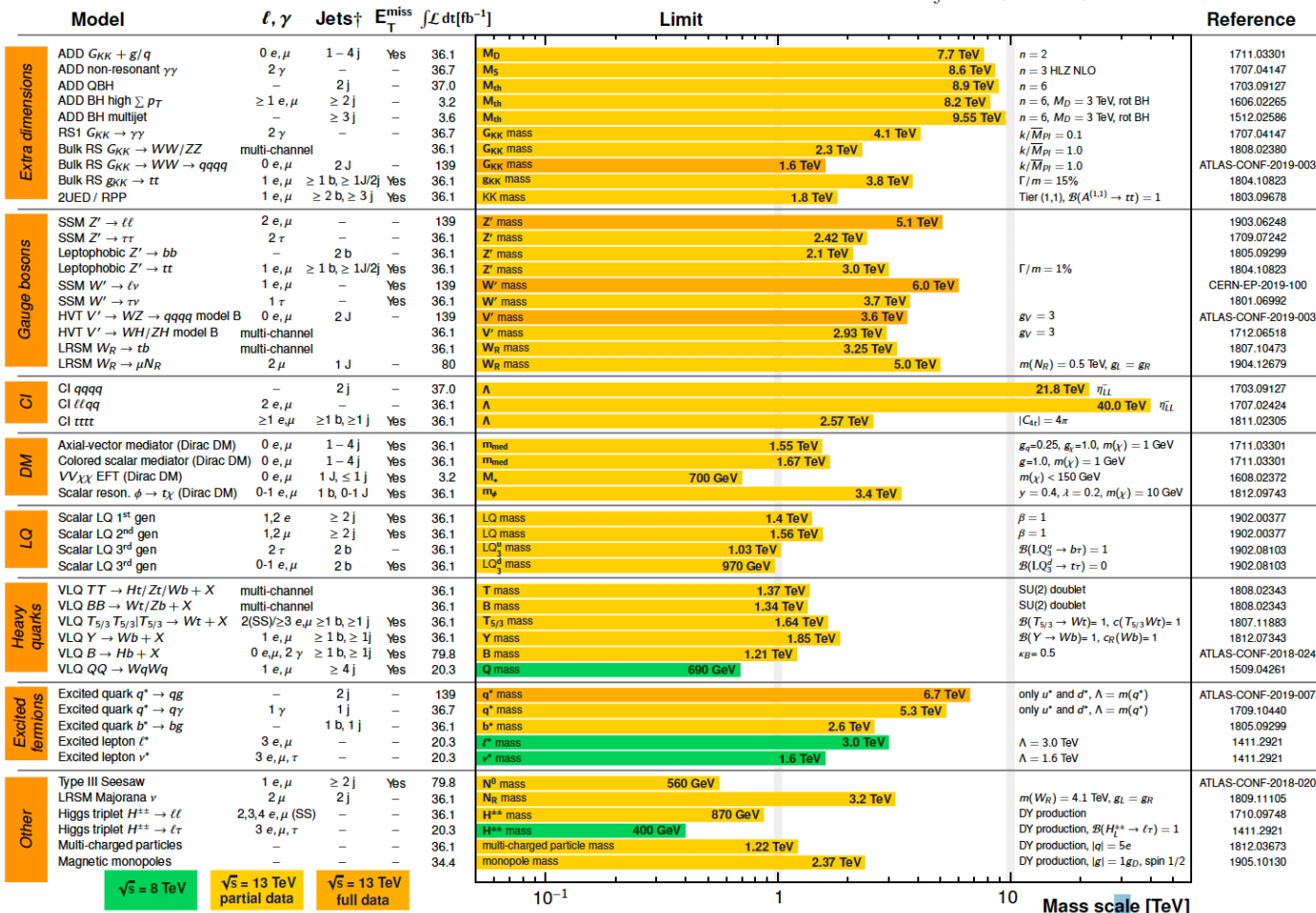
Search for New Physics at ATLAS

ATLAS Exotics Searches* - 95% CL Upper Exclusion Limits
Status: May 2019

ATLAS Preliminary

$\int \mathcal{L}\, dt = (3.2 - 139)\ \text{fb}^{-1}$ $\sqrt{s} = 8, 13\ \text{TeV}$

	Model	ℓ,γ	Jets†	E_T^{miss}	$\int \mathcal{L}\, dt[\text{fb}^{-1}]$	Limit		Reference
Extra dimensions	ADD $G_{KK} + g/q$	$0\ e,\mu$	$1-4$ j	Yes	36.1	M_D 7.7 TeV	$n=2$	1711.03301
	ADD non-resonant $\gamma\gamma$	2γ	–	–	36.7	M_S 8.6 TeV	$n=3$ HLZ NLO	1707.04147
	ADD QBH	–	2 j	–	37.0	M_{th} 8.9 TeV	$n=6$	1703.09127
	ADD BH high $\sum p_T$	$\geq 1\ e,\mu$	≥ 2 j	–	3.2	M_{th} 8.2 TeV	$n=6$, $M_D = 3$ TeV, rot BH	1606.02265
	ADD BH multijet	–	≥ 3 j	–	3.6	M_{th} 9.55 TeV	$n=6$, $M_D = 3$ TeV, rot BH	1512.02586
	RS1 $G_{KK} \to \gamma\gamma$	2γ	–	–	36.7	G_{KK} mass 4.1 TeV	$k/\overline{M}_{Pl} = 0.1$	1707.04147
	Bulk RS $G_{KK} \to WW/ZZ$	multi-channel			36.1	G_{KK} mass 2.3 TeV	$k/\overline{M}_{Pl} = 1.0$	1808.02380
	Bulk RS $G_{KK} \to WW \to qqqq$	$0\ e,\mu$	2 J	–	139	G_{KK} mass 1.6 TeV	$k/\overline{M}_{Pl} = 1.0$	ATLAS-CONF-2019-003
	Bulk RS $g_{KK} \to tt$	$1\ e,\mu$	≥ 1 b, ≥ 1 J/2j	Yes	36.1	g_{KK} mass 3.8 TeV	$\Gamma/m = 15\%$	1804.10823
	2UED / RPP	$1\ e,\mu$	≥ 2 b, ≥ 3 j	Yes	36.1	KK mass 1.8 TeV	Tier (1,1), $\mathcal{B}(A^{(1,1)} \to tt) = 1$	1803.09678
Gauge bosons	SSM $Z' \to \ell\ell$	$2\ e,\mu$	–	–	139	Z' mass 5.1 TeV		1903.06248
	SSM $Z' \to \tau\tau$	2τ	–	–	36.1	Z' mass 2.42 TeV		1709.07242
	Leptophobic $Z' \to bb$	–	2 b	–	36.1	Z' mass 2.1 TeV		1805.09299
	Leptophobic $Z' \to tt$	$1\ e,\mu$	≥ 1 b, ≥ 1 J/2j	Yes	36.1	Z' mass 3.0 TeV	$\Gamma/m = 1\%$	1804.10823
	SSM $W' \to \ell\nu$	$1\ e,\mu$	–	Yes	139	W' mass 6.0 TeV		CERN-EP-2019-100
	SSM $W' \to \tau\nu$	1τ	–	Yes	36.1	W' mass 3.7 TeV		1801.06992
	HVT $V' \to WZ \to qqqq$ model B	$0\ e,\mu$	2 J	–	139	V' mass 3.6 TeV	$g_V = 3$	ATLAS-CONF-2019-003
	HVT $V' \to WH/ZH$ model B	multi-channel			36.1	V' mass 2.93 TeV	$g_V = 3$	1712.06518
	LRSM $W_R \to tb$	multi-channel			36.1	W_R mass 3.25 TeV		1807.10473
	LRSM $W_R \to \mu N_R$	2μ	1 J	–	80	W_R mass 5.0 TeV	$m(N_R) = 0.5$ TeV, $g_L = g_R$	1904.12679
CI	CI $qqqq$	–	2 j	–	37.0	Λ 21.8 TeV η_{LL}		1703.09127
	CI $\ell\ell qq$	$2\ e,\mu$	–	–	36.1	Λ 40.0 TeV η_{LL}		1707.02424
	CI $tttt$	$\geq 1\ e,\mu$	≥ 1 b, ≥ 1 j	Yes	36.1	Λ 2.57 TeV	$|C_{4t}| = 4\pi$	1811.02305
DM	Axial-vector mediator (Dirac DM)	$0\ e,\mu$	$1-4$ j	Yes	36.1	m_{med} 1.55 TeV	$g_q = 0.25$, $g_\chi = 1.0$, $m(\chi) = 1$ GeV	1711.03301
	Colored scalar mediator (Dirac DM)	$0\ e,\mu$	$1-4$ j	Yes	36.1	m_{med} 1.67 TeV	$g = 1.0$, $m(\chi) = 1$ GeV	1711.03301
	$VV\chi\chi$ EFT (Dirac DM)	$0\ e,\mu$	1 J, ≤ 1 j	Yes	3.2	M_* 700 GeV	$m(\chi) < 150$ GeV	1608.02372
	Scalar reson. $\phi \to t\chi$ (Dirac DM)	0-1 e,μ	1 b, 0-1 J	Yes	36.1	m_ϕ 3.4 TeV	$y = 0.4$, $\lambda = 0.2$, $m(\chi) = 10$ GeV	1812.09743
LQ	Scalar LQ 1st gen	$1,2\ e$	≥ 2 j	–	36.1	LQ mass 1.4 TeV	$\beta = 1$	1902.00377
	Scalar LQ 2nd gen	$1,2\ \mu$	≥ 2 j	–	36.1	LQ mass 1.56 TeV	$\beta = 1$	1902.00377
	Scalar LQ 3rd gen	2τ	2 b	–	36.1	LQ_3^u mass 1.03 TeV	$\mathcal{B}(LQ_3^u \to b\tau) = 1$	1902.08103
	Scalar LQ 3rd gen	0-1 e,μ	2 b	Yes	36.1	LQ_3^d mass 970 GeV	$\mathcal{B}(LQ_3^d \to t\tau) = 0$	1902.08103
Heavy quarks	VLQ $TT \to Ht/Zt/Wb + X$	multi-channel			36.1	T mass 1.37 TeV	SU(2) doublet	1808.02343
	VLQ $BB \to Wt/Zb + X$	multi-channel			36.1	B mass 1.34 TeV	SU(2) doublet	1808.02343
	VLQ $T_{5/3}T_{5/3}/T_{5/3} \to Wt + X$	2(SS)/$\geq 3\ e,\mu$	≥ 1 b, ≥ 1 j	Yes	36.1	$T_{5/3}$ mass 1.64 TeV	$\mathcal{B}(T_{5/3} \to Wt) = 1$, $c(T_{5/3}Wt) = 1$	1807.11883
	VLQ $Y \to Wb + X$	$1\ e,\mu$	≥ 1 b, ≥ 1 j	Yes	36.1	Y mass 1.85 TeV	$\mathcal{B}(Y \to Wb) = 1$, $c_R(Wb) = 1$	1812.07343
	VLQ $B \to Hb + X$	$0\ e,\mu$, 2γ	≥ 1 b, ≥ 1 j	Yes	79.8	B mass 1.21 TeV	$\kappa_B = 0.5$	ATLAS-CONF-2018-024
	VLQ $QQ \to WqWq$	$1\ e,\mu$	≥ 4 j	Yes	20.3	Q mass 690 GeV		1509.04261
Excited fermions	Excited quark $q^* \to qg$	–	2 j	–	139	q^* mass 6.7 TeV	only u^* and d^*, $\Lambda = m(q^*)$	ATLAS-CONF-2019-007
	Excited quark $q^* \to q\gamma$	1γ	1 j	–	36.7	q^* mass 5.3 TeV	only u^* and d^*, $\Lambda = m(q^*)$	1709.10440
	Excited quark $b^* \to bg$	–	1 b, 1 j	–	36.1	b^* mass 2.6 TeV		1805.09299
	Excited lepton ℓ^*	$3\ e,\mu$	–	–	20.3	ℓ^* mass 3.0 TeV	$\Lambda = 3.0$ TeV	1411.2921
	Excited lepton ν^*	$3\ e,\mu,\tau$	–	–	20.3	ν^* mass 1.6 TeV	$\Lambda = 1.6$ TeV	1411.2921
Other	Type III Seesaw	$1\ e,\mu$	≥ 2 j	Yes	79.8	N^0 mass 560 GeV		ATLAS-CONF-2018-020
	LRSM Majorana ν	2μ	2 j	–	36.1	N_R mass 3.2 TeV	$m(W_R) = 4.1$ TeV, $g_L = g_R$	1809.11105
	Higgs triplet $H^{\pm\pm} \to \ell\ell$	2,3,4 e,μ (SS)	–	–	36.1	$H^{\pm\pm}$ mass 870 GeV	DY production	1710.09748
	Higgs triplet $H^{\pm\pm} \to \ell\tau$	$3\ e,\mu,\tau$	–	–	36.1	$H^{\pm\pm}$ mass 400 GeV	DY production, $\mathcal{B}(H_L^{\pm\pm} \to \ell\tau) = 1$	1411.2921
	Multi-charged particles	–	–	–	36.1	multi-charged particle mass 1.22 TeV	DY production, $|q| = 5e$	1812.03673
	Magnetic monopoles	–	–	–	34.4	monopole mass 2.37 TeV	DY production, $|g| = 1g_D$, spin 1/2	1905.10130

$\sqrt{s} = 8$ TeV $\sqrt{s} = 13$ TeV partial data $\sqrt{s} = 13$ TeV full data

**Mass scale [TeV]** 10^{-1} 1 10

*Only a selection of the available mass limits on new states or phenomena is shown.
†Small-radius (large-radius) jets are denoted by the letter j (J).

- A lot of model-dependent searches ongoing at ATLAS

- New limits on mass and life-time values with increasing precision

- But still, no proof of their existence

[1] ATLAS Collaboration,
Summary Plots for Exotics Heavy Particle Searches and Exotics/SUSY Long-lived Particle Searches. *ATL-PHYS-PUB*-2019-023, July 2019. url : http://cds.cern.ch/record/2682064?ln=en
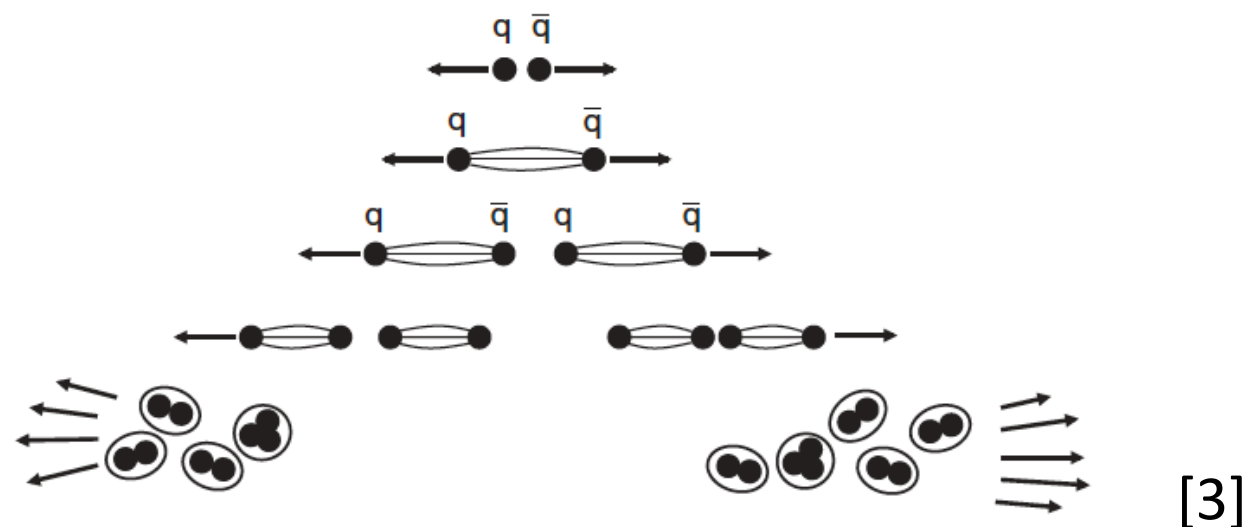
The ATLAS Detector
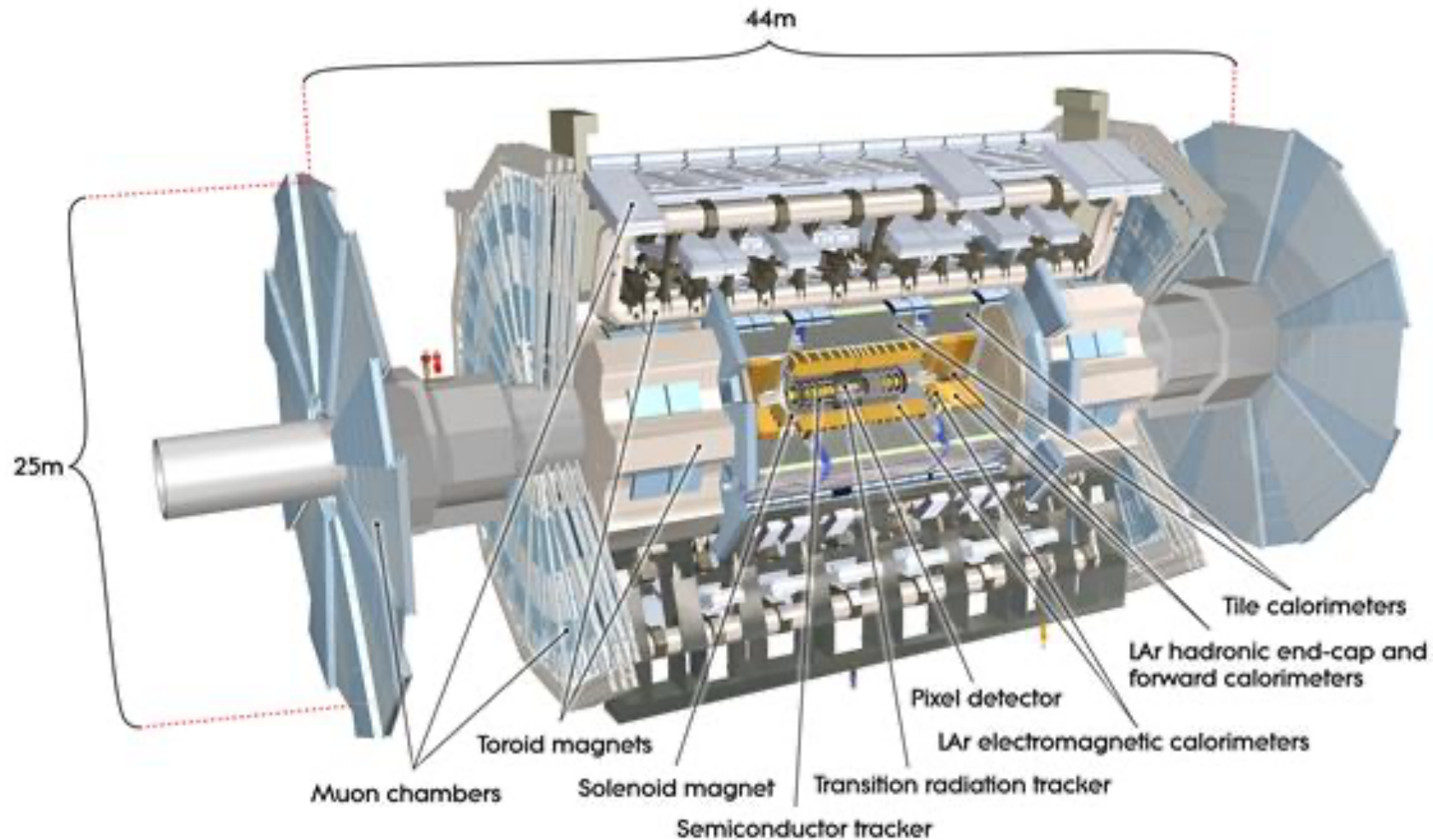
[2]

Jets in the Detector

A jet is a collimated flow of particles resulting generally from a high-p_T quark or gluon :
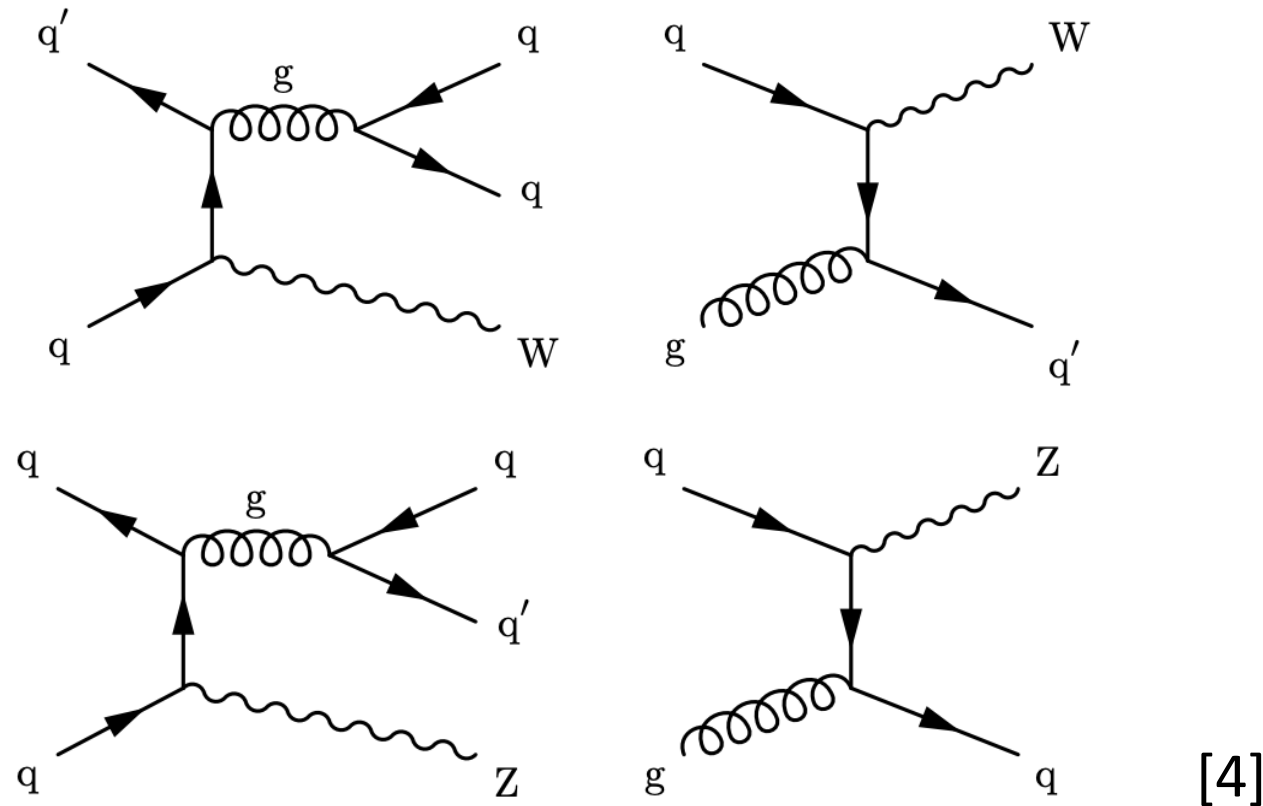
[3]

Jets happen a lot at the LHC (high center of mass energy)

Jets can be produced by multiple ways : parton (quark/gluon) collisions, or by the decay of a massive particle
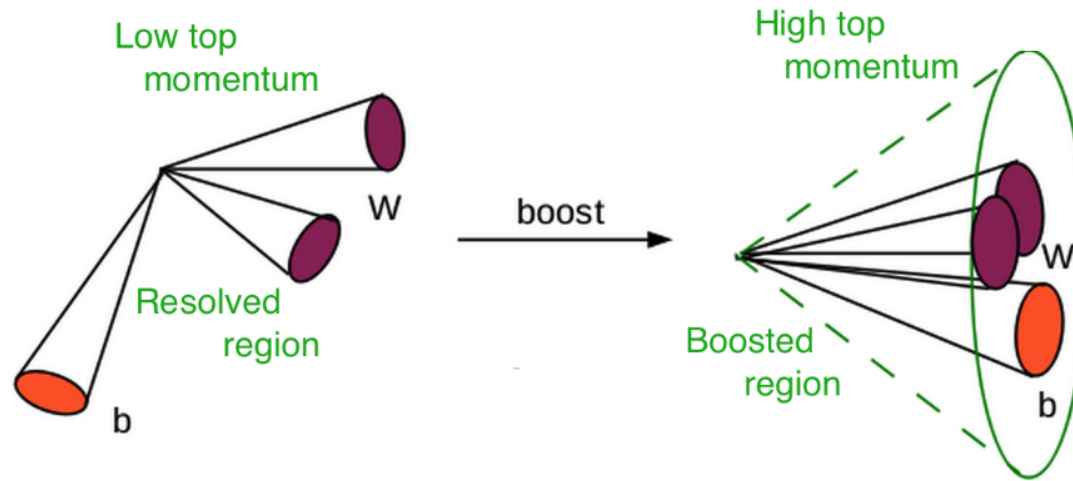
Jets in the Detector

Some massive particles (ex : W/Z) also decay to approximately 2/3 quarks and can form jets :

[4]

Jets in the Detector

If the jets are produced with high momentum, their decay products can be collimated and they can be reconstructed inside a single (large-radius) jet.

[5]

Why Jets ? Why Machine Learning?

First question :
- Are all jets produced at the LHC according to the SM?
- Are there unknown massive particles decaying to jets at the LHC?

Second question :
- All the events that happened at the LHC produce a whole lot of data : 60 TB/s produced, but 1.5 GB/s registered!
- General searches for new physics like in boosted jets over full p_T-spectrum have never been done

The goal : Search for new physics inside jets, but without searching for a specific model.
The method : Use deep learning as an anomaly detection technique (unsupervised method)

Variational Auto-Encoder (VAE) for Jet Physics
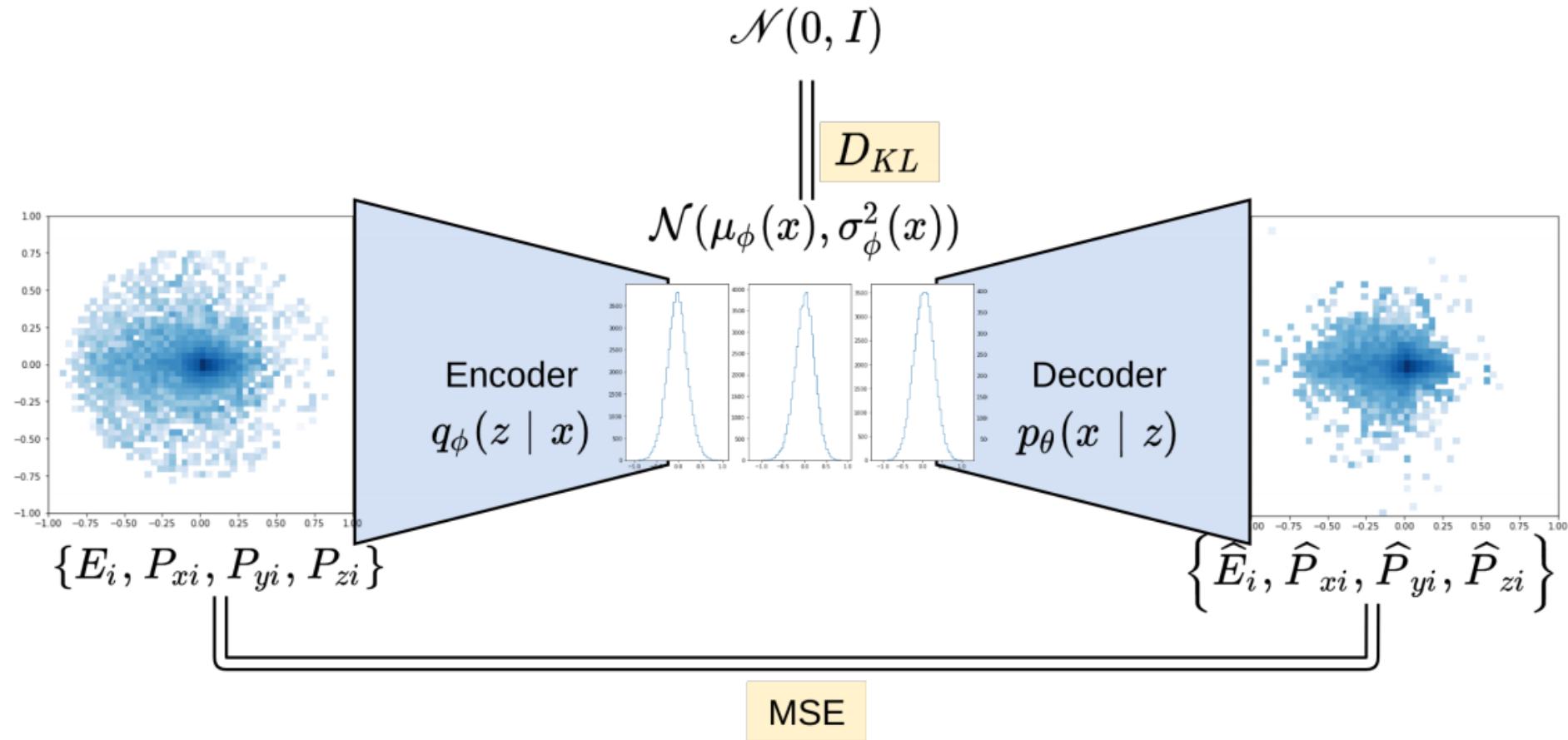
[6]

The Principle

For the first phase of the project, we will look for unknown massive particles decaying to jets. We will thus try to perform a "bump hunting" on the mass spectrum of jets by cutting on the anomaly score.

Before the Cut

After the Cut

SM background

New physics signal

SM background reduced + new signal visible

m_j

m_j
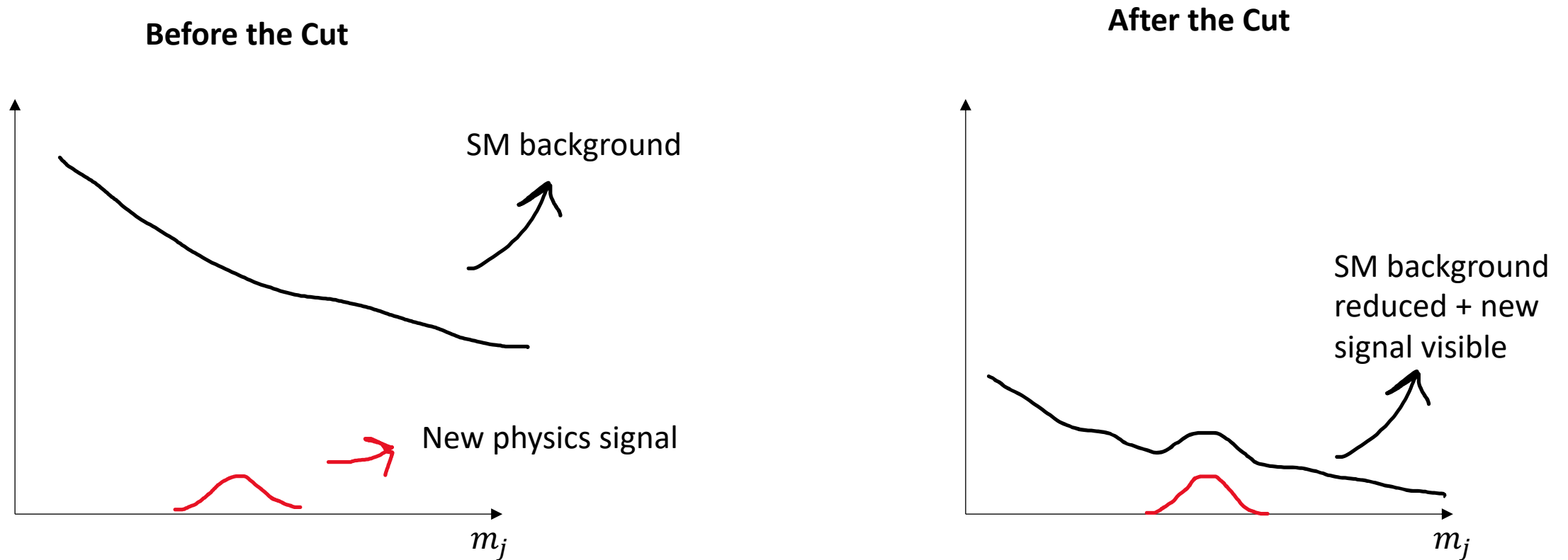
Simulation Samples

We want to know if our algorithm performs well. We choose a test signal to find :

Our background : QCD dijets (gluon jet or light-quark jet, excluding top jets)

Our signal : Boosted $t\bar{t}$ jets (from SM)

Simulated from Monte Carlo :

- Boosted jet (high-p_T) requirement :
  - |η| < 2, no leptons, N(jet), N(jets) with p_T > 200GeV >= 2, N(jets) with p_T > 450GeV >= 1
- We use only the leading large-radius jet

Our inputs are the 4-vectors of the jet constituents.

We compute the anomaly score between the VAE's output and the input.

Discrimination

Our model seems to discriminate reasonably well between our background and signal.

Reconstruction Loss for the VAE
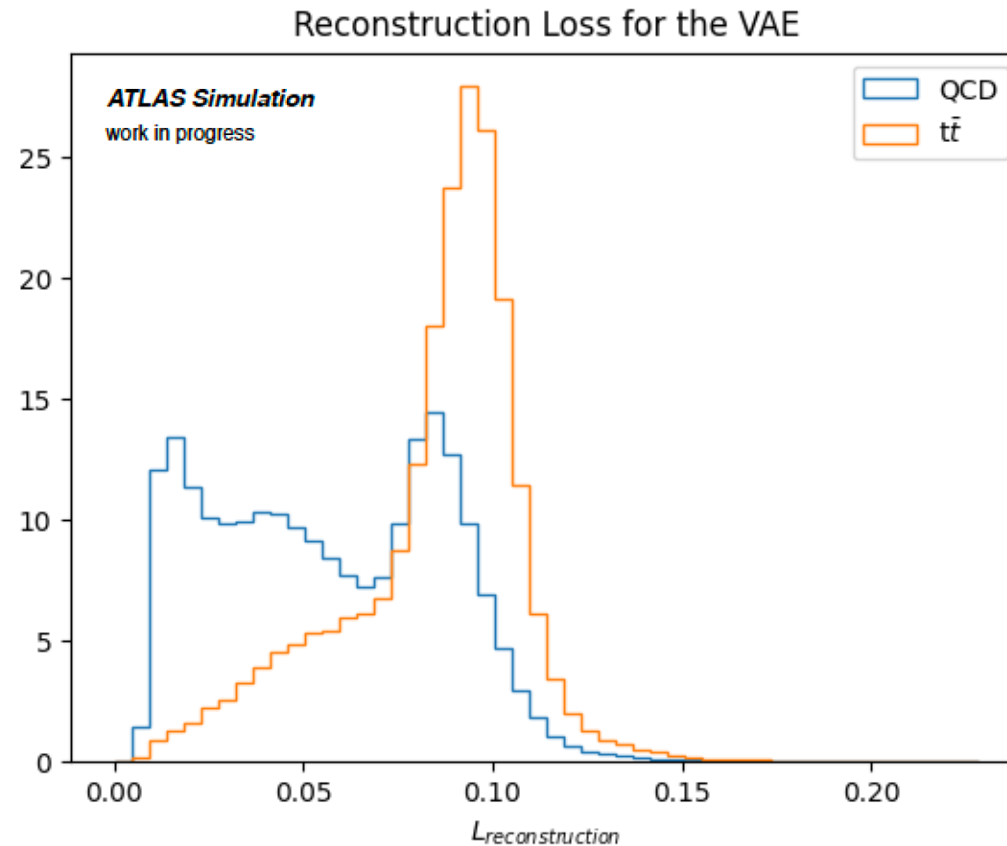
Mass Correlation

If we look at how our background behaves when we cut on the anomaly score:
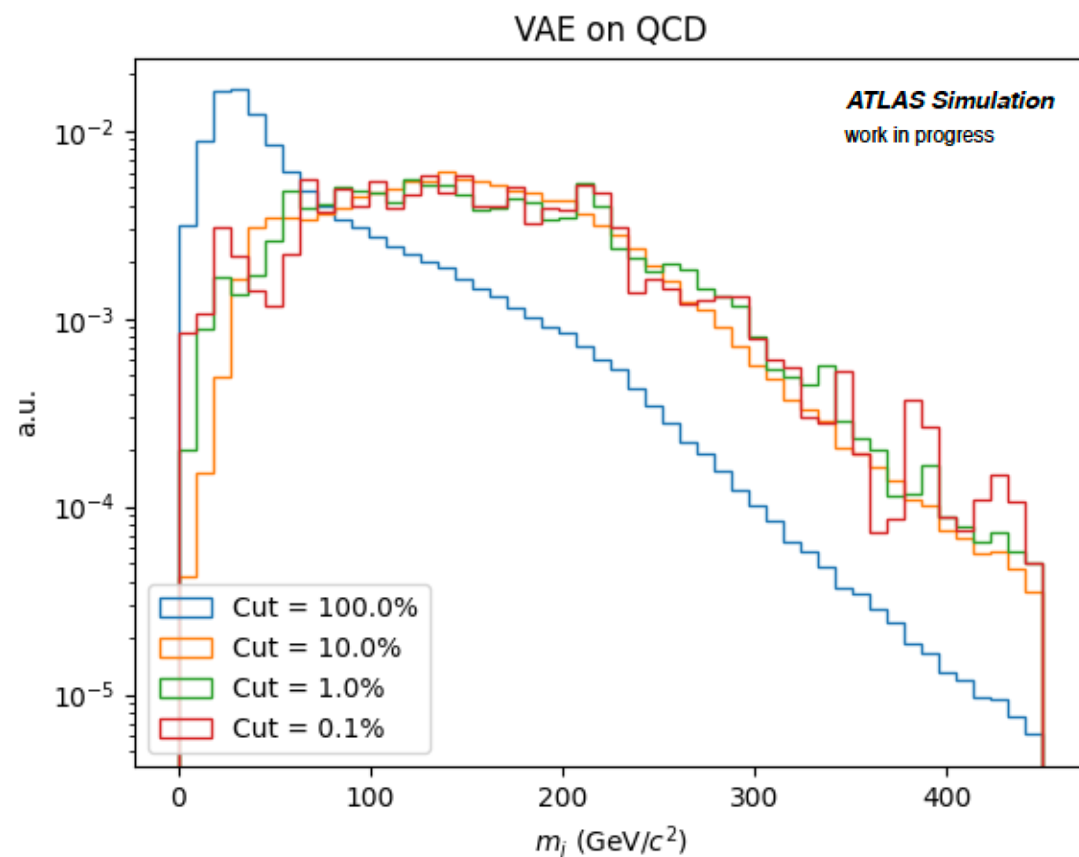
Outlier Exposure

- Semi-supervised method.

- Inject some out of distribution samples to the training.

- The goal is that the VAE gain in sensitivity to outlier jets, and to decorrelate the jet mass from the anomaly score.

- To do this decorrelation, we reweight our outlier sample to match the mass spectrum of our QCD background. «This prevents the VAE from learning the mass of the jet as an important feature, and rather make it focus on the complexity of the jet itself.» [6]

- Outlier = boosted W jet sample

Preliminary Results

Background only (with mass decorrelation)
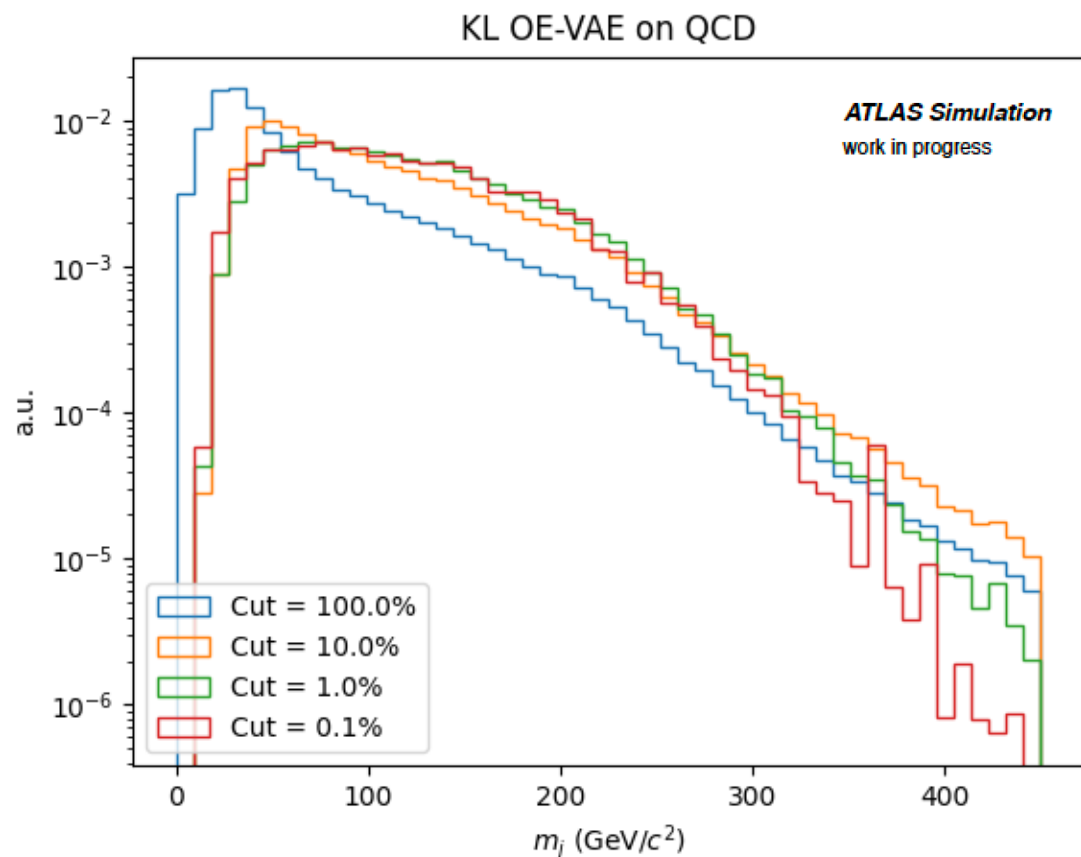
Background + signal
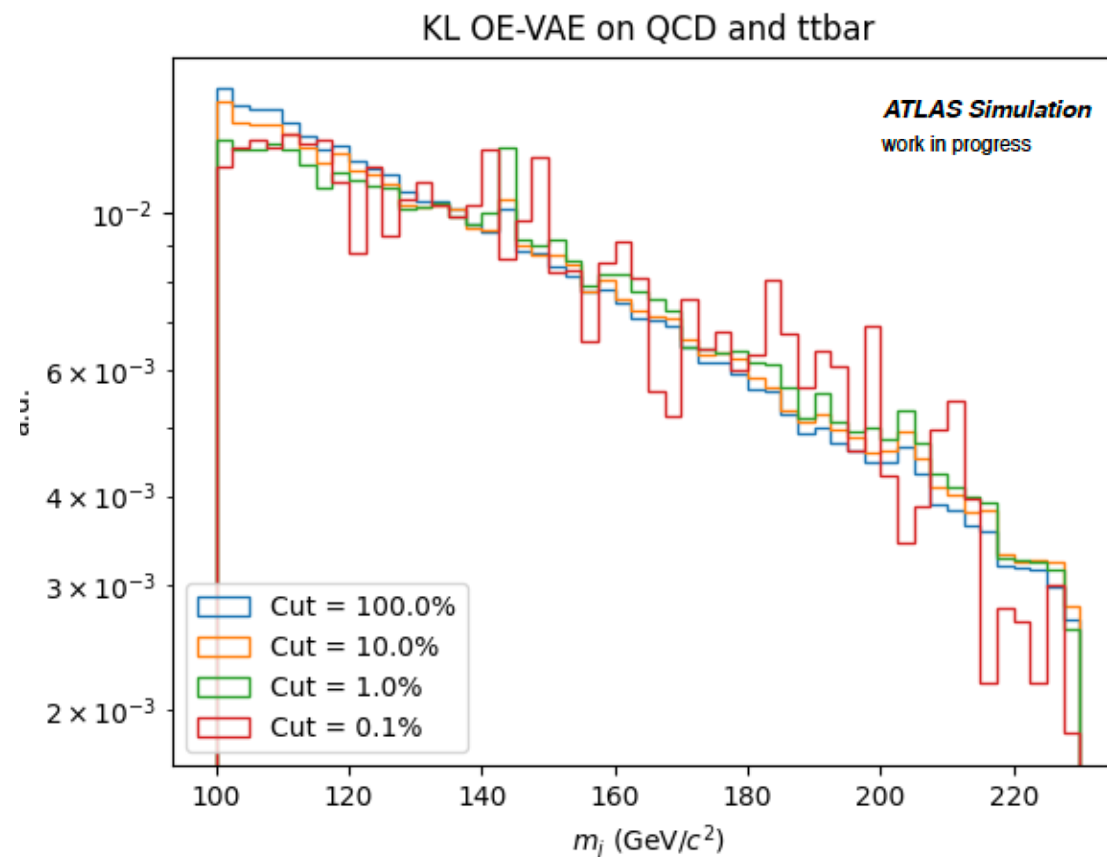
Conclusion

- Machine learning could be a useful tool for general new physics searches in boosted jets

- Anomaly detection with unsupervised methods is a new and innovative way to search for new physics

- To suppress the dominant QCD background, we need better performance from our Variational Auto—Encoder with Outlier Exposure

References

[1] ATLAS Collaboration. (2019). Summary Plots for Exotics Heavy Particle Searches and Exotics/SUSY Long-lived Particle Searches. *ATL-PHYS-PUB*. url : http://cds.cern.ch/record/2682064?ln=en

[2] Pequenao, J. : Computer generated image of the whole ATLAS detector. 2008. url: https://cds.cern.ch/record/1095924.

[3] Quigg, C. : Gauge Theories of the Strong, Weak, and Electromagnetic Interactions. Princeton University Press, 2sd edition, 1983

[4] Spettel, F. M. (2017). *Measurement of the boosted WW+WZ production cross section in the semileptonic decay channel with ATLAS* [PhD Thesis, Universität Tel Aviv]. CERN-THESIS-2017-072. http://cds.cern.ch/record/2271216

[5] Martínez Solaeche, G. : Top tagging at the LHC experiments with proton-proton collisions at 13 TeV. PhD thesis. 2015. doi: 10.13140/RG.2.1.4521.4560.

[6] Cheng, T., Arguin, J-F., Leissner-Martin, J., Pilette, J., Golling, T. : Variational Autoencoders for Anomalous Jet Tagging. arXiv:[hep-ph] : 2007.01850. 2020.