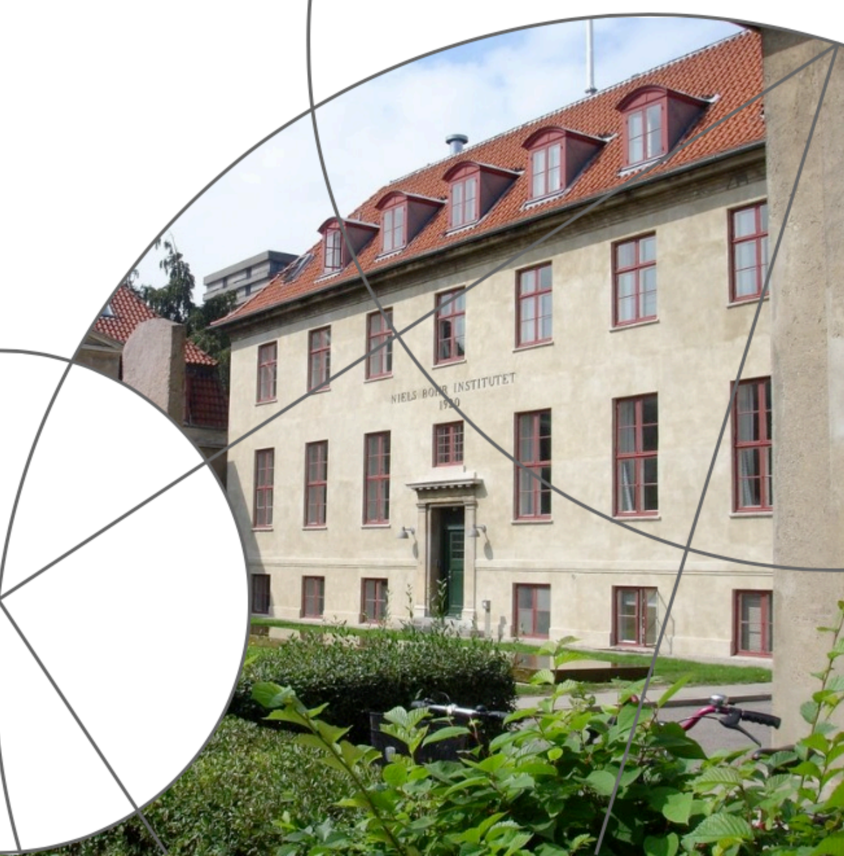
Rethinking searches for new physics at the LHC

Flavia de Almeida Dias

Nordic Conference on Particle Physics - Spaatind 2020

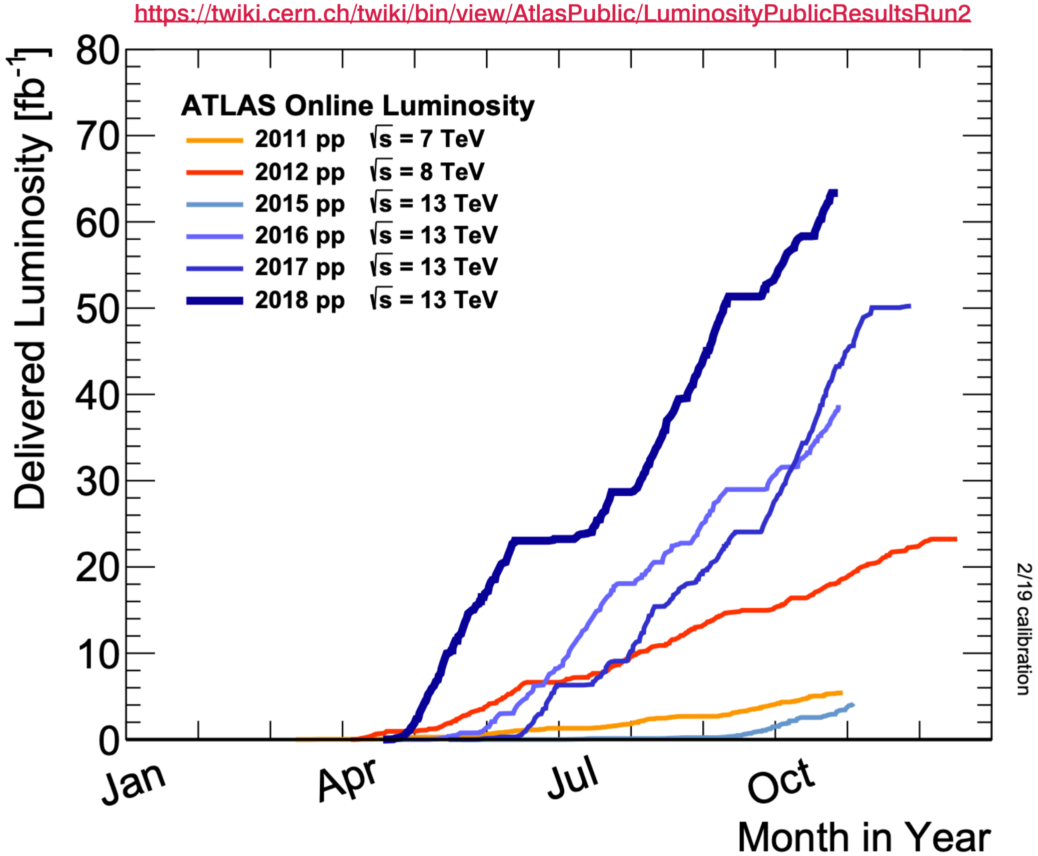
03 January 2020



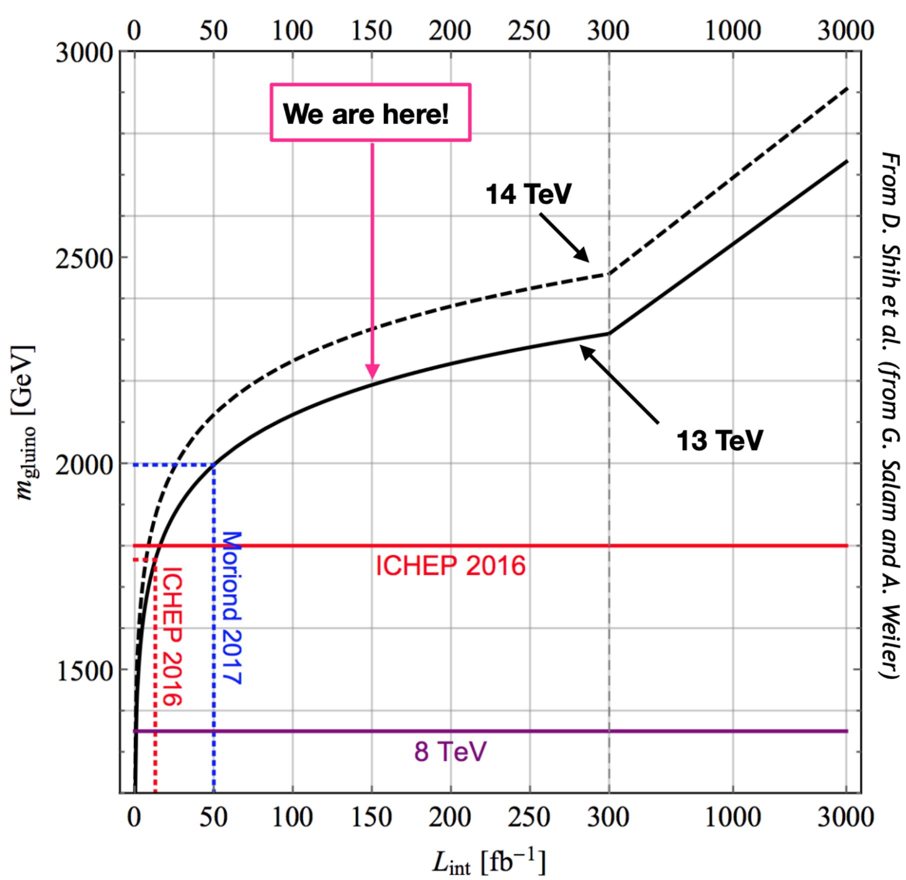
LHC Run 2 (2015 - 2018)

- Increase in energy from 8 → 13 TeV
- Major new-physics sensitivity opened up, specially at high masses
- Integrated luminosity: 140 fb^{-1}

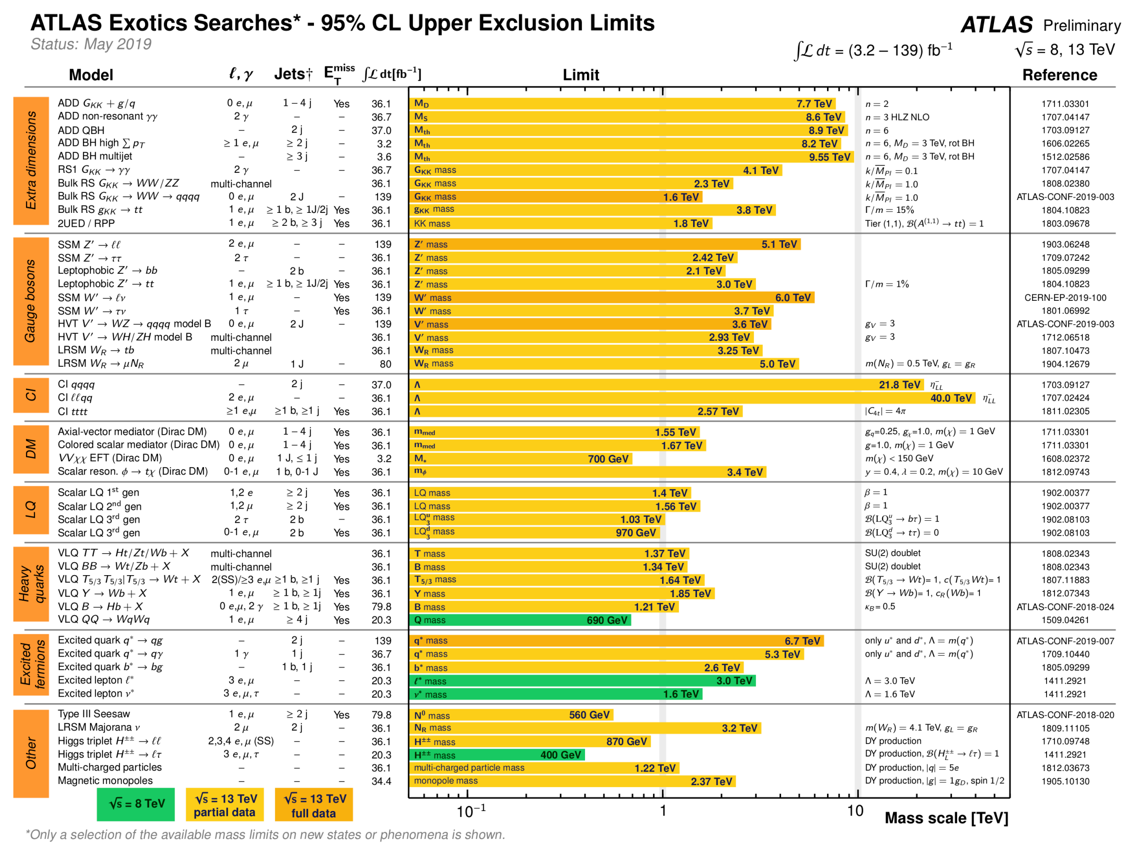
https://twiki.cern.ch/twiki/bin/view/AtlasPublic/LuminosityPublicResultsRun2

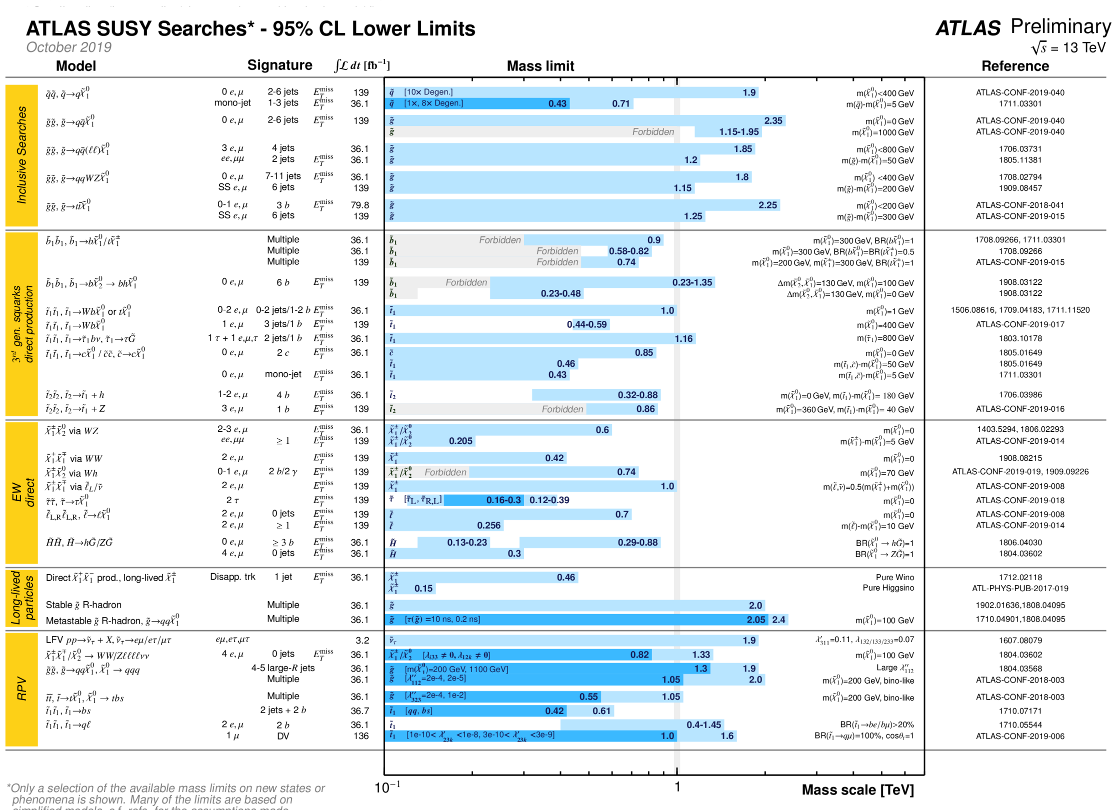


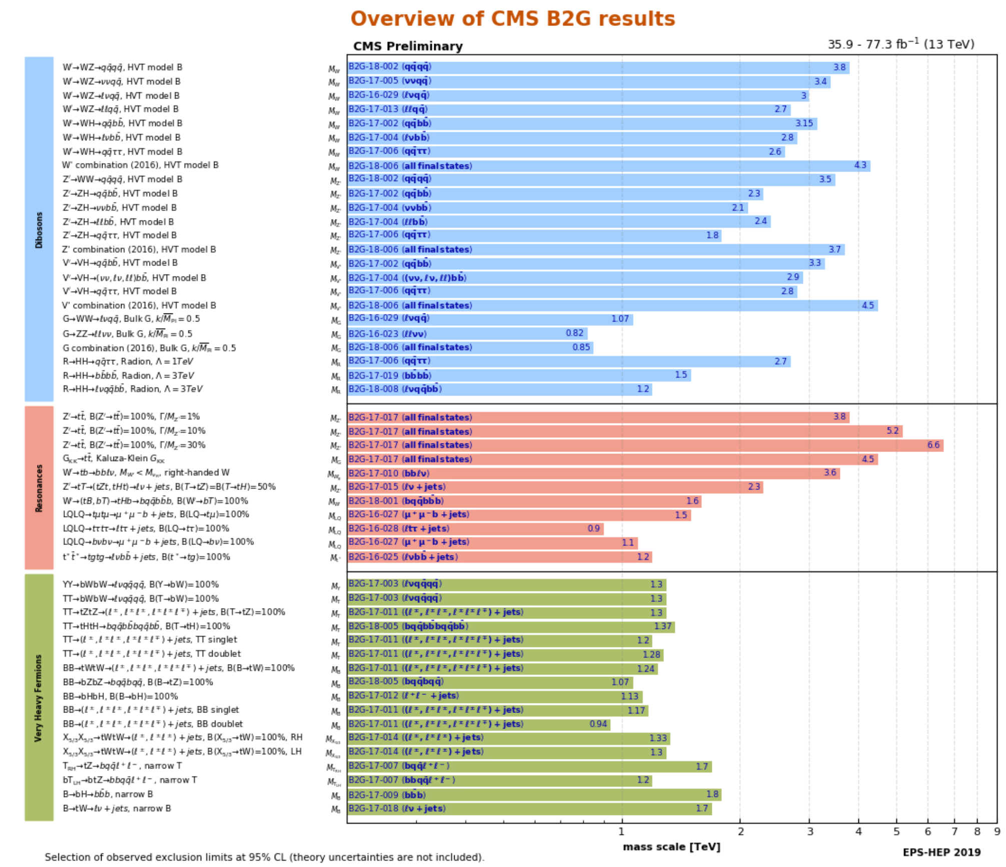
From Marumi's talk earlier today

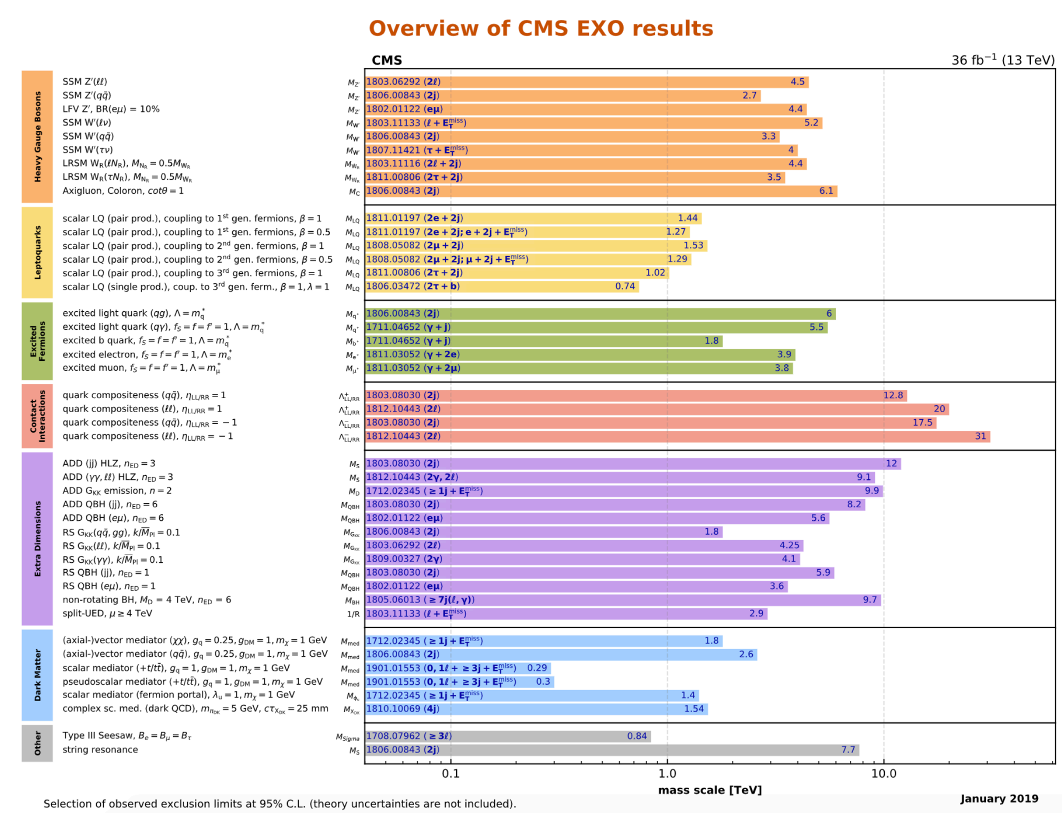


Hundreds of searches performed

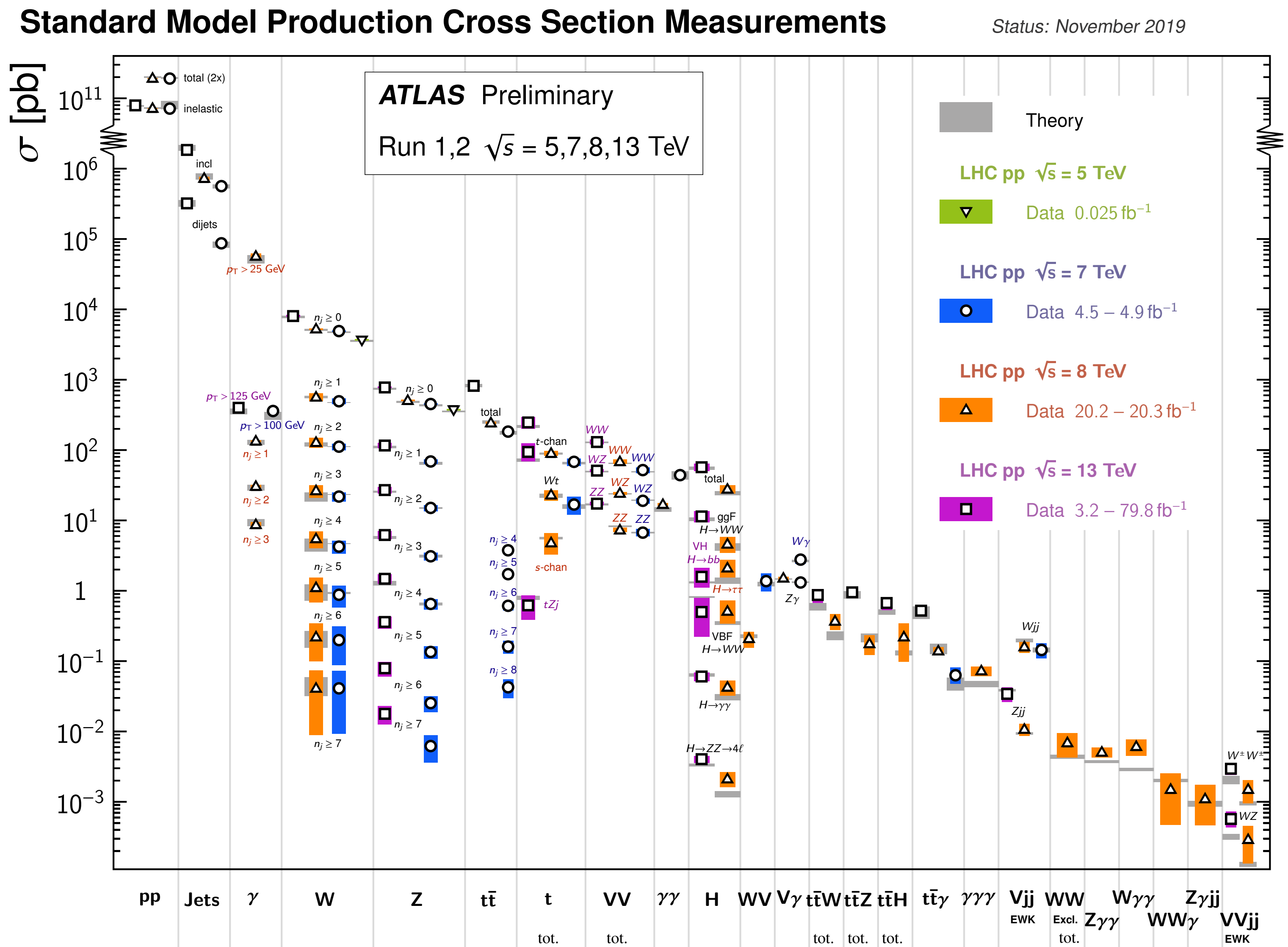


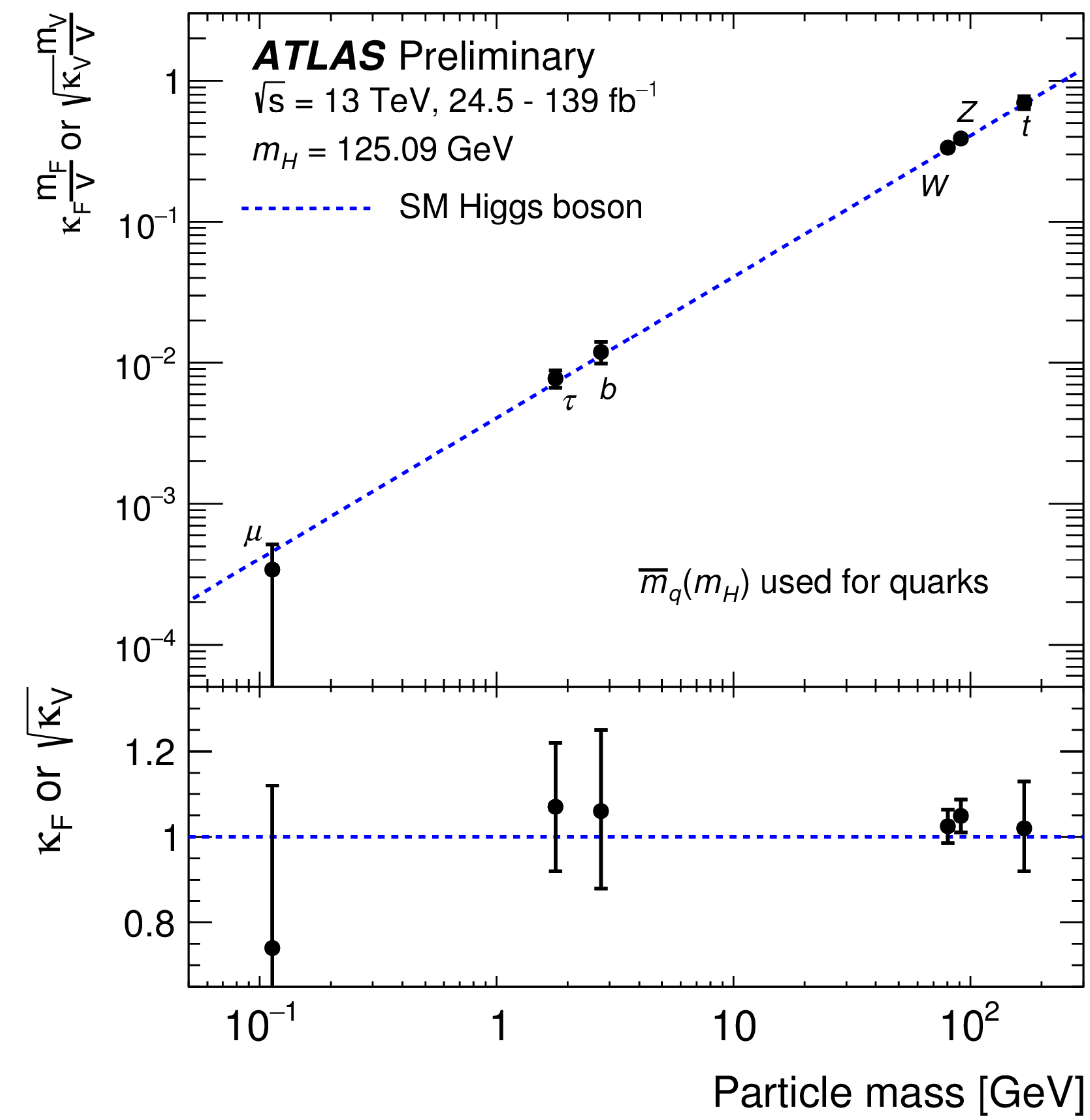






Many measurements to probe the SM





- The Standard Model persists being unchallenged by LHC data so far

What's next?

No BSM

BSM very rare

What's next?

Looking in the wrong place!

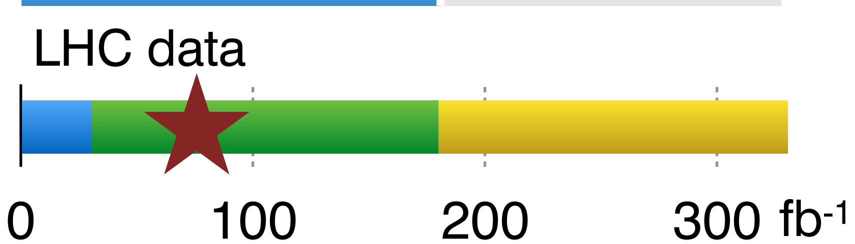
No BSM

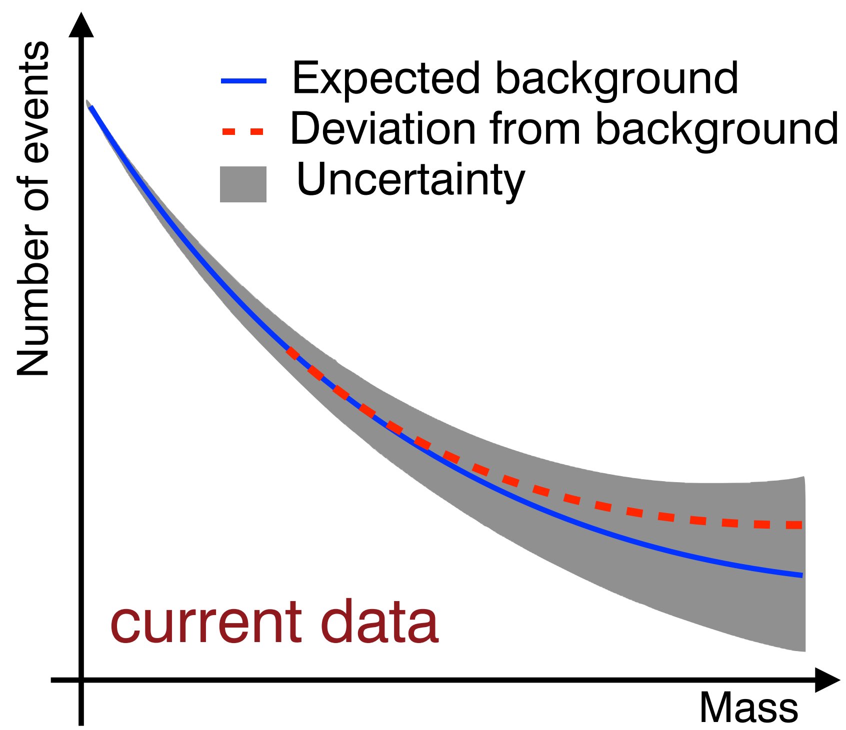
- Assume that: neutrino masses does not lead to any new physics; there is no particle composition to dark matter; ignore all b-jet anomalies; hierarchy of masses/forces just are what they are;

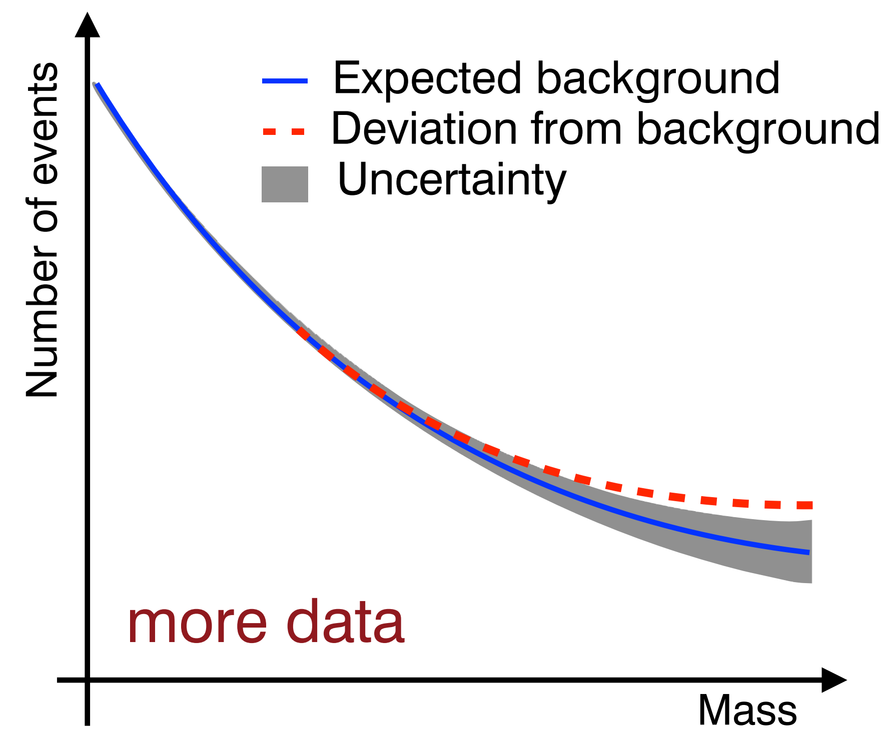
- Keep performing searches as we do;
- Precision measurements to look for deviations
  - ➡ Use of effective field theories (SMEFT) to parameterise a large class of BSM models

BSM very rare

ATLAS Higgs Results	Combined signal strength
At discovery July 2012	1.2 ± 0.3
March 2019 (with 8x more data)	$1.11^{+0.09}_{-0.08}$







- Development of generic, less model-dependent[1] 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 ⇨ falsification of the SM

Looking in the wrong place!

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

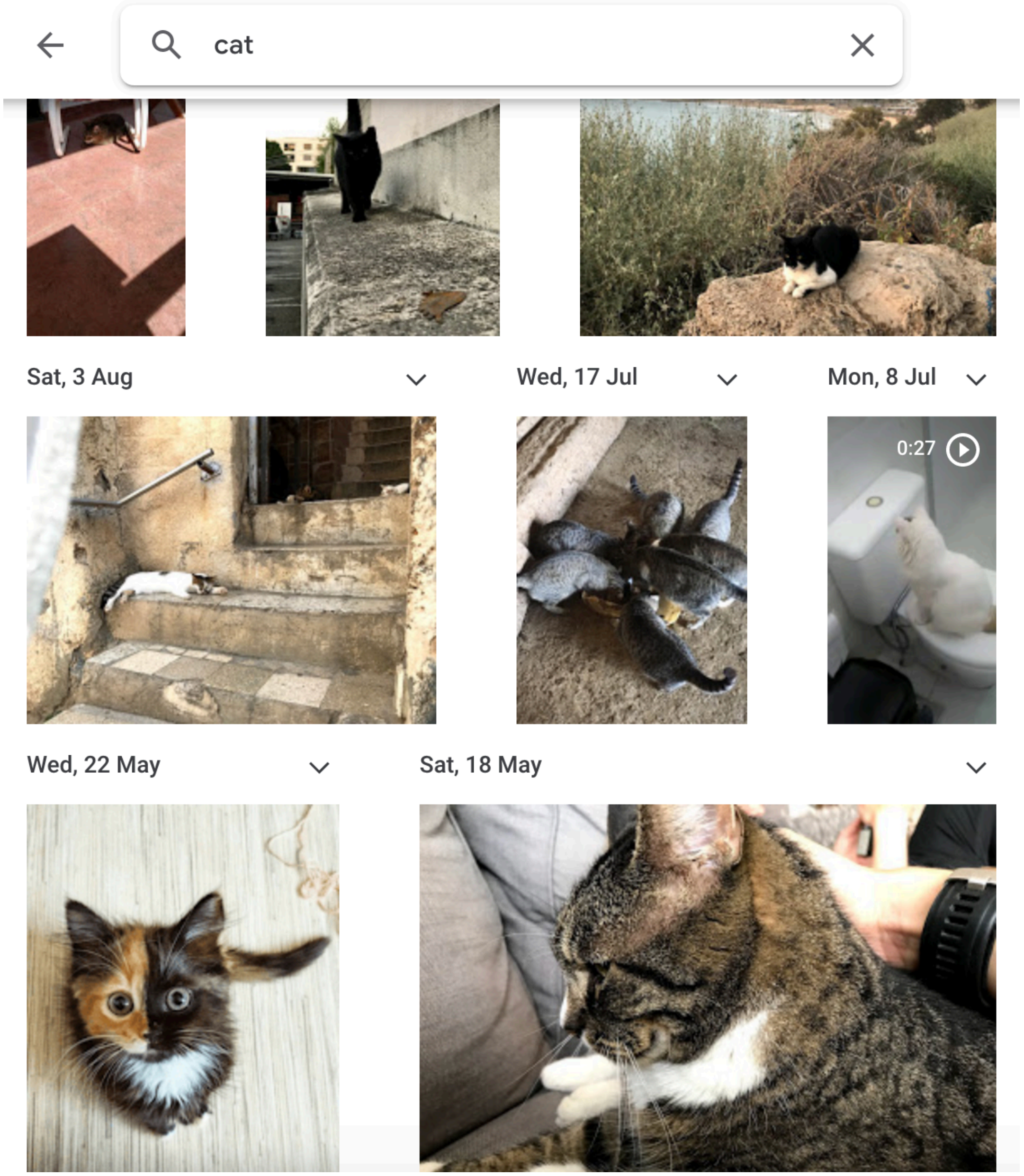
Machine Learning Tools

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

Machine Learning Tools

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

Image Recognition



Google Photos search

Machine Learning Tools

- 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

COMPLETE TEXT

https://talktotransformer.com/

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."

Machine Learning Tools

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

Image and video generation

https://thispersondoesnotexist.com/

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
- …

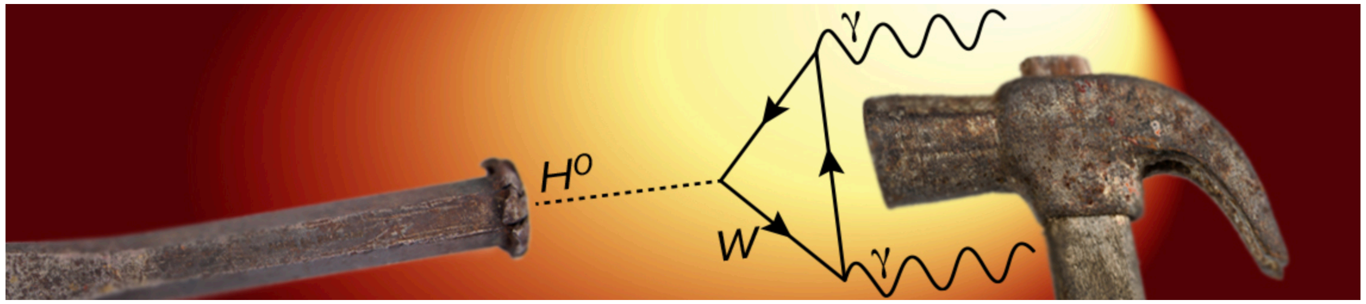
Guest, Cranmer, Whiteson
Annu. Rev. Nucl. Part. Sci. 2018. 68:1–22

Nature 560, 41-48 (2018)

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 P values	Additional data required
CMS[24] $H \to \gamma\gamma$	2011–2012	2.2σ, $P = 0.014$	2.7σ, $P = 0.0035$	4.0	51%
ATLAS[43] $H \to \tau^+\tau^-$	2011–2012	2.5σ, $P = 0.0062$	3.4σ, $P = 0.00034$	18	85%
ATLAS[99] $VH \to bb$	2011–2012	1.9σ, $P = 0.029$	2.5σ, $P = 0.0062$	4.7	73%
ATLAS[41] $VH \to bb$	2015–2016	2.8σ, $P = 0.0026$	3.0σ, $P = 0.00135$	1.9	15%
CMS[100] $VH \to bb$	2011–2012	1.4σ, $P = 0.081$	2.1σ, $P = 0.018$	4.5	125%

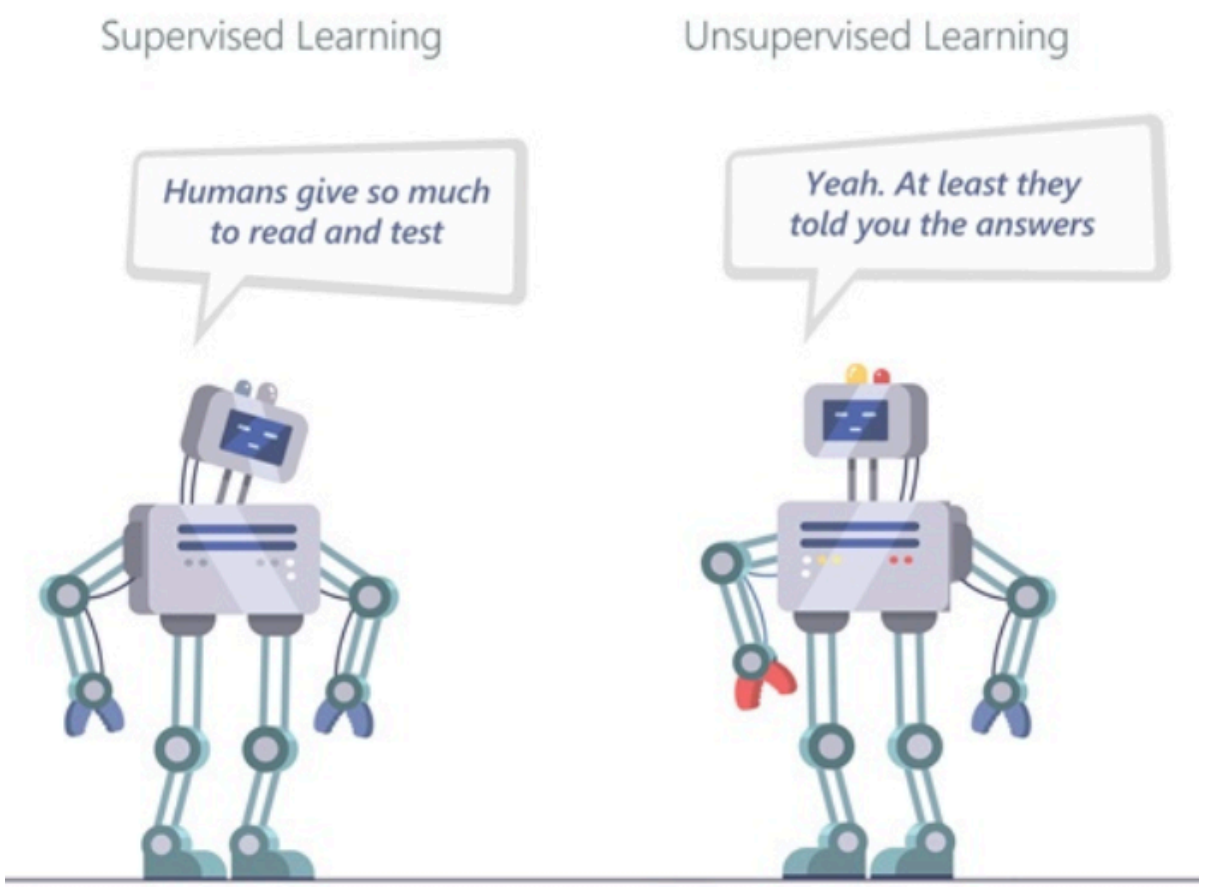
Five key measurements of three decay modes of the Higgs boson H for which machine learning greatly increased the sensitivity of the LHC experiments, where V denotes a W or Z boson, γ denotes a photon and b a beauty quark. For each analysis, the sensitivity without and with machine learning is given, 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



https://www.immuniweb.com/

- Unsupervised:
  - ➡ 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

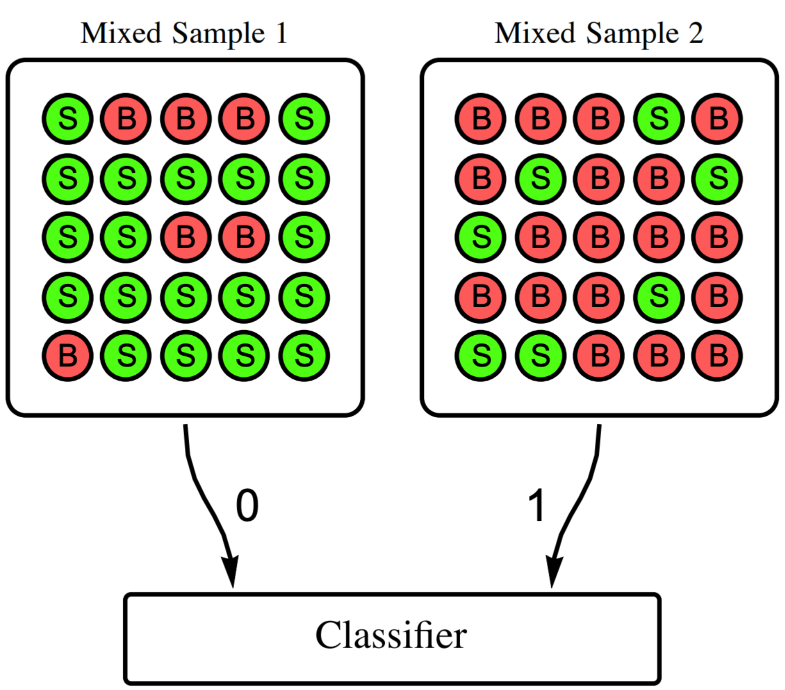
Classification Without Labels (CWoLa)

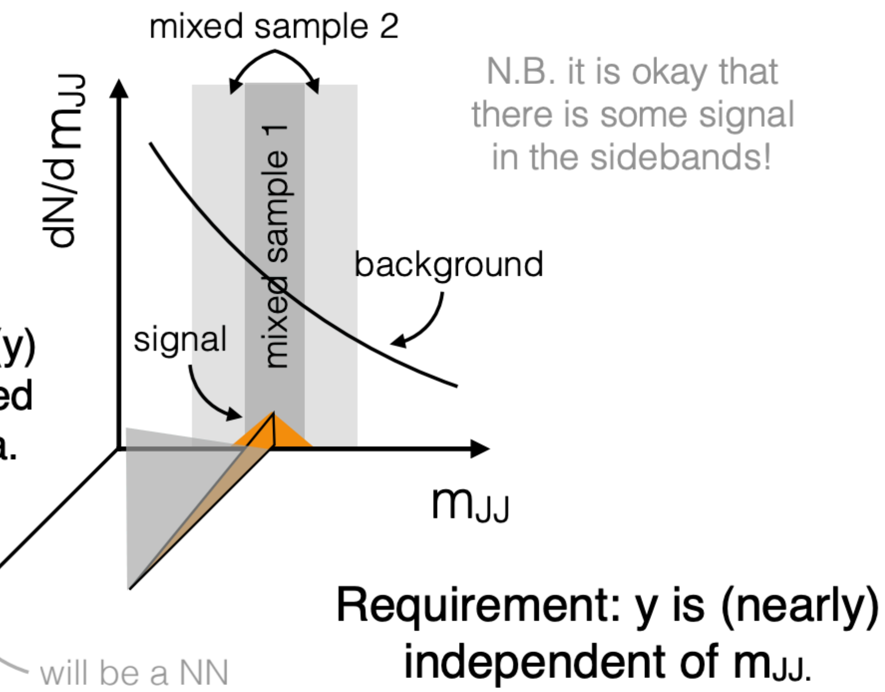
- Look into di-jet (large-R jets) resonance searches
  - ➡ Regular search looks for X → W/Z → J J
  - ➡ CWoLa: X → Y → J J

CWoLa

Classification Without Labels

From Ben Nachman

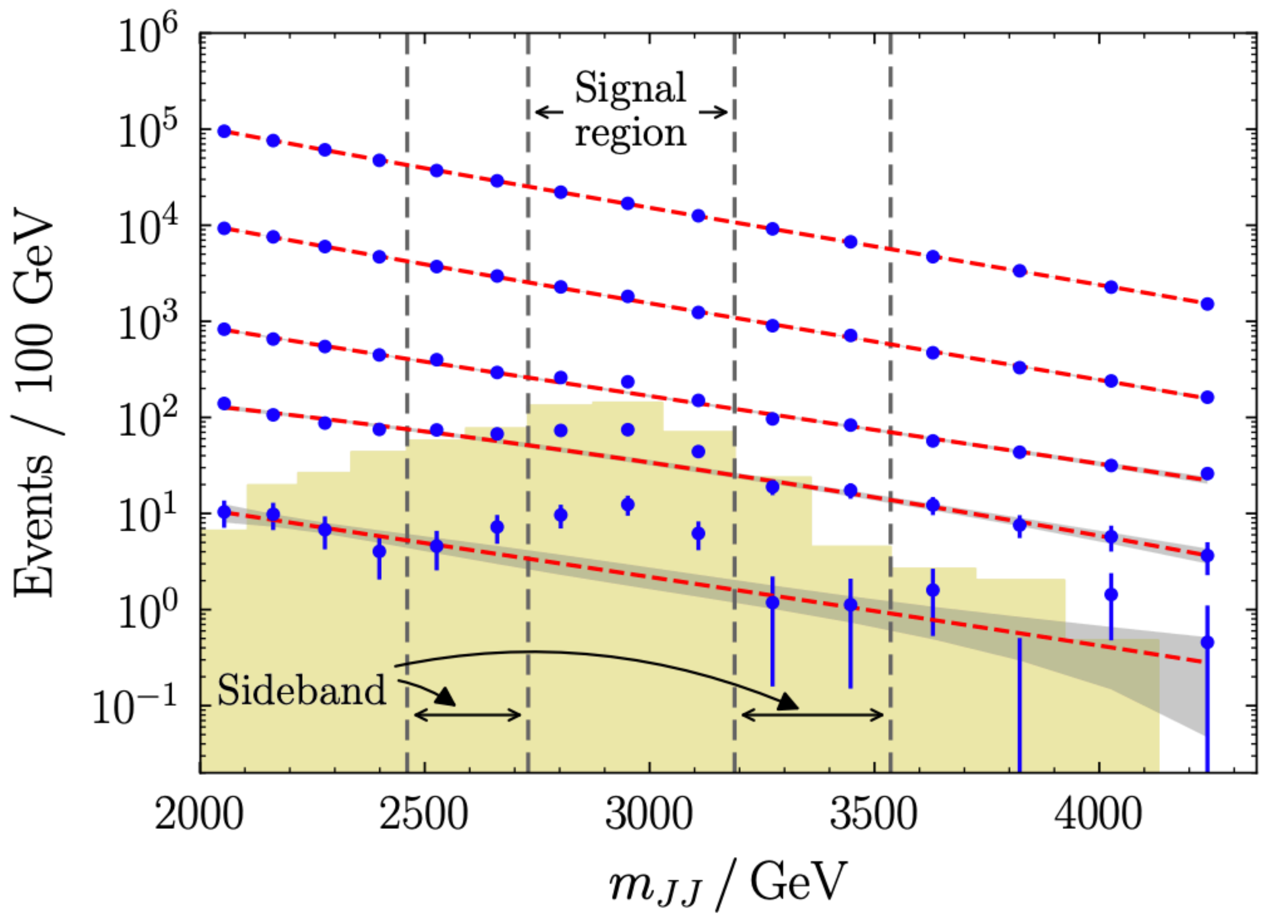


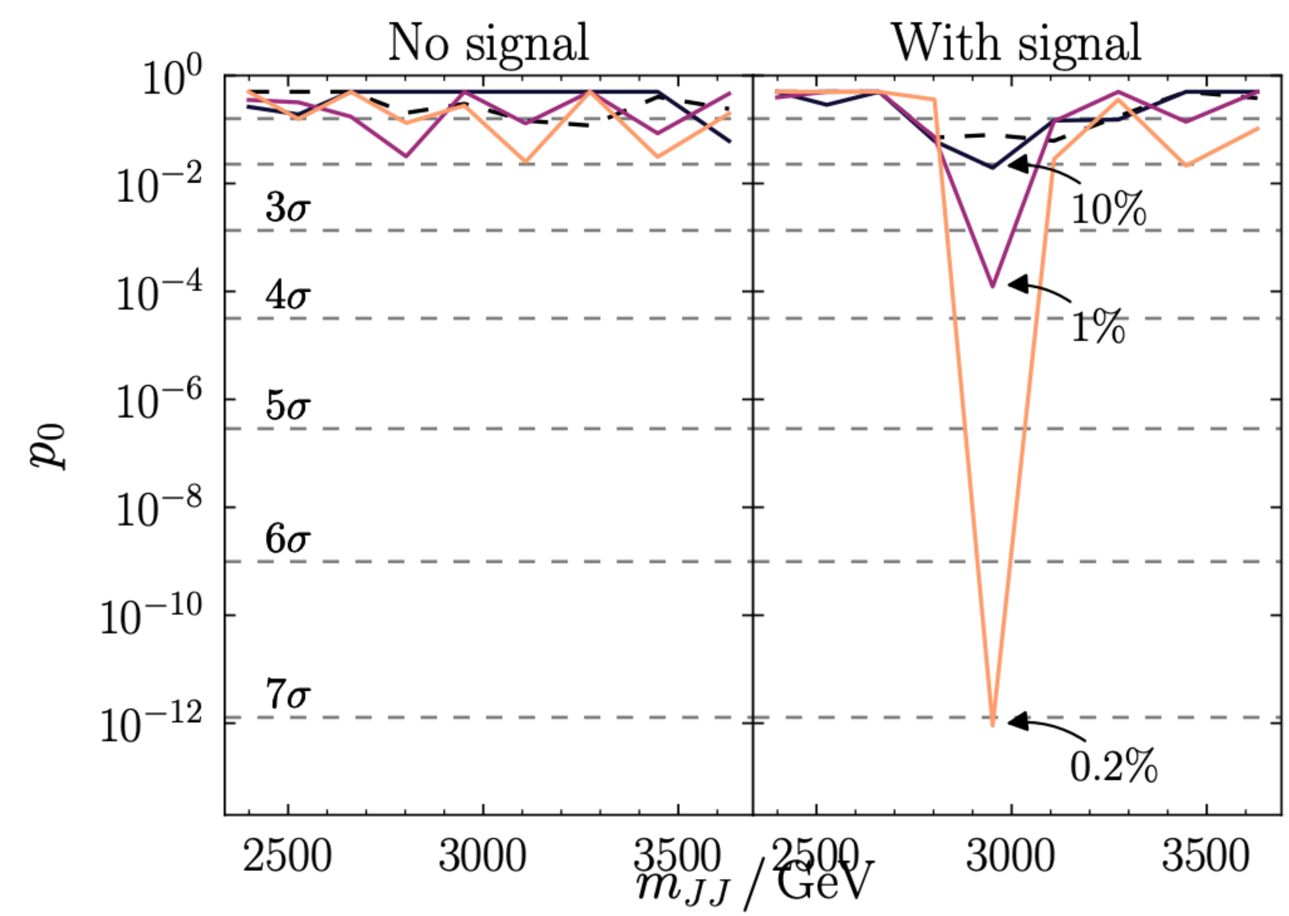


Selection on classifier output

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

Classification Without Labels (CWoLa)



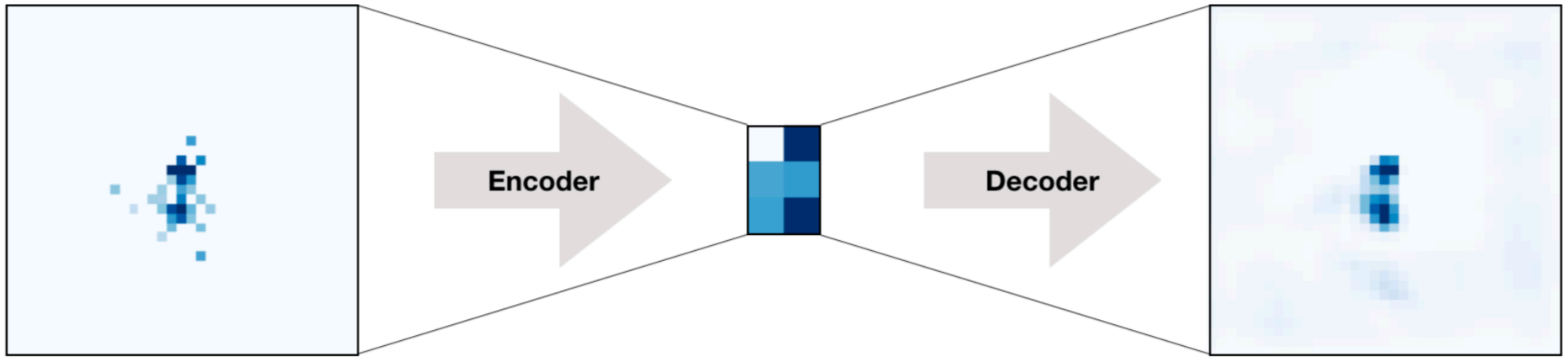


- ✓ Independent of model (limited to a specific signature)
- ◉ Limited application for very weak signals
- ◉ There can be complications decorrelating *y* features from final discriminant variable

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

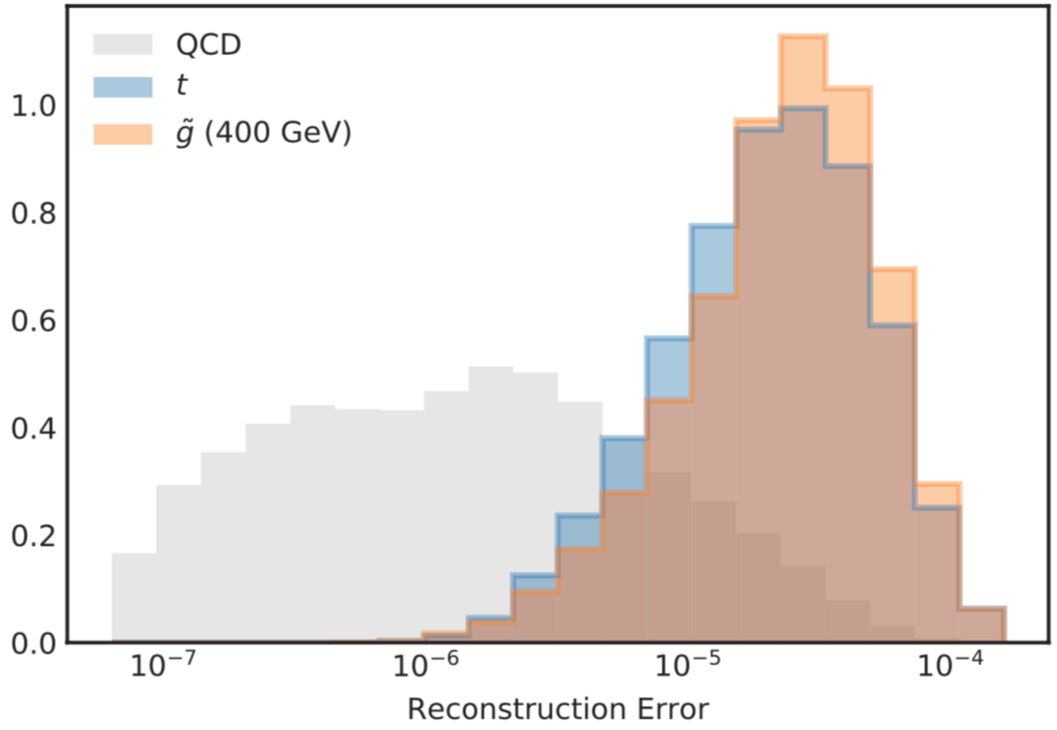
Anti-QCD Taggers

- Autoencoders (AE)



➡ Map "normal" events back to themselves, but fails to reconstruct "anomalous" events that it has never encountered before.

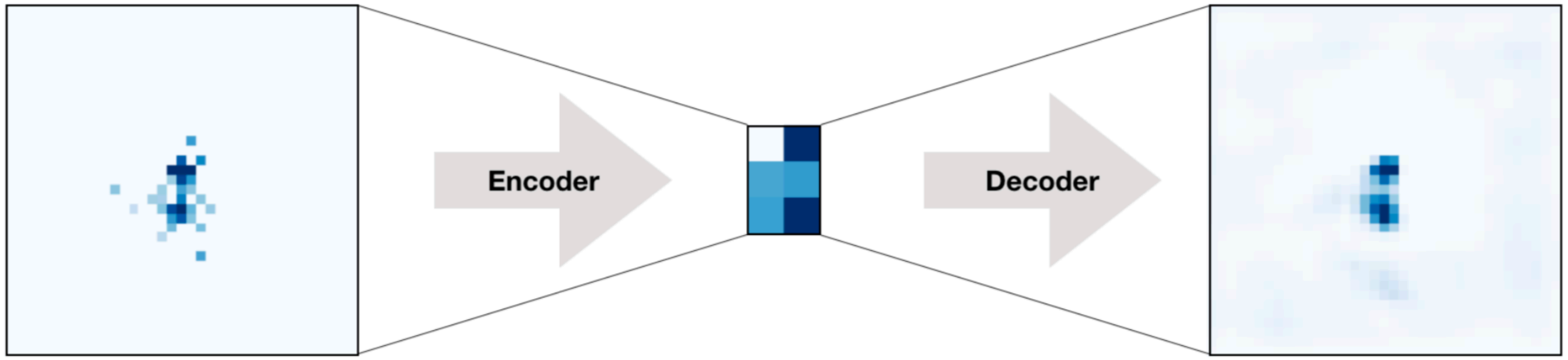
➡ Reconstruction error ⇒ anomaly threshold



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.
  - ➡ Reconstruction error ⇒ anomaly threshold

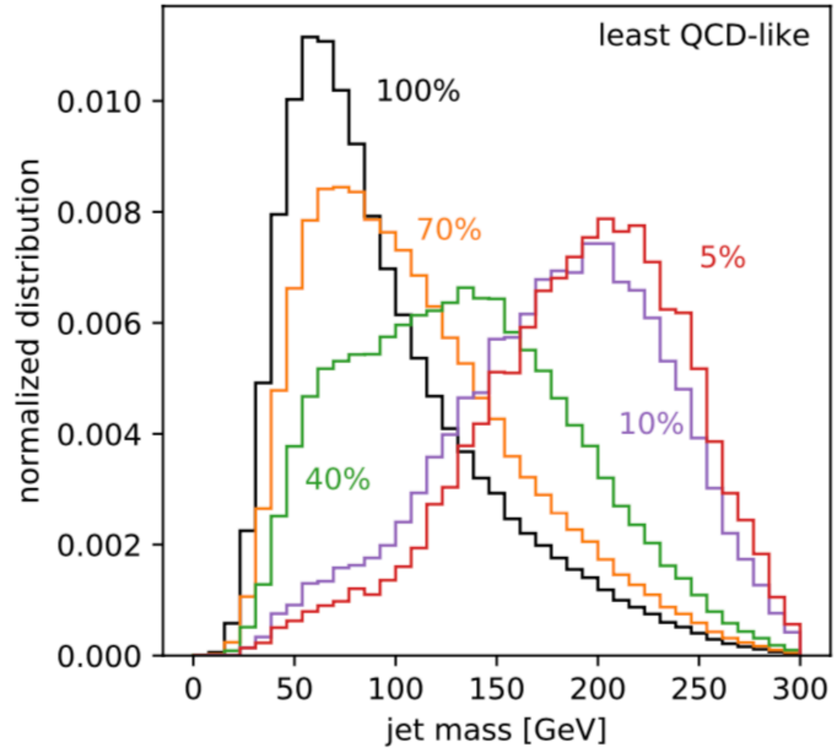
- Train on MC background only (weakly supervised) and in data with ~small amounts of signal (typical control region - unsupervised)
- Test on Monte Carlo with top/BSM signals
- Look into correlation effects with the jet mass (control with choice of architecture [1] or with adversarial network [2])

[1] Farina, Nakai, Shih
arXiv: 1808.08992

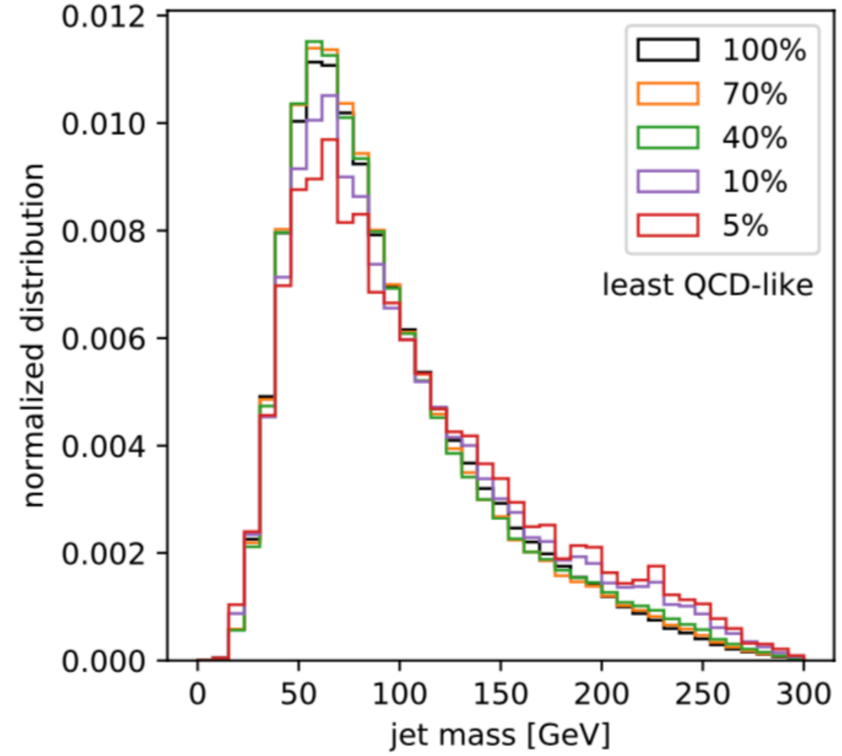
[2] Heimel, Kasieczka, Plehn, Thompson
SciPost Phys. 6, 030 (2019)

Anti-QCD Taggers

No adversarial

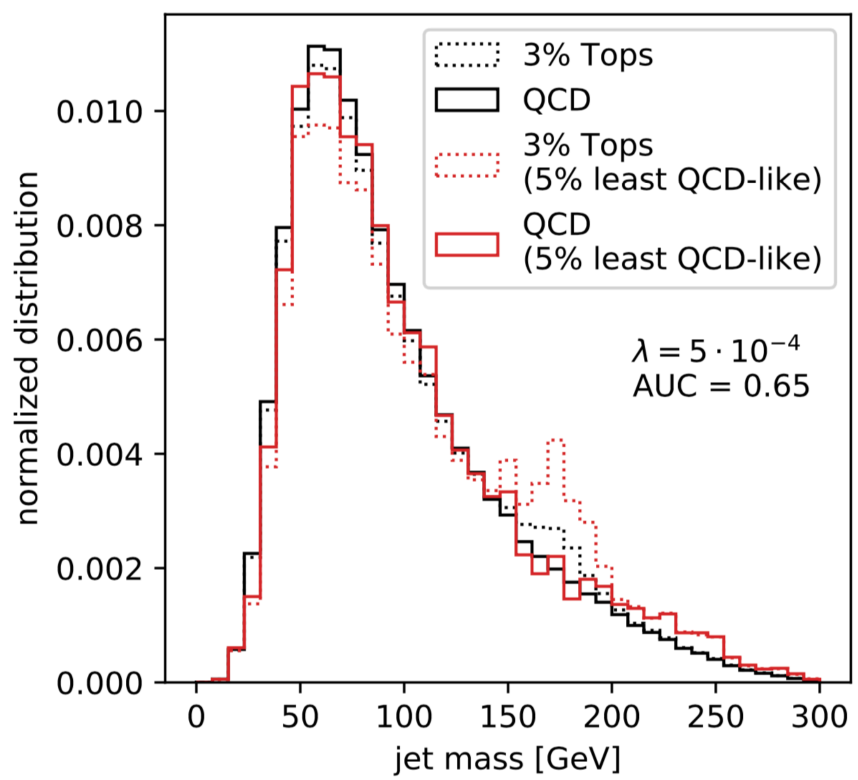


Adversarial



all events
anomalous

- - contaminated
— pure QCD



Training made with mixed sample:
QCD + 3% top quarks

Adversarial makes background stable (full lines)

Signal is enhanced in the above threshold events even if present in training (dashed red)

Heimel, Kasieczka, Plehn, Thompson
SciPost Phys. 6, 030 (2019)

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

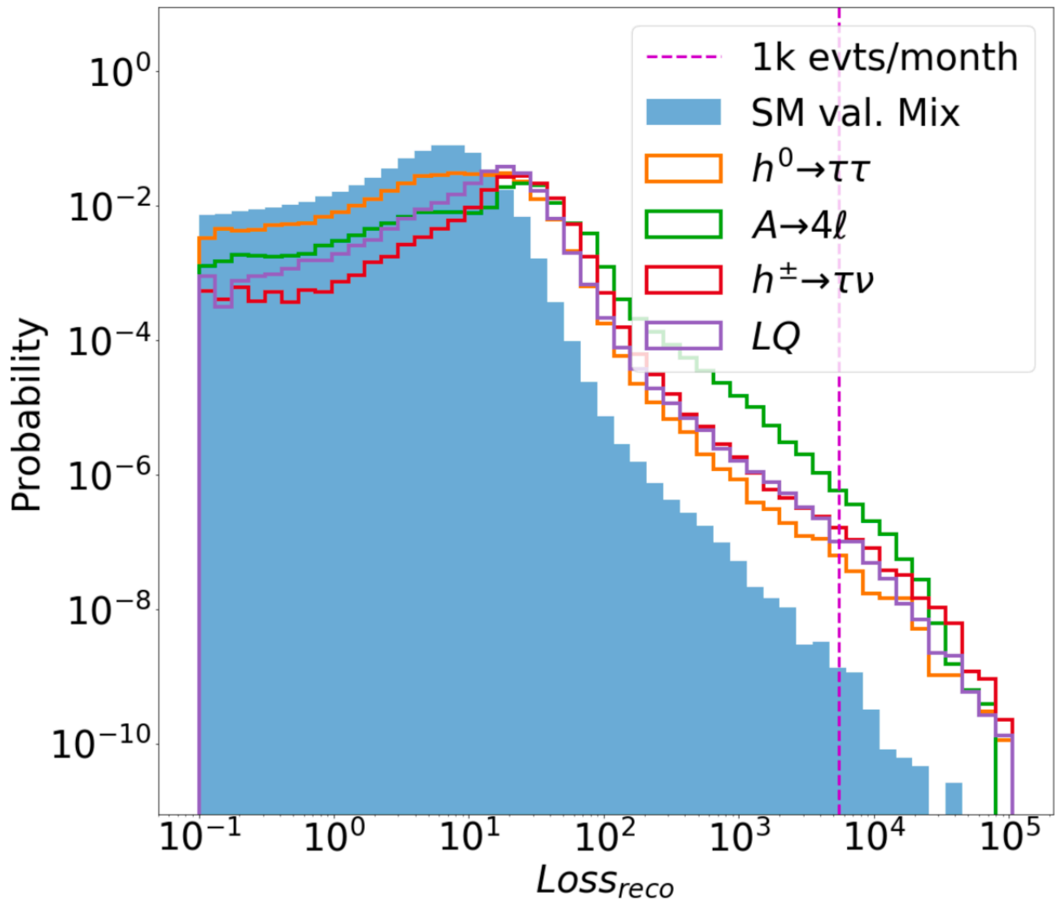
Full-Event Training - Trigger Level

- VAE[1] 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

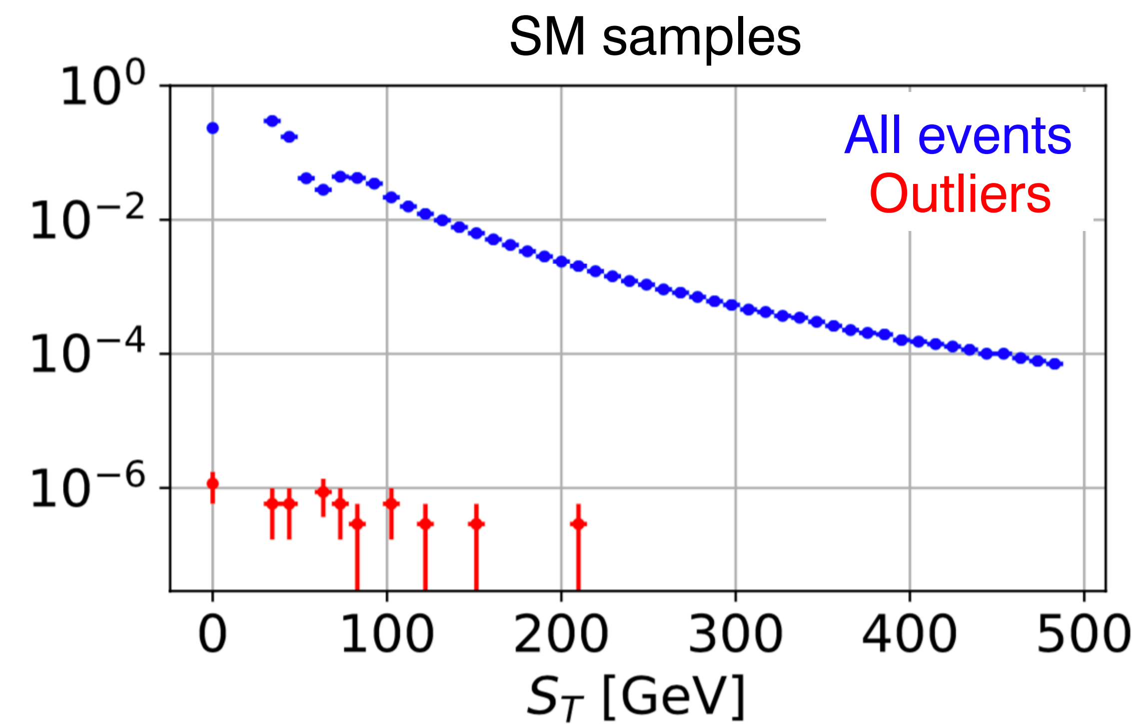
[1]: Variational Autoencoder: similar to AE but allows a stochastic modelling of late space

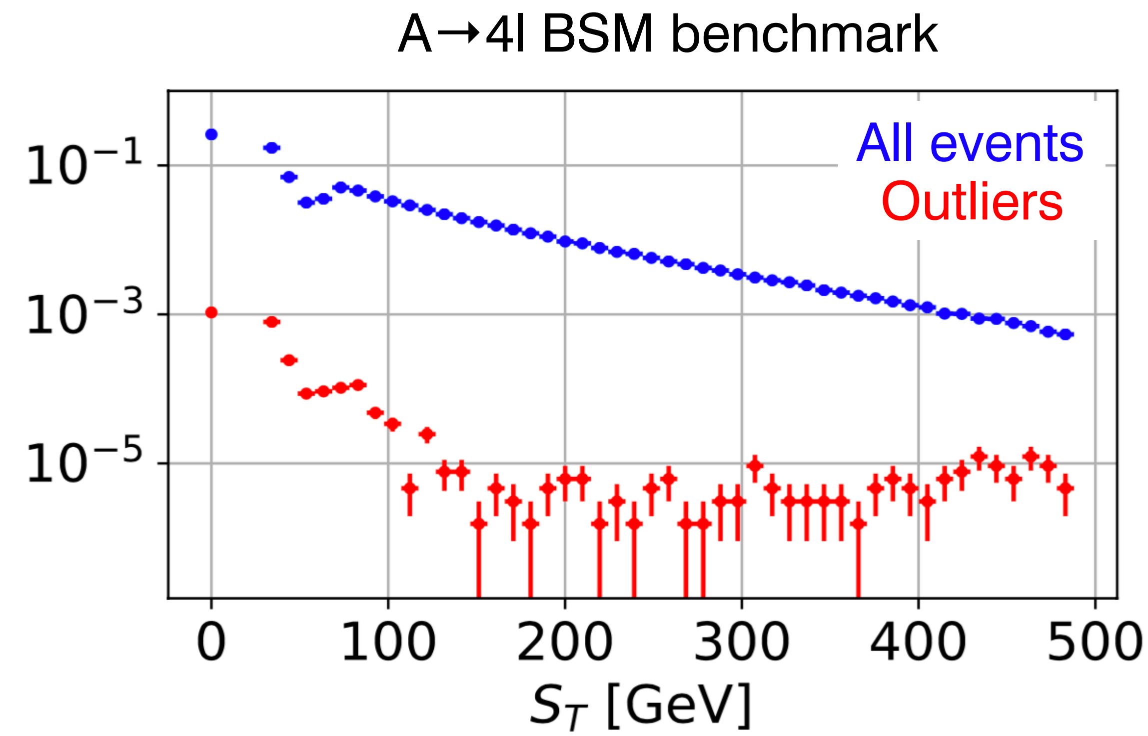
Full-Event Training - Trigger Level



Reconstruction loss function for SM and signal benchmarks

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





Not trivially samples from tails

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

Full-Event Training - Trigger Level

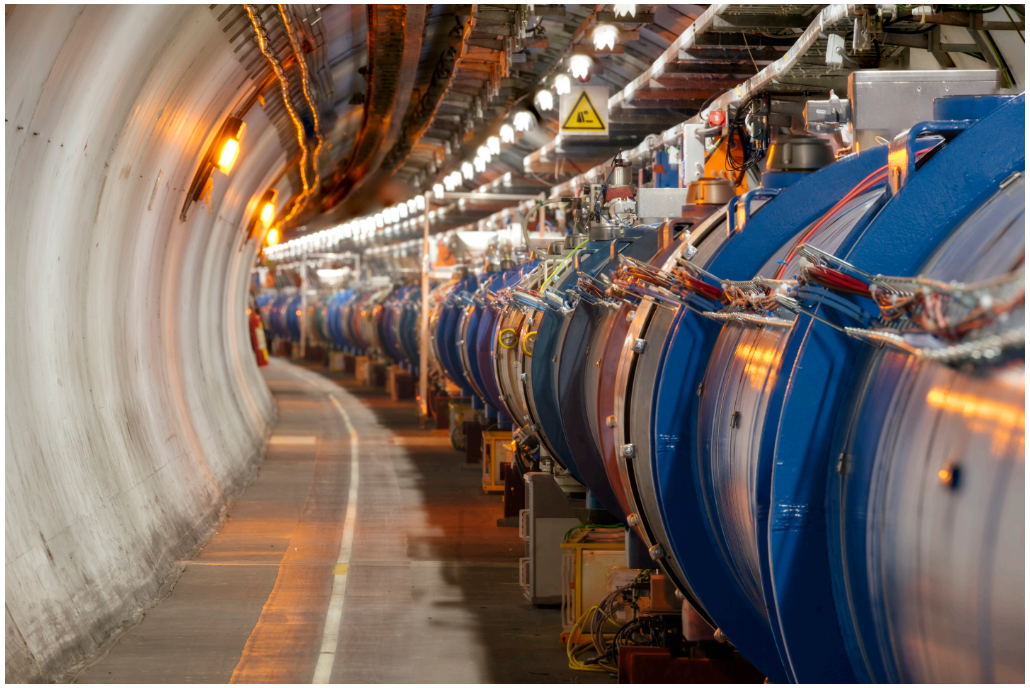
- ✓ Identify anomalies that would escape detection due to trigger selection
- ✓ High purity sample of potentially interesting events
- ◉ Small signal efficiency
- ◉ Strong bias in dataset definition (not possible to perform traditional data-driven and supervised search)
- ✓ Repeated patterns to motivate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

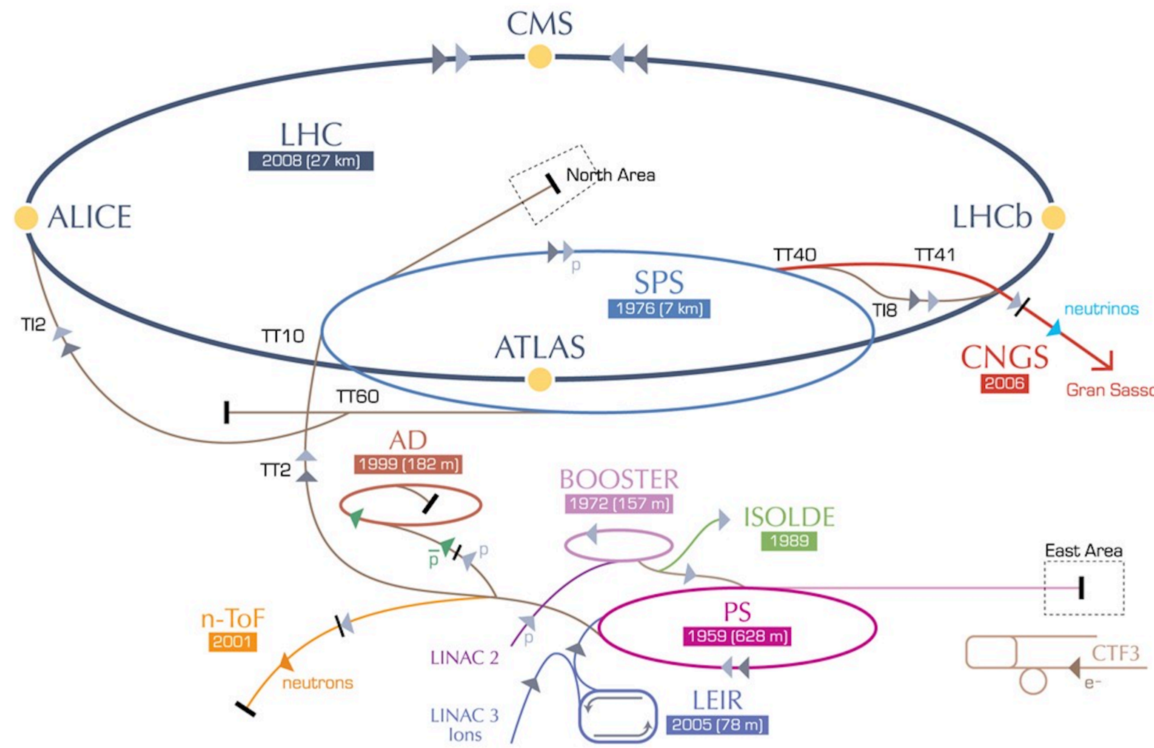
Summary and Outlook

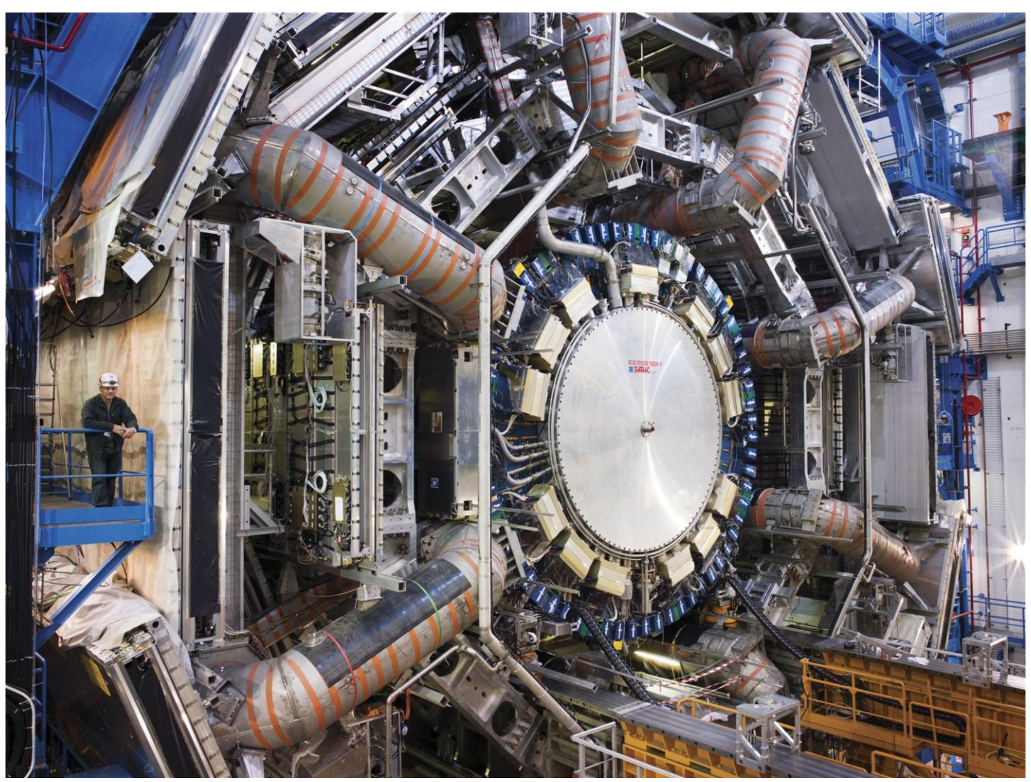
- Current scenario at the LHC motivates searches other than supervised testing of specific BSM models
- Deep learning can provide tools to look for generic new physics looking into specific final states objects or full events
  - ✓ Possibility to find not yet thought of scenarios
  - ◉ Still poses challenges 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

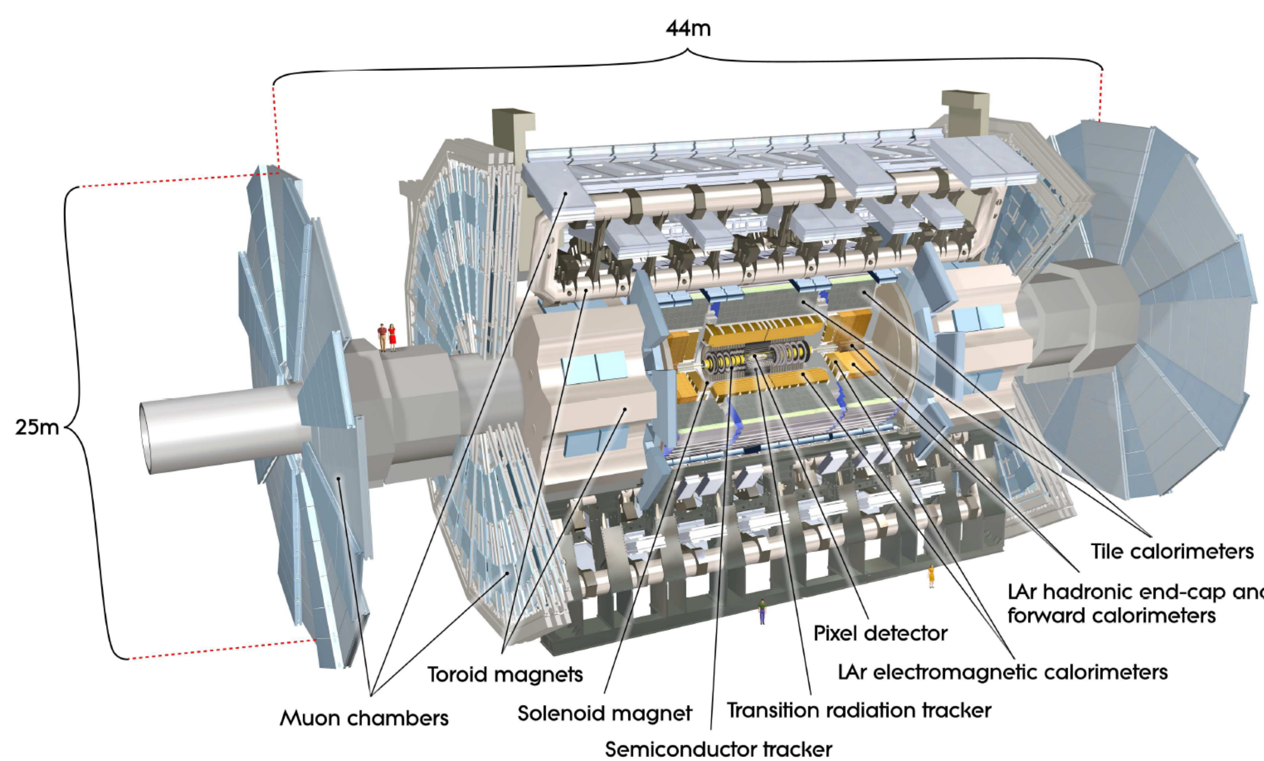
Backup Slides

LHC and ATLAS





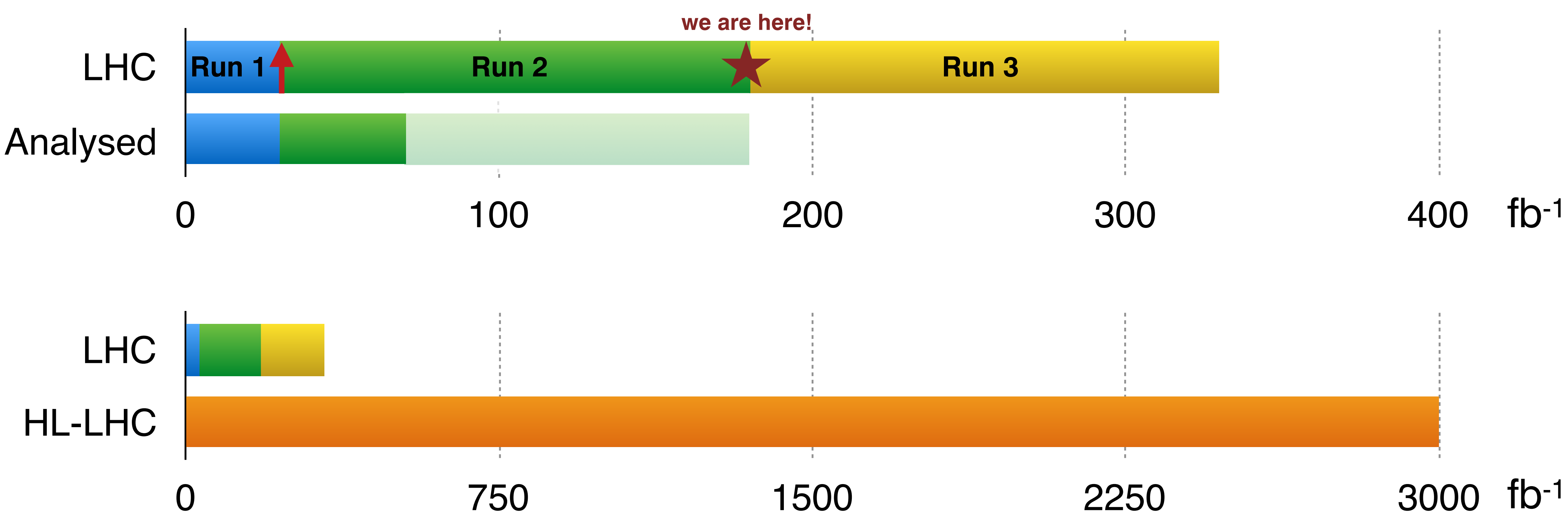




Credit: CERN

The Large Hadron Collider Schedule

LHC Data



Effective Field Theories

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

Full-Event Training - Trigger Level