



From collider data to fundamental physics: the role of an experimentalist*

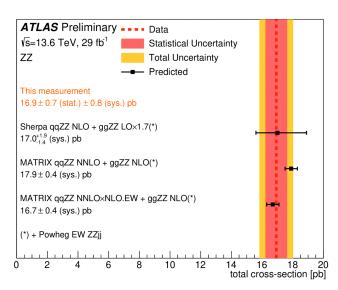
Inês Ochoa

Course on Physics at the LHC 2025

Introduction

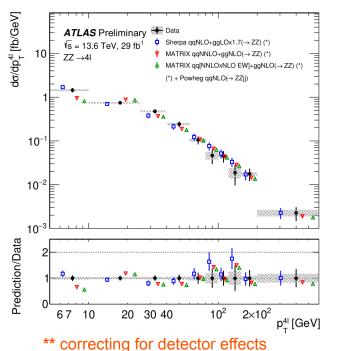
- The role of an experimentalist is to piece together all the elements in the chain that links theory and data.
- Main topics:
 - 1. Event reconstruction
 - 2. Trigger and detector operations
 - 3. Simulation
 - 4. Calibrations
 - 5. Computing & Software
 - 6. Case study: measuring the WH cross-section
 - 1. Simulation-based backgrounds, global fit,
 - 7. Case study: searching for new physics resonances
 - 1. Data-driven background estimation methods
 - 2. Anomaly detection

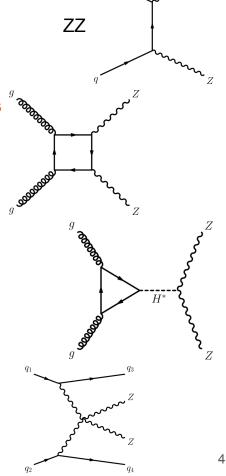
Total, fiducial* cross-sections

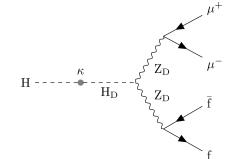


*in the detector's acceptance

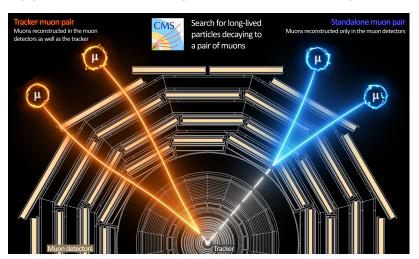
Unfolded** differential cross-sections



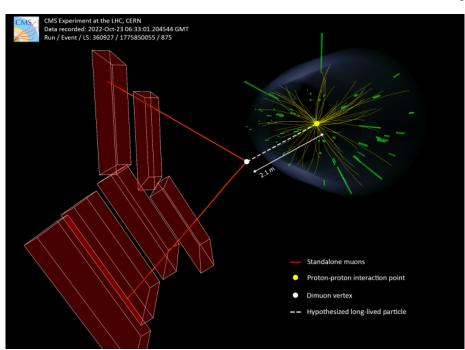


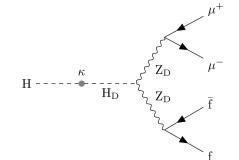


Upper limits on the production of new particles

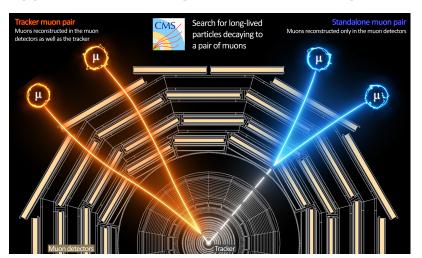


Long-lived particles

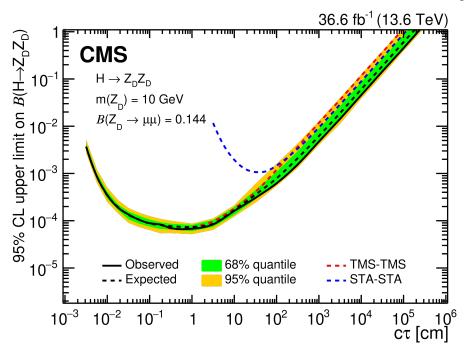


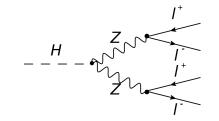


Upper limits on the production of new particles

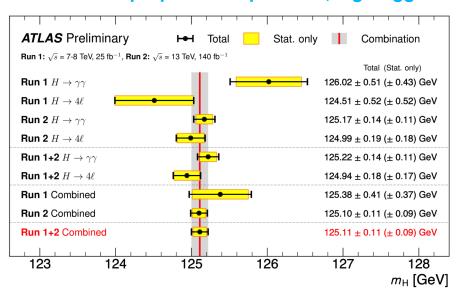


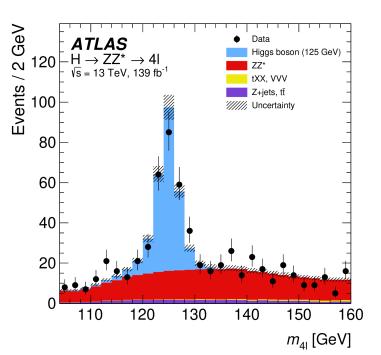
Long-lived particles

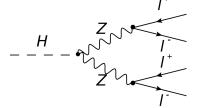


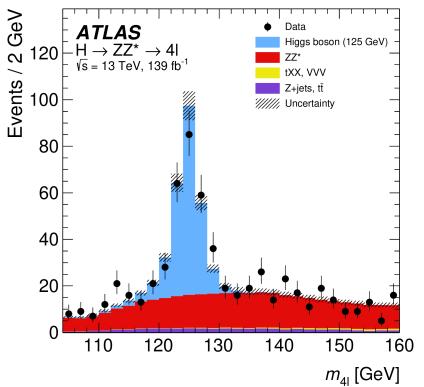


Fundamental properties of particles, e.g. Higgs boson mass

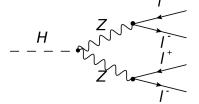


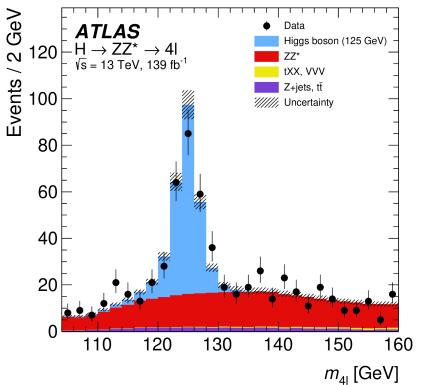




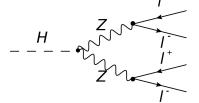


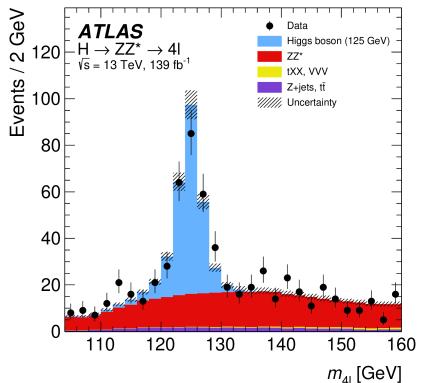
- Data
- Simulation





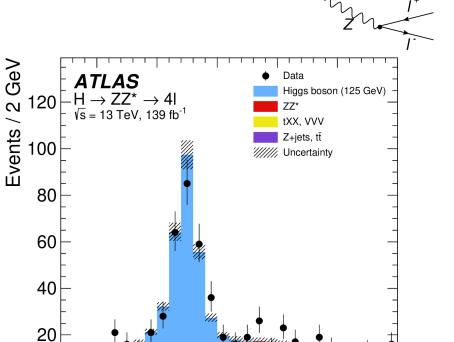
- Data
- Simulation
- ★ an invariant mass
- Lepton reconstruction & identification





- Data
- Simulation
- ★ an invariant mass
- Lepton reconstruction & identification
- Calibrations, detector alignment, pile-up, much more...

How do we get to this plot?



130

140

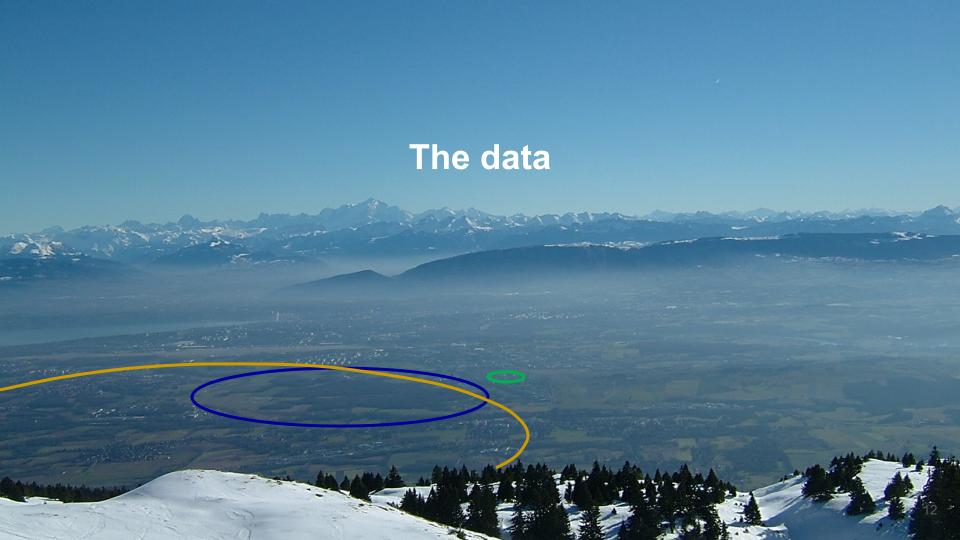
150

 m_{41} [GeV]

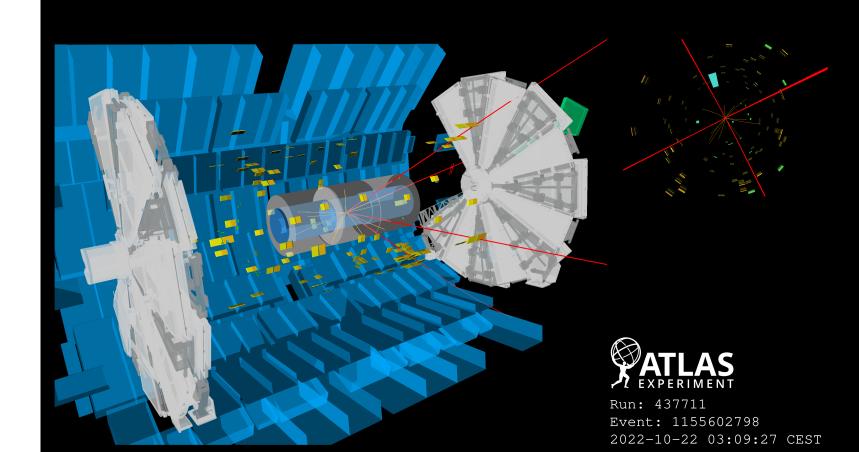
120

110

160



A H to 4µ candidate



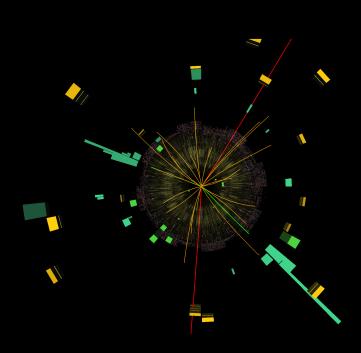
A H to 2µ2e candidate

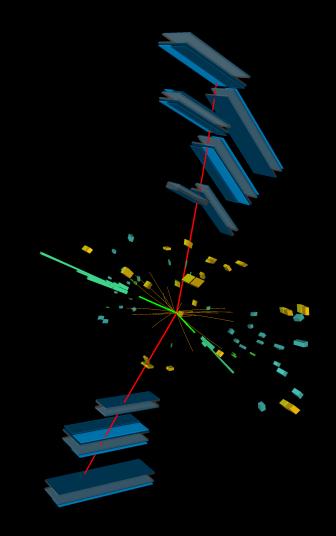


Run: 439798

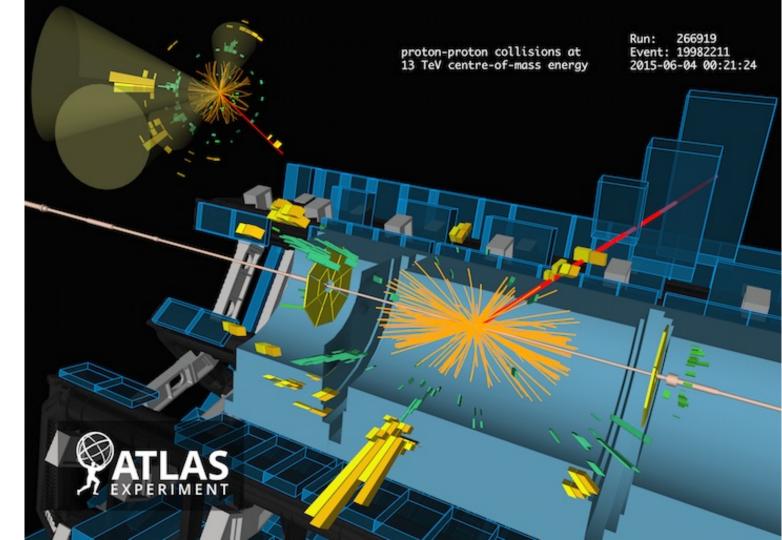
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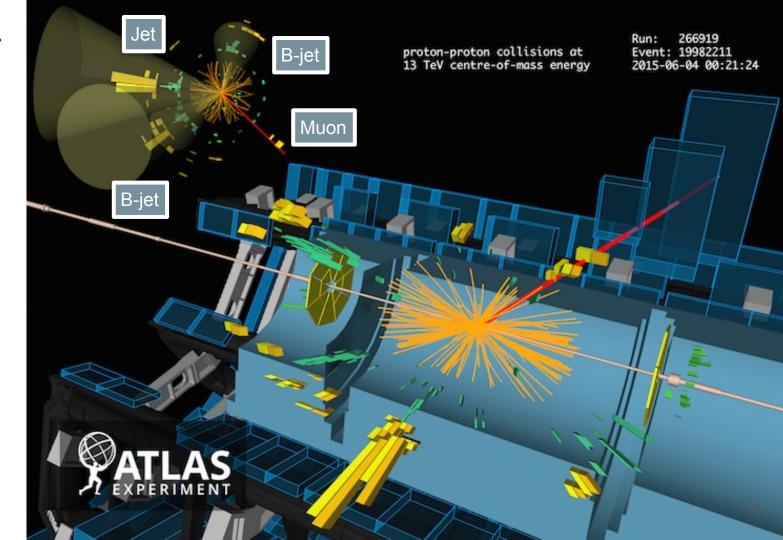




A pair of topquarks produced in ATLAS

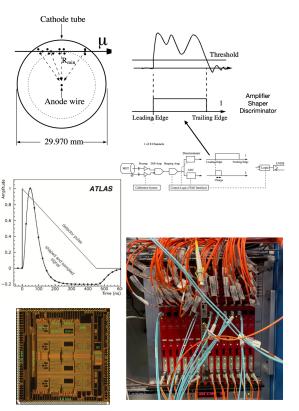


A pair of topquarks produced in ATLAS

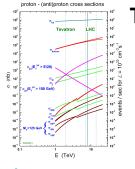


A simplified picture

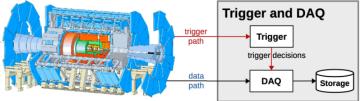
Data Acquisition









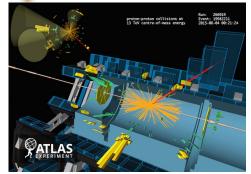


Raw data

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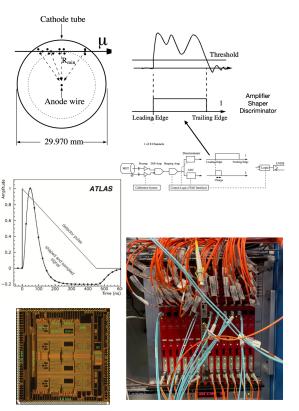
Reconstruction



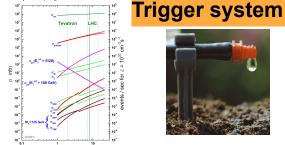
Taken from ATLAS Lectures on DAQ, Trigger, Data Processing Workflow: slides, slides, slides

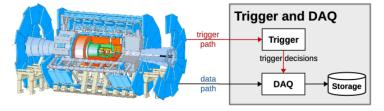
A simplified picture

Data Acquisition





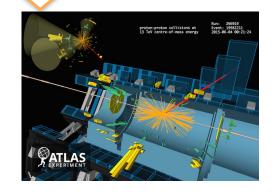




Raw data

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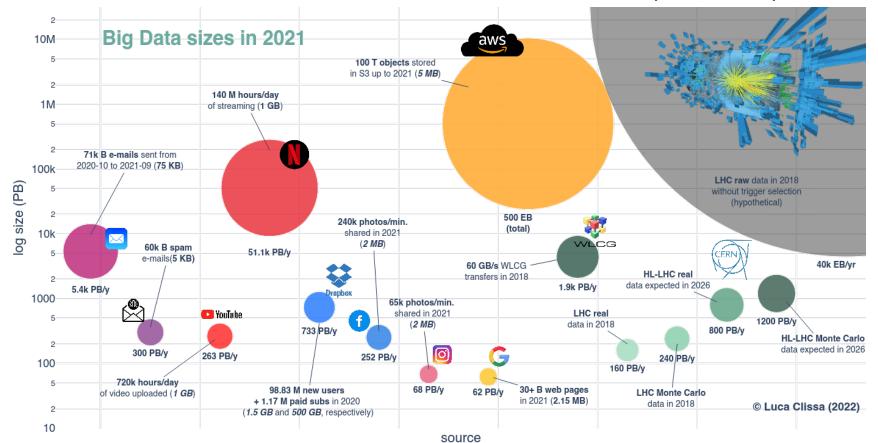




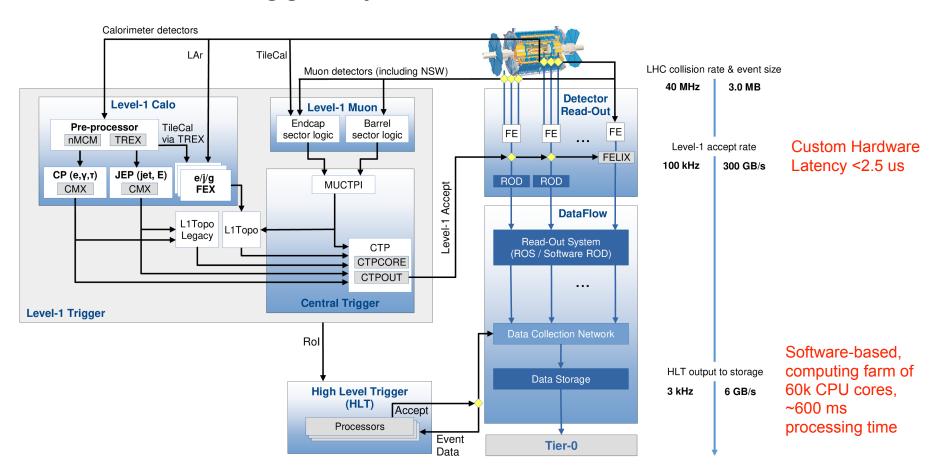
Taken from ATLAS Lectures on DAQ, Trigger, Data Processing Workflow: slides, slides, slides

Data volumes at the LHC

- Up to 40 million collisions per second (MHz)
- ~1 MB of data per collision
- 40 MHz * 1 MB = 40 TB/s
- 40 TB/s * 1e6 s/year = 40 000 EB/year



The ATLAS trigger system



THE ATLAS **RUN 3 TRIGGER**

OUR SIGNATURES

ELECTRONS

290 HZ

TAUS

160 HZ

JETS & MET 630 HZ



ON BEHALF OF THE

ATLAS TRIGGER GROUP

ABOUT US

ATLAS runs a two-level triggering strategy:

- I1 → Hardware-based, coarse reconstruction, total accepted rate is 90-100 kHz
- HIT → Software-based, reconstruction precision approaching offline reconstruction

The Trigger Menu is limited by:

- L1 RATE → Constrained by dead time Impacts the range of physics accessible
- Limits the execution rate of high-precision reconstruction algorithms
- Limits the data volume that can be reconstructed TO CPU → promptly for endpoint analysis

L1/HLT limitations scale with luminosity:

 END OF FILL → Enhance signatures limited by L1 rate and/or HLT rate & CPU

OUR STREAMS



For prompt reconstruction Rate limited by L1. CPU & T0 Resources

1.7 KHZ



B-Physics

Delayed Processing when T0 CPU available 900 HZ



TRIGGER-LEVEL Jets, Photons, ANALYSIS (TLA)

Reduced event content, HLT Objects only.



Minimal burden on bandwidth



PARTIAL EVENT Jets, Photons, BUILDING (PEB) flavour-tag

Regional data around near physics objects identified by trigger



EMERGING JETS

HIGHLY IONIZING TRACK ISOLATED TRACK

10 HZ

1 HZ

5 HZ **DISPLACED OBJECTS**

PARTIAL EVENT BUILDING

DISAPPEARING TRACK

4 HZ **40 HZ**

200 HZ

HEAVY IONS: RUN 2 THRESHOLDS PRESERVED!

New trigger strategies: how to make the most out of the data

Bandwidth = event rate x event size



MAIN

For prompt reconstruction Rate limited by L1. CPU & T0 Resources 1.7 KHZ



ELAYED Hadron B-Physic

Delayed Processing when T0 CPU available

900 HZ



TRIGGER-LEVEL Jets, Photo b-tag

Reduced event content,
HLT Objects only.
Minimal burden on bandwidth



PARTIAL EVENT Jets, Photon RIIII DING (DER) flavour-tag

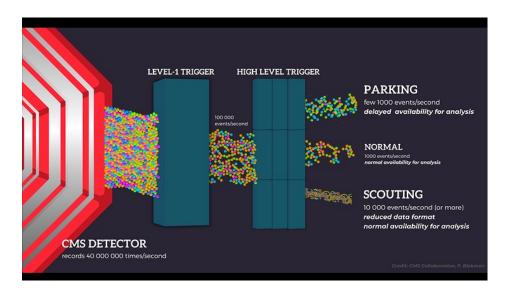
Regional data around near physics objects identified by trigger

Delayed reconstruction ("Parking")

- Park and wait.
- Process events when resources are available.

Do analysis in real-time (TLA, "Scouting")

• Save only the trigger objects, smaller event size.



New trigger strategies: how to make the most out of the data

Bandwidth = event rate x event size



MAIN For prompt reconstruction Rate limited by

1.7 KHZ







TRIGGER-LEVEL Jets, Photons b-tag

Reduced event content,
HLT Objects only.
Minimal burden on bandwidth



PARTIAL EVENT Jets, Photons, RIIII DING (PFR)

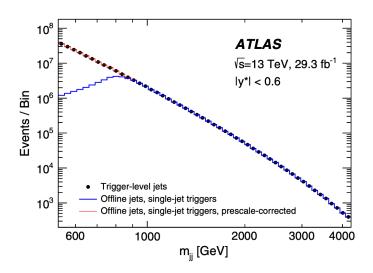
Regional data around near physics objects identified by trigger

Delayed reconstruction ("Parking")

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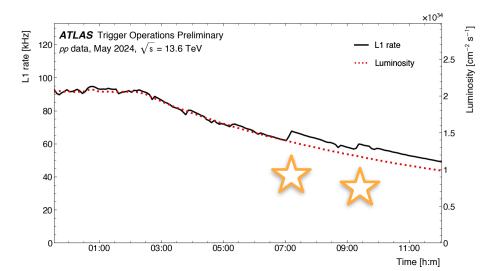
Trigger Operations

- Real-time constraints during any data-taking run:
 - At L1: maximum rate of 100 kHz (detector readout capability)
 - At HLT: bandwidth + CPU resources of the HLT farm
 - Offline prompt processing capabilities



Trigger menu and prescales are continually adjusted to optimise the available resources.

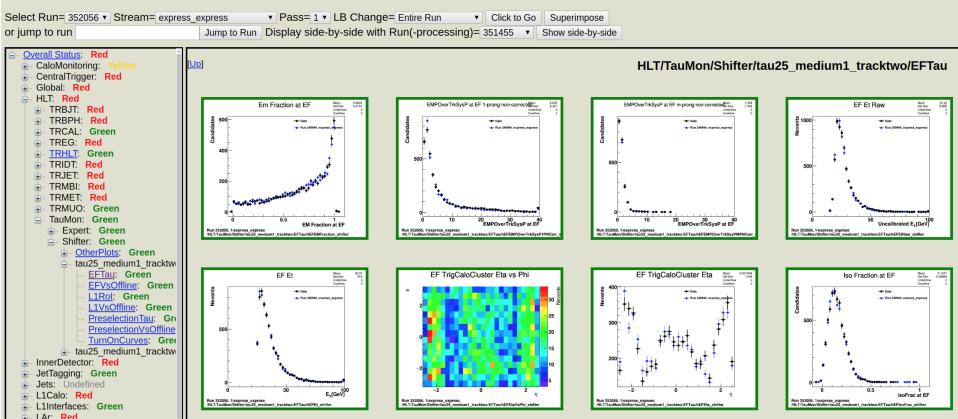
- Prescale factors are applied to L1 and HLT triggers
 - Triggers can be executed for a fraction of events and to be enabled/disabled; can be changed during datataking to adapt to decreasing luminosity
- End-of-fill (EOF) strategies:
 - Enable/unprescale additional/resource-heavy triggers when luminosity declines



Data Quality shifts

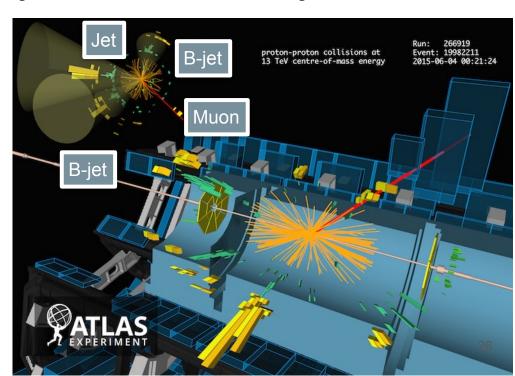
ATLAS

Run 352056, 1/express_express

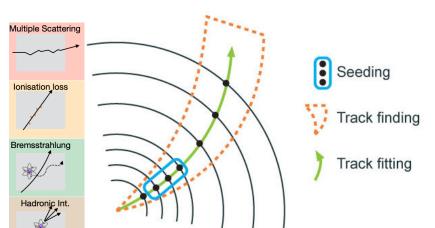


Event Reconstruction

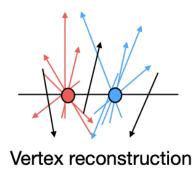
- Going from raw data to analysis objects.
- Important: data and simulation pass through the same reconstruction algorithms.
- Raw data reconstructed into:
 - Tracks
 - Calorimeter deposits
- Which are then reconstructed into "physics" objects:
 - Jets, electrons, muons, taus
 - Photons, missing transverse energy

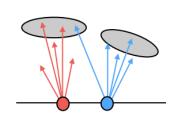


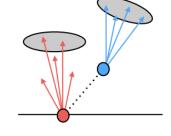
From hits to physics: tracking



- Efficiently and precisely reconstructing charged particles:
 - Under a non-uniform magnetic field (equations of motion have to be solved numerically)
 - With hundreds to thousands of particles per event.
 - With tight CPU timing constraints.
- Used in almost every element of reconstruction.





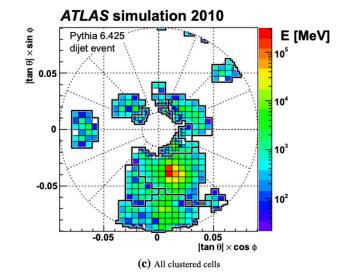


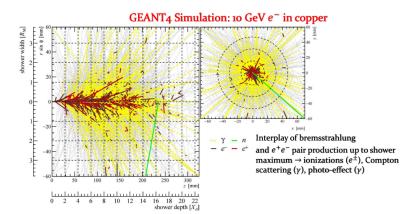
Pile up removal

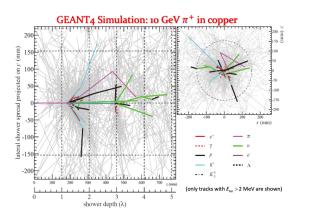
Jet flavour tagging

From hits to physics: clustering

- Three-dimensional topological clustering (topo-clustering) of individual calorimeter cell signals.
- Algorithm sensitive to the nature of the shower producing the cluster signal:
 - EM showers are more compact, smaller intrinsic fluctuations
 - HADdronic shower have larger shower-by-shower fluctuations and are located deeper in the calorimeter.









From hits to physics: clustering

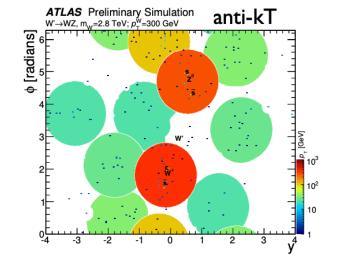
 Calorimeter topoclusters are one of the ingredients to jet clustering

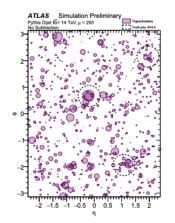
2.2.5 The anti- k_t algorithm

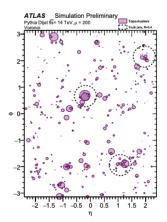
One can generalise the k_t and Cambridge/Aachen distance measures as [33]:

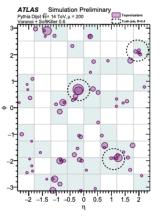
$$d_{ij} = \min(p_{ti}^{2p}, p_{tj}^{2p}) \frac{\Delta R_{ij}^2}{R^2}, \qquad \Delta R_{ij}^2 = (y_i - y_j)^2 + (\phi_i - \phi_j)^2,$$
 (10a)

$$d_{iB} = p_{ti}^{2p} \,, \tag{10b}$$



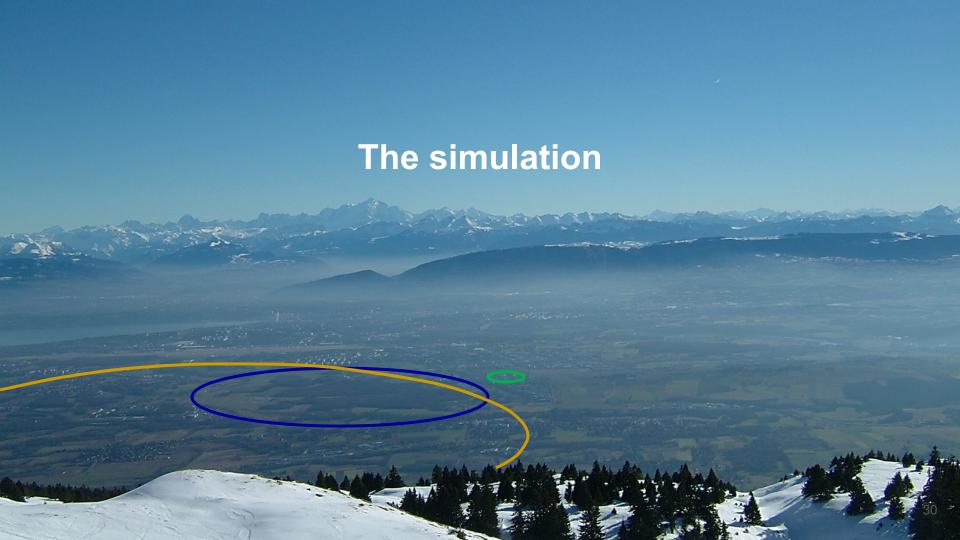






Different techniques to handle pile-up:

- At constituent-level, e.g. subtracting lowpt constituents
- At jet-level, subtracting energy density x jet area, cut on jet timing, etc...



Physics analyses at the LHC

The power of factorisation of physics at different energy scales.

Inclusive* cross-section

for the production of the final state X in the collision of hadrons h₁,h₂

$$\sigma_{h_1,h_2\to X} = \sum_{a,b\in\{a,a'\}} \int dx_a \int dx_b f_a^{h_1}(x_a,\mu_F^2) f_b^{h_2}(x_b,\mu_F^2) \int d\Phi_{ab\to X} \frac{d\hat{\sigma}_{ab}(\Phi_{ab\to X},\mu_F^2)}{d\Phi_{ab\to X}}$$

Partons a,b in the PDF with momentum fraction x_a,x_b

Parton distribution functions (PDFs) at factorisation scale μ_F^2 **Differential partonic** cross-section

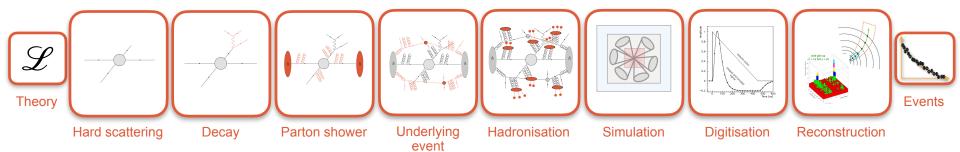
$$d\hat{\sigma}_{ab}(\Phi_{ab\to X}, \mu_F^2) \over d\Phi_{ab\to X}$$

From collisions to physics results

Theory and data can be linked through **precise simulations** of:

- The hard scatter interaction.
- The parton showering and hadronization
- The detector itself

The goal is to have a twin set of collision data to compare to the real collisions.



Detector simulation (I)



No. of steps ∝ simulation time

Simulation of the passage of particles through the detectors.

Particle ionisation in the trackers

Energy deposition in the calorimeters

Intermediate particle decays, radiation and scattering...

Typically done using the *GEANT4* software, taking into account:

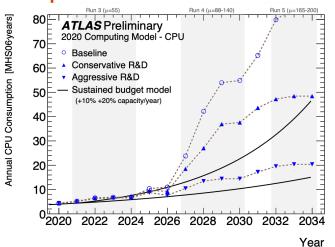
Dense hit content in the inner trackers.

Electromagnetic and hadronic shower development.

Effect of the magnetic fields.

Complex geometry with multiple sub-detectors, support structures, cooling pipes, cables, ...

A problem...



One of the most computational expensive steps in the entire Monte Carlo generation chain: ~40% of ATLAS resources in Run 2.

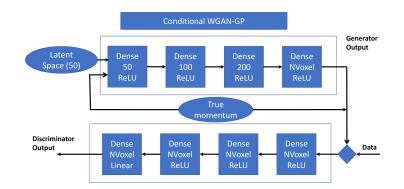
Detector simulation (II)

Can also be done using a *fast* simulation:

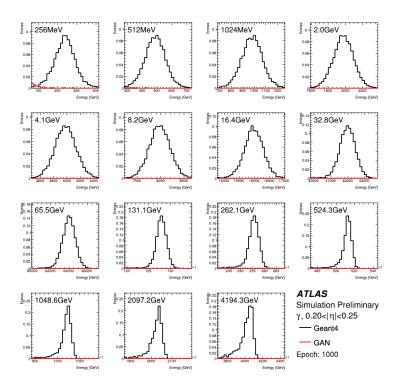
Parameterising the calorimeter response to single particles (smearing 4-vectors)

New: improved methods using machine learning!

e.g. Generative Adversarial Networks (GANs)



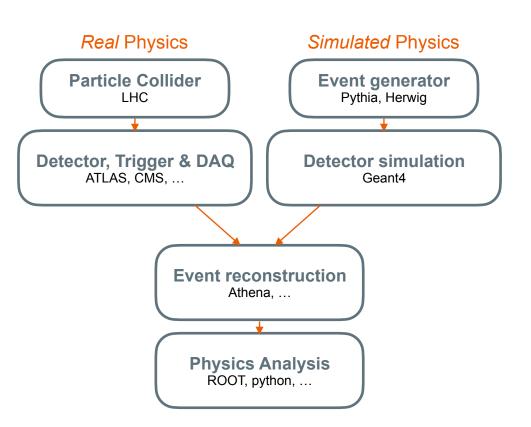
Calorimeter energy response to photons

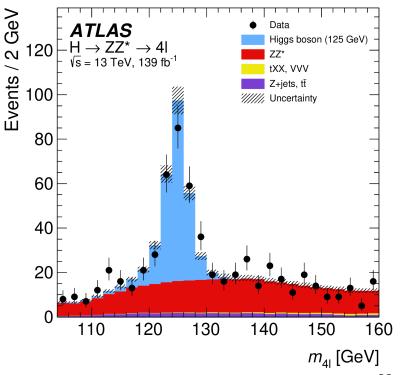


Fast simulation provides speed gains of O(500) for calorimeter simulation!

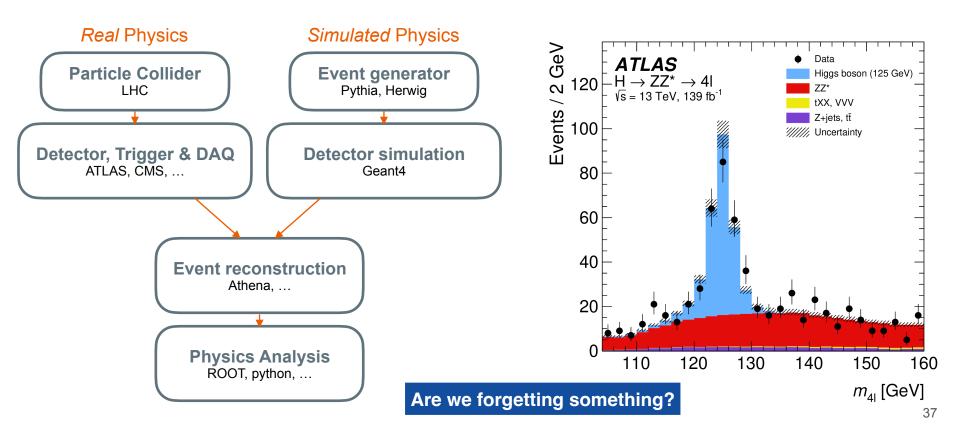






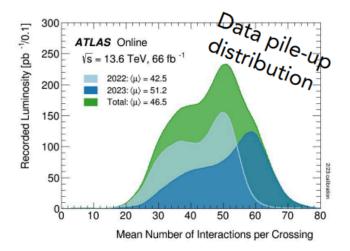


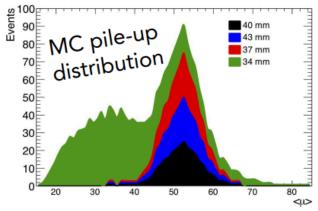
What's in a plot?



Overlaying pile-up collisions

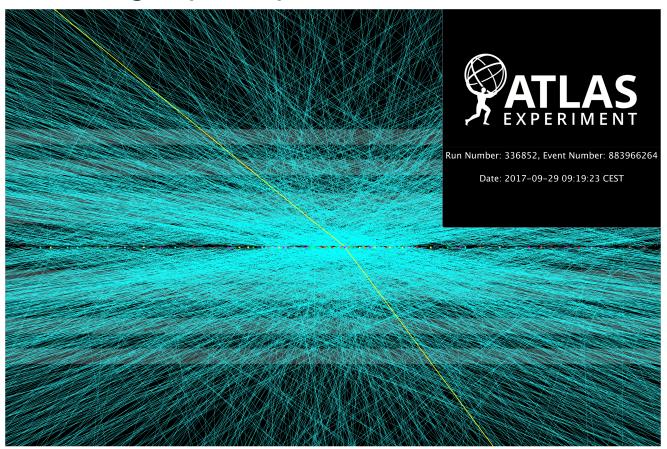
- Pile-up comes "for free" in our data. It needs to be modelled in our Monte Carlo as well, for a fair comparison to data.
- In ATLAS Run 3, this is done by MC pile-up overlay:
 - Minimum-bias and single neutrino events are generated using Pythia8.
 - GEANT4 is run on these events to simulate detector response.
 - Digitisation is then run on a combination of these events, including shifts in time to reproduce in-time and out-of-time pile-up.
 - The digitisation output of a pile-up event is then overlaid with the hard-scatter MC.
- Proton bunch structure and luminosity based on that of real data.





 $<\mu>$ = mean number of interactions per crossing 38

Challenge: pile-up



A Z boson decays to 2 muons in an event with 65 (!) additional pile-up collisions.

$$\sqrt{\hat{s}} = 13 \text{ TeV}$$

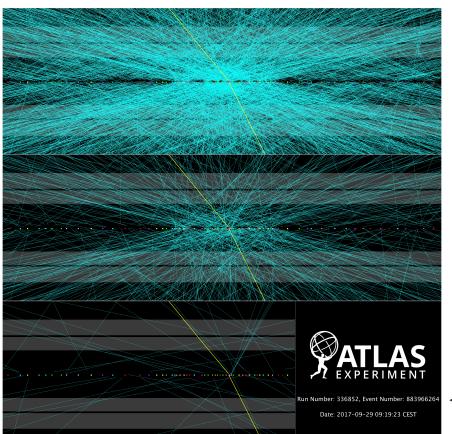
 $<\mu>$ = mean number of interactions per crossing

Challenge: pile-up

Track $p_T > 100 \text{ MeV}$

Track p_T > 1 GeV

Track p_T > 5 GeV



A Z boson decays to 2 muons in an event with 65 (!) additional pile-up collisions.

$$\sqrt{\hat{s}} = 13 \text{ TeV}$$

 $<\mu>$ = mean number of interactions per crossing

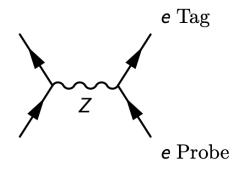
What else?

MC WARNING

- The real world need to be reflected in the Monte Carlo simulation.
 - E.g. a section of the calorimeter readout dies and cannot be repaired until the detector is opened during an LHC shutdown.
 - If this impacts x% of the data, we need a representative slice of the problem in our MC.
 - But x is usually hard to know until we know how much data we will collect until the shutdown. At that point we need to reprocess the MC.
- Even then, MC often doesn't describe the data.
 - Improving MC (e.g. via tuning of input parameters) is an ever on-going (and time consuming task.
 - Another way to deal with inaccurate modeling is to correct / calibrate the MC.
 - We can correct:
 - An efficiency (event-level correction).
 - An object's energy scale or resolution (object-level correction).

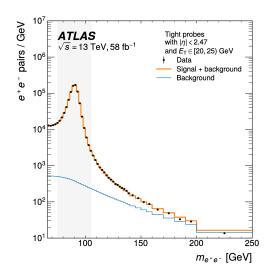
Example #1: tag & probe method

How efficiently do we identify an electron?



Use a Standard Model candle like $Z \rightarrow ee$

- ✓ We know the Z decays to one electron and a positron.
- ✓ We know the Z invariant mass very well
- ✓ We "tag" one electron and study the "probe" electron



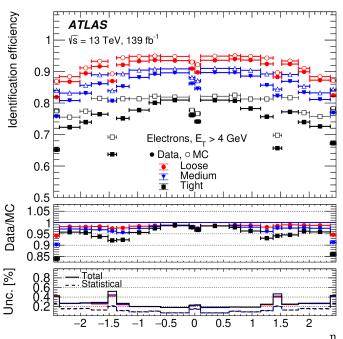
For example, the identification efficiency can be calculated as:

$$\epsilon = \frac{\text{probe is identified}}{\text{all probes}}$$

Only the tag electron is used to select events.

Example #1: tag & probe method

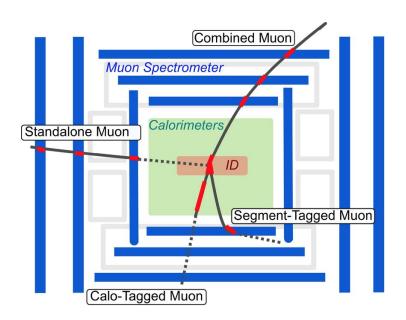
How efficiently do we identify an electron?



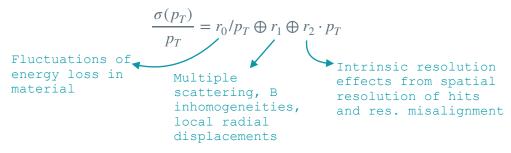
- Electrons are identified with tracks and EM topo-clusters.
- Id efficiency shown as a function of electron η :
 - Also studied as a function of electron E_T, pile-up...
- Data and simulation have different efficiencies, an approximately 5% effect.
 - Weights or scale-factors are derived as a function of η, E_T, ...
 - We reweight the simulation to achieve the same efficiencies as in the data.

Example #2: smearing the MC

• How well do we measure the momenta of muons?



- Muons are typically reconstructed using the ATLAS inner detector and the muon spectrometer.
- Each detector has its own momentum resolution:

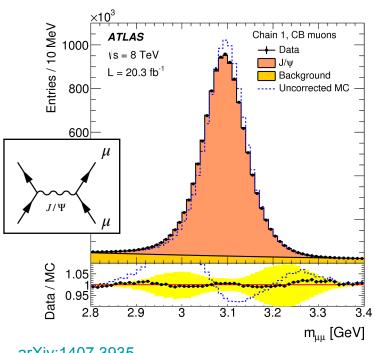


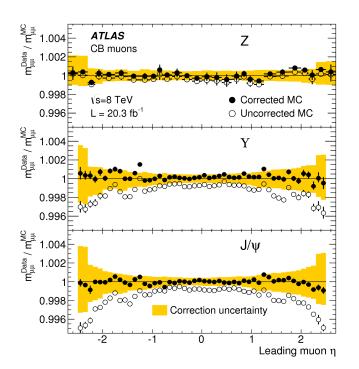
 We smear the MC (depending on detector region) to reproduce the muon momentum resolution and scale of data at high precision.

arXiv:1407.3935

Example #2: smearing the MC

• How well do we measure the momenta of muons?

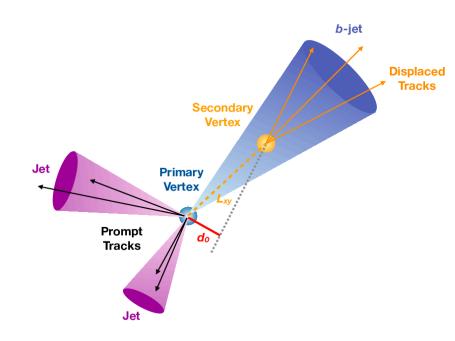




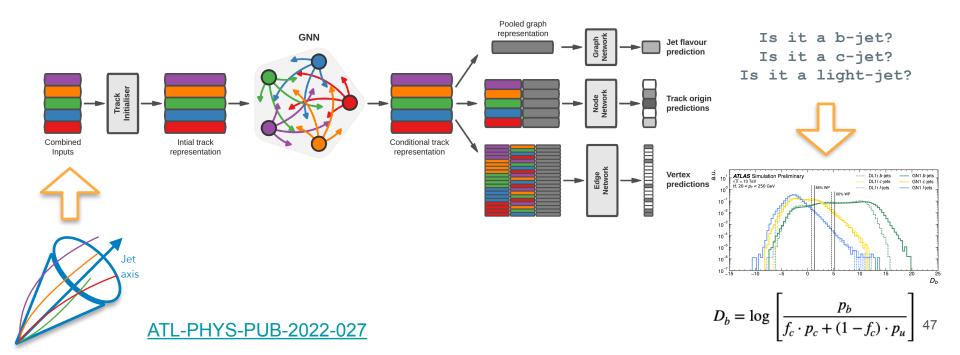
Example #3: measuring tag rates, fake rates

• How do we identify b-jets?

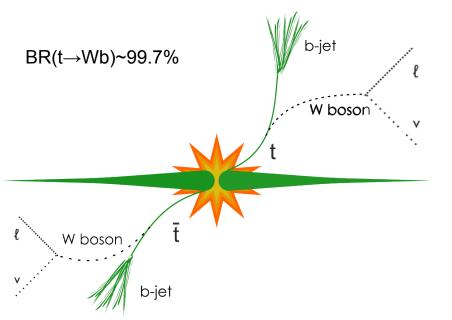
- b-jets contain the decay particles of longlived b-hadrons and some additional particles
- Key properties:
 - Relatively large b-hadron mass ~5 GeV
 - Significant b-hadron lifetime ~1.5 ps
- This leads to unique characteristics that distinguish them from light (u,d,s,g) and to a lesser extent charm (c) jets:
 - A secondary vertex
 - Tracks with large impact parameters
 - Leptons from the b-hadron decay



State-of-the-art b-tagging in ATLAS

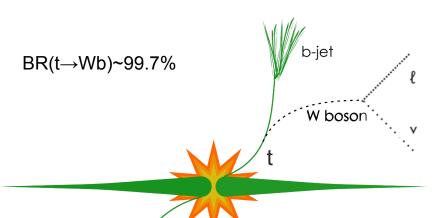


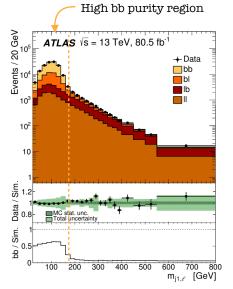
How efficiently do we tag a b-jet?

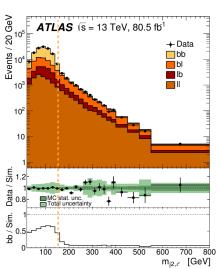


- Use a highly-enriched sample of top-pair events to:
 - Measure the jet flavour composition.
 - Measure the b-tagging efficiency vs jet p_T.
- Invariant mass of each of the top systems:
 - $\bullet \qquad m_{t1} = m_{j1,\ell}$
 - $m_{t2} = m_{j2,\ell}$
- Real top-pair events will have $m_{j1,\ell}, m_{j2,\ell}$ distributions with an upper limit around the top-quark mass of 172.5 GeV
 - In practice smaller due to the undetected neutrino.

How efficiently do we tag a b-jet?







Expected number of events in a

given bin and. b-tagging selection: $v_{SR}(T^m, T^n, O^k, O^p) = c_{bb}^{m,n} v_{SR,bb}^{m,n} \cdot \mathcal{P}_b(O^k | T^m) \cdot \mathcal{P}_b(O^p | T^n)$

$$+c_{bl}^{m,n}v_{SR,bl}^{m,n}\cdot\mathcal{P}_b(O^k|T^m)\cdot\mathcal{P}_l(O^p|T^n)$$

$$+ c_{lb}^{m,n} v_{SR.lb}^{m,n} \cdot \mathcal{P}_l(O^k | T^m) \cdot \mathcal{P}_b(O^p | T^n)$$

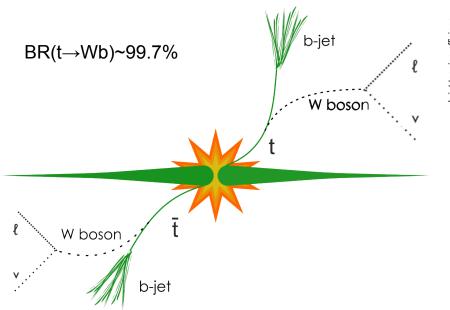
 $+ c_{ll}^{m,n} v_{SR,ll}^{m,n} \cdot \mathcal{P}_l(O^k | T^m) \cdot \mathcal{P}_l(O^p | T^n),$

 $\mathcal{P}_h = \text{b-tagging probability}$

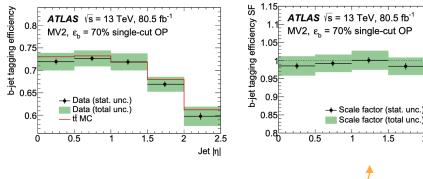
W boson

b-jet

How efficiently do we tag a b-jet?



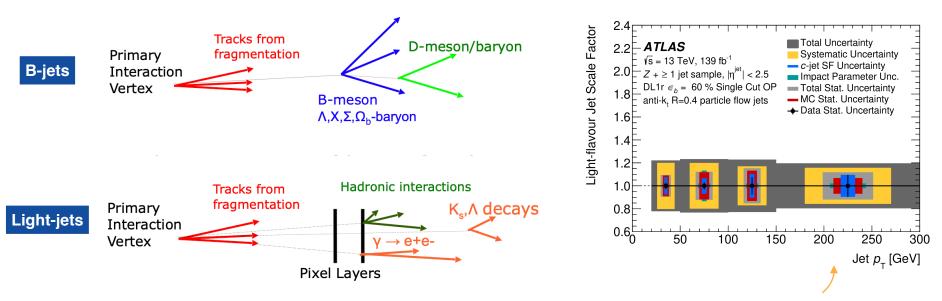
FTAG-2018-01



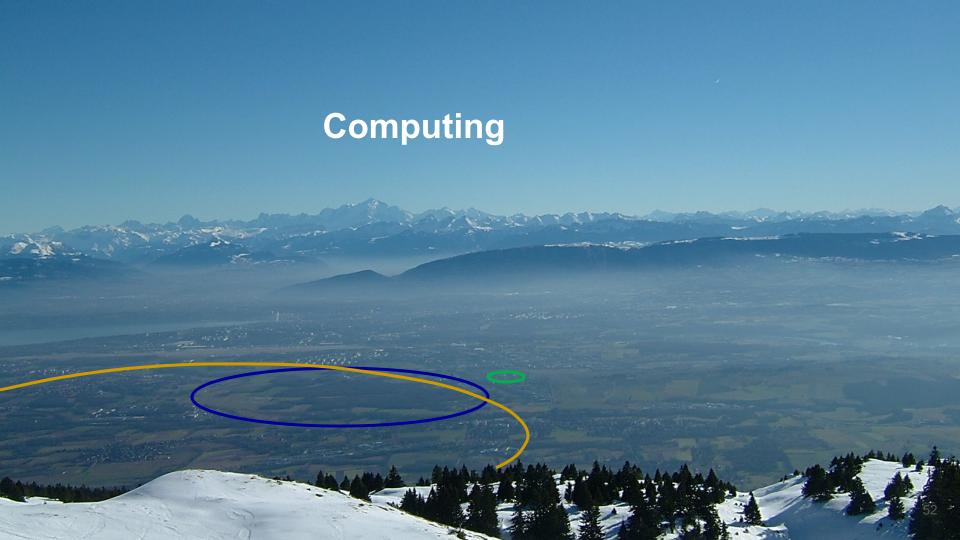
Scale-factors to correct b-tagging efficiency in MC as a function of pseudo-rapidity (also transverse momentum).

Jet |n|

And how often do we tag a light or a c-jet instead (mis-tag)?



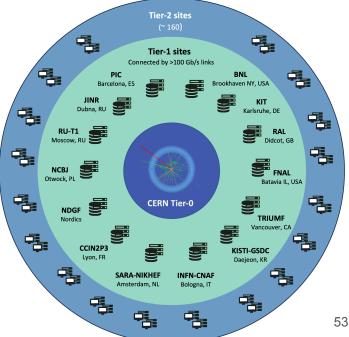
Scale-factors to correct light mis-tag rate in MC as a function of jet transverse momentum.



The grid

- Processing data and simulation poses huge computing, storage and analysis challenges.
- We rely on the World LHC Computing Grid (WLCG), and international organisation of computing centres.
 - Tier-0: the CERN Data Centre where O(100) PB of data are stored on magnetic tapes.
 - Tier 1: 14 large data centres for intensive computing tasks and secondary storage.
 - Tier 2: ~160 smaller processing centres, like universities or labs that can provide storage and computing power for specific analysis tasks.





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An ATLAS example:

- DAOD	129 PB
- AOD	80.2 PB
- HITS	51.4 PB
- RDO	17.9 PB
- EVNT	13.0 PB
- RAW	11.9 PB
- ESD	2.27 PB
- DESD	1.52 PB
- log	1.43 PB
no_name	1.24 PB
- TXT	1.00 PB
- HIST	886 TB
- DRAW	787 TB
- user	697 TB
- NTUP	263 TB

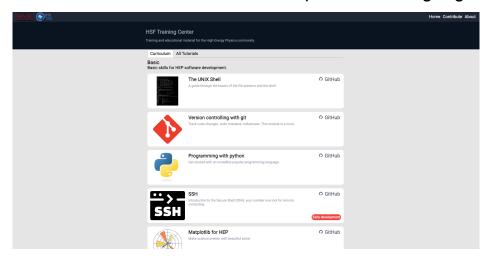
HEP Software Foundation

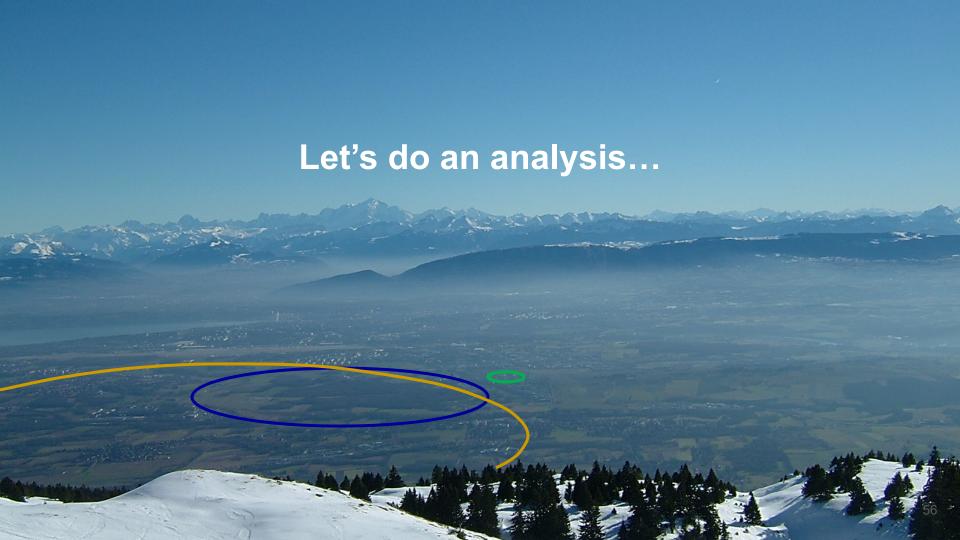


The HEP Software Foundation facilitates cooperation and common efforts in High Energy Physics software and computing internationally.

Lots of training resources:

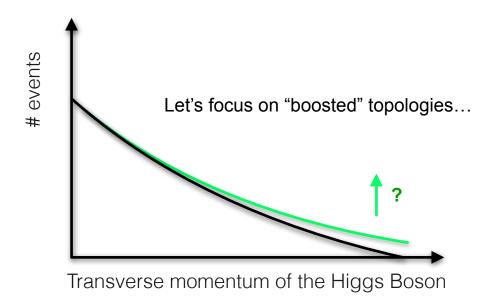
https://hsf-training.org/

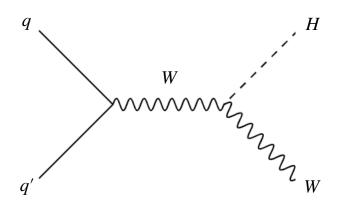




☑ Physics motivation

 Precise measurements of the cross-section and decays of Higgs boson as a test of Standard Model predictions and probe of New Physics.





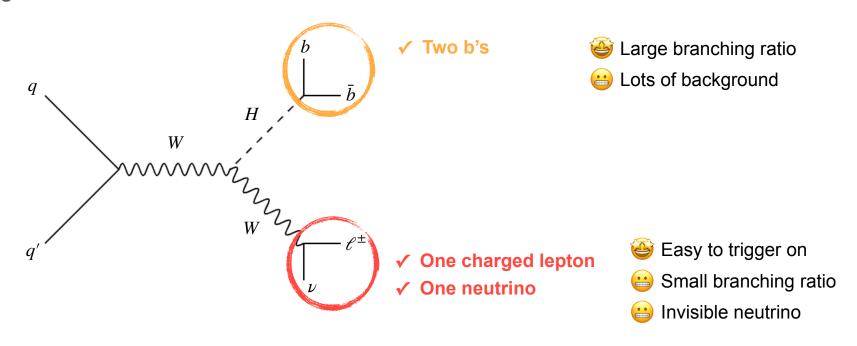
SM Higgs Boson decay modes

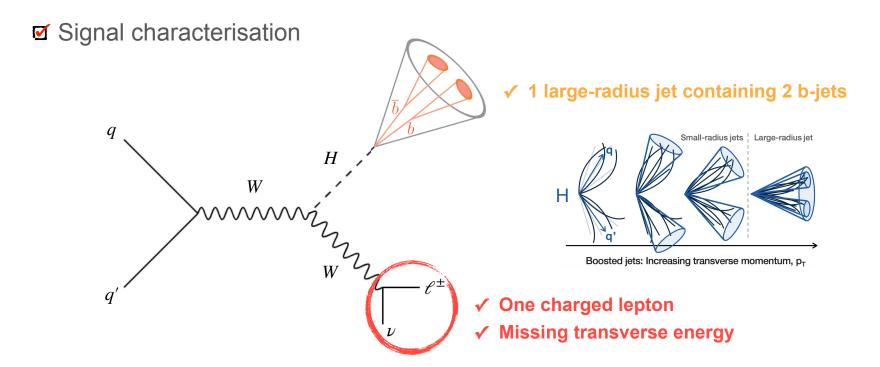
Decay channel	Branching ratio
$H \to \gamma \gamma$	2.27×10^{-3}
H o ZZ	2.62×10^{-2}
$H \to W^+W^-$	2.14×10^{-1}
$H \to \tau^+ \tau^-$	6.27×10^{-2}
$H o b ar{b}$	5.84×10^{-1}
$H o Z \gamma$	1.53×10^{-3}
$H \rightarrow \mu^+ \mu^-$	2.18×10^{-4}



w boson decay modes	Fraction (Γ_i/Γ)		
$\ell^+ \nu$	[<i>b</i>]	(10.86± 0.09) %	
$e^+ u$		$(10.71 \pm 0.16) \%$	
$\mu^+ u$		$(10.63 \pm \ 0.15) \%$	
$ au^+ u$		$(11.38 \pm \ 0.21) \%$	
hadrons		$(67.41 \pm 0.27) \%$	





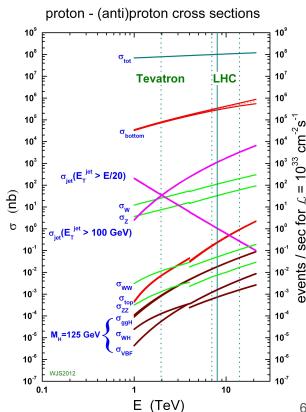


- **Background:** it is crucial to correctly estimate the expected background and its uncertainty.
- Common strategy (for many backgrounds):

1. Use Monte Carlo estimate (yields and shapes) during analysis optimisation.

2. Use data to correct and constrain MC estimate.*

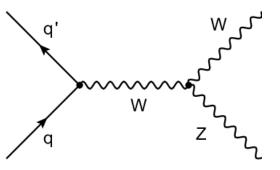
when there is an appropriate control region.



☑ What are the (dominant) backgrounds? How can we reduce them?



WZ production



- $W \rightarrow \ell V$
- ✓ One charged lepton
- Missing transverse energy

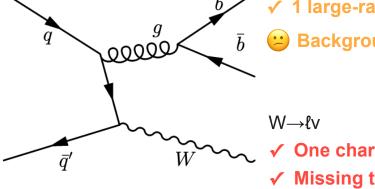
- Z→bb
- ✓ 1 large-radius jet containing 2 b-jets
- Background from cc faking bb



☑ What are the (dominant) backgrounds? How can we reduce them?



W+jets production



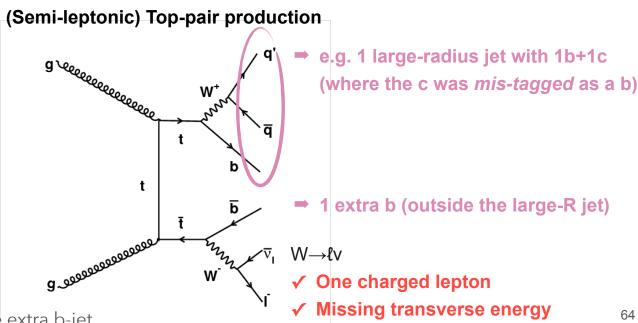
- large-radius jet containing 2 b-jets
- Background from cc faking bb

- One charged lepton
- Missing transverse energy



☑ What are the (dominant) backgrounds? How can we reduce them?

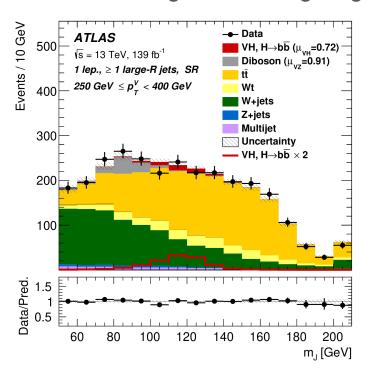


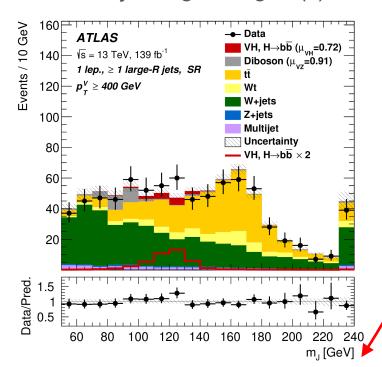




Can take advantage of the extra b-jet.

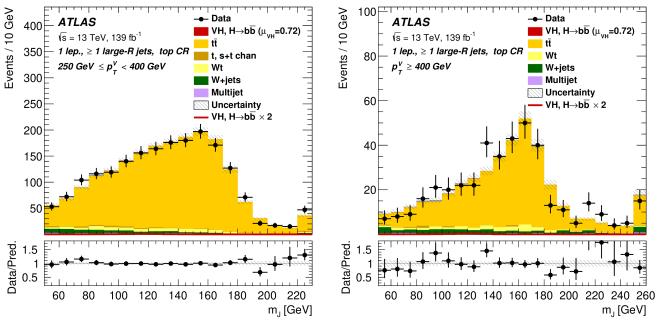
☑ Event selection: regions with high signal efficiency ⇒ signal region(s)





m_J = mass of the largeradius jet

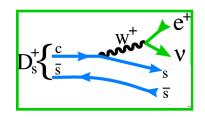
☑ Event selection: regions with high background purity ⇒ control region(s)

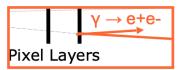


Top CR: events with 1 extra b (outside the large-R jet)

☑ Background from non-prompt / fake leptons:

- Non-prompt: from semi-leptonic decay of hadrons or photon conversions.
- Fake leptons from misidentified jets.
- Very challenging to model these processes in simulation:
 - Depend strongly on details of physics simulation, often in nonperturbative regions.
 - Depend on modeling of material composition and response.
 - Very low probability for hadronic jets to fake a lepton, yet multi-jet cross section is huge and simulating this effect would be prohibitive.







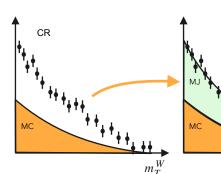


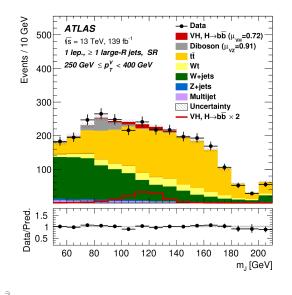
Non-prompt leptons can be reduced by requiring isolated leptons.

☑ Background from non-prompt / fake leptons:

- Use data-driven methods!
- E.g. template method:
 - Extract a background template from a control region enriched in multi-jet events.
 - Built by inverting the lepton isolation and missing transverse energy requirements.
 - Assumption: shape SR = shape CR
 - Determine its normalisation in fits to the W transverse mass distribution in the signal region.

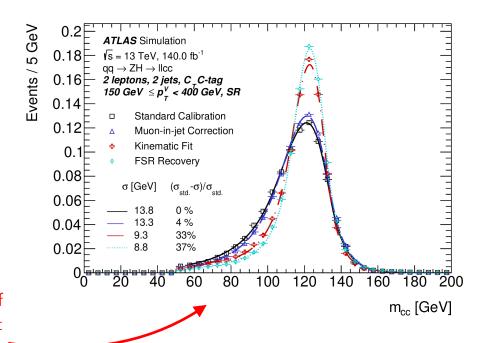
$$m_T^W = \sqrt{2p_T^{\ell} E_T^{miss} (1 - \cos \Delta \phi(\ell, E_T^{miss}))}$$





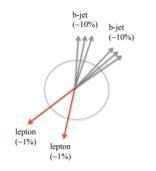
~2% in the electron channel (with a 55% uncertainty)

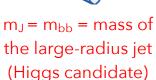
☑ Analysis specific: improvements to the invariant mass resolution



- Correct b-jets semi-leptonic decays with muon four-vector.
- ✓ Correct for missing energy from neutrinos.
- ✓ In the ZH(IIbb) channel, a kinematic fit.

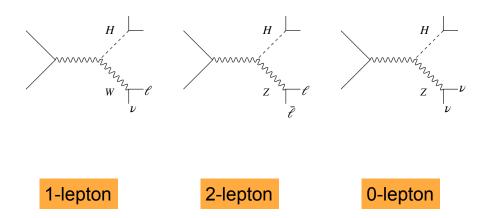
In the end, a 37% improvement.

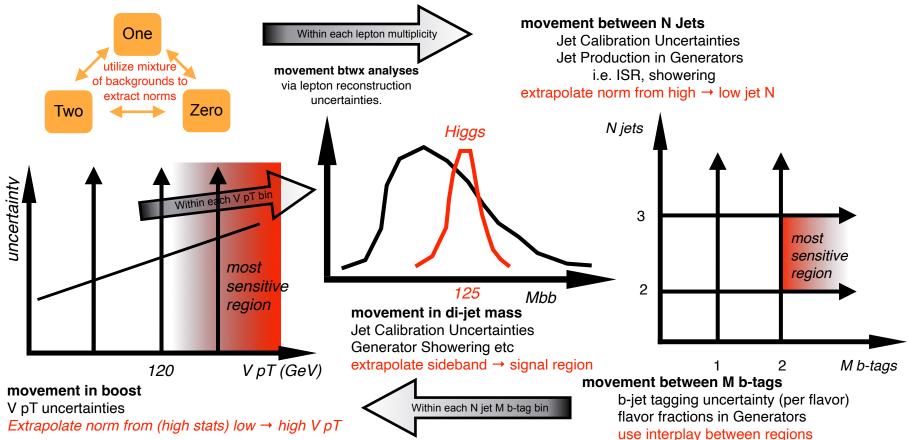




☑ All together now!

 The data, the simulated and datadriven backgrounds, as well as the Higgs boson signal go into a likelihood fit of the signal and control regions, considering theoretical and experimental uncertainties.



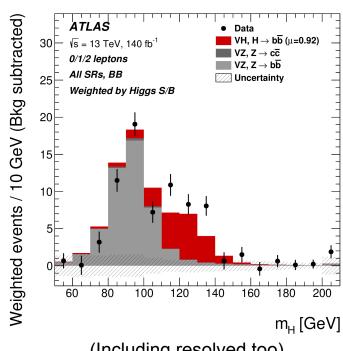


☑ All together now

 In this case, a strength parameter of the signal is measured:

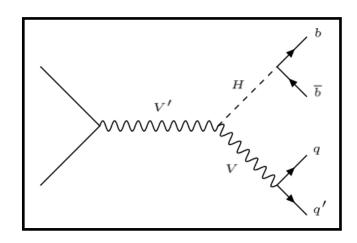
$$\mu_{VH} = \frac{\sigma_{\text{meas}}}{\sigma_{\text{SM}}} = 0.92 \pm (\text{stat.})^{+0.13}_{-0.11} (\text{syst.})$$

 We take advantage of the diboson peak for validation, before unblinding the data.



(Including resolved too)

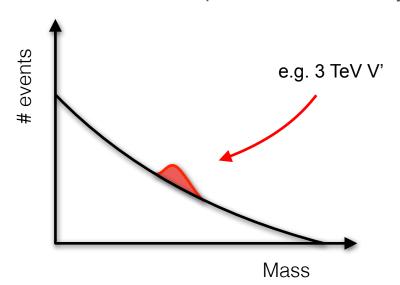
- Let's make it more interesting...
 - ✓ Make it a resonance: $W' \rightarrow WH$
 - ✓ Make it all hadronic

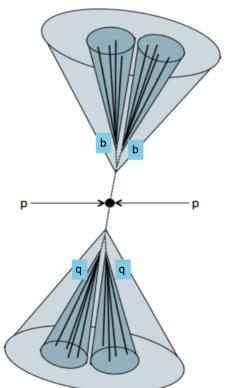




W', Z': heavier versions of the W and Z bosons

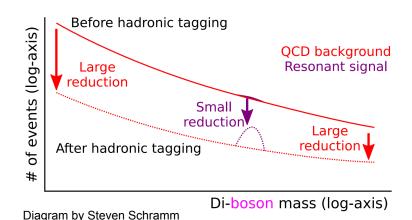
- 2 large-radius jets: 1 boosted H→bb jet and 1 boosted W→qq jet
- A resonant peak above the multijet background, ~TeV scale





☑ Dominant background: multi-jet production

- Huge cross-section!
- Tagging of boosted Higgs and boosted W bosons rejects a lot of background, but what remains is tricky and expensive to simulate precisely.



We do a fully data-driven background estimation 😭



- In other words, we interpolate or extrapolate from a background dominated CR into a SR.
- We use data directly (in some cases using MC but only in defining regions or checking assumptions).

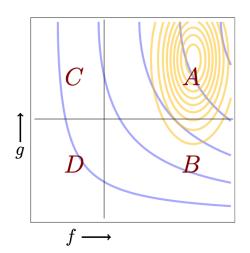
Example #1: the ABCD method

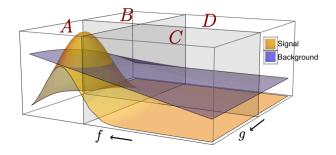
- 1. Pick two observables **f** and **g** which are:
 - Approximately statistically independent for the background.
 - ☑ Effective discriminators of signal vs background.
- 2. Apply thresholds on these observables to define 4 regions:
 - · A: signal region
 - B, C, D: background regions
- 3. If **f** and **g** are independent then the background in A can be predicted from the other three regions:

$$N_A = \frac{N_B N_C}{N_D}$$

 N_i = number of events in region i

E.g. f,g = mass, missing ET, ...

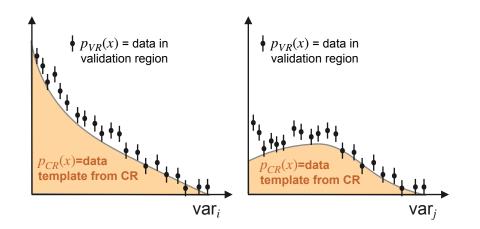




Example #2: multi-dimensional reweighting with ML

- Let's say we extrapolate the background from control region to signal region.
- We cross-check modelling in validation region and observe discrepancies.
- Then, do a **reweighting**: use one sample with distribution $p_{CR}(x)$ to model sample $p_{VR}(x)$, via a density ratio r(x)

$$p_{VR}(x) = r(x)p_{CR}(x)$$
 How do we determine $r(x)$?



Example #2: multi-dimensional reweighting with ML

• *Likelihood-ratio trick:* a classification model (NN, BDT, ...) trained to discriminate between samples A and B can also estimate their probabilities.

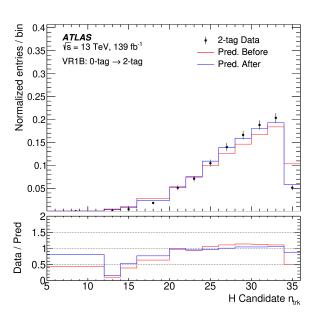
$$r(x) = \frac{p_A(x)}{p_B(x)} = \frac{p(x|A)}{p(x|B)} = \frac{p(A|x)}{p(B|x)} = \frac{h(x)}{1 - h(x)}$$

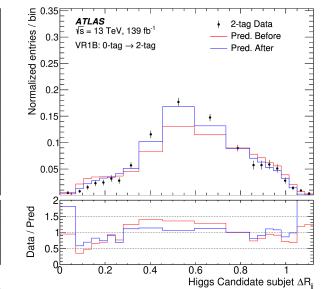
 $p_{VR}(x)$ = data in validation region p_{V

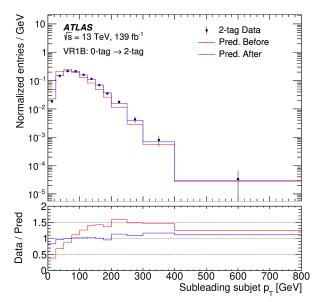
h(x) is the classifier output

Example #2: multi-dimensional reweighting with ML

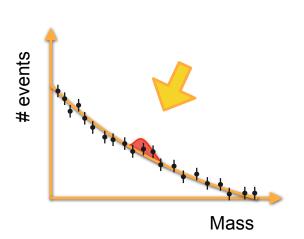
Before BDT reweighing After BDT reweighting



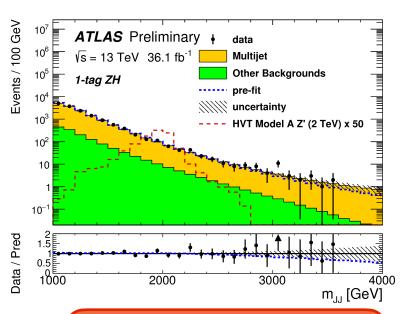




☑ Results:



Finally, we have a background model for the signal region (shape and yields) and systematic uncertainties on that model, to compare against data.



Signs of new physics / statistical fluctuations?

When do announce a discovery?

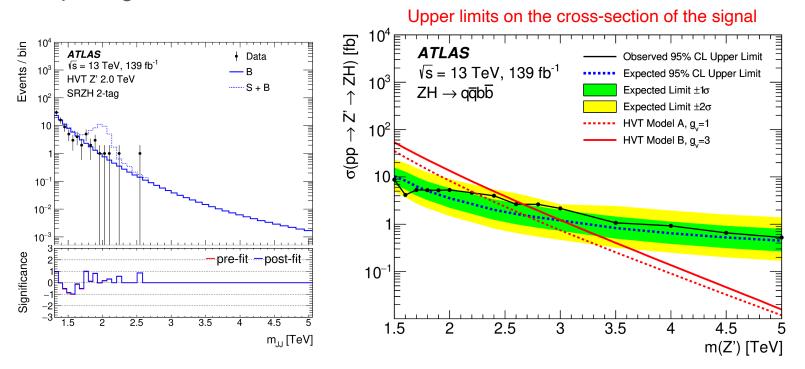
• To find out if our data is compatible with the presence of new physics, we can compute the probability for our observation with no signal present.

- Suppose we observe \mathbf{n}_b background events and \mathbf{n}_s signal events.
- Suppose ${\bf n}={\bf n_b}+{\bf n_s}$ is distributed according to a Poisson distribution with mean ${\bf s}+{\bf b}$: $P(n;s,b)=\tfrac{(s+b)^n}{n!}e^{-(s+b)}$

If b=0.5 and n=5, do we claim discovery?

p-value =
$$P(n > 5; b = 0.5, s = 0) = 1.7 \times 10^{-4}$$

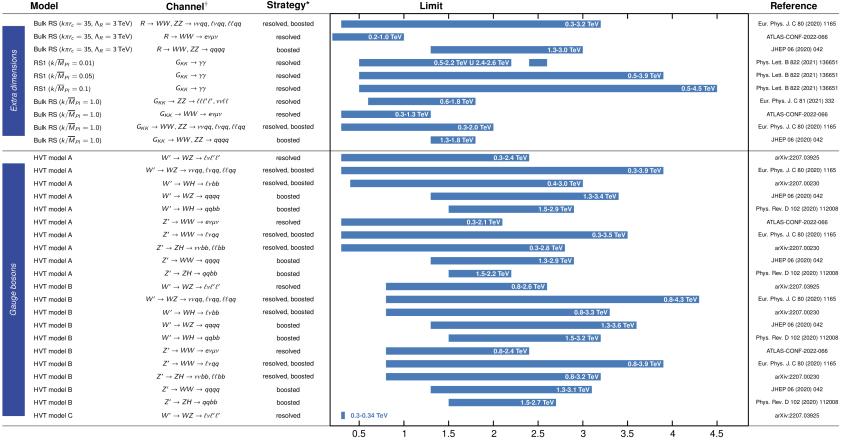
☑ Interpreting the results in the absence of an excess:



ATLAS Diboson Searches - 95% CL Exclusion Limits

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



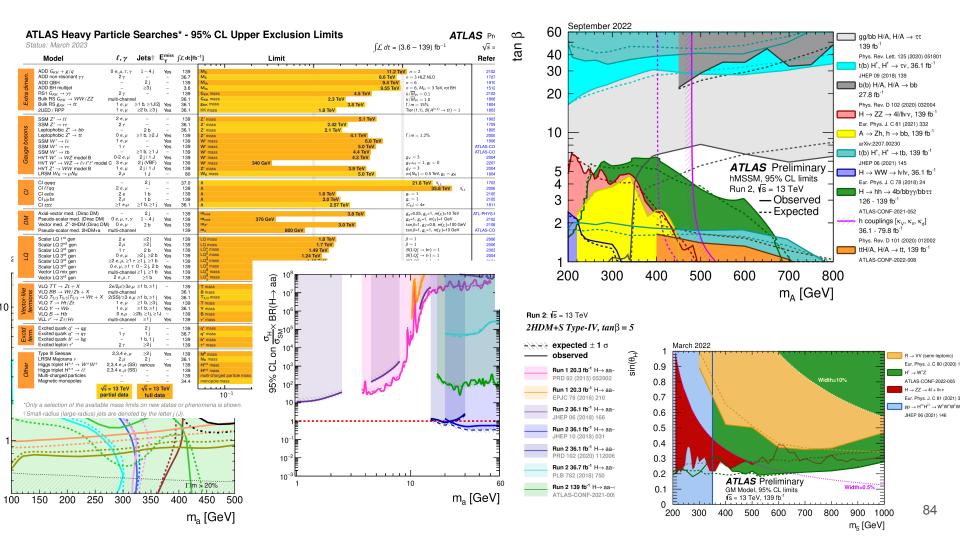


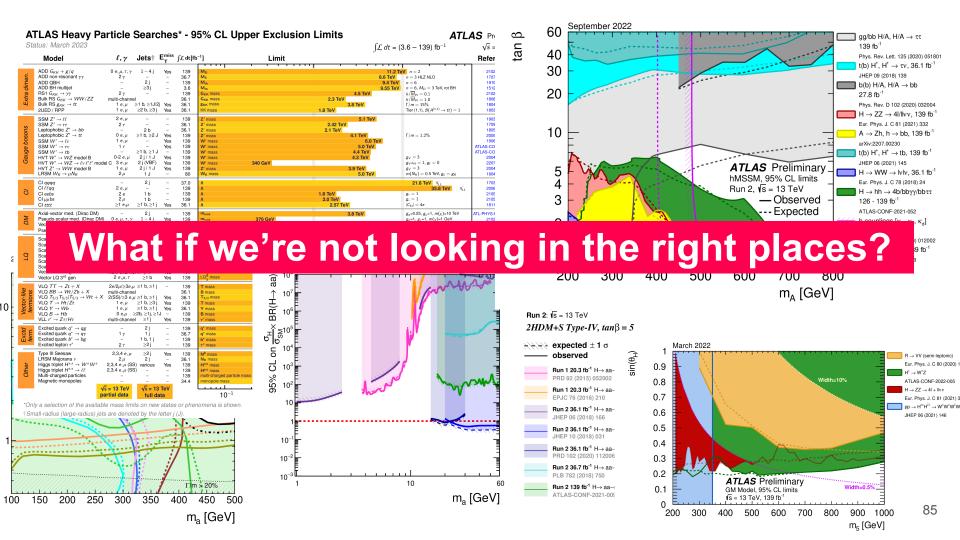
HVT model A: $g_F = -0.55$, $g_H = -0.56$ HVT model B: $g_F = 0.14$, $g_H = -2.9$

HVT model C: $g_F = 0$, $g_H = 1$

*small-radius (large-radius) jets are used in resolved (boosted) events

 † with $\ell=\mu$. e



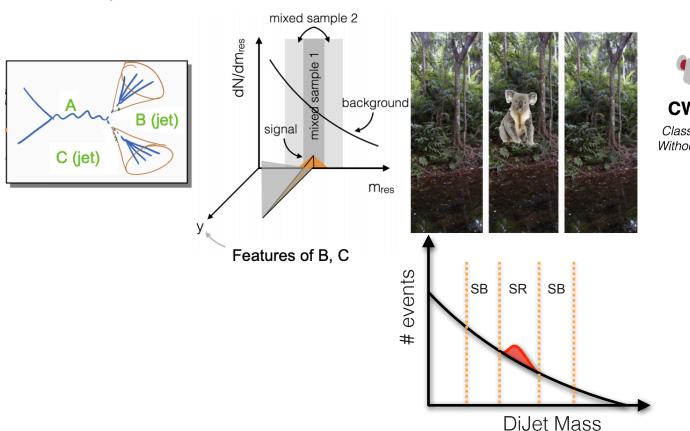


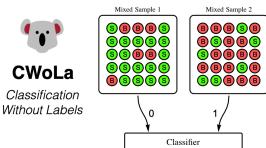
Bonus: anomaly detection

CERN seminar

https://arxiv.org/abs/2005.02983

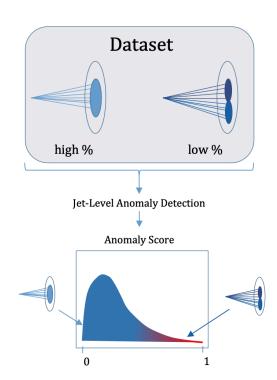
Weak supervision

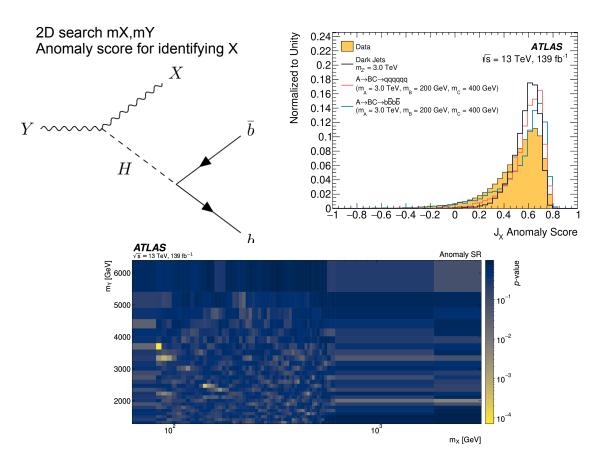




Bonus: anomaly detection

Unsupervised learning





Bonus: anomaly detection in the *trigger*

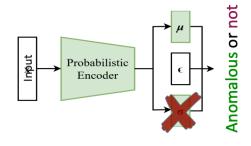
CICADA and AXOL1TL

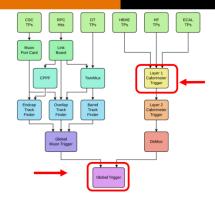






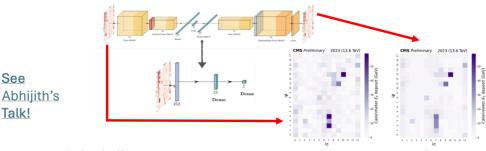
- Uses L1T objects as input
- Uses variational autoencoder
 - Latent space is Gaussian distributed
- Uses anomaly metric μ^2





CICADA

- Uses bare calorimeter inputs
- Uses convolutional autoencoder
 - Suited for image inputs
- Uses mean squared error as metric, and smaller model to predict final score

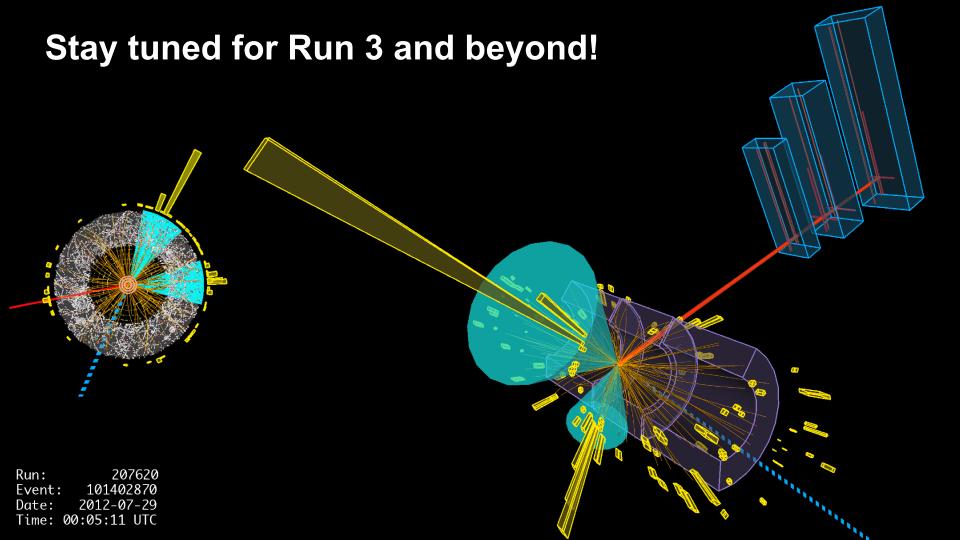


7/18/2024

Andrew Loeliger

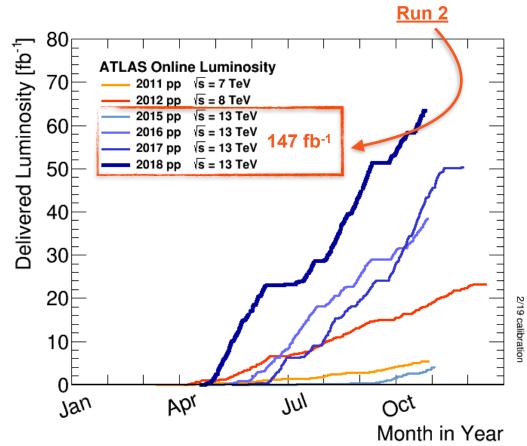
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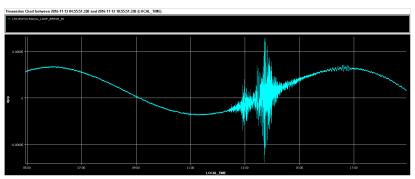




The LHC datasets







The New Zealand earthquake (2016).

LHC beam orbit displacement.