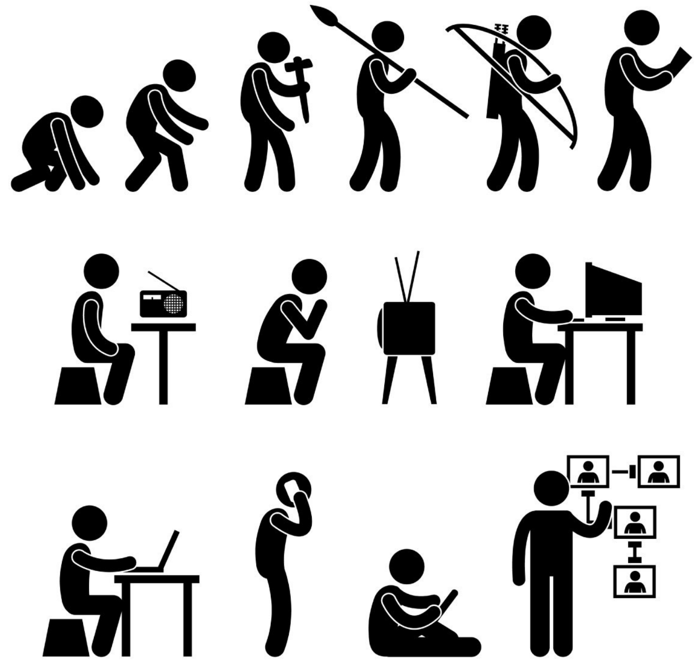
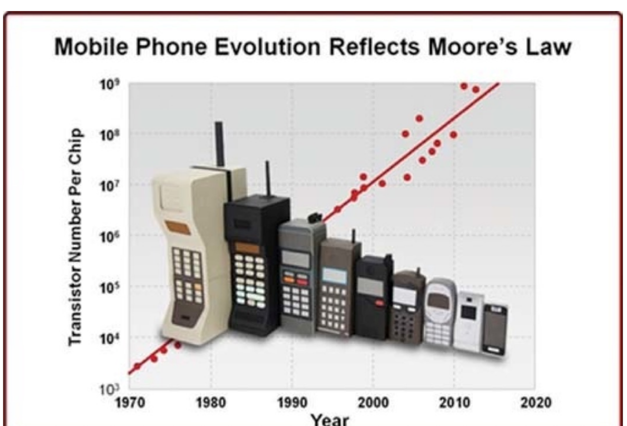
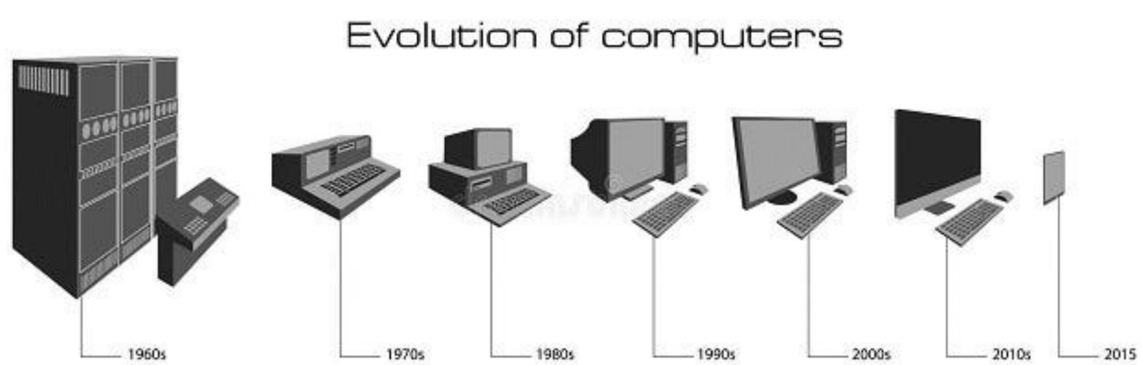


Trend and novelty on tools used for BSM searches at LHC

Stephanie Beauceron
LPNHE





Looking for the less obvious

Large search program but except the Higgs, nothing new so far

→ Machine Learning to improve calibration

→ Decay not automatic

→ Form of the decay not ‘usual’

→ Looking for anomalies

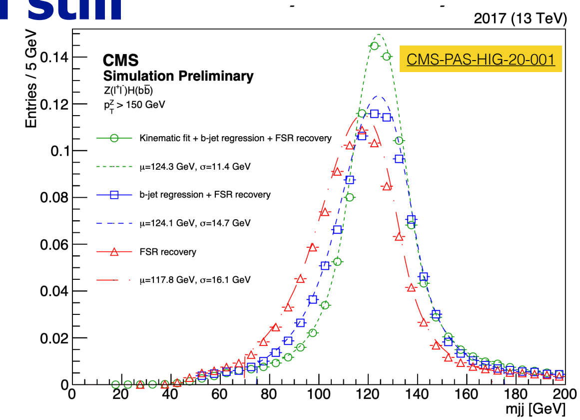
→ Machine Learning to help the selection

→ Improving background shape

Many Processes in Reality

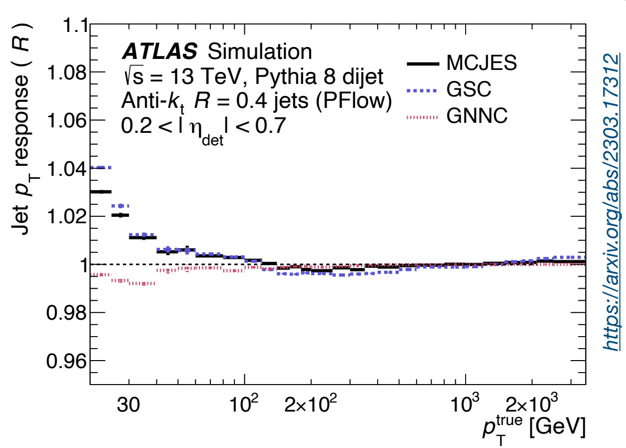
Increase PU, irradiation → increase noise etc, and still looking for extremely rare processes (di-Higgs production + searches)

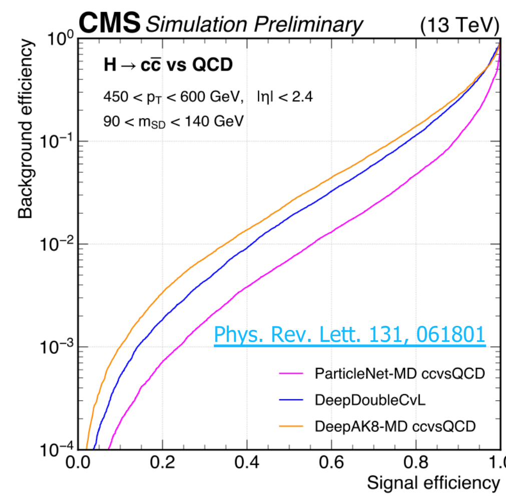
→ Constant need to carry on improving the reconstruction



→ Improving the understanding of the detector thanks to machine learning:

- **Regression method to improve energy measurement**
- **Better jet tagging**
- **Calibration at the level of jet constituents**
- **Improve track reconstruction (mostly HL-LHC)**



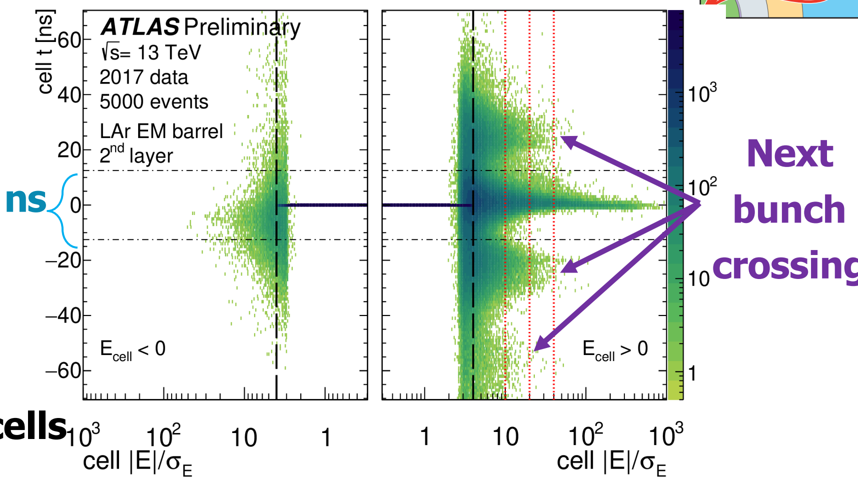


The cell ‘time cut’

Time resolution is good for large enough E significance

$$\begin{cases} |E_{\text{cell}}|/\sigma_E > 4 \\ |t_{\text{cell}}| \leq 12.5 \text{ ns} \end{cases} \quad \text{OR} \quad |E_{\text{cell}}|/\sigma_E > X_{\text{UL}}$$

±12.5 ns

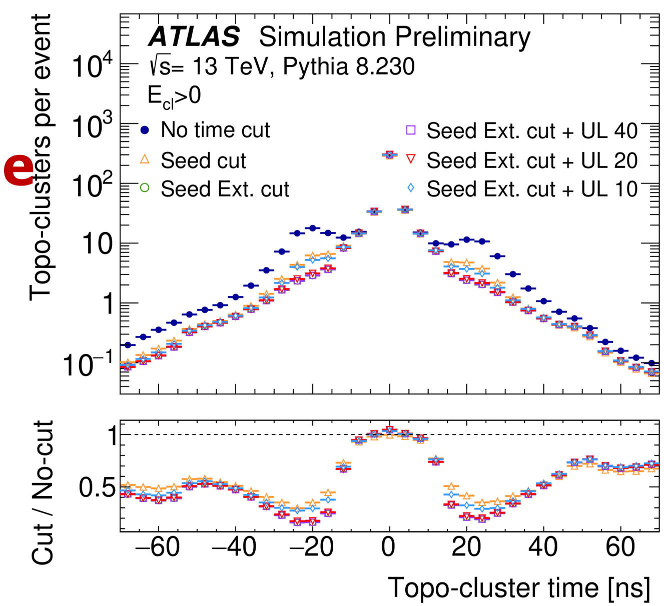


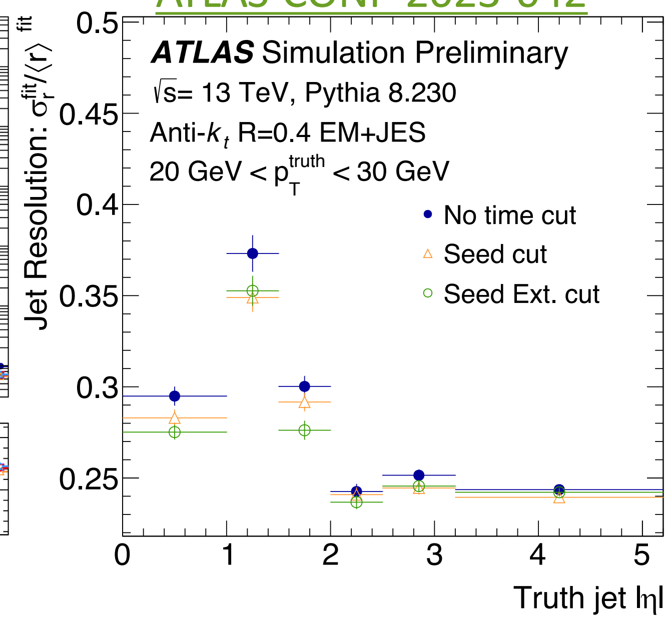
- **Cells passing $|E_{\text{cell}}|/\sigma_E > 4$ but failing $|t_{\text{cell}}| < 12.5$ ns are also vetoed from being collected as neighbouring cells**

Cut switched off for E significance greater than x_{UL} to avoid rejecting phase space potentially sensitive to Long-Lived-Particle

ATLAS-CONF-2023-042

Suppresses out-of-time jets while preserving in-time signals
➔ ~ -60% at p_T=20 GeV



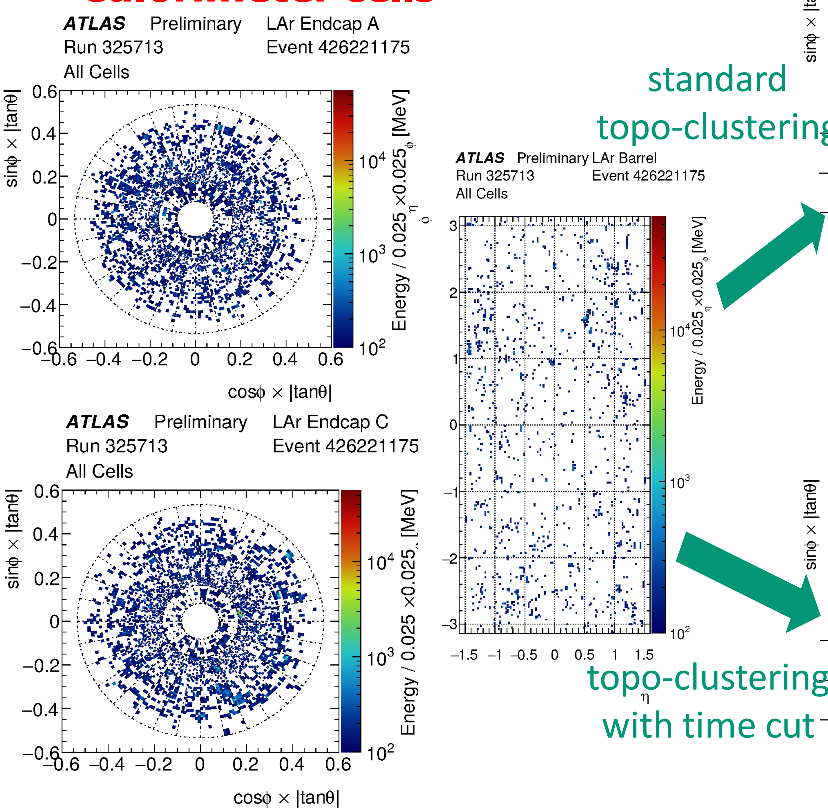


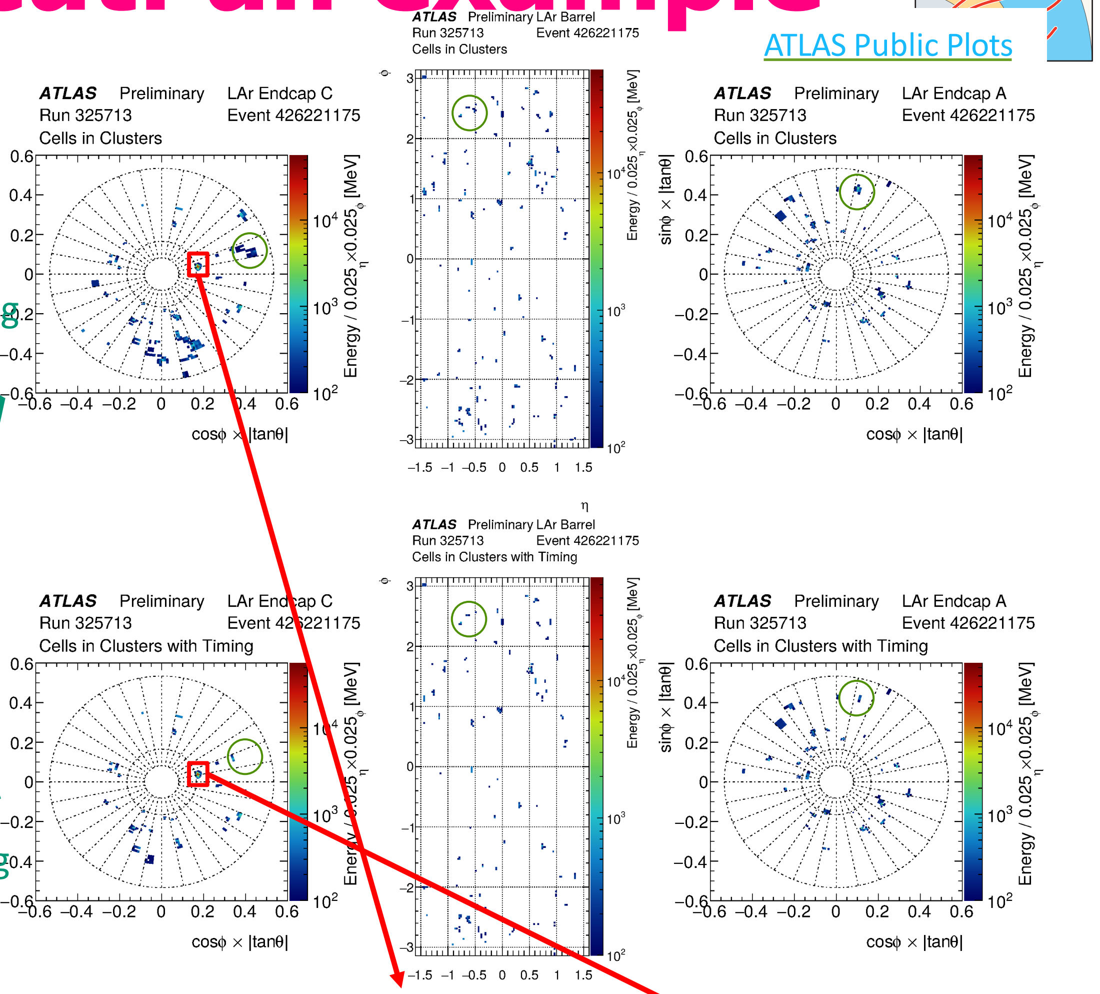
The time cut: an example

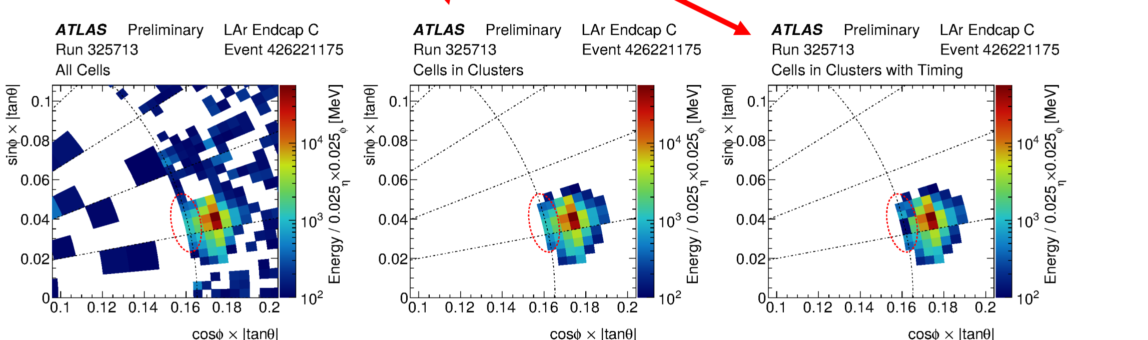
[ATLAS Public Plots]

➢ **One event from Run 2**

Calorimeter cells



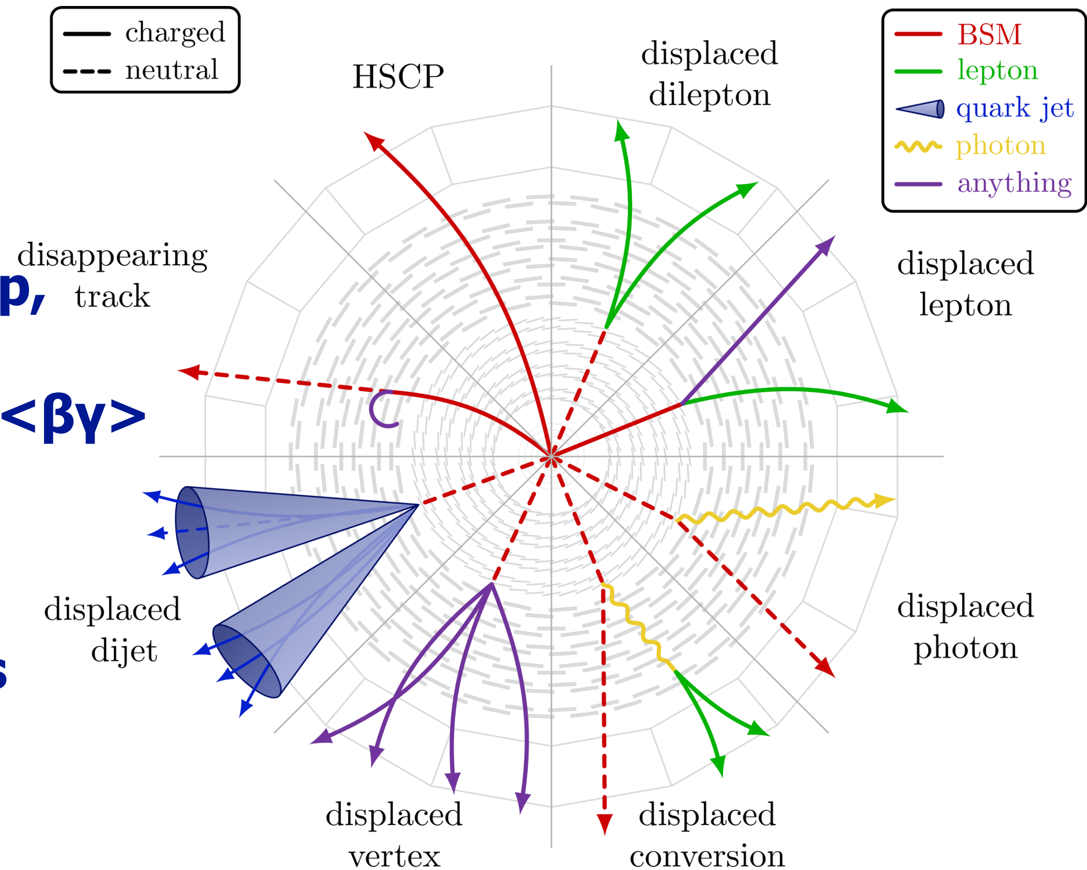




Spurious contributions are removed
Signal cluster becomes cleaner

Long Lived Particles

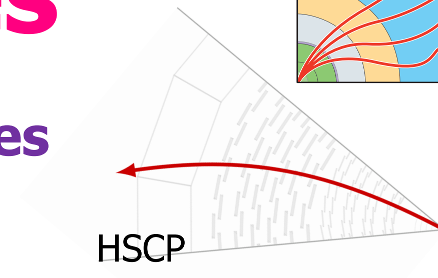
Detector signatures are unconventional, delayed and displaced:
- **Often similar to noise, pile-up, misreconstruction**
- **Dependent on LLP mass, cτ, <βγ> and decay channel**



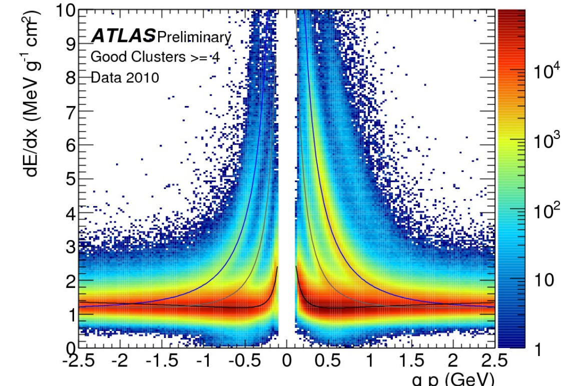
Request:
- **Innovative trigger strategies**
- **Custom reconstruction and identification methods**
- **Sophisticated ML techniques**

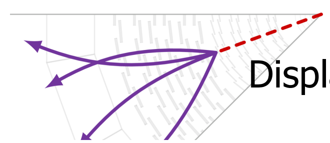
Long Lived Particles

R-hadrons: bound state of SUSY & SM colored particles
Gluinos (split SUSY) or stops (electroweak baryogenesis)



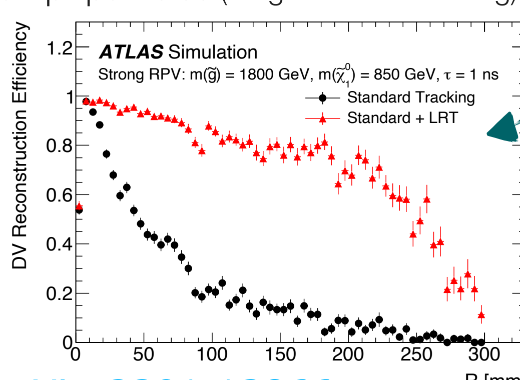
HSCP: Measure candidate velocity (β) and mass ($m = p/\beta\gamma$) from dE/dx or ToF
Particles can be detected via high ionization.
Anomalously high dE/dx is measured by the Inner Tracker.





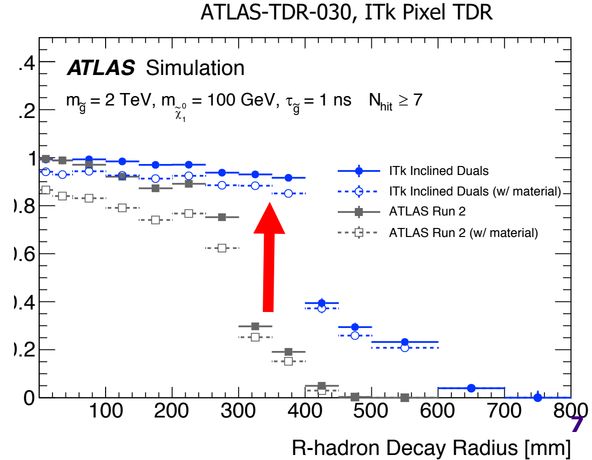
Neutral or charged LLP which decays within tracker to at least one vertex with many tracks
Searches will benefit from Pixel Upgrades

Dedicated secondary-vertex reconstruction for DVs benefitting from **dedicated track reconstruction** for non-prompt particles (Large Radius Tracking)



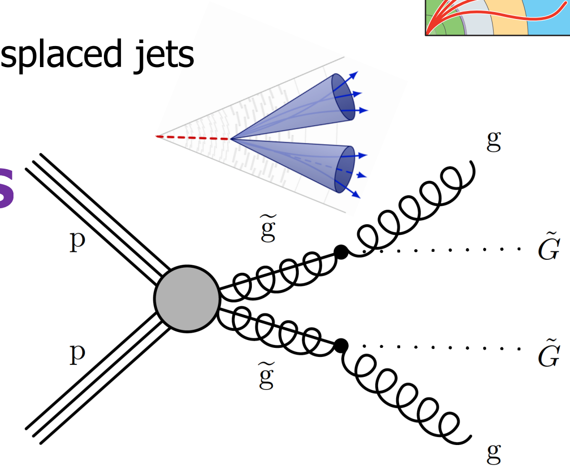
arXiv:2301.13866

ATLAS-TDR-030, ITk Pixel TDR



Specific Reconstruction

Displaced jets



Delay jets + p_T^{miss} ,
Gauge mediated supersymmetry breaking (GMS

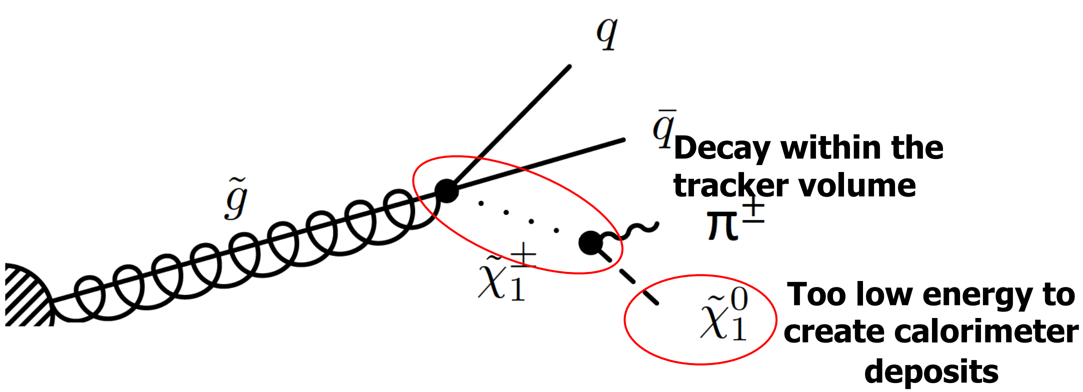
Rely on high precision of timing of CMS Electromagnetic Calorimeter

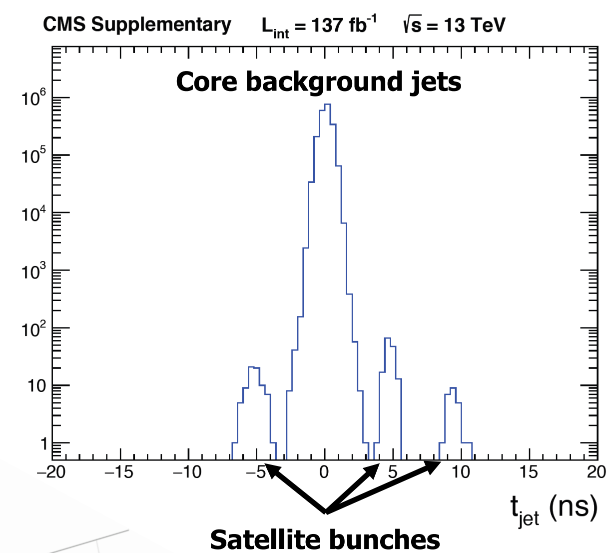
CMS-PAS-EXO-19-001

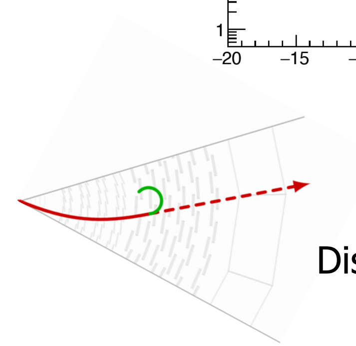
Disappearing tracks + jets,
Compress SUSY with $\Delta m(\tilde{\chi}^{\pm}_1, \tilde{\chi}^0_1) \sim 100$ MeV

Looking for a « short track »

CMS-PAS-SUS-19-005

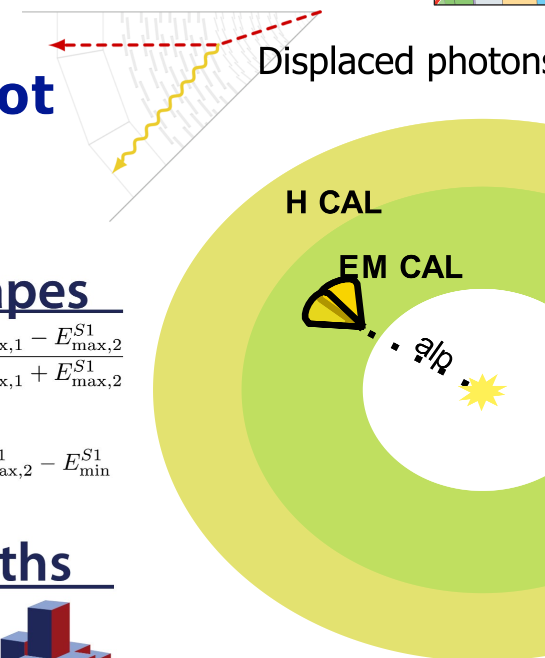






Disappearing track

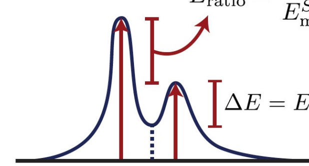
Displaced and Merged Photons



Standard E-Gamma objects reconstruction not suitable for displaced/merged photons
→ Usually expect symmetries in the variables used

Shower Shapes

$$E_{\text{ratio}} = \frac{E^{S1}_{\text{max},1} - E^{S1}_{\text{max},2}}{E^{S1}_{\text{max},1} + E^{S1}_{\text{max},2}}$$

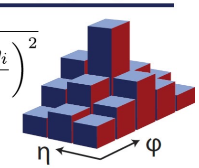


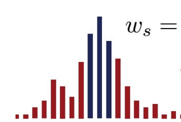
$$\Delta E = E^{S1}_{\text{max},2} - E^{S1}_{\text{min}}$$

Widths

$$w_{\eta,2} = \sqrt{\frac{\sum E_i \eta_i^2}{\sum E_i} - \left(\frac{\sum E_i \eta_i}{\sum E_i}\right)^2}$$

Width in a 3×5 (Δη×Δφ) region of cells in the second layer.





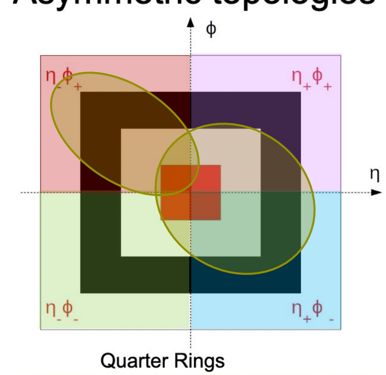
$$w_s = \sqrt{\frac{\sum E_i (i - i_{\text{max}})^2}{\sum E_i}}$$

ws3 = w_1 uses 3 strips in η; wstot is defined similarly, but uses 20 strips.

→ Allow asymmetric information by summing energies on lower level clusters to look for second/third maxima

→ Usage of Machine Learning techniques to maximise the usage of the information, promising results

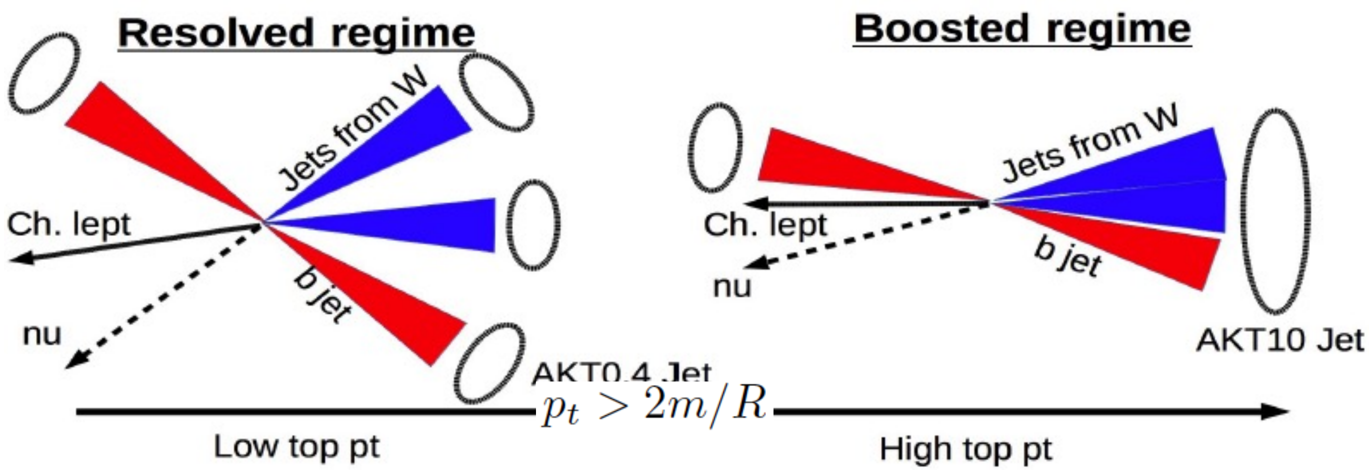
Asymmetric topologies



Quarter Rings

Boost

I.e. ttbar pair production:



Higher boost is given, more collimated are the decay:

Adjust reconstruction/identification variable:

Lepton isolation: with a cone size depending on pT:

i.e. Atlas: $I = \sum_{R} p_T^{trk}$ with $R = \min\left(\frac{10\,\mathrm{GeV}}{p_T}, 0.2\ (0.3)\right)$ **electron/muon**

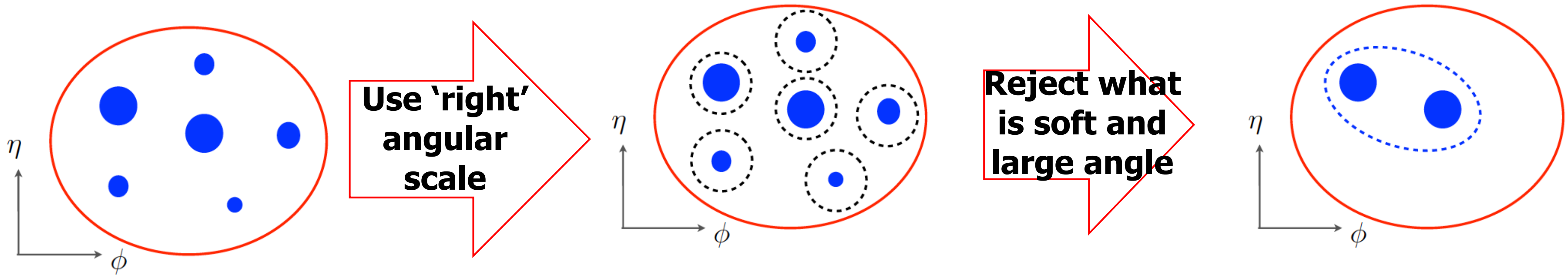
Using larger cone size for jets to get all decay in

→ Look at jet sub-structure to identify

Jets sub-structure

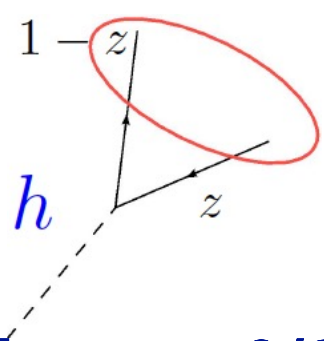
Exploit jet substructure: grooming and tagging

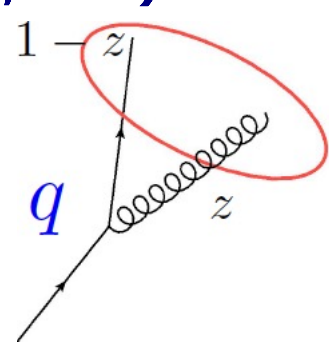
Grooming:



Tagging:
identify the features of hard decays and cut on them
core-idea for 2-body tagging: min(z, 1 - z) > zcut

symmetric sharing of the energy



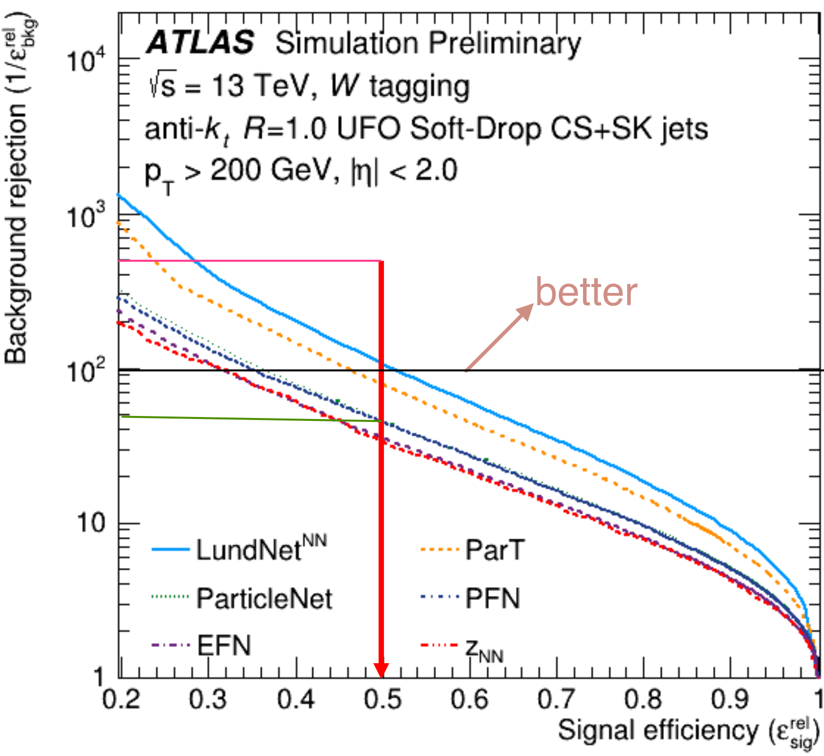


asymmetric sharing of the energy

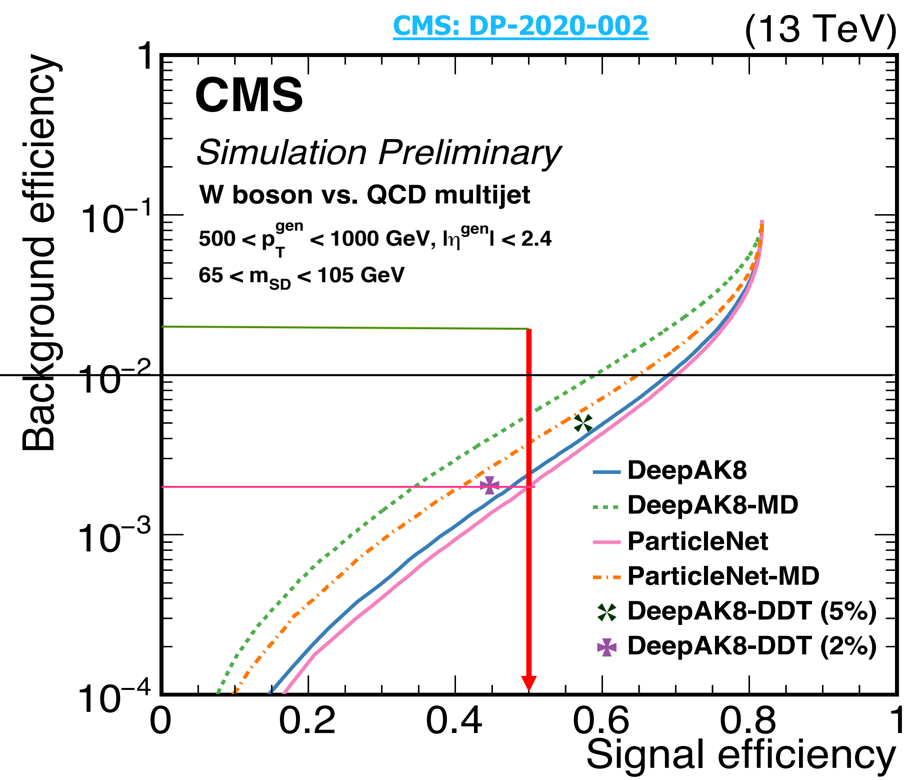
discriminate between 0/2/3/4 subjets inside the wide jet
→N-subjettiness

Results

ATL-PHYS-PUB-2021-029

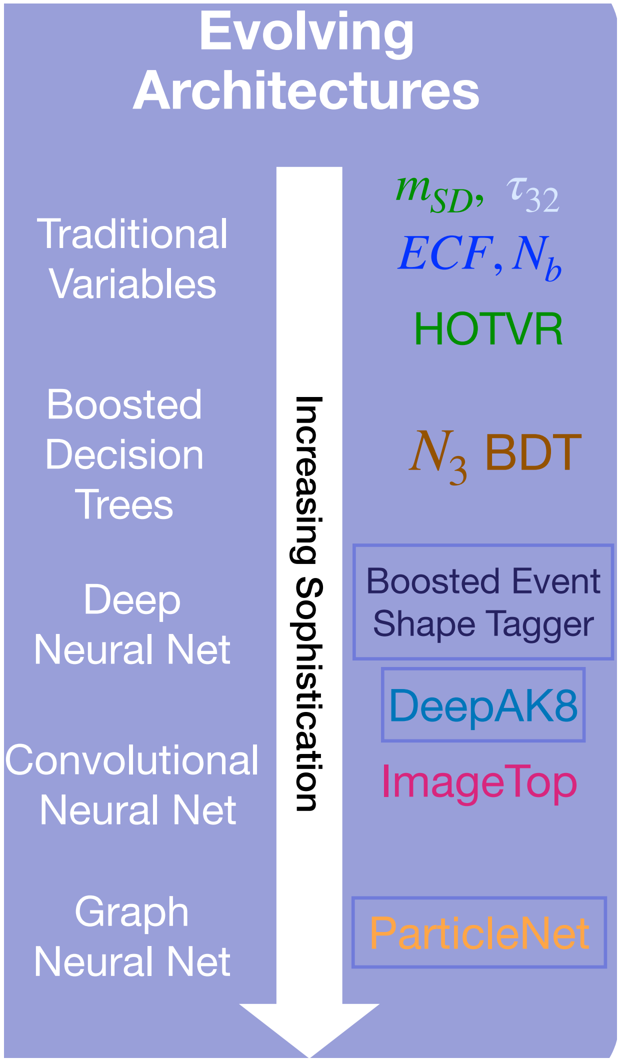


CMS: DP-2020-002



LundNet is x2 time more efficient for Atlas and in general CMS seems to be more efficient with particleNet (coming from different phase space? Pt?)

Machine Learning



Going from calibration/regression to object identification to event categorisation…

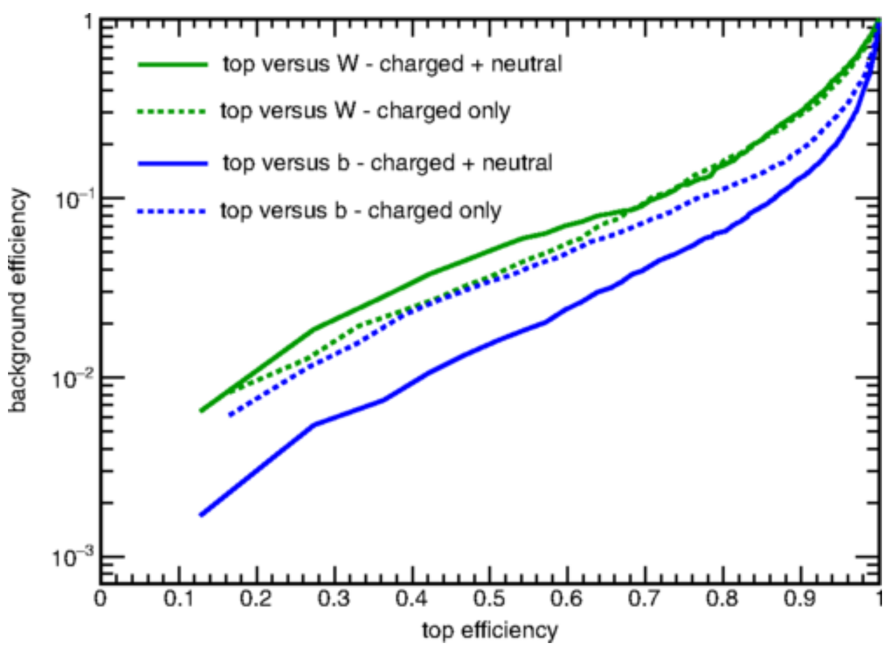
Machine learning is also used to select events wrt to background (many example)

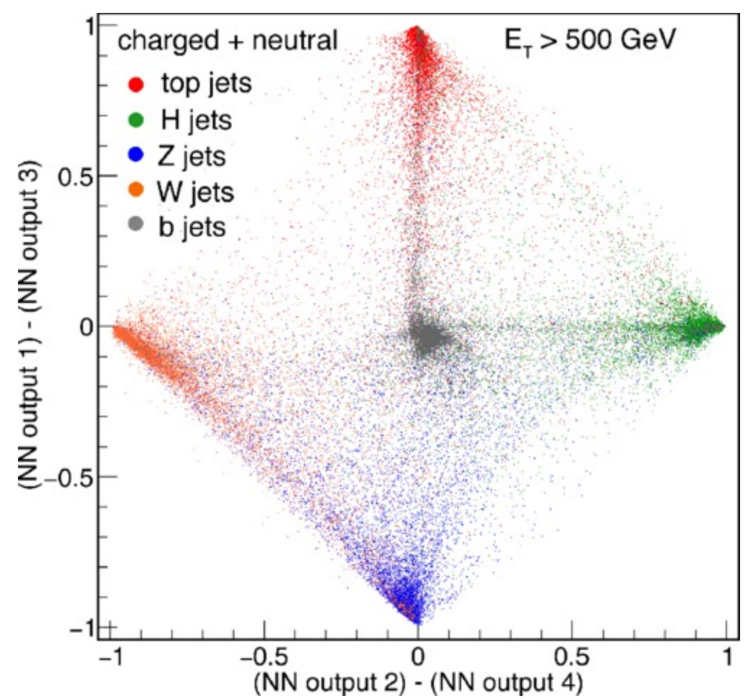
Focus on trying to have full event interpretation…

Jets Multiple Taggers

[Phys. Rev. D 94, 094027]

BEST algorithm = Boosted Event Shape Tagger
Using machine learning to classify a wide jet into W, Z, H, top, b or light quark jet
Main ideas:
- **Move to the rest frame of the assumed particle**
- **Use several variables to build a neural network discriminant**





→ Use in case multiple wide jets in final state

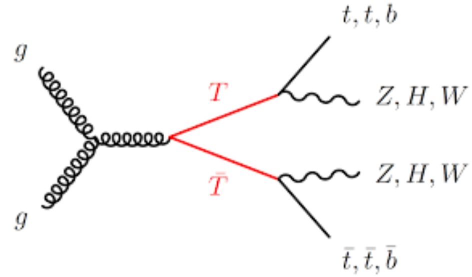
Multiple Identification

Simultaneously identify 6 jets category: BEST (Boosted Event Shape Tagger) [NN] CMS-PAS-B2G-18-005

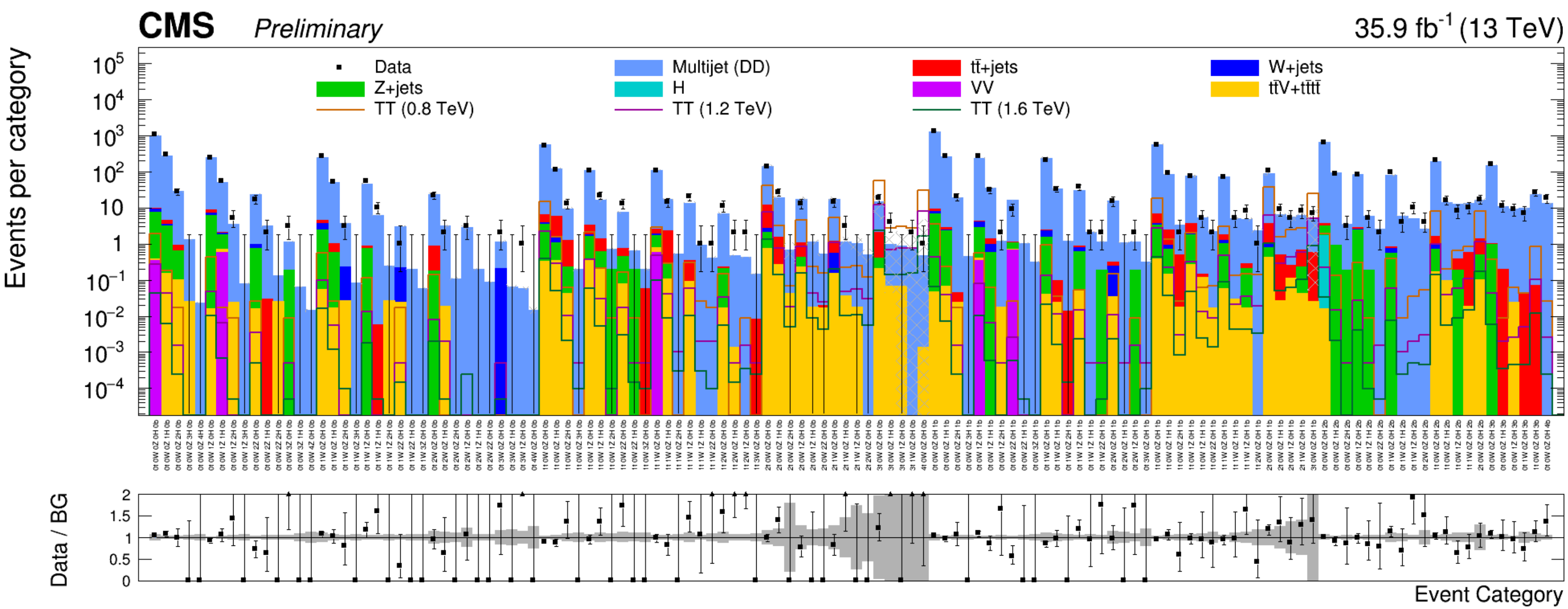
→Search for pair produced Vector Like Quark (T/B) all hadronic:

All decay channels in one go

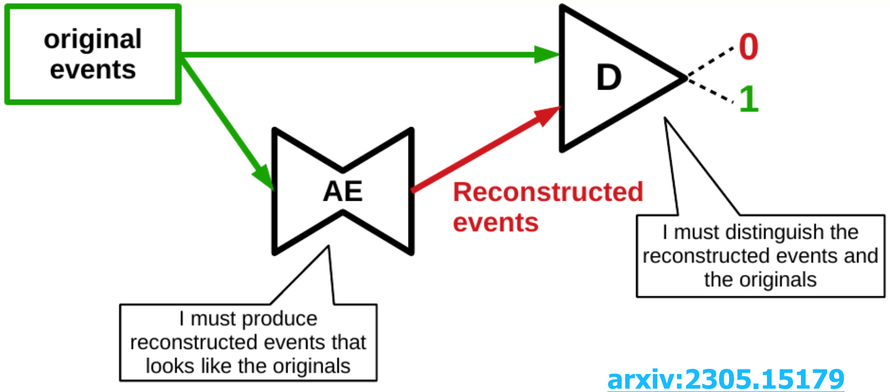
4 ak8 jets p_T>400 GeV



VLQ	W-decay	Z-decay	h-decay
T	Wb	Zt	ht
B	Wt	Zb	hb
$T_{5/3}$	Wt	-	-
$Y_{-4/3}$	Wb	-	-

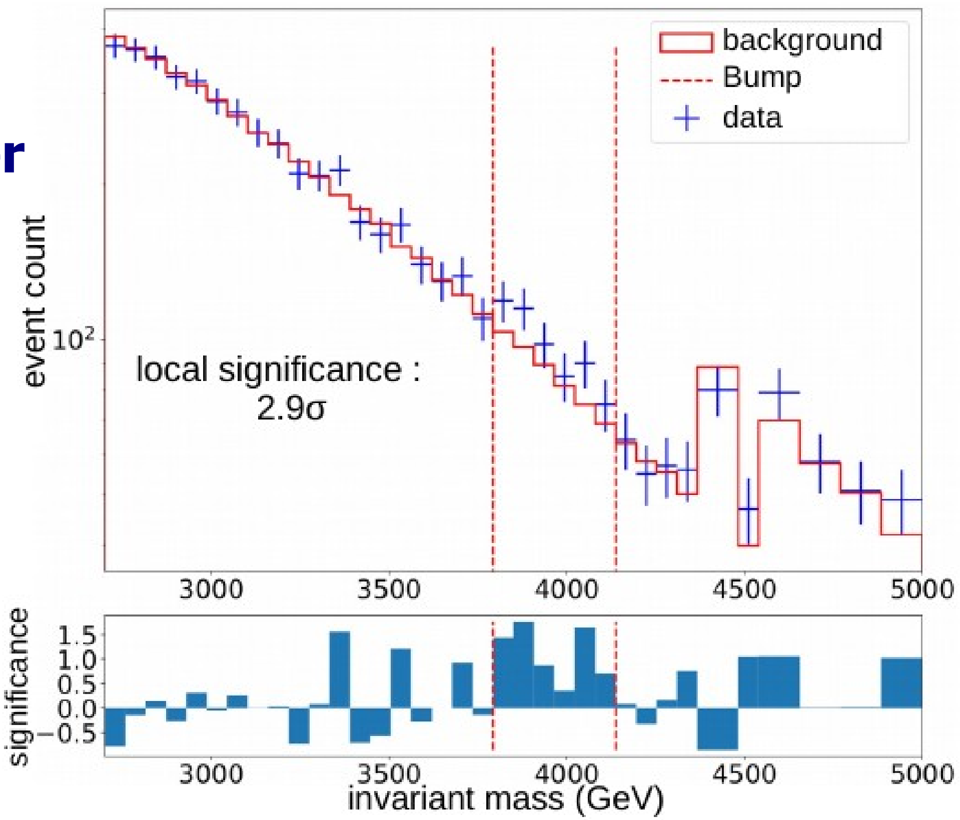


ML: Looking for Anomalies



Unsupervised training:
Generative Adversarial Network-based auto-encoder
Established an abnormal score from the data:
Selection of abnormal data containing potentially high rate of signal
Predict the background shape
Search of bump via pyBumpHunter algorithm

arxiv:2305.15179
arxiv:2107.11573



Observed excess in agreement with the injected one

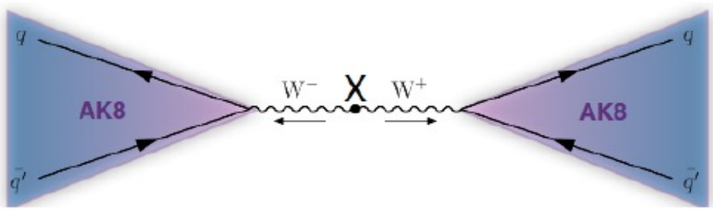
(Ratio S/B x 20 after the selection on the abnormal score)

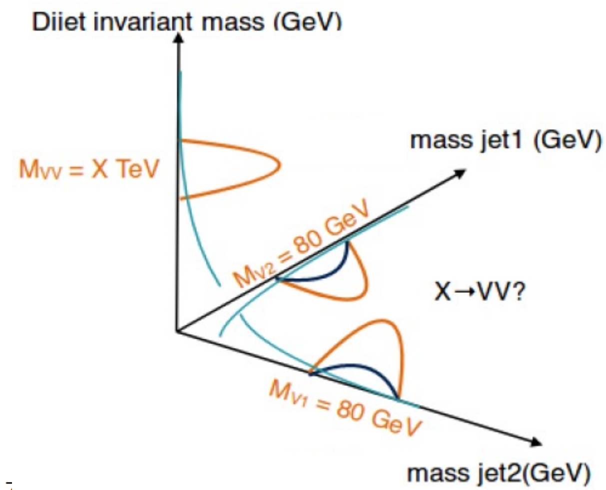
And Not ML: Multi-Dimensional Fit

CMS-PAS-B2G-18-002

Search for VV resonnances (V=W/Z) [Mass> 1TeV]:

3D maximum likelihood fit: $m(V_1V_2)$, $m(V_1)$, $m(V_2)$

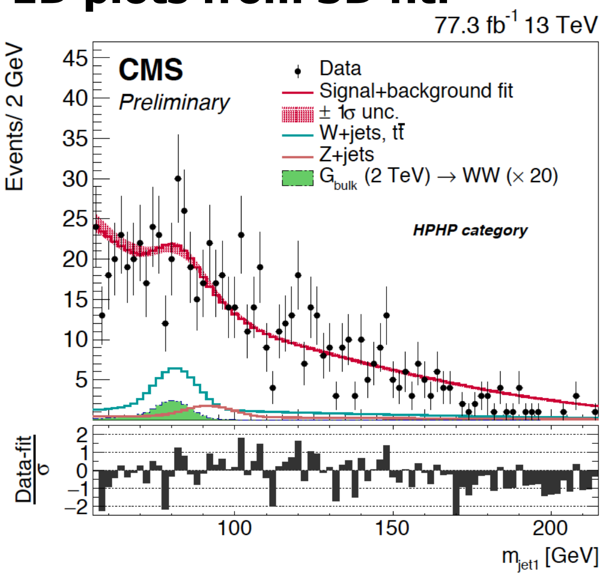


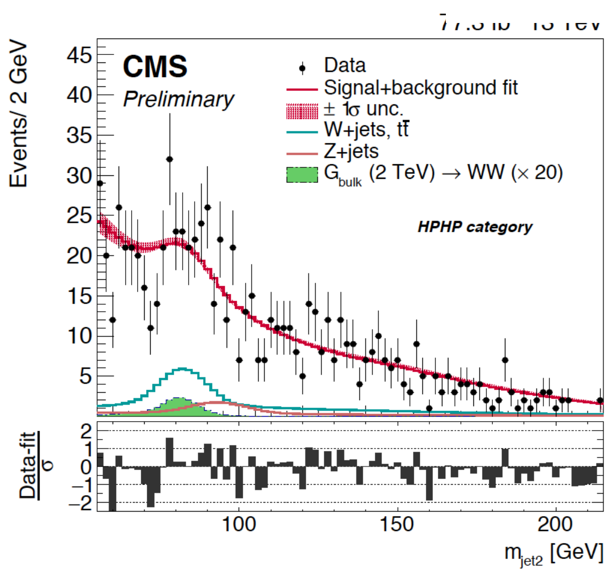


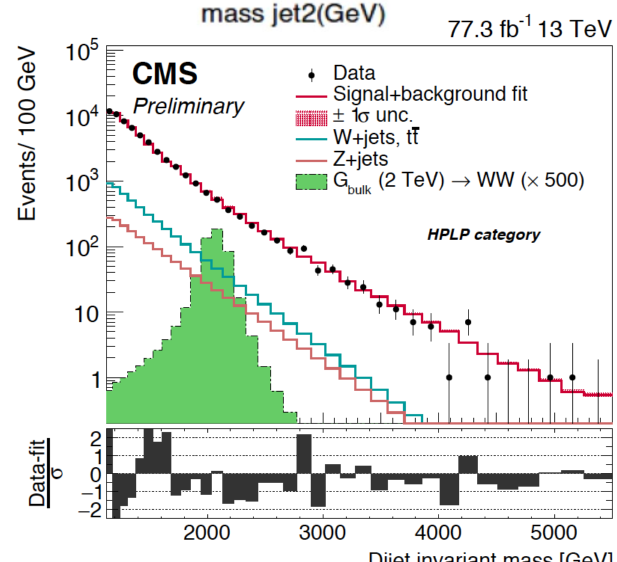
2 ak8 jets p_T>200 GeV

$|\Delta\eta|$<1.3

1D plots from 3D fit:

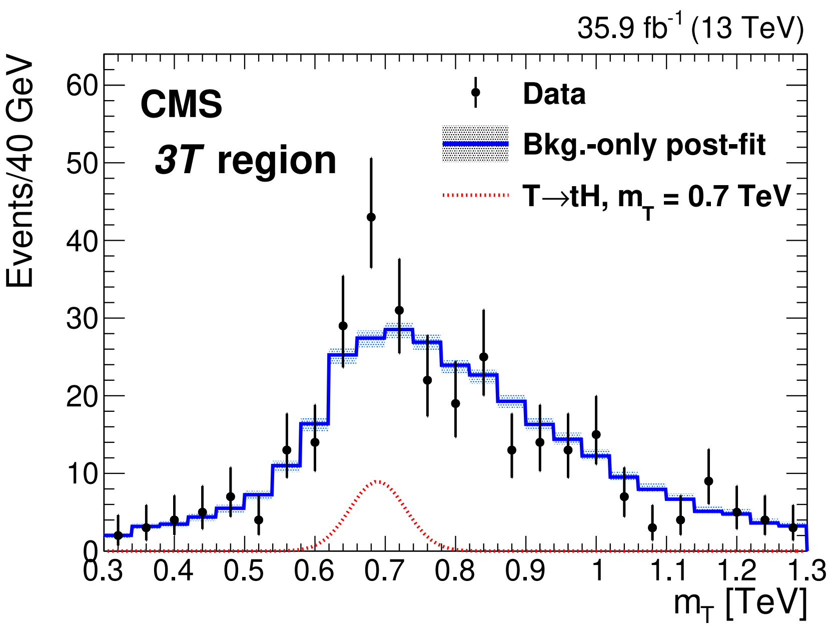


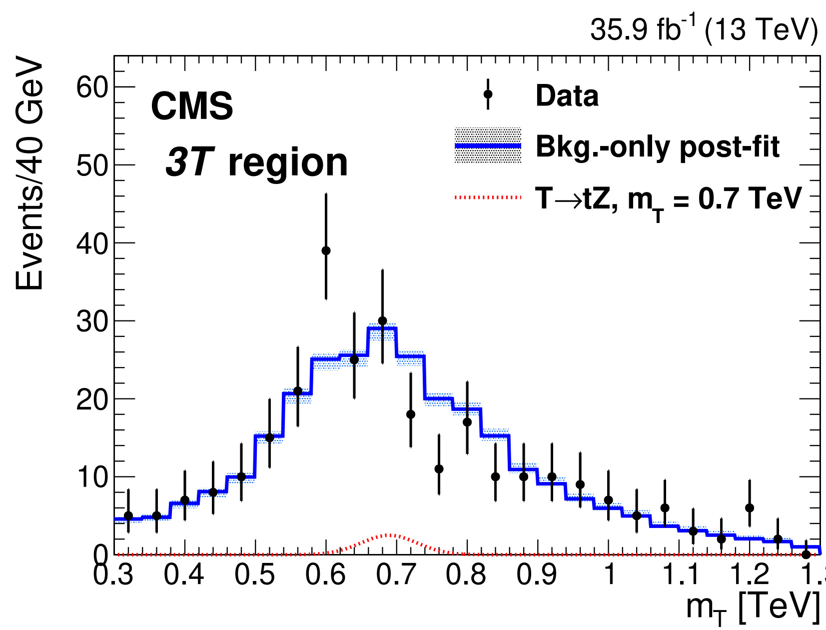




Not ML: Removing Selection Bias

An excess was observed on variable shaped by the selection, defined a second selection to remove the shaping
➔ more robust analysis





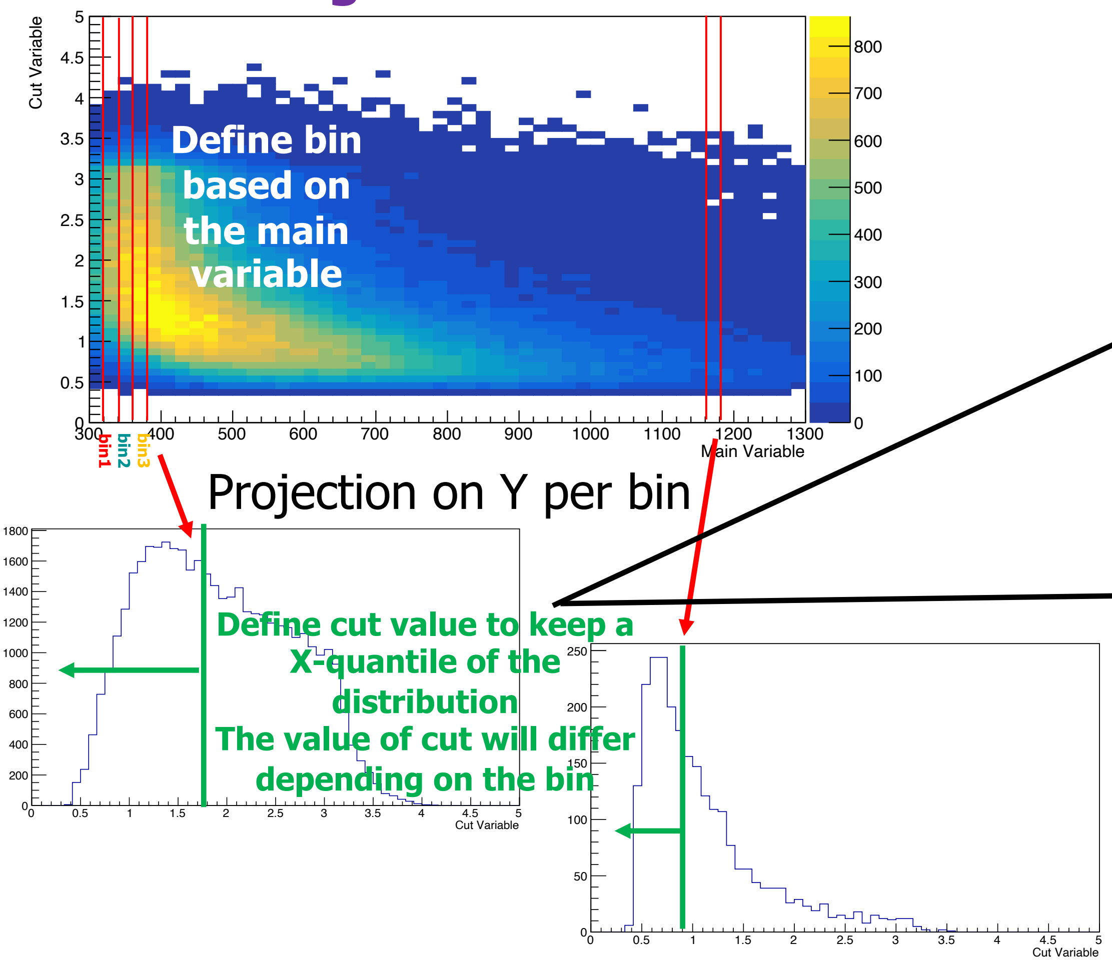
JHEP01(2020)036

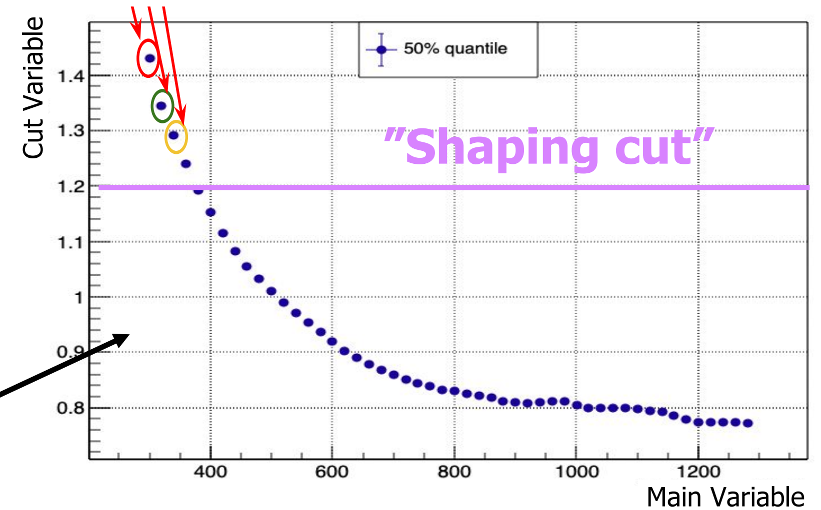
➔ Obtain a falling background

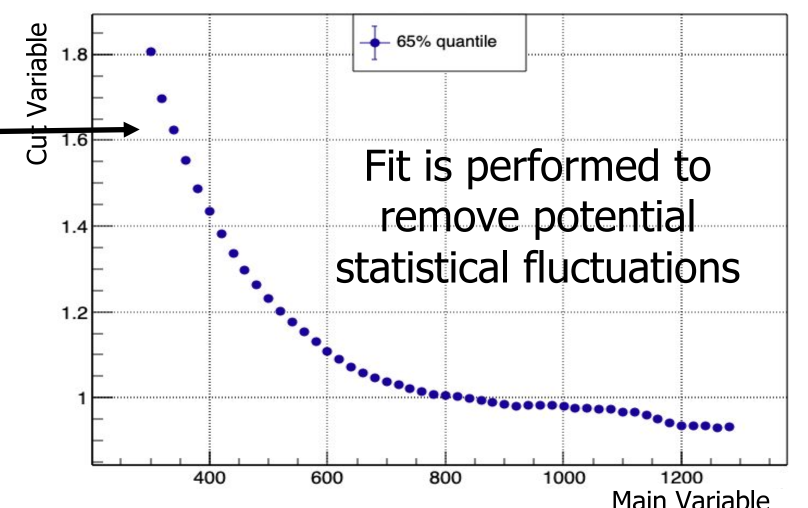
Remove Selection Bias

The same criteria than before are used, simply modify the cut value:
Define a cut as function of the main variable to keep a quantile of events from the previous cut
➔ Preserving the shape as just reducing the shape by a given quantile

How to design the new cut value:

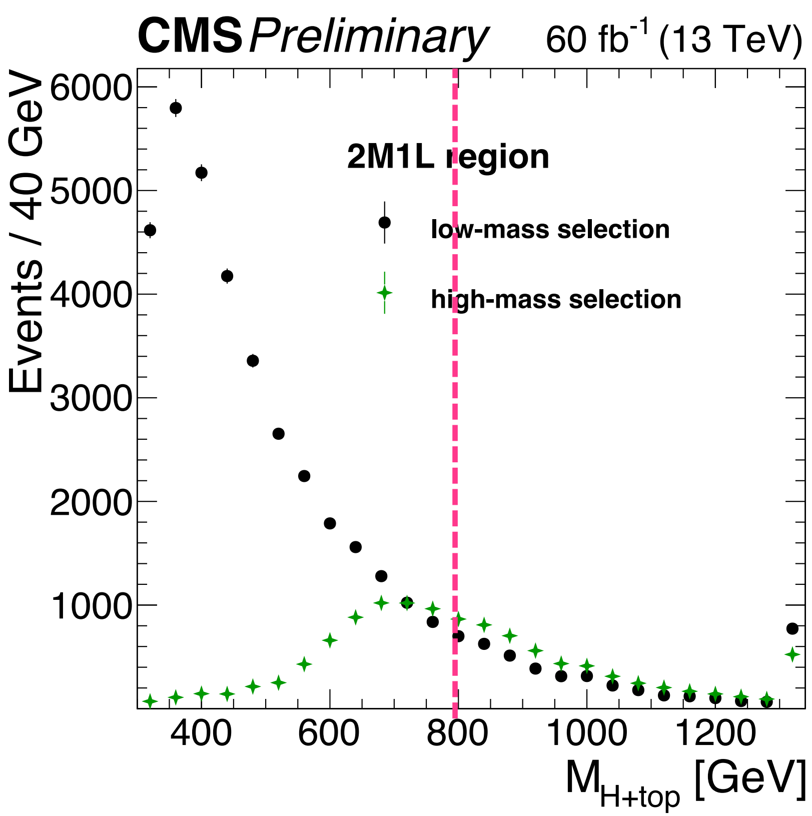


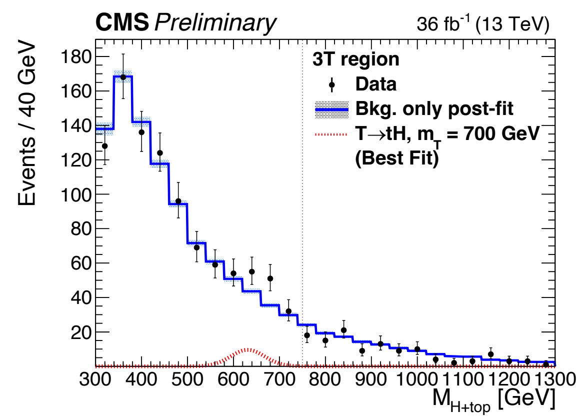




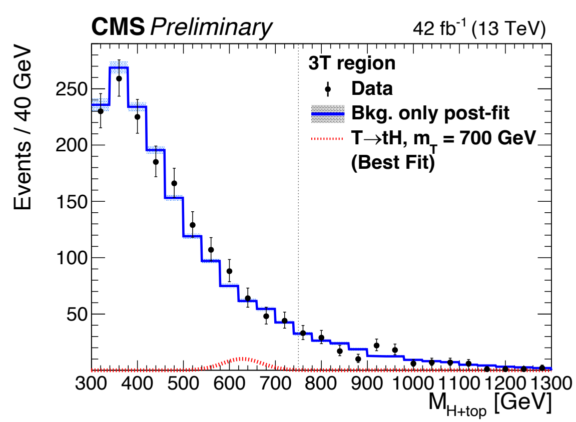
Removing Selection Bias

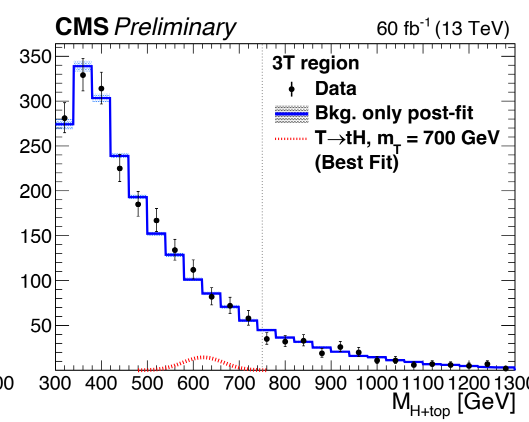
Keep the same efficiency for the signal than the optimized cuts (shaped analysis), still optimized cuts have better S/B at high values





B2G-19-001





➔ The background is clearly a falling background

➔ Better control of the background, easier to see a potential excess…

Conclusion

Searches are challenging → looking in the corner/tail of SM physics
→ New searches of non-standard final state
Detector are aging → Need to keep high performance

- ➔ Usage of Machine Learning to keep/improve calibration of objects
- ➔ Improve the reconstruction for non-standard objects
- ➔ Machine learning can help in reducing the new kind of background
- ➔ More energy → More boost! Adapt algorithms with sub-structure!
- ➔ Machine learning learning about the 'non-standard'
- ➔ Improve analysis technics also for cut based

- ➔ Extremely large number of new tools to cope for the new challenges, machine learning is highly present at many different stage
- ➔ Hopefully, finding something new soonish?!

(Recall, machine learning [neural networks] is used in particle physics since ~1970…)
CAREFUL: Full machine learning analysis request care when willing to share with theoriticians…

Optionnal

Lund Plane

- An abstract representation of the jet formation, initially developed by theorists to better understand it

- Each emission represented by a point in the kT-emission angle plane (log scale)

- Hard scattering, collinear and large-angle emissions populate different regions of the plane

- Experimentally, we can have an approximate reconstruction of the Lund Plane by running back the CA jet clustering and using the jet merging information

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