



# ICHEP ATLAS & CMS highlights

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# ICHEP 2024

## 42nd International Conference on High Energy Physics (In Prague, Czechia)

Huge conference that happens once every two years. It has many topics within the realm of particle physics. 18 parallel sessions (13 running in parallel at any given time during three days)



**281 posters, 918 parallel talks, 40 plenary talks**

**1388 Participants in total!**

*I tried to collect interesting ATLAS and CMS results that were shown or discussed there but as you can imagine, it's a lot of material and I missed lots of it even being there! I will only highlight some interesting/fun things that I found, with not that much detail*

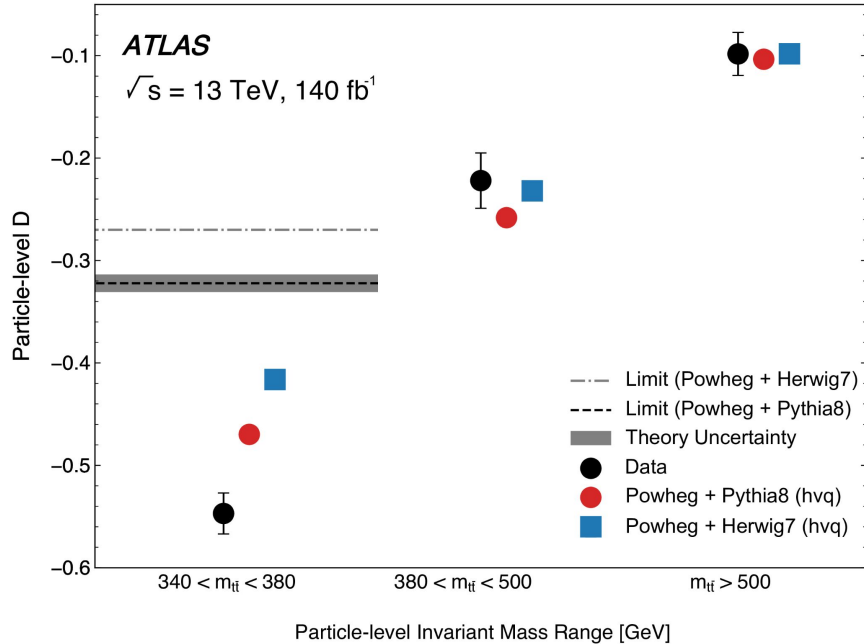


# Physics results

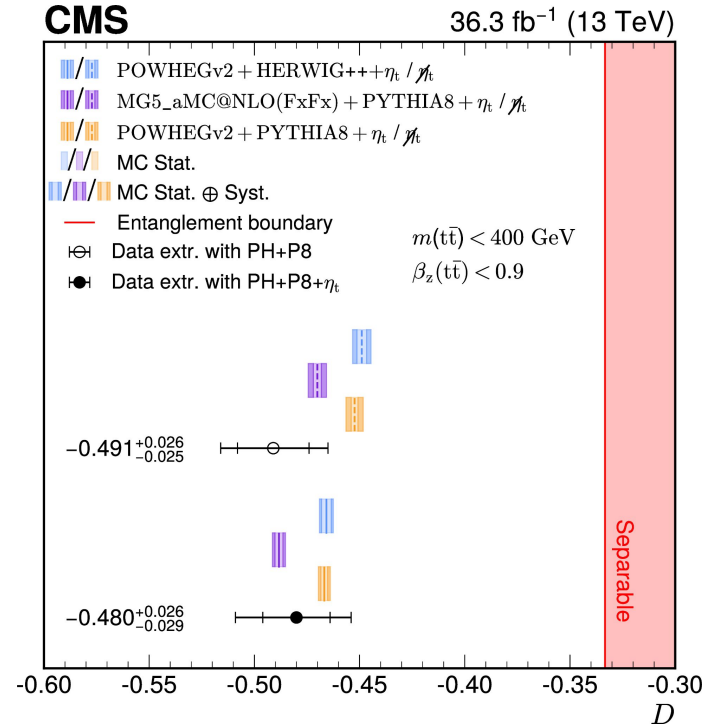
# Quantum entanglement results

[Link to talk](#)

Measuring entanglement-related observables in  $t\bar{t}$  pairs. New CMS result similar to a previous ATLAS results from late last year



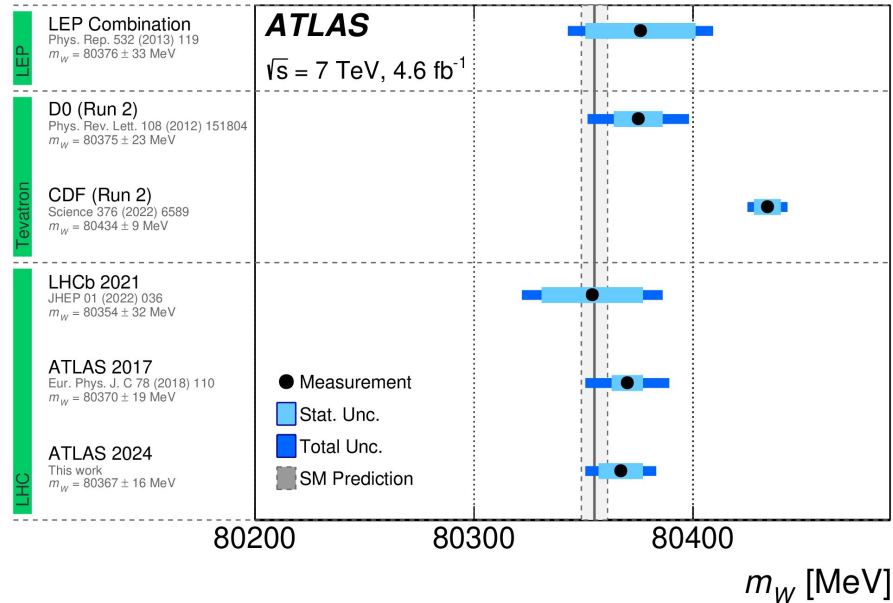
**D is connected to the distance in phi of the decay products of the two top quarks**



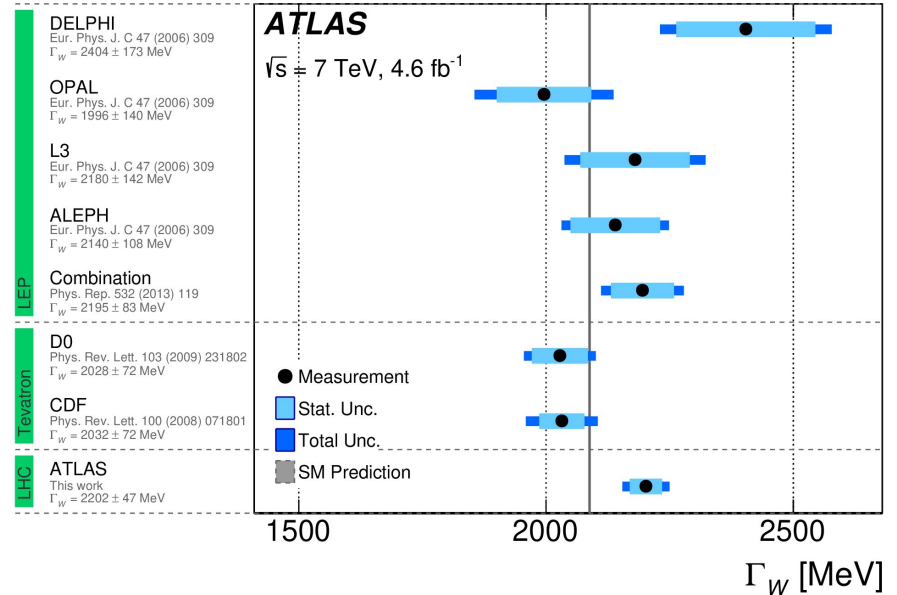
# The $M_W$ mystery is still unsolved

[Link to results](#)

Overview of  $m_W$  measurements



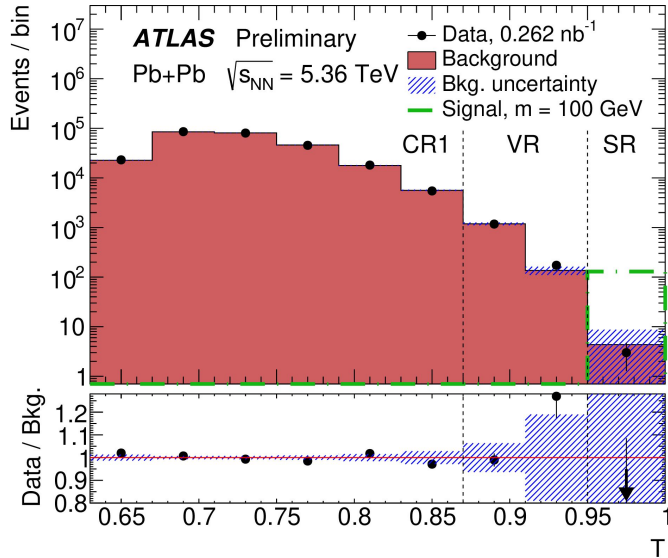
Overview of  $\Gamma_W$  measurements



*Eagerly awaiting CMS results, hopefully soon !  
 The final paper from ATLAS didn't change the picture much from last year... but introduced a bit of extra 'fun' given the width measurement disagreement with SM predictions*

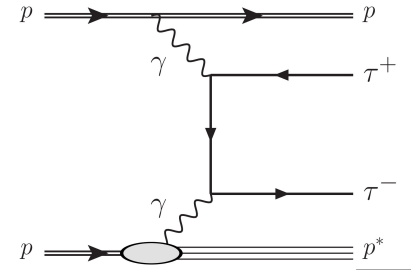
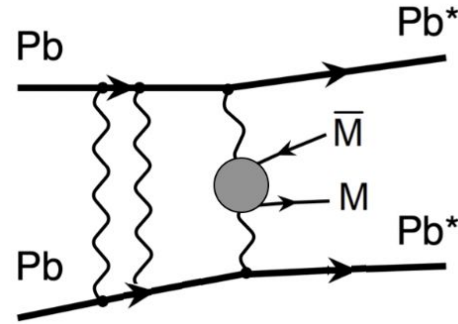
# Colliding more than protons/HI

Using the LHC as a photon-photon collider !



ATLAS: Looking for monopoles

CMS: Measuring anomalous magnetic and electric dipole moments of taus



**CMS**  $138 \text{ fb}^{-1} (13 \text{ TeV})$   
 • Observed — 68% CL — 95% CL

**OPAL**  
 $ee \rightarrow Z \rightarrow \tau\tau\gamma$   
 PLB 434 (1998) 188

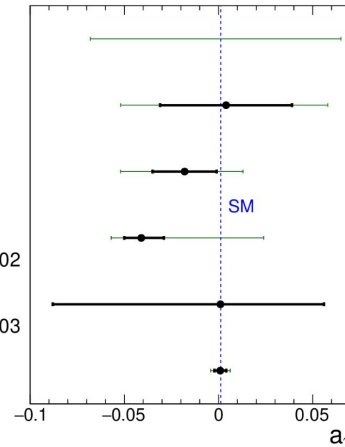
**L3**  
 $ee \rightarrow Z \rightarrow \tau\tau\gamma$   
 PLB 434 (1998) 169

**DELPHI**  
 $\gamma\gamma \rightarrow \tau\tau$  ( $\gamma$  from e)  
 EPJC 35 (2004) 159

**ATLAS**  
 $\gamma\gamma \rightarrow \tau\tau$  ( $\gamma$  from Pb)  
 PRL 131 (2023) 151802

**CMS**  
 $\gamma\gamma \rightarrow \tau\tau$  ( $\gamma$  from Pb)  
 PRL 131 (2023) 151803

**CMS**  
 $\gamma\gamma \rightarrow \tau\tau$  ( $\gamma$  from p)  
 This result



**CMS**  $138 \text{ fb}^{-1} (13 \text{ TeV})$   
 • Observed — 68% CL — 95% CL

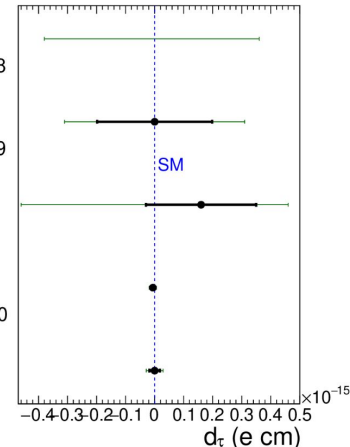
**OPAL**  
 $ee \rightarrow Z \rightarrow \tau\tau\gamma$   
 PLB 431 (1998) 188

**L3**  
 $ee \rightarrow \tau\tau\gamma$   
 PLB 434 (1998) 169

**ARGUS**  
 $ee \rightarrow \gamma^* \rightarrow \tau\tau$   
 PLB 485 (2000) 37

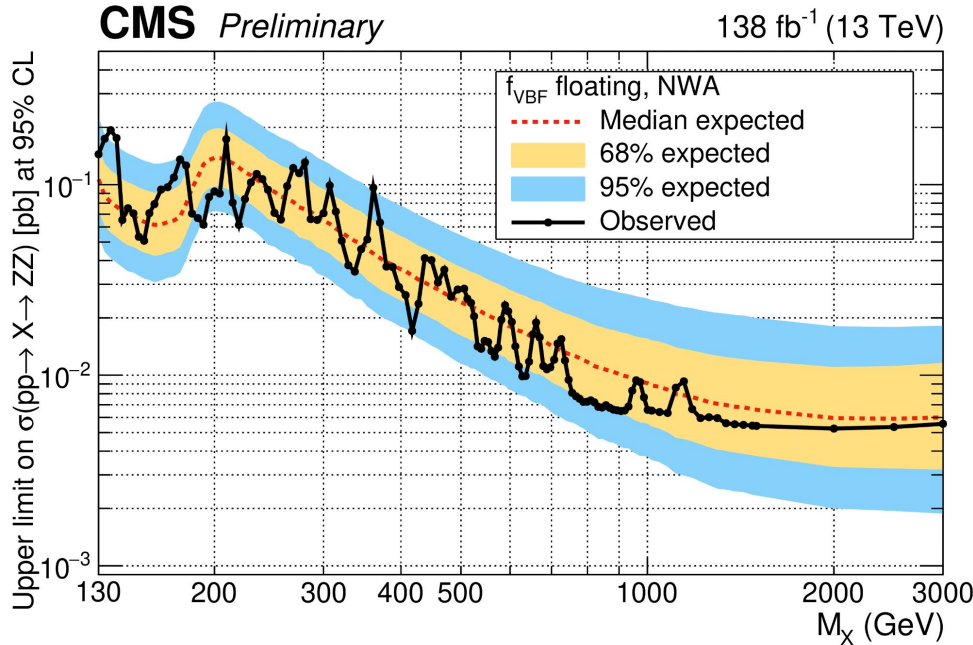
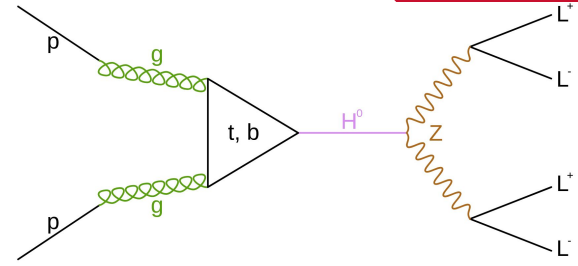
**Belle**  
 $ee \rightarrow \gamma^* \rightarrow \tau\tau$   
 JHEP 04 (2022) 110

**CMS**  
 $\gamma\gamma \rightarrow \tau\tau$  ( $\gamma$  from p)  
 This result

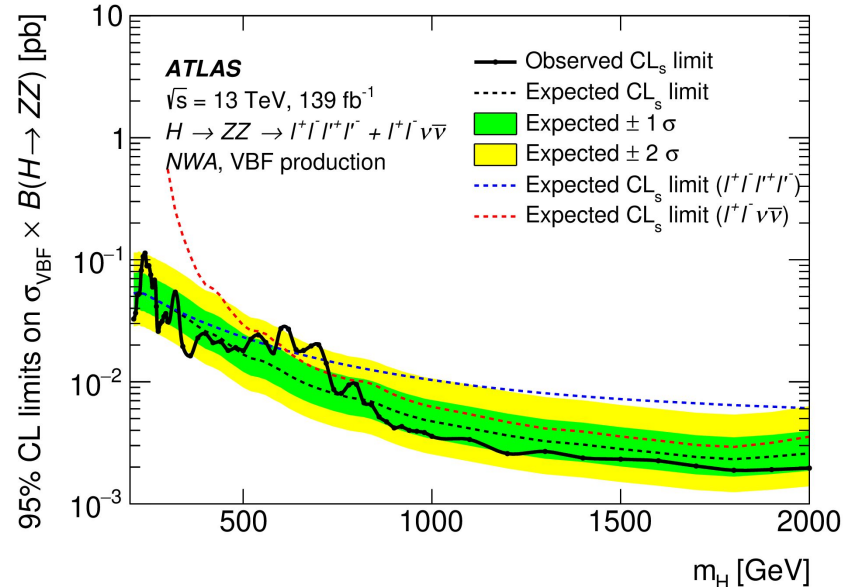


# Cross checking results

Complementarity between ATLAS and CMS is crucial for BSM searches



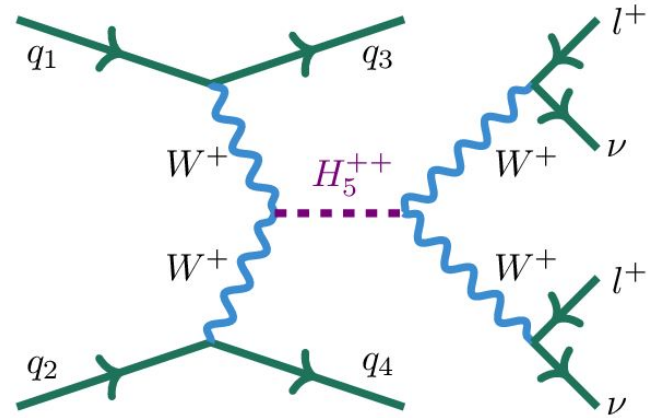
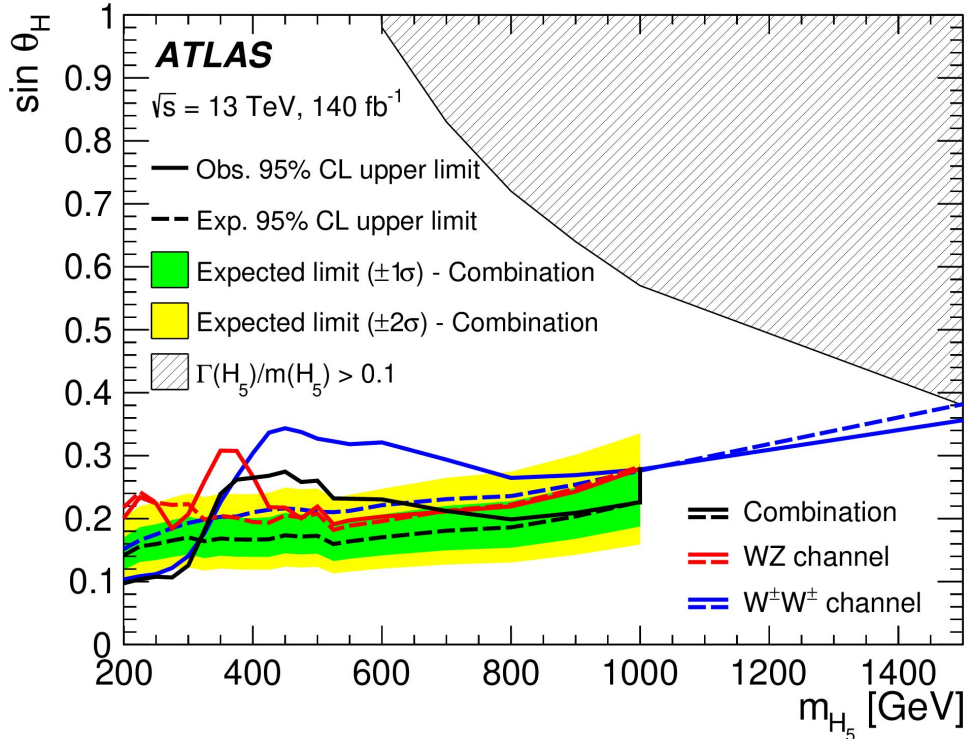
**4-lepton search of heavy scalar to cross-check a previous hint in ATLAS results that had some buy-in from the theory community**



H. de la Torre, Northern Illinois University



# Maybe new hints?



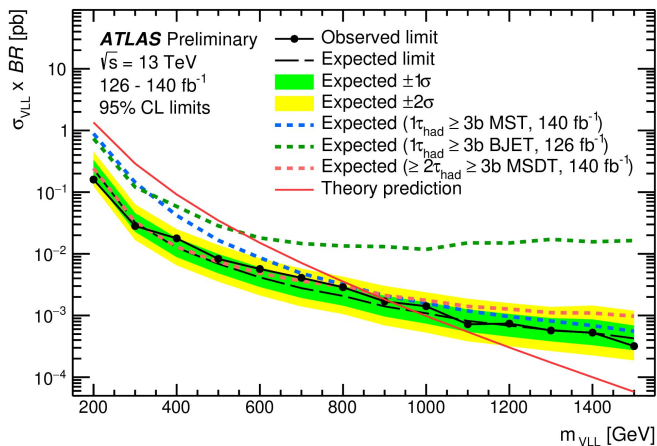
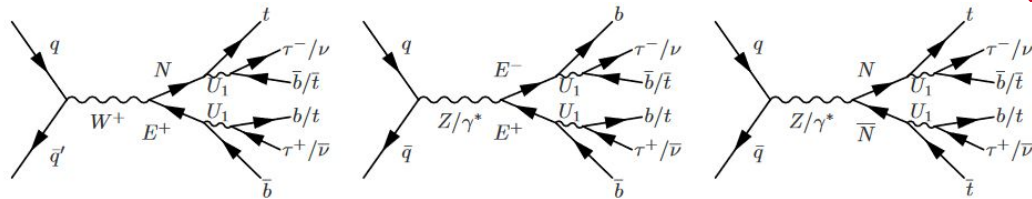
Bit of an excess in the  $H^{++}$  search in ATLAS, around  $3.3\sigma$  local ( $2.5\sigma$  global!)  
 One of the largest I remember as of late. Around 400 GeV



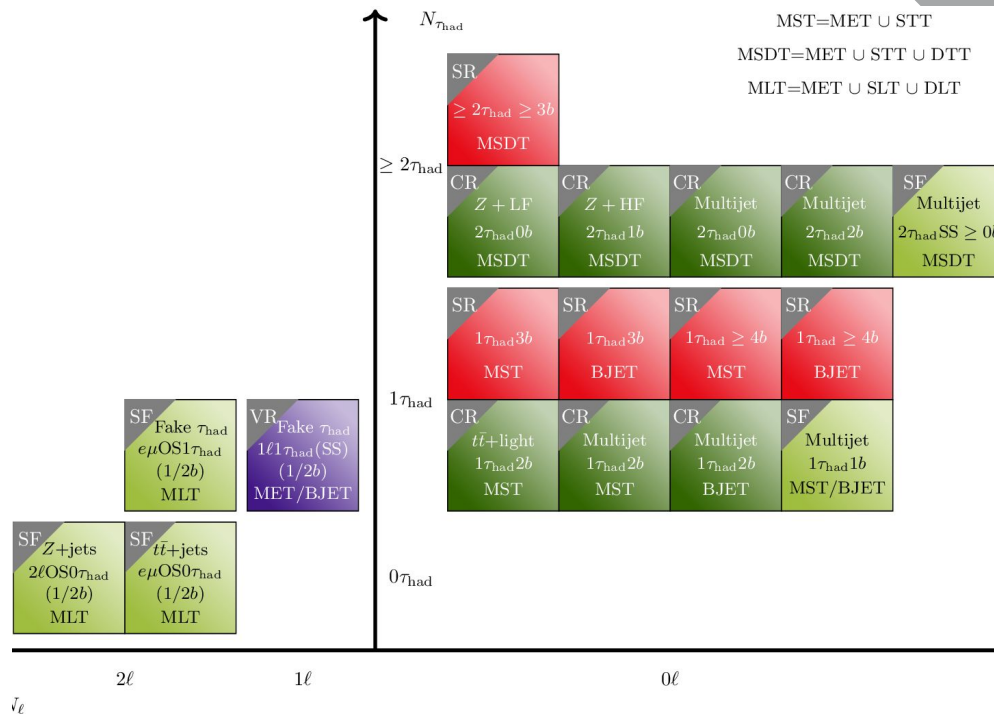
# Really looking everywhere (I promise)

[Link to talk](#)

Vector-like (non-chiral) charged and neutral leptons search focused on the 4321 model

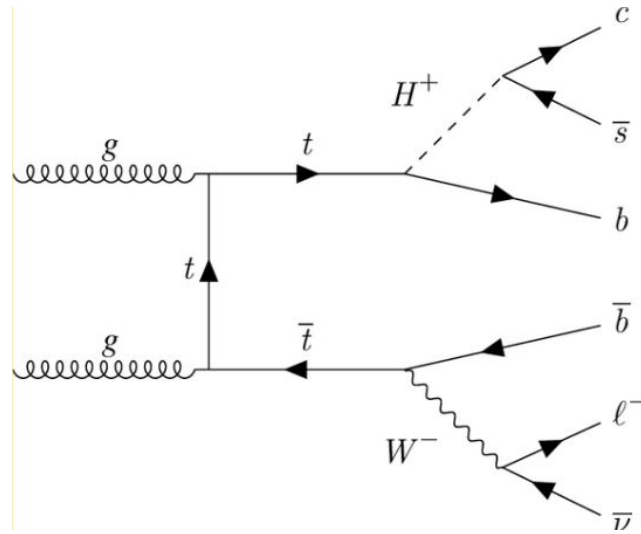


Very complicated model with very complicated final states. We are not dealing with two body resonance decays anymore

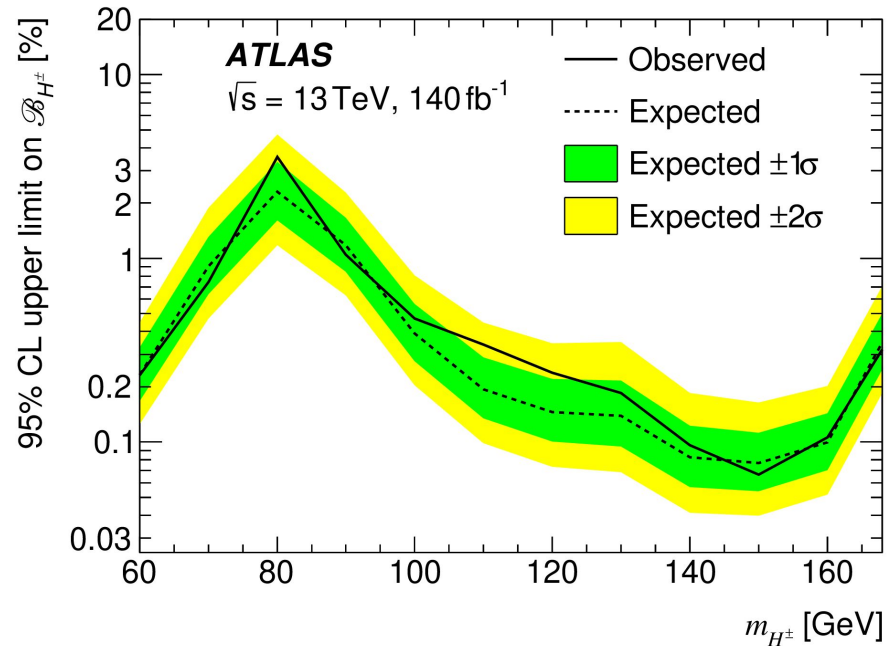


# Really looking everywhere (I promise)

[Link to talk](#)



Flipping the script, usually we search for BSM decaying into SM particles... but a light  $H^+$  can appear in top quark decays creating an anomalous top decay

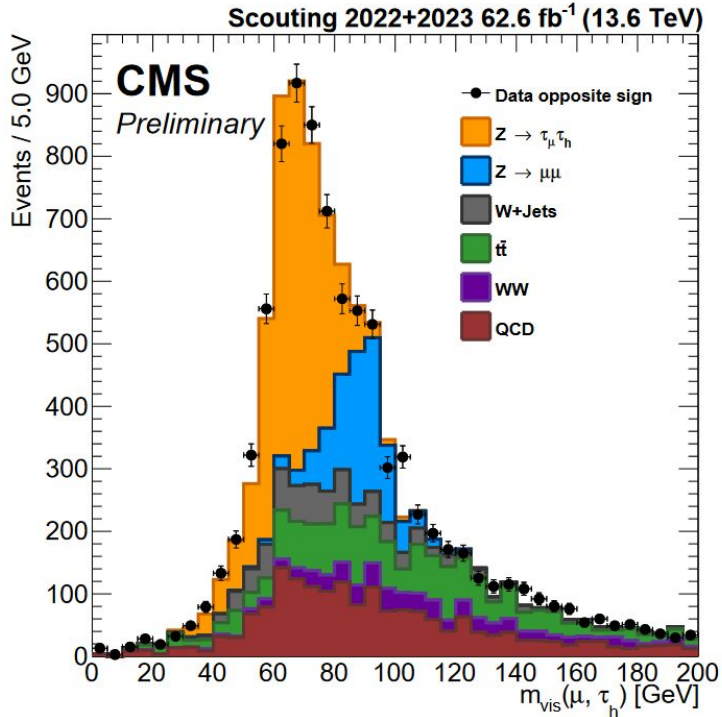




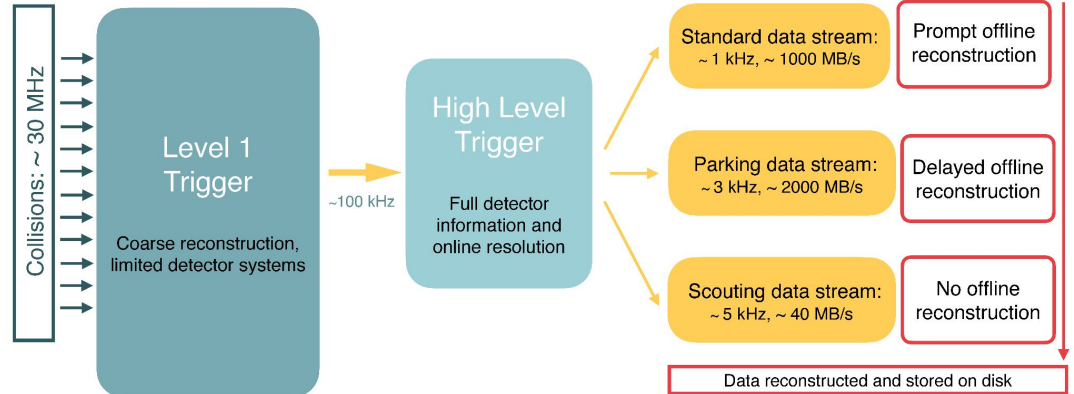
# Performance highlights

# More data with the same collisions

Heavy emphasis from CMS on data Scouting (Similar to ATLAS Trigger Level Analysis).  
Additional dataset with small (in terms of size) events using only Trigger-level objects



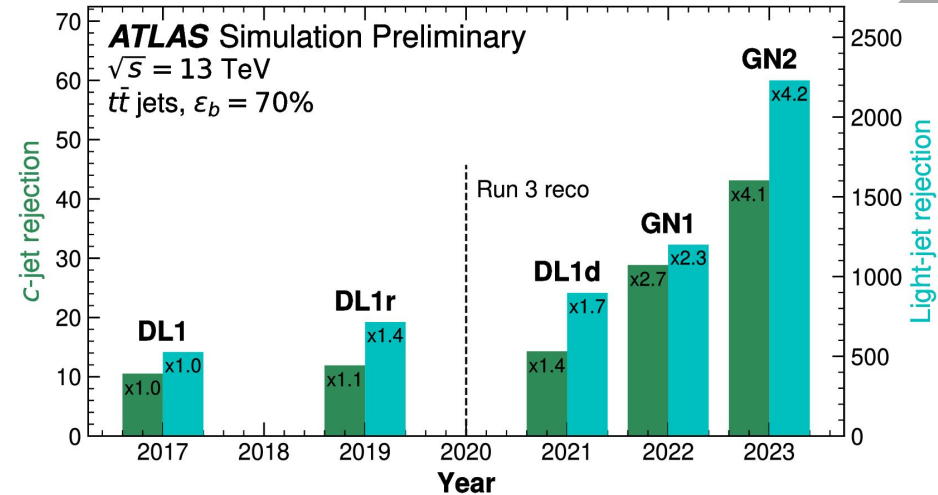
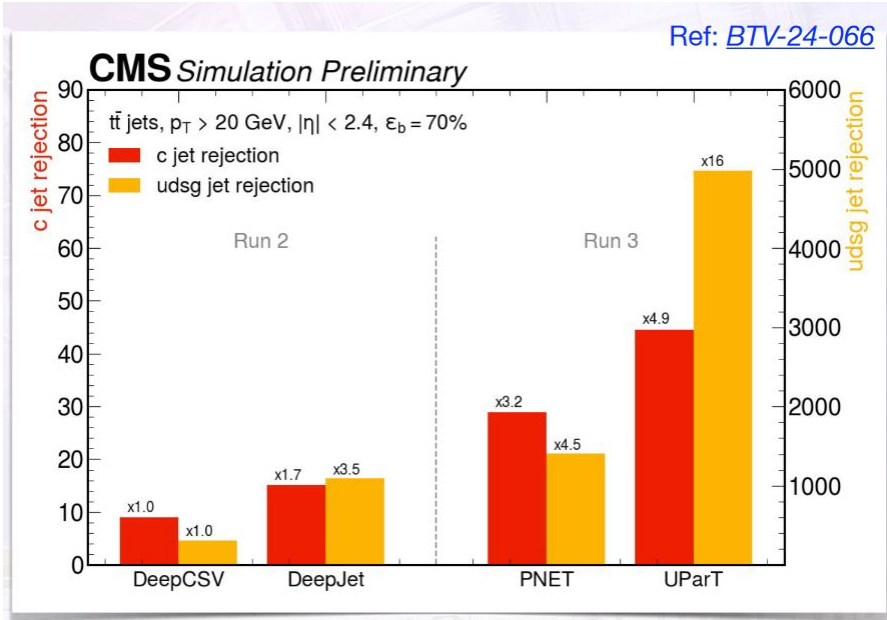
Data flow for a typical 2018 data-taking scenario



ATLAS has this capability too but so far mainly focused on dijet resonances at low mass. CMS scouting program uses jets/taus/muons/electrons... much more extensive !

# B-tagging improvements\*

Talk at ICHEP



New evolution of taggers in both collaboration, using a transformer approach.

Real arms race that is leaving the run-2 taggers in the dust for both collaboration! Similar multipliers in c-jet rejection, last iteration seems to have a higher multiplier for CMS

**CMS intends to use this tagger for general small-R jet classification (Including taus !) -> Advantage of a particle-list approach**

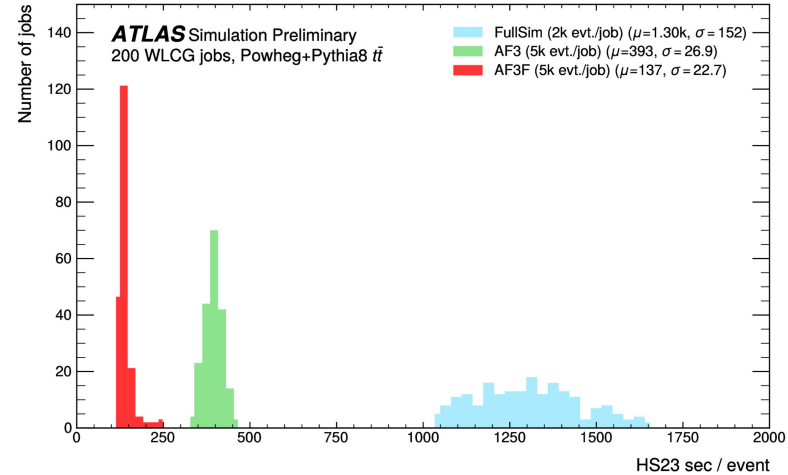
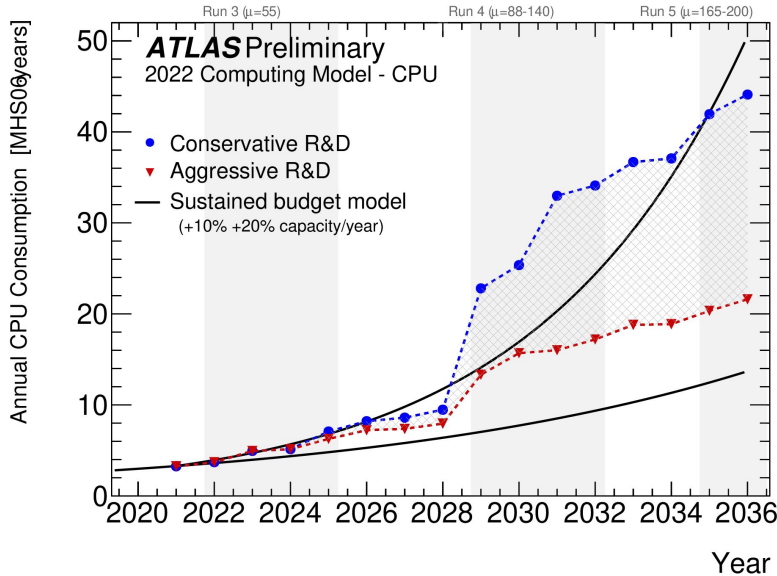


**Anything else**



# We need faster (and better) simulations

Simulating collisions at the LHC and the detector response takes a lot of resources. It's the dominant source of computing usage in ATLAS and CMS and will exceed our budget as we go into HL-LHC and beyond



*Lots of efforts to improve and validate Fast simulations that can reduce the computational cost with negligible (or reasonable) performance loss !*

[Link to talk](#)

# Publishing likelihoods

CMS is starting to go into the direction of publishing full likelihoods for some analysis.

What that actually means: Publishing the full set of numbers that go in the likelihood in a way that people can modify them easily (datacards in this case) + publish the software so that you can process those inputs (CMS combine)

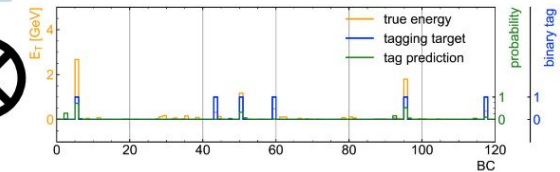
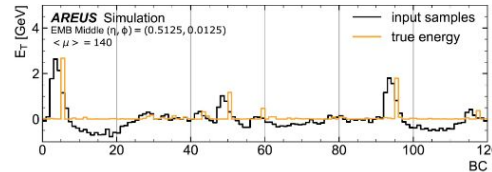
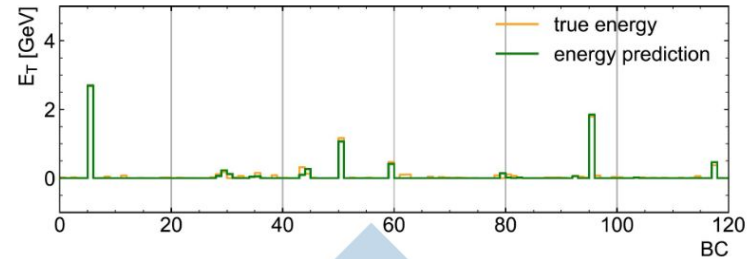
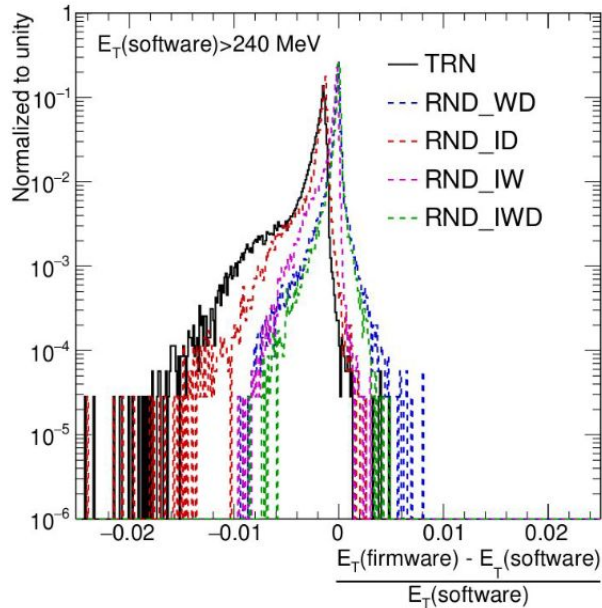
The screenshot shows a Zenodo publication page for 'CMS Higgs boson observation statistical model'. The page includes a header with the CMS logo and title, a 'Model' tag, and a green 'Open' button. It displays '2K VIEWS' and '175 DOWNLOADS'. The 'Versions' section shows 'Version v1.0' with a DOI of 10.17181/c2948-6875. The 'Details' section provides the DOI (10.17181/c2948-6875) and the DOI for all versions (10.17181/c2948-6875). The 'Resource type' is 'Model', the publisher is 'CERN', and the DOI for all versions is 10.17181/c2948-6875.

ATLAS has already done so for SUSY analysis starting in 2020 using pyHF. Unfortunately both collaborations use different tools and standards!

Neat publication in the form of a website for the Higgs combination!

*H. de la Torre, Northern Illinois University*

# Many ML in FPGA talks and posters..



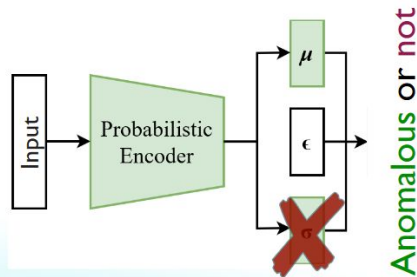
**One example: RNN / CNN implementations in firmware for calorimeter reading (LAR calorimeters in ATLAS for HL-LHC)**

# Anomaly detection for triggering

## Shrinking the Autoencoders



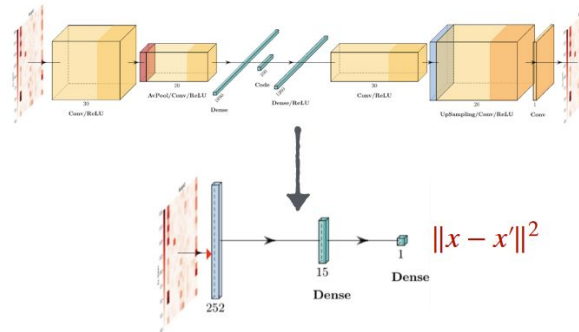
- Uses variational autoencoder
  - In training require the latent space is gaussian distributed  $\sim \mathcal{N}(0,1)$
  - For *atypical* events from  $\sim \mathcal{N}(0,1)$
- **Solution:** Deploy only the encoder



$$\text{Anomaly Metric} = \mu^2$$



- Uses convolutional autoencoder
  - Most suited for image like inputs
- Knowledge distillation to compress the autoencoder to a smaller model size



- Compressed model outputs the reconstruction error

*CMS deploying two dedicated anomaly detection triggers to trigger on anomalous events! running concurrently with more standard trigger strategies*

# Language models for physics

## Generating Lagrangians for Particle Theories

Elieel Camargo-Molina, Yong Sheng Koay  
Department of Physics and Astronomy, Uppsala University,  
Box 516, SE-751 20 Uppsala, Sweden

When AI Starts To Learn Particle Theory!



UPPSALA  
UNIVERSITET

If Lagrangians are Particle Physicists' Language, can LLMs learn it? **YES!**

<p><b>How?</b></p> <ul style="list-style-type: none"> <li>Transformers + seq-to-seq : Works!</li> <li>Lagrangian Sampling : Important!</li> <li>Math Tokenization : Important!</li> </ul>	<p>Large LLM = <i>Lagrangian</i> Model</p>	<p>In Language : Mary Had A Lit <small>P(mad   Mary) P(A   Mary had) P(Lit   ...)</small></p>
<p><b>Why?</b></p> <p>Foundational Model for Particle Theory Understanding</p> <ul style="list-style-type: none"> <li>Auto Lagrangian Completion</li> <li>Model Extraction from Literature</li> <li>Symbolic Manipulation</li> <li>Direct Theory Inference from Data</li> <li>...</li> </ul>		<p>In Lagrangians : <math>D_\mu \Phi^\dagger D^\mu \Phi + m^2 \Phi^\dagger \Phi + \dots</math> <small>P(m^2   D_\mu \Phi^\dagger \Phi)</small></p> <p>Model Task : <math>\Phi_{(3,3,1)}, \Phi'_{(1,2,1/6)} \rightarrow \dots + \lambda</math></p>

<p><b>BART</b> Bidirectional and Auto-Regressive Transformers</p>	<p><b>Dataset</b> What and How to teach AI Part</p>
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## ChatQCD: Let Large Language Models Explore QCD

Antonin Sulc (HZB), Patrick L.S. Connor (UHH)

Quantum chromodynamics (QCD) has yielded a vast literature spanning distinct phenomena. We construct a corpus of papers and build a generative model. This model holds promise for accelerating the capability of scientists to consolidate our knowledge of QCD by the ability to generate and validate scientific works in the landscape of works related to QCD and similar problems in HEP. Furthermore, we discuss challenges and future directions of using large language models to integrate our scientific knowledge about QCD through the automated generation of explanatory scientific texts.

Many posters and talks mentioned or had transformers and language models in them

<p><b>MOTIVATION</b></p> <ul style="list-style-type: none"> <li>Broad QCD literature</li> <li>Modern tools can accelerate knowledge acquisition in QCD</li> <li>LLMs could enhance QCD research accessibility.</li> <li>Potential model for knowledge consolidation in other fields.</li> </ul>	<p><b>FINETUNING</b></p> <p><b>Unsloth Framework [2]</b> : A lightweight framework optimized for efficient fine-tuning of LLMs.</p> <p><b>LoRA [3]</b> (Low-Rank Adaptation): Parameter efficient fine-tuning via matrix multiplication</p>	<p><b>PARAMETERS</b></p> <pre> LORA(   r = 32,   target_modules = ["q_proj",     "k_proj", "v_proj", "o_proj",     "gate_proj", "up_proj", "down_proj"],   lora_alpha = 8,   lora_dropout = 0,   bias = "none")  TrainingArguments(   per_device_train_batch_size = 16,   gradient_accumulation_steps = 32,   warmup_steps = 5,   num_train_epochs = 1, </pre>
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**DATASET**

- The training dataset consist of





***Conference was full of nice ideas and plenty of results that I didn't cover here. Take a look at the summary slides if you have the chance!***