

ATLAS Report 2022

MDP a nome del gruppo ATLAS Napoli

Chi siamo

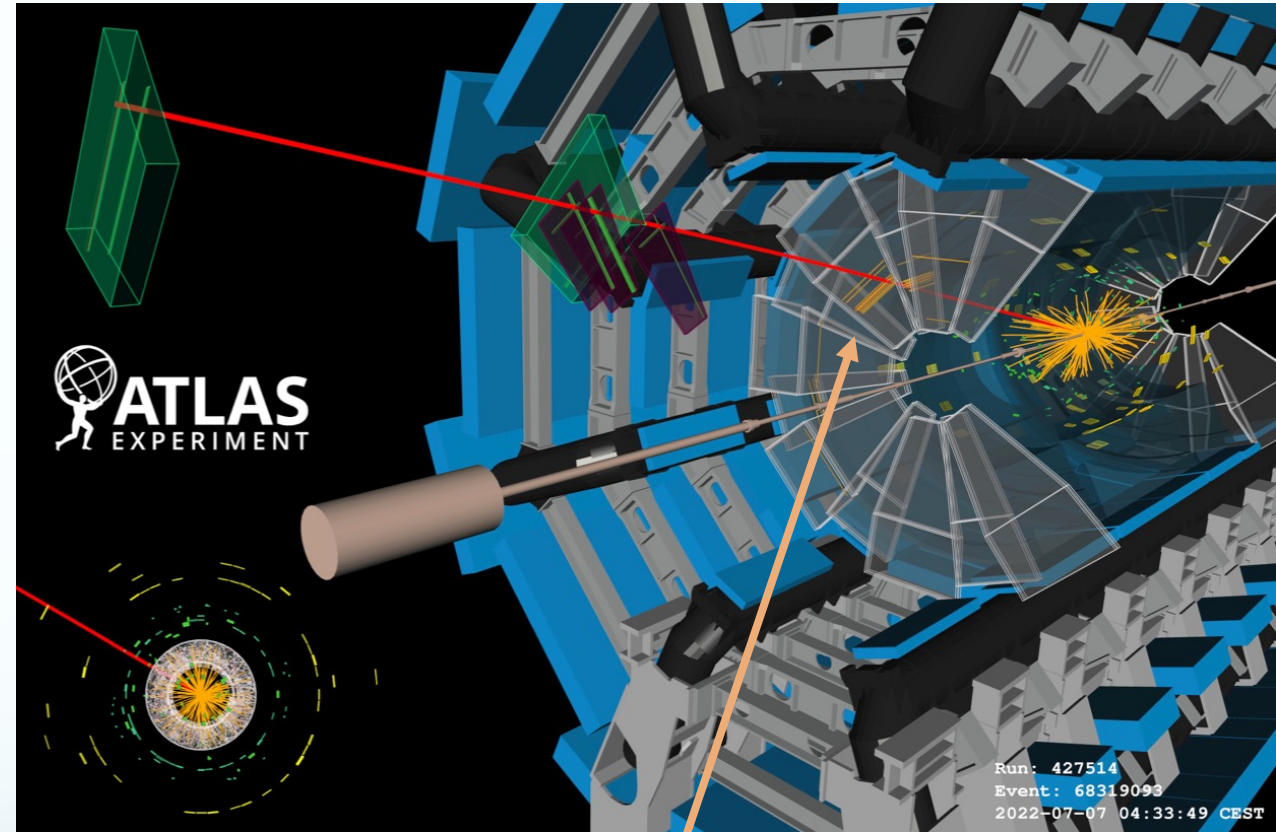
- Acampora Giovanni
Aloisio Alberto
Alviggi Mariagrazia
Auricchio Silvia *<-- fine PhD*
Camerlingo Maria Teresa
Canale Vincenzo
Carlino Gianpaolo
Ciotto Francesco
Conventi Francesco
D'Avanzo Antonio *<-- Borsista
neolaureato*
de Asmundis Riccardo
Della Pietra Massimo

Di Donato Camilla
Doria Alessandra
Iengo Paolo
Izzo Vincenzo
Massarotti Paolo
Merola Leonardo
Rossi Elvira
Russo Guido
Schiattarella Roberto
Spisso Bernardino
Sekhniaidze Givi
Vitiello Autilia

Grazie a tutti quelli che hanno contribuito a mettere su questo report!

ATLAS RUN 3

- LHC:
 - Nuova energia: 13.6 TeV
 - Massimizzazione della luminosità integrata (β^* leveling)
- ATLAS
 - Nuovi detector + elettronica installati (NSW, L1Muon, LAr + L1Calo, L1Topo, CTP)
 - Upgrade del TDAQ
 - Programma di fisica vasto su RUN3 e completamento delle analisi per il RUN2



Event display con NSW!

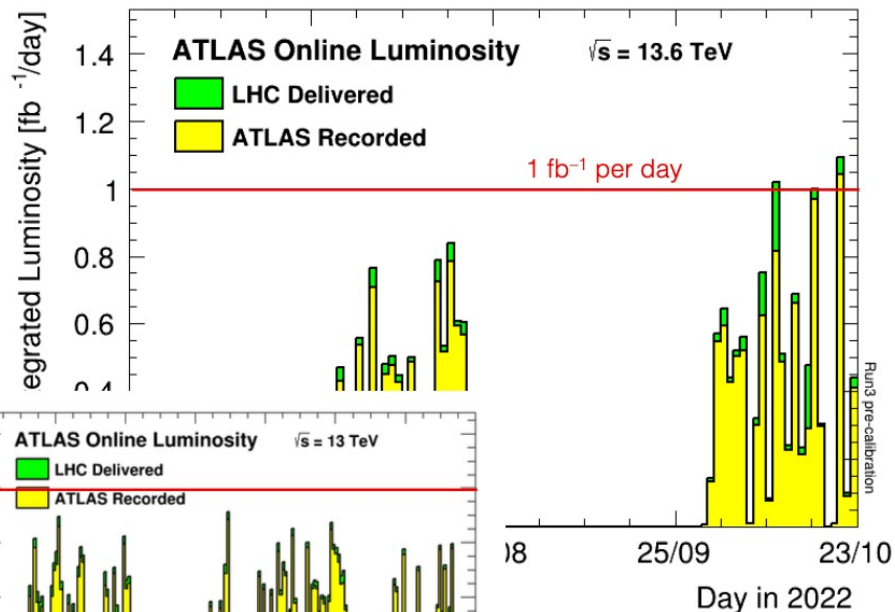
LHC luminosity production

LHC β^* levelling operates reliably and successfully

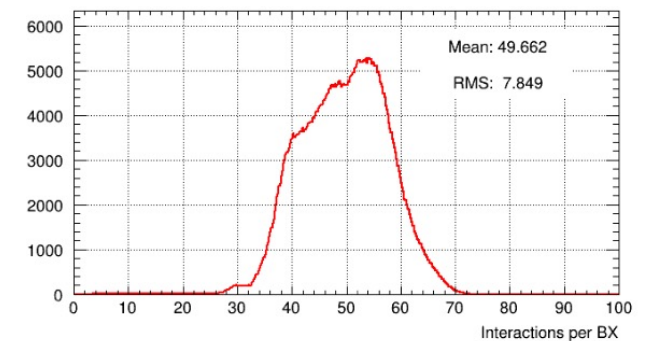
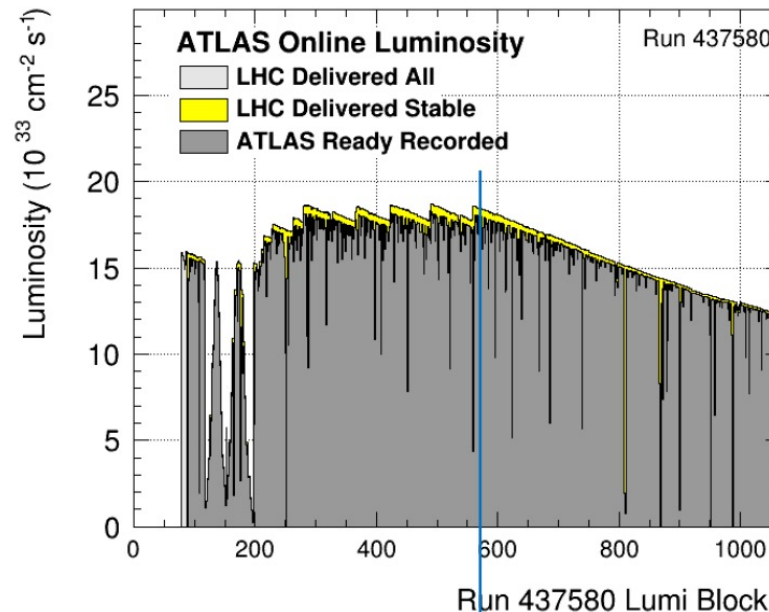
Peak luminosity limited by LHC cooling power to absorb heat load from beams

Mixed filling schemes are being explored to maximise integrated luminosity within cooling and pileup constraints

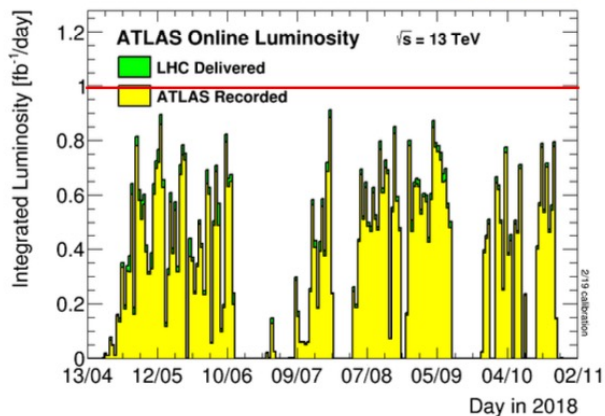
Passed new record of $> 1 \text{ fb}^{-1}$ per day
(Run-2 record: 0.91 fb^{-1} taken on 22 July 2018)



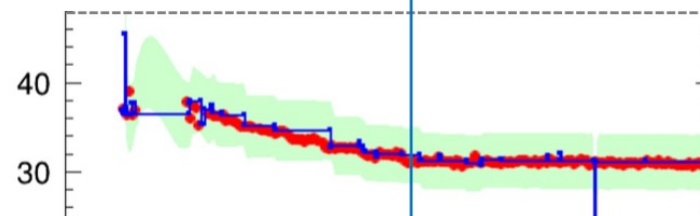
Run taken on 20/21 October 2022



Pileup profile of run 437580



Longitudinal
beamspot width

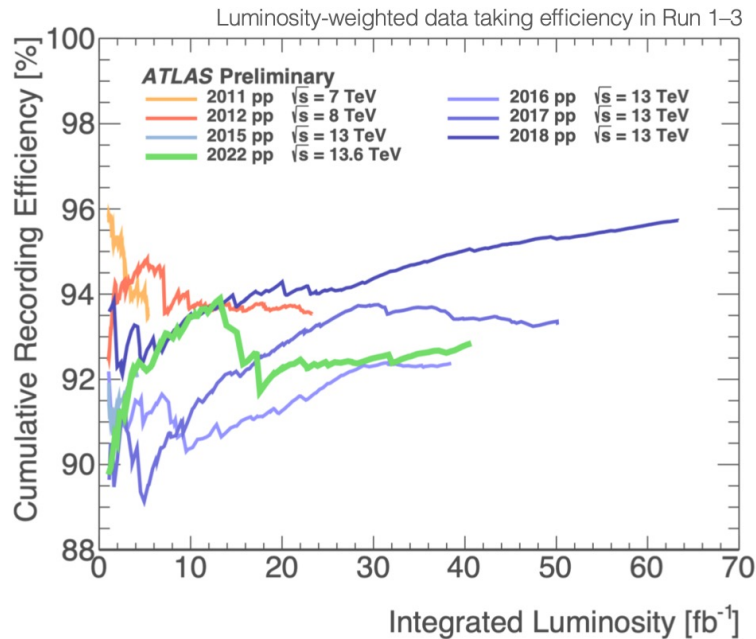
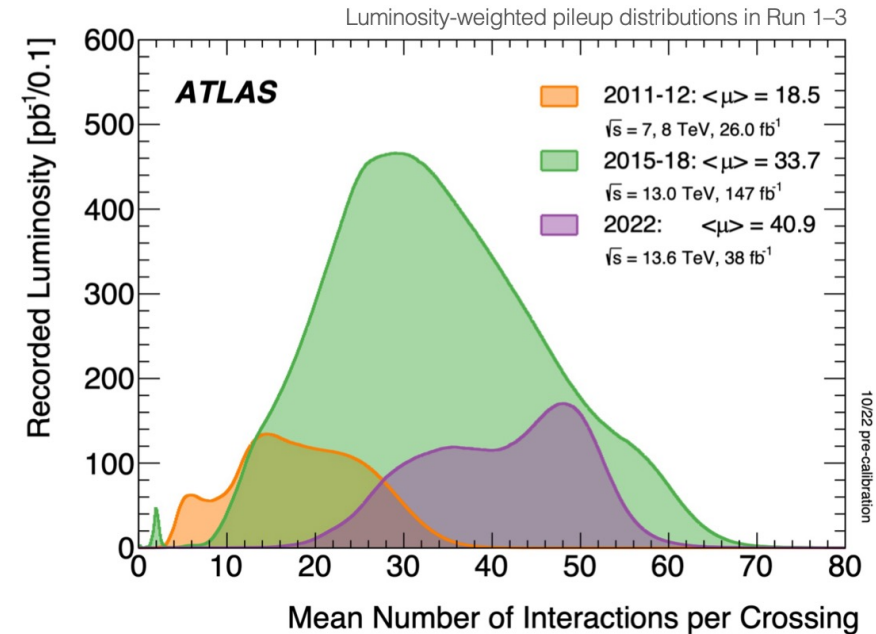
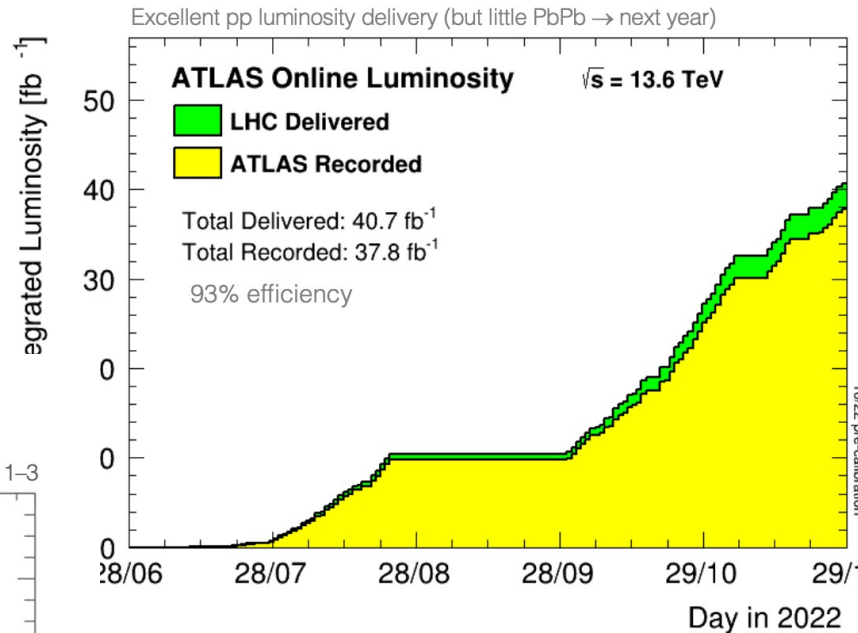


β^* levelling squeezes
longitudinal beamspot size

ATLAS Data taking

Livello finale di efficienza DAQ dell'ordine del 93%

Remarkable 2022 data taking completed



Buon livello di performance raggiunto nonostante l'elevato pile-up

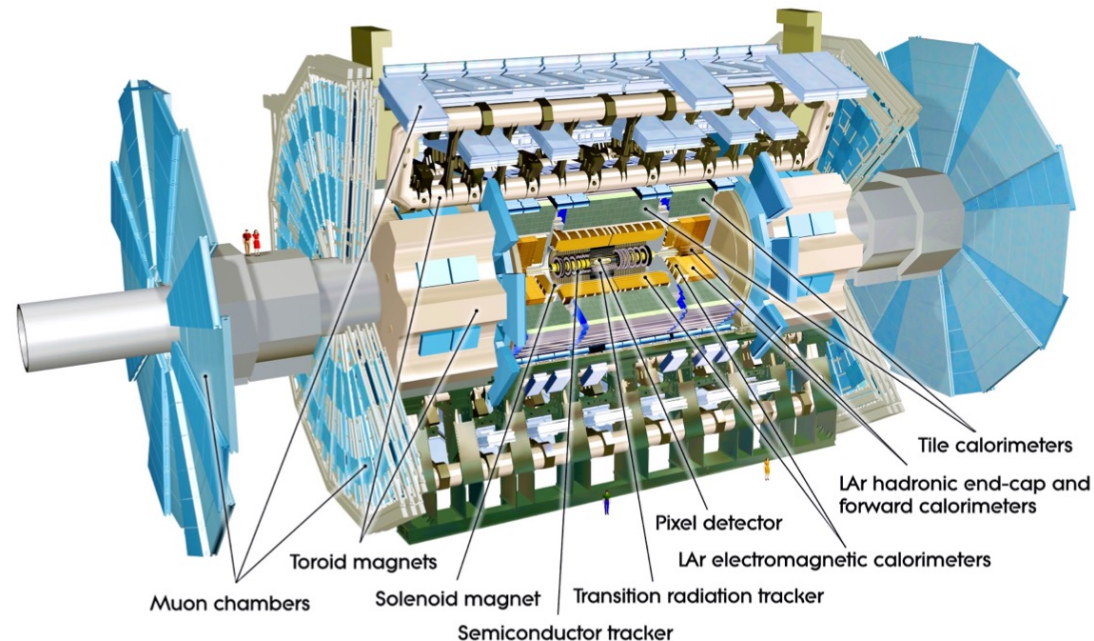
Alcuni degli upgrade di Fase I ancora non al meglio del funzionamento, ma buon funzionamento generale

Limiti strutturali al DAQ/Dataflow che saranno risolti durante YETS

Detector Status

Executive summary

- Legacy systems operating well, some limitations (dead time) at highest pileup / trigger rate
- Issues with RPC HV stability (improved), and FE electronics cooling in TRT and Tile Calorimeter (ongoing)
- Phase-I systems regularly included in data taking, their commissioning is ongoing
- Trigger, online and offline data quality monitoring, calibration loop, and prompt reconstruction fully operational



Detector Status

Pixel: initial hit efficiency problem resolved

SCT: good

TRT: “resync storms” mitigated (more work needed), FE cooling leaks are a worry

LAr: good, initial digital trigger readout limitation solved

Tile: good, FE electronics cooling leaks under control

Muon: MDT & TGC good; RPC efficiency first low (HV), now improved but not yet nominal

NSW: both wheels with MM and sTGC sectors in runs, DAQ stability improving, trigger (sTGC Pad and MM) progressing, several ICS (LV) & VTRx hardware failures

Forward: LUCID good, AFP: SiT good, ToF being commissioned, ALFA water accident, ZDC ran with LHCf

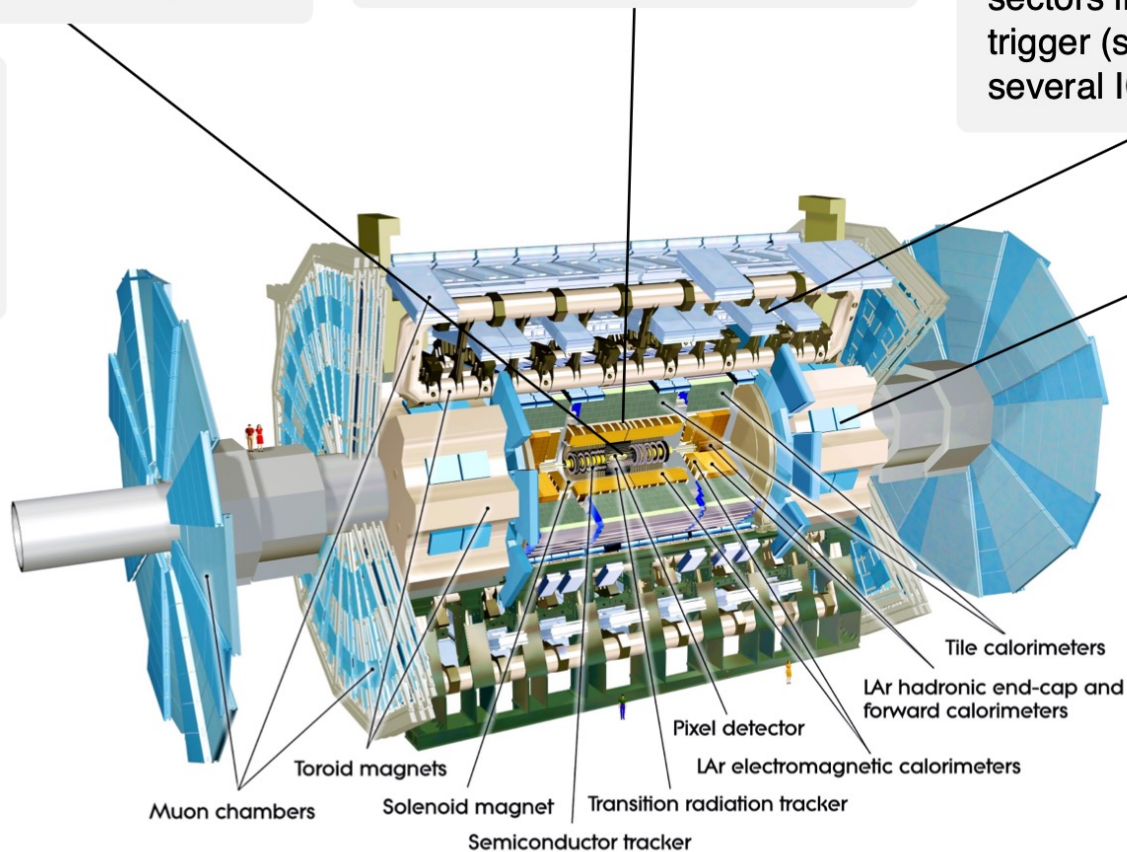
DAQ: initial ROS limitations solved

Trigger: L1 & HLT good, HLT at CPU limit, MDT calibration issue led to low muon efficiency in early data

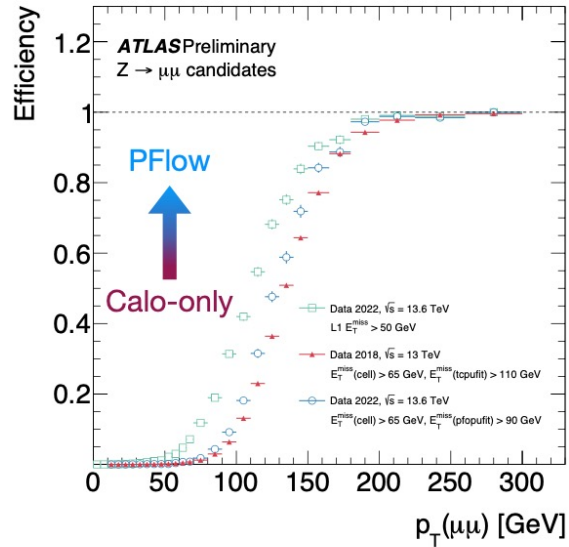
Phase-I systems: good progress, eFEX boards complete

Magnets: good, but three accidental toroid cycles, must avoid power blackouts

Offline: Tier-0 reconstruction with release 22 good, some early condition problems fixed with fast data reprocessing

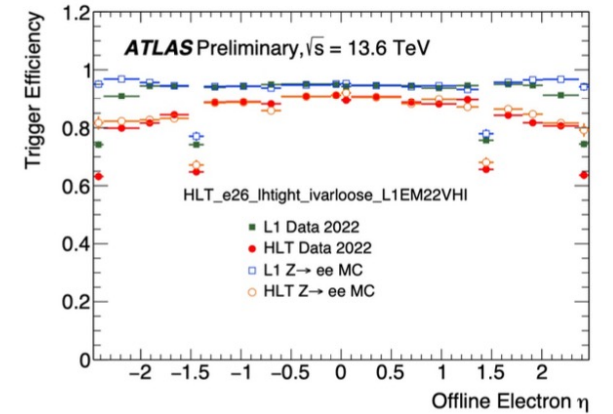
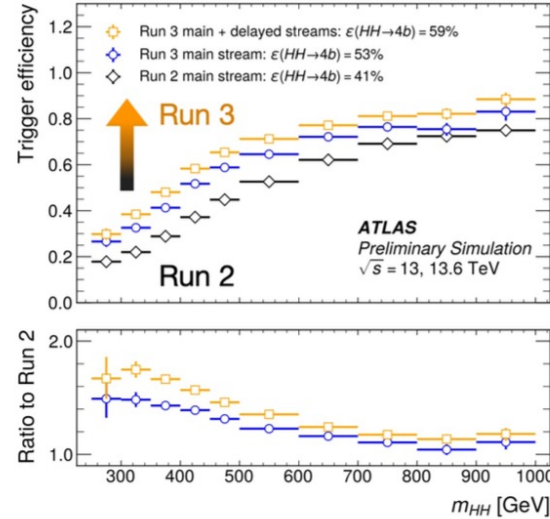


Trigger and reconstruction status



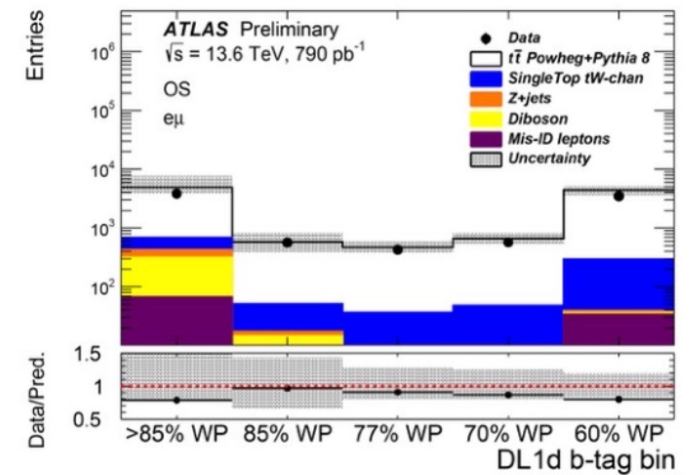
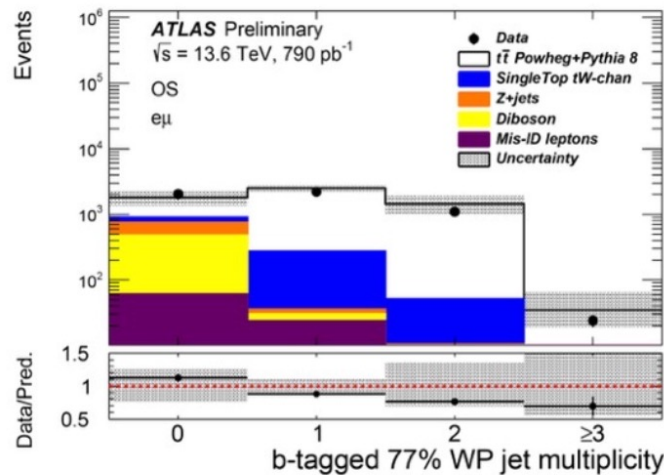
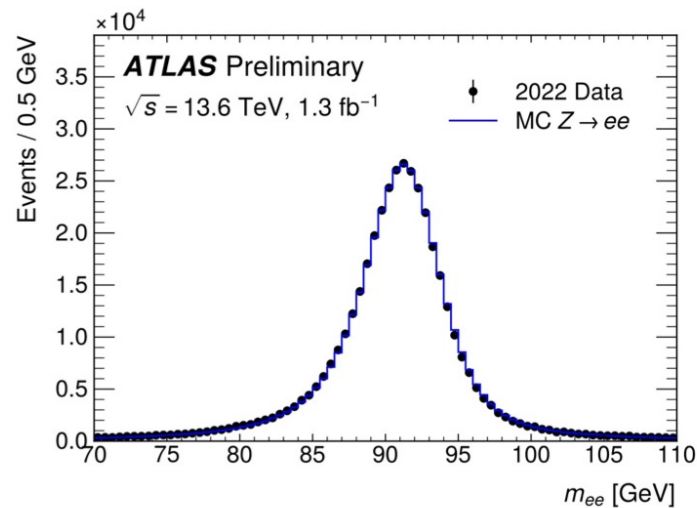
Left: Jet & E_{Tmiss} trigger efficiency enhanced with particle flow reconstruction

Right: 50% signal efficiency increase from reoptimized $HH \rightarrow 4b$ trigger with PFlow + ML b-taggers



Top: Electron triggers commissioned

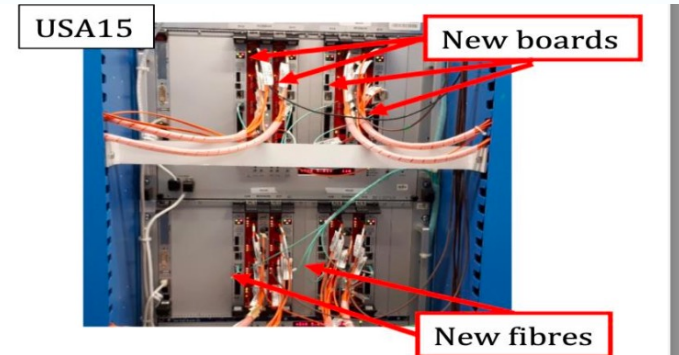
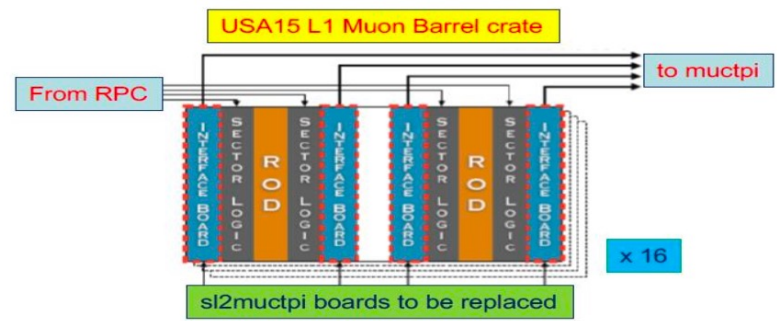
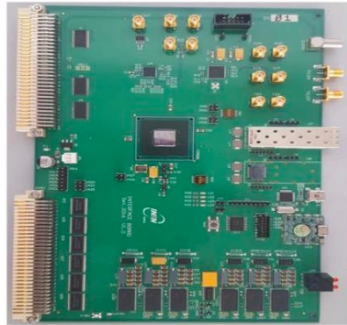
Bottom: physics analysis validation plots with Z \rightarrow ee peak data/MC (left) and top-antitop \rightarrow e μ candidates in early data (center and right)



ATLAS NA Contribution to L1 Trigger and operation

Della Pietra M, Izzo V, Rossi E., Conventi F, D'Avanzo A

Hardware Phase I upgrade in L1MuonBarrel

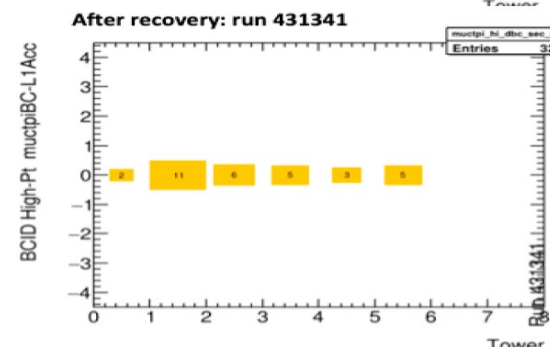
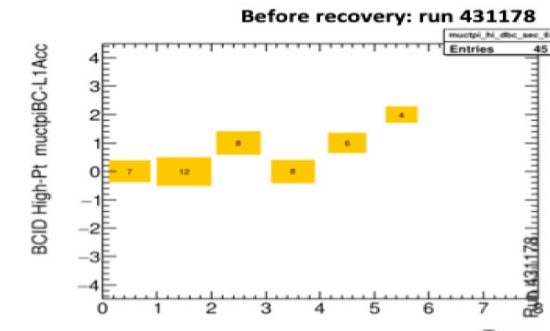


New SL2MUCTPI* Interface boards

- ◉ SL2MuCTPI boards and optical fibres installed in USA15 since 2020.
- ◉ Successfully used during Milestone Weeks Data Taking (Nov. 2021).
- ◉ SL2MuCTPI Firmware new version loaded in August:
 - Allows to set BCID offset values independently for each SL2MuCTPI board.
 - Timing of MuCTPI RPC inputs alignment seems to be OK.
- ◉ No major FW changes foreseen
 - Few other firmware fixes for minor bugs, already uploaded.

Sector Logic boards:

- ◉ Recovered the timing of 6 Trigger towers thanks to VME firmware reload for Sector Logic SL06 (a spare, with an old FW).

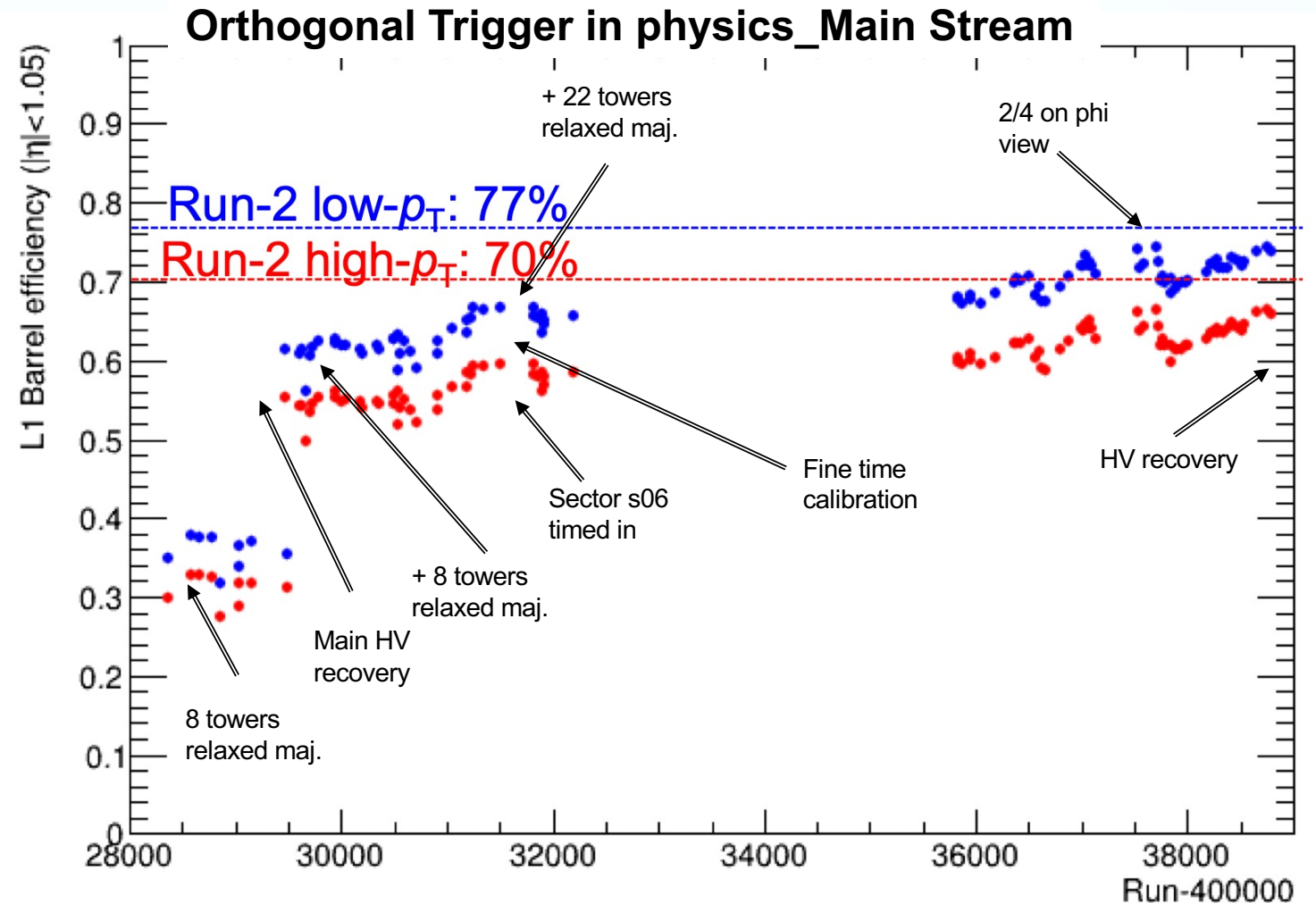


*Sector Logic to Muon Central Trigger Processor Interface

L1 Trigger efficiency recovery

At the beginning of RUN3 the L1MUB efficiency was very poor due to RPC problems with gas volumes

- Big effort of whole community
- RPC gas recovery campaign
- Relaxed majority
- Problem with resynchronization of problematic RPC towers:
 - The whole sector started to trigger at wrong BC after resynch. This was eventually solved with the help of MuCTPi software.
- In best runs, efficiency for high-PT was close to 67%
- Comparable results using T&P method
- After technical stop efficiency still increasing thanks to relaxed majority keeping rate under control



ATLAS NA Contribution to NSW

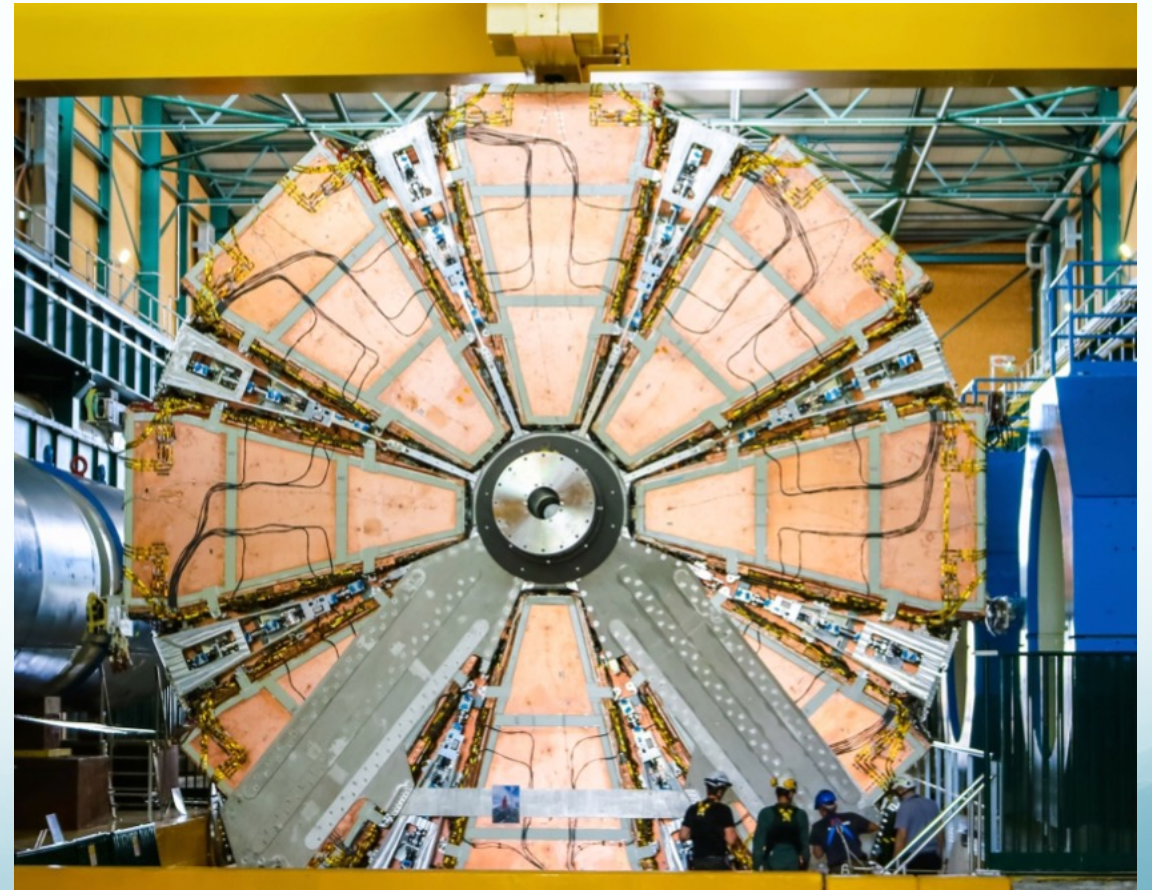
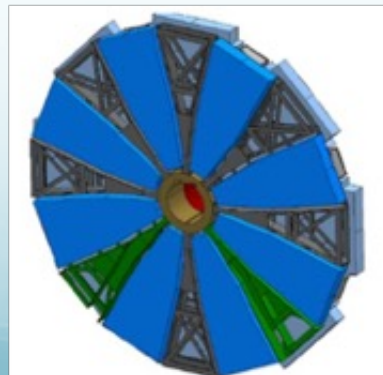
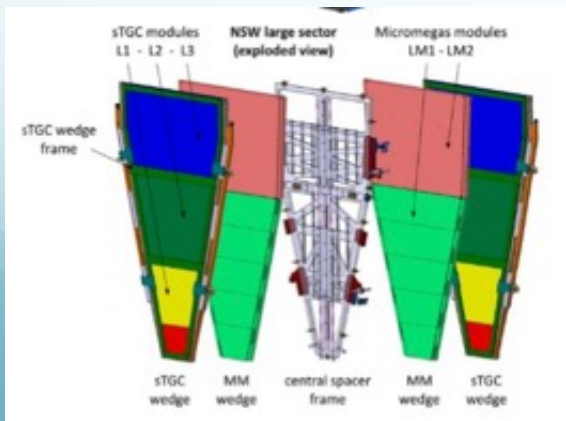
Alviggi MG, Camerlingo MT, Canale V, Della Pietra M, Di Donato C, Iengo P, Izzo V, Massarotti P,
Sekhniaidze G

C. Cassese, B. De Fazio, L. Panico, D. Trotta

Current responsibilities (P. Iengo): NSW Deputy PL, Micromegas project coordinator, Micromegas
operation coordinator

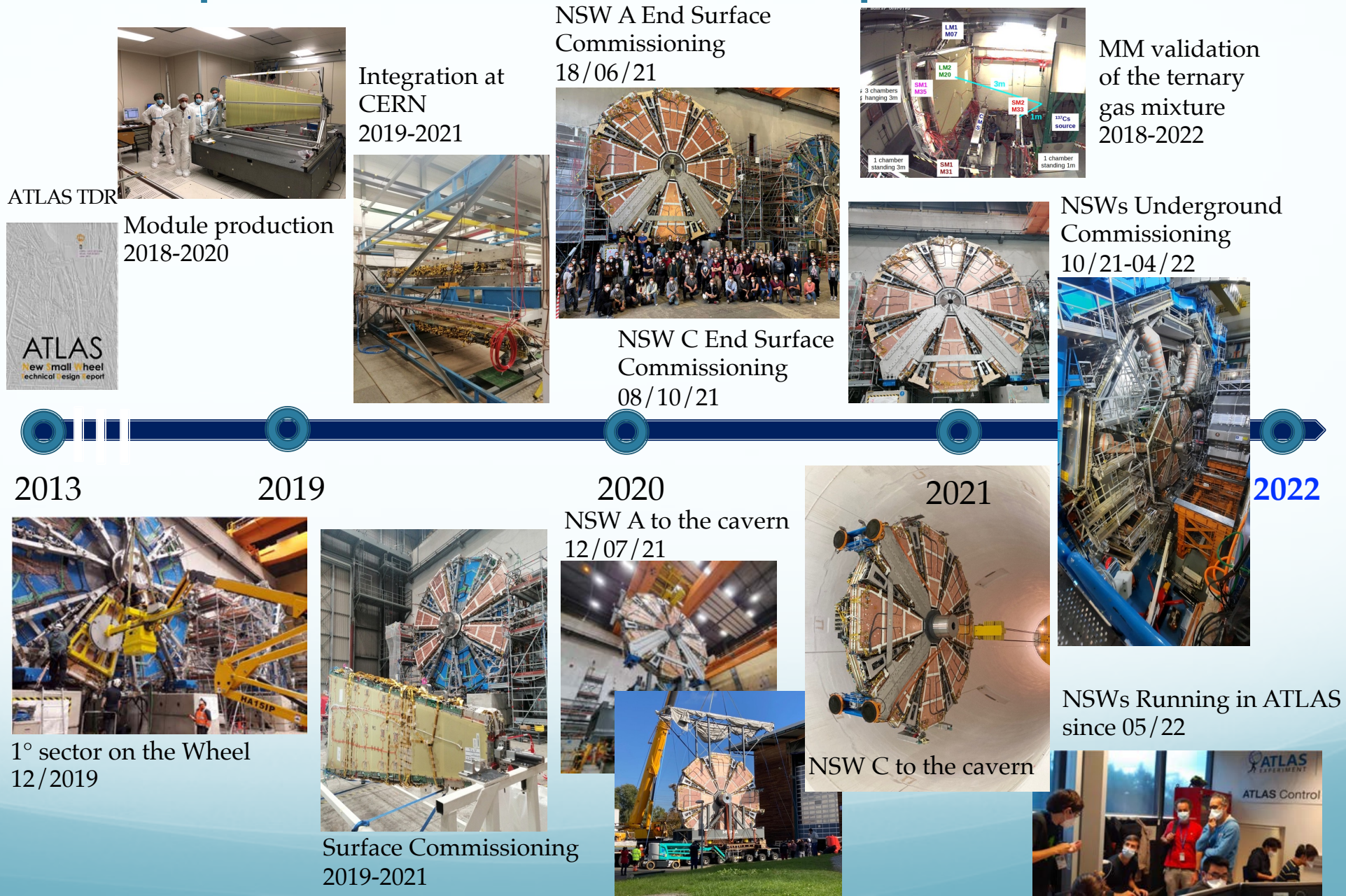
ATLAS NSW

- New Small Wheel: largest ATLAS Phase-1 project
- 2 end cap muon stations.
16 detector sectors per station (8 large, 8 small).
16 detector planes per sector:
- 8 small-strip Thin Gap Chambers wedges (sTGC)
- 8 micromegas (MM) wedges



Roadmap from TDR to Operation!

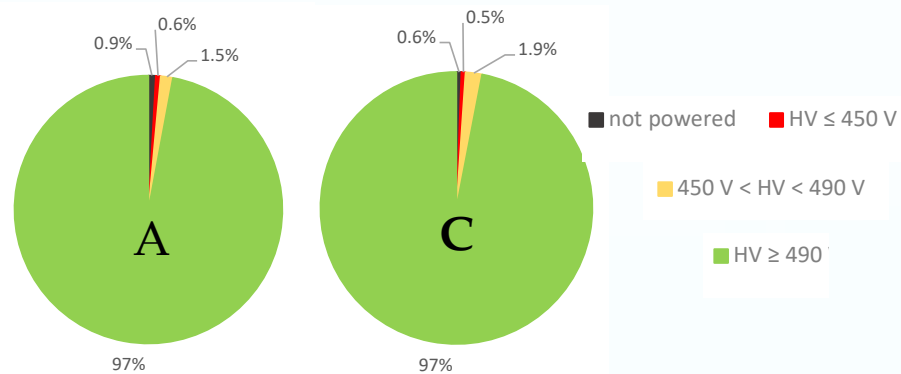
- 9 anni di impegno del gruppo di Napoli



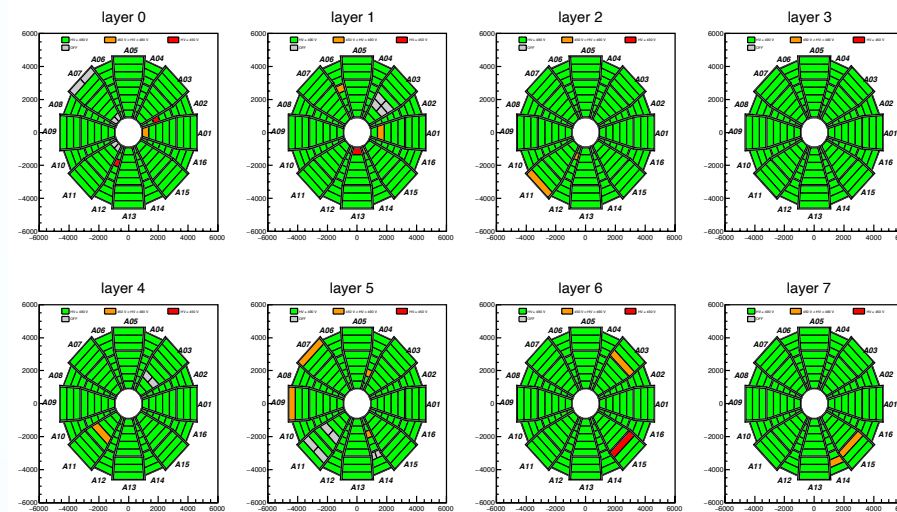
NSW HV/LV Status

NSW HV and LV status:

HV



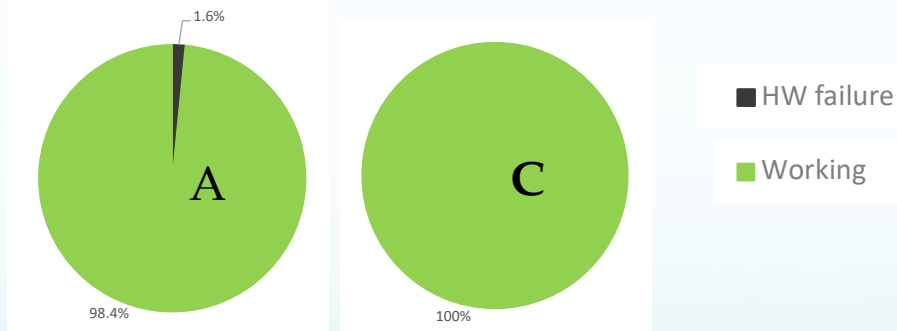
A: HV pcb by pcb



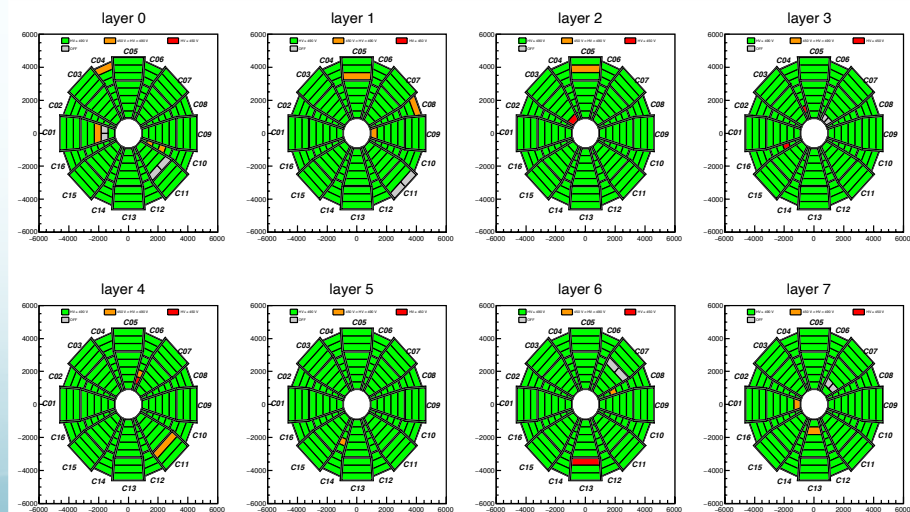
2 Drifts not working:

A2 SM1 IP Layer 3, C15 LM1 IP Layer 2

LV



C: HV pcb by pcb



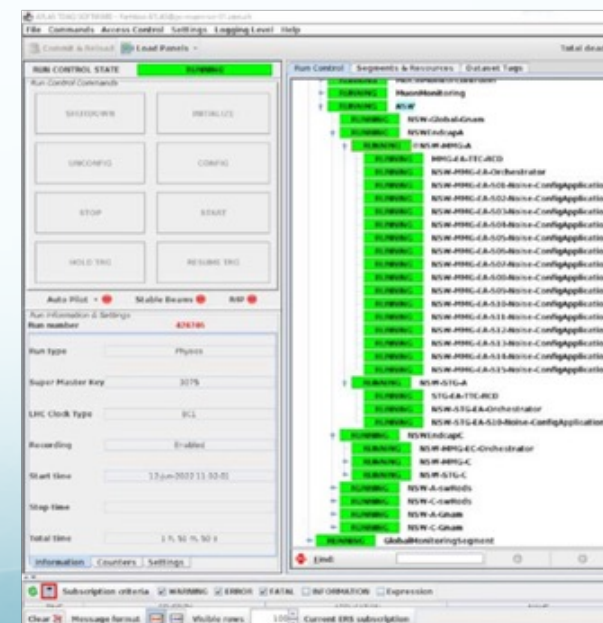
Hardware failure as from Low Voltage known issues that cannot be solved during standard interventions.

Wheel A:

- A4 affecting 8 MMFE8
- A6 affecting 16 MMFE8
- A14 affecting 8 MMFE8

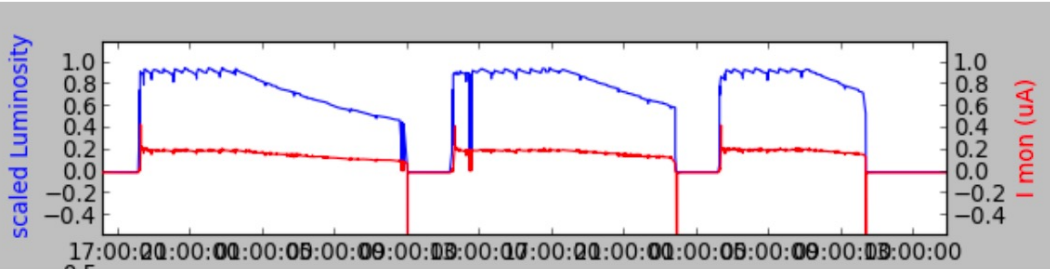
DAQ Status

- NSWs successfully integrated into the ATLAS Muon Central DCS and in the ATLAS TDAQ
- DCS fully working and stable
- Some instabilities observed in the DAQ
 - NSW employs new generation DAQ developed for the ATLAS Run-3: FELIX (Front End Link eXchange) system + software ROD (swROD) —> Extremely tight schedule for DAQ commissioning
 - Many calibrations required for the detector and DAQ operation: optimization of Front-end analog circuits, correct timing of detectors, data communication stabilities...
 - Experienced DAQ instabilities with Felix buffer filling and data link de-synchronization while including more sectors or at higher (>10kHz) trigger rate —> expert work continuing to improve stability
 - Integration in the ATLAS TDAQ partition since May: from a few sectors to entire wheel.
 - 5/Jul-Nov22 -> Early Run3 started! NSW have been joining the ATLAS data taking with nice results!

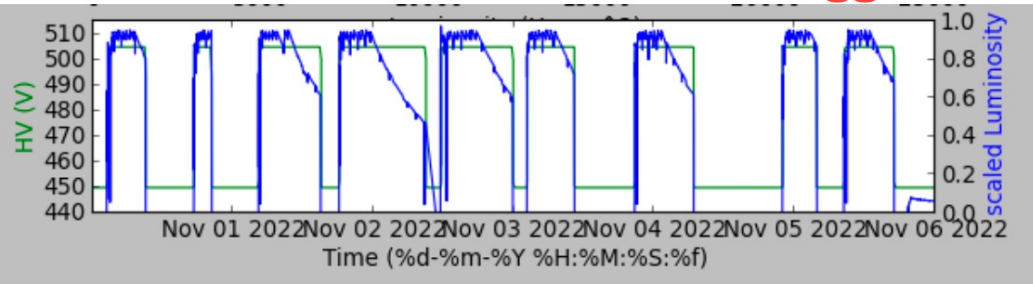


Detector response

- Current vs LHC luminosity



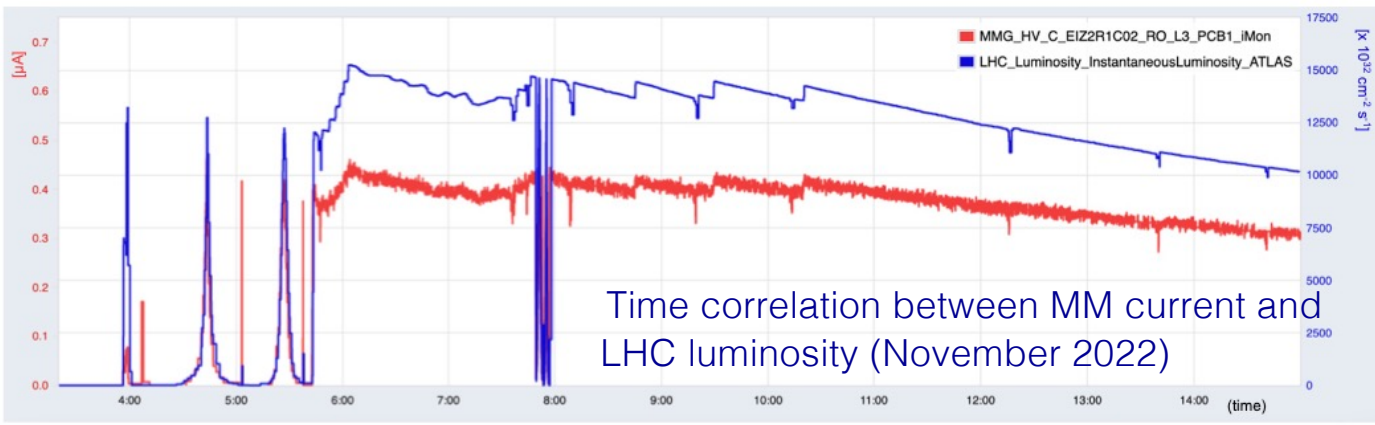
- HV stability (time evolution)



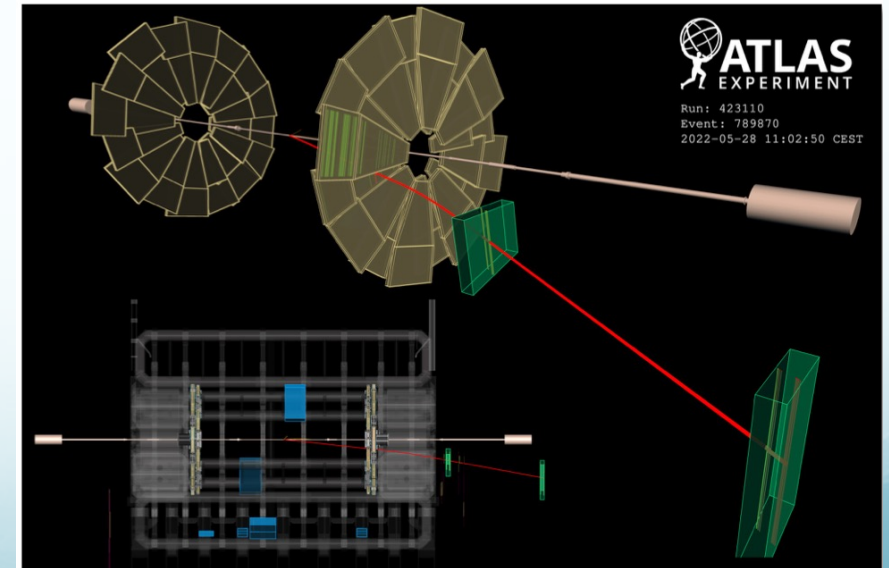
Napoli è impegnata nel monitoraggio della stabilità del detector



- ◆ Splash events (7 May 2022) seen by the Micromegas: current peaks at each event



Time correlation between MM current and LHC luminosity (November 2022)

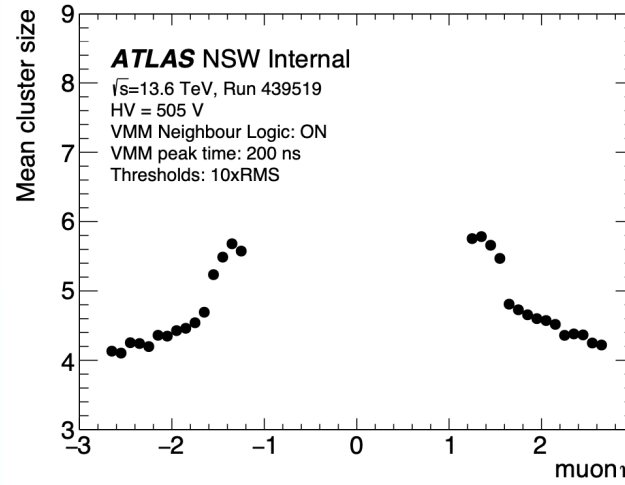


Muon reconstructed in the NSW Micromegas from pp collisions (28 May 2022)

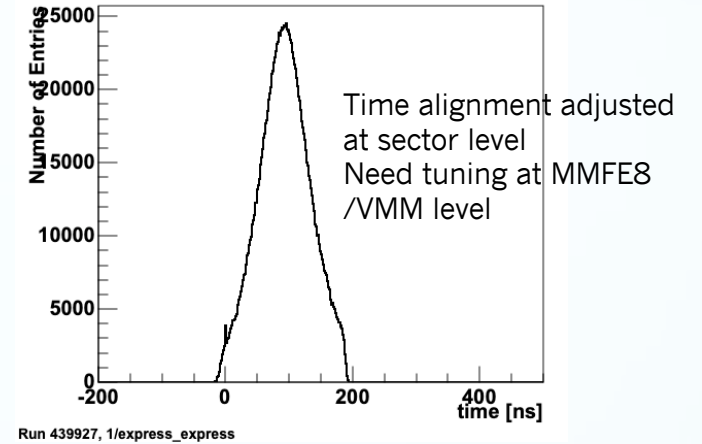
Preliminary performance studies

- ◆ Performance studies are affected by DAQ instabilities
- ◆ Software and reconstruction under optimisation
- ◆ Results are very preliminary
—> Full system still undergoing tuning and optimisation

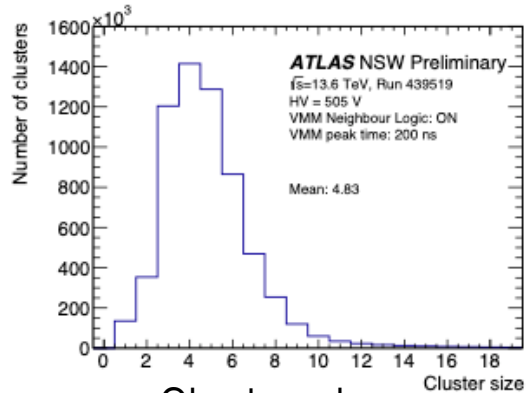
Cluster size vs Eta



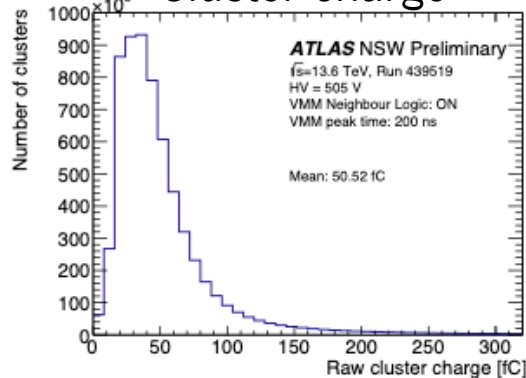
cluster time on track



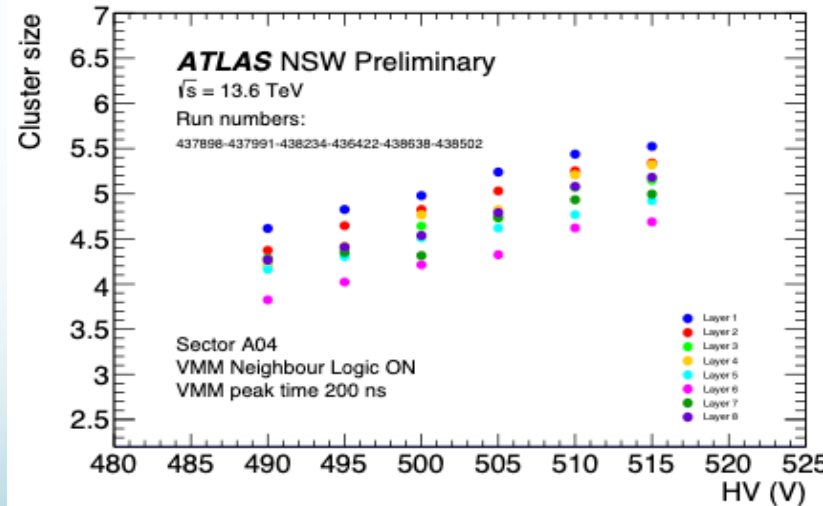
Cluster size



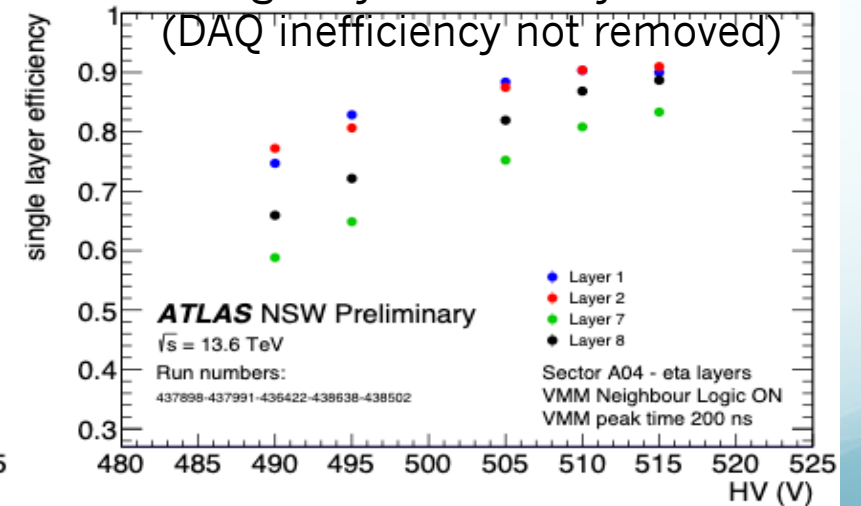
Cluster charge



Cluster size vs HV



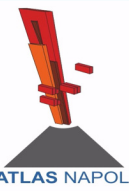
Single layer efficiency vs HV



ATLAS NA Contribution to PHYSICS

F. Conventi – E. Rossi – F. Cirotto – A. D'Avanzo – S. Auricchio - R. Schiattarella – G. Acampora – A. Vitiello

VBS VV semi-leptonic



Study EW $WW/WZ/ZZ$ production in semi-leptonic final states

- Limits on anomalous-QGC (Quartic Gauge Coupling) in EFT
- Focus on SM Vector Boson Scattering (VBS)
- Previous analysis on 36 fb⁻¹ dataset with observed 2.7σ ([PhysRevD.100.032007](#))
- ML approach to build the final discriminant with RNN
- **Background:** V+jets; ttbar

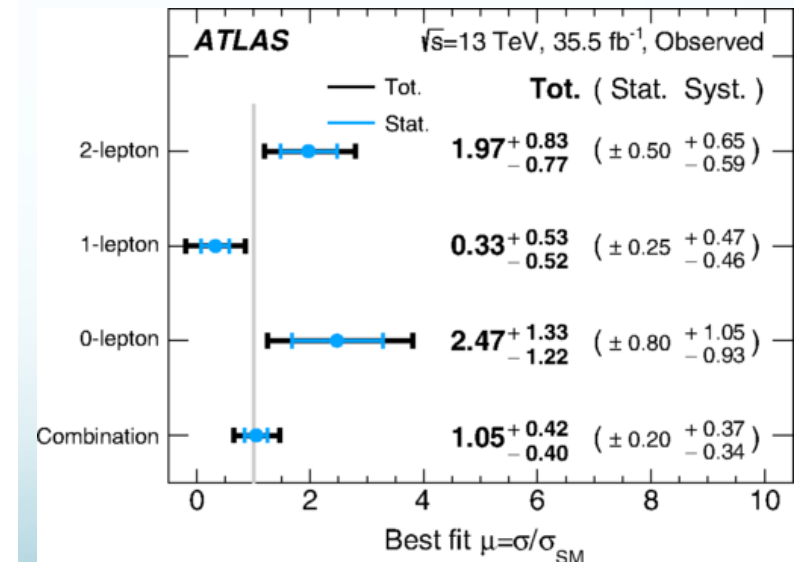
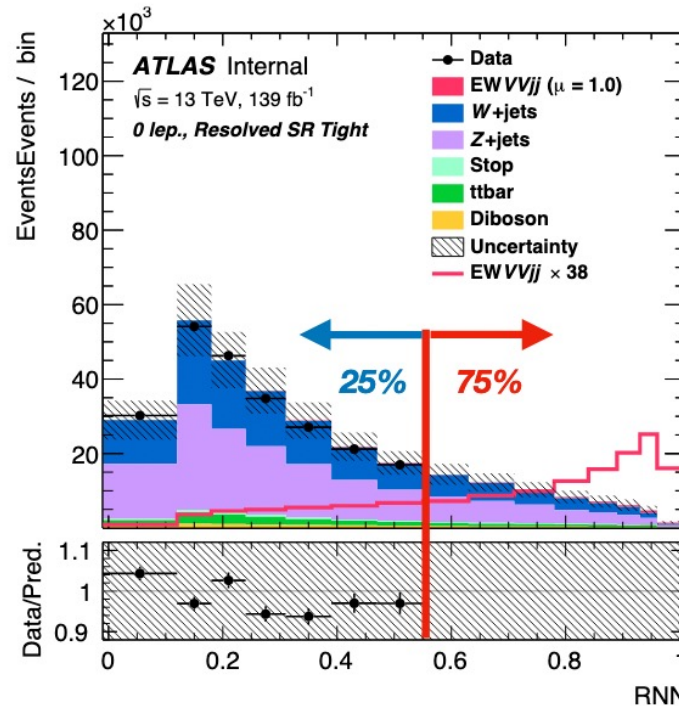
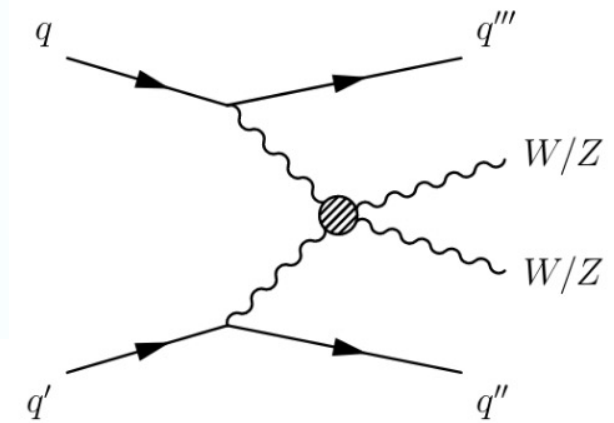
➔ **Aim for observation!**

Limits on anomalous QGC:

- ✓ VBS is a key diagram for probing QGC of EWK sector
- ✓ New physics introduced by anomalous-QGC can be described via EFT:

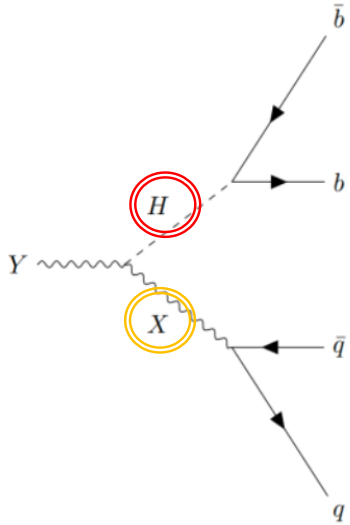
$$\mathcal{L} = \mathcal{L}_{sm} + \sum_i \frac{c_i}{\Lambda^2} \mathcal{L}_i + \sum_n \frac{f_n}{\Lambda^4} \mathcal{L}_n$$

- ✓ Limit on Wilson coefficients for different operators



soon updated public results ➔ Elvira paper's editor, analysis in final stages of approval

Fully-hadronic $Y \rightarrow Xh$: First application of Anomaly detection in ATLAS



- **Model-independent discovery region** introduced with novel data-driven anomaly score (**AS**)
- AS determined from fully unsupervised **variational recurrent neural network (VRNN)** trained over jets modeled as sequence of constituent four-vectors.

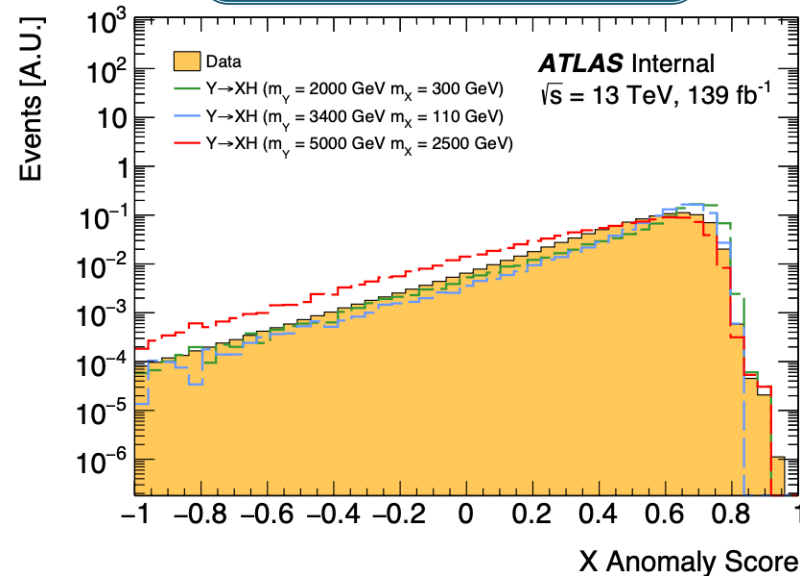
High ($\sim 1-6\text{TeV}$) Y mass resulting in X and H boosted

• Y Reconstructed with two large- R jets

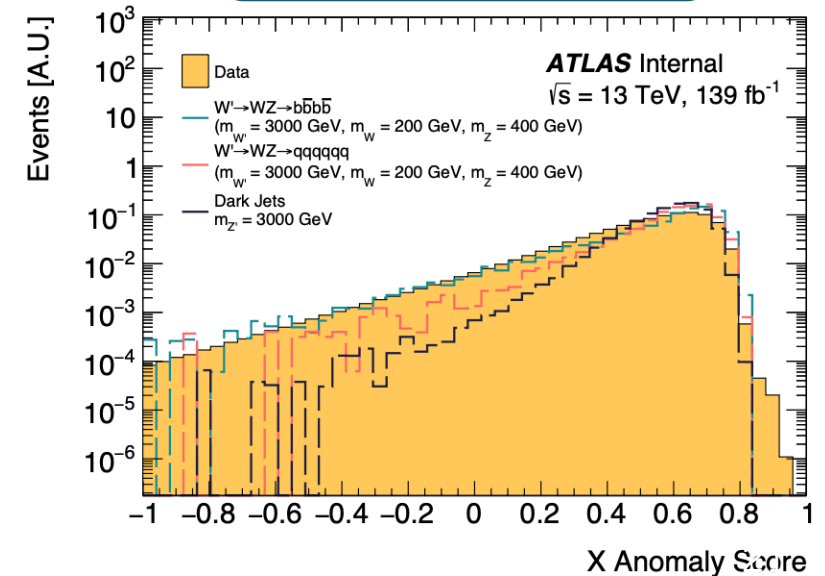
Object Reconstruction:

H Candidate: Xbb Tagger @60% WP + mass window ($75\text{GeV} < m_H < 145\text{GeV}$)

Tested on YXH signal samples



Tested for NON-2 prong signal jets

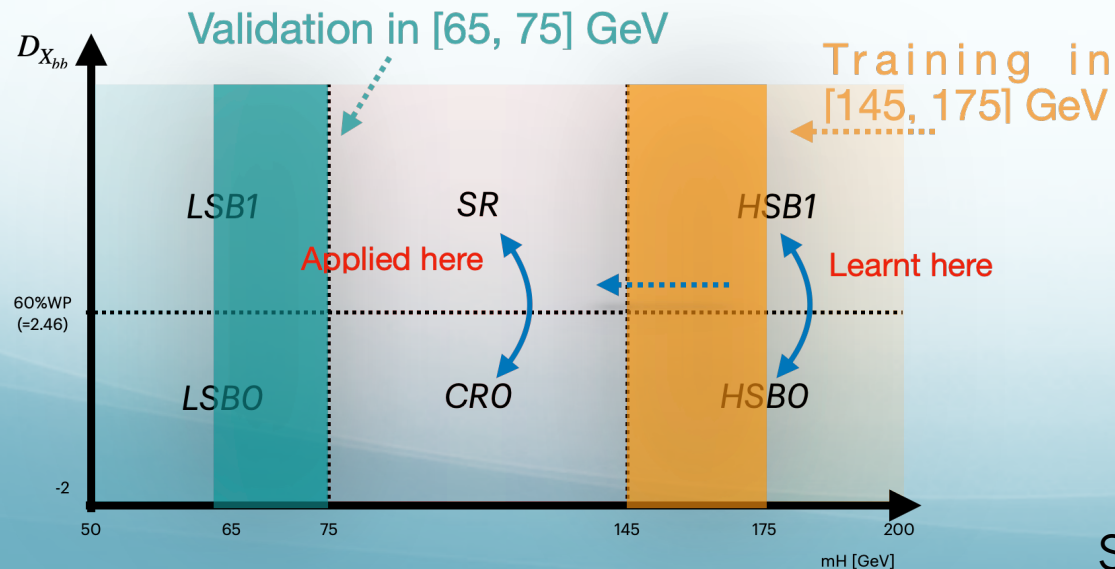


A Deep Neural Network for background reweighting

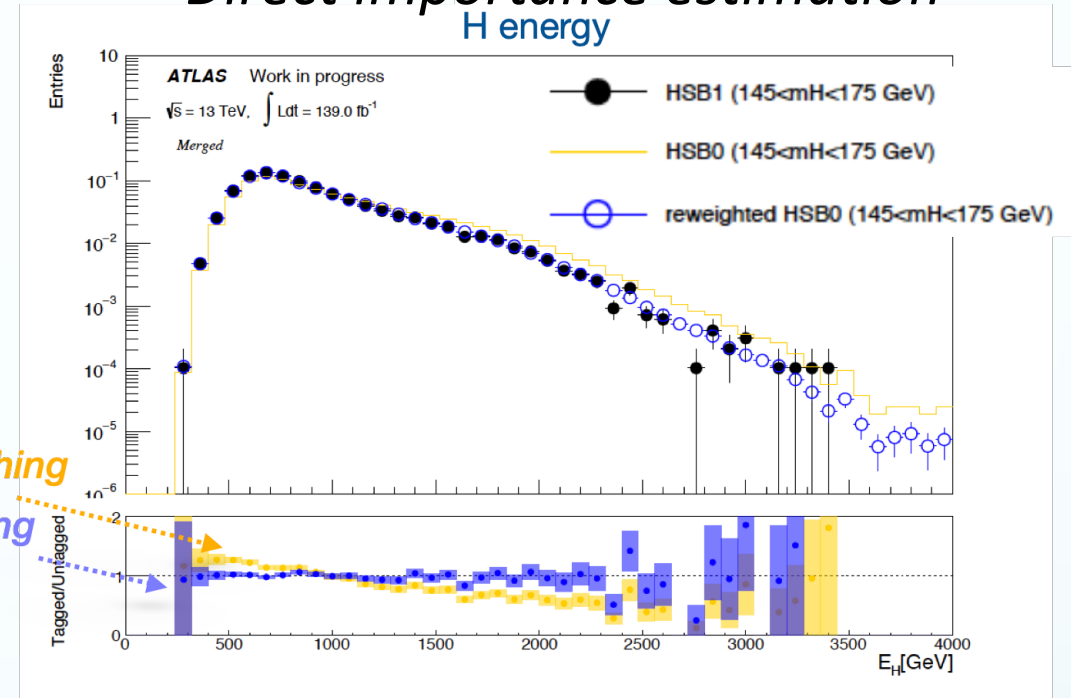
(Ref: [1] [2])

In the YXH analyses a DNN has been applied for estimating the likelihood ratio between two kinematic regions and obtaining reweighting factor for the background estimation in the signal region

$$p_1 = w \cdot p_0 \Rightarrow \text{Rearranging: } w = \frac{p_1}{p_0}$$



Direct importance estimation



Before reweighing

After reweighing

DNN trained on Data inputs:

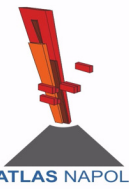
- H four-momentum
- Ntracks associated to H
- Leading and subleading track jets associated to H:

Minimized loss function

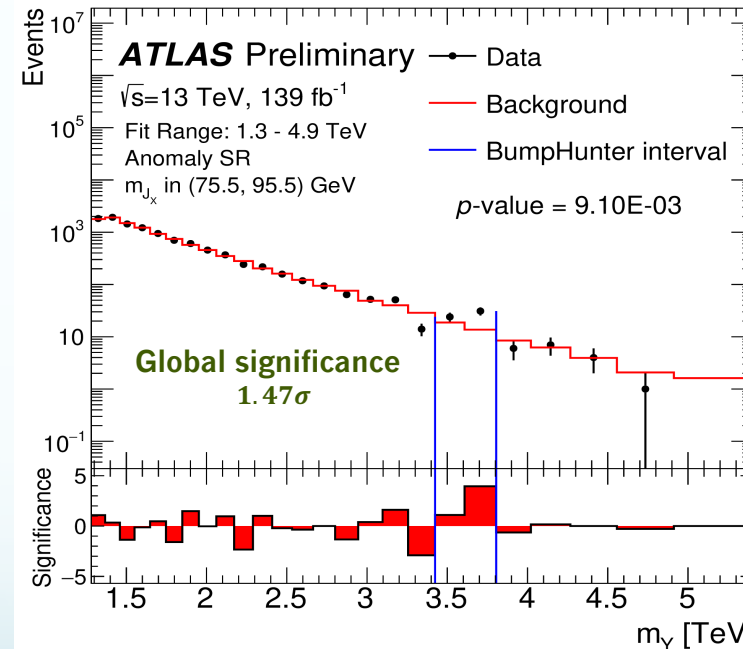
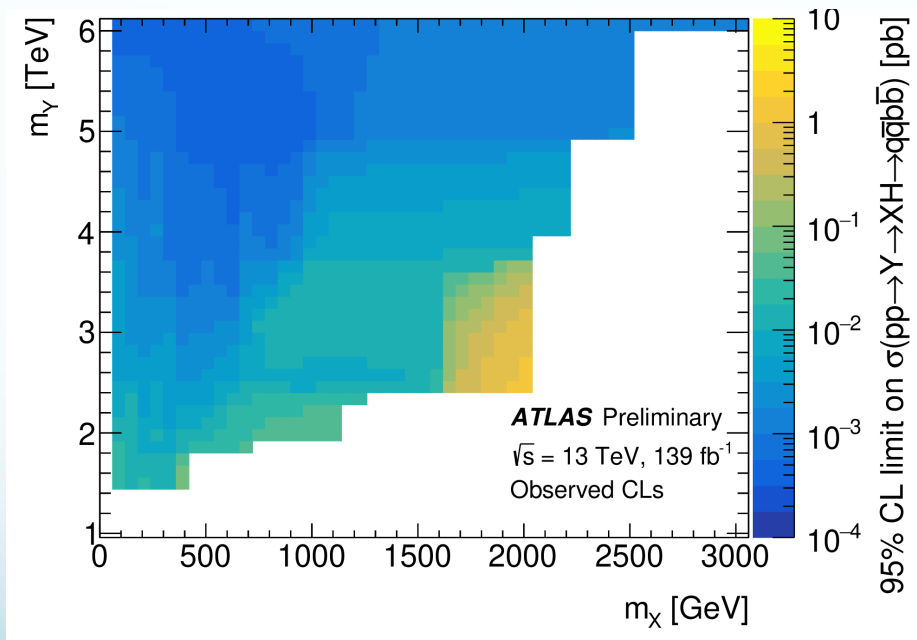
$$J(\theta) = E_{p_0} \sqrt{e^{u(\bar{x}, \theta)}} + E_{p_1} \frac{1}{\sqrt{e^{u(\bar{x}, \theta)}}}$$

Fully-hadronic $\Upsilon \rightarrow Xh$ results

ATLAS-CONF-2022-045



- The m_{JJ} distribution is fitted in bins of the X candidate mass
- A search for excesses of data over the expected background is performed
- Two-dimensional 95%CLs upper limit on the cross section of the $\Upsilon \rightarrow Xh \rightarrow q\bar{q}b\bar{b}$ HVT process of HVT signals have been calculated in the plane $\{m_Y, m_X\}$



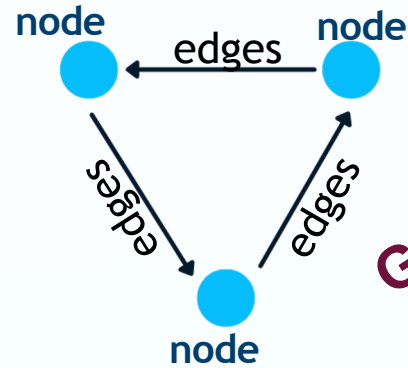
Good compatibility found for background-only fit, largest excess in the m_X window [75.5, 95.5] GeV with a local p-value 0.0091 (corresponding to a global significance of 1.47σ)

Francesco Conventi paper's editor, Francesco Cirotto internal note's editor, paper almost ready (2nd circulation)

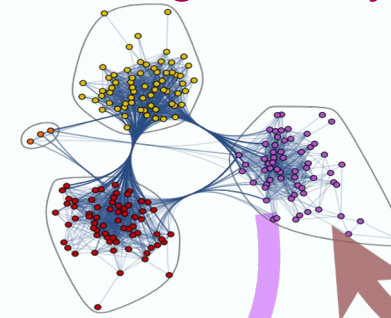
Graph anomaly detection in Diboson searches

Applying Graph Neural Network for performing anomaly detection

A **Graph** is the type of data structure that contains nodes and edges. A node can be a person, place, or thing, and the edges define the relationship between nodes. The edges can be directed and undirected based on directional dependencies.



Graphs



Anomaly detection



Graph Neural Network (GNN) is a deep learning model that handles a graph as input data. Graph-structured data are ubiquitous across science and they are used to describe and analyse relations and interactions and they can encapsulate object or event information

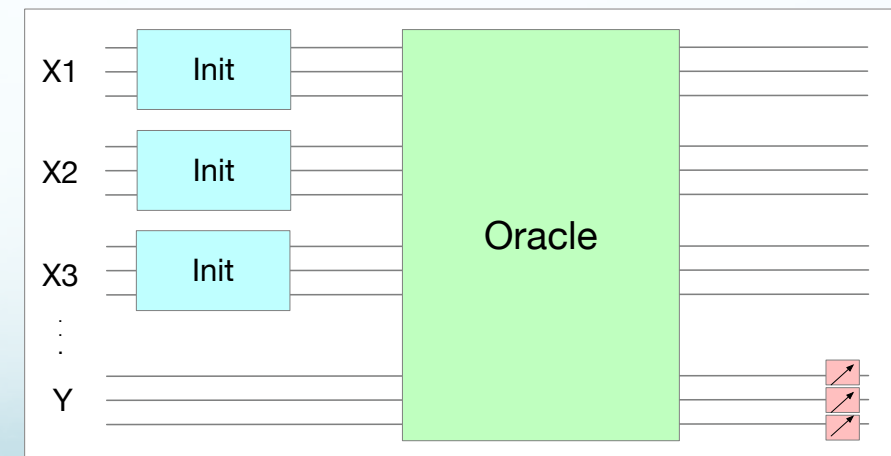
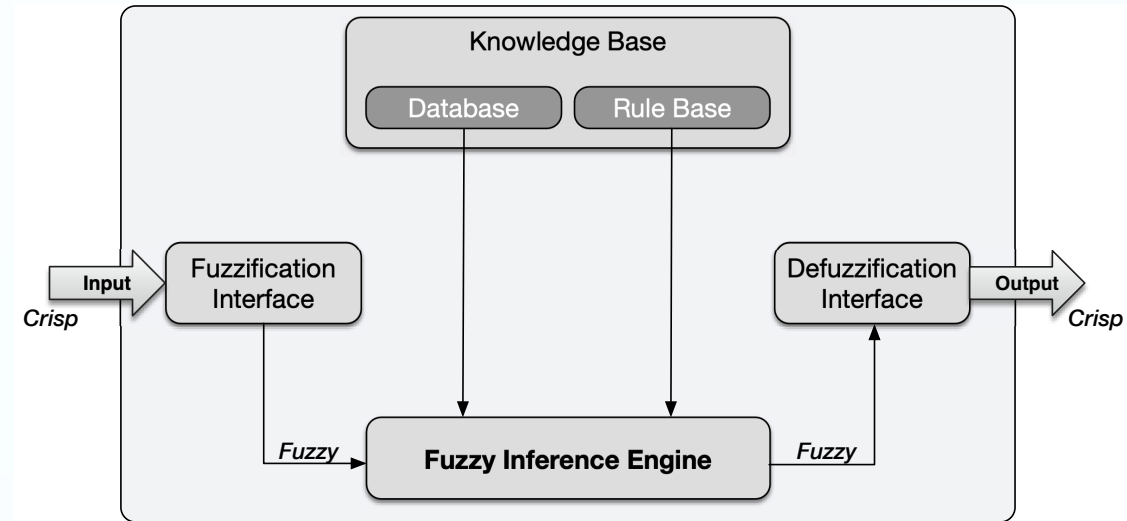
Anomaly detection: Identification of rare items, events or observations which deviate significantly from the majority of the data and do not conform to a well defined notion of normal behaviour

→ In HEP language: identify features of the data that are inconsistent with a background-only model or deviation from known SM processes

- Our strategy: to represent jets as graphs and then apply machine learning to build an anomaly detection algorithm
 - ↳ Provide easier extension to variable multiplicity (many jets in the event)
 - ↳ Targeting heavy resonance searches with hadronic final states ($A \rightarrow BC \rightarrow \text{hadronic}$)
- Implementing a Graph Neural Network and testing on hadronic final states
 - ↳ Two approaches under study for signal/background discrimination: supervised and unsupervised
 - ↳ First GNN event level application in ATLAS!

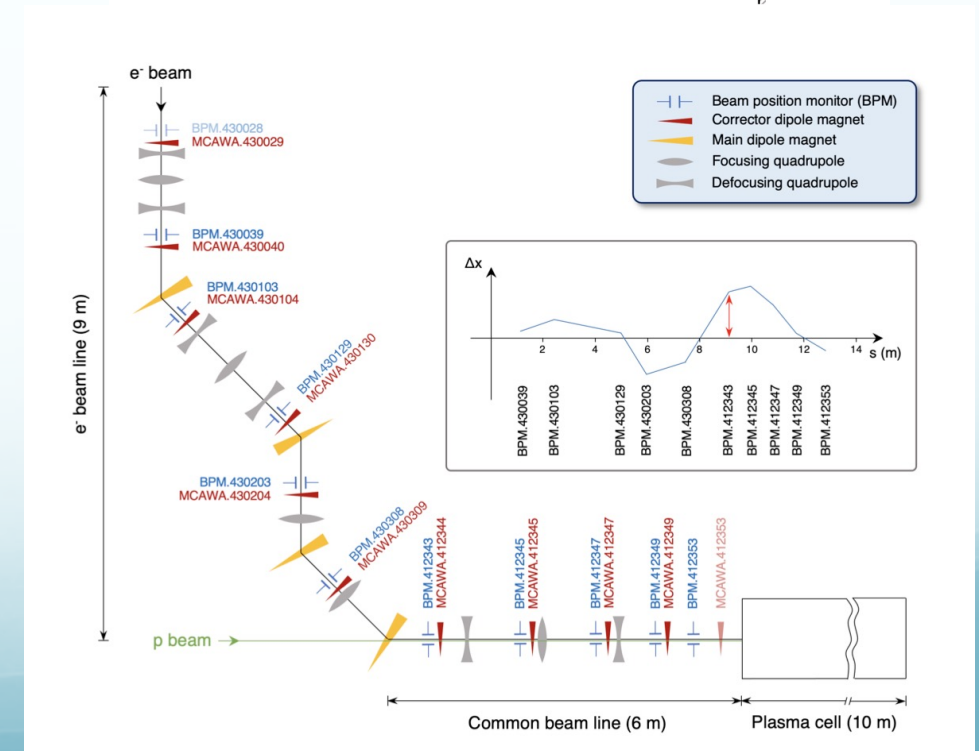
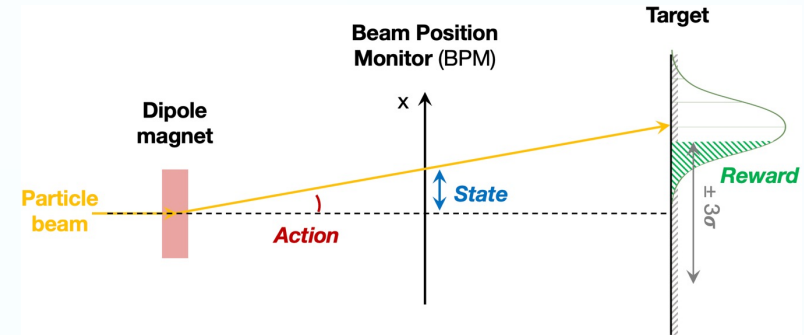
More information in [Antonio's lightning talk!](#)

- Classical **Fuzzy Logic** is a theory introduced by Lofti Zadeh with the idea to give computers the capability of dealing with **uncertainty**.
- Fuzzy Logic is used to develop **Control Systems** based on **linguistic rules**, which are therefore highly **interpretable**.
- In [1] a **Quantum Fuzzy Control System** is proposed. The main goal achieved by this approach is the **exponential advantage** in computing fuzzy rules on quantum computers over their classical counterpart.



Quantum Fuzzy Control Systems For Particle Accelerators

- The Quantum Fuzzy Control System proposed in [1] has been tested for **controlling the trajectory of particle beams** in two real particle accelerator facilities at CERN:
 - **T4 target station** at the CERN SPS fixed target physics beam line
 - Advanced Proton Driven Plasma Wakefield Acceleration Experiment (**AWAKE**)
- **Experimental results** carried out on the **real accelerators** show the suitability of this approach in controlling these systems.



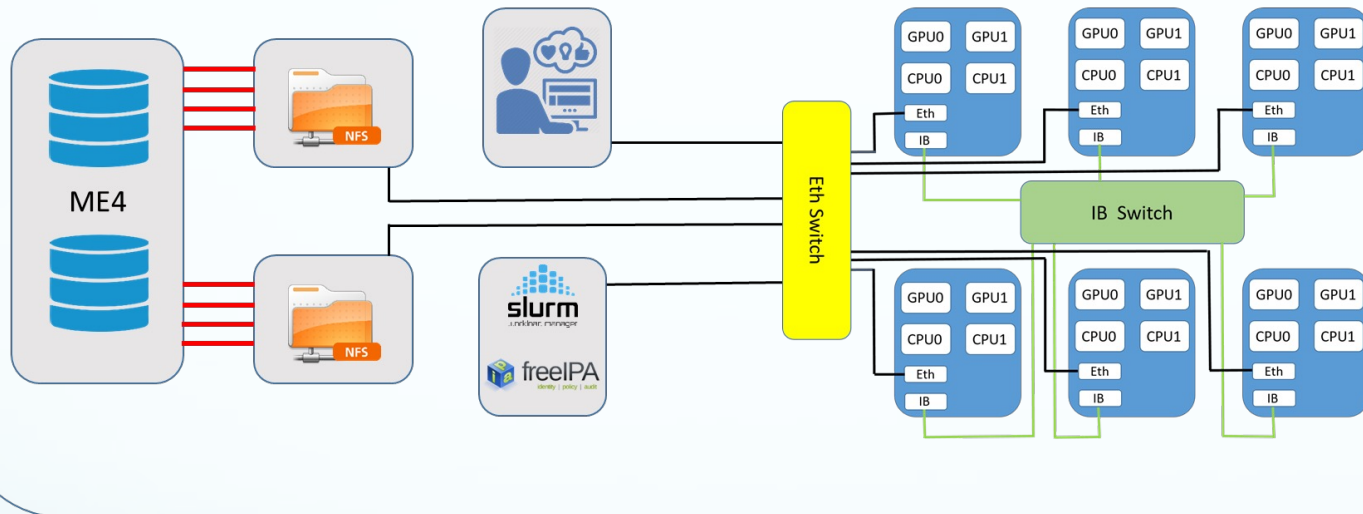
ATLAS NA Computing Activity

A. Doria – B. Spisso – G- Carlino – G. Russo

Cluster HPC INFN Napoli


Sistema in fase di pre-produzione – risorse del progetto IBiSCo

Resources



- 6 nodi di calcolo PowerEdge R7525
 - 2 CPU AMD EPYC 7742 128 core
 - 2 GPU NVIDIA V100 32GB
 - Memoria 1200 GB
- Interconnessione Infiniband 100 GB
- Sistema di Storage per il breve e medio termine circa 500 TB raw, diviso tra partizione all flash e partizione meccanica

Scelte architetturali

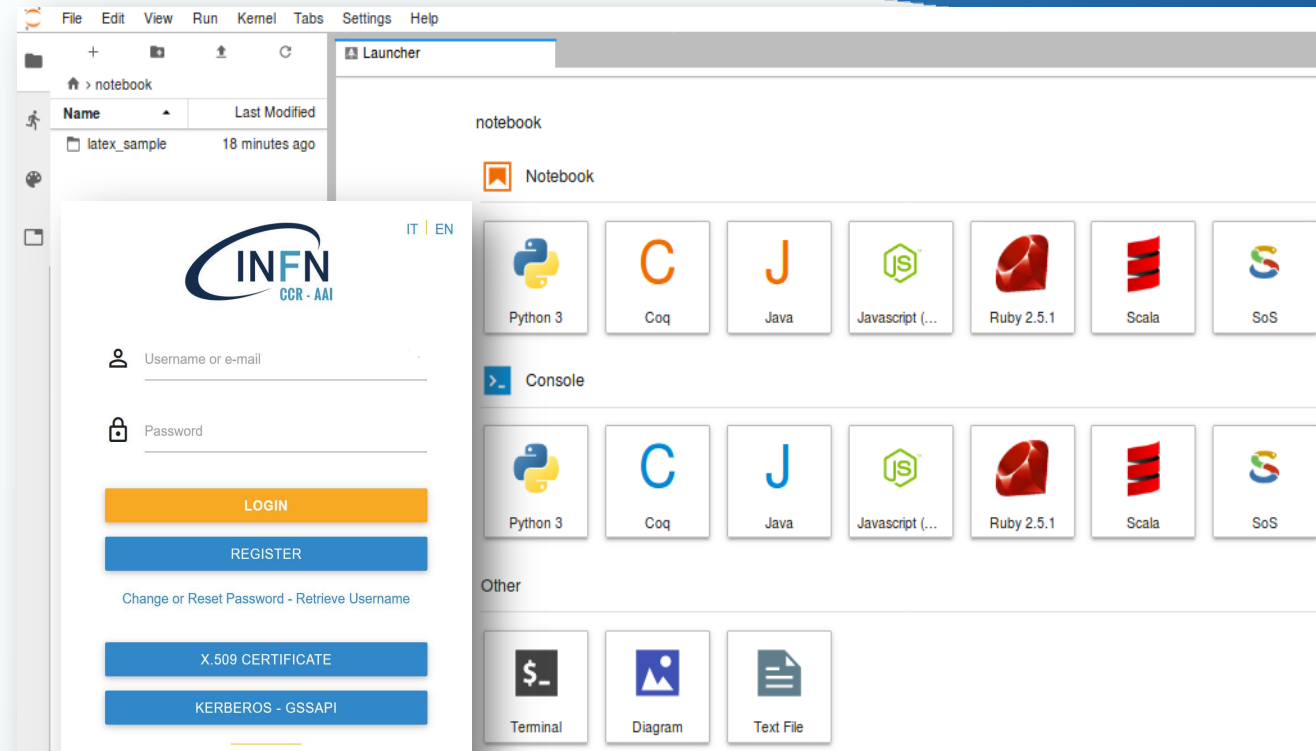
-  **Rocky Linux™ 9** come sistema operativo (Red Hat 9 based)
- **NFS** installato per la condivisione di spazio utente, scratch e software applicativo.
- **SLURM** per la gestione dell'accesso alle risorse e lo scheduling dei job.

Accesso utenti (User interface)

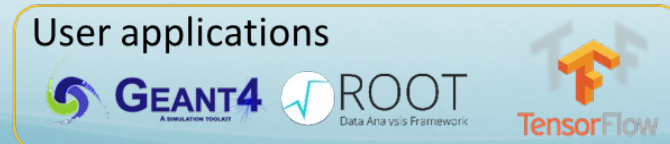
- Autorizzazione utenti locali
- Prevista autenticazione AAI (utenti INFN)
- Accesso tramite Command Line
- Accesso tramite JupyterLab

Attualmente il cluster è in pre-produzione.

Utenti «beta tester» benvenuti per provare i workflow dei diversi esperimenti.



```
JOBID PARTITION NAME USER ST TIME NODES NODELIST(REASON)
24955 myNodes slurm_py spotter5 PD 0:00 1 (Resources)
24956 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24957 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24958 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24959 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24960 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24961 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24962 myNodes slurm_py spotter5 PD 0:00 1 (Priority)
24952 myNodes slurm_py spotter5 R 0:01 1 parrot103
24953 myNodes slurm_py spotter5 R 0:01 1 parrot102
24954 myNodes slurm_py spotter5 R 0:01 1 parrot101
```



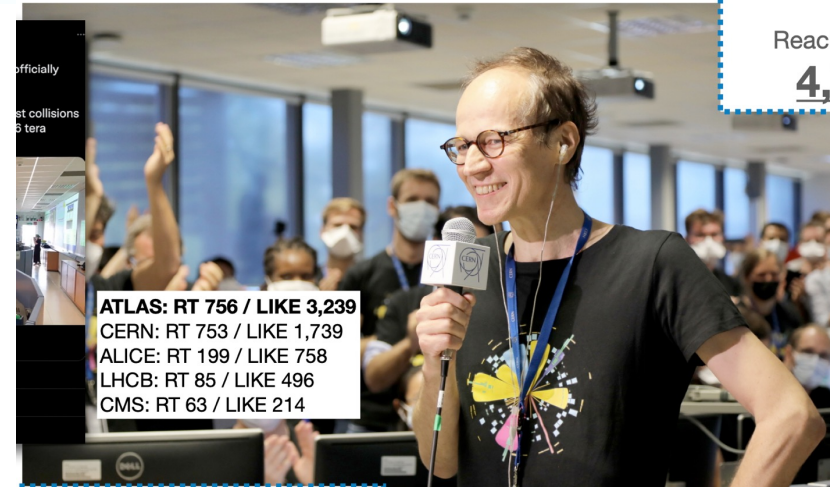
ATLAS NA Outreach Activity

C. Di Donato – P. Massarotti – et. al.

Outreach

- Grande attenzione della collaborazione per l'Outreach e la presenza sui Social Media:
 - 2022 pieno di eventi: Higgs10, Run-3 start, ATLAS 30th anniversary!
 - Grande presenza della collaborazione e di ATLAS IT sui principali social media (FB – IG – Twitter) e discreto successo in termini di followers.
- Gruppo di lavoro "Outreach" Atlas Italia (Coordinatore G. Gaudio – PV):

- Web Site (A. Sidoti) <https://web.infn.it/atlas/>
- Social channels (E. Ricci)
 - Facebook <https://www.facebook.com/esperimentoATLASitalia>
 - Instagram <https://www.instagram.com/atlasitalia/>
 - Twitter https://twitter.com/atlas_italia
- Translations (G. Mancini)
- Masterclasses (M. Capua)
- Repository Talk/Photo/Video (C. Di Donato)
- Wikitalia (G. Introzzi) https://it.wikipedia.org/wiki/Esperimento_ATLAS



Run 3 live
Reached 11,557,580 people
4,732,869 views

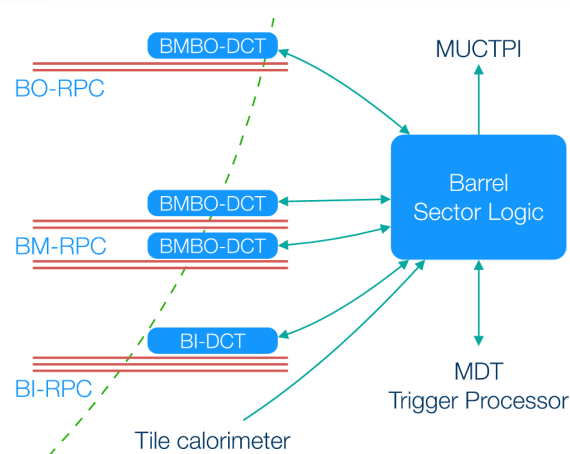
Peak seen in Instagram,

- Il gruppo di ATLAS – NA è stato sempre molto attivo nelle Masterclass.
 - Ripresa nel 2023 degli appuntamenti Masterclass in sede

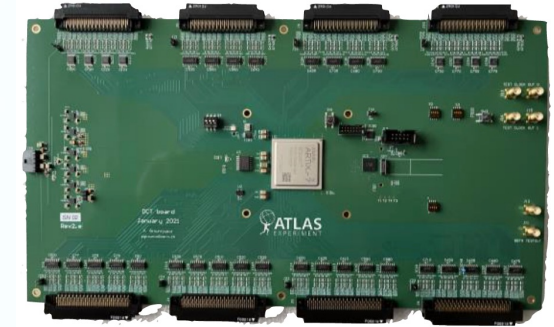
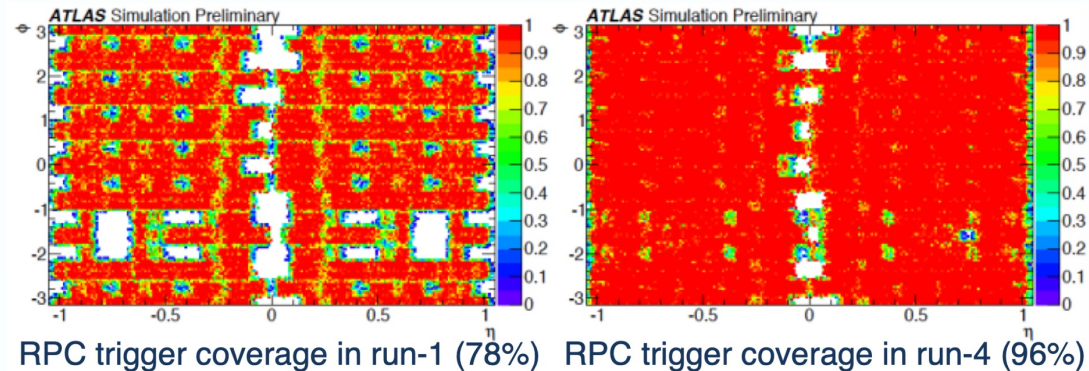
ATLAS NA Phase II

Uno sguardo al futuro

Attività di Upgrade per L0 Muon Barrel



L1 Muon Barrel Trigger schema



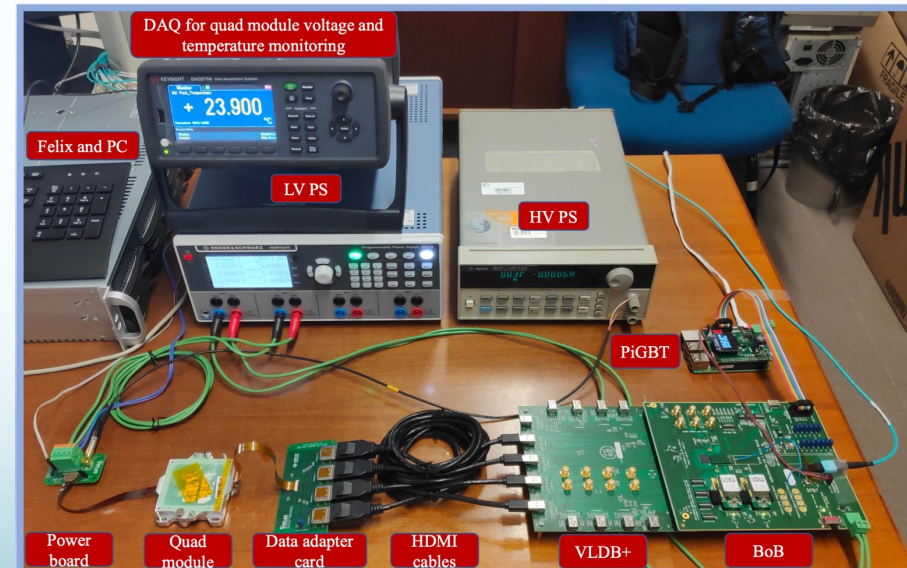
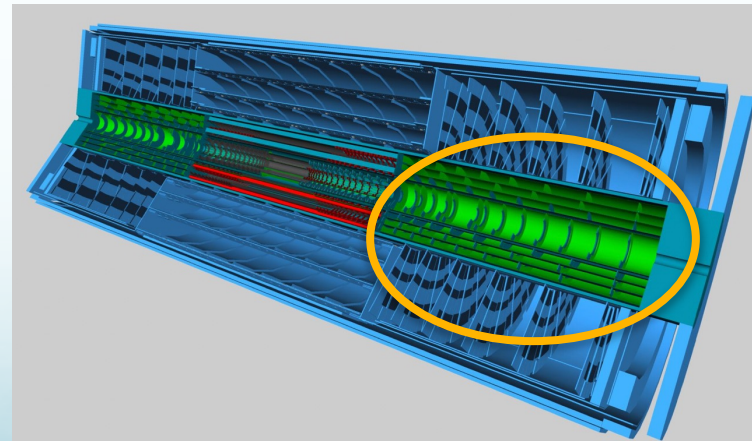
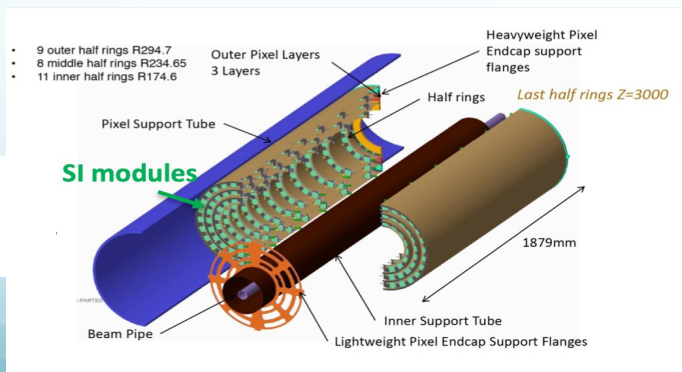
BM-BO DCT

Elettronica per il trigger di Livello1 degli RPC

- Schede **DCT (1570)** ricevono i segnali dal front-end degli RPC e inviano i dati digitalizzati alle schede **Sector Logic (32)** off-detector
- La scheda Sector Logic riceve i dati dai DCT ed esegue l'algoritmo di trigger di Livello-0 nel barrel e la logica di readout degli RPC.
- Test del prototipo DCT mostrano una corretta funzionalità della scheda
- Test di qualificazione dei componenti per radiazioni completati nel 2022.
- Test delle prestazioni della logica (TDC e readout) con un rivelatore RPC previsti nel 2023
- Elevato tempo di consegna (~ 1 anno per gli FPGA) di componenti elettronici (FPGA, regolatori di tensione, trasduttori ottici, ...)
 - Alto rischio di ritardi nella produzione dei prototipi

Avvio attività ITK

- Alla fine del 2022 alcuni membri del gruppo hanno preso contatti con la comunità italiana di ITK per capire se e come entrare in ITK
 - Interesse nel seguire i test di integrazione a Frascati del detector di responsabilità italiana con l'ausilio dei servizi tecnici
 - Interesse allo sviluppo del sistema di DAQ ed integrazione nel TDAQ di ATLAS (ancora allo stato embrionale)
 - Attività in sede con messa a punto di un testbench per lo sviluppo del sistema di DAQ



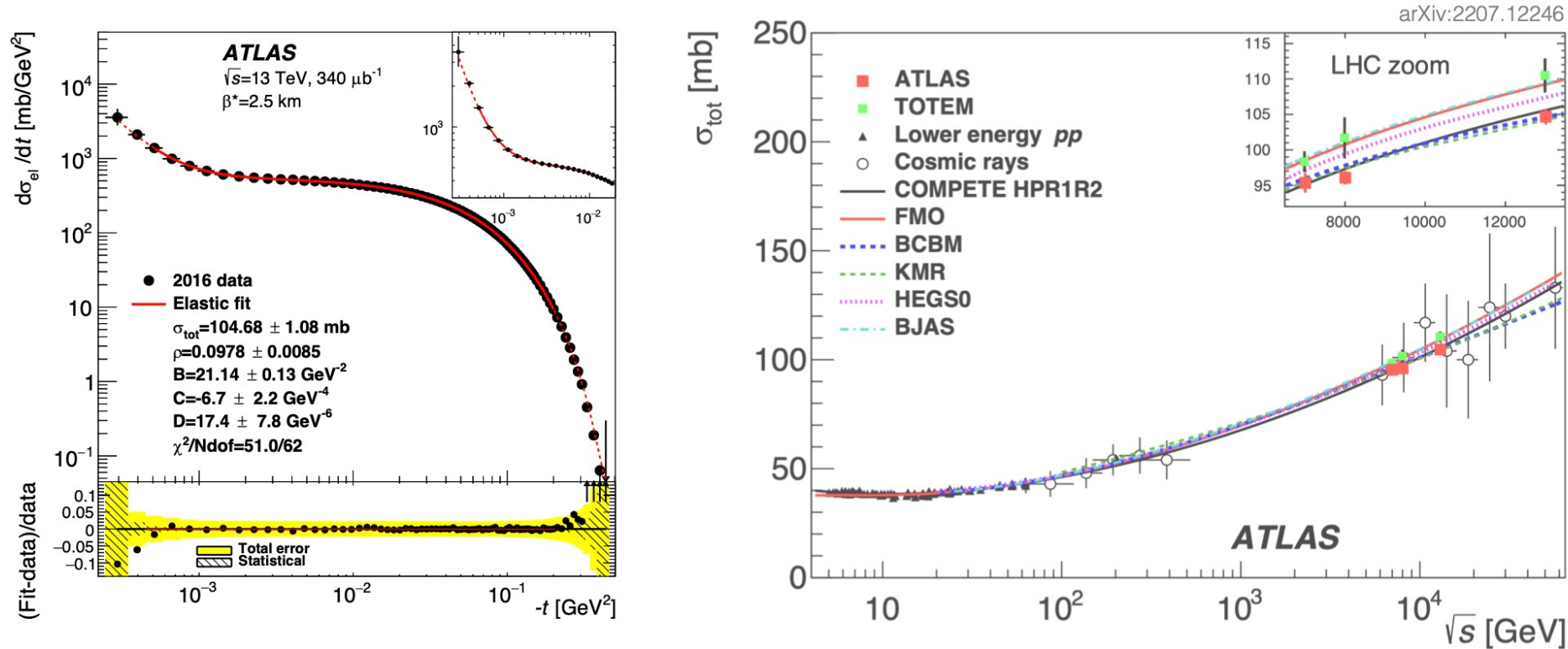
Outer pixel endcap di responsabilità italiana

Backup

New 13 TeV elastic cross-section measurement

Differential pp → pp elastic cross section as function of t-channel momentum transfer

Scattered protons in $\beta^* = 2.5$ km run (2016) measured in Roman Pot stations 237 m & 245 m on either side of ATLAS (ALFA)



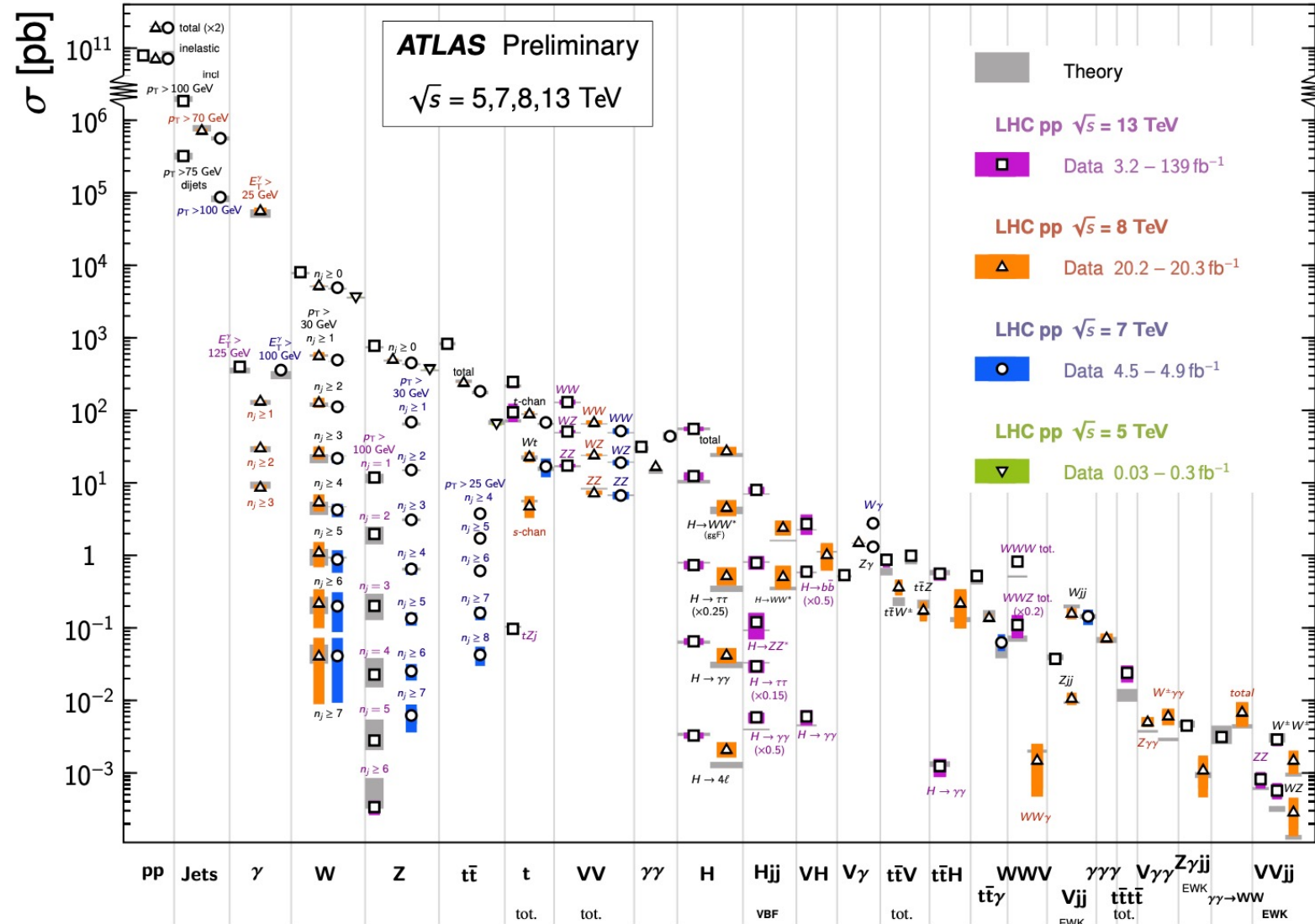
Measured inelastic cross section: $77.41 \pm 1.07_{\text{exp}} \pm 0.18_{\text{theo}}$ mb

Measured ρ value: $0.0978 \pm 0.0085_{\text{exp}} \pm 0.0064_{\text{theo}}$, confirming lower value than model expectation

SM picture

Standard Model Production Cross Section Measurements

Status: February 2022



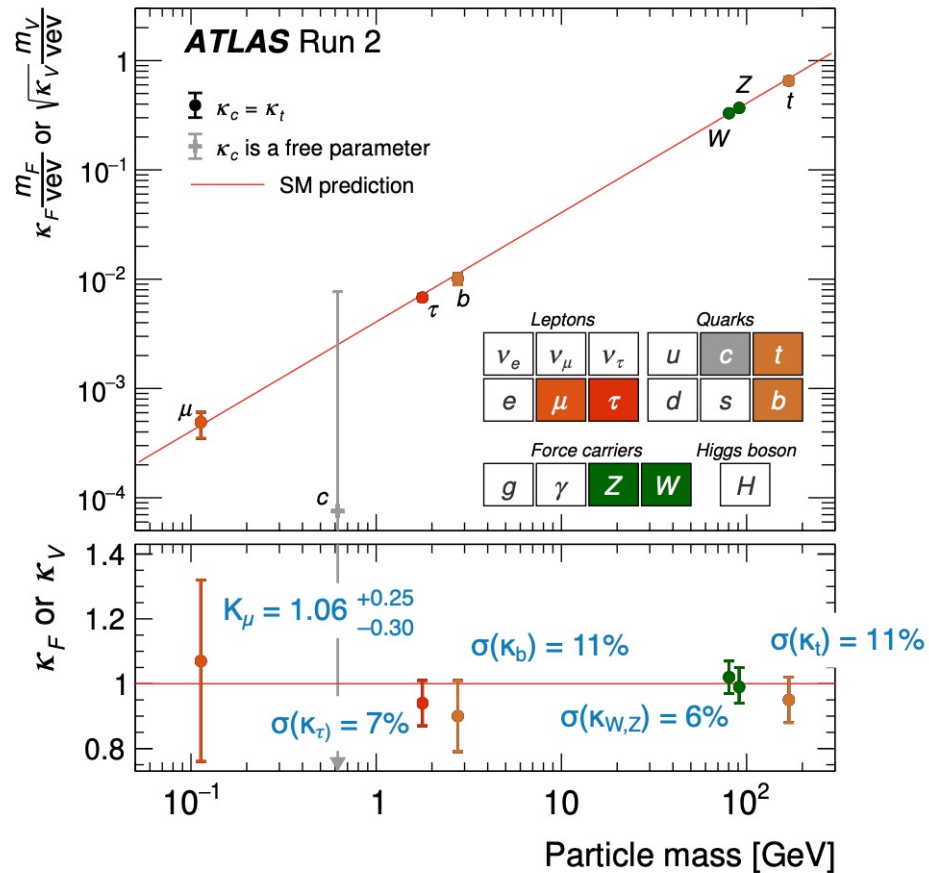
Measurements confirm the predictive power of the Standard Model

Large benefits from recent theory developments and computations

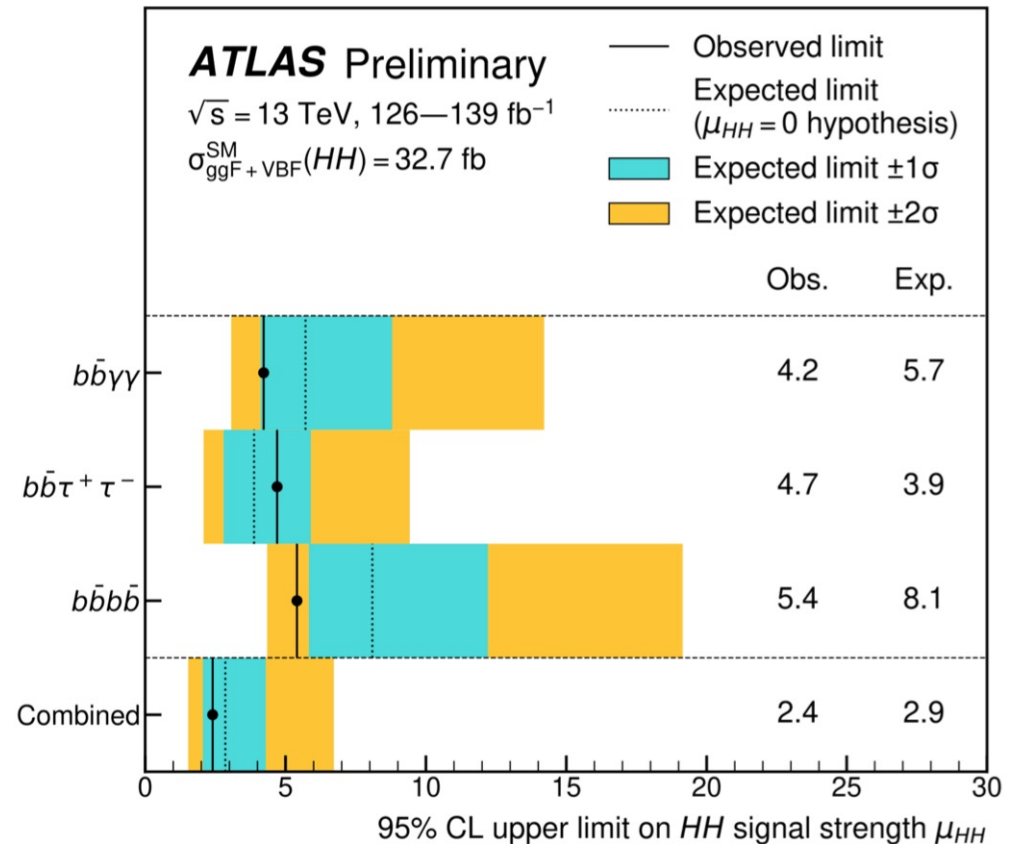
Higgs Status Run2

Higgs combination papers and di-Higgs combination conference note (ATLAS)

$\kappa_\gamma = 1.01 \pm 0.06$, $\kappa_g = 0.95 \pm 0.07$, $\kappa_{Z\gamma} = 1.38^{+0.31}_{-0.37}$, $H \rightarrow \text{inv} < 13\%$ (8% exp.)



[arXiv:2207.00092](https://arxiv.org/abs/2207.00092), [Nature 607, 52–59 \(2022\)](https://doi.org/10.1038/s41586-022-0350-4)

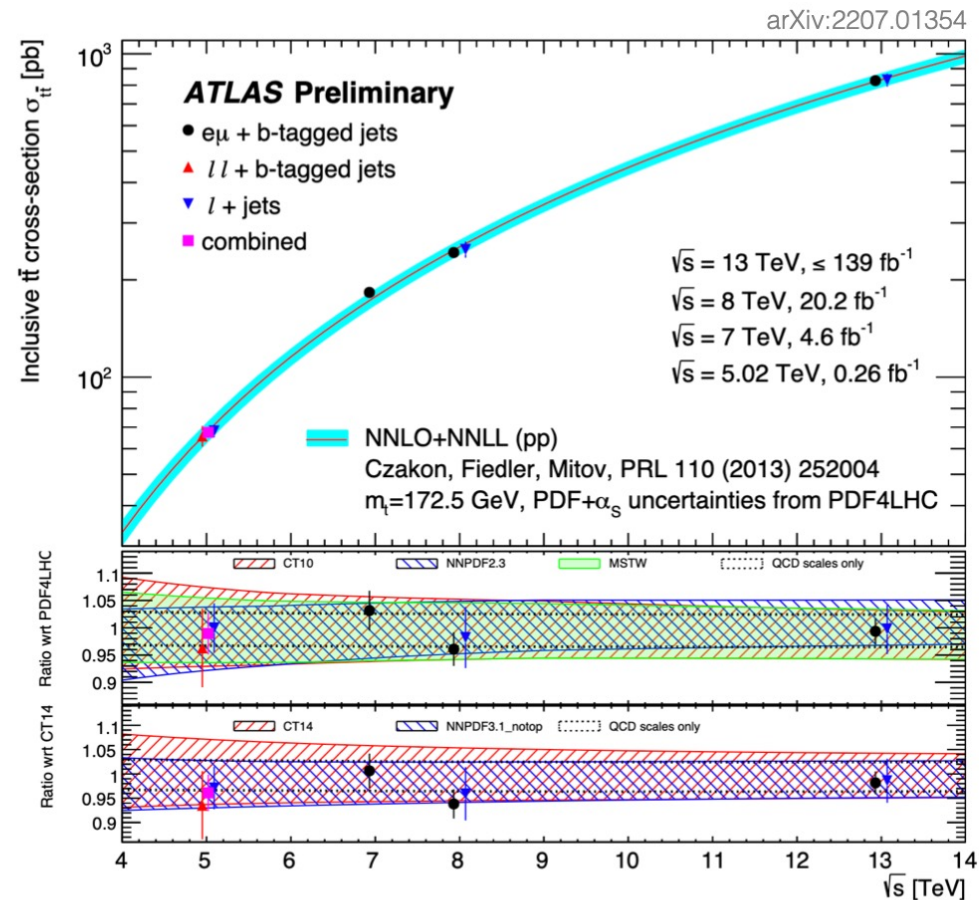


[ATLAS-CONF-2022-050](https://arxiv.org/abs/2207.00092), [Physics briefing](https://arxiv.org/abs/2207.00092)

Top Pair production

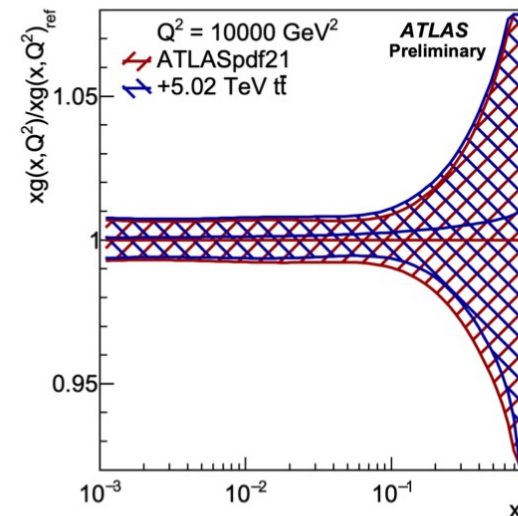
Top-pair production cross-section measurement in low pileup run at 5.02 TeV

Excellent precision (3.9%) reached with small 2017 dataset of 257 pb⁻¹



$$\sigma_{t\bar{t}} = 67.5 \pm 0.9 \text{ (stat.)} \pm 2.3 \text{ (syst.)} \\ \pm 1.1 \text{ (lumi.)} \pm 0.2 \text{ (beam) pb}$$

In excellent agreement with the NNLO-NNLL TOP++ prediction: $68.2 \pm 4.8^{+1.9}_{-2.3} \text{ pb}$



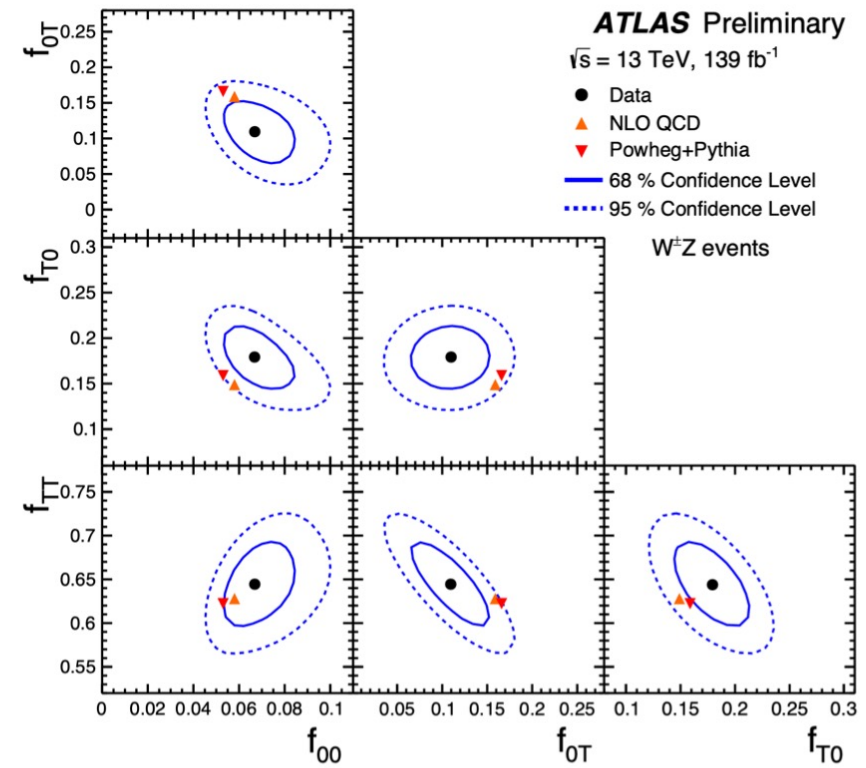
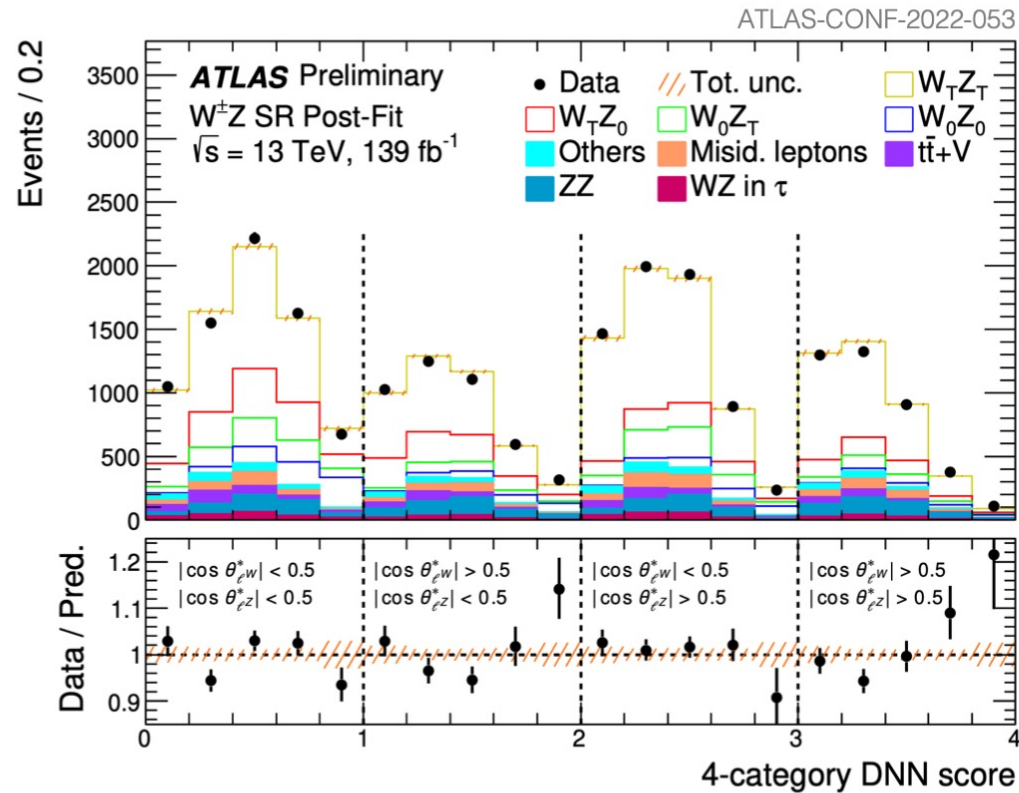
Energy dependence can be used to improve gluon PDF by 5%

→ Helpful for Higgs cross-section prediction

Joint WZ polarization studies

Joint measurement of W and Z polarization in WZ production

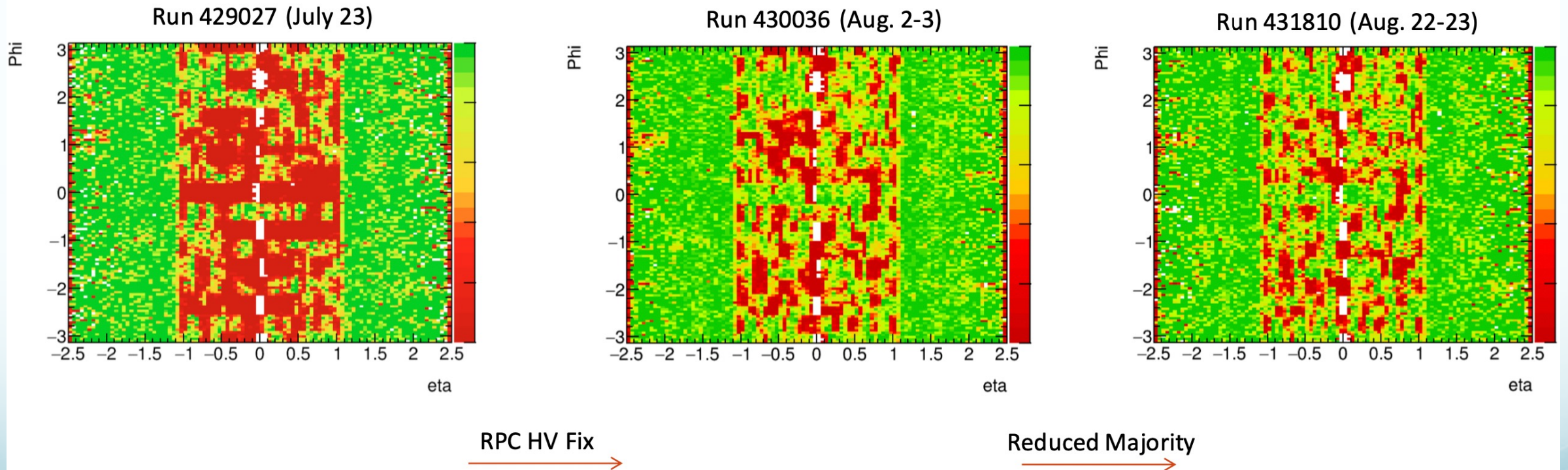
First observation of simultaneous production of longitudinally polarised W and Z bosons with 7.1σ



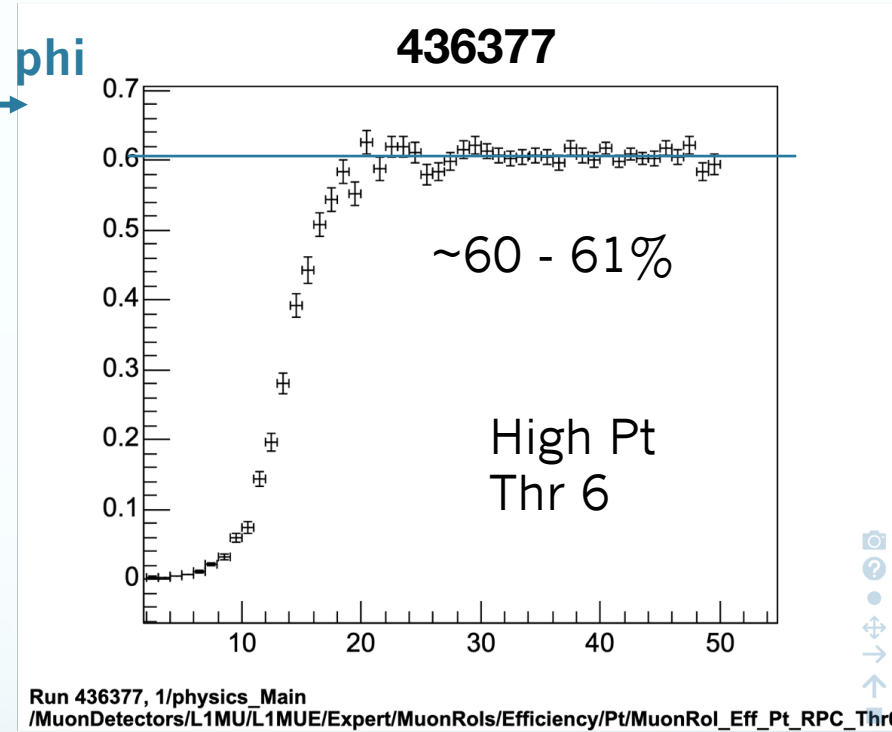
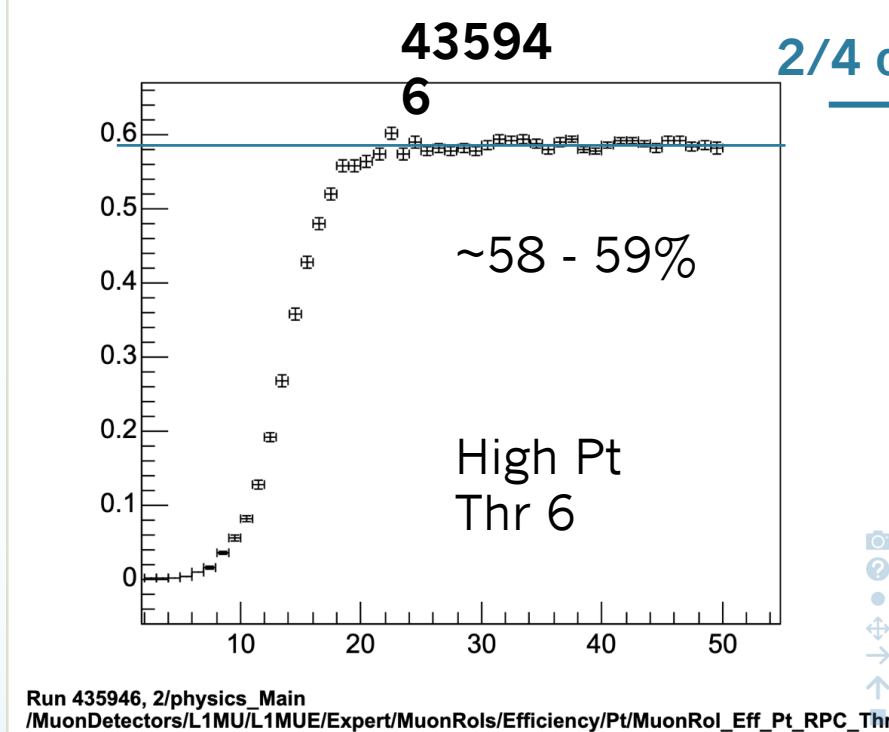
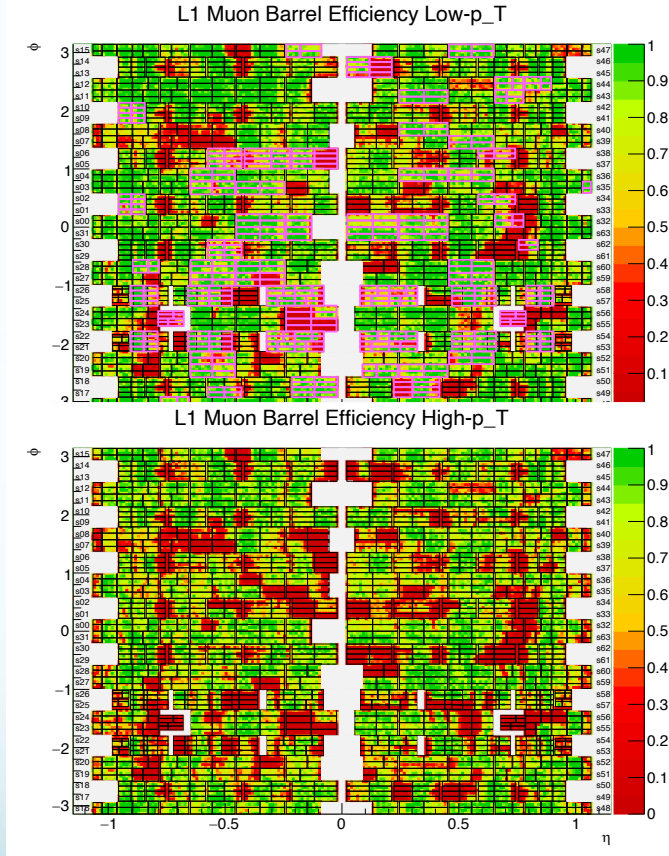
Measured longitudinal polarisation fraction: $f_{00} = 0.067 \pm 0.010$

L1 Muon Barrel High-PT Efficiency

- Barrel region is from -1.05 to $+1.05$



L1 Muon Barrel Efficiency: very last update

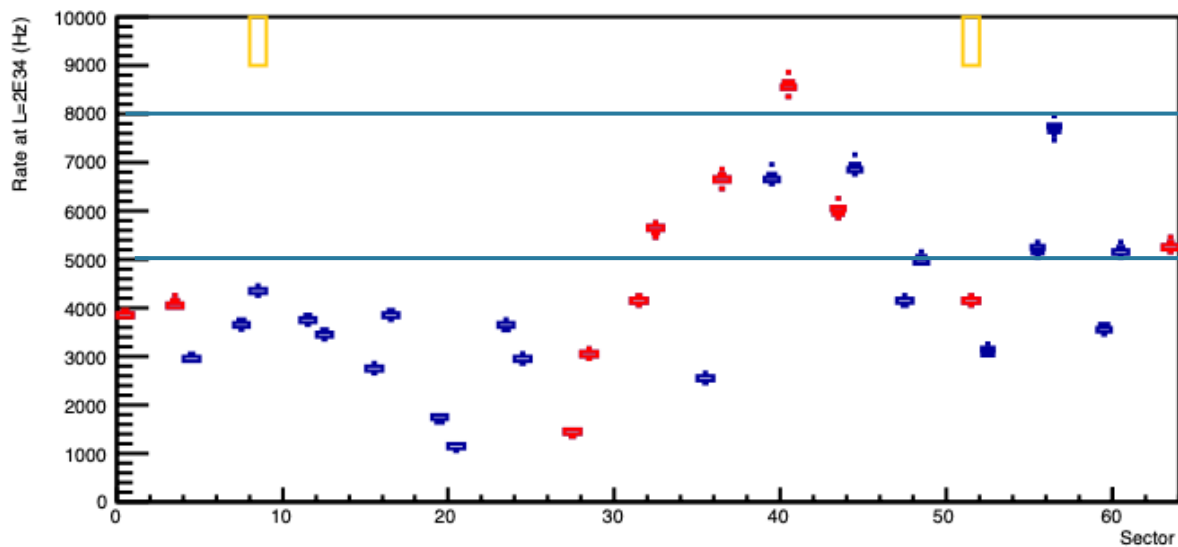


- 92 Towers with 2/4 majority in both eta and phi views over more than 400
- Few days ago 2/4 added only on phi view on almost all towers: waiting for physics_Main processing:
 - expecting 2 % more without increasing too much the rate.

L1 Muon Barrel rates

Before 2/4 on phi view

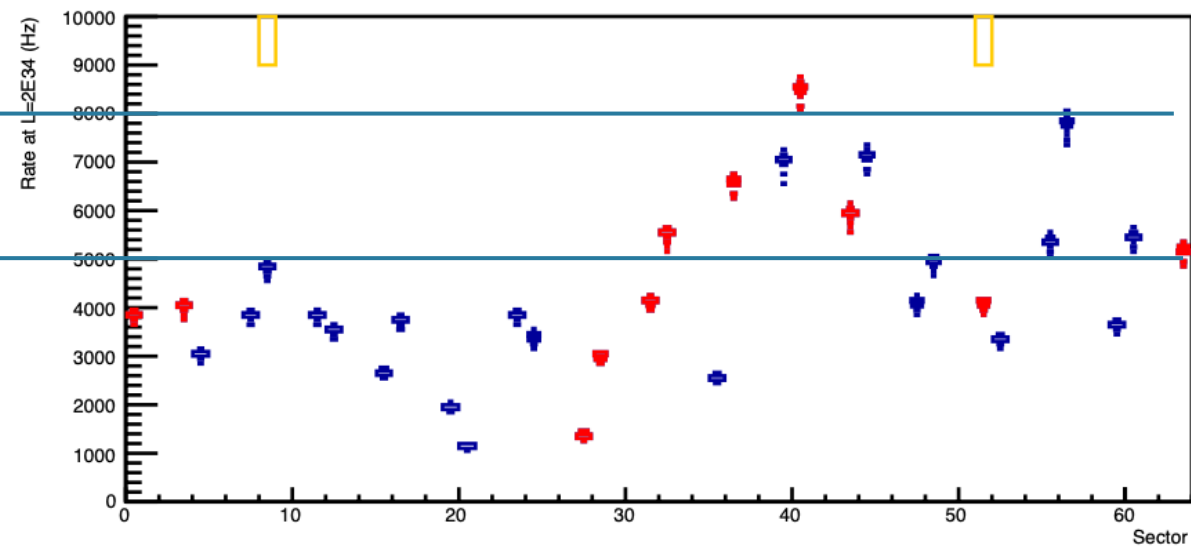
Tower 1



- Large sectors with 3/4
- Large sectors with 2/4
- Noisy channels

After 2/4 on phi view

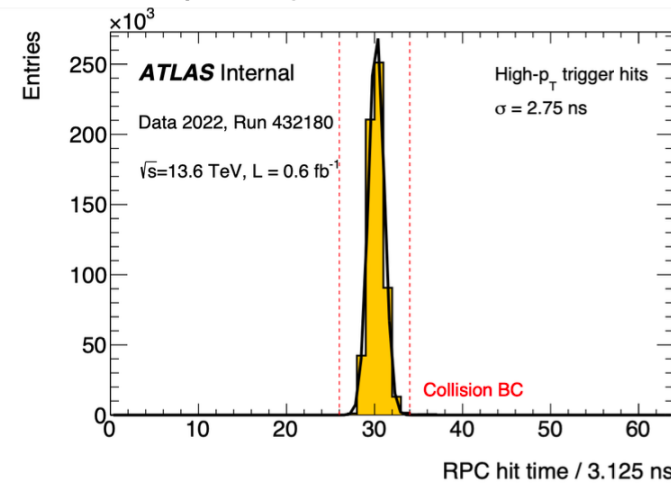
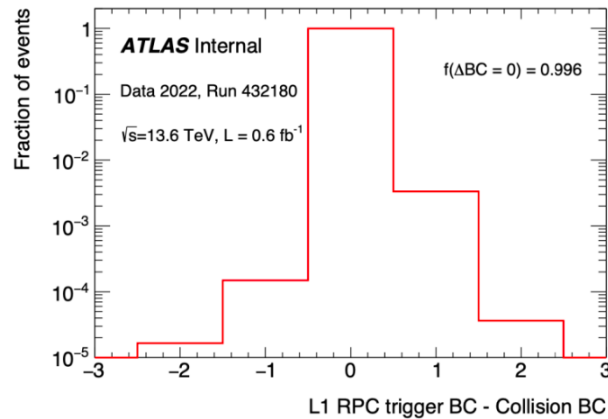
Tower 1



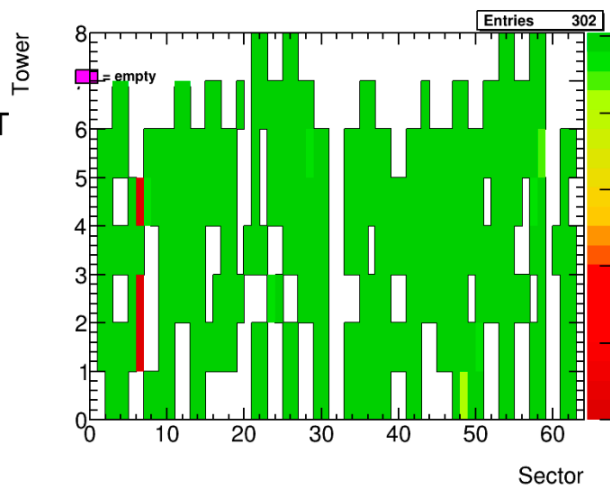
Rates under control even in the worst case (Tower 1 for Large sectors)

L1 Muon trigger timing

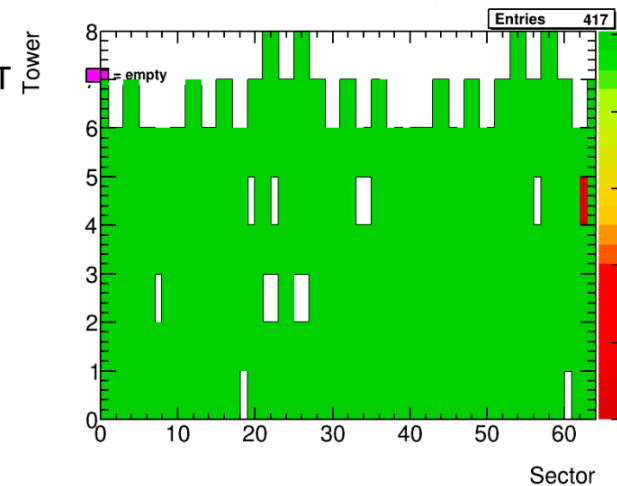
- All towers are triggering in correct BC
 - (some issue with sector S06, where the Sector Logic board was replaced)



Fraction of high- p_T
Rol in correct BC
- Run 428353

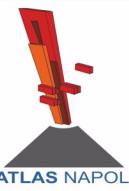


Fraction of high- p_T
Rol in correct BC
- Run 432810



Fully-hadronic $Y \rightarrow Xh$

ATLAS-CONF-2022-045



◆ Search for a narrow-width heavy resonance (Y) decaying into a SM Higgs $h(b\bar{b})$ and a new particle X in a fully hadronic final state

◆ Mass ranges investigated: m_Y in (1500-6000) GeV, m_X in (65-3000) GeV

◆ Model-independent search, [HVT](#) model used as a benchmark for $Y \rightarrow X$

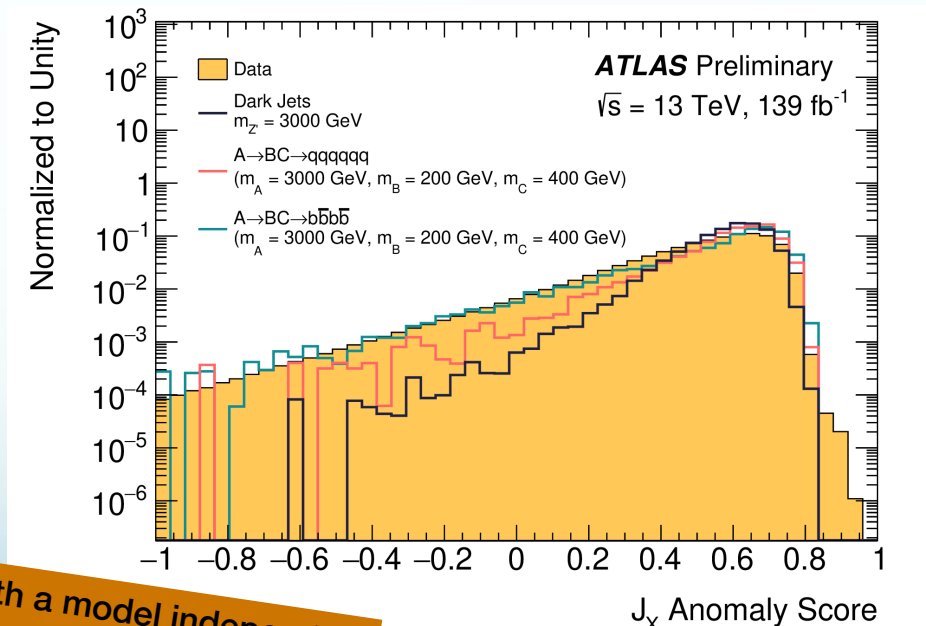
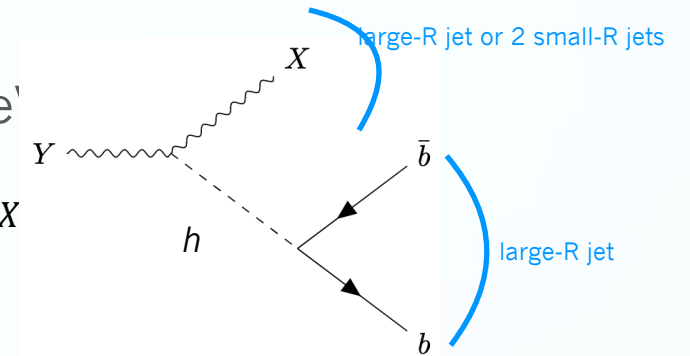
◆ Single large-R jet trigger (large-R jet collection [TCC R=1](#))

◆ **Higgs candidate** tagged with the new [Xbb tagger](#)

◆ **For X candidate** two tagging approaches are carried out:

1. **Discovery Region** based on a [jet-level anomaly score](#) (from a **variational Recurrent-Neural-Network trained on jets collection in data at preselection level**)

◆ sensitive to an X with any hadronic decay, model-independence assessed

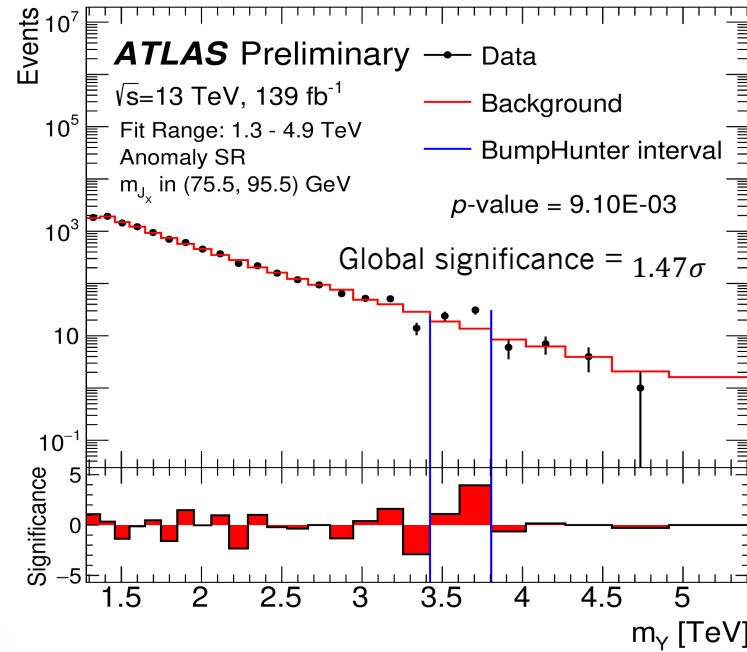
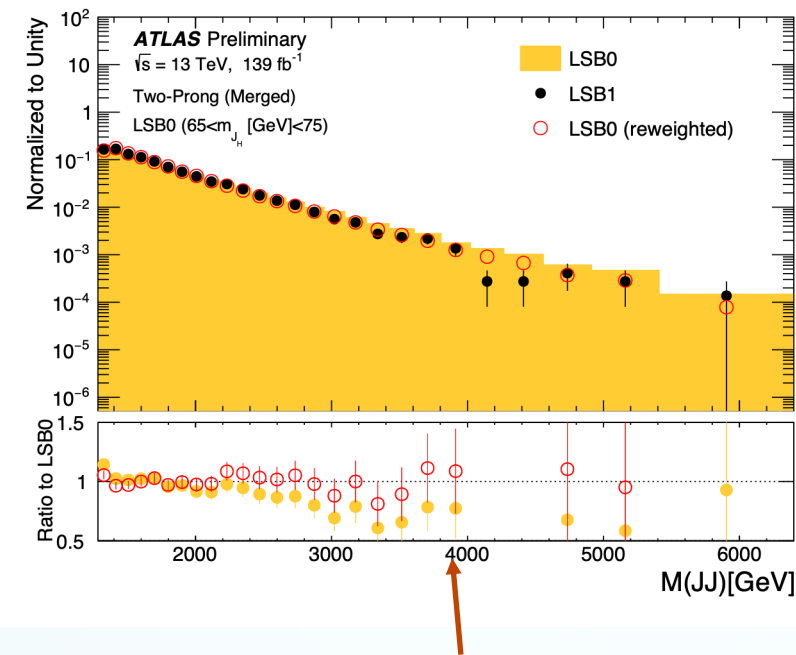
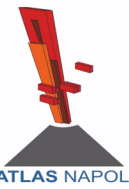


1st ATLAS analysis with a model independent (unsupervised) autoencoder!

2. **Exclusion Regions** for two-prong jets $X \rightarrow q\bar{q}$

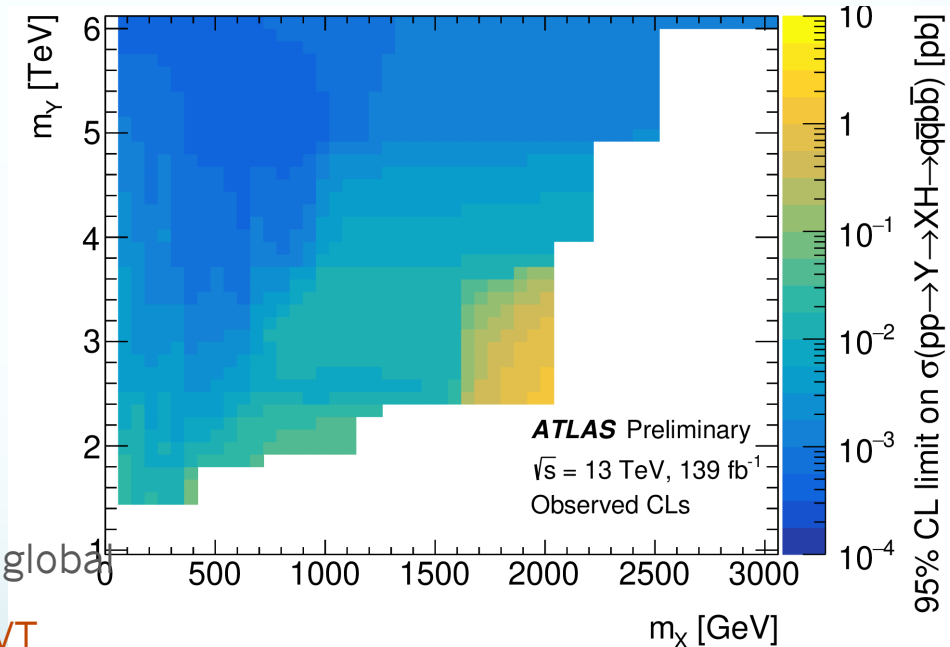
Fully-hadronic $\Upsilon \rightarrow Xh$ results

ATLAS-CONF-2022-045



Model independent search

HVT upper limits



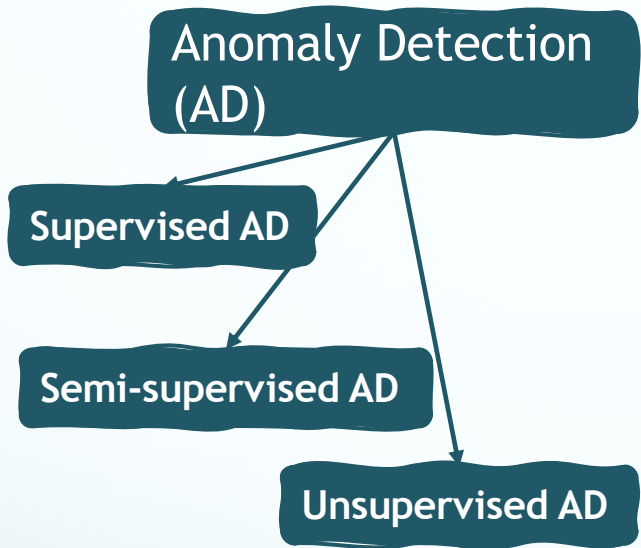
- ◆ Deep Neural Network (DNN)-based data-driven background reweighting
- ◆ The m_{JJ} distribution is fitted in overlapping bins of the X candidate mass
- ◆ A [BumpHunter](#) search for excesses of data over the expected background is performed
 - ◆ Good compatibility found for background-only fit, largest excess in the m_X window [75.5, 95.5] GeV with a local p-value 0.0091 (corresponding to a global significance of 1.47σ)
- ◆ Two-dimensional 95%CLs upper limit on the cross section of the $\Upsilon \rightarrow Xh \rightarrow q\bar{q}b\bar{b}$ HVT process of HVT signals have been calculated in the plane $\{m_Y, m_X\}$

Francesco Conventi paper's editor, Francesco Cirotto internal note's editor, paper almost ready (2nd circulation)

Anomaly Detection

Identification of rare items, events or observations which deviate significantly from the majority of the data and do not conform to a well defined notion of normal behaviour

□ In HEP language: identify features of the data that are inconsistent with a background-only model

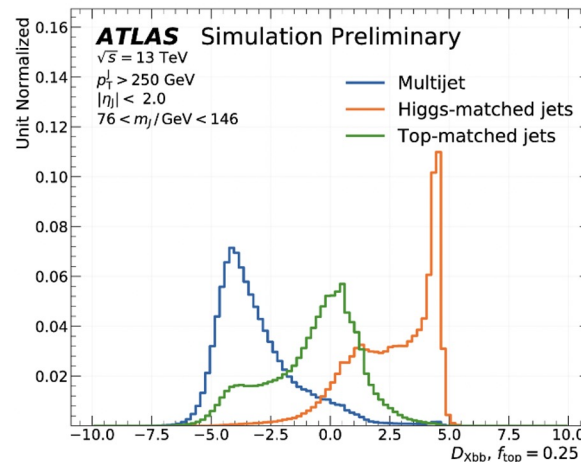


Supervised learning (labeled training datasets) has a long & effective history in HEP:

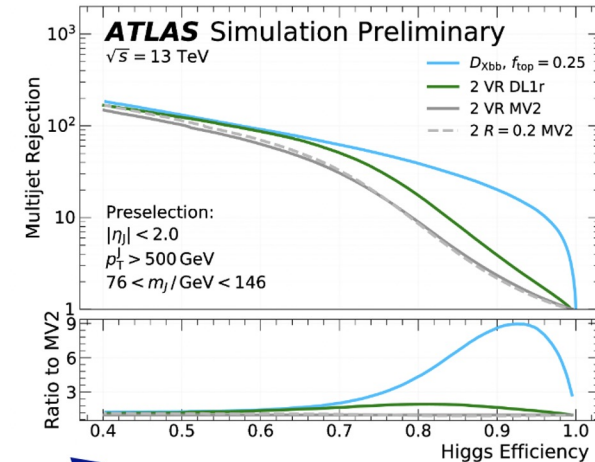
- High statistics, complex dataset with many correlated features
- Examples: neural net to classify boosted Higgs bosons from QCD/top backgrounds (ATLAS)

$H \rightarrow bb$

NN Output Scores



Background Rejection vs. Signal Efficiency



Identification of Boosted Higgs Bosons
Decaying Into bb With Neural Networks and
Variable Radius Subjets in ATLAS

Anomaly Detection

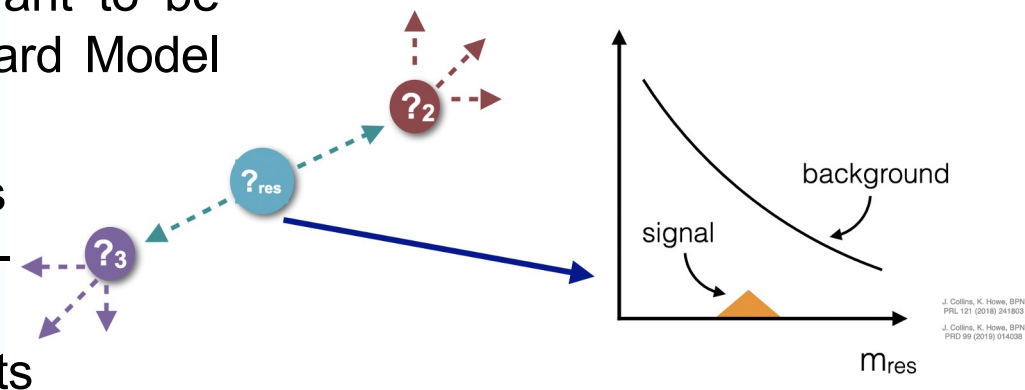
Identification of rare items, events or observations which deviate significantly from the majority of the data and do not conform to a well defined notion of normal behaviour

□ In HEP language: identify features of the data that are inconsistent with a background-only model

But, what if we don't know the characteristics of our signal?


A broad search for “new physics” means we want to be sensitive to anything not predicted by the Standard Model (and perhaps, not even predicted by us)

- **Semi-supervised approach:** labels for some events
- **Weakly supervised approach:** noisy labels (“signal-enriched” instead of pure)
- **Unsupervised approach:** train over unlabeled events




Unsupervised approach

Autoencoders
I know how to predict all collisions



Are there any collisions that I cannot predict?

Weakly-Supervised
I know regions where new physics does not exist



I want to leverage those regions against other parts of the data to find differences

Weakly supervised approach

Anomaly Detection

Identification of rare items, events or observations which deviate significantly from the majority of the data and do not conform to a well defined notion of normal behaviour

▫ In HEP language: identify features of the data that are inconsistent with a background-only model

ML for anomaly detection: a physics cases

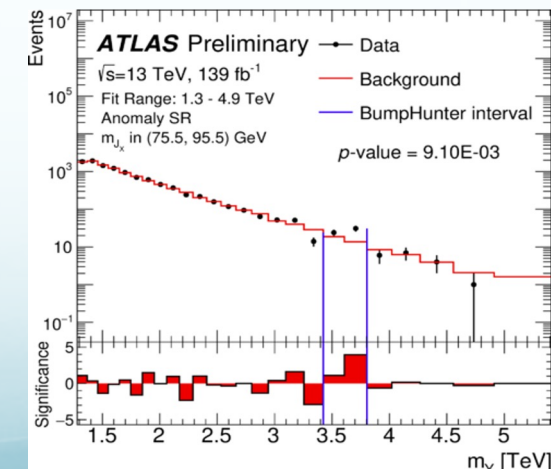
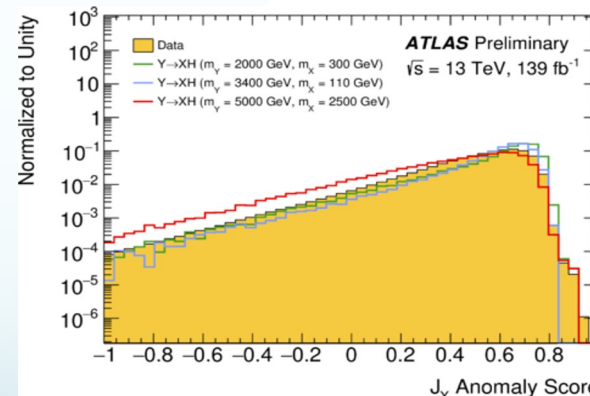
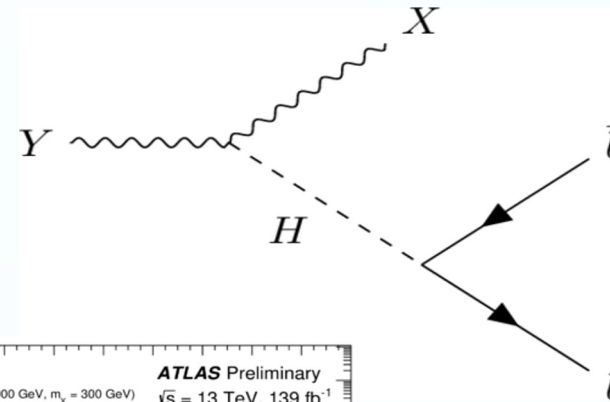
Search for heavy resonance Y decaying into SM Higgs and new particle X in a fully hadronic final state

- Targeting high Y mass regime
- Boosted H and X with collimated decay products

Variational recurrent neural network (VRNN) trained on jets in data

- Selection of X based on incompatibility of jet sub-structure with background jets

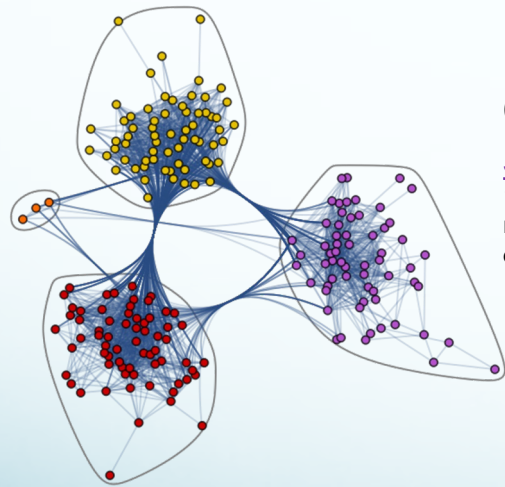
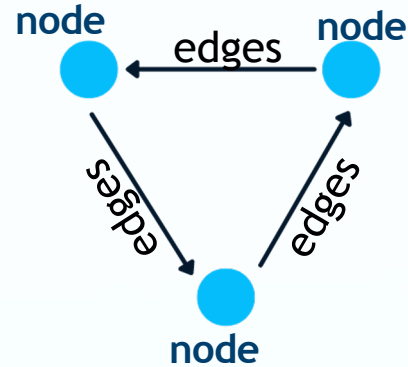
First application of ML technique fully unsupervised for anomaly detection to ATLAS analysis



Graph Neural Network

Graph Neural Network (GNN) is a deep learning model that handles a graph as input data.

A **Graph** is the type of data structure that contains nodes and edges. A node can be a person, place, or thing, and the edges define the relationship between nodes. The edges can be directed and undirected based on directional dependencies.



Community Graph Plot by dataset

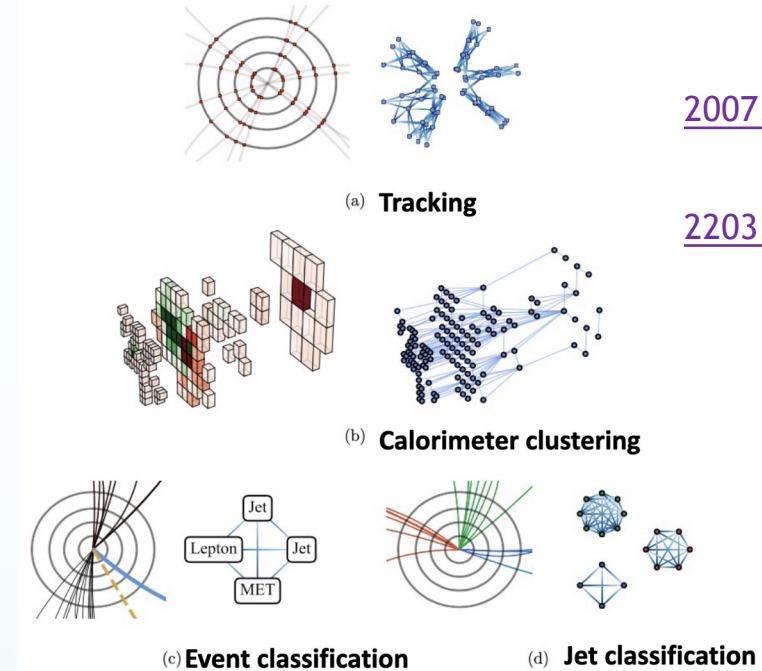
Jazz Musicians Network

198 nodes and 2742 edges: different colors of nodes represent various communities of Jazz musicians and the edges connecting them

Graphs are excellent in dealing with complex problems with relationships and interactions.

They are used in pattern recognition, social networks analysis, recommendation systems, and semantic analysis. **Creating graph-based solutions is a whole new field that offers rich insights into complex and interlinked datasets.**

Data structure in HEP



[2007.13681](#)

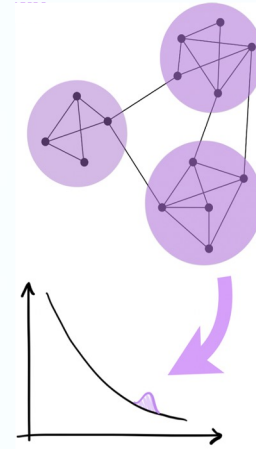
[2203.12852](#)

Task Definition: the first step is to decide what function one wants to learn with the GNN. In some applications this is trivial - for example jet, event or particle classification. In those cases a GNN is used to learn some representation of the node or the entire graph/set and a standard classifier is trained on that representation. For tasks such as segmentation or clustering this definition is less trivial.

Anomaly detection e Graph Neural Network

Roma/Napoli/INFN

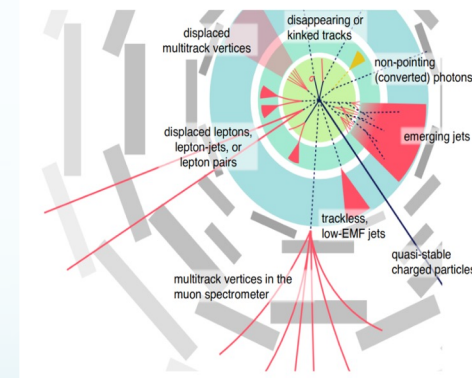
Contatti: Valerio Ippolito (INFN Roma 1), Elvira Rossi (Federico II),
Descrizione: Sviluppo di algoritmi basati su graph neural networks, con applicazioni per anomaly detection a livello di oggetto ricostruito e di classificazione dell'evento. Implementazione a livello di trigger e di analisi, e possibile implementazione su acceleratori tipo FPGA.
Stato: Fase prototipale iniziata basata su OpenData ([LHC Olimpics](#))
Esperimento: ATLAS
Tecnologie: GPU, FPGA, DataLake



Anomaly Detection to be more sensitive to New Physics:

Online algorithms to select (and for not discarding) interesting event @ trigger level

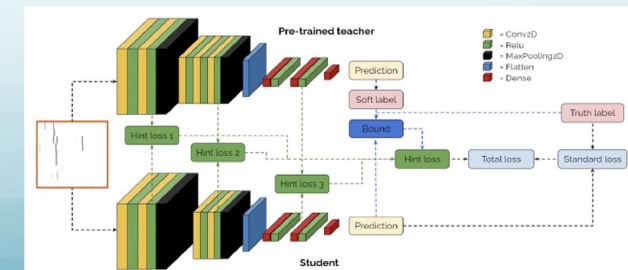
Low level trigger: Ready to implement the method on FPGA with more flexibility than traditional algorithms (like pathfinder) → Ultra-small CNN models (700 parameters) trained and performance loss is recovered thanks to compression techniques; Synthesis on XCV13P FPGA performed through *HLS4ML* library but only with a serial input (for now)



HLT-Physics motivations: What if we are not sensitive to select beyond SM events @ trigger level and, instead, we discard these events?

New Physics could have unconventional anomalous signature

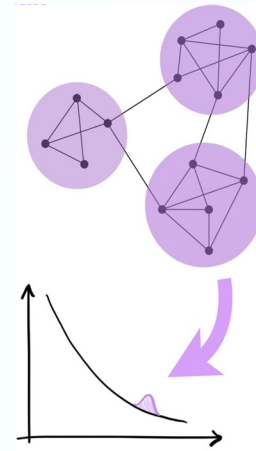
High level trigger: Test with Long Living Particles (LLP) decay tracks in the MS using CNN; work on a full chain from ML model to FPGA implementation is ongoing (Implementation on Xilinx Alveo U50 FPGA with *Vitis AI*)



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Anomaly Detection to be more sensitive to New Physics:

Offline algorithms to perform analysis, e.g. **heavy diboson resonances**

The idea for analysis with AD:

- Create **graphs** from energy deposits and track hits
- Build **unsupervised graph-based autoencoder** and **Anomaly Score**
- **Train only on background (Standard Model events)**
- Test on anomalous events
- Compare Standard Model distribution in Anomaly Score

Graph NN code - Up to now:

Input data: Diboson Resonance and QCD multijet events for an anomaly detection task (LHC Olympics dataset)

Net: **GIN (graph isomorphism network)** and we are evaluating the performance approaches against more conventional (**DNN without graph**): a graph neural network is implemented for the classification of large-radius jets. The network starts from the **topological clustering** in the calorimeters (topoclusters) used to build each jet and **uses the spatial information to connect N neighbors (nodes) with weights on their distance in ΔR (edge)**; the code run on Rome server with 2 GPU RTX 3090 24GB RAM

Computing time:

- bottleneck: building the graph itself as it starts from energy deposit clusters ~50 events a second
- training ~hours/ 1day but it strongly depends on the size of the dataset