





# Tracking, particle flow and muon performance at CMS and ATLAS

Marco Vanadia, on behalf of the ATLAS and CMS collaborations LHCP 2024 June 7<sup>th</sup> 2024, Boston (USA)

### **ATLAS and CMS detectors: tracks & muons**





- Silicon + gas tracker in 2T solenoid
- Muon Spectrometer in toroid

- Silicon tracker in 4T solenoid
- Muon spectrometer in **return yoke** of solenoid





<u>ATLAS</u> in Run-3 : upgrade of endcap muon spectrometer (among other things)





Shutdown/Technical stop Protons physics Ions Commissioning with beam Hardware commissioning

<u>CMS</u> in Run-3: upgrade of Pixel tracker (among other things)

### Coming soon...



For HL-LHC we need better performance and resilience vs pileup and aging

- New trackers, full Si, up to  $|\eta| \sim 4$
- New chambers in muon spectrometers
- New detectors with high granularity/better timing resolutions  $\rightarrow$  particle flow
- Electronics, claorimeters, trigger...

See the dedicated plenary session!





### **Improving software performance**

#### CMS-DP-2023-075



**Improvement** in reconstruction software  $\rightarrow$ more space for physics ATLAS added displaced ID and muon tracks to **standard data flow** in Run-3



### **Displaced tracks reconstruction**

ATLAS Large Radius Track (LRT) Run-3 vs Run-2:

- 10 times less CPU
- 50 times smaller event size
- Now included in standard data processing







New results from CMS calibration on Run-2 data on  $K_s$  show good agreement with simulation for displaced track reconstruction

### **Tracking @ HL-LHC:** software and algorithms



- New trackers designed for high PU @ HL-LHC
- Both new detector design and improvements in the software to profit from that ensure linear behaviour vs pileup



- Tracking for trigger @ HLT demanding due to **combinatorics**
- Requires improved algorithms + parallel computing

## <u>Tracking with</u> <u>Machine Learing</u>



#### Machine Learning R&D ongoing



#### GNN-based pattern recognition with ITK

- New result with improved algorithms and updated detector simulation
- Performance close to standard algorithms
- Work ongoing to evaluate computing performance

**CNN-based** tracking within  $high-p_T$  jets (Run-3 detector)

- Challenging due to cluster merging & combinatorics
- Updated CNN algo analyses pixel maps
- Standard vs ML-based algorithms performance differ in phase space regions
  - **combining** both has best performance

### Muon reco, identification & isolation

- Muons reconstructed separately in **Tracker**(ID)/**Spectrometer** (MS)
- In most cases a **combined track** (CB) is then produced
  - different strategies of reconstruction and single-detector or partial trk to recover acceptance





- Different Working Points for different use cases
- Isolation criteria for muons from prompt resonances
- Different momentum measurement strategies available:
  - $\circ$  ~ ID+MS or CB for ATLAS
  - $\circ$  Tune-P algorithm for CMS picks best measure





### **Muon performance ATLAS**



$[\mu m]$	$\sigma_{ m ali}(\mu_0)$	$\sigma_{\rm ali}(\mu_{\theta})$	$\sigma_{\rm ali}(\mu_{\phi})$	$\sigma_{\rm ali}({\rm total}$
BA large	$25\pm2$	$9\pm1$	$10 \pm 1$	$29\pm2$
BA small	$25 \pm 4$	$19\pm3$	$21 \pm 4$	$38 \pm 4$
EC large	$69 \pm 3$	$20 \pm 1$	$28\pm2$	$77\pm2$
EC small	$95 \pm 4$	$28 \pm 2$	$26 \pm 2$	$103\pm3$
EE large	$106\pm10$	$22\pm3$	$52\pm 6$	$121\pm9$
EE small	$66 \pm 9$	$36 \pm 9$	$58\pm8$	$94 \pm 9$
BEE	$59\pm8$	$50\pm7$	$33\pm6$	$84\pm7$

Alignement in Run-3 MDET-2024-03

- Significant ε improvement in 2023 after commissioning of NSW
- Important to correct for **detector effects** for precision measurements

### <u>Muon performance CMS</u>

- Recently published results on muon **online** & **offline** performance
- Detailed studies using Z→µµ events show high performance and good data/MC agreement
- High-p<sub>T</sub> results based on **Drell-Yan** data

**CMS** Preliminary 13.6 TeV L1+HLT Efficiency  $|m^{offline}| < 2.4$ Isolated muon with p\_ > 24 GeV Run2022 Data (35 fb<sup>-1</sup>) - Run2023 Data (27 fb<sup>-1</sup>) 0.8 0.6 0.4 0.2 2023/2022 1.05 0.95 0.9 120 140 160 180 80 100 Offline muon p\_ [GeV]

CMS-DP-2024-005

CMS-DP-2024-019

CMS-DP-2024-023



### <u>Muon developments</u>

Machine Learning offers great potential for improving muon performance

New isolation based on a **transformer neural network** from ATLAS





### <u>JINST 19 P02031</u> (2024)

CMS published new results for **muon identification** with **MVA** techniques:

- Major improvement in signal eff vs bkg rejection
- Performance
   calibrated in
   data, using also
   non-prompt
   muons enriched
   selections

### **Particle Flow**

- Particle Flow algorithms currently used in ATLAS mostly for jet reconstruction
  - Pflow isolation used for leptons <u>EPJC 81</u>
     (2021) 578
  - Ongoing effort towards a ML-based PFlow implementation <u>ATL-PHYS-PUB-2022-040</u>



- Particle Flow algorithms used by CMS for global event reconstruction <u>JINST</u> <u>12 (2017) P10003</u>
- Studies for ML-based Pflow J. Phys.: <u>Conf. Ser. 2438 012100</u> with heterogeneous architectures

   Based on a scalable GNN model



### **PFlow news from CMS**

 New result on hadronic PFlow clusters reconstruction @ HLT using the <u>Alpaka library</u> show significant improvement when CPUs → GPUs



- PFlow will go through a **major overhaul for HL-LHC** to profit from new detectors (HGCAL and MTD above all) providing info with **high granularity** and great **timing resolution**
- New reconstruction framework (TICL) for HGCAL being developed <u>J. Phys.:</u> <u>Conf. Ser. 2438 012096</u>



Clustering step removing noise around back-to-back muon tracks

### **Conclusion**

- Presented most recent results for **tracking**, **muon** and **PFlow** performance from ATLAS and CMS
  - Performance measurements are **challenging analyses** with demanding precision requirements
  - They provide **crucial inputs** for physics measurements and searches
- Soft collisions makes life hard; more and more challenging conditions must be addressed with:
  - $\circ$  Better detectors  $\rightarrow$  Phase-1 upgrades in, Phase-2 upgrades on their way
  - $\circ$  Better algorithms  $\rightarrow$  optimised usage of resources can significantly impact physics output
  - $\circ \quad \text{Better tools} \to \text{Machine Learning techniques, parallel computing...}$
- Run-3: high performance in demanding conditions
- **HL-LHC** is not so far now, crucial work ongoing for that

# BACKUP

### **ATLAS detector**







### **CMS Tracking**

- Seeding from pixels/strips
- Pattern recognition from outward KF + inward search for additional hits
- Fit: outward KF followed by a smoother filter, weighted average, iteration to remove outliers
- Track selection DNN-based
- Online tracking:
  - $\circ$  Streamlined version of offline
  - $\circ \quad \text{HLT ported to GPUs, heterogenous CUDA-based} \\ \text{architecture} \rightarrow \text{CKF algo seeded by Patatrack pixel} \\ \text{tracks} \\ \end{cases}$
  - $\circ$  ~ Improved fake rejection and IP reso wrt Run-2 ~
- Offline tracking:
  - Iproved parallelized and vectorized algorithm (mkfit)
  - $\circ$  ~ Similar perf to Run-2 CKF, significant speed-up ~





### ATLAS Tracking

- Primary tracking  $Inside \rightarrow Out$ 
  - Seeding from Si Hits
  - $\circ$   $\,$  CKF to extend up to all SCTs  $\,$
  - Track ambiguity solver based on track quality+ NN
  - Global fitting + extension to TRT with refit
- Back-tracking Outside  $\rightarrow$  In
  - Used e.g. for photon conversion
  - Seeding from TRTs
  - Then add hits/segments not included by primary tracking
- LRT tracking
- Improvements for Run-3
  - Tighter selections to reuce combinatorics
  - New PV algorithm: Adaptive multi-vertex fitter (AMVF): better efficiency and lower fake rate



### **CMS Muon Recostruction**

- Standalone reconstruction: uses Kalman filter
- If MS compatible with ID track  $\rightarrow$  global muon
- ID track + MS segment(s)  $\rightarrow$  tracker muon
- Then muons fed to PFlow algorithm
- Loose muons (i.e. global or tracker) are passed to MVA
  - Prompt-muon MVA: used for isolated prompt muons
  - Muon MVA ID: used for generic muon id vs hadrons, developed in the paper for more general usage
  - $\circ \quad \mbox{Work focus on } p_{\rm T} {>} 10 \mbox{ GeV, for soft muons there is a} \\ \mbox{different Soft Muon MVA algorithm developed in Run 2} \\$

General muon MVA: Random forest using pt, eta, number of this, chi-squares etc... Prompt muon MVA: BDT using kinematics, isolation, closest jet information, impact parameter

19 P020

(2024)

### **ATLAS Muon Recostruction**

- Hough transform to build segments in MS
- Segments combined in preliminary track, then a 3D candidate is formed combining both views, then a global chi2 fit is performed
- Now outliers are removed and missing hits on the trajectory are added and a refit performed
- Ambiguities are resolved, and a final refit is performed with loose IP constraint and calo information
- Muons can be globally reconstructed as:
  - $\circ$  CB: ID+MS (neluding SiF in fwd region)
  - $\circ$  IO: ID track + MS hits combined
  - $\circ \quad MS \ only \\$
  - Segment tagged: ID track tagged by MS segment
  - CaloTagged: ID track tagged by calorimeter deposit



### CMS Muon Momentum measurement 2018 JINST 13 P06015

Tune-P algorithm selects best measurements among:

- Inner Track fit: ID only, best at low  $p_T$
- Tracker-Plus-First-Muon-Station fit: ID + first MS station
- Pick fit: for muons with showering in one chamber, selects MS hits compatible with extrapolated track
- Dynamic-Truncation fit: treats cases with high energy loss by iteratively adding stations to track

The PF algorithm finally refines measurement from Tune-P

Momentum calibration:

- from  $Z \rightarrow \mu \mu$  using  $< 1/p_T^{\mu} >$
- from  $J/\Psi$  and  $\Upsilon$  using a Kalman filter technique
- from cosmic rays
- from Drell-Yan events using q/p<sub>T</sub>



### **ATLAS Muon Momentum measurement**

- Data correction: sagitta bias correction using Z
  - Ο
  - from variance of  $M_{\mu\mu}$ from local effects on  $< M_{\mu\mu} >$ Ο
- MC calibration from iterative procedure to determine calib constants using
  - Z events Ο
  - $J/\Psi$  events Ο
  - $\Upsilon$  events for validation Ο



#### Eur. Phys. J. C 83 $(2023)\ 686$



- Individual particles produce several PF elements in various subdetectors
- Reconstructions via a *link algorithm* connecting the different contributions
- Particles reconstructed by standard reconstruction algorithms are selected in sequence and connected appropriately
- A postprocessing cleans up and further corrects difficult cases



### **PFlow CMS**

<u>JINST 12 (2017)</u> <u>P10003</u>





Pflow algorithm diagram for overlap removal between tracker and cluster

## PFlow ATLAS

Eur. Phys. J. C 77 (2017) 466



#### CMS Tracking performance in 2023: localised issue



In 2023 the proton-proton physics data taking at 13.6 TeV was from May 6th to July 16th. An extended LHC downtime from June 13th to July 1st splits the data taking in two periods. In the second period readout problems were observed in the layer 3 and 4 of the barrel pixel tracker both in the same sector in  $\varphi$  on the negative half along beamline, with track coverage within  $-1.5 < \eta < -0.2$ and  $-1.1 < \phi < -0.9$ . Dedicated MC samples are used for the two periods.



In Run 3, track reconstruction at the CMS High-Level Trigger (HLT) is based on a single iteration of the Combinational Kalman Filter (CKF), using hits recorded by both the pixel and strip detectors. The track reconstruction needs an initial estimate of the track parameters, i.e. a trajectory seed. The single iteration is seeded by pixel tracks reconstructed by the *Patatrack* algorithm, which can be offloaded to GPUs [1,2].

Heterogeneous architecture based on CUDA platform exploiting GPUs for parallel computing <u>Front.Big Data 3</u> (2020), 601728



Performance of Track Reconstruction at the CMS High-Level Trigger in 2023 <u>CMS-DP-2024-013</u>

#### CMS-DP-2024-013













#### Performance of Track Reconstruction at the CMS High-Level Trigger in 2023 <u>CMS-DP-2024-013</u>

### **ATLAS Muon & Tracking software**





### **ATLAS Muon & Tracking software**



#### <u>CMS-DP-2023-075</u>

### <u>Improved Performance of Line Segment Tracking</u> <u>Using Machine Learning @ HL\_LHC</u>



- Hits from outer tracker combined using local information
  - Parallelized on GPUs
- Objects with more and more hits are subsequently built and finally combined with inner tracker

The LST algorithm creates the following objects in OT through linking of objects [1]:

- MiniDoublet (MD): linked pair of hits in individual p<sub>T</sub> modules
- Line Segments (LS): linked pair of MDs in neighboring layers
- Triplet (T3): linked pair of LSs with a common MD
- Quintuplet (T5): linked pair of T3s with a common MD

Using a subset of inner tracker (IT) pixel seed iterations, (i.e. *initial* iteration seed, and *highPtTriplet* iteration seed [3, 4]), LST algorithm creates following objects through linking of OT objects with IT seeds:

- pixel + Quintuplet (pT5): linked pair of a pixel seed and a T5
- pixel + Triplet (pT3): linked pair of a pixel seed and a T3 (both not in a pT5)

#### CMS-DP-2023-075

Improved Performance of Line Segment Tracking Using Machine Learning @ HL\_LHC



#### T5 DNN input features

Object	Feature	
	рт	
T3 (x2)	Inner anchor hit r, z, φ, η, layer	
	Middle anchor hit r, z, φ, η, layer	
	Outer anchor hit r, z, φ, η, layer	
	Radius of circle fit	
TT and date	<b>ρ</b> τ, η, φ	
15 candidate	Radius of circle fit for "Bridge T3"	

Both T5-level and T3-level features are provided to the DNN as input.





### ATLAS LRTs

#### Eur. Phys. J. C 83 (2023) 1081





Table 2: Most important selection criteria that differ between the primary tracking (*inside-out* sequence only) and LRT setups. Common selection criteria that were changed from the legacy implementation are also shown.

Selection criteria	Primary (inside-out)	LRT					
max. $ d_0 $ [mm]	5	300					
max. $ z_0 $ [mm]	200	500					
min. $p_{\rm T}$ [GeV]	0.5	1					
max. $ \eta $	2.7	3.0					
max. silicon holes	2	1					
max. double holes	1	0					
max. holes gap	2	1					
road width [mm]	12	5					
seeding	Pixels and SCT	SCT only					
max. seeds per middle Pixel SP	1						
max. seeds per middle SCT SP	5	1					
Common selection criteria							
min. silicon hits	8						
min. unshared silicon hits	6						
max. track $\chi^2/n_{\rm DoF}$	9						
keep all confirmed seeds	true						

### ATLAS LRTs



### **CMS displaced tracking calibration**

#### <u>CMS-DP-2024-010</u>



### <u>CMS displaced tracking calibration</u>

#### <u>CMS-DP-2024-010</u>





12 14 16 18 20  $\Delta_{2D}$  (cm) Reconstructed vertices (/ 0.5 cm)

Data/Sim.

105

0 2

CMS

Preliminary

#### Pre-legacy





18

 $\Delta_{2D}$  (cm)

#### **Expected tracking performance of the ATLAS Inner Tracker Upgrade for Phase-II**

#### IDTR-2023-05





#### <u>Performance of the Line Segment Tracking</u> <u>Algorithm in the CMS Phase-2 High Level Trigger</u> <u>Tracking</u>

Detector modules in OT consist of two closely spaced silicon sensors per layer. This configuration provides a handle for hits in adjacent sensors to be correlated and allows for an estimation of the local transverse momentum ( $p_T$ ) of the track. The resulting local hit pairs, called MiniDoublets (MDs), provide an opportunity to reduce occupancy of the detector. MDs with  $p_T$  more than 0.8 GeV are considered in the following implementation of LST. Below, a qualitative representation of the expected Phase-2 CMS tracker geometry [2] is given:



CMS-DP-2024-014



#### <u>CMS-DP-2024-014</u>

Performance of the LineSegment TrackingAlgorithm in the CMSPhase-2 High LevelTrigger Tracking





#### CMS-DP-2024-003

DeepCore 2.0: Convolutional Neural Network for Tracking in Jets with High Transverse Momentum

#### DeepCore2.0: Target and Prediction

- Target and prediction format: three 30  $\times$  30 Track Crossing Point (TCP) maps and three 30  $\times$  30 Track Parameters (TP) maps.
- TCP maps:
  - Target TCP map: every BPIX2 pixel is assigned a value of 1 if a particle crossed a pixel and 0 otherwise.
  - Prediction TCP map: every BPIX2 pixel is assigned a score between 0 and 1 reflecting the likelihood of a track crossing point being within the boundaries of that pixel.
- TP maps:
  - Track Parameters are Δx and Δy between the center of a pixel and a TCP, relative azimuthal angle (Δφ) and relative pseudorapidity (Δη) between the center of a pixel and the merged-cluster axis, and p<sub>T</sub> of the reconstructed track associated to the TCP. The TCP charge is positive by default and adjusted as needed when testing candidate tracks.
  - Target TP maps: track parameters of TCP pixels and pixels within 2-pixel radius.
  - Prediction TP maps: predicted track parameters for every TCP pixel.
- If 2 particles cross the same pixel, the second set of Target TCP/TP maps (Overlap maps 2) is filled with the second TCP information. Similarly, Overlap maps 3 are used if 3 particles cross the same pixel. Prediction TCP/TP Overlap maps 2 and 3 are always filled.



An example of the pixel maps used as input for DeepCore2.0 is shown above. For each BPIX layer, the normalized ADC count per pixel is shown as a function of the pixel position within the  $30 \times 30$  window. The BPIX2 pixel map also shows multiple target TCPs (red) and the TCPs predicted by DeepCore (black) for a calo-jet with  $p_T^{jet} = 1786$  GeV and  $\eta^{jet} = -0.08$ . DeepCore predicts the same number of TCPs as the number of target TCPs (7), including 6 TCPs (2 – 7) in the same cluster and 2 TCPs (4 and 5) in the same pixel (x = 2, y = -2). The position of the predicted TCPs is relatively close to the position of target TCPs, which shows that DeepCore2.0 makes good predictions.





#### <u>MUON-2023-02</u>





#### 





### <u>CMS Muon Performance</u> <u>2022</u>

CMS-DP-2024-019



#### CMS Muon Online Performance 2022

CMS-DP-2024-005



#### <u>CMS MVA muon</u> <u>identification</u>

JINST 19 P02031 (2024)



Comparison of 3 point deep DL algo:

- Deep Sets
- GNN
- Transformers

With image-based CNN and DNN. Tested options with and without tracking. Identification and energy response are evaluated.



#### **<u>Point Cloud Deep Learning Methods for Pion</u>** <u>**Reconstruction in the ATLAS Experiment**</u>



<u>ATL-PHYS-PUB-2022-040</u>



PFElements per event

#### <u>Machine Learning for Particle</u> <u>Flow Reconstruction</u> <u>at CMS</u>

J. Phys.: Conf. Ser. 2438 012100

- heterogeneous architectures based on a scalable GNN model
- Task is to identify  $y_k$ particles, described as  $(ID,p_T,\eta,\phi,E,q)$ , from  $x_i$ detector signals
- Performance mostly in line with standard PF
- Computing scales linearly vs multiplicity, comparison with standard PF not trivial

- We port steps producing hadronic barrel and endcap (HBHE) PF clusters to GPU as a first step of PF reconstruction acceleration.
  - GPU porting is done with the Alpaka portability library, allowing future hardware flexibility [2]
  - This PF clustering step is relatively slow on CPU (a few % of timing of recent Run-3 CMS High Level Trigger (HLT) menus).



HeterogeneousReconstruction ofHadronic Particle FlowClusters with AlpakaPortability LibraryCMS-DP-2024-026

Data converted to format optimized for GPUs

The Alpaka-based implementation was included in HTL menu at beginning of 2024



### <u>The Iterative Clustering framework for</u> <u>the CMS HGCAL Reconstruction</u>

J. Phys.: Conf. Ser. 2438 012096

TICL: modular software framework for HGCAL reconstruction, with configurable:

- Seeding region production and layer-cluster selection
- Pattern recognition
- Linking

Integrated in CMS software and suited for integration with ML techniques

Comparison of Trcksters produced during pattern recognition with different algorithms