DeepCore:
Convolutional Neural Network for high p_T jet tracking

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On behalf of CMS Collaboration

Connecting The Dots and Workshop on Intelligent Trackers

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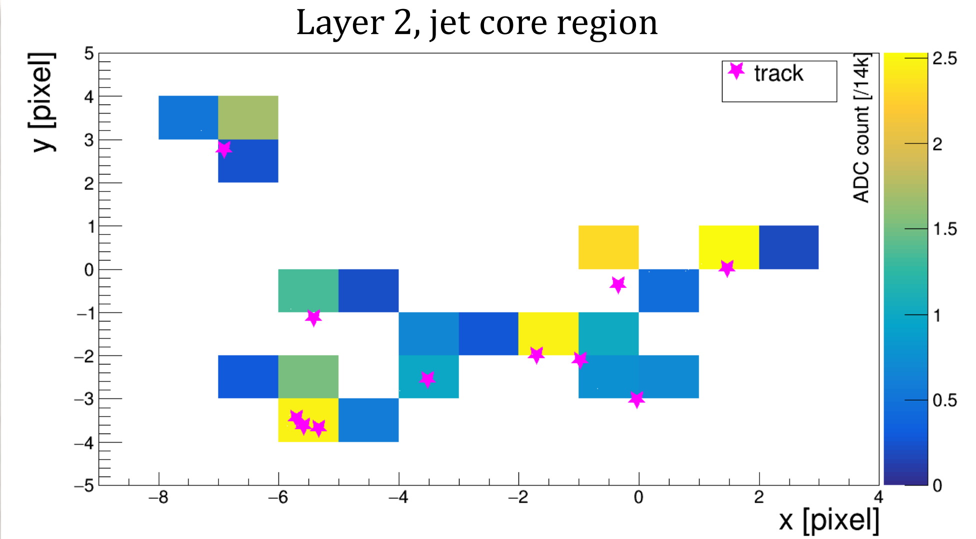
Outlook

- High-Pt jet tracking: motivation and strategy
- DeepCore
  - Input, target, architecture
  - Loss functions and training
  - Event Display and training performance
- Integration in CMS reconstruction
- Tracking Performance with DeepCore

Tracking in high p_T jets



Why?

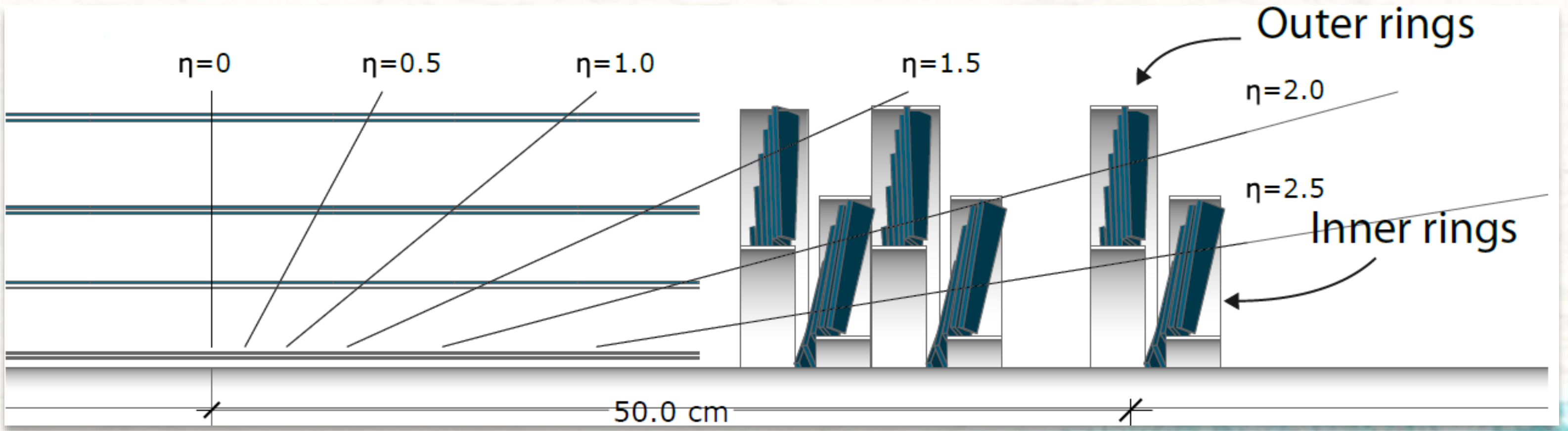
- Jet reconstruction with Particle Flow[1]
- b-tagging
- Substructures

Issues

- Tracking (based on **combinatorial Kalman Filter**) inside jets starts to become inefficient over 500 GeV
- Critical step is the **splitting of the clusters** in the pixel detector

Low quality seeding for the cKF

CMS Pixel detector Phase 1



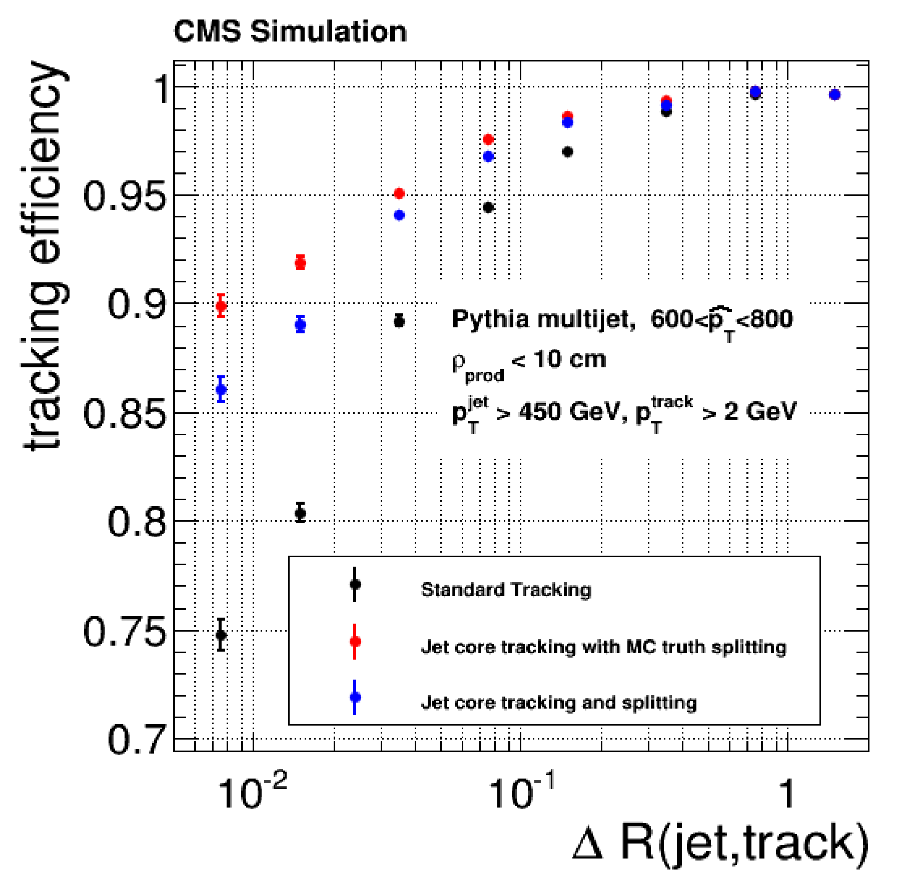
[Picture from CMS-TDR-11]

1 all the references in the backup slides

Previous solution of the seeding inefficiency

Before this work has been developed a K-means based algorithm

- Efficiency gain, but still present inefficiencies due to the splitting
- each layer analyzed separately



Strategy

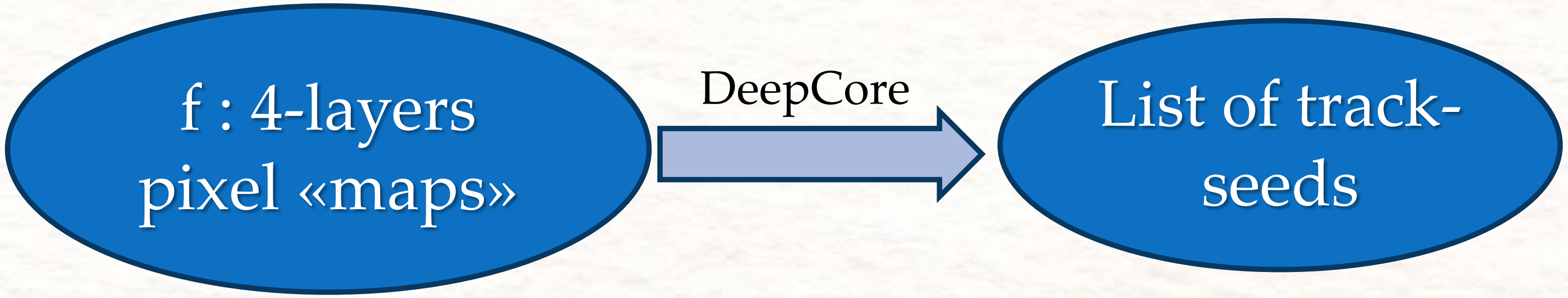
Goal:

Improve the jet-tracking seeding→ *Eyes on the ball*: track parameters

- Efficient clustering is an issue? Let's skip it!
- From raw pixel info obtain directly track parameters **(seed)** of the tracks around the jet axis

Strategy:

- Develop a Convolutional Neural Network (**CNN**) to reproduce the «function»:

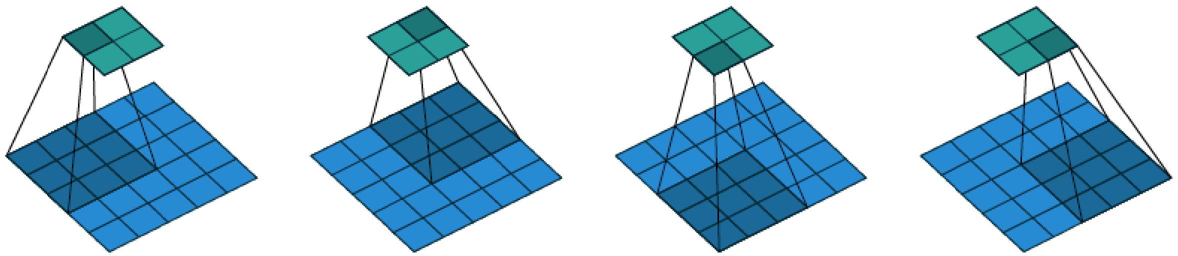


Convolutional NN approach

- Input / Target as 2D pictures
- Each node is a pixel
- Each node looks only in a small zone of the layer (**filter**)
- Discovered features **shared between filters**→looks for pattern

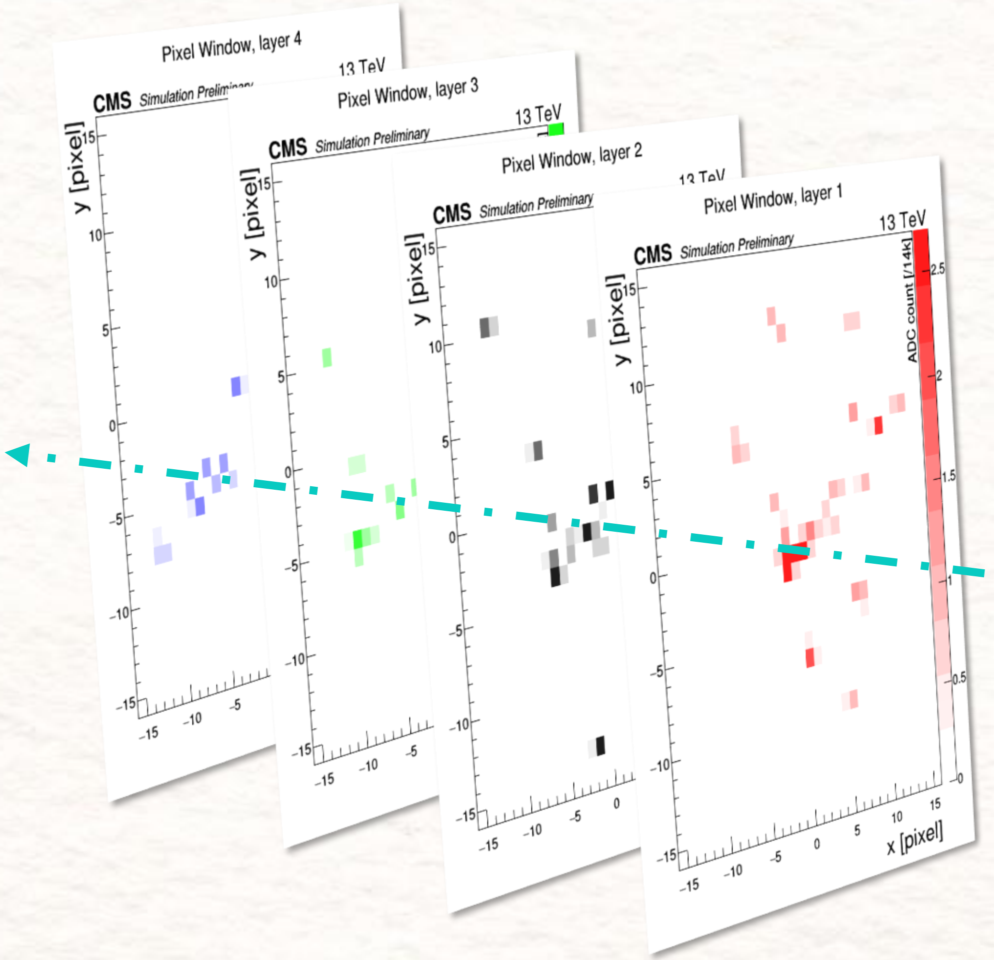
- 4 layer as «**RGB channels**» of same picture
- All the track seeds predicted **at same time**
  - **Independent of the number** of seeds/tracks
  - Indipendent of the **dimension** of the map

[Picture from arXiv:1603.07285v1]



Input of DeepCore

- 4 **pixel detector maps**, merged clusters centered
  - interception of calo-jet axis with layer 1,
  - open a cone of $\Delta R = 0.1$ → list of merged clusters on layer 1
  - If layer 1 module is broken → list of merged clusters on layer 2
  - for each merged cluster → open a **window 30x30 pixel** in each layer (primary vertex- merged cluster direction)
  - Added to list of the direction the jet axis from calorimeter information
  - save **x; y; charge** information for each pixel in the 4 windows for each merged cluster
  - Charge info normalized to order of magnitude 1
- jet η (for each merged cluster of the list)
- jet p_T (for each merged cluster of the list)



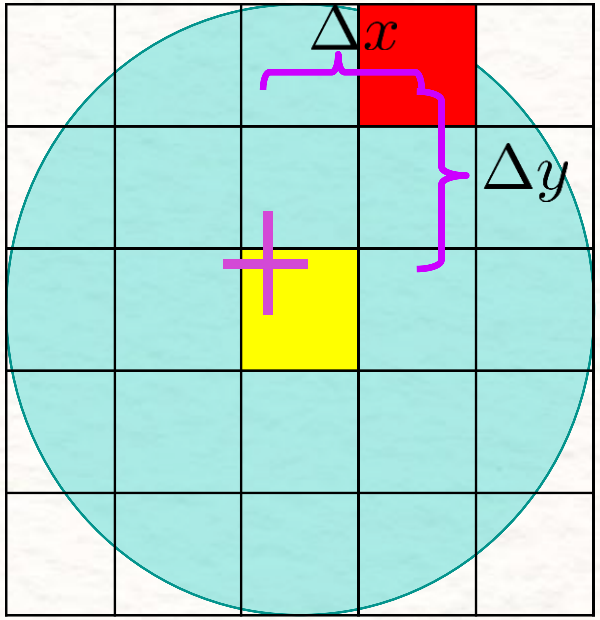
Target of DeepCore

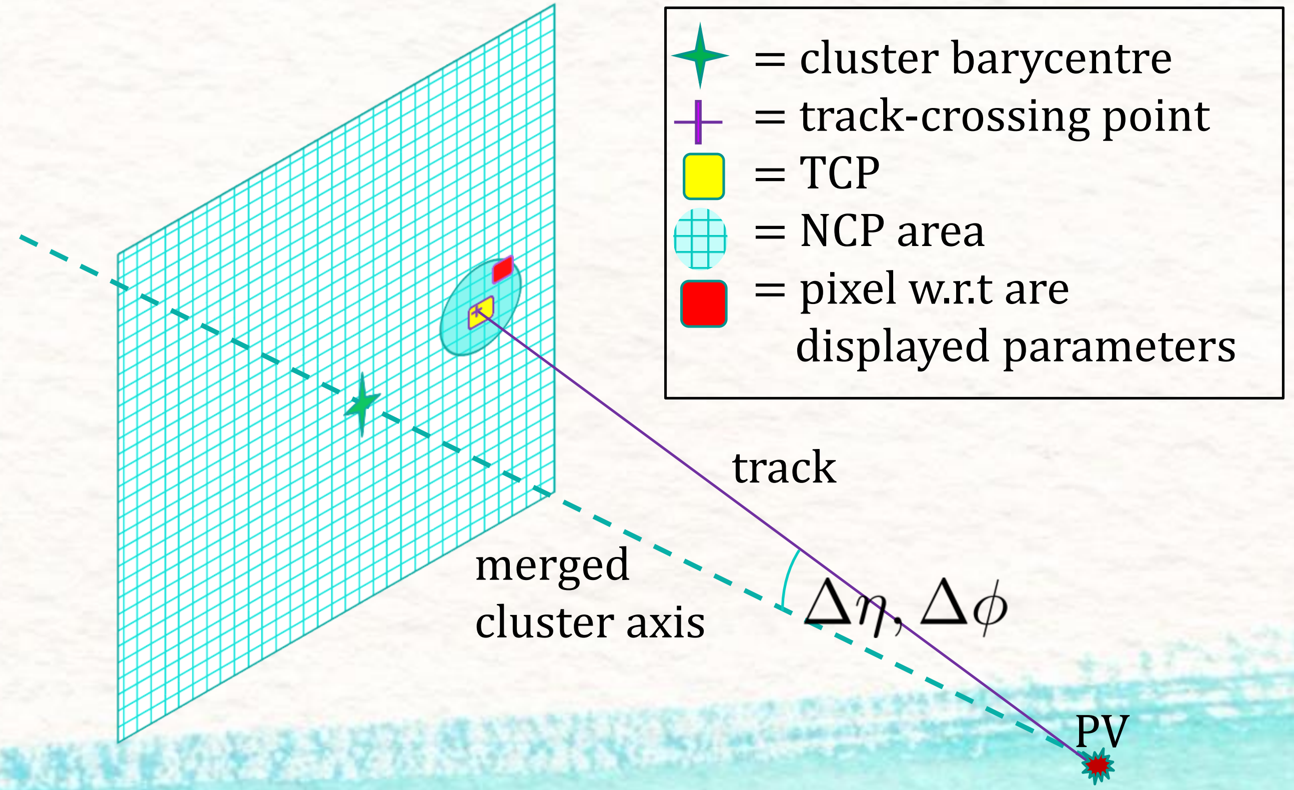
For each pixel in 30x30 window of layer 2:

- 1 if a track cross that pixel (**Track Crossing Point**), 0 otherwise
- **Track parameters** in local parametrization: (Δx, Δy, $\Delta\varphi$, $\Delta\eta$, p_T)
  - For the track-crossing pixels (TCP)
  - In a circle of radious 4-pixel (NCP)

Overlap: additional 1/0 + track parameters info if a second or third track cross the pixel

p_T range: tracks with p_T>1 GeV





Network architecture

Input Pixel 4-map, η^{jet}, p_T^{jet}

1. CONV: 50 filters, 7x7
2. CONV: 20 filters, 5x5
3. CONV: 20 filters, 5x5
4. CONV: 18 filters, 5x5
5. CONV: 18 filters, 3x3

6. CONV: 18 filters, 3x3
7. CONV: 18 filters, 3x3
8. CONV: 18 filters, 3x3
9. CONV: 18 filters, 3x3

Track Parameters Map

6. CONV: 12 filters, 3x3
7. CONV: 9 filters, 3x3
8. CONV: 7 filters, 3x3
9. CONV: 6 filters, 3x3

TCP Map

Activation Functions:
all ReLU except Sigmoid on last probability layer

Number of parameters: 77373

Training

Loss functions:

- Crossing Points → weighted **Binary Cross Entropy:**
  – $\frac{1}{N}\sum_{i=1}^{N}\left[y_i^{true}\ln(y_i^{perd}) + (1-y_i^{true})\ln(1-y_i^{pred})\right]$ but
  – Different weights:
    - TCP[2]-pixel counts 10
    - NCP[3] pixel counts 1
    - Other pixel counts 0.01
- Parameters → **mean squared error:**
  – clipped between [-5; 5]
  – Averaged between TCP and NCP only

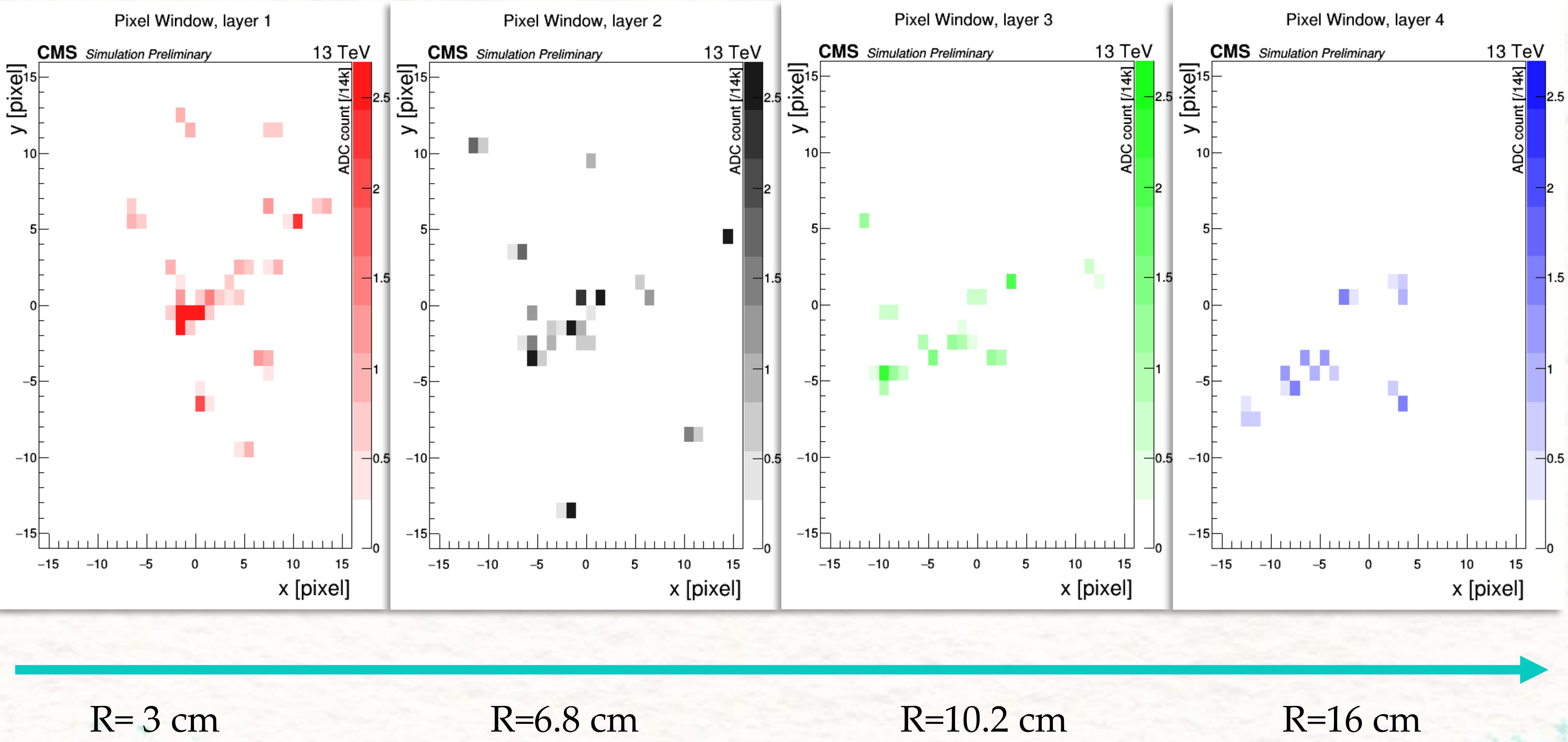
$$\frac{\sum_{p\in TCP,NCP}\min[(p_{\rm pred}-p_{\rm targ})^2, 25]}{N_{TCP+NCP}}$$

Training:

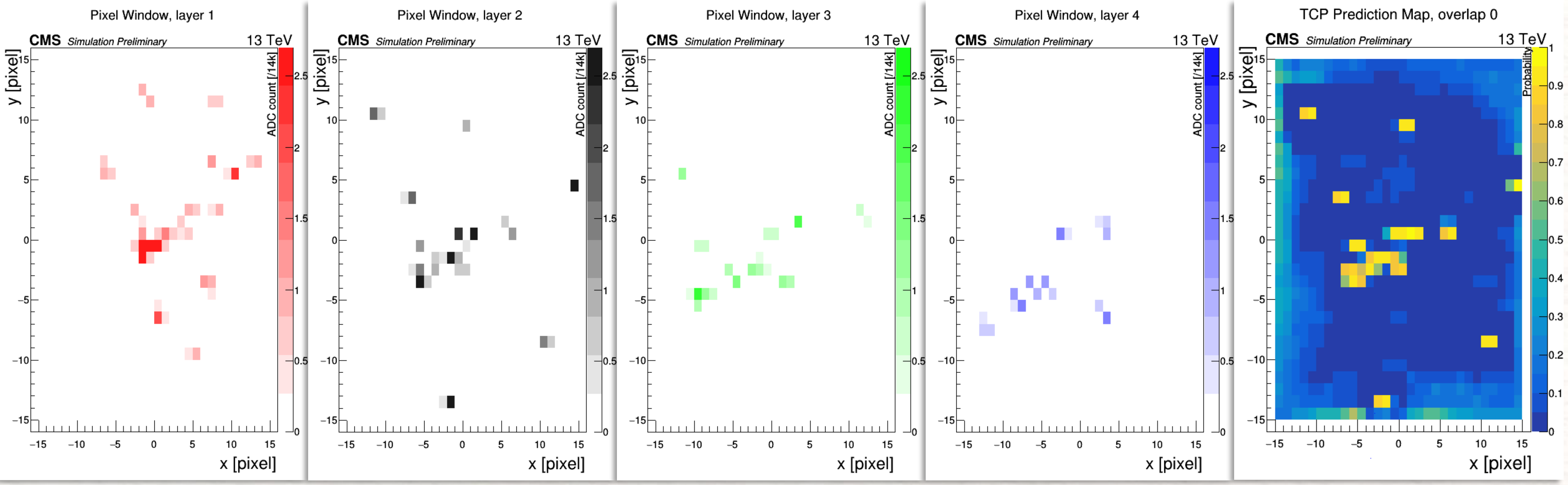
- Sample composition:
  - QCD events 1.8 TeV < $\hat{p}_T$ < 2.4 TeV,
  - p_T^{jet}> 1 TeV, $|\eta^{jet}|$<1.4
- Sample dimension: **22M input (2M jets)**, 2M input for validation
- Batch size: **32**
- Optimizer: **Adam**
- Learning Rate: reduced during training: $2{\cdot}10^{-4} \rightarrow 1{\cdot}10^{-4} \rightarrow \ldots \rightarrow 1{\cdot}10^{-7}$
- Relative weights of losses: same weight

2 TCP = Track Crossing Point, where the TCP map target = 1.
3 NCP= pixel inside a circle of radius 2 pxiel centered in the TCP

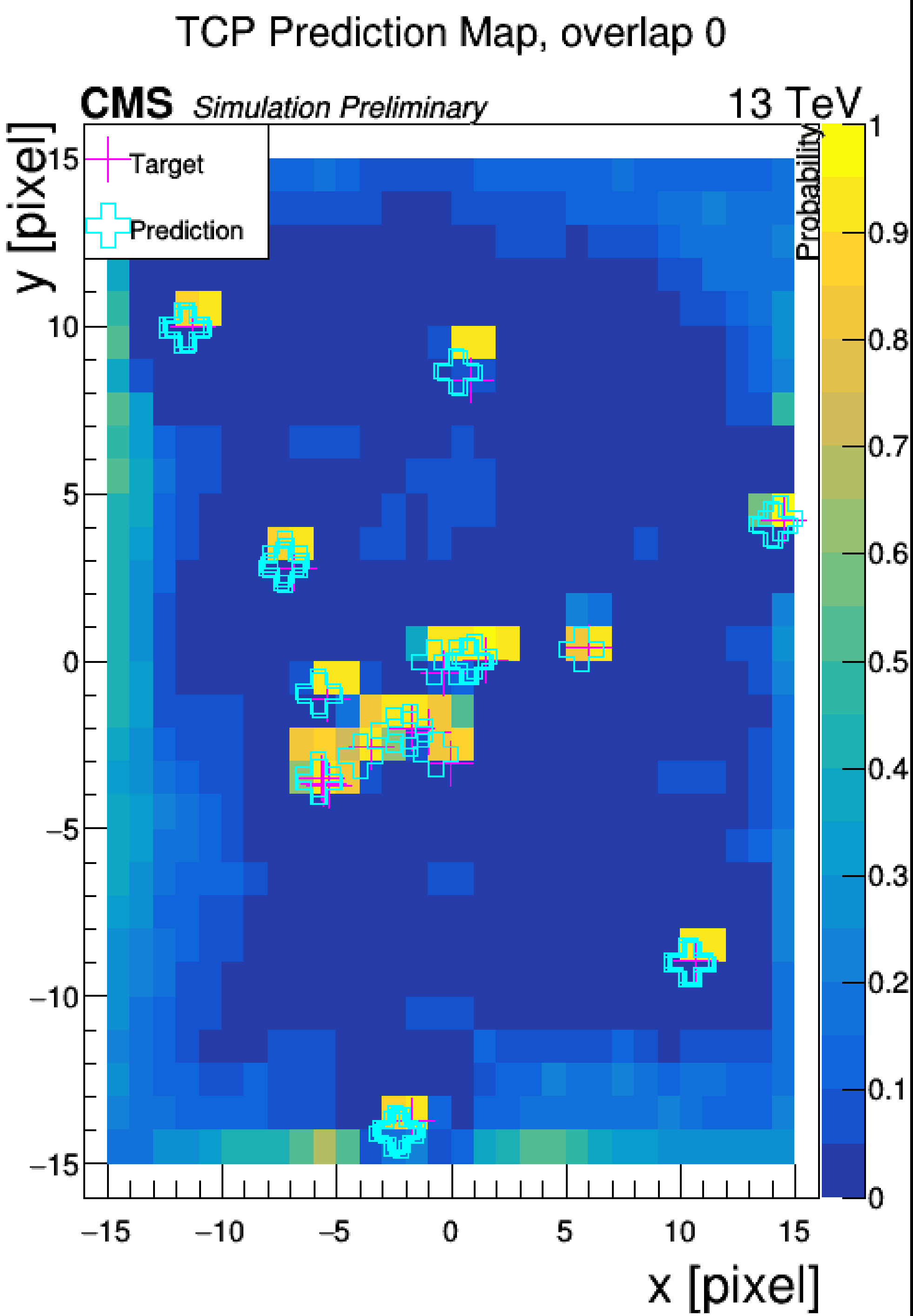
The “Event Display” of DeepCore

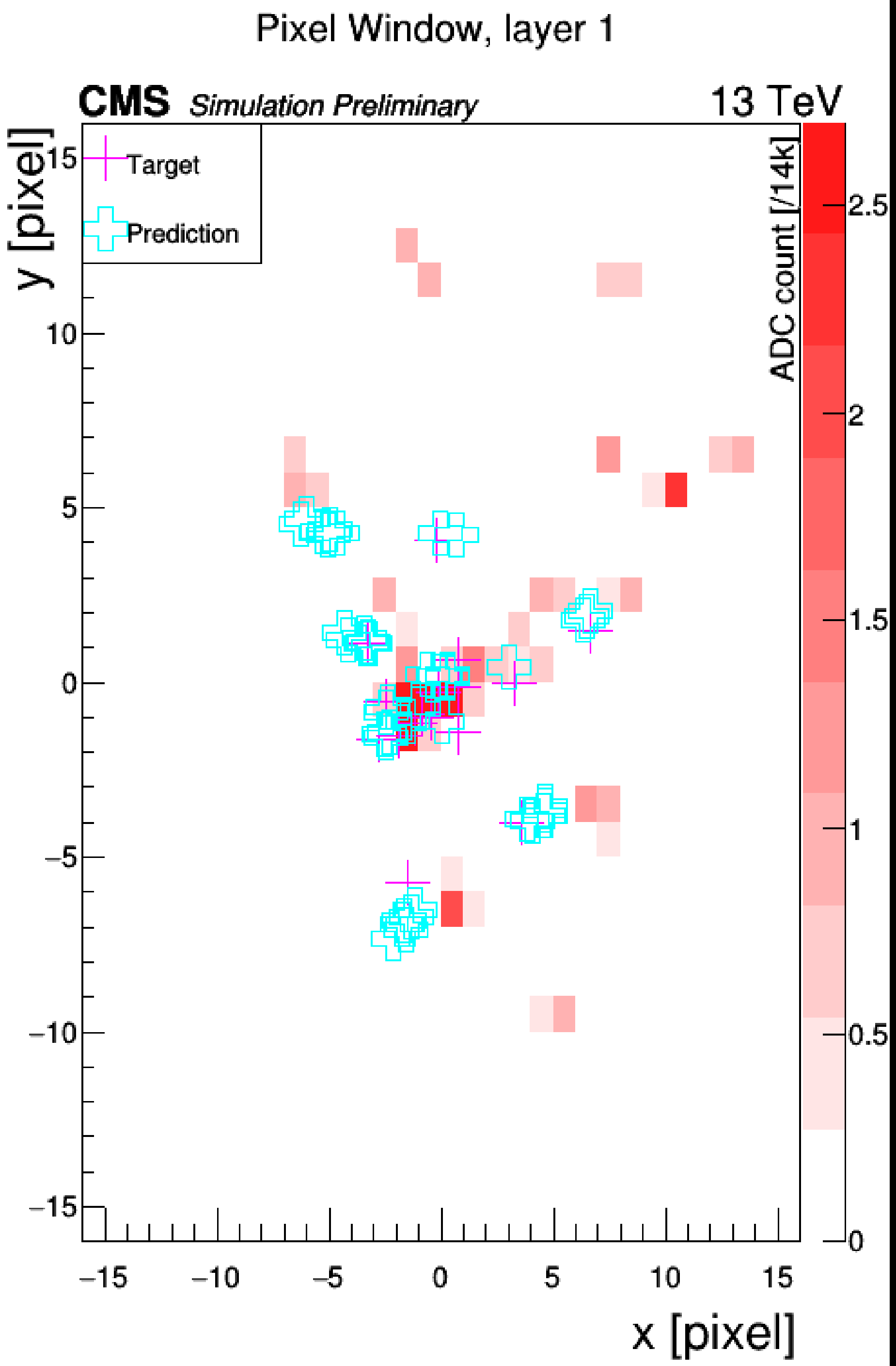


The “Event Display” of DeepCore

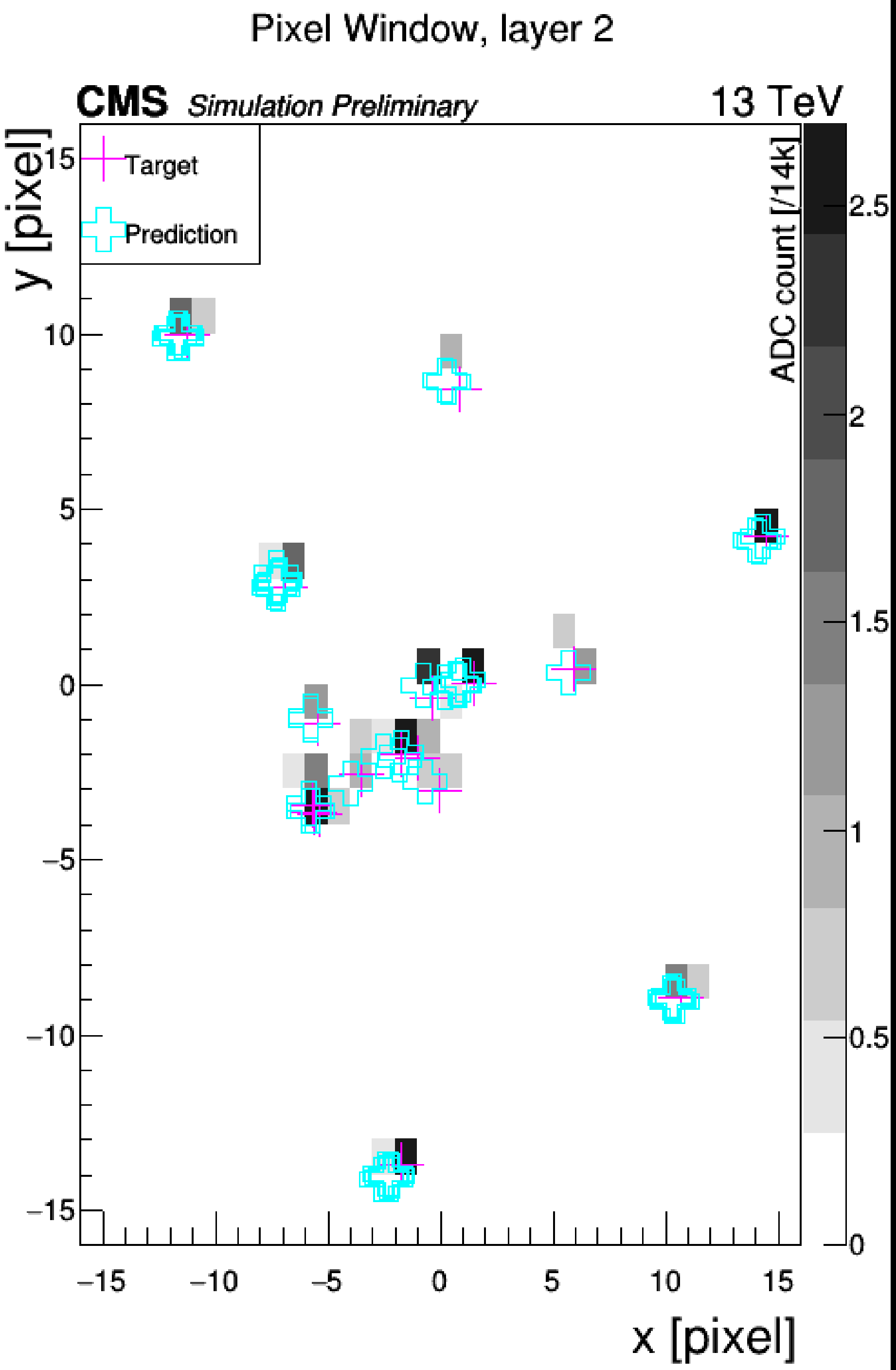


R= 3 cm R=6.8 cm R=10.2 cm R=16 cm

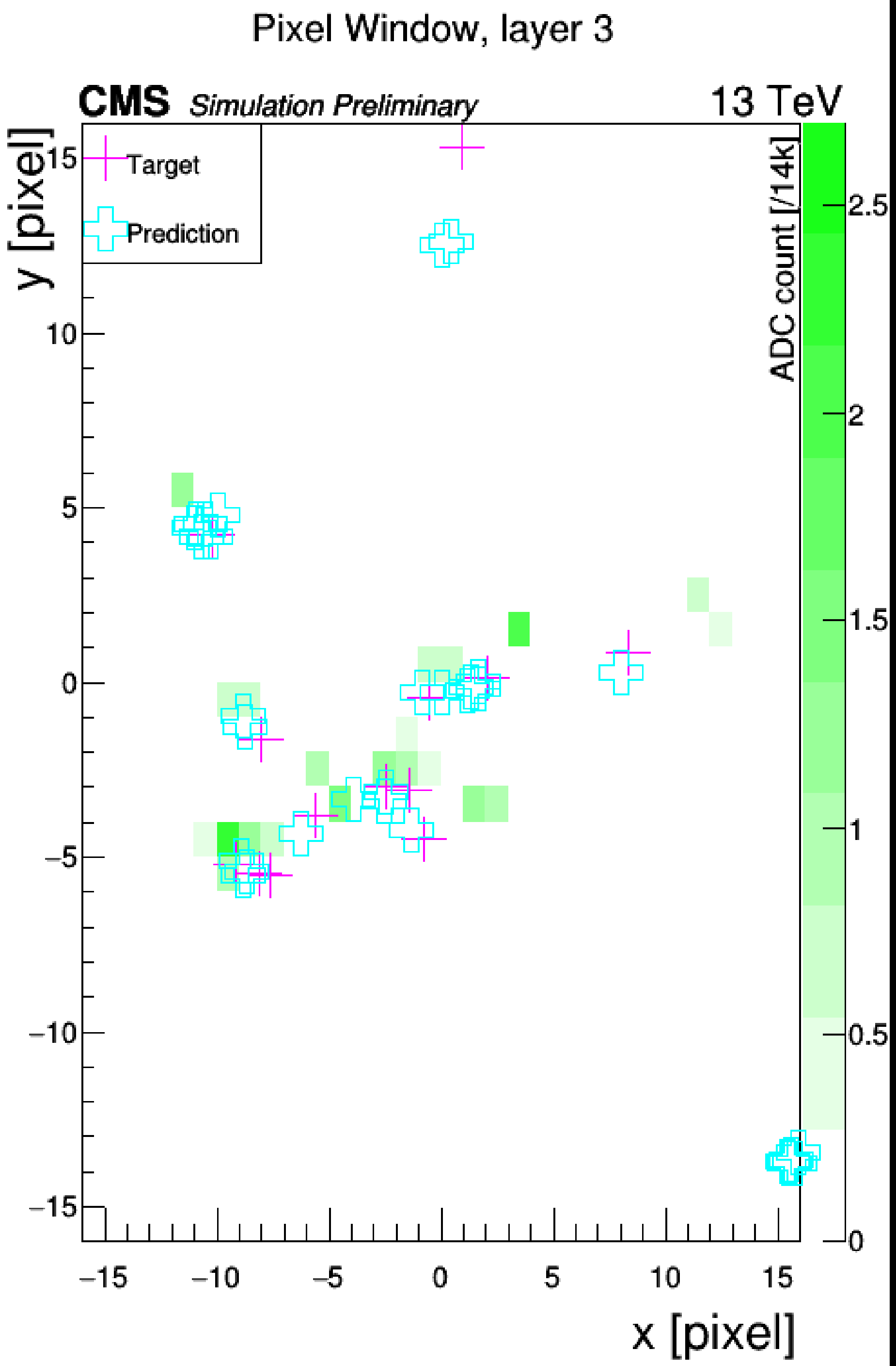

TCP Prediction Map, overlap 0
CMS Simulation Preliminary
13 TeV
Target
Prediction
Probability
y [pixel]
x [pixel]



Pixel Window, layer 1
CMS Simulation Preliminary
13 TeV
Target
Prediction
y [pixel]
x [pixel]
ADC count [/14k]

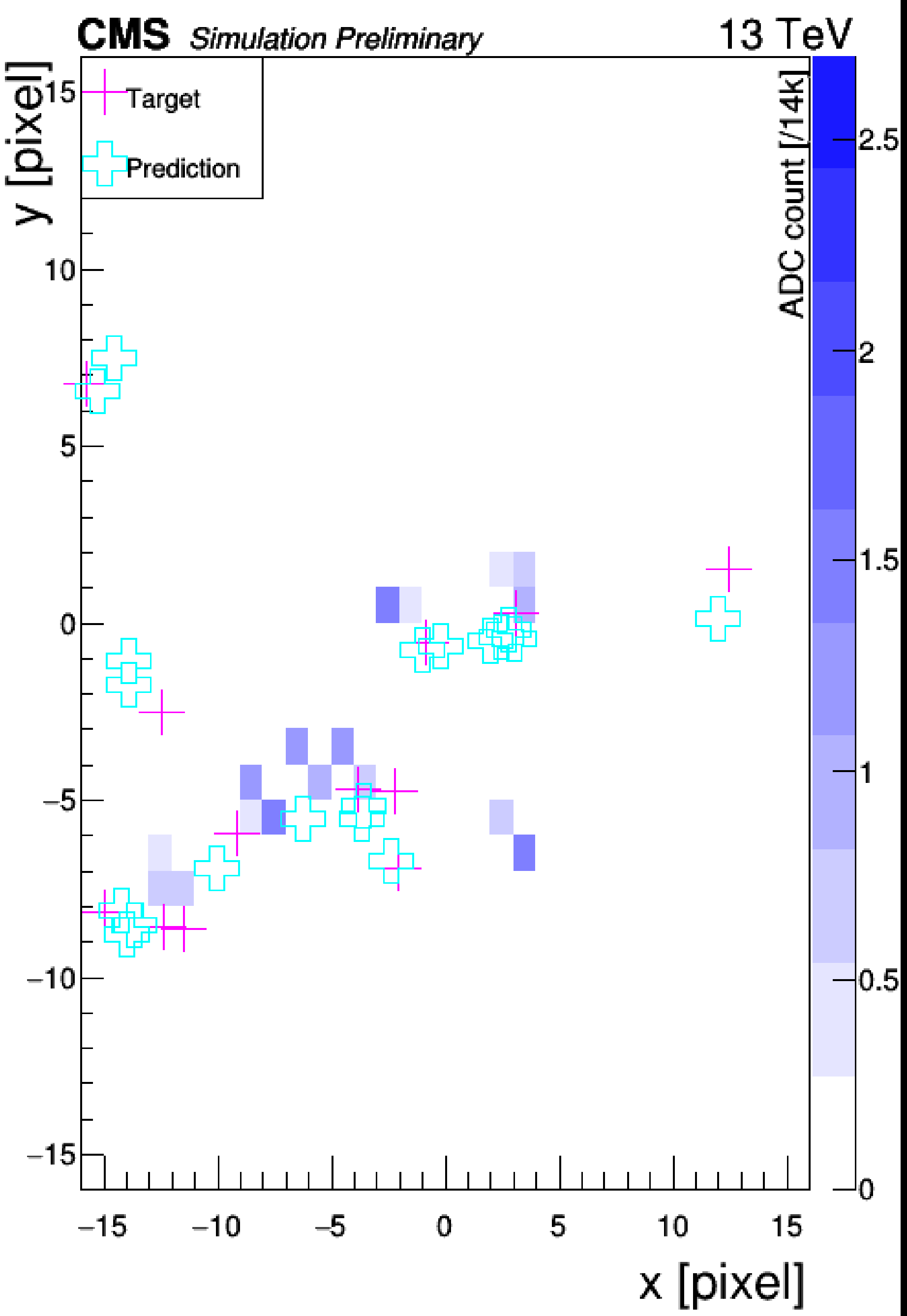


Pixel Window, layer 2
CMS Simulation Preliminary
13 TeV
Target
Prediction
y [pixel]
x [pixel]
ADC count [/14k]

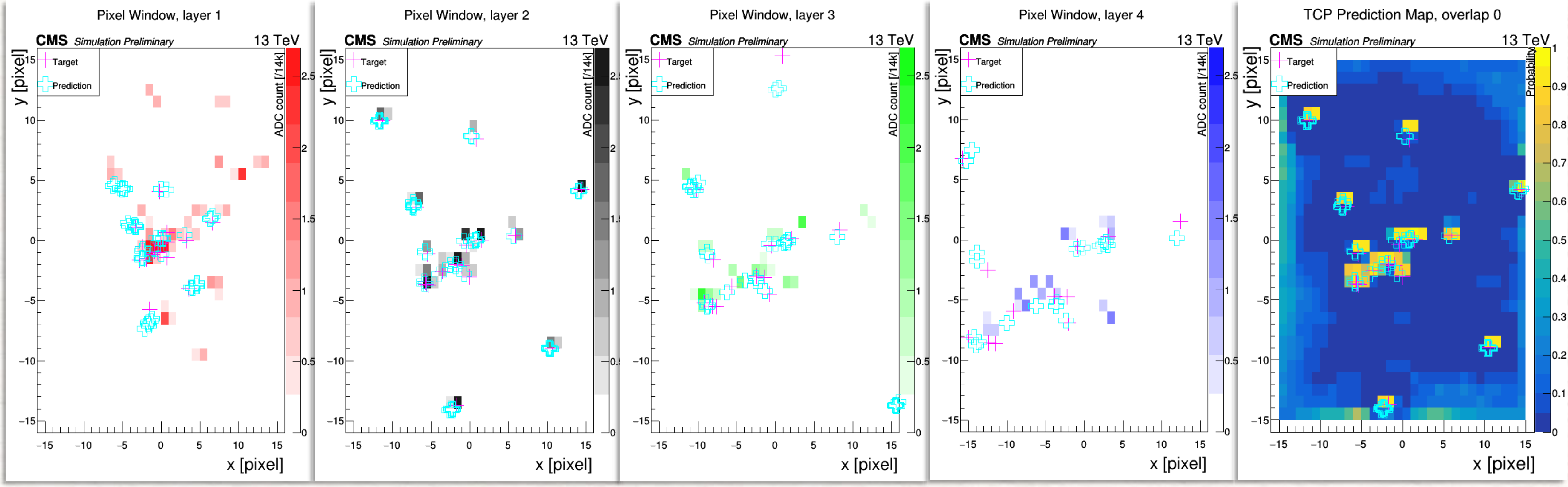


Pixel Window, layer 3
CMS Simulation Preliminary
13 TeV
Target
Prediction
y [pixel]
x [pixel]
ADC count [/14k]
15
10
5
0
−5
−10
−15
2.5
2
1.5
1
0.5

Pixel Window, layer 4

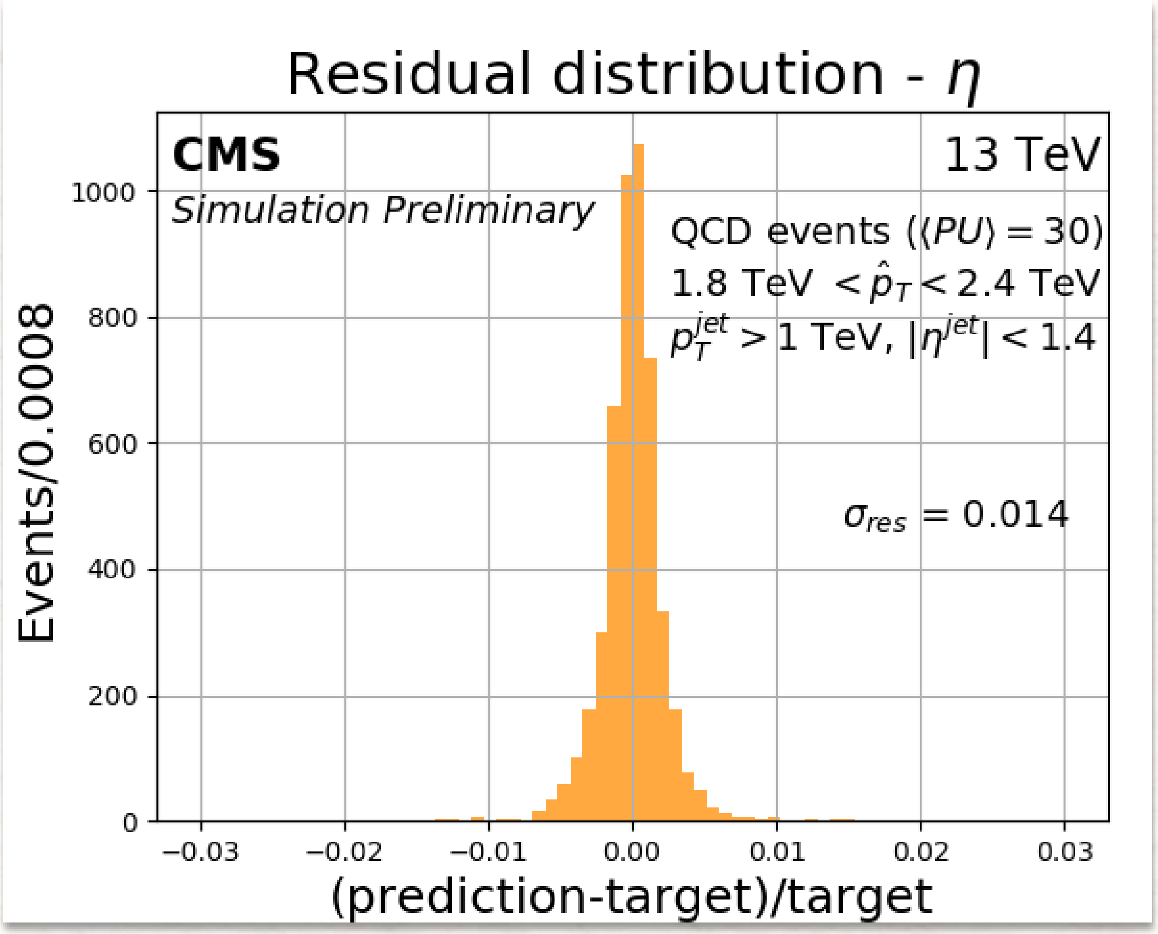


The "Event Display" of DeepCore

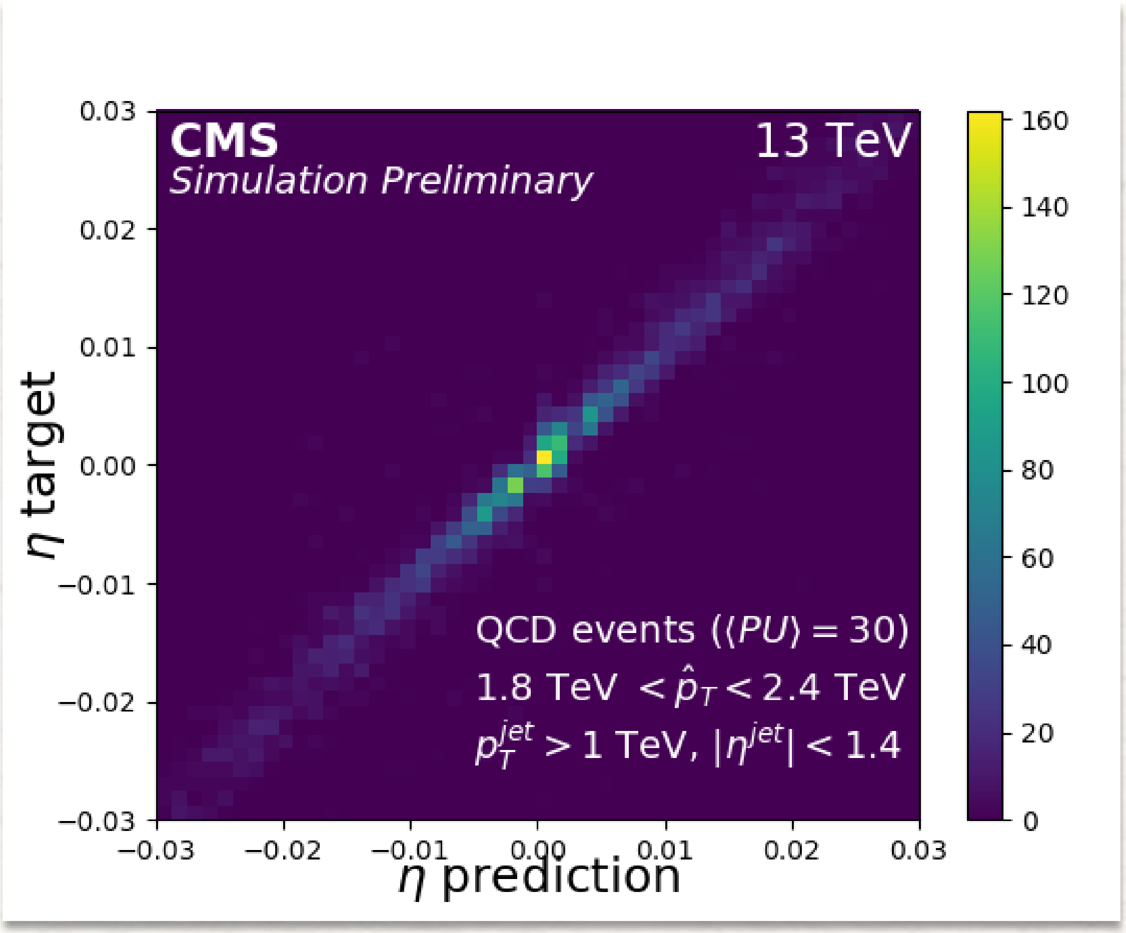


R= 3 cm R=6.8 cm R=10.2 cm R=16 cm

Performance of DeepCore training



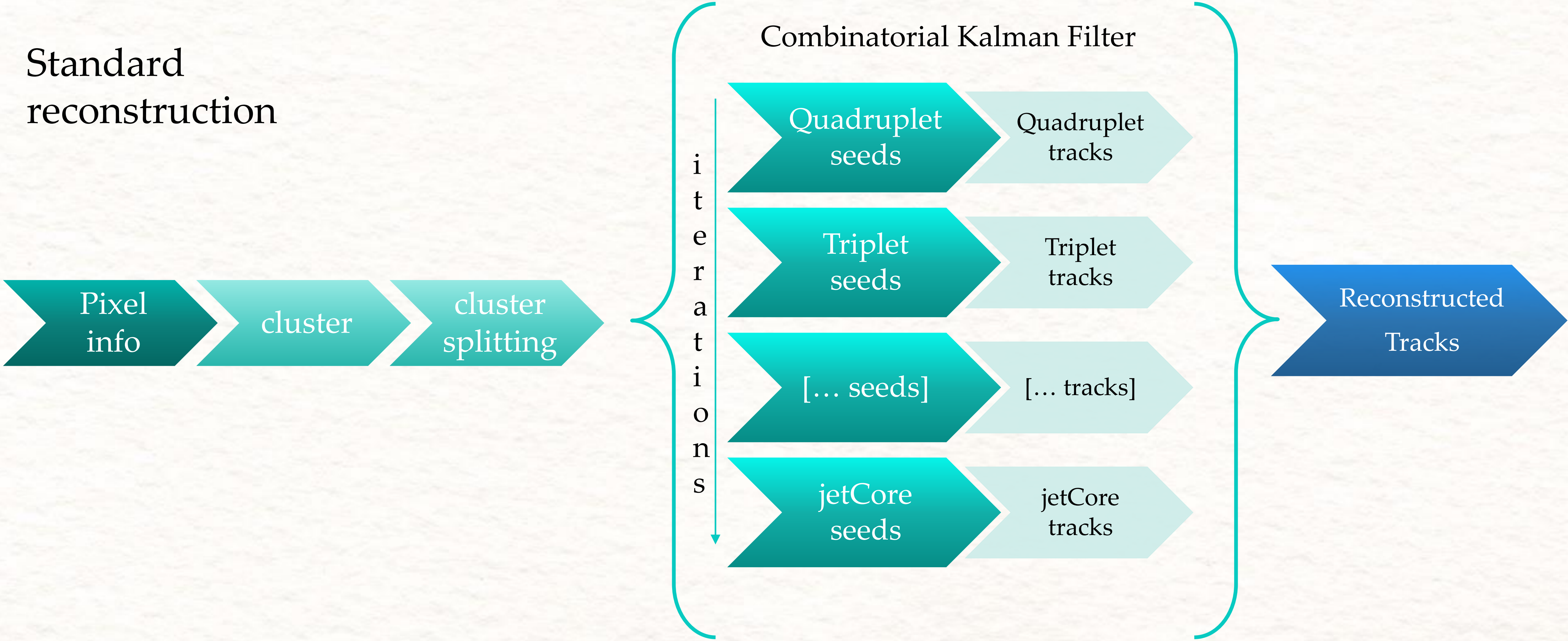
Residual between the seed η parameter predicted by DeepCore and the target (simulated) track η parameter.



Correlation between prediction of DeepCore and target parameters shown with seed η parameter predicted against the simulated track η parameter.

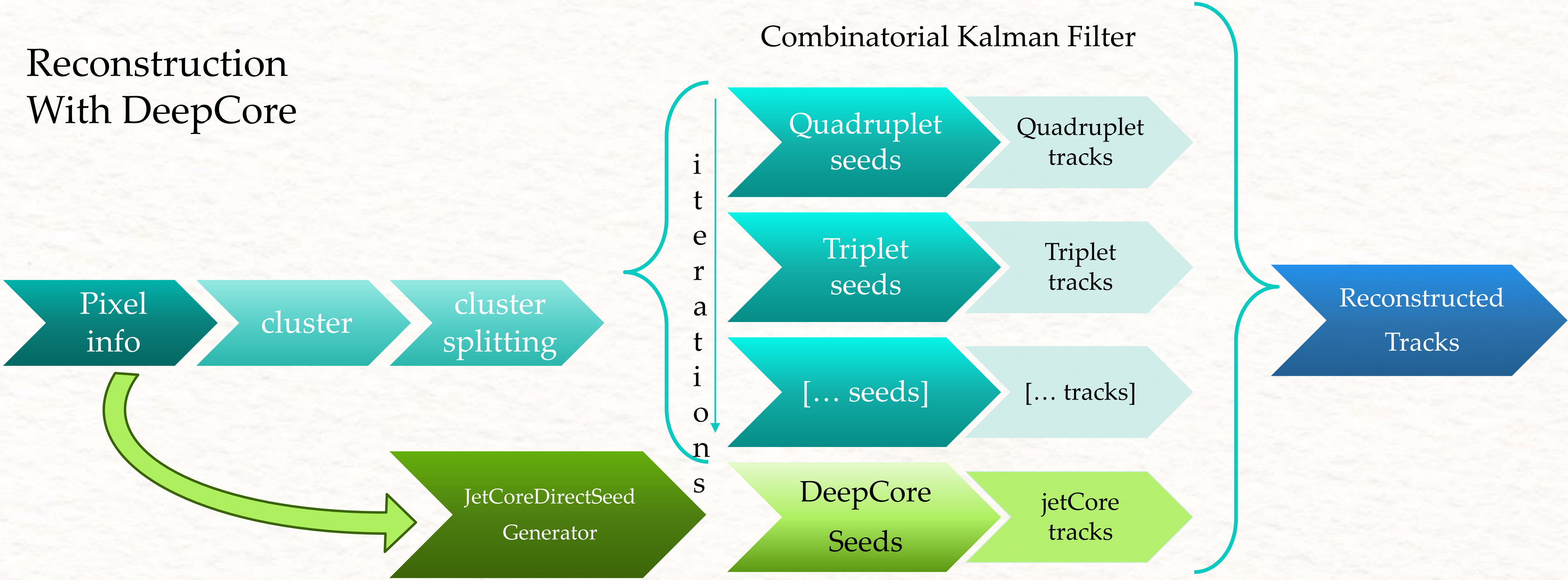
Inside CMS Reconstruction

Standard reconstruction



Inside CMS Reconstruction

Reconstruction
With DeepCore



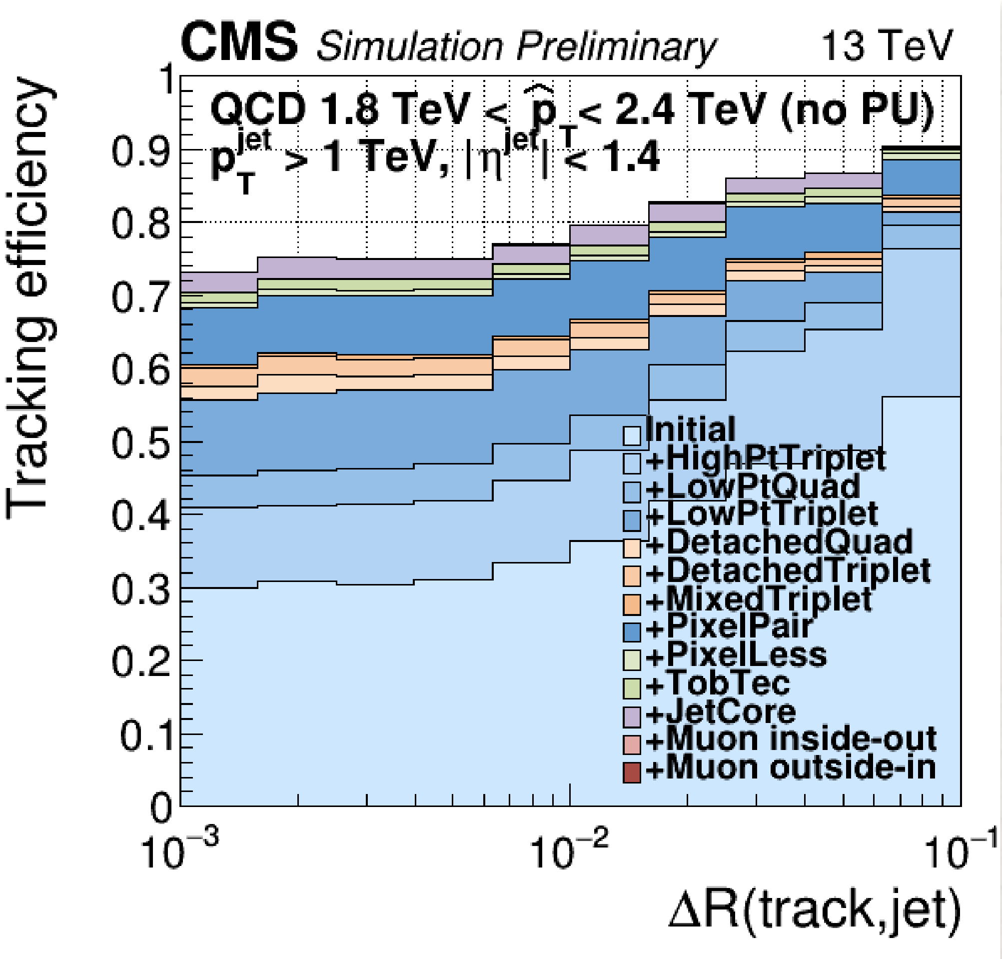
Inside CMS Reconstruction: DeepCore seeds

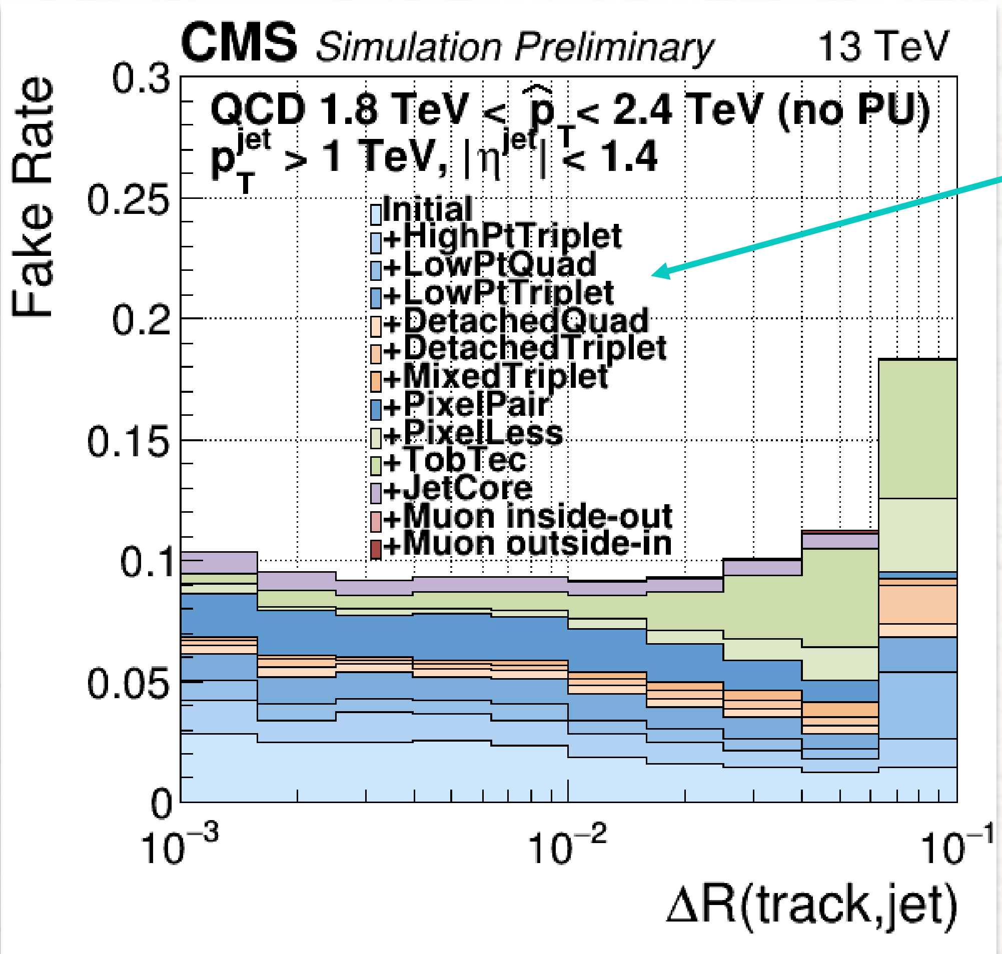
1. Loop over calorimeter-jets with **p_T>0.3 TeV**
2. For **each cluster** with DeltaR(jet, cluster)<0.1 →new direction
3. Built a NN input: four 30x30 pixel windows around the found direction + (η^{jet}, p_T^{jet})
4. Prediction of the NN→List of DeepCore Seeds

How the seed list built from the NN output?

- Saved 5 parameters of most probable pixels
- **Most Probable** = TCP>0.85, 0.75, 0.65 in the 3 repetitions, or 0.50,0.40,0.30 if layer 2 is missing
- **Cleaning**: if two seed have x,y closer than 50 μm, η, φ closer than 0.002 rad → remove one
- Uncertainty: **the same** for all the seeds: (σ_{p_T}=0.15 GeV, $\sigma_\eta=\sigma_\varphi$=0.002, $\sigma_{xy}=\sigma_z$=44 μm)

DeepCore performance in CMS reconstruction





Stacked cKF iterations

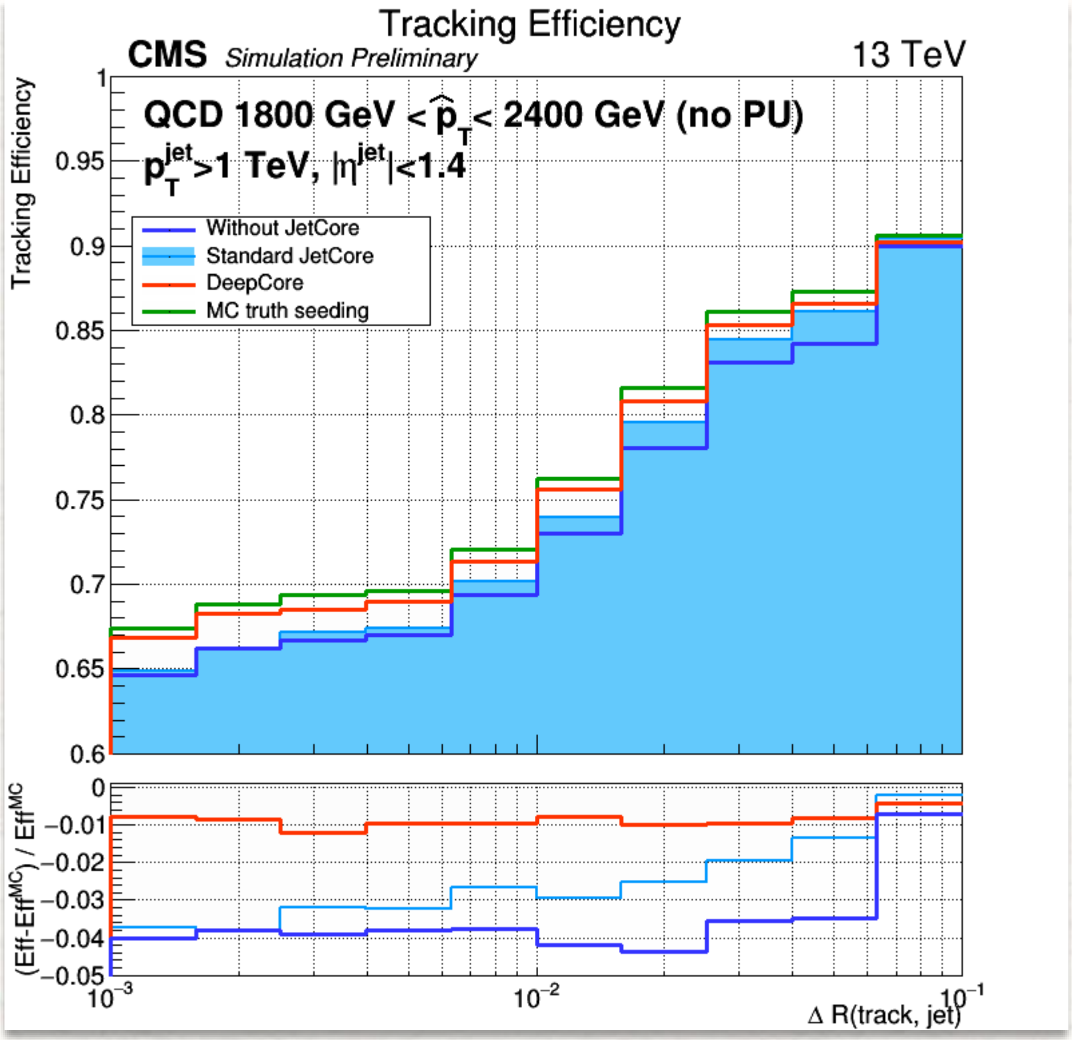
$$\varepsilon = \frac{N_{\text{reco}\to\text{sim}}}{N_{\text{sim}}}$$

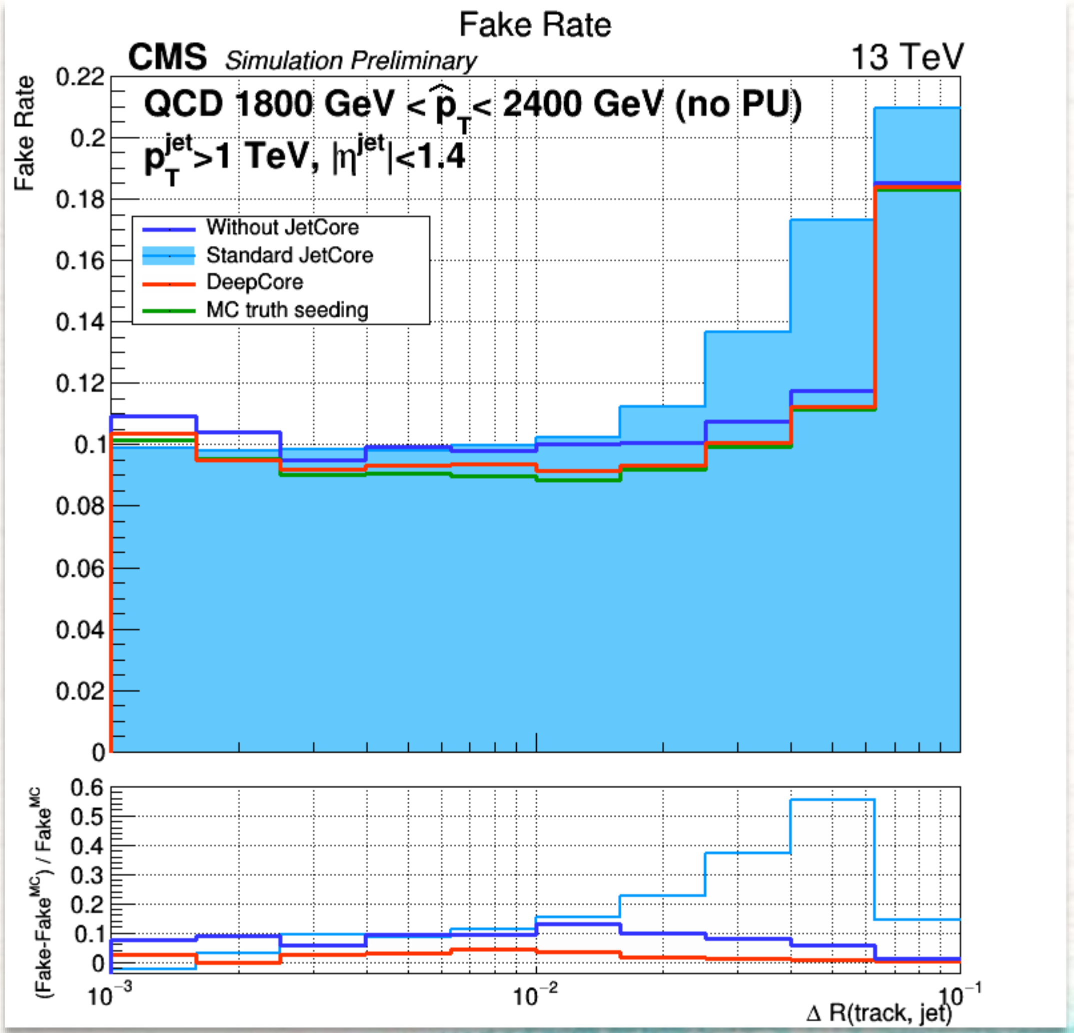
$$R_{\text{fake}} = \frac{N_{\text{reco}\not\to\text{sim}}}{N_{\text{reco}}}$$

$$\text{reco} \to \text{sim} \Leftrightarrow \chi^2 < 25$$

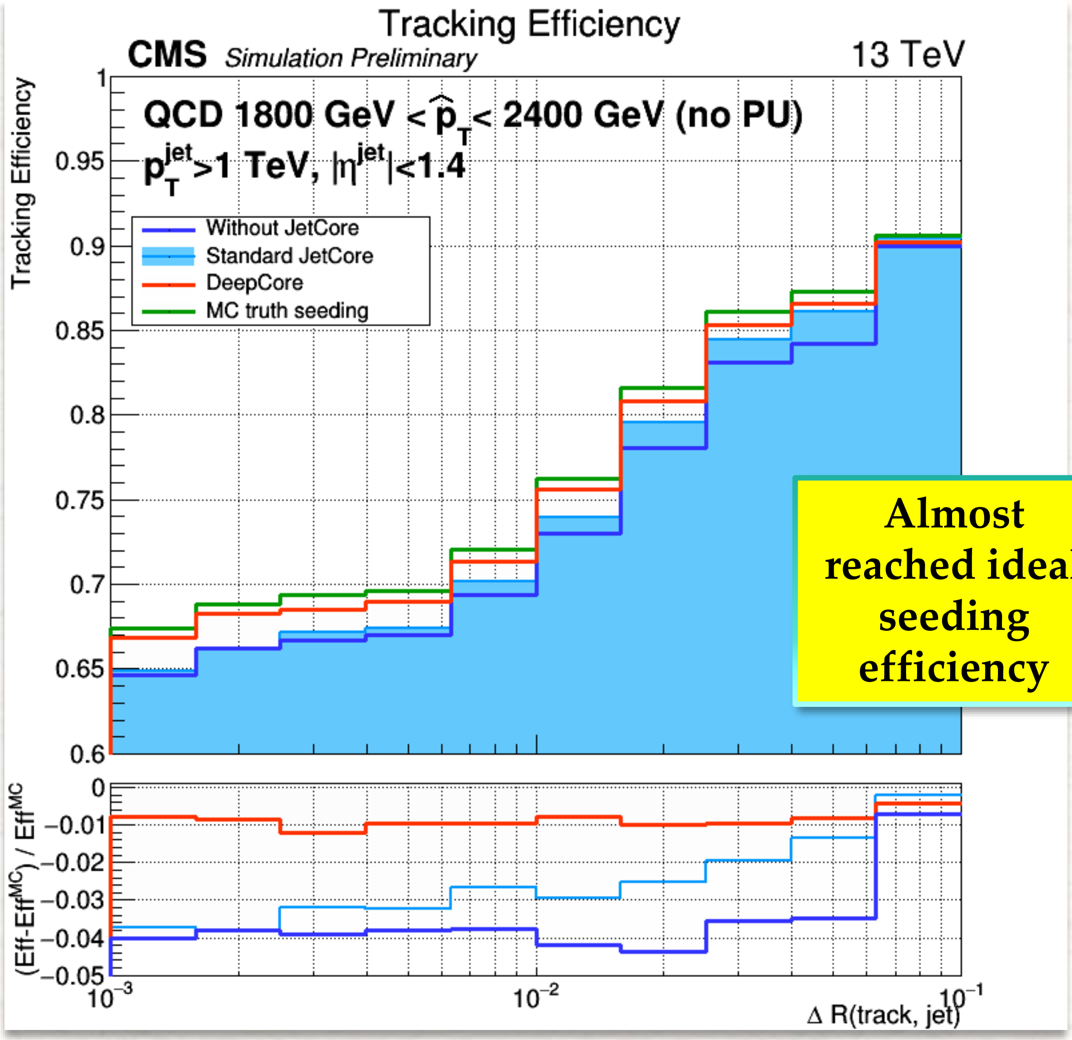
NB: in the efficiency the shared reconstructed tracks (duplicated) between various iterations are not removed.

DeepCore compared performance in CMS reconstruction

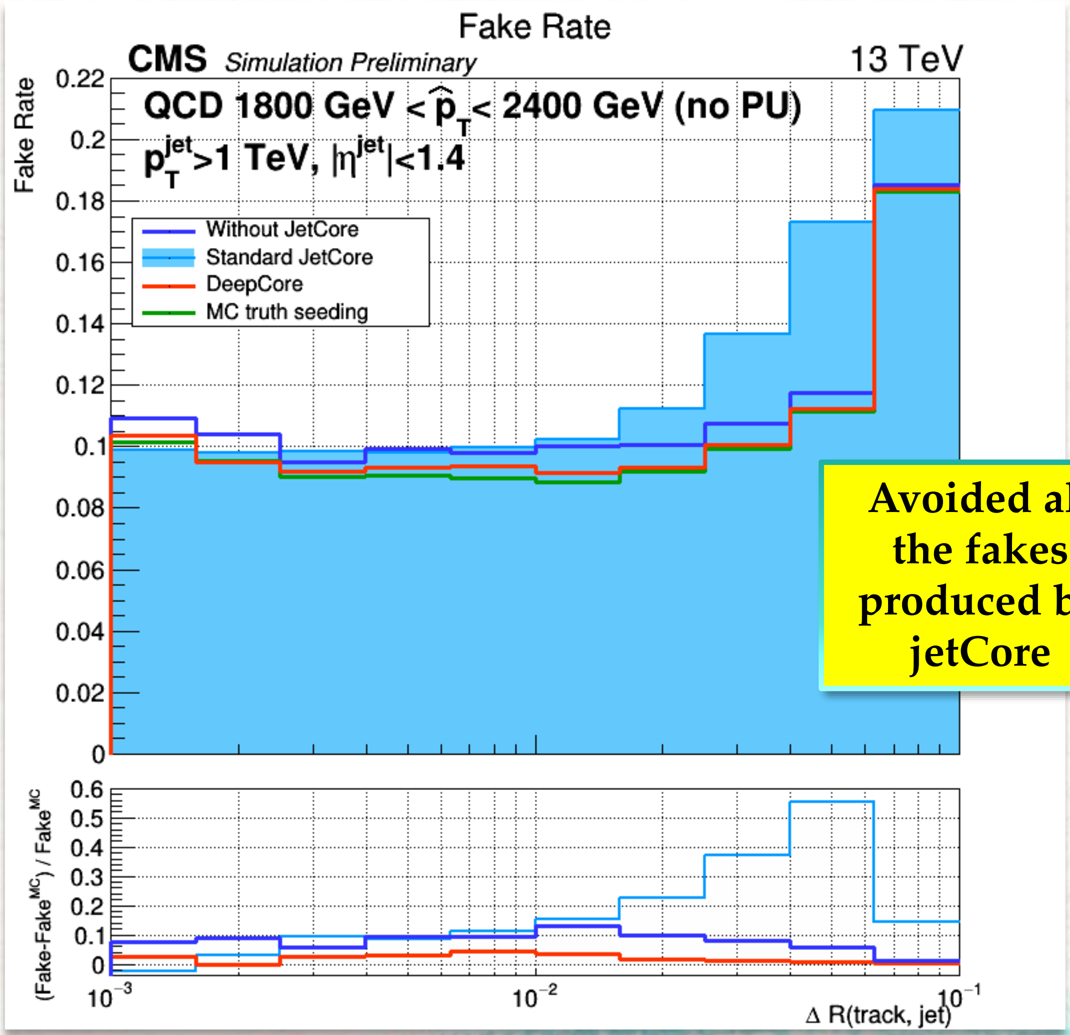




DeepCore compared performance in CMS reconstruction

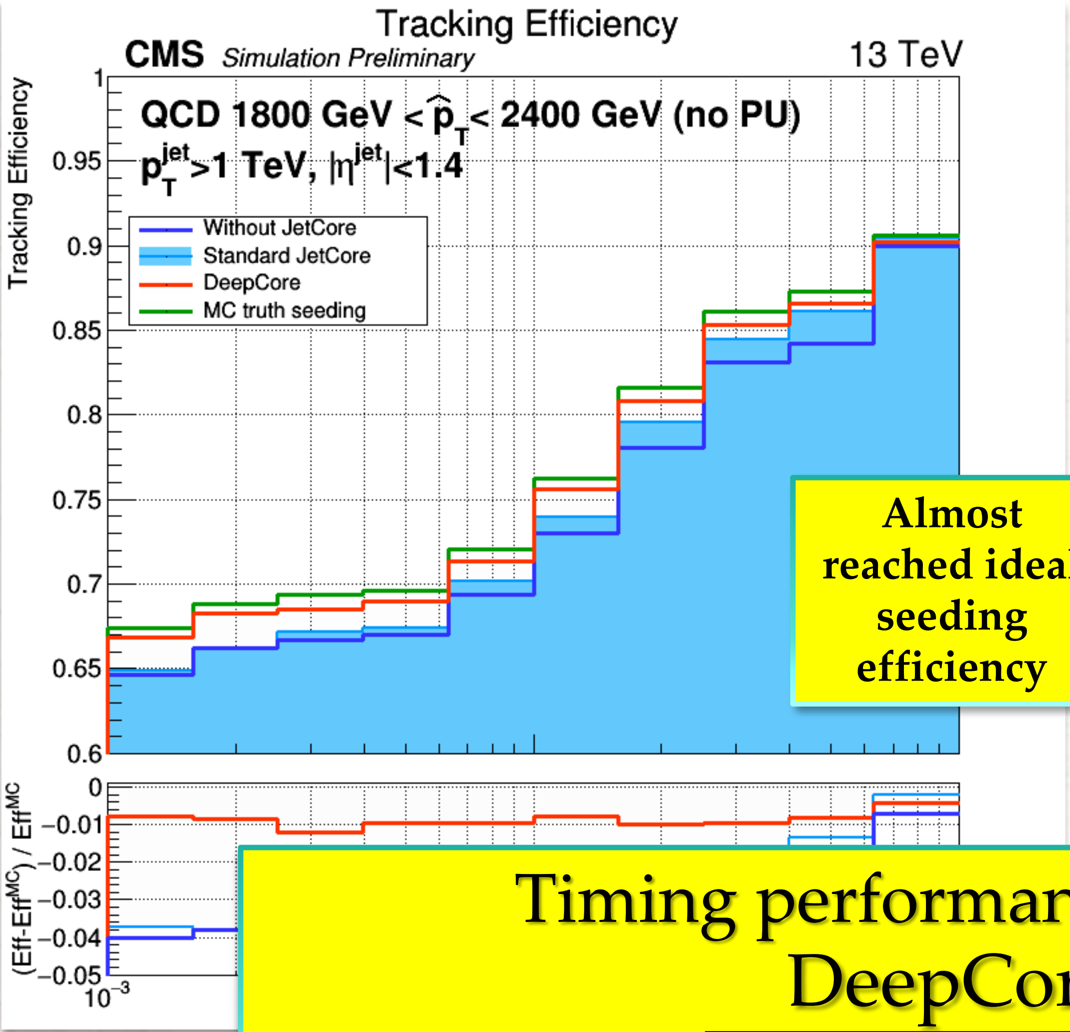


Almost reached ideal seeding efficiency



Avoided all the fakes produced by jetCore

DeepCore compared performance in CMS reconstruction



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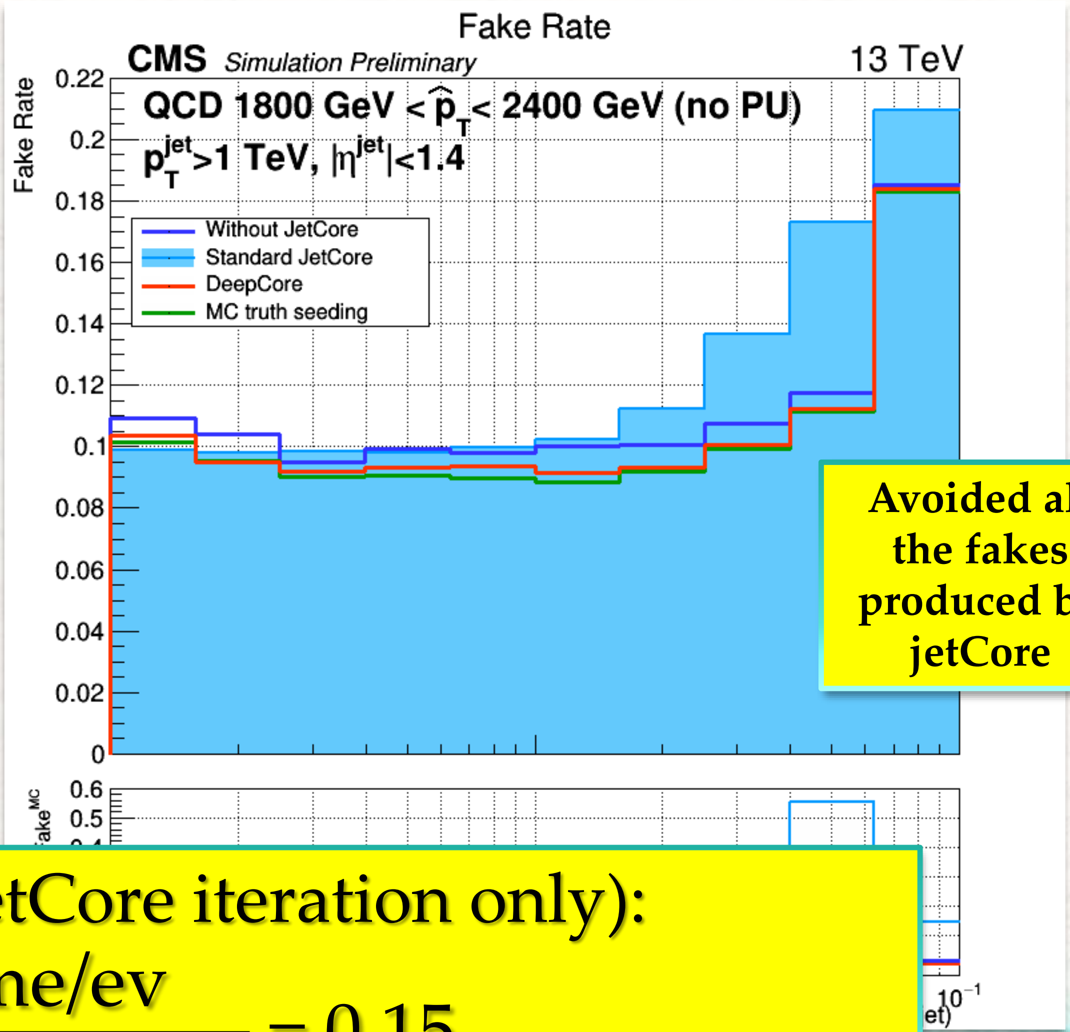

Avoided all the fakes produced by jetCore

Timing performance (JetCore iteration only):

$$\frac{\text{DeepCore Time/ev}}{\text{default JetCore Time/ev}} = 0.15$$

CONCLUSIONS

- The **CNN approach works** for tracking at seeding level
- The DeepCore implementation for CMS reconstruction gives (in jet core regions):
  - **almost cancelled seeding inefficiencies**
  - **fake rate reduction** up to 60%
  - **seeding time reduced** by 85%
- The result is very **preliminary**:
  - Barrel only → must be extended, expect higher gain in **endcaps**
  - **Further optimization** on training (LR, batch size, architecture)
  - Extension to other steps of pattern recognition

BACKUP SLIDES

Standard seeding details

Why outward?
- Pixel→Lower occupancy
- Pixel→3D measurement
- Higher efficiency (low energy tracks, energy losses, interactions with material)

Seed parameters:
- 5 track parameters
- From three 3D hits or two 3D hits+vertex constraint

Algorithm:
- For each iteration defined 2 sets of parameters
  - Seeding layer: the used detectors
  - Tracking regions: optimized set of cuts to define good combinations of hits (on p_T, d_0, $|z_0|$, charge)
- If seeding layer is a pair of detector: look for pair of hits and applied cuts of the region
- If seeding layer is a triplet/quadruplet: Cellular Automaton seeding (see Felice's talk)

Iteration (some):
- Pixel triplets: for prompt tracks
- Pair+vertex: also from Endcap strips, for forward tracks
- Mixed triplets: strips+pixel, for displaced tracks (b tracks, photon conversion, nuclear interaction)
- Strip Pairs: weaker constraints, recover efficiency for tracks produced outside pixel detector
- jetCore: pairs+axis constraint, high p_T jet tracking

Details of the training

- Ep 0-11 →200k ev, LR=0.0002
- Ep. 11-40 → 200k ev, LR=0.0001
- Ep. 40-191 → 200k ev, LR=0.00007

Small sample (200k events)
BCE with 0 out of NCP

- Ep 191-200 → 200k ev, LR=0.00007, new loss
- Ep. 200-233 →200k ev, LR= 0.000001, new loss

Small sample
Complete BCE

- Ep 233-239 → 22 M events, LR= 0.000001, new loss
- Ep 239-246 → 22 M events, LR =0.0000001, new loss, epochs of 1M ev.

Complete Sample
Complete BCE

Definitions

Tracking Efficiency

Number of reconstructed tracks associated to a simulated one divided by the number of simulated tracks. A reconstructed track is flagged as "associated" if the χ^2 between its parameters and the simulated is lower than 25.

Fake Rate

Number of reconstructed tracks not associated to a simulated one divided by the number of reconstructed tracks.

Duplicate rate

Number of tracks duplicate divided by the number of reconstructed tracks. A reconstructed track is flagged as "duplicate" if at least another reconstructed track is associated to the same simulated track of the first one.

Track selection

The typical selection for simulated tracks used in validation: $|\eta^{jet}|<2.5$, $r_{prod}<3$ cm, $|z_{prod}|<30$ cm, $p_T> 0.9$ GeV.

Technicalities and references

YOLO (You Only Look Once)

Our source of inspiration for CNN approach

References:

- https://pjreddie.com/darknet/yolo/
- arXiv:1506.02640v5
- arXiv:1612.08242v1

Adam Optimizer

Extension to stochastic gradient descent (adaptive per-parameter LR, use of the second moment of gradients)

References: https://arxiv.org/abs/1412.6980

CMS references

- Track Reconstruction: arXiv:1405.6569v2
- Particle Flow: arXiv:1706.04965v2
- b-tagging and vertexing: arXiv:1712.07158v2
- Jet substructures: arXiv:1803.06991v2

Activation functions:

- ReLU: $f(x)=max(0,x)$
- Sigmoid: $f(x)=1/(1+e^{-x})$

Timing Performance:

Unofficial absolute values for jetCore iteration only:

- DeepCore: 2.5 sec./ev.
- Standard JetCore: 16.6 sec./ev.