Deep learning tracks in the CMS detector

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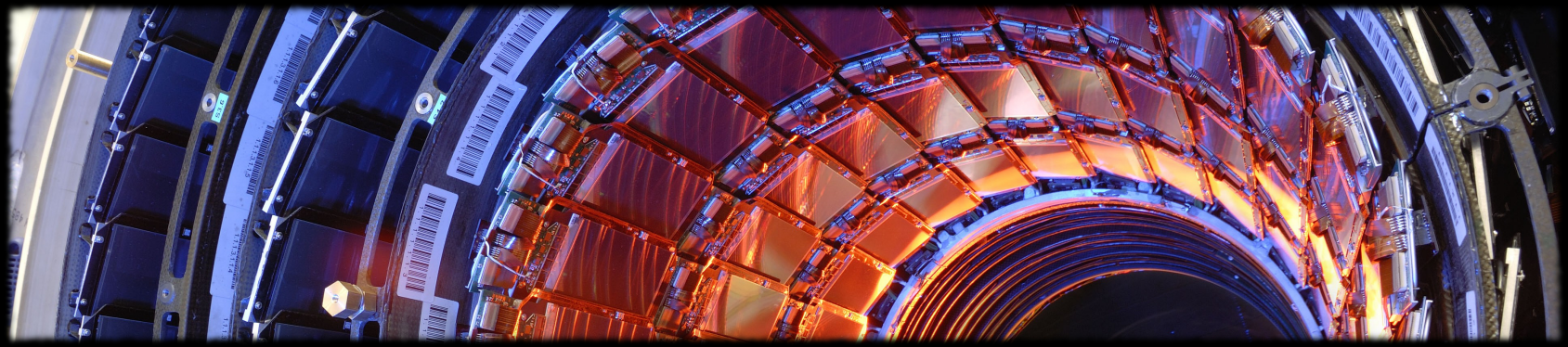
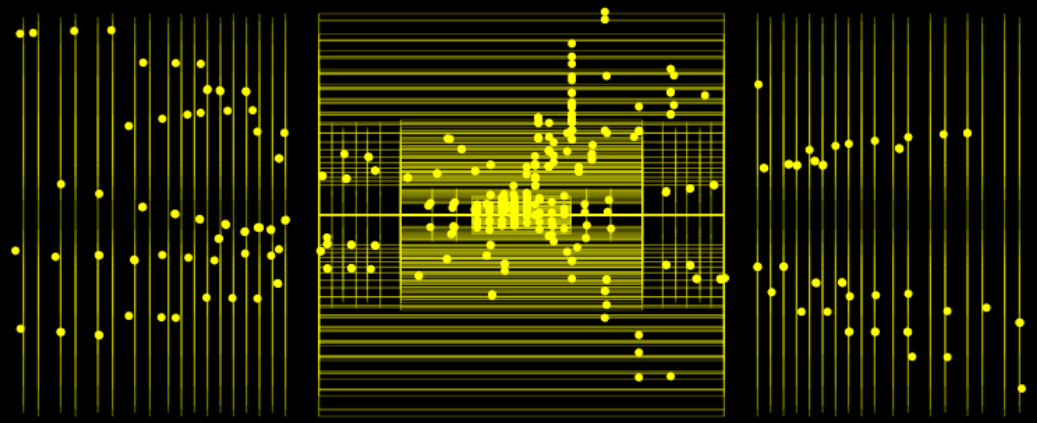
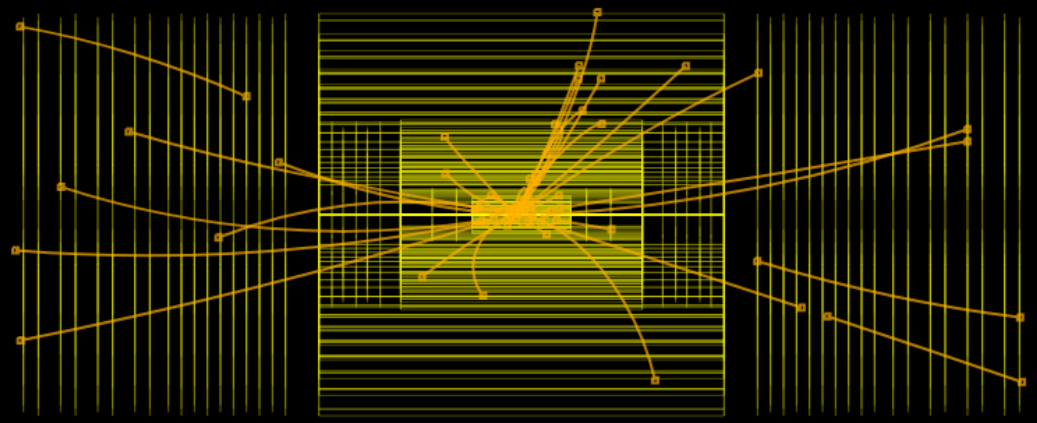


Track reconstruction – Connecting the dots

Measured hits



Reconstructed tracks



Inferring **trajectories** of charged particles from measurements

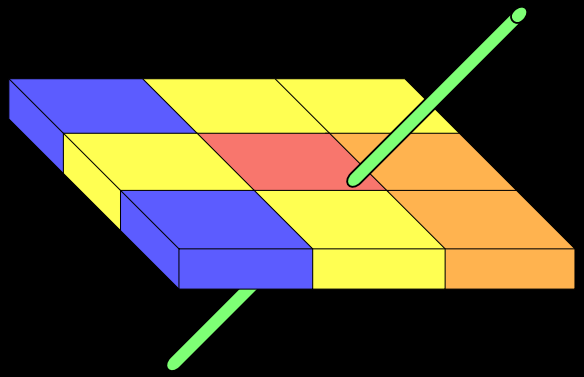
Tracks are used to determine properties of the particles

- p_T
- electric charge
- particle type

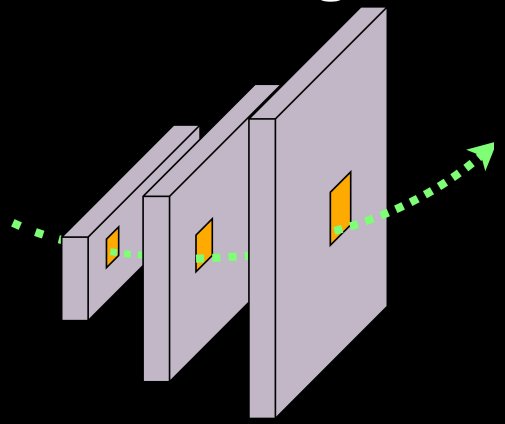
Tracking is vital for almost every type of physics analysis done at hadron colliders

Track reconstruction – Stages

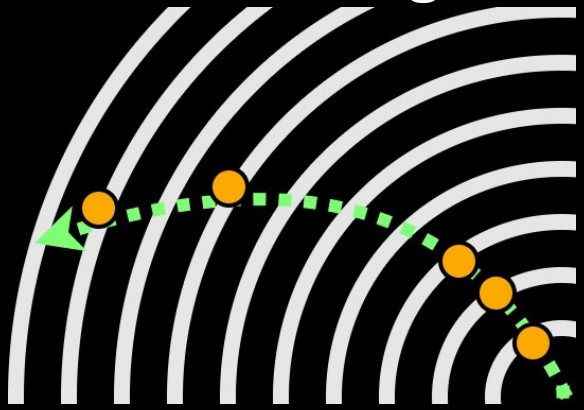
1. Hit clustering



2. Track seeding



3. Track building



4. Track fitting

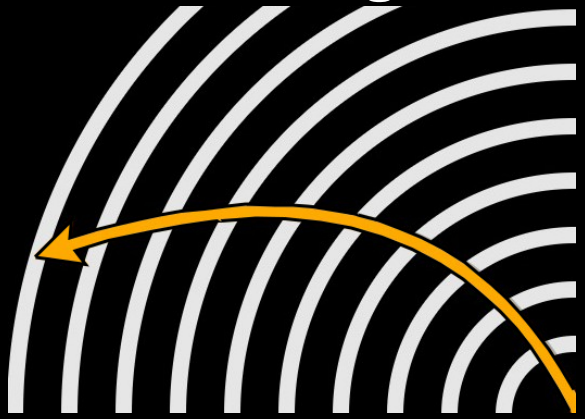


Figure 1: **1.** Hit locations are determined from energy deposits in the tracker.
2. Compatible sets of three hits in different layers are used as track seeds.
3. Seeds are extended with additional hits that suit the track hypothesis.
4. Final track fit is done on the found hits.

Track reconstruction – Challenges

Parts of the reconstruction process scale badly with respect to number of tracks in an event. Current tools have worked so far, but the pile-up is foreseen to increase with predicted $\mu = 140 - 200$ at the HL-LHC.

Machine learning methods have potential for tackling some of the issues

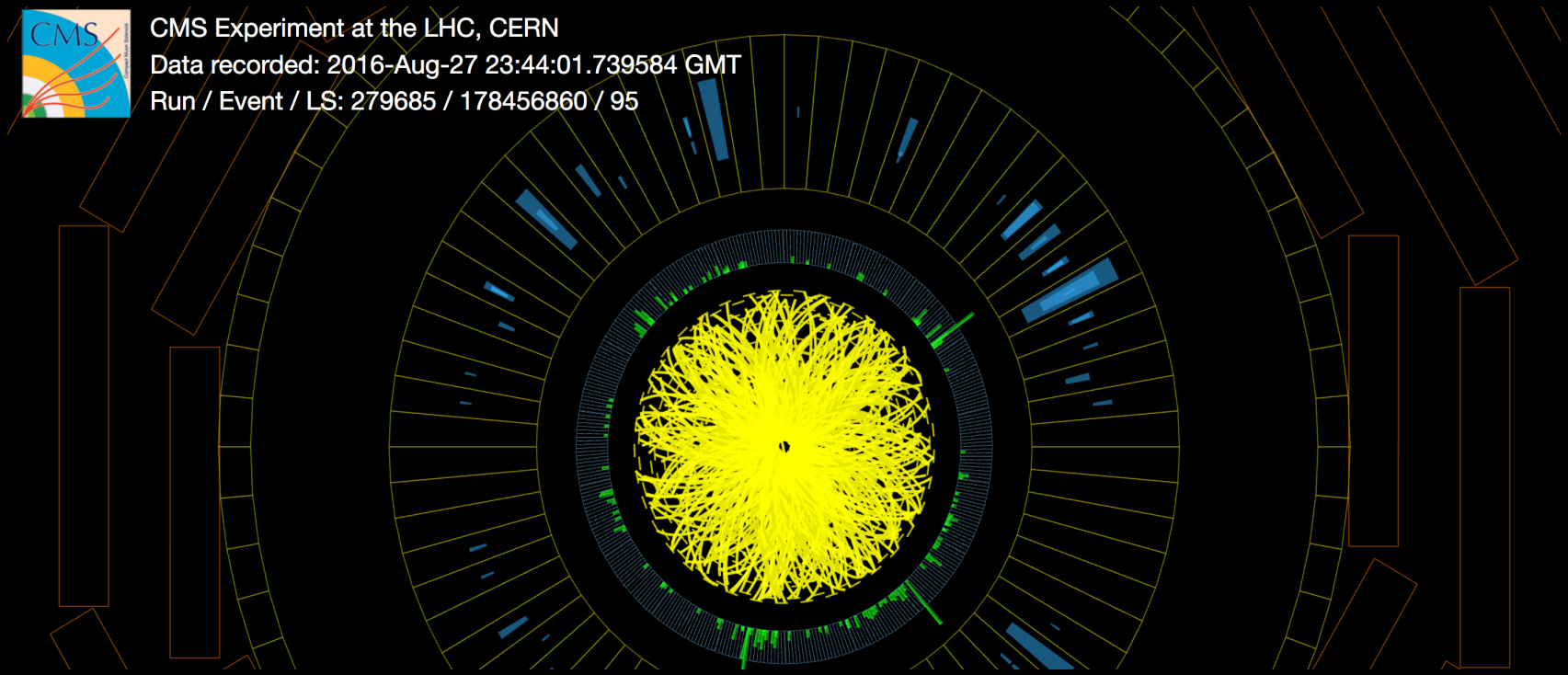


Figure 2: An event at the CMS with 30 pile-up vertices during Run 2 resulting in O(100) tracks.

Deep learning

Deep learning techniques have achieved great results in pattern recognition tasks. These methods rely on learning useful **representations** for data, often using very low level inputs such as pixels in an image.

While training a deep neural network can take a long time, evaluating inputs on a pretrained network is usually fast.

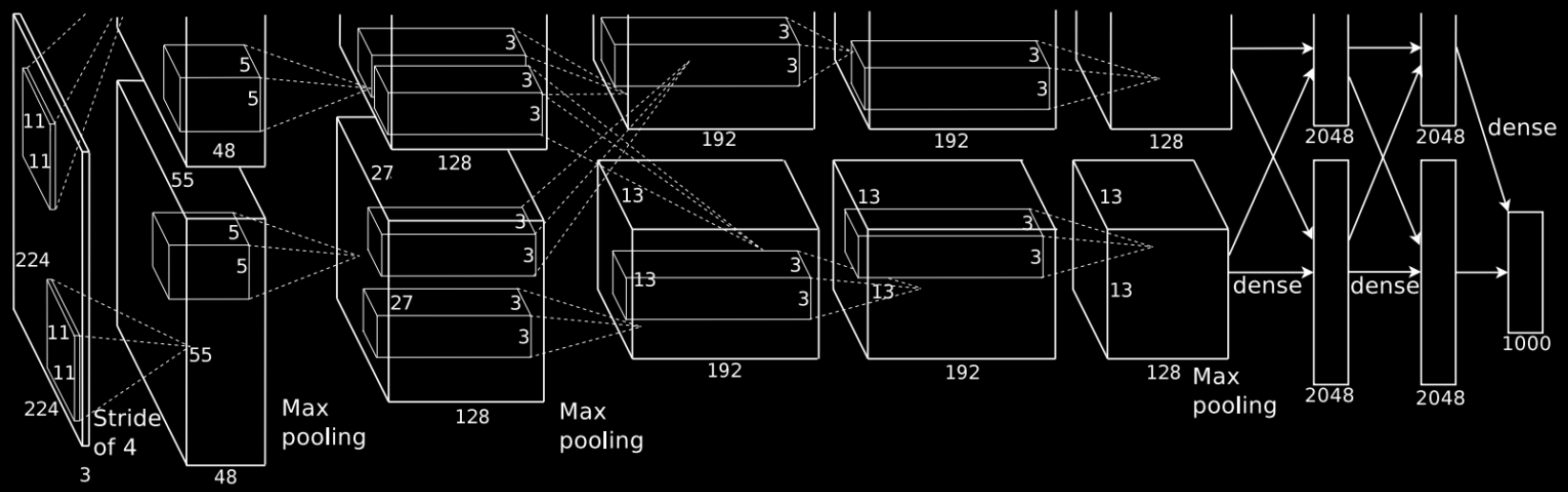
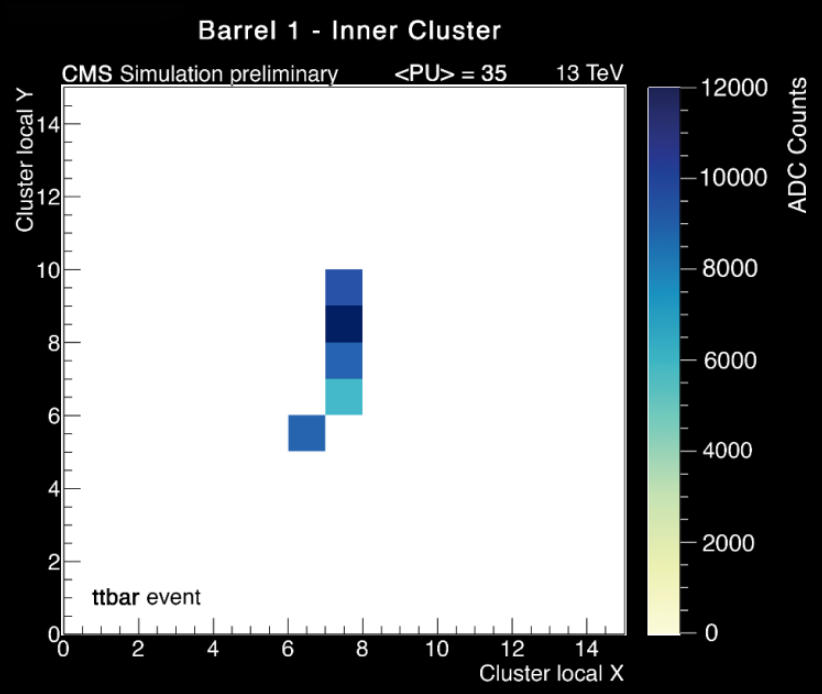


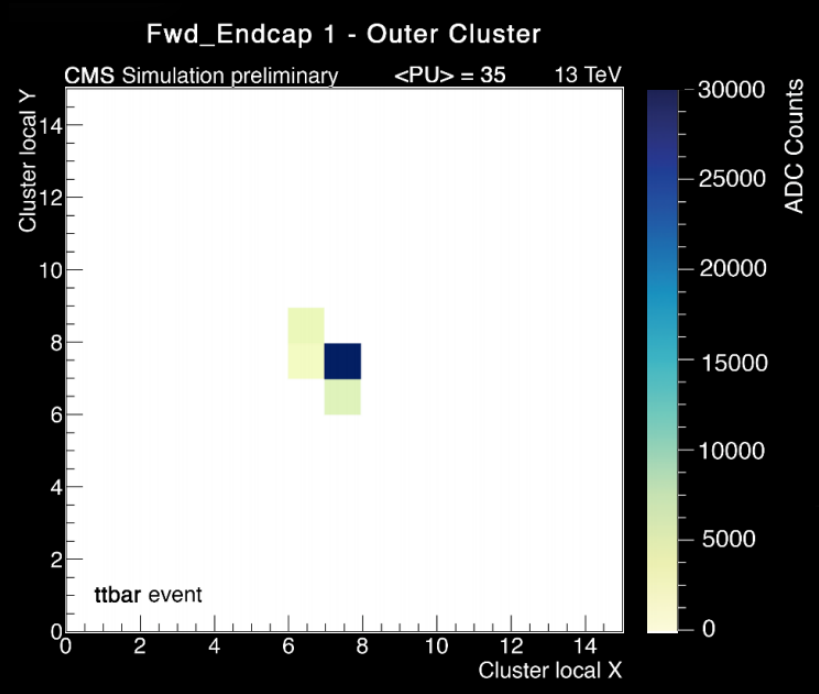
Figure 3: Example of ConvNet topology used to classify high resolution images. The network has 60 million trainable parameters.[1]

[1] A.Krizhevsky I.Sutskever,G.E.Hinton : ImageNet Classification with Deep Convolutional Neural Networks, https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks

Deep learning tracks – Track seeding

Track building demands a lot of computational resources, so one should choose carefully which seeds to use. Convolutional Neural Networks have shown[2] good results in rejecting seeds that do not correspond to real tracks by comparing the shapes of the hit clusters used in the seed.





[2] A. Di Florio: Convolutional Neural Network for Track Seed Filtering at the CMS HLT, ACAT2017. https://indico.cern.ch/event/567550/contributions/2638698/

Deep learning tracks – Dense regions

Boosted objects like jets can have a large number of tracks in a small section of the tracker. Reconstructing these is difficult as allowing shared hits increases reconstruction of fake and duplicate tracks.

Neural network classifier identifying if hits are caused by single or multiple tracks has been shown to increase tracking efficiency in dense regions[3].

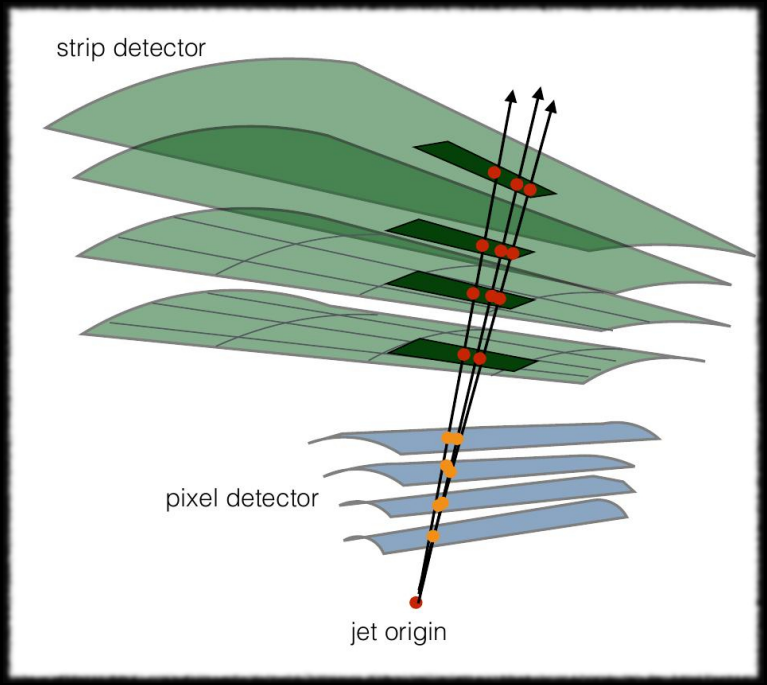


Figure 4: Multiple tracks can share hits in dense regions such as cores of jets.[4]

[3] The ATLAS Collaboration: The Optimization of ATLAS Track Reconstruction in Dense Environments, https://cds.cern.ch/record/2002609

[4] A.Salzburger: Tracking at HL-LHC and FCC, https://indico.hephy.oeaw.ac.at/event/86/session/2/contribution/4

Deep learning tracks – Track quality and classification

Fitted tracks pass through a classifier that rejects fake tracks not corresponding to a real particle. Use of deep neural networks (DNN) instead of boosted decision trees (BDT) as classifiers improves efficiency and reduces the fraction of fake tracks.

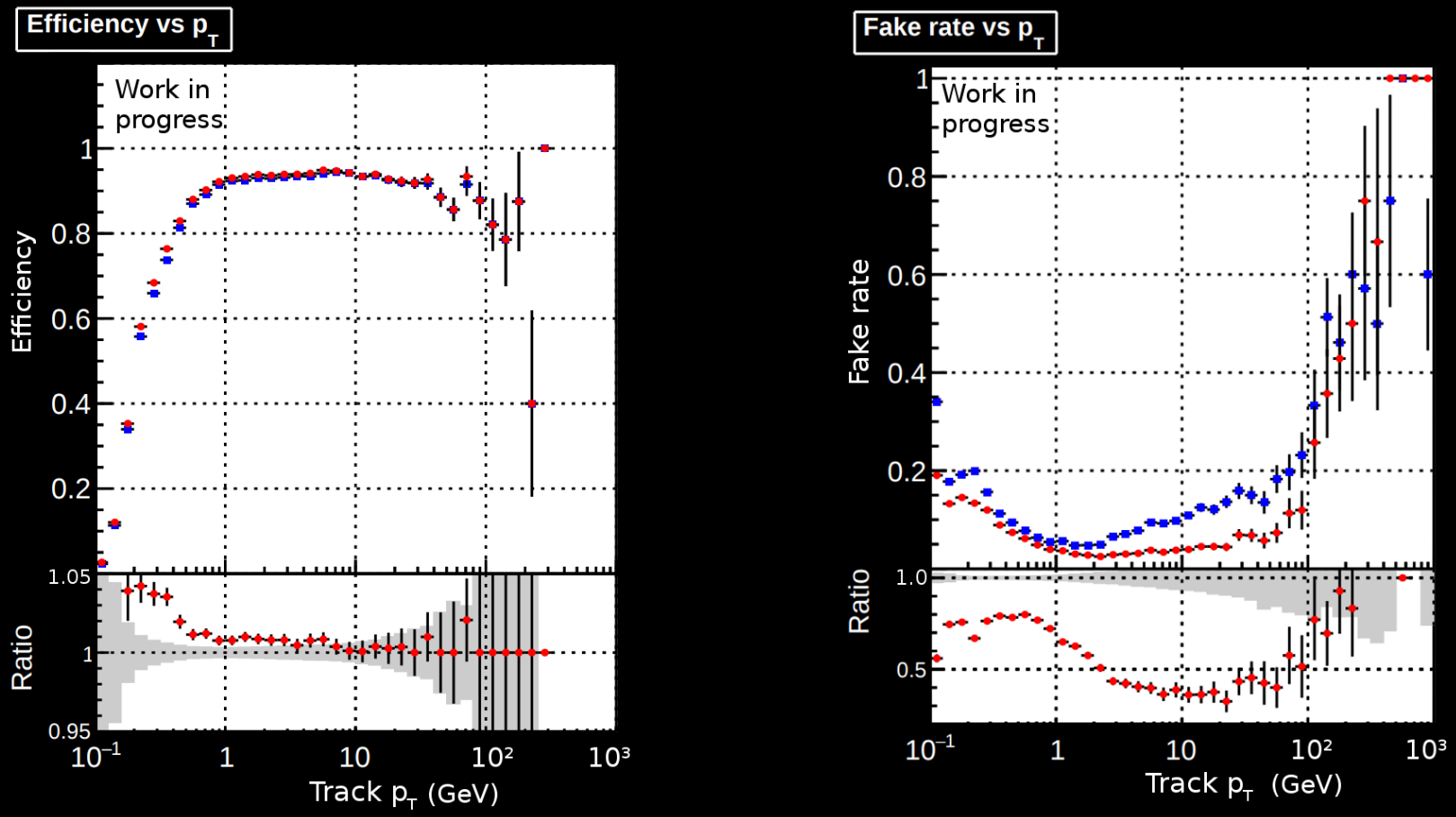


Figure 5: Comparison of DNN and BDT classification on simulated $t\bar{t}$ events with pile-up 50 in CMS. Efficiency (left) and fake rate (right) as a function of track p_T

Deep learning tracks – End-to-end track reconstruction

Reconstructing tracks by learning the track parameters directly from the detector input has been demonstrated on a 2D toy model[5]. Such an approach could improve the speed of track reconstruction process enormously.

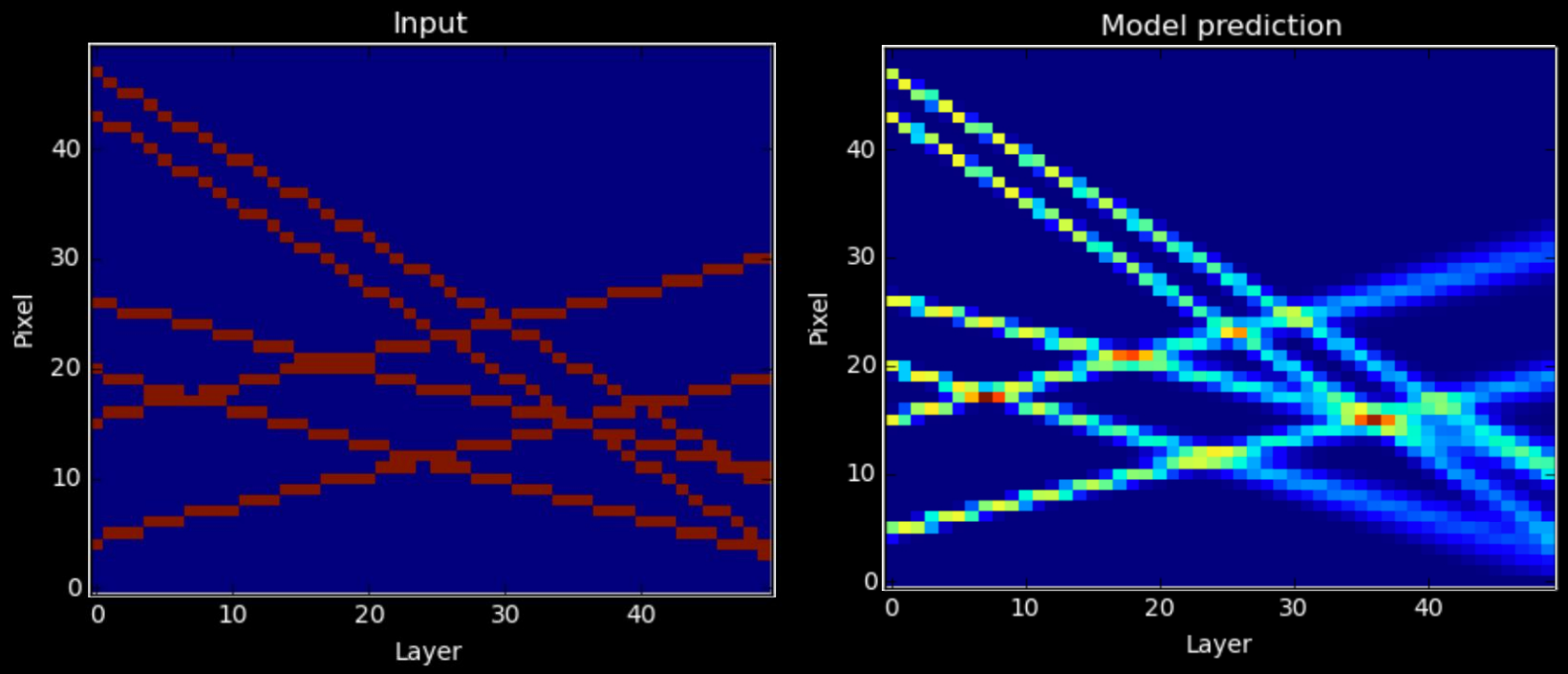


Figure 6: **Left:** The input hits given to the network. **Right:** Tracks reconstructed using the parameters learned from the input.

[5] The HEP.TrkX Project: deep neural networks for HL-LHC online and offline tracking, CTD/WIT 2017, https://doi.org/10.1051/epjconf/201715000003

Summary

- Track reconstruction needs to adapt to higher track multiplicities
- Promising results from deep learning approaches in tracking
- Many interesting projects on-going, many more to follow