Machine Learning techniques for long lived Dark Photon at ATLAS

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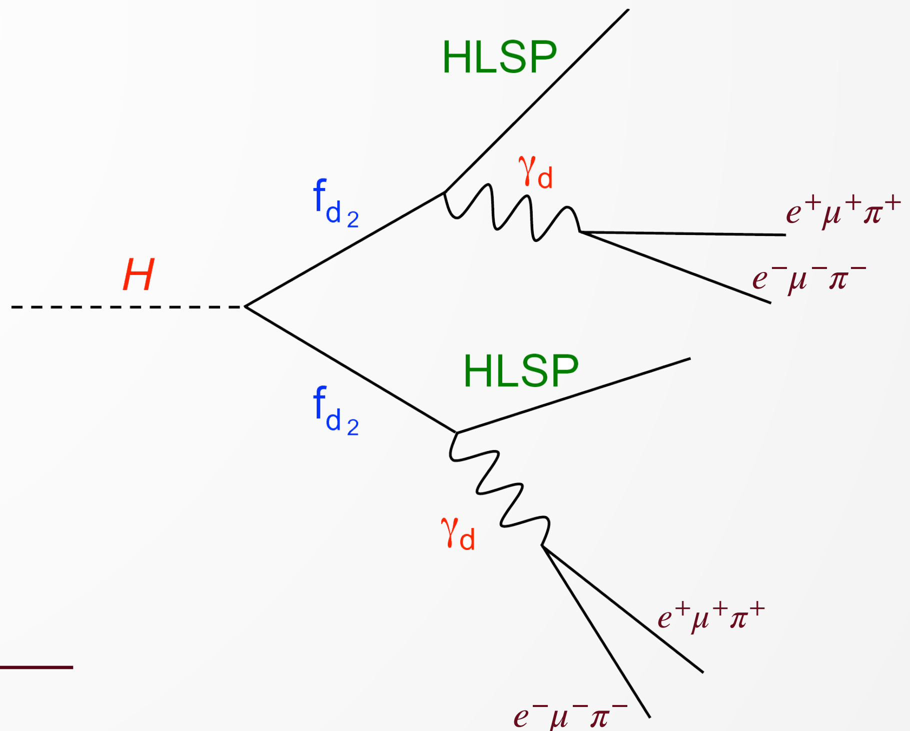
ATLAS EXPERIMENT

INFN

Benchmark model

- Hidden sector weakly coupled with SM
- Minimal model!
  - No direct coupling to SM - new U(1) gauge invariance
  - Kinetic mixing with only one parameter (ε)
  - Search oriented to small ε and mass, highly collimated decay products

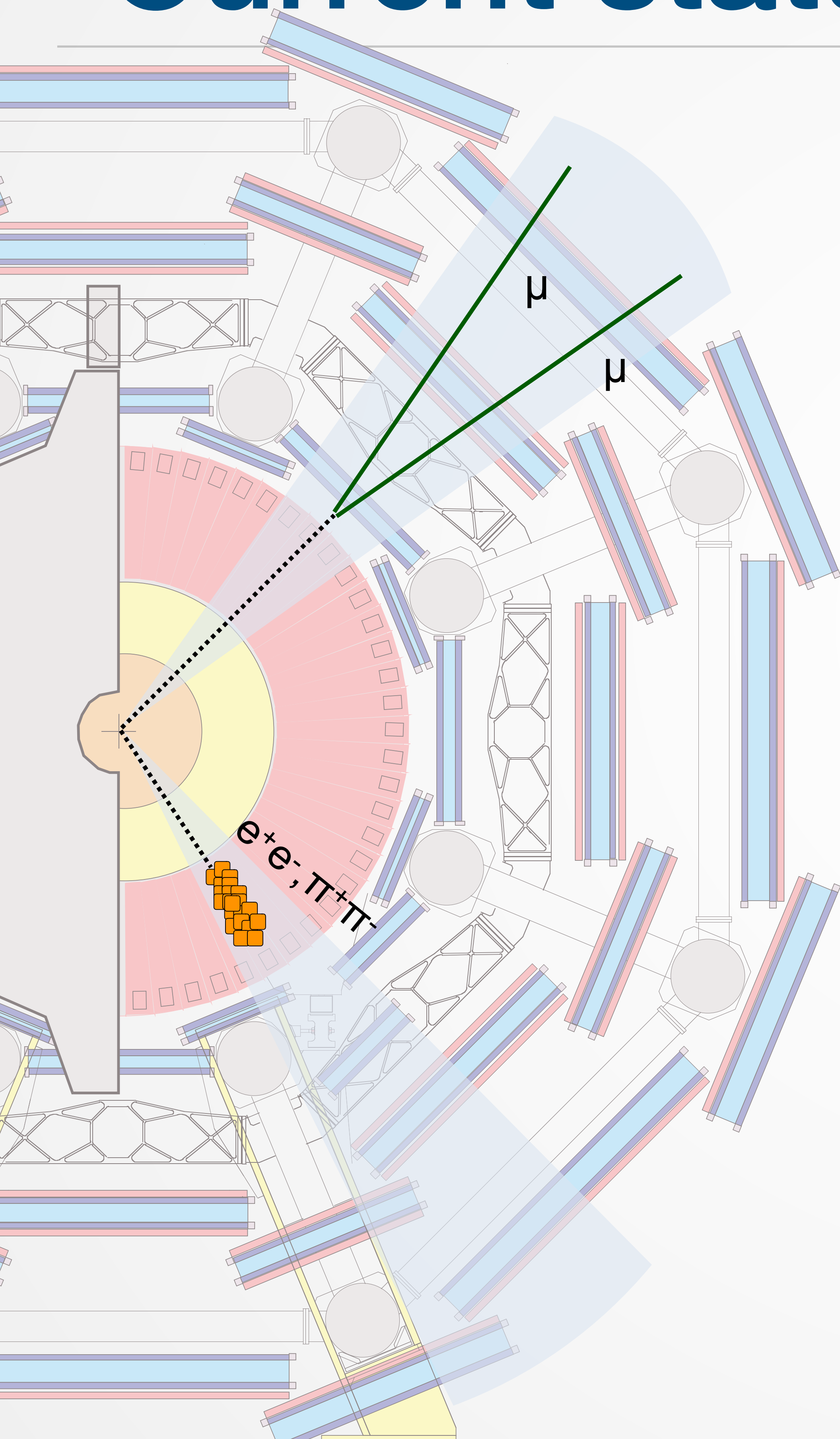


Dark-QED U(1)

$$\mathcal{L} \propto \epsilon e \gamma_d^\mu J_\mu^{em}$$

$$c\tau = \frac{1}{\Gamma_{\gamma_d}^{\mathrm{tot}}} \propto \frac{1}{\epsilon^2 m_{\gamma_d}}$$

Current status in ATLAS



- Muonic Lepton Jets:
  collimated muon bundle in the MS with no tracks in the ID
  main background: cosmic

- Hadronic Lepton Jets:
  Low E_{ECAL}/E_{HCAL} jets with no tracks in the ID
  main background: QCD multijet, beam induced background

Event Selection
Dedicated Triggers, Quality cuts, PV

LJ Selection
2 LJ per event, Cuts on LJ, BDT selection

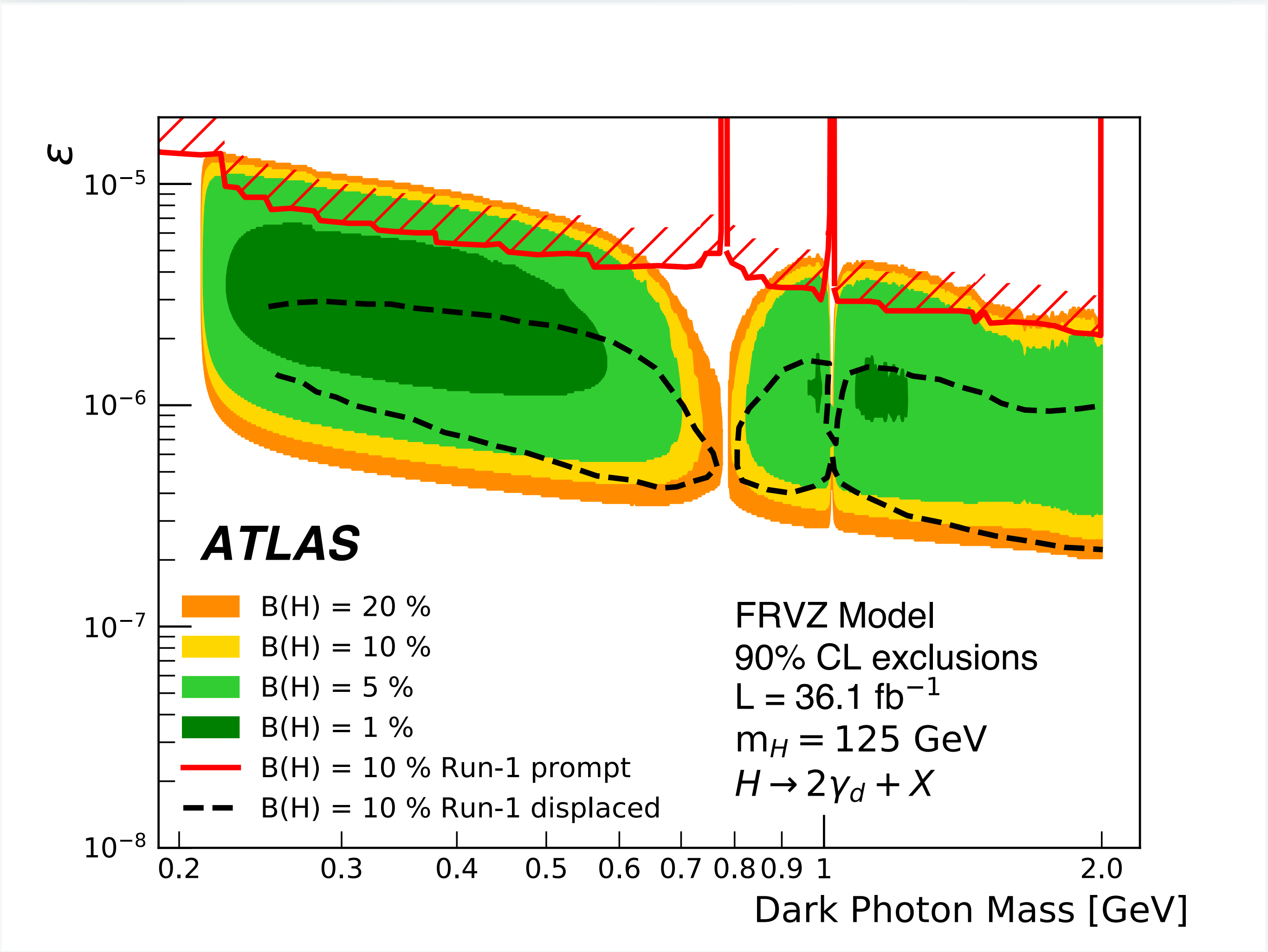
ABCD plane
Isolation in ID, $\Delta\phi$ between LJ

CERN-EP-2019-140

Current status in ATLAS

Results on 36 fb^{-1} data collected in 2015-2016 at $\sqrt{s}$ = 13 TeV

Exclusion possible only in muonic Lepton Jet case due to low sensitivity!



Main Limitations

Muonic channel:

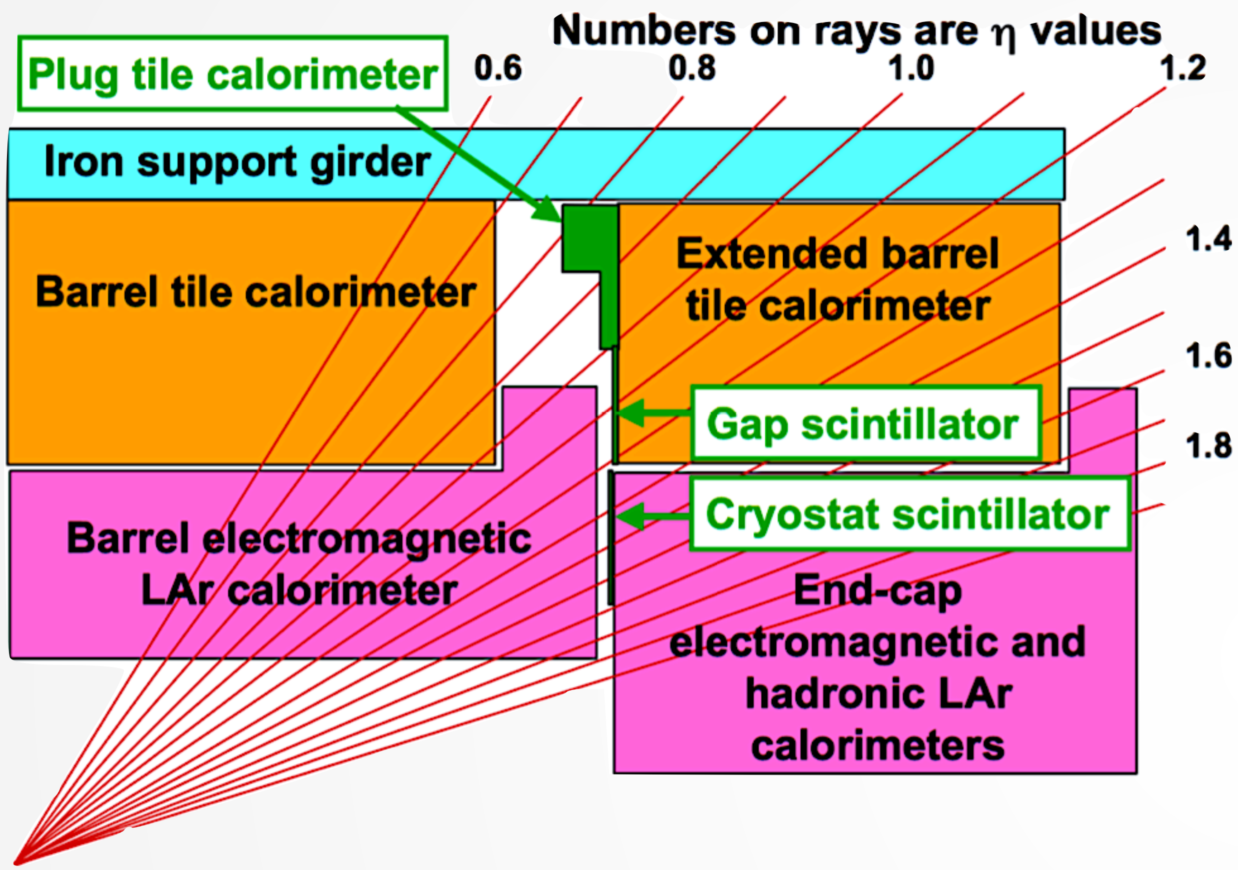
- LLP triggers limited due to p_T requirements to keep rate low.
- maximum number of muons in the same RoI
- Intrinsic pointing to IP

Hadronic channel:

- BDT not enough powerful to discriminate signal from background

Deep Learning can help us to overcome these limitations!

Learn from RAW data!



The idea:
Make a map of jet energy deposits!

A Convolutional Neural Network could process RAW information obtained from jet deposits relative position and energy distribution

Processing this information, additional LLP features may be learnt and used alongside of jet-level variables
(jet p_T, jet timing, jet mass, JVT, charge ...)

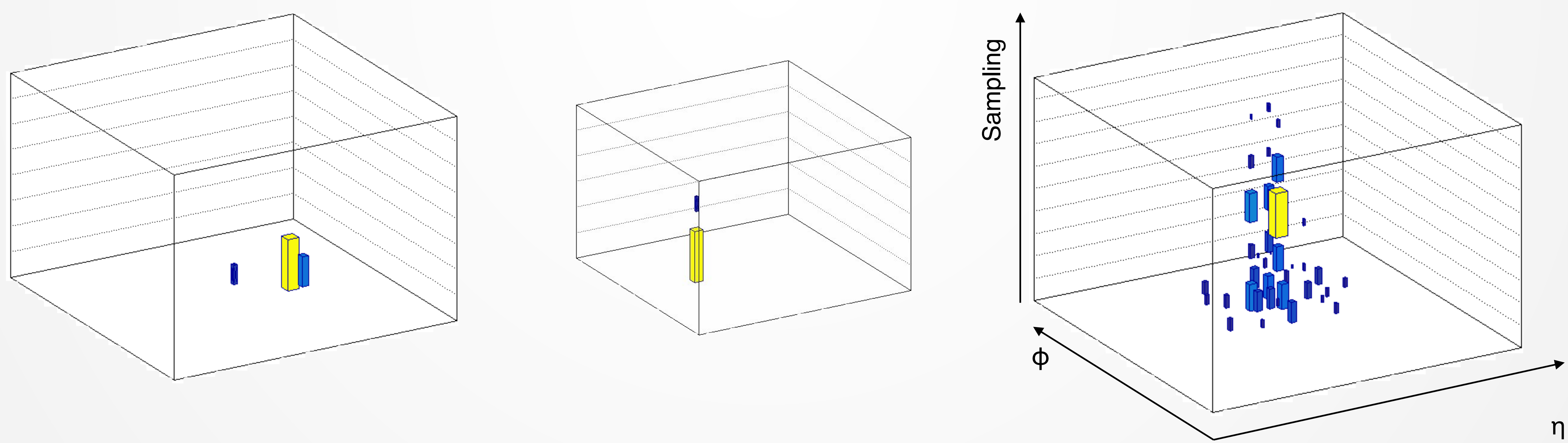
This information could be obtained from:
Jet associated cells position (x,y,z) of calorimeter cell
Jet associated calocluster information
(eta, phi, E in each calo sampling)

This study

Calorimetric jet images

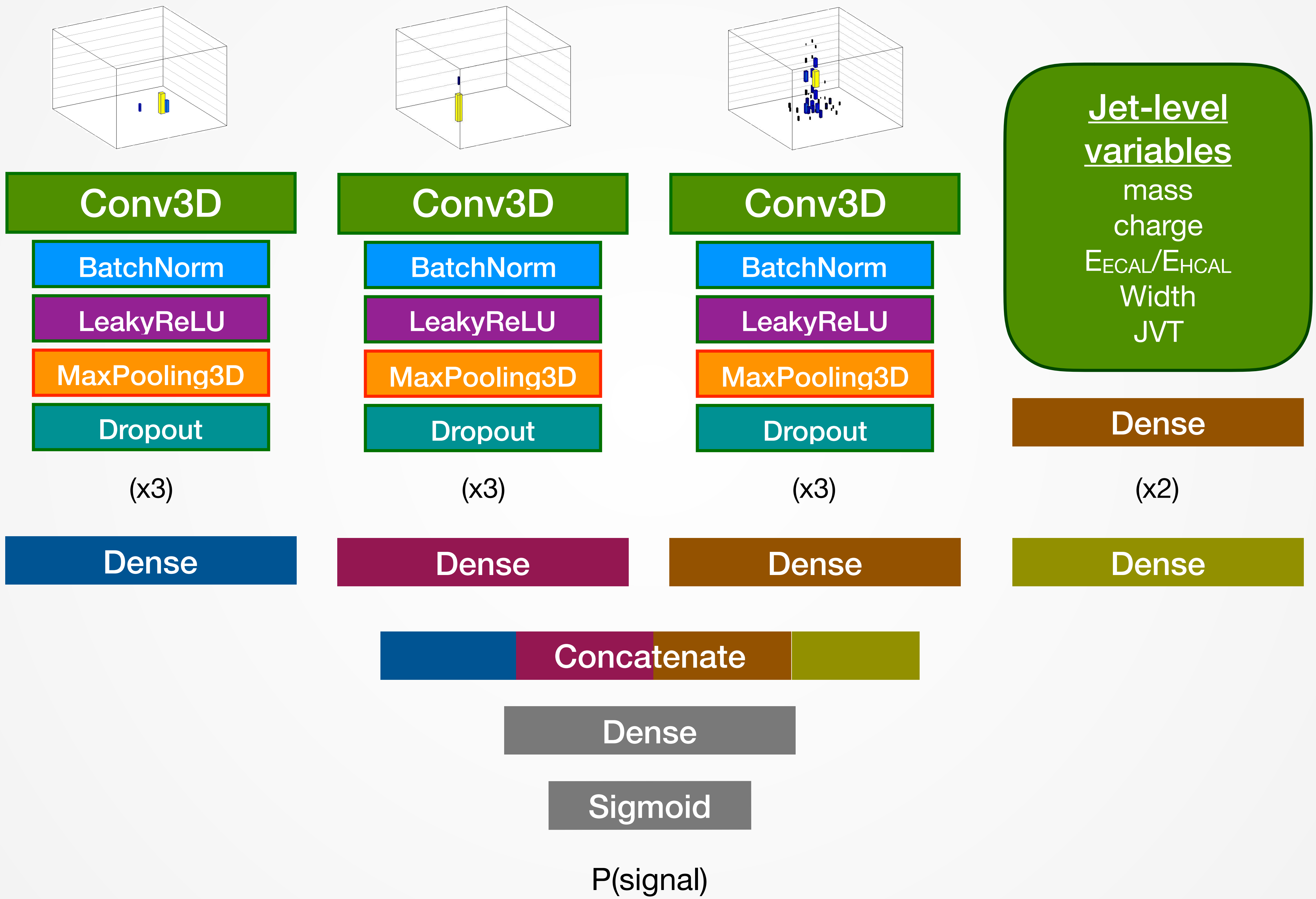
Jet clusters

TileBar2	TileExt2	HEC3
TileBar1	TileExt1	HEC2
TileBar0	TileExt0	HEC1
preSamplerB + EMB		HEC0
		preSamplerE + EME



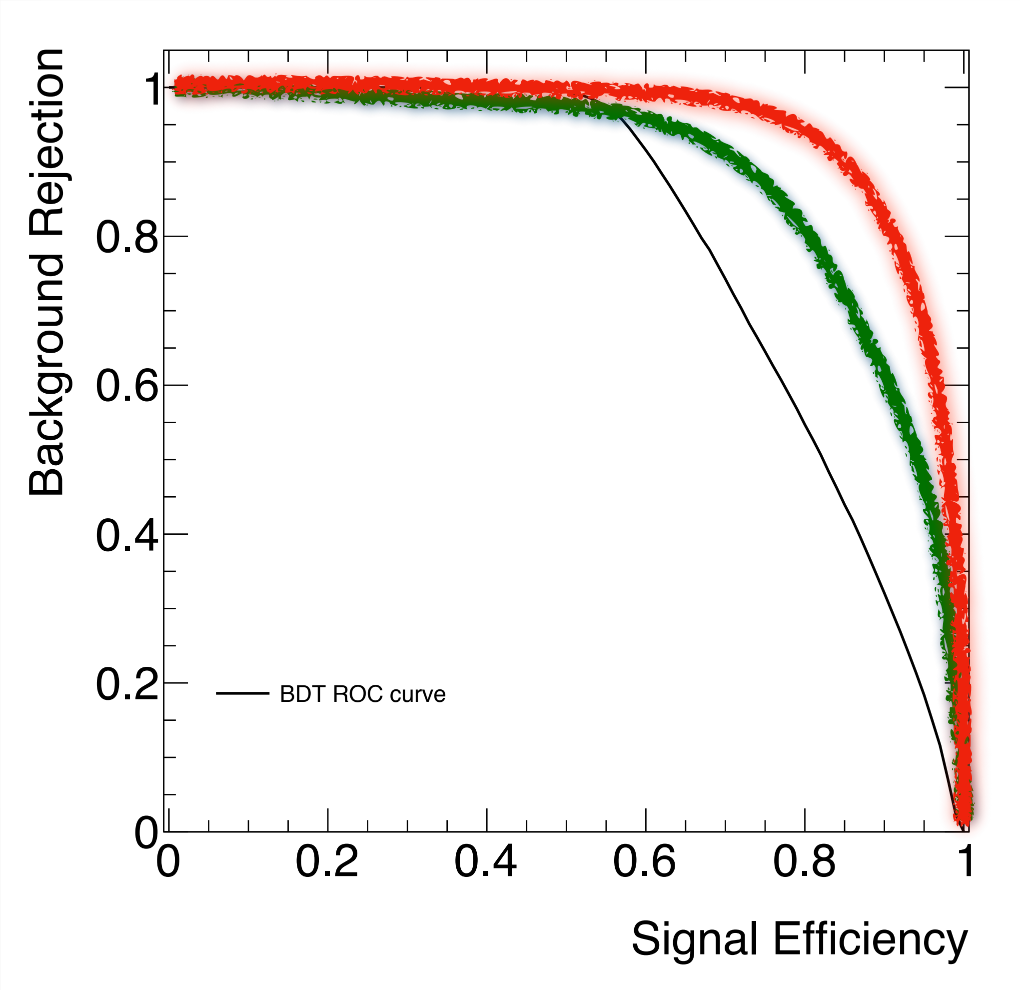
Images corresponds to a 25x25 binned $\eta x \phi$ = [1.4;1.4] window centred around the jet axis

CNN architecture



CNN expected performance

- Improvement to BDT possible due to use of ConvNets
- Standard Network architecture, many optimisation possible



Expected performances

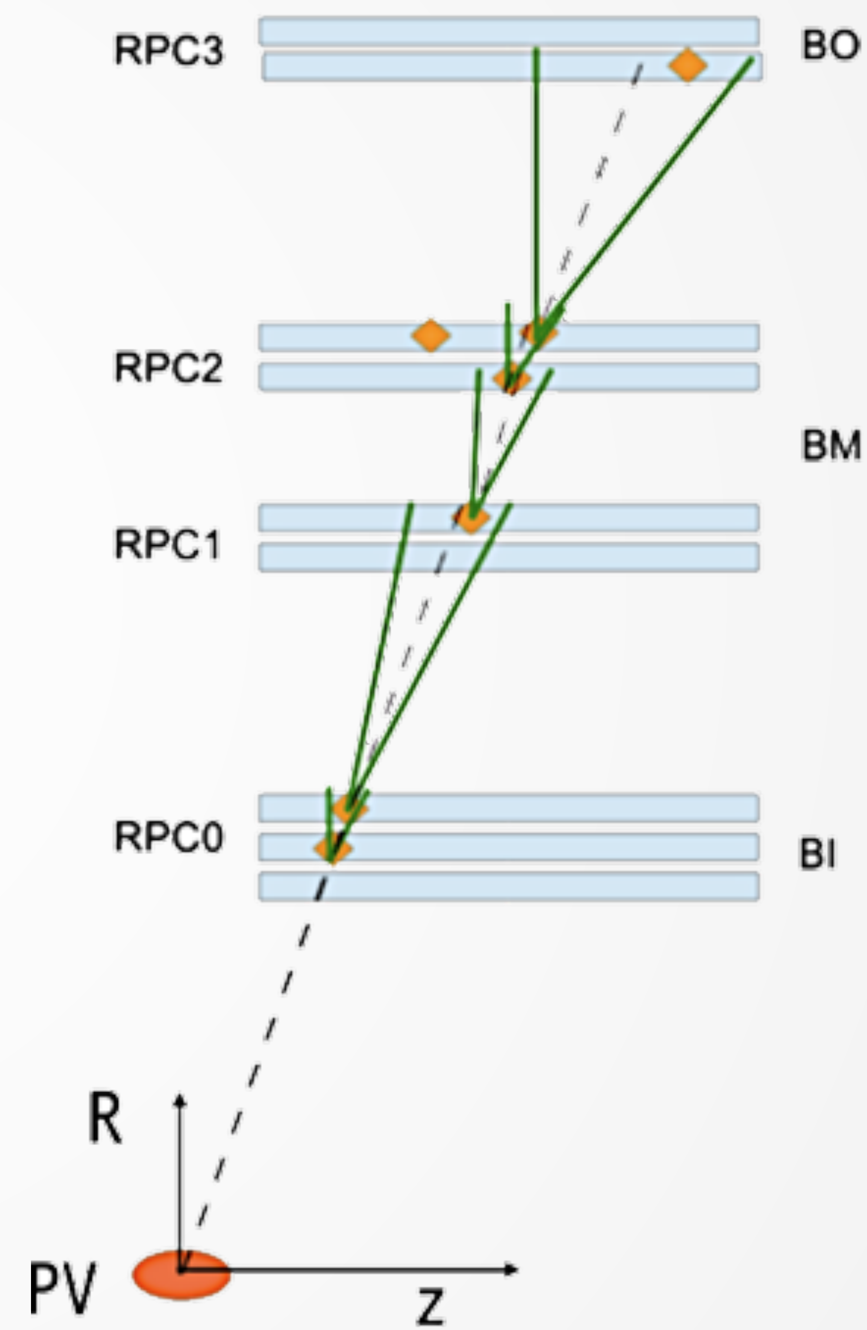
CNN without jet-level variables as input

CNN with jet-level variables as input

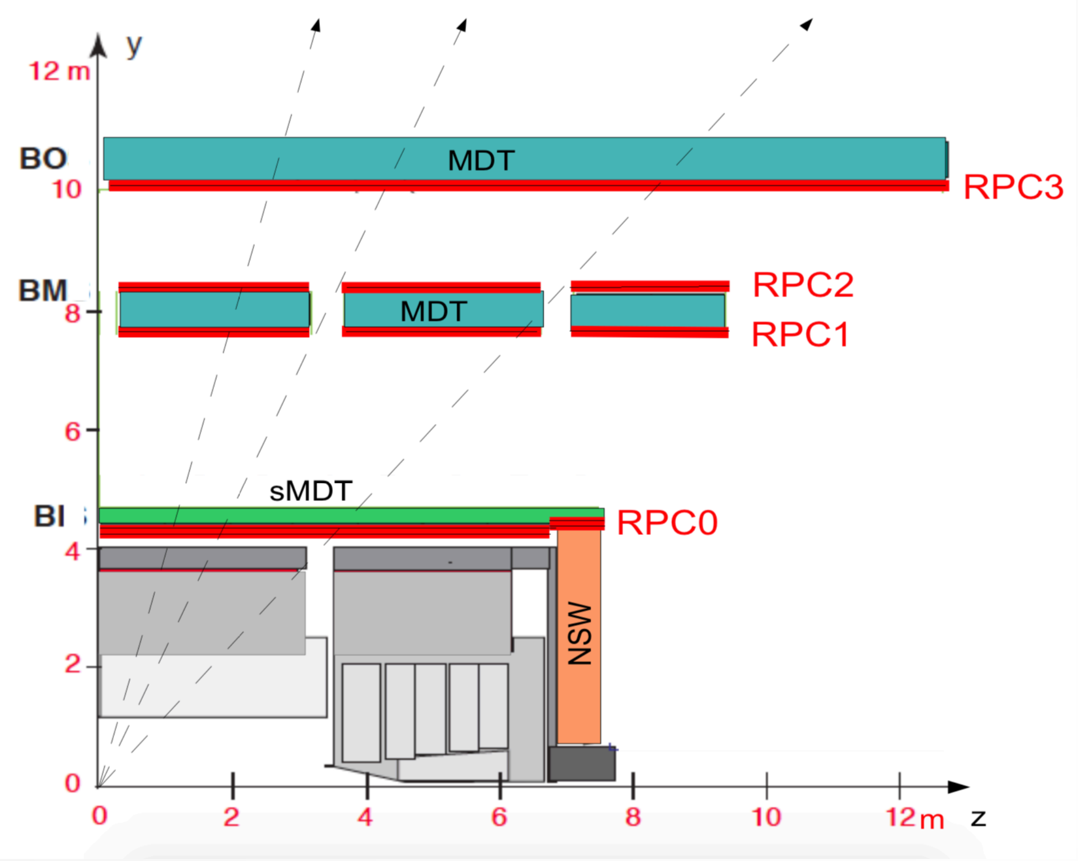
accuracy ~ 88% on test sample

What about trigger?

- Searches for displaced decays in the MS are highly sensitive to triggering algorithms
- Common trigger strategy
  - Recursive search for hits in corresponding coincidence windows
  - Stable and reliable with good performances
  - Momentum estimation limited to a p_T range
  - Pointing constraint to primary vertex

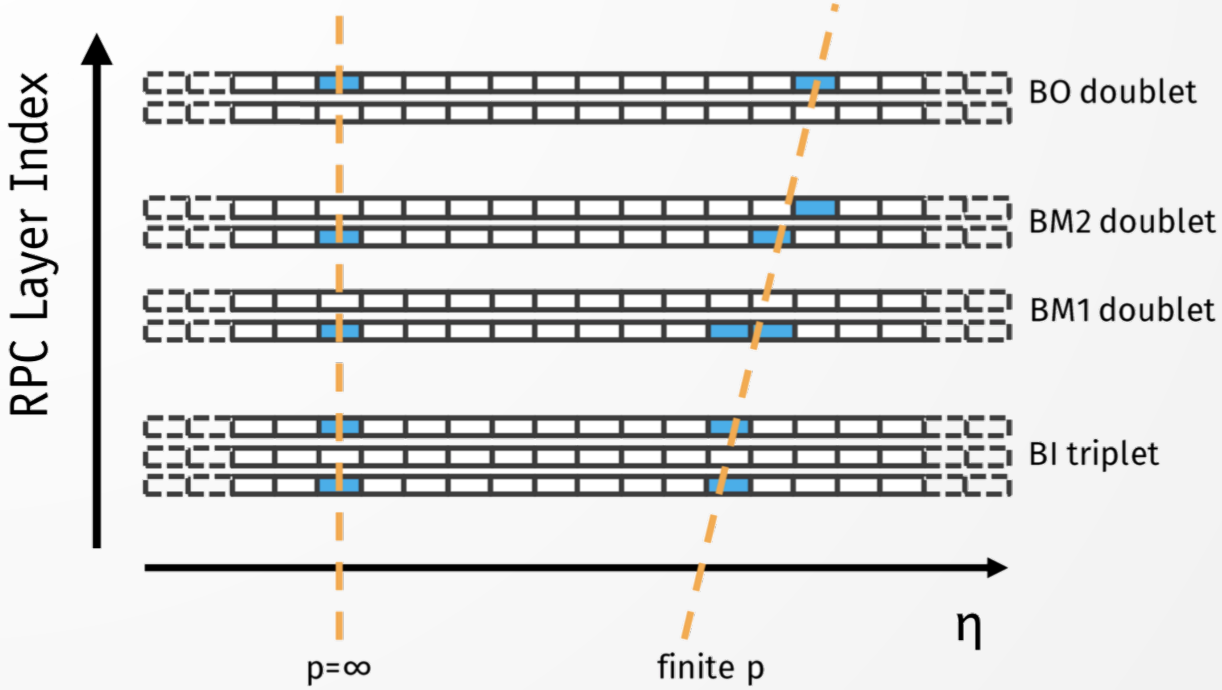


Learn from RAW data!



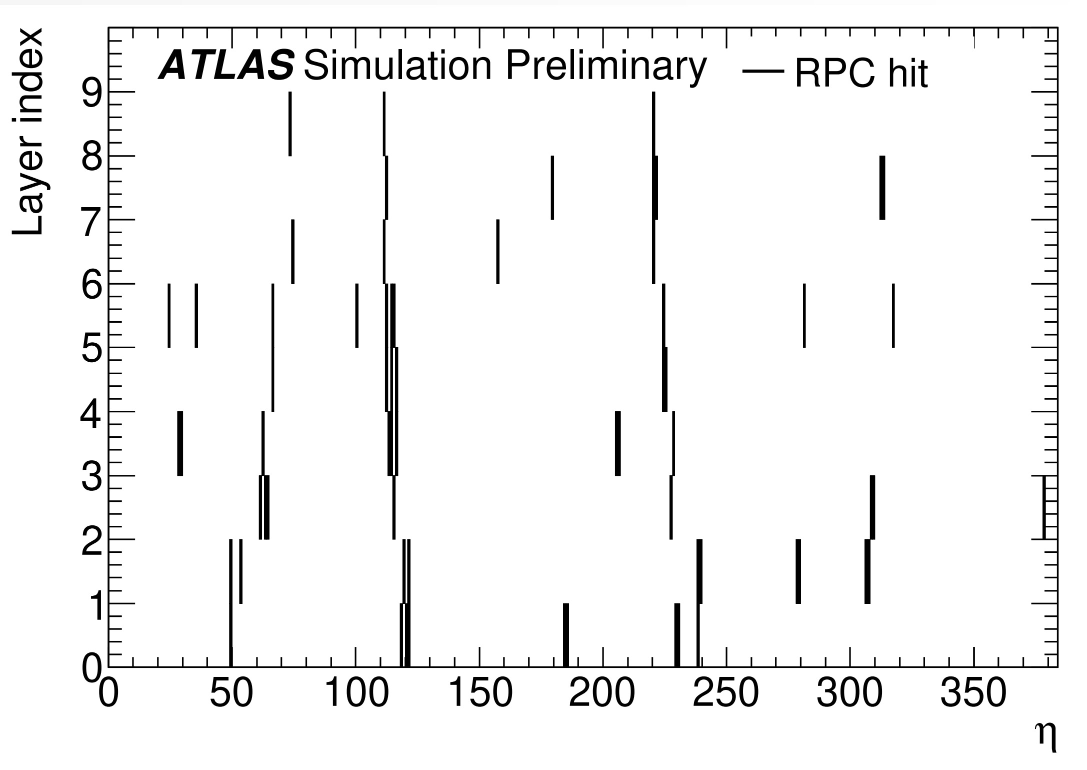
- Phase II ATLAS trigger will be based on high performance Xilinx FPGAs
- Main requirement is on processing time (latency ≤ few μs)
- This opens the possibility to run Deep Learning model at Level-0 trigger

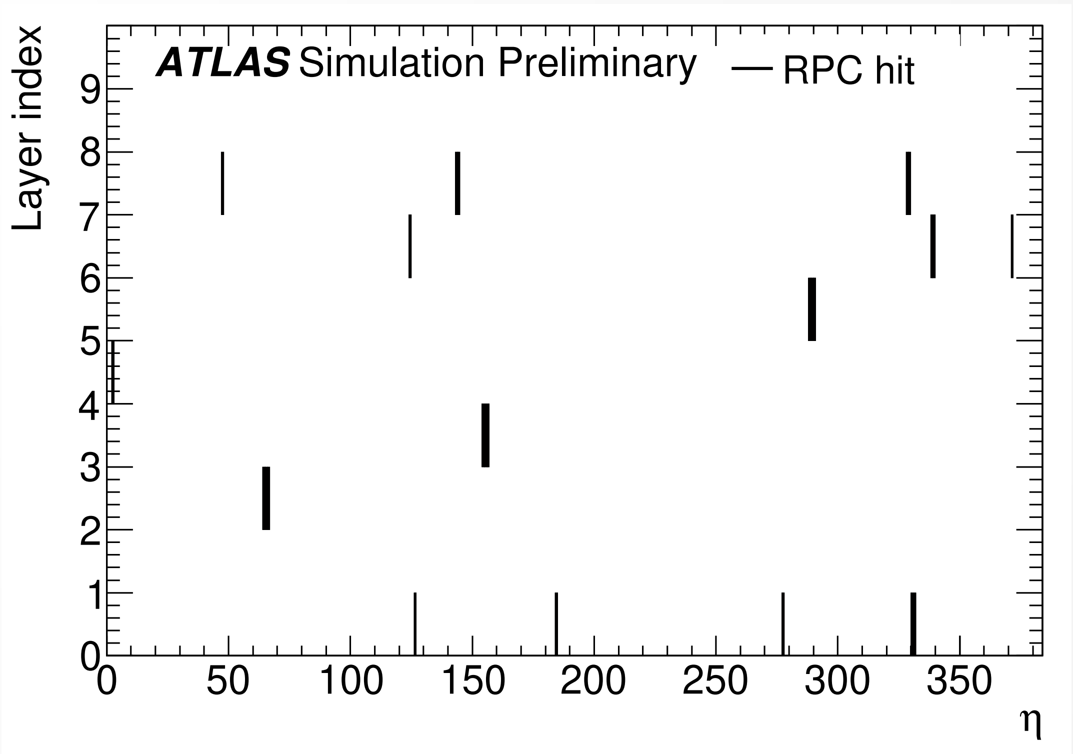
- Signals from RPC mapped to images, which can be processed by a CNN
- Additional features such as secondary vertex, precise p_T measurement, higher trigger efficiency



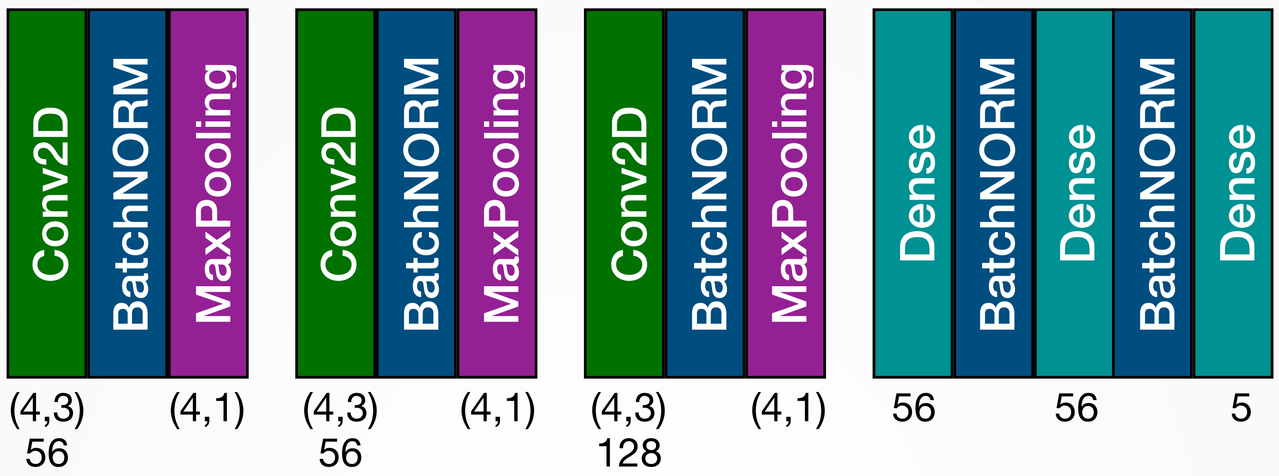
RPC hit maps

- 384 bins in η x 9 RPC station
- Training sample from Phase II FullSim
  flat η,ϕ, p_T distribution ([0; 20] GeV)
  balanced sample with 0 to 3 muons per image





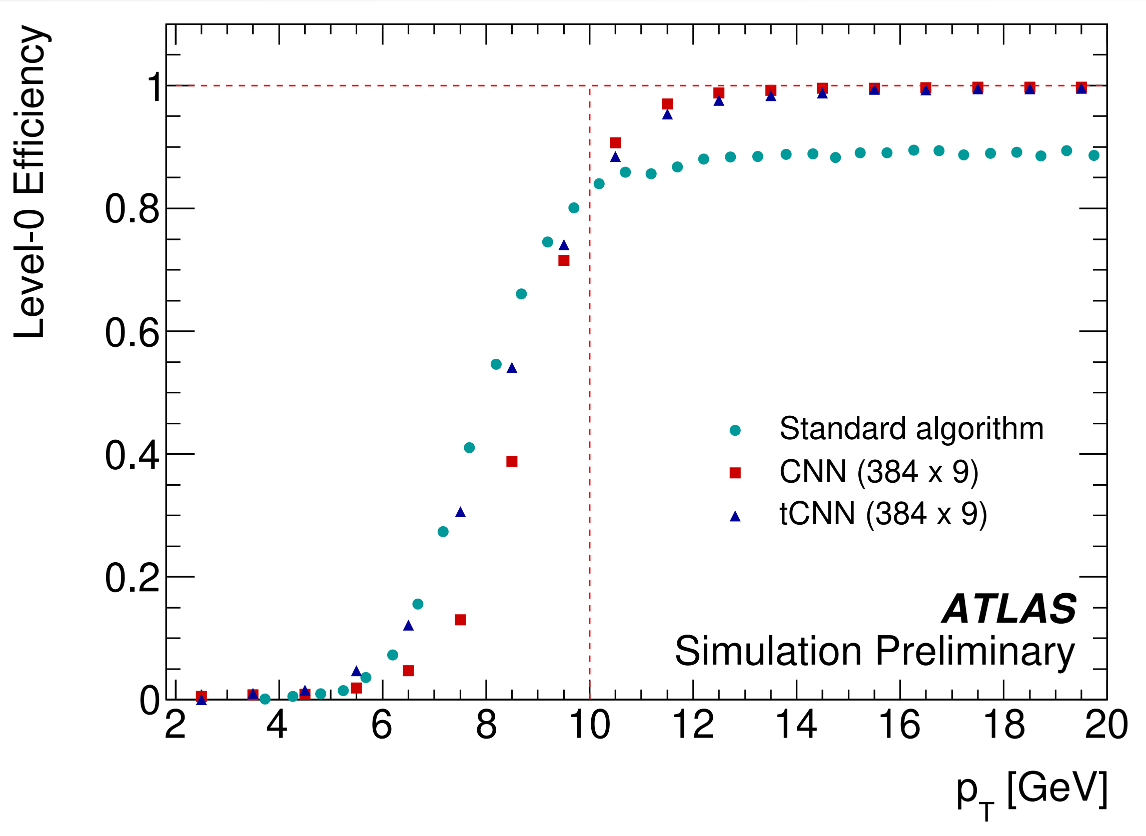
Ternary ConvNet on FPGA



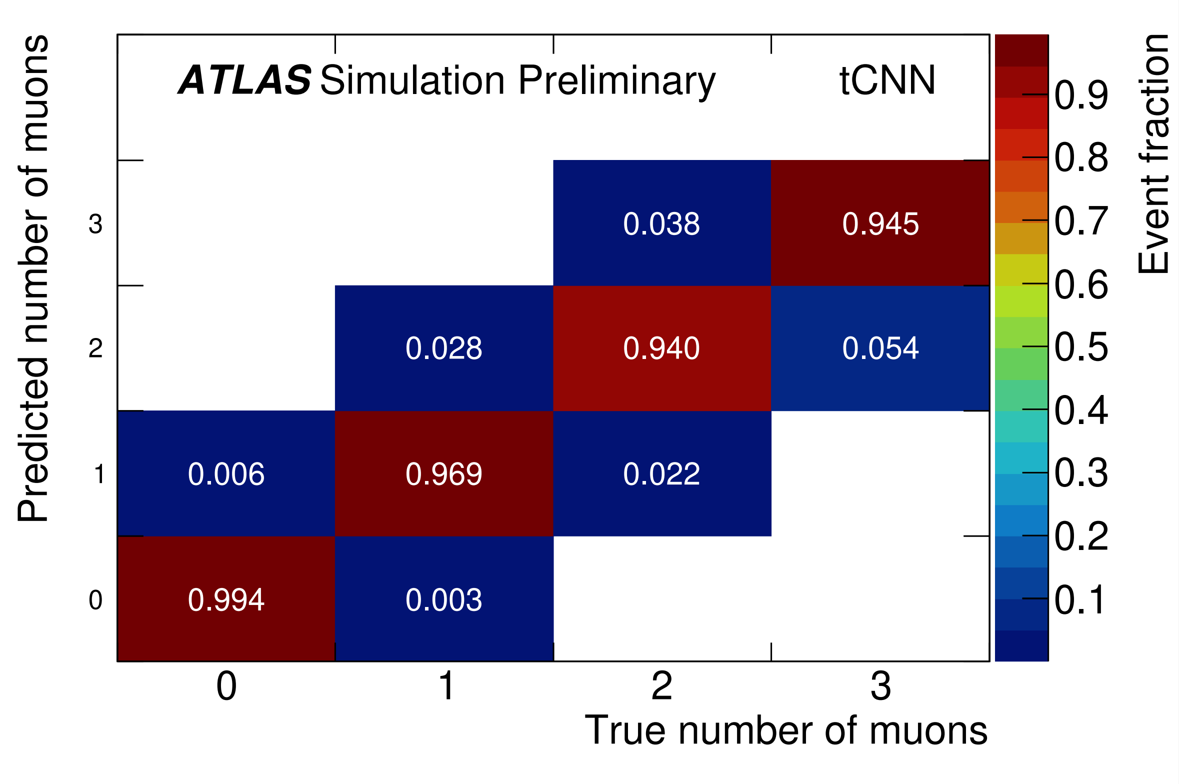
- Limited resources on FPGA → ternary network!
  - {-1, 0, 1} as network weights to reduce memory usage
  - Lower number of operations: no multiplication if w=0
  - Parallelisation of the input for smarter FPGA usage
  - Simplified VGG-like network

Trigger performance

efficiency for p_T = 10 GeV threshold



Confusion matrix



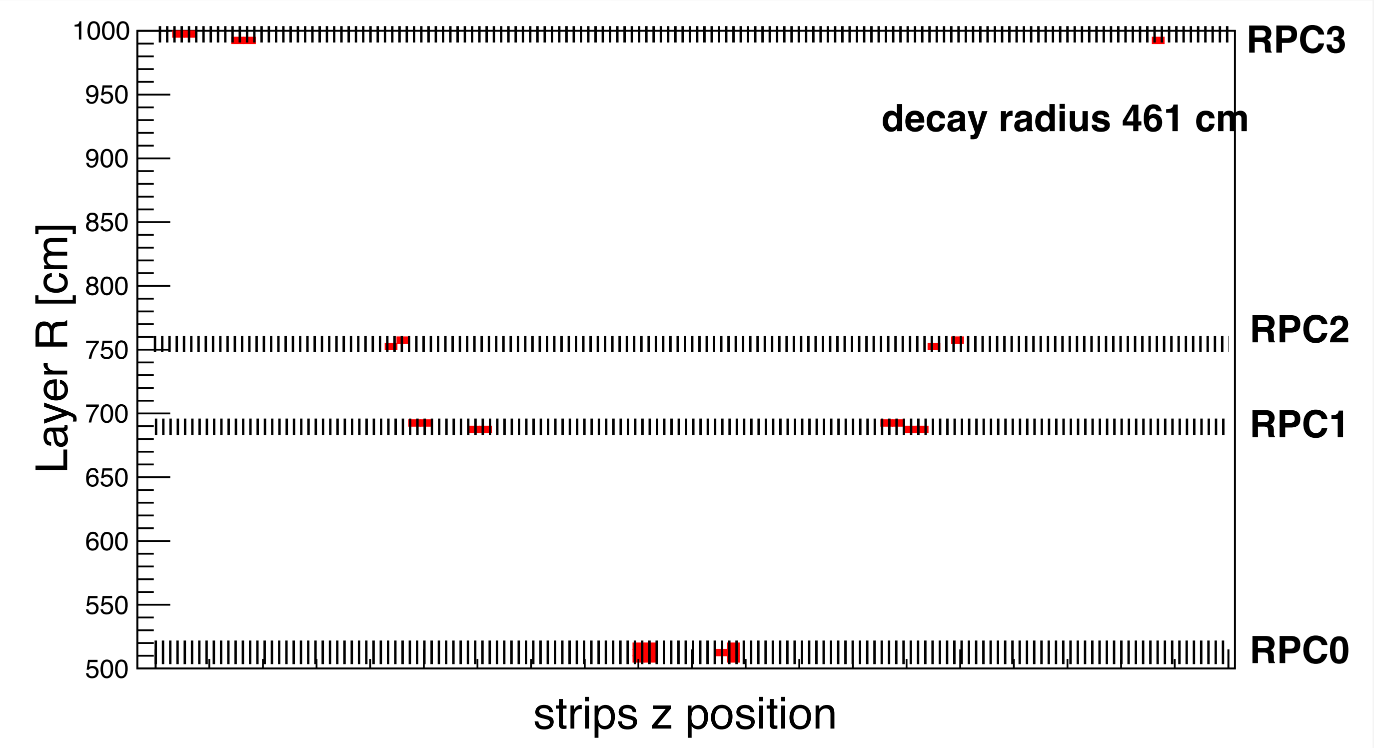
fake rate of 0.6% without p_T requirement
reduced to 0.01% for p_T = 10 GeV threshold

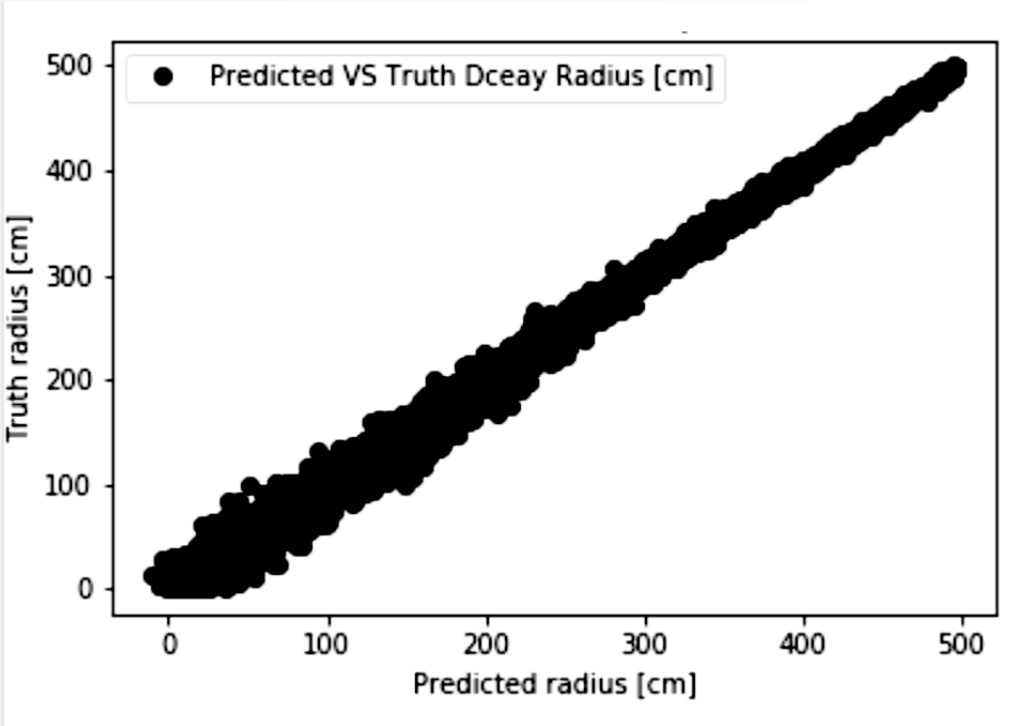
Secondary vertices

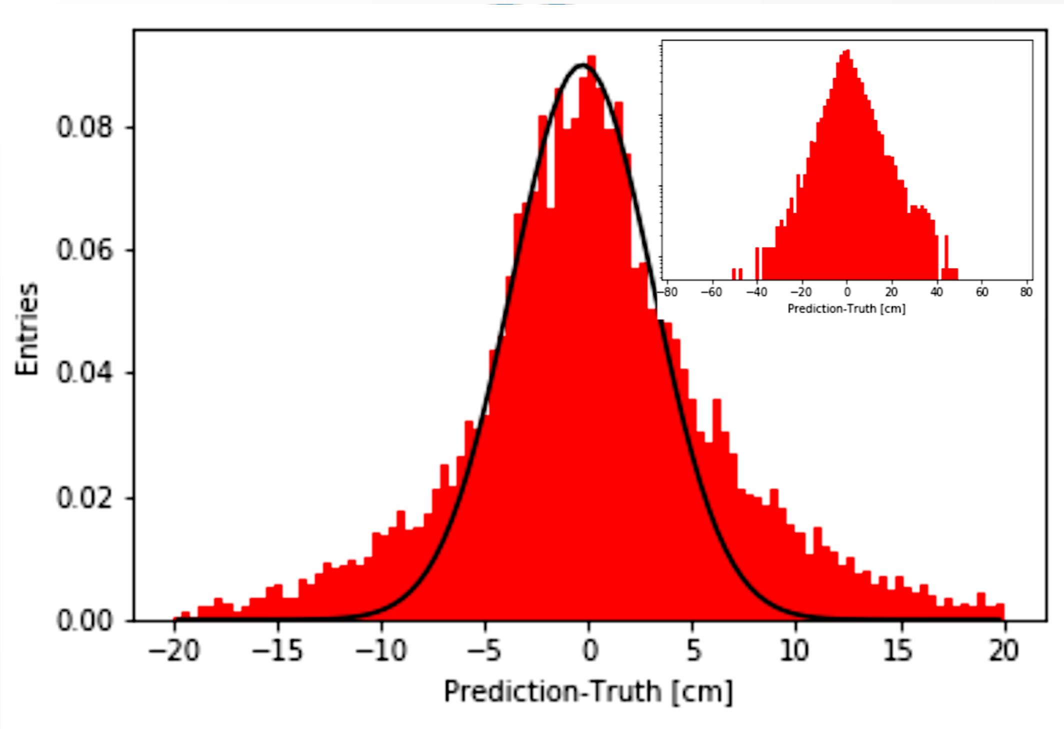
Toy images for displaced vertex identification

$p_T > 20$ GeV
$L \in [0,5]$ m
$\Delta\Phi \in [0.05,0.2]$ rad

Ongoing studies on FullSim events







σ~ 3.5cm, μ~-0.3cm

Wrapping up

- Dark Photon searches can be heavily improved with better object identification and trigger ability to identify secondary vertices
- **(Deep) Learning using RAW information can be the key!**
- 3D jet image ConvNet can exploit key features from jet cluster topology providing a highly efficient selection
- Exploiting FPGA CNN at L0 for precise p_T measurement and secondary vertexing
- Trigger features already implemented for prompt muons!