Study of energy deposition patterns in hadron calorimeter for prompt and displaced jets using convolution neural network

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Abstract

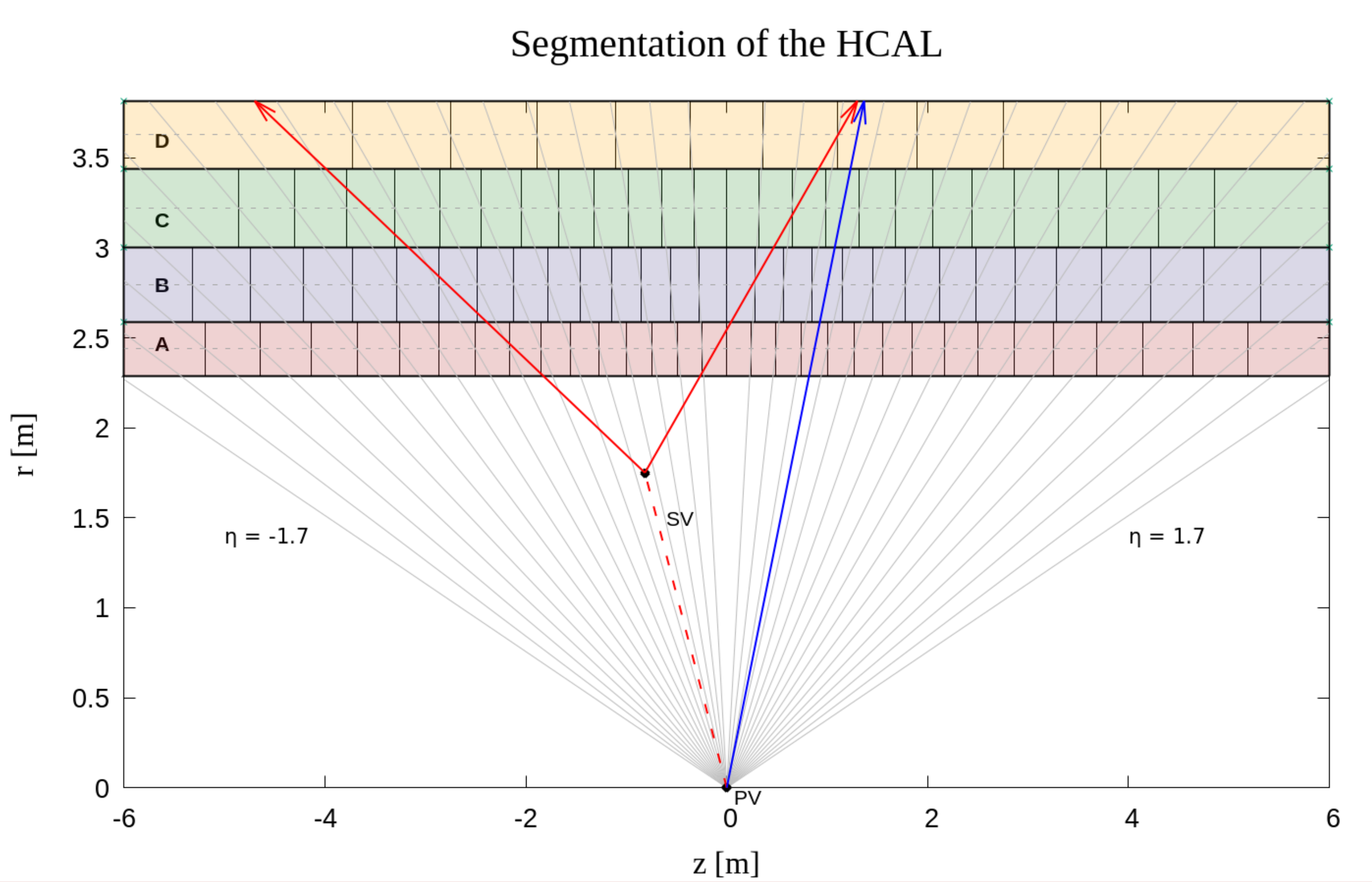
Sophisticated machine learning techniques have promising potential in search for physics beyond Standard Model in Large Hadron Collider (LHC). Convolutional neural networks (CNN) can provide powerful tools for differentiating between patterns of calorimeter energy deposits by prompt particles of Standard Model and long-lived particles predicted in various models beyond the Standard Model. We demonstrate the usefulness of CNN by using a couple of physics examples from well motivated BSM scenarios predicting long-lived particles giving rise to displaced jets. Our work suggests that modern machine-learning techniques have potential to discriminate between energy deposition patterns of prompt and long-lived particles, and thus, they can be useful tools in such searches.

Questions we're trying to address

- **How is the energy deposition pattern of displaced jets different from prompt jets in the HCAL?**
- **Can CNN learn these features and discriminate prompt jets from displaced jets?**

Simplified simulation of energy deposition in HCAL

- Fast detector simulation (eg. Delphes) will not work because:
  1. no layered calorimeter structure
  2. no segmentation in the physical Z direction.
- So we simulated a simplified calorimeter closely resembling barrel HCAL of ATLAS.



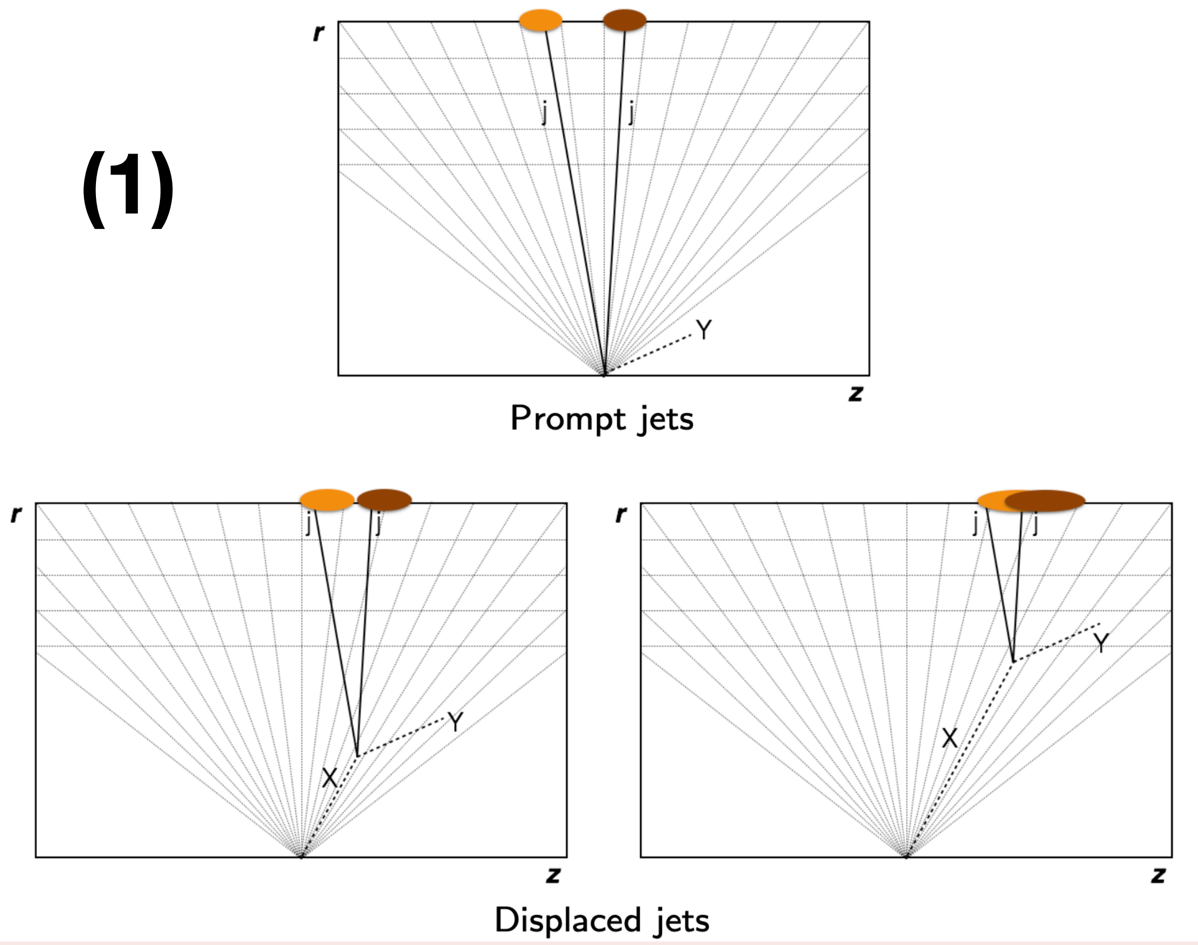
How is the energy deposition pattern of displaced jets different from prompt jets in the HCAL?

Physics Scenarios

Scenario 1:

$X_{LLP} \rightarrow Z_{SM} + Y_{invisible}$ and $Z_{SM} \rightarrow jj$, where $m_X = 800$ GeV .

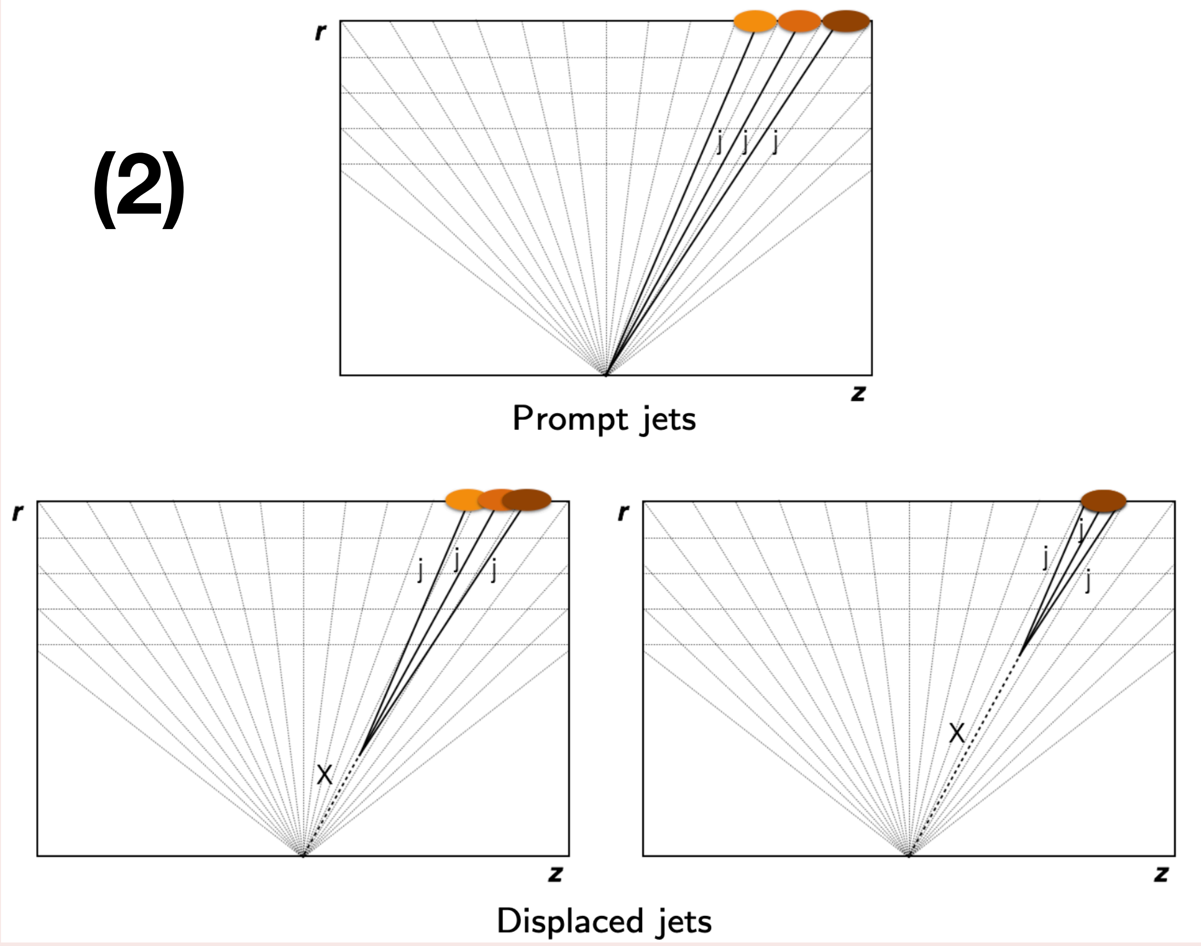
- X_{LLP} can be neutralino in GMSB model.
- Jets ensuing from displaced Z_{SM}.



Scenario 2:

$X_{LLP} \rightarrow jjj$, where $m_X = 100$ GeV .

- X_{LLP} can be neutralino in RPV SUSY model.

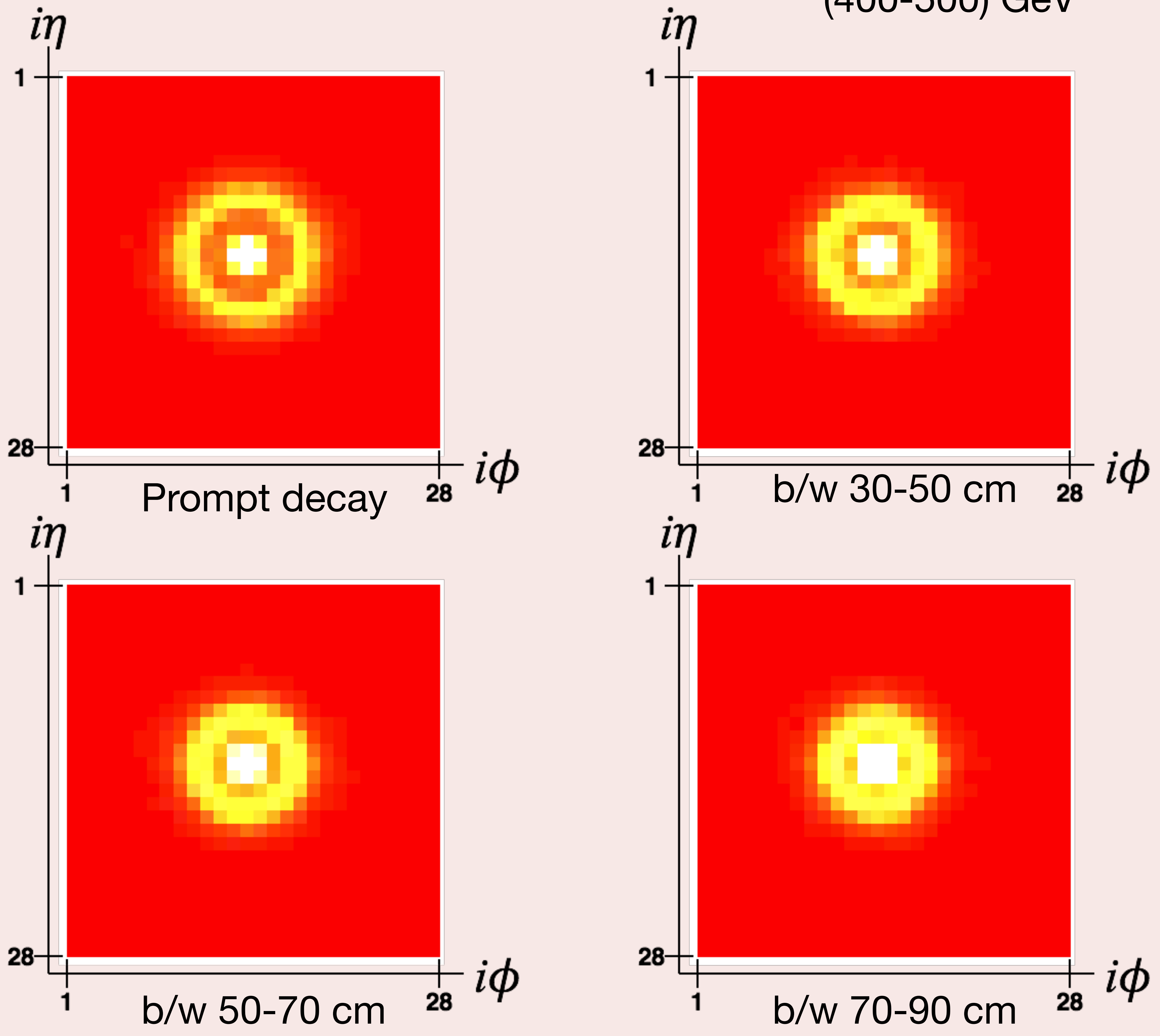


- **Later the decay of X_{LLP}, smaller the physical region in which the deposited energy is contained in HCAL.**
- **Due to mismatch of particle's actual η - ϕ and detector segmentation, more elongated energy deposits in HCAL.**

Energy deposition pattern: Average over many events

Scenario 1:

Total energy deposited: (400-500) GeV



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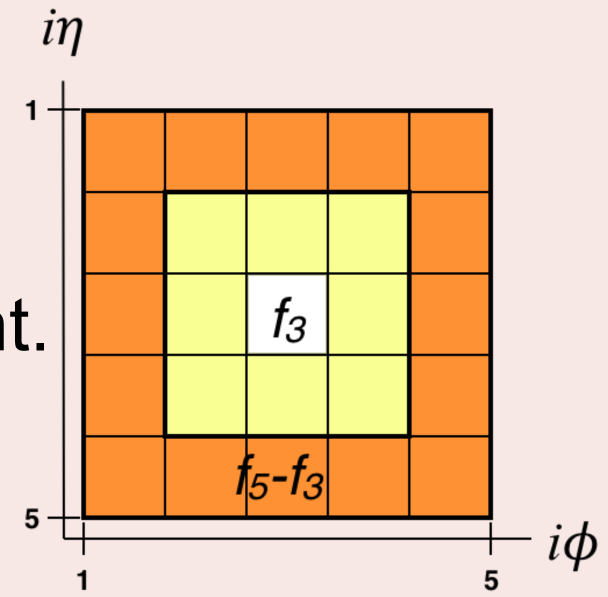
How is the energy deposition pattern of displaced jets different from prompt jets in the HCAL?

Energy fraction histograms

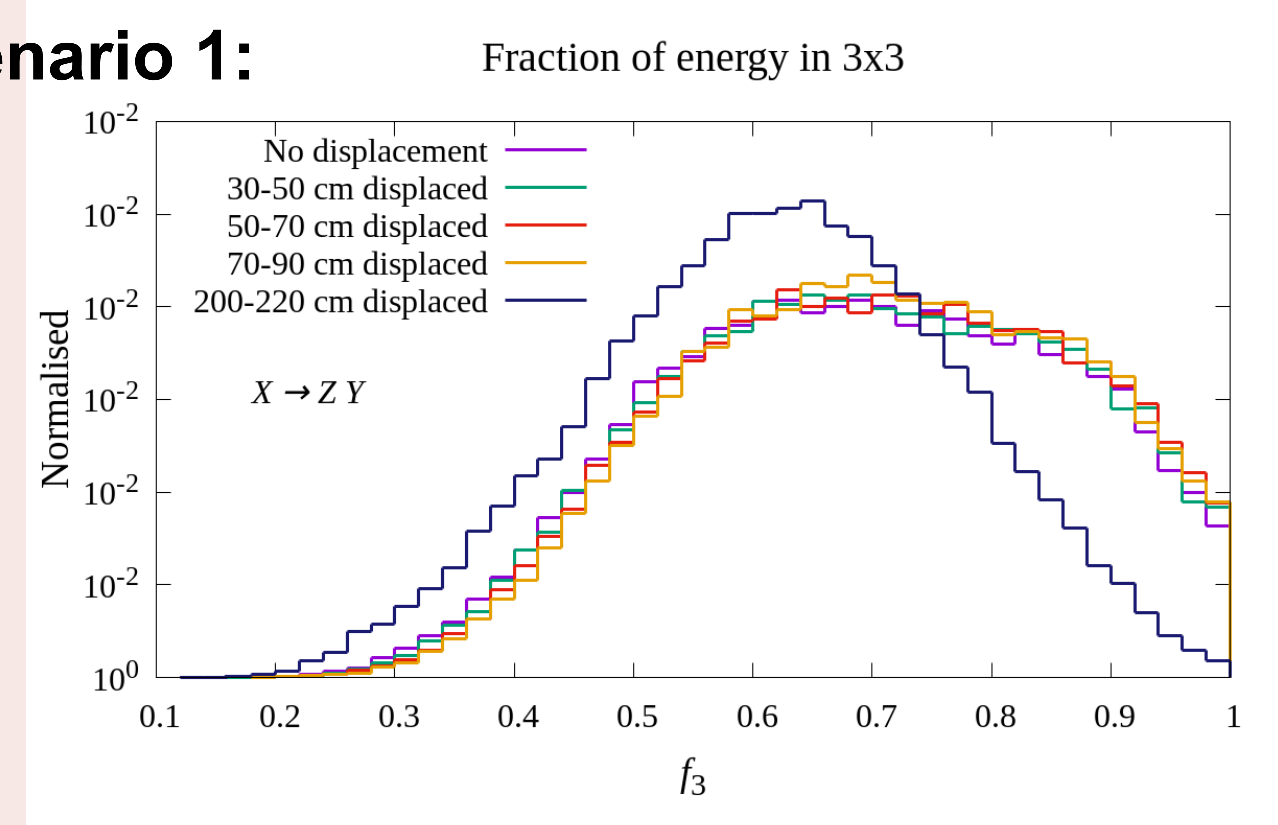
$$f_i = \frac{\text{Energy deposited in } i \times i \text{ block of image}}{\text{Energy deposited in } 28 \times 28 \text{ image}} \quad \text{where } i = 3,5,9,11$$

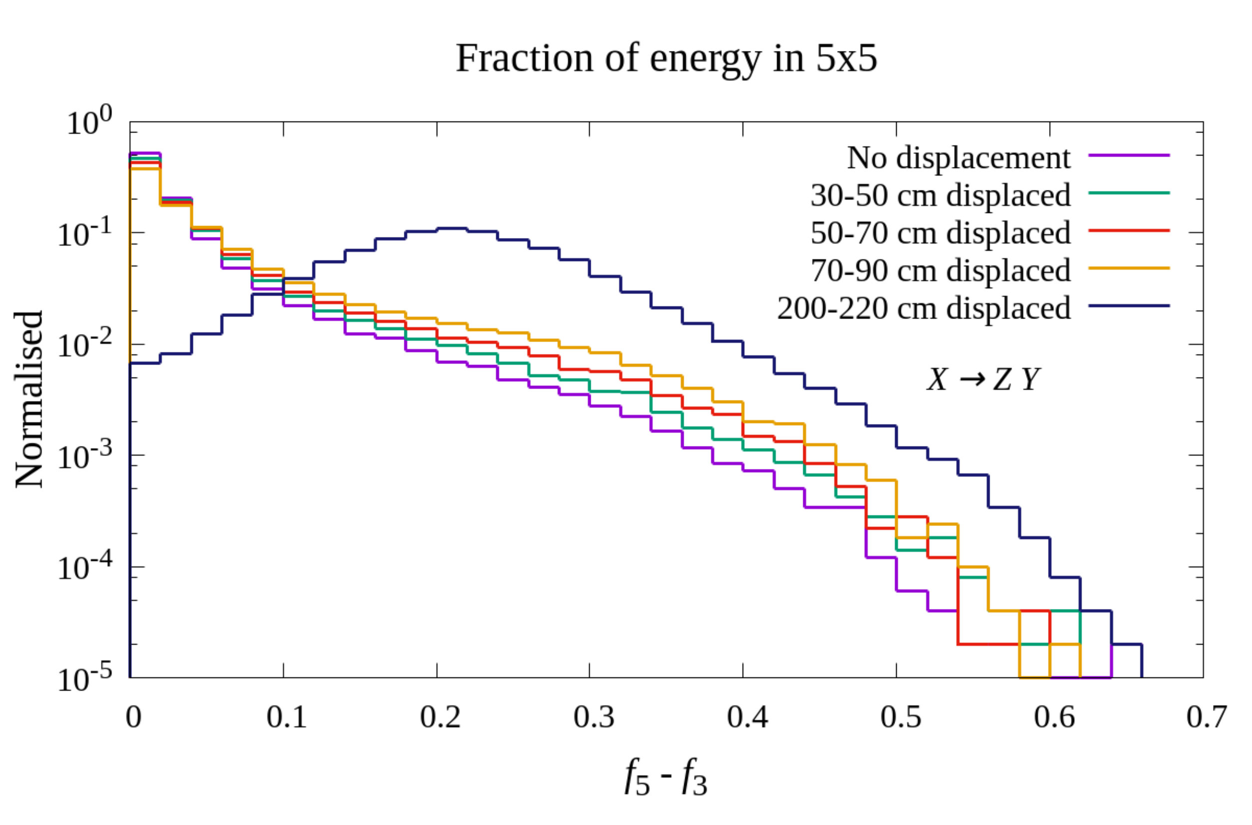


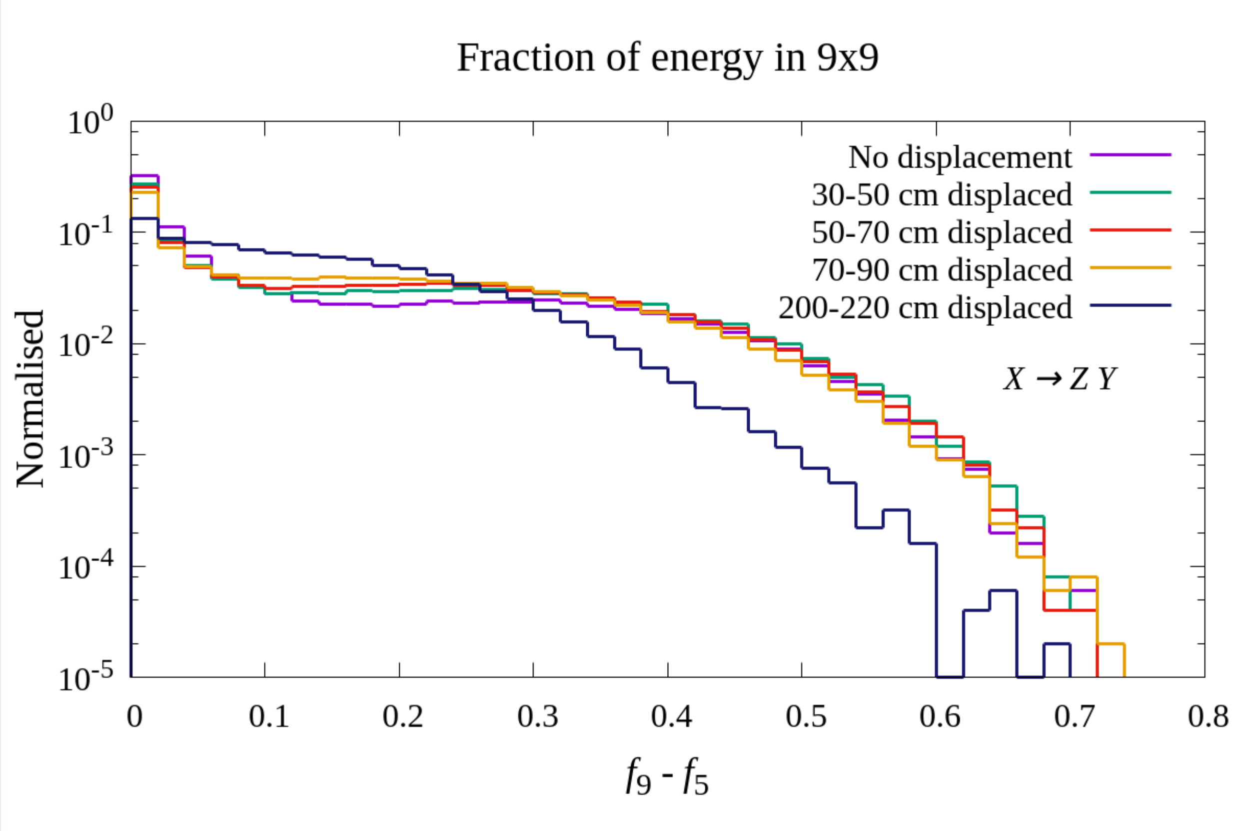
Poor discrimination power — only exception 200-220 cm displacement.

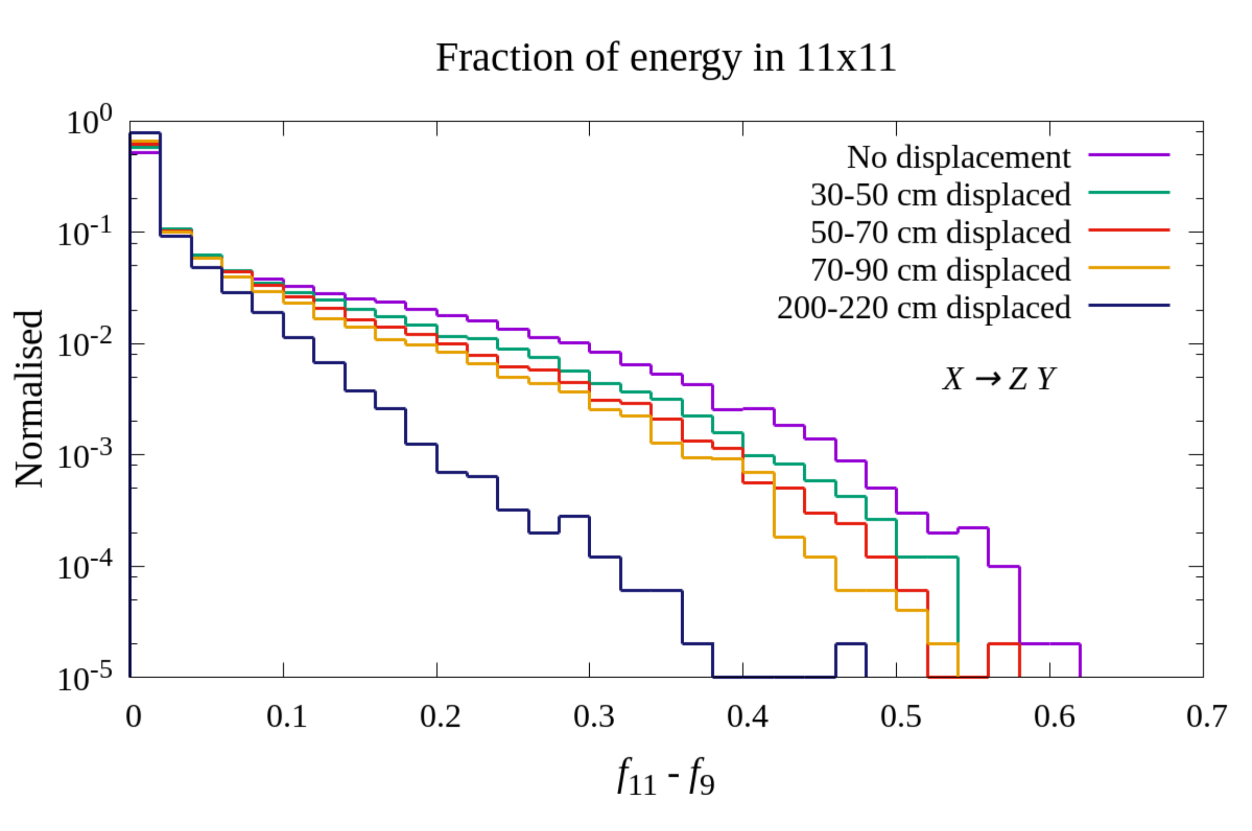
Cut-based analysis not optimal choice.
Deploy computer vision techniques.

Scenario 1:



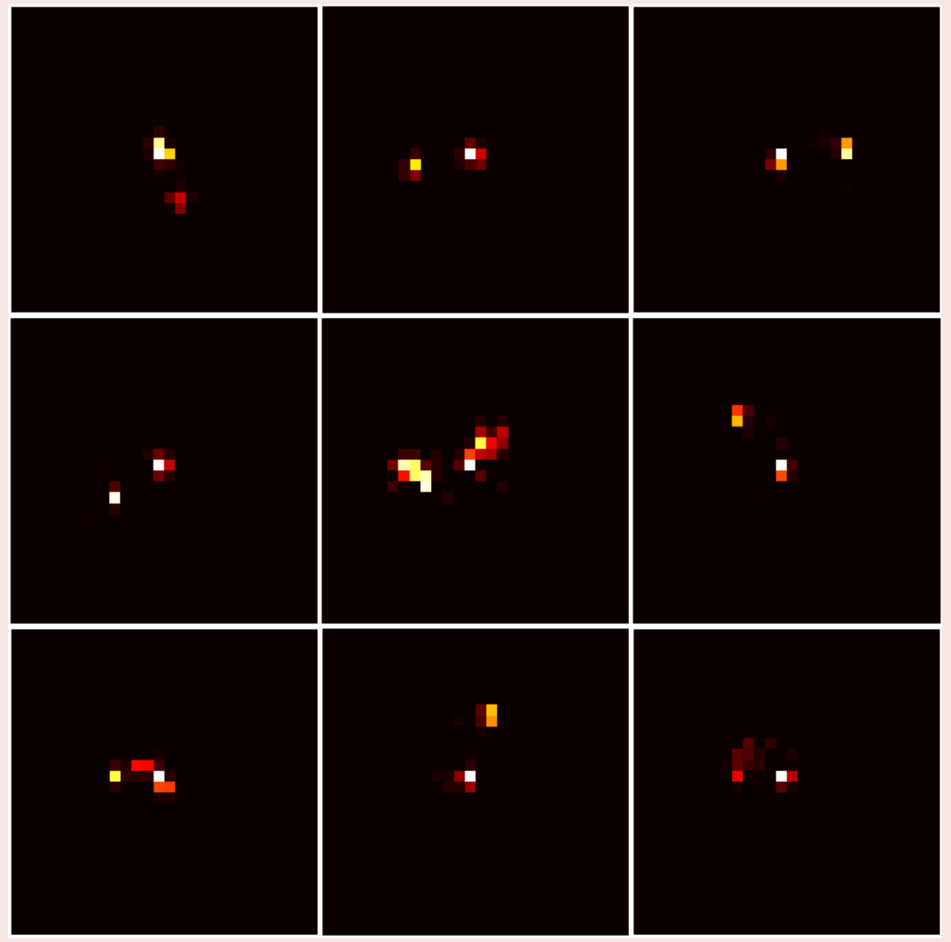




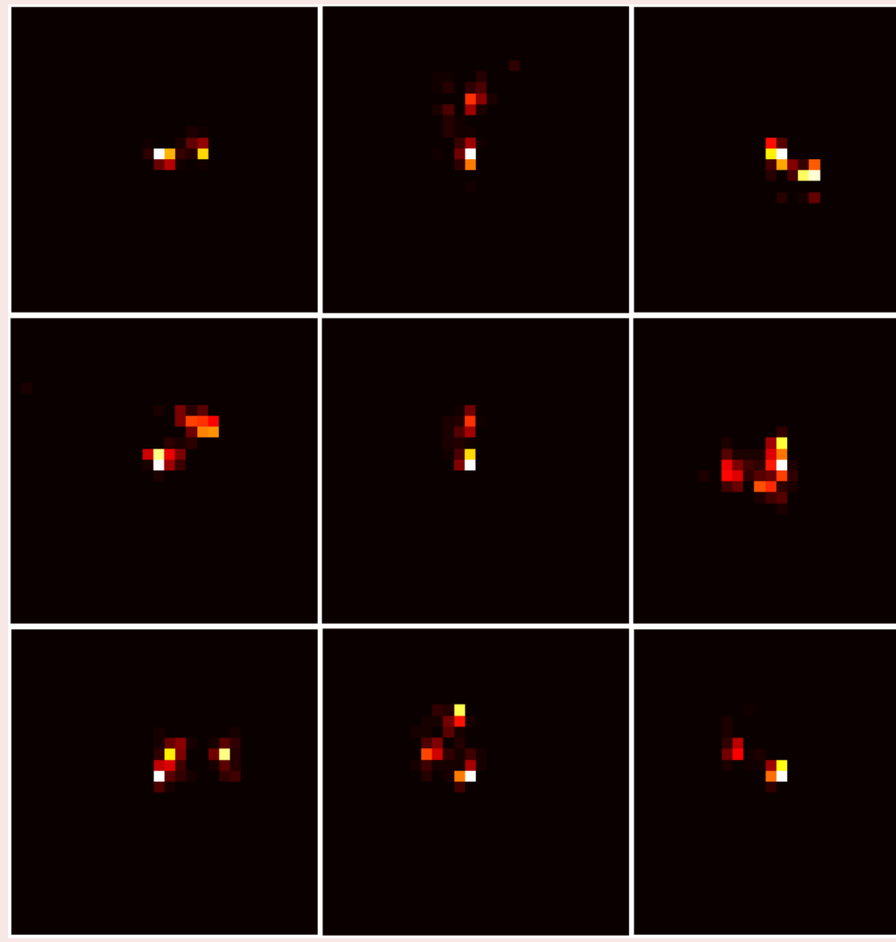


Energy deposition pattern: Individual events

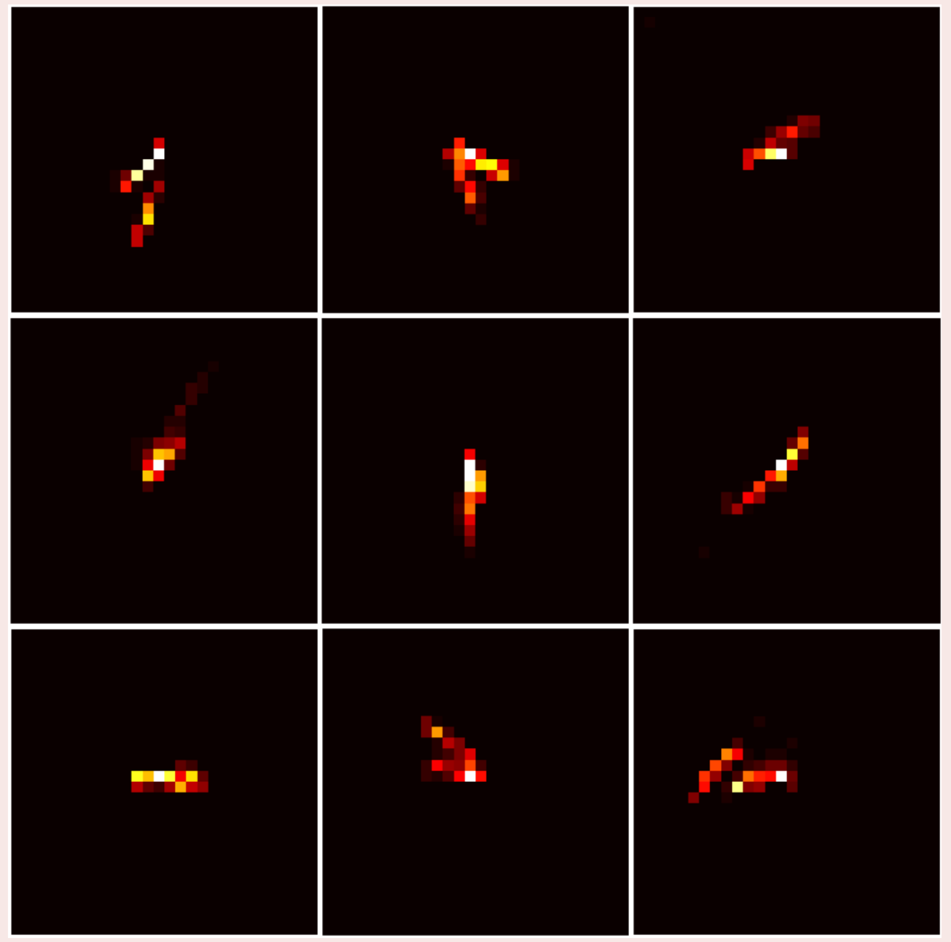
Scenario 1:



Prompt decay



b/w 50-70 cm



b/w 200-220 cm

HCAL energy deposition pattern in η-ϕ plane.

These images used for CNN training.

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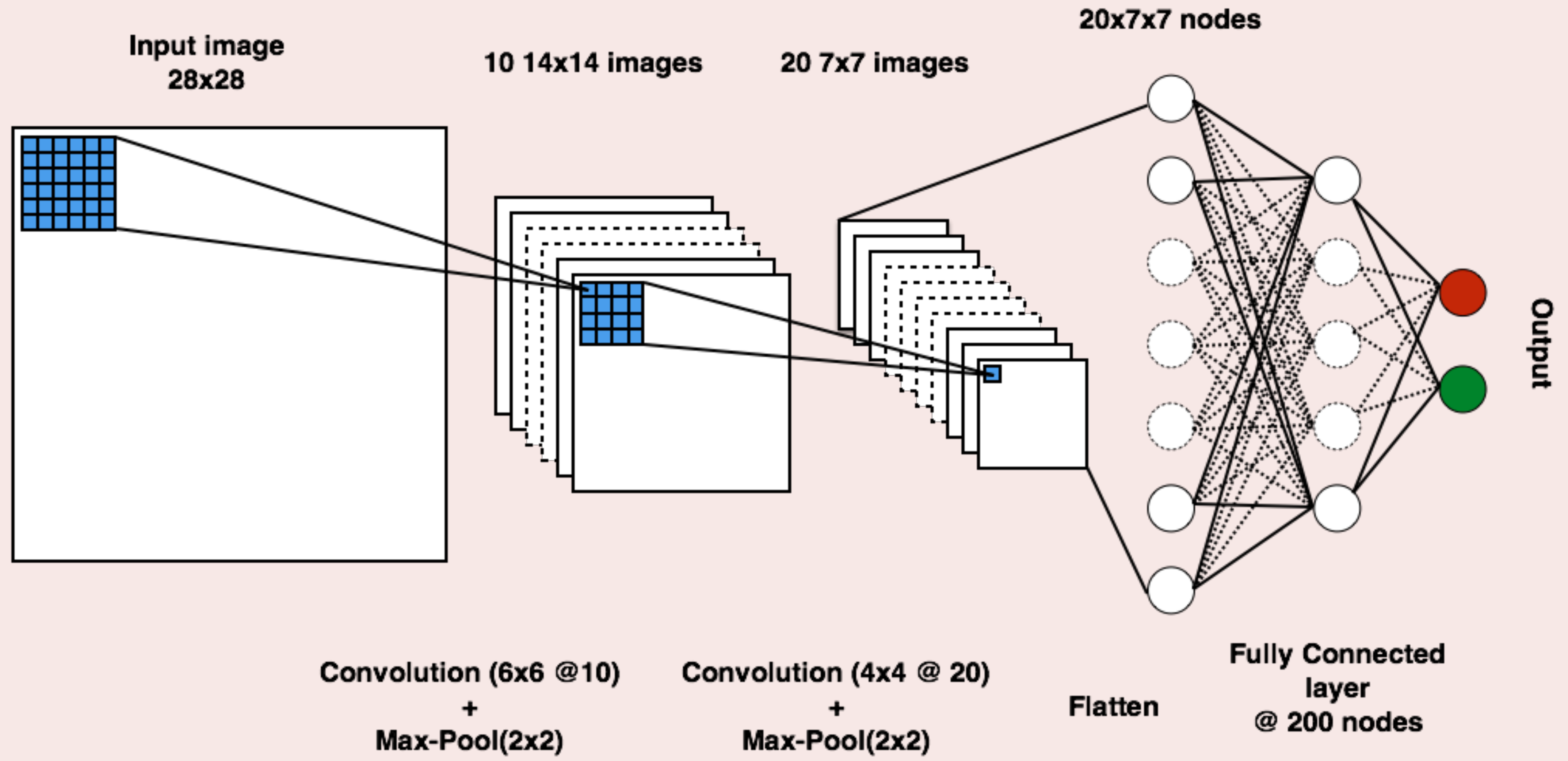
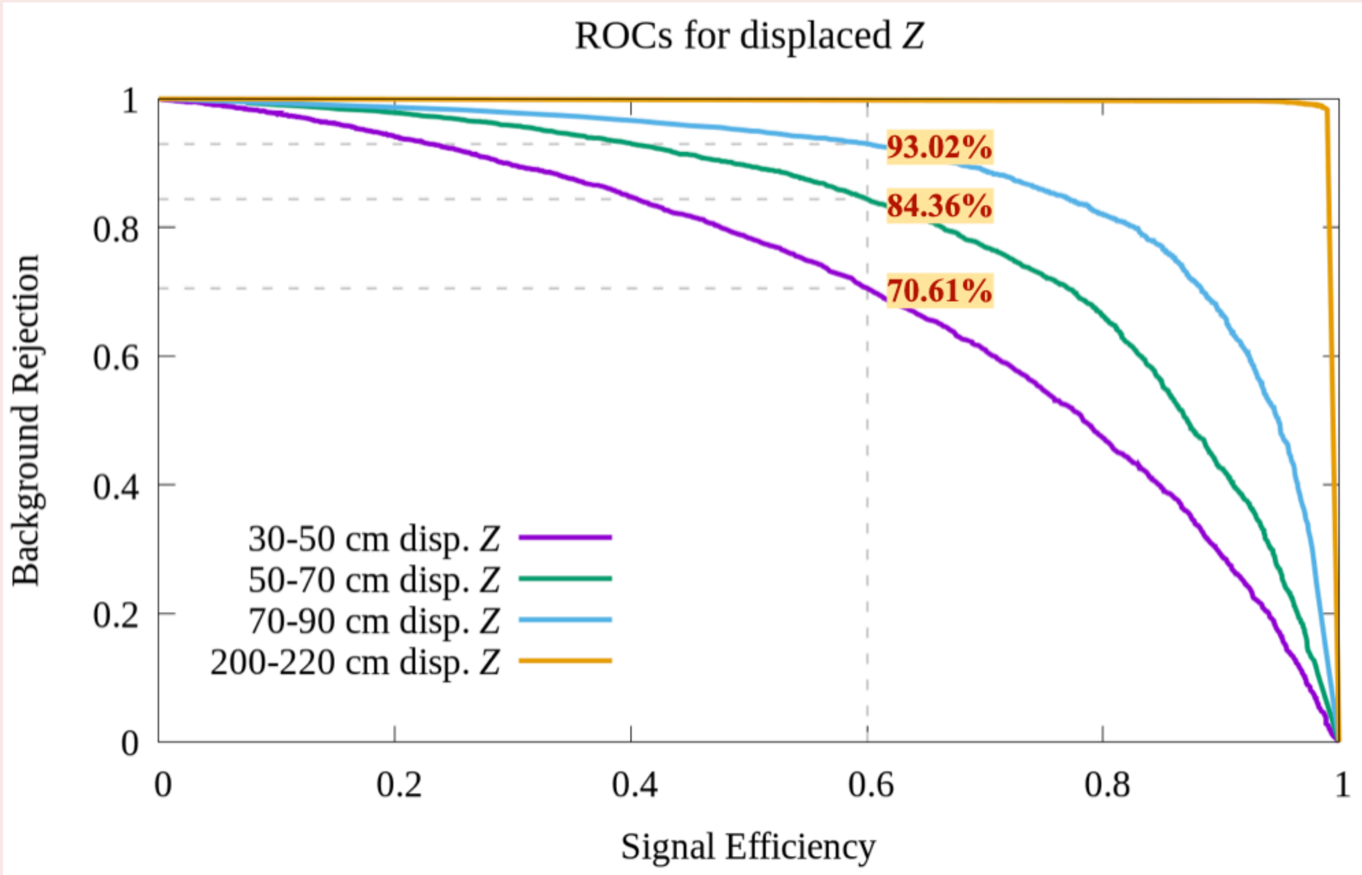
Can CNN learn these features and discriminate prompt jets from displaced jets?

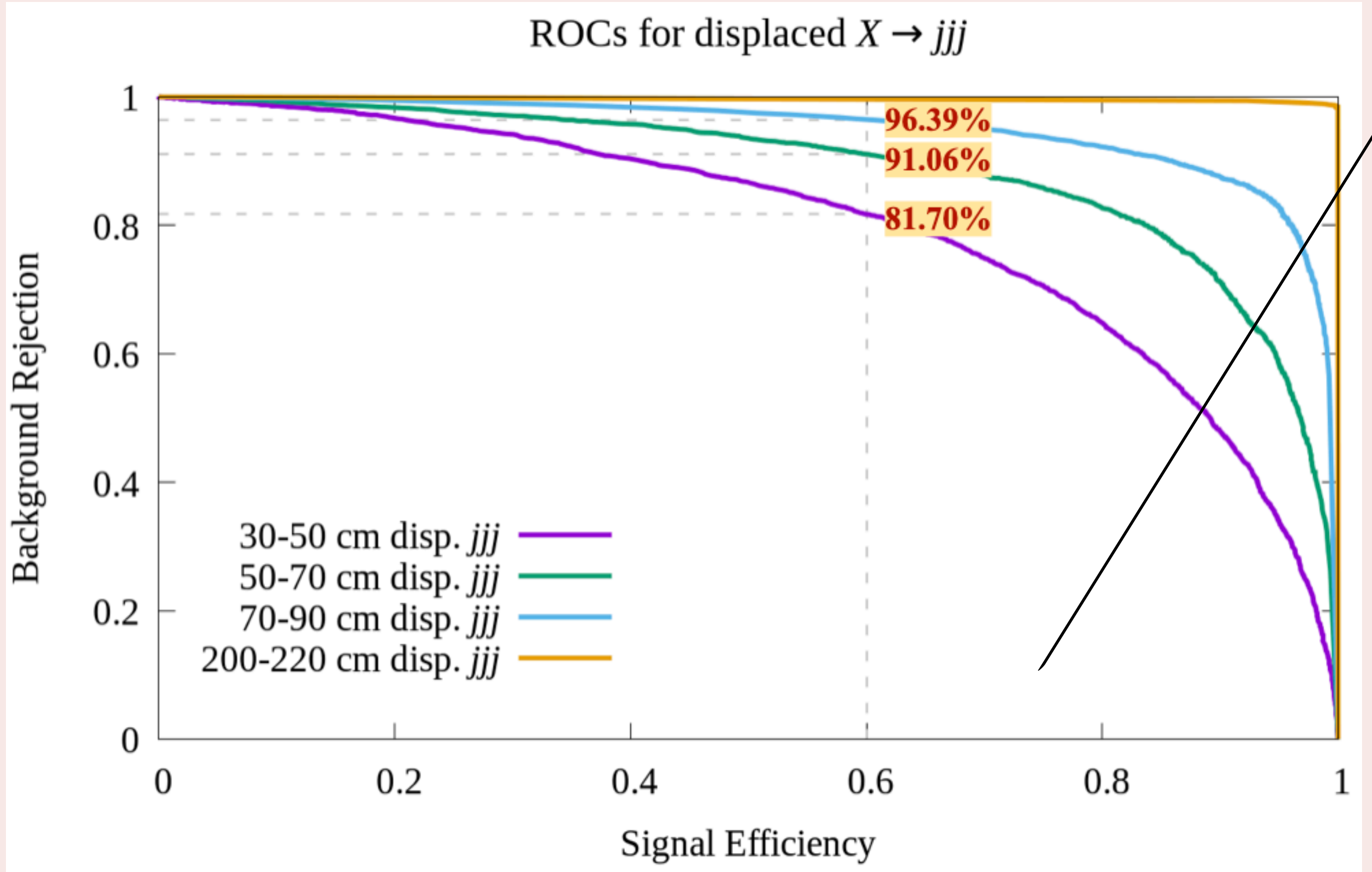
CNN architecture

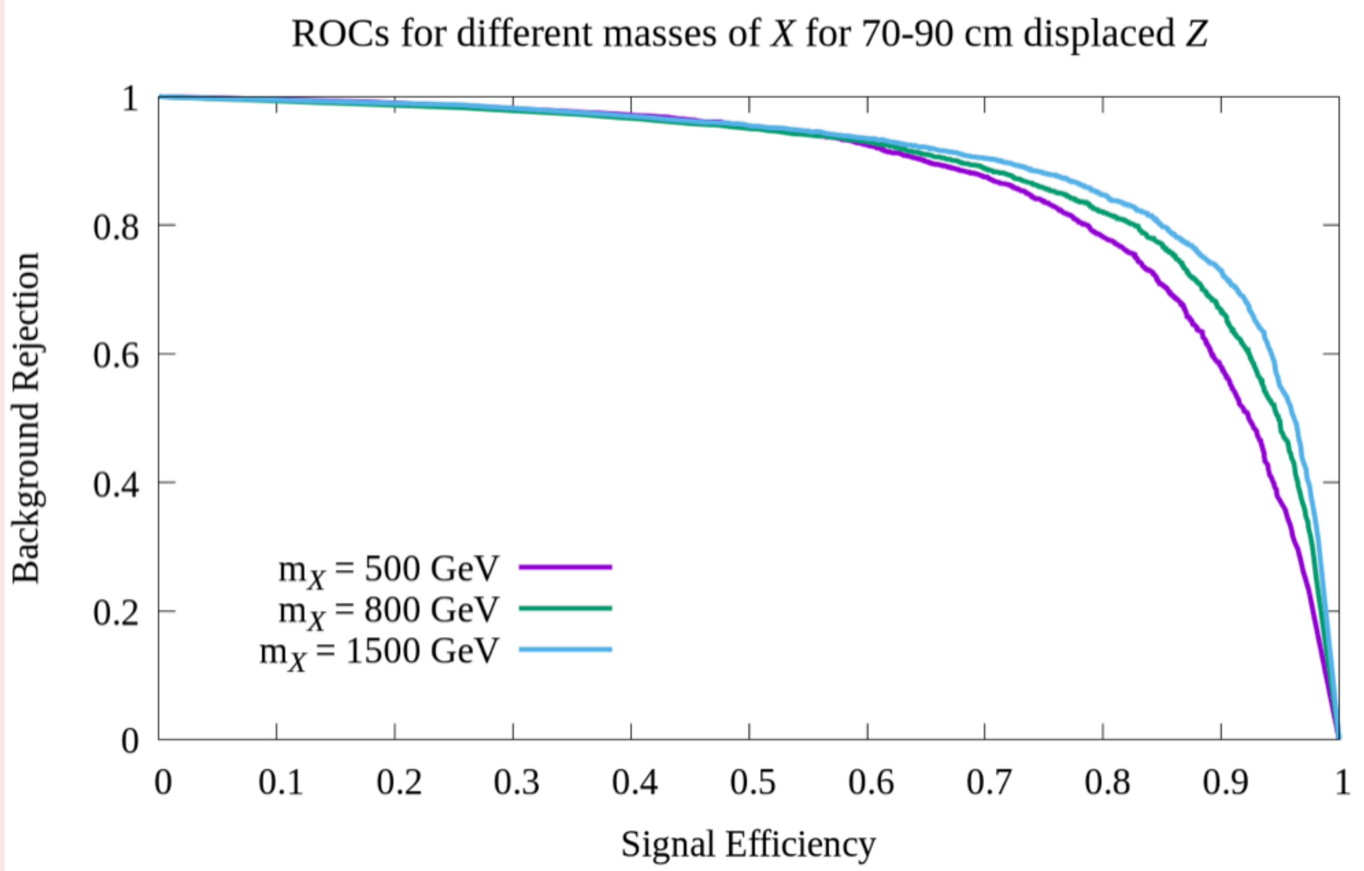


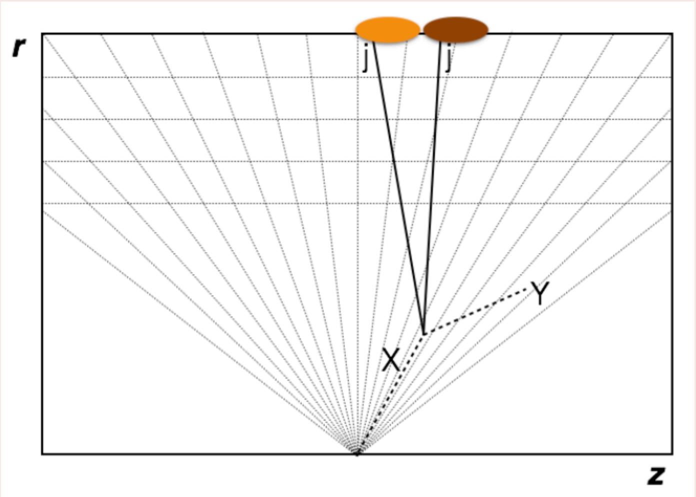
- Minimal preprocessing of images.
- Adam optimiser; Activation by RELU.
- Learning rate 0.001; Dropout 50%.
- 60,000 images for training, 20,000 each for validation and testing.
- Batch size 200.

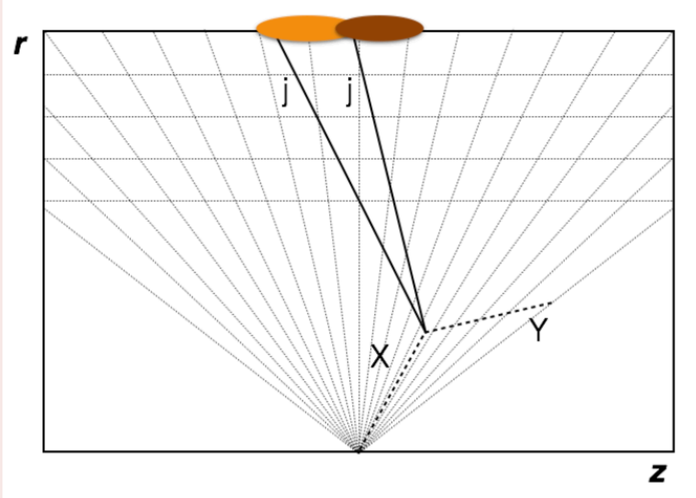
CNN performance: ROC curves











Separation power increases with displacement of LLP.

Separation power increases slightly with mass of LLP in scenario 1.

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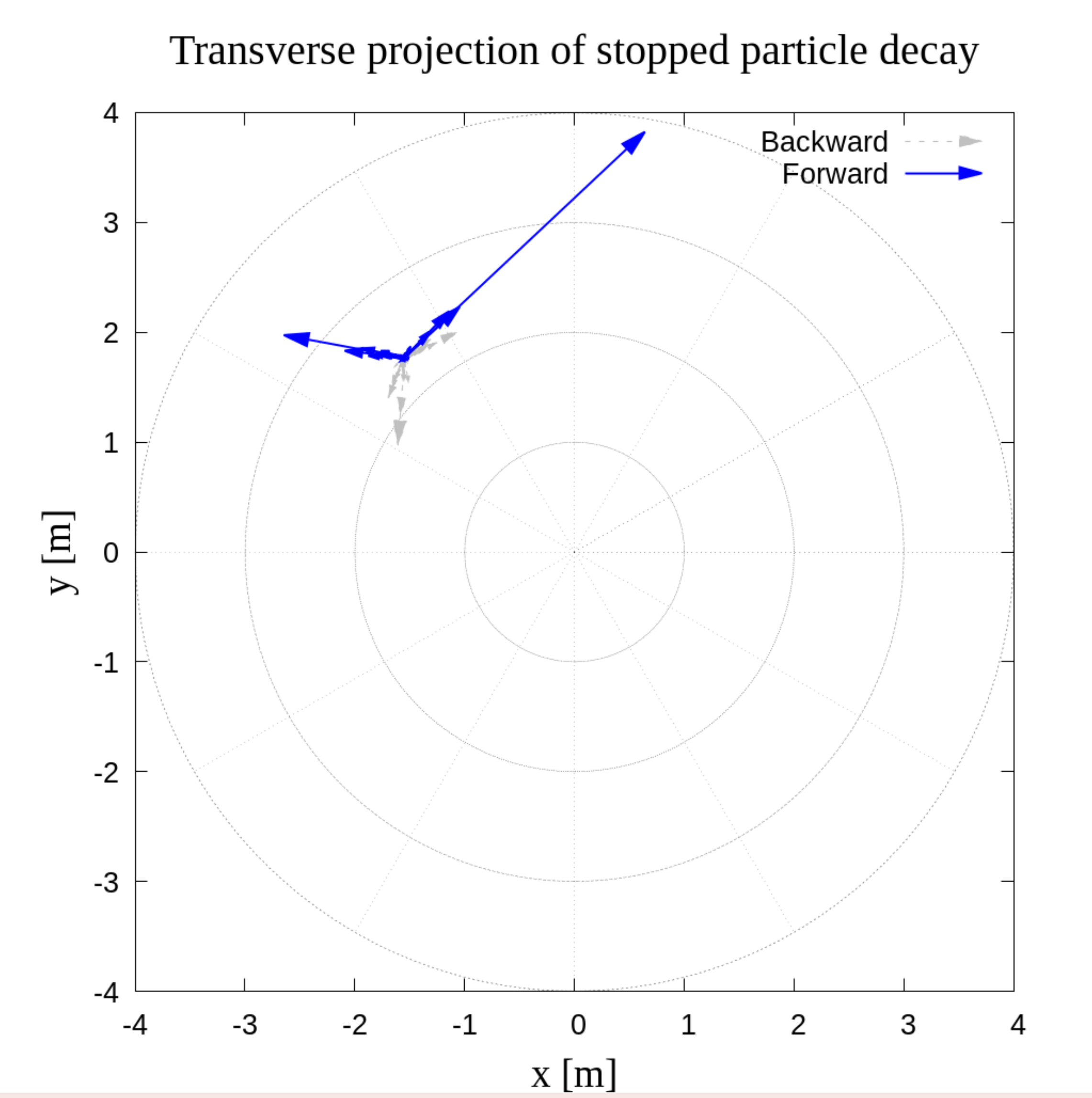
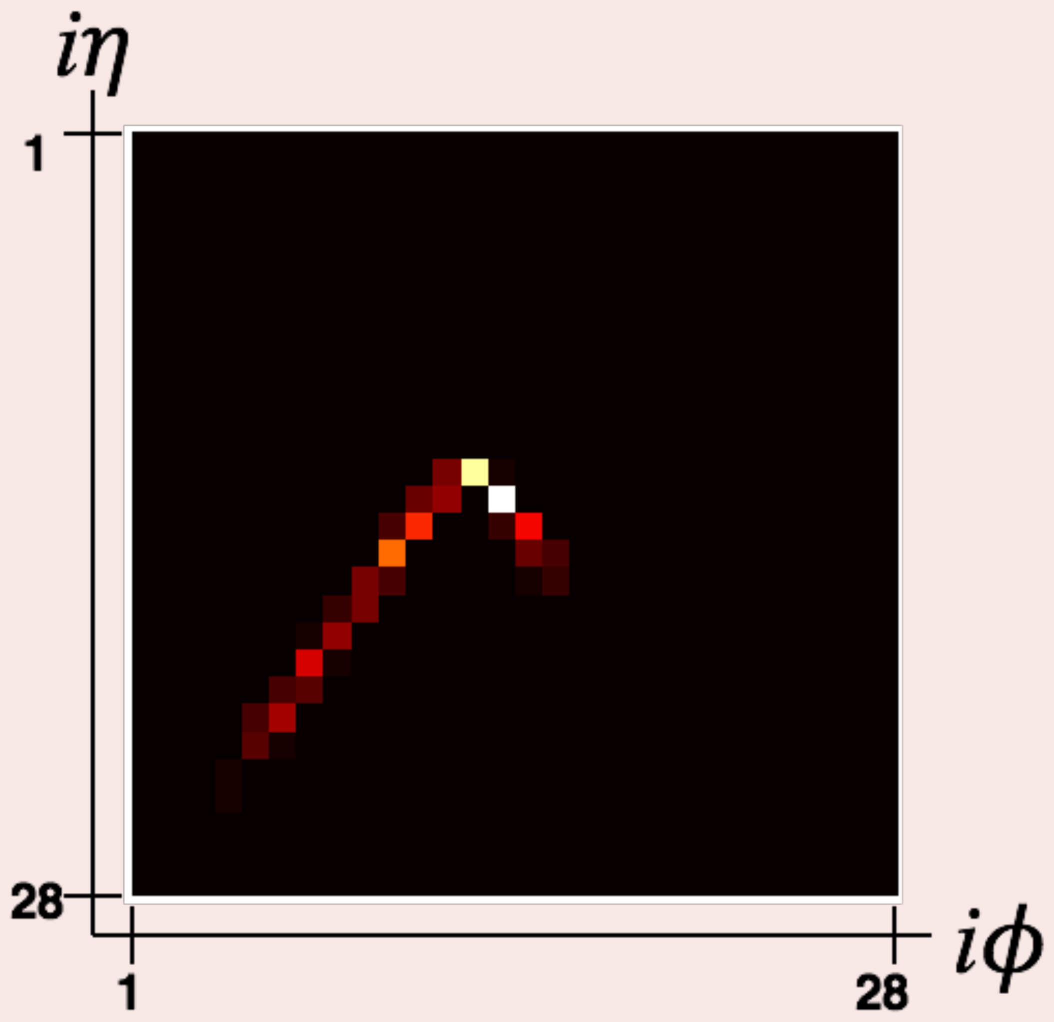
Can CNN learn these features and discriminate prompt jets from displaced jets?

Scenario 3: Stopped particles





- LLP comes to rest in HCAL due to interaction with the detector material (R-hadrons). Decays hours/days later.
- Decay products can go in any direction, even backward (towards beam-pipe).
- Backward moving objects more complicated, studies done in Ref.[2].
- In this work, we only consider energy deposition of forward-moving particles.

Very distinct signature compared to the prompt decay of boosted objects.

Summary

- **First application of CNN in long-lived particle search.**
- We studied the energy deposition pattern of displaced jets from LLP decays.
- Fast detector simulations not suitable to study displaced jets.
- We simulated simplified version of the segmentation following ATLAS HCAL.
- Key feature of displaced jet: Elongated and physically smaller region of energy deposit.
- **This study indicates that CNN works well to discriminate displaced jets from prompt jets.**

References

1. B. Bhattacherjee, S. Mukherjee, and R. Sengupta, "Study of energy deposition patterns in hadron calorimeter for prompt and displaced jets using convolutional neural network," JHEP 11 (2019) 156, arXiv:1904.04811 [hep-ph].
2. S. Banerjee, G. Bélanger, B. Bhattacherjee, F. Boudjema, R. M. Godbole, and S. Mukherjee, "Novel signature for long-lived particles at the LHC," Phys. Rev. D 98 no. 11, (2018) 115026, arXiv:1706.07407 [hep-ph].

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