UNIVERSITÉ
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Identification of Jets and Regions of Interest in the ATLAS Calorimeter with Deep Convolutional Neural Networks

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MARIE CURIE ACTIONS

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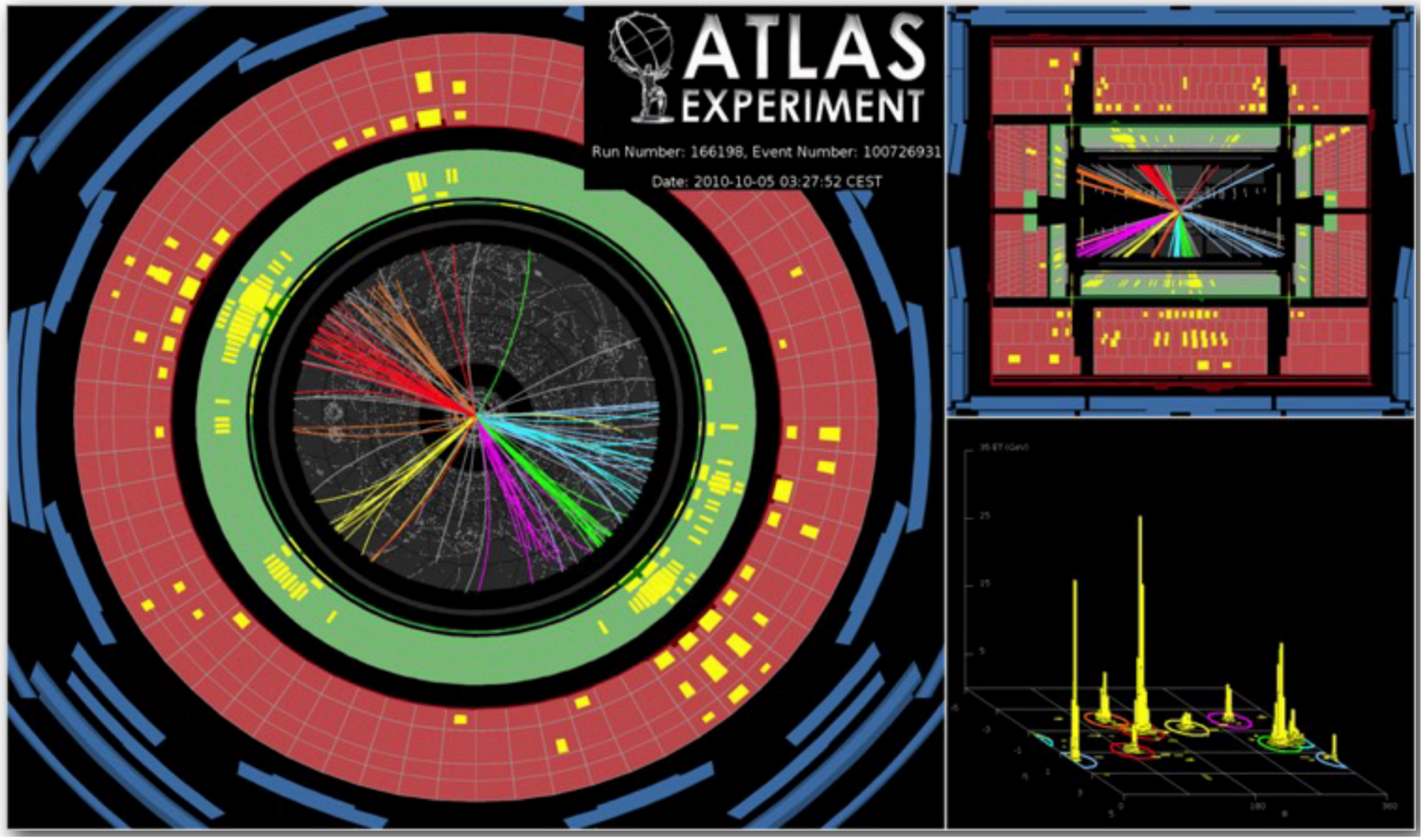
Presentation Outline

- Motivation and objectives
- A typical LHC trigger system
- What is object detection?
- Results
  - Calorimeter clusters
  - Jets
- Conclusion and outlook

Project Objectives

What and why?

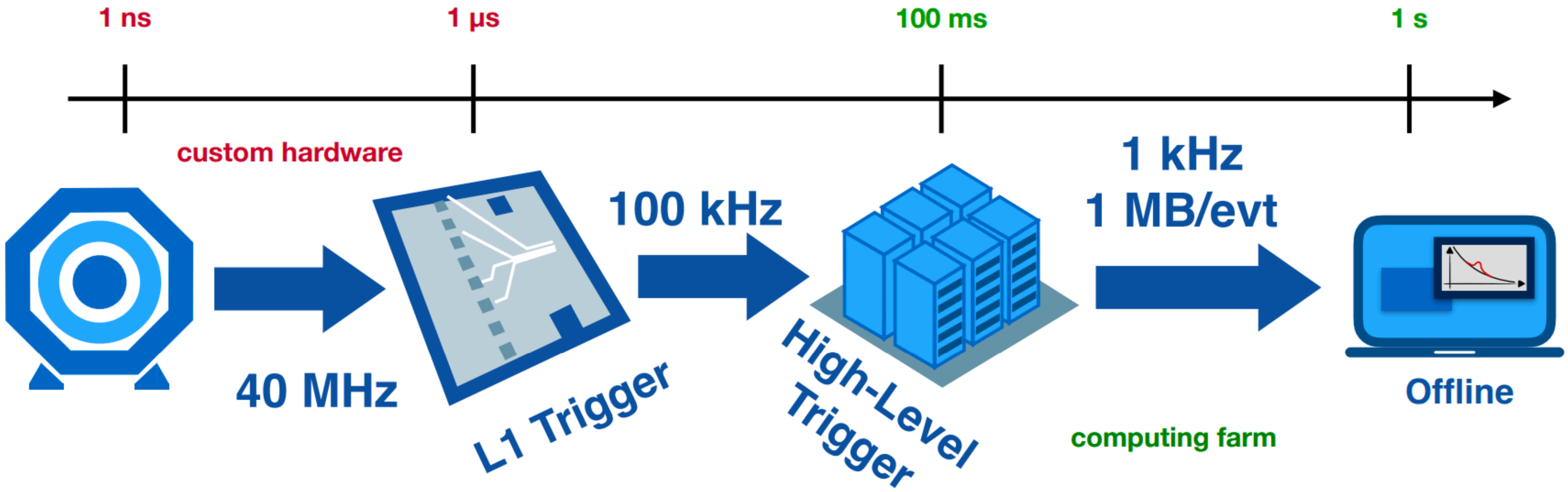
- Is it possible to use ML models to identify regions of interest (RoIs) or jets using *just* calorimeter information?
- Can this be accelerated → **faster** than current iterative methods.
- Can we save time in the trigger, a **preselection** step, quickly rejecting events that are “uninteresting”?
- Will a CNN be able to cope in the conditions of HL-LHC?



Ever wondered what these yellow blobs are?

Typical Trigger Dataflow @ LHC

*In Run 3 (as conditions are now)



- Trigger algorithms are preferentially ordered from simple to complex.
- This project aims to go directly from calorimeter cells → physics.

Image: S. Summers, indico.cern.ch/event/1389765/attachments/2815819/4915639/sps_ds_8-3-24.pdf

Object Detection

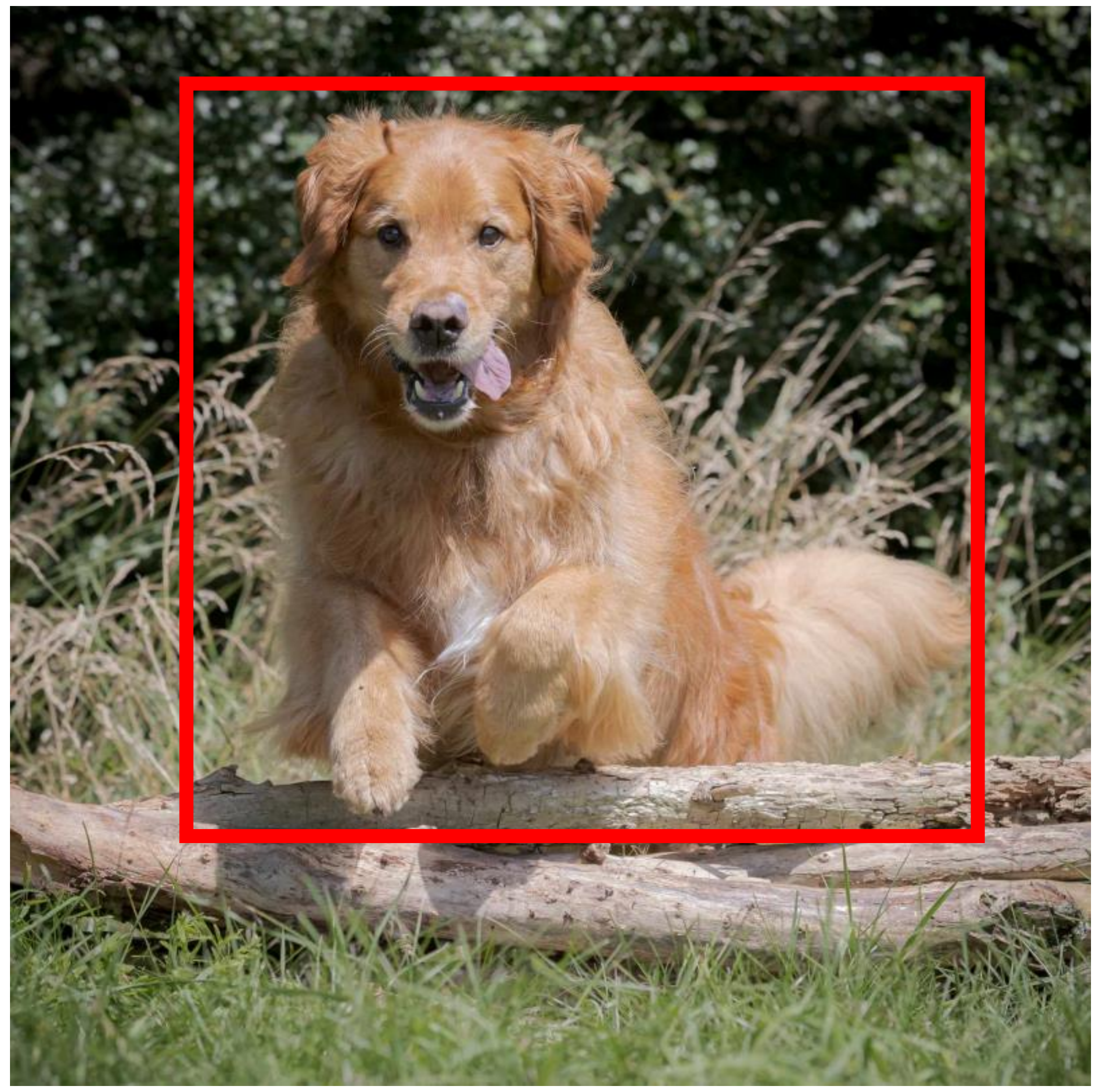
Object Detection

A more traditional example

Classification

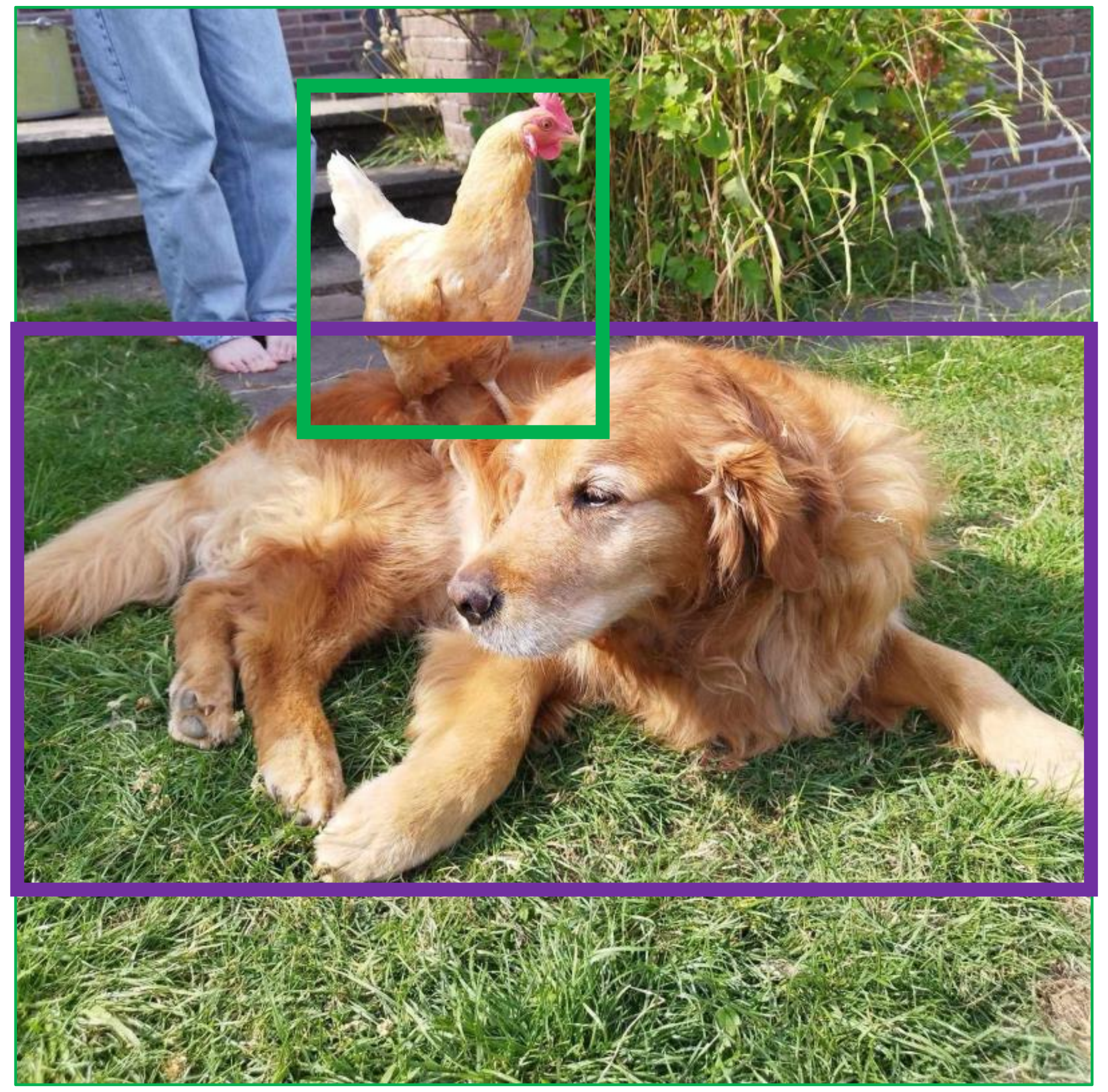
The Most Beautiful Dog in the World, named Heaven

Classification + Localisation



The Most Beautiful Dog in the World, named Heaven

Object Detection



The Most Beautiful Dog in the World, named Heaven and A Very Friendly Hen, named Abigail

Image: M. Moors

See also: https://arxiv.org/abs/2105.05785
CMS JetSSD

Object Detection

Single Shot Multibox Detector (SSD) Network Architecture

- **Backbone**
  - VGG16 CNN architecture used as feature extractor, original design for classification
  - 35 million parameters, large + relatively old
- **6 Additional Feature (Auxiliary) Layers**
- **Residual connections between the layers and outputs**
- **Two output heads, regression + classification**

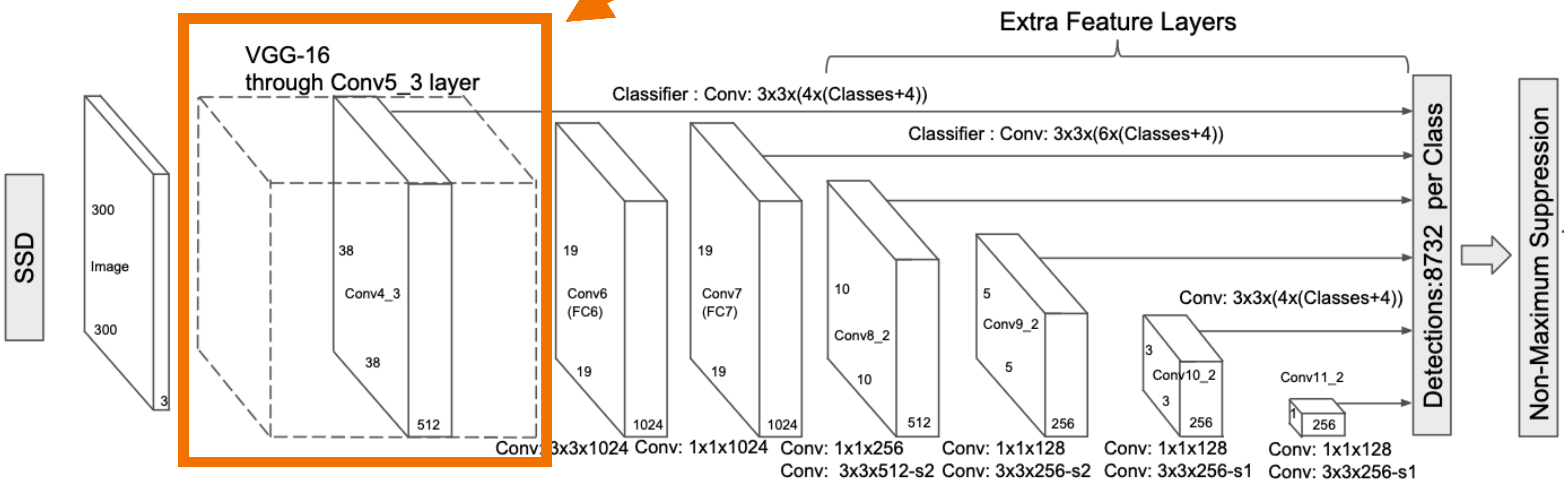
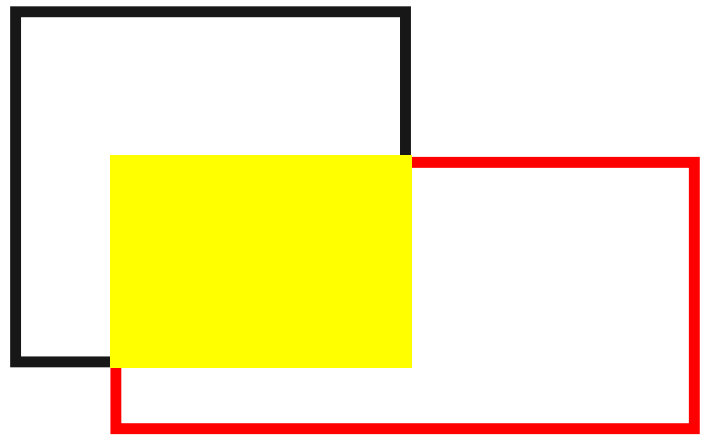


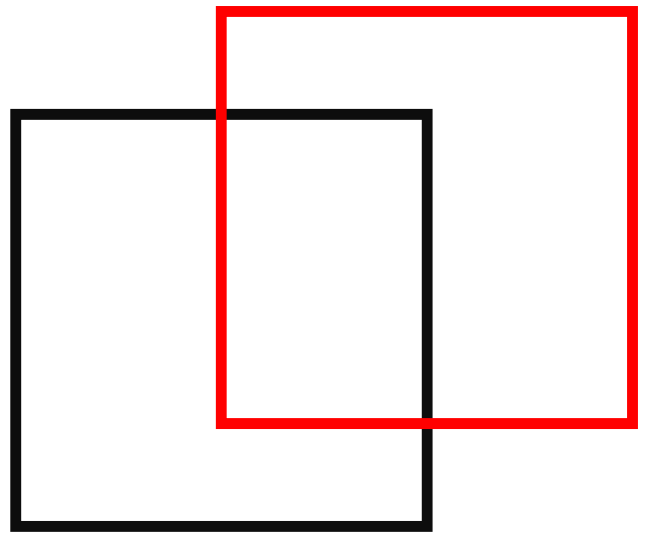
Image: https://arxiv.org/abs/1512.02325

Matching Predictions and Truth

How to judge good identification performance?

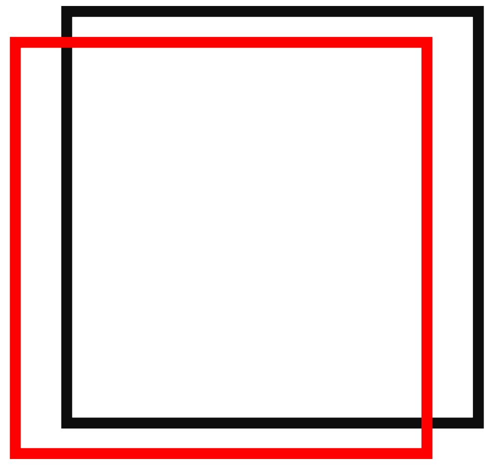


$$IoU = \frac{\textit{Area of Overlap}}{\textit{Area of Union}}$$



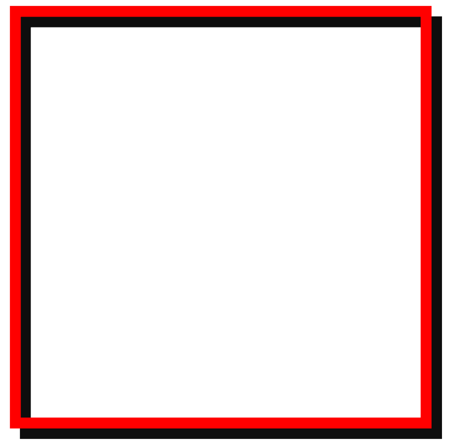
Poor

IoU = 0.23



Good

IoU = 0.68



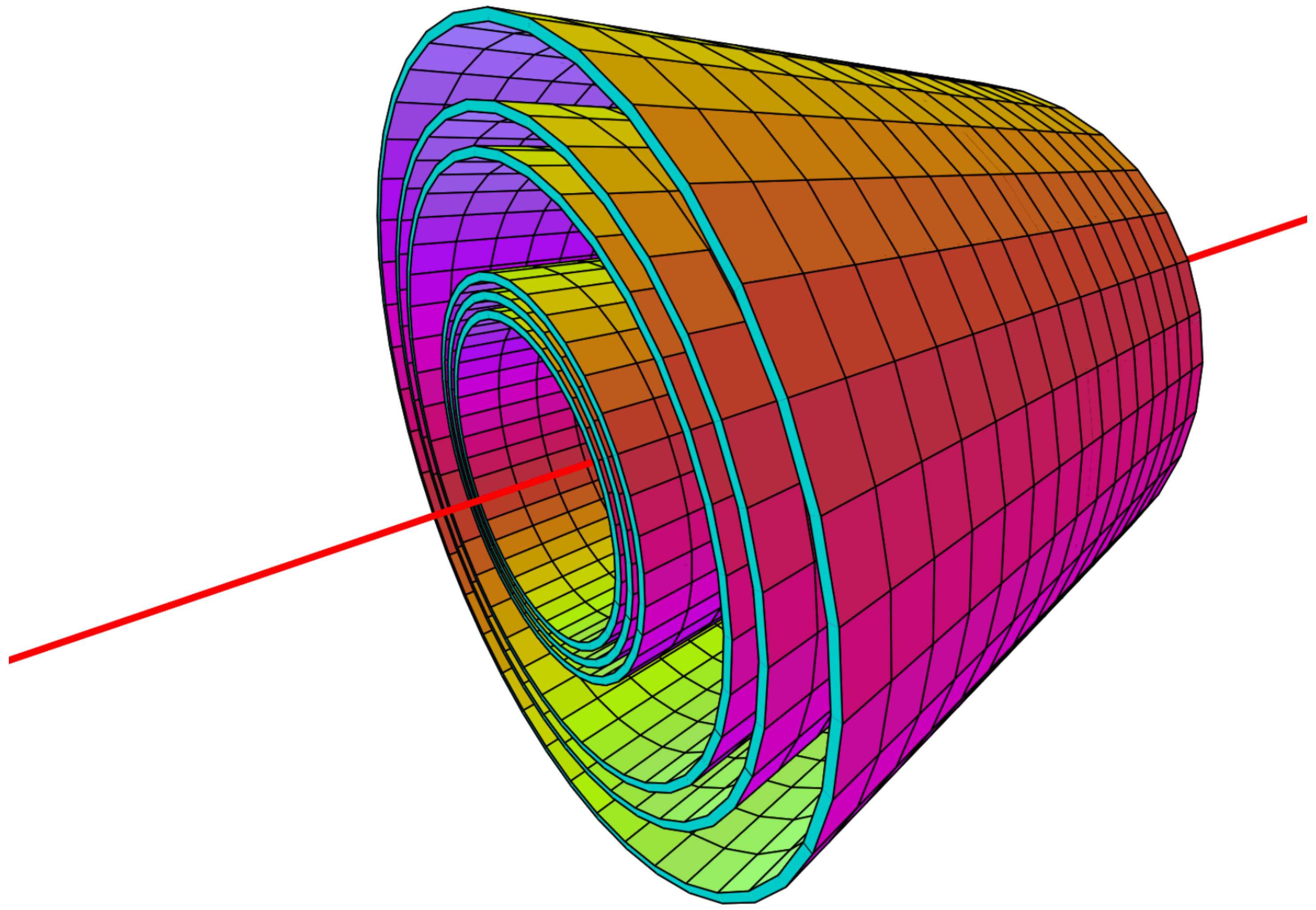
Excellent

IoU = 0.90

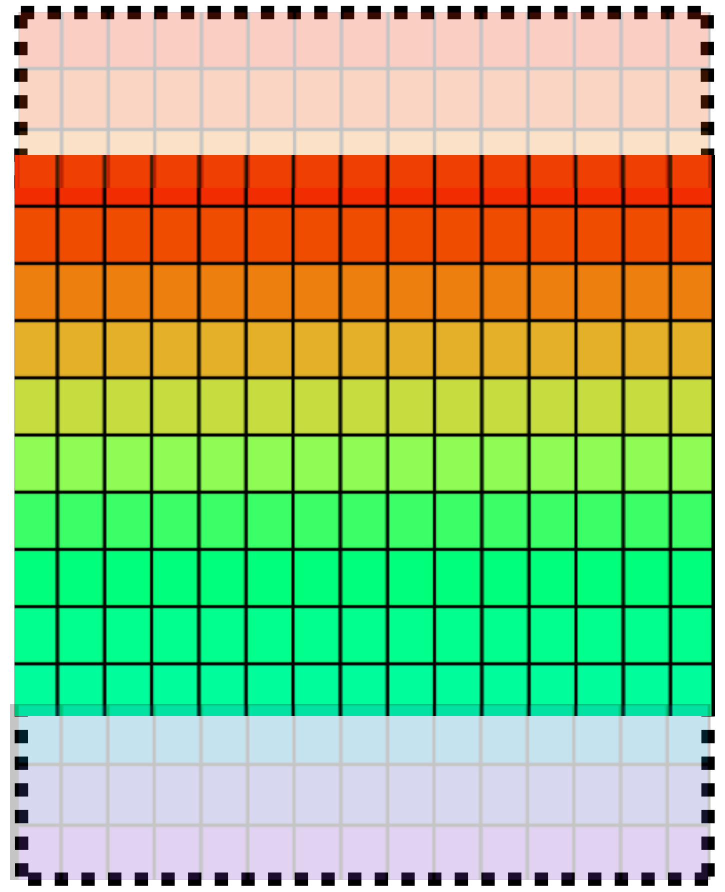
Image: M. Moors

Data Preparation

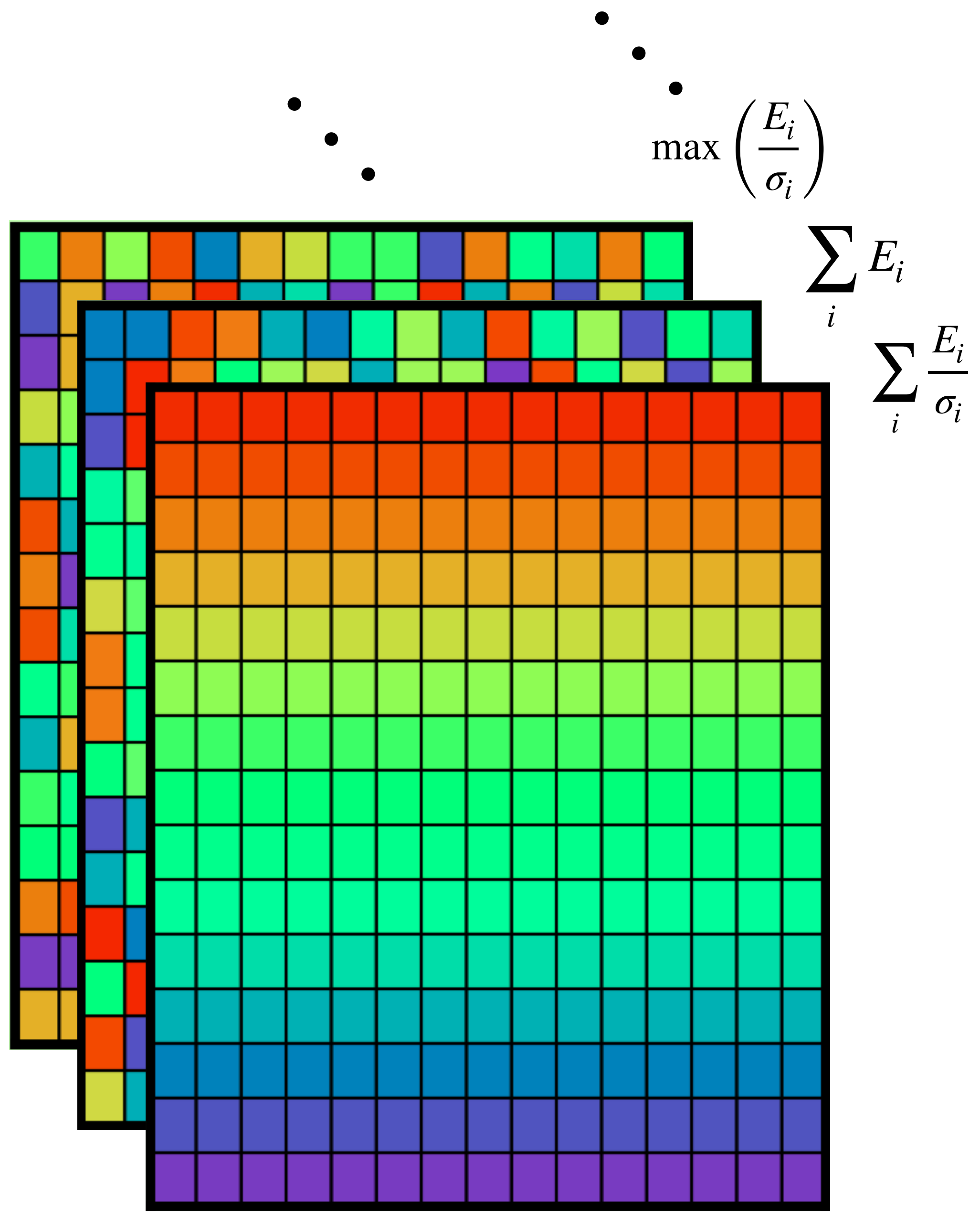
Making Calorimeter “Images”



Project in $\eta - \phi$



“Wrap” boundary regions



Calculate separate channels using cell information

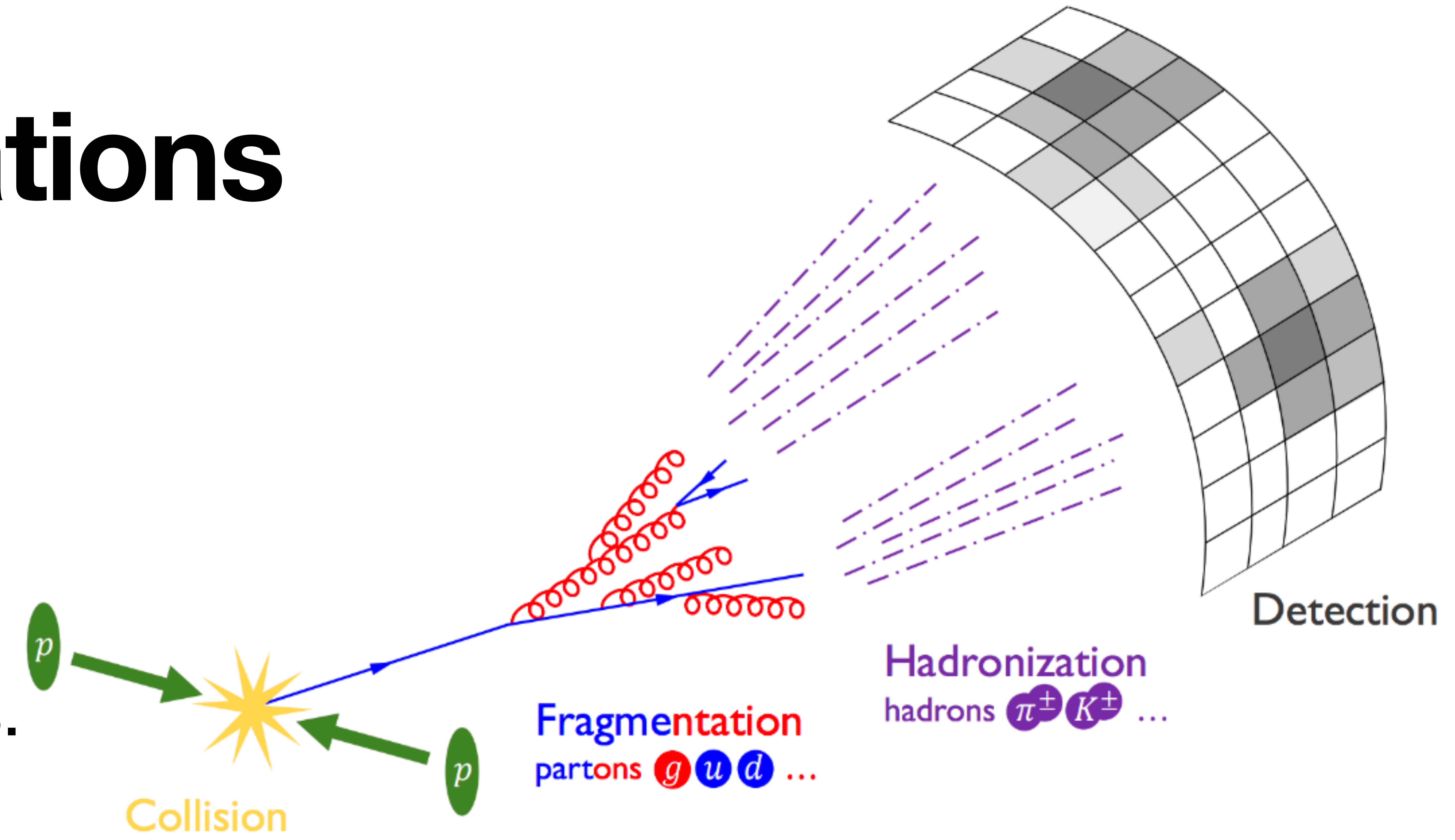
Making Truth Annotations

- We use jets to group the quarks or gluons in a shower. Jets may contain many different particles.

- We typically use jet algorithms to sequentially combine jet constituents.

- In the calorimeter these constituents are clusters. (The yellow “blobs”).

- The jets or their constituents are used as target/truth boxes for our CNN.



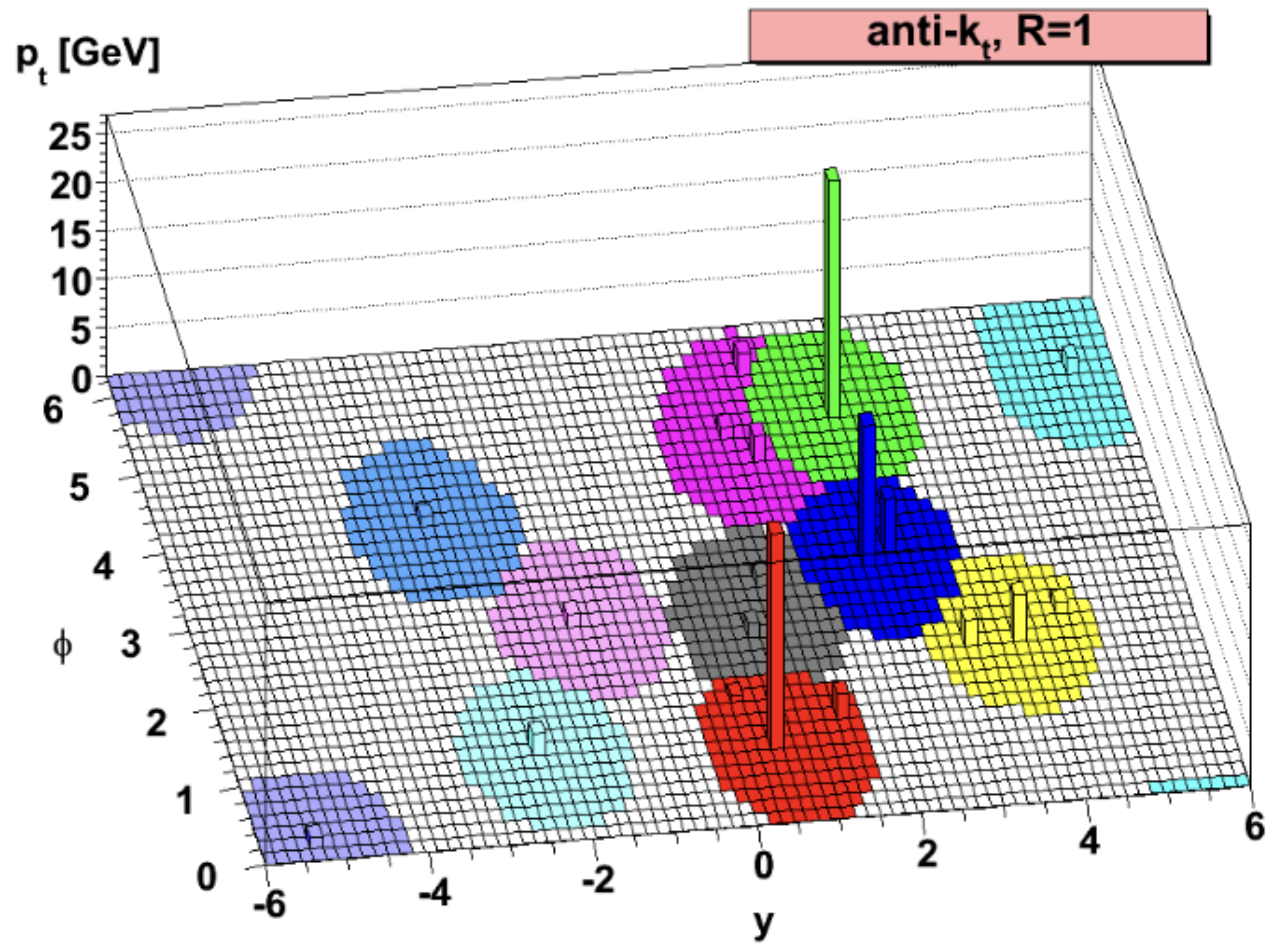
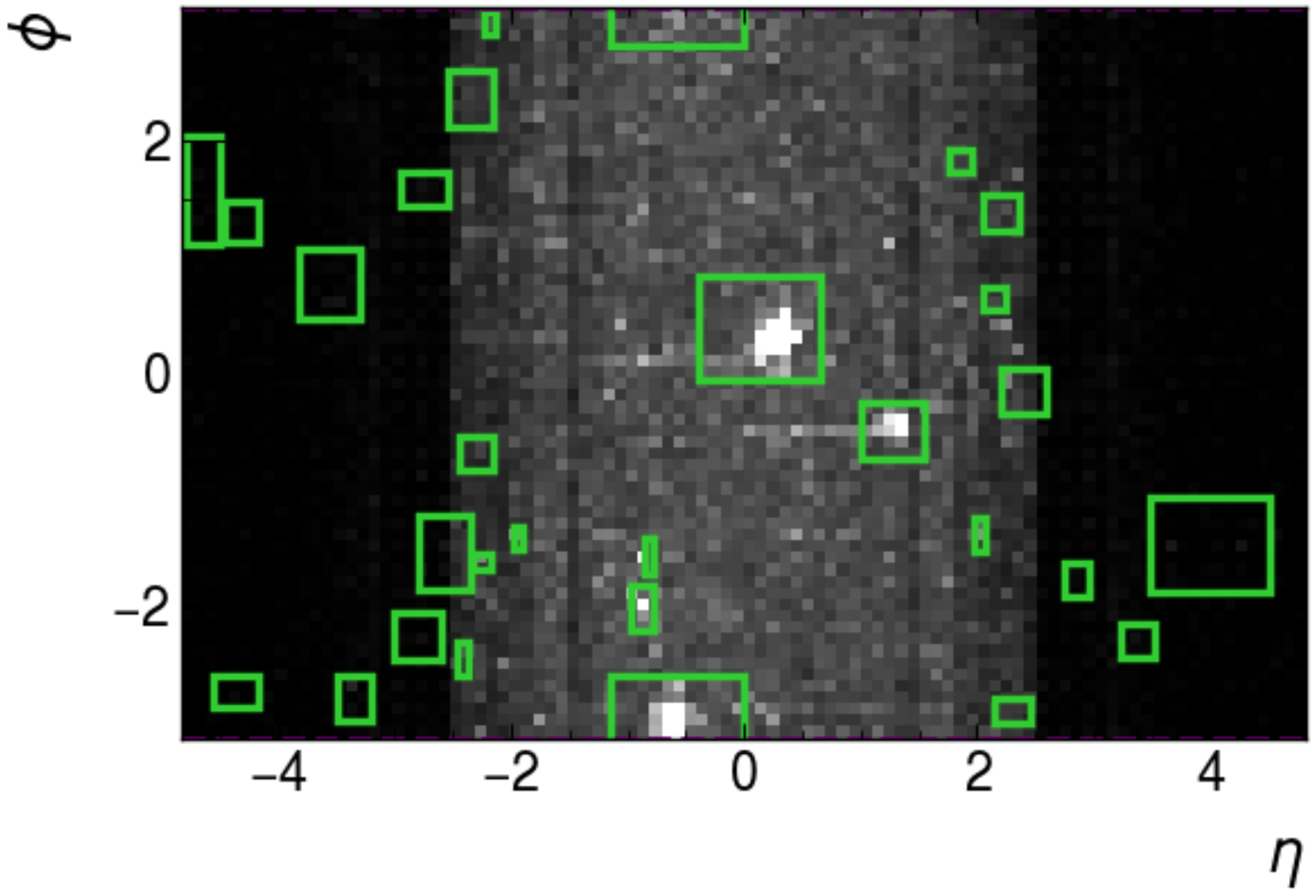


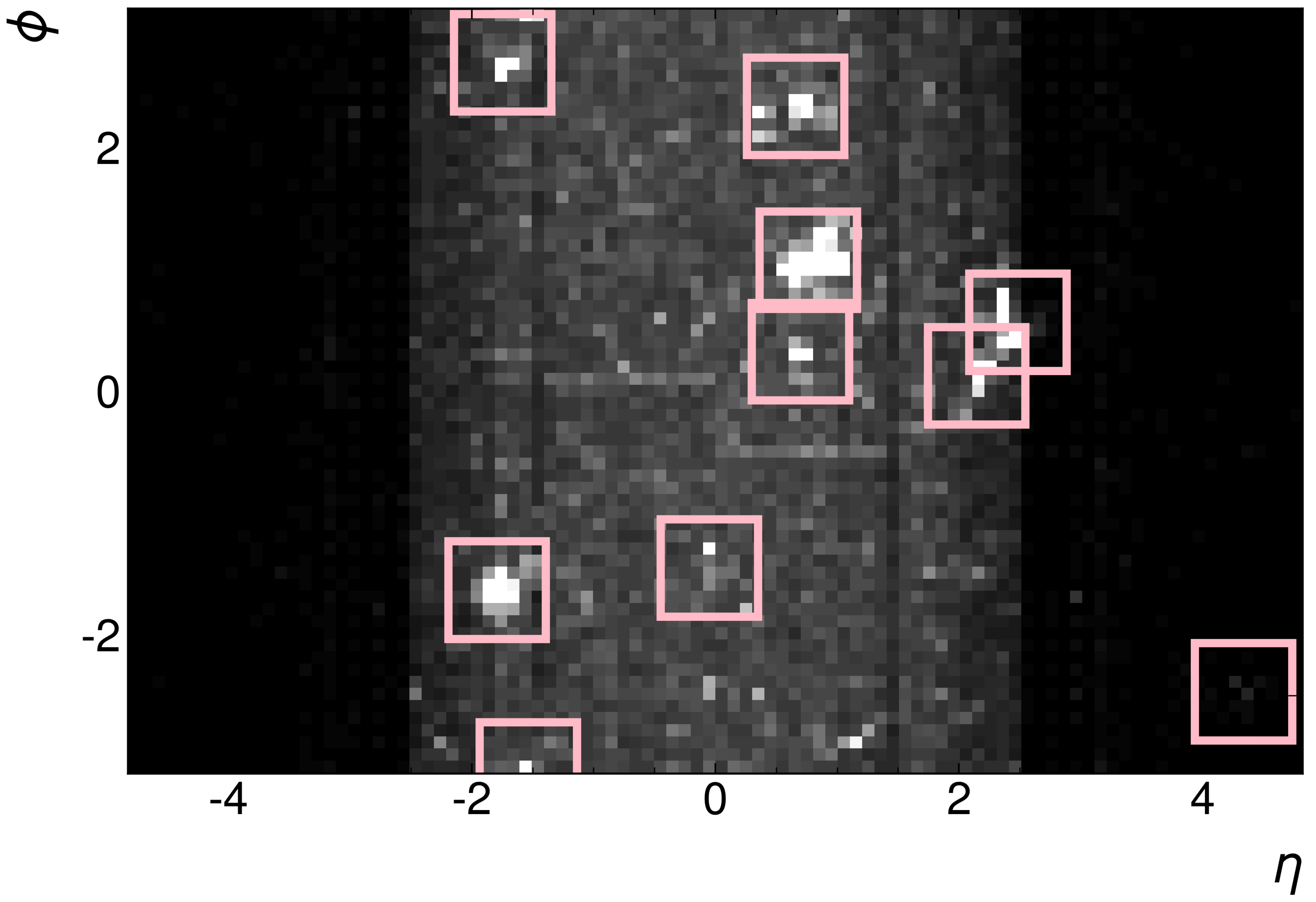
Image: https://www.ericmetodiev.com/post/jetformation/ Image:https://arxiv.org/abs/0802.1189

Marking Calorimeter Target Boxes

With jet *constituent* targets:



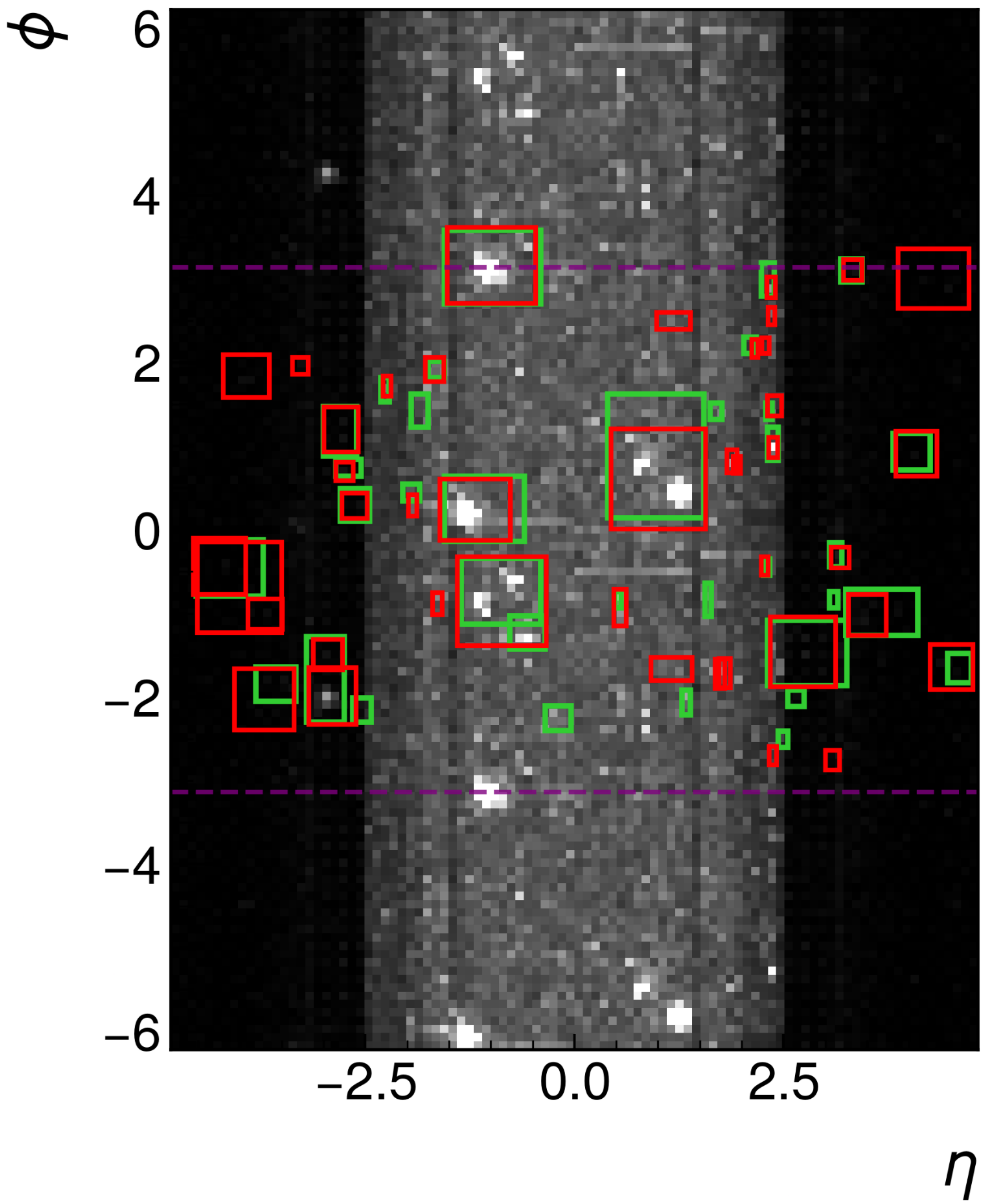
With jet targets:



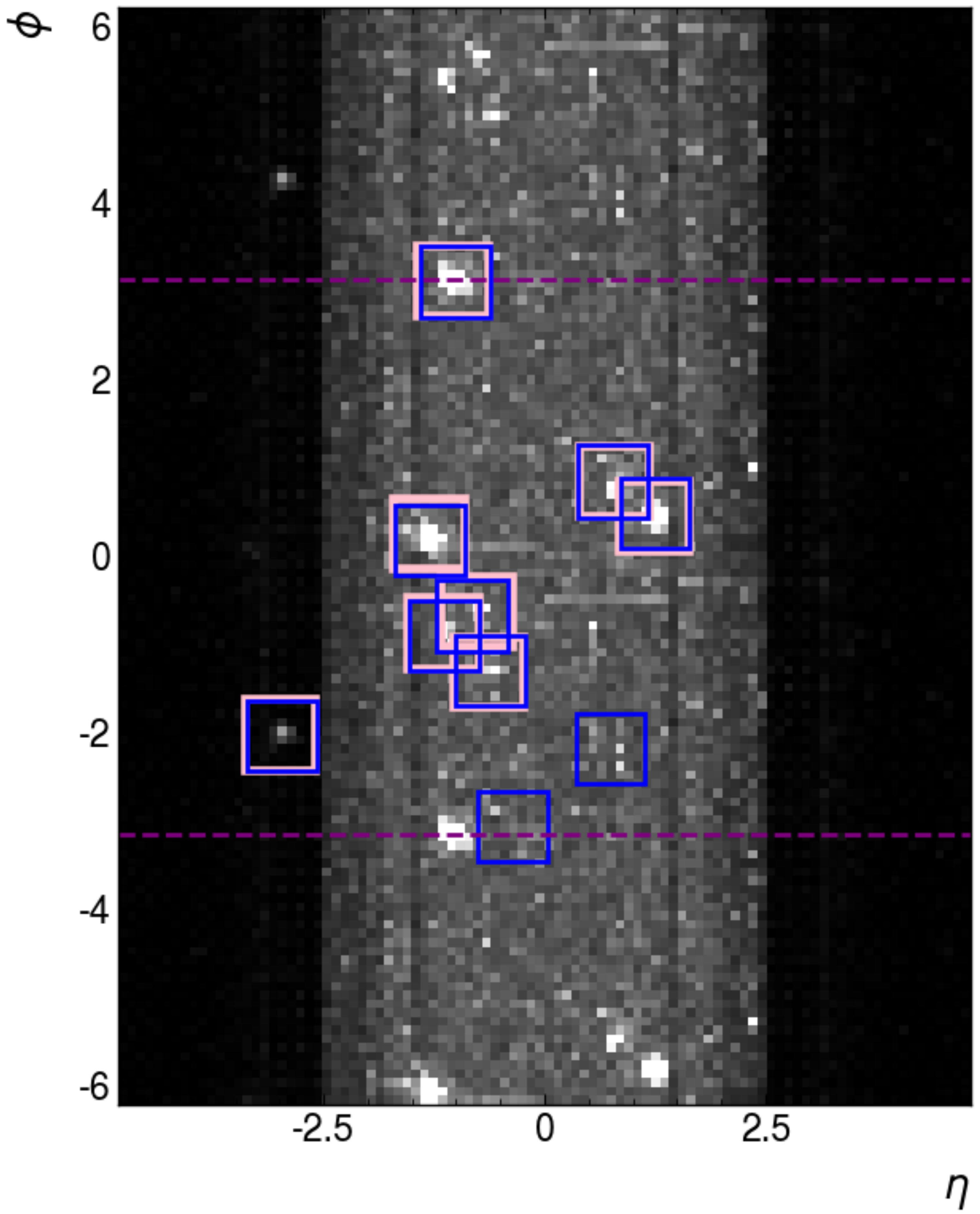
Results

Detection Performance for 1 event

With jet *constituent* targets:



With jet targets:



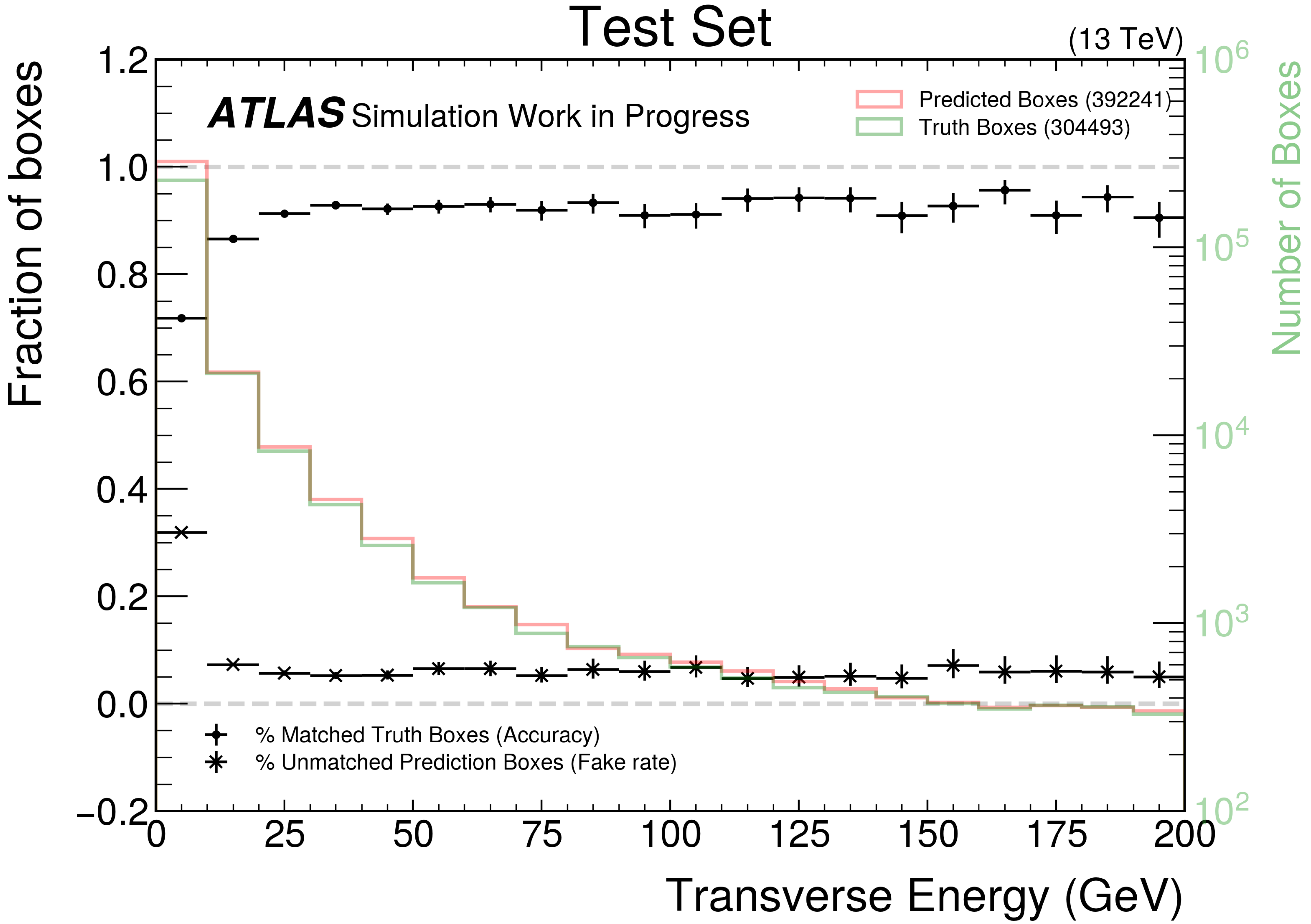
Detection Performance on Test Set

With jet *constituent* targets:

Detection performance as a function of the transverse energy of the box prediction. Displaying only target/prediction boxes with transverse energy up to 200GeV.

Match fraction: $\dfrac{\text{\# matched truth}}{\text{\# truth}}$

Unmatch fraction: $\dfrac{\text{\# unmatched pred.}}{\text{\# pred.}}$

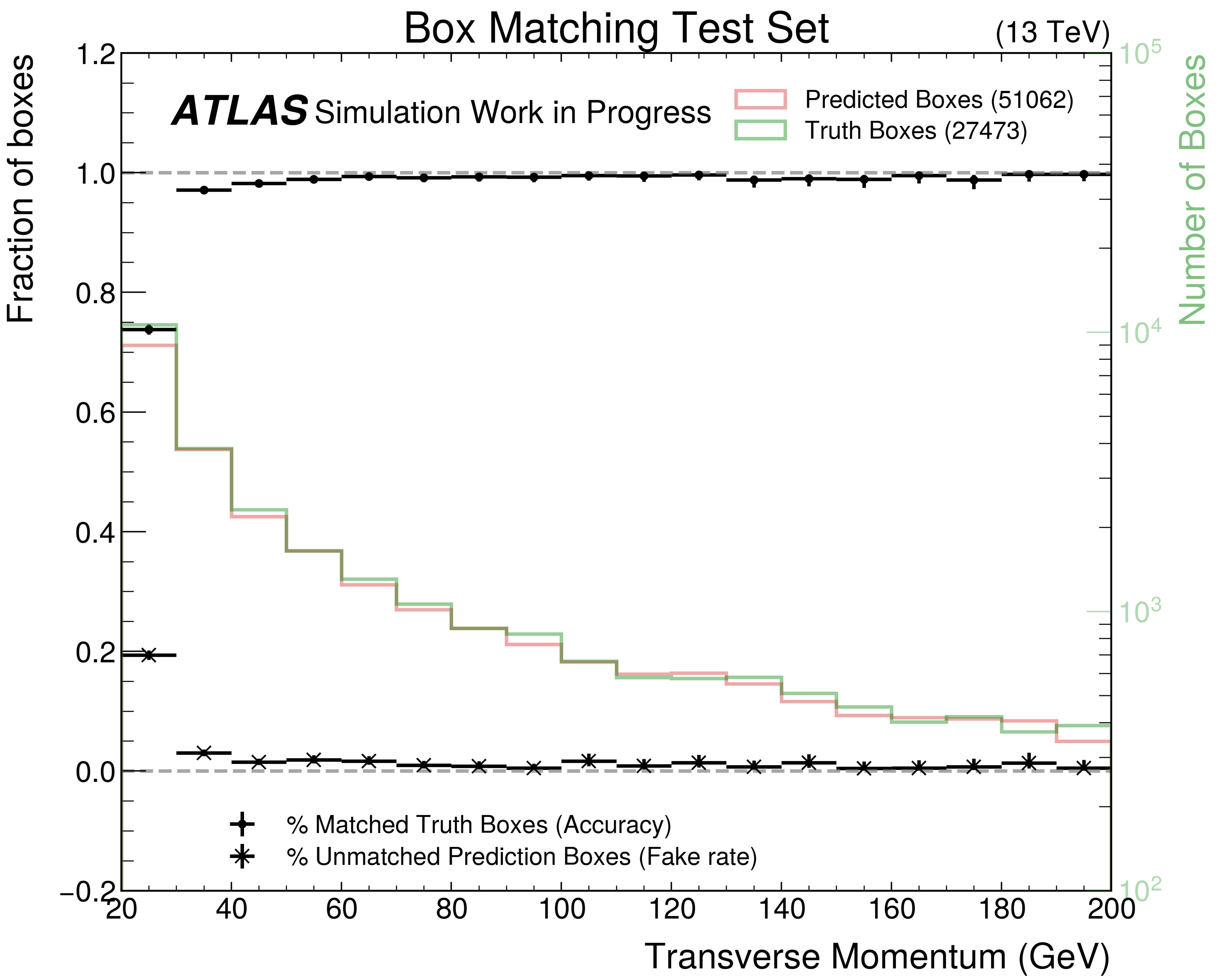


Detection Performance on Test Set

With jet targets:

With the same detection performance metrics we see that the CNN model looking for jets has higher matching efficiency, as well as reduced unmatched prediction rate in comparison to the jet constituent task.

This is intuitive since the jet targets are a subset of the constituent targets, and show clearer signatures in the calorimeter via large energy depositions.



Outlook & Next Steps

- It is possible to use an object detection CNN to identify jets/RoIs using just the calorimeter cell information.

- The efficiency increases as a function of the jet/RoI p_T or E_T. Conversely the fake prediction rate decreases with the p_T or E_T.

- Continue to study the effect of different network architectures (backbones), fewer parameters $\rightarrow$ faster inference. Initial timing studies are promising!

- Validate results in the context of HL-LHC conditions, with increased detector occupancy and pile-up.

Thank you for listening

Backup

A quick word on timing

*Subject to change!

Post-processing timing includes retrieving cells from the predicted jet bounding box (circle), sharing overlaps and calculating kinematic variables.

For reference, currently topoclustering takes an average of ~ 80ms, while Anti-kt jet finding another $20-25$ms per event.

	Inference (RTX 2080 Ti GPU)	Post-processing (incl. cell retrieval)
CNN (SSD with VGG backbone, 35.6m param)	35ms	14ms
CNN (SSDLite MobileNet Backbone, 3.4m param)	14ms	14ms