

Deep Learning Methods for Jet Tagging and Process Classification Using Image Processing

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Jet tagging

Introduction

What is the purpose of jet tagging?

- Jets are proxies to partons
- Understand where the jet comes from
- Reveal the physics behind its production^[1]
 - Precision measurements of the SM
 - Heavy quarks
 - Higgs boson
 - Top quark
 - Electroweak decays
 - Probe medium properties in A+A collisions
 - Searches for BSM physics
 - Background rejection

[1] The ATLAS Collaboration, "[Transforming jet flavour tagging at ATLAS](#)", Nature Communications, vol. 17, p. 541, Jan. 2026

Motivation and objectives

The issue

- Massive amounts of raw data generated by detectors (e.g. in Run 3 the ALICE Experiment was giving a readout of **3.5 TB/s**)^[2]
 - Demands a **fast skimming** of the data, especially in the **triggering** systems
- How can we reduce data size and extract events of interest?
 - **Machine learning** perform **quick** predictions and are already used for triggering
 - Reduce, or get rid of, steps that can slow the process down
 - Best case scenario: trigger directly from raw data
- Mechanisms of data processing
 - Track reconstruction
 - Particle identification
 - **Jet reconstruction**

[2] D. Rohr on behalf of the ALICE Collaboration (2022). “Overview and 2022 data taking the experience of ALICE online and offline processing in Run 3”, [Talk presented at the Kruger 2022: Discovery Physics at the LHC]. Johannesburg, South Africa

Objectives

→ Develop an **AI model** that can “sense” the **presence of jets** (and their flavor) in an event just by looking at **low level particle variables**

◆ **Without jet reconstruction**

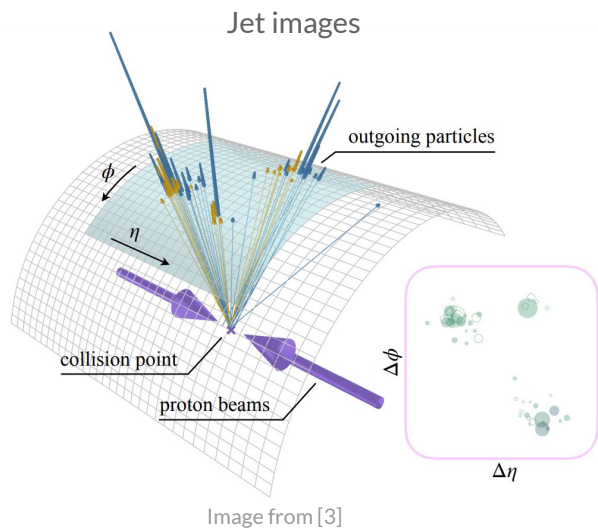
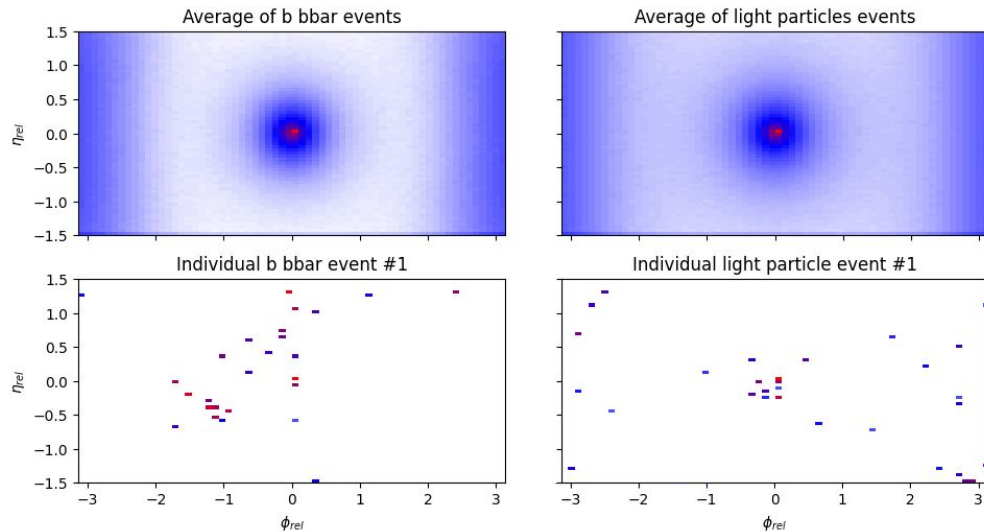


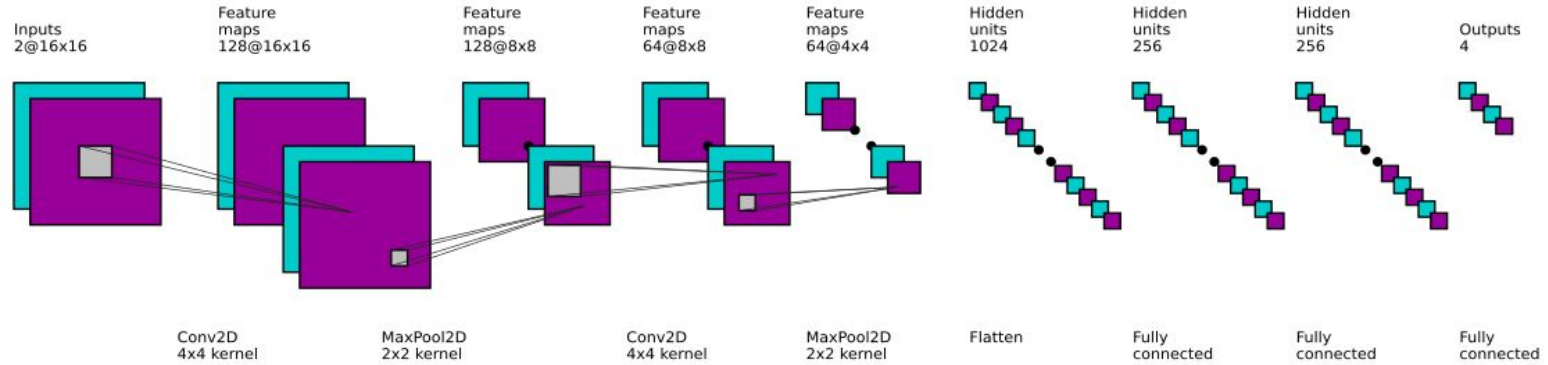
Image from [3]



The ability to tag events

Preliminary results

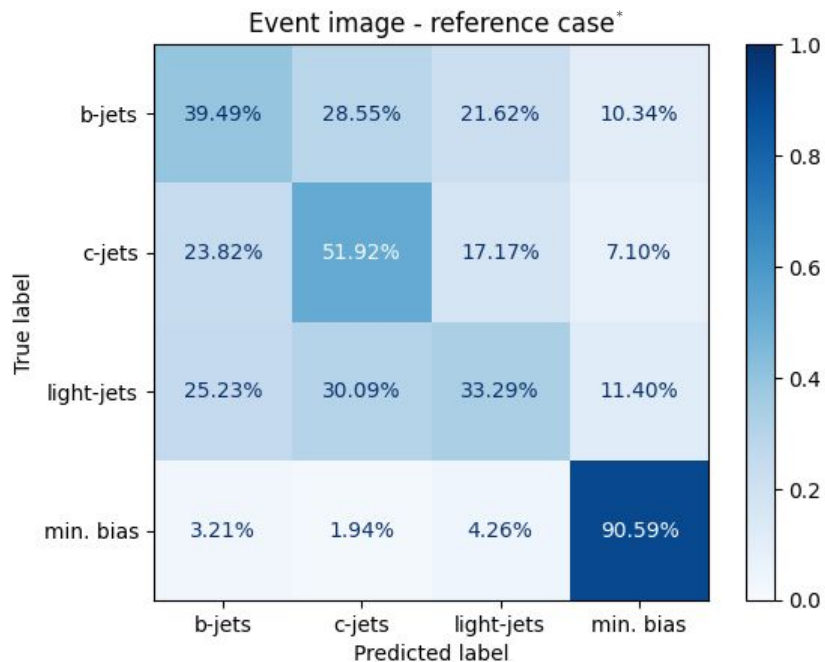
Main framework



Adapted from [4]'s top tagger

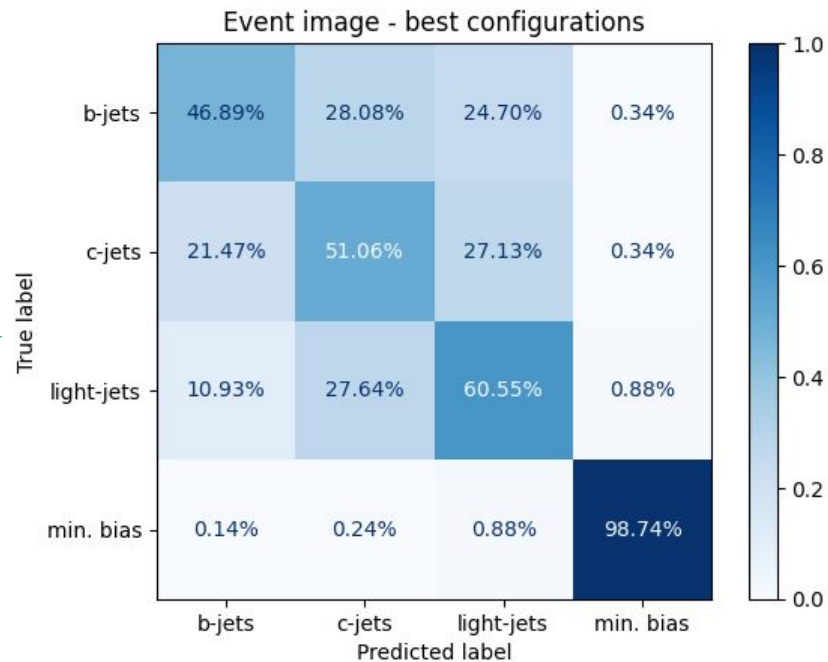
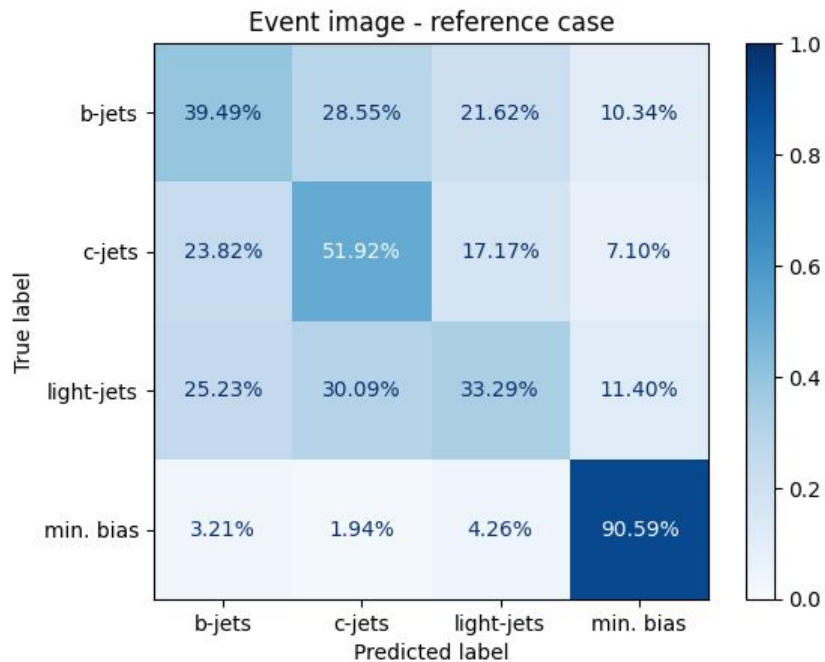
- Activation functions: tanh and softmax
- Epochs: 25
- Optimizer: Adam
- Learning rate: 0.00005, halving each 10 epochs
- Loss function: Categorical cross entropy

Event images



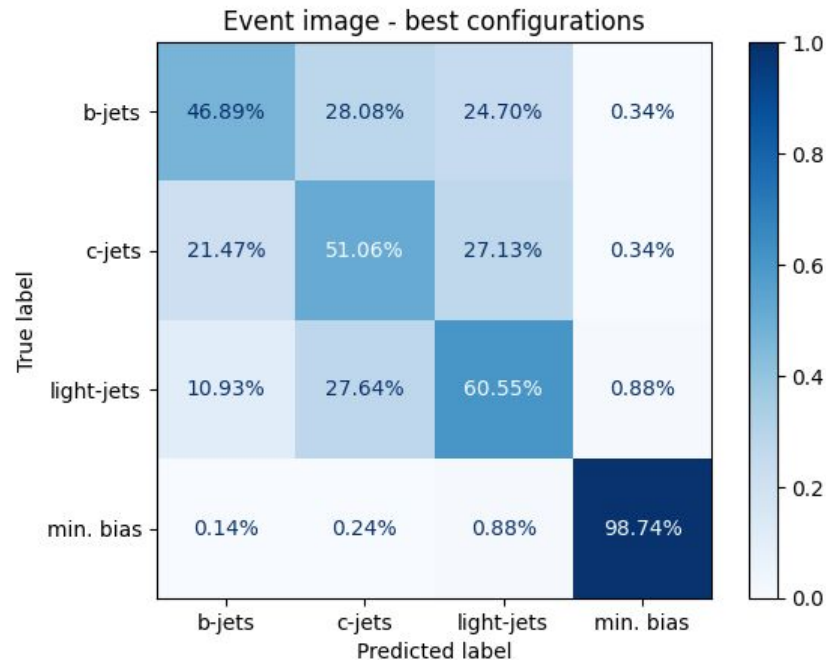
- 16x16 pixels
 - $R \simeq 1$ ($\Delta\eta_{\text{rel}} = \Delta\varphi_{\text{rel}} = 0.7$)
 - Different $\hat{p}_T$ ranges mixed
 - 2 color channels: p_T and charge
- Flavor tagging needs further improvement
- Excels at background separation!

Event images

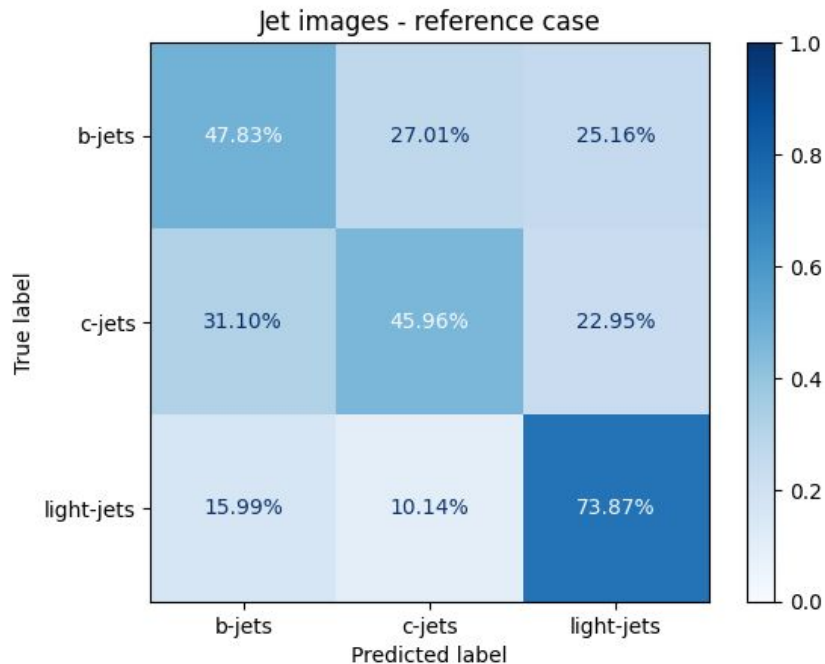


Event images

- $R \simeq 2.8$ ($\Delta\eta_{\text{rel}} = \Delta\varphi_{\text{rel}} = 2$)
- Highest $\hat{p}_T$ range (90 - 110 GeV/c)
- 5 color channels: p_T , charge, baryon, lepton and “meson” number



Jet images



- 16x16 pixels
- $R = \sqrt{2}$ ($\Delta\eta_{\text{rel}} = \Delta\phi_{\text{rel}} = 1$)
- No cuts in p_T
- particle p_T and charge color channels

→ Similar performance for the heavy jets

→ Light tagging improved!

Insights from reconstructed jets

Discussion and outlook

Questions and (possible) answers

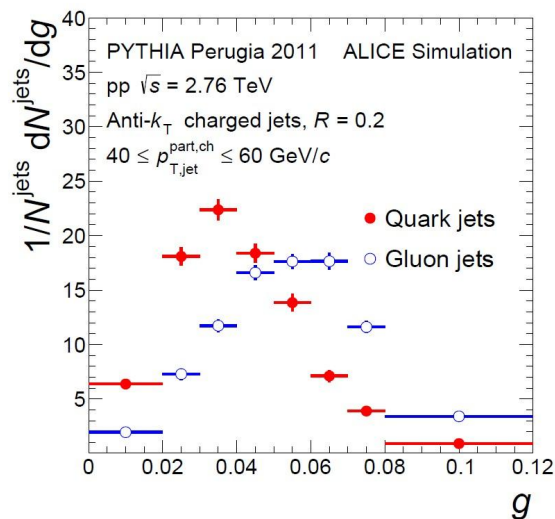
- ❖ Shouldn't the reconstructed jets yield a (even) better result?
 - b and c jets are much more similar than light jets
 - Results given by direct network outputs, discriminant(s) should improve^[1]

$$D_{q_i} = \log \left(\frac{p_{q_i}}{f_{q_j} p_{q_j} + (1 - f_{q_j}) p_{q_k}} \right)$$

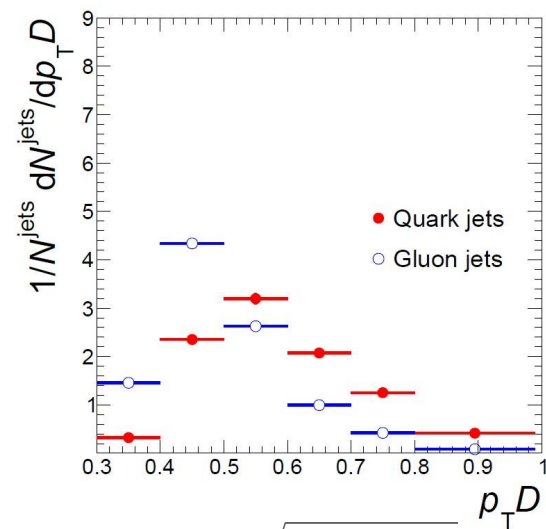
- Same low level variables as before, but jet properties could help
- ❖ Where does this put event images?

Extracting jet information

- Jet shape is sensitive to jet flavor^[5]:



$$g = \sum_{i \in jet} \frac{p_{T,i}}{p_{T,jet}} \Delta R_{jet,i}$$

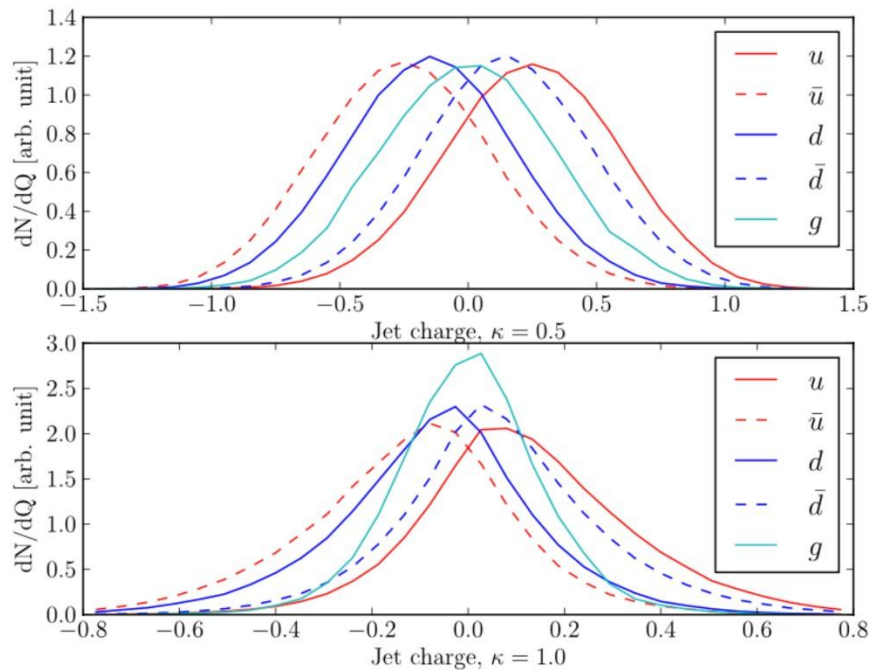


$$p_T D = \frac{\sqrt{\sum_{i \in jet} p_{T,i}^2}}{\sum_{i \in jet} p_{T,i}}$$

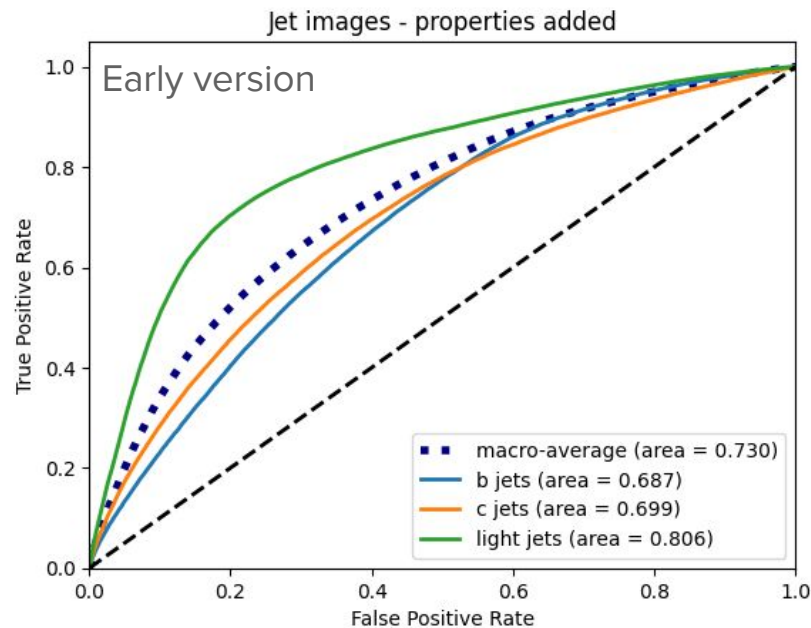
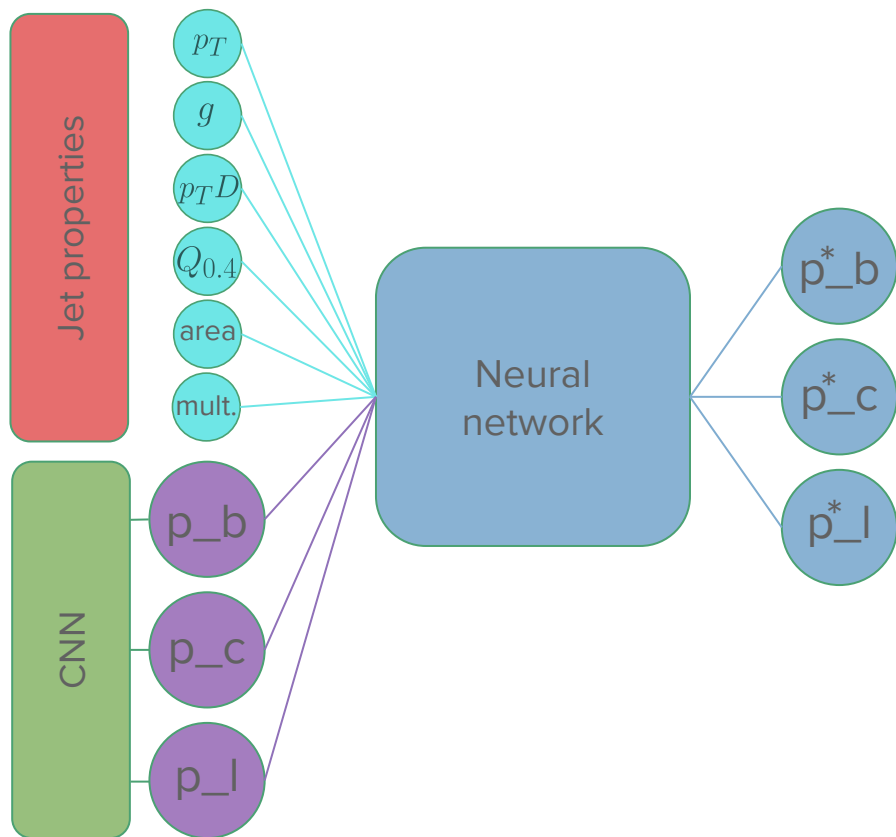
Extracting other jet information

- Other jet properties as well^[6]

$$Q_k = \sum_{i \in \text{jet}} \left(\frac{p_{T,i}}{p_{T,\text{jet}}} \right)^k Q_i$$



Adding a second network



Outlook

- Improve the secondary network
- Adapt observables to event landscape
- Hope for the best!



Thank you!



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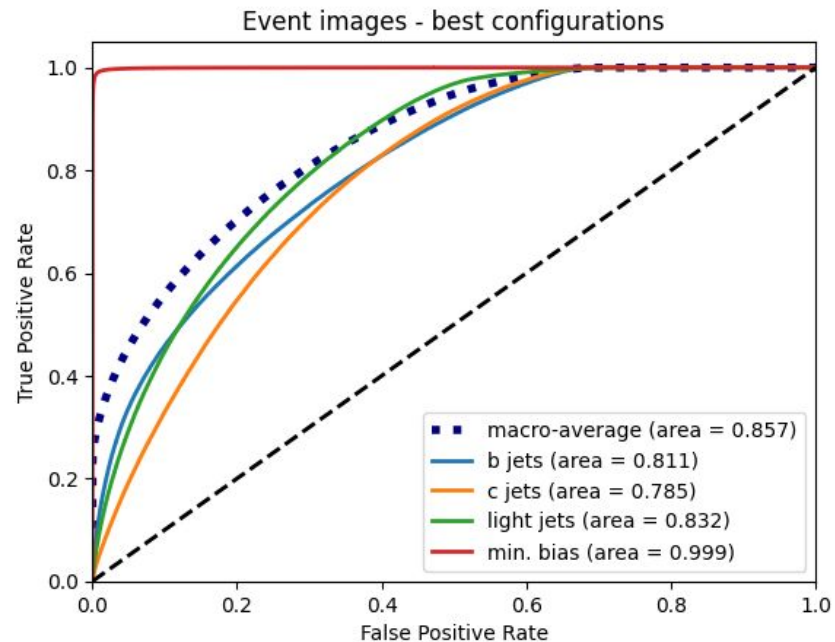
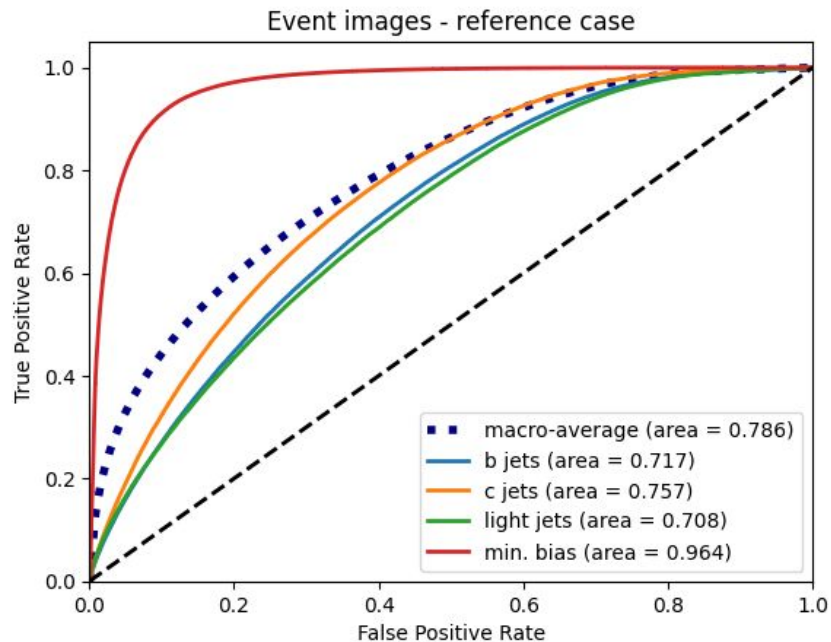
Backup

The database

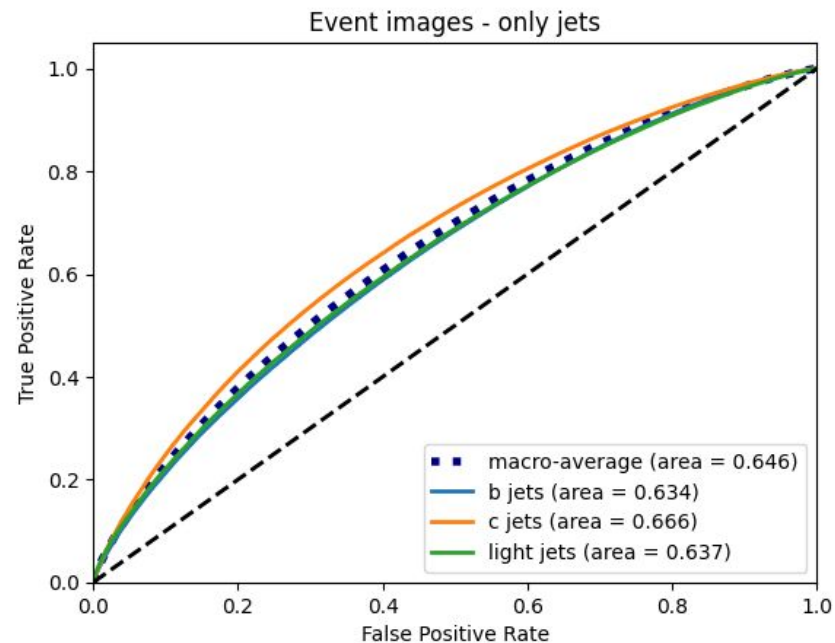
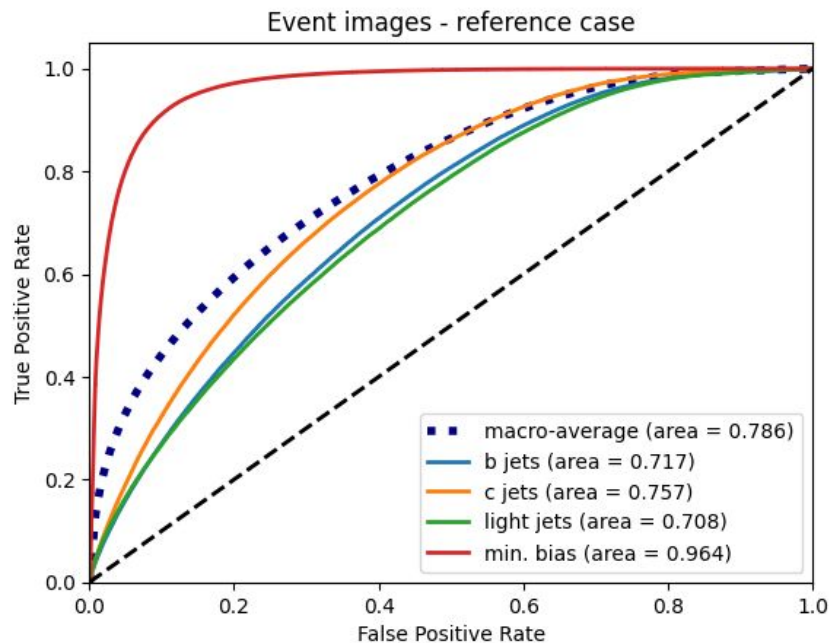
- Simulated collisions
 - ◆ Pythia 8.3 Monash Tune with CT10 PDFs
 - ◆ p+p with 13 TeV
- Selected processes
 - ◆ One process per event
 - ◆ Production of bottom, charm, light particles (light quark + gluons)
 - ◆ Minimum bias for background
- Defining our jets
 - ◆ Charged final state particles (detectable)
 - ◆ 50 most energetic particles
 - ◆ Hard processes (except background)
- Cuts in $\hat{p}_T$ phase space
 - ◆ 20 to 30 GeV
 - ◆ 40 to 60 GeV
 - ◆ 90 to 110 GeV

ROC curves

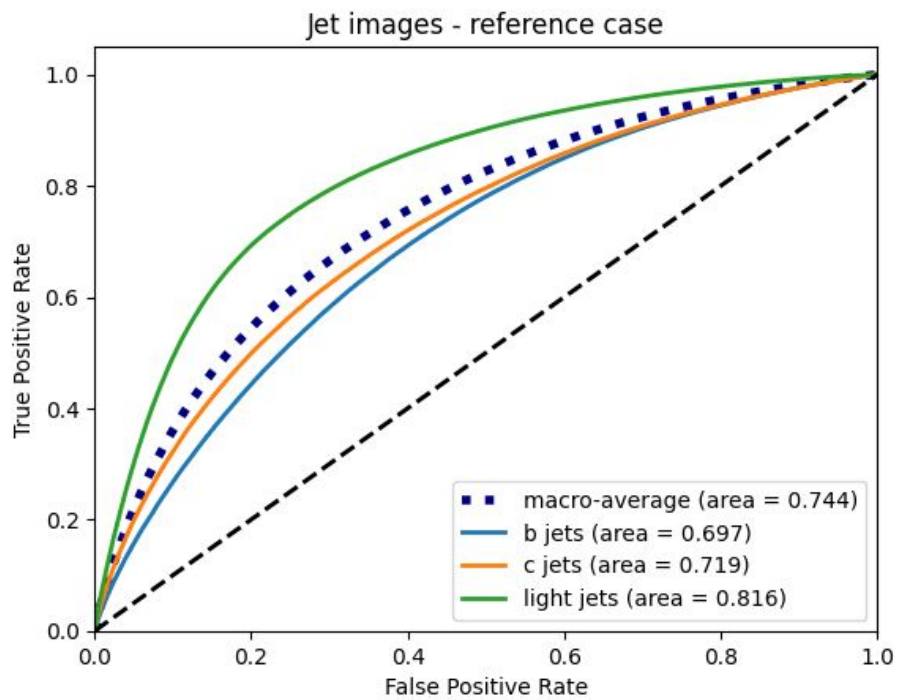
Event images



Event images



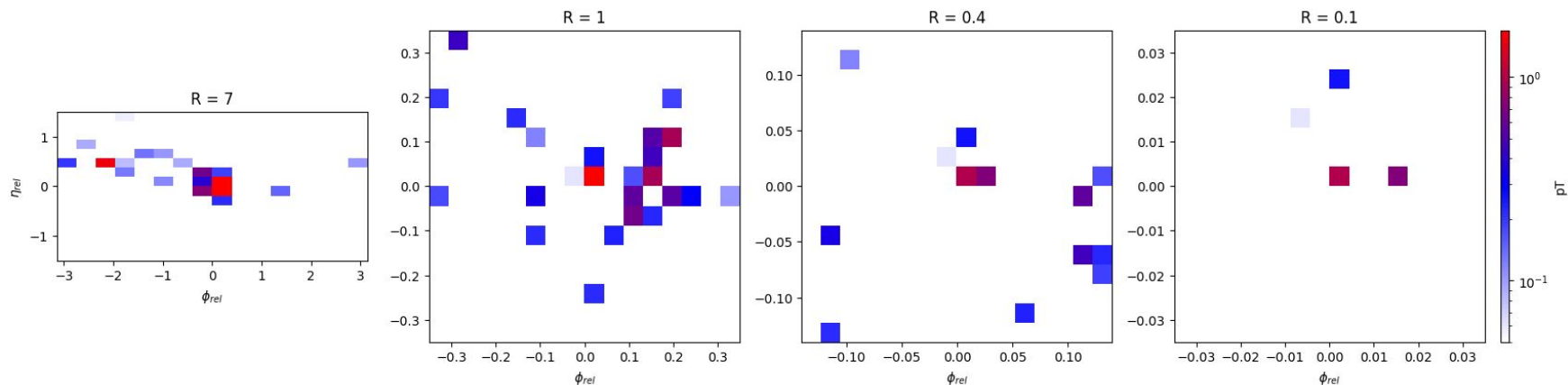
Jet images



Studies in event images configuration

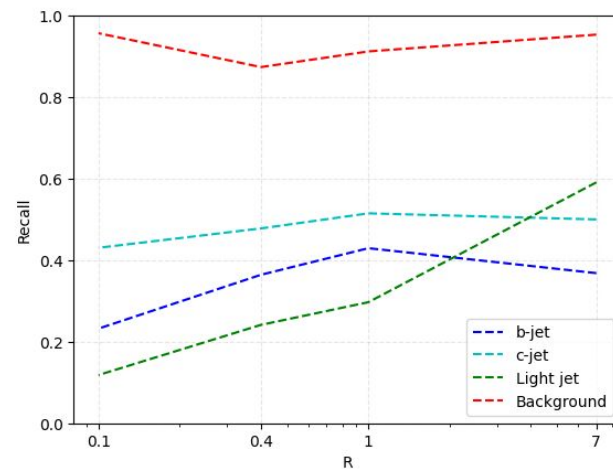
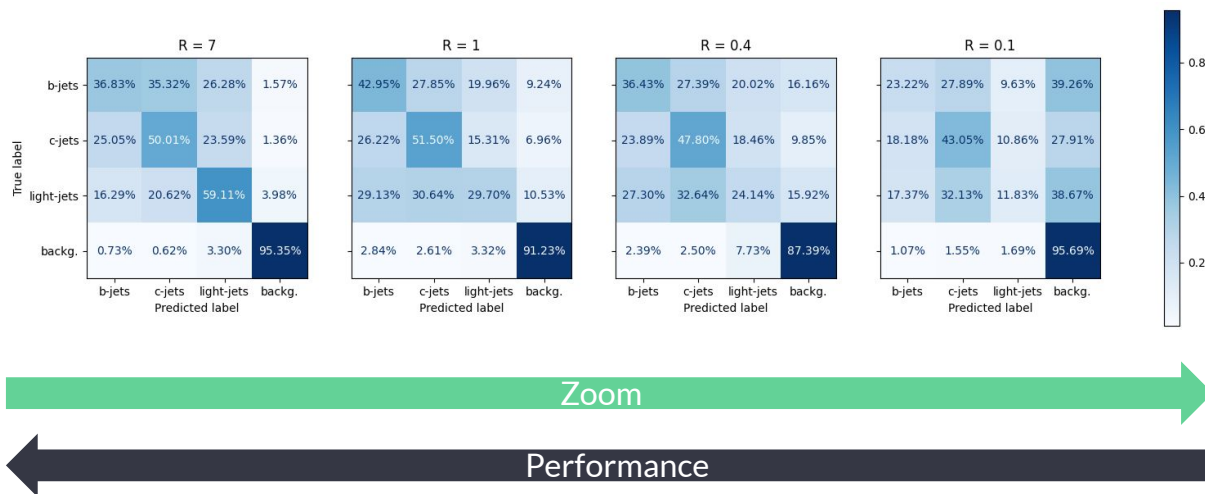
Applied models

- Configuration studies
 - ◆ Images zoom (R factor)



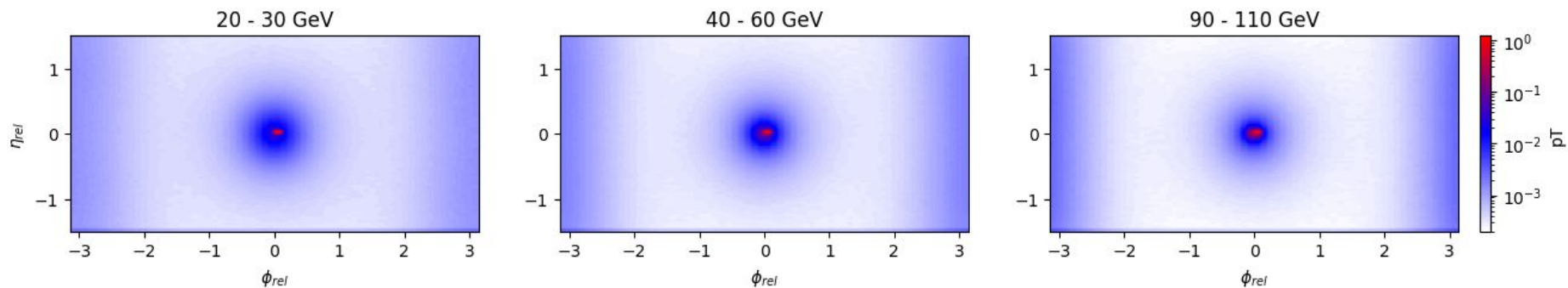
Applied models

- Configuration studies
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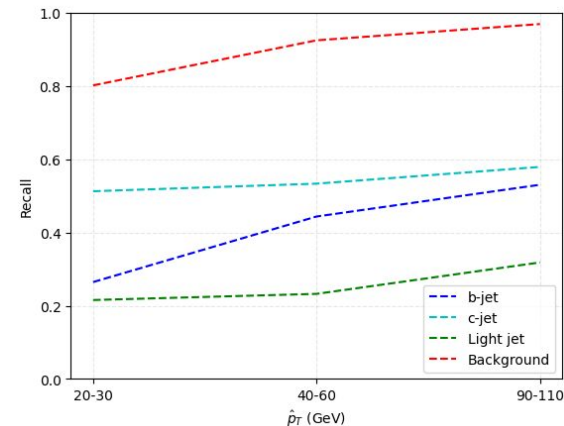
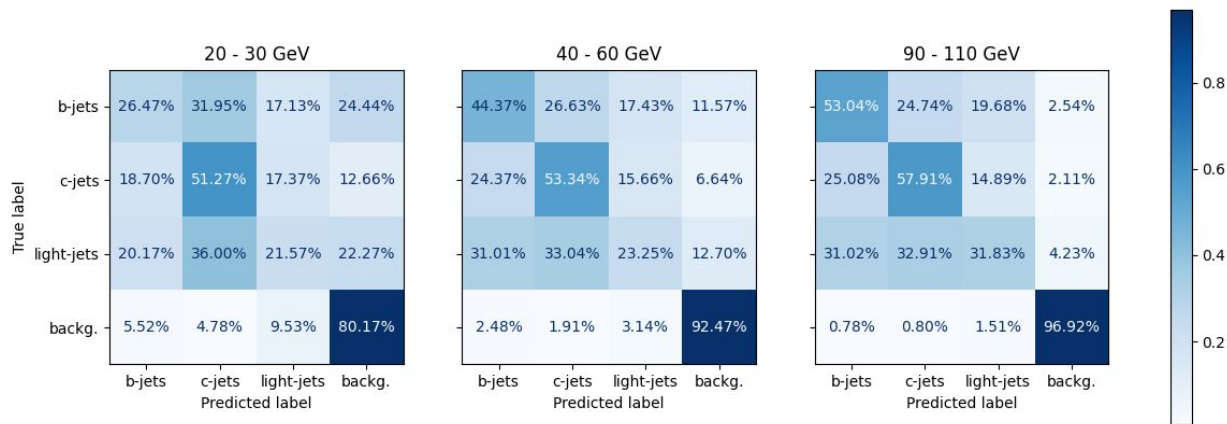
Applied models

- Configuration studies
 - ◆ Separation by $\hat{p}_T$



Applied models

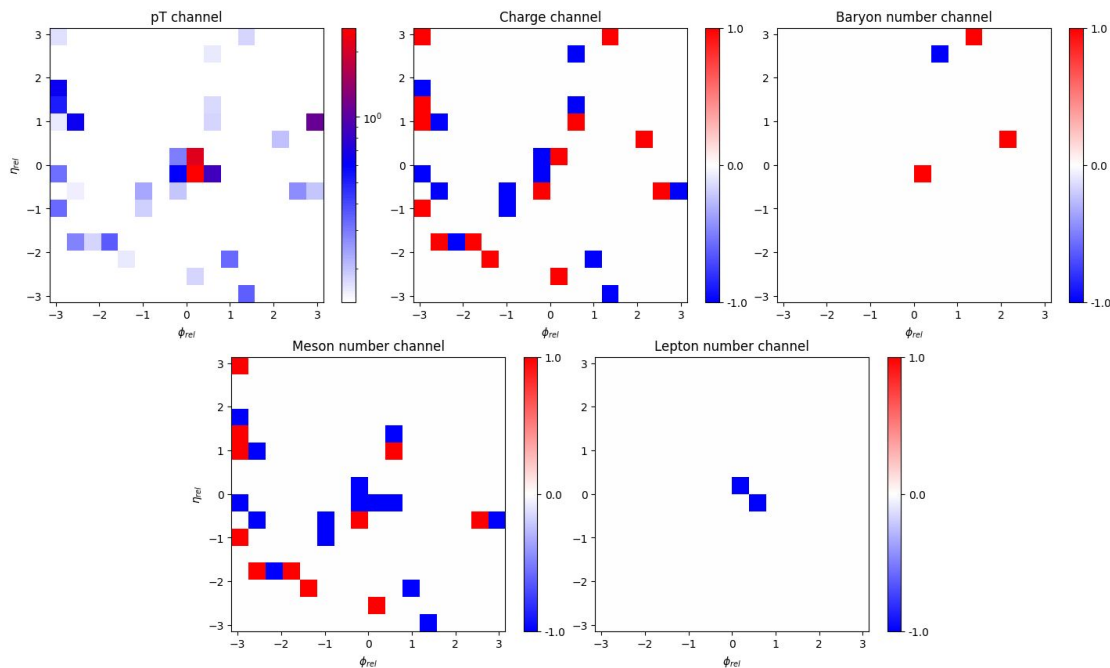
- Configuration studies
 - ◆ Separation by $\hat{p}_T$



Higher energy → More particles → Better results

Applied models

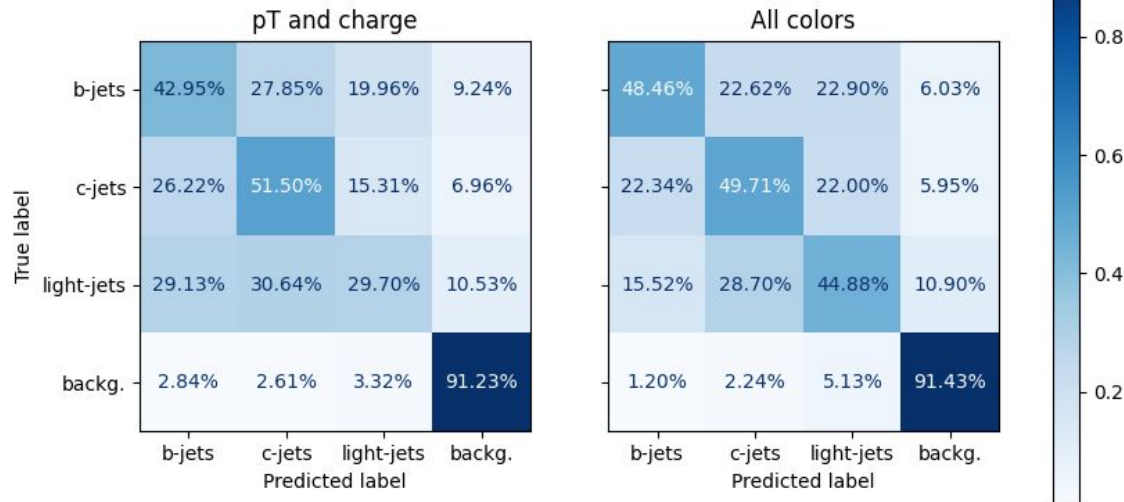
- Configuration studies
 - ◆ Addition of colors (particle identification)



Applied models

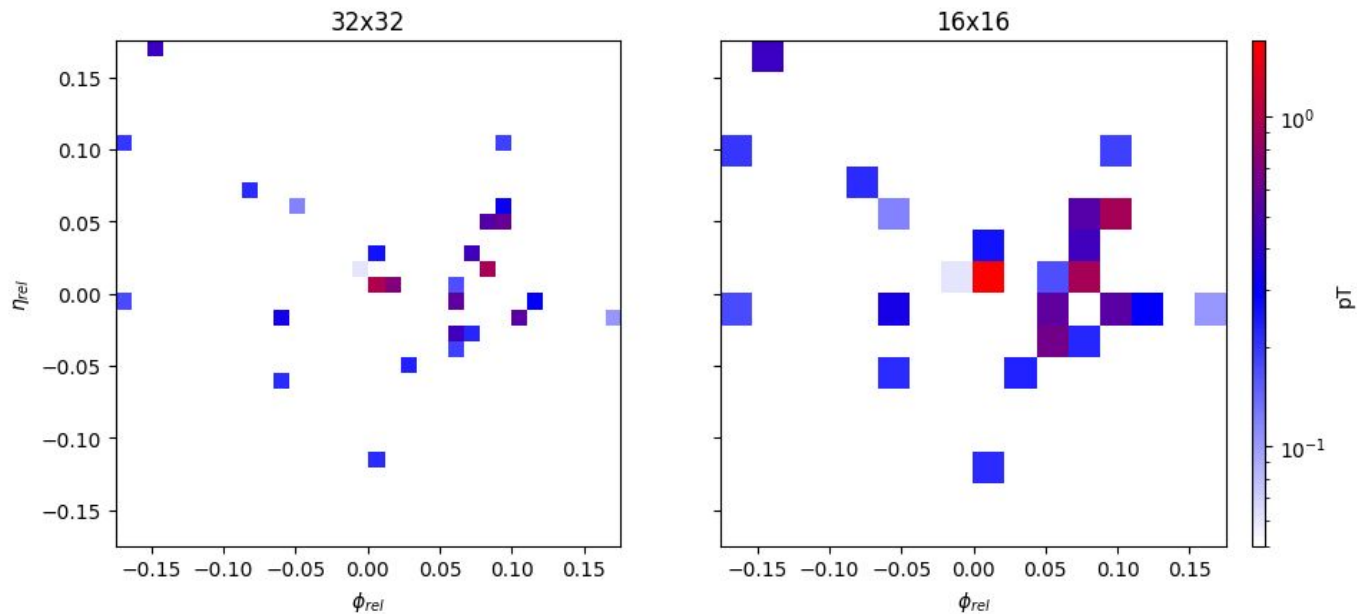
- Configuration studies
 - ◆ Addition of colors (particle identification)

- Light jets reach the same level as heavy jets
- The recall on b-tagging gets better
- False positive rates of several classes improve as well



Applied models

- Image settings
 - ◆ Pixel resolution



Applied models

- Image settings
 - ◆ Pixel resolution

→ Higher granularity improves the performance too little for the computational cost

