Upper limits on the isotropic diffuse flux of PeV photons from Carpet-3 data using Domain Adaptation

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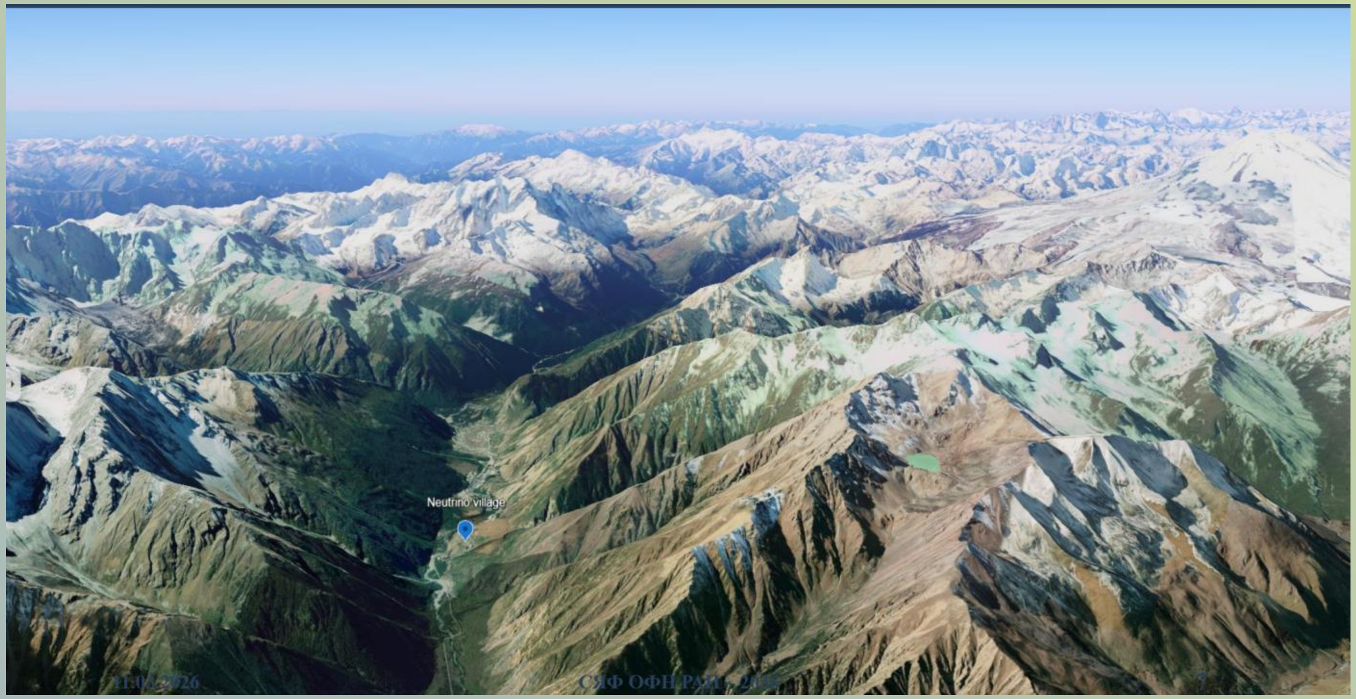
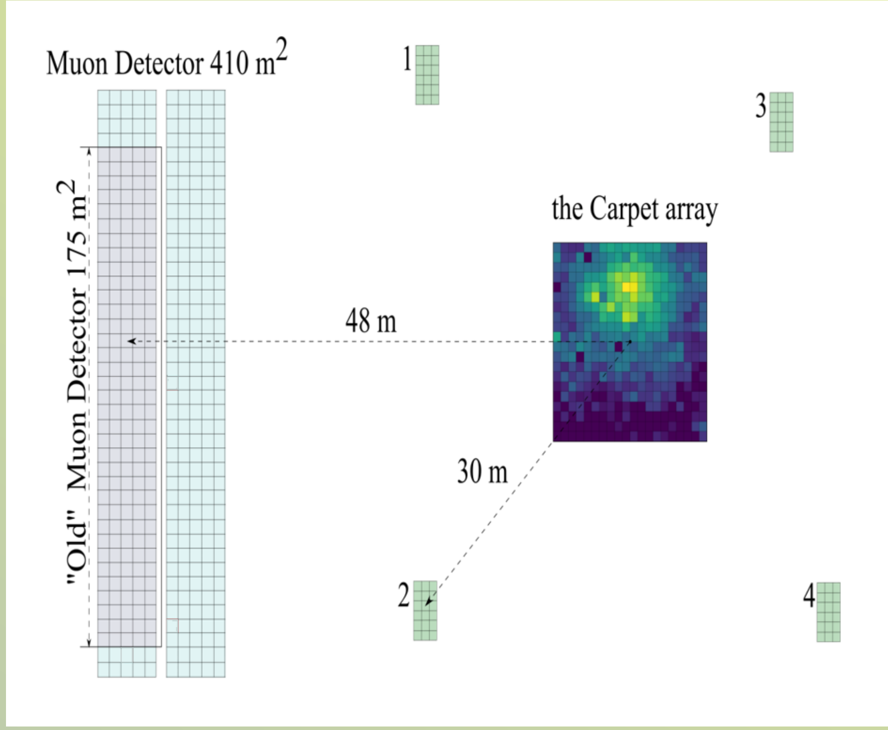
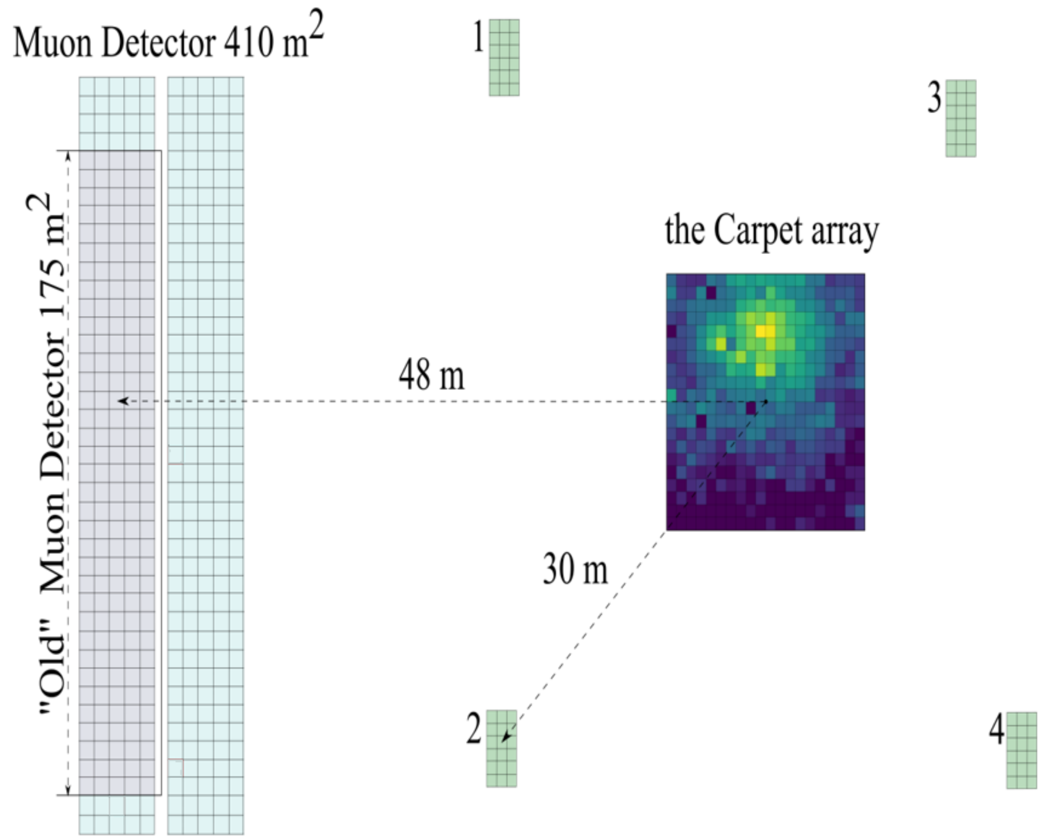
Carpet-3





Russia, Baksan Valley, Neitrino village
1 700 m above sea level

Carpet-3



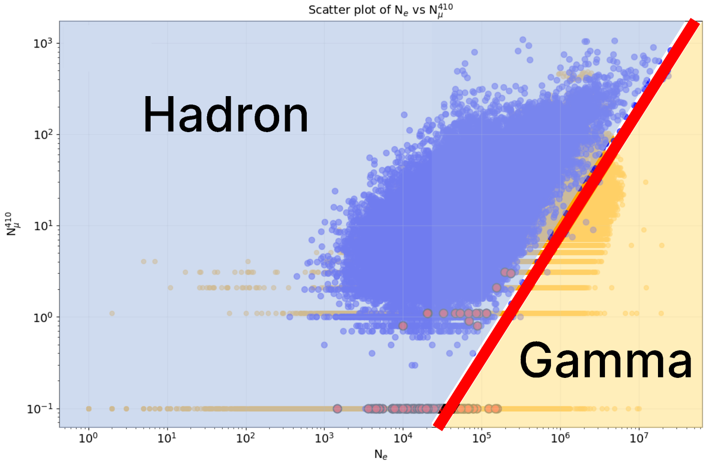
Ground array
400 liquid scintillator detectors
Total area of 196 m^2

4 outer stations with plastic scintillator detectors 9 m^2 each

Underground muon detector
175 m^2 **old** and 235 m^2 **new**
Total area of 410 m^2

Gamma/hadron separation

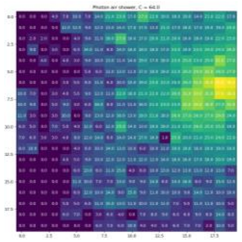
Reconstructed
N_e, N_μ



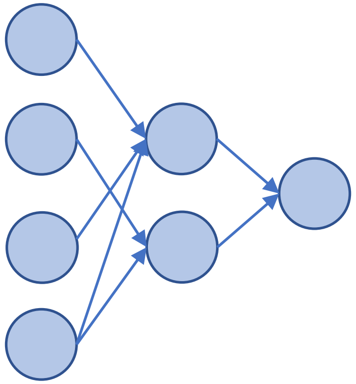
Photon-like events = muon-poor events

Easy physical interpretation, but imposes a very harsh cut.
Needs accurate muon density modeling

We can do better – use everything that's measured!



Reconstructed parameters



Particle type prediction

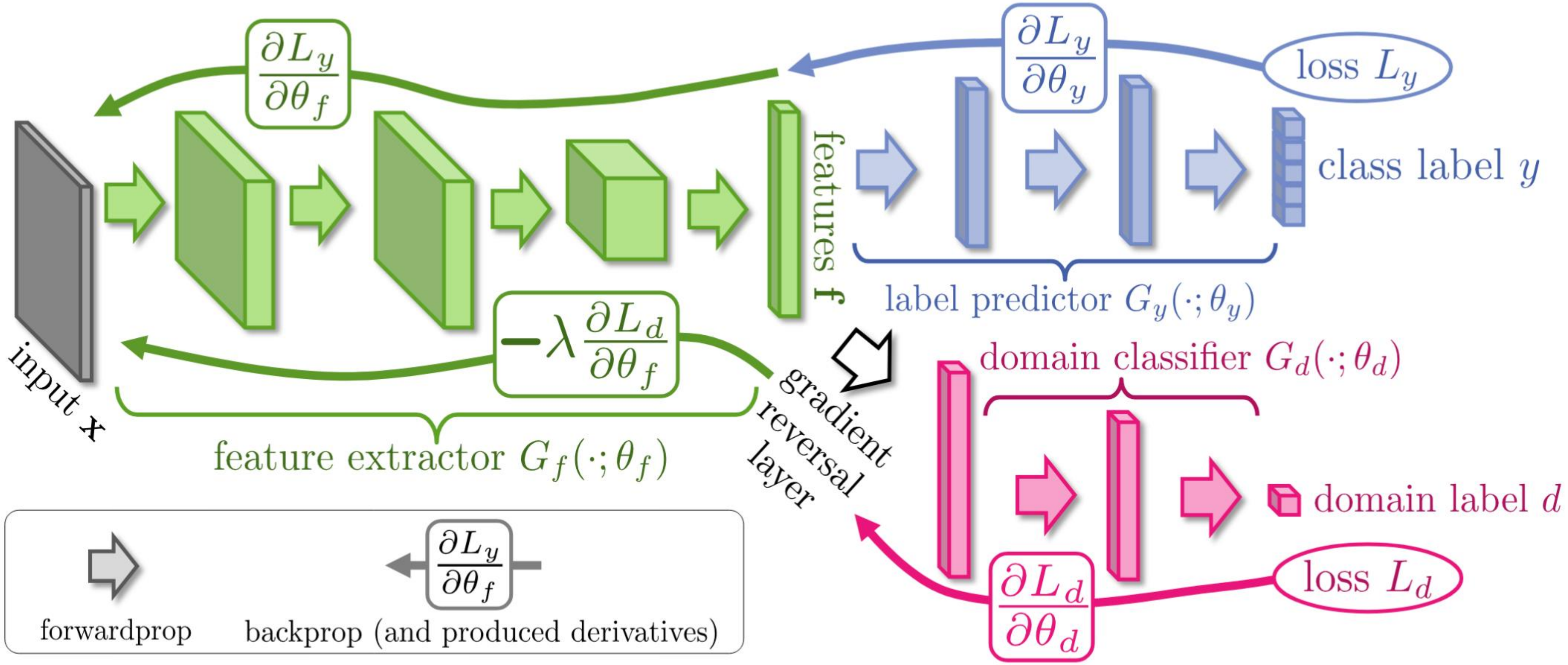
Can separate muon-poor events better due to more features.
Can capture more intricate differences

Domain adaptation

Neural networks require large amounts of training data. Usually, Monte Carlo simulations are used. But what if the target domain is different from the source domain?
Answer: Domain Adaptation!

The goal is to make the network use domain-invariant features, so examples from MC and Data look the same to the network. Then you can trust the source domain statistics when using it on the target domain.

Domain adaptation-2



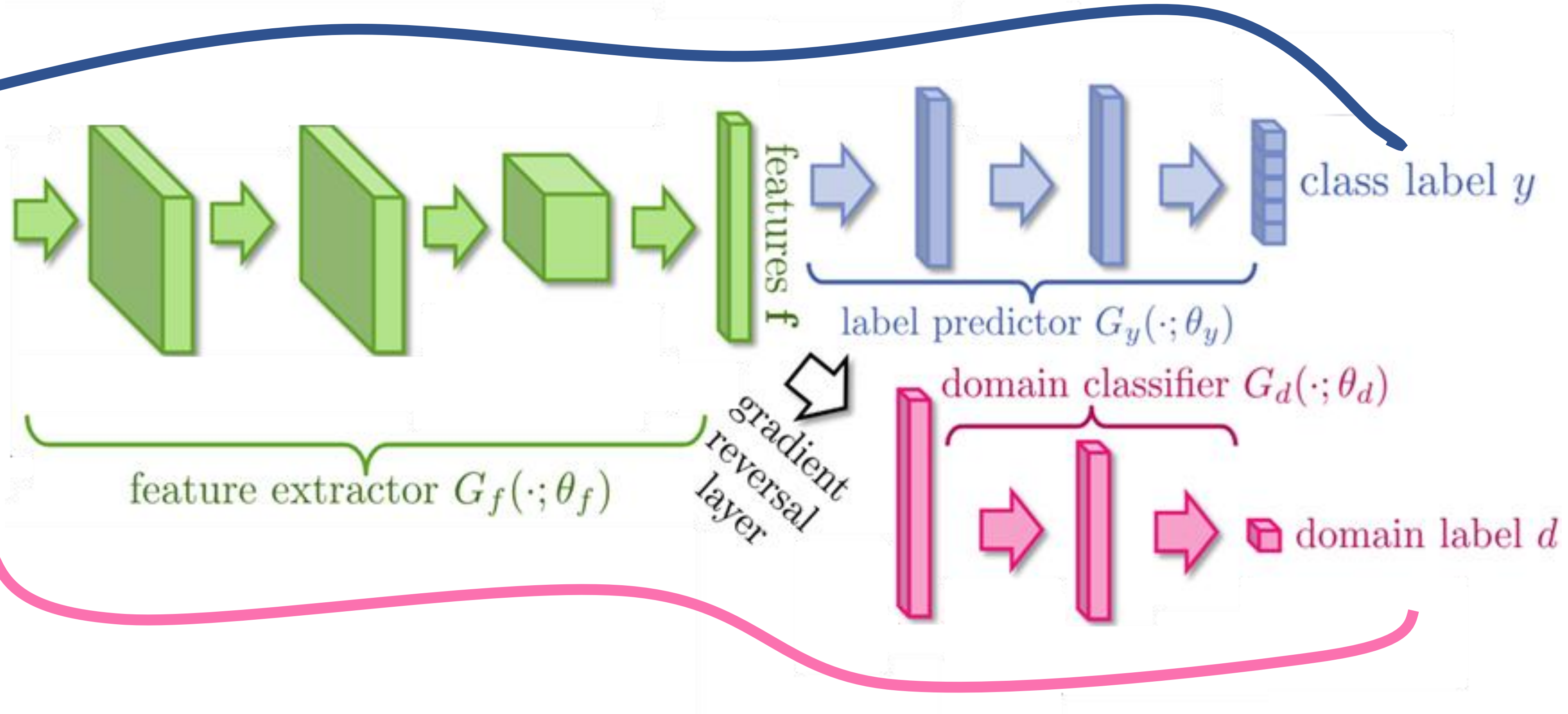
Unsupervised domain adaptation (Ganin, Lempitsky 2015) – train the network with examples from both domains to predict the class and domain. Gradient reversal maximizes the domain loss gained from the feature extractor – this makes the feature distributions similar and excludes domain-specific features.

Data Flow

50 % p/γ MC E^{-1}

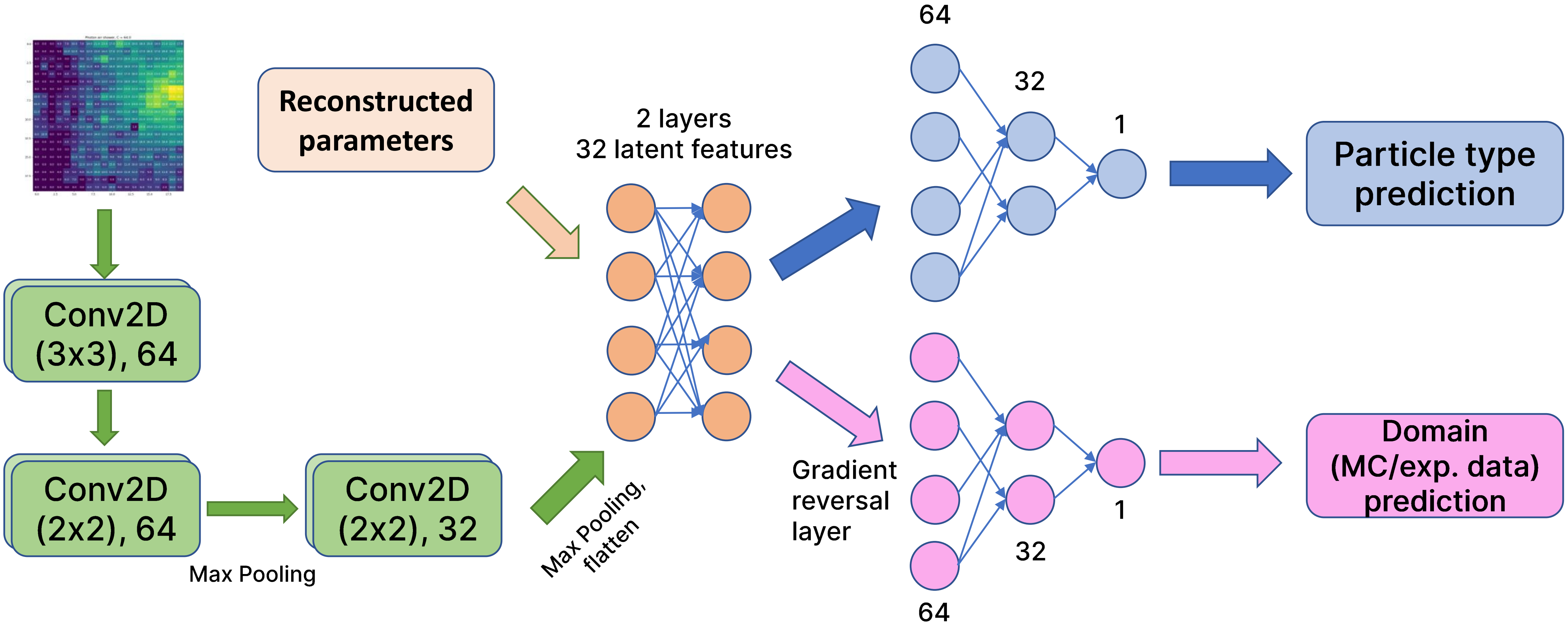
25 % p MC $E^{-\alpha}$

25 % Exp. data $E^{-\alpha}$



Monte-Carlo and real data are separate – the network learns to predict the class only on MC, but learns to predict the domain on data and proton MC similar to data. This is important because of different energy spectra.

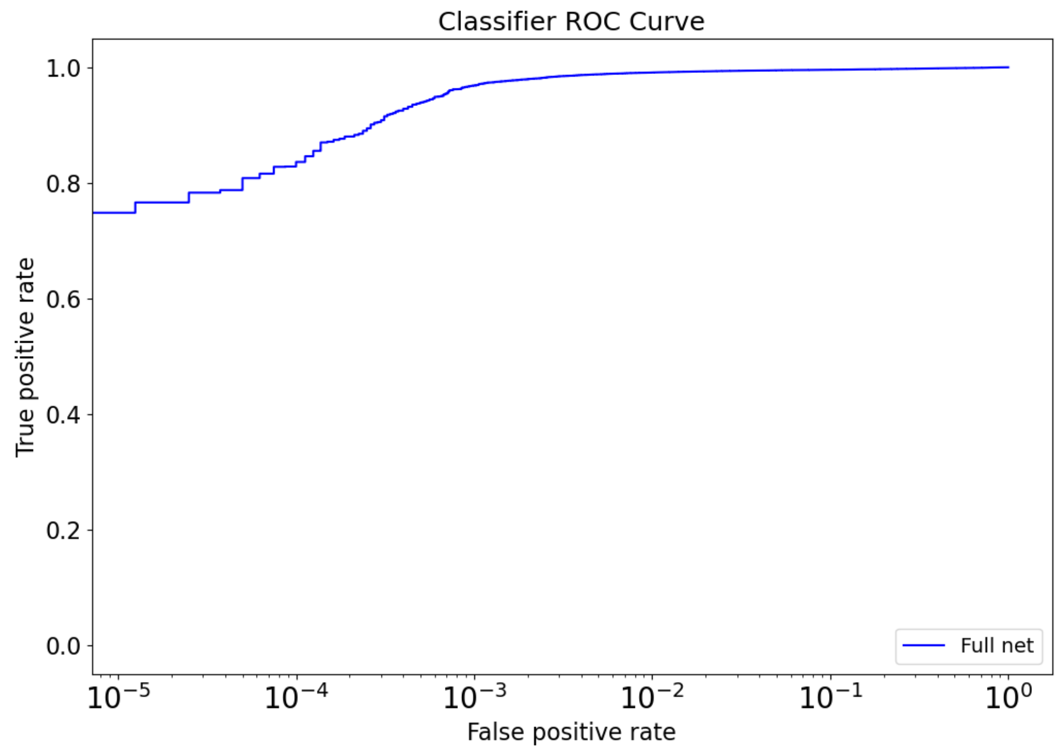
Network Architecture

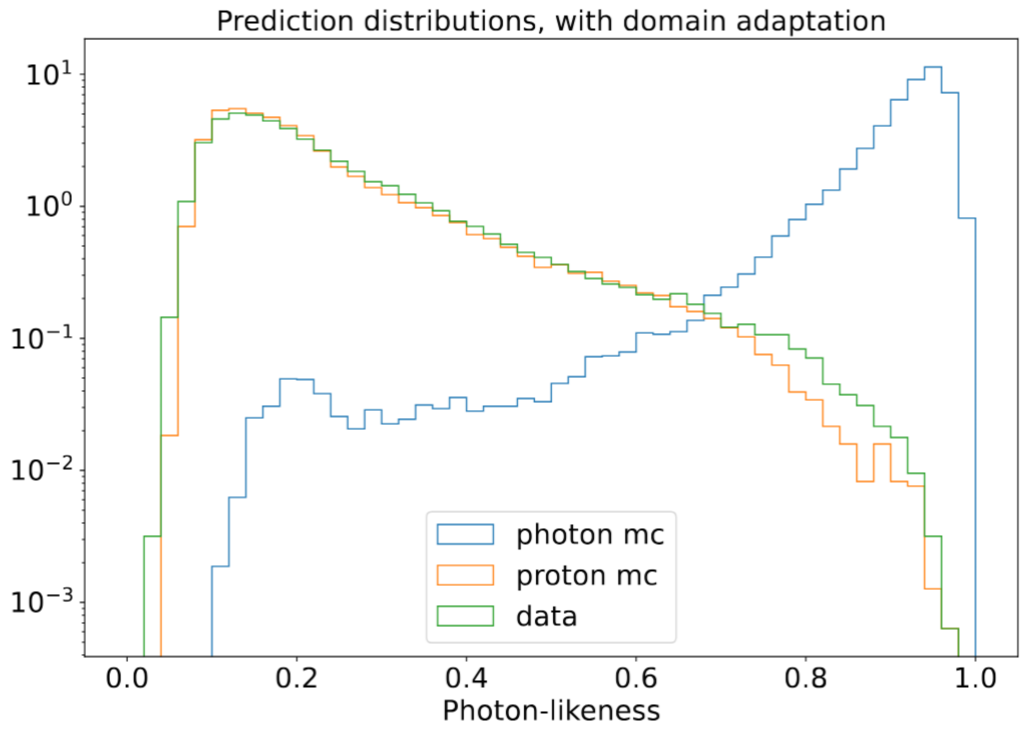


Hybrid network – central detector array is processed by CNN, reconstruction added later

Both prediction heads are identical, both have **32** latent features as input

Classifier metrics

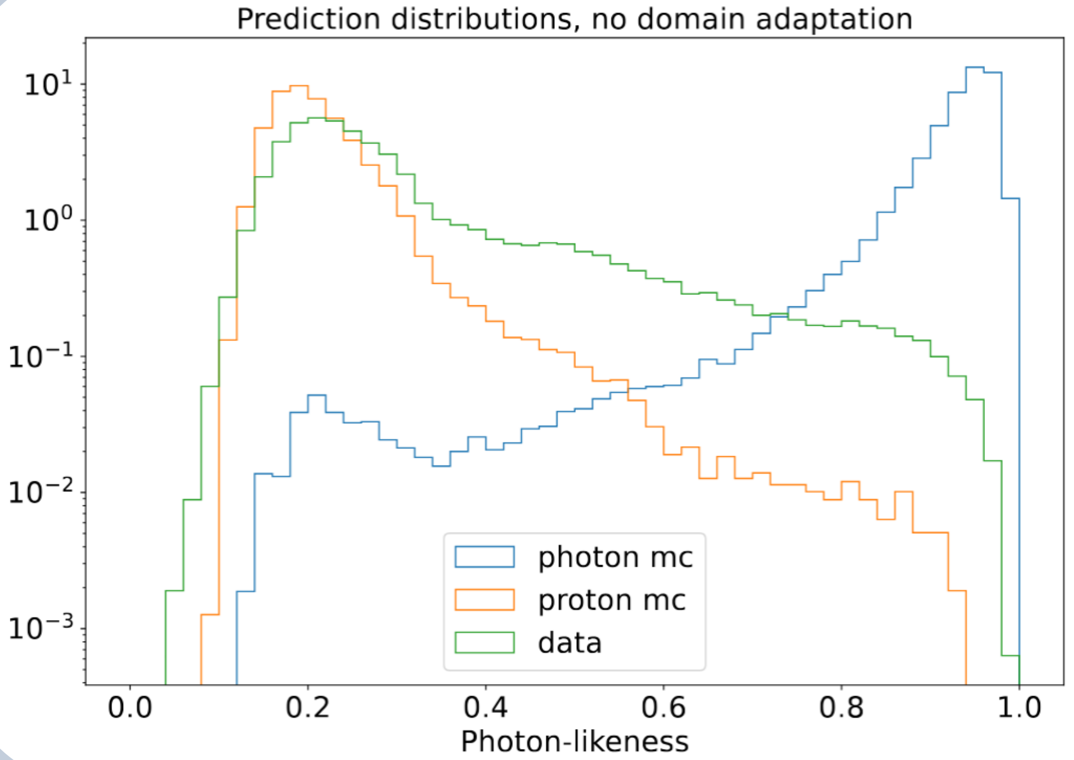


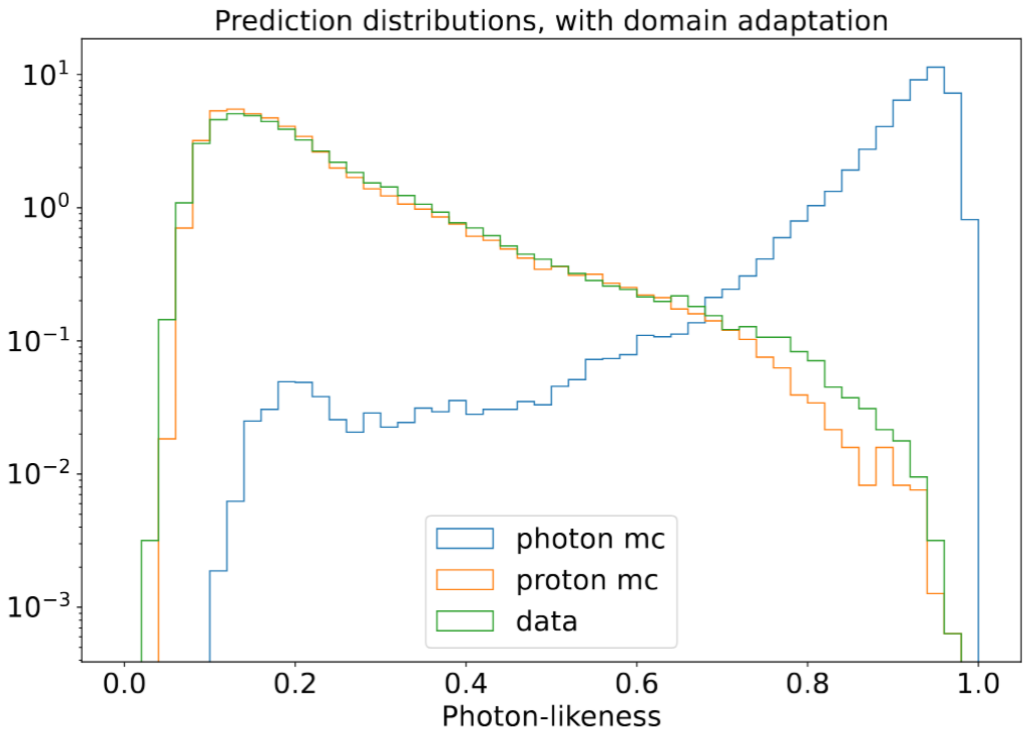


ROC curve on the test set
(160 000 events)

Predictions distribution on data,
proton mc and proton/gamma mc

Classifier metrics - 2



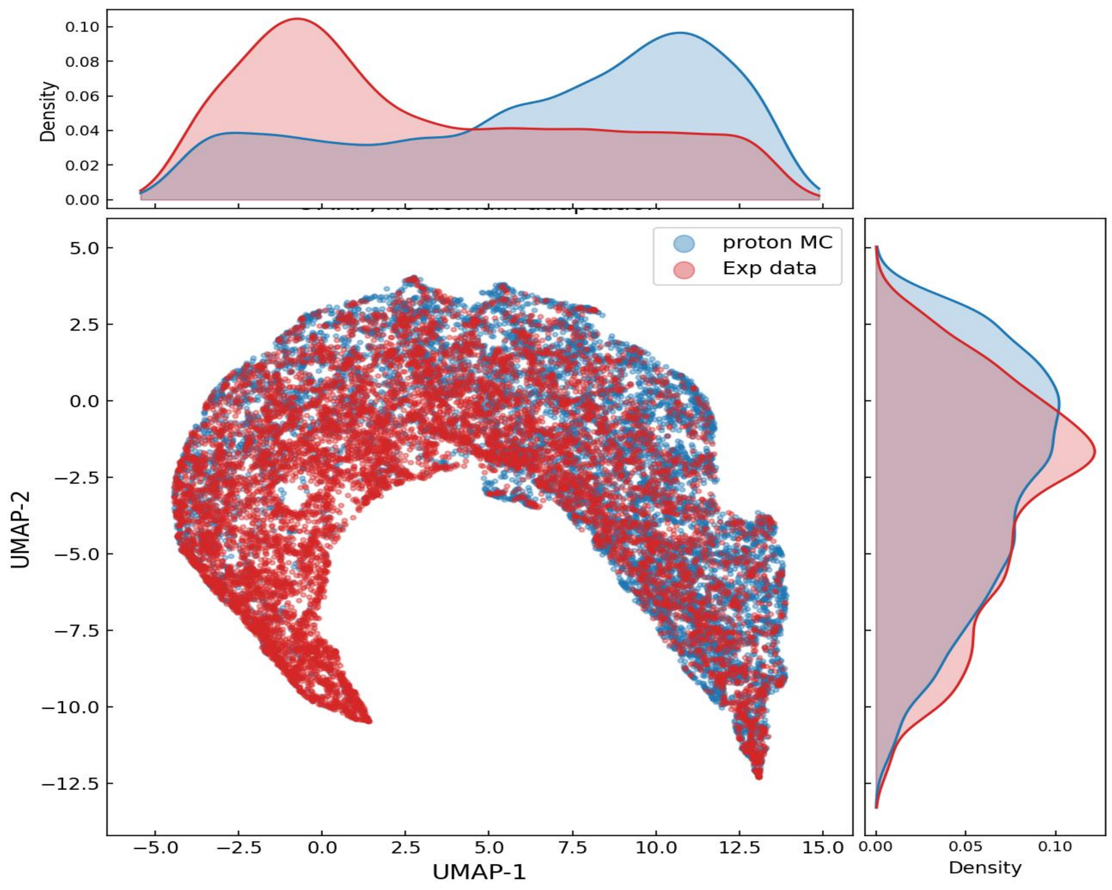


Predictions distribution on data, proton mc and gamma mc (no domain adaptation)

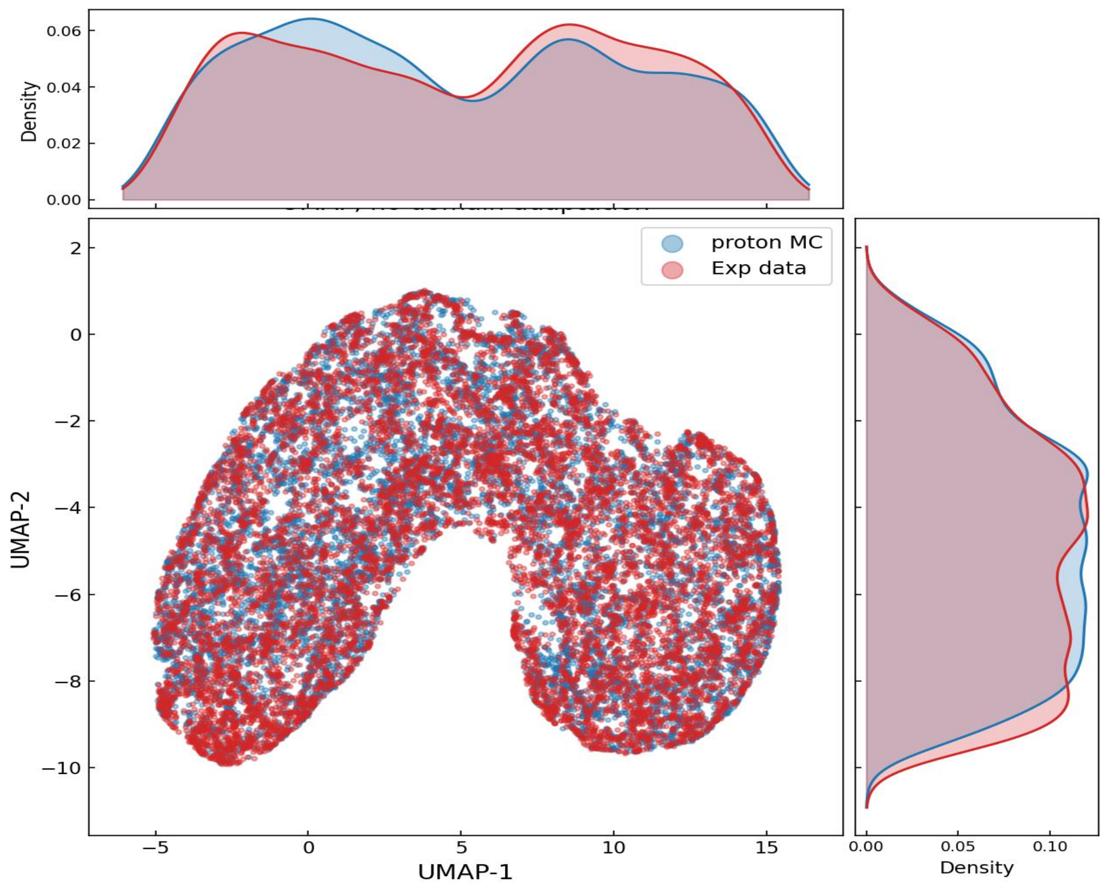
Predictions distribution on data, proton mc and gamma mc (with domain adaptation)

Domain adaptation effects

UMAP without domain adaptation



UMAP with domain adaptation



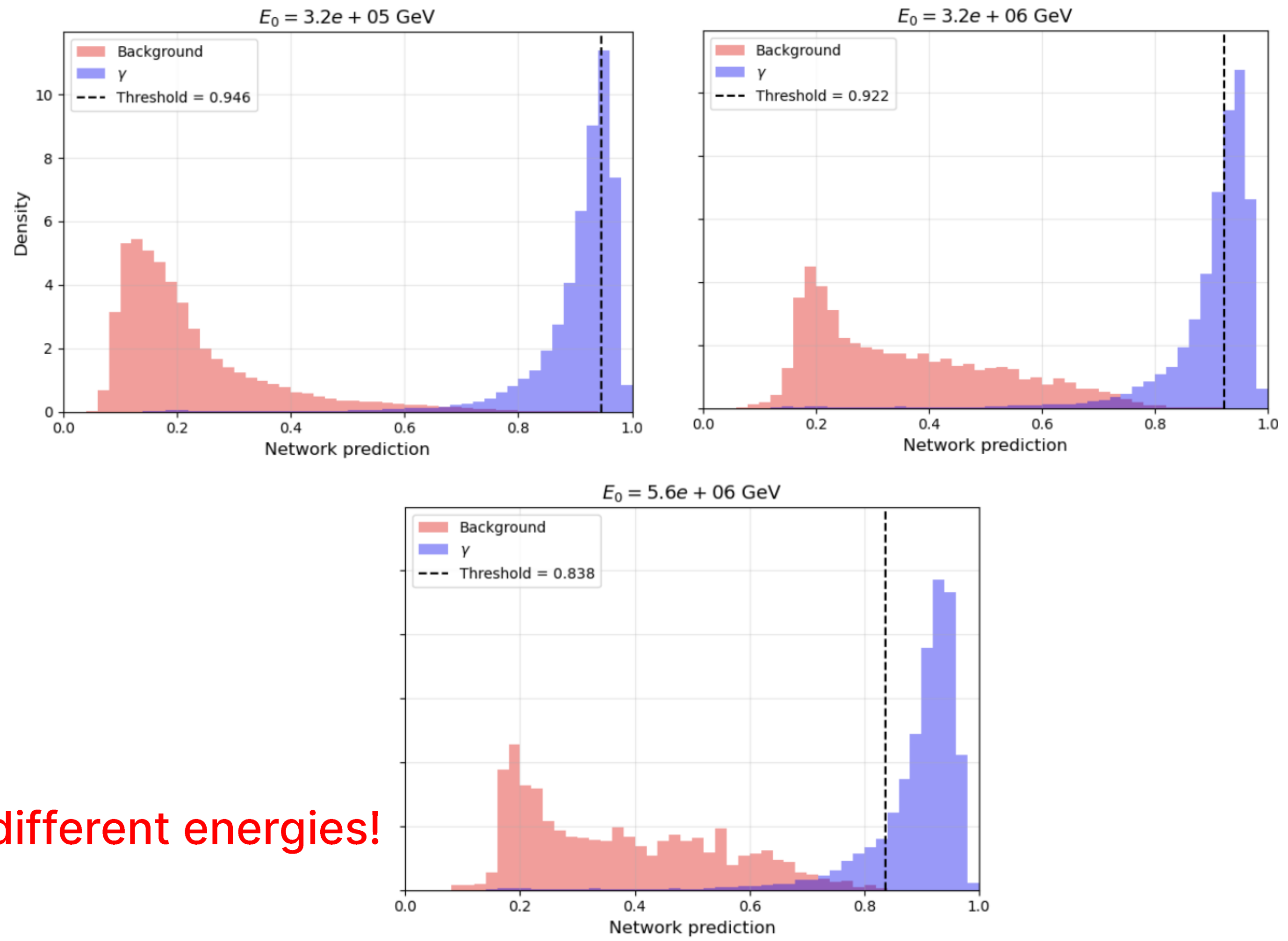
Domain adaptation makes the feature distributions closer

Isotropic diffuse photon flux upper limits

Limits are set mainly by background events

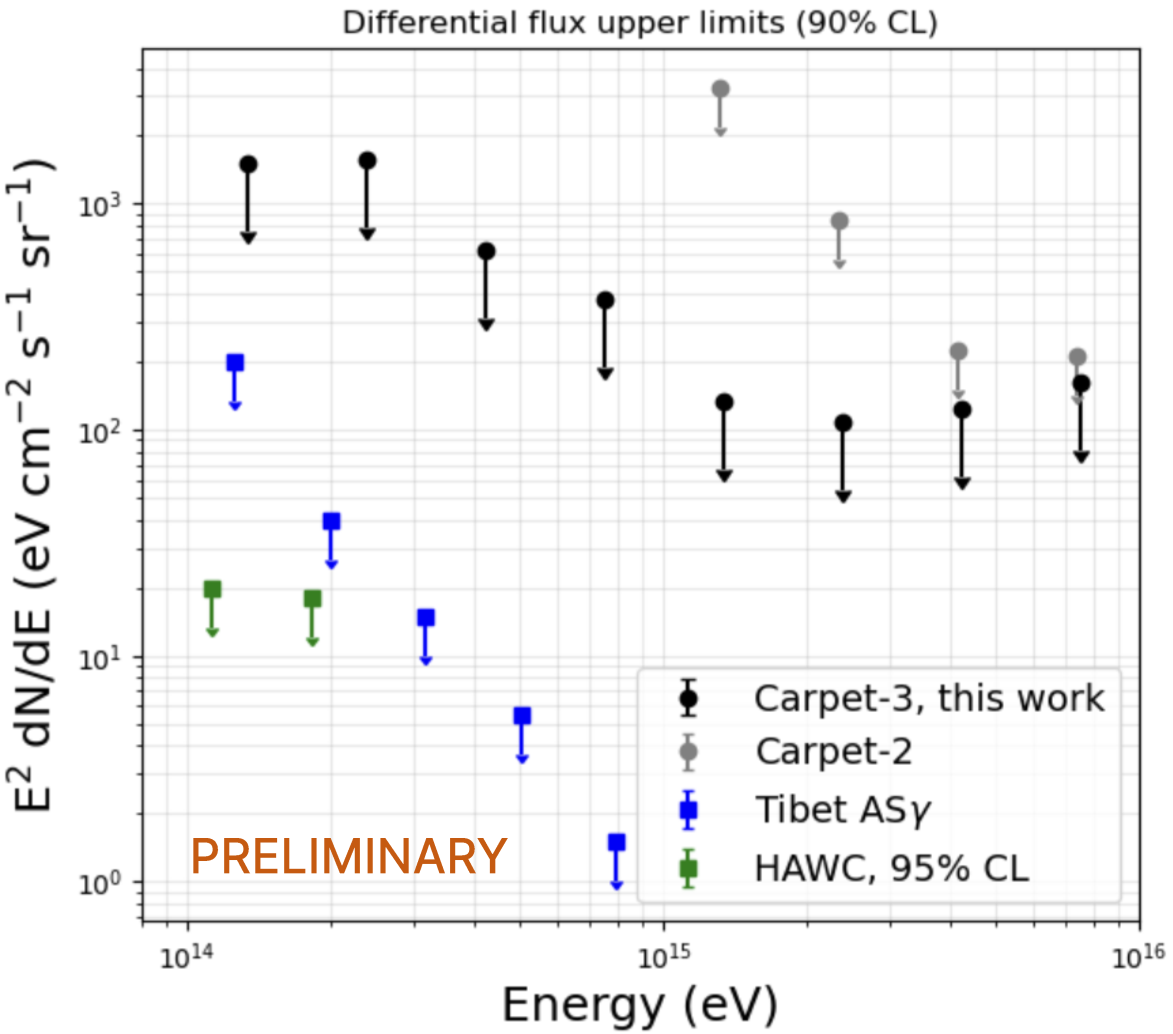
Main procedure:

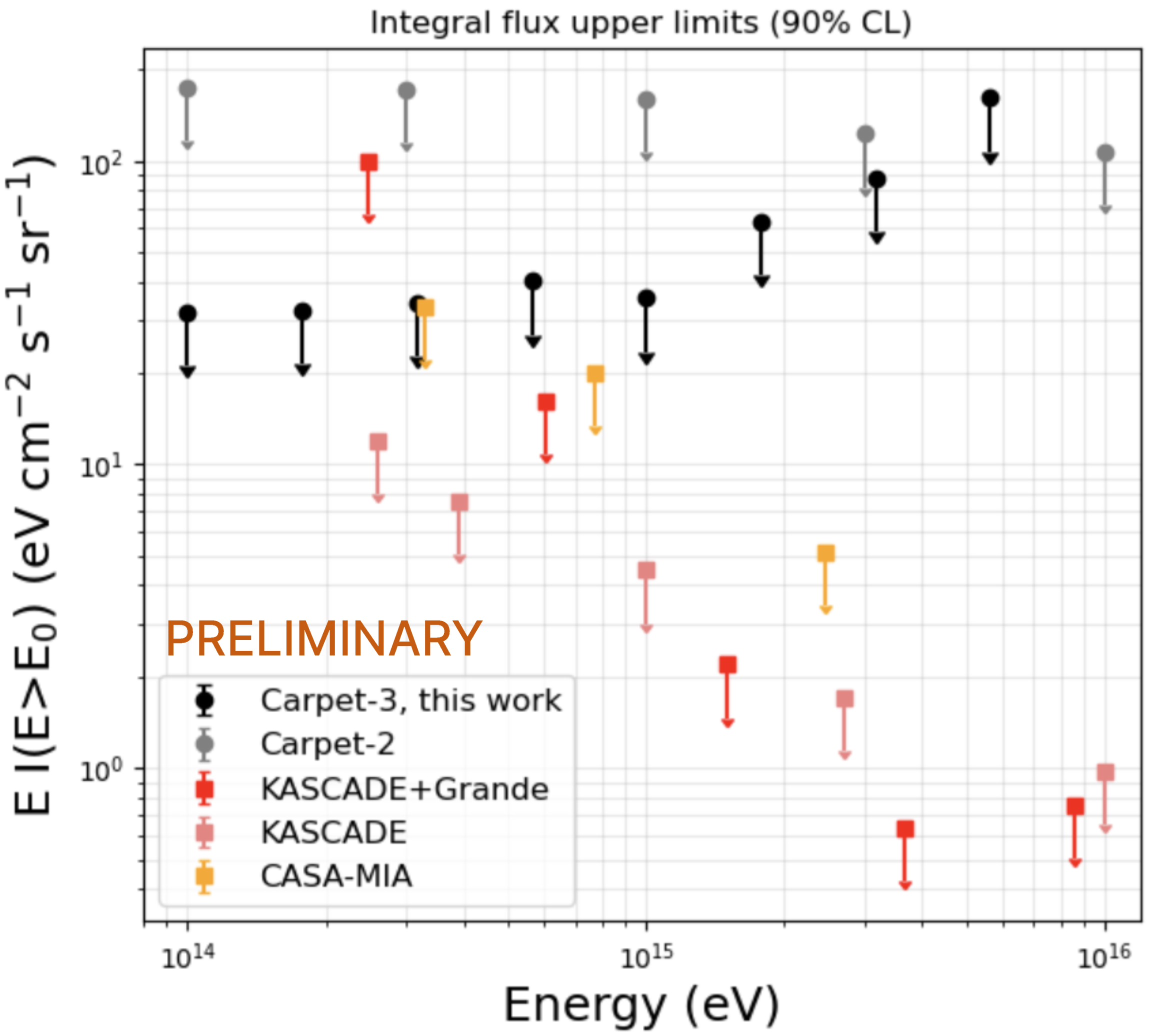
- Run predictions on experimental-like MC
- Calculate N_{bkg}^{90} at 90% CL in each energy bin (assuming Poisson statistics)
- Minimize $\dfrac{N_{bkg}^{90}(\xi)}{Efficiency(\xi)}$ for each bin



Different thresholds at different energies!

Isotropic diffuse photon flux upper limits





Differential (left) and integral (right) diffuse photon flux upper limits.
This work – in black. Carpet-2 limits – in grey.
E^{-2} spectrum is assumed. Exposure time is 1076 days.

Conclusions

Neural networks improve gamma/hadron discrimination, especially at lower energies

Domain adaptation is crucial in making network predictions reliable when training on imperfect Monte-Carlo

First Carpet-3 upper limits on diffuse isotropic photon flux are presented. Neural networks allowed it to outperform Carpet-2 in a shorter time. New strongest integral limits at E > 100 TeV, differential limits at E > 1 PeV

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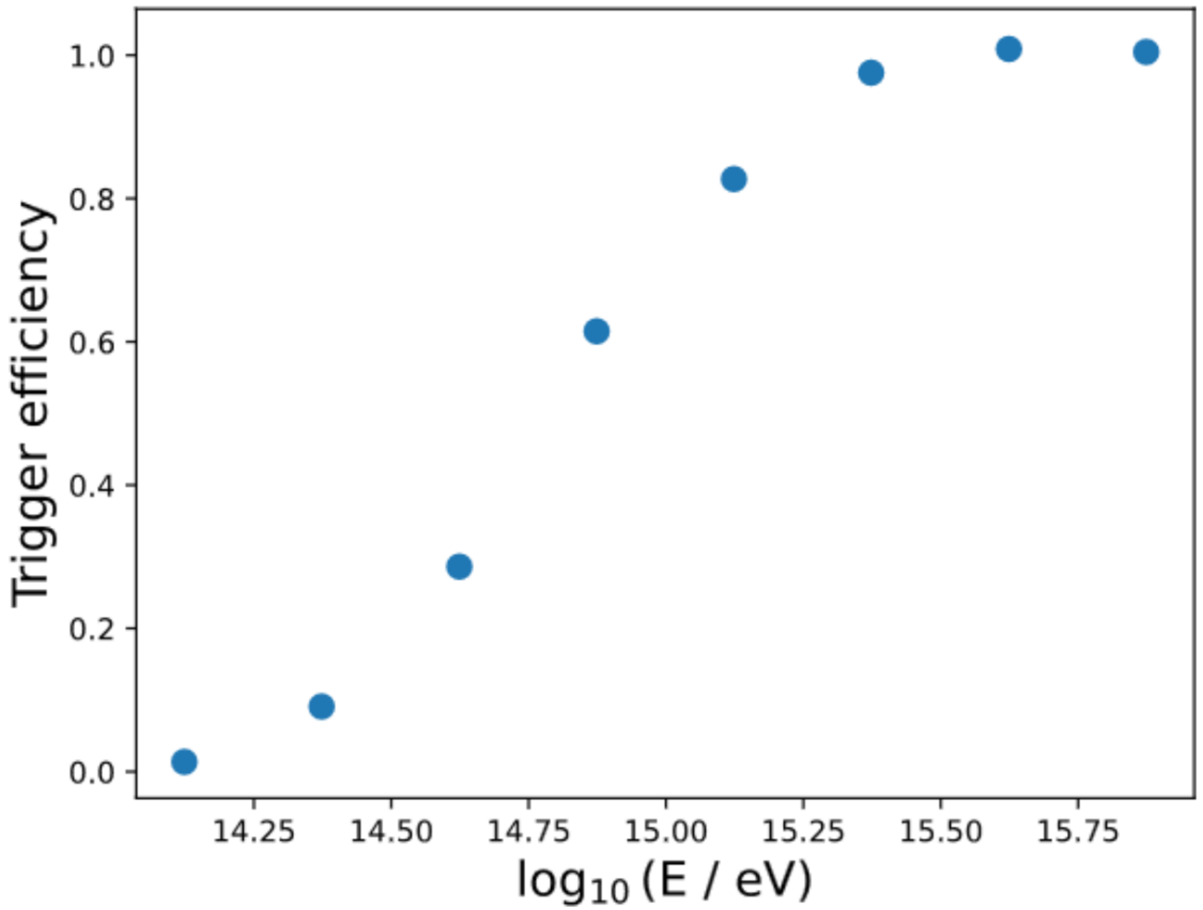
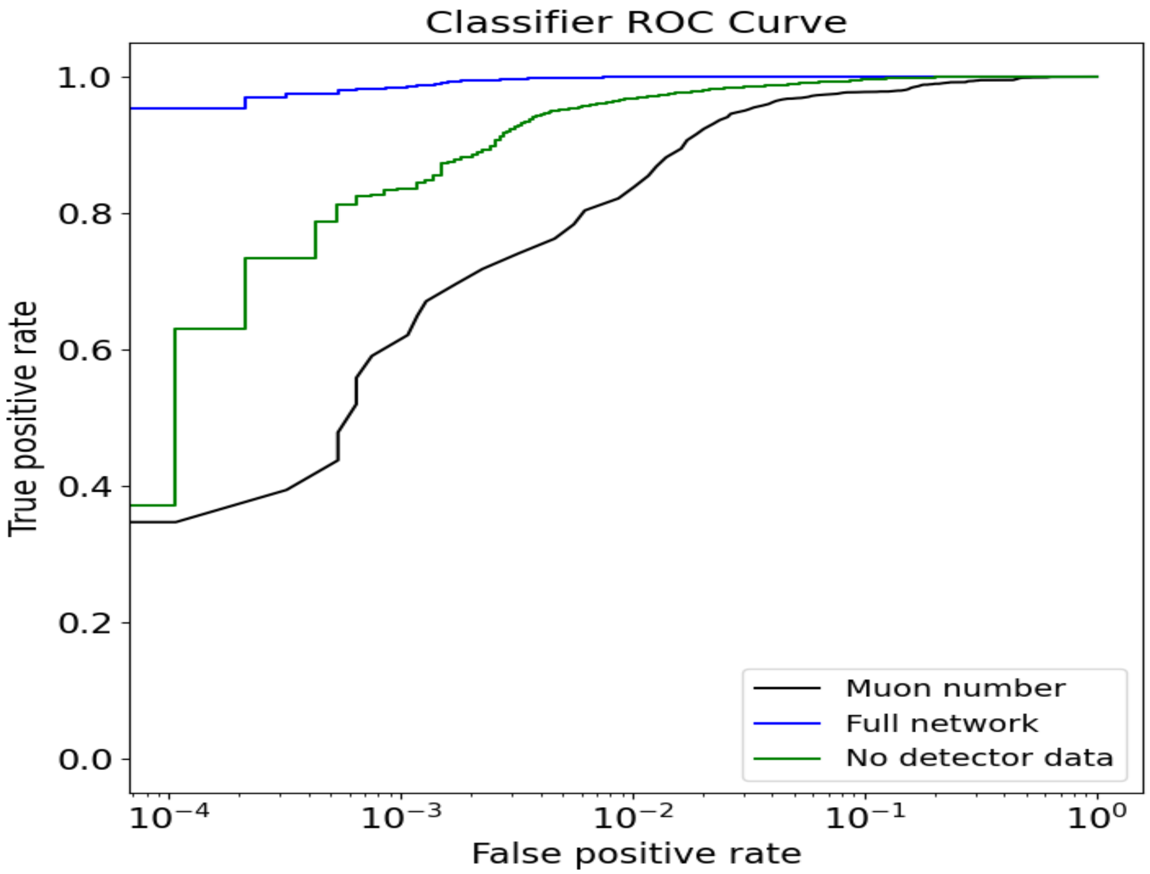
Backup slides

Carpet-3 efficiency



Carpet-3 trigger efficiency for gamma-ray primaries

Comparison with simpler methods



ROC-curves. Blue – full network (described earlier), green – no central array data, black – muon number only.

Raw central detector data improves background rejection by an order of magnitude!

Monte-Carlo simulations

CORSIKA+QGSJETII-04:
15 000 proton and 15 000 gamma showers

100 TeV – 10 PeV, E^{-1} spectrum

$\sim$**500 000** events after passing all the quality cuts and reconstruction

Neural network architecture

Convolutional part for the central array, fully connected classifier network

Used features: energy deposition in central carpet detectors (20x20 detector grid),

N_e, N_μ^{175}, N_μ^{410}, shower axis coordinates, arrival direction, shower clumpines C

TODO: Cool and fancy architecture picture

Shower «clumpinnes»

A parameter that measures the non-uniformity of the lateral particle density [Conceicao et al:2022]:

$$C = \sum_k \frac{2}{N_k(N_k - 1)} \cdot \frac{1}{< S_k >} \sum_{i<j} (S_{ik} - S_{jk})^2$$

This variable is sensitive to clusters in the lateral particle distribution

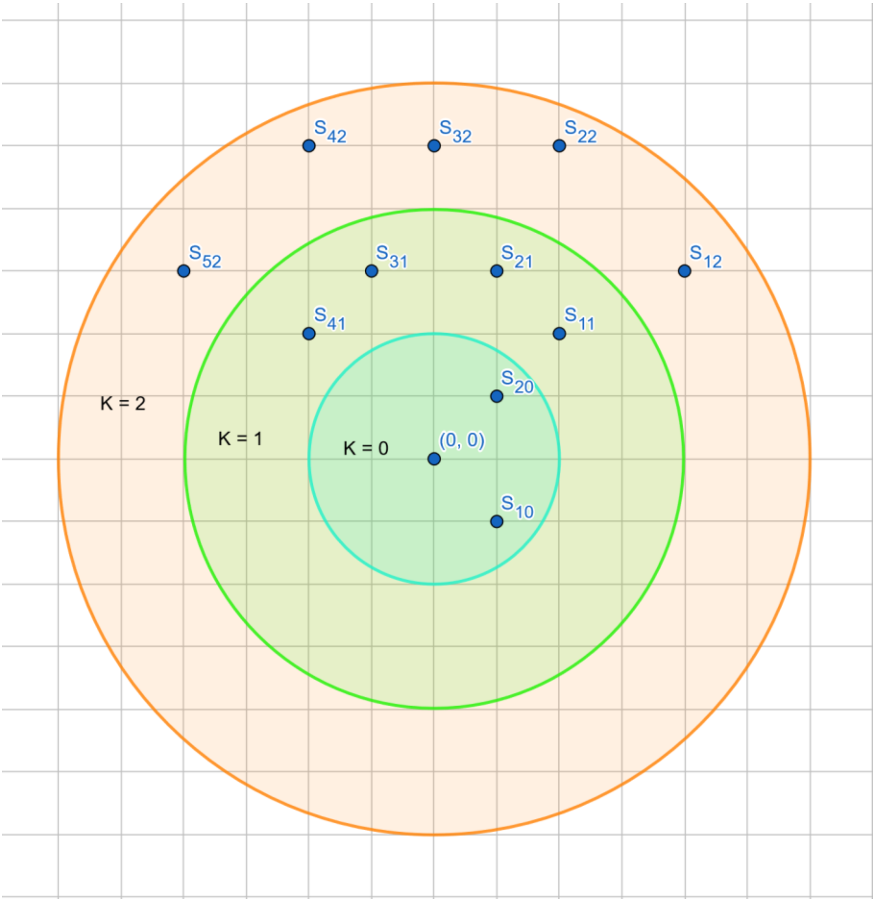
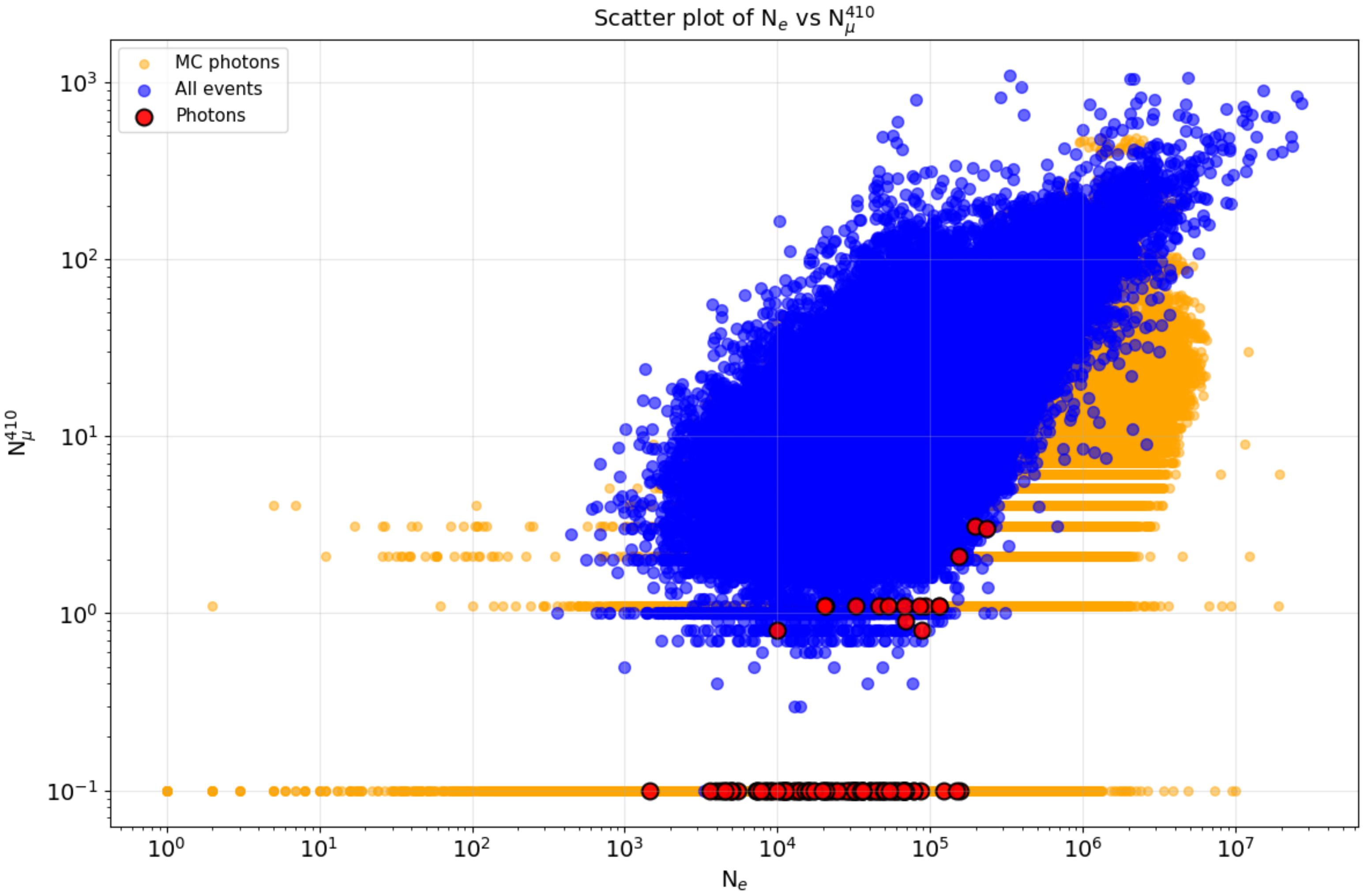


Illustration. Rings are centered on the shower axis.

Photon candidate events



Photon events (in red) on a N_e – N_mu scatter plot.

Photon MC in orange