Reducing model bias in a deep learning classifier using domain adversarial neural networks in the MINERvA experiment

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On behalf of the MINERvA collaboration

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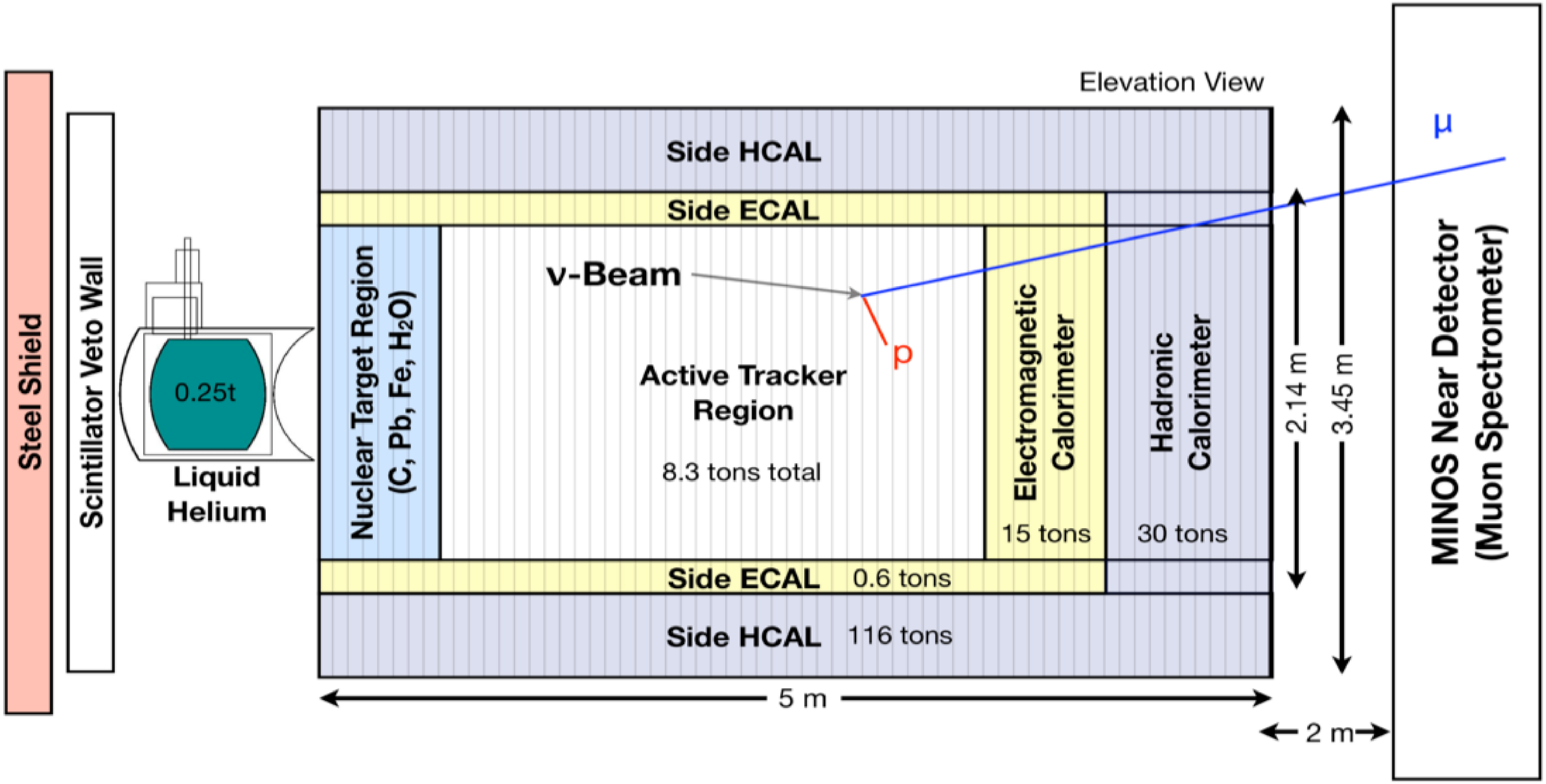
MINERvA Experiment

- MINERvA is a dedicated neutrino-nucleus experiment situated at Fermilab's NuMI Beam along with other two experiments MINOS and NOvA

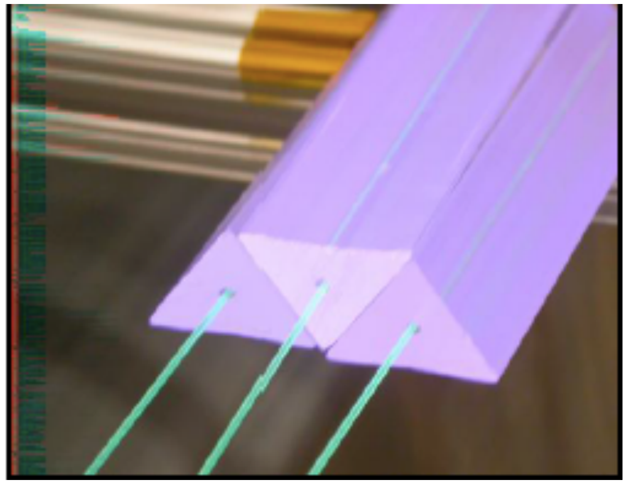
- A precise understanding of the A-dependence of the neutrino-nucleus cross section is important to reduce systematic uncertainties in the measurements of oscillation experiments.

- MINERvA having different nuclear targets (iron, carbon, lead, water, helium, scintillator) and excellent tracking ability , is able to provide high precision measurement of neutrino interactions on various nuclei in the 1-10 GeV energy range.

MINERvA Detector

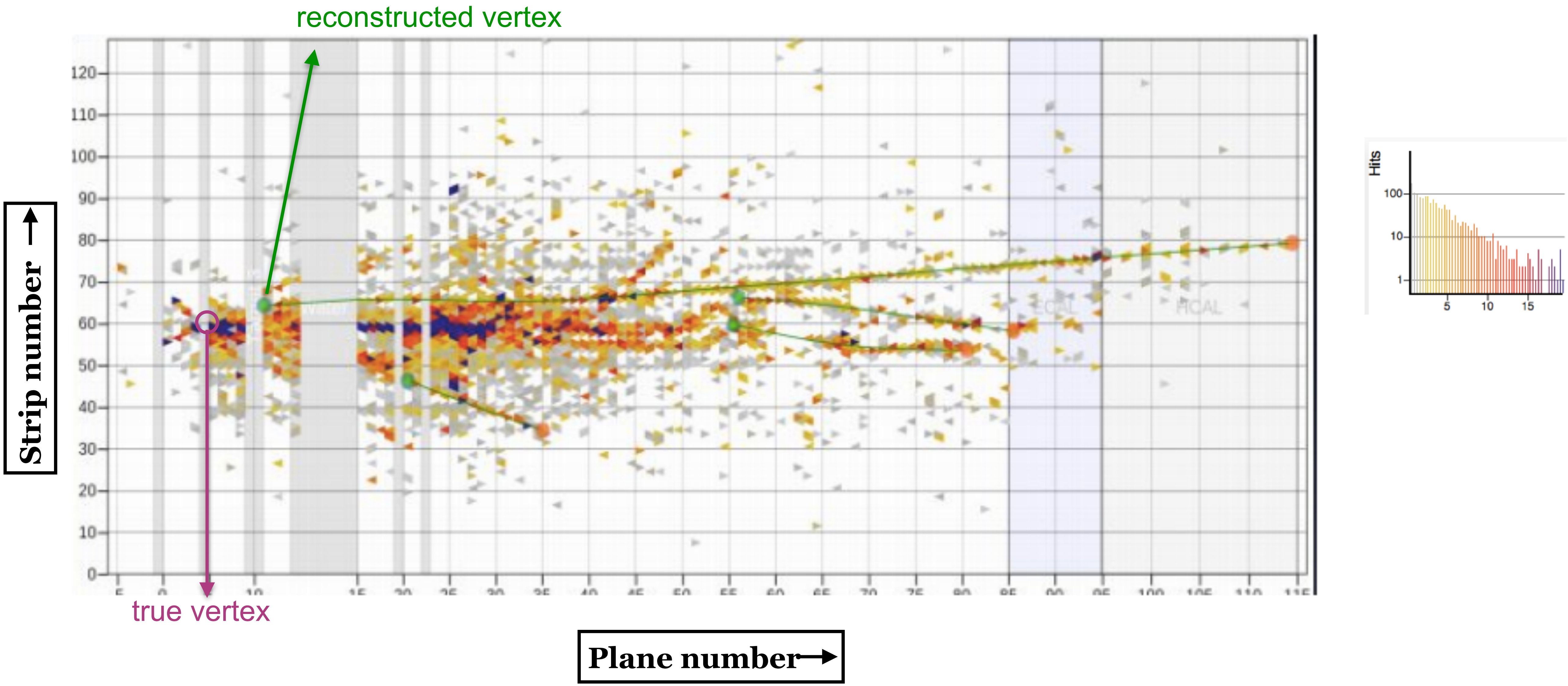


- Consists of a core of scintillator strips surrounded by ECAL and HCAL
- MINOS Near Detector for muon charge and momentum



Problem with vertex finding: motivation behind ML technique

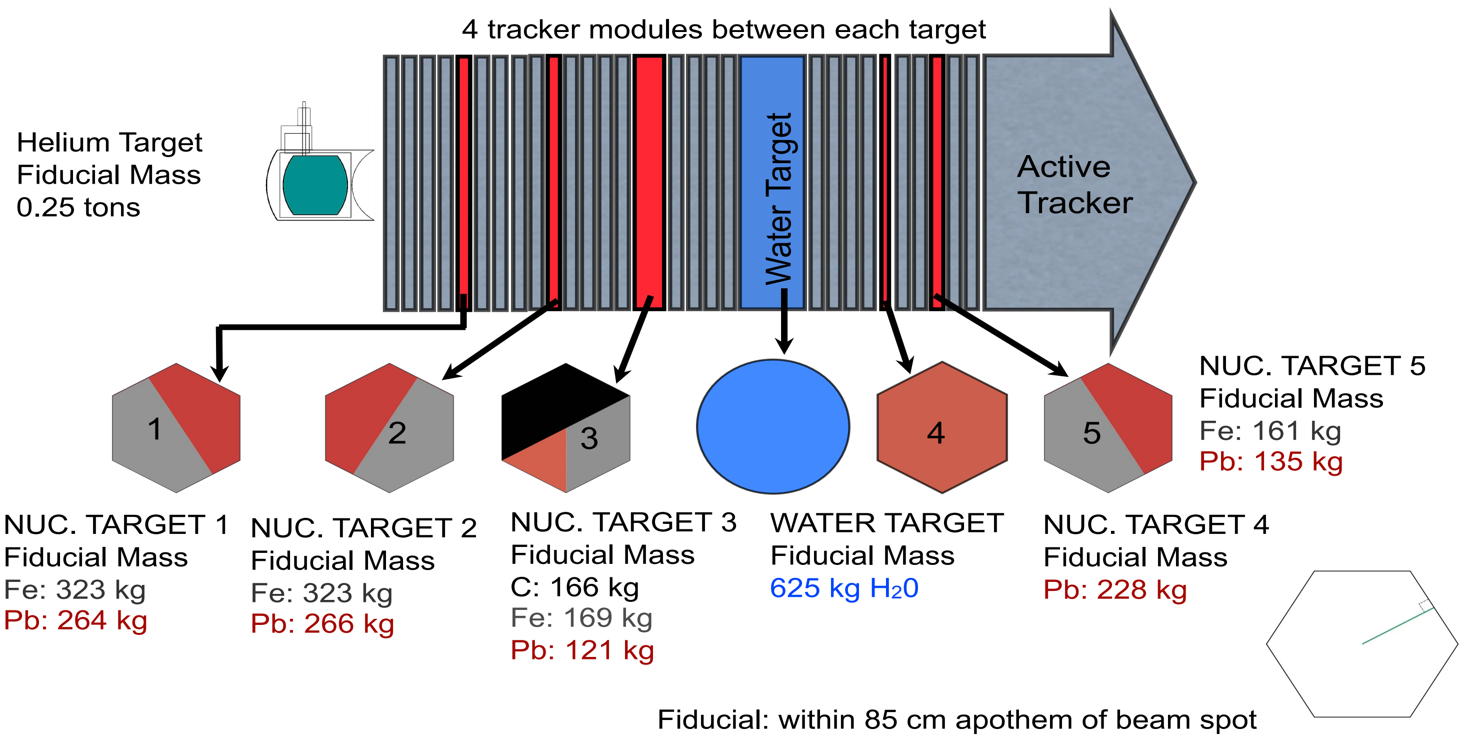
- With the increase of our beam energy, there is an increase in the hadronic showers near the event of interactions.
- Cause more difficulty in vertexing with increase rates of failure in getting the correct vertex position

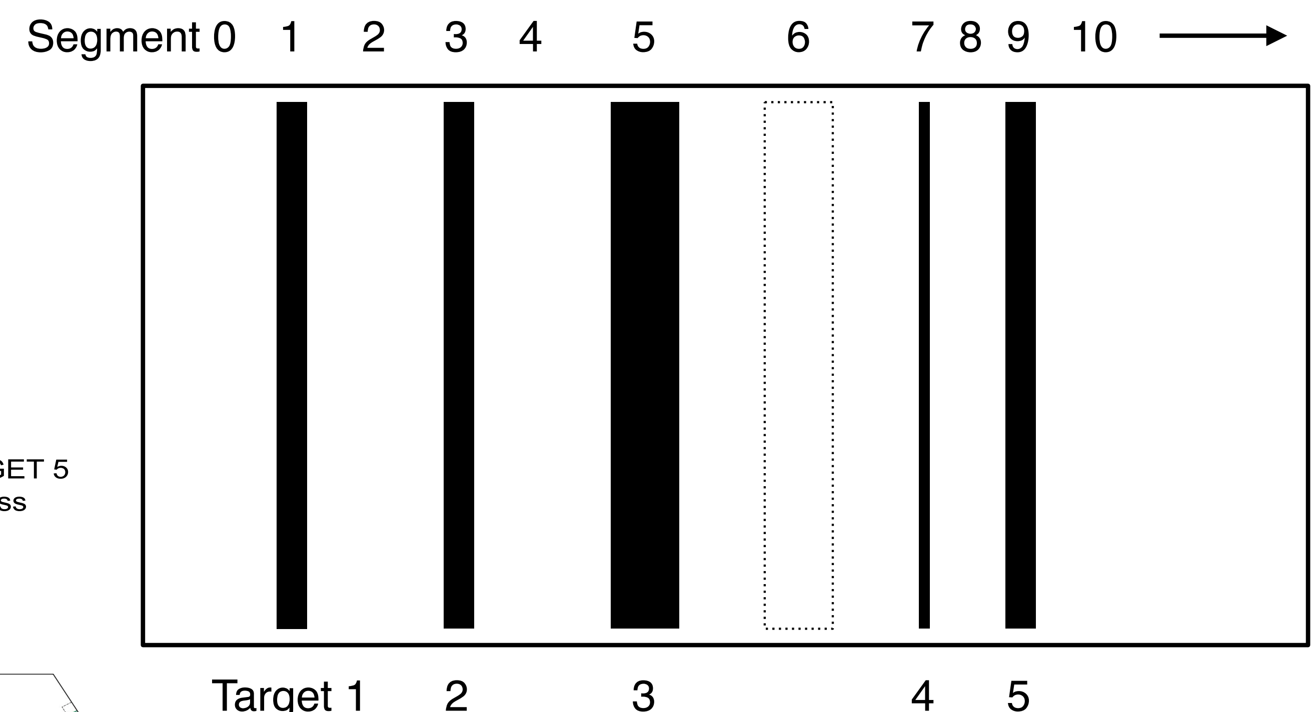


ML Approach To Determine Event Vertex

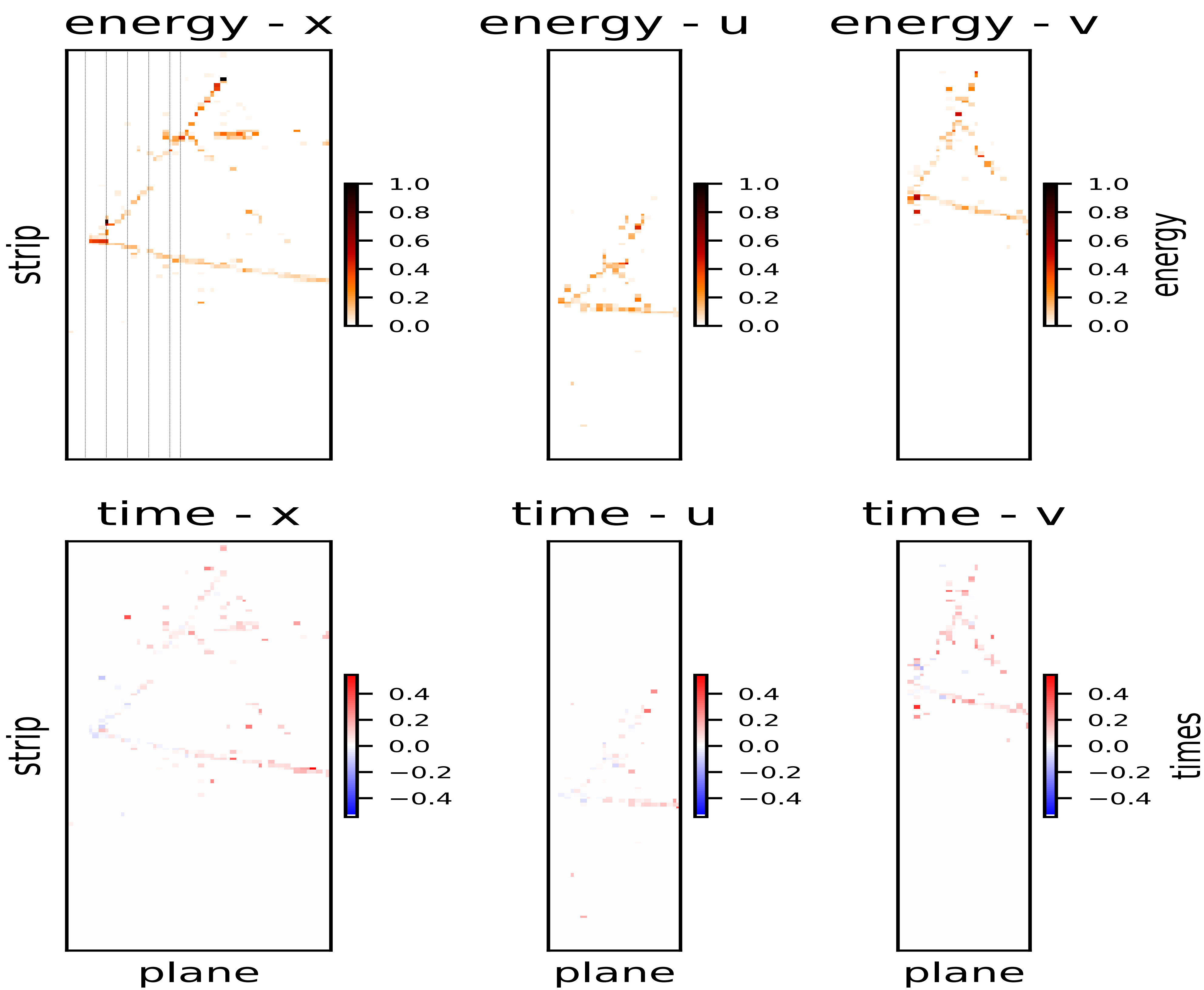
- Goal: Find the location of the event vertex

  -Treat the localization as a classification problem



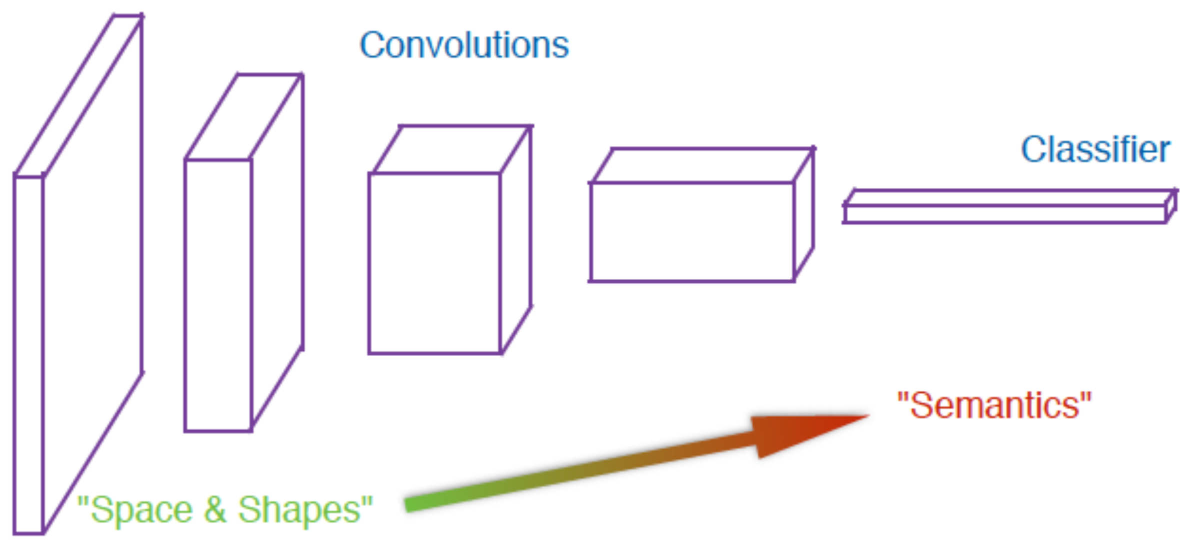


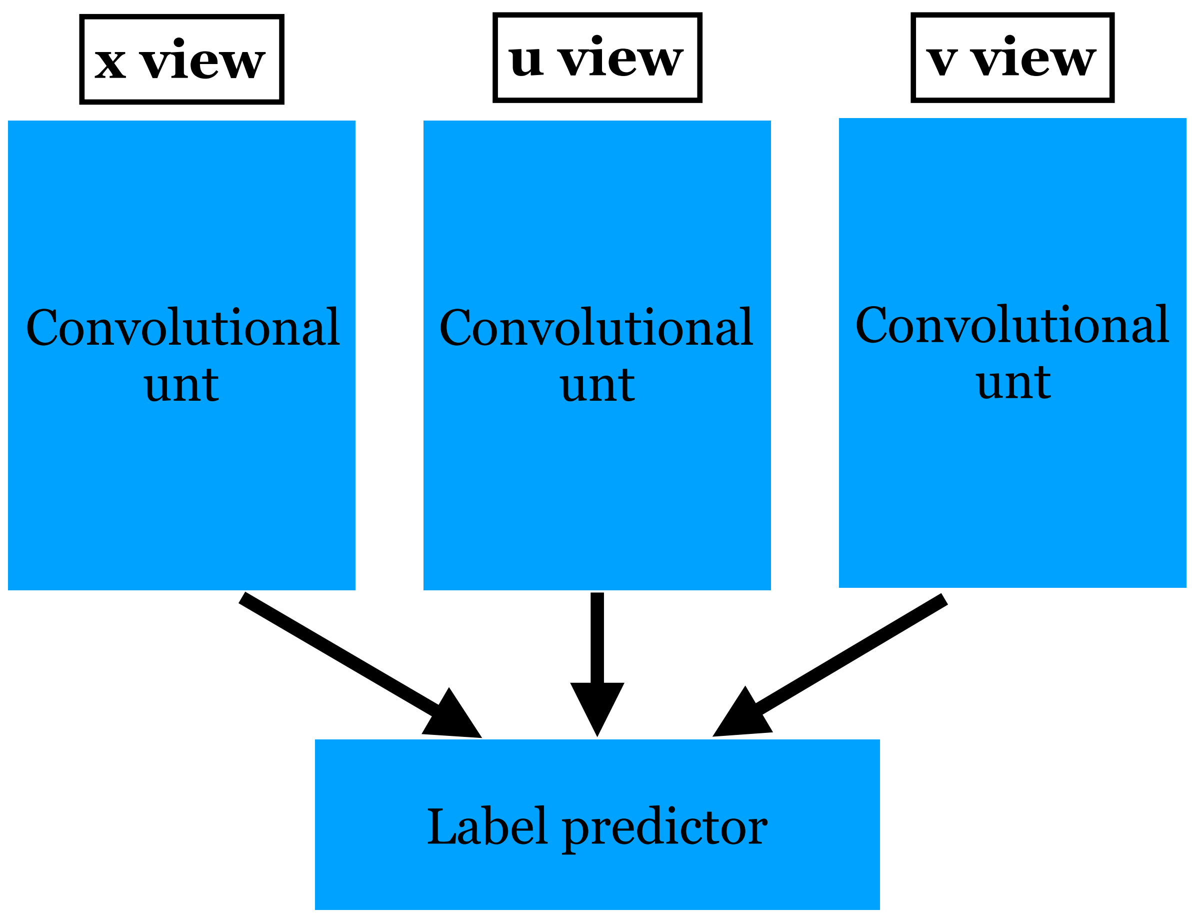
Make images for three different views →	DNN(Convolutional neural network) →	Prediction at which segment an interaction occurs


energy - x
energy - u
energy - v
time - x
time - u
time - v
strip
strip
plane
plane
plane
energy
times
1.0
0.8
0.6
0.4
0.2
0.0
0.4
0.2
0.0
−0.2
−0.4

Convolutional neural network (CNN)

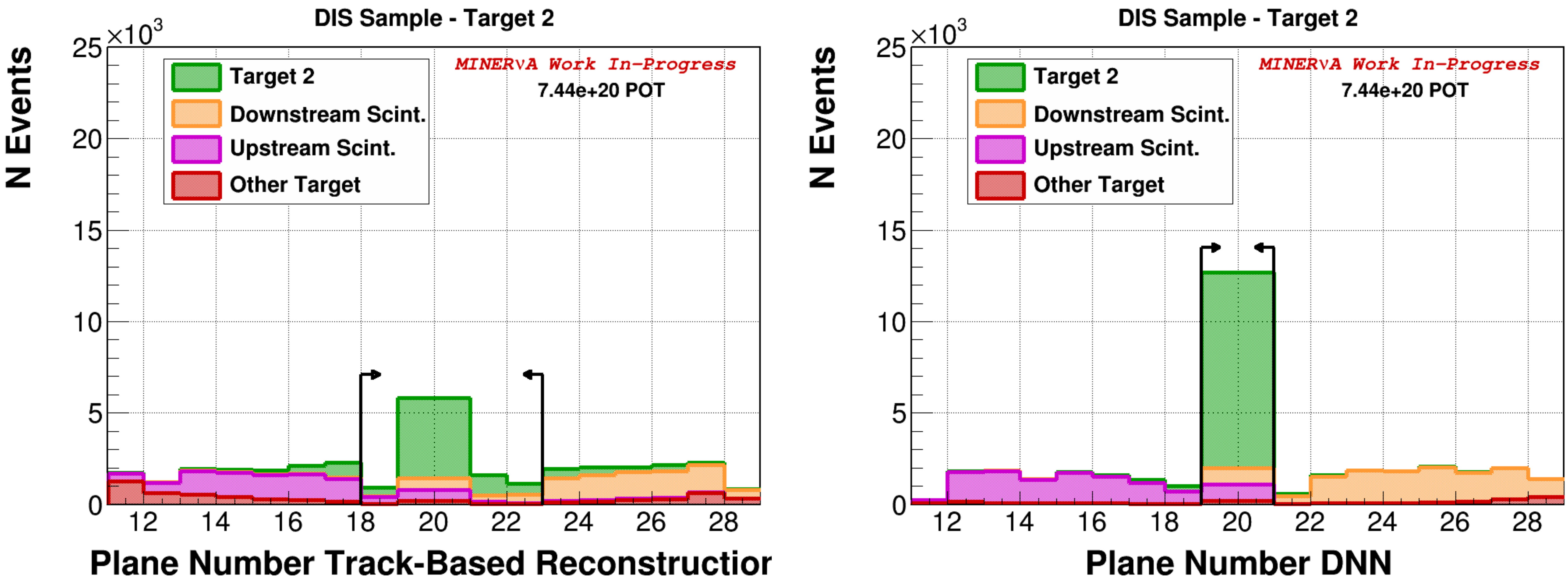
Stacking layers of convolutions leads from geometric / spatial representation to semantic representation:





We have three separate convolutional towers that look at each of the X, U, and V images.

Track-based approach vs ML approach



Signal purity has been improved by the factor of 2-3 using ML technique compared to track based approach

Domain Adversarial Neural Network (DANN)

http://adsabs.harvard.edu/cgi-bin/bib_query?arXiv:1505.07818

CNN:

- Train with labeled data: in our case it is Monte Carlo
- Test with unlabeled data: in our case it is real data

Limitation:

Labeled simulated data for training >> unlabeled real data for testing

Our models are not perfect ->domain discrepancies arises

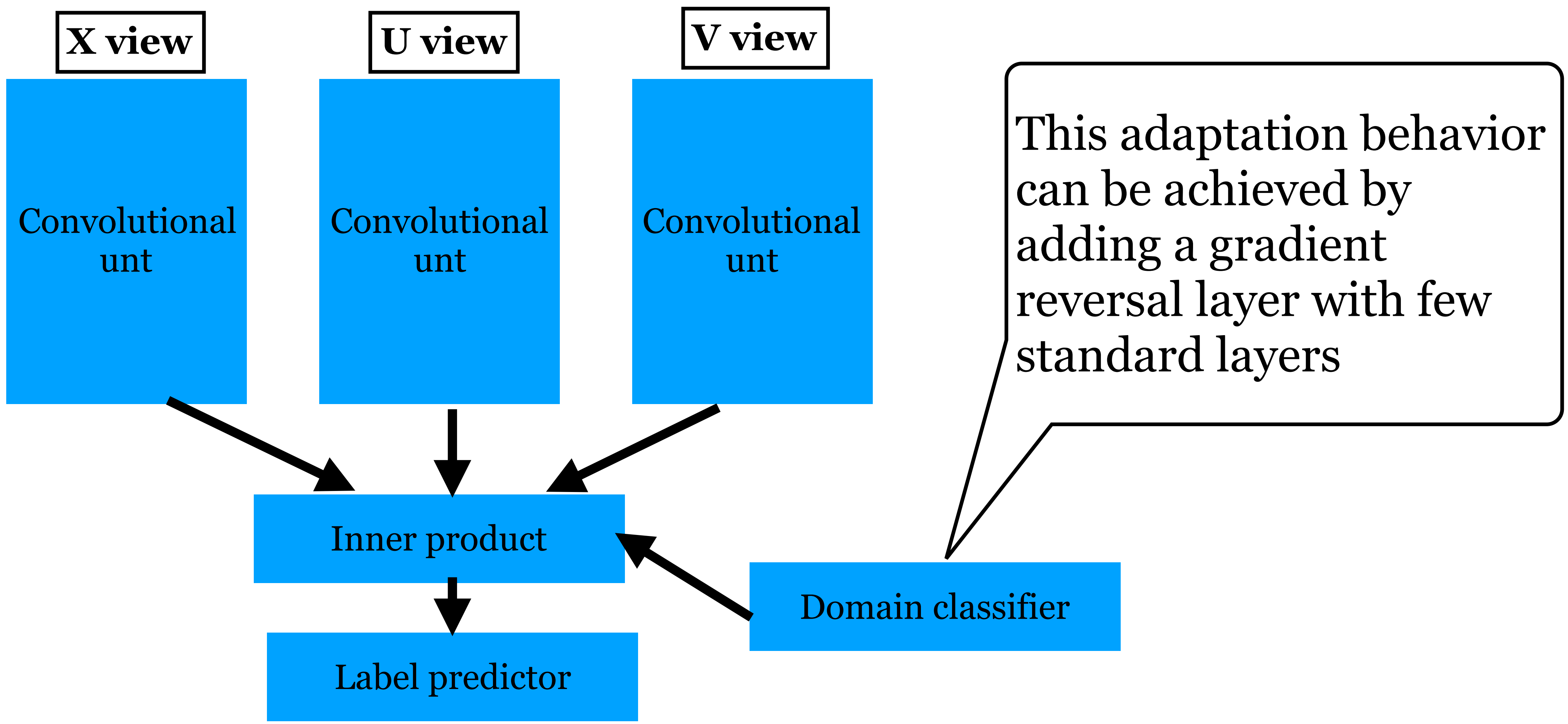
Need strategy to reduce any biases in the algorithm that may come from training our models in one domain and applying them in another

Here DANN comes into the picture

DANN

Train from the ***labeled source domain (MC)*** and ***unlabeled target domain (real data)***

Goal to achieve the features:
1) ***discriminative*** for the main learning task on the source domain
2) ***indiscriminate*** with respect to the ***shift between domains***



DANN

- Two classifiers into the network:

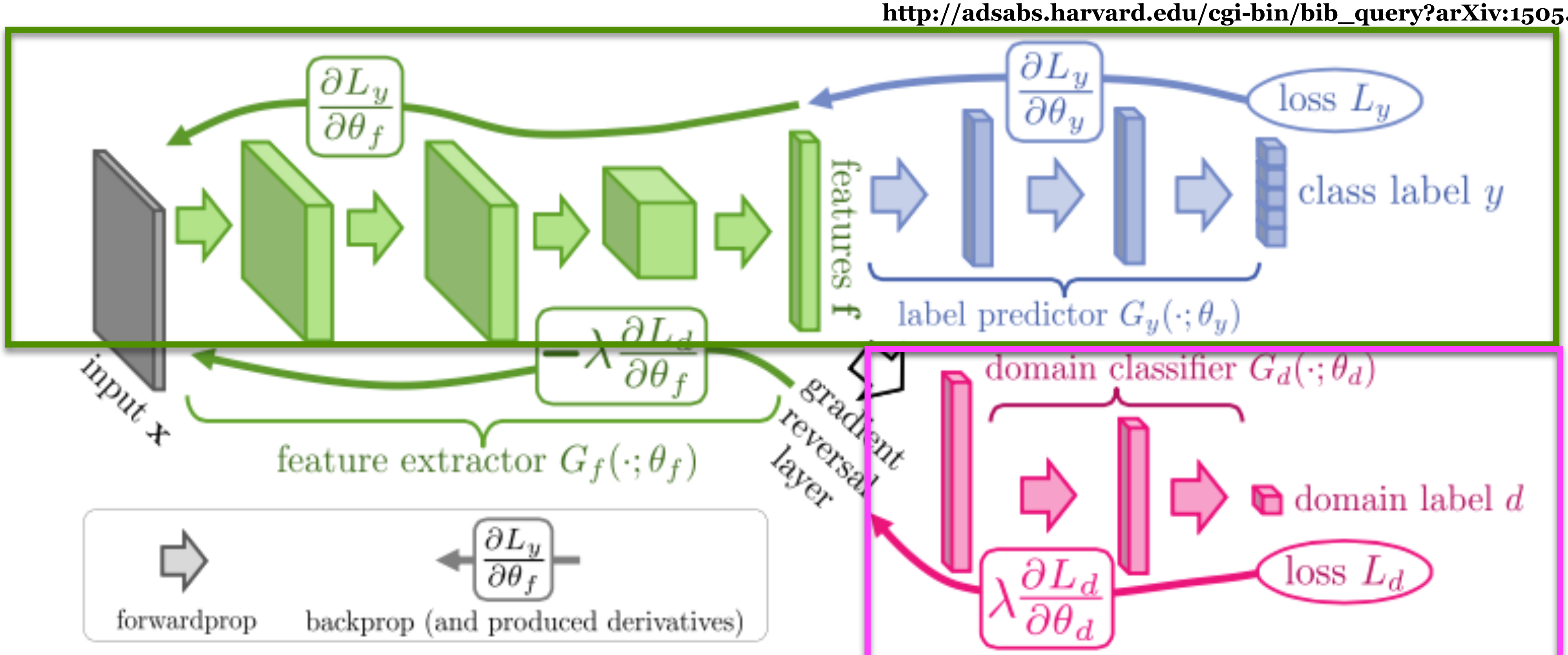
  Label predictor: output

  Domain classifier: works internally

- ***Minimize the loss of the label classifier:*** network can predicts the input level
- ***Maximize the loss of the domain classifier***: network can not distinguish between source and target domain

The network develops an ***insensitivity to features that are present in one domain but not the other*****, and train only on features that are common to both domains**

http://adsabs.harvard.edu/cgi-bin/bib_query?arXiv:1505.07818



How to test DANN ?

- Find source and target with distinct features.

  -our source and target domains may be too similar for the domain classifier to be able to distinguish between them.

- We train with Monte Carlo (MC) events and use different MC as target

- We tried by few ways to get the target sample having different features than source: changing the flux, physics model, kinematic division etc.

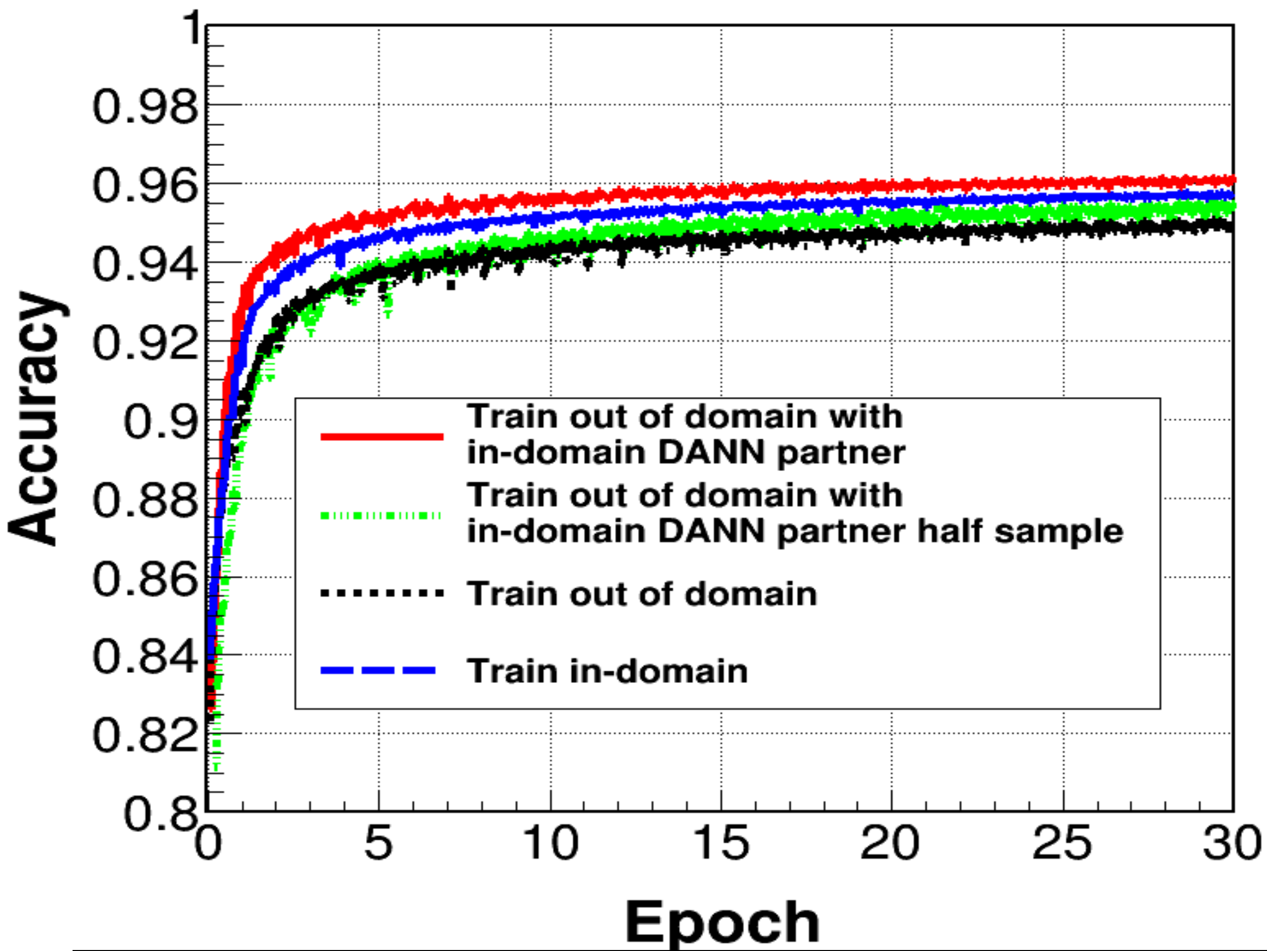
Final state interaction(FSI) On/Off

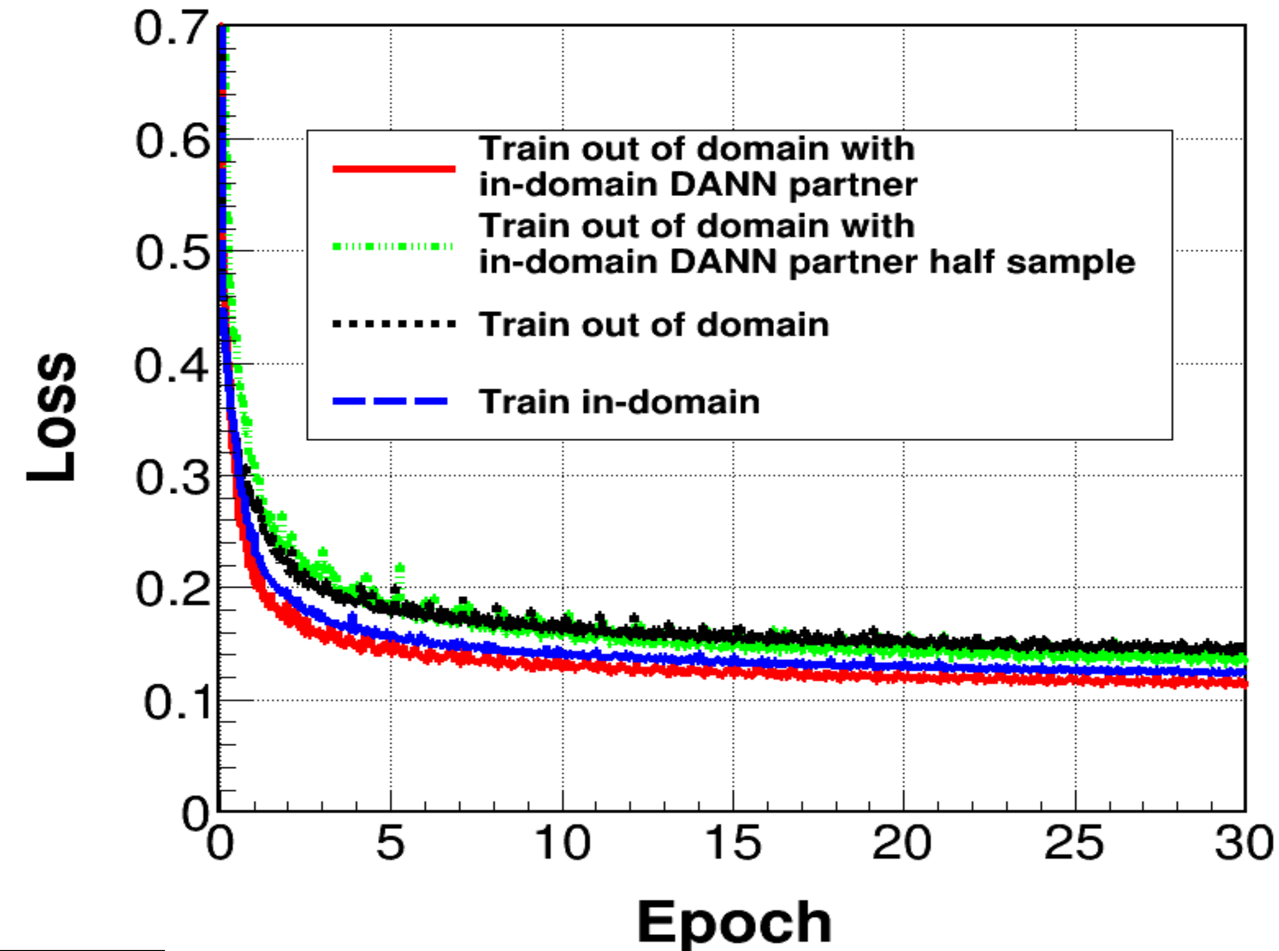
- We assume that "***FSI is on***" in real world and so we ***turned on FSI*** in our ***testing sample***

Training sample (Source domain)	DANN partner (target domain)	Testing sample	Model
FSI on (1.2M)	**N/A**	**FSI on**	**In domain**
FSI off(1.2M)	**N/A**	**FSI on**	**out of domain**
FSI off(1.2M)	**FSI off(1.2M)**	**FSI on**	**Out of domain with in domain DANN partner**

The expectation: ***CNN in domain*** will perform *better* than ***CNN out of domain***.

The expectation: though model is trained "out of domain", it would show the ***similar performance*** as ***"CNN in domain"*** since we consider ***"in domain" DANN partner.***





Source domain	Target domain	Testing sample	Model
FSI on (1.2M)	N/A	FSI on	In domain
FSI off(1.2M)	N/A	FSI on	out of domain
FSI off(1.2M)	FSI off	FSI on	Out of domain with in domain DANN partner
FSI off(0.6M)	FSI off(0.6M)	FSI on	Out of domain with in domain DANN partner(half sample)

Red curve: Adding a DANN partner to the model trained in the out-of domain we are able to ***recover the performance*** of the model natively trained in the correct domain

Green curve:

- ***Perform worse*** than red curve as the sample size is reduced by half
- ***Perform better*** than than black curve as it has information ***from the correct domain***

DANN helps to recover the domain information

Summary

- We see ***improvement factor of ~2-3*** with DNN based reconstruction over track-based reconstruction

- We simulated with different FSI behavior and we saw the cross-domain performance degradation. However, ***by using DANN*** to restrict the feature extraction only to features in both domains ***we can train a domain-invariant classifier***

- MINERvA is expanding ML infrastructure in other studies like hadron multiplicity, particle identification and we will use ***DANN to reduce the bias coming from the physics model.***

From MINERvA Collaboration:

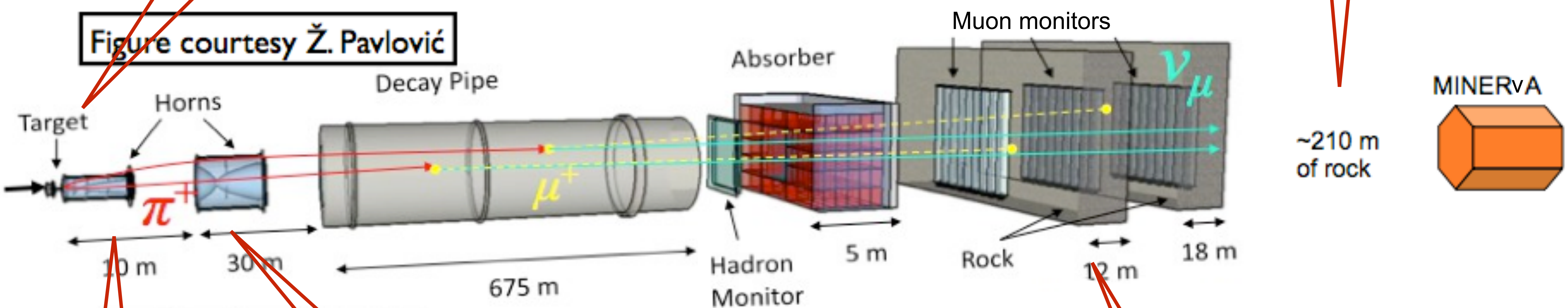
Thank you!

Backup slides

NuMI Beam

120
GeV proton beam
from
the main injector on

Neutrinos

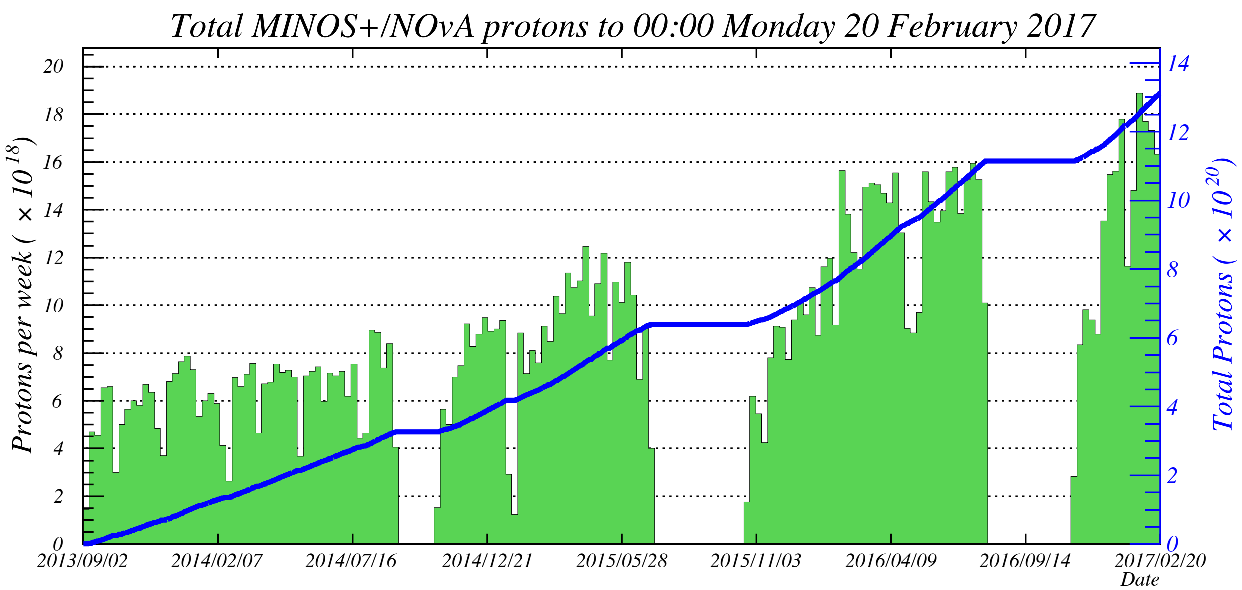


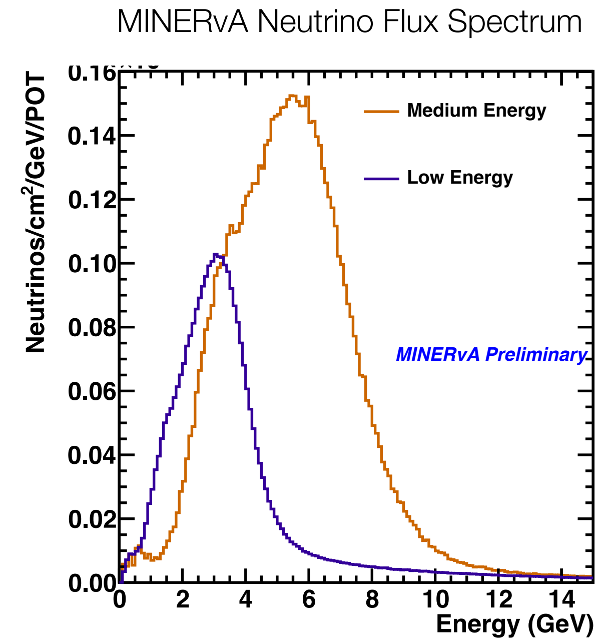
Focus π^+ and K^+ (π^- and K^-) to get the ν_μ ($\bar{\nu}_\mu$)beam

Beam energy can be changed by moving the horns with respect to each other

Rock removes muon from beam

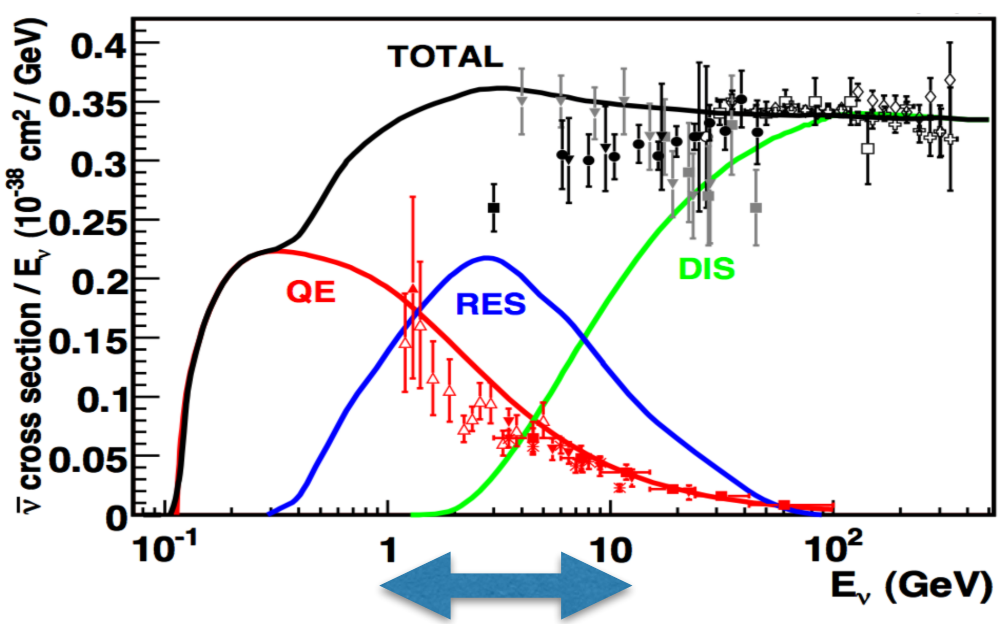
NuMI beam: medium energy regime





- NuMI beamline currently running with increased beam energy mode which peaks at ~6 GeV (ME mode).
- We have taken ~12E20 POT in neutrino mode and currently taking data in anti-neutrino mode.
- About factor of 3 increase from LE data at 3.9E20 POT!

J.A. Formaggio, G. Zeller, Reviews of Modern Physics, 84 (2012)

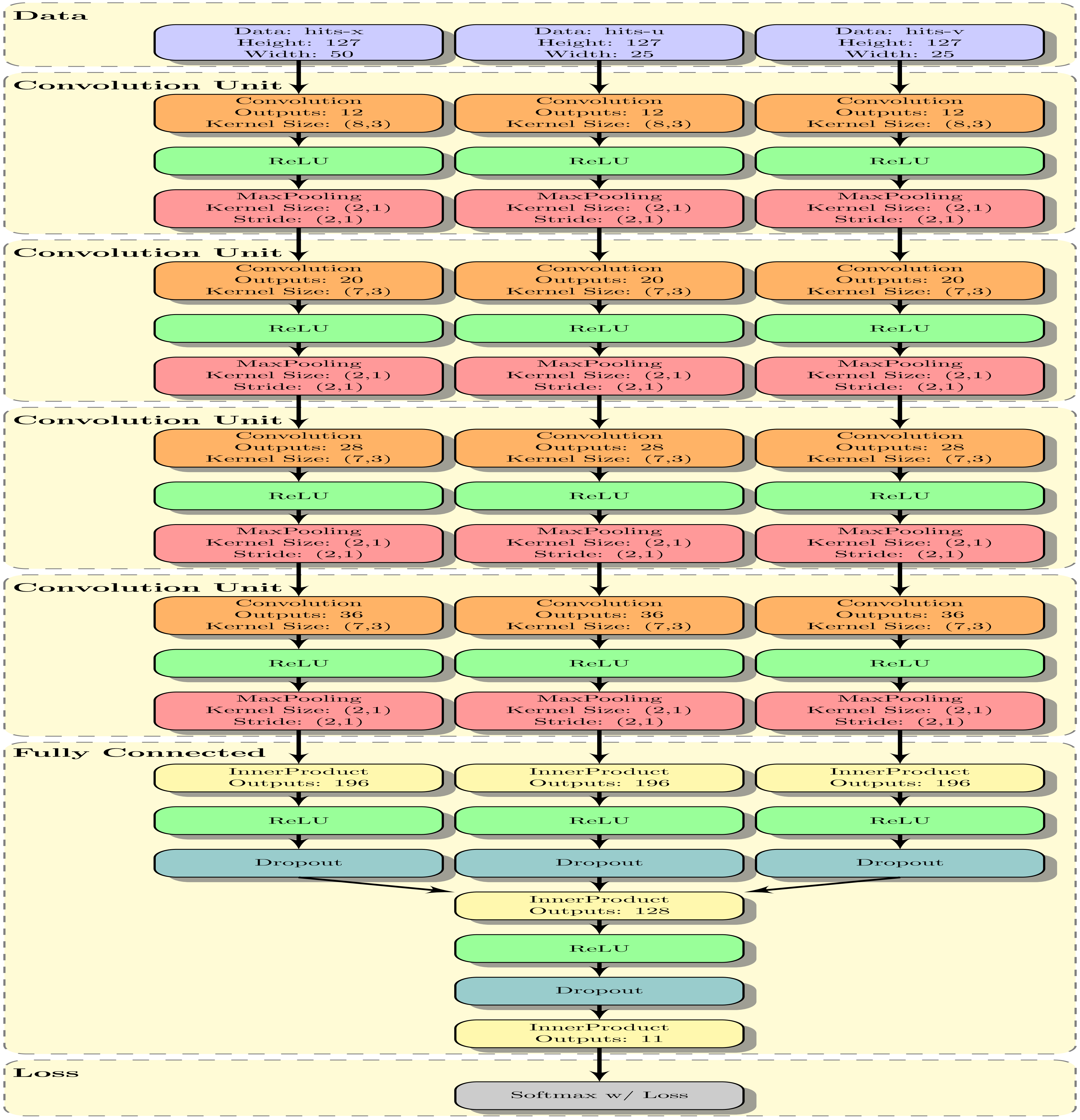


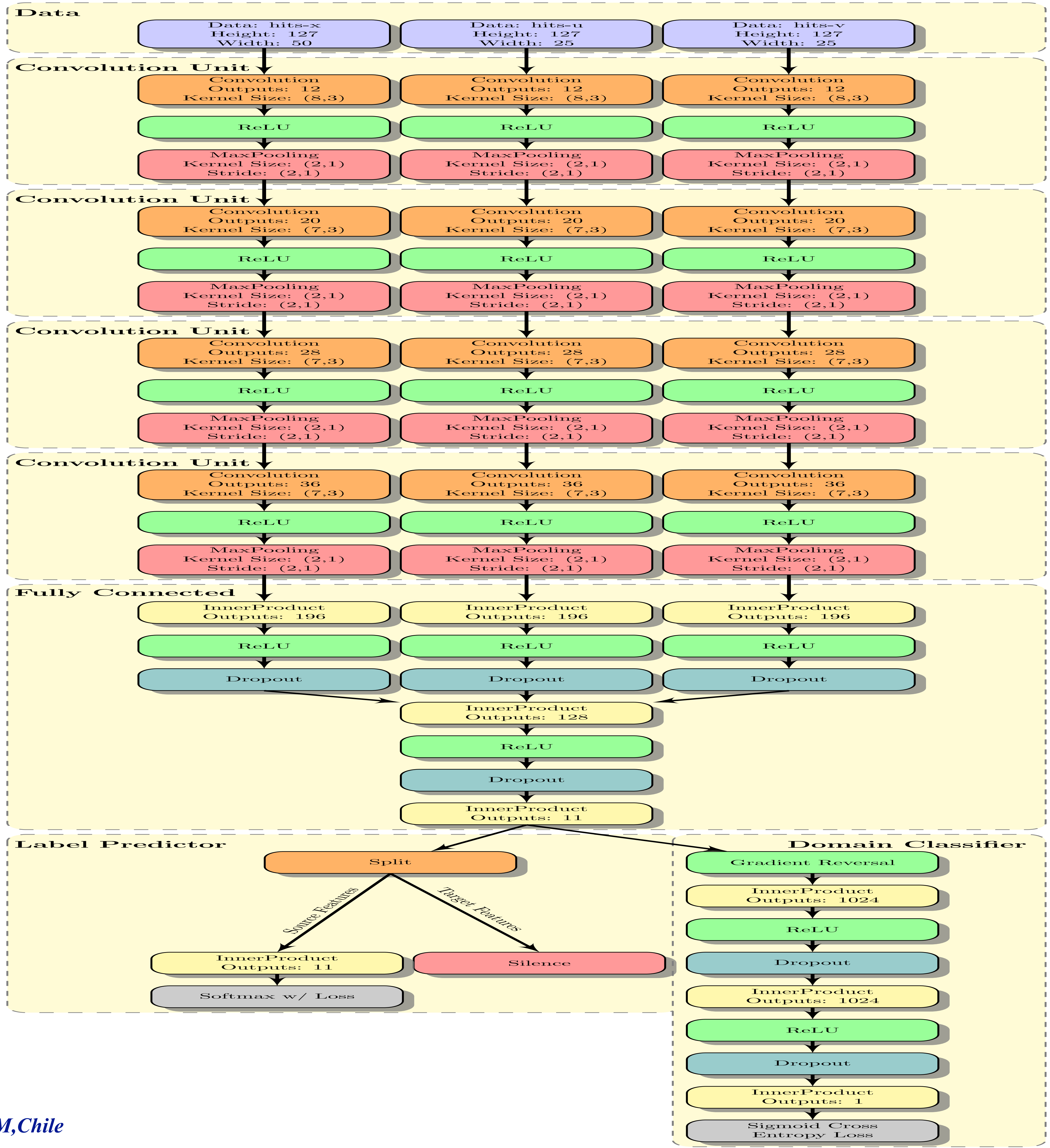
MINERvA, DUNE, NOvA

- Higher statistics yields improve comparisons across nuclei
- The peak of energy now moves to the DIS-rich kinematic region. *Access to expanded kinematics and nuclear structure functions.*

Network structure

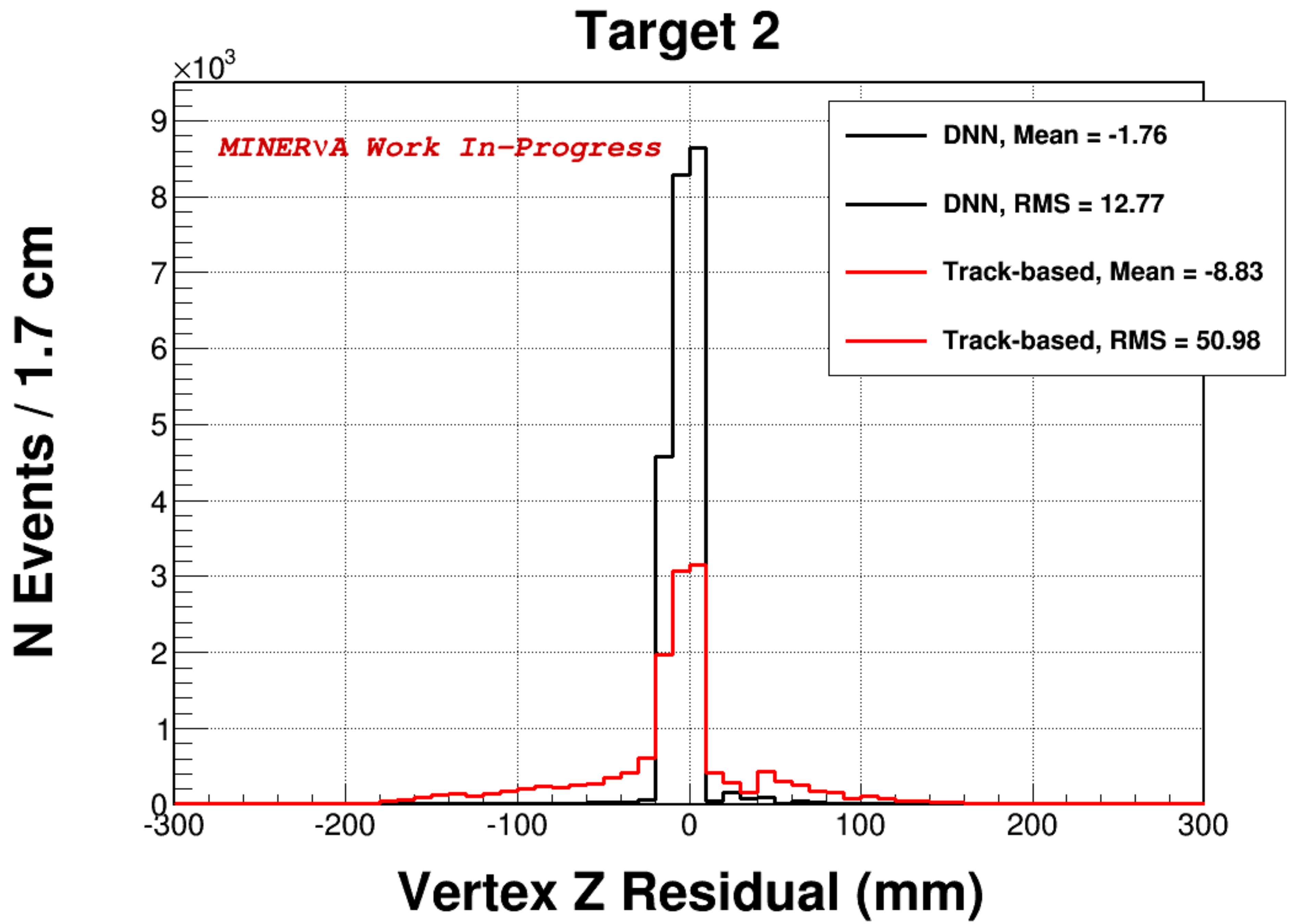
- Each view represents a different angle of the interaction, hence, a pixel location in one view does not correspond to that same pixel location in another view
- So, we have three separate convolutional towers that look at each of the X, U, and V images.
- Each tower consists of four iterations of convolution and max pooling layers with ReLUs acting as the non-linear activations and after that there is a fully connected layer
- The out of three views are concatenated and fed into another fully connected layer .This is the input to the final fully connected layer with 11(67) output -> input to the softmax layer.
- We use non-square kernels, they are much larger along the transverse direction than along the z direction-> localization information contained directly in the energy distribution along Z. So, we allow the images to shrink along the transverse dimension but largely preserved the image size along the Z axis. Also, we pooled the tensor elements together only along the transverse axis, not along the z axis.


Data
Data: hits-x
Height: 127
Width: 50
Data: hits-u
Height: 127
Width: 25
Data: hits-v
Height: 127
Width: 25
Convolution Unit
Convolution
Outputs: 12
Kernel Size: (8,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Convolution Unit
Convolution
Outputs: 20
Kernel Size: (7,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Convolution Unit
Convolution
Outputs: 28
Kernel Size: (7,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Convolution Unit
Convolution
Outputs: 36
Kernel Size: (7,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Fully Connected
InnerProduct
Outputs: 196
ReLU
Dropout
InnerProduct
Outputs: 128
ReLU
Dropout
InnerProduct
Outputs: 11
Loss
Softmax w/ Loss

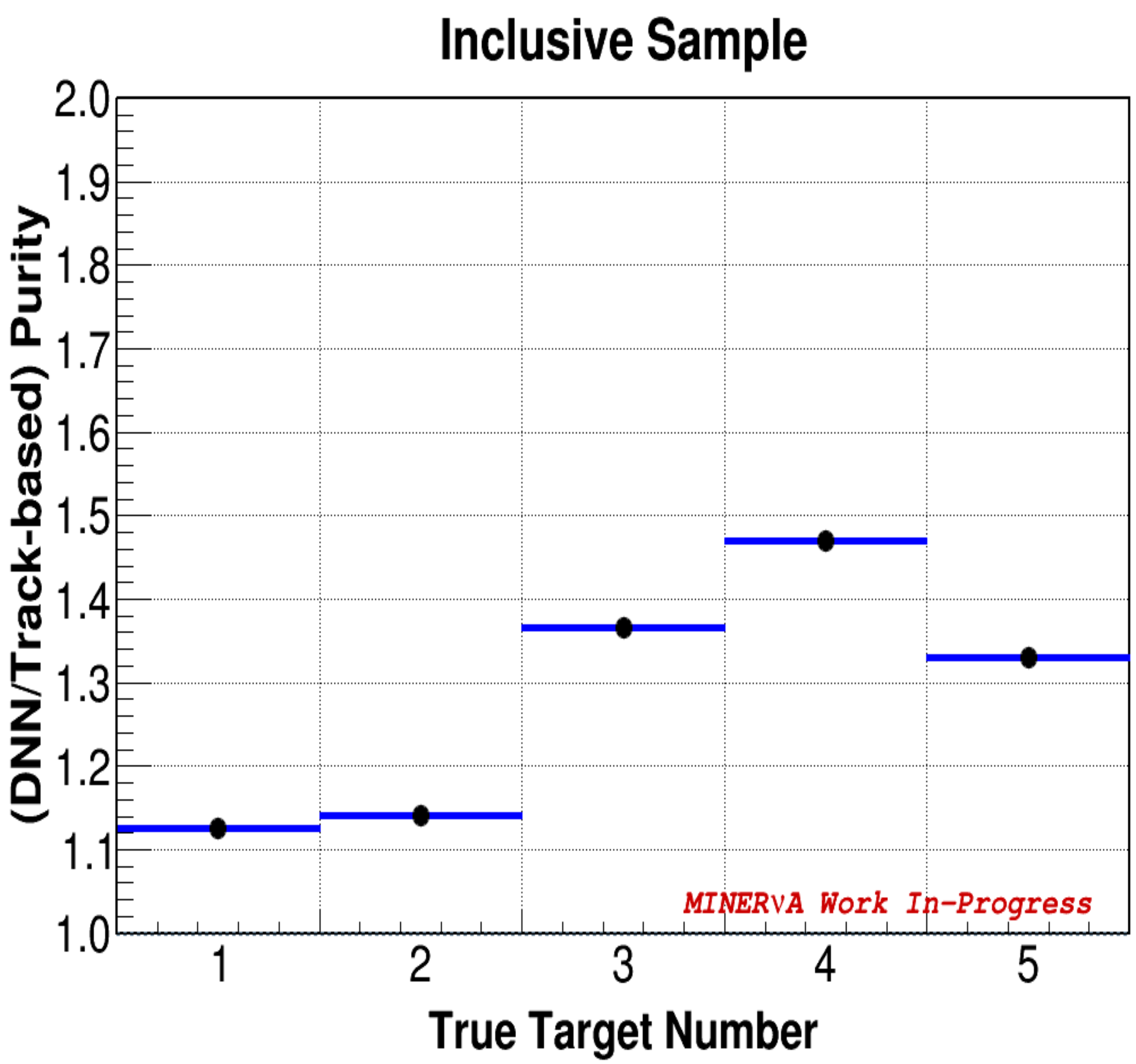

Data
Data: hits-x
Height: 127
Width: 50
Data: hits-u
Height: 127
Width: 25
Data: hits-v
Height: 127
Width: 25
Convolution Unit
Convolution
Outputs: 12
Kernel Size: (8,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Convolution Unit
Convolution
Outputs: 20
Kernel Size: (7,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Convolution Unit
Convolution
Outputs: 28
Kernel Size: (7,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Convolution Unit
Convolution
Outputs: 36
Kernel Size: (7,3)
ReLU
MaxPooling
Kernel Size: (2,1)
Stride: (2,1)
Fully Connected
InnerProduct
Outputs: 196
ReLU
Dropout
InnerProduct
Outputs: 128
ReLU
Dropout
InnerProduct
Outputs: 11
Label Predictor
Split
Source Features
Target Features
InnerProduct
Outputs: 11
Softmax w/ Loss
Silence
Domain Classifier
Gradient Reversal
InnerProduct
Outputs: 1024
ReLU
Dropout
InnerProduct
Outputs: 1024
ReLU
Dropout
InnerProduct
Outputs: 1
Sigmoid Cross
Entropy Loss

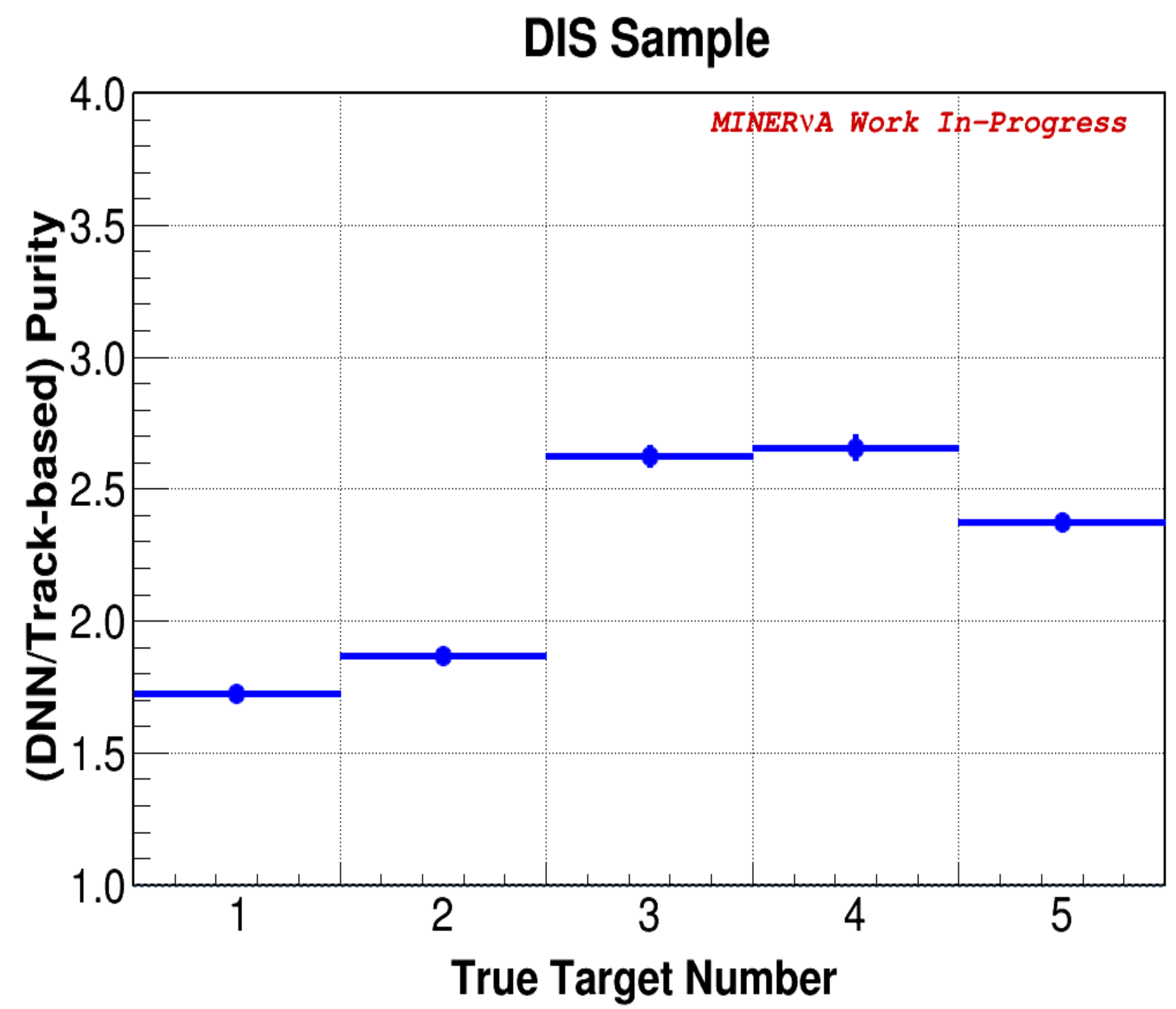
DNN vertex Z residual: True vertex Z - Z center of predicted plane

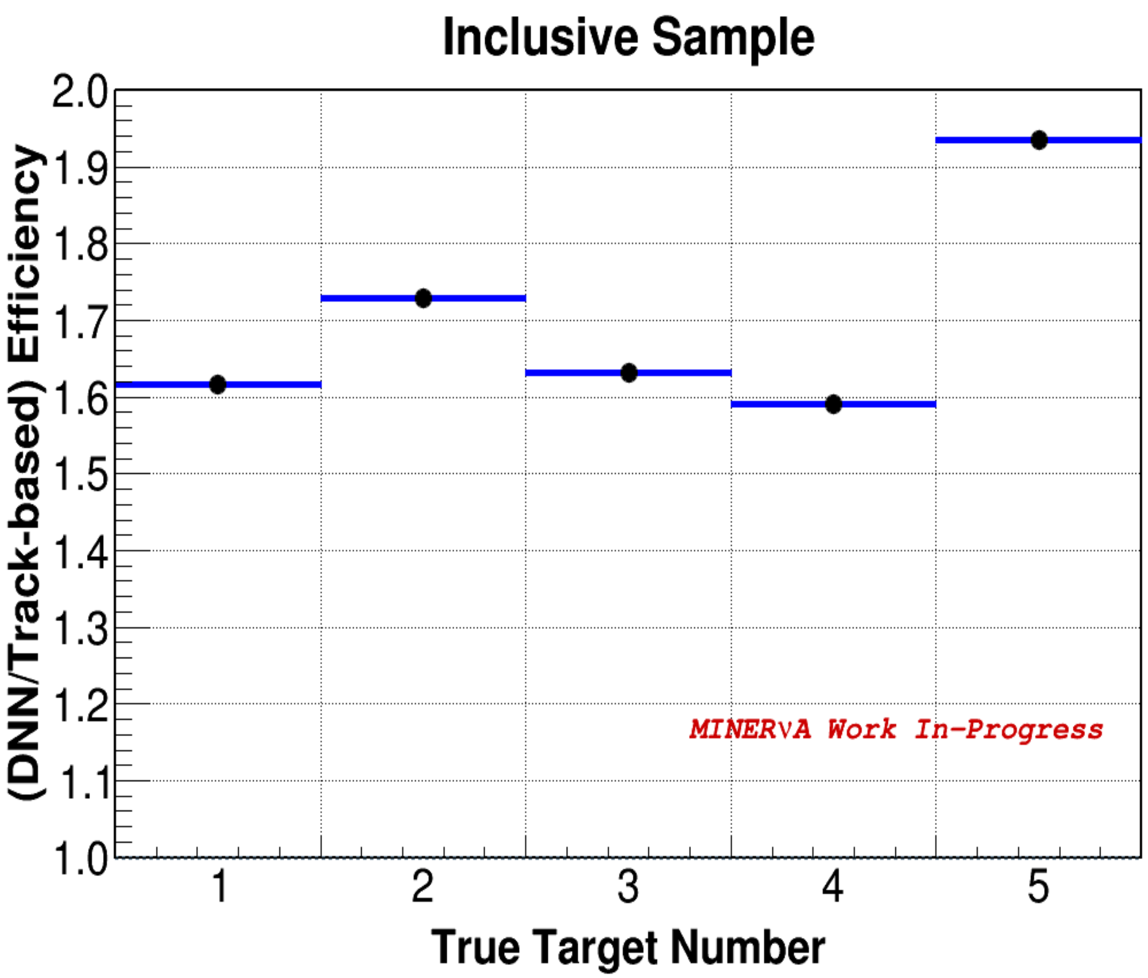
Track based vertex Z residual: True vertex Z - reconstructed vertex Z

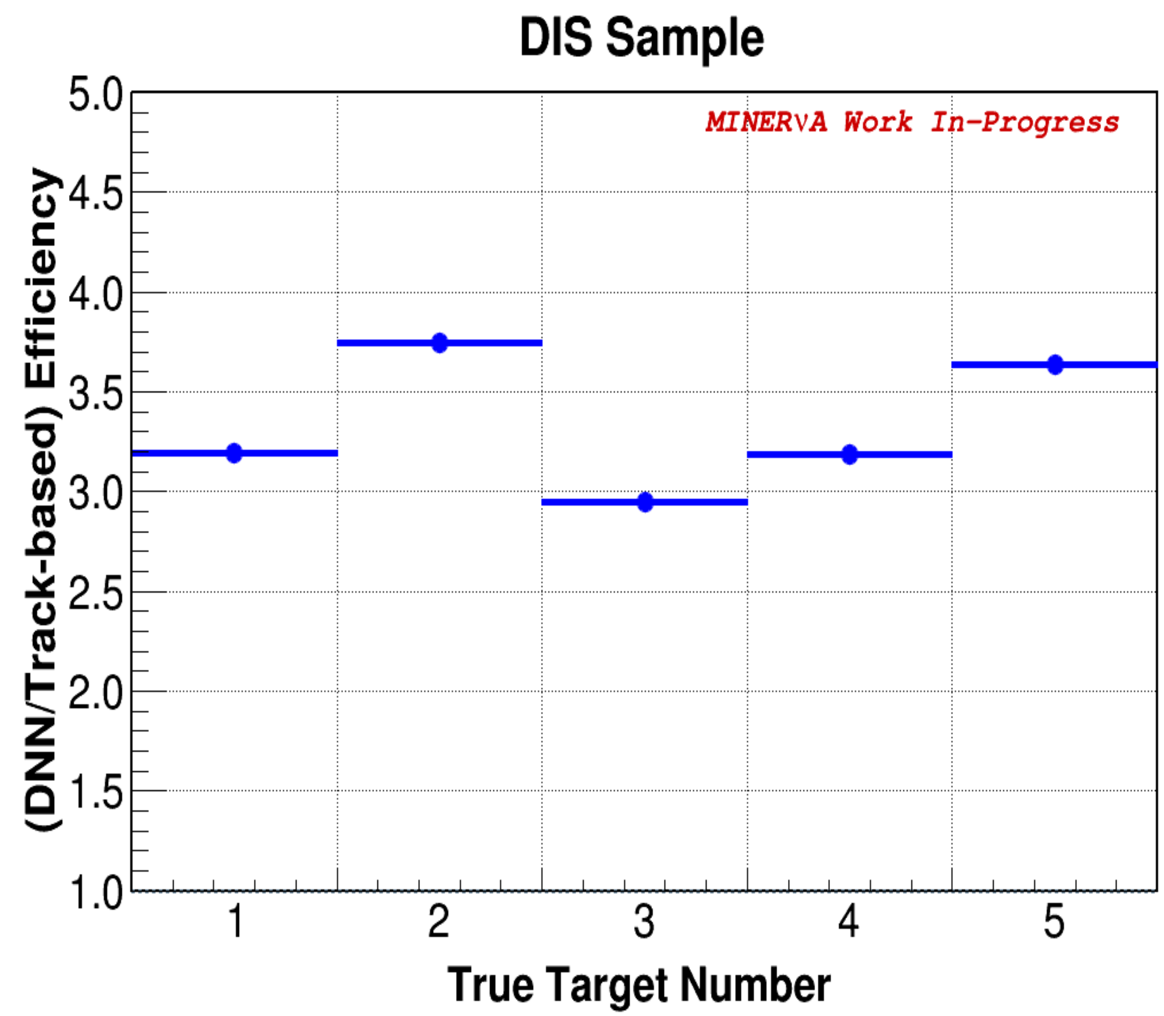


Classifying events in plane number


Inclusive Sample
(DNN/Track-based) Purity
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
1
2
3
4
5
True Target Number
MINERνA Work In-Progress

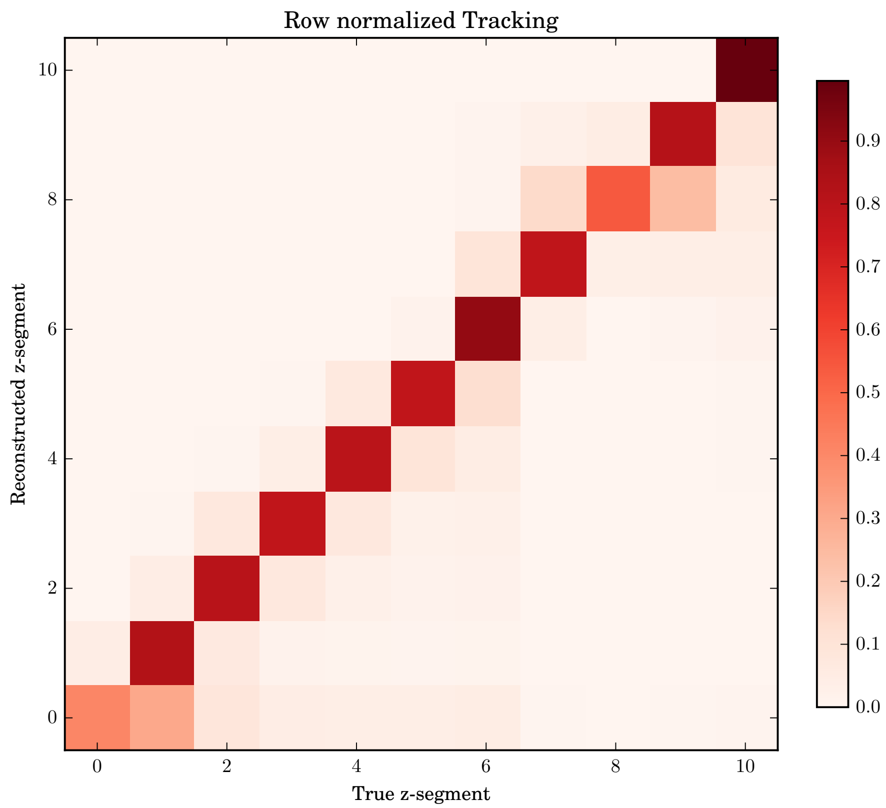

DIS Sample
(DNN/Track-based) Purity
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
2
3
4
5
True Target Number
MINERνA Work In-Progress

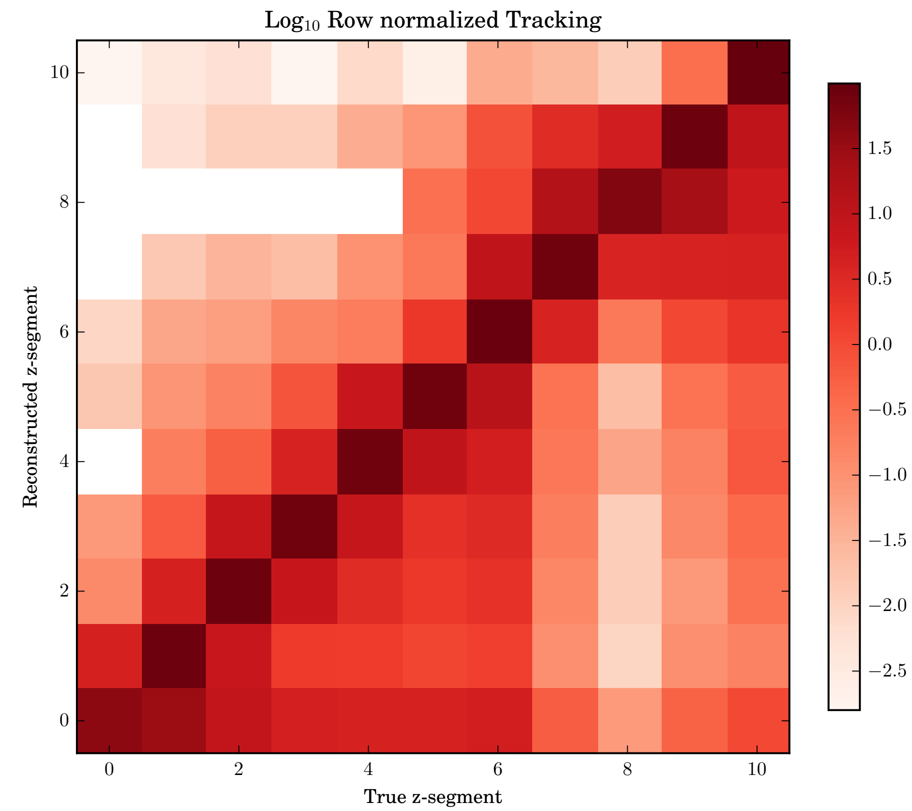

Inclusive Sample
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
(DNN/Track-based) Efficiency
MINERvA Work In-Progress
1
2
3
4
5
True Target Number

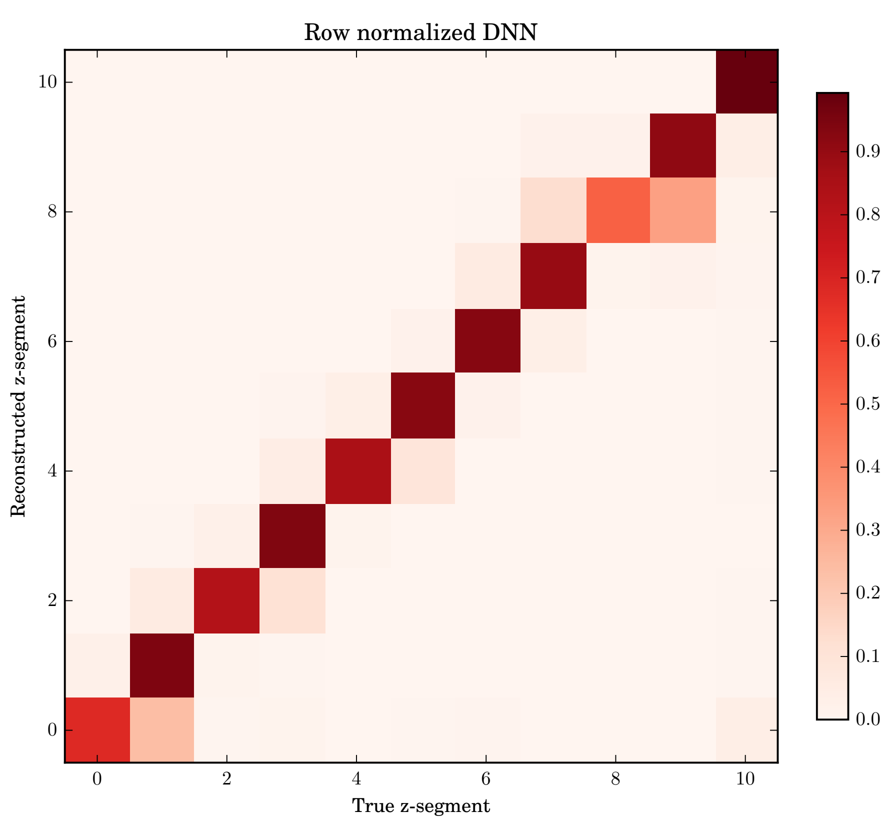

DIS Sample
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
(DNN/Track-based) Efficiency
MINERvA Work In-Progress
1
2
3
4
5
True Target Number

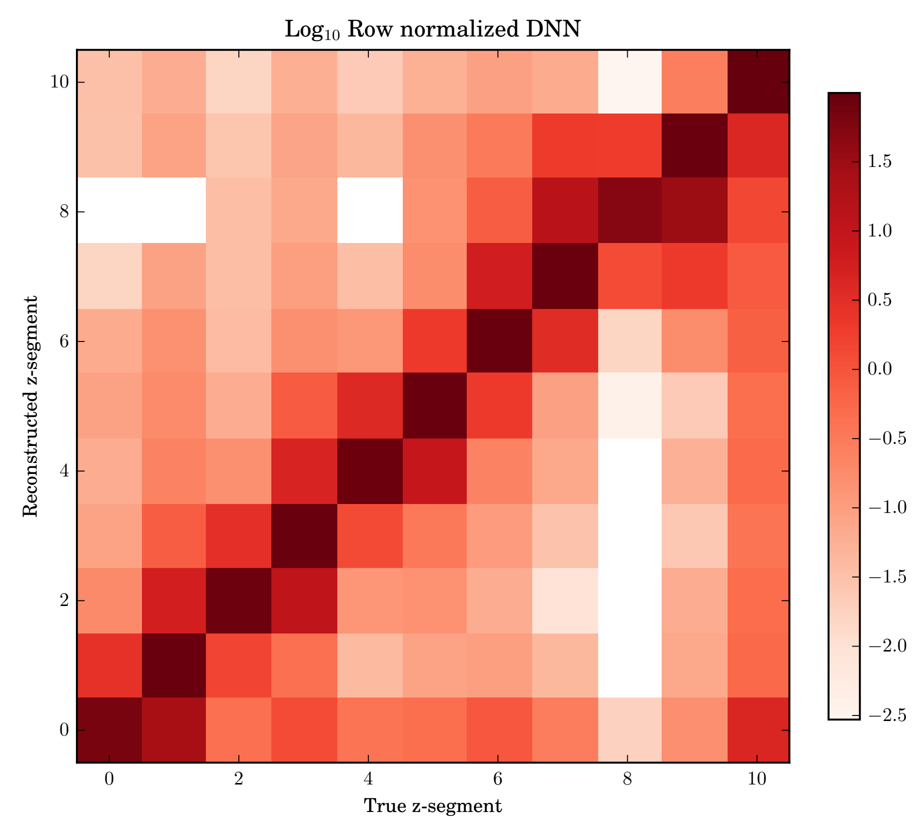
Confusion matrix

Classifying events in 11 segments









classifying events in 11 segments

Target	Track-Based Row Normalized Event Counts +stat error (%)	DNN Row Normalized Event Counts+stat error (%)	Improvement+ stat error (%)
Upstream of Target 1	41.11±0.95	68.1±0.6	27±1.14
1	82.6±0.26	94.4±0.13	11.7±0.3
Between target 1 and 2	80.8±0.46	82.1±0.37	1.3±0.6
2	77.9±0.27	94.0±0.13	16.1±0.3
Between target 2 and 3	80.1±0.46	84.8±0.34	4.7±0.6
3	78±0.3	92.4±0.16	14.4±0.34
Between target 3 and 4	90.5±0.2	93.0±0.14	2.5±0.25
4	78.3±0.35	89.6±0.22	11.3+0.42
Between target 4 and 5	54.3±1.12	51.6±0.95	-2.7±0.15
5	81.6±0.3	91.2±0.18	9.5±0.34
Downstream of target 5	99.6±0.01	99.3±0.13	-0.3±0.02