Generative Adversarial Networks in Liquid Argon

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Project Description

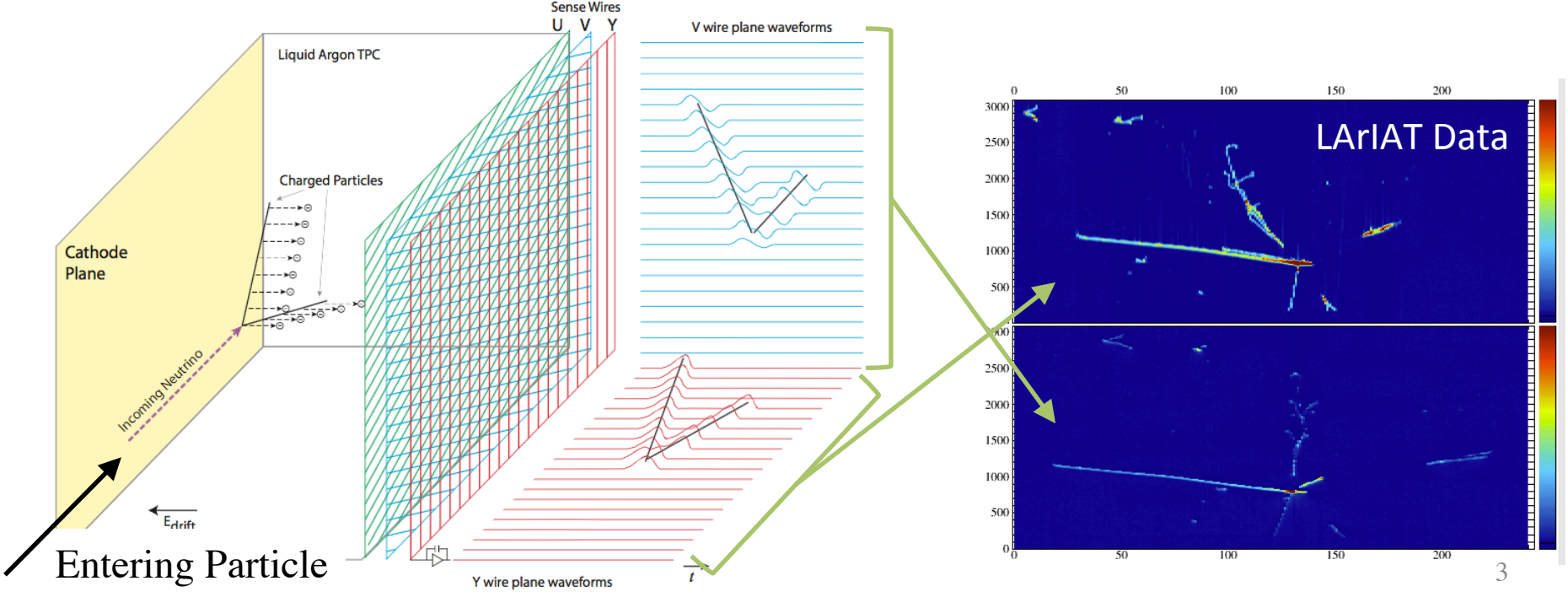
Use MC-Trained CNNs to classify hits as shower-like or track-like in Liquid Argon TPC (LArTPC) events

Develop methods to make MC-trained networks perform as well on data as they have proven to perform on MC.

Apply Generative Adversarial Network (GAN) to create a data-driven filter that will add noise and missing physics in the MC to make it more similar to data

LArTPCs

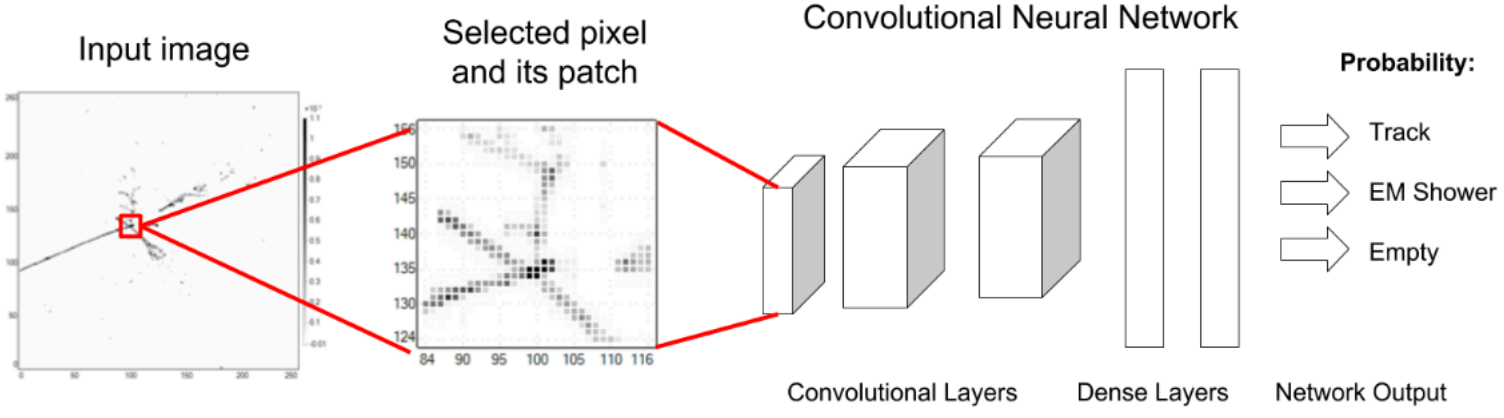
Liquid Argon Time Projection Chambers (LArTPCs)
Being developed on the large scale for neutrino and proton decay experiments
Two Wire Planes and Dimension of Time allows full 3D Reconstruction of Particle Tracks



Classification in Reconstruction

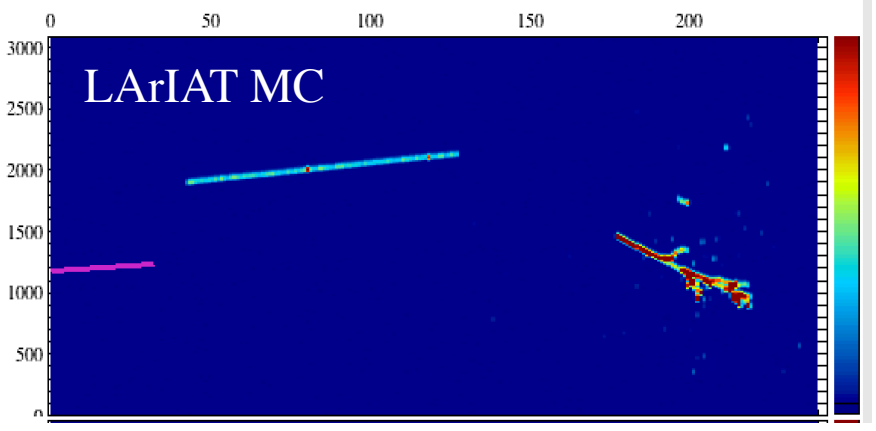
MC-Trained CNN to classify each hit created as shower-like or track-like

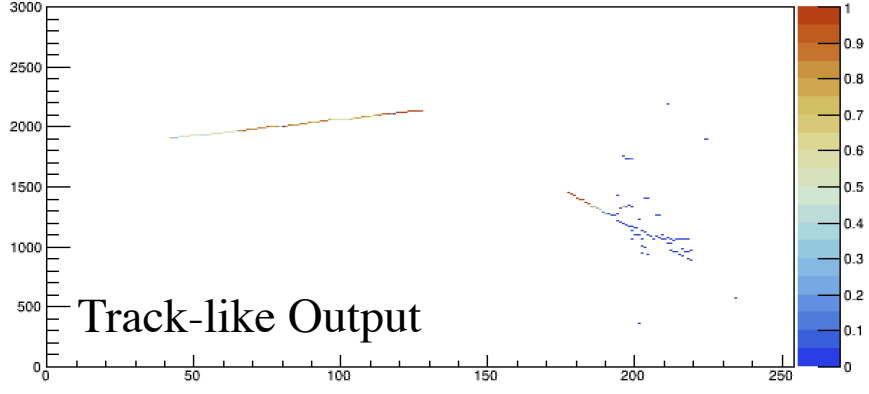
Performed on noise-filtered ADC values and
only after hit finding, making it one of the first reconstruction steps

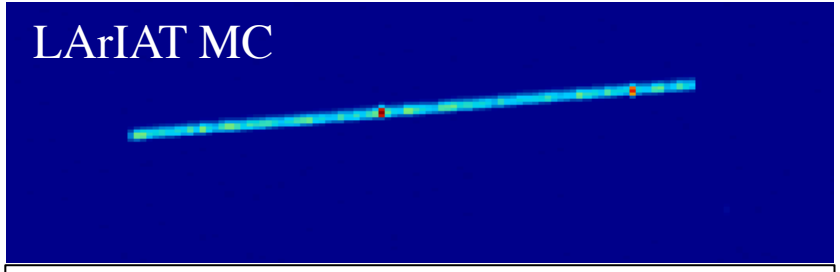


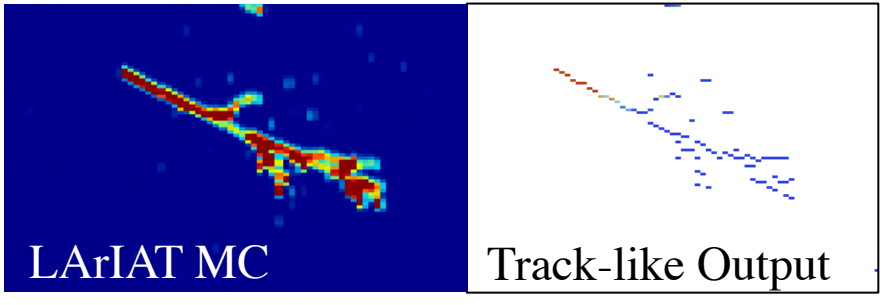
Greatly speeds up tracking and makes shower clustering possible

MC Classification Performance

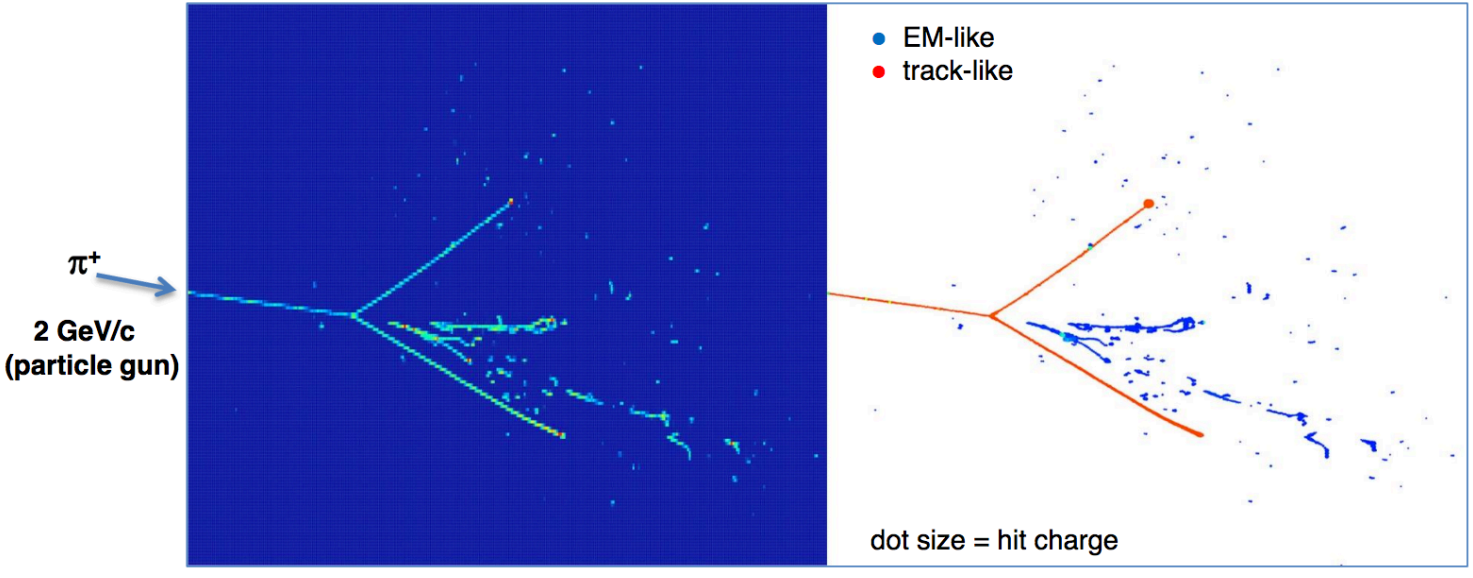






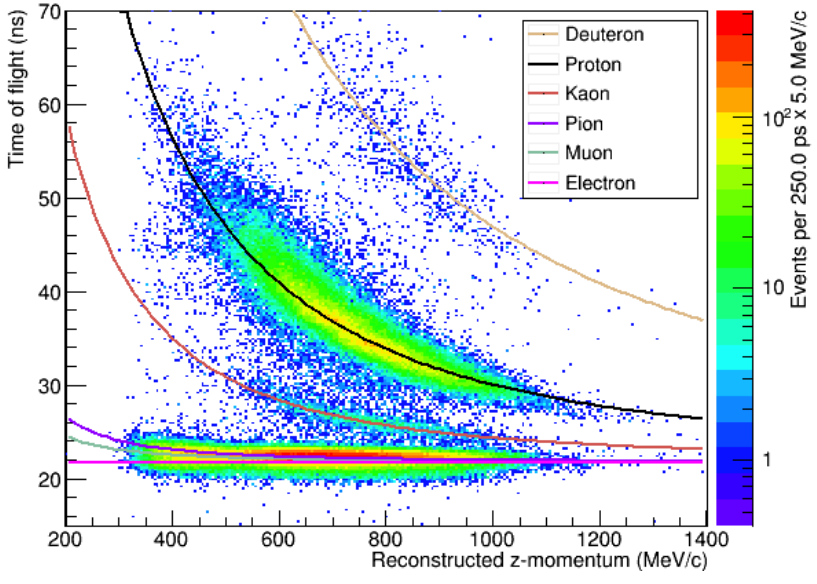


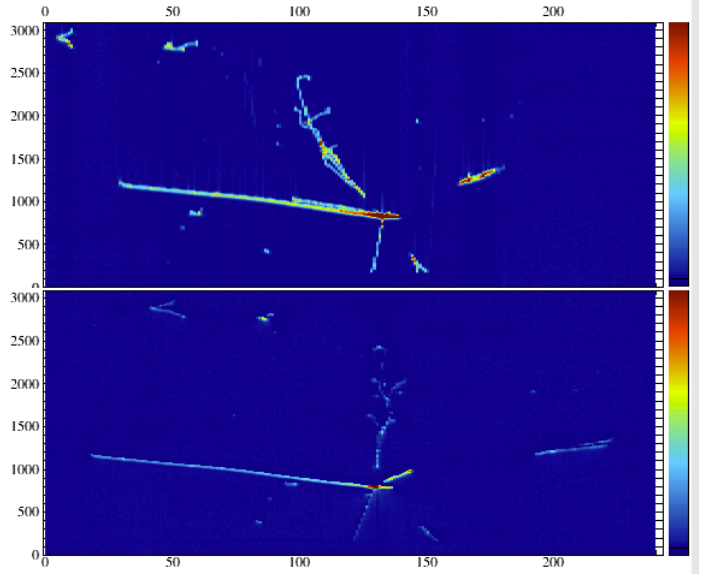
MC Classification Performance



LArIAT Experiment & Data

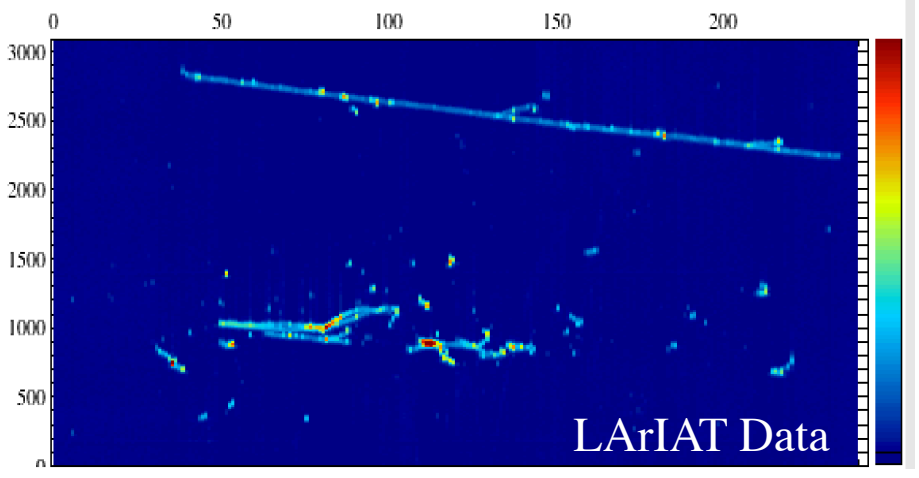
LArIAT (Liquid Argon TPC in a Testbeam) – Beamline LArTPC experiment at Fermilab
3 years of LArTPC data events

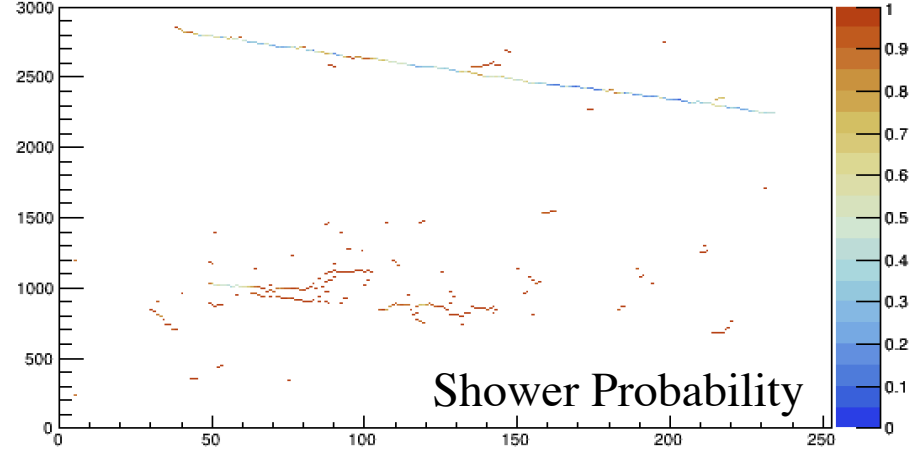


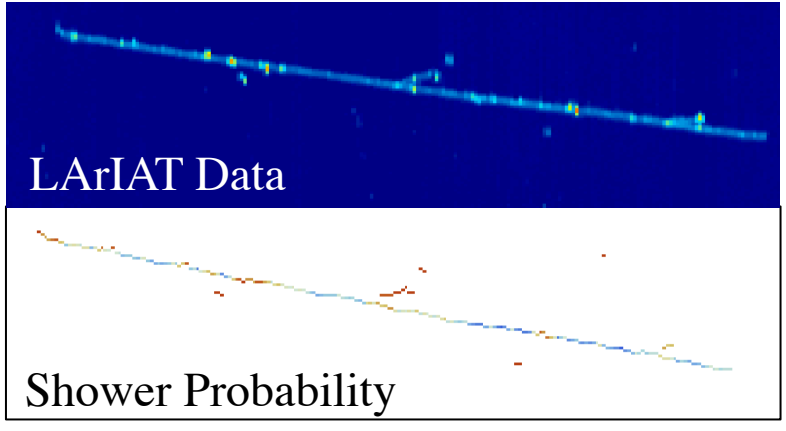


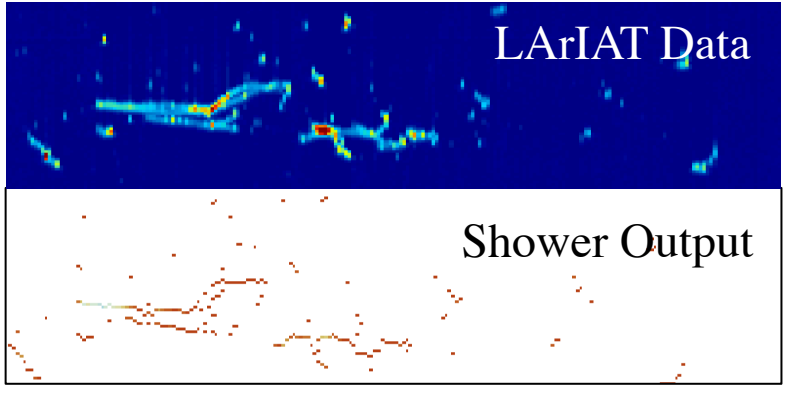
Beamline TOF and Wire-Chamber Momentum
allow us to select for desired particle species

Data Classification Performance



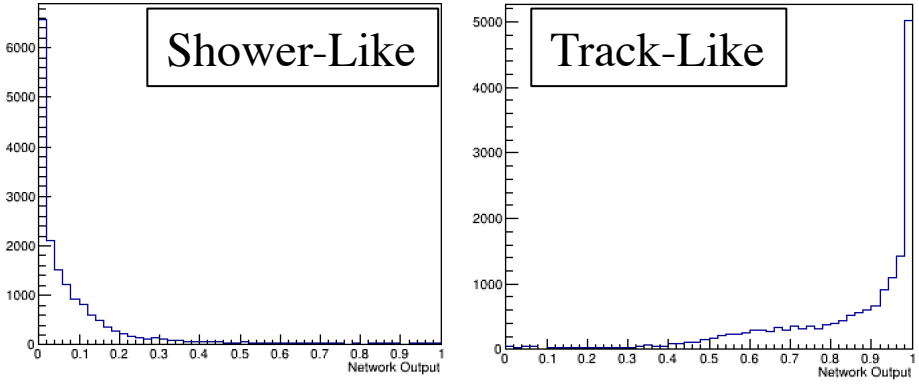




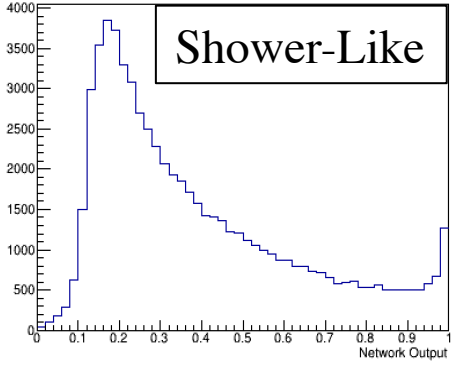


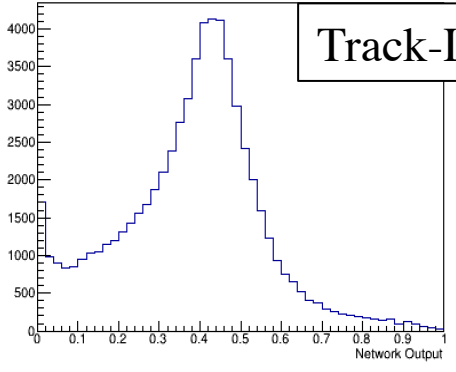
Data Classification Performance

200 π- MC events



638 π- data events with μ/e contamination





Distribution of network output for only tracks-like hits

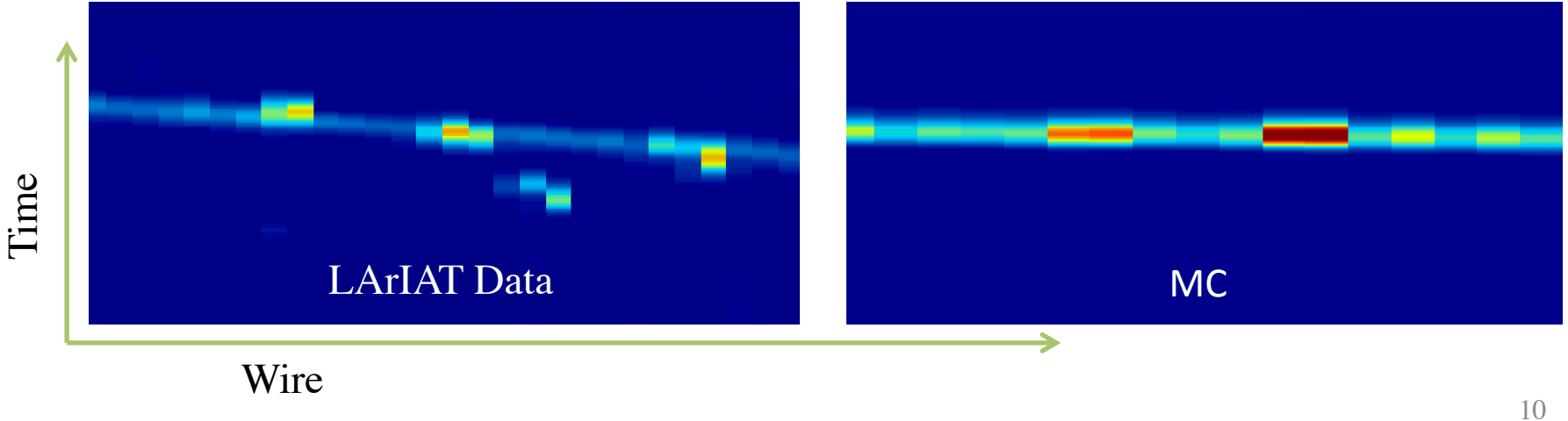
Track-like hits from MC truth or from matched track entering TPC in data after electron / shower vetos

MC shows good separation as expected however, the data is simply not working

Cause - Cross-talk in MC

Network sensitive to differences between training and applied sample –
difference between MC and data affect the network in unpredictable ways

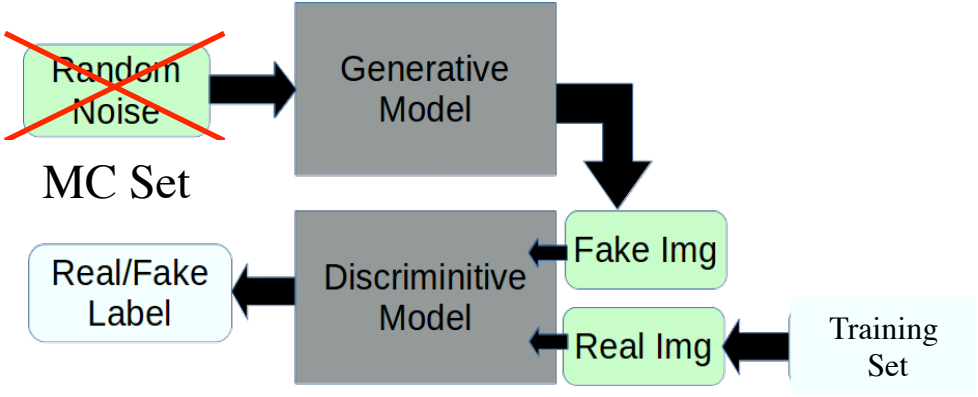
Known differences are in wire-to-wire cross-talk
wire-to-wire inductance, physics of wire charge deposition range, electronic noise,
wire-to-wire variance are all not simulated in MC



Potential Solution - Modified GAN

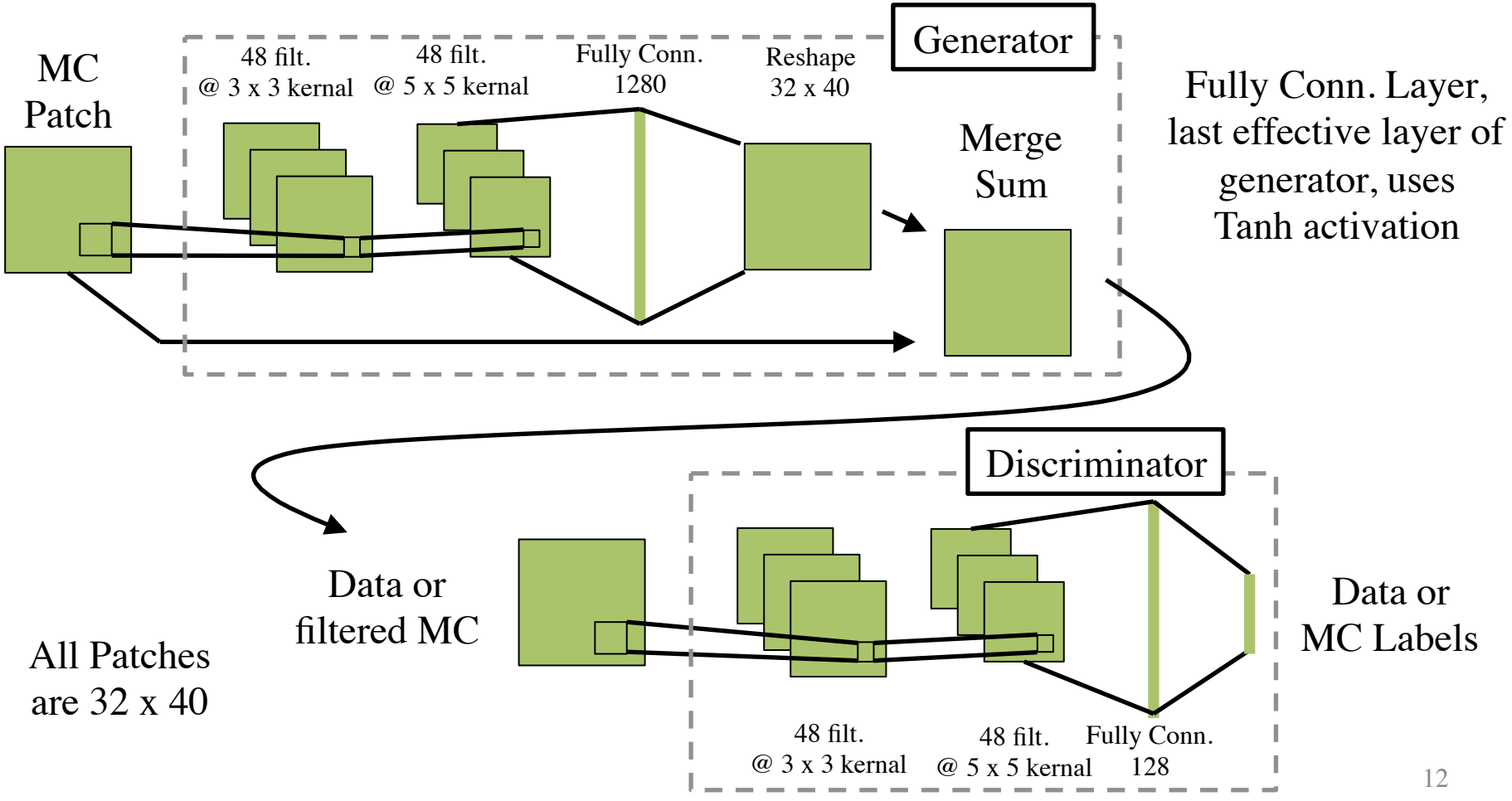
Generative Adversarial Networks (GANs) are a promising unsupervised machine learning method used to generate images similar to a training set.

I propose modifying the GAN to pass in a MC sample into the generator, functionally turning it into a filter



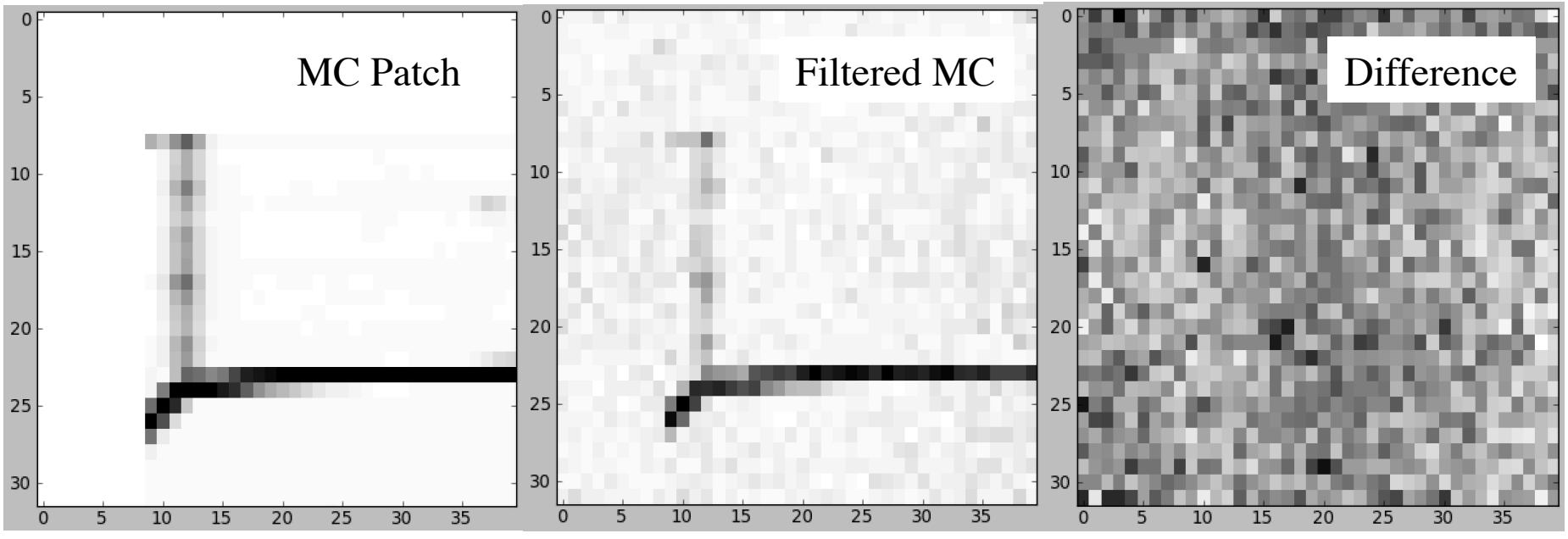
Training against data will create a data-driven filter for MC, allowing one to create a filtered MC sample that is very similar to data

Modified GAN Architecture



First Trails – Low Entropy

In training, system tends to prefer lower entropy systems
if the training data is too stochastic

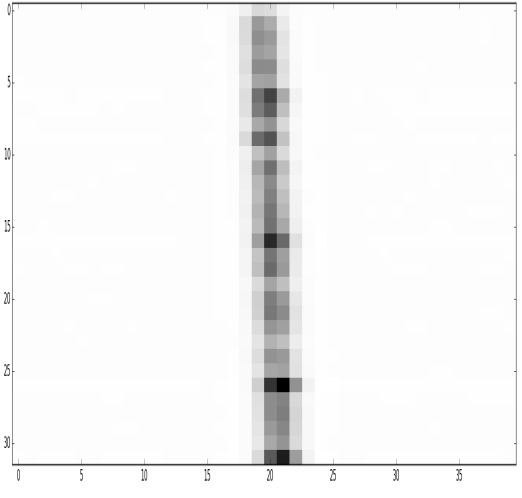


Minibatches – Train on a select of very similar patches to increase entropy in system, encoraging more input-specfic output and prevent collapse of output

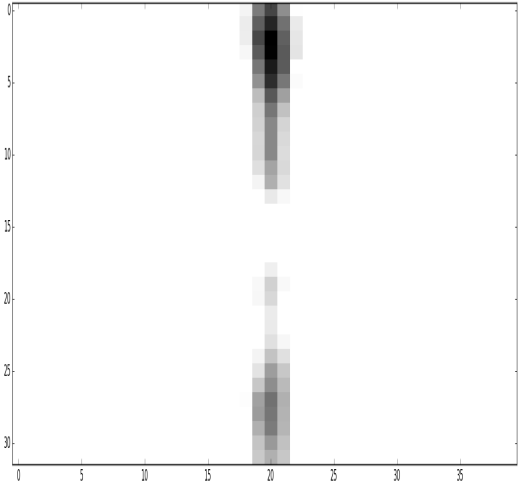
First Trails – Seeing Spots

Generator began to systematically ‘erase’ the center of images

MC Patch



Filtered MC

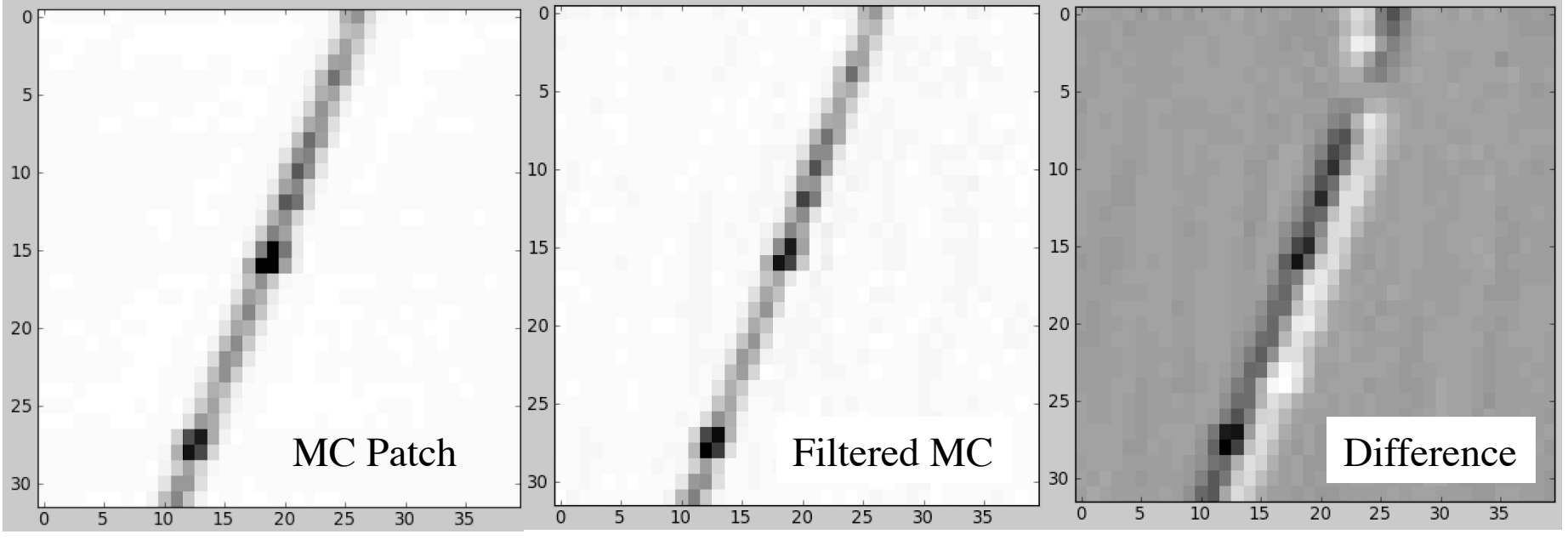


The cause – training dataset was almost never centered on hits while MC events were almost always centered.

A failure mode, but very promising as sign of GAN replicating a sample

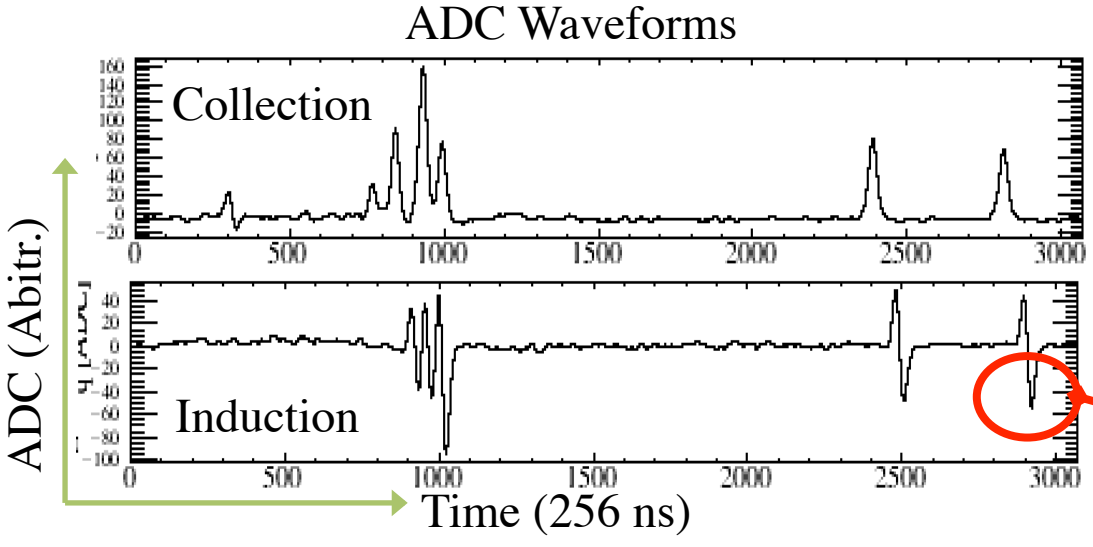
Collection to Induction Plane

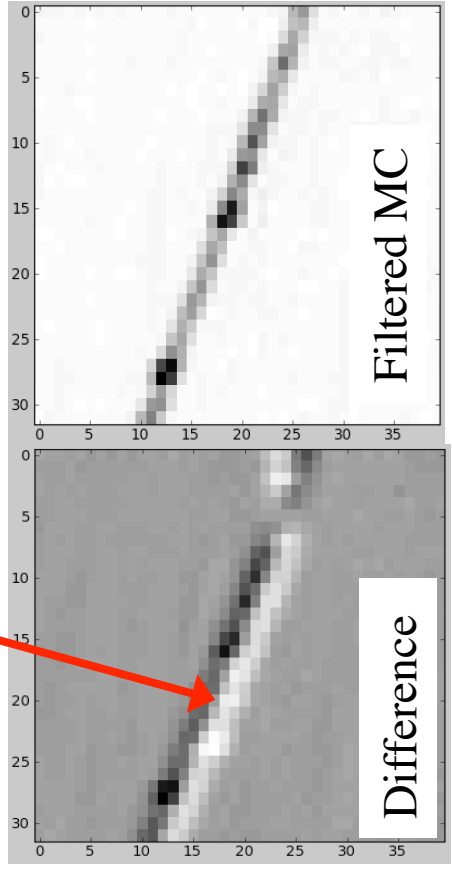
Generator began putting a ‘shadow’ under tracks



Collection to Induction Plane

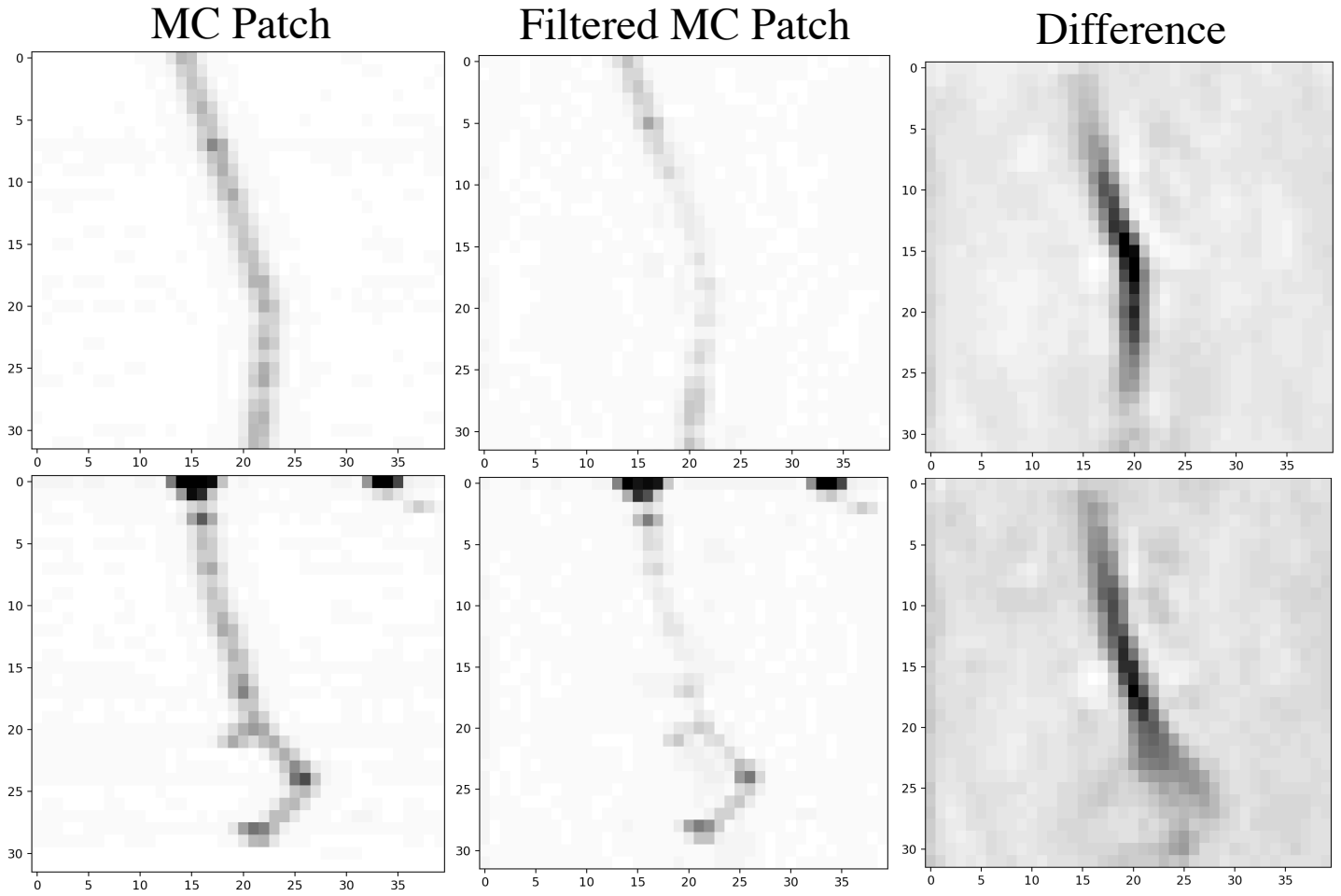
This shadow is due to a mix up in training.
Passed in **Collection Plane MC** events and
trained on **Induction Plane Data** events





Only training using collection plane data going forward
but this is very promising because it is emulating physics

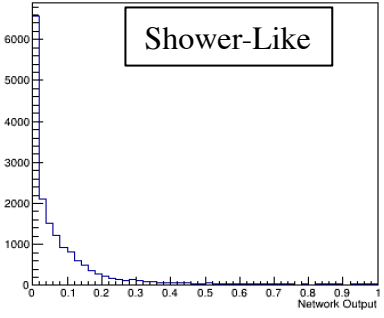
Latest Trial Result

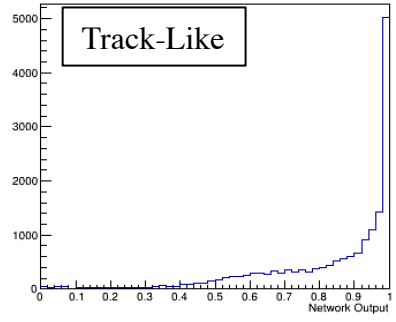


Filtered MC Classifier Performance

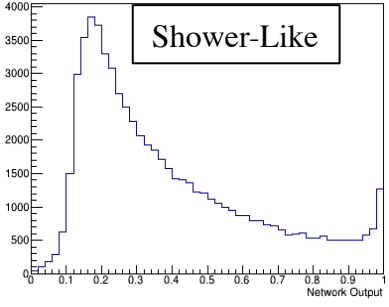
Using the most recent filtered, created a filtered MC set, trained a new classifier and looked into the results

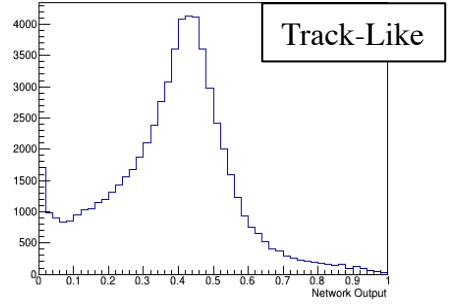
200 π- MC events





638 π- data events





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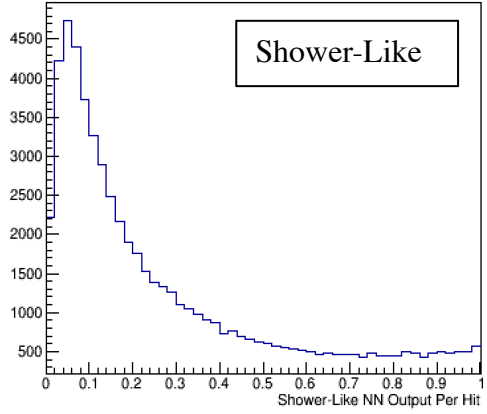
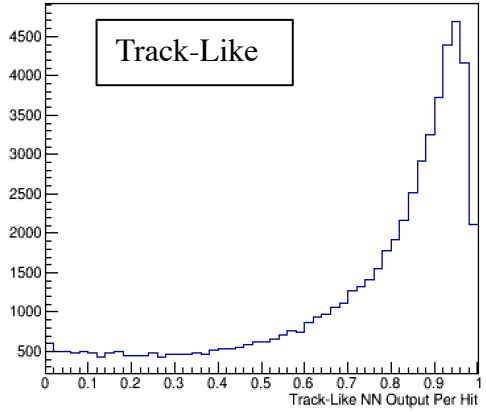




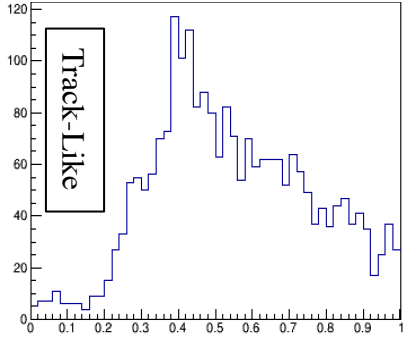
Using filtered MC, the network is performing much closer to that seen in MC studies

Filtered MC Classifier Performance

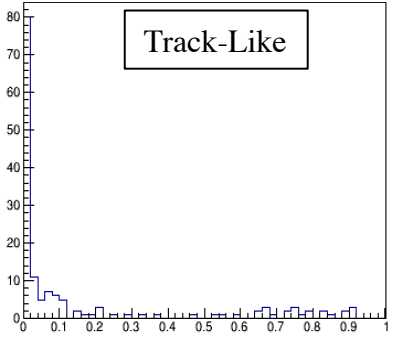
After eyescanning a hand full of data events, plotted network output for

Unfiltered-MC Trained Classifier

Tracks:

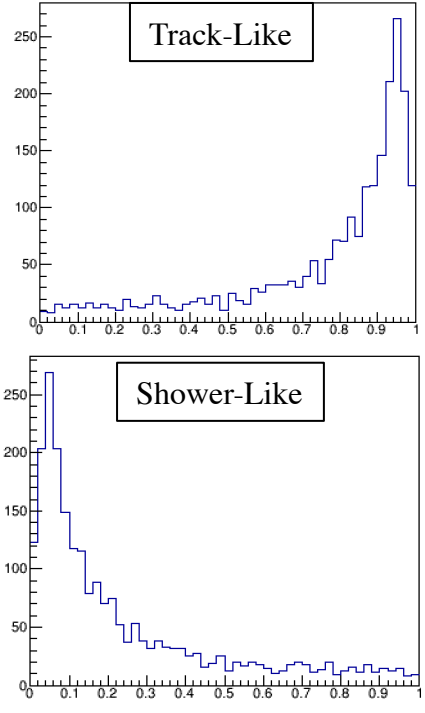


Showers:



Filtered-MC Trained Classifier

Tracks:



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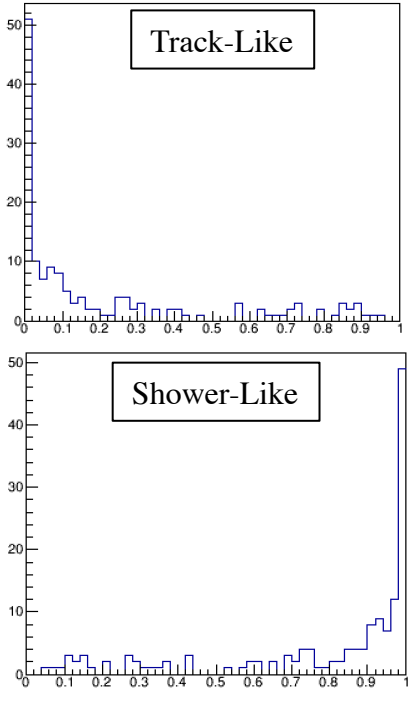
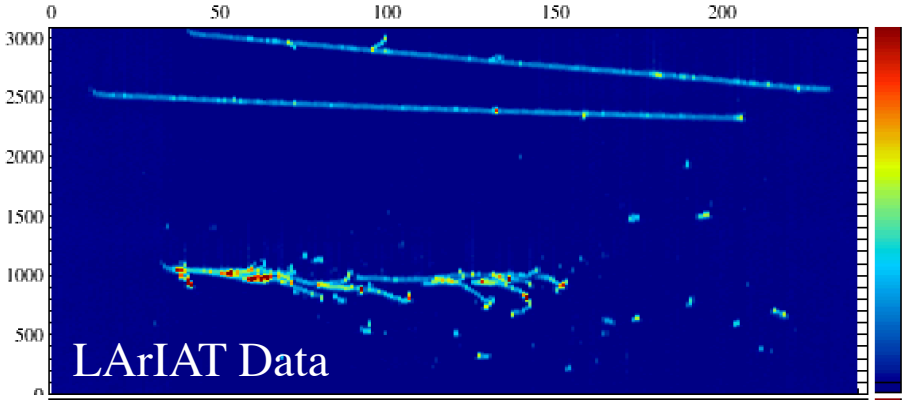
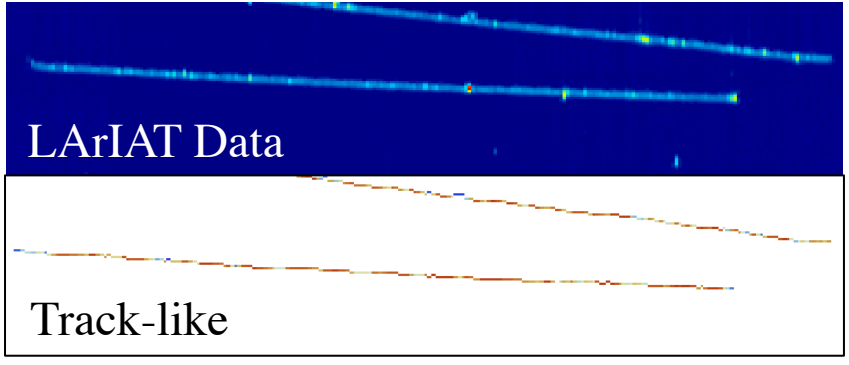
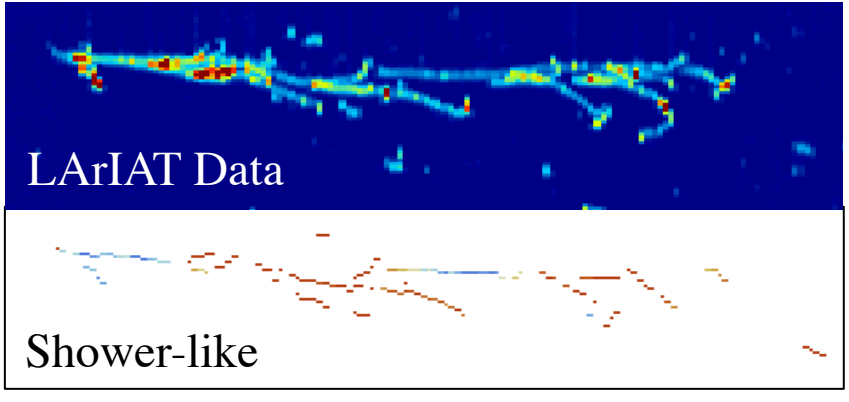


Filtered MC Classifier Performance





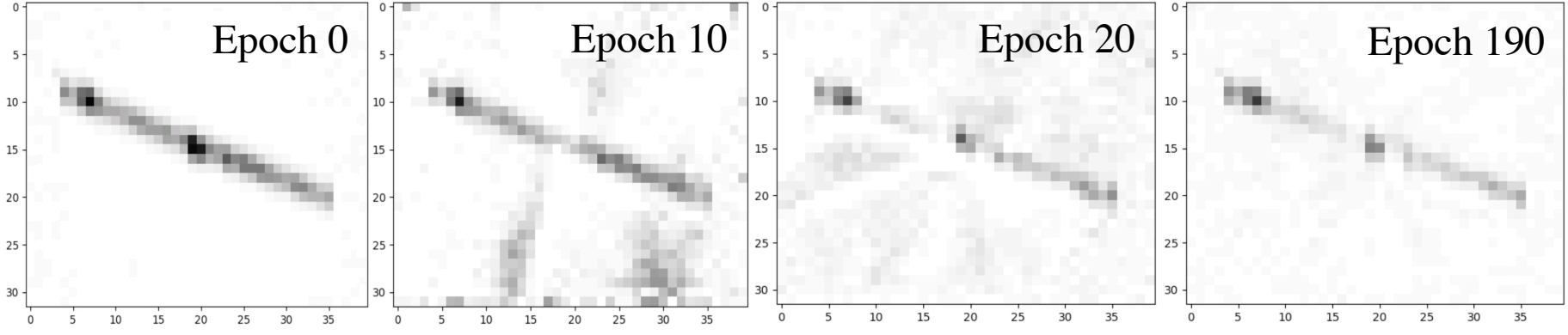


Conclusions and Future Work

GAN proving to be effective in filtering
MC to be more similar to data

Work to do:

- Investigate differences that GAN highlights
- Optimize GAN training using other techniques in literature
- Explore applications for filter

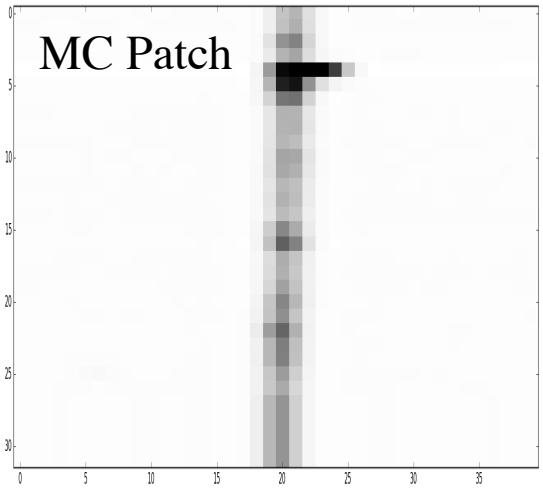


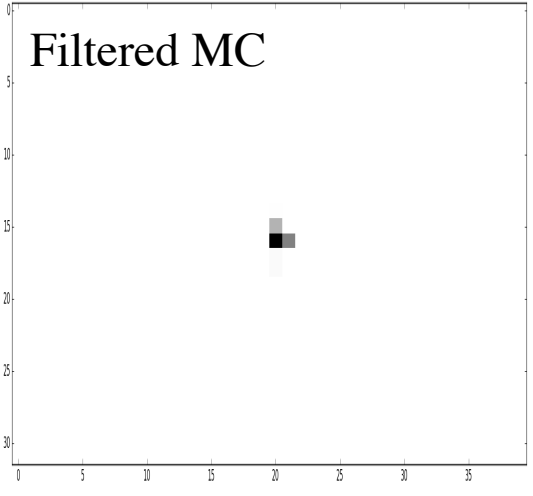
Thank you!

Backup

First Trails – Training Stability

As is common in GANs, there are stability issues including overtraining





Combat this by carefully regularizing the training including training the generator until it reaches a level of loss before retraining the discriminator

LArIAT Experiment

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Beamline LArTPC experiment at Fermilab
3 years of LArTPC data events