Challenges in AI/ML at the Intensity Frontier

SLAC SSI 2023

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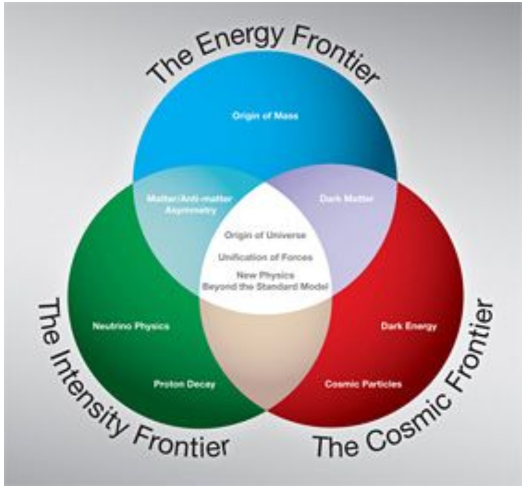
Outline

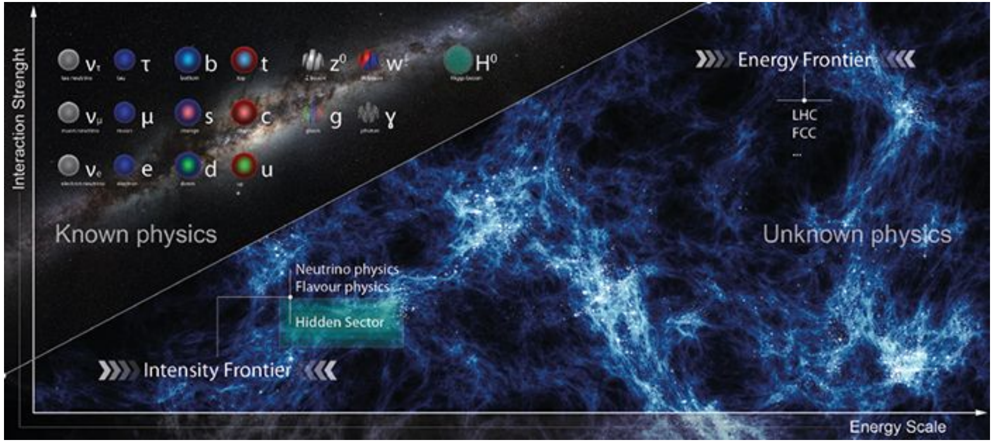
- What is the Intensity Frontier (IF)?
- A subset: Neutrino Experiments
- What are some of the physics questions we are after?
- What are the challenges to answering those questions?
    - w/ a bias on one question: measuring neutrino oscillations



The Intensity Frontier

From Snowmass 2013

> “The Intensity Frontier explores fundamental physics with intense sources and ultra-sensitive detectors. It encompasses searches for extremely rare processes and for tiny deviations from Standard Model expectations. Intensity Frontier experiments use precision measurements to probe quantum effects. They typically investigate new laws of physics that manifest themselves at higher energies or weaker interactions than those directly accessible at high-energy particle accelerators.”



Intensity Frontier 2.0 = Neutrino + Rare Process/Precision

NEUTRINO FRONTIER

NF01: Neutrino Oscillations
NF02: Understanding Experimental Neutrino Anomalies
NF03: Beyond Standard Model (BSM)
NF04: Neutrinos from natural sources
NF05: Neutrino properties
NF06: Neutrino Interaction Cross Sections
NF07: Applications
NF08/TF11: Theory of Neutrino Physics
NF09: Artificial Neutrino Sources
NF10: Neutrino Detectors

RARE PROCESSES AND PRECISION MEASUREMENTS FRONTIER

RF1: Weak decays of b and c quarks
RF2: Weak decays of strange and light quarks
RF3: Fundamental Physics in Small Experiments
RF4: Baryon and Lepton Number Violating Processes
RF5: Charged Lepton Flavor Violation
RF6: Dark Sector Studies at High Intensities
RF7: Hadron Spectroscopy

Intensity Frontier 2.0 = Neutrino + Rare Process/Precision

Snowmass 21 Frontiers

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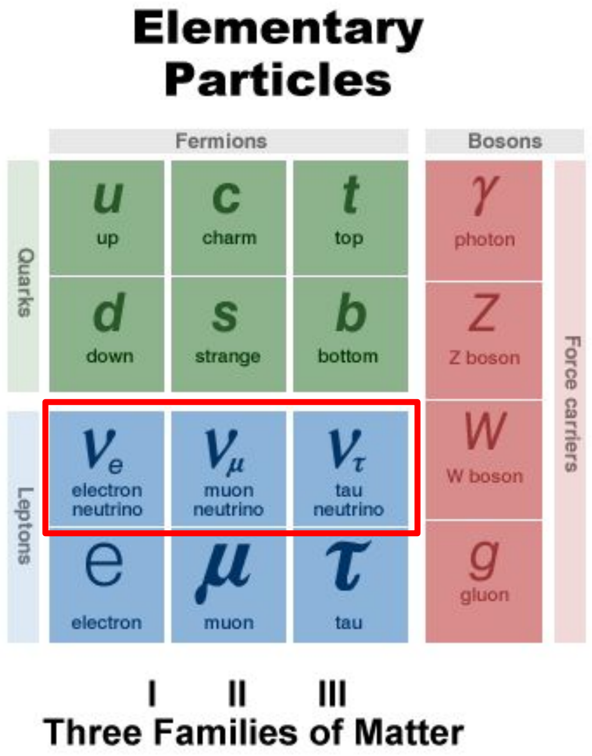
A very vast field to survey – I will stick closely to areas I am most familiar, i.e a subset of Neutrino Frontier

Neutrinos

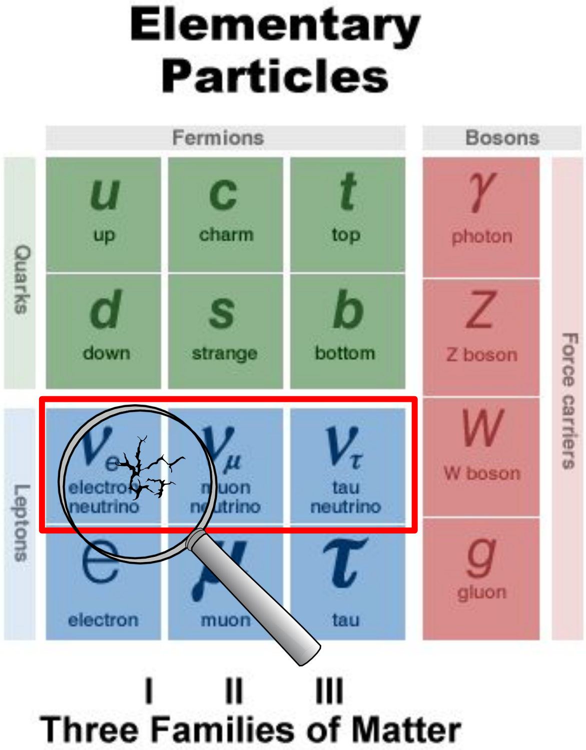
Key properties

- No electric charge
- Interacts only via weak force (and gravity)
- Very, very small mass: <eV
- Come in three “flavors” -- named from what lepton made during certain interactions (Charged-Current)



Why Neutrinos

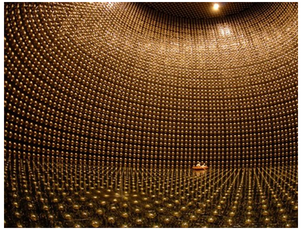
- The hope is that precision measurement of neutrino properties and behavior will show cracks in the SM which point the way to new physics
- These efforts center around the neutrino mass …



Neutrino Oscillations: a brief History

- A long saga
- Starting with the Homestake Experiment (1970 until 1994) and culminating with measurements in Super-Kamiokande (1999) and the Sudbury Neutrino Observatory (2001)
- Showed that neutrinos can change flavor as they propagate

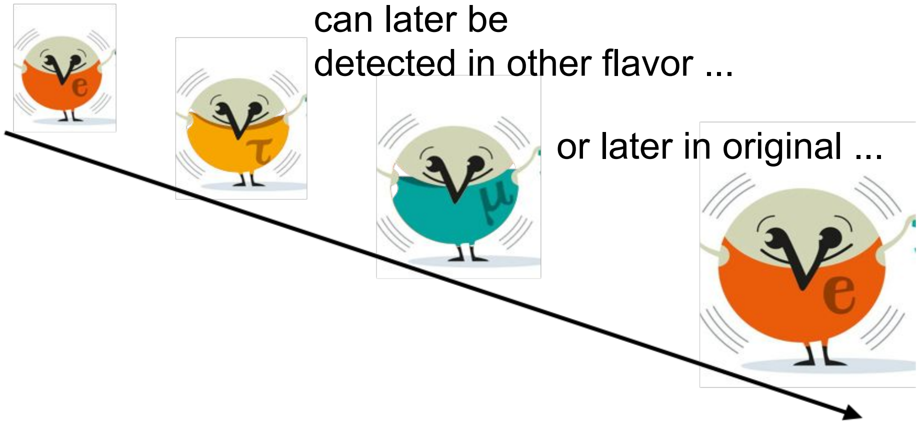
Homestake



Super-Kamiokande

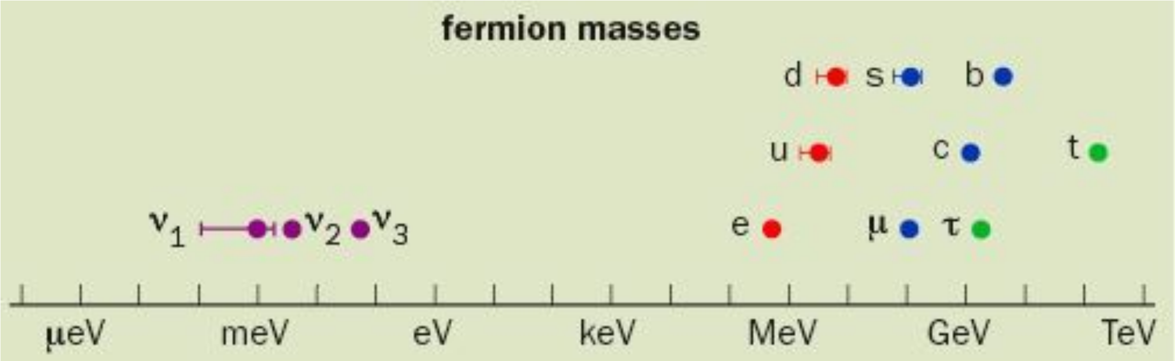
SNO

Neutrino created in certain flavor ...

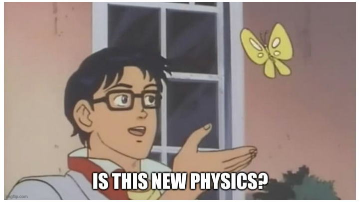


Mass induced Flavor Oscillations

- Several ways to explain neutrino flavor changing, but accepted model that has explained nearly all of the data* is that if <u>neutrinos have a non-zero mass, then the flavors of neutrinos can mix</u>
- Furthermore, constraints tell us that this mass is <u>very small</u>
- ***Is the neutrino mass mechanism different?***



NB: this seems weird – but universe allowed to be weird



Connection to Old and New Physics

Ways to explaining very small Neutrino masses:

- Neutrinos are similar to the other leptons and quarks, i.e. are Dirac Fermions, and have a **very small coupling to the Higgs**
- Neutrinos are different – Majorana Fermions – and couple with **a different Higgs Boson**
- Neutrinos are Majorana and small mass due to effective couplings to new **physics at a very different energy scale** (See Saw Mechanisms)

> * Quick def: A Majorana Neutrino would mean a neutrino and antineutrino are the same
> (Majorana condition: $\Psi_M^C = C\gamma_0\Psi_M^* = \Psi_M$)

From de Gouvea, PITP 2017

Other Questions

- Can we determine if the neutrino is **Dirac or Majorana**? (Yes! By seeing neutrino-less double beta decay)
- Neutrino flavors mix: will quantifying their **mixture give us hints for new symmetries**?
- Do **neutrinos exhibit** ring the matter/anti-matter asy
  (but so far, SM neutrino CF
- **How many neutrinos**
- Do neutrinos have sho
- Neutrino experiments require intense sources and large detectors – can search for evidence of new particles (e.g. **dark matter/dark sector**)

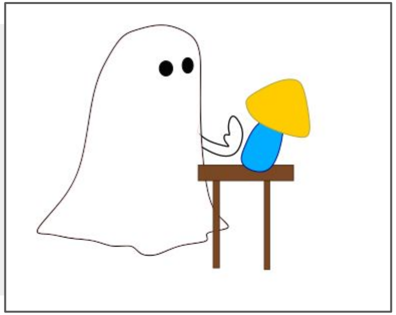
It's unclear if any of these questions will point us to new physics - we need more information.

ML/AI Techniques have already improved our ability to answer such questions with the experiments we have – and we really on just begun

Observing Neutrinos

Neutrino properties dictate how we search for them. Two key ones:

No electric charge
=> ***observe indirectly***



Only Weak Force
=> ***rare process***

Try to **observe and identity as many of the particles as possible** coming from neutrino interactions.

(Avoid background particles if possible: underground facilities, capabilities for rejection)

Need **intense source** of neutrinos and/or **large detector**

Neutrino Sources

Neutrinos are produced in several different sources – natural and artificial – and over a vast energy range

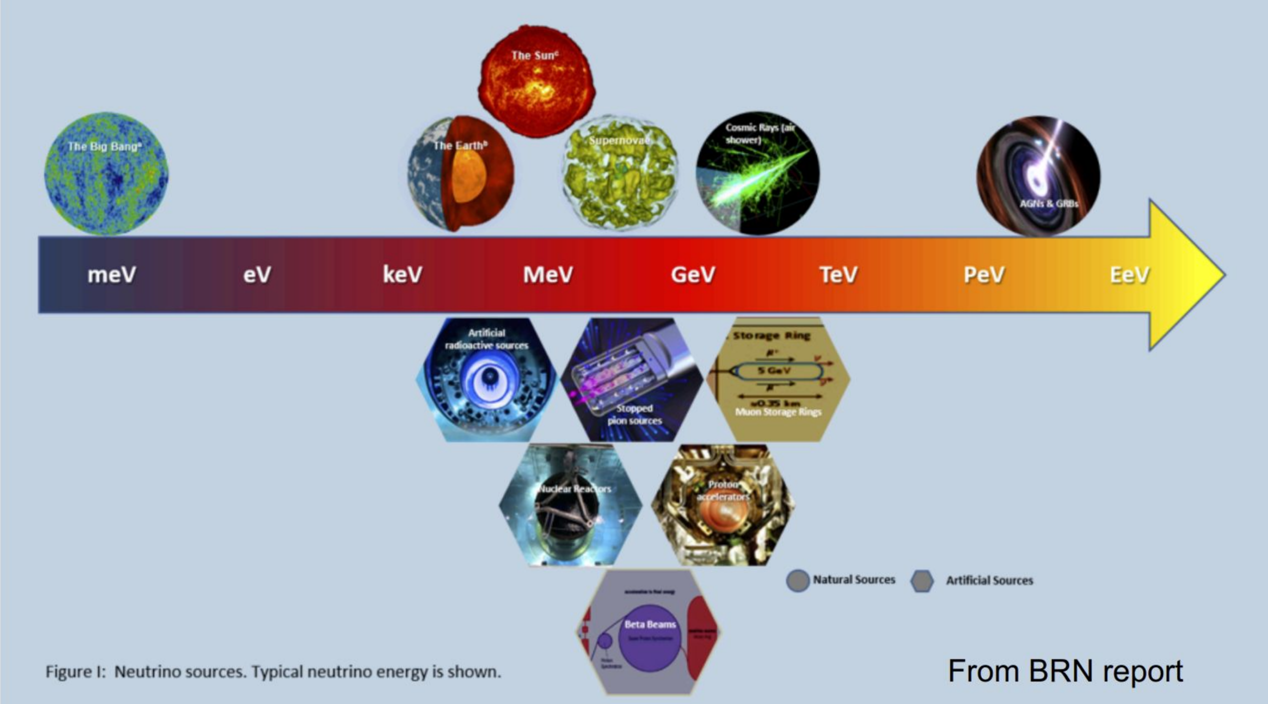


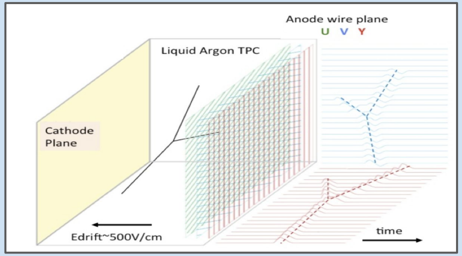
Figure I: Neutrino sources. Typical neutrino energy is shown.

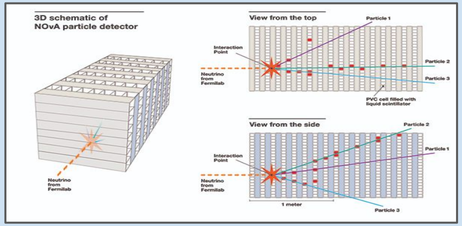
From BRN report

Detector Types

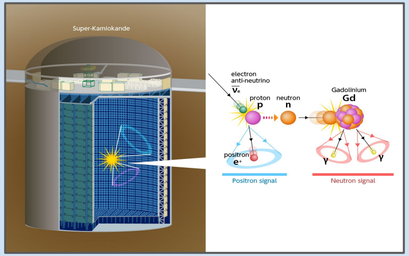
A wide-variety. Here are four broad classes though experiments often mix elements.

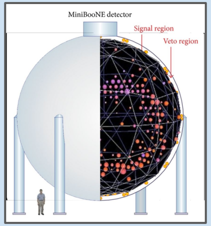
Trackers

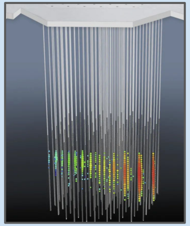




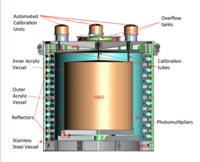
Cherenkov Detectors

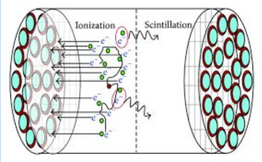




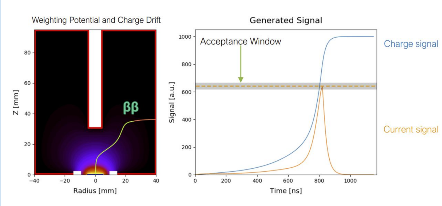


Scintillators





Solid-State/Crystals



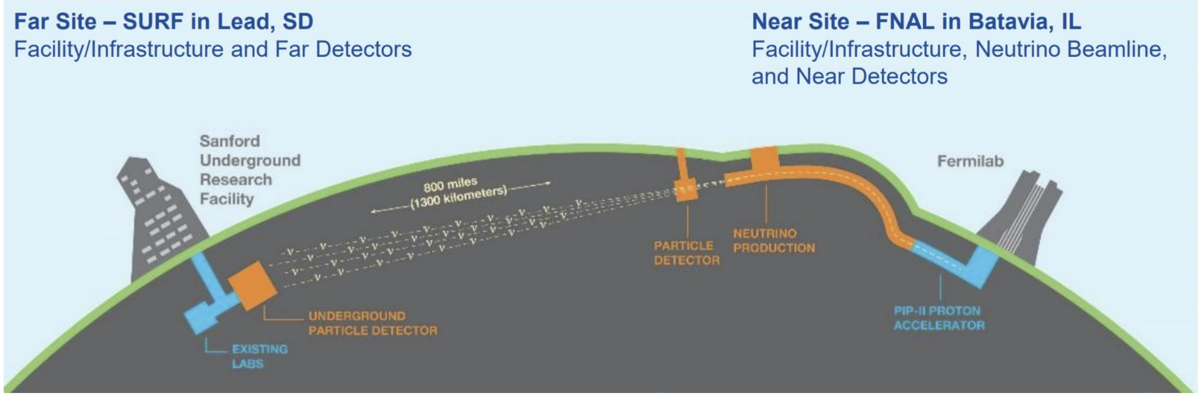
Accelerator Neutrino Experiments

Many of the research challenges that ML has highly impacted have to do with experiments accelerator neutrino experiments – and many in other experiments as well

Of their many physics goals, a primary objective is to make ***precision measurements of neutrino oscillations***.

Example DUNE

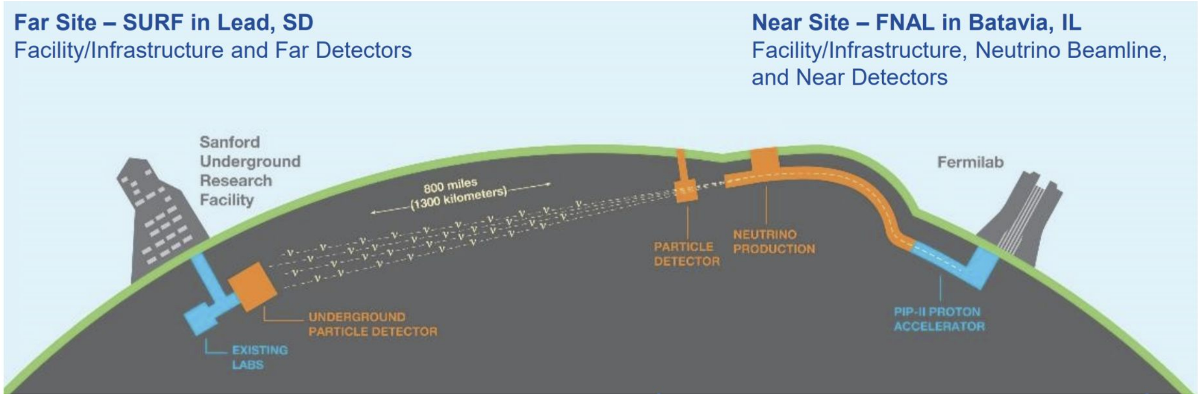
one part of the program: $\nu_\mu \rightarrow \nu_e$ and $\bar{\nu}_\mu \rightarrow \bar{\nu}_e$ in order to look for **CP-violation**



Strongest oscillation effect expected after 1300 km: need really intense beam + large detector (40kt LArTPC)

Preferably large monolithic detector (scalable) with good particle discriminating power.

Accelerator Neutrino Experiments



Note two detector design:

***Near** detector measures rate of neutrino interactions before oscillations near beam source*

***Far** detector measures rate after oscillations*

Both are Liquid Argon Time Projection Chambers - are class of tracking detectors

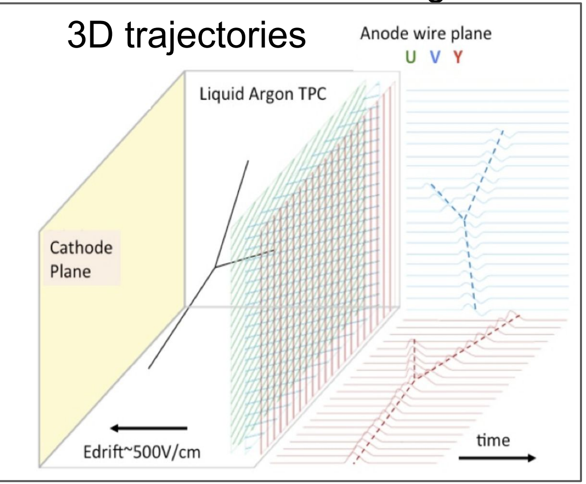
Trackers

Promising applications of ML/AI in Neutrino physics applied to tracking detectors

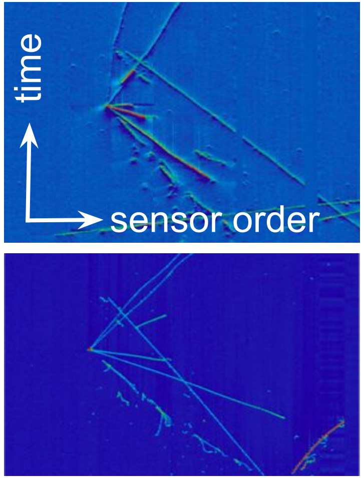
Record 3D energy depositions as 2D projections which are very image-like: sensor measurements naturally arranges into regular 2D array.

Pattern of energy deposits can help us infer a lot: particle type, momentum

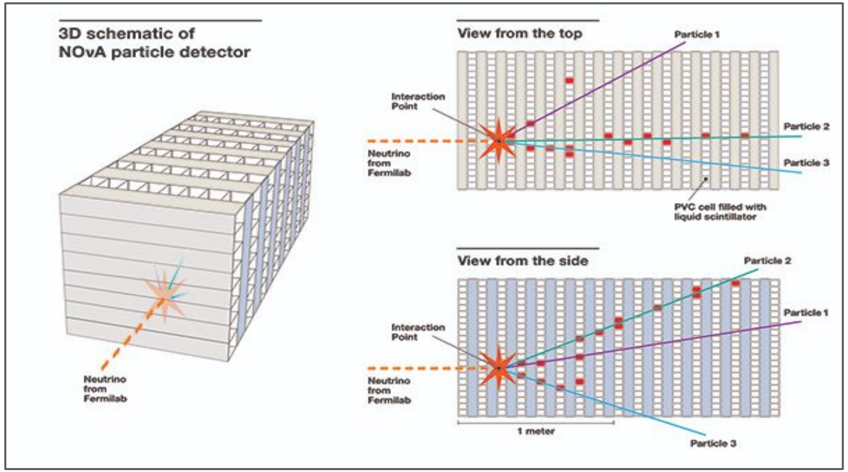
LArTPCs: e.g. DUNE



Multiple 2D projections



Segmented Scintillators: e.g. Nova/Minerva



Challenges

ML/AI impacting research challenges common to many experiments

Reconstruction: are we getting all the information that we can from our data, precisely and accurately?

Simulation/Modeling: can we translate physics to observables faster? Can we better use data-driven methods?

Inference: are we testing our models against data as best as we can while accounting properly for and mitigating our model uncertainties?

Operations: are we saving the right events? Is the experiment running optimally? Can we detect and make decisions faster?

Challenges

Reconstruction: are we getting all the information that we can from our data, precisely and accurately?

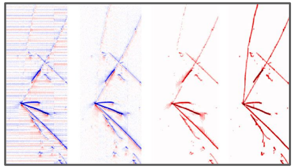
The bulk of the development in ML has been here

Reconstruction

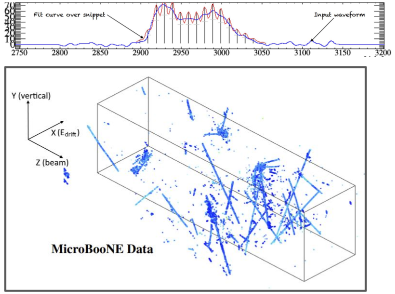
Broadly, reconstruction involves a sequence of algorithms to take raw detector data to relevant observables.

Reduction of data into increasingly higher-level/summary representations.

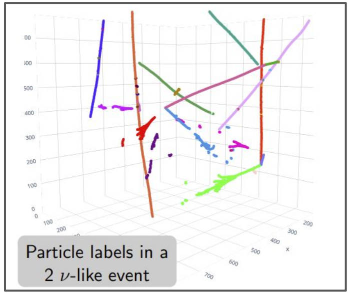
Example: Reconstruction stages for parsing LArTPC data to find neutrinos



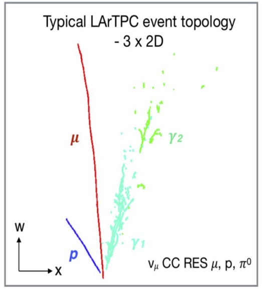
Signal conditioning



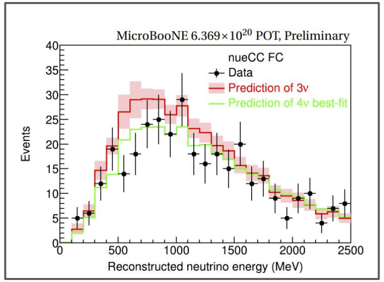
"Hit" finding (first-stage summary)



Clustering (particles)



Interaction

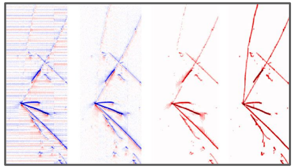


Measurement Observable

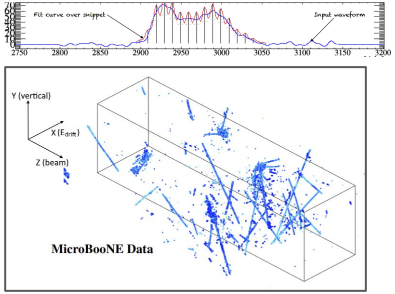
ML Reconstruction

ML Approaches have been applied to several of these stages, effectively proposing higher-level outputs directly from low-level inputs.

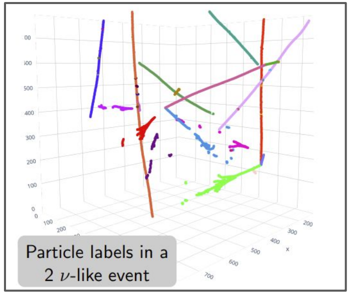
Taking advantage of “data” as algorithm, i.e. intermediate representations (features) are learned through training a model to best output a given objective



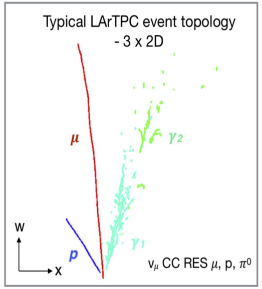
Signal conditioning



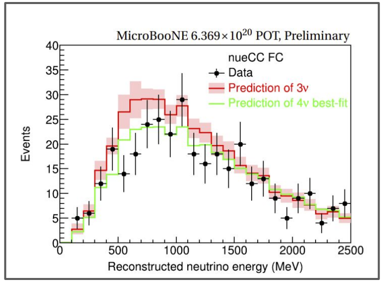
“Hit” finding (first-stage summary)



Clustering+particle ID



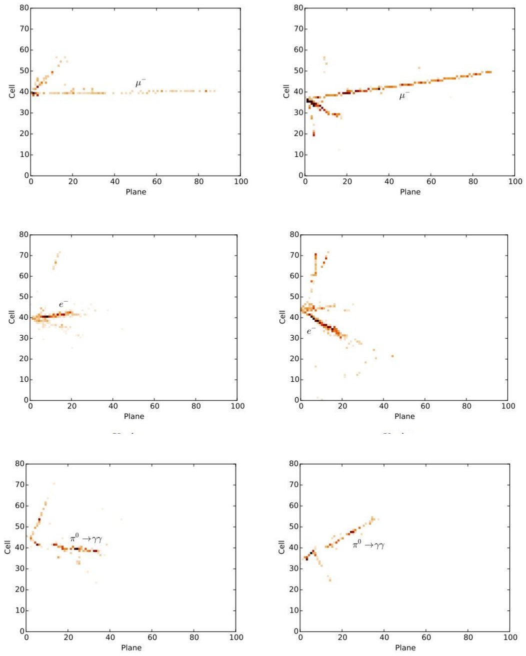
Interaction



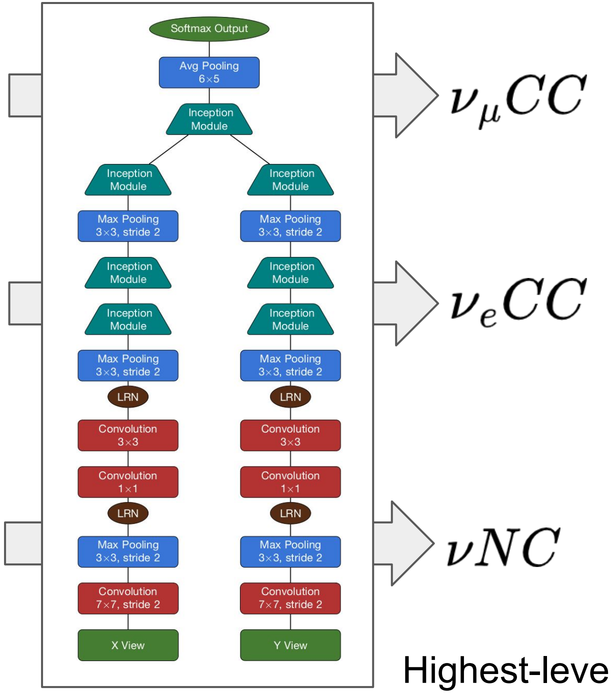
Measurement Observable

Neutrino Flavor/Interaction Classification

X view | Y view



Nearly raw data



Highest-level physics concept

Two projections of neutrino interaction passed into Convolutional Neural Network to determine interaction type.

Used in analysis measuring

$$\nu_\mu \to \nu_e$$

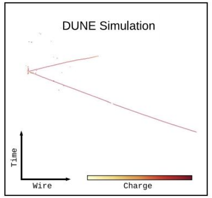
oscillations, so signal are $\nu_e CC$ events

35% increase in signal efficiency over previous methods.

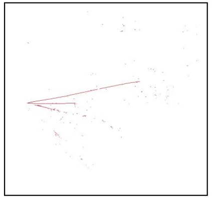
JINST 11 P09001(2016)

Neutrino Flavor/Interaction Classification

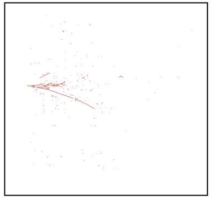
Classification CNN also applied to **DUNE**: Upcoming oscillation experiment aiming to measure CP-violation



(a) 1.6 GeV CC ν_μ.

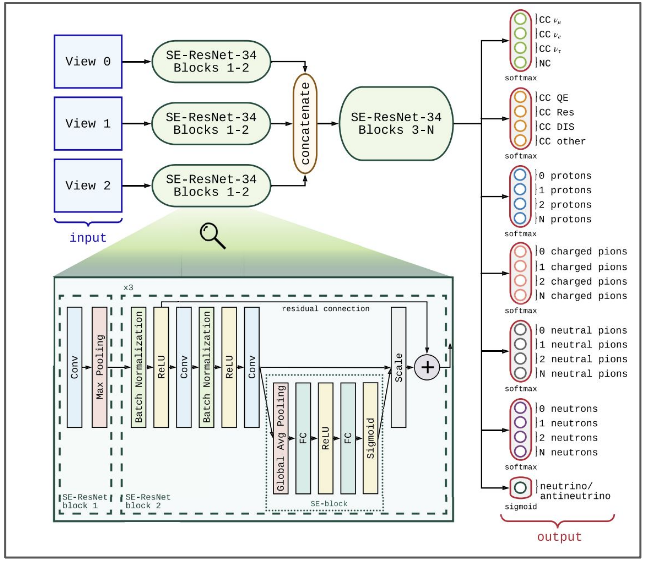


(b) 2.2 GeV NC $1\pi^+$.

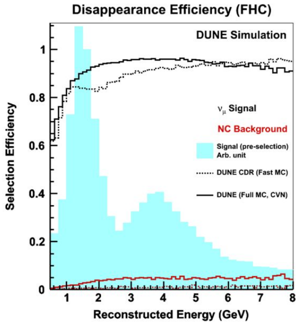


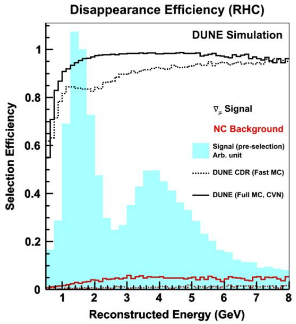
(c) 2.4 GeV NC $1\pi^0$.

Updated architecture, multi-task output



Improvement to previous selection. Used in sensitivity estimates for DUNE Technical Design Report





See talks by S. Monsalve on Computer vision techniques and L. Whitehead on Intensity Frontier Computer Vision Applications for more details

PhysRevD.102.092003

Low/Intermediate-level Representations

CNNs have also found use producing lower-level outputs for downstream algorithms.

Why? Didn't you show me how to get the answer already?

Reasons to produce low/intermediate-level representations

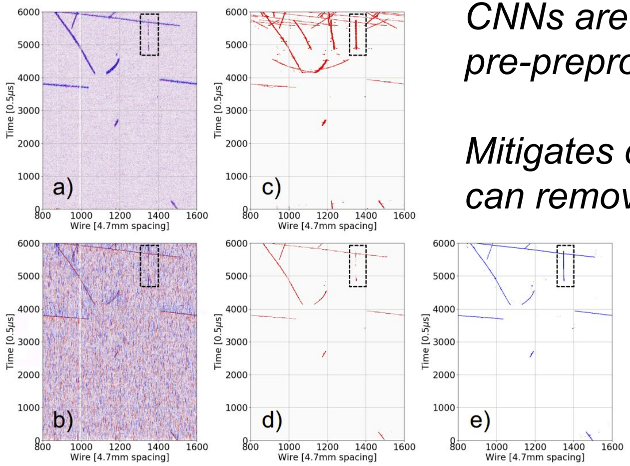
- Feed high-quality outputs more easily incorporated into downstream algorithms ("traditional" or ML-based)
- "Getting the right answer" uses physics which we have more confidence modeling:
  e.g. particle propagation in matter vs. to neutrino-nucleus interactions
- Can find side-bands in data to check for effects from domain shift, i.e training on sim, applying on data
  NB: Nova had a means for checking network using a control sample provided by another "near" detector

Examples:

- Producing 3D energy deposits from 2D projections
- Keypoints useful for seeding particle reconstruction
- Labeling hits by particle type
- Individual particle clusters

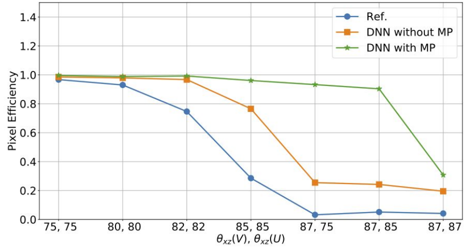
PhysRevD.102.092003

Signal Processing/ROI Finding



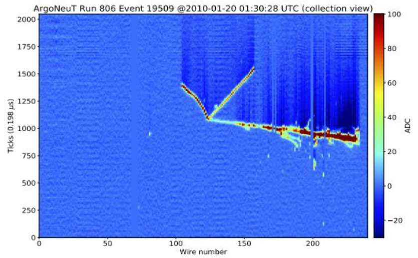
CNNs are helping to refine pre-preprocessing of waveforms

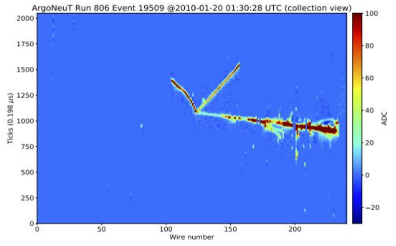
Mitigates detector effects that can remove signals

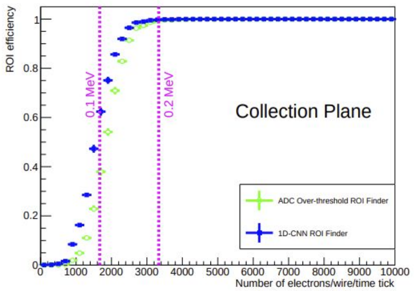


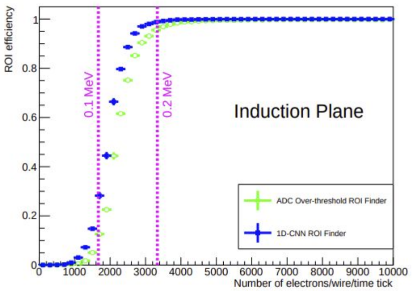
[JINST 16 P01036 (2021)](#)

CNNs helping to also find lower energy signals: potentially addresses challenge of measuring low energy deposits associated to neutrons or providing charge calibration in DUNE



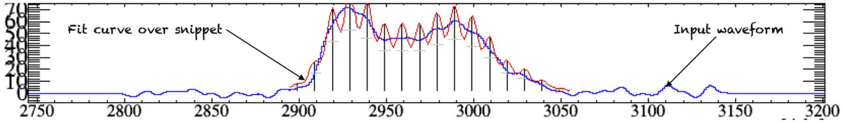






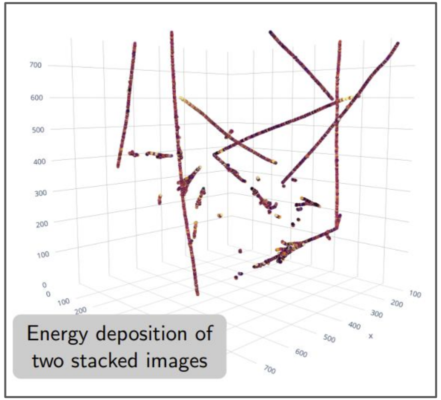
[JINST 17 P01018 (2022)](#)

Low-Level "Hit" Finding



Options: 2D vs. 3D

2D Hit finding: Fit Gaussians to Waveforms in MicroBooNE LArTPC, reduction of event data size from 20 Megapixel image to ~15k hits



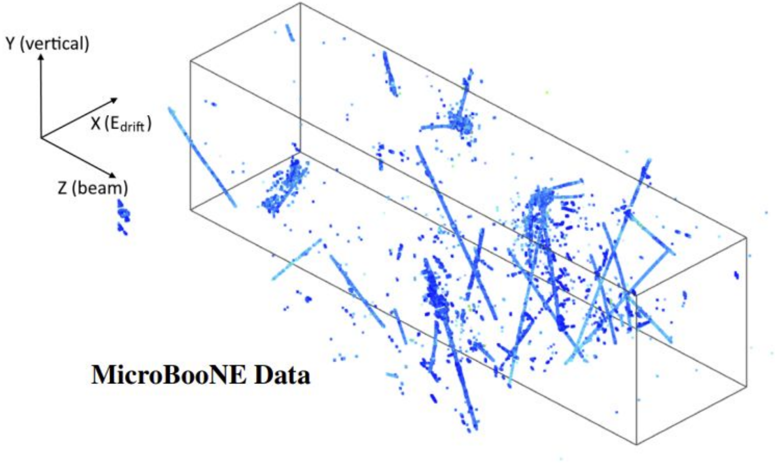
From 2D to 3D: producing 3D hits, or spacepoints, as first-level representation has advantages

- Primarily, clustering particles is easier as due to less overlap/close clusters in 3D
- Can use additional modality – optical information – to reject backgrounds at earlier stage [JINST 16 P06043 (2021)]

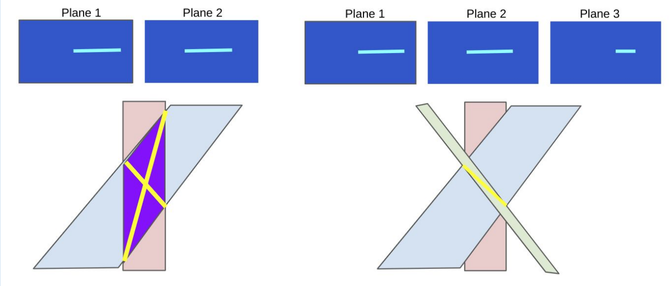
PhysRevD.102.092003

Low-Level "Hit" Finding

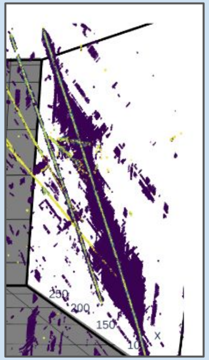
For inferring 3D spacepoints: requires solving an underspecified inverse problem – a prior is needed to make progress. E.g. sparsity [JINST 16 P06043 (2021)]



Example: track parallel to the wire plane → Pixels for track all show up in same row



Highly degenerate combinations for matching pixels across wires to infer Y,Z position: leads to large number of ghost points

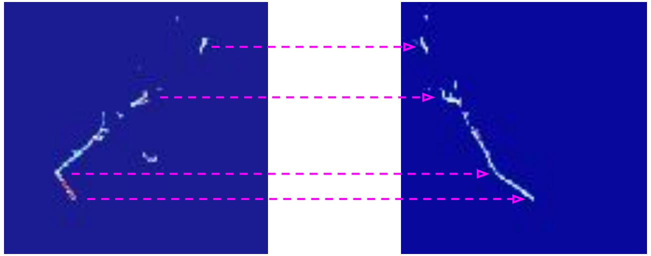


Low-Level "Hit" Finding

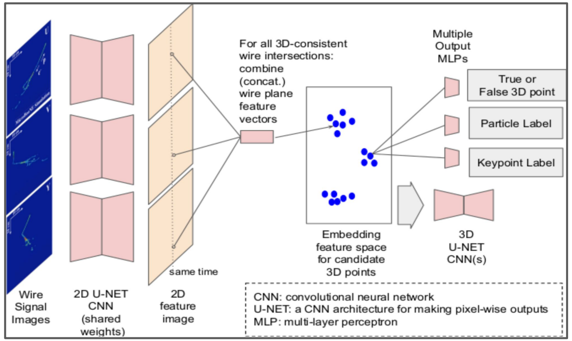
Here DL is a good fit: learn patterns from data to form "prior" to better resolve degeneracies

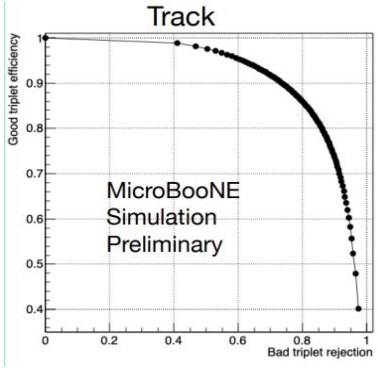
Matching more than charge: learn correlated patterns across planes

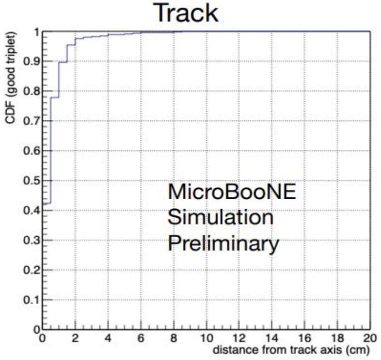
Plane 1 Plane 2

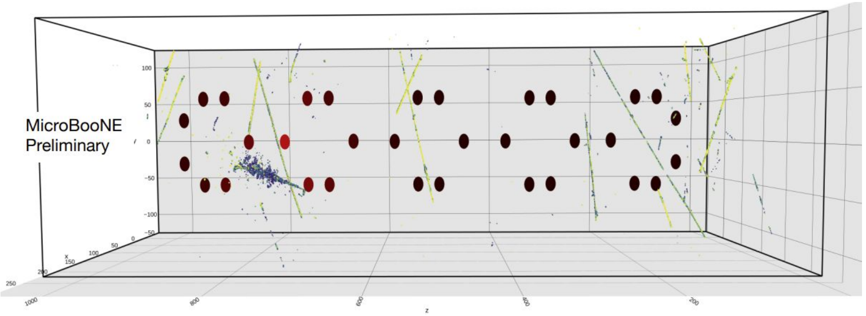


LArMatch Net
CNN represents content around given pixel and uses it to determine ghost/true









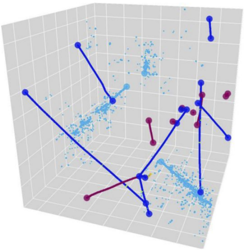
NPML 2020

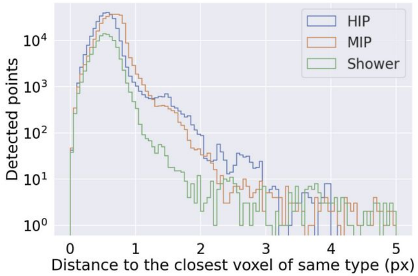
Keypoints

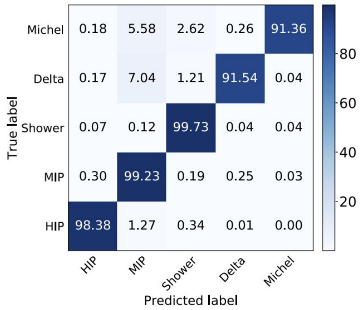
Certain 2D or 3D locations are useful to seed reconstruction

- Track starts and End
- Shower starts
- Location of Michel/Delta rays
- Neutrino Interaction vertex

Point Proposal Network (on 3D voxels): subpixel resolution and high classification accuracy

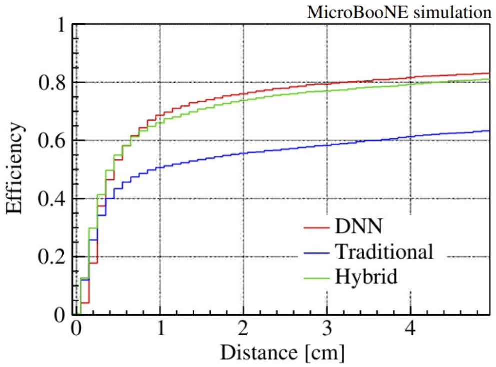






Phys. Rev. D 104, 032004 (2022)

Neutrino Vertex finding in LArTPC



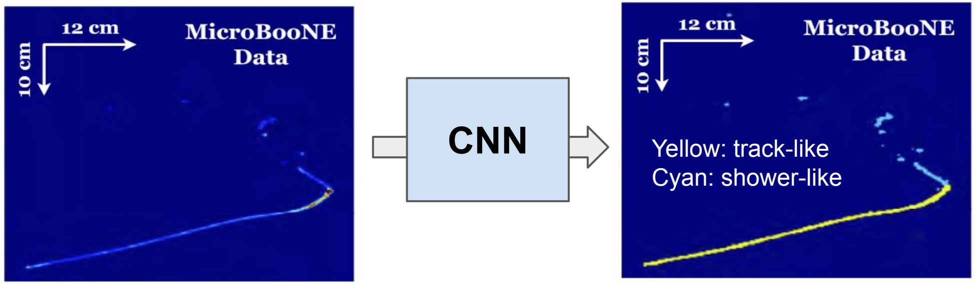
JINST 17 P01037 (2022)

Different IF effort, ***Minerva***, focused on understanding neutrino-nucleus interactions: mproved vertex finding using DNN + adversarial network to reduce bias from out-of-domain events JINST 13 P11020 (2018)

Automated architecture optimization
JINST 17 T08013 (2022)

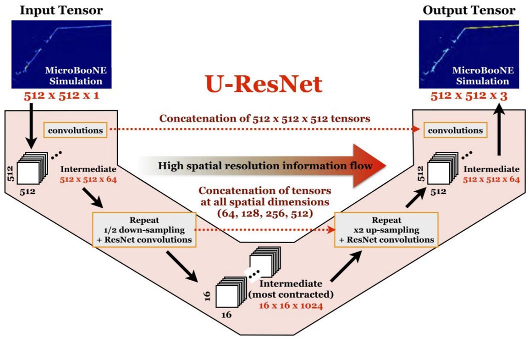
Intermediate Targets: Shower/Track labeling

Goal: separate pixels into track-like (proton,muon,pion) and shower-like (electron, photon)



Clustering/reco algorithms for tracks and showers are different due to much different topologies

NB: Improvements from per-image class-balancing and importance weighting for pixels with neighbors of a different class



Used architecture that can produce per-pixel labels.

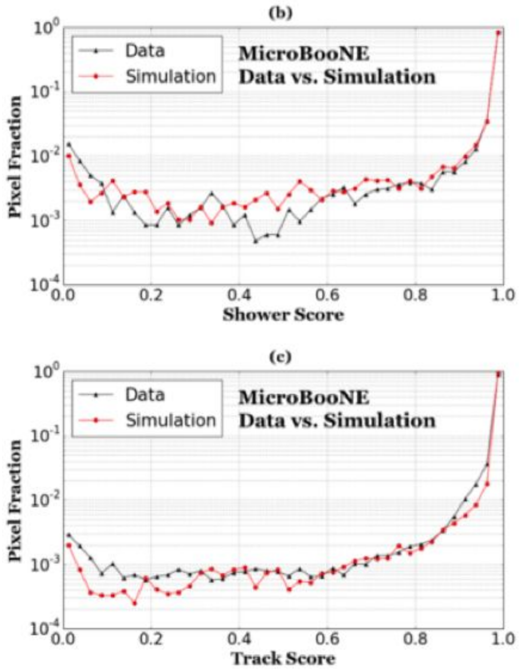
U-(Res)Net builds in paths for features at multiple resolution to flow

[PhysRevD.99.092001]

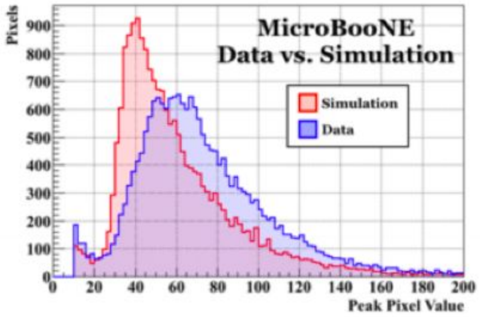
For an approach using Graph Neural Networks see:

[EPJ Web of Conferences (CHEP 2021) 251, 03054 (2021)]

Checking Output on Data



- Sample: stopping muons
- Score distributions similar
- Robust to moderate difference in images as shown by peak pixel distributions



Acquired sample of cosmic particles that come to rest in the detector – both in data and simulation

Mostly muons, many of which decay into electrons

Use to check track and shower labeling

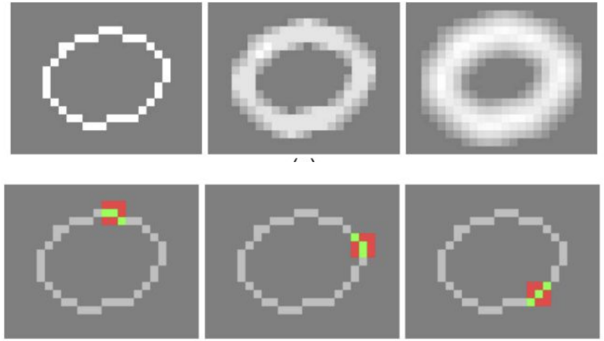
Sparse Submanifold Convolutions

LArTPC (and many other experiments) have sparse data, i.e. a vast majority (90%+) of sensor output is zero or below threshold.

For CNNs - a lot of wasted computation where operations performed on input with all zeros.

Can perform efficient convolutions on sparse representation of images, i.e. a list of above threshold pixels, but this efficiency is lost due to information “bleeding” across image

Sparse ***submanifold*** convolutions (SSC) preserve sparsity – and thus efficiency – by requiring that new information produced only at locations of original input.



Sparsity reduced with regular convolutions

Sparsity conserved with submanifold convolutions

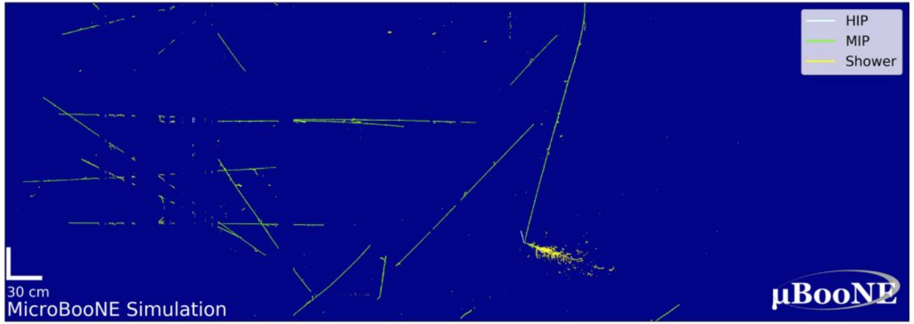
arxiv:1711.10275

Sparse Submanifold Convolution Application

A SSC Network trained as an upgrade for MicroBooNE

- Performance improvement: Showers acc. 95.9%→99.6% and track 97.4% → 99.2%
- Why? Hypotheses: no need to determine dominating background class, information maintains locality, larger input so less information loss due to being on the boundary
- Much more efficient: 10x lower in CPU time (~5 → ~0.5 s), 6x less RAM (~6 → ~1 GB)
- **Deployable**: Fit onto more FermiGrid nodes, can run on entire event image

Output of network on entire wireplane image

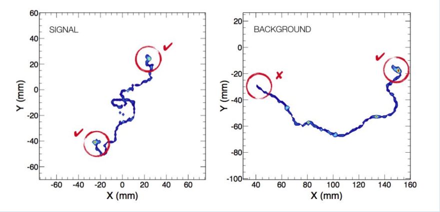


PhysRevD.103.052012

Additional SSC studies for 3D LArTPC data

PhysRevD.102.012005

Different IF effort: SSC Network used on 3D voxel data for finding signal events for $0\nu\beta\beta$ - 10% improved background rejection



PhysRevD.103.052012

Sparse SSNet for LArTPC analysis

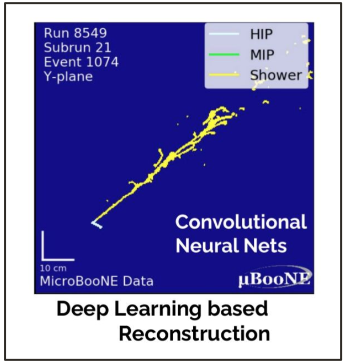
Sparse SSNet key in search for $\nu_e CC$ 1 electron + 1 proton exclusive channel

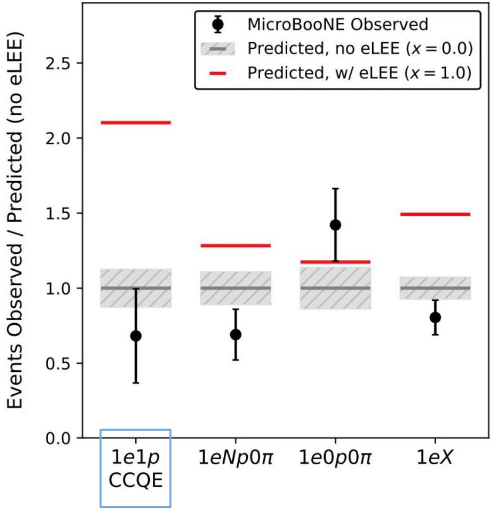
Aim was to search for signs of a low-energy electron neutrino excess – another experiment (MiniBooNE) had seen such an anomaly in the same neutrino beam line [PhysRevD.103.052002]

Shower+track pixels fed into a mixture of DL and traditional algorithms

Algorithms relatively simple: using neighboring shower and track pixel clusters [JINST 16, P02017 (2021)]

Analysis competitive with other reco. algorithms for given LEE signal model





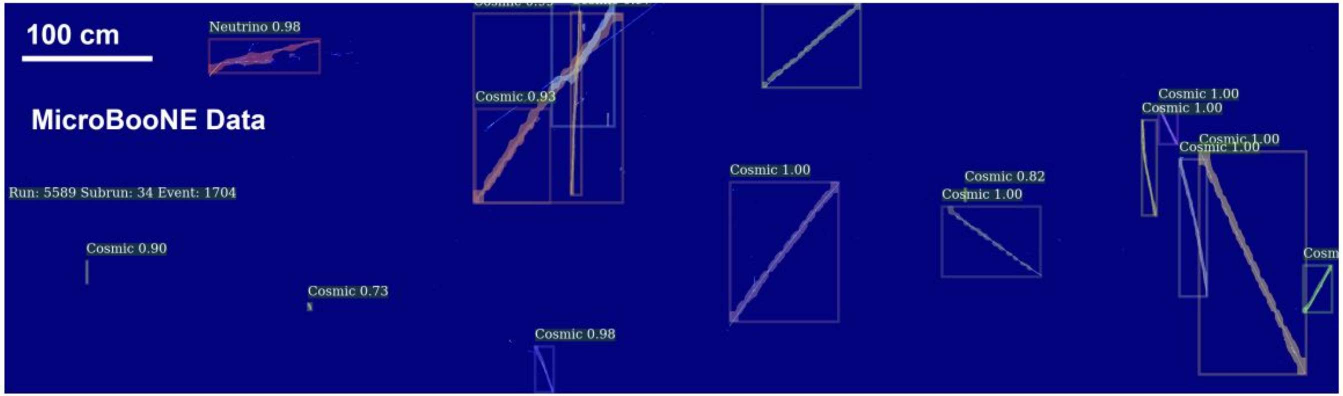
Phys. Rev. Lett. 128, 241801

Phys. Rev. D 105, 112003

Clustering+Classification: Sparse Mask-RCNN

A key task is clustering hits (2D or 3D) into individual particles or into meaningful groups of particles

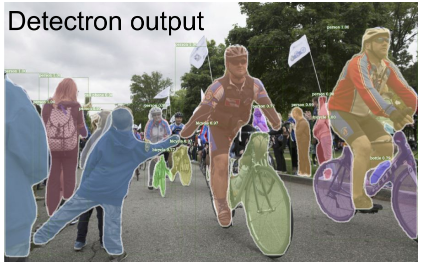
For detectors near the surface, neutrino interactions are a very small fraction of the cosmic background that passes through the detector



2022 JINST 17 P09015

Sparse Mask-RCNN outputs bounding box, mask, and class score

A modified version of the *Detectron* network trained to locate cosmic clusters and neutrino interactions.

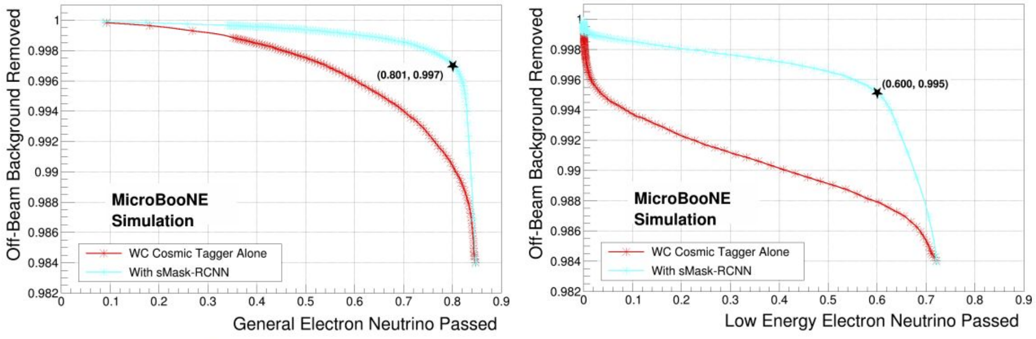


Changed several components of this network to use ***sparse submanifold convolutions***

Sparse Mask-RCNN for addressing backgrounds

Output from network can be used in minimal selection scheme to augment baseline cosmic taggers

Note that baseline tagger already good, but incorporates timing information from optical sensors to use (non-)coincidence between clusters and the beam



(a) General electron neutrino sample

(b) Low energy electron neutrino sample

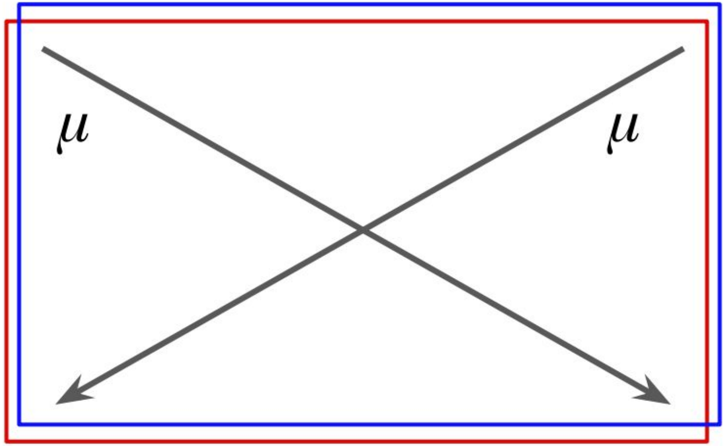
Reasons to believe Mask-RCNN and similar object detection methods will have trouble with particles within interactions

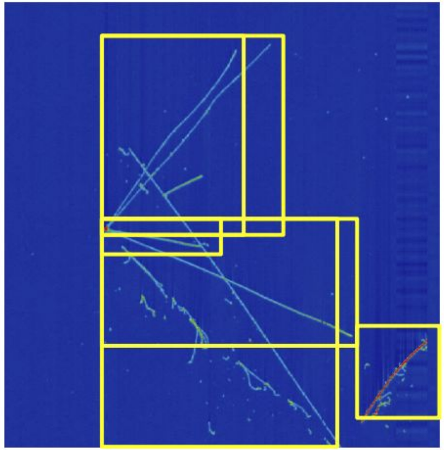
2022 JINST 17 P09015

Object Detection Methods for Individual Particles

Issues derive from mismatch between bounding box and trajectories

- Two distinct objects can have essentially the same bounding box
- Objects often overlap
- These type of top-down detection methods often have trouble with small objects
- Potentially solvable with rotatable boxes …





Instance+Semantic Segmentation

- Three component loss: pull together points that belong to the same cluster, keep distance between clusters, and regularization

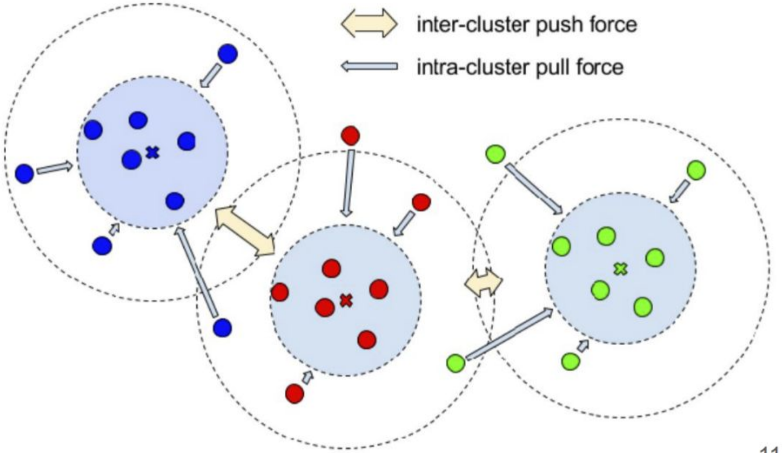
$$L = \alpha L_{var} + \beta L_{dist} + \gamma L_{reg},$$

$$L_{var} = \frac{1}{C}\sum_{c=1}^{C}\frac{1}{N_c}\sum_{i=1}^{N_c}[\max(0, \|\mu_c - x_i\| - \delta_v)]^2$$

$$L_{dist} = \frac{1}{C(C-1)}\sum_{\substack{c_A, c_B = 1 \\ c_A \neq c_B}}^{C}[\max(0, 2\delta_d - \|\mu_{c_A} - \mu_{c_B}\|)]^2$$

$$L_{reg} = \frac{1}{C}\sum_{c=1}^{C}\|\mu_c\|$$

Equation credit: Dae Hyun K. @ Stanford



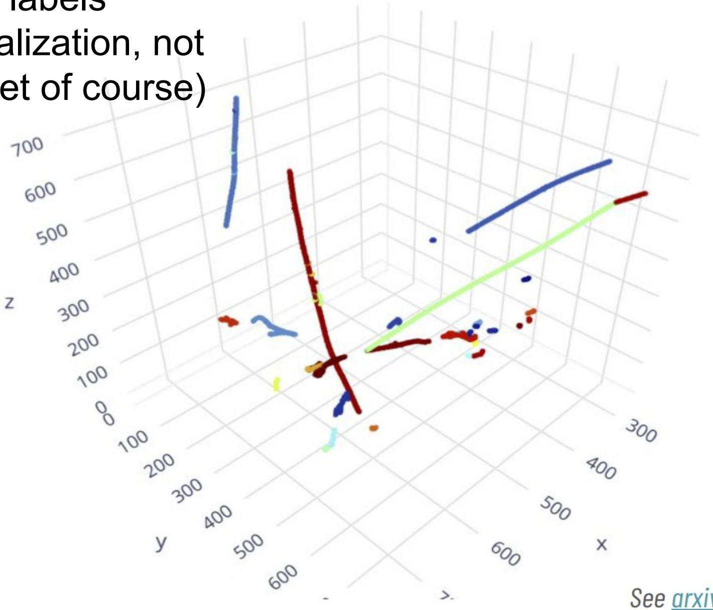
117

Image credit: arXiv 1708.02551

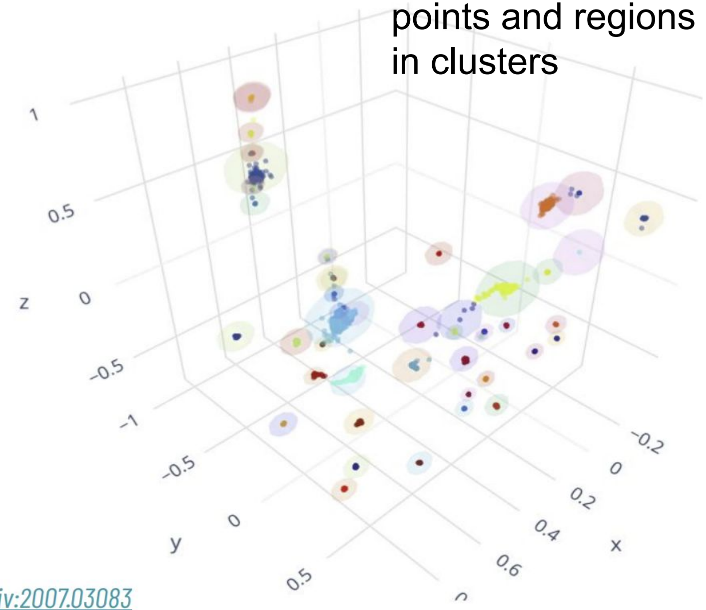
SPICE Output

Network learns to push spacepoints from same particle into ball and provides a centroid and radius to cluster the ball

Input w/ truth labels
(only for visualization, not provided to net of course)



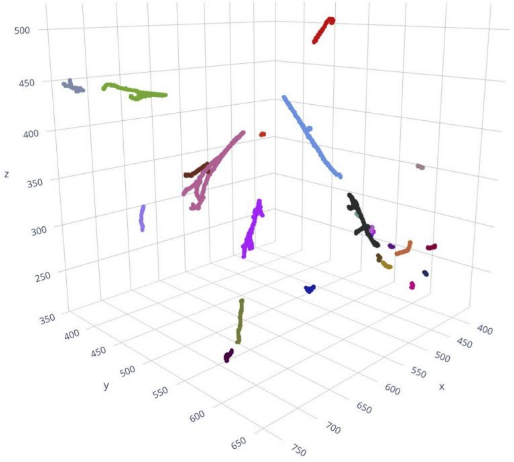
Output of Net: re-embedded points and regions to include in clusters



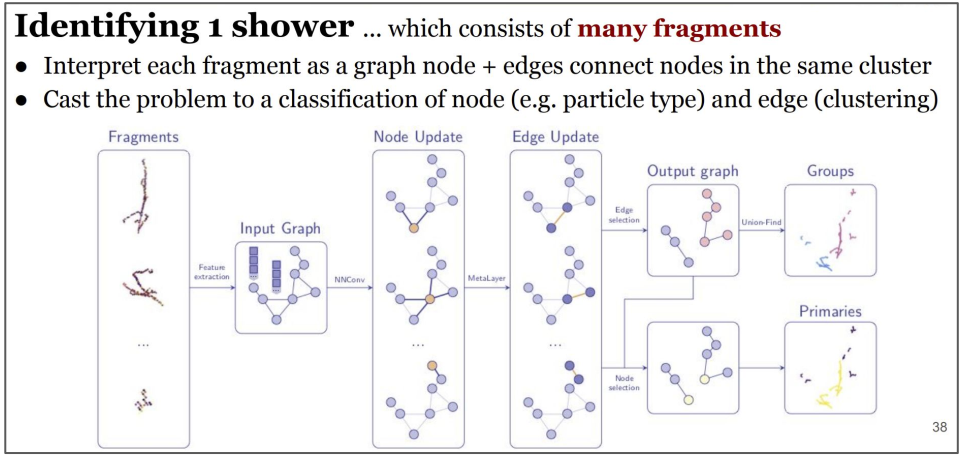
See arxiv:2007.03083

Shower Clustering

One challenge to shower clustering is that at the lower (<~1 GeV neutrino energies) of DUNE or for experiments like MicroBooNE showers are actually disconnected



One strategy is to use SPICE to find contiguous shower sub-clusters and then piece together entire shower



Slide credit: K. Terao

Interaction Clustering

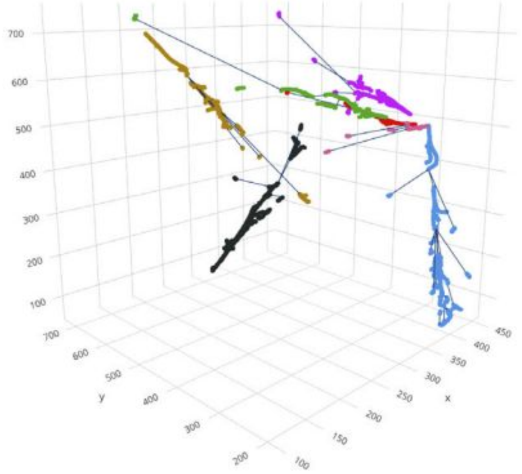
See F. Drielsma's talk on Graph Neural Networks Applications I (IF) for more!

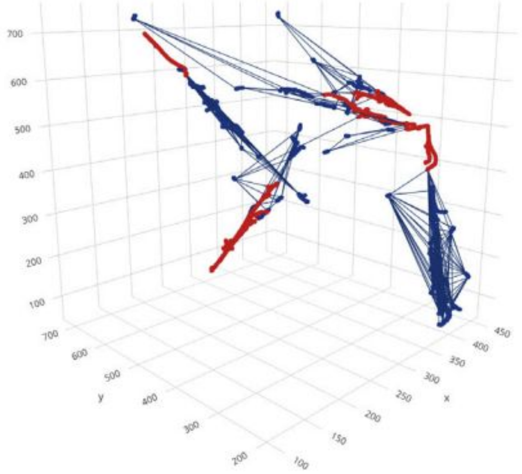
Truth

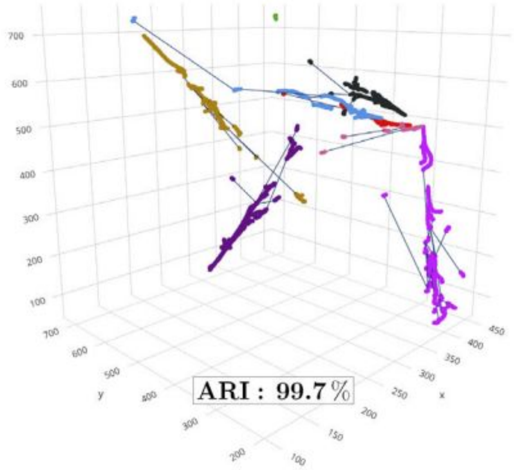
Edges with score > 0.5

Output of net is also primary label for subfragments representing the start of the shower

Predicted clusters

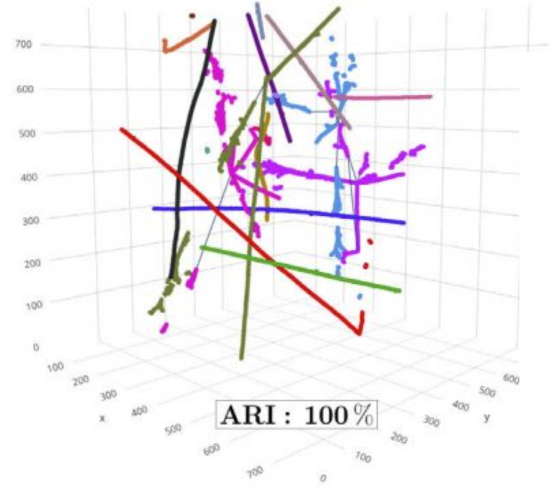




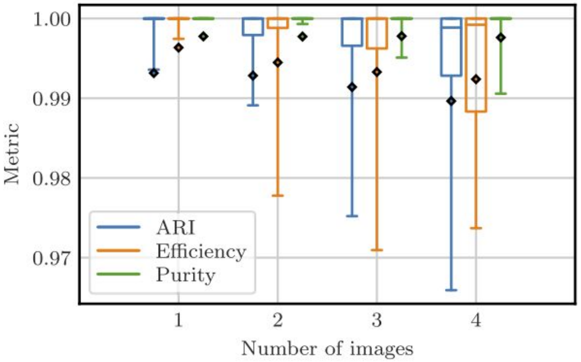


Interaction Clustering

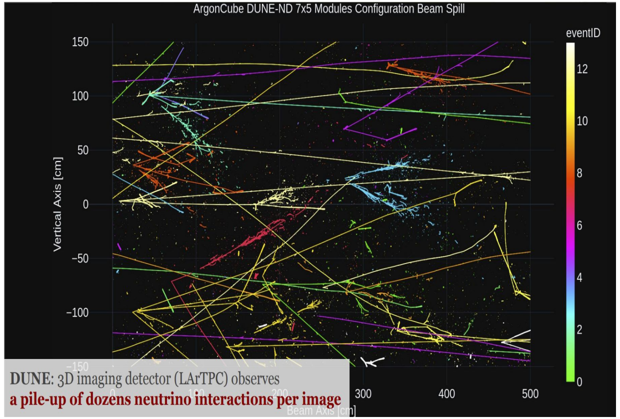
Can extend this to clustering interactions



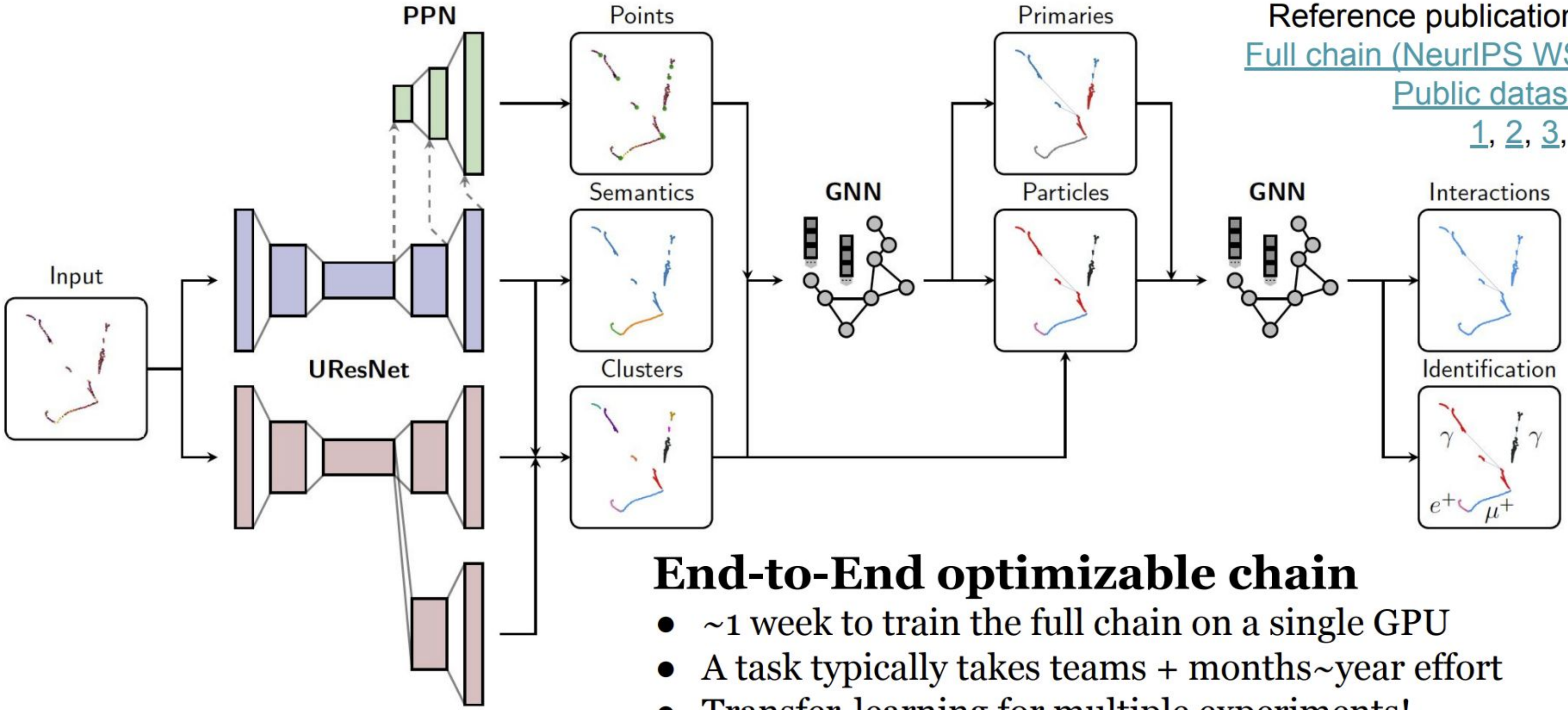
Performance remains high, even with higher multiplicities of interactions



Addresses a big challenge in DUNE: high multiplicity of neutrino interactions in the near detector!



End-to-End 3D Voxel-based DL Chain



Reference publications
[Full chain (NeurIPS WS)]
[Public dataset]
1, 2, 3, 4

End-to-End optimizable chain

- ~1 week to train the full chain on a single GPU
- A task typically takes teams + months~year effort
- Transfer-learning for multiple experiments!

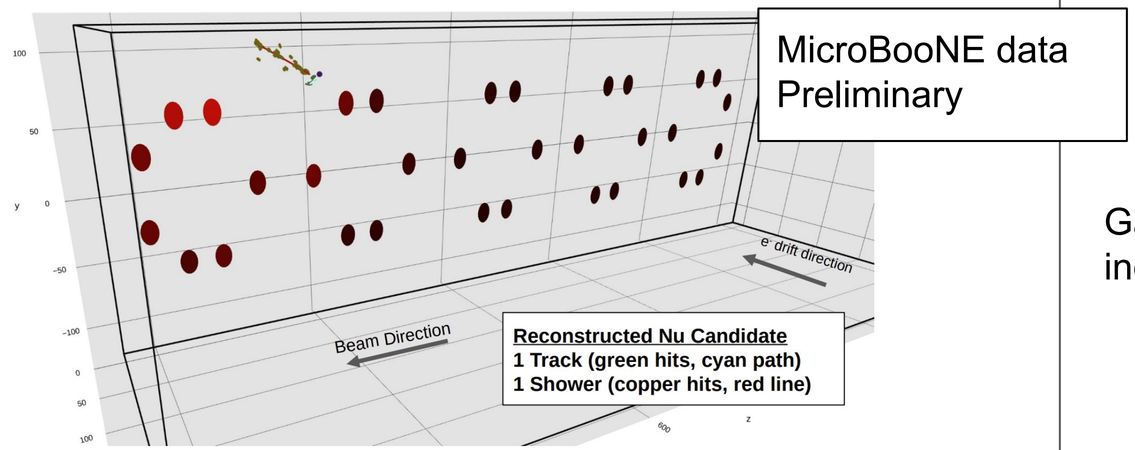
2D Particle Classification

Going back to raw 2D images – potentially still useful in conjunction with reconstruction in 3D

Here shower object missing trunk because of detector issues:
In two planes beginning of shower obscured for different reasons

Example LArMatch Event:
Run 5339 Subrun 115 Event 5764

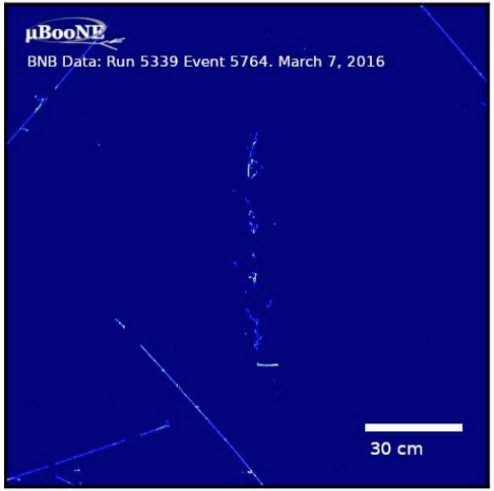
Shower trunk obscured in both U and V plane → leads to missing shower trunk in 3d hits, but seen by 2D CNN in Y plane



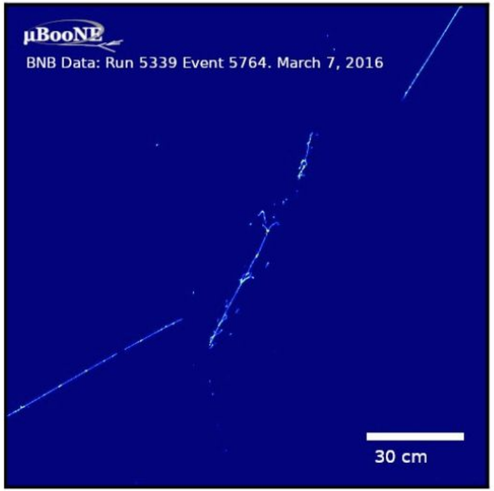
Gap between vertex and shower usually indicates the shower is a photon

2D Particle Classification

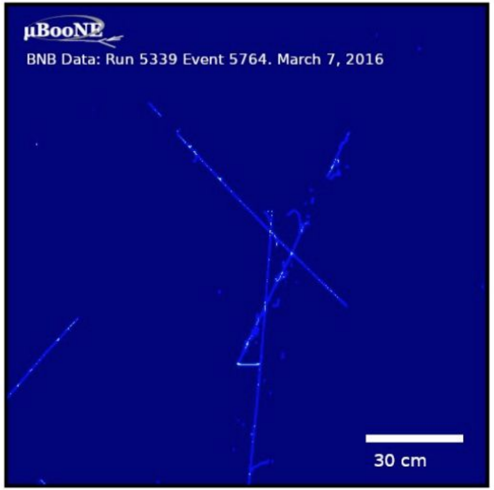
U-plane missing because of effect involving long ionization clouds moving past induction wire



V-plane obscured due to unresponsive wires



Y-plane clearly shows ionization between shower and vertex
→ suggests shower is from electron



2D Particle Classification

Provide "Prong CNN" both a masked "prong image" containing only those pixels consistent with 3D cluster

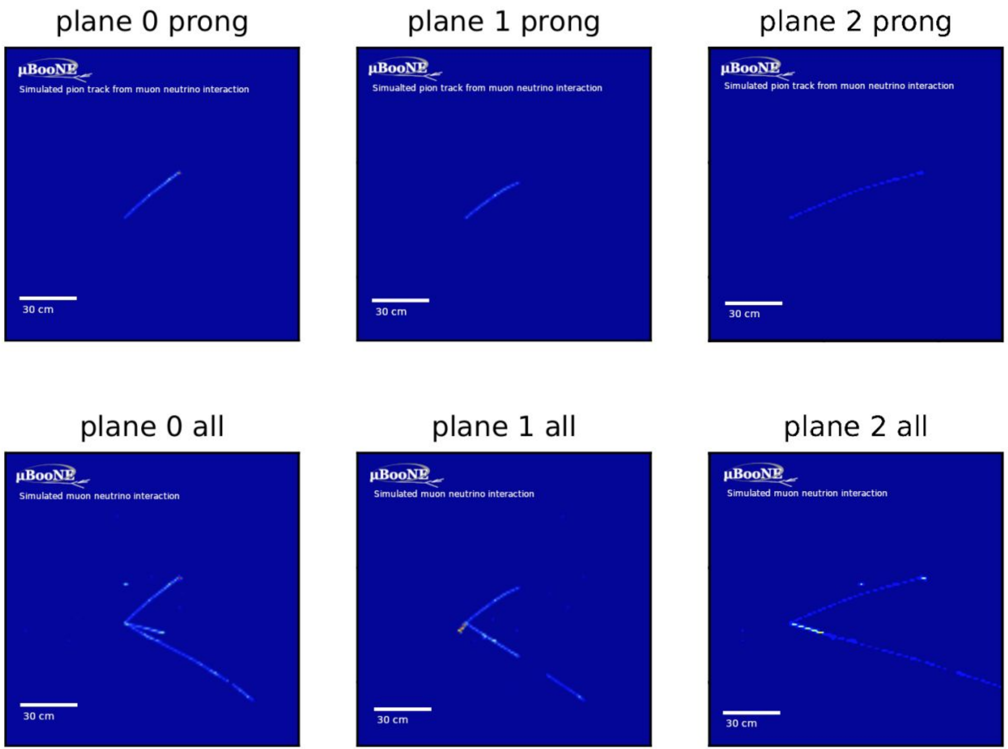
AND

"Context" image with crop around interaction

(cosmic tagged clusters are masked in both)

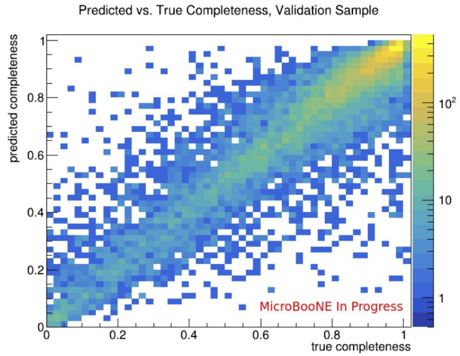
Allow network to recognize and estimate upstream clustering errors

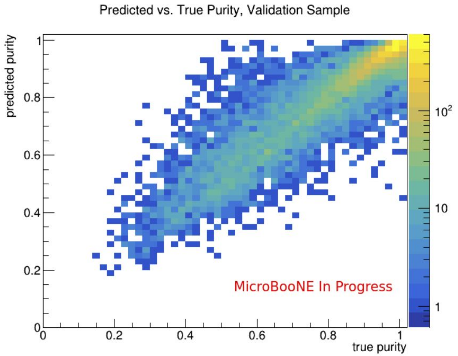
*Nova does something similar



2D Particle Classification

Performance Metrics





Validation Sample Accuracy Statistics

	True electrons	True photons	True muons	True pions	True protons
Fraction classified as electrons	**83.5%**	4.8%	0.1%	0.4%	0.1%
Fraction classified as photons	13.3%	**94.7%**	0.1%	0.2%	0.2%
Fraction classified as muons	0.4%	0%	**93.6%**	12.1%	0.2%
Fraction classified as pions	2.7%	0.4%	6.1%	**85.9%**	1.4%
Fraction classified as protons	0.2%	0.2%	0.2%	1.5%	**98.2%**

*Output of network used in next-generation MicroBooNE analysis - that combines larmatch outputs + 3D clustering: early results suggest its competitive with current state-of-art analysis for nue-inclusive selection

2D Particle Classification

Doing image manipulations to study use of context

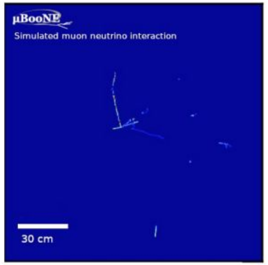
plane 1 prong

Prong under consideration seems attached to vertex, but gap potentially obscured

However, there is a second shower in the context image

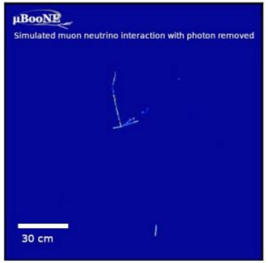
plane 1 prong

plane 1 all



Remove second photon, prong photon score drops

plane 1 all



Using such physics is good - but must be careful with understanding biases coming from neutrino interaction generator

Currently exploring

electron score = -3.63, $\boxed{\text{photon score = -0.03}}$

electron score = -1.53, $\boxed{\text{photon score = -0.25}}$

Challenges

Lot's of progress over less than a decade or so

… still lot's of areas to tackle for which lot's of ongoing effort

Simulation/Modeling: can we translate physics to observables faster? Can we better use data-driven methods?

Inference: are we testing our models against data as best as we can while accounting properly for and mitigating our model uncertainties?

Operations: are we saving the right events? Is the experiment running optimally? Can we detect and make decisions faster?

Fast ML on FPGAs to implement special rare process triggers

frai.2022.855184

Challenges

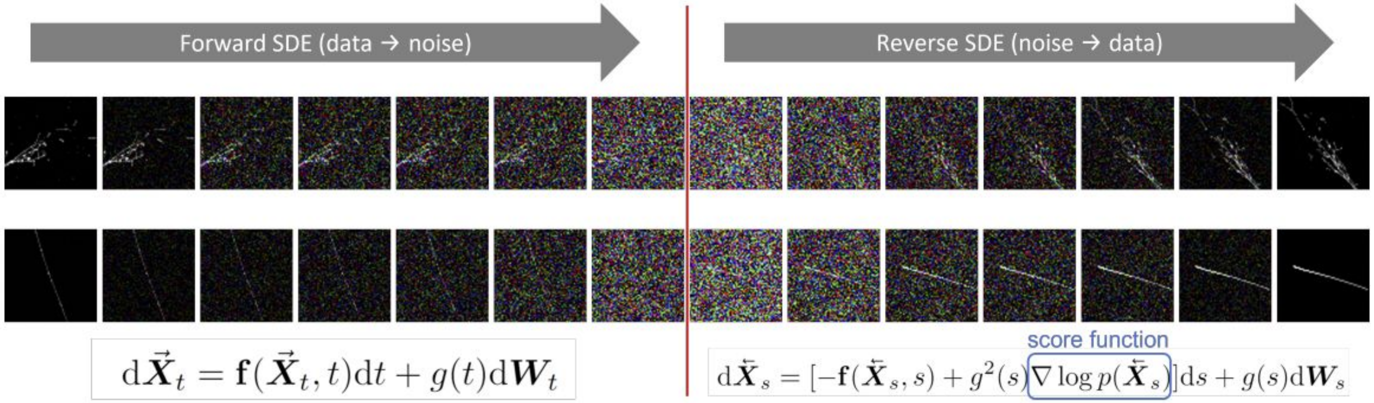
Simulation/Modeling: can we translate physics to observables faster? Can we better use data-driven methods?

Like in other frontiers, generating simulated data is a bottleneck of analyses

- Individual events can take upwards of ~5 mins/event+ for MicroBooNE TPC with simulated cosmics + neutrino interaction
- Data driven methods are used to get better estimate: in MicroBooNE and SBN experiments which are on surface, cosmic background data is collected and used in simulated data by adding neutrino interaction – but cannot save enough of these events due to processing and storage constraints

Simulations - Generative Models

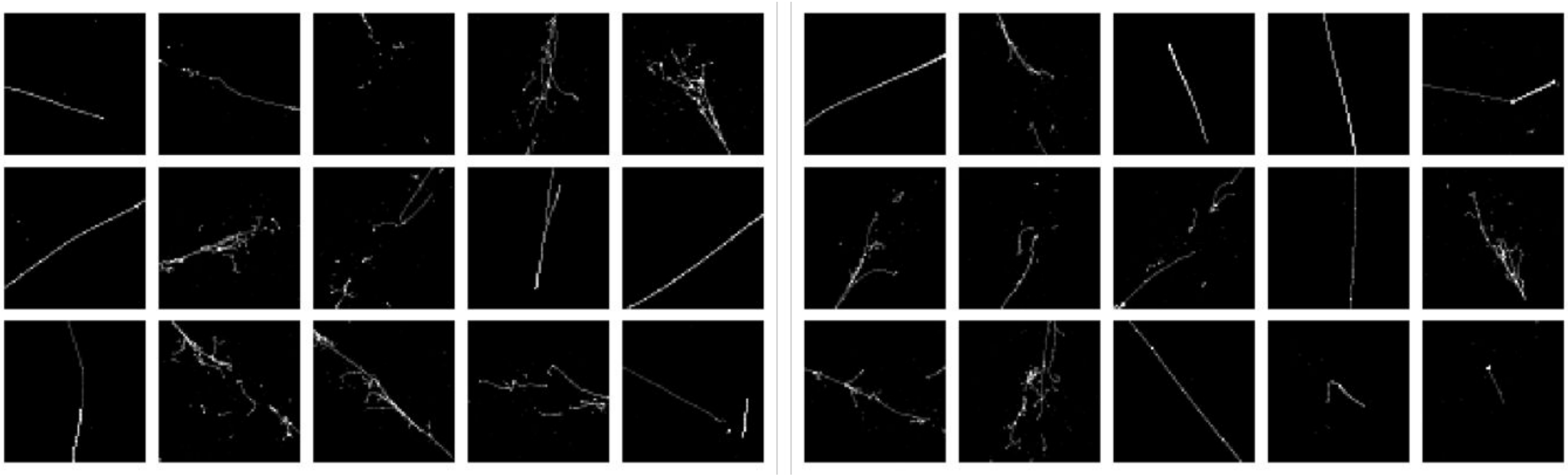
Score-based Generative Modeling shows promise for generating LArTPC-like images



Model generation as the reverse of a diffusion process bringing data images to noise

Simulations - Generative Models

Which set, left or right, is training images – which are generated?



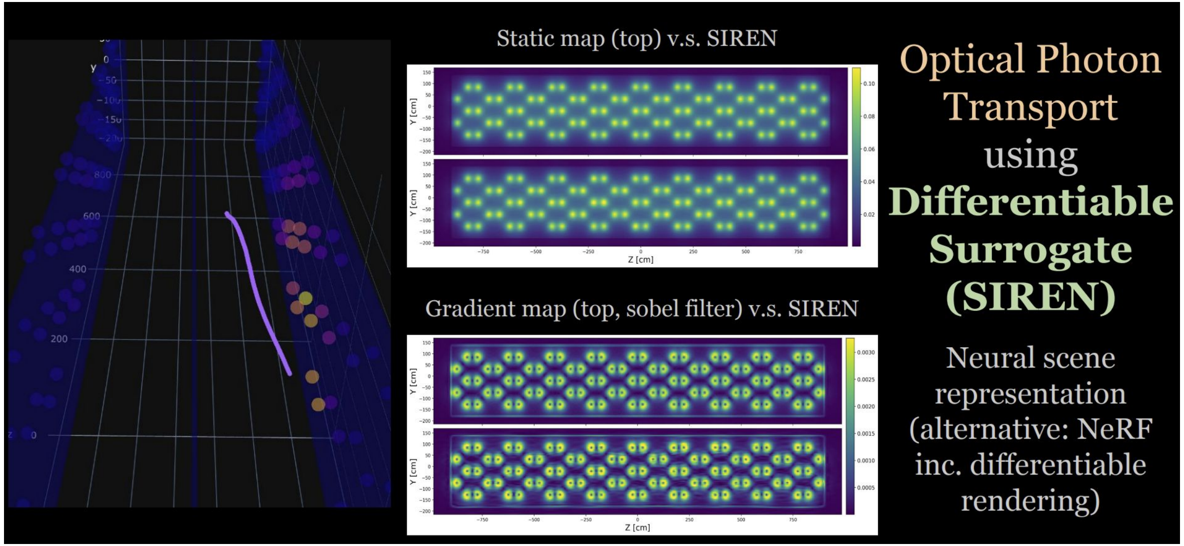
More details in next Wed. talk: “Generative Model Applications 3”

Simulations - Data Driven/Differentiable

Differentiable (surrogate) simulations save time by allowing a way to possible reweight MC events rather than generating additional samples with variation in detector physics parameters

Also enables simulation-based inference for a number of exciting applictions

https://arxiv.org/abs/2211.01505



One more Challenge

Accelerating Development: Are we providing enough tools to the community to enable new ideas and new contributors?

LArTPC Neutrino Interaction (Simulation) Dataset

MicroBooNE has released some LArTPC simulations: cosmic data overlaid with simulated neutrino interaction

Access point

- Entry point is the MicroBooNE website:
  - https://microboone.fnal.gov/documents-publications/public-datasets/

About MicroBooNE

- MicroBooNE Code of Conduct
- Physics
- Detector
- Collaboration
- R&D Program
- Documents and Publications
- Images and videos
- In the News
- Contact

For Collaborators (password required)

µBooNE

Search this site... Search

Related Experiments

- Short Baseline Neutrino Program
- LArIAT – Test Beam
- DUNE – Long Baseline
- ArgoNeuT
- More Fermilab Neutrino Experiments

Public Datasets

Two MicroBooNE datasets are opened to the public. They contain simulated neutrino interactions, overlaid on top of cosmic ray data. Both simulate neutrinos in the Booster Neutrino Beam (BNB). The first sample includes all types of neutrinos and interactions (taking place in the whole cryostat volume), with relative abundance matching our nominal flux and cross section models. The second sample is restricted to charged-current electron neutrino interactions within the argon active volume of the time projection chamber.

Samples are provided in two different formats: HDF5, targeting the broadest audience, and artroot, targeting users that are familiar with the software infrastructure of Fermilab neutrino experiments and more in general of HEP experiments. The HDF5 files and a file with the list of xrootd urls providing access to the artoot files are stored on the open data portal Zenodo, and can be accessed from the DOI links in the table below. Artroot files contain the full information available to members of the collaboration, while HDF5 files have a reduced and simplified content. Each HDF5 sample is provided in two versions: with and without wire information. The reason is that, when present, the wire information largely dominated the file size. A second set of datasets is therefore created without the wire information, thus allowing storage of a significantly larger number of *events* for applications that do not use the wire information (where events are defined as independent detector read outs).

Description

Sample	DOI	N events	N HDF5 files	HDF5 size	N artroot files	artroot size
Inclusive, NoWire	10.5281/zenodo.7261798	141,260	20	34 GB	3400	787 GB
Inclusive, WithWire	10.5281/zenodo.7262009	24,332	18	44 GB	720	136 GB
Electron neutrino, NoWire	10.5281/zenodo.7261921	89,339	20	31 GB	2151	761 GB
Electron neutrino, WithWire	10.5281/zenodo.7262140	19,940	20	39 GB	540	170 GB

Links to Zenodo

Detailed documentation for accessing the datasets is provided at https://github.com/uboone/OpenSamples.

Link to documentation

Samples are released under CC-by license, allowing users to freely reuse the data with the requirement of giving appropriate credit to the collaboration for providing the datasets.

Suggested text for acknowledgment is the following:
We acknowledge the MicroBooNE Collaboration for making publicly available the data sets [data set DOIs] employed in this work. These data sets consist of simulated neutrino interactions from the Booster Neutrino Beamline overlaid on top of cosmic data collected with the MicroBooNE detector [2017 JINST 12 P02017].

In addition, although not enforced by the license, we request that software products resulting from the usage of the datasets are also made publicly available.

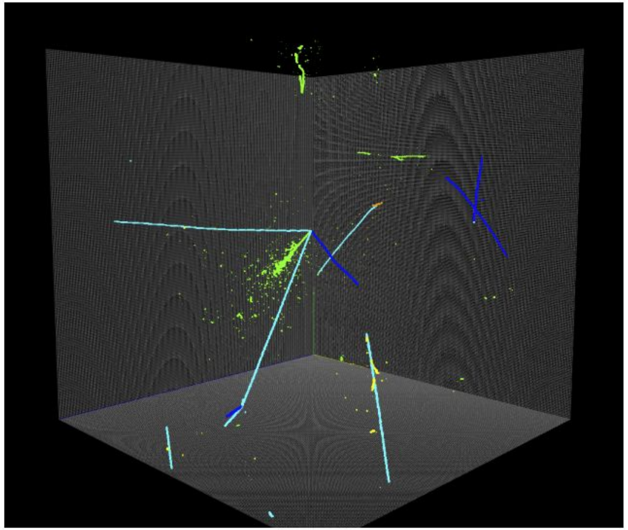
Info about license and citation

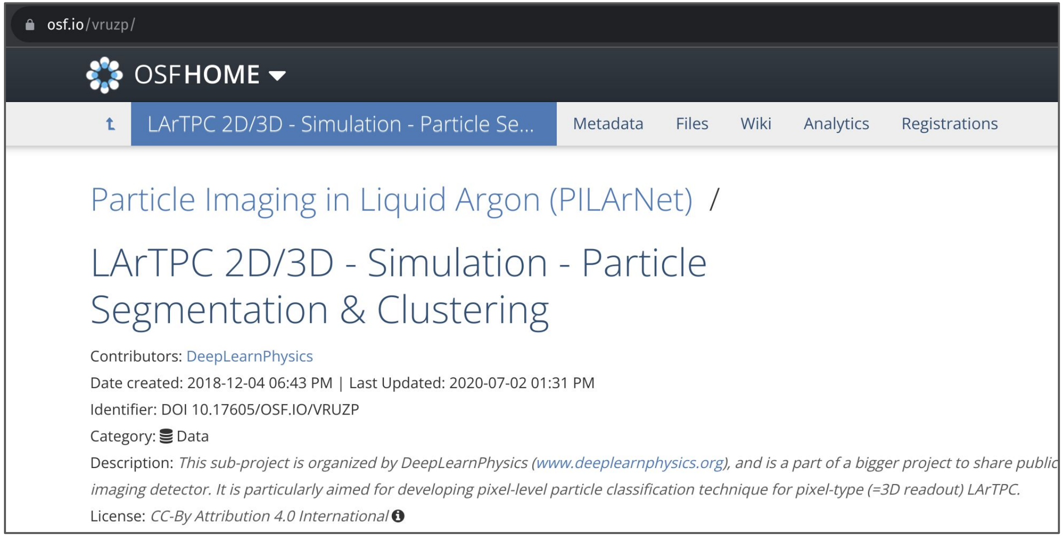
Fermilab

10 2023/05/09 G. Cerati (FNAL)

LArTPC Neutrino Interaction (Simulation) Dataset

Another public dataset of 3D voxels along with simple 2D projections





https://arxiv.org/abs/2006.01993

https://osf.io/vruzp

Conclusions

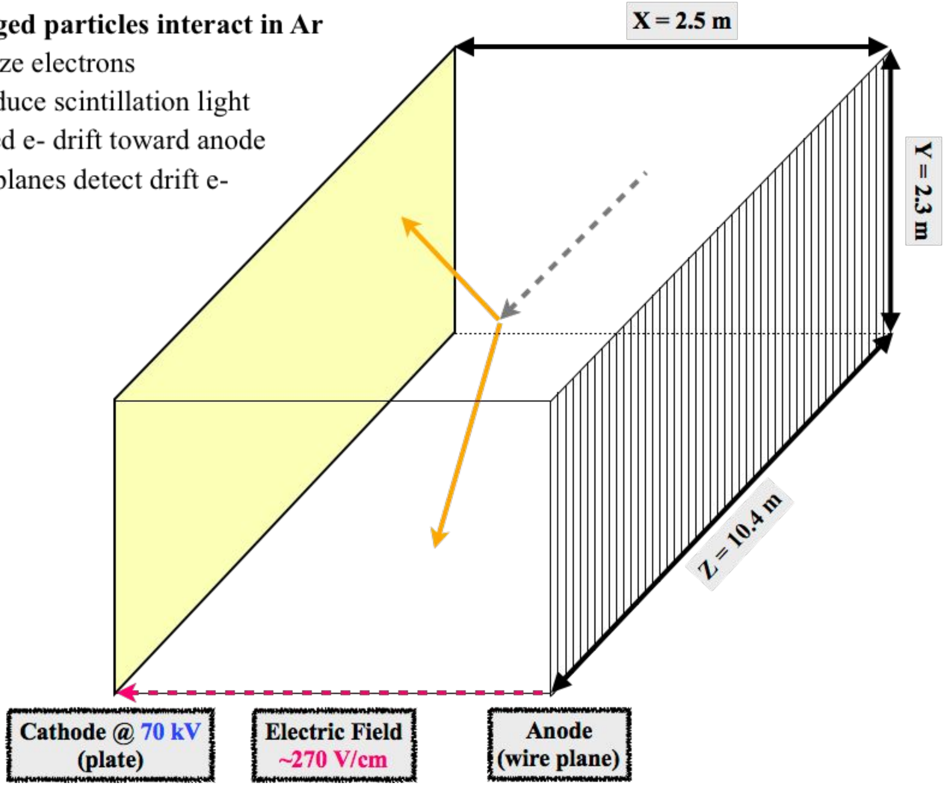
- ML techniques have already impacted the physics program of several neutrino experiments
- Many develops across experiments should provide further impact
- Developments have been somewhat focused on reconstruction
- But there are still other research challenges that ML might help to advance
- Cross pollination between experiments and frontiers will surely accelerate progress

Backups

LArTPC Primer

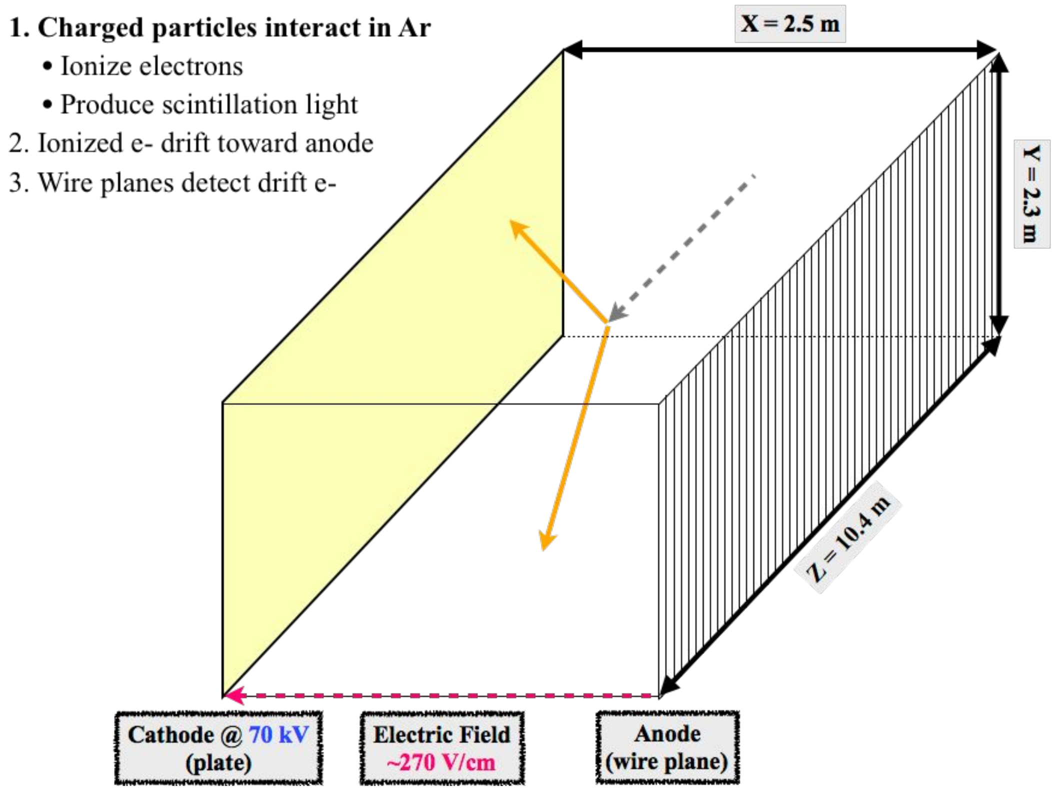
Capturing Neutrino Interaction Images w/ LArTPCs

1. Charged particles interact in Ar
    - Ionize electrons
    - Produce scintillation light
2. Ionized e- drift toward anode
3. Wire planes detect drift e-



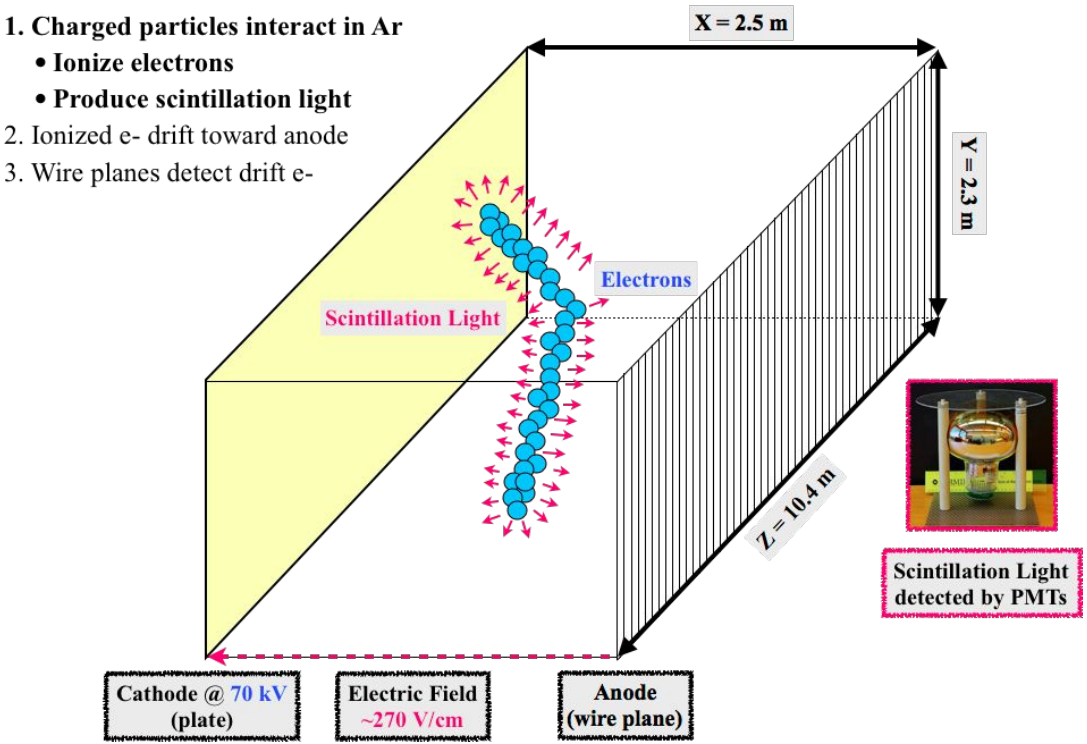
MicroBooNE TPC

Capturing Neutrino Interaction Images w/ LArTPCs

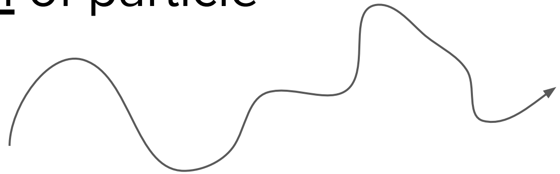


A neutrino (dashed grey) passes into the detector and interacts producing charged particles (solid yellow)

Capturing Neutrino Interaction Images w/ LArTPCs

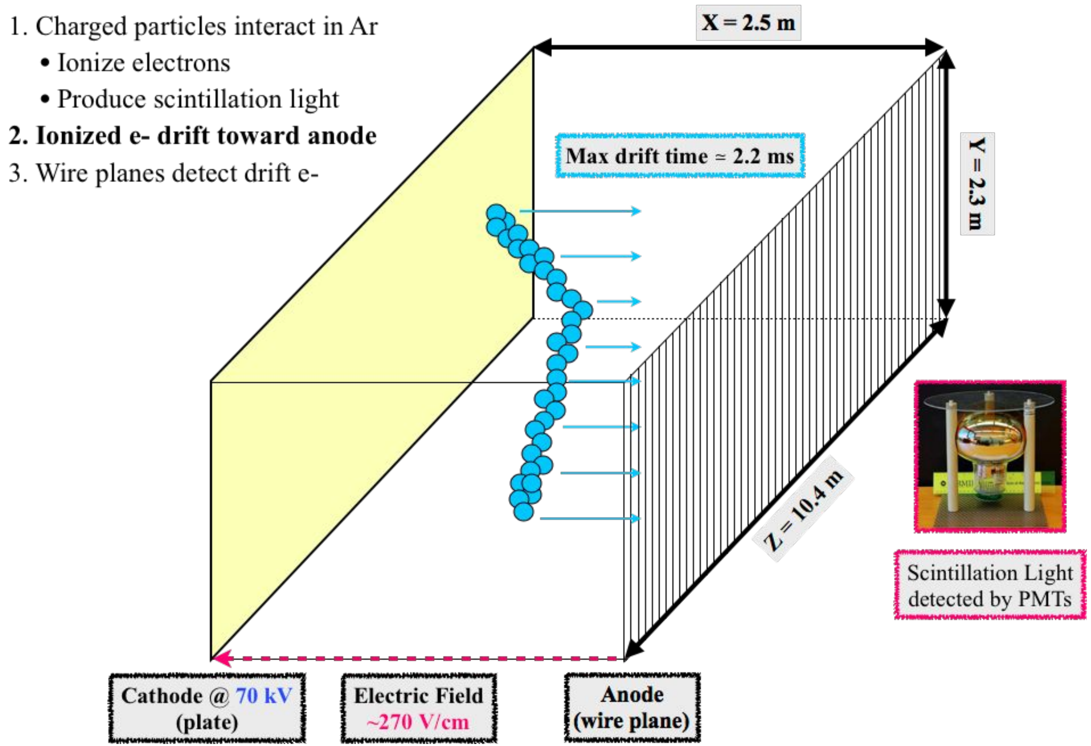


Charged particles produce ionization electrons: tell us path of particle



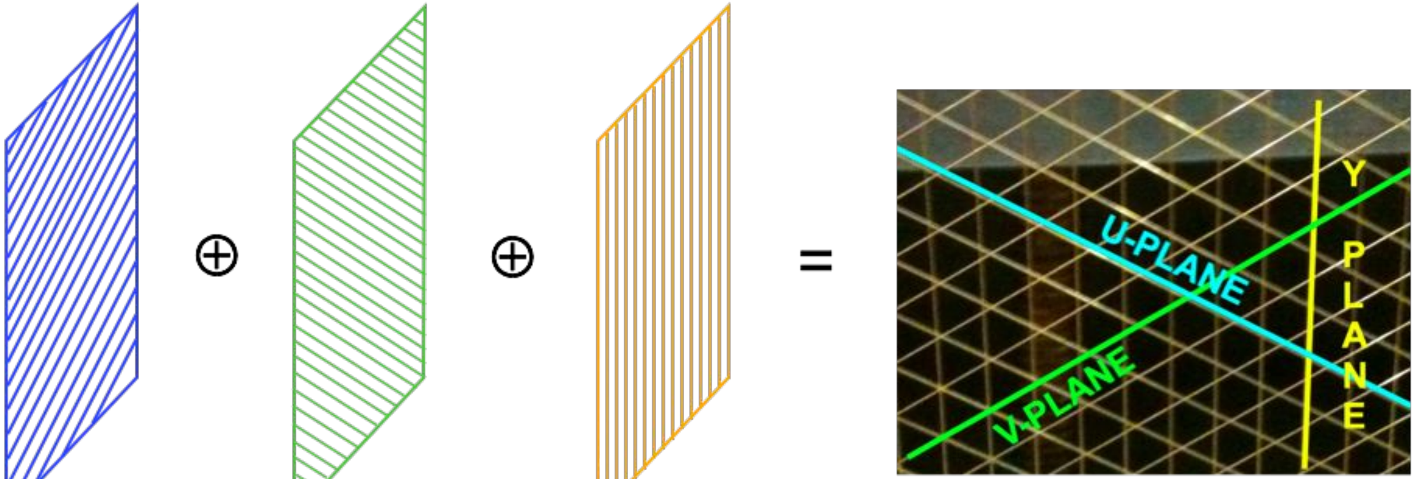
Also produces *light*: tells us time of the event

Capturing Neutrino Interaction Images w/ LArTPCs



Ionization electrons drift towards wireplanes

Capturing Neutrino Interaction Images w/ LArTPCs



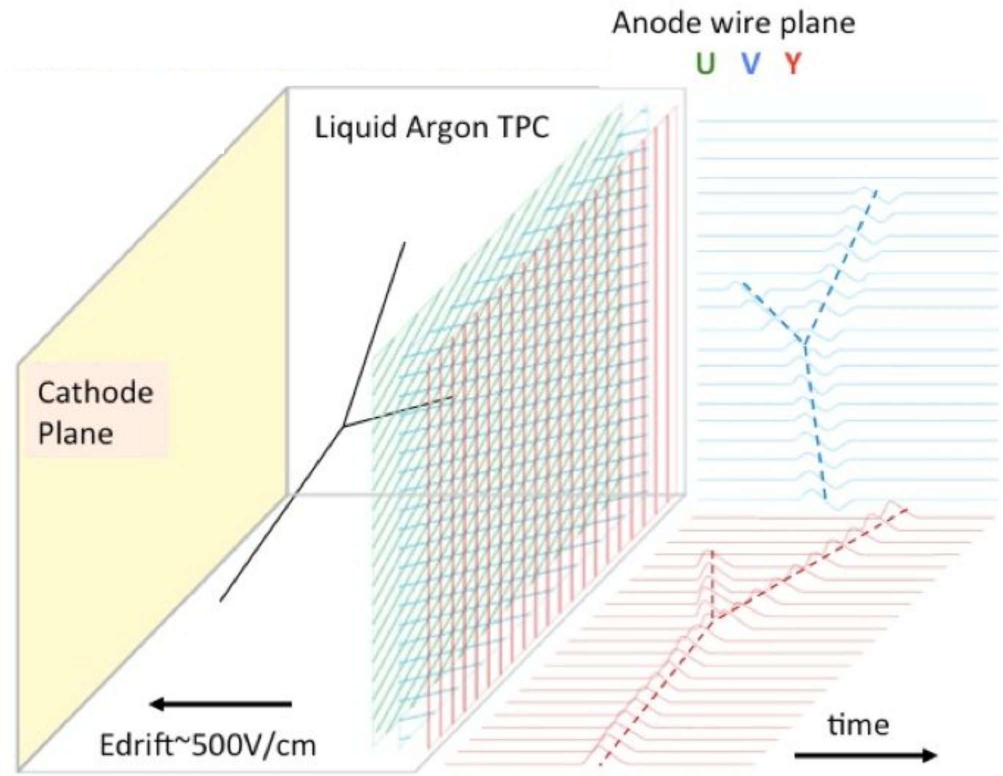
U plane (induction)

V plane (induction)

Y plane (collection)

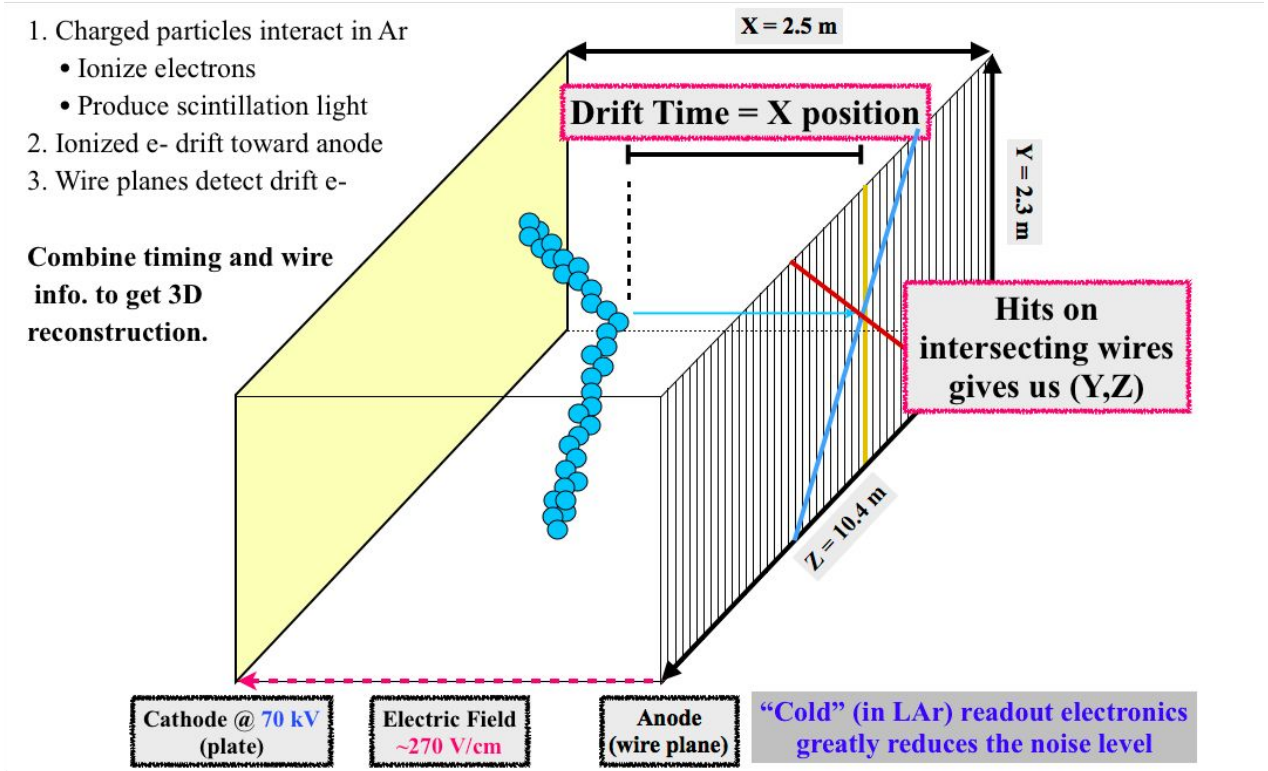
8256 wires w/ pitch = 3mm
(Y, Z) = coincidence on wire

Capturing Neutrino Interaction Images w/ LArTPCs



Recording wire signals over time, detector produces image-like data

Capturing Neutrino Interaction Images w/ LArTPCs



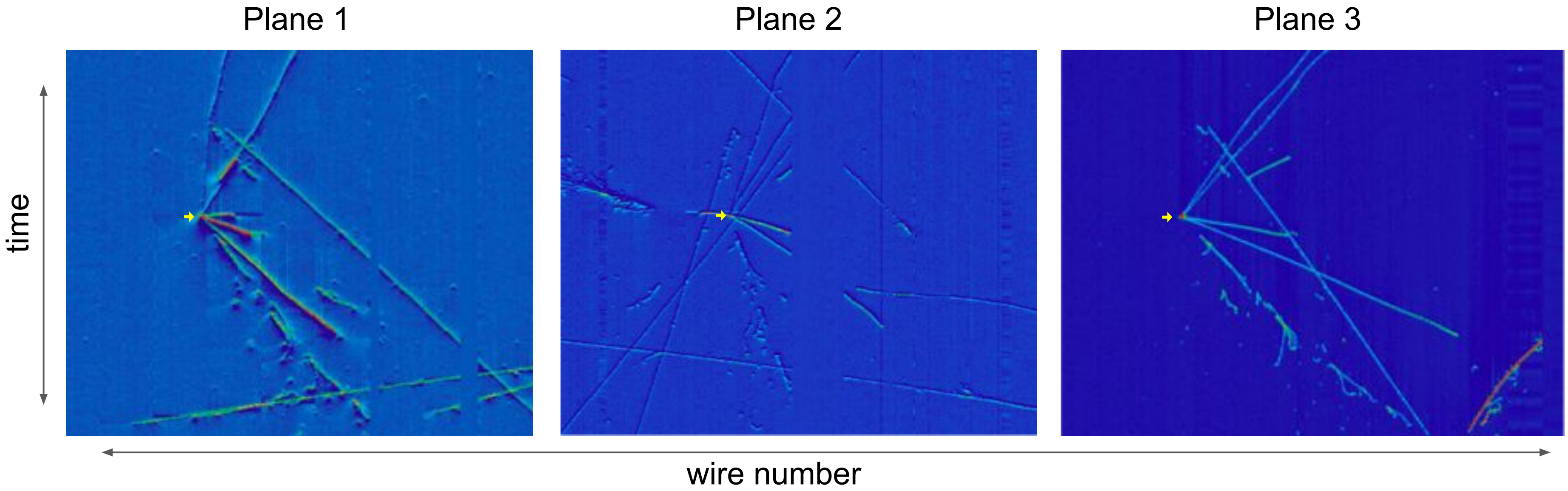
Capture 3 projection images with wire planes

Can solver inverse problem to recover 3D energy deposits

Ionization signals on wires coincident in time provide info for (Y,Z) position

X position given by time delay from light signal

Capturing Neutrino Interaction Images w/ LArTPCs



Example of data event in MicroBooNE. View of same event for each projection.

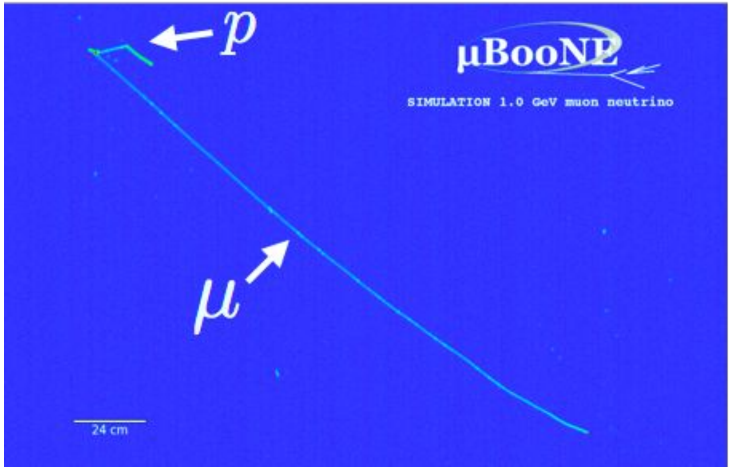
Color scale indicates amount of ionization electrons seen on wire at given time

Capturing Neutrino Interaction Images w/ LArTPCs

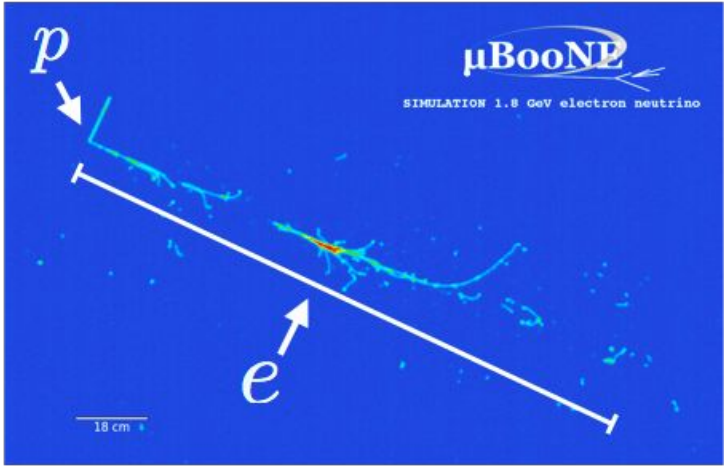
Flavor determined from finding partner lepton (muon,electron) produced in interaction

Neutrino energy inferred from momenta of resulting particles

$$\nu_\mu + n \rightarrow \mu + p$$



$$\nu_e + n \rightarrow e + p$$



Neutrino Oscillation Analysis

Δm^2
θ

+

ν Flux model

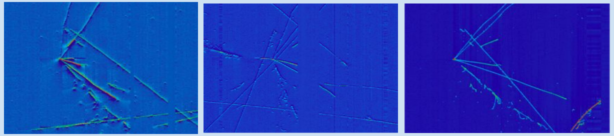
ν-nucleus interaction model

(Truth) final-state particles
$\{p_1, p_2, p_3, \ldots p_n\}$

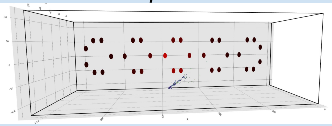
Detector Sim

Detector Outputs

Ionization



Optical

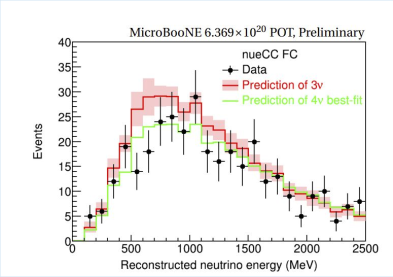


Reconstruction

(reco) final-state particles
$\{\tilde{p}_1, \tilde{p}_2, \tilde{p}_3, \ldots \tilde{p}_m\}$

Calculate observables

Observables



Neutrino Oscillations

Neutrino oscillations occur because

- neutrinos have mass
- and flavor states are mixture of mass states

Neutrinos created/interact in flavor states
They propagate in their mass states

Don't have to line up!

Neutrino Oscillation: 2-flavor example

Neutrino oscillations occur because

- neutrinos have mass
- and flavor states are mixture of mass states

Flavor States | **Mixing Matrix (*U*)** | Mass States

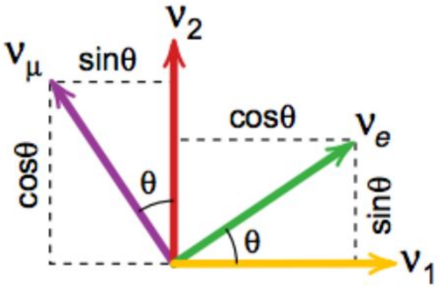
Example 2 ν model

$$\begin{pmatrix} \nu_a \\ \nu_b \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} \nu_1 \\ \nu_2 \end{pmatrix} \begin{matrix} \text{w/mass } m_1 \\ \text{w/mass } m_2 \end{matrix}$$

In 2D, simple rotation

$$|\nu_e\rangle = \cos\theta|\nu_1\rangle + \sin\theta|\nu_2\rangle$$

$$|\nu_\mu\rangle = -\sin\theta|\nu_1\rangle + \cos\theta|\nu_2\rangle$$



Neutrino Oscillation: 2-flavor example

Let's start with a neutrino created in flavor state $|\nu_\mu\rangle$

Neutrino Oscillation: 2-flavor example

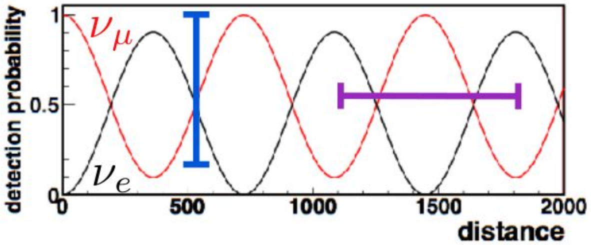
Probability of transition from flavor ν_μ to ν_e :

$$P(\nu_\mu \to \nu_e) = |\langle \nu_e | U_{PNMS} U(t) U^{-1}_{PNMS} | \nu_\mu \rangle|^2$$

$$= \sin^2 2\theta \sin^2 \left(([1.27 \text{ GeV km}^{-1}] \Delta m^2 \boxed{\frac{L}{E}} \right)$$

Key signature is oscillatory prob function of L/E

Result is sinusoidal probability, function of L/E



mixing angle, θ, governs amplitude

mass splitting, Δm^2, governs frequency

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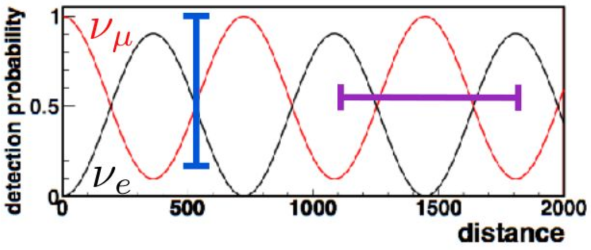


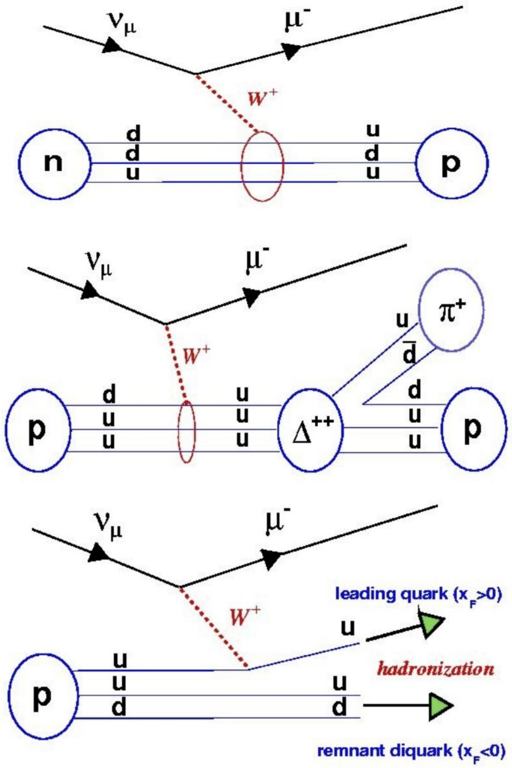
mixing angle, θ, governs amplitude

mass splitting, Δm^2, governs frequency

Neutrino nucleon Interactions

Never scattering on a free quark.

Dominant interactions at ν_μ at $E_\nu \sim 1\,\mathrm{GeV}$ (typical flavor and energy for accelerator ν)



Neutrino Oscillations

Want to know state at time, *t*, so we need to apply the propagator, *U(t)*, on the $|\nu_\mu\rangle$ in the mass basis

$$U(t)U^{-1}_{PMNS}|\nu_\mu\rangle = -\sin\theta e^{-iE_1 t}|\nu_1\rangle + \cos\theta e^{-iE_2 t}|\nu_2\rangle$$

$$E = \sqrt{p^2 + m^2}$$

Neutrino Oscillations

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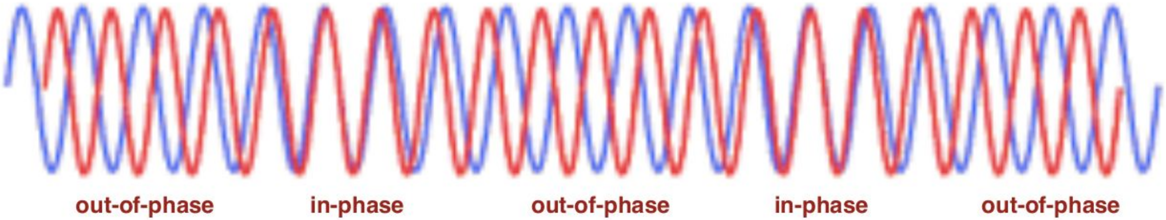
$$E = \sqrt{p^2 + m^2}$$

what we have are two states oscillating at slightly two frequencies due to the slightly different masses



with a slight shift in frequency, you get periods where two waves in phase for some time, and out of phase for others

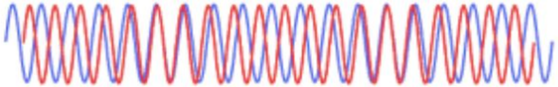
Neutrino Oscillations

Want to know state at time, *t*, so we need to apply the propagator, *U(t)*, on the $|\nu_\mu\rangle$ in the mass basis

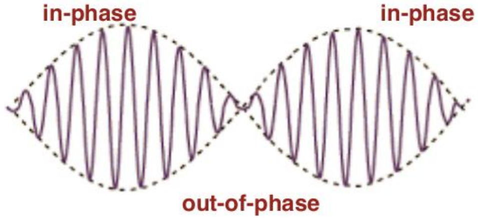
$$U(t)U_{PMNS}^{-1}|\nu_\mu\rangle = -\sin\theta e^{-iE_1 t}|\nu_1\rangle + \cos\theta e^{-iE_2 t}|\nu_2\rangle$$

$$E = \sqrt{p^2 + m^2}$$

what we have are two states oscillating at slightly two frequencies due to the different masses



Classical analogue is the beat-frequency phenomenon



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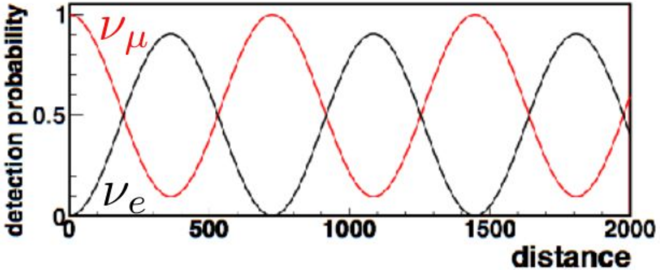
$$= \sin^2 2\theta \sin^2 \left(([1.27 \text{ GeV km}^{-1}] \Delta m^2 \frac{L}{E} \right)$$

Result is
sinusoidal
probability,
function of L/E

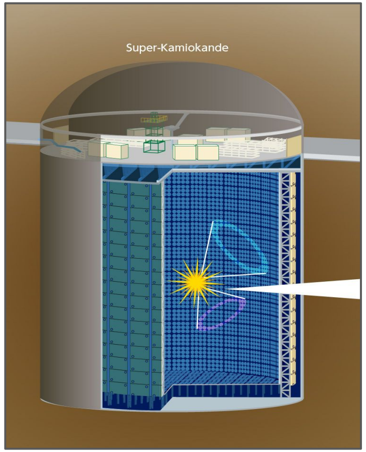


Cherenkov

Other experiments analyze the pattern of Cherenkov Radiation to infer particle momenta and type.

Spatial arrange of optical sensors not grid-like

Example: Super-Kamiokande, T2K, Hyper-K

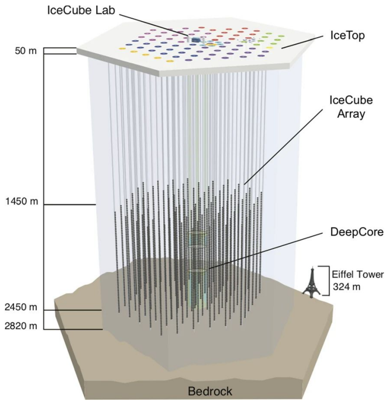


Muons
(sharp ring)

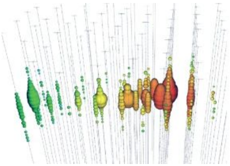
EM showers
(fuzzy ring)

Example: IceCube

Observing atmospheric + astrophysical neutrinos



Muon
(from $\nu_\mu CC$)



Electron or Tau
(from $\nu_e CC$ or $\nu_\tau CC$)