

Enforcing Self-Consistent Kinematic Constraints in Neutrino Energy Estimators

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Neutrino Oscillations & Interactions

Neutrinos oscillate their flavor

- Dependent on $\{E_\nu, L(\theta_\nu)\}$
- Most neutrino beams begin with ν_μ flavor
- Created from meson decays following spallation
- Oscillate into ν_τ principally and some ν_e

Measure ν interaction counts in our detectors...

Must use an interaction model to deconvolute the ν flux

$$N_\alpha(E_{rec}, L) = \sum_{i=\text{Nucleus Type}} \sum_{j=1}^{\text{Nuclei}} \int \Phi_\alpha(E_{true}, L) \sigma_{\alpha i}(E_{true}) R_{\sigma_{\alpha i}}(E_{true}, E_{rec}) dE_{true}$$

Measured in Far Detector

Required! ν flux

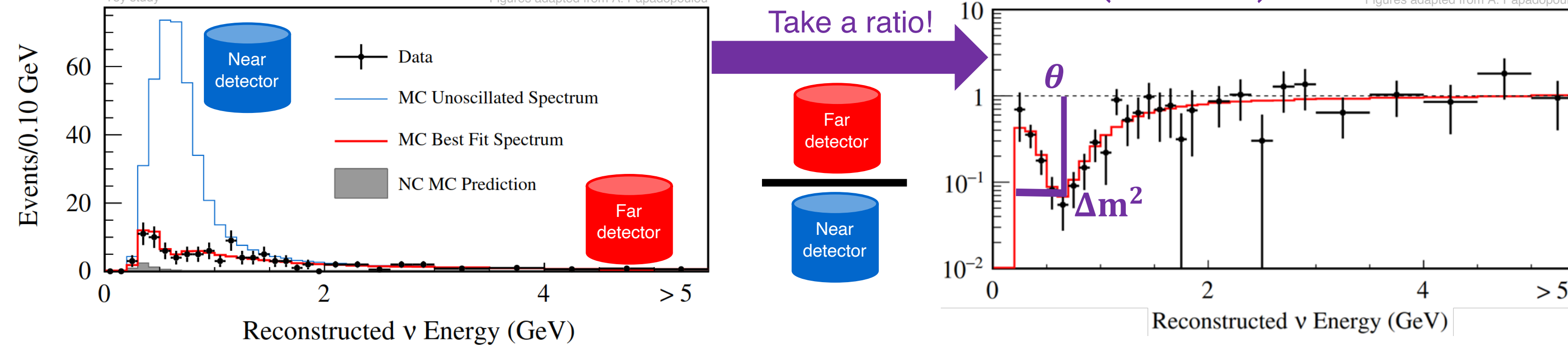
Interaction Model—i.e. GENIE

$$\Phi_\alpha(E_{true}, L) \propto \left[1 - P_{\nu_\beta \rightarrow \nu_\alpha}(E_{true}, L) \right] \Phi_\alpha(E_{true}, \sim 0)$$

\propto Oscillation parameters!

Near detector constraint

$$P_{\nu_\beta \rightarrow \nu_\alpha}(E_{true}, L) \approx \sin^2(2\theta) \sin^2\left(\frac{\Delta m^2 L}{E_{true}}\right)$$



A ratio of Far to Near Detector event spectra shows dependencies on...

- Flavor mixing angle θ (not ν direction!) & mass state splitting Δm^2
- Event spectra are in E_ν^{reco} , but we calculate oscillations given E_ν^{true} !
- Understand mapping between these with ν event generators, reconstruction software
- Machine learning ν energy estimators can perform this reconstruction
- Improvements possible in ML algorithms with physics motivations at heart!

Self-(In)Consistent Kinematics in ν Energy Estimators

$$E_{v1}^{pred} = E_{v2}^{pred}$$

$$p_{v1}^{pred} \neq p_{v2}^{pred}$$

$$\theta_{1}^{pred} \neq \theta_{2}^{pred}$$

Most ν energy estimators do not consider the full kinematics of the ν

- Optimize a single loss function of a single variable, s_ν :

$$L(s_\nu^{true}, s_\nu^{pred}) = \dots = L(E_\nu^{true}, E_\nu^{pred})$$
- ν should be defined by more than simply their E_ν ...need momenta info!

$$(E_\nu, p_{x_\nu}, p_{y_\nu}, p_{z_\nu}) \propto (E_\nu, \theta_\nu) \propto (E_\nu, L(\theta_\nu))$$
- Should continue training until four-vector components are kinematically consistent!
- Must include new inputs to loss function!**
- Otherwise:** $E_\nu \approx |p_{v1}^{pred}| \approx |p_{v2}^{pred}|$ while $\theta_\nu \approx \theta_{1}^{pred} \neq \theta_{2}^{pred}$
- There is no automatic guarantee that angular correlations are respected in a kinematically consistent way without a loss function which penalizes such behavior

Composite Loss Functions for Kinematic Estimators

Seek to encourage faster, accurate, kinematically consistent learning

- Instead: make the loss composite and multivariate**
- Utilize possibly many kinematic variables *simultaneously*: $\{s_\nu, x_\nu, \dots\}$

$$\mathcal{L}(\{s_\nu^{true}, s_\nu^{pred}\}, \{x_\nu^{true}, x_\nu^{pred}\}, \dots) = \alpha L_s(s_\nu^{true}, s_\nu^{pred}) + \beta L_x(x_\nu^{true}, x_\nu^{pred}) + \dots$$
- Can use this to imbue more physics into the loss function!
- "Physics motivated loss functions", "Physics informed machine learning" (PIML)
- Individual loss functions $\{L_s, L_x, \dots\}$ create a composite \mathcal{L} with
- Composite loss \mathcal{L} optimized

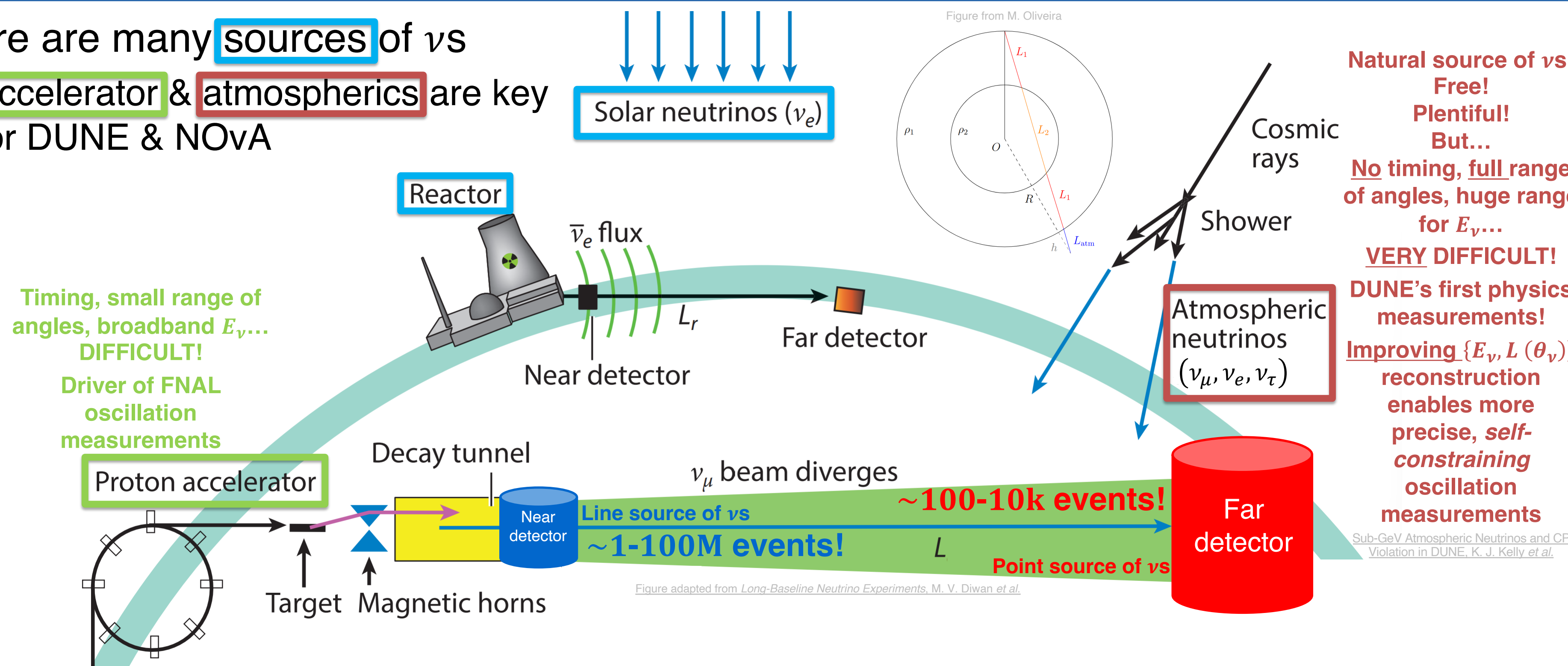
Initial loss variable combinations to be considered during trainings

- "Target" variables for predictions which enter losses against truth values

$$(E_\nu, p_{x_\nu}, p_{y_\nu}, p_{z_\nu}), (p_{x_\nu}, p_{y_\nu}, p_{z_\nu}), (E_\nu, \cos \theta_\nu), (E_\nu, \theta_\nu)$$
- Can calculate angular values from predicted/true momenta
- Will compare to single variable trainings: $E_\nu, \cos \theta_\nu, \theta_\nu$

There are many sources of ν_s

- Accelerator & atmospheric are key for DUNE & NOvA

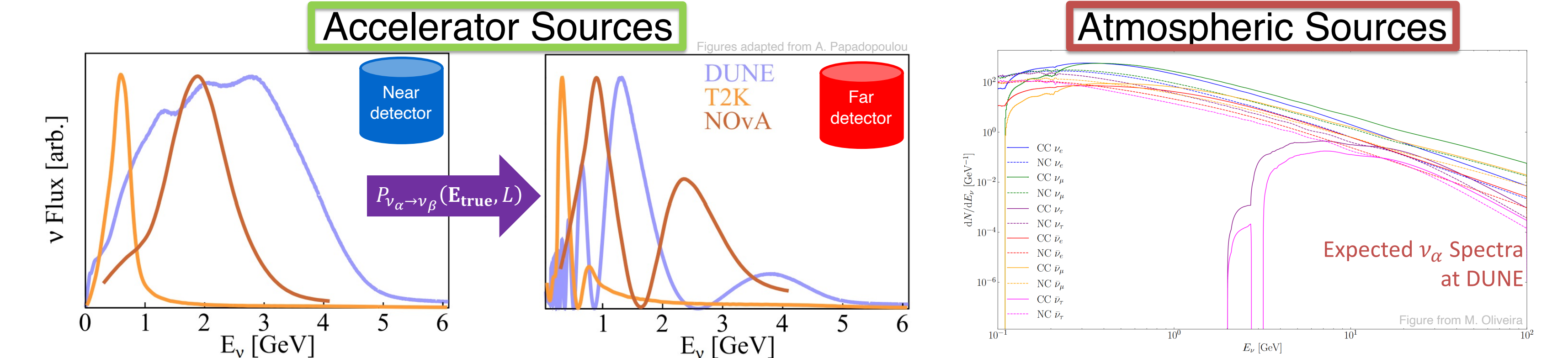


Accelerator sources usually have small range of energy: $\sim \{0.1, 10\}$ GeV

- ν beam energies are tuned to oscillation maxima given chosen baseline
- Many possible interactions: CC/NC, quasielastic, resonant production...
- Well-known incoming direction** from geometrically diverging beam
- No historic need to reconstruct θ_ν , only E_ν
- Timing from proton beam pulse helps eliminate backgrounds

Atmospherics have huge range of energy: $\sim \{0.1, 1000\}$ GeV

- Even more high energy processes possible! Containment issues abound...and τ s!
- Many baselines** from all around the globe! Like having many accelerators all over!
- Many baselines from **many incoming angles**! Not just one...
- No timing info to quell backgrounds—detectors deep underground to avoid cosmic μ s
- These ν_s become **very hard to reconstruct** because of these factors...



Training Sample Preparation w/GENIE Simulation

Large, truth level samples of ν interactions available

- GENIE used by ν experiments to predicted final state particles from initial state neutrino interactions on nuclei
- Can simulate beam and atmospheric neutrinos across many energies
- Initial challenge of this project: improve atmospheric ν reconstruction
- Utilize Inclusive, CC, NC, $NpN\pi$, $1p0\pi$, $Np0\pi$... selections for topologies
 - Make realistic selections on final state particles only above kinematic thresholds
- All done at truth-level—will utilize reconstructed values w/experiments!

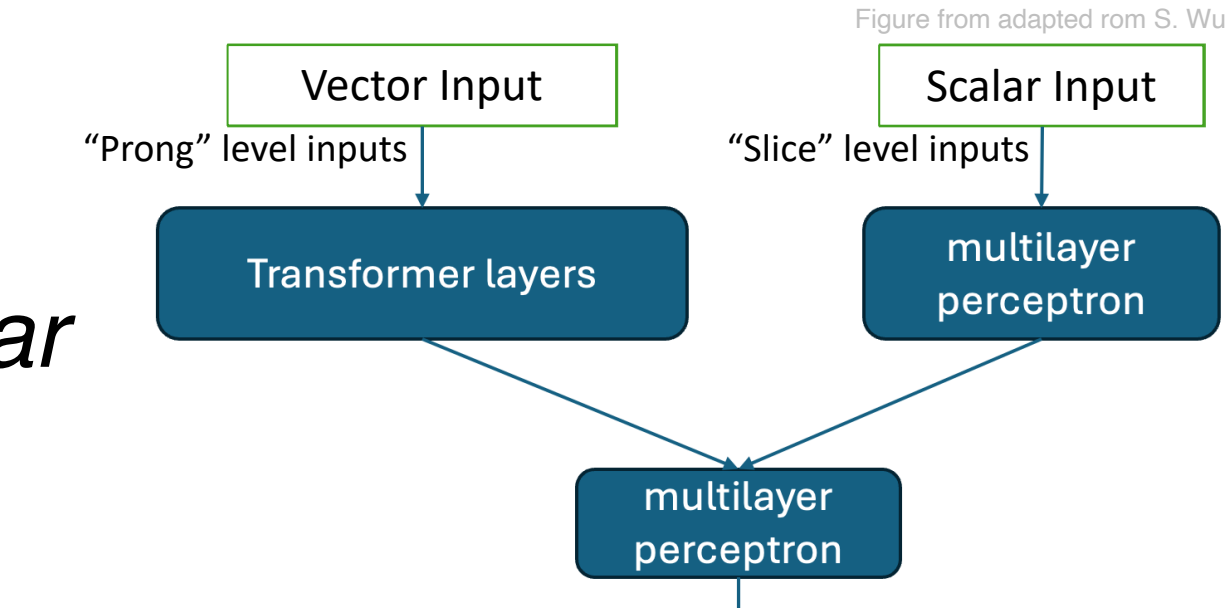
Transformer Training Variables

Transformer network used for initial studies

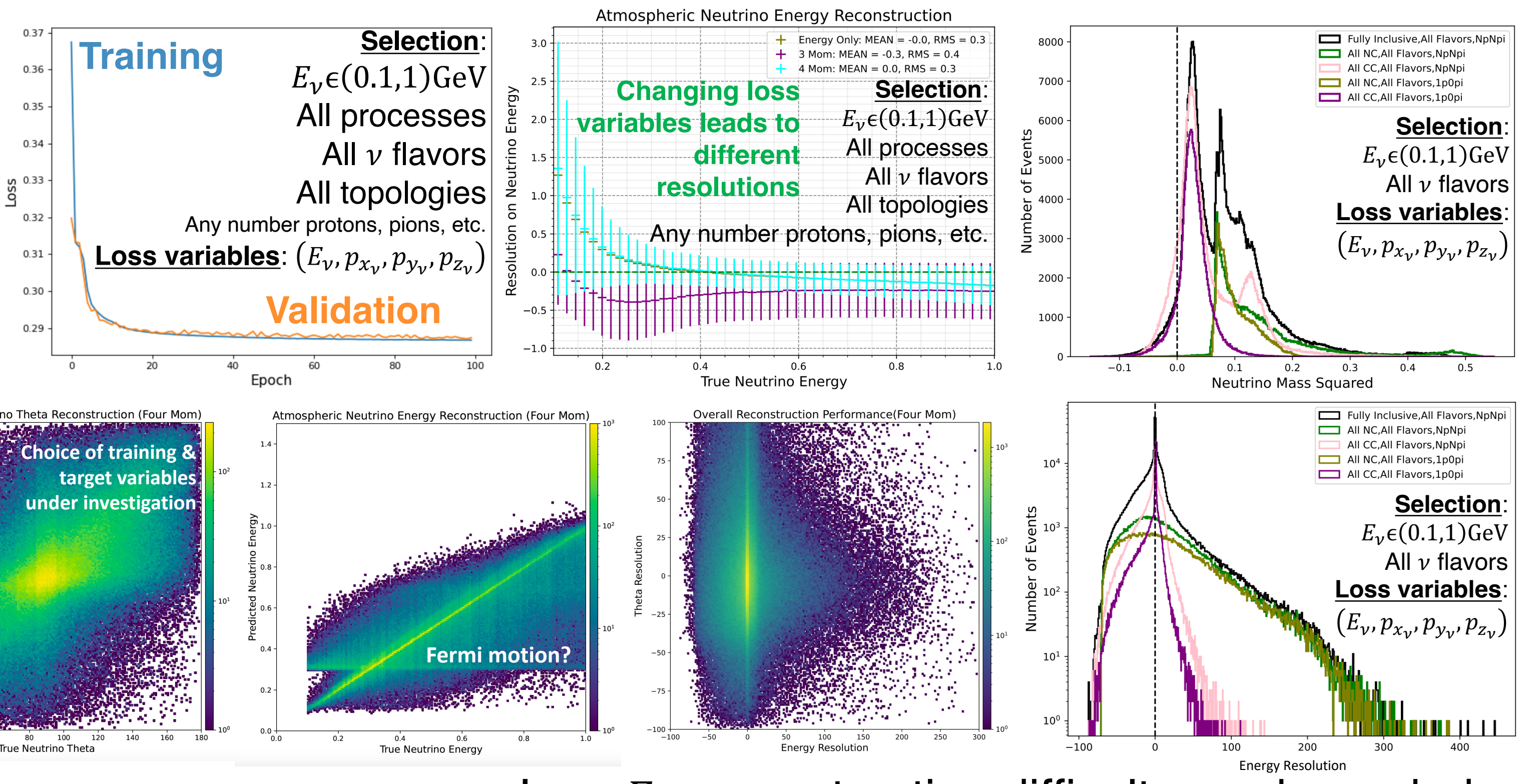
- Training variables organized as *vector* & *scalar*
 - Scalar: whole, event-level kinematic variables

$$P_{Tot}, KE_{Tot}, P_{Miss}$$
 - Vector: "visible" (above threshold) final state particle kinematics

$$PDG_i, Mass_i, KE_i, P_{x_i}, P_{y_i}, P_{z_i}, \cos \theta_i, \theta_i$$



Initial Comparisons: Atmospherics w/ $E_\nu < 1$ GeV



- Low- E_ν reconstruction difficult...work needed on θ !
- Fermi motion, Intranuclear cascade, many incoming θ_ν^{atmo}
- Targeting GENIE-oriented publication *first*
- Both atmospheric & beam comparisons
- DUNE-&-NOvA-oriented publications to follow w/fully reconstructed inputs