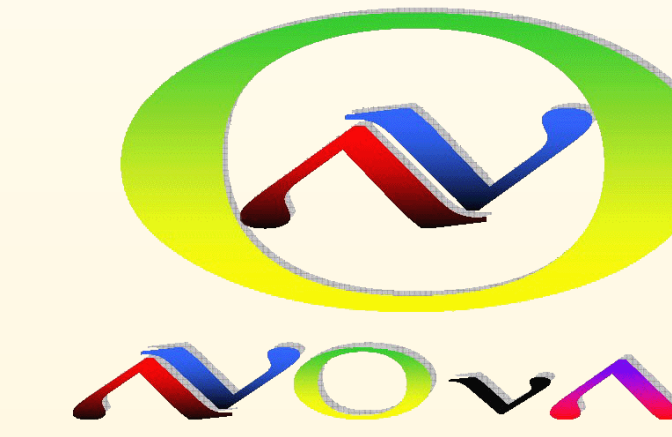


Transforming the ν World: A New Multivariate Transformer Energy Estimator for NOvA

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Energy Estimation in Neutrino Experiments

Accurate reconstruction of neutrino energy is crucial to enable precision oscillation studies

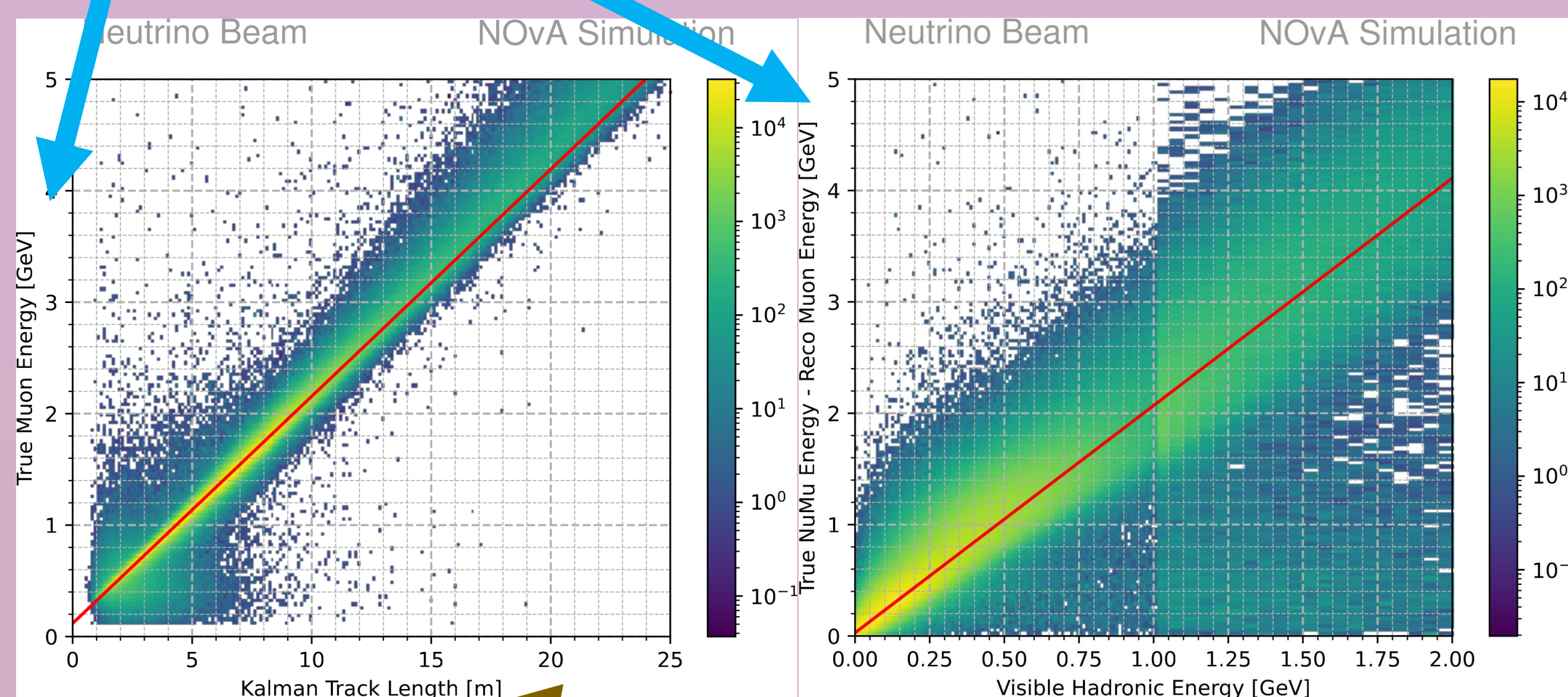
Incoming neutrinos are invisible, so initial kinematic inferences can only be made via resultant final state particles

$$P_{\alpha \rightarrow \beta} = \delta_{\alpha\beta} - 4 \sum_{j>k} \mathcal{R}_e \left\{ U_{\alpha j}^* U_{\beta j} U_{\alpha k} U_{\beta k}^* \right\} \sin^2 \left(\frac{\Delta_{jk} m^2 L}{4E} \right) + 2 \sum_{j>k} \mathcal{I}_m \left\{ U_{\alpha j}^* U_{\beta j} U_{\alpha k} U_{\beta k}^* \right\} \sin \left(\frac{\Delta_{jk} m^2 L}{2E} \right)$$

Traditional Methods

Traditionally, neutrino energies are estimated by fitting components of the **true energy** to **reconstructed variables** in Monte Carlo.

True Energies



Reco Variables

Spline's Shortcomings:

- Overly *rigid* fitting
- Fails to utilize full array of information available for each event
- Depends strongly on accuracy of MC
- Highly susceptible to systematic errors

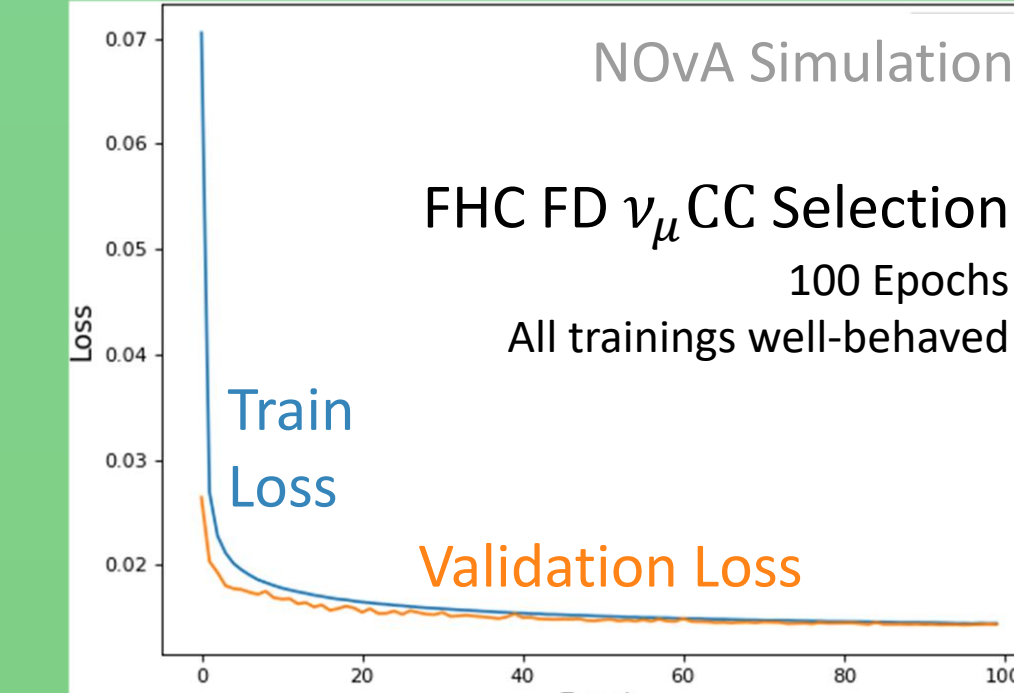
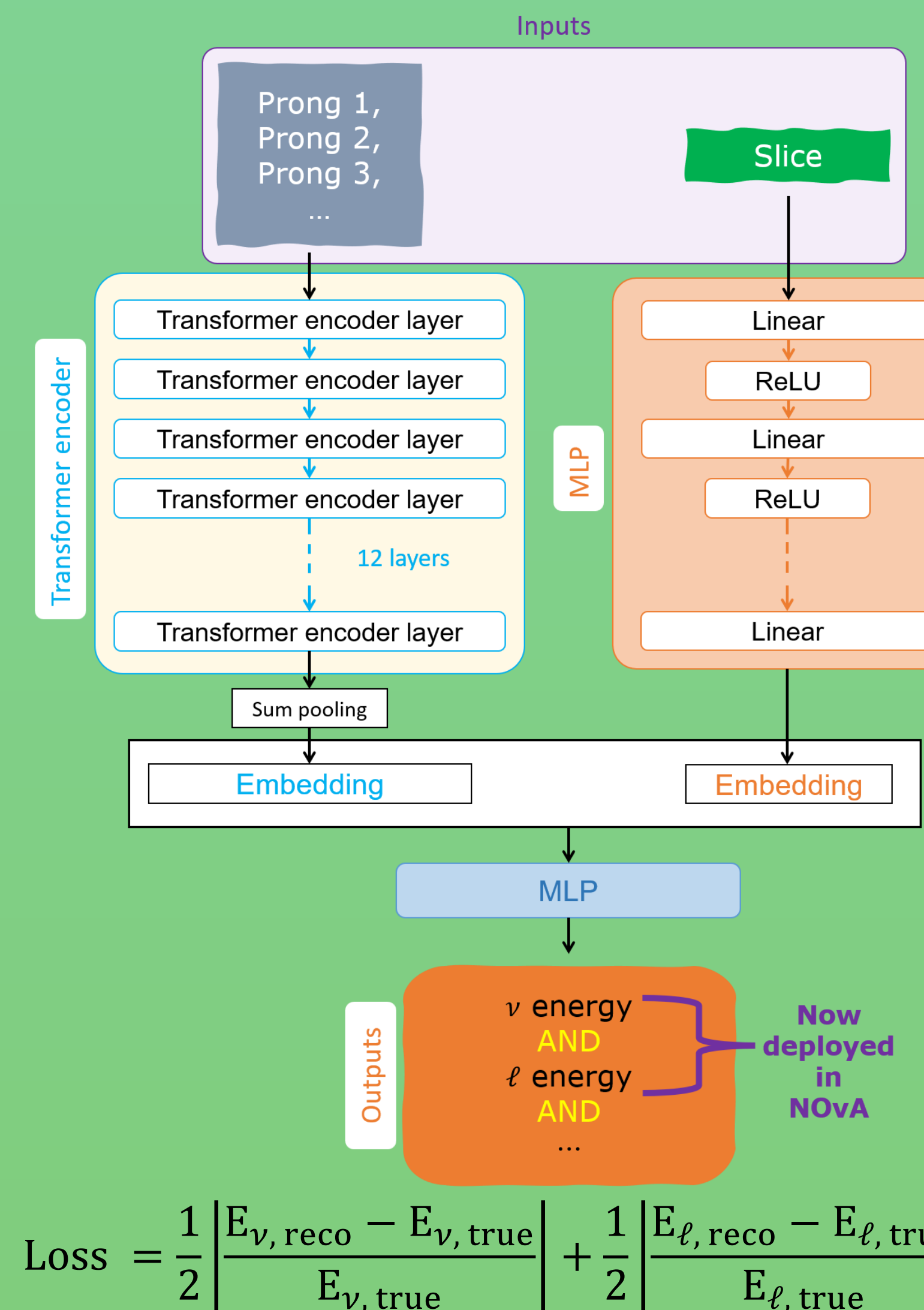
Fits used for NOvA's Spline energy estimator: $E_{\nu, \text{Spline}} = a \cdot \text{Track Length} + b \cdot E_{\text{had, vis}}$
(Left) True muon energy is fit against reconstructed muon track length (slope = a)
(Right) The remaining true neutrino energy is fit against visible hadronic energy (slope = b)

Transformer

Our transformer (**TransformerEE**) utilizes prong (reconstructed 3D tracks and showers) and slice (event-level) variables to estimate incoming neutrino and outgoing lepton energy.

Features:

- Architecture allows an arbitrary number of prong inputs.
- Makes use of purpose-built upstream prong reconstruction algorithms, including other neural networks.
- Transformers' defining attention mechanism allows associations to be made between prongs.
- Can be trained to predict any number of correlated output variables.



Training

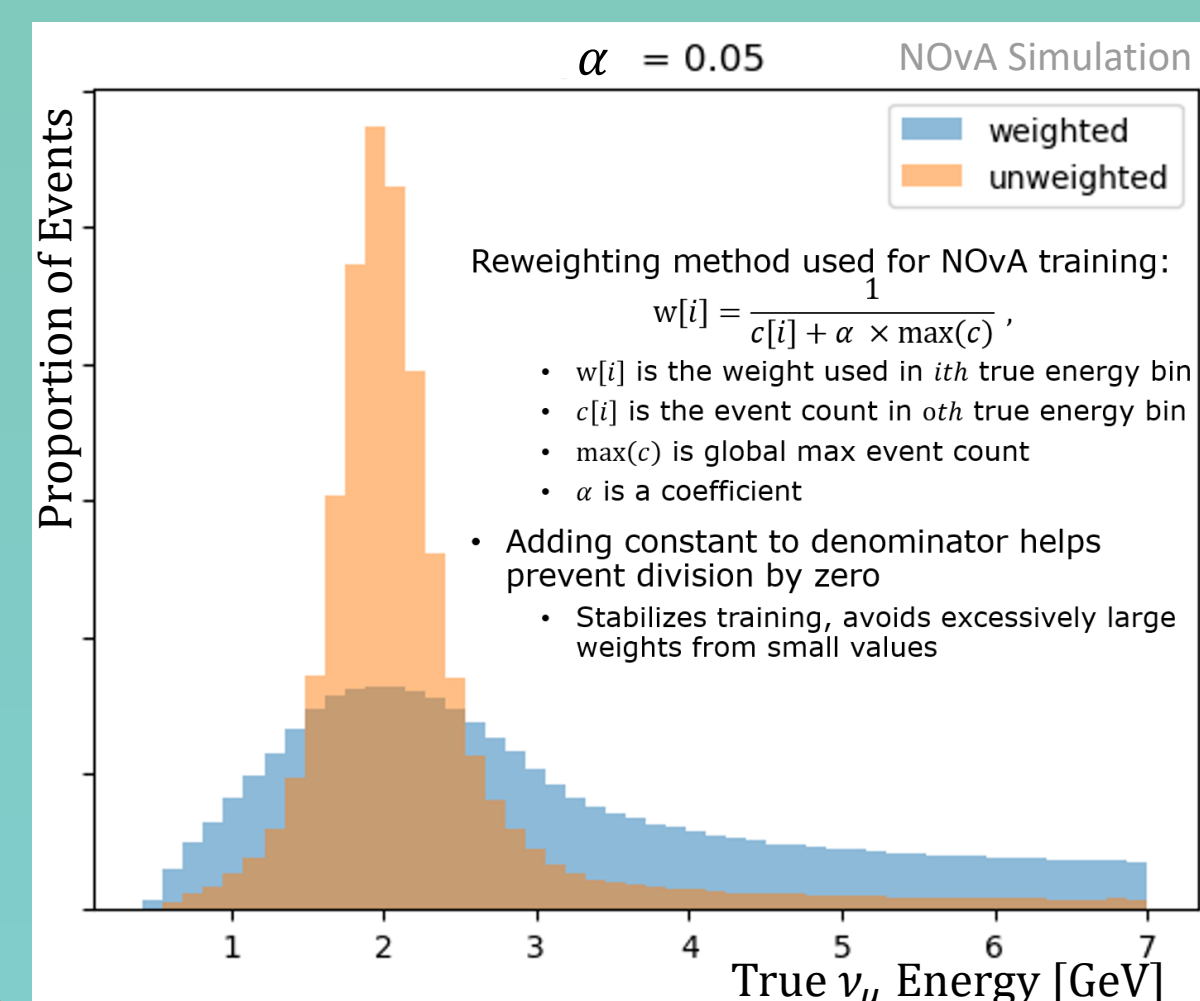
- ~1.7M trainable parameters
- Trains on 1.7M events
- Single 40GB A100 GPU
- In just ~2.5hrs!

Mitigating Bias

TransformerEE trained & tested on ν_{μ} CC events in NOvA ND/FD

To mitigate bias from the MC and upstream reconstruction, we implement the following:

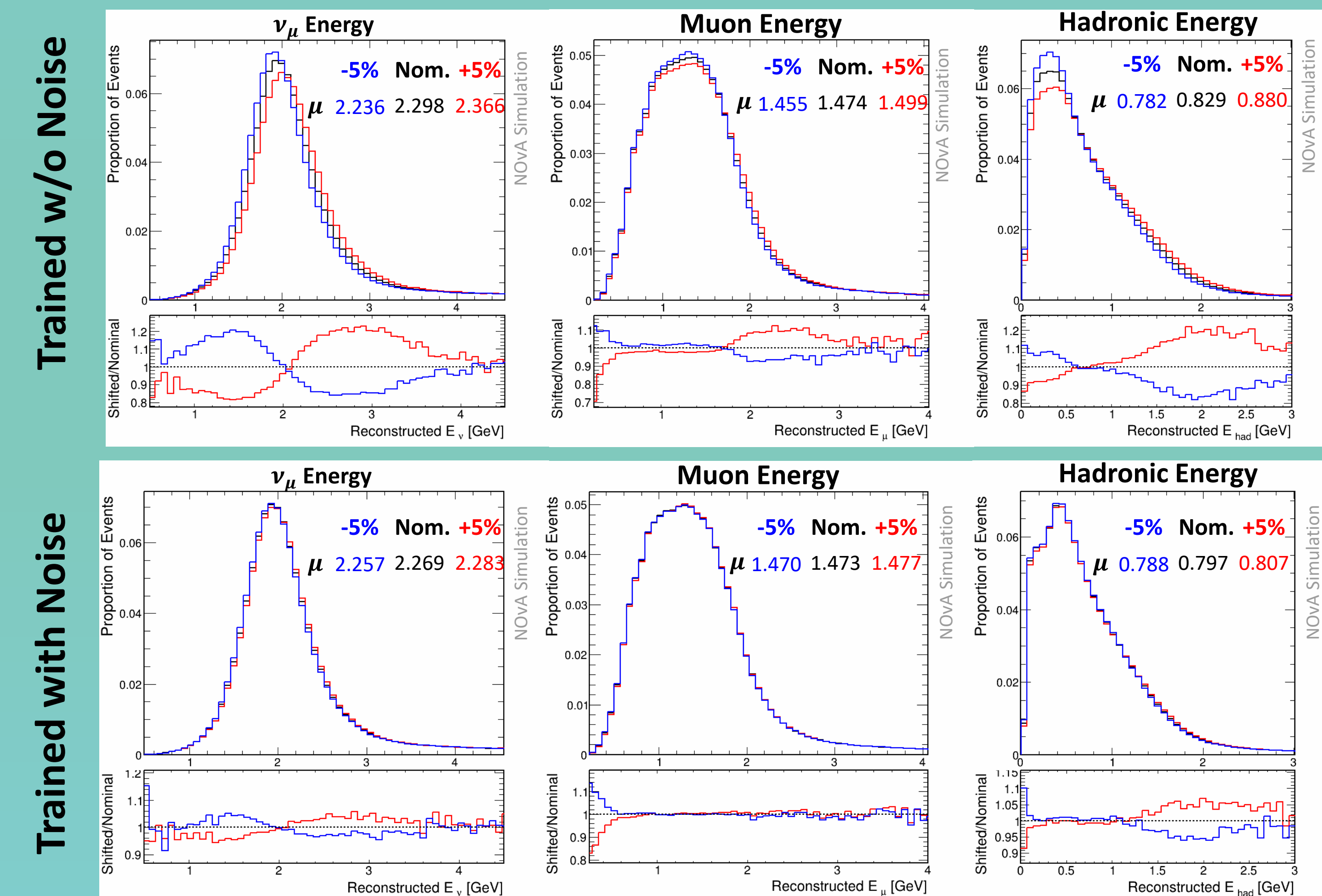
1. Events are weighted to train on a flattened spectrum
 - Reduces bias towards the MC truth peak value
 - More importance in tails



2. 20% Gaussian fluctuations on calorimetric-based input variables
 - "Noise" directly builds in robustness to energy calibration errors!

Inference on FD datasets with a fixed $\pm 5\%$ shifts in calorimetric energy

- Represents expected calibration uncertainty in NOvA detectors:

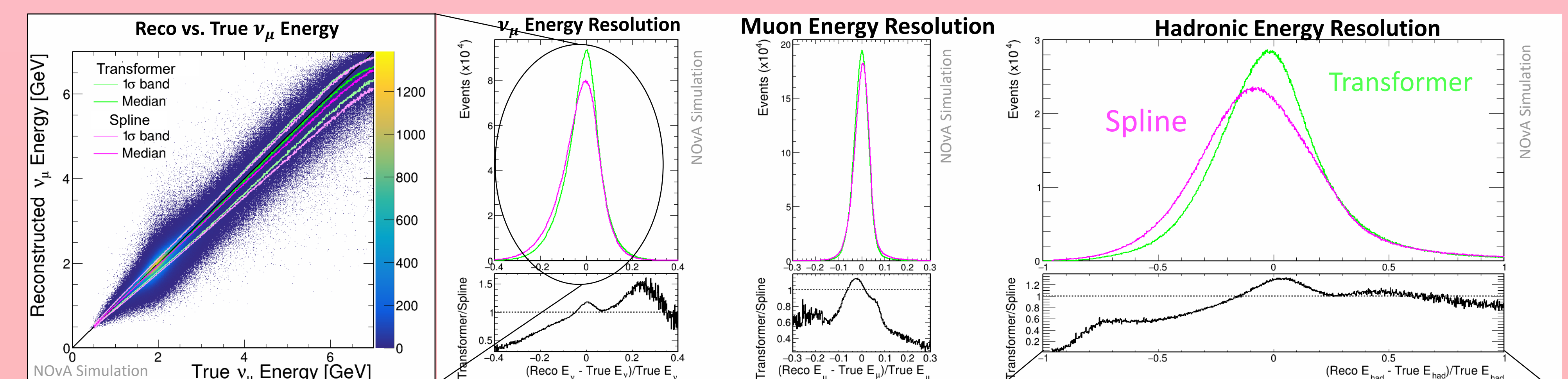


Reconstructed ν_{μ} energy shifts reduced by ~80%!

Performance

The percent error in TransformerEE predictions was compared to that of Spline

- Spread of percent errors representative of energy resolutions for each method
- **TransformerEE exhibits lower bias and better resolution at all energies!**



Note: Underlying 2D histogram is for TransformerEE only.

Legend: Spline / Transformer

	Bias	Standard Dev.
ν_{μ} Energy Res.	-2.80%/-1.58%	9.68%/8.46%
Muon Energy Res.	0.40%/-0.13%	6.69%/4.73%
Had. Energy Res.	-4.82%/-1.03%	28.73%/25.97%

Inference results on full NOvA production set with 7.7 million contained ν_{μ} CC far detector, forward horn current events.

