

Unbinned Unfolding Method with Machine Learning



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Neutrino Interaction

The nature of neutrino is measured by oscillation measurement. A main source of its uncertainty is originated from the interaction with the nucleus. To understand the effects, it is important to measure the cross section of channels with hadron(s). \rightarrow A key part of the cross section measurement : Unfolding

<u>Unfolding</u>

Unfolding is a process of cross section measurement to deconvolute the smearing effect due to the detector resolution.

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Binned unfolding : unfolding is done after filling events in a histogram

True space





Dataset

In this study, the T2K near detector (ND280) MC dataset[2] is used for application of the Omnifold. The main tracker of ND280 is consist of two scintillator detectors and three time projection chambers (TPC). A signal event is defined as events w/ one muon and w/o pion (CC0 π)



TPC FGD TPC FGD TPC



An instance of CC0piNp event

<u>A conventional method : Iterative Bayesian Unfolding (IBU)</u> An iterative method with Bayes theorem and the prior distribution $T^{(0)}$:

$$U_{ji}^{(n)} = S_{ij} \frac{T_j^{(n)}}{\sum_k^N S_{ik} T_k^{(0)}} \quad \longleftarrow \quad T_j^{(n+1)} = \sum_i^N U_{ji}^{(n)} R_i$$

Unbinned Method

Reweighting dataset B (sampled from $p_{B}(x)$) to dataset A $p_{A}(x)$ without binning dataset B with weight w(x) := $p_A(x) / p_B(x)$ is statistically identical to dataset A.

A neural network classifying two datasets minimizes the following loss function called binary cross entropy :

$$Loss(p_i, q_i) := -w_i \{ p_i \log q_i + (1 - p_i) \log(1 - q_i) \}$$

The prediction minimizing the loss function gives the ratio of their

Pseudo Data for the Performance Evaluation

Single Transverse variables (STV) is used to see the transverse kinematic imbalance. The pseudo data used to evaluate the performance is made by weighting the nominal MC dataset match to T2K data for a certain STV.

Performance

To evaluate the performance of Omnifold, nominal MC is unfolded to the pseudo data. The unfolding is done using 100 statistic and systematic variations and the deviation of the result is considered as the uncertainty of the method.

The left plot shows the result which a certain variation is unfolded onto the pseudo data with the shape only change



Conceptual figure of STV



probability densities :



Omnifold [1]



•Nominal to a pseudo data w/ shape only change (δp_{τ})



•Nominal to a pseudo data w/ shape and normalization change (δp_{τ})



Omnifold is an iterative process and it consists of two steps:

Step 1 :

A NN which distinguishes data and MC in the reconstructed space

 \rightarrow gives weights to match MC to data Step 2 :

Another NN which distinguish the nominal MC and updated MC by Step1

 \rightarrow gives weights to match Nominal MC to truth

Network structure input 3D momenta of particles two hidden layers w/ 100 nodes •one output (prediction)



As a metric to evaluate the performance χ^2 is adopted :

$$\chi^2 = (\mathbf{p}-\mathbf{q})^T \mathrm{Cov}^{-1} (\mathbf{p}-\mathbf{q})$$

χ^2	unfolding method	muon (p,θ)	δp _T	δα _τ	$\delta \phi_{T}$
shape only δρ _τ	IBU	12.5	10.3	2.1	2.7
	Omnifold	28.2	3.4	3.5	1.3
shape + norm. δρ _τ	IBU	66.7	18.5	15.6	21.0
	Omnifold	48.9	11.0	1.7	6.5

[1] A. Andreassen, P. T. Komiske, E. M. Metodiev, B. Nachman and J. Thaler, Phys. Rev. Lett. 124, 182001 (2020)

[2] K. Abe et al. (T2K collaboration), Phys. Rev. D 108, 112009 (2023)