



AI IN PARTIAL WAVE ANALYSIS

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Partial Wave Analysis



- A python-based software framework designed to perform Partial Wave and Amplitude Analysis with the goal of extracting resonance information from multi-particle final states.
- In development since 2014 and has been significantly improved with each revision - Version 3.4 just released!
- Efficient amplitude analysis framework including multithreading and CUDA support
- Optimizers include: Minuit, Nestle (or add your own!)

Group Members

Carlos Salgado (NSU/Jlab)

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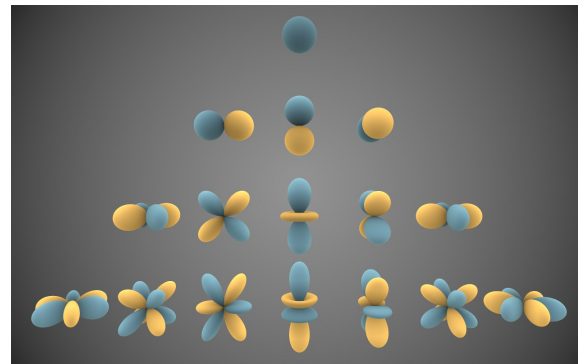
Brandon DeMello

Website: <https://pypwa.jlab.org>

GitHub: <https://github.com/JeffersonLab/PyPWA>

Preliminary Studies using Neural Networks

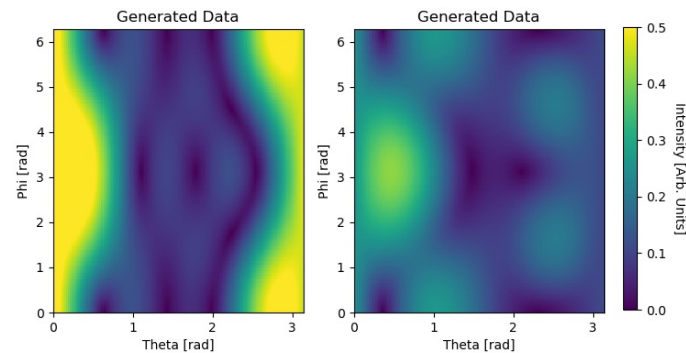
- Generate datasets using decay amplitudes (linear combination of spherical harmonics) with the following quantum numbers
 - $L = 1, 2, 3$
 - $m = 0, 1$
 - $\epsilon_R = -1, +1$
 - 9 total waves (“fit parameters”)



$$I(\Omega) = \sum_k \sum_{\epsilon_R} \sum_{l, |m|, l', |m'|} \epsilon_R Y_l^{|m|}(\Omega) \epsilon_R V_{l, |m|}^k \epsilon_R V_{l', |m'|}^{k*} \epsilon_R Y_{l'}^{|m'|*}(\Omega)$$

Production Amplitudes

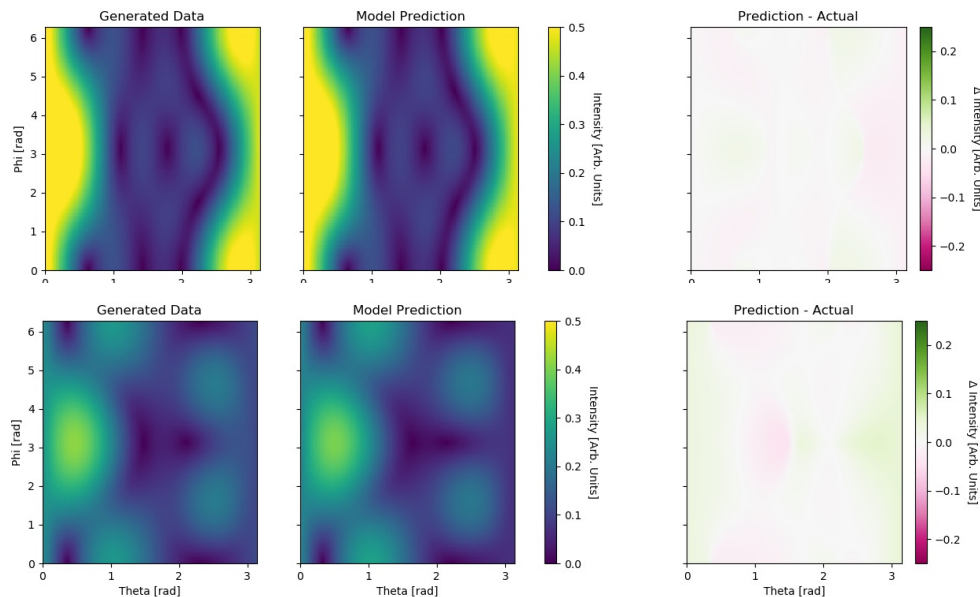
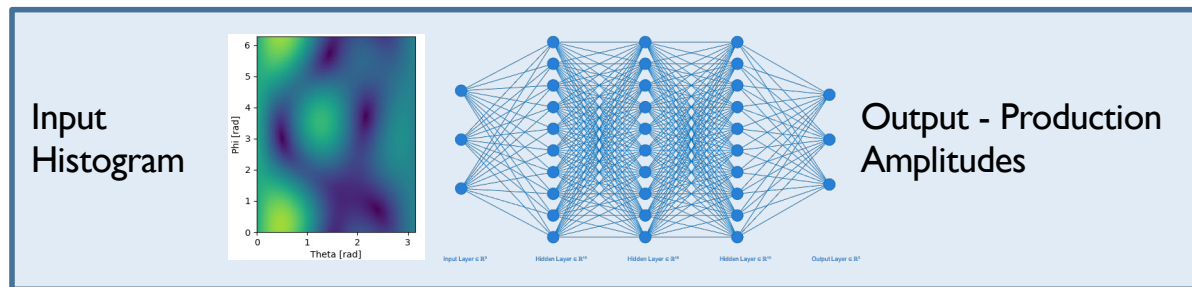
Decay Amplitudes



Early Results



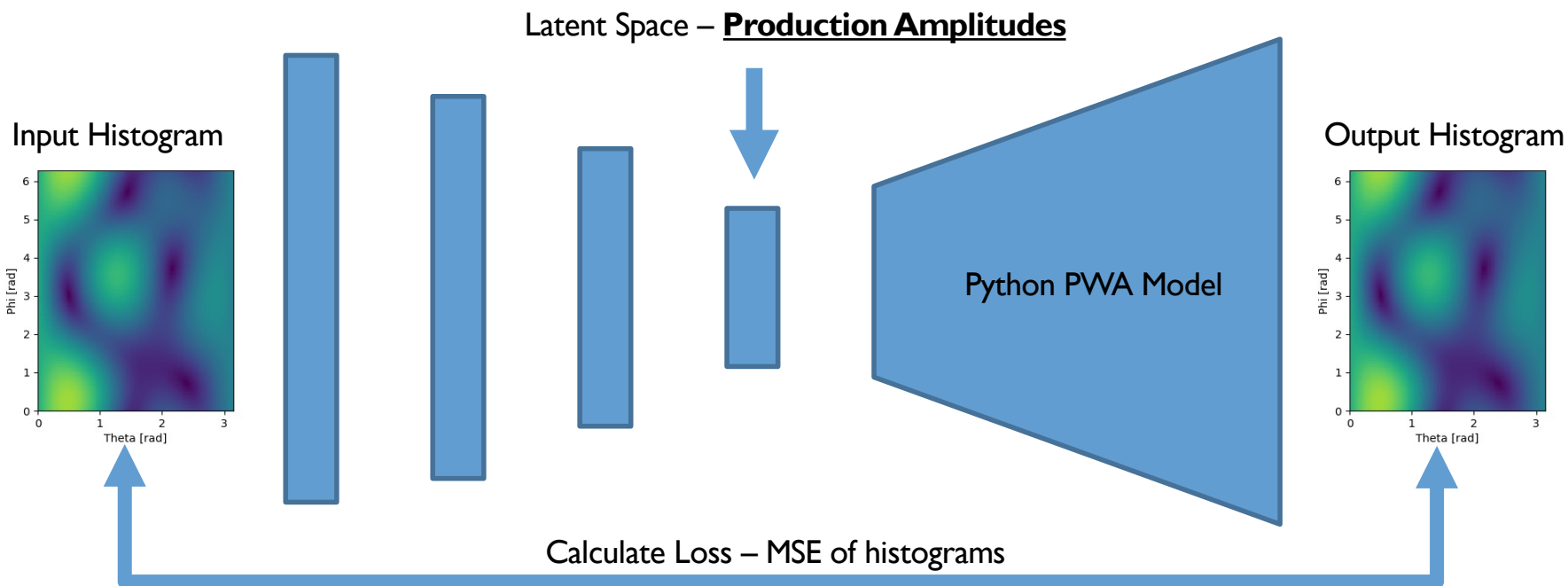
- We compare the intensity function and compare it to the model prediction
- Model Architecture:
 - 128x128 2D histogram as input
 - 9x128 Dense Layers – Relu activation
 - 9 production amplitudes as output
- In order to deal with the vast amounts of data we used generators to generate data for each epoch on the fly



Interesting Tools: Generators,
Complex Valued Deep Learning

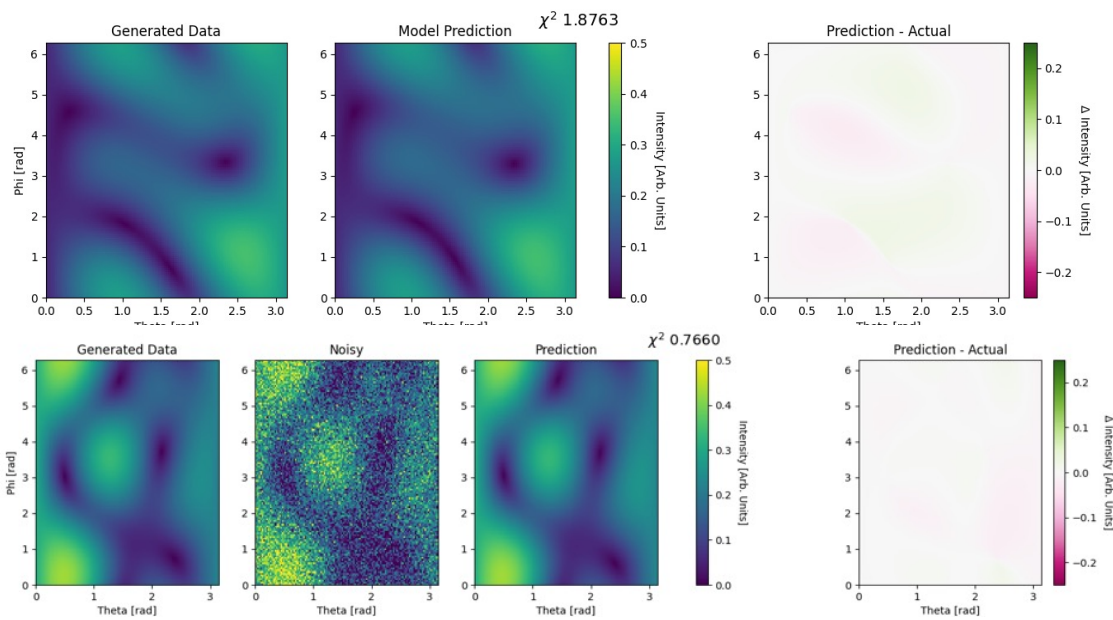
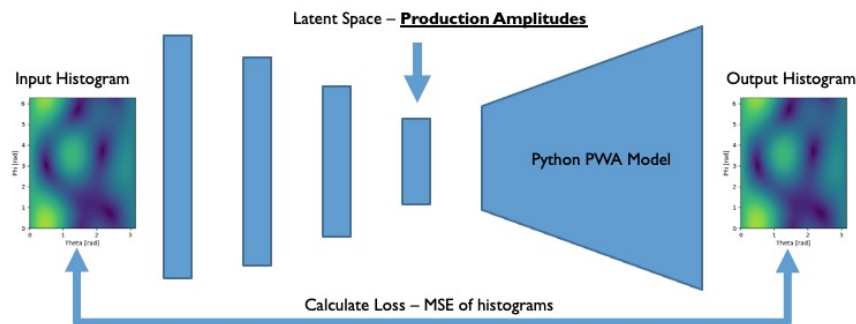
Autoencoder for PWA

Unsupervised learning!



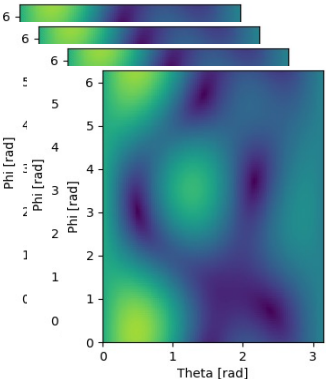
Autoencoders for PyPWA

- Encoder portion is a standard MLP, but without labels!
- Decoder is a PyPWA model that takes in production amplitudes and produces a histogram
- Autoencoders *dramatically* improved the accuracy!
- Even works well for noisy data



Future Autoencoder work for PWA

Input Histogram
(20x) Histograms



Latent Space – Production Amplitudes

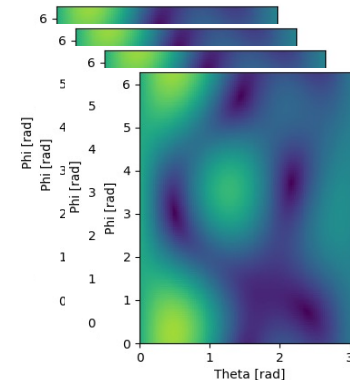


Python PWA Model

Latent Space p.2 – Resonance Mass and Width

Calculate Loss – MSE of 20 histograms

Output Histogram
(20x) Histograms



Summary

- We have been able perform PWA “fits” with neural networks
- Autoencoders dramatically improved the performance
- Future work includes adding mass and t as parameters to have a global fit

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