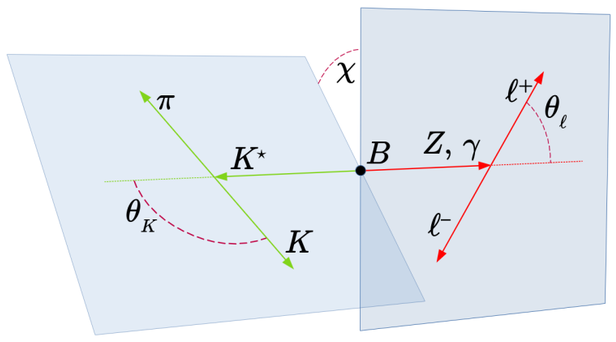
Machine Learning for New Physics in $B \to K^*\mu^+\mu^-$ Decays

Shawn Dubey
sdubey@hawaii.edu
Department of Physics and Astronomy
University of Hawai'i at Mānoa,
Honolulu, HI, USA

Abstract

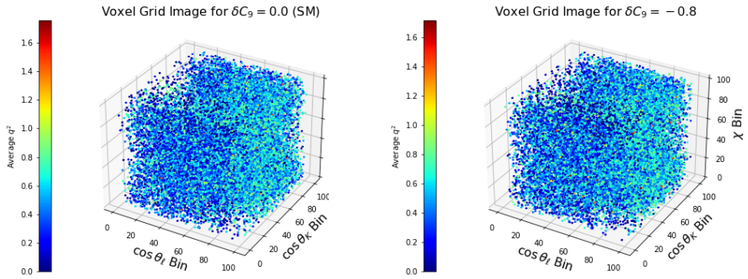
We report the status of a neural network regression model trained to extract new physics (NP) parameters in Monte Carlo (MC) data. We utilize a new EvtGen NP MC generator to generate $B \to K^*\mu^+\mu^-$ events according to the deviation of the Wilson Coefficient C_9 from its SM value, δC_9, for different δC_9 values. We train a three-dimensional ResNet regression model, using images built from the the angular observables and the invariant mass of the di-muon system, to extract values of δC_9 directly from MC data samples. This work is intended for future analyses at the Belle II experiment but may also find applicability at other experiments.

Decay Topology



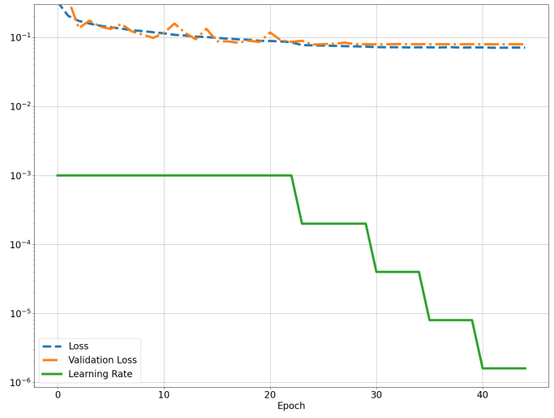
Decay topology of a generic $B \to K^*\ell^+\ell^-$ decay,
showing the relevant angular observables used in neural network training.

Images

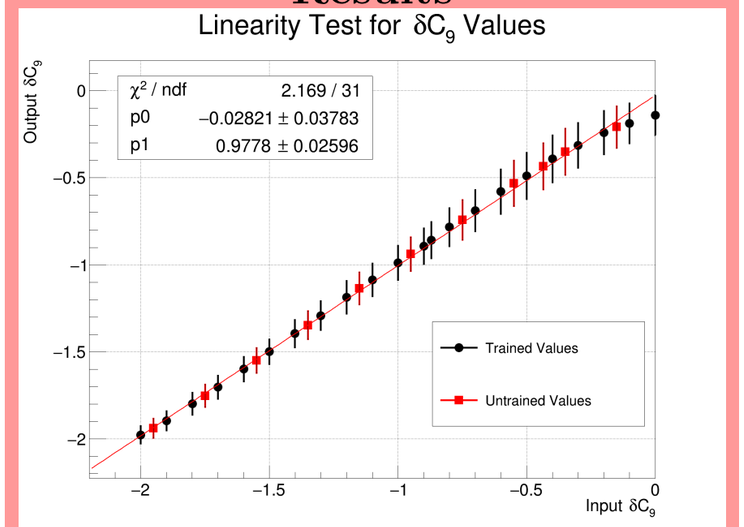


We produce "images" from generator-level MC, according to [1], that are used to train our neural network. Images are $q^2 \equiv M^2(\mu^+\mu^-)$ values binned in bins of the angular observables. Our model is a three-dimensional, 34-layer, ResNet [2] trained to perform *regression* to extract Wilson Coefficient information, $\delta C_i \equiv C_i^{\rm BSM} - C_i^{\rm SM}$, directly from data[3].

Training History



Results



From ensemble experiments, it is seen that the trained ResNet is able to correctly extract the different δC_9 values, from independent and unlabeled images. The black points are from experiments where the images are generated according to δC_9 values the ResNet has been trained with and the red points are from experiments where the images are generated according to δC_9 values with which the ResNet has *not* been trained.

References

[1] A. Sibidanov et al *Detecting lepton universality violation in angular distributions of $B \to K^*\ell^+\ell^-$ decays*, arXiv:2202.06827v4 (2023)

[2] K. He et al *Deep Residual Learning for Image Recognition*, arXiv:1512.03385 (2015)

[3] Done in collaboration with the authors of [1]