

Training Deep 3D Convolutional Neural Networks to Extract BSM Physics Parameters Directly from HEP Data: a Proof-of-Concept Study Using Monte Carlo Simulations

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Abstract

We report on a novel application of computer vision techniques to extract beyond the Standard Model (BSM) parameters directly from high energy physics (HEP) flavor data. We develop a method of transforming angular and kinematic distributions into “quasi-images” that can be used to train a convolutional neural network to perform regression tasks, similar to fitting. This contrasts with the usual classification functions performed using ML/AI in HEP. As a proof-of-concept, we train a 34-layer Residual Neural Network (ResNet) to regress on these images and determine the Wilson Coefficient C_9 in MC (Monte Carlo) simulations of $B \rightarrow K^* \mu^+ \mu^-$ decays. The technique described here can be generalized and may find applicability across various HEP experiments and elsewhere.

Problem

- Want to determine Wilson Coefficient deviation from SM value $\delta C_i \equiv C_i^{\text{BSM}} - C_i^{\text{SM}}$, for $B^0 \rightarrow K^{*0} \mu^+ \mu^-$.
- Want to use related angular and kinematic information: θ_K , θ_μ , χ , and $q^2 \equiv M^2(\mu^+ \mu^-)$. See Fig. 1 for definitions.
- High-dimensional fits, in the angles and q^2 , become complicated in the presence of backgrounds and detector effects.
- Here, focus is on C_9 as measurements demonstrate a potential BSM signal [1, 2].

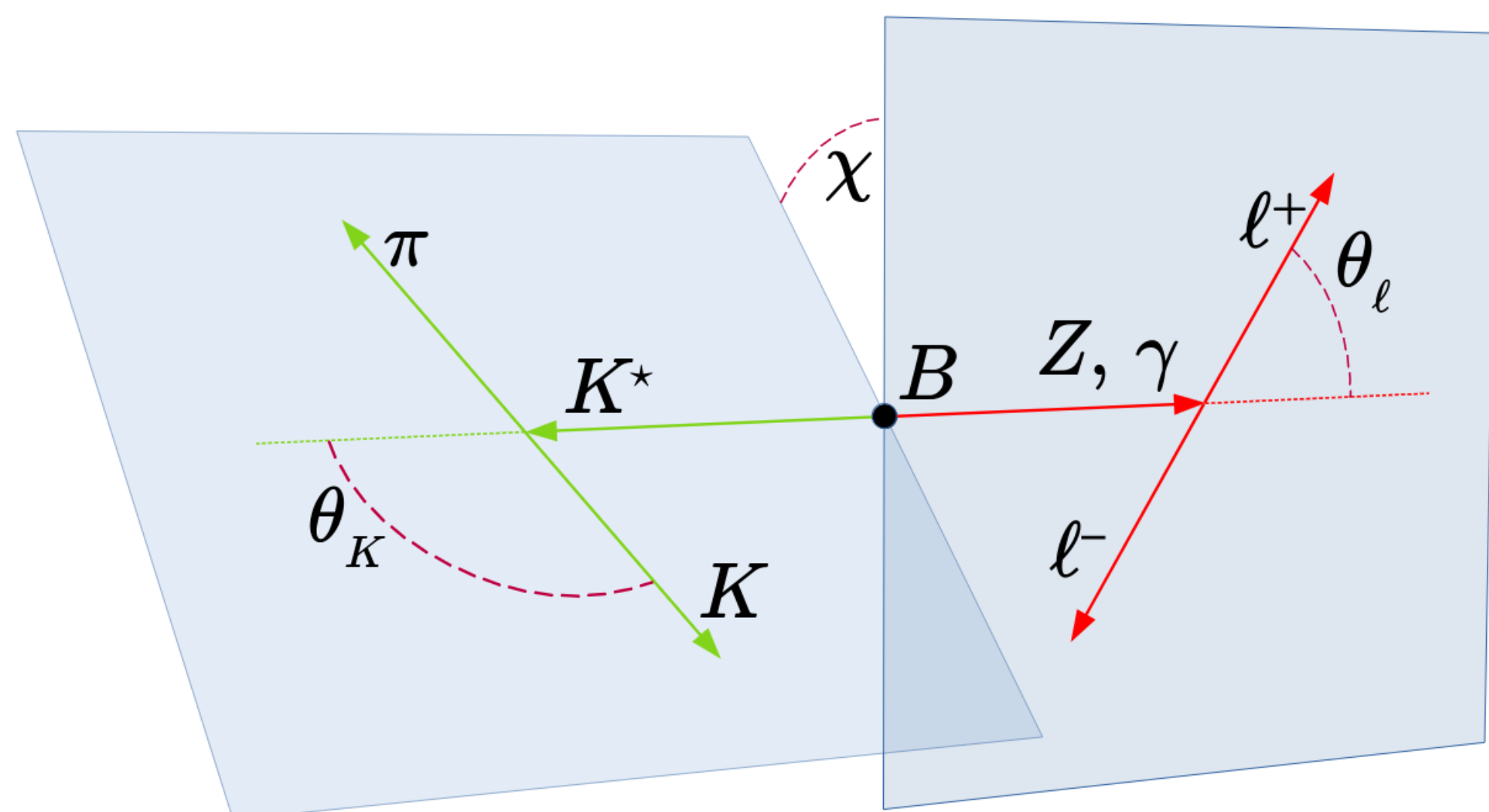


Figure 1: Topology for generic $B \rightarrow K^* \ell^+ \ell^-$ decays [3]

Solution

- Model developed, implemented in MC software [3].
- Model is tunable in terms of δC_i .
- Produce high-statistics, generator-level, MC simulations for different values of δC_9 , without backgrounds.
- Bin average, normalized, q^2 values in 50 equal-width bins of $\cos \theta_K$, $\cos \theta_\mu$, and χ (“quasi-images”/voxel grids, see Fig. 2).
- Quasi-images used to train a 3D, 34-layer ResNet [4].
- ResNet used to perform a regression task to predict δC_9 [5].

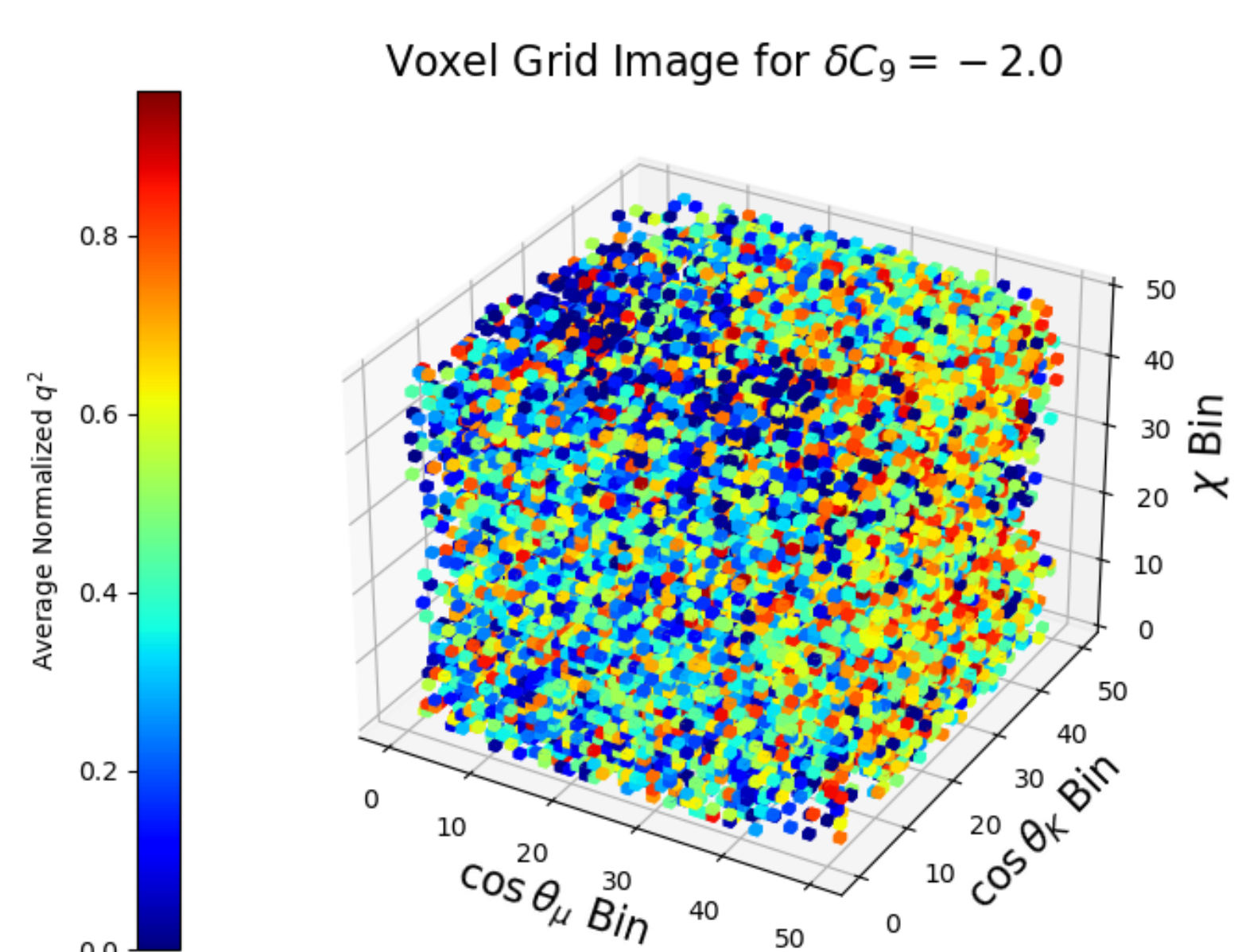


Figure 2: Example of a quasi-image generated with $\delta C_9 = -2.0$ [5]

Results

- Test the trained ResNet on a test set of unseen images.
- Statistically independent ensembles of test images generated for different δC_9 values.
- Median δC_9 inference values and the left and right standard deviations are determined.
- Plotted against the actual, generated, δC_9 values of the test set images. See Fig. 3.
- ResNet performs well at predicting δC_9 on unseen test set images.

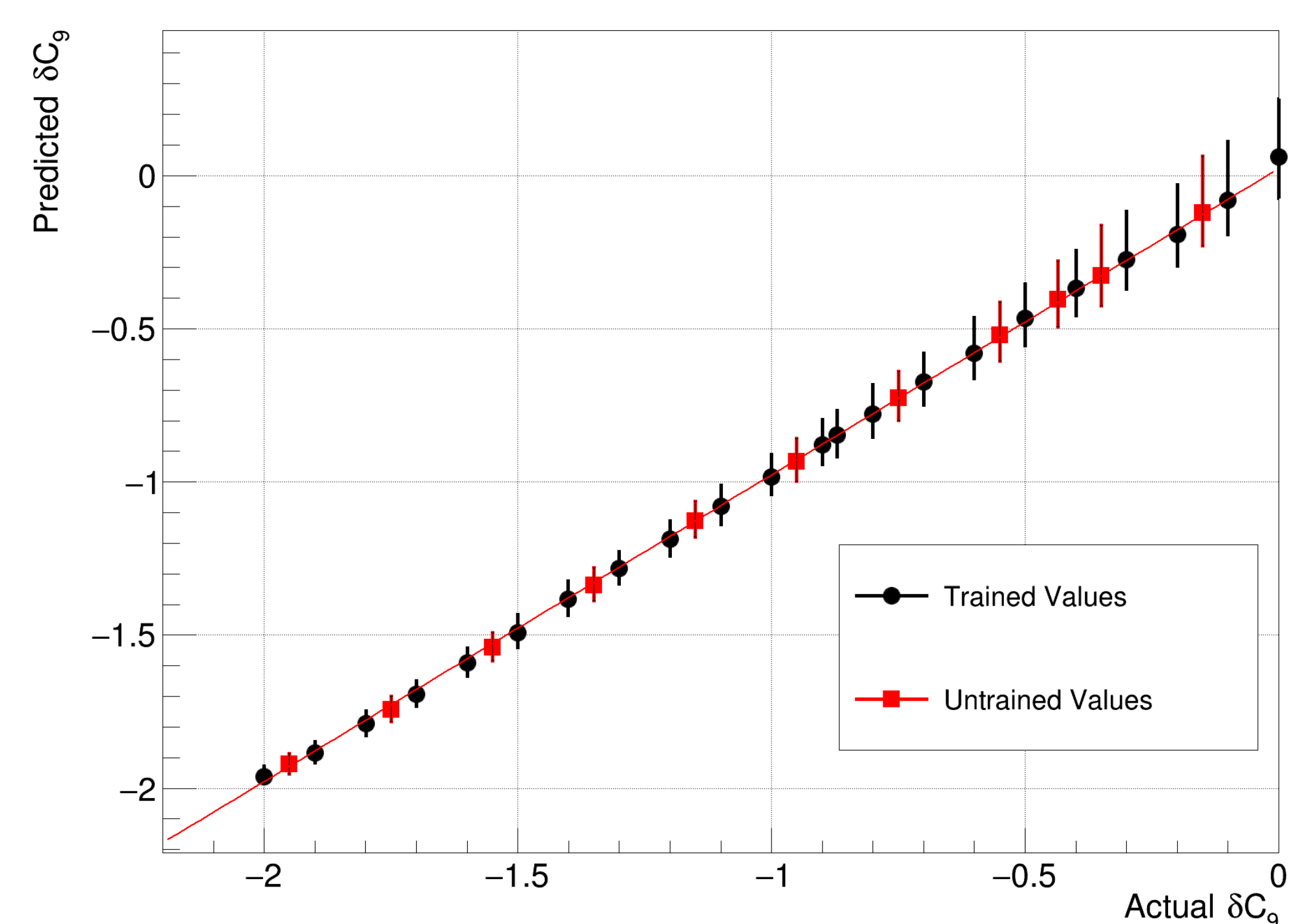


Figure 3: Linearity Test from Test Set [5]

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