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Gaussian Processes: Machine Learning for Observable Interpolation & Data Analysis

Current studies of the hadron spectrum are limited by the accuracy and consistency of datasets. Information derived from theory models often requires fits to measurements taken at specific values of kinematic variables, which needs interpolation between such points. In sparse datasets the quantification of uncertainties is problematic. Machine Learning is a powerful tool that can be used to build an interpolated dataset, with quantification of uncertainties. The primary focus here is one type of machine learning called a Gaussian Process (GP).

By calculating the covariance between known datapoints, the GP can predict the mean and standard deviation of other, unknown, datapoints, with no theoretical model dependence. The GP model presented here uses a bespoke method to find the optimal hyperparameters, using Bayesian inference. Checking and testing is performed using Legendre polynomials to ensure it is unbiased and gives accurate predictions.

The GP can also be used to give a probability density prediction between conflicting, and potentially inconsistent, datasets of the same physics observable. This enables theorists to test their models using the largest likelihood available from data.

AI keywords

Bayesian inference; uncertainty quantification; dataset creation

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