Data Fusion of Multi-fidelity Systems via Latent Variable Gaussian Process for Active Learning Applications

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High-fidelity models can achieve remarkable accuracy but come with high computational costs. Conversely, low-fidelity models are inexpensive to evaluate but lack accuracy. To attain high accuracy while minimizing computational expenses, multi-fidelity methods have gained popularity in recent times. These methods leverage the relationships between high-fidelity and low-fidelity models so that only a small amount of data is needed from the high-fidelity models to predict system responses. However, many existing multi-fidelity methods rely on simple predefined correlations between high-fidelity and low-fidelity models. They employ sequential training, starting from the lowest fidelity to the highest, to learn the correlations between successive fidelity models. This sequential training architecture not only dilutes the information from the low-fidelity training samples but also amplifies uncertainty propagation across the training stages. Consequently, constructing a multi-fidelity surrogate that effectively captures arbitrary correlations with minimal assumptions is generally a challenging task.

In this work, we develop a new multi-fidelity modeling method based on the Latent Variable Gaussian Process (LVGP), a Gaussian Process (GP) based approach that can accommodate mixed-variable (quantitative and qualitative) variables as predictors. LVGP can straightforwardly handle the multi-fidelity modeling problem by representing the fidelity level of different models as a qualitative variable. The LVGP learns the correlations between fidelity models through a Gaussian kernel and represents them with latent variables. Unlike the sequential training architecture, the LVGP only requires one training to construct a single hypersurface that simultaneously accommodates all fidelity models and their correlations. This representation enables the direct conditioning of high-fidelity model predictions on all low-fidelity models, minimizing the dilution of information and uncertainty propagation.

By representing the multi-fidelity surrogate model in a single LVGP model, our proposed method effectively learns the correlations between fidelity levels without requiring prior knowledge of fidelity hierarchy and inherits the advantages of GP modeling in uncertainty quantification applications such as global fitting (GF) and Bayesian optimization (BO). In this work, we demonstrate the combination of multi-fidelity LVGP and the pre-posterior analysis to perform active learning by explicitly utilizing the correlations to guide the sampling strategy. Through numerical cases, we show that the proposed method outperforms the state-of-the-art multi-fidelity methods in both GF and BO. It provides a more powerful solution for multi-fidelity modeling, and shows great potential in active learning applications.