Function-on-Function Prediction via Deep Generative Models

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Abstract

Function-on-function prediction involves using one sequence to predict another sequence. It is a problem commonly seen in many scientific fields. Its model is trained on paired sequence data. However, sequences may have different lengths, observed at irregular spaces and at different locations. These irregularities make model training difficult to proceed. In this talk, we present a graph-based method for training deep generative models to tackle function-on-function prediction problems. This method addresses a common challenge in training data, where functional sequences are only partially observed at irregular locations. Under this method, a functional sequence is represented as a graph in which each node corresponds to a location–value pair, and each link is defined in terms of the distance between locations of two nodes. This formulation allows training data to have functional sequences with different lengths and observed at different locations. Simulation results show that deep generative models trained under our method outperform the ground-truth model when only incomplete observations are available. This work is joint with Chia-Tse Wang, Ming-Chung Chang, Su-Yun Huang, and Tailen Hsing.

Keywords: Denoising Diffusion Probabilistic Models; Functional data; Graph neural networks.