Enriching Non-Parametric Models for Practical Robot Policies

Name Shuyuan Wang

Laboratory's name Robot Learning Laboratory

Supervisor's name Takamitsu Matsubara

Abstract

Robotic control policies must handle complex tasks in dynamic environments, yet traditional parametric and non-parametric models face significant limitations. Semi-parametric models combine their strengths but often struggle with multimodality, local discontinuities, and low-probability behaviors. This work enhances semi-parametric models by advancing their non-parametric components with Bayesian techniques to improve adaptability, accuracy and efficiency. We propose two novel approaches: (1) Composite Gaussian Processes Flows (CGP-Flows), which integrate Overlapping Mixtures of Gaussian Processes (OMGPs) and Non-Gaussian Gaussian Processes (NGGPs) to model multimodality. These composite distributions are transformed using Conditional Continues Normalizing Flows (CCNFs) to handle smoothness and local discontinuities, achieving a balance between computational efficiency and expressiveness for non-linear tasks. (2) Model Select Gaussian Processes Flows (MSGP-Flows), which combine Robust Gaussian Processes (RGPs) and NFs to assign lower weights to low-probability modes in multimodal data. This approach reduces the impact of rare actions while retaining diverse expert strategies, improving learning efficiency.