A DISTRIBUTIONALLY ROBUST AND TASK-ADAPTIVE DATA-FREE META-LEARNING APPROACH

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Abstract

Data-Free Meta-Learning (DFML) has emerged as a promising paradigm for enabling few-shot adaptation without requiring access to original training datasets, leveraging only multiple pre-trained models. However, existing DFML approaches largely overlook robustness challenges arising in real-world deployments. Inspired by recent robustness analyses in distributional learning, this study proposes a trust-aware and distributionally robust DFML framework designed to address two critical vulnerabilities: (i) Task-Distribution Shift (TDS), which leads to catastrophic forgetting due to evolving synthetic task distributions, and (ii) Task-Distribution Corruption (TDC), where the inclusion of deceptive or low-quality pre-trained models undermines meta-learner generalization. To mitigate TDS, we introduce a task-memory interpolation mechanism that reconstructs and replays interpolated historical synthetic tasks, ensuring stable meta-knowledge retention across sequential task streams. To address TDC, we propose a trust-aware automatic model selection strategy that assigns adaptive trust weights to pre-trained models using reinforcement learning-based policy optimization. Synthetic task reconstruction is performed using generator-based model inversion with distribution alignment regularization to ensure high-fidelity data synthesis. Extensive evaluations on benchmark few-shot datasets demonstrate that the proposed framework significantly improves robustness, stability, and generalization performance compared to conventional DFML methods. The results confirm that integrating trust modeling, memory-aware interpolation, and distributionally robust optimization provides a reliable pathway toward secure and scalable data-free meta-learning systems suitable for real-world, privacy-constrained environments.