

COMPLEMENTARY SUBNETWORKS FOR PARAMETER-EFFICIENT CLASS-INCREMENTAL LEARNING

Author's: S. Sajitha Banu¹, G. Thilipkumar², K. Sujith³, N. Vanjulavalli⁴

Abstract

Class-Incremental Learning (CIL) aims to enable intelligent systems to continuously learn new classes over time without forgetting previously acquired knowledge. However, conventional deep neural networks suffer from catastrophic forgetting when trained sequentially on evolving tasks. Additionally, retraining or fine-tuning the entire network for each new class introduces substantial computational and memory overhead. To address these challenges, this work proposes a parameter-efficient Class-Incremental Learning framework based on Complementary Learning Subnetworks (CL-Subnets). The proposed approach integrates a frozen backbone feature extractor with lightweight adapter modules and complementary subnetworks that are trained incrementally. Instead of updating the entire model, the backbone parameters remain fixed to preserve previously learned representations, while compact adapter layers enable efficient adaptation to new tasks. The complementary learning mechanism consists of two parallel subnetworks that capture diverse and complementary feature transformations. A learnable gating module dynamically fuses their outputs, allowing the system to adaptively emphasize the most informative subnetwork during incremental updates. This structure enhances representational diversity and robustness without significantly increasing parameter count. To further mitigate catastrophic forgetting, a hybrid continual learning strategy is employed. A bounded replay buffer stores representative samples from earlier classes, enabling rehearsal during subsequent training sessions. In addition, knowledge distillation is applied to align the current model's predictions with those of a previously saved teacher model, preserving decision boundaries for old classes. A complementary diversity regularization term encourages the subnetworks to learn non-redundant feature mappings, promoting balanced knowledge retention and plasticity.