DEEP FEATURE UNSUPERVISED DOMAIN ADAPTATION FOR TIME-SERIES CLASSIFICATION

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Abstract

Time-series classification plays a critical role in numerous real-world applications such as healthcare monitoring, industrial fault diagnosis, financial forecasting, and IoT-based sensing systems. Deep learning models, particularly convolutional and recurrent architectures, have significantly improved classification performance by automatically learning hierarchical temporal representations from raw signals. However, a major limitation of conventional supervised learning approaches is their sensitivity to domain shift, where the statistical distribution of deployment (target) data differs from the training (source) data. This distribution mismatch often leads to substantial performance degradation when models are applied in new environments. Moreover, obtaining labeled data in the target domain is frequently expensive, time-consuming, or impractical.To address this challenge, this project proposes a Deep Feature Unsupervised Domain Adaptation (UDA) framework for time-series classification based on the Domain-Adversarial Neural Network (DANN) architecture. The proposed system leverages labeled source domain data and unlabeled target domain data to learn domain-invariant temporal representations through adversarial training. A shared 1D Convolutional Neural Network (CNN) serves as the feature extractor, while a label classifier predicts class labels using source supervision. Simultaneously, a domain discriminator, connected via a Gradient Reversal Layer (GRL), enforces feature alignment between source and target domains by minimizing domain distinguishability. This adversarial mechanism encourages the extraction of features that are both discriminative for classification and invariant across domains.