The paper you provided is titled "Self-Supervised Contrastive Pre-Training for Time Series via Time-Frequency Consistency" authored by Xiang Zhang, Ziyuan Zhao, Theodoros Tsiligkaridis, and Marinka Zitnik. It was presented at the 36th Conference on Neural Information Processing Systems (NeurIPS 2022).

Abstract:

The paper addresses the challenge of pre-training on time series data, considering the potential mismatch between pre-training and target domains. The authors propose a method called Time-Frequency Consistency (TF-C) for self-supervised pre-training on time series. The method aims to accommodate target domains with different temporal dynamics without seeing any target examples during pre-training. They introduce a decomposable pre-training model that utilizes time-based and frequency-based representations and applies contrastive estimation for training. The proposed method is evaluated on eight datasets in various domains, including electrodiagnostic testing, human activity recognition, mechanical fault detection, and physical status monitoring. The results demonstrate the effectiveness of TF-C in improving downstream performance compared to state-of-the-art methods.

Introduction:

The introduction highlights the importance of time series in various fields and the challenges associated with learning generalizable representations for temporal data. The authors emphasize the benefits of pre-training in time series analysis and the need for pre-training models that can effectively transfer knowledge to target datasets. They discuss the complexity of time series data, including variations in temporal dynamics, semantic meaning, sampling rates, and system factors, which can hinder knowledge transfer. The paper proposes the concept of Time-Frequency Consistency (TF-C) as a guiding principle for self-supervised pre-training in time series.

Methodology:

The proposed TF-C method leverages time-based and frequency-based representations of time series examples. The authors employ contrastive learning to generate time-based and frequency-based embeddings. The objective is to minimize the distance between the embeddings in the time-frequency space, ensuring consistency between the two domains. The self-supervised loss is used to optimize the pre-training model, which is then fine-tuned on target datasets.

Evaluation:

The TF-C model is evaluated on eight diverse time series datasets in one-to-one and one-to-many settings. The datasets cover different scenarios and signal types, such as EEG, EMG, ECG, acceleration, and vibration. The performance of TF-C is compared against eight state-of-the-art baselines. The results demonstrate significant improvements in terms of F1 score and precision, indicating the effectiveness of TF-C in achieving positive transfer and outperforming existing methods.

Related Work:

The authors discuss related work on self-supervised representation learning for time series and highlight the limited research on self-supervised pre-training specifically for time series data. They mention the challenges in applying pre-training models from computer vision and natural language processing to time series due to modality mismatch. The paper distinguishes TF-C as a novel approach designed to capture generalizable representations in time series pre-training.

Please note that the content of the paper beyond this point has been truncated and is not available.