# Advanced Machine Learning

Research Paper Assignment

# Progress Evaluation

Name - Ninduwara K.G.M.
Index - 210429K

## 1. Introduction

Time Series Classification (TSC) is a critical task in machine learning with wide-ranging applications, from medical diagnosis using EEG signals to financial forecasting and industrial sensor monitoring. Historically, methods like Dynamic Time Warping (DTW) have been effective but are often computationally intensive. The advent of deep learning has introduced powerful models like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) that can automatically learn hierarchical features from raw time series data.

However, the performance of these supervised models is heavily reliant on large, meticulously labeled datasets, which are often expensive or impractical to acquire. To address this limitation, self-supervised learning has emerged as a powerful paradigm. SSL methods learn meaningful data representations from unlabeled data, which can then be used for downstream tasks with much less labeled data.

A state-of-the-art SSL method in the time series domain is Temporal Neighborhood Coding (TNC). TNC utilizes a contrastive learning objective to learn robust representations by ensuring that embeddings from a signal's temporal neighborhood are closer to each other than to embeddings from other, dissimilar signals.

While TNC has proven effective for representation learning, its performance under data-scarce conditions, specifically in few-shot learning scenarios, remains an area ripe for exploration. In a few-shot setting, a model must learn to classify new categories given only a handful of examples. This project aims to bridge this gap by enhancing the TNC framework to improve its performance on few-shot time series classification tasks using the benchmark UEA Archive.

My primary objective is to develop and validate a targeted enhancement to the TNC model that makes it more effective and sample-efficient for few-shot TSC.

## 2. Literature Review

Unsupervised representation learning for time series has recently gained attention as a critical research area in machine learning. Unlike supervised learning, which requires large amounts of labeled data, unsupervised learning focuses on extracting meaningful patterns without labels. This is especially valuable in real-world applications such as healthcare, where obtaining high-quality annotations is costly or impractical. Time series data present unique challenges such as high dimensionality, non-stationarity, and variable lengths, making representation learning both difficult and important. The following section reviews the major categories of methods and key state-of-the-art contributions.

### 2.1 Autoencoder-Based Methods

Early research applied autoencoders and sequence-to-sequence models to time series. These models jointly train an encoder and decoder to reconstruct the input, forcing the encoder to capture compressed representations. Examples include *Choi et al. (2016)*, *Amiriparian et al. (2017), and Malhotra et al. (2017)*. Variational autoencoders (VAEs) were later introduced to encourage disentangled and interpretable features. However, direct reconstruction of complex signals proved challenging, leading to a shift toward methods that learn representations without reconstruction objectives.

### 2.2 Contrastive Learning Approaches

Contrastive learning has become a dominant self-supervised strategy. The key idea is to bring representations of similar samples (positives) closer, while pushing apart dissimilar ones (negatives). Although initially popular in computer vision, adapting contrastive frameworks to time series required careful treatment of temporal dependencies and augmentations.

Contrastive Predictive Coding (CPC) *(Oord et al., 2018*) introduced the idea of predicting future latent representations from past contexts. CPC works well on structured datasets like Human Activity Recognition but struggles with highly non-stationary signals.

Triplet Loss (T-Loss) (*Franceschi et al., 2019*) proposed a triplet-based sampling strategy tailored for time series, using causal dilated convolutions for variable-length inputs. While effective in simple settings, T-Loss often fails when states are generated from similar dynamics.

Temporal Neighborhood Coding (TNC) (*Tonekaboni et al., 2021*) addressed these issues directly. TNC defines temporal neighborhoods segments with locally stationary properties and employs a debiased contrastive loss inspired by Positive-Unlabeled learning. By treating non-neighboring samples as unlabeled rather than strictly negative, TNC reduces false negatives and learns smoother temporal embeddings. The encoder in TNC can be an RNN or CNN depending on the dataset. TNC demonstrated superior performance over CPC and T-Loss, particularly in medical applications where non-stationarity is common.

TS-TCC (*Eldele et al., 2021*) extended contrastive methods with a dual-module framework that combines temporal and contextual contrasting, often with a Transformer backbone. This model outperformed CPC and SimCLR, especially in few-label and transfer scenarios.

TS2Vec (*Yue et al., 2021*) pushed the field further by introducing hierarchical contrastive learning at multiple semantic levels (timestamp, instance). It demonstrated strong improvements across classification, forecasting, and anomaly detection, achieving state-of-the-art performance on both UEA and UCR benchmarks.

BTSF (*Yang & Hong, 2022*) incorporated both temporal and spectral features via bilinear fusion, arguing that spectral properties are often ignored in prior work. This approach improved performance across tasks and emphasized the value of frequency-domain information.

### 2.3 Architectures for Time Series Representation Learning

Different frameworks adopt different encoders. Recurrent Neural Networks (RNNs) are intuitive but suffer from vanishing gradients and limited parallelization. Dilated Convolutional Neural Networks (CNNs), used in T-Loss and TS2Vec, capture long-range dependencies more efficiently. Transformers have also been explored, such as in TS-TCC, but CNN backbones often remain more efficient for long time series.

### 2.4 Evaluation Metrics and Benchmarks

Representation learning methods are typically evaluated on downstream tasks,

- Classification - Accuracy and AUPRC on datasets like UCR and UEA archives.
- Clustering - Silhouette score and Davies-Bouldin index.
- Forecasting - Mean Squared Error (MSE) on benchmarks such as ETT and Weather.
- Anomaly Detection - Precision, Recall, and F1 score on datasets like Yahoo KPI and SWaT.

### 2.5 Few-Shot Learning in Time Series

Few-shot learning (FSL) is another critical direction, addressing scenarios where only a handful of labeled samples are available per class. FSL methods are typically grouped into,

- Metric-Based Learning, Prototypical Networks (*Snell et al., 2017*), which compute class prototypes and classify queries based on distance.
- Optimization-Based Learning, MAML, which adapts model parameters with a few gradient steps.
- Data Augmentation Approaches, which expand limited labeled data through transformations.

In time series, metric-based approaches are particularly attractive due to their simplicity and robustness under small data regimes.

### 2.6 Research Gap

Despite strong progress, most existing self-supervised time series models, including TNC, were not explicitly designed for few-shot classification. Their typical evaluation relies on training a linear classifier on top of frozen embeddings. While this works when ample labels are available, it becomes suboptimal under extreme data scarcity. There is a clear opportunity to integrate few-shot methods such as Prototypical Networks directly into frameworks like TNC. This combination would better exploit learned representations in low-label settings, providing a more sample-efficient solution to Time Series Classification (TSC).

The literature shows a clear evolution from reconstruction-based methods to advanced contrastive learning and hybrid approaches that incorporate temporal, contextual, and spectral information. Methods like TNC, TS2Vec, and BTSF represent the cutting edge of unsupervised time series representation learning. However, the integration of these powerful encoders with few-shot classification strategies remains underexplored. Addressing this gap forms the motivation for our project, which enhances TNC by replacing its standard linear classifier with a Prototypical Network head, aiming to improve performance in few-shot time series classification tasks.

## 3. Methodology

My approach is designed as an improvement to the existing TNC framework, with a special focus on few-shot classification. The process is divided into two phases:

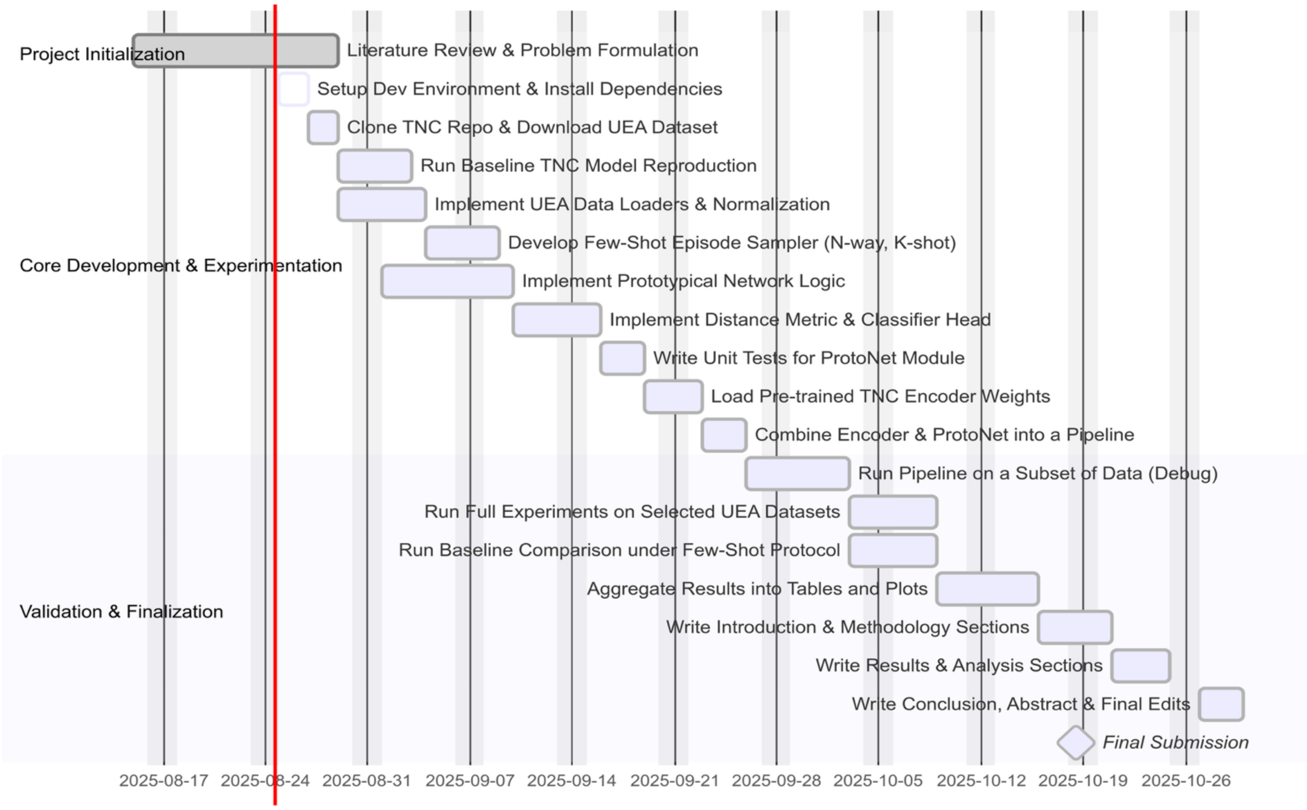
**Phase 1 - Self-Supervised Representation Learning (Pre-training)**

- **Baseline Replication:**
  I first implement the original TNC model using the official GitHub repository. This model is trained on large amounts of unlabeled time series data from the UEA Archive datasets.
- **Objective:**
  The model is trained using the same self-supervised contrastive objective as described in the TNC paper. In simple terms, the model learns to tell apart time segments that are close together (neighbors) from those that are far apart (non-neighbors).
- **Outcome:**
  After training, I obtain a powerful encoder that can transform any raw time series into a meaningful, compact representation. The weights of this encoder are kept fixed and used in the next phase.

**Phase 2 - Few-Shot Classification with Prototypical Networks (Fine-tuning)**

- **Why this change?**
  Instead of using a simple linear classifier (as done in the original TNC baseline), I use Prototypical Networks. This is a metric-based method that works very well for few-shot learning tasks, where only a small number of labeled examples are available.
- **Task Setup:**
  I evaluate the model using the standard N-way, K-shot format. For example, in a "5-way 1-shot" task, the model must classify a new sample into one of five possible classes, but it only gets one labeled example per class as guidance.
- **Prototype Creation:**
  For each class in the support set, the encoder creates an embedding (a compact representation). We then take the average of embeddings for each class, which acts as that class's "prototype" or representative point.
- **Classification:**
  When a new (unlabeled) query sample comes in, we encode it using the same encoder. We then compare its embedding to each class prototype and assign it to the class that is most similar (closest in distance).
- **Validation:**
  We test this approach on multiple UEA Archive datasets. We directly compare our method (TNC + Prototypical Head) against the baseline (TNC + Linear Classifier) under identical few-shot settings such as 5-way 1-shot and 5-way 5-shot. The main evaluation metric is average classification accuracy across many test episodes.

## 4. Project Timeline

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