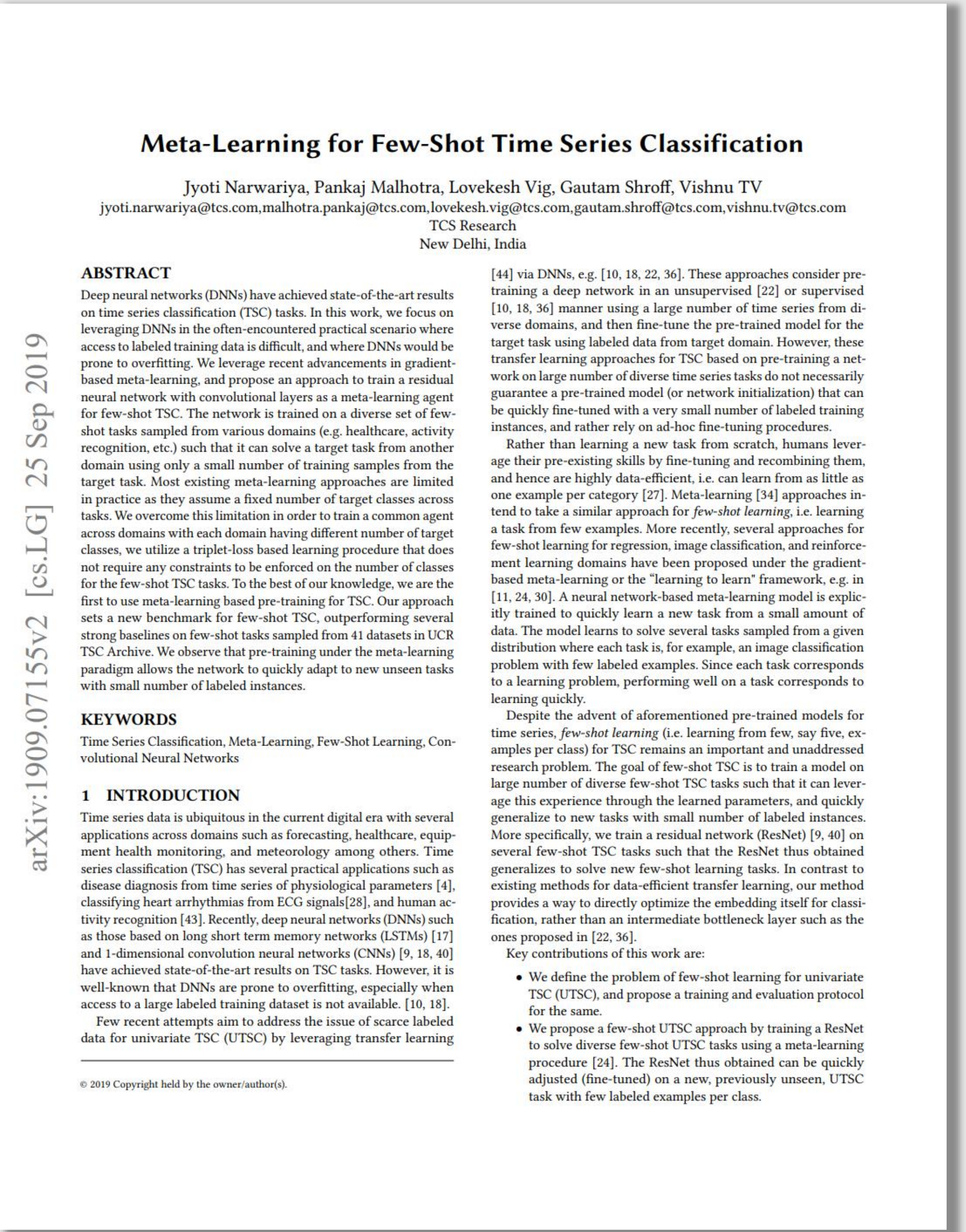
Meta-Learning for Few-Shot Time Series Classification

Presented by Erik Olsvik Dengerud



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ABSTRACT

Deep neural networks (DNNs) have achieved state-of-the-art results on time series classification (TSC) tasks. In this work, we focus on leveraging DNNs in the often-encountered practical scenario where access to labeled training data is difficult, and where DNNs would be prone to overfitting. We leverage recent advancements in gradient-based meta-learning, and propose an approach to train a residual neural network with convolutional layers as a meta-learning agent for few-shot TSC. The network is trained on a diverse set of few-shot tasks sampled from various domains (e.g. healthcare, activity recognition, etc.) such that it can solve a target task from another domain using only a small number of training samples from the target task. Most existing meta-learning approaches are limited in practice as they assume a fixed number of target classes across tasks. We overcome this limitation in order to train a common agent across domains with each domain having different number of target classes, we utilize a triplet-loss based learning procedure that does not require any constraints to be enforced on the number of classes for the few-shot TSC tasks. To the best of our knowledge, we are the first to use meta-learning based pre-training for TSC. Our approach sets a new benchmark for few-shot TSC, outperforming several strong baselines on few-shot tasks sampled from 41 datasets in UCR TSC Archive. We observe that pre-training under the meta-learning paradigm allows the network to quickly adapt to new unseen tasks with small number of labeled instances.

KEYWORDS

Time Series Classification, Meta-Learning, Few-Shot Learning, Convolutional Neural Networks

1 INTRODUCTION

Time series data is ubiquitous in the current digital era with several applications across domains such as forecasting, healthcare, equipment health monitoring, and meteorology among others. Time series classification (TSC) has several practical applications such as disease diagnosis from time series of physiological parameters [4], classifying heart arrhythmias from ECG signals[28], and human activity recognition [43]. Recently, deep neural networks (DNNs) such as those based on long short term memory networks (LSTMs) [17] and 1-dimensional convolution neural networks (CNNs) [9, 18, 40] have achieved state-of-the-art results on TSC tasks. However, it is well-known that DNNs are prone to overfitting, especially when access to a large labeled training dataset is not available. [10, 18].

Few recent attempts aim to address the issue of scarce labeled data for univariate TSC (UTSC) by leveraging transfer learning [44] via DNNs, e.g. [10, 18, 22, 36]. These approaches consider pre-training a deep network in an unsupervised [22] or supervised [10, 18, 36] manner using a large number of time series from diverse domains, and then fine-tune the pre-trained model for the target task using labeled data from target domain. However, these transfer learning approaches for TSC based on pre-training a network on large number of diverse time series tasks do not necessarily guarantee a pre-trained model (or network initialization) that can be quickly fine-tuned with a very small number of labeled training instances, and rather rely on ad-hoc fine-tuning procedures.

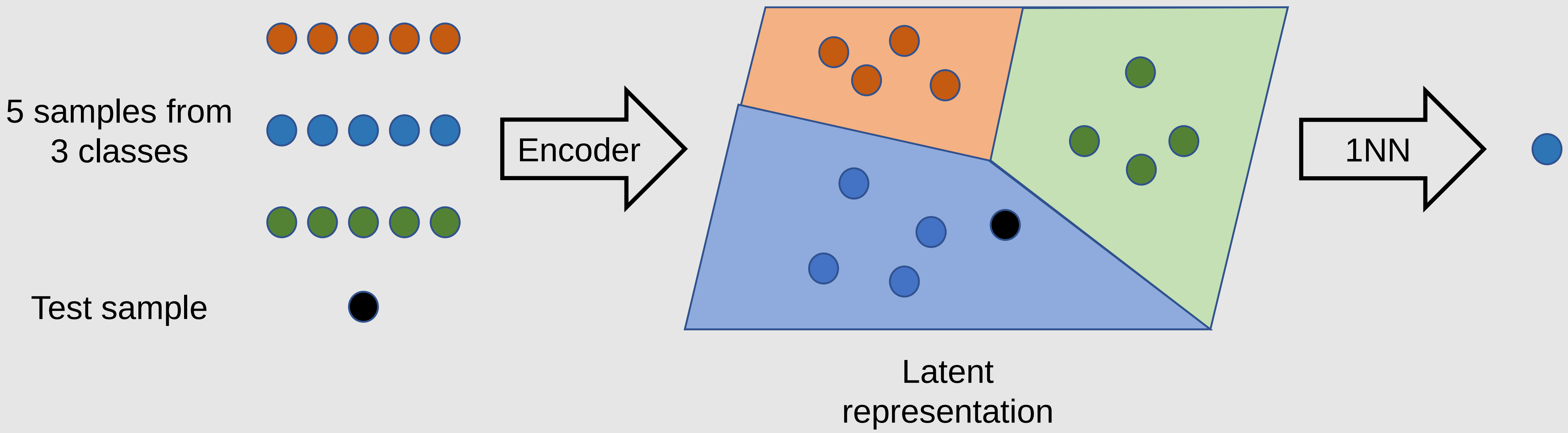
Rather than learning a new task from scratch, humans leverage their pre-existing skills by fine-tuning and recombining them, and hence are highly data-efficient, i.e. can learn from as little as one example per category [27]. Meta-learning [34] approaches intend to take a similar approach for *few-shot learning*, i.e. learning a task from few examples. More recently, several approaches for few-shot learning for regression, image classification, and reinforcement learning domains have been proposed under the gradient-based meta-learning or the "learning to learn" framework, e.g. in [11, 24, 30]. A neural network-based meta-learning model is explicitly trained to quickly learn a new task from a small amount of data. The model learns to solve several tasks sampled from a given distribution where each task is, for example, an image classification problem with few labeled examples. Since each task corresponds to a learning problem, performing well on a task corresponds to learning quickly.

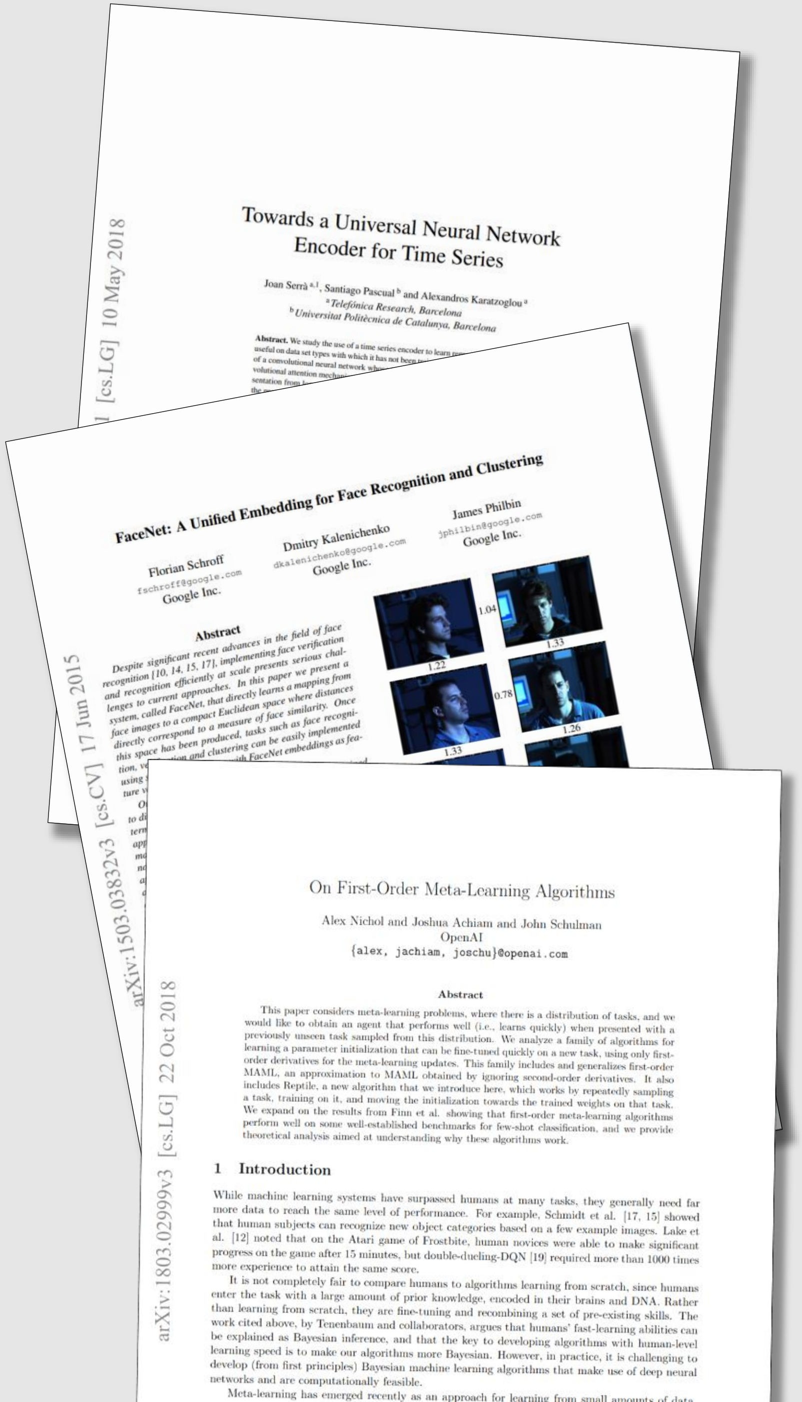
Despite the advent of aforementioned pre-trained models for time series, *few-shot learning* (i.e. learning from few, say five, examples per class) for TSC remains an important and unaddressed research problem. The goal of few-shot TSC is to train a model on large number of diverse few-shot TSC tasks such that it can leverage this experience through the learned parameters, and quickly generalize to new tasks with small number of labeled instances. More specifically, we train a residual network (ResNet) [9, 40] on several few-shot TSC tasks such that the ResNet thus obtained generalizes to solve new few-shot learning tasks. In contrast to existing methods for data-efficient transfer learning, our method provides a way to directly optimize the embedding itself for classification, rather than an intermediate bottleneck layer such as the ones proposed in [22, 36].

Key contributions of this work are:

- We define the problem of few-shot learning for univariate TSC (UTSC), and propose a training and evaluation protocol for the same.
- We propose a few-shot UTSC approach by training a ResNet to solve diverse few-shot UTSC tasks using a meta-learning procedure [24]. The ResNet thus obtained can be quickly adjusted (fine-tuned) on a new, previously unseen, UTSC task with few labeled examples per class.

The **goal** is to classify time series with **limited** access to **labeled** data





Towards a Universal Neural Network Encoder for Time Series (2018)

Pre-training: Training an encoder on many datasets.

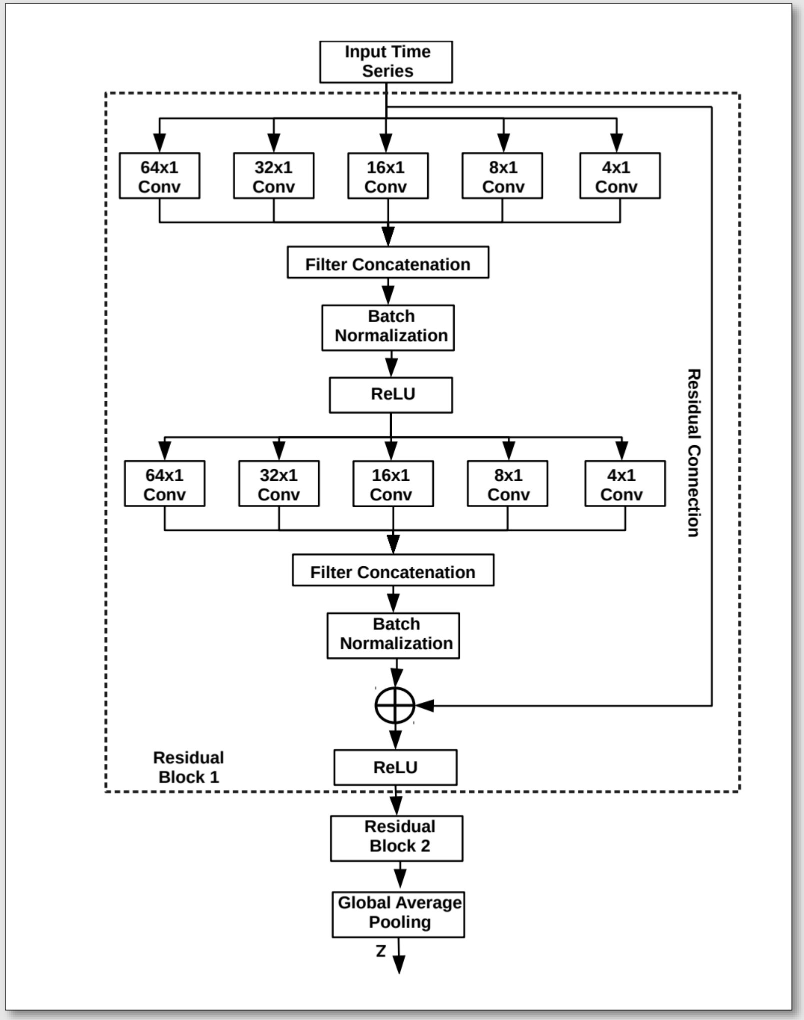
FaceNet (2015)

Triplet loss: Optimizing the latent embeddings directly.

On First-Order Meta-Learning Algorithms (2018)

Gradient descent based meta-learning: Learning to learn few shot tasks.

ResNet is a **successful** architecture for time series classification



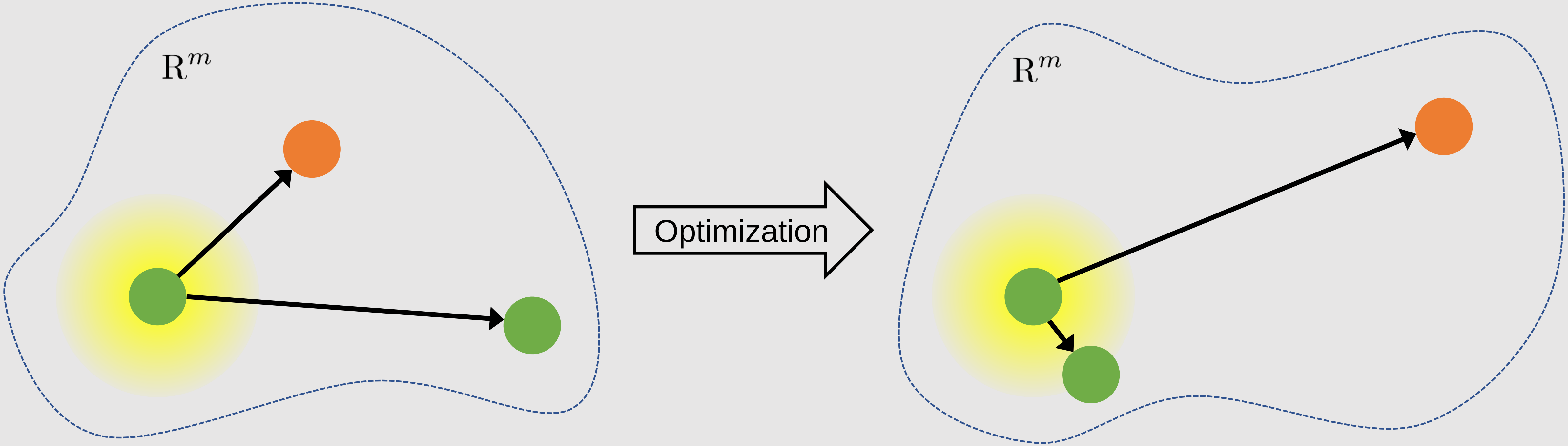
Time series classification from scratch with deep neural networks: A strong baseline (Wang, Z., Yan, W., & Oates, T. , 2017)

Towards a Universal Neural Network Encoder for Time Series (Serrà, J., Pascual, S., & Karatzoglou, A. , 2018).

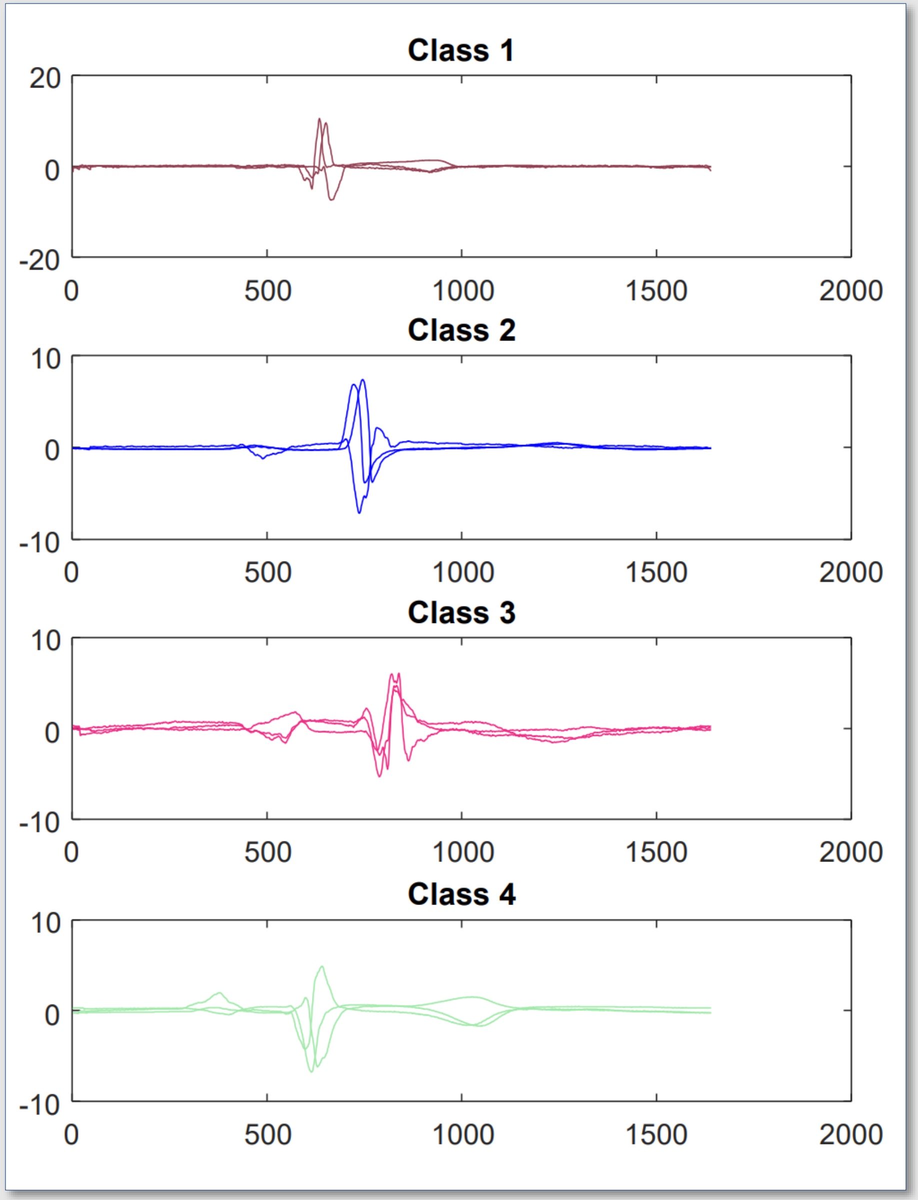
ConvTimeNet: A pre-trained deep convolutional neural network for time series classification (Kashiparekh, K., Narwariya, J., Malhotra, P., Vig, L., & Shroff, G. ,2019)

The triplet loss **optimize** the latent **embedding** directly

Triplets of one anchor, one of same class, and one of different class.



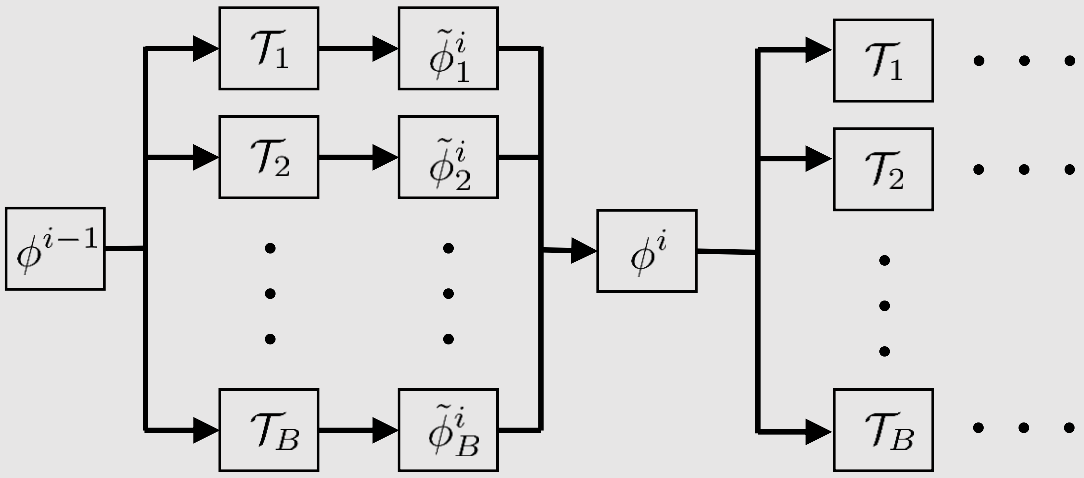
The UCR archive



Gradient descent based **meta-learning**

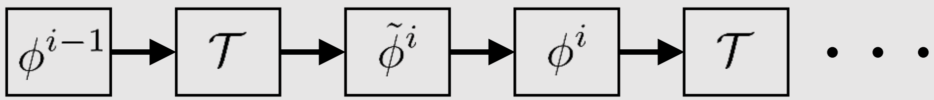
Optimization: $\tilde{\phi}^i_j = U^k_{\mathcal{T}_j}(\phi^i_j)$

Meta



Few-Shot-1
(FS-1)

Normal



Few-Shot-2
(FS-2)

Fine-tuning and inference on specific datasets

Fine-tuning

A new ResNet is initialized with the weights from pre-training.

Fine-tuning on the train split of the specific dataset.

Inference

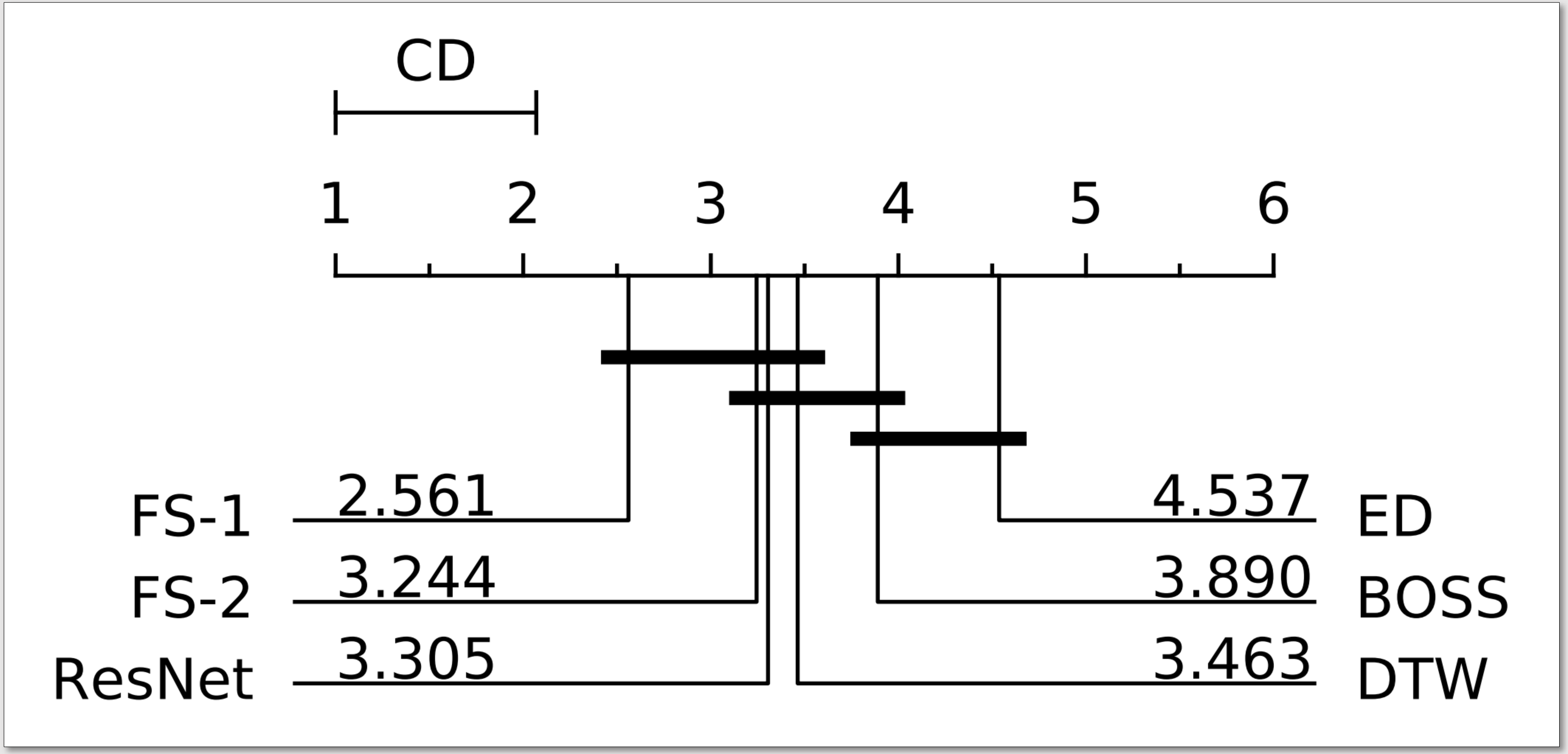
Encode the K time series from the train split of the dataset.

Use an 1NN classifier for each new embedded time series in the test split.

The method outperforms other typical representations

K	ED	DTW	BOSS	ResNet	FS-2	FS-1
2	4.232	<u>2.976</u>	3.902	3.805	3.207	**2.878**
5	4.537	3.463	3.890	3.305	<u>3.244</u>	**2.561**
10	4.573	3.476	3.646	3.683	<u>3.427</u>	**2.195**
20	4.439	3.354	<u>2.927</u>	3.902	3.793	**2.585**

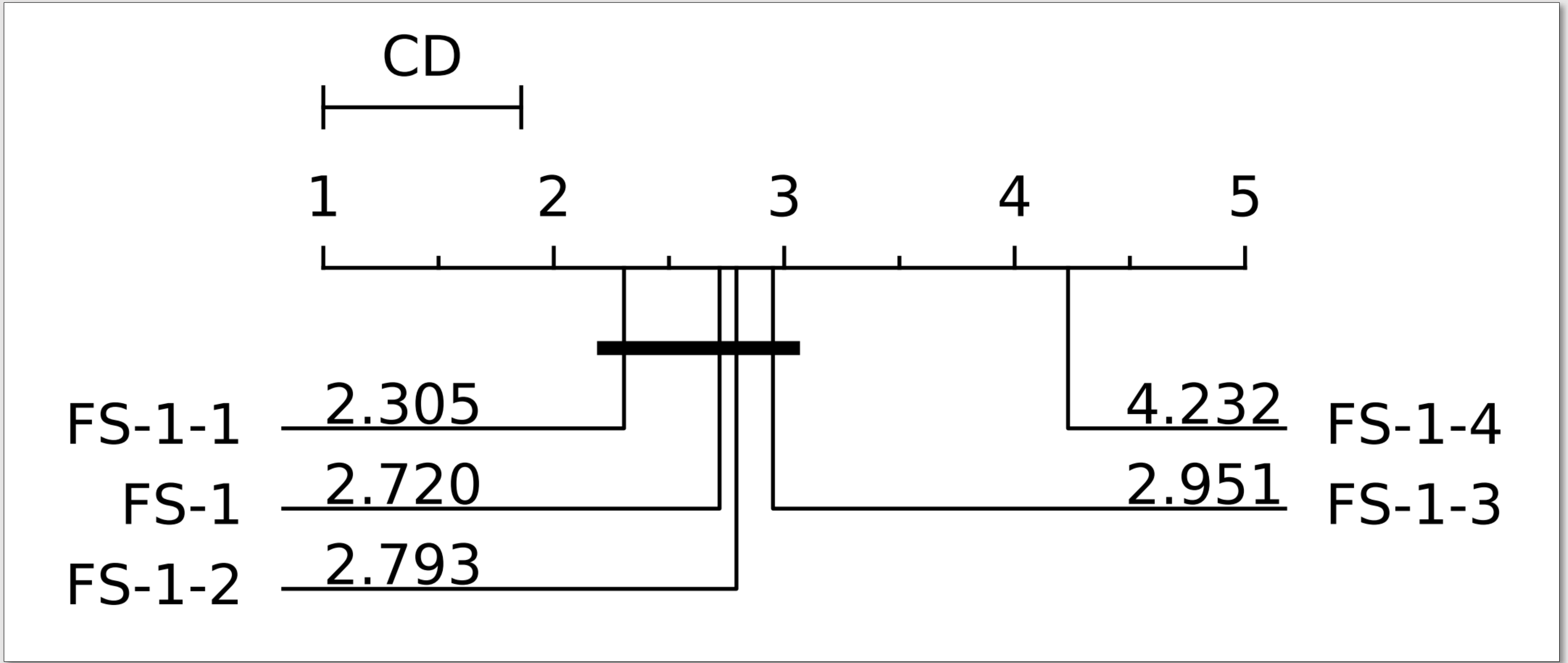
It is not significantly better than DTW



Performance is dependent on the **number** of classes

N	n	ED	DTW	BOSS	ResNet	FS-2	FS-1
2-5	24	4.167	4.083	3.375	3.458	<u>3.042</u>	**2.875**
6-10	9	4.778	**2.333**	5.333	<u>2.389</u>	3.778	<u>2.389</u>
>10	8	5.375	2.875	3.812	3.902	3.875	**1.812**
Overall	41	4.537	3.463	3.890	3.305	<u>3.244</u>	**2.561**

Freezing the first **layer** during fine tuning increase the performance



Important aspects of the paper

1. Triplet loss optimizes the latent embeddings directly and removes the need for a multi-head network.

2. Gradient descent based meta-learning learns to learn tasks and is different from “normal” learning.

3. Pre-training makes the network generalize better.