Contrastive self-supervised learning for climate spatio-temporal data

Alexander Marusov [1]

Abstract

The aim of the representation learning problem is to obtain *universal* and *high-quality* representations of the data. One of the ways to solve a such problem is to use Self-Supervised Learning (SSL). SSL is a fundamental paradigm originating from computer vision that now underlies numerous methods in different domains, including time series processing. In particular *contrastive-based methods* have become widespread because of their practical effectiveness and simple working idea — to make similar (*positive*) objects *closer* and distancing different (*negative*) ones. Such an approach naturally allows to prevent mode *complete collapse* when all representations of different objects are the same. Despite the wide usage of the self-supervised learning paradigm for different domains application of SSL for climate spatio-temporal data is scarce. We aim to fill this gap by proposing a new contrastive-based SSL approach for climate spatio-temporal data. The code is available in the Github. [1]

1. Introduction

Nowadays, more and more Deep Learning (DL) algorithms are being used to solve different kinds of tasks. Typically, it is about supervised DL methods, which rely on labelled data. However, many real applied objectives lack a sufficient amount of annotated data, resulting in poor quality of the supervised model. Self-supervised learning (SSL) methods show great potential to reduce this quality gap using a massive amount of unlabeled data available for many scenarios (Ericsson et al., 2022; Lin et al., 2023). The primary purpose of SSL methods is to obtain an encoder that produces *universal* representation (embedding) of an input signal that generalizes across various *downstream* tasks (Gálvez et al., 2023).

Generally, SSL approaches can be divided into generative and discriminative (Grill et al., 2020). The last one consists of contrastive and non-contrastive algorithms. Contrastive methods make *closer* representations of *similar* objects and *further* for *different* ones (Joshi & Mirzasoleiman, 2023). Such an approach naturally avoids the *complete collapse* problem, i.e., when representations of different objects are the same (Jing et al., 2022).

Many different algorithms such as SimCLR (Chen et al., 2020), MoCo (Chen et al., 2021), BYOL (Grill et al., 2020), Barlow Twins (Zbontar et al., 2021), VICReg (Bardes et al., 2021), DINO (Caron et al., 2021) were originally developed for **computer vision (CV)** domain. Moreover, current theoretical fundamental papers are also devoted to the SSL methods from the CV area (Balestriero & LeCun, 2022; Jing et al., 2022; Tian et al., 2021; Ji et al., 2023). Some of those methods were adapted to the time series domain. For example, BYOL (Marusov & Zaytsev, 2023; Niizumi et al., 2021) and Barlow Twins (Anton et al., 2023) provide quality representations for audio; a variant of the Triplet model (Romanenkova et al., 2022) shows promising results for the industrial sensors data analysis. However, a naive adaptation of those methods does not account for the peculiarities of dependent data.

Classic SSL approach for **time series** is Contrastive Predictive Coding (CPC) (Oord et al., 2018). CPC uses compressing and autoregressive techniques to create a low-dimensional embedding space and make predictions for several steps in the future. More recent TS2Vec (Yue et al., 2022) positions itself as a universal approach for any time series (Foumani et al., 2024). They use hierarchical contrastive loss to learn representations at different time scales. CoST (Woo et al., 2022) framework decomposes the original signal into season and trend components with a transition to the frequency domain.

Creating high-quality embeddings for spatio-temporal data—data that combines both spatial and temporal components—using self-supervised learning (SSL) is both challenging and essential. In particular climate data has its own peculiarities that should be accounted in SSL models. Available research efforts (Wang et al., 2022; 2023; Lee et al., 2024) present different approaches to handle climate spatio-temporal data. However most of those methods were straightforwardly adapted from computer vision domain thus being ineffective to process temporal dependency in the data.

[1] https://github.com/Astralex98/Contrastive-self-supervised-learning-for-climate-spatio-temporal-data

Novelty. Given the existing body of work, we aim to propose a new spatio-temporal SSL method that should properly handle both spatial and temporal correlation in the data. In particular we propose to generalize TS2Vec model from time series to spatio-temporal case. Since TS2Vec was originally developed for time series this method should properly handle *temporal correlations*. By applying different spatial augmentations that have already shown their effectiveness in (Wang et al., 2022) and using spatio-temporal encoder ConvLSTM (Shi et al., 2015) we handle *spatial correlations*.

2. Related work

2.1. Climate spatio-temporal SSL

Climate-related tasks require special attention among spatio-temporal problems because of their critical importance to human well-being. The authors (Wang et al., 2022) adapted SimCLR to classify weather systems in East China. To create a positive pair for each sample x_i within the randomly sampled batch, they take a sample t_i hours later than x_i from the original dataset. The gap t_i is taken from the distribution that monotonically decreases with time. After the sample is taken, spatial augmentations (like resizing, cropping, and Gaussian blur) are applied, resulting in a positive pair and treating all other samples as negatives. However, such an approach has several issues. Firstly, batches consist of random samples. Hence, there is a possible situation where many truly positive examples can be considered as negatives. Secondly, contrasting occurs in a mixed way, without separately dividing the penalties for each dependency among themselves. Another approach (Lee et al., 2024) is to apply generative modeling to reconstruct masked spatio-temporal data and test their representations for rainfall probability estimation downstream task. The authors (Wang et al., 2023) adapted different approaches from computer vision (MoCo, DINO, MAE) to a large corpus of the satellite imagery to solve standard computer vision downstream tasks — scene classification and semantic segmentation. However, those methods mostly concentrate on handling only spatial dependency rather then temporal one.

2.2. Benchmarks

According to our research we found the following benchmarks for spatio-temporal data:

Drought dataset. The first benchmark is from (Marusov et al., 2024). This dataset collects the recordings of the drought index (Palmer Drought Severity Index, PDSI (Alley, 1984)) for different regions from various climate zones — Madhya Pradesh (India), Missouri(USA), Northern Kazakhstan, and Goias (Brazil) considering a time span from 1958 to 2022 with a monthly resolution.

WeatherBench. The authors (Tan et al., 2023) proposed a benchmark for different spatio-temporal tasks including climate domain. For weather forecasting tasks researchers used *WeatherBench* dataset containing history of different climatic variables (temperature, precipitation and etc.). The researchers considered different spatial resolutions (32×64 and 128×256) and different setups — single variable (*WeatherBench-S*) and multi-variable (*WeatherBench-M*). For the first setup authors used data from 2010 to 2018 with one hour temporal resolution while for the second one time range encompassed time period from 1979 to 2015 with six hour resolution.

SSL4EO-S12. The authors (Wang et al., 2023) shared an unlabeled dataset **SSL4EO-S12** corpus of various satellite images from different sources including Sentinel-1, Sentinel-2. The overall size of the dataset is $251,079$ images. The downstream tasks are mostly related to computer vision - scene classification, semantic segmentation.

2.3. Research gap

According to our review, we see that most of SSL-approaches for climate data are more concentrated on spatial dependencies without proper handling of temporal dependency.

3. Experiments

3.1. Downstream problems

3.1.1. Drought prediction.

Problem importance. Among different climate-related problems, the drought prediction task is in particular demand these days since it is crucial in the global climate-changing context (Xiujia et al., 2022). Given the available history of the drought index for a particular region, our aim is to predict the spatial distribution of drought over the area up to twelve months ahead. This task belongs to long-term drought forecasting.

Drought Target variable. The most suitable drought indicator target for our task is the Palmer Drought Severity Index, PDSI (Alley, 1984). Indeed, (McPherson et al., 2022) use PDSI as a suitable drought index for long-term drought forecasting. Moreover, PDSI is freely available in Google Earth Engine (Gorelick et al., 2017). We consider a time span from 1958 to 2022 with a monthly resolution. To make the forecast more interpretable, the regression task (predicting drought index directly) transforms into a binary classification problem by dividing PDSI values into two classes: drought or its absence. In particular, the case is considered as a drought if the PDSI value is less than -2 aligning with (Marusov et al., 2024; McPherson et al., 2022).

Drought prediction model. The general formalized description of the model for drought prediction is the following:

- Input: PDSI's history for a particular region — 3D-tensor: time, longitude, and latitude.
- Output: Predicted drought probability distribution over the given area — a 2D tensor for a selected forecasting horizon.

To solve the target task using the SSL paradigm, we divide our model into two parts: a **SSL-pretrained encoder** and a **downstream classifier**. Using the contrastive SSL architecture described below, we pretrain the encoder. After SSL pretraining, we freeze the weights and provide feature representations of the input tensors for downstream problems. Then, a gradient boosting as the downstream classifier (Chen & Guestrin, 2016) solves a binary classification task based on representations from the encoder.

3.2. Model architecture

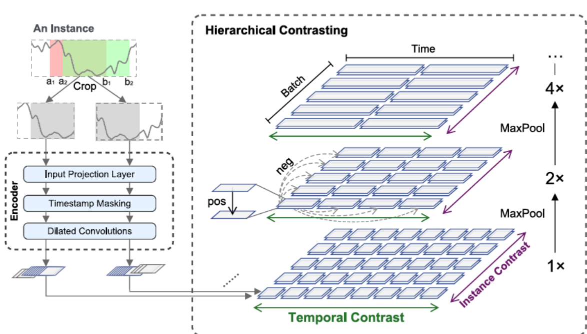

Figure 1: Original TS2Vec

The architecture of original TS2Vec is depicted in Figure 1. We generalized TS2Vec for the spatio-temporal case in the following way:

- **Augmentations.** We use standard spatial augmentations from computer vision following (Wang et al., 2022): Resizing (all regions reduce to one spatial size — 60×60), Gaussian blur, average pooling.
- **Encoder.** To account for both spatial and temporal dependencies, we use ConvLSTM architecture (Shi et al., 2015). The output dimension from ConvLSTM is $H \times W \times C_{cell}$ where H, W are spatial sizes of the region and C_{cell} is the embedding size of a single cell. We use one-dimensional convolutions and a fully connected layer to transform the tensor from $H \times W \times C_{cell}$ to $B \times T \times C$ dimension.

3.3. Implementation details

General setting. We mostly follow the training protocol from the original paper (Yue et al., 2022). The maximum number of epochs is 100. The training stops if, during ten consequent epochs, the loss function on the validation set doesn't decrease. Learning rate is 0.001 following TS2Vec.

Encoder. The hidden dimension and embedding size for each cell are set to 8. The embedding size of the region is 512. Kernel size is $(3, 3)$. The number of layers is 3.

Augmentations. The optimum resize shape for all regions is 60×60. The kernel size for Gaussian blur and average pooling is 5.

3.4. Results

Below you can find current intermediate results. In particular we vary only length of the history since its one of the crucial hyperparameters.

	ROC-AUC (first month)			
History	Madhya	Missouri	Kazakstan	Europe
10	0.59	0.74	0.65	0.62
20	0.63	0.76	0.7	0.56
30	0.61	0.75	0.67	0.54

Table 1: Selection of the optimal history length

4. Conclusions

TODO.

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