Impact of Negative Sample Scaling on Time-Series Forecasting Accuracy in Self-Supervised Contrastive Learning

Assignee Research

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Abstract

In recent years, the introduction of self-supervised contrastive learning (SSCL) has demonstrated remarkable improvements in representation learning across various domains, including natural language processing and computer vision. By leveraging the inherent benefits of self-supervision, SSCL enables the pre-training of representation models using vast amounts of unlabeled data. Despite these advances, there remains a significant gap in understanding the impact of different SSCL strategies on time series forecasting performance, as well as the specific benefits that SSCL can bring. This paper

1 Introduction

This paper examines: What Constitutes Good Contrastive Learning in Time-Series Forecasting?. Research question: What is the impact of scaling the number of negative samples in self-supervised contrastive learning on the downstream forecasting accuracy of time-series models evaluated on the Monash University Time Series Repository?.

2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.7/10.

3 Results

9 papers retrieved. 14 claims extracted; 12 independently verified. Quality review score: 7.7/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The ETT datasets consist of data from six power load features and measurements of oil temperature.	✓	0.23
The ECL dataset contains the electricity consumption of 312 clients.	✓	0.16
The ECL dataset was converted into hourly-level measurements, following previous work (Yue et al., 2022).	✓	0.28
MSE is used as the main evaluation metric, while MAE results are also reported.	×	0.12
The overall performance of each model is represented by averaging the MSE across all prediction lengths and the three da	×	0.14
The LSTM-based encoder includes five uni-directional LSTM layers with a hidden dimension of 320 in each layer, totaling	✓	0.33
The TCN-based encoder consists of 10 dilated convolution layers with a hidden dimension of 320 and a kernel size of 3 pe	✓	0.35
The Transformer-based encoder contains 5 Informer layers with a hidden size of 128 and 8 attention heads, totaling 655K	✓	0.30
All three models use a linear layer as the first embedding layer to map the input features into hidden dimensions.	✓	0.23
All models are trained with a peak learning rate of 0.001 and use a cosine learning rate scheduler for MoCo2-framework m	✓	0.22
Each model trains for 30 epochs with early stopping based on the Dev performance to prevent overfitting.	✓	0.25
For two-step learning, the encoder is trained on the training set with SSCL for 600 training iterations.	✓	0.21
When fine-tuning a pre-trained encoder, the same training hyper-parameters as in end-to-end training are used.	✓	0.19
The LSTM, TCN, and Informer architectures are evaluated for their effectiveness in exploiting SSCL in time series foreca	✓	0.15

References

- http://arxiv.org/abs/2112.13755v1
- http://arxiv.org/abs/2311.11335v1
- http://arxiv.org/abs/2306.12086v2