Self-supervised contrastive learning for chaotic time-series classification

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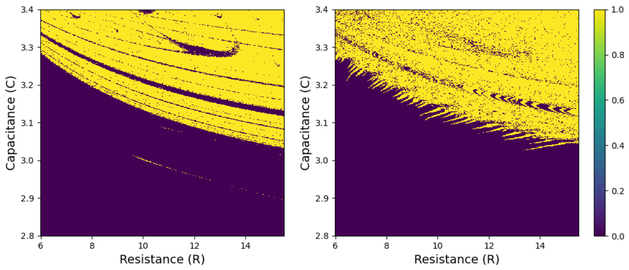
Abstract. We apply a self-supervised contrastive learning approach to reconstruct a two-parameter bifurcation diagrams of the chaotic nonlinear dynamical systems. By using only 1% of the dataset labels we can reconstruct the diagrams with the accuracy of about 92%. Furthermore, the method does not require a prior knowledge of the system or the labeling of the whole nonlinear time-series dataset, which makes it as useful as other statistical methods, for example, the surrogate data ones, 0-1 test for chaos, and others. We use the transformed Temporal and Contextual Contrasting (TS-TCC) framework and apply the residual components and scaling as our data augmentation techniques to train the TS-TCC framework. We test our approach against the regular TS-TCC model and the supervised approach, obtaining very promising results.

Introduction

It is often crucial to compute bifurcation diagrams in order to assess the stability and effects of multiple parameters on the overall dynamical properties of nonlinear systems. The case of one-parameter bifurcation diagrams is fairly easy to deal with, but it is more difficult (due to computational requirements) to do so when two or more parameters change at once. Many studies have been published in recent years suggesting employing various machine learning techniques to handle such multi-parameter cases, for example, the Extreme Learning Machines, Time Series Forests with Entropy, LKCNN and LSTM networks, and others. Although those models perform well on the training datasets, they have two major drawbacks: firstly, they need a large amount of labeled data and, secondly, they tend to overfit while tested on the new datasets as shown in [1, 2]. These drawbacks lead us to **the main objective of this work**, which is improving the generalization abilities of the machine learning models in order to make them applicable in the real problems with decreased amount of the labeled data needed to achieve satisfactory results. We achieved that by applying the Temporal and Contextual Contrasting (TS-TCC) framework [3], using the residual components, and scaling as the data augmentation techniques to train the TS-TCC framework.



1% of labeled data						
	dataset $L=1$		dataset $L=1.1$		dataset $L=2$	
Baseline	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score
Random Initialization	61.82	10.08	79.27	75.73	67.45	0.00
Supervised	81.52	72.17	87.26	87.63	68.17	5.37
TS-TCC	81.66	72.00	88.52	87.58	85.56	74.57
TS-TCC Residual	**91.66**	**89.61**	**89.30**	**88.65**	**90.65**	**85.25**
5% of labeled data						
	dataset $L=1$		dataset $L=1.1$		dataset $L=2$	
Baseline	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score
Random Initialization	63.85	19.25	77.95	73.47	67.45	0.00
Supervised	94.69	93.22	94.39	94.18	**94.67**	**91.57**
TS-TCC	89.25	84.66	90.74	89.65	90.48	84.49
TS-TCC Residual	**95.52**	**94.35**	**94.59**	**94.50**	93.86	90.49

Figure 1: From left: two-parameter bifurcation diagram generated using the method (similar to Poincaré section) described in [4]; reconstructed two-parameter bifurcation diagram with the TS-TCC Residual Framework using 1% of labeled data; tables with the results, using 1% and 5% of labeled data for three sets of $R \times C \times L$ parameters: (a) $(6, 15.5) \times (2.8, 3.4) \times 1$, (b) $(6, 15.5) \times (2.8, 3.4) \times 1.1$, and (c) $(20, 29.5) \times (2.2, 2.8) \times 2$. The best results are in bold, and the second best are underlined.

Results and discussion

The results of the TS-TCC and TS-TCC Residual frameworks are presented in Figure 1. We obtained very high-performance metrics for both TS-TCC networks trained on only 1% and 5% of labeled data for all three sets of parameters. The TS-TCC Residual achieved around $89-91\%$ accuracy trained on 1% of labeled data, while the TS-TCC achieved accuracy between $81-88\%$. The results clearly show that training the TS-TCC framework on residual components for the nonlinear chaotic arc RLC circuit is much more stable and less impacted by the parameter changes. Similar conclusions can be made for the training on 5% of labeled data. The reconstructed diagram shown in Figure 1 gives fairly good approximation of the original diagram. We conclude that (1) the TS-TCC framework trained on the residual components of the considered signals achieves better accuracy than the original TS-TCC framework; (2) taking only a handful of labeled data, the self-supervised methods perform very well and are more useful than the supervised machine learning methods for oscillatory time-series classification; (3) by improving the accuracy of the TS-TCC framework, we can obtain the general method for multi-parameter bifurcation diagrams generation, that can compete with the currently used statistical methods.

References

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