Towards Similarity-Aware Time-Series Classification

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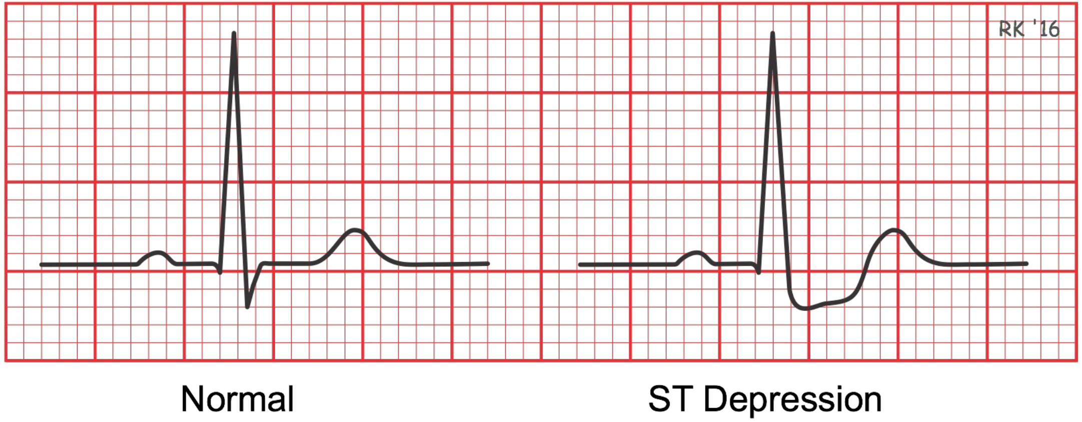
Time-Series Classification (TSC) Problem

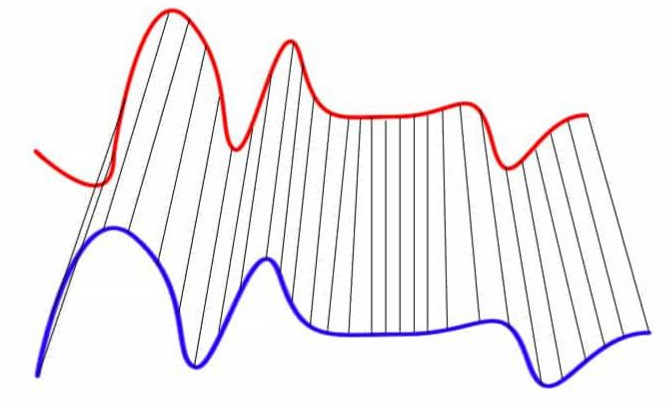
- **Problem setting**
  - Given a collection of time-series with the attached labels, TSC aims to train a classifier to classify unseen time-series.
- **Main challenge**
  - How to model and incorporate the temporal information in the classification?



Source: https://www.cvphysiology.com/uploads/images/CAD012%20ECG%20ST%20depression.png

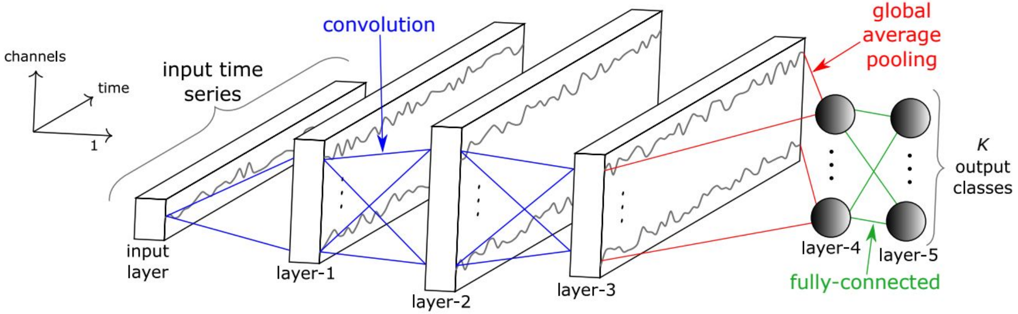
Existing Solutions

- **Existing studies approach TSC in two major directions**
  - **Similarity-based:** Combine a k-NN classifier with a similarity measure for classification.
  - **Deep learning:** Perform end-to-end training on the raw time-series and learn the representations to do classification.



Dynamic Time Warping Matching

Source: https://commons.wikimedia.org/wiki/File:Euclidean_vs_DTW.jpg

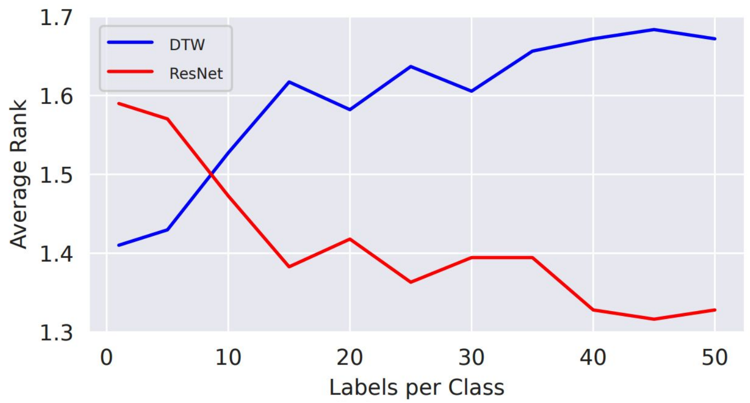


ResNet with 1-D convolution

Source: https://arxiv.org/pdf/1809.04356.pdf

Motivation

- **Preliminary experiments**
  - We compare **DTW** (a representative similarity-based method) and **ResNet** (a representative deep learning approach) on **the full 128 UCR datasets**. We report the average ranks. The lower the better.



Average ranks of ResNet and DTW on the full 128 UCR datasets, where different numbers of labels per class is given.

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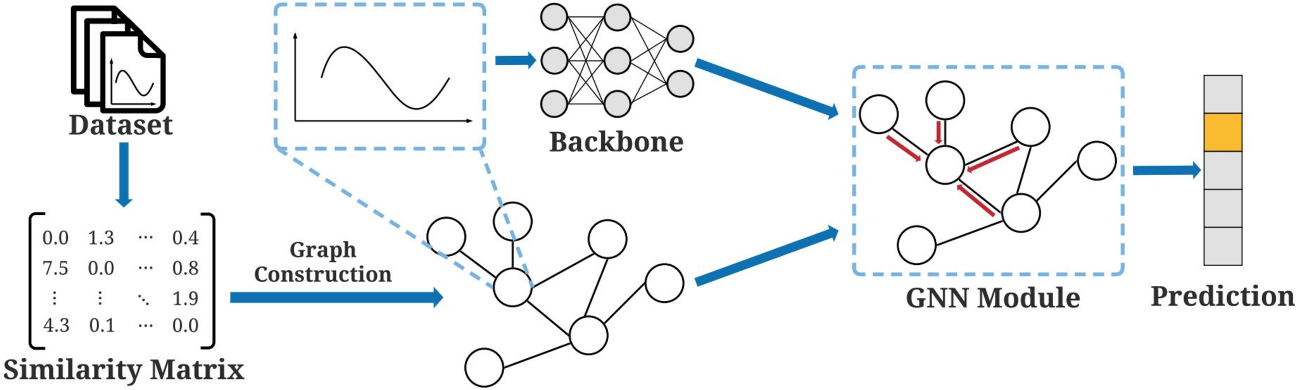
Research Question and Challenges

- **Our research question**
  - Can we connect the two research lines in such a way as to jointly model time-series similarities and learn the representations?

- **Challenges**
  - How can we incorporate similarity information into representation learning?
  - Even though we can enable similarity in deep learning models, how can we balance similarity information and the original representation learning?

SimTSC Framework

- **Our simple yet effective solution**
  - We propose Similarity-Aware Time-Series Classification (SimTSC) framework based on Graph Neural Networks.
  - Time-series -> node
  - Similarity of time-series -> edge
  - TSC -> node classification



Each time-series is first processed by a backbone, and enhanced by GNN with aggregation.

Our Instantiation

- **Backbone**
  - We use **ResNet** as the backbone since it has strong performance.
- **Similarity Measure**
  - We use **DTW** as the the similarity measure because it is the most popular one.
- **Graph Neural Networks**
  - We use **Graph Convolutional Networks (GCN)** because it is the most basic one.
  - We only use 1-layer GCN. We find that it delivers the best performance.
- **Other Tricks**
  - We use **negative sampling** to sample a half batch of labeled time-series and a half batch of unlabeled time-series.

Results on Univariate Time-Series

- **Experimental Setting**
  - We compare SimTSC with the existing **similarity-based** and **deep learning** methods on the **full 128 UCR datasets**. We report average rank and Wilcoxon signed rank test ($p < 0.05$) for the significance test.

	Algorithm \ Labels	1	5	10	15	20	25	30	35	40	45	50
Similarity-based	DTW	3.776	4.163	4.465▲▽	4.738▲▽	4.824†▲▽	5.048†▲▽	4.965†▲▽	5.160†▲▽	5.309†▲▽	5.199†▲▽	5.211†▲▽
Deep Learning	MLP	5.504†▲▽	5.496†▲▽	5.438†▲▽	5.309†▲▽	5.316†▲▽	5.256†▲▽	5.367†▲▽	5.477†▲▽	5.195†▲▽	5.402†▲▽	5.348†▲▽
	FCN	4.630▲▽	4.310	4.383▲▽	4.508▲▽	4.723†▲▽	4.803†▲▽	4.699†▲▽	4.910†▲▽	4.773†▲▽	4.883†▲▽	4.852†▲▽
	ResNet	4.846†▲▽	4.857†▲▽	4.617†▲▽	4.047	4.449▲▽	4.039	4.102	4.090	4.086	3.840	3.895
	InceptionTime	5.484†▲▽	5.302†▲▽	5.438†▲▽	5.434†▲▽	5.215†▲▽	5.145†▲▽	5.168†▲▽	4.914†▲▽	4.941†▲▽	5.066†▲▽	5.039†▲▽
Ours	SimTSC-S	4.224▲	4.278▲▽	4.074	4.277▲▽	4.141▲▽	4.044▽	4.148▲	3.988	3.887	3.918	4.047
	SimTSC-I	**3.724**	3.817	3.793	**3.836**	3.746	4.031▲▽	**3.762**	3.734	**3.852**	3.867	**3.797**
	SimTSC-T	3.811	**3.778**	**3.781**	3.852	**3.586**	**3.632**	3.789	**3.727**	3.957	**3.824**	3.812

Results on Multivariate Time-Series

- **Experimental Setting**
  - We conduct experiments on 4 multivariate time-series classification tasks, including **Character Trajectories**, **ECG**, **KickVsPunch**, and **NetFlow**.

Similarity-based

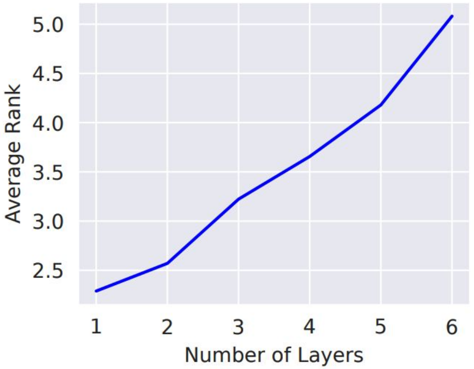
Deep Learning

Ours

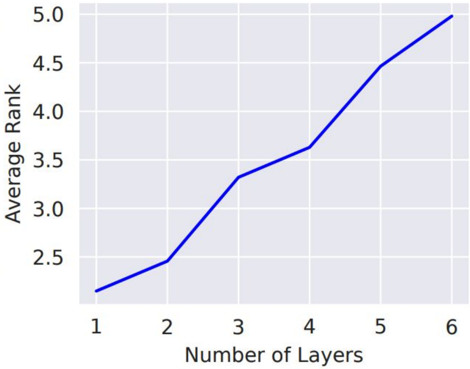
Dataset	Labels / Algorithm	5	10	15	20	25	30	35	40	45	50
Character Trajectories	DTW	.847±.014	.881±.005	.895±.009	.900±.014	.908±.014	.907±.013	.906±.010	.906±.007	.909±.010	.913±.008
	ResNet	.834±.024	.898±.017	.920±.010	.937±.010	.939±.008	.941±.009	.949±.008	.956±.011	.958±.007	.958±.007
	InceptionTime	.883±.010	.939±.007	.947±.006	**.968±.006**	.964±.003	.974±.005	.979±.003	.978±.005	.979±.001	**.986±.003**
	TapNet	-	-	-	-	-	-	-	-	-	-
	SimTSC-S	.894±.020	.939±.009	.949±.007	.947±.017	.964±.011	.975±.003	.977±.011	.975±.004	.981±.007	.982±.005
	SimTSC-I	**.914±.012**	.944±.009	.951±.015	.953±.012	**.969±.011**	**.978±.006**	**.981±.007**	.979±.005	.977±.008	.980±.003
	SimTSC-T	.903±.014	**.946±.005**	**.957±.011**	.964±.009	.967±.012	.973±.009	.976±.009	**.981±.006**	**.983±.008**	**.986±.004**
ECG	DTW	.605±.124	.670±.086	.740±.112	.755±.103	.805±.043	.825±.050	.805±.053	.800±.057	.805±.053	.800±.057
	ResNet	.745±.048	.795±.037	.805±.058	.800±.079	**.860±.030**	**.855±.048**	.850±.052	**.855±.029**	.830±.037	**.870±.029**
	InceptionTime	.750±.045	.805±.033	.785±.020	.800±.037	.820±.037	.830±.043	.825±.016	.850±.027	**.855±.0010**	.850±.016
	TapNet	.770±.043	.780±.012	.755±.025	.795±.048	.810±.037	.795±.029	.785±.025	.815±.037	.830±.019	.845±.024
	SimTSC-S	.795±.043	.810±.020	**.855±.040**	**.840±.051**	.830±.056	.840±.020	**.860±.041**	.825±.047	.830±.071	.860±.025
	SimTSC-I	.790±.062	.765±.072	.830±.070	.730±.159	.740±.087	.800±.091	.830±.048	.750±.052	.790±.108	.735±.108
	SimTSC-T	**.810±.041**	**.815±.046**	.770±.108	.815±.115	.730±.118	.745±.075	.745±.099	.780±.051	.775±.071	.710±.101
KickvsPunch	DTW	.433±.082	.433±.082	.433±.082	-	-	-	-	-	-	-
	ResNet	.667±.183	**.833±.149**	.833±.183	-	-	-	-	-	-	-
	InceptionTime	.667±.000	.533±.125	.567±.226	-	-	-	-	-	-	-
	TapNet	.700±.125	.767±.082	.733±.013	-	-	-	-	-	-	-
	SimTSC-S	**.733±.200**	.767±.133	**.867±.125**	-	-	-	-	-	-	-
	SimTSC-I	.700±.125	**.833±.105**	.800±.125	-	-	-	-	-	-	-
	SimTSC-T	.600±.133	.767±.133	.767±.082	-	-	-	-	-	-	-
NetFlow	DTW	.611±.016	.559±.128	.607±.132	.595±.118	.546±.103	.568±.125	.523±.154	.481±.203	.503±.217	.504±.214
	ResNet	.613±.074	.714±.063	.749±.022	.763±.038	.739±.058	.767±.050	.769±.054	.767±.049	.787±.026	.797±.039
	InceptionTime	.418±.052	.456±.046	.484±.058	.618±.049	.642±.036	.657±.024	.678±.014	.675±.036	.681±.018	.681±.015
	TapNet	-	-	-	-	-	-	-	-	-	-
	SimTSC-S	.519±.108	.720±.071	.705±.055	.709±.089	.738±.082	.786±.036	.765±.091	.790±.045	.784±.063	.799±.047
	SimTSC-I	.766±.043	.788±.036	.689±.139	**.776±.042**	.731±.084	.755±.104	**.834±.037**	.798±.066	.810±.065	.839±.035
	SimTSC-T	**.769±.052**	**.805±.035**	**.785±.101**	.766±.095	**.745±.092**	**.825±.029**	.801±.065	**.827±.059**	**.847±.023**	**.852±.028**

Impact of the Number of GCN Layers

- **Experimental Setting**
  - We vary the number of GCN layers when we have 10 or 20 labels



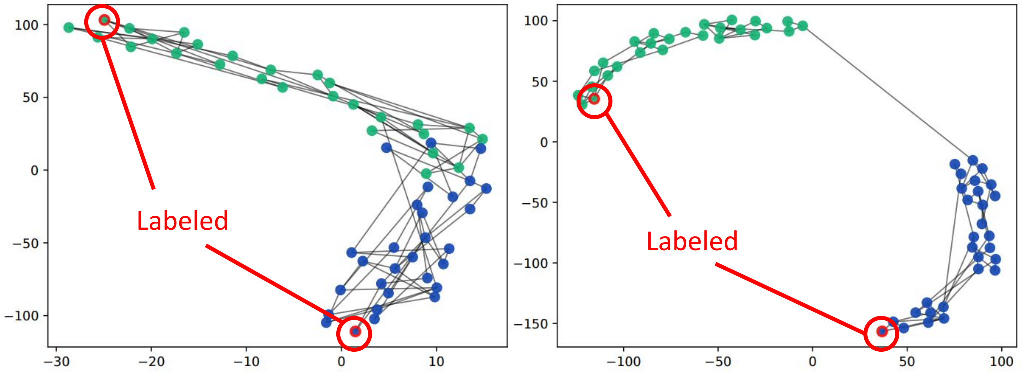
10 Labels



20 Labels

- **Observation**
  - One GCN layer achieves the best performance.
  - Possibly because the graph is dense and more layers lead to over-smoothing.

Visualization



(a) ResNet (83% accuracy) (b) SimTSC (100% accuracy)

Learned representations of ResNet and SimTSC on Coffee with 56 time-series. The two classes are marked in blue and green. Only one time-series is labeled.

Summary and Q & A

- **Takeaways**
  - SimTSC is a conceptually simple yet effective framework to join the research efforts of similarity-based and deep learning methods for time-series classification.
  - We demonstrated the effectiveness of graph neural networks in time-series classification.
- **Future Work**
  - Larger dataset, sparse graph, other tasks in time-series.
  - Differentiable similarity learning.
- **Acknowledgement**

  - This work is supported by National Science Foundation (NSF).

Paper   Code