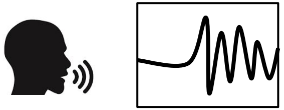
Paper ID 154

ICML | 2021
Thirty-eighth International Conference on Machine Learning

Voice2Series: Reprogramming Acoustic Models for Time Series Classification



International Conference on Machine Learning (ICML), July, 2021

Huck Yang
Georgia Institute of Technology, USA

Team

Huck Yang
Georgia Tech

Yun-Yun Tsai
Columbia

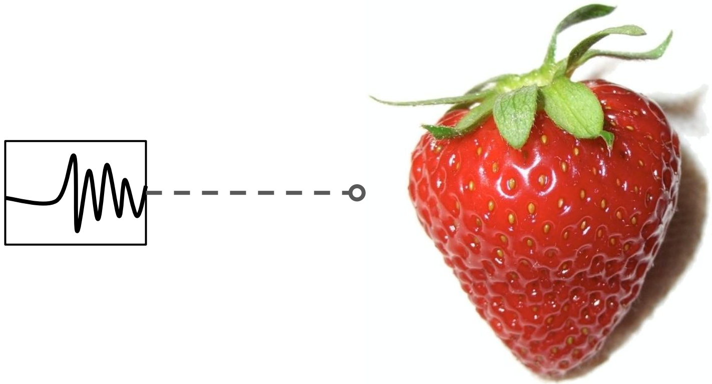
Pin-Yu Chen
IBM Research

Feel free to contact us for collaboration. (huckiyang@gatech.edu)

Challenges of Applying Deep Learning for Time Series

Time Series Samples are Shallow and often **Insufficient**

“Strawberry” Dataset (e.g., Spectrum)



(Holland et al., 1998) and Image Source: UCR Archive

From “Speech” Model to “Time Series” Model?

Speech Corpora and Acoustic Models

- Large-Scale Training Data (>100k Samples)
- Power of Deep Representation Learning
- Domain Difference (e.g., Phonetic Information)

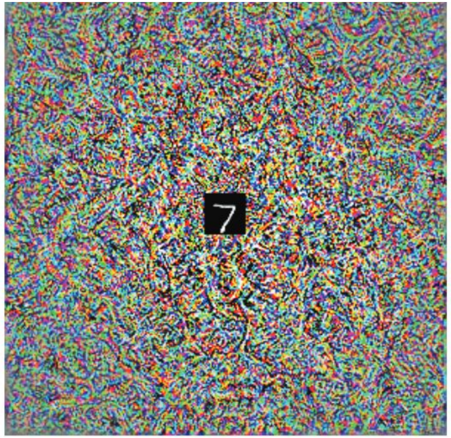
Some Efforts in Transfer Learning for Time Series Classification

- Pretrained on Different Time Series Model [D1, D2]

What is Model (Adversarial) Reprogramming?

Reprogramming works for Image to Image Classification (*Elsayed et al. 2018*)

- Training Weights (Perturbation) and Freeze a Pretrained Model



→ Inception V3 ImageNet model → “Seven”

Reprogramming for a MNIST Classifier

Our Contributions in this Work

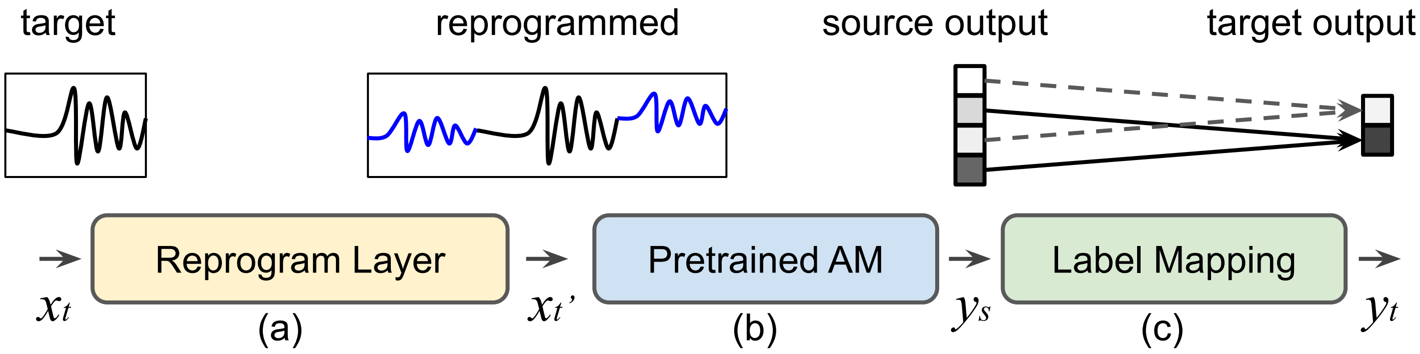
1. We propose **Voice-to-Series (*V2S*)**. To the best of our knowledge, V2S services as the **first** method that enables reprogramming for time series tasks.

2. Tested on a standard UCR time series classification benchmark with 30 different univariate tasks, ***V2S*** outperforms or is tied with the best reported results on 20 datasets and improves their average accuracy by **1.84%.**

3. We develop a **theoretical risk analysis,** which can be used to assess the performance of reprogramming.

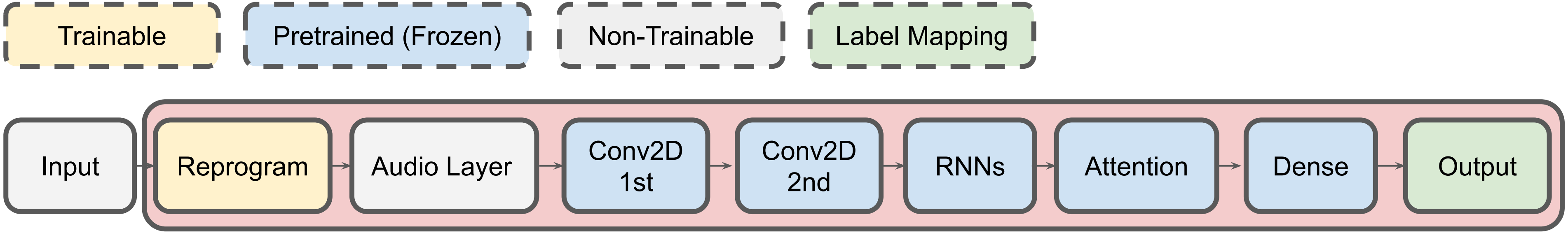
I. Introduce Voice-to-Series (V2S)

- Schematic illustration of the proposed Voice-to-Series

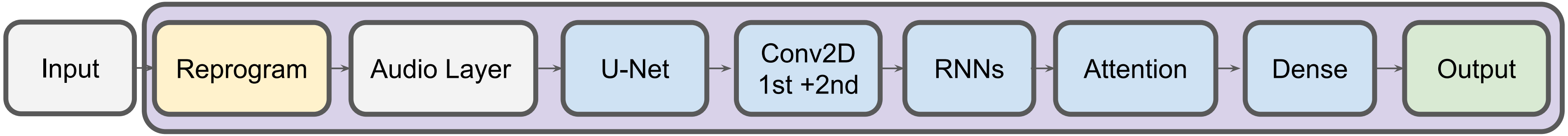


I. Voice-to-Series (V2S) Design

- Schematic illustration of the proposed Voice-to-Series



(a) Voice-to-Series with Transformer-based Attention (V2Sa)



(b) Voice-to-Series with U-Net Transformer-based Attention (V2Su)

Open Source Implemented Layer and Code: https://github.com/huckiyang/Voice2Series-Reprogramming

I. Voice-to-Series (V2S) Performance on UCR Archive

Table 2. Performance comparison of test accuracy (%) on 30 UCR time series classification datasets (Dau et al., 2019). Our proposed V2S$_a$ outperforms or ties with the current SOTA results (discussed in Section 5.3) on 20 out of 30 datasets.

Dataset	Type	Input size	Train. Data	Class	SOTA	V2S$_a$	V2S$_u$	TF$_a$
Coffee	SPECTRO	286	28	2	**100**	**100**	**100**	53.57
DistalPhalanxTW	IMAGE	80	400	6	**79.28**	79.14	75.34	70.21
ECG 200	ECG	96	100	2	90.9	**100**	**100**	**100**
ECG 5000	ECG	140	500	5	**94.62**	93.96	93.11	58.37
Earthquakes	SENSOR	512	322	2	76.91	**78.42**	76.45	74.82
FordA	SENSOR	500	2500	2	96.44	**100**	**100**	**100**
FordB	SENSOR	500	3636	2	92.86	**100**	**100**	**100**
GunPoint	MOTION	150	50	2	**100**	96.67	93.33	49.33
HAM	SPECTROM	431	109	2	**83.6**	78.1	71.43	51.42
HandOutlines	IMAGE	2709	1000	2	**93.24**	**93.24**	91.08	64.05
Haptics	MOTION	1092	155	5	51.95	**52.27**	50.32	21.75
Herring	IMAGE	512	64	2	**68.75**	**68.75**	64.06	59.37
ItalyPowerDemand	SENSOR	24	67	2	97.06	**97.08**	96.31	97
Lightning2	SENSOR	637	60	2	86.89	**100**	**100**	**100**
MiddlePhalanxOutlineCorrect	IMAGE	80	600	2	72.23	**83.51**	81.79	57.04
MiddlePhalanxTW	IMAGE	80	399	6	58.69	**65.58**	63.64	27.27
Plane	SENSOR	144	105	7	**100**	**100**	**100**	9.52
ProximalPhalanxOutlineAgeGroup	IMAGE	80	400	3	88.09	**88.78**	87.8	48.78
ProximalPhalanxOutlineCorrect	IMAGE	80	600	2	**92.1**	91.07	90.03	68.38
ProximalPhalanxTW	IMAGE	80	400	6	81.86	**84.88**	83.41	35.12
SmallKitchenAppliances	DEVICE	720	375	3	**85.33**	83.47	74.93	33.33
SonyAIBORobotSurface	SENSOR	70	20	2	**96.02**	**96.02**	91.71	34.23
Strawberry	SPECTRO	235	613	2	**98.1**	97.57	91.89	64.32
SyntheticControl	SIMULATED	60	300	6	**100**	98	99	49.33
Trace	SENSOR	271	100	4	**100**	**100**	**100**	18.99
TwoLeadECG	ECG	82	23	2	**100**	96.66	97.81	49.95
Wafer	SENSOR	152	1000	2	99.98	**100**	**100**	100
WormsTwoClass	MOTION	900	181	2	83.12	**98.7**	90.91	57.14
Worms	MOTION	900	181	5	80.17	**83.12**	80.34	42.85
Wine	SPECTRO	234	57	2	**92.61**	90.74	90.74	50
Mean accuracy (↑)	-	-	-	-	88.02	**89.86**	87.92	56.97
Median accuracy (↑)	-	-	-	-	92.36	**94.99**	91.40	53.57
MPCE (mean per class error) (↓)	-	-	-	-	2.09	**2.01**	2.10	48.34

Achieve or outperform SOTA in 20 out of 30 datasets

II. Proposed Theoretical Analysis for Reprogramming

- Population Risk via Reprogramming (Optimal Transport)

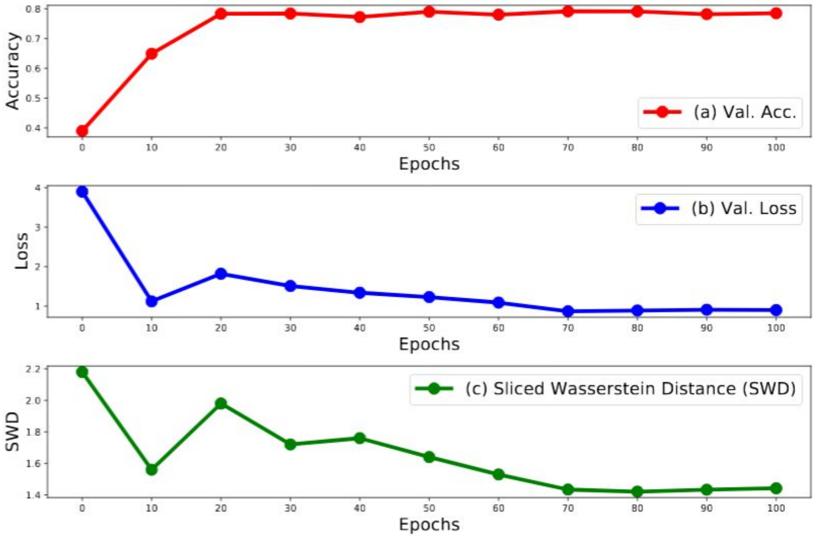
Theorem 1: Let δ^* denote the learned additive input transformation for reprogramming. The population risk for the target task via reprogramming a K-way source neural network classifier $f_{\mathcal{S}}(\cdot) = \eta(z_{\mathcal{S}}(\cdot))$, denoted by $\mathbb{E}_{\mathcal{D}_{\mathcal{T}}}[\ell_{\mathcal{T}}(x_t + \delta^*, y_t)]$, is upper bounded by:

$$\mathbb{E}_{\mathcal{D}_{\mathcal{T}}}[\ell_{\mathcal{T}}(x_t + \delta^*, y_t)] \leq \underbrace{\epsilon_{\mathcal{S}}}_{\text{source risk}} + 2\sqrt{K} \cdot \underbrace{\mathcal{W}_1(\mu(z_{\mathcal{S}}(x_t + \delta^*)), \mu(z_{\mathcal{S}}(x_s)))_{x_t \sim \mathcal{D}_{\mathcal{T}},\, x_s \sim \mathcal{D}_{\mathcal{S}}}}_{\text{representation alignment loss via reprogramming}}$$

This results suggest that reprogramming can perform **better** (lower risk) when the source model has a lower source loss and smaller representation loss.

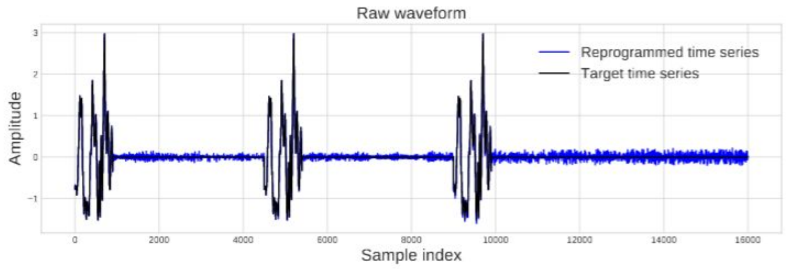
II. Proposed Theoretical Analysis for Reprogramming

- Training-time reprogramming analysis using V2S and DistalPhalanxTW dataset (Davis, 2013)

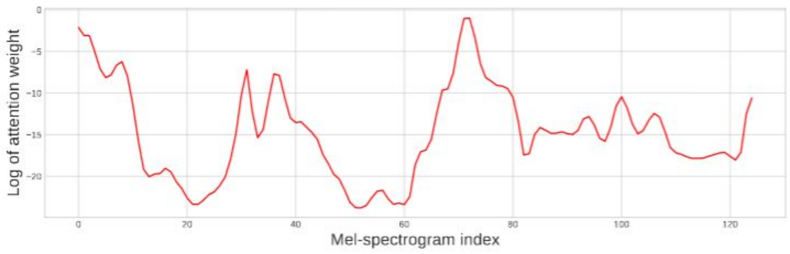


III. Voice-to-Series (V2S) Visualization - (1)

- Proposed Voice-to-Series on the Worms dataset (Bagnall et al., 2015)



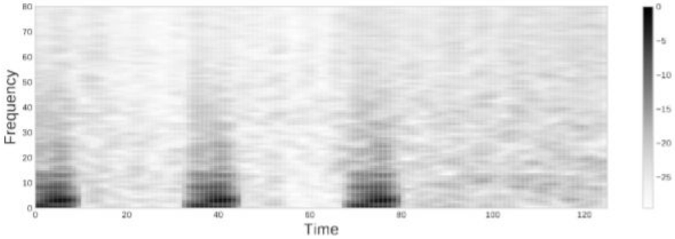
(a) Targeted (blue) and reprogrammed (black) time series



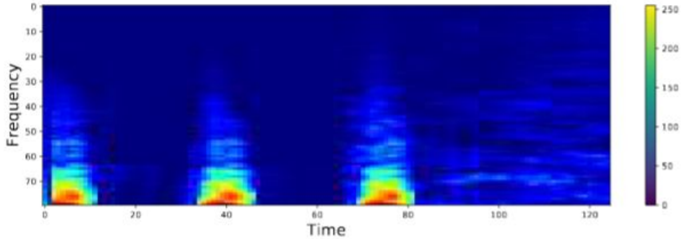
(b) Attention weight of reprogrammed input

III. Voice-to-Series (V2S) Visualization - (2)

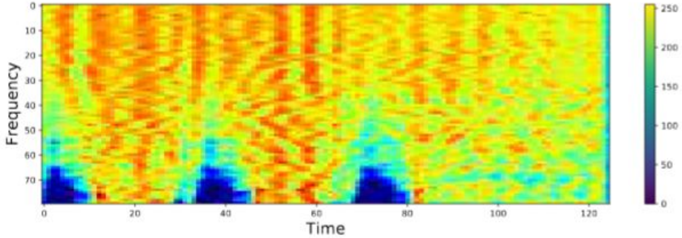
- Proposed Voice-to-Series on the Worms dataset (Bagnall et al., 2015)



(c) Mel-spectrogram of reprogrammed input



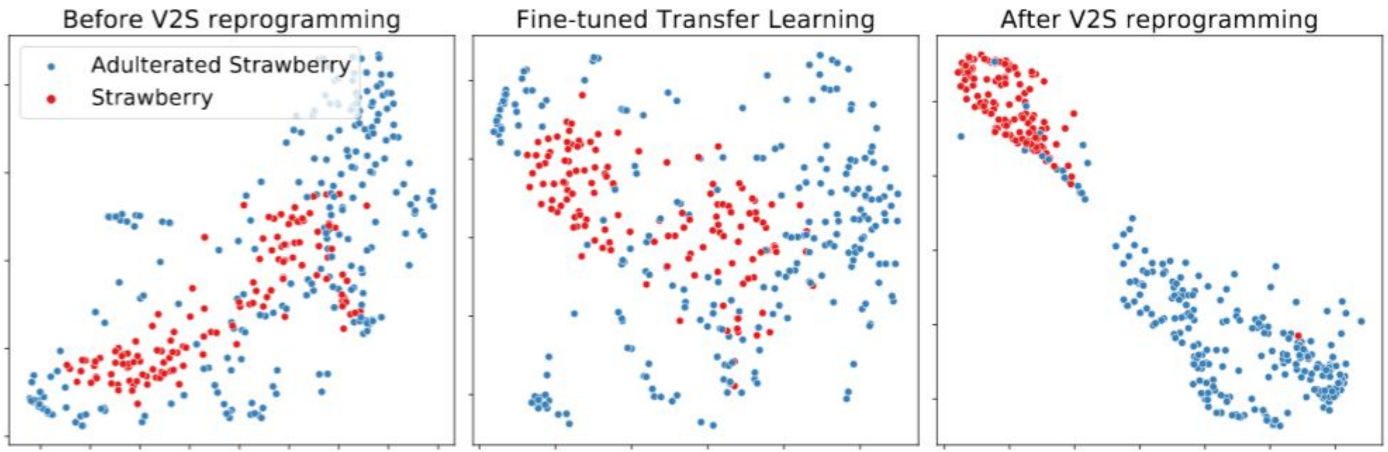
(d) Class activation mapping of (c) from 1_{st} conv-layer



(e) Class activation mapping of (c) from 2_{nd} conv-layer

III. Voice-to-Series (V2S) Visualization - (3)

- tSNE plots of the logit representations using the Strawberry (Holland et al., 1998)



Future Work - Different Time Series (e.g., Regression) and Speech Processing Tasks.

Acknowledgement

A. Large-Scale Pretrained Speech and Acoustic Models

1. *Choi et al.* "Kapre: On-GPU Audio Preprocessing Layers for a Quick Implementation of Deep Neural Network Models," ***ICML Workshop* 2017**
2. Yang *et al.* "Decentralizing feature extraction with quantum convolutional neural network for automatic speech recognition," ***ICASSP 2021***, Code
3. *Hu et al.* "A Two-Stage Approach to Device-Robust Acoustic Scene Classification," ***ICASSP 2021, DCASE 20 Task-1 Best System,*** Code

B. Time Series Classification

1. *Wang et al.* "Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline," **IJCNN 2019**
2. *Dau et al.* "The UCR Time Series Archive," ***IEEE/CAA Journal of Automatica Sinica***

References

C. Adversarial Reprogramming

1. *Elsayed et al.* "Adversarial reprogramming of neural networks," ***ICLR 2018***
2. *Tsai et al.* "Transfer learning without knowing: Reprogramming black-box machine learning models with scarce data and limited resources," ***ICML 2020***
3. *Neekhara et al.* "Adversarial Reprogramming of Text Classification Neural Networks," ***EMNLP 2019***

D. Transfer Learning in Time Series Classification

1. *Fawaz et al.* "Transfer learning for time series classification" ***Big Data 2018***
2. *Kashiparekh et al.* "ConvTimeNet: A pre-trained deep convolutional neural network for time series classification. ***IJCNN 2019***