Adacket: ADAptive Convolutional KErnel Transform for Multivariate Time Series Classification

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ABSTRACT

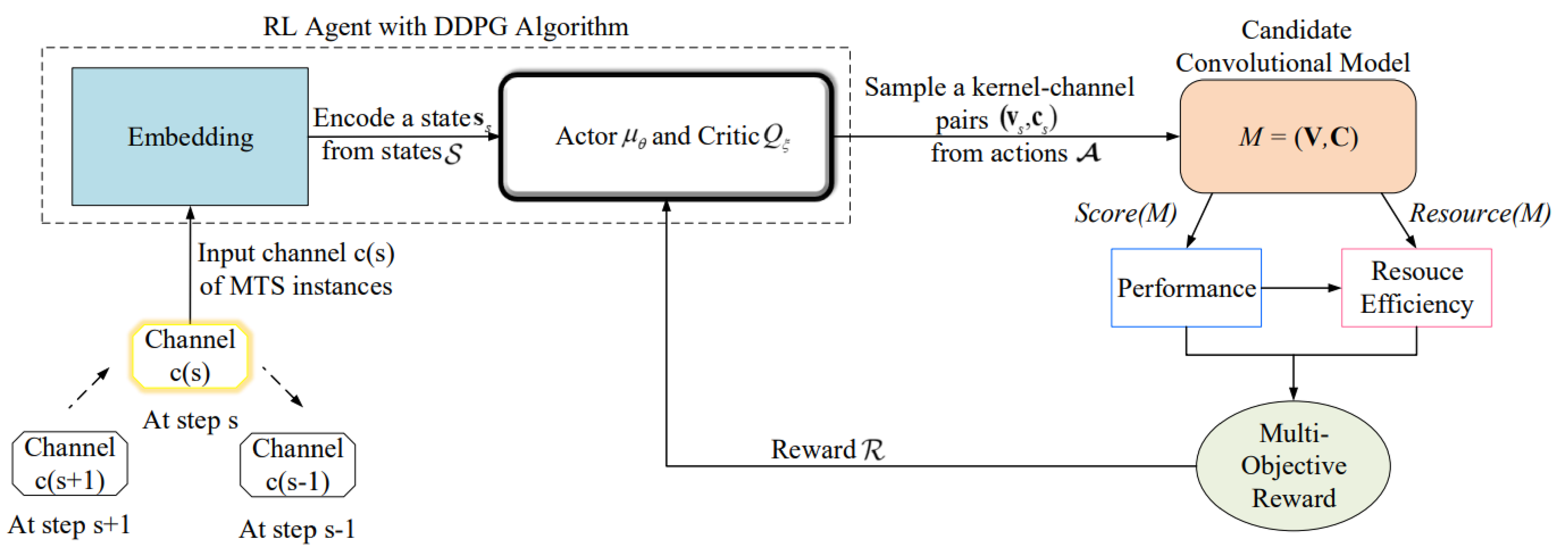
Current multivariate time series classification (MTSC) methods frequently utilize resource-intensive convolutional kernels with a rigorous trial-and-error design, limiting their overall effectiveness. We introduce Adacket, a pioneering approach for automatically designing efficient 1D dilated convolutional kernels tailored specifically for MTSC tasks. Adacket balances performance and resource efficiency through a reinforcement learning (RL) agent, offering a comprehensive search. Empirical evaluations on UEA archives show Adacket outperforms other methods.

INTRODUCTION

- **Background** 1D convolutional kernels have shown promise for MTSC tasks. However, existing methods use resource-intensive and empirical approaches for designing convolutional kernels.
- **Challenges** MTSC models use trial-and-error or focus on specific hyperparameters, instead of comprehensive exploration of the 1D convolutional kernels design space. Popular RL-based methods require significant computational resources and encounter memory bottlenecks when searching for parameters in a large space.
- **Adacket** is an automatic method for designing efficient 1D dilated convolutional kernels tailored to MTSC scenarios.

-- A multi-objective search method
-- Model the problem as sequential decision-making using RL
-- Conducts a comprehensive search of the kernel design space
-- Achieve excellent performance in terms of accuracy & resource efficiency

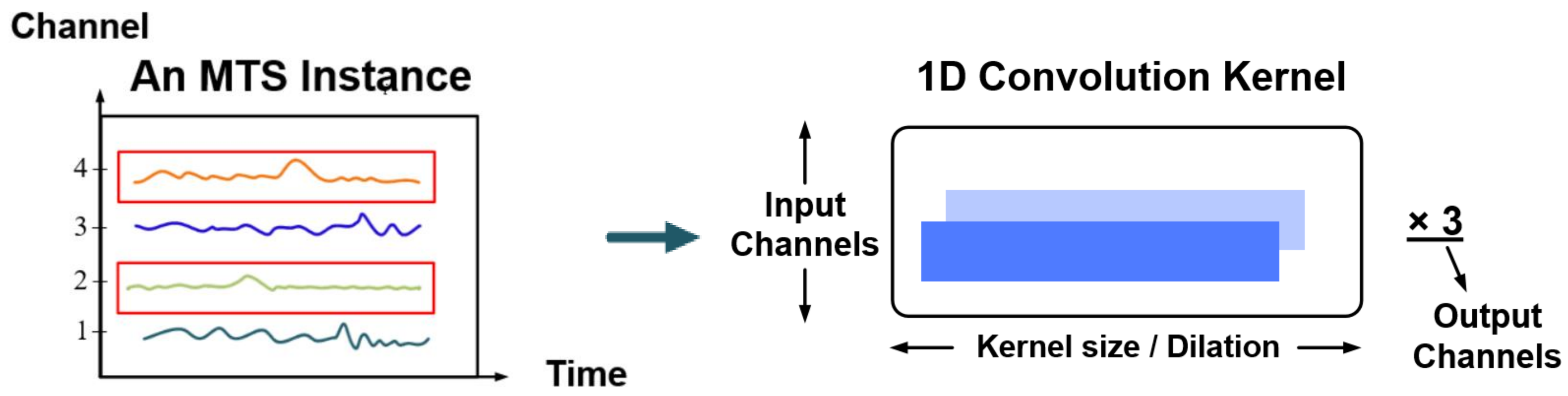
METHOD



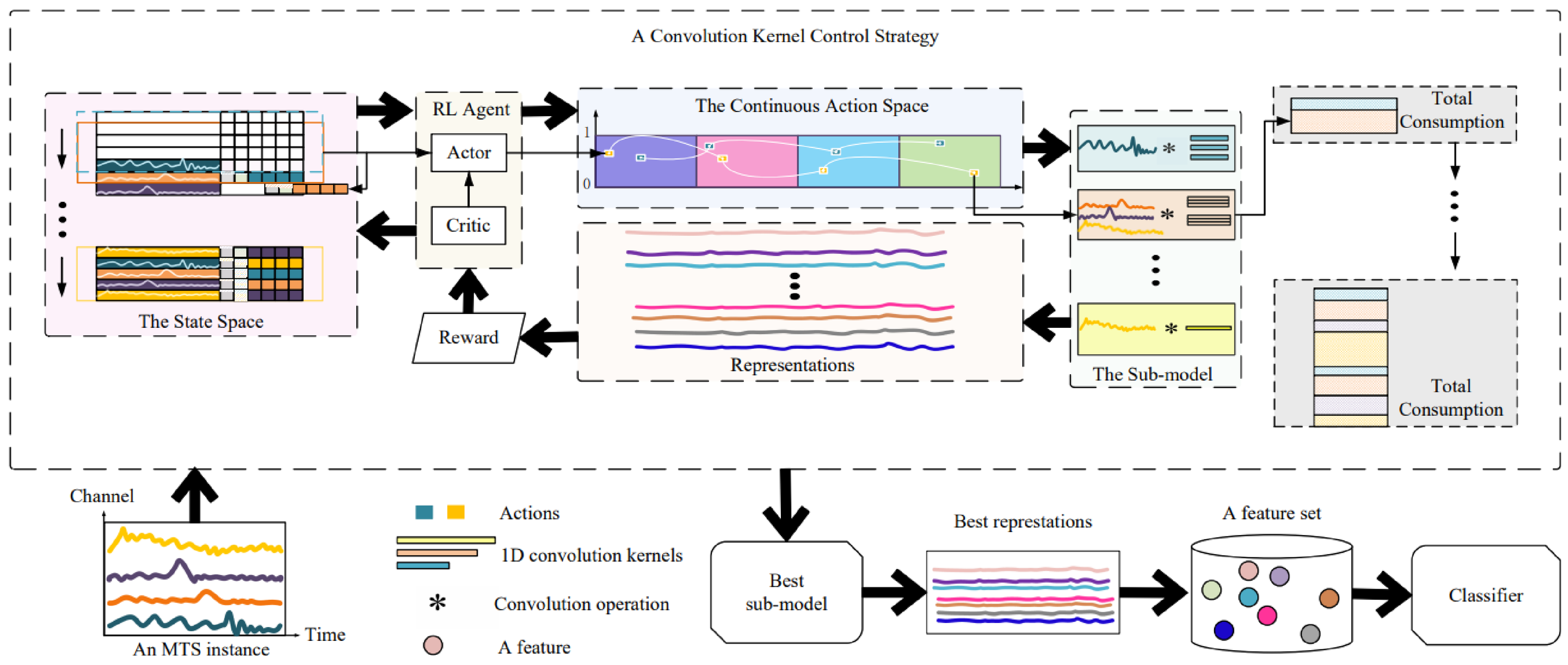
Automatically generate 1D convolutional kernels to transform specific channels of input time series data into discriminative representations

- **State Space** The channel encoding for current state identification in decision-making, including attribute features and environmental property.
- **Action Space** Form a kernel-channel pair to specify the input channels of the MTS data for a set of convolutional kernels.
- **Reward** A multi-objective metric of candidate convolutional models:

$$Reward(M) = \underbrace{\boxed{Score(M)}}_{\text{Model performance}} \times \epsilon + \underbrace{\boxed{\frac{Score(M)}{\log Resource(M)}}}_{\text{Resource efficiency}} \times (1-\epsilon).$$



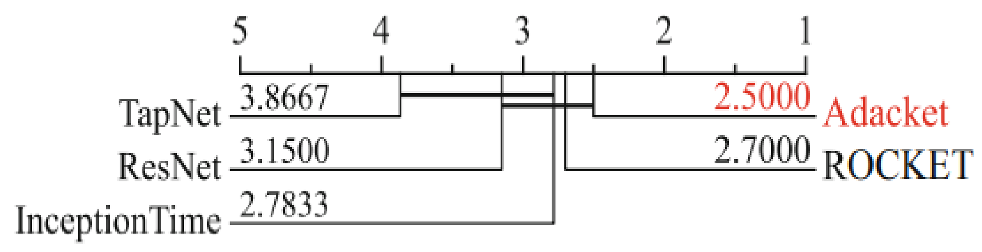
Input specific channels of a multivariate time series (MTS) instance for the designed 1D convolutional kernels



Overall instruction of Adacket-designed MTSC models for feature extraction and classification

EXPERIMENTS

- **Accuracy**

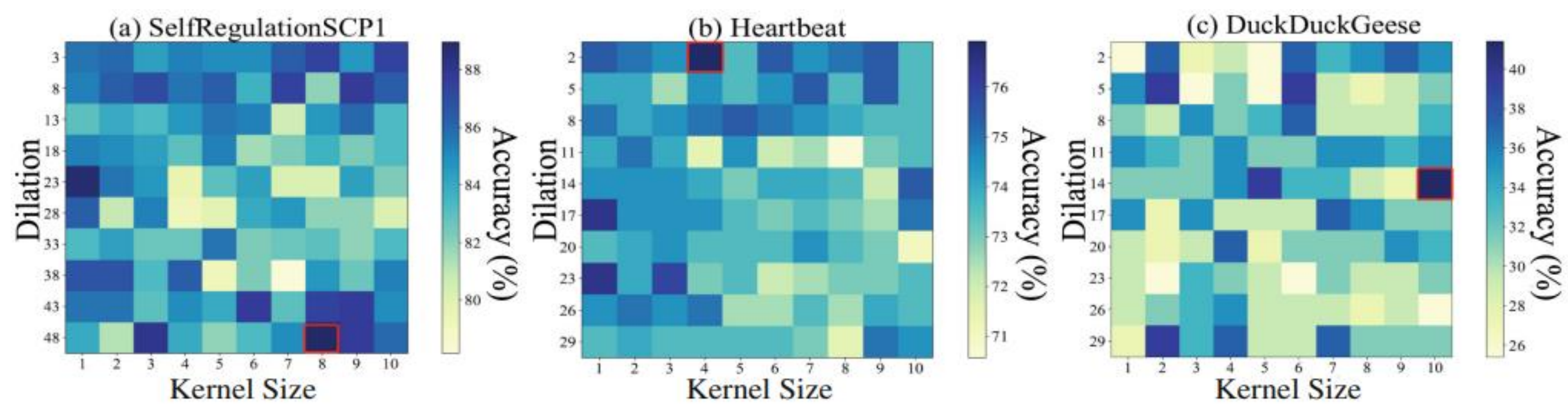


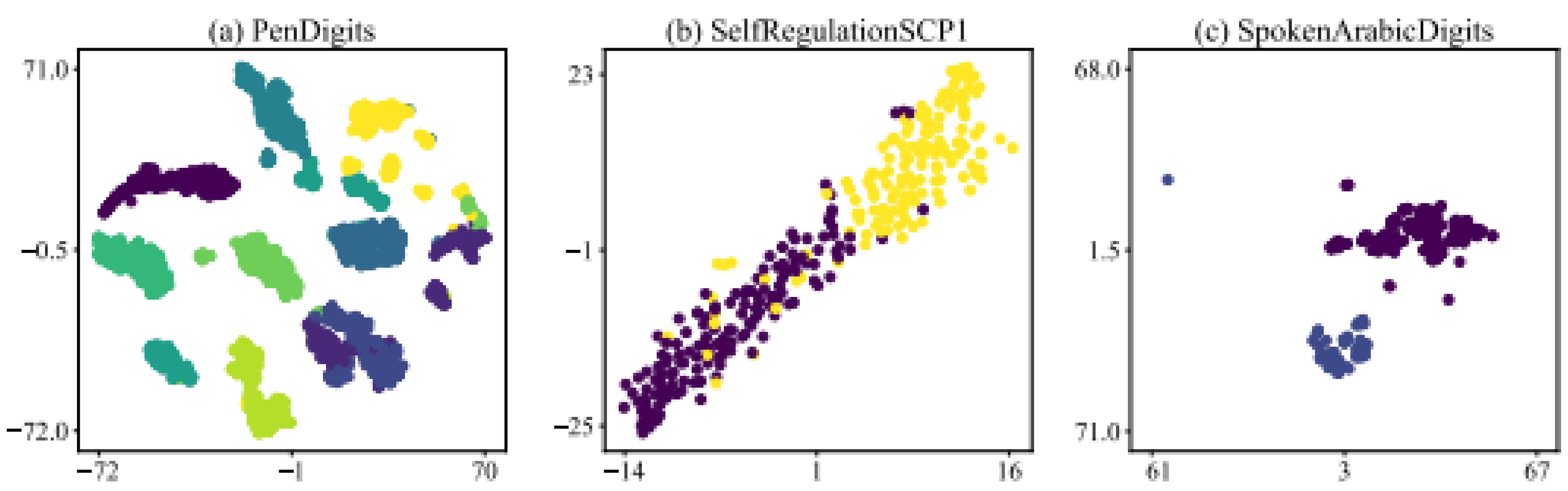
- **Computational Efficiency**

Method	Train Time	Inference Time
InceptionTime	48.55	1.61
ROCKET	**1.25**	1.58
Adacket	1.61	**0.68**

- **Resource Efficiency**

Dataset	Method	Acc	Params	Mem
SRS	InceptionTime	86.55	4.685	-
	ROCKET	84.69	-	42.88
	Adacket	**89.42**	**0.021**	**3.34**
HB	InceptionTime	73.20	4.810	-
	ROCKET	71.76	-	32.64
	Adacket	**77.07**	**0.012**	**0.58**
DDG	InceptionTime	54.00	7.754	-
	ROCKET	46.13	-	8.00
	Adacket	**58.00**	**0.003**	**0.68**





CONCLUSIONS AND FUTURE WORK

Adacket shows tremendous promise in MTSC scenarios and presents intriguing possibilities for future research. One potential avenue is to expand termination conditions in each episode to accurately meet strict budget constraints. This would enhance the method's applicability and efficiency in real-world settings. Furthermore, exploring the application of Adacket's principles to other time series models, such as forecasting and anomaly detection, holds significant potential.