Guest Editorial: AutoML for Nonstationary Data

DEVELOPING high-performance machine learning models is a difficult task that usually requires expertise from data scientists and knowledge from domain experts. To make machine learning more accessible and ease the labor-intensive trial-and-error process of searching for the most appropriate machine learning algorithm and the optimal hyperparameter setting, automated machine learning (AutoML) was developed and has become a rapidly growing area in recent years. AutoML aims at automation and efficiency of the machine learning process across domains and applications. Nowadays, data is commonly collected over time and susceptible to changes, such as in Internet-of-Things (IoT) systems, mobile phone applications and healthcare data analysis. It poses new challenges to the traditional AutoML with the assumption of data stationarity. Interesting research questions arise around whether, when and how to effectively and efficiently deal with non-stationary data in AutoML.

This special issue brings together five accepted articles (out of 22 submissions in total) that address different aspects of AutoML from fundamental algorithms to real-world applications.

In the article titled, "Explainable Attention Pruning: A Meta-Learning-Based Approach" [1], the authors propose a meta-learning algorithm that prunes transformer-based language models for efficient inference. It can adaptively identify and eliminate insignificant attention weights. The algorithm shows good performance in inference latency, loss, and Matthew's correlation coefficient.

The article titled, "A Dense Multicross Self-Attention and Adaptive Gated Perceptual Unit Method for Few-Shot Semantic Segmentation" [2], provides an automated end-to-end method for few-shot semantic segmentation (FSSS) with a limited number of annotated samples. It demonstrates great potential in segmenting previously unseen objects in images.

For more general cases, in the article titled, "An Automated Few-Shot Learning for Time Series Forecasting in Smart Grid Under Data Scarcity" [3], the authors present an AutoML framework that automates the optimal design of a few-shot learning pipeline from a bi-level programming perspective. The framework uses a lower-level meta-learner to mitigate data scarcity, and an upper-level optimization component to automatically tune hyperparameters for lower- and upper-level learners. It allows easy integration through a plug-in mechanism and demonstrates effectiveness in obtaining a high-performance few-shot learning pipeline in real-world energy forecasting tasks.

The article titled, "Learning-Driven Dynamic Multimodal Optimization Algorithm for Real-Time Traceability of Water Pollution" [4] studies an applied task of how to locate pollution sources in real-time based on water quality sensors, and proposes a dynamic multimodal optimization algorithm integrated with machine learning. It tackles the challenges arising from large-scale and uncertain water supply networks.

In "Self-Guided Autoencoders for Unsupervised Change Detection in Heterogeneous Remote Sensing Images" [5], the authors tackle the problem of unsupervised change detection in heterogeneous remote sensing images. A self-guided autoencoder framework is proposed with a concise structure. It discovers the discriminating features automatically to guide the network learning for change detection.

The special issue sheds lights on where this area is heading toward. While more focus has been given to applications that make use of AutoML approaches to automate decision making in combination with challenges in real-world data (e.g., multimodality and data scarcity), the fundamental aspects are also following up with new challenges, e.g., explainability, timeliness and change detection. We further envision that future work in this area will align with the agenda of trustworthy artificial intelligence, e.g., explainability, robustness aspects, data privacy, etc. We hope that this special issue opens up interesting and promising avenues for future AutoML research.

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