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CIS Publication Spotlight

IEEE Transactions on Neural Networks and Learning Systems

Survey on Multi-Output Learning, by D. Xu, Y. Shi, I. W. Tsang, Y. Ong, C. Gong, and X. Shen, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 31, No. 7, July 2020, pp. 2409–2429.

Digital Object Identifier: 10.1109/TNNLS.2019.2945133

“The aim of multi-output learning is to simultaneously predict multiple outputs given an input. It is an important learning problem for decision-making since making decisions in the real world often involves multiple complex factors and criteria. In recent times, an increasing number of research studies have focused on ways to predict multiple outputs at once. Such efforts have transpired in different forms according to the particular multi-output learning problem under study. Classic cases of multi-output learning include multi-label learning, multi-dimensional learning, multi-target regression, and others. From our survey of the topic, we were struck by a lack in studies that generalize the different forms of multi-output learning into a common framework. This article fills that gap with a comprehensive review and analysis of the multi-output learning paradigm. In particular, we characterize the four Vs of multi-output learning, i.e., volume, velocity, variety, and veracity, and the ways in which the



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four Vs both benefit and bring challenges to multi-output learning by taking inspiration from big data. We analyze the life cycle of output labeling, present the main mathematical definitions of multi-output learning, and examine the field’s key challenges and corresponding solutions as found in the literature. Several model evaluation metrics and popular data repositories are also discussed. Last but not least, we highlight some emerging challenges with multi-output learning from the perspective of the four Vs as potential research directions worthy of further studies.”

Extracting Relational Explanations From Deep Neural Networks: A Survey From a Neural-Symbolic Perspective, by J. Townsend, T. Chaton, and J. M. Monteiro, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 31, No. 9, September 2020, pp. 3456–3470.

Digital Object Identifier: 10.1109/TNNLS.2019.2944672

“The term “explainable AI” refers to the goal of producing artificially intelligent agents that are capable of providing explanations for their decisions. Some models (e.g., rule-based systems) are designed to be explainable, while others are less explicit “black boxes” for which their reasoning remains a mystery. One example of the latter is the neural network, and over the past few decades, researchers in the field of neural-symbolic integration (NSI) have sought to extract relational knowledge from such networks. Extraction from deep neural networks, however, has remained a challenge until recent years in which many methods of extracting distinct, salient features from input or hidden feature spaces of deep neural networks have been proposed. Furthermore, methods of identifying relationships between these features have also emerged. This article presents examples of old and new developments in extracting relational explanations in order to argue that the latter have analogies in the former and, as such, can be described in terms of long-established taxonomies and frameworks presented in early neural-symbolic literature. We also outline potential future research directions that come to light from this refreshed perspective.”

IEEE Transactions on Fuzzy Systems

Probabilistic Forecasting With Fuzzy Time Series, by P. C. L. Silva, H. J. Sadaei, R. Ballini, and F. G. Guimarães, *IEEE Transactions on Fuzzy Systems*, Vol. 28, No. 8, August 2020, pp. 1771–1784.

Digital Object Identifier: 10.1109/TFUZZ.2019.2922152

“In recent years, the demand for developing low computational cost methods to deal with uncertainties in forecasting has been increased. Probabilistic forecasting is a class of forecasting in which the method provides intervals or probability distributions as outcomes of its forecasting. The aim of this paper is, therefore, proposing a new forecasting approach based on fuzzy time series (FTS) that takes advantage of fuzzy and stochastic patterns on data and is capable to deal with point, interval, and distribution forecasts. The method proposed was empirically tested with typical financial time series, and the results were compared with other standard FTS and statistical methods. The results show that the proposed method obtained accurate results and outperformed standard FTS methods. The proposed method also combines versatility, scalability, and low computational cost, making it useful on a wide range of application scenarios.”

Patch Learning, by D. Wu and J. M. Mendel, *IEEE Transactions on Fuzzy Systems*, Vol. 28, No. 9, September 2020, pp. 1996–2008.

Digital Object Identifier: 10.1109/TFUZZ.2019.2930022

“There have been different strategies to improve the performance of a machine learning model, e.g., increasing the depth, width, and/or nonlinearity of the model, and using ensemble learning to aggregate multiple base/weak learners in parallel or in series. This article proposes a novel strategy called patch learning (PL) for this problem. It consists of three steps: first, train an initial global model using all training data; second, identify from the initial global model the patches that contribute the most to the learning error, and train a (local) patch model for each such patch; and, third, update the global model using training data that do not fall into any patch. To use a PL model, we first determine if the input falls into any patch. If yes, then the corresponding

patch model is used to compute the output. Otherwise, the global model is used. We explain in detail how PL can be implemented using fuzzy systems. Five regression problems on one-dimensional (1-D)/2-D/3-D curve fitting, nonlinear system identification, and chaotic time-series prediction, verified its effectiveness. To our knowledge, the PL idea has not appeared in the literature before, and it opens up a promising new line of research in machine learning.”

IEEE Transactions on Evolutionary Computation

A Multifactorial Evolutionary Algorithm for Multitasking Under Interval Uncertainties, by J. Yi, J. Bai, H. He, W. Zhou, and L. Yao, *IEEE Transactions on Evolutionary Computation*, Vol. 24, No. 5, October 2020, pp. 908–922.

Digital Object Identifier: 10.1109/TEVC.2020.2975381

“Various real-world applications with interval uncertainty, such as the path planning of mobile robot, layout of radio frequency identification readers and solar desalination, can be formulated as an interval multiobjective optimization problem (IMOOP), which is usually transformed into one or a series of certain problems to solve by using evolutionary algorithms. However, a definite characteristic among them is that only a single optimization task can be caught up at a time. Inspired by the multifactorial evolutionary algorithm (MFEA), a novel interval MFEA (IMFEA) is proposed to solve IMOOPs simultaneously using a single population of evolving individuals. In the proposed method, the potential interdependency across related problems can be explored in the unified genotype space, and multitasks of multiobjective interval optimization problems are solved at once by promoting knowledge transfer for the greater synergistic search to improve the convergence speed and the quality of the optimal solution set. Specifically, an interval crowding distance based on shape evaluation is calculated to evaluate

the interval solutions more comprehensively. In addition, an interval dominance relationship based on the evolutionary state of the population is designed to obtain the interval confidence level, which considers the difference of average convergence levels and the relative size of the potential possibility between individuals. Correspondingly, the strict transitivity proof of the presented dominance relationship is given. The efficacy of the associated evolutionary algorithm is validated on a series of benchmark test functions, as well as a real-world case of robot path planning with many terrains that provides insight into the performance of the method in the face of IMOOPs.”

IEEE Transactions on Games

Adaptive Music Composition for Games, by P. E. Hutchings and J. McCormack, *IEEE Transactions on Games*, Vol. 12, No. 3, September 2020, pp. 270–280.

Digital Object Identifier: 10.1109/TG.2019.2921979

“The generation of music that adapts dynamically to content and actions has an important role in building more immersive, memorable, and emotive game experiences. To date, the development of adaptive music systems (AMSs) for video games is limited both by the nature of algorithms used for real-time music generation and the limited modeling of player action, game-world context, and emotion in current games. We propose that these issues must be addressed in tandem for the quality and flexibility of adaptive game music to significantly improve. Cognitive models of knowledge organization and emotional effect are integrated with multimodal, multiagent composition techniques to produce a novel AMS. The system is integrated into two stylistically distinct games. Gamers reported an overall higher immersion and correlation of music with game-world concepts with the AMS than that with the original game soundtracks in both the games.”