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CIS Publication Spotlight

IEEE Transactions on Neural Networks and Learning Systems

When Gaussian Process Meets Big Data: A Review of Scalable GPs, by H. Liu, Y. -S. Ong, X. Shen, and J. Cai, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 31, No. 11, November 2020, pp. 4405–4423.

Digital Object Identifier: 10.1109/TNNLS.2019.2957109

"The vast quantity of information brought by big data as well as the evolving computer hardware encourages success stories in the machine learning community. In the meanwhile, it poses challenges for the Gaussian process regression (GPR), a well-known nonparametric, and interpretable Bayesian model, which suffers from cubic complexity to data size. To improve the scalability while retaining desirable prediction quality, a variety of scalable GPs have been presented. However, they have not yet been comprehensively reviewed and analyzed to be well understood by both academia and industry. The review of scalable GPs in the GP community is timely and important due to the explosion of data size. To this end, this article is devoted to reviewing state-of-the-art scalable GPs involving two main categories: global approximations that distillate the entire data and local approximations that divide the data for subspace learning. Particularly, for global approximations, we mainly focus on sparse approximations comprising prior approximations that modify the prior but perform exact inference, posterior approximations that retain exact prior but perform approximate inference, and structured sparse approximations that exploit specific structures in kernel matrix; for local approximations, we highlight the mixture/product of experts that conducts model averaging from multiple local experts to boost predictions. To present a complete review, recent advances for improving the scalability and capability of scalable GPs are reviewed. Finally, the extensions and open issues of scalable GPs in various scenarios are reviewed and discussed to inspire novel ideas for future research avenues."

Continual Learning of Recurrent Neural Networks by Locally Aligning Distributed Representations, by A. Ororbia, A. Mali, C. L. Giles, and D. Kifer, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 31, No. 10, October 2020, pp. 4267–4278.

Digital Object Identifier: 10.1109/TNNLS.2019.2953622

"Temporal models based on recurrent neural networks have proven to be quite powerful in a wide variety of applications, including language modeling and speech processing. However, training these models often relies on backpropagation through time (BPTT), which entails unfolding the network over many time steps, making the process of conducting credit assignment considerably more challenging. Furthermore, the nature of backpropagation itself does not permit the use of nondifferentiable activation functions and is inherently sequential, making parallelization of the underlying training process difficult. Here, we propose the parallel temporal neural coding network (P-TNCN), a biologically inspired model trained by the learning algorithm we call local representation alignment. It aims to resolve the difficulties and problems that plague recurrent networks trained by BPTT. The architecture requires neither unrolling in time nor the derivatives of its internal activation functions. We compare our model and learning procedure with other BPTT alternatives (which also tend to be computationally expensive), including real-time recurrent learning, echo state networks, and unbiased online recurrent optimization. We show that it outperforms these on-sequence modeling benchmarks such as Bouncing MNIST, a new benchmark we

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denote as Bouncing NotMNIST, and Penn Treebank. Notably, our approach can, in some instances, outperform full BPTT as well as variants such as sparse attentive backtracking. Significantly, the hidden unit correction phase of P-TNCN allows it to adapt to new data sets even if its synaptic weights are held fixed (zero-shot adaptation) and facilitates retention of prior generative knowledge when faced with a task sequence. We present results that show the P-TNCN's ability to conduct zero-shot adaptation and online continual sequence modeling."

IEEE Transactions on Fuzzy Systems

A New Approach for Transformation-Based Fuzzy Rule Interpolation, by T. Chen, C. Shang, J. Yang, F. Li, and Q. Shen, *IEEE Transactions on Fuzzy Systems*, Vol. 28, No. 12, December 2020, pp. 3330–3344.

Digital Object Identifier: 10.1109/TFUZZ.2019.2949767

"Fuzzy rule interpolation (FRI) is of particular significance for reasoning in the presence of insufficient knowledge or sparse rule bases. As one of the most popular FRI methods, transformation-based fuzzy rule interpolation (TFRI) works by constructing an intermediate fuzzy rule, followed by running scale and move transformations. The process of intermediate rule construction selects a user-defined number of rules closest to an observation that does not match any existing rule, using a distance metric. It relies upon heuristically computed weights to assess the contribution of individual selected rules. This process requires a move operation in an effort to force the intermediate rule to overlap with an unmatched observation, regardless of what rules are selected and how much contribution they may each make. It is, therefore, desirable to avoid this problem and also to improve the automation of rule interpolation without resorting to the user's intervention for fixing the number of closest rules. This article proposes such a novel approach to selecting a subset of rules from the sparse rule base with an embedded rule weighting scheme for the automatic assembling of the intermediate rule. Systematic comparative experimental results are provided on a range of benchmark datasets to demonstrate statistically significant improvement in the performance achieved by the proposed approach over that obtainable using conventional TFRI."

SFCM: A Fuzzy Clustering Algorithm of Extracting the Shape Information of Data, by Q-T. Bui, B. Vo, V. Snasel, W. Pedrycz, T-P. Hong, N-T. Nguyen, and M-Y. Chen, *IEEE Transactions on Fuzzy Systems*, Vol. 29, No. 1, January 2021, pp. 75–89.

Digital Object Identifier: 10.1109/TFUZZ.2020.3014662

"Topological data analysis is a new theoretical trend using topological techniques to mine data. This approach helps determine topological data structures. It focuses on investigating the global shape of data rather than on local information of high-dimensional data. The Mapper algorithm is considered as a sound representative approach in this area. It is used to cluster and identify concise and meaningful global topological data structures that are out of reach for many other clustering methods. In this article, we propose a new method called the Shape Fuzzy C-Means (SFCM) algorithm, which is constructed based on the Fuzzy C-Means algorithm with particular features of the Mapper algorithm. The SFCM algorithm can not only exhibit the same clustering ability as the Fuzzy C-Means but also reveal some relationships through visualizing the global shape of data supplied by the Mapper. We present a formal proof and include experiments to confirm our claims. The performance of the enhanced algorithm is demonstrated through a comparative analysis involving the original algorithm, Mapper, and the other fuzzy set based improved algorithm, F-Mapper, for synthetic and real-world data. The comparison is conducted with respect to output visualization in the topological sense and clustering stability."

IEEE Transactions on Evolutionary Computation

A Hybrid Deep Grouping Algorithm for Large Scale Global Optimization, by H. Liu, Y. Wang, and N. Fan, *IEEE Transactions on Evolutionary Computation*, Vol. 24, No. 6, December 2020, pp. 1112–1124.

Digital Object Identifier: 10.1109/TEVC.2020.2985672

"Many real-world problems contain a large number of decision variables which can be modeled as large scale global optimization (LSGO) problems. One effective way to solve an LSGO problem is to decompose it into smaller subproblems to solve. The existing works mainly focused on designing methods to decompose separable problems, while seldom focused on the decomposition of nonseparable large scale problems. Also, the existing decomposition methods only learn the interaction (correlation or interdependence) among variables to make the decomposition. In this article, we make the decomposition deeper: we not only consider the variable interaction but also take the essentialness of the variable into account to form a deep grouping method. To do this, we first design an essential/trivial variable detection scheme to support the deep decomposition for both separable problems and nonseparable problems. Based on it, we propose a new decomposition method called deep grouping method. Then, we design a new differential evolution (DE) algorithm with a new mutation strategy.

By integrating all these, we propose a hybrid deep grouping (HDG) algorithm. Finally, the experiments are conducted on the widely used and most challenging LSGO benchmark suites,

and the comparison results of the proposed algorithm with the state-of-the-art algorithms indicate the proposed algorithm is more effective."

IEEE Transactions on Games

Correlating Psychophysiological Responses of Exergaming Boxing for Predictive Heart Rate Regression Models in Young Adults, by N. A. Mohd Jai, M. Mat Rosly, and N. A. Abd Razak, *IEEE Transactions on Games*, Vol. 12, No. 4, December 2020, pp. 398–405.

Digital Object Identifier: 10.1109/TG.2020.3039838

"The purpose of this article is to validate the correlations between the heart rate (HR) and rating of perceived exertion (RPE) during exergaming boxing in sitting and standing positions. Thirty healthy adults, whose mean age was 25.10 and standard deviation (SD) 2.95 years, were recruited to play 10 minutes of exergaming boxing in sitting and standing positions. HR measurements were obtained at rest and during gameplay. RPE was assessed using Borg's modified (1–10) and original (6–20) scales. A paired-sample t-test, bivariate Pearson's, and Spearman's rho correlations were used to analyze the results. Mean HR was significantly higher while exergaming in standing position (130.79 SD23.18 bpm) as compared to sitting position (116.46 SD19.08 bpm) (p \$¥leq 0.05\$). There was a significant correlation between HR and RPE values while playing boxing exergaming in the standing position. A regression model that can be fitted into an equation to predict HR from reported RPE was derived from the significant values of Pearson's correlations. However, HR and RPE values did not significantly correlate with each other during exergaming boxing in the sitting position. The formula extracted from the linear regression models provides reliable predictions in estimating HR from the reported RPE while exergaming boxing in the standing position."

IEEE Transactions on Cognitive and Developmental Systems

Toward Improving Engagement in Neural Rehabilitation: Attention Enhancement Based on Brain-Computer Interface and Audiovisual Feedback, by J. Wang, W. Wang, and Z.-G. Hou, *IEEE Transactions on Cognitive and Developmental Systems*, Vol. 12, No. 4, December 2020, pp. 787–796.

Digital Object Identifier: 10.1109/TCDS.2019.2959055

"Both motor and cognitive function rehabilitation benefits can be improved significantly by patients' active participation. To this goal, an attention enhancement system based on the brain-computer interface (BCI) and audiovisual feedback is proposed. First, an interactive position-tracking riding game is designed to increase the training challenge and neural engagement. Subjects were asked to drive one of the avatars to keep up with another by adjusting their riding speed and attention. Second, the subject's electroencephalogram (EEG)-based attention level is divided into three regions (low, moderate, and high) by using the theta-to-beta ratio (TBR). According to the subject's attention states, different speed adjustment strategies are adopted to adjust the tracking challenge and improve the subject's attention. Besides, if the subject's attention focused on the training is moderate or low, an auditory feedback will be given to remind the subject to pay more attention to the training. The contrast experimental results show that subjects' performance indicated by overall attention level and average muscle activation can be improved significantly by using the attention enhancement system, which validates the feasibility of the proposed system for improving the neural and motor engagement."

IEEE Transactions on Emerging Topics in Computational Intelligence

Multidomain Features Fusion for Zero-Shot Learning, by Z. Liu, Z. Zeng, and C. Lian, *IEEE Transactions on Emerging Topics in Computational Intelligence*, Vol. 4, No. 6, December 2020, pp. 764–773.

Digital Object Identifier: 10.1109/TETCI.2018.2868061

"Given a novel class instance, the purpose of zero-shot learning (ZSL) is to learn a model to classify the instance by seen samples and semantic information transcending class boundaries. The difficulty lies in how to find a suitable space for zero-shot recognition. The previous approaches use semantic space or visual space as classification space. These methods, which typically learn visual-semantic or semantic-visual mapping and directly exploit the output of the mapping function to measure similarity to classify new categories, do not adequately consider the complementarity and distribution gap of multiple domain information. In this paper, we propose to learn a multi-domain information fusion space by a joint learning framework. Specifically, we consider the fusion space as a shared space in which different domain features can be recovered by simple linear transformation. By learning a *n*-way classifier of fusion space from the seen class samples, we also obtain the discriminative information of the similarity space to make the fusion representation more separable. Extensive experiments on popular benchmark datasets manifest that our approach achieves state-of-the-art performances in both supervised and unsupervised ZSL tasks."

IEEE Transactions on Artificial Intelligence

A Recommender System for Metaheuristic Algorithms for Continuous Optimization Based on Deep Recurrent Neural Networks, by Y. Tian, S. Peng, X. Zhang, T. Rodemann, K. C. Tan, and Y. Jin, *IEEE Transactions on Artificial Intelligence*, Vol. 1, No. 1, September 2020, pp. 5–18.

Digital Object Identifier: 10.1109/TAI.2020.3022339

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Publication Spotlight

(continued from page 13)

"Real-world optimization problems, such as aerodynamic design of turbine engines and automated trading, have been successfully solved by metaheuristics. However, practitioners are confronted with the challenge of how to choose an appropriate metaheuristic algorithm to solve a particular instance of these problems. This paper proposes a recommender system that can automatically select a best-suited metaheuristic algorithm without trial and error on a given problem. The proposed method develops a generic tree-like data structure for representing the difficulties of optimization problems and then trains a deep recurrent neural network to learn to choose the best metaheuristic algorithm, making automated algorithm recommendation practical for real-world problem-solving. The method will make metaheuristic optimization techniques accessible to industrial practitioners, policy makers, and other stakeholders who have no knowledge in metaheuristic algorithms."