Guest Editorial

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Models of Representation in Computational Intelligence

Computational Intelligence (CI) provides a set of powerful tools to effectively tackle complex computational tasks: global optimization methods (e.g., evolutionary computation, swarm intelligence), machine learning (e.g., neural networks), fuzzy reasoning, and so on. While CI research generally focuses on the improvement of algorithms (e.g., faster convergence, higher accuracy, reduced error), another promising research direction concerns the representations and models in CI. This can be in the form of search space transformation, that is, dilating, shrinking, stretching, collapsing, or remapping the fitness landscape, leading to the simplified formulations of optimization problems. The use of surrogate modeling can further reduce the complexity – or the computational effort – of a CI task, by providing the optimization algorithm with a simplified or approximated version of the fitness landscape. Moreover, in discrete domains, the simplification of the problem can be obtained by embedding implicit or explicit assumptions into the structure of candidate solutions, so that the feasible search space can be explored by genetic operators in a "smarter" way, reducing the overall computational effort. In the contexts of machine learning or fuzzy modeling, the focus can be on interpretability and explainability, the two open issues that currently affect the trust in AI solutions and hamper the adoption of such techniques in some disciplines (in particular, biomedical applications).

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Although many problem-specific strategies have been used in the past, there is still a general lack of universal theories and results for the best way of selecting or building a representation of a particular problem, including the possibility of automatically generating representations. Both theoretical and applied research can be performed in this novel field, driving new discoveries, novel perspectives in the context of fitness landscapes analysis, solutions representation, and generation of representation models, improving the performance and our understanding of existing algorithms, and considering the power of transcending search of a fitness landscape to generate novel fitness landscapes that transform the solubility of difficult problems.

This Special Issue have been supported by the IEEE CIS Task Force on Advanced Representation in Biological and Medical Search and Optimization, whose aim is to promote research on representation of solutions (and the dual perspective of fitness landscape manipulation) in CI, with a particular focus on biomedical and health-related disciplines. However, the scope of this special issue is not limited to global optimization, but embraces all kinds of representation methods exploited in CI research and welcomes any exotic ideas like non-conventional representations (e.g., adaptive, state-conditioned, generative/procedural, implicit, or relative representations), interpretable/explainable representations, graph-based approaches, fitness landscape transformation, simplifications and restrictions, alternative semantics, surrogate models, and novel evolutionary operators. Eventually, this special issue attracted 14 submissions which reported state-of-the-art contributions on the latest research and development, up-to-date issues, challenges, and applications in the field of representation in CI. Following a rigorous

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peer review process, four papers were finally accepted for publication in IEEE Computational Intelligence Magazine.

The first paper, titled "Simplifying Fitness Landscapes using Dilation Functions evolved with Genetic Programming", is based on the idea of using deformations of the fitness landscape to simplify the optimization problem by "expanding" and "compressing" specific regions. The concept behind Dilation Functions (DFs) is to remap the parameters of candidate solutions to perform a better exploration of the most promising areas, while avoiding regions characterized by worse fitness. This task is clearly problem-dependent. To have arbitrary DFs tailored on the fitness optimized, the authors proposed a novel approach based on Genetic Programming named GP4DFs, which evolves a specific DF for each dimension of the search space. The performance of GP4DFs was compared against a bilevel optimization algorithm named GA-FSTPSO, which exploits an outer layer based on a $(\mu + \lambda)$ genetic algorithm to evolve the structure of the DFs, while an inner layer uses the self-tuning swarm intelligence algorithm FST-PSO to identify the optimal parameters. The performance of the two methods was compared using a variety of benchmark functions (including the CEC'17 suite) of up to 100 dimensions. According to the authors, GP4DFs outperformed GA-FSTPSO in the majority of the tests. Moreover, GP4DFs seems to require a smaller budget (in terms of fitness evaluations) than GA-FSTPSO to achieve similar results.

The second paper, titled "Graph Lifelong Learning: a survey", proposes a thorough review of methods for the lifelong learning of graph-structured data. As a matter of fact, the vast majority of articles on graph learning assumes a static representation, in which the complete structure of the graph is known since the beginning of the training process. However, this is not possible in the case of continuously changing or expanding graphs, where new instances and/or new classes might emerge incrementally. The paper organizes the discussions in four groups: architectural, rehearsal, approach, and hybrid approaches. The state-of-the-art is presented and tested on various scenarios, addressing the open issues of lifelong graph learning, including catastrophic forgetting that afflicts continual machine learning algorithms. Covering more than one hundred works on graph lifelong learning, this survey presents a valuable starting point for all researchers interested in this emerging hot topic on the boundary between lifelong learning and graph learning.

The third paper, titled "A Multi-Transformation Evolutionary Framework for Influence Maximization in Social Networks", tackles the problem of finding the "influencers" in a social network in a more efficient way than the usual one of modeling the spread of information via a diffusion process, which requires a large number of simulations via a Monte Carlo process. In particular, the task is to find the optimal subset of nodes that are able to spread the most information in the network. The approach used by the authors is to define a multi-transformation evolutionary framework to avoid an a priori selection of a proxy model where the optimization is performed. The individuals in the multiple transformations are not independent but are instead used to perform a knowledge transfer process. The paper presents an improvement in solving the problem of influence maximization while using less computational resources than the existing methods.

The fourth paper, titled "Self-supervised Fusion for Multi-modal Medical Images via Contrastive Auto-encoding and Convolutional Information Exchange", concerns the combination of medical images with different methods while preserving the complementary information from different sources. This method aims to help in the diagnoses and treatments of patients. The authors formulate the multi-modal image fusion problem as a contribution estimation problem, making use of a convolutional autoencoder – being able to merge local and global features – and a multi-convolutional information exchange network, to allow the estimation of the contribution of each source image. The experimental results show the superiority of the proposed approach compared to the state-of-the-art, demonstrating a clear improvement on the state of multi-modal image fusion.

The guest editors of this special issue would like to thank Professor Chuan-Kang Ting, Editor-in-Chief of IEEE Computational Intelligence Magazine, for the great support in developing this special issue. We also take the opportunity to thank all the authors for submitting their valuable research outcomes, as well as the reviewers, who have critically evaluated the papers.

We would like to thank Prof. Daniel "Dan" Ashlock, who suddenly left this world during the development of this special issue. His visions and contributions were fundamental to develop this area of research.