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Editorial

# Advances in intelligent systems

The power of different intelligent techniques, such as Artificial Neural Networks (ANNs), have been demonstrated over the years by their successful use in many types of problems with different degrees of complexity and in different fields of application. However, the use of a machine learning solution involves choosing a particular model and properly tuning a set of parameters that, together, can effectively and efficiently solve the specific problem. Some difficulties arise in this process, such as the existence of several machine learning algorithms, the exponential number of combinations of parameter values, and also the need for a priori knowledge on the problem domain. Moreover, certain complex learning problems cannot be solved by a single intelligent technique and each intelligent technique has particular computation properties that can be complementary.

This special issue has a collection of papers on intelligent systems design and applications. The papers have a combination of many different techniques including neural networks, fuzzy systems, evolutionary computation, evolving systems and meta-learning. Applications examples are from multiobjective and many objective optimization problems, time-changing data and others.

The Extreme Learning Machine (ELM) is an efficient training algorithm for single hidden layer feedforward neural networks, known to obtain neural network models with better generalization performance while consuming far less time than other traditional learning algorithms. Nonetheless, the generated models tend to present more neurons in the hidden layer, which affects the time taken for future predictions. Particle Swarm Optimization (PSO) algorithms can be used to find good performing ELM networks with a lower number of neurons. Paper 1, *Investigating the use of alternative topologies on performance of the PSO–ELM by Elliacking Figueiredo and Teresa Ludermir*, presents an ELM-PSO hybridization, considering different PSO topologies. While the performance of the PSO depends strongly on its topology, there is no outright best topology for all problems. Therefore, the authors investigate the effect of the PSO topologies on the performance of the PSO–ELM for training single hidden layer neural networks. Experimentally, the frequently used global topology showed better results compared to the other topologies tested regarding the root mean squared error on validation data.

Learning from data streams is a contemporary and demanding issue because of the constantly increasing rate in size and temporal availability of data. Paper 2, *Uninorm Based Evolving Neural Networks and Approximation Capabilities by Fernando Bordgnon and Fernando Gomide*, suggests a structure and introduces a learning approach to train uninorm-based hybrid neural networks using extreme learning concepts. Uninorms bring flexibility and generality to fuzzy neuron models as they can benefit from triangular norms, triangular conorms, or operations in between by adjusting identity elements. The Fuzzy c-means is used to granulate the input space, and a scheme based on extreme learning is employed to compute the weights of the neural network approximating any continuous functions in compact domains. Subsequently, an evolving version of the network is developed exploring recursive clustering methods and extreme learning. It is postulated, and computational experiments endorse, that the evolving neuro fuzzy network share equal or better approximation ability in dynamic environments than its static counterpart.

The response of natural and artificial systems to external signal has been studied deeply, especially in biological systems. This response to a weak signal can be enhanced in the presence of a specific intensity of stochastic input noise. Such phenomenon highlights that noise may play a constructive role in signal processing. As noise is a common feature in nature, there are many research works concerning on the positive impact of noisy factors, with the objective to explore and understand the phenomenon of stochastic resonance. Some works suggested that the use of excitable neuronal system profited from the noise of the neurons themselves to optimize the response to external stimulus, where the noise is not from the environment fluctuations but from the intrinsic diversity of neurons. The third paper, *Effect of nonidentical signal phases on signal amplification of two coupled excitable neurons by Xiaoming Liang and Liang Zhao*, investigates the response of two coupled excitable neurons to external subthreshold periodic signals. The neuron's response to the subthreshold signals can be enhanced when the signal phases are nonidentical. Moreover, the response can be strongly improved if the level of nonidentical signal phases is at an intermediate value and thus resulting in a resonance-like phenomenon. Under the influence of nonidentical signal phases the response also exhibits a resonance-like dependency on the coupling coefficient. This paper presents an analysis to understand the mechanism of these two types of resonance behaviors. The robustness of the resonances induced by nonidentical signal phases to neuronal diversity, noise perturbation and different neuron models is verified and can be useful for understanding neural information processing.

Most machine learning and data mining techniques consider a scenario where data are centralized. This includes the popular *k*-means algorithm for clustering data. For dealing with data distributed in separated repositories, distributed versions of *k*-means have been proposed. Paper 4, *Evolutionary k-means for distributed data sets by Murilo Naldi and Ricardo Campello*, uses a hybrid evolutionary *k*-means algorithm for clustering distributed data. The evolutionary algorithm evolves clustering partitions that are refined by the *k*-means algorithm. A master node combines the information from multiple data nodes, which distribute the data. This algorithm is called Distributed Fast Evolutionary Algorithm for Clustering (DF-EAC). Two different distribution approaches are

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adopted: the first obtains a model identical to the centralized version of the clustering algorithm; the second generates and selects clusters for each distributed data subset and combines them afterwards. Both algorithms are compared experimentally considering two perspectives: theoretical, through asymptotic complexity analyses; and experimental, through a comparative evaluation of results obtained from a collection of experiments and statistical tests. The obtained results allows to conclude that the first approach is robust to different types of data distribution, and requires reasonable transmission speeds for interactively transmitting data between distributed parts of the algorithm. The second approach reduces the data amount and the number of transmissions of the algorithm, causing a slight quality loss, and is recommended for systems with low transmission rates.

Semi-supervised learning can be employed in domains where few labeled instances are available, while there is a vast amount of unlabeled instances. Therefore, the information of such data can be used to help in the supervised model induction. In Paper 5, *A Semi-Supervised Classification Technique Based on Interacting Forces by Thiago Cupertino and Liang Zhao*, the authors propose a nature-inspired semi-supervised learning technique based on attraction forces. Instances are represented in a $k$-dimensional space, and they move according to dynamical rules. Data items with the same label cooperate with each other, while data items with different labels compete among them to attract unlabeled points. Throughout, all unlabeled data items can be classified when the system reaches stability. By using this collective dynamics, the elements of the system interact locally, and a global pattern emerges. The authors also propose some heuristics for parameter setting. Experimentally, the proposed technique showed results comparable to other well-known semi-supervised algorithms when applied to both artificial and benchmark data sets.

There exists several machine learning algorithms that can be applied to a learning problem. As there is no single best algorithm for all possible cases, an important question is how to choose the best algorithm to a given problem. Meta-learning provides a suitable technique for the selection of promising optimization algorithms for a specific problems. In paper 6, *MetaStream: a meta-learning based method for periodic algorithm selection in time-changing Data by André Rossi, André Ponce de Leon F de Carvalho and Carlos Soares*, it is presented a meta-learning based method for periodic algorithm selection in time-changing environments, named MetaStream. MetaStream works by mapping the characteristics extracted from past and incoming data to the performance of regression models in order to choose between single learning algorithms or their combination. Several experiments illustrate the performance of the meta-learning based approach proposed.

Multiobjective Optimization Problems (MOP) have several objectives, normally conflicting with each other. Usually, approaches to solve MOP consider only a single objective to simplify the problem. In these cases two main alternatives are possible: (i) the use of a specific objective to be optimized, while the remaining are normally handled as constraints; (ii) to aggregate one-dimensional cost/utility function by taking a weighted sum of the various objectives. Recently, approaches assume that all objectives are considered simultaneously and aim to find a set of solutions (called efficient solutions) with different trade-offs among the objectives instead of a unique optimal solution. Evolutionary algorithms seem particularly suitable to solve MOP, because they deal simultaneously with a set of possible solutions. This allows finding several members of optimal solutions in a single run of the algorithm. Paper 7, *ADEMO/D: Multiobjective Optimization by an Adaptive Differential Evolution Algorithm by Sandra Venske, Richard Aderbal Gonçalves and Myriam Delgado*, presents an approach for continuous multiobjective optimization. The approach incorporates concepts of Multiobjective Evolutionary Algorithms based on Decomposition (MOEA/D) and mechanisms of strategies adaptation. Two methods were investigated to perform adaptive strategy selection: Probability Matching (PM) and Adaptive Pursuit (AP). The Differential Evolution strategy is chosen from a candidate pool according to a probability that depends on its previous experience in generating promising solutions. The proposed solution is confronted with its non-adaptive counterparts and with four important multi-objective optimization algorithms in the same application context.

Many-Objective Optimization Problems are problems that have more than three objective functions. The interest for Many-Objective Optimization has grown due to the limitations of Pareto dominance based Multi-Objective Evolutionary Algorithms when dealing with problems that have a high number of objectives. Paper 8, *Using Reference Points to Update the Archive of MOPSO Algorithms in Many-Objective Optimization by Andre B. de Carvalho and Aurora Pozo*, presents a study of the behavior of Multi-Objective Particle Swarm Optimization (MOPSO) algorithms in many-objective problems. In this paper, the I-MOPSO is extended to achieve an in-depth evaluation of the I-MOPSO algorithm in different many-objective scenarios and it uses a new archiving method that guides the search to different regions of the Pareto Front using reference points. The algorithms proposed are evaluated with several Many-Objective Problems in terms of their convergence and diversity to the Pareto front. The experimental results are compared applying quality indicators and statistical tests and showed that the solutions generated by the algorithms were close to the selected reference point.

This special issue includes eight papers selected among the best contributions to the XII Brazilian Symposium on Neural Networks, XII SBRN, which took place in Curitiba, Brazil, from October 20 to October 25, 2012. The SBRN in 2012 was held as part of the First Brazilian Conference on Intelligent Systems (BRACIS 2012). The Symposium covered topics related to Computational Intelligence, including Artificial Neural Networks, Evolutionary Computation, Fuzzy Systems and other Computational Intelligence approaches. XII SBRN received papers related with theoretical and practical aspects of Computational Intelligence. SBRN is an international conference, with papers written in English, an international program committee composed by well-known researchers from all over the world, and proceedings published by IEEE Computer Society.

The XII SBRN received 79 submissions from several different countries. Among these submissions, 42 full papers were accepted for oral presentation. All papers were reviewed by, at least, two independent specialized referees. The authors of the papers with the best reviews were invited to submit an extended and updated version for this special issue. The selection process emphasized three main aspects: originality, relevance and technical contribution. The papers selected from SBRN are listed in the references [1–8]. The new versions were submitted to a rigorous peer review process conducted by international reviewers. Only the papers recommended by the reviewers were accepted for this special issue. We believe that this issue presents a set of very high quality papers. As a result, this edition will provide the readers a rich material of current research on Intelligent Systems and related issues.

We would like to thank all the authors for their effort to submit high quality papers and the referees for their meticulous and useful reviews with relevant comments and suggestions that surely improved the quality of this special issue. We would also like to thank the Neurocomputing Editor-in-Chief Tom Heskes, the Journal Editorial Board and Elsevier for the opportunity and for efficiently handling the publication procedure. Finally, we would further like to acknowledge Vera Kamphuis and Vijayakumar Raman for their help and careful edition of this issue.

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