Guest Editorial Learning in Nonstationary and Evolving Environments

RESEARCH on machine learning and computational intelligence has significantly advanced over the last two decades by providing well assessed methods and theories, as well as real-world applications that show the effectiveness of learning solutions directly from data. In this direction, the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, formerly IEEE TRANSACTIONS ON NEURAL NETWORKS, has been providing one of the most visible and effective platforms to disseminate the knowledge and wisdom gained from those studies. However, much of the research in this field relied on two fundamental assumptions: 1) there is a sufficiently large and representative dataset to configure and assess the model performance, and 2) data are drawn independently from a fixed - albeit unknown distribution. Alas, these assumptions often do not hold in many real-world applications, such as those where available data are limited and the process generating the data is time variant, e.g., in analysis of climate or financial data, network intrusion, spam and fraud detection, power demand and pricing, industrial quality inspection and complex dynamical systems, among others.

Efforts towards incremental and online learning allowed researchers to relax the "sufficiently large data set" requirement by continuously updating a model to learn from small batches or online data, yet, did very little for addressing the "fixed distribution" assumption. More recently, approaches based on the so called concept drift - and to some extend domain adaptation – algorithms, in some cases in collaboration with change detection tests, have attempted to relax the fixeddistribution hypothesis by accommodating a stream or batches of data whose underlying distribution might change over time. However, early efforts have made other assumptions, such as restricting the type of faults, or changes affecting the system or the distribution. Against this background, the need for more general frameworks to learn from - and adapt to - nonstationary and evolving environments can be hardly overstated. Hence, we felt that a special issue that discusses the stateof-the-art approaches, latest results on detecting and adapting to changes in underlying data distributions, and learning in complex dynamic environments is very timely.

Shortly after we announced the special issue, we came to the surprisingly pleasant – but also alarming – realization that "timely" was a gross understatement in describing the need for this special issue: nearly 100 original manuscripts were submitted in response to our call-for-papers for this special issue, and thence started the long, laborious but rewarding review process to select those highest quality papers pertinent to this special issue. The review process involved over 400 reviews that led to the final selection of the nineteen papers composing this special issue. Two of these papers have recently appeared in a regular issue of this journal due to timing and space constraints, and the remaining seventeen are published in this issue. We provide a brief overview of all 19 papers below.

The papers included in this special issue encompass a broad spectrum of scenarios and problems, including some of the new challenges and fundamental problems that are encountered in learning in nonstationary and evolving environments. Perhaps one of the more challenging problems in machine learning is unsupervised or semi-supervised learning from unlabelled or limited labelled data, made even more challenging when such data are also drawn from nonstationary distributions. Such a learning setting gives rise to the extreme case of the so-called verification latency problem, a machine learning scenario that is quite practical, yet surprisingly missing in the machine learning literature: learning concept drift in a streaming nonstationary environment that provides only unlabelled instances after an initial training set. In COMPOSE: COMpacted POlytope Sample Extraction - A Semi-Supervised Learning Framework for Initially Labelled Non-Stationary Streaming Environments, Dyer, Capo and Polikar propose a computational geometry based approach for this challenging problem. Another challenging situation is explored in Active Learning with Evolving Streaming Data, where Žliobaitė et al. take on the often encountered but rarely addressed issue of choosing most informative instances for learning in nonstationary settings, providing a compelling argument why an active learning algorithm - as opposed to a standard online learning algorithm that can naturally handle nonstationary environments - should be used in the face of concept drift. They offer several strategies based on various uncertainty metrics for choosing the most informative instances to be labelled when obtaining labelled data is expensive, and there is a fixed budget for labelled data. In Online Bayesian Learning with Natural Sequential Prior Distribution, on the other hand, Nakada et al. show that a theoretically well-justified prior specifically designed for nonstationary environments can be used effectively in an online Bayesian learning setting. In PANFIS: A Novel Incremental Learning Machine, Pratama et al. propose a neurofuzzy approach for incremental learning from nonstationary data, where fuzzy rules can be automatically added or removed from the knowledge-base of the machine based on the

drifting assumption for the data distribution. Salazar, Adeodato and Arnaud then address the very challenging problem of time series forecasting in their paper *Continuous Dynamical Combination of Short and Long Term Forecasts for Nonstationary Time Series.* They show that a short term forecasting approach based on model ensembles, combined with a long term forecasting, improves over a more straightforward ensemble method.

Another important group of papers address the issues of feature extraction, change detection, and adaptation to drifting environments. In PCA Feature Extraction for Change Detection in Multidimensional Unlabelled Data, Kuncheva et al. propose a simple but effective principal component analysis (PCA) based feature extraction approach for improving the performance of a subsequent change detection algorithm. They prove that in a PCA based dimensionality reduction process, components with the lowest variance should be retained as the extracted features, as those components are more likely to be affected by a change. In Reacting to Different Types of Concept Drift: The Accuracy Updated Ensemble Algorithm, Brzezinski and Stefanowski provide an overview and competitive comparison of several state-of-the-art single and ensemble based approaches for learning concept drift, and offer a unique perspective in improving the performance of ensemble based approaches. In Mining Recurring Concepts in a Dynamic Feature Space, Gomes et al. also propose an ensemble based approach that adds classifiers to an ensemble as new data arrive. The novelty of their approach lies in the active selection of a subset of features for each context induced by concept drift. Alippi, Boracchi and Roveri propose a justin-time change detection approach in Just-in-time classifiers for recurrent concepts (which appeared in the April 2013 issue of these Transactions) to address the situation where recurrent concept drift arise. There, learning is active and new states are added to the recurrent concept drift state machine whenever needed.

A number of papers discuss challenges of uncertain dynamic environments, such as stable but adaptive tracking of control systems. In Dynamic Learning from Adaptive Neural Network Control of a Class of Non-Affine Nonlinear Systems, Dai, C. Wang and M. Wang discuss their adaptive radial basis function neural network-based approach for controlling nonaffine nonlinear systems. Faults and system failures are common types of concept drift that might drastically or subtly change the behaviour of the process generating the data, e.g., the environment or a plant. In this direction, Chen et al. propose incremental one-class learning specifically for fault detection applications in Learning in the Model Space for Fault Diagnosis. An alternative approach that incorporates a change detection test to detect faults based on hidden Markov models, augmented with a cognitive level process, taking advantage of spatial and temporal dependencies in sensor networks is introduced by Alippi et al. in A Cognitive Fault Diagnosis System for Distributed Sensor Networks (which appeared in the August 2013 issue of these Transactions).

Reppa, Polycarpou and Panayiotou address the relevant issue of multiple fault detection and isolation in a large class of

dynamic systems whose description is assumed to be known. In their paper Adaptive Approximation for Multiple Sensor Fault Detection and Isolation of Nonlinear Uncertain Systems, the authors propose a novel method for sensor fault detection based on nonlinear observers and a combinatorial logic for fault isolation; unknown parameters and thresholds are learned from the data. Bose *et al.*, also look at concept drift and its many variations, but specifically focus on process mining and process discovery applications in Dealing with Concept Drifts in Process Mining, where they propose a unique feature extraction mechanism, applied in conjunction with a dynamic drift detection approach. Che Ujang et al. provide an interesting discussion for adaptation mechanisms in complex dynamic systems. Specifically, in An Adaptive Convex Combination Approach for the Identification of Improper Quaternion Processes, the authors propose a novel data-adaptive modelling of sensor data with model order selected in the quaternion domain.

This special issue also includes a group of contributions on application research that go beyond evaluating new nonstationary learning algorithms on synthetic and benchmark datasets, but rather describe various novel and challenging real-world applications that naturally generate non-stationary/time variant data. Anthropomorphic robots constitute the real-world testbed in the contribution from Saegusa et al., titled Action-Driven Development of Self and Action Perception, where the developed framework allows the robot - when provided with very rudimentary initial knowledge about motor synergies to recognize its own body, generate voluntary actions and perceive the changing effects its actions generate on the environment. Again, within the robotic framework, He et al., in Linguistic Decision Making for Robot Route Learning propose a novel method for robot route learning. The robot behaviour is adaptively determined by exploiting information coming from a linguistic decision tree. Juang et al.'s contribution, An Interval Type-2 Neural Fuzzy Chip with On-Chip Incremental Learning Ability for Time-Varying Data Sequence Prediction and System Control is unique in the sense that it combines the development of a computationally efficient neurofuzzy incremental learning algorithm with its system-on-chip implementation for use in nonstationary online prediction and system control applications. Finally, in Learning Geo-Temporal Non-Stationary Failure and Recovery of Power Distribution, Wei et al. address the problem of system failure in the power distribution. A novel formulation for the system failure and recovery is provided, which takes into account both spatial and temporal available information.

With 19 selected contributions, this special issue includes, perhaps, a larger selection of papers than a typical special issue. We believe that this wider presence is a testament to the sheer magnitude (depth) and the broad spectrum (breath) of the work being done in developing new approaches for learning in nonstationary and evolving environments, and identifying novel applications that can benefit from such approaches. We hope that the papers in this special issue will generate an engaging forum for discussing novel approaches, and also provide a solid foundation for future novel approaches and applications. We would like to thank all authors for their contributions, the 400+ reviewers who helped us in reviewing these manuscripts and, most importantly, our Editor-in-Chief, Dr. D. Liu, for his support, guidance and wisdom throughout this process. This special issue would not have been possible without all their efforts. ROBI POLIKAR, *Guest Editor* Rowan University Glassboro, NJ 08028, USA

CESARE ALIPPI, *Guest Editor* Politecnico di Milano 20133 Milan, Italy



AND LEARNING SYSTEMS.

Robi Polikar (S'93–M'00–SM'08) received the B.Sc. degree in electronics and communications engineering from Istanbul Technical University, Istanbul, Turkey, in 1993 and the M.Sc. and Ph.D. degrees in electrical engineering and biomedical engineering from Iowa State University, Ames, IA, USA, in 1995 and 2000, respectively.

He is a Professor of electrical and computer engineering with Rowan University, Glassboro, NJ, USA, where he is currently serving as the Department Chair. He has published over 140 peer-reviewed papers in journals and conference proceedings. His current research interests include incremental and online learning, learning in nonstationary and evolving environments, ensemble-based systems, and various applications of computational intelligence in bioinformatics and biomedical engineering.

Dr. Polikar is a member of the ASEE, Tau Beta Pi, and Eta Kappa Nu. His recent and current works are funded primarily through NSF's CAREER and Energy, Power, and Adaptive Systems Programs. He is an Associate Editor of the IEEE TRANSACTIONS ON NEURAL NETWORKS



Cesare Alippi (SM'94, F'06) received the Degree (*cum laude*) in electronic engineering and the Ph.D. from Politecnico di Milano, Milano, Italy, in 1990 and 1995, respectively.

He is currently a Full Professor of information processing systems with Politecnico di Milano. He was a Visiting Researcher at University College London, London, U.K., Massachusetts Institute of Technology, Cambridge, MA, USA, ESPCI, Paris, France, and CASIA, Beijing, China. He holds five patents and has published over 200 papers in international journals and conference proceedings. His current research interests include adaptation and learning in nonstationary environments and intelligent embedded systems.

Dr. Alippi is a Vice-President for education of the IEEE Computational Intelligence Society, an Associate Editor (AE) of the *IEEE Computational Intelligence Magazine*, past AE of the IEEE TRANSACTIONS ON NEURAL NETWORKS and the IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENTS from 2003 to 2009, and a member and chair of other IEEE Committees, including the IEEE Rosenblatt Award. In 2004, he received the IEEE

Instrumentation and Measurement Society Young Engineer Award. He has been awarded the Knight of the Order of Merit of the Italian Republic in 2011. He received the IBM Faculty Award in 2013.