Guest Editorial

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Computational Intelligence for Changing Environments

Over the past decade or so, biologically inspired computational intelligence techniques have been highly successful in solving big data challenges in changing environments. In particular, there has been growing interest in so called biologically inspired learning (BIL), which refers to a wide range of learning techniques, motivated by biology, that try to mimic specific biological functions or behaviors. Examples include the hierarchy of the brain neocortex and neural circuits, which have resulted in biologically inspired features for encoding, deep neural networks for classification, and spiking neural networks for general modeling.

There has been growing interest in biologically inspired learning (BIL), which refers to a wide range of learning techniques, motivated by biology, that try to mimic specific biological functions or behaviors.

To ensure these models are generalizable to unseen data, it is common to assume that the training and test data are independently sampled from an identical distribution, known as the sample i.i.d. assumption. In dynamic and non-stationary environments, the distribution of data changes over time, resulting in the phenomenon of 'concept drift' (also known as population drift or concept shift), which is a generalization of covariance shift in statistics. Over the last few years, transfer learning and multitask learning have been used to tackle this problem. Fundamental analyses using probably approximately correct (PAC) and Rademacher complexity frameworks have explained why appropriate incorporation of context and concept drift can improve generalizability in changing environments.

It is possible to use human-level processing power to tackle concept drift. Concept drift is a real-world problem, usually associated with online concept learning, where the relationships between input data and target variables dynamically change over time. Traditional learning schemes do not adequately address this issue, either because they are offline or because they avoid dynamic learning. However, BIL seems to possess properties that would be helpful for solving concept drift problems in changing environments. Intuitively, the human capacity to deal with concept drift is innate to cognitive processes, and the learning problems susceptible to concept drift seem to share some of the dynamic demands placed on plastic neural areas in the brain. Using improved biological models in neural networks can provide new insights into cognitive computational phenomena.

However, a main outstanding issue in using BIL for concept drift and domain adaptation is how to build complex networks, or how networks should be connected to the features, samples, and distribution drifts. Manual design and building of these networks are beyond current human capabilities. Recently, BIL has been used to address concept drift, with promising results. A Hebbian learning model has been used to handle random, as well as correlated, concept drift. Neural networks have been used for concept drift detection, and the influence of latent variables on concept drift in a neural network has been studied. In another study, a timing-dependent synapse model has been applied to concept drift. These works mainly apply biologically-plausible computational models to concept drift problems. Although these results are still in their infancy, they open up new possibilities to achieve brain-like intelligence for solving concept drift problems in changing environments.

Taking the current state of research in concept drift and BIL into account, the objective of this special issue, a first on this multi-disciplinary subject, is to collate this emerging research to help unify the concepts and terminology of BIL in changing environments, and to survey

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state-of-the-art BIL methodologies and the key techniques investigated to date.

The Special Issue Call for Papers led to a total of fourteen submissions, all of which were subject to a rigorous multi-stage peer review process. The paper by Poria, Cambria, Gelbukh, Bisio and Hussain was handled independently by the Editor-in-Chief. The final review and selection of papers were made by the magazine's editorial board, and a total of three papers were included in the Special Issue, representing diverse challenging areas where BIL is gaining particular attention.

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The first paper by Ditzler, Roveri, Alippi, and Polikar reviews state-of-the-art learning in nonstationary environments. In such types of changing environments, particularly those that generate streaming or multi-domain data, the probability density function of the data-generating process is known to potentially change (drift) over time. The authors start by highlighting the fundamental and rather naïve and non-realistic assumption made by most conventional computational intelligence approaches that the training and testing data are sampled from the same fixed, albeit unknown, probability distribution. Learning in such challenging non-stationary environments requires adaptive or evolving approaches that can monitor and track the underlying changes, and adapt a model to accommodate those changes accordingly. In this pioneering survey paper, the authors provide a succinct and comprehensive survey and tutorial of both established and state-of-the-art approaches, highlighting the two primary perspectives, active and passive, for learning in nonstationary environments. Finally, the authors provide an invaluable inventory of existing real and synthetic datasets, as well as tools and software for getting started, evaluating and comparing different approaches.

In the second paper by Poria, Cambria, Gelbukh, Bisio and Hussain, the authors aim to exploit dynamic linguistic patterns for sentiment data flow analysis in natural language text. Specifically, the authors demonstrate how computational intelligence and linguistics can be blended in order to better understand sentiment associated with natural language text in very large, heterogeneous, noisy, and ambiguous environments such as the Web. In a changing and complex world of the Open Internet, where needles of useful information are buried in haystacks of ever growing floods of Big Data, the authors argue that conventional natural language processing (NLP) systems are in urgent need to fast "jump the curve" to catch up with the many new challenges. Relying on arbitrary keywords, punctuation and word co-occurrence frequencies have worked fairly well so far. However, the explosion of Web contents and the outbreak of deceptive phenomena such as Web trolling and opinion spam are increasingly exposing the inefficiency of conventional NLP algorithms. In order to effectively extract and dynamically manipulate text meanings, a truly intelligent NLP system must have access to a significant amount of knowledge about the real noisy, ambiguous world and the domain of time-varying discourse. The authors show how their novel analysis algorithm, based on the flow of sentiment from concept to concept through dependency relations enhances the understanding of the contextual role of each concept in natural language text. Further, they demonstrate how their proposed system achieves a dynamic polarity inference that outperforms state-of-the-art statistical methods, in terms of both accuracy and training time.

The final paper by Widrow, Kim and Park, combines different learning paradigms to develop a new unsupervised learning algorithm that has practical engineering applications and provides insight into learning in living neural networks. Specifically, the authors demonstrate how a form of the well-known, 'supervised' Least Mean Squares (LMS) algorithm can be constructed to perform 'unsupervised' learning and, as such, be used in a more natural way to implement Hebbian learning. Unsupervised Hebbian learning is widely accepted in the fields of psychology, neurology, and neurobiology, and is one of the fundamental premises of neuroscience. On the other hand, the supervised LMS algorithm of Widrow and Hoff is the world's most widely used adaptive algorithm, fundamental in the fields of signal processing, control systems, pattern recognition, and artificial neural networks. These very different learning paradigms, can be combined to create a new unsupervised learning algorithm, that according to the authors, can help address the fundamental question: "how does learning take place in living neural networks? "Nature's little secret," the learning algorithm practiced by nature at the neuron and synapse level, may well be the Hebbian-LMS algorithm proposed by the authors.

Finally, the guest editors are grateful to the reviewers for their insightful and timely reviews and to the Editor-in-Chief for giving us the opportunity to propose and guest edit this exciting special issue.