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EDITORIAL

Adaptive and on-line learning in non-stationary environments

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The computerization of many life activities and the advances in data collection and storage technology lead to obtain mountains of data. They are collected to capture information about a phenomena or a process behavior. These data are rarely of direct benefit. Thus, a set of techniques and tools are used to extract useful information for decision support, prediction, exploration and understanding of phenomena governing the data sources.

Learning methods use historic data points about a process past behavior to build a predictor (classifier, regression model, time-series model). The latter is used as an old experience to predict the process future behavior. However, the predictor needs to adjust itself (self-correction or adaptation) as new events happen or new conditions/system states occur (e.g. during on-line operations). The goal is to ensure an accurate prediction of process behavior according to the changes in new incoming data characteristics. This requires a continuous learning over long period of time with the ability to evolve new structural components on demand and to forget data becoming obsolete and useless. Incremental and sequential learning are essential concepts in order to avoid time-intensive re-training phases and account for the systems dynamics/changing data characteristics with low computational effort and virtual memory usage (enhancing on-line performance). This is because data is processed in sample-wise and single-pass manner.

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It is important that the update of model parameters and structure be achieved without a "catastrophic forgetting". Therefore, a balance between continuous learning and "forgetting" is necessary to deal with non-stationary environments.

A considerable body of research has been previously devoted to the design of models (e.g. classifiers, cluster models, time-series models) whose operating environments are supposed to be static—there, the system behavior and operating conditions/modes in static environments does not change over time. However, this is a quite strong restriction as usually the characteristics of systems and environmental conditions change, evolve over time. A typical example of changing environments is the spam detection and filtering. The descriptions of the two classes "spam" and "non-spam" evolve over time due to the changes of user preferences and "spammers" techniques to trick spam classifiers. Another example is the behavior of human beings, which may be affected by different experiences, moods, daily conditions etc.—mimicking their cognitive capabilities in form of neural models thus require a permanent adaptation and regulation of the induced networks. In case of condition monitoring systems employing multi-sensor networks, new sensors may be added whose measured variables or classes should be ideally integrated on-the-fly into a large networks of identified models describing the relations and dependencies being present within the system. In many applications, the models rely on off-line training cycles from historic data samples, which are often costly to obtain or need to be pre-annotated to establish an initial model (e.g. in case of classifiers), especially when intending to guarantee a sufficient coverage of the feature space—issues which are cost-intensive for companies and thus decreasing the applicability and attraction of data-driven models in industrial and healthcare systems. Training the models on a small initial portion of the data and further autonomous adaptation during real on-line mode for refining their definition space and improving their significance helps to overcome this unpleasant situation. System drifts making older relations obsolete requires a dynamic change of the models trained on the preliminary states (before the drifts).

In order to tackle the aforementioned problems, models need to adjust their parameters in order to refine their appearance and behaviors as well as evolve their structures take into account the actual changes in the operating environments. This self-adaptation is necessary to preserve the model's accuracies and thus guarantee their stability. Modeling in evolving environments is thus a central research topic for current machine learning methods, which heavily emerged during the last 10–12 years, as anchored in various publication and organization activities. Recent challenges in adaptive and on-line learning concern the handling of drifts and shifts appropriately and accordingly due to their sudden appearance in streams, semi-supervised and active learning to keep annotation efforts and costs at a minimal possible level, enhanced human–machine interaction strategies for on-line model adaptations and user's behavior modeling, on-line dimension reduction issues assuring smoothness and convergence, ensemble-based methods for noise reduction and improved stability, granular modeling and clustering, interpretability issues during on-line modelling, as well as recent methods in incremental and evolving neuro-fuzzy and neural networks approaches employing various model architectures and applying it for time series modeling problems in non-stationary environments.

This special issue aims at discussing novel efficient techniques, methods and tools in these directions in order to be able to manage, to exploit and to interpret correctly the increasing amount of data in environments that are continuously changing. It thus includes some recent methods going beyond state-of-the-art and addressing the advances and challenges of learning in non-stationary environments. In particular, it handles several real-world applications that require on-line and evolving learning capabilities which have been hardly tackled before in this context.

In the following, a short summary of each accepted paper in this special issue is presented.

The paper "Affect Detection from Non-stationary Physiological Data using Ensemble Classifiers" (*Paper #1*) by O. AlZoubi, D. Fossati, S. D'Mello, and R. A. Calvo, proposes a classifier ensemble approach to detect affect from physiological signals. The latter exhibit considerable variation over time. The non-stationarities of physiological signals is a major challenge for building a reliable classifier over time. Therefore, the proposed ensemble classifier combines decisions from the ensemble members based on their weights. The latter depend on the performance of each ensemble member. These weights are updated over time automatically based on incoming data. The members that make a correct decision are promoted and the ones that make incorrect decisions are demoted.

The paper "Penalized Ensemble Feature Selection Methods for Hidden Associations in time series Environments" (*Paper #2*) by A. Aloraini, addresses the problem of revealing hidden and informative dependencies between Equity Companies that appear in Saudi Stock Exchange Market. The latter is a strong non-stationary environment generating a huge volume of daily time series datasets. The paper proposes penalized ensemble feature selection techniques in order to capture hidden associations between predictors from daily time series stock market data sets. These techniques are based on the combination of univariate filtering feature selection, wrapper feature selection and the lasso regularization feature selection from which the most optimal penalized features are learned in parallel.

The paper "On-line Incremental Learning for Unknown Conditions during Assembly Operations with Industrial Robots" (*Paper #3*) by J. L. Navarro-Gonzalez, I. Lopez-Juarez, K. Ordaz-Hernandez and R. Rios-Cabrera, handles the problem of controlling autonomous industrial robots for the assembly operations in non-stationary environments. The latter comprise uncertainties associated to sensing, to control, to the model errors, to disturbances, aging etc. which make the assembly task very complex. Therefore, this paper proposes a Fuzzy Adaptive Resonance Theory MAP Artificial Neural Network (ARTMAP-ANN) to overcome these uncertainties and consequently to accomplish successfully the assembly task. The fuzzy ARTMAP is composed of two fuzzy ART modules connected by an inter-ART module that controls the learning of an associative map from the two ART modules.

The paper "Hybrid Dynamic Data-driven Approach for Drift-like Fault Detection in Wind Turbines" (*Paper #4*) by H. Toubakh and M. Sayed-Mouchaweh, proposes an online self-adaptive learning scheme in order to achieve the fault diagnosis in early stage in wind turbines. To achieve that, the learning scheme uses two indicators in order to monitor a drift in the characteristics of normal operating conditions. The first indicator detects the drift and the second indicator confirms it. The drift of the operating conditions of a wind turbine component from normal towards a failure represents component degradations due to aging effect and/or to the wind turbine environment conditions. The detection of this drift allows achieving the fault diagnosis in early stage before the failure.

The paper "On-line Learning with Minimized Change of the Global Mapping—Optimized Local Learning by Incremental Risk Minimization." (*Paper #5*) by A. Buschermoehle and W. Brockmann, treats the problem of online learning regression, which is able to deal with all kinds of nonlinear model structures. The adaptation is achieved online in order to ensure low computational cost or restricted computation time suitable for real applications as for example embedded systems with real-time constraints. The key challenge lies on the problem of localizing the adaptation strategy of a single training datum in a way to minimize its effect on the global model structure, omitting catastrophic forgetting and over-fitting on sparse data, without the request of a concrete setting of the forgetting factor, which is hardly possible in an adequate and appropriate way in advance. Therefore, it develops an incremental risk minimization algorithm continuously adapting the learning process itself to the data at hand.

At the end, we hope that this special issue sheds light on some novel works on adaptive and online learning in non-stationary environments. In particular, we would like to gratefully acknowledge and sincerely thank all the reviewers for their insightful comments and criticism of the submitted papers. We would like also to thank all the authors for their contributions and collaboration. Finally, we are grateful to the Editor-in-chief Plamen Angelov and the editorial office assistants of Evolving Systems for their suggestive and insightful editorial comments and support during the review and production process of this special issue.

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