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(eds.)

The first workshop on
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Proceedings

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Program

10.00-10.10 Opening (Chairs: Gabriella Casalino and Katarzyna Kaczmarek-Majer)
10.10-11.00 Keynote Talk:
Plamen Angelov, Online Learning of Interpretable Deep Models from Uncertain Data (streams)

11.00-12.00 Session 1 (Chair: Giovanna Castellano)

- *P. V. Campos Souza and E. Lughofer*, An explainable evolving fuzzy neural network in position identification of basketball players
- *B. Li and E. Müller*, STAD: State-Transition-Aware Anomaly Detection Under Concept Drifts
- *D. Leite*, State-Space Evolving Granular Control of Unknown Dynamic Systems

14.00-15.00 Session 2 (Chair: Daniel Leite)

- *J. L. Corcuera Bárcena, P. Ducange, F. Marcelloni, A. Renda, F. Ruffini*, Hoeffding Regression Trees for Forecasting Quality of Experience in B5G/6G Networks
- *P. Ardimento, L. Aversano, M. L. Bernardi, M. Cimitile*, Fuzzy-based process mining to discover the coding behavior: challenges and future works
- *G. Casalino, P. Ducange, M. Fazzolari, R. Pecori,* Fuzzy Hoeffding Decision Trees for Learning Analytics

15.00-16.00 Session 3 (Chair: Katarzyna Kaczmarek-Majer)

- *P. Grzegorzewski and A. Kedzierski*, Time series classification using F-transform
- *K. Kaczmarek-Majer, A. Rutkowska, O. Hryniewicz*, Evolving membership functions in fuzzy linguistic summarization
- *J. Onderi Orero*, Typicality based fuzzy gradual rules model for real-time emotions assessment through physiological signals

Online Learning from Uncertain Data Streams: Editorial

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Abstract

This editorial note provides an overview of the papers accepted to the First Workshop on Online Learning from Uncertain Data Streams (OLUD 2022) and related sub-areas. The OLUD workshop was intended to facilitate interdisciplinary discussion on recent advancements of state-of-the-art online machine learning and incremental pattern recognition methods. The uncertainty inherent to the data, model parameters and learning procedures, as well as the implication of the uncertainties on applied domains, was a concern of the discussions. Model explainability, especially by means of a rule base and linguistically-translated elements, was also emphasized. The workshop was held in Padua (Italy), on July 18, 2022, in conjunction with the IEEE World Congress on Computational Intelligence (IEEE WCCI 2022). This preface summarizes the motivations of the meeting, the contributing papers and their findings, and the open topics discussed by the participants, which may stimulate new research.

1. Area Overview and OLUD Motivations

Nowadays, applications in various domains (computer science, engineering, medicine, economy, etc.) are based on sensor data and/or depend on data transmission in the cloud. Effective modeling approaches to address such a massive amount of dynamically-changing data in a feasible period of time are of utmost importance. Traditional first principles and offline data-driven modeling approaches for static datasets are very often insufficient or ineffective in online data stream environments. In such environments, fast recursive procedures to capture spatio-temporal patterns and concept drifts and shifts from the data are needed. Often, the data flow brings instances in high frequency. Narrow time and memory constraints are available for an incremental machine learning step per instance, or per a small set of instances.

Models should be parametrically and structurally updated as a consequence of multiple types of changes that may occur in the data sources. Moreover, data streams may carry statistical, possibilistic and fuzzy uncertainties that arise in specific technical and contextual domains, which need to be adequately addressed. Finally, computational models that present a higher level of human-understandability have been demanded in several domains. For example: (i) in

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domains in which the final users are non-technicians; (ii) to support expert decision making in medicine, engineering, meteorology, energy, logistics; (iii) to explain the actions taken by unmanned vehicles and mobile robots, which affect the human environment. Thus, new methods to linguistically explain the approximate reasoning behind the outcomes of a model are needed to achieve trustful and reliable results. The OLUD (Online Learning from Uncertain Data Streams) workshop (sites.google.com/view/olud) addressed topics on uncertainty in online machine learning, leaving room to several open questions:

- How explainability can be achieved in online learning?
- How uncertainty handling can improve online learning?
- How hybrid methods and elements from different theories can be combined to exploit their benefits for online learning?

The workshop brought together theorists and practitioners who apply computational intelligence, statistics, and control methods for sequential and uncertain data analysis to exchange and discuss ideas that enrich traditional approaches useful for static datasets. The workshop was attended by experts and an audience from different research communities – such as: (i) incremental learning from stream data; (ii) soft methods for stream data; (iii) fuzzy statistics; (iv) Big data; (v) uncertainty modeling; (vi) evolving neural and neuro-fuzzy networks.

2. Event Synopsis

The workshop started with a keynote talk by Plamen Angelov titled *Online Learning of Interpretable Deep Models from Uncertain Data Streams*, which is based on his recent findings [1, 2]. Current machine learning methods are often focused on accuracy, whereas overlook aspects such as explainability, semantic meaning of the internal model representation, reasoning, and the model link with the problem domain. They also overlook the efforts to collect and label training data and rely on assumptions about the data distribution that are often unsatisfactory. The keynote speaker has addressed open issues on developing highly efficient and accurate algorithms; and models that are transparent, explainable, and fair by design. Such models are able to continuously learn and improve their estimates or actions over time. Complete model re-training after significant changes is needless. Learning can start from a few training instances, and never-before-seen patterns can be detected on the fly. Such evolving models would be able to collaborate with humans and other such algorithms.

The OLUD workshop attracted 12 full-length papers from computational intelligence, control and statistics, from which 9 were accepted. The contributions are:

1) *An Explainable Evolving Fuzzy Neural Network in Position Identification of Basketball Players*, by Paulo Vitor Campos Souza and Edwin Lughofer. This paper applies an evolving fuzzy neural network to identify the position of players on a basketball court. The Spanish Basketball League dataset contains 4 classes (point guard, shooting guard, small forward, and center). An instance related to a player is described by 13 features (height, blocks, rebounds, assists, points, personal fouls committed and received, free throw percentage, 2-point and 3-point field goal percentages, turnovers, steals, and global assessment). In addition to provide accurate classification, the evolving neuro-fuzzy model displayed

interpretable information to help decision making. For example, the model indicated that the player height is a determining factor for his position on the court. The ability on blocking, rebounding, and 3-point shooting can also facilitate the player's on-court functionality. See [3, 4] for further applications and different types of evolving neuro-fuzzy networks studied by the authors.

2) *STAD: State-Transition-Aware Anomaly Detection Under Concept Drifts*, by Bin Li and Emmanuel Muller. This paper proposes an autoencoder-based approach called STAD for anomaly detection under potential concept changes. A state-transition-based model is used to map different data distributions within windows of the data stream into states, thereby addressing the model adaptation problem in an interpretable way. The state transition process was empirically evaluated and demonstrated for detecting anomalies in a Covid-19 dataset from Germany. While typical offline-designed autoencoders for unsupervised anomaly detection become invalid after distributional drifts of the data stream, STAD overcomes this issue by exploring the temporal context. For additional information of the research area refer to [5, 6].
3) *Fuzzy Hoeffding Decision Trees for Learning Analytics*, by Gabriella Casalino, Pietro Ducange, Michela Fazzolari and Riccardo Pecori. This paper presents a case study of explainable stream data analysis in the educational domain. Students' interactions with Virtual Learning Environment together with students' information, have been proved to be suitable predictors of the students' outcomes [7]. In this paper the intrinsic evolving nature of the students' learning has been exploited though a stream data analysis algorithm. Particularly, Fuzzy Hoeffding Decision Trees, proposed in [8], have been used to describe the students' learning behaviors over sequential semesters, in form of "IF-THEN" rules, and to predict their outcomes. This is an innovative research topic combining stream data processing, explainability and fuzzy logic for the educational domain. These topics are individually addressed in the literature [9, 10, 11].
4) *Hoeffding Regression Trees for Forecasting Quality of Experience in B5G/6G Networks*, by José Luis Corcuera Bárcena, Pietro Ducange, Francesco Marcelloni, Alessandro Renda, and Fabrizio Ruffini. This paper describes the use of Hoeffding Regression Trees (HRTs) to evaluate the end-user satisfaction in terms of "Quality of Experience" (QoE). They measure the capability to play high-definition videos in real-time with B5G/6G networks. Standard Regression Trees (RTs) have been compared with HRTs to forecast real data. Different parameters have been considered in evaluating the two approaches, such as, accuracy, time for model updating, model complexity and memory occupancy. For additional information on forecasting QoE in networks refer to [12, 13, 14]
5) *Fuzzy-based Process Mining to Discover the Coding Behavior: Challenges and Future Works*, by Pasquale Ardimento, Lerina Aversano, Mario Luca Bernardi, and Marta Cimitile. This paper describes a learning environment for object-oriented coding, that is able to identify patterns in students' coding behaviours, through a fuzzy logic based process mining approach. The interactions between students and the learning environment are collected over the time and are stored in form of logs. For additional information of the process mining applied to the educational and coding domain refer to [15, 16, 17].
6) *State-Space Evolving Granular Control of Unknown Dynamic Systems*, by Daniel Leite. The paper describes a State-Space Evolving Granular Control method (SS-EGC) for unknown

nonlinear dynamic systems. The approach is based on elements of granular computing, discrete state-space systems, and online machine learning. The structure and parameters of a granular model is developed from a stream of state data. The model is formed by information granules comprising first-order difference equations. A granular controller is derived from the granular model for parallel distributed compensation. Instead of difference equations, the content of a control granule is a gain matrix, which can be redesigned in real-time from the solution of a relaxed locally-valid linear matrix inequality derived from an energy Lyapunov function. For information on the research area of evolving granular control, and applications in stabilization of nonlinear systems refer to [18, 19, 20, 21, 22].

7) *Time series classification using F-transform*, by Przemysław Grzegorzewski and Antoni Kędzierski. This paper describes a new method for time series classification. Two techniques were evaluated: (i) the fuzzy transform (F-transform), which provides a simple approximate representation of functions; and (ii) the well-known decision tree classifier. The objective is to compare the best distance measures to be used in both the proposed method and the most popular 1-NN method. Numerical experiments confirmed that the proposed F-transform-based classification method reveals the smallest standard deviation of the error, and one of the smallest mean errors. For further results on the use of F-transforms in time-indexed data refer to [23, 24].
8) *Evolving Membership Functions in Fuzzy Linguistic Summarization*, by Katarzyna Kaczmarek-Majer, Aleksandra Rutkowska, and Olgierd Hryniewicz. Inspired by the general concept of evolving fuzzy systems, this paper introduces a time-dependent procedure for the construction of membership functions in linguistic summarization. Linguistic terms are automatically derived from a mathematical model to compose membership functions. In particular, stationary autoregressive and moving average (ARMA) models are estimated. Then, components of linguistic summarization are gradually changed by online learning from new data instances and statistical inference. The usefulness of the proposed approach is illustrated in an economic time series prediction problem. For additional information on the research area, refer to [25].
9) *Typicality based Fuzzy Gradual Rules Model for Real-Time Emotions Assessment through Physiological Signals*, by Joseph Onderi Orero. This paper addresses online affective computing in order to enhance the quality of human-computer interactions. The essential idea is that computational models should automatically adapt themselves based on human affective states. Emphasis is put on promoting empathy between machine and autistic people. Emotional responses were accessed by means of uncertain and imperfect physiological measures using bio-sensors. As physiological patterns change over time and change from person to person, a fuzzy rule-based model supported by the concept of typicality of the flowing data was developed and updated gradually to characterize different affective states over the time. For additional information about online learning applied to emotion recognition and affective computing refer to [26, 27, 28, 29].

Overall the OLUD contributions highlighted the ability of online machine learning methods and evolving fuzzy and neuro-fuzzy systems to handle complex nonstationary and uncertain data; thus indicating multiple avenues for future research. Particularly, in addition to the paper

topics, the on-site participants leveraged and discussed future and open research issues. Some issues are mentioned in the following.

3. Open Topics

Interesting and persuasive practical solutions have been achieved in the area of intelligent modeling of uncertain data streams in the last decade. Some future directions for making adaptive and evolving methods suitable to a broader field of applications, especially for Big data processing, Internet of Things, eXplainable Artifcial Intelligence, Cyber-Physical Systems, and Smart Industry, are described in the following.

Propositions, lemmas, theorems and assurance that certain conditions are fulfilled are still lacking, in large part, in the field of online clustering and evolving fuzzy and neuro-fuzzy modeling from data streams [30]. For instance, necessary and sufficient conditions to guarantee short-term adaptation and long-term survivability are still to be found. This is a major challenge because concept shift and concept drift affect the structure of the hypothesis space [30]. Systematic and formal methods to deal with the models' structural stability-plasticity trade-off are still needed.

Characterization, design of experimental setups, and construction of workflows to guide development, performance evaluation, testing, validation, and comparison of methods in nonstationary environments require further elaboration. The evolution of rough-set models, Dempster-Shafer models, second-order granular rule-based models, and aggregation functions are also important topics to expand the current scope of the area [30]. T-norms and S-norms, Uni-norms and null-norms, and averaging functions are generally chosen *a priori* and kept fixed during model evolution. Approaches to switch aggregation operators based on properties of the data, and to update associated operator parameters are still to be undertaken.

Evolving and adaptive systems in parallel high-performance computing frameworks should be explored. The rule-base modular and granular structure of fuzzy models is an interesting aspect to be exploited in high-frequency stream applications. Moreover, a variety of particularities of different applications and evolution aspects in hardware using low resources – aiming at smarter evolving models – are still to be addressed.

We have witnessed the expansion of the OLUD topics to the area of deep learning, image processing, and autoencoders [1]; streams of text and sentences, and log parsing [31]; decision and regression trees in the educational domain [32]; autonomous robots with evolving capabilities [33]; linguistic summarization for augmented interpretability [34]; brain-computer interfaces [27, 28, 35]; weather prediction [36]; power systems [37]; fault detection in engineering systems [38, 39]; and patient monitoring and medical decision support [25, 40].

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