A Self-organizing Multi-agent System for Adaptive Continuous Unsupervised Learning in Complex Uncertain Environments

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Introduction. Continuous learning and online decision-making in complex dynamic environments under conditions of uncertainty and limited computational recourses represent one of the most challenging problems for developing robust intelligent systems. The existing task of *unsupervised clustering* in statistical learning requires the maximizing (or minimizing) of a certain similarity-based objective function defining an optimal segmentation of the input data set into clusters, which is an NP-hard optimization problem for general metric spaces and is computationally intractable for real-world problems of practical interest (Davidson and Ravi 2005). The task of continuous online learning in complex dynamic environments assumes *near real-time* mining of streaming data continually arriving at the system, which imposes additional requirements for continuous clustering algorithms. This paper describes the developed computationally efficient adaptive multi-agent approach to continuous online clustering of streaming data in complex uncertain environments and a knowledge-based self-organizing multi-agent system for implementing it.

A multi-agent approach to adaptive continuous learning. We address the problem of continuous online learning in changing environments by developing a hybrid learning approach to be both *intelligible* and *computationally efficient* that combines multiagent distributed resource allocation and model-based reinforcement learning of POMDPs. The developed multi-agent approach to adaptive online unsupervised learning of streaming data is based on an asynchronous message-passing method of continuous agglomerative hierarchical clustering and a knowledge-based competitive multi-agent system for implementing it.

The proposed computationally efficient multi-agent algorithm for online agglomerative hierarchical clustering of streaming data is different from conventional unsupervised learning methods by being *distributed*, *dynamic*, and *continuous*. Distributed clustering process provides the ability to perform efficient run-time learning from both centralized and decentralized data sources without an additional centralized algorithm of aggregating partial mining results. Both the input dataset of decentralized sources and decision criteria for learning (e.g. similarity matrices and expert knowledge) are not fixed and can be changed at run-time during execution of the dynamic algorithm. The continuous adaptive process of distributed learning is originally sensitive to environmental variations and provides a fast dynamic response to changes with event-driven incremental improvement of learning results. Clustering results of the adaptive learning algorithm are available at any time and continuously improved to achieve a global solution to the constrained optimization problem of clustering, trading off operating time and result quality.

As opposed to previous work, we propose a different multi-agent approach to continuous online learning by modeling the task of unsupervised clustering as a dynamic distributed resource allocation problem and implementing the concept of *clustering by asynchronous message-passing* (Frey and Dueck 2007) whereby an implicit global quasi-optimal solution to the constrained optimization problem of clustering is obtained by satisfying a dynamic distributed constraint network defined for data elements. The data-driven self-organizing process of dynamic continuous optimization is based on the constant distributed search to maintain a dynamic balance among the interests of all self-interested participants in the interaction by means of a decentralized market-based method for multi-agent coordination.

A market-based algorithm of continuous agglomerative hierarchical clustering. Autonomous agents of records and clusters negotiate with each other in the virtual clustering marketplace (competitive computational environment) to enhance their satisfaction levels with minimal costs and establish semantic links of the highest utility, according to the following ongoing algorithmic process. (1) *Continuous arriving of data elements at the system.* For each data and cluster element continuously arriving at the system at run-time, the Biosphere Agent of the special service type continually parses a description of a clustering situation, constructs the initial ontological scene (instances and relationships) in the mining ontology, and produces a population of corresponding mining agents in the virtual clustering marketplace. (2) *Locating candidate agents for allocation negotiations (semantic-based pre-matching).* Once created, an agent examines the mining ontology to find appealing candidate agents to initiate allocation negotiations inside its limited field of vision, considering domain-specific heuristics. (3) *Allocating a record to the existing cluster*. To accomplish the allocation goal a record agent can participate in three types of allocation negotiation processes: it can interact with the existing cluster agents to join it, or negotiate with either other record agents or cluster agents

to create a new cluster to be allocated to (algorithmic steps #3, #4, #5 respectively). (3.1) *Requesting membership in a cluster by a record agent (task announcement).* A record agent sends a membership request to selected cluster agents. An autonomous agent of a candidate cluster can proactively sends a membership proposal to an appealing single record agent without receiving a membership request (algorithmic step #7). (3.2) *Proposing membership in a cluster by a cluster agent (bidding for allocation).* A cluster agent evaluates the value of the possible allocation option (ontological relationship) with the partner according to the agent criterion of the corresponding negotiation type ("allocating a record to a cluster"). (3.3) *Establishing a membership contract by a record agent (allocation bid processing).* The record agent selects a single candidate cluster agent with the most profitable allocation variant that increases the value of its current agent state and sends to it a membership contract. (3.4) *Performing allocation of a record to a cluster by a cluster agent (membership contract processing).* Once a membership contract has been awarded to a cluster agent, the initiator and participant of the negotiation process commit to the target allocation goal to establish a mutually profitable ontological relationship and produce a new mining agent. (4) *Creating a cluster by record agents*; (5) *Creating a cluster of the higher level by record and cluster agents.* A record agent can consider the option of creating a cluster of a higher level to be allocated to with another record or cluster agent, in case there are either no cluster agents that can increase the value of the current state of a record agent or all of them refuse a membership request since such an allocation option is not profitable for them. (6) *Creating a cluster of the higher level by cluster agents*. Besides negotiating with record agents to enhance its quality, a cluster agent has the second goal of establishing the most profitable allocation with the agents of clusters. To achieve this goal a cluster agent participates in a negotiation process of the synthesis type with other cluster agents to create a cluster of a higher level to be a part of it. (7) *Agent proactive improvements of mining results*. The agents exhibit not only reactive behavior by simply responding to system events, but also proactively search for the most profitable allocation variants and initiate negotiations to establish and reconsider ontological relationships with other agents, thereby enhancing results of the dynamic clustering process. During the active state of agent proactive improvements, agents can restrictively regulate a depth of their vision and consider allocation options with the increased length of the "ripple-effect", which is a decision reconsideration chain that improves the overall clustering results (adaptation). Additionally, different centralized and distributed control mechanisms for self-organization are applied to control the transition of the dynamic optimization process toward the global quasi-optimal state while avoiding undesirable local attractors (Kiselev et al. 2007). (8) *Terminating algorithm execution.* For situations when no changes of ontological relationships and cluster memberships can increase values of the agents, the system eventually settles down to a new quasi-optimal state and the distributed learning process turns to the inactive state. The algorithm is terminated either when a predefined amount of time elapses or it is known that the operating environment is static and no more input data elements will arrive at the system.

Agent decision-making strategies. Goal-driven behavior of autonomous agents is supported by the developed microeconomic multi-objective decision-making model, which makes it possible for the learning algorithm to operate on the basis of nonstandard optimization criteria and to be suitable for exploratory data analysis using unusual measures of similarity. Currently supported agent decision-making strategies are based on the following agent criteria: a distance-based measure of similarity, the Chebychev similarity metric, and the angle metrics defining polarization ("shape") of agent communities (multilevel and multicultural) in decision-space. Agent decision-making strategies can be applied dynamically at run-time to the whole agent society (global level), to a single agent (individual level), or to agent groups in different areas of the virtual clustering marketplace (several polarization vectors).

Conclusion and future work. Conducted experiments demonstrated the strong performance of the developed multi-agent learning system for online hierarchical clustering of both synthetic datasets and datasets from the RoboCup Soccer and Rescue domains. Nevertheless, the developed system prototype revealed the current limitation of the algorithm to efficiently perform massive data processing of high-dimensional data (gene expression datasets). To address this issue we have been working on the approach to reducing the problem dimension while maintaining the essential characteristics of the original system (the concept of renormalization) by modeling a multi-agent system in incomplete decision space as decentralized partially observable Markov decision processes (DEC-POMDPs) and applying Bayesian statistical methods. Additionally, further research is being conducted on extending the adaptive learning approach to support online semi-supervised classification by continuously deducing semantic-based classification rules from clustering results and performing automatic rule-based classification at run-time.

References

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