EVOLVING STRUCTURES FOR PREDICTIVE DECISION MAKING IN NEGOTIATIONS

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Abstract: Predictive decision making increases the individual or joint gain of negotiators, and has been extensively studied. One particular skill of predicting agents is the forecast of their opponents' future offers. Current systems focus on enhancing learning techniques in the decision making module of negotiating agents, with the purpose to develop more robust systems. Empirical studies are conducted in bounded problem spaces, where data distribution is known or assumed. Our proposal concentrates on the incorporation of learning structures in agents' decision making, capable of forecasting opponents' future offers even in open problem spaces, which is the case in most negotiation situations.

1 INTRODUCTION

Electronic Marketplaces (E-markets), is an important component of e-business that brings demand and supply of commodities and services into balance. The term e-market is used in a broad sense and incorporates the various types and configurations of markets, stores, agoras and other meeting places where transactions about tangible or intangible objects take place (Kersten, Chen, Neumann, Vahidov, and Weinhardt, 2008). Our focus lies on the negotiation mechanism, which is defined as an iterative communication and distributed decision-making process, where participants, humans or agents acting on their behalf, are searching for an agreement. Several scientific fields have made contributions to the development of negotiation theory. In particular models that follow normative, prescriptive or descriptive approaches derived from the application of economic theories, management and social sciences respectively. The current trend concentrates on the development of learning techniques, incorporated either in support systems that assist human negotiators, or in software agents that are capable to fully automate the process. It is proved that humans or agents that act in open, dynamic environments where minimal knowledge is available are particularly benefited by learning techniques that seem to "extend" their cognitive abilities. In section 2 we give a brief review of the learning techniques employed by negotiators, and particularly focus on forecasting opponents' offers. In section 3 we discuss limitations and weaknesses and in section 4 we propose a structure that is expected to advance the state-of-the art in predictive decision-making. Finally, in section 5 we describe the expected results of this proposal.

2 LEARNING IN NEGOTIATIONS

The majority of research efforts regarding the learning techniques in order to support the various negotiation activities are concentrated in the adoption of optimal or satisfying strategies, in understanding negotiating partners and in identifying individual preferences and objectives. This is due to the fact that negotiators deal with vague and incomplete information. The common case is to be ignorant about their opponents' preferences and strategy. Nevertheless negotiation result, measured in terms of individual or joint satisfaction, highly depends on the negotiating behaviors of the engaged parties, reflected through the different strategies. We devise current state-of-the-art agents into those that follow explorative, repetitive or predictive strategies.

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The former category consists of agents that search the strategy space usually through trial-and-error learning processes, the second category consists of agents who repeat strategies that have proved efficient in past similar situations, while the third category consists of agents who adopt a strategy, based on estimations of environmental parameters and/or opponent. We focus on the latter category and particularly to the issue of estimating opponents' future offers, which has proved to add value to negotiators in various domains. The learning methods used to provide opponent's forecasts summarize to statistical models, mathematical models and neural networks. In section 2.1 we present current systems of negotiation forecasts.

2.1 Forecasting Opponent's offers

Forecasting opponents' offers has proved valuable for various reasons. We discriminate between single and multi-lag predictions. Single-lag predictions, which involve the estimation of the opponents' next offer, encourage more sophisticated decision making mechanisms. Oprea (2003) discusses the development of SmartAgent enhanced with a feed forward artificial neural network, to facilitate trading scenarios via an internet platform. The agent uses the predicted value of his opponents' next offer in order to refine his proposal and increase individual gain. Carbonneau, Kersten, and Vahidov (2008) depict the development of a neural network predictive model in order to facilitate "What-if" analysis and generate optimal offers. It is proved that even small variations in the current offer can have important impact on the expected counter-offer from the opponent. A similar negotiation support tool is applied by Lee and Ou-Yang (2009) in a supplier selection auction market, where the demander benefits from the suppliers' forecasts, by selecting the most appropriate alternative in each round. Papaioannou, Roussaki, and Anagnostou (2006) discuss a predictive model, based on neural networks (MLPs and RBFs), with the purpose to refine the agents' pre-final offering decision and produce more beneficial outcomes. The difference with this approach is that the prediction mechanism is run only once, when agent is approaching his deadline. Brzostowski and Kowalczyk (2006) implemented a non-linear regression model to forecast opponents' next offer; they describe an iterative procedure in order to foresee the whole negotiation thread, based on standard concessions. The objective is to identify the optimal strategy in order to attain the most beneficial discourse.

Moving to the realm of multi-lag predictions, an interesting approach based on non-linear regression can be found in Hou (2004), where prediction of opponents' future offers, combined with the estimation of his strategic parameters, has been used to effectively detect and withdraw from pointless negotiations, where agreement could not have been established. This line of inquiry has also been followed by Roussaki, Papaioannou and Anagnostou (2007), where the decision of the agents to withdraw or not from the current negotiation was taken at an early round through the forecast of the providers' offer before the clients' deadline, with the use of MLPs and RBFs. Finally, predictions have been used to avoid negotiation breakdown whilst making a best deal at the opponents' deadline (Hou, 2004). Current systems have been assessed by a series of experiments with opponents who use pure and in some cases mixed static strategies in various domains, and it has been proved that predicting agents gain in utility compared to the non-predicting ones.

3 PROBLEM STATEMENT

When it comes to forecasting the partners' future offers, techniques can be summarized into those based on statistical approaches (non-linear regression), mathematical models, based on arithmetic analysis and connectionist approaches, particularly some special types of neural networks (MLPs and RBFs). We are not concerned with mathematical models, since experiments have proved that they give poorer results when compared to non-linear regression or neural networks. The agents enhanced with non-linear regression methods are more restrictive than those who use artificial neural networks, in that they are particularly tied to specific offer generation functions which have been described by Faratin, Sierra, and Jennings (1998). On the contrary neural networks do not assume a known function form and this makes them more robust in the general case. We trust that the current trend on providing offer forecasts lies on neural networks, also due to the fact that they have been applied in different negotiation problems and domains.

Nevertheless, in all aforementioned systems, the networks are trained once in an off-line mode and are set to operate in a real environment. This implies high dependency of the predictors' accuracy to the available training data which are initially presented. In reality, an electronic market place is a highly turbulent environment; data distributions may change as stakeholders enter and leave the e-market, or as individual preferences and strategies change over time. If an agent changes the negotiable attributes' reservation values, his concession strategy or the available time to negotiate, a different negotiation thread, series of offers, will be produced. As the predicting agent uses the neural network with different data, the accuracy of the system is expected to decrease. Neural networks that are used for predictions comprise of a hidden layer with sigmoid or tangent hyperbolic transfer functions and of an output layer with linear transfer functions. The transfer function of the nodes in the hidden layer acts as a squashing function which returns values in [-1,1]. Therefore if the new input deviates from min and max values of input data in the training vector, the network will not be able to produce accurate results. Existing systems have not been tested in dynamic environments with changing data distributions. Since they are trained only once, how can we expect to provide the network with data that exhaust all possible interactions?

To tackle with the problem of changing distributions, it is evident that models must engage in on-line learning, where learning takes place during operation, as new input patterns are presented. A stated risk of this approach is catastrophic forgetting; previously learned patterns are forgotten with the presentation of new data. Albesano Gemello, Laface, Mana, and Scanzio (2008) state that catastrophic forgetting is particularly high when a connectionist network is adapted with new data that do not adequately represent the knowledge included in the original training data. The question we pose is the following: how can the accuracy of a model engaged in on-line, life-long learning be preserved even in an environment with unknown data distributions?

4 PROPOSAL

In order to advance the current state of the art we propose the use of a model capable of adapting to new data of unknown distributions without forgetting previously learned patterns. The above characteristics are met by Evolving Intelligent Systems (EIS), which trace and understand the dynamics of the modeled processes, automatically evolve rules, solve problems of complex domains and continuously improve performance. Methods of (EIS) are consolidated in Evolving Connectionist Systems (ECoS), and have been studied in various domains. "An ECOS is an adaptive, incremental learning and knowledge representation system that evolves its structure and functionality, where in the core of the system is a connectionist architecture that consists of neurons and connections between them" (Kasabov, 2007). ECoS have the following attractive features: they may evolve in open space, engage in incremental lifelong learning in an online mode, learn both as individual systems and as evolutionary populations of such systems, partition the problem space locally, allowing for fast adaptation, have evolving structures and trace the evolving processes over time. We propose the integration of Evolving Fuzzy Neural Networks (EFuNNs) (Kasabov 2007), which are evolving connectionist structures, in the decision-making mechanism of negotiating agents. EFuNNs translate the input and output space to fuzzy input and fuzzy output space. The objective is to provide appropriate mappings of input to output subspaces. This is realized with the use of intermediate rule nodes which move as new patterns are presented and the data associations change. Additionally new rule nodes may be created to represent new associations. With this technique the system is always consistent with current data, without any assumptions of data distributions. In more detail EFuNNs have a five layer structure as shown in figure 1, where new nodes and connections are created and connected as data examples are presented. The first layer represents the input variables and the second represents fuzzy quantization of each input variable. The third layer contains rule nodes that evolve through supervised learning and represent prototypes of input-output data associations. The fourth layer represents fuzzy quantization of the output variables and the fifth layer represents the values of the output variables.

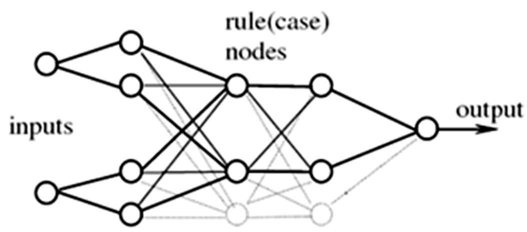

Figure 1: Evolving fuzzy neural network (Kasabov, 2007).

Rule nodes move to accommodate new input-output examples. The networks' structure is not predefined but changes according to incoming data (rules are updated or new rules are inserted). This special characteristic of EFuNNs allows for adaptation to dynamic environments. Additionally each rule node is separately trained (implements local learning), and this allows for learning new patterns without forgetting the previously learned ones. Our belief that EFuNNs are appropriate to guide predictive decision making in negotiations is strengthened by the fact that they can learn any dataset in various problems (function approximation, time-series prediction, and classification) and have been tested in various domains. For example, (Kasabov, 2007) demonstrates that EFuNNs are capable to learn complex chaotic functions through incrementally adaptive learning from one-pass data propagation.

5 EXPECTED RESULTS

Our research attempts to advance the state of the art in predictive decision making with the proposal of agents that are capable of providing predictions even in dynamic environments with changing data distributions. We distinguish two cases, bounded and open problem spaces: (a) “in bounded problem spaces, if sufficient examples are presented after a time moment, the input and output space will be covered by hyperspheres of the evolved rules, and the system will reach the desired accuracy” (Kasabov, 2007). It has been proved that EFuNNs are universal function approximators in bounded problem spaces; the proof is based on the well-known Kolmogorov theorem and is analogous to the proof that MLPs with two layers are universal function approximators. In such cases we expect EFuNNs to be as accurate as MLPs in the task of forecasting opponents’ offers. (b) “In open problem spaces, where data dynamics and distribution may change over time in a continuous way, the error of EFuNNs will depend on the closeness of the new input to the existing rule nodes” (Kasabov, 2007). Such spaces have not been considered in existing literature and we argue that current systems are not adequate to model evolving lifelong learning processes. The use of EFuNNs in the decision-making of existing negotiating agents adds value to the field, as more accurate results are expected even in open problem spaces. Empirical evaluation of our proposal will be provided through a number of experiments simulating different situations.

REFERENCES

Albesano, D., Gemello, R. Laface, P., Mana, F., Scanzio. S. (2006) Adaptation of Artificial Neural Networks Avoiding Catastrophic Forgetting. In *Proceedings of IJCNN 2006* (pp. 1554-1561).

Brzostowski, J. and Kowalczyk, R. (2006). Adaptive Negotiation with On-Line Prediction of Opponent Behaviour in Agent-Based Negotiations. In *Proceedings of the IEEE/WIC/ACM international Conference on intelligent Agent Technology* (pp. 263-269). Washington, DC: IEEE Computer Society.

Carbonneau, R., Kersten, G. E., and Vahidov, R. (2008). Predicting opponent's moves in electronic negotiations using neural networks. *Expert Systems with Applications: An International Journal,* 34 (2), 1266-1273.

Faratin, P., Sierra, C. and Jennings, N. R. (1998). Negotiation Decision Functions for Autonomous Agents. *Int. Journal of Robotics and Autonomous Systems*, 24 (3 - 4), 159-182.

Hou, C. (2004). Predicting Agents Tactics in Automated Negotiation. In *Proceedings of the intelligent Agent Technology, IEEE/WIC/ACM international Conference* (pp. 127-133). Washington, DC : IEEE Computer Society.

Kasabov, N. (2007). *Evolving Connectionist Systems: The Knowledge Engineering Approach*. London: Springer-Verlag,

Kersten, G. E, Chen, E., Neumann, D., Vahidov, R., Weinhardt, D. (2008). On Comparison of Mechanisms of Economic and Social Exchanges: The Times Model, *Negotiation, Auctions and Market Engineering*. Heidelberg: Springer Berlin.

Lee, C. C. and Ou-Yang, C. (2009). A neural networks approach for forecasting the supplier's bid prices in supplier selection negotiation process. *Expert Systems with Applications,* 36(2), 2961-2970

Oprea, M. (2003) The Use of Adaptive Negotiation by a Shopping Agent in Agent-Mediated Electronic Commerce. In: *Proceedings of the 3rd International Central and Eastern European Conference on Multi-Agent Systems, CEEMAS03*. (pp. 594-605). Heidelberg: Springer Berlin.

Papaioannou, I. V., Roussaki, I. G., and Anagnostou, M. E. (2006). Comparing the Performance of MLP and RBF Neural Networks Employed by Negotiating Intelligent Agents. In *Proceedings of the IEEE/WIC/ACM international Conference on intelligent Agent Technology (*602-612). Washington, DC: IEEE Computer Society.

Papaioannou, I., Roussaki, I., and Anagnostou, M. (2008). Detecting Unsuccessful Automated Negotiation Threads When Opponents Employ Hybrid Strategies. In D. Huang, D. C. Wunsch, D. S. Levine, and K. Jo, (Eds.), *Proceedings of the 4th international Conference on intelligent Computing* (pp. 27-39). Heidelberg: Springer Berlin.

Roussaki, I., Papaioannou, I., Anagnostou, M. (2007). Building Automated Negotiation Strategies Enhanced by MLP and GR Neural Networks for Opponent Agent Behaviour Prognosis. In Sandoval, F., Gonzalez Prieto, A., Cabestany, J., Grana, M. (eds.) IWANN 2007 (pp. 152-161) Heidelberg: Springer Berlin.