Data Assimilation Technique for Social Agent-Based Simulation by using Reinforcement Learning

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***Abstract*—This paper presents a data assimilation technique for social agent-based simulation to fit real world data automatically by a reinforcement learning method. We used the hidden Markov model in order to estimate the states of the system during the reinforcement learning. The proposed method can improve simulation models of the social agent-based simulation incrementally when new real data are available without total optimization. In order to show the feasibility, we applied the proposed method to a housing market problem with real Korean housing market data.**

Keywords—data assimilation, agent-based, social simulation, reinforcement learning, hidden Markov model

I. Introduction

In spite of many merits of agent-based simulations, it is hard to get exact agent-based simulation models for social systems due to lots of latent and non-stationary driving factors in terms of system dynamics. When new data arrive, the model validation process of the social systems is usually performed via human hands periodically, which is expensive and time-consuming to give imprecise models before modification. Data assimilation for social agent-based simulation has been difficult problem due to absence of optimization of mathematical models. Some optimization approaches have been studied to optimize the simulation models of agent-based simulation like the Kalman or Particle filter, evolutionary algorithms and reinforcement learning [1][2][3].

In spite of many optimization techniques for agent-based simulation, there were few studies to consider the data assimilation of social agent-based simulation systematically. We proposed the reinforcement learning technique to get data assimilation of social agent-based simulation beforehand [4]. In this paper, we improve the state selection for the reinforcement learning by using hidden Markov model. We apply the proposed method to a housing market problem with real Korean housing market data in order to show the feasibility.

II. Proposed Data Assimilation Technique with Reinforcement Learning

A. Self-evolving Simulation Framework

The framework for self-evolving agent-based simulation is composed of the modules of simulation engine, model validity detection, data assimilation, data/model management, model reconfiguration [5]. The models have configurable structures which include formal components. Candidate components are made during modeling process of simulation models beforehand and managed via the data/model management module. The framework makes data assimilation of agent-based simulation into the problem to select the best model components among the candidates.

B. Reinforcement Learning

The data assimilation of the agent-based simulation can be converted into the reinforcement learning problem to derive the optimal policy by selecting the best candidate components for some states of the system from rewards of the Markov decision process. It has been the open issue how to define the states of the Markov decision process of the system and we defined the states by hand in a heuristic way in [4].

C. Hidden Markov Model for State Estimation

It is hard to define the states and the corresponding policy structure for the reinforcement learning mechanism systematically because the domain and heuristic knowledge is required. In this paper, we use the hidden Markov model to estimate the states to find effects of latent and time-varying factors of real system as in Fig. 1. The hidden Markov model has been applied to find the market regimes of the social systems. In this paper, we combine the estimation of system states via hidden Markov model with the previously proposed heuristic way of the state design [4].

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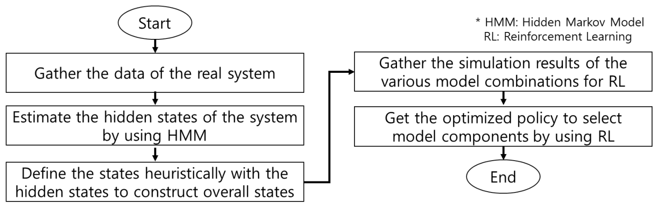

Fig. 1. The optimization process of model selection by the state estimation of the hidden Makrkov model.

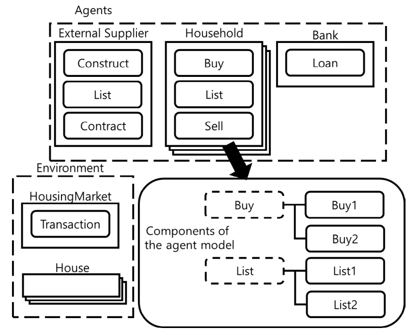

Fig. 2. Agent-based simulation component models of the housing market.

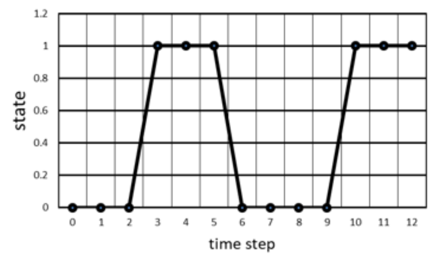

Fig. 3. Estimation of states via hidden Markov model .

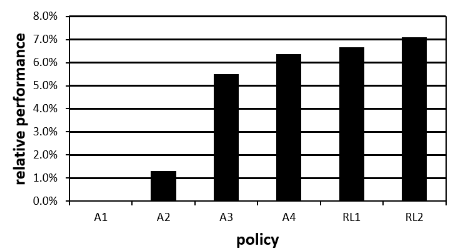

Fig. 4. The peformance comparison of the policies.

III. APPLICATION TO AN HOUSING MARKET PROBLEM

A. The Housing Market Problem

We designed the agent-based model for the housing market problem with real Korean housing market data of 48 months [4]. The agent model for a household has actions of 'buy', 'sell', and 'list'. The 'buy' and 'list' actions have two candidates for each as depicted in Fig. 2. Since we can get the housing market data of 12 months every year via panel survey and statistics from the Korean government, we use the data of 12 months for data assimilation.

B. Markov Decision Process for Reinforcement Learning

We estimated regime states with two state values for the policy by using hidden Markov model as in Fig. 3. We combined these two states with three error states between simulation results and the real data of house trading. Therefore, four action sets are selected for six overall states. That means 4,096 policy combinations are possible. We use the Q-learning method as the reinforcement learning.

C. Simulation Results

The 500 households and the 1,114 houses are used for the simulation. We compared some possible policies in terms of simulation errors as shown in Fig. 4. The symbols of the A1 ~A4 mean the results of four models with fixed actions during simulation. The RL1 means the result of reinforcement learning with heuristic state definition and RL2 means the result with hidden Markov model for state estimation. The relative performances are measured via sum of absolute errors between simulation results and real data values as an average of ten simulations in comparison with the worst performance with the A1 policy. RL2 has 7.1% better performance than one of A1, and better than one of RL1.

IV. CONCLUDING REMARKS

In this paper, reinforcement learning was used to optimize the policy of Markov decision process for data assimilation of social agent-based simulation. By using hidden Markov model to estimate states of the policy, the reinforcement learning process can be designed systematically. Although the performance of the model of the proposed method is better than the heuristic one in this paper, the bad selection of the hyper parameters of the method may result in worse models. For future research, we will study how to select the hyper parameters effectively.

ACKNOWLEDGMENT

This research was supported by the Korean ICT R&D program of MSIT/IITP, (No. R7117-17-0219, Development of Predictive Analysis Technology on Socio-Economics using Self-Evolving Agent-Based Simulation embedded with Incremental Machine Learning)"

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