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Social Simulation Based on Human Behavioral Data Collected from Web-Based Experimental System

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and Shigeru Matsumoto[2, 3, 4]

Abstract

In this paper, we propose some models to simulate human choice behavior to select facilities. In order to develop models for human behavior, first we develop a web-based experimental system to collect the data of human choice behavior in facility selection. Using the developed system, human subjects act their facility selection according to the information such as the congestion level of the facility selected last time. We examine several models to simulate human choice behavior based on the data collected from the experimental system. From our examination, we find that developing models according to experimental results improves simulation results.

Keyword: human choice behavior, web-based experimental system, machine learning

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1. Introduction

In this paper, we propose some models to simulate human choice behavior to select facilities. When a national or a local government try to have a plan to build some public facilities such as library or community center, they try to build them to give fair services to all parts of its territory. Post offices or ATMs (automatic teller machine) are also placed to give fair services to residents in their service territory. In order to build or place such facilities for their service, the congestion level of the facility is really matter. If the level of congestion is high in a facility, another one should be added in that place. On the other hand, the level is low in another one, it should be contracted or removed in order not to pay too much running expense for the facility.

In this paper, we try to build models to simulate human choice behavior using a machine learning technique. Here we employ a table to express the relation between state and action. State is defined by an agent using his perception. That is, if he percepts some information around his environment, that becomes his perception. In the state and action table, one of several actions is selected according to his perception. Using this expression, we try to simulate human choice behavior in this paper. The state and action table is commonly employed in reinforcement learning [1]. However, in many trials of reinforcement learning, a reward for an agent is given from an environment that is designed by a programmer of the system. An agent learns the best state and action table automatically by obtaining rewards from the environment. This is well known approach in reinforcement learning, however, the environment is built by a programmer as a creator of the world. If the world is not built appropriately, the table learned by an agent through his try and error seems meaningless for observers to learn something from the table. In this paper, we try to build a state and action table based on actual data of human subjects who join our facility selection experiment.

In order to obtain a state and action table based on real data from experiments with human subjects, we first develop a system to collect data of experiments of human choice behavior. Section 2 shows a design of our experiment for human choice behavior. Then Section 3 introduces our web-based experimental system to collect data of human choice behavior. Section 4 shows brief results obtained by our web-based experimental system. Then, we show several attempts to express human choice behavior using a state and action table in Section 5. Finally we conclude some findings in Section 6.

2. Experiment of Human Choice Behavior

We design our laboratory experiment of human choice behavior based on the experiment conducted by Selten et al. [2]. They analyze commuters' route choice behavior in the laboratory. They find that subjects keep changing their routes even in the substantially long experiment. Then they conclude that fluctuation around the pure equilibrium is a much better explanation about commuters' route choice behavior. Their results show the optimal allocation of the commuters can be achieved by choices of subjects, however, they will not be maintained. Next, they show that commuters change their routes less frequently when additional feedback information (congestion information) is provided.

In our experiment, we extend the analysis of Selten et al. [2] by allowing cost heterogeneity across agents. When the chosen facility is congested, an agent should wait for his or her turn to receive a service in the facility. Waiting costs vary across agents. That is, some do not mind spending a reasonable amount of time in the facility, but others are less patient. In a real world, both high-cost and low-cost agents use the same public facility. Therefore, it is worthwhile to examine how the cost variation influences the human choice behavior.

We can predict an equilibrium of the problem using the game theory [3,4]. In this paper, however, we don't focus on the process to obtain an equilibrium of the problem. The result using our experimental system for the problem (the system is introduced in the next section) was not the same to the theoretical equilibrium of the problem. This shows that, in order to simulate human choice behavior, we can not employ a result of the game theory because it leads only to an equilibrium that can not be found in the real world.

We design our experiment of human choice behavior as follows: Subjects are 40 students from the Department of Informatics, Kansai University, Japan. They were divided into 5 groups, with 8 subjects in each group. We conducted the same experiment for each group. The experiment had 5 sessions. In each session subjects had to choose one of two facilities (either Facility A or Facility B) 30 times repeatedly.

It is assumed that both facilities proved an identical service. However, the cost of using facility changes with the congestion level of a chosen facility. If Subject *i* chooses Facility A and the number of the subjects who choose Facility A is n^A, then the period payoff (the unit is Japanese yen) becomes.

$$v_i = 70 - c_i n^A . \qquad (1)$$

Here c_i is the subject-specific cost of using the facility. Instead, if Subject *i* chooses Facility B, then the period payoff becomes

$$v_i = 70 - c_i n^B, \quad (2)$$

where $n^B = 8 - n^A$ is the number of the subjects who choose Facility B. Therefore, the expected cost and benefit of using the two facilities are the same. In addition to the payoffs, every participant received a show-up fee of 2,000 yen. Before the experiment, we provided the participants with the instruction that explained the purpose and the procedure of the experiment. The leaflet can be found in Figure 1.

The first session is designed as the baseline case. We set $c_i = 6$ for all 8 subjects. In the remaining four sessions, we equally split 8 subjects into two subgroups. In the second session, we set $c_i = 8$ for the subjects in the former subgroups while we set $c_i = 4$ for the subjects in the latter subgroup (each subgroup consists of 4 subjects). In the third session, we swapped the costs between two subgroups and conducted the same experiment as in the second session.

The main purpose of this experiment is to examine whether the cost variation of using facilities influences the agents' facility choice behavior. We model the experiment as a repeated game. In our framework, only the congestion level influences the expected payoff. Regardless of their cost, all players equally evaluate the two facilities.

In the first three sessions, the subjects received feedback at the beginning of each period after the first one about the following items:

1. The number of the current session,
2. The number of the current period,
3. Last chosen facility,
4. Payoff received at the last period,
5. Cumulative payoff in the session

Selten et al. [2] examined whether commuters route choice behavior was influenced by the provision of additional feedback. Following their work, we provided the subject with addition feedback in the last two sessions (Sessions 4 and 5). The amount of the payoff of the non-chosen-facility in the last period was informed to the subject.

2009/2

About Today's Experiment

We thank you for your participation to the PG Lab experiment. The purpose of this experiment is to examine how an individual changes his or her behavior using provided information. There are a few things to note about this experiment. Please read this instruction first.

Examples

Imagine the situation in which you are waiting for your turn in the line to obtain a service at a particular facility. For example, you are waiting your turn in front of ATM to withdraw your money or you are waiting your turn at the postal office to send your parcel. In these situations, you will obtain the same service regardless of the facility. Therefore, you will choose the least crowded facility.

Instruction of this experiment

- ✧ In this experiment, we will ask you to choose one of the two facilities repeatedly.
- ✧ If you choose the facility that a small number of people choose, then the waiting time becomes shorter. Consequently, your payoff becomes larger.
- ✧ Your cumulative payoff constantly changes with your facility selection.
- ✧ The cumulative payoff you obtained is shown on the PC screen in each period.
- ✧ The maximum payoff you can obtain through this experiment is 9,600 yen while the minimum one is 3,300.
- ✧ After each session, please fill your payoff in the prescribed form.
- ✧ In addition to the payoff you will obtain through the experiment, you will receive 2,000 yen remuneration.

Cautions

1. All instructions are provided on the PC screen. When you cannot understand them, please raise your hand and ask your questions to the instructor directly.
2. Please do not talk to other persons during this experiment.
3. Please do not look at the other persons screen during this experiment.
4. Once this experiment begins, you cannot go to the bathroom for about one hour. Please go to the bathroom now if you want to.

Thank you for your cooperation.

Fig. 1. Instruction to Subjects (Original one is in Japanese)

3. Web-based Experimental System of Human Choice Behavior

In order to collect data of human choice behavior, we develop a web-based experimental system. In research regions for sociology, psychology, economics, or politics, many experiments with human subjects are designed to collect data of human behavior. When those experiments are conducted, and data of the experiments are recorded by subjects themselves or human observers, it took time and there are possibilities of human errors in recording data. In order to avoid such human error in experiments, it is better to use computers to record them. There are several computer-aided experimental systems. In order to conduct such computer-aided experiments, several centers are developed. For example, New York University established the Center for Experimental Social Science that has 20 workstations for experiments on economic theory, social psychology, and political science in Manhattan [5]. Hokkaido University, Japan, has the Center for Experimental Research in Social Sciences that includes three systems called “(a) the group experiment lab”, “(b) the worldwide network experiment lab” and “(c) the experiment lab for perception/sensation system” for collecting experimental data in social psychology [6]. Both centers have specially designed laboratory for their experimental systems as shown in Figs. 2 and 3.

Fig. 2. Experimental system in New York University
(A picture found in their website).



(a) (b) (c)

Fig. 3. Experimental systems in Hokkaido University
(Pictures found in their website).

In order to collect data of human choice behavior, we develop a web-based experimental system. Since we don't have specially designed room for conducting our experiment, we design our system that can be used with several computers connected in LAN. The system is outlined in Fig. 4. Each subject sees a screenshot sent from the controller of an experimenter who is conducting his experiment. Figs. 5 and 6 shows sample screenshots that are provided to subjects.

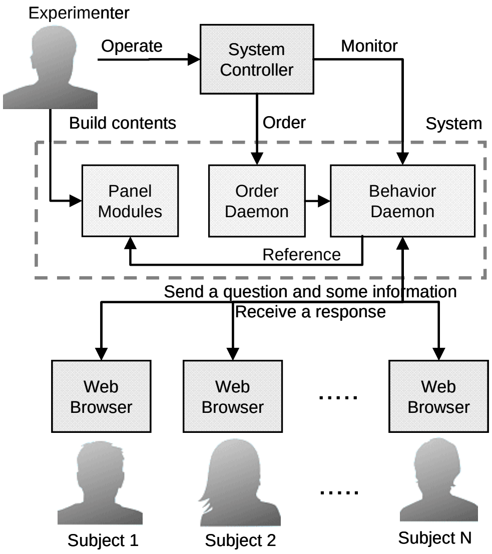

Fig. 4. Overview of the developed web-based experimental system.

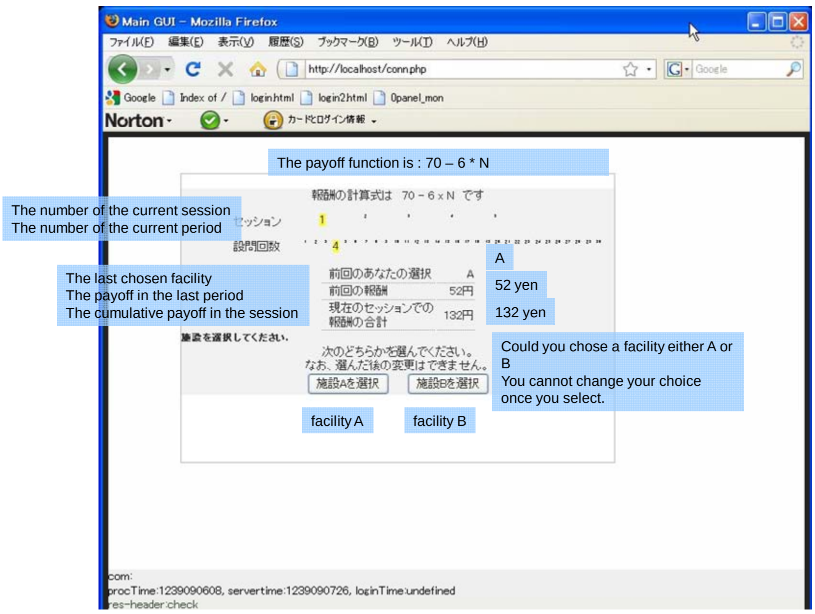

Fig. 5. Screenshot example of the first three sessions (Sessions 1, 2, 3).

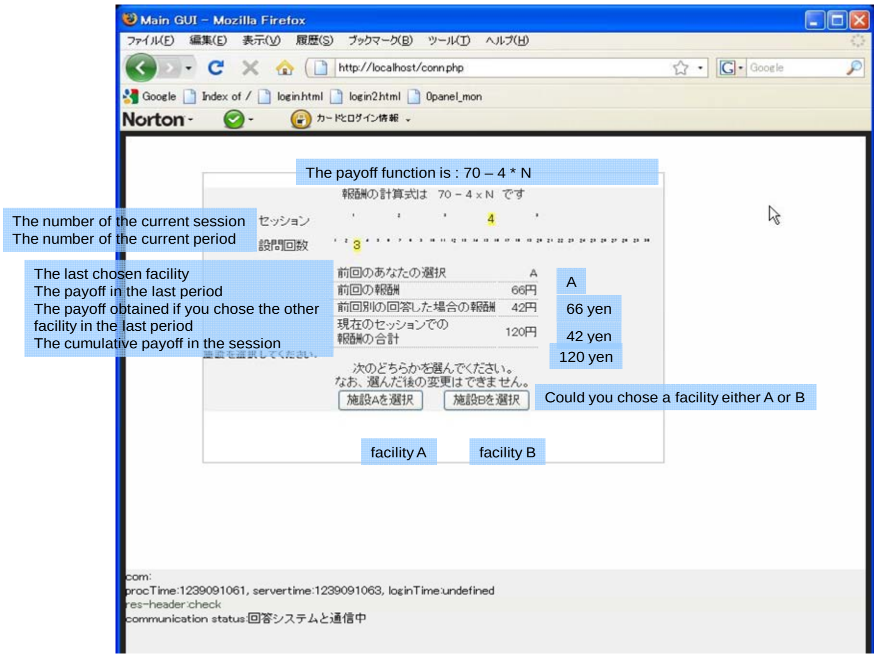

Fig. 6. Screenshot example of the last two sessions (Sessions 4, 5).

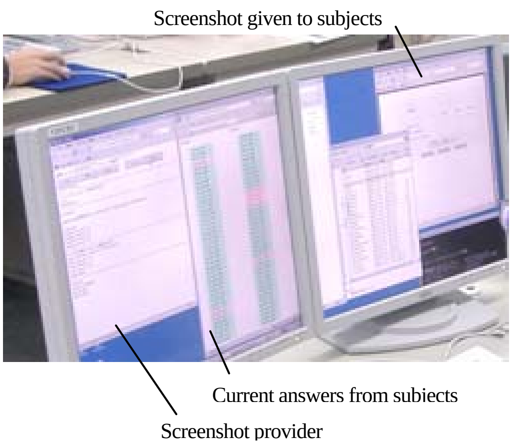

Fig. 7. Desktop of the controller for the experimenter.

Since the congestion level of facilities are determined after all subject decided their facility selection, the experimenter should synchronize screenshots shown to subjects. In order to control the experiment progression, the system shows the experimenter the current status of selections from subjects and the screenshot currently given to subjects. Fig. 7 shows the desktop that was used during the experiment by the experimenter. Using these systems we conduct our experiments.

Fig. 8. A picture of our experiment.

4. Experimental Results

We conducted our experiment with 40 students of the Department of Informatics, Kansai University in February, 2009. As shown in Section 2, we divided them into 5 groups, and each experiment is conducted with a single group. Fig. 8 shows a picture of our experiment conducted in a laboratory that is normally used for graduate students. Although the laboratory is not designed for the experiment, we put some partitions in order to have subjects not to see screens of other subjects.

Fig. 9 shows the number of subjects in Group 3 who chose Facility A in the first three sessions. This figure shows that substantial fluctuations persist until the end of the session. Convergence to the theoretical equilibrium was not observed in all three sessions.

Fig. 10 shows the number of subjects who changed the facility in the first three sessions. In the symmetric mixed equilibrium, the expected number of facility changes of all 8 subjects within a session is 116. The averages actually observed are 80.2 in Session 1, 87.2 in Session 2, and 83.2 in Session 3. The difference between the theoretical expectation and the observed value is greater than in all three sessions. Therefore, like Selten et al. [2], the frequency of facility changes is much lower than the prediction by the symmetric mixed equilibrium. As for the difference of the value of cost in each subject, we compare the numbers of subjects who changed the facilities in each session. The null-hypothesis of no difference in changing behavior between two types of subjects cannot be rejected based on a Wilcoxon matched-pairs signed-rank test. The result implies that the cost difference does not influence the agent’s facility choice behavior.

5. Simulation Models

From the results shown in Section 4, we can see the difference between the observed results and the theoretical predictions. Therefore, in order to see consequences of facility selection by multiple agents, we need to have some other method than the game theory. In this paper, we try to develop several simulation models to simulate human choice behavior based on the actual data obtained from our experiments.

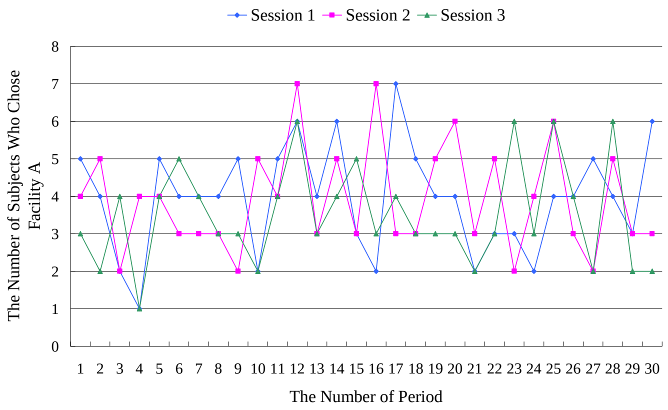

Fig. 9. The number of subjects who chose Facility A (Sessions 1, 2, 3 of Group 3).

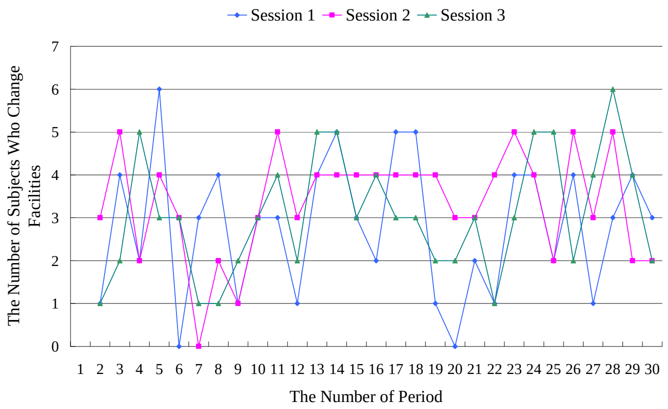

Fig. 10. The number of subjects who change facilities (Sessions 1, 2, 3 of Group 3).

In order to select an expression for the decision model of an agent in human choice behavior, we employ a state and action table. Using this table, each agent can make his decision to choose one of facilities. We examine several values as the state of an agent. Since the state should be perceived by each agent, the state information should be based on the information given to subjects. We examine one of the following information in our models as the state information.

1. The payoff
2. The number of users who chose the same facility
3. Increase or decrease of the payoff
4. The level of increase or decrease of the payoff

According to the description of our experiment in Section 2 and the screenshot in Fig. 3, only the first information is directly given to subjects. The others should be calculated by subjects. For example, the second one can be calculated from the values of payoff and his cost in Equation (1) or (2). The third and fourth ones are calculated by comparing the current and the previous payoffs by subjects.

As for actions in the state-action table, we specify “stay” or “move”. When a subject decides one of facilities, he might think that he should stay the facility he chose, or move to the other facility. According to the data we collected from our experiments, the state-action tables are constructed as shown in Tables 1 through 4. Frequency shows the amount of cases where a subject took either action at a certain state. Probability shows the ratio of stay or move according to the frequencies. We utilized the data of all sessions since we did not find any significant difference among sessions with different costs or information provision. Using one of these tables, every agent makes his decision to stay or to move in his facility selection.

Table 1 State-action table (Payoff value).

	Frequency		Probability	
Payoff	Stay	Move	Stay	Move
0 – 9	4	4	0.500	0.500
10 – 19	44	47	0.484	0.516
20 – 29	234	181	0.564	0.436
30 – 39	1003	559	0.642	0.358
40 – 49	884	550	0.616	0.384
50 – 59	1436	699	0.673	0.327
60 – 69	115	40	0.742	0.258

Table 2 State-action table (The number of subjects in the same facility).

	Frequency		Probability	
# of subjects	Stay	Move	Stay	Move
1	23	16	0.590	0.410
2	212	64	0.768	0.232
3	691	323	0.681	0.319
4	1144	520	0.688	0.313
5	1040	656	0.613	0.387
6	461	361	0.561	0.439
7	140	133	0.513	0.487
8	9	7	0.563	0.438

Table 3 State-action table (Increase/decrease of payoff).

	Frequency		Probability	
Payoff	Stay	Move	Stay	Move
Decrease	1282	911	0.585	0.415
Same	803	435	0.649	0.351
Increase	1493	676	0.688	0.312

Table 4 State-action table (Level of increase/decrease of payoff).

	Frequency		Probability	
Payoff	Stay	Move	Stay	Move
Decrease more than 15	306	225	0.576	0.424
Decrease less than 15	976	686	0.587	0.413
Same	803	435	0.649	0.351
Increase less than 15	1106	497	0.690	0.310
Increase more than 15	387	179	0.684	0.316

We employ one of these tables for decision making of each agent in our simulation. In order to compare simulated results in our simulation and actual results collected from our experiments, we introduce the following measures.

$$AverageDifference = \frac{1}{P}\sum_{p=1}^{P}\frac{1}{M}\sum_{m=1}^{M}| capacity_m - user_{m,p} |, \quad (3)$$

$$SelectionInclination = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{M}\left(\sum_{m=1}^{M}| s_{i,m} - P/M |\right), \quad (4)$$

where P is the number of periods, M is the number of facilities, $capacity_m$ is the capacity of Facility m, $user_{m,p}$ is the number of users who use Facility m at period p, N is the number of subjects, and $s_{i,m}$ is the number of visits for agent i who visits Facility m during P periods.

Therefore the *AverageDifference* is a measure for the facilities that indicates the difference between the target capacity of a facility and the actual congestion. Having too many or too few users in a facility is not desirable for the facility. If all facilities have the number of users that is equal to their own capacity, this value becomes zero. On the other hand, *SelectionInclination* shows an average inclination over agents to select one facility. If all agents averagely visit all facilities, this value becomes zero.

In our experiments, we set the value of $capacity_m$ is four because we have eight subjects in a group. From the data collected in our experiments, the average value of *AverageDifference* was 1.0 and its standard deviation was 0.11, and the average value of *SelectionInclination* was 9.4 over

150 periods, and its standard deviation was 8.91.

In order to realize the tendency found from the experiments in our simulation, we examine the value of *AverageDifference* and *SelectionInclination* in our simulation. In order to compare the four models with a simple transition model, we develop a simple table that has probabilities calculated from the number of stays and moves in the experiments. The probability for stay is 0.641 and that for move is 0.359. Table 5 shows the difference between actual data and simulated data with five models. The values italicized are the closest values to the actual data. From this table, we can see that any models can give similar value of *AverageDifference* to the actual data. On the other hand, there is much difference in *SelectionInclination*. From this result, we should say that the tendency for the facility can be simulated by our models, but behaviors for each subject can not be simulated by our models.

In order to make our models to simulate each agent accurately, we examine a state-action table developed by the data from each subject. That is, each agent makes his decision using his own state-action table that is developed by the corresponding subject. Table 6 shows the simulation results obtained by these models developed by actual data by each subject. From this table, we can see that the modification in making state-action tables slightly improve the values of *AverageDifference* and *SelectionInclination*. However, there is still difference in *SelectionInclination*.

Table 5 The difference between actual data and simulated data.

Method	*AverageDifference*	*SelectionInclination*
Actual data	1.023	9.450
Payoff	1.061	6.486
The number of users	*1.037*	*6.546*
Payoff increase/decrease	1.061	6.437
Detail payoff increase/decrease	1.061	6.442
Simple probability	1.094	6.466

Table 6 The difference between actual data and simulated data using own state-action tables.

Method	*AverageDifference*	*SelectionInclination*
Actual data	1.023	9.450
Payoff	1.047	*7.666*
The number of users	*1.013*	7.603
Payoff increase/decrease	1.054	7.363
Detail payoff increase/decrease	1.049	7.394
Simple probability	1.094	7.437

Table 7 The difference between actual data and simulated data using facility-based state-action tables.

Method	*AverageDifference*	*SelectionInclination*
Actual data	1.023	9.450
Payoff	1.043	11.230
The number of users	*1.014*	10.972
Payoff increase/decrease	1.051	*10.590*
Detail payoff increase/decrease	1.044	10.909
Simple probability	1.086	10.858

We suppose that there may be some difference in actions from Facility A or Facility B. That is, although both facilities have no difference in their function subjects may stick to one facility rather than the other. Based on this assumption, we develop state-action table separately for Facility A and Facility B. Table 7 shows simulation results obtained using these tables. We can see that *SelectionInclination* is improved while *AverageDifference* is kept close to the actual data.

5. Conclusion

In this paper, we examine several models to simulate human choice behavior. Before making simulation, we developed the web-based experimental system to collect human choice behavior. In order to simulate not only facility congestion but also decision making of each agent, the data of individual subjects can be used for modeling state-action tables for each agent in the simulation. Although this conclusion may leads to collect all data from those who are involved in a social simulation, it is impossible. In order to avoid such thorough collection of data, we should develop some method to categorize data and extract representative data for the simulation.

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