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Model-based Approach with ACT-R about Benefits of Memory-based Strategy on Anomalous Behaviors

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Abstract

Users sometimes face anomalous behaviors of systems, such as machine failures and autonomous agents. Predicting such behaviors of systems is difficult. We investigate the benefits of the memory-based strategy, which focuses on memorization of instances to predict anomalous and regular behaviors of the system, with ACT-R simulations with a cognitive model. In this study, we presumed the parameters defining the encoding processes on anomalous instances and regular instances in the model of the memory-based strategy and performed simulations to verify how these two parameters influence prediction performance. The results of simulations showed that (1) regular instances are not encoded as default values in the memory-based strategy and that (2) such inactivity on regular instances suppresses commission errors of regular instances and does not suppress commission errors of anomalous instances nor omission errors.

Keywords: memory-based strategy; prediction; anomalous behavior; regular behavior; ACT-R

Introduction

There are many various systems around us, and users often predict their behaviors. It is relatively easy for users to predict systems' stationary behaviors by applying schemas (henceforth referred to as "regular behaviors"). However, users sometimes observe that systems' behaviors deviate from regular behaviors (henceforth referred to as "anomalous behaviors"). Predicting anomalous behaviors is effortful (e.g., Besnard & Bastien-Toniazo, 1999; Casner, Geven, & Williams, 2013) and requires users to execute much cognitive processing such as reallocation of cognitive resources (Meyer, Reisenzein, & Schützwohl, 1997). Therefore, it is necessary to process anomalous behaviors and regular behavior differently in order to predict systems' behaviors precisely.

One of the strategies to predict systems' behaviors is the "inference-based strategy," which focuses on inferences and understandings regarding the causal structure from systems' behaviors. The literature from various areas of research show that users apply the inference-based strategy spontaneously when encountering anomalous instances (e.g., Baker et al., 2009; Clary & Tesser, 1983; Howard & Holcombe, 2010; Tremoulet & Feldman, 2000, 2006). Inferences contribute to users' understanding of systems, but these inferences include advanced integration processes of the knowledge and the environment (Darabi, Nelson, & Palanki, 2007); therefore, the inference-based strategy is not always effective for highly complex systems.

We define the "memory-based strategy," which focuses on memorization of instances to predict systems' behaviors without understandings regarding causal structure. A knowledge base, such as a database of prior failure instances, is an example of the memory-based strategy. Experimental studies have demonstrated that the benefits of the memory-based strategy appear in the test situations, which is the same as the learning situations (e.g., Lane, Mathews, Sallas, Prattini, & Sun, 2008).

Our previous study reveals that the memory-based strategy is effective in a high-complexity task and the inference-based strategy is effective in a low-complexity task (Matsubayashi, Miwa, & Terai, in press). This study indicates that the benefits of the memory-based strategy are likely to be provided by the activity in which the instances representing the regular behaviors (henceforth referred to as "regular instances") are not encoded as default values, whereas the instances representing the anomalous behaviors (henceforth referred to as "anomalous instances") are intentionally encoded. In this study, we investigate these features of the memory-based strategy in detail, with a cognitive model.

First, we review our argument that regular instances are not encoded in the memory-based strategy by reproducing the human data in the psychological experiment. We presume the two parameters defining the encoding processes on anomalous instances and regular instances, and then examine whether the simulated data with inactivity of encoding regular instances provide a good fit to the human data. Second, we reveal why the benefits of the inactivity of encoding regular instances appear by confirming the performance with settings of two encoding parameters. Specifically, when the parameters are set for encoding not only anomalous instances but also regular instances, what happens to the simulated performance data?

Experimental Task

Stimulus

The experimental task required participants to predict the final position of the ball based on its observed movement.

The screen used in this task comprises a visible region and an invisible region (see Figure 1). A hidden object is placed in the invisible region. If the ball makes contact with the object, it changes its direction, whose trajectory is defined as an anomalous instance. Conversely, a regular instance is generated when the ball goes straight without direction changes. The ball is ejected from a certain initial position in the outer frame and at a certain angle. The ball is temporarily invisible while it passes through the invisible region. The ball becomes visible again when it enters the visible region. The ball's movement finally stops at the outer frame. Hereafter, an initial position and an initial angle of the trajectory are defined as "input," and a final position and a final angle are defined as "output."

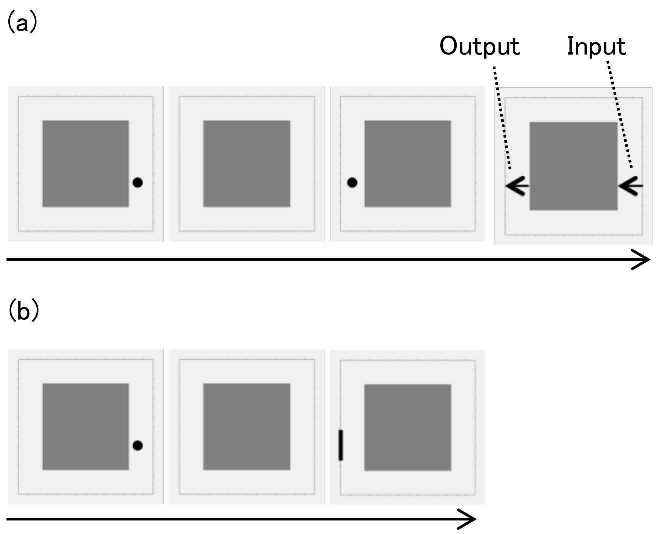

Figure 1: Overview of the task. (a) In the observation phase, the movement of the ball is presented and then the confirmation screen is displayed. (b) In the test phase, participants can move the paddle.

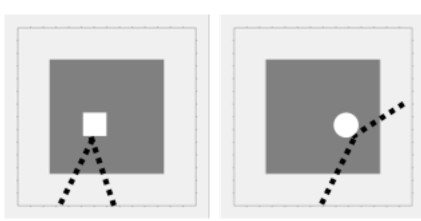

Figure 2: Difficulty settings of the task. Shapes of hidden objects and examples of trajectories in a low-complexity task (left) and in a high-complexity task (right).

Table 1: Composition of the trials in blocks 2–5.

Phase	Instance	Experience
Observation	Anomalous (3)	
	Regular (9)	
Test	Anomalous (6)	Novel (3)
		Experienced (3)
	Regular (6)	Novel (3)
		Experienced (3)

The observation phase and the test phase are alternated repeatedly in this task. In the observation phase, participants observe the movement of the ball from its ejection (i.e., input) until its stoppage in the outer frame (i.e., output). Participants are also shown the confirmation screen with two arrows representing the input and the output (see Figure 1a).

In the subsequent test phase, the ball stops as soon as it enters the invisible region, and a paddle is also displayed (see Figure 1b). To predict the final position of the ball and catch it with the paddle, participants are required to move the paddle with a left click button and determine its position with a right click button. The paddle is displayed at the same location in which the ball would arrive if it went straight without direction changes. In other words, it is not necessary to move the paddle in regular instances but is necessary to move the paddle in anomalous instances to catch the ball. The number of correct trials in which the range of the paddle includes the genuine final position of the ball is regarded as the prediction performance. No feedback on the predictions is provided to participants.

The shapes of the hidden objects in the invisible region determine the complexity of the tasks (see Figure 2). Anomalous instances follow a simple trajectory in a low-complexity task with a square-shaped object and a complex trajectory in a high-complexity task with a circular object.

Procedure

Prior to the observation phase, participants were informed that they were required to predict, as precisely as possible, the final position of the ball in the test phase. Participants were instructed to focus on and memorize the two arrows representing the input and the output in the confirmation screen in the observation phase. Participants are expected to use the memory-based strategy and encode the combination composed of an initial position, an initial angle, and a final position as an instance comprised of the input and the output.

The movement of the ball constituted one sequence, and each sequence constitutes one trial. A block comprised 12 trials in the observation phase and 12 trials in the test phase. All trials in block 1 corresponded to regular instances in the observation phase and in the test phase. Trials comprised three anomalous instances and nine regular instances in the observation phase in blocks 2–5. In the test phase, trials comprised six anomalous instances and six regular instances. In addition, each trial in the test phase comprised three novel instances, which were shown only at this time, and three experienced instances, which had been shown in the previous observation phase (see Table 1).

Participants implemented a 5-block low-complexity task and a 5-block high-complexity task. The positions and the shapes of hidden objects are consistent throughout all the trials in each task.

Summary of Psychological Experiment Results

Overall, the data of 24 participants were analyzed. A summary of the results is described here, and the details are mentioned with the simulation results (see Figure 3).

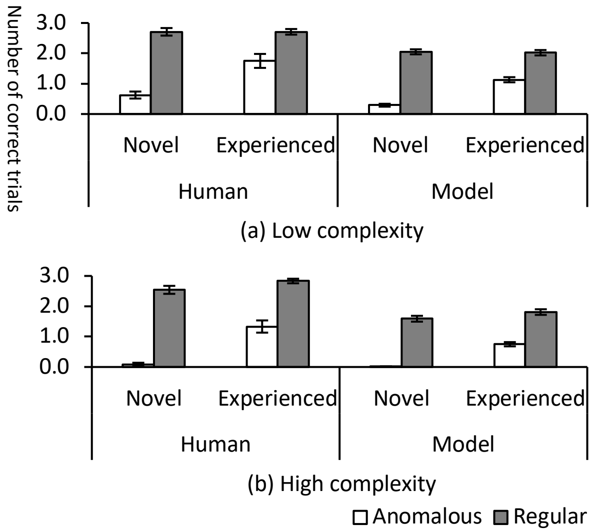

Figure 3: Prediction performance in block 5. Error bars represent standard errors.

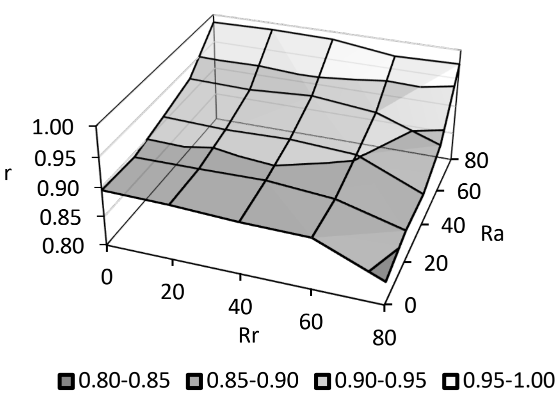

Figure 4: Correlation coefficients on prediction performance in block 5 between the simulated data and human data. Ra represents the rehearsal probability of anomalous instances and Rr represents the rehearsal probability of regular instances.

Statistical results show that the interaction of the instance factor (anomalous/regular) and the experience factor (novel/experienced) was significant for the prediction performance in each task in block 5 (low-complexity: $F(1, 23) = 13.8$, $p < .005$, $\eta^2 = .60$; high-complexity: $F(1, 23) = 10.7$, $p < .005$, $\eta^2 = .47$). Specifically, the performances for anomalous-experienced instances are higher than those for anomalous-novel instances (low-complexity: $F(1, 46) = 27.6$, $p < .001$; high-complexity: $F(1, 46) = 41.6$, $p < .001$). This result indicates that anomalous instances were encoded in the observation phase. Additionally, no differences are observed in the performance for regular-novel instances and for regular-experienced instances (low-complexity: $F(1, 46) = 0.0$, $p = 1.0$, $r = .00$; high-complexity: $F(1, 46) = 2.2$, $p = .13$, $r = .32$). This result indicates that regular instances were not encoded in the observation phase; therefore, they were not retrieved even for regular-experienced instances in the test phase.

Simulations with Cognitive Model

This study adopts ACT-R simulations (Anderson, 2007) with a cognitive model to investigate the details of processing. Two retrieval errors critical to the memory-based strategy are available in ACT-R, that is, commission errors representing that wrong instances are retrieved and omission errors representing that encoded instances are not retrieved.

In this study, we examine the following two points with simulations. First, we reveal the features of the memory-based strategy by performing simulations with two parameters defining the encoding processes of anomalous instances and regular instances. If the simulated data with the parameters meaning inactivity of encoding regular instances provide a good fit to the human data, our argument regarding such an inactivity is supported. Second, we reveal the reason why the benefits of inactivity of encoding regular instances appear in the memory-based strategy. Two research questions are drawn: How does the parameter on encoding regular instances decrease the prediction performance? What type of retrieval error is the cause of such decline in performance?

Simulation Settings

The following is the outline of the memory-based strategy model. In the observation phase, the model detects an input arrow and an output arrow, reads the position and the angle of each arrow, and then encodes them as a chunk in the declarative memory. This chunk comprises three slots—the initial position, the initial angle, and the final position. Next, the model runs rehearsals by repeating retrievals of the chunk. The rehearsal probability parameters determine whether the model continues to run a rehearsal on every rehearsal. There are two types of rehearsal probability parameters. If an input angle is different from an output angle, the model regards this trial as "an anomalous instance" and runs rehearsals on the basis of the rehearsal probability of anomalous instances (henceforth referred to as "Ra"). Additionally, if an input angle is the same as an output angle, the model regards this trial as "a regular instance" and runs rehearsals on the basis of the rehearsal probability of regular instances (henceforth referred to as "Rr").

In the subsequent test phase, the model reads the position and the angle of an input arrow and makes a retrieval request to declarative memory with them as a clue. If the model fails to retrieve an instance or the retrieved final position is included in the range of the paddle, the model does not move the paddle. Otherwise, the model moves it to the retrieved final position with left click button. After that, the model confirms the position of the paddle with a right click button.

Making retrieval errors on two adjacent initial positions is likely because these two positions are highly similar and difficult to distinguish from each other. Therefore, the similarity parameters between two adjacent initial positions are set to −0.5. Other similarity parameters are set to −1.0 as default.

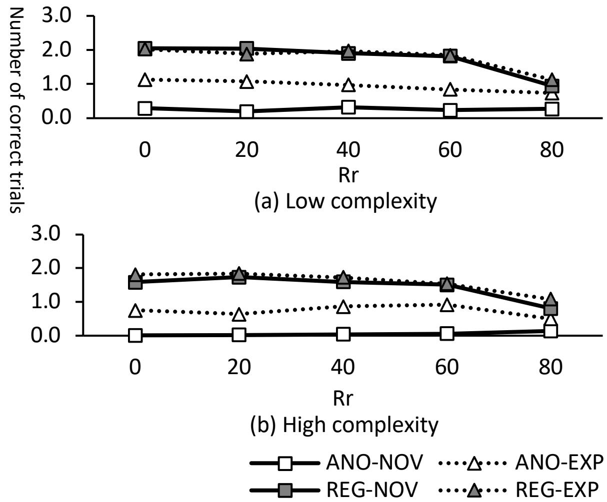

Figure 5: Variations of prediction performance on a function of the rehearsal probability of regular instances (Rr). ANO, REG, NOV, and EXP represent anomalous, regular, novel, and experienced respectively.

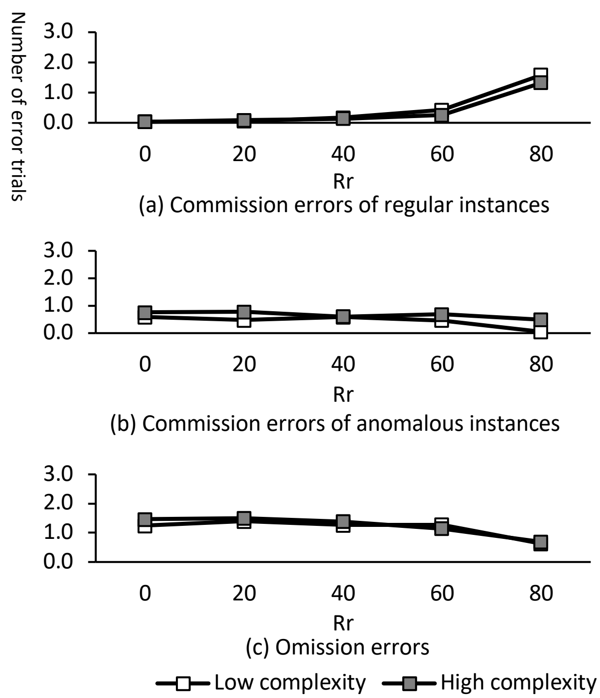

Figure 6: Variations of retrieval errors on anomalous-experienced instances on a function of the rehearsal probability of regular instances (Rr).

Each Ra and Rr has five levels; therefore, 25 parameter combinations are simulated. The five levels of rehearsal probability correspond to 0%, 20%, 40%, 60%, and 80%, that is, the expected values of the number of rehearsals are 0.00, 0.25, 0.67, 1.50, and 4.00 respectively.

Results of Simulations

Best Parameters First, in order to investigate the features of the memory-based strategy, we calculate correlation coefficients between the simulated data and the human data on prediction performance in block 5. Figure 4 shows that the simulated data in which anomalous instances are encoded sufficiently and regular instances are not encoded provide a best fit to the human data. Prediction performance at Ra 80% and Rr 0% is reproduced well. Specifically, there is no difference in the performance for regular-experienced instances and for regular-novel instances, and the performance for anomalous-experienced instances is higher than that for anomalous-novel instances (see Figure 3). These results support our argument that regular instances are not encoded and anomalous instances are encoded. Notably, the simulated data are wholly lower than the human data. We will discuss this topic in Discussion and Conclusion.

Effects of Encoding Regular Instances Second, we investigate the reason why the benefits of the inactivity of encoding regular instances appear in the memory-based strategy. What happens to the prediction performance when the Rr parameter is set to 20% or higher?

Figure 5 represents the variations of the prediction performance based on a function of Rr. The results show that the performances for anomalous-experienced instances decrease gradually as Rr increases and that the performances for regular instances decrease rapidly when Rr increases to 80%.

We verify what retrieval error is the cause of decline in performance. There are three types of errors on anomalous instances—commission errors in which regular instances are retrieved incorrectly, commission errors in which another anomalous instances are retrieved, and omission errors, in which no instance is retrieved. On the other hand, there are three types errors on regular instances—commission errors in which another regular instances are retrieved, commission errors in which anomalous instances are retrieved incorrectly, and omission errors. However, the omission errors on regular instances do not correspond to retrieval errors because participants can catch the ball even if they do not move the paddle and such trials are regarded as successful prediction. Therefore, we verify the only two commission errors on regular instances as possible causes of decline in performance for regular instances.

Figure 6 represents the variations of retrieval errors on anomalous-experienced instances. The results show that commission errors of regular instances increase as Rr increases to 80%. Additionally, there is no change on commission errors of anomalous instances and on omission errors from Rr 0% to 60%, but rapid drops appear in these errors at Rr 80% in each task. We found that the cause of declines in performance for anomalous-experienced instances is the commission errors in which regular instances are retrieved inappropriately.

Subsequently, Figure 7 represents the transitions of retrieval errors on regular instances. The results show that commission errors of regular instances increase as Rr increases to 80% and that commission errors of anomalous instances decrease at 80%. As a result, the cause of declines in performance for regular instances is the commission errors in which another regular instance is retrieved.

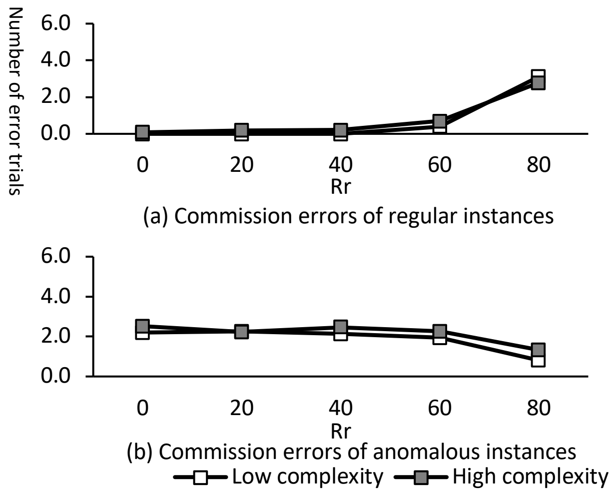

Figure 7: Variations of retrieval errors on regular instances on a function of the rehearsal probability of regular instances (Rr).

In summary, we found that the commission errors of regular instances contribute to the declines in performances on anomalous-experienced instances and on regular instances. That is, encoding regular instances in the memory-based strategy leads to increases in retrieval of inappropriate regular instances. In other words, participants using the memory-based strategy are likely to inhibit the commission errors of regular instances by not encoding regular instances. Additionally, and notably, commission errors of anomalous instances and omission errors do not increase according to Rr and decrease at Rr 80%. We will discuss this topic in Discussion and Conclusion.

Discussion and Conclusion

In this study, we performed the simulations of the processing of the memory-based strategy with a cognitive model and revealed the following two points in the context of the prediction on anomalous behaviors. First, by reproducing the human data, we found that the results support our argument that regular instances are not encoded as default value, and anomalous instances are encoded in the memory-based strategy. Second, the simulations in prediction performance with settings of encoding parameters show that the benefits of the memory-based strategy appear when such inactivity on regular instances inhibits commission errors of inappropriate regular instances and does not inhibit commission errors of anomalous instances nor omission errors.

Processes of Memory-based Strategy

We found that the simulated data in which regular instances are not encoded provide a best fit to the human data. This result confirms our argument that regular instances are not encoded in the memory-based strategy. Additionally, this result corresponds to the results in our previous experiment about participants' subjective evaluations toward anomalous instances and regular instances (Matsubayashi et al., in press).

Although the tendencies on prediction performance in simulations are reproduced well, the simulated data are wholly lower than the human data. This result indicates that participants in the memory-based strategy could perform other additional processing than the encoding processing that we presumed in the current model when they observed various instances. For example, participants might integrate some similar instances into one chunk, make an inference regarding the causal structure through the anomalous trajectories, or revise relevant schema (Meyer et al., 1997).

The studies on category learning have presumed the models that implement multiple processing when observing an instance (Nosofsky, Palmeri, & McKinley, 1994). Furthermore, our previous study indicates that participants adopt the inference-based strategy and the memory-based strategy when not provided explicit instructions about strategies (Matsubayashi et al., in press). The human data cited in this article correspond to the data when participants were urged to use the memory-based strategy, but we cannot dismiss the possibility that the participants use the inference-based strategy alongside. However, the inference-based strategy is possible to consume much cognitive resources (Darabi et al., 2007); therefore, using both strategies could reduce prediction performance. Notably, the trade-off between the costs and the benefits on two strategies must be verified for future work.

Benefits of Memory-based Strategy

The benefits of the memory-based strategy appear because of the inhibition of retrieval errors of inappropriate regular instances. The inactivity on regular instances inhibits commission errors in which regular instances are retrieved incorrectly on anomalous instances and commission errors in which another inappropriate regular instances are retrieved on in-situ regular instances. In summary, such inactivity of the memory-based strategy has a critical role in preventing confusion in encoded instances when they are retrieved and in saving cognitive resources to encode instances. The results of the simulations show that when regulars are encoded as frequently as anomalous instances are, more commission errors of regular instances occur, which indicates that it is critical not to encode regular instances in the memory-based strategy.

On the other hand, the commission errors of anomalous instances or the omission errors do not increase even if regular instances are encoded. Furthermore, we found that these two errors decrease only if regular instances are encoded as frequently as anomalous instances are. These decreases seem to occur, confounded with the effect of the increase in the commission errors of regular instances. If regular instances are encoded as frequently as anomalous instances are, the current model stores three anomalous instances and nine regular instances in the declarative memory in each block, with similar activation levels. Consequently, regular instances are more likely to be retrieved than anomalous instances, which results in a relative decrease in the commission errors of anomalous instances and omission errors. However, the benefits of encoding regular instances do not appear because the whole prediction performance decreases even if these two errors decrease.

The features of cognitive processing on anomalous instances have been verified with visual search tasks. Studies have revealed that the objects incongruent with the schema of the scene are difficult to identify (Mudrik, Deouell, & Lamy, 2011) and these objects are represented internally prior to the objects congruent with the schema (Hollingworth & Henderson, 2000). Our findings that there are no benefits of encoding regular instances are not contradictory to such studies. Furthermore, our study reveals the cognitive processing on regular instances, which are congruent with the schema, while other studies have referred to that on anomalous instances, which are incongruent with the schema. Model-based approaches can clarify the internal cognitive processes that are difficult to observe and have been used in various areas, such as category learning (Erickson & Kruschke, 1998). Particularly, studies on the cognitive model about instance-based learning have revealed decision making processes from experience (Gonzalez & Dutt, 2011; Paik & Pirolli, 2013). Our findings regarding regular instances could not have been obtained without the simulations with a cognitive model.

In this study, we performed simulations of the processing of the memory-based strategy with a cognitive model from a perspective of predicting anomalous behaviors. First, by reproducing the human data, we found the results that support our argument that regular instances are not encoded as default values and anomalous instances are encoded in the memory-based strategy. Second, simulations in performance with encoding parameters clarified that the benefits of the memory-based strategy appear when such inactivity on regular instances inhibits the commission errors of inappropriate regular instances and does not inhibit the commission errors of anomalous instances nor the omission errors.

Acknowledgments

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