Stochastic Independence Between Recognition and Completion of Spatial Patterns as a Function of Causal Interpretation

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Abstract

A common view in the research on dynamic system control is that human subjects use exemplar knowledge of system states – at least for controlling small systems. Dissociations between different tasks or stochastic independence between recognition and control tasks, have led to the assumption that part of the exemplar knowledge is implicit. In this paper, I propose an alternative interpretation of these results by demonstrating that subjects learn more than exemplars when they are introduced to a new system. This was achieved by presenting the same material – states of a simple system – with vs. without causal interpretation. If subjects learned exemplars only, then there should be no differences between the conditions and stochastic dependence between various tasks would be expected. However, in an experiment with N=40 subjects the group with causal interpretation is significantly better at completing fragmentary system states and in judging causal relations between switches and lamps, but not in recognizing stimuli as studied. Only in the group without causal interpretation, the contingency between recognition and completion was close to the maximum memory dependence, estimated with Ostergaard's (1992) method. Thus, the results resemble those of other studies only in the condition with causal interpretation. The results are explained by the assumption that subjects under that condition learn and use a second type of knowledge, which is construed as a rudimentary form of structural knowledge. The interpretation is supported by a computational model that is able to reproduce the set of results.

Dynamic system control (DSC) is a paradigm of great interest for applied and basic research likewise. In applied contexts, researchers address questions about how human operators learn to operate new technical systems efficiently, how training should be designed, or what errors operators are likely to commit. In basic research, DSC is one of the paradigms for studying implicit learning. It has been argued that subjects control dynamic systems predominantly with exemplar knowledge about system states, part of which is considered implicit (Dienes & Fahey, 1998). This conclusion was derived from studies with systems characterized by small problem spaces, such as the "Sugar Factory" (a dynamic system with one input and one output variable, connected by a linear equation; Berry & Broadbent, 1988). However, studies with more complex systems have delivered evidence that structural knowledge (i.e. knowledge about the variables of a system and their causal relations) can be more effective for controlling these systems (Vollmeyer, Burns, & Holyoak, 1996; Funke, 1993), although it is not easy to apply and use this type of knowledge (Schoppek, 2002). But even for small systems, the question about what type of knowledge is learned in an implicit manner, is still open. Simulation studies that have proven the sufficiency of exemplar knowledge for controlling the Sugar Factory (Dienes & Fahey, 1995; Lebiere, Wallach, & Taatgen, 1998) have as yet not reproduced effects that point to implicit learning. An example of such effects is the stochastic independence between recognition of system states of the Sugar Factory as studied and performance in one-step control problems, found by Dienes & Fahey (1998). Since exemplar knowledge is typically construed as explicit rather than implicit, it cannot account for these dissociations.

This paper addresses the question if a rudimentary form of structural knowledge is acquired in addition to exemplar knowledge, albeit implicitly or explicitly. The different use of exemplar knowledge and structural knowledge in different tasks can explain dissociations between tasks. The basic strategy for separating the two

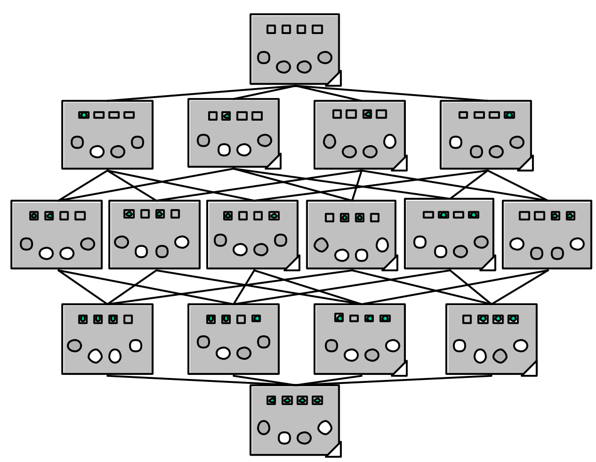

Figure 1: Problem space of the Switches & Lamps system; the states with white triangles were studied in the learning phase

knowledge types rests on using material that can be interpreted as states of a system or simply as spatial patterns. Therefore, I designed a system consisting of four lamps operated by four switches. Each switch affects one or two lamps. Two of the effects were negative, which means that the corresponding lamp is switched off when the switch is turned on. The problem space of 16 possible states is depicted in Figure 1. Subjects under both conditions (causal interpretation vs. no causal interpretation) are shown possible states and asked to memorize them.

In a previous experiment with that paradigm (Schoppek, 2001), I found positive effects of causal interpretation on recognition of patterns as studied and on causal judgment. The effects were attributed to a preliminary form of structural knowledge, namely associations between switches and lamps, acquired by the group with causal interpretation. This knowledge enables subjects to reconstruct a system state in cases where no exemplar representation of the state can be retrieved. The pattern of results was reproduced by a computational model that instantiates these assumptions. The model is written in ACT-R (Anderson & Lebiere, 1998), a cognitive architecture that distinguishes between subsymbolic and symbolic levels of processing, with associative learning residing on the subsymbolic level.

The experiment also delivered some hints that there was stochastic independence between recognition of states as studied and a completion task in the group with causal interpretation, but dependence in the other group. Again, this supports the assumption that more than one knowledge type is used in the causal condition. However, to judge the empirical contingency between tasks, it should be compared with the maximum possible memory dependence, estimated with a method proposed by Ostergaard (1992). This method requires answers to nonstudied items in the completion task, but all items that could be reasonably used in that task (i.e. all possible system states) have been studied in Schoppek (2001). Therefore in the present experiment, subjects studied only a subset of system states. This fact implies a different prediction for recognition of states as studied: The set of possible states and the set of studied states were identical in the previous experiment, whereas they are different in the present experiment. This makes the strategy of reconstructing system states susceptible to errors, because classifying any possible state as studied would result in many false alarms. Thus in the present experiment, I expected no differences in recognition performance between the two conditions.

Experiment

The experiment started with a learning phase where subjects saw 60 system states in intervals of four seconds. The sequence consisted of ten out of sixteen possible system states that were repeatedly shown in a "natural" order, i.e. only one switch changed its status from item to item. The ten states where selected such that all causal relations between switches and lamps could be concluded from them. All subjects were instructed to memorize the "states" (in the condition "causal interpretation" or ci group) or the "patterns" (in the condition "no causal interpretation" or nci group). The learning phase was followed by a speeded recognition task. 20 items, including the ten studied states, six nonstudied states, and four impossible states, had to be classified as studied or nonstudied. Next, subjects worked on the completion task, where they saw arrays of switches in certain states and were asked to complete the patterns by clicking on the correct lamps. All possible states, except the one where no switch is on, were administered. Then the subjects of the group without causal interpretation were debriefed about the meaning and the causal nature of the material. Finally, in a causal judgment task, subjects were asked to estimate the causal strength of all 16 combinations between switches and lamps on a scale ranging from -100 (strong negative relation), through 0 (no relation), to 100 (strong positive relation). N=42 students from the University of Bayreuth, participated in the experiment. One subject had to be excluded because of erroneous administration of the tasks; one other subject was excluded because he had misunderstood the instructions.

I expected medium to large effect sizes ($d \approx 0.65$) in this experiment. With the given sample size of $n=20$ for each group, the α-level is set to $p<0.1$ to get an acceptable power of 0.67. All significance tests were two-tailed[1].

Recognition

I expected no differences in discrimination between the two groups. This can be explained as follows. For the nci group, conditions are not much different to the previous experiment (Schoppek, 2001), except that fewer states where shown and each state was shown equally often. In the ci group, however, the fact that not all possible system states were shown in the learning phase is expected to lead to some confusion. Subjects who know about the causal structure of the material may recognize nonstudied system states as regular states and mistake them as studied. Thus, in contrast to the previous experiment, there is no advantage of knowing the causal structure. It is hard to predict if subjects use the strategy of reconstructing system states at all. An indicator for using the strategy is a longer response time.

[1] The power analysis was calculated with the G-Power program by Faul & Erdfelder (1992).

As expected, discrimination indices for recognition (calculated according to the two-high-threshold model by Snodgrass & Corvin, 1988) are almost equal in both groups (ci: d=0.46, s=0.19; nci: d=0.43, s=0.17; t=0.53). However, mean response times rt for hits are significantly longer in the ci group (ci: rt=2325 ms, s=1159 ms; nci: rt=1699 ms, s=513 ms; t=2.21, p<0.05). This result, including the difference in the standard deviations, closely replicates the findings of Schoppek (2001). It supports the assumption that at least some of the subjects in the ci group used the strategy of reconstructing system states on the basis of structural knowledge.

Completion

Since all possible system states had to be completed in this task, I expected the ci group to be better than the nci group. Subjects in the latter group have only a small chance to complete nonstudied items correctly.

Performance in the completion task is measured by summing up deviations from the correct solution over all items (variable td). For each lamp, a deviation is counted when the lamp is in the wrong state, resulting in a maximum deviation of four per item. Thus, the total deviation td ranges between 0 and 60 (4 · 15 items). The expected deviation for chance performance is 30 (0.5 · 4 · 15). As expected, there is a significant difference in total deviation between the groups: The ci group deviates less from the correct solutions than the nci group (ci: td=21.9, s=6.7; nci: td= 25.3, s=4.6; t=1.88, p<0.1). Generally, performance in the completion task was low: In terms of correct items, the ci group solved an average of 3.9 items (26%), the nci group an average of 2.9 items (19%). However, these values are close to those found by Dienes and Fahey (1998) in their one-step control problems with the Sugar Factory.

Causal Judgment

Subjects of the ci group are expected to be much better in judging causal relations between switches and lamps. At first glance, this hypothesis appears straightforward. However, if causal knowledge is learned implicitly in the form of associations between switch-events and lamp-events, it is possible that subjects of the nci group are able to judge some of the relations after they have been debriefed about the causal nature of the material.

As a measure for causal judgment, the median of the 16 absolute deviations between judgments and correct answers was calculated (variable md) for each subject. The ci group was significantly better at judging the causal relations between switches and lamps (ci: md=27.9, s=31.1; nci: md= 64.7, s=25.1; t=3.91, p<.01). This result makes it unlikely that many of the nci subjects had learned associations between switches and lamps implicitly.

Contingency analysis between recognition and completion task

If subjects used exemplar knowledge only, we expect performance in the two memory tasks to be correlated. If, however, subjects used exemplar knowledge and structural knowledge, performance in the two tasks may well be independent from each other. To judge the contingency between two memory tasks, Ostergaard (1992) has proposed a method for estimating the maximum possible memory dependence for a given data set. The method is based on the contingency tables crossing the answers in both tasks. Stochastic independence is shown when there is a significant difference between appropriate measures of the observed contingency and the contingency assuming maximum memory dependence.

The contingency analysis was applied separately for each subject, yielding distributions of observed and estimated values of the joint probability of giving a correct response to both tasks, and of the contingency measure Δp. Analyses with the data collapsed over all

Table 1: Overview over results of the experiment

	Causal interpretation (ci)	No causal interpretation (nci)	Significance
Recognition			
discrimination index	0.46	0.43	ns
response time for hits	2325 ms	1699 ms	**
Completion			
total deviation	21.9	25.3	*
Causal judgment			
median of deviation	27.9	64.7	***
Correlation			
completion – causal judgment	.62***	.21	

Significance levels: *: p<0.10 **: p<0.05 ***: p<0.01

subjects of each condition were conducted to cross-check the results. Both analyses yielded equivalent results.

In the ci group, the observed joint probability of giving a correct response to both tasks equals 0.31, a value lying right between 0.27, the joint probability of the independence model and 0.34, the joint probability of the maximum memory dependence (MMD) model. Although the absolute difference between the value for the MMD and the observed value is rather small, it is still reliable ($t(19)=2.41$, $p<0.05$). The contingency measure Δp also discriminates between the different models. The $\Delta p = 0.22$ observed in the ci group is significantly smaller than the $\Delta p = 0.37$ of the MMD model ($t(18)=2.26, p<0.05$).

Things are different in the nci group, where the joint probabilities of the observed data and the MMD model are 0.23 and 0.24, respectively ($t(19)=0.53$, $p=0.60$). The difference between $\Delta p=0.22$ (observed) and $\Delta p=0.23$ (MMD model) is not significant either ($t(19)=0.11, p=0.92$).

The result that in the ci group the observed contingency between recognizing states as studied and completing fragments of these states correctly is significantly below the maximum, indicates that different memories have been used for both tasks. In the nci group, the observed contingency between the tasks is almost at its theoretical maximum, indicating that only one type of knowledge was used for answering the items. The interpretation of these results is that both groups use exemplar knowledge in both tasks, but that subjects of the ci group also use structural knowledge, especially in the completion task. This conclusion is supported by different correlations between measures of causal judgment and completion, which are $r=0.62$ ($p<0.01$) in the ci group, and $r=0.21$ (ns) in the nci group.

Discussion

The present experiment confirmed predictions about the differential impact of causal interpretation on memory for states of a simple system. In part, these predictions were derived from a computational model that formalizes a set of assumptions about acquisition and use of two types of knowledge. Exemplar knowledge about system states is assumed to be acquired and used in all tasks, regardless of causal interpretation. With causal interpretation, subjects can additionally learn structural knowledge based on associations between switch events and lamp events (Schoppek, 2001). This knowledge can be used to reconstruct system states in cases where no relevant exemplar can be retrieved from memory. For reasons described above, this type of knowledge was expected to be useful in a causal judgment task and a fragment completion task, but not in a recognition task, resulting in stochastic independence between recognition and completion in the condition with causal interpretation.

This approach has much in common with implicit learning paradigms. Similar to those paradigms, subjects are presented with material based on a structure they do not know. In contrast to many implicit learning experiments, subjects of the nci group of the present experiment did not learn much about that structure (see the results of the causal judgment task). However, the view that structure is always learned implicitly, as soon as there is one, is not unchallenged. Wright and Whittlesea (1998) argue against the hypothesis that implicit learning is passive and independent of the intentional processes during learning. According to them, this is a misconception resulting from the fact that in most implicit learning experiments there is little or no variation in the learning phases. Wright and Whittlesea provided evidence that even small variations in the presentation of stimuli, or in the induction task can result in differences of what is learned implicitly. Causal interpretation can be viewed as one of these variations that affects processing in the learning phase.

Other examples of the effect that providing additional information about stimuli enhances memory or other kind of performance are found in classification learning (Nosofsky, Clark, & Shin, 1989) or schema acquisition (Ahn, Brewer, & Mooney, 1992). Common to all these examples is subjects' reluctance to use the additional hints. Ahn et al.'s (1992) subjects used the experimentally provided background knowledge only when they were engaged in tasks requiring the active use of that knowledge. Nosofsky et al. (1989) found that even simple rules defining a concept were only used when subjects were explicitly told to do so.

In the group with causal interpretation, the results resemble those typically found in implicit learning experiments. So does the stochastic independence in that group indicate implicit learning? It is not a new claim, but still useful to analyze the acquisition processes, the knowledge resulting from these processes, and the retrieval processes separately (Frensch, 1998), rather than calling the whole thing "implicit learning". Doing so in the present context results in a detailed web of hypotheses. According to the ACT-R model, the processes for acquiring associations between switches and lamps can be characterized as implicit, because associative learning is an autonomous process that occurs without awareness. That does not mean that it is independent from attentional processes. In fact, what associations are learned depends on the sequence in which perceptional or memory elements are focused on. In the Switches & Lamps System, the condition for acquiring useful associations is a processing sequence that focuses on the changes first (i.e. encode the switch that has changed since the last item, then encode the lamps that have changed, then encode the rest). The assumption that such a sequence occurs more likely in the ci group, whereas in the nci group, subjects adopt other strategies such as processing the images from top left to bottom right, is plausible, although it was not tested empirically. When the critical difference between ci and nci groups lies in the processing sequence of stimuli, one can conclude the testable prediction that differences between the groups should disappear when nci subjects are instructed to focus on changes and are debriefed after the learning phase.

These deliberations are well in line with the view of Wright and Whittlesea (1998), who claim that "the only major difference between implicit and explicit learning may be that consciously knowing that a domain possesses some important structural property can cause one to learn specifically about that property, whereas the processing performed when unaware that such a property exists may focus selectively on less relevant properties" (p. 419).

As a form of subsymbolic knowledge, associations can be viewed as implicit knowledge. In ACT-R, subsymbolic knowledge exerts its influence through activation processes, but is not directly accessible by production rules. The explanatory potential of the subsymbolic level of ACT-R for implicit memory phenomena has also been demonstrated by Taatgen (1999) with a model of word recognition and completion. In his model it is the dynamics of baselevel learning rather than associative learning that accounts for dissociations.

Only at the stage of applying the knowledge a conscious strategy of utilizing the associations between switch events and lamp events is assumed, a strategy of retrieving the most active lamp event with a given switch-turned-on event as cue.

Since the system I used here was a static one, some considerations about the generalization of the results to dynamic systems are indicated. Dynamic systems are characterized by dependence on their own state, which gives them momentum. This is not the case in the Switches & Lamps System. However, similar to dynamic systems, its output variables depend on multiple input variables. The momentum is an important property that makes it hard to handle dynamic systems (Funke, 1993). This might be one of the reasons why subjects typically focus on the relations between input and output variables, often disregarding the output-output relations that establish the momentum (Schoppek, 2002). Thus, from the point of view of many subjects, the Switches & Lamp System can appear very similar to small dynamic systems like the Sugar Factory.

If one accepts "Switches & Lamps" as a model for small dynamic systems, the work presented here questions the common interpretation that controlling those systems is accomplished with exemplar knowledge only (Dienes & Fahey, 1995; Lebiere, Wallach & Taatgen, 1998). For obvious reasons, proving the sufficiency of this type of knowledge does not prove that human subjects are making do with this type, too. The findings of the group with causal interpretation parallel those of Dienes and Fahey (1998), who found stochastic independence between recognition and a completion task and arrived at similar conclusions. The present experiment extends Dienes and Fahey's approach by demonstrating that without causal interpretation the contingency between these tasks is close to its possible maximum, indicating that in that case only one type of knowledge is used. Moreover, it involves a real dissociation in the sense that the experimental manipulation affected one task (causal judgment, completion), but not another (recognition). It would be interesting to see if a variation of causal interpretation with the Sugar Factory yielded similar results.

Although many of the predictions were derived from a cognitive model, I have as yet not succeeded in reproducing the whole set of results with the model. For example, the present model overestimates discrimination between old and new states. The main reason for this is the simplified assumption that every state is encoded by three chunks in a one trial fashion: One chunk representing all switches, one representing all lamps, and one grouping the two other chunks together. This assumption has to be replaced by an appropriate theory about how humans form chunks from unfamiliar material, such as the competitive chunking theory (Servan-Schreiber & Anderson, 1990), or EPAM successors like CHREST (Gobet & Jackson, 2001). Nevertheless, even when a model does not reproduce all aspects of the data, the cognitive modeling perspective forces the analyst to explicate assumptions on all stages of processing, thus helping to draw a detailed picture of reality that goes far beyond the simple distinction between implicit and explicit learning.

Acknowledgments

I would like to thank Wayne Gray for valuable hints regarding the paradigm, and Nha-Yong Au for carrying out the experiment.

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