Teaching Structural Knowledge in the Control of Dynamic Systems: Direction of Causality makes a Difference

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Abstract

Recent publications about humans controlling dynamic systems have emphasized the role of specific rules or exemplar knowledge. Although it has been shown that small systems can be controlled with these types of knowledge, there is evidence that general knowledge about the structure of a system plays an important role, too, particularly when dealing with systems of higher complexity. However, teaching structural knowledge has often failed the expected positive effect. The present work investigates details of acquisition and use of structural knowledge. It is hypothesized that guiding subjects to focus on dependencies rather than effects supports them in applying structural knowledge, especially when the application is practiced in a strategy training. An experiment with N=95 subjects supported the hypothesis of the usefulness of the dependency perspective, but revealed an adverse effect of the strategy training. Differences between subgroups studying different majors have been found that give rise to questions about the relation between prior knowledge and instruction. The results have interesting implications for models of how structural knowledge is represented as well as for methods of teaching system control efficiently.

Humans have to deal with dynamic systems throughout their lives. Especially in industrial environments, people are confronted with new systems such as production lines frequently. Therefore it is worthwhile to study how humans learn to control dynamic systems, and how instruction can support the learning process.

In cognitive psychology, a common paradigm for studying the control of dynamic systems can be characterized by the following features: The systems simulate some fictitious device or environment that most people have no specific experience with (e.g. a tank with sea animals in a biology lab, used by Vollmeyer, Burns, & Holyoak, 1996). This is to ensure an equally low level of prior knowledge. Discrete linear additive equations are used for simulation, one equation per output variable. There is the opportunity to assign values to the input variables in each simulation step, which is referred to as "trial". A number of trials, e.g. six simulated hours, make up a "round". The objective for participants is to attain a specific goal state either at the end of a round, or as soon as possible and to maintain the state. A prominent, yet simple example is the "Sugar Factory" (Berry & Broadbent, 1984) that has been used to investigate questions about implicit vs. explicit knowledge and about rule vs. exemplar learning (e.g. Dienes & Fahey, 1995; Fum & Stocco, 2003; Lebiere, Wallach, & Taatgen, 1998)

Research with this paradigm has shown that subjects largely prefer acquiring and using exemplar knowledge rather than structural knowledge, i.e. subjects memorize specific actions taken in specific situations together with their outcomes. This strategy can be successful under certain conditions: First, when the system has a small problem space like, for example, the Sugar Factory (144 states); second, when the same goal state has to be attained repeatedly (Vollmeyer et al., 1996), which means that only a small fraction of a possibly large problem space is relevant. Simulation studies with the Sugar Factory have shown that it can be successfully controlled by using either declarative representations of specific actions (Lebiere et al., 1998), or learned production rules that also represent specific interventions (Fum & Stocco, 2003). In conditions, however, where subjects have to deal with huge problem spaces (e.g. because the system is more complex and subjects have to attain a number of different goal states), the exemplar strategy is no longer useful[1]. Instead, it is more reasonable to use general knowledge about the causal structure of the system to navigate through the problem space. I will refer to this type of knowledge as "structural knowledge".

In principle, complete structural knowledge is sufficient to control a system even without specific experience. Although correlations between structural knowledge and performance have been reported (Funke, 1993), experiments where structural knowledge was taught, usually failed to demonstrate its superiority (Putz-Osterloh, 1993; Schoppek, 2002). One reason for this is that deriving

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[1] The inclination to use exemplar knowledge even when it is inappropriate may explain why subjects generally perform at very low levels when they are asked to control complex dynamic systems that are new to them.

specific actions from structural knowledge is a skill that has to be practiced in addition to learning the structure. This view is corroborated by results from studies where the application of structural knowledge has been practiced extensively (Preussler, 1998). A second reason for the difficulties of applying structural knowledge is that knowledge about causal relations is acquired under a different perspective than it is applied when controlling a system. This issue is elaborated in the following paragraphs.

Verbal protocols of successful system controllers and simulation studies (Schoppek, 2002) have helped identify efficient strategies for acquisition and application of structural knowledge. A good strategy for exploring the causal structure of a system is to vary input variables one at a time to identify the immediate effects of the input variables and the momentum of the system, which is produced by effects of output variables onto each other. For example, a subject could put some lime into the animal tank to observe the effect onto the oxygen content of the water, then set lime input back to zero and observe how the oxygen content changes on its own.

A common application strategy starts with (1) predicting the next state of the system under the assumption of no interventions, continues with (2) calculating the differences between the predicted and the desired state, (3) selecting a free input variable, (4) calculating the input value, and ends with (5) applying the intervention. In the course of this strategy, for each output variable all their dependencies are considered in turn. This consideration of dependencies is a marked difference compared with the focus on effects that is prevalent during acquisition of structural knowledge.

Thus we can distinguish two perspectives on causal relations: One looking for effects of a given cause, the other looking for possible causes of a given effect. The first perspective is prevalent during exploration of a new system, the second is more adaptive during system control. In the following, I will use the word "effects" to characterize constructs related to the first perspective, and "dependencies" to characterize the second perspective.

The distinction of perspectives on causal relations has a number of implications. The first has to do with the question what given information cues the retrieval of what other information. During exploration, when input variables are manipulated and effects are observed, associations from cause to effect are learned, resulting in a structure where representations of input manipulations act as cues for representations of changes in output variables. When the task is to control a system and the dependencies of output variables are considered, output variables should be learned as cues for input variables.

A second implication concerns the mechanism of chunking, which plays an important role in successful problem solving (Newell, 1990, Gobet & Simon, 1996). The effect perspective suggests chunking together single effects of a variable (which can be an input or an output variable), whereas the dependencies perspective suggests chunking together all dependencies of an output variable. Again, the second possibility seems to be more adaptive in system control, because having all dependencies in one chunk relieves the problem solver from extensive memory search, a process that consumes much time, poses high demands on working memory, and is thus error prone.

A second issue in the context of helping humans to use structural knowledge has to do with strategy instruction. Undoubtedly, extensive practice under supervision of experienced operators is effective, but also very costly. Thus it is important to find ways of leveraging structural knowledge efficiently. The way followed here was to base a training program on a strategy that has proven successful in a computer simulated cognitive model of controlling a system similar to the present one (Schoppek, 2002).

To summarize, the aim of the present work is to investigate ways of teaching structural knowledge about dynamic systems, either indirectly by manipulating the perspective on causal relations, or directly by practicing the application of structural knowledge. Specifically, I tested the hypothesis that guiding subjects to focus on dependencies rather than effects enhances performance. By measuring access to causal knowledge with a speeded judgment task I investigated if the different perspectives are also reflected in the representation of structural knowledge. The results may show new ways of teaching structural knowledge and extend our understanding of the use of this type of knowledge.

Experiment

The system I used in this experiment is a simulation of the influences of three fictitious medicines onto the levels of three fictitious peptides in the blood. The medicines are called MedA, MedB, and MedC; the peptides are called Muron, Fontin, and Sugon. The effects of the substances onto each other are simulated with the following discrete linear equations:

(1) $\text{Muron}_t = 0.1\,\text{Muron}_{t-1} + 2\,\text{MedA}_t$
(2) $\text{Fontin}_t =$
    $\text{Fontin}_{t-1} + 0.5\,\text{Muron}_{t-1} - 0.2\,\text{Sugon}_{t-1} + \text{MedB}_t$
(3) $\text{Sugon}_t = 0.9\,\text{Sugon}_{t-1} + \text{MedC}_t$

In a neutral state with Muron = Sugon = 0 and Fontin = x, the system is stable. Once some of the medicines are administered, the system gains momentum. Note that the

amount of Fontin in the blood can only be reduced through Sugon, which depends on MedC. Since Sugon decomposes slowly, large time delays of changes in medication have to be dealt with. Subjects interacted with the system through an interface consisting of two tables showing the states of the variables in all trials, and input boxes where they could enter values for the medicines. One round comprised six trials, introduced to the subjects as "simulated hours".

Structural knowledge was tested with a speeded causal relation judgment task. All names of input and output variables were shown on a screen in a spatial arrangement that matched that of the simulation interface. This was done to assure that variables could be identified by both, their names and their locations. Then the name of an output variable was highlighted on the right side of the screen, followed by the highlighting of another variable name on the left side with an ISI of 500 ms. The subject was asked to respond with pressing one of two keys as quickly and accurately as possible to indicate her judgment if there was a causal relation between the highlighted variables or not. All 18 possible input-output and output-output relations were shown in one test. Eight of these relations had to be answered with yes, 10 with no. The procedure was arranged such that knowledge of dependencies should result in faster judgments compared with pure knowledge of effects. This is expected because the variable that was highlighted first (the effect) is assumed to act as a prime for the variable highlighted second (the cause) only when causal relations have been memorized under the perspective of dependencies.

Subjects and Design
N=95 subjects, studying different majors at the University of Bayreuth, participated in the experiment. Subjects were paid 10 €for their participation.

The factor "type of knowledge" with the levels "knowledge of effects" (Eff) and "knowledge of dependencies" (Dep), and the factor "strategy training" with the levels "no training" and "training" were varied between subjects. A third, quasi-experimental factor "field of study" with the three levels arts/humanities, law/economy, and science was also analyzed. In principle, subjects were randomly assigned to one of the four conditions. A few exceptions from complete randomization were due to the objective to have approximately equal distributions of field of study in each condition.

Procedure
The experiment began with a general instruction about the system. All subjects went through a standardized exploration phase guided by the experimenter. The exploration was designed to demonstrate all causal relations between the variables of the system. Subjects were guided to analyze the observed effects and asked to enter them in cards provided by the experimenter. The procedure in this phase was different for the two knowledge conditions: In the Dep condition, the experimenter consistently asked for dependencies, and the cards were sorted by the "dependent" variables Muron, Fontin, and Sugon. In the Eff condition, the experimenter consistently asked for effects, and the cards were sorted by the "independent" variables MedA, MedB, and MedC. At the end of this phase, the experimenter examined the knowledge of the subject orally, again consistently asking either for dependencies or for effects. Subjects had to recall all possible relations with the respective numeric weights before moving on to the next phase (all subjects achieved that).

Subjects in the "no strategy training" condition could then explore the system for one round (six simulated hours) on their own. Subjects in the "strategy training" condition went through a number of exercises where they practiced a method of predicting future states of the system. As mentioned above, this was the first part of a strategy tested earlier in a cognitive model. Only a part of the complete strategy was selected to keep the training short. Nevertheless, all effects (condition Eff) or dependencies (condition Dep) were needed and rehearsed in these exercises.

Next, all subjects were given the control problems. All problems comprised six simulated hours and were given with the objective that the goal states had to be reached as soon as possible, and to be maintained. Table 1 shows the initial states and the goal states for the four control problems. Initially, all variables except Fontin were zero. In order for the subjects to familiarize themselves with the control task, they were given two rounds for Problem 1.

Table 1: The four control problems given to the subjects

Problem 1: Fontin = 50 → Muron = 200 , Fontin = 1000
Problem 2: Fontin = 900 → Muron = 100
Problem 3: Fontin = 2000 → Fontin = 1000
Problem 4: Fontin = 50 → Muron = 400 , Fontin = 900

Results
To measure control performance, the solution error was calculated by summing the natural logs of the absolute differences between the goal values and the actual values for each time step of a round (Müller, 1993). A perfect solution is indicated by a solution error of zero. Since the results of Problem 2 were close to ceiling, they were excluded from the analysis. I analyzed the mean solution error of the remaining problems as dependent variable in

an ANOVA with the factors "type of knowledge" (knowledge about effects, "Eff" vs. knowledge about dependencies, "Dep"), "strategy training" (with vs. without training), and the quasi-experimental factor "field of study" of the participant (arts/humanities, law/economy, science). The means aggregated across all fields of study are listed in Table 2.

The ANOVA yielded significant main effects of all three factors, "type of knowledge" ($F = 3.94$, $df = 1$, $MSE = 5.57$, $p = .05$), "strategy training" ($F = 5.97$, $df = 1$, $MSE = 8.45$, $p < .05$), and "field of study" ($F = 13.24$, $df = 2$, $MSE = 18.75$, $p < .01$). As expected, subjects who were guided to acquire knowledge of dependencies were more successful in controlling the system (mean solution error = 2.1, SD = 1.3) than subjects who were guided to acquire knowledge of effects (M = 2.6, SD = 1.5). Contrary to expectation, subjects who underwent the strategy training performed lower (M = 2.6, SD = 1.5) than those without strategy training (M = 2.0, SD = 1.3). Subjects studying arts or humanities performed worst (M = 3.2, SD = 1.4, n = 33), followed by subjects studying law or economy (M = 2.3, SD = 1.2, n = 30). Most successful in controlling the system were science students (M = 1.6, SD = 1.1, n = 32).

There is a significant interaction between "field of study" and "type of knowledge" ($F = 3.29$, $df = 2$, $MSE = 4.65$, $p < .05$). Detailed analyses revealed that a strong effect of "type of knowledge" was only present in the group of subjects who studied arts/humanities (see Figure 1). No other effects reached statistical significance (all p > .05).

Table 2: Solution error of system control in the various conditions of the experiment

		Eff	Dep	
Strategy training	yes	**2.9** (1.5) n = 24	**2.4** (1.5) n = 26	**2.6** (1.5) n = 50
	no	**2.4** (1.5) n = 22	**1.7** (0.9) n = 23	**2.0** (1.3) n = 45
		2.6 (1.5) n = 46	**2.1** (1.3) n = 49	**2.4** (1.4) n = 95

To test the expectation that knowledge of dependencies results in faster response times in the speeded structural knowledge test, I calculated an ANOVA with the same factors as described above and the mean response times for hits in the first test as dependent variable. (Three subjects with mean response times of greater than 3800 ms were excluded from the analysis. Raw values were ln-transformed for the ANOVA). The expected effect of
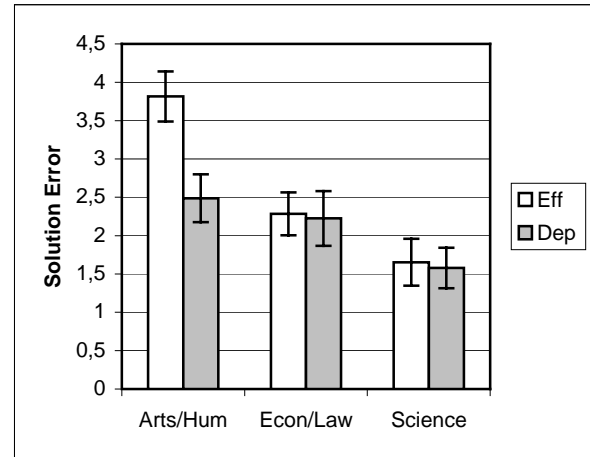

Figure 1: Means and standard errors of solution error of controlling the system (smaller values indicating better performance)

"type of knowledge" was confirmed by the analysis ($F = 7.83$, $df = 1$, $p < .01$), (1559 ms vs. 1237 ms, Dep faster). However unexpectedly, there was also a main effect of "strategy training" ($F = 11.24$, $df = 1$, $p < .01$), (1576 ms vs. 1236 ms, with training faster). No other effects were significant at the level of $\alpha = .05$. The results of the second structural knowledge test were analogous to the first test.

Similar analyses with the discrimination index (an index of how well subjects can discriminate between relations and no relations, cf. Snodgrass & Corvin, 1988) as dependent variable yielded no significant effects. Discrimination indices were relatively high in all conditions (di = 0.89).

Discussion

The experiment has confirmed the hypothesis that guiding subjects to focus on dependencies of output variables rather than on effects of input variables can enhance performance in controlling a complex dynamic system. Although there is an effect in the complete sample, the major contribution came from the subjects studying arts/humanities. Presumably, this group has the least experience with abstract representations of dynamic systems and thus learned something new when focusing on dependencies instead of effects. If the other groups did not benefit from the manipulation because they take the dependencies perspective on their own, or because of some other strategy cannot be told with the present data.

The results of the speeded causal judgment task indicate that focusing on dependencies vs. effects affects the

mental representation of causal relations. The task was arranged to enable priming from output to input variables, but not the other way round. Subjects in the Dep condition were significantly faster in judging the relations, supporting the assumption that they have established stronger associations between output to input variables than subjects in the Eff condition.

The two findings are raising the question about their relation. Are these stronger associations a cause for better performance or are they just a side effect of the experimental manipulation? If the relation was causal, there should be a substantial (negative) correlation between response time in the causal judgment task and solution error in the control problems. The respective correlation is $r=.05$ in the whole sample. Hence, the faster reaction times in the Dep condition are probably a side effect of the manipulation. This, in turn, supports the hypothesis that the positive effect of knowledge of dependencies on performance is based on the chunking aspect, i.e. the integration of single effect representations according to output variables. It is possible that especially science students have built such chunks on their own, even in the Eff condition. (Note that subjects in the Eff condition were not prevented from gaining knowledge of dependencies). Figure 2 shows a sketch of the hypothetical structure of a dependency chunk "Dep01" (the causal weights are omitted for clarity). The shaded substructure "Eff01" is a chunk that represents the single causal relation between MedC and Sripon. The structure, whose construction in a learning process appears straightforward, mirrors the equations defining the behavior of the system remarkably. The solid lines indicate slot-value
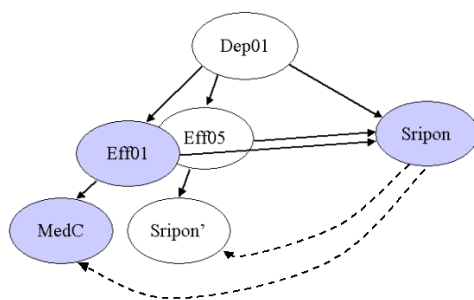

Figure 2: Hypothetical structure of a dependency chunk; solid lines indicate slot-value relations, dotted lines indicate associations.

relations. Dotted lines indicate the associations between the name of the dependent variable and names of influencing variables, which may have been learned under the Dep condition. These associations can explain the effects in the speeded judgment task, but are not necessary for the usefulness of dependency chunks in control tasks. This interpretation is in line with the assumption of Boucher & Dienes (2003) that there are two ways of learning associations, one resulting in activating relations, the other resulting in chunks that combine the associated information. Baker, Murphy and Vallée-Tourangeau (1996) suppose that these two ways may be attributed to different modules of the mind. Research on causal reasoning has discovered many other cases where concept-driven symbolic processing must be assumed in addition to pure associative learning to explain the phenomena (Waldmann, 1996).

Unexpectedly, the strategy training had an effect on answering speed in the causal judgment task (with training faster). According to the above interpretation subjects must have rehearsed relations between each output variable y and the variables affecting y during the training. In the Dep condition, this is obvious. Since in the Eff condition subjects were asked for all variables that had an effect on the output variable in question, they had to search memory for names of input variables while the name of the output variable was present in working memory. Thus, subjects have learned associations from output to input in that condition, too.

The adverse effect of the strategy training was also unexpected. The training had been inspired by results from cognitive tutoring that subskills can effectively be trained based on single production rules (Anderson, 1993), and thus, practicing only the most difficult part of a larger strategy appeared reasonable. However, the success of this kind of training depends on the compatibility of the practiced subskills with the subjects' own strategies. This condition seemed to be hurt in the present case. Subjects might have applied the practiced method of predicting the next state, and after successful completion were unclear about what to do next and how to use the result. An alternative explanation is that the practiced strategy has interfered with the subjects' own strategies, resulting in mixtures of incompatible strategy fragments. (see e.g. Vosniadou, 1997 for the difficulties of integrating new knowledge with prior knowledge).

In future efforts to train the application of structural knowledge it should be assured that subjects have at least an idea of the whole strategy. This could be achieved by introducing abstract labels for all subgoals and practicing the whole strategy at least once before possibly focusing on the most difficult part of it (Catrambone, 1998).

In general, the results of the experiment show that variations of structural knowledge do affect performance in the control of dynamic systems. This extends the view that mainly exemplar knowledge or very specific rules are used for controlling systems (Dienes & Fahey, 1995; Fum & Stocco, 2003; Lebiere et al., 1998). It is important to note that not knowledge about single causal relations as measured by the discrimination index of the causal judgment task makes the difference (there were no effects of the experimental factors on di), but rather the way of using it, obviously depending on prior knowledge, and the way of chunking it into larger units.

Acknowledgments

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