Mixed Effects of Training on Transfer

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Abstract

The study of learning transfer yields conflicting patterns of results. While some research shows strong effects of previous learning, others show no such effects. This is a consequence of the absence of consensus on what parts of a skill is transferred. In the present paper, we suggest that learning can be divided into general task-related components and specific stimulus-related ones. In one condition, participants were transferred to a new set of stimuli while continuing to perform the same task. Results show an absence of benefit right after the transfer and the presence of long-lasting interference. In the opposite condition, the results show no effects of previous training. These diverging results are best explained by a model of higher-level skill acquisition: knowledge partitioning.

Introduction

The decomposition of performance has a long history in psychology. It was first proposed by Donder (1868), who proposed the subtractive method to measure the speed of "psychological acts". This method was further developed by Sternberg in the late sixties (Sternberg, 1969) and more recently using the mean interaction contrast model (Thomas, 2000). In all these models, the decomposition occurs at the level of a single response and the goal is to identify the sequence of operations between the stimulation and the response (e.g. encoding, decision, response selection, etc.).

More recently, other researchers have proposed another way of decomposing cognitive processes. In this approach, the performance is decomposed by whether improvement results from repeated exposure to the stimuli or repeated exposure to the task (Haider & Frensch, 1996, 1999). Therefore, it does not aim at identifying the stimulus-response chain of processing. However, this level of analysis is particularly interesting in the study of learning transfer because, during transfer, either the stimuli or the task are changed in part or in whole.

Hillstrom and Logan (1998) have tested this approach using memory search vs. visual and memory search. In the two conditions of their Experiment 1, participants first had to memorize a set of letters prior to a block of trials. On each trial, participants saw letters in the test display and had to decide whether there was an element from the memorized set or not. The only difference between the two conditions was the test display. In the memory search condition, a single letter appeared in the display. In the visual and memory search condition, an array of letters appeared in the display. Half of the participants were trained in the memory search task and transferred to the visual and memory search task while the other half did the opposite. The results showed that training in visual and memory search fully transferred to memory search. On the other hand, training in memory search transferred only partially to the visual and memory search task. Hillstrom and Logan concluded that there is a global component, common to both tasks, and a private component, present only in visual and memory search. Moreover, results from their Experiment 3 suggested that the private component was closely related to the stimuli used. However, in Hillstrom and Logan's experiments, the memory search condition was entirely embedded in the visual and memory search condition. Therefore, the observed transfer is not a surprise.

Another task in which learning transfer was found is the string verification task (Haider & Frensch, 1996; 1999; 2002). In Haider and Frensch's experiments, participants were asked to verify the validity of letter strings of the kind "A [4] F G H". The task was to determine if the letters were an ordered segment from the alphabet. In the second position, a number always appeared in brackets. It indicated the number of letters skipped between the first and third positions. The string length varied between three and seven. The important points are that the number was always four, it was always in the second position and, if the string was not an ordered segment of the alphabet, the problem was always at the third position.

Haider and Frensch (1996; 1999) postulated that participants would notice the consistency of the error position and ignore the remaining of the string (the reduction of information theory). Results supported their hypothesis: After extensive training, participants were presented with new strings and the ability to ignore useless information transferred to these new strings. Nevertheless, response times of the new strings were still slower then those of the original (training) strings. They concluded that these slower response times revealed the presence of another component, specific to the stimuli, which did not transfer.

Haider and Frensch's decomposition of skills (1996) was further studied in a perceptual learning setting (Goldstone, 1998, Doane et al., 1996). Doane and her colleagues independently tested stimulus-related and task-related knowledge in same-different tasks (Bamber, 1969) involving abstract polygons. Specifically, the discrimination difficulty in the learning phase was varied in order to measure its effect on transfer. Results showed that a harder learning phase lead to better performance on novel stimuli.

In all studies mentioned (Doane et al., 1996; Haider & Frensch, 1996; Hillstrom & Logan, 1998), skills were decomposed in general proficiencies, which are transferable to new situations, and specific proficiencies, unique to each experimental condition. Accordingly, the aspects manipulated in this paper are task-related and stimulus-related. Task-related aspects are everything held constant from trial to trial (tempo, responses keys, etc.) while stimulus-related aspects are everything that may change from one trial to the next (here, the stimulus shown).

The studies just described had shortcomings related to these particular aspects. First, in the study by Hillstrom and Logan (1998), one task was embedded into the other: we avoided this problem by using two different tasks: visual search and categorization. Second, in Haider and Frensch's study (1996), the stimuli used (the letter strings) remained of the same nature during training and transfer; the same was true of Doane et al.'s (1996) study. It is therefore difficult to distinguish general stimulus-related knowledge from task-related knowledge (Doane et al., 1996). In the present work, we avoided this problem by using two different sets of stimuli: radial stimuli and Gabor patches.

Two additional issues were explored. The first one bears directly on the following primary question: What underlies the improvement in performance? Several studies have shown that mean response times tend to diminish with practice (Cousineau & Larochelle, 2004; Shiffrin & Schneider, 1977). But, how is this measure getting smaller? Is it because the fastest times get faster or is it because the slower response times become less frequent? One way of addressing this issue is by examining response time distributions. The Weibull distribution is likely to resolve this issue because it separates changes in spread from changes in position (Cousineau, Goodman & Shiffrin, 2002; Weibull, 1951). The probability density function (PDF) of a response time t is given by:

$$f(t) = \beta^{-\gamma}\gamma(t-\alpha)^{\gamma-1} e^{-(\frac{t-\alpha}{\beta})^{\gamma}} \qquad (1)$$

where α is the position parameter and represents the minimum RT, β is the spread parameter and γ is the shape parameter.

The second issue considered is the duration of the transfer phase. Although previous studies (Doane et al., 1996; Haider & Frensch, 1996; Hillstrom & Logan, 1998) included extensive training, they all used a short transfer period[1]. This issue might be critical because the effects of an extensive period of transfer are unknown. As Haider and Frensch (2002) pointed out, strategic changes might happen at any time during training or transfer. In the present, transfer was studied for as long as training, revealing the long-term impact of previous training.

[1] The exception is Hillstrom and Logan's (1998) Experiment 1, in which the transfer phase lasted as long as training. However, transfer duration was not the focus of their paper.

Experiment

An experimental design, where some participants could use previously acquired knowledge of the stimuli during transfer while others could use previously acquired knowledge of the task, was used. Two tasks and two stimulus sets were required to achieve this. The two tasks were visual search and categorization. The two stimulus sets were composed of radial stimuli and Gabor patches. Each task was performed with each stimulus set, resulting in four conditions: (1) visual search with Gabor patches (VS × Gabor), (2) visual search with radial stimuli (VS × radials), (3) categorization with Gabor patches (Cat × Gabor) and (4) categorization with radial stimuli (Cat × radials).

The participants were trained in one of these four conditions for four sessions. After training, all participants transferred to the same Cat × Gabor condition for four additional sessions. Therefore, one group changed task while keeping the same stimuli (VS × Gabor), another kept doing the same task with new stimuli (Cat × radials) and the other two were controls. One of them changed both task and stimuli (VS × radials) and the other kept doing the same task using the same stimuli (Cat × Gabor).

The perceptual learning literature (Goldstone, 1998) predicts a training effect specific to both the task and the stimuli used. Therefore, no transfer should occur whatsoever. However, Doane et al. (1996) have shown that learning a task which requires finer-grain discrimination should lead to better transfer. Therefore, the VS × Gabor condition should transfer well to the Cat × Gabor task. The former requires the participants to discriminate between every single stimulus whereas the latter only needs category boundaries. However, one might argue that the categorization task requires a more complex decision procedure than visual search: the exclusive-OR (XOR). Therefore, the discrimination skills acquired during training in the VS × Gabor condition do not fully prepare participants for the categorization task. As will be shown, none of these predictions were correct.

Participants

Twenty-four undergraduates from the Université de Montréal participated in this experiment. Two participants quitted and were replaced to keep groups of equal size. All participants were paid for their participation.

Apparatus and Stimuli

Two stimulus sets were used, each covered by Gaussian envelops. The first set was composed of sixteen Gabor patches. Two dimensions were varied to individually define the patches: frequency and orientation. The second set was also composed of sixteen stimuli, each created by applying a sine-wave function on a radial space. These radial stimuli were individually created by varying their curvature and their frequency. The two stimulus sets are shown in Figure 1.

Each stimulus occupied 3.7 × 3.7 degrees of visual angle. They were presented on a 17-inches SVGA monitor. The Experiment was conducted on Pentium-III PCs.

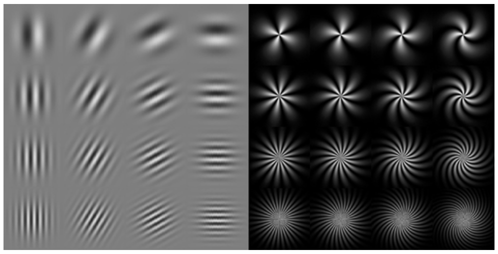

Figure 1: Stimuli used in the Experiment. The left panel shows Gabor patches while the right panel shows radial stimuli.

Procedure

Visual Search: In the visual search task, participants were asked to detect the presence or absence of a target stimulus as fast as possible. A trial went as follow: First, a black foreground occupying 12.55 × 12.55 degrees of visual angle appeared in the center of the display. Second, the target stimulus appeared in the center of the foreground for 500 ms and disappeared for 500 ms. Third, three stimuli appeared at random locations in the foreground. Participants had to press "y" if the target was present and "n" if it was absent. Finally, a feedback was displayed, informing participants about their accuracy and their response time. The target was present on 50% of the trials. Each session contained four blocks of 128 trials. At the end of each block, the mean response time and mean response accuracy of the last block was displayed and participants were invited to take a break. Participants were asked to answer as fast as possible without sacrificing accuracy.

Categorization: In the categorization task, participants had to classify the stimuli in two groups using the exclusive-OR logical rule: A Gabor patch was an "A" if it had a near vertical orientation or high frequency but not both. For radial stimuli, an "A" had small curvatures or high frequency but not both. A trial went as follow: A stimulus appeared in the center of the display. The participant classified the stimulus either as an "A" or a "B", by pressing "a" or "b" accordingly. A feedback similar to the one described in the visual search task was displayed after each answer. Half of the trials were "A"s and half were "B"s. Each session was composed of four blocks of 128 trials. At the end of each block, a recapitulative feedback was given (mean response time and accuracy) and the participant was invited to take a break. Participants were asked to answer as fast as possible without sacrificing accuracy.

The sessions were completed on consecutive working days but the transfer could not occur after a week-end. The participants were told that they were enrolled for two distinct experiments and two distinct experimenters briefed them prior to training and prior to transfer. Further, training and transfer were completed in two different laboratories. Hence, the context varied as well as the task[2].

Results

Three sessions from three different participants are missing due to computer problems. A training Task × training Stimuli × Session ANOVA was performed on the participants' accuracy at transfer. This analysis confirmed an improvement with practice ($F(3, 51) = 51.13$, $p < .01$). Mean accuracy was 67% in the first transfer session and 82% in the last. Because error rates were similar across conditions (all other Fs < 0.99), the following analysis concentrates on responses times.

Response Times

The following response time analyses included only hits. In the visual search task, hits were correct responses in which the target was present. In the categorization task, hits were defined as "A" trials in which participants answered correctly[3]. Two participants failed to significantly improve their response times and were eliminated from further analyses[4]. Figure 2 shows the learning curves for each group. A Task × Stimuli × Session ANOVA was performed on the training phase. First, all groups improved their response times ($F(3, 51) = 16$, $p < .01$). Mean response time on Session 1 was 762 ms. Second, the interaction Task × Session was significant ($F(3, 51) = 3.07$, $p < .05$). Response times in both tasks were similar in the first three sessions of training (all Fs < 2.24) but the visual search task was performed significantly faster (568 ms) in the fourth session than the categorization task (720 ms, $F(1, 17) = 9.38$, $p < .01$). Other main effects and interactions were not significant (all Fs < 3.11).

The switch to the transfer phase generated a discontinuity in the learning curves clearly seen between session four and five. The exception is the control group Cat × Gabor, for which the Experiment continued unchanged. Further, Figure 2 shows that all performances were equally degraded (mean response times of 905 ms in the first block of transfer). Therefore, prior knowledge of the task or the stimulus set did not provide any short term advantage in the new settings (performing a categorization task with Gabor patches). In order to better visualize the effect of previous learning on transfer, the transferring groups must be compared with the first four sessions of the control group which categorized Gabor patches as a first task (Cat × Gabor). This comparison is shown in Figure 3.

Figure 3 highlights what Figure 2 hinted: there was no effect of previous learning during the first block of transfer. This result was confirmed by the absence of a significant

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[2] These precautions were taken in order to prevent participants from anticipating the link between both conditions, which might have artificially elicited transfer.

[3] The "A" responses were defined as hits because the categorization rule given to the participants stated what an A was. The B category was defined as its complement.

[4] One of the excluded participants was from the VS × Gabor condition and the other was from the control group Cat × Gabor.

difference between transferring groups and the control group Cat × Gabor ($t(21) = 0.85$, $p > .05$). A training Task × training Stimuli × Session ANOVA was performed on the response times. The interaction training Task × training Stimuli × Session was significant ($F(3, 51) = 3.68$, $p < .05$). Therefore, we proceeded to decompositions within each session. The training Task × training Stimuli interaction failed to be significant in both Session 1 ($F(1, 17) = 0.44$, $p > .05$) and Session 2 ($F(1, 17) = 1.94$, $p > .05$). These results show that performance was similar for all groups early in transfer. However, divergences become significant later, as seen next.

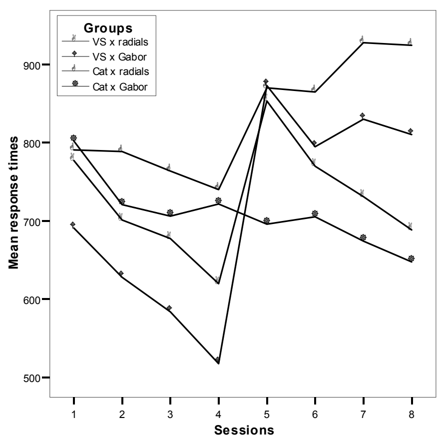

Figure 2: Learning curves averaged by session.

In the third and fourth sessions, the training Task × training Stimuli interaction were significant (both $F(1, 17) > 9.18$, $p < .01$). They were further decomposed. In the third session of transfer, response times of participants trained in the visual search task were not affected by their training stimuli ($F(1, 17) = 2.05$, $p > .05$). However, response times in the control group (Cat × Gabor) were significantly faster (671 ms) than those of participants trained in the categorization task using radial stimuli (923 ms, $F(1, 17) = 7.97$, $p < .05$). The same pattern of results was found in the fourth session: Response times of participants trained in the visual search task were not affected by their training stimuli ($F(1, 17) = 2.12$, $p > .05$) whereas response times of the control group (Cat × Gabor) were significantly faster than response times of the group trained in categorization with radial stimuli ($F(1, 17) = 8.02$, $p < .05$).

Post hoc comparisons showed that the two control groups, Cat × Gabor (during the first 4 sessions) and VS × radials (when transferred to categorization with Gabor patches) had identical performance. This result was expected on logical grounds since both groups had no prior knowledge of the task and the stimulus set. It indicates that when both task and stimuli were changed, nothing was left to be transferred. Retrospectively, it also indicates that our manipulations were performed correctly.

In sum, analysis of response times suggests two important results. First, there is no short term benefit of previous learning when categorizing Gabor patches. Second, and more importantly, there is interference of previous task-related knowledge on the learning of new stimuli and this interference is only visible after an extended period of transfer.

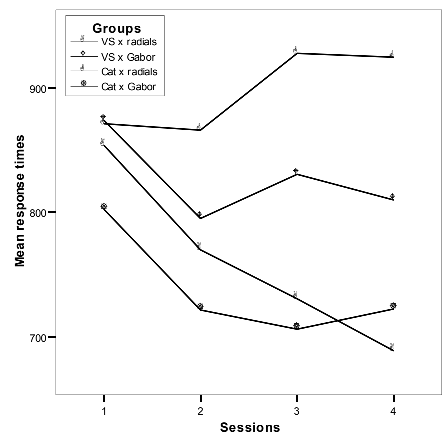

Figure 3: Learning curves at transfer. The four transfer sessions are shown for every group except Cat × Gabor, for which the four training sessions are shown.

Distributions Analysis

So far, a differential effect of previous training on transfer has been shown. However, by simply looking at the mean response times, it is difficult to assess responsibility for these changes. In this section, we examine whether improvements happened because slow responses no longer occurred or because fast responses became faster.

Table 1 shows the parameters of the best fitting Weibull distributions estimated for each session of transfer using PASTIS (Cousineau, Brown and Heathcote, 2004; Cousineau & Larochelle, 1997). A training Task × training Stimuli × Session ANOVA was performed on each estimated parameter.

Analysis on the position parameter (α) yielded no significant effect of the factors (mean $\alpha = 371$ ms, all Fs < 1.63) as well as no interaction. Therefore, minimum response times were not affected by the previous phase or by retraining within the transfer phase.

Analysis on the spread parameter (β) showed some effects. First, it diminished with practice ($F(3, 51) = 4.61$, $p < .01$). Mean β was 540 ms in the first session and 418 ms in the last. Because the position α did not change, the improvement in means must be related to a smaller number of longer response times. Second, the training Task × training Stimuli interaction reached significance ($F(1, 17) = 9.1$, $p < .01$). Decomposition of the effect showed that, for participants trained in the VS conditions, training stimuli did not affect the spread of response times ($F(1, 17) = 2.31$, $p > .05$). However, the spread of the response times of participants trained in the categorization task was affected by their training stimuli ($F(1, 17) = 8.25$, $p < .05$). Response times of participants trained to categorize radial stimuli were more sparse (β = 581 ms) than those of participants trained to categorize Gabor patches (β = 418 ms). The interference previously detected in mean response times for the Cat × radials condition is thus explained by a failure to eliminate longer response times.

Table 1: Estimated parameters of the best fitting Weibull distributions

	α		β		γ	
	Mean	SD	Mean	SD	Mean	SD
Session 1						
VS × radials	401	97	479	82	1.92	0.23
VS × Gabor	335	181	598	136	1.93	0.14
Cat × radials	347	166	564	133	2.49	0.34
Cat × Gabor	317	175	517	123	2.16	0.25
Session 2						
VS × radials	415	38	393	162	1.92	0.22
VS × Gabor	362	192	471	140	1.6	0.2
Cat × radials	243	206	656	243	2.36	0.45
Cat × Gabor	335	153	391	94	2.06	0.51
Session 3						
VS × radials	387	104	349	125	1.98	0.52
VS × Gabor	426	151	456	83	1.93	0.58
Cat × radials	407	212	576	230	2.2	0.92
Cat × Gabor	337	182	373	81	1.89	0.41
Session 4						
VS × radials	387	67	342	94	1.89	0.32
VS × Gabor	444	53	410	106	1.62	0.18
Cat × radials	447	73	529	89	2.02	0.33
Cat × Gabor	350	156	391	98	1.91	0.44

Finally, analysis on the shape parameter (γ) revealed a main effect of training task ($F(1, 17) = 4.73$, $p < .05$). On a Weibull distribution, a γ parameter approaching the value 3 reveals a symmetric distribution and a $\gamma < 3$ means a positive asymmetry. In the present case, mean γ was 1.85 for participants trained in the VS task and 2.14 for those trained in the categorization task. Thus, participants trained in the VS conditions had more positively skewed response times than participants trained in the categorization conditions. This difference in skew suggests that the processes being used to solve the transfer task were different (Haider & Frensch, 2002), generating qualitatively different shapes of response time distributions.

Discussion

In this paper, two types of decomposition were performed: The first was functional and examined the cognitive processes to partition their inputs as whether it was task-based or stimulus-based. The goal of this decomposition was to test whether these processes transferred differently. The second type of decomposition was simply descriptive: was the improvement caused by a change in position (fast responses became faster) or by a change in scale (slow responses were eliminated)? To be certain that the effects would be visible, the transfer phase lasted for as long as the training phase.

The functional decomposition revealed some interesting effects that would not have been predicted by standard models of perceptual learning (Goldstone, 1998) or transfer (Doane et al., 1996; Haider & Frensch, 1996). First, contrary to the analysis performed by Doane and her colleagues, the finer-grain discrimination training in the VS × Gabor condition did not give any short or long term advantage in the transfer phase (Cat × Gabor). However, this finding is consistent with previous research, which found no effect of the specific stimulus-related component in the learning of a new task (Haider & Frensch, 1996; Hillstrom & Logan, 1998). In fact, participants trained in the visual search task using Gabor patches did not differ from the control groups in learning to categorize Gabor patches. Therefore, prior knowledge of the stimuli does not provide any short-term or long-term advantage in learning a new task.

Findings concerning the general task-related component did show a surprising effect. Training on the categorization task with different stimuli did not seem to have any effect on subsequent learning at first. However, after a few hours of practice, previous knowledge impaired the learning of new stimuli in this same task. Similar results were previously found in A-B / A-Br transfer situations (Rehder, 2001). However, this pattern of results is counterintuitive in the present experiment for several reasons: First, learning of the decision process (the categorization rule) did not transfer to new stimuli. Second, the stimuli in the Cat × radials condition were changed: Therefore, the stimuli could not wrongfully be used as retrieval cues (as is the case in the A-B / A-Br transfer paradigm). Therefore, task-related latent interference affected performances when learning a new class of stimuli in an already practiced task. This framework suggests that stimulus-related knowledge is encapsulated within the general task-related knowledge (Hillstrom et Logan, 1998). Furthermore, our results suggest that each task can hold a single class of stimuli at any given time. Therefore, when learning a new class of stimuli in an already practiced task, one must unlearn the previously stored stimuli before learning the new ones. This extra work explains the lack of improvement in the Cat × radial condition. However, when learning already known stimuli in a new task (VS × Gabor), no advantage of previous learning is present because every tasks are independent.

Surprisingly, our results, found in a perceptual learning (Goldstone, 1996) setting, are best explained by a higher-level skill learning theory: knowledge partitioning (Lewandowsky, Kalish & Ngang, 2002). According to this theory, the association between a stimulus and the desired response is learned according to a particular context. Moreover, these parcels of knowledge are independents and different responses can be associated to a single stimulus in different contexts. This emphasis on the role of the context in learning a task was anticipated by Tulving and Thompson (1971). In the present work, the task constituted a constant context that can easily be used by participants.

The second finding of this study is a better description of the improvement in response times. A diminution in the spread (variance) of the response times is responsible for the smaller means. Such a diminution with training had already been observed by Logan (1988) and by Cousineau and Larochelle (2004). Moreover, the distribution analyses showed no improvement for the position (the minimum response times).

To conclude, it is worth mentioning that all our findings would not have been visible if the transfer phase had lasted a single session[5]. An absence of transfer on the first session does not mean that the manipulation did not affect performances, as was clearly the case in this experiment. Similarly, the presence of transfer on the first session does not imply a stable effect through time. Therefore, transfer must be studied for as long as training in order to reveal its full impact (Haider & Frensch, 2002). It is our hope that longer examination of skill transfer will resolve some of the inconsistencies found in the past literature.

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[5] It is important to note that, although many studies have used more than one transfer session, the number of transfer trials was never greater than one session of our experiment. Again, Hillstrom and Logan's Experiment 1 is the exception, with the equivalent of five of our sessions of transfer (Hillstrom and Logan, 1998).