Intelligent Systems Program Comprehensive Examination

Human Problems Solving and Skill Acquisition

Noboru Matsuda
March 14, 2003

Questions from Kurt VanLehn:

Write a short essay (no more than 10 pages) addressing all three questions below, and taking into account the two notes that follow them.

1. Solving problems by analogy to other solved problems (examples) is often described as if it were a completely different process from the one underlying transfer of cognitive skills. In both cases, the students have solved problems earlier, and this somehow affects their cognitive processes while solving problems now. Distinguish the two views, and indicate what kinds of studies are typically used for each. Explain the relationship between the two views (e.g., is one a special case of the other? a subprocess of the other? or are they two competing theories for the same phenomena? In what ways are the two theories dissimilar? etc.). Support your explanation by referring carefully to the studies in your readings.

2. Consider the following theory of cognitive skill acquisition: "The novice first learns the basic operators of the task domain, and these estabish the problem space for a given problem. However, novices are only able to solve extrmely simple problems because they have no knowledge about how to control their search. With pratice, two developments aid problem solving. First, they develop heuristics and other knowledge that can be used to select operators more successfully. This reduces the time wasted going down dead-end paths. Second, they develop macro-operators, each of which is composed of several more basic operators. Using macro operators reduces the number of steps in a solution path. Both developments can reduce search, thus allowing students to solve more difficult problems." First, what evidence in your reading can you find that is consistent with theis theory? Second what evidence in your reading is inconsistent this theory of learning? Can the theory be restricted to a subset of tasks in such a way that it remains plausible, that is, that the evidence agaimts it in your readings is excluded?

3. An ancient design principle for instruction in problem solving is to start by giving the student simple problems then gradually increase the difficulty of the assigned problems. This should expedite the student's learning. Based on your readings, can you propose two more specific design principles for selecting and ordering instructional exercises so that the student's learning is increased? For each one, explain how the evidence in the readings supports your hypothesis.

Note1 : In answering these questions, try to refer only to evidence in the readings. If you must use other evidence to support your point, it should be widely accepted facts, such as "experts can solve more difficult problems than novices." If there is any doubt about a "fact," then you should not use it. For instance, you might be tempted to argue that "experts make fewer errors than novices," except it turns out that in some task domains (e.g., algebra equation solving) this is not true; they make errors with equal frequency. Thus, you should stick almost exclusively to the evidence in the readings.

Note 2: You should argue like a psychologist. That is, when you lay out a line of reasoning, you should support as many steps as possible by referring to your readings. Speculation should be MINIMAL.

Answer for question #1:

Although both analogy and transfer potentially enhance and hinder performance on a target task[1], they can be representing different cognitive phenomena. The persuasiveness of this claim, however, varies depending on the definition of "transfer" and "analogy," which is certainly very confusing (or, very flexible, if you will) even in the readings assigned for this examination. So, we start with inspecting the phenomena, and then define transfer and analogy as labels representing different phenomena. We then briefly review cognitive studies on transfer and analogy. Finally we compare similarity and dissimilarity between transfer and analogy.

1. Definition of the Terms & Overview of the Phenomena

In some abstract sense, both phenomena can be described as influence of an experience in a preceding task upon a succeeding task. In this essay, the preceding task is called the *source task*, whereas the succeeding task is called the *target task*. The tasks can be solved by *domain principles*. Problem solving might involve a control mechanism for principle applications (e.g., planning, strategy, schema, etc.). Hence the experience in the source task would affect not only *principle application* but also the *control mechanism* in the target task. There might be only a single principle or a single element in the controlling mechanism that is affected by the experience on the source task. Or, several of them might be affected, but from different experiences with the source task.

The source task and the target task share common features such that underlying domain principles (e.g., two problems that are dissimilar on the surface can be solved by the same domain principles), abstract goal structure (e.g., two very different text editors obeying the same concept of text editing such as cut and past), physical objects (e.g., driving a car in different countries where the cars run on the opposite side of streets). Hence, one may find *mapping* between those common features in the source and the target task.

There are several ways that application of a domain principle or execution of control mechanism is influenced by the experience on a source task; principle or plan is applied in a one-to-one mapping basis, or some kind of memory retrieval is invoked based upon the surface features (e.g., the second-order features advocated by Chi, Feltovich, & Glaser, 1981). Performance on the target task might be

[1] *Misapplication* of analogy hinders problem solving. Analogously, a *negative* transfer slows down the performance on the target task.

influenced by *general principles* or *general controlling mechanism*, which can be applied to several different tasks, or by *task specific principles* or *task specific controlling mechanisms*, which work only on a specific kind of task.

Given these observations, we now define "analogy" and "transfer" to make the arguments in remaining sections meaningful.

In this short essay, we define analogy as *mapping*, namely, "finding a set of one-to-one correspondences (often incomplete) between aspects of one body of information and aspects of another" (Gick & Holyoak (1983) quoted in Caplan & Schooler, 1999). There usually exists a *single principle* (a *target principle*) to be applied by analogy. More precisely, the target principle will be applied to the target task in such a way that mapping between the source and the target task holds. Hence, the term "problem solving by analogy" here means to solve problems by means of the domain principles and/or the control mechanism, learned in the source task, applied upon mapping between the source and the target tasks.

Transfer is defined as an improvement of performance in the target task on a basis of the experience in the source task, but not necessarily due to explicit mapping between two tasks neither not necessarily by a single principle application. So, transfer will be observed between tasks without explicit (or conscious, if you will) use of mapping technique, or it will be done by applying more than one principles hence a whole problem solving process can not be mapped back onto any single instance of training in source task domain.

These definitions provide a partial answer for the original question: Analogy, by definition, can be viewed as a special case of transfer where only a single application of domain principle is studied in terms of the mapping between the source and the target tasks. Because they, again by definition, represent different aspects of influence of the source tasks over the target tasks, they also have dissimilarities. These issues are discussed in the following sections in detail.

2. Cognitive Studies on Analogy and Transfer

Basically, cognitive studies on transfer and/or analogy follows a general procedure: training subjects in one task (the training task) and measure the performance on another task (the target task). They have different focus of investigation, though: studies on analogy expect subjects to use particular principles in different tasks, whereas studies on transfer put greater interests on the quality (usually speed and accuracy) of performance on the target task.

Since one-to-one correspondence is not the central issue in transfer studies, a common norm in studies on transfer is to show a speed-up (or, a slow-down in a case of negative transfer studies) of the performance on the source task as compared with the performance on the same task without prior experience on the source task. For example, transfer between different types of text editors has been defined as "reductions in total time, keystrokes, residual errors, and seconds per keystroke" (Singley & Anderson, 1985). To explain a mechanism of speed up, researchers may identify features that are shared with the source and the target tasks. For example, the identical-element theory of transfer attributes the degree of transfer to the amount of shared principles (Singley & Anderson, 1985).

3. Dissimilarity

As the definitions in the first chapter read, we intentionally defined analogy and transfer to hold different aspects hence not surprisingly they have dissimilarities. The major disagreement is in the *single vs. multiple* principle applications, and *mapping* between two tasks.

In some sense, analogy can be easily applied than transfer, because it is easier to learn single principle than multiple principles. For example, students tend to *copy* a solution from example and apply it to a problem in hand (i.e., problem solving by analogy). On the other hand, even when a student have learned a set of principles, he/she would have great difficulty to apply to a novel problem in a different combination than the one learned in the source task (i.e., transfer needs extra work). In other words, transfer may require applying domain principles in a different way than once learned (VanLehn, 1996, p.522).

Analogy, by definition, requires a single domain principle to be applied to both tasks in such a way that explicit mapping between the source and the target application can be defined. Transfer, on the other hand, would occur with more vague correspondence among two tasks. Because of this loose connection between the source and the target tasks, researchers often are puzzled about what exactly would have caused transfer. To address this question, transfer is often split into two subcomponents: domain general transfer and domain specific transfer (Caplan & Schooler, 1999; Singley & Anderson, 1985).

Not a direct response to the question, but one interesting dissimilarity is that "transfer" also represents an amount of speed up in *learning* on the target task (VanLehn, 1996, p.532), but the word "analogy" is hardly used to describe learning phenomenon (at least in the readings). Namely, transfer can be measured as a ratio of the time saved in learning on one task (i.e., the target task) due to earlier learning on a different task (the source task) (VanLehn, 1996, p.532). In such context, the amount of transfer would be reduced even when a substantial amount of knowledge is shared between tasks. This would happen when repeating practice on a task eventually leads the learner a *strategy change* (VanLehn, 1996, p.533). Transfer might suffer with the *use specificity*, which decrease amount of transfer as practice on the training task increases. These issues are hardly discusses in analogy studies (again, at least in the readings).

4. Similarity

As described in the very beginning of this short essay, both analogy and transfer address same abstract phenomena in problem solving. So, it is not a great surprise to see that they actually share many common features and research issues. Some even uses the words "analogy transfer" or "analogical transfer" to express what we have been discussing (Caplan & Schooler, 1999).

In fact, with a slight generalization of the definitions, analogy can be seen as a special case of transfer where only single domain principle is involved. In other words, transfer could be seen as a problem solving with analogical reasoning in sub-procedures. Namely, each sub-procedure can be just a matter of mapping for principles applications learned in the training task onto the target task. One distinctive characteristic in the transfer in such a view is that one must take into account control mechanism, which may or may not have learned in the target task (i.e., different tasks require different control mechanism over the same set of principles), hence even if most of the domain principles can be transferred, one would not see much improvements on a performance in the target task.

These presuppositions lessen the impact of surprise on similarities among analogy and transfer, because they now both governed by a single phenomenon, i.e., domain-principle application (may or may not include control mechanism) in two different situations.

First, both transfer and analogy could occur via an implicit mechanism of priming (Schunn & Dunbar, 1996). The human problem solvers would solve problems without noticing that they are influenced by the previous problem-solving activities.

Second, they both fit in the power curve of learning (Newell & Rosenbloom, 1981); "skill learning," which is defined as an improvement in problem solving that requires both a direct application of analogy and learning new concepts, has been shown to follow the power curve (Gupta & Cohen, 2002). Transfer can be modeled as a composite of general and specific skills, each of which follows the power curve (Singley & Anderson, 1985).

Third, as an analogous to *negative transfer*, “negative analogy” namely misapplication of analogy would bring false solution or impasse.

Lastly, although no empirical study is found in the readings hence this must be counted as a speculation, the theory of second-order features (Chi et al., 1981), which explains memory retrieval, would apply in both cases as a mechanism of memory retrieval. This is because both types of problem solving are based on a similarity of tasks, and the theory of second-order features is to explain how human problem solvers “see” those similarities.

Answer for question #2:

A theory of two-phased skill acquisition is proposed: (1) The novices first learn basic operators, which establish problem space, (2) they then develop search heuristics and acquire macro operators, which reduce a search hence enable to solve more difficult problems. The question is then asking to provide supporting as well as conflicting evidence for the proposed theory.

1. Supporting Evidence

The proposed theory of learning is actually a rephrase of the theory of problem solving as search (Holyoak, 1995, p.268-276). Not so much amount of evidence can be find in the readings, but there are many studies that support that human problem solvers develop so called *search heuristics* that is a set of criterion to *select* better operators among competing operators, which in turn prevent the search from facing combinatorial explosion (Holyoak, 1995, p.271-272).

In the readings, ACT theory, a version of state-space search model, also provides positive support for the proposed theory (Anderson, 1982; Anderson & Fincham, 1994). ACT theory advocates that all knowledge first come into the learning system in a declarative form, then with practice at using the knowledge in a particular context, production rules would develop. These process corresponds to “learning the basic operators of the task domain” in the proposed theory. ACT theory further claims that once productions are formed, a set of productions that fires together in a certain context will be put into a larger production, which is called *knowledge composition* (Anderson, 1982, p.382). This process corresponds to the development of macro-operators in the proposed theory. The *principle of conflict resolution* in ACT theory corresponds to the heuristics in the proposed theory. This principle provides criterion to select a production among equally plausible productions; select most specific production, select production that refers to the working memory element that has been modified most recently, select production that was used least recently, etc.[2]

How about the known phenomenon that despite enormous amount of expertise and experience that experts usually have, it is often observed that they can only solve familiar problems (Ericsson & Lehmann, 1996)? I claim that this is a positive support, because the proposed theory predicts that the operators and search heuristics would be more and more adapted to the familiar problems along with the practice. On the other hand, unfamiliar problems should be solved without macro-operators and the heuristics hence the performance would be as low as novices' performance.

As described in the next section, there are many aspects reported in the readings that do not fit into the proposed theory of cognitive skill acquisition. Hence, my basic attitude toward the theory is that it is overly simplified and describing only a part of phenomena.

2. Conflicting (or unfitted) Evidence

The proposed theory does not explain much about the process of being a skilled problem solver, i.e., an expert. Let define an expert as an experienced problem solver who can solve problems quicker and more accurate than novice problem solvers. The mechanisms in the proposed theory that explains such improvement are composition of macro-operators and search heuristics. There are known phenomena in the readings that these mechanisms can not sufficiently explain.

First, it has been claimed that improvement of problem solving is not only the result of acquiring heuristics and bigger chunk of productions, but the productions themselves are modified to adapt to the environment (Singley & Anderson, 1985, p.419), so called a *self-modifying production systems*. In such a system, *proceduralization* first takes place to strip the domain specific declarative information off the composite production. Second, *generalization and discrimination* expand and restrict the scope of production application. And third, the *strengthening* mechanism adjusts the probability of successful production application that further contribute to resolving competing productions (Anderson, 1982). This cannot be done just putting operators together to make macro-operators.

---

[2] I can not find a citation for this principle from the readings. But, I do remember I read an article in the readings describing about the principle of conflict resolution in ACT that further goes like "the least frequency is especially effective when a solution requires most productions to be applied."

Second, for some tasks (e.g., algebra or text editing), when novices are given enough practice with a particular type of problem, then they eventually memorize a stereotypic procedures and solutions. Once they acquire such things, then they start to just retrieve a solution for a particular problem from memory instead of applying normal search (VanLehn, 1996, p.532). This phenomenon cannot be explained neither by macro-operators nor by search heuristics.

Third, there are plenty of studies showing that experts tend to apply *schema-driven* technique, which is knowledge about problem types that further provides a clue to application of known productions (Ericsson & Lehmann, 1996, p.275; VanLehn, 1989, p.545-553). A problem schema consists of information about the class of problems the schema applies to as well as information about their solutions. Hence it is a composite knowledge of feature of problems and solutions. It has been also shown that novices and experts utilize different mechanism to retrieve schemas. Chi et al found that novices categorize problems with respect to the problem's literal features whereas experts relies on the underlying principles (Chi et al., 1981). These studies show that expert performance is not achieved merely by selecting better operators, but schematic insight for a solution also takes place during problem solving.

As the fourth claim, another known characteristic in expert problem solving is that they learn different *strategies* as experience in problem solving proceeds. For example, there are several different strategies for multiplication; memory retrieval, repeated addition, counting a set of objects, writing an equation either horizontally or vertically, and saying "I don't know."[3] A study shows that when 2nd graders learn multiplication, they would learn more and more strategies and tend to apply more and more effective strategies (Lemaire & Siegler, 1995). Since different strategies can be modeled as different operators, the proposed theory could be expanded to acquire new operators along with the increase of experience.

3. Can the proposed theory be valid in a restricted phenomenon?

The counterarguments in the previous section are all about expert performance. Hence, if we only concern about the novice learning process just before they obtain expert level performance, then the proposed theory will explain how novices acquire problem-solving skills.

---

[3] Yes, in some study, "I don't know" is considered as an answer, and saying that is considered as a valid strategy.

Answer for question #3:

There is only a small amount of direct evidence in the assigned readings that support designing effective ordering of instructional materials (i.e., *selection* and *ordering* of problems provided to students during learning by solving problems). Nonetheless some studies in the readings seem to support at least two different design schemata: ordering problems with respect to their cognitive load, and ordering problems so that the structural decomposition (goal-subgoal relationship) is held for all domain principles. Here, the term “domain principles” represents what students must learn to solve problems in the subject domain.

1. Ascending Cognitive Load

There are many empirical studies that investigate effectiveness on learning from worked examples and problems. The former means that students learn how to apply domain principles by reading solutions that somebody else made, whereas the latter means that the students practice applying domain principles by actually solving problems. However, since most of these studies are not in the reading list, I can not include them here as supporting evidence (Note 2 specified in the exam question), but some of them are mentioned in VanLehn (1996, p.517): three studies showing students’ preference for learning from worked examples to other form of instruction, and three studies showing superiority of efficiency in skill acquisition by learning from worked examples to learning from problem solving. The question then is how to order worked examples and when to switch the learning material from worked examples to problem solving.

The cognitive load theory explains a reason for novice student's failure on learning from problem solving. The dominant strategy used to solve problem, i.e., means-ends analysis, “places heavy demands on limited working memory and can easily result in cognitive overload that interferes with learning” (Kalyuga, Chandler, Tuovinen, & Sweller, 2001, p.579). The theory further goes to suggest that providing worked examples instead of problems should reduce cognitive load hence facilitate learning. Thus, it should be better to use worked examples first followed by problem solving. When should the learning phase be changed?

Kalyuaga et al show that the most efficient mode of instruction depends on the level of experience of learners (Kalyuga et al., 2001, p.584). This means that learning from worked examples is superior to learning from problem solving at the beginning, but the superiority reverses at the later stage. Namely, as experience increased, the relative improvement in performance of the problem solving group is superior to the worked example group. But they end up with the same performance level.

Does this mean that learning by problem solving is just a "slow-starter" who goes further lately (hence, in a long view, learning by problem solving brings better gain)? No. The second experiment in (Kalyuga et al., 2001) shows that repeating exposure to worked out examples would eventually brings no learning gain at all, hence the above observation (i.e., both learning groups ended up with the same level) merely means that the problem solving group took much longer time than the worked example group to reach to the same skill level. This slackness of learning gain is called the *redundant effect*; once learners reach an expert level, which is defined by a lack of learning gain from worked examples, then further learning with worked examples is ineffective (possibly due to its redundancy, hence named as the redundant effect).

In sum, starting with the worked examples and continue to provide them until the redundant effect is observed, and then switch to the problem solving should bring a better learning gain than any other combination of examples and problem solving.

Not relating to ordering nor selection, but it is shown that explication of goal structure facilitate learning from worked examples (Catrambone, 1996). In teaching a calculation of probability, he found that providing a meaningful label to a set of problem-solving steps that corresponds to a subgoal of the procedure to calculate probability results in a better learning gain than providing not-so-meaningful label as well as than not showing the subgoal steps at all. Hence, the goal structures should be explicated in the worked examples.

It is also known that making spontaneous explanation (called *self-explanation*) facilitates learning from worked examples (Chi et al 1989 cited in VanLehn, 1996, p.523). VanLehn et al (1992 cited in VanLehn, 1996) found that self-explanation is a crucial component for learning from worked example, because only less than half of the rules needed to solve problems are mentioned in the worked examples whereas remaining rules can be noticed by self-explanation. Hence, students should be asked to self-explain given worked examples.

2. Hierarchical Structuring

A domain principle may consist of several subskills, i.e., a domain principle may be able to decompose into several other domain principles. To understand a composite domain principle, all component principles (i.e., subskills) must be learned prior to the composite principle. For example, addition with carrying involves an addition with single digits. The addition with single digits must be learned prior to the addition with carrying.

The identical-elements theory of transfer says that the degree of transfer is directly proportional to the number of shared productions (Singley & Anderson, 1985). That is, the more component principles are learned, the faster the composite principle would be learned.

The model tracing tutor, which is known to be an effective tutor for problem solving, let students follow solution path step-by-step either top-down or bottom-up (Anderson, Corbett, Koedinger, & Pelletier, 1995).[4] This learning environment represents domain principles as a set of production rules, which clearly hold hierarchical structure of domain principles. Hence the students in this learning environment inevitably learn (or, at least correctly perform) component principles prior to the composite principle. Although there is no evidence in the literature that attributes the known effectiveness of this learning environment to the proposed design principle (i.e,. prior component learning followed by composite principle), it is worth studying if it is the case.

For this design principle, masterly learning (Bloom, 1985) should be a plus. It is not included in the readings, but there is a study that shows that mastery learning at each skill results in higher scores on posttests than tutoring based on fixed problem sets (Anderson et al 1989 cited in VanLehn, 1996, p.529).

3. A little thought: Not for filling up a space

There is a little thought for this question; namely, what does “simple” and “difficulty” mean?

In some sense, the more cognitive load an example or a problem has, the more “difficult” to understand or solve it. Similarly, the more unlearned component principles involved, the more “difficult” to understand the composite principle. Hence, both design principles discusses above could fall into the simple-to-difficult design principle specified in the question.

The examinee interpreted the “difficulty” of examples and problems as the amount of time required to understand an example or solve a problem given the same set of domain principle involved. For example, for addition with carrying, the difficulty is proportional to the number of digit to be added. Hence the simple-to-difficult design principle says to order addition problems from least number of digits to most number of digits.

[4] This paper is not included in the readings for “Human Problem Solving and Skill Acquisition,” but borrowed from the readings for “Intelligent Tutoring Systems.”

Reference:

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review, 89*(4), 369-406.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. *Journal of the Learning Sciences, 4*(2), 167-207.

Anderson, J. R., & Fincham, J. M. (1994). Acquisition of procedural skills from examples. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20*(6), 1322-1340.

Bloom, B. S. (1985). Learning for Mastery. In C. W. Fisher & D. C. Berliner (Eds.), *Perspectives on Instructional Time* (pp. 73-93). White Plains, NY: Longman.

Caplan, L. J., & Schooler, C. (1999). On the use of analogy in text-based memory and comprehension: The interaction between complexity of within-domain encoding and between-domain processing. *Journal of the Learning Sciences, 8*(1), 41-70.

Catrambone, R. (1996). Generalizing solution procedures learned from examples. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22*(4), 1020-1031.

Chi, M. T. H., Feltovich, P. J., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5*, 121-152.

Ericsson, K. A., & Lehmann, A. C. (1996). Expert and exceptional performance: Evidence of maximal adaptation to task constraints. *Annual Review of Psychology, 47*, 273-305.

Gupta, P., & Cohen, N. J. (2002). Theoretical and Computational Analysis of Skill Learning, Repetition Priming, and Procedural Memory. *Psychological Review, 109*(2), 401-448.

Holyoak, K. J. (1995). Problem solving. In E. E. Smith & D. N. Osherson (Eds.), *Thinking: An invitation to cognitive science* (2nd ed., Vol. 3, pp. 267-296). Cambridge, MA: The MIT Press.

Kalyuga, S., Chandler, P., Tuovinen, J., & Sweller, J. (2001). When problem solving is superior to studying worked examples. *Journal of Educational Psychology, 93*(3), 579-588.

Lemaire, P., & Siegler, R. S. (1995). Four aspects of strategic change: Contributions to children's learning of multiplication. *Journal of Experimental Psychology: General, 124*(1), 83-97.

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of Skill Acquisition and the Law of Practice. In J. R. Anderson (Ed.), *Cognitive Skills and Their Acquisition* (pp. 1-55). Hillsdale, NJ: Erlbaum.

Schunn, C. D., & Dunbar, K. (1996). Primary, analogy, and awareness in complex reasoning. *Memory and Cognition*, *24*(3), 271-284.

Singley, M. K., & Anderson, J. R. (1985). The transfer of text-editing skill. *International Journal of Man Machine Studies, 22*(4), 403-423.

VanLehn, K. (1989). Problem solving and cognitive skill acquisition. In M. I. Posner (Ed.), *Foundations of cognitive science* (pp. 527-579). Cambridge, MA: The MIT Press.

VanLehn, K. (1996). Cognitive skill acquisition. *Annual Review of Psychology, 47*, 513-539.

Appendix: Assigned Reading List:

Theory of Problem Solving

Holyoak, K. J. (1995). Problem solving. In E. E. Smith & D. N. Osherson (Eds.), Thinking: An invitation to cognitive science (2nd ed., Vol. 3, pp. 267-296). Cambridge, MA: The MIT Press. [30p]

Hutchins, E. (1995). How a cockpit remembers its speeds. Cognitive Science, 19(3), 265-288.

Kotovsky, K., & Simon, H. A. (1990). What makes some problems really hard: explorations in the problem space of difficulty. Cognitive Psychology, 22, 143-183.

VanLehn, K. (1989). Problem solving and cognitive skill acquisition. In M. I. Posner (Ed.), Foundations of cognitive science (pp. 527-579). Cambridge, MA: The MIT Press. [53p]

Theory of Skill Acquisition

Gupta, P., & Cohen, N. (2002). Theoretical and Computational Analysis of Skill Learning, Repetition Priming, and Procedural Memory. Psychological Review, 109(2), 401-448. [48p]

VanLehn, K. (1996). Cognitive skill acquisition. Annual Review of Psychology, 47, 513-539. [27p]

Lemaire, P., & Siegler, R. S. (1995). Four aspects of strategic change: Contributions to children's learning of multiplication. Journal of Experimental Psychology: General, 124(1), 83-97.

Voss, J. F., Wiley, J., & Carretero, M. (1995). Acquiring intellectual skills. Annual Review of Psychology, 46, 155-181.

Anderson, J. R. (1982). Acquisition of cognitive skill. Psychological Review, 89(4), 369-406. [38p]

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of Skill Acquisition and the Law of Practice. In J. R. Anderson (Ed.), Cognitive Skills and Their Acquisition (pp. 1-55). Hillsdale, NJ: Erlbaum. [55p]

Learning from Examples & Problems

Kalyuga, S., Chandler, P., Tuovinen, J., & Sweller, J. (2001). When problem solving is superior to studying worked examples. Journal of Educational Psychology, 93(3), 579-588. [10p]

Rittle-Johnson, B., Siegler, R. S., & Alibali, M. W. (2001). Developing conceptual understanding and procedural skill in mathematics: An iterative process. Journal of Educational Psychology, 93(2), 346-362. [17p]

Anderson, J. R., & Fincham, J. M. (1994). Acquisition of procedural skills from examples. Journal of Experimental Psychology: Learning, Memory, and Cognition, 20(6), 1322-1340. [19p]

Transfer

Phye, G. D. (2001). Problem-solving instruction and problem-solving transfer: The correspondence issue. Journal of Educational Psychology, 93(3), 571-578. [8p]

Caplan, L. J., & Schooler, C. (1999). On the use of analogy in text-based memory and comprehension: The interaction between complexity of within-domain encoding and between-domain processing. Journal of the Learning Sciences, 8(1), 41-70. [30p]

Catrambone, R. (1996). Generalizing solution procedures learned from examples. Journal of Experimental Psychology: Learning, Memory, and Cognition, 22(4), 1020-1031.

Schunn, C. D., & Dunbar, K. (1996). Primary, analogy, and awareness in complex reasoning. Memory and Cognition, 24(3), 271-284.

Singley, M. K., & Anderson, J. R. (1985). The transfer of text-editing skill. International Journal of Man Machine Studies, 22(4), 403-423.

Expertise

Vicente, K. J., & Wang, J. H. (1998). An ecological theory of expertise effects in memory recall. Psychological Review, 105(1), 33-57.

Ericsson, K. A., & Lehmann, A. C. (1996). Expert and exceptional performance: Evidence of maximal adaptation to task constraints. Annual Review of Psychology, 47, 273-305. [33p]

Bloom, B. S. (1985). Learning for Mastery. In C. W. Fisher & D. C. Berliner (Eds.), Perspectives on Instructional Time (pp. 73-93). White Plains, NY: Longman. [21p]

Chi, M. T. H. (1981). Categorization and representation of physics problems by experts and novices. Cognitive Science, 5, 121-152. [32p]