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Two principles for connectionist learning

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At the crossroad between cognitive psychology and artificial neural networks, this work is about learning complex behaviors? Indeed, current connectionist algorithms can only learn simple tasks, and can only model limited and isolated human abilities. Two principles to overcome these limits are proposed.

Progressivity

To make a network learn a complex ability, computer scientists usually use a single network with a single training set. Conversely, we argue that learning should take place in a temporal framework, where the training set evolves during learning. In particular, if successive training sets are carefully chosen, such a temporal organization of learning can facilitate learning, thanks to *progressive learning* (Cloete & Ludik, 1993; Elman, 1993; Szilas & Ronco, 1995). Such a progressivity effect, based on the notion of transfer, is often observed in human learning. Beyond the intuitive obvious fact that the whole schooling is based on progressive acquisition of knowledge, laboratory experiments have demonstrated the efficiency of progressive learning, in a large variety of tasks, like human-computer interaction, motor learning, concept learning, etc.

Polyvalency

However, the success of both computer and psychological experiments mentioned above entirely relies on how the task designer organizes the learning environment. We intend to design models of *autonomous* learning, where the learning system is able to select what to learn and when. Straightforward finding, without a priori knowledge, the proper ordering of tasks is unrealistic, if the system is not allowed to use some kind of trials and errors strategy. Such a strategy requires polyvalency. Polyvalency reefers to the ability of a system to have several distinct skills, which correspond to distinct training sets in connectionist models. In a pure progressive learning situation, the current learning only have the previous skill at its disposal, because progressive learning is characterized by a "fixed processing channel" (Clark & Thornton 1997), whereas in progressive *and* polyvalent learning, there is a wide panel of tasks, available for transfer. Thus, progressive learning can occur in an autonomous way; the system acquires, in a bottom up way, a variety of skills incrementally connected one with the others.

About optimality

Interestingly, those two principles, when combined, imply that the resulting structure is sub-optimal, from a computational point of view. Indeed, progressive and polyvalent systems need to maintain their old abilities which constrained the space of solutions (Szilas 1997). Conversely, the multitask approach (Caruana, 1993) aims at better architectures, in terms of generalization, because in multitask learning, all skills are acquired simultaneously, in a non progressive way. We just claim that multitask learning is not suited to highly complex tasks. Non optimality has been observed in human learning (see (Ben-Zeev, 1995) for example): in the course of development, old erroneous procedures remain during the whole life, while new procedures are just superimposed to them. According to these psychological data and the two proposed principles, we claim that the current race of computer scientists for optimality does not hold: non optimal structures form a necessary stage in learning.

References

Ben-Zeev, T. (1995). The nature and Origin of *rational Errors* in Arithmetic Thinking: Induction from Examples and Prior Knowledge. *Cognitive Science*, 19, 341-376.

Caruana, R. A. (1993). Multitask Connectionist Learning. *Proceedings of the 1993 Connectionist Summer School* (pp. 657-664). Hillsdale, NJ: Lawrence Erlbaum Associates.

Clark, A., & Thornton, C. (1997). Trading Spaces: Computation, Representation and the Limits of Uninformed Learning. *Behavioral and Brain Sciences*, to appear.

Cloete, I., & Ludik, J. (1993). Increased Complexity Training. *Proceedings of the International Workshop on Artificial Neural Networks* (pp. 267-271) Sitges, Spain.

Elman, J. F. (1993). Learning and development: the importance of starting small. *Cognition*, 48, 71-99.

Szilas, N., & Ronco, E. (1995). Action for learning in non-symbolic systems. *Proceedings of the European Conference on Cognitive Science* (pp. 55-63) Saint-Malo, France.

Szilas, N. (1997). Apprendre dans le temps: un nouvel éclairage sur l'apprentissage connexionniste. *Informations Incognito*, 7, 17-24.