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Toward a Large-Scale Characterization of the Learning Chain Reaction

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Abstract

Designing an agent that can grow cognitively from a child to an adult human level of intelligence is the key challenge on the roadmap to human-level artificial intelligence. To solve this challenge, it is important to understand general characteristics of the expected learning process at a level of mathematical models. The present work makes a step toward this goal with a simple abstract model of a long-term learning process. Results indicate that this process of learning is characterized by two distinct regimes: (1) limited learning and (2) global learning chain reaction. The transition is determined by the set of initially available learning skills and techniques. Therefore, the notion of a ‘critical mass’ for a human-level learner makes sense and can be determined experimentally.

Keywords: human-level artificial intelligence; self-regulated learning; teachable systems.

Introduction

Since the 1956 Dartmouth conference, researchers are taking seriously the challenge of creating machines capable of general human-level intelligence, human-like learning and self-improvement (McCarthy et al., 1955), yet the distance toward this goal has hardly decreased since 1955 (in fact, it is practically difficult to evaluate to make any judgment). Main progress made since the beginning is visible in reassessment of the difficulties, in emergence of new approaches, e.g., cognitive architectures (Newell, 1990; Gray, 2007), and in a new understanding of the goal. Yet, despite growing interest to the field, it is not clear what the final goal is and what would be the impact of achieving it.

Here four different views and associated with them schools of thought can be named: (1) computational neuroscience, that tries to understand how the brain works in terms of neurophysiological mechanisms and neuroarchitectures; (2) cognitive modeling, pursuing higher-level computational description of human cognition and behavior based on more abstract cognitive architectures; (3) human-level artificial intelligence, aiming at generally intelligent artifacts that can replace humans at work; and (4) a new emergent paradigm (that can be called “machine consciousness”, or “human-like learners”, etc.) aiming at artificial minds that can be understood by humans intuitively, that can learn like humans, from humans and for human needs. All these are fundamental scientific problems. While (1) and (2) are focused on understanding the roots of human cognition, and therefore allow for validation of their progress using brain-and-behavior data, (3) and (4) are oriented toward creation of an expected phenomenon that does not exist yet: a computational replica of the human mind capable of human-like learning and cognitive growth.

From this point of view, defining a success criterion for (3) and (4) is the key challenge on the roadmap to a human-level learner. Examples of practically inefficient guiding criteria include ambitious global challenges like the Turing test (Turing, 1950; Korukonda, 2003) and limited challenges like beating humans in chess or poker. As a result of the missing clear understanding of the overarching goal, the original high spirit appears to be lost in specific, incremental steps that together did not produce a quantum leap and seem to lead nowhere. On the other hand, both, computational neuroscience and microelectronics made tremendous progress in recent decades. Today there is no big mystery in functioning of the brain elements, in the sense that the generally accepted view of the brain is that of a natural information processing device. Capabilities of the modern computing hardware are approaching or have already exceed computational resources of the human brain, therefore, hardware is not a bottleneck on the road to human-level intelligence. Then, what are we missing?

Several recent conferences, e.g., the BICA symposia (Samsonovich, 2008, 2009, members.cox.net/bica2010) addressed this question. To summarize the situation: it becomes clear that biologically inspired cognitive architectures (BICA) provide the most promising approach to creating a functional replica of the human mind, and the key to solving this challenge is in replication of the human ability to learn. In other words, having a machine that can be taught virtually anything that a human child can be taught would imply the achievement of the grand overarching goal. Therefore, in order to successfully steer research toward this goal, it is necessary (a) to better understand principles and characteristics of human learning at a big scale: e.g., in educational practice, rather than in limited behavioral laboratory experiments, and (b) to match the same characteristics of learning in artifacts.

From this point of view, the overarching goal should be formulated as a challenge in terms of scalability laws characterizing the learning process over a long period of time, when previously learned knowledge and skills enable the acquisition of new knowledge and new learning techniques, and so on. This large-scale process of bootstrapped learning can be visualized as a chain reaction (e.g., as depicted in Figure 1). Understanding details of this bootstrapped learning process, such as principles of self-regulated learning (SRL: Zimmerman, 2002), is vital for achieving the goal. At the same time, description of the general laws and their mathematical understanding is possible at an abstract level. Indeed, this is a task of high priority on the roadmap toward general human-level artificial intelligence, or artificial human-like minds.

Similarly to the history of the study of the nuclear chain reaction, models and theories are needed to describe and understand the learning chain reaction in detail in order to make it achievable. The key task is to clarify the difference between solutions leading to small incremental steps and solutions leading to a big quantum leap, and to identify conditions (e.g., the ‘critical mass’ of the initially available capabilities, if it makes sense) that make the leap possible.

The present work presents an attempt to start developing the necessary theory by constructing and simulating a general model of large-scale learning of the above sort, using learning of an abstract curriculum as an example.

Methods

First, in this section a challenge scenario is outlined that can serve as a goal for designing a general-purpose human-like learner and at the same time as an example justifying abstract modeling. Then, based on this scenario, an abstract model is constructed that will be studied numerically in the next section.

An Example Challenge Scenario

The following challenge scenario for an artificial learner can be viewed as an operational definition of certain key aspects of the human learning ability that needs to be replicated in artifacts: in particular, scalability, robustness, cross-domain transferability, and most importantly, its metacognitive nature. This paradigm will also allow experimenters to measure the “critical mass” of initial knowledge and skills that enable human-level bootstrapped learning.

Settings: The agent is embedded in a virtual learning environment with the study material (the textbook and supplementary materials normally available to students) encoded electronically and made available to the agent. All interactions between human instructors and the agent are mediated by an interface implemented at a symbolic level. The agent is expected to make progress in study of the curriculum, being taught by human instructor(s) via the high-level symbolic interface. The domain of study can be limited, e.g., to high school algebra. The agent together with instructors will go through chapters of the textbook (e.g., Algebra 1 and Algebra 2: Larson et al., 2007a,b) in their electronic representation, will learn new concepts, will ask questions, will take quizzes, will do exercises, and will be able to explain the learned material.

Approach: The approach to implement an artificial student capable of learning how to solve high school algebra problems can be based on a biologically-inspired cognitive-metacognitive architecture implementing principles of SRL (e.g., Samsonovich, De Jong and Kitsantas, 2009; Samsonovich, 2010).

Metrics and Criteria: The challenge for the agent is (i) to demonstrate a long-term ability to learn the curriculum step-by-step, starting from basic concepts available initially

(examples: an integer number, a variable, a function) and gradually moving to their practical usage and to complex constructs based on them, and (ii) to demonstrate improvement of meta-learning skills over time, in particular, SRL skills (Zimmerman, 2002). The agent performance improvement over time at the task level will be measured using standard tests and metrics used for evaluation of student academic progress. The agent will be evaluated not only based on its task-level learning and problem solving performance, but also based on changes in the approach to problem solving, using general metrics for SRL (Winne & Perry, 2000). A particularly interesting question relates to the measure of initial intelligence (the “critical mass”) that enables learning of the curriculum.

Generalizations: This example of a challenge scenario entails a generalization. Taking a step to the abstract level, it makes sense to introduce of elements of an abstract curriculum as a system of interrelated abstract units (skills, facts, etc.) that the agent may have the ability to learn, depending on its current knowledge and experience. This is done below.

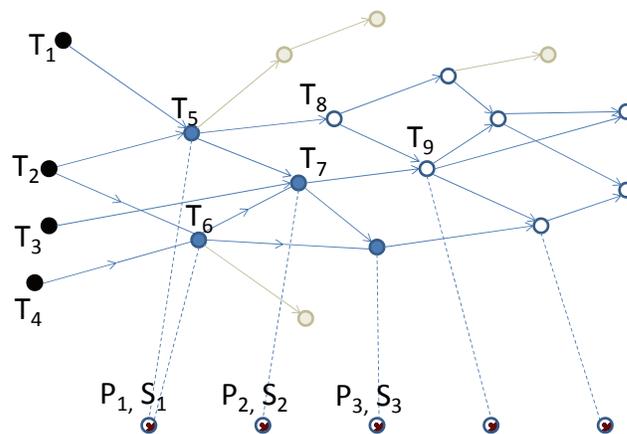


Figure 1: A possible curriculum structure. Solid circles (black and blue) represent available techniques.

Designing an abstract Model

A simple abstract model of a learning process consistent with the above scenario can be defined as follows. Elements of the model are abstract problems P , abstract facts and techniques T applicable to the problems, and abstract solutions S understood as subsets of techniques associated with problems. It is assumed that the set of techniques $\{T\}$ is ordered based on their mutual dependence, excluding a possibility of circular dependence. This ordering can be understood as resulting from a process of adding new techniques one by one to the set, as follows. Given a set of available $i-1$ techniques, the new technique T_i is defined as an abstract function f_i of a subset of the available $i-1$ techniques:

$$T_i = f_i(\{T_j : 0 < j < i, W_{ij} = 1\}), \quad \sum_j W_{ij} = m, \quad (1)$$

where W is a randomly generated, sparse Boolean matrix with zero elements for all $i \leq j$. To simplify the modeling study, it is assumed that each row of W (except the first m rows) has exactly m nonzero elements that are uniformly sampled in the part of the row before the diagonal. Each of the first m rows has the maximal number of nonzero elements satisfying (1). Therefore, a typical matrix W looks like the example plotted in Figure 2 B.

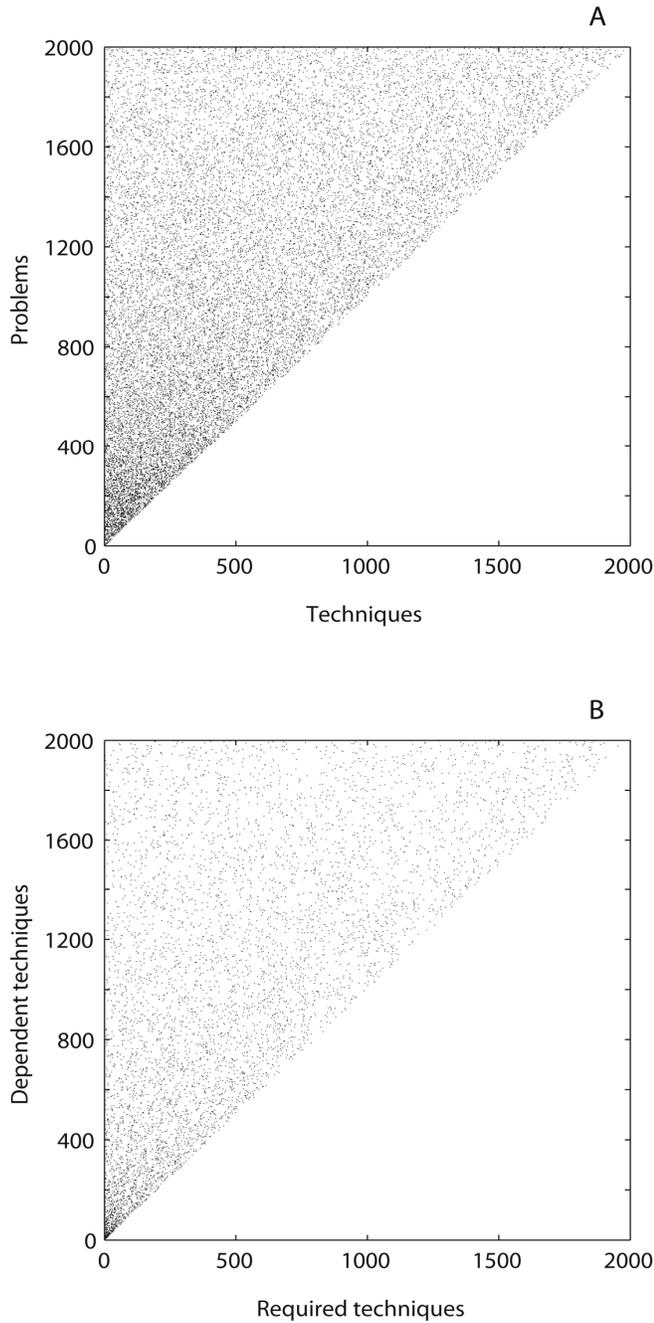


Figure 2: Examples of the abstract curriculum materials used in simulations. A: Example set of solutions for each of the 2,000 abstract problems. B: Example set of dependencies among the 2,000 abstract techniques.

Next, it is assumed that the set of problems $\{P\}$ is ordered similarly, and solutions S to problems are described by a matrix W' defined by a duplicate of (1), only with a different parameter m' :

$$S_i = \{T_j : 0 < j < i, W'_{ij} = 1\}, \quad \sum_j W'_{ij} = m', \quad (2)$$

To simplify the study, each problem is assumed to have exactly one solution, which is defined as a certain set of m' techniques. Of course, in real life, knowing a set of techniques that together are sufficient for solving a given problem does not imply the ability to solve the problem: one needs to know in what order and how to apply those techniques. For now, however, we assume that this part of solution is available automatically whenever each of the set of techniques that are necessary to solve the problem is mastered. Therefore, a typical matrix defining solutions of problems looks like the plot in Figure 2 A.

Naturally, there should be also an abstract notion of applicability of techniques to problems: each technique is either applicable to a given problem or not. In this sense, a solution must be a subset of techniques applicable to the given problem. The matrix of applicability $A = \{A_{ij}\}$ tells us whether T_i is applicable to P_j . The matrix A is again generated as a Boolean random matrix with given sparsity.

Model Dynamics

From the learner's perspective, each problem in this simplistic model is either solved or not. Similarly, each technique has three possible states: unavailable, available (yet not mastered), and mastered. The model dynamic rules of learning are defined as follows. A technique becomes (and forever remains) available when all techniques on which it depends are mastered. A technique becomes (and forever remains) mastered when it is successfully used to solve a problem. A technique can be used to solve a problem when it is available. A problem that is already solved is not considered again (indeed, with exactly one solution for each problem, its consideration would change nothing).

Experimental Paradigm

The abstract learning paradigm is the following. Given a set of n techniques and n problems (having the same n just simplifies the consideration), of which initially k techniques are available and zero problems are solved, the learner tries to solve as many problems as possible by randomly picking problems that are not solved yet and trying to apply available techniques to them. This is done in discrete steps. At each step, one problem is selected, and if the solution is contained within the set of available applicable techniques, then the problem is considered solved, and those techniques that constitute the solution become mastered. Simultaneously, states of all techniques are updated based on the above stated dynamic rules: this may result in the emergence of new available techniques. The process ends after a fixed number of steps N_{max} . The progress made in

learning is measured by the final numbers of solved problems, available and mastered techniques.

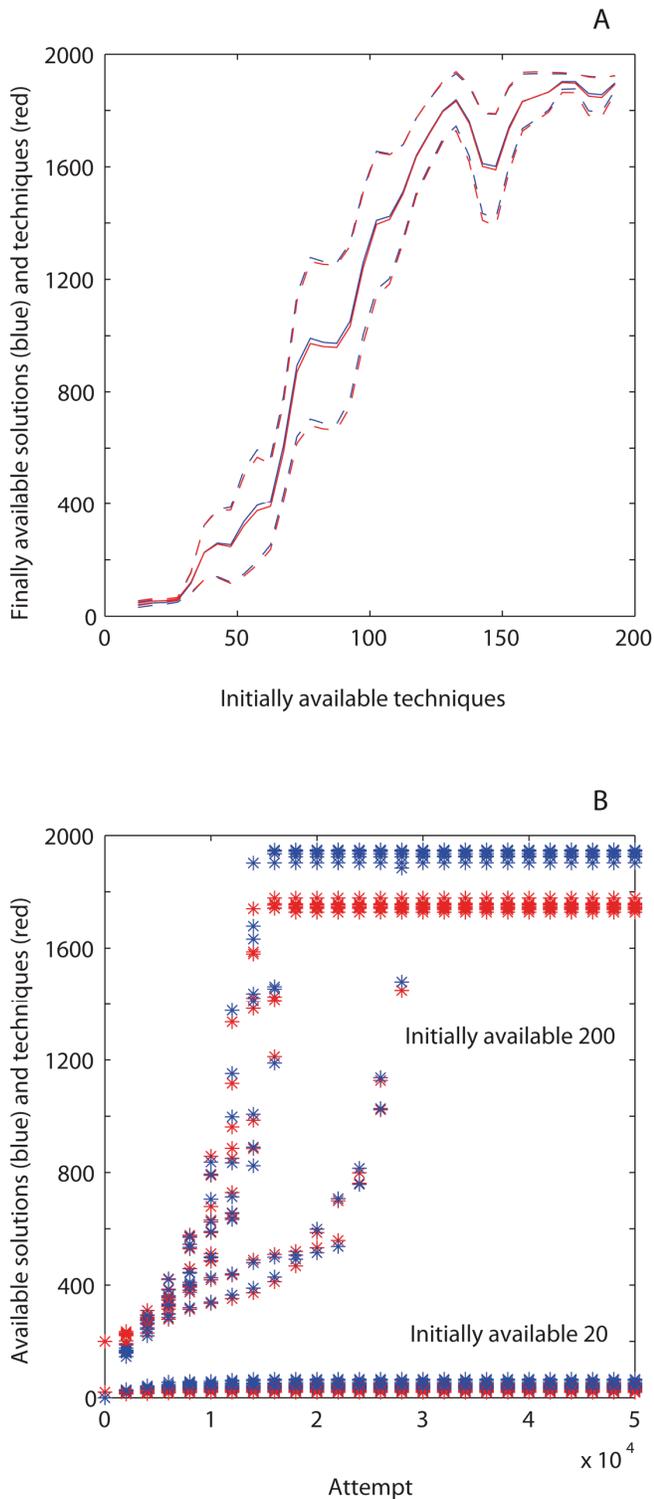


Figure 3: Simulation results. A: Results of learning as a function of initially available techniques. The dotted lines indicate the standard error. B: Learning curves for different numbers of initially available techniques.

Simulation Results and Analysis

The model described above was simulated on a computer with the following parameters. The number of techniques and problems was $n=2,000$, the maximal number of dependencies for techniques $m=3$, the maximal length of a solution = 10, the sparsity of the applicability matrix = 0.05, the number of steps $N_{max} = 50,000$, and the number of initially available techniques was $k=200$ and $k=20$ in two sets of trials. The results were averaged over 10+10 trials. Results of simulations are summarized in Figure 3.

Figure 3A shows the dependence of the number of finally available solutions (blue) and techniques (red) as functions of the number k of initially available techniques that was varied gradually from 20 to 200. Figure 3B shows multiple learning trajectories for two different values of k : 20 and 200. In this case, the numbers of available solutions (blue) and techniques (red) are plotted as functions of the number of learning attempts.

Results indicate two distinct regimes: “limited learning” ($k < 70$) and “global chain reaction” ($k > 100$). As Figure 3A shows, limited learning is characterized by the number of finally available solutions and techniques that is commensurate with the number of initially available techniques. By contrast, the chain reaction regime is characterized by the number of finally available solutions and techniques that is close to the maximal given number of solutions and techniques n . Figure 3B demonstrates clear clustering of the learning trajectories corresponding to the two regimes.

The qualitative observation of the two regimes is robust with respect to variation of parameters of the model. The transition is clearly visible in Figure 3 and shows a tendency to become sharper as the number of learning steps and the number of problems and techniques n are increased (not shown in Figure 3). The null hypothesis, that dynamics of learning produces results linearly increasing as a function of the amount of initial intelligence, can be ruled out based on the sigmoid appearance of the curve in Figure 3A: residuals of the linear fit exhibit the standard error several times along a substantial fraction of the curve (not shown in Figure 3A). A more rigorous validation of the result will be presented elsewhere.

Speaking generally, the observed chain reaction behavior resembles the phenomenon of percolation, which is characterized by threshold dynamics (a phase transition: see Ziman, 1979). The present limited study, however, does not allow for a detailed investigation of the phase transition characteristics.

Discussion

The presented study and its results are limited in many aspects. For example, from the cognitive psychological perspective, this approach may seem to be fundamentally lacking in an appreciation for the difficulty in understanding human cognition and learning and how they vary as a function of many variables (experience, context, personality differences, etc.). It is nevertheless always reasonable to

start with a simple general model, and then correct the findings by including missing details. This was the motivation behind the choice of the presented model and its simulation. In the present version, the model and its simulation results do not tell us precise details about how humans learn throughout their lifetimes, and this was not the intent. On the other hand, the present work opens a new topic in cross-disciplinary discussions: only through meaningful interactions between hardcore computer scientists and mathematicians and psychologists and cognitive neuroscientists we will be able to achieve the overarching goals described in the Introduction. Certainly, more formal analysis informed by all related disciplines will benefit artificial intelligence, psychology and neuroscience, as well as other disciplines.

The study and its analysis presented here constitute a first step of its kind, paving the way to finding general scalability criteria for intelligent learning systems intended to achieve the human level of performance. In this respect, it would be very interesting to compare results of this study with available data from educational studies and from machine learning: this will be done elsewhere. The questions to be addressed in future studies include: Do we see the same kinds of limited learning and global learning chain reaction regimes in human children? How this model might be made less abstract and more related to existing specific models of learning? How to include cross-discipline learning into the model? How to specifically describe the role of metacognition within the abstract formalism? And so on.

Returning to the topic of the Introduction, the present study outlined a new kind of scalability criteria that will be useful guiding the design of human-level learners. The knowledge that learning dynamics have a threshold nature allows in principle to identify the threshold (the “critical mass”) for a given learning system based on its abstract modeling and then to set the achievement of this “critical mass” as the goal of development.

Conclusions

Designing an agent that can master one specific cognitive skill in specific settings may be feasible today based on traditional approaches in artificial intelligence, regardless of the level of the selected cognitive skill. At the same time, designing an agent that can grow cognitively from a child to an adult human level of general intelligence is challenging. To solve the challenge, it is important to understand the different nature of the two tasks in terms of mathematical characteristics of the expected learning process. The present work addressed this goal with a simple abstract model of a long-term learning process. Results indicate that this process of learning is characterized by two distinct regimes: (1) limited learning and (2) a learning chain reaction that extends through the entire learning material.

The transition between the two regimes is determined by the ‘mass’ of initially available learning skills and techniques. Therefore, the notion of a ‘critical mass’ for a human-level learner makes sense and can be determined

experimentally. Therefore, this criterion can be used to guide research in human-level teachable systems.

Stated simply, while an intelligent learning agent may be successful in learning starting from any amount of initial knowledge, it needs to begin with a “critical mass” of knowledge and skills in order to successfully self-teach to learn much more than was conceived during its design – up to the human level of general knowledge.

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