ARTIFICIAL INTELLIGENCE VERSUS HUMAN TALENTS IN LEARNING PROCESS

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Abstract

To highlight the differences between conventional educational systems and CBLS - computer based learning systems. It is useful to consider CBLS, as the class of a system most closely related to artificial intelligence - AI. In such a system, the ultimate goal is to create a virtual duplicate of reality for learning, analysis, training, experimentation, or other purposes. Simulating reality is an approach that may or may not be useful at creating experience. This distinction yield several consequences. In CBLS, behaviour should be as realistic as possible, the representation of environment tends to be uniform and consistent and allowing users to act freely within that environment.
To teach users through realistic experience CBLS design techniques can make the experience much more memorable. In such an environment the context and control afforded by design techniques allow the integration of technologies and evaluation of the overall experience. Perhaps it is time to take lessons of CBLS and AI in a learning design and teaching tools seriously.
At the beginning we will point out one simple question: could the ideas, methodology and techniques of AI also be applied to a development of relatively serious mind applications and can they substitute human teachers? And the answer will be continued in our paper.
Keywords: *education, intelligent tutors, artificial intelligence, CBLS, brain based learning.*

Introduction

A wave of innovation is being stimulated by the Information Technology (IT) and AI revolution that promises to revitalise our schools (Aberšek, 2005, Aberšek, Kordigel Aberšek, 2010). Outcome-based teaching methods, a problem and experience based learning, a brain base learning and a collaborative group work are becoming popular phrases in the today's progressive educational milieu. Moreover, new discoveries in the field of developmental AI and cognitive neuroscience hold a great promise for improving current teaching methods despite a significant gap between the scientific discoveries that could improve our education system and the application of this knowledge.

These changes are proving so effective that they signal the need for a major reconceptualization of the learning and teaching process. The goal of a school system must focus on instilling that vital desire of “learning to learn” into today's students. To accomplish this, teachers must involve the student as an active, self-directed learner. Powerful new forms of a knowledge distribution create an information-rich and effective learning environment in which students and teachers can explore and get experience and not merely learn or teach. More than thirty studies have shown that this new approach improves learning over 50 percent compared to the traditional approach. The use of an intelligent computer tutoring system, as our research shows, improves learning and provides better knowledge (with our students, approx. from 20% to 40%, depending on a type and generation of a tutoring system) (Aberšek, Kordigel Aberšek 2010).

How to solve the educational problem of young generations of students, i.e. how to

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IN THE 21st CENTURY
Volume 37, 2011

motivate them to explore and experience? In this paper it will be hand out the concrete activities that will indicate answers to this question. It is important to use methods which enable students to actively participate in an educational process through which they acquire skills necessary to function in the tomorrow's world, especially, in the technological society of tomorrow. As it is mentioned previously we would restrict our attention in this paper only on two of four pillars (Aberšek, Ploj Virtič, 2009) of an educational system: the learning/teaching process and the educational environment.

New Paradigm of Education

Learning denotes changes in the system that is adaptive in the sense that they enable the system to do the same task or tasks drawn from the same population more efficiently and more effectively the next time.

*Herbert A. Simon (*Simon, 1976)

Humans learn throughout their whole life, practically every day, which means that our knowledge is changing, broadening and improving all the time. Beside humans animals learn also. The ability to learn depends on the evaluative stage of species. Investigating and interpreting the natural learning is the domain of *psychology of learning* and *educational psychology*. The former investigates and analyses principles and abilities of learning whereas the latter investigates methods of human learning and education and aims to improve the results of the educational process. Educational psychology considers attention, tiredness and motivation to be of a crucial importance for a successful educational process and takes carefully into the account the relation between a teacher and students suggesting thereby various motivation and rewarding strategies (Anderson, 2007; Aberšek, Ploj Virtič, 2009).

For many years now, neuroscience has held a distance with reference to education (Morris, 2003). Many authors have discussed them with the excitement albeit direct neuroscience-education links have not been an issue (Anderson, 2007, Bear, 2006, Schwartz, 1990). However, perhaps now cognitive neuroscience and cognitive science of education have progressed enough that such links are possible. At the University of Maribor we examine closely new methods of conducting training interventions that are directly informed by cognitive neuroscience of learning as well as training methods that use real-time neuroscience data to guide the instruction.

New discoveries in the field of developmental cognitive neuroscience hold a great promise for improving current teaching methods. Yet there remains a significant gap between the scientific discoveries that could improve our education system and the application of this knowledge (Anderson, 2007).

Educational Neuroscience

The world has learned more about the human brain in the past 10 to 15 years than in the rest of the recorded history. And that information is leading to revolutionary changes in how each of us uses his own "individual brain-based computer" to learn much better, faster and easier. Educational neuroscience (also called Mind Brain and Education - MBE) is an emerging scientific field that brings together researchers in cognitive neuroscience, developmental cognitive neuroscience, educational psychology, educational technology, education theory and other related disciplines to explore the interactions between biological processes and education (Ansari, Coch, 2006; Ansari, Coch, 2008; Goswami, 2006). Researchers in educational neuroscience investigate the neural mechanisms of reading (Goswami, 2006), numerical cognition (Ansari, 2008), attention etc. as they relate to education. Researchers in this area may link basic findings in cognitive neuroscience with educational technology to help at the curriculum implementation in mathematics, science, technology and reading education. The aim of educational neuroscience is to generate the basic and applied research that will provide a new transdisciplinary account of learning and teaching, which is capable of informing education. A major goal of educational neuroscience is to bridge the gap between the two fields through a direct dialogue between researchers and educators, avoiding the "middlemen of the brain-based learning industry". These middlemen have a vested commercial interest in the selling of "neuromyths" and their supposed remedies (Goswami, 2006).

The potential of educational neuroscience has received varying degrees of support from both cognitive neuroscientists and educators. Pettito and Dunbar (Petitto, Dunbar, 2004) point out that educational neuroscience provides the most relevant level of analysis for resolving today's core problems in education. Howard-Jones and Pickering (Howard-Jones, Pickering, 2007) surveyed opinions of teachers and educators on the topic and found out that they were generally enthusiastic about the use of neuroscientific findings in the field of education and that they thought these findings to influence their teaching methodology more than the curriculum content. Some other researchers take an intermediate view and say that the direct link from neuroscience to education is a "bridge too far" but that a bridging discipline, such as cognitive psychology or educational psychology, can provide the neuroscientific basis for the educational practice (Morris, 2003; Mason, 2009). The prevailing opinion, however, appears to be that the link between education and neuroscience is at best in its infancy, and whether through a third research discipline or through the development of new neuroscience research paradigms and projects, much work is required in order to apply neuroscientific research findings to education in a practically meaningful way (Ansari, Coch, 2006; Goswami, 2006, Meltzoff et al, 2009).

Brain Based Learning Strategy

Education and educators are in the spotlight as never before. Parents, politicians, business, and the media are calling for better "results". And yet almost no attention is being publicly paid to how people learn naturally, and what sort of teaching best addresses the natural learning (Caine, Caine, 1991; Dryden, Voss, 1999; Meltzoff et al, 2009)

In the early 1990s the brain based learning has been introduced in the educational milieu. The brain based learning theory is routed in the structure and function of the brain. As long as the brain is not prohibited from fulfilling its normal processes learning will occur. Since the introduction of the brain based learning (Caine, Caine, 1991) the science has been following it with a great attention. Although the Principles have been modified a little they have stood the test of time very well. They provide, more than ever, an understanding of what actually happens when people learn and a foundation for a great teaching (Morris, 2003).

Foundations: Learning as Integrated Process

The research is calling into question the fundamental belief that has survived for four hundred years. Since the writings of Descartes in the 17th century it has been somewhat assumed that body and mind are separate. This approach is now being challenged in a new way.[1] Neuroscientists, such as Antonio Damasio, linguists, such as George Lakoff and cognitive scientists, such as Mark Johnson, are showing that body, brain and mind are deeply interconnected. Even though a specific function (such as hearing sounds or seeing faces) may be separate in some respects the bottom line is that each person is an undissociated whole that interacts with the world as a complete system (Morris, 2003).

1 It has been questioned previously also but merely on theoretical/philosophical grounds (e.g. Gassendi, 1985; Kim, 1996).

ISSN 1822-7864

Brain/Mind Learning Principles – Systems Principles of Natural Learning

If body, brain and mind are conceived as a dynamic unit then it becomes possible to identify core general principles of a learning system.
For the purpose of improving education a principle has to meet the following four criteria:

1. The phenomena described by a principle should be universal and applicable to all human beings;
2. The principle should emerge out of research from several different disciplines;
3. The principle should anticipate the future research;
4. The principle should have implications for educational practice.

They need to be read as gateways to a vast body of the research and as working at several different levels simultaneously. In essence, they show how the many aspects of a human being are engaged in the overall learning process in any field, subject or domain. The Principles are as follows (Caine, Caine, 1991):

1. Learning is physiological;
2. The brain/mind is social;
3. The search for the meaning is innate;
4. The search for the meaning occurs through patterning;
5. Patterning involves emotions;
6. The brain/mind works with parts and wholes simultaneously;
7. Learning involves both, a focused attention and peripheral perception;
8. Learning is both, conscious and unconscious;
9. There are at least two approaches to memory: archiving isolated facts and skills and making sense of experience;
10. Learning is developmental;
11. Learning is inhibited by threat associated with helplessness and/or fatigue;
12. Each brain is uniquely organized.

There sequence of principles is not necessary; it is rather that each supports and connects with all the others. Accordingly, often it is shown in a circle (Caine, Caine, 1991).

From Understanding Natural Learning to Understanding Great Teaching

It is good to have a solid theoretical foundation of how people learn. However, the question is how to make it practical? An introductory answer is that each principle has some practical implications. For instance, if learning is psychological then learning is enhanced when students use their senses and take actions. That is just one reason why brain based teaching is so powerful.

Computational Neuroscience

Computational neuroscience is the study of brain function in terms of the information processing properties of the structures that make up the nervous system (Schwartz, 1990). It is an interdisciplinary science that links the diverse fields of neuroscience, cognitive science and psychology with engineering, computer science, mathematics and physics.

Computational neuroscience is somewhat distinct from psychological connectionism and theories of learning, such as machine learning, neural network and computational learning theory, in that it emphasizes descriptions of functional and biologically realistic neurons (and neural systems) and their physiology and dynamics. These models capture the essential features of the biological system at multiple spatial-temporal scales, from membrane currents, protein and chemical coupling to network oscillations, columnar and topographic architecture and learning and memory. These computational models are used to frame hypotheses that can be directly tested by current or future biological and/or psychological experiments (Chklovskii, 2004).

Educational Environment – Tutoring Educational Systems

From Smart to Intelligent Self- Learning Tutoring System – Hasty Glance into Future

Nowadays, most of the researchers agree that there is no intelligence without learning. Learning by a living system is called *natural learning*; if, however, the learner is a machine – a computer, learning is called *machine learning*. The purpose of developing machine learning methods is, beside a better understanding of natural learning and intelligence, to enable the algorithmic problem solving that requires specific knowledge. In order to solve problems we obviously need knowledge and the ability to use it. Often such knowledge is unknown or is used by a limited number of human experts. Under certain preconditions, i.e. by using machine learning algorithms, we can efficiently generate such knowledge which can be used to solve new problems.

Even the whole natural evolution can be regarded as learning: with a genetic crossover, mutation and natural selection it creates better and better systems, capable to adapt to different environments. The principle of evolution can also be used in machine learning to guide the search in the hypothesis space through the so called *genetic algorithms* (Aberšek, Popov, 2004).

Artificial Intelligence

A long term goal of machine learning research, which currently seems unreachable, is to create an artificial system that could through learning achieve or even surpass the human intelligence. A wider research area with the same ultimate goal is called *artificial intelligence*. Artificial intelligence (AI) research deals with the development of systems that act more or less intelligently and are able to solve relatively hard problems.[2] Its methods are often based on the imitation of the human problem solving. AI areas, beside machine learning, are knowledge representation, natural language understanding, automatic reasoning and theorem proving, logic programming, qualitative modelling, expert systems, game playing, heuristic problem solving, artificial senses, robotics and cognitive modelling (Copeland, 1993, Peroš, 2000).

Neural Networks and Neuroscience

Theoretical and computational neuroscience is the field concerned with the theoretical analysis and computational modeling of biological neural systems. Since neural systems are intimately related to cognitive processes and behavior the field is closely related to the cognitive and behavioral modeling.

The aim of the field is to create models of biological neural systems in order to understand how biological systems work. To gain this understanding, neuroscientists strive to make a link between observed biological processes (data), biologically plausible mechanisms for the neural

2 "Artificial intelligence is the science of making machines do things that would require intelligence if done by men" (Copeland, 1993:1).

processing and learning (biological neural network models) and the theory (the statistical learning theory and information theory).

Future of Inteligent Tutoring System – Neural Network?

The original inspiration for the term *Artificial Neural Network* comes from the examination of central nervous systems and their neurons, axons, dendrites and synapses, which constitute the processing elements of biological neural networks investigated by neuroscience. In an artificial neural network simple artificial nodes, variously called "neurons", "neurodes", "processing elements" (PEs) or "units", are connected together to form a network of nodes mimicking the biological neural networks — hence the term "artificial neural network".

Because neuroscience is still full of unanswered questions and since there are many levels of abstraction and therefore many ways how to be inspired by the brain there is no single formal definition of what an artificial neural network is. Generally, it involves a network of simple processing elements that exhibit a complex global behavior determined by connections between processing elements and element parameters. While an artificial neural network does not have to be adaptive per se, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

These networks are also similar to the biological neural networks in the sense that functions are performed collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned.[3] Currently, the term Artificial Neural Network (ANN) tends to refer mostly to the neural network models employed in statistics, cognitive psychology and artificial intelligence. Neural network models designed with emulation of the central nervous system (CNS) in mind are a subject of theoretical neuroscience and computational neuroscience.

In modern software implementations of artificial neural networks the approach inspired by biology has been largely abandoned for a more practical approach based on statistics and signal processing. In some of these systems neural networks or parts of neural networks (such as artificial neurons) are used as components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such adaptive systems is more suitable for the real-world problem solving it has far less to do with the traditional artificial intelligence connectionist models. What they do have in common, however, is the principle of non-linear, distributed, parallel and local processing and adaptation (Peroš, 2000).

Models

Neural network models in artificial intelligence are usually referred to as artificial neural networks (ANNs); these are essentially simple mathematical models defining a function $f: X \rightarrow Y$ or a distribution over X or both X and Y, but sometimes models are also intimately associated with a particular learning algorithm or learning rule. A common use of the phrase ANN model really means the definition of a *class* of such functions (where members of the class are obtained by varying parameters, connection weights or specifics of the architecture, such as the number of neurons or their connectivity) (Peroš, 2000).

The word 'network' in the term 'artificial neural network' refers to the inter-connections between the neurons in the different layers of each system. A paradigmatic system has three layers. The first layer consists in input neurons which send data via synapses to the second layer of neurons and then via more synapses to the third layer of output neurons. The more complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The synapses store parameters called "weights" that manipulate the data in the calculations.

3 See also connectionism, e.g. Bechtel, Abrahamsen (2002).

The ANN is typically defined by three types of parameters:

1. The interconnection pattern between different layers of neurons;
2. The learning process for updating the weights of the interconnections;
3. The activation function that converts a neuron's weighted input to its output activation.

Mathematically, the neuron's network function $f(x)$ is defined as a composition of other functions $g_i(x)$, which can further be defined as a composition of other functions. This can be conveniently represented as a network structure, with arrows depicting the dependencies between variables. A widely used type of composition is the *nonlinear weighted sum*

$$f(x) = K\left(\sum_i w_i g_i(x)\right)$$

where K (commonly referred to as the activation function) is some predefined function, such as the hyperbolic tangent. It will be convenient for the following to refer to a collection of functions $g_i(x)$ simply as a vector $g_i = (g_1, g_2, g_3, \ldots g_n)$.

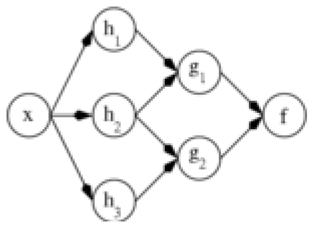

Figure 1: ANN dependency graph.

Figure 1 depicts such a decomposition of f with dependencies between variables indicated by arrows. This can be interpreted/viewed in two ways:

(i) The first view is *the functional view*: the input x is transformed into a 3-dimensional vector h, which is then transformed into a 2-dimensional vector g, which is finally transformed into f. This view is most commonly encountered in the context of optimization.

(ii) The second view is *the probabilistic view*: the random variable $F=f(G)$ depends upon the random variable $G = g(H)$, which depends upon $H = h(X)$, which depends upon the random variable X. This view is most commonly encountered in the context of graphical models.

The two views are largely equivalent. In either case, for this particular network architecture the components of individual layers are independent of each other (e.g., the components of g are independent of each other given their input h). This naturally enables a degree of parallelism in the implementation (Peroš, 2000).

Learning

What has attracted the most interest in neural networks is the possibility of *learning*. Given a specific *task* to solve, and a *class* of functions F learning means using a set of *observations* to find $f^* \in F$, which solves the task in some *optimal* sense.

This entails defining a cost function $C : F \rightarrow \mathbf{R}$ as such that for the optimal solution f^* $C(f) \leq C(f) \vee f \in F$ (i.e., no solution has a cost less than the cost of the optimal solution).

The cost function C is an important concept in learning, as it is a measure of how far away a particular solution is from an optimal solution to the problem to be solved. Learning algorithms search through the solution space to find a function that has the smallest possible cost.

For applications where the solution is dependent on some data the cost must necessarily be a *function of the observations*; otherwise we would not be modeling anything related to the data. It is frequently defined as a statistic to which only approximations can be made. As a simple example, consider the problem of finding the model f, which minimizes

$$C = E\,[(f(x) - y)]^2$$

for data pairs (x, y) drawn from some distribution D. In practical situations we would only have N samples from D and thus, for the above example, we would only minimize

$$\widehat{C} = \frac{1}{N}\sum_{i=1}^{N}(f(x_i) - y_i)^2$$

Thus, the cost is minimized over a sample of the data rather than the entire data set. When $N \to \infty$ some form of online machine learning must be used, where the cost is partially minimized as each new example is seen.

So, when the neural network methods are used, some form of online machine learning is frequently used for finite datasets.

Applications

The advantage of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particularly useful in applications where the complexity of the data or tasks makes the design of such a function by hand impractical.

Application areas include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess), pattern recognition (radar systems, face identification, object recognition and more), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications (automated trading systems), data mining (or knowledge discovery in databases, "KDD"), visualization and in educational purposes as decision making, sequence recognition and data mining (Aberšek, Popov, 2004; Aberšek, 2005; Aberšek, Kordigel Aberšek, 2010).

Conclusion

The information technology play and will play through networking, knowledge-based systems, artificial intelligence etc. an increasingly important role in the way that education is taught and delivered to the student.

For this reason in this paper is presented some ideas of such learning-training environment for education. Like the researchers in other countries we tend to develop a user-friendly general system made particularly for solving problems based on experience-based tutoring systems, primary for executing better lessons and for students self-learning.

There is no doubt that intelligent computer based tutors will very likely substitute teachers in some respects, for example as transmitters of new knowledge. But it is still an open question to what extent technologies can overtake the teacher's roles of being a mediator and a human being; and this is indispensable since such a mediation generates students' cognitive and social processes and is a highly important factor for the whole learning process. We cannot be sure what the future will bring but we can be sure that if somebody wishes to substitute a human teacher for a "computer" he must do it carefully. Like all powerful tools also this one could be very useful but it could also be very dangerous. Without a carefully designed experience and extensive testing these systems could easily result in unwanted outcomes (such as a negative training or increased phobia anxiety). Despite the promise of the early efforts the best approaches to design an artificial tutor are still a subject of the research and debate.

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Received: *September 18, 2011* Accepted: *October 24, 2011*

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