Using the Computational Model of the Mind to Design Educational Methodologies: Solving Problems More Efficiently in the Classroom

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***Abstract*—The developed countries of the world have a unified curriculum for primary and secondary schools. The performance of the educational systems of these countries is evaluated every three years with the global Pisa Test. This Test is of great research value. It allows to draw two fundamental conclusions: the curriculum is obsolete, and the performance of the students around the world is extremely poor. Recent developments in cognitive sciences provide resources that can ameliorate these two deficiencies. A computational model of the mind provides the framework for the development of a new school curriculum and a new set of educational methodologies. This paper presents the fundamental ideas of a computational model of the mind and its implications in the development of new school content and school teaching and learning methods. We use a set of examples to illustrate the new framework and its effects in a more effective classroom.**

***Index Terms*—computational theory of the mind, blank slate, education, new approaches to problem solving**

I. Introduction

For the last two decades, the curriculum of the developed countries of the world, in primary and secondary education, has been unified by virtue of having a common test that is used to evaluate the performance of the individual countries [1]-[3]. These periodic tests are used to rank the world standings of national educational systems and national student constituencies. They also allow each country the evaluation of the progress of their educational system over time by analyzing their position in the world ranking, monitoring their relative position with respect to other countries.

These PISA tests, at the same time, offer a rich set of research data that allows the formal description of the content of the tests, and by implication, the content matter studied in the classrooms of the world.

An analysis of this content, in turn, allows the study of two research questions: 1) is the content of education relevant for the needs of modern society? And 2) is the content of education appropriate for the mind of the student?

The PISA tests, with 540,000 participating students in 72 countries in 2015, also offer an extremely valuable research tool to study the cognitive performance of students around the world. These data allow the study of two additional research questions: 3) is there a cognitive limit to the minds of these students that justifies the poor results of these PISA tests? And 4) if the answer to question 3 is no, what are the causes that produce the poor cognitive performance identified by these tests?

This paper studies these four research questions, and proposes a framework, the computational model of the mind [4], [5], as the best platform to address them.

In addition, it introduces some fundamental cognitive concepts that will illuminate these studies in three areas of interest.

In the area of education content, this paper introduces the concept of cognitive complexity: how to define a measure for the level of difficulty of a problem (is a problem easy or difficult.) This concept of cognitive complexity is intended to substitute the current measurement: the probability that a student fails to solve the problem (regardless of the cognitive reasons that caused the error.)

In the area of human cognitive capabilities, this paper introduces the concept of cognitive primitives and a layered model of cognition. This concept of cognitive primitives is intended to substitute the current model of the Blank Slate: students are characterized by an intrinsic general ability (g) [6] to solve general problems, as measured by IQ. (IQ, like PISA, is also a statistical measure of probability of incorrect answers [7], [8].)

In the area of educational methodology, this paper introduces the concept of cognitive virtual machines. This concept of cognitive virtual machines is intended to substitute the current educational methodologies (resolution of Type-A problems, intensive use of System-2, lack of formal cognitive model.) An educational system will have to address Type-A problems, but more substantially, it will have to address the more relevant and cognitively more complex Type-B problems [9]. It

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will make substantial use of System-1. It will also make substantial use of fast, automatic and reliable retrieval of immediate-access permanent-memory.

Finally, an educational system must include a formal and detailed computational model of the content and process of learning.

II. Computational Model of the Mind and Related Cognitive traps

This paper presents alternative views on cognitive topics. Our view is that many of the ailments of the current educational systems find their genesis in incorrect design decisions caused by the inability to think clearly.

This section introduces some reflections on how the mind assesses alternatives and arrives to decisions. Some of these reflections are drawn from the work of Kahneman and others [10] which constitute one of the most significant advances in cognitive science of the last decades. The work of Kahneman and others was recognized with the Nobel Prize in Economics in 2002 [11]. This work has implications not only in economics but also in areas where decisions need to be made.

A reader may benefit from a summary of Kahneman's findings as we proceed in this paper with the rationalization of cognitive concepts and the proposition of alternative models.

We will use the metaphor of mathematical theorems to encapsulate the main concepts introduced in this section, and we will number them for better identification.

A. Kahneman and the Principle of the Hidden Decision Process

The work that won Kahneman the prestigious Nobel Price could be summarized in his own words with a very simple sentence:

- Often, when we make decisions, (Proposition-1, P1) we think that we reason, (P2) but in fact we don't. (P3) Instead, we use simple heuristics.
- (P4) These heuristics are often biased, and (P5) this lead us to error.

B. The Superior Model of Our Perceptions (P1, P2)

According to propositions P1 and P2, many of our decisions are implemented with simple "if then" heuristics, but we have the strong believe that we arrived to them through an exhaustive reasoning process.

In the economic world where Kahneman implemented his research, large companies make financial, economic, investing, marketing decisions based on simple heuristics. However, they believe that they arrived to them through their detailed plans, long board discussions, market analysis, etc.

The world of academic administrators and policy makers is not immune to the same illusion. The theorem (T1) of *"The Superior Model of Our Decisions"* encapsulates the gap between our believes and the reality underlying many of our decisions.

The pervasive presence of this gap should guide the study of alternative models in education.

A second piece of knowledge intrinsic from propositions (P1) and (P2) is our lack of knowledge about how our mind really works. This could be called (T2), the theorem of *"Dear Mind: I think I know you, but I don't know you at all."*

An economist may know well the markets, but fails to know his own mind. However, in the area of teaching and learning, the mind is a fundamental component of the system, and not knowing how the mind works is a fundamental failure.

C. The Simple Model of Our Decisions (P3)

The fact that our mind makes decisions based on simple heuristics is a consequence of our evolutionary past. Thinking needs to be fast, economical, and automatic. It does not need to be accurate; rather, it needs to provide advice that protects our welfare.

In order to apply the architecture of our evolutionary brain to solve novel problems, we need to create heuristics that process information accurately. It is possible to use our evolutionary mind to solve problems fast, economically, and automatically and at the same time accurately. This requires massive experience, through repetition and immediate and correct feedback. We will search for process that value precision over safety.

These two fundamental ideas can be summarized in these two theorems:

(T3) Theorem of the *"Fast and safe, but not necessarily accurate evolutionary mind",*

and,

(T4) theorem of the *"Fast and accurate mind through massive training with immediate and accurate feedback."*

A third theorem highlights the paradox of our own perceptions: we have profound intuitions that our decisions have been designed through careful considerations of goals and available information, while the reality is that a simple heuristic was used.

(T5) Theorem of *"The perceived complexity of our mind hides the simplicity of our computational behavior."*

D. The Heuristics Are Often Biased (P4)?

As we have already introduced, there are fundamental evolutionary forces in the creation of simple and fast heuristics to make decisions. The sources of bias have also evolutionary origins: safety.

In an environment with low probability but high-risk events, conservative heuristics, even with many false positives, are preferred over those that may miss the low probability event. This bias values safety over accuracy and its architecture extends to modern life cognitive heuristics.

E. This Leads Us to Error (P5)

Even when we learn how unreliable the insight on our mental processes is, we largely fail to benefit from this knowledge. It is a cognitive trap that also has evolutionary foundations. This cognitive trap is described in the book "Why everyone else is a hypocrite" [12], and it can be summarized in:

(T6) The theorem of *"Others may be in error, but not me."*

The essence of this evolutionary cognitive trap is called Strategic Error (the strong feeling that we are correct when in fact we are wrong) and it provides great advantages when negotiating with others.

We highlight this theorem (T6) because when discussing alternatives to new concepts, ideas and mythologies, it is important to identify the cognitive trap if we want to make progress in a rational deliberation.

F. A Brief Model of the Cognitive Theory of the Mind

The concepts introduced in this section provide an introductory path to the Cognitive Theory of the Mind, the philosophical ideas that underlie it, and some of the cognitive traps that have impeded progress in the past and in some areas progress in the present time.

The Body-Mind problem [13] and related philosophical enterprises were met in their time with obstacles of perception and poor understanding of computation. Turing [14], Shannon, and many others have downgraded the mind-body mysteries to computational problems [15].

III. Education Content and Cognitive Complexity

Many great advances in communications during the last decades find their roots in the Theory of Information [16]. The idea that all kinds of signals, music, voice, films, video, books, paintings, photographs, could be formally described by a common reference that measured the amount of information they conveyed, and the application of the same idea to the systems that stored or transmitted those signals, are at the center of today's revolution in multimedia communications.

Thinking is a process of manipulating symbols in our mind in order to produce other symbols [4], [5]. Therefore, there must be a way to describe both the amount of information in the symbols manipulated when we think, and the amount of information in the mental processes that manipulate existing symbols into new ones.

This proposal is fundamental, and at the same time addresses a vast set of signals, symbols and processes. Therefore, it will require a great deal of research and effort. Here we propose a few guidelines that can lead to incremental progress.

A. System1 vs System2

The amount of information that can reliably be stored in System2 is very small [17]. System 2 is also limited to implementing one algorithm at a time because the performed algorithm interferes with any other potential task [10]. These two fundamental cognitive limitations of System2 indicate that when we model the cognitive complexity of a problem we will focus on Type-B problems implemented in System1. These problems are complex in nature and include multiple objects and multiple processes.

B. Number of Objects

The more objects one problem has, all things being equal, the more complex a problem is. In a problem with an object in motion, we can calculate its velocity, trajectory, etc. In a problem with two objects in motion, to find the moment in which their trajectories intersect it is required to know each individual trajectory.

In an environment with one self-driving car, the problems to be addressed will have to deal with the car and the static environment. When we add a second object, a second car, to the environment, the problems of either car now include collision avoidance with each other, racing strategies, competition, etc. The interactions increase exponentially with the number of objects.

C. Number of States of the Objects

The complexity of each object is a function of the number of states in which it can find itself. In a geometry problem, the area of a square is an invariant of the system. The equation of the area does not change with the details of the problem. It has only one state.

However, the object of a self-driving can be in multiple states: driving forward, going uphill, using third gear, stopped in a traffic light, etc. The transitions between states are a subset of all possible transitions. The goals and functionalities of the object car vary according to the state.

The object of a human person can be in multiple emotional states: angry, tired, afraid, bored, motivated, etc. In this example, each state represents a different environment. In addition, the goals and functionalities in each state will differ.

D. Number of Irreducible Procedures of the Objects

In each state, the object will have access to a set of data, goals and functionalities. For example, a simple self-driving car (Fig. 1) is able to detect turns on the road and steer accordingly. It can accelerate when it is allowed and safe, or reduce the speed when approaching a turn.

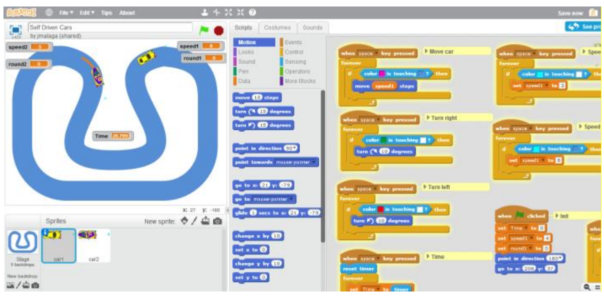

Figure 1. Irreducible procedures of the object self-driving car implemented in the scratch programming environment.

The procedures that implement these functionalities can be described computationally. Multiple procedures may provide a similar set of functionalities. When these procedures are decomposed into set irreducible proto-procedures, we can estimate their cognitive complexity.

E. Number of Links to Other Objects

In most problems of the traditional curriculum, the objects live in isolation. However, in almost all Type-B problems the objects are related to other objects explicit in the problem or to other remote object.

For example: Think of upper case D. Turn it 90 degrees to the left. Put it on top of an upper case J. What kind of weather does it remind you of?

The obvious answer is rain, but the object “umbrella” is not an explicit element in the problem. There is link between the letters J and D and umbrella without which the problem cannot be successfully solved [15.]

The complexity of the problem increases with the number of links to other objects. As the set of links increases its size, so does the entropy of the set, and with it, the complexity of the problem.

In Fig. 2, the object Oedipus is directly or indirectly connected to several objects: Laius, Jocasta, Freud, Lehrer, Sophocles, song, theory, etc. [18]

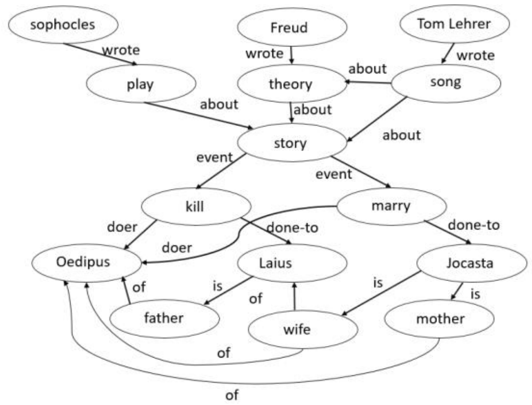

Figure 2. Web diagram of the object oedipus and linked objects

IV. Human Cognitive Capabilities: Cognitive Primitives

The structure of the current human brain, as it is transmitted from generation to generation, has been evolving during many millions of years, even before Homo sapiens became a separate species.

During that time, the brain has developed a vast set of mind modules designed to implement tasks of general purpose or tasks with specific goals. These modules are layered in a hierarchical architecture, allowing new tasks to be supported by modules that perform sub-tasks.

This hierarchical architecture has been replicated in modern computation in order to provide integrated functionalities to a vast number of applications within the same system.

Following this parallelism, we refer to these hierarchical brain modules as cognitive primitives.

A. Cognitive Primitives for the Representation of Data

The mind operates with symbols, which in turn are a representation of the external world and the internal states of the mind.

It is not necessary to know how the brain encodes these symbols, but it is important to know the capabilities and limitations on the mind’s ability to encode data.

For example, a young child has an advanced and complex encoding of the concept of dog in her mind. This is apparent when the child is able to recognize a dog among other animals. In addition, the child is able to retrieve information from this encoding and respond to questions such as: which is larger, a dog or an elephant, even when no dog or elephant are in her presence.

The child is also able to encode the characteristics of a particular dog, for example her dog ‘Ruff’, that she will identify without effort among many other dogs.

The child also encodes more abstract concepts, such as fear or happiness. It encodes properties of these concepts, and has preferences, goals and related feelings about them.

On the other hand, humans have difficulty, for very good evolutionary reasons, to easily and reliably encode other types of data, such as a long set of numbers, or the formula for the number of corners of a prism.

B. Manipulating Data

Other mind modules have evolved to manipulate symbols and produce from them new symbols. For example, in an earlier section the reader manipulated the upper case letters J and D to jump to the concept umbrella and from there to the concept rain.

Most of the fast symbol manipulation of the mind is performed in this form. If we see a snake on the road, we automatically decide to stay away.

Even small children perform basic arithmetic with cognitive primitives. When the experimenter moves one puppet behind a curtain in front of a child, and then moves a second puppet, and finally lifts the curtains to reveal only one puppet (the other was carefully hidden), the child is startled with surprise. When one plus one was expected, and only one appeared, the mind was surprised by the different states of the mind and reality.

Think of this question: The trophy did not fit into the suitcase because it was too small. Which was too small, the trophy or the suitcase?

The problem may seem easy because of the ease with which the mind manipulated these symbols to find the correct answer. However, the problem is far from simple. No computer in existence today can solve this problem and others of this type. These problems, used in the Winograd Schema Challenge [19], highlight the cognitive complexity of some of the mind’s primitives.

C. Space, Motion, Vision and Language

The search and formal description of these cognitive primitives will enhance the ability to design educational methodologies by recruiting their computational capabilities.

Evolutionary biology could help us by suggesting cognitive areas where many and complex primitives could be found.

In particular, the areas of space, motion, vision and language are likely to include many of these cognitive primitives.

The work of Adriaan de Groot [20] in the area of chess, indicates that space primitives are the fundamental tools of chess masters, while amateur players rely mainly on search. This example of chess also reveals the great gap between the perception of intelligence (deep search in a world of many paths) and the reality of chess masters (they recognize the spatial layout of the board, because they have been in that 'city' and that particular 'street' before, and they automatically know what the best way to get Post Office is. In their own words: 'The answer comes to them.')

V. Cognitive Virtual Machines

In computing, a virtual machine is a process designed to perform a task by delegating work to resources available in the system. Imagine a chef that asks one of her assistants to go to the market and buy all the ingredients, another to chop the vegetables, a third one to debone and fillet the fish, and a fourth one to prepare the pan and all the spices. Finally, the chef, in only a few minutes, sautés all the ingredients, and creates a perfect dish.

This example captures one of the concepts of virtual machines: how much time and effort is saved by delegating work to others.

A second fundamental concept of virtual machines is described in one metaphor attributed to Isaac Newton: "If I have seen further it is by standing on the shoulders of Giants." It is the ability of see further, to reach new frontiers that advanc the cognitive capabilities of humans. Virtual machines sit atop giant architectures of computation that allow them to see further.

We define a cognitive virtual machine as the group of objects and related algorithms that delegate tasks to existing human primitives in order to solve efficiently complex problems, or to extend the scope of the complexity of past problems.

A. Layered Systems and Virtual Machines

Virtual machines delegate many of their tasks to existing human primitives. We conceptually represent the data and algorithms of the virtual machine as sitting on top of a layered architecture. The cognitive primitives have been developed by evolution to solve specific problems, but they offer a general structure that we can interface by renaming the interface parameters. The example of the following section illustrates this operation.

We introduce also the concept of isomorphism or isomorphic problems in order to formally represent the operation of a cognitive virtual machine and its operation. Two problems are isomorphic if their formal computational description is identical. In general, we will use an object oriented programming language to describe isomorphic problems.

B. Example of Virtual Machine: Energy Distribution of Photons

We have identified paradigmatic problems from selected scientific literature to create cognitive virtual machines that illustrate this fundamental concept of learning and teaching.

The first example is selected from the publication Science Magazine [21] where students of a college level Physics course were exposed to two different learning methodologies in order to compare their performance. From this study, we selected one of the difficult problems of the test.

The low percentage of students that successfully solved the problem (regardless of the teaching methodology used) indicates that the problem has a high level of difficulty for college engineers. It also indicates that there are Physics problems that are beyond the cognitive levels of many college students.

The problem stated:

The wavelength lambda of a laser is slowly changed from a lower value of 450nm (blue color) to 750 nm (red color). While the wavelength of the laser is changed, the output power is maintained at exactly 1 watt.

What can be said of the amount of photons emitted by the laser every second?

a) *The number of photons emitted by the laser per second decreases when we increase their wavelength;*
b) *The number of photons emitted by the laser per second increases when we increase their wavelength;*
c) *The number of photons emitted by the laser per second remains constant when we increase their wavelength;*
d) *There is not enough information.*

We created a java program that represented the data provided in the problem [9]. The program also includes the equations that relate the power of the laser, the wavelength of the photons and the number of their set.

Using the formal description of the problem in a java program, we developed an isomorphic problem: it had the same number and type of input data, same number and type of output data, and same mathematical equations relating the former with the later.

In addition, we framed the problem in a context (a seal in a zoo, eating fish) that would automatically invoke a set of cognitive virtual machines appropriate for this problem: in particular the relationship between total energy, wavelength and frequency of photons.

The statement of the isomorph problem stated:

The seal in the zoo of our town is the preferred animal of all the children. Each day he eats a bucket full of fish. To optimize his diet, each day of the week he is fed a different variety of fish. On Monday, the bucket is full of large fish. As the week progresses the bucket is filled with fish of smaller and smaller size. On Sunday, the seal eats a bucket full of the smallest fish in the market.

What day of the week does the seal eat a larger number of individual fish:

a) On Monday.

b) On Thursday.

d) On Sunday.

d) There is not enough information.

This experiment provides data in several areas of cognition and traditional educational research.

C. To Know is to Be Able to Describe the Process of Discovery

In the research study published in Science Magazine, where the question of the photons and other similar questions were evaluated under two different teaching systems, the measured variable was the percentage of students that correctly answered the question. This often was less the 50%.

These studies are required to achieve some statistical significance in order to eliminate the effect of unintended variables in the study.

This seems to imply that statistical analysis is the only method to arrive to a valid conclusion. But, in fact, to determine if a student has acquired a particular knowledge, a more robust and simple method needs to be used: ask the student to explain how the problem was solved. By doing so, the student shows that he has direct access to his knowledge, is able to describe it, and is able to use is to solve a problem.

Statistical analysis is necessary when there is no direct access to the behavior of a system, for example how the immune system would respond to a new drug. The reason why we still use this method in educational research is because we lack formal descriptions of the knowledge we teach, and we assume students do not have direct access to it.

Ask a person to explain the rational of how the problem of the seal and the fish was solved and the response will be a description of the internal knowledge used.

One could probe the person further and ask why some parts of the knowledge are correct, for example, why a bucket full of big fish, while having the same weight as the same bucket full with small fish, has fewer fish, and the explanation is a description of why that knowledge is correct.

D. The Paradox of Effort and Knowledge

Even if the two versions of the photons/seal problem are described as isomorph, and reading their java computational description makes it evident that they are computationally the same problem, people have difficulty comprehending they are isomorph, because one seems difficult and the other is in fact very easy.

This cognitive trap is one fundamental reason why traditional and obsolete educational systems last. If a problem is only solved correctly by a small percentage of student, the problem is deemed difficult. In the opposite case, the problem is easy.

One standard notion is that higher-level cognition is abstract cognition, where abstract means devoid of any recognizable pattern.

Einstein, Feynman, Watson, and many others used and continue to use intuitively cognitive virtual machines to access the great computing potential of the mind to advance the sciences of relativity, quantum mechanics, DNA structure, etc.

This paradox will disappear in our educational systems when we formally describe the cognitive complexity of a problem. If photon-problem = java_problem, and seal_problem = java_ problem, then photon_problem= seal_problem.

E. Standing on the shoulders of Giants

Imagine that you have not one but five lasers. Some increase their wavelength while others decrease them. The output powers are different, and we want to analyze the system in order to predict the overall rate of photons.

The virtual machine created previously becomes now part of our set of primitives. For each of the five lasers we fork a new virtual machine. Earlier a single photons/seal virtual machine seemed simple. Now the set of five machines starts to require additional attention. Then the problem is solved and a higher-level virtual machine is created. Next, we have five sets of five lasers, and so on.

A layered architecture allows this process of exponential growth in complexity, and the goals of definitions described earlier for the formal definition of complexity start to become clearer.

Newton's three laws of motion were developed with the collaboration of many people throughout many centuries: from Archimedes and Euclid to Galileo, Copernicus and Kepler. Now those laws are available to all of us. They are virtual machines that allow all of us to build upon them. Unfortunately, our students do not possess those virtual machines, and we do not provide them to them. Galileo and Newton represented these laws in their minds as two boats on a lake. They also had the intuition of using cognitive primitives to access the cognitive potential of their minds. In our classrooms we could do the same.

VI. Conclusions

In this paper we present a novel cognitive platform designed to address four research questions: 1) is the content of education relevant for the needs of modern society? 2) Is the content of education appropriate for the mind of the student? 3) Is there a cognitive limit to the minds of these students that justifies the poor results of these PISA tests? And 4) in the case when the answer to question 3 is not, what are the causes that produce the poor cognitive performance identified by these tests?

The platform introduces a computational theory of the mind: how the mind represents symbols and operates them in order to produce new symbols. The work of Kahneman is highlighted to identify these representations and operations, as well some fundamental cognitive traps that hide them from researchers.

The traditional theory of the mind provides a tool of analysis. Three additional novel components are incorporated to this computational theory in order to provide tools for the design of new teaching methodologies.

These components are design to substitute three obsolete concepts of standard educational systems: the measure of complexity by profanity of student error, the standard Blank Slate model as measured by IQ, and curriculum based on Type-A problems.

These components are replaced by: a formal model of the concept of cognitive complexity, in the area of education content; the concept of cognitive primitives and a layered model of cognition, in the area of human cognitive capabilities, and a paradigm of virtual cognitive machines in the area of educational methodology

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