Discussion Paper

A Framework for Computational Thinking for the Transition to a Super Smart Society

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Questions

Q1: Is Computational Thinking present in the curriculum of your economy?

Q2: In what grade levels?

- Elementary
- Middle
- High school

Q3: Which type of Computational Thinking is present in the curriculum of your economy?

- Programing
- Computational models
- Machine Learning
- Other

Q4: Is Society 5.0 (Super Smart Society) mentioned in the curriculum of your economy?

Q5: What are the curriculum contents of computational thinking in the curriculum of your economy?

Q6: What are the values and attitudes of computational thinking in the curriculum of your economy?

Q7: Name some activities of computational thinking in the curriculum of your economy

Q8: Do you have textbooks of computational thinking adjusted to the curriculum of your economy?

Q9: Write the web pages with the computational thinking curriculum of your economy

Q10: Does your economy have a national standardized test of computational thinking?

Abstract

As never before, technological change is accelerating and it is doing so in areas that will have a strong impact on the nature of work. The central role is brought by the computer, which is increasingly present and ubiquitous at all times, but also *actively taking the initiative* to interact with the citizen and his networks. This technological change has strong social consequences, displacing many workers and leaving them practically irrelevant. But, at the same time, it provides other workers with enormous job opportunities. This means that we urgently need to start designing a curriculum that prepares all of our students for this new super smart ecosystem. We need a framework that teaches them to think like the early adopters: computer scientists and engineers. Students have to learn to use that way of thinking, as a tool to improve their understanding of nature and society, and to design and build solutions. But in addition, we need students to join this new super smart environment as critical citizens, with values and attitudes that allow them to handle the anxieties that come with this huge transition.

Who takes the initiative? You, me, or our computers?

Imagine a super smart ecosystem, where your smartphone not only talks to you and give you instructions to turn next street in order to help you effectively reach in minimum time to the place of your meeting, but it also takes the initiative to suggest you changes in your presentation and strategy given the update of the participants attending the meeting, their recent viewpoints and the news of the day. Why would you follow these suggestions? What happens if a second system also takes the initiative and gives you different suggestions? What happens if the systems take the extra initiative to talk each other and discuss pondering their arguments, but don´t agree on certain key strategies? What would you do if you if ten different systems take the initiative to interact with you and between themselves in order to help you? Welcome to a new fascinating world. The Super Smart Society.

How do we prepare for this world? On the one hand, the natural response is studying more time. Yes, this solution is already happening. For example, in Chile every year all parents of fourth grade students are asked what academic grade their children will achieve. This is a question about their expectations (as opposed to their aspirations). More precisely the question was the following:

What do you think is the highest level of education that your student will achieve in the future?

1. Elementary School (Incomplete)
2. Elementary School (Complete)
3. High School (Incomplete)
4. Vocational High School (Complete)
5. Regular High School (Complete)
6. Technical College (Complete)
7. University Degree
8. Postgraduate Degree

From a total of 2,376,690 parents, 2,158,925 has answered the question. As shown in Figure 1, (Araya et al. 2017), in the last 10 years, parental expectations have grown systematically. They have grown for parents from all socioeconomic (SES) backgrounds, and for all levels of their children's academic performance (measured in the SIMCE national test).

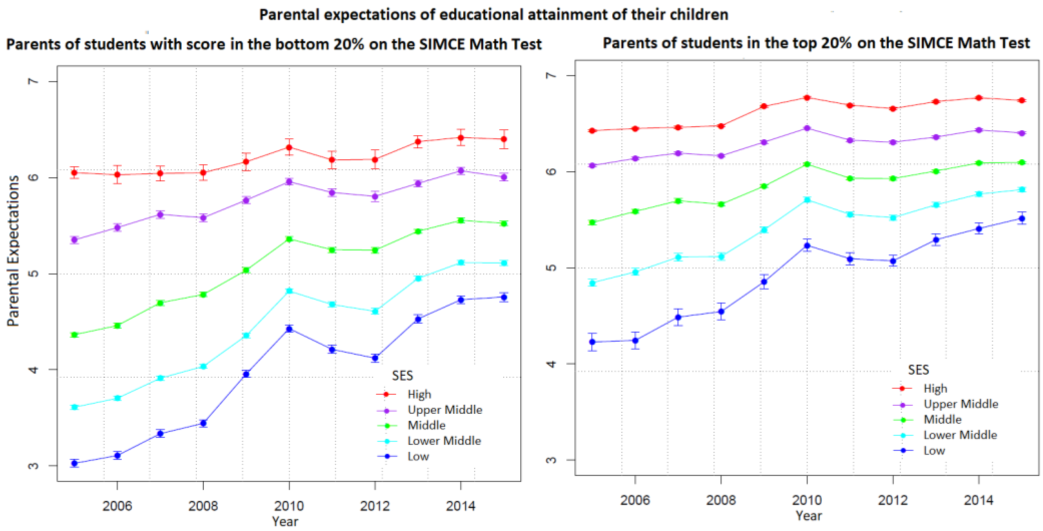

Figure 1. For years 2005 and 2015, average parental expectations for their child's academic future as a function of their score on the SIMCE Math Test, broken down by SES.

Is studying more years enough? More of the same? Or rather, we have to learn other contents and practices? To help answer this question, it helps to review human history and the main transitions in society. We can visualize the evolution of human society in 5 main types of societies, as shown in figure 2.

Figure 2. Five types of societies. Society 1.0 is the hunter-gatherer stage of human development. Society 2.0 is the agrarian society. Society 3.0 is the industrial one. Society 4.0 is the information society we are living on, but we are entering Society 5.0, the Super-Smart Society.

Let's follow the transitions on Figure 2. Imagine that you were living in the transition from the hunter-gatherer to the agricultural society. How would you prepare the youth? How do you design the curriculum for this transition? What contents and skills should this new curriculum have? More studies and practices on how to hunt? Imagine now that you were in the middle of the next transition, that of the agricultural society to the industrial one. What new contents should the curriculum have? Clearly there are important new knowledge and skills. The same happens in the transition from industrial society to the information society. It is not enough to increase the number of years of schooling.

In all these social transitions, it is convenient to know how the first ones adapt. The successful ones. Hunter-gatherers had to learn from the first farmers, from those who adapted quickly and successfully. They need to acquire the agricultural thinking. Learn to think like successful farmers. Incorporate their attitudes and values. This is much more than the knowledge on how to grow plants. The family, property and values also changed. Knowledge and values go together. Likewise, in the next transition, it is convenient to learn to think like the first industrialists. Acquire their industrial thinking. Learn things like the measurement of time, the division of labor, the conveyor belt, accounting and the efficiency metrics. Again, values and attitudes also changed. Population crowded in large cities, and we had to learn to live with others, where most people are not familiar. They are completely unknown people, whom one sees once and never again. For the next transition, to the information society, we needed to learn another way of thinking. It starts with universal literacy and numeracy. But now we need to handle much more information, coming from manuals, reports, newspapers, books, and the internet. They are very powerful and enormous databases. Values also changed. Just think on your trust on credit cards and virtual money.

Even when the information we already have is huge, and continues to grow, it is information without initiative. These huge data bases are waiting to be consulted. They do not act on their own and do not talk to each other autonomously. In the Super Smart Society, information and devices have initiative. They are constantly working for you. They are analyzing information, deliberating with others, and also making decisions for you. Decisions that affect you, and they decide whether to notify you or not.

What type of thinking do we need now for the transition to the super smart society? The natural strategy is to learn the type of thinking from the actors that are already successful in the transition to the super smart society. These are computer scientist and computer engineers. Welcome to Computational Thinking

Are You Anxious?

Peter Turchin, in his book *Ultra Society: How 10,000 years of war made humans the greatest cooperators on earth*, emphasizes that projectile weapons are one of the most important technologies that shaped human evolution, but they rarely get the credit they deserve. People tend to be much more preoccupied with fire. With a spear you have a huge advantage over the rest of the members of your tribe. Your hunting productivity explodes. No one comes close. But you also achieve enormous power. Now, you rule the world. However, if others learn to make spears and use them, then something magical occurs: it emerges much more equality of power. In this situation, there appears more egalitarianism than there was before anyone had spears. Before, the strongest person hunted more and imposed his will over others. However, if everyone has spears and knows how to use them, the differences in productivity disappears. Society is equalized. As Turchin puts it: it is hard to see how this egalitarianism could have evolved without projectile weapons.

What is going on here? Apparently, a new technology disrupts society, brings huge inequality. During a time window an almost unfair advantage is gained by early adopters. But once it is assimilated by all, society equalizes. The initial advantage disappears and the advantages are equal for all. Is this always like that?

In their influential paper *The Race between Education and Technology*, Claudia Goldin and Lawrence Kats argue that the full twentieth century contains two inequality tales—one declining and one rising: a sharp decline of college wage premium from 1915 to 1950, jaggedness from 1950 to 1980, and a rapid increase after 1980. According to them in recent decades the lion’s share of rising wage inequality can be traced to an increase in educational wage differentials. They conclude that technological change creates winners and losers and can sometimes have adverse distributional consequences that may foment social tension. Is this the same phenomena as with the projectile weapon?

Nobel Prize economist, Angus Deaton, in his book, *The Great Escape*, has documented the enormous improvement in poverty and life expectancies in the last centuries. However, there is now an increasing inequality. According to Deaton, economist attribute the recent rise of wage inequality to the relentless increase in the skills required to work with new information-based technologies. Acceleration in skill-biased technical progress over the past thirty years is the main engine driving increased inequality in earnings. Therefore, we must not only seek the new knowledge and thinking skills of early adopters and the values and attitudes that accompany them. We must do it quickly and help transfer to everybody, in order to avoid an imbalance and the social tensions that can occur between early adopters and the rest that is left behind.

Framework for Computational Thinking

In this Discussion Paper we propose to include Computational Thinking in the curriculum. We also illustrate the proposal with some exemplars. This proposed framework is meat to serve as a tool to develop basic human characters, creative human capital, and well qualified citizens through computational thinking. A more complete version can be found in Araya et al. 2019.

First, we consider the classical conception of computational thinking. It is explained by the attitudes of attempting to think computationally by philosophers and mathematicians such as Ramón Llull, Gottfried Wilhelm Leibniz, Alan Turing, and John Holland. For example, in a letter to Philip Spencer in 1685 Leibniz wrote “The only way to rectify our reasoning is to make them as tangible as those of the mathematicians, so that we can find our error at a glance, and when there are disputes among persons, we can simply say: Let us calculate, without further ado, to see who is right”. Leibnitz was Influenced by the work of 14^{th} century Majorcan philosopher, Ramon Llull, who designed a mechanical machine to reformulate arguments and ideas in terms of a characteristica universalis, or universal language, so that to have them computable. According to Llull, the machine could prove for itself the truth or the lie of a postulate. This means, decomposing arguments in term of thousands of simple units, which can be recombined and thus able to be expressed and performed as mechanical computations. Later, in 1936 Alan Turing proposed a sequential machine, the Turing machine, which provides a precise definition for computational steps and algorithms. This is the core of computational thinking as expressed today by computer scientist Jeannette Wing: “Computational Thinking is the thought processes involved in formulating a problem and expressing its solution(s) in such a way that a computer – human or machine – can effectively carry out”.

Imagine you have write the instructions to represent quantities with an abacus Is this an example of computational thinking? How about writing instructions to translate the annotations in the abacus into Arabic positional notation in paper?

Figure 3. Goes the use of abacus require computational thinking?

Consider now the text in figure 4. If you have to write an instruction manual to read and translate the text to English. Is this computational Thinking? How about an instruction manual to do text to speech on any text in English. Is this an example of computational thinking? And, if you consider the converse case: speech to text. Is this computational thinking? Does your smartphone do computational thinking when it uses Text to Speech or Voice Recognition Apps?

Figure 4. Reading text requires computational thinking?

A second conception of Computational thinking comes from science, where it is viewed as building computational models. According to computer scientist Peter Denning, in the 1960s and 1970s we allowed, and even encouraged, the perception "Computer Science = programming," which is now to our dismay widely accepted outside the field. Rather, he consider computational thinking as the thought processes in doing computational science—designing, testing, and using computational models. According to Denning, computational thinking, came into wide use during the 1980s, during the development of computational models that produced startling new discoveries in physics that leads to a Nobel Prize. Building models not only relies in abstractions like number and computation with numbers. It uses also the human ability that capture patterns and the dynamic of unfolding actions.

Imagine the floor of the classroom with lots of large and small balls, and each student holding a paperclip in their hands as shown in figure 5. Some students have a large paperclip, which can grab any ball. Other students have small paperclips. These paperclips can only grab small balls. When the whistle blows, each student has a few seconds to grab a ball. If he does not grab any, then his paperclip goes to a bag of the paperclips without offspring in generation 1. If he has grasped a ball, then his paperclip goes to a bag of paperclips with offspring in Generation 1, and those students get another paperclip similar to the previous one. With this new paperclip he is able to play in the next turn. This is, the turn corresponding to generation 2. Assuming that the grasped balls are retired from the floor, what will happen after several generations? Are there any patterns? Is this activity a computational thinking activity? Is it like something analogous to the size of bird beaks that Charles Darwin observed in the Galapagos Islands? Is this the natural selection algorithm?

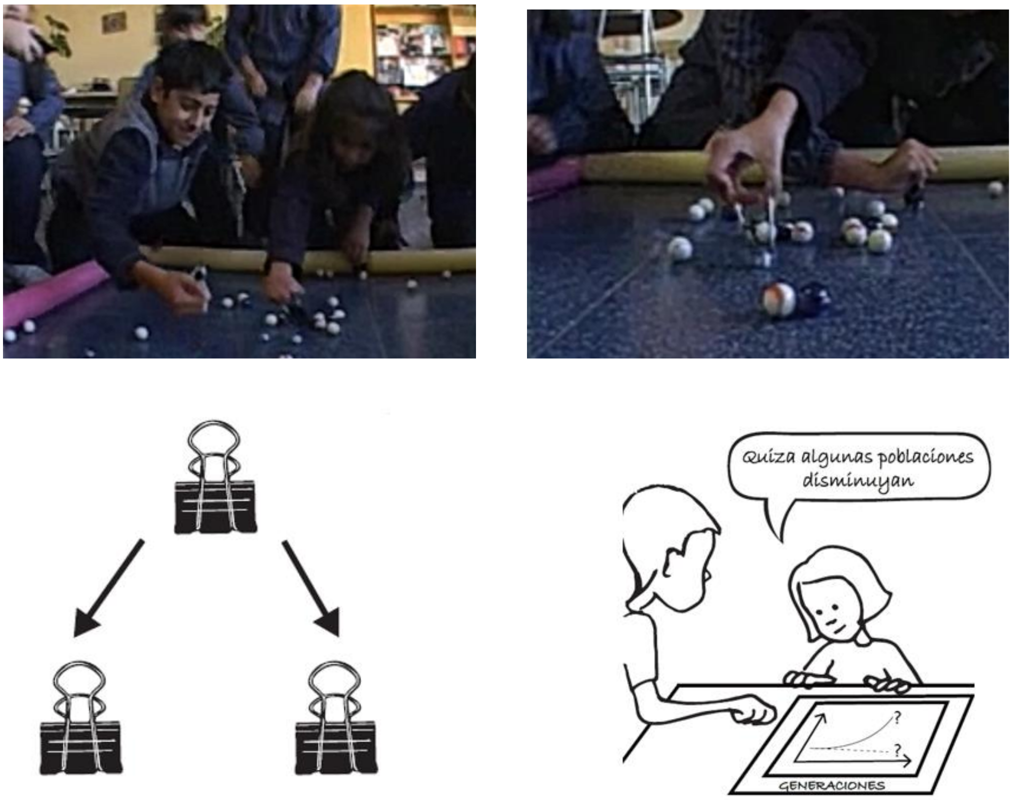

Figure 5: Students grasping balls with paperclips. Some paperclips reproduce and have similar offspring. Students have to predict eventual patterns in the population of paperclips.

The computational thinking attitude is behind the current progress in biology, where increasingly accurate computational models of cells and organisms are being built. According to John Holland, pioneer in the application of cellular automata to biology and the creator of genetic algorithms, patterns are normally expressed with board games: "Board games are not usually accorded the same primacy as numbers, but to my mind they are equally important cornerstone to the scientific endeavor. I think board games, as well as numbers, mark a watershed of human perception of the world". Holland also introduced computational models that can evolve, like in natural selection and thus are able to solve problems that their creators do not fully understand.

Let´s think that the world is like a board, and people are like beads that move around following certain rules. Is this an example if computational thinking? Nobel Prize Thomas Schelling, placed blue and red beads on a chess board and moved them around according to various rules. He interpreted the board as a city, with each square of the board representing a house or a lot. He interpreted the beads as agents representing any two groups in society, such as two different races of people. With this model of segregation Schelling showed that even when individuals didn't mind being surrounded or living by agents of a different race, they would still choose to segregate themselves from other agents over time! Why?

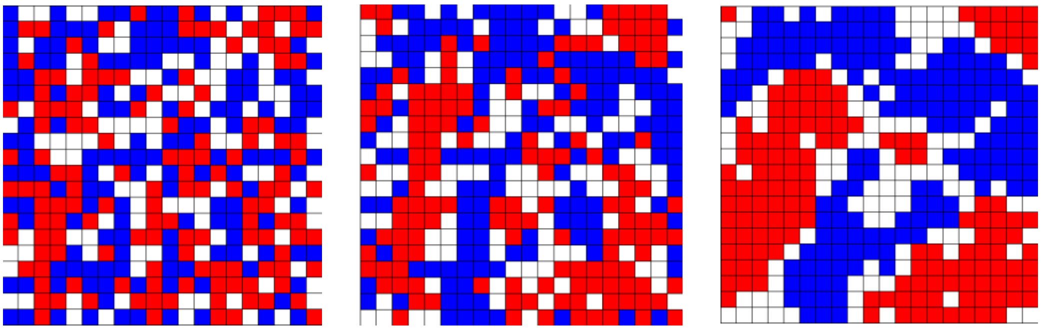

Figure 6. Initial, intermediate and final stages of a board with agents of color blue and red. At each iteration an agent review her adjacent locations. If majority is a different color than hers, the she randomly jumps to any free location.

Is this model an example of computational thinking? Consider now Figure 7. Here, red agents are not professionals. They have only up to high school education. Blue agents are professionals. The have college degrees. If you run a model, with an initial stage with agents distributed randomly, after several iterations it converges to a board where the blue agents accumulates in certain regions. What can of rules can generate this behavior? Is this an example of computational thinking? Does this behavior resembles somehow a known social phenomena occurring recently in some countries? Why?

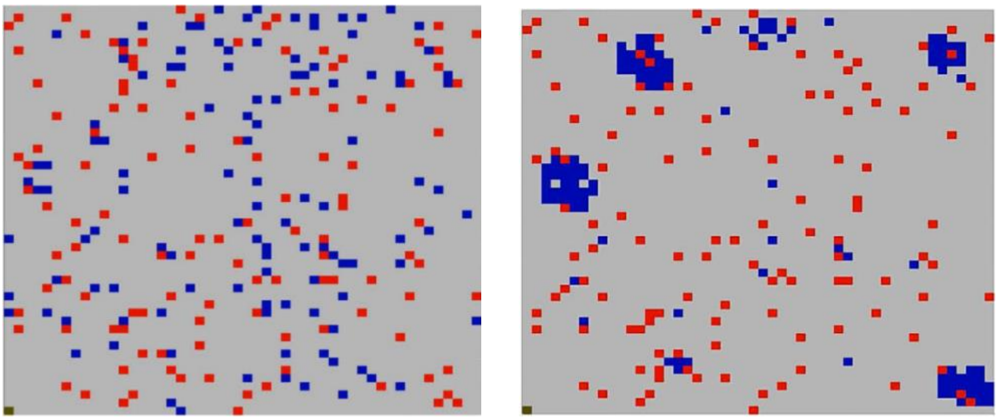

Figure 6: Initial and final stages of a board with agents of color blue and red

A third conception of computational thinking comes from Data Science and Machine Learning. Machine learning is growing very fast and transforming an increasing number of industries, from credit risk to medical diagnosis. This transformation will have a huge impact on the nature of job and on employment. We need to anticipate this transformation and avoid the fear expressed by the historian Noah Harari: the main struggle in the 21st century will be about irrelevance. Many people are being pushed aside. What is the nature of this transformation? According to the Fields Medal mathematician, Cedric Villani, “Machine learning techniques mark a break with the classic algorithm. In particular, as they mark the gradual transition from a programming logic to a learning logic. That's what led Wired magazine to prophesize in June 2016 ´*The end of the code*´: in the future, we will no longer program computers, we will train them". This is a different computational thinking. For example, the National Academies, see the need to analyze new and greater volumes of information, along with its variety and velocity, compound long-standing challenges of data analysis—and raise new ones. There are critical issues all citizens has to consider. For example the Bias problem in Machine Learning. Data is not neutral and thus the computer will learn stereotypes present on the data. This means, machine learning will learn sexist or racist programs if the data has these bias. There are also important ethical issues about the use of data, privacy and its consequences on people. On the other hand, given the huge impact of automatizing tasks, Villani view here an historic opportunity of de-automation of human labor: "Indeed the automation of tasks and trades can constitute a historical chance of de-automatization of human labor: it allows to develop human capacities (creativity, dexterity manual, abstract thinking, problem solving). We have to seize artificial intelligence to develop the capabilities of each, we have the opportunity".

Imagine now that you are taking out one box after another, and each time you open a box you look at what is inside. It turns out that you always find a white rabbit or a black rabbit. They were set with a criterion, but the criterion is totally unknown to you. You can measure the length, width and depth of each box, and record those characteristics along with the color of the box. With this information you can bet on the color of the rabbit that is inside the box that is now in front of you. You can say that you do not know, and you earn one point. If you bet on one color and hit, then you earn two points. If it does not hit then you earn zero points.

Figure 7: Student trying to guess what color is the rabbit inside the box.

Additionally, you have the option to bet with a rule. For example, a rule like the following one;

IF
Length + 2.5 x width > 3
THEN
Color = white
ELSE
Color = black.

If you decide to bet with a rule, then you must apply the rule to the characteristics of the box in front of you. If you compute the output of the rule and it predicts correctly the color of the rabbit, then you earn 4 points. If you use a rule but does not agree with the color then you lose 4 points. Figure 8 illustrates the score of hundreds of students (Araya et al, 2015)

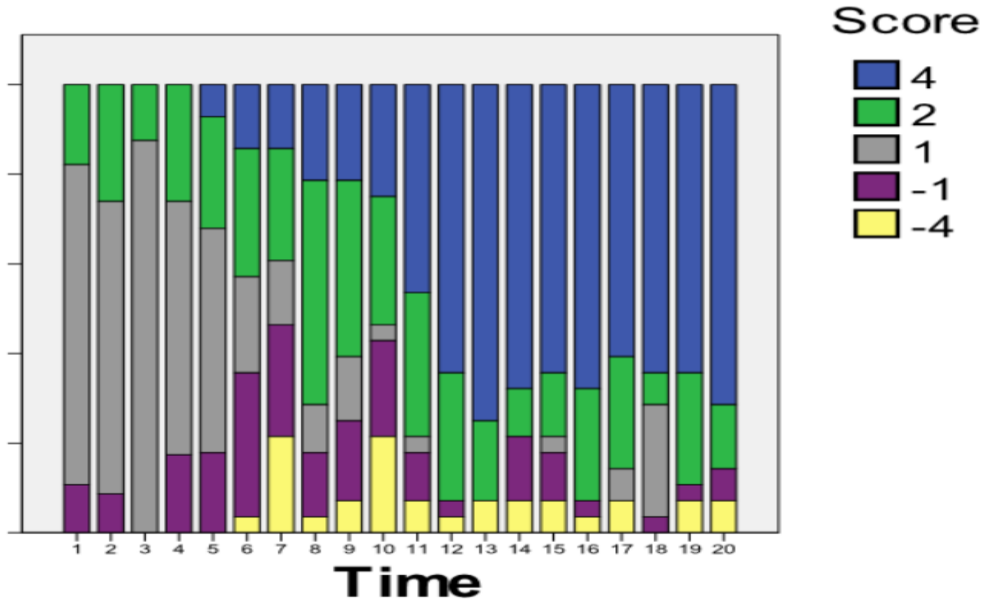

Figure 8: Results of a cluster of students of 7th and 8th grade that bets with rules. Across 20 turns, proportion of students gaining score 4, 2, 2, -1 and -4. Score 4: student bets and hits following a rule; score 2: student bets white or black and hits; score 1: student bets gray; score −1: student bets black or white and does not hit, score −4: student uses a rule but does not hit.

Consider now that instead of a Box you have a truck engine, and when you open the engine you can find a malfunction or not. The feature of the boxes are now features obtained from the engine, like viscosity and presence of different chemical components on the engine oil. Your bets are now about the health of the truck engine. How do you build a system that diagnoses the state of the engine? Is a pattern finding algorithm as the one used on the game to guess the color of the rabbit inside the box? Is it a different computational thinking than the one used for programming?

These three conceptions of computational thinking bring two key values: understanding and objectivity. Deep understanding requires powerful tools. The microscope and the telescope enhance human vision. Similarly, the computer enhance human reasoning. It also brings objectivity. It forces you to make explicit your assumptions. The computer still cannot do mind reading. Moreover, you can compute the consequences of your assumptions, and everybody else can do it also. Everybody can carefully inspect your models and your thinking. They can read your code or algorithms, run them, search for bugs and debug.

According to philosopher Daniel Dennett, we are Popperian creatures with the habit of permanently creating forward models and using them to make decisions. However we need not understand this process. Only with thinking tools, like the tools of computational thinking, we can do systematic explorations and attempt higher order control of mental searches.

It is very important to remember that computational thinking is much more than programing. According to Tedre and Denning (2016): “Computational Thinking initiatives that focus solely on programming tools and techniques market a tasteless, scentless view of computing that emphasizes analytical abstract world far distant from the hands-on dirty complexities of the real world. In the early stages of the computer revolution, the focus on calculation may have justified a programming-and-techniques view, but since the 1980s the revolution has produced radical changes in the way we see the world and move in it.”

Can we all learn Computational Thinking?

In the Super Smart Society the central role is brought by the computer. It is increasingly present and ubiquitous at all times. Moreover, it is actively taking the initiative to interact with the citizen and his networks. This is a completely new phenomena, where the machine is autonomous and takes the initiative. To understand this situation citizens need to acquire the strategies and knowledge of the successful early adopters of this era. Computer scientist and computer engineers tell us that Computational Thinking is the key. It is essential for developing creative human capital adapted to the challenges of the 21st century.

Computational thinking processes are just strategies for successful reasoning. It contains strategies like discretizing, decomposing, modularizing, factorizing, and forward and backward chaining reasoning. These are very powerful strategies. It also contains fundamental concepts, like lists, arrays, iteration, recursion, state, pseudocodes, data and datamining. They all lead to a richer and deeper backbone to support reasoning. The ability to iterate, simulate, operate, perform and debug algorithms enables efficient ways to build computational models and solve real world problems. Pattern detection is also key. This is computational thinking working together with statistical thinking. A very powerful mix, that is behind machine learning. Given the enormous quantity of applications and tits impact in voice recognition, visual recognition, and autonomous vehicles, students need to understand the central ideas of machine learning. But computational thinking is not only powerful in technical problems. It is also powerful in general reasoning. It can help the citizens in argumentation and deliberation, in order to detect usual reasoning errors like causal attribution and confirmation bias.

The transition to the Super Smart Society brings enormous challenges and anxieties. One anxiety is educational. We are starting to see the less educated rebelling against the more educated (Collier, 2018). Artificial Intelligence technology is automating the more repetitive tasks, leaving jobs only for the more complex tasks and the ones that integrate humans with machines. These tasks require more knowledge and higher skills. Many are left behind. Thus, we need urgently to start teaching computational thinking to young kids. In the year 1,100 CE only 2% of the male population of the West was full literate (Morris, 2015), and practically 0% of the females. For a common citizen of that time, learning to read and write was probably considered a very complex endeavor, and not for everyone. But today we all learn it. It is now the turn to teach computation thinking.

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