Interdisciplinary Aspects of Cognition

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Abstract. This position paper analyses the multidisciplinarity of cognitive research and its challenges from three perspective: the *foundations* of cognitive science, which draw from logic and neuroscience and their interconnections in studying human logic; *computation* as a means to identify mathematical patterns in human cognition, represent them symbolically and use such representations in computer emulations of human cognitive activities and possibly verify properties of such activities; *education*, devising and implementing learning models that exploit as well as address human cognition.

Keywords: Cognitive Science; Logic; Human-computer Interaction; Neuroscience; Cognitive Learning; Formal Methods

1 Introduction

The online Oxford Dictionary [43] defines cognition as "The mental action or process of acquiring knowledge and understanding through thought, experience, and the senses." This is the definition of the *mass* or *uncountable* noun, which denotes the abstract concept. There is also a countable meaning of the word cognition, which the Oxford Dictionary defines as "A perception, sensation, idea, or intuition resulting from the process of cognition." The English word "cognition" comes from the Latin verb "cognoscere", which means "to get to know". The English mass noun accurately describes how the action expressed by the Latin verb takes effect in the human mind in the form of a process. The English count noun refers to all possible entities that are the result of such a process. The wide range of these possible cognition outcomes, which may belong to the external world, experienced through the human capabilities (e.g. perception, sensation), but may also originate within the mind itself (e.g. idea, intuition), makes cognition an intrinsically interdisciplinary discipline of study.

Although cognitive science is quite a recent discipline of study, nevertheless the deep interest in understanding and explaining cognition goes back to the origin of western philosophy, with Plato focussing on the ideas and Aristotle on the experiences. Plato's distinction between perfect *ideas*, or *forms*, and their imperfect copies in the experienceable world evolved through the centuries and found a turning point in Descartes' mind-body dualism, which can be seen as the origin of a new discipline, which had to wait for over two centuries to find a name, psychology, and even more to have a recognition as a science. It is, in fact, the double intent to study both mind and behaviour, that made it difficult for psychology to acquire its own identity as a science. And when this started to happen, around the end of the 19th century and the beginning of the 20th century, psychology was split into two main schools, *structuralism*, whose object of study was the human mind, observed through introspection, and *functionalism*, which later evolved to *behaviourism*, whose object of study was the observed human behaviour. This opposition went on for several decades until in the mid 20th century. The building of the first computers and the development of its theoretical bases in terms of logic and computability theories offered an alternative way of looking at cognition, namely as a mental process similar to a computer process. This is the *computer analogy* or *computer metaphor*, in which the human mind is compared to a computer with processing unit, input and output "devices" and different kinds of memories for short-term and long-term storage. This way of understanding the human mind went beyond scientific circles and, with popular publications of eclectic scientists like Noam Chomsky and Douglas R. Hofstadter, also captivated ordinary people. Hofstadter's 800-page bestseller [25] shows how cognition is related to mathematics, logic, computer science, biology and art, specifically Escher's figurative art and Bach's music. Interestingly, Hofstadter manages to do this without even using the word 'cognition'.

Furthermore, the relation between cognition and computer science actually goes both ways. Not only can cognition be modelled in a computer-science fashion but is also largely affected by the way computer science has spread throughout the human living environment. The increasing complexity of this environment is no longer restricted to its natural components and the humans populating it, but is permeated by the ubiquitous presence of technology, which includes physical systems, computational systems, virtual worlds and robots. Such an extended human environment has modified the way humans live, work, interact with each other and learn.

Although the study of cognition split from philosophy almost two centuries ago, there are philosophical foundations of cognition which are still actual nowadays. In Section 2 we start from such philosophical foundations and we introduce a fundamental dilemma, which is also a first rule underlying human reasoning and logic. Then we explore some foundational challenges relating human logic and neuroscience and we illustrate future research applications. In Section 3, we move from the notions of symbolic manipulation and recursion and their use in mathematical proofs as the basis for modelling cognitions to an overview of cognitive architectures and their application. Then we discuss how to enrich cognitive architectures with findings from research in human logic and enable them to perform formal verification in order to tackle the most recent challenges encountered in human-computer interaction (HCI). In Section 4 we show how new learning environments, inspired by cognitive science, improve knowledge development and produce cognitive skills in students fostering their transition to adulthood and their involvement in lifelong learning. Finally, in Section 5 we draw some conclusions on the interrelation among the considered perspectives.

2 Foundations: From Logic to Neuroscience

Cognition is both a theoretical and natural phenomenon. We humans have evolved as the only species in the observable universe known to be capable of reasoning at its highest levels: we make abstractions, place thoughts as subjects of other thoughts, erect in our own minds a higher-order theory of other minds, and have evolved to communicate with the most expressive of human innovations: natural language. As the result we are able, at least in principle, to constantly improve our own mental instruments of thought, repair reasoning when it is ill, and elevate levels of critical and innovative thinking to new, unprecedented heights.

Yet the enormous complexity of the human brain and the mind gives rise to a fundamental dilemma. We fail to be sufficiently cautious when the task at hand is not to fool those who are the easiest ones to be fooled: ourselves. This fact—that we should not take it for granted that we are proficient enough when exercising our own critical faculties—is *the First Rule of Reason*. It is also the first rule of logic in human mind and cognition to be expected to be able to re-invent self-controlled thoughts and to implement long-lasting solutions.

What does the future of intelligent cognition look like in the world? Abject failures of this rule are evident in today's world: we meet irrational and inconsistent behavior that discounts the future; biases that have led to collective erosion of reason such as in-group favouritism, out-group prejudice, deindividuation and group narratives that only advance causes no different from self-serving attitudes; overconfidence boosted by ignorance, and widespread resistance to radical solutions when they clash with uncriticised appeals to the Precautionary Principle. Such feats are trumped only by the abundance of Type I errors we make when our apophenic neural relics kick in. Acts that harm others simply because of the possession of different belief systems are just some examples of dire consequences of uncriticised reasoning among many.

Various and well-documented logical, behavioural, economic, sociological, philosophical, psychological and cognitive theories can be adduced to explain extreme wrongdoings of human cognition and reason. These include *game theory*, *social dilemmas*, incomplete *evolutionary developments* such as the work-in-progress status of the evolution of our mammalian neuroendocrinological system, *inter-group conflict theories*, *dual-process theories of cognition*, and the intrinsically confusing mechanisms that *natural language* has created, churning *paradoxes* out of its system of propositional meaning and reference. Add the frailty and intractability of the consistency-maintenance of our belief systems and a living time-nuke may be ticking around the corner.

Section 2.1 illustrates how these issues can be studied logically.

2.1 Logics for Cognition

What is needed are future-oriented logical and formal representations and models appropriate for the study of general intelligence and cognition. This has to be done by resetting the scope of logic and reasoning and to have it incorporate the full spectrum not only of the integrated human, machine and algorithmic *deductive* reasoning, but also the integrated *inductive* and *abductive* modes of inference modelling intelligent interactive systems [14, 18, 60]. But here is where the future looks promising: in the experimental world of cognitive neuroscience, one might expect to find much new and interesting neural and behavioural correlates to those expanded and interconnected logical modes and modalities.

The aims and challenges in the future studies of logic in cognition are thus three-fold:

- *Develop new forms of logic as the basis of cognitive and substrate-independent studies of intelligent interaction.* One needs an integrated logical, cognitive, algorithmic and philosophical perspective to understand human reasoning, (ir)rational action and generalized computational thought. New notational innovations, such as diagrams and icons, have to occur in information production and in rational acts of signification, independently of systems of linguistic meaning and reference. Such innovations are likely to impact how we perceive both the scope and the formal and mathematical structures of logic in ways that apply to cognitive theories of reasoning and mind.
- *Achieve new theoretical insights to human reasoning and decision-making.* Game-theoretical studies of behaviour and reasoning are common, but need a sea change: human strategic reasoning is after all at bottom an abductive, not a deductive, undertaking. Players deliberate on possible future histories and take positions that according to standard common belief of rationality approaches will never actually be reached as 'the surprising facts'. Prompted to reason to antedating actions under which such positions would be rendered comprehensible, less surprising, or utterly facile and natural, the change in view to abductive reasoning means to imaginatively look for where those perturbations, such as trembles or quantal responses, could take place. The conclusion is a conjecture about such perturbations [47].
- *Study experimental validations of the above.* Different forms of reasoning, pragmatic and naturalized logics may be exposed through the advice of neurocognitive studies. In particular, one could predict that various novel brain measurement methods such as fNIRS (functional near-infrared spectroscopy) produce data providing important insights into issues such as
  - the performance of linear vs. non-linear (iconic, diagrammatic and visual) reasoning tasks;
  - optimal logical representation tasks in different areas of pre-frontal cortex;

- how inventions of new solutions come about (abduction and anticipation);
- verifications of cognitive economy of reasoning;
- how particular formal systems (such as negation-free conditional logic [6]) could explain a host of cognitive biases without resorting to dual-process theories.

Three observations can be made from these desiderata:

1. The advent of modern logic has made the study of reasoning and higher executive tasks a remarkably *platform-independent* endeavor not limited to traditional theories of rational behavior.
2. A key benefit of the application of logic in cognitive science is that we can now study the *non-deductive* and *imagistic* sides of such reasoning better than before [2, 3, 12, 28, 36, 46], including modes of reasoning encountered in automatized decision-making systems, to reset the bounds of logic. This is not to hasten to deny that all good reasoning is justified, at bottom, by deductive patterns of inference.
3. *New experimental analyses* promise to reveal a cortical differentiation between the three major reasoning modes (deduction, induction and abduction). Measurements by fNIRS can reveal biological differences between these three modalities, in which case differences in solving various reasoning tasks have neural correlates in the prefrontal cortex. A hypothesis yet to be tested is that *frontal lobes are most active in deduction, occipital lobes in abduction, and there is increased activation in parietal lobes in induction.* Also, one can study symbolic vs. iconic representations of logical tasks (such as graphical logics) and observe to what extent the latter excites increased activities in the right hemisphere and occipital lobes.

Future applications of research in logic and cognition are valuable not only in cognitive sciences but also in general artificial intelligence. For example, computations in various important hierarchies are non-monotonic, and are commonly used in logic, mathematics and their applications. Known examples are neural networks and expert systems, where information recovered during computations increases non-monotonically with time, as information previously obtained may later be defeated and strategies of computation need reflect those changes. In mathematical logic, such processes are known as "trial and error" processes. Interestingly, they are related to abduction in ways not yet fully understood.

The future harbours new notational and empirical distinctions concerning integrated human and artificial reasoning both at their theoretical and neurophysiological levels. This, if successful, will in turn result in improved methods that apply such distinctions to creation of artificial models of cognition and computational structures that reflect those distinction and could hence become inventive, ampliative and generalisable when confronted with various critical reasoning tasks independently of the particularities of the human, social, mathematical or machine contexts.

Future insights may also include why conspiracy ‘theories’ have become so widespread and what symptoms, factors and theoretical explanations, such as hyper-rationalizability, they correlate with, namely exactly where and why certain executive areas in the prefrontal cortex assume abnormal functions. Theoretical activities and findings in logic and cognition are thus expected to have translational and clinical impacts.

2.2 Brain-computer Interfaces

A brain-omputer interfaces (BCI) is a direct communication pathway between an enhanced or wired brain and an external device. Since the early prototypes in the 70’s [57], the field of BCI has witnessed a rapid growth, and a large number of neuroimaging technologies have been employed, such as Electroencephalography (EEG) [5], Magnetoencephalography (MEG) [58], Electrocorticography (ECoG) [7], functional magnetic resonance imaging (fMRI) [34], near-infrared spectroscopy (NIRS) [56] as well as combinations thereof [16, 15]. Early BCI systems were based on operand conditioning [4], where the subject had to adapt to the BCI in order to give meaningful commands. However, these types of systems required weeks of adaptation on the subject side. More recently, a machine learning approach has been adopted by the community in order to reduce setup times of real-time feedback sessions [5, 17]. While BCIs have originally been proposed as a communication tool for patients with disabilities, such as paraplegia or locked-in syndrome [4], a whole range of other applications have been proposed, which use BCI decoding techniques such as gaming, biometrics [13], workload detection and driver fatigue [21].

The field of BCIs can play an important role for further advances in cognitive sciences, since a number of technologies that have been developed are applicable beyond this field of research. A recent BCI study that employed multi-modal neuroimaging for intention decoding found that EEG and NIRS can lead to higher decoding accuracy when combined and more importantly, that their information is complementary [16]. In another study, a machine learning approach of mental state decoding was applied to the Libet experiment [51]. Generally, BCI techniques are tools for decoding mental states and intentions in real time. Clearly, these mental states underlie higher order cognitive processes, which can be disseminated further by careful experimental design.

3 Computation: From Mathematics to Computer Science

Hofstadter’s 800-page bestseller [25] aims to show how *self-reference*, which essentially corresponds to the mathematical notion of *recursion*, is the basis of *self-awareness*. Hofstadter considers the diagonal argument used by Kurt Gödel to prove his two incompleteness theorems: the use of a property that refer to itself to prove that (1) there is no axiomatic system capable to prove all properties of the arithmetic and (2) no consistent axiomatic system which includes Peano arithmetic can prove its own consistency.

Gödel's results may be seen as an evidence that there is no objective reality and that there are questions that cannot have an answer. Hofstadter writes in the preface to the 20th-anniversary edition of his book: 'Something very strange thus emerges from the Gödelian loop: the revelation of the causal power of meaning in a rule-bound but meaning-free universe. [...] When and only when such a loop arises in a brain or in any other substrate, is a *person* — a unique new "I" — brought into being.' This means that symbolic computation, especially through recursion, potentially allows meaning to emerge from the manipulation of meaningless symbols, up to the complexity of human reasoning. The fact that recursion is the fundamental mathematical tool in mechanising reasoning is not a surprise for a computer scientist. After all, programming languages used in artificial intelligence, either Lisp-like functional languages or Prolog-like declarative languages, heavily exploit recursion.

3.1 A Philosphical Digression

It is interesting to note that Gödel's results inspired, on the one hand, Penrose's claim that *human consciousness* is non-algorithmic, and thus is not capable of being modeled by a conventional Turing machine, which includes a digital computer [45] and, on the other hand, Hofstadter's identification of what emerges from Gödel's diagonalisation, i.e. from an algorithmic process, as self-awareness [25, 26]. If we put the two things together, then it may be true that, as Penrose believes, human consciousness cannot be modelled algoritmically, but, following Hofstadter, self-awareness, i.e. the recognition of that consciousness and its limitations, emerges from a recursive algorithm. Although, this may appear as a paradox, in reality, Gödel's proving procedure uses self-reference, i.e. a recursive algorithm to understand the limitations of highly expressive formal systems. And this "understanding process" is nothing else than *cognition*.

We can then conclude this philosophical digression by stating that symbolic manipulation, i.e. algorithms, may potentially be used to model human cognition. However, a first important question is whether this potential power of symbolic manipulation together with the high performance of today's computers can effectively be used to emulate human cognition. Then, if this is possible, a second question is what would be the purpose and the real-life usage of a computational emulation of human cognition. We will look for answers to these questions in Sections 3.2–3.3.

3.2 Cognitive Architectures

A cognitive architecture has to be intended as a comprehensive model of the human mind, with a computational power that supports the in silico replication of experiments carried out in cognitive psychology as well as some form of prediction and analysis. A cognitive architecture is based on and implements a theory of cognition, which conceptualises the structure of mind in terms of its processing and storage components and the way such components work together to produce human thinking and behaviour [1]. Cognitive architectures originated from the research carried out in artificial intelligence during the 1950s with the aim of creating computer programs that could solve a wide range of problems across several domains and adapt themselves to new contexts and new situations and, finally, in line with the Hofstadter's Gödelian loop, to reason about themselves.

A number of cognitive architectures have been proposed since the 1970s [50, 33], following three approaches: *symbolic* (or *cognitivist*), such as Soar, which are based on a set of predefined general rules to manipulate symbols, *connectionist* (or *emergent*), such as DAC, which count on emergent properties of connected processing components (e.g. nodes of a neural network), and *hybrid*, such as CLARION, which combine the two previous approaches. However, there is no clear agreement on the categorisation of specific architecture in this taxonomy. For example, ACT-R [1] is often classified as symbolic but, in fact, explicitly self-identifies as hybrid.

Kotseruba and Tsotsos [33] note that most cognitive architectures have been developed for research purposes rather than for real-life usage. Nevertheless, they consider several major categories of application:

- *Psychological experiments* is the largest category comprising more than one third of the architectures and supports the replication of a large number of psychophysiological, fMRI and EEG experiments with the aim of demonstrating the capability of adequately modelling and possibly explaining psychological and physiological phenomena.
- *Robotics* includes nearly one quarter of the architectures and mostly involves relatively simple forms of behaviour, such as navigation, obstacle avoidance and object search and manipulation, but, in some instances, incorporates multiple skill to perform a complex behaviours.
- *Human performance modelling (HPM)* to perform a quantitative analysis of the human behaviour in carrying out specific tasks.
- *Human-robot interaction (HRI) and human-computer interaction (HCI)* to analyse the interaction process in which the human is assisted by a robot or machine.
- *Natural language processing (NLP)* to model various processing aspect from low-level auditory perception to high-level conversation, though the latter only in limited domains.
- *Categorisation and Clustering* comprises mostly connectionist architectures and aims at processing noisy sensory data.
- *Computer vision* comprises most of connectionist architectures and aim at solving computer vision problems.
- *Games and puzzles* to demonstrate reasoning and learning ability.
- *Virtual agents* to model human behaviour in a domain in which experiments might have lethal consequence such as military and counter-terrorism.

3.3 Human-computer Interaction and Cognitive Errors

Human-computer interaction is the study, planning, and design of the interaction between humans (users) and computers. A system that involves such an interaction is called *interactive system*. Interactive systems may appear to work correctly and safely when analysed in isolation from the human environment in which they are supposed to work. In fact, the same cognitive skills that enable humans to perform complex tasks may also become the source of critical errors in the interaction with systems and devices designed as supports for such tasks [27].

These kinds of errors are called *cognitive errors*. Normally, cognitive errors occur when a mental process aiming at optimising the execution of a task causes instead the failure of the task itself. The existence of a cognitive cause in human errors started to be understood already at the beginning of the 20th century, when Mach stated that "knowledge and error flow from the same mental sources, only success can tell the one from the other" [37]. It is, in fact, at the beginning of the 20th century, when human errors in interacting with machines have started to be studied. However, we had to wait until the 1990's to clearly understand that "correct performance and systematic errors are two sides of the same coin" [48].

The systematic analysis of human errors in interactive systems has its roots in Human Reliability Assessment (HRA) techniques [31], which mostly emerged in the 1980's. However, these first attempts in the safety assessment of interactive systems were typically based on *ad hoc* techniques [35], with no efforts to incorporate a representation of human cognitive processes within the model of the interaction. With the increasing use of computers in safety-critical domains, such as avionics, aerospace, transportation and medicine, during the second half of the 20th century, the increased complexity of overall systems consisting of both computer and human components made it difficult to predict the range of possible human errors that could be observed (*phenotype errors*) and even more difficult to relate them to their cognitive causes (*genotype errors*).

3.4 Using Formal Methods in Human-computer Interaction

In the critical contexts considered in Section 3.3 it is thus essential to verify the desired properties of an interactive system using a model that not only includes a user-centered description of the task, but also incorporates a representation of human cognitive processes within the task execution. However, although cognitive architectures can mimic many aspects of human cognitive behaviour and learning, including some aspects of human interaction with machines, they could never be really incorporated in the system and software verification process.

In contrast, the important role played by formal methods in the modelling and verification of computer systems in general, and of safety and security systems in particular, cannot be questioned. In fact, in safety-critical domains, it is explicitly dictated by standards that verification of critical modules must be formal. However, the use of formal methods in HCI has often been restricted to specific domains or applications, with the unfounded hope to be able to identify most human errors which may occur.

Nonetheless, the way the validity of both functional and non-functional properties is affected by the user behaviour is quite intricate. It may seem obvious for functional properties that an interactive system can deploy its functionalities only if it is highly usable. However, usability may actually be in conflict with functional correctness, especially in applications developed for learning or entertainment purpose. More in general, high usability may be in conflict with user experience, whereby the user expects some challenges in order to test personal skills and knowledge, enjoy the interaction and avoid boredom.

Usability is also strictly related to critical non-functional properties such as safety [27] and security [11]. Moreover, safety and security are two critical context in which human error may lead to catastrophic consequences, in term of loss of properties, injuries and even loss of life.

The relationship between usability and critical non-functional properties is actually two ways. On one side improving usability increases safety and/or security. On the other side introducing mechanisms to increase safety and/or security may reduce usability and, as a result, may lead to an unexpected global decrease in safety [27] and/or security [11]. Although in an ideal world human errors may be avoided through a rigorous user-centred design, in the real world humans have to frequently deal with inappropriate operating environments [9, 27], constraining social contexts [11, 27] and cultural differences [23], thus building up experiences that may then produce expectation failures and result adverse in the interaction with "correctly" designed systems [9]. Moreover, the individual analysis of different aspects of cognition, such as specific cognitive errors [30], pattern of behaviours [9], specific cognitive processes such as automatism and attention [8, 53] and social interaction [11] fails to capture failures that may emerge from the combination of these aspects [27]. Furthermore, the context in which the interaction occurs and its effect on the human behaviour are often unpredictable; thus they cannot be modelled a priori. This complex situation determines a number of important research challenges in developing a methodology for the modelling and analysis of interactive systems:

1. non-functional properties that are in conflict with each other or with functional properties must be "cognitively weighted";
2. the correctness of a system depends also on the effect on the human of previous environments or context, that is, on learning;
3. system failures depend on multiple aspects of cognition, which need to be dealt with during analysis in a holistic way;
4. the intrinsic unpredictability of human behaviour requires the validation of any a priori model on real data;
5. the use of formal methods for system modelling and analysis requires high expertise in mathematics and logic, which is not common among typical users, such as interaction design and usability experts as well as psychologists and other social scientists.

We believe that these challenges can only be tackled through an interdisciplinary approach in which computer scientists cooperate with logicians, neuroscientists, cognitive scientists and social scientists. Cognitive architectures are already the result of interdisciplinary efforts, but additional efforts are needed to make them usable not just for emulating aspects of the human behaviour but also to prove properties of the human behaviour and its interaction with machines. That is, to reason about the same behaviour they model or, in the spirit of Hofstadter's "golden braid", to reason about themselves.

In this respect, the new forms of logic discussed in Section 2 would provide expressive, appropriate languages to describe properties that, on the one hand, have visual characteristic fostering human intuition and, on the other hand, are also apt to the symbolic manipulation needed for formal analysis. We claim that the realisation of cognitive architectures able to carry out formal analysis is a promising way to tackle the five challenges above [10].

4 Education: Cognitive Learning

The field of cognitive science has greatly enhanced our understanding of many areas of human thought processing including but not limited to memory, intelligence, brain research, problem solving, expert-novice continuum, information processing and pattern recognition. This in turn has greatly affected education and its practices. Cognitive learning (i.e., cognitive education) could be defined as an educational approach that has its basis in cognitive science research and is focused on the teaching and learning of the cognitive processes and skills connected to reasoning [22, 54]. Thus, the subsequent instruction engages students in learning and helps them to make connections between new and older concepts in order to make learning more meaningful.

In the previous sections we have already very much emphasised the multidisciplinary nature of cognitive science and its subdisciplines. The field of cognitive learning is no exception. It is multidisciplinary and draws from the findings in a number of fields (e.g., human computer interaction, cognitive linguistics, neuroscience and cognitive psychology) in order to design learning environments that produce the most effective learning possible so that learning occurs not only more effectively but in a deeper fashion. These cognitive processes or skills are mechanisms used by everyone to navigate their everyday lives. Which means that these redesigned learning environments will allow for not only increases in understanding in specific fields but also allow for the production of lifelong learners and thinkers in all areas of life. While a traditional learning environment is teacher directed and centered on knowledge transmission, memorization, based in facts and usually competitive in nature, a cognitive approach is student centered and focused on knowledge construction, development of reasoning skills, collaborative and practical in nature.

4.1 Learning Environments for Multiple Disciplines

The findings from these multiple fields have led to numerous new, effective learning environments. Drawing from HCI, cognitive tutors have been shown to be highly effective in mathematical classes [49]. Cognitive tutors make use of findings drawn from interactions that include just in time scaffolding to assist students as they construct their knowledge of arithmetic. Other approaches have been developed that have been successfully used in multiple disciplines to teach reasoning skills such as problem-based learning [59] and project-based learning [32]. Project-based learning has been shown to be highly effective and makes use of student-led projects. These projects are tasks that are highly challenging, which allows students to engage in activities such as problem solving and decision making while allowing students to work independently for extended periods of time [55]. Tan and Chapman [55] found that this learning method encouraged students to learn to work collaboratively while gaining cognitive skills in problem solving.

4.2 Modelling in Science — A Cognitive Learning Environment

One learning environment that has been utilised in the field of science education and has its base in cognitive science is the use of models in science classrooms [24, 44]. These methods make use of the work done by cognitive psychologists to discover the cognitive activities and tools that practicing scientists make use of on a daily basis. Giere [20] postulated that the tools used by scientists to make sense of the world cannot be much different from those used by people in everyday life. Nersessian [42] studied historical and contemporary scientists to determine that the construction and use of science models was at the center of scientific thought.

Mental models are constructions in each individual brain which they can encode into multiple representations to share with others thus producing what Hestenes calls a conceptual model [24]. These conceptual models consist of multiple reprehensions that can take many forms such as that of diagrams, algebraic equations or graphical depictions of reality. The conceptual models can then become shared within a group of individuals to make predictions and refinements in thinking. The use of mental models for meaning making is also quite well known in cognitive linguistics [19]. Modelling in science is basically model-based reasoning. It is the production of models from empirical data and the use of these models to produce predictions whose failure leads to refinements of the original model. Thus, it is an iterative cycle [52]. It has been shown to be highly effective at producing conceptual gains in physics [29] and biology [40] as well as gains in student understanding of models [61].

The problem solving of students has been shown to become more expert like and allow students the ability to undertake productive error analysis [38]. In addition, in some fields it is difficult to produce empirical data within the context of classrooms simply because there is not enough time. In these cases, computer modeling has been used to produce simulations that help students 'collect' data on which to base their initial models [41, 39]. These simulations then allow for further analysis of the strategies used by students by cognitive psychologists. Finally, modelling in science has been shown to increase student fascination with science over that of traditionally taught students [41].

In conclusion, cognitive learning in the educational field has produced gains in knowledge development as well as producing students with the cognitive skills to become effective reasoning adults no matter what path they take in life.

5 Conclusion

We have considered cognitive research and its challenges from three perspectives: *foundations*, *computation* and *education*. Within each of these perspectives. we have identified important relations and complementarity among different disciplines.

Foundations of cognition can be in terms of either logic description of high-level reasoning modalities or low-level neurological signals. We have proposed the use of new experimental analyses to map reasoning modes to areas of the prefrontal cortex. From a computational perspective, cognitive architectures can be enriched with formal analysis mechanisms to carry out the verification of the overall interactive system. Furthermore, as a transversal relation across foundations and computation, symbolic and visual aspects of new logics for human cognition may be exploited to enable formal analysis and facilitate user understanding, respectively.

Finally education is a perspective in which research in cognition can be applied to any discipline by defining the appropriate learning environment.

Acknowledgments. The authors would like to thank the four anonymous reviewers whose comments and suggestions greatly contributed to improve the paper.

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