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Editorial

The cognitive modeling of human behavior: Why a model is (sometimes) better than 10,000 words

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1. Introduction

This special issue of Cognitive Systems Research presents a collection of remarkable papers on cognitive modeling based on communications delivered at ICCM-2006, the Seventh International Conference on Cognitive Modeling (Fum, Del Missier, & Stocco, 2006) held in Trieste, Italy, from April 5th to 8th, 2006. Being the organizers and chairmen of the conference, we have been invited to serve as guest editors for this issue. We therefore solicited some participants to reexamine their contributions, and to change them in form of journal articles. In particular, we asked authors to review what they had presented during the conference focusing on the benefits cognitive modeling could provide to cognitive science. The issue you are reading is the result of this editorial process.

In this introductory commentary we would like to set the stage for what follows by illustrating the advantages and disadvantages of cognitive modeling, and by presenting a minimal set of requirements for a good modeling practice. Then, we will briefly preview the papers composing this special issue, and we will emphasize how they deal with the issues discussed in the previous sections.

2. The joys and sorrows of cognitive modeling

The aim of science, of every science, is to describe and explain the events that occur in the world. If the descriptions and explanations we come to are adequate, they will allow not only to understand the how and why of the old things, but also to predict the happening of new ones.

Within cognitive science we are trying to uncover how the mind works. Aiming toward this end, cognitive scientists have been developing an impressive array of empirical methods encompassing observational and correlational studies, human and animal experimentation, case studies of brain-damaged patients, physiological recordings and, more recently, neuroimaging techniques. Here we are interested in using modeling to advance our knowledge of cognition.

Modeling is used when we are investigating a system (or phenomenon) that is too complex, too difficult, or, sometimes, simply impossible to deal with directly. In such cases, we build a simpler and more abstract version of the system—i.e., a *model*—that keeps its essential features while omitting unnecessary details. If the model is a good one, the results obtained by working and experimenting with it could be applied to the original system. "Intuitively, a model is an artifact that can be mapped on to a phenomenon that we are having difficulty understanding. By examining the model we can increase our understanding of what we are modeling" (Dawson, 2004, p. 5).

A particularly useful class of models is represented by *computational* models. A computational model is a model that is implemented as a computer program. Differently from statistical and mathematical models, which describe a phenomenon but they do not reproduce it, computational models *behave*, and they allow us to observe and measure their behavior. "With the advent of powerful computers, it has become possible to combine deductive and experimental methods in a single computational approach. A model of the object in question is created in the form of a computer program, which is then actually run on the

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computer, simulating behavior. In this way experiments can be designed with the model, and the dynamic properties of the model can be examined through studying its actual behavior." (Goldberg, 2001, p. 45).

In *cognitive* modeling we build computational models of cognitive processes. "The computer is given input and then must perform internal operations to create a behavior. By observing the behavior, the researcher can assess how well it matches behavior produced by a real mind. [...] As such, computer simulations provide a useful tool for testing theories of cognition. Successes and failure of models give valuable insights to a theory's strengths and weaknesses" (Gazzaniga, Ivry, & Mangun, 2002, pp. 102–103).

Several authors (e.g., Dawson, 2004; Lehman, 1977; Lewandowsky, 1993) have examined the advantages of building computational models of cognition, and they generally agree about its benefits.

2.1. Clarity and completeness

An important benefit of articulating scientific generalizations in form of computer programs is the increase in the clarity of theoretical statements that is obtained. This enhancement can assume different forms.

First, the statements composing a program cannot, by definition, be vague or imprecise. To get a program run, it is necessary to specify how the information is represented and manipulated by it. All the steps must be clearly defined and there is no room for cloudiness or ambiguity: all the variables must be operationalized, the relationships between them have to be fully specified, all the parameters must be set.

A beneficial side effect of this clarification process is the fact that it forces modelers to make their hidden assumptions fully explicit: "... [computational modeling] techniques lead to precise statements of theory by forcing the detailed specification of all aspects essential to the theory's implementation, including many aspects which might otherwise be overlooked" (Cooper, Fox, Farringdon, & Shallice, 1996, p. 4). Verbally expressed statements are sometimes flawed by internal inconsistencies, logical contradictions, theoretical weaknesses and gaps. A running computational model, on the other hand, can be considered as a sufficiency proof of the internal coherence and completeness of the ideas it is based upon.

2.2. Better exploration and evaluation

A strictly related benefit of expressing theories in a computational form is the possibility to explore their consequences in depth. With a theory expressed only in verbal form we have to resort to logical inference to figure out whether a certain proposition is entailed by it, and there are known limits to the complexity of the inferences we can perform. Computational models do not suffer from these shortcomings. Running a model makes in fact the ramifications of the theory explicit and allows a thorough evaluation of it. Through computational modeling it is possible to tackle problems that do not allow closed-form analysis, it is possible to include random and stochastic components, it is possible to manage a huge number of parameters and variables, and deal with complex forms of dynamic interaction. Moreover, computational models provide an ideal environment for experimentation. Once a model is operating correctly it is relatively easy to run experiments. "With modeling a new minitheory can often be developed rather quickly, certainly much more quickly than by the traditional approach of a series of experimental studies to explore a new explanatory conception. The model can serve as a kind of rough draft of the theory allowing a quick preliminary check on many of the consequences of a theory. If the model makes predictions that are obviously incorrect, that difficulty can often be uncovered in a less painful and time consuming fashion when simulating" (Lehman, 1977, p.13). The model can therefore be used to ask "what-if" questions, and to produce answers that are compared with the results of real experiments whose findings motivate more sophisticated models which are used to produce still more interesting results, thus giving raise to a virtuous circle that will advance our understanding.

2.3. Serendipity and emergence

The most relevant advantage of computational modeling derives, however, from the heuristic power that is associated with it. This idea has been stated clearly by James McClelland: "The key point here is that an explicit computational perspective often leads to new ways of understanding observed phenomena that are apparently not always accessible to those who seek to identify subsystems without giving detailed consideration to the mechanisms involved" (McClelland, 2000, p. xxi). These new ways of understanding may assume several forms. They can derive, for instance, from the discovery of a single unifying principle that will explain a set of hitherto seemingly unrelated facts. They can lead to the emergence of complex, holistic forms of behavior from the specification of simple local rules of interaction. New ways of understanding can arise from unexpected results that defy the modelers' intuition. They could be obtained by pushing the model beyond its limits and by applying it to situations that it was not originally intended to face.

Computational modeling presents, however, also some disadvantages and side-effects, of which modelers should be aware. Almost paradoxically, these disadvantages constitute the complementary side of the benefits.

2.4. Irrelevant specification

While a running model guarantees the completeness of the underlying formulation (if a program is incompletely specified, it will simply refuse to run), it could engender what Lewandowsky (1993) called the irrelevant specification problem, i.e., the fact that sometimes it is necessary to make design decisions on issues that, while being theoretically irrelevant from the modeler's point of view, could have a significant impact on the model performance. In many circumstances, these decisions are likely to involve aspects of the problem the modeler is not interested in. Because these choices are made only to be able to implement the model, they should be considered theoretically neutral and fully interchangeable with any viable alternative: whatever decision is made, it should not have any influence on the model's results. This is however not always the case, and the model behavior could be strongly affected by "irrelevant" details such as the data structures being used or the idiosyncratic features of the scheduler that drives the simulation.

2.5. Accessibility and comprehensibility

A second problem constitutes the back side of the clarity and precision obtained through computational modeling. While a verbal formulation could be loose and underspecified, it is also generally understandable without too much effort by people having the sufficient background knowledge. Computational models are more precise. If there exist any doubts in the interpretation of a specific detail it is always possible to look back at the code. Unfortunately, while everybody is capable to follow a discussion stated in verbal form, access to code requires specific competence and skills that are not universally shared.

2.6. Bonini's paradox

The possibility to test complex domains has its counterpart in what is known as the Bonini's paradox: "As a model of a complex system becomes more complete, it becomes less understandable. Alternatively, as a model grows more realistic, it also becomes just as difficult to understand as the real-world processes it represents" (Dutton & Starbuck, 1971, p. 4). In other words, the risk we run in developing intricate and elaborate models is that they are no more understandable than the phenomena they are intended to explain.

3. Hints for a good modeling practice

To take full advantage of the benefits and to limit the shortcomings associated with computational modeling, several pieces of advice have been put forward. Most of these concern two critical points in the modeling endeavour, i.e., model validation and the choice among competing models.

3.1. Model validation

One of the most important and most debated aspects of cognitive modeling is *validation*, i.e., the problem of establishing how adequately the model reflects those aspects of the real world it has been designed to model. Conceptually the problem seems simple: if the results obtained by running the model match those obtained by running experiments with human participants, the model is validated, otherwise it should be rejected. Traditionally, several measures have been used to show that the model fits the data, i.e., that the model parameters can be adjusted so that the output of the model replicates the real results.

In the last years this practice has met several criticisms which are summarized in a paper by Roberts and Pashler (2000). Basically, three objections have been raised to goodness of fit: (a) it is often unclear which specific predictions the model makes, i.e., how much it constrains the data to be fitted; (b) data variability is often not clearly defined, i.e., it is not evident whether the data agree not only with the model predictions but also with the outcomes ruled out by the model; (c) the a priori likelihood that the theory will fit—i.e., the likelihood that it will fit whether or not it is true—is ignored. From these criticisms three pieces of advice immediately follow, i.e. the modeler should: (a) determine the model predictions by varying each free parameter over its entire range (or by parameter space partitioning: Pitt, Kim, Navarro, & Myung, 2006), (b) report the variability in the data, and (c) show that there are plausible results the model cannot fit.

The Roberts and Pashler (2000) paper gave raise to a lively debate. Schunn and Wallach (2005) argued that exploring the fit of a model to data is an important goal by itself and that obtaining a good fit is not a trivial result. In the same vein, Stewart (2006) proposed a methodology to be used to address some of the issues that Roberts and Pashler found to be problematic. By relying on all these contributions, it is possible to draw some guidelines for the model validation processes. We mention here only the most important pieces of advice you can find in them:

1. Take both deviation and trend measures into account. It is important that the evaluation of a model be based on two different kinds of measures: those that quantify the deviation of predicted data from the observed ones (e.g., MAD, RMSD, and RMSE) and those (like r^2) that take into account the trend relative magnitude.

2. Take the data variability into account. More than producing values that are similar to the sample means, a good model should produce "*statistically equivalent* data. In other words, good models should produce data with the same statistical distribution we find in the real world." (Stewart, 2006, p. 818). In order to evaluate these distributions, Stewart suggests the use of the equivalence testing procedure which assumes as the null hypothesis that the difference between the means of the data being compared, instead of the usual zero, is greater than some amount.

3. Avoid overfitting. We talk of overfitting when the model is too good to be true, i.e., when it fits perfectly a particular data set but does not generalize to new ones. This happens when the model captures not only the general aspects of a phenomenon but also the noise contained in the data. Some statistical and machine-learning techniques

(e.g., use of separate training and test sets, cross-validation, bootstrapping, etc.) allow to appraise and avoid the overfitting situations.

4. Apply relative, not absolute, standards of goodness of fit. In some circumstances, it is easy to obtain unnatural and excessive measure of goodness of fit that do not reflect the real value of the model. For instance, if the data lie on a straight line it is easy to obtain a perfect fit with a linear model with only two free parameters. Thus, according to Schunn and Wallach (2005), absolute standards should not be applied in assessing the quality of a particular goodness of fit value. The fit of a model should be instead evaluated in comparison to those obtained by alternative models, and in relation to the complexity of the data being modeled.

5. Minimize the number of free parameters. With a sufficient number of parameters any model may fit almost perfectly any data. To counteract this argument, Schunn and Wallach (2005) proposed a number of potential solutions such as: (a) the adoption of standard parameter values to be used in all the modeling efforts, (b) giving semantic meaning to the parameters, (c) discussing complex models in terms of more abstract, and approximate, models that have fewer free parameters and clearer predictions, and (d) conducting sensitivity analyses to ascertain how much the fit depends on the particular parameter values.

3.2. Model comparison and selection

Distinct from evaluating the validity and the goodness of fit of a single cognitive model is the problem of comparing several models to choose the one that best describes a given set of results. Its apparent simplicity notwithstanding, this problem, the so-called *identification problem*, is simply unsolvable. This point was put forward more than 30 years ago by John R. Anderson. "Unique identification of mental structures and processes was once my goal and it seems that it is also the goal of other cognitive psychologists. However, I have since come to realize that unique identification is not possible. There undoubtedly exists a very diverse set of models, but all equivalent in that they predict the behavior of humans at cognitive tasks." (Anderson, 1976, p. 4). Anderson's argument is based on the fact that, because there are problems of uniqueness in the formal automata subspace—where for any well specified behavior there exist many different automata which can reproduce it—there will be even greater problems in the full space of cognitive theories which, even it is not well specified, can presumably include all the types of machines that are studied in the formal automata theory.

Given the fact that there are many different models capable of explaining and reproducing the same behavioral data and that, therefore, asking which is the "true" one is futile, the question of the criteria that should be adopted to choose among competing models becomes critical. Having banned the truth criterion, the theoretical and practical utility seems the most agreed-upon one. "A very important point is that in this particular kind of work, the postulates built into a model need not represent the beliefs of the modeler; rather, they may represent a particular set of choices the modeler has made to try to gain insight into the model and, by proxy, the associated behavioral [...] phenomenon" (McClelland, 2000, p. xxii).

Anderson (1976) breaks down the utility criterion into four subcriteria: (a) *parsimony*, which provides both a relative and an absolute standard for comparing models; (b) *effectiveness*, which refers to the fact that there should be explicit procedures for deriving prediction from the model; (c) *broad generality*, and, obviously, (d) *accuracy*. Following his suggestions, we can articulate some additional recommendations for the modeling practice.

6. Prefer models which are based on general cognitive theories. This means that, in choosing between a model providing a specific explanation for results obtained with a constrained research paradigm and one deriving from a theoretical view addressing a broad range of phenomena, we should prefer the latter. This is the idea underlying the architectural approach to modeling, inspired by the seminal paper of Newell (1973). Cognitive architectures "are task-general theories of the structure and function of the complete cognitive system. They are general theories of how perceptual, cognitive and motor processes interact in producing behavior, rather than specific theories of behavior on a single task (e.g., the Stroop task) or behavior in a single functional domain (e.g., working memory)" (Cooper, 2006, p. 200). It should be noted that developing a model within an existing architecture also helps to reduce the impact of the irrelevant specification: model features that need to be specified but are not immediately related to the task are usually provided by the architecture, and have undergone independent verification. Relying on cognitive architectures, moreover, contributes to reducing the number of free parameters of a model and seriously bounds the dangerous practice of ad hoc theorization. The architectural approach has gained consensus in the cognitive modeling community. Several architectures such as ACT-R (Anderson et al., 2004; Anderson & Lebiere, 1998), Soar (Newell, 1990), 4-CAPS (Just, Carpenter, & Varma, 1999), EPIC (Meyer & Kieras, 1997) and Clarion (Sun, 2002) have been developed in the last two decades and models based on them are used to address specific tasks within a unified theoretical framework.

7. Prefer simple models. As we saw in the previous section, an arbitrarily complex model can fit almost everything. A feature to be taken into account in evaluating models is therefore their complexity (Myung, 2000). To this end, several criteria (e.g., Minimum Description Length, Akaike information criterion, Bayesian information criterion) have been proposed that assess the goodness of fit values in relation to the model complexity.

8. Prefer interesting and counterintuitive models. Under the assumption that "... if a model doesn't have any surprises, then it may not be a very good model" (Dawson, 2004, p. 24) we should prefer models that provide a novel

and original contribution to our understanding and that do not simply repeat and refine what is already known.

9. Prefer precise and easily falsifiable models. Scientific models should be falsifiable (Bamber & van Santen, 2000). The more precise the predictions made by a model, the easier is to falsify it. Bold, sharp and risky predictions are virtues for a model.

10. Prefer integrated models, i.e., models that take into account, or are possibly inspired or compatible with, different data and different knowledge. Researchers may divide on the level they prefer to see and explain human behavior, but a good model should in principle be compatible with all of them.

4. The papers in this issue

The papers contained in this issue represent an interesting array of the results that could be obtained by following a good modeling methodology.

The paper by **Grecucci, Cooper, and Rumiati** is an example of a strain of connectionist models (e.g., O'Reilly & Munakata, 2000; Rolls & Treves, 1998) which devote increasing attention to the biology and physiology of the systems they try to reproduce. Building upon a notable example of integrated framework within the connectionist approach (i.e., Leabra: O'Reilly & Munakata, 2000), Grecucci et al. model the impact of emotion in the execution of motor actions which are either identical to or different from the perceived ones. It has been pointed out in the previous section that the complexity of computational models often obscures their real value in fitting experimental data. This, in turn, prevents a real understanding of the proposed explanation and a deeper examination of the models themselves. Taking seriously these issues, Grecucci et al. have been extremely careful in their approach. Being their model inherently complex, the authors choose to explicitly lay down each of its individual underlying assumptions, and to justify them on the basis of previous research and neuropsychological findings. Consistently, they did not simply report how well the model reproduces human data, but tested independently each of the assumptions, thus providing the reader with a deeper insight of the empirical findings and of how well the model captures them. Finally, they successfully enriched their model with an additional layer representing the dorsolateral prefrontal cortex providing important cues on how the model can be broadened and how it can be interfaced with other aspects of cognition.

The paper by **Chuderski, Stettner and Orzechowski** constitutes an important example of how psychological theory and computational modeling can be fruitfully integrated. Starting from the need to provide a convincing explanation for a complex (and puzzling) set of results in a classical short-term memory paradigm—Sternberg (1969) task—Chuderski et al. developed a model that is partly grounded on the ACT-R (Anderson et al., 2004; Anderson & Lebiere, 1998) cognitive architecture. However, their model combines basic assumptions drawn from this theory with a detailed account of search processes. The model assumes that search is initially targeted to elements under the focus of attention. If this first stage of search fails, then participants may try to retrieve items from declarative memory. This model is able to offer a good account for a complex pattern of experimental results (latency *and* accuracy data). Moreover, the model is able to capture individual differences in search modes through the variation of a single, theoretically grounded, parameter which controls the extent of the focus of attention.

This paper is an example of how a single model can offer an explanation for a complex pattern of data. As we have previously stated, the capacity to provide a unitary explanatory framework for an apparently disparate constellation of phenomena represents one of the most valuable advantages of cognitive modeling based on cognitive architectures. It is noteworthy that also the analysis of individual differences assumes a significant role in Chuderski et al.'s work. This paper shows how it is possible to seamlessly integrate the analysis of individual differences in cognitive models, thus increasing their explanatory capacity.

Chuderski et al. followed a number of good methodological practices. First, extensive psychological justification for the model assumptions is provided. This practice is unfortunately not very common in cognitive modeling, despite the fact that only a convincing psychological/neural justification of the model assumptions may support its plausibility. Next, the model is fitted to a complex pattern of data, thus creating the conditions for its potential falsification. Finally, the authors suggest other research problems and situations in which the predictions of the model can be tested. As we previously reminded, the capacity to formulate novel and counter-intuitive predictions is a critical dimension to be considered in the evaluation of models. Cognitive modeling can help the researchers to figure out novel predictions, given that it is relatively easy to explore how a model would face a novel situation and to generate predictions on that situation before starting to collect behavioral data.

The paper by **van Maanen and van Rijn** exemplifies the tendency towards integration in yet another way. These authors investigated a widely known and extensively researched experimental task (the picture-word interference paradigm) and modeled participants' behavior within the ACT-R integrated cognitive architecture. The architecture provided them with background constraints on how the task could be performed and participants' behavior be reproduced. Then, they argued for an extension of the architecture itself by examining the time course of interference, where the experimental results suggest the existence of effects that lie beyond the scope of ACT-R's retrieval mechanism. The extension is a modified, non-ballistic retrieval algorithm, which is again informed by a connectionist model of recent generation (in this case, the leaky accumulator model by Usher & McClelland, 2001), and is capable of explaining interference effects occurring in the small interval between the initiation and the completion of retrieval. To accomplish this, the authors successfully abstracted the algorithm to a level where it can be smoothly integrated within an existent framework for more complex behaviors.

The paper by **Tamborello and Byrne** shows another fruitful way to exploit cognitive architectures and their embedded constraints to increase the explanatory power of cognitive modeling. The authors investigated a visual search of menu displays, a well-studied paradigm in the field of Human Computer Interaction. Human behavior is sensitive to the statistical structure of the task and, in particular, to the degree to which highlighted items in a display correspond to the information sought for. An existing successful algebraic model of visual search (Fisher & Tan, 1989) already existed, but it failed to capture the ongoing learning process which eventually shapes the search behavior. Tamborello and Byrne adopted ACT-R to provide a reliable background against which alternative leaning strategies could be tested, and they put forward convincing evidence about the (micro) level at which learning occurs and how it shapes behavior. The use of an architecture is doubly useful in clamping down behavioral constraints and in providing an integrated statistical learning algorithm for human behavior.

Both the contributions by van Maanen and van Rijn and of Tamborello and Byrne nicely exemplify two trends in current computational modeling of cognitive processes. The first is the careful attention paid to alternative strategies and their relevance also in simple, and apparently irreducible, tasks. Even in the Stroop task, for instance, competing strategies may be used to capture and reproduce the interference and facilitation effects (Lovett, 2005) and are compatible with the existence of individual differences in performance (e.g., Long & Prat, 2002). The second is the awareness that even simple experimental paradigms are affected by factors which lie beyond the domain of investigation and often are inconspicuous to the modeler. In the case of van Maanen and van Rijn, it is the interference occurring after retrieval from declarative memory has been initiated. In the case of Tamborello and Byrne, it is the underlying procedural learning and how it exactly shapes the visual search strategy.

The paper by **Kong and Schunn** shows how cognitive modeling can be used to explain human behavior in a complex problem solving task. In their model of the traveling salesman problem (TSP), Kong and Schunn explore how well their hypothesis about the integration of global and local visuo-spatial information processing is supported by the data. In its willingness to tackle complex phenomena, this paper on the TSP reminds the spirit of the prestigious tradition of computational theories of problem solving, which traces back to Newell and Simon (1972).

The first general lesson we can learn from the paper by Kong and Schunn is that cognitive models are unique tools for understanding whether our theories of complex phenomena can stand the reality test (i.e., successfully predict experimental data). In fact, as we have previously pointed out, cognitive modeling allows drawing precise predictions from complex theories, even in situations that cannot be handled by mathematical models. Kong and Schunn investigated the TSP and showed that their model, based on a limited number of clearly stated assumptions, represents a plausible explanation of participants' behavior. Additionally, this paper proves that cognitive modeling is not limited to verbal tasks, but can be also profitably applied to visuo-spatial cognition.

From the methodological viewpoint, two important aspects can be underlined. First, the paper by Kong and Schunn exemplifies how precise and detailed the description of a model should be. Second, this paper applies a core methodological guideline in modeling: i.e., comparing alternative accounts in their capacity to fit the data. Kong and Schunn contrasted their model and four alternative explanations of human performance in the TSP. Competitive modeling is useful because it forces the researchers to be clear about differences between theories. Moreover, in order to set the ground for critical tests and falsification, it leads the researchers to be explicit about what each theory does and does not predict.

The paper by **Dzaack, Trösterer, Pape and Urbas** applies cognitive modeling to time estimation. Dzaak et al. propose a model of retrospective time estimation that can be integrated as a module in the ACT-R architecture. Then, they evaluate the model capacity to fit the data on retrospective estimation of trials composed by D2-Drive task performance and idle periods.

This work shows how cognitive modeling requires a detailed specification of the processes involved in a task (unlike verbal theories, generic neural theories, and box-and-arrows accounts). Additionally, it is an example of incremental modeling. Incremental construction of theories, from the methodological point of view, reduces significantly the number of assumptions and free parameters that are used to explain the data.

Finally, it is worth underlining that the model presented by Dzaac et al. deals with time estimation processes, which do play a major role in real-word contexts. Well-supported and plausible models of retrospective and prospective time estimation can be very useful in applied research settings and in the real world. In fact, they allow predicting and simulating human performance in a variety of important contexts (e.g., reactions to waiting times in Human Computer Interaction/Human Machine Interaction or for services, behavior in queues, time estimation while driving or piloting). This reminds us that cognitive modeling can be used also as a prescriptive device, supporting prototyping and design of technological artifacts and displays, but also complementing more traditional types of environmental, economic, and social planning.

The paper by **Baughman and Cooper** proposes a simple and elegant explanation of the differences in performance between two groups of children (3–4 vs. 5–6 years old) working on the Tower of London task where younger children show a tendency to break more task rules and to produce more incomplete solutions. The authors claim that this tendency could be explained in terms of the development of the executive functions, more precisely by postulating a stronger role of inhibition in the older group.

The authors developed two computational models, implemented in the Cogent modeling environment (Cooper, 2002) that simulate two different solution strategies employed by the groups. The models are based on the theory of control of cognitive processed developed by Norman and Shallice (1986). Being expressed only verbally, the theory was not sufficiently specified to allow the construction of a fully mechanistic account of the problem solving processes. Its implementation in the Cogent environment, however, allowed the authors to derive precise predictions that match the behavior of the two groups. By basing their models on a sound theory, the authors were able to show the emergent nature of control that arises from the interaction of the two structures hypothesized by the theory, i.e., the contention scheduling and the supervisory attentional system, offering thus a bridge between the traditional approaches to problem solving and the accounts based on theories of executive functions and data from the neurosciences.

One of the questions modelers often ask themselves is how the performance of their model changes when some of its features are changed. This generally means to adjust the numerical parameters of the model. Another interesting, but less studied, aspect is that of establishing how the results vary if we modify some of structural aspects of the model.

The paper by **Stewart and West** deals with this issue by providing en environment which facilitates the exploration of the space of the possible models based on ACT-R. Relying only on the theoretical description of the architecture and not on the standard implementation, the authors rebuilt a version of ACT-R in Python, a clean programming language which is robust, easy to maintain, and effective as a rapid prototyping tool. The new system, Python-ACR emphasizes a clear separation between the theoretical and implementational part of ACT-R, solving at least partially the irrelevant implementation problem.

An interesting side effect of this effort is that, during the reimplementation phase, the authors developed a new vision of how the architecture could be used. ACT-R is normally considered as comprising a set of separate modules, a set of buffers used for communication, and the traditional components of declarative memory (with its chunks) and procedural memory (with its productions). These last elements could be used, according to Stewart and West, to describe a ‘‘generic’’ module instead of being limited to define the different kinds of knowledge held in memory. In other words, it should be possible, in principle, to describe other modules each having its own declarative and procedural subpart.

Building a Python ACT-R model could thus consist in defining the production systems (please, note the plural), the associative learning systems (as before), the buffers and the connections between these systems. The different models created in this way can then be compared, just as models with different numerical parameters settings are compared in most other cognitive modeling research.

The paper by **Kennedy and Trafton** deals with a problem that is rarely addressed in the cognitive modeling community, i.e., exploring an important phenomenon or an interesting task by using different architectures. Because a model combines general architectural constraints with domain-specific knowledge, the failure of the model to replicate empirical data is generally attributed to the latter and not to the former. There is a widespread belief that cognitive architectures should be viewed not as theories subject to Popperian falsification, but rather as Lakatosian research programs based on cumulative growth (for an insightful discussion of this issue—raised by Newell, 1990—see: Cooper, 2006).

Kennedy and Trafton investigated the characteristics of long-term symbolic learning in Soar and ACT-R by running cognitive models of simple tasks in the blocks world domain. They examined whether symbolic learning continues indefinitely, how the learned knowledge is used, and whether computational performance degrades over the long term.

As far as the first question is concerned, it was found that in finite domains symbolic learning eventually stops in both Soar and ACT-R, a finding that, according to the authors, suggests that learning will stop in humans, too. The two architectures differ, on the other hand, in the use of learned knowledge, with Soar that makes immediately available the new acquired procedures and ACT-R that requires many learning episodes before a new production would be usable. Finally, both architectures suffer from computational performance problems with long term learning.

Kennedy and Trafton's work is thus an interesting example of how it is possible to compare and contrast different architectures to advance our knowledge of cognition.

To summarize, we think that the papers composing this issue constitute a significant case for cognitive modeling and a clear illustration of the advantages modeling could provide to cognitive science. We hope you will enjoy reading them and, possibly, get inspiration for your own work.

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