How to Assess ACT-R Models Predicting BOLD Curves for a Complex Problem

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Introduction

Cognitive architectures provide a modeling framework with constraints preventing modelers from creating unrealistic models of human cognitive processes (Gray, 2007; Gluck, Pew, 2005). One of the most prominent architectures is the ACT-R-architecture (Anderson, 2007). It has a long tradition, dating back at least to 1983 (Anderson, 1983).

The ACT-R (Atomic Components of Thought-Rational) cognitive architecture (Anderson, 2004; 2007) consists of eight modules: The Visual, Aural, Manual, Vocal, Declarative, Imaginal, Goal, and Production modules. Obviously, they perform specific functions: The Visual and Aural modules control the perceptual input of an ACT-R model, while the Manual and Vocal modules constitute its action apparatus. The Goal module stores the current goal, while the Imaginal module represents working memory. The Declarative module's purpose is to retrieve facts from long-term memory. All of these modules interface to the Production module via buffers. A buffer may hold a single chunk (i.e. fact) at a time. The Production module represents the procedural memory and matches, selects, and executes production rules, which compare and manipulate the buffers' contents. Each action triggered by a production in a specific module consumes a certain amount of time. A model based on this architecture is an executable program in the form of production rules which may be used to determine predict a participant's performance in various tasks on trials of various domains, such as algebraic problem solving.

Anderson's Brain Mapping Hypothesis (Anderson, 2007) maps the activity of the ACT-R modules onto specific brain regions. Thus, ACT-R implements a tooling that enables Blood-Oxygen Level-Dependent (BOLD) signal predication for these brain regions. However, these regions only cover a very small volume of the brain, and most studies were conducted using simple tasks with a limited strategy space.

Research Question

The first research question of our sub-project was to study the robustness of the Brain Mapping Hypothesis towards a non-algebraic task, a multidimensional strategy space, and programming or modeling errors.

Methods

A trial problem consists of the visual and auditory presentation of a name for a chemical compound and two structural formulae which were presented to the left and the right on the screen. The participant has to decide which one of these matches the compound name (for task details see Anschütz et al. this volume). The following constraints are known to the participant (Möbus, Lenk et al., 2011).

1. The abbreviation for an element is defined by two letters
2. The first letter of the abbreviation is the same as the first letter in the name of the element.
3. Both letters appear in the element's name.
4. An element may have a multiplicity from 1 to 4 in the compound. Distinct three letter words served as numerals to denote the multiplicity:
    a. 1 /–
    b. 2 /pli
    c. 3 /pla
    d. 4 /plo
5. The position of a numeral is always in front of the owning element in the compound name.
6. The central element of the structural formula is always the first in the compound name.

We used data from 62 children, ages 10 to 13, who took part in the fMRI experiment (see Özyurt and Thiel, this volume for details on the fMRI experiment). Each participant underwent a total of 80 trials during two sessions.

The chemical formula language is usually not known to children of that age group. Nevertheless, fictitious chemical elements and their abbreviations as well as numerals were used to prevent carry-over effects. The children were familiarized with the above constraints by undergoing an extensive instruction and training phase.

Models

During the task analysis, it became clear that this seemingly simple problem may be solved by applying a multitude of strategies. For instance, the participant may constrain him- or herself to study either only the left or the right structural formula exclusively and subsequently decide whether it matches or not. Alternatively, the participant could check characteristics on both formulae until a violation of the above constraints is detected for one formula. Also, some aspects of the trial may be processed multi-threaded as opposed to single-threaded processing. Still, there is a great degree of freedom for the ACT-R modeler to implement these strategies. A participant may change the strategy across trials, or in the worst case, during a single trial.

Out of these considerations, six ACT-R models were implemented. Model S1a and S1b were multi-threaded and evaluated only one structural formula, either the left or the right. Model S2 is also multi-threaded, but checks certain characteristics on both formulae for violations. Along these lines, S3a and S3b were single-threaded counterparts of S1a and S1b evaluating only one formula. S4 is single-threaded and again checks both formulae.

Data Aggregation

Individual BOLD curves were extracted for each participant from the regions defined by Anderson. Each module was mapped onto two regions for each brain hemisphere. Then, the individual BOLD curves were aggregated. For this purpose, we constructed a Bayesian Belief Network (BBN), which allowed us to infer the probability that a specific strategy had been used by a participant based on the participant's response time (RT) and characteristics of the trial (Figure 1). The BBN had been trained prior with ACT-R model data. These probabilities were used as weights for the aggregation of the individual BOLD curves, which resulted in a strategy-specific BOLD curve that was then compared with the BOLD prediction of the corresponding model.

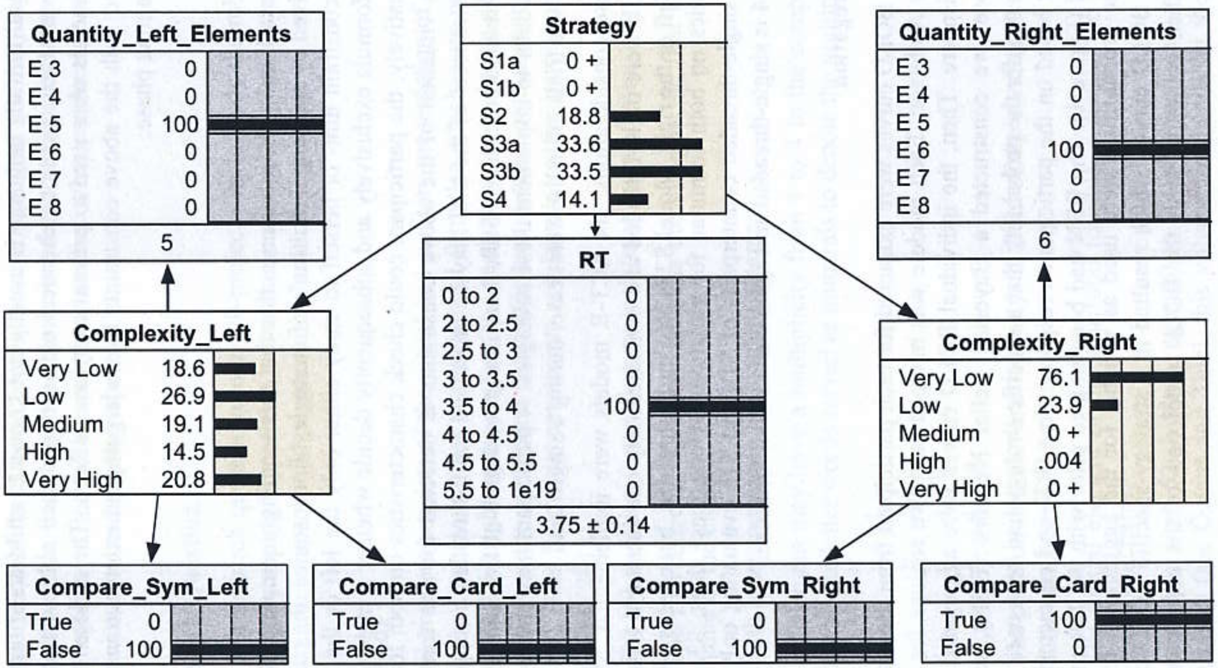

Fig. 1 The Bayesian Belief Network used to infer a participant's likely used strategy

We first compared the complete time series of the time series with about 400 data points which showed generally low correlations (Möbus, Lenk et al., 2010). We then applied the aggregation method from Carter, Anderson et al. (2008), which allowed us to align the scans from different trials and individuals onto a template and subsequently aggregate the data. However, we modified the method by using the probabilities from the BBN as weights in the aggregation again. Model predictions were likewise aggregated and Pearson's correlation coefficients have been computed for strategy model predictions and strategy-specific BOLD curve aggregations.

Results

These coefficients (Table 1) are high for all modules but the Goal module. This indicates a faulty assumption in the modeling process. Indeed, all strategies place a single chunk in the Goal buffer at the start of each trial and thus produce little activity in this module. Generally, most correlation coefficients were heightened by the weighting process. This is especially the case for the Manual module, which may be easily explained as the RT (triggered by manual action) is the prime indicator for a strategy in the BBN.

Tab.1 Correlation coefficients between models' BOLD predictions and brain regions in the left hemisphere for weighted (w.) and unweighted (Uw.) aggregation (Möbus, Lenk et al., 2011)

	Production		Imaginal		Goal		Declarative		Visual		Aural		Manual	
	Uw.	w.	Uw.	w.	Uw.	w.	Uw.	w.	Uw.	w.	Uw.	w.	Uw.	w.
S1a	0.985	0.992	0.858	0.892	-.917	-.930	0.938	0.966	0.888	0.827	0.917	0.916	0.733	0.840
S1b	0.983	0.990	0.858	0.890	-.917	-.931	0.934	0.966	0.888	0.824	0.917	0.919	0.740	0.856
S2	0.977	0.974	0.858	0.861	-.917	-.930	0.934	0.941	0.981	0.982	0.917	0.930	0.600	0.665
S3a	0.894	0.888	0.870	0.876	-.917	-.914	0.875	0.858	0.862	0.854	0.918	0.924	0.302	0.351
S3b	0.891	0.886	0.870	0.875	-.917	-.912	0.871	0.853	0.863	0.856	0.918	0.923	0.295	0.345
S4	0.829	0.851	0.870	0.822	-.917	-.837	0.825	0.778	0.500	0.480	0.918	0.896	0.074	0.320

Also, asymmetries can be found in the data. Most module and region pairs correlate higher with the left hemisphere (Figure 2), with the notable exception of the Imaginal module, which correlates slightly higher with the right. The Manual module correlates negatively with the right hemisphere. This is in accordance with the literature (Mattay et al., 1998), as the participants responded with their right hand. No model performs best for all module/region pairs, but generally the multi-threaded model S1a, S1b, and S2 show the most accurate BOLD predictions.

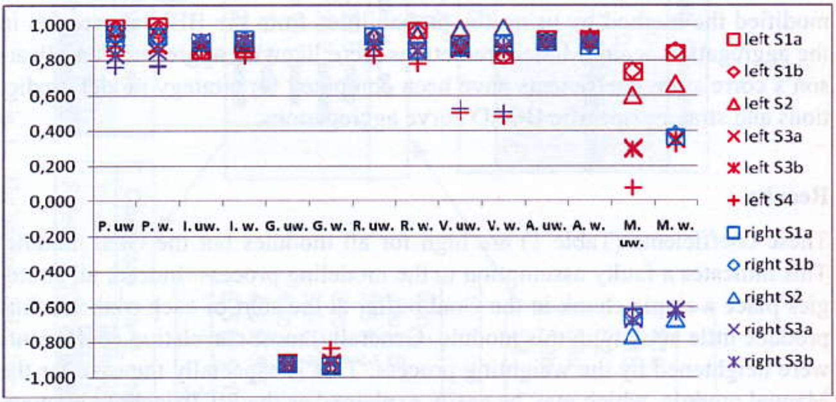

Fig. 2 Correlation coefficients for both hemispheres. On the horizontal axis are the module/region pairs and weighted (w.) vs. unweighted (uw.) aggregation. The vertical axis shows the correlation coefficient ranging from -1 to 1

Conclusion

We were able to show that the ACT-R Brain Mapping Hypothesis also holds in large parts for tasks with multi-dimensional strategy spaces. However, it has been shown that an ACT-R model which explains behavior does not necessarily predict fitting BOLD curves, and thus, due to ACT-R being underconstrained, the modeler cannot hope to conceive a valid model, even if based on fit to behavioral data, for BOLD prediction in the first run. Thus, we suggest four options for our further research: First, one could try to simplify the problem, in order to separate the cognitive functions (such as transformation, perception, and goal setting) in time. But this would also mean missing out on the opportunity to study the Brain Mapping Hypothesis in relation to complex problems, and this is also already a prominent approach in prior research by Anderson and others.

Second, one could try to tune the parameters of ACT-R's BOLD prediction tooling (Anderson et al., 2008). This is an interesting approach as these seem to affect shape and magnitude of the predicted BOLD curves greatly.

The third approach is to find alternative Regions-of-Interest (ROIs) in an independent data set since the current ACT-R Brain Mapping Hypothesis covers only a small fraction of the brain. This could be done for example by Independent Component Analysis (ICA) (McKeown et al., 1998; Friston, Büchel, 2007). Such approach would enable to identify feedback-related brain regions and to incorporate these in to the model. Finally, the modeling itself may be questioned. We implemented only six ACT-R models, but many more are conceivable. Indeed, the goal setting strategy has to be refined, which is clearly shown by our results.

The models we presented here may be called first-pass models (Carter et al, 2008). Our second-pass models will incorporate the findings from the fMRI analysis, and should, along with Bayesian strategy classification, provide better insight on how to handle ACT-R's BOLD prediction capabilities within multidimensional strategy spaces.

Furthermore, we had to realize that at the present moment it is not within the state of the modeling art to generate an ACT-R model of a human student with motivational states as curiosity, happiness, or frustration. This is due to the fact that the granularity of process descriptions that ACT-R requires and that educational psychologists are willing to provide differs widely.

Literature

Anderson, J. R. (1983). *The Architecture of Cognition*. Cambridge, MA: Harvard University Press.

Anderson, J. R. (2007). *How Can the Human Mind Occur in the Physical Universe*. Oxford: Oxford University Press.

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., Qin, Y. (2004). An integrated theory of the mind. *Psychological Review, 111*, 1036–1060.

Anderson, J. R., Fincham, J. M., Qin, Y., Stocco, A. (2008). A central circuit of the mind. *Trends in Cognitive Science, 12*, 136–143.

Carter, C. S., Anderson, J. R., Fincham, J. M., Ravizza, S. M., Rosenberg-Lee, M. (2008). Using fMRI to test models of complex cognition. *Cognitive Science, 32*, 1323–1348.

Friston, K. J., Büchel, C. (2007). Functional connectivity: Eigenimages and multivariate analyses. In: K. J. Friston, J. T. Ashburner, S. J. Kiebel,

T. E. Nichols, W. D. Penny (Eds.), *Statistical parametric mapping: The analysis of functional brain images* (pp. 492–507). Amsterdam: Elsevier.

Gluck, K. A., Pew, R. W. (2005). *Modeling Human Behavior with Integrated Cognitive Architectures*. Mahwah, N. J.: Lawrence Erlbaum Associates.

Gray, W. D. (2007). *Integrated Models of Cognitive Systems*. Oxford: Oxford University Press.

Mattay, V. S., Callicot, J. H., Bertolino, A., Santha, A. K. S., Van Horn, J. D., Tallent, K. A., et al. (1998). Hemispheric control of motor function: A whole brain echo planar fMRI study. *Psychiatry Research*: 924 Neuroimaging Section, 83, 7–22.

McKeown, M. J., Makeig, S., Brown, G. G., Jung, T.-P., Kindermann, S. S., Bell, A. J., et al. (1998). Analysis of fMRI data by blind separation into independent spatial components. *Human Brain Mapping, 6*, 932 160–188.

Möbus, C., Lenk, J. C. (2009). Bayesian identification of problem-solving strategies for checking the ACT-R/Brain-mapping hypothesis. In: U. Schmid, M. Ragni, M. Knauff (Eds.), *Proceedings of the KI 2009 Workshop on Complex Cognition* (pp. 37–47). Retrieved from http://www. opus-bayern.de/uni-bamberg/volltexte/2009/212/ (last access: 2010-10-28).

Möbus, C., Lenk, J. C., Claassen, A., Özyurt, J., Thiel, C. M. (2010). Checking the Brain Mapping Hypothesis: Predicting and Validating BOLD Curves for a Complex Task Using ACT-R. In: D. D. Salvucci, G. Gunzelmann (Eds.), *Proceedings of the 10th International Conference on Cognitive Modeling* 2010 (pp. 163–168). Philadelphia, PA: Drexel University.

Möbus, C., Lenk, J. C., Özyurt, J., Thiel, C. M., Claassen, A. (2011). Checking the ACT-R/Brain Mapping Hypothesis with a complex task: Using fMRI and Bayesian identification in a multi-dimensional strategy space. *Cognitive Systems Research*, in: press, Date accepted 24 Nov. 2010, corrected proof, available online 6 Jan 2011, ISSN 1389-0417, DOI: 10.1016/j.cogsys.2011.01.001.

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Interdisciplinary Perspectives on Cognition, Education and the Brain

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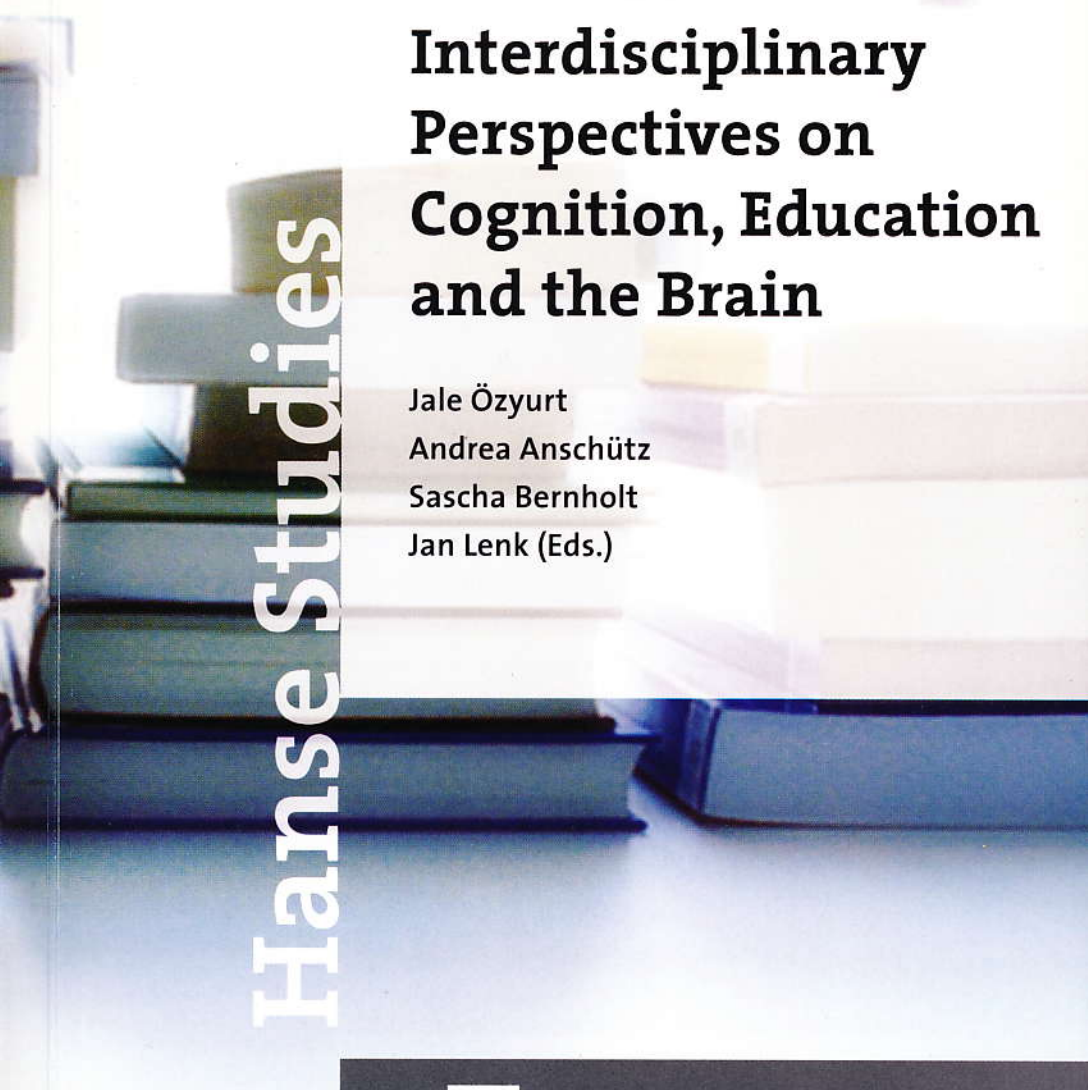

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The Cognitive Neurosciences, with the rapidly growing field of brain imaging in particular, have generated a wealth of findings that bear an interesting potential for the field of Learning and Instruction. Notably, the practical use of neuroscientific data for education has been proven to be modest at present and conjoint effort is needed to integrate neuroscientific findings in educational theory. The current reader, as the result of an international and interdisciplinary workshop at the Institute for Advanced Study in Delmenhorst, aims to provide an insight into the wide diversity of the Educational Neurosciences. It combines recent empirical findings from researchers highly interested in an interdisciplinary exchange at the intersection of the Cognitive Neurosciences, Educational Research, and Cognitive Modeling. The inclusion of the Cognitive Modeling research constitutes a fruitful widening of the field, providing valuable tools for representing and testing cognitive models relevant for both the Educational Sciences and the Cognitive Neurosciences.

Ergebnisse der Kognitiven Neurowissenschaften, insbesondere der funktionellen Bildgebung des Gehirns, haben Erkenntnisse hervorgebracht, die ein interessantes Potenzial für die Lehr- und Lernforschung bergen. Der praktische Nutzen dieser Erkenntnisse ist jedoch gegenwärtig eher begrenzt und für die Integration neurowissenschaftlicher Befunde in die pädagogische Theorie und Praxis bedarf es gemeinsamer Anstrengungen mehrerer Disziplinen. Vorliegendes Buch, das aus einem internationalen und interdisziplinären Workshop am Hanse-Wissenschaftskolleg in Delmenhorst hervorgegangen ist, gibt einen Einblick in die Breite und Vielfalt des Forschungsfeldes »Neurowissenschaften und Lehr- und Lernforschung«. Es vereint neuere empirische Befunde von Wissenschaftlerinnen und Wissenschaftlern, die an einem interdisziplinären Austausch an der Schnittstelle zwischen Kognitiven Neurowissenschaften, Lehr- und Lernforschung und Kognitiver Modellierung interessiert sind. Die Einbeziehung der Kognitiven Modellierung stellt eine fruchtbare Erweiterung des Forschungsfeldes dar. Modellierungsansätze können wertvolle Instrumente für die Repräsentation und Testung kognitiver Modelle bereitstellen, die sowohl für die Lehr- und Lernforschung als auch für die Kognitiven Neurowissenschaften relevant sind.

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