

Further Commentary on Weitz, Durnin and More Generally Deep Infrastructures in TICL

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I would like to commend Weitz et al for their thoughtful and productive critique of deep infrastructures in TICL. While the focus is on production systems and constraint based modeling, they also make a number of worthwhile suggestions having general relevance. The two most important are: a) the need for more scientifically valid comparisons of intelligent and other highly adaptive tutoring systems and b) the suggestion that investigators publish details of the productions and/or other deep infrastructures on which their systems are based. Without this, it is impossible to compare alternative systems. Since it often is not practical to publish details in Journal format, their suggestion that these be made available on referenced websites is certainly desirable.

In commenting on SLT, Weitz et al are also correct that the “proof of the pudding is in the eating”. I certainly wouldn’t disagree that SLT provides a comprehensive and integrated theoretical foundation. I am not sure, however, whether the authors are familiar with the considerable progress that has been made recently in the development of actual intelligent (which I have called “highly adaptive”) tutoring systems.

In this context I would like to comment at three levels:

1. Why existing tutorials based on SLT are unique in not requiring empirical testing in the same sense as others (e.g., those based on production systems, constraint based modeling or relational models).
2. How TutorIT tutorials developed using AuthorIT and based on existing SLT can naturally be extended to deal with more complex domains.
3. An intriguing, non-obvious but highly speculative analogy between classical Newtonian and relativity theory in physics, on the one hand, and production system based theories and SLT in TICL, on the other.

Considering the ground to be covered, my comments will be brief. They draw heavily on recently published material on SLT and the current status of associated technologies. Scandura (2005) summarizes much of the work on AuthorIT and TutorIT up to that time. My recent monograph on SLT (Scandura, 2007) is fairly comprehensive, and familiarity with that is essential for full understanding of what I say below.

1. *Need for Empirical Testing* -- Currently, our AuthorIT authoring and TutorIT delivery systems are being used in a low budget environment partly funded by the National Science Foundation to develop a series of highly adaptive TutorIT tutorials. These tutorials are targeted at well defined basic math skills (e.g., column subtraction, multiplication facts, long division) -- with the utopian goal of guaranteed learning. Rather than traditional empirical evaluation, this guarantee is based on what measurement folks call “construct validity”: Any student who enters with pre-specified prerequisites and who completes a given tutorial will necessarily

have mastered the skill taught. There is no other way a learner can successfully complete one of these tutorials (other than having someone feed answers to the student).

In effect, TutorIT tutors are self evaluating by design. Having said this, guaranteed learning requires complete analysis of the skill to be taught using AuthorIT's AutoBuilder component. While the theory and technologies make this possible in principle, practical considerations may often preclude full analysis. TutorIT is specifically designed to allow for this possibility. Instead of testing each sub-skill on a single test item (which research shows is sufficient given a full analysis), TutorIT can easily be configured to allow for uncertainty. Specifically, TutorIT can be configured to require that each such sub-skill be tested more extensively before mastery can be assumed (Scandura, 2005, p. 213-4). It would be very interesting to compare the respective benefits of this approach in comparison with more traditional statistical methods. Please let me know at scandura@scandura.com if we can be of any help in pursuing such research.

There is no reason in this context (other than time and costs) not to test TutorIT tutorials empirically. For example, a student may not complete a given tutorial for any number of reasons. The results of such studies, for example, may motivate improved questions, instruction, positive or corrective feedback, and/or in the media used to convey such information (e.g., to make them more interesting). Accordingly, I strongly encourage the TICL community to undertake such evaluation independently. Toward this end, we will happily make these tutorials available for research purposes.

2. Extension to More Complex Domains.-- AuthorIT and TutorIT currently deal only with well defined skills. These skills can be arbitrarily complex. Nonetheless, one must specify what is to be learned in all cases. The only kind of inference currently supported is simple chaining (of arbitrarily complex SLT rules rather, for example, than simple productions). While supporting the chaining of SLT rules represents an advance of sorts, SLT goes much further. As recently extended and refined (Scandura, 2007, p. 194-216), Structural (domain) Analysis offers a well defined method for detailing higher (as well as lower) order knowledge necessary in complex problem solving. This includes complex domains where it is impossible (or impractical) to identify any finite set of SLT solution rules.

Another key distinction between SLT and other deep infrastructure theories (e.g., various versions of ACT) is that SLT assumes a single Universal Control Mechanism (UCM). Others, such as ACT, have introduced multiple and varying learning mechanisms through their long history, with no firm conclusion in sight (see Ohlsson & Mitrovic, 2007). AuthorIT and TutorIT were designed with the above in mind so extension to support ill-defined problem solving is essentially a matter of time and resources.

In this context, let me make one further comment on higher order knowledge. In my recent monograph (Scandura, 2007, p. 190), I listed schematics for several basic types of higher order rules (e.g., composition/chaining, analogy, generalization, selection, automation/chunking). The higher order rules resulting from SA of any particular (complex) domain typically will involve variations and/or combinations of such types. Automation rules, involving the conversion of procedural knowledge to structural knowledge, represent one important type. I did not, however, include any examples illustrating what is involved (p. 259). I take this opportunity to add some clarity.

According to SLT, automation rules play an essential role in acquiring expertise in any given area. The question is how automation rules are acquired and used. The short answer is in the same way as every other SLT rule. Automated SLT rules are created by application of SLT rules acting in higher order fashion relative to (on) other rules. The mechanism by which automated (versus non-automated) SLT rules are invoked involves higher order selection rules. Consider simple column subtraction: Most of us have learned how to perform column subtraction using the well-known method of borrowing (or regrouping). Others have learned what is known as the equal addition method. As educated adults, we also know any number of short cuts – e.g., an SLT rule, whereby any pair of numbers ending in the same digits (e.g., 38) is subtracted by reference to the significant digits (e.g., $738 - 238 = 500$).

There are any number of similar “tricks”, where the procedure involved is relatively simple and the structure being operated on is relatively complex. Such tricks are learned over time in the same way as any other SLT rule – by application of higher to lower order SLT rules. Once learned, what we know as “automation” essentially involves rule selection. In this case, for example, a higher order rule might select SLT solution rules based on comprehensiveness of their structures (or simplicity of their procedures).

3. An Intriguing, Highly Speculative Analogy with Relativity Theory.-- Let me also take this opportunity to make a highly speculative observation: I'm not prepared to defend or fully elaborate the idea here, but there is an intriguing analogy involving 20th century developments in physics and choices we must make today in TICL. In Newtonian theory a fundamental assumption is that all motion is relative to a fixed set of coordinates. In 1905, Einstein argued to the contrary that motion is properly measured relative to whatever coordinate system may be relevant (Einstein, 1961). This in itself would not have done very much. However, the empirical fact that light travels at a constant speed in all directions led to fundamental changes in the way we view our universe, including what every schoolboy knows as $E = mc^2$.

It would be foolish of me to make more of this than circumstances warrant. On the other hand, the following analogy is potentially intriguing. I put it forth in this context primarily to help motivate deeper thinking in TICL. Why now ? By happenstance, while at my daughter's home, I came across a popular treatment of the essentials and motivations leading to relativity written years later by Einstein himself.

This analogy derives from the fact that contemporary instructional systems can be based either on:

- a) modeling psychological learning theories (e.g., based on ACT or similar theory based on production systems and/or constraints in learner minds), or
- b) SLT, based on abstract syntax trees (SLT rules), which combine both declarative and procedural knowledge and represent what is to be learned.

In the former case, a fixed set of assumptions is made regarding to be learned elements (e.g., productions) and learning mechanisms. Instructional decisions are based thereon. Each such learning system begins with a fixed set of components and some fixed set of learning mechanisms. (It makes no difference whether or not those components include error as well as correct productions.) All are fixed once and for all. Adding or eliminating, even changing the order of productions, may require reworking the entire system. Changing learning mechanisms typically requires even more fundamental revision.

In SLT, on the other hand, SLT rules, whether of higher or lower order, are derived directly from whatever a content domain requires. Moreover, SLT rules associated with any given domain are not identified in the abstract. Rather, they depend on a knowledgeable observer – a subject matter expert, for example, who is doing the analysis. Different experts may have different views on what is important to learn. Indeed, the same subject matter expert may be, in fact frequently is able to view the same subject matter from more than one perspective – involving multiple sets of SLT rules.

Each of these views is roughly analogous to a different coordinate system in relativity theory. In such a diverse system, then, is there anything corresponding to the speed of light that holds things together? As it turns out, the answer is “yes”. The Universal Control Mechanism (UCM) in SLT serves precisely that role (pp. 175-77, 216-31). UCM provides a common denominator of sorts, which is invariant and does not change as do the SLT rules and higher order rules representing knowledge associated with any given domain.

There is significant empirical support for UCM going back to my first attempt to formulate SLT as a unified theory (1971). Research over the years is summarized in my recent monograph (Scandura, 2007). Perhaps most significant are several core experiments published in the *Journal of Experimental Psychology*, which caused a lot of debate (and confusion) when first published. Implications of UCM in conjunction with interacting higher and lower order SLT rules is perhaps best illustrated by a series of experiments conducted by Wally Wulfeck. In these studies lower and higher order rules were learned in different orders effecting the amount of derivation required on specific problems. It is hard to imagine predicting the differential solution times cited on p. 261-4 in Scandura (2007) by any other means.

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