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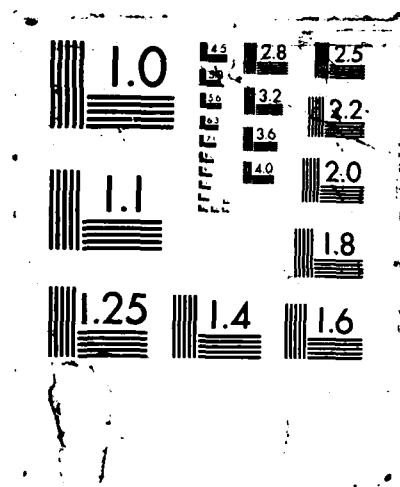
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IMPLICATION OF REAL TIME PROBLEM SOLVING:

FINAL REPORT

EARL HUNT

University of Washington

NOVEMBER 1987

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19 ABSTRACT (Continue on reverse if necessary and identify by block number) Hybrid computer simulations of problem solving can be constructed by combining the production system architecture with a semantic activation process for selecting productions. This technique has been used to construct simulations of problem solving done under time pressure, and in the presence of interruptions. The power of the simulations is limited by the pattern recognition capacity of the semantic networks. This has been analyzed and some mathematical limits obtained. Whether these (or analogous) limits apply to connectionist networks is to base pattern recognition on case-based memory models, which store specific experiences rather than statistical associations between features of experiences. A study is presented showing that case based models may be an alternative to semantic networks. <i>Key words: ...</i>				
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Figure 2.3. Report Documentation Page, DD Form 1473.

1. Introduction

This is the final report for ONR contract N00014-84K-5553, between the Office of Naval Research (Personnel and Training program) and the University of Washington Earl Hunt was the principal investigator. This report covers work from Jan. 1, 1984 through 30 September 1987

The purpose of this project was to investigate the utility of "hybrid" production-system and semantic activation models as models of problem solving under time pressure. We define a hybrid system as a computer simulation of human problem solving in which the basic steps are represented by pattern-action pairs ('productions', as originally described by Newell, 1973). The system is a hybrid because the selection of the productions themselves is guided by the activation level of nodes in a network. The essential idea is that each production can be thought of as a node in a network, and that the nodes pass activation between them as a function of (a) the extent to which the current situation is an appropriate context for a production and (b) the extent to which nodes (productions) related to the production in question have been activated in the recent past.

To illustrate this idea, consider a simple example from automobile driving. The rudimentary "rules of the road" may be summarized in the productions

- (1) If light is green → go
- (2) If light is red → stop
- (3) If light is yellow → caution.

Each production is obviously associated with a specific context. Productions (1) and (2) also have negative associations, i.e. they inhibit each other. Therefore whenever the activation level associated with production (1) goes up the activation level associated with production (2) should go down, and vice versa. Production (3) is a logical predecessor of production (2). Therefore whenever production (2) is activated the activation level of production (3) should be raised. Similarly, since green lights typically precede yellow lights, activation of production (1) should raise the activation level of production (3), though hopefully to the point at which it is ready to be executed but is not actually executed. The result is a system in which a driver will approach a green light, but be prepared to show caution, be cautious and prepared to stop at a yellow light, and will inhibit accelerating as he/she stops at a red light.

Production system simulations of human problem solving are

well known, so no attempt will be made to describe them here. (See Neches, Langley, and Klahr (1987) for an excellent discussion.) Similarly, semantic networks have been studied extensively (Anderson, 1983). The contribution of this project lies in (a) a combination of the two ideas, in a manner similar to Anderson's (1983) ideas, and (b) extension of the technology to the simulation of tasks in which decision making and memory references have to be made under extreme time pressure.

The overall project can be thought of as being divided into related subprojects. The main theme of the research was set in a paper by Hunt and Lansman (1986) which summarized previous research and established a general theoretical position. Subsequent projects by Richardson and Hunt (1985), Reed and Hunt (1985), and Lundell and Loden (1987) expanded on Hunt and Lansman's ideas by extending them to new areas. The Lundell and Loden paper, in particular, developed a number of new ideas relating this work to the study of parallel distributed processing systems (Rumelhart and McClelland, 1986). A fourth paper, by Hogden and Hunt (1986) presented a mathematical analysis of the behavior of the activation networks considered both in the Hunt and Lansman work and in PDP modeling.

A Ph.D. thesis, by McSpadden (in preparation) has introduced a new theoretical development. In order to understand this development it is useful to consider the general thesis of work involving hybrid systems, such as Anderson's (1983), Thibodeau, Carpenter, and Just's (1982) and our own. That thesis is that human problem solving is based on two systems: a system for transformations of internal representations in working memory and a system that supports the transformation system by pattern recognition and selective activation of information stored in long term memory. The transformational system is well suited for modeling using the production system notation. "Semantic networks," and, more generally, PDP models, are used to represent pattern recognition, the arousal of memories, and learning. Therefore PDP models have served as virtually the only representation of the memory component of hybrid models.

PDP models are based upon the idea that memory stores explicit associations between elements of perceived objects and idea. To return to the traffic illustration, we assumed an explicitly memorized association between yellow and red lights. Hintzman (1986) in a publication that coincidentally appeared in the same issue of Psychological Review as the Hunt and Lansman paper, has proposed an alternative model, in which memory stores specific experiences. We will refer to this assumption as "instance-based memory," where an instance refers to a stored experience.

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Hintzman showed that at least some associations would be implied by retrieval processes used in an instance-based memory. M. McSpadden, in his thesis research, used Hintzman's instance based memory model as the memory and pattern recognition part of a general problem solving model. He then used the combined model to simulate individual subjects' behavior as they learned to operate a computer simulation of a simplified nuclear power plant.

Finally, Hunt and Banaei (1987) have prepared a "general interest" paper, in which the hybrid model was used as a device to explain cross-cultural observations about the relationship between language and thought.

In the subsequent sections of this report each subproject is explained in somewhat more detail. Where appropriate, references are made to technical reports or other publications. Work now in progress (but not funded by ONR) that is extending the ideas developed will also be described. Finally, in the interests of making this report a useful scholarly document as well as a report on past studies, most sections contain a brief retrospective comment evaluating the project and considering issues that it raised.

2. A Unified Model of Attention and Problem Solving:

Hunt and Lansman (1986) describe a hybrid production execution and semantic activation model intended to unite phenomena typically studied under the rubrics of "information processing" and "problem solving." The architecture of the system they considered is shown in Figure 1. It consists of a 'blackboard area' and a long term memory area. Loosely speaking the blackboard area contains data structures defining the model's representation of the current situation. Long term memory contains productions (pattern-action rules) for recognizing patterns within the situation representation and for changing that representation when an appropriate pattern is recognized. To continue the driving example illustrated earlier, consider the following extension of the production rules.

Figure 1 here

- (3') If light is yellow -> place "caution" in working memory.
- (4) If "caution" is in working memory -> scan cross streets.
- (5) If light is yellow and there is traffic in the cross

streets -> decelerate

Production 3' illustrates a change in the working memory area that is produced by the system itself, rather than by observation of the outside world.

The production system just described is a trivial illustration of the standard production notation described by Neves et al. (1987), and used in many simulations. Hunt and Lansman introduced three elaborations on the standard notation. First, production selection was determined by evaluation of the activation level of a production, where activation was determined both by the match between the pattern part of the production and information in the blackboard and by the level of activation of a node in a semantic network of related productions. See the illustration given in the introductory section of this report. The techniques for selection were similar to those used by Anderson (1983) in his ACT* model, with one important exception. Anderson bases production selection upon the state of the model after the semantic network has stabilized. Hunt and Lansman considered activation based upon transient states of the network.

Hunt and Lansman's second innovation was the division of the blackboard area into separate areas, corresponding to buffer areas for perceptual representations driven by the outside world and a working memory, which contained data structures that are constructed by the system itself. Thus the buffer area contains the perceived world, and the working memory area contained the model's interpretation of that world. The production system part of the model could be driven either by the "perceptual" or "conceptual" parts of the blackboard model.

A third innovation was the use of codes. Any data structure was assumed to be written in just one of three codes. Hunt and Lansman considered "visual," "auditory," and "semantic" codes. The first two refer to information coded as visual or auditory percepts (or images), while the third refers to an abstract propositional representation. Data structures in the visual or auditory codes could appear in the appropriate buffer or in working memory. Data structures written in the semantic code could appear only in working memory. The model assumes that the pattern-action cycle takes place in parallel within each code type. Roughly, their model can listen to something, look at something, and think about something, all at the same time, but it can only look at one thing at a time, hear one thing at a time, or think about one thing at a time.

Hunt and Lansman tested the model by determining whether or not it could reproduce a number of well-known results from the attention and performance literature. For instance, they considered the choice reaction

time (CRT) paradigm. In which a person decides, as rapidly as possible, which of N possible stimuli has been presented. CRT studies can be represented by trivial production systems, since the intellectual component of the task is simple. What is interesting is how reaction times vary as a function of the stimulus presentation conditions. It is well known that reaction time increases logarithmically with the number of potential stimuli (Hick's law). Hunt and Lansman showed that their model reproduces the logarithmic relation as a result of the competition between productions due to the spread of semantic activation. Similarly, Hunt and Lansman were able to reproduce certain findings concerning the serial presentation of items in a CRT study, the effect of competition between two simple scanning tasks upon the accuracy of each task, and the resolution of response conflict in "Stroop" experiments, in which a person must suppress highly overlearned response tendencies in order to select the response required within the special context of the experimental situation.

The Hunt and Lansman paper has received considerable comment, as it is (to our knowledge) the first computational model of the interaction between consciously cognitive processes and the "cognitively impenetrable" processes of basic information processing. The model has been extended to cover real time tasks in arithmetic computation, reading, and more complicated response conflict situations. These applications are detailed below.

Some critics have argued that the model is trivial because it is not falsifiable in any obvious way. This is a subtle issue. The Hunt and Lansman model, like Anderson's (1983) ACT*, Rumelhart & McClelland's (1986) PDP models, and virtually all computer simulations, has enough free parameters so that it could be made to model virtually any situation. Therefore it is not appropriate to argue for the model on the basis of any one experimental test. On the other hand, the model has been used to simulate a number of different situations, with very little alteration. But what counts as "little alteration." This is not the sort of issue that can be decided by appeal to statistical tests. The correct statement is that the model has proven to be a useful way to summarize findings from disparate fields of inquiry in Psychology. The issue of whether or not models that summarize should also be falsifiable, in the narrow sense of being rejectable in a specific experiment, is beyond the scope of the current report.

3. Simulation of a complicated real-time problem solving task.

A simulation study by Richardson and Hunt (1985, 1987) has extended Hunt and Lansman's basic model to the simulation of a much more

cognitively complex task. The purpose of doing so was to show that the basic approach developed by Hunt and Lansman could be applied to tasks that were not designed solely to isolate a few cognitive functions.

Richardson and Hunt considered a situation in which a person had to respond to an interruption that arrived during processing of a complex, time driven task. The complex task Richardson and Hunt studied was ternary (base three) arithmetic. This is a task that people can learn to do relatively well, but that is much less practiced than conventional arithmetic. College students were asked to read ternary numbers displayed on a computer screen, and to keep a running total of those numbers. Periodically a tone was presented. The participant was to press a button to turn off the bell, while still maintaining the running total in the arithmetic task. For a (only slightly whimsical) extra-laboratory analog, the reader might imagine the phone ringing while he or she was balancing a checkbook. The only difference is that in the experiment the participants did not have access to paper and pencil. All arithmetic had to be done in the head.

Although this task is certainly less complex than many tasks that people do, it does offer interesting complexities. The participant must execute a moderately complicated rule-governed task, ternary arithmetic. In executing the task the participant must suppress the highly overlearned rules of conventional decimal arithmetic. The short term memory requirements of the arithmetic task vary considerably, depending upon the number of carries required. When the interrupting tone sounds the participant must temporarily suspend arithmetical operations, respond to the tone, and then resume the arithmetic task.

Richardson and Hunt wrote a simulation of this task based on the Hunt and Lansman model. The major differences were that in the Richardson and Hunt simulation five internal code types were used, corresponding to visual, auditory, semantic, motor, and metacognitive codes. The motor code was added to keep track of the status of the button pressing response, and is of little theoretical importance. The metacognitive code is somewhat different. This code was used to keep track of the status of operations in the problem solving process itself. For instance, metacognitive operations were included to control the decision to respond to a tone immediately or to rehearse the status of the arithmetic problem before responding to the tone. The introduction of metacognitive operations represents a theoretically interesting extension of the Hunt and Lansman model.

Three dependent variables were examined, the occurrence of errors in the arithmetic task, the time required to compute and speak a new sum as a

function of the complexity of the arithmetic problem and the presence or absence of the probe tone, and the time to respond to the probe tone as a function of the complexity of the concurrent arithmetic problem. The program made all the types of errors observed in the participant's actions. As the absolute frequency of errors by people was low, further statistical tests based on errors were not possible.

For each possible response time measure and condition of observation the mean of the median response made by participants was compared to the number of computing cycles the simulation program used to compute the same response. (Note that this is not equivalent to the number of productions executed, because the Hunt and Lansman model considers variables that will alter the time required to execute a given production.) There was a remarkably good agreement, the correlation between participant response times and simulation results was slightly over 95. A similar degree of agreement was exhibited on a subject by subject basis. Richardson and Hunt concluded that the Hunt and Lansman model could profitably be extended to deal with situations more complex than conventional information processing tasks.

A preliminary report of this work was presented at the 1985 Cognitive Science Society meeting (Richardson and Hunt, 1985). A paper describing the complete project is now being reviewed by the journal *Cognitive Science*.

4. Studies of response conflict in the Stroop Paradigm:

One of the major theoretical advances in information processing psychology in the past fifteen years has been the elaboration of the distinction between "controlled" and "automatic" processes. Hunt and Lansman (1986) pointed out that this distinction was paralleled in their theoretical model by the distinction between the activation of productions through recognition of patterns in working memory compared to the activation of productions solely by spreading activation within a semantic network. To illustrate this distinction they showed that their model could simulate the behavior typically observed in the Stroop paradigm. This is an experimental situation in which an observer must make a response to one aspect of the stimulus, while suppressing a highly overlearned, incompatible response to some other aspect of the stimulus. The name of the paradigm is derived from Stroop's (1935) experiments, in which participants had to name the ink color of a printed color name, e.g. respond "Red" to the word GREEN printed in red ink. Stroop situations are of interest because they represent a conflict between controlled and automatic responding.

Hunt and Lansman modeled the classic color-naming experiment just described. Reed and Hunt (1985) extended this work to consider a number of other Stroop-like simulations. Marcel (1983) had shown that Stroop interference did not depend upon overt recognition of the word. He did this by exposing a color word followed by a masking stimulus and then a color patch. Marcel found that the time required to name the color patch was increased if the patch was preceded by a contradictory color name, even though the color name-mask interval was so small that observers did not report seeing the color name. Reed and Hunt produced this effect within the Hunt and Lansman model by "presenting" a color word form to the simulation program for such a brief period that the program could not reliably retrieve the word name, i.e. it was unable to translate from the visual form code to the auditory name code. Nevertheless, the program's network of productions was sufficiently activated in the wrong direction...so that the number of cycles required to retrieve the color name was increased.

Shimamura (1986) has reported a rather unusual form of the Stroop phenomenon. Shimamura recorded the performance of native Japanese readers who attempted the Stroop task using either the Japanese ideographic symbol for colors (the kanji script) or using the Japanese phonetic color symbol (the kana script). Shimamura found that although native Japanese could name the kana script more rapidly than the kanji script, the kanji script interfered more with an incompatible color naming response. (Shimamura went on to make similar observations about ideographic symbols in American culture, such as responding with the left hand to a stimulus on the right hand side of the observer.) Reed and Hunt simulated Shimamura's results by using a semantic network in which the flow of activation for the kana script (and for the earlier work on English script) was from the visual form to the auditory form, and then to the semantic concept, while the flow of activation for the kanji script was from the visual form directly to the semantic concept, and from there to the auditory form of the word.

The Reed and Hunt work was criticized by external reviewers, who felt that the model was inadequate because it did not seem capable of dealing with two additional Stroop phenomena. The first was a "release from interference" phenomenon reported by Klein (1964). Klein had people name the word, and then the color name. For instance, if the word were GREEN printed in red ink Klein's participants would respond "Green-Red." Klein reported that this destroyed the Stroop phenomenon, since he found that the time required to say the color name was not longer than the time required to say the form and color name for color neutral words, such as "BOX" printed

in green, where the response would be "Box-green." The reviewers correctly observed that there is no place for such a phenomenon in the Hunt and Lansman model.

We were at a loss as to how to proceed, since it did not seem possible to produce any believable model for the Klein results. We also noted that Klein used a somewhat crude technology (although typical of its day), in that he had participants read a long list of Stroop color-name pairs. The dependent variable was the time taken to read the entire list, rather than the time required to respond to individual items. Therefore we repeated the Klein studies using modern, computer-driven displays. Unlike Klein, we recorded response times to individual items. We utterly failed to replicate Klein's results. Every subject that we ran showed the normal Stroop pattern in Klein's double-naming paradigm. We are now preparing a brief empirical note, reporting this non-replication.

A second criticism raised against Reed and Hunt's work is that the model could not reproduce the results of Kahneman and Chajzyck's (1983) "dilution" studies. Kahneman and Chajzyck presented observers with stimuli consisting of a color name, a color bar, and a neutral word. For instance, they might present a red color bar between the words GREEN and BOX. The task would be to name the color bar. Kahneman and Chajzyck found that the Stroop phenomenon was reduced by approximately one half when the neutral word was present. This study has been widely cited as an illustration that word naming is not an automatic phenomenon.

We attempted to replicate the Kahneman and Chajzyck studies and observed an interesting phenomenon. Averaged over subjects, we observed the dilution phenomenon that Kahneman and Chajzyck reported. (They report data averaged over subjects.) On the other hand, our individual subjects either showed a normal Stroop phenomenon or showed no interference whatsoever. We are somewhat puzzled by this result. Kahneman has informed us, privately, that he did observe dilution within individual subjects. He has also visited our laboratory and suggested some minor changes of procedure. Before publishing our results we wish to replicate them, using Kahneman's suggested modifications, and establishing a larger sample. The work will be continued without ONR support.

While the Reed and Hunt model probably will not be reported further, it has served its purpose in two ways. First, it has led to two new experimental studies, both of which may result in significant modifications of our knowledge about the Stroop phenomenon. Second, it raised an important question not mentioned by any reviewer. This is the problem of

establishing a correspondence between the times to complete actions in different logical portions of a simulation. Any model of the Stroop phenomenon has to consider three different types of information processing, analyses in the visual system, the arousal of semantic information, and response selection. The Reed and Hunt model (and for that matter, all other formal models of which we are aware, including a variety of connectionist models) treat each type of information processing as proceeding on the same time scale. Yet there is considerable evidence that the visual system is faster than the semantic, which in turn is faster than the motor selection system. If we are able to assign different time parameters to each system virtually any result could be modeled. On the other hand, if different time parameters are not assigned the simulation is probably going to be unrealistic. We feel that this problem has not received the attention in the literature that it deserves.

5. Simulation of comprehension and problem solving:

The final simulation study to be reported deals with a rather different sort of real time problem solving activity, modeling the incorporation of information into logical problem solving. Lundell and Leden (1987) wished to extend hybrid models to a situation in which a person was required to read information, grasp it quickly, and then use the information to solve a problem.

Lundell and Leden took a somewhat different approach to problem solving than that illustrated by the Hunt and Lansman model. Following Schank and Abelson (1975), and a number of other theorists (stretching back to Bartlett (1932)), they argue that much problem solving is based upon the activation of scheme representing prototype problems. Problems are then solved by filling in values for the "variables" represented by slots in a schema. Lundell and Leden proposed that the schema themselves are activated by a semantic network, which is cued initially by lexical references to items contained in the schema. Once the schema becomes active it acts as a primer for productions designed to analyze the incoming text in a particular way, in order to extract the information that is needed to complete the activated schema.

In their initial work (reported in Lundell and Leden, 1987) they constructed a model of reading during problem solving that works along the lines just described. They found that this model correctly predicted reading times for subjects who were presented with "three term series" problems, such as "Fred is shorter than Bill. Tom is taller than Bill. Is Fred shorter than Tom?" These are very simple problems but they can be stated in ways

that make them differentially difficult. For example, in the illustrative problem the first sentence establishes a schema for ordering based on the "shorter than" relation. This is reversed in the second sentence. Therefore, according to the model, there must be a pause in reading time while the information based on two different schemas is resolved. In fact, such pauses do occur. More generally, Lundell and Laden were able to use their hybrid model to simulate a number of the phenomena found in reading sentences during solution of three term series problems.

This work has now been extended to an analysis of reading times while solving simple algebra word problems. Laden (who has a substantial amount of training in musicology) has proposed a further extension of these ideas to recognition of major keys in musical phrases. In general, Lundell and Laden's work has proven to be a useful extension of the development of hybrid models to situations in which text must be analyzed in the course of problem solving. A technical report on the work that has followed Lundell and Laden's initial studies is not feasible, as the follow-on work had not been completed prior to expiration of this contract. However this work will certainly lead to several publications.

6. The Mathematical Analysis of Networks

Both the Hunt and Lansman and Lundell and Laden simulations depend heavily upon "appropriate" configurations of activations being achieved by a semantic activation network. Just what are the configurations that these networks can achieve? The same question can be asked of virtually all of the many recent studies of parallel distributed processing systems; just what configurations can be achieved. To put the question in historical perspective, consider the situation in the early 1960s, when there was a great deal of interest in a class of activation networks known generically as "perceptrons" (Rosenblatt, 1962). One of the most interesting findings was that a simple learning rule algorithm was sufficient to bring a perceptron network into any configuration that it could achieve, regardless of the starting point. This finding excited many people, until Minsky and Papert (1969) showed that the networks themselves could only reach a limited number of configurations. More psychologically, there were certain psychologically interpretable decision rules (e.g. decision rules based on "A implies B and vice versa" relationships) that could not be represented by any configuration of perceptron activation networks.

The classes of networks considered in our own work, and much more generally, in the Parallel Distributed Processing research that is now so popular (Rumelhart and McClelland, 1986) are more general than the

restricted perceptron networks analyzed by Minsky and Papert. The new networks are known to be free of many of the restrictions that applied to the perceptrons considered by Minsky and Papert. But do any analogous restrictions apply and, if so, what are they?

As an initial approach to this question, John Hogden and (now at Stanford University) and Earl Hunt considered a mathematical analysis of the situations under which activation networks of the type considered by Hunt and Lansman would reach any stable configuration. Hogden and Hunt found that these networks were stable only if the matrix of associations satisfied the following mathematical constraint.

Let C be the matrix of associations between elements, with c_{ij} being the weight of the connection between the i th and j th element in the network. Let I be the identity matrix. Furthermore, let $a(i)$ be the vector of activation levels at time t , i.e. the state of the matrix. The network is said to stabilize (i.e. reach a resting configuration) in response to an input stimulus only if, for some t , $a(t) = a(t+1)$. Hogden and Hunt showed that this condition is met if and only if all the eigenvalues of the matrix $(I-C)^{-1}$ are positive real numbers. In a very loose psychological analogy, this means that an activation network of the type considered by Hunt and Lansman will go into "hysterical behavior" (either looping or moving to ever increasing activation values) unless the connection matrix obeys a fairly restrictive mathematical condition.

Hogden and Hunt presented their work at the 1986 Mathematical Psychology Society meetings. It was pointed out, on the one hand, that this would be a fairly serious result if it applied to all parallel distributed processing networks and, on the other, that it is by no means clear that the restrictions do or do not apply. There are two differences between the activation networks considered by Hunt and Lansman and most of those considered by PDP theorists. Hunt and Lansman considered networks in which the output of each element was a linear function of its input, providing that the input exceeded a threshold level. In most PDP simulations the output is "squeezed" to a value between fixed limits, say -1 and $+1$. This means that in PDP networks with n elements, the vector $a(t)$ is restricted to the space defined by the n dimensional hypercube with corners at all possible $+1$ and -1 combinations. Therefore by fiat the network activation cannot go off into infinity, one of the pathological conditions considered by Hogden and Hunt. What is not known is (a) whether there may be connection matrices that drive the network arbitrarily close to the corners of the hypercube, for all stimuli, or (b) whether there are connection matrices that produce cycling behavior. It would not be

appropriate to speculate one way or the other. The answer simply is not known

One might argue that if such pathological conditions could exist, the now extensive empirical studies of PDP networks would have uncovered them. It is not at all clear that this would be the case. Hogden and Hunt considered the completely general case, in which connections were permitted between any units. In practice, most PDP simulation studies have been of networks with restricted connection matrices, chosen to be the experimenter's best guess as to how the final network might look. In particular, the experimenter initially sets certain connection values to zero, and the mechanism of connection adjustment assures that once a value is identically zero it remains there. In response to a question following Rumelhart's 1987 Cognitive Science meeting presentation on how PDP networks derive semantic concepts, Rumelhart acknowledged that setting up the initial networks is, in his words, "a black art." We do not know if the black artists have managed to avoid networks that would go into closed loops, because we do not know if such networks exist.

The questions raised by the Hogden and Hunt paper are fundamental to understanding of PDP networks in general. However, we feel that it would be premature to publish the partial results, that apply to the more limited networks. Unfortunately, due to Hogden's move to Stanford University it has not been possible to continue our collaboration. Therefore this work is currently "on hold" until time can be freed for analysis. Hunt hopes to conduct some of these analyses while on leave at the University of Texas (Austin) during the first half of 1988.

7. The Simulation of Complex Learning Through Memory

In all the studies considered thus far a production system model has been augmented by the inclusion of a "semantic activation" model of memory. This remark is true both of our own work and the work by most other authors in the field. The basic characteristic of a semantic activation model is that it stores (some function of) correlations between feature occurrences. For instance, much PDP modeling can be thought of as a demonstration that a neural net model can reorganize itself to represent statistical associations between stimulus features, e.g. between the occurrence of the sound "ed" and semantic markers for the past tense. Recently Hintzman (1986) published an alternative to the network model of memory, which we shall refer to as "case based memory." The idea behind case based memory is that the information stored in memory is a record of specific instances, rather than associations between features. Hintzman

showed, by simulation, that a case based memory model could be used to derive many of the phenomena of memory usually thought to be based on the storage of information about feature association.

McSpadden extended Hintzman's ideas to the field of problem solving. Most models of how people learn to solve problems in various fields assume that as a person acquires expertise he/she acquires more efficient rules for handling situations. See, for instance, the discussion of "compiling knowledge" in Anderson's (1982, 1987) discussions of learning. Hintzman's approach suggests another alternative. Perhaps what people do is to acquire specific experiences. Upon encountering a new situation people may simply try to recall what they did before, in similar situations, and whether or not their efforts were successful. Their recall of previous efforts can then be used as a starting place for the construction of a response to a new situation.

To make this concrete, let us consider the situation McSpadden actually studied. Participants in his experiment learned to play a complex computer game (RELTDOWN) based on the operation of nuclear power plants. At the start of the game the player is given a brief introduction to how a (vastly simplified) power plant operates. Instruction is given in terms of state variables and control variables. The state variables indicate the current condition of the plant, in terms of temperature of various processes, levels of coolant, power being produced, and settings of control rods. The player then sets the control variables, essentially the level of fuel exposure and the flow of coolants. The state variables are then recalculated and the cycle begins again. In fact, the state variables are determined by difference equations based on the control settings and the history of the state variables. For instance, the plant will react differently to a control variable setting depending upon whether the plant is heating up or cooling down.

The goal of the game is to maximize power output, subject to the constraint of not burning down the plant. A "perfect operator" would do this by discovering the equations used to calculate state variables from control variables, but in practice we have not heard of anyone ever doing this. Instead people get surprisingly good playing the game, but do not develop particularly sophisticated rules. (McSpadden showed that there was no correlation between a test of knowledge of the system and performance while playing the game.) What might they be doing?

McSpadden wrote a model of player's performance based largely on Hintzman's case based model of memory. The simulation program stores explicit situations...e.g. when system variables were in state X and control

variables were set in position Y, then Z happened. Each time a new situation is encountered (i.e. state variables recognized, but control settings not yet made) the program "probes" its memory following Hintzman's definition of probing to retrieve information about what happened when similar state variable settings were encountered. The program uses this information to construct new responses.

At first, such information is of little use, so the simulation often fails to make an adequate response, eventually causing a "Melt-down." So do human subjects. As the simulation and the subjects acquire more information they do progressively better. What is more to the point is that they get better in the same manner. McSpadden was able to show a reasonably close correspondence between individual subject's decisions and the decisions made by the modified Hintzman model, when provided with the same information. Both system and subjects learned, but they learned by acquiring experience, not by sharpening procedures. The only procedural information (i.e. production rules) contained in McSpadden's model consists of rules for interrogating the system's own memory, i.e. for constructing probes. There are no procedural rules for operating the game as such...nor do they seem to be needed to simulate subjects' behavior.

The latter conclusion probably overstates the case. It seems unlikely that people do not learn any production type rules based on instruction in the game itself. Therefore, if possible, a second simulation of the data will be attempted using a simplified problem solving model in addition to the memory model. It is interesting, however, to see that in a situation involving very complex learning problem solving behavior could be modeled by assuming that people learned solely "what to do," without developing any internal model of the device they were trying to operate. This is a very different assumption than that made by most psychologists interested in how people learn to use devices. Most theories of device learning assume that the operator is trying to construct a mental model of the device itself.

It is probably not appropriate to argue that people always learn to operate complex systems by developing mental models. McSpadden's results clearly question such an extreme form of the "learning through mental models" approach. On the other hand, it seems equally unlikely that people never make mental models of a system that they are trying to control. What we need to do is to establish the situations under which people learn solely by recording experience, and the situations in which they attempt to process that experience into a mental model.

Related research on this point is now being conducted by Ms. Jenny Epps, in a master's thesis that examines the range of learning effects that can be simulated by a case based memory model. This is an important step in the further analysis of the powers of case based vs. feature association memory systems.

8. Language and Problem Solving

The final paper to be described here is a speculative, general interest paper written by E. Hunt and M. R. Baneji (Yale University). Hunt and Baneji were invited to consider how modern views of cognition, such as those represented here, could be related to cross-cultural aspects of cognition. Hunt and Baneji responded to this request by reconsideration the "Whorfian hypothesis" in terms of computational models of problem solving.

The Whorfian hypothesis (Whorf, 1956) is that language controls thought. The strongest view of the hypothesis is that one's external language is taken to be virtually identical to the internal language of thought. If this is true, concepts that cannot be expressed in the external language cannot appear as objects of perception or cognition. The strong view of the hypothesis has been falsified by observation. For instance, it has been shown that perceptual confusions between colors are not related to the particular color terms used in the respondent's language. The weak form of the language is that the external language influences thought. Virtually no one disputes this. But can anything more be said? Hunt and Baneji responded to this challenge by considering how some facts about language might be interpreted on the assumption that the Hunt and Lansman (1986) model really is a correct model of how people think.

Hunt and Baneji argued that symbols and symbol structures in the external language serve to construct a listener's "mental representation" of a speaker's (or writer's) intention. Various languages provide symbol systems that vary in the efficiency of constructing this representation. Varied efficiency can come in several ways. In the simplest case, the speaker may have available a symbol that indicates to the comprehender that the mental representation should contain a reference to a (possibly complex) mental structure that the comprehender already has. This is one way that common words are used. Consider, for instance, the references contained in the American phrase "The I.R.S. is after me." (Hunt and Baneji considered a number of such examples, including the use of acronyms in government and military communications.) Compact references can be used to produce very complex mental representations in the comprehender, with minimum burden on the comprehender's computational resources. In other

cases complexes of words must be used to express an idea. This does not mean that the comprehender cannot comprehend the idea, but it does mean that the comprehender has to do additional computations in order to make up for a lack of reference in the language itself. For instance, in English a conditional conclusion is usually expressed by the subjunctive, as in "If the IRS were after me, I would see my lawyer." Mandarin Chinese does not have a subjunctive. Hunt and Banaji argue that Chinese can reason counterfactually (after all, they have a 5000 year history of diplomacy!) but that comprehending a counterfactual is computationally more difficult for a Chinese speaker than for an English speaker.

Hunt and Banaji further pointed out that syntactical structures must be analysed by transforming candidate structures in working memory. Languages vary in the extent to which surface markers provide aids for such computation. English is a weakly inflected language, which relies heavily on word order to indicate syntactic role. Thus English comprehenders must keep word order information present in working memory while parsing a sentence. In more strongly inflected languages (e.g. Spanish), where syntactic function is often indicated by word form, the requirement for recall of order information is reduced. Similarly, languages differ in the extent to which the forms of words can be used to reduce memory requirements in the resolution of anaphors. Hunt and Banaji point out that English is quite precise in specifying gender resolution, since in English "he," "she," and "it" can be mapped onto nouns in a way predicted by biology. This contrasts with German, where (as Mark Twain complained) "A young lady has no sex but a turnip has." English has its own ambiguities. In particular, the all-purpose "you" in English is an anaphor that can be difficult to resolve. Several other languages break "you" down into forms that depend upon the social relation of the referent to the speaker, as in the "tu-vu" forms in the Romance languages. These observations are certainly not original with Hunt and Banaji. Their contribution was to consider how and with what difficulty various ambiguities in different languages could be resolved by a precisely stated computational model of language comprehension. The result was a reformulation of the Whorffian hypothesis in terms of the relative difficulty of constructing different sorts of mental representations in different natural languages.

As indicated, the Hunt and Banaji paper was intended to be a thought-provoking piece rather than a completed program of research. At present we have no further activities underway related to this paper.

9. Conclusions

The research program was initiated to see if hybrid production-system and semantic activation models could be used to tackle "hard" problems in areas ranging from time pressured problem solving to language comprehension. The answer to this question is a tentative "yes." The Richardson and Hunt work showed that the model could be applied, exactly, to a situation that involved complicated, time-interrupted reasoning. On the other hand, our work with the Stroop paradigm revealed an important problem that applies to all production system models of which we have knowledge. There is no clearcut way to represent real time in the system. In particular, any realistic model has to allow for parallel actions in the visual, auditory, and perhaps semantic systems. Each of these systems runs on their own clocks, and we have no way of relating the clock speed of one system to the clock speed of the others. Until we can find principled method for defining "clock cycles" within a computer simulation it will be difficult to apply any production system methodology to the study of real-time problem solving involving information processing in different sensory systems.

One of the more interesting developments in our work has been the use of case based models of memory. These models have proven to be surprisingly powerful. In other work (not sponsored by ONR) we hope to extend these models to the simulation of a variety of problem solving situations in which people act sometimes as rule-governed systems and sometimes as systems essentially "muddle through" on the basis of specific past experiences. We suspect that such situations are far more common than a person who values logical reasoning would care to admit.

10. Summary of publications

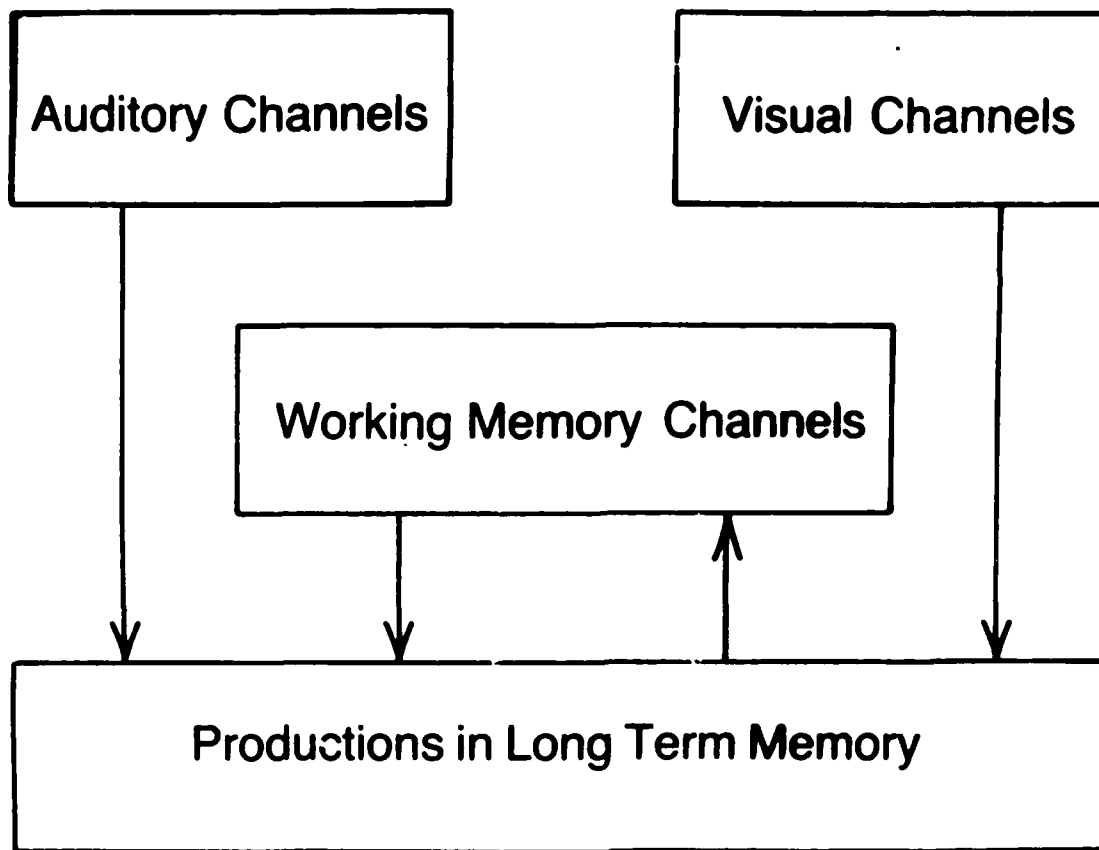
Hunt, E. Science, technology, and intelligence. In R. Ronning, J. Glover, J.C. Conoley, and J.C. Witt (Eds.) *The Influence of Cognitive Psychology on Testing*. Buras-Nebraska Symposium on Measurement and Testing, Volume 3. Lawrence Erlbaum Associates, Inc., 1987.

Hogden, J. and Hunt, E. (1986) An analysis of models of memory based on activation.

Hunt, E. & Banaji, M.R. (1987) The Whorffian Hypothesis Revisited: A Cognitive Science View of Linguistic and Cultural Effects on Thought. In Berry, J.W., Irvine, S.H., & Hunt, E. (Eds.) *Indigenous Cognition: Functioning in a Cultural Context*. The Netherlands: Martinus Nijhoff.

- Hunt, E. & Lansman, M. (1986) A unified model of attention and problem solving. *Psychological Review* 93 (4) 446-461
- Lundell, J. & Loden, B. (1987) A dynamic connectionist model of problem solving. *Proceedings of the 9th Annual Conference of the Cognitive Science Society*, 663-674
- McSpadden, M. (in preparation) Remembering the Future: A model predicting future decisions from past experience
- Peed, P. & Hunt, E. (1986) A production system model of response selection in the Stroop Paradigm. ONR Technical Report
- Richardson, M. & Hunt, E. (1985) Problem solving under time constraints. Mathematical Psychology Society Annual Conference
- Richardson, M. & Hunt, E. (1985b) Problem solving under time constraints. ONR Technical Report
- Richardson, M. & Hunt, E. (1987) Dealing with interruptions during problem solving. Submitted to *Cognitive Science*
- 10. Additional references**
- Anderson, J.R. (1982) Cognitive Skills and their acquisition. *Psychological Review* 89 359-406
- Anderson, J.R. (1983) *The Architecture of Cognition*. Cambridge, MA: Harvard Press
- Anderson, J.R. (1987) Skill Acquisition. Compilation of Weak Method Problem Solutions. *Psychological Review* 94(2) 192-210
- Bartlett, F. C. (1932) *Remembering*. Cambridge, Eng. Cambridge U. Press
- Hintzman, D. L. (1986) "Schema Abstraction" in a Multiple-Trace Memory Model. *Psychological Review* 93 (4) 411-428
- Kahneman, D. & Chajczyk, D. (1983) Tests of the automaticity of reading: Dilution of Stroop effects by color-irrelevant stimuli. *Journal of Experimental Psychology: Human Perception and Performance* 9 (4) 497-509

- Klein, G.S. (1964) Semantic power measured through the interference of words with color naming. *American Journal of Psychology* 77, 576-588
- Marcel, A. J. (1983) Conscious and Unconscious Perception: Experiments on Visual Masking and Word Recognition. *Cognitive Psychology* 15(4) 197-237
- Minsky, M. & Papert, S. (1969) *Perceptrons*. Cambridge, MA: MIT Press
- Neches, R., Langley, P., and Klahr, D. (1987) Learning, Development, and Production Systems. In D. Klahr, P. Langley, and R. Neches (eds.) *Production System Models of Learning and Development*. Cambridge, MA: MIT Press
- Newell, A. (1973) Production Systems: Models of Control Structures. In W. G. Chase (Ed.) *Visual Information Processing*. New York: Academic Press
- Rosenblatt, F. (1962) *Principles of Neurodynamics*. New York: Spartan
- Rumelhart, D. E. & McClelland, J. L. (1986). *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* Vol. 1. Cambridge, MA: MIT Press
- Schank, R. C. & Abelson, R. P. (1977) *Scripts, plans, goals, and understanding*. Hillsdale, N.J. L. Erlbaum Assoc.
- Shimamura, A. P. (1987) Word comprehension and naming: an analysis of English and Japanese orthographies. *American Journal of Psychology* 102, 15-40.
- Stroop, J.R. (1935) Studies of interference in serial verbal reactions. *Journal of Experimental Psychology* 18, 643-662
- Thibadeau, R., Just, M.A., & Carpenter, P.A. (1982) A model of the time course and content of reading. *Cognitive Science* 6, 157-203
- Whorf, B.L. (1956) *Language, thought, and reality*. Cambridge, MA: MIT Press



Marcel, A. J. (1983) Conscious and Unconscious Perception Experiments on Visual Masking and Word Recognition. *Cognitive Psychology* 15(4) 197-237

Minsky, M. & Papert, S. (1969) *Perceptrons*. Cambridge, MA: MIT Press

Neches, R., Langley, P., and Klahr, D. (1987) Learning, Development, and Production Systems. In D. Klahr, P. Langley, and R. Neches (eds.) *Production System Models of Learning and Development*. Cambridge, MA: MIT Press

Newell, A. (1973) Production Systems: Models of Control Structures. In W. G. Chase (Ed.) *Visual Information Processing*. New York: Academic Press

Rosenblatt, F. (1962) *Principles of Neurodynamics*. New York: Spartan

Rumelhart, D. E. & McClelland, J. L. (1986) *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* Vol. 1. Cambridge, MA: MIT Press

Schank, R. C. & Abelson, R. P. (1977) *Scripts, plans, goals, and understanding*. Hillsdale, N.J.: L. Erlbaum Assoc.

Shimamura, A. P. (1987) Word comprehension and naming: an analysis of English and Japanese orthographies. *American Journal of Psychology* 102, 15-40

Stroop, J. R. (1935) Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, 18, 643-662

Thibodeau, R., Just, M. A., & Carpenter, P. A. (1982) A model of the time course and content of reading. *Cognitive Science* 6, 157-203

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