Title
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A Distributed Representation and Model for Story Comprehension and Recall

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Abstract

An optimal control theory of story comprehension and recall is proposed within the framework of a "situation" state space. A point in situation state space is specified by a collection of propositions each of which can have the values of either "present" or "absent". Story comprehension is viewed as finding a temporally-ordered sequence of situations or "trajectory" which is consistent with story-imposed constraints. Story recall is viewed as finding a trajectory consistent with episodic memory constraints. A multistate probabilistic (MSP) machine representational scheme is then introduced for compactly and formally assigning a "degree of belief" (i.e., a probability value) to each trajectory in the state space. A connectionist model is also introduced which searches for trajectories which are highly probable with respect to a set of constraints and an MSP machine representation. Like human subjects, the model (i) recalls propositions with greater causal connectivity as retention interval is increased, and (ii) demonstrates how misordered propositions tend to "drift" more towards their canonical position in a text as retention interval is increased.

General Theory

We have currently been approaching the problem of story comprehension and recall within the framework of a special high dimensional state space which is called the "situation" state space. A point in situation state space consists of a collection of d facts about the world, each of which can be classified as being either "present" or "absent." The reader's current mental state is therefore modelled as a single point in a d-dimensional situation state space. At some later point in time, the reader's mental state would be modelled as another point in the same d-dimensional situation state space. It will be convenient, therefore, to order these points according to a time index. Thus, the "unfolding" or "evolution" of the reader's mental state as a function of time, may be represented as an ordered sequence of points or *trajectory* in situation state space.

Some trajectories in situation state space will be more likely to occur than others. For example, a trajectory in a four-dimensional situation state space might be specified by the sequence of three four–dimensional situation state vectors depicted in Table 1. World knowledge is represented by a belief function which assigns a specific "degree of belief" to different trajectories in the situation state space. In particular, trajectories which are more likely are assigned values close to one, while trajectories which are less likely are assigned values close to zero.

A story is a set of constraints upon the class of possible trajectories in situation state space. The features possessing the value "present" along the trajectory are fixed in value. The remaining features possessing the value "absent" may have their values modified.

The problem of story comprehension is now formally defined as finding a trajectory in situation state space which is *most probable* with respect to some probabilistic belief function (for some closely related ideas see Rumelhart, 1977). We suggest that readers may find highly probable trajectories by "running" their probabilistic mental models forwards and backwards in time. The resulting trajectory is then used to update the parameters of the belief function via some learning process, and then a reconstructed story trajectory is recalled from memory by using another partially specified trajectory (perhaps the title of the story) as a retrieval cue, and "rerunning" the probabilistic mental model. Note that once a trajectory has been constructed following the comprehension process or reconstructed following the recall process, the resulting representation may be used by other systems to answer questions about the story, summarize the story, or recall the original story.

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Story Feature	t=1	t=2	t=3
Hear (M, IC Music)	1	1	0
Desire (M,Eat(M,IC)	0	1	0
Eat (M, IC)	0	0	1
Sleep (M)	0	0	0

Table 1. A situation state space trajectory. M=Mary. IC=Ice-Cream. 1 = Feature Present. 0=Feature Absent.

Representation and Model

Multi-state probabilistic machines.

Gabrielian and his colleagues (for a review see Gabrielian and Iyer, 1991) have been developing the theoretical foundations of a new class for machines known as *hierarchical multi-state machines* for specifying the performance requirements of complex high-dimensional systems. We have found that a probabilistic extension of the multi-state machines studied by Gabrielian and his colleagues provides a useful way of implicitly, yet precisely, representing complex belief functions that assign degrees of belief to specific trajectories in situation state space. We will call this special notation for representing complex probabilistic knowledge structures a MSP (multi-state probabilistic) machine.

A MSP machine consists of three distinct types of entities: local states, transitions, and controls. The *local states* of the MSP machine correspond to the set of d features required to specify a point in a d-dimensional situation state space. The set of all states of the MSP machine is sometimes referred to as a *global state* of the machine. A *marking* of the MSP machine indicates the values of local states of the machine at an instant in time. Thus, a marking of the machine identifies a point in the d-dimensional situation state space. The *transitions* and the *controls* of the MSP machine specify how the global state of the machine evolves from one instant of time to the next.

Table 2 and Figure 1 show a more complicated example where the multi-state probabilistic machine notation is used to represent the causal knowledge structure underlying an actual story. The story was parsed into propositions following Trabasso, Secco, and Van Den Broek (1984). All probabilistic transitions are designed to "fire" with probability 0.9. Close inspection of Figure 3 reveals a very compact notation for specifying complex causal relations over time. Like the notation of Trabasso and his colleagues, the links in this representation are derived from a combination of intuitive considerations supported by counterfactual arguments. This notation has the advantage, however, of permitting multiple local states to be simultaneously active, and permitting multiple local transitions to simultaneously fire. We also exploit a Markov random field framework to formally link the firing of the "local probabilistic" transitions, with the global subjective probability function which assigns a probability to each trajectory in the system. Thus, once the probabilistic causal chain representation has been constructed, it is possible to implicitly assign a degree of belief to all possible trajectories in situation state space through the use of interpretable local probability distributions.

The parallel distributed processing model.

The theory of story comprehension and recall we have been describing is based on a two-step process. First, a highly probable (believable) trajectory is computed by the reader which is consistent with the constraints of the story. This story trajectory is the reader's mental model of the story. The reader then learns the constructed mental model. During the recall process, the reader is given the initial portion of the trajectory (story) as a retrieval cue, and the remainder of the story is retrieved.

Network Architecture. We have devised a recurrent parallel distributed processing model which searches for highly probable trajectories where the probability of a trajectory is formally defined with respect to a MSP representation consisting of d local states or propositions.. Figure 1 shows a convenient way of thinking about this system. Instead of trying to visualize the complex temporal dynamics of a d-unit system, a system of dM units is considered where the unit in the ith row and jth column of the array corresponds to the value (absent or present) of the ith feature at time j. Thus, the each column of the array represents a point in the d-dimensional situation state space, and the M columns of the array correspond to an ordered sequence of M points in situation state space.

Feature #	Sentence Fragment associated with Story Feature
1.	Once there was a little boy
2.	who lived in a hot country.
3.	One day his mother told him to take some cake to his grandmother.
4.	She warned him to hold it carefully
5.	so it wouldn't break into crumbs.
6.	The little boy put the cake in a leaf under his arm
7.	and carried it to his grandmother's.
8.	When he got there
9.	the cake had crumbled into tiny pieces.
10.	His grandmother told him he was a silly boy
11.	and that he should have carried the cake on top of his head
12.	so it wouldn't break.
13.	Then she gave him a pat of butter to take back to his mother.
14.	The little boy wanted to be very careful with the butter
15.	so he put it on top of his head
16.	and carried it home.
17.	The sun was shining hard
18.	and when he got home
19.	the butter had all melted.
20.	His mother told him that he was a silly boy
21.	and that he should have put the butter in a leaf
22.	so that it would have gotten home safe and sound.

Table 2. Situation State Space Representation of Epaminondas Story

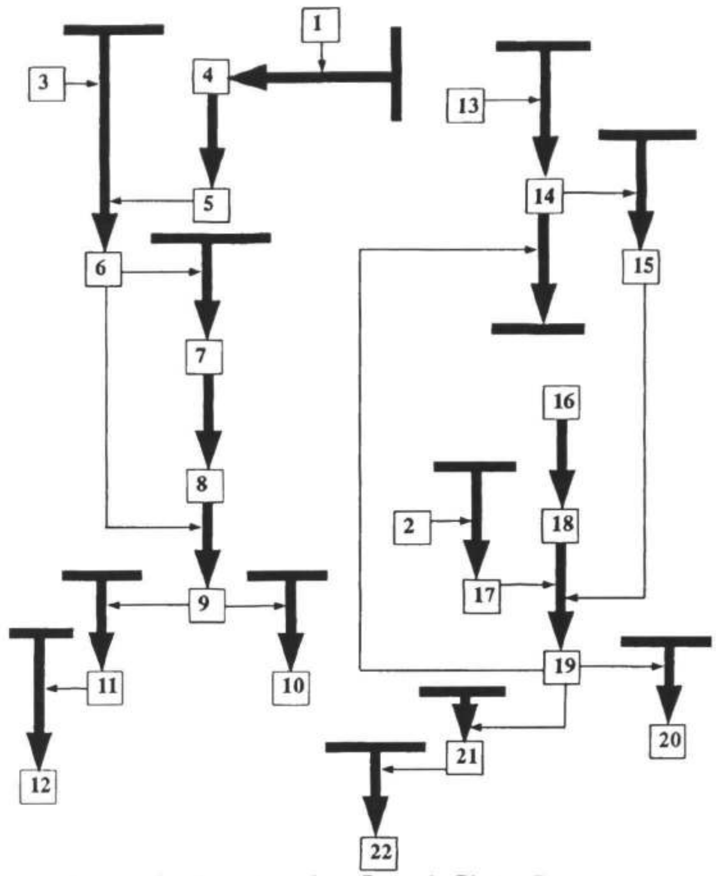

Figure 1. Epaminondas Causal Chain Representation. The numbered states refer to propositions in Table 2.

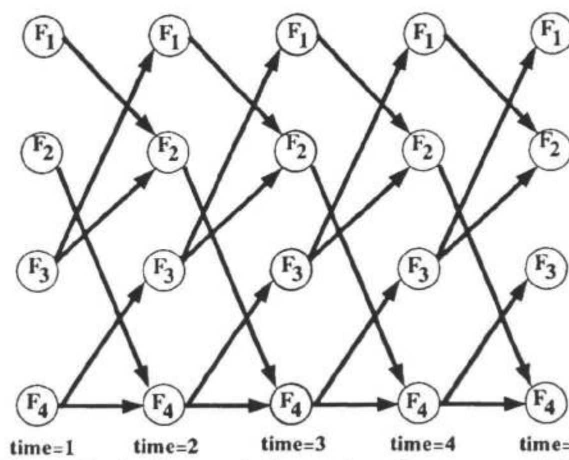

Figure 2 An "expanded" version of a recurrent PDP network. The recurrent network may be visualized as a matrix of units where the pattern of connectivity from one time instant to the next is identical. In this example, a four unit recurrent network has been rewritten as a sequential 20 unit network which can reconstruct state space trajectories of length five or less.

Notice that the connectivity pattern between units at adjacent time intervals is identical because this two-dimensional array is intended to model a two-layer recurrent network. The network shares important similarities with recurrent back-propagation (Rumelhart, Hinton, and Williams, 1986) and the brain-state-in-a-box model (Anderson et al., 1977; Golden, 1986). Golden (submitted) has found a discrete-time Liapunov function for this algorithm which explicitly states when all trajectories will converge to the set of system equilibrium points.

Comprehension Process. The comprehension process is modelled by beginning with a story which has already been parsed into a situation state space trajectory as in Table 1. If situation feature i at time j is equal to one (indicating feature i at time j is present), then the activation value of the unit in the ith row and jth column of the array in Figure 4 is clamped to the value of one during the comprehension process. The term *clamped* refers to the case where the activation of a unit is not permitted to change. The unclamped unit representing situation feature i at time j then computes a weighted sum of the activations of the units at time $j-1$ and time $j+1$, and uses this weighted sum to increment or decrement the unclamped unit's activation value. The unclamped unit's activation value is also decremented by an amount inversely proportional to ρ so that the system searches the high-dimensional trajectory space in a region near the original story trajectory. Finally, the activations of all units in the system are constrained to lie in the range of zero to one. When the activations of the unclamped units are updated in this manner, then the network may be formally viewed as seeking a trajectory in situation state space which is highly probable with respect to a probability (belief) function. The system updates the activations of the units for some pre-determined maximum number of iterations, or until the system stabilizes. The resulting pattern of activation over the dM units is the constructed story trajectory, and represents the system's "understanding" of the story.

Learning and Recall Processes. It is assumed that people learn the story trajectory (mental model) which they constructed during the comprehension process. Rather than attempt to model the details of this learning process, we are currently content to model the end results of that process. In particular, it is assumed that when people are asked to recall a story from memory, an episodic memory trace of the story trajectory is available to guide the recall process. In the model, the strength of this episodic memory trace is the ρ parameter. Large values of ρ correspond to long retention intervals so the strength of the episodic memory trace of the story trajectory is strong. Small values of ρ correspond to short retention intervals so the strength of the episodic memory trace of the story trajectory is weak.

The recall process is then similar to the comprehension process, except that only the first few features of the story in the first three time steps of the trajectory are clamped as a retrieval cue. The network must then reconstruct the remainder of the trajectory. Although this is a very high dimensional parameter estimation problem, the introduction of the learning constraint helps by restricting the search to trajectories close in an Euclidean distance sense to the original story trajectory. In particular, each unit at time t uses a weighted sum of the activations of the units at times $t-1$ and $t+1$ to update its activation value, but each unit at time t also has its activation value modified by the episodic memory trace of the story weighted by the ρ parameter.

The reconstructed recall trajectory is then used to generate the model's free recall responses. In particular, the "most active" unit in each situation is assumed to be the model's summary of that situation. Moreover, since the situation vectors are ordered in the recall trajectory, the responses of the model will be ordered as well. If the maximally active unit's value was less than 0.5, the model does not recall a situation feature summarizing that situation. If several units in a situation are maximally active, then exactly one of the units is randomly chosen to summarize the situation.

Simulation Experiments

Human memory for simple causally coherent stories is characterized by at least four fundamental phenomena (Trabasso, Secco, & Van Den Broek, 1984; Van Den Broek & Trabasso, 1985). First, propositions with more causal connections are more likely to be on the main causal chain of the story and are more likely to be recalled. Second, as the retention interval between reading and recalling the story is increased, the percentage of propositions recalled decreases but those propositions will be more likely to lie on the main causal chain of the story. And third, more propositions will be recalled from stories which are more causally coherent (i.e., stories possessing more propositions on the main causal chain of the story). In this first set of simulations, we were interested in whether the proposed model would exhibit some of these qualitative phenomena.The average *causal connectivity* of a group of propositions was computed by counting the number of forward and backward connections in the MSP representation each statement in the group possessed, and then averaging over the group of propositions.

Each of the four stories were individually "comprehended" by the model, "learned" by the model, and "recalled" by the model as previously described. The ρ parameter during the recall process was varied, and took on the values: $\rho = 0.1$, $\rho = 0.2$, and $\rho = 0.3$ corresponding to short, medium, and long retention intervals respectively.

Effects of causal connectivity.

Figure 3 shows how variation of the retention interval parameter of the model affects which propositions are recalled by the model from memory. The dependent measure was *relative causal connectivity* which was defined as the average number of causal connections per proposition in a story subtracted from the average number of causal connections per proposition in the set of propositions recalled by the subjects. Like human subjects (e.g., Trabasso et al., 1984; Van Den Broek & Trabasso, 1985), propositions with greater causal connectivity (greater causal cohesiveness) are more likely to be recalled as retention interval increases. We would expect to see these effects in the model since the algorithm is minimizing an energy function which becomes more closely related to the relative causal connectivity as the retention interval parameter ρ is increased (Golden, submitted).

An analysis of variance of the data using a story by retention interval design where the story factor was treated as random, however, did not support the hypothesis that statements with greater causal connectivity are more likely to be recalled as retention interval increases although the effect was marginally significant ($F(2,6) = 4.2$, $p < 0.10$). On the other hand, the average relative causal connectivity was significantly greater than zero ($t(11) = 2.4$, $p < 0.05$), indicating statements with greater causal connectivity are more likely to be recalled (e.g., Trabasso et al., 1984; Trabasso and Van Den Broek, 1986) was replicated by the model.

Migration of misordered propositions.

Another important aspect of human memory for stories with a strong causal structure is that if propositions in such stories are "displaced," they will "migrate" back towards their canonical positions in the text (Bischofshausen, 1985; Bower, Black, and Turner, 1979; Mandler, 1978). Moreover, the magnitude of these effects tend to increase as retention interval is increased (Bischofshausen, 1985). We would expect to see these effects in the model as well since as the retention interval factor is decreased, the local probability of predicting a feature at the next instant of time becomes less dependent upon the episodic memory trace of the story formed during the comprehension process.

To model these phenomena, the simulations described above were repeated using exactly the same four causal knowledge structures (i.e., sets of connections among the units), but using stories which were slight distortions of the original four stories. For example, a "distorted" story was generated from the original *Fox and Bear* story by switching statement #8 with statement #21. Three distorted stories for each of the original four stories were generated in this manner, and the recall of the model for each of the twelve stories was recorded. Because the retention interval factor was varied in this experiment as well, thirty six independent simulation runs of the model were done. The number of steps along the recalled trajectory a misordered statement "drifted" towards its canonical position was used as a dependent measure.The results of these experiments are shown in Figure 4.

An analysis of variance of the data using a story by retention interval design where the story factor was treated as random supported the hypothesis that as retention interval increased, the magnitude of the drift increased as well ($F(2,6) = 15.6$, $p < 0.01$). Also the drift measure was significantly greater than zero ($t(11) = 6.1$, $p < 0.01$) indicating that misordered statements did indeed "drift" towards their canonical positions in the text rather than in the opposite direction.

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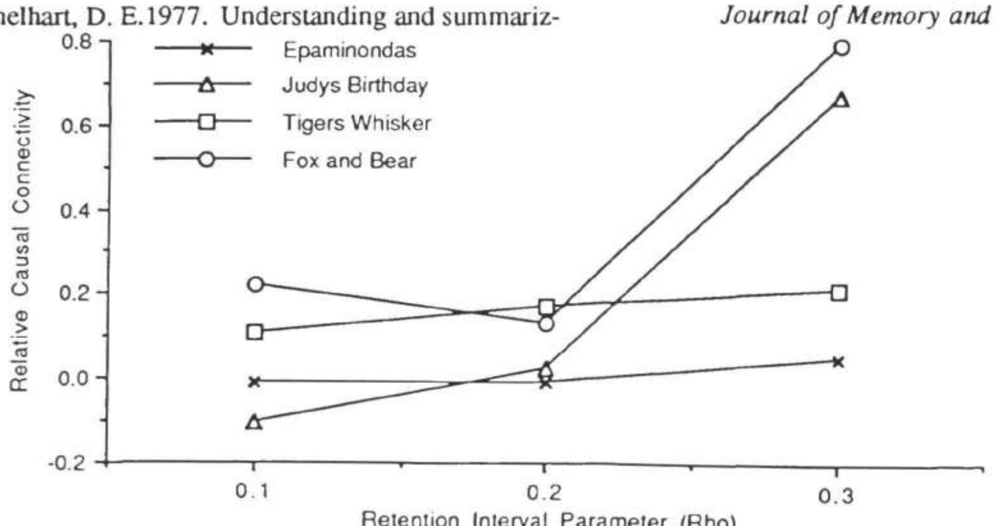

Figure 3 Relative causal connectivity as a function of the retention interval parameter ρ.

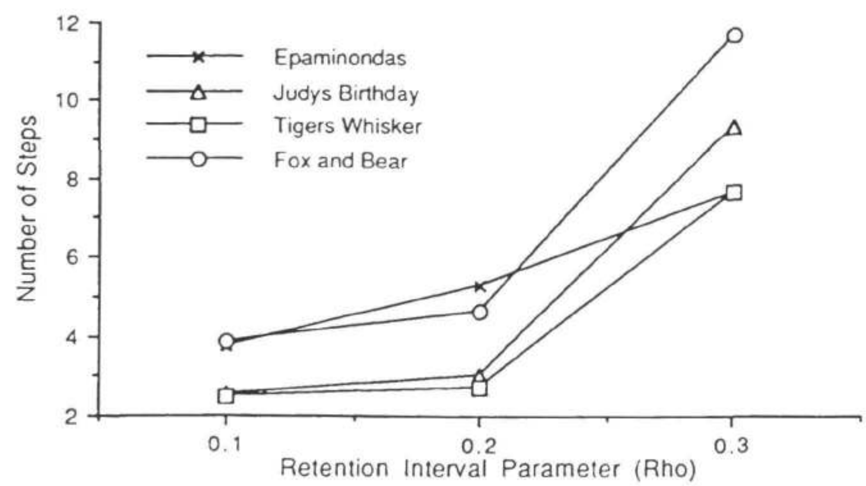

Figure 4 Number of steps a misordered statement "drifted" towards its canonical position as a function of the retention interval parameter ρ.