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The role of long-term working memory in text comprehension

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Abstract:
A distinction is made between short-term working memory, which is capacity limited, and long-term working memory , which is available to experts in their domain of expertise . Text comprehension is viewed as expert performance. The role of long-term working memory in text comprehension is analyzed, with an emphasis on the activation of relevant knowledge during comprehension . Latent semantic analysis used to model knowledge activation in text comprehension.

Ever since the days of Ebbinghaus (1985), a plethora of research results have poured from the laboratories of memory researchers. As the experimental evidence accumulated, several fairly comprehensive theories of human memory emerged which provide a reasonably good account of the major memory phenomena that had been studied in the experimental laboratories. Gillund & Shiffrin (1984), Murdock (1993), and Hintzman (1988) are good examples of these comprehensive theories of memory, but we should also note more specialized theories, such as that of Baddeley (1996) on working memory. While neither these theories nor the data on which they are based are able to answer all questions about memory experiments or settle all disputes, they represent a solid achievement and one can say with confidence that memory is one area of psychology about which we know a great deal, in a fairly systematic way. Nevertheless, while the laboratory study of memory thus flourished, this experimental research failed to address everyday memory problems and phenomena. Therefore, this laboratory based research was repeatedly attacked by psychologists who were interested in memory for stories, not word lists, memory for autobiographical events, not contrived laboratory stimuli, memory in ecologically relevant situations, not in controlled experiments. Experimental psychologists for a long time had very little to answer these critics, the more radical of whom declared the laboratory study of memory as irrelevant and were ready to discard it.

To heed these critics would be a major mistake, however. The rich knowledge we have gained about memory processes from laboratory studies during the past 100 years can very well inform and constrain our understanding of memory processes in ecologically significant situations. It is the same memory we study in a controlled laboratory experiment with artificial stimuli and in complex real-life situations – but we must figure out just how the evidence from the memory laboratory applies to everyday memory phenomena. The theory of long-term working memory of Ericsson & Kintsch (1995) does that for one important problem: how memory is used in complex cognitive processes from skilled performance to text understanding. There appeared to be an unbridgeable gap between what we know about memory in the laboratory and how memory is ostensibly used in such tasks, requiring perhaps a completely different theory of memory than what experimental psychologists had been working on for the past 100 years. Ericsson & Kintsch showed, however, that this was by no means the case. They argued that classical memory theory did not even have to be modified, just elaborated, in order to account for the observed memory use in higher cognitive processes.

Within the standard working-memory framework, it is not possible to explain how memory is used in many cognitive tasks, such as playing chess or text comprehension.

Given the severe capacity constraints of short-term memory and working memory, how do people perform tasks for which the memory demands greatly exceed these constraints? Or put in another way, why is memory so poor in the laboratory but so easy in many real-life situations?

Consider the memory demands in text comprehension. Van Dijk & Kintsch (1983, p. 347) list the following components of the memory system involved in text comprehension: perceptual features, linguistic features, propositional structure, macrostructure, situation model, control structure, goals, lexical knowledge, frames, general knowledge, and episodic memory for prior text. Each of these components by itself would exceed short-term working memory, but it is clearly needed in text understanding and people have no memory problems in understanding well-written, familiar texts. Similarly, a person memorizing a list of 100 random word requires at least one hour of hard work. To memorize a text of 100 words is trivial, however, and a person reading a novel for an hour could reproduce and reconstruct quite well what was read.

The theory of long-term working memory (LTWM) addresses this dilemma. It does so by specifying the conditions under which working memory capacity can become greatly expanded and by describing the mechanisms that are responsible for this expansion of working memory. The theory was first proposed by Ericsson & Kintsch (1995) and further elaborated by Kintsch (1998), Kintsch (in press), and Ericsson, Patel, & Kintsch (in press). Herte, the recent elaborations of the theory will be emphasized, with a focus on text comprehension rather than on skilled performance, the other primary domain of the theory.

LTWM is restricted to well practiced tasks and familiar knowledge domains. With novel tasks and in unfamiliar domains people must do with the severely capacity restricted short-term working memory. Since the typical laboratory tasks were unfamiliar to the subjects of memory experiments – like memorizing a list of paired-associates - and the materials used were relatively meaningless – word lists, or, in the extreme case, nonsense syllables - most laboratory studies of memory never involved more than short-term working memory. Hence the ubiquitous findings of severe capacity limitations. However, in some real life situations people perform tasks at which they are highly skilled and well practiced, involving well-known knowledge domains. Performance does not suffer from memory limitations in these tasks. Skilled, expert performance provides many examples of such situations – playing chess or medical diagnosis, for instance. Of course, not everyone playing chess will have a memory advantage. Only the real expert shows exceptional memory in such tasks. Novice chess players can remember briefly presented chess positions no better than the capacity limitations of short-term memory allow them. Only master chess players who have devoted a decade or so to the study of chess will show truly superior memory in these situations. Indeed, part of becoming an expert in a skill consists in the development of superior memory in the expert domain. These memory skills are entirely domain specific, however. The chess master on all memory tasks outside their expertise perform no better than people normally do.

Thus, LTWM is an expert skill. There are, however, tasks at which most adults in our society are experts. Text comprehension is an example. As long as the texts to be comprehended are simple, reasonably well written and about familiar, everyday topics, we are all experts. The reading (or listening) skills involved are highly practiced over a lifetime. The subject matter of many texts often concerns everyday events and human actions and relations – subjects in which our lifelong experience qualifies us as experts. A text on atomic physics needs a physicist to comprehend, but for a simple story or item in the newspaper we all have the necessary expertise. Thus, we comprehend such texts readily, retrieve relevant knowledge or personal experiences automatically without special effort, and remember what we read, also without special effort. The LTWM mechanisms is behind this achievement, and explains why our memory is so good here and so poor when we read something in an unfamiliar domain or are trying to acquire a new skill.

The LTWM theory claims that superior memory in expert domains is due to LTWM, whereas in non-expert domains LTWM can be of no help. Thus, working memory has two components: short-term working memory, which is available under all conditions, but is severely limited in its capacity. This is what has been studied in most laboratory memory tasks. The second component of working memory is LTWM, which is not capacity limited but available only in expert domains. LTWM is conceived as a subset of long-term memory[1] that is directly retrievable via cues in short-term working memory. Any cue in short-term memory – alternatively we could talk about contents of consciousness, or items in the focus of attention – that is linked by a stable memory structure to long-term memory nodes makes available these nodes in a single, automatic and quick retrieval operation. The retrieval is fast and automatic in that it does not require mental resources (such as an intentional, conscious memory search does). Thus, the contents of short-term memory automatically create LTWM: a zone in long-term memory that is directly linked to these contents and immediately retrievable. The crucial restriction is that the items in short-term working memory and the items in long-term memory are linked by stable, fixed memory structures that permit direct retrieval. This is the case only in very well practiced domains – where we are experts. Without these expert memory links, retrieval can be a protracted and resource demanding process and is controlled rather than automatic.

Long-term memory is a relatively permanent system. Additions and modifications occur, as well as forgetting, but the system as a whole changes only slowly. Short-term memory, the focus-of-attention or content- of-consciousness, on the other hand, changes from moment to moment. Since LTWM is generated dynamically by the cues that are present in short-term memory, LTWM mirrors the changes in short-term memory. A flashlight metaphor has often been used to describe short-term memory: a small beam that lights up 3 or 5 nodes in long-term memory. Imagine each of these nodes is linked to nodes in the unlit part of the long-term memory network. The linked nodes form LTWM. Working memory consists of the lit nodes plus the linked nodes in the dark part of long-term memory. The flashlight is able to jump immediately to any of these linked nodes, without external guidance.

The above represents the simplest case of LTWM. The links pre-exist in long-term memory (stable associations or other memory structures such as schemata, frames, etc.). LTWM in this case involves no more than a set of cues in short-term memory plus the long-term memory nodes they are linked to in long-term memory. But this is only part of the story, because the ongoing cognitive process results in the generation of new nodes, which greatly enrich and complicate LTWM. These nodes are first generated in short-term working memory, but as the focus of attention shifts away, they fade from consciousness. Depending on the nature of these nodes, they may be more or less permanent or subject to forgetting.

Consider what happens in reading comprehension: Comprehension results in the formation of new nodes in memory (propositions derived from the text) which are linked in a complex pattern determined by the nature of the text and the comprehension strategies of the reader. Figure 1 shows both episodic memory nodes generated in the process of comprehension, and long-term memory nodes linked with them. The links among newly formed propositions (those are the links that are being formed in the comprehension process, as described, for instance by the construction-integration model of text comprehension of Kintsch, 1998) are shown as thick black lines, whereas pre-existing links in long-term memory are shown as thin lines. Broken lines, linking newly formed propositions and long-term memory nodes indicate the memory links that generate LTWM. Working memory in Figure 1 then consists of the text nodes still active in short-term memory (short-term working memory), plus older text nodes no longer in the focus of attention but linked to the active nodes by the links established between text nodes in the process of comprehension, and the long-term memory nodes linked to active nodes by pre-

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[1] The term long-term memory is used broadly here; it includes personal experiences as well as general

existing memory structures (LTWM). Not any link will do, however, to generate a LTWM node: the link must be stable and strong, permitting automatic retrieval.

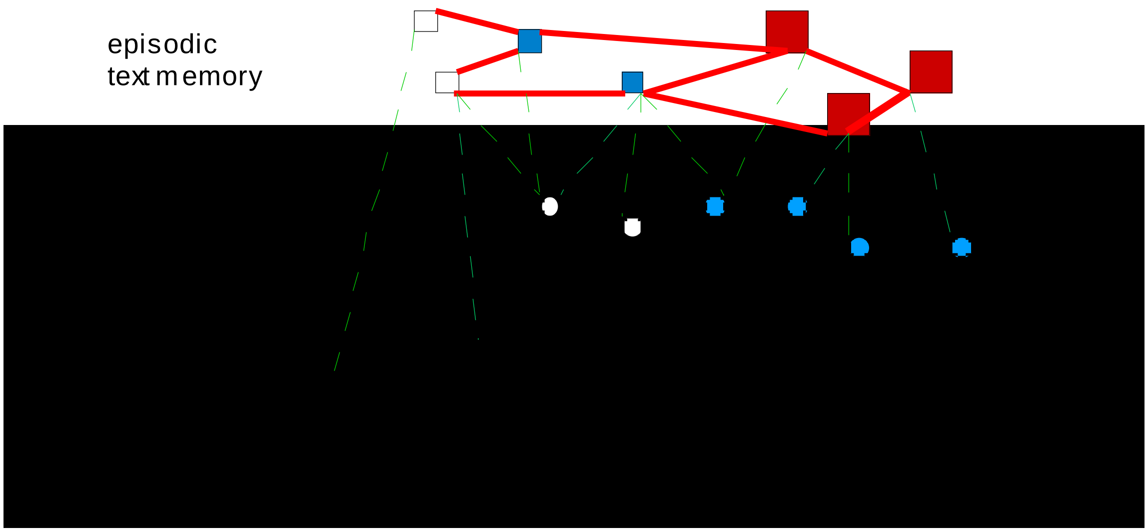

Figure 1. Three propositions (large squares) are held in short-term working memory; the other four squares represent text propositions already out of short-term working memory. Filled in nodes are long-term memory nodes that are directly linked to contents of short-term memory and comprise LTWM. Thick lines are strategically established links during comprehension; dashed lines represent links between episodic nodes and long-term memory nodes.

How are the links that generate LTWM formed? The newly formed links in text comprehension are the result of the reader’s comprehension strategies, as specified by the construction-integration-model. Some links are strong, some are weak, some nodes are tightly interconnected and some are sparsely interconnected, depending on how the mental representation of a text has been built up. The structure that supports retrieval is not being formed for the purpose of memory retrieval. Rather, the ability to retrieve is incidental to comprehension: if one comprehends a text properly, a mental structure has been generated

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knowledge.

that supports memory retrieval via LTWM. What is required for LTWM, therefore, are appropriate comprehension strategies (e.g., as described in van Dijk & Kintsch, 1983), and the knowledge (linguistic knowledge, world knowledge, specific topic knowledge) and skills (language skills) necessary for the use of these strategies.

LTWM is not always incidental. There is a continuum between some processes where LTWM is incidental, as in text comprehension or chess, and other processes where it is intentional, as in the case of the retrieval structures used in mnemonic techniques. Thus, the memory artist studied by Chase & Ericsson (1981) employed a set of specific encoding strategies for digit strings for the sole purpose of memorizing them, and used a body of knowledge (about running times) that was needed for the operation of these encoding strategies. Another example is the method of loci where a complex schema is used over and over again, together with specialized imagery encoding strategies for the sole purpose of memory retrieval. It is important to realize, however, that the deliberate retrieval structures involved in mnemonic techniques are but one type of structures that support LTWM. Incidental structures that arise from text comprehension processes or planning moves in a chess game represent quite different cases which are ecologically more important.

Two types of links are involved in LTWM: links among newly formed nodes as a text is being comprehended, and links between these newly formed nodes and other nodes in long-term memory. For new nodes and links in text comprehension the process assumed here is the following: certain features of a text elicit an appropriate processing strategy; the application of this strategy results in the creation of new memory nodes, links among them, and links among the new nodes and the body of long-term-memory; the whole process is automatic. Thus, faced with a particular text, an expert speaker of the language automatically recognizes which comprehension strategies are appropriate, applies them, and generates a network of propositions linked to prior knowledge. A chess player looks at a board and applies appropriate planning strategies, creating a network of representations that enable later recall. A memory artist "sees" a random digit string as a meaningful running time and stores it at a particular place in his reusable retrieval structure. An expert physician recognizes a patient's signs and symptoms, which are stored as a pattern for subsequent decisions about disease, therapy, and management. The performance is quick and effortless in each case, but limited to the specific domain in question. In each case an episodic memory structure is created that supports LTWM. The nature of these strategies, and the resulting structures, is the object of study in psycholinguistics, the psychology of chess, the psychology of clinical reasoning, or mnemonics, respectively, and differs widely between these domains. Although we know something about these strategies and their use, much remains to be learned.

But what about the links between newly generated memory nodes and other nodes in long-term memory – the dashed lines in Figure 1? Calling them associations and schemata does not really explain anything. What is needed is a process model for the automatic elicitation of relevant knowledge nodes. Myers et al. (1994) attempt to do so with their "resonance model" which specifies a mechanism for such automatic knowledge retrieval in discourse comprehension (and, presumable, other higher cognitive processes). Their model lacks, however, a way to specify the huge and complex long-term memory network upon which this resonance process must operate. Latent Semantic Analysis (LSA) can fill this gap in that it allows us to simulate human knowledge structures on a large scale.

How is it possible to simulate human knowledge, its wealth, its richness, and its complexity, its organization and structure? Human knowledge is the result of our interaction with the world. The nature of that interaction is constrained by the nature of the human body and human mind. Human knowledge contains information at different levels of representation, starting with the level of action and sensory experience which we share with some animals, to linguistically coded information and the abstract-symbolical level which are distinctly human. Language has come to be a dominant factor in the way human knowledge is encoded and structured. It is certainly not the case that all human knowledge is linguistic, but much of what we know is indeed represented linguistically, either because the original information was in linguistic form or because we have recoded linguistically a type of experience that was non-linguistic to begin with: an action, sensation, emotion, or abstraction. Thus, while human knowledge may take on many forms, linguistic representations play a particularly important role. The arguments for these claims about the nature of knowledge representations are summarized and discussed in some detail in Kintsch (1998).

How could such a knowledge-based system be modeled? Since it is too large and too opaque for hand coding, the only way would be to design an algorithm that acquires knowledge through experience in the way humans do. However, because computers are by nature very different from humans, they cannot interact with the world and learn from it in the way humans do. There is no solution to this dilemma.

There is a solution, however, to a more limited problem. Suppose we model not all of human knowledge, but only its linguistically encoded component, or more precisely, only that part of human knowledge that is reflected in written language. While this is undoubtedly a nontrivial restriction, the portion of human knowledge that is representable by the written word is a large one. It does not comprise all knowledge, and the written representation may sometimes introduce distortions - but if we could successfully model this section of human knowledge, this would be a major advance. Latent Semantic Analysis, or LSA, permits us to do so.

LSA is a fully automatic computer method for the construction of a knowledge representation in the form of a high-dimensional semantic space based on the analysis of a large corpus of written text. The computer reads a large amount of text - millions of word tokens - consisting of thousands of documents and ten thousands of word types. From this input it constructs a huge word-by-document matrix, the entries of which are the frequencies with which each word type appeared in each document. Thus, word co-occurrences are the input to LSA, much like percept-action-word co-occurrences are the input to the human cognitive system. This input is processed and transformed in two ways: first, through the mathematical technique of singular value decomposition, and then through dimension reduction. Singular value decomposition is a technique which allows one to express any matrix as the product of three matrices, one of those being the singular values matrix. If one multiplies the three matrices together, one simply gets back the original one. But we don't want the original matrix of word co-occurrences, because that matrix contains too much information. The fact that an author used this particular word in this particular place is not important; rather, we want to know what kinds of words could be used in that place. In other words, we want to represent the basic meaning relationships, not particular word choices. LSA achieves that through dimension reduction: it throws away most of the information it has computed and retains only the information associated with the 400 or so largest singular values of the matrix. Thus, it keeps the essence of the semantic relationships in the texts it has read, but discards the incidental and irrelevant detail.

The rationale for this analysis and its details are described elsewhere (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990; Landauer & Dumais, 1997; Landauer, Foltz, & Laham, 1998). Here, a simple example must suffice to indicate the flavor of this method. For instance, in a large corpus of texts, the singular and plural forms of a noun are not very highly correlated: in general, when one talks about a particular *mountain* one does not also talk about *mountains* in the same context, and vice versa. Thus, the correlation between *mountain* and *mountains* is probably low in the texts that LSA reads, perhaps around r = .1 or .2; after dimension reduction, however, this correlation is much higher (r = .84 in this case): LSA has inferred that *mountain* and *mountains* are closely related semantically (though by no means identical).

Although LSA starts with word co-occurrences (much like a child listening to an adult's speech), it infers from these co-occurrences a semantic space that reflects the meaning relationships among words and sentences, no longer their co-occurrences. In other words, the result of dimension reduction is an abstract knowledge space representing the structure of the information underlying the texts it had read.

Having constructed a high-dimensional semantic space of typically 300-400 dimensions in this way, we can express words, sentences, and whole texts as vectors in that space, with all the advantages this mathematical representation affords. That is, we can readily compute the semantic relatedness of vectors in terms of the cosine (a measure that can be interpreted much like the familiar correlation coefficient), and we can find out what other vectors are located in the semantic neighborhood we are interested in. For instance, around *mountain* we find *peaks, rugged, ridges,* and *climber,* whereas around *mountains* we find *peaks, rugged, plateaus,* and *foothills.* This is the kind of information we need to model knowledge activation via LTWM in comprehension.

According to the construction-integration model of text comprehension (Kintsch, 1988; 1998) knowledge activation is a bottom-up, associative process, followed by contextual integration. LSA permits us to model the bottom-up associative component of this two-stage process objectively and in detail. We assume that the LSA space is the long-term working memory structure within which automatic knowledge activation in comprehension takes place. Thus, the memory structure that is responsible for the generation of LTWM is the semantic space: items close in the semantic space are accessible in LTWM, whereas items removed in the semantic space require more elaborate and resource consuming retrieval operations.

Specifically[2], each word in a text will automatically generate a LTWM consisting of its immediate semantic neighborhood. The likelihood that an item of the semantic neighborhood will be included in LTWM is a function of the cosine between the source vector and the target vectors. The exact nature of that function cannot be specified at this point, however.

Propositions, in addition to words, also activate knowledge from their semantic neighborhood, in the same way as words do. For LSA, propositions are disambiguated and appropriately parsed word groups. Examples will be described later.

Macro-units of a text can also be represented as vectors in the LSA space. Indeed, once a text has been parsed into its constituent words and propositions, the vector representing the text as a whole is simply the centroid of the constituent vectors. Thus, the

[2] The discussion of knowledge activation in text comprehension is based on Kintsch (in press).

macrostructure of the text is given for free as soon as the text's microstructure has been computed (assuming that the appropriate macro-units are clearly signaled in the text). Hence macro-units can also participate in the knowledge activation process, exactly as words and propositions do. Indeed, items activated from the neighborhood of macro-units will usually turn out to be particularly important for the final interpretation of the text (the situation model that is constructed from the text), because they will tend to be widely interconnected. In contrast, locally activated knowledge items may become deactivated in the integration process if they are not linked to other items in the text.

How much knowledge elaboration does occur in comprehension? Technically speaking, how many items from the semantic neighborhood of each text unit are included in LTWM? These are not questions that can be answered in general. Reader activity will depend on many factors. In the extreme case of no elaboration, the resulting mental representation of the text will be a pure textbase; if a substantial amount of knowledge elaboration occurs, the mental representation is called a situation model in the terminology of Kintsch (1998.)

Once a textbase has been constructed and knowledge has been activated in the manner described above, a constraint-satisfaction or integration process takes over according to the construction-integration model. Integration ensures that only related items play a role in the final knowledge representation, and that all the irrelevant and contradictory information that necessarily has been included in the bottom-up construction process is rejected.

To illustrate the control of knowledge activation - that is, the construction of a LTWM - according to the CI model, consider a simple sentence like (example from Kintsch, in press)

The band played a waltz.

According to the CI model, we first construct a network representing the sentence itself as well as the items of knowledge that were retrieved from long-term memory by the text elements. Figure 2 shows the three word groups that make up the sentence as well as the corresponding proposition. I have also indicated knowledge activation in Figure 2. Three close neighbors for each of the four original sentence constituents were selected (with some overlap, so that the total number of items is less than 12) and connected to their sources and each other with links whose strengths were set equal to the cosines of the corresponding vector pairs in the LSA space. These nodes form the LTWM created by the sentence "*The band played a waltz*," or rather a segment of LTWM, because LTWM may contain a larger neighborhood than just three nodes. The links between the three content words and the proposition node were assigned a strength value of 1 to make sure that they will dominate the resulting network. Note that the network thus constructed contains relevant (e.g., *dance*) as well as irrelevant (e.g. *game*) nodes. After integration, however, the irrelevant nodes are deactivated (their activation values are low), while the relevant knowledge items as well as the original sentence constituents remain strongly activated, as seen in Figure 3. A network with strength values as in Figure 3 would be the situation model the CI model has formed, given that the LSA space functions like a retrieval structure and given that the particular knowledge items were included in LTWM as in Figure 2. We can express this situation model as a vector in the LSA space, too: the vector representation of the sentence is the centroid of all the component vectors, weighted by the activation values shown in Figure 3.

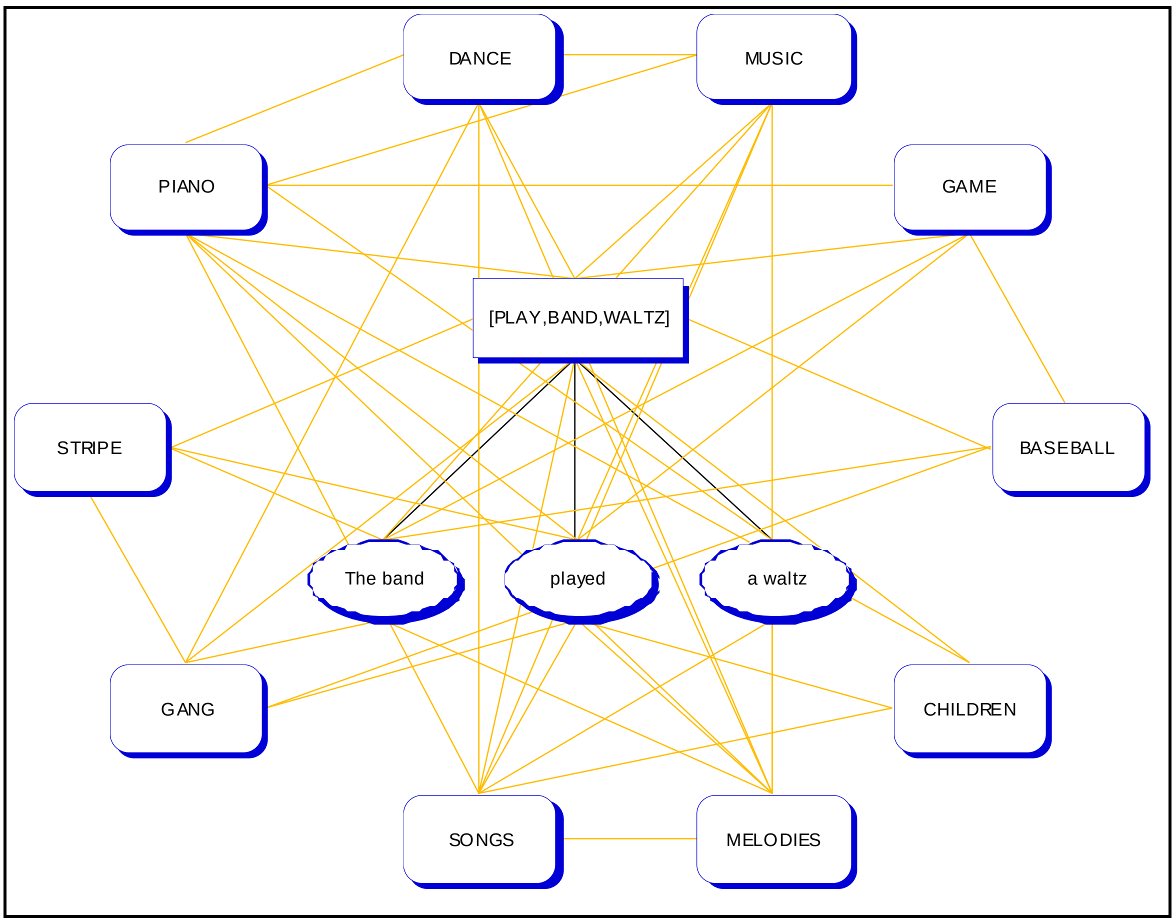

Figure 2. Knowledge activation for the sentence *The band played a waltz*. Words are enclosed by ovals, the underlying proposition by a rectangle, and the concepts retrieved from long-term memory, which form LTWM by rounded rectangles. Only links above a certain strength are shown. (From Kintsch, in press).

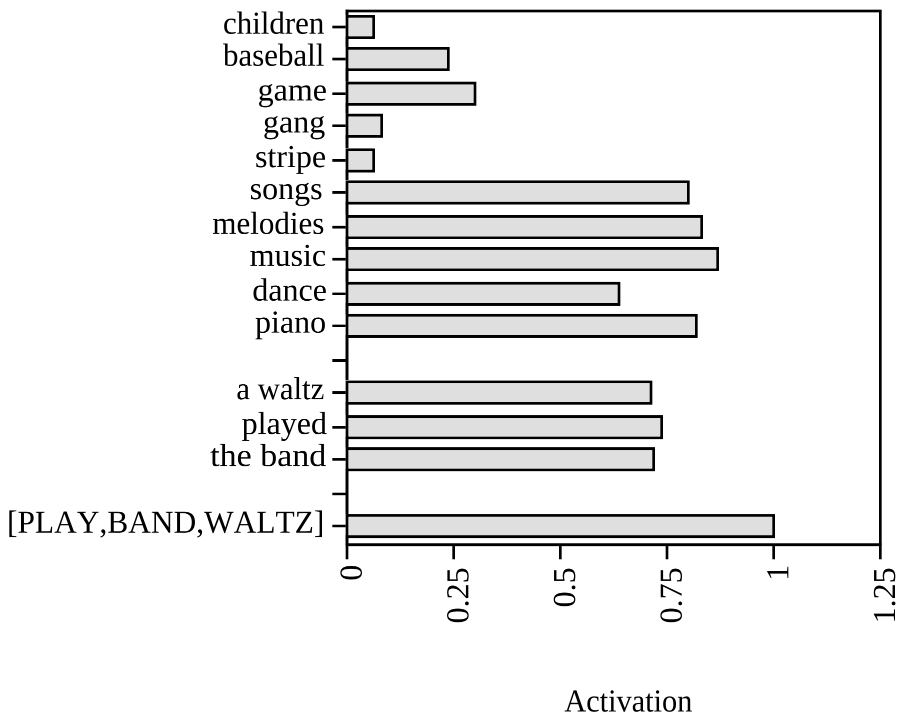

Figure 3. Final activation values for the nodes in Figure 1. (From Kintsch, in press).

Now consider the two-sentence mini-text

The band played a waltz. Mary loved to dance.

There are no direct links between these two sentences, but the sentences are nevertheless indirectly coherent (Kintsch, 1998). LSA lets us assign a non-arbitrary value to the coherence link between these two sentences, the cosine between their corresponding vectors, which turns out to be .45 in this case. No inference is required to connect these sentences: the very fact that they both are situated in the same semantic space provides a link of a certain strength between them.

A slightly more complex case, the often-cited newspaper headline *Iraqi head seeks arms* is shown in Figure 4. There are two propositional interpretations[3] of this sentence*: A head from Iraq seeks arms,* which does not make any sense, *and The government of Iraq wants weapons*, which is the intended meaning. The two propositional interpretations interfere with each other (the broken lines indicate a link strength of -1). If the network consisting only of the sentence and the two antagonistic propositions is integrated, neither

[3] In Figure 1 the proposition was not really needed - the sentence itself would have served just as well. In general, propositions are needed to clarify the psychologically most relevant meaning relations in complex or ambiguous sentences (as in Figure 4), neglecting, however, some semantic and syntactic detail.

interpretation wins out. Furthermore, the process of associative knowledge elaboration, in this case, fails to disambiguate this sentence. If we add, like in Figure 2, three associates from the neighborhood of each node (not shown in Figure 4), the integration process is not helped. What is needed in this case is a more directed inference process: not only the propositions shown in rectangular boxes must be constructed as part of the original parsing process, but also the intermediate propositions shown in the rounded-off rectangles that provide the missing links between the words and the eventual propositions *(Iraq is a country; countries have governments; governments have heads* - etc.). If these inferences are included in the network, the network settles on the intended interpretation: the *want-government-weapons* proposition receives a final activation value of .89, the *have-Iraq-government* proposition ends up with .66, and both unintended propositions receive an activation value of zero.

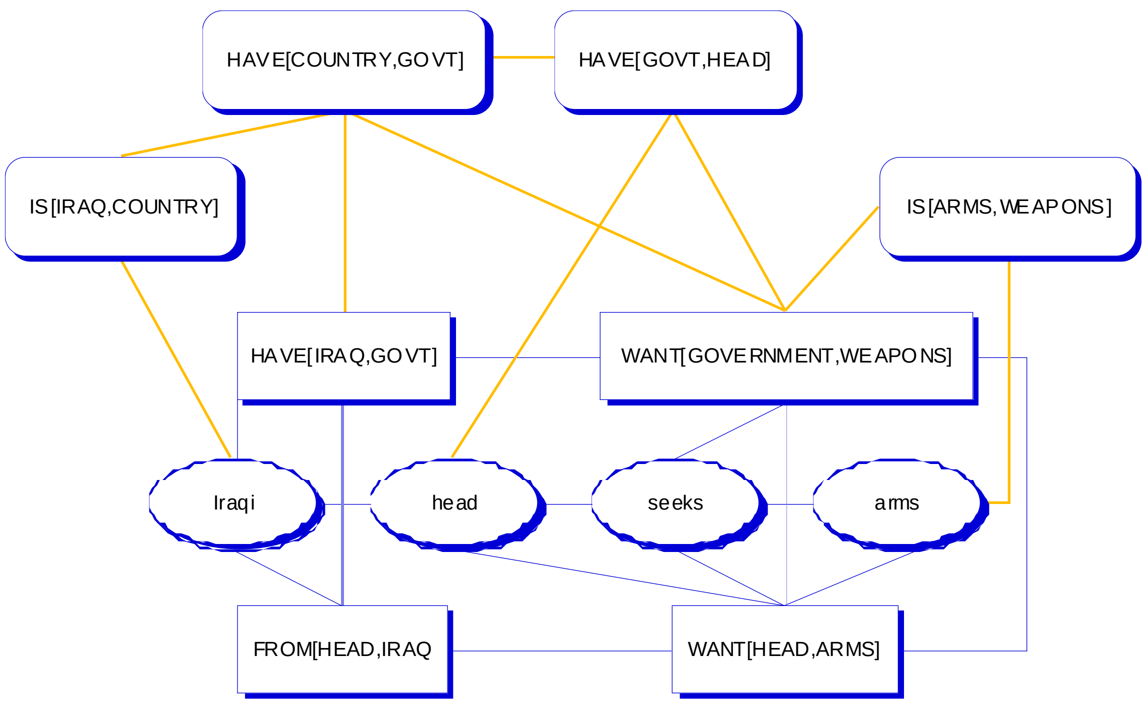

Figure 4. The sentence “Iraqi head seeks arms” with two opposing propositional interpretations and bridging inferences. Words are enclosed by ovals, the propositions by rectangles, and inferred propositions by rounded rectangles. (From Kintsch, in press).

The two examples discussed here illustrate how LTWM is generated automatically in text comprehension according to the CI model . In the first example the LSA-CI model provided a good account of the process of knowledge activation. However, as the second example shows, this is not always sufficient: sometimes the process of bottom-up associative knowledge elaboration must be supplemented by more a goal-directed inference process to generate a coherent representation of a text. LSA is a model of knowledge representation and it must be combined with theories that specify the precise processes that operate on this representation. The CI model - discussed in detail in Kintsch (1998) - is one such process theory, but to completely model human thinking and language understanding, more than that will be required - for instance, an explicit account of how sentences are parsed in the first place, as well as the analytic, goal directed problem solving that is involved in the formation of inferences in text comprehension.

Text comprehension is therefore one area where it is in fact possible to formulate a computational model of LTWM. Even though that model is still incomplete in some respects, it specifies clearly the nature of the memory structures involved in LTWM . It is important to note that these structures are not uniform, either in their nature or in the manner of their generation. The episodic part of LTWM in text comprehension springs from the comprehension process itself, the details depending on the strategies of the comprehender as well as the characteristics of the to be comprehended text. A LTWM is generated in comprehension as long as the strategies are well-practiced and automatic, and result in the establishment of strong links among the propositions of a text. The other part of LTWM that makes available relevant portions of long-term memory in LTWM , depends on a quite different mechanism. Here, the semantic space itself functions like a retrieval structure, making close neighbors of newly generated text propositions automatically available in LTWM, as long as they can be successfully integrated with the existing episodic structure.

What defines LTWM is the existence of strong links in memory that can support automatic retrieval. How these links are generated, and, indeed, how the nodes themselves are generated which are linked in LTWM, are important and interesting questions that must be answered by the study of text comprehension, medical diagnosis, chess playing and other cognitive skills in which LTWM plays a role. LTWM is not always a matter of schemata, or retrieval structures, or strong associations. It can be any of these and more under the right circumstances. Anything that guarantees automatic retrieval will do, as long as it can be generated automatically within the context of the cognitive process requiring the use of LTWM. That is a serious restriction, because it essentially limits the use of LTWM to expert performance.

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