Inhibition Needs No Negativity: Negative Links in the Construction-Integration Model

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Abstract

The Construction-Integration (CI) model represents sentence comprehension using nodes composed of propositions, words, and other information connected by links. These representations include multiple possible structures for a sentence. Successful simulation of sentence comprehension requires that inappropriate or irrelevant structures are not selected by the model. The standard CI model contains inhibitory links between possible structures to aid in the selection of the appropriate alternative. An alternative account of the CI model, the knowledge-based account, proposes the use of positive links only to disambiguate alternative structures instead of inhibitory links. This study compared these two accounts and found both models worked equally well with respect to number of iterations needed for the network to settle on a pattern of activation, the amount of activation for the selected nodes, and the node selected between mutually exclusive representations of a text, suggesting that both accounts produce similar representations of a sentence.

Comprehension and Disambiguation

An important process in reading comprehension is disambiguation: the ability to select a single representation from multiple possible representations. Even simple sentences typically contain words and phrases with multiple meanings as well as multiple possible syntactic structures (e.g., flying kites can be dangerous). To successfully comprehend the sentence, the correct representation must emerge as the most highly activated among all possible representations. The Construction Integration (CI) model (Kintsch, 1988; 1998) provides a simulation of reading comprehension instantiated within a hybrid connectionist architecture. The CI model relies on architectural features (e.g., the connections between information units) to facilitate appropriate representations of a text and inhibit inappropriate representations. The model typically relies on facilitatory links between related units of information and negative links between alternative, conflicting representations. The negative links effectively inhibit the weaker representation (e.g., Gernsbacher & St. John, 2000; Kintsch, 1998). However, a modified version of the CI model has been proposed that does not use negative links between alternative representations, relying solely on facilitation between related units of information. (McNamara, 1997; McNamara & McDaniel, 2004).

While the work by McNamara (McNamara, 1997; McNamara & McDaniel, 2004) suggested that negative links were not necessary to explain inhibitory processes, there have been no comparisons of the two versions of the CI model. The purpose of the current study was to compare the CI model with and without negative links when simulating comprehension of an ambiguous sentence.

The standard CI model is based on the assumption that negative links are required for the simulation of comprehension to select the appropriate structure for a sentence (Kintsch, 1998). The negative links remove activation from nodes in order for disambiguation to occur. In contrast, the knowledge-based account promotes a disambiguation process that relies solely on competition for association between nodes (McNamara, 1997). Equitable results of sentence simulations for both accounts would mean that the same phenomenon could be simulated by two accounts with different underlying assumptions.

Construction-Integration Model

The CI model of comprehension includes two separate, but interdependent stages (Kintsch, 1998; Kintsch & van Dijk, 1978). During the first stage, construction, a mental representation (instantiated as nodes and links) is formed from the text and the reader’s knowledge (Kintsch, 1998). This initial representation is formed by generating all possible meanings of the words in the sentence, and all possible sentence structures. Creating this representation therefore involves promiscuous generation of information, with no regard to plausibility or contextual appropriateness.

During the second stage, integration, nodes within the network are strengthened and weakened in iterations until reaching a stability criterion (i.e., less than .001 change in node strength between iterations). Activated nodes send activation through positive links to other nodes and take away activation through negative links during each iteration. This process generally results in the elimination of superfluous information and a coherent text representation that includes primarily relevant information.

The CI model uses propositions as a basic unit of representation. Propositions are situated in the model as nodes and connected to one another through links. Propositions are predicate-argument units that represent the relations found within a text in the form of Predicate [Argument1, Argument2,…]. The slots (i.e., predicate, argument1, etc.) in the predicate-argument structure are
reserved for specific elements of a text. The predicate is typically a verb (e.g., run), though it can also be a modifier of a noun (e.g., red).

Links connect the nodes created from the propositions and words in a text. Positive links connect related nodes such as propositions and the words present within them. Positive links supply activation from one node to another. Negative links form between mutually exclusive nodes (Kintsch, 1998). Mutually exclusive nodes are competing representations of a text created during construction, such as alternative meanings for words in the sentence or alternative propositions created from the sentence (e.g., a river bank and a money bank). Unlike positive links where activation to one node would feed the other, activation to a node with a negative link removes activation from the other making it weaker thereby suppressing its activation.

The integration phase is completed when the activation across all nodes has stabilized. The resulting pattern of activation is the representation of the sentence. Information with high activation is included in the representation, while information with low activation is excluded. For example, when a reader encounters a word with multiple possible meanings such as bug, all of the meanings are initially activated. Due to the interconnectivity of the words in the sentence, the possible associates of the words in the sentence, and prior knowledge of the reader, one of the possible meanings is strengthened above the others.

The Knowledge-Based Account
McNamara (1997; McNamara & McDaniel, 2004) proposed the knowledge-based account as an alternative to suppression/inhibitory link based models. The knowledge-based account relies on the activation of knowledge and their associations within the framework of the CI model. McNamara based the model on the grounding assumption that better readers make more inferences and make more associations and knowledge-based elaborations while reading (Long, Oppy, & Seely, 1994; Oakhill & Yuill, 1996). McNamara (1997) simulated the findings by Gernsbacher and colleagues (Gernsbacher & Faust, 1991; Gernsbacher, Varner, & Faust, 1990) showing that skilled readers more quickly suppress irrelevant meanings of words. McNamara demonstrated, contrary to theoretical assumptions made by Gernsbacher and colleagues, that these results could be simulated without inhibitory links, and solely with a greater number of associations and links within the network. McNamara and McDaniel (2004) in turn demonstrated that participants with greater knowledge about a sentence topic, but who were not skilled readers, showed the same pattern as skilled readers – they quickly suppress irrelevant meanings of words. These results support an explanation of disambiguation that relies more on context and the enhancement of relevant information than an inhibitory mechanism that turns off irrelevant information.

The models with and without negative links both rely on the interconnections of their nodes to provide disambiguation. The standard CI model with negative links relies on processes that inhibit mutually exclusive alternatives. The connections between their nodes weaken the strength of the node that is inappropriate. Through the negative links, the more highly activated nodes deactivate nodes that are mutually exclusive. Alternatively, the knowledge-based model without negative links relies solely on constraint satisfaction. The most highly activated nodes essentially steal away activation from weaker nodes. Nodes that are more relevant tend to have more connections to other nodes in the network. Those nodes are fed more activation from other nodes, and during the integration phase, normalization of the network results in the weaker nodes losing strength. The normalization process is predicated on the assumption that the total amount of activation is limited (i.e., working memory capacity is limited). Thus, the network is normalized during each iteration, wherein the total amount of activation is kept constant such that nodes with more links become stronger and those with few links lose strength. This aspect of the model is common to both versions used here, but it is the sole feature of disambiguation in the version without negative links.

Current Experiment
There are two arguments for why the inclusion of negative links may not be necessary. There is little doubt that inhibition occurs at a neuronal level; individual neurons in the brain have excitatory and inhibitory connections to one another. What is unclear is the assumption that inhibition appears at higher orders of representation than that of the neuron. When establishing the CI model representations for a sentence, words are added in as associates of the propositions. These words are short-hand representations of patterns of activity, not individual nodes unto themselves. Therefore, negative links between two nodes would in effect be negative links between entire patterns. At this point, the neuronal metaphor fails to be adequate. The nodes are no longer individual neurons, but clusters of neurons. In this case, the negative links act as a representation of the overall inhibition between nodes of the network.

The second argument concerns the actual purpose of the negative links. The CI model does not have an instantiated knowledge base (Kintsch, 1998). The negative links may serve as a substitute for the associations provided by a knowledge base. The negative links funnel activation away from inappropriate representations, making the appropriate representation stronger. The stronger of two negatively linked representations would weaken the other. This phenomenon makes the appropriate representation the stronger of the two. If a knowledge base were incorporated in the model the strengthening of a node is the function of the links to associations. The more associations connected to a representation the more activation it would receive, increasing its activation level. Thus, negative links are not needed if a knowledge base is included in the network.
The current study examined two different CI model architectures; one model with negative links, the other without. These two models provide different explanations for text comprehension. The model with negative links includes a mechanism that removes activation from nodes when activation is supplied to a competing node. The model without negative links settles on a possible representation of text through positive links that feed activation to nodes.

The current study was a replication of the text comprehension cycle found in McNamara (1997). The exclusion of added associations and negative links corresponded to McNamara’s (1997) low-knowledge simulation, whereas the simulation with negative links corresponded to a basic instantiation of the CI model. This study extended the McNamara (1997) study in two ways. First, this study directly compared simulations of text comprehension with and without negative links. Second, this study used multiple texts as opposed to the single text used in McNamara’s (1997) study.

The two accounts of inhibition were compared for differences in terms of the number of iterations needed to settle on a representation of a sentence and the agreement of the representation between models. Simulations created by Kintsch (1988) investigating text comprehension achieved stability in approximately 10 iterations. This number of iterations corresponds to McNamara’s (1997) findings. Therefore, both accounts are expected to settle in the same number of iterations. However, if differences are found between models, word and sentence features may provide insight into why the models were different. As such, word and sentence level features (e.g., polysemy, average meaning frequency for a sentence and sentence complexity) were coded in order to identify any factors integral in the differences between models.

Methods

Apparatus and Stimuli

The CI model was run on an Apple Performa 5200 computer using the CI simulator created by Mross and Roberts (1992). Eighteen short texts of either a single sentence or a short paragraph were excerpted from several previous studies (Kintsch, 1988; Kintsch, 1998; Kintsch & Van Dijk, 1973; Kintsch & Welsch, 1991). Since there is currently no automated method for simulating the construction stage of the CI model, the sentences had been transformed into node and link structures by hand in previous studies. Only sentence structures that were already transformed into node and link structures by hand in the construction stage of the CI model, the sentences had been currently no automated method for simulating the CI model Coding

Sentences were coded into node and link representations. Nodes represent the information present in the sentence and information already present within the system (e.g., prior knowledge). The link between two nodes represents the way in which the two pieces of information are related. For example, if a node and link structure for traffic lights were constructed, the nodes representing red and stop would be positively connected, whereas green and stop would not be connected or negatively connected (see Figure 1).

Nodes represented possible propositions created from the sentence, individual words in the sentence, and information already present within the system. Alternative representations of sentence structure were modeled as possible propositional structures. For example, the janitor cleaned the room with the window could be one proposition (CLEAN[JANITOR, ROOM, WINDOW]) or two connected propositions (CLEAN[JANITOR, ROOM] and WITH[ROOM, WINDOW]) (Kintsch, 1998, p. 170). The first representation would mean that the room was cleaned using a window, whereas the second indicates the type of room being cleaned. Similarly, alternative meanings for ambiguous words were represented as separate nodes. For example, in the sentence he dug with a spade the word spade can be associated with a type of playing card (ISA[SPADE, CARD]) or a garden tool (ISA[SPADE, GARDENTOOL]).

These alternative structures represent possible interpretations of the sentence as well as information the system already knows. Alternative interpretations of words and structures must be present in the network before a distinction between them can take place. Thus, the network also contains information that is not explicitly represented in the sentence. The third type of node present in the network

Figure 1. Example network with alternative link structures
is information already present in the system, such as prior knowledge.

These three types of nodes were linked to one another in two ways. Some links between nodes were positive, meaning the activation of one node would facilitate activation in the other. Other nodes were negatively linked, meaning activation of one node would inhibit activation of the other. Information nodes were connected to associated words and propositions to facilitate disambiguation. More interconnected alternatives would be provided more activation through a superior number of positively linked nodes.

Representations of the sentences were given an initial activation of 1.0. This activation represents the perception and creation of the propositions from the text. The knowledge contained within the network not directly representative of the propositions (e.g., apples are red, but red is not mentioned in the sentence) was given an initial activation of 0.0. Any activation for the knowledge in the system was provided by the activated nodes through links to the sentence representation. A zero level of activation requires activation to be supplied to the node, rather than the node supplying activation. Once activated, these nodes supply activation to a corresponding alternative representation. The stability criterion value was set at the default of 0.001 change in activation. After the network reached a stable activation level, the simulation ceased.

Sentence Coding

The stimuli for this study were composed of single and multiple sentence texts. The CI model does not simulate comprehension of multiple sentences at once. Instead, sentences are comprehended individually with the most activated nodes remaining active between sentences. Thus, an active network contains the sentence currently being comprehended and the most activated node from a previous sentence. The final sentence contained the mutually exclusive nodes and was the focus of the study. Sentence features were coded for all last sentences.

In order to ensure that any differences found were not a result of sentence level features, an on-line analytical tool for texts called Coh-Metrix (Graesser, McNamara, Louwerse, & Cai, 2004) was used to obtain indices of word and sentence complexity. These indices included maximum polysemy, average polysemy, number of modifiers appearing before the verb, number of words, number of noun phrases in the sentence, minimum frequency and average frequency of content words. These measures were used to evaluate word complexity and sentence complexity.

Word complexity was obtained using frequency and polysemy values. Word frequency is a measure of the occurrence of a word in corpora, usually measured in occurrences per million words. Uncommon and rare words are less likely to be encountered or known by the readers. Such rare words would make the task of sentence comprehension difficult. Word frequency was acquired from the Brown (Nelson & Kucera, 1982), Kucera-Francis (Kucera & Francis, 1967), and Thorndike-Lorge (Thorndike & Lorge, 1944) corpora. Each frequency for content words was logarithmically standardized.

Just because a word occurs more frequently does not mean that it is easier to comprehend. High frequency words tend to have more meanings than low frequency words, increasing ambiguity, and causing the comprehender to rely more on context to process the word. Polysemy provides a measure of the number of different meanings a word has affecting the number of instances in which the word may be applicable, which can be taken as an approximate measure of how difficult the word might be to disambiguate.

Sentence complexity was measured using indices related to the structure of the sentence. The number of words before the main verb provides a measure of potential for imbedded clauses, hence greater complexity. Similarly, the number of noun phrases helps identify how many possible structures could be created from the sentence. Although highly correlated with number of noun phrases, number of words in the sentence was also obtained as a measure of sentence complexity. For the latter two indices, it is usually the case that the more words (or noun phrases) present, the more complex the structure.

Results and Discussion

Model Performance

Table 1 presents the number of iterations and the activation level of the selected node for the models with and without negative links. No significant differences were found between models ($\eta(34) = -0.805$, n.s.; $\eta(34) = 0.026$, n.s., respectively). In fact, all simulations except one settled on the same representation, with the same mutually exclusive node being selected as the appropriate representation for the sentence. The two models were nearly identical in the number of iterations taken to settle and the final activation of the selected nodes.

<table>
<thead>
<tr>
<th>Model with Negative Links</th>
<th>Number of Iterations</th>
<th>Activation of Selected Node</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model without Negative Links</td>
<td>11.89</td>
<td>0.760</td>
</tr>
<tr>
<td>Model without Negative Links</td>
<td>10.67</td>
<td>0.763</td>
</tr>
</tbody>
</table>

These results support the claim that both accounts for the CI model simulate similar representations for a text. Therefore, two alternative accounts of the disambiguation mechanism within the CI model with fundamentally contradictory assumptions provide similar representations of text. This does not mean that the standard model is wrong, but that the mechanisms underlying disambiguation need to be explored further.
The only differences in results found between the models were for the sentence The linguist knew the solution of the problem would not be easy. The structure selected by the model without negative links was the representation attaching not be easy to nothing rather than the noun solution. One possible reason for this error is the sparseness of the network in the original model of the sentence (Kintsch, 1998). There were no other nodes present in the model other than those representing the text. The CI model without negative links will fail without some representation of prior knowledge. Likewise, humans would likely fail to disambiguate sentences if they possessed no prior knowledge. Thus, this result highlights the critical assumption of the knowledge-based account: the activation of knowledge is necessary and sufficient to inhibit irrelevant information.

**Model and Sentence Factor Comparison**

Correlations between the model factors and sentence factors are presented in Table 2. Model factors included number of nodes, number of links, strength of chosen node, number of iterations, and criterion value met by model. Sentence factors included content word frequency (from three corpora), number of words before the main verb, polysemy of words in the sentence, number of words in the sentence, and number of noun phrases. The correlations for both models were examined individually for sentence and word factors.

Table 2. Correlations between activation level of activated choice and three sentence characteristics for the standard CI model with negative links and the knowledge-based version without negative links.

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of nodes</th>
<th>Words per sentence</th>
<th>KF Content word frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative Links</td>
<td>0.138</td>
<td>-0.594*</td>
<td>-0.514*</td>
</tr>
<tr>
<td>No Negative Links</td>
<td>0.267</td>
<td>-0.632*</td>
<td>-0.503*</td>
</tr>
</tbody>
</table>

* = p < 0.05

In both models the activation values for the chosen nodes were negatively correlated with the same two features: number of words and Kucera-Francis average content word frequency. These correlations imply that the more words in a sentence or the higher the average frequency of the content words in a sentence, the lower the activation value of the nodes. When there are more words in a sentence, activation across those words is spread more thinly. If one node (or word) does not emerge as more highly activated, then the normalization process results in the activation being spread thinly among all of the nodes. Essentially, a fan effect occurs. Thus, sentences with more words emerged with less activation than those with fewer words resulting in the negative correlation between number of words in a sentence and the activation level of the model’s final choice.

Similarly, the average frequency of the content words in the sentence was negatively correlated with the activation level of the selected node. This result indicates that the selected alternative nodes in networks containing less frequent words were more likely to have higher activation levels. This result may be due to the structure of the sentences used. All the sentences used were ambiguous with respect to either sentence structure or a specific content word. The ambiguity would be unresolvable if taken in isolation. The sentences do have a specific interpretation if all the words in the sentence are used together. As such, there are two types of words present. First, there are ambiguous words which would have more possible meanings and thus potentially higher frequency in language due to use. Second, there are focused words related to the intended meaning of the ambiguous word. These words are often specific with respect to meaning and less frequent. There are more focused words than ambiguous words in sentences, thus the average word frequency would be lower overall. These focused words are all feeding activation to one alternative representation of the sentence or word. Therefore, the activation level would be higher while the average frequency of the words would be lower.

Overall, the sentence level factors were nearly identical between models. These results support the assumption that both models are effective in simulating comprehension and the structure of the sentence alone cannot account for the results. Although nonsignificant, the correlation between number of nodes and activation level of the selected alternative node does show a higher correlation for the knowledge-based account over the standard CI model. This correlation is to be expected because inhibitory links remove activation from connected nodes. Similarly, the knowledge-based account is more highly correlated with the number of words (nodes) in a sentence as would be expected given that this account relies heavily on the interconnectivity of the network to successfully simulate comprehension.

**Conclusion**

This study explored the mechanisms within the CI model related to disambiguation. Ambiguity is present at multiple levels of text comprehension, and thus the mechanisms required to disambiguate text are fundamental to understanding how readers comprehend text. Two accounts of the CI model provide different mechanisms responsible for disambiguation. The basic CI account simulated comprehension with positive links between associated nodes and negative links between mutually exclusive representations of texts. Ambiguity was resolved due to the weakening of less activated nodes by more activated nodes. Conversely, the knowledge-based account simulated text comprehension with positive links between associated nodes, but without negative links. The interconnectivity of the nodes in a network provides representations with sufficient activation to distinguish one mutually exclusive representation from the other and allow the network to settle...
on a single representation. Previous simulations using both accounts (Kintsch, 1988; McNamara, 1997) settled on a representation of a text around 10 iterations, regardless of the presence or absence of negative links. Overall, the current study also settled on a representation of a text in the same number of interactions. Both accounts did not significantly differ in the number of iterations or the selected representation of a text.

As was found in McNamara’s (1997) simulation the exclusion of negative links did not prevent the model from settling on a representation for a text. The current study expanded this finding in two ways: 1) by increasing the number of texts simulated and 2) directly comparing simulations of the same text with and without negative links. The texts used for the simulations contained different ambiguity types resulting in different types of mutually exclusive nodes, such as the selection between propositions, selection between activated associates from prior knowledge, and selection between multiple meanings. Because comprehension of the texts was simulated similarly between both models, both accounts are plausible explanations of comprehension. Therefore, the removal of negative links does not affect the CI model’s ability to simulate text comprehension regardless of the type of ambiguity found in the text if there is some form of prior knowledge present within the network. However, the knowledge-based account, without negative links, is more parsimonious.

It is important to note that the structure of the network for both accounts is not identical. The models did differ, although not significantly, in the number of links between nodes. The models with negative links contained at least 1 more link in comparison to those without negative links because it contained negative link(s) between mutually exclusive nodes. The removal of the negative links altered the actual structure of the network and the activation levels of the nodes, but did not change the resulting selection of one alternate representation over another. The two accounts both provided accurate comprehension simulations even though their underlying structures differed. These results imply that the use of negative links in models to represent inhibition may be superfluous, particularly for models that rely on constraint satisfaction, and in particular, the normalization of activation during the integration phase. In any case, the result reported here suggests that the use of negative links or inhibition may not be the only possible explanation for a disambiguation mechanism in sentence comprehension.

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References


