Towards a Textual Cohesion Model that Predicts Self-Explanations Inference Generation as a Function of Text Structure and Readers' Knowledge Levels

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Abstract

The Interactive Strategy Trainer for Active Reading and Thinking (iSTART) is an intelligent tutoring system that provides students with automated training on reading strategies. In particular, iSTART trains students to self-explain target sentences so as to integrate encoded information into a coherent mental representation. The goal of this study was to investigate the relation between text structures and the generation of bridging and elaborative inferences during self-explanation. We developed a computational model in which textual cohesion was interpreted as matrices of textbase cohesion values, such as argument overlap or semantic similarity, but also as matrices of situation model cohesion values such as causality. The model successfully predicted the different types of self-explanations as a function of the textual cohesion. We also found that students' prior knowledge interacts with the textual cohesion effect when cohesion was based on situation model indices.

Keywords: bridging; elaboration; iSTART; textbase; situation; dependency; cohesion.

Self-explanations in iSTART

The Interactive Strategy Trainer for Active Reading and Thinking (iSTART) is a computational tool that provides students with automated training on appropriate reading strategies (van Dijk & Kintsch, 1983) to use while reading difficult texts (McNamara, Levinstein & Boonthum, 2004). iSTART is grounded on the success of Self-Explanation Reading Training (SERT, McNamara & Scott, 1999). SERT incorporates theories of text comprehension (Kintsch, 1998) and active thinking (Chi, Sotta, & de Leeuw, 1994) to train students on reading strategies that help them understand difficult texts.

Students work with iSTART in a three-step sequence, including the introduction phase, demonstration phase, and practice phase. During the introduction phase, students watch a discussion on self-explanation strategies between artificial agents (a teacher and two students). In the demonstration phase, students are asked to identify and locate strategies used in computer-generated examples of self-explanations. Finally, during the practice phase, students self-explain sentences from texts while attempting to use the reading strategies learned in the previous steps.

McNamara (2004) described six different reading strategies that the trainees use when producing self-explanations. At a *surface level*, readers represent a text segment by (i) repeating the wording, without enriching its meaning (repeating) or (ii) by generalizing the content of a text segment (paraphrasing). At a *textbase level*, readers make inferences in order to (iii) maintain the coherence of the mental representation of the text, and use the encoded information from the text read so far (bridging). At the *situation model level*, readers (iv) create explicit and enriched relations in the text (elaborating), and/or (v) try to construct an efficient situation model by making logical links between text segments (using logic) or (vi) by predicting facts or upcoming events (prediction).

As a function of readers' knowledge and skills, it is more or less difficult to go beyond a textbase representation to construct an elaborated self-explanation. Elaborated self-explanation contains inferences that not only maintain the text-based coherence of the mental representation (i.e., by bridging) but also the continuity of the situation exposed by the text (i.e., by elaboration). As such, the ability to make elaborative inferences is an indication of higher-order text comprehension. While prior knowledge has been shown to play a role in the types of inferences readers make (Caillies Denhière, & Kintsch, 2002), there is also evidence that the structure of the text favors one type of inference over another (Magliano, Zwaan & Graesser, 1999; Zwaan, Langstone & Graesser, 1995). Thus, in this study, we examine the contribution of prior knowledge and text structure in predicting when students make bridging or elaborative inferences in iSTART.

Bridging and Elaboration

A large body of research has addressed how the linguistic representation of a text guides the formation of a bridging or elaborative inference during text comprehension (Gernsbacher, 1990; Kinstch, 1993; McKoon & Ratcliff, 1992; McNamara & Kinstch, 1996; Zwaan et al., 1995). Based on Kintsch (1998) we can distinguish between inferences that *bridge* or *elaborate* information at a textbase level, and those which *integrate* the content of a text at a situation model level.

At a textbase level, both bridging and elaborative inferences are generated. Textbase coherence is mainly maintained by the presence of argument or semantic overlaps (Foltz, Kintsch, & Landauer, 1998). When local coherence can be maintained automatically, readers are able to make bridging inferences automatically without generating elaborative inferences unless the readers' goal is to strategically make elaborative or forward inferences (McKoon & Ratcliff, 1992). However, when bridging information is not readily accessible, knowledge elaborations can be accessed rapidly (retrieval time of about 400 ms) through long-term working memory (Ericsson & Kintsch, 1995; Kintsch, 1993). For example, in "A car stopped. The door opened", knowing that a door is a part of car is quite effortless.

When local coherence cannot be maintained automatically in working memory, it is well accepted that a new mental text sub-structure can be formed (Gernsbacher, 1990; Ericsson & Kintsch, 1995). Indeed, at some point of reading, students often need to make a link between a main topic and a subtopic of the text. In such circumstances, students need to rely on a highly integrated representation (i.e., a situation model) to create links between propositions currently processed and previously encoded information. As such, situation model coherence tends to follow different rules than textbase coherence rules. A theory of situation model coherence has been described by Zwaan and Radvansky (1998) that incorporates five dimensions of coherence: temporal, causal, intentional, spatial and agentive information. By using a task in which participants needed to explicitly self-explain narratives, Magliano et al. (1999) demonstrated that a deficit of *situational cohesion* in a text resulted in readers making more elaborations than bridging inferences.

Because of the difference between local coherence and situation model coherence, we can predict that bridging inferences are more likely to be generated when texts are cohesive because local coherence can be maintained automatically and there is no need to add a new sub-structure to the mental representation of the text. We can also predict that elaborative inferences are generated when, for example, the local coherence cannot be preserved automatically or when the text is directed toward a new subtopic: the textual cohesion is disturbed or lowered, and readers are forced to rely on their domain knowledge to self-explain the text.

Knowledge, Levels of Understanding and Cohesion

McNamara, Kintsch, Songer, and Kintsch (1996) have shown how text cohesion and prior knowledge interact to influence comprehension. High knowledge readers are more accurate than low knowledge readers on text comprehension assessments. The authors assessed comprehension at two levels of understanding, textbase and situation model, and found that high knowledge readers were able to take advantage of low cohesion texts to improve accuracy on situation model measures. In contrast, low knowledge readers benefits from high cohesion texts were more apparent on textbase measures than on situation model measures. Therefore, high knowledge readers benefited from low cohesion texts when they were able to elaborate their mental representation, mostly at a situation model level.

In other studies, it was also found that the interaction between cohesion and prior knowledge was modulated by readers' skills: high knowledge and low skilled readers benefited from low cohesion texts; in contrast, high knowledge and high skilled readers benefited from high cohesion texts (McNamara, 2001; O'Reilly, & McNamara, 2006). Moreover, the authors found that reading skill tended to help low knowledge readers build a situation model when reading a high cohesive text. They also found that prior knowledge helped less skilled readers comprehend low cohesive texts when comprehension was assessed at a textbase level.

The findings of McNamara et al. (1996), McNamara (2001) and O'Reilly and McNamara (2006) are consistent with theories of encoding such as long-term working memory (Ericsson & Kintsch, 1995; Kintsch, 1998). Long-term working memory theory predicts that readers are able to encode information by associating it with cues that belong to a mental retrieval structure. At a textbase level, reading skill is mainly needed to associate information with previously encoded information by means of argument overlap (Kintsch, 1988; Kintsch & van Dijk, 1978) or semantic distance (Foltz, et al., 1998; Shapiro & McNamara, 2000). In particular, related information in the textbase representation plays the role of retrieval cues. At a situation model level, when a rupture disturbs the smooth process of text comprehension, skilled and/or knowledgeable readers are able to link the non-related information to a general representation of the text by elaborating a macrostructure that results from the generalization of the encoded information based on their prior knowledge (Bellissens & Denhière, 2004; Ericsson & Delaney, 1999). When knowledge is necessary or sufficient to fill in gaps in the linguistic representation of the text, elaboration plays the role of semantic cue associated with encoded information in long-term working memory.

Hypotheses

Text comprehension and memory theories lead us to formulate the following hypotheses: (i) When *textual cohesion* is preserved, bridging inferences are more likely to be generated. In contrast, (ii) when textual cohesion is disturbed, elaborative inferences are more likely to be generated. Moreover, based on McNamara et al. (1996) and O'Reilly and McNamara (2006), we assume that, reading medium cohesive texts, (iii) high and low knowledge readers are able to understand and explain a text at a textbase level, but it seems high knowledge readers can show an advantage for a medium zone of performance and deeply understand at a situation model level too, hence we expect an interaction between prior knowledge and textual cohesion when the textual cohesion indices includes a measure of situational cohesion. Finally, (iv) high knowledge readers should generate more inferences than low knowledge readers.

Textual Cohesion and Sentence Dependency Model

We address these hypotheses in the construction of a model that is intended to evaluate sentences' dependencies to previous sentences as a function of textual cohesion (local and situation-based). Our goal is to predict the conditions that lead students to elaborate self-explanation with information from previous text or their own knowledge.

Textual Cohesion and Coh-Metrix

Coh-Metrix is a computational tool that measures more than 400 cohesion indices (Graesser, McNamara, Louwerse & Cai, 2004). All those measures can be taken to define a *textual cohesion* factor.

Textual cohesion is viewed in two complementary ways. First, text sentences are more or less related to preceding sentences by means of many kinds of relationships, such as semantic similarity, argument overlap, co-reference, causality, and so on, which can be classified either as *textbase* or *situation model* relationships. Second, in order to define *textual cohesion* we state that the dependency of a target sentence s_i corresponds to a value that is a function of all relationships that it shares with preceding sentences in the text.

Sentence Dependency Model

Our primary goal was to determine the *dependency* of text sentences as a function of *textual cohesion*. We used a network model in which each node was a text sentence and links between sentences were weighted by *cohesion values. Textual cohesion* was defined as the connectivity in the network, such that, the higher the connectivity, the greater the textual cohesion. The cohesion values were defined by Coh-Metrix cohesion indices.

Partly based on the integration phase of the Construction-Integration model (Kinstch, 1988; 1998), the model operationalized the hypothesis that the greater the textual cohesion between a target sentence s_i and preceding sentences, the more that s_i is *dependent*. Conversely, the lower the textual cohesion, the more that s_i is *independent*.

Hence, in the model, the sentence dependency was an activation value, resulting from a *relaxation process* (Rumelhart & McClelland, 1986) applied to a network in which each node was a text sentence and each link was weighted by a measure of sentence relationship, obtained from Coh-Metrix.

Sentence Cohesion Values We distinguished two types of cohesion values: (i) *textbase cohesion measures,* which were co-referential cohesion and semantic similarity measures in Coh-metrix; and (ii) *situation model measures* that combined cohesion measures to create causality, temporality, spatiality, and intentionality relationships. Both types were used in this study. The first type included a measure of the proportion of *word stem overlap* between sentences and a measure of the *semantic similarity* between sentences, given by LSA (Landauer & Dumais, 1997), using the General-Reading-up-to-1st-year-college TASA corpus (Touchstone Applied Science Associates, Inc.). For the second type of measures, we computed a *situation model measure* that includes a causality index.

The original Coh-Metrix causality index is computed by considering the number of causal verbs and causal particles per 1000 words. That measure is an approximation of the amount of causality relationships in a text. Because we wanted to get an approximation of the causal links between pairs of sentences, we combined these counts with other measures. The rationale behind this combination was based on the postulate that if there was a causal link between two sentences, then there should be, at the very least, argument overlap and/or sufficient semantic similarity between the two sentences. As a result, a causal relationship C between two sentences was defined as:

$$C = \frac{c(S + L)}{2} \tag{1}$$

where c is a normalized causal link approximation from Coh-Metrix, S is a normalized stem overlap measure, and L a normalized semantic similarity measure between two sentences.

To summarize, we computed *textual cohesion* at two levels of understanding. At a *textbase level*, textual cohesion relied on (i) stem overlap, and on (ii) semantic similarity, between sentences; at a *situation model level*, textual cohesion relied on a causality measure expressed by equation (1).

Textual Cohesion Network For a given text of n sentences, a relationship value was calculated between each pair of sentences. As a result, we had an original nXn matrix, with sentences in rows and columns and their relationship value in the cells. Textual cohesion determined the dependency of each sentence. Hence, we used the original matrix to construct one matrix per target sentence, with all preceding sentences and the target sentence in rows and columns and their cohesion values in the cells. For example, if the text comprised five sentences, the original matrix was a 5X5 matrix. From this matrix we constructed a 2X2, 3X3, 4X4 and 5X5 matrices to eventually compute the dependency of the second, the third, the fourth and the last sentences of the text, respectively. For each matrix, we referred to the last sentence as the *target sentence*.

Dependency Computation As we depicted it, textual cohesion is connectivity in a network, where each node is a sentence, and the links between nodes are weighted by cohesion values. In such a net, after the relaxation process, which simulates spreading activation in the network, greater connectivity results in greater final activation values of the target sentence. Hence, a *dependent* sentence is a sentence that receives relatively more activation, and an *independent* sentence is a sentence that receives little activation. An *intermediate* level of dependency for a sentence is defined relative to the average of the activation values.

Experiment and Simulation

Participants

Participants were 77 high school students who were paid to participate in the experiment.

Procedure of the Experiment

Participants were asked to read six texts that were approximately 400 words in length. Texts were extracted from science, history and literature textbooks. The participants wrote a self-explanation for eight of the sentences in each text. These eight *target sentences* were, signaled by red font on the computer screen. Hence, 3696 self-explanations were collected.

We also assessed participants' prior knowledge by asking them to answer questions on a prior knowledge assessment test. The test consisted of 30 four-option multiple-choice questions that covered topics on science, history and literature.

Self-explanations Coding

Two experts scored the 3696 self-explanations in terms of the presence of bridging and elaborative inferences. They determined whether the participants added information in their self-explanation in comparison to the target sentence, and whether added information came from the text itself (i.e., bridging inferences) or from information outside of the text (i.e., elaborative inferences). The coding scheme considered three dimensions: (i) the extent to which a self-explanation overlapped with the text, and particularly the last sentence read (i.e. the *target sentence)*; (ii) the extent to which a self-explanation added information to the text or the target sentence, and (iii) whether the source of any added information was from the text itself or from the reader's prior knowledge. When the information contained in a self-explanation came only from the target sentence, it was coded as a *paraphrase* or a *repeat*. When it came from previous sentence, they coded it as a *bridging* inference. When the information was not present in the text, they coded it as an *elaborative* inference. Reliability was established between two raters on the basis of a sample of the self-explanations (kappa = 0.67), then each of the raters coded half of protocols.

Of the 3696 self-explanations; 9% contained both *bridging* and *elaborative inference*s, 49% consisted of only *paraphrasing* or *repeating* the target sentences, 21% contained *bridging* inferences but no *elaborative inference*s, and 21% contained *elaborative inference*s but no *bridging* inferences. Hence, in this study, 77 high school students produced an equal number of *bridging* and *elaborative inference*s.

Textual Cohesion Model

The Textual Cohesion Model was applied to the six texts used in the experiment. For each text, we used the three measures of sentence relationships between all text sentences that we specified earlier: (i) word stem overlap; (ii) LSA semantic similarity; and (iii) causal cohesion calculated by equation (1).

For each of the three measures of sentence relationships, eight textual cohesion networks were constructed per text, one for each target sentence. The dependency value of the eight target sentences was calculated after spreading activation in each textual cohesion network. Sentences with high final activation values were categorized as *Dependent*, and those sentences with the low final activation values were categorized as *Independent*. Sentences with medium values were categorized as *Intermediate*.

Results

Textbase Cohesion Measure

As described above, textbase cohesion was represented here by stem overlap and semantic distance. For each index, we conducted a two-way within-subjects ANOVA, including sentence dependency (Dependent, Intermediate, Independent) and type of generated inference (Bridging, Elaborations), with the number of generated inferences as the dependent variable.

Stem Overlap Cohesion Sentence dependency, based on stem overlap continuity, did not have a significant effect on the number of inferences generated in self-explanations, $F(2, 152) = 1.14$, $p = .32$. However, sentence dependency had a significant effect on the type of inferences generated. Indeed, as predicted, more *Elaborations* than *Bridging* were generated when the target sentence was *Independent*; and fewer *Elaborations* than *Bridging* were generated when the target sentence was *Dependent*, .33 *vs*. .27 and .28 *vs*. .33, respectively, $F(2, 152) = 12.34$, $p < .01$.

Semantic Similarity Cohesion Sentence dependency, based on semantic similarity, had a significant effect on the number of inferences made in self-explanations, $F(2, 152) = 4.05$, $p = .01$. The quadratic contrast was also significant, indicating that significantly more inferences were produced for *Dependent* and *Independent* target sentences than for *Intermediate* target sentences, .31, .30, .28, respectively, $F(1, 76) = 7.39$, $p < .01$.

Sentence dependency also had a significant effect on the kind of inferences produced in self-explanations: more *Elaborations* than *Bridging* were generated for *Independent* target sentences, whereas the reverse was found for *Dependent* target sentences, .32 *vs.* .30 and .28 *vs.* .32, respectively, $F(2, 152) = 3.16$, $p < .05$.

Situational Cohesion Measure

Sentence dependency based on causal relationships had a significant effect on the number of generated inferences, $F(2, 152) = 4.07$, $p < .05$. The linear contrast was significant, indicating that more inferences were generated after *Dependent* target sentences than after *Intermediate* and *Independent* target sentences, .32, .30, .29, respectively, $F(1, 76) = 7.25$, $p < .01$.

Sentence dependency also exerted a significant effect on the type of inferences made in self-explanations: here again, more *Elaborative* than *Bridging* inferences were generated for *Independent* target sentences, whereas the reverse was found for *Dependent* target sentences, .33 *vs.* .24 and .28 *vs.* .35, respectively, $F(2, 152) = 24.85$, $p < .01$.

Knowledge Effects

To better understand the effect of prior knowledge on the number and the type of generated inferences, we used a mixed model with *Sentence dependency* and *Inference type* as within-subjects factors and *Prior knowledge* as a between-subjects factor. Three categories were formed based on the prior knowledge test (high, medium, low). Generally, *Prior knowledge* had an effect on the number of generated inferences: *High knowledge* participants produced more inferences than *Intermediate* and *Low knowledge* participants, .39, .30, .20, respectively, $F(2, 74) = 8.38$, $p < .01$.

Prior knowledge significantly influenced the effect of *Sentence dependency* on the type of generated inference only within the situational cohesion model. Specifically, the two-way interaction including *Sentence dependency*, *Inference type* and *Prior knowledge* was significant: $F(4, 148) = 4.29$, $p < .01$. In a separate *Sentence dependency* x *Inference type* analysis, *High knowledge* participants made significantly more *Bridging* inferences with *Dependent* than with *Independent* sentences, and more *Elaborations* with *Independent* than with *Dependent* sentence, $F(2,44) = 27.50$, $p < .01$. The same trend was found for *Intermediate knowledge* participants. However, *Low knowledge* participants generated the same number of *Elaborative* and *Bridging* inferences after an *Independent* target sentence, .21 *vs*. .22, respectively, in a separate analysis, the interaction between *Sentence dependency* and *Inference type* was not significant, $F(2, 40) < 1$.

Discussion

Predicting inference generation as a function of text cohesion and knowledge can be very useful when the goal is to train students to use particular reading strategies, such as bridging and elaboration. In order to predict the number of bridging and elaborative inferences that students would generate while self-explaining a text, we constructed a Textual Cohesion Model that automatically determines target sentence dependencies. As defined in the model, a dependent sentence at a textbase level shares arguments and meaning with previous sentences in the text, whereas, a dependent sentence at the situation model level is continuous with previous text in terms of causal cohesion.

We predicted that self-explaining a *dependent* sentence would not necessitate a lot of elaboration, because information relevant to bridging was in the text itself. In contrast independent sentences would necessitate greater elaboration by the reader in order for it to be linked with the text. Therefore, iSTART trainees would generate more bridging than elaborative inferences when they encountered dependent sentences, and more elaborative than bridging inferences when they encountered independent sentences. We also expected that textbase elaboration required less knowledge than situation model elaboration. Hence we predicted an interaction between prior knowledge and textual cohesion only when the textual cohesion measure included a index of situational cohesion.

Indeed, as a function of target sentence dependency, determined by the Textual Cohesion Model, participants did not generate the same type of inferences. As predicted, when target sentences were independent, participants produced more elaborative than bridging inferences; and when target sentences were dependent, they generated more bridging than elaborative inferences. Finally, high knowledge participants generated more inferences than intermediate and low knowledge participants, and prior knowledge interacted with sentence dependency effects when the dependency was computed on the basis of a situation model cohesion measure, such as the causality calculated by the equation (1).

In future research, we will vary levels of cohesion and vocabulary complexity in texts in order to examine whether greater effects of textual cohesion occur. It is expected that a greater range of cohesion variation should allow further investigation on the interaction between skills, knowledge, and cohesion.

As a conclusion, we demonstrate that it is possible to automatically predict the number and type of inferences generated during self-explanations by taking into account target sentence dependencies and participants' prior knowledge. We implemented this process into the Textual Cohesion Model by computing different types of textual cohesion networks. Thus, it is possible to assess effects of different kinds of independent textual cohesion on inference generation in students' self-explanations. Knowing how students are able to use text-based and/or knowledge-based information to self-explain a text, as well as knowing the level of understanding they can use to better express their comprehension, could be key information that helps teachers and tutoring technologies to improve diagnostics and remediation.

Acknowledgements

The research was supported an Institute for Educational Sciences (IES R305G020018-02) and a National Science Foundation (NSF REC0241144) awards to the 4th author. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the IES or the NSF. We would like to thank all the CSEP Lab members who participated in the collect of the data, and particularly Yasuhiro Ozuru.

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