

*Auto Prop:*  
**A Tool to Automate the Construction of Psychological Propositions**

Stephen W. Briner, Philip M. McCarthy, and Danielle S. McNamara  
Department of Psychology  
University of Memphis  
Memphis, TN 38152

A prototype of an automated tool to construct a propositional textbase, *AutoProp*, is described and qualitatively assessed. The tool is specifically designed to propositionalize texts for experimental studies that collect and analyze participants' recall of text. The procedure for creating the propositionalized text is explained, followed by a descriptive analysis of the tool's propositions as compared to 29 hand-coded propositions. In initial testing, all of *AutoProp*'s propositions differed from the hand-coded propositions at a superficial level; however, no differences deemed *uncorrectable* were encountered. Based on the success of these initial results, we conclude that *AutoProp* is a viable tool worthy of continued examination and development. Limitations of the tool, along with future developmental plans and requirements addressing these limitations are also discussed.

## **1. Introduction**

Propositions are psychological representations of textual units that capture the overall gist of a sentence or clause (Kintsch & van Dijk, 1978; Kintsch, 1988; Kintsch, 1998). Whereas the *surface code* of the text, or the exact words and phrases, is usually not retained by the reader, the *textbase*, or propositional representation of the text, is more likely to be retained in the readers' working memory (Graesser, Millis, & Zwaan, 1997) and retained after a delay (Ericsson, Kintsch, & Ericsson, 1995). Propositions essentially represent the underlying meaning of sentences in text. Although propositions are widely used in studies of text comprehension and knowledge representation, (e.g., McDaniel, Schalmhofer, & Keefe, 2001; McNamara, 2004), they have traditionally been coded by hand, a process that can be quite time-consuming.

Why has an automated tool to propositionalize text not yet been developed? One obvious answer to that question concerns the complex nature of language and the inability of computer-based programs to *understand* deep semantics. That is, it has seemed a daunting and perhaps unrealistic goal to automate the process of turning sentences into propositions.

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A second reason concerns the focus of attention. Although the utility of an automated tool to propositionalize text has long been recognized, the primary focus for most researchers has been on the theoretical aspects of propositions (e.g., Kintsch, 1998). Additionally, for many researchers, the need for an automated tool was relatively minimal, particularly if their purpose was restricted to the simulation of text comprehension, such as using the Construction-Integration model to simulate comprehension processes (e.g., Kintsch, 1998; McNamara, 1997). Propositionalizing the amount of text required to conduct a computer simulation is hardly worth automating. If it had been, perhaps we would have seen an automated tool long ago.

Recently, however, the advent of major computational projects such as iSTART (McNamara, Levinstein, & Boonthum, 2004) and Coh-Metrix (Graesser, McNamara, Louwerse, & Cai, 2004) has highlighted the need for an automated tool capable of converting thousands of sentences into propositional units. This need is two-fold. First, in both projects, we have been collecting a large number of recall protocols from young children and adults to assess comprehension. Scoring these protocols requires not only propositionalizing the texts, but also the participants' recall of the text (see section 1.3 for an example). Second, in the Coh-Metrix project, in which we are developing computational algorithms to assess text *cohesion*, *coherence*, and *difficulty*, we need an automated technique for determining the underlying propositions within a text. Because the second need is more challenging, we concentrate here on the development of a tool that can be used to aid in the scoring recall protocols. We hope in its development and testing that this will lead us to a tool that reveals the underlying meaning of text through its propositional structure. In this paper, we describe our starting point. We introduce a working prototype of a propositionalization tool, called *AutoProp*, and assess its automated output of propositions against a corpus of published hand-coded propositions.

## 1.1 The Construction of Propositions

Propositions consist of *arguments*, *predicates*, and *frames* (Kintsch, 1998). *Arguments* consist of important elements of a sentence, including (but not limited to) subjects, objects, and locations. *Predicates* modify arguments, and can be verbs, adverbs, adjectives, or connectives. The *arguments* modified by any particular predicate are enclosed within a *frame*, which is modified by the *predicate*.

For example, consider the following sentence and its propositional representation (taken from Kintsch, 1988):

- (1) a. The lawyer discussed the case with the judge.
- b. DISCUSS[LAWYER,JUDGE,CASE].

Here, LAWYER, JUDGE, and CASE serve as the *arguments* being modified by the *predicate* DISCUSS, while the set of brackets represents the *frame*. There are other ways to represent a proposition, such as a tree diagram (Kintsch, 1998). However, the bracketed style is the style most easily replicated when processing raw text, so we have chosen to emulate this text-within-brackets scheme when developing our tool.

While a sentence's propositional representation can be constructed in a number of ways, certain ambiguous sentences can also have more than one propositional representation. In such a case, each propositional representation reflects an interpretation of the ambiguous sentence. For example, take the following phrase and its two possible representations (Kintsch, 1988).

- (2) a. the old men and women
- b. OLD[MEN,WOMEN]
- c. OLD[MEN], [WOMEN]

So (a) could be interpreted in at least two ways; either it could mean, "The old men and the old women," as in (b), or it could mean, "The old men and the (not necessarily old) women," as in (c). Such ambiguous sentences, along with multi-clausal sentences, can be problematic for researchers interested in developing a propositional tool. The current study attempts to address these issues.

Although the concept of propositions has recently been somewhat controversial, particularly in the circle of embodiment theorists (e.g., Glenberg, 1997), their utility in text research is undeniable. Also, empirical studies have clearly supported the psychological basis of propositions. For example, the results reported by Forster (1970) indicated that the number of propositions in a sentence affects the number of words recalled from the sentence, with fewer words being recalled from sentences containing more propositions, even when controlling for sentence length. Kintsch and Keenan (1973) demonstrated that when the number of words in a sentence is controlled, reading time increases approximately 1.5 seconds for each proposition in the sentence. Also, a priming study by Ratcliff and McKoon (1978) provides more evidence for the existence of propositional representations.

## 1.2 Propositions in Text Recall

Propositions are often constructed in order to score the recall of a text (Barnes, Dennis, & Haefele-Kailvaitis, 1996; Graesser, Olde, & Kletke, 2002; Neuman & Weizman, 2003). A propositional textbase is first constructed, and then participant recall is matched against the textbase. The proportion of recall that closely resembles the textbase is scored as recall. Scorers can also measure the number of inferences generated by a participant (e.g., Best, Floyd & McNamara, 2003). Take, for example, the to-be-recalled sentence in a text along with its propositional representation:

- (3) a. The dog was loud
- b. LOUD[DOG]

Compare that with a hypothetical recall of that sentence and its propositional representation:

- (4) a. The dog was barking
- b. BARK[DOG]

The discrepancy between the propositional representation of the textbase (3b) and recall (4b) may reflect an inference on the reader's part. Specifically, the reader draws on prior knowledge (a dog's bark can be loud) to draw an inference (the dog was loud, so it must have been barking).

## 1.3 The Need for a Propositional Tool

The hand-coding of a propositional textbase has certain limitations. Construction of propositions by hand not only limits the sample size in studies that require propositional representations of text, but also limits the type of research that can be conducted using such a textbase (Landauer, Foltz, & Laham, 1998). Coding a propositional textbase by hand can also be time consuming if a researcher is converting participant recall of a text into propositional form. Individual preferences and random errors may cause researchers to propositionalize the same texts inconsistently. These inconsistencies can jeopardize a study's reliability or replicability.

A computational tool capable of assisting a researcher in converting a text into a propositional representation provides a distinct advantage over hand-coding. Considerably less time is needed to propositionalize a text automatically. In

addition, an automatic tool will provide a standard procedure for constructing a textbase, increasing the reliability of the propositions within a study.

The current study describes and qualitatively assesses our first version of *AutoProp*, an automated tool to assist researchers in the construction of a propositional textbase. The tool was designed with particular emphasis on automating the process of scoring free recall of text, such that a propositionalized text will be compared to a propositionalized verbal recall of the text to assess the correspondence between the two, and thus the quality of the recall. For now, the process of comparing the two sets of propositions (from the text and the human recall) is manual, but we hope to eventually automate that process as well.

Our goal in developing the tool was to capture the major elements within a text, as opposed to perfectly mimicking the Kintsch (1998) method of propositionalization. These major elements of the text will be compared against recall of a text in order to compare similarity between text and recall. Although the tool's output may differ visually from a hand-constructed textbase, its function remains the same: describing which predicates and arguments are important within the text, and how those arguments are modified by predicates.

#### **1.4 Alternative approaches to propositionalization.**

A number of alternative methods currently exist that allow researchers to bypass the construction of a propositional framework altogether. Latent Semantic Analysis (LSA, Landauer, Foltz, & Laham, 1998), for example, is a computational method that can be used to measure meaning in a text. Although LSA may be useful for measuring cohesion and for other purposes such as reading strategy assessment (Magliano et al., 2002) or the analysis of a textual structure (McCarthy, Briner, Rus, & McNamara, in press), it is less ideal when used to analyze recall of a text. First, the results from LSA are untraceable; that is, an LSA score does not indicate what the individual recalled, but rather an overall correspondence between the text and the recall protocol. LSA is also more useful for scoring the textbase knowledge or understanding than conceptual knowledge or inferences (Shapiro & McNamara, 2000).

## **2. *AutoProp*: A Prototype Propositional Tool**

Our propositional tool, *AutoProp*, combines a Charniak based parser (Charniak, 2000) with a Visual Basic interface (see Figures 1 & 2). As a first instantiation of *AutoProp*, texts are initially processed by calling the Charniak parser, before the output is loaded through the Visual Basic interface. As an example, consider the following sentence and its output in *AutoProp*:

- (5) a. The customer wrote the company a complaint  
b. [Sentence 1]  
(S1 (S NP (DT The (NN customer))  
(VP (VBZ) wrote)  
(NP (DT the) NN company))  
(NP (DT a) (NN complaint)))  
(..)))

In this parsing, the abbreviations represent the parts of speech as designated by the Charniak Parser, where NP denotes *noun phrase*, VP denotes *verb phrase*, DT denotes *determiner*, and NN denotes *noun*. After the text has been parsed, it is loaded into AutoProp. No further user-action is required as the tool automatically creates and outputs all parses as sequential propositions and sub-propositions, which indicate which information is most directly relevant to text recall. The AutoProp process is outlined below:

- (a) Check for *question forms* and *multi-clausal sentences*. (The current model asks the user to reform these sentences into single clause non-questions. These sentence structures are discussed below.)
- (b) Identify main verb and retain as *predicate* for final proposition.
- (c) Add marker to head verb if it is a negative clause.
- (d) Add modal and multi-element verb elements (e.g. *is going to*, *can help*).
- (e) Identify noun elements as propositional elements, displayed as *{pe}*.
- (f) Identify arguments of all *{pe}* as sub-propositions.

The final proposition is displayed on *AutoProp's* interface, and can be saved to a file or printed upon request. As such, the tool's output for the above example sentence would be:

- (5) c. [Proposition 1]  
wrote (the {pe} customer, the {pe} company, a {pe} complaint)  
sub prop: the ({pe} customer)  
sub prop: the ({pe} company)  
sub prop: a ({pe} complaint)

The current version of the tool requires the user to make slight modifications to multi-clausal sentences. For example, the following sentence would require a reparse:

- (6) a. An air mass is a large body of air that has about the same temperature and humidity throughout.

The above sentence would be divided into the following two sentences by AutoProp:

- (6) b. 1. An air mass is a large body of air [sbar]  
2. That has about the same temperature and humidity throughout.

Once reparsed, *AutoProp* automatically remodels the parse as an integrated proposition with the second proposition identified within the first. For example:

- (6) c. 1. [Proposition 1]  
is (an {pe} air mass, a large {pe} body, of {pe} air,  
Proposition 2)  
sub prop: an ({pe} air mass)  
sub prop: a large ({pe} body)  
sub prop: of ({pe} air)
2. [Proposition 2]  
has (that, about the same {pe} temperature, and  
{pe} humidity, throughout)  
sub prop: about the same ({pe} temperature)  
sub prop: and ({pe} humidity)

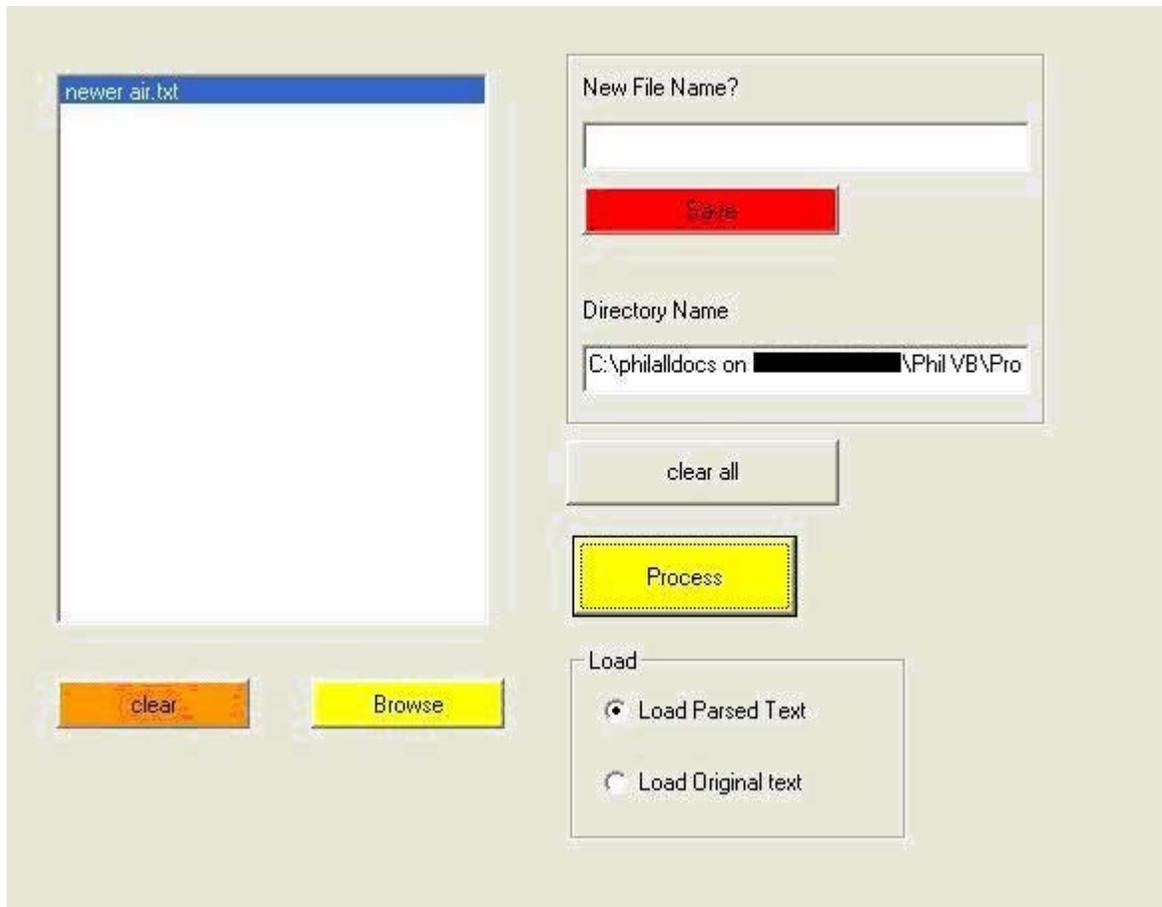


Figure 1: Load window for *AutoProp*.

Only preliminary work has been conducted on these more complex sentence forms and much work remains to be done. Naturally, the English language contains many complex syntactical forms and the purpose of the current tool is merely to offer workable propositions for the majority of sentence types. The degree to which complex sentences will be tackled is largely dependent on the success of forthcoming experiments. However, even with the limitations described above, *AutoProp* is already robust enough to conduct this initial line of testing.

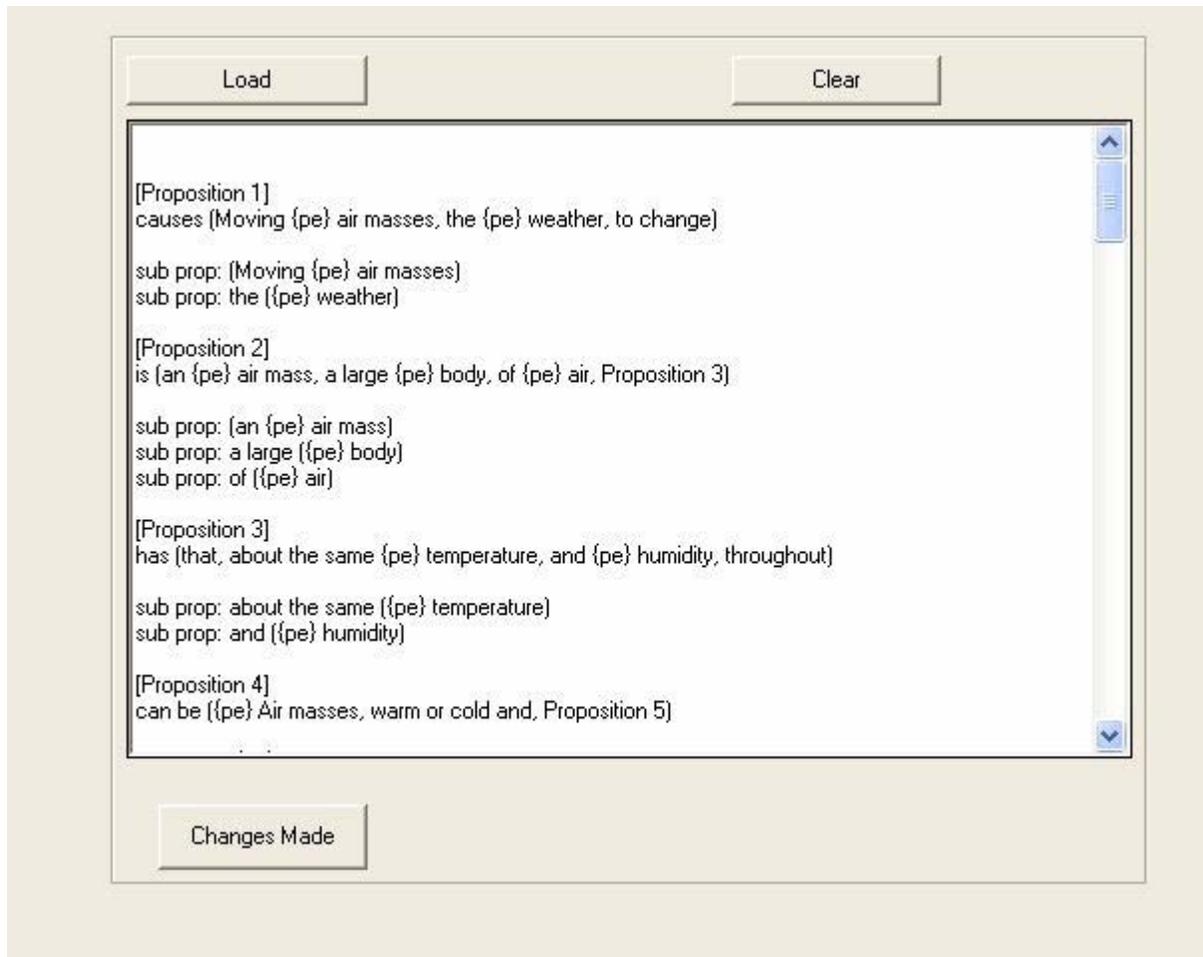


Figure 2: Propositional window for *AutoProp*.

## 2.1 Testing the Tool

To test the effectiveness of the tool, we constructed a test corpus of 29 published sentences that had been converted into propositions (Kintsch, 1998). Twenty of these representations were left in their original form, while 9 were originally presented in a representation other than the text-within-brackets model described above, and needed to be modified to fit the propositional representation that the tool attempts to emulate. All necessary modifications followed the guidelines of Kintsch (1998) for constructing a propositional representation of a text. However, the guidelines presented in Kintsch (1998) were relatively brief, so a more comprehensive guide (Turner & Greene, 1987) was used as a supplement for modifying the propositions. The same sentences were then processed by AutoProp to derive the tool's propositional representations.

To compare AutoProp's output to the Kintsch's propositions, a set of criteria were adapted from Hempelmann, Rus, Graesser, and McNamara (2006). The types

of contrasts (i.e., output differences) between the tool and the Kintsch model were categorized *a priori* as follows:

*Type 1: Minimum, superficial contrasts.* Contrasts in the surface structure of the propositions' representations that preserve the psychological representation of the textbase. This follows Kintsch (1998), in which a propositional representation may take a wide variety of forms.

*Type 2: Easily correctable contrasts.* Contrasts that might not accurately capture the representation of the Kintsch model, but that can be changed with little difficulty in the next instantiation of the tool.

*Type 3: Systematic contrasts due to limitations of the parser.* Contrasts that do not accurately capture the representations of the Kintsch model, that occur due to some limitation of the parser rather than the tool technology used, and have no clear, immediate solution.

*Type 4: Systematic, but correctable contrasts.* Contrasts that do not accurately capture the psychological representation of the standard, but are not due to a programming error. These are contrasts that are correctable, but will take some amount of reprogramming to correct.

*Type 5: Systematic, difficult to correct contrasts.* Contrasts that do not accurately capture the psychological representation of the standard, which are not due to programming error, which reflect a serious flaw in AutoProp. These contrasts may be correctible, but would take much time and effort to rectify.

A particular proposition could potentially have more than one type of contrast. Based on these criteria, we analyzed contrasts between the propositional tool and the hand-coded Kintsch textbase. Our goal in constructing AutoProp was to capture the same information found in a hand-coded textbase, not the aesthetic representation. Because of this goal, we expected to find many Type 1 contrasts, but considered such contrasts unimportant for our purposes. We also expected that Type 2, 3, and 4 contrasts would be minimal.

### **3. Results**

The results of the analysis are summarized in Table 1, which lists the number of contrasts found along with an index of contrasting sentences found over total number of sentences.

#### **3.1 Type 1 Contrasts**

Type 1 contrasts were encountered for all of the tool's representations. These include the preservation of non-argument words which are typically omitted in the Kintsch model. The following example demonstrates the difference between the

original sentence, the sentence as propositionalized by AutoProp, and the sentence as propositionalized according to the Kintsch model, respectively:

- (7) a. *The hemoglobin carries the oxygen*, was represented by the tool as:  
b. [Proposition 1]  
          carries (the {pe} hemoglobin, {pe} oxygen)  
          sub prop: the ({pe} hemoglobin)  
          sub prop: ({pe} oxygen)  
c. CARRY[HEMLGLOBIN,OXYGEN]

In this example, the tool's representation preserves the article *the*, which would be deleted for the sake of abbreviation in the Kintsch (1998) model. Additionally, the Kintsch model does not preserve tense or aspect in propositions (Graesser, Millis, & Zwaan, 1997), whereas AutoProp's representation preserves these features. These sorts of contrasts were encountered in each of the tool's representations. However, if desired, the tool can be easily modified by applying, for example, a lemmatizer. A lemmatizer could help transform *carries* in (7b) to the CARRY found in (7c), though such a change would be only superficial.

The tool also produces a number of *sub propositions* that would not necessarily be hand-coded. These were included to aid researchers in identifying the most important information within a proposition, and also to identify which arguments modify other arguments within a proposition. Such sub propositions assist scorers when evaluating recall of a text (Best, Floyd, & McNamara, 2004). Below is another example of a sentence, its AutoProp representation, and its representation in the Kintsch model:

- (8) a. The blood arrives at the right atrium  
b. [Proposition 1]  
          arrives (the {pe} blood, at the right {pe} atrium)  
          sub prop: the ({pe} blood)  
          sub prop: at the right ({pe} atrium)  
c. ARRIVE[BLOOD,Right[ATRIUM]]

In (8c), the argument RIGHT modifies the argument ATRIUM. Compare this to the tool's representation (8b), where the main proposition does not explicitly indicate that *right*, modifies *atrium*, this relationship is expressed in the second sub proposition.

TABLE 1: Number of sentences that resulted in contrasts between the hand-coded and AutoProp propositions as a function of the type of contrast.

Contrast Type	Number	Proportion
Type 1	29	1.00
Type 2	0	0
Type 3	1	0.03
Type 4	11	0.38
Type 5	0	0

### 3.2 Type 2 Contrasts

No Type 2 contrasts occurred.

### 3.3 Type 3 Contrasts

We encountered only one Type 3 contrast. Below is the sentence, along with its AutoProp representation and two possible representations according to the Kintsch Model:

- (9) a. They are flying planes.  
 b. [Proposition 1]  
     are (They, flying {pe} planes)  
     sub prop: flying ({pe} planes)  
 c. 1. FLY[THEY,PLANES]  
     2. ISA[THEY,FLYING[PLANES]]

Sentence (9a) is ambiguous, and could mean at least two things: *Those people are operating airplanes* (9c.1), or *Those things are airplanes in flight* (9c.2). The representation generated by AutoProp (9b) more closely resembles Kintsch’s second construction (9c.2).

Though the tool only generates one possible interpretation of the sentence, this representation accurately reflects Kintsch’s construction of that interpretation. However, this example was given without context in Kintsch (1998), so it is impossible to tell which version is the “correct” one.

### 3.4 Type 4 Contrasts

These contrasts fell into two basic sub-categories: Type 4a contrasts (where the tool presents a verb as a predicate and Kintsch represents an adjective, adverb, or some other non-verb word as the predicate), and Type 4b contrasts (where Kintsch (1998) has placed an argument within brackets while the tool does not).

#### 3.4.1 Type 4a Contrasts

There were 5 Type 4a contrasts. One of the contrasts, its AutoProp representation, and the Kintsch representation are as follows.

- (10) a. The blood returns to the heart quickly.  
b. [Proposition 1]  
returns (the {pe} blood, to the {pe} heart, quickly)  
sub prop: the ({pe} blood)  
sub prop: to the ({pe} heart)  
c. QUICK[RETURN[BLOOD,HEART]].

In (10c) QUICK serves as the predicate for rest of the proposition, as adjectives and adverbs take a predicate position in Kintsch's representation. However, (10b) considers the adverb to be an argument, rather than a predicate.

#### 3.4.2 Type 4b Contrasts

There were 6 sentences that resulted in Type 4b contrasts. These contrasts represented differences in the parsing of adjectives and adverbs within a propositional frame. For example:

- (11) a. The first chamber is the right atrium.  
b. [Proposition 1]  
is (the first {pe} chamber, the right {pe} atrium)  
sub prop: (the first {pe} chamber)  
sub prop: the right ({pe} atrium)  
c. IS[FIRST[CHAMBER],RIGHT[atrium]]

In (11c), the Kintsch representation, FIRST modifies CHAMBER, and RIGHT, modifies ATRIUM. Compare this to the tool's representation. But in (11b), the AutoProp representation, *right* explicitly modifies *atrium*, but *first* does not explicitly modify *chamber*, as indicated by the lack of brackets.

### **3.5 Type 5 Contrasts.**

No Type 5 Contrasts occurred.

## **4. Discussion**

In this study, we assessed the level of similarity between Kintsch's (1998) representation of a textbase, and a representation of the same text as created by AutoProp. While we were interested in looking for general contrasts between the tool's output and a hand-crafted representation, we were primarily concerned with developing a representation that could be used in order to assess a reader's recall of a text.

While a number of contrasts were detected between AutoProp's propositions and those of Kintsch (1998), the tool's output should still be effective for scoring text recall, and future studies will empirically test this hypothesis. All Type 1 contrasts detected were not only expected, but should have little if any impact on the tool's ability to process a text for recall. All of the major elements of the text are preserved in the tool's representation, although the tool's preservation of less important words (such as articles) could possibly present "false targets," for a researcher scoring recall. A minimal amount of training, however, would enable a scorer to identify the portions of the tool's propositions that are important to comprehension. (i.e., verbs, adverbs, adjectives, connectives, subjects, and objects).

The Type 3 contrast found, where the tool produces only one propositional representation for a sentence that could be interpreted in more than one way, may not be as troubling as it first seems. First, the current model still captures all the major information within a sentence. Also, when comparing recall to textbase, a scorer's knowledge of the correct interpretation of an ambiguous sentence (as judged by the sentence's context) will most likely mitigate this contrast's effect. Therefore, these contrasts present little difficulty for a researcher interested primarily in using the tool to score recall data.

The Type 4 contrasts, where contrasts were detected between the predicates of AutoProp and the hand-coded propositions, require our attention but can be corrected. Kintsch's method of propositionalization places adjectives and adverbs in the predicate positions, whereas AutoProp currently only predicates verbs. However, since adjectives and adverbs are detectable in the Charniak parser, we are confident that Type 4 contrasts can be eliminated with further development of the tool.

The absence of Type 5 contrasts suggests the overall feasibility of our tool. All the observed contrasts can be adjusted with relative ease. This allows us to

continue development on the *AutoProp* project, and work toward the ultimate goal of assessing the feasibility of using AutoProp to assist in the scoring of text recall.

While the current study focuses on a descriptive analysis of the tool, future research will empirically test the tool's utility in scoring text recall. Specifically, we intend to examine the correspondence between recall scores emanating from AutoProp and scores based on manually coded propositions. A close correspondence in scores using the traditional method and using AutoProp will validate its utility. We also intend to compare both these methods to an LSA-based approach. Considerations will include not only correspondence with the hand-coded method, but also construct validity (e.g., correlations with other comprehension measures) and the time required to complete the scoring.

Our long term goal is to have a fully automated tool that scores recall protocols. Thus, we also intend to build a scoring utility that matches the text-based propositions to recall-propositions. The tool will assess a string of nearest matching proposition pairs and score the pairs for similarity along a researcher initiated scoring rubric.

This research initiates a response to a growing need for an automated proposition tool. The current version of the tool is the first step toward building an automated tool capable of converting a wide range of sentence types into propositional units. Later versions will also assess recall-propositions for their similarity to text-based propositions. Although this early version is not fully automated, the tool substantially decreases the amount of work needed to produce a propositional representation of a text. While much work is still needed, we are confident that AutoProp will contribute to the field by substantially reducing preparation time and substantially increasing the accuracy and reliability of scores generated from recall data.

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Stephen W. Briner  
Department of Psychology  
The University of Memphis  
Memphis, TN 38152  
*sbriner@mail.psyc.memphis.edu*

Danielle S. McNamara  
Department of Psychology  
The University of Memphis  
Memphis, TN 38152  
*d.mcnamara@mail.psyc.memphis.edu*

Philip M. McCarthy  
Department of Psychology  
The University of Memphis  
Memphis, TN 38152  
*pmccarthy@mail.psyc.memphis.edu*