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Integrating Marker Passing and Connectionism for Handling Conceptual and Structural Ambiguities*

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Abstract

This paper discusses the problem of selecting the correct knowledge structures in parsing natural language texts which are conceptually and structurally ambiguous and require dynamic reinterpretation. An approach to this problem is presented which represents all knowledge structures in a uniform manner and which uses a constrained marker passing mechanism augmented with elements of connectionist models. This approach is shown to have the advantage of completely integrating all parsing processes, while maintaining a simple, domain-independent processing mechanism.

1. Introduction

A major problem in parsing natural language texts is the selection of the correct knowledge structures from the large number of inappropriate ones in memory. This problem is especially difficult in the case of texts which are highly ambiguous and which require the reader to correct an initially mistaken interpretation, since structures which are only potentially relevant must also be found. Consider, for example, the following sentence: **S1. John put the pot on the stove.** This seems to indicate that John is preparing to use a container for cooking on a stove. However, after reading the next sentence: **S2. He picked it up and smoked it**, it appears that John was actually using the stove as a supporter (or lighter) for a marijuana cigarette (not a cooking pot). In addition note that S1 and S2 are potentially ambiguous at the structural level, e.g. <X picked it up> could mean <X learned new information>, while <X put object on> could mean <X wear object>.

Previous approaches to parsing natural language texts have largely been unsuccessful at handling ambiguous sentences such as those presented above. These approaches can generally be divided into four groups: (1) **Expectation-based conceptual analyzers (CAs)**, such as [Dyer,1983], associate each word with one or more knowledge structures, which have rules attached indicating how they can be connected to other structures. This approach has been successful for parsing large pieces of connected text. However, the processing mechanism is overly complex, since each type of knowledge structure generally requires its own set of rules. Parsing highly ambiguous sentences such as S1 and S2 above is particularly problematic since sophisticated back-up and recovery rules are needed. (2) **PDP/Connectionist systems**, examples of which include [Waltz and Pollack,1985], [Cottrell and Small,1985], [McClelland and Kawamoto,1986], have emerged as an alternative to such rule-based approaches. These systems use only simple rules for spreading and combining activation (and in some cases inhibition). Since they are highly parallel and employ scalar activations, complicated backtracking rules are not needed. Unfortunately, these models currently lack operations which are fundamental in higher level NLP systems, specifically: variables, role bindings, instantiations, and inheritance. (3) **Marker passing systems** [Charniak,1986], [Granger et. al, 1986] and [Norvig, 1987], which find connections between concepts by propagating markers over a local semantic network, are a similar approach which provides these high-level operations. Such systems however, generate too many inappropriate connections and typically employ a filter mechanism with its own set of inference rules to weed them out. The complexity of this mechanism negates the simplicity that is the

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advantage of the marker passing approach. (4) **Definite Clause Grammars (DCGs)**, such as [McCord, 1982], unlike the above approaches, focus primarily on the syntactic and structural features of natural language texts, such as conjuncts, quantifiers and agreement. These systems view parsing as a two step process which first constructs a syntactic parse tree through unification and then performs semantic processing. The strength of these systems is their ability to analyze complex linguistic constructs. However, they lack the conceptual information necessary to analyze texts at deeper conceptual levels.

This paper presents CAIN (Conceptual Analyzer for multiple re-INterpretations), which parses highly ambiguous texts while avoiding the problems of the above approaches. CAIN overcomes these problems by: (1) representing all knowledge (both conceptual and structural) in a uniform manner in a local semantic network, (2) using constrained marker passing for all parsing processes, and (3) using link weights, activation values, and thresholds from connectionist models for indicating relative strengths of activations between concepts. Representing all knowledge at the symbolic level provides higher level symbolic operations and allows all parsing processes to be integrated. The marker passing mechanism depends only upon knowledge of the different link and marker types used, so the processing mechanism is simple and independent of the content of memory. Also, since only certain types of marker intersections are considered important and since elements of connectionist models are employed, the problem of spurious connections is avoided. CAIN is implemented in T [Slade, 1987], a Scheme-based dialect of Lisp, and can parse sentences S1 and S2 above.

2. Parsing Using Constrained Marker Passing

The parsing process can be divided into 4 steps: (1) from the input, mark the lexical items and their associated conceptualizations, (2) find the knowledge structures which connect the marked nodes together, (3) bind the roles of these structures, and (4) refine them to be as specific as possible.

The following sections describe how memory is organized and how the above processes are realized using a constrained marker passing and activation mechanism.

2.1 Memory Organization

All knowledge in the system, whether conceptual or structural, is represented using a semantic network, such as that shown in figure 1* below:

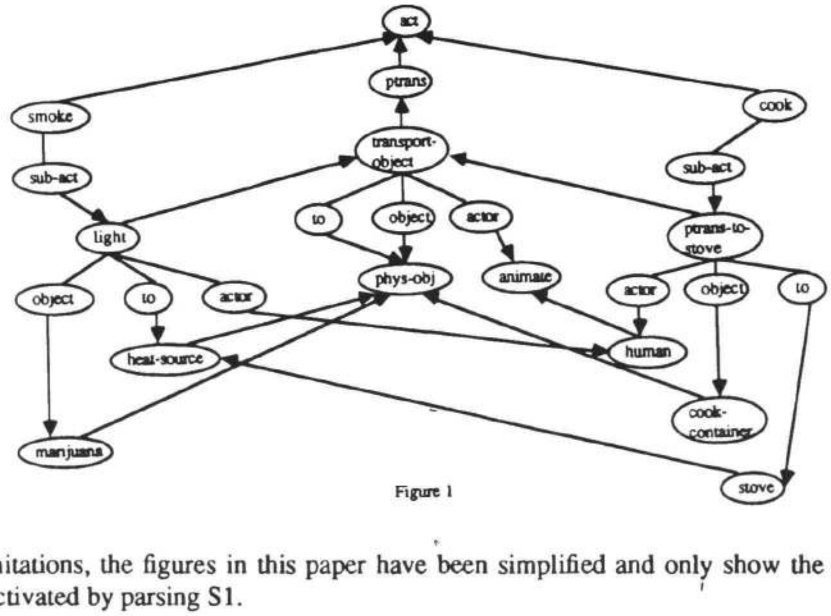

Figure 1

* Due to space limitations, the figures in this paper have been simplified and only show the small portion of the network which is activated by parsing S1.

This figure shows the representation for putting a cooking container on a stove and for lighting a marijuana cigarette. Is-a links, which connect a node to its parents, are represented by the arrows in the figure, and has-a links, which connect a node to its roles, are represented by straight lines. For example, to indicate that lighting a marijuana cigarette is a sub-act of smoking, the node for SMOKE is connected by a has-a link to the node for sub-act, and by an is-a link to the node representing the lighting action. Note that the components of a single act are represented in the same manner. To indicate that the object of the transport action is a physical object, TRANSPORT-OBJECT is connected by a has-a link to its object role, which is in turn connected by an is-a link to PHYS-OBJ. Structural information is represented in the same manner and using the same link types, as illustrated in Figure 2*, which shows the representation for the phrase <person put OBJ1 on OBJ2>, used in parsing S1:

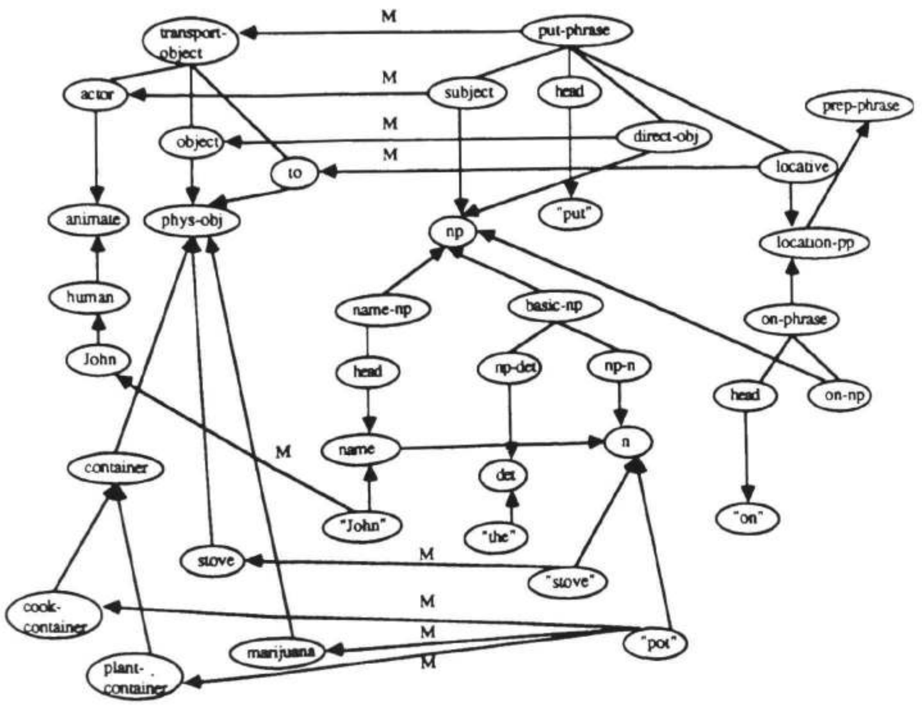

Figure 2

The arrows labeled M (for meaning) in the figure indicate the link between structural and conceptual information.

2.2 Marking the Input Concepts

As the input is read, the occurence of each word and its conceptualizations is indicated by placing an *activation marker (AM)* on the appropriate node. For example, in figure 2, reading the word "pot" results in the placement of AMs on the lexical node "pot" and on the nodes representing the concepts cook-container, plant-container and marijuana. Marking the occurence of a concept also results in the marking of its ancestors, to indicate their implicit occurence. The AM which is placed on COOK-CONTAINER, for example, is also placed on the nodes for container and phys-obj. The rules for marking concepts from the input are therefore:

R-1: When a word is read, an AM is placed on its corresponding lexical node.
R-2: When a lexical or phrasal node receives an AM *of sufficient strength*, an AM is passed across an M link to its associated conceptualizations.
R-3: When a node receives an AM, an AM is passed to its parents.

* This representation is based primarily upon [Gasser, 1988] and [Jacobs, 1985].

AMs which are passed to ancestor nodes contain information indicating the descendant that was the source of the marker. In addition, AMs from lexical nodes also maintain information indicating their meaning(s). This information will later be used to perform role bindings. The reason for the strength constraint on rule R-2 will become clear in subsequent sections.

2.3 Connecting the Input Concepts

How can the correct knowledge structures, connecting the input concepts, be selected? Each node which was activated (received an AM) from the input suggests potentially relevant structures based on the various roles that it plays. This is true for both syntactic and semantic information. For example, since a stove plays the role of an instrument in the cooking schema, activating STOVE suggests that COOK may be applicable. Similiarly, activating the node for determiner indicates that BASIC-NP may be appropriate. *Search Markers (SMs)* are used to indicate knowledge structures which are suggested in this fashion. SMs are propagated according to the following rule:

R-4: SMs are passed from an activated node, down is-a links to all of its descendants that are role nodes, and across has-a links to the owners of the roles.

Applying the above rule will result in the marking of the correct knowledge structures. However, a large number of inappropriate structures will also receive SMs. For example, when the lexical node for "put" is activated in sentence S1, the above rule will mark the nodes for other phrases involving "put", such as <person-put-up-with-person> and <person-put-on-clothing>, in addition to marking the node for the desired put-phrase shown in figure 2. The solution to this problem is to utilize elements of connectionist models, specifically link weights, activation values and thresholds. Each SM is assigned a *strength value* which depends upon the *weights of the links* over which it is propagated. In general, nodes representing more specific concepts will pass stronger SMs than their ancestors. Thus, the SM that COOK-CONTAINER passes to PTRANS-TO-STOVE in figure 1 will be much stronger than the SM that PHYS-OBJ passes to TRANSPORT-OBJECT. When an SM is propagated to a node representing a knowledge structure, its strength value is added to that of the other SMs on the node. If their combined strengths exceed the node's *threshold level*, then there is strong evidence that the structure is applicable, and it therefore attempts to bind its roles. *Using activation values and thresholds allows a large number of structures to be suggested, while only a few are actively pursued.*

2.4 Role Binding

Binding a role of a structure involves determining whether its filler is activated. If so, then the concept which activated the filler is bound to the role. To bind the subject role of PUT-PHRASE in figure 2, for example, the NP node is checked to determine whether it was previously activated. If it was, the descendant which activated it is then bound to the subject role. The check for whether the filler has an AM is made using a *Role marker (RM)*, which is propagated according to the following rule:

R-5: When a node's threshold is exceeded, RMs are passed across has-a links to each of its roles, and up is-a links to the fillers of those roles

Note that RMs may be used to indicate roles which should already have been filled or which are expected to become filled. In the latter sense, RMs are very similar to the prediction marker used in DMAP [Riesbeck and Martin, 1986]. Role binding is performed by the rule:

R-6: When an AM and an RM of sufficient strength intersect*, an AM is placed on the role node

* If it is possible to bind more than one role of a structure to a single concept, then sequencing information, indicating the order in which the roles normally occur, is used to determine which binding is appropriate.

Since an AM maintains information indicating the descendant that was its source, merely placing it on the role has the effect of binding it.

Our confidence in a structure's relevance to the input increases as its roles are bound. For example, as sentence S1 is read and each component of the put-phrase in figure 2 is recognized, it becomes apparent that it correctly represents the input. Thus, binding the subject role should activate the put-phrase node, binding the head role increases its activation level, and similarly for the remaining roles. The amount of the increase depends upon how important the role is to the structure. Role importance is reflected in the strength of the connection between the structure and its roles and therefore in the strength of the RM which is passed by rule R-5. The rule for activating a structure is:

R-7: When an RM and an AM intersect, activate the source of the RM
by placing on it a new AM if one (representing this instance) is not already present,
or by increasing the activation level of the AM which is already there

Syntactic information can be used to help bind roles in semantic structures using rule R-2. For example, when PUT-PHRASE is sufficiently activated by rule R-7, the actor role of TRANSPORT-OBJECT receives an AM (which has John as its meaning) from SUBJECT. Figure 3 shows the AMs which are placed on the structures shown in figure 2, as a result of reading S1.

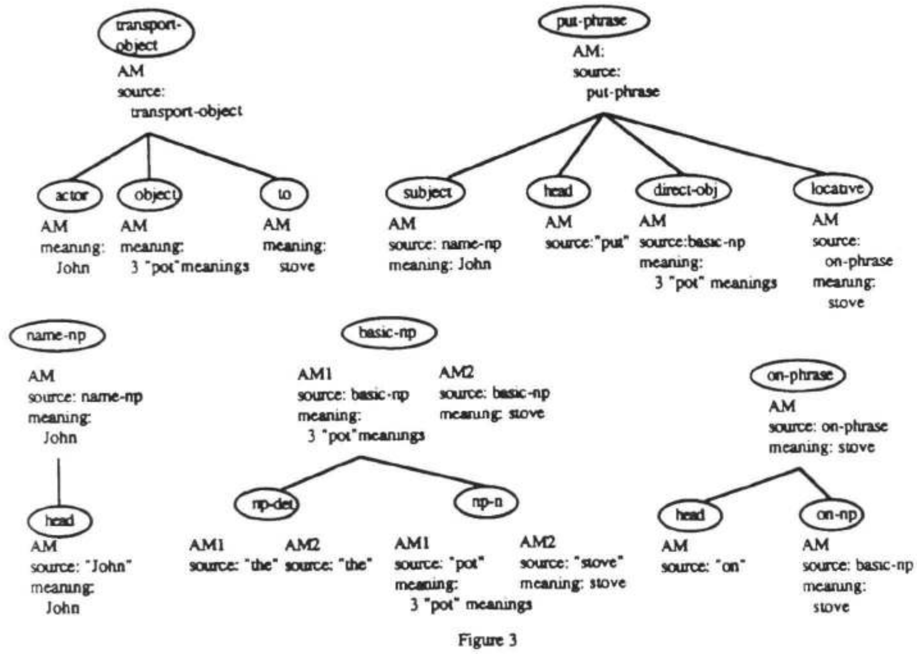

Figure 3

2.5 Concept Refinement

The *most specific* structures possible must be found in order for the input to be completely parsed. A node which is activated by rules R-2 or R-7 may need to be refined to a more specific one using contextual information supplied from the input. Refinement involves searching for a descendant whose equivalent roles have more specific, activated fillers. For example, when the put-phrase is recognized and TRANSPORT-OBJECT is activated by R-2, it can be refined to PTRANS-TO-STOVE as shown in figure 1. The search process is performed using a *descendant marker (DM)* which is spread by the rule:

DM-1: When a node is sufficiently activated by rules R-2 or R-7, a DM is passed down
is-a links to each of its descendants

How is a descendant with more specific fillers found? Recall that each concept which was activated from the input supplies contextual information in the form of SMs, whose strengths are combined when they intersect. A descendant whose fillers are more specific will have SMs with a stronger combined strength. For example, PTRANS-TO-STOVE in figure 1 will receive SMs from HUMAN, COOK-CONTAINER, and STOVE while TRANSPORT-OBJECT will receive SMs from ANIMATE, PHYS-OBJ, and PHYS-OBJ. Since the connection from the roles of PTRANS-TO-STOVE will be much stronger than for TRANSPORT-OBJECT, the former will have a much greater SM strength. Thus, TRANSPORT-OBJECT should be refined to PTRANS-TO-STOVE. The rule which implements concept refinement, then, is:

> DM-2: When a DM is placed on a node whose combined SM level is greater than that of the source of the DM, then bind its roles using the procedure described in section 2.4

Note that after reading S1, TRANSPORT-OBJECT in figure 1 can be refined to either PTRANS-TO-STOVE or LIGHT, so both will be activated. However, since the concept stove suggests cooking much more strongly than HEAT-SOURCE suggests lighting a marijuana cigarette, PTRANS-TO-STOVE will be much more strongly activated. Therefore, it represents the result of the parse. When sentence S2 is read, however, it is recognized as another sub-act of SMOKE. SMOKE will therefore be more strongly activated than COOK, since it receives SMs from two of its sub-act roles, while COOK is unrelated to S2. This causes S1 to be reinterpreted as lighting a marijuana cigarette.

2.6 Marker Removal

As with connectionist systems, markers are removed using a decay process. DMs decay very quickly since they do not have to wait for other nodes to become activated and therefore do not need to remain between sentences. This is not true for the other types of markers, so they decay much more slowly.

3. Related Work

The work presented here was inspired by direct memory access parsing, particularly DMAP [Riesbeck and Martin, 1986]. DMAP attempts to find the most specific knowledge structures that connect the input concepts, using a marker passing algorithm based on recognizing concept sequences. Despite the similarity between DMAP's markers and ours, there are major operational differences. The biggest difference is that DMAP is only able to recognize structures whose roles are encountered in the correct sequence, beginning with the first item. While this works well for syntactic structures which are typically encountered in their entirety and in the correct order, it is not well suited to recognizing higher level conceptual structures such as MOPs [Schank, 1982]. For example, DMAP would not be able to recognize that the COOK context is appropriate after parsing sentence S1, since the intial act, PTRANS-FOOD-TO-CONTAINER, was not encountered. Our work also extends direct memory access parsing (1) to handle ambiguities, reinterpretations, and role bindings, (2) to include more information about syntax, and (3) to represent relative strengths of activations between concepts.

We believe that learning (i.e. adding new nodes and links to the network) will be facilitated by the simplicity of our memory representation. This contrasts to approaches which simplify the processing mechanism by adding extra link types to the network (for example, DMAP uses a special concept refinement link). Our approach is to use only those link types which are necessary for the representation itself and add extra markers where necessary. Since markers are dynamically created during processing and decay with time, adding new ones has no effect on the complexity of the learning mechanism. Similarly, link weights in our model *only* represent relative strengths of connections between concepts and (unlike connectionist systems) are *not* used to control processing.

This work also bears some similarity to SCISOR [Rau, 1987], a system for conceptual information retrieval. The process presented in section 2.3 (for finding the correct structures in memory connected to input concepts) is similar to the priming rules used in SCISOR. However, SCISOR only addresses the problem of finding episodes in memory, and uses a separate module for parsing. In our work, *parsing and memory search are completely integrated.* Thus, the memory search process described here is more general since SMs can be used to retrieve different types of knowledge structures (such as syntactic information) in addition to retrieving episodes.

4. Conclusions

In this paper, we have presented an approach to parsing natural language texts which integrates a constrained marker passing mechanism with properties of connectionist systems: link weights, activation values and thresholds. This approach is particularly attractive for three reasons. First, it is capable of parsing texts which have proved to be difficult for previous parsing systems, specifically those which are highly ambiguous and require the reader to correct an initially mistaken interpretation. Second, it uses a simple processing mechanism whose rules are independent of the actual content of memory. Thus, new knowledge structures can be added without changing the processing mechanism. Finally, it completely integrates all parsing processes, such as memory search, disambiguation and inferencing.

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