Steps Toward Knowledge-Based Machine Translation

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Abstract—This paper considers the possibilities for knowledge-based automatic text translation in the light of recent advances in artificial intelligence. It is argued that competent translation requires some reasonable depth of understanding of the source text, and, in particular, access to detailed contextual information. The following machine translation paradigm is proposed. First, the source text is analyzed and mapped into a language-free conceptual representation. Inference mechanisms then apply contextual world knowledge to augment the representation in various ways, adding information about items that were only implicit in the input text. Finally, a natural-language generator maps appropriate sections of the language-free representation into the target language. We discuss several difficult translation problems from this viewpoint with examples of English-to-Spanish and English-to-Russian translations; and illustrate possible solutions as embodied in a computer understander called SAM, which reads certain kinds of newspaper stories, then summarizes or paraphrases them in a variety of languages.

Index Terms—Artificial intelligence, computational linguistics, inference, knowledge representation, language generation, machine translation, natural language processing, scripts, summarization.

I. Introduction

FOR competent automatic translation of natural-language text to be possible, it seems obvious that the computer will have to "understand," in some reasonably deep sense, what it is reading. A necessary ingredient in human, and therefore machine, story comprehension is access to a rich base of common-sense knowledge about people, things, and events as they happen in the real world. This paper discusses a paradigm for knowledge-based machine translation (MT), and reports work in implementing such a system.

In a survey of the early machine translation efforts, Bar-Hillel [1] conjectured that the problem of competent automatic translation of a text is equivalent to the problem of full understanding of that text. Because of the tremendous amount of information required for understanding, and the complexity of applying such information, Bar-Hillel concluded that "true" MT was not feasible.

Since the time of that survey, several important practical and theoretical advances have been made which suggest that some progress toward knowledge-directed MT may now be possible. On the practical side, of course, available computing hardware is much more powerful than one could reasonably have expected in 1960, and improvements in memory size and processing speed continue to be made. More significantly, we have greater knowledge about memory organization and accessing techniques for "intelligent" systems than we did in 1960.

One important class of theoretical contributions from artificial intelligence (AI) research has been concerned with *representation of meaning.* Wilks' preference semantics [45], Schank's conceptual dependency theory [38], Rieger's commonsense algorithms [34], and semantic network representations [32], [13], [22] are representative examples. Several theories of commonsense *inference* in natural language processing have been proposed [11], [33]. Perhaps most importantly, methods for structuring and applying large amounts of *world knowledge* have been devised, based upon representational constructs such as frame-systems [30], [12], knowledge representation language (KRL) [2], and knowledge structures, including scripts, plans, and goals [39]. Brachman [4] attempts to unify some of these methods in a comprehensive representational scheme.

Using methods such as the above, AI researchers have had a fair degree of success in devising working analyzers [49], [47], [35], [28], [19], [17] and generators [20], [29] of natural language sentences. In several instances these modules have been combined with a model of some type of real-world knowledge to create "complete" understanding systems that achieve a reasonable depth of comprehension in limited domains. Examples of complete systems include: SOPHIE [5] and SCHOLAR [6], which supply semantic networks; NUDGE, the frame-based scheduling assistant [21]; PAM, which uses plans [43]; SAM, the script-based story understander [14], [15], described later in this paper; and POLITICS, which combines several types of knowledge sources [9].

These developments have triggered a revival of interest in MT in the AI community. For example, Wilks constructed an experimental English-French MT system [44], based on the preference semantics scheme for representation and inference. "Practical" MT has not been a primary working goal with SAM and the other understanding systems built within the conceptual dependency/knowledge structure framework. Never-

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theless, a rudimentary capability for English-Mandarin Chinese translation [42] was incorporated in an early version of SAM, and more recent efforts have produced limited English-Spanish translations of newspaper articles. We have continued to experiment in SAM with translating newspaper reports into Dutch, Russian, and Arabic.

This paper examines some important problems in knowledge-based MT in the light of our recent experience with these programs. We describe possible solutions to some of these problems, illustrating these with Spanish and Russian summaries or paraphrases of English newspaper articles read by SAM. Then we proceed to describe how scripts, as a form of *episodic context*, comprise a necessary part of a process model for accomplishing meaning-preserving translation.

Before we proceed, a basic remark concerning our approach to MT needs to be made. Technically speaking, our computer programs do not perform strict translation, but rather *retell* or *summarize* the source text in the target language. Professional-level translation strives to maintain invariant all relevant properties of the source text. For example, the translator attempts to convey the meaning content of the source sentences, the intentions of the writer, certain stylistic elements and specific details, "exact" lexical substitutions, and syntactic structure as far as is possible. Early MT efforts (e.g., see Locke and Booth, [27]) strove to preserve the latter three criteria with the hope that the former two criteria would be preserved "automatically." Unfortunately, this approach led to many cases where meaning and intent were either subtly altered or totally violated. MT work in the conceptual dependency paradigm has been concerned with holding meaning invariant above all else. When it can be discerned, we also strive to preserve the intent of the writer. We also replace the criterion of "exact" lexical substitution with "meaningful and appropriate" lexical substitution.

Our task, therefore, is one of making certain that meaning is preserved as the programs retell and paraphrase the source text in the target language. We consider this to be an essential first step toward fully automated MT. Clearly, this type of machine translation would fail if applied to literature or poetry, but it succeeds measurably in conveying the meaning of mundane newspaper stories where "style" and "syntactic beauty" are of peripheral interest at best. Rather than inventing new jargon, we will use the term "translation" in this paper to refer to our meaning-preserving process of retelling the source text in a different target language, at the risk of causing some small confusion to the reader.

II. Translation and Understanding

A. Knowledge Sources for MT

What kind of knowledge is needed for the translation of texts? Consider the task of translating the following simple story about eating in a restaurant from English into Russian or from English into Spanish:

> *Story 1:*
> John went into a restaurant. He ordered a hamburger. When the hamburger came, he ate it.

In Russian, one cannot say the equivalent of WHEN THE HAMBURGER CAME. Instead, a Russian speaker would say something like: WHEN THE HAMBURGER WAS SERVED (BYL PODAN). Similarly, in Spanish, one would have to say CUANDO SE LO SIRVIERON (WHEN IT WAS SERVED TO HIM) or CUANDO SE LO TRAJERON (WHEN IT WAS BROUGHT TO HIM). Therefore, direct lexical translation with "syntactic" rules is insufficient to form a meaningful translation of Story 1 in either Russian or Spanish.

Context-free "semantic" rules alone will not suffice for meaning-preserving translation, either, as the examples following will show. We will argue that in addition to semantic rules, detailed knowledge of the domain is necessary for correct translations.

Let us look at the English-Russian translation process first. We could try to solve the problem caused by the special sense of the verb "to come" in Story 1 with a translation rule such as:

> *Rule 1:*
> If, in the clause "x came...," x is an inanimate object, then translate the clause as "x was served."

This rule, of course, is much too simplistic. For example, it would not work in the following story:

> *Story 2:*
> John ordered a book by mail. When the book came, John realized it was not what he wanted.

Here, a Russian speaker would use an expression similar to the English THE BOOK CAME (KNIGA PRISHLA). We could try to fix Rule 1 by requiring the subject of the verb "to come" to be "food" instead of just "an inanimate object," but this would not help, since if in the same story John had asked for an extra plate, a Russian speaker would have still used a phrase equivalent to THE PLATE WAS SERVED.

The important factor in the above examples is the context in which the verb "to come" appears. The fact that the story takes place in a restaurant context is crucial for the correct translation of Story 1. Thus, we could modify Rule 1:

> *Rule 2:*
> If we encounter the clause "x came..." in a restaurant context, translate it as "x was served" if x is an inanimate object.

There are, however, difficulties even with this rule. Consider the following story:

> *Story 3:*
> John and Mary ordered lobster in a restaurant. The waiter told them a shipment of fresh lobsters was expected any minute. They decided to wait. When the lobsters came, the waiter asked them how they should be prepared.

Here, the phrase WERE SERVED is an inappropriate translation of WHEN THE LOBSTERS CAME. In order to translate Story 3 correctly, we have to know not merely that we are in the restaurant context, but also what exactly can happen in a restaurant. In our example we need to know who can serve whom, and under precisely what circumstances "serving" can take place. Thus, we could further modify Rule 2:

> *Rule 3:*
> Use the Russian verb for "to serve" only when a waiter brings something to a customer.

Rule 3 will suffice for certain simple restaurant stories, but, unfortunately, it is not applicable even to our original story. Story 1 does not say explicitly who brought the hamburger to whom. To apply Rule 3 in translating the story, we need a detailed account of what can actually happen in a restaurant. Story 1 does not say that it was the waiter who brought the hamburger. It is our knowledge of restaurants that supplies us with this information. For instance, we would need to know something like:

> If something which is normally served by the waiter (e.g., food, utensils, etc.) arrives at the location of the customer, then it was probably the waiter who brought it there.

Only by applying this information in conjunction with Rule 3 can we arrive at a correct Russian translation.

Analogous problems arise in formulating a Spanish translation of Story 1. In Spanish one must specify the recipient case in the lexical realization of sentences containing verbs such as "to serve." In our example, a Spanish speaker must say the equivalent of THE HAMBURGER WAS SERVED *TO HIM* (or TO JOHN). This presents a serious problem in that the original English sentence gives no hint as to who received the hamburger. The solution is, once again, to apply knowledge about the workings of a restaurant. We must know not only who serves the food but also who receives it in the restaurant context. If food is brought to somebody in a restaurant, then that person is probably the customer. Thus, if we had earlier identified John as the customer, we could apply this rule to identify him as the recipient of the hamburger, and produce the proper Spanish translation.

The main conclusion to be drawn here is that competent translation of even simple texts requires (among many other things!) access to a source of detailed knowledge concerning what usually happens in situations such as eating in restaurants, including the order in which things happen, and the roles that various actors play. We model this type of episodic knowledge for the computer in a data structure called a script [39]. Section II-B gives a more detailed analysis of the kinds of knowledge needed to solve the problems arising in the translation of simple newspaper stories. Section III describes our solution to some of these problems, as embodied in a working computer program called SAM.

B. *Translating Newspaper Articles*

We have suggested that professional-quality translation is based upon a bilingual speaker's ability to retell a story written in one language in a desired level of detail in a second. Our model for this process (which we will call "translation" in this paper) is graphically illustrated in Fig. 1. First, we analyze the source text into a language-free semantic representation. Second, we apply contextual knowledge of the subject matter to fill in the things that were left unsaid in the source text. The meaning structures for the sentences of the text, together with

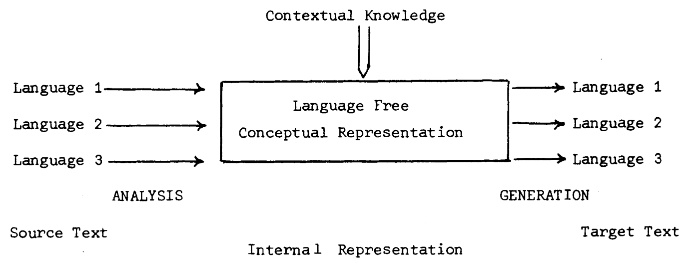


Fig. 1. Machine translation paradigm.

the interconnecting inferences, comprise a complete "conceptual" representation of the text. Third, we choose appropriate parts of the conceptual representation and express them in the target language. In this paradigm, the same language-free representation is used to generate many different target-language realizations. Because the contextual knowledge is language independent (with some exceptions which will be discussed later), it can be used to translate stories in a given domain between different pairs of languages. This translation paradigm is implemented in the SAM system.

Let us consider some of the kinds of knowledge that need to be applied to produce correct translations of simple English "newspaper" stories into Spanish and Russian.

Story 4:
(4a) An automobile hit a tree Friday evening.
(4b) David Hall, 27, a New Jersey man, died.
(4c) Frank Miller, the driver, was slightly injured.
(4d) The police department did not file charges.

To translate the first sentence from English to Spanish, we must disambiguate the word "hit." There are at least three different Spanish verbs meaning "to hit," and each is much more specific than the English verb. The translator must choose among the three alternatives.

PEGAR: The actor (usually the subject in the active voice) applies a force to the object with the explicit intention of realizing a state change in the object. Hence, the actor must be a human. There is a strong expectation that the object is animate (i.e., that it will feel the force and its aftereffects). For example, the sentence JOHN *HIT* MARY will be translated as JUAN *LE PEGO* A MARIA.

GOLPEAR: In default, it is assumed that the actor is higher animate (e.g., human). There is a strong expectation that the actor will propel an instrument whose physical state will remain unchanged, and that the object with which the instrument comes into physical contact may suffer a state change. No restrictions are placed on the object. Thus, the sentence JOHN *HIT* THE NAIL WITH A HAMMER will be translated as JUAN *GOLPEO* EL CLAVO CON UN MARTILLO.

CHOCAR: It is assumed that the actor did not intend for the act to occur. There is an expectation that the actor will be self-propelled but mindless. There is a strong expectation that the actor suffers a state change, but only a weak expectation that the object does likewise.

A Spanish speaker will use the verb CHOCAR to translate the first sentence of Story 4:

(5) El viernes al anochecer un auto *choco* contra un arbol.

Thus, in order for the Spanish generation module of an MT system to properly select the verb CHOCAR, it must have access to a memory representation for Story 4 which contains information about the intentionality of entities such as vehicles and trees. In SAM, the language-free representation built for this type of story includes the necessary information. Section III describes how this representation is created, and how SAM's Spanish generator uses it to produce the correct translation.

A dictionary-based approach to MT would typically rely on such information's being available under the lexical entry in the target language dictionary. We note, however, that the needed data are not explicitly provided in ordinary bilingual dictionaries. For instance, an unabridged Spanish-English dictionary lists no less than 60 Spanish verbs and expressions as possible translations of "to hit," with no hint concerning how one selects the appropriate translation. The University of Chicago English-Spanish Dictionary, designed expressly for teaching, lists 13 ways to say "hit" in Spanish (omitting the obscure, poetic, or regional-dialect translations). Eight of these are associated with English phrases which suggest *by example* the appropriate usage (e.g., to hit the mark–acertar). In translation, of course, one cannot rely on the presence of the suggested phrase in the source text. Moreover, these are not necessarily fixed idiomatic expressions. For example, "to hit a bullseye/target" is also translated using "acertar," but this rule must be induced by the reader from the previous example. Finally, the three Spanish verbs "pegar," "golpear," and "chocar" are listed as "basic" in the University of Chicago dictionary, with no means provided to discriminate among them.

A similar target-language verb selection problem is encountered when one tries to translate sentence (4a) into Russian. We need to apply information about cars, trees, and car accidents to choose the Russian verb NALETET' as the appropriate translation of the English verb TO HIT. (NALETET' literally means TO FLY ONTO.)

Translating sentence (4b) into Spanish presents no verb-selection problem regarding the state-change of a person going from being alive to being dead. A Russian speaker, however, will have to choose among UMER (died), SKONCHALSYA (passed away), or BYL UBIT (was killed) to express a person's death in a particular context. The first verb is not sufficiently "formal" to be used in a newspaper account. The second will be used if the death occurred some time after the accident. The third expression will be used if the death occurred during the accident or as an immediate result of it. In all cases, the Russian sentence will be incomplete unless the place, the time, or some other circumstances of the death are given. Once again, a detailed representation must be available of what *actually happened* in the accident, derived from a "complete" understanding of Story 4.

"Full" understanding is also needed to complete the translation of sentence (4b). We must determine that the number "27" in the English is the age of David Hall in years, since this must be made explicit in Spanish and Russian. Similarly, the second appositive to David Hall's name, "a New Jersey man," must be interpreted as a reference to Hall's residence. A literal Spanish translation of "a New Jersey man" into Spanish (i.e., UN HOMBRE DE NUEVA JERSEY), may be easily misunderstood to mean "a man who was born in New Jersey." Furthermore, the literal Russian translation "chelovek iz New Jersey" is not only ambiguous, but also inappropriate in a car accident context. The understander realizes Hall is no longer alive, and this enables the choice of the *past* tense of the Spanish verb VIVIR and Russian PROZHIVAT' (to reside). We want to say "who *lived* in New Jersey" rather than "who *lives* in New Jersey".

The Spanish and Russian versions of (4b), then, are as follows:

(6) David Hall, de 27 anos, que vivia en Nueva Jersey, se murio.

(7) David Hall, 27 let, prozhivavshii v shtate N'yu-Dzhersi, bye ubit.

Since the original sentence does not specify the place or time of David Hall's death, the Russian generator chooses the most general expression, BYE UBIT (WAS KILLED).

Now consider the phrase WAS INJURED in sentence (4c). Spanish gives a choice of the expressions ESTABA HERIDO and QUEDO HERIDO. One can say ESTABA HERIDO if there is no known connection between "being hurt" and the actions described in the story, or QUEDO HERIDO if "being hurt" was a result of these actions. If the context of automobile accidents is not considered, we may miss a *causal* connection between the injury and the events described earlier. That is, we may assume that Miller was injured *before* the other events, rather than as a *result* of an event in the story. Yet, it is clear to readers of (4c) that Miller was injured as a result of the car (in which, by inference, he was riding) hitting the tree. Such causal information is part of the episodic representation built by SAM, which is used by the Spanish generator to produce the following translation of (4c):

(8) El chofer, Frank Miller, quedo un poco herido.

The Russian version of (4c) is

(9) Vodidel', Frank Miller, seriozno ne postradal.

The appropriate translation of the phrase WAS SLIGHTLY INJURED in this context is SERIOZNO NE POSTRADAL which literally means "did not seriously suffer." The verb and the negative mode are normally used in accident descriptions to contrast with the very strong statement ("David Hall died") in the previous sentence. Thus, the program which generates (9) has to know not only what happened in the story, but also what is said previously.

Sentence (4d), "the police did not file charges," cannot be translated directly into either Spanish or Russian. In this situation, a Spanish speaker would have to say

(10) La policia no accuso a nadie.

which literally means "the police did not accuse anybody."[1] In many Spanish-speaking countries, the legal procedure fol-

[1]Sentence (10) literally means "the police did not accuse nobody." In Spanish, double negatives are used to emphasize that an expected event did *not* occur. That is, although the reader of Story 4 may have expected somebody to be accused of a wrongdoing, there was no accusation made.

lowing a serious accident calls for the police to make an accusation very shortly after the accident if they believe a crime may have been committed. There is then a period of several days during which the police conduct an investigation, prior to the formal filing of charges. Hence, a newspaper account of a recent accident would not normally refer to the prosecution procedure, but to the accusation. In English-speaking countries, an official accusation must be accompanied by initiating a formal prosecution, without a delay. Accordingly, competent translation of (4d) into Spanish requires that the translator understand the difference between the knowledge structures describing accusations and prosecutions in English- and Spanish-speaking countries.

A Russian speaker will have even more serious difficulties in translating sentence (4d). We consulted six native speakers of Russian, two of whom are professional translators. All were puzzled as to how this sentence should be translated. The difficulty here is that in Russia the police never file charges themselves. Accusations can be made only by the prosecutor's office. The role of the police in such cases is to gather and present the available evidence. Moreover, the fact that no charges were filed sounds very odd to a Russian. Someone must always be at fault, and the authorities will always find out who. Otherwise, a Russian would normally assume that a cover-up must have taken place. Thus, a Russian who understands English but is not familiar with the Western judicial system will not even understand the meaning of sentence (4d). When forced to translate, he will do it literally:

(11) Polizia ne pred'yavila nikakikh obvinenii.

This, native speakers agree, does not mean much to a Russian. Sentence (11), although syntactically and even semantically correct, does not correspond to any knowledge structure in the mind of the Russian listener. A Russian speaker who is familiar with Western judicial practice will use sentence (11) only when speaking in Russian to another person with the same background about a car accident *in the U.S.A*. Only in this situation will neither speaker nor listener notice any anomaly in (11). A good translator, of course, will be aware of these cultural differences, and will briefly explain them in his translation. In most cases, however, the fact that the police did not file charges would be considered unimportant, and hence would be omitted from the Russian translation.

C. Some Conclusions

At this point, we are in a position to make several claims about the necessity for applying world knowledge in MT. Basically, we believe that competent translation of a connected text is impossible unless the text has first been understood, in some reasonably deep sense.

Specifically, we argue that translation cannot be done purely on the basis of syntactic manipulations, even if these are augmented by "context-free" semantic rules. Every story is placed in some well-defined knowledge domain, and a translator constantly applies information from that domain.

This has two significant implications. First, for MT to be possible at all, the knowledge context, or a large part of it, must be shared between the speakers of the source and target languages. There is no sense, for example, in trying to translate a radio report of an American football game for a Koi-Koi or a Cambodian peasant.

The second major implication of the need for a knowledge context is that translation of isolated sentences is at best unreliable, and often impossible, since single sentences may not unambiguously establish a context. For example, the Spanish sentence JUAN SE LO COMIO is translated into four radically different English sentences depending on the surrounding context.

(12s) Juan tenia un refuerzo de jamon. *Juan se lo comio*.
(12e) John had a ham sandwich. *John ate it*.
(13s) Juan estaba manejando su auto de noche. En el medio de la calle habia un arbol caido. *Juan se lo comio*.
(13e) John was driving his car at night. There was a fallen tree in the middle of the road. *John ran into it*.
(14s) Juan estaba buscando su anillo en el cajon. Aunque el anillo estaba debajo de unos papeles, en su busqueda apurada *Juan se lo comio*.
(14e) John was looking for his ring in the drawer. Although the ring was underneath some papers, in his hurried search *John missed it*.
(15s) Juan estaba jugando ajedrez con Pedro. Pedro movio su alfil al medio del tablero. *Juan se lo comio*.
(15e) John was playing chess with Peter. Peter moved his bishop to the center of the board. *John captured it*.

Thus, in order to translate sentences from simple stories we first need to understand the story. But what does it mean for a computer program to "understand" a story? This question will be addressed in the next section, in terms of the model of machine translation embodied in the SAM system.

III. An Example of Script-Based Machine Translation

SAM (script applier mechanism) [14] is a system of computer programs that uses a knowledge structure called a script to "understand" newspaper stories about factual events. By "factual," we mean descriptions of "overt" or "physical" activities, such as car accidents, plane crashes, natural disasters and state visits. More "interesting" stories, of course, refer to all sorts of nonphysical information, such as political or ideological beliefs (see, e.g., [7]). Every story, however, has at least some factual component which a script can account for.

Scripts are a medium for representing people's everyday knowledge about stereotyped activities such as going to birthday parties or museums, driving cars or riding the subway. This knowledge is expressed in conceptual dependency [38], a formalism for language-free meaning representation. SAM uses an extension of the script idea to encode what ordinary people know about certain kinds of events they see in the newspaper. For example, the motor-vehicle accident script, $VEHACCIDENT,[2] contains a detailed account

[2] In this paper, uppercase names preceded by "$" are names of scripts. Names preceded by "&" refer to script variables, that is, to props and roles from the script. For example, &BUSDRIVER is the "bus driver" role from the bus script, $BUS.

of the happenings in a crash and its aftermath, including actions of the police, ambulance service, and hospital.

The accident script is a structure of event sequences, called causal chains [39]. Each causal chain characterizes one well-understood happening ("episode") from the situation. The episodes contain well-defined roles, or script variables, which prescribe who can be doing what, and the episodes are grouped into scenes by the importance of the activity in the accident context. There is, for example, a "crash" scene, which describes the various ways that a vehicle can go out of control and run into something. Script variables in these events include the functions for "vehicle," "driver," and "obstruction."

The example car-accident story (Story 4) considered in the last section is a shortened version of a summary formed by SAM. The story below was the input to SAM, which generated the following English and Spanish summaries as part of its output:

Story 5:
Friday evening a car swerved off Route 69. The vehicle struck a tree. The passenger, a New Jersey man, was killed. David Hall, 27, was pronounced dead at the scene by Dr. Dana Blauchard, medical examiner. Frank Miller, 32, of 593 Foxon Rd, the driver, was taken to Milford Hospital by Flanagan Ambulance. He was treated and released. No charges were made. Patrolman Robert Onofrio investigated the accident.

English Summary:
AN AUTOMOBILE HIT A TREE NEAR HIGHWAY 69 FOUR DAYS AGO. DAVID HALL, AGE 27, RESIDENCE IN NEW JERSEY, THE PASSENGER, DIED. FRANK MILLER, AGE 32, RESIDENCE AT 593 FOXON ROAD IN NEW HAVEN, CONNECTICUT, THE DRIVER, WAS SLIGHTLY INJURED. THE POLICE DEPARTMENT DID NOT FILE CHARGES.

Spanish Summary:
UN AUTO CHOCO CONTRA UN ARBOL CERCA DE LA CARRETERA 69 EL VIERNES AL ANOCHECER. DAVID HALL, DE 27 ANOS, QUE VIVIA EN NEW JERSEY, EL PASAGERO, SE MURIO. FRANK MILLER, DE 32 ANOS, QUE VIVIA EN 593 CALLE FOXON EN NEW HAVEN, CONNECTICUT, EL CHOFER, QUEDO UN POCO HERIDO. EL DEPARTMENTO DE POLICIA NO ACUSO A NADIE.

The details of SAM's operation are given in [14]. In the following section we briefly describe the various processes used to understand Story 5. The summaries above were generated by SAM. Our analysis below concentrates on how a portion of the Spanish summary was generated.

A. The Understanding Process

The machine-translation configuration of SAM is sketched in Fig. 2. As shown in the figure, MT is accomplished in two phases: 1) understanding the source-language text and building a language-free representation for it; and 2) formulating a language-free summary or paraphrase of the story from the memory representation and expressing it in a target language.

SAM operates during story understanding as a collection of "experts," each module consulting a specialized knowledge source (see Fig. 2). One, called ELI (English language interpreter, [35], [17]), analyzes the text into a meaning representation. A second module, PP-memory, tags and identifies references to picture producers (PP's: people, places, and things having a definite, static memory reference). Finally, the script applier finds the inputs in its database of scripts.

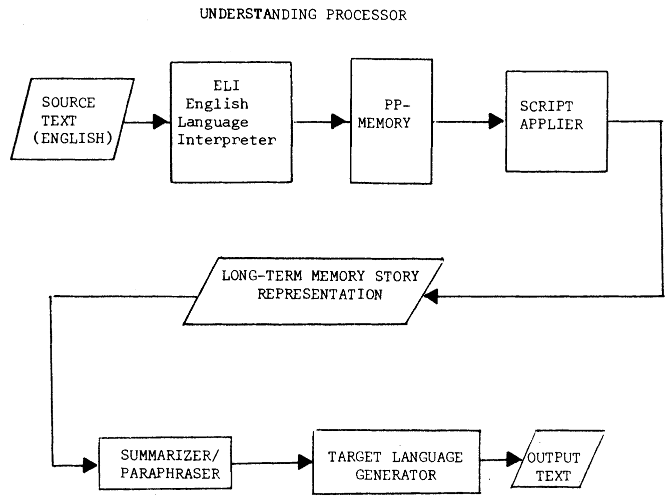


Fig. 2. Machine translation configuration of the SAM system.

ELI is the only module of SAM that is concerned with linguistic input. It is a dictionary-based system which uses "expectations" as its control mechanism. The input is read from left to right one word at a time. The meaning and syntactic function of each word have to satisfy the expectations set up by the conceptual structures built by previous words and context requirements. The analyzer, however, does not have a separate syntactic preprocessor. Syntactic constraints are applied only as needed to attain the main goal of the analyzer—to assemble a semantically well-formed conceptual dependency representation of the input. A detailed discussion of the workings of ELI is beyond the scope of this paper.

ELI builds two types of conceptualizations: PP's and complex relations among the PP's whose central elements are the ACT's and STATE's of conceptual dependency. PP-memory's job is to find the PP's in a conceptualization and assign tokens to them. Tokens are tags or handles by which the PP's will be known to the rest of SAM. This module also supplies tokens for script variables which the script applier encountered in building the story representation, but which the story text did not mention. The basic problem PP-memory must deal with is that of "reference": is an input PP something or someone SAM has seen before, is it a reference to a "permanent" token known to the system (e.g., a well-known person such as "President Carter"), or is it something totally new to the system?

The script applier is the repository for episodic information about what can happen in a known context. It performs the basic task of "understanding" in SAM: locating an input in the currently accessible parts of an active script, linking the new input up with what has come before, and making predictions about what is likely to be read next in the story. In each of these activities, the script applier uses world knowledge to make explicit the connections, or *inferences*, which are only implicit in the text.

The most important kind of inference SAM makes is *filling in a causal chain.* In reading Story 5, the structure of $VEHACCIDENT tells the script applier which sequence of causally connected events to select and instantiate in order to connect explicitly mentioned events. We read about a crash, then about a person being taken to the hospital. How can these events be connected? SAM applies its knowledge about car accidents and the functions of ambulance companies (the ambulance script) to fill in the probable causal relations that someone saw the crash and called an ambulance, that the ambulance came to the scene, that the ambulance attendants placed the person on a stretcher and put the stretcher into the ambulance, etc. It also makes the crucial connection, never stated in the story, that the person who was taken to the hospital in Story 5 must have been injured in the crash. The reason it can do this is because it "knows" what ambulances and hospitals are for, in the sense that the appropriate scripts connect together for the purpose of aiding people who are sick or hurt, and cannot get to the hospital under their own power. A necessary part of filling in causal chains is role-instantiation: specifying the necessary properties a PP must have to fill a specified role in an event. An example of role-instantiation can be seen in the summary of Story 5, which asserts that the "police department," as the organization responsible for investigations and arrests, chose not to file charges in this instance.

Another basic class of inferences in the SAM system is *reference specification.* The need for this process arises when a script variable which has already been bound to a PP is mentioned in a subsequent input. At this point a decision has to be made: can the new PP be an instance of an old one? The classic reference problem occurs with pronouns, e.g., can "he" be the "John" we heard about earlier? In newspaper stories, a more complicated reference problem arises because of what we call "paraphrastic reference": the use of arbitrarily complex noun groups to refer to the same PP. An example of this type of inference is the process of recognizing that the man from New Jersey mentioned in the third sentence of Story 5 must be David Hall, age 27.

SAM also uses the *time/place setting* of a story for inferences about where things are happening and how long they take. A script's causal chains have associated default values for the length of time they typically use up, or where they would be expected to occur. SAM uses these defaults in Story 5 to infer that the crash must have occurred on the same day as the "swerve," namely, Friday evening. Cars simply cannot stray from roads for very long (on the order of seconds) before encountering an obstruction. Similarly, the crash must have occurred "near Route 69," although the story does not explicitly say so. This is because roads are provided with all sorts of nearby objects for cars to run into.

Finally, SAM makes various kinds of *delayed inferences.* Sometimes a story will leave a point of interest to a reader hanging for a while, only clearing up the problem in a later sentence. The inferences needed in these cases have the nature of "demons" [11], hovering around and waiting for a feature of an input that satisfies their expectations. In car accidents, for example, we want to know whether anyone was killed; if someone was hurt, how badly; what the police did, etc. In Story 5, although we know that the man taken to the hospital was hurt (because we know that this is what ambulances are for), we cannot initially be sure how seriously. Will the person be operated on and spend some time in the hospital? Was he so badly injured as to die there? This decision cannot be made until the sentence stating "He was treated and released" is interpreted, at which point SAM concludes that he must not have been too badly hurt.

The understanding phase of SAM is completed when all the sentences of a story have been read, located in a script, and connected together by script-driven inferencing. The results of understanding are stored in a "permanent," language-free memory representation. Let us look at some of the memory structures constructed for Story 5.

The story representation is placed in a hierarchical property-list structure, accessed through the global variable !STORY. Story 5 is represented as a "sequential" (SEQ) instantiation of certain episodes of the accident script, each episode having a most important event, or Maincon. Additionally, the story itself has a Maincon (the crash), and certain events have happened which "interfere" with the flow of the script, or the well-being of one of the participants. In this story, the accident has interfered with the health of "Hall" and "Miller," but Miller's condition, by inference, was relieved (i.e., the interference was resolved) at the hospital. (Hall, being dead, cannot be helped.) Interference and resolution events are marked in the story representation with PATHVALUE INT and RES, respectively. Finally, the SCORECARD property in the story representation points to an event of especial interest to the script, viz., what the police did:

```
!STORY: (SEQ SCLAB3)

SCALB3:
   SCRIPTNAME $VEHACCIDENT                  The active script.
   MAINCON EVNT4                            Story Maincon
   SCENECONS (EVNT4 EVNT17 EVNT33)          Episode Maincons
   INTERFERENCE ((EVNT20 EVNT26)            Interference/resolution events
                 (EVNT14))
   SCORECARD (EVNT33)                       An "interesting" event, what the police did
```

Each event in the story representation is a conceptual dependency structure containing a reference to one of the primitive conceptual dependency ACT's or STATE's, and pointers to the PP-tokens which figured in the event. This is the structure representing the story Maincon, the crash, which is based on the ACT *PROPEL*:

EVNT4:	The Maincon of the script: the crash
VALUE ((ACTOR STRUCT0	
⇔ (*PROPEL*)	
OBJECT PHYS0)	
TIME (TIME5))	
LASTEVENT (EVNT3)	The causal predecessor of the crash and its
NEXTEVENT (EVNT20 EVNT14 EVNT7)	causal successors, including "someone died" and "someone was hurt"
STRUCT0:	
CLASS (#STRUCTURE)	The PP is a structured physical object
TYPE (*CAR*)	A pointer to the def. of "car" in PP-memory
SUPERSET (*VEHICLE*)	Its functional superset
ELEX (AUTOMOBILE)	An English lexeme
SLEX (AUTO)	A Spanish lexeme
SROLES	Pointer to the script roles:
(($VEHACCIDENT . &VEHICLE1)	1) accidents
($DRIVE . &VEHICLE1))	2) driving
PHYS0:	
CLASS (#PHYSOBJ)	The PP is an unstructured physical object
TYPE (*TREE*)	A pointer to the def. of tree in PP-memory
ELEX (TREE)	An English lexeme
SLEX (ARBOL)	A Spanish lexeme
SROLES	
(($VEHACCIDENT . &OBSTRUCTION))	

Connected to the crash conceptualization is a cluster of inferences, defined by the script, for events which causally can follow it. Here are some inferences made in this story:

EVNT14:	One result of the crash is that someone
VALUE ((ACTOR HUM0	died
FROM (*HEALTH* VAL (*NORM*)))	
TOWARD (*HEALTH* VAL (-10)))	
TIME (TIME17))	
PATHVALUE INT	This is an interference event in the script
EVNT20:	Another result is that somebody was
VALUE ((ACTOR HUM3	injured
FROM (*HEALTH* VAL (*NORM*))	
TOWARD (*HEALTH* VAL (NIL)))	
INC (-3))	
PATHVALUE INT	Another interference
EVNT26:	This is the resolution for EVNT20: treat-
VALUE ((⇔ ($TREATMENT	ment at a hospital. This is a scene of
DOCTOR HUM9	the hospital "script," with doctor and
PATIENT HUM3))	patient (here, Miller) as the most im-
TIME (TIME31))	portant roles
PATHVALUE RES	This is a resolution event for the "interfering" injury
HUM0:	This is the person who died
CLASS (#PERSON)	
SURNAME (HALL)	
PERSNAME (DAVID)	
GENDER (*MASC*)	
AGE (UNIT0)	His age, 27 years.
RESIDENCE (POLIT0)	This is his residence, the political unit "New Jersey."
SROLES (($VEHACCIDENT . &DEADGRP)	
(DRIVE . &PASSGRP1))	

```
HUM3:                                          This is the person who was injured
   CLASS (#PERSON)
   SURNAME (MILLER)
   PERSNAME (FRANK)
   GENDER (*MASC*)
   AGE (UNIT1)                                 His age, 32 years, and where he lives.
   RESIDENCE (LOC1)
   SROLES (($VEHACCIDENT . &HURTGRP)
           ($DRIVE . &DRIVER1))
```

Finally, we show an "interesting" event, the Maincon of the investigation episode. This event is marked as being of special importance because of the SCORECARD property:

```
EVNT33:     [Onofrio decides not to prosecute]
   VALUE ((ACTOR HUM7 ⇔ (*MBUILD*)                This event states that the patrolman decided
               MOBJECT ((⇔ ($PROSECUTION            not to execute the prosecution "script," one
                           CHARGE (NIL)             of the activities of the organization he is an
                           CHARGOBJ (NIL)           agent for
                           CHARGEE (ORG3)))
                          MODE (MMODE3))
          TIME (TIME319))
   [MMODE3 = (*NEG*)]
HUM7:
   CLASS (#PERSON)
   SURNAME (ONOFRIO)
   PERSNAME (ROBERT)
   GENDER (*MASC*)
   TITLE (PATROLMAN)
   OCCUPATION (*POLICEMAN*)
   SROLES (($VEHACCIDENT . &POLSTAFF))
ORG3:                                           The police department executes the police
   CLASS (#ORGANIZATION)                          "script" and has the role "investigator of
   ORGOCC ($POLICE)                               accidents" in the vehicle-accident script.
   SROLES (($VEHACCIDENT . &POLORG))
```

B. The Target Language Generation Process

After a source text has been analyzed, understood, and represented in memory, a version of the text must be generated in the chosen target language. The generation process may be conceptually divided into two phases: deciding what to say, and then deciding how to say it. We often want to say in the target language essentially the same things that were said in the source text. In other circumstances it may be necessary or desirable to paraphrase or summarize the meaning representation before generating its target linguistic realization.

Summary and paraphrase by computer are tasks containing major unresolved problems. SAM's summary module works on a language-free basis with the "important" events stored in the memory representation, such as the Maincon, interference events and events on the scorecard. It does not, however, embody solutions to such problems as culture-dependent judgments concerning the importance of events, or the idiosyncratic viewpoint of the reader. As such, SAM's summarizer must be considered as only a first step toward the solution of the problem of automatic summary/paraphrase. A more detailed description of how SAM does summary and papaphrase is given by DeJong and Stutzman in [39].

In this paper, we emphasize the problem of how to generate natural language text from conceptual descriptions of events, assuming that the summary module has already done its job. We have built generators of varying degrees of sophistication for English, Spanish, Mandrin Chinese, Russian, Arabic, and Dutch. This section will concentrate on script-based Spanish generation.

The first event from the story representation to be expressed in the summary is the Maincon of the accident script, EVNT4 from the story representation. An "expanded" conceptual dependency (CD) representation for this event is:

(16) [A car hit a tree Friday evening.]

```
((ACTOR (#STRUCTURE TYPE      (*CAR*)
                    SUPERSET  (*VEHICLE*)
                    TOKEN     (STRUCT0))
      ⇔ (*PROPEL*)
  OBJECT (#PHYSOBJ TYPE (*TREE*)))
  TIME   ((WEEKDAY FRIDAY) (DAYPART EVENING)))
```

Spanish translation:

(17) EL VIERNES AL ANOCHECER UN AUTO CHOCO CONTRA UN ARBOL.

The Spanish generator is based on Goldman's [20] CD-to-English generator. Its input is the CD diagram presented above; its output is the Spanish sentence (17). The generator has access to the full meaning representation of the accident story produced by SAM in its script application phase, including the accident script and any other scripts referenced therein. Neither the original English sentence (4a) nor any of the original English words are accessible to the generator. It has no need for them, as SAM has already extracted all the relevant meaning from the input text.

We are not claiming here that accurate, professional-quality translation (see Section IV) has no need to refer to the intact source text after it has been understood by the translator. Wilks [45], [46], for example, argues that both meaning representation and at least certain aspects of the original surface source text may be required to competently generate in the target language. While this is an open issue, we are inclined to agree with Wilks when translation means faithful reproduction of the style and syntax of the source text, as well as content and precise meaning. However, recall that our task is primarily one of retelling and summarizing stories in different languages, maintaining invariance only of the meaning of the source (and therefore target) text. In this paradigm, once the meaning has been reliably extracted and encoded, there is no need to refer to the original source text, as it can provide no additional information that can be utilized by the target language generator.

SAM's generator is action-oriented. Upon receiving a conceptualization, it must first decide on the appropriate verb-sense in the target language that best expresses the action or change of the state in the input conceptualization. A verb-sense is a semantically unambiguous entity associated with a particular verb in the target language. There may be many verb-senses associated with a single verb, one for each different meaning (or usage) of the verb. "Take1" and "take2," for example, are two senses of the verb "take." "Take1" means to take possession of an object, as in "John took the book from Mary," and "take2" means to take someone or something to a new location, as in "Mary took John to his house." The reason for selecting a verb-sense is that once the verb-sense is chosen, there are severe semantic and syntactic constraints placed upon the linguistic cases of the verb. These constraints are usually strong enough to specify a unique mapping from the conceptual cases in the CD-diagram to the linguistic cases in a grammatical case structure generated for the target language.

Once the linguistic case-structure is generated, a grammar for the target language (encoded as an augmented transition network [48]) is applied to generate its surface linguistic realization. We shall focus our attention on the verb-sense selection and related processes, as the grammatical generation stages are relatively well understood. Further details on the linguistic aspect of generation can be found in [20].

We mentioned in Section II-B that there are three possible Spanish translations of the English verb "to hit," only one of which is correct in a given context. The CD-representation (17) gives access to all the information necessary to choose the appropriate Spanish verb sense. The CD-ACT PROPEL defines a set of possible verb-senses. Selecting a member of this set is accomplished using a discrimination network (D-net).

The simplest example of a D-net is a binary decision tree. The root node of the PROPEL D-net asks whether the ACTOR of the PROPEL is human. If the answer to this question is YES, then we proceed to the left-hand descendant of the root node. If the answer is NO, as in (17), we proceed to the right-hand descendant. This node asks whether the OBJECT is self-PROPELled. In (17), the answer is YES. Hence, we proceed to the next left-hand descendant. The new node tests whether the OBJECT is much smaller than the ACTOR. The answer is NO and the right-hand descendant is tested. In this manner, we determine that the ACTOR is self-propelled and not human, and that the OBJECT is not particularly fragile. (The latter information comes not from (17), but from a query to PP-memory about the properties of trees.) At this point, we reach a leaf-node in the tree, that is, *not* a node containing a question whose answer directs the program onward into the tree, but one which yields the unique verb sense CHOCAR. Fig. 3 is the full discrimination-net for Spanish verb senses expressing the conceptual act PROPEL.

Each question in the D-net of Fig. 3 divides the set of possible verb senses for PROPEL into two (roughly equal) sets. The process is repeated for each new set until the working set contains only one candidate (i.e., the D-net reaches a leaf-node). The leaf node CHOCAR defines a unique mapping of the conceptual cases from (16) into the linguistic case structure of (17). The Spanish grammar linearizes the linguistic case-structure representation, adding the adverbial time clause in the appropriate place, and substituting the Spanish lexical items for "small motorized vehicle" and "tree."

The second conceptualization to be expressed in the summary is the "interfering" event, EVNT14, from the story representation:

(18) [David Hall, 27, a New Jersey Man, died]

```
((ACTOR (#PERSON PERSNAME (DAVID)
                 LASTNAME (HALL)
                 AGE (#UNIT TYPE     (*YEAR*)
                            AMOUNT (27)
                            TOKEN  (UNIT0))
                 RESIDENCE (#POLITY TYPE      (*STATE*)
                                    POLNAME  (NEW JERSEY)
                                    TOKEN    (POLIT0))
                 GENDER (*MASC*)
                 TOKEN  (HUM0))
  TOWARD (*HEALTH* VAL (-10))
  FROM   (*HEALTH* VAL (*NORM*)))
  TIME   (( BEFORE *NOW* X))
```

(19) DAVID HALL, DE 27 ANOS, QUE VIVIA EN NUEVA JERSEY, SE MURIO.

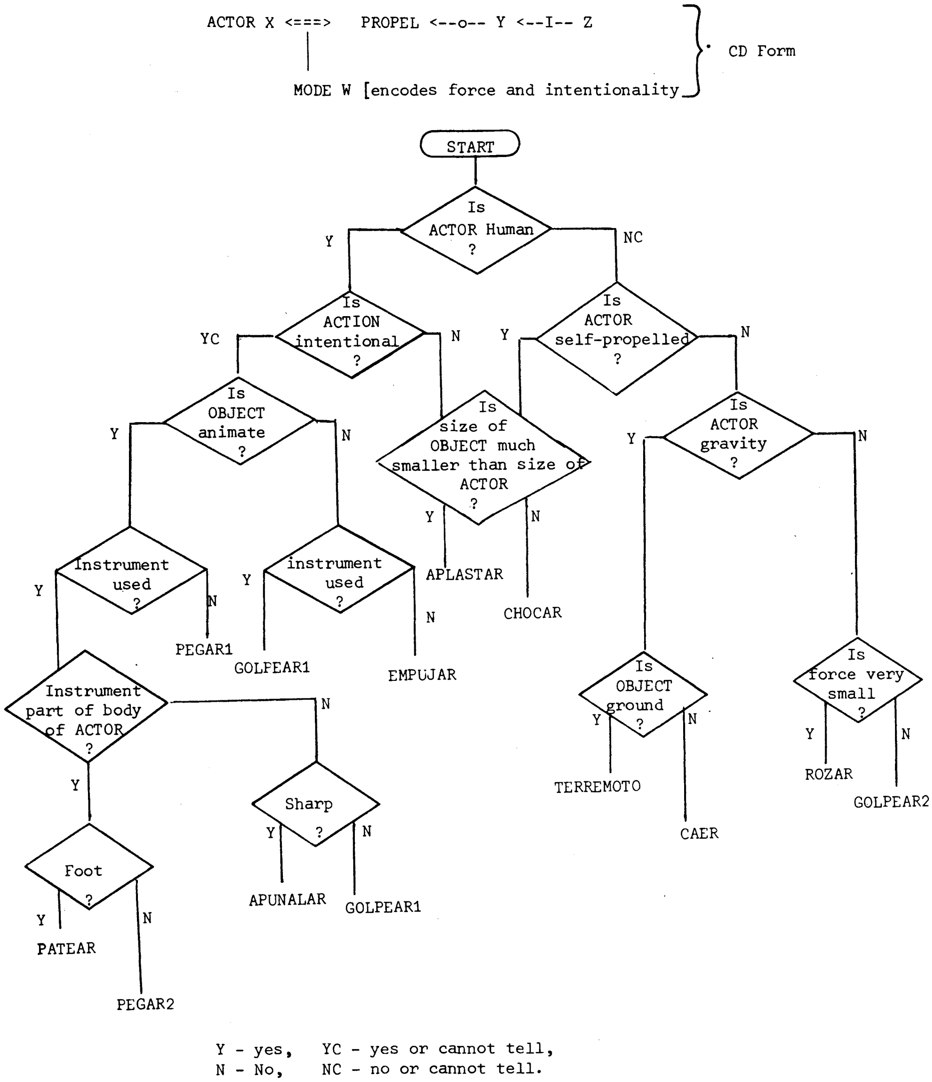


Fig. 3. Discrimination network for Spanish verbs expressing PROPEL conceptualizations.

The Spanish verb sense MORIR2 is chosen by applying the D-net associated with the HEALTH state to conceptualization (18) in the same manner as (16). The conceptual ACTOR case is mapped into the linguistic AGENT case. We mentioned in Section I that translating the age and residence would present severe problems to a system that did not recognize them as such. Once the CD-diagram (18) has been created, some of the difficult problems are automatically resolved. Others are greatly simplified. For instance the "27" in Story 5 was resolved as Hall's age in years by the conceptual analyzer, ELI. The fact that sufficient information is provided beforehand makes the task of the Spanish phrase generator straightforward. It maps "AGE (#UNIT TYPE (*YEAR*) AMOUNT (27))" into "DE 27 ANOS," since a person's age can always be expressed the same way in Spanish.

The problem of expressing "a New Jersey man" in Spanish is greatly simplified by the representation "RESIDENCE (#POLITY POLTYPE (*STATE*) POLNAME (NEW JERSEY))." The generator must decide whether the reference is to Hall's residence, birthplace, present location or destination, since each of these alternatives would require a different Spanish expression. The grammatical construction that needs to be generated in Spanish differs from the original English expression. The former is an appositive noun phrase, while the latter is a relative clause. Given that Spanish normally expresses residences as relative clauses, we need to determine the verb of the relative clause and its proper conjugation. A D-net is used to determine whether it is known that David Hall owns the house he lives in, rents an apartment, or was temporarily passing through. If the first were true, we would say the equivalent of "Hall owns a residence in NJ"; if the second were the case, we would generate something like "Hall rents in NJ," etc. Since we have no information to allow us to answer any of the above questions, we resort to the most general verb expressing the idea of residence, namely VIVIR2, meaning "to live in."

The conjugation of this verb is determined by the subject of the sentence and the proper time modality. Determining the time modality involves determining when it was true that Hall's residence is/was in New Jersey. This involves consulting the entry in PP-memory for David Hall (accessed through the token HUM0) created during the understanding process. We find that his HEALTH is at -10, meaning he has died. Therefore, he can no longer "live" at his New Jersey residence, and we conjugate VIVIR2 in the past tense.

Alternatively, we could have checked the conceptualization being generated to see whether Hall was still a resident of New Jersey. This would also have yielded the right answer in this instance. In general, however, the current conceptualization does not contain the data that are needed. Consider, for example, translating; "George Washington, a Virginia man, led the Continental Army." Here, only the PP-memory entry for George Washington can tell us that he can no longer be a resident of Virginia.

The next summarizing conceptualization to be expressed is the second "interfering" event from Story 5:

(20) [Frank Miller, the driver, was slightly injured]

```
((ACTOR (#PERSON PERSNAME (FRANK)
                 LASTNAME (MILLER)
                 GENDER   (*MASC*)
                 SROLES   (($VEHACCIDENT . &HURTGRP)
                           ($DRIVE . &DRIVER1))
                 TOKEN    (HUM3))
  TOWARD (*HEALTH* VAL (NIL))
  FROM   (*HEALTH* VAL (*NORM*)))
  INC    (-3)
  TIME   ((BEFORE *NOW* X)))
```

(21) EL CHOFER, FRANK MILLER, QUEDO UN POCO HERIDO.

To select the Spanish verb-sense QUEDAR3, the generator, as before, applies a state-change D-net. The CD representation (20), however, does not contain all the necessary information for choosing the appropriate verb-sense. One of the questions asked by the D-net is whether the change in Miller's health occurred as a result of his scriptal ROLE. That is, did Miller's getting hurt have anything to do with his being the driver of a vehicle? This question is answered by a program that searches the instantiated $VEHACCIDENT script. This finds a causal connection in the story representation between the crash, EVNT4, and the event of Miller's injury, EVNT20. Therefore, QUEDAR3 is chosen. The negative INCrement in the HEALTH scale and its final value (3 points below normal) yields the Spanish adjective HERIDO. The small magnitude of the increment tells the generator to modify the adjective with UN POCO, meaning "a little." Example (21) is thus generated in a straightforward manner, aside from the necessary query to the instantiated script.

The final event passed by the summarizer to the generator for expression is the "scorecard" event (EVNT33) which records what the police decided to do as a result of the accident:

(22) [The policeman in charge did not press charges]

```
((ACTOR (#PERSON SURNAME (ONOFRIO)
                 TITLE   (PATROLMAN)
                 GENDER  (*MASC*)
                 TOKEN   (HUM7)
                 SROLE   (($VEHACCIDENT . &POLSTAFF)))
      <=> (*MBUILD*)
 MOBJECT ((ACTOR HUM7
          <=> ($PROSECUTION CHARGEE  (NIL)
                            CHARGOBJ (NIL)
                            CHARGER  (#ORGANIZATION
                                      ORGOCC ($POLICE)
                                      TOKEN  (ORG3)))
          MODE (*NEG* *TS*)))
  TIME ((BEFORE *NOW* X)))
```

(23) LA POLICIA NO ACUSO A NADIE.

The Spanish generator in SAM contains certain heuristics to avoid "verbose" expressions for events. One of these applies to conceptualization (22):

Generation Rule 1:
If the CD to be expressed matches the pattern
(ACTOR X ⇔ MBUILD MOBJECT Y)
and Y is an action with ACTOR = X, MODE = NEG,
then express instead CD Y.

This rule essentially states that persons deciding not to do something usually can be assumed not to have done it. Unless something further is said, we assume that they do not change their minds: "John decided not to go" versus "John didn't go." The generator extracts the conceptualization in the MOBJECT of (22) (i.e., the decision arrived at by the policeman), and attempts to express it.

At this step, it runs into a problem not encountered in the first three examples: there is no correct way to directly express the subconceptualization, which in English means "the police did not initiate prosecution (file charges)." D-nets are attached, in general, to CD ACT's or STATE's. In CD diagrams, ACT's appear to the right of a "⇔". The generator discovers that there is no way to directly express (22) when it finds no D-net indexed under $PROSECUTION.

Since $PROSECUTION is a script, it applies the following script-based generation heuristic:

Generation Rule 2:
```
IF there is no D-net attached to a script name,
   THEN IF MODE = NEG
        THEN search the script in temporal order for
             the first event that is a "precondition"
             for the rest of the script to take place.
             Bind the script roles in this event, add
             MODE NEG, and generate that event
        ELSE retrieve the script Maincon, bind roles
             and generate.
```

Applying this rule, the generator searches the $PROSECUTION script (as it exists in the minds of many Spanish speakers), and finds that its first scene describes the police deciding whom to accuse for the alleged crime. This event must be completed before succeeding events in $PROSECUTE can take place (e.g., the police must have a suspect before making an arrest and proceeding to initiate a trial). Since the search is successful, the generator adds MODE ((*NEG*)) (meaning that the event did not take place). The negated accusation event, represented below, is easily generated in Spanish:

(24) [Police do not accuse someone]
```
((ACTOR (#ORGANIZATION ORGOCC ($POLICE)
                       TOKEN  (ORG3))
    ⇔ (*MTRANS*)
 MOBJECT ((⇔ ($ACCUSATION CHARGOBJ (NIL)
                          CHARGER  ORG3
                          CHARGEE  (NIL))))
   FROM (*CP* PART ORG3)
     TO (*CP* PART (NIL)))
   MODE ((*NEG*)))
```

Using the D-net attached to the ACT MTRANS, the Spanish generator selects the verb-sense ACUSAR1, and subsequently generates sentence (23).

IV. How Much Understanding is Needed for Machine Translation?

In this section we address the crucial issue of whether "full" understanding is necessary for the correct translation of a text from one language into another (and, if not, just how much understanding is needed). By full understanding, we mean the mapping of a text into some semantic representation adequate for competent question answering.

A. Translation with Minimal Understanding

Perhaps the most common attitude of past and present MT researchers is expressed in the following excerpt from Kittredge *et al.* [25]:

> ... even if lexical decomposition proves theoretically possible, it is far from clear that it will prove efficient in semantically complex subject areas. Thus the designers of heavy-duty translation systems, those which must actually produce readable translations of texts formed over an extensive vocabulary, are more or less faced with the necessity of leaving the lexical unit intact. Translation then requires relating the lexical units of the two languages within the framework of empirically established syntactic structures, and the inventory and use of such structures invariably differs between languages.

The first sentence of the above passage states that understanding, even if possible, may be inefficient. Therefore, the authors conclude that a practical, "heavy-duty" translation system will consist of a dictionary of the source language in which every word-entry will contain instructions on how to translate it into the target language. These instructions will use such information as the syntactic structure of the sentence, the syntactic role of the word in the sentence, and the constraints the corresponding expression in the target language places on the structure of the resulting sentence. Thus, the English verb OCCUR is translated into French as SE RENDRE COMPTE if the second complement is present, as is the case in IT OCCURRED TO RAY THAT MAX MIGHT HAVE LIED. The entry for OCCUR must also specify that, if the above translation has been chosen, then the translation of the first complement (RAY in our example) should become the subject of the verb SE RENDRE COMPTE.

The above rule is, of course, a simplification of Kittredge *et al.*'s scheme. In practice, the input is first converted into some tree-like structure that explicates some, but not all, of the underlying syntactic relations of the source-language sentence. The structure focuses on those relations that are considered relevant for the task of translation between the particular pair of languages. Sometimes these structures are annotated with some rudimentary semantic information. At the second stage, these structures are *transformed* into the corresponding "syntax-tree" structures of the target language, from which the output is then generated.

The rules governing this transformation are organized in what is called a *transfer grammar* [3], [25], [31]. The characteristic features of this approach are 1) there us no "understanding" of the input text, since these systems are in principle unable to answer even the simplest questions about the input; and 2) all structures and rules used in the translation are established "empirically" for each pair of languages, and thus are necessarily different for each pair. Moreover, the word "empirically" often reflects the researcher's ingenuity in finding ad hoc heuristics, rather than any principles of language organization and use. It is clear that this approach to FAHQT (fully automatic high quality translation—Bar-Hillel's terminology) is inadequate, as has been argued repeatedly in the last 18 years, beginning with [1] and continuing with the examples in Section II.

In recent years, efforts have been made in two directions to overcome the inadequacies of the above approach: 1) more extensive use of semantics and 2) relaxation of the requirements for FAHQT. Let us examine each of these directions in turn.

B. A Little More Semantics

The main objection to MT models which try to "understand" is that this task is so complex as to lead necessarily to inefficient MT. Thus, some MT researchers propose the use of as "little understanding" as is needed for an adequate translation between a given pair of languages. Wilks [44] proposes a specialized intermediate representation system for *every* pair of languages. This representation system is basically an extention of the source language (English in this case), which includes all the information necessary for the correct translation of the input into the target language (French). Each meaning of a word in the source language is described by a special data structure, called a formula, and each formula has a set of functions associated with it that choose the appropriate target language expression. These functions can test the structures in the intermediate representation of the text. Thus, in some sense, each English word in this schema has a set of specialized routines which "know" how to translate the word into French. In "hardship" cases, when the information necessary for correct translation is not explicitly mentioned in the source text, Wilk's system would call the "real" understander (never implemented). This understander would have to translate the intermediate representation into a "real" meaning representation, make the necessary inferences, and then translate the results back into the intermediate language.

Certain MT researchers in the Grenoble group [3], [31] take a similar approach, retaining, however, the transfer stage of the process. They propose several levels of transfer corresponding to different levels of the system's syntactic and semantic sophistication. Such a system attempts to translate the input on the lowest possible level. If this is inadequate, it goes to a higher level. As in Wilks' system, the structures and transfer functions need to be defined for each different pair of languages.

C. Relaxing Requirements

The conclusion that one can draw from our examination of these efforts is not surprising. The more semantics one puts in the system, the better (but possibly slower) it works. This conforms to Bar-Hillel's original assertion that FAHQT is possible only with full understanding. This observation leads us back to the second item in our discussion: perhaps by relaxing some of the requirements for FAHQT we can find a reasonable solution to the efficiency problem in MT. But what does it mean to relax requirements for FAHQT? In the early days of MT, this meant translations which were smoothly readable but not always correct. The slogan in those days was "95 percent accuracy." This is clearly naive and misleading. What does it mean for a human translation to be 95 percent accurate? Over what class of texts do we make these measurements? Even a very good UN translator is likely to be helpless at a mathematics congress.

The inadequacy of this approach was discussed at length by Bar-Hillel [1]. However, the main objection to it was not the emptiness of the criterion, but rather the fact that the reader of such a translation would not be able to detect the mistakes. A similar fear of undetectable mistakes was voiced in [23]. But is this not the case with human translators as well? Even good human translators sometimes misunderstand the input or choose an inappropriate word or expression, making it difficult for the reader to find the mistake. One must apply criteria based upon human-level translation, or the whole idea of "fully automatic high quality translation" becomes vacuous. We discuss the problem of reliability in MT in the next section.

As an alternative to the "frequency" methods Bar-Hillel proposed replacing FAHQT with a MACHINE-MAN partnership in which the computer supplies a specially trained human editor with all translations of all the words in the input sentence, with suggestions for a few possible versions of the target sentence. In the best case, the suggestion would be unique and grammatical. The editor would then compile the "real" translation in the target language. Alternatively, the users themselves would have to learn how to read and make sense of such computer output. Thus, Josselson in his 1970 survey of MT wrote:

> Since it is quite obvious that the product of any functioning MT system will never look the same as human translation, man will also have to expend some effort in reading the output. This process will, however, require less effort than the acquisition of reading skill of another language. . .

Such a computer tool might be useful, but no one would call it "translation" in the strict sense of the word.

D. The Problem of Reliability

We believe that the output of an MT system should be comparable to a reasonable human translation. To make this possible, the MT system must have a reasonable ability to understand what it is translating. But how can one be sure that translations produced by computer are "reliable?" We take the standpoint that this is equivalent to answering the question: how can we be sure that human translations are reliable? Our experience with an individual translator can only tell us that, when he understands a text, he can usually recreate reliably its content in another language. We cannot expect even a good translator to translate *reliably* a text in an unfamiliar area. One can verify the accuracy of human translations in two different ways: compare the results of two different translators, or ask the translator to expand the meaning of the original text, when there is doubt as to the accuracy of a particular passage. The latter method is preferred for real-time human translation. As an example of this mode of translation, consider the highly publicized error in English-Polish translation that occurred during a trip by former President Carter to Poland. Carter stated that people in the United States "desired to have closer ties to the Polish people." The sleepy translator expressed the Polish equivalent that the United States "lusted after the Polish people." On a lexical/syntactic level it is difficult to determine why this translation was incorrect. But, if asked, the translator would quickly have realized his error, and explained what the American President had really meant. Thus, we establish a criterion for reliable translation: the translator must be able to answer questions about the meaning of the source text and elaborate the target text to make the meaning clear to readers. This criterion is met by our programs, since they can answer at least certain questions about things they can understand.

E. Depth of Understanding and Reliability of Translation

A possible objection to our schema for MT is that some limited form of translation is possible, although the translator may fail to fully understand the source text. For example, one can imagine a person without deep medical training translating a highly professional conversation between two doctors from different countries. In this scenario, translation is only possible if the doctors refrain from using technical jargon. Our claim is not that such a translation would be impossible, but that it would be *unreliable.* We have argued that people's ability to produce a *reliable* translation of a text is limited by their ability to understand it. The interpreter in the above example would have to have some model of the medical universe, however naive and unsophisticated, to produce any kind of coherent translation at all. The reliability of his translation would depend on how closely his model corresponds to the real model shared by the two professionals.

Let us consider an example in which "common sense" understanding (i.e., equivalent to that of an ordinary person rather than a specialist) would be sufficient to generate reasonable translations of these newspaper headlines:

(25a) Israel seized large quantities of new weapons from the U.S.S.R.

(25b) Israel seized territory from Syria.

To produce accurate Russian translations of (25a) and (25b), a translator needs to understand only that:

1) The weapons were seized *not* from the Soviet Union, but presumably from a neighboring Arab country.
2) The weapons were manufactured in the Soviet Union.
3) The territory was indeed seized from (*not* manufactured by) Syria.

In (25a), a Russian would make these distinctions by preceding the name of the country by the preposition "iz" while in (25b) he would use the preposition "u."

A more comprehensive understanding of (25), while possible, is not necessary for the purpose of ordinary translation. For instance, a political scientist might consider the U.S. *reaction* to (25) as part of his understanding process, but this goes beyond the minimal understanding necessary to answer questions about what actually happened in (25). While producing a detailed political analysis of a situation is beyond the capabilities of our computer programs (although POLITICS has produced some preliminary results in this area), they are, nevertheless, able to produce a translation roughly equivalent to that of a human with a similar "factual" knowledge base.

Translation can be achieved on various levels of understanding, from extremely primitive to very advanced. For example, a program called FRUMP [16] has been developed at Yale which uses a knowledge structure called a "sketchy script" to process a great variety of news items taken directly from the UPI wire. FRUMP produces simple one, two, or three sentence summaries in English, Dutch, French, Spanish, and Russian. FRUMP's understanding and expressive abilities are limited, but the program works very quickly and can answer questions about what it has understood. It simulates a person *skimming* through a newspaper.

One might argue that this is not, strictly speaking, translation. Nevertheless, this is what people often do with foreign language newspapers, and, therefore, FRUMP models a minimal order of understanding as applied to MT. It is also a useful tool in reducing the enormous flow of information in different languages that humans have to handle. The SAM system, described in Section III, is one of the best developed understanding systems at Yale to date. It represents a middle range of sophistication among our systems. Currently, work is in progress on exploring MT in intelligent computer systems such as PAM [43] and POLITICS [7].

F. "Professional" versus "Ordinary" Translation

Our basic approach to MT in all these systems is what might be called a "retelling" of the text in a different language, rather than a translation in the professional sense of the word, with its close correspondence to the structure and style of the original. We are not trying to simulate a professional translator. The ability to translate professionally is a highly specialized skill, which requires many years of training in addition to a particular talent. Instead, we are trying to simulate an average nonprofessional person with a working knowledge of two languages who is asked to read a text and then to reproduce its content at a desirable level of detail. As far as the professional skill is concerned, we believe that it is based on this more "mundane" ability to translate.

Thus, when a good translator hears an intentionally ambiguous expression, e.g., in a political speech or a literary composition, he will first find both meanings, analyze why the speaker used the ambiguous expression in the first place, and then search for an expression in the target language which preserves the ambiguity. Ambiguity on purely syntactic and lexical grounds is never preserved for its own sake, as semantic considerations imposed by the context will invariably rule out spurious interpretations. Attempts to preserve lexical and syntactic ambiguities in an MT system without proper understanding of the source text must often produce unreliable translations.

It must be said, however, that in order to produce a professional quality translation with its close correspondence to the structure and style of the original, we will have to keep the original text as a complement to its meaning representation at all stages of the translation process. See Wilks [45] for a detailed discussion of this subject.

G. A Few Words about Efficiency

Finally, some comments on the question of efficiency of MT systems need to be made. One of the main objections to the "understanding-first" schema of MT is its alleged inefficiency. In answer to this, one can only say that, as is the case with humans, efficiency depends on the desired quality of translation. FRUMP works very quickly and "efficiently." SAM works more slowly, but it produces better translations. Our experience with SAM, however, suggests that the increase in SAM's understanding abilities does not lead to any serious decrease in its speed. The combinatorial "explosion" feared by Boitet [3] has not come to pass. SAM uses a hierarchical representational scheme, so that processing time grows by a less than linear function of the increased information in the system. However, in a syntax-based system that allows several rewrite rules to be applicable at any one time and generates many alternative syntactic parses (or transformations) of a sentence, the combinatorial explosion in processing time (and space) as a function of the number of applicable rules is indeed a serious consideration.

A different inefficiency problem arises in transfer grammars and in Wilks' translation paradigm. Such systems require specialized routines to translate between *every pair of languages.* The number of pairs of languages increases as the *square* of the number of languages. Hence, if one wishes to translate among 11 different languages one would need 110 transfer grammars! In our understanding paradigm, source text is mapped into a language-free representation, and that representation is mapped into the target language. This process would requires 11 language analyzers and 11 generators, for a total of 22 routines. Moreover, the memory model mediating between analysis and generation would be the same in each case (ignoring small cultural differences). Thus, the extra memory space required to add another language would be expected to increase only linearly with the number of languages.

We are not claiming that we have solved the problem of knowledge-based machine translation. Far from it—we feel that we have only scratched the surface. Three different classes of problems need to be addressed in our approach to MT: 1) understanding the input text, 2) generating a coherent, readable text in a given language from a conceptual representation of the text, and 3) generating an output which conforms to the standards of professional translation. We have concentrated mostly on the first set of problems, since we consider them critical to the whole approach. Our generators are admittedly primitive. We have consciously chosen to attack the problem of "what to say," rather than the problem of "how to say it." In SAM our summarizers work with conceptual memory on the one hand, and with various natural-language generators on the other to produce reasonable summaries of the stories SAM has understood. We are only beginning to work on the second set of problems, and we do not yet have a model of language generation which is comparable to the sophistication of our models of understanding. We have not even touched the third group of problems.

H. Concluding Remarks

Our work on MT grew out of our research on natural language understanding, human memory mechanisms and natural language generation. When we put these modules together we got our first working MT system. The main advantage of the "understanding-generation" schema of MT is that every problem can be put in the context of human problem-solving, and attacked by all known memory and inference mechanisms. Another advantage of this approach is that the psychological plausibility of the proposed mechanisms can be used as a guiding principle. But more importantly, this approach makes the work on MT not an isolated effort to develop a set of task specific heuristics but a part of a general investigation of language and thinking.

References

[1] Y. Bar-Hillel, "The present status of automatic translation of languages," *Advances Comput.*, vol. 1, pp. 91-163, 1960.

[2] D. G. Bobrow and T. Winograd, "An overivew of KRL: A knowledge representation language," *Cognitive Sci.*, vol. 1, no. 1, 1977.

[3] C. Boitet, "Problemes actuels en TA: Un essai de response," in *Proc. 6th Int. Conf. Computational Linguistics*, Ottawa, Canada, 1976.

[4] R. J. Brachman, "A structural paradigm for representing knowledge," Bolt Beranek and Newman, Inc., Cambridge, MA, Rep. 3878, 1978.

[5] J. S. Brown and R. R. Burton, "Multiple representations of knowledge for tutorial reasoning," in *Representation and Understanding*, Bobrow and Collins, Eds. New York: Academic, 1975.

[6] J. R. Carbonell, "AI in CAI: An artificial intelligence approach to computer-aided instruction," *IEEE Trans. Man-Mach. Syst.*, vol. MMS-11, pp. 190-202, 1970.

[7] J. G. Carbonell, "POLITICS: Automated ideological reasoning," *Cognitive Sci.*, vol. 2, no. 1, 1978.

[8] J. G. Carbonell, R. E. Cullingford, and A. V. Gershman, "Towards knowledge-based machine translation," in *Proc. 7th Int. Conf. Computational Linguistics*, Bergen, Norway, 1978.

[9] J. G. Carbonell, "Subjective understanding: Computer models of belief systems," Ph.D. dissertation, Yale Univ., Computer Science Report 150, 1979.

[10] C. Castillo and O. Bond, *University of Chicago Spanish Dictionary.* Chicago, IL: Univ. Chicago Press, 1972.

[11] E. Charniak, "Towards a model of children's story comprehension," Ph.D. dissertation, M.I.T., Cambridge, MA, Rep. AITR-266, 1972.

[12] —, "A framed painting—Representation of a commonsense knowledge fragment," *Cognitive Sci.*, vol. 2, no. 1, 1978.

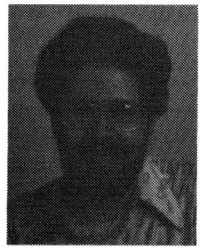
[13] A. M. Collins and M. R. Quillian, "How to make a language user," in *Organization of Memory*, Tulving and Donaldson, Eds. New York: Academic, 1972.

[14] R. E. Cullingford, "Script application: Computer understanding of newspaper stories," Ph.D. dissertation, Yale University, New Haven, CT, Comput. Sci. Res. Rep. 116, 1978.

[15] —, "Pattern-matching and inference in story understanding," *Discourse Processes*, vol. 2, no. 2, 1979.

[16] G. F. DeJong, "Skimming stories in real time: An experiment in integrated understanding," Ph.D. dissertation, Yale University, New Haven, CT, Comput. Sci. Res. Rep. 158, 1979.

[17] A. Gershman, "Analyzing English noun groups for their conceptual content," Comput. Sci. Res. Rep. 110, Yale Univ., New Haven, CT, 1977.
[18] —, "Knowledge-based parsing," Ph.D. dissertation, Yale Univ., New Haven, CT, Comput. Sci. Res. Rep. 156, 1979.
[19] J. Ginsparg, "Natural language processing in an automatic programming domain," Stanford Univ., Stanford, CA, Stanford AI Memo AIM-316, 1978.
[20] N. M. Goldman, "Conceptual generation," in *Conceptual Information Processing,* R. Schank, Ed. Amsterdam, The Netherlands: North-Holland, 1975.
[21] I. P. Goldstein and R. B. Roberts, "NUDGE, a knowledge-based scheduling program," in *Proc. 5th Int. Conf. Artificial Intell.*, Cambridge, MA, 1977.
[22] G. G. Hendrix, "Expanding the utility of semantic networks through partitioning," in *Proc. 4th Int. Joint Conf. Artificial Intell.*, Tbilisi, U.S.S.R., 1975.
[23] Th. Hoffman, "Semantics in aid of automatic translation," in *Proc. 6th Int. Conf. Computational Linguistics*, Ottawa, Canada, 1976.
[24] H. H. Josselson, "Automatic translation of languages since 1960: A linguist's view," *Advances Comput.*, vol. 10, pp. 1-58, 1970.
[25] R. Kittredge, L. Bourbeau, and P. Isabelle, "Design and implementation of an English-French transfer grammar," in *Proc. 6th Int. Conf. Computational Linguistics*, Ottawa, Canada, 1976.
[26] W. Lehnert, "The process of question answering," Ph.D. dissertation, Yale Univ., New Haven, CT, Dep. Comput. Sci. Rep. 88, 1977.
[27] W. N. Locke and A. D. Booth, Eds., *Machine Translation of Languages.* Boston, MA: Technology Press, 1957.
[28] M. Marcus, "Theory of syntactic recognition for natural language," Ph.D. dissertation, M.I.T., Cambridge, MA, 1977.
[29] D. D. McDonald, "Language generation: The linguistic component," in *Proc. 5th Int. Conf. Artificial Intell.*, Cambridge, MA, 1977.
[30] M. Minsky, "A framework for representing knowledge," in *The Psychology of Computer Vision*, P. H. Winston, Ed. New York: McGraw-Hill, 1975.
[31] N. Nedobejkine, "Niveaux d'interpretation dans une traduction multilingue: Application a l'analyse du Russe," in *Proc. 6th Int. Conf. Computational Linguistics*, Ottawa, Canada, 1976.
[32] M. R. Quillian, "Semantic memory," in *Semantic Information Processing*, M. Minsky, Ed. Cambridge, MA: M.I.T. Press, 1968.
[33] C. Rieger, "Conceptual memory," *Conceptual Information Processing*, R. Schank, Ed. Amsterdam, The Netherlands: North-Holland, 1975.
[34] —, "The commonsense algorithm as a basis for computer models of human memory, inference, belief and contextual language comprehension," in *Proc. Theoretical Issues in Natural Language Processing*, Cambridge, MA, 1975.
[35] C. Riesbeck, "Conceptual analysis," in *Conceptual Information Processing*, R. Schank, Ed. Amsterdam, The Netherlands: North-Holland, 1975.
[36] —, "An expectation-driven production system for natural-language understanding," in *Pattern-Directed Inference Systems*, D. A. Waterman and F. Hayes-Roth, Eds. New York: Academic, 1978.
[37] R. C. Schank, "Understanding paragraphs," Instituto per gli Studi Semantici e Cognitivi, Castagnola, Switzerland, Tech. Rep. 6, 1974.
[38] —, *Conceptual Information Processing.* Amsterdam, The Netherlands: North-Holland, 1975.
[39] R. C. Schank and R. P. Abelson, *Scripts, Plans, Goals and Understanding.* Hillsdale, NJ: Erlbaum, 1977.
[40] R. C. Schank and K. M. Colby, *Computer Models of Thought and Language.* San Francisco, CA: Freeman, 1973.
[41] R. Simmons and J. Slocum, "Generating English discourse from semantic networks," *Commun. Ass. Comput. Mach.*, vol. 15, no. 10, 1972.
[42] W. J. Stutzman, "Organizing knowledge for English-Chinese translation," in *Proc. 6th Int. Conf. Computational Linguistics*, Ottawa, Canada, 1976.
[43] R. Wilensky, "Using plans to understand natural language," in *Proc. Ann. Conf. ACM*, Houston, TX, 1976.
[44] Y. Wilks, "An artificial intelligence approach to machine translation, in *Computer Models of Thought and Language*, R. Schank and K. Colby, Eds. San Francisco, CA: Freeman, 1973.
[45] —, "A preferential, pattern-seeking, semantics for natural language inference," *Artificial Intell.*, vol. 6, 1976.
[46] —, "Natural language understanding systems within the AI paradigm: A survey and comparison," *Amer. J. Computational Linguistics*, 1976.
[47] T. Winograd, *Understanding Natural Language.* New York: Academic, 1972.
[48] W. A. Woods, "Transition network grammars for natural language analysis," *Commun. Ass. Comput. Mach.*, vol. 13, no. 10, pp. 591-606, 1970.
[49] W. A. Woods *et al.*, "The lunar sciences natural language information system: Final Report," Bolt, Beranek and Newman, Cambridge, MA, Rep. 2378, 1972.



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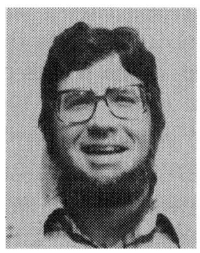

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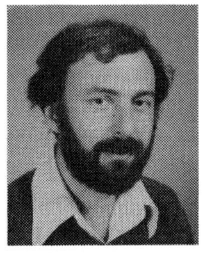

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