CHAPTER 3

Learning Word Meanings from Examples

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INTRODUCTION

This chapter describes an experimental computer program that deduces the meaning of novel verbs from the context of story descriptions. The key idea is a variation on Winston's (Winston, 1975) program that learned the structural descriptions of block world scenes. Instead of learning descriptions of toy block assemblies like ARCH and TOWER, the word-learning program acquires frame-based descriptions of English verbs like MURDER or DONATE. The program works by assuming that similar verbs will play similar causal roles in common story plots. For example, ASSASSINATE is like MURDER because both MURDER and ASSASSINATE cause similar things to happen and are caused by similar patterns and events. Intuitively, we learn about a new verb like ASSASSINATE as a kind of family resemblance variation on a core verb like MURDER. The program works in a similar way. Syntactic constraints derived from the parsing of story plots are used to drive an analogical matching procedure. Analogical matching gives a way to compare descriptions of known words to unknown words. The "meaning" of a new verb is learned by matching part of the causal network description of a story précis

containing the unknown word to a set of such descriptions derived from similar stories that contain only known words. The best match forges an assignment between objects and relations such that the unknown verb is matched to a known verb. The causal network surrounding the unknown item is then used as a scaffolding to construct a network representing the meaning of the novel word in a particular context. In some ways, the model is similar in spirit to that of Granger (1977), who also extracted context-based descriptions to acquire meaning descriptions of novel words. As we see, this way of describing word meaning has several advantages over definitional approaches.

A second aim of this research is to explore the interaction between syntax and semantics in learning. The word-learning program is embedded into a larger system that can acquire new syntactic rules for English, as described in Berwick (1979, 1980, 1982, 1985). The word-learning component uses the larger system's determination of the syntactic category of a new word and its predicate-argument structure. These last two abilities are based on the $\bar{X}$ theory of Jackendoff (1977) and a theory of syntax that assumes a strong principle of lexical transparency (roughly, that the semantic argument structure of a verb appears at all levels of representation). Here, *syntax* means simply the grammatical *form* of sentences, whereas *semantics* refers to such notions as case relationships (Agent, Affected Object), as well as the causal description language used for word matching itself. Although some have emphasized either syntax or semantics as a key to word learning, the position taken here is that either may serve as a constraint on the other. It is the interaction between syntax and semantics that drives word leaning. In some cases, syntax helps semantics. We see several examples of this here, where prior knowledge of sentence structure plays a vital role in figuring out the candidate words for a causally based match. Recently, Landau and Gleitman (1985) have independently confirmed this theoretical finding by studying a blind child's acquisition of verb meanings. They found that syntactic constraints were crucial for successful acquisition of verbs such as *look at* or *see*. Language acquisition involves the complex interplay between these two sources of constraint.

Third, this chapter suggests a concrete computational model for the acquisition of word protoypes from positive examples. In addition, it also suggests a way of automatically generating A K O ("a-kind-of") hierarchies from positive examples. Importantly, this method follows a natural formal and empirically justified constraint on the evolution of categorizations first explored by Keil (1979).

The moral of this chapter is that *constraints* make learning possible. A learning theory can be built only if one has a good representation of what it is that is learned, and some idea of the constraints on that target state. For our theory, the constraints include a restricted vocabulary of *thematic relations* (a "case system") plus a causal description language. The hardest part of constructing a theory of word learning is figuring out just how to represent the "meaning" of a word. Fortunately, a variety of linguistic constraints can help us here. The second moral is that learning does not seem possible unless one almost already knows what is to be learned—a principle of "incremental learning." Whether all learning abides by these principles is not certain, but it seems true that so far all successful artificial intelligence (AI) learning programs have followed them.

Our first job, then, is to describe the representation for word meaning to be used by the learning program. Before we do so, however, it would be best to give an example of the kind of competence we want our word-learning system to display. As mentioned, a key underlying assumption is that the meaning of a word is determined by the role it plays in a causal network description of an event, and that similar words are those that play similar roles in the description of similar events. Consider the following scenario:

> Suppose we are given two versions of the story of Macbeth, one reporting that "Macbeth murders Duncan" and the other that "Macbeth assassinates Duncan." Further suppose that MURDER is a known word but not ASSASSINATE. We should conclude that ASSASSINATE is most like MURDER, because, comparing stories, it seems to us that ASSASSINATE plays the same role that MURDER does in the Macbeth plot. We should also conclude that ASSASSINATE has political overtones, because we note that the Macbeth story includes such relations as *Macbeth wants to be king* and *Macbeth becomes king*. Probing further, later stories should inform us that the uses of ASSASSINATE and MURDER are slightly different, because MURDER need not carry that political connotations that ASSASSINATE does. We should also be able to use the story of Hamlet to deduce the same kind of relationship between MURDER and ASSASSINATE.

Here is the actual input for the Macbeth story:

> MA is a story about Macbeth Lady-macbeth Duncan and Macduff.
>
> Macbeth is an evil noble. Lady-macbeth is a greedy ambitious woman. Duncan is a king. Macduff is a noble.
>
> Lady-macbeth persuades Macbeth to want to be king because she wants him to be king. She wants him to be king because she is greedy.

She can convince him because Macbeth loves her and also because Macbeth is wimpy.

Macbeth assassinates Duncan with a knife. Macbeth assassinates Duncan because Macbeth wants to be king. Lady-macbeth becomes insane. She kills herself because she is insane.

Macduff becomes angry because the king was assassinated. Macduff kills Macbeth because Macbeth assassinated Duncan and because Macduff is loyal to Duncan.

Remember MA.

Using the techniques described in Winston (1980) and Katz and Winston (1982) the system builds a causal network description of the story, as shown in Figure 3.1. This network is basically an object-oriented semantic network, with objects, agents, and qualities (and sometimes propositional attitudes like beliefs or desires) serving as the nodes in the network, and verbs serving as the links between nodes.

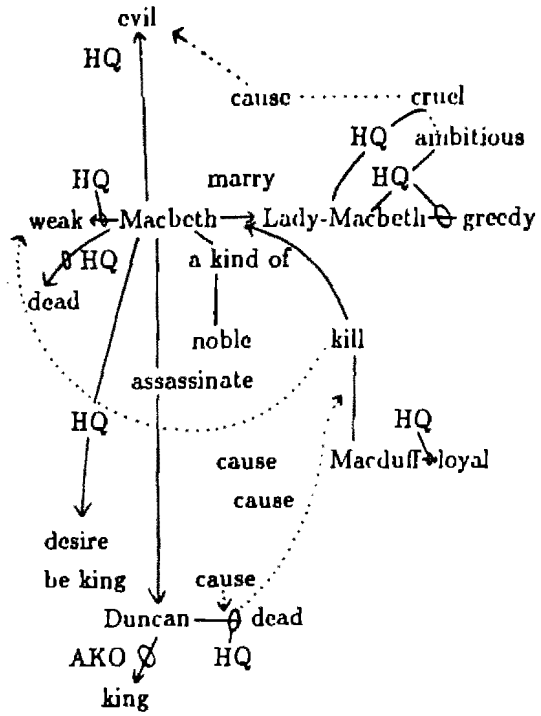


Figure 3.1. Causal networks describe stories

Now suppose that a number of other stories have been previously analyzed and stored in causal network form (e.g., Macbeth, Hamlet, Julius Caesar, and the Taming of the Shrew, as discussed in Winston, 1980), and that none of these previous plot summaries used the word *assassinate*. (Alternatively, the *Macbeth* story could be considered unknown, as long as other examples of murders, say, in *Hamlet*, were already analyzed.)

A causal network representation can be built for each of these stories. For the old Macbeth and Hamlet stories, this network will be nearly identical to the network built previously, but with some key differences that flow from the lack of understanding of *assassinate*. Still, as we see, syntactic constraints permit the entire network to be built, because the connections between objects and actions are actually syntactic.

The learning procedure then takes the causal network descriptions of each of the candidate stories and runs an analogy matching program, pairing objects and relations in the new story against objects and relations in each of the candidates until the best match is obtained. Note that the system can use either similar stories for an attempted match or exactly the same story (but with unknown words).

This is a graph matching problem. It tries all possible combinations of nodes (objects) and links (labeled with verbs, prepositions, or CAUSE) until it finds one that lines up best with the old story. This best match will pair up corresponding objects and links in the network representation of the new Macbeth story and the network of one of the other stories. In this case, the best match weds *murder* and *assassinate*, because these have the most causal links in common. This is the first step in forging a representation of the meaning of the new verb *assassinate*.

This is what we want our system to do; the rest of the chapter says just how it is done. In the first Section, following much recent work on concept acquisition, I discuss why dictionary definitions are inappropriate for this task. The next section follows with an outline of a causal description language that does seem more suited for representing verb meanings and a definition of semantic similarity. The third section outlines the syntactic constraints used by the acquisition program and their connection to semantic representations. A detailed discussion of the program implementation and some examples of the system in action is given in the fourth section. It also compares the current system to an earlier attack on this problem, by Granger (1977). The final section is a discussion of current limitations and some proposed extensions for the learning of Nouns.

THE INADEQUACY OF DEFINITIONS

If the key to any learning program is a good representation of what is learned, then we must have a good representation of word meanings before we can learn them. In fact, this has been the biggest stumbling block for word learning. What is the meaning of a word?

One common analysis has been *decompositional*. Words are viewed as chemical compounds, built out of constituent primitives. So for example, *dog* might be labeled Animate, Four-legged, Mammal. . . . This "word chemistry" is a classical technique that aims to account for our apparent "generative" ability with words—our ability to represent the meaning of a potentially unlimited number of words with finite means. Researchers as diverse as Schank and (much earlier) Katz and Fodor have embraced this method. For instance, as should be familiar, Schank takes the "meaning" of verbs as representable by a graphic language consisting of primitives like PTRANS (physical movement) assembled into a picture of the relationship between objects in an event representation of a sentence.

The difficulties with a "pure" compositional account of word meanings are by now well known. There is a familiar skeptical tradition in 20th century philosophy of language, stemming in part from the later work of Wittgenstein, arguing that it is impossible to give definitions—necessary and sufficient conditions—for words. In a classical passage, Wittgenstein observed, for example, that there can be no definition of a *game*, because there is nothing held in common between board games, sports games, and the like. The most that can be said is that there is a kind of "family resemblance" between the members of the group of games. More recently, psychological arguments have been advanced that mitigate against definitional accounts of meaning. Fodor, Garrett, Walker, and Parkes (1980) pointed out that it is impossible to find "if-and-only-if" conditions for words, aside from examples of such words as jargon or kinship terms. (Note that AI programs for word acquisition have often focused on just these sorts of items, such as *bachelor*.) They also provide psycholinguistic evidence—based on reaction time tests—that feature decomposition into primitive elements is not carried out in on-line processing.

. Whatever the status of these experiments and others like them (see, for example, Hayes-Roth and Hayes-Roth, 1977, who present similar evidence against decompositional theories), it is plain that "if-and-only-if" conditions for word definitions must be rejected. Definitions should admit exceptions and graded categorization judgments, as well as networks of family resemblances. What is the alternative? One approach that has been emerging out of work in AI and

psychological analysis is that of *prototype* theory. Prototype theory holds that the criterial features of a word—say, *apple*—are described via some paradigm or core example. We picture an apple by conjuring up a familiar red object in our mind's eye. Even so, this prototypical apple admits exceptions and gradations in each of its characteristic qualities: the skin may be green, if the shape is right; the apple may be mis-shapen, if it is otherwise applelike; a huge apple is still an apple, and so on. In the traditional AI parlance, we may connect these various sorts of apples by means of *difference pointers* (Winston, 1975) indicating how and by how much the various members of the apple family deviate from core apple-ness.

Difference-pointer families avoid the pitfalls of necessary sufficient conditions because there are no necessary and sufficient conditions for any definitions. Indeed, there are no definitions at all, in the "if and only if" sense. Viewed this way, what we learn when we learn a new word is not some set of conditions, but a connection of some network of already-known words. This viewpoint is not novel, of course, being part of most network-based theories of semantic representation. What is new is a demonstration of just how this approach can be used for word learning.

At the same time, it is worth pointing out that these claims about word decomposition are controversial. An opposing, long-standing approach attempts to chop up word meanings, particularly those for verbs, into primitives. So for example, *kill* might be written as CAUSE *to die*. This is a tack favored by Gruber (1965), Schank (1973), and Jackendoff (1972), among others. In this chapter we straddle both sides of this difficult fence. Rejecting if-and-only-if conditions, we adopt a family resemblance model for meaning. At the same time, we decompose verbs into causal network diagrams.

THE ACQUISITION PROCEDURE

The Causal Description Language

Having adopted a "family resemblance" model for meaning, we have still to say just what our network descriptors should be. As is well known, the choice of a semantic network vocabulary is a hazardous game. Ideally, one should follow empirical constraints on descriptors, but little is known about what these should be. Is color a basic element of our semantic descriptions? If so, what colors? What about geometric shapes? Such conditions can be multiplied endlessly. It would be useful to have criteria analogous to those for grammatical categories and features that would let us know that *red* is just as much a part of semantic descriptions as *Noun* is for syntactic

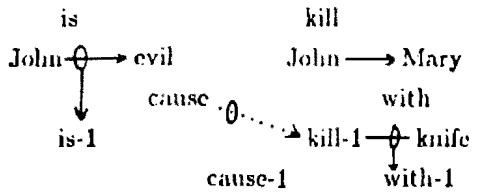


Figure 3.2. A causal network fragment

descriptions. The last section of this chapter explores one way of attacking these problems, based on work by Jackendoff (1977), but we defer the question for now.

Given that we do not know just what the right primitive elements should be, or even that there are primitive elements at all, in this work we have simply adopted the position that *all* elements are allowable as potential descriptors on our semantic network. The actual representation for the simple English stories in our database is called an *extensible-relation* representation. It was developed by Winston (1980).

This semantic net is object oriented, with agents, objects, and qualities serving as nodes and verbs tying them together. If more than one object is involved in an act, additional descriptions can be associated with the act-specifying relation. These additional descriptions are nodes that are related to other nodes. For example, the sentence *John killed Mary with a knife because John is evil* is depicted in Figure 3.2.

Note that in this scheme all individual words such as *knife* or *kill* are considered unanalyzable wholes. Nevertheless, it is still possible to relate one word to another word, by comparing the networks in which each is embedded.

Causality

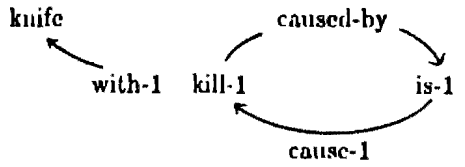
There is one more ingredient to add to our representational language that is a primitive, however. One of the key elements in describing a situation seems to be *causality*. To know what an event is about it is important to know what causes what and what is caused by what. Evidence for this view comes from a variety of sources. Developmental psychologists have discovered that even very young children are disposed to analyze complex mechanical scenes in causal terms, and they can do so correctly (Gelman & Gallistel, 1979). For example, a long row of standing dominoes can be successfully analyzed as capable of knocking open a jack-in-the-box, if the leftmost domino is

rapped with a rigid swinging stick long enough to reach it. Evidently quite young children know enough about causality to reason about even these complex situations.

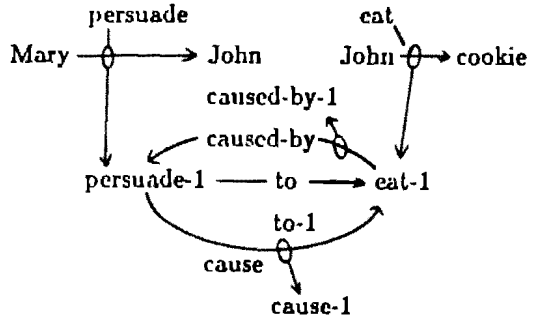
Then too, the ability to explain what happened depends on a causal description. It is no surprise that many AI programs that reason about physical processes rely on causal descriptions. Causality plays a prominent role in other representational languages for predicates, particularly in the work of Schank and Wilks. Finally, causality adds an implicational structure to an otherwise static description network. Without before-and-after links of some kind, it is impossible to describe a chain of events. Otherwise, words are just linked to each other without any directionality.

Given the central role of causality in the description of events, special *cause* links are included in the network description language. Because causes are so important, there is an extra mechanism, demons, associated with them. The following conventions for CAUSE demons are obeyed:

- If A causes B, then B is caused by A, where A can be people, relations, or objects and B can be other relations or acts. The caused-by links are automatically generated when causal relations are inserted in the database. In our previous example, there should be a caused-by link from kill-1 to is-1.



- If A persuades B to do C, then clearly, A causes C and C is caused by A. The appropriate links are added to the database. For example, *Mary persuaded John to eat a cookie* is pictured as:



Demons are also used to make certain simple deductions as relations are added to the database. For instance, if we add *Macbeth kills Duncan* to our database, a demon adds *Duncan is dead*. From a theoretical standpoint, these demons are simply meaning postulates, in Carnap's (1952) sense. But why does one add some set of meaning postulates rather than another? Why, for instance, add just "Romeo has-quality dead" rather than a whole list of additional deductions likely to be true if Romeo kills himself? The idea here is that the added deductions are the "simplest" meaning postulates associated with predicates, where "simplest" is a one-step deduction according to a common-sense language of description. In other words, folk psychological terms are used rather than a sophisticated language of scientific descriptions for depicting events: We say that Macbeth killed Duncan because Macbeth is evil, not because of some account averting to biochemical imbalances. To be sure, this way of limiting deduction is not perfect, but it at least aims to stay close to the deductions people make.

Although the AKO and causal-based representation has been a useful testbed, it is not without problems. We use a preexisting set of AKO descriptors, such as *king* or *knife*. Ideally, these too should be learned. Also, it is not clear that *cause* suffices to describe all verbal relationships. Stative verbs like *be* that describe changes in properties or motion verbs like *run* are not so easily cast in terms of causal interactions with objects. A cause-based matcher will have nothing to work with here, and so will fail. In the fourth section of this chapter we propose modifications to handle some of these difficulties.

Thematic Role Structure and Meaning

In addition to the causal network description, there is one other component of word meaning used by the learning program. This is the linguistic notion of *thematic roles*, also called *case frames*. Thematic-role descriptions have been discussed in detail by Fillmore (1968) and Gruber (1965), but in fact are part of almost every linguistic theory. Intuitively, we think of a verb as requiring several thematic arguments that flesh out a picture of the event the verb describes. For example, *eat* takes at least three arguments: the eater, the thing eaten (sometimes tacit); and optionally the manner, instrument, or place of eating. For our purposes here, what is important is that particular thematic roles are ordinarily linked to specific grammatical positions in a particular language. In English, the subject position is canonically the "doer" of the action or the agent. Importantly, the notion of subject is syntactic in English, because it is the first noun phrase under the sentence in a parse tree. Likewise, the object position canonically plays the *affected object* or *patient* role. This correspondence between form and meaning implies that thematic structure can be recovered from syntactic form, at least in clear cases.

Interestingly enough, possible form-meaning assignments vary parametrically within narrow limits. That is, although other languages (unlike English) do not link the subject syntactic position with the thematic role of agent,the allowed variations are quite limited. Linguistic analysis suggests a twofold division of the world's languages, into either the *accusative languages*, with a subject-agent and object-patient connection; or the *ergative languages*, with the reverse object-agent and subject-patient links. Once this pattern is fixed for a given language, it need not be relearned for individual verbs, although there may be exceptions to, for example, the generally accusative character of a language. In English, for instance,there is a systematic class of verbs whose subjects are affected objects rather than agents; this data and the table here are from Levin (1983).

- The glass broke.
- The puddle disappeared.
- The book fell off the shelf.

This analysis carves up English verbs into a few classes according to their argument structure. Basically, there are two argument verbs with the accusative pattern; one argument verbs with a subject-agent link; and the ergative one argument verbs like those just mentioned:

2 arg. verbs	1 arg. verbs (Agent only)	1 arg. verbs (Patient only)
hit	talk	come
kick	cough	break[1]
push	wave	appear
give	sing	fall
take	sniff	go

The learning program exploits these regularities by using the form-meaning correspondence to guide network matching. No matter what the meaning of a novel verb, and unless there are specific syntactic clues that indicate otherwise, one can assume that the subject will be the agent and the object will be the patient. But this means that the subject-verb-object links so crucial for the meaning

representation can be partially built even for an unknown verb. Syntactic constraints are enough in most cases. Then, the network matching program can use this information to attempt to pair up only agents with other agents, patients with patients, and so forth. This filtering saves a good deal of effort. For example, if we have that "X kills Y," then naturally X and Y will wind up playing different causal roles later in the story. Given "W assassinates Z" it would thus be a waste of time to try to pair the person killed in one story with the assassinator in the other. Thematic filtering prevents this. Granger (1977) used a similar method within a very different semantic representation. He too found that thematic roles were a crucial factor in looking for a representation for a novel word. Granger did not use thematic roles directly, but instead looked at prepositional types and their noun phrase objects. In English, this amounts to the same thing as a thematic role. For example, *by* plus an animate noun phrase often corresponds to an agent thematic role. This would not work in a language where thematic roles are unmarked by prepositions. It also fails in cases where thematic role varies from its canonical prepositional assignment; for example, in *the vase broke*, *vase* is not the agent. This is one reason why it is better to work through a mediating syntactic theory that directly defines thematic roles, and then use these for filtering candidate matches.

With the basics of the syntax-semantics connection described, some details are in order. The techniques described in Berwick (1985), based on the Marcus (1980) parser, are used to syntactically analyze the input. Consider a sentence such as *Macbeth assassinates Duncan*. How can we assign the correct thematic roles in this case if *assassinate* is an unknown word?

First of all, we may assume that all normal English sentences are known to be in the form noun phrase—verb phrase. Unless there is evidence to the contrary, the parser will predict that a noun phrase (*Macbeth*) begins this sentence as well. With the NP disposed of, the parser now predicts that an a verb phrase (VP) should be found. Given that English verb phrases must be headed by verbs, *assassinate* is forced to be a verb. In this way, syntax actually constrains the lexical category of the unknown word. (There are, of course, other possibilities. Suppose that an adverb intervened between NP and verb, as in, *Macbeth quickly dispatched Duncan*. In this case, given that *quickly* is known as an adverb, again a VP is predicted, and *assassinate* must be its head. Note that *Duncan* is assumed known as a noun, hence cannot be the verb heading the verb phrase.)

Finally, *Duncan* is parsed as an NP and noted as an object of the unknown verb, as it is by definition. Given the canonical relationship between thematic arguments and syntactic positions, we also know that the object is the patient and that *Macbeth* is the agent. So we already know quite a bit about *assassinate* without really understanding its meaning.

Semantic Similarity and Matching

We are now ready to describe the matching criteria used for judging when two verbs are "close" in meaning. Two verbs are judged semantically identical if:

1. Their thematic role structures and selectional restrictions are the same;
2. The same objects are present in the causal representations of both verbs; and
3. Their causal links overlap exactly.

Selectional restrictions amount to simply the type checking of arguments. For example, *admire* demands an animate subject (*John admires sincerity* but not *Sincerity admires John*). (The final section discusses in more detail how selectional restrictions may be learned.)

These three conditions are identical to what Salveter (1982) used in the MORAN system for learning Schank-type representations of words. Plainly, however, these exact-match conditions are too strong. Similar verbs can violate any or all of conditions (1)–(3). Verbs may differ in argument structure and yet be alike in meaning: *Eat* takes an object argument and *dine* does not (*John ate an apple* vs. *John dined an apple*). Similar verbs may have different selectional restrictions: *Assassinate* differs from *murder* in that it requires the thing killed to be a person and a political figure. The requirement of object identity is also too strong. It is clear that two verbs may be nearly synonymous, and yet one verb might appear in a story mentioning only Hamlet, whereas the other verb occurs with Macbeth. Finally, similar verbs may have causal structures that do not exactly overlap (e.g., *steal* usually leads to a pattern of causes and effects that is distinct from *take*, yet the two verbs are alike in some ways).

All of these considerations suggest that one give up the tight constraint of exact matches for a graded system of inexact matching. Computationally, the problem is one of (directed) graph isomorphism. We want to find the best possible correspondence between graphs G_1 and G_2 labeled with cause, verb, and preposition links.

Aside from this labeled correspondence, then, the matching process is completely syntactic; only the pattern of the graphs matters in matching. In addition, two nodes are not considered for matching unless they play the same thematic roles (agent, patient, and so forth) in the graph representations (in particular, two objects may be matched if they denote different instances of the "same" object, e.g., KNIFE-1 and KNIFE-3). (It might also be reasonable to use a weakened condition here that permits two objects to be matched even if they do not fill the same thematic roles, if they are the same object or nearly the same kind of object, but this change has not been investigated.)

The matching process is in general computationally intractable. There are *n* factorial possible 1-1 mappings of *n* nodes to *n* other nodes; there are more possible matches if a 1-1 correspondence is not required. Worse yet, the program must search as many graphs as there are possible stories with candidate verbs. We conclude that some potential matches must be filtered out in advance and the size of matches should be restricted if at all possible. Two heuristics have been adopted to implement this strategy.

The first heuristic limits the number of stories considered by the matcher. It is currently under development. The key idea is to look only at a few stories that are broadly similar to the story with the unknown verb. Similarity of stories is judged in terms of plot units, in the sense of Lehnert (1981). Roughly, plot-unit theory assumes that the causal relationships in a story can be summarized by extracting out the "molecular structure" of the causal network. This is done by imposing a theory of plot "molecular structure" onto the more basic causal network. Given a network description we can form a corresponding description in terms of basic plot units like *loss*, *gain*, or *intentional problem resolution*. The advantage of this approach is that it boils down entire stories to supergraphs of just a few nodes and links each. For instance, Lehnert showed how a complex story like *The Gift of the Magi* can be reduced to just 10 linked nodes. Applied to our current problem, the idea is to index all stories by their plot summaries and to retrieve only those that happen to closely match the current story under analysis. Of course, this extra indexing and retrieval matching itself takes time, but typically far fewer nodes are involved for matching. One difficulty is that Lehnert's plot summaries are based on a vocabulary of affective reactions, which may not be suitable for indexing causal regularities. What is needed is an approach like Lehnert's but with a different summarization vocabulary. This has not yet been done. Because it is not yet completely implemented, this heuristic currently replaced

by an oracle—a programmer who decides what stories to match against the network with the unknown verb.

The second heuristic reduces the number of nodes matched by considering only the local graph structure around the unknown verb. Specifically, we force the matching algorithm to consider only nodes directly linked to the unknown verb plus any nodes linked to these directly connected nodes, but no others. Intuitively, this makes sense: This means that distantly related events and relations are not brought in for matching at all. This is a brute force approach that directly reduces the number of matched nodes. In practice, although a full story could have a 100 or so nodes, this constraint reduces the nodes for matching down to 10 or so—an order of magnitude savings, with a corresponding savings in computation time. Finally, as mentioned, we do not consider match candidates that do not meet the tests of thematic role identity.

Difference Pointers

Having found a match, the last job of the acquisition procedure is to calculate just how the new word differs from the old. This is at least as important as finding the best match, for only by finding differences do we learn anything new. The calculation is straightforward. We take the graphical representation of the local network around the old verb and add an annotated link indicating how the new verb differs from old. Alternatively, one could add pointers to the network representation of the new network, indicating differences. In this way, the system actually builds up a set of family resemblances. Words that are more distant from the "core" member of a family will have more difference pointers than words that are "closer" to the core. Note that this way of storing information already admits a prototype with allowable exceptions. A wormy or overly large apple can still be an apple because it will not violate enough of the prototypical apple qualities to be ruled out.

Constructing the appropriate difference pointers is often difficult. *Assassinate* differs from murder in that a political figure is involved, but how is the program to know (or learn) this? Currently, the difference pointer constructed in this example reveals two different AKO structures: for *assassinate* the murdered figure is AKO *king*, whereas for *murder* it is just AKO person. Eventually, we would like the system to connect a group of similar *assassinates* by lumping *king*, *president*, and so forth into a more general AKO *political* class.

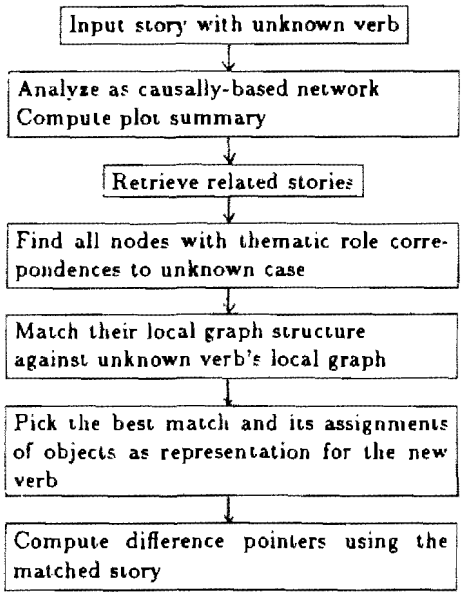


Figure 3.3. Flowchart for word learning

In general, human abilities at forming such natural classes are not well understood; some ways of handling this are discussed in the section on Learning AKO Hierarchies.

Flowchart

We can now give a complete flow diagram of the learning procedure (see Figure 3.3).

IMPLEMENTATION AND EXAMPLES

With the entire acquisition procedure described, this section presents some examples of the system in action. In order to fix the meaning of an unknown verb, stories are first translated into their respective extensible-relation representation. Then it provides our matcher with the unknown verb, the name of the story in which it appears, and the name of the stories to be used as precedents. The pieces of the network local to the known verb (the extent of the pieces is controlled by the user) are superimposed, one at a time, to

the piece of the network local to the unknown verb. The verb that is probably the closest in meaning to the unknown verb will have the greatest number of matching links.

The examples use three Shakespearean plots, Hamlet (HA), Macbeth (MA), and Julius Caesar (JU):

HA is a story about a ghost Hamlet Gertrude Claudius and Laertes.

Hamlet is a prince. The ghost is a dead king. Claudius is an evil king. Gertrude is a queen. Gertrude is a naive woman. Laertes is a man. The ghost was married to Gertrude.

Claudius, who is married to Gertrude, murdered the ghost because Claudius wanted to be king and because Claudius was evil. The ghost persuades Hamlet to kill Claudius because Claudius murdered the ghost. The ghost can persuade Hamlet to kill Claudius because Hamlet loves the ghost. Hamlet is unhappy because the ghost is dead. Claudius wants to kill Hamlet because Claudius is afraid of Hamlet. Claudius kills Gertrude. Hamlet kills Claudius because Claudius murdered the ghost and because Hamlet is loyal to the Ghost. Hamlet kills Claudius with a sword. Claudius persuades Laertes to kill Hamlet. Laertes kills Hamlet with a sword. Hamlet kills Laertes.

Remember HA.

MA is a story about Macbeth Lady-macbeth Duncan and Macduff.

Macbeth is an evil noble. Lady-macbeth is a greedy ambitious woman. Duncan is a king. Macduff is a noble.

Lady-macbeth persuades Macbeth to want to be king because she wants him to be king. She wants him to be king because she is greedy. She can convince him because Macbeth loves her and also because Macbeth is wimpy.

Macbeth assassinates Duncan with a knife. Macbeth assassinates Duncan because Macbeth wants to be king. Lady-macbeth becomes insane. She kills herself because she is insane.

Macduff becomes angry because the king was assassinated. Macduff kills Macbeth because Macbeth assassinated Duncan and because Macduff is loyal to Duncan.

Remember MA.

JU is a story about Caesar Brutus Anthony and Cassius.

Caesar is a general. He is an ambitious and foolish emperor. He is a man. Brutus who is an honest and unhappy man loves Rome. Antony is a man. Cassius is a thin man.

Cassius convinces Brutus to murder Caesar because Cassius hates Caesar and also because Brutus is weak. Brutus murders Caesar with a knife. Brutus murders Caesar because Cassius told Brutus that Caesar was evil. Brutus is unhappy because Brutus murdered Caesar and because Brutus loved Caesar. Antony who loved Caesar persuades some people to attack Brutus because Brutus murdered Caesar. Brutus

attacks the people because the people attacked him. Cassius also attacks the people. Brutus kills himself. He kills himself because he is unhappy. Cassius kills himself also.

Remember JU.

To begin matching, we need to obtain the relations that are linked to the verbs. An auxiliary function, GET-RELATIONS, returns the root of each different relation linked to each verb. Invoking this function on MURDER-1 returns the list (CAUSE CAUSED-BY). Note that MURDER-1 can be thought of as premeditated, first degree murder.

In this implementation, two nodes or links in a network are possible matches if:

- they are the same object or
- they fill the same thematic roles or
- they are connected by AKO links (i.e., Macbeth and Gertrude are both a-kind-of persons) or

Macaisa (1984) is chiefly responsible for the matcher's implementation, and we follow her description of its next steps:

> Because verbs frequently have multiple instances of the same relations, we risk not finding the best match were we to pair up the instances randomly. How do we decide whether CAUSE-15 or CAUSE-21 matches better with, say, CAUSE-2000? We make this decision by matching the objects of each relation to the objects of the relations of the candidate verbs. In practice, most conflicts are settled at this level. However, if there is still uncertainty, we choose the first match. The consequences of this choice will be examined later.
>
> The routine that performs the steps indicated above is called DO-MATCH, and it returns the matching relations and matching objects. Returning the objects is necessary because we allow the user to control the extent of the local network which is to be matched. The variable controlling the locality of the match is *MATCH-LEVEL, and if its value is greater than 1, DO-MATCH is called on each pair of matching objects. The matching relations are collected into a list by the procedure calling DO-MATCH. This procedure checks membership before adding a new pair of matching relations since our extensible-relation representation allows cycles. When there are no more new matches, or when we have reached the specified *MATCH-LEVEL, the scoring function is applied to the list of matching relations. We use a simple scoring function, one which merely counts the number of pairs of relations. (p. 5)

Let us run through an example. Let us assume that *Hamlet* is retrieved as the story closest to *Macbeth* in terms of plot summaries

or causal similarity. We then try to find a verb closest to *murder*, where the *score* is defined as described previously, by the number of matching pairs of relations.

```
(setq *match-level 1)
1.
(define-verb 'murder-1 'ha 'ma)
Matching MURDER-1 with KILL-1 scores 1.
Matching MURDER-1 with ASSASSINATE-1 scores 2.
(setq *match-level 2)
2.
Matching MURDER-1 with ASSASSINATE-1 scores 3.
```

Two verbs score well: KILL-1 and ASSASSINATE-1. If we increase the local distance of matching, then ASSASSINATE-1 does better still. Most relations are eliminated by the case filter: 41 out of 66 in this example.

If we carry out the symmetric match we get this:

```
(setq *match-level 1)
1.
(define-verb 'assassinate-1 'ma 'ha)
Matching ASSASSINATE-1 with KILL-7 scores 1.
Matching ASSASSINATE-1 with MURDER-1 scores 2.
Matching ASSASSINATE-1 with KILL-4 scores 1.
```

Next, the program adds difference pointers connecting *murder* and *assassinate*. In this case, there really is no difference at all. All figures in both plots play political roles; indeed, both persons killed/assassinated (as matched) are rulers. A more interesting example is the matching of *assassinate* to *murder* in, for example, Romeo and Juliet. Here also, the match scores 2, but this time the players are not political. A difference pointer is constructed to indicate this subtlety (see Figure 3.4).

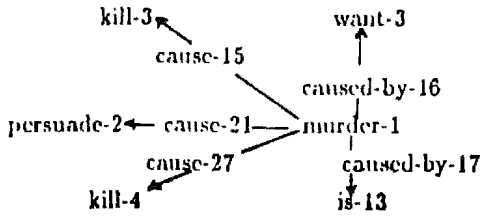


Figure 3.4. Two networks with difference pointers

Further stories should prompt the relevant generalization of the A K O RULER difference to a political classification. Note how this method builds up prototypes automatically. A causal network that reappears in many different plots will be richly connected to other networks of verbs, whereas a rarely occurring verb will be woven only weakly to other stories. Thus, what a "typical" verb is falls out automatically as a consequence of the matching procedure: it is simply a densely connected verb. (It will therefore be easily accessible, under whatever measure of access one uses, again as suggested by psycholinguistic work.)[1]

Macaisa (1984) carried out some other interesting experiments with the matcher. *Love* and *hate* were similar, as were *persuade* and *convince*. Macaisa's summary table runs as follows. The *score* is defined as previously stated, as the number of matching relations. The column labeled *filter* shows the number of relations in the two stories before and after a subcategorization filter is applied that removes relations that do not have the same case frame structure. Some of these results deserve further comment. Note that *attack* and *kill* are considered to match each other in *Julius Caesar* and *Hamlet*. Careful examination of the relevant subnetworks reveals that this conclusion is correct. *Attack* plays a big role in *Julius Caesar*. Here is the relevant excerpt:

> Antony who loved Caesar persuades some people to attack Brutus because Brutus murdered Caesar. Brutus attacks the people because the people attacked him.

This is similar to *kill* in *Hamlet* because of a similar causal role. Both verbs are the result of a persuasion prompted by a death and love of another entity:

> The ghost persuades Hamlet to kill Claudius because Claudius murdered the ghost. The ghost can persuade Hamlet to kill Claudius because Hamlet loves the ghost.

Initial tests of this method proved successful enough to encourage a full-scale test with a large verb computer database currently being

[1]Jackendoff (1983) correctly observed that because brains are finite we cannot store an infinite number of such prototypes. However, it is still possible to store rules to generate an arbitrary number of prototypes. It remains to investigate a "grammar" of this kind.

Verb	*Story and Precedent*	*No. of Rels Before and After Filter*	*Matching Verbs*	*Score*
murder-1	HA, MA	66, 25	kill-1	1
			assassinate-1	2
murder-1	HA, JU	70, 25	kill-10	1
			murder-2	2
assassinate-1	MA, HA	83, 31	kill-7	1
			murder-1	2
			kill-4	1
attack-1	JU, HA	83, 30	kill-7	1
			kill-4	1
love-1	MA, JU	70, 25	hate-3	1
hate-1	JU, MA	66, 24	love-1	1
persuade-4	JU, HA	83, 21	persuade-2	2
			persuade-3	1

developed by the MIT Linguistics Department. This database includes languages other than English. Among these are some ergative-type languages whose different syntactic-thematic linkages should provide a good test of the flexibility of the approach.

LEARNING NOUNS AND CLASS HIERARCHIES

Having seen the learning procedure in action, it is time to step back and assess its competence. One complaint might be that people certainly do not learn the meaning of verbs in the manner suggested. For example, one could just use a dictionary. But this comment misses several points. Miller (1984) noted first of all that many verbs are learned before mastery of reading. Even so, examination of dictionary-reading behavior reveals that children will substitute known words rather than say an unknown word that is being defined by the very entry they are reading. This is only suggestive, but it hints that context-learning plays a dominant role even given learning from dictionary definitions. It certainly fulfills Wittgenstein's admonition "don't tell me the meaning, tell me the use" of a word.

More pointedly, there are many other aspects of the procedure subject to question. In this section, we review two parts of the learning systems behavior that are most open for revision. The first weak point is our choice of representational language, and the second our predefined set of AKO relationships. Two corresponding remedies are suggested: a modified representational language with some primitives, and a systematic method of generating class hierarchies.

Beyond Causal Verbs

The system as designed so far performs adequately on verbs that have a rich causal structure, primarily verbs such as *love*, *murder*, or *persuade*. This is to be expected. The matcher uses causal relations, and so is sensitive to them. Verbs without rich causal relationships cannot be distinguished, because there is nothing to match. It is not clear, then, a simple causal structure is the right way to describe stative verbs like *be* or *become*, or motion verbs like *run*.

One alternative here is a description language outlined by Jackendoff (1983), originally proposed by Gruber (1965) and extended by Schank (1972) and Jackendoff (1972). It decomposes verbs of state or motion into primitives along a few principle axes or semantic "fields" such as temporal, possessional, or identificational, combined with three primitive verb types: STAY, GO and BE. BE denotes a state, STAY lack of motion, and GO, motion (over the semantic field). Jackendoff observed that a wide variety of verbs are modeled on the same scaffolding as these three verbs, but with modifications depending on the semantic field involved. For example, consider the temporal field. We find the following sorts of verbs:

is: BE *The book is on the table*
move: GO *John moved the book to the table*
kept: STAY *The book was kept on the table*

The same three primitives work for possessional verbs:

give: GO *John gave a book to Mary*
sell: GO object to recipient; "money" from recipient to agent
keep: STAY *John kept the book*

Finally, we have identificational examples:

is: BE *John is a teacher*
become: GO *John became a teacher*
remain: STAY *John remained a teacher.*

How can we graft this modified vocabulary onto our previous word-learning algorithm? All that really must be done is to expand our formerly atomic verb names such as *become* or *give* into their parts. This alters just the arc labels on the network descriptions. Matching will be modified to take note of GO, STAY, and BE labels, as well as semantic subfields. Consider the following example. *Macbeth got a knife* has the two representations depicted in Figure 3.5. Now consider a verb like *obtain*. Not only does it participate in the same causal network as *get*, but it decomposes in the same way. The question is: How is this learned? Once again, we can simply use the network matching algorithm to tell us that *obtain* and *go* POSSESS are paired up.

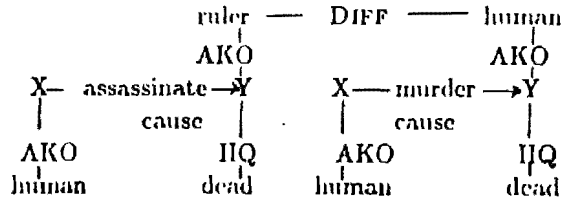


Figure 3.5. Old and new representations for *got*

What are the advantages to this modification? Evidently, to fix a verb decomposition we must fix (at least) two parameters: first, one of the proto-verbs GO, BE, or STAY; second, one of the semantic fields. One positive example fixes one possible variant of the verb's meaning, but it is easy to get others simply by choosing another parameter. For instance, if we set the semantic field to IDENTIFICATIONAL, then we get the verb *get* used in the sense, *Macbeth got religion*. Thus, given this decomposition, we can delineate a space of parametric variation outlining the space of possible verbs of this kind.[2]

It is interesting to compare this approach with another model for word acquisition, that of Granger (1977). Granger also determined the meaning of an unknown word via a matching procedure that extracted similar network representations across stories. Granger's work is founded on the same nondefinitional, context-based theory of meaning as ours, but differs in significant ways. Unlike our causally based representation, Granger's model used a conceptual dependency representation of a story. As mentioned earlier, Granger filtered story matches by (indirectly) computing the thematic roles for nouns, and retaining only those candidate matches whose thematic roles align with those of the unknown input. This representation language takes a stronger stand on decomposition than the one we adopted earlier, but is otherwise would be quite close to the modified decomposition model as just suggested. Granger's system had more trouble with verbs than nouns because its matching procedure

[2]Miller and Johnson-Laird (1976) probed further into a decompositional approach of this kind.

was grounded on a conceptual dependency representation that in turn required one to know what verb one was analyzing. With an unknown verb, much information is absent, and so it is difficult to start matching. In addition, the system explicitly does not build a syntactic representation of a sentence; this makes it all the more difficult to bootstrap a match. In contrast, the system described in this chapter makes explicit use of syntactic constraints to drive matching. It also directly uses thematic role constraints. Finally, the causally based description says that what causes what is more important to a word's meaning than any primitive decomposition into a series of "physical transfers."

Both models benefit from a parameter-setting approach. First, the essentially combinatoric character of parameter setting immediately accounts for the productivity of word meanings. If recursive devices are some kind are allowed, then an indefinite number of word meanings can be accommodated. Second, a theory of parameter setting translates directly into a learning theory. "All" that must be learned is the settings of the various parameters. Berwick (1985) presented one model of parameter setting under the restriction that only positive examples are given. The key idea is that if positive-only examples are used, then at no time should the learner make a general guess that leaves open the possibility that the correct answer is a subset of the guess just made. The reason for this constraint should be apparent. If a subset of the hypothesis *can* be the correct "target," then there is now no way for the learner to find this out. Why? If the correct target is indeed a subset of the hypothesis, then any *positive* example will be compatible with the now overly general hypothesis. In fact, the constraint that one cannot interpolate a subset between one guess and the next turns out to be necessary and sufficient for learning using positive examples.

Learning AKO Hierarchies

The second weak point of the learning model is that it depends on a preexisting set of AKO descriptors. It would be better if these could themselves be learned. Why, for instance, should be class RULER or HUMAN be given rather than POLITICAL? Yet the choice of these descriptors figures crucially in what the matcher does and what difference pointers are created.

In the remainder of this section we outline one possible method of inducing the AKO categories themselves. The central idea rests on

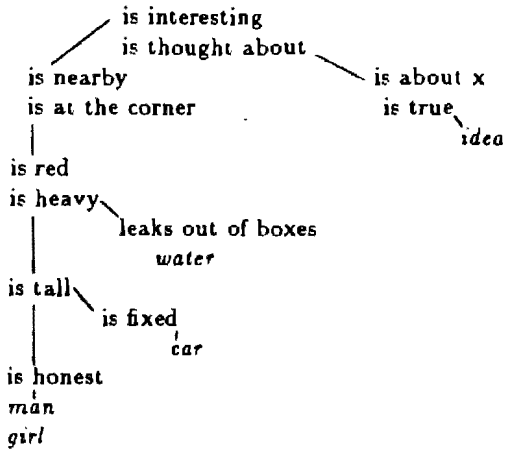
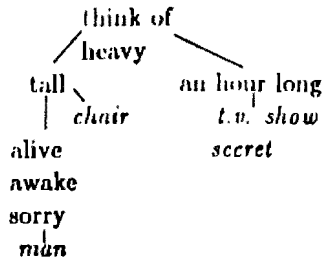


Figure 3.6. The M constraint

an observation of Sommers (1971) about semantic networks, explored in detail by Keil (1979).

Briefly, Sommers has suggested that if one arranges terms such as *dog, cat, love,* and so on into a graph structure whose terminal leaves are terms and where each node is an item that can sensibly be predicated of all terms below it in the graph, then one never, or rarely, finds human intuitions of sensibility resulting in M shaped graphs—the so-called "M" constraint. Rather, the graph structures take the form of hierarchical trees. For instance, the tree in Figure 3.6 (reproduced from Keil 1979, p. 15, Figure 1) is typical of one that comports with human intuitions; an idea can be predicated as being true, hence lies under a node labeled true in a predication tree, but cannot be at the corner, or red, hence does not lie under nodes labelled with these predicates. In contrast, a car can be nearby, at the corner, red, tall, and fixed, but not true. The resulting tree of predicates is called a *predicability* tree.

The "M" constraint relates to acquisition in the following way. Keil found through empirical studies of children that the hierarchical tree structures demanded by the "M" constraint developed the foliation of the trees—that is, children formed new categories by splitting old ones, rather than creating entirely different tree structures. For instance, at the earliest ages studied (5–6 years), some children's predicability trees looked like that in Figure 3.7.



(This is a single individual's tree.)

Figure 3.7. Tree at early age

When second graders were tested, their trees were foliated versions of initial trees of this kind. Figure 3.8 shows the result.

We can use the foliation constraint to learn new AKO categories as follows. Assume at step *n* that the system has built some predicability tree. For concreteness, we shall use the tree given in Figure 3.9.

The root node corresponds to a universal predicate P_0 that applies to all things. Several layers below it is a chain of predicates that apply Duncan, Macbeth, Romeo, and Juliet. That is, these predicates apply to all these items as a class; we could call this the class HUMAN. Call the last predicate node dominating all of these P_i.[3]

Now suppose that the system acquires a network representation of *assassinate*. The network indicates explicitly that *Duncan* can be assassinated, and the difference pointer notes this as distinct from *Romeo's* murder. To abide by the "M" constraint, the predicability tree should be bifurcated at P_i, carving *Duncan* away from its old class. Now we have the situation as depicted in Figure 3.10.

We could name the new category "political entity," but actually there is no need to name it explicitly. The class is *defined* by the predicates that can apply to it. A "ruler," for example, is simply something to which one can apply the predicates ALIVE, CAN REIGN, CAN BE ASSASSINATED, and so forth. Class formation follows the general principle of acquisition from positive evidence cited earlier. Suppose we define a predicability tree as a set of direct domination relations among predicates P_i: We say that dom (P_i, P_j) if and only if

[3]One remark in passing: this way of defining a noun in terms of the predicates that can apply to it is quite close to Montague's (1973) analysis.

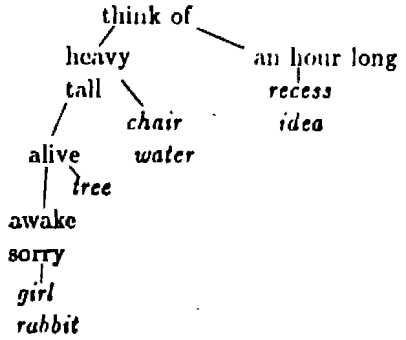


Figure 3.8. Foliated tree

P_i directly dominates P_j. Then according to the class refinement scheme defined earlier, any new predicate is not permitted to destroy existing *dom* relations; it can only add new *dom* relations (between it and old *P*'s).

The justification for this monotonic refinement follows from the general principle of acquisition from positive-only evidence cited earlier.[4] Recall that if a learner is not to overgeneralize, then a new hypothesis should not allow the possibility of a correct target that is a proper subset of the new hypothesis. But this precisely the situation previously described: If a correct target predicability tree could include interpolated P_i's then such trees would be subsets of the hypothesized trees (see Figure 3.11). The criterion of learning from positive-only examples would be violated.

To a certain extent, then, the empirical fact that the evolution of children's predicability trees does not allow for interpolated new predicates constitutes evidence that the constraint of acquisition from positive evidence has played a role. To make predicability trees learnable, they are constrained to obey the "M" principle. By following this constraint, the learning procedure too can make use of positive-only example, without relying on explicit negative correction. This is just a particular illustration of the general point that if negative examples are not allowed, then additional constraints are required.

[4]For examples of monotonic refinement in other domains of learning, see Berwick (1985).

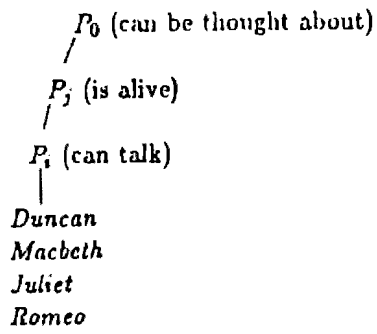


Figure 3.9. A predicability tree fragment for the Shakespeare world

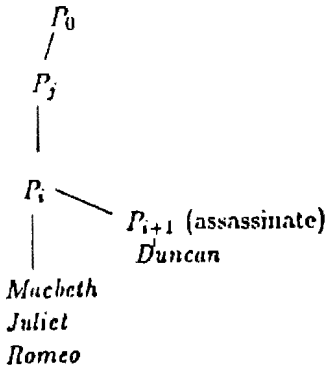


Figure 3.10. New predicability tree

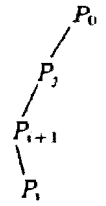


Figure 3.11. An impossible predicability tree

CONCLUSIONS

To sum up, the acquisition theory for words described here seems to meet Wittgenstein's challenge for a theory of word meaning that does not depend on dictionary definitions, but instead on a "family resemblance" model of word relationships. It successfully acquires causally based network models of verbs by the analogical analysis of story contexts containing them. Some extensions of the method for noncausally based verb descriptions were also presented. A method for learning AKO hierarchies (class descriptions) using positive-only evidence was presented. All of these learning procedures work because they are tightly constrained. The verb-learning model uses only causal links and syntactic filtering to guide it. The extension to other verbs depends on a limited set of descriptors closely linked to a spatial vocabulary. Finally, AKO learning depends on monotonic tree refinement obeying the "M" constraint. Future success of natural-language learning hinges on the discovery of constraints like these that make learning possible.

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APPENDIX 1: THE STORIES

```
;;This is for the Shakespeare story file - slavish attention to consistent
;;usage was avoided on the ground the programs should be robust enough
;;to deal with some variety and some error -- much of the initial
;;stuff sets up demons and establishes the A-KIND-OF tree

;;initialize


(reset)

;;do not insert PART relation automatically

(setfv *insert-part* nil)

;;read new-style demons

(fread "<analog>demons.lsp")

;;read demons for Macbeth-HW analogy

;;(fread "<analog>xcross.lsp")

;;create some demons

(make-if-affirmed murder
     (affirm reference 'cause (affirm subject 'kill object))
     (affirm subject 'hate object))

(make-if-affirmed kill
     (affirm reference 'cause (affirm object 'is 'dead)))

(make-if-affirmed cruel (when (eq relation 'is) (affirm subject 'is
'evil)))

(make-if-affirmed loyal (when (eq relation 'is) (affirm subject 'is
'good)))

(make-if-affirmed honest (when (eq relation 'is) (affirm subject 'is
'good)))

(make-if-affirmed married

(cond ((eq (relation reference) 'is)
       (let ((partner (get-one-object reference 'to)))
 (cond ((and partner (true? (consider reference 'to partner)))
```

```
(affirm (affirm partner 'is 'married)
'to
(subject reference))))))))


;;build ako tree

Person is an instance of a people.
Man woman and masochist are instances of a person.
Father son boy gentleman and bastard are instances of a man.
Mother daughter girl lady hag and witch are instances of a woman.
Shrew is an instance of a bitch.
General and colonel are instances of a soldier.
Emperor Empress King and Queen are instances of a ruler.
Prince Noble Ruler Emperor and King are instances of a man.
Prince is an instance of a noble.
Empress Queen and Princess are instances of a Woman.
Knife and sword are instances of a weapon.


;;insert PART relation automatically

(setfv *insert-part* t)

(make-if-affirmed ako
  (loop for class in (get-classes subject)

do (affirm subject 'ako class)))
```

APPENDIX 2: THE MATCHING FUNCTION

The following code is from Macaisa (1984).

```
  (p '|Matching | verb '| with | rel '| scores | score))
      (setq *given-matches current-matches)
      ))
   ()
   ))

;; Is the given verb in story1 "close in meaning" to any verb in story2?

(defun word-match (word1 word2)
  ;; MATCHES contains all the matching objects; NEXT-MATCHES contains
  ;; the matching objects at each level, including ones which are
  ;; already in MATCHES; NEW-MATCHES contains all the matching objects,
  ;; not already in MATCHES, at each level.
  (declare (special *nesting-level))
```



```
  (if (not (or (matching? word1 word2) (subj-obj-match? word1 word2)))
 ()
      (add-to-matches word1 word2) ;;  Assume the two words match.
      (let ((matches (list (list word1 word2)))
    (new-matches (list (list word1 word2)))
    (new-match? nil))
 (loop for i from 1 to *nesting-level
       with relations and next-matches
       do (let ((rels-and-objs (get-next-matches new-matches)))
   (add-matches (car rels-and-objs) 'relations)
   (setq next-matches (cadr rels-and-objs))
   (setq new-match? nil) (setq new-matches nil)
   (loop for match in next-matches
 do (if (add-match match 'matches)
 (progn
  (setq new-match? T)
  (setq new-matches (cons match new-matches))))
  ))
      if (and (not new-match?) (> i 1) relations)
      ;;do (p '|***No matches past level| i) and return relations
      return nil
      finally (return relations)
))
  ))

(defun get-next-matches (old-matches)

;;  (print old-matches)
  (loop for match in old-matches
with relations and next-matches
do (let ((rels-and-objs (do-match (car match) (cadr match))))
;;       (p '|Rels:| (car rels-and-objs) '|Objs:| (cadr rels-and-objs))
     (setq relations (append relations (car rels-and-objs)))
     (setq next-matches (append next-matches (cadr rels-and-objs))))
finally (return (list relations next-matches))
))

(defun do-match (word1 word2)
  ;; Works with all relations one link away from word1 and word2;
  ;; Adds the matching relations to *matching-relations;
  ;; Adds the matching  objects to *matching-objects;
  ;; Returns an alist of the matching objects at this level.
  (declare (special *uninteresting-relations *uninteresting-objects))
  (let ((rels1 (get-relations word1))
(rels2 (get-relations word2))
(matching-rels1) (matching-rels)
(matching-objs1) (matching-objs))
    (setq matching-rels (lists-match
```

```
(list-difference rels1 *uninteresting-relations)
(list-difference rels2 *uninteresting-relations)))
   (loop for rels in matching-rels
 with objs1 and objs2
 do (let ((objs1 (get-objects word1 (car rels)))
  (objs2 (get-objects word2 (cadr rels))))
      (setq matching-objs
    (lists-match
     (list-difference objs1 *uninteresting-objects)
     (list-difference objs2 *uninteresting-objects)))
      ;; MATCHING-RELS1 will contain the actual instanstiations
      ;; of the matching relations.  MATCHING-OBJS1 will contain
      ;; a list of objects matched at this level.
      (loop for objs in matching-objs
    do (let ((rel1 (consider word1 (car rels) (car objs)))
     (rel2 (consider word2 (cadr rels) (cadr objs))))
 (if (not (subj-obj-match? rel1 rel2)) ()
     (add-match (list rel1 rel2) 'matching-rels1)
     (add-match objs 'matching-objs1))
))
      ))
   (list matching-rels1 matching-objs1)))

(defun add-match (item list-name)
  (let ((fcn-value t)
(list (eval list-name)))
    (loop for item1 in list
  if (or (equal (car item) (car item1))
 (equal (cadr item) (cadr item1)))
  do (setq fcn-value nil) and return fcn-value
  finally (set list-name (cons item list)))
    fcn-value))

(defun add-matches (list1 list-name)
  (loop for item in list1
do (add-match item list-name)
))

(defun add-to-matches (word1 word2)
  (declare (special *given-matches))
  (add-match (list word1 word2) '*given-matches)
  (let ((root1 (get word1 'root))
(root2 (get word2 'root)))
    (if (and root1 root2)
(add-match (list root1 root2) '*given-matches))
    ))
```



```
(defun apply-filters (verb relations)
  (let ((root (get verb 'root))
(properties (list 'transitive))
(pattern) (rels))
    (loop for prop in properties
  do (setq pattern (cons (get root prop) pattern)))
    (setq rels (&sort-relations relations properties pattern))
    (car rels)
    ))

(defun lists-match (list1 list2)
  (let ((match-list))
    (loop for element1 in list1
  do (loop for element2 in list2
   when (matching? element1 element2)
   do (setq list2 (delq element2 list2)) and
   return (setq match-list
(cons (list element1 element2) match-list))
   ))
   match-list))

(defun subj-obj-match? (node1 node2)
  (let* ((subj1 (get node1 'subject)) (obj1 (get node1 'object))
 (subj2 (get node2 'subject)) (obj2 (get node2 'object)))
    (and (matching? subj1 subj2) (matching? obj1 obj2))
    ))

(defun matching? (object1 object2)
  (let ((answer (matching1? object1 object2)))
    (if answer ()
(setq answer (matching1? (get object1 'root) (get object2 'root))))
    answer))

(defun matching1? (object1 object2)
  (declare (special *given-matches))
  (cond ((or (null object1) (null object2)) nil)
((eq object1 object2) T)
((or (member (list object1 object2) *given-matches)
     (member (list object2 object1) *given-matches)) T)
((a-kind-of-join object1 object2) T)
(t nil)))

(defun sublist? (list1 list2)
  (let ((b1 (sublist1? list1 list2))
(b2 (sublist1? list2 list1)))
    (if (and b1 b2)
```

```
nil ;; return nil if the two sets are "equal"
b1) ;; otherwise, return the value of the first boolean
    ))

(defun sublist1? (list1 list2)
  (cond ((null list1) t)
((member (car list1) list2) (sublist? (cdr list1) list2))
(t nil)
))

(defun scoring-fcn (matching-rels)
  (let ((true-matches (eliminate-inverses matching-rels)))
    (length true-matches)))


(defun eliminate-inverses (matching-rels)
  (let* ((sorted-rels (sort-rels matching-rels))
 (cause-rels (car sorted-rels))
 (caused-by-rels (cadr sorted-rels))
 (other-rels (caddr sorted-rels)))
    (loop for cb-rels in caused-by-rels
  do (let ((cb-rel (car cb-rels)))
       (loop for c-rels in cause-rels
     do (let ((c-rel (car c-rels)))
  (if (inverse? c-rel cb-rel) (del c-rels 'cause-rels))
  ))
       ))
    (append cause-rels (append caused-by-rels other-rels))
    ))

(defun sort-rels (matching-rels)
  (loop for rels in matching-rels
with cause-rels and caused-by-rels and other-rels
do (let* ((rel (car rels))
  (root (get rel 'root)))
     (cond ((eq root 'cause) (add rels 'cause-rels))
   ((eq root 'caused-by) (add rels 'caused-by-rels))
   (t (add rels 'other-rels))
   ))
finally (return (list cause-rels caused-by-rels other-rels))
))

(defun inverse? (rel1 rel2)
   (and (eq (get c-rel 'subject)
    (get cb-rel 'object))
(eq (get c-rel 'object)
    (get cb-rel 'subject))
))
```

CHAPTER 4

An Introduction to Plot Units

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UNDERSTANDING AND REPRESENTATION

Representational Systems for Text Understanding

If a computer is to be said to understand a story, we must demand of it the same demonstrations of understanding that we require of people. When a person reads a story, an internal representation for that story is constructed in memory. For a computer to read and understand a story, it too must represent the story's content in memory. We can test both human and computer understanding by using various natural-language tasks such as answering questions or summarization. Each task will help us examine a different piece of the understanding process and the underlying representation. Question answering provides us with a method for examining the contents of the memory representation, but tells us very little about how it is structured. We can only guess at how the various pieces fit together. Summarization, on the other hand, requires concentration on the central elements of a story while ignoring peripheral information. As such it provides an excellent tool for investigating the global structure of a memory representation.

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