A THEORY OF LANGUAGE ACQUISITION BASED ON GENERAL LEARNING PRINCIPLES

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Abstract

A simulation model is described for the acquisition of the control of syntax in language generation. This model makes use of general learning principles and general principles of cognition. Language generation is modelled as a problem solving process involving prmciply the decomposition of a lo-be-communicated semantic structure into a hierarchy of subunits for generation. The syntax of the language controls this decomposition. It is shown how a sentence and semantic structure can be compared to infer the decomposition that led to the sentence. The learning processes involve generalizing rules to classes of words, learning by discrimination the various contextual constraints on a rule application, and a strength process which monitors a rule's history of success and failure. This system is shown to apply to the learning of noun declensions in Latin, relative clause constructions in French, and verb auxiliary structures in English.

INTRODUCTION

This research has its background in past work on language acquisition (for reviews, see Anderson. 1976; Pinker. 1979—see also Langley. 1981), especially in my previous work on LAS (Language Acquisition System—see Anderson. 1977). For various reasons that will be explained, there were problems with LAS and a more general concept of human cognition was developed called ACT (Anderson, 1976). The system to be reported here is an attempt to merge the ideas in the ACT project and the LAS project. It is called ALAS for ACT's Language Acquisition System. First in this paper I will review those aspects of the LAS and ACT systems that are relevant to understanding the current project and then I will turn to describing the ALAS system.

THE LAS SYSTEM

LAS accepted as input strings of words, which it treated as sentences, and scene descriptions encoded as associative networks. When learning, the program attempted to construct and modify augmented transition networks which described the mapping between sentence and scene descriptions. This assumption, that the program has access to sentence-meaning pairings, is the basic assumption underlying most of the recent attempts at language acquisition. This assumption might be satisfied in the circumstance where the child is hearing a sentence describing a situation he is attending to. Even here it is likely that the child will represent aspects of the situation not described and fail to represent aspects described. In LAS we worked out mechanisms for filtering out the non-described aspects of the meaning representation by comparison with the sentence. In the current ALAS system there is a discrimination mechanism for bringing in aspects of the situation not initially thought by the learner to be part of the sentence. So. we have worked out mechanisms for achieving sentence-meaning pairings in simple ostensive learning situations. However, much of what a child must learn about language will lack simple ostensive referents. For instance, most of the verb auxiliary system refers to non-ostensive meaning. How a child (or any system) would come up with sentence-meaning pairings in these situations is not clear and remains an issue for future research.

A major assumption of the LAS model that is maintained in the current system is that the system already knows the meaning of a base set of words. LAS was unable to learn the meaning of any words in context while the current system can; however the basic learning algorithm in both still requires that a substantial number of words in the sentence have their meanings previously learned. In principle (see Anderson, 1974). it would be possible to call to bear statistical learning programs to extract the meaning of the base set of words from a sufficiently large sample of meaning-sentence pairings. However, the evidence (McWhinney, 1980) is that children accomplish their initial lexicalization by having individual words paired directly with their referents.

Identifying Phrase Structure: The Graph Deformation Condition

A major problem in language learning is to identify the phrase structure of the sentence. There are a number of reasons why inducing the syntax of language becomes easier once the phrase structure has been identified: (1) Much of syntax is concerned with placing phrase units within other phrase units. (2) Much of the creative capacity for generating natural-language sentences depends on recursion through phrase structure units. (3) Syntactic contingencies that have to be inferred are often localized to phrase units, bounding the size of the induction problem by the size of the phrase unit. (4) Natural language transformations are best characterized with respect to phrase units as the transformational school has argued. (5) Finally, many of the syntactic contingencies are defined by phrase unit arrangements. So. for instance, the verb is inflected to reflect the number of the surface structure subject

A major mechanism for identifying phrase structure in LAS (and which is continued in ALAS) is use of the graph-deformation condition. The idea is to use the structure of a sentence's semantic referent to place constraints on surface structure. The application of the graph deformation condition is illustrated in Figure 1. In part (a) we have a semantic network representation for a series of propositions and in part (b) we have a sentence that communicates this information. The network structure in (a) has been deformed in (b) so that it sits above the sentence but all the node-to-node linkages have been preserved. As can be seen, this captures part of the sentence's surface structure. At the top level we have the subject clause (node X in the graph), *give, book,* and the

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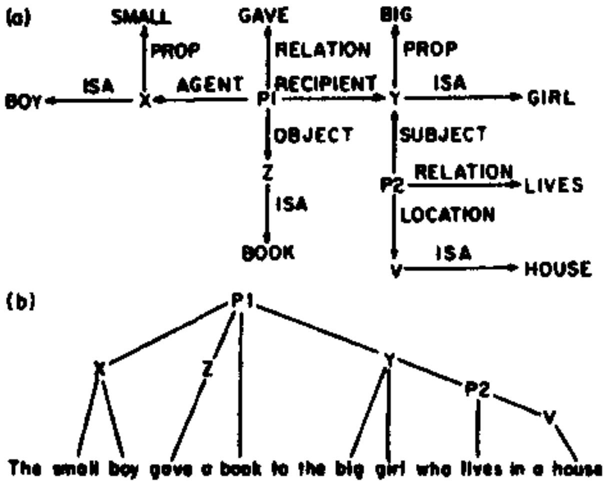
Figure 1



recipient (node Y) identified as a unit The two noun phrases are segmented into phrases according to the graph structure. For instance, the graph structure identifies that the words *lives* and *house* belong together in a phrase and that *big, girl, lives,* and *house* belong together in a higher phrase.

The graph deformation in part (b) identifies the location of the terms for which meanings are possessed in the surface structure of the sentence. However, terms like *the* before *big girl* remain ambiguous in their placement. It could either be part of the noun phrase or directly part of the main clause. Thus, there remains some ambiguity about surface structure that will have to be resolved on another basis. In LAS the remaining morphemes were inserted by a set of ad hoc heuristics that worked in some cases and not in others. One of the goals in ALAS was to come up with a better set of principles for determining the boundaries of phrases.

The graph deformation condition is violated by certain sentences which have undergone structure-modifying transformations that create discontinuous elements. Examples in English are:

1. The news surprised Fred that Mary was pregnant.
2. John and Bill borrowed and returned, respectively, the lawnmower.

Transformations which create discontinuous elements are more common in languages that use word order less than English. However, the graph deformation condition remains as a correct characterization of the major tendency m all languages. The general phenomena has been frequently commented upon and has been called Behaghers First Law (see Clark & Clark, 1977). A problem with LAS was that it had no means of dealing with exceptions to the graph deformation conditions or of learning transformations in general. Another goal for the ALAS current enterprise is to be able to delect sentences that violate the graph deformation condition and to use these as opportunities for learning transformations.

A major source of my dissatisfaction with LAS is that its processing discipline and learning mechanisms are specific to language and it was hard to imagine how they would relate to other types of skill learning. While many people believe the principles underlying language acquisition are unique, 1 do not I think the other problems with the LAS enterprise could be repaired but 1 felt a fresh start was needed if we were to show that general skill acquisition principles could plausibly apply to natural language as a special case. This led to the development of the ACT theory (Anderson, 1976; Anderson, Kline, & Lewis, 1977) and to a set of learning principles for that theory.

ACT

As originally formulated. ACT was s production system without any commitment to the mechanisms of skill organization or skill acquisition. However, a set of principles have emerged in our more recent work (Anderson. Kline. & Beasley. 1980; Anderson & Kline. 1979: Anderson. Greeno. Kline. *SL* Neves. 1981) and it is these developments which are essential for the current application. These ideas have been developed ID non-linguistic domains—schema abstraction, acquisition of proof skills in geometry, and most recently in the acquisition of programming skills.

We see any skill as being hierarchically organized into a search of a problem space in which there is a mam goal, which is decomposed into subgoals. and so on until the decomposition reaches achievable subgoals. Much of what is distinctive about a particular skill is the way in which the problem space is searched for a solution. In our model of language generation, this is seen as a simple top-down generation of subgoals (corresponding to phrases) where there is no real search needed unless transformations have to be applied. We will illustrate this application to language shortly.

In simulating language acquisition we have focused on the learning mechanisms concerned with operator selection: generalization, discrimination, and strengthening. Generalization takes rules developed from special cases and tries to formulate more general variants. Discrimination is responsible for acquiring various contextual constraints to delimit the range of overly general rules. Strength reflects the success of a rule in the past and controls its probability of future application. In combination, these mechanisms function like a statistical learning procedure to determine which problem features are predictive of a rule's success. They have been extensively documented in our efforts to model the literature on schema abstraction (Anderson & Kline, 1979: Eho *SL* Anderson, in revision), but they have had a richer application to acquisition of proof skills (Anderson, submitted: Anderson, Greeno. Kline, & Neves. 1981). 1 will sketch their application to the language acquisition domain, but the reader should go to these other sources (and particularly Anderson, Kline, & Beasley. 1980) for a fuller development

CURRENT FRAMEWORK FOR LANGUAGE LEARNING

The language learner is characterized as having the goal of communicating a particular set of propositions. This set of propositions is organized into a mam proposition and subpropositions. So. for instance, the goal behind the generation of *The girl kicks the boys* might be a communication structure which we can represent as (KICK (GIRL x) (BOY y)> where x is tagged as singular and y is tagged as plural. To achieve the goal, the learner tries to decompose this higher level goal into subgoals. according to the units of the overall communication structure. So. he will decompose this into the subgoals of communicating *kick,* of communicating <G1RL x), and of communicating (BOY y). He looks to his language for some means of organizing these subgoals. So. he might have learned a rule of the form:

```
   IF the goal is to communicate (LVrelation LVobjectl
            LVobject2)
      and LVrelation is in the VERBX class
THEN set as the subgoals to
            communicate LVobjectl
            say the morpheme for LVrelation
            say "S"

            and to communicate LVobject2
```

or we might more compactly denote this rule:

(1 2 3) --> 2 + 1* + 8 + 3 if 1 in VERBX

in the above, the 1, 2, and 3 match the three elements in the meaning structure-KICK, (GIRL x), and (BOY y). The right side of the arrow specifies their order in the sentence and the insertion of mophemes like S. The star above the 1 indicates its lexical form is to be retrieved. The other elements will have to be further unpacked.

If it is early in the language learning history and the learner does not have a rule for realizing this construction, then he might try to invent some principle. He may only produce a fragment (e.g.. girl hit) or a non-allowed order (e.g., girl boy hit). There is some evidence in first language acquisition that children will use word orders not frequent in adult speech (Clark, 1975; de Villiers & de Villiers. 1978; McWhinney. 1980). For instance, there is a tendency to prefer agents first even when one's language does not. Also, it is well known that second language learners fall back on their first language word orders when knowledge of word order fails.

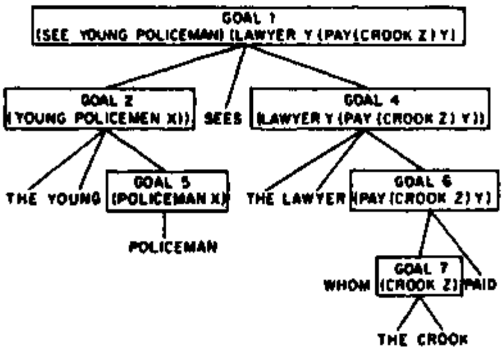
The embedded subgoals are unpacked into actions or further subgoals in the same way that the top level structure is unpacked. For instance, if the object to be communicated were (girl x (like x (sailor z))), the top level of this structure might be communicated by the rule:

(1 2 3) --> the + 1 + 3   if 1 is a noun

where \(like x (sailor z)) is item 3 in the above and would be communicated by the rule:

(1 2 3) --> who + 1" + 3   if 1 is a verb and the construction is embedded

Figure 2 illustrates the hierarchy of subgoals ID the generation of s relatively complex sentence: *The young policeman sees the lawyer whom the crook paid.* It should be clear that if sentences are generated by setting subgoals to reflect the structure of the referent, then the graph deformation condition will tend to be satisfied in natural language.



The learning that occurs in ALAS is basically learning by doing. The learner generates an utterance and it is assumed that he has access to feedback about the correctness of the construction he generated and perhaps information about what the correct utterance should have been if he has made an error. There are many ways this can happen. The learner may generate a sentence and be corrected by a teacher. He may generate a sentence and remember a sentence or sentence fragment heard earlier. He may hear a sentence, infer its meaning, and compute how he would express the meaning. By whatever means the learner sometimes identifies some fragment of his generation to be in error and sometimes has a hypothesis as to the correct utterance. This is the stimulus for learning. In the actual simulations that will be reported, the program is given a model sentence along with each meaning and the program compares its generation with the model sentence. No doubt this is an unrealistically ideal assumption and results in a considerable speed up of the learning process in ALAS, However, the same learning mechanisms would apply in more psychologically realistic situations where the program was given only occasional information and often fragmentary information about what the correct target sentences were.

Formation of Initial Rules

The initial rules that the system acquires are, of course, quite specific. So, for instance, consider the rules it might form upon receiving a pairing of the Latin sentence ((Equ i)(agricol as)port ant) and the meaning representation (carry (horse x)(farmer y)>. With a partially complete lexicalization, ALAS knows the meaning of *equ* is horse, the meaning of *agricol it* farmer, and the meaning of *port* is carry). ALAS then formulates the following rules:

(1 2 3) --> 2 + 3 + 1 + ant   if 1 = carry
(1 2) --> 1- + i   if X = horse
(1 2) --> 1' + as   if 1 = farmer

Thus, its acquired rules are exact encodings of the relations at each level in the meaning hierarchy. The evidence is that children also start out with rules specific to individual words (Mac Whinney. 1980; Maratsos & Chalkley, 1981) and indeed the nature of natural language makes this a wise policy in that rules are quite specific to various lexical items (Bresnan, 1981; Maratsos & Chalkley, 1980; Pinker, 1981). This also is exactly how learning proceeds in other areas to which we have applied ACT. Initially, the system acquires rules that encode the exact goal structure of specific examples. Later, generalizations are formed.

While, on one hand, these rules are too specific, on the other hand, they are too general. The inflections associated with the nouns and verbs are only correct for the specific case and number combinations but these rules do not reflect that constraint. The system will have to acquire discriminating features that will properly constrain the range of application of these rules. Again that corresponds to child language. Children initially use words with a single inflection in all situations and only later acquire the contextual constraints. It also corresponds to our other learning endeavours where contextual constraints on goal decomposition are acquired through discrimination.

Discrimination

To illustrate the discrimination process consider again the rule for realizing *farmer:*

(1 2) —> 1* + as   if 1 ■ farmer   (a)

Suppose the system encounters a second instance of farmer in the meaning-sentence. pairing (call (farmer u) (girl v)> - ((agricol a) (puell am) voc at). It would detect a conflict between its generation of *agricol+as* and the target *agricol*a.* In this case it would look for differences between the context of its current application and the previous. The relevant differences are:

1. *y* in the previous application is lagged as plural while *u* in the above structure is singular
2. The object structure was in third position in the embedded clause of the first meaning structure, but now it is in second position.

However, there are any number of other potential differences such as

3. The previous verb was *port* and the current *voc*
4. The second position of the embedded clause was plural and the current is singular.
5. The current sentence involves a feminine object.

LAS has an ordering of distance (to-be-explained) such that 4 and 5 above would be definitely less preferred but there is no clear basis for choosing 1 and 2 over 3. A feature to discriminate upon is chosen at random and a new rule is formed such as: (b)

(1 2) --> 1*+ a   if 1 * farmer   (b)
(1 2) -->   and 2 is singular

Note that tins if a discrimination for the current context, not the previous. ALAS can also form a rale for the old context

(1 2) — > 1' + as If 1 = farmer and 2 is plural (c)

but only if the old rule (a) exceeds a threshold of strength to indicate that it has applied successfully more often than not and is therefore not a pure mistake.

The correct rules above need another round of discrimination before they pick up the semantic position feature. Then they will become

(1 2) — > *V* ♦ a if 1 = fanner and 2 is singular' and this occurs in second position in the semantic referent (d)

(1 2) — > 1' ♦ as if 1 = fanmer and 2 is plural and this occurs in third position in the semantic referent (e)

The set of possible features for discrimination is defined by a network that includes the semantic referent the goal structure, and any properties tagged to terms in the semantic referent or the goal structure. The program does a breadth first search out from the current position in this network looking for features that distinguish between current and past applications of the rule. It chooses the features it first finds in that search. This means that the system is sensitive to both syntactic and semantic contingencies of the context of application.

Generalization

Let us consider what would happen if the currently implemented ACT generalization process were to apply to rule (e) from before and to the following rule that the system might derive in a similar manner:

(1 2) —> 1* + as if 1 = girl and 2 is plural and this occurs in the third position in the sonantic referent

ACT would generalize these two rules by simply dropping the constraint that 1 be farmer or girl. This would yield:

(1 2> — > 1* + as if 2 is plural and this occurs in third position of the semantic referent

This would lead to an enormous overgeneralization in that the above rule u only valid for first-declension nouns.

Thus, we have had to assume that generalization cannot occur in language by the wholesale replacement of a constant by a variable. Rather what we assume is that generalization occurs by replacing a constant by s word class. So. the proper form of the above rule becomes

(1 2) — > l* + as if 1 is in class X and 2 is plural and this occurs in third position in the semantic referent

where class X will contain *firmer* and *girl* among others. It is unclear at present whether this is s true instance of where language acquisition differs from other cognitive learning or whether the generalization mechanism should be set up to produce constrained variables in all situations.

A major issue in ALAS concerns when words should be merged into the same class. It is not the case that this occurs whenever there is the potential to merge two rules as above. The existence of overlapping declensions and overlapping conjugations in many languages would result in disastrous overgeneralizations. Rather we have brought to bear an extension of our schema abstraction ideas (Anderson & Kline. 1979). What ALAS does is look at the pattern of rules that individual words appear in. It will merge two words into a single class when

J. The total strength of the rules for both words exceeds a threshold indicating a satisifactory amount of experience

2. A traction (currently 2/3> of the rules that have been formed for one word (as measured by strength) have been formed for the other word.

When such a class is formed, the rules for the individual words can be generalized to that class. Also, any new rules acquired for one word will generalize to the other. Once a class is formed new words can be merged with the class according to the same criteria (1) and (2) for merging words. Further, two classes can be merged together, agsin according to the same criteria. Thus, it is possible to gradually build up large classes like first declension.

The word-specific rules are not lost when the class generalizations appear. Furthermore, one form of discrimination is to propose that there is a rule special to a word. Because of the specificity ordering in production selection, these word-specific rules will be favored when applicable. This means that the system can live with a situation where a particular word (such as *dive)* can be in a general class but still maintain some exceptional behavior.

Thus, the system begins with a lot of word-specific rules which gradually expand in their scope of application. This is basically the development observed in child language.

It should be noted that there is another dimension in which the system's behavior starts out very general. The rules for communicating a particular construction, such as an object construction (eg. noun phrase) or qualifying proposition (e.g.. a relative clause), are assumed to apply in every location. Thus, the system automatically assumes rules are recursive and does not need, as did LAS, to verify such points of recursion. Rather, the learning here takes the form of constraining this assumption where overgeneral— as we have discussed Correspondingly, children seem not reluctant to venture old constructions in new syntactic contexts.

Phrase Structure Segmentation

Up to this point we have assumed that the target sentences were segmented into phrase structure units. The graph deformation condition can be used to assign the words whose meaning u known to phrase units but this leaves unspecified the other morphemes. To take an example from my work with Latin consider the following meaning-sentence pairing:

(praise (friend u (have (man v) u)) (field x (have (farmer y) x))) 1

amic us vir I ager os agricol ae laud at 2

(translated: The man's friend praises the farmer's fields).

Clearly, the semantic structure indicates *vtr* (man) associates with *amic* (friend) as a modifier and not with ager (field) since *man* is contained in the same meaning unit as *friend.* However, the semantic structure provides us no way of deciding whether the non-meaning-'bearing morpheme *us* associates with *vir* or *emit.* Similarly, it is ambiguous how to locate the other noun inflections: /. OS, and a*. On the other hand, *et* occurring at the end of the sentence definitely must associate with *laud.* Thus, by means of the graph deformation coodition and only taking unambiguous cases, we get the following hierarchical organization for the Latin string:

((amic (<vir))) (ager ((agricol))) laud at) 3

where the indeterminate morphemes are left out. At one point in its application of the graph deformation condition ALAS calculates just this structure. If nothing more can be done, this is the form of the string provided to the learning system-i.e., with the ambiguous morphemes deleted.

How can this string be improved upon to insert the non-meaning bearing morphemes? In the literature there are three suggestions. First, there may be pauses in the speech signal to indicate the correct associations. There would be no ambiguity if there were long pauses after *us, l*, *os,* and as in the above message. Normal speech does not always have such pauses in correct places and sometimes has pauses in wrong places. Still, this basis for segmentation would be correct more often than not and ALAS's error correcting facilities have the potential to recover from the occasional missegmentaion. Also, it is argued that parent speech to children is much better segmented than adult speech to adults (see de Villiers & de Villiers. 1978). In ALAS pausing is used when given, but the system does not require pause segmentation.

A second suggestion is to use past instances of successful segmentation to segment in the current case. Thus, if the system has previously identified *agricol+se* as associating together it can assume they associate together now. The past experience could derive from bearing the word in isolation or from other sentences where some other basis could be applied for segmentation. Memory for words spoken in isolation is a particularly useful solution to the problem of identifying which morphemes belong together to define a word. The evidence is quite clear that children do bear many words in isolation (McWhinney, 1980). This is less helpful in identifying phrase boundaries for structures like noun phrases or relative clauses—both because these structures are less likely to be spoken in isolation and because the same word sequence is rarely repeated. This may explain why missegmentalion of morphemes within words is rare in child speech relative to missegmentalion of words with phrases (Slobm, 1973). Although we could in principle use this strategy, our simulation that attempted to segment without pause structure was not given words in isolation.

The third basis for segmentation relies on the use of statistics about morpheme-to-morphenie transitions. For instance, the segment ae will more frequently follow *agricol* with which it is associated than it will precede *laud* with which it is not. The differences in transitional frequencies would be very sharp in a language like Latin with a very free word order but they also exist in English. Thus, ALAS can associate a*e* with the *agricol* if it has followed *agricol* more frequently than it has preceded *laud.* This requires keeping statistics about word-to-word transitions. Currently, the system will favor one association of a morpheme over another if there is a difference in frequency of two. This might seem a rather small threshhold but I have gotten satisfactory performance out of ALAS, partly because ALAS can recover from occasional missegmentations. Again the evidence is that children do occasionally missegment (McWhinney. 1980) and. of course, recover eventually. It strikes some as implausible to suppose that people could keep the statistical information required about word to word transitions. However, Hayes and Clark (1970) have shown that subjects in listening to nonsense sound streams can use differential transition probabilities as a basis for segmentation. Such information has also proven useful in computational models of speech recognition (Lesser, Hayes-Roth, Birnbaum. & Cronk, 1977).

It is possible and frequently has been the case that none of the ALAS segmentation mechanisms could apply to assign a morpheme to a level in the phrase structure. In such cases the non-assigned morpheme was simply omitted from the phrase structure. Thus, the initial utterances produced by ALAS, like the utterances produced by young children, arc telegraphic in character. That is. they are missing many functors.

Latin: The issue of segmentation

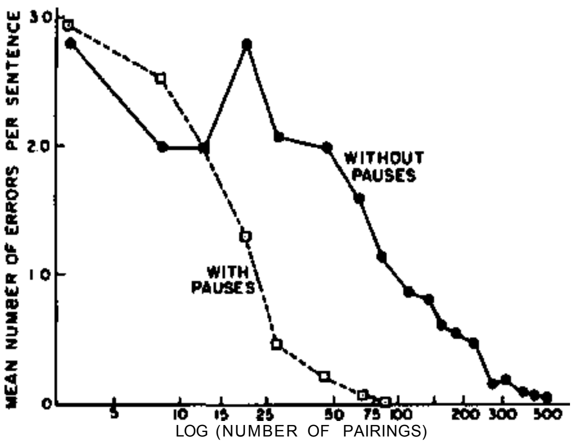
Our first endeavour was to learn a fragment of Latin that involved first and second declension nouns, inflected for the nominative, accusative, and genitive cases and for plural and singular. An example of the input to ALAS is

Agricol ae puel am legat I laud ant
(praise (farmer x) (girl u (have (lieutenant v) u>)
where x is plural, u and v are singular

That is, the input was a string of Latin morphemes that comprised the target sentence and a hierarchical representation of the meaning of this sentence. The program was provided with a long sequence of such pairings. Over the sequence all syntactic possibilities were realized. With each pairing, ALAS consulted its rules to see if they would map the meaning structure onto the target string. Its learning principles were evoked to modify the rules if they failed to produce the right mapping. In this simulation (and the others) we provide the strings segmented into morphemes. Acquisition of morpheme segmentation is thus being ignored. The verbs used were *8* first-conjugation verbs; the nouns were *8* first-declension nouns and 7 second-declension nouns. One of the things our simulation was going to get at was the adequacy of our class heuristics to separate our first and second declension nouns. We performed two simulations over this target language subset. In the first we provided the system with no information about segmentation and it was forced to use the graph-deformation condition and transitional probabilities to segment into surface structure units. In the second simulation we provided pause information to indicate with which words the inflections were associated.

To avoid any possible biasing in input order, the sentence-meaning pairs were generated by a randomization program. The simulation without the pause information required 525 pairings before it has identified all the needed grammatical rules and ran a criterion 25 pairings with no mispredictions of the target strings. With pause information, only 100 sentences were required to reach the same criterion. Figure 3 illustrates the mean number of errors for the two conditions plotted as a function of the logarithm of number of pairings experiences. An error was defined as a misordering of elements at any phrase level, the insertion of an incorrect morpheme, or the ommission of a morpheme.

Figure 3



In the case where the system was not given information about pause structure, it had to use transitional frequency to segment. After the first 25 sentences it was correctly associating about 50% of the noun inflections with the nouns. Most of the remaining 50% were failures to insert the morphemes but there were occasional missegmentations. Despite the fact that it was correctly segmenting over half of the input to the learning program after the 25th trial, it was only after 75 trials that any learning of inflections showed up in its performance (i.e.. it started using these inflections with significantly greater than chance accuracy). Even after 150 sentences ALAS is failing to segment some nouns in 10% of the sentences. The difficulty in segmentation is what is accounting for the slow learning of the program. The examples that follow present first the Latin morpheme string that the program generated to express a meaning structure (not shown) and, second, the target string that was correct. I have given a non-random selection of these to give the reader a sense of the progress of the system throughout the course of the 525 pairings:

Sentence 2: PUGN NUNTI LEGAT
vs. NUNTI I LEGAT OS PUGN ANT

Sentence 28: AGRICOL PUELL AE LEGAT AM ANT
vs. AGRICOL AE PUELL AM LEGAT I AM ANT

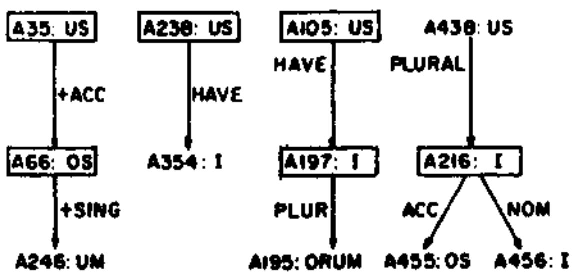
Sentence 83: LEGAT I POET A NUNTI I LAUD ANT
vs. LEGAT I POET AM NUNTI ORUM LAUD ANT

Sentence 129: LEGAT US NUNTI UM AM SPECT AT
vs. LEGAT US NUNTI UM SPECT AT

Sentence 203: VIR I AMIC OS NATUR AE OCCUP ANT
vs. VIR I AMIC OS NATUR AE OCCUP ANT

The class formation heuristics worked quite well in these simulations. Both with and without pause information, the two declensions were identified as two word classes and all the verbs were brought together into another word class. Figure 4 illustrates the history of discrimination that led to correct use of inflections for the second declension in the simulation with pause information. Time goes to the right and down in the figure. It turned out that on four occasions the system proposed an unconstrained rule for the *us* inflection. This is reflected in the horizontal dimension. Going down we have the history of discrimination for each rule. Arrows lead from a rule to a discriminated rule. The label on the arrow indicates the feature added in the discrimination. Thus, for instance, A35 is a rule that calls for the *us* inflection (appropriate for nominative singular). It was used incorrectly in an accusative plural situation and an *os* rule. A66, was formed with the discriminating test that the noun be in accusative case (i.e.. third position in the semantic structure). This rule misapplied in an accusative singular situation and so a singular feature was added. Rules in boxes are ones that were so weakened by misapplication that they were removed.

Figure 4



Note that there are four rules with all the necessary features: A246 for accusative singular, A195 for genitive plural. A455 for accusative plural, and A456 for nominative plural. On the other hand. A354 for genitive singular only tests that it is in a possessive context and not for number. However, because of the specificity ordering on production selection, the more specific genitive plural rule (A195) will apply whenever applicable leaving A3 54 only the genitive singular situations in which to apply. Similarly, A438 which has no discriminating features will only apply when no other rule is applicable—which is to say it will apply only the nominative singular case for which it gives the appropriate inflection.

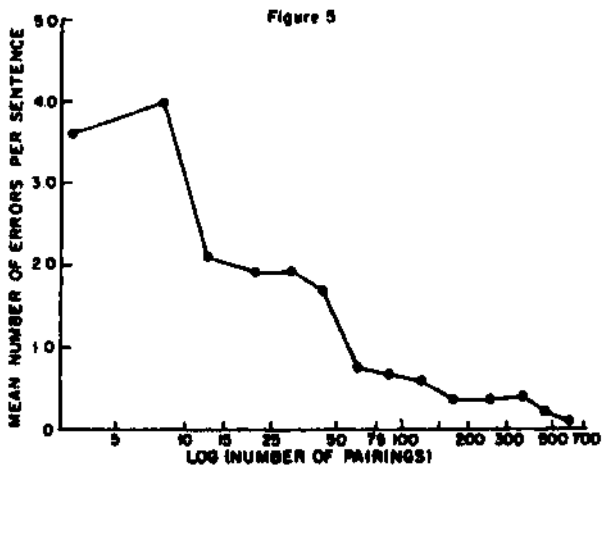
We ran another simulation training ALAS on the same subset of French that LAS (Anderson, 1977) had been trained on. This subset is interesting because it introduces the recursive properties of natural language through relative clause recursion. ALAS successfully learned this subset The detail* of this simulation are being omitted because of space constraint*. However, it is mentioned here to note that ALAS can reproduce the success of the previous program. Information about this simulation can be obtained by writing to the author.

Verb Auxiliaries

The third simulation was an attempt to have ALAS learn the verb auxiliary system of English. This is one of the standard language fragments used to introduce and motivate transformational grammar <e.g., Cuhcover. 1976). This is interesting because the verb auxiliary system does not involve any violations of the graph deformation condition and should be learnable by ALAS without resorting to transformations. The models we used were *CM, could, should, would, will,* and *may* with corresponding meaning components of present-able, past-able, obligation, intention, future, and possibility. These meaning components were not assigned to the terms but rather had to be learned from context The sentences were also marked for tense and, optionally for perfect, progressive, and stative, We used sets of four adjectives, eight nouns, six transitive verbs, and four intransitive verbs. Among the verbs were *hit, shoot,* and *run* which all have irregular inflections. Therefore, another problem for the simulation will be to learn the special inflections associated with these terms. We provided these strings with the pause structures to permit segmentation. Space limitations prevent a detailed specification of the semantic representation, but the author can be written to for a fuller report

Figure 5 plots the performance of the system for 700 pairings which is the number of pairings required to reach 25 trials of errorless performance. Examples of sentences it generated are:

Sentence 1: Jump angry debutante
Sentence 10: A tall lawyer s could jump ed
Sentence 16: Some smart actress have tickle ed the sailor s
Sentence 30: Being smart a angry lawyer
Sentence 51: The sailor s were dance ing
Sentence 75: A smart sailor tickle ing a bad lawyer
Sentence 148: The farmer may have shoot ed some Arab s



Sentence 195: The fat doctor s should dance ed
Sentence 213: A fat lawyer can be tall ed
Sentence 228: Some smart lawyer s should be tickle ing the angry actress s
Sentence 253: A sailor are tickle ed by some good lawyer s
Sentence 354: Some sad ed lawyer s have run
Sentence 370: The sad doctor s are kick ed by the angry farmer s
Sentence 426: Some lawyer s were being hit ed.

These sentences illustrate one of the unexpected developments in the simulation. ALAS collapsed adjectives, transitive verbs, and untransitive verbs into a single word class over time because all these are involved in numerous similar auxiliary structures. This accounts for the appearance of constructions like "sad ed lawyers" and "can be tall ed" where the "ed" inflection has generalized from the verbs to adjectives. Then ALAS had to go through a number of discriminations in which it used the action-quality property distinction between verbs and adjectives to properly restrict the rules.

An important feature of the verb auxiliary system is that, if we consider the verb matrix sequenced tense-modal ity-perfect-progresstve-verb, tense coaditions an inflection in the term that immediately follows it, perfect an inflection in the term that follows it, and similarly progressive. This is interesting because the modality, perfect, and progressive terms are all optional. This means that the term inflected for tense or perfect will vary. So. for instance, depending on the verb matrix we inflect perfect (has/had), progressive (is/was), or verb (kicks/kicked) for tense. This is handled in standard transformational analysis by a transformation called affix hopping. This is handled in our simulation by making the prior term part of the rule. So, for instance. ALAS learned the rule:

```
1 + 2 --> 1 + s ♦ 2        if 1 is progressive
                           and the context is present
                           and the syntactic subject
                           is singular
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It is not a simple matter to judge whether the affix hopping transformation (together with its many support rules) provides a more parsimonious characterization of verb auxiliary structure or whether our context-sensitive rules do. However, the ALAS rules seem much easier to learn. This is one illustration of many where learning considerations can be used to guide linguistic description.

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