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Typicality and its correlates, a Whorfian view.

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TYPICALITY AND ITS CORRELATES: A WHORFIAN VIEW

by

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We, the undersigned faculty, do hereby certify that we have read this thesis and that in our opinion it is fully adequate, both in scope and quality, as a thesis for the degree of Master of Arts in Social Relations at Lehigh University.

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ABSTRACT

This study explores the correlates of semantic typicality. The major question is whether it is experiential or linguistic familiarity that underlies our interpretations of typicality, or category representativeness.

Previous studies emphasize the role of direct experience in cognitive development, and they have shown that typicality corresponds closely with how perceptually familiar we are with instances of a category. In other words, if we have seen instances of a segregate often and can produce mental images for it, we are also likely to regard it as a very typical example of its semantic domain.

This study approaches typicality from a different perspective. Typicality is regarded as a purely linguistic phenomenon, in the sense that people's judgments regarding the best examples of a domain are predisposed by the social tradition as passed on through language. This is the Whorfian perspective. Whorf believes that as we learn our language, we impose categories on the world. It would follow that the language we speak not only determines the boundaries of categories, but also their best examples, or their most typical instances.

In general terms, Whorf's hypothesis of linguistic relativity states that the link between language and thought

is stronger than that between language and reality or between reality and thought. The results of this experimental study generally support a Whorfian interpretation of typicality. The major findings are as follows:

1. The correlation between cognitive salience and linguistic variables is stronger than that between salience and perceptual familiarity and/or object knowledge.

2. The correlation between typicality and linguistic familiarity is stronger than that between typicality and perceptual familiarity and/or object knowledge.

3. The correlation between object knowledge and perceptual familiarity is stronger than the correlation between object knowledge and linguistic measures, although this does not rule out some linguistic influence on the measure of object knowledge.

INTRODUCTION

Language influences the way we interpret the world, and it is through language that people learn their cultural categories. Whorf quotes Sapir who said, "The fact of the matter is that the 'real world' is to a large extent unconsciously built up on the language habits of the group. ... We see and hear and otherwise experience very largely as we do because the language habits of our community predispose certain choices of interpretation" (Whorf 1978:134).

Whorf develops this idea further. He believes that language shapes thought. More specifically, he feels that as we learn our language we impose categories on the world and, therefore, that the norms of reality reflect the grammatical structures and categories of our language. This postulate of linguistic relativity may encompass not only the boundaries of categories -- or how we carve up the world -- but also degrees of representativeness within categories, for as our concepts differ cross-culturally so too might their best examples.

In a Whorfian view, typicality, another name for category representativeness, would be regarded as a purely linguistic phenomenon, in the sense that people's judgments regarding the best examples of a category derive from the definitional structure of concepts themselves. Thus, elms may be rated a very typical kind of tree, but people may have never seen an elm and know very little about them. Conversely, many people may know the silhouette of coconut palms and be able to recognize them, but they may regard coconut palms as an atypical variety of tree.

An alternative view is that typicality arises from differential experience with members of a category. Those varieties with which people have more experience, the more perceptually familiar kinds, are also regarded as more typical of the category. Such a model emphasizes the role of direct experience in cognitive development rather than the effects of the social tradition as passed on through language.

What, then, underlies typicality? Does perceptual familiarity with exemplars lead us to think the more frequently encountered instances are also the most typical, or does typicality arise from the purely semantic structuring of categories? In other words, which best accounts for our opinions of category representativeness: experiential or linguistic familiarity? These are the questions addressed in this study. Unlike Whorf, however, who employed cross-cultural evidence and argumentation, I focus on typicality and its correlates within one language group.

The paper consists of four main parts, beginning with a literature review. The second section describes the methods and measures used. The third section presents the results, and the last section discusses the implications of my findings in light of previous studies.

PREVIOUS RESEARCH ON TYPICALITY

The amount of research directly related to this study is fairly limited. There has not been a great deal published on the topic of typicality and its measures, but there have been publications on related fields, which are the background for typicality research. These include the topics of category norms, semantic distance, and property dominance effects in semantic memory.

One particular article by Battig and Montague (1969), called "Category Norms for Verbal Items in 56 Categories: A Replication and Extension of the Connecticut Category Norms," is widely cited. This article has no particular hypothesis that the authors are trying to support, but is rather a data bank for others to use in their studies. The authors felt it was important to re-do and bring up to date the 43 categories used in the Connecticut Category Norms collected by Cohen, Bousfield, and Whitmarsh (1957).

Battig and Montague collected data for the 43 categories used in the Connecticut study plus 13 additional categories which they felt were relevant. Subjects were shown a category heading and asked to list as many individual members, or segregates, as they could for each. The only thing Battig and Montague did differently than Cohen, Bousfield, and Whitmarsh was to give the subjects 30 seconds to write down as many segregates as they could, whereas the previous study instructed subjects to list only 4 items for each category heading.

For all responses with a frequency of 10 or greater in each of the 56 categories, the following measures were reported: the total frequency of occurrence in the entire sample of 442 subjects, how many times the response was listed first, the total frequencies for each sub-sample of subjects (172 from the University of Illinois and 270 from the University of Maryland), and the mean-position in free-recall lists from the Maryland sub-sample.

The principal findings were that some individual items, or segregates, were consistently listed more often than others and that these also tend to be produced earlier in a free-recall task. For example, for the category of trees, 394 of the 442 subjects listed oak, and of those 394 listings, 202 subjects listed oak first in their lists. By contrast, only 50 of the subjects listed hickory, and only 2 of those 50 listed it first.

The Battig and Montague research is relevant to the current study because it is one of the early examples of people using a free-recall task (or a production task) to study conceptual domains and categorization. The data from these 56 categories have been used extensively in free-recall, memory, and typicality studies.

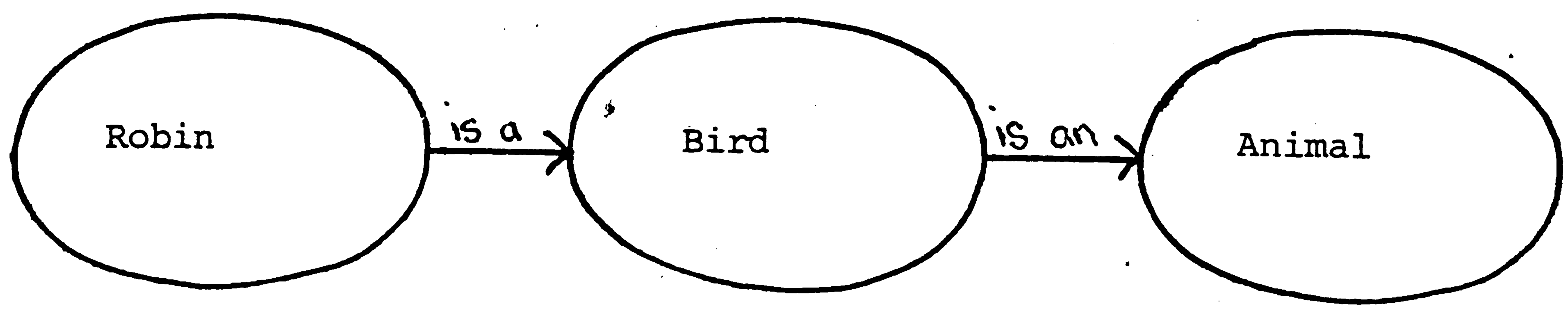
Another preliminary article is Rips, Shoben, and Smith (1973), who studied how semantic relations are represented in memory. In particular, they studied semantic verifications and reaction times (RT). A subject was shown a pair of nouns, in the form of "an X is a Y", and was asked to make a quick semantic decision about the relation. A common example, used in several articles, is "a robin is a bird." Using this method, it is possible to compare the verification times for phrases containing the same X but different Y's. For example, the verification time for "a robin is a bird" is usually much shorter than for "a robin is an animal." This is called the "semantic distance effect" or the "subset effect" (Rips, et al. 1973:1).

Explanations for this effect are derived from two different models of semantic memory — the network and the set-theoretic models-- each having more than one version. Early versions of the network model made the assumption that words or references exist as independent units, or nodes, in semantic memory, connected, as the name implies, by a network of relations. As an illustration, "a robin is a bird" is represented as two nodes, one corresponding to robin and one to bird, and by the "is a" relation between them. Collins and Quillian's (1969) network model accounts for the semantic distance effect in terms of the number of pathways that must be retrieved. In a later study, Collins and Loftus (1975) account for the effect in terms of the length of the pathway between the two references. Figure 1 illustrates each version of the general network model.

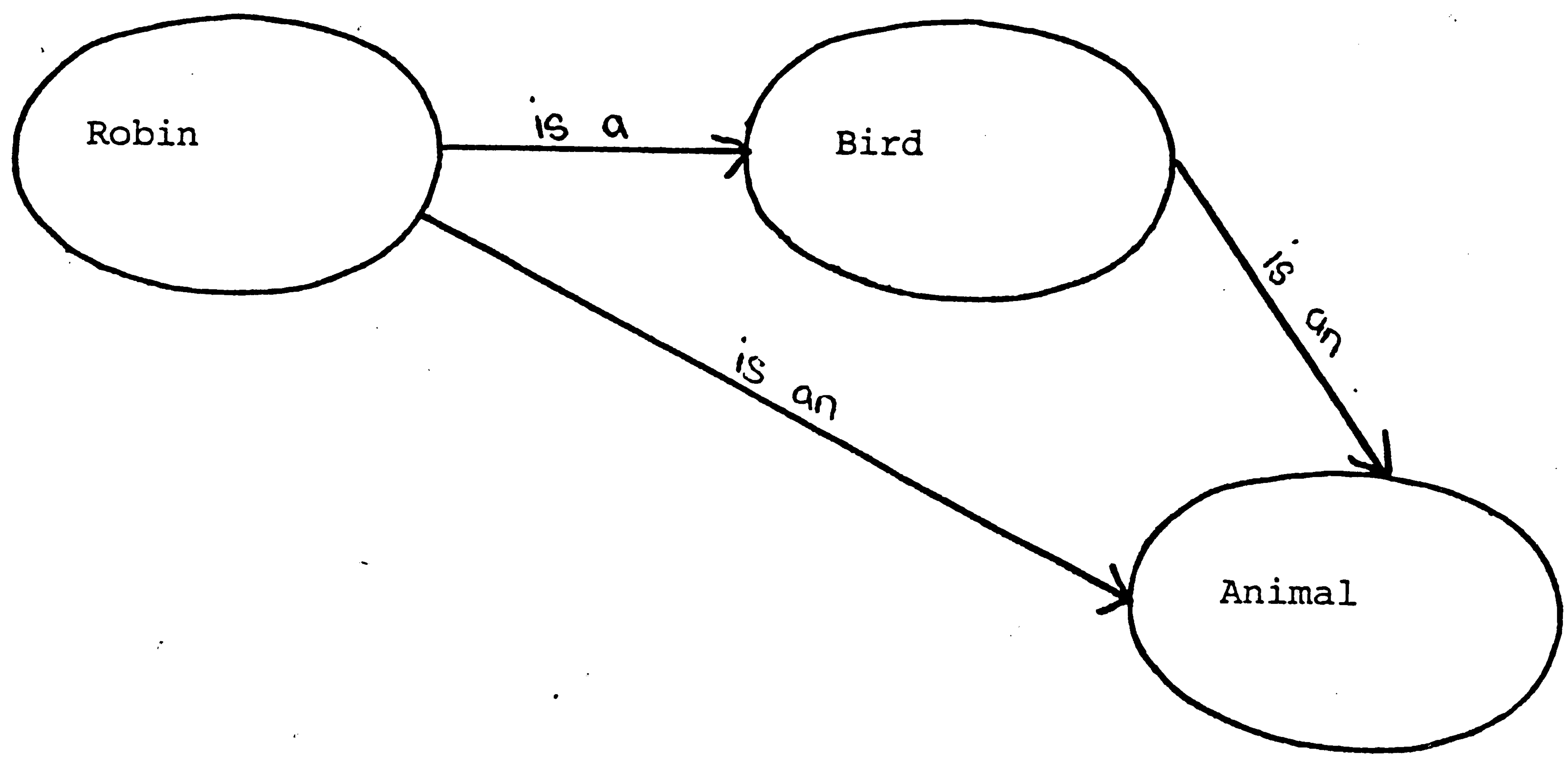
Both network accounts are consistent with the results commonly found. For the phrases "a robin is a bird" and "a robin is an animal", the first version explains the semantic distance effect as follows: "If the connection between robin and animal is indirect (robin is connected to animal via the intermediate node bird) verification of the latter statement involves the retrieval of two relations, while verification of the former involves retrieval of only one relation" (Rips, et al. 1973:2). Thus, if verification time is a function of the number of relations that must be retrieved, then because the latter sentence requires the retrieval of two relations, it should take longer to verify than the first sentence. The second version, using length of a pathway, is very similar. It says there are pathways between robin and bird,

Figure 1. Network Models

1. Network-Retrieval Model



2. Network-Pathway Model



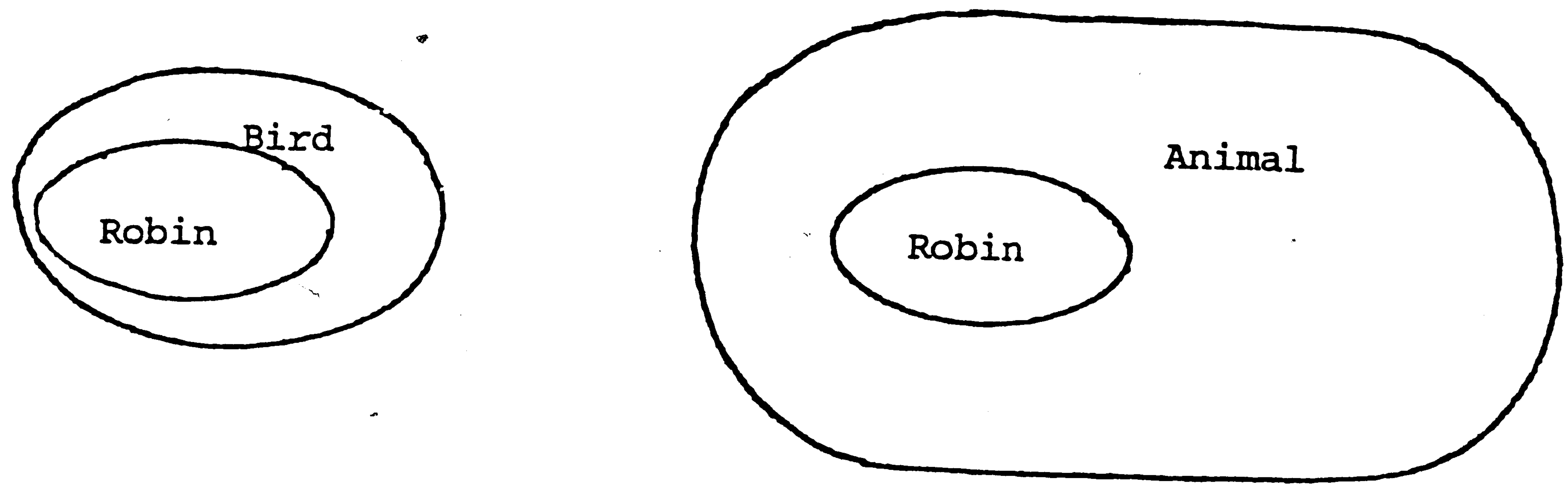
bird and animal, and robin and animal. Since the pathway from robin to bird is shorter than that between robin and animal, the former will be verified much faster than the latter.

An early version of the set-theoretic model for verification or reaction time is the set-comparison model. "In set models, concepts such as robin, bird, and animal are represented by a set of elements where elements might be exemplars, attributes, subsets, or supersets of the concept" (Meyer 1970:2). As an illustration, if robin, bird, and animal are the categories, "then verification of 'a robin is a bird' occurs when a comparison process indicates that each robin-exemplar matches some bird-exemplar. Similarly, verification of the statement 'a robin is an animal' requires that each robin-exemplar match some animal-exemplar. Since there are more animal-exemplars than bird-exemplars, then, given specific assumptions about the comparison process, more comparisons would have to be made to verify the robin-exemplar" (Rips, et al. 1973:2). In this model, reaction time is a function of the number of comparisons that must be made, and the less restricted the comparison, the longer it takes. Thus, the statement "a robin is an animal" takes longer to verify than does "a robin is a bird" because the former places fewer restrictions on the comparisons than the latter (see Figure 2).

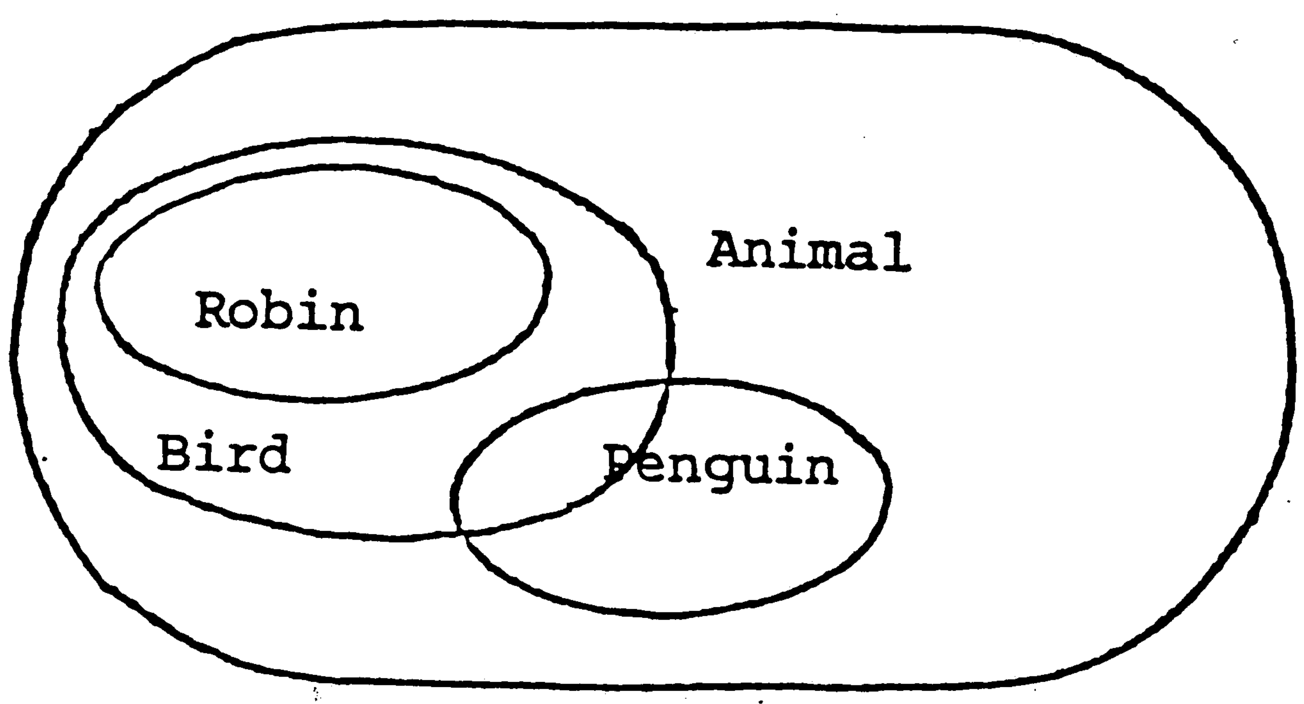
Rips, Shoben, and Smith (1973) attempted to test network versus the set-comparison models. Their approach to this problem was "to measure semantic distance independently of verification times and then determine the extent to which semantic distance influences the verification of instance-category and inter-instance relations in several tasks before

Figure 2. Set-Theoretic Models

1. Set-Comparison Model



2. Feature Overlap Model



relating it to the relevant models" (1973:3). In their Experiment I, they established categories in which all or almost all of the instances showed the semantic distance/subset effect.

In Experiment II, they obtained ratings of semantic similarities (distances) for many of the statements previously used in Experiment I. To do this, they collected instance-category ratings, or the semantic similarity ratings between X (instance) and Y (category). Each subject was given a 16-page booklet. Each page contained a standard word and a group of comparison words taken from Experiment I. They were instructed to indicate the degree of relatedness, on a 4-point scale, between the standard word and each comparison word. The ratings were combined and evaluated to obtain the final ratings of semantic similarity for instance-category pairs. Their results showed that rated semantic similarity can account for differences in verification times in cases where network models and their rather ungraded representations of category distance make either no predictions or faulty predictions.

Rips, et al. (1973) also found that instance-category ratings are related to typicality ratings, where the latter is a measurement of how representative an instance is of a category. This finding is similar to that of Heider (1973). Using instances from several different categories in a True-False verification time experiment, she found that those instances which were rated as highly typical had shorter verification times than instances rated as atypical. They conclude that "representativeness appears to be an important construct, and Experiments I and II, like the experiment of Heider (1973), demonstrate the importance of representativeness for sentence verification and word classification tasks" (Rips, et al, 1973:19).

Expanding on the relationship between the subset effect and typicality, Smith, Rips, and Shoben (1974) develop a second version of the general set-theoretic model. They define semantic relatedness as the degree of feature overlap between concepts (see Figure 2) and explain variation in verification times as a function of the semantic relatedness between categories. Thus, because the feature overlap between a superordinate category and its varieties decreases as the typicality of the variety decreases, the reaction time to atypical category members will be slower than reaction time to typical members.

Ashcraft wrote several articles expanding on the idea of semantic distance and verification times. He notes in passing that the phenomenon of typicality does not by itself rule out network models in favor of set-theoretic models (Ashcraft 1978a:155-156). Degrees of typicality may be represented in terms of the length of the superordinate pathway from the concept to its category name. Atypical concepts are connected by a longer pathway, which, therefore, takes longer to verify.

Instead of focusing on taxonomic relations between categories using the form "an X is a Y," he measured reaction time to verify property statements like, "robin has feathers" as they varied with respect to two semantic distance/relatedness factors, one factor being the concept's typicality and the second being the number of times a given property is generated in production tasks for a category (property dominance). The design included three within-subject variables: typicality, whether typical or atypical; property dominance, either high or low; and a true-false judgment. He found that reaction time to sentences with atypical category members was slower than reaction time to those with typical members, and that sentences with low dominance properties were also verified more slowly than sentences with high dominance properties.

Ashcraft's interpretation of these results explicitly links typicality and the kind of knowledge a person has of referents, suggesting that typical varieties of a domain are regarded as such because they have high dominance properties. Further, he feels it is possible that access to information within concepts in semantic memory depends on the amount of information stored for that concept. Therefore, "such an interpretation suggests that concepts for which more information is accessible, that is the 'typical' concepts to which people can generate more properties, may present a more easily searched target in the semantic space" (Ashcraft 1978a:162).

In Ashcraft (1978b), the first major variable of interest is property dominance, and the second is typicality or goodness-of-exemplar (Rosch 1975). In his study, property dominance, or the property's frequency of association with a category in a production task, is considered the basic measure of semantic relatedness between concepts and their properties. The concept of an item's typicality is presented in terms of:

1. the number of common properties (Collins & Loftus 1975) or the amount of feature overlap (Smith, et al. 1974) between category member and its superordinate,
2. the degree of dominance or criteriality between a category member and its superordinate (Collins & Loftus 1975),

3. the amount of accessible information stored about a category member, and
4. the uniformity of a concept's semantic representation across individuals (Ashcraft 1978b:227).

For his experiment, Ashcraft used 17 categories from the Battig and Montague (1969) norms. After identifying the items considered typical and atypical using Rosch's (1975) procedures, he selected 3 typical and 3 atypical members for all 17 categories. The total word sample consisted of the 102 category members, 17 category names, and the words "plant" and "animal." Subjects were given 40 seconds to write down the properties and characteristics for each labeled category in the stimulus set. Property responses that were generated only once for a word were eliminated from subsequent analyses.

Stepwise multiple regressions were used to evaluate the responses. The single most important variable in accounting for the variance in property verification times was the property dominance measure (Ashcraft 1978b:228). Also, the average production frequency of the superordinate as a property or characteristic was significantly higher for typical members than it was for atypical members, indicating that the semantic link between typical members and their superordinate category is stronger than it is for atypical members. Finally, Ashcraft found a significantly higher overlap of properties between typical members and superordinates than between atypical members and superordinates. This is consistent with Smith, et al. (1974), who argued that items considered as typical in a category should have higher feature overlap with their superordinate than those considered atypical.

Two additional assumptions are made, although they are not included as measures in these results. First, Ashcraft states that it is commonly assumed that objects frequently encountered are more familiar or salient, and therefore become regarded as typical members of their categories. So, he feels it is likely that typical members would be represented more completely and elaborately in semantic memory, permitting the generation of more properties in such a task. In support of this prediction, typical category members were significantly higher than atypical members in the number of properties generated.

The second assumption is that typical items are likely to be more uniformly represented in memory across individuals (Rosch & Mervis 1975), yielding a higher incidence of agreement across subjects on the properties of typical category members. In support of this assumption, Ashcraft found that the number of these "high-dominant" (generated by at least 50% of the subjects) properties is greater for typical members than it is for atypical members.

After a second stepwise multiple regression, using typicality as the dependent variable, Ashcraft found that the mean number of properties is the most important predictor of rated typicality. In both Ashcraft (1978a) and Ashcraft (1978b), this effect was interpreted as indicating that more information is accessible for typical than atypical members, and that there are more interconnections among properties and members at the typical level of category membership. According to Collins and Loftus (1975), both of these conditions should lead to faster verifications of property statements. "In combination with the present results, it may in fact be the case that a greater amount of accessible information both allows for faster verification and also serves as the semantic determinant of higher typicality per se" (Ashcraft 1978b:229).

The purpose of the study done by Glass and Meany (1978) was to examine the relationship between instance typicality and reaction time for a true category judgment. Glass and Meany believe that both the set-comparison model and the network-retrieval model correctly predict results in certain situations. They also speculate that there are two kinds of low-typicality ratings, which are the main concern of their study. So, this analysis suggests that there are total of three types of instances rather than two.

Instead of the usual high-typicality versus low-typicality, Glass and Meany (1978) classify instances as high-typicality, low-typicality (atypical), and low-typicality (unfamiliar). "Thus, this model assumes that some low-typicality instances are categorized more slowly than typical instances because it takes longer to retrieve their descriptions, while others are categorized more slowly because it takes longer to compare their descriptions to that of the category. This will be labeled a 'mixed model' of semantic categorization" (Glass & Meany 1978:622).

In order for Glass and Meany to demonstrate that instances are categorized differently, they first had to identify examples of the three types of instances. To do this, instances were selected on the basis of how they were rated by a normative subject group on the two dimensions of typicality and imagery. Imagery was chosen as the second dimension because pilot studies indicated that it was the best measure of how much a subject knew about an item. The three kinds of instances identified were those of high-typicality high-imagery, like robin, low-typicality high-imagery, like penguin, and low-typicality low-imagery, like grackle. The low-typicality high-imagery instances would elsewhere be referred to as "atypical," and the low-typicality low-imagery would be referred to as "unfamiliar."

The three kinds of instances were then presented in a categorization task. Glass and Meany state that in all previous categorization tasks, except one (Loftus 1973), the category was always presented either before or simultaneously with the instance. But, Glass and Meany feel if they present the instance first, enough time should be provided for all instances to retrieve the information necessary for a categorization judgment. Once the instance is recognized, the reaction time to a categorization task can be measured more accurately.

Glass and Meany made several predictions about the outcome of their results. First, high-imagery instances, like robin and penguin, would be recognized more quickly than low-imagery instances, like grackle, because the high-imagery instances are closely associated to descriptions whereas low-imagery instances are not. Second, high-typicality instances should be categorized quickly because they are closely associated with, and have similar descriptions to the category itself. Next, "unfamiliar instances (e.g., grackle) should be categorized quickly because they are only associated to the category, and hence, the category description should have been retrieved when the instance was recognized" (Glass & Meany 1978:623). And finally, atypical instances should be categorized slowly because the description they are closely associated with is not similar to the category description. So, typical and unfamiliar instances should be categorized more quickly than atypical instances.

In testing these ideas, Glass and Meany conducted three very similar experiments. The methods and procedures were the same for each, only the directions were varied slightly between groups. All predictions held true for each experiment. An additional finding was also made: it takes longer to recognize unfamiliar instances, but once recognized, it takes no longer to categorize an unfamiliar instance than a typical instance.

Glass and Meany believe that their results are inconsistent with either a simple network-retrieval model or a set-comparison model. Each simple model can only account for the results of one of the low-typicality instances. They combine retrieval and comparison models into one mixed model "in which a categorization decision is influenced by both the kind of information accessed by the instance and the speed with which it is accessed" (Glass & Meany 1978:626). In their conclusion they state that their results strongly suggest that differences in both the retrieval and the comparison of semantic descriptions contribute to the observed RT differences between the high-typicality and low-typicality instances in a categorization task.

The foregoing review covers the essential background to research on typicality and its correlates. The following three articles, however, are more directly related to the current research.

Malt and Smith (1982) begins by stating that "all members of a semantic category are not equally representative or typical of that category: a peach is a more typical fruit than a pomegranate, and a robin is a more typical bird than a roadrunner" (1982:69). They feel that by understanding what determines typicality, a better understanding will be achieved of how information is acquired and organized in semantic memory.

Prior to their study, the primary focus in typicality studies had been on the property structure of categories, evaluating the properties of the category members by those of the category itself (Rosch & Mervis 1975; Smith, et al. 1974), in other words, how typical an item is in comparison to the category of which it is a member. Rosch and Mervis (1975) suggest that typicality is based on the distribution of properties among category members, where typical members have properties that are common to many category members and atypical members have properties common to only a few. This description is very similar to the feature overlap model discussed earlier. An alternative suggestion is that typicality is based on familiarity, meaning those category members encountered most frequently and interacted with most often, are those judged as typical category members.

As already stated, Ashcraft (1978a, 1978b) concluded that the larger number of properties listed for typical than for atypical category members indicates that people are more familiar with and can produce more information for typical items than they can for atypical category members. The Malt and Smith (1982) article reports on three experiments designed to assess Ashcraft's claim.

Their first study was implemented to determine whether or not a positive correlation exists between typicality and the number of properties produced for category members. In Experiment 1, 20 subjects generated property lists for category members within a 75 second time limit. Nineteen additional subjects rated the category members for typicality on a scale from 1 to 7, with 7 being the highest typicality rating. Pearson correlation coefficients were computed between the mean number of properties listed and the mean typicality ratings for each item. For both categories, bird and furniture, the correlation between the number of properties and typicality turned out to be negative, meaning the number of properties increased as typicality decreased.

These results are in complete opposition to what Ashcraft (1978b) found in his study, so a second experiment was executed. "Experiment 2 tested whether, for a random sample of 15 items from each of 8 categories, a positive correlation between typicality ratings and number of properties listed would be found" (Malt & Smith 1982:71). This time 240 subjects provided property lists and 20 provided typicality ratings.

Again, correlation coefficients were calculated for the mean number of properties and the mean typicality ratings for each item. Contrary to the results in Experiment 1, the correlation coefficients were positive for all 8 categories. For 5 categories the correlations were significant, and for the remaining 3, the correlations were positive but not significant. "The familiarity explanation of typicality assumes that subjects have at least a rough idea of the appearance of the referent of the item they are rating as low in typicality; it is the relative infrequency of that referent in the environment that leads it to be perceived as less typical" (Malt & Smith 1982:71).

The authors make the point that if subjects have no idea what the referent of a word is, they cannot make a typicality judgment about the referent itself and perhaps resort to a strategy of assigning low ratings to such words (Malt & Smith 1982:72). Experiment 3 was designed and implemented to compensate for this possibility. For Experiment 3, a new set of typicality ratings, which included the option of "U" as a choice was collected. "U" indicates that the subject is too unfamiliar with an item to rate it on the typicality scale.

They found that the "U" ratings did correspond to those category member ratings from Experiment 2 that were found at the lower end of the typicality scale. "The Experiment 2 correlations between typicality and mean number of properties were recalculated, omitting all items that received a 'U' rating from 4 or more subjects in Experiment 3" (Malt & Smith 1982:72). Although the correlations generally remained positive, they dropped below significance for the 5 categories that included "U's" in the typicality scale. The authors note that omitting the "U" items from the sample reduced the range of the number of properties produced but not the range of typicality ratings. The results of Experiment 3 concluded that familiarity with the referents may very well influence typicality ratings, as suggested by Ashcraft (1978b).

This masters thesis is a direct development out of two studies done by Gatewood, "Loose Talk: Linguistic Competence and Recognition Ability" (1983) and "Familiarity, Vocabulary Size, and Recognition Ability in Four Semantic Domains" (1984). Much of the data used in the current study was collected previously in conjunction with these two articles.

In his first article, Gatewood (1983) investigates the significance of the fact that a person may know and use a word without being able to recognize its empirical referent. He states that the ability to talk about and the ability to recognize are independent skills. In making this point, he studied Americans' linguistic versus recognition abilities within the narrow domain of trees.

Data were collected from 40 college students in a free-recall task during a class period. They were asked to list all the kinds of trees they could think of and were given as much time as necessary, although none took longer than 15 minutes. When all the students were finished with the first task, they were asked to go back through their own lists and to check off all those kinds of trees they could recognize in a natural setting, with the restriction that fruit, nut, and flowering trees should be claimed as recognizable only if identifications were possible without using their fruits, nuts, or flowers as a clue.

Gatewood found that at least within the domain of trees, the average American knows the names for more varieties than he or she is able to recognize. Of those students studied, they could, on the average, recognize only 50% of the trees appearing in their free-recall lists. "This would imply that there is a lot of loose talk when Americans discuss trees" (Gatewood 1983:379). In trying to explain why Americans know the names for many more kinds of trees than they can recognize, he suggests that a proximate cause for the persistence of unrecognizable category labels is the prevalence of written language in modern society. In other words, people learn the names for many things in the world and even a large amount of information about them without being exposed to a concrete example. This kind of knowledge is purely semantic. It is learned through words and extends no further than words

(Gatewood 1983:384).

The second article (Gatewood 1984) investigated the relation between cultural emphasis and lexicon by studying the interrelationships among familiarity, personal vocabulary size, and recognition ability at the level of interindividual differences. He suggests that "whether familiarity is experiential, linguistic, or both, we might expect that the more 'familiar' a person is with a domain, the larger his or her vocabulary for that domain. Further, we might expect those persons who are more experientially familiar with a domain to evidence greater recognition abilities as well as larger vocabularies" (Gatewood 1984:508).

The data collection tasks were much the same as in his earlier study, except that the categories included not only trees, but also musical instruments, fabrics, and hand tools. Each of 9 research assistants collected the data from 6 informants. The results showed that, indeed, self-rated familiarity with a domain was highly correlated with measures of vocabulary size, though not as greatly with measures of recognition ability.

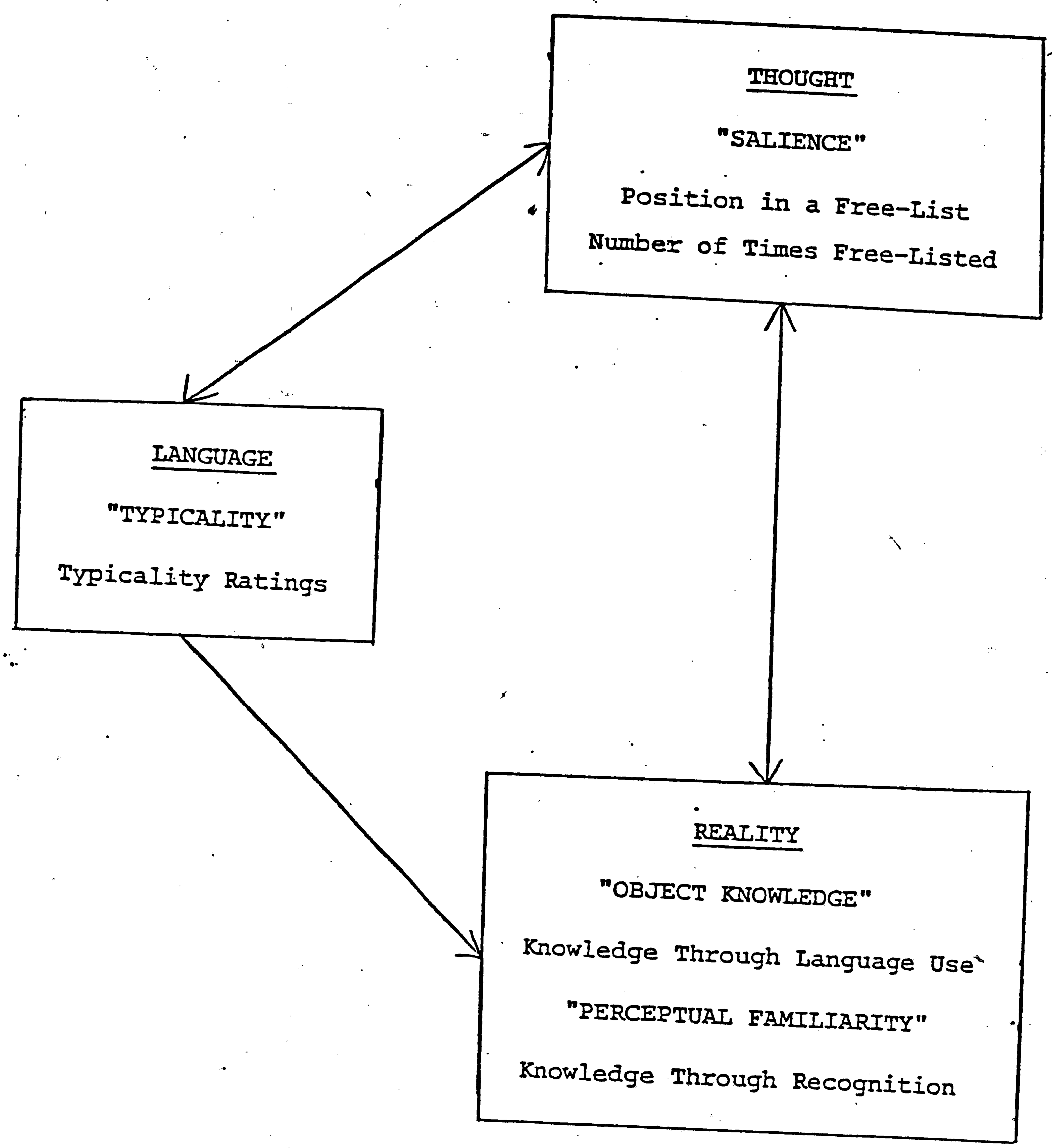
There are two major differences between those studies done by psychologists and the articles by Gatewood (1983, 1984). The first concerns the meaning, or perhaps the implications, of one of the commonly used measures of familiarity. Ashcraft and, to a lesser extent, Malt and Smith regard the number of properties subjects produced for a segregate (PROP) as a measure of perceptual familiarity, or, in other words, a measure of knowledge derived from direct experience with the referent. Thus, if a subject could list properties for a segregate, it was tacitly assumed that that knowledge came from the subject's ability to recognize the referent. Gatewood's findings, however, indicate that property lists could equally well reflect subjects' linguistic competence because people can list properties of unrecognizable trees, including varieties they have never actually seen. Hence, the ability to generate property lists for a given category does not necessarily imply perceptual familiarity; it may be another manifestation of "loose talk."

Second, the number of times an item occurs in free-recall lists (FLL) has generally been regarded, along with verification time, as a measure of salience, or memory accessibility (Rosch, et al. 1976). Extrapolating from Ashcraft's demonstrations that reaction time, typicality, and referential knowledge are highly intercorrelated, one might suppose that FLL would also correlate highly with typicality and experiential familiarity and, especially, that the causal chain goes from experience to salience to typicality. It follows from Gatewood's studies, however, that frequency of appearance in free-recall lists may reflect subjects' familiarity with the communicational uses of a category rather than direct experience with the category's referent. In other words, salience may reflect linguistic and/or perceptual familiarity.

Differences of interpretation aside, Figure 3 illustrates how the measures discussed so far fit into the larger Whorfian framework of language, thought, and reality.

Whorf's hypothesis of linguistic relativity states that the link between language and thought is stronger than that between language and

Figure 3. The Distribution of Previously Used Measures in a Whorfian-Framework



reality or between reality and thought. The purpose of the current study is to evaluate the relations between various measures of the variables language, thought, and reality with emphasis placed on the following specific hypotheses.

1. The correlation between cognitive salience and linguistic variables is stronger than that between salience and perceptual familiarity and/or knowledge about the referents of labeled categories (object knowledge).
2. The correlation between typicality and linguistic familiarity is stronger than the correlation between typicality and perceptual familiarity and/or object knowledge.
3. The correlation between object knowledge and linguistic familiarity is stronger than that between object knowledge and perceptual familiarity (recognizability), i.e., knowledge about referents is more a reflection of verbal learning than of direct perceptual experience.

METHOD

The study was designed to integrate the ideas put forth by Gatewood (1983, 1984) and Malt and Smith (1982). Gatewood (1984) found a positive, though not significant, correlation between subjects' self-ratings of "familiarity" with a domain and their recognition ability of instances within that domain. Two out of three experiments in Malt and Smith (1982) found positive and significant correlations between typicality and familiarity, meaning, in their case, perceptual familiarity or recognition ability.

Rather than collecting a small amount of data for several categories, I analyze a wide variety of data for one category, that of trees. I reassess the relationships just mentioned and include correlations between typicality and the following measures: the position in which the tree is listed, the number of times a segregate is free listed, recognition ability, and the number of properties listed. Most of these measures were available from previous studies done by Gatewood. The data I personally collected were typicality ratings and property listings.

Subjects

To collect my data I made use of the undergraduate subject pool. The original request was for 50 students. Forty-five subjects showed up for part one, and of those 45, 42 showed up for part two. The subjects were told they would receive two experiment credits as long as they were present for both parts. Subjects performed their tasks in small groups, numbering from 1 to 8 persons.

Data Collection Procedures

Part one of the experiment was designed to collect typicality ratings of trees. The instructions for part one are in Appendix A. The stimulus was one of two lists of trees. The list of 100 trees was the standardized list used in previous studies by Gatewood, and the list of 109 trees was a cumulative list of trees produced in free-recall tasks in those same earlier studies. Both lists are presented in Appendices B and C, respectively.

The names of all the trees were written on 3 x 5 cards, one to a card, keeping each card in its respective standardized pile. The trees were written on cards to avoid any effect due to the standardized order of the trees in their original lists. To randomize the order, the cards were shuffled several times before each session.

The 45 students who participated in part one were randomly divided into two groups, each group performing typicality ratings for one of the two lists of trees. Twenty-three students were shown the set of 100 trees and 22 were shown the set of 109. Each group was shown the trees one at a time and asked to write down the tree name in the space provided. Then they were instructed to rate the typicality of the tree just shown. A scale from 1 to 7 was provided next to each space, where 1 meant "very atypical" and 7 meant "very typical." Another option of "unfamiliar" was provided as a choice, if the subject was completely unfamiliar with the tree being shown. Part one took between 20 and 25 minutes.

There is an overlap of 59 tree names between the two lists of 100 and 109 trees. For part two, 50 of those 59 trees were used as stimuli. The list of 50 trees was randomly divided into two sub-sets of 25. The list of 50 trees used for part two is listed in Appendix D. Again, the names of the trees were written on 3 x 5 cards, one to a card, keeping each in its proper pile. The task of part two was property listing. Instructions for this part are displayed in Appendix E.

Only 42 of the 45 original subjects participated in part two. Twenty-one subjects were randomly placed in each group. Group A was shown one sub-set of 25 trees and Group B was shown the second. Again, the cards were shuffled several times before each session to randomize the order. As I showed a card to the subjects, they were instructed to write the tree name at the top of their paper, in the space provided. When all had finished writing the name, they were given 75 seconds to list as many properties as they could. Part two took between 35 and 40 minutes to complete.

Measures and Their Definitions

Seven measures were used in this research, and of those seven the first four measures, POS, FLL, SDL, and SDR were taken from previous research done by Gatewood with a sample of 72 subjects. The measures are defined as follows.

1. POS - Mean position (percentage from top) where tree is free-listed.

The measure POS is used to indicate where in a list a segregate was free listed by the subjects. It is the average position of a segregate and was calculated by numbering all the trees in each free list, choosing a particular tree, and averaging the position where it was listed. Because the free lists varied in length, the mean position in a list was reported in percentages, where a lower number represents an earlier position in the list, and a higher number indicates that the item was listed closer to the end of the list.

2. FLL - Number of times a tree is free-listed.

FLL stands for the total number of times subjects free list a particular segregate. This measure is obtained simply by counting the number of times a tree was listed by the subjects.

3. SDL - Number of times a tree was "heard of" from standard list.

SDL is a linguistic measure. It represents the number of times a tree, on a standard list of 100 trees, was indicated as being heard of. The subjects were each given a standard list of trees and asked to check off those trees that they had heard of, whether through conversation or by reading about it.

4. SDR - Number of times a tree was "recognizable" from standard list.

For a measure of recognizability, the subjects were given a standard list identical to the previous list and asked to check off those trees they thought they could recognize if it were encountered in a natural setting, with the restrictions that a fruit, nut, or flowering tree could be recognized without its fruit, nuts, or flowers as a clue.

5. TYP1 - Mean typicality ("Unfamiliar" not included).

Typicality was averaged in two ways. In the first method, referred to as TYP1, blanks were left where the subjects had circled "unfamiliar" as their typicality rating. This way, the blanks would not be counted and used in averaging the typicality ratings. This was done because we only wanted ratings from those who were familiar with the tree. If the subject was not familiar with a tree, how could he compare it to the other trees and give it a typicality score? A subject has to be familiar with a tree to give it a typicality rating.

6. TYP2 - Mean typicality ("Unfamiliar" equated with "very atypical").

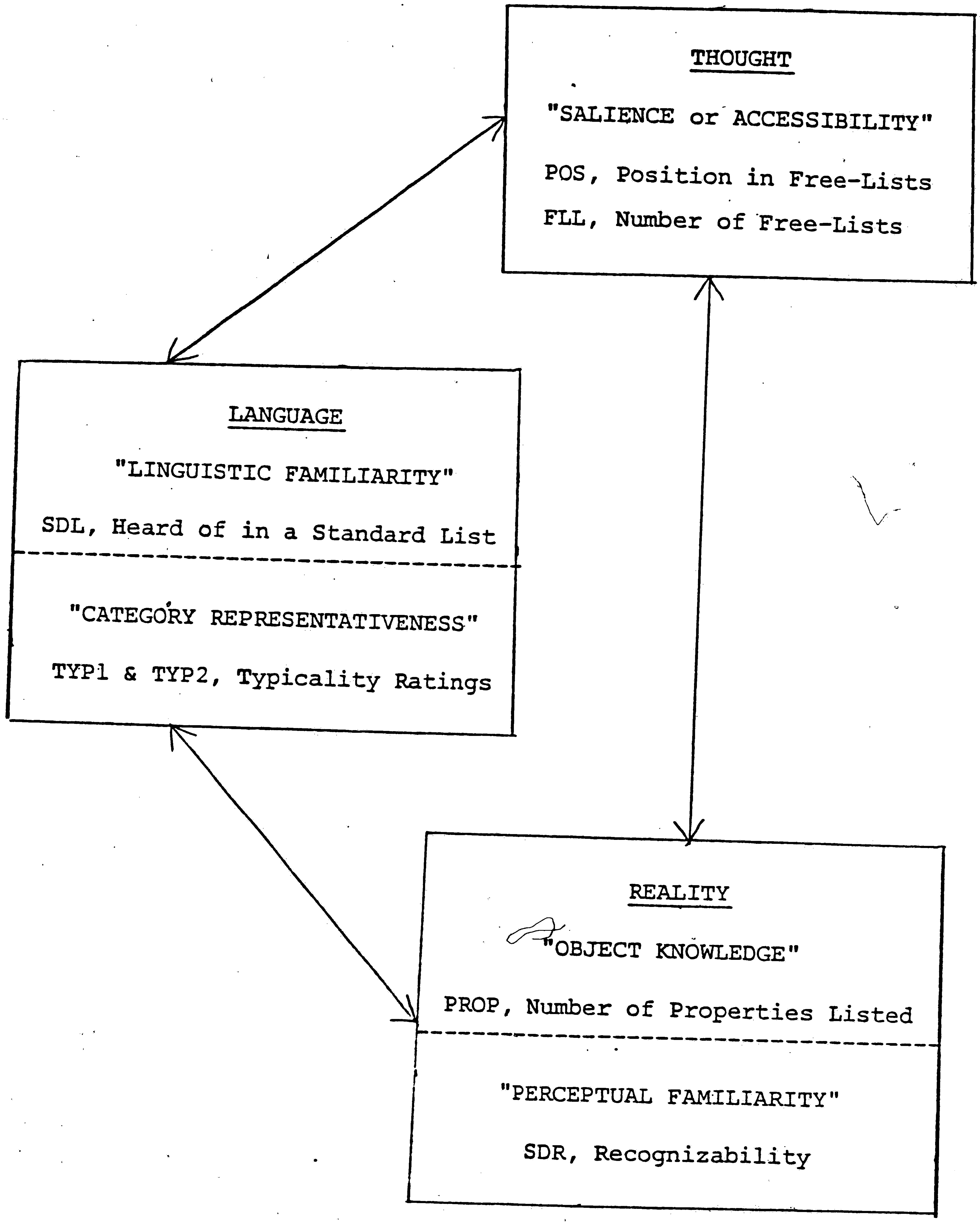
For the second method, referred to as TYP2, we replaced the blanks (or unfamiliars) with 1's, the rating for very atypical, and recalculated the average typicality ratings. This was done to enable comparisons with previous research, in particular Malt and Smith (1982).

7. PROP - Mean number of properties listed.

The measure PROP represents the average number of properties listed for each tree. In averaging the number of properties listed, a value of zero was included when a subject listed nothing or stated he knew nothing about that tree, because a blank sheet tells us just that. So, the totals for each tree were all divided by the same number, 21. Appendix F notes some of the problems I encountered when trying to count the number of properties embedded in a subject's lists. It is not as simple and straightforward a procedure as the published articles make it seem. Nonetheless, using certain rules-of-thumb, I counted properties and calculated the mean number of properties listed for each of the 50 tree names used as stimuli in part two. The table of property numbers is listed in Appendix G.

Figure 4 shows the conceptual variables and their measures that constitute the basic model underlying the subsequent analyses. In discussing the results, linguistic familiarity, SDL, and typicality ratings, TYP1 and TYP2, will be considered measures of Whorf's language

Figure 4. The Seven Measures in a Whorfian-Framework



variable. The measures of salience, POS and FLL, will represent the variable thought, and reality will be represented by the measures PROP and SDR.

The sample size, ranges, means, and standard deviations for all seven measures are presented in Table 1. The 50's under the heading N represent those fifty trees used in part two of the experiment, for which I collected property listings. In obtaining the means and standard deviations for these fifty trees, the various measures had differing sample sizes and ranges of numbers from which they were calculated. For example, the measures POS, FLL, SDL, and SDR were taken from earlier studies done by Gatewood involving 72 subjects.

Table 1. Descriptive Statistics for all Seven Measures

VARIABLE	N	RANGE	MEAN	STD DEV
POS	50	.18 - .91	.5226	.1473
FLL	50	3 - 65	18.1800	16.7986
SDL	50	14 - 72	60.5800	14.1235
TYP1	50	2.80 - 6.65	4.7166	.8757
TYP2	50	1.70 - 6.65	4.4144	1.1198
PROP	50	.67 - 7.57	4.0644	1.5966
SDR	50	1 - 65	18.1600	15.8454

In calculating POS, the possible range is from 0.00 to 1.00, where smaller percentages represent an earlier average position in a list and numbers closer to 1.00 indicate that the segregate was listed near the end of the lists in which it occurred.

The average number of people who free-listed (FLL) a given variety of tree is 18.18. In other words, an average of 18 people out of 72 subjects free-listed each of the fifty trees used in part two of the experiment. Likewise, 61 out of 72 indicated on the standard list of 100 trees that they had heard of each of the fifty trees, and 18 out of 72 said they could recognize each tree if it were encountered in a natural setting.

The possible range for both TYP1 and TYP2 is one to seven. The two means differ, however, reflecting the different way each measure treats "unfamiliar" judgments. When "unfamiliar" judgments are not included in a segregate's average rating (TYP1), the mean typicality for the fifty segregates is 4.72. When "unfamiliar" judgments are coded as "very atypical" (TYP2), the mean typicality drops to 4.41. The number of properties listed for the fifty segregates ranges from zero to twelve with the mean number of 4.07 properties listed for the segregates.

RESULTS

In evaluating the results, only typicality ratings from the standard list of 100 trees were used. (The list of 109 trees will be evaluated at a later date.) Typicality ratings for each of the 100 trees comprising the "standard list" are provided in Appendix H, and the values across all seven measures for each of the 50 trees used in the property list task appear in Appendix I.

We used Pearson correlation coefficients with a two-tailed test of significance, Fisher's r-to-z transformation and subsequent z-tests, and two-tailed partial correlations in the statistical analysis of the data. The full matrix of zero-order Pearson correlation coefficients presented in Table 2 shows that the measures in this study are highly intercorrelated.

Table 2. Matrix of Zero-Order Pearson Correlation Coefficients among all Seven Measures Used in this Study

	POS	FLL	SDL	TYP1	TYP2	PROP
FLL	-.4079 (.003)					
SDL	-.2780 (.051)	.5192 (.001)				
TYP1	-.3977 (.004)	.7322 (.001)	.7076 (.001)			
TYP2	-.3964 (.004)	.7025 (.001)	.7810 (.001)	.9681 (.001)		
PROP	-.1551 (.282)	.6015 (.001)	.5869 (.001)	.6762 (.001)	.7571 (.001)	
SDR	-.2365 (.098)	.5802 (.001)	.4122 (.003)	.5730 (.001)	.5599 (.001)	.6247 (.001)

Hypothesis 1

The correlation between cognitive salience and linguistic variables is stronger than that between salience and perceptual familiarity and/or object knowledge.

The measures POS and FLL and their correlations with the remaining measures will be used in investigating the first hypothesis. The position where a segregate is listed, either early or late in a free-recall task, and how many times a segregate is free-listed have been considered measures of salience in some previous studies. The inter-correlation between these two measures of salience is -.4079, which means that those segregates listed most often also tend to appear near the beginning of subjects' lists.

Apart from the number of times a segregate was free-listed, the greatest predictor of position in free-recall lists is the segregate's typicality (see Table 3). When typicality is computed as TYP1, the correlation coefficient is -.3977; and when computed as TYP2, it is also a relatively strong -.3964. This means that the more typical segregates tend to appear earlier in subjects' lists than do the less typical varieties of trees.

Table 3. Zero-Order Pearson Correlation Coefficients between both Measures of Salience and the Other Measures

	SDL	TYP1	TYP2	PROP	SDR
POS	-.2780 (.051)	-.3977 (.004)	-.3964 (.004)	-.1551 (.282)	-.2365 (.098)
FLL	.5192 (.001)	.7322 (.001)	.7025 (.001)	.6015 (.001)	.5802 (.001)

The correlations of POS with PROP and SDR are insignificant (-.1551 and -.2365, respectively), which indicates that there is no relation between position in a list and recognition ability, measured as either object knowledge or as perceptual familiarity.

To evaluate further the relationships between POS and the remaining measures, Fisher's r-to-z transformation (Winkler & Hays 1975:653-655) and partial correlations were used. Z-tests performed on the Fisher-transformed correlation coefficients showed that all of the differences in the first row of Table 3 are statistically insignificant.

Table 4 shows the partial correlations between POS and each measure while controlling for all the other measures. All the partial correlations drop significantly from the zero-order correlation coefficients noted above. One positive Pearson correlation, that of POS and PROP, even changes to a negative partial correlation, meaning that as a segregate's position in a list gets closer to the end, the number of properties generated for that segregate increases. This and all other partial correlations in Table 4 are very weak and insignificant, meaning they could have just as easily been caused by chance as by a real relationship between the measures.

Table 4. Partial Correlation Coefficients between Position in Free-Recall Lists and each Measure Controlling for all the Others (df = 44)

	FLL	SDL	TYP1	TYP2	PROP	SDR
POS	-.2193 (.143)	-.0448 (.768)	-.1871 (.213)	-.2675 (.072)	.2192 (.143)	-.0379 (.802)

FLL, or the number of lists a given segregate appears in, is the second measure of cognitive salience. The Pearson correlation coefficients between FLL and the other measures in Table 3 are all greater than +.50 and are significant at the p=.001 level. Scattergrams show that, with one exception, the relations between this second measure of salience and the linguistic and object knowledge measures are generally linear. FLL and SDL, i.e., salience and linguistic familiarity, seem to be highly correlated, but not in a linear fashion (see Figure 5), as assumed by Pearson correlations. Compounding the matter is that this relation is logically truncated: subjects could free-list a variety of tree only if they had also heard of it. If the relation between these measures were calculated by another method, e.g., curve-fitted, the correlation may very well turn out to be stronger than the current linear correlation of +.5192. Nevertheless, the correlation between FLL and SDL is still significant, meaning that those segregates heard of most often on the standard list are also those listed most often in a free-recall task.

Figures 6 to 8 illustrate, in order of decreasing strength, the correlations between FLL and the remaining measures. The strongest correlation of +.7322 occurs between FLL and TYP1. The correlation decreases to +.6015 with PROP, and even further to +.5802 with SDR.

The zero-order correlations, thus, suggest that typicality is the best predictor of salience, and that the correlation between cognitive salience and the definitional structure of categories is stronger than the correlation between salience and object knowledge or perceptual familiarity. In other words, the relative strengths of these

Figure 5. F.L. Listings by S.D. Listings
(.5192)

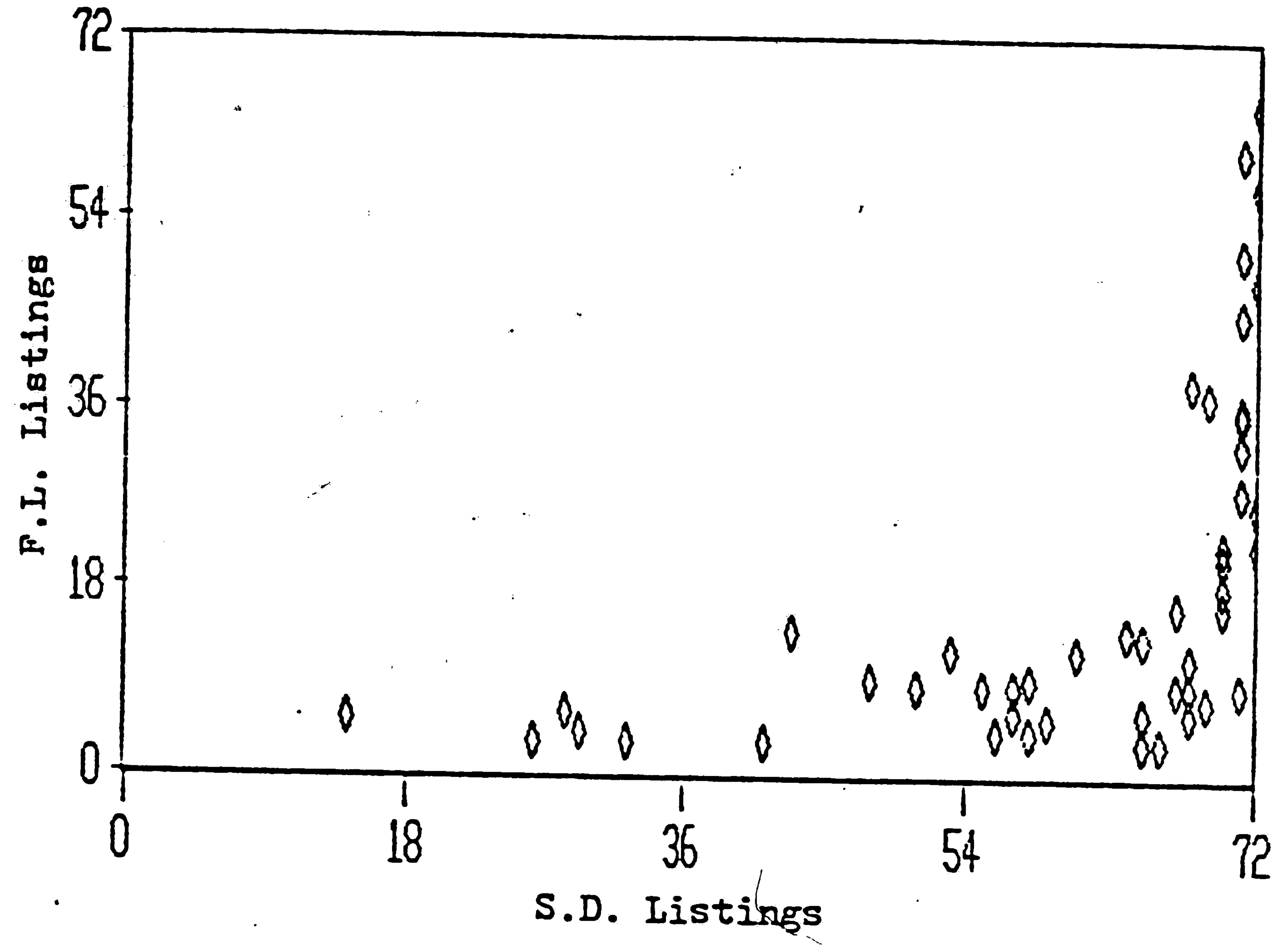


Figure 6. F.L. Listings by Typicality 1
(.7322)

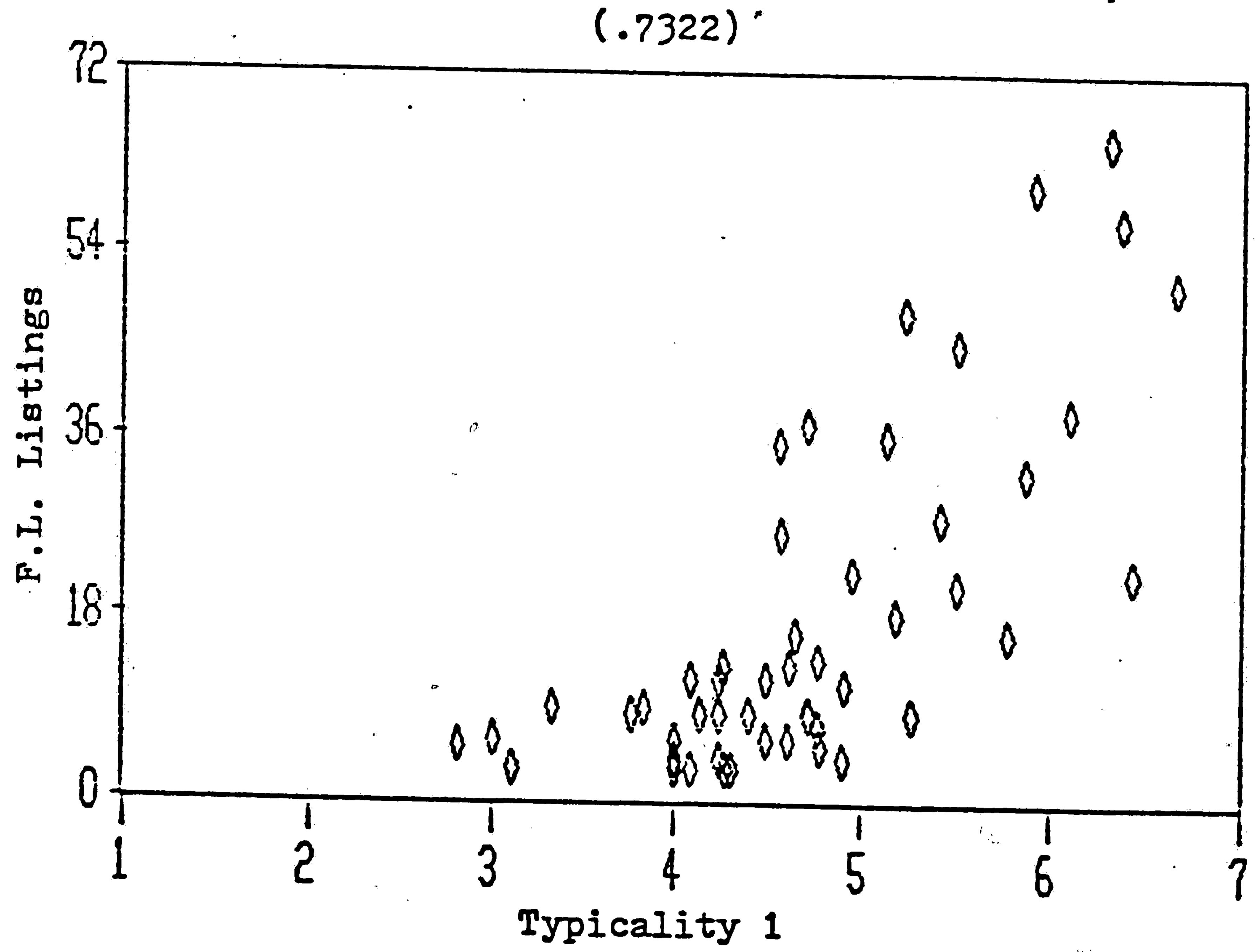


Figure 7. F.L. Listings by No. of Properties
(.6015)

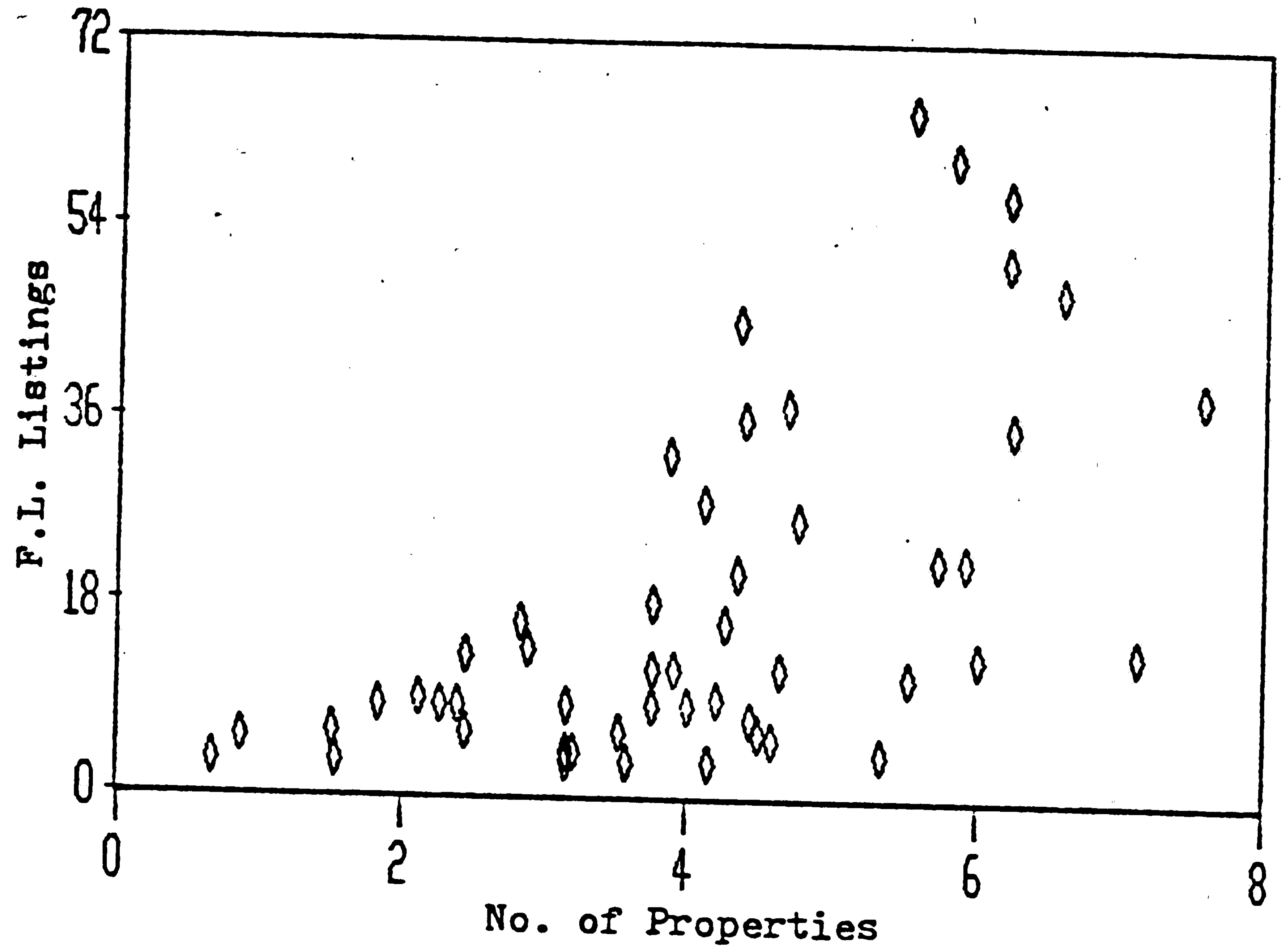
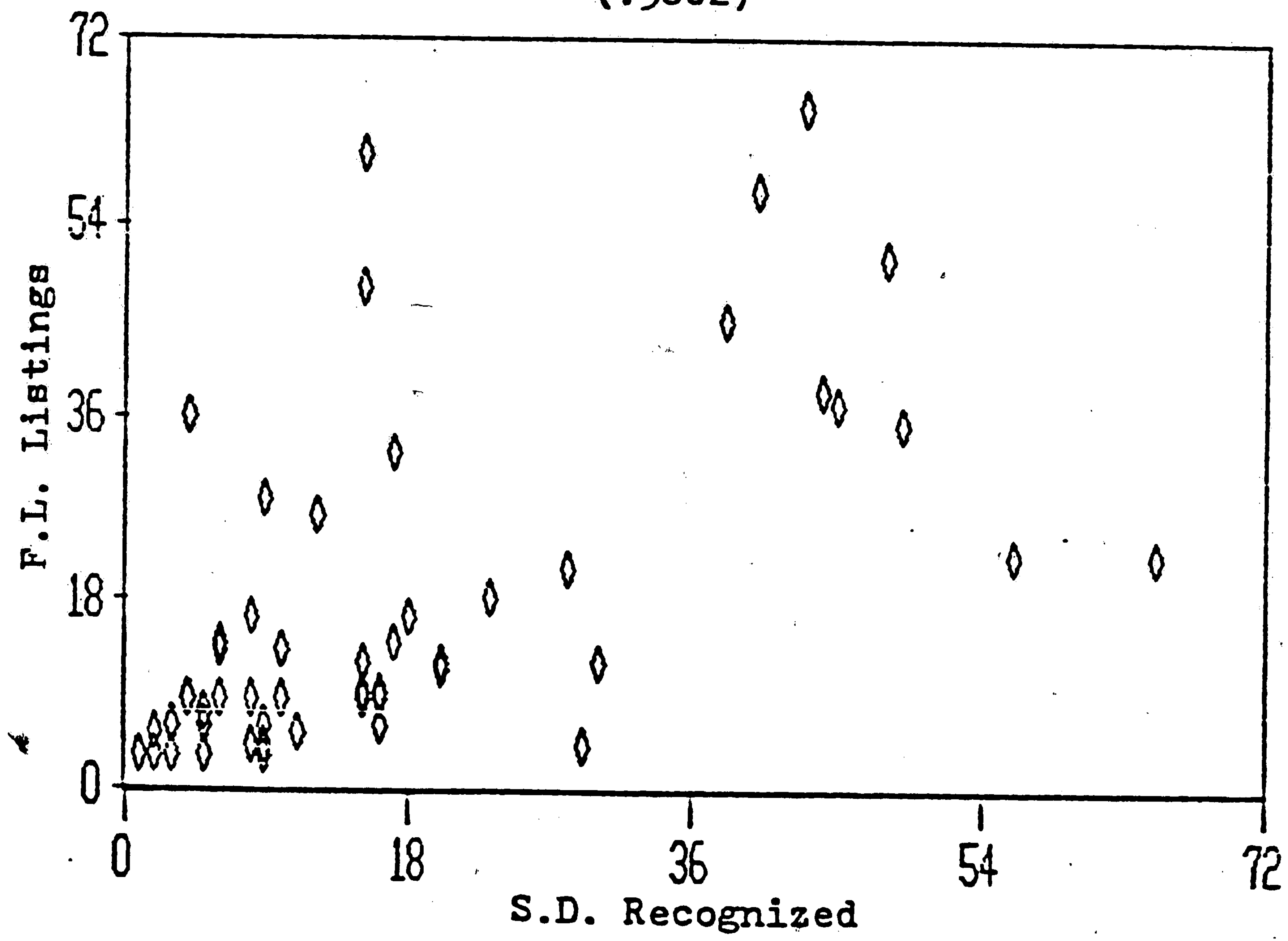


Figure 8. F.L. Listings by S.D. Recognized
(.5802)



correlations support Whorf's hypothesis that the link between language and thought is stronger than the link between thought and reality.

Fisher's r-to-z transformation was used to determine whether there were significant differences among Pearson correlation coefficients in the second row of Table 3. Z-tests show that the difference between the strongest correlation (+.7322 for FLL x TYP1) and the lowest correlation (+.5192 for FLL x SDL) is not beyond chance. In other words, although the strengths of the correlations are in the right direction to support hypothesis 1, the differences are statistically insignificant.

Finally, partial correlations were used to investigate the relations between salience and the remaining measures. Table 5 shows that when FLL is partially correlated with each measure while controlling for all the others, the only correlation which remains significant is that between FLL and TYP1 (TYP2 was excluded from this analysis because of its near redundancy with TYP1). This finding provides additional support for the hypothesis that salience is more strongly related to linguistic factors than it is to object knowledge or perceptual familiarity.

Table 5. Partial Correlation Coefficients between Frequency in Free-Recall Lists and each Measure Controlling for all the Others (df = 45)

	SDL	TYP1	PROP	SDR
FLL	-.0269 (.857)	.4636 (.001)	.1157 (.439)	.2250 (.128)

Hypothesis 2

The correlation between typicality and linguistic familiarity is stronger than the correlation between typicality and perceptual familiarity and/or object knowledge.

As stated before, typicality was calculated in two ways. In contrast to Malt and Smith's (1982) findings, when we recoded the "unfamiliar" ratings of typicality (not included in calculation of TYP1) with scores of "1" corresponding to "very atypical" (i.e., TYP2), all the correlations remained positive and significant (see Table 6).

Table 6. Zero-Order Pearson Correlation Coefficients between both Computations of Typicality and the Other Measures

	FLL	SDL	PROP	SDR
TYP1	.7322 (.001)	.7076 (.001)	.6762 (.001)	.5730 (.001)
TYP2	.7025 (.001)	.7810 (.001)	.7571 (.001)	.5599 (.001)

Because the two calculations of typicality behave in very similar ways, we shall concentrate mainly on the correlates of TYP1, which we regard as the better computation of typicality, but shall include some discussion of TYP2.

The scattergrams in Figures 9 and 10 show that typicality is very highly correlated with salience and the linguistic measure SDL. The correlation between TYP1 and SDL is +.7076, meaning that those segregates heard of most often in the standard list are also those

Figure 9. Typicality 1 by F.L. Listings
(.7322)

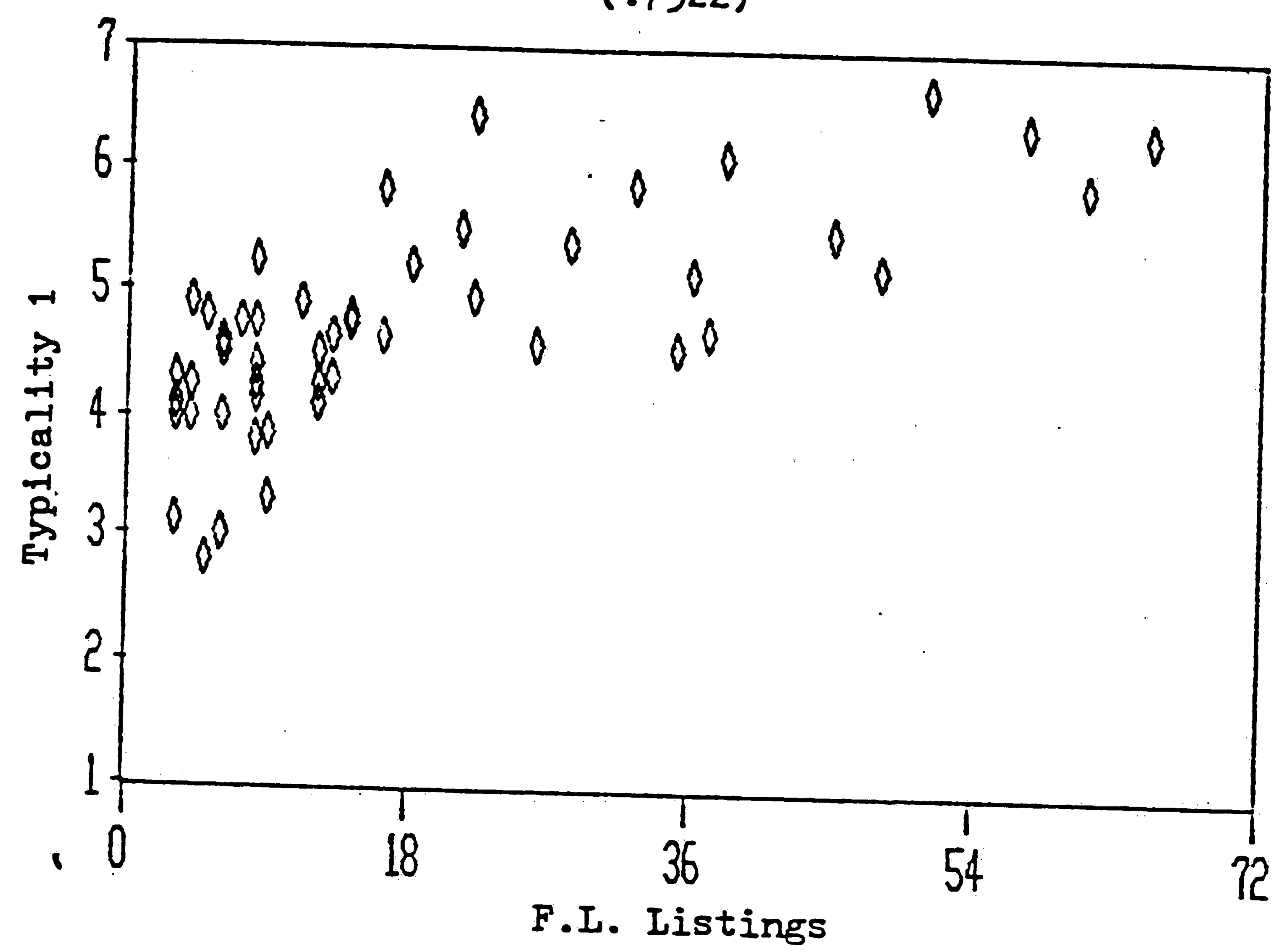


Figure 10. Typicality 1 by S.D. Listings
(.7076)

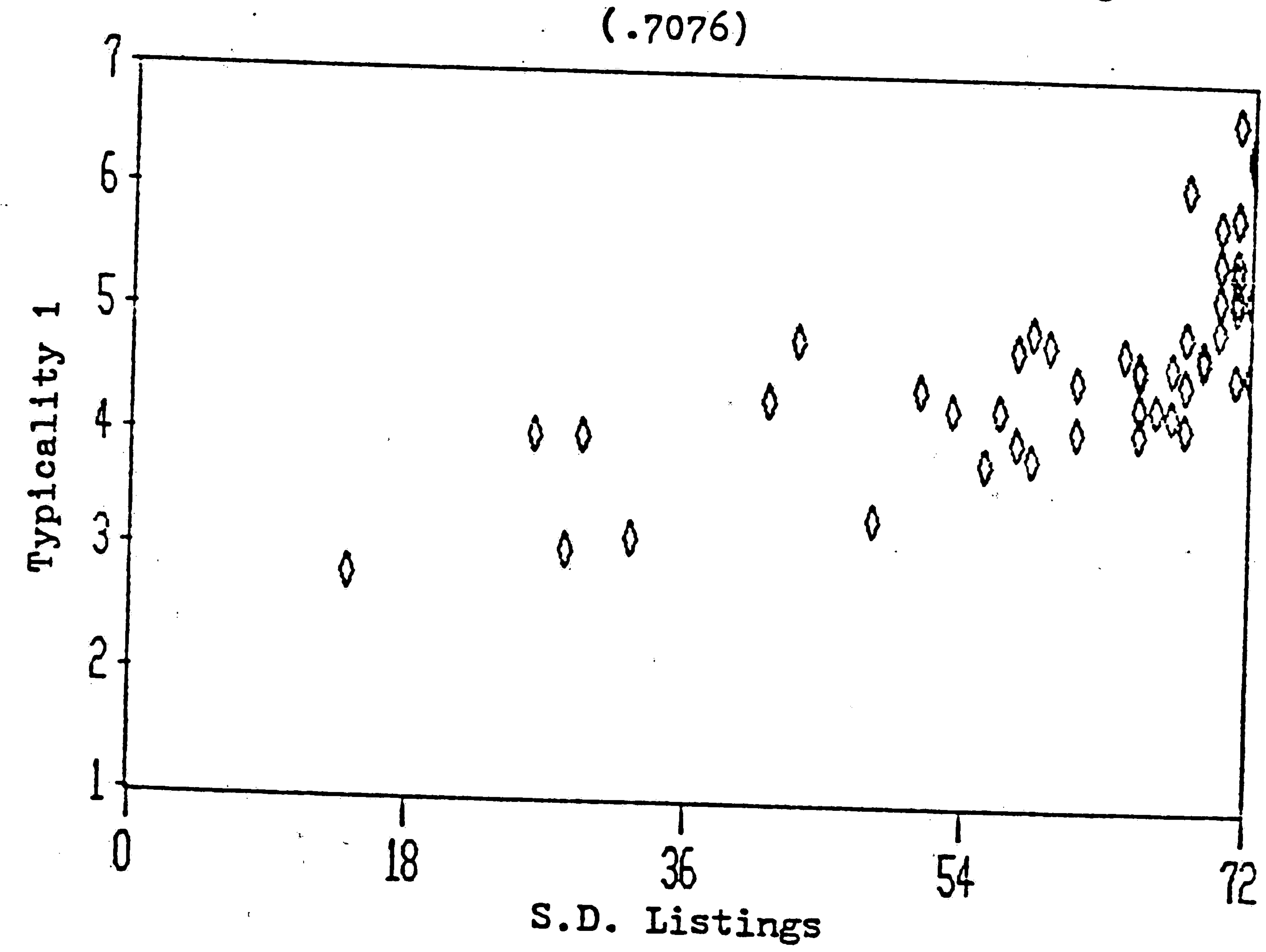


Figure 11. Typicaltiy 1 by S.D. Recognized
(.5730)

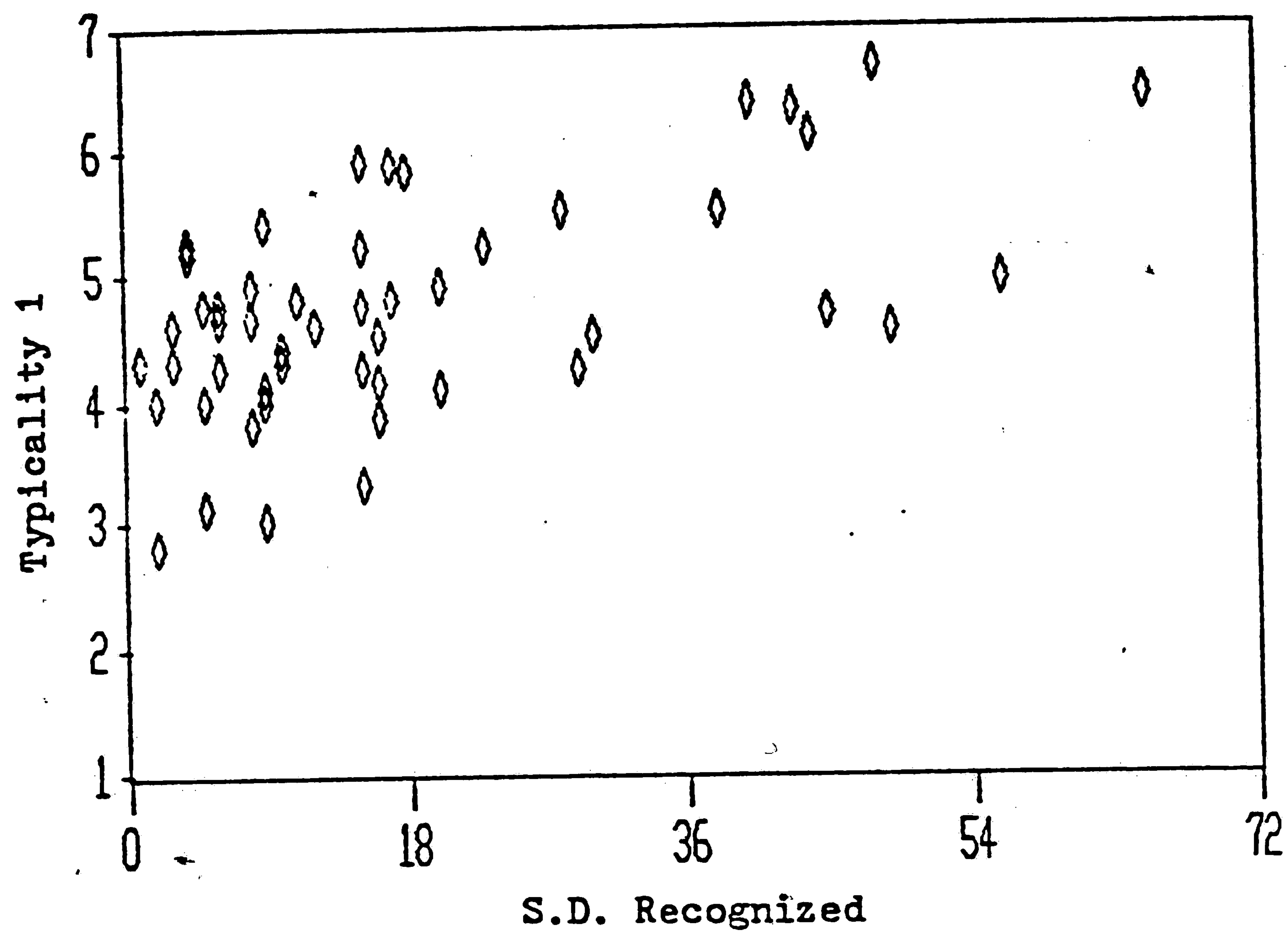
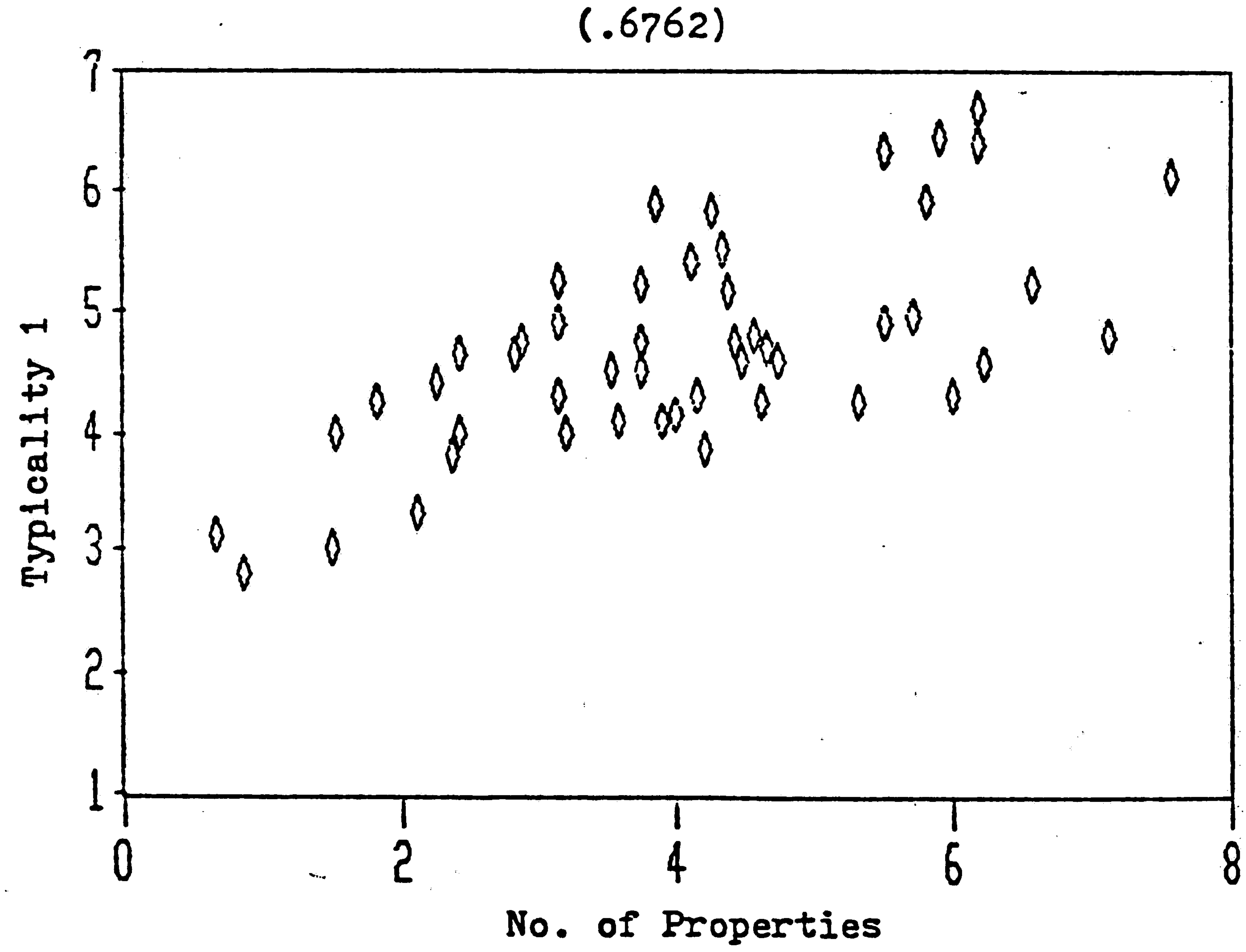


Figure 12. Typicality 1 by No. of Properties
(.6762)



segregates rated as most typical. The relation between TYP1 and SDR (r=+.5730) is graphed in Figure 11. In contrast to Malt and Smith's (1982) Experiment 1 and in support of Ashcraft (1978b), a high correlation (r=+.6762) was found between typicality ratings and the number of properties listed for a segregate (see Figure 12).

The Whorfian hypothesis predicts that the correlation between typicality and linguistic familiarity (SDL) should be stronger than that between typicality and recognition ability (SDR), and the zero-order correlations bear this out. To determine whether the difference between TYP1 x SDL (+.7076) and TYP1 x SDR (+.5730) is statistically significant, we again used Fisher's r-to-z transformation. Z-tests on the transformed coefficients reveal that these two relations do not differ more than one might expect by chance. The difference does achieve statistical significance, however, when TYP2 x SDL (+.7810) is compared with TYP2 x SDR (+.5599).

Partial correlations were used to look at typicality and its correlates in greater detail. Whereas all the zero-order Pearson coefficients between TYP1 and the remaining measures are significantly correlated, the only partial correlations that remain significant, when controlling for all other measures, are those between TYP1 and FLL and SDL (see Table 7). The partial correlations of TYP1 with PROP and SDR drop below significance. These findings further support the Whorfian hypothesis that typicality is better predicted by linguistic familiarity and is more highly correlated with salience than it is with recognition ability. However, due to the definition of TYP2, when it is used, the partial correlation between TYP2 and PROP also remains significant.

Table 7. Partial Correlation Coefficients between both Computations of Typicality and each Measure Controlling for all the Others (df = 45)

	FLL	SDL	PROP	SDR
TYP1	.4636 (.001)	.4745 (.001)	.2088 (.159)	.1231 (.410)
TYP2	.3894 (.007)	.6051 (.001)	.4285 (.003)	.0331 (.825)

Hypothesis 3

> The correlation between object knowledge and linguistic familiarity is stronger than that between object knowledge and perceptual familiarity (recognizability).

The number of properties listed is straightforwardly a measure of object or referential knowledge, but only indirectly a measure of perceptual familiarity. If subjects can list properties of a segregate, they may also know what it looks like and therefore be able to recognize it. But, it is quite possible for subjects to list properties of a given kind of tree based solely on what they have heard about it. In other words, property lists may reflect perceptual familiarity, purely linguistic knowledge, or both.

As shown in Table 8, the mean number of properties listed is highly correlated with all other measures. PROP is most strongly correlated with the typicality measures. The strongest predictor is TYP2 with a correlation of +.7571, the second strongest being TYP1 with a correlation of +.6762 (see, also, Figure 12). Contrary to the hypothesis being tested, however, the measure of perceptual familiarity, SDR, is more highly correlated at +.6247 with the number of properties listed than is the measure of linguistic familiarity, SDL at +.5869 (see Figures 13 and 14).

Table 8. Zero-Order Pearson Correlation Coefficients between Number of Properties Listed for Segregates and the Other Measures

	FLL	SDL	TYP1	TYP2	SDR
PROP	.6015 (.001)	.5869 (.001)	.6762 (.001)	.7571 (.001)	.6247 (.001)

Again, to see if the difference between the Pearson correlation coefficients is significant, Fisher's r-to-z transformation was used. The results show that the difference between the zero-order correlations in Table 8 are insignificant and could therefore have been caused by chance.

Figure 13. No. of Properties by S.D. Listings
(.5869)

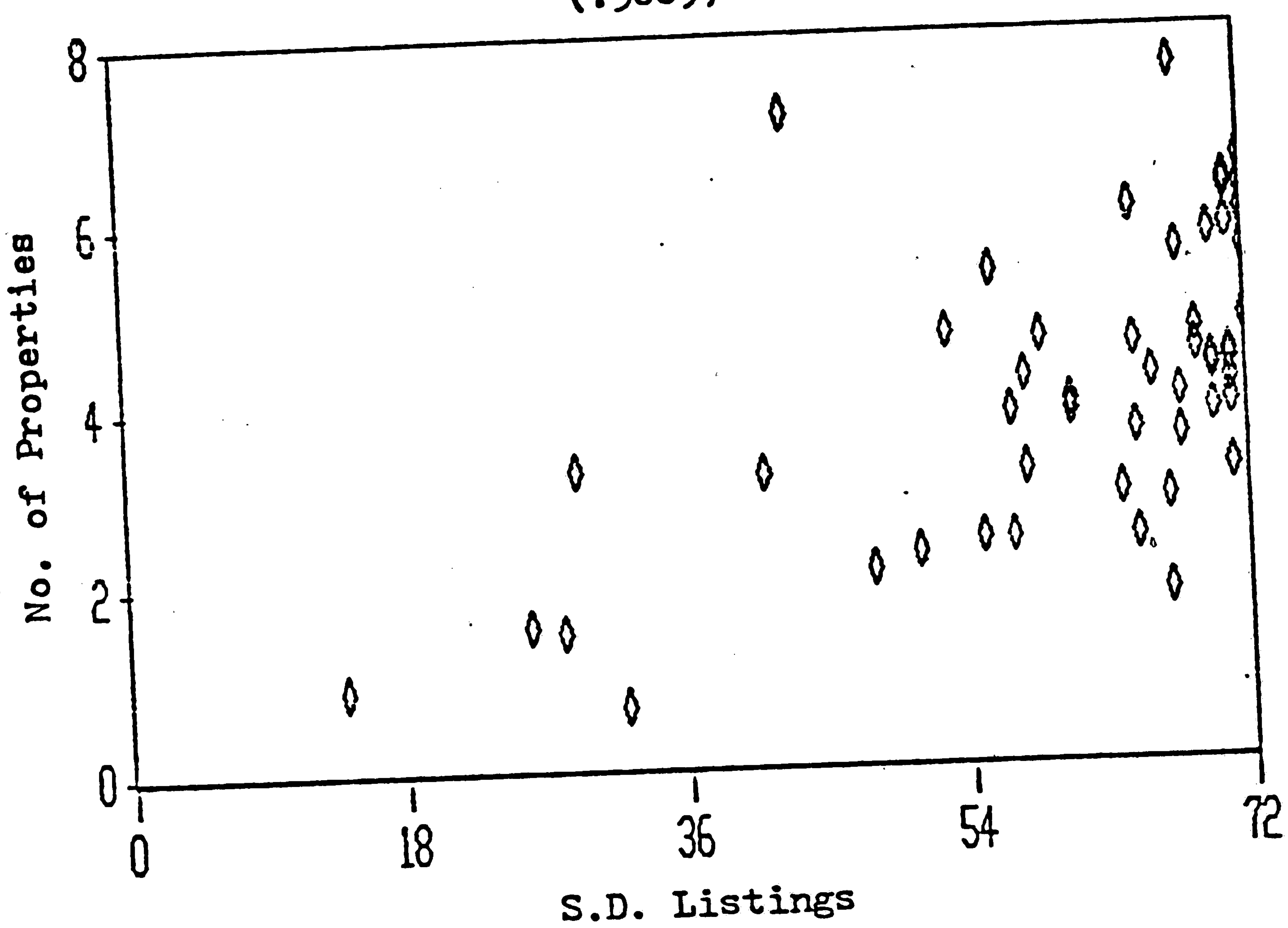
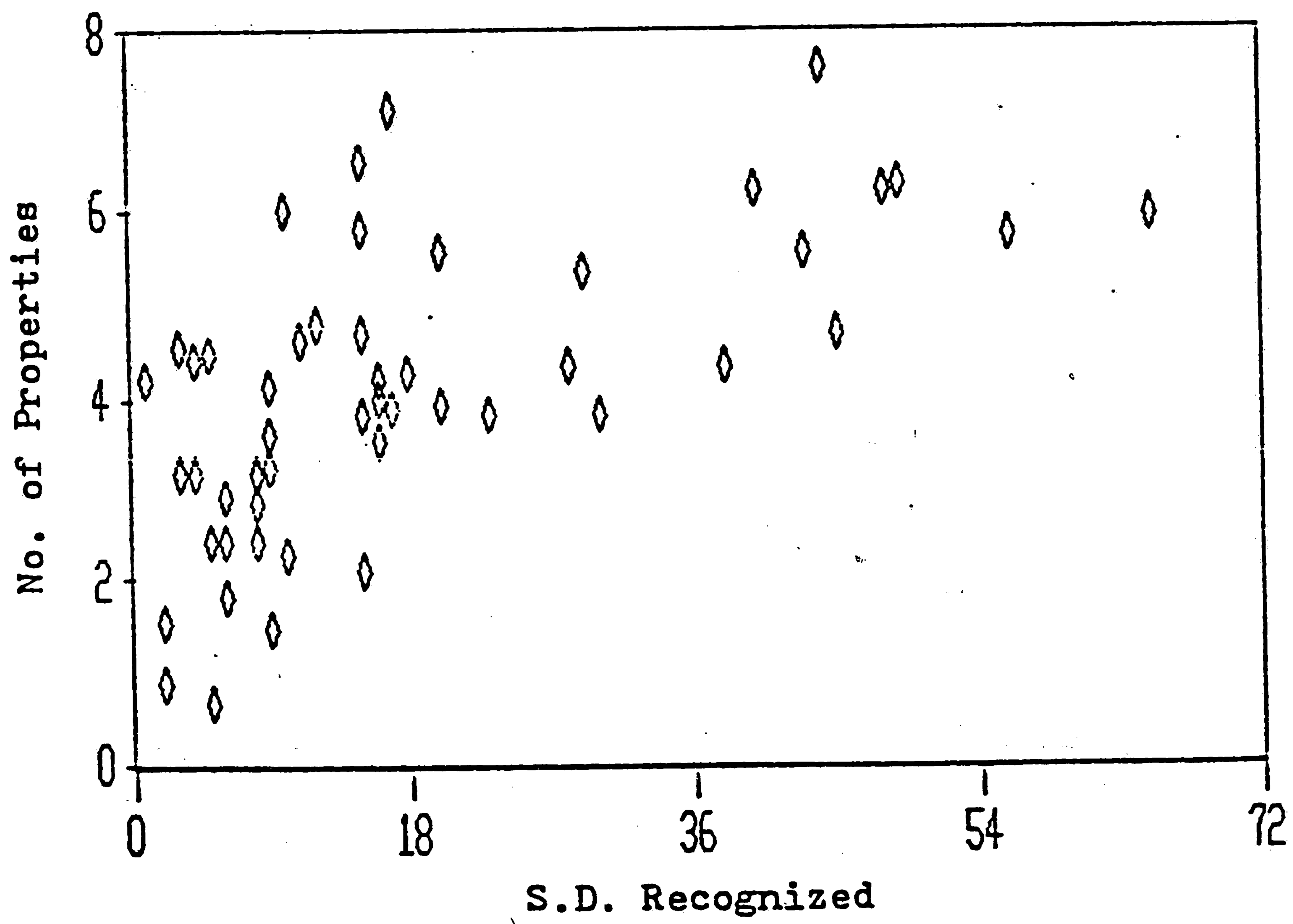


Figure 14. No. of Properties by S.D. Recognized
(.6247)



The partial correlations in Table 9 show that SDR is the only measure that remains significant when all other measures are controlled for, increasing the evidence against the hypothesis that linguistic measures are a better predictor of object knowledge is than perceptual familiarity.

Table 9. Partial Correlation Coefficients between Number of Properties Listed and each Measure Controlling for all the Others (df = 45)

	FLL	SDL	TYP1	SDR
PROP	.1157 (.439)	.2231 (.132)	.2088 (.159)	.3603 (.013)

DISCUSSION

As previously stated, all the measures used in this study are highly interrelated, and almost all of the zero-order Pearson correlations are significant. Because the variables are so intercorrelated, Fisher's r-to-z transformation and partial correlations were included in the evaluation of the results.

The investigation of salience and its correlates used both POS and FLL as measures of salience. First, a percentage calculation of the position where a tree is listed was used. When this measure is used, the only significant Pearson correlations are with FLL, TYP1, and TYP2. The correlation with the linguistic measure SDL at -.2780 approaches, but does not quite reach significance (p=.051). These correlations provide some support for the first hypothesis. Both linguistic measures and typicality ratings are better predictors of salience than are object knowledge (PROP) or perceptual knowledge (SDR).

When partial correlations were calculated, all correlations dropped below the level of significance. The correlation between POS and PROP changed from a non-significant positive correlation to a non-significant negative correlation. The negative correlation means that as a segregate's position in a list gets closer to the end, indicating lower salience, the number of properties generated for that segregate actually increases. Because this and all partial correlations between POS and the remaining measures were so weak and insignificant, the second measure of salience (FLL) provides better results to evaluate the first hypothesis.

The zero-order correlation coefficients between FLL and the remaining measures are all significant, but the strongest correlation with FLL is TYP1 at +.7322. This means that the best predictor of salience is typicality, or the definitional structure of categories. The second best predictor of salience is object knowledge, with the correlation between FLL and PROP being +.6015. The measure of direct perceptual familiarity, SDR, is correlated with FLL at +.5802, and the weakest predictor of how many subjects free-listed a segregate is the number of subjects who had simply heard of it when presented with the standard list (r=+.5192). This last relation is, however, clearly non-linear and problematic because of a logical non-independence between the two measures.

Fisher's r-to-z transformations and z-tests show that the difference between the Pearson correlations of FLL with TYP1, PROP, and SDR are statistically insignificant. In other words, neither the difference between +.7322 and +.6015 nor the difference between +.7322 and +.5802 are statistically significant. Thus, although the relative strengths of the zero-order correlation coefficients support the first hypothesis, they are not sufficiently different to be conclusive.

The strongest support for the first hypothesis are the partial correlations between FLL and each of the measures while controlling for all the others. When these are examined, the only correlation that remains significant is that between salience and typicality. This supports the Whorfian hypothesis that the relation between cognitive salience and language is stronger than the relation between salience and object knowledge or perceptual familiarity.

The second hypothesis -- that the relation between typicality and linguistic familiarity is stronger than the relation between typicality and object knowledge or perceptual familiarity — is the main hypothesis under study in this paper. All the results support this hypothesis and, by extension, the larger Whorfian framework emphasizing the importance of language rather than direct experience in shaping thought.

Like Ashcraft's studies, we found a strong relationship between typicality and the number of properties subjects could list for a segregate. But, because this study included additional measures, ones that distinguish linguistic from perceptual knowledge (SDL and SDR, respectively), the conclusions concerning the importance of direct perceptual experience as a determinant of typicality differ from his. Before discussing these results, however, it is worth noting some subtle differences in the ways previous researchers have measured typicality.

Ashcraft did not collect his own typicality ratings, nor was his measure of typicality a seven-point scale. Instead, he selected items from Rosch's (1975) results that he coded as simply "typical" or "atypical" examples. Rosch's average typicality ratings were computed like our measure TYP2, or so it would seem from her description of method. Malt and Smith (1982), however, showed that TYP2's computational procedure, i.e., recoding a subject's "unfamiliar" rating with a "1" (very atypical), conflates two very different responses and in so doing confounds typicality with linguistic familiarity. When a subject assigns a segregate "1," the presumption is that he has heard of the tree and on the basis of his knowledge, limited as that may be, judges it a very atypical variety. "Unfamiliar," however, means precisely that the subject has never heard of it. Thus, TYP2 incorporates our measure SDL in its typicality ratings.

When Malt and Smith used TYP1 instead of TYP2, they found that their correlations between typicality and property lists dropped below statistical significance. In our data, the effect of including unfamiliar ratings in average typicality is less dramatic, but the confounding of typicality and linguistic familiarity inherent in the calculation of TYP2 explains why the TYP2 x SDL correlation (+.7810) is higher than the TYP1 x SDL correlation (+.7076).

In a less obvious way, this confounding also explains why the correlation between TYP2 and PROP (+.7571) is stronger than that between TYP1 and PROP (+.6762). If, as Gatewood suggests, property lists reflect both perceptual and linguistic familiarity, something Ashcraft overlooked, then it follows that a typicality measure that inadvertently includes linguistic familiarity (i.e., TYP2) will correlate more strongly with PROP than a "pure" measure of typicality.

The most direct evaluation of hypothesis 2, thus, uses neither TYP2 or PROP, but rather the relative strength of the correlations between TYP1 and SDL (+.7076) versus TYP1 and SDR (+.5730). The direction of these zero-order correlations for TYP1 (and TYP2 as well) clearly support the hypothesis, but when Fisher's r-to-z transformation is used, the differences are statistically significant only when the comparison involves TYP2.

Partial correlation analysis provides perhaps the strongest support for the second hypothesis. Of the partial correlations between TYP1 and each measure, controlling for all other measures, only those of TYP1 with FLL and SDL remain significant. Correlations with both SDR and

PROP drop below significance. (The partial for TYP2 and PROP does remain significant, but this probably reflects the confounded nature of TYP2 discussed above.)

What all this means is that the best predictor of a segregate's typicality rating is the number of people who have heard of it, not how many properties they can list or whether they can recognize its referent. This agrees with the Whorfian perspective on typicality: knowledge transmitted through language is more important in establishing typicality judgments than is direct experience with the referents.

The third hypothesis — that the correlation between object knowledge (PROP) and linguistic familiarity (SDL) is stronger than that between object knowledge and recognizability (SDR) — is not supported by the data. Contrary to a strong interpretation of Gatewood's "loose talk" argument, subjects' recognition ability is a better predictor of how many properties they can list for a kind of tree than is familiarity with the segregate label. On the other hand, the data make it abundantly clear that purely linguistic knowledge of segregates has considerable influence property lists.

CONCLUSIONS

Most of the research on typicality and its correlates has been done by psychologists whose theoretical paradigm emphasizes the role of direct experience in the construction of categories. Ashcraft well exemplifies both this approach and the sort of conclusions prevalent in the field.

In his view, objects that are encountered frequently are more (perceptually) familiar or salient and, therefore, become regarded as typical members of their categories. He feels it is likely that typical members are represented more completely and elaborately in semantic memory, which is why subjects tend to generate more properties for typical exemplars than they do for atypical exemplars. In support of this reasoning, his experiments showed that typical category members are indeed significantly higher than atypical members in terms of the number of properties generated.

The results of the current study, especially if one considers only the relationship between TYP2 and PROP, confirm those found by Ashcraft. But, by including additional measures that reduce the conceptual ambiguities of Ashcraft's two measures, my interpretation of the results differs from his.

Subjects' ability to list properties for a segregate is not restricted only to those segregates they have seen or could recognize. The number of properties listed is also a reflection of how much a subject has heard about the segregate, whether or not he has actually encountered an instance of the category in question. In consequence, a segregate's typicality corresponds more closely to how many people have simply heard of it before than to the number of properties subjects can generate for it (hypothesis 2). Further, salience is more closely related to typicality than it is to referential knowledge (hypothesis 1). Thus, although a segregate's recognizability accounts for the number of properties generated better than simple linguistic familiarity (contrary to hypothesis 3), the relation between direct experiential knowledge and typicality is much less direct than Ashcraft's model suggests.

The basic problem with Ashcraft's perception-salience-typicality model is that it underplays, or ignores, the extent to which people's definitions of categories are learned via symbolic communication with other members of society. In a very real sense, category systems are social constructions. While no one doubts that individuals as such construct their own versions, interpretations of private experience are guided and mediated by the talk of one's fellows. This is the Whorfian perspective on typicality and its correlates, and the results reported here generally confirm such a view.

One suggestion for future research is a cross-cultural study of typicality. It would be interesting see whether the correlational patterns found in this study are replicated by similar studies among English speakers from different geographical-botanical areas. For example, in my sample, the average typicality rating for "eucalyptus" was 4.09 and the average number of properties listed was 3.57. American subjects knew about the tree and listed properties for it, but would Australians rate the eucalyptus tree as more representative of trees in general? Conversely, do Americans rate evergreens and pine trees as more typical than Australians? The answers to questions such as these would help clarify the main question of this study: What makes us rate an item as typical in a category? Is it experiential or linguistic familiarity?

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APPENDIX A

INSTRUCTIONS FOR TYPICALITY RATING TASK

This session is the first of two related parts. It is imperative that you are present for both sessions. You will be given two experiment credits, as long as you're here for both parts. Before you leave this afternoon, I need you to sign up for your second session. The data I'm collecting will be used for my master's thesis and also in a larger study of Dr. Gatewood's.

Your task in this part is to rate trees on how typical you think they are. I have the names of trees written on these cards. As I show them to you, write down the name of the tree in the blank provided. Then circle your typicality rating for each item, in comparison to the entire domain of trees. The choice of "UNFAMILIAR" is there for you to use if you have never heard of the tree or you have no idea how typical it is.

Please put your names on your paper, if you don't mind. This is for my records only. Once the data is collected, names will no longer be used. I just want to make sure everybody gets credit for being here.

Any questions?

Please hand in your papers. The times I have scheduled for part two are the following;

Tues. Feb. 24 11:10, 12:10, & 1:10
Wed. Feb. 25 11:10, 12:10, & 1:10
Thurs. Feb. 26 11:10, 12:10, & 1:10

Thank you for showing up. When I see you next time I will hand out your debriefing statements.

APPENDIX B

The following is an alphabetical listing of the 100 trees used in part one of this experiment.

acacia
alder
apple
apricot
areca palm
ash
aspen
avocado
balsa
banana
banyan
baobab
beech
birch
black ash
blach oak
black walnut
blue spruce
boxwood
broadleaf
burr oak
catalpa
cedar
cherry
chestnut
citrus
coconut (palm)
cottonwood
crabapple
cutleaf maple
cypress
date
dogwood
Douglas fir
ebony
elm
eucalyptus
evergreen
fig
fir
fruit
ginkgo
golden chain
golden delicious apple
grapefruit
gum
hawthorn
hazelnut
hickory
holly
honey locust
horse chestnut
japonica
larch
lemon
lilac
locust
lodgepole pine
Lombardy poplar
magnolia
mahogany
maple
McIntosh apple
mimosa
oak
olive
orange
palm
peach
pear
pecan
persimmon
pin oak
pine
plum
Ponderosa pine
poplar
red cedar
red maple
redwood
rubber
Scotch pine
screw palm
shaggy-bark hickory
silver birch
silver maple
smooth-bark hickory
spruce
sugar maple
sycamore
tulip
walnut
water chestnut
white ash
white oak
white pine
willow
yellow birch
yellow cedar
yew

APPENDIX C

The following is an alphabetical listing of the 109 trees used in part one of this experiment.

acorn
almond
apple
ash
aspen
avocado
balsa
balsam fir
bamboo
banana
banana palm
baobab
beech
birch
black cherry
black oak
black walnut
blue spruce
bonzai
brazil nut
breadfruit
briar
cactus
cedar
cherry
cherry blossom
chestnut
China berry
coconut
coconut palm
coniferous
coniferous pine
crabapple
crepe myrtle
cypress
date palm
dogwood
Douglas fir
ebony
elm
eucalyptus
evergreen
fern palm
fig
fir
flowering peach
ginkgo
grapefruit
gum
hazelnut
hickory
holly
juniper
laurel
lemon
lime
locust
macadamia
magnolia
mahogany
mango
mangrove
maple
mayberry
mimosa
miniature apple
mulberry
mustard
nectarine
Norfolk pine
oak
oleander
olive
orange
palm
peach
pear
pecan
pine
pineapple
plum
poplar
red maple
redbud
redwood
rosewood
rubber
sage
sassafras
Scotch pine
scrub pine
sequoia
spruce
sugar maple
sweet cherry
sweetgum
sycamore
tangerine
taro
teak
tulip
tulip poplar
walnut
weeping cherry
weeping willow
white pine
willow
wisteria
woody pine

APPENDIX D

The 50 Kinds of Trees for which Property Lists Were Elicited in Jane Gretz's Experiment

GROUP A:

apple
ash
beech
blue spruce
boxwood
cedar
chestnut
coconut
date
dogwood
Douglas fir
eucalyptus
evergreen
hickory
holly
locust
magnolia
mahogany
oak
pear
red maple
redwood
sugar maple
sycamore
white pine

GROUP B:

aspen
balsa
banana
birch
cherry
crabapple
cypress
elm
fig
fir
ginkgo
larch
maple
mimosa
palm
pin oak
pine
poplar
rubber
Scotch pine
spruce
tulip
walnut
willow
yew

APPENDIX E

JANE GRETZ
Master's Experiment 1987

INSTRUCTIONS FOR PROPERTY LIST TASK

\- - - - - - - - - -

Please take a moment to number the pages in your packet in the upper left-hand corner from 1 to 25 (do not use the "#_____" spaces).

\- - - - - - - - - -

On this deck of cards, I have written the names of 25 kinds of trees. In a moment, I'll start showing them to you one at a time and ask you to write down all the characteristics you can think of for each tree presented.

By "characteristics" I mean what you know about that kind of tree. For example, how big it is, what its bark or leaves look like, what special uses it has (if any), where it is usually found, and so forth.

The procedure is as follows:

a. When I show you a card, write the name of the tree at the top of a sheet of paper, then look up and wait for my signal to begin.

b. When I say, "Go," you will have 75 seconds to list as many properties of the tree as you can think of.

c. If you finish ahead of time, do not go back to previous lists.

d. Finally, please don't look to see what your neighbor is doing.

APPENDIX F

The following are some problematic examples taken from subjects' property listings and an explanation of how they were dealt with.

PROBLEM: "short green bristles"

SOLUTION: Counted as two properties - short bristles and green bristles.

RATIONALE: When there's more than one adjective before a noun, count each as a separate property, unless the adjectives go together like reddish-brown, dark green, or 5-pointed.

PROBLEM: "the tallest tree"

"very tall but not too thick a trunk"

[Listed by same subject for same segregate.]

SOLUTION: When an adjective is used twice, only count it one time.

PROBLEM: "beautiful pink and white flowers"

SOLUTION: Counted as pink flowers and white flowers.

RATIONALE: Personal opinions are not counted.

PROBLEM: "small (miniature)"

SOLUTION: Counted as one.

RATIONALE: Subject is just clarifying what he/she meant by small.

PROBLEM: "grown in areas with lots of sun and warmth like California"

SOLUTION: Counted as three, i.e., sun, warm, and California.

PROBLEM: (weeping willow) "is a willow tree"

(blue spruce) "is a spruce tree"

(redwood) "is a pine tree"

SOLUTION: The first two examples are simply not counted as properties, but the third counts as one property.

RATIONALE: If the tree name is repeated as a description, do not count the name, but if it not (as in redwood "is a pine tree") do count it as a property.

PROBLEM: "grows peach fruit"

"pit of fruit is seed"

[Listed by same subject for same segregate.]

SOLUTION: Counted as two.

RATIONALE: When a person describes the fruit in greater detail, it is like describing the types of wood a tree produces in greater detail. All properties describing wood and its uses are considered separate properties of the tree being described.

PROBLEM: "sheds its leaves in the fall"

SOLUTION: Counted as two.

RATIONALE: When a particular season is mentioned for an occurrence, count the season, too.

PROBLEM: "more slender trunk and branches than an oak tree say"

SOLUTION: Counted as three.

RATIONALE: When another tree is used as a comparison, count the comparison made as a property.

PROBLEM: "it stays green all year, it doesn't shed leaves"

SOLUTION: Counted as one.

RATIONALE: When a person says the same thing twice, count only once.

PROBLEM: "good for smoking fish and game"

SOLUTION: Counted as one, because smoking is the process used for both fish and game.

PROBLEM: "migrates to Miami in Winter months"

"likes the outdoors and water sports"

SOLUTION: Do not count what are obviously intended as sarcastic remarks or attempts at humor.

APPENDIX G

STANDARD LIST OF 50 TREES	Numbers of Properties for Trees (2 Groups of 21 Sub) MEAN	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
apple	5.81	1.84	4	6	9	4	4	7	8	5	9	6	4	7	4	6	2	7	4	7	5	6	8
ash	2.86	2.27	0	0	7	1	5	2	7	4	7	3	4	1	4	2	0	1	1	5	1	3	2
beech	2.43	2.04	1	0	3	3	0	1	7	3	6	2	2	3	0	2	3	0	2	2	3	1	7
blue spruce	3.76	2.41	0	5	1	3	0	3	9	6	5	0	6	3	5	7	3	7	5	3	3	3	2
boxwood	1.52	2.54	0	3	4	0	0	0	0	0	6	0	0	1	0	3	0	0	0	0	7	0	8
cedar	4.24	2.58	2	4	7	4	3	3	8	4	10	2	6	2	3	0	3	0	4	7	7	3	7
chestnut	4.76	2.37	4	4	2	6	1	2	9	3	7	4	6	5	2	7	3	3	4	7	10	4	7
coconut (palm)	7.10	2.49	5	1	6	5	6	9	11	6	7	11	6	8	3	8	6	8	9	8	9	6	11
date	4.14	2.08	3	0	7	4	6	2	7	5	7	3	4	3	3	3	2	7	4	8	3	2	4
dogwood	4.67	3.11	0	0	8	5	1	2	7	8	5	0	8	5	2	9	0	5	4	7	8	6	8
Douglas fir	3.76	2.37	5	0	3	1	5	3	6	6	6	0	7	5	0	5	2	0	5	6	4	3	7
eucalyptus	3.57	2.28	2	6	6	4	7	7	5	3	6	1	2	5	2	1	0	1	2	6	6	2	1
evergreen	5.90	1.95	7	1	9	7	3	7	6	8	6	5	2	5	5	8	5	7	6	7	6	6	8
hickory	3.14	2.23	2	0	6	1	1	2	7	3	9	1	1	4	5	3	2	2	3	3	2	3	6
holly	5.33	3.55	5	0	1	6	2	6	6	7	6	0	6	7	1	9	3	0	7	10	11	7	12
locust	2.38	2.30	0	3	4	2	0	0	6	0	6	3	1	5	0	0	6	1	1	0	6	2	4
magnolia	3.52	2.38	2	1	2	2	0	0	6	7	3	4	4	2	4	5	3	0	5	4	9	4	7
mahogany	4.48	2.08	1	5	5	3	6	2	5	4	10	4	4	5	5	3	0	6	5	6	5	3	7
oak	5.52	1.84	3	5	9	4	5	6	7	6	8	6	4	2	4	5	4	7	4	8	7	4	8
pear	4.38	1.50	4	2	4	3	3	5	8	4	6	6	3	4	2	5	3	6	4	6	4	4	6
red maple	3.90	1.74	5	4	3	3	3	3	5	3	7	0	5	6	3	2	1	4	4	7	4	4	6
redwood	6.24	2.00	6	3	8	4	10	3	8	5	8	5	7	6	7	7	4	8	6	7	5	4	10
sugar maple	4.57	1.76	2	5	4	4	5	2	6	4	8	5	5	5	4	8	1	4	3	6	7	4	4
sycamore	2.81	1.84	0	0	4	3	1	4	6	3	6	2	2	4	1	2	2	3	3	5	1	6	1
white pine	4.62	1.70	4	6	5	4	5	2	8	5	8	3	3	2	6	5	2	3	6	6	5	5	4
aspen	3.14	2.53	0	4	1	1	5	0	4	6	7	0	3	2	2	0	3	3	7	0	5	5	8
balsa	2.43	1.71	3	5	2	4	3	0	2	4	6	3	0	1	1	0	2	3	3	1	4	4	0
banana	6.00	2.45	6	10	3	3	7	4	5	6	6	9	7	5	9	3	7	3	12	5	7	6	3
birch	4.33	2.48	2	7	3	3	3	2	6	5	0	5	4	2	5	2	5	3	10	9	3	4	8
cherry	6.57	2.38	2	6	4	5	8	7	8	5	9	8	8	3	6	6	9	8	12	3	5	7	9
crabapple	5.52	2.36	0	7	5	4	4	1	7	6	6	6	6	3	7	7	7	4	8	4	6	7	11
cypress	3.14	2.71	4	4	1	0	3	0	3	4	0	0	4	0	3	1	9	1	9	4	7	5	4
elm	3.86	1.70	3	6	2	4	0	3	6	4	7	5	3	3	7	4	5	2	4	4	2	4	3
fig	4.43	2.44	3	7	2	3	3	6	5	4	1	4	4	1	7	1	8	4	9	2	5	5	9
fir	3.76	2.09	3	4	2	3	5	0	5	6	4	4	3	1	4	1	6	3	9	2	6	2	6
ginkgo	1.48	1.99	0	4	0	0	0	0	3	3	0	0	0	0	5	0	5	0	6	2	2	0	1
larch	0.86	1.55	0	4	0	0	0	0	4	5	0	0	0	0	0	0	0	2	0	1	0	2	0
maple	6.19	1.50	2	6	6	7	8	5	7	7	7	6	6	7	9	5	7	5	8	4	5	7	6
mimosa	2.10	2.39	0	4	0	0	3	0	4	7	0	0	0	0	3	0	4	2	2	4	8	3	0
palm	7.57	2.06	10	8	5	5	10	7	5	7	12	6	8	7	5	9	7	5	11	8	10	7	7
pin oak	3.19	2.08	2	2	4	0	5	0	5	5	5	5	2	2	0	2	3	5	6	0	4	3	7
pine	6.19	1.99	6	5	5	6	8	2	7	5	7	5	5	6	4	5	9	4	10	5	8	9	9
poplar	1.81	2.11	0	4	4	0	0	0	2	3	0	0	0	1	5	0	1	2	8	3	3	2	0
rubber	4.00	2.02	2	7	3	1	6	0	3	3	5	2	4	5	4	4	5	2	8	4	6	3	7
Scotch pine	4.19	2.24	5	4	4	1	6	0	5	5	8	6	2	1	5	0	4	5	5	3	8	5	6
spruce	4.33	2.92	1	6	6	1	4	2	6	7	0	0	6	4	8	0	6	4	7	2	6	4	11
tulip	2.24	1.80	2	4	0	0	2	2	5	4	0	3	1	2	0	1	7	3	1	1	4	2	3
walnut	4.10	2.04	2	7	5	5	7	1	4	5	0	2	3	1	7	3	4	4	6	7	4	4	5
willow	5.71	1.86	5	3	4	5	4	3	9	7	7	5	5	7	4	6	7	5	8	5	10	4	7
yew	0.67	1.17	0	3	0	0	0	0	3	1	0	0	0	0	0	0	3	0	0	1	3	0	0

APPENDIX H

STANDARD LIST OF 100 TREES	23 Subjects' Typicality Ratings: X as a "Tree"																									
	n	MEAN	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
acacia	12	3.17	1.86		6		5	3		1		4				2	2					3	2	7	2	1
alder	10	3.30	1.27				2		4	3		5				4						5	3	1	2	4
apple	23	5.91	1.35	5	7	2	4	4	7	5	5	6	4	7	6	7	6	7	7	6	7	7	7	7	6	7
apricot	22	4.27	1.21		4	3	3	3	6	4	3	6	4	3	3	4	3	5	3	5	4	5	6	7	5	5
areca palm	16	3.19	1.42			3	3	3		4	5	1	2	3	5	1	4			4		6	1		3	3
ash	21	4.76	1.51	4		4	5	3	6	3	6	7	4	4	5	6	6		4	4	6	4	4	1	7	7
aspen	20	4.30	1.05			5	3	4	6	4	4	3	4	3	4	5	3		4	5	4	5	3	5	5	7
avocado	23	4.30	1.40	4	7	3	3	4	4	4	3	5	3	5	3	2	2	4	4	6	4	5	6	7	6	5
balsa	20	4.00	1.26		6	1	3	4	3	3	3	5	6	2	5	4	4		4		5	5	3	5	5	4
banana	23	4.26	1.62	4	7	2	2	3	6	3	3	6	3	2	4	4	3	3	4	6	4	5	7	7	4	6
banyan	9	2.44	1.34				2			5		1	3			1				3			2		4	1
baobab	6	2.17	1.07				2					3				4						2			1	1
beech	21	4.62	1.70			2	3	3	4	5	6	4	3	4	5	7	4	6	3	7	7	5	6	1	7	5
birch	22	5.50	1.34	3		5	4	5	7	5	3	7	6	5	5	6	5	6	7	6	7	5	7	3	7	7
black ash	18	3.33	1.41			3	1	2	2	3	4	4	3		5	3	3			3	2	6	3	3	7	3
black oak	21	3.62	1.50		1	5	2	1	3	5	5	5	3	3	4	4	5		1	6	3	5	5	4	4	2
black walnut	20	3.65	1.39			4	2	1	3	5	5	5	4	2	3	2	5		3	5	2	6	5	3	3	5
blue spruce	21	4.48	1.65			2	3	2	6	6	7	5	4	4	6	4	5	5	4	6	1	6	4	6	6	2
boxwood	12	4.00	1.35			5				4	3	2				2	6			5		6	5	3	4	3
broadleaf	14	3.43	1.95	3		4			1	7		7		2		1	3			1		4	5	3	5	2
burr oak	18	3.78	1.47			5	3	2	1	5	5	4	3			1	3		2	5	5	4	5	5	6	4
catalpa	7	2.43	1.05			3	1					3											3	4	2	1
cedar	23	5.78	1.28	3	3	6	5	4	7	6	6	6	6	6	6	3	6	6	7	7	7	6	6	7	7	7
cherry	23	5.22	1.47	1	6	4	4	4	7	5	4	6	5	4	6	7	3	5	7	6	7	5	6	7	5	6
chestnut	23	4.57	1.56	1	2	5	5	2	5	2	5	6	5	4	4	5	7	5	4	4	6	4	6	6	5	7
citrus	22	5.86	1.29		7	3	5	7	4	5	5	7	7	6	7	3	5	5	7	6	7	7	6	6	7	7
coconut (palm)	22	4.77	1.04		7	4	4	3	5	4	4	5	5	5	5	3	5	4	3	5	6	6	5	6	6	5
cottonwood	16	3.56	1.73			4	1	2	1	3	2	4				2	3	4		7		5	4	6	6	3
crabapple	23	4.91	1.64	4	1	7	3	4	6	4	5	3	4	5	4	5	3	6	7	6	7	6	6	3	7	7
cutleaf maple	19	3.37	1.22		2		2	3	5	3	5	4	2		5	1	5	3	2	3	3	5	4		4	3
cypress	20	4.90	1.09		5	3	5	4	4	5	5	5	6	5	3	4	4	6		4	7	5	5		6	7
date	22	4.27	1.48	3		2	5	3	2	4	4	4	4	5	3	4	2	3	5	6	7	6	6	7	4	5
dogwood	20	4.70	1.62			6	3	3	4	5	4	5	4	4		5	6	5	7	6	2	6	7	1	4	7
Douglas fir	18	4.72	1.73			3	3	6	2	4	5	6	5	3		5	6		5	4	1	6	7		7	7
ebony	18	3.50	1.21	5	5	5	1			3	3	5		3		4	3	5	2	3	2		3	3	3	5
elm	22	5.86	1.06		6	7	4	4	7	5	6	7	6	5	4	6	7	6	7	5	7	6	7	5	5	7
eucalyptus	23	4.09	1.47	5	7	2	2	5	3	4	2	5	3	3	2	5	3	3	5	4	7	5	6	5	4	4
evergreen	23	6.43	1.01	4	3	7	6	6	7	7	7	6	6	7	7	6	7	7	7	7	7	7	7	7	6	7
fig	21	4.76	1.34			3	5	4	4	3	3	4	4	5	3	5	3	6	7	5	7	6	6	5	5	7
fir	22	5.18	1.37	4		4	3	6	7	6	6	7	5	4	2	6	6	5	6	4	3	6	6	5	6	7
fruit	22	6.32	0.87		6	5	6	7	6	7	7	7	7	7	7	6	7	6	7	6	5	7	4	7	5	7
ginkgo	8	3.00	1.41			3					4	4				1						4	2		5	1
golden chain	6	3.00	1.29									2										3	3	5	4	1
golden del. apple	21	4.76	1.41	5	5	2	3	3	6	4	4	4	3	5	6	4	5	7	6		4	6	7		4	7
grapefruit	23	4.74	1.19	6	4	3	4	3	5	3	5	5	4	5	4	5	3	4	7	5	6	6	6	5	4	7
gum	20	3.15	1.42		6	2	3	3	1	5	4	4	3	2		2	2		3	1	5	3	2	6	3	3
hawthorn	13	3.08	1.14			3	1	2	3			2				5	3	3		3		4		2	5	4
hazelnut	21	3.57	1.37	4			2	2	2	3	3	3	5	2	3	3	2	3	2	5	4	5	6	6	5	5
hickory	22	5.27	1.25	4		6	3	2	6	5	6	5	5	4	5	6	4	5	6	6	7	6	7	6	5	7
holly	22	4.23	1.04	3		4	3	3	5	6	4	6	4	4	3	4	5	3	5	3	4	5	5	3	5	6
honey locust	14	3.07	1.49				1	2	2			5				1		3	1	3	3	5	5	3	4	5
horse chestnut	18	3.39	1.46			3	3	2	1	2	5	4	3		4	2	4		2	5		5	4	2	7	3
japonica	6	1.17	0.37					1				1				2								1	1	1

larch	10	2.80	1.60				1					2				2				2	6	5	3	1	2	4
lemon	23	4.43	1.56	2	7	2	5	2	3	4	3	5	5	4	4	3	3	3	6	6	5	6	6	6	5	7
lilac	20	4.25	1.22			3	2		3	5	4	4	3	3	6	3	5	5	4	4	6	6	3	6	5	5
locust	20	3.75	1.30	3		3	3		4	2	3	5		3	3	2	4	2	2	5	5	5	5	6	6	4
lodgepole pine	20	3.90	1.26		5	4		4	4		4	6	2	5	5	1	3	4	2	6	4	5	4	4	3	3
Lombardy poplar	6	3.50	1.71									2				3						4	3		7	2
magnolia	21	4.48	1.71		6	3	4	2	5	3	2	6	5		5	2	3	6	2	3	7	5	6	7	6	6
mahogany	20	4.60	1.62			4	2	3	4	4	2	6	6		5	5	4	6	7	2	6	4	3	7	5	7
maple	22	6.36	0.88		5	7	5	4	7	6	5	7	6	7	7	7	6	6	7	6	7	7	7	7	7	7
McIntosh apple	22	4.86	1.42	4		4	3	2	3	4	5	5	5	6	4	6	2	6	6	6	5	5	6	6	7	7
mimosa	16	3.31	1.53			1	1	3	5	3	2	4	2			4	2				5	5	2	6	3	5
oak	23	6.30	1.04	5	5	7	5	3	7	7	6	7	6	6	6	7	7	5	7	7	7	7	7	7	7	7
olive	23	4.57	1.50	3	6	1	4	3	6	3	3	5	5	6	5	3	4	6	5	5	6	4	3	7	5	7
orange	23	5.70	1.40	2	7	5	6	4	6	4	4	6	6	7	6	4	5	7	7	6	7	7	7	7	4	7
palm	23	6.09	1.06	5	7	5	6	5	7	7	5	6	6	6	7	7	5	5	7	6	7	7	3	7	7	7
peach	22	4.86	1.32		7	2	3	4	6	4	3	6	4	5	5	5	3	6	6	6	5	5	5	7	4	6
pear	23	5.13	1.42	4	7	2	3	4	7	4	4	5	3	5	5	6	4	6	7	7	6	6	6	5	5	7
pecan	22	4.05	1.19		6	2	2	3	4	4	4	6	5	4	4	4	3	4	3	6	4	5	5	2	4	5
persimmon	14	2.93	1.28				2	3	1	3	3	2				3			1		3	5	3	5	5	2
pin oak	21	4.00	1.69	4		6	1	2	3	4	4	6	3		3	5	6	3	2	5	2	6	6	2	7	4
pine	23	6.65	0.87	3	7	7	6	7	7	6	7	7	6	7	7	7	6	7	7	7	7	7	7	7	7	7
plum	22	4.50	1.41	2		2	4	3	6	3	3	3	4	5	4	5	4	5	4	6	6	6	6	6	5	7
Ponderosa pine	20	4.15	1.46			4	2	5	2	2	5	4	5	3	4	2	5	5	3	3		6	5	7	5	6
poplar	17	4.24	1.66			2	4		1	5	3	7			3	4	3	5	3	5	5	7	4		7	4
red cedar	22	4.73	1.25	5	2	6	2	3	5	5	6	5	4	6	4	6	5		3	6	5	6	5	4	6	5
red maple	22	4.09	1.59		1	3	2	2	5	3	5	4	4	3	4	4	5	3	7	5	4	6	6	2	5	7
redwood	22	4.55	1.92	4		6	2	2	7	3	2	6	5	1	2	7	3	4	6	5	5	5	7	7	4	7
rubber	22	4.14	2.01	1	7	2	1	5	2	4	2	4	6	2	5	5	2		5	6	7	2	6	7	4	6
Scotch pine	23	3.83	1.69	1	1	2	2	3	4	3	5	5	4	3	5	4	3	5	1	6	4	6	6	3	5	7
screw palm	16	3.13	1.62		6		2	2	2	3	4	4	2	1	5	2	3					5	2		6	1
shaggy-bark hickory	14	3.14	1.64				1	1		4	6	4	2	3		3			1	5		5	4		1	4
silver birch	19	3.58	1.43			4	1	1	2	3	2	5	4	4		2	4	4	3	6		6	4	4	4	5
silver maple	20	3.65	1.59				1	1	4	4	4	4	4	2	5	3	4	4	1	4	2	6	5	3	7	5
smooth-bark hickory	16	3.19	1.13				2	2	4	3	4	4	3	2	3	2	3			5		5	4		1	4
spruce	22	5.50	1.16	4		5	3	4	5	4	7	6	5	4	6	6	6	6	5	5	7	7	6	6	7	7
sugar maple	23	4.78	1.56	6	3	3	3	2	6	4	5	5	4	4	6	6	4	5	6	7	3	7	6	2	6	7
sycamore	22	4.64	1.72	3		6	2	3	7	3	4	5	3	4	3	6	4	6	5	5	7	5	7	6	7	1
tulip	20	4.40	1.53		6	3	5	3	2	4	6	5	4			3	3	6	2	5	3	6	3	7	6	6
walnut	22	5.41	1.30	5		4	4	2	7	6	5	7	5	5	5	5	7	4	5	4	7	6	6	7	6	7
water chestnut	20	3.65	1.39			3	2	3	3	2	4	5	3		4	3	4	3	3	4	5	3	3	2	7	7
white ash	20	3.65	1.35	2		6	1	2	5	3	4	4	4		3	5	3	3	2	4	5	5	3		6	3
white oak	21	4.48	1.68	4		4	1	1	3	5	5	4	4	7	3	4	6	4	6	5	6	5	3		7	7
white pine	21	4.24	1.72		6	5	2	2	4	5	6	4	4	3		6	6	4	3	4	1	7	4	1	6	6
willow	22	4.95	1.49	5		6	5	4	5	5	3	5	4	1	5	6	4	6	7	2	7	5	6	5	6	7
yellow birch	22	3.64	1.11	2		4	2	2	3	3	3	4	4	4	2	3	4	4	3	6	4	4	4	5	4	6
yellow cedar	20	3.75	1.37			2	2	2	3	3	5	4	3	3		2	4	4	2	6	4	5	5	4	6	6
yew	10	3.10	1.58				2	2		4	4	5				2						5		1	5	1

APPENDIX I

SEGREGATES	POS	FLL	SDL	TYP1	TYP2	PROP	SDR
apple	0.43	61	71	5.91	5.91	5.81	15
ash	0.57	14	64	4.76	4.43	2.86	6
aspen	0.33	3	41	4.30	3.87	3.14	3
balsa	0.44	6	57	4.00	3.61	2.43	5
banana	0.62	13	65	4.26	4.26	6.00	10
beech	0.38	13	65	4.62	4.30	2.43	6
birch	0.47	45	71	5.50	5.30	4.33	38
blue spruce	0.46	12	61	4.48	4.17	3.76	30
boxwood	0.91	3	26	4.00	2.57	1.52	2
cedar	0.51	16	70	5.78	5.78	4.24	18
cherry	0.52	48	72	5.22	5.22	6.57	15
chestnut	0.58	26	72	4.57	4.57	4.76	12
coconut (palm)	0.76	14	43	4.77	4.61	7.10	17
crabapple	0.64	11	68	4.91	4.91	5.52	20
cypress	0.48	4	58	4.90	4.39	3.14	8
date	0.72	3	66	4.27	4.13	4.14	1
dogwood	0.50	37	69	4.70	4.22	4.67	45
Douglas fir	0.56	8	57	4.72	3.91	3.76	15
elm	0.29	32	71	5.86	5.65	3.86	17
eucalyptus	0.69	3	65	4.09	4.09	3.57	9
evergreen	0.60	22	72	6.43	6.43	5.90	65
fig	0.70	7	69	4.76	4.43	4.43	5
fir	0.46	18	70	5.18	5.00	3.76	23
ginkgo	0.41	6	28	3.00	1.70	1.48	9
hickory	0.58	8	71	5.27	5.09	3.14	4
holly	0.61	4	56	4.23	4.09	5.33	29
larch	0.47	5	14	2.80	1.78	0.86	2
locust	0.60	8	55	3.75	3.39	2.38	8
magnolia	0.61	6	68	4.48	4.17	3.52	16
mahogany	0.48	6	65	4.60	4.13	4.48	3
maple	0.25	57	72	6.36	6.13	6.19	40
mimosa	0.79	9	48	3.31	2.61	2.10	15
oak	0.18	65	72	6.30	6.30	5.52	43
palm	0.55	38	68	6.09	6.09	7.57	44
pear	0.58	36	71	5.13	5.13	4.38	4
pin oak	0.51	4	29	4.00	3.74	3.19	9
pine	0.42	51	71	6.65	6.65	6.19	48
poplar	0.41	8	67	4.24	3.39	1.81	6
red maple	0.40	12	61	4.09	3.96	3.90	20
redwood	0.62	35	71	4.55	4.39	6.24	49
rubber	0.47	8	68	4.14	4.00	4.00	16
Scotch pine	0.55	9	58	3.83	3.83	4.19	16
spruce	0.43	21	70	5.50	5.30	4.33	28
sugar maple	0.24	5	59	4.78	4.78	4.57	11
sycamore	0.53	16	67	4.64	4.48	2.81	8
tulip	0.55	8	51	4.40	3.96	2.24	10
walnut	0.49	28	71	5.41	5.22	4.10	9
white pine	0.48	12	53	4.24	3.96	4.62	15
willow	0.43	22	70	4.95	4.78	5.71	56
yew	0.87	3	32	3.10	1.91	0.67	5

VITA

Jane Anne Gretz was born in Rantoul, Illinois, on April 2, 1963, to Herbert and Shirley Gretz. She attended Niskayuna High School in Schenectady, New York, where she graduated in 1981. In 1985, she completed her B.A. degree, with a major in social relations and minors in studio art and classics, from Lehigh University.