

An Investigation on Polysemy and Lexical Organization of Verbs

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Abstract

This work investigates lexical organization of verbs looking at the influence of some linguistic factors on the process of lexical acquisition and use. Among the factors that may play a role in acquisition, in this paper we investigate the influence of polysemy. We examine data obtained from psycholinguistic action naming tasks performed by children and adults (speakers of Brazilian Portuguese), and analyze some characteristics of the verbs used by each group in terms of similarity of content, using Jaccard's coefficient, and of topology, using graph theory. The experiments suggest that younger children tend to use more polysemic verbs than adults to describe events in the world.

1 Introduction

Lexical acquisition is restrained by perception and comprehension difficulties, which are associated with a number of linguistic and psycholinguistic factors. Among these we can cite age of acquisition (Ellis and Morrison, 1998; Ellis and Ralph, 2000), frequency (Morrison and Ellis, 1995), syntactic (Ferrer-i-Cancho et al., 2004; Goldberg, 1999; Thompson et al., 2003) and semantic (Breedin et al., 1998; Barde et al., 2006) characteristics of words. In terms of semantic features, acquisition may be influenced by the polysemy and generality of a word, among others.

In terms of semantic features, acquisition may be influenced by the generality and polysemy of a word, among others. For instance, considering acquisition of verbs in particular, Goldberg (1999) observes that verbs such as *go*, *put* and *give* are

among those to be acquired first, for they are more general and frequent, and have lower “semantic weight” (a relative measure of complexity; Breedin et al., 1998; Barde et al., 2006). These verbs, known as light verbs, not only are acquired first: they are also known to be more easily used by aphasics (Breedin et al., 1998; Thompson, 2003; Thompson et al. 2003; Barde et al. 2006; but see Kim and Thompson, 2004), which suggest their great importance for human cognition. The preference for light verbs may be explained by the more general meanings they tend to present and their more polysemic nature, that is their ability to convey multiple meanings, since the more polysemic the verb is, the more contexts in which it can be used (Kim and Thompson, 2004; Barde et al., 2006). The importance of the number of relationships a word has in the learning environment has been pointed out by Hills et al. (2009), regardless of generality. Several factors may influence acquisition, but in this paper we will focus on polysemy.

Understanding how characteristics like polysemy influence acquisition is essential for the construction of more precise theories. Therefore, the hypothesis we investigate is that more polysemous words have a higher chance of earlier acquisition. For this purpose, we compare data from children and adults from the same linguistic community, native speakers of Brazilian Portuguese, in an action naming task, looking at lexical evolution by using statistical and topological analysis of the data modeled as graphs (following Steyvers and Tenenbaum, 2005, and Gorman and Curran, 2007). This approach innovates in the sense that it directly simulates the influence of a linguistic factor over the process of lexical evolution.

This paper is structured as follows. Section 2 describes relevant work on computational modeling of language acquisition. Section 3 presents the materials and methods employed in the experiments of the present work. Sections 4 and 5 present the results, and section 6 concludes and presents future work.

2 Related Work

In recent years, there has been growing interest in the investigation of language acquisition using computational models. For instance, some work has investigated language properties such as age-of-acquisition effects (Ellis and Ralph, 2000; Li et al., 2004). Others have simulated aspects of the acquisition process (Siskind, 1996; Yu, 2005; Yu, 2006; Xu and Tenenbaum, 2007; Fazly et al, 2008) and lexical growth (Steyvers and Tenenbaum, 2005; Gorman and Curran, 2007).

Some authors employ graph theory metrics to directly analyze word senses (Sinha and Mihalcea, 2007; Navigli and Lapata, 2007). In this paper, word senses are implicitly expressed by graph edges, thus being considered indirectly. Graph theory has also been successfully used in more theoretical fields, like the characterization and comparison of languages (Motter et al., 2002; Ferrer-i-Cancho et al., 2004; Masucci and Rodgers, 2006). For example, the works by Sigman and Cecchi (2002), and Gorman and Curran (2007) use graph measures to extensively analyze WordNet properties. Steyvers and Tenenbaum (2005) use some properties of language networks to propose a model of semantic growth, which is compatible with the effects of learning history variables, such as age of acquisition and frequency, in semantic processing tasks. The approach proposed in this work follows Steyvers and Tenenbaum (2005), and Gorman and Curran (2007) in the sense of iterative modifications of graphs, but differs in method (we use involutions instead of evolutions) and objective: modifications are motivated by the study of polysemy instead of production of a given topological arrangement. It also follows Deyne and Storms (2008), in the sense that it directly relates linguistic factors and graph theory metrics, and Coronges et al. (2007), in the sense that it compares networks of different populations with the given approach.

As to Brazilian Portuguese, in particular, Antiquera et al. (2007) relate graph theory metrics and

text quality measurement, while Soares et al (2005) report on a phonetic study. Tonietto et al. (2008) analyze the influence of pragmatic aspects, such as conventionality of use, over the lexical organization of verbs, and observe that adults tend to prefer more conventional labels than children.

In this context, this study follows Tonietto et al (2008) in using data from a psycholinguistic action naming task. However, the analysis is done in terms of lexical evolution, by using graph and set theory metrics (explained below) to understand the influence of some linguistic characteristics of words, especially polysemy.

3 Materials and Methods

3.1 The Data

This paper investigates the lexical evolution of verbs by using data from an action naming task performed by different age groups: 55 children and 55 young adults. In order to study the evolution of the lexicon in children, children's data are longitudinal; participants of the first data collection (G1) aged between 2;0 and 3;11 (average 3;1), and in the second collection (G2), between 4;1 and 6;6 (average 5;5) as described by Tonietto et al. (2008). The adult group is unrelated to the children, and aged between 17;0 and 34;0 (average 21;8). The longitudinal data enabled the comparison across the lexical evolution of children at age of acquisition (G1), two years later (G2), and the reference group of adults (G3). Participants were shown 17 actions of destruction or division (Tonietto et al, 2008); answers were preprocessed in order to eliminate both invalid answers (like "I don't know") and answers with only 1 occurrence per group. The selection of this particular domain (destruction and division) is due to its cognitive importance: it was found to be one of the four conceptual zones, grouping a great amount of verbs¹ (Tonietto, 2009).

There were a total of 935 answers per group, out of which 785, 911 and 917 were valid answers to G1, G2 and G3, respectively. These made averages of 46.18, 53.59 and 53.94 valid answers per action, respectively. The average numbers of distinct valid answers per action, before merging (explained in section 3.2), were 6.76, 5.53 and 4, respectively.

¹ The others are evasion, excitation, and union.

The answers given by each participant were collected and annotated two polysemy scores, each calculated from a different source:

- Wscore is the polysemy score of a verb according to its number of synsets (synonym sets) in WordNetBR (Dias-da-Silva et al., 2000, Maziero, 2008), the Brazilian Portuguese version of Wordnet (Fellbaum, 1998).
- Hscore is the number of different entries for a verb in the Houaiss dictionary (Houaiss, 2007).

Information about these two scores for each group is shown in Table 1.

	G1	G2	G3
Average type Wscore	10.55	10.64	10.48
Average token Wscore	16.25	14.66	11.13
Average type Hscore	21.59	20.84	16.26
Average token Hscore	26.93	23.02	17.82

Table 1: Score per group and per participant.

We notice that most scores, i.e., type and token Hscores, and token Wscore, decrease as age increases, which is compatible with the hypothesis investigated. However, due to the limited coverage of WordNetBR², some verbs had a null value, and this is reflected in type Wscore. This is the case of “*serrar*” (to saw) which appears in both G1 and G2, but not in G3.

A comparative analysis of linguistic production across the different groups is presented in Table 2. There is a significant similarity across the groups, with 12 verbs (out of a total of 44) being common to all of them. In each column, the second graph is compared to the first. In the “G1-G2” column, there are 16 verbs common to both graphs, which represents 64% of the verbs in G2 (with 36% of the verbs in G2 not appearing in G1). As expected, due to the proximity in age, results show a higher similarity between G1 and G2 than between G2 and G3.

	G1-G2	G2-G3	G1-G3	All
Common verbs	16	17	12	12
Verbs only in older group (%)	36	45.16	58.06	-

Table 2: Comparisons between groups³.

3.2 Simulation Dynamics

Linguistic production of each group was represented in terms of graphs, whose nodes represent the verbs mentioned in the task. Verbs uttered for the same action were assumed to share semantic information, thus being related to each other. The existence of conceptual relationships due to semantic association is in accordance with Nelson et al. (1998), where implicit semantic relations were shown to influence on recall and recognition. Therefore, for each age group, all the verbs uttered for a given action were linked together, forming a (clique) subgraph. The subgraphs for the different actions were then connected in a merging step, through the polysemic words uttered for more than one action.

As the goal of this research is to investigate whether a factor such as polysemy has any influence on language acquisition, we examine the effects of using it to incrementally change the network over time. Strategies for network modification, such as network growth (Albert and Barabási, 2002), have been used to help evaluate the effects of particular factors by iteratively changing the network (e.g., Steyvers and Tenenbaum, 2005; Gorman and Curran, 2007). Network growth incrementally adds nodes to an initial state of the network, by means of some criteria, allowing analysis of its convergence to a final state. The longitudinal data used in this paper provides references to both an initial and a final state. However, due to differences in vocabulary size and content between the groups, network growth would require complete knowledge of the vocabulary of both the source and target groups to precisely decide on the nodes to include and where. Network involution, the strategy adopted, works in the opposite way than network growth. It takes an older group graph as the source and decides on the nodes to iteratively remove, regardless of the younger group graph, and uses the latter only as a reference for compari-

² WordNetBR was still under construction when annotation was performed.

³ Relevant comparisons are for G1-G2 and G2-G3 pairs. Values for G1-G3 are only presented for reference.

son of the structure and content of the resulting graph.

For comparison, graph theory metrics allow us to measure structural similarity, abstracting away from the particular verbs in the graphs. Since graphs represent vocabularies, by these metrics we aim to analyze vocabulary structure, verifying whether it is possible for structures to approximate each other. The graphs were measured in relation to the following:

- number of vertices (n),
- number of edges (M),
- average minimal path length (L),
- density (D),
- average node connectivity (k),
- average clustering coefficient (C/s)⁴,
- average number of repetitions (r).

L assesses structure in the sense of positioning: how far the nodes are from one another. D and k express the relation between number of edges and number of nodes in different ways; they are a measure of edge proportion. C/s measures the distribution of edges among the nodes, assessing the structure *per se*. The division by the number of disconnected subgraphs extends the concept to account for partitioning. Finally, r captures the number of different actions for which the same verb was employed.

Although all metrics are useful for analyzing the graphs, a subset of four was selected to be used in the involution process: k , D , L and C/s . With k and D , we measure semantic share, since that is what relations among nodes are supposed to mean (see above). L and C/s are intended to measure vocabulary uniformity, since greater distances and lower clusterization are related to the presence of subcenters of meaning (again, taking relations as effect of semantic share).

In order to compare the contents of each graph as well, we employed a measure of set similarity; in this case, Jaccard’s similarity coefficient (Jaccard, 1901). With these measures, we analyze how close vocabularies of each two groups are in respect to their content. Given two sets A and B, the Jaccard’s coefficient J can be calculated as follows:

$$J(A, B) = \frac{x}{(x+y+z)},$$

where “ x ” is the number of elements in both A and B, “ y ” is the number of elements only in A, and “ z ” is the number of elements only in B. For this purpose, graphs were taken as verb sets, regardless of their inner relations.

To verify the hypothesis that more polysemic verbs are more likely to be acquired, by node elimination, verbs were ranked in increasing order of polysemy (from less to more polysemic verbs). Therefore, at each step of graph involution, a verb was selected to be removed, and the resulting graph was measured. In case of a tie, verbs with the same polysemy value were randomly selected until all of them have been removed. Results are reported in terms of the averages of 10-fold cross-validation.

4 Results

A topological analysis of the graphs is shown in Table 3. As expected, vocabulary size, represented by n , increases with age, with G1 and G2 being closer in age and size than G2 and G3. A concomitant decrease in the average connectivity (k) of the nodes with age suggests vocabulary specialization. This decrease is even more clearly shown by density (D), since it measures the proportion of edges against the theoretical maximum. As age increases, so does the average minimal path length (L), with less paths through each node, which leads to a more structured and distributed network. Specialization is again represented by a decrease in r , the average number of actions for which each verb was mentioned (the more repeatedly it is mentioned, the less specialized the vocabulary tends to be).

	G1	G2	G3
n	22	25	31
L	1.46	1.6	1.98
D	0.55	0.42	0.27
M	128	126	126
C/s	0.84	0.78	0.78
k	$\mu = 11.64,$ SD = 6.73	$\mu = 10.08,$ SD = 4.86	$\mu = 8.13,$ SD = 4.76
r	$\mu = 5.23,$ SD = 4.41	$\mu = 3.76,$ SD = 3.15	$\mu = 2.19,$ SD = 1.58

Table 3: Properties of graphs.

⁴ We adopt the local clustering coefficient of Watts and Strogatz (1998), but as the graphs may become disconnected during network modification, this value is further divided by the number of subgraphs.

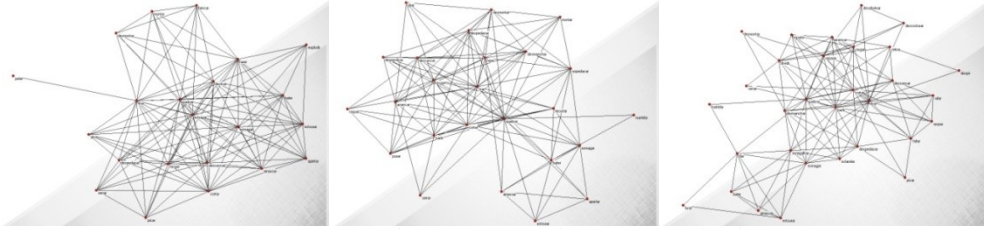


Figure 1. Graphs G1, G2 and G3 respectively.

Results suggest a greater similarity between G1 and G2 than between G2 and G3. Jaccard's coefficient reinforces this result, with a score of 0.52 between G1 and G2, and of 0.44 between G2 and G3.

Figure 1 shows the graphs for each group, where progressive structuring and decentralization can be seen.

The effect of polysemy is observed in the proportion of verbs with a higher degree: G1 is structured by highly connected verbs (there is a low proportion of verbs with low degree), while in G3 more than 80% of the nodes have a degree of 11 or less (Figure 2).

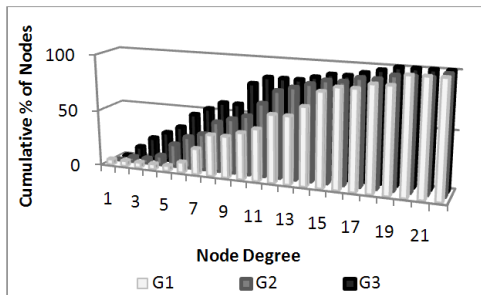


Figure 2. Cumulative histogram of node degree.

5 Simulation Results

This research investigates the relation between the number of meanings and ease of learning, hypothesizing that the more meanings a verb has, the easier it is to be learned, and the earlier children will use it. Particularly considering graph theory metrics, if we remove the verbs with fewer meanings from the graph of an older group, the overall structure will approximate to that of a younger group. Considering set theory metrics, as we remove these verbs, there should be an increase in the similarity between the contents of the graphs.

Therefore, the most relevant part of each chart is its initial state. The verbs to be first removed are expected to be those that differentiate graphs concerning both structure and content.

Although the previous results in section 4 suggest an influence of polysemy on the lexical organization of verbs, we intend to use involutions to confirm these tendencies. Each involution is compared to a random counterpart, making the interpretation easy.

5.1 Network Involution Topology

The graph theory metrics (k , L , C/s and D) of the collected data are shown in Figures 3 and 4 in terms of 2 lines: network involution with node removal (a) by using the selected criterion, and (b) by using random selection (10-fold cross validation). In addition, each figure also shows the measure for the younger group as reference (a dashed, straight, thick line).

In each figure, charts are displayed in four columns and two rows. Each column represents a graph theory metric, and each row refers to the use of a different score. For example, the first chart of each figure is the result of average connectivity (k) in a complete involution, using Wscore. Each legend refers to all eight charts in the figure.

The results of the simulations from G2 to G1 (Figure 3) show that the four metrics are clearly distinct from random elimination from the beginning, indicating that polysemy plays a role in the process. C/s is particularly distinct from random elimination: while the former remains constant almost to the end, indicating a highly structured (clustered) graph, even during node removal, the random elimination shows effects of graph partitioning. The remaining metrics presented their greatest approximations to the reference line before the middle of the chart, suggesting that the initial verbs were actually the ones differentiating both graphs. These results suggest an initial increase in semantic share, as the proportion of edges by node increases (k and D), and in uniformity, as nodes get closer to one another (L) and remain clustered (C/s).

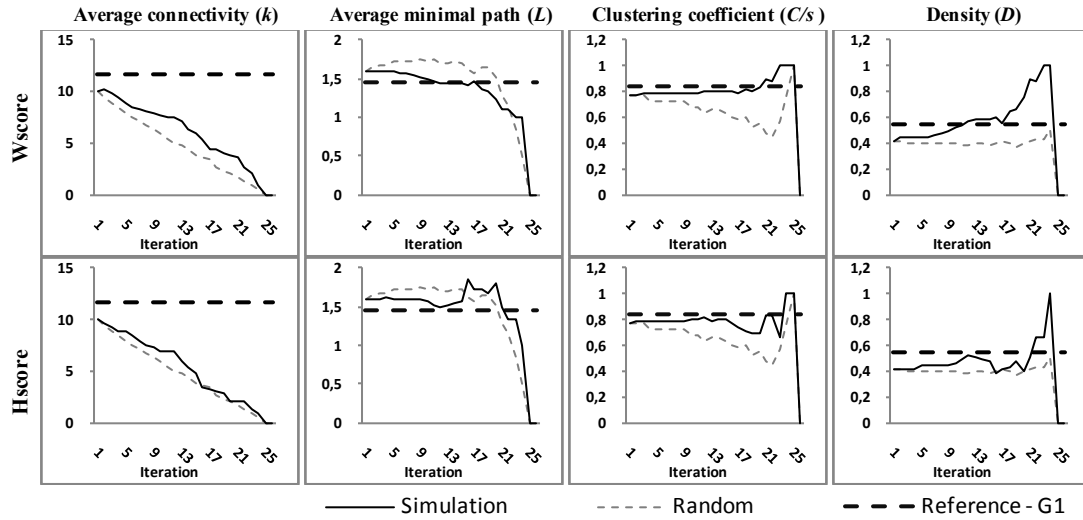


Figure 3. Network involution from G2 to G1 using two scores for node removal: graph theory metrics

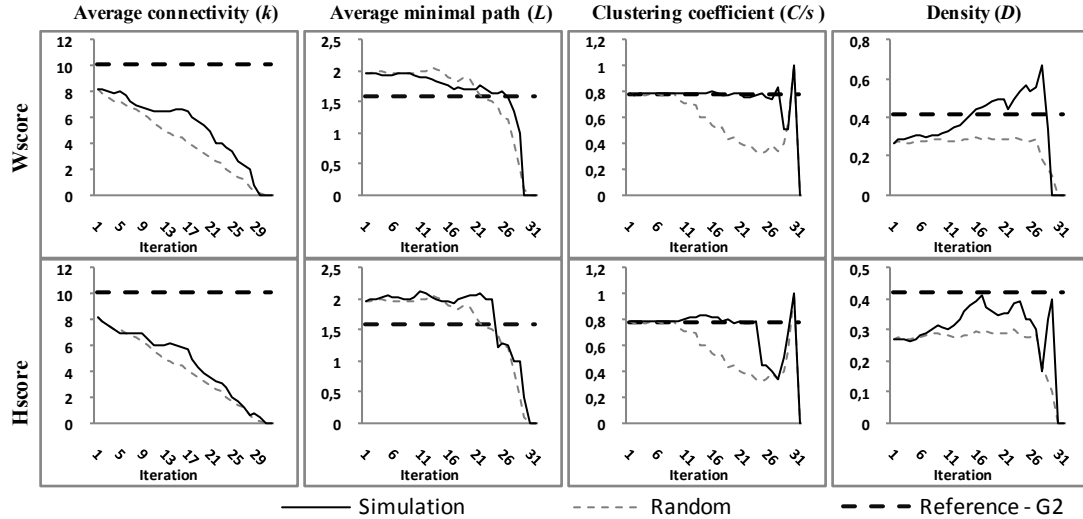


Figure 4. Network involution from G3 to G2 using two scores for node removal: graph theory metrics

Looking at the involution charts of G3, taking G2 as reference, the same tendencies are maintained, although not as clearly as the previous results (Figure 4). The greatest approximations between k and D happen in the first half of the chart, but much closer to the middle when compared with Figure 3. C/s still behaves steadily, remaining stable during most of the simulation, suggesting maintenance of the clustered structure.

The quasi-random behavior of L can be explained by the initial structure of the graphs. They become progressively sparser as age increases, but the difference between G3 and G2 is greater than between G2 and G1 (this was both visually and

statically confirmed). Therefore, G3 would require too many removals until the most distant nodes were eliminated, even in an ideal elimination simulation, thus preventing a descent from the beginning. The same can be said about average connectivity: since G3 has such a low initial score, and low deviation, even if the nodes with the lowest degrees were eliminated, it would not result in a much better result.

5.2 Network Involution Similarity

The main metric to analyze set similarity is Jaccard's coefficient. There are two important factors

influencing it: the number of verbs common to both sets (the “x” component of the formula), “common verbs” hereby; and the number of verbs which are exclusive for the older group, the “different verbs” (the “z” component of the formula, where the older group is represented by “B”). In the charts, a rise means that “different verbs” were eliminated one by one (increasing set similarity),

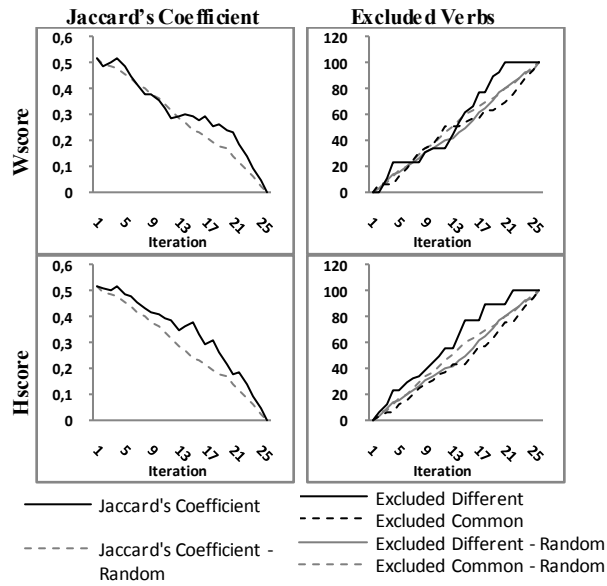


Figure 5. Network involution from G2 to G1 using two scores for node removal: set theory metrics.

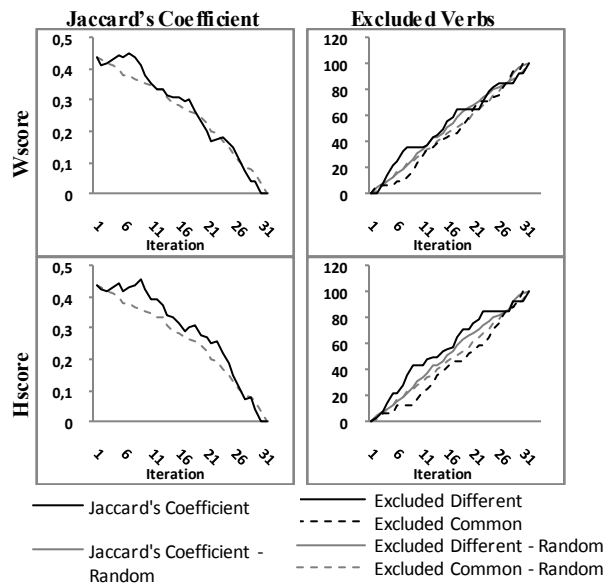


Figure 6. Network involution from G3 to G2 using two scores for node removal: set theory metrics.

and a descent means that “common verbs” were eliminated instead.

In addition to Jaccard’s coefficient, we included the measures for “excluded different” verbs and “excluded common” verbs (and their random counterparts) in percentage. In this sense, the “Excluded Different” line presents the percentage of the “different verbs” excluded so far, and similarly in the “Excluded Common” line. By doing so, it is possible to measure the exact evolution of both sets despite the proportion between them (there are much more “common” than “different” verbs). A rise in the “Excluded Different” line means that sets are getting similar, while stabilization (since descents are not possible) means that they are getting different. The opposite applies to the “Excluded Common” line. All lines start at 0% and end at 100%.

In the figures, charts are arranged in columns (the parameter being measured) and rows (the score being used). This time, each legend is particular to each parameter (one to Jaccard’s coefficient and another to the excluded verbs).

Both simulation sets (Figures 5 and 6) confirm the expected pattern: an initial increase in the proportion between “different” and “common” verbs. Jaccard’s coefficient behaves more satisfactorily in the second simulation set (Figure 6), where a sharp rise is observed before the middle of the chart, thus indicating that many “different verbs” were excluded. In the first set (Figure 5), Wscore behaves ambiguously with two rises: one before and another after de middle of the chart. Hscore behaves the same way, but the second rise is much sharper than the first. Even so, the positive effect of polysemy is clear in the “Excluded Different” and “Excluded Common” lines. We notice that the “Excluded Different” line is usually above the “Excluded Common” in the beginning and far from the random values. Wscore in Figure 5 is an exception, although a significant rise is observed in the beginning.

5.3 Discussion

Results show that metrics behaved in a consistent manner, considering the natural variation of different sources of information.⁵ Concerning graph

⁵ Since the measures were taken from the whole graph, it was not possible to determine a measure of significance without other graph configurations to compare to. However, the com-

theory metrics, the early graph disconnection in the random simulation alone (in the C/s metric) confirmed a structural stability by using polysemy.

The regular behavior of the Jaccard's coefficient in the simulations may be attributed to a high similarity between the pair of sets: just 45.16% of the verbs in G3 were able to increase the index, and just 36% of the verbs in G2 (Table 2). Even so, an analysis of the "Excluded Different" curves made it clear that the results were better than they appeared to be.

6 Conclusions and Future Work

This study investigated the influence of polysemy on verb acquisition and organization using both graph and set theory metrics. In general, results from the topological analysis showed a tendency towards the reference value, and the greatest similarities were mostly collected in the beginning, as expected, pointing for a preference of children to use more polysemous verbs. The static analysis of the initial graphs (Tables 1, 2 and 3) corroborate the hypothesis. As a result, we note that not only does the evolution of human vocabulary lead to a decrease in the average polysemy measure, but its structure also evolves according to this linguistic factor. So we conclude that both the model of involution and the given analysis are appropriate for linguistic studies concerning vocabulary evolution.

The analyses highlighted also some interesting properties reflected in the graphs, such as vocabulary growth and specialization with the increase of participants' age. In addition, the analysis was useful in showing that the graphs of the two groups of children were more similar to each other than to that of adults, both in structure and content.

For future work, we intend to apply the same approach to other parameters, such as frequency, concreteness, and syntactic complexity. As they may simultaneously influence acquisition, we also plan to investigate possible combinations of these factors. We also intend to apply this methodology to investigate lexical dissolution in the context of pathologies, such as Alzheimer's disease, and in

comparisons with random elimination can be seen as a tendency. Additionally, the experiments consist of two simulations, over three different data sets, by using two different sets of polysemy, two kinds of metrics, and five different metrics, which provide robustness to the results.

larger data sets, in order to further confirm the results obtained so far.

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