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Research Paper: Small-world Structure in Children's Featured Semantic Networks

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ABSTRACT

Background: Knowing the development pattern of children's language is applicable in developmental psychology. Network models of language are helpful for the identification of these patterns.

Objectives: We examined the small-world properties of featured semantic networks of developing children.

Materials & Methods: In this longitudinal study, the featured semantic networks of children aged 18-30 months were obtained using R software version 3.5.2 and the igraph software package. The data of 2000 English (British)-speaking children, half boy and half girls, were gathered from existing databases of MCDI (between 2000 and 2007) and McRae feature norms. The growth pattern of these networks was illustrated by graph measures. Comparing these measures with those of the reference random networks, the small-world structure can be examined.

Results: To have a comparison between path length and clustering coefficient of featured semantic networks with those of random networks, we computed the Q quotient. The results showed that the values of the Q quotient at 18, 22, 26, and 30 months of age were all more than 1, which confirms the small-world characteristic of the networks.

Conclusion: Featured semantic networks of children exhibited a small-world structure, in which there was a local structure in the form of clusters of words. For global access, some words act as bridges connecting semantically distant clusters. These networks possess small-world property from the early months of age. The small-world structure cannot be seen in the less dense networks built with a higher cut-off threshold.

Keywords: Semantics, Child development, Language acquisition

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Highlights

- Network models of language reveal the development pattern of children's language.
- Graph theory measures of developmental semantic networks detect and explain language growth.
- Featured semantic networks of children exhibit a small-world structure from the early months of age.
- Small-world structure makes the children capable of having both global and local access to their mental lexicon.

Introduction

Pair-wise interactions between entities can be modeled using complex networks. In recent years, this approach has been successful in studying how a large number of complex systems, such as social networks, brain networks, and biological webs work [1-4]. More lately, complex networks have also been vastly considered in cognitive sciences. Outstanding cases in point are the representation of structural or functional patterns of connectivity in the human brain [5, 6] or studies of molecular relationships, such as gene regulatory network [7]. Furthermore, complex networks offer a fruitful quantitative tool for modeling the human mental lexicon [8, 9]. The semantic connections among the words in the human mental lexicon play an essential role in the processing and comprehension of the language [10, 11]. These connections are often studied using semantic networks [11, 12]. The semantic networks may be built from various sources of data, such as spoken or written corpus, free association data, and word-embedding models [9, 12-14]. In the meantime, network science helps us understand how semantic networks modify as they grow. Steyvers and Tenenbaum built semantic networks of adult language users based on the free association database. Roget's Thesaurus and WordNet have some small-world structures [9].

A small-world characteristic is a combination of local structure as well as efficient global access. In small-world networks, there are often some densely connected clusters. The connections between the nodes of a cluster tend to connect to nodes in a similar cluster, which contributes to the high local structure. On the other hand, there are also a few hub nodes in these dense clusters with links to the nodes in other potentially far-away clusters. This leads to global access that allows easy connection and transition from one cluster to another. Numerically, these characteristics of small-world networks are represented by having a high clustering coefficient (a measure of local connectivity) and the same average geodesic distance (the average shortest path between pair of nodes) with a random network of the same size and link density [1, 15].

Adult semantic networks exhibit a small-world characteristic [9]. Here, we examined the networks' small-world structures of children's language under two and a half years old at different intervals during development. We tried to know whether the small-world property emerges in children's semantic networks or not. Furthermore, we explored if the emergence time of small-world structure depends on acquiring a specific number of English words or children's semantic networks show small-world characteristics for any vocabulary size from the relatively early stages of development. We also examined how the density of children's semantic networks affects their small-worldness. Accordingly, we evaluated the connectivity within the featured semantic networks of typically developing children. The featured semantic networks are built from feature norms and the children's language data prior to the age of 30 months. We studied some network statistics, such as path length and clustering coefficient calculated over nodes [7]. By comparing these measures with those of the reference random networks, it was identified that featured semantic networks of children possess a small-world structure, which helps the children to have both local and global access to their mental lexicon. This capability is the basis of making phrases and sentences.

Materials and Methods

We studied children's language development by implementing the network model of their language. As it is explained below, we used early-learned nouns of 2000 English-speaking children in Britain, half boys and half girls aged 18 to 30 months as the nodes in the network model. Due to the shared features of these nouns, we made the connections to build featured semantic network. We acquired the data of the nouns and their shared features respectively from the MCDI database (the data were gathered between 2000 and 2007) and the McRae dataset. For building, visualizing, and analyzing featured semantic networks, we used R software version 3.5.2 and the igraph software package.

Nodes: The nodes of the featured semantic networks were 118 nouns selected from the MacArthur-Bates Communicative Developmental Inventory (MCDI), Toddler version [16]. MCDI is longitudinal data collected from more than 2000 parents. Using questionnaires, they were asked to monthly report the words their children had said. After some statistical analysis, the inventory provides month-by-month norms specifying the proportion of children) aged 18 to 30 months(who have each noun in their productive vocabulary. Building semantic networks from these nouns require an index of semantic association that indicates the semantic relations between the set of nodes. In this regard, we used some feature norms to build featured semantic networks of developing children.

Links: Developmental studies have indicated that children know about the features that are characteristic of general categories [12]. To construct developmental featured networks, we used the McRae feature norms [17]. This is a normed experimental study, in which participants were asked to record features of objects in an open-ended manner. This dataset contains several types of relations that have been categorized into mutually exclusive categories, such as 1) functional (e.g., can be eaten) 2) perceptual (e.g., has hands), 3) taxonomic (e.g., is a vehicle), and 4) encyclopedic features (e.g., was invented by Thomas Edison). Also, 118 early learned nouns in our networks were found in this database. We only considered perceptual and functional features, excluding encyclopedic and taxonomic features because they were unlikely to be experienced by children [12, 17].

Featured Semantic Networks: In the featured semantic networks, nodes represented nouns, and links between nodes represented their feature relationships. For a 4-month period from 18 to 30 months of age, we included only nouns that were in the productive vocabulary of more than 50% of the children in the MCDI at that interval. Consequently, a developmentally ordered set of four featured networks were constructed. Links between nodes are put in the network as follows: a link exists between two nouns if they shared one or more features (F=1). For example, the bird and plane are linked as they share the feature “can fly”.

Small-world Structure: To study the small-world structure of developmental networks, first, we calculated the path length and clustering coefficient of the featured semantic networks. Then, we generated 1000 Erdős-Rényi random networks of the same density and size with the featured semantic networks of 18, 22, 26, and 30 months of age. A network has a small-world property when its clustering coefficient is highly relative to its equivalent random network, but its mean path length is as low as that of the equivalent random network. To have this comparison, we calculated the small-world quotient, Q, as follows [18, 19]:

$$Q=\frac{C}{L}\times\frac{L_r}{C_r}$$

Where, C is the featured semantic networks’ clustering coefficient, L is the mean path length, Cr is the clustering coefficient of the reference random networks, and Lr is the mean path length. Values of Q> 1 indicate the small-world structure because it means that the featured semantic network’s mean path length is similar to that of the random reference network and/or its clustering coefficient is larger than that of a random reference network. For calculating all network measures and the small-world quotients, we used R software version 3.5.2 and the igraph software package.

Results

The featured semantic network of children was constructed (by R software version 3.5.2 and the igraph package) using the feature sharing method at 18, 22, 26, and 30 months of age. Figures 1 and 2 respectively present the featured networks at 18 and 26 months of age. The links existed between pairs of nouns if they shared at least one feature (F=1). We calculated some graph theory metrics of these networks to show their properties and possible changes through development.

The measures’ statistics for the featured semantic networks are presented in Table 1. In this table, N is the network size, <k> is the average of node degrees, D is network density (the ratio of the number of links to the number of possible links), L is the mean path length between nodes, and C is the mean clustering coefficient. The path length is the shortest path between two nodes, and the clustering coefficient quantifies how close neighbors of a node make a complete graph [1]. From 18 to 30 months of age and during language development, the number of learned words raised from 10 words at 18 months of age to 118 words at 30 months of age. The average degree of the nodes (<k>) also had an incremental pattern through the network growth, while oth-

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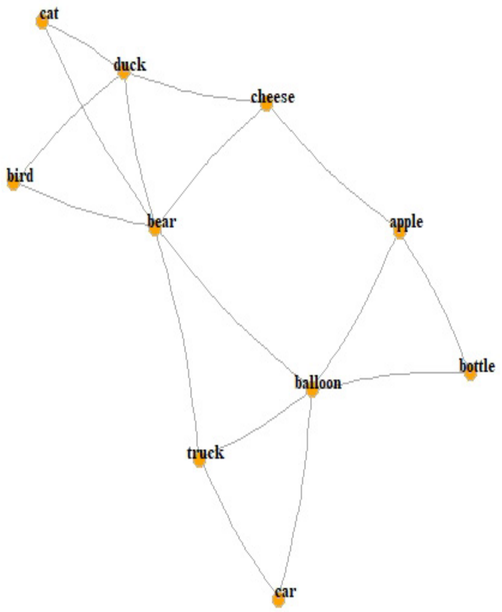

Figure 1. Featured semantic networks of children at 18 months of age

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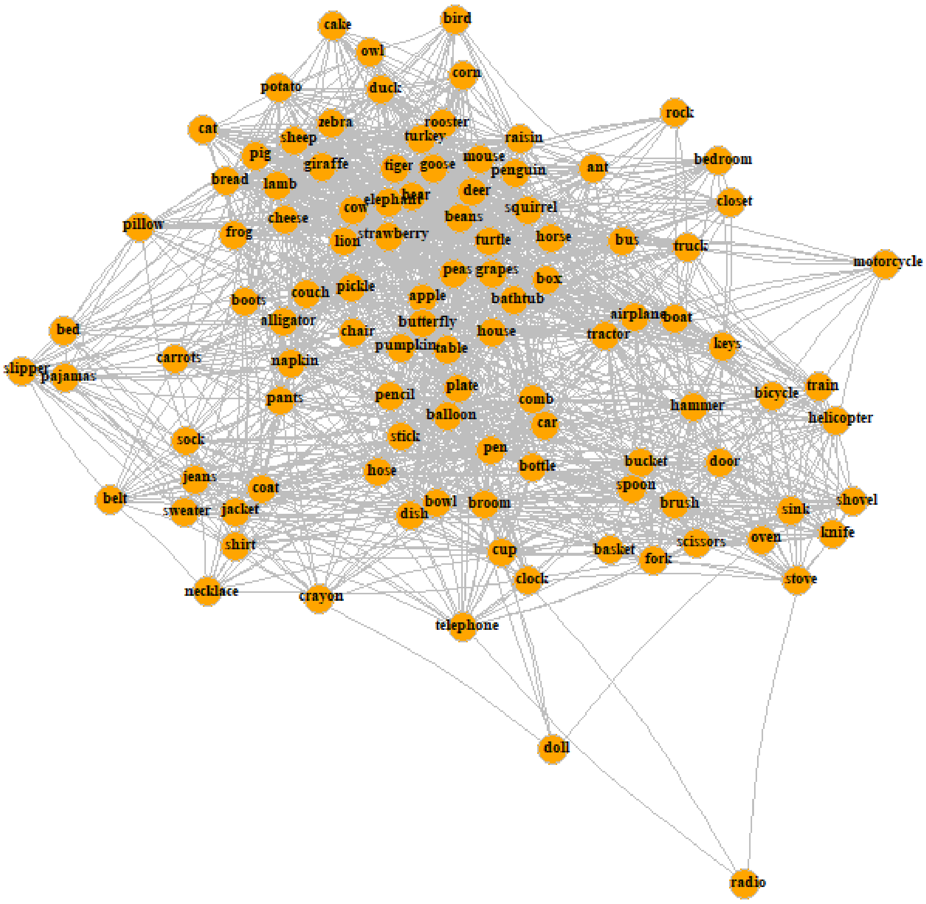

Figure 2. Featured semantic networks of children at 26 months of age

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Table 1. Featured semantic networks' measures

Age (Month)	18	22	26	30
N	10	53	106	118
<k>	3.2	16.03	31.66	36.37
L	1.84	1.75	1.74	1.72
D	3	3	3	3
C	0.64	0.591	0.610	0.621

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Network size <k>: Average of the node degrees, D: Network density, L: Mean path length between nodes, C: Mean clustering coefficient.

Table 2. Averaged measures of 1000 Erdős -Rényi random networks

Age (Month)	18	22	26	30
Lr/Mean±SD	1.93(0.056)	1.703(0.000)	1.702(0.000)	1.691(0.000)
Cr/Mean±SD	0.317(0.025)	0.301(0.000)	0.298(0.000)	0.308(0.000)

Lr: Path length; Cr: Clustering coefficient of random networks.

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er measures, such as density, average path-length, and clustering coefficient of the featured semantic networks did not change significantly while the network grows. The relatively low amount of d (0.301-0.355) shows that featured semantic networks were not dense. To study the small-world property of these networks, we generated 1000 Erdős-Rényi random networks, which their size and density were similar to their relevant featured semantic networks at 18, 22, 26, and 30 months of age. Then, we computed two graph measures, i.e., average path length and clustering coefficient of these 1000 random networks, and obtained the average for each measure. Table 2. shows the average of these measures for Erdős-Rényi random networks. Lr is the mean path length and Cr is the mean clustering coefficient of 1000 random networks. The small-world networks have global access to random graphs, i.e., small path length. In addition to the high global access, small-world networks show a high local structure by having a greater clustering coefficient in comparison with the random graph of the same size and density [1]. To have a comparison between path length and clustering coefficient of featured semantic networks (L and C) with those of random networks (Lr and Cr), we computed the Q quotient, which is shown in Table 3. It can be seen that the values of the Q quotient at 18, 22, 26, and 30 months of age were all more than 1, which confirms the small-world characteristic of the featured semantic networks.

We showed that featured semantic networks had a small-world structure at 18 months of age with a network size of 10. The links between these featured networks were found when the words shared at least one feature. Here, we asked this question that what will be happened to the small-world property of our networks if we increase the threshold to two features (F=2). To answer this question, we constructed the developmental featured networks considering F=2. Figure 3 illustrates the featured networks at 18 and Figure 4 at 26 months of age considering F=2. It can be seen that these networks were not connected dense networks and sub-graphs emerged. To examine the small-worldness of these networks, we calculated the Q quotients at 18, 22, 26, and 30 months of age, which are listed in Table 4. It can be seen that the featured networks at none of these ages were small. At 18 months of age, as is clear in Figure 3,

Table 3. Q quotient of the featured semantic networks

Age (Month)	18	22	26	30
Q	2.117	1.910	2.002	1.982

Q: Small-world quotient

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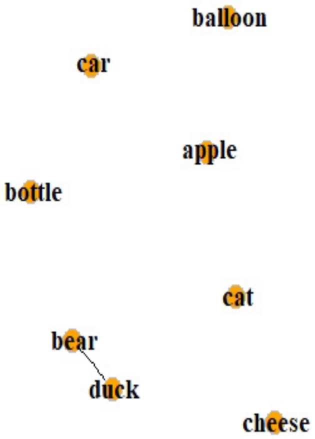

Figure 3. Featured semantic networks of the children (F=2) at 18 months of age

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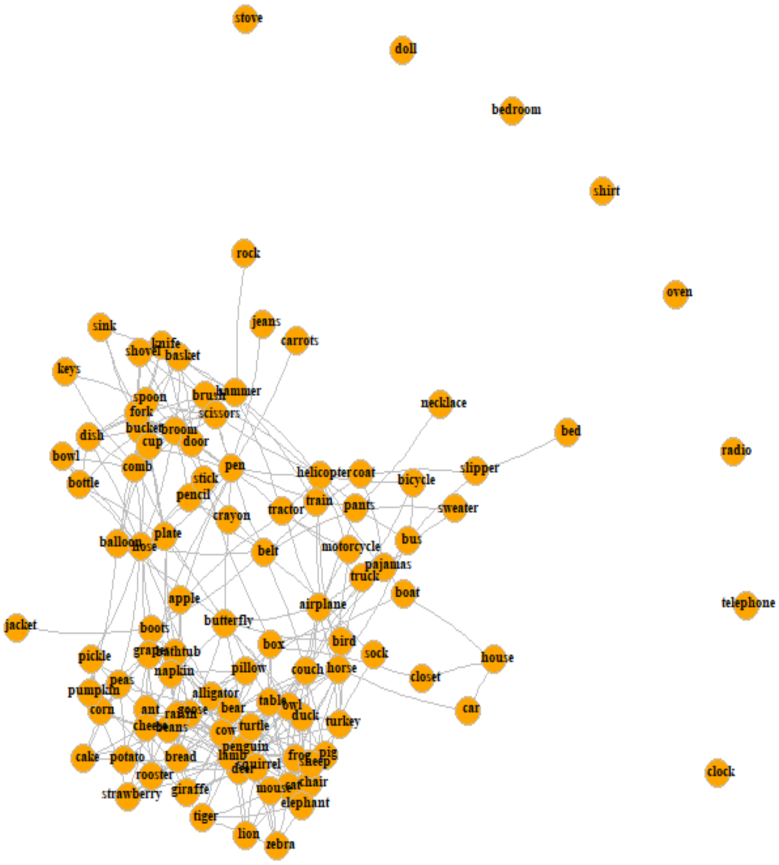

Figure 4. Featured semantic networks of the children (F=2) at 26 months of age

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Table 4. Q quotient of the featured semantic networks (F=2)

Age (Month)	18	22	26	30
Q	-	0.121	0.289	0.267

Q: Small-world quotient

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Q was inapplicable because we did not have triangles in our unconnected network and could not calculate the clustering coefficient. At 22, 26, and 30 months of age, all the Q quotients had values less than 1, which shows that the featured networks with F=2 had not the small-world property.

Discussion

As reported in the results section, featured semantic networks of children (F=1) showed a small-world structure characterized by the combination of dense clusters of the nodes and a short mean path length between them. In these networks, the small-world property even emerges at 18 months of age. This is in accordance with the results reported by Beckage et al. regarding the developmental co-occurrence networks of children. Featured semantic networks show the efficient local and global access of children to their mental lexicon and semantic memory to produce the phrases. This dual access lets the children make a structure from the words that are semantically near or distant to convey their meaning. Small-world characteristic is a possible property of featured categories because: 1) words are in local clusters of the objects that are categories and conceptually the same but may differ from having links with random words, and 2) some words are as hubs and go to multiple clusters. This property can be discrimination between a typical and delayed language development. The small-world characteristic may emerge later in the semantic networks of children diagnosed with language impairment or delayed language development. This delayed small-world structure can be either because of a smaller lexicon or limited ability of language processing or words' feature perception.

By examining the small-world property of early featured networks, we evaluated the contributions of features in the growth of semantic networks. It is revealed that the featured semantic networks with links if their relevant nodes share at least two features, do not show a small-world structure. This means that increasing the cut-off threshold leads to a network, which does not have the efficient property of small-worldness. It can be concluded that for developing children, it is necessary to link the words in their mental lexicon while they share at least one feature. Nevertheless, their featured semantic networks are not small. As a consequence, they would not have efficient local and global access to their mental lexicon and their language cannot be developed typically. In children with delayed language development, the limited capability of language processing can be modeled in the featured semantic networks by changing the cut-off threshold.

Conclusion

Featured semantic networks of children were constructed using the developmental MCDI dataset and McRae's feature norms. Some graph metrics, such as path length and clustering coefficient were obtained from these semantic networks of children prior to 30 months of age. By computing the Q quotient to compare path length and clustering coefficient of featured semantic networks to mean path length and clustering coefficient of random graphs of the same size and density, it was discovered that these developmental semantic networks, even from the early months of age, had a small-world structure. We showed that the small-world structure of featured semantic networks depended on the binarization criteria and these networks were not small anymore while connecting the words that share two or more features.

Ethical Considerations

Compliance with ethical guidelines

All study procedures were done in compliance with the ethical guidelines of the Declaration of Helsinki, 2013. We gathered all data from online datasets; thus, there was no need for a moral code.

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Authors' contributions

Conceptualization, methodology, investigation, writing of the original draft: Somayeh Sadat Hashemi Kamangar; Writing, review, and editing, funding acquisition, resources: All authors; Supervision: Fatemeh Bakouie and Shahriar Gharibzadeh.

Conflict of interest

The authors declared no conflicts of interests.

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