The Aging Lexicon: Differences in the Semantic Networks of Younger and Older Adults

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Abstract

How does the mental lexicon, the network of learned words in our semantic memory, change in old age? To address this question, we employ a new network inference method to infer networks from verbal fluency data of a group of younger and older adults. We find that older adults produce more unique words in verbal fluency tasks than younger adults. In line with recent theorizing, this suggests a larger mental lexicon for older than for younger adults. Moreover, we find that relative to the mental lexicon of younger adults, the mental lexicon of older adults is less small-world-like. Based on several findings linking network clustering to processing speed, this finding suggests that not only the size, but also the structure of the mental lexicon may contribute to apparent cognitive decline in old age.

Keywords: Semantic representation, networks, small world, verbal fluency, aging.

Introduction

Cognitive science commonly depicts semantic memory as a random walk traversing a network of concepts or words, often called the mental lexicon (Abbot, Austerweil, Griffith, 2015; Anderson, 1983; Collins & Loftus, 1975; De Deyne, Verheyen, & Storms, 2014; Hills, Todd, & Jones, 2012; Miller, 1995; Vitevich, 2011). A corollary of this view is that the structure of the network should impact memory performance (Jones, Hills, Todd, 2015; Vitevich, 2008; Borge-Holthoefer & Arenas, 2010). Several studies have attempted to measure the mental lexicon using memory productions from free association or natural language (Ferrer-i-Cancho & Sole, 2001; Steyvers & Tenenbaum, 2005; Morais, Olssen, & Schooler, 2013). They concluded that the macroscopic structure of the mental lexicon follows, similar to networks is other domains, a small-world structure, implying higher clustering and equal average path length than found in random networks (Humphries & Gurney, 2008; Steyvers & Tenenbaum, 2005; Watts & Strogatz, 1998). However, whether this aggregate pattern also characterizes the mental lexica of individuals is far from understood. As a first step toward answering this question, we will apply in this investigation a new network inference method to study and compare the small world-ness of younger and older adults' mental lexica based on verbal fluency data.

The Aging Mental Lexicon

Semantic memory follows a unique developmental trajectory across later age. Whereas episodic memory and fluid abilities, such as working memory capacity, peak in early adulthood, the performance of semantic memory, as measured by vocabulary tests, increases until age 65 to 70 (Hartshorne & Germine, 2015; Keuleers, Stevens, Mandera, & Brysbaert, 2015) or even beyond (Kavé & Halamish, 2015)[1]. Recently, it was argued that the positive trend for semantic memory might actually be responsible for the poor performance of older adults in other cognitive variables (Ramscar, Hendrix, Shaoul, Milin, & Baayen, 2014). Specifically, if older adults have access to an increasing number of words, then their mental lexicon must be larger. As with finding a book in a large as compared to a small library, retrieving information from a large mental lexicon

[1] Moreover, linguistic analyses suggest that common vocabulary tests underestimate the true vocabulary size for older adults (Baayen, 2001).

should take more time and be more error prone, than in a small mental lexicon. The apparent cognitive decline in older adults – usually attributed to a general cognitive slowing for older adults due to neuronal deterioration (Light, 1991) – may thus arise from changes in older adults mental lexica.

As size of the mental lexicon can impact the performance of the memory system, so should its structure (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013). Previous research has successfully connected a network's clustering coefficient to processing speed (Nematzadeh, Ferrara, Flammini, & Ahn, 2014; Vitevich, et al., 2011), enhanced priming effects (Nelson & Goodmon, 2002), as well as facilitated recognition and recall (Nelson, Bennett, Gee, Schreiber, & McKinney, 1993; Nelson, Zhang, & McKinley, 2001). Furthermore, the structure of the mental lexicon is naturally related the meaning of words, categorization, and language itself (Borge-Holthofer & Arenas, 2010; De Deyne, Verheyen, & Storms, 2014; Jones & Mewhort, 2007).

To our knowledge, no previous study assessed the effect of aging on the structure of the mental lexicon. Existing research rather focused on the early developmental trajectory of the mental lexicon in children (e.g., Hills, Maouene, Maouene, Sheya, & Smith, 2009; Beckage, Smith, & Hills, 2011). Hills and colleagues (2009) found evidence in favor of preferential acquisition process, in which words are learned as a function the words' degree of connectedness in the learning environment. More research is needed to corroborate this finding and it is unclear whether these trends can be extrapolated to later life. We therefore aim to help investigate the structural development of the aging mental lexicon.

Present Study

In this investigation we provide a first peek into the mental lexicon's adult development by comparing mental lexica of younger and older adults as inferred from verbal fluency data. Doing this we will focus on the average local clustering coefficient, the average shortest path length, and the small world-ness of young and older adults' semantic networks. Out of the many network statistics, the clustering coefficient is most prominent. It is also the only network statistic that has been causally connected to memory performance (Vitevich et al., 2011). The average shortest path length has not been linked to memory performance, however, it carries an intuitive interpretation: Networks with larger average shortest path lengths should lead to slower and less flexible recall performance. Finally, as a composite measure of the clustering coefficient and the average shortest path length, small world-ness speaks to the global structure of a network. Many natural occurring networks exhibit a small world structure, including importantly word occurrences in natural language (Ferrer-i-Cancho & Solé, 2001). Small world networks have been found to "display enhanced signal-propagation speed, computational power, and synchronizability" (Watts & Strogatz, 1998, p. 440).

Method

Data

The data for our analysis was comprised of 60 seconds animal fluency data from a total of 332 participants. Verbal fluency tests ask participants to list within a defined time window as many members of a natural category as they can think of. The dataset was composed of the data from two independent studies, 228 (18.6 animals on average) participants from Hills, Mata, Wilke, and Samanez-Larkin (2013) and 104 participants (21.8 animals on average) from a subsample from the Midlife in the United States study (MIDUS; Lachman, Agrigoroaei, Tun, & Weaver, 2013). The data of the latter was transcribed by us from audio recordings using the Penn TotalRecall[2] software. Following Lerner, Ogrocki, and Thomas (2009), the datasets were subjected to preprocessing, in which variants of the same animal were combined ('kitten' and 'kitty'), but alternate forms of the same species were retained ('cow' and 'calf'). We removed 36 participants for low scores on a dementia screener (value < 26; Folstein, Folstein, & McHugh, 1975) and 16 for producing too few animals (n < 10). A total of 284 participants entered the analysis, with age ranging from 29 to 94 and number of produced animals from 10 to 39. Figure 1 illustrates the sample. For the comparison of older and younger adults we performed a median split on age, resulting in a group of 142 younger adults, aged 29 to 65, producing on average 22 animals, and a group of 142 older adults, aged 66 to 94, producing on average 18.8 animals (see also Table 1).

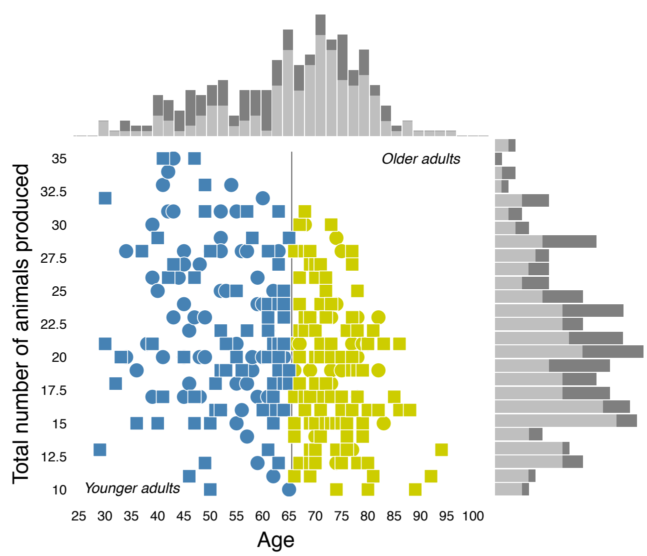

Figure 1: Illustration of the data used to infer the mental lexica of younger and older adults.

Table 1: Description of the raw data after median split.

[2] http://memory.psych.upenn.edu/TotalRecall

Group	N	Age	Mean recalled	Unique recalls N_U	N_U / N_T
Younger Adults	142	19 – 65	22	287	.091
Older Adults	142	66 – 94	18.8	284	.106

Legend: N_U /N_U – Number of unique/total words

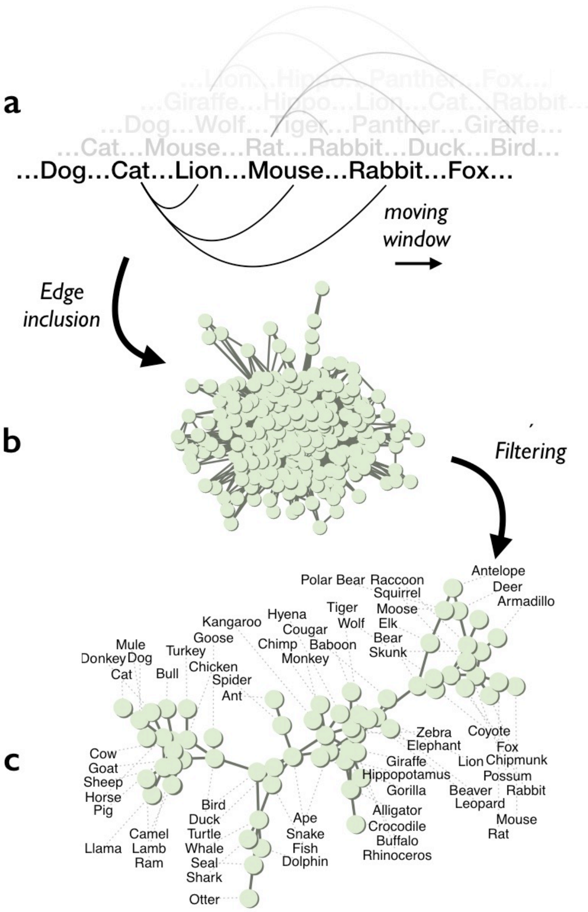

Figure 2. Illustration of the network inference method.

Network Inference Method

To infer the mental lexicon of younger and older adults from verbal fluency data, we borrow from the statistical procedure developed by Goñi et al. (2011). The method assesses for every two words whether they co-occur more frequently than would be expected by chance. Figure 2 illustrates the three steps of the procedure. In the first step (a), a window of size *w* moves through all verbal fluency sequences of one group and records the number of times two words co-occur within the window. For instance, if w = 3, then all pairs of words with no more than one intervening word entered the next step of the analysis. In the second step (b), a non-weighted, undirected graph is created from the pairs that co-occurred more often than a minimum threshold of *m*. For example, if $m = 2$, then all pairs of words that co-occurred at least twice entered the final step of the analysis. Finally, in the third step (c), the recorded frequency of co-occurrence is tested against the random expectation based on the marginal frequencies of words and the lengths of the verbal fluency sequences[3]. Specifically, an edge between a pair of nodes is retained whenever likelihood of the frequency of co-occurrence under the random model surpasses a lower threshold *c*. As can be seen in the example given, in the bottom panel of Figure 2 the method produces highly intuitive networks. The network shown is based on the older adults data and $w = 3$, $m = 3$, and $c = .05$.

Relative to other methods that are used to construct networks from verbal fluency data, our method has two important advantages. First, it is the only method based on the common contention that related words co-occur within relatively small window sizes, often no more than two or three words apart (Abbot et al., 2015; Troyer et al., 1997; Hills, Jones, & Todd, 2012, Wulff, Hills, & Hertwig, 2013). Second, the flexible parameterization allows to map different parts of the mental lexicon. Specifically, increasing the minimum co-occurrence parameter *m* means that only the strongly connected core network will be assessed (Baronchelli et al., 2013). A similar case can be made for the window size parameter *w*.

A critical aspect of investigations into the macroscopic properties of networks is statistical inference. When the endpoint of the investigation is a single network, one cannot rely on standard statistical procedures. Often the only possibility to generate standard errors lies in bootstrap methods that repeatedly construct subnetworks from randomly selected nodes and edges. The reliability of such methods is, however, contested (Sneijders & Borgatti, 1999). To circumvent these issues, we chose to bootstrap participants instead of subnetworks. Specifically, we inferred as many networks as there were participants in a group according to a leave-one-out procedure (Efron & Efron, 1982; Sneijders & Borgatti, 1999). We then compared network measures between the groups based on the pooled standard deviations computed across the 142 leave-one-out-networks for each of the groups.

Network Measures

We focus in our analyses on the two network measures constituting a small world: The average (local) clustering coefficient and the average shortest path length. The clustering coefficient *C*, sometimes also called transitivity, refers to the proportion of cases in which the neighbors of a node are neighbors themselves. The shortest path length of two nodes *L* refers to the length of the shortest possible way to traverse from one node to the other. The average clustering coefficient and the average shortest path length

[3] For details see Goñi et al. (2011).

are both computed as the arithmetic mean of their respective measures.

To counter known dependencies of the clustering coefficient and the shortest path length on the size and connectedness of the network (von Wijk, Stam, & Daffertshofer, 2010), we measure both variables relative the expectations of a Erdos-Renyi random graph (Bollobas, 2001). In addition, to prevent influences from the outset of the analysis, we match the data of younger and older adults. Specifically, we implemented the following matching scheme: First, we included older and younger adults with exact matches in samples size of fluency productions. Second, for all participants that could not be matched in the first round, we identified for each older adult the younger counterpart whose number of productions lay closest, cropped the extra productions at the end produced by the young adult, and included the pair. The matched data included 5230 productions, representing about 90% of the original 5802 productions. All of the following results hold for an alternative matching scheme in which young adults' extra productions were cropped at the beginning.

We also include in our analysis the small-world-ness index *S* developed by Humphries and Gurney (2008). This measures combines the clustering coefficient and the average shortest path into a single metric, while controlling for the expectations of a Watts-Strogatz small world network. The measure indicates small-world-ness for values > 1.

Results

Unique Productions

First, we turn to the number of unique productions. Although younger adults produced slightly more unique animals in total, older adults produced more unique items per production, which was both, significant and substantial, according to a bootstrap test ($d = -1.9$, $p < .001$). This finding is consistent with the idea that a larger mental lexicon slows the productions of older adults (Ramscar et al., 2012).

Network Comparison

Figure 3 shows the results of our network inference for the number of nodes in the resulting graph (N), the average clustering coefficient relative to random (C/C_{rand}), the average shortest path length relative to random (L/L_{rand}), and the small-world-ness index S. Specifically, the figure displays for each measure the median result of the 142

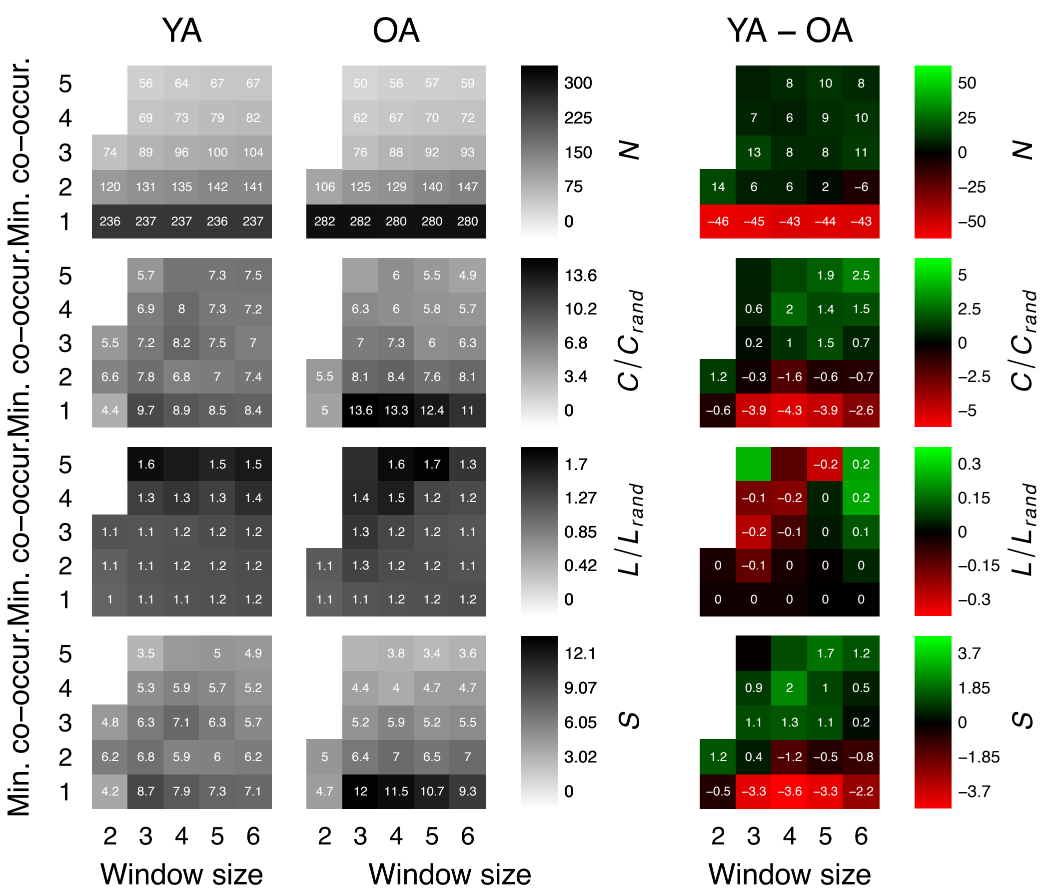

Figure 3. Macroscopic properties of the mental lexicon of older and younger adults as inferred from verbal fluency data.

leave-one-out runs per group. The results are shown for five levels of the minimum co-occurrence parameter *m*, five levels of the window size parameter *w,* and a single criterion value of $c = .05$. The left two columns show the results for the younger (YA) and older adults (OA), while the rightmost column displays their difference. The figure only displays boxes when a giant components comprised of at least 90% of all nodes could be recovered, and numbers, when the statistical test yielded significance at the level of .05.

As can be seen from the figure, the networks and their differences across groups are markedly influenced by the choice of minimum co-occurrence, but not window size. Specifically, the analysis of all data, including pairs of words that only co-occurred once, resulted in about 20% larger networks for the older adults than for the younger adults. Responsible for this pattern is that, consistent with more unique productions for older adults, the older adults frequency distribution of productions has a longer tail of highly infrequent items. Under most circumstances, such infrequent items will likely form unique pairs with the words they are paired with. As it is impossible to discern whether such pairings are the result of a systematic association between the words or mere chance, we followed Goñi et al. (2011) in disregarded co-occurrences that occurred no more than once ($m \geq 2$).

Evaluating the networks for $m \geq 2$ revealed a very clear pattern: The networks of younger adults exhibit more clustering, mostly shorter average path lengths and mostly larger small-world-ness indices. This suggests that the structure of the younger adults mental lexicon resembles more closely a small world structure than that of older adults.

Discussion

To our knowledge our investigation represents the first comprehensive comparison of younger and older adults mental lexica. Consistent with previous research (Ramscar et al., 2014), we have shown that relative to younger adults, older adults produce more unique words in the verbal fluency task, suggesting a larger underlying mental lexicon. Critically, we have also shown that relative to the mental lexicon of younger adults, the mental lexicon of older adults exhibits a less small-world-like structure, implying less clustering. Based on previous findings that associate network clustering with processing speed (e.g., Nematzadeh, Ferrara, Flammini, & Ahn, 2014), this result suggests that the structure of the mental lexicon of older adults might contribute to the apparent cognitive decline in old age.

The inference of a mental lexicon from memory productions is, however, not without caveats. Most importantly, one must consider that memory productions are the process not only of the underlying network, but also a search process operating on the network (Jones, Hills, & Todd, 2015; Raaijmakers & Shiffrin, 1981). This means that one cannot easily attribute differences in inferred networks to the underlying structure. This holds in particular as it has been proposed that the search process is affected by age (Hills et al., 2013). Future studies should aim to disentangle search process and network, possibly by means of simulation. Future studies should also aim to corroborate the present findings by extending the analysis of mental networks to other methods (e.g., similarity ratings) and content (e.g., other natural categories).

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