Structural differences in the semantic networks of younger and older adults

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Abstract

Cognitive science invokes semantic networks to explain diverse phenomena from reasoning to memory retrieval and creativity. While diverse approaches are available, researchers commonly assume a single underlying semantic network that is shared across individuals. Yet, semantic networks are considered the product of experience implying that individual who make different experiences should possess different semantic networks. By studying differences between younger and older adults, we demonstrate that this is the case. Using a network analytic approach and diverse empirical data, we present converging evidence of age-related differences in semantic networks of groups and, for the first time, individuals. Specifically, semantic networks of older adults exhibited larger degrees, less clustering, and longer path lengths. Furthermore, the edge weight distributions of older adults individual networks exhibited significantly more skew and higher entropy across node pairs and, except for unrelated node pairs, less inter-individual agreement, suggesting that older adults networks are generally more distinct than younger adults networks. Our results challenge the common conception of a single semantic network shared by individuals and highlight the importance of individual differences in cognitive modeling. They also present valuable benchmarks to discern between theories of age-related changes in cognitive performance.

Keywords: Semantic memory, Network analysis, Mental Lexicon, Cognitive Aging

1. Introduction

Semantic networks are a key ingredient of research in diverse areas of cognitive science [1, 2, 3]. With diverse cognitive processes operating on them, they have delivered explanations to important cognitive phenomena concerning reasoning [4], free associations and similarity ratings [5], language development [6, 7, 8], creativity [9, 10], or search in memory in healthy individuals [11, 12] and patients [13]. For instance, De Deyne et al. [14] showed that a random walk process spreading through a semantic network will take account of indirect connections between concepts permitting better prediction of human judgments of similarity than any modeling focusing alone on the two concepts at hand. Key such approaches of modeling human cognition is the availability of semantic networks. Studies have relied on networks derived from multiple sources including man-made taxonomies [4, 15], human association data [16, 17], network growth models [7, 18], or machine learning algorithms learning from natural language [19, 20]. Commonly, such approaches take a one-size-fits-all approach in that they assume a single semantic network to describe all individuals or, at least, groups of individuals. However, this introduces the problems of aggregation. Semantic networks are the product of experience and learning [21, 22]. Assuming that everyone possesses the same semantic network is, thus, equal to assuming that people have made identical experiences in their. While some consistency is expected due social forces, such as communuication and coordination [23], one must individuals' semantic networks to differ in both content and structure. This should be particularly the case in comparisons younger and older adults. Older adults have been exposed to more and more different experiences, which should have left traces in their semantic networks. To date little is known on how aging or other individual differences impact people's semantic networks. To fill this gap, we use network analytic approaches and diverse empirical data to uncover age-related differences in semantic networks of groups and individuals.

1.1. The Aging Mental Lexicon

Compared to the ability to solve abstract problems or to quickly process incoming information, which tend to decline with age [24], individuals' store of words and concepts, also known as the mental lexicon [14], takes a different trajectory. Research on vocabulary has found vocabulary size to grow into late age [25, 26]. These results imply that semantic networks of older adults should be larger than those of younger adults. This finding alone has inspired a provocative hypothesis [27], namely that memory search demands associated with larger semantic networks may account for the decline observed in other cognitive capacities that otherwise commonly attributed to cognitive slowing [24, 28]. Simulation studies have shown that age-related effects on, e.g., picture-naming or paired associative learning, can indeed been modeled as resulting from a growing semantic network [27, 29], underlining the importance of understanding individual differences in semantic networks. Network size is one aspect of semantic networks that is subject to change to across age. Another is structure. Analogous to networks in other domains [30], the structure of semantic networks exhibits small-world structure [31, 32, 33], implying high local clustering and moderate average shortest path length, and a (near) scale-free degree distribution, implying few words with many connections and many words with few connections [34, 32]. Some evidence exist that such macroscopic properties of networks are affected by aging. Using data from free word associations, that require individuals to produce associates to word cues presented to them, two recent studies both found older adults networks to exhibit a lower average degree ($\langle k \rangle$) and larger average shortest path length (L), but they did not produce consistent results concerning which network exhibited the larger average local clustering coefficient (C) [35, 36]. See Materials and Methods for details on network measures. Similar to network size, network structure can be expected to impact psychological functioning [37, 38, 39, 40]. Work on creativity, for instance, suggests a link between the creative abilities and lower path lengths and higher clustering [41].

Based on previous research, semantic networks can be expected to undergo noticeable and consequential age-related changes in terms of both size and structure. How exactly these changes come about, however, is still relatively unclear. Approaches to model the growth of semantic networks have either focused on language learning during childhood [18, 7, 42] or paid no attention to developmental at all [17, 19]. Yet, it seems useful, as a first attempt to understand aging in semantic networks, to derive predictions from existing growth models. To this end, we simulated growth using [32]'s model, which was proposed to account for the small-worldness and scale-freeness of adult semantic networks. Aside from the size of the network $|V|$, this model has one parameter m governing the number of edges created for every new node in the network. As we have no assumption, how this parameter, which is intimately related to the average number of edges in the network, would change across the lifespan we implemented three regimes: growing, constant, and declining. Figure 1 how growth effects three key indicators of network structure. Crucially, the figure shows that non-increasing ms are able to produce the same pattern of results observed by empirical studies [36, 35]. This result, which arises from natural unavoidable dependencies between $\langle k \rangle$, C, and L [43, 44] implies that a single process may underlie the currently observed differences between younger and older adult semantic networks. One candidate for this process is network degradation [45, 46, 47]. That is, similar to the neuronal networks, the semantic network could be subject to deterioration. A technically similar, but, in spirit, very different explanation, is that $\langle k \rangle$ declines as a function of increased discrimination [27]. By providing further evidence on the structural differences between younger and older adults we seek to shed some light on the plausibility of either explanation.

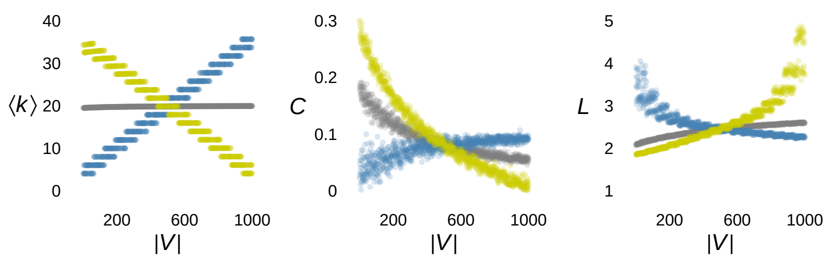

Figure 1: Simulation of semantic network aging using the Steyvers-Tenenbaum growth model. The figure shows changes in average degree (k, left panel), average local clustering coefficient (C, middle panel) and average shortest path length (L, right panel) as a function of three regimes of network growth: stable, declining, and increasing connectivity, in which the number of newly established connections per node is constant (grey), declines (yellow), or increases over time (blue). Results are based on 1,000 repetitions per number of nodes.

1.2. Measuring age-related differences in semantic networks

In this study, we will, first, compare semantic networks of older and younger adults derived from several verbal fluency data sets [48] using a novel network inference approach. Verbal fluency tasks require participants to report in a limited time window as many elements of a natural category, such as animals or countries [49]. Using this data, we seek to confirm the existing findings using a different method and different data sets. Second, we extend existing findings by measuring individual-level semantic networks via a similarity rating tasks. This allows us to sidestep two methodological problems associated with aggregate networks. First, there is no good way to average across the presence and absence of edges and nodes. As a result, aggregate networks usually reflect the union of individual networks rather than their average, rendering the aggregate network unrepresentative of individual networks. Second, aggregate networks prevent standard statistical inferences, as they provide only a single observation of its structural properties. We overcome these problems by letting individuals provide similarity ratings on the same large set of word pairs using a continuous scale. This will allow us to create comparable, weighted, and individualized networks that can be subjected to standard statistical analyses. Finally, the distribution of similarity ratings and how it differs between younger and older adults will provide valuable insights on the processes underlying the age-related changes in semantic networks.

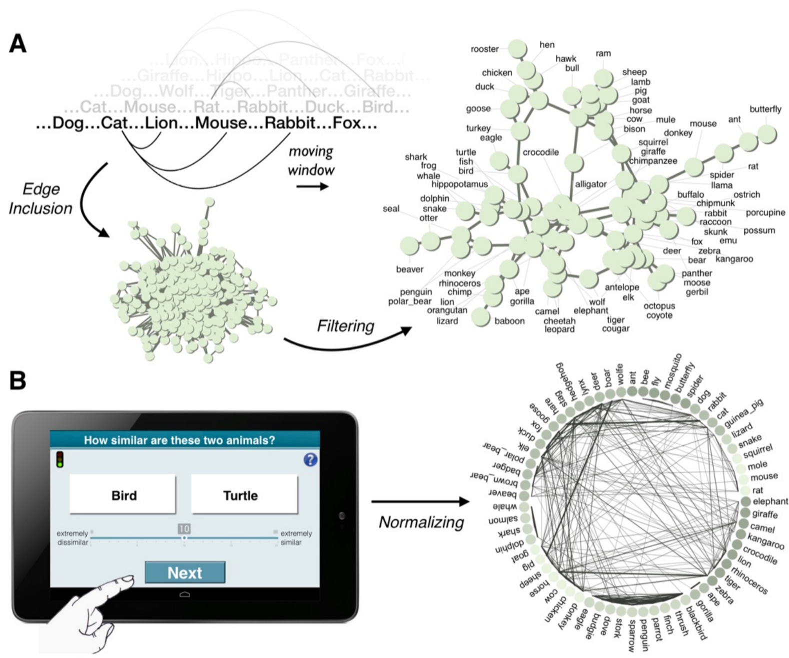

Figure 2: Methodological approach. Panel A illustrates the steps, edge inclusion and filtering, involved in inferring networks from verbal fluency sequences. For details see Materials and Methods. The resulting network is based on 142 sequences of the older adults group of study 1. Panel B illustrates the creation of networks from similarity ratings, involving merely normalization of individual's responses. The weighted network is based on the average ratings of the older adults group of study 3.

2. Methods

2.1. Fluency data

A total of four data sets from three studies were used to infer networks from fluency data. The first data set was obtained from [**?**], who analyzed the data of two published studies, i.e., from Hills et al. [50] and the Midlife in the United States (MIDUS3) longitudinal study. The data of Hills et al. [50] contains three waves of responses to one minute animal fluency task collected at Stanford University, CA, in 2011. At time point one, the data included a total of 201 participants aged 27 to 99 (Mdn = 68). To avoid practice effects and problems associated with participant attrition, we used only the first wave. The MIDUS3 data contained one minute animal fluency data - recorded in phone interviews - from 104 individuals aged 34 to 83. Audio recordings were transcribed by us (see Supplementary Material). In order to obtain a sufficient amount of data to infer fluency networks, we joined the two data sets, but eliminated individuals with fewer than 10 fluency productions and mini-mental state values lower than 26, which is indicative of either low attention to the task or beginning age-related disorders. Groups of younger and older adults were created by splitting the data at the median age. This resulted in groups of 142 individuals each aged 29 to 65 years old and 66 to 94 years old, respectively. Our first study with original data was collected in the context of another study on age-difference in decision making running in the laboratories of the Max Planck Institute (MPI) for Human Development, Berlin. We collected 10 minute fluency data for both animals and countries from 71 older adults and 41 younger adults. Responses were recorded using a microphone and transcribed by us. Participants were recruited through the internal participant database of the MPI of Human Development. The older adults group ranged from 65 to 80 years with a median age of 70 years, the younger adults age ranged from 17 to 33 with a median age of 25. Participants were paid 10/hour for participation. The second study was also collected at the Max Planck Institute for Human Development using participants from the MPIs internal database. We collected 10 minute fluency data for animals from 36 older adults and 36 younger adults. Responses were recorded using a microphone and transcribed by us. The older adults group ranged from 65 to 78 years with a median age of 70 years, the younger adults age ranged from 18 to 32 with a median age of 24. Participants were paid 10/hour for participation. Study 1, 2 and 3 were approved by the internal review board of the Max Planck Institute for Human Development.

Fluency data was subjected to minimal preprocessing. Responses were scrutinized for category membership and spelling. A lenient criterion was used to assess category membership to retain as much of the original data as possible. In the case of animals, all non-fictional entries that described entire, non-human, and non-fictional animals were retained. This lead us to exclude few cases from the data, such as Godzilla, cat eye, or animal trainer. Similarly, in the case of countries, we retained all existing and named territories such as Istrien, a region of Italy, Croatia and Slovenia, the desert Sahara or cities, but not non-existing, fictional territories such as Middle-earth. Spelling was hand-corrected on the basis of the Merriam Webster online dictionary. Overall 96.8% to 99% of responses were retained in the analysis.

2.2. Measures of macroscopic network structure

The average degree of a network $G = (V, E)$, with nodes (or vertices) V and edges E, is defined as $\langle k \rangle = \frac{2|E|}{|V|}$ for unweighted networks and as $\langle k \rangle = \frac{2}{|V|(|V|-1)} \sum_{i,j \in V; i \neq j} a_{ij} w_{ij}$, where $a_{i,j}$ denotes the presence of an edge between nodes i and j and $w_{i,j}$ the according edge weight. The average degree or strength, as it is commonly referred to for weighted networks, describes the average connectivity in the network. The average local clustering coefficient for unweighted networks is defined as $C = \frac{1}{|V|} \sum_{i \in V} C_i$ with $C_i = \frac{2}{|k_i|(k_i-1)} \sum_{j,h \in N_i} a_{jh}$ and k_i being the degree of node i and N_i the set of neighbors to i. For weighted networks, $C_i^w = \frac{1}{|s_i|(k_i-1)} \sum_{j,h \in N_i} \frac{w_{ij}+w_{ih}}{2} a_{ij} a_{ih}, a_{jh}$ with $s_i = \sum_{j \in N_i} w_j$ being the strength of node i, the weighted analog to k_i. The local clustering coefficient describes the degree of transitivity in the network and is related to network modularity [51]. It is often conceived as an indicator of the structured-ness of a network [52]. The average shortest path length is defined as $L = \frac{2}{|V|(|V|-1)} \sum_{i,j \in V; i \neq j} L_{ij}$ where L_{ij} is the length of shortest path between nodes i and j, also known as the geodesic distance. For weighted networks, L_{ij} is the sum of weights rather than the length. The average shortest path length describes the average distance between nodes. Low average shortest path lengths have been associated with efficient information processes [53, 54].

2.3. Networks inference approach

Networks were inferred from verbal fluency data based on the community model developed by **?**] and studied by Zemla and Austerweil [55]. The model is based on a two-step procedure. First, nodes and edges are included for every pair of responses that occurred within a distance of l responses. For instance, for the response sequence dog, cat, mouse, rabbit and a criterion of $l = 2$, edges would be included for all pairs less than three responses apart, excluding only the pair dog and rabbit, which are three responses apart. Second, an edge is identified as a true edge, if the frequency of the connected words occurring with l or fewer steps apart exceeded a frequency threshold t_{min} reflecting the required minimum frequency of co-occurring within l responses to be considered in the first place, as well as a frequency threshold t_{chance}. The latter is derived from the probability p_{ij}^{linked} of two words occurring within l responses by chance, which is calculated as $p_{ij}^{linked} = p_i j^{co-occur} * p_{ij}^{\geq l}$. Furthermore, $p_{ij}^{co-occur}$, the probability of two words to co-occur within a fluency sequence, and $p_{ij}^{\geq l}$, the probability that two responses are no more than l responses apart, are being calculated as $p_{ij}^{co-occur} = \frac{f_i f_j}{MM}$ and $p_{ij}^{\geq l} = \frac{2}{N(N-1)}(-lN\frac{l(l+1)}{2})$ with f_i, f_j denoting the number of times two responses occur across M sequence and N denotes the average number of productions per sequence. t_{chance} is then defined as the $1 - \alpha$ quantile of the binomial distribution $B(M, p_{ij}^{linked})$. Based on the simulations reported in the Supplementary Material, we found a minimal model with $l = 1$, $t_{min} = 1$, and $\alpha = 1$ to the best recover the underlying network structure.

2.4. Similarity ratings

Similarity ratings were collected in the context of study 2 and prior to participants completing the verbal fluency task. Participants took home a tablet to provide, over the course of roughly one week, on a scale from 1 to 20 similarity, ratings for 2268 pairs of animals, consisting of each possible pair of 63 frequently occurring animals and 315 repeated pairs. The 63 animals were selected on the basis of the verbal fluency responses of study 1 in manner that equated word frequency across younger and older adult age groups. See Supplementary Material. Reliability was found to be high for both younger and older adults with respective correlations of $r = .76$, $r = .74$. Participants were paid 10/hour for participation in the lab session and a flat fee of 44.1 for providing the similarity ratings.

3. Results

3.1. Differences in networks inferred from verbal fluency data

We inferred networks from verbal fluency sequences using the community model, which has recently been found to predict human similarity ratings very well and likely better than other approaches available [**?** 55]. As illustrated in 2, the approach is based on two steps: First, edges for every pair of items that occurred withing a distance of l responses from another and, second, edges are retain that occurred more often than a minimum criterion t_{min} and what would be expected by chance given a false alarm rate of α. For details see Methods. To validate this approach, we ran extensive simulation analyses based on the specifications of our four fluency datasets. For details see the Supplementary Material. These showed that a minimum model of $l = 1$, $t_{min} = 0$, and $\alpha = 1$, essentially a random-walk threshold model [13, 55], was able to best recover underlying networks. Assuming a moderate network size and a censored random walk retrieval process [56, 55], this model detected 70.5% of the edges that could have been detected given the available data, while committing only 6.8% of the edge false alarms that the more lenient, random-walk model ($t_{min} = 0$) would commit. Moreover, this model recovered the macroscopic structure of the underlying network well, as indicated by correlations of .95 and .79 between inferred and true values of C and L, respectively. Finally, the presence and absence of edges in the inferred animal fluency networks was able to predict well the similarity ratings collected in study 2 ($d = (.88, 1.32, 1.53)$).

Networks were inferred for younger and older adult groups of four fluency datasets. The data sets varied in terms of domain (animal vs. country), design (lifespan vs. cohort), and fluency duration (1 minute vs. 10 minute). Among those factors, duration exerted a strong influence on performance, with 10-minute fluency leading to 4 to 5 times as many responses per sequence than 1-minute fluency. Notably, the longer duration allowed older adults to produce as many, if not more, items than younger adults, contradicting the typical observation of declining performance in verbal fluency [57, 58, 50]. Moreover, we found that older adults, as a group, produced more unique responses both in total and per response, consistent with the notion that adults possess larger vocabularies and, thus, may possess larger semantic networks (see Table 1).

In order to account for differences in network sizes, which could obfuscate differences in structure [43], we compared the macroscopic structure younger

Table 1: An Overview of Fluency Data and their Inferred Macroscopic Network Structure

Dataset	N	Age	$\bar{N}$	$\frac{N_u}{N^a}$	$\lvert V \rvert$	$\langle k \rangle$	C	L
Wulff et	142	29-65	22.00	.09b	84	3.85	0.46	2.53
al. (2016)	142	66-94	18.60	$.11^b$	87	3.33	0.38	2.83
Study 1 -	41	18-34	93.10	$.15^b$	165^c	1.85	0.24	4.72
Animal	71	66-81	101.80	$.18^b$	155^c	1.69	0.24	5.09
Study 1 -	41	18-34	77.60	$.08^b$	132^c	2.94	0.36	3.67
Country	71	66-81	80.30	$.11^b$	135^c	2.49	0.35	4.12
Study 2 -	36	18-32	97.50	.17	141	1.72	0.26	4.66
Animal	36	65-78	98.10	.19	123	1.62	0.31	5.06

[a] Ignoring duplicate productions. [b] Proportions were found to be significantly different between younger and older adults according to permutation tests. [c] To equate the amount of data per group, the older adults results are rounded averages of 200 random samples of 41 older individuals.

and older adult's networks only for the shared set of nodes, i.e, their common subgraph. We found the pattern of results to be consistent with previous results Zortea et al. [35], Dubossarsky et al. [36]. Older adult networks were characterized by smaller average degrees and higher average path lengths than networks of younger adults. Older adults' networks also exhibited a smaller average clustering coefficient than younger adults in two data sets and a larger clustering coefficient in the other two data sets, mirroring the inconsistent findings of previous studies [35, 36]. See Figure 3. These results confirm previous findings and strongly suggest age-related differences in semantic networks.

3.2. Differences in networks based on similarity ratings

To test whether the results from fluency networks extend to the level of the individuals and to rule out any influence of aggregation biases, we measured networks of younger and older individuals using similarity ratings. Specifically, we had individuals rate all 1953 pairs of 63 animals on a scale from 1 (extremely unsimilar) to 20 (extremely similar) plus 315 repeated pairs in order to assess reliability, which was found to be high (older adults: $r = .76$, younger adults: $r = .74$). Before creating the networks, we mapped

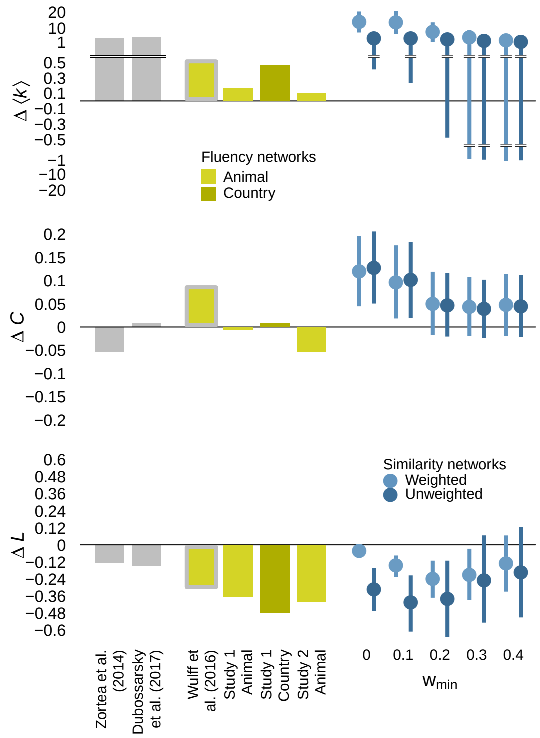

Figure 3: Differences in the macroscopic structure of younger and older networks. Grey bars show the the difference between the young and old age group in Zortea et al. [35] and that of age 30 and 70 in Dubossarsky et al. [36], respectively. Yellow bars show differences in networks inferred from the four fluency data sets. Blue points show differences in weighted and unweighted similarity rating networks, with blue bars showing 95% bootstrapped confidence intervals.

individuals' minimum ratings to 0 and maximum ratings to 1, in order to account for differences in scale use. Weighted and unweighted networks were then constructed by including edges larger than w_{min}. The threshold w_{min} was needed for two reasons. First, clustering can only be evaluated for networks that are not fully connected. Second, by varying the treshold we were able to evaluate the robustness of the results. Across various values of w_{min}, we found older adults' networks to consistently exhibit lower average degrees ($\langle k \rangle$), higher average shortest path length (L), and also lower local clustering coefficients (C), irrespective of whether the networks were analyzed as a weighted or unweighted network. For highly inclusive values of w_{min} that retain more than 50% of all edges, i.e., $w_{min} \in (0, .1)$ moderate to large effects were observed, each reaching statistical significance. Effects for more restrictive values of w_{min}, i.e., $w_{min} > .1$ pointed in the same direction, but they were smaller in size and, due to larger variance, did not consistently reach significance. These results confirm and extend findings from fluency networks. Moreover, they demonstrate, for the first time, systematic age-related differences in the structure of semantic networks on the level of the individual.

Table 2: Average Macroscopic Structure of Similarity Networks for $w_{min} \in (0, .1, .2)$

		Weighted			Unweighted		
	$\|V\|$	$\langle k \rangle$	C	L	$\langle k \rangle$	C	L
$w_{min} = 0$							
YA	63	16	.87	.13	50.7	.86	1.16
OA	62.9	12.5	.75	.18	37.0	.73	1.47
d	.42	$.51^a$	$.73^a$	-.46	$.94^a$	$.74^a$	$-.93^a$
$w_{min} = .1$							
YA	63	15.5	.77	.24	42.4	.76	1.31
OA	62.7	12	.67	.38	29	.66	1.72
d	.34	$.50^a$	$.56^a$	$-.88^a$	$.85^a$	$.56^a$	$-.93^a$
$w_{min} = .2$							
YA	62.8	13.6	.64	.56	28.5	.62	1.66
OA	61.8	11	.59	.80	21.2	.57	2.04
d	.30	.39	.33	$-.85^a$	$.54^a$	.31	$-.63^a$

$^a p < .05$

3.3. Comparison of edge weights

What drives the structural differences between networks of younger and older adults? To shed light on this question, we compared the distribution of edge weights in the similarity networks. As illustrated in Figure 4A adults' edge weight distributions were found to be significantly more skewed ($t_{53.8} = -2.02$, $p = .049$, $d = -.48$) and of significantly smaller entropy ($t_{56.9} = 3.46$, $p = .001$, $d = .82$) than those of younger adults. The same pattern was observed on the level of individual nodes. Nodes in older adults networks exhibited edge weight distribution that also were significantly more skewed ($t_{114.2} = -3.89$, $p < .001$, $d = -.69$) and of significantly smaller entropy ($t_{107.7} = 5.33$, $p < .001$, $d = .95$) than nodes in younger adult networks. We also compared the distribution of edge weights between younger and older adults' networks (Figure 4B) and found that older adults' networks show lower edge weights than younger adults' networks, particularly, for those edges that possess moderate weights in the younger adults networks. Consistent with results obtained for aggregate networks [36], these results suggest higher discrimination of semantic relatedness in older as compared to younger adults. Specifically, in older adults networks, items of medium relatedness appear to have been driven further away from maximum similarity than in younger adults networks.

We evaluated compared within-group consistency by measuring the interquartile ranges (IQR_w) for each edge within a group. We found that older adults' networks showed a nearly three times higher dispersion of IQRs than younger adults ($\hat{\sigma^2}_{older} = .029$, $\hat{\sigma^2}_{younger} = .011$). This higher dispersion stems from older adults showing significantly higher consistency ($d = -9.04, p < .001$) for weakly related node pairs, i.e., $0 < w < .2$, and significantly lower consistency highly for related noted pairs, i.e, $.2 < w < 1$, showing maximum inconsistency for $.4 < w < .6$ ($d = 1.57, p < .001$). Thus, except for relatively unrelated node pairs, such as rat and fly, older adults semantic networks tend to be more different from one another than those of younger adults.

4. Discussion

Semantic networks are a key ingredient of many models of cognition. They provide the underlying knowledge base that allow cognitive processes to reason whether a penguin is bird or to remember the name of a person, you have just met. This knowledge base is the product of learning from experience [19, 59]. Individuals who make different amounts and different kinds of experiences should, thus, possess different semantic networks. In this investigation, we have demonstrated that this assertion holds true. Studying the association of age and semantic networks, we have found structural differences in networks of groups and individuals. Group-level analyses using verbal fluency data have replicated previously observed [35, 36] differences between networks of younger and older: Older adults' networks exhibited larger average degrees and lower average shortest path lengths than younger adults' networks and they did not systematically differ in terms average clustering

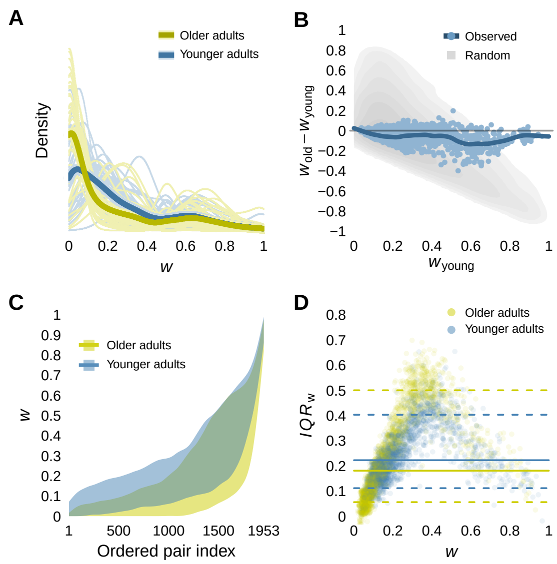

Figure 4: Comparison of edge weights in younger and older adults' networks. Panel A shows the individual and aggregate density distribution of edge weights for younger (blue) and older adults (yellow). Panel B shows the differences in edge weights between younger and older adults as a function of the younger adults edge weights (in blue). The grey background shows the expected result distribution (determined by simulation) assuming the marginal distributions in panel A and independence between edge weights of younger and older adults. Panel C illustrates within-group differences in edge weights by showing as polygons the edge weights interquartile range across individuals for all 1953 pairs ordered by the pair's average weight across both groups. Panel D shows the relationship between the a pairs' average edge weights and the associated interquartile ranges

coefficients. Individual-level analyses of weighted and unweighted networks based on similarity ratings confirmed the differences in average degrees and lower average shortest path lengths and also revealed systematic differences in terms of average clustering coefficients, pointing to lower clustering in older adults semantic networks. These results establish, for the first time, conclusive evidence for structural, indivudal-level differences in semantic networks of younger and older adults.

Our results have important implications for understanding and modeling human cognition. It is generally assumed that differences in size and structure of semantic networks can manifest in differences in cognitive performance [37, 38, 39, 40, 27, 29, 19]. This creates a thorny problem: Both network structure and cognitive process can independently be powerful explanations of behavior, which can render it difficult to decide between competing models. Recently, a version of this problem has been at the core of a debate concerning models of human memory search. It was found that a simple random walk process operating on a network generated from free association data was able to explain verbal fluency data just as well as previously proposed, more complex cue-based search process operating on a network generated from natural language data using machine learning [56, 21, 11]. Thus, different choices concerning the underlying semantic network can critically impact conclusions drawn from data regarding the cognitive process, not even considering individual differences. A key challenge for future research is, thus, to develop new methodological approaches to reliably measure the semantic network of groups and individuals free of influences of process [21, 60]. This will involve characterizing the linguistic and physical environment of individuals and to develop appropriate learning mechanisms that build a realistic image of a person's semantic network.

4.1. What drives age-related differences in network structure?

Another, related challenge is the development of models of age-related differences. Both Zortea et al. [35] and Dubossarsky et al. [36] had studied semantic networks across the entire lifespan, including children, and observed inverted U-shaped trends with inflection points at around 30 years of age. Because of this, it seems unlikely that network growth models, such the one by Steyvers and Tenenbaum [17], are able to capture the full developmental trajectory, as they tend to grow monotonically. A probably more fruitful approach is the use of models of computational semantics (e.g., [19]), which learn representations from natural language, and a language corpus that is age-specific. The input to the cognitive system, in this case text, is often ignored and may account for some of the observed developmental non-linearities. The goal of such an agenda should be how much of the observed findings can be explained through natural learning, in order to find out whether and which additional aging process need be assumed [45, 46, 47].

For this agenda, it will be useful to consider the complex edge-weight differences between younger and older adults. Compared to younger adults networks, We found the distribution of edge weights in older adults networks to be considerably more right-skewed and most different from younger adults networks for moderate edge weights. Moreover, we found older adults networks to be more similar to each other for unrelated node pairs, and more distinct from each other for related node pairs as compared to younger adults networks. These patterns can, at least in parts, arise from natural development. Models of continued discriminative learning predict that related and unrelated concepts are driven further apart from each other over time [29]. Moreover, the fact that younger adults will likely have spend about half their life in educational institutions and, thus, in highly similar environments, whereas the relevance of education is much lower for older adults, may explain the considerably lower dispersion among younger than among older adults. Thus, the demonstrated structural differences between younger and older adults may not reflect decline, but continued learning and a possibly quite useful adaptation to the requirements of older adults life [61].

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