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The Hyper-Modular Associative Mind: A Computational Analysis of Associative Responses of Persons with Asperger Syndrome

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Abstract
Rigidity of thought is considered a main characteristic of persons with Asperger syndrome (AS). This rigidity may explain the poor comprehension of unusual semantic relations, frequently exhibited by persons with AS. Research indicates that such deficiency is related to altered mental lexicon organization, but has never been directly examined. The present study used computational network science tools to compare the mental lexicon structure of persons with AS and matched controls. Persons with AS and matched controls generated free associations, and network tools were used to extract and compare the mental lexicon structure of the two groups. The analysis revealed that persons with AS exhibit a hyper-modular semantic organization: their mental lexicon is more compartmentalized compared to matched controls. We argue that this hyper-modularity may be related to the rigidity of thought which characterizes persons with AS and discuss the clinical and more general cognitive implications of our findings.

Keywords
Asperger syndrome, semantic networks, modularity, thought rigidity, network science

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Introduction

Persons with Asperger syndrome (AS) (according to the DSM-IV) have impairments in social interaction and flexibility of thinking. While they exhibit intact formal language (syntax, morphology, phonology) and general learning abilities, they express a deficit in high level non-literal aspects of linguistic processing (Boucher, 2003; Gernsbacher & Pripas-Kapit, 2012; Hermelin & O'Connor, 1970; Minshew, Goldstein, & Siegel, 1997). Extensive research has shown that persons with AS show difficulty in understanding irony (Martin & McDonald, 2004), semantic ambiguity (Le Sourn-Bissaoui, Caillies, Gierski, & Motte, 2011), humor (Emerich, Creaghead, Grether, Murray, & Grasha, 2003; Samson & Hegenloh, 2010), context-related linguistic interpretations (Jolliffe & Baron-Cohen, 1999) and figurative language (Gillberg & Gillberg, 1989; Gold & Faust, 2010, 2012; Gold, Faust, & Goldstein, 2010). To date, the cause of this deficit is still unclear. However, it is clear that it involves difficulties in semantic processing (Boucher, 2012; Hobson, 2012). This apparent inflexibility in thought and processing of creative aspects of language is often referred to as concrete or rigidity of thought (Hobson, 2012).

Attempting to explain the difficulties in processing figurative language typically exhibited by persons with AS, Gold and Faust (2012) proposed an extension to Baron-Cohen's empathizing–systemizing theory (Baron-Cohen, 2009). This extension argues that in the language domain, conventional language processing is rule-based and thus considered as the "systemized" part of semantic processing, which remains intact in persons with AS. Figurative language processing, on the other hand, involves some degree of semantic rule-violation strategies. These strategies involve the ability to violate conventional dominant meanings and connect remote associations into a new and appropriate linguistic product, also related to creative ability (Benedek, Konen, & Neubauer, 2012; Gold, Faust, & Ben-Artzi, 2011; Mednick, 1962). As such, the authors argue that figurative processing can be considered similar to the "empathized" system, which is much less rule-based and considered to be disrupted in persons with AS. This disrupted flexible ability in breaking away from a strict rule-based semantic system, as suggested by these authors, may explain the rigidity of thought expressed in persons with AS and, as a result, their specific difficulties in processing aspects of language that require some degree of semantic rule violation. Nevertheless, to date, this perspective has not been directly empirically investigated. The present study applied computational network tools to investigate the structure of the mental lexicon of persons with AS compared to a group of matched controls (MC). This was done in order to examine whether differences in the structure of the mental lexicon may shed quantitative light on the rigidity of thought expressed by persons with AS. To the best of our knowledge, this is the first network research conducted on the semantic organization of this population.

Previous research conducted on autistic persons has hinted at the deficit they experience in breaking apart from a rule-based language system. Boucher (1988) investigated the verbal fluency ability of high functioning autistic children compared to MCs. In this research, participants had to generate as many words as they could think of either to a semantically well-defined category (i.e., animals) or simply generate miscellaneous words. Results showed that while high functioning autistic children performed as well as the controls on the semantic categories task, they performed significantly worse than the controls on the miscellaneous word generation task. The poor performance exhibited by the autistic children in the undefined task may reflect difficulty with unstructured -non rule based -verbal tasks. Similarly, Turner (1999) examined the ability of autistic persons compared with a group of learning disabled persons to generate novel ideas, via three different fluency tasks–verbal (phonological and semantic), ideational and design (for a full description, see Turner, 1999). This research found that autistic persons generated a significantly

lower number of responses in the ideational tasks compared to the group of learning disabled persons. Furthermore, autistic persons generated significantly fewer novel responses. Craig and Baron-Cohen (1999) examined the creative abilities of children with autism, children with AS, and typically developing children. The authors found that both clinical groups tended to generate fewer novel ideas. Furthermore, these two groups generated more reality based suggestions for what ambiguous shapes could be, compared to the control group. The authors therefore concluded that autism is related to deficiency in imaginative ability.

Overall, the above findings exemplify the difficulties persons with autism have in generating new ideas, in both creative and verbal fluency tasks. These studies may be explained in terms of the organization of their mental lexicon. This difference in organization could underlie their deficit in flexibility of thought, which may have a negative effect on their abilities to process figurative language (Boucher, 1988; Craig & Baron-Cohen, 1999; Turner, 1999). Yet, this difference in organization does not seem to disrupt substantive category structure (Boucher, 1988). Thus, investigating the difference in the organization of semantic memory of persons with AS compared to a group of MC may shed new light on the nature of cognitive and linguistic deficits in persons with AS.

Semantic memory is the system of human memory that stores concepts and facts, regardless of time or context. In a more meticulous definition, semantic memory is responsible for the storage of semantic categories and of natural and artificial concepts (Budson & Price, 2005; McRae & Jones, 2013; Patterson, Nestor, & Rogers, 2007). However, the way in which semantic memory is organized into categories and subcategories remains an open question (Jones, Willits, & Dennis, in press; Rogers, 2008). Recently, a growing amount of research in neurocognitive domains is being conducted through the use of computational network science tools. Network science is based on mathematical graph theory, in which networks represent complex systems (such as the mental lexicon) via a set of nodes and links connecting them (for an extensive recent review, see Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013). The nodes in such networks represent the basic unit of the system (i.e., concepts) and the links signify the relations between them (such as semantic relatedness; Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006; Borge-Holthoefer & Arenas, 2010). Of the various network models developed in network science theory, the network model that has been widely used to examine complex systems is the small world network model (SWN) (Milgram, 1967; Watts & Strogatz, 1998). This model has successfully described a wide range of sociological, technological, biological and economical networks (Boccaletti et al., 2006; Bransburg-Zabary et al., 2013; Cohen & Havlin, 2010; Kenett et al., 2010; Newman, 2010). Two main characteristics of SWN are the networks clustering coefficient and its average shortest path length. The clustering coefficient (CC) refers to the probability that two neighbors (a neighbor is a node *i* that is connected through an edge to node *j*) of a node will themselves be neighbors. The average shortest path length (ASPL) refers to the average shortest number of steps (nodes being traversed) needed to be taken between any two pairs of nodes. A related structural property of networks examined is the network diameter (D), which represents the longest path in the network. Thus, the diameter is related to the spread of the network, which has been shown to be important in cognitive systems (i.e., Kenett, Anaki, & Faust, 2014). A SWN is characterized by having a large CC and a short ASPL.

At the cognitive level, the application of network science tools is developing, mainly to investigate complex systems of language and memory structure (Baronchelli et al., 2013; Borge-Holthoefer & Arenas, 2010; Chan & Vitevitch, 2010; De Deyne, Kenett, Anaki, Faust, & Navarro, in press; Vitevitch, 2008; Vitevitch, Chan, & Goldstein, 2014; Vitevitch, Chan, & Roodenrys, 2012). In the linguistic domain, lexicons of different languages display SWN characteristics, considered to be a fundamental principle in lexical organization (Borge-Holthoefer & Arenas, 2010; De Deyne & Storms, 2008; Kenett, Kenett, Ben-Jacob, & Faust, 2011; Steyvers & Tenenbaum, 2005). Network

research has also been recently used to investigate individual differences in creative ability. Such research has shown how the semantic network of high creative persons is less structured and more flexible than the network of low creative persons (Kenett, Anaki, et al., 2014). This higher flexibility and lower structure of their mental lexicons allows higher creative persons to generate creative ideas (Mednick, 1962; Schilling, 2005). Finally, clinical research using network science tools to examine deficits at the cognitive level in clinical populations is beginning to emerge. Such research examines the mental lexicon organization of clinical populations suffering from speech, language and thought disorders and provides novel insights into the nature of their deficiencies (i.e., Beckage, Smith, & Hills, 2011; Cabana, Valle-Lisboa, Elvevåg, & Mizraji, 2011; Holshausen, Harvey, Elvevåg, Foltz, & Bowie, 2014; Kenett et al., 2013; Lerner, Ogrocki, & Thomas, 2009; Mota et al., 2012; Voorspoels et al., 2014). Currently, the research conducted on autism using network science focuses on the analysis of brain networks (Barttfeld et al., 2011, 2012; Rudie et al., 2013). Although prior behavioral research has indicated altered memory organization in persons with AS (Bowler, Gaigg, & Gardiner, 2008, 2009; Poirier, Martin, Gaigg, & Bowler, 2011), to the best of our knowledge, network research has not been conducted on the cognitive level of persons with autism or AS. Such research has great value, as it can provide a quantitative method to examine the cognitive difficulties exhibited by this population, such as their rigidity of thought.

Recently, Faust and Kenett (2014) proposed a novel theory which relates lexicon structure to typical and atypical semantic processing. This theory proposes a cognitive continuum of lexicon structures, ranging from extremely rigid to extremely chaotic lexicon structures. According to this theory, efficient semantic processing is achieved via a balance between rigid structured semantic processing and more chaotic, flexible semantic processing (Faust & Kenett, 2014). On one extreme of this continuum lies chaotic, unstructured lexicon networks, such as those exhibited in persons with schizophrenia (Zeev-Wolf, Goldstein, Levkovitz, & Faust, 2014). On the other extreme of this continuum lies rigid, structured lexicon networks. Such lexicon structure is overly structured, allowing efficient ordered, rule-based, structured lexical processing. However, such a lexicon structure is extremely inflexible, greatly inhibiting the ability to create novel combinations and break apart from rule-based processing. The authors promote the use of network science methods to examine such structural lexicon differences between typical and atypical populations. One such method is via the investigation of the community structure of the mental lexicon.

Community structure research examines how a complex system, comprised of many nodes and edges, break apart (or partition) into smaller sub-networks (Fortunato, 2010). This area of research has been promoted, to a great extent, by Newman (2006), who introduced the notion of modularity (Q). The modularity measure is a statistical measure that quantifies how much a network partitions into sub-communities. The larger the modularity measure is, the more the network is comprised from sub-communities (Newman, 2006). The notion of modularity is extensively investigated at the neural brain organization level to examine neuronal connectivity and functional networks (Bullmore & Sporns, 2012; Hilgetag & Hütt, 2014; Meunier, Lambiotte, & Bullmore, 2010). However, a limited amount of research has been conducted using this quantitative measure in the study of the mental lexicon (Kenett, Anaki, et al., 2014; Siew, 2013). Furthermore, while previous studies have shown the effect of modular disruption in regard to clinical populations (Stam & van Straaten, 2012), research on possible negative aspects of a network being extremely, or hyper, modular is lacking (Arenas, Borge-Holthoefer, & Moreno, 2012; Shai et al., 2014). This hyper-modularity, resulting from extreme structuring of the networks into smaller sub-parts, may hinder the flexibility of the network, thus increasing its rigidity. According to the theory proposed by Faust and Kenett (2014), persons with AS may have a hyper-modular mental lexicon organization compared to the lexicon of MCs.

To examine this theory, we used the approach developed by Kenett et al. (2011) to represent and compare the semantic networks of both groups. This approach defines connections between concepts in the mental lexicon by the similarity of association responses generated to these concepts, or alternatively, as the overlap of "association clouds" (Kenett et al., 2011). This notion is in accord with classic cognitive theory on the organization of semantic memory (Collins & Loftus, 1975), and thus differs from standard methods of extracting semantic similarity based on standard statistical properties (Kenett et al., 2011). Studying the mental lexicon with the use of complex network methodology, based on free association responses, poses great merit. This is due to the general agreement, from a psychological point of view, that associations are one of the organizing principles of semantic memory (Borge-Holthoefer & Arenas, 2010; De Deyne et al., in press). Thus, this approach can be used to examine the organization of the mental lexicon in persons with AS compared to MCs and to quantitatively examine the nature of their rigidity of thought. This was achieved via two major steps: first, both AS and MC groups generated free association responses to 96 cue words. Second, the semantic networks of both groups were calculated based on the overlap of association responses ("associative clouds") between the cue words. Finally, we quantitatively analyzed and compared the two networks to examine any possible differences between them. We hypothesized that the AS network would be more modular than the MC network (higher Q). Furthermore, in accordance with Gold and Faust (2012), we hypothesized that the AS group would generate a smaller number of unique associative responses ("associative clouds") as compared to the MC group.

2 Materials and methods

2.1 Participants

Nineteen individuals with Asperger syndrome participated in this study (12 men, 7 women; average age in years = 26, SD = 5.54). In line with previous research (Gold & Faust, 2010; Gold et al., 2010), diagnosis of persons with AS was carried out by an independent psychiatrist with extensive experience in this area, following DSM-IV criteria (American Psychiatric Association, 1994). To confirm this diagnosis, they completed the autism-spectrum quotient (AQ) (Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001). All participants scored above 26, which has been suggested in two separate studies as a more sensitive cut-off point for this quotient (Kurita, Koyama, & Osada, 2005; Woodbury-Smith, Robinson, Wheelwright, & Baron-Cohen, 2005), and fits the cut-off point distinguishing the general Israeli population and Israeli persons diagnosed on the autistic spectrum (Golan, Gold, & Fridenzon, 2009). In addition, according to parental report, all participants with AS had no significant delay in language development. Parents were asked to report at what age major language developmental milestones were reached, for both expression and comprehension. Specifically, regarding expressive language development they were asked at what age first words were acquired and at what age two words were combined. Regarding language comprehension they were asked to indicate whether as a child their son/daughter could understand simple questions and follow simple directions. Participants who suffered from co-morbid mental illness, reading disabilities, or substance abuse were excluded. Substance abuse and comorbidities were assessed as exclusion criteria by the psychiatrist who conducted the diagnostic procedure (excluding six participants). Reading disability was assessed as exclusion criteria by asking participants whether they were ever formally diagnosed as having a reading disability. In addition, participants were asked to subjectively report if they encounter reading difficulties. Participants with AS had an average verbal IQ score (mean IQ = 103, STD = 16), which was shown in a previous study to resemble that of a similar sample of matched comparable controls (Gold et al., 2010). The

research was conducted prior to the release of the DSM-V, thus participants were diagnosed according to the DSM-IV. The strict inclusion criteria resulted in a relatively small AS group sample size.

Fifty individuals participated as MCs (33 men, 17 women; average age in years = 25.2, SD = 3.03). All control participants were psychology students at Bar-Ilan University. Due to the long experimental procedure, IQ tests were not administered to controls. We assumed the two groups were IQ-matched based on the previous study mentioned above (Gold et al., 2010). In that previous study, a similar group of students (also from the psychology program) served as controls, and for them IQs were obtained and found to match those of the AS group. All participants were native Hebrew speakers who had completed at least 12 years of formal education, and were rewarded with 70 ILS or with partial fulfillment of their academic requirements.

2.2 Methods

2.2.1 Free association task. The free association task is based on the method used in Rubinstein, Anaki, Henik, Drori, and Farn (2005). Participants are presented with a cue word and have one minute to generate as many associative responses they could for that cue word. This method differs from classical association tasks, where subjects are only required to generate the first associative response to a cue word (Nelson, McEvoy, & Schreiber, 2004). This method is superior to previous methods in collecting association norms, as it exposes a greater part of the mental lexicon, helping to statistically strengthen significant associations with cue words within the network (De Deyne, Navarro, & Storms, 2013; Kenett et al., 2011). The duration of time for the generation of associative responses per cue word was chosen to be one minute. This was chosen based on the procedure conducted by Rubinstein et al. (2005). Some objections have been raised that this duration is too short for such tasks (Wixted & Rohrer, 1994). However, these objections focus on free recall tasks, which demand structured retrieval from memory. The continuous free association paradigm does not pose any constraints on retrieval. Furthermore, Beaty and Silvia (2012) examined the trajectory of numbers of responses in a 10-minute divergent thinking task. The authors show that the majority of responses are generated within the first minute of responses.

Persons with AS exhibit a strong reliance on concrete nouns combined with difficulties in processing abstract words (Gold & Faust, 2012). Therefore, we controlled for the concreteness of the cue words chosen for the free association task. The construction of the list of cue words used in this study involved several steps. First, words were drawn from a list of categorical norms gathered by Henik and Kaplan (2005), who asked their participants to generate words in a verbal fluency task. The words were generated based on 36 categories (e.g., fruits, trees, countries). The top four high frequency words from each category were selected. These high frequency words were then tested for their degree of concreteness. Ten independent persons were selected to judge the level of concreteness of each of these words. These judges were age matched to the AS group and did not participate in the experiment. Each word was judged for its level of concreteness on a 7-point Likert scale, in which 1 represented low concreteness (i.e., abstract) and 7 represented high concreteness (i.e., concrete). Based on this pretest, only words with an average score of 5 and above on the concreteness scale were selected. The final word pool thus consisted of 96 words from 24 categories.

2.2.2 Association correlation networks. The free association data were analyzed using the approach developed by Kenett et al. (2011). In these association correlation networks, nodes represent the cue words and edges represent the association correlation between words or the similarity of associations generated by a pair of cue words. The association correlation networks were constructed by the following four steps.

First, raw association matrices were separately constructed for the associative responses of the two groups. These matrices were constructed such that each row was an associative response generated by any of the participants to any of the cue words and each column was a different cue word. In these raw association matrices, each cell contains the value "1," indicating that a specific participant generated a specific associative response *i* to a cue word *j*.

Second, we conducted a pre-processing stage. The aim of this stage was to standardize the associative responses across participants (by converting plural into singular, i.e., fruits to fruit) and to eliminate any possible typing errors (i.e., aplle to apple). Next, identical associative responses were merged using the Minitab software (www.minitab.com). This resulted in unique association matrices for both groups. In these unique association matrices, each row *i* is a unique associative response given by the entire sample, each column *j* is a different cue word, and a cell contains the number of participants generating a unique association response *i* to cue word *j*.

Third, the association correlation matrix is computed from the unique association matrices. The correlations between the cue word associations profiles (the associative responses given to the cue words by all participants), are calculated by Pearson's correlation. This correlation is based on the contribution of two parameters–the extent of similar associative responses given to a pair of cue words and the number of participants generating these similar associative responses to these cue words. Thus, the more similar associations generated and the larger number of participants generating these association responses to a pair of cue words, the higher the association correlation between this pair of words is (see Kenett et al., 2011 for a full description).

For example, if a pair of cue words are *cat* and *dog* we examine the overlap of associative responses for these two cue words. A possible overlap of associative responses given to both the cue word *cat* and the cue word *dog* can be *pet* (given by *a* number of participants to *cat* and *b* number of participants to *dog*), *home* (given by *c* number of participants to *cat* and *d* number of participants to *dog*), *friend* (given by *e* number of participants to *cat* and *f* number of participants to *dog*) and so on. Then, each of these association responses given to both cue words and the number of participants generating these associative responses for both cue words contributes to the strength of the association correlation between these cue words. The association correlation matrix can be studied in terms of an adjacency (connectivity) matrix of a weighted, undirected network. In this view, each cue word is a node in the network, and an edge (link) between two nodes (cue words) is the correlation between these two nodes.

Fourth, we used a filter to remove spurious correlations. Since most of the edges have small values (weak correlations), the relevant information about the network can be obscured. Several methods have been developed to overcome this obstacle by constructing from the complete network a sub-graph that captures the most relevant information embedded in the original network. Here we use the planar maximally filtered graph method (PMFG) (Tumminello, Aste, Di Matteo, & Mantegna, 2005). The resulting sub-graph of this method includes all of the nodes in the network whose edges represent the most relevant association correlations. To construct the planar graph, the N(N–1)/2 values of the correlation matrix are ordered in decreasing rank. The method starts from the pair of nodes *i* and *j* with the highest correlation and draws a link between them. This reiterates according to correlation strength where in each iteration a link is added, if and only if the resulting graph is still planar, that is, can be drawn on the surface of a sphere without links crossing (Tumminello et al., 2005). This results in a filtered sub-graph after eliminating possible spurious correlations. Since we are interested in the structure of the network, we binarized the network (by converting all edges to uniform weight = 1) and analyzed the network as an unweighted undirected network.

Finally, it is important to note that this method can only examine group sample networks and is not sensitive to the individual differences of specific participants. When applying this method to

compare two networks (for example, AS versus MC semantic networks), this method focuses on how the responses generated by all cue words by all participants in one group differ from those of the second group. Thus, if the same cue words are presented to both groups in a free association task, this computational method analyzes the general difference of the network structure arising from each complete sample.

2.2.3 Network analysis. The network parameters, calculated with the brain connectivity toolbox for Matlab (Rubinov & Sporns, 2010), were the following: the CC, the ASPL and the network's diameter (D). Furthermore, in order to examine the network's CC and ASPL, a random network was created with the same number of nodes and edges. For this random network, we calculated its clustering coefficient (CCrand) and its average shortest path length (ASPLrand). To examine the modularity of each network, we made use of Newman's modularity measure (Newman, 2006) to investigate how each network divides into sub-clusters of words, by calculating its modularity index (Q).

Statistical hypothesis testing methods to compare between networks is currently lacking (Moreno & Neville, 2013). Such methods are required when conducting empirical network research to determine whether two (or more) networks are significantly different from each other or not (null hypothesis). This lack of network comparison hypothesis testing is mainly due to difficulties in estimating or collecting a large sample of empirical networks and due to few statistical methods that compare between networks (see Moreno & Neville, 2013). To statistically analyze our findings, we used three complementing approaches. First, we simulated random networks to determine that the network measures calculated for both networks did not result from a random network null hypothesis. To this end, we generated a large sample of Erdös–Rényi random networks with a fixed edge probability (Boccaletti et al., 2006) and compared the network measures to the values resulting from the simulated random distributions for each measure. The Erdös–Rényi random network model was chosen as it does not make any assumptions regarding the structure of the network (Erdös & Rényi, 1960).

Second, we examined whether differences between the AS and MC network measures were statistically significant by applying the bootstrap method (Efron, 1979) to simulate partial random AS and MC networks and compared these networks (Kenett et al., 2013; Kenett, Anaki, et al., 2014). This procedure had a twofold rationale: (1) if the two networks truly differ from each other, then any sub-network consisting of the same nodes in both networks should also be different; and (2) the bootstrap method enables the generation of many simulated partial AS and MC networks, allowing for statistical examination of the difference between the two networks. In order to conduct the bootstrapping procedure, half of the cue words (nodes) were randomly chosen. Then partial AS and MC networks were constructed separately using these random nodes, based on the entire sample. This method is known as the without replacement bootstrap (Bertail, 1997; Politis & Romano, 1994; Shao, 2003). Finally, for each partial AS and MC network, CC, ASPL, D and Q measures were computed. This procedure was simulated with 1000 realizations.

Third, we used the non-parametric bootstrap method to conduct sample-matched analysis (Efron, 1979; Shalizi, 2010). As the association correlation matrix is constructed from the associations generated by the entire sample, sample size might affect the association correlations which determine the links in the network. As sample size grows, the number of associations generated to cue words over the entire sample grows. As such, this can flesh out more of the mental lexicon, by strengthening correlations between cue words and "revealing" links between nodes in the network. However, when comparing groups with unequal sample size, such effects of the "association clouds" on the association correlation matrix may provide an alternative explanation of the results. As individual semantic networks of participants consistently exhibit SWN properties (Morais, Olsson, & Schooler, 2013), we can assume that such a possible artifact is not due to individual differences within the MC sample. Since the MC sample is more than double the size of the AS group

(50 MC participants compared to 19 AS participants), we used the bootstrap method (Efron, 1979) to create bootstrapped-MC raw association matrices matched in size to the AS raw association matrix. This method is known as the *m* out of *n* bootstrap (Bickel, Gotze, & van Zwet, 1997; Bickel & Sakov, 2008). This was done by randomly choosing a row *i* from the original MC raw association matrix, with equal probability for every row and with replacement (the same row could be chosen more than once). The result of this process was a new bootstrapped-MC raw association matrix which matched the size of the AS raw association matrix (4821 rows × 96 columns). The associative network of this bootstrapped size-matched MC association matrix was computed and its network measures were calculated. This process was reiterated 1000 times and resulted in a referenced empirical bootstrapped distribution (Kenett, Zack, & Amberti, 2014) for each network measure examined in this research (CC, ASPL, D, and Q). These reference distributions allowed us to examine the statistical probability of the AS network measures' value falling within the reference simulated distribution for each statistical measure separately, thus controlling for possible sample size contamination.

Finally, we analyzed the difference in the number of unique associations generated ("association clouds") by the two groups. If the AS group's semantic rigidity is related to their mental lexicon organization and its lack of flexibility, we would expect that their ability to generate associative responses to cue words would be significantly lower than that of the MC group. As sample size can affect this analysis, we also examined the bootstrapped-MC average number of associations generated for every cue word. Thus, we conducted ANOVA and correlation analyses on the mean number of unique associations generated by the three groups (AS, MC, bootstrapped-MC), averaged over cue words and participants.

2.3 Procedure

The cue words were presented to participants via Microsoft PowerPoint slide software (www.microsoft.com) on a cathode ray tube screen, positioned 50 cm from the participant. Each cue word was presented on a separate slide, in a large font over a white background. The slideshow began with four slides containing written instructions and examples. The experimenter went through the written instructions with the participants, added oral explanations and encouraged questions. The experiment began only after it was clear that the participants understood the task. Participants were given a booklet containing a chart with word numbers and space to write the associations they came up with. They were asked to fill in their associations in the box corresponding to the word number appearing on the slide. The slideshow was pre-programmed to run automatically so that each word was presented on the screen for one minute. After the word was presented for 45 seconds, a short bell sound was heard and the words "15 seconds remaining" appeared on the screen to signal to the participants that time was almost over and to notice the following word. Once a full minute elapsed, the following word appeared and a soft "swoosh" sound was heard to ensure that participants attended to the new word. After 48 minutes (half of the experiment), the participant had a short break before continuing for another 48 minutes. All of the participant's free associations were later manually coded into an Excel sheet.

3 Results

3.1 Associative network construction

We constructed the associative networks based on the steps described above. First, we coded the data into raw association matrices. This resulted in 12,225 (association responses) × 96 (cue words) for the AS group and 19,186 (association responses) × 96 (cue words) for the MC group. Next, we

Table 1. Small world network measures calculated for the Asperger syndrome (AS) and the matched control (MC) semantic network.

Parameter	AS	MC
CC	0.69	0.67
ASPL	3.95	3.66
D	9	8
CCrand	0.06	0.08
ASPLrand	2.74	2.73
Q	0.71	0.70

CC: clustering coefficient; ASPL: average shortest path length; *D*: diameter; CCrand: clustering coefficient of random graph; ASPLrand: average shortest path length of random graph; *Q*: modularity measure.

verified that the length of the paradigm did not cause fatigue and thus confound the data. This was achieved by comparing the number of association responses for the first 25% of the cue words versus the last 25% of the cue words presented to the participants in both groups. This analysis found no significant differences between the number of associations generated by the first and last cue words in both groups.

Second, we conducted the pre-processing stage in order to create the unique association matrices. This resulted in 4821 (unique association responses) × 96 (cue words) for the AS group and 8280 (unique association responses) × 96 (cue words) for the MC group. Such a compression rate of 66% for the AS group and 50% for the MC group is consistent with prior applications of this approach (Kenett et al., 2011; Kenett, Anaki, et al., 2014). This is a result of the tendency of a specific associative response to be generated for a larger number of cue words by a larger portion of the sample. For example, the associative response *tree* was generated by the AS group for 44 different cue words for a total of 152 responses. For the MC group, this associative response was generated for 45 cue words for a total of 483 responses. Finally, we calculated the association correlation matrices for each group independently. We then used the PMFG method to filter out any possible spurious correlations.

3.2 Network analysis

The different SWN properties of the semantic networks of both groups were calculated and compared (Table 1). To visualize the networks, we plotted the graphs using the force-directed layout of the Cytoscape software (Shannon et al., 2003), and in order to present the Hebrew cue words as the labels of the nodes, we translated them into English (Figure 1). In these 2D visualizations, nodes (words) are represented as circles and links between them are represented by lines. Since these networks are unweighted and undirected, the links merely convey symmetrical relations between two nodes.

Both the quantitative analysis of the calculated network measures and the qualitative examination of the networks visualization reveal differences between the AS and MC networks. The network analysis revealed that the AS network had a larger ASPL and D than the MC network. This indicates that the AS network is more spread out than the MC network. This is evident in the network visualization, whereas the AS network is much more spread out than the MC network. Furthermore, this analysis revealed that the AS network had a higher modularity Q value than the MC network. This indicates that the AS network is more modular than the MC network. This is evident in the network visualization, whereas the AS network breaks apart into more sub-parts than

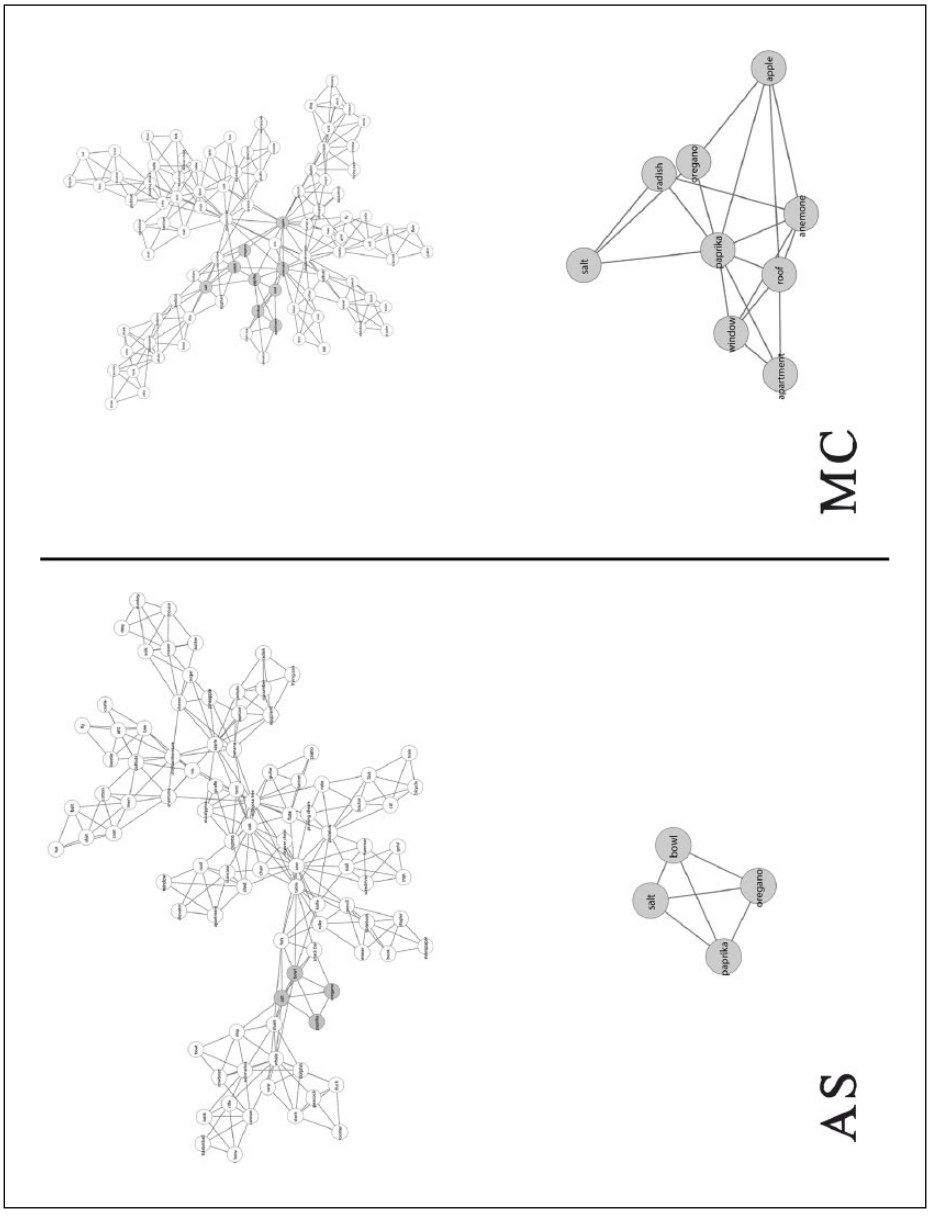

Figure 1. A 2d visualization of the Asperger syndrome and the matched control semantic networks.
Nodes are the 96 cue words translated into English. The links between nodes represent an unweighted, undirected connection between nodes.
Upper panels – full semantic networks; lower panels – the cue word *paprika* and its directly connected neighbors. The cue word *paprika* and its directly connected neighbors are also marked in gray in the full network shown in the upper panels.

Table 2. Small world network measures calculated for the partial Asperger syndrome and matched control semantic networks.

Parameter	P-AS	P-MC	*t*-score
CC	0.69 (0.01)	0.68 (0.01)	3.87***
ASPL	3.12 (0.24)	3.08 (0.24)	4.42***
D	3.74 (0.6)	3.68 (0.6)	2.08*
Q	0.55 (0.05)	0.54 (0.03)	2.16*

Standard deviations in brackets.
CC: clustering coefficient; ASPL: average shortest path length; *D*: network diameter; *Q*: modularity measure; P-AS – mean partial bootstrapped Asperger syndrome networks; P-MC: mean partial bootstrapped-matched control networks.
* $p < 0.05$; *** $p < 0.001$.

the MC network. For example, in the AS network the cue word *paprika* is connected to its directly related category members (i.e., *salt* and *oregano*). In the MC network, however, the cue word *paprika* is connected to its category members but also to other cue words which are associatively related, such as *window*, *apartment*, *roof*, *anemone*, *apple*, and *radish* (Figure 1).

Since both networks are comprised from the same nodes, our null hypothesis is that the networks' measures should not differ. To verify that the AS and MC networks do not result from null hypothesis random networks, we conducted the simulated random network method. This analysis revealed that for both AS and MC networks, all four network measures (CC, ASPL, D and Q) were significantly different than their simulated random measures (all *p*s < 0.001).

To examine the significance of the differences found between the networks, we applied the partial networks analysis (Bertail, 1997; Kenett, Anaki, et al., 2014). An in-house Matlab code was written for the partial networks procedure. This code randomly chose half of the nodes comprising the network. Next, AS and MC networks were constructed for this subset of nodes, based on the associative responses given by each group to these cue words. Network measures were computed for each partial network and this procedure was reiterated 1000 times. This resulted in a sample distribution of 1000 samples for all measures (CC, ASPL, D, and Q). An independent samples *t*-test was conducted on each network measure to test the difference between the partial networks' distribution of the two groups. These analyses revealed significant differences between all of the network measures, in the sense that the CC, ASPL, D and Q of the partial AS network was significantly larger than that of the partial MC network (Table 2). Thus, while these differences were numerically small, they were significantly different and replicated the structural differences revealed in the main analysis.

To control for any possible sample size contamination, we conducted the bootstrapping approach to generate size-matched MC networks (Bickel & Sakov, 2008; Bickel et al., 1997). An in-house Matlab code was written for the bootstrapped size-matched procedure. This code randomly chose, with replacements, 4821 rows out of the original MC raw association matrix to create a bootstrapped size-matched MC raw association matrix. The associative network was computed from this matrix (as described above) and its network measures (CC, ASPL, D, and Q) were calculated. This process was reiterated 1000 times and a reference bootstrap distribution for each network measure was created. Each AS network measure value was than compared to its relevant bootstrapped reference distribution. This provides an examination of the statistical probability of the AS measure value falling within its referenced bootstrapped measure distribution, controlling for sample size contamination (Kenett, Zack, et al., 2014). The analysis revealed that the AS modularity measure Q is significantly out of range, falling to the right of the positive tail of its reference bootstrapped distribution (Table 3).

Table 3. Statistical comparison of Asperger syndrome semantic network measures to size-matched matched controls reference distributions.

Parameter	AS score	SMC score	z-score
CC	0.69	0.69 (0.01)	0.02
ASPL	3.95	3.92 (0.32)	0.07
D	9	8.91 (1.24)	0.07
Q	0.71	0.6 (0.05)	2.06*

Each measure is statstically compared to the 1000 sample simulated size-matched matched control reference distribution for that measure. Statistical comparison is done via a two-tailed *z*-score analysis. AS score: the AS network values for a specific measure; SMC score: mean score of the simulated size-matched matched control network measure distribution (standard deviations in barckets); *z*-value: *z*-score for the AS measure value compared to the bootstrapped reference distribution for that measure; CC: clustering coefficient; ASPL: average shortest path length; *D*: diameter; CCrand: clustering coefficient of random graph. * $p < 0.05$.

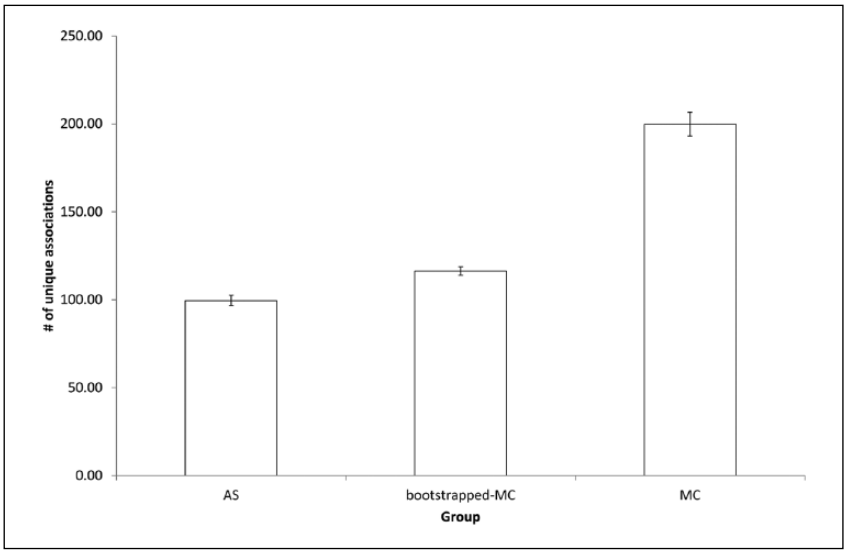

Figure 2. Average unique association responses of the three groups (AS, MC, bootstrapped-MC), averaged over cue words and participants.
X-axis: examined groups; *Y*-axis: mean number of unique association responses (error bars depict standard error); AS: Asperger syndrome group; MC: matched control group.

Finally, we examined the difference in the mean number of unique association responses ("association clouds") generated by the three groups (AS, MC, bootstrapped-MC). A one-way analysis of variance conducted on the effect of group on mean association responses per cue word revealed a significant main effect of group, $F(2, 285) = 628.921$, $p < 0.01$, $\eta^2 = 0.815$. A planned contrast revealed that this main effect is due to a significant difference between the AS group and both MC and bootstrapped-MC groups (all *p*s < 0.001; Figure 2). To exclude any possible sample size contamination, we examined the difference in unique association generation between the AS group and the bootstrapped-MC group. A simple effect analysis (corrected for multiple comparisons using the Benjamini–Hochberg correction (Thissen, Steinberg, & Kuang, 2002) was conducted on the AS unique association responses compared to their bootstrapped-MC unique association distribution for a specific cue word. This analysis revealed a significant effect for 66% of the cue words

Table 4. Correlation analysis of number of unique associations generated by cue words by the three groups (AS, MC, bootstrapped-MC).

Variables	1	2	3
1 – AS	–	.56***	.56***
2 – MC		–	1***
3 – bootstrapped-MC			–

AS: Asperger syndrome group; MC: matched control group. *** $p < .001$.

(all ps < 0.01), in the sense that the AS group generated significantly fewer associative responses to a cue word than the bootstrapped-MC group. Finally, we conducted a correlation analysis between the mean number of unique associations generated for each of the cue words in the three groups (Table 4). This analysis revealed high significant positive correlations between the AS and both MC and bootstrapped-MC groups.

4 Discussion

The present study is the first network analysis of the mental lexicon structure of persons with AS, compared to MCs. The similarities between words based on their free association responses were calculated and used to construct the association correlation matrix separately for each group. These association correlation matrices were used to model the associative networks of both groups, thus representing the organization of the cue words in their mental lexicon. This analysis was conducted in order to investigate the rigidity of thought exhibited in persons with AS from a computational network approach.

Our analysis uncovered several network differences which relate to the structure of the mental lexicon of the two groups. This was evident in higher ASPL and D measures for the AS network, indicating that the AS network is more spread out than the MC network. Furthermore, the AS network had a higher modularity value than the MC network, indicating that the AS network breaks apart into more sub-communities than the MC network. We examined these differences by simulating a large sample of partial networks constructed from subsets of nodes comprising the full network (Bertail, 1997; Kenett, Anaki, et al., 2014). This partial networks analysis found significant differences between all network measures examined, as found in the comparison of the full networks. To control for any possible sample size contamination on the structure of the semantic networks, we used the bootstrapping method (Efron, 1979). This method was used to simulate a large number of size-matched MC association responses matrices, matched to the size of the AS association responses matrix. For each such bootstrapped size-matched MC association responses matrix, we computed its semantic network and calculated its network measures. We then examined how the values of the AS network measures fall within their specific measure distribution (Bickel & Sakov, 2008; Bickel et al., 1997). This analysis revealed that the modularity measure of the AS network was significantly different compared to its bootstrapped distribution, extremly right to the positive tail of the distribution. Thus, the AS modularity measure is hyper-modular compared to the bootstrapped size-matched MC networks and is also significantly higher in the partial networks analysis and larger in the full networks analysis.

Finally, we analyzed the mean number of unique association responses generated by both groups to the cue words. To avoid any possible sample size contamination, we also calculated the mean number of bootstrapped-MC unique association responses for every cue word. Therefore, we compared the mean number of unique associative responses, averaged over cue words and

participants for the three groups (AS, MC, bootstrapped-MC). This was done to further examine whether the deficit in figurative processing (Gold & Faust, 2012) and novel generation (Turner, 1999) typically exhibited by persons with AS may be a result of a hyper-modular mental lexicon. If the AS mental lexicon is hyper-modular, it might be harder for them to generate a wider array (larger breadth) of associative responses to a cue word, thus having a "narrower associative cloud" for a cue word as compared to MCs. This analysis revealed that persons with AS generate a significantly lower number of unique association responses, even when compared to a size-matched bootstrapped sample. Correlation analysis between the number of unique associations generated to the cue words by the three groups revealed significantly high correlations between the AS and MC and bootstrapped-MC group. This correlation analysis provides further support for narrower "associative clouds" to the cue words in the AS group. In general, the AS and MC groups appear to have a similar trend in the breadth of associations generated by the cue words. However, the range of unique associations in the AS is much narrower compared to the MC group.

Taken together, our results indicate that persons with AS have a hyper-modular mental lexicon structure, which may disrupt associative processing and might be related to their rigidity of thought. How may this hyper-modular mental lexicon network organization be related to this rigidity of thought? Kenett et al. (2011) proposed a theoretical account which relates the network structure of the mental lexicon with thought processes, such as those required in creative problem solving (Mednick, 1962). This theory argues that when attempting to solve a creative problem, a search process is activated throughout the mental lexicon. Thus, the structure of the mental lexicon may determine the extent to which this search activation succeeds. How might this theory explain the rigidity of thought expressed by persons with AS? We suggest that the hyper-modular mental lexicon network organization may hinder their ability to break apart from a specific module in the network and spread into other modules. Thus, activation within a dense module might get "trapped" and, combined with its rapid dissipation, result in rigidity of thought. Recent work by Kenett, Anaki, et al. (2014) provided empirical support for this theory. The authors examined the difference in semantic networks of low and high creative individuals. This examination revealed how the semantic network structure of low creative individuals is more modular and spread out than that of high creative individuals (Kenett, Anaki, et al., 2014). Thus, the more modular the structure of the lexicon is, the less flexible it is. Related to this theory, Siew (2013) has recently applied a network community detection approach to investigate the community structure of the phonological network (Siew, 2013). The author describes how densely connected phonological modules "trap" spreading activation of phonological processing.

From a broader perspective, our work highlights the complex relation between the modularity of the mental lexicon and dynamical processes operating upon it (Kenett, Anaki, et al., 2014; Shai et al., 2014; Siew, 2013). The constraints imposed by the structure of the mental lexicon on the dynamical processes operating upon it may explain the dissociation persons with AS exhibit in processing structured compared to unstructured semantic tasks (Boucher, 1988; Turner, 1999). While persons with AS exhibit typical performance within a specific module in the network, their hyper-modular organization disrupts their ability to spread into other parts of the lexicon. This hypothesis may explain why persons with AS exhibit difficulties in higher order linguistic abilities that require access to a wide range of associations and semantic features (Faust, 2012).

Our findings are well integerated with current theories of autism. According to the empathizing–systemizing theory of autism (Baron-Cohen, 2009), autistic persons exhibit a deficit in their empathizing system, while preserving an intact systemized, rule-based system. According to the fine–coarse semantic processing model (Jung-Beeman, 2005), the left hemisphere (the specialized hemisphere for processing language) activates dominant, strong semantic meanings, while the right hemisphere non-specialized system activates a coarse, or weak, unconventional range of

meanings. It is through the interaction of these two systems that optimal semantic processing is achieved. Our finding of the hyper-modular organization of the AS semantic network suits the left hemisphere strategy of processing dominant, strong meanings, which we suggest is facilitated through the partitioning of the network into modules. This is in line with research on persons with autism, demonstrating a right hemisphere deficit in coarse semantic processing (Gold & Faust, 2010). Our results are also directly related to the theory proposed by Faust and Kenett (2014), which relates lexicon structure to typical and atypical semantic processing. This theory proposes a cognitive continuum of lexicon structures, ranging from extremely rigid to extremely chaotic. Our findings are related to the extreme rigid end of this continuum. According to this theory, extreme rigid lexicon structure is characterized as overly structured and modular, allowing efficient ordered, rule-based, structured lexical processing. Such a structure, however, is extremely inflexible, inhibiting breaking away from structured, rule-based processing. Thus, our findings are directly related to the extreme rigid end of this semantic continuum (Faust & Kenett, 2014).

The application of network tools to study language processing in autism and particularly in AS may provide a novel quantitative way to further elucidate the nature of this disorder. Our research adds to the developing field of research which uses network science tools to investigate the mental lexicon and thought processes of clinical populations (i.e., Beckage et al., 2011; Cabana et al., 2011; Holshausen et al., 2014; Kenett et al., 2013; Lerner et al., 2009; Mota et al., 2012; Voorspoels et al., 2014). From a clinical point of view, our findings might serve as a clinical tool by preparing protocols which encourage free association generation. These protocols might attenuate the hyper-modular organization of the mental lexicon of persons with autism, thus aiding in lowering their rigidity of thought and possibly helping them to better process the more creative aspects of language, including metaphors, humor, ambiguity and connotations. Furthermore, such network measures can be used to quantify the severity of the rigidity of thought expressed by persons with AS in relation to treatment methods, thus serving as a unique clinical diagnostic tool.

Alongside the contributions of this study, a few limitations to it exist. First, the network method used here can only represent the network of the sample, and cannot relate to individual participants. In order to be used in clinical applications, this method must be developed to allow the investigation of the semantic network of an individual (see Morais et al., 2013 for a novel approach to investigating individual semantic networks). Second, while the cue words were chosen carefully to control for concreteness and to be strong category representatives, these words were chosen based on MCs responses. While unlikely, it might be that the chosen words were less known to the AS sample, which resulted in fewer association responses. Thus, although both groups were controlled for verbal IQ, and no AS participant reported any difficulties with the cue words, future research should select cue words based on persons with AS norms, in order to eliminate any such contamination and replicate our findings. Finally, in our research we had unequal sample sizes of the two groups–19 persons with AS compared to 50 MCs. As our approach is sample based, we controlled for any sample size contamination by using the bootstrap method to simulate sample-matched raw association matrices. Further research with a larger and size-matched sample will allow the replication and verification of our findings.

In summary, the work presented here is the first network analysis on the structure of the mental lexicon in persons with AS. This was done to investigate the rigidity of thought expressed by this population. We found that the mental lexicon of persons with AS is more compartmentalized and hyper-modular than that of MCs. We suggest that this hyper-modularity might be related to the rigidity of thought expressed by these persons. Our findings provide further evidence for the constraints the structure of the mental lexicon imposes on the dynamical processes operating upon it. As such, network science provides a powerful approach to shedding further light via quantitative means on the thought processes of typical and atypical populations.

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