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Alternative Empirical Directions To Evaluate Schemata Organization And Meaning

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Abstract
It has been reported [1] that a neural network can be implemented to identify whether students have integrated into their lexicon schemata related concepts by the contents of a school course. Specifically, a neural net is trained to discriminate between successful and unsuccessful students´ semantic priming latencies of schemata related words obtained by a semantic priming study at the beginning and end of a course. This neural network discrimination capacity is based on the idea that once a student has integrated new knowledge in long-term memory then a semantic priming effect is obtained from schemata related words (single word schemata priming; e.g., 2]. The current paper constitutes the first of three documents providing a more in-depth analysis to this approach for cognitive assessment of learning. For instance, the mental representation technique used to obtain natural semantic networks from students and teachers (as opposed to idiosyncratic or artificial semantic nets) to study computer simulated schemata behaviour is put under academic scrutiny. Here, it is argued that statistical properties regarding the kind of semantic net (small world structure, scale free degree) as well as the implicit distributed schema through semantic connectedness among concepts relate to emergent connectionist schemas underlying schemata priming that can be identified by a neural net.

Keywords: Schemata behaviour, meaning, natural semantic networks, learning.

INTRODUCTION

In his accusations to cognitive science the famous behavioural scientist Skinner noted [3]:

> *"I accuse cognitive scientists of misusing the metaphor of storage… I accuse cognitive scientists of speculating about internal processes… They have no appropriate means of observation… I accuse cognitive scientists of emasculating the experimental analysis of behavior… I accuse cognitive scientists as I would psychoanalysis, of inventing explanatory systems which are admired for profundity which is more properly called inaccessibility…… I accuse cognitive scientists of relaxing standards of definition and logical thinking and releasing a flood of speculation... "*

Certainly, regarding the case for the "Knowledge Schema" concept, some of Skinner´s accusations toward cognitive science seem to hold. For instance, no definitive definition on this mental phenomenon has been achieved yet. Even when it is clear that a schema (schemata for plural) refers to our capacity to dynamically represent inside our minds internal and surrounding events by using a specific data structure, this theoretical construct is admired more for its profundity than its theoretical specificity, even though the schemata concept is at the core of modern cognitive psychology theorization, and it is a relevant explanatory construct to other academic fields like artificial intelligence, linguistics and even philosophy.

Inside psychology the schema concept was introduced by Piaget [4] to explain how children develop thinking through age. On his part, Bartlet [5] used this mental construct to explain how people tended to reconstruct stories. Early empirical evidence for schemata behaviour in humans [e.g., 6] led to cognitive modelling development like the so called schema-plus-tag model [7]. Later definitions on the schemata data structure provided evidence for human schemata to be constituted with attribute value lists where attributes varied in importance [8], lists of concepts with weighted attributes [9], default values for some attributes [10], and schemata with lists of slots and filters [for a review see 11,12].

A most striking theoretical development regarding the schemata concept was presented by Rumelhart, Smolensky, McClelland and Hinton [13]: they proclaimed that no schemata mental representations exist in our mind; rather, these data representations emerge as required by cognitive processing demands like trying to understand a text [e.g., 14]. Then, for no apparent reason, academic empirical research efforts to explore the schemata conceptual organization seemed to disappear after the beginning of this millennium. Only some isolated efforts to explore the emergent schemata hypothesis have been provided.

A connectionist approach to schemata conceptual organization.

The assumption that a schema can represent knowledge at all levels of abstraction, from ideologies to the meaning of a simple word [15], led Lopez and Theios [16] to look for evidence of emergent schemata behaviour affecting concept organization in the human lexicon. These authors obtained concept definers to Schema related target concepts from persons by using a technique called Natural Semantic Networks [17, 18]. Theoretical foundations for this kind of technique can be tracked to summary representations or feature lists of prototypes [for a review see 12]. Then they used a Constrained Satisfaction Neural Net (CSNN) like the one used by Rumelhart et al. [13] to obtain schemata behaviour from the obtained concept definers.

A typical study on natural semantic nets requires participants to provide single concept definers to target concepts that are related by some knowledge schema of interest. As a result, a set of lists is obtained, each containing the ten highest pondered definers for a target concept (more on this in the method section). The probability for two concepts to co-occur through these lists of definers becomes their weight association in a rectangular matrix, with k possible connections with N concepts such that $k = N(N-1)/2$.

Thus, in a CSNN like the one used by Rumelhart et al. [13], the weight association between two concepts is computed by the following derivative of the Bayesian formula:

$$W_{ij} = -\ln [p(X=0 \,\&\, Y=1)\, p(X=1 \,\&\, Y=0)]\, [p(X=1 \,\&\, Y=1)\, p(X=0 \,\&\, Y=0)]^{-1} \quad (1)$$

where X represents one of the concepts of the pair of concepts to be associated, and Y another concept. In determining association values among concepts in a natural semantic network like the one appointed before, the joint probability value $P(X=1 \,\&\, Y=0)$ can be obtained by computing how many times the definer X of a pair of concepts appeared in a list of definers in which Y did not appear, and the same for the other probability values. These association values were used as an input matrix to the CSNN to simulate the schema of a room. These authors found that if schemata related words selected from the computer simulations (like BRICK-

BUILDING) were tested in a semantic priming experiment against associative and categorical words, then semantic priming is obtained for schemata related words [16, 19, 20, 21]. Moreover, it is argued that this schema priming effect is obtained only after knowledge of a topic has been integrated in long-term memory [e.g., after an academic course 2]. Interestingly enough, neural net classifiers can be taught to discriminate between successful students and non-successful students by analyzing schemata priming effects [1].

In this paper, it is argued that specific structural properties of the implied semantic network as well as memory retrieval processes activated by the definition task in a natural semantic net study produce implicit schema behaviour that is made explicit by connectionist computer simulations. In order to express these ideas in a more formal and deeper style the following natural semantic net study regarding the schema on Piaget´s theory is presented. This will empower a discussion on how this kind of research provides insights into schemata behaviour research by following the questions on how knowledge structure serves meaning formation and in turn how by exploring meaning we can identify mental representation properties of schemata behaviour.

METHOD

A mental representation study using a natural semantic network was used to explore learning of concepts from a psychology course on Piaget´s Theory. By doing this, several unedited properties of this technique will presented as a platform to explore a relation between meaning formation and schemata behaviour that is assumed suitable for cognitive assessment of learning.

Participants

A sample of 43 first semester psychology bachelor's degree students provided conceptual definitions to build a natural semantic net based on Piaget's cognitive theory.

Instruments

Piaget´s related words to be used in the semantic priming study were obtained from a "natural semantic network" technique as follows: Participants were presented with a complete set of instructions and 10 Piaget´s theory concepts to define. These are called "target concepts" and they were: SCHEMA, ACOMMODATION, ASSIMILATION, ADAPTATION, CONCRETE, FORMAL, STAGES, PREOPERATOY, SENSORYMOTOR, and EQUILIBRIUM. These concepts were obtained from three active teachers in charge of a course on this topic and from two experts on this knowledge domain. All of them agreed that these concepts are central to schema acquisition of Piaget´s Theory.

These target concepts were randomly presented in a computer screen to each participant. Subjects were asked to define the 10 target concepts one by one, using other single word concepts as definers. After definition of a target concept (subjects are allowed 90 seconds for this definition task) each definer (which could be any noun or adjective, but not a complete phrase, pronouns, articles, prepositions or conjunctions) has to be rated according to its relevance as a definer on a scale ranging between 1 (lowest relevance) and 10 (highest relevance). This technique, called natural semantic network technique, has been tested [e.g., 17, 18, 22] and shown to produce definitions for the represented objects based on their meaning and not on free associations or pure semantic category membership.

By using this technique, at least the following values can be computed for each of the 10 target concepts:

M value: The sum of the ranks assigned by all the subjects to each definer concept. This is a relevant measure to each concept as the definition relevance of a target concept.

SAM (Semantic Analysis of M value) group: This is a basic group of 10 definers with the highest M values for the target concept. This is the set of 10 definers that construct most of the meaning of the target concept in a network

Frequently, some concepts serve as definers for more than one target concept. These concepts are called common definers and groups of definers are interconnected through them. High numbers of common definers tend to appear whenever there is a close relation among target concepts.

RESULTS AND ANALYSIS

Table 1 shows the SAMs groups for each target concept of the current study; that is, the highest ten definers of a target schema concept regarding Piaget´s theory.

Table 1. Definition groups (SAM) for schema related targets.

TARGET : STAGES		
DEFINER	M	IRT
SENSORYMOTOR	293	22
PREOPERATIONS	245	28
FORMAL	237	32
STAGES	199	10
ACHIEVEMENT	196	34
CONCRETE	159	33
STRUCTURES	157	31
DEVELOPMENT	154	33
EQUILIBRIUM	120	38
OPERATTIONS	103	33

TARGET : SENSORYMOTOR		
DEFINER	M	IRT
REFLEXS	287	15
EGOCENTERED	250	31
SENSORY	201	17
MOTOR	158	22
STAGES	150	15
SUCTION	110	32
ACTION	109	31
SCHEMA	92	37
RC	89	24
GRABING	78	39

TARGET : PREOPERATIONAL		
DEFINER	M	IRT
EGOCENTERED	168	45
LANGUAGE	158	
ANIMISM	141	
YUXTAPOSITION	140	
CENTRATION	112	
STAGES	112	
CHILD	101	
PRECONCEPT	101	
SYMBOLIC	85	
SYNCRETISM	65	

TARGET : CONCRETE		
DEFINER	M	IRT
OPERATIONS	193	14
STAGES	142	22
LOGIC	78	29
GROUPUNG	72	27
CHILD	64	25
HETEROGENY	52	25
LOGIC_MAT	46	24
CLASIFICATION	43	29
GROUPS	43	38
DE-CENTRATION	41	54

TARGET : FORMAL		
DEFINER	M	IRT
ABSTRACTION	219	21
OPERATIONS	160	24
STAGES	156	21
EGOCENTERED	104	31
REBELD	99	38
LOGIC	94	25
ADOLESCENCE	75	37
DEDUCTIVE	70	32
HYPOTETIC	62	22
HYPOTHESIS	61	31

TARGET : ADAPTATION		
DEFINER	M	IRT
ASIMILATION	350	13
ACOMODATION	323	17
EQUILIBRIUM	260	21
INELIGENCE	122	29
ORGANIZATION	119	35
INVARIANTS	117	27
ENVIRONMENT	80	41
BIOLOGY	75	26
KNOWLEDGE	75	41
DEVELOPMENT	68	38

TARGET : ASIMILATION		
DEFINER	M	IRT
ADAPTATION	229	24
ACOMODATION	196	23
EQUILIBRIUM	147	33
INCORPORATE	115	17
KNOWLEDGE	110	37
SCHEMA	107	24
INVARIANTS	104	29
STRUCTURES	66	28
OLD-NEW	59	31
INFORMATION	53	14

TARGET : ACOMODATION		
DEFINER	M	IRT
ADAPTATION	264	23
ASIMILATION	208	18
ORGANIZATION	159	22
SCHEMA	147	31
EQUILIBRIUM	137	35
REORGANIZATION	125	24
STRUCTURES	114	27
INVARIANTS	88	33
KNOWLEDGE	71	38
INTELLIGENCE	61	43

TARGET : EQUILIBRIUM		
DEFINER	M	IRT
ADAPTATION	185	21
EQUILIBRIUM	174	14
ASIMILATION	148	22
STRUCTURES	141	31
ACOMODATION	127	22
STAGES	111	37
INTELLIGENCE	98	28
ORGANIZATION	91	21
ACHIEVEMENT	83	33
STAGE-OF	80	19

TARGET : SCHEMA		
DEFINER	M	IRT
ACTION	270	14
STRUCTURES	231	21
ORGANIZATION	133	30
KNOWLEDGE	107	34
SEQUEL	81	25
REPETITION	80	28
ACOMODATION	79	30
STAGES	72	35
ASIMILATION	68	28
DEVELOPMENT	65	45

It is argued by users of a natural semantic net that it is possible to construct a semantic net if desired. For example, a given target concept would have links to each of its definers, having the M value as a weighted link between the definer and the target concept and common definers serving as links among target concepts. This network structure proposition, as obvious as it seems to be, does not specify the type of net minimizing the close relation between network structure and meaning. Contrary to a hierarchical semantic net [e.g., 23] or to an unstructured net [24], the natural semantic network of concepts resembles a small-world structure characterised by the combination of highly clustered neighbourhoods and a short average path length where a relatively small number of well-connected nodes serve as hubs, and the distribution of node connectivity follows a power function [25]. This kind of semantic net structure seems to arise from a scale-free organization that can be found in many other non-biological and biological systems [26]. Figure 1 shows the hub clustered organization of concepts for the current natural semantic net on Piaget´s theory.

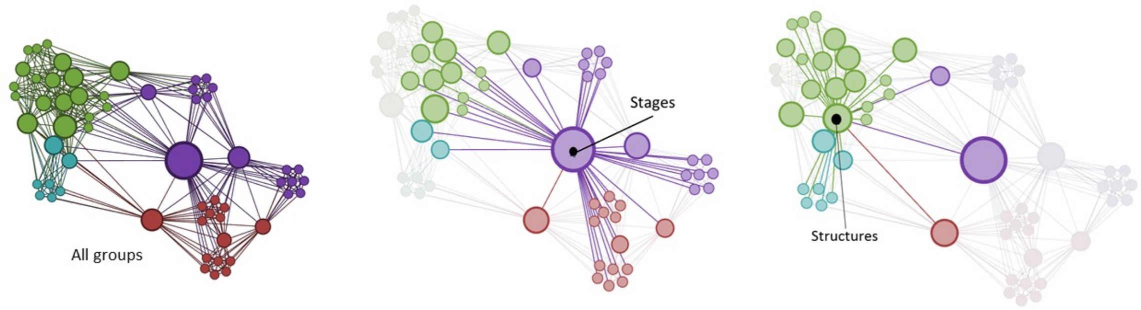

Figure 1. By using a GEPHI force Atlas method [27], a natural semantic network shows clustered concepts with short paths among concepts.

Specification of the network structure like the one shown in Figure 1 empowers a researcher not only with metrics regarding concept organization [e.g., here the Cluster Index was moderately high: C: 0.69; for a review in network metrics see 28] but also with a tool to define the relationship between semantic concept activation and schemata behaviour. For example, the concept definer “stages” was used as the most common definer to link SAM groups, which in turn provides strong connectivity among target concepts of a schema. The second most frequent second definer was “structures” and its grouping influence can be visualized.

Computer simulated schemata behaviour based on concept co-occurrence (formally defined by equation 1) through lists of concept definers seems to implicitly rely on statistical properties typical of a specific small world semantic net structure. For example, common definers in a natural semantic net seem to provide the in- betweenness centrality required to support proper schemata behaviour in this kind of semantic net.

The only difference between Rumelhart´s model [13] and the one presented by Lopez and Theios [29] was that the first one was idiosyncratic, that is, definers and targets are provided by a researcher, whereas in simulated schemata based on natural semantic nets, the schema targets are provided by teachers and definers are obtained from students´ definitions. Thus, emergent schemata behaviour is greatly defined by network structure and concept in/out degree of connectivity.

Lopez and Theios [29, 30] strongly suggested that the M value used to rank a concept should be used to modify weight of association among concept definers. However, if the position where a definer tends to appear in a SAM group is considered, that is, the Inter Response Time (IRT), another picture emerges. Figure 2 clearly shows that the highest ranked definers tend to always to appear between the third and fifth positions.

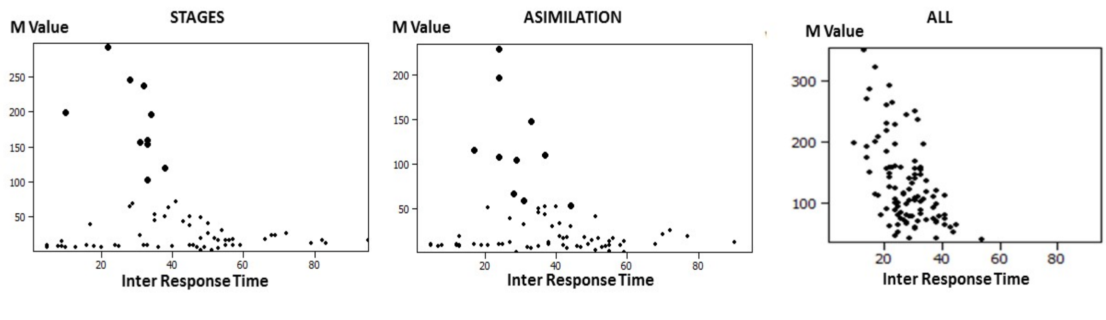

Figure 2. The highest ranked definers in the current study for a target concept tend to appear between 20 and 40 seconds in a definition task. All the concept M values are shown for the

target concept STAGES as well as for the target concept ASSIMILATION. The right panel shows the case for the highest ranked definers from all SAM groups in the current study.

After several natural semantic net studies regarding environmental issues (120 subjects, 20 concepts), schema of rooms (85 subjects, 10 concepts), computer usability (300 subjects, 10 concepts), self-concept and self-esteem in adolescence (190 subjects; 20 concepts), and aging (120 subjects, 10 concepts), it has been observed that the M value in a semantic natural network can be predicted by a 98% accuracy if IRT and concept frequency (F) are considered as follows:

$$M = \mathrm{A} * e^{(\mathrm{B}/F + \mathrm{C} * IRT)} + \mathrm{D} * \ln(F)$$

Where A, B, C y D are only constant values obtained by a Fit analysis. In other words, word position in a SAM group is only needed to know which definer is ranked higher since the concept frequency has already been used to filter the SAM group. It is still unknown if this applies to all knowledge domains. However, it seems that conceptual co-occurrence as expressed by equation 1 is sufficient to reflect implied structural connectivity that underlies schemata behaviour, with no need for considering ranking values, since the M value is implied by concept position within a SAM group. What ITR means in psychological terms is not clear yet; however, ITR is a well-known effect in free recall concept organization studies [31].

DISCUSSION

It is possible to determine how a small world semantic network structure grows or develops over time [e.g., 25]. New nodes are assimilated in a net depending on its connectivity degree (preferential attachment) to clustered nodes. Several studies have been carried out under this assumption to study human development [e.g., 32, 33, 34]. Indeed, this is a desirable property to be considered if a researcher wants to study human learning of schema concepts. Unfortunately, neither the natural semantic network technique nor the reviewed connectionist schemata model have the possibility to explore learning, other than by observing qualitative changes on concept activation or appearance/disappearance of concepts in the net.

By considering statistical properties and metrics of a long denied specific network structure underlying meaning formation and emergent schemata it is possible to identify mechanisms of learning. For instance, Gonzalez et al. [2] showed that high school students enrolled in a moral development course recognized moral schemata related words significantly faster than non-related words in a semantic priming study only after the course. These moral related words were obtained from computer simulated moral schemata that was based on teachers' and students' natural semantic networks from 10 moral concepts. However, teachers did not expect this fast recognition effect for word pairs like POLICE – PARENTS after the course, since the course was designed to break this kind of semantic relation. If teachers were asked about this persistent semantic effect they generally argued that this was related to a typified students´ moral age (e.g., Piaget´s heteronymous moral state). This kind of rationale denies specification on semantic network development and schema behaviour analysis (Skinner's criticism is correct in this sense). For example, to say that students changed from a heteronymous moral state to an autonomous moral state is now an observation on schema development that can be explored with more specification.

This is also the case when Lopez et al. [1] argue that recognition times of learned schema related words are enough for a trained neural net to identify whether a student has integrated new schema related concepts into the lexicon. Even when this is an appealing opportunity for cognitive assessment of long term learning we have to struggle not to promote a new kind of obscure mental phenomena (e.g., schemata priming and learning).

As Steyvers et al. [25] argue, a specific network structure cannot account for all kinds of meaning formation. Here, it can be the case that limitations on small world semantic nets to account for meaning formation relate to a neural net capacity to discriminate appropriately between successful and non-successful students´ learning. Considerations in this issue are explored in a second paper, as well as potential implications for implementing an alternative new way for cognitive assessment of online learning.

References

Lopez, R. E. O., Morales, M. G. E., Hedlefs, A.M.I., Gonzalez, T. C. J. [2014]. New empirical directions to evaluate online learning. International Journal of Advances in Psychology, 3, 40-47. doi: 10.14355/ijap.2014.0302.03 http://www.ij-psychol.org/paperInfo.aspx?ID=12125

Gonzalez, C.J, Lopez, E.O. Morales, G.E. [2013]. Evaluating moral schemata learning. International Journal of Advances in Psychology, 2(2), 130-136. http://www.ij-psychol.org/paperInfo.aspx?ID=1981

Skinner, B. F. [1984]. Representations and misrepresentations. The Behavioral and Brain Sciences, 7, 502-510.

Piaget, J. (1926). The Language and Thought of the Child. New York: Harcourt Brace & Company.

Bartlet, F. C. [1932]. Remembering. Cambridge: Cambridge University Press.

Brandsford, J. D. & Johnson, M. K. [1973]. Considerations of some problems of comprehensions. In W.G. Chase [Eds.], Visual Information Processing [383-438]. New York: Academic Press.

Graesser, A. C., and Nakamura, G. V. [1982]. The impact of a schema on comprehension and memory. In G. Bower (Ed.) The psychology of learning and motivation: Advances in research and theory Vol.16 [60-110]. New York: Academic Press.

Hampton, J. [1979]. Polymorphous concepts in semantic memory. Journal of Verbal Learning and Verbal Behavior, 18, 441–461.

Smith, E. E., Osherson, D. N., Rips, L. J., & Keane, M. [1988]. Combining prototypes: A selective modification model. Cognitive Science, 12, 485–527.

Franks, B. [1995]. Sense generation: A “quasiclassical” approach to concepts and concept combination. Cognitive Science, 19, 441–505.

Medin, D.L. & Rips, L. J. [2005]. Concepts and Categories: Memory, meaning, and methaphysics. In Keith J. Holyoak and Robert G. Morrison. The Cambridge Handbook of Thinking and Reasoning [37-72]. Edinburgh, UK. Cambridge University Press.

Murphy, G.L. [2002]. The big book of concepts. Cambridge, Massachussets: MIT Press.

Rumelhart, D. E., Smolensky, P., McClelland, J. L., & Hinton, G.E. [1986]. Schemata and sequential thought processes. In McClelland, J.L., Rumelhart, D. E. & the PDP research group. Parallel distributed processing: Explorations in the microstructure of cognition Vol. 2: Psychological and biological models. [7-57]. Massachussetts: MIT Press.

Holley, C.D., & Danserau, D.F. [1984]. Networking: The technique and the empirical evidence. In Charles, D. Holley & Donald F. Danserau. Spatial learning strategies: Techniques, applications and related issues [81-108]. New York: Academic Press.

Rumelhart, D. E., & Ortony, A. [1977]. The representation of knowledge in memory. In R. C. Anderson, R. J., Shapiro, & W. E. Montague [Eds]. Schooling and the acquisition of knowledge [99-136]. Hillsdale, N. J.: Lawrence Erlbaum Associates.

Lopez, R.E. O. & Theios, J. [1996]. Single word schemata priming: a connectionist approach. The 69th Annual Meeting of the Midwestern Psychological Association, Chicago, IL.

Figueroa, J. G., Gonzales, G. E. & Solis, V. M. [1976]. An approach to the problem of meaning: Semantic networks. Journal of Psycholinguistic Research, 5(2), 107�115.

Perez, C.N., Hernandez, C. D. Hernandez, B.C. & Figueroa, N.J. [2012]. Model of natural semantic space for ontologies´ construction. International Journal of combinatorial Optimization Problems and Informatics, 3(2), 93-108.

Lopez, R. E. O. [1996]. Schematically related word recognition: Ph.D. dissertation abstract. Michigan: UMI Dissertation Abstracts International.

Padilla, M.V.M., López, R.E.O. & Rodríguez, N. M. C. [2006]. Evidence for schemata priming. 4th International Conference on Memory. University of New South Wales, Sydney, Australia.

Lopez, R.E.O., Padilla, M.V.M. & Rodriguez, N. M. C. [2006]. Connectionist schemata based behavior based on subject conceptual definitions: The role of inhibitory mechanisms. 4th International Conference on Memory. University of New South Wales, Sydney, Australia.

Figueroa, J.G., Solís, V.M. & Gonzalez, E. [1974]. The possible influence of imaginery upon retrieval and representation in LTM. Acta Psicologica, 38, 423-428.

Collins, A. M., & Quillian, M. R. [1969]. Retrieval time from semantic memory. Journal of Verbal Learning and Verbal Behavior, 8, 240–248.

Collins, A. M., & Loftus, E. F. [1975]. A spreading-activation theory of semantic processing. Psychological Review, 82, 407–428.

Steyvers, M. & Tenembaum, B.J [2005]. The Large-Scale Structure of Semantic Netwoks: Statistic Analysis and a Model of Semantic Grothw. Cognitive Science, 29, 41 -77.

Barabási, A. L., & Albert, R. [1999]. Emergence of scaling in random networks. Science, 286, 509–512.

GEPHI force Atlas method. http://gephi.github.io

Bersano, M.N.I., Schaefer, S.E. & Bustos, J. J. [2012]. Metrics and models for social networks. In Ajith Abraham, Aboul-Ella Hassanien [Eds]. Computational Social Networks: Tools, Perspectives and Applications [115-142]. London: Springer Verlag.

Lopez, R. E. O. & John Theios [1992]. Semantic Analyzer of Schemata Organization [SASO]. Behavior Research Methods, Instruments, & Computers, 24 (2), 277-285.

Lopez, R. E. O. & John Theios [1991]. Semantic Analyzer of Schemata Behavior [SASO]. Paper presented in The Society for Computers in Psychology. Twenty-first Annual Conference. San Francisco.

Friendly, M [1979]. Methods for finding graphic representations of associative memory structures. In C. Richard Puff (Ed.) Memory organization and structure. New York: Academic press.

Nematzadeh, A., Fazly, A., & Stevenson, S. [2011]. A computational study of late talking in word-meaning acquisition. In Proc. of CogSci'11.

Nematzadeh, A., Fazly, A., & Stevenson, S. [2012]. Interaction of word learning and semantic category formation in late talking. In Proc. of CogSci'12.

Nematzadeh, A., Fazly, A. & Stevenson, S. [2014]. Structural Differences in the Semantic Networks of Simulated Word Learners. COGSCI 2014. The Annual Meeting of the Cognitive Science Society.