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A COMPLEX NETWORK MODEL OF SEMANTIC MEMORY IMPAIRMENTS

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ABSTRACT

In the last decades, several models have been proposed to describe the functions and the structure of human memory. Many of these agree in representing semantic memory, i.e. the part of memory which contains the general knowledge about the world, as a network. On the other hand, the study of complex networks is a new and emerging field at the intersection of physics, mathematics and computer science which aims at characterizing the topological properties of large networks.
The paper proposes a quantitative study of the large-scale properties of semantic memory, modelled as the knowledge base of an automatic concept classifier of images.
This approach allows us to probe the topological properties of the network, showing that it exhibits the marks of *complexity*, and provide us with a suitable mathematical framework to study memory impairments. These alterations are firstly modelled as nodes removals and secondly as links modifications, producing markedly different results.

***Index Terms*—** Complex Networks, Semantic Memory Model, Human Memory, Image Analysis

1. INTRODUCTION

Many papers and studies are available on how memory works, trying to simulate and mock up the behaviour of the synapses and to propagate, store and retrieve pieces of information. On the other hand Information Retrieval (in the following IR) is a well established research branch, working on low level information (features) that can be extracted from digital contents. Retrieval is based on the indexing of the low level content features in an appropriate digital structure and recall is based on similarity, i.e. distance functions applied to multidimensional spaces. Looking at the human memory behaviour [1][2] there are no universally accepted conceptual model. There are several studies and suggested models on memory which typically divide human memory into [2]: *semantic memory*, the general knowledge about the world, mental thesaurus, organized knowledge a person possesses about words and other verbal symbols, etc; *episodic memory*, the memory for events occurring at a specific time in a specific place. The episodic memory is intrinsically connected with the semantic memory which rules its behaviour. The very first attempt to describe the structure of semantic memory, i.e. of the human knowledge base, is Collins and Quillian's groundbreaking work of 1969 [3]. Despite its great impact and innovativity, the hierarchical tree-shaped network of [3] did not provide enough flexibility and was successively modified by Collins and Loftus [4].
The latter model can be described in terms of a weighted network.
In the following we propose a mathematical model to describe the topological features of semantic memory, in order to characterize quantitatively memory impairments. Some studies already exploit the possibility of studying the large-scale properties of brain networks, mapped through neuroimaging techniques, to analyze lesions and disorders [5, 6]. Although some significant efforts have been made to link the psychological study of memory with the brain systems that underpin it [2], a clear map of the organization of concepts in the brain still does not exist at the present time, making difficult to translate brain damages in cognitive impairments. Therefore, we follow the widely accepted model of [4], a network of concepts, losing biological accuracy, but yielding results that can be interpreted and tested more easily.

2. BACKGROUNDS

In this section we briefly recall some concepts from complex networks theory that are useful for the following analyses.

2.1. Complex networks

The study of *complex networks* is a new and emerging field, born in the late 90s as a consequence of the discovery that many real networks (WWW, Internet, science collaboration graph, the web of human social contacts,...) share (at least) three important global properties [7, 8].
Small world: despite a large number of nodes, the average

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distance between two nodes (i.e. the minimum number of edges separating them) is relatively small. Mathematically, the typical behaviour is $l = klog(N)$, where l is the average distance, N is the number of nodes in the network and k is an appropriate constant.
Clustering: the clustering coefficient measures the probability that, given that A is connected to C and B is connected to C, A is connected to B. In words, it is an assessment of the density of ties inside the network, of the presence of highly connected clusters, representing groups or communities. In complex networks this coefficient is normally much larger than that of a random network.
Degree distribution: the degree of a node is the number of connections that the node has. It is a first measure of centrality, that is of the importance of the node in the network. The spread in the value of degree can be characterized by the $P(k)$, the distribution of degree, giving the probability that a random selected node has degree k. In complex networks, $P(k)$ is considerably different from binomial, poissonian or gaussian distributions, since it is markedly right-skewed and fat-tailed, often well approximated by a power-law distribution.

2.2. Weighted networks

Since in the following we deal with a weighted network, we introduce here the concepts of distance, clustering coefficient and degree of a weighted network (for an extensive dissertation see [9] [10]). The distance between two nodes can be extended to a weighted network, taking in consideration that the larger the weight is, the stronger is the association and the shorter should be the distance, defined as follows:

$$d_{ij} = \frac{1}{w_{ij}} \tag{1}$$

For what concerns the clustering coefficient, as discussed in [10], several generalizations are possible. In our study we use the following definition:

$$C_i = \frac{1}{k_i(k_i-1)} \sum_{j,k} (w_{ij}w_{ik}w_{jk})^{\frac{1}{3}} \tag{2}$$

where k_i is the degree of the node i and w are weights.
Finally, we need to broaden the notion of degree, i.e. the number of connections of a node. To this end, we introduce the *strength* of a node:

$$s_i = \sum_j w_{ij} \tag{3}$$

The strength of a node is then the sum of the weights over all the links of a node. Note that in the case of an unweighted network ($w = 1$), $s_i = k_i$, the strength is reduced to the degree. Another important property of a node is its *betweenness*, namely its capacity of connecting different portions of the web. It is defined as the fraction of shortest paths passing through the node, where the notion of "short" depends on the definition of distance. In an unweighted network it will simply be the smallest number of hops connecting two nodes and in a weighted network will be the previously defined (1).

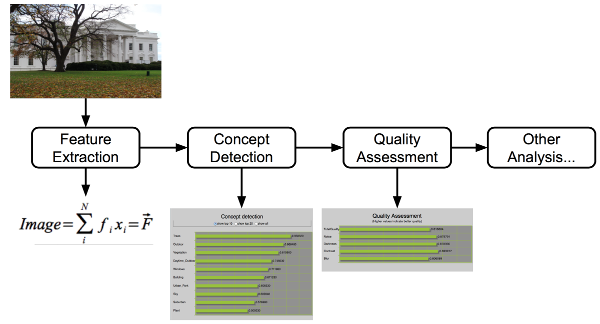

Fig. 1. *The information extraction (IE) from the image involves several processes such as low level feature extraction, concept detection, quality assessment and other analysis such as automatic contextualization [11][12]*

3. THE MODEL

Figure 1 shows a classic IR image processing flow, based on extracting low level features and applying some reasoning on them in order to extract some latent semantic such as concept detection or quality assessment. "Other analysis" is a placeholder for further reasonings and elaborations made on summary representation of the image as well as information collected by referenced sources. From the human being perspective, images can be considered as part of an episodic element and must be archived together with their frame: we need to represent the digital image together with the associated knowledge base, namely our model of semantic memory. In order to be able to best represent the knowledge base and related computations, we introduce the concept of *graph*. A graph is the mathematical description of a network and is defined by a pair of sets $G = (C, A)$ where C is the set of nodes and A is the set of edges, i.e. links between nodes. In a weighted graph every link is assigned a weight, normally a real number representing the strength of the interaction. In our context, C is the set of concepts and A is the set of weighted associations. Networks of this kind are usually referred to as "weighted semantic graphs". Notable examples of semantic graphs are language networks [13], such as Dictionaries (e.g. WordNet [14]), Thesauri (e.g. Roget's Thesaurus [15]), Word Association networks [16]. A first link between *complex* and semantic networks is individuated in [17], where the authors show that the afore-mentioned networks can be considered *complex*. Other studies confirm these findings on other Word Association Networks [18] and on co-occurring tag network [19]. Analogous results are obtained in [20].

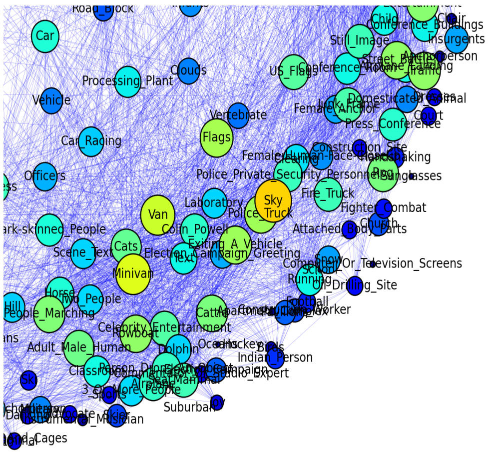

Fig. 2. A portion of the knowledge base built using CERTH's concept detector.

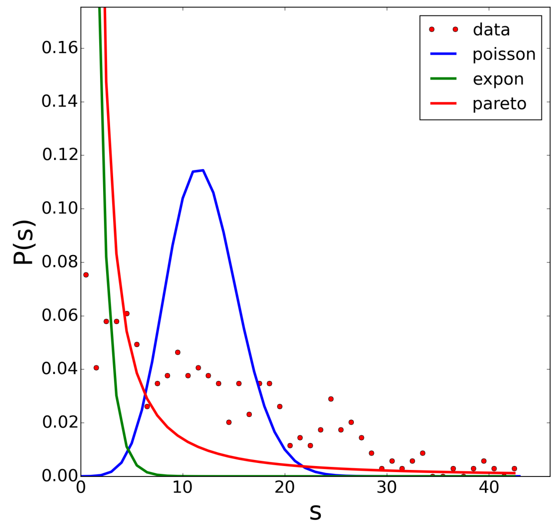

Fig. 3. *The strength distribution is represented by the red dots. As we can see, the tail of the distribution is thick, even compared to a Pareto's distribution.*

4. BUILDING THE KNOWLEDGE BASE NETWORK

Our model of knowledge base is simple, if compared to models as those of [13]. Nonetheless, it is perfectly suitable to the analyses we want to perform and it takes into account an aspect often neglected of semantic memory: its subjectivity. It stresses how the personal knowledge of the world must to some extent depend on personal experiences. It is based on CERTH's concept detector [12] developed within the ForgetIT project, which has 346 categories and assigns to each one of them confidence scores, real numbers in the [0,1] interval. We had the classifier analyze the ForgetIT dataset made up of 11270 images and for each one of them collected the confidence score of each of the 346 concepts, stored into a 11270x346 matrix. We converted the matrix in a weighted semantic graph using the following procedure:

1 Identify the nodes of our graph with the 346 categories of the classifier

2 Compute a 346x346 correlation matrix R_{ij}, i.e. Pearson's correlation coefficient r_{ij} between the concepts c_i and c_j in the 11270 images sample

3 Draw an edge between c_i and c_j if $r_{ij} > \alpha$, where α is a fixed threshold

4 Assign the weight $w_{ij} = r_{ij}$ to the edge.

The result is depicted in Fig. 2. The assumption behind this method is that links are simple associations, due to the fact that two concepts often occur together. We may conceive the 11270 images as a set of episodic elements, personal experiences, from which the semantic memory, that is the personal knowledge of the world, is built. Differently from [3][4] and the models employed for natural language processing, there are no logical relationships embedded in the links. It is also worth noting that the network is undirected, as a consequence of the fact that correlations are symmetric. Therefore, we shall not consider directed associations in what follows.

5. ANALYSES

We have obtained a network made of 346 nodes and 6239 edges, setting the threshold $\alpha = 0.2$ as a good compromise between the necessity of having a well connected network and that of neglecting irrelevant correlations.

In this section we briefly summarize the results of the quantitative analyses that we have carried out.

5.1. Complexity

The network can be considered for many reasons similar to a *complex network*. It presents a little average path length, sign of the property of small world, and a high clustering (both considering and neglecting the role of the weights). The strength distribution $P(s)$, i.e. the frequency of nodes with strength s, shows a high variance in the values of s, being notably different from a Poissonian or an exponential distribution (Fig. 3). This implies that the architecture of the network is far from being random and it is distant from a homogeneous picture, where every node is almost alike and has the same importance in the system. On the contrary, the presence of fat tails hints at the role of hubs, very important nodes, holding together a large number of other concepts and essential for

Measure	Value
Components	5
$< l >$	2.8
$< s >$	12.0
$< c >$	0.22
s_{max}	42.4
$\frac{\sigma^2}{<s>}$	7.0
$\frac{<s^2>}{<s>}$	19.0

Table 1. *$< l >$ is the average path length, which is even smaller than log$(N) = 5.8$, sign of the property of small world. $< c >$ is the average clustering coefficient, significantly higher than those of random graphs. The other parameters show the heterogeneity in the values of strength s (for a Poissonian distribution $\frac{\sigma_s^2}{<s>}$ = 1.)*

the connectivity of the whole network. This conclusion is in line with what observed in [19, 18, 17, 20], confirming the strong connection between complex and semantic networks. The numerical values obtained are reported in Table 1.

5.2. Resilience

One of the greatest advantages of a complex network approach to modelling semantic memory is the possibility to evaluate quantitatively its resistance to damages, failures, attacks. The idea is to remove one node at the time from the network and to observe how the global structure reacts. Therefore, we need to introduce a way to quantify the state of health of the network. If we neglect the role of links' weights, this can be done simply by computing the fraction of nodes in the largest connected component f_c in function of the fraction of nodes removed f [8]. Connectivity being a crucial property for most of the dynamical processes occurring on a network, f_c provides an intuitive way to quantify the robustness of the web. Nevertheless, when dealing with weighted networks f_c is not enough, for it does not account for the heterogeneity in the links [9]. For this reason we replace f_c with s_c, i.e. the total strength (summed over all the nodes) of the largest connected component of the network. We have compared the weighted and the non-weighted case and for each case we have used different strategies of nodes removal: random, degree (nodes with a higher degree are removed first), betweenness (nodes with a higher betweenness are removed first). As we can see in Fig. 4, the network proves to be much more vulnerable to targeted attacks (degree and betweenness) than to random failures. This result is consistent with what is known about complex networks, in which just a few nodes, often called *hubs*, are really important to keep the whole structure together and are characterized by a high value of degree, betweenness and other measures of centrality. These hubs are not likely to be extracted randomly, thus random attacks are

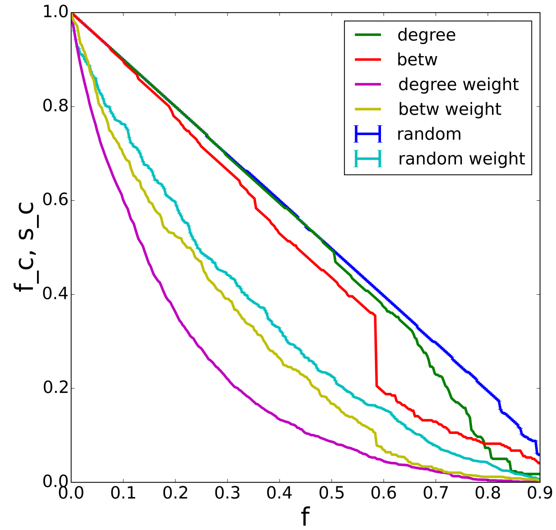

Fig. 4. *The curves labeled with 'weight' correspond to s_c, the others to f_c in function of the f. The curves corresponding to random strategies have error bars representing an interval of 2σ*

ineffective. On the contrary, targeted attacks are extremely dangerous.
Moreover, we can observe that the total strength s_c drops much earlier than the f_c, showing that neglecting the role of weights brings us to overstate the robustness of the network. This finding is in line with the conclusions of [9]. We believe that this analysis may prove to be useful to characterize from a mathematical viewpoint the nature of memory impairments. The node removal, i.e. the removal of a concept in semantic network, may be due to ageing or to a disease and in this framework it is possible to describe how the whole structure reacts to this loss. Note that the same type of technique can be applied to *links* instead of nodes, investigating how the global structure of semantic memory reacts consequently to a forgotten conceptual association.

5.3. Average shortest path change

Another relevant property of a network is its average shortest path length l, that is the average, computed on every pair of nodes, of the length of the shortest path connecting them. This quantity provides an intuitive measure of the size of the network, as it tells us how long it would take, on average, to go from a node to another, i.e. from a concept to another. Let us suppose that the starting node is *tree* and the final node is *building*: a path in the network is a set of conceptual associations, e.g. $tree \rightarrow citypark \rightarrow urban \rightarrow building$.. l is thefore a measure of the facility of conceptual associations: the smaller its value, the easier it is to go from a concept to another. With this in mind, we have studied how l evolves in function of the weights of the links (recall that we have defined the distance to be inversely proportional to the weight). The idea is to see how the ability of conceptual leaps is modified when a certain amount of connections are reinforced or weakened. To this end, we have considered $\delta d = \frac{1}{\delta w}$, the variation of distance as a parameter and we have plotted $l(f; \delta d)$ where f is the fraction of links whose distance have been changed, for a set of possible values of δd, ranging from -0.8 to 0.8 (the use of δd as a parameter instead of δw is absolutely equivalent from the theoretical point of view, but simpler for computational reasons). In Figure 5 it is possible to observe how l tends to increase with f when $\delta d > 0$ and to decrease when $\delta d < 0$. This behaviour is rather intuitive: if the distance of a fraction f of links raises, the average distance will raise accordingly and viceversa. Nonetheless, it is possible to underline a few remarkable properties: a marked asymmetry in curves corresponding to $\delta d' = -\delta d$ (e.g. $\delta d = 0.8$ to $\delta d = -0.8$) and a non-linear behaviour as f increases. This can be explained taking into account that l, being the average *shortest* path, is a result of a process of minimization. For every pair of nodes it is computed the length of the possible paths connecting them. Among these, the shortest is selected. l is then the average of the minimum lengths for every pair of nodes in the network. We can imagine how this procedure will tend to rule out the paths whose distance have been increased and to select those whose distance have been decreased. Thus the asymmetry emerges as a consequence of this mechanism: l is much more sensitive to $\delta d < 0$ than to $\delta d > 0$. The non-linearity can also be interpreted as a consequence of this behaviour: discontinuities occur when the shift of d produces a new minimum. These results provide us with non-trivial insights on the problem we are tackling. Recall that we have said that l can be seen as a measure of the facility of conceptual associations. We can now say that, if we reinforce the strength of a number of associations between pairs of concepts, this will strongly influence the value of l. Conversely, if we reduce the strength of a number of conceptual associations, e.g. as a consequence of an injury or a trauma, the value of l will change slightly. The minimization offers a sort of *shield*, of insurance against brain damage: links whose weights have been decreased tend to be avoided and a more efficient path of conceptual associations is found.

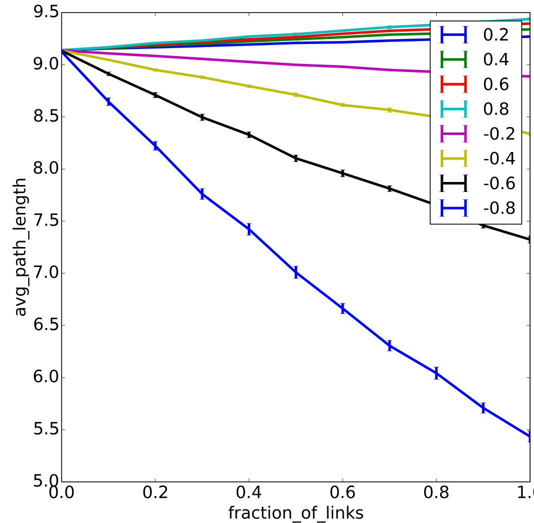

Fig. 5. *Average path weight in function of the fraction of links whose weight has been changed of a fixed quantity* $\delta d = \frac{1}{\delta w}$. *The error bars represent an interval of* 2σ

6. CONCLUSIONS AND FUTURE WORK

We have presented a novel mathematical model of semantic memory based on the theory of complex networks. Even if simple enough for a preliminary analysis, it allowed to discover specific behaviour that are particularly important in the study of semantic memory. On the one hand we exploited the processing flow of digital contents (such as images) set up within the ForgetIT project, on the other hand we tried to investigate how is working the human memory, making the machine learn from the concepts extracted (automatically) from the acquired images. Differently from most models of semantic graphs, we have proposed a bottom-up construction, relying completely on an automatic images concept detector. Upon this structure, we have performed a set of analyses aimed at determining its statistical properties. We have shown how the heterogeneity of its connections, its high clustered nature and the property of small world makes it comparable to a complex network. This result bears important consequences on the reaction of the network to attacks, i.e. threats to the semantic memory. We have observed two remarkable effects:

- the network is extremely robust against random attack and weak against targeted attack. This is a consequence of the heterogeneity of the centrality of the nodes: a small number of hubs are holding together the global structure of the web.
- the possibility of conceptual associations, measured as the average shortest path length, is sensitive to weights' reinforcements, but resilient to weights' weakening. Indeed, the possibility to find shortest paths tends to select the former and avoid the latter.

At this stage, possible future developments are countless. First of all, it is necessary to assess the robustness and the generality of our conclusions. How would semantic networks such as words association networks, WordNet, Roget's thesaurus [17][13] respond to the analyses we have performed? Moreover, our model allows a certain degree of flexibility, since different webs may be obtained from different sets of images: what would happen if we changed the sample set of images? Is a network built from heterogeneous images stronger than one built using images belonging to a unique context? Are our predictions confirmed by experimental tests on subjects affected by semantic memory diseases? Secondly, we think that our approach paves the way to an integrated model of episodic and semantic memory, which would include processes of archival and retrieval of memories, as well as the possibility of reinforcing and forgetting associations. In this framework, it would be possible to describe also memory impairments due to a failed information retrieval and not only to a structural degradation of the semantic information. Finally, we believe that our work may have an array of applications in the field of machine learning: concept based information retrieval, clustering, similarity measures and so on. We deem that these questions set up the bases of a new and appealing research scenario.

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