# The Brain is a Social Network

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**Abstract.** Social Network Analysis is employed widely as a means to compute the probability that a given message flows through a social network. This approach is mainly grounded upon the correct usage of three basic graph-theoretic measures: degree centrality, closeness centrality and betweeness centrality. We developed a model, using Semantic Social Network Analysis, that overcomes the drawbacks of general indices and we found that this model can be applied, after appropriate adaptations, to a very different domain such as brain connectivity.

## 1 Introduction

Social Networks are considered, on the current panorama of web applications, as the principal virtual space for online communication. Therefore, it is of strong relevance for practical applications to understand how strong a member of the network is with respect to the others.

Traditionally, sociological investigations have dealt with problems of defining properties of the users that can value their relevance (sometimes their importance, that can be considered different, the first denoting the ability to emerge, and the second the relevance perceived by the others). Scholars have developed several measures and studied how to compute them in different types of graphs, used as models for social networks. This field of research has been named *Social Network Analysis*. Sometimes the same name is attributed to a wider context, where we also mean to include analysis of the ways in which such values arise (for instance, processes able to change importance of members), or to provide methods for employing these measures in applications.

Majorly, scholars dealt with the Social Network Analysis from the viewpoint of *information flow*, namely they provide models of importance (and other aspects as well) to understand how probable would be that a piece of information passed through a given node. Mainly, the information flow has been studied for propagation of viruses (both in medical and in computer security contexts), news spread-out (and hence, studies about viral marketing as well), and message passing in certain application contexts.

The analysis model we propose in this paper can be extended to the study of brain, with potentials for for a deeper understanding of neurological disorders.

In particular, in the last two decades, the study of brain functional connectivity (FC) from multivariate neuroimaging data (eletroencephalography [EEG], functional magnetic resonance imaging [fMRI] etc.) has become an increasingly active field of research providing novel and crucial insights into normal brain functions in resting state as well as during tasks and their disruption in brain pathologies. Network modeling and analysis applied in this field of research enable the study of functional brain connections by extracting significant aspects of network organization. In this paper we provide a model, the social semantic analysis [6] that associates vertices with regions of the brain, signals are weights on the edges connecting regions of the brain, and activities are mapped onto topics of the semantic analysis. On this basis we can rapidly evidentiate the regions that are involved in a given activity, since they exhibit a greater centrality measure related to that topic. On the contrary, when a region is involved in more than one single topic, it exhibits a great transtopic centrality measure. When we assume that a specific topic represents a pathological condition, as for instance epilepsy, a centrality measure would allow detecting the source of the seizures. These "hub" nodes would play a leading role in the seizure generation and propagation[16]. Transtopic concept could further validate this hypothesis: we could distinguish between a source that affects other higher functions (high transtopic centrality measure) and an isolated source of such activity (low transtopic centrality measure).
The purpose of this paper is to give account to the aspects showed above. We provide a model of Social Network Analysis that takes into account topics, and show that it can foresee information flow for message treating those topics in a more accurate way than classical topic-free social network analysis. We also name Semantic Social Network Analysis the techniques we studied in this investigation to cover a part of research that some previous studies did not cover satisfactorily.

The rest of the paper is organised as follows: in Section 4 we discuss related work on the subject. Further we employ Section 2 to provide the actual technical part of the paper and in Section 3 . Finally Section 5 takes some conclusions and sketches further work.

## 2 Semantic Social Network Analysis

In this section we introduce the theme of graph theory, we apply to Social Network Analysis and then we show how the model may be applied to the study of human brain connections. The basis of both is the very general notion of a labelled graph, that we assume to be known to the reader, and specify in terms of form of the labels in Subsection 2.1. Social Network Analysis is extended in semantic terms in Subsection 2.2 and the model for brain connectomics is explained in Subsection 2.3.

### 2.1 Graph theory preliminaries and Social Network Analysis

A *graph* is a pair $G = \langle \mathcal{V}, \mathcal{E} \rangle$, where $\mathcal{V}$ is a finite set of vertices, and $\mathcal{E}$ is a set of edges. A graph $G$ is labelled when to each vertex or to each edge is associated a label, determined by $\Lambda$, a function that associates vertices and edges to the label sets (that are thus denoted by $\Delta(\mathcal{V})$ and $\Delta(\mathcal{E})$, or simply by $\Delta$, meant to be the union of the above). We use the term node and the term vertex indifferently.

In this paper we concentrate ourselves onto indirected graphs, and delay the investigation on directed graphs to further work. We also assume that the graphs we deal with have no circular edge (although we do not assume them to be acyclic).

To treat the notion of distance we employ notions derived from classic algorithmic graph theory, as widely discussed in [10]. The distance between two vertices $v_1$ and $v_2$, denoted by $\delta(v_1, v_2)$, in a graph, is the length of the shortest path connecting $v_1$ and $v_2$.

*W*e now introduce three basic measures of Social Network Analysis, and discuss several flaws they exhibit.

**Definition 1.** *A node $v$ of a graph is said to have* absolute degree centrality $k$ *when the number of edges incident to $v$ is $k$.*

From absolute degree centrality we can easily derive relative degree centrality, as the absolute degree centrality weighted by the size of the graph. In other terms, if a graph has $n$ vertices, and a node $v$ has absolute degree centrality $k$, the relative degree centrality of $v$ is $\frac{k}{n}$.

We now introduce the second measure of social network analysis.

**Definition 2.** *A node $v$ of a graph is said to have* farness $f$ *such that:*

$$f(v_i) = \sum_{k=1, k \neq i}^{N} \delta(v_i, v_k)$$

*The* closeness centrality *of a vertex is the reciproce of the farness of $v$:*

$$c(v) = \frac{1}{f(v)}$$

Closeness centrality only works for connected graphs. Conceptually, however, two vertices that are not connected ar as far as infinite, thus being closeness centrality of these equivalent to 0. This is clearly faulty. There have been several proposals to solve this aspect, mainly by means of techniques that are based upon weights. For the purpose of this research we assume that networks are connected.

The third measure we consider here is *betweeness centrality.* It is obtained as the number of pairs of vertices that are traversed by a path containing the measured vertex, or such that the vertex is between the elements of the pair.

**Definition 3.** *The betweeness centrality of a vertex $v$ is the number $K$ of pairs in the graph for which $v$ is between.*

Analogously to the previous analysis about degree centrality we can note that large networks may exhibit wider spectrum of betweeness centrality than smaller ones, and conversely, less wide.

### 2.2 Semantic Social Network Analysis

Social Network Analysis starts from unlabelled and, for the settings of this investigation, indirected graphs.

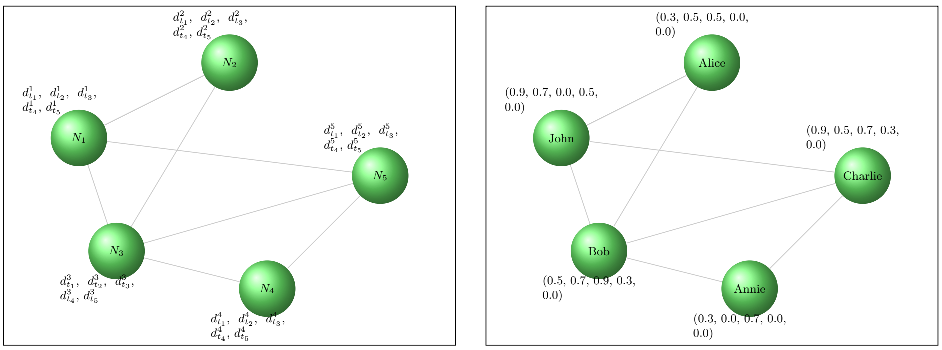
This, as discussed in Section 1 is unrealistic. An individual can be connected to another over a certain topic, but definitively disconnected over another topic [17, 5]. Moreover, the link between individuals can be indipendent from the shared topics. These concepts are known as *homophily* and have been discussed in Section 4.

If we measure centralities by means of unlabelled graphs, we may be rather misleading in defining the relevance (or importance, in some sense) of a vertex in the graph, since an individual can exhibit strong connections on one specific topic and weak ones on other topics, providing therefore a differentiated degree centrality, in particular, and analogously for closeness and betweeness measures.

Consider two individuals *John* and *Alice* belonging to the same school but not sharing a hobby like music. A message regarding a class has a good probability of being forwarded from *John* to *Alice* while one regarding the hobby hasn't.

So we can say that *John* and *Alice* are connected over a topic *school* but are disconnected over topic *music*.

A method to provide this is to add a label to vertices in the graph with label corresponding to a measure of *depths* relative to a set of topics $T = \{t_1, \ldots, t_k\}$. The label will be vector $D = \{d^1_{t_1}, \ldots d^n_{t_k}\}$ whose component $d^i_{t_j}$ is the *depth* over the topic $t_j$ of the individual represented by vertex $i$ as can be seen in Figure 2a. The goal of centrality measures is to provide a tool for foreseeing information




a)Introducing labels for depth in topics. b)Example of s.n. with labels on topics

Fig. 2: Social networks (s.n) as labelled graphs

flow. The basic assumption we make here is that when someone is not involved in a specific topic, it is rather unlikely that she promotes the flow of a piece of information through the vertex she occupies.

Considering the aforementioned two individuals *John* and *Alice*, their interests in the set of topics $T = \{gossip, music, sport, cooking, politics\}$ can be expressed as $D^a = (0.3, 0.5, 0.5, 0.0, 0.0)$ for *Alice* and $D^j = (0.9, 0.7, 0.0, 0.5, 0.0)$ for *John*, meaning that while both are interested in *gossip* and *music* and not interested in *politics*, *Alice* is keen to *sport* and *John* is not but he likes *cooking* while *Alice* does not, as is expressed in Figure 2b in which topic labels are about *gossip, music, sport, cooking, politics.*

An individual has *depth* on a certain topic measuring the degree of involvement on it; an individual has also an *activation threshold* which describes the inverse of the likelihood of that individual of becoming active when "hit" by a message. The notion introduced here is inspired by that used in scientific evaluation as proposed in [18].

### 2.3 The model for the Human Brain

This model can in our opinion be extended to the field of brain connectomics, in which brain regions are studied along with their connections one to each other. Each brain region can be represented as a vertex in our graph, while the arcs represent the connections. Several studies have represented data of brain connectivity as matrices of correlation values between pairs of signals from different brain regions. These experiments are relative to several brain activities, such as memory, language, motor tasks, or even to resting-state conditions (rest). *We make the assumption that these correlation matrices represent semantic graphs in which the specific brain activity can be regarded as a topic.* Our labeled graph model can be adopted seamlessly to this assumption so that brain regions and their connections, both physical and functional, can be represented with our labeled graph. The weights in the arcs are the values of the correlation matrix for the specific brain activity which we call equivalent to topic.

From the Semantic Closeness centrality of a node on various topics is possible to derive a new measure, that we named *Transtopic Centrality* (TC), in order to quantify the actuation of a region considering all topics. We can define it as a cross-topic measure. To explain, the TC can be defined as the good chance that an region becomes engaged when a signal regarding different topics arrives to it.

For a node $v$, we can express this as: $TC(v) = \sum_{i=1}^{r} \alpha_i \cdot SC(v_i)$ where $r$ is the number of topics and $SC(v)$ is the Semantic Centrality of node $v$. The *Transtopic Centrality* of a region is defined as the weighted sum of the Semantic Closeness centralities in all topics. Intuitively, the formula finds the actors that are closer to all other actors in the network for all topics.

In the human brain, the weights associated with the links can also have negative values, while our model for the social network assumes only values between zero and one. There are two possible alternative solutions: considering the data as a transform from positive values only and considering two different possible origin for the data: the positive and the negative network. The first case is named "softening" while the latter "reaction" and will both be explained in the following paragraph. A third approach can be to consider and study the positive and the negative network separately.

**Softening** Here we consider the hypothesis of the negative value between two nodes to have a meaning of "attenuation" of the semantic value of the message flowing between two nodes, meaning the node *softens* the message.

A negative value is therefore indicating that the meaning of the message is somehow "softened" or attenuated. A positive message means that the meaning of the message is made "stronger" or sharper , while a zero means that the message is passed through as it has been seen in input.

This interpretation leads to a model with threshold at 'zero' which might as well be mapped in a similar one in which values are all above zero.

As our data are all in the range $[-1, 1]$ we can define a mapping function from this range to $[0, 1]$ without loss of generality

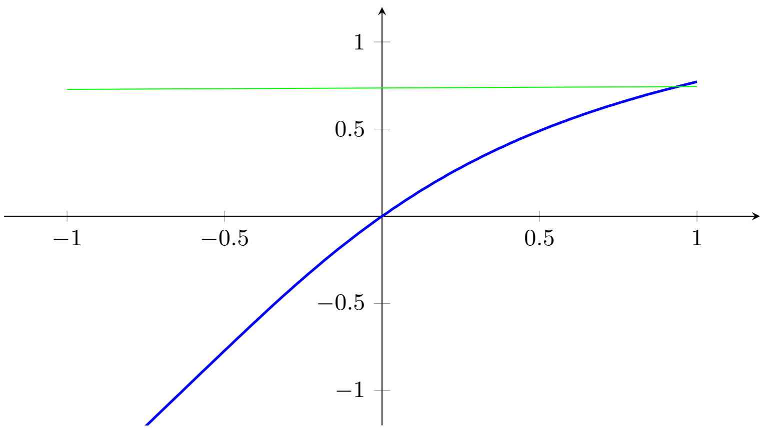



Fig. 3: A possible mapping function for the softening hypothesis

**Reaction** Here we consider the hypothesis of the negative value between two nodes to have a meaning of "reaction" or inversion of the polarity of the semantic value of the message flowing between two nodes, meaning the node *reacts* to the message.

A negative value is therefore indicating that the meaning of the message is somehow "inverted". A positive message means that the meaning of the message is kept with bigger values pointing to a stronger meaning, while a zero means that the message is passed through as it has been seen in input.

This interpretation leads to a model in which the network is the result of the superimposition of two different networks, the *positive* one and the *negative* one.

In this model our *positive* network is obtained from the original *neutralizing* all connections with negative values, while the *negative* one is obtained from the original neutralizing all connections with positive values and keeping the absolute values of the others. With *neutralizing* we mean set the value to zero.

This leads to two different *Centrality* measures, the *positive centrality* ($C_p$) and the *negative centrality* ($C_n$) so that our centrality can be obtained as

$$C = f(C_p, C_n)$$

where $f$ can be any reasonable function that considers weights of positive and negative values, for instance $f = C_p - 2C_n$

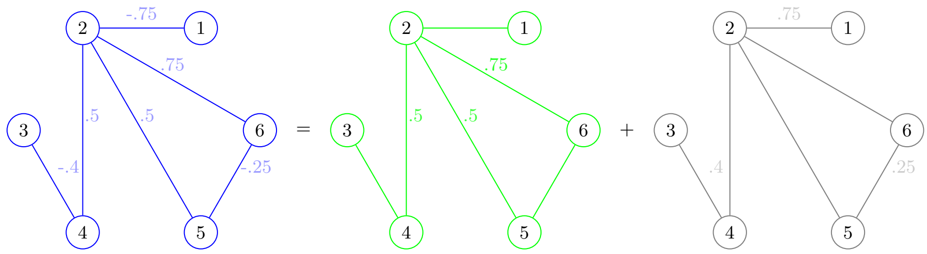



Fig. 4: The resulting graph can be considered the composition of the *positive* and the *negative* graphs.

## 3 Experiments

To test the expressivity of the methods introduced above in section 2, we applied our model to a magnetic resonance imaging (MRI) dataset[1] composed of structural and functional exams of several conditions of a single subject.

We assess how eight major domains ("topics"), that sample the diversity of neural systems, modulate a connectivity network of 139 brain regions. The topics include: 1) Emotion processing; 2) Gambling: designed to assess reward processing and decision making; 3) Language processing (semantic and phonological processing); 4) Motor: visual, motion, somatosensory, and motor systems; 5) Relational processing; 6) Resting state condition; 7) Social cognition (Theory of Mind) and 8) Working Memory (WM): working memory/cognitive control systems. The image acquisition, protocols and data preprocessing are described in detail in [3]. Stimuli were projected onto a computer screen behind the subject's head within the imaging chamber. Brain parcellation, based on the Harvard-Oxford Probabilistic MRI Atlas (HOA) and the cerebellar Atlas[2] as included in FSL, was performed. From these atlases, 139 regions were extracted. In details: cortical and subcortical regions, considering separately the right and left hemispheres, along with cerebellar ROIs divided into left, vermis and right regions. For each of these regions, a representative mean time series was extracted by

[1] HCP dataset (http://www.humanconnectome.org)
[2] https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/FSL

Table 1: Most Central brain regions in different topics

| Rank | *Emotion* | *Gambling* | *Language* | *Motor* | *Relational* | *Rest* | *Social* | *WM* |
|---|---|---|---|---|---|---|---|---|
| 01 | ***OLs.R*** | PRG.R | Crus II.L | AG.R | ***OLs.R*** | ***OLi.L*** | OP.R | ***OLs.R*** |
| 02 | PRG.L | FP.R | ***OLi.R*** | Crus I.R | ***F2.L*** | Crus II.L | PRG.R | PRG.R |
| 03 | VI.R | Crus II.L | LG.R | PCN.L | POG.R | LG.L | SGa.R | FP.R |
| 04 | POG.L | ***OLs.R*** | OP.R | ***OLs.L*** | Crus II.L | PRG.L | PRG.L | Crus I.R |
| 05 | CO.L | ***OLs.L*** | ***OLs.R*** | PCN.R | FP.R | CO.L | VI.L | PCN.L |
| 06 | TO2.R | FP.L | PRG.L | LG.R | ***F1.R*** | Crus I.L | SGp.L | Crus II.R |
| 07 | SGa.L | ***F2.R*** | PRG.R | PT.R | Crus I.R | TOF.L | OF.L | ***F2.R*** |
| 08 | AG.R | Crus II.R | ***F2.R*** | OF.L | CALC.R | Crus II.R | SGp.R | VI.R |
| 09 | ***F2.R*** | Crus I.R | LG.L | ***F1.L*** | VI.R | AG.L | Crus II.L | ***F1.R*** |
| 10 | SGp.R | CN.R | ***F1.R*** | TOF.L | ***OLi.R*** | VI.L | PT.R | TO2.R |
| 11 | VI.L | ***OLi.R*** | ***F1.L*** | SGp.R | PRG.L | SMC.R | VIIb.L | AG.R |
| 12 | SPL.L | VI.R | OF.L | Crus II.R | ***F2.R*** | VI.v | SGa.L | LG.R |
| 13 | ***F2.L*** | VI.L | PT.R | POG.L | CALC.L | T1p.L | VI.R | SGp.R |
| 14 | IX.L | ***F2.L*** | CGa.L | CGp.R | Crus I.L | OF.L | POG.L | ***OLi.R*** |
| 15 | CGa.R | AG.R | Crus II.R | SPL.R | AG.R | INS.L | Crus I.R | ***OLs.L*** |

averaging the time series of all voxels within the area and used as reference. A $139 \times 139$ symmetric connectivity matrix was then derived for each topic by calculating the Pearson correlation coefficient between pairs of nodes. These matrices can be considered as the matrices defining our graph, in which the activities are regarded as “topics”.

Generally, Emotion processing task involves activation of amygdala extending into the hippocampus, as well as bilateral activation in medial and lateral orbital frontal cortices, and some activation of ventral temporal cortex. Gambling task is designed to assess reward processing and decision making and involves striatum, insula, ventral medial prefrontal and orbitofrontal. Language processing elicits robust activation in ventral lateral prefrontal cortex and in both superior and inferior temporal cortices, including the anterior temporal poles bilaterally. Activation is expected to be stronger on the left than on the right. Motor task comprises right and left hand, foot and tongue movements and involves primary motor, premotor, striatum, retinotopic visual areas, and cerebellum. Relational elicits consistent activation in bilateral anterior prefrontal cortex, including temporal parietal junction and superior temporal cortex regions. Social task involves medial prefrontal cortex, temporal parietal junction and inferior and superior temporal sulcus. Finally, working memory should activated dorsolateral and anterior prefrontal, inferior frontal, precentral gyrus, anterior cingulate, and dorsal parietal regions (Barch). Finally the Resting state elites the so-called resting state networks. Moving from simple regional activations toward a deeper understanding of the communication patterns between brain regions and network organization, our results showed that there is extensive activation of visual regions (OL) in most of the tasks, which is not surprising given the use of visual stimuli (Fig.11). In addition to these visual areas, Transtopic highlights the common regions between tasks involving the frontal and parietal lateral cortex.

In Figure 14 the transtopic value of 30 regions is projected into a cortical surface (L, left side; R, right side): an increase in node size (sphere radius) represents the increase in transtopic value.

In table 1 regions with the highest degree of semantic centrality are exposed: for the sake of readability we highlighted a few example regions that appear in more than one topic. It can be easily noted that some regions appear in this top fifteen but at different position while there are regions that selectively appear only on certain topics but not in the others.

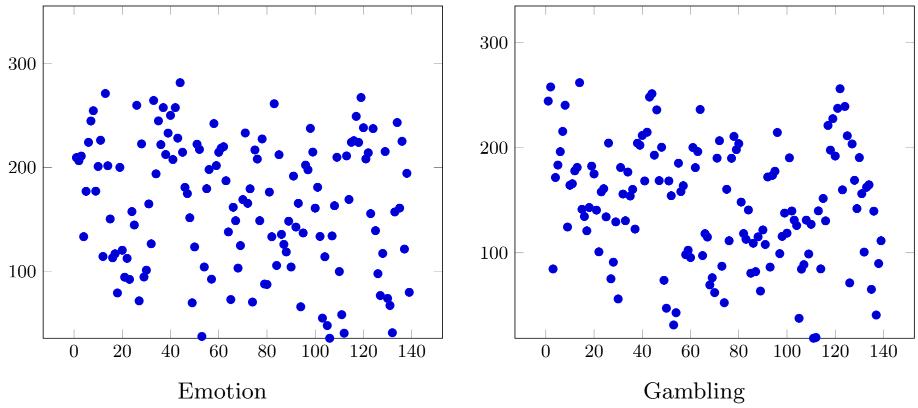



Fig. 6: Semantic Centrality of brain regions for *topic* Emotion (left) and Gambling (right)

In figures 6, 8, 10, 12 the centrality value for each region is shown: on the $x$ axis the region number and on the $y$ one the centrality value. For the sake of space we show only the images with centrality values of the positive matrix.

As can be easily seen different regions have different centrality values depending on the topic.

The values of the Transtopic Centrality for the test subject are shown in Figure 13; It is worthy of note that the calculation has been done with equal weights for each topic.

The picture shows how the transtopic centrality can be an efficient instrument for quick confrontation with single topics: if a node has a high centrality in a certain topic and also in transtopic it is likely to have high centrality also on other topics whereas otherwise in other topics the odds are it has a low centrality.

## 4 Related Work

The reference literature can be considered as articulated in three themes:

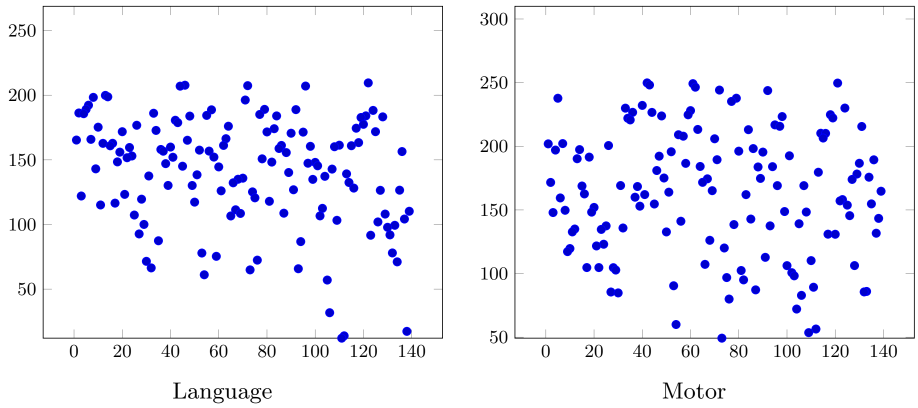



Fig. 8: Semantic Centrality of brain regions for *topic* Language (left) and Motor (right)

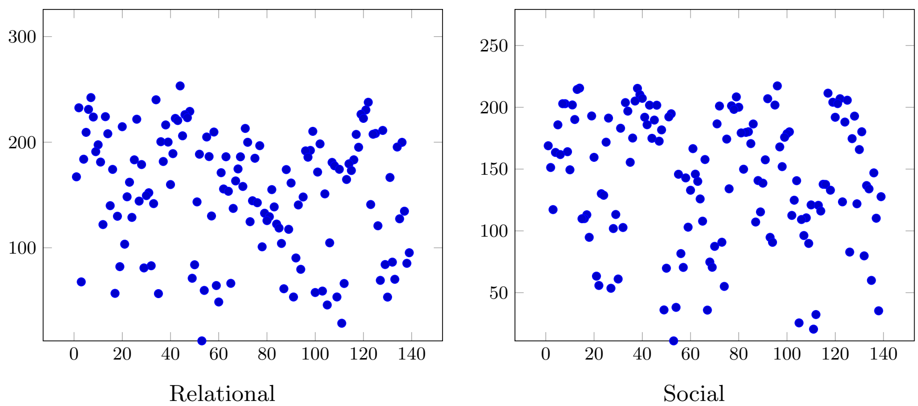



Fig. 10: Semantic Centrality of brain regions for *topic* Relational (left) and Social (right)

– Studies about implicit social links that exist among users of the internet (or of an internet application), or about enrichment of social web;
– Investigations of the semantics of social networks;
– Research about Social Network Analysis and relationships to semantic issues.

Regarding the first topic, we can look at methods for social link extraction, as discussed below, as one of the best structured investigations on the theme. This specific method for extracting social networks from the web using similarity between collective contexts is proposed in [2]. The authors construct three social networks on the same set of named entities. They use Jaccard, overlap and Normalized Google Distance (NGD) [4] coefficients to retrieve degree of closeness between entities. They show how actors may be assigned different relevance degrees and that actors having higher ranking results may be assigned lower ranks and inversely by choosing another measure to perform the ranking. In our

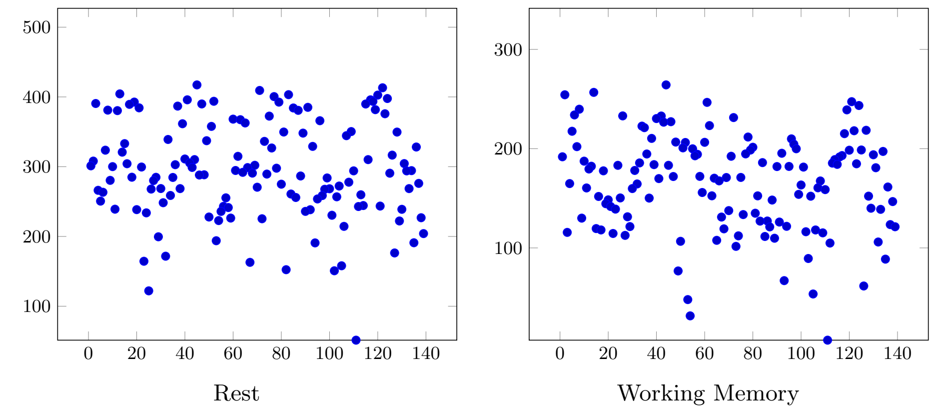



Fig. 12: Semantic Centrality of brain regions for *topic* Rest (left) and Working Memory (right)

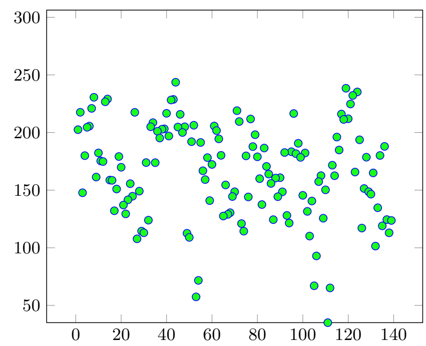



Fig. 13: Transtopic Centrality

perspective their work is solid, but lacks in one important aspect, the authors build homophily on the based of the contents.

This is a technique to *build* a network, and not an *analysis* of the network itself, as we do in this work. Suffering the same issue is the work of [11], where the authors present a new framework for applying Social Netork Analysis to RDF representations of social data. In particular, the use of graph models underlying RDF and SPARQL extensions enables us to extract efficiently and to parameterize the classic Social Network Analysis features directly from these representations.

The main criticisms to the proposed approach lie on the fact that, as already shown in many practical cases, it makes a lot of difference, in terms of understading of the structure of similarity between nodes, to know the relevance of the two nodes. In fact, similarity can be used, as done, for instance in [7], for community detection, where members are related to each other based on their

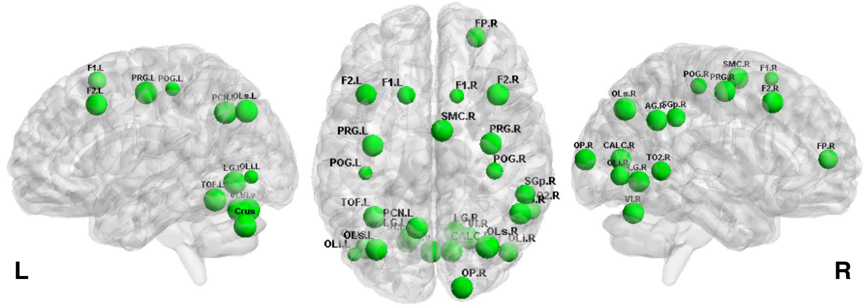



Fig. 14: Node cortical transtopic of 30 regions projected into a cortical surface (L, left side; R, right side): an increase in node size (sphere radius) represents the increase in transtopic value.

similarity in semantic terms. This is different in terms of relationship, with respect to measuring the relevance and study attactivity. Clearly, being interested in Football lies on liking it, but the community is formed around *authoritative* persons, for instance journalists. A more practical research has been documented in [19] where an application of semantic social networks and attraction theory to web based services is carried out. The relation between trust and Social Network Analysis has been investigate in [20] and specified as a means for understanding deeply the meaning of centrality and other measures as related to authority. The same concept is employed to provide a framework for the general interpretation of the logic bases of recommendation systems in [8].

The studies cited above all aim at discovering network links by means of mining techniques. On the other hand, the introduction of notions derived from semantic web into social networks is the core quest of many recent studies, including [21]. As a complete reference to the current literature about meaning of social links, and relationships between social web and semantics, readers can look at [13]. More deeply, in [14] a direct and explicit comparison between social networks and the semantic web is carried out. This paper proposes a parallel between networked knowledge of members in a network and the basic notions of semantic web. The same issue is dealt with, with the specificity of a known technique, the semantic networks, in [9]. More generally, the semantic web methods are employed for understanding the meaning of social networks as sharing platforms for common knowledge, in [15].

The idea of using Social Network Analysis as a means for forecasting the probability of a message to pass through a given member of the network itself is not novel at all. Base of our analysis is the criticisms to the roughness of the employed measures, criticisms that are not novel anyhow. This has been dealt in two distinct ways: by using semantic methods for habilitating the forecast processes: in particular in [22], authors use semantic networks for foreseeing the behaviour in facebook.

On the other hand, many criticisms are applied to centrality measures ([12]). The main criticisms, that are met by the above mentioned investigations as well as by researches tending to correct the flaws of the general methods for centrality measures, and the measures themselves, lie on the weakness of the notion of similarity derived from the notion of centrality. The above mentioned notion of similarity as derived from centrality measures, and its applications to the notion of reciprocity, a concept that has a crucial importance, for instance, in asymmetric social networks (Instagram, Twitter) are dealt with in [1]. Authors show that centrality measures as used so far are unsuccessful in forecasting the information flows.

## 5 Conclusions

In this paper we investigated the application of a model of Semantic Social Network analysis, based on topic centrality, to the description of the brain functional connectivity evoked by different conditions of the spectrum of human behaviours. We presented preliminary experimental data, that, by some examples of these connections, show that the proposed model can be effective in enhancing the understanding of the shared brain functioning during different tasks or resting state condition.

In further work, we shall investigate also ways in which this diagnostic process will be expressed by means of large experiments, and verify its usefulness with medical teams.

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