The network of concepts in written texts

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Abstract

Complex network theory is used to investigate the structure of meaningful concepts in written texts of individual authors. Networks have been constructed after a two phase filtering, where words with less meaning contents are eliminated, and all remaining words are set to their canonical form, without any number, gender or time flexion. Each sentence in the text is added to the network as a clique. A large number of written texts have been scrutinized, and it is found that texts have small-world as well as scale-free structures. The growth process of these networks has also been investigated, and a universal evolution of network quantifiers have been found among the set of texts written by distinct authors. Further analyzes, based on shuffling procedures taken either on the texts or on the constructed networks, provide hints on the role played by the word frequency and sentence length distributions to the network structure. Since the meaningful words are related to concepts in the author’s mind, results for text networks may uncover patterns in communication and language processes that occur in the mind.

1 Introduction

Concepts of complex networks have proven to be powerful tools in the analysis of complex systems [1,2,3,4,5]. They have been applied to modelling purposes as well as to search for properties that naturally emerge in actual systems due to their large-scale structure. Unlike random graphs, complex networks reveals ordering principles related to their topological structure. This way, if complex systems are mapped onto networks, it is possible to use their conceptual framework to identify and even to explain features that seem to have universal character.
Several complex networks have been proposed in the scientific literature associated with real systems: the biological food web[6], technological communication networks as the Internet, information networks as the World Wide Web[7], social networks defined by friendship relations among individuals, etc. [8].

Word networks have been used to address complex aspects of human language. In such studies, words are connected according either to semantic associations [11,12,13] or even by nearness in the text [14,15,16], i.e., based on what is commonly called word window with a fixed number of words. Those works intend to establish the structure of a given language as a whole. Because of this, they deal with a huge amount of texts, independently of their authors, what is called corpora.

Language is obviously a product of brain activity and, to this regard, we would like to call the attention to works revealing the presence of neuronal networks in the brain by direct physiological measurements. In a recent work[17], functional magnetic resonance of human brains has established networks whose vertices are regions of the cerebral cortex that are activated by external stimuli according to a temporal correlation of activity.

In this work, we investigate the relations between the concepts in individual written texts, by using them as starting point to construct significant networks. Projecting both the concepts present in the text, as well as the way they are related among them, onto a network gives the opportunity to use the tools and concepts developed within the network framework to characterize, in a quantitative way, how the concepts in a written text appear, how ordered and connected they are, how close to each other they are within the text, and so on.

2 Network concepts and text network construction

An undirected network is defined by a set of elements, called vertices or nodes, represented graphically by points, some of which are joined together by an edge, represented by a line between these points. The topological structure of many networks displays a large-scale organization, with some typical properties like: highly sparse connectivity, small minimal paths between vertices and high local clustering.

To analyze a network, a number of indices (or quantifiers) have been proposed, which allow for a quantification of many of the properties quoted above. In this work we will use the most important of them: number of vertices $N$, number of edges $M$, average connectivity $< k >$, average minimal path length
ℓ, diameter L, degree distribution \( p(k) \), and the Watts and Strogatz clustering coefficient \( C \) (for a thorough discussion of these indices see, e.g., [5]). If the node degree distributions follow power laws, \( p(k) \sim k^{-\gamma} \), the exponent \( \gamma \) becomes an important index for the network characterization.

Two important network scenarios, characterized respectively by the small-world [9] and scale-free structures [10], have been identified to be present in several complex networks, including those related to the subject of this work, namely the analysis of corpora and of brain activity. The first one is related to the concomitant presence of small average value for \( \ell \) and high \( C \), while the second is related to a power law distribution of node degree.

To map the texts onto networks that reflect the structure of meaning concepts within it, we have preserved only the words with an intrinsic meaning, eliminating words which have a merely grammatical function, as to arrange the syntactical structure of sentences in the text (articles, pronouns, prepositions, conjunctions, abbreviations, and interjections). Afterwards, we have reduced the remaining words to their canonical forms, i.e., we have disregarded all inflections as plural forms, gender variations, and verb forms. Such procedures are common in studies on language[18]. In order to perform a computer implementation, we have used some routines, dictionaries, and grammatical rules from UNITEX package[19]. Unknown words to the program were preserved in their original forms. After this filtering treatment, we have constructed a network for each individual text, where each distinct word corresponds to a single vertex. Since we consider the sentence as the smaller significant unit of the discourse, two words are connected if they belong to the same sentence. Thus, sentences are incorporated into the network as a complete subgraph, that is, a clique of mutually connected words. Sentences with common words are connected by the shared words. The method we propose offers a natural way to analyze the growth process of the network evolution. We have investigated both the network behavior in this step by step evolving process, what we call dynamical analysis, as well as the behavior of the entire network in its final form, corresponding to the entire text, called the static analysis. Both methods reveal important properties and they shall be discussed further on. In Figure 1, we show an example of a text filter process together with the evolving process of network construction for a well known jingle.

In order to guarantee an uniform and comprehensive sample, we have chosen a collection of 312 texts [20], which can be cast into different classes as: genre (59% technical, 41% literary), language (53% in Portuguese, 47% in English), gender (72% male authors, 28% female authors). Finally we have also classified the texts according to their size (55% with less than 1,000 sentences, 45% with more than 1,000). The smaller text has 169 and the larger, 276,425 words; in the average, the texts have 32,691 words.
3 Results

The texts were individually analyzed, based on the evaluation of the indices quoted in the previous section: $N$, $M$, $<k>$, $\ell$, $C$, $L$, and degree distribution $p(k)$, which we have found to obey a power law $p(k) \sim k^{-\gamma}$. We have also followed how the number and size of independent clusters varies in the growth process. Average values of such indices based on the entire texts of the whole sample have been computed and are shown in Table I. The analyzed networks are very sparse, with average connection index $2M/[N(N - 1)] < 0.1$ for the networks with $N \geq 100$.

We have verified that the degree distributions, for all analyzed texts, exhibit an early maximum around $k = 10$, which is followed by crossover to a long right-skewed tail, approximating a power law distribution with average exponent $\langle \gamma \rangle = 1.6 \pm 0.2$. We have found no evidence of correlation between the value of $\gamma$ and the length of the analyzed text. These features are illustrated in Figure 2, where we show $p(k) \times k$ for a very large text and the smallest one we analyzed.

The dynamical analysis also reveals very interesting results. In Figure 3(a), points indicate the evolution of $C$ for 15 large texts, as function of the network sizes, showing that they converge to a value around 0.75. We have identified
the data of two specific texts (in color) to emphasize such phenomenon. This peculiar behavior of $C$ is also exhibited when we plot its value as function of the number of sentences $s$ in the different texts, as shown in Figure 3(b). A functional dependence between $C$ and $s$ can be written as $C \approx 1 - 0.08 \log_{10} s$.

The investigation of the cluster structure of the network during its growth has shown that texts evolve mostly in the form of a very large single cluster, which is formed since the very beginning of the network evolution. New words are likely to adhere to it rather than starting other significant clusters, what leads to the presence of a single giant cluster for the entire text. Another aspect we have analyzed was the evolution of the indices in the network growth process with respect to the same text in different languages. As an example we compare, in Figure 4, the evolution of $C$ and $\ell$ for the network associated to James Joyce’s Ulysses, in the original English version and in its translation to Portuguese.

A partial discussion of the results we have obtained to this point indicates that the networks we analyzed have highly sparse connectivity, small $D$ and $\ell$, but high $C$, what constitute evidences of a small-word network scenario. Besides, since $p(k)$ decay according to power laws, we conclude they also behave as scale-free networks (see values in Table I). It is important to emphasize that the filtering treatment does not modify the network general behavior. In order to verify this fact, we have also performed the same measurements for the networks obtained from the original texts, without any kind of treatment. We have verified that, notwithstanding to the fact that we obtain different values for the same indices (see Table I), the very frequent presence of articles, prepositions and other words does not alter the small-world and scale-free character of the text networks! The small-world behavior is characterized by a great compactness and by the presence of some vertices with high local clustering. Such aspect in these networks means that they have words that are often used along the text. That fact explains the small values of $D$ and $\ell$. The scale-free behavior results from the presence of nodes with high connectivity degree in a much greater amount in comparison to that of a random graph. This aspect is obviously expected in a written text, due to the presence of an organization principle which controls the construction of the text. The most connected words are associated with recurrent concepts around which the text is constructed.

4 Shuffling procedures

There are several agents that contribute to determine the measured indices in the analyzed networks. For example, since each sentence is added to the network as a complete subgraph, their lengths may interfere in the cluster-
Fig. 3. (a) Behavior of $C$ as function of the number of vertices compared with two texts. (b) The same index as function of the number of sentences, for 15 texts.

Fig. 4. Clustering coefficient and average shortest path length evolution, according to the number of sentences in James Joyce’s Ulysses, in the original English version and in a Portuguese translation.

ing coefficient. In the same way, the own structure of the sentences and the frequency of the words along the whole text affects $C$ and other indices as well. In order to evaluate the role of these main agents in the determination of the indices, we have re-analyzed the filtered texts after submitting them to four shuffling processes, which are so characterized: ($SA$) In this process, the beginning and the end of sentences are kept fixed, however the position of the words along the whole text is randomly changed. This procedure breaks completely the structure of concepts in the sentences, but their lengths and the frequency of the words in the whole text are kept unchanged. ($SB$) Here, the original sequence of the words along the text remains unchanged, but all sentences are forced to have the same average length, as obtained from the analysis of the unperturbed text. ($SC$) As in $SA$, the beginning and the end of sentences are kept fixed, and words are randomly chosen from the same vocabulary of the text. However, the words frequency is changed to a white distribution, so that all the words have the same choice probability. ($SD$) Here, we randomly distribute the same number of links as in the network of the filtered text among the nodes, i.e., obtaining an Erdös-Renyi network.

A summary of results is also included in the Table I. They show that the networks are affected in different ways but, as expected, for all but the $SD$ procedure, they are very far from random networks. The indices for $SA$ and $SB$ are not significantly altered. In the first case it shows that, without changing
the structural aspects of sentence sizes and word frequencies, the network is not essentially affected. In the second one, breaking sentence sizes but keeping words in their original places is not sufficient to alter, in a meaningful way, the network structure. These traits are corroborated by Figure 5, where we show the 4 cumulative degree distribution

$$P(k) = \frac{1}{k} \int_k^\infty p(k')dk',$$

for a given text and three shuffled versions of it. We realize that the scale-free character, expressed by a linear decay in the $k$ interval $[10,300]$ for $P(k)$ remains almost unchanged. These results remind Zipf’s universal result about distribution frequency of words in texts since, when Zipf’s law is not followed, e.g., $SC$ and $SD$, the network structure is broken. Indeed, not only the power law for $P(k)$ is lost, but also the indices in Table I have been altered. Nevertheless we emphasize the fact that, despite the change in word frequency caused by $SC$ sets up a deep modification in the text, its value for $C$ is much higher than that one for $SD$. This indicates that the unchanged distribution of sequence sizes still keeps the $SC$ network far away from the Erdös-Renyi scenario.

The results of the dynamical analysis call our attention to general aspects of network growth. Barabási and Albert[10] observed that the scale-free behavior may be explained by a special kind of growth process, known as preferential attachment. They proposed a model that captures such behavior: vertices are added to the network, systematically, by connecting them to some just existing vertices, which are selected in accordance with a probability distribution that depends on their degrees. However, the values obtained for $C$ are much lower than those in small-world networks. On the other hand, the Watts and Strogatz small-world, obtained by randomly rewiring a regular network, does
Table 1
Average values for the indices. Filtered texts were used as standard subjects, and shuffling operations were carried out on networks generated by them. Original means text without filtering, used just for the purpose of comparison.

<table>
<thead>
<tr>
<th>Text</th>
<th>$L$</th>
<th>$\ell$</th>
<th>$C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filtered</td>
<td>5±1</td>
<td>2.3±0.2</td>
<td>0.77±0.05</td>
</tr>
<tr>
<td>$SA$</td>
<td>4±1</td>
<td>2.2±0.2</td>
<td>0.77±0.04</td>
</tr>
<tr>
<td>$SB$</td>
<td>4±1</td>
<td>2.4±0.3</td>
<td>0.74±0.05</td>
</tr>
<tr>
<td>$SC$</td>
<td>4±1</td>
<td>2.2±0.3</td>
<td>0.40±0.20</td>
</tr>
<tr>
<td>$SD$</td>
<td>3±1</td>
<td>2.2±0.3</td>
<td>0.05±0.06</td>
</tr>
<tr>
<td>Original</td>
<td>4±1</td>
<td>2.0±0.1</td>
<td>0.82±0.03</td>
</tr>
</tbody>
</table>

not reproduce the scale-free feature[9] Therefore, we may suggest that the growth process we employ here is essential to capture both quoted behaviors. It is characterized by the addition of a new sentence, i.e., a complete subgraph or clique in each step. Due to the frequency distribution of words along the text, the attachment of these complete subgraphs is still preferential, but the new vertices are highly clustered, what contributes to the coexistence of both small-world and scale-free network scenario. Thus, the model of preferential attachment by complete subgraphs according to a pre-established frequency of vertices seems to be more suitable to describe the concomitant emergence of these behaviors.

To conclude, we would like to stress that our major purpose, to analyze network structure among concepts expressed by significant words in written texts, has been successfully addressed. The obtained indices point to the presence of both small-world and scale-free features. Moreover, we also characterized important aspects observed as the text grows, and studied the influence of distinct shuffling procedures of words and sentence size distribution. As expressed in the first paragraphs, our results may be of significance to shed light into the deeper problem of how the human mind works. We have briefly mentioned some efforts concerning the construction and analyzes of networks that represent the relations between neurons in brain cortex[17], such networks presenting both small-world and scale-free behavior.

The relation mind-brain is a subject of great controversy, but we wonder whether the universal character of the network behavior we have found in our work does not point out to some patterns present in the human mind. Indeed, due to the intense intellectual activity required to produce texts, it is natural to expect that the results may help understanding the way our mind works.

Patterns that might control the way we store concepts in our minds and could
reveal aspects of the structure of our brains. It is also worthy to remember that
similar patterns to those we obtained here have been observed in networks of
semantically related words. Thus, it is natural to conjecture that the results
we found do reveal the existence of links between all these research areas.
Certainly, there is much to be explored in such text networks, as this is a
vast field and the possibility of a joint effort from several different areas of
investigation is open.

Acknowledgements: The authors would like to thank Fernanda Regebe, Gesiane
Teixeira and Charles Santana for helpful discussions and assistance by code
programming.

References

[1] D. J. Watts, Small Worlds: The dynamics of networks between order and

[2] M. Buchanan, Nexus: small world and the groundbreaking science of networks,


(2002).


065102 (2002).


[20] Literary texts have been mostly obtained from Gutenberg Project website at www.gutenberg.org