UNIVERSIDADE DE SÃO PAULO
INSTITUTO DE FÍSICA DE SÃO CARLOS

Renato Fabbri

Topological stability and textual differentiation in human interaction networks: statistical analysis and linked data

São Carlos

2016

Renato Fabbri

Topological stability and textual differentiation in human interaction networks: statistical analysis and linked data

Thesis presented to the Graduate Program in Physics at the Instituto de Física de São Carlos, Universidade de São Paulo, to obtain the degree of Doctor in Science.

Concentration area: Applied Physics
Option: Computational Physics

Supervisor: Prof. Dr. Osvaldo Novais de Oliveira Junior

Original version

São Carlos

2016

É possível elaborar a ficha catalográfica em LaTeX ou incluir a fornecida pela Biblioteca. Para tanto observe a programação contida nos arquivos USPSC-modelo.tex e fichacatalografica.tex e/ou gere o arquivo fichacatalografica.pdf.

A biblioteca da sua Unidade lhe fornecerá um arquivo PDF com a ficha catalográfica definitiva, que deverá ser salvo como fichacatalografica.pdf no diretório do seu projeto.

Folha de aprovação em conformidade
com o padrão definido
pela Unidade.
No presente modelo consta como
folhadeaprovacao.pdf

This work is dedicated to God and my family, whose constant support made it possible.

ACKNOWLEDGEMENTS

I thank Prof. Dr. Osvaldo Novais de Oliveira Junior and Prof. Dr. Luciano da Fontoura Costa whose research inspired this thesis.

I thank the members of the São Carlos Physics Institute, including the instructors, the administration and the secretariat for the mindfulness and patience whenever I needed to reach them.

I thank the Brazilian Presidency and the United Nations Development Program for the partnership established with this research in the year of 2014. I thank Ricardo Poppi for his time and experience, which was of great help in this endeavor.

I thank the labMacambira.sf.net collective for numerous discussions and guidance with regards to free and digital culture. Namely, I thank Ricardo Fabbri, Vilson Vieira, Daniel Penalva, Caleb Luporini, Danilo Shiga, Antonio Pessotti and Carlos Lobo for insights and fruitful discussions.

I thank my family for the invaluable support in every step.

I thank the open source and free software communities for sharing their work, which made possible the developments presented in this thesis.

"Call to me and I will answer you and tell you great and unsearchable things you do not know."
Jeremiah 33:3

ABSTRACT

FABBRI, R. **Topological stability and textual differentiation in human interaction networks: statistical analysis and linked data**. 2016. 99p. Thesis (Doctor in Science) - Instituto de Física de São Carlos, Universidade de São Paulo, São Carlos, 2016.

This work reports on stable (or invariant) topological properties and textual differentiation in human interaction networks, with benchmarks derived from public email lists. Activity along time and topology were observed in snapshots in a timeline, and at different scales. Our analysis shows that activity is practically the same for all networks across timescales ranging from seconds to months. The principal components of the participants in the topological metrics space remain practically unchanged as different sets of messages are considered. The activity of participants follows the expected scale-free outline, thus yielding the hub, intermediary and peripheral classes of vertices by comparison against the Erdös-Rényi model. The relative sizes of these three sectors are essentially the same for all email lists and the same along time. Typically, 3-12% of the vertices are hubs, 15-45% are intermediary and 44-81% are peripheral vertices. Texts from each of such sectors are shown to be very different through direct measurements and through an adaptation of the Kolmogorov-Smirnov tests. These properties are consistent with the literature and may be general for human interaction networks, which has important implications for establishing a typology of participants based on quantitative criteria. For guiding and supporting this research, we also developed a visualization method of dynamic networks through animations. To facilitate verification and further steps in the analyses, we supply a linked data representation of data related to our results.

Keywords: Complex networks. Text mining. Pattern recognition. Statistics. Social network analysis. Typology. Data visualization. Linked data. Semantic web.

RESUMO

FABBRI, R. **Estabilidade topológica e diferenciação textual em redes de interação humana: análise estatística e dados ligados**. 2016. 99p. Tese (Doutorado em Ciências) - Instituto de Física de São Carlos, Universidade de São Paulo, São Carlos, 2016.

Este trabalho relata propriedades topológicas estáveis (ou invariantes) e diferenciação textual em redes de interação humana, com referências derivadas de listas públicas de e-mail. A atividade ao longo do tempo e a topologia foram observadas em instantâneos ao longo de uma linha do tempo e em diferentes escalas. A análise mostra que a atividade é praticamente a mesma para todas as redes em escalas temporais de segundos a meses. As componentes principais dos participantes no espaço das métricas topológicas mantêm-se praticamente inalteradas quando diferentes conjuntos de mensagens são considerados. A atividade dos participantes segue o esperado perfil livre de escala, produzindo, assim, as classes de vértices dos hubs, dos intermediários e dos periféricos em comparação com o modelo Erdös-Rényi. Os tamanhos relativos destes três sectores são essencialmente os mesmos para todas as listas de e-mail e ao longo do tempo. Normalmente, 3-12% dos vértices são hubs, 15-45% são intermediário e 44-81% são vértices periféricos. Os textos de cada um destes setores são considerados muito diferentes através de testes de Kolmogorov-Smirnov. Estas propriedades são consistentes com a literatura e podem ser gerais para redes de interação humana, o que tem implicações importantes para o estabelecimento de uma tipologia dos participantes com base em critérios quantitativos. De modo a guiar e apoiar esta pesquisa, nos também desenvolvemos um método de visualização para redes dinâmicas através de animações. Para facilitar a verificação e passos seguintes nas análises, nós fornecemos uma representação em dados ligados dos dados relacionados aos nossos resultados.

Palavras-chave: Redes complexas. Mineração de texto. Reconhecimento de padrões. Estatística. Análise de redes sociais. Tipologia. Visualização de dados. Dados ligados. Web semântica.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

HTML	HyperText Markup Language
HTTP	HyperText Transfer Protocol
URI	Uniform Resource Identifier
RDF	Resource Description Framework
SPARQL	SPARQL Protocol and RDF Query Language
W3C	World Wide Web Consortium
LOSD	Linked Open Social Database
IRC	Internet Relay Chat
AA	Algorithmic Autoregulation
POS	Part-Of-Speech

CONTENTS

1 INTRODUCTION

The first studies dealing explicitly with human interaction networks date from the nineteenth century while the foundation of social network analysis is generally attributed to the psychiatrist Jacob Moreno in mid twentieth century.[4,5] With the increasing availability of data related to human interactions, research about these networks has grown continuously. Contributions can now be found in a variety of fields, from social sciences and humanities[6] to computer science[7] and physics,[8,9] given the multidisciplinary nature of the topic. One of the approaches from an exact science perspective is to represent interaction networks as complex networks,[8,9] with which several features of human interaction have been revealed. For example, the topology of human interaction networks exhibits a scale-free outline, which points to the existence of a small number of highly connected hubs and a large number of poorly connected nodes. The dynamics of complex networks representing human interaction has also been addressed,[10,11] but only to a limited extent, since research is normally focused on a particular metric or task, such as accessibility or community detection.[12,13]

There are numerous articles, books, websites and software tools about complex and social networks and about text mining in social media. There are fewer endeavours to characterize these networks beyond general features such as the scale-free aspect or to deal with text produced by social networks from the complex networks background. Research on network evolution is often restricted to network growth, in which there is a monotonic increase in the number of events.[10] Network types have been discussed with regard to the number of participants, intermittence of their activity and network longevity.[10] Two topologically different networks emerged from human interaction networks, depending on whether the frequency of interactions follows a generalized power law or an exponential connectivity distribution.[14] In email list networks, scale-free properties were reported with $\alpha \approx 1.8$[7] (as in web browsing and library loans[8]), and different linguistic traces were related to weak and strong ties.[15]

The fact that unreciprocated edges often exceed 50% in human interaction networks[11] motivated the inclusion of symmetry metrics in our analysis. No correlation of topological characteristics and geographical coordinates was found,[16] therefore geographical positions were not considered in our study. Gender related behavior in mobile phone datasets was indeed reported[17] but it is not relevant for the present work because email messages and addresses have no gender related metadata.[18]

1.1 Related knowledge

1.1.1 Complex networks

Although not universally accepted, it is commonplace to define a complex network to be a "graph with non-trivial topological features".[5] We might add to this definition that a complex network is also a large graph (even while there seems not to be a consensus to what *large* means in such context) and that it is a graph representation of a system found in natural, real or empirical systems. Another way to approach the definition of "complex networks" is to define it as complex systems modeled as networks. This second definition is also useful but is even more problematic as there is no consensus of what a *complex system* is. Even so, one should keep in mind that authors often define a complex system to be a system composed with many parts in which "the whole is more than the sum of its parts". Authors also often consider complex systems to have capabilities to "process information", to adapt and to reproduce.[19]

A graph is a structure that consists of a set of objects (called vertices) and a set of binary/dual relations of the objects (called edges). A graph might be unweighted and undirected (the simplest possibility), weighted and undirected, unweighted and directed, or weighted and directed.

The most usual representations of graphs (and networks) are the matrix, list and node-edge representations. In the matrix representation, each entry a_{ij} is non-zero if i is linked to j; entries might be other than 0 and 1 in weighted graphs; undirected graphs yield symmetric matrices. There are two common list representations of graphs, one lists each pair of vertices that are connected, the other holds a list for each vertex in which are all the vertices connected to it (a list of lists). In the node-edge representation, each node represented as a point while each edge is represented by a line between correspondent nodes. The matrix representation is essential for algebraic reasoning and for deriving measures while the node-edge representation is important for illustration and intuitive guidance in characterizing the systems.

1.1.1.1 A good justification for applying the complex networks theory

The estimated number of atoms in the universe is often used as a reference of largeness and is $\approx 10^{80}$. Let us find the number of vertices needed to reach such number of possible networks. Consider the simplest case of the unweighted and undirected networks. Each edge can exist or not (i.e. it is a Bernoulli variable) and with n vertices there are at

most $\binom{n}{2}$ edges. Therefore:

$$2^{\binom{n}{2}} > 10^{80} \Rightarrow log_2[2^{\binom{n}{2}}] > log_2(10^{80}) \Rightarrow \binom{n}{2} > \frac{log_{10}(10^{80})}{log_{10}2} \Rightarrow$$
$$\Rightarrow \frac{n.(n-1)}{2} > \frac{80}{log_{10}2} \Rightarrow N > 23,5988$$

That is, with only 24 vertices we have more possible networks than the estimated number of atoms in the universe. We should also add that the number of possible networks grows very fast with the number of vertices. This is a good reason for characterizing such systems by means of paradigmatic networks and generic measures for nodes and the network (and edges, but it is less often).

1.1.1.2 Basic measures

Section 2.2.3 gives a mathematical account of the following measures, which are here for characterizing basic types of networks in the next section. Such measures are:

- Degree k_i: number of edges linked to vertex i.
- In-degree k_i^{in}: number of edges ending at vertex i.
- Out-degree k_i^{out}: number of edges departing from vertex i.
- Strength s_i: sum of weights of all edges linked to vertex i.
- In-strength s_i^{in}: sum of weights of all edges ending at vertex i.
- Out-strength s_i^{out}: sum of weights of all edges departing from vertex i.
- Betweenness centrality bt_i: fraction of geodesics that contain vertex i.
- Clustering coefficient cc_i: fraction of pairs of neighbors of i that are linked, i.e. the standard clustering coefficient metric for undirected graphs.

In the following discussion, we also use the concept of distance between a pair of nodes, which is the number of edges between the nodes.

1.1.1.3 Basic types of networks

Complex networks are often characterized in terms of paradigmatic models. There are diverse models, but we can glimpse the background theory with the following ones[20]:

- The Erdös-Rényi model*: each pair of nodes is connected with a fixed random probability p. This model presents a characteristic degree ($n.p$ where n is the number of nodes), low clustering and low average distance between nodes.

- Spatial network, also called geographic network or geometric graph: nodes are located in a metric space and the probability that two nodes are connected is greater as the distance between nodes gets smaller. These networks present characteristic degrees, high clustering and large average distance between nodes.

- Small-word network: defined as a network where the typical distance between nodes grows with the logarithm of the number of nodes while the average clustering coefficient is not small (larger than e.g. in the Erdös-Rényi model). One method for constructing a small-world network is to start with a regular lattice in which each node is connected to k nearest neighbors. Each link is then rewired with probability p. With intermediate values of p such as $0.01 < p < 0.1$, we obtain a network with both short average distance between nodes (as in the Erdös-Rényi model) and a high average clustering coefficient (as in the spatial network). This model presents a characteristic degree.

- Scale-free networks: in which the degree distribution $p(k)$ follows a power law ($p(k) = C.k^{-\alpha}$ where C and α are constants). These networks are qualitatively characterized by the presence of a large number of poorly connected and of few highly connected hubs. Important is the absence of a characteristic degree, thus the name 'scale-free network'.

- Other networks: among important models of networks are exponential networks, networks with community structure and hybrid models.

Real networks most often exhibit scale-free and small-world properties. This is the case of most e.g. social, gene and food networks. However, one should be cautious about such statement because the networks derived from the real systems depend heavily in what is considered a node and a link, i.e. on how the system is modeled as a graph. Another noteworthy remark is that the Erdös-Rényi networks, i.e. graphs of the Erdös-Rényi model, are frequently pin-pointed as the networks with trivial topological properties. Even though, it is posed as a paradigmatic "complex network", concept often defined as graphs with non-trivial topological properties, which is a contradiction and exposes that complex networks is not a very well defined notion, as is the case with the *complexity theory* in general.

* This name is also used for the model in which, for a fixed number of nodes and a fixed number of links, all networks are equally likely. This is the model originally introduces by Paul Erdös and Alfréd Rényi.[21] We choose the definition given inline, which is closely related to the one given in this footnote, because it is more commonly used nowadays.

1.1.2 Text mining of social data

Text mining is a multidisciplinary field, it is an extension of data mining to (often unstructured) textual data with the goal of discovering structure and meaning.[22] A general outline of a text mining endeavor involves structuring input text, deriving patterns and the evaluation of the output. There are actually numerous models of such outline, as e.g. considering document collection and obtaining a final report in the start and end respectively.[23] Text mining tasks include document summarization, sentiment analysis and natural language processing techniques such as part of speech tagging.[24] Among application are social media monitoring, automated ad placement, publishing and making tools for semantics, sentiment and general natural language.[23] It is believed that applying text mining to social media can yield interesting findings in human behavior.[22] Although there is no clear cut, text mining is sometimes divided into linguistic and non-linguistic.[22] In the first case, techniques borrowed from linguistics are present, such as the analysis of discourse and part of speech tagging, and it is often mingled with natural language processing or computational linguistics (see Section 1.2 for a coherent distinction of the fields). In the non-linguistic text mining, text is analyzed by means of statistical features derived from e.g. the size of tokens and sentences, and might be more easily related to the intuitive concept of data mining of text. On this thesis we use both perspectives.

1.1.3 Visualization of static and dynamic graphs

Static graph visualization is achieved in many ways, most usually through the node-link (often called network diagram) and matrix representations. Representing graphs as node-link diagrams has a long tradition which remotes at least to the works of Ramon Llull in the 13th century.[25] To glimpse at the theory involved in visualizing networks,[26] we mention three aspects:

- criteria for the quality of layouts might include the number of crossing edges or the area of the drawing relative to closest distance between two vertices.
- Layout methods are derived e.g. by placing vertices in a circular fashion, by using the eigen vectors from a worked out variant of the adjacency matrix as coordinates, or by force-based methods. For large graphs, including a number of social networks, the force-based networks are reported as useful. Therefore, we illustrate this method with the simplest model we could find in the well known literature. Be f_a the attraction force, f_r the repulsion force, d the distance between the vertices and k a constant. The model introduced by Fruchterman and Reingold[27] defines the forces as:

$$f_a = \frac{d^2}{k} \tag{1.1}$$

$$f_d = -\frac{k^2}{d} \tag{1.2}$$

On a computer software, one usually starts with a random layout and performs a number of iterations updating the position of nodes using these forces to obtain the intended force-directed layout.

- Graph drawings are often developed for specific applications e.g. in biology (as for protein and gene interactions), in social networks, in tree diagrams.

The core difference of dynamic graphs to static graphs is that vertices and edges can be added and removed over time. If we define the static graph G as $G := (V, E)$ where V are the vertices as E are the edges in G, a dynamic graph might be defined as $\Gamma := (G_1, G_2, ..., G_n)$ where $G_i := (V_i, E_i)$ are static graphs and indices refer to a sequence of time steps $(t_1, t_2, ..., t_n)$. In dynamic graph visualization most usually graphs are represented as animated diagrams or charts based on a timeline.[28] In this thesis we make use of node-link diagrams of both static and dynamic graphs.

1.1.4 Linked (open) data

The fields of social network analysis and complex networks are widely researched. However, there is a lack of open datasets for benchmarking results, especially associated with the complex networks field, yielding diverse results from poorly related sources. Recently, a myriad of results have been reported which are based in diverse datasets most often not accessible to researchers other than the publishing authors. In this thesis we present resources for having open databases to provide the scientific community with a friendly and common repertoire. We chose to use the linked data technology and follow W3C best practices for publishing data.

Linked data refers to data published in the web in such a way that it is machine readable and complies with a set of best practices. The web of data is constructed with documents on the web such as the web of HTML documents. In practice, the idea of linked data can me summarized by 1) the use of RDF to publish data on the web and 2) the use of RDF links to interlink data from different sources. The web is expected to be interconnected and to grow by the systematic application of four steps[29]:

- Use URIs to identify things.[30]
- Use HTTP URIs.
- Provide useful information when an URI is accessed via HTTP.
- Provide other URIs in the description of resources so human and machine agents can perform discovery.

The Linked Open Data[31] builds an ever growing cloud of data, the global data space, which is usually conceived as centered around the DBPedia, a linked data representation of data from Wikipedia.[32,33]

1.1.4.1 RDF

The Resource Description Framework (RDF), a W3C recommendation, is a model for data interchange. It is based on the idea of making statements about resources in the form of triples, i.e. expressions in the form "subject - predicate - object". RDF can be serialized in several file formats, including RDF/XML, Turtle and Manchester, all of which, in essence, represent a labeled and directed multi-graph. RDF may be stored in a type of database referred to as a triplestore.[34]

As an example of an RDF statement, the following triple in the Turtle format asserts that "the paper has color white":

```
http://example.org/Things#Paper http://example.org/hasColor
http://example.org/Colors#White .
```

Integration and uniformity of access is obtained through linked data representation, as explained in Section 3.3.5.

1.1.5 Social participation

A significant share of our endeavor was oriented towards social participation, i.e. to facilitate civil engagement in a community, most significantly in State affairs. More concretely, we published data from a social participation federal portal,[2] applied complex networks and text mining criteria for resources recommendation[35–37] and proposed a ranking algorithm for voted proposals in another federal participation portal.[38] Such works were performed within a United Nations Development Program consulting contract, in partnership with the Brazilian Presidency of the Republic and published publicly mainly as technical reports.[35–37] This aspect of our research was important for maturing topics and understanding the extent to which they are applied in pragmatic contexts and is left mostly to auxiliary documents of this thesis to promote simple expositions.

1.1.6 Other

Given the multidisciplinary condition of our work and of the implied topics, many other fields of knowledge could be further explored in this introduction or the methods chapter. To name just a few of the most directly related fields: statistics, principal component analysis, big data, social network analysis, social media mining, mathematical sociology, datasets, free culture, open source software, computer programming.

Of particular relevance are the typologies for human personality, such as the ones derived from the Myers-Briggs type indicator[39] and from authoritarian personality[40]

theories, because we present a new typology of human participants in social networks in Section 3.0.4. Another topic we should highlight is what we called "anthropological physics"[41,42]: the observation of natural/physical laws in human social systems. The term should not be confused with physical anthropology, which is a synonym for biological anthropology, a subfield of anthropology concerned with the evolution of humans.[43]

1.2 Polysemy and synonyms

In the context of complex networks, the words *network* and *graph* are often used interchangeably, although the word graph might refer to the mathematical structure of vertices and edges and the word network might refer to the real system being represented as a graph or to the graph obtained by means of representing a real system. Furthermore, the word graph can be used to refer to a *graph of a function* (mathematics) or to an abstract datatype (computer science). This parallelism between network and graphs also apply to network visualization and graph visualization. One might add here the term *graph drawing*, another synonym for the visualization of graphs, although the term seems to be more traditional in relation to the achievement of node-edge network diagrams. Evolutionary graph visualization or evolutionary network visualization are examples of variants of *dynamic graph visualization*. The nomenclature of vertices and edges vary widely among interested fields (mathematics, physics, biology, sociology, etc). A vertex might be called e.g. a node, a point, an agent, an actor, a participant. An edge might be called e.g. a link, a bond, a relation, a tie, a connection.

The terms *text mining*, *natural language processing* and *computational linguistics* are often used for similar endeavors. A distinction might be made in that text mining refers to data mining of text, natural language processing is concerned with the interactions between the computer and the human natural languages, and computational linguistics aims for statistical or rule-based modeling of natural language from a computational perspective. Such fields are multidisciplinary and there is no sharp distinction between them.

Examined as fields of knowledge, the *linked data* and the *semantic web* terms are often used without distinction. Tim Berners-Lee coined both terms: the semantic web was conceived as a web of data that can be processed by machines,[44] the expression linked data appeared in a 2006 design note about the Semantic Web project[29] and refers to structured data that emphasizes interlinking and usefulness through semantic queries.

Social participation, *social envolvement* and *social engagement* are synonyms that refer to the participation of an individual or group in a community or society. In Brazilian Portuguese, *controle social* can refer to the antagonist concepts of social participation or of a social control (played by the State or companies in the civil society).

1.2.1 More specific terminology problems in the complex networks field

Given that this thesis involves multidisciplinary and new knowledge, it might be of no surprise that the nomenclature is not very well defined. Here we pin-point some more specific conflicts that arise in the literature of complex networks to both exemplify this issue and to avoid some problems in interpreting the methods and results in this thesis:

- The *hubs* are, by the usual definition, the more connected vertices. In the context of the HITS (Hyperlink-Induced Topic Search) algorithm, for attributing centrality to vertices, most traditionally to web pages, the hubs are the vertices with greater out-degree (greater in-degree yield *authorities*).
- In some contexts, the center of network is the collection of vertices whose the maximum distance to other vertices is the radius (i.e. the minimum maximum difference between vertices). In the same framework, the periphery of a network is the collection of vertices whose the maximum distance to other vertices is the diameter (i.e. the maximum distance between vertices). By extension, the intermediary might be regarded as the set of vertices that are not in the center or the periphery. These definitions yield fractions of members that do not agree with the literature with respect to hubs, intermediary and periphery. We present a suitable method for deriving such classification, in the sense that it fits the literature prediction, in Section 2.2.4.
- Lace, loop, selfloop and autoloop are terms used to designate an edge from a vertex to itself.

1.3 Historical note

The knowledge fields involved in this thesis are very recent. To point just the main areas, complex networks has emerged in the final years of the 1990s decade[5]; text mining first workshops were held in 1999[45]; as an independent field, graph drawing arose in the 1990s[28]; the term linked data was coined in 2006.[29]

1.4 Further considerations

An initial proposal of this research was to enable the use of complex and social networks scientific knowledge by the participant of the networks. This motivated the open software, data and texts produced, conferences attended, and the endeavors with the United Nations, Brazilian Presidency and civil parties. As this was a practical goal, we found by hands-on processes that many fields are deeply related to the subject, which reflected in the number of fields tackled in this thesis and related documents.[2,35–38,41,42,46,47] Furthermore, we understand that the open software, texts, videos and processes provided

by our work contributes for the popularization of the knowledge and technologies implied by the empowerment of civil individuals and groups through the management of the networks in which they exist.

1.5 Structure of the thesis

Next Chapter presents data and methods while the results and discussion are in Chapter 3. Conclusions and further work are stated in Chapter 4. Appendixes display auxiliary tables, figures and other results.

2 MATERIALS AND METHODS

2.1 Core data and scripts

Email list messages were obtained from the Gmane email archive, which consists of more than 20,000 email lists (discussion groups) and more than 130×10^6 messages.[48] These lists cover a variety of topics, mostly technology-related. The archive can be described as a corpus along with message metadata, including sent time, place, sender name, and sender email address. The usage of the Gmane database in scientific research is reported in studies of isolated lists and of lexical innovations.[7,15]

We observed various email lists and selected five of them together with data from Twitter, Facebook and Participabr for a thorough analysis, from which general properties can be inferred. These lists are as follows:

- Linux Audio Users list*,with participants from different countries with artistic and technological interests. English is the prevailing language. Abbreviated as LAU from now on.
- Linux Audio Developers list†, with participants from different countries; a more technical and less active version of LAU. English is the prevailing language. Abbreviated as LAD from now on.
- Developer's list for the standard C++ library‡, with computer programmers from different countries. English is the prevailing language. Abbreviated as CPP from now on.
- List of the MetaReciclagem project§, a Brazilian email list for digital culture. Portuguese is the prevailing language, although some messages are written in Spanish and English. Abbreviated as MET from now on.
- List for de discussion of the election reform¶. English is the prevailing language. Abbreviated ELE from now on.

The first 20,000 messages of each list were considered, with basic attributes of total timespan, authors, threads and missing messages indicated in Table 1. We considered 140

* gmane.linux.audio.users is list ID in Gmane.
† gmane.linux.audio.devel is list ID in Gmane.
‡ gmane.comp.gcc.libstdc++.devel is list ID in Gmane.
§ gmane.politics.organizations.metareciclagem is list ID in Gmane.
¶ gmane.politics.election-methods is list ID in Gmane.

Table 1: Columns $date_1$ and $date_M$ have dates of first and last messages from the 20,000 messages considered in each email list. N is the number of participants (number of different email addresses), Γ is the number of discussion threads (count of messages without antecedent), $\overline{M}$ is the number of messages missing in the 20,000 collection ($100\frac{23}{20000} = 0.115$ percent in the worst case).

list	$date_1$	$date_M$	N	Γ	$\overline{M}$
LAU	2003-06-29	2005-07-23	1147	3374	5
LAD	2003-07-03	2009-10-07	1232	3114	4
MET	2005-08-01	2008-03-07	477	4607	23
CPP	2002-03-12	2009-08-25	1036	4506	7
ELE	2002-03-18	2011-08-31	302	6070	54

Source: Prepared by the authors.

additional email lists to report on the interdependence between the number of participants and the number of discussion threads. Furthermore, 12 networks from Facebook (8), Twitter (2) and Participabr (2) were scrutinized, and their analysis is given in the Supporting Information document for the purpose of testing the generality of the results. We systematicaly used 18 lists for taking text-related measures.

2.1.1 Linked Open Social Database for scientific benchmarking

Beyond core data used to derive topological and text related results, we provided a database for scientific benchmarking and to derive further results in our research. The data used here were obtained from Facebook, Twitter, IRC, Email lists and the detached instances of ParticipaBR, AA and Cidade Democrática. These were represented as linked data to homonenize access, complying with current best practices and facilitationg analyzes which integrate third party and provided instances.

Data was gathered from:

- public APIs (Twitter, Email);
- public logs (IRC and AA);
- Netvizz software[49] and subsequent donation by users (Facebook);
- donation by system administrators (AA, ParticipaBR, Cidade Democrática).

This section introduces the underlying data in a very concise fashion. Further information is available in the Appendix **??** and in an article.[2]

2.1.1.1 Snapshots

Of central importance to the provided database is the concept of a snapshot. A snapshot is herein a set of data gathered together, at a contiguous time span. For example:

the first 20 thousand email messages of an email list comprises a snapshot; the tweets from the MAMA music event are a snapshot; the friendship, interaction and posts structures of a facebook group, prospected at the same time, are a snapshot.

2.1.1.2 Facebook data

Friendship ego networks (networks whose constituents are friends of a user) were donated from individual users in 2013 and 2014. Friendship and interaction networks from groups were gathered from groups where the author was a participant. Additionally, some groups have post texts along some metadata, such as the number of likes.

2.1.1.3 Twitter data

Tweets were gathered through the Twitter streaming public API. Each snapshot is unified by a distinct hashtag. Edges are canonically yield by retweets but replies and user mentions are also kept in the database.

2.1.1.4 IRC data

Public IRC logs were used to render IRC snapshots. The database has records of users to which the message is directed or mentions.

2.1.1.5 Email data

Email snapshots refer to individual email lists. All messages were obtained from the Gmane public email database.[50] Each message has the original text and the text without some of the lines from previous messages or that are software code. Most importantly, each message instance holds the ID of the message it is a reply to, if any.

2.1.1.6 ParticipaBR data

The ParticipaBR is a Brazilian federal platform for social participation. Texts are derived from blog posts and networks are derived from friendship and interaction criteria.

2.1.1.7 Cidade Democrática data

Cidade Democrática is a Brazilian civil society social participation portal. Data gathered is complex with many types of instances and no intuitive criteria for deriving networks, such as friendships or replies.

2.1.1.8 AA data

The Algorithmic Autoregulation[51] is a software development methodology based on testifying and sharing ongoing work. The data was gathered from different versions of the system and from an IRC log.

2.1.2 Availability

The data and scripts used to derive the results, figures and tables are publicly available. Email messages are downloadable from the Gmane public database.[48] Data annotated from Facebook and Twitter are in a public repository.[52] Data from Participabr was used from the linked data/semantic web RDF triples,[37] available in.[53] Computer scripts are delivered through public domain Python PyPI packages and open Git repositories.[18] This open approach to both data and scripts reinforces the scientific aspect of the contribution[54] and mitigates ethical and moral issues involved in researching systems constituted of human individuals.[41,55]

2.2 Methods

2.2.1 Temporal activity statistics

Messages were counted over time as histograms in the scales of seconds, minutes, hours, days of the week, days of the month, and months of the year. Most standard measures of location and dispersion, e.g. the usual mean and standard deviation, hold little meaning in a compact Riemannian manifold, such as the recurrent time periods that we are interested in. Similar measures were taken using circular statistics,[56] in which each measurement t is represented as a unit complex number, $z = e^{i\theta} = \cos(\theta) + i\sin(\theta)$, where $\theta = t\frac{2\pi}{T}$, and T is the period in which the counting is repeated. For example, $\theta = 12\frac{2\pi}{24} = \pi$ for a message sent at $t = 12h$ and given $T = 24h$ for days. The moments m_n, lengths of moments R_n, mean angles θ_μ, and rescaled mean angles θ'_μ are defined as:

$$\begin{aligned} m_n &= \frac{1}{N}\sum_{i=1}^{N} z_i^n \\ R_n &= |m_n| \\ \theta_\mu &= Arg(m_1) \\ \theta'_\mu &= \frac{T}{2\pi}\theta_\mu \end{aligned} \tag{2.1}$$

θ'_μ is used as the measure of location. Dispersion is measured using the circular variance $Var(z)$, the circular standard deviation $S(z)$, and the circular dispersion $\delta(z)$:

$$\begin{aligned} Var(z) &= 1 - R_1 \\ S(z) &= \sqrt{-2\ln(R_1)} \\ \delta(z) &= \frac{1 - R_2}{2R_1^2} \end{aligned} \tag{2.2}$$

Also, the ratio $r = \frac{b_l}{b_h}$ between the lowest b_l and the highest b_h incidences on the histograms served as a further clue of how close the distribution was to being uniform. As expected, a positive correlation was found in all $r, Var(z)$, $S(z)$ and $\delta(z)$ dispersion measures, which can be noticed in Section **??**. The circular dispersion $\delta(z)$ was found more sensitive and therefore preferred in the discussion of results.

2.2.2 Interaction networks

Edges in interaction networks can be modeled both as weighted or unweighted, as directed or undirected.[7,57,58] Networks in this thesis are directed and weighted, the most informative of the possibilities. We did not investigate directed unweighted, undirected weighted, and undirected unweighted representations of the interaction networks.

The interaction networks were obtained as follows: a direct response from participant B to a message from participant A yields an edge from A to B, as information went from A to B. The reasoning is: if B wrote a response to a message from A, he/she read what A wrote and formulated a response, so B assimilated information from A, thus $A \rightarrow B$. Edges in both directions are allowed. Each time an interaction occurs, the value of one is added to the edge weight. Selfloops were regarded as non-informative and discarded. Inverting edge direction yields the status network: B read the message and considered what A wrote worth responding, giving status to A, thus $B \rightarrow A$. This thesis considers by convention the information network as described above ($A \rightarrow B$) and depicted in Figure 1. These interaction networks are reported in the literature as exhibiting scale-free and small-world properties, as expected for a number of social networks.[5,7]

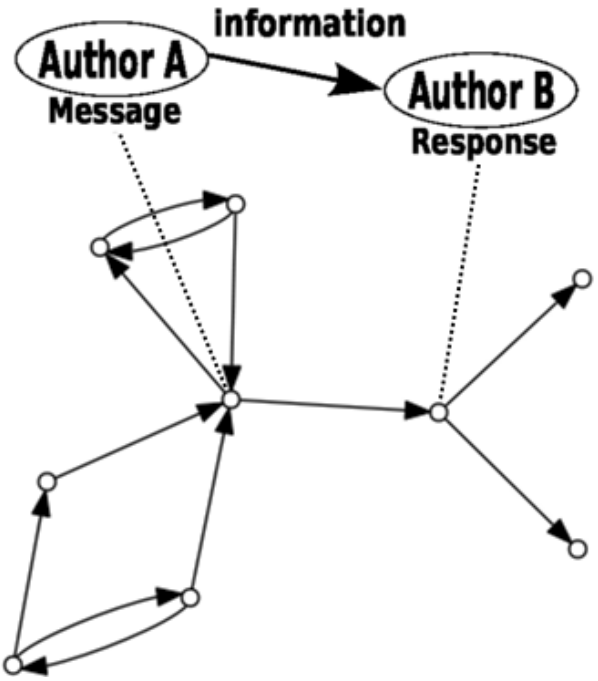
2.2.3 Topological metrics

The topology of the networks was characterized from a small selection of the most basic and fundamental measurements for each vertex,[5] as introduced in Section 1.1.1.2. The betweenness centrality index was computed for weighted digraphs as specified in.[59]

The non-standard metrics below were formulated to capture symmetries in the activity of participants:

- Asymmetry of vertex i: $asy_i = \frac{k_i^{in} - k_i^{out}}{k_i}$.
- Average asymmetry of edges at vertex i:
  $\mu_i^{asy} = \frac{\sum_{j \in J_i} e_{ji} - e_{ij}}{|J_i|}$, where e_{ij} is 1 if there is an edge from i to j, and 0 otherwise, and J_i is the set of neighbors of vertex i.
- Standard deviation of asymmetry of edges:
  $\sigma_i^{asy} = \sqrt{\frac{\sum_{j \in J_i} [\mu_i^{asy} - (e_{ji} - e_{ij})]^2}{|J_i|}}$.
- Disequilibrium: $dis_i = \frac{s_i^{in} - s_i^{out}}{s_i}$.

Figure 1: The formation of interaction networks from exchanged messages. Each vertex represents a participant. A reply message from author B to a message from author A is regarded as evidence that B received information from A and yields a directed edge. Multiple messages add "weight" to a directed edge. Further details are given in Section 2.2.2.



Source: Prepared by the authors.

- Average disequilibrium of edges:
  $\mu_i^{dis} = \frac{\sum_{j \in J_i} \frac{w_{ji} - w_{ij}}{w_{ji} + w_{ij}}}{|J_i|}$, where w_{xy} is the weight of edge $x \to y$ and zero if there is no such edge.

- Standard deviation of disequilibrium of edges: $\sigma_i^{dis} = \sqrt{\frac{\sum_{j \in J_i} \left[\mu_i^{dis} - \frac{w_{ji} - w_{ij}}{w_{ji} + w_{ij}}\right]^2}{|J_i|}}$.

Standard metrics are used for the Erdös sectioning (described in the next section). Both standard and non-standard metrics are used for performing principal component analysis (PCA) (as described in Section 2.2.5).

2.2.4 Erdös sectioning

It is often useful to think of vertices as hubs, peripheral and intermediary. We have therefore derived the peripheral, intermediary and hub sectors of an empirical network from the comparison against an Erdös-Rényi network with the same number of edges and vertices, as depicted in Figure 2. We refer to this procedure as *Erdös sectioning*, with the resulting sectors being named as *Erdös sectors*. The Erdös sectioning was recognized as a

theoretical possibility by M. O. Jackson in his video lectures,[1] but to our knowledge it has not as yet been applied to empirical data.

The degree distribution $\widetilde{P}(k)$ of a real network with a scale-free profile $\mathcal{N}_f(N, z)$ with N vertices and z edges has less average degree nodes than the distribution $P(k)$ of an Erdös-Rényi network with the same number of vertices and edges. Indeed, we define in this work the intermediary sector of a network to be the set of all the nodes whose degree is less abundant in the real network than on the Erdös-Rényi model:

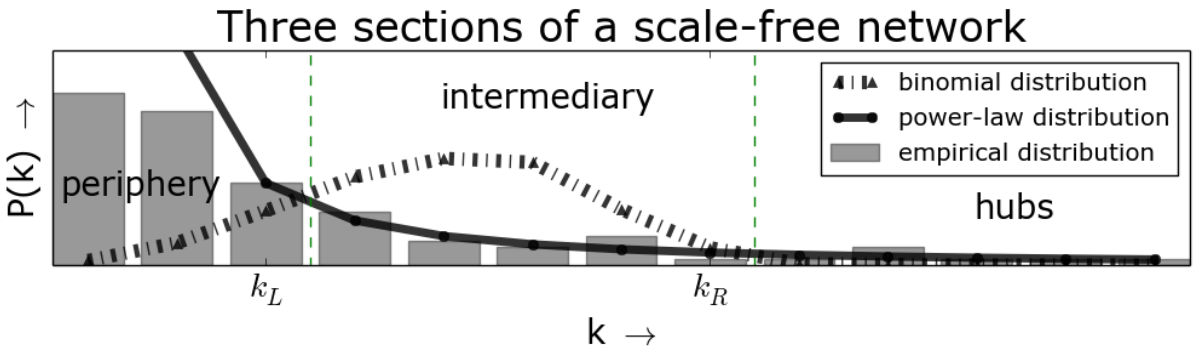
$$\widetilde{P}(k) < P(k) \Rightarrow \text{k is intermediary degree} \tag{2.3}$$

If $\mathcal{N}_f(N, z)$ is directed and has no self-loops, the probability of the existence of an edge between two arbitrary vertices is $p_e = \frac{z}{N(N-1)}$. A vertex in the ideal Erdös-Rényi digraph with the same number of vertices and edges, and thus the same probability p_e for the presence of an edge, will have degree k with probability

$$P(k) = \binom{2(N-1)}{k} p_e^k (1-p_e)^{2(N-1)-k} \tag{2.4}$$

The lower degree fat tail corresponds to the border vertices, i.e. the peripheral sector or periphery where $\widetilde{P}(k) > P(k)$ and k is lower than any value of k in the intermediary sector. The higher degree fat tail is the hubs sector, i.e. $\widetilde{P}(k) > P(k)$ and k is higher than any value of k in the intermediary sector. The reasoning for this classification is as follows: vertices so connected that they are virtually nonexistent in the Erdös-Rényi model, are coherently associated to the hubs sector. Vertices with very few connections, which are way more abundant than expected in the Erdös-Rényi model, are assigned to the periphery. Vertices with degree values predicted as the most abundant in the Erdös-Rényi model, near the average, and less frequent in the real network, are classified as intermediary.

Figure 2: Classification of vertices by comparing degree distributions.[1] The binomial distribution of the Erdös-Rényi network model exhibits more intermediary vertices, while a scale-free network, associated with the power-law distribution, has more peripheral and hub vertices. The sector borders are defined with respect to the intersections of the distributions. Characteristic degrees are in the compact intervals: $[0, k_L]$, $(k_L, k_R]$, $(k_R, k_{max}]$ for the periphery, intermediary and hub sectors, the "Erdös sectors". The connectivity distribution of empirical interaction networks, e.g. derived from email lists, can be sectioned by comparison against the associated binomial distribution with the same number of vertices and edges. In this figure, a snapshot of 1000 messages from CPP list yields the degree distribution of an interaction network of 98 nodes and 235 edges. A thorough explanation of the method is provided in Section 2.2.4.



Source: Prepared by the authors.

To ensure statistical validity of the histograms, bins can be chosen to contain at least η vertices of the real network. The range Δ of incident values of degree k should be partitioned in m parts $\Delta = \cup_{i=1}^{m} \Delta_i$, with $\Delta_i \cap \Delta_j = \emptyset \; \forall \; i \neq j$ and:

$$\Delta_i = \Bigg\{ k \;\Big|\; \overline{\Delta}_{i-1} < k \leq l \text{ and } \Bigg[\Bigg[N - \sum_{k=0}^{\overline{\Delta}_{i-1}} \eta_k < \eta \text{ and } l = \overline{\Delta} \Bigg] \text{ or } \Bigg[\sum_{k=\overline{\Delta}_{i-1}+1}^{l} \eta_k \geq \eta \text{ and } \Bigg(\sum_{k=\overline{\Delta}_{i-1}+1}^{l-1} \eta_k < \eta \text{ or } l = \overline{\Delta}_{i-1} + 1 \Bigg) \Bigg] \Bigg] \Bigg\} \tag{2.5}$$

where η_k is the number of vertices with degree k, while $\overline{\Delta}_{(i)} = max(\Delta_{(i)})$, and $\overline{\Delta}_0 = -1$.

Equation 2.3 can now be written in the form:

$$\sum_{x=min(\Delta_i)}^{\overline{\Delta}_i} \widetilde{P}(x) < \sum_{x=min(\Delta_i)}^{\overline{\Delta}_i} P(x) \Leftrightarrow$$
$$\Leftrightarrow \Delta_i \text{ spans intermediary degree values.} \tag{2.6}$$

If the strength s is used for comparison of the real network against the Erdös-Rényi model, P remains the same, but $P(\kappa_i)$ with $\kappa_i = \frac{s_i}{\overline{w}}$ should be used, where $\overline{w} = 2\frac{z}{\sum_i s_i}$ is the average weight of an edge and s_i is the strength of vertex i. For in and out degrees (k^{in}, k^{out}), the real network should be compared against

$$\hat{P}(k^{way}) = \binom{N-1}{k^{way}} p_e^k (1-p_e)^{N-1-k^{way}}, \tag{2.7}$$

where *way* can be *in* or *out*. In and out strengths (s^{in}, s^{out}) are divided by $\overline{w}$ and compared also using $\hat{P}$. Note that p_e remains the same, as each edge yields an incoming (or outgoing) edge, and there are at most $N(N-1)$ incoming (or outgoing) edges, thus $p_e = \frac{z}{N(N-1)}$, as with the total degree.

In other words, let γ and ϕ be integers in the intervals $1 \leq \gamma \leq 6$, $1 \leq \phi \leq 3$, and each of the basic six Erdös sectioning possibilities $\{E_\gamma\}$ have three Erdös sectors $E_\gamma = \{e_{\gamma,\phi}\}$ defined as

$$\begin{aligned} e_{\gamma,1} &= \{\ i \mid \overline{k}_{\gamma,L} \geq \overline{k}_{\gamma,i}\} \\ e_{\gamma,2} &= \{\ i \mid \overline{k}_{\gamma,L} < \overline{k}_{\gamma,i} \leq \overline{k}_{\gamma,R}\} \\ e_{\gamma,3} &= \{\ i \mid\ \ \overline{k}_{\gamma,i} > \overline{k}_{\gamma,R}\}, \end{aligned} \tag{2.8}$$

where $\{\overline{k}_{\gamma,i}\}$ is

$$\begin{aligned} \overline{k}_{1,i} &= k_i \\ \overline{k}_{2,i} &= k_i^{in} \\ \overline{k}_{3,i} &= k_i^{out} \\ \overline{k}_{4,i} &= \frac{s_i}{\overline{w}} \\ \overline{k}_{5,i} &= \frac{s_i^{in}}{\overline{w}} \\ \overline{k}_{6,i} &= \frac{s_i^{out}}{\overline{w}} \end{aligned} \tag{2.9}$$

and both $\overline{k}_{\gamma,L}$ and $\overline{k}_{\gamma,R}$ are found using $P(\overline{k})$ or $\hat{P}(\overline{k})$ as described above and illustrated in Figure 2.

Since different metrics can be used to identify the three types of vertices, more than one metric can be used simultaneously, which is convenient when analysing small networks, such as the cases where only 50 messages are considered in Section **??**. After a careful consideration of possible combinations, these were reduced to six:

- Exclusivist criterion C_1: vertices are only classified if the class is the same according to all metrics. In this case, vertices classified do not usually reach N (or 100%), which is indicated by a black line in Figure 4.
- Inclusivist criterion C_2: a vertex has the class given by any of the metrics. Therefore, a vertex may belong to more than one class, and the total number of memberships may exceed N (or 100%), which is indicated by a black line in Figure 4.
- Exclusivist cascade C_3: vertices are only classified as hubs if they are hubs according to all metrics. Intermediary are the vertices classified either as intermediary or hubs with respect to all metrics. The remaining vertices are regarded as peripheral.
- Inclusivist cascade C_4: vertices are hubs if they are classified as such according to any of the metrics. The remaining vertices are intermediary if they belong to this category for any of the metrics. Peripheral vertices are those which are classified as such with respect to all metrics.
- Exclusivist externals C_5: vertices are hubs if they are classified as such according to all the metrics. Vertices are peripheral if they are peripheral or hubs for all metrics. The remaining nodes are intermediary.
- Inclusivist externals C_6: hubs are vertices classified as hubs according to any metric. The remaining vertices are peripheral if they are classified as such according to any metric. The rest of the vertices are intermediary.

Using Equations (2.8), these *compound criteria* C_δ, with δ integer in the interval $1 \leq \delta \leq 6$, can be specified as:

$$
\begin{aligned}
C_1 &= \{c_{1,\phi} = \{i \mid i \ \in e_{\gamma,\phi},\ \forall\, \gamma\}\} \\
C_2 &= \{c_{2,\phi} = \{i \mid \exists\ \gamma : i \in e_{\gamma,\phi}\}\} \\
C_3 &= \{c_{3,\phi} = \{i \mid i \ \in e_{\gamma,\phi'},\ \forall\, \gamma,\ \forall\, \phi' \geq \phi\}\} \\
C_4 &= \{c_{4,\phi} = \{i \mid i \ \in e_{\gamma,\phi'},\ \forall\, \gamma,\ \forall\, \phi' \leq \phi\}\} \\
C_5 &= \{c_{5,\phi} = \{i \mid i \ \in e_{\gamma,\phi'},\ \forall\, \gamma, \\
&\qquad\qquad \forall\, (\phi'+1)\%4 \leq (\phi+1)\%4\}\} \\
C_6 &= \{c_{6,\phi} = \{i \mid i \ \in e_{\gamma,\phi'},\ \forall\, \gamma, \\
&\qquad\qquad \forall\, (\phi'+1)\%4 \geq (\phi+1)\%4\}\}
\end{aligned}
\tag{2.10}
$$

Notice that the exclusivist cascade is the same sectioning of an inclusivist cascade from periphery to hubs, but with inverted order of sectors. The simplification of all possible compound possibilities to the small set listed above might be formalized in strict mathematical terms, but this was considered out of the scope for current interests.

2.2.5 Principal Component Analysis of topological metrics

Principal Component Analysis (PCA) is a well documented technique[60] and is used here to address the following questions: 1) which metrics contribute to each principal component and in what proportion; 2) how much of the dispersion is concentrated in each component; 3) which are the expected values and dispersions for these quantities over various networks. This enables one to characterize human interaction networks in terms of the relative importance of network metrics and the way they combine.

Let $\mathbf{X} = \{X[i,j]\}$ be a matrix where each element is the value of the metric j at vertex i. Let $\mu_X[j] = \frac{\sum_i X[i,j]}{I}$ be the mean of metric j over all I vertices, $\sigma_X[j] = \sqrt{\frac{\sum_i (X[i,j]-\mu_X[j])^2}{I}}$ the standard deviation of metric j, and $\mathbf{X}' = \{X'[i,j]\} = \left\{\frac{X[i,j]-\mu_X[j]}{\sigma_X[j]}\right\}$ the matrix with the *z-score* of each metric. Let $\mathbf{V} = \{V[j,k]\}$ be the matrix $J \times J$ of eigenvectors of the covariance matrix $\mathbf{C}$ of $\mathbf{X}'$, one eigenvector per column. Each eigenvector combines the original metrics into one principal component, therefore $V'[j,k] = 100\frac{|V[j,k]|}{\sum_{j'}|V[j',k]|}$ is the percentage of the principal component k that is proportional to the metric j. Let $\mathbf{D} = \{D[k]\}$ be the eigenvalues associated with the eigenvectors $\mathbf{V}$, then $D'[k] = 100\frac{D[k]}{\sum_{k'} D[k']}$ is the percentage of total dispersion of the system that the principal component k is responsible for. We consider, in general, the three largest eigenvalues and the respective eigenvectors in percentages: $\{(D'[k],\ V'[j,k])\}$. These usually sum up between 60 and 95% of the dispersion and reveal patterns for a first analysis. In particular, given L snapshots l of the interaction network, we are interested in the mean $\mu_{V'}[j,k]$ and the standard deviation $\sigma_{V'}[j,k]$ of the contribution of metric j to the principal component k, and the mean $\mu_{D'}[k]$ and the standard deviation $\sigma_{D'}[k]$ of the contribution of the component k to the dispersion of the system:

$$\begin{aligned}
\mu_{V'}[j,k] &= \frac{\sum_{l=1}^{L} V'[j,k,l]}{L} \\
\sigma_{V'}[j,k] &= \sqrt{\frac{\sum_{l=1}^{L}(\mu_{V'} - V'[j,k,l])^2}{L}} \\
\mu_{D'}[k] &= \frac{\sum_{l=1}^{L} D'[k,l]}{L} \\
\sigma_{D'}[k] &= \sqrt{\frac{\sum_{l=1}^{L}(\mu_{D'} - D'[k,l])^2}{L}}
\end{aligned} \tag{2.11}$$

The covariance matrix $\mathbf{C}$ is the correlation matrix because $\mathbf{X}'$ is normalized. Therefore, $\mathbf{C}$ is also directly observed as a first clue for patterns by the most simple

associations: low absolute values indicate low correlation (and a possible independence); high values indicate positive correlation; negative values with a high absolute value indicate negative correlation. Notice that in this case the variable k is not the degree value but a principal component. In the results, the principal components are numbered according to the magnitude of associated eigenvalue and k is incorporated into the notation (e.g. PC2 for metrics of $\mu_{V'}[j, 2]$).

2.2.6 Evolution and audiovisualization of the networks

The evolution of the networks was observed within sequences of snapshots. In each sequence, a fixed number of messages, i.e. the window size ws, was used for all snapshots. The snapshots were made disjoint in the message timeline, and were used to perform both PCA with topological metrics and Erdös sectioning. Figures and tables were usually inspected with $ws = \{50, 100, 200, 400, 500, 800, 1000, 2000, 2500, 5000, 10000\}$ messages. Variations in the number of vertices, edges and other network characteristics, within the same window size ws, are given in Section **??**.

2.2.7 The Versinus graph visualization method

Network structures were mapped to video animations, sound and musical structures developed for this research.[61]Such *audiovisualizations* were crucial in the initial steps and to guide the research into the most important features of network evolution. Versinus is a visualization method for dynamic graphs based on experimental observations. This method received dedicated attention by recurrence of the suggestion, by fellow researchers, to write about it. In visualizing a network, the method consists of creating an animation, of a fixed-size message sliding window (e.g. 400 messages) and partitioning the network in two fixed-layout segments: a sinusoid for the most connected vertexes (hubs and intermediary) and a straight line for the less connected (peripheral). A vertex holds the same position throughout the animation. Also, visual cues of properties - such as color, height and width, and rank of vertex with degree criteria - play a central role. Numbers with individual measures for each vertex blink periodically. Versinus differs from the few works on the visualization of dynamic graphs because it is a simple method that has developed for practical needs and is the result of experimentations, although a number of criteria have guided its development.[62–64]

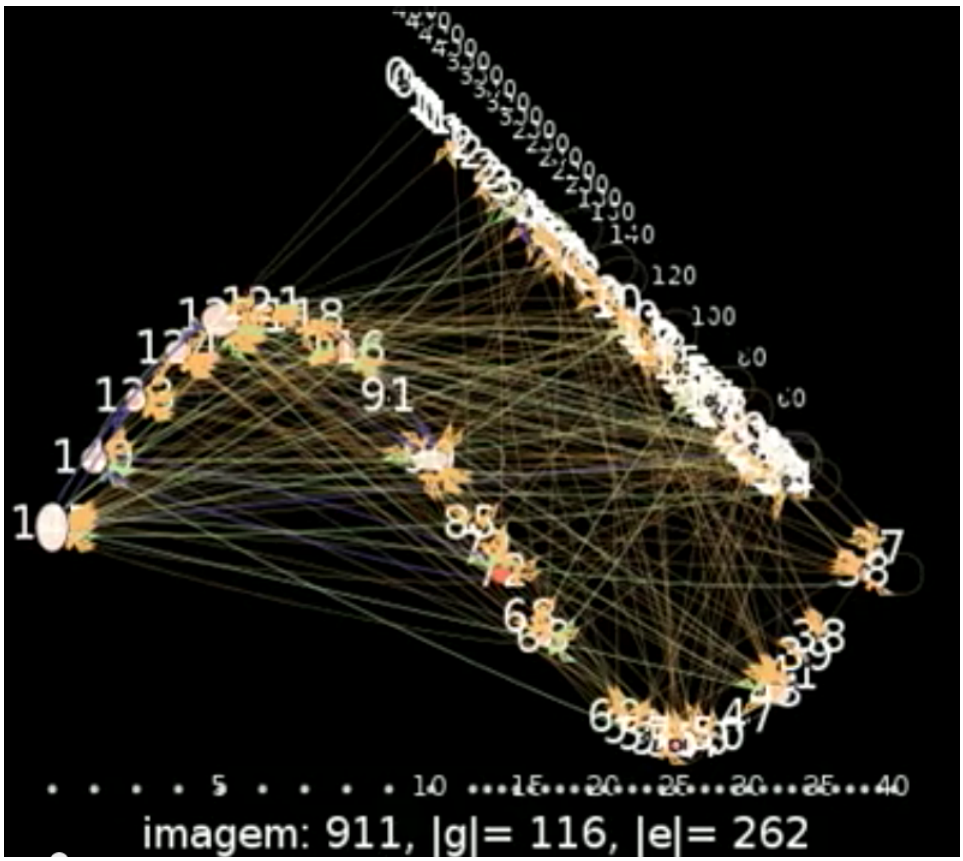
Let Δ be a fixed number of messages (e.g. $\Delta = 400$). Let also $s_i^{i+\Delta}$ be sets of Δ consecutive email messages along time. A sequence $S^{\Delta,M}$ of such sets, with the first message positioned in each the M messages (e.g. $M = 20000$), can be written as:

$$S^{\Delta,M} = \{s_i^{i+\Delta}\}_{i=0}^{M-\Delta} \tag{2.12}$$

Each set s_i yields an interaction network, as described in Section 2.2.2. Each of such sequence $S^{\Delta,M}$ of sets presents stable properties, while each participant exhibits a wide variation of characteristics. Understanding the mechanisms of this compatibility (unstable vertices and stable network) led to experimenting with a series of layouts and visualization techniques, from which Versinus emerged.

Taking advantage from the fact that vertices are roughly split into usual 80% of peripheral, 15% of intermediary and 5% of hubs, hubs are laid on the first half of a sinusoid, intermediary on the second half, and peripheral on the straight line. This configuration can be improved in various forms, to which Section 3.2.3 is dedicated. Figure 3 has an image of such a layout. The fixed position of each vertex is defined by the overall structure, i.e. with respect to all M messages.

Figure 3: The Versinus visualization method in use. 5% of the most connected vertexes (hubs) are on the left half-period of the sinusoid. 15% of the most connected remaining vertices are on the right half-period. 80% of the least connected vertices are on the straight line, above the sinusoidal shape. White dots in the bottom with numbers keep track of node position in the overall degree ordering. Measures blink periodically near the vertices they are related to.



Source: Prepared by the authors.

2.2.8 Textual measures

This work focuses on very simple metrics derived from texts as they have been sufficient for current interests. Such metrics are:

- Frequency of characters: letters, vowels, punctuations and uppercase letters.
- Number of tokens, frequency of punctuations among tokens, frequency of known words, frequency of words that have Wordnet synsets, frequency of tokens that are stopwords.
- Mean and standard deviation for word, token sentence and message sizes.
- Fraction of morphosyntactic classes, such as adverbs, adjectives, nouns and other POS (Part-Of-Speech) tags.
- Fraction of words in each Wordnet[65] top-most hypernyms, such as abstraction and physical entities for nouns or act for verbs.
- Mean and standard deviation of the number of Wordnet synset relations, such as holonyms and meronyms, domains, lemmas and verb groups.

This choice is based on: 1) the lack of such information in the literature, to the best of our knowledge; 2) potential relations of these incidences with topological aspects, such as connectivity; 3) the interdependence of textual artifacts suggests that simple measures should reflect complex and more subtle aspects. A preliminary study, with the complete works from the Brazilian writer Machado de Assis (in Section **??**), made clear that these metrics vary with respect to style.

2.2.8.1 About Wordnet

In this thesis, we made use of the statistics derived from the incidence of Wordnet synsets and their characteristics. This calls for a brief description of what is Wordnet, what is a synset and what are such characteristics:

- Wordnet: a lexical database for the English language released in a BSD style license. It groups synonyms into synsets, provides a number of relations among the synsets, definitions and use examples.
- Synset: defined by Wordnet documentation as a set of one or more synonyms that are (somewhat) interchangeable without changing the true value of the proposition in which they occur.
- Synset characteristics: a synset is associated to other synsets by a number of semantic relations which differ with the POS tag attributed to them. Examples of such relations

are yield by hyponyms and hypernyms (respectively less and more general terms), meronyms and holonyms (respectively is part of and has part), lemmas (canonical forms of a word), similar words by semantic criteria, entailments. Some characteristics are derived from the synset in relation to the whole Wordnet network. In this respect, we used only the maximum and minimum depth of the synset, which are respectively the maximum and minimum number of hypernyms from the synset to the root synset (e.g. 'thing' for nouns).

2.2.8.2 Relating text and topology

The topological and textual measures were related by:

1. textual measures in hub, intermediary and peripheral network sectors, which are delimited by topological criteria as described in Section 2.2.4.
2. Correlation of measures of each vertex, facilitating pattern detection involving topology of interaction and language.
3. Principal components formation derived from usual Principal Components Analysis.

An adaptation of the Kolmogorov-Smirnov test was used to observe differences in textual content, as follows. Let $F_{1,n}$ and $F_{2,n'}$ be two empirical distribution functions, where n and n' are the number of observations on each sample. The two-sample Kolmogorov-Smirnov test rejects the null hypothesis if:

$$D_{n,n'} > c(\alpha)\sqrt{\frac{n+n'}{nn'}} \tag{2.13}$$

where $D_{n,n'} = sup_x[F_{1,n} - F_{2,n'}]$ is the Kolmogorov-Smirnov statistic and $c(\alpha)$ is related to the significance level α by:

α	0.1	0.05	0.025	0.01	0.005	0.001
$c(\alpha)$	1.22	1.36	1.48	1.63	1.73	1.95

Source: Wikipedia
<https://en.wikipedia.org/wiki/Kolmogorov%E2%80%93Smirnov_test>.

We need to compare empirical distribution functions, therefore $D_{n,n'}$ is given, as are n and n'. All terms in equation 2.13 are positive and $c(\alpha)$ can be isolated:

$$c(\alpha) < \frac{D_{n,n'}}{\sqrt{\frac{n+n'}{nn'}}} = c' \tag{2.14}$$

When c' is high, low values of α favor rejecting the null hypothesis. For example, when c' is greater than ≈ 1.7, one might assume that $F_{1,n}$ and $F_{2,n'}$ differ. We used c'

as a measure of how much the distributions differ[66] and for deriving hypotheses about how different are the underlying mechanisms of generation of texts. We made systematic measurements of the c' statistic in Section **??** which illustrate that c' and $D_{n,n'}$ are useful in considering the similarity or difference in the distributions underlying sets of samples. A note of caution should be given here: what is a difference in distributions might vary with context. A $D_{n,n'}$ of only 0.0001 will yield a very large c' if n and n' are large enough On the other hand, a large $D_{n,n'}$ with a small c' is not a strong evidence that the distributions differ. Therefore, we consider both $D_{n,n'}$ and c' simultaneously in our analysis.

3 RESULTS AND DISCUSSION

3.0.1 Activity along time

Regular patterns of activity were observed along time in the scales of seconds, minutes, hours, days and months. Histograms in each of the time scales were computed as were circular average and dispersion values, and the results are given in Tables 2-6. For example, uniform activity is found with respect to seconds, minutes and days of the months. Weekend days exhibit about half the activity of regular weekdays, and there is a peak of activity between 11am and noon.

In the scales of seconds and minutes, activity is uniform, with the messages being slightly more evenly distributed in all lists than in simulations with the uniform distribution*. In the networks, $\frac{min(incidence)}{max(incidence)} \in (0.784, .794)$ while simulations reach these values but have on average more discrepant higher and lower peaks, i.e. if $\xi = \frac{min(incidence')}{max(incidence')}$ than $\mu_\xi = 0.7741$ and $\sigma_\xi = 0.02619$. Therefore, the incidence of messages at each second of a minute and at each minute of an hour was considered uniform. In these cases, the circular dispersion is maximized and the mean has little meaning as indicated in Table 2. As for the hours of the day, an abrupt peak is found between 11am and 12pm with the most active period being the afternoon, with one third of total daily activity, and two

* Numpy version 1.8.2, "random.randint" function, was used for simulations, algorithms in <https://github.com/ttm/percolation>.

Table 2: The rescaled circular mean θ'_μ and the circular dispersion $\delta(z)$, described in Section 2.2.1, for different timescales. This example table was constructed using all LAD messages, and the results are the same for other lists, as shown in Section **??** of the Supporting Information document. The most uniform distribution of activity was found in seconds and minutes. Hours of the day exhibited the most concentrated activity (lowest $\delta(z)$), with mean between 2 p.m. and 3 p.m. ($\theta' = -9.61$). Weekdays, days of the month and months have mean near zero (i.e. near the beginning of the week, month and year) and high dispersion. Note that θ'_u has the dimensional unit of the corresponding time period while $\delta(z)$ is dimensionless.

scale	mean θ'_μ	dispersion $\delta(z)$
seconds	–//–	9070.17
minutes	–//–	205489.40
hours	-9.61	4.36
weekdays	-0.03	29.28
month days	-2.65	2657.77
months	-0.56	44.00

Source: Prepared by the authors.

Table 3: Activity percentages along the hours of the day. Nearly identical distributions were observed on other social systems as shown in Section **??** of the Supporting Information document. Highest activity was observed between noon and 6pm (with 1/3 of total day activity), followed by the time period between 6pm and midnight. Around 2/3 of the activity takes place from noon to midnight but the activity peak occurs between 11 a.m. and 12 p.m. This table shows results for the activity in CPP.

<table>
<tr><th></th><th>1h</th><th>2h</th><th>3h</th><th>4h</th><th>6h</th><th>12h</th></tr>
<tr><td>0h</td><td>3.66</td><td rowspan="2">6.42</td><td rowspan="3">8.20</td><td rowspan="4">9.30</td><td rowspan="5">10.67</td><td rowspan="12">33.76</td></tr>
<tr><td>1h</td><td>2.76</td></tr>
<tr><td>2h</td><td>1.79</td><td rowspan="2">2.88</td></tr>
<tr><td>3h</td><td>1.10</td><td rowspan="3">2.47</td></tr>
<tr><td>4h</td><td>0.68</td><td rowspan="2">1.37</td><td rowspan="5">3.44</td></tr>
<tr><td>5h</td><td>0.69</td></tr>
<tr><td>6h</td><td>0.83</td><td rowspan="2">2.07</td><td rowspan="3">4.35</td><td rowspan="7">23.09</td></tr>
<tr><td>7h</td><td>1.24</td></tr>
<tr><td>8h</td><td>2.28</td><td rowspan="2">6.80</td><td rowspan="5">21.03</td></tr>
<tr><td>9h</td><td>4.52</td><td rowspan="3">18.75</td></tr>
<tr><td>10h</td><td>6.62</td><td rowspan="2">14.23</td></tr>
<tr><td>11h</td><td>7.61</td></tr>
<tr><td>12h</td><td>6.44</td><td rowspan="2">12.48</td><td rowspan="3">18.95</td><td rowspan="4">25.05</td><td rowspan="5">37.63</td><td rowspan="12">66.24</td></tr>
<tr><td>13h</td><td>6.04</td></tr>
<tr><td>14h</td><td>6.47</td><td rowspan="2">12.57</td></tr>
<tr><td>15h</td><td>6.10</td><td rowspan="3">18.68</td></tr>
<tr><td>16h</td><td>6.22</td><td rowspan="2">12.58</td><td rowspan="5">23.60</td></tr>
<tr><td>17h</td><td>6.36</td></tr>
<tr><td>18h</td><td>6.01</td><td rowspan="2">11.02</td><td rowspan="3">15.88</td><td rowspan="7">28.61</td></tr>
<tr><td>19h</td><td>5.02</td></tr>
<tr><td>20h</td><td>4.85</td><td rowspan="2">9.23</td><td rowspan="5">17.59</td></tr>
<tr><td>21h</td><td>4.38</td><td rowspan="3">12.73</td></tr>
<tr><td>22h</td><td>4.06</td><td rowspan="2">8.36</td></tr>
<tr><td>23h</td><td>4.30</td></tr>
</table>

Source: Prepared by the authors.

Table 4: Activity percentages along weekdays. Higher activity was observed during work-week days, with a decrease of activity on weekend days of at least one third and at most two thirds.

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
LAU	15.71	15.81	15.88	16.43	15.14	10.13	10.91
LAD	14.92	17.75	17.01	15.41	14.21	10.40	10.31
MET	17.53	17.54	16.43	17.06	17.46	7.92	6.06
CPP	17.06	17.43	17.61	17.13	16.30	6.81	7.67

Source: Prepared by the authors.

thirds of activity are allocated in the second 12h of each day. Days of the week revealed a decrease between one third and two thirds of activity on weekends. Days of the month were regarded as homogeneous with an inconclusive slight tendency of the first week to be more active. Months of the year revealed patterns matching usual work and academic calendars. The time period examined here was not sufficient for the analysis of activity along the years. These patterns are exemplified in Tables 3-6.

3.0.2 Stable sizes of Erdös sectors

The distribution of vertices in the hub, intermediary and periphery Erdös sectors is remarkably stable along time if the snapshots hold 200 or more messages, as it is clear in Figure 4 and in Section **??** of the Appendix. Activity is highly concentrated on the hubs, while a very large number of peripheral vertices contribute to only a fraction of the activity. This is expected for a system with a scale-free profile, as confirmed with the distribution of activity among participants in Table 7.

Typically, $[3\% - 12\%]$ of the vertices are hubs, $[15\% - 45\%]$ are intermediary and $[44\% - 81\%]$ are peripheral, which is consistent with other studies.[67] These results hold for the total, in and out degrees and strengths. Stable sizes are also observed for 100 or less messages if the classification of the three sectors is performed with one of the compound criteria established in Section 2.2.4. The networks often hold this basic structure with as few as 10-50 messages, i.e. concentration of activity and the abundance of low-activity participants take place even with very few messages, which is highlighted in Section **??** of the Appendix. A minimum window size for the observation of more general properties might be inferred by monitoring both the giant component and the degeneration of the Erdös sectors.

In order to support the generality of these findings, we list the Erdös sector sizes of 12 networks from Facebook, Twitter and Participabr in Table **??** of the Appendix. The fractions of hubs, intermediary and peripheral nodes are essentially the same as for the email list networks but with exceptions and a greater variability.

3.0.3 Stability of principal components

The principal components of the participants are very stable in the topological space, i.e. in the space of network metrics. Table 8 exemplifies the formation of principal components by providing the averages over non-overlapped activity snapshots of a network. The most important result of this application of PCA, the stability of principal components, is underpinned by the very small dispersion of the contribution of each metric to each principal component.

The first principal component is an average of centrality metrics: degrees, strengths and betweenness centrality. On one hand, the similar relevance of all centrality metrics is

Table 5: Activity along the days of the month cycle. Nearly identical distributions are found in all systems as indicated in Section **??** of the Supporting Information. Although slightly higher activity rates are found in the beginning of the month, the most important feature seems to be the homogeneity made explicit by the high circular dispersion in Table 2. This specific example and empirical table correspond to the activity of the MET email list.

<table>
<tr><th></th><th>1 day</th><th>5</th><th>10</th><th>15 days</th></tr>
<tr><td>1</td><td>3.05</td><td rowspan="5">18.25</td><td rowspan="10">35.24</td><td rowspan="15">50.96</td></tr>
<tr><td>2</td><td>3.38</td></tr>
<tr><td>3</td><td>3.62</td></tr>
<tr><td>4</td><td>4.25</td></tr>
<tr><td>5</td><td>3.94</td></tr>
<tr><td>6</td><td>3.73</td><td rowspan="5">16.98</td></tr>
<tr><td>7</td><td>3.17</td></tr>
<tr><td>8</td><td>3.26</td></tr>
<tr><td>9</td><td>3.56</td></tr>
<tr><td>10</td><td>3.26</td></tr>
<tr><td>11</td><td>3.81</td><td rowspan="5">15.73</td><td rowspan="10">31.98</td></tr>
<tr><td>12</td><td>2.91</td></tr>
<tr><td>13</td><td>3.30</td></tr>
<tr><td>14</td><td>2.75</td></tr>
<tr><td>15</td><td>2.95</td></tr>
<tr><td>16</td><td>3.36</td><td rowspan="5">16.25</td><td rowspan="15">49.04</td></tr>
<tr><td>17</td><td>3.16</td></tr>
<tr><td>18</td><td>3.44</td></tr>
<tr><td>19</td><td>3.36</td></tr>
<tr><td>20</td><td>2.93</td></tr>
<tr><td>21</td><td>3.20</td><td rowspan="5">15.79</td><td rowspan="10">32.78</td></tr>
<tr><td>22</td><td>3.11</td></tr>
<tr><td>23</td><td>3.60</td></tr>
<tr><td>24</td><td>2.74</td></tr>
<tr><td>25</td><td>3.13</td></tr>
<tr><td>26</td><td>3.13</td><td rowspan="5">16.99</td></tr>
<tr><td>27</td><td>3.07</td></tr>
<tr><td>28</td><td>3.61</td></tr>
<tr><td>29</td><td>3.60</td></tr>
<tr><td>30</td><td>3.57</td></tr>
</table>

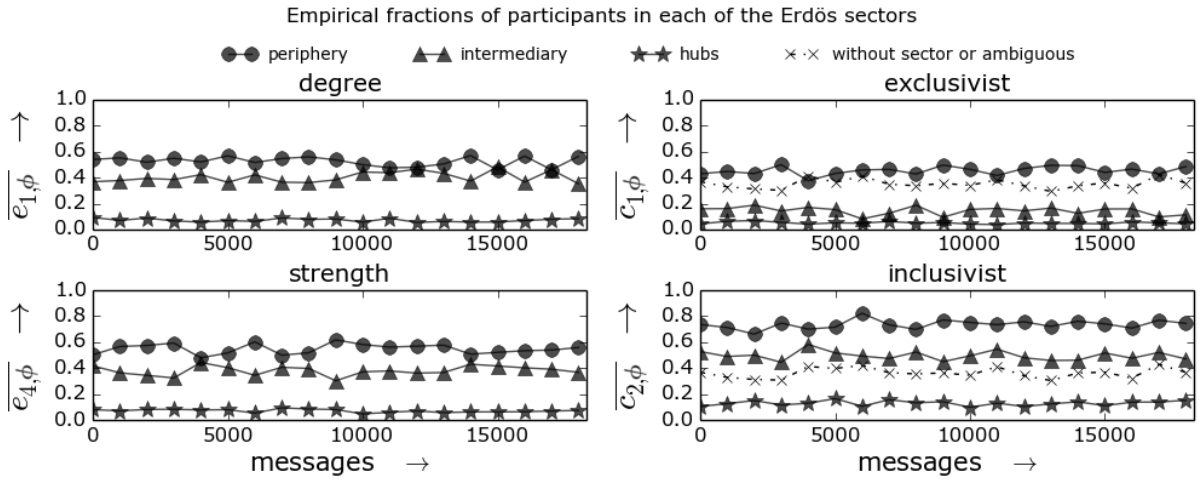
Source: Prepared by the authors.

Table 6: Activity percentages on months along the year. Activity is usually concentrated in Jun-Aug and/or in Dec-Mar, potentially due to academic calendars, vacations and end-of-year holidays. This table corresponds to activity in LAU. Similar results are shown for other lists in Section **??** of the Supporting Information document.

<table>
<tr><th></th><th>m.</th><th>b.</th><th>t.</th><th>q.</th><th>s.</th></tr>
<tr><td>Jan</td><td>10.22</td><td rowspan="2">19.56</td><td rowspan="3">28.24</td><td rowspan="4">35.09</td><td rowspan="6">49.16</td></tr>
<tr><td>Fev</td><td>9.34</td></tr>
<tr><td>Mar</td><td>8.67</td><td rowspan="2">15.53</td></tr>
<tr><td>Apr</td><td>6.86</td><td rowspan="3">20.93</td></tr>
<tr><td>Mai</td><td>7.28</td><td rowspan="2">14.07</td></tr>
<tr><td>Jun</td><td>6.80</td><td rowspan="4">30.36</td></tr>
<tr><td>Jul</td><td>8.97</td><td rowspan="2">16.29</td><td rowspan="3">24.47</td><td rowspan="6">50.84</td></tr>
<tr><td>Ago</td><td>7.32</td></tr>
<tr><td>Set</td><td>8.18</td><td rowspan="2">16.25</td><td rowspan="5">34.55</td></tr>
<tr><td>Out</td><td>8.06</td><td rowspan="3">26.36</td></tr>
<tr><td>Nov</td><td>7.64</td><td rowspan="2">18.30</td></tr>
<tr><td>Dez</td><td>10.66</td></tr>
</table>

Source: Prepared by the authors.

Figure 4: Stability of Erdös sector sizes. Fractions of participants derived from degree and strength criteria, E_1 and E_4 described in Section 2.2.4, are both on the left. Fractions derived from the exclusivist C_1 and the inclusivist C_2 compound criteria are shown in the plots to the right. The ordinates $\overline{e_{\gamma,\phi}} = \frac{|e_{\gamma,\phi}|}{N}$ denote the fraction of participants in sector ϕ through criterion E_γ and, similarly, $\overline{c_{\delta,\phi}} = \frac{|c_{\delta,\phi}|}{N}$ denotes the fraction of participants in sector ϕ through criterion C_δ. Sections **??** and **??** of the Supporting Information bring a systematic collection of such timeline figures with all simple and compound criteria specified in Section 2.2.4, with results for networks from Facebook, Twitter and Participabr.



Source: Prepared by the authors.

Table 7: Distribution of activity among participants. The first column shows the percentage of messages sent by the most active participant. The column for the first quartile (Q_1) gives the minimum percentage of participants responsible for at least 25% of total messages with the actual percentage in parentheses. Similarly, the column for the first three quartiles Q_3 gives the minimum percentage of participants responsible for 75% of total messages. The last decile D_{-1} column shows the maximum percentage of participants responsible for 10% of messages.

list	hub	Q_1	Q_3	D_{-1}
LAU	2.78	1.19 (26.35%)	13.12 (75.17%)	67.32 (-10.02%)
LAD	4.00	1.03 (26.64%)	11.91 (75.18%)	71.14 (-10.03%)
MET	11.14	1.02 (34.07%)	8.54 (75.64%)	80.49 (-10.02%)
CPP	14.41	0.29 (33.24%)	4.18 (75.46%)	83.65 (-10.04%)

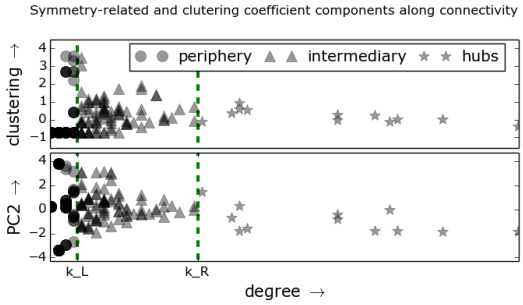
Source: Prepared by the authors.

Table 8: Loadings for the 14 metrics into the principal components for the MET list, 1000 messages in 20 disjoint positions. The clustering coefficient (cc) appears as the first metric in the table, followed by 7 centrality metrics and 6 symmetry-related metrics. Note that the centrality measurements, including degrees, strength and betweenness centrality, are the most important contributors for the first principal component, while the second component is dominated by symmetry metrics. The clustering coefficient is only relevant for the third principal component. The three components have in average more than 85% of the variance. The low standard deviation σ implies that the principal components are considerably stable.

	PC1		PC2		PC3	
	μ	σ	μ	σ	μ	σ
cc	0.89	0.59	1.93	1.33	21.22	2.97
s	11.71	0.57	2.97	0.82	2.45	0.72
s^{in}	11.68	0.58	2.37	0.91	3.08	0.78
s^{out}	11.49	0.61	3.63	0.79	1.61	0.88
k	11.93	0.54	2.58	0.70	0.52	0.44
k^{in}	11.93	0.52	1.19	0.88	1.41	0.71
k^{out}	11.57	0.61	4.34	0.70	0.98	0.66
bt	11.37	0.55	2.44	0.84	1.37	0.77
asy	3.14	0.98	18.52	1.97	2.46	1.69
μ^{asy}	3.32	0.99	18.23	2.01	2.80	1.82
σ^{asy}	4.91	0.59	2.44	1.47	26.84	3.06
dis	2.94	0.88	18.50	1.92	3.06	1.98
μ^{dis}	2.55	0.89	18.12	1.85	1.57	1.32
σ^{dis}	0.57	0.33	2.74	1.63	30.61	2.66
λ	49.56	1.16	27.14	0.54	13.25	0.95

Source: Prepared by the authors.

Figure 5: The first plot highlights the well-known pattern of degree versus clustering coefficient, characterized by the higher clustering coefficient of lower degree vertices. The second plot shows the greater dispersion of the symmetry-related ordinates dominant in the second principal component (PC2). This larger dispersion suggests that symmetry-related metrics are more powerful, for characterizing interaction networks than the clustering coefficient, especially for hubs and intermediary vertices. This figure reflects a snapshot of the LAU list with 1000 contiguous messages.



Source: Prepared by the authors.

not surprising since they are highly correlated, e.g. degree and strength have Spearman correlation coefficient $\in [0.95, 1]$ and Pearson coefficient $\in [0.85, 1)$ for window sizes greater than a thousand messages. On the other hand, each of these metrics is related to a different participation characteristic, and their equal relevance for variability, as measured by the principal component, is noticeable. Also, this suggests that these centrality metrics are equally adequate for characterizing the networks and the participants.

According to Table 8 and Figure 5, dispersion is larger in symmetry-related metrics than in clustering coefficient. We conclude that the symmetry metrics are more powerful, in terms of dispersion in the topological metrics space, in characterizing interaction networks and their participants, than the clustering coefficient, especially for hubs and intermediary vertices (peripheral vertices have larger dispersion with regard to the clustering coefficient). Interestingly, the clustering coefficient is always combined with the standard deviation of the asymmetry and disequilibrium of edges σ^{asy} and σ^{dis} in the third principal component.

Similar results are presented in Sections **??** and **??** of the Appendix for other email lists and interaction networks. A larger variability was found for the latter networks, which motivated the use of interaction networks derived from email lists for benchmarking.

3.0.4 Types from Erdös sectors

Assigning a type to a participant raises important issues about the scientific cannon for human types and the potential for stigmatization and prejudice. The Erdös sector to which a participant belongs can be regarded as implying a social type for this participant. In this case, the type of a participant changes both along time and as different networks

are considered, despite the stability of the network. Therefore, the potential for prejudice of such participant typology is attenuated.[40] In other words, an individual is a hub in a number of networks and peripheral in other networks, and even within the same network he/she most probably changes type along time.[61]

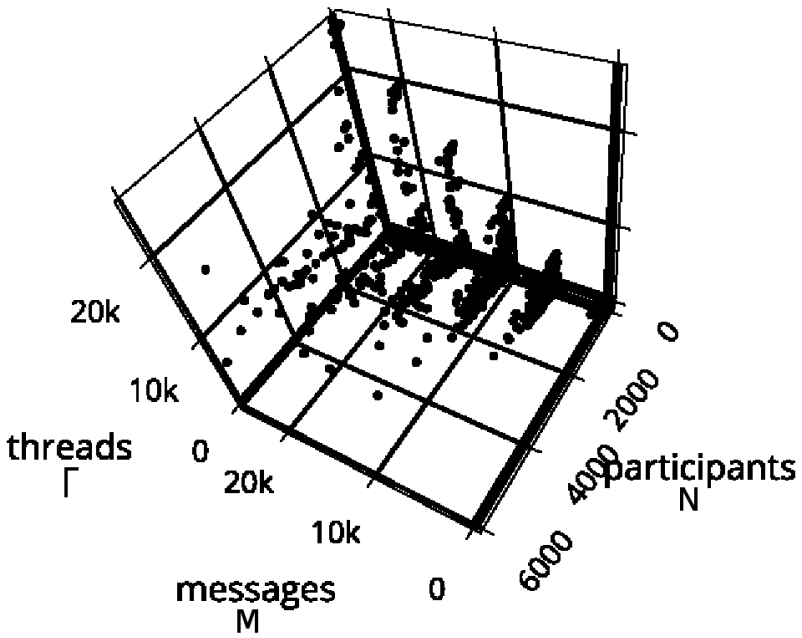
The importance of this issue can be grasped by the consideration of static types derived from quantitative criteria. For example, in email lists with a small number of participants, the number of threads has a negative correlation with the number of participants. When the number of participants exceeds a threshold, the number of threads has a positive correlation with the number of participants. This finding is illustrated in Figure 6 and can also be observed in Table 1. The assignment of types to individuals, in this latter case, has more potential for prejudice because the derived participant type is static and one fails to acknowledge that human individuals are not immutable entities.

Further observations regarding the Erdös sectors and the implicit participant types were made, which are consistent with the literature[10]: 1) hubs and intermediary participants usually have intermittent activity, and stable activity was found only in smaller communities. For instance, the MET list had stable hubs while LAU, LAD and CPP exhibited intermittent hubs. 2) Network structure seems to be most influenced by the activity of intermediary participants as they have less extreme roles than hubs and peripheral participants and can therefore connect to the sectors and other participants in a more selective and explicit manner.

3.0.5 Implications of the main findings

The findings reported in this thesis arose from an exploratory procedure to visually inspect the networks and to analyze considerable amounts of interaction networks data. While this procedure has certainly an ad hoc nature, the statistics in the data are sufficiently robust for important features from these interaction networks to be extracted. Temporal stability, in the sense that interaction networks could be considered as stationary time series, is the most important feature. Also relevant is the significant stability found on the principal components, on the fraction of participants in each Erdös Sector and on the activity along different timescales. In fact, these findings confirm our initial hypothesis - based on the literature[5] - that interaction networks should exhibit some stability traces. The potential generality of these findings is suggested by the analysis of networks derived from diverse systems, with interaction networks from public email lists serving as proper benchmarks. Indeed, with such benchmarks one can compare any social network system. Furthermore, this analysis enables us to establish an outline of human interaction networks. It takes the hub, intermediary and periphery sectors out of the scientific folklore and into classes drawn from quantitative criteria. It enables the conception of non-static human types derived from natural properties.

Figure 6: A scatter plot of number of messages M versus number of participants N versus number of threads Γ for 140 email lists. Highest Γ is associated with low N. The correlation between N and Γ is negative for low values of N but positive otherwise. This negative correlation between N and Γ can also be observed in Table 1. Accordingly, for $M = 20000$ messages, this inflection of correlation was found around $N = 1500$, while CPP, LAU, LAD, MET lists present smaller networks.



Source: Prepared by the authors.

We envisage that the knowledge generated in the analysis may be exploited in applications where the type of each participant and the relative proportion of participants in each sector can be useful metadata. Just by way of illustration, this could be applied in semantic web initiatives, given that the Erdös sectorialization is static in a given snapshot. These results are also useful for classifying resources, e.g. in social media, and for resources recommendation to users.[37] Finally, the knowledge acquired with a quantitative treatment of the whole data may help guide the creation through collective processes of documents to assist in participatory democracy.

Perhaps the most outreaching implications are related to sociological consequences. The results expose a classification of human individuals which is directly related to the concentration of wealth and based on natural laws. The derived human typology changes over different systems and over time in the same system, which implies a negation of the absolute concentration of wealth. Such concentration exists but changes across different wealth criteria and with time. Also, the hubs stand out as dedicated, sometimes enslaved, components of the social system. The peripheral participants have very limited interaction with the network. This suggests that intermediary participants tend to dictate structure,

legitimate the hubs and stand out as authorities.

With regard to the limitations of our study, one should emphasize that not all types of human interaction networks were analyzed. Therefore, the plausible generalization of properties has to be treated with caution, as a natural tendency of such systems and not as a rule. Also, the stable properties in the networks were not explored to the limit, which leaves many open questions. For example, what are the maximum and minimum sizes of the networks for which they hold? What is the outcome of PCA when more metrics are considered? What is the granularity in which the activity along the timescales is preserved? Do the findings reported also apply to other systems, beyond human networks?

3.1 Text-related results and discussion

The most important result of including textual metrics in our analysis is the statistical evidence of extreme differentiation of each Erdös sector with respect to the texts produced. This conclusion can be reached by observing the differences in the measurements of textual features in each sector, but is reached with greater theoretical background from the adaptation of the Kolmogorov-Smirnov test we presented in Section 2.2.8.2. Other relevant results are:

- the achievement of references for the amount of nouns, adverbs, sizes of words, depth of Wordnet synsets and other linguistic traces, used in social networks. We did not find in literature any indication for such values and understood useful to acknowledge e.g. that about 15% of the characters are spaces and more than 50% of tokens are nouns. These values are available in[?] and not in the body of the text, since we focus in this thesis in the evidence that the texts from distinct sectors differ.

- Indicatives of what is different in the texts produced by each of the Erdös sectors. For example: hubs were found to use more contractions, more common words, and less punctuation if compared to the rest of the network, especially the peripheral sector. In general, the rise or fall of a text-related metric is not relevant or is monotonic along connectivity, but some of them reaches extreme values in the intermediary sector.

The next sections summarize results of immediate interest and further insights can be obtained by skimming through the tables and figures of[?,78] and the Conclusions chapter. We illustrate with just one table of each kind, and from networks obtained with 2000 messages. In[?] we display tables for various networks. In the same document, we relate the email lists to each numerical TAG in the tables of the following sections. The scale of 1000 and 2000 messages was chosen for deriving results, as the networks in this scale are found with stable topological structure, as exposed in Section 3.0.2. The findings

with 1000 messages are the same as with 2000 messages, and there are many tables. This motivated the exclusion of the tables with measurements in networks of 1000 messages.

3.1.1 General characteristics of activity distribution among sectors

Before we dig into the findings derived from text-related measures, let us look once more at the general structure of these networks, now giving emphasis on the activity of the sectors. In almost all our observations, the peripheral sector is responsible for starting most of the discussion threads, i.e. messages to the list which are not replies. This is surprising since the peripheral sector is responsible for fewer messages. This suggests a complementarity between peripheral diversity and hub specialization which, on its turn, deepens the understanding of the interaction network as a meaningful system. These assertions are condensed in Table 9. Less often, the intermediary sector is responsible for the greatest number of messages and of threads. Also meaningful is that the hubs sector is responsible for most of the messages, which is not completely obvious: hub participants are far more active but way less numbered. Interestingly, in such a setting where every characteristic differs with respect to distinct sectors, there was no evidence of difference on the size of the threads started by each sector.

Table 9: Distribution of participants, messages and threads among each Erdös sector: (p. for periphery, i. for intermediary, h. for hubs) in a total timespan of 0.72 years (from 2003-11-30T20:21:32 to 2004-08-19T18:11:24). N is the number of participants, M is the number of messages, Γ is the number of threads, and γ is the number of messages in a thread. The % denotes the usual 'per cent' with respecto to the total quantity (100% for g.) while μ and σ denote mean and standard deviation. TAG of list in[?]: 10

	g.	p.	i.	h.
N	131	80	46	5
$N_{\%}$	100.00	61.07	35.11	3.82
M	1000.00	136.00	361.00	503.00
$M_{\%}$	100.00	13.60	36.10	50.30
Γ	292.00	76.00	147.00	69.00
$\Gamma_{\%}$	100.00	26.03	50.34	23.63
$\frac{\Gamma}{M}\%$	29.20	55.88	40.72	13.72
$\mu(\gamma)$	2.74	2.76	2.81	2.58
$\sigma(\gamma)$	0.44	0.43	0.39	0.49

Source: Prepared by the authors.

3.1.2 Evidence that the texts from Erdös sectors differ

Results from our adaptation of the Kolmogorov-Smirnov test (see Section 2.2.8.2) present substantial evidence that the texts produced by each sector are different. Tables 10-

19 illustrate three results:

- There is statistical evidence that the textual production of the Erdös sectors are different. This can be noticed from the high values of c' on these tables, beyond reference values used for the acceptance of the null hypothesis. Also, we regarded as non-negligible the values often above 0.1 for the Kolmogorov-Smirnov statistic (the maximum difference between the cumulative distributions), which we recognized as relevant for assuming differences in the underlying distributions in our study (see Section 2.2.8.2).
- Intermediary sectors sometimes exhibit greater differences from periphery and hubs than these extreme sectors between themselves (Tables 10 and 14). This differentiation of the three sectors is an indicative that the Erdös Sectioning described in Section 2.2.4 reveals meaningful sectors of the networks.
- Evidence of differences between sectors on the same network (Tables 10-**??**) is often greater than differences between the same sector from distinct lists (Tables 16-19).

Table 10: KS distances on size of tokens. TAG: 6

	g.	p.	i.	h.
g.	0.000	4.327	17.168	7.851
a	0.000	0.014	0.115	0.044
p.	4.327	0.000	18.907	7.833
	0.014	0.000	0.129	0.045
i.	17.168	18.907	0.000	15.540
	0.115	0.129	0.000	0.129
h.	7.851	7.833	15.540	0.000
	0.044	0.045	0.129	0.000

Source: Prepared by the authors.

Table 11: KS distances on size of known words. TAG: 1

	g.	p.	i.	h.
g.	0.000 0.000	5.904 0.043	5.264 0.040	5.549 0.150
p.	5.904 0.043	0.000 0.000	9.547 0.083	7.073 0.193
i.	5.264 0.040	9.547 0.083	0.000 0.000	4.058 0.111
h.	5.549 0.150	7.073 0.193	4.058 0.111	0.000 0.000

Source: Prepared by the authors.

Table 12: KS distances on size of sentences. TAG: 2

	g.	p.	i.	h.
g.	0.000 0.000	0.733 0.020	2.077 0.038	2.834 0.059
p.	0.733 0.020	0.000 0.000	1.642 0.048	2.589 0.080
i.	2.077 0.038	1.642 0.048	0.000 0.000	4.139 0.097
h.	2.834 0.059	2.589 0.080	4.139 0.097	0.000 0.000

Source: Prepared by the authors.

Table 13: KS distances on use of adjectives on sentences. TAG: 3

	g.	p.	i.	h.
g.	0.000 0.000	0.461 0.011	0.564 0.010	0.617 0.010
p.	0.461 0.011	0.000 0.000	0.385 0.011	0.800 0.021
i.	0.564 0.010	0.385 0.011	0.000 0.000	0.986 0.020
h.	0.617 0.010	0.800 0.021	0.986 0.020	0.000 0.000

Source: Prepared by the authors.

Table 14: KS distances on use of substantives on sentences. TAG: 1

	g.	p.	i.	h.
g.	0.000 0.000	0.642 0.023	1.791 0.067	6.936 0.537
p.	0.642 0.023	0.000 0.000	1.007 0.044	6.970 0.560
i.	1.791 0.067	1.007 0.044	0.000 0.000	7.510 0.607
h.	6.936 0.537	6.970 0.560	7.510 0.607	0.000 0.000

Source: Prepared by the authors.

Table 15: KS distances on use of punctuations on sentences. TAG: 8

	g.	p.	i.	h.
g.	0.000 0.000	1.380 0.039	3.583 0.069	2.894 0.046
p.	1.380 0.039	0.000 0.000	1.718 0.054	2.871 0.085
i.	3.583 0.069	1.718 0.054	0.000 0.000	5.398 0.114
h.	2.894 0.046	2.871 0.085	5.398 0.114	0.000 0.000

Source: Prepared by the authors.

Table 16: c' values for substantives. Comparison of the same sector between lists, each author is an observation. See subsection 3.1.2 for discussion and directions.

	CPP-LAD	CPP-LAU	CPP-ELE	LAD-LAU	LAD-ELE	LAU-ELE
P	1.35	4.05	5.80	3.00	5.41	4.94
I	1.27	0.78	4.01	0.84	3.84	3.94
H	0.98	1.94	3.17	1.32	3.82	4.47

Source: Prepared by the authors.

Table 17: c' values for adjectives. Comparison of the same sector between lists, each author is an observation. See subsection 3.1.2 for discussion and directions.

	CPP-LAD	CPP-LAU	CPP-ELE	LAD-LAU	LAD-ELE	LAU-ELE
P	0.44	0.34	2.57	0.20	2.32	2.37
I	0.74	0.99	3.72	0.32	3.37	3.10
H	0.26	0.32	3.72	0.29	4.36	4.24

Source: Prepared by the authors.

Table 18: c' values for stopwords. Comparison of the same sector between lists, each author is an observation. See subsection 3.1.2 for discussion and directions.

	CPP-LAD	CPP-LAU	CPP-ELE	LAD-LAU	LAD-ELE	LAU-ELE
P	3.31	3.26	6.68	0.57	5.36	5.41
I	1.45	1.08	5.16	0.91	5.00	4.92
H	0.98	0.68	4.35	1.05	4.73	5.01

Source: Prepared by the authors.

Table 19: c' values for punctuations/char. Comparison of the same sector between lists, each author is an observation. See subsection 3.1.2 for discussion and directions.

	CPP-LAD	CPP-LAU	CPP-ELE	LAD-LAU	LAD-ELE	LAU-ELE
P	5.74	4.88	8.28	2.23	5.37	6.60
I	3.23	2.49	4.16	0.96	3.40	3.51
H	2.49	1.87	4.02	1.36	3.05	3.71

Source: Prepared by the authors.

3.1.3 What and how the texts from the sectors differs

In the next sections we will look through text-related measures and summarize the findings about what might be different in the textual features of the sectors. One should keep in mind that our core result is the evidence that the texts from distinct sectors differ. The following discussion of what differs and how it differs is interesting but is both derived from less strong statistical evidence and less crucial for our current stage of researching these structures. Nonetheless, for the sake of clarity, we state the main findings:

- Peripherals use more nouns while hubs use more verbs and adverbs. The fraction of adjectives did not change systematically with respect to connectivity, but given that the nouns are more numerous in the periphery, there are more adjectives per noun in the hubs sector texts.
- The size of tokens and words were found greater in the more connected sectors, which might be related to the use of a more specialized vocabulary. Sentences and messages were found smaller in the more connected sectors.
- The differences found with respect to Wordnet synsets were found less well behaved. Often, the sectors exhibit noticeable differences but greater and smaller incidences are found in all sectors (but in different networks). Some incidences are more systematic and this analysis assisted by Wordnet is semantic, reasons that motivated our inclusion of these results by means not of example tables but by explicit counts of greater incidence in each sector throughout the networks.

3.1.4 Characters

Most often, peripheral and intermediary sectors use more digits and upper case letters. Hubs use more letters and vowels among letters. The use of white spaces, for example, does not seem to have any relation to connectivity. These results are illustrated in Table 20.

Table 20: Characters in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 6

	g.	p.	i.	h.
$chars$	1485813	552986	554328	378499
$chars_{\%}$	100.00	37.22	37.31	25.47
$\frac{spaces}{chars}$	12.94	12.79	12.82	13.35
$\frac{punct}{chars-spaces}$	9.54	10.53	10.15	7.20
$\frac{digits}{chars-spaces}$	4.49	7.13	3.87	1.54
$\frac{letters}{chars-spaces}$	83.95	80.09	83.95	89.65
$\frac{vowels}{letters}$	36.94	36.10	36.98	38.00
$\frac{uppercase}{letters}$	4.49	4.60	4.68	4.07

Source: Prepared by the authors.

3.1.5 Tokens and words

In most of the networks analyzed, hubs use longer words, which might be related to the use of a specialized vocabulary. Hubs use more contractions and known words, while peripheral sector exhibit a greater incidence of punctuations among tokens. Although the token diversity ($\frac{|tokens\neq|}{|tokens|}$) found in peripheral sector is far greater, this result has the masking artifact that the peripheral sector corpus is smaller, yielding a larger token diversity. This can be noticed by the token diversity of the whole network, which is lower than in any of the sectors. The same observation apply to the lexical diversity ($\frac{|kw\neq|}{kw}$). These results are exemplified in Table 21.

Table 21: Tokens in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 1

	g.	p.	i.	h.
$tokens$	286232	146472	134852	4908
$tokens_{\%}$	100.00	51.17	47.11	1.71
$tokens \neq$	3.00	4.01	3.66	24.08
$\frac{knownw}{tokens}$	25.76	25.11	26.21	32.84
$\frac{knownw \neq}{knownw}$	4.51	6.22	5.92	42.80
$\frac{stopw}{knownw}$	42.46	38.92	43.60	98.33
$\frac{punct}{tokens}$	33.18	34.09	32.56	23.11
$\frac{contrac}{tokens}$	0.16	0.10	0.18	1.67
$\mu(\overline{tokens})$	3.19	3.10	3.26	3.65
$\sigma(\overline{tokens})$	2.53	2.54	2.52	2.60
$\mu(\overline{knownw})$	4.89	4.69	5.06	5.50
$\sigma(\overline{knownw})$	2.37	2.41	2.31	2.28
$\mu(\overline{knownw \neq})$	6.53	6.39	6.27	6.16
$\sigma(\overline{knownw \neq})$	2.53	2.50	2.46	2.42
$\mu(\overline{stopw})$	2.83	2.83	2.83	2.81
$\sigma(\overline{stopw})$	0.87	0.84	0.86	1.17

Source: Prepared by the authors.

3.1.6 Sizes of sentences

Hubs present the lowest average sentence size, in characters, tokens or known words. This result is illustrated in Table 22 and might be considered counterintuitive given that punctuation is more abundant in the texts of less connected participants.

Table 22: Sentences sizes in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 16

	g.	p.	i.	h.
$sents$	10757	1252	4529	4978
$sents_{\%}$	99.98	11.64	42.09	46.27
$\mu_S(chars)$	113.88	143.37	120.21	100.65
$\sigma_S(chars)$	318.65	750.47	276.21	88.88
$\mu_S(tokens)$	24.78	28.83	26.72	21.98
$\sigma_S(tokens)$	40.56	77.72	42.08	20.23
$\mu_S(knownw)$	7.81	8.37	8.26	7.25
$\sigma_S(knownw)$	8.18	9.38	9.30	6.56
$\mu_S(stopw)$	7.78	7.61	7.92	7.70
$\sigma_S(stopw)$	6.88	6.94	7.36	6.39
$\mu_S(puncts)$	4.29	5.42	5.04	3.33
$\sigma_S(puncts)$	9.92	13.08	12.13	5.82

Source: Prepared by the authors.

3.1.7 Messages

Connectivity was found correlated to smaller messages in terms of characters and tokens. Connectivity was also found correlated to smaller messages in terms of the number of sentences, but it was less consistent. This result is exemplified in Table 23.

Table 23: Messages sizes in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 0

	g.	p.	i.	h.
$msgs$	1992	286	841	865
$msgs_{\%}$	100.00	14.36	42.22	43.42
$\mu_M(sents)$	5.21	6.08	6.43	3.74
$\sigma_M(sents)$	6.78	4.03	9.40	3.26
$\mu_M(tokens)$	145.82	230.45	186.07	78.71
$\sigma_M(tokens)$	260.61	291.17	326.68	127.13
$\mu_M(knownw)$	38.83	56.29	48.87	23.29
$\sigma_M(knownw)$	50.54	58.28	58.67	31.16
$\mu_M(stopw)$	34.29	41.96	42.42	23.84
$\sigma_M(stopw)$	41.11	32.32	52.81	25.35
$\mu_M(puncts)$	36.34	66.11	47.66	15.49
$\sigma_M(puncts)$	103.42	114.84	135.49	39.61
$\mu_M(chars)$	637.40	977.77	811.14	355.94
$\sigma_M(chars)$	1054.36	1195.70	1290.46	566.92

Source: Prepared by the authors.

3.1.8 POS tags

We found that lower connectivity yields more nouns and less verbs and adverbs. Also, the fraction of adjectives does not change, but given that peripherals use more nouns, we can conclude that hubs use more adjectives per noun. This suggests that the networks gather issues through the peripheral sector. These issues are qualified and proposed to be acted upon by the more connected participants. This is a further indicative that peripheral sectors are related to diversity while hubs relate to specialization. These results are exemplified in Table 24. Weaker evidence was found that hubs use more *adpositions*, determinants and 'particles and other functional words' while peripherals use more numerals.

Table 24: POS tags in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). Universal POS tags[3]: VERB - verbs (all tenses and modes); NOUN - nouns (common and proper); PRON - pronouns; ADJ - adjectives; ADV - adverbs; ADP - adpositions (prepositions and postpositions); CONJ - conjunctions; DET - determiners; NUM - cardinal numbers; PRT - particles or other function words; X - other: foreign words, typos, abbreviations; PUNCT - punctuation. TAG: 13

	g.	p.	i.	h.
NOUN	51.86	63.77	48.31	37.37
X	0.08	0.14	0.02	0.07
ADP	7.25	5.23	7.86	9.69
DET	7.48	6.47	7.43	9.28
VERB	16.93	11.93	20.01	20.54
ADJ	3.97	3.37	3.83	5.18
ADV	4.02	2.41	4.45	6.05
PRT	3.17	3.98	2.37	3.05
PRON	3.16	1.29	3.64	5.55
NUM	0.43	0.30	0.38	0.74
CONJ	1.65	1.11	1.70	2.49
PUNC	0.00	0.00	0.00	0.00

Source: Prepared by the authors.

3.1.9 Wordnet-related results

For correctly analyzing text production in terms of the Wordnet lexical database, we only considered words that had synsets of with the POS tag obtained with the POS tagger. This resulted in portions of tokens considered of $\approx 30\%$, but of more than 90% of all tokens with Wordnet synsets. This yields less strong results, but which we found still relevant. Measures regarding Wordnet synsets often reach an extreme value (maximum or minimum) in the intermediary sector, which we understood as evidence that:

- the Erdös sectioning of the networks into peripheral, intermediary and hubs sectors are in fact relevant for human social structures, at least to the ones analyzed in this thesis.
- Human social networks present relations between connectivity and semantics.
- The intermediary sector might hold a deeper identity than that of a sector bounded by hubs and periphery sectors.
- The analysis of social networks texts using Wordnet reveals aspects of the structures which are not clear with the non-semantic analysis we performed.

Furthermore, the analysis of the measures we obtained by means of the Wordnet is not trivial because of the number of different measures and because differences in

measures are not obviously relevant. In order to obtain consistent results, we considered *weak evidence of difference* in sectors in a network if maximum measure is at least 10% greater than minimum measure, i.e. $\frac{maximum\ measure}{minumum\ measure} > 1.1$. We considered *evidence of difference* in sectors in a network if $\frac{maximum\ measure}{minumum\ measure} > 1.2$. When $\frac{maximum\ measure}{minumum\ measure} > 1.5$, we considered *strong evidence of difference*. We than looked through each measure in all networks to reach compelling observations about the differences of sectors through all networks. Also useful here is the definition of lower sectors (peripheral and intermediary), upper sectors (intermediary and hubs) and extreme sectors (peripheral and hubs). We should also point when measurements peak at the intermediary sector, be it a maximum or minimum peak.

Noteworthy is that extra skepticism should be kept in mind about these results because of the unquantified noise in the measurements. Observations seem consistent and meaningful, but only about a third of total tokens were considered. This is because tokens were discarded if not having a Wordnet synset or when not having a synset with a POS tag true to the POS tag attributed by the POS tagger. Besides that, there are often more than one synset with the same POS tag for each word, and we chose the most frequent synset as ranked by Wordnet. In the positive side, we observe that $\approx 95\%$ of tokens which had synsets were considered. Examples of types tokens without synsets are stopwords, punctuations, numerals, acronyms and typos.

3.1.9.1 Wordnet POS tags

The observations here are somewhat consistent with those in Section 3.1.8: peripherals use more nouns and less verbs and adverbs. The variation here is regarding adjectives, which was found more frequent in hubs texts in this reduced set of tokens. These results are illustrated in Table 25.

Table 25: Percentage of synsets with each of the POS tags used by Wordnet. The last lines give the percentage of words considered from all of the tokens (POS) and from the words with synset (POS!). The tokens not considered are punctuations, unrecognized words, words without synsets, stopwords and words for which Wordnet has no synset tagged with POS tags. Values for each Erdös sectors are in the columns p. for periphery, i. for intermediary, h. for hubs. TAG: 12

	g.	p.	i.	h.
N	58.82	59.32	61.81	49.90
ADJ	10.62	10.44	10.17	12.06
VERB	5.06	4.85	4.38	7.16
ADV	25.50	25.39	23.64	30.89
POS	33.10	32.91	32.94	33.74
POS!	92.51	93.21	91.83	93.94

Source: Prepared by the authors.

3.1.9.2 Wordnet synsets characteristics

Wordnet synsets with different POS tags have different relations. Therefore, we made separate observations about each POS tag:

- Nouns, exemplified in Table 26.
  - Minimum and maximum depth: differences were found in the mean of minimum and maximum depth of a synset between email lists, but not once among sectors of a network. Differences between the variance of minimum and maximum depth of synsets of sectors was found mostly nonexistent or weak.
  - Holonyms: differences in the number of holonyms per word were present in $\approx 85\%$ of the networks and were more incident in the lower sectors in $\approx 90\%$ of the observations in which we found such differences. Differences in the variance in the number of holonyms was also found with the same regularity, but were greater in the upper sectors in $\approx 80\%$ of the networks. Both mean and variance of the number of holonyms peaked in the intermediary sector in $\approx 50\%$ of the observations.
  - Meronyms: words with more meronyms were present in $\approx 90\%$ of the networks and were more incident in the lower sectors in $\approx 80\%$ of the observations in which we found such differences. Differences in the variance in the number of meronyms was found in 100% of the networks and was often strong. The variance was greater in the periphery in 66.66% and in the lower sectors in $\approx 90\%$ of the observations.
  - Domain: differences in the mean and variance of the number of domains of words were found respectively in 90% and 50% of the networks and maximum values were found evenly distributed across sectors. Peaks were found in the intermediary sector in $\approx 50\%$ of the networks.
  - Lemmas: differences in the mean and variance of the number of lemmas of words were found respectively in 40% and 55% of the networks. In $\approx 90\%$ of the cases where there was difference in the mean, the maximum number of lemmas was found in the periphery. Peaks in the intermediary sector were less often, occurring only in $\approx 35\%$ of the observations.
  - Hyponyms: differences in the mean and variance of the number of hyponyms of words were found respectively in 77.77% and 88.88% of the networks. In $\approx 93\%$ of the cases where there was difference in the mean, the maximum number of hyponyms was found indistinctly in the upper sectors. In 75% of the cases where there was difference in the variance, the maximum variance was found indistinctly in the upper sectors. Peaks occurred for both mean and variance in the intermediary sector in $\approx 75\%$ of the observations.

  - Hypernyms: between the sectors of all networks analyzed, we found no differences in the mean of the number of hypernyms. There were differences in the variance of the number of hypernyms of the words used by the sectors in ≈ 72% of the networks. Greatest values occurred indistinctly in all sectors and peaked in the intermediary sector in ≈ 50% of the observations.

Table 26: Measures of wordnet features of nouns in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 13

	g.	p.	i.	h.
$\mu(min\,depth)$	6.60	6.40	6.72	6.68
$\sigma(min\,depth)$	1.99	1.96	2.11	1.76
$\mu(max\,depth)$	6.95	6.64	7.15	7.09
$\sigma(max\,depth)$	2.28	2.19	2.42	2.10
$\mu(holonyms)$	0.17	0.10	0.24	0.17
$\sigma(holonyms)$	0.43	0.36	0.49	0.38
$\mu(meronyms)$	0.41	0.25	0.53	0.44
$\sigma(meronyms)$	1.38	1.12	1.47	1.57
$\mu(domains)$	0.12	0.13	0.12	0.10
$\sigma(domains)$	0.33	0.34	0.33	0.31
$\mu(lemmas)$	2.63	2.51	2.46	3.16
$\sigma(lemmas)$	2.30	2.30	2.02	2.66
$\mu(hyponyms)$	6.67	5.95	7.21	6.85
$\sigma(hyponyms)$	21.70	19.05	22.92	23.36
$\mu(hypernyms)$	1.01	1.01	1.01	1.01
$\sigma(hypernyms)$	0.10	0.11	0.10	0.10

Source: Prepared by the authors.

- Adjectives, exemplified in Table 27.

  - Domain: differences in the mean and variance of the number of domains of words were found respectively in 88.88% and 61.11% of the networks. In 87.5% of the cases where there was difference in the mean, the maximum number of domains was found indistinctly in the upper sectors. In ≈ 82% of the cases where there was difference in the variance, the maximum variance was found indistinctly in the upper sectors. Peaks occurred in the intermediary sector in 68.75% of the observations for the mean and in ≈ 54.55% of the observations for the variance.

  - Similar: differences in the mean and variance of the number of similar synsets relations of adjectives were found respectively only in 44.45% and 61.11% of the networks. In ≈ 90% of the cases where there was difference in the mean, the maximum number of domains was found in the hubs sector. In ≈ 90% of the cases where there was difference in the variance, the maximum number

of domains was found indistinctly the extreme sectors. Peaks occurred in the intermediary sector in 50% of the observations for the mean and in ≈ 36.37% of the observations for the variance.

– Lemmas: differences in the mean and variance of the number of lemmas of adjectives were found respectively only in 27.78% and 72.22% of the networks. Maximum values occurred indistinctly in all sectors and peaks were found in the intermediary sector in ≈ 50% of the observed cases.

Table 27: Measures of wordnet features of adjectives in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 9

	g.	p.	i.	h.
$\mu(domains)$	0.05	0.06	0.05	0.06
$\sigma(domains)$	0.22	0.24	0.21	0.23
$\mu(similar)$	5.78	5.49	5.46	6.09
$\sigma(similar)$	6.78	6.45	6.55	7.00
$\mu(lemmas)$	1.65	1.71	1.63	1.66
$\sigma(lemmas)$	1.29	1.38	1.24	1.31

Source: Prepared by the authors.

- Verbs, illustrated in Table 28.

  – No significant differences were found in the mean and variance verb synset relations of minimum and maximum depth, verb groups, lemmas and hypernyms.

  – Domains and entailments: differences were often strong (i.e. > 1.5) in both mean and variance. Due to the reduced number of verbs and the small values of mean and variance, we considered these measures as not significant.

  – Hyponyms: differences in the mean and variance of the number of hyponyms of verbs were found respectively in 50% and 72.23% of the networks. In ≈ 90% of the cases where there was difference in the mean, the maximum number of hyponyms was found in the upper sectors (66.67% in the hubs sector). In ≈ 85% of the cases where there was difference in the variance, the maximum number of domains was found indistinctly the upper sectors (61.54% in the hubs sector). Peaks occurred in the intermediary sector in ≈ 35% with respect to both mean and variance.

Table 28: Measures of wordnet features of verbs in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 3

	g.	p.	i.	h.
$\mu(min\,depth)$	1.41	1.48	1.46	1.35
$\sigma(min\,depth)$	1.41	1.42	1.46	1.37
$\mu(max\,depth)$	1.42	1.50	1.46	1.35
$\sigma(max\,depth)$	1.42	1.44	1.47	1.37
$\mu(domains)$	0.03	0.04	0.04	0.03
$\sigma(domains)$	0.18	0.19	0.19	0.16
$\mu(verb\,groups)$	0.45	0.46	0.47	0.44
$\sigma(verb\,groups)$	0.62	0.62	0.62	0.62
$\mu(lemmas)$	3.18	2.95	3.17	3.33
$\sigma(lemmas)$	2.15	2.06	2.17	2.18
$\mu(entailments)$	0.05	0.04	0.04	0.06
$\sigma(entailments)$	0.22	0.20	0.20	0.23
$\mu(hyponyms)$	14.39	11.45	15.42	15.47
$\sigma(hyponyms)$	42.12	31.44	46.49	44.58
$\mu(hypernyms)$	0.71	0.73	0.71	0.70
$\sigma(hypernyms)$	0.46	0.45	0.46	0.46

Source: Prepared by the authors.

- Adverbs, exemplified in Table 29.
  - Domains: differences in the mean and variance of the number of domains of adverbs were found respectively in $\approx 95.45\%$ and $\approx 66.67\%$ of the networks. In $\approx 82.35\%$ of the cases where there was difference in the mean, the maximum number of domains was found in the upper sectors (58.82% in the hubs sector). In $\approx 92\%$ of the cases where there was difference in the variance, the maximum number of domains was found indistinctly the upper sectors (50% in the intermediary sector). Peaks occurred in the intermediary sector in $\approx 64.71\%$ and 75% in the mean and variance respectively.
  - Lemmas: no systematic difference was found in the mean and variance of the number of lemmas of adverbs.

Table 29: Measures of wordnet features of adverbs in each Erdös sector (p. for periphery, i. for intermediary, h. for hubs). TAG: 17

	g.	p.	i.	h.
$\mu(domains)$	0.09	0.09	0.08	0.09
$\sigma(domains)$	0.28	0.28	0.27	0.28
$\mu(lemmas)$	3.23	3.07	3.29	3.23
$\sigma(lemmas)$	2.23	2.20	2.33	2.22

Source: Prepared by the authors.

3.1.9.3 Wordnet synset hypernyms

- Noun synsets: differences in the use of nouns with physical entity hypernyms was found indistincly in all sectors. In deeper layers, more systematic differences arises. With depth 2, hubs use more nouns related to attribute and psycological features. Lower sectors use more nouns related to measure, with 62.5% of the lists where this difference was found having greater values in the peripheral sector. Communication related nouns were found mostly in extreme sectors. With depth 3, hubs presented more nouns related to written communication, event and cognition. Peripherals showed greater use of nouns related to definite quantity. Message related nouns often peaked at the intermediary sector. These results are shown in Table 30.

Table 30: Wordnet synset hypernyms from nouns in each Erdös sector.

synset	p.	i.	h	peaks	total	depth
abstraction.n.06	2	0	1	1	18	1
physical_entity.n.01	3	3	4	4	18	1
attribute.n.02	4	2	11	6	18	2
communication.n.02	7	2	5	5	18	2
causal_agent.n.01	5	2	7	4	16	2
psychological_feature.n.01	2	1	11	6	18	2
object.n.01	5	3	4	4	18	2
measure.n.02	10	5	1	6	18	2
written_communication.n.01	1	3	8	6	13	3
definite_quantity.n.01	12	4	2	6	18	3
event.n.01	2	1	11	7	17	3
person.n.01	4	2	6	5	16	3
message.n.02	7	4	7	10	18	3
whole.n.02	6	2	9	6	18	3
cognition.n.01	3	0	12	6	17	3

Source: Prepared by the authors.

- Adjective synsets: the use of adjectives was found less systematic. The synsets varied greatly among lists and differences were not strong. We obseved weak evidence that hubs use more adjectives related to certainty, and that the use of such adjectives always peaked at the intermediary sector. Even weaker evidence was found that hubs use more adjectives related to newness. These results are shown in Table 31.

Table 31: Wordnet synset hypernyms from adjectives in each Erdös sector.

synset	p.	i.	h	peaks	total	depth
certain.a.02	0	3	8	4	11	1
new.a.01	2	1	4	4	9	1

Source: Prepared by the authors.

- Verbs synset hypernyms of move and travel was found more numerous in the peripheral sector. Verbs related to change was found more common in the hubs sector. Verbs related to making was found with differences in the frequency of use among sectors, but had greatest incidence in all sectors (but in distinct networks). With depth 2, hubs exhibited greater use of verbs related to state and evaluate while peripherals exhibited greater use of verbs related to keeping and putting. With depth 3, in the upper sectors was found a greater use of verbs related to thinking. Hubs used more increase-related verbs. Periphery presented more verbs related to running and communication. With depth 4, lower sectors used more verbs related to informing, peripherals might be regarded as using more verbs related to recording (set in a permanent form), and hubs as using more verbs related to adding. These results are shown in Table 32.

Table 32: Wordnet synset hypernyms from verbs in each Erdös sector.

synset	p.	i.	h	peaks	total	depth
move.v.02	9	2	2	4	14	1
travel.v.01	10	0	1	5	15	1
change.v.02	3	1	9	5	13	1
make.v.03	5	5	4	8	16	1
use.v.01	4	0	6	2	16	1
change.v.01	1	4	8	6	15	1
state.v.01	0	3	13	5	16	2
keep.v.03	9	3	2	4	14	2
interact.v.01	8	5	4	8	18	2
evaluate.v.02	1	3	13	5	18	2
put.v.01	10	1	1	3	14	2
think.v.01	1	6	10	7	17	3
run.v.01	9	0	3	5	14	3
increase.v.01	3	3	10	6	16	3
communicate.v.02	10	4	4	8	18	3
inform.v.01	8	7	3	12	18	4
record.v.01	8	3	4	6	15	4
add.v.01	2	4	10	6	17	4

Source: Prepared by the authors.

- Adverb synsets was found with particularly interesting patterns as greater use of adverbs related to possibility and stillness was found in the intermediary sector. Adverbs related to however and even were more frequent in the peripheral sector while adverbs related to well (good way to perform) was more used by hubs. These results are shown in Table 33.

Table 33: Wordnet synset hypernyms from adverbs in each Erdös sector.

synset	p.	i.	h	peaks	total	depth
however.r.01	7	2	4	8	13	1
even.r.01	7	3	5	9	16	1
possibly.r.01	1	8	5	12	14	1
well.r.01	2	2	7	6	13	1
still.r.01	2	9	1	11	13	1

Source: Prepared by the authors.

3.1.10 Correlation of topological and textual metrics

Overall, small correlation is found between textual and topological metrics. An exception is that, in the hubs sector, strengh was very often negatevely correlated to the mean and variance of the number of punctuations (and sometimes with the number of known words or stopwords) with values bellow -0.4, but a few positive and high values (above 0.5) were also found. Interestingly, the number of punctuations per sentence was most often correlated to the number of stopwords while most often *not* correlated to the number of known words. Noteworthy is that degree is negatively correlated to clustering coefficient in intermediary and hubs sectors, which is consistent with the literature, but it is positively correlated for peripheral sectors. Other strong correlation associations of textual and topological measures were found but not systematically and might be indicatives of style from the different lists analyzed. These results are exemplified in Table 34.

3.1.11 Formation of principal components

Principal components formation of textual and topological metrics seems to be the less stable of all results reported in this study. The concentration of dispersion often peaked in the intermediary sector. Components are most often composed of topological or textual features. Other than that, we observe that PCA is sensitive to metrics included and should reveal other insights in other settings. These results are exemplified in Table 35.

3.1.12 Results still to be interpreted

Histogram differences of incident word sizes with and without repetition of words are constant. That is, in each email list, when a histogram of word sizes were made with all

Table 34: Pierson correlation coefficient for the topological and textual measures. TAG: 9

	cc	d	s	$\mu_S(p)$	$\sigma_S(p)$	$\mu_S(kw)$	$\sigma_S(kw)$	$\mu_S(sw)$	$\sigma_S(sw)$
cc	1.00	-0.03	-0.08	0.04	0.10	0.05	0.10	0.09	0.21
(p.)	1.00	0.64	0.42	0.12	0.19	0.09	0.22	0.08	0.22
(i.)	1.00	-0.58	-0.51	-0.10	-0.08	-0.26	-0.11	-0.24	-0.19
(h.)	1.00	-0.86	-0.85	0.33	0.09	0.14	0.21	0.14	0.11
d	-0.03	1.00	0.98	-0.05	0.00	0.04	0.05	0.09	0.12
	0.64	1.00	0.78	0.11	0.16	-0.00	0.16	0.06	0.22
	-0.58	1.00	0.86	0.10	0.14	0.29	0.18	0.30	0.28
	-0.86	1.00	1.00	-0.51	-0.25	-0.42	-0.34	-0.47	-0.35
s	-0.08	0.98	1.00	-0.05	-0.01	0.02	0.02	0.05	0.09
	0.42	0.78	1.00	0.10	0.15	0.10	0.19	0.21	0.35
	-0.51	0.86	1.00	0.13	0.07	0.29	0.10	0.32	0.35
	-0.85	1.00	1.00	-0.50	-0.25	-0.40	-0.32	-0.47	-0.34
$\mu_S(p)$	0.04	-0.05	-0.05	1.00	0.82	0.65	0.61	0.19	0.52
	0.12	0.11	0.10	1.00	0.96	0.65	0.86	0.18	0.59
	-0.10	0.10	0.13	1.00	0.84	0.77	0.76	0.34	0.50
	0.33	-0.51	-0.50	1.00	0.78	0.93	0.96	0.92	0.97
$\sigma_S(p)$	0.10	0.00	-0.01	0.82	1.00	0.58	0.92	0.16	0.52
	0.19	0.16	0.15	0.96	1.00	0.54	0.89	0.11	0.62
	-0.08	0.14	0.07	0.84	1.00	0.73	0.98	0.26	0.44
	0.09	-0.25	-0.25	0.78	1.00	0.89	0.84	0.85	0.76
$\mu_S(kw)$	0.05	0.04	0.02	0.65	0.58	1.00	0.64	0.73	0.67
	0.09	-0.00	0.10	0.65	0.54	1.00	0.73	0.71	0.65
	-0.26	0.29	0.29	0.77	0.73	1.00	0.76	0.74	0.72
	0.14	-0.42	-0.40	0.93	0.89	1.00	0.94	0.97	0.95
$\sigma_S(kw)$	0.10	0.05	0.02	0.61	0.92	0.64	1.00	0.27	0.56
	0.22	0.16	0.19	0.86	0.89	0.73	1.00	0.30	0.79
	-0.11	0.18	0.10	0.76	0.98	0.76	1.00	0.31	0.48
	0.21	-0.34	-0.32	0.96	0.84	0.94	1.00	0.88	0.96
$\mu_S(sw)$	0.09	0.09	0.05	0.19	0.16	0.73	0.27	1.00	0.61
	0.08	0.06	0.21	0.18	0.11	0.71	0.30	1.00	0.53
	-0.24	0.30	0.32	0.34	0.26	0.74	0.31	1.00	0.74
	0.14	-0.47	-0.47	0.92	0.85	0.97	0.88	1.00	0.94
$\sigma_S(sw)$	0.21	0.12	0.09	0.52	0.52	0.67	0.56	0.61	1.00
	0.22	0.22	0.35	0.59	0.62	0.65	0.79	0.53	1.00
	-0.19	0.28	0.35	0.50	0.44	0.72	0.48	0.74	1.00
	0.11	-0.35	-0.34	0.97	0.76	0.95	0.96	0.94	1.00

Source: Prepared by the authors.

words written, and another histogram made with sizes of all *different* words, the cumulative absolute difference of the two histograms throughout the bins were found constant for all lists analysed. When all known English words were considered, the difference sums up to ≈ 1.0. When stopwords are discarded, the difference found was different, but still constant, slightly above 0.5. When only stopwords were considered, the difference is ≈ 0.6. When

Table 35: PCA formation TAG: 11

	PC1	PC2	PC3	PC4	PC5
cc	1.56	5.55	5.27	66.36	4.43
(p.)	2.07	21.29	-3.09	-16.58	-30.47
(i.)	3.53	-5.95	-6.72	51.70	8.40
(h.)	9.65	-14.73	3.26	14.54	27.15
d	3.28	39.23	-2.42	-3.75	1.71
	2.31	29.69	-4.90	7.49	10.16
	6.23	18.94	16.55	7.89	-1.65
	-10.34	13.75	-14.11	5.08	9.43
s	2.89	39.14	-2.73	-6.53	2.19
	2.30	29.95	-4.12	6.71	9.55
	6.37	19.06	16.00	10.14	-1.42
	-9.80	13.47	-14.84	6.58	13.35
$\mu_S(p)$	11.87	-6.88	-23.79	0.56	19.99
	-12.99	-3.75	-21.38	18.20	-12.48
	8.32	-18.13	13.89	6.33	-6.38
	10.80	-6.99	-19.67	0.26	6.55
$\sigma_S(p)$	11.31	-0.30	-25.29	10.55	-14.13
	-10.90	-0.79	-27.98	-9.77	8.49
	10.21	-14.05	15.44	-6.84	12.95
	8.72	-6.76	-21.47	2.17	-16.46
$\mu_S(kw)$	19.19	-6.59	-2.36	-5.99	11.85
	-19.64	0.08	-0.64	7.86	-7.62
	17.95	-8.73	0.93	-2.42	-16.55
	14.15	7.50	-7.33	-20.52	6.85
$\sigma_S(kw)$	17.26	-1.70	1.16	0.48	-24.22
	-17.26	1.60	-1.20	-18.84	10.50
	16.92	2.12	-4.56	-13.03	22.97
	13.31	10.62	-1.67	19.42	-11.12
$\mu_S(sw)$	15.36	-0.55	19.90	-4.40	14.27
	-14.96	6.19	21.48	9.07	-5.17
	15.77	4.76	-12.12	0.29	-20.25
	12.34	12.79	7.28	-15.30	8.15
$\sigma_S(sw)$	17.31	-0.06	17.07	-1.37	-7.20
	-17.57	6.65	15.22	-5.48	5.55
	14.70	8.27	-13.80	-1.36	9.42
	10.89	13.38	10.37	16.12	-0.94
λ	36.91	22.07	16.02	11.02	7.75
	37.77	25.85	14.81	8.29	7.11
	33.74	23.23	20.12	10.67	6.77
	40.07	27.24	20.10	6.53	3.68

Source: Prepared by the authors.

only known English words that does not have Wordnet synsets are used, this difference

is ≈ 1.2. We considered this result a number of times in the past years and presented it to other researchers, but reached no conclusions about its meaning. Appendix **??** are dedicated to this histogram differences.

3.2 Results from visualization

Results from Versinus are divided in two groups: observations on features that made it useful for the task of hypothesizing about general properties of human interaction networks, and the network properties it made possible to grasp.

3.2.1 Useful visualization features for dynamic networks

Among the numerous insights related to Versinus, a few of them seem more fundamental, others seem simply useful. Such insights were incorporated to Versinus as the result of tests which presented clear benefits within the context of our research. The following list is an attempt to present them in an importance-first order:

1. Vertices need to remain static. Even if they move smoothly, one tends to notice solely transient artifacts from the structure.

2. Very connected sectors (hubs and intermediary) need to be in a curve, otherwise the edges enclose each other and reasoning about the network becomes harsh.

3. Height and width of a vertex are very informative, specially if measures mapped to them have a strong relation, such as out-degree (mapped to height in Versinus) and in-degree (mapped to width).

4. The color of nodes is also informative although less than height and weight, as differences in the latter are more noticeable.

5. An ordering of nodes, related to their fixed position, is very useful. Among all tests, ordering of vertices by degree was considered the most informative, which led to the hub, intermediary and peripheral sectioning of the network delineated in Section 2.2.4. As node position in the layout is fixed throughout an animation which comprises consecutive but distinct network activity, such ordering is done with respect to the resulting network of all the activity. Numbering these positions with respect to the order of the vertices in the larger structure (i.e. all M messages) is useful for understanding how much a vertex preserves the position in different scales of activity.

Many other insights were derived from Versinus, such as possible visualization tools, other kind of convenient layouts and glyph elaborations. These receives dedicated attention in Section 3.2.3.

3.2.2 Understanding of network properties through Versinus

A number of hypotheses were drawn about the networks for which Versinus was designed. As suggested by Palla, Barabási and Vicsek,[10] stability of participant activity in social networks is more incident in smaller networks. In accordance with this result, all hubs have intermittent activity in the settings analyzed, except for the email list with the smallest number of participants (the Metareciclagem email list). The intermitence of hubs was one of the top hypotheses which motivated Versinus development. The stability of the network structure, concomitant with the instability of the activity of each participant, motivated a deeper analysis.[78] In doing so, we also found evidence for another hypothesis drawn from Versinus: that in- and out-degree differences in each vertex are important for network characterization. Furthermore, the visualization suggests that there are modes of operation of the network. As an example, the intermediary sector often communicates mostly with the hubs or with the peripheral vertices. Other hypotheses, such as discrepancies in the authority and the degree of a vertex, are numerous but need further research to be valuable.

3.2.3 Refinement of Versinus

Versinus was convenient for obtaining insights about how to enhance its layout and use. It was immediate to think of a tool for using Versinus in real-time, but less obvious are some ideas about the layout and visual guides. To further enable visualization of hubs and intermediary vertex, the sinusoid can have many periods with a decaying frequency. The upper straight line can also have an oscillating outline. The two halves of the sinusoidal period could be moved independently. The waveform need not to be a sinusoid. One can think of many ways to make more informative glyphs. Also, visual and auditory signals for specific occurrences can be interesting (e.g. when a new vertex appears, when one vanishes, when an ordering of vertices changes). Measures of each vertex can be exposed with a vertical displacement, to enable multiple measures, to avoid the need to blink the numbers and to keep network visualization free from occlusion. Working with Versinus has also suggested other kinds of layout for vertices, specially geometric figures and iterative force-based methods for positioning vertex in a fixed layout. The traditional matrix representation of the graphs has been gazed upon as support to Versinus as has been some recent approaches to network visualization.[62]

3.3 Linked data results

Current results include data selection and preparation for knowledge discovery. In this respect, the main result is the data made available, which enables benchmarking of scientific results and easy experimentations. Secondary results include data outline through figures and tables, software support and example SparQL queries.

3.3.1 Standardization

The data is embedded into standard URIs and triples, i.e. translated to RDF. URIs are built in the namespace <http://purl.org/socialparticipation/participationontology/> which are identified herein with the prefix `po:`. Classes and properties are built by adding a suffix to the root, as in the class `po:Participant` or in the property `po:text`. Classes have "UpperCamelCase" suffixes while properties have "lowerCamelCase" suffixes. All class instances, such as participants, messages, friendships and interactions, are linked to snapshots through the triple `<instance> po:snapshot <snapshot_uri>`. Message texts, including comments, are objects in the triple: `<message_id> po:text <message_text>`. Pre-processed texts are objects of triples: `<message_id> po:cleanText <message_text>`. More specialized predicates are used for delivering text when necessary, such as `po:htmlBodyText` and `po:cleanBodyText` used for ParticipaBR articles (instances of the class `po:Article`. A participant URI is unique throughout the provenance (e.g. the same for the same participant in all Twitter snapshots). To enable annotations which differ when the snapshot changes, `po:Observation` class instances are used in the triple `<participant_uri> po:observation <observation_uri>`. The observation instances are then linked to the snapshot and the data.

Instances are built on top of the class they derive from plus a hashtag character, a provenance string (e.g. `facebook-legacy` or `participabr-legacy`) of the snapshot they refer to, and an identifier; i.e. `po:Participant#<provenance-legacy>-<id>`. All snapshot URIs follow the formation rule: `po:<SnapshotProvenance>#<snapshot_id>`. All snapshot ids follow the formation rule: `<platform>-legacy-<further_identifier>`; e.g. `irc-legacy-labmacambira` or `email-legacy-linux.audio.devel1-20000`.

3.3.2 Data outline

The database consists of 34,120,026 triples, 3,172,927 edges yield by interactions or relations, 382,568 participants and 253,155,020 characters. Among all snapshots, 63 are ego snapshots, 54 are group snapshots; 49 have interaction edges, 89 have friendship edges; 43 have text content from messages.

3.3.3 Software tools

The database is released with software for rendering itself, analyses and multimedia artifacts.

3.3.3.1 Triplification routines

For each social platform there is a *triplification* routine, i.e. a script for translating data to RDF. Original formats and further observations are presented in Table 37.

Table 36: Number of snapshots from each provenance.

social protocol	**number of snapshots**
Algorithmic Autoregulation	3
Cidade Democrática	1
Email	4
Facebook	88
IRC	4
ParticipaBR	1
Twitter	16
all	117

Table 37: Social platforms, original formats and further observations for the database.

social platform	**original format**	**further observations**	**toolbox**
AA	MySQL and MongoDB databases; IRC text logs	donated by AA users	Participation[68]
Cidade Democrática	MySQL database	donated by admins	Participation
Email	mbox	obtained through Gmane public database	Gmane[50]
Facebook	GDF, GML and TAB	obtained through Netvizz[49]	Social[69]
IRC	plain text log	obtained through Supybot logging	Social
ParticipaBR	PostgreSQL database	donated by admins	Participation
Twitter	JSON	obtained through Twitter streaming API	Social

Source: Prepared by the authors.

3.3.3.2 Topological and textual analysis

Routines are available for taking the topological and textual measures from the database. Auxiliary routines, such as performing principal component analysis and taking Kolmogorov-Smirnov measures, are available to ease pattern recognition. All the analysis routines used for this thesis are in these publicly accessible scripts.

3.3.3.3 Multimedia rendering

It is a core purpose of the framework to provide routines for rendering audiovisualizations of the data. Social structures are rendered into music, images and video animations through the Percolation toolbox[70] in association with the Music and Visuals toolboxes.[71,72]

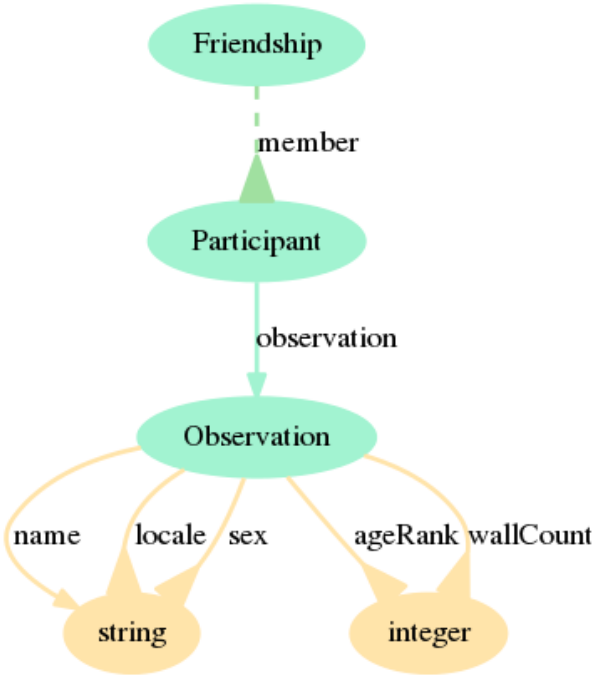
3.3.3.4 Migration from deprecated toolboxes

Routines mentioned in Sections 3.3.3.2 and 3.3.3.3 are being migrated from deprecated toolboxes[73,74] into newly designed toolboxes.[70,72]

3.3.4 Diagrams of the data and auxiliary tables

The database exploration can be assisted through diagrams which expose the structure from each provenance. Such diagrams are exemplified in the Appendix **??** and fully available in a dedicated article[2] with some tables to make it easier to understand the data provided. A simplified example is given in Figure 7 where the friendship structure of the Facebook snapshots are exposed.

Figure 7: A diagram of the structure involved in the friendship networks of the Facebook snapshots. A green edge denotes an OWL existential class restriction; an inverted nip denotes an OWL universal class restriction; a full (non-dashed) edge denotes an OWL functional property axiom. Further information and complete diagrams for each provenance are in the dedicated article.[2]



Source: Prepared by the authors.

3.3.5 SPARQL queries

There are numerous useful and general purpose SPARQL queries to be performed against the database. Here we write some of such queries selected by their simplicity and potential to be varied. All queries assume the use the preamble `PREFIX po: <http://purl.org/socialparticipation/po/>`.

1. Retrieve the number of participants:
   ```
   SELECT (COUNT(DISTINCT ?author) as ?c) WHERE { ?author a po:Participant . }
   ```
2. Retrieve the number of relations, be them interactions or friendships:
   ```
   SELECT (COUNT(?interaction) as ?c) WHERE {
   ```

```
  { ?interaction a po:Friendship } UNION { ?interaction a po:Interaction } UNION
  { ?interaction po:retweetOf ?message } UNION { ?interaction po:replyTo ?message
}
  UNION { ?interaction po:directedTo ?participant }
}
```

3. Retrieve all text produced by an specific user:

```
SELECT (CONCAT(?text) as ?texts) WHERE {
  ?activity po:author <user_uri> . ?activity po:text ?text .
}
```

4. List 1000 users (URIs and names) with the most friendships and the number of friendships in descending order by the number of friendships:

```
SELECT DISTINCT ?participant (COUNT(?friendship) as ?c) WHERE {
  ?friendship a po:Friendship . ?friendship po:member ?participant .
} ORDER BY DESC(?c) LIMIT 1000
```

5. Retrieve text messages with the word "pineapple" (case insensitive):

```
SELECT ?text WHERE {
  ?activity po:text ?text . FILTER regex(?text, 'pineapple', 'i')
}
```

6. List participants and respective full names whose name has the substring "Amanda":

```
SELECT DISTINCT ?participant ?name WHERE {
  ?participant po:observation ?obs . ?obs po:name ?name .
  FILTER regex(?name, 'Amanda', 'i')
}
```

7. Return all pairs of friends of a participant which are friends themselves:

```
SELECT DISTINCT ?friend1 ?friend2 WHERE {
  ?friendship1 po:member <participant_uri> . ?friendship1 po:member ?friend1 .
  ?friendship2 po:member <participant_uri> . ?friendship2 po:member ?friend2 .
  ?friendship3 po:member ?friend1 . ?friendship3 po:member ?friend2 .
}
```

8. Return all interactions from replies in a snapshot:

```
SELECT ?from ?to WHERE {
  ?message1 po:snapshot <snapshot_uri> . ?message2 po:replyTo ?message1 .
  ?message1 po:author ?from . ?message2 po:author ?to .
}
```

3.3.6 License issues

The database presented in this thesis is released under public domain. Computer scripts are in git repositories and PyPI Python packages, also under public domain. Although most data is already in open licenses (Twitter, Email, Participabr, Cidade Democrática, and AA data), IRC and Facebook data was collected and donated by the individuals which yield the data. This rises the understanding of the right to study such data as the right to access the self, in parity with anthropological endeavors.[42,75]

3.3.7 Data-driven ontology synthesis

OWL Ontologies are critical tools to describe taxonomies and the structure of knowledge. Most ontologies are created by domain experts even though there often is data they organize that is given by a software system and which has a predefined structure.

We developed a simple ontology synthesis method that probes the ontological structure in data with SPARQL queries and post-processing. The results are OWL code and diagrams which are exemplified in the Appendix **??** and fully available in a dedicated article.[2] The method can be extended to comprise further OWL axioms and restrictions, but is currently performed to fit present needs with maximum simplicity. Present needs are limited to informative figures and the steps implemented are as follows:

1. Obtain all distinct classes with the query:
   ```
   SELECT DISTINCT ?class_uri WHERE { ?s a ?class_uri }
   ```

2. For each class, obtain the properties that occur as predicates in triples where the subject is an instance of the class:
   ```
   SELECT DISTINCT ?property_uri WHERE { ?s a <class_uri> . ?s ?property_uri ?o . }
   ```
   Such properties are used to assert existential and universal restrictions for the class.

3. Compare the total number of individuals (`?cs1`) of the class (`class_uri`) with the number of such individuals (`?cs2`) that are subjects of at least one triple where the predicate is the property (`property_uri`). If the numbers match, there is an existential restriction for the class. The queries are:
   ```
   SELECT (COUNT(DISTINCT ?s) as ?cs1) WHERE { ?s a <class_uri> }
   SELECT (COUNT(DISTINCT ?s) as ?cs) WHERE {
     ?s a <class_uri>. ?s <property_uri> ?o .
   }
   ```

4. Find the number of instances which are subjects of triples where the predicate is the property but are not instances of the class. If there is zero of such instances, there is an universal restriction:
   ```
   SELECT (COUNT(DISTINCT ?s)=0 as ?cs) WHERE {
   ```

```
  ?s <property_uri> ?o . ?s a ?ca . FILTER(str(?ca) != 'class_uri')
}
```

5. To keep a record of the restrictions (and occurring triples), get all object classes or datatypes where the subject is an instance of the class and the predicate is the property:
```
SELECT DISTINCT ?co (datatype(?o) as ?do) WHERE {
  ?s a <class_uri>. ?s <property_uri> ?o . OPTIONAL { ?o a ?co . }
}
```

6. Obtain all distinct properties:
```
SELECT DISTINCT ?p WHERE { ?s ?p ?o }
```

7. Check if each property is functional, i.e. if it occurs at most once with each subject. This is performed by counting the objects and further verifying that they are at most one. The query is:
```
SELECT DISTINCT (COUNT(?o) as ?co) WHERE { ?s <property_uri> ?o } GROUP BY ?s
```

8. For each property, find the incident range and domain with the queries:
```
SELECT DISTINCT ?co (datatype(?o) as ?do) WHERE {
  ?s <property_uri> ?o . OPTIONAL { ?o a ?co . }
}
```
and
```
SELECT DISTINCT ?cs WHERE { ?s <property_uri> ?o . ?s a ?cs . }
```

9. Render diagrams as exposed in the next section and in the Supporting Information file.

4 CONCLUSION AND FUTURE WORK

The very small standard deviations of principal components formation (see Sections 2.2.5 and 3.0.3), the presence of the Erdös sectors even in networks with few participants (see Sections 2.2.4 and 3.0.2), and the recurrent activity patterns along different timescales (see Sections 2.2.1 and 3.0.1), go a step further in characterizing scale-free networks in the context of the interaction of human individuals. Furthermore, the importance of symmetry-related metrics, which surpassed that of clustering coefficient, with respect to dispersion of the system in the topological measures space, might add to the current understanding of key-differences between digraphs and undirected graphs in complex networks. Noteworthy is also the very stable fraction of participants in each Erdös sector when the network reaches more than 200 participants. Benchmarks were derived from email list networks and the supplied analysis of networks from Facebook, Twitter and ParticipaBR in the Appendix might ease hypothesizing about the generality of these characteristics.

4.1 Textual analysis final remarks

This is a first systematic exploration of the relation between topological and textual metrics in human interaction networks, as far the authors know. Different textual features were scrutinized and were found to present evident patterns, specially in relation to topological measures and the Erdös sectors. Furthermore, results show that peripheral participants use more nouns while hubs use more verbs, which suggests that less connected participants bring content and concepts, while hubs propose action on them. Such findings have potential applications in the collection and diffusion and information, resources recommendation in linked data contexts, and open processes of document elaboration and refinement.[35–37,76–78]

Most importantly, we understand reasonable to conclude, from all the distinct textual characteristics found between the Erdös sectors, that, as a rule of thumb, the texts from each of the sectors differ. Surely there should be exceptions and it is a fact that we left out of the analysis more subtle textual aspects e.g. those related to low percentages (<5%) or to small differences. These might be the subject of future contributions.

4.2 Linked data final remarks

The database presented in this thesis constitutes a large database with diverse provenance. Even so, the database should be expanded in upon need or requests from feedback. All data should be available online in the <http://linkedopensocialdata.org>

address in near future to fulfill the purpose of being a common repertoire in current research. One should reach the diagrams and tables of the articles produced in this research[2,46,78,79] for further directions on the available structures and for an overview complement.

4.3 Future work

Further work should expand the analysis to include more types of networks and more metrics. The data and software needed to attain these results received dedicated and in-depth documentation as they enable a greater level of transparency and work share, which is adequate for both benchmarking and specifically for the study of systems constituted by human individuals (see Section 2.1). The derived typology of hub, intermediary and peripheral participants has been applied for semantic web and participatory democracy efforts, and these developments might be enhanced to yield scientific knowledge.[2,36,37] Also, we plan to further explore and publish the audiovisualizations used for this research[46,61] and the linguistic differences found in each of the Erdös sectors.[79]

Similarity measures of texts in message-response threads has been thought about by us, and some results should be organized in near future. In this respect, there are two core hypotheses obtained from recent experiments:

- the existence of information "ducts", observable through similarity measures. These might coincide with asymmetries of edges between vertex pairs, with homophily or with message-response threads, to point just a few possibilities.
- Valuable insights might be obtained from the self-similarity of messages by same author, of messages sent at the same period of the day, etc. This includes incidences of word sizes, incidences of tags and morphosyntactic classes, incidences of particular Wordnet synset characteristics and distances.

Current results suggest that diversity and self-similarity should vary with respect to connectivity. Literature usually assumes that periphery holds greater diversity,[?] which can be further verified, for example through the diversity of entries (e.g. tokens, sentence sizes).

Other potential next steps are:

- The observation of most incident words and word types, such as words related to cursing, food or body parts.
- Interpretation of the constant difference found from incident and existent tokens histograms, exposed in Section 3.1.12.
- Extend word class observations, e.g. to include plurals, gender, common prefixes and suffixes.

- The observation of date and time in relation to textual production of interaction networks and to activity characteristics (e.g. dispersion of sent time along the day or weekdays).
- A careful analysis of each textual feature distribution which is likely to reveal multimodal outlines and other non-trivial characteristics.
- Extend analysis of textual measures to the windowed approach along the timelines, where hub, peripheral and intermediary sectors where topologically characterized.[?]
- For ELE list, the more connected the sector, the longer the messages are. This is the inverse of what was found in the other lists, and was considered a peculiarity of the culture bonded with the political subject of ELE list. This hypothesis should be further verified.
- Tackle the same analysis on networks with languages other than English. This is especially important for easing applications[76] and should rely on dedicated implementation of tokenization, lemmatization and attribution of POS tags.
- Observe a broader set of human interaction networks and the resulting types of networks and participants with respect to topological and textual features.
- Analyze interaction networks from other platforms such as LinkedIn, Diáspora, etc.
- Sentiment analysis was not used in this work, but might be a good endeavor since the subject has received considerable attention from the scientific literature but has not included topological features as far as we know.
- This thesis focused on differences of texts among Erdös sectors but we envisage that comparison of texts from social networks with canonical texts (e.g. Shakespeare or the King James Bible) might yield other powerful insights.

BIBLIOGRAPHY

1 JACKSON, M. O. **Social and Economic Networks: Models and Analysis**. 2013. <https://class.coursera.org/networksonline-001>.

2 FABBRI, R.; JUNIOR, O. N. O. **Linked Open Social Data for Scientific Benchmarking**. [S.l.]: GitHub, 2016. <https://github.com/ttm/linkedOpenSocialData/raw/master/paper.pdf>.

3 PETROV, S.; DAS, D.; MCDONALD, R. A universal part-of-speech tagset. **arXiv preprint arXiv:1104.2086**, 2011.

4 MORENO, J. L. Who shall survive?: A new approach to the problem of human interrelations. **The Journal of Social Psychology**, Nervous and Mental Disease Publishing Co, v. 6, p. 388–393, 1935.

5 NEWMAN, M. **Networks: an introduction**. [S.l.]: Oxford University Press, 2010.

6 LATOUR, B. Reassembling the social. an introduction to actor-network-theory. **Journal of Economic Sociology**, National Research University Higher School of Economics, v. 14, n. 2, p. 73–87, 2013.

7 BIRD, C.; GOURLEY, A.; DEVANBU, P.; GERTZ, M.; SWAMINATHAN, A. Mining email social networks. In: ACM. **Proceedings of the 2006 international workshop on Mining software repositories**. [S.l.], 2006. p. 137–143.

8 VÁZQUEZ, A.; OLIVEIRA, J. G.; DEZSÖ, Z.; GOH, K.-I.; KONDOR, I.; BARABÁSI, A.-L. Modeling bursts and heavy tails in human dynamics. **Physical Review E**, APS, v. 73, n. 3, p. 036127, 2006.

9 BALL, B.; NEWMAN, M. E. Friendship networks and social status. **arXiv preprint arXiv:1205.6822**, 2012.

10 PALLA, G.; BARABÁSI, A.-L.; VICSEK, T. Quantifying social group evolution. **Nature**, Nature Publishing Group, v. 446, n. 7136, p. 664–667, 2007.

11 LEICHT, E. A.; CLARKSON, G.; SHEDDEN, K.; NEWMAN, M. E. Large-scale structure of time evolving citation networks. **The European Physical Journal B**, Springer, v. 59, n. 1, p. 75–83, 2007.

12 TRAVENÇOLO, B.; COSTA, L. d. F. Accessibility in complex networks. **Physics Letters A**, Elsevier, v. 373, n. 1, p. 89–95, 2008.

13 NEWMAN, M. E. Modularity and community structure in networks. **Proceedings of the National Academy of Sciences**, National Acad Sciences, v. 103, n. 23, p. 8577–8582, 2006.

14 ALBERT, R.; BARABÁSI, A.-L. Topology of evolving networks: local events and universality. **Physical review letters**, APS, v. 85, n. 24, p. 5234, 2000.

15 MAREK-SPARTZ, K.; CHESLEY, P.; SANDE, H. Construction of the gmane corpus for examining the diffusion of lexical innovations. 2012.

16 ONNELA, J.-P.; ARBESMAN, S.; GONZÁLEZ, M. C.; BARABÁSI, A.-L.; CHRISTAKIS, N. A. Geographic constraints on social network groups. **PLoS one**, Public Library of Science, v. 6, n. 4, p. e16939, 2011.

17 PALCHYKOV, V.; KASKI, K.; KERTÉSZ, J.; BARABÁSI, A.-L.; DUNBAR, R. I. Sex differences in intimate relationships. **Scientific reports**, Nature Publishing Group, v. 2, 2012.

18 FABBRI, R. **Python package to observe temporal stability in the GMANE database**. 2015. <https://github.com/ttm/percolation>.

19 HOLLAND, J. H. **Complexity: A very short introduction**. [S.l.]: OUP Oxford, 2014.

20 COSTA, L. d. F.; RODRIGUES, F. A.; TRAVIESO, G.; BOAS, P. V. Characterization of complex networks: A survey of measurements. **Advances in Physics**, Taylor & Francis, v. 56, n. 1, p. 167–242, 2007.

21 ERDÖS, P.; RÉNYI, A. On random graphs, i. **Publicationes Mathematicae (Debrecen)**, v. 6, p. 290–297, 1959.

22 ORDENES, F. V.; THEODOULIDIS, B.; BURTON, J.; GRUBER, T.; ZAKI, M. Analyzing customer experience feedback using text mining: A linguistics-based approach. **Journal of Service Research**, SAGE Publications Sage CA: Los Angeles, CA, v. 17, n. 3, p. 278–295, 2014.

23 GUPTA, V.; LEHAL, G. S. et al. A survey of text mining techniques and applications. **Journal of emerging technologies in web intelligence**, Academy Publisher, PO Box 40 Oulu 90571 Finland, v. 1, n. 1, p. 60–76, 2009.

24 BIRD, S.; KLEIN, E.; LOPER, E. **Natural language processing with Python: analyzing text with the natural language toolkit**. [S.l.]: " O'Reilly Media, Inc.", 2009.

25 WILSON, R.; WATKINS, J. J. **Combinatorics: ancient & modern**. [S.l.]: OUP Oxford, 2013.

26 EADES, P.; KLEIN, K. Graph visualization. **EDBT School**, 2015.

27 FRUCHTERMAN, T. M.; REINGOLD, E. M. Graph drawing by force-directed placement. **Software: Practice and experience**, Wiley Online Library, v. 21, n. 11, p. 1129–1164, 1991.

28 BECK, F.; BURCH, M.; DIEHL, S.; WEISKOPF, D. A taxonomy and survey of dynamic graph visualization. In: WILEY ONLINE LIBRARY. **Computer Graphics Forum**. [S.l.], 2016.

29 BERNERS-LEE, T. **Linked data, 2006**. 2006.

30 MASINTER, L.; BERNERS-LEE, T.; FIELDING, R. T. Uniform resource identifier (uri): Generic syntax. 2005.

31 UMBRICH, J.; DECKER, S.; HAUSENBLAS, M.; POLLERES, A.; HOGAN, A. Towards dataset dynamics: Change frequency of linked open data sources. CEUR, 2010.

32 BIZER, C.; LEHMANN, J.; KOBILAROV, G.; AUER, S.; BECKER, C.; CYGANIAK, R.; HELLMANN, S. Dbpedia-a crystallization point for the web of data. **Web Semantics: science, services and agents on the world wide web**, Elsevier, v. 7, n. 3, p. 154–165, 2009.

33 AUER, S.; BIZER, C.; KOBILAROV, G.; LEHMANN, J.; CYGANIAK, R.; IVES, Z. Dbpedia: A nucleus for a web of open data. In: **The semantic web**. [S.l.]: Springer, 2007. p. 722–735.

34 CYGANIAK, R.; WOOD, D.; LANTHALER, M. Rdf 1.1 concepts and abstract syntax. **W3C Recommendation**, v. 25, p. 1–8, 2014.

35 FABBRI, R. **United Nations Development Programme: Tools for content classification in the ParticipaBR Brazilian federal portal of social participation**. [S.l.]. <https://github.com/ttm/pnud3/blob/master/latex/produto.pdf?raw=true>.

36 _____. **United Nations Development Programme: Adaptations and increments for the ParticipaBR Brazilian federal portal of social participation)**. [S.l.]. <https://github.com/ttm/pnud4/blob/master/latex/produto.pdf?raw=true>.

37 _____. **Content extraction through API from the Brazilian Federal Portal of Social Participation and its tools to a social participation cloud**. [S.l.], 2014. (Desenvolvimento de Metodologias de Articulação e Gestão de Políticas Públicas para Promoção da Democracia Participativa). <https://github.com/ttm/pnud5/blob/master/latex/produto.pdf?raw=true>.

38 FABBRI, R.; POPPI, R. Continuous voting by approval and participation. **arXiv preprint arXiv:1505.06640**, 2015.

39 MACDAID, G. P.; MCCAULLEY, M. H.; KAINZ, R. I. **Atlas of type tables: Myers-Briggs Type indicator**. [S.l.]: Center for Applications of Psychological Type, 2005.

40 ADORNO, T. W.; FRENKEL-BRUNSWIK, E.; LEVINSON, D. J.; SANFORD, R. N. The authoritarian personality. Harpers, 1950.

41 FABBRI, R. **What are you and I? [Anthropological physics fundamentals]**. 2015. <https://www.academia.edu/10356773/What_are_you_and_I_anthropological_physics_fundamentals_>.

42 ANTUNES, D.; FABBRI, R.; PISANI, M. M. Anthropological physics and social psychology in the critical research of networks. **International Conference on Complex Systems (2015)**, 2015.

43 STANFORD, C.; ALLEN, J. S.; ANTÓN, S. C. **Biological anthropology: the natural history of humankind**. [S.l.]: Pearson, 2016.

44 BERNERS-LEE, T.; HENDLER, J.; LASSILA, O. et al. The semantic web. **Scientific american**, New York, NY, USA:, v. 284, n. 5, p. 28–37, 2001.

45 WITTEN, I. H. **Text Mining.** 2004.

46 FABBRI, R. Versinus: a visualization method for graphs in evolution. **arXiv preprint arXiv:1412.7311**, 2013. <http://arxiv.org/abs/1412.7311>.

47 _____. **A distance metric between histograms derived from the Kolmogorov-Smirnov test statistic: specification, measures reference and example uses**. [S.l.]. <https://github.com/ttm/kolmogorov-smirnov/raw/master/paper.pdf>.

48 WIKIPEDIA. **Gmane — Wikipedia, The Free Encyclopedia**. <http://en.wikipedia.org/wiki/Gmane>.

49 RIEDER, B. Studying facebook via data extraction: the netvizz application. In: ACM. **Proceedings of the 5th Annual ACM Web Science Conference**. [S.l.], 2013. p. 346–355.

50 INGEBRIGTSEN, L. M. **Gmane**. 2008.

51 FABBRI, R.; FABBRI, R.; VIEIRA, V.; PENALVA, D.; SHIGA, D.; MENDONÇA, M.; NEGRÃO, A.; ZAMBIANCHI, L.; THUMÉ, G. S. The algorithmic autoregulation software development methodology/a metodologia de desenvolvimento de software autorregulação algorítmica. **Revista Electronica de Sistemas de Informaçao**, Faculdade Cenecista de Campo Largo-FACECLA, v. 13, n. 2, p. 1, 2014.

52 FABBRI, R. **A Python package to deliver social linked data**. 2015. <https://github.com/ttm/social>.

53 _____. **Data from Participa.br, Cidade Democrática and AA, in XML/RDF and Turtle/RDF**. [S.l.]: Datahub, 2014. (Desenvolvimento de Metodologias de Articulação e Gestão de Políticas Públicas para Promoção da Democracia Participativa). <http://datahub.io/organization/socialparticipation>.

54 WOELFLE, M.; OLLIARO, P.; TODD, M. H. Open science is a research accelerator. **Nature Chemistry**, Nature Publishing Group, v. 3, n. 10, p. 745–748, 2011.

55 ANTUNES, D. C.; FABBRI, R.; PISANI, M. M. **Anthropological physics and social psychology in the critical research of networks**. 2015. CSDC'15 online conference, Conference on Complex Systems. <https://www.youtube.com/watch?v=oeOKYc3-nbM>.

56 MARDIA, K. V.; JUPP, P. E. **Directional statistics**. [S.l.]: John Wiley & Sons, 2009. v. 494.

57 LEICHT, E. A.; NEWMAN, M. E. Community structure in directed networks. **Physical review letters**, APS, v. 100, n. 11, p. 118703, 2008.

58 NEWMAN, M. Community detection and graph partitioning. **arXiv preprint arXiv:1305.4974**, 2013.

59 BRANDES, U. A faster algorithm for betweenness centrality*. **Journal of Mathematical Sociology**, Taylor & Francis, v. 25, n. 2, p. 163–177, 2001.

60 JOLLIFFE, I. **Principal component analysis**. [S.l.]: Wiley Online Library, 2005.

61 FABBRI, R. **Video visualizations of email interaction network evolution**. 2013–5. <https://www.youtube.com/playlist?list=PLf_EtaMqu3jVodaqDjN7yaSgsQx2Xna3d>.

62 ELZEN, S. van den; HOLTEN, D.; BLAAS, J.; WIJK, J. J. van. Reordering massive sequence views: Enabling temporal and structural analysis of dynamic networks. In: IEEE. **Visualization Symposium (PacificVis), 2013 IEEE Pacific**. [S.l.], 2013. p. 33–40.

63 _____. Reordering massive sequence views: Enabling temporal and structural analysis of dynamic networks. In: IEEE. **Visualization Symposium (PacificVis), 2013 IEEE Pacific**. [S.l.], 2013. p. 33–40.

64 KOOP, D.; FREIRE, J.; SILVA, C. T. Visual summaries for graph collections. In: IEEE. **Visualization Symposium (PacificVis), 2013 IEEE Pacific**. [S.l.], 2013. p. 57–64.

65 MILLER, G. A. Wordnet: a lexical database for english. **Communications of the ACM**, ACM, v. 38, n. 11, p. 39–41, 1995.

66 WIKIPEDIA. **Kolmogorov–Smirnov test — Wikipedia, The Free Encyclopedia**. 2015. [Online; accessed 26-September-2015]. Disponível em: <https://en.wikipedia.org/w/index.php?title=Kolmogorov%E2%80%93Smirnov_test&oldid=682456076>.

67 BOCCALETTI, S.; LATORA, V.; MORENO, Y.; CHAVEZ, M.; HWANG, D.-U. Complex networks: Structure and dynamics. **Physics reports**, Elsevier, v. 424, n. 4, p. 175–308, 2006.

68 FABBRI, R. **participation toolbox**. [S.l.]: GitHub, 2015. <https://github.com/ttm/participation>.

69 _____. **social toolbox**. [S.l.]: GitHub, 2015. <https://github.com/ttm/social>.

70 _____. **Percolation toolbox**. [S.l.]: GitHub, 2015. <https://github.com/ttm/percolation>.

71 _____. **Music toolbox**. [S.l.]: GitHub, 2015. <https://github.com/ttm/music>.

72 _____. **Visuals toolbox**. [S.l.]: GitHub, 2015. <https://github.com/ttm/visuals>.

73 _____. **Gmane legacy repository**. [S.l.]: GitHub, 2015. <https://github.com/ttm/gmaneLegacy>.

74 _____. **Percolation legacy repository**. [S.l.]: GitHub, 2015. <https://github.com/ttm/percolationLegacy>.

75 _____. What are you and I? [Anthropological physics fundamentals]. 2015.

76 _____. Ensaio sobre o auto-aproveitamento: um relato de investidas naturais na participação social. **arXiv preprint arXiv:1412.6868**, 2014.

77 FABBRI, R.; LUNA, R. B. de; MARTINS, R. A. P. et al. Social participation ontology: community documentation, enhancements and use examples. **arXiv preprint arXiv:1501.02662**, 2015.

78 FABBRI, R.; FABBRI, R.; ANTUNES, D. C.; PISANI, M. M.; JR, O. N. O. Temporal stability in human interaction networks. **arXiv preprint arXiv:1310.7769**, 2013.

79 FABBRI, R. A connective differentiation of textual production in interaction networks. 2013. <http://arxiv.org/abs/1412.7309>.