Complex Networks

Master of Science in Electrical Engineering

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March 13, 2019

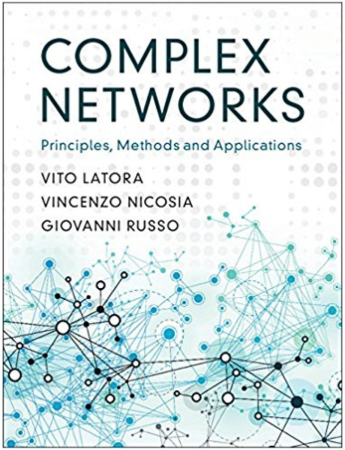
Teaching Plan

Content

1. Graphs and Graph Theory
2. Centrality Measures
3. Random Graphs
4. Small-World Networks
5. Generalised Random Graphs
6. Models of Growing Graphs
7. Advanced topics

Reference

- V. Latora, V. Nicosia, and G. Russo, *Complex Networks: Principles, Methods and Applications*. Cambridge University Press, 2017.



Assessment

- $N_1 = 80$ points : Conference paper.
- $N_2 = 20$ points : Activities
- $N = N_1 + N_2$ points
- **If** $N \geq 60$ **then** *Succeed*.
- **If** $N < 60$ **then** *Failed*.

Introduction

- A social system is a typical example of what is known today as a complex system.

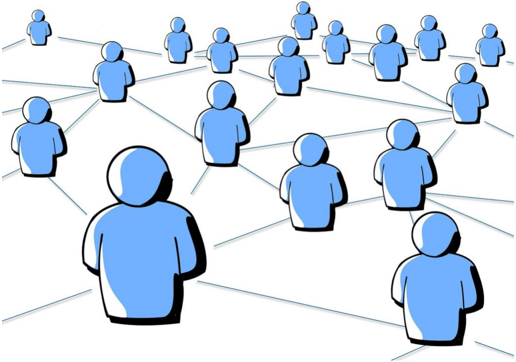


Figure 1: A social system. Source: https://corefinder.dk/the-social-system/

- The study of complex systems is a new science, and so a commonly accepted formal definition of a complex system is still missing.
- A complex system is a system made by a large number of single units (individuals, components or agents) interacting in such a way that the behaviour of the system is not a simple combination of the behaviours of the single units.
- Some collective behaviours emerge without the need for any central control.
- Over the years, the main focus of scientific research has been on the characteristics of the individual components of a complex system and to understand the details of their interactions.
- Less explored: structure of the interactions among the units of a complex system: which unit is connected to which others.
- The most representative and beautiful complex system: the human brain.

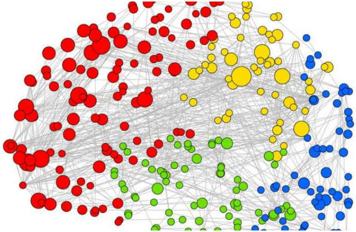


Figure 2: Brain network. Source: Dr. Petra Vertes (University of Cambridge).

- 100 billion neurons.
- Each connected by synapses to several thousand other neurons.
- Each node of the network represents a different brain region and is colour-coded according to the larger area is located in. Pairs of nodes are linked if the activity of the two regions is found to synchronize a lot of the time during an fMRI brain scan. [Video-01].
- Social network [Video-02].

- Some sub-structures of a network propagate information faster than others.
- What also matters in a complex system is the architecture of the network of interactions. It is precisely on these complex networks.
- **Complex networks are all around us.**
  1. Think in a typical day of any person.
  2. Wake-up: Power grid.
  3. Family: Social network.
  4. Take a shower: Water distribution network.
  5. Go to work: street network
  6. Take the underground: transportation network.
  7. Use your laptop: network of logic gates.
  8. Check your emails: email communication network.
  9. Meet a colleague: collaboration network.
  10. Paper cited: citation network.
  11. Lunch time - news on the web: World Wide Web.
  12. Facebook: online social network.
  13. Receive a phone call: phone call network.
  14. Invitation to go to a lake: food web network.

15. Thoughts on lake: network of words association.
16. Book a flight to Prague for a conference: air transportation system
17. Drive back home - tired: network of blood vessels, metabolic networks...
18. Dinner - news about economics: commercial relationship.
19. Relaxing time - moview : actor collaboration network.
20. Going to bed - think about the day using your brain network.

- **Why Study Complex Networks?**
  - In the following slides a couples of papers are going to testify the importance of the Network Science.

letters to nature

typically slower than $\sim 1\,\mathrm{km\,s^{-1}}$) might differ significantly from what is assumed by current modelling efforts[27]. The expected equation-of-state differences among small bodies (ice versus rock, for instance) presents another dimension of study; having recently adapted our code for massively parallel architectures (K. M. Olson and E.A, manuscript in preparation), we are now ready to perform a more comprehensive analysis.

The exploratory simulations presented here suggest that when a young, non-porous asteroid (if such exist) suffers extensive impact damage, the resulting fracture pattern largely defines the asteroid's response to future impacts. The stochastic nature of collisions implies that small asteroid interiors may be as diverse as their shapes and spin states. Detailed numerical simulations of impacts, using accurate shape models and rheologies, could shed light on how asteroid collisional response depends on internal configuration and shape, and hence on how planetesimals evolve. Detailed simulations are also required before one can predict the quantitative effects of nuclear explosions on Earth-crossing comets and asteroids, either for hazard mitigation[28] through disruption and

Collective dynamics of 'small-world' networks

Duncan J. Watts* & Steven H. Strogatz

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Networks of coupled dynamical systems have been used to model biological oscillators[1–4], Josephson junction arrays[5,6], excitable media[7], neural networks[8–10], spatial games[11], genetic control networks[12] and many other self-organizing systems. Ordinarily, the connection topology is assumed to be either completely regular or completely random. But many biological, technological and social networks lie somewhere between these two extremes. Here we explore simple models of networks that can be tuned through this middle ground: regular networks 'rewired' to intro-

Figure 3: D. J. Watts and S. H. Strogatz, "Collective dynamics of 'small-world' networks," Nature, vol. 393, no. 6684, pp. 440–442, Jun. 1998. GS: 38306.

For ALO and ALO/STO barriers, a predominant tunneling of s-character electrons (see arrow in Fig. 2B) is the usual explanation of the positive polarization (*6–8*). The rapid drop with bias (Fig. 3B) is similar to what has been observed in most junctions with ALO barriers, and completely different from what is obtained when the tunneling is predominantly by d-character electrons (Fig. 3A). The origin of this rapid decrease of the TMR at relatively small bias has never been clearly explained. This is roughly consistent with the energy dependence of the DOS induced by sp-d bonding effects on the first atomic layer of ALO in the calculation of Nguyen-Mahn *et al*. (*8*) for the Co-ALO interface. But Zhang *et al*. (*13*) have also shown that a large part of the TMR drop can be attributed to the excitation of spin waves.

The experiments reported here and in several recent publications (*3, 4*) demonstrate the important role of the electronic structure of the metal-oxide interface in determining the spin polarization of the tunneling electrons. The negative polarization for the Co-STO interface has been ascribed to d-d bonding effects between Al and Ti (*4*). This interpretation is similar to

Emergence of Scaling in Random Networks

Albert-László Barabási* and Réka Albert

Systems as diverse as genetic networks or the World Wide Web are best described as networks with complex topology. A common property of many large networks is that the vertex connectivities follow a scale-free power-law distribution. This feature was found to be a consequence of two generic mechanisms: (i) networks expand continuously by the addition of new vertices, and (ii) new vertices attach preferentially to sites that are already well connected. A model based on these two ingredients reproduces the observed stationary scale-free distributions, which indicates that the development of large networks is governed by robust self-organizing phenomena that go beyond the particulars of the individual systems.

The inability of contemporary science to describe systems composed of nonidentical elements that have diverse and nonlocal interactions currently limits advances in many disciplines, ranging from molecular biology to computer science (*1*). The difficulty of describing these systems lies partly in their topology: Many of them form rather complex networks whose vertices are the elements of the system and whose edges represent the interactions between them. For example, liv-

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Figure 4: A. Barabási and R. Albert, “Emergence of Scaling in Random Networks,” Science, vol. 286, no. 5439, pp. 509–512, Oct. 1999. GS: 33041.

SIAM REVIEW
Vol. 45, No. 2, pp. 167–256

The Structure and Function of Complex Networks*

M. E. J. Newman†

Abstract. Inspired by empirical studies of networked systems such as the Internet, social networks, and biological networks, researchers have in recent years developed a variety of techniques and models to help us understand or predict the behavior of these systems. Here we review developments in this field, including such concepts as the small-world effect, degree distributions, clustering, network correlations, random graph models, models of network growth and preferential attachment, and dynamical processes taking place on networks.

Key words. networks, graph theory, complex systems, computer networks, social networks, random graphs, percolation theory

AMS subject classifications. 05C75, 05C90, 94C15

PII. S0036144503424804

Figure 5: M. E. J. Newman, “The structure and function of complex networks,” Society for Industrial and Applied Mathematics, vol. 45, no. 2, pp. 167–256, 2003. GS: 18289.

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Complex networks: Structure and dynamics

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Accepted 27 October 2005
Available online 10 January 2006
editor: I. Procaccia

Figure 6: S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D. Hwang, "Complex networks: Structure and dynamics," Physics Reports, vol. 424, no. 4–5, pp. 175–308, Feb. 2006. GS: 8842.

ARTICLE

DOI: 10.1038/s41467-018-04287-5 OPEN

Dynamically induced cascading failures in power grids

Benjamin Schäfer [1,2], Dirk Witthaut [3,4], Marc Timme [1,2] & Vito Latora [5,6]

Reliable functioning of infrastructure networks is essential for our modern society. Cascading failures are the cause of most large-scale network outages. Although cascading failures often exhibit dynamical transients, the modeling of cascades has so far mainly focused on the analysis of sequences of steady states. In this article, we focus on electrical transmission networks and introduce a framework that takes into account both the event-based nature of cascades and the essentials of the network dynamics. We find that transients of the order of seconds in the flows of a power grid play a crucial role in the emergence of collective behaviors. We finally propose a forecasting method to identify critical lines and components in advance or during operation. Overall, our work highlights the relevance of dynamically induced failures on the synchronization dynamics of national power grids of different European countries and provides methods to predict and model cascading failures.

Figure 7: B. Schäfer, D. Witthaut, M. Timme, and V. Latora, “Dynamically induced cascading failures in power grids,” Nature Communications, vol. 9, no. 1, p. 1975, Dec. 2018. GS: 9.

Importance of topology

- WS1998 and BA999 provided clear indications, from different angles, that:
  - the networks of real-world complex systems have non-trivial structures and are very different from lattices or random graphs, which were instead the standard networks commonly used in all the current models of a complex system.
  - some structural properties are universal, i.e. are common to networks as diverse as those of biological, social and man-made systems.
  - the structure of the network plays a major role in the dynamicsof a complex system and characterises both the emergence and the properties of its collective behaviours.

Datasets

Table 1 A list of the real-world complex networks that will be studied in this book. For each network, we report the chapter of the book where the corresponding data set will be introduced and analysed.

Complex networks	Nodes	Links	Chapter
Elisa's kindergarten	Children	Friendships	1
Actor collaboration networks	Movie actors	Co-acting in a film	2
Co-authorship networks	Scientists	Co-authoring a paper	3
Citation networks	Scientific papers	Citations	6
Zachary's karate club	Club members	Friendships	9
C. elegans neural network	Neurons	Synapses	4
Transcription regulation networks	Genes	Transcription regulation	8
World Wide Web	Web pages	Hyperlinks	5
Internet	Routers	Optical fibre cables	7
Urban street networks	Street crossings	Streets	8
Air transport network	Airports	Flights	10
Financial markets	Stocks	Time correlations	10

Figure 8: If there is no other mention, table and figures in these slides come from the adopted textbook.

Appendix

- Contains a detailed description of all the main graph algorithms discussed in the various chapters of the book, from those to find shortest paths, components or community structures in a graph, to those to generate random graphs or scale-free networks.
- All the algorithms are presented in a C-like pseudocode format.
- Access to both the most famous data sets of real-world networks and to the numerical algorithms to compute network properties and to construct networks.
- Accompanying website of the textbook: www.complex-networks.net.
- Data Sets: (html).
- Book's Programs (NetBunch) in C Language: (html).

Use of C code

ER_A(1) WWW.COMPLEX-NETWORKS.NET ER_A(1)

NAME

er_A - Sample a random graph from the Erdos-Renyi model A

SYNOPSIS

er_A *N* *K* [*fileout*]

DESCRIPTION

er_A samples a random graph with *N* nodes and *K* edges from the Erdos-Renyi model A, i.e. the ensemble of random graphs where K links are placed uniformly at random among N nodes. The program dumps the edge list of the resulting graph on output. If the optional *fileout* is provided, the output is written on a file with that name.

PARAMETERS

N Number of nodes in the final graph.

K Number of edges in the final graph.

fileout The (optional) name of the filename where the edge list of the graph will be saved.

Figure 9: Source: (Web textbook)

Use of C code

EXAMPLES

The following command:

```
$ er_A 1000 3000
```

samples an undirected random network with *N=1000* nodes and *K=3000* edges using the Erdos-Renyi model A. The output of the command **er_A** will be the edge-list of the resulting graph, where each (undirected) edge is reported only once. In order to be useful, such edge-list should be saved into a file. The following command:

```
$ er_A 1000 3000 > er_A_1000_3000.net
```

will save the resulting graph in the file er_A_1000_3000.net. Notice the usage of the symbol ">" to redirect the output of the program to a file.

SEE ALSO

er_B(1), ws(1)

Figure 10: Source: (Web textbook)

Code in Matlab

- Executable function in C: `er_A.exe`
- Matlab call: `system('er_A.exe 10 5');`
- Result:

```
>> system('er_A.exe 10 5');
8  3
8  4
9  0
9  6
9  8
```

- `system('er_A.exe 10 5 > er_A_10_5.net');`
- `A=load('er_A_10_5.net');`