Structure and dynamical behavior of non-normal networks

Malbor Asllani1,2, Renaud Lambiotte1, Timoteo Carletti2*

We analyze a collection of empirical networks in a wide spectrum of disciplines and show that strong non-normality is ubiquitous in network science. Dynamical processes evolving on non-normal networks exhibit a peculiar behavior, as initial small disturbances may undergo a transient phase and be strongly amplified in linearly stable systems. In addition, eigenvalues may become extremely sensible to noise and have a diminished physical meaning. We identify structural properties of networks that are associated with non-normality and propose simple models to generate networks with a tunable level of non-normality. We also show the potential use of a variety of metrics capturing different aspects of non-normality and propose their potential use in the context of the stability of complex ecosystems.

INTRODUCTION

Network science (1–3) has emerged, in the past 20 years, as an essential framework to model and understand complex systems in a variety of disciplines, including physics (1), economics (4), biology (5), and sociology (6). At its core, network science views a system as a set of nodes that may be connected directly by an edge or indirectly by a succession of edges, thereby forming paths of interactions. The bridge between network structure and dynamics is generally unraveled by defining a linear dynamical model on the nodes; take, for instance, a random walk process as a simple model of diffusion or the linearization around a critical point of a nonlinear dynamical system (7–10). In each case, the process is determined by a matrix, somehow related to the adjacency matrix of the underlying network. In addition, critical aspects of the system, such as its stability and characteristic time scales, are usually described by the properties of its spectrum (11). Central network concepts such as the spectral gap, spectral radius, and master stability conditions all build on this interpretation. Relatedly, network spectra also appear in network algorithms, such as in community detection (12) or in network comparison (13).

The characterization of a linear system by its spectrum is canonical, but it is unreliable in situations when the linear operator is non-normal; namely, its eigenvectors do not necessarily form an orthonormal basis, and the transformation to eigenvector coordinates may involve a strong distortion of the phase space. Non-normality has a long tradition in linear algebra and dynamical systems, from early studies in hydrodynamics (14) to more recent works on the robustness of non-normal ecosystems (15) and in neuronal dynamics (16, 17). Yet, these results remain focused on limited areas of science, and a systematic study of the prevalence of non-normality in real-world networks, as well as its potential impact on dynamics, is still lacking. Here, we call non-normal a network whose adjacency matrix A is non-normal (18). By definition, A is non-normal if it verifies AA† ≠ A†A. It is thus clear that A needs to be asymmetric to be non-normal or, equivalently, the network needs to be directed to be non-normal, but, as we will discuss in more detail later, asymmetry is not sufficient and certain types of network architectures are necessary to determine a strong non-normality. Given a non-normal network, other standard matrices, such as its Laplacian L, are also non-normal. Non-normality can hence be quantified using a standard spectral measure borrowed from matrix theory, such as Henrici’s spectral abscissa, which provides a direct measure of the size of the transient amplification (see Table 1).

| Corresponding author. Email: timoteo.carletti@unamur.be |

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definition, a complex number $z$ is an eigenvalue of $M$ if a bounded inverse of $zI - M$ does not exist. The pseudospectrum is based on a less strict definition and defines regions of the complex plane where $|| (zI - M)^{-1} ||$ is larger than a prescribed positive number $\epsilon^{-1}$. By its very first definition, the pseudospectrum defines regions of the complex plane where eigenvalues of a matrix can be found because of a small perturbation, $M + \Delta M$, with $|| \Delta M || < \epsilon$. These perturbations lead to small variations of the spectrum in the case of normal matrices, but they can become much more important in the case of non-normal matrices. In particular, even small perturbations can make a linearly stable system unstable. Note that this effect may have important practical consequences for networks, as the precise value of edge weights is often unknown (21), and empirical measurements of networks are prone to missing edges (22).

As we have discussed, non-normality may strongly affect linear and nonlinear dynamical systems on networks and, more generally, their behavior. The contributions of this work are manifold. First, we show that a strong non-normality is widespread in complex networks empirically observed in a variety of domains. As a second step, we reveal the organization behind non-normality and show that non-normality is associated with a combination of absence of cycles (23), low reciprocity (24), and hierarchical organization (25). We also propose a simple model for growing networks based on preferential attachment reproducing our observations. Last, we consider in detail a Lotka-Volterra model applied to a real-world network and show that the use of network metrics for non-normality helps to understand the dynamics of the system.

**RESULTS**

**Non-normal networks: Empirical data and the shape of non-normality**

As a first step, we have considered a large set of directed, real-world networks from different disciplines, including biology, sociology,
communication, transport, and many more. Results reported in Table 2 (see also the more complete table presented in the Supplementary Materials) show values of standard measures of non-normality, including the numerical abscissa, the \( \varepsilon \)-pseudospectral abscissa, and the normalized Henrici’s departure from normality, \( d_F(M) = d_F(\|M\|_F) \), all revealing that the networks present a strong non-normality.

As a next step, we investigate the type of network organization associated with non-normality. The directedness and low reciprocity of a network are necessary conditions for non-normality, but they are by no means sufficient. For instance, a \( k \)-regular directed ring, whose adjacency matrix is circulant, is normal because of its rotational symmetry (18). The condition \( AA^T \neq A^T A \) is instead satisfied when the network is hierarchical, that is, when nodes have a rank and edges with a strong weight tend to flow from nodes with a small rank to nodes with a high rank (or vice versa). These organizations are known to be prevalent in different types of networks (25–28), for instance, through the concepts of dominance hierarchies in social ecology, trophic levels in food webs, and social status in social networks. The inequality becomes maximum when the network is a directed acyclic graph (DAG), such that the matrix takes an upper triangular form after proper relabeling of the nodes. Again, DAGs find several applications, for instance, in the case of citation or causal networks. On the basis of these intuitions, we estimate the level of hierarchy of a real-world network as follows. Given an adjacency matrix, we search for the best nodes ordering such that the

### Table 2. Some figures for a selected set of real webs.

<table>
<thead>
<tr>
<th>Network name</th>
<th>Nodes</th>
<th>Links</th>
<th>( \omega )</th>
<th>( \omega - \alpha )</th>
<th>( \alpha_e )</th>
<th>( \Delta )</th>
<th>( \hat{d}_F )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Foodwebs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cypress wetlands South Florida (wet)</td>
<td>128</td>
<td>2016</td>
<td>296.71</td>
<td>132.11</td>
<td>167.46</td>
<td>0.83</td>
<td>1.00</td>
</tr>
<tr>
<td>Cypress wetlands South Florida (dry)</td>
<td>128</td>
<td>2137</td>
<td>217.60</td>
<td>152.50</td>
<td>62.20</td>
<td>0.89</td>
<td>1.00</td>
</tr>
<tr>
<td>Little Rock Lake (Wisconsin, USA)</td>
<td>183</td>
<td>2494</td>
<td>21.69</td>
<td>14.69</td>
<td>10.02</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td><strong>Biological</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transcriptional regulation network (Escherichia coli)</td>
<td>423</td>
<td>578</td>
<td>5.11</td>
<td>4.11</td>
<td>2.52</td>
<td>0.81</td>
<td>0.93</td>
</tr>
<tr>
<td>Metabolic network (Caenorhabditis elegans)</td>
<td>453</td>
<td>4596</td>
<td>13.44</td>
<td>12.44</td>
<td>12.44</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>Pairwise proteins interaction (Homo sapiens)</td>
<td>2239</td>
<td>6452</td>
<td>15.79</td>
<td>13.02</td>
<td>4.01</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td><strong>Transport</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>U.S. airport 2010</td>
<td>1574</td>
<td>28,236</td>
<td>1.19 ( \times 10^7 )</td>
<td>79.30</td>
<td>1.19 ( \times 10^7 )</td>
<td>0.01</td>
<td>1.00</td>
</tr>
<tr>
<td>Road transportation network (Rome)</td>
<td>3353</td>
<td>8870</td>
<td>2.40 ( \times 10^4 )</td>
<td>120.05</td>
<td>2.39 ( \times 10^4 )</td>
<td>0.08</td>
<td>0.28</td>
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<tr>
<td>Road transportation network (Chicago)</td>
<td>12,982</td>
<td>39,018</td>
<td>4.23</td>
<td>4.29 ( \times 10^{-4} )</td>
<td>4.54</td>
<td>0.04</td>
<td>0.19</td>
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<tr>
<td><strong>Communication</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Email network Democratic National Committee</td>
<td>2029</td>
<td>39,264</td>
<td>28.00</td>
<td>2.00</td>
<td>26.37</td>
<td>0.53</td>
<td>0.89</td>
</tr>
<tr>
<td>Enron email network (1999–2003)</td>
<td>87,273</td>
<td>1,148,072</td>
<td>85.14</td>
<td>14.54</td>
<td>71.05</td>
<td>0.30</td>
<td>0.99*</td>
</tr>
<tr>
<td>Email network European institution</td>
<td>265,214</td>
<td>420,045</td>
<td>76.02</td>
<td>6.09</td>
<td>70.30</td>
<td>0.30</td>
<td>0.84*</td>
</tr>
<tr>
<td><strong>Citation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Articles from Scientometrics (1978–2000)</td>
<td>3084</td>
<td>10,416</td>
<td>10.32</td>
<td>8.32</td>
<td>5.28</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>Citation network Digital Bibliography and Library Project</td>
<td>12,591</td>
<td>49,743</td>
<td>21.50</td>
<td>16.82</td>
<td>4.45</td>
<td>0.87</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Social</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypernetwork of 2004 U.S. election blogs</td>
<td>1224</td>
<td>19,025</td>
<td>45.37</td>
<td>10.95</td>
<td>34.95</td>
<td>0.72</td>
<td>0.98</td>
</tr>
<tr>
<td>Reply network of the news website Digg</td>
<td>30,398</td>
<td>87,627</td>
<td>15.92</td>
<td>6.56</td>
<td>10.18</td>
<td>0.61</td>
<td>0.97</td>
</tr>
<tr>
<td>Trust network from the website Epinions</td>
<td>75,879</td>
<td>508,837</td>
<td>123.00</td>
<td>16.47</td>
<td>106.96</td>
<td>0.13</td>
<td>0.80*</td>
</tr>
</tbody>
</table>
imposing that 0 included in different ways, either by endowing edges with a weight and 

rocat ing and creating a link directed at 

ability proportional to its in-degree. Note that this type of process is 

node 

ture. We thus consider a growing network where, at each step, a new 

reciprocity of the directed edges and the presence of a hierarchical struc-

tural hierarchy and dynamical non-normality (see also Methods). Last, 

real-world networks, hence reinforcing the connection between struc-

tural hierarchy and dynamical non-normality (see also Methods). Last,

note that non-normality and a hierarchical structure are global proper-

ties of a network. As an illustration, we have considered in the Sup-

plementary Materials the case of networks built from different 

combinations of the same constituting blocks or motifs (25, 29–31), 

and we observe that different levels of non-normality can emerge from 

the combination of two directed motifs, from strong non-normality 

and a DAG structure for the whole graph to weakly non-normal patterns, 

where the presence of a cycle prevents the dynamical flow to accumulate 

on a small number of nodes.

Mechanistic model

Here, we propose a simple mechanistic model, denoted by the nSF 

network, leading to the formation of networks with tunable levels of 

non-normality. The model builds on the seminal ideas of de Solla Price 

(32), later leading to the family of preferential attachment models (33).

As discussed before, critical ingredients of the model should be the low 

reciprocity of the directed edges and the presence of a hierarchical struc-

ture. We thus consider a growing network where, at each step, a new 

node j draws a directed edge to a previously existing node i, with a prob-

ability proportional to its in-degree. Note that this type of process is 

expected to lead to the formation of power-law in-degree distributions, 

but this is not our concern here. Node i also has the possibility of recipro-

rocat ing and creating a link directed at j, as in (34). Asymmetry can be 

included in different ways, either by endowing edges with a weight and 

imposing that 0 ≤ wji ≪ wij or by considering unweighted edges and 

assuming that the reciprocal edge is created with a probability p_j→i ≪ 1,

see Fig. 2. Hierarchy is then induced by the ordering of the nodes 

terms of their arrival time. As expected, the stronger the inequalities,

the stronger the non-normality of the resulting networks. We have 

investigated the non-normality of the resulting networks and found a 

notable similarity with the relation between Δ and Henrici’s departure 

from normality observed in real-world networks, as shown in Fig. 1.

Note that we have also considered variants of other classical network 

models, such as Erdös-Rényi (ER) (35) and Watts-Strogatz (WS) (36) 

(see the Supplementary Materials), but their lack of hierarchical structure 

prevents the formation of strong non-normality, as can be seen in their 
pseudospectral properties (see Fig. 3 and the Supplementary Materials).

Application to the stability of complex ecosystems

The hierarchical structure of non-normal networks allows for the intro-
duction of interesting connections with dynamical systems. Here, we 

focus on stability, a central concept to understand the emergence of col-

lective phenomena (10). The importance of network structure for sta-

bility is well established since the seminal works of May (7) and Alle
sina and Tang (8) in the context of ecology. For instance, choosing the in-

teraction strengths from a normal distribution N(0, σ), May proved 

that an ecosystem loses its stability above a critical size, as a consequence 
of the circular law (37). To understand the interplay of non-normality 

and dynamics, we analyze the master stability function (3, 10), which is 
a general tool that allows one to infer about the (in)stability of a net-

worked dynamical system; it often relies on the use of the spectrum of 
some suitable linearization, while hereby conditions for (in)stability 

are determined through the pseudospectrum of the linearized system 

(1). The latter represents the generalized Lotka-Volterra (GLV) model, 

which is popular for understanding competition and mutualism among 

interacting species (7–9). The set of equations governing the dynamics 
of trophic interactions is given by (9)

\[
\frac{dx_i}{dt} = x_i \left( r_i - s x_i + \sum_{j \neq i} M_{ij} x_j \right). \quad \forall i = 1, 2, \ldots N
\]  

(1)
Here, $r_i$ are the intrinsic rates of (i) birth if $r_i > 0$, meaning that species $i$ can reproduce itself in absence of other species and in abundance of resources; (ii) death if $r_i < 0$ in the sense that the population of species $i$ will decline in absence of other species (e.g., preys). The positive constants $s_i$ represent the finite carrying capacity of the ecosystem (limited resources) and prevent the species $i$ from growing indefinitely. An important role is played by the community matrix $M$, whose entries $M_{ij}$ (respectively $M_{ji}$) represent the influence of species $j$ on $i$ (respectively $i$ on $j$). We also assume that $M_{ii} = 0$, $\forall i$; namely, the community matrix describes only interspecies interactions, and intraspecies interactions have been cast into $s_i$. In the following, we adopt the method of Chen and Cohen (38), as already explained in the literature (8, 9). More precisely, we hypothesize the existence of a positive equilibrium solution $x^*$ that, without loss of generality, can be assumed to be of the form $x^*_i = 1$, for all $i$, after a suitable choice of the growth/death rates $r_i$. At this point, the master stability function of the GLV model depends solely on the spectrum (pseudospectrum) of the matrix $M - \text{diag}(s)$, namely, the community matrix from which we remove the matrix whose diagonal contains the interspecies strengths $s_i$. The problem is hence mapped to a framework where stability directly depends on species interactions.

The vulnerability of the system is visible in Fig. 4, where the spectra (black dots) shift from the left to the right of the imaginary axis once mutualism increases. Although the system remains stable for a strong competitive setting (Fig. 4, A and B), we can observe (colored curves) that the $\epsilon$-pseudospectral abscissa [see (19) and Table 1] is positive and larger for structured systems than for random ones (8). To represent the former systems, we used the nSF networks obtained with the generation model previously presented, the latter exhibiting features very similar to the real trophic relations. This implies that the system can easily be destabilized by (relatively) small fluctuations due to demographic, thermal, or endogenous noise that are always present in the surrounding environment and are amplified because of the non-normality (see the Supplementary Materials). This remark can have important consequences in the understanding of the problem of coexistence of multiple species in a harsh competitive environment, e.g., in the case of the paradox of the plankton (39), for which field observations are at odds with the principle of competitive exclusion (8).

**DISCUSSION AND CONCLUSIONS**

We have shown that a large number of real-life networks are strongly non-normal and that a characterization of their properties solely by spectral methods may be misleading. Non-normality induces a strong dependency on fluctuations and needs to be considered with care when performing a linear stability analysis of nonlinear systems. Despite the fact that the non-normality is well studied and that its importance has been recognized in a variety of domains, a systematic analysis of its importance and effect in large-scale networks was still lacking. Our first contribution is thus not only the identification of what appears to be a ubiquitous property of directed networks but also the introduction of new methods in the toolbox of network science to generate non-normal networks and capture the effect of non-normality on their dynamics. Potential applications have recently been explored, for instance,
in pattern formation on networks (18) and in epidemic spreading in metapopulation models (18). Overall, these findings emphasize that non-normality is a critical component of complex systems and that specific tools are necessary to complement standard methods based on eigenspectra, which are prevalent in network science. More specifically, this new perspective may shed light on how to explain the diversity of species in ecosystems (40), the origin of cascade failures in power grids (41), or the spread of epidemics in mobility networks (42), just to mention a few possible applications.

METHODS

Measures of non-normality
A real matrix \( M \) is said to be non-normal if it is not diagonalizable by a unitary matrix; namely, its eigenvectors are not orthogonal to each other (19). The numerical abscissa has been introduced in population dynamics (15) with the term of reactivity, and it is defined by \( \alpha(M) = \text{sup}\{H(M)\} \), where \( H(M) = (M + M^T)/2 \) is the Hermitian part of \( M \). This is a very natural concept; however, it does not allow the computation of the maximum amplification of the initial conditions exhibited by linear stable non-normal systems. For this reason, one has to resort to the pseudospectrum (19), \( \sigma_\varepsilon(M) \), which is defined for all \( \varepsilon > 0 \) as the spectrum of the perturbed matrix \( M + \varepsilon I \), for any matrix \( \| I \| \leq \varepsilon \). From the \( \varepsilon \)-pseudospectral abscissa, \( \alpha_\varepsilon(M) = \text{sup}\Re\sigma_\varepsilon(M) \), we can obtain the Kreiss constant, \( K(M) = \sup_{\varepsilon>0} \alpha_\varepsilon(M)/\varepsilon \), and eventually the lower bound on the orbit size

\[
\sup_{t \geq 0} |x(t)| \geq K(M) |x(0)|
\]

\[ (2) \]

Let us observe that the latter provides a straightforward bound on the amplification envelope defined in (15). Moreover, \( K(M) \) is more informative that reactivity, in fact a stable system, can exhibit a small amplification even if \( \alpha(M) > 0 \) is very large.

Henrici’s index is based on the observation that the Frobenius norm of a normal matrix is given by \( \| M \|_F^2 = \text{tr}(M^2) = \sum_{i} \lambda_i^2 \), where \( \lambda_i \) are the eigenvalues of the matrix; one can thus define Henrici’s departure from normality (19) for a non-normal matrix \( M \) by

\[
d_F(M) = \sqrt{\| M \|_F^2 - \sum_{i} |\lambda_i|^2}
\]

\[ (3) \]

It attains its minimum once the matrix is normal and then increases as long as the matrix deviates from normality. To compare systems with different sizes, we define the normalized index \( d_F(M)/\| M \|_F \)

For a generic matrix with binary (respectively positive) entries, one can define the imbalance between the number (respectively the total sum) of entries in the upper and lower triangular part, using the language of networks

\[
\Delta(M) := \frac{\left| \sum_{i<j} \tilde{M}_{ij} \right|}{\left( \sum_{i<j} \tilde{M}_{ij} + \sum_{j<i} \tilde{M}_{ji} \right)}
\]

\[ (4) \]

where \( \tilde{M}_{ij} \) are the entries of the final relabeled matrix.

Fig. 4. GLV model: \( x_i = x_i(r_i - s_i x_i + \sum_j M_{ij} x_j) \). We consider an ecosystem composed of 25 species. For the sake of simplicity, the intraspecies interactions are all set equal, \( s_i = 1 \) \( \forall i \), and \( M \) is the (weighted and signed) adjacency matrix of an nSF for the structured case (main panels) or a random matrix (insets) whose weights are drawn from a normal distribution \( \Re(0, 1/5) \). In the structured cases, the strengths in the upper triangular part of the matrix \( M \) are 15 times larger than those in the lower one, thus enhancing non-normality, as can be seen from the pseudospectrum levels [computed using the software EigTool (44)]. In the top panels, we show the master stability function close to the asymptotically stable equilibrium point, based on the use of the pseudospectra. The corresponding dynamical evolution is shown in the bottom panels, where different colors correspond to different levels of \( \varepsilon \) in log scale (as in the top panels); initial conditions have been uniformly randomly chosen. Different cases are considered depending on the signs of the interaction strengths: (A) competition (\(-/-\)), (B) prey-predator (\(-/+\)), and (C) mutualism (\(+/+\)). We observe that, even if the system is asymptotically stable (A1 and B1), the \( \varepsilon \)-pseudospectral abscissa is positive for sufficiently large \( \varepsilon \), thus inducing an unstable system behavior if the perturbation (in the adjacency matrix and/or in the initial conditions) is strong enough (A2 and B2). Yet, the unstructured systems still converge to the homogeneous equilibrium [see insets in (A2) and (B2)]. Overall, this effect is more pronounced in the structured systems than in the random ones, as the \( \varepsilon \) levels are much larger in the former case, for a fixed value of \( \varepsilon \).
While it can be relatively easy to determine a DAG and compute $\Delta$, once we have a drawing of a (small enough) network, this task becomes hard starting from the adjacency matrix or a large network. We observed that the simple operation of relabeling the nodes can change the value of $\Delta$ and that the latter increases the larger the number of entries in the adjacency matrix in the upper triangular part, namely, links $i \to j$, where $j > i$. Having in mind these observations, we designed an algorithm aiming at maximizing $\Delta$ once couples of nodes are relabeled; i.e., rows and columns of the adjacency matrix are swapped. To overcome the combinatorial difficulty of the problem, we resorted to a simulated annealing method (43) to get an accurate solution in a relatively short time. A pseudocode is presented in the Supplementary Materials, and the generic convergence behavior of the maximization process is shown in fig. S2.

**SUPPLEMENTARY MATERIALS**

Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/4/12/eaau9403/DC1

Section S1. Non-normal matrices and their pseudospectra
Section S2. Global structure of non-normal networks
Section S3. Models for generation of non-normal networks
Section S4. An intuitive meaning of the pseudospectrum
Section S5. Pseudospectra of real non-normal networks
Section S6. Extended table of real non-normal networks

**REFERENCES AND NOTES**

References and notes for this article are available at http://advances.sciencemag.org/cgi/content/full/4/12/eaau9403/DC1

Section S6. Extended table of real non-normal networks
Section S5. Pseudospectra of real non-normal networks
Section S1. Non-normal matrices and their pseudospectra

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