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# Conservative vs. non-conservative diffusion towards a target in a networked environment

Ernesto Estrada

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**Abstract** The networked nature of complex systems determines the way in which 'information' navigates the system from a source to a target. This navigation is governed by the lack of central controllers and the fact that every individual entity ignores the global structure of the system. Consequently, targeted shortest-path searches are almost automatically excluded in these systems, leaving the more blind diffusive processes as the main mechanism for navigating complex networks. Here we show that non-conservative diffusion has some advances over the 'classical' (conservative) diffusion for searching a target in a network. The non-conservative nature of the diffusion process is given by the possibility that the network 'communicates' with the environment in which it is embedded. We use analytical and computational methods to show that non-conservative diffusion uses trajectories which are more prone to find a target than the conservative one. We illustrate the existence of this mechanisms in systems as varied as traffic in urban environments, volume transmission in the brain and communication through online social networks.

**Keywords:** non-conservative diffusion; graph Laplacians; communicability distance; diffusion distance; complex networks; circum-Euclidean distance matrices

## 1 Introduction

"The Target Problem" seems to be an easy problem when it deals with searching strategies toward an efficient target identification on a networked environment. This environment can be represented by the discrete space created by a graph  $G = (V, E)$ , in which a set of vertices  $V$  are interconnected by pairs forming a set of edges  $E$  [22]. Therefore, once a target has been identified in the graph, e.g., the vertex  $w \in V$ , our task can be thought to be reduced to find the shortest topological path connecting our current location, e.g., the vertex  $v \in V$ , with the target. A path refers to a sequence of different vertices and edges between two corresponding vertices. Among all existing paths between two vertices, the one having the minimum length, in terms of the number of edges in the path, is the shortest path. There are several algorithms for finding the

shortest path between two vertices in a graph [43, 82, 88]. The Bellman-Ford-Moore algorithm [4, 37, 67] allows to find the shortest paths from the source vertex to all other vertices in a graph in which edges can be weighted by positive numbers. The algorithm has a time complexity of  $O(V \cdot E)$ , which because  $\#E \geq \#V - 1$  in connected graphs makes the complexity relatively large, i.e., in general larger than  $O(V^2)$ . The most popular algorithm for finding shortest paths is the Dijkstra [18] which finds the shortest paths from the source vertex to all other vertices in the graph with time complexity  $O(V^2)$ . Finally, the Floyd-Warshall algorithm [36, 83] finds the shortest paths between all pairs of vertices in a graph in  $O(V^3)$  allowing weights in the edges, which can be positive or negative.

Let us now see the target problem from the perspective of a single vertex in a network representation of a complex system [25]. Think for instance about a neuron which is interconnected to others in a human brain composed by about  $10^{10}$  neuronal cells and  $10^{14}$  interconnections [55]. Can this single neuron find the shortest path to a target neuron in this network? If the neuron is going to use a routing/navigation process to find the shortest path to a specific target it needs to have a “global knowledge about the network topology” [45]. This is exactly what the previously mentioned algorithms use: global information about the network. It is hard to digest that a every single neuron has a map of the 86 billion neurons in the brain. In spite of this, there are authors that believe that [58] “the shortest path plays an important role in the information transmission of a brain network, and it is a very important measure to describe the internal structure of the brain network”. The claim is mainly based on the apparent fact that “the shortest path can transmit the information more quickly and reduce brain consumption.” For such a thing to be possible it is necessary the existence of a central controller with “global knowledge about the network topology” [45] to direct the information through the shortest paths connecting pairs of brain regions. But even in this “mystical” scenario, the use of the shortest path could be inefficient from an energetic point of view. Tomasi et al. [80] have found experimentally that “a higher degree of connectivity was associated with nonlinear increases in metabolism”. That is, the more connected a vertex is, the highest its energy consumption. It is evident that a highly connected vertex supports many shortest paths crossing it—a vertex of degree  $k$  supports  $k(k-1)/2$  shortest paths of length two between its nearest neighbors, apart from the rest. Therefore, it is not true that the use of shortest paths “reduces brain consumption” as claimed in [58].

How is then possible that information finds its way from a specific source to a specific target in such complex networked environments like a human brain? Diffusion may be a plausible solution. At the end, a diffusive process can transmit information between a source and a target without any “knowledge about global network topology” [45]. This strategy will also avoid the problem of increasing glucose consumption because it “prevents particles or messages from taking shortest paths” [45]. Diffusion is ubiquitous in nature and in many man-made systems, even in those in which it seems to be counterintuitive [62]. For instance, when navigating a city at rush hour, drivers in general know the shortest topological paths between origin-target pairs. However, it has been seen statistically that they frequently avoid such paths for several reasons [2]. The first is that such routes contain, with high probability, highly interconnected intersections. Therefore, traveling through shortest topological paths necessarily would imply more complicated maneuvers and more waiting time due to traffic signals, jams, etc. In navigating between origin-target pairs, drivers frequently use their own “cognitive maps”, which allow them “establishing locations, understanding distances between

locations, comprehending the direction of one location from another, linking locations in sequence, and transferring knowledge from the mental arena to the surrounding physical environment” [44]. We can think that every driver in the same city has his own cognitive map to go from one place to another, particularly at rush hour. Indeed, Golledge and Gärling [44] have found in travel-related literature more than 20 different strategies used by drivers to find their routes. Their search include reports in fields such as travel behavior, operations research, transport geography, and behavioral travel modeling. Such mental algorithms include strategies like: using the “longest leg first”, or using the “shortest leg first”, selecting the route that has “fewest turns”, or “fewest lights or stop signs”, or “fewest obstacles or obstructions”, etc. If we assign randomly and independently these algorithms to the drivers in a city at rush hour, what we will observe are patterns similar to those of a diffusive motion [2, 53, 87].

When we talk about diffusion we typically talk about a series of different physical phenomena, which include classical conservative diffusion, non-conservative diffusion, and anomalous diffusion (sub- and superdiffusion) [14, 41, 52, 56, 74]. By conservative we mean that the amount of diffusive particles is constant in the graph, while in a non-conservative diffusion such number of diffusive particles can change with time. The reason for the last is that some particles are created/annihilated in the graph, maybe because they escape to the environment in which this graph lives. Here, we study the similarities and differences between conservative and non-conservative diffusion on graphs. We discover here that the non-conservative diffusive strategy present certain advantages for a single vertex in a network to send information to a target in a faster way relative to the conservative one. The main reason behind this advantage of non-conservative diffusion over the conservative one resides in the trajectories that diffusive particles follow in both processes. These trajectories are found here by means of a geometrization of the graphs using the Euclidean distances induced by the diffusive processes. We found here that non-conservative diffusive particles follow trajectories involving low-connected vertices, which coincide with the bypasses recently found to play an important role in complex networks navigation [27], while the conservative ones can follow trajectories more similar to those of the shortest topological paths. We finalize this chapter with some examples of complex systems in which such non-conservative diffusive strategies are used.

## 2 The setting

Here we only consider simple, undirected and unweighted graphs  $G = (V, E)$ , where  $V = \{v_1, \dots, v_n\}$  is the set of vertices with  $\#V = n$ , and  $E = \{(v_i, v_j) \mid v_i, v_j \in V\}$  is the set of edges with  $\#E = m$ . We use indistinctly the terms graphs and networks to refer to  $G$ , although the term “network” is mainly reserved to the skeleton of complex systems in the real-world. The terms vertex and node are also used indistinctly.

A walk of length  $l$  in a graph is a sequence of (not necessarily different) vertices  $v_1, v_2, \dots, v_l, v_{l+1}$  such that for each  $i = 1, 2, \dots, l$  there is an edge from  $v_i$  to  $v_{i+1}$ . The walk is known as closed if  $v_{l+1} = v_1$ . If all the vertices and edges of the walk are different we say that it corresponds to a path. Among all the paths that connect a pair of vertices, the one having the minimum length is the shortest path. The shortest path between two vertices is a distance. A graph for which there is at least a path between every pair of vertices is said to be connected. We will consider here only connected graphs.

Two vertices are adjacent in the graph if they share a common edge. Then the square symmetric matrix  $A$ , whose entries are defined as

$$A_{i,j} = \begin{cases} 1 & (i,j) \in E \\ 0 & (i,j) \notin E, \end{cases} \quad (2.1)$$

represents the adjacency between pairs of vertices in the graph and it is known as the adjacency matrix.

The following is a very well-known result (see for instance [5]):

**Theorem 1** *Let  $G$  be a simple connected graph. Then,  $(A^l)_{ij}$  counts the number of walks of length  $l$  between the vertices  $i$  and  $j$ .*

The number of vertices adjacent to a vertex  $i$  is known as the degree of  $i$  and denoted by  $k_i$ . The diagonal matrix  $K$  of the degree of the vertices in  $G$  is known as the degree matrix. Then, the matrix  $L = K - A$  is defined as the graph Laplacian matrix of  $G$ , see further for a “first-principles” definition.

### 3 Normal diffusion

Let us consider a simple undirected graph as the one illustrated in Fig. 3.1 in which there is a “concentration” of a given “item” at the nodes at a time  $t = 0$ . At every edge  $(i, j)$  there will be a gradient  $u_i(0) - u_j(0)$  of concentrations. As time evolves, there is a “movement” of the “items” from high concentration to low concentration. Let us pick a vertex of  $G$ , let say  $A$  and analyze how the concentration of the items at this vertex changes in time. Because  $A$  is connected to  $B$  and to  $C$  we have that the change of concentration at  $A$  is proportionally to the sum of the gradients with both  $B$  and  $C$ :

$$\frac{dC_A(t)}{dt} = \gamma [(C_B(t) - C_A(t)) + (C_C(t) - C_A(t))], \quad (3.1)$$

where  $\gamma$  is a proportionality coefficient known as diffusivity or diffusion coefficient [41]. We can rearrange this equation for the node  $A$  as:

$$\frac{dC_A(t)}{dt} = \gamma [C_B(t) + C_C(t) - 2C_A(t)], \quad (3.2)$$

where  $C_B(t) + C_C(t)$  is the sum of the concentrations at the nearest neighbors of  $A$  and  $2C_A(t)$  is the concentration at  $A$  multiplied by the number of nearest neighbors it has, i.e., its degree. Let us hereafter consider  $\gamma = 1$ . Then, we can write generically the following equation:

$$\dot{C}_i(t) = \left( \sum_{(j,i) \in E} C_j(t) \right) - k_i C_i(t), \quad (3.3)$$

where  $k_i$  is the degree of vertex  $i$ .

Let us now defined the following.

**Definition 1** Let  $\mathcal{H} := \ell^2(V)$  be a Hilbert space and let  $f \in \mathcal{H}$  be a function. Then, the adjacency operator  $\mathcal{A}$  of  $G$  is defined as [60]:

$$(\mathcal{A}f)(v) := \sum_{(w,v) \in E} f(w). \quad (3.4)$$

Notice that if  $G$  is infinite but locally finite, i.e.,  $k_i < \infty$  for all vertices of  $G$ , the adjacency operator is a bounded selfadjoint operator in  $\mathcal{H}$  [60]. If the graph is finite the adjacency operator coincides with the adjacency matrix  $A$  of the graph.

**Definition 2** Let  $\mathcal{H} := \ell^2(V)$  be a Hilbert space and let  $f \in \mathcal{H}$  be a function. Then, the degree operator  $\mathcal{K}$  of  $G$  is defined as:

$$(\mathcal{K}f)(v) := k_v f(v). \quad (3.5)$$

If the graph is finite the degree operator is realized by the diagonal matrix  $K$  of vertices degrees of the graph.

Let  $\dot{C}(t) := [\dot{C}_{v_1}(t) \dots \dot{C}_{v_n}(t)]^T$  and let  $C(t) := [C_{v_1}(t) \dots C_{v_n}(t)]^T$ . Then, we can write the set of diffusion equations for all the vertices of the graph in the following matrix-vector form:

$$\begin{aligned} \dot{C}(t) &= AC(t) - KC(t) \\ &= (A - K)C(t) \\ &= -LC(t), \end{aligned} \quad (3.6)$$

where  $L := K - A$  is the Laplacian of the graph, which can be formally defined as:

**Definition 3** Let  $\mathcal{H} := \ell^2(V)$  be a Hilbert space and let  $f \in \mathcal{H}$  be a function. The Laplacian operator  $\mathcal{L}$  of  $G$  is defined as [47]:

$$(\mathcal{L}f)(v) := \sum_{(w,v) \in E} (f(w) - f(v)). \quad (3.7)$$

When the graph is finite, then  $L$  is the matrix representation of this operator.

We then have the diffusion equation of the graph as:

$$\dot{C}(t) = -LC(t) \quad (3.8)$$

where  $L := K - A$  is the graph Laplacian and  $K$  is a diagonal matrix of vertex degrees, and where the initial condition is  $C(0) = C_0$ .

### 3.1 Some properties of $L$

Here we state some of the general properties of the graph Laplacian matrix  $L$  (see [48, 49, 63, 66]).

**Definition 4** Let  $m$  be the number of edges and  $n$  be the number of vertices. Then the incidence matrix  $\nabla$  is the  $m \times n$  matrix given by:

$$\nabla_{v,e} = \begin{cases} -1 & e = (v, w) \text{ and } v > w \\ 1 & e = (v, w) \text{ and } v < w \\ 0 & \text{otherwise.} \end{cases} \quad (3.9)$$

**Lemma 1** *The Laplacian matrix of the graph  $L$  is given by*

$$L = \nabla^T \nabla, \quad (3.10)$$

*such that the incidence matrix can be considered as a gradient matrix of a graph where concentrations are arbitrarily but fixed at the nodes.*

The following resume some of the general properties of the Laplacian.

**Theorem 2** *The Laplacian matrix  $L$  of a graph:*

1. *is a positive semidefinite matrix, indeed  $f^T L f = \sum_{(v,w) \in E} (f(v) - f(w))^2 \geq 0$ ;*
2. *always has an eigenvalue equal to 0;*
3. *the multiplicity of the zero eigenvalue is equal to the number of connected components of the graph.*

### 3.2 Conservative nature of the graph diffusion

**Definition 5** A diffusion process is said to be conservative if the number of diffusive particles is constant along the time. That is, if and only if  $\mathbf{1}^T C(t_i) = \mathbf{1}^T C_0$  for any  $0 \leq t_i \leq \infty$ . Otherwise the process is said to be non-conservative

**Lemma 2** *The diffusion (3.8) on a connected graph is always conservative.*

*Proof* The solution of the diffusion equation is:

$$C(t) = e^{-tL} C_0. \quad (3.11)$$

Let us take the sum of the entries of  $C(t)$  at an arbitrary time  $t$ ,

$$\mathbf{1}^T C(t) = \mathbf{1}^T e^{-tL} C_0 \quad (3.12)$$

and let us expand the matrix exponential in its Taylor series

$$\mathbf{1}^T C(t) = \mathbf{1}^T C_0 - t \mathbf{1}^T L C_0 + \frac{t^2}{2!} \mathbf{1}^T L^2 C_0 + \dots + \left( \frac{(-1)^k t^k}{2!} \right) \mathbf{1}^T L^k C_0 + \dots \quad (3.13)$$

Because  $L$  is positive semidefinite, we have that  $\mathbf{1}^T L = 0$  and so  $(\mathbf{1}^T L) L^{k-1} = 0$ , so that  $\mathbf{1}^T C(t) = \mathbf{1}^T C_0$  for any  $t$ .  $\square$

In plane words, the previous result means that at any time  $t$  the sum of concentrations of particles at the nodes of the graph is exactly the same, independently of  $t$ .

Let us now see what is the steady state of the diffusive dynamics in a graph.

**Lemma 3** *Let  $C_0(i)$  be the state of the vertex  $i$  at time  $t = 0$ . Then, when  $t \rightarrow \infty$  the solution of the diffusion equation of the graph converges to  $C_t(i) = \frac{1}{n} \sum_{i=1}^n C_0(i)$ , i.e., to the average of the state of nodes in the initial condition. The rate of convergence of the diffusion is dictated by the smallest nontrivial eigenvalue of  $L$ .*

*Proof* Let  $0 = \mu_1 < \mu_2 \leq \dots \leq \mu_n$  be the eigenvalues of  $L$  and let  $\varphi_i$  the orthonormalized eigenvector associated with  $\mu_i$ . Then, we can write

$$\begin{aligned} C(t) &= e^{-tL} C_0 \\ &= \varphi_1 e^{-t\mu_1} \left( \varphi_1^T C_0 \right) + \varphi_2 e^{-t\mu_2} \left( \varphi_2^T C_0 \right) + \dots + \varphi_n e^{-t\mu_n} \left( \varphi_n^T C_0 \right). \end{aligned} \quad (3.14)$$

When  $t$  is sufficiently large we have

$$\begin{aligned} \lim_{t \rightarrow \infty} C(t) &= \varphi_1 e^{-t\mu_1} \left( \varphi_1^T C_0 \right) \\ &= \frac{1}{\sqrt{n}} \mathbf{1} \left( \frac{1}{\sqrt{n}} \mathbf{1}^T C_0 \right) \\ &= \mathbf{1} \left( \frac{1}{n} \sum_{i=1}^n C_0(i) \right), \end{aligned} \quad (3.15)$$

which proves the first part of the result. Because  $\mu_2$  is the second smallest eigenvalue of  $L$ , it will dictate the rate of convergence of the process.  $\square$

### 3.3 Intuition of the conservative diffusion on graphs

We start here by writing an iterative form of the diffusion dynamics on graphs in discrete-time:

$$C_i(r+1) = C_i(r) - \varepsilon C_i(r) k_i + \varepsilon \sum_{(j,i) \in E} C_j(r). \quad (3.16)$$

If we introduce the following matrix  $P := I - \varepsilon L$ , which was proposed to be called the Perron matrix by Olfati-Saber et al. [69], we can write the discrete-time diffusion dynamics as:

$$C(r+1) = PC(r). \quad (3.17)$$

This formulation allows us to interpret what is happening in the diffusive process on a graph in a step-by-step basis. That is, if the ‘‘concentration’’ of an item at the vertex  $i$  at time step  $r$  is equal  $C_i(r)$ , then the node  $i$  will transfer the amount  $\varepsilon C_i$  to every of its nearest neighbors at time step  $r+1$ , at the same time that it will receive  $\varepsilon C_j(r)$  from every of its  $j$ th nearest neighbors. This means that at every time step there is a trade off in which pairs of connected vertices interchange concentrations between each other, but such a process goes in the direction of lower concentration.

Let us explain this with an example based on the graph illustrated in Fig. 3.1. Let us consider the following initial condition:  $C_0 = [3, 2, 5, 4, 1]^T$ . That is, the vertex  $A$ , which is connected to vertices  $B$  and  $C$ , has an initial concentration of  $C_A(0) = 3$ . At the next time step,  $r = 1$ ,  $A$  will transfer to  $B$  the amount  $\varepsilon C_A(0) = 3\varepsilon$  and will receive from  $B$  the amount  $\varepsilon C_B(0) = 2\varepsilon$ . This means that the net balance of  $A$  for its trade off with  $B$  is:  $C_{A=B}(1) = -3\varepsilon + 2\varepsilon = -\varepsilon$ , which implies that  $A$  has transferred more to  $B$  than what it has received from that vertex. If we do the same analysis for the trade off between  $A$  and  $C$ , which has initial concentration 5, we have:



$C_{A=C}(1) = -3\varepsilon + 5\varepsilon = 2\varepsilon$ , clearly indicating that  $A$  receives more from  $C$  than what it transfers to that node. Because  $A$  is connected only to  $B$  and  $C$ , we have:  $C_A(1) = C_A(0) + C_{A=B}(1) + C_{A=C}(1) = 3 - \varepsilon + 2\varepsilon = 3 + \varepsilon$ , indicating that in the first step  $A$  increases its concentration in spite of the fact that it has transferred more to  $B$  than what it has received from it, but such a loss is compensated by the gains from  $C$  which has a high initial concentration. The process continues with these “negotiations” of concentrations between pairs of connected vertices so that the steady state is eventually reached as illustrated in Fig. 3.1. This kind of negotiation is the main reason why this process is known in engineering as the “consensus protocol” (see for instance [64]).

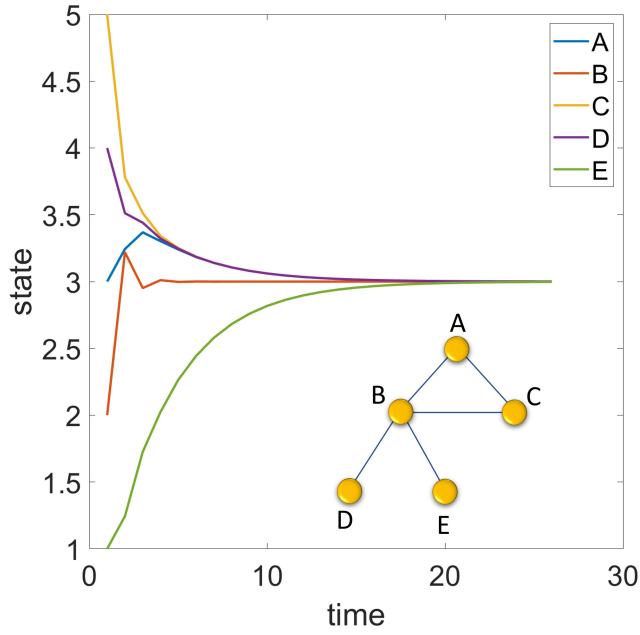


Fig. 3.1

#### 4 Non-conservative diffusion

Let us consider the following matrix:  $\mathcal{L}_\chi := \chi I - A$ , which was first analyzed in [39] (see also [40]) and I therefore propose here to call it the Lerman-Ghosh Laplacian of a graph. Let us then consider the following diffusive process

$$\dot{C}(t) = -(\chi I - A)C(t) = -\mathcal{L}_\chi C(t). \quad (4.1)$$

At the local level, the concentration of items at a vertex  $i$  at time  $t$  is given by

$$\dot{C}_i(t) = \left( \sum_{(i,j) \in E} C_j(t) \right) - \chi C_i(t). \quad (4.2)$$

We now analyze the solution of this dynamics.

**Theorem 3** *Let  $\mathcal{L}_\chi = \chi I - A$  be the Lerman-Ghosh Laplacian and let*

$$\dot{C}(t) = -\mathcal{L}_\chi C(t) \quad (4.3)$$

*with initial condition  $C(t) = C_0$ . Then,*

$$\lim_{t \rightarrow \infty} C(t) = \begin{cases} \left( \psi_1^T C_0 \right) \psi_1 e^{t(\lambda_1 - \chi)} = \infty \text{ for } \chi < \lambda_1 \\ \left( \sum_j C_0(j) \psi_1(j) \right) \psi_1 \text{ for } \chi = \lambda_1 \\ \left( \psi_1^T C_0 \right) \psi_1 e^{-t(\chi - \lambda_1)} = 0 \text{ for } \chi > \lambda_1. \end{cases} \quad (4.4)$$

*Proof* The solution of the diffusion equation is given by

$$C(t) = e^{-t(\chi I - A)} C_0, \quad (4.5)$$

which can be written as

$$C(t) = e^{t(\lambda_1 - \chi)} \left( \psi_1^T C_0 \right) \psi_1 + e^{t(\lambda_2 - \chi)} \left( \psi_2^T C_0 \right) \psi_2 + \dots + e^{t(\lambda_n - \chi)} \left( \psi_n^T C_0 \right) \psi_n. \quad (4.6)$$

Then, when  $\chi < \lambda_1$  we have

$$\lim_{t \rightarrow \infty} C(t) = e^{t(\lambda_1 - \chi)} \left( \psi_1^T C_0 \right) \psi_1, \quad (4.7)$$

which diverges as  $t \rightarrow \infty$ .

If  $\chi = \lambda_1$  we have that the first term of Eq. (4.6) is zero, and the rest are negative, such that

$$\lim_{t \rightarrow \infty} C(t) = \left( \psi_1^T C_0 \right) \psi_1, \quad (4.8)$$

which indicates that the solution is proportional to the entries of the eigenvector associated with the spectral radius of  $A$ . Because the second smallest eigenvalue of  $(\lambda_1 I - A)$  is  $\lambda_1 - \lambda_2$ , it determines the rate of convergence of the diffusive process. Notice that if  $C_0 = \psi_1$ , then the diffusion process is conservative because:

$$\mathbf{1}^T C(t) = \left[ \mathbf{1}^T \psi_1 \right] = \mathbf{1}^T C_0. \quad (4.9)$$

Finally, if  $\chi > \lambda_1$  then,

$$\lim_{t \rightarrow \infty} C(t) = e^{-t(\chi - \lambda_1)} \left( \psi_1^T C_0 \right) \psi_1, \quad (4.10)$$

which goes to zero as  $t \rightarrow \infty$ .  $\square$

**Corollary 1** *Let  $G$  be a regular graph. Then, the diffusion model (4.1) with  $\chi = \lambda_1$  is conservative for any initial condition, where  $\lim_{t \rightarrow \infty} C(i) = \frac{1}{n} \sum_j C_0(j)$  for all  $j \in V$ . If the graph is not regular and  $C_0 \neq \psi_1$  then the process is non-conservative and  $0 < C(t) < C_0 < \infty$ .*

*Remark 1* The diffusion process (4.1) is non-conservative for all values of  $\chi$  and initial conditions  $C_0$ , except for the specific case in which  $\chi = \lambda_1$  and  $C_0 = \psi_1$ .

In Fig. 4.1 we illustrate the three examples of non-conservative diffusion modeled by Eq. (4.1) using the Lerman-Ghosh Laplacian for the graph and initial condition of the Fig. 3.1 with  $\chi < \lambda_1$  (a),  $\chi = \lambda_1$  (b) and  $\chi > \lambda_1$  (c). Notice that when  $\chi = \lambda_1$  and  $C_0 \neq \psi_1$  the process can be said to be quasi-conservative as the number of particles when  $t \rightarrow \infty$  is just a bit smaller than at  $t = 0$ .

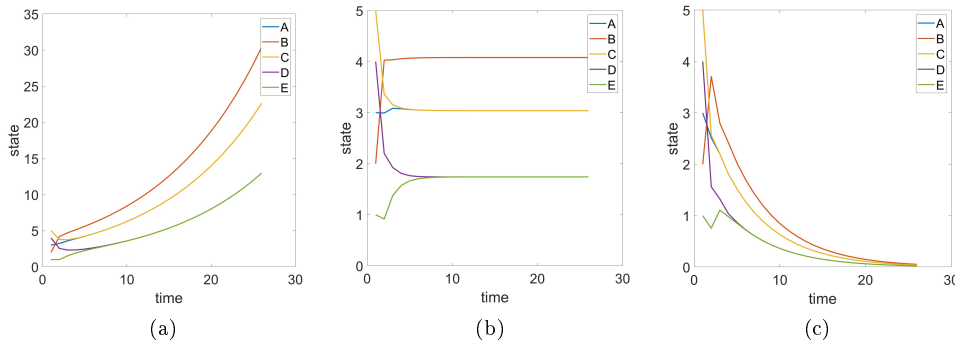


Fig. 4.1: Illustration of the non-conservative diffusion process on the graph illustrated in Fig. 3.1 for  $\chi < \lambda_1$  (a),  $\chi = \lambda_1$  (b) and  $\chi > \lambda_1$  (c).

#### 4.1 On the intuition of the non-conservative diffusion

In the discrete time setting the Eq. (4.1) indicates that the resulting concentration at every vertex of the graph at the discrete time step  $r + 1$  is given by

$$C_i(r+1) = C_i(r) - \varepsilon\chi C_i(r) + \varepsilon \sum_{(j,i) \in E} C_j(r). \quad (4.11)$$

If we introduce the following matrix  $Q := I - \varepsilon(\chi I - A) = (1 - \varepsilon\chi)I + A$ , then we can write the discrete-time diffusion dynamics as:

$$C(r+1) = QC(r). \quad (4.12)$$

In order to gain intuition on what is happening let us start by considering that a graph is submerged into a given reservoir in which there could be an infinite reserve of the item to be diffused across the graph. Every vertex of the graph is connected to the reservoir by mean of a semi-edge, which has one endpoint at the vertex and the

other one is freely dangling in the reservoir. We then consider a two-steps diffusion process as follows. First every vertex  $i$  expels  $\varepsilon\chi C_i(r)$  to the reservoir, where  $\chi$  is a constant such that  $\varepsilon\chi \leq \max_i C_0(i)$  to guarantee that no vertex is left with a negative concentration. This first step creates a pool of the item being diffused in the reservoir (in case it exists). In the second step of the process every vertex sucks from the reservoir an amount equal to  $\varepsilon \sum_{(j,i) \in E} C_j(r)$ .

For instance, let us consider the graph of Fig. 3.1, which has  $\lambda_1 \approx 2.343$ , and let us use  $\chi = 3$  and  $\varepsilon = 0.25$  as before. Then, vertex  $A$  expels  $\varepsilon\chi C_A(0) = 2.25$  of its initial concentration to the reservoir. The amounts expelled by the other vertices are: 1.5; 3.75; 3.0; 0.75. In total, the vertices have expelled 11.25 of its initial total concentrations that sum 15. At every vertex remains concentrations equal to: 0.75; 0.50; 1.25; 1.0; 0.25, respectively, as can be seen in Fig. 4.2(a). In the second step, the vertex  $A$  has to suck  $\varepsilon \sum_{(j,A) \in E} C_j(0) = 1.75$ , while the others will suck: 3.25; 1.25; 0.50; 0.50; respectively, for a total of 7.25. This amount to be sucked from the reservoir is smaller than the one expelled previously to it. Therefore, in the reservoir it will remain  $11.25 - 7.25 = 4$  and the sum of the concentrations at the nodes will be 11 instead of the 15 that there was initially. This is illustrated in Fig. 4.2(b). The repetition of this process makes that the vertices get empty as time evolves because in every time step there are more “items” deposited in the reservoir than the ones extracted from it. Notice that in this case the reservoir at  $t = 0$  may be empty.

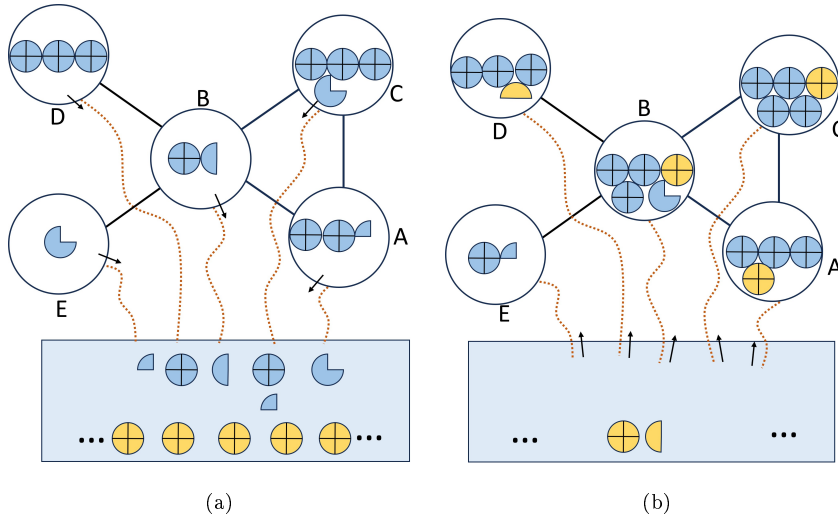


Fig. 4.2: Schematic representation of the non-conservative diffusive process when  $\chi > \lambda_1$ .

If  $\chi < \lambda_1$  the amount  $\varepsilon\chi C_i(r)$  expelled by the vertices to the reservoir is smaller than the amount  $\varepsilon \sum_{(j,i) \in E} C_j(r)$  that the vertex has to suck from the reservoir. For instance if we use  $\chi = 1$ , the vertices will expel in total 3.75 to the reservoir as illustrated in Fig. 4.3(a). However, the vertices have to extract 7.25 from the reservoir,

which means they will take the 3.75 previously expelled plus 3.5 from the reserve in the reservoir. Here the total amount at the vertices at  $t = 1$  is 19 (see Fig. 4.3(b)) instead of the amount equal to 15 which existed at  $t = 0$ . The consequence of the repetition of this process is that the concentrations at the vertices grow to infinity as time evolves due to the fact that vertices extract “items” from the reservoir.

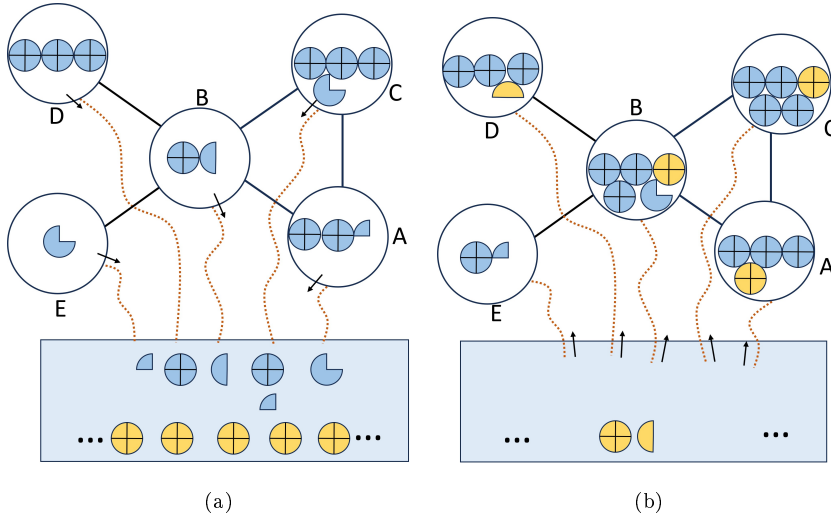


Fig. 4.3: Schematic representation of the non-conservative diffusive process when  $\chi < \lambda_1$ .

#### 4.1.1 Avoiding the blow-up

It is certainly weird to think about a non-conservative process in which the concentration at the vertices of a complex system grows to infinity with time. To avoid this unrealistic situation we introduce here the following reaction-diffusion equation:

$$\dot{C}(t) = -\mathcal{L}_\chi C(t) + \alpha C(t) \left(1 - \frac{C(t)}{\mathcal{C}}\right), \quad (4.13)$$

where the new term on the right-hand side of the equation models the reproduction of the items at nodes. That is, we allow that the vertices create or annihilate items as to avoid that their concentrations go to zero or to infinity. Here,  $\alpha$  is the growth rate and  $\mathcal{C}$  is the carrying capacity. This equation is a version of the Fisher equation [35] for a graph in which the Lerman-Ghosh Laplacian is used instead of the standard Laplacian one. The reproduction term in the Fisher equation—also known as the Kolmogorov–Petrovsky–Piskunov equation [54] (see also [19])—represents the linear growth of the particle population in proportion to its current size, and the negative quadratic one has the effect of curtailing the items population growth. Hereafter, we will call this model the non-conservative graph Fisher–Kolmogorov–Petrovsky–Piskunov equation.

Although we do not study this equation in details in this Chapter, we provide some examples on how changing the values of the growth rate changes the behavior of the system showing different steady states even for a simple graph as the one depicted in Fig. 3.1. As can be seen in Fig. 4.4 the system can behave in an oscillatory way (panels b and c) and in all cases the solution is non-conservative, but stable, i.e., there is not blow-up.

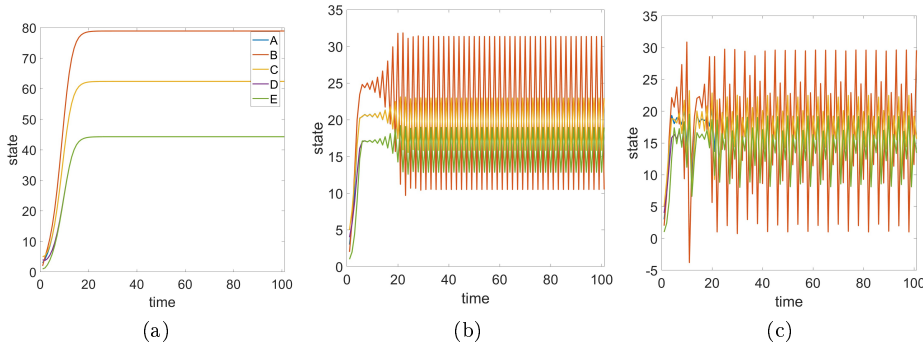


Fig. 4.4: Illustration of the time evolution of the Fisher–Kolmogorov–Petrovsky–Piskunov equation on the graph and initial condition illustrated in Fig. 3.1 using the following parameters:  $\mathcal{C} = 15$  and  $\alpha = 0.1$  (a),  $\alpha = 0.8$  (b) and  $\alpha = 1.2$  (c).

## 5 Sending “information” to a target

In order to compare the two diffusion processes considered here, conservative and non-conservative ones, we select a graph formed by two cliques, which are interconnected by a path. This kind of graphs are known as dumbbell graphs and they are a good example of a difficult networked environment in which a particle in one of the cliques have to diffuse to find a target in the other clique. While it is relatively easy for a diffusive particle to navigate one of the cliques, it is more difficult to find the only path communicating the two cliques to move to the other. The dumbbell graph built here has 10 vertices in each clique and 10 vertices in the path connecting them. In Fig. 5.1(a) we illustrate the temporal evolution of the conservative diffusion of a particle initially located in a clique vertex different from the one connecting the clique to the path. For the sake of comparison we illustrate in Fig. 5.1(b) the same process in a random graph having the same number of vertices and edges as the dumbbell one. That is, this is a graph in which the difficulties inherent to the structure of the dumbbell graph have been changed by an environment in which the particle can navigate in an easier way, although having the same number of vertices and edges. As can be seen in Fig. 5.1 the conservative diffusion takes about 100 times more steps to reach the steady state in the dumbbell graph than in its random analogous.

Let us now consider what happens with the non-conservative diffusion. To consider a process in which a steady state is reached we will use the non-conservative Fisher–Kolmogorov–Petrovsky–Piskunov equation on graphs which has been defined here. It

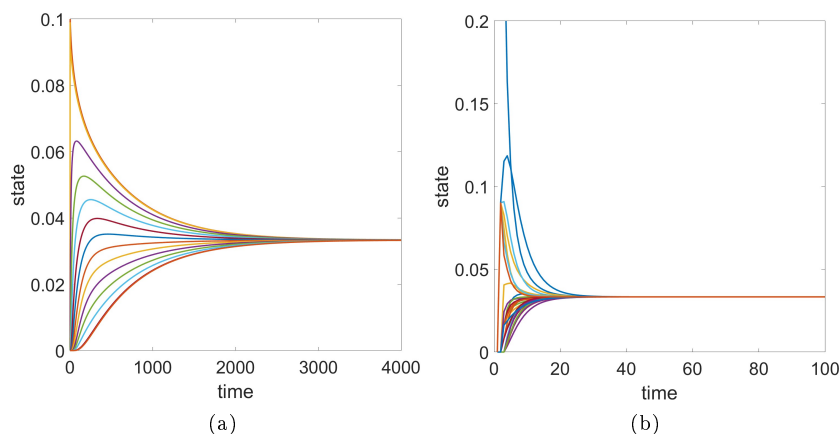


Fig. 5.1: Time evolution of conservative diffusion dynamics on a dumbbell graph (a) with two cliques of 10 vertices interconnected by a linear chain of 10 vertices, and in the random graph (b)–of the Erdős-Rényi type– having the same number of vertices and edges like the graph in (a).

is remarkably to notice that the non-conservative diffusion only takes two times more steps to reach the steady state in the dumbbell graphs than in its random analogous. This is illustrated in Fig. 5.2 where, by comparison with Fig. 5.1. If we compare this non-conservative process with the conservative one in the dumbbell graph we observe that the first is more than 50 times faster than the second one.

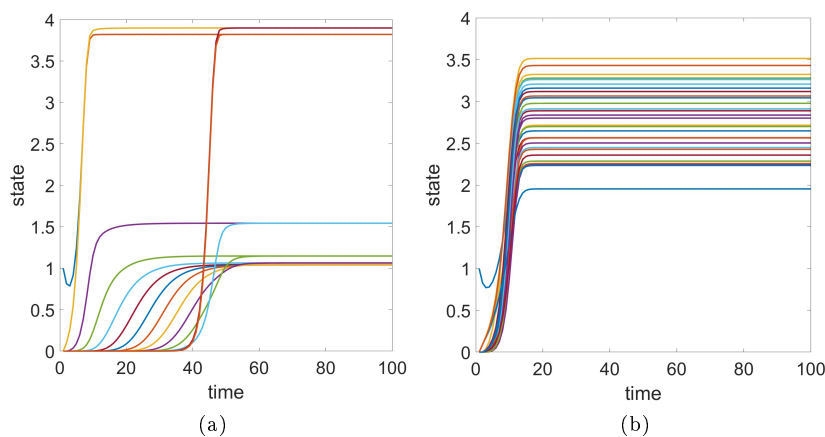


Fig. 5.2: Time evolution of non-conservative Fisher-Kolmogorov-Petrovsky-Piskunov diffusion dynamics on a dumbbell graph (a) with two cliques of 10 vertices interconnected by a linear chain of 10 vertices, and in the random graph (b)–of the Erdős-Rényi type– having the same number of vertices and edges like the graph in (a).

A distinctive characteristic of the non-conservative models defined with the use of the Lerman-Ghosh Laplacian relative to the standard diffusion equation is the following. In the steady state of the conservative diffusion, all the vertices have exactly the same concentration, which as we have proved before, is equal to the mean of their initial concentrations. Contrastingly, in the non-conservative diffusion processes studied here the steady state is proportional to the eigenvector associated with the spectral radius of  $A$ :  $C(t \rightarrow \infty) \sim \psi_1$ . This eigenvector was introduced by Bonacich [6–8] as a centrality index of the vertices in a graph and it is nowadays known as the eigenvector centrality. Therefore, the current framework provides a dynamics interpretation of this centrality index in term of the concentration reached by a vertex at the steady state of a non-conservative diffusion controlled by the Lerman-Ghosh Laplacian matrix.

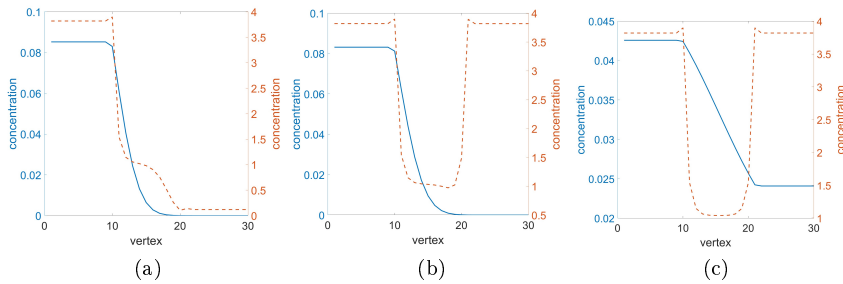


Fig. 5.3: Time evolution of the conservative (blue solid line) and non-conservative Fisher–Kolmogorov–Petrovsky–Piskunov diffusion dynamics (red broken line) on a dumbbell graph with two cliques of 10 vertices interconnected by a linear chain of 10 vertices at three different times: (a)  $t = 40$ ; (b)  $t = 50$  and (c)  $t = 1000$ .

## 6 Trajectories of “items” to a target

Both the conservative classical diffusion model and the non-conservative one studied here have solutions in which the term depending on the structure of the network is:  $\exp(\beta M)$ , where  $\beta$  is a parameter usually depending on time and diffusivity coefficient and where  $M = \{-L, A\}$ . Hereafter we will consider only the case  $\beta = 1$  for the sake of simplicity. Let us focus on a couple of vertices designated by  $u$  and  $v$ . Then, at a given time the concentration at these nodes are:

$$C_u(t) = \sum_j (\exp(M))_{uj} C_j(0) \quad (6.1)$$

and

$$C_v(t) = \sum_j (\exp(M))_{vj} C_j(0). \quad (6.2)$$

Then, let  $\mathcal{F}_{uv} = C_u(t) - C_v(t)$  be the diffusive flow from  $u$  to  $v$  in a graph when the initial concentration is totally located at the vertex  $u$ ,  $C_0 = \delta_{u,j}$  and let the same



be in the other direction when the initial concentration is completely located at the vertex  $v$ ,  $\mathcal{F}_{vu} = C_v(t) - C_u(t)$  when  $C_0 = \delta_{u,j}$ . Then, we have that

$$\mathcal{F}_{uv} = [(\exp(M))_{uu} - (\exp(M))_{uv}] C_u(0), \quad (6.3)$$

and

$$\mathcal{F}_{vu} = [(\exp(M))_{vv} - (\exp(M))_{vu}] C_v(0). \quad (6.4)$$

For the sake of simplicity we consider  $C_u(0) = 1$  in the first case and  $C_v(0) = 1$  in the second one.

### 6.1 Inducing a geometric embedding

**Definition 6** Let  $\mathcal{F}_{uv}$  and  $\mathcal{F}_{vu}$  as defined previously. Then, let us define the sum of the flows between the two nodes in both directions, which is given by:

$$\mathcal{D}_{uv}(M) := \mathcal{F}_{uv} + \mathcal{F}_{vu} = (\exp(M))_{uu} + (\exp(M))_{vv} - 2(\exp(M))_{uv}. \quad (6.5)$$

We then have the following result [20, 46, 71].

**Proposition 1**  $\mathcal{D}_{uv}(M)$  is a squared Euclidean distance between the pairs of vertices  $u$  and  $v$ .

*Proof* Let us consider that  $M = U^T \Lambda U$  where  $\Lambda$  is a diagonal matrix of eigenvalues of  $M$  and  $U$  is an orthogonal matrix of eigenvectors. Then, if  $\varphi_i$  is the  $i$ th column of  $U^T$ , we have

$$\begin{aligned} \mathcal{D}_{uv}(M) &= (\varphi_u - \varphi_v)^T e^\Lambda (\varphi_u - \varphi_v) \\ &= \left( e^{\beta\Lambda/2} \varphi_u - e^{\Lambda/2} \varphi_v \right)^T \left( e^{\Lambda/2} \varphi_u - e^{\beta\Lambda/2} \varphi_v \right) \\ &= (x_u - x_v)^T (x_u - x_v) \\ &= \|x_u - x_v\|^2. \end{aligned} \quad (6.6)$$

□

**Definition 7** Let  $s = \text{diag}(e^M)$ . Then, we define the diffusion Euclidean Distance Matrix (EDM) as the matrix

$$\mathcal{M} = s\mathbf{1}^T + \mathbf{1}s^T - 2e^M. \quad (6.7)$$

An EDM is called [3, 51, 57, 77] spherical EDM or circum-EDM if the points  $p^1, p^2, \dots, p^n$  that generate the EDM lie on a hypersphere.

**Proposition 2**  $\mathcal{M}$  is a circum-Euclidean distance matrix.

*Proof* We follow Gower [?] who proved that the points that generate the matrix  $M$  lie on the surface of a hypersphere if and only if  $\mathbf{1}^T M^{-1} \mathbf{1} \neq 0$ . Thus, we have to prove that  $M^{-1}$  exists. We first use the Sherman-Morrison-Woodbury formula (see p. 50 in [42]) to have

$$\begin{aligned}
\mathcal{M}^{-1} &= \left( (-2e^M + \mathbf{1}s^T) + s\mathbf{1}^T \right)^{-1} \\
&= -\frac{1}{2}e^{-M} - \frac{\left( e^{-M} \mathbf{1}s^T e^{-M} \right)}{4 - 2s^T e^{-M} \mathbf{1}} - \frac{\left( -\frac{1}{2}e^{-A} - \frac{\left( e^{-M} \mathbf{1}s^T e^{-M} \right)}{4 - 2s^T e^{-M} \mathbf{1}} \right) s\mathbf{1}^T \left( -\frac{1}{2}e^{-M} - \frac{\left( e^{-M} \mathbf{1}s^T e^{-M} \right)}{4 - 2s^T e^{-M} \mathbf{1}} \right)}{1 + \mathbf{1}^T \left( -\frac{1}{2}e^{-M} - \frac{\left( e^{-M} \mathbf{1}s^T e^{-M} \right)}{4 - 2s^T e^{-M} \mathbf{1}} \right) s} \\
&= -\frac{1}{2}e^{-M} - \frac{ab}{4 - 2\varepsilon} - \frac{\left( -\frac{1}{2}b^T - \frac{ac}{4 - 2\varepsilon} \right) \left( -\frac{1}{2}a^T - \frac{db}{4 - 2\varepsilon} \right)}{1 + \left( -\frac{1}{2}\varepsilon - \frac{dc}{4 - 2\varepsilon} \right)},
\end{aligned} \tag{6.8}$$

from which we get

$$\mathcal{M}^{-1} = -\frac{1}{2}e^{-A} + \frac{caa^T - (\varepsilon - 2)b^T a^T - (\varepsilon - 2)ab + db^T b}{2(cd - (\varepsilon - 2)^2)}, \tag{6.9}$$

where  $a = e^{-A}\mathbf{1}$ ,  $b = s^T e^{-M}$ ,  $c = s^T e^{-M} s$ ,  $d = \mathbf{1}^T e^{-M} \mathbf{1}$ , and  $\varepsilon = s^T e^{-M} \mathbf{1}$ . We still need to prove that the denominator is not zero:  $cd - (\varepsilon - 2)^2 \neq 0$ . It is easy to see that  $c \geq \varepsilon$ , with equality if and only if  $s = \mathbf{1}$  which only happen if the graph is trivial, which is excluded here as the graphs are connected. Therefore,

$$-\varepsilon^2 + cd + 4\varepsilon - 4 > -\varepsilon^2 + (d + 4)\varepsilon - 4 > 0, \tag{6.10}$$

where the last inequality is obvious from the roots of the quadratic equation.

We now obtain  $\mathbf{1}^T \mathcal{M}^{-1} \mathbf{1}$ , as

$$\mathbf{1}^T \mathcal{M}^{-1} \mathbf{1} = -\frac{1}{2}d - \frac{d\varepsilon}{4 - 2\varepsilon} - \frac{\left( -\frac{1}{2}\varepsilon - \frac{dc}{4 - 2\varepsilon} \right) \left( -\frac{1}{2}d - \frac{d\varepsilon}{4 - 2\varepsilon} \right)}{1 + \left( -\frac{1}{2}\varepsilon - \frac{dc}{4 - 2\varepsilon} \right)} \tag{6.11}$$

$$= \frac{2d}{cd - (\varepsilon - 2)^2}. \tag{6.12}$$

Because  $d = \mathbf{1}^T e^{-M} \mathbf{1}$  is the sum of all the entries of  $e^{-M}$  and  $M \neq 0$  (because the graph is not trivial), we have that  $d > 0$  and because we have proved before that  $cd - (\varepsilon - 2)^2 > 0$ , we have proved that  $\mathcal{M}$  is a nonsingular spherical EDM.  $\square$

*Remark 2* For properties of the circum-EDM  $\mathcal{M}$  when  $M = A$ , the reader is referred to [24, 30, 32]. For analysis of the circum-EDM  $\mathcal{M}$  when  $M = L$ , the following is recommended [13, 72].

## 6.2 Diffusive trajectories

In order to analyze the trajectories of the diffusive particles in a graph we need to convert the distances generated in the previous section into geodesics which can be traversed by these particles. That is, we need a geometrization of the graph. A graph is geometrized if we consider every edge  $e = uv$  in  $E$  as a compact 1-dimensional manifold with boundary  $\partial e = u \cup v$ . We then assign to  $e = uv$  the metric  $\mathbb{L}_{uv}(M)$ , such that,  $\tilde{e}_{uv}(M) \cong [0, \mathcal{D}_{uv}(M)]$  if  $e \in E$  or zero otherwise. In this way we transform the network into a space which is locally compact, complete and geodetic [12, 61].

Technically, what we need is to create the corresponding distance matrix  $\mathcal{D}(M)$  and then multiply it in an entrywise way by  $A$ , creating a weighted adjacency matrix  $W$  in which every weight corresponds to the length of the corresponding edge. We now can obtain the weighted shortest paths (SP) connecting every pair of vertices. While the unweighted shortest paths correspond to the topological ones, those based on  $\mathcal{D}(-L)$  correspond to the conservative diffusive SP and the ones based on  $\mathcal{D}(A)$  are the non-conservative diffusive SP, also known as communicability SP.

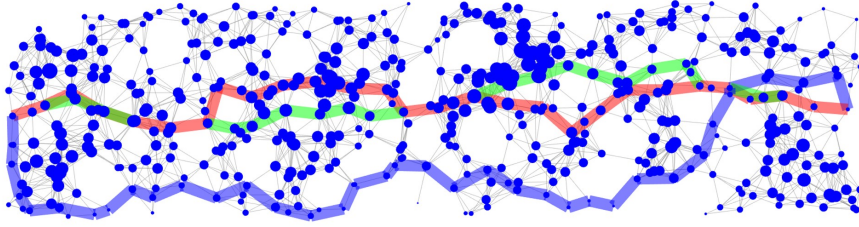


Fig. 6.1: Illustration of the diffusive paths between two vertices in a random rectangular graph. Blue: shortest non-conservative path; Red: shortest conservative path; Green: shortest topological path.

To understand the differences between the conservative and non-conservative diffusion trajectories let us first consider the non-conservative case. The non-conservative diffusion trajectory between two vertices corresponds to the path with the minimum sum of the corresponding distances  $\mathcal{D}_{uv}(A)$  along the path. The distance between individual pairs of vertices can be written as

$$\begin{aligned} \mathcal{D}_{uv}(A) &= e^{\lambda_1} (\psi_{1u} - \psi_{1v})^2 + e^{\lambda_2} (\psi_{2u} - \psi_{2v})^2 + h.o. \\ &= e^{\lambda_1} (\psi_{1u}^2 + \psi_{1v}^2 - 2\psi_{1u}\psi_{1v}) + e^{\lambda_2} (\psi_{2u} - \psi_{2v})^2 + h.o. \\ &= e^{\lambda_1} (EC_u^2 + EC_v^2 - 2\psi_{1u}\psi_{1v}) + e^{\lambda_2} (\psi_{2u} - \psi_{2v})^2 + h.o., \end{aligned}$$

where  $EC_j$  indicates the eigenvector centrality of the corresponding vertex. Therefore, selecting the path that minimizes  $\mathcal{D}_{uv}(A)$  necessarily means a path that minimizes the eigenvector centralities of the vertices along the path. Let us now give a walk-based interpretation of the eigenvector centrality (see p. 25 on [15] and a proof in p.161 on [31]).

**Theorem 4** Let  $N_r(i)$  be the number of walks of length  $r$  starting at vertex  $i$ . Let

$$p_r(i) = \frac{N_r(i)}{\sum_j N_r(j)}, \quad (6.13)$$

be the  $i$ th element of the vector  $\mathbf{p}_r$ . Then, if  $G$  is not bipartite there is a scalar  $\alpha$  such that as  $r \rightarrow \infty$ ,  $\mathbf{p}_r \rightarrow \alpha\psi_1$ .

This result indicates that the eigenvector centrality of the vertex  $i$  can be interpreted as the probability of intercepting at this vertex an infinitely long walk among all the walks of such length traversing the graph.

On the case of the conservative diffusion the distance is expressed as:

$$\begin{aligned} \mathcal{D}_{uv}(-L) &= e^{-\mu_2} (\varphi_{2u} - \varphi_{2v})^2 + h.o. \\ &= e^{-\mu_2} (\varphi_{2u}^2 + \varphi_{2v}^2 - \varphi_{2u}\varphi_{2v}) + h.o., \end{aligned}$$

where  $\varphi_2$  is the Fiedler vector [33, 34]. The entries of the Fiedler vector may be positive or negative and the sign of this vector is frequently used to partitionate a graph into two communities. Therefore, large entries of  $\varphi_2$  correspond to vertices with a large number of neighbors in the same cluster. In fact, the entries of  $\varphi_2$  are positively contributed by the number of incluster neighbors that the vertex has, minus the number of its out-cluster neighbors. This indicates clearly that the Fiedler vector is not necessarily related to the degree of the vertices like in the case of the eigenvector centrality. For instance, in the graph illustrated in Fig. 6.2 the vertex with the largest degree has the same number of connections with vertices of one cluster (red vertices) than with those of the other (blue vertices). Therefore,  $\varphi_{2,i} = 0$  for this vertex. The vertices with the largest values of the Fiedler vector are those having only two connections, but they are both only connected with vertices in their same cluster. In [16] more details about the structural interpretation of the entries of the Fiedler vector and its role on spectral clustering are provided.

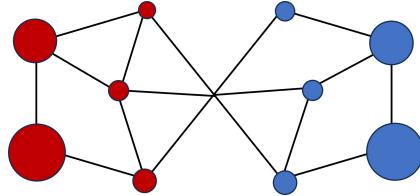


Fig. 6.2: Illustration of a simple graph having two clusters according to the sign of the Fiedler vector (vertices in red and vertices in blue). The size of the vertices is proportional to the square of the magnitude of the entries of the Fiedler vector.

In closing,  $\mathcal{D}_{uv}(A)$  avoids the vertices with the highest  $EC$ , implying that the shortest non-conservative diffusive paths traverse the graph by using relatively low degree (more precisely low cliquishness) vertices. For a blind navigator of the graph, these trajectories are easier to navigate than those having vertices with large degrees in which they have to decide which of the many routes ahead they have to select to

continue to the next step (see [27]). This may be the case of the shortest conservative diffusive paths where sometimes the vertices with the lowest entries of the Fiedler vector coincide with those of high degree, difficulting the blind navigation of the graph.

### 6.3 Where to find non-conservative diffusion in graphs

We have seen in this chapter that the non-conservative diffusion has some advantages relative to conservative diffusion for finding a target on a networked environment. Namely, the steady state in the non-conservative process is reached much faster than in the conservative one by tracing trajectories that avoids the potentially most connected vertices. Then, it is not surprising to find real-world systems in which non-conservative diffusion is present, some of which are described below.

The most intuitive of these examples is the one of traffic at rush hour that we have described in the Introduction. But, where the “non-conservative” part comes from? The number of cars departing from one intersection is not necessarily the same that arrives at the next one. The reason is that a few cars will end up their trajectory in the street leg between two intersections due to the existence of parking spaces in them. In a similar way some cars can emerge from these spaces, such that the number of cars can increase/decrease from one vertex to another.

A second illustrative example is the diffusive neurotransmission by means of chemical synapses in neuronal systems [68, 81]. Nowadays it is well-established that chemical synapses do not only take place by the wiring intercellular communication in which two neurons interchange neurotransmitters [1]. Apart from this conservative process, neurons and brain regions also communicate by means of a volume transmission (VT), which uses the extracellular fluid filling channels of the extracellular space (ECS) and the cerebrospinal fluid filling ventricular space and sub-arachnoidal space [1, 10, 38, 75, 76, 84, 85]. That is, some amounts of the neurotransmitters are spilled over to the ECS in the perisynaptic region and from there it can be retaken by other neurons, or they can even be transported by blood and/or cerebrospinal fluid to long distances where they can also be retaken. From the point of view of the network of neuronal or brain regions, the process is clearly non-conservative, although at the organ-level it is of course a conservative process.

A third example of networked non-conservative diffusion is the communication in social media [59, 70, 86] like Twitter or Facebook where an user can post a message which can be read by her followers, but also (if not constrained by the user) by non-followers, all of whom can propagate such information to others [78]. By constructing the network of followers, the propagation of information is non-conservative because part of the information goes out the network and some other information is subsequently received by the users from outside the network.

Other areas in which non-conservative diffusion on networks is present include, for instance, diffusive processes in ecology [9, 11, 73], diffusion of microplastics and other materials in the ocean [50] where the locations can be recorded by means of interconnected nodes, among others.

## 7 Conclusions

When referring to transmission principles in the brain, Tognoli and Scott-Kelso [79] stated that they “do not scale well upward from simple “channels” of synaptic interactions to the larger and more complex web of evolved brains. Thus, it is without surprise that the brain betrays an essential communicational etiquette: its parts do not behave in a sequential—one-talks-at-a-time—manner”. This statement can be extended to most complex systems where the sender of information does not necessarily know the global topology of the network in which it is embedded.

The lack of a sequential one-talks-at-a-time communication is a characteristic feature of diffusive processes in which the sender of information spreads it across all potential routes to find its target(s). We have seen here that even a conservative diffusive way in which one-talks-to-everybody is not the most efficient way of reaching potential targets in networked environments. The discovery presented here by first time that the non-conservative diffusion is more efficient in communicating a source and a target in a network is somehow surprising. On the light of this discovery it is then clear why some new ways of social communication, such as online social networks, are so efficient in spreading information. They certainly use non-conservative diffusive ways of finding their targets. However, we should not forget that this process may be more costly energetically than a conservative one, particularly when diffusive particles need to be constantly created at the nodes of the network.

The current work also opens new avenues that should be explored to better understand the ways in which source-to-target communication occurs in complex systems. For instance, anomalous diffusion on graphs described by means of the  $d$ -path Laplacians [21, 23, 28, 29] and its combination with fractional temporal derivatives [17], are all conservative processes. The extension of  $d$ -path Laplacians to  $d$ -path Lerman-Ghosh Laplacians seems to be a necessary extension of the current work. This will allow us to investigate, for instance, if the non-conservative anomalous diffusion is more efficient than its conservative analogous in finding a target on a graph. Similarly, the Lerman-Ghosh Laplacians can be used in degree-biased advection--diffusion models on undirected graphs/networks [65] to simulate realistic scenarios in complex systems. Another avenue is to investigate non-conservative diffusion in metaplexes [26], where not only the particles diffuse across a discrete space, but also in a continuous one existing inside the nodes. All in all, we hope this Chapter helps the reader in their particular “Target Problems” for understanding complex systems.

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