Network dynamics of innovation processes

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We introduce a model for the emergence of innovations, in which cognitive processes are described as random walks on the network of links among ideas or concepts, and an innovation corresponds to the first visit of a node. The transition matrix of the random walk depends on the network weights, while on turn the weight of an edge is reinforced by the passage of a walker. The presence of the network naturally accounts for the mechanism of the “adjacent possible”, and the model reproduces both the rate at which novelties emerge and the correlations among them observed empirically. We show this by using synthetic networks and by studying real data sets on the growth of knowledge in different scientific disciplines. Edge-reinforced random walks on complex topologies offer a new modeling framework for the dynamics of correlated novelties and are another example of co-evolution of processes and networks.

Creativity and innovation are the underlying forces driving the growth of our society and economy. Studying creative processes and understanding how new ideas emerge and how novelties can trigger further discoveries is therefore fundamental if we want to devise effective interventions to nurture the success and sustainable growth of our society. Recent empirical studies have investigated the emergence of novelties in a wide variety of different contexts, including science [1, 2], knowledge and information [3, 4], goods and products [5], language [6], and also gastronomy [7] and cinema [8]. In particular, the authors of Refs. [9–12] have looked at different types of temporally ordered sequences of data, such as sequences of words, songs, Wikipages and tags to study how the number $S(t)$ of novelties grows with the length of the sequence $t$. They have found that the Heaps’ law, i.e. a power law behaviour $S(t) \sim t^\beta$ originally introduced to describe the number of distinct words in a text document [13], applies to different contexts, producing different values of $\beta$. In parallel to the empirical analyses, various models have been proposed to reproduce the innovation dynamics in specific domains, such as the vocabulary growth and the writing process in linguistics [14, 15], or the emergence of collective knowledge in social systems [16] or in self-organized critically (SOC) mechanisms [17]. Other approaches have modeled the emergence of innovation as an evolutionary process, such as the Schumpeterian economic dynamics proposed by Thurner et al. [18] and the evolutionary game among innovators and developers proposed by Armano and Javarone [19]. Urn models are another successful framework which has been widely applied to study innovation processes in evolutionary biology, chemistry, sociology, economy and text analysis [20, 21]. In the classic Polya urn model [22, 23], a temporal sequence of discoveries is generated by drawing balls from an urn that contains all possible inventions at the time of extraction. Several variations have been proposed, such as the urn model with memory, to model the dynamics of collaborative tagging [11], or the more recent model by Tria et al. [9, 24], which incorporates a reinforcement mechanism and the concept of the adjacent possible [25, 26] into the Polya’s urn framework.

Here, we propose to model the dynamical mechanisms leading to discoveries and innovations as an edge-reinforced random walk (ERRW) on an underlying network of relations among concepts and ideas. Random walks on complex networks [27–31] have been studied at length [32]. In the context of innovation, they have been used to build exploration models for social annotation [33], music albums popularity [34], knowledge acquisition [35] and evolution in research interests [36]. A special class of random walks are those with reinforcement [37, 38], which have been successfully applied to biology [39] and mobility [40, 41]. In particular, the concept of random walks with edge-reinforcement [42, 43] was introduced in the mathematical literature by Coppsmith and Diaconis [44]. Here, we will make use of edge-reinforced random walks to mimic how different concepts are explored moving from a concept to an adjacent one in the network, with innovations being represented, in this framework, by the first discovery of previously unvisited nodes. As supported by empirical observations, we expect indeed the walkers to move more frequently among concepts which are already known and, from time to time, to discover new nodes. For this reason, we introduce and study a model in which the network is co-evolving with the dynamical process taking place over it. In our model: i) random walkers moves over a weighted network whose edge weights represent the strength of the association among couples of concepts; ii) the network evolves in time through a reinforcement mechanism in which the weight of an edge is increased every time the edge is traversed by a walker, making a traversed edge

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FIG. 1. Edge-reinforced random walks produce a co-evolution of the network with the dynamics of the walkers. At time $t$ (left) the walker is on the red node and has already visited the gray nodes, while the shaded nodes are still unexplored regions of the network. The widths of edges are proportional to their weights. At time $t + 1$ (right) the walker has moved to a neighbor node (in red) with a probability given by Eq. (1), and the weight of the used edge has been reinforced by a quantity $\delta w$. At this point, the walker will preferentially go back to one of the old nodes, although has now also the possibility to access a new set of nodes, shown in green, representing the new “adjacent possible”.

more likely to be traversed again in the future. As we will show in the following, this basic model is able to reproduce the statistical properties observed in real data of innovation processes, i.e. the Heaps’ law [13], and by tuning the amount of reinforcement can give rise to different scaling exponents. Furthermore, correlations in the temporal sequences of visited concepts and innovations will appear as a natural consequence of the interplay between the network topology and the reinforcement mechanism that controls the exploration dynamics.

The model. Let us consider a random walker over a weighted connected graph $G(V, E)$, where $V$ and $E$ are respectively a set of $N = |V|$ nodes and a set of $K = |E|$ links. Each node of the graph represents a concept or an idea, and the presence of a link $(i, j)$ denotes the existence of a direct relation between two concepts $i$ and $j$. The values of $N$ and $K$ and the topology of the network are assumed to be fixed, while the weights of the edges can change in time according to the dynamics of the walker, which, as we will see below, is in turn influenced by the underlying network. The graph at time $t$, with $t = 0, 1, 2, \ldots$, is fully described by the non-negative time-dependent adjacency matrix $W^t \equiv \{w_{ij}^t\}$, where the value $w_{ij}^t$ is different from 0 if the two concepts $i$ and $j$ are related, and quantifies the strength of the relationship at time $t$. We initialize the network assuming that at time $t = 0$ all the edges have the same weight, namely $w_{ij}^0 = 1 \forall (i, j) \in E$. The dynamics of the walkers is defined as follows: at each time step $t$, a walker at node $i$ jumps to a randomly chosen neighboring node $j$ with a probability proportional to the weight of the connecting edge. Formally, the probability of going from node $i$ to node $j$ at time $t$ is:

$$ \text{Prob}^t(i \to j) = \pi^t_{ij} = \frac{w_{ij}^t}{\sum_j w_{ij}^t} \quad (1) $$

where the time-dependent transition probability matrix $\Pi^t \equiv \{\pi^t_{ij}\}$ depends on the weights of all links at time $t$ [45]. The transition probabilities satisfy the normalization $\sum_j \pi^t_{ij} = 1 \forall i$ and $\forall t$, and we assume that $G$ has no self-loops, so that the walker changes position at each time step. On the other hand, the network co-evolves with the random walk process, since every time a walker traverses a link, it increases its weight by a quantity $\delta w > 0$, as illustrated in Figure 1. This mechanism mimics the fact that the relation between two concepts is reinforced every time the two concepts are associated by a cognitive process. Formally, the dynamics of the network is the following. Every time an edge $(i, j) \in E$ is traversed at time $t$, the associated weight is reinforced as:

$$ w_{ij}^{t+1} = w_{ij}^t + \delta w \quad (2) $$

The quantity $\delta w$, called reinforcement, is the only tunable parameter of the model. The idea of a walker preferentially returning on its steps is in line with the classical rich-get-richer paradigm, which has been extensively used in the network literature to grow scale-free graphs [46], and is here implemented in terms of reinforcement of the edges, instead that as a random walker biased on node properties [37, 47, 48].

The co-evolution of the network with the motion of the walker induces a long-term memory in the trajectories which reproduces, as we will show below, the empirically observed correlations in the dynamics of innovations [9]. In fact, if $i_t$ is a realization of the random variable $X_t$ denoting the position of the walker at time $t$, the conditional probability $\text{Prob}[X_{t+1} = i| i_0, i_1, \ldots, i_t]$ that, at time step $t + 1$, the walker is at node $i$, after a trajectory $S = (i_0, i_1, i_2, \ldots, i_t)$, depends on the whole history of the visited nodes, namely on the frequency but also on the precise order in which they have been visited [41].

The strongly non-Markovian [49] nature of the random walks comes indeed from the fact that the transition matrix $\Pi^t$ co-evolves in time together with the rearrangement of the weights. This makes our approach radically different from the other models based on Polya-like processes. For instance, in the Tria et al. Urn Model (UM) [9], where an innovation corresponds to the extraction of a ball of a new color, the probability of extracting a given color (colors correspond to node labels in our model) at time $t + 1$ only depends on the number of times the color has been extracted up to time $t$, and not on the precise sequence of colors. Moreover, the use of an underlying network (see Fig. 1) is a natural way to include the concept of the adjacent possible in our model, without the need of a triggering mechanism and further parameters, which are instead necessary in the UM (balls of new colors added into the urn whenever a color is drawn out for the first time) and in its mapping in terms of growing graphs considered in the SI of Refs. [9, 10].

Results. We will first test our model on synthetic networks, and then we will show an example of a real case
where the underlying network of relations among concepts can be directly accessed and used. As a first experiment, based on the idea that concepts are organized in dense clusters connected by few long-range links, we model the relations among concepts as a small-world network (SW) [50]. Our choice is supported by recent results on small-world properties of word associations [51] and semantic networks of creative people [52]. To construct SW networks we use the procedure proposed in Ref. [53]. Namely, we start with a ring of $N$ nodes, each connected to its $2m$ nearest neighbors, and then we add, with a tunable probability $p$, a new random edge for each of the edges of the ring. The first thing we want to investigate is the Heaps’ law for the rate at which novelties happen [9, 13]. We therefore looked at how the number of distinct nodes $S(t)$ in a sequence $S$ generated by a walker grows as a function of length of the sequence $t$. Figure 2(a) shows the curves $S(t)$ obtained by averaging over different realizations of an ERRW process with reinforcement $\delta w$ on a SW network with rewiring probability $p = 0.02$. All the curves can be well fitted by a power law $S(t) \sim t^{\beta}$, with an exponent $\beta$ which decreases when the reinforcement $\delta w$ increases. Finding the average number of distinct sites visited by a random walker is a well-known problem in the case of graphs without reinforcement. In particular, it has been proven that, in absence of reinforcement, the average number of distinct sites $S(t)$ visited in $t$ steps scales as $S^{ring}(t) \sim (8t/\pi)^{1/2}$ [54] in a 1-dimensional lattice and as $S^{ER}(t) \sim t$ [55] in an Erdős-Rényi (ER) random graph [56]. The transition between these two regimes has been investigated in Refs. [57, 58] for SW networks with different values of $p$. In Figure 2(b) we report the fitted values of the exponent $\beta$ obtained in the case of ERRW with different strength of reinforcement. The four curves refer to SW networks with rewiring probabilities $p = 0, 0.02, 0.1$ and 1. Notice that the previously known results, $\beta^{ring} = 1/2$ and $\beta^{ER} = 1$, are recovered as limits of the two curves relative to $p = 0$ and $p = 1$ when $\delta w \to 0$. Furthermore, for values of $p$ in the small-world regime [59], it is possible to get values of $\beta$ spanning the entire possible range $[0, 1]$ by tuning the amount of reinforcement $\delta w$. This means that the reinforcement mechanism we propose is able to reproduce all the Heaps’ exponents empirically observed [9].

The cognitive growth of science. To show how the model works in a real case, we have extracted the empirical curves $S(t)$ associated with a discovery process on an underlying network whose topology can be directly accessed. Specifically, we studied the growth of knowledge in modern science by analyzing 20 years (1991-2010) of scientific articles in four different disciplines, namely Astronomy, Ecology, Economy and Mathematics. Articles were taken from core journals in these four fields, and bibliographic records were downloaded from the Web of Science database. Details on data collection and the list of core journals are given in Ref. [60]. From a text analysis of each abstract, we have used an algorithm to extract relevant concepts as multi-word phrases [61] and constructed the real temporal sequence $S$ in each field (see Fig. 3(a)) based on the publication date of the papers. Fig. 3(b) shows that the number $S(t)$ of novel concepts in Astronomy grows with the length $t$ of $S$ as a power-law with a fitted exponent $\beta = 0.82$. Together with the real exploration sequences we have also extracted the underlying networks of relations among concepts from their co-occurrences in the abstracts, so that we do not need to rely on synthetic small-world topologies, or on the graph version of the UM (see SI of Refs. [9, 10]). Table I reports basic properties, such as number of nodes $N$, average node degree $\langle k \rangle$, characteristic path length $L$ and clustering coefficient $C$, for the largest components of the four networks we have constructed. Notice that different disciplines exhibit values of $\langle k \rangle$ ranging from 19 for Mathematics to 172 for Astronomy, but all of them have high values of $C$ and low $L$. We have then run the ERRW on each of the four networks, tuning the strength of the reinforcement $\delta w$, the only parameter of the model, so that the obtained curves for the growth of the number of distinct nodes visited by the walkers reproduces the empirical values of the exponent $\beta$. Fig. 3(b) shows

FIG. 2. ERRW on SW networks with $N = 10^6$ and $m = 1$. (a) Heaps’ law and associated exponents $\beta$ obtained for different values of reinforcement $\delta w$ on a network with $p = 0.02$. (b) Exponent $\beta$ as a function of the reinforcement $\delta w$ for networks of different rewiring probabilities $p$. 

FIG. 3. Growth of knowledge in science (case of Astronomy shown). (a) An empirical sequence $S$ of concepts in a scientific field is extracted by concatenating them in the temporally ordered sequence of abstracts. (b) The ERRW model over the network of relations among concepts is tuned to the empirical data by selecting the reinforcement $\delta w$ that reproduces the Heaps’ exponent $\beta$ obtained by fitting the Heaps’ curve as a power law.
that, for the case of Astronomy, the curve \( S(t) \) of our model with \( \delta w = 330 \) has a power-law growth with exponent \( \beta = 0.82 \), equal to the one extracted from the real sequence of concepts. The values of reinforcement obtained for the other scientific disciplines are reported in Table I. As expected, networks with higher values of \( \langle k \rangle \) require stronger reinforcement.

**Correlations.** In addition to the Heaps’ law, our model naturally captures also the correlations among novelties proper of real exploration sequences [9, 10]. Figure 4(a) shows that the frequency distribution \( f(\Delta t) \) of inter-event times \( \Delta t \) between couples of consecutive occurrences of the same concept is a power-law, like the ones found for novelties in Wikipedia and in other data sets in Refs. [9, 10]. Furthermore, the shape of \( f(\Delta t) \) in our model significantly differs from that obtained by randomly reshuffling the sequence (either locally, after the first appearance of the considered concept, or globally). We have also looked at how the number \( M_l \) of distinct subsequences of \( S \) of length \( l \) grows with \( l \) [62]. In Fig. 4(b) the curve \( M_l \) generated by the ERRW model with \( \delta w = 0.01 \) is compared to those obtained by reshuffling the sequences. The value of \( M_l \) grows with \( l \), until it reaches a plateau (equal to \( T - l \), where \( T = 5 \times 10^4 \) is the number of steps of the walker in the simulation) as a consequence of the finite length of \( S \). Interestingly, the analogous curves for the null models immediately approach the saturation value, meaning that a process without reinforcement would generate all the possible sub-sequences in a sequence of length \( T \), while with the reinforcement this number drops down because of the correlations. In our model, these correlations in the sequence of visited nodes are produced by the co-evolution of the walker dynamics with the network, while the Urn Model proposed in Ref. [9] requires the introduction of an additional semantic triggering mechanism to replicate the correlations found in the data. To better characterize the correlations we studied how homogeneously concepts occur in the sequence \( S \) after their first appearance. Following Tria et al. [9], we have divided the sequence \( S \) in \( n^{(A)} \) sub-sequences of the same length, with \( n^{(A)} \) being the total number of occurrence of \( A \) in \( S \), and we have evaluated the Shannon entropy \( H^{(A)} \) of a concept \( A \) as:

\[
H^{(A)} = - \sum_{s=1}^{n^{(A)}} p_s^{(A)} \log p_s^{(A)}
\]

where \( p_s^{(A)} = n_s^{(A)}/n^{(A)} \) denotes the probability of finding concept \( A \) in the sub-sequence \( s \). The maximum value \( H^{(A)}/\log n^{(A)} \) is reached for a concept equally distributed along \( S \). Fig. 4(c) shows the normalized average entropy \( H(n) \) of concepts appearing \( n \) times. Again, the large differences with respect to the null models defined above reveal the correlated dynamics of our model.

In summary, the mechanism of co-evolution of network and random walks we have introduced in this work naturally reproduces all the properties observed in real innovation processes, including the correlated nature of exploration trajectories. Being the topology of the network a key ingredient of the model, we hope our framework will result particularly useful in all such cases where the network can be directly reconstructed from empirical data, as in the study of scientific innovations reported here.

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![Figure 4](image)

**TABLE I.** Basic statistics for the network of concepts in the four considered research field. For each field is also reported the empirical Heaps’ exponent \( \beta \) and the reinforcement \( \delta w \) to plug in our model that reproduce it.

| Research Field | Papers | \( N \) | \( \langle k \rangle \) | \( C \) | \( L \) | \( \beta \) | \( \delta w \) |
|---------------|--------|--------|----------------|-------------|--------|--------|--------|
| Astronomy     | 97,255 | 103,069| 172 | 0.41 | 2.48 | 0.82 | 330    |
| Ecology       | 18,272 | 289,061| 52  | 0.89 | 2.98 | 0.85 | 105    |
| Economy       | 7,100  | 60,332 | 20  | 0.91 | 3.69 | 0.91 | 6      |
| Mathematics   | 7,874  | 48,593 | 19  | 0.89 | 3.69 | 0.87 | 20     |

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