Evolution of Patent Citation Networks

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Abstract—Can we use the framework of evolution to understand technological innovation? This question has been explored in the past using different approaches. Here, we propose that the convergence of computer science, evolutionary biology and statistical physics is a promising approach to study technological evolution. Using this novel framework, we show that the patterns of interactions between inventions show strong regularities shared by many physical, natural, and man-made systems. These patterns can be explained with a generic model of network growth that combines preferential attachment and ageing. The implications of these studies are discussed.

I. INTRODUCTION

Many technological inventions have a purpose, they are the product of rational design. While we recognise the important and unique features of cultural systems, the comparison of biological and man-made systems indicates that they share many common features [1]. Our knowledge of the underlying processes is still incomplete, but artefacts, like species, came about by a similar process: differential replication followed by unintended, more or less mindless mutations. Technological evolution is a process of cumulative transmission of information from one generation of inventors to another. There are only a few examples of complex artefacts actively designed by a single inventor. Moreover, complex artefacts are the outcome of collaborative efforts and often require many iterations until a stable, functional design is reached [2]. Amidst this level of complexity, it is clear that we need a novel, more systematic way to understand technological evolution.

George Basalla pointed out that rationality alone cannot explain the huge diversity of inventions [3]. Accidents and contingency play an important role in the history of technology. The paths towards many inventions are full of twists and turns [4]. For example, innovation requires a stimulating environment that provides a minimum amount of resources. During the 1960s, revenues from the selling of the Beatles by the Electric and Musical Industries (EMI) company enabled Godfrey Hounsfield to conduct independent research in computer tomography (CT) [5]. The combination of X-rays with a computer capable of interpreting data scans enabled physicians to visualise the internals of bodies without the need to open them. This technology was possible only because Hounsfield had a solid, previous expertise in computer technology: he helped to build the first all-transistor computer. EMI sold its computer division in 1962, at the same moment when they signed the Beatles, thus securing the funding for Hounsfield’s research. In retrospective, it seems easy to explain why some inventions have succeeded while others have failed. But how likely was CT to appear at that particular moment in history? Are innovations inevitable or just happy accidents?

Similar questions have been explored in the literature of evolutionary biology. A successful approach to evolution studies the behaviour and structure of organisms in the search of links between them. By comparing species’ anatomies, biologists find important clues of descendant relationships linking the species. For example, palaeontologists have devoted considerable efforts to find the links connecting past to extant species in order to get a deeper understanding of the causes of evolution. Darwin dreamed that one day it would be possible to reconstruct the history of life by assembling all the knowledge gathered about species. In the only figure of the "Origin of Species" [5], Darwin suggested that all the species are interrelated by the tree of life rooted in a very ancient, common ancestor. We still don’t have the full picture but scientists are assembling more and more pieces of information of the tree [6].

II. MAPS OF TECHNOLOGICAL EVOLUTION

Like evolutionary biologists, we would like to obtain maps of technological evolution (see below). Maps are useful tools that simplify the system under observation while capturing important relationships between their components. As we will see, features of these maps reflect our assumptions about underlying processes. Historical timelines are one common example of technological maps that focus the sequence of events. Figure 1A recapitulates the history of CT technology, from the initial attempts of detecting the tiniest variations in the strength of radiations, to accurate measures of thickness by X-rays, to computer-assisted tomography. These timelines are constructed to highlight major trends or design goals, e.g., the history of CT can be described as an attempt towards reduced scanning times (indicated by arrows in the figure), less exposure time of patients to X-ray sources and increased imaging resolution. However, the simplified nature of the timeline might be misleading because technological evolution is not a simple ladder of progress.

Perhaps the shape of technological evolution resembles more a tree, like natural phylogenies. This representation is associated to a mode of branching evolution, where each artefact yields a number of "descendant" inventions. For example, figure 1B shows the evolution of electronic digital computers from the early ENIAC (first electronic computer) up to the 1970s [7]. The main feature of this diagram is the separation between serial (represented by EDVAC, left branch) and parallel computers (ORDVAC, right branch). The separation should

1In 1979, Godfrey Hounsfield and Allan McLeod Cormack were awarded the Nobel prize in Physiology for developing this technology.
Roentgen discovered X-Rays in 1895. These early inventions laid the foundation for modern technology and are rich sources of information about the process of invention. AEC Dose reduction was a significant milestone in the timeline of computer tomography, which progressed through several generations from 1963 to 1992. The US Patent Trademark Office (USPTO) is a very rich source of information about the process of invention and contains more than $3 \times 10^6$ patents. This database has different sources of information: text documents, inventor-patent associations, and networks of patent citations. Using the listing of references included in patent descriptions we can obtain a graph with nodes representing patents and links depicting citations. This patent citation network gives a global picture of the flow of knowledge exchanged between old and new inventions. Technological evolution (as given by the architecture of the patent citation network) cannot be described with a tree [9] (see figure 1C). This map suggests an important difference between technology and evolution: inventors can transfer solutions between different domains (horizontal transfer) while species are more constrained when borrowing genetic information from another, remote species.

III. SCALE-FREE NETWORKS

Many laws in nature have a statistical origin. The fundamental components of society are not particles, but humans, and the number of individual interactions is very small compared to the total number in the system. Still, we can find strong regularities in the behaviour and organisation of human societies, like power laws [10]. How can we explain them? Statistical physics is the natural approach to study macroscopic features of complex systems, i.e., understand large-scale patterns as the collective outcome of the interaction between many individuals. In the 1960s, Derek J. de Solla Price pioneered the study of citation networks by describing a strong regularity in their structural organisation. The analysis of citation networks is important for a number of reasons. For many years, we have been measuring publication impact by counting how many times it is cited by other publications. Empirical studies by de Solla Price showed that the distribution of citations in scientific publications follows a robust pattern, that is, the frequency of any publication having $k$ citations follows a power-law:

$$P_i(k) \sim k^{-\gamma}$$

where the exponent $\gamma$ varies between 2 and 3 [11]. Other related attributes, like the frequency of publication of authors, also behave as power-law [12]: a small fraction of authors (around 25%) publishes the majority of publications (around 75%)[13]. Scaling laws like the above can be found in a wide variety of physical, biological and artificial phenomena, from word frequencies in English texts to the sizes of earthquakes. The ubiquity of this behaviour suggests that a general mechanism is capable of reproducing this pattern.

IV. MODELLING NETWORK EVOLUTION

A difference between natural and man-made systems is the latter are not (yet) capable of self-reproduction. The abundance of artefacts, like species, depends on some external measure of success (a notion analogous to “adaptation”). Assuming that the number of citations is a valid measure of relevance, we can interpret the power-law distribution of citations (see above) as an indication of inequality between innovations. What mechanisms drive the popularity of patents? In 1965, de Solla Price proposed the so-called “cumulative advantage” mechanism for citation networks: “there is a probability that the more a paper is cited the more likely is to be cited

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2 The geometry of evolutionary trees is also not a perfect tree. Simple organisms like bacteria can exchange genetic material within the same generation. However, recombination is harder in complex multicellular organisms where developmental plan imposes many constraints.
Thereafter” [11]. This mechanism was based on the analogous concept of “rich get richer” suggested by Yule [14] and Simon [15] (and more recently “preferential attachment” [16]). This is consistent with empirical observations. In many fields, a few publications (so called “hubs”) receive many more citations than the average publication. For example, figure 2 shows the emergence of hubs in the evolution of the CT technology.

We can incorporate this mechanism of “cumulative advantage” in a model of growing networks. From the perspective of any node, the rate of incoming citations is proportional to the number of links (or popularity):

$$\Pi(k) \sim k^\beta$$

(2)

where $\beta$ is the attachment exponent that controls the strength of citation reinforcement. It can be shown that such model yields a power-law distribution of connections [11][16]. However, the actual distribution of citations in patent networks is not a simple power-law (1). Instead, we have found that an extended power-law form (described by a Zipf-Mandelbrot function) provides a better fitting for the distribution of patent citations:

$$P_i(k) \sim (k + k_0)^{-\gamma}$$

(3)

where $k_0 = 19.46 \pm 0.22$ is the “initial attractivity” and the exponent $\gamma = 4.55 \pm 0.04$. The missing ingredient here is the preferential attachment model does not consider the temporal dependencies between inventions. For example, the tablet computer has an historical precedent in the 1970s (Dynabook) but until the 2000s it was not a commercial success (iPad). Why did it take some 35 years for this invention to succeed? A component of the explanation is that invention qualities are not the only determinant for success but the environment has to be right. DynaBook was conceived around 1968 by Alan Kay from Xerox (see figure 3A). DynaBook was meant to be a revolutionary keyboard-less, wireless tablet computer [17]. But, in their specifications, it was supposed to be permanently connected to an online library containing all the world’s accumulated knowledge. However, in 1968 there was no microprocessors, let alone the internet. And more fundamentally, there were no widespread, affordable wireless communications.

By combining ageing and preferential attachment, we can write a general law describing the evolution of the rate of citations. The following model predicts the observed distribution of patent citations, i.e., an extended power-law (3):

$$\Pi(k) \sim k^\beta \tau^{\alpha - 1} \exp(\frac{\tau}{\tau_0})^\alpha$$

(4)

where $\tau$ indicates patent age, the exponent $\alpha > 0$ weights how fast the ageing is affecting the likelihood of attachment, and $\tau_0$ is the scale parameter that controls the rightward extension of the ageing curve [18]. We have validated the assumptions of the ageing component with the full USPTO dataset (see fig. 3 B) (see [8] for details). The shape of the ageing curve indicates that patents do not tend to cite recent patents. There is a characteristic temporal separation between the average patent and its followers (indicated by the hump of the distribution) suggesting that (in average) any patent “must be around” some time before it gets noticed and starts to gather citations. Interestingly, the slow decay of the ageing curve

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3Charles Darwin proposed that the function of a trait might shift during its evolutionary history (exaptation).

4The term Wi-Fi was commercially used at least as early as August 2000, coined by a brand consulting firm.
indicates that some old patents have reached an "immortal" status and they are cited presumably because of their high importance.

V. INNOVATION BY RECOMBINATION

An important feature of citation networks is their clustered organization: there is a nested hierarchy of interconnected clusters (so-called communities or modules) of related inventions (see fig. 1C). An active area of research combines statistical physics with computational approaches to develop algorithms for automatic community detection [19]. These algorithms have the potential to provide the basis for explaining technological development and the emergence of new technological areas (which should map structural modules) [20]. Our partial exploration of modularity suggests there is a good correlation between their structural features and the properties that define the sets of patents within them. There is, however, a lack of robust patterns ("laws") describing the modular organisation of citation networks. The emergence of correlations is a natural consequence of the specialised features shared by related patents. But how these features emerge? Inventors use available, previous inventions as an essential part of their work, e.g., by copying designs inherited from their ancestors. It has been suggested that technology evolves mainly by combining previous inventions [21].

We think this conjecture can be studied by extending the models discussed in this paper. A starting point is to further investigate the actual interactions between concepts and artefacts. For example, we can explore collections of technical documents at different scales. An example is shown in figure 4, which shows the evolution of video camera technology at three different levels. The problem of photographic lens design was addressed well before the invention of the first cameras in the early 19th century. Lens is a common word for almost 200 years while the abundance of the word "camera" grows linearly with time. During the 1930's, the earliest video cameras used in television experiments were large and heavy. The emergence of microprocessors (early 1970s) enabled both a drastic reduction of camera size and digital storage of images. More recently, there is a strong clique formed by "digital", "video" and "camera" in the cultural network. The behaviour of word frequencies at the tail of the time-series suggests a coupling between structure and dynamics.

VI. CONCLUSION

We have started to explore the parallelisms and differences between biology and technology, by developing the basis of a theory of technological evolution [22]. In this context, network theory is a powerful framework to test our hypotheses. Our study is part of the current trend of using statistical physics to study the dynamics and organisation of social systems. The final validation for our models is to test their capacity to predict. In this context, forecasting the emergence of innovations (both technology and biology) is a very difficult (and perhaps impossible) task. For example, citations have been used as building blocks for computing indexes of scientific performance (e.g., h-index). The framework described might be useful when assessing the implications and the predictive capacity of citation-based indexes [23].
Perhaps the best-known policy to ensure future innovation is to invest sufficient resources in public research. Interestingly, not only EMI but British tax payers possibly contributed much more to the development of this medical technology [24]. The other requirement for evolving complex technology is the quality of knowledge available to their inventors. In the era of search engines, being able to locate relevant information is the key to success. USPTO database is a very rich corpus and offers a lot of potential to studies of technological evolution. But extracting relevant knowledge from very large databases (including several millions of text documents) remains a challenging and formidable task. The robust detection of trends is both a technical and theoretical problem. Ultimately, the solution will require not only powerful computers but also a theoretical framework that enable us to understand the origin of innovation.

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