# On the Temporal Analysis of Scientific Network Evolution

Frederic Amblard*, Arnaud Casteigts†, Paola Flocchini † Walter Quattrociocchi‡ and Nicola Santoro§

* IRIT-CNRS, Toulouse, France frederic.amblard@univ-tlse1.fr
† University of Ottawa, Canada, {casteig,flocchin}@site.uottawa.ca
‡ University of Siena, Italy, walter.quattrociocchi@unisi.it
§ Carleton University, Ottawa, Canada, santoro@scs.carleton.ca

***Abstract*—In this paper we approach the definition of new methodologies for the visualization and the exploration of social networks and their dynamics. We present a recently introduced formalism called TVG (for time-varying graphs), which was initially developed to model and analyze highly-dynamic and infrastructure-less communication networks, and TVG derived metrics. As an application context, we chose the case of scientific communities by analyzing a portion of the arXiv repository (ten years of publications in physics). We discuss the dataset by means of both static and temporal analysis of citations and co-authorships networks. Afterward, as we consider that scientific communities are at the same time communities of practice (through co-authorship) and that a citation represents a deliberative selection of a work among others, we introduce a new transformation to capture the co-existence of citations' effects and collaboration behaviors.**

***Index Terms*—Social Networks Evolution, Temporal Metrics, Visualization, Time-Varying Graphs**

## I. Introduction

Social networks are systems based upon several interconnected (and interdependent) dynamic networks where the elements join, participate, attract, compete, cooperate, disappear, and affect the shape and strength of the system and its relationships. Despite the common agreement about the fact that these networks, during their life time, are characterized by the occurrence of complex phenomena that are the emerging global effects induced by local interactions at play among their elements, not much is qualitatively known yet concerning the dynamical patterns that are produced by such an interplay. Several questions arise from the studies approaching the modeling and analysis of such complex dynamics: a) is it possible to generalize and characterize global emerging properties in terms of the local behaviors (e.g. local interactions) among the components of the system? and reciprocally, what are the consequent effects caused by these global phenomena upon the local levels of the interaction space? b) what are the driving forces behind the evolution of these networks and their articulations within the system dynamics? In this paper we approach the definition of new methodologies for the visualization and the exploration of the dynamics in real dynamic social networks. As an example, we chose the case of scientific communities by analyzing a portion of the arXiv repository (ten years of publications in physics). The analysis addresses the co-existence of co-authorships' and citations' behaviors of scientists by focusing on the most proficient and cited authors interactions' patterns and, in turn, on how they are affected by the selection process of citations.

## II. Related Work

The research efforts in the area of dynamic networks strive to understand what are the driving forces behind the evolution of social networks and how they are articulated together with social dynamics, e.g., opinion dynamics, the epidemic or innovation diffusion, the teams formation and so on ([7], [8], [11], [14], [21], [23]). However, the current instruments (definitions, models, metrics) are mainly drawn for static networks and therefore generally fail to capture the evolution of phenomena and their dynamical properties – *temporal dimension*. In fact, as stated in [15], the central problem in this area is the definition of mathematical models able to capture and to reproduce properties observed on the real networks. However, the increasing availability of real social network datasets, as well as recent or impending deployments of mobile ad hoc communication networks have fostered research on dynamic networks and caused the emergence of both fine-grained (e.g. journey, temporal distance, connectivity over time) and coarse-grained (e.g. densification, emergence of structural properties, formation of communities) concepts capturing network dynamics [26].

From a coarse-grain perspective, studies on scientific network dynamics deal with understanding the factors that play a significant role in their evolution, not all of them being neither objective nor rational - e.g., the existence of a star system [1], [18], [19], [28] the blind imitation concerning the citations [16], the reputation and community affiliation bias [10]. Among the available data to analyze the scientific system, a subset of the publications in a given field is the most frequently used such as in [13], [20], [22] and [24]. Classical analyses concern either the co-authorships network ([1], [18]) or the citation network ([12], [25]), more rarely the institutional network ([21]). Moreover, such networks are often considered as static and their structure is rarely analyzed overtime. In [18] the network of scientific collaborations, explored upon several databases, shows a clustered and small world structure. Moreover, several differences between the collaborations' patterns of the different fields studied are captured. Such differences have been deepened in [19] with respect to the number of papers produced by a given group of authors, the number of collaborations and the topological distances between scientists.

## III. Preliminaries

This section gives background information related to the present work, including concepts and notations for the analysis of dynamic networks (based on the *time-varying graph* formalism from [6]), and a description of the arXiv dataset we used for experimentations.

### A. The TVG Formalism

Consider a set of entities $V$ (or *nodes*), a set of relations $E$ between these entities (*edges*), and an alphabet $L$ accounting for any property such a relation could have (*label*); that is, $E \subseteq V \times V \times L$. The definition of $L$ is domain-specific, and therefore left open –a label could represent for instance a particular type of relation in a social network, a type of carrier in a transportation networks, or a communication medium in communication networks. For generality, $L$ is assumed to possibly contain multi-valued elements (e.g. *<satellite link; bandwidth of 4 MHz; encryption available;...>* ). The set $E$ enables multiple relations between a given pair of entities, as long as these relations have different properties, that is, for any $e_1 = (x_1, y_1, \lambda_1) \in E, e_2 = (x_2, y_2, \lambda_2) \in E$, $(x_1 = x_2 \wedge y_1 = y_2 \wedge \lambda_1 = \lambda_2) \implies e_1 = e_2$.

The relations between entities are assumed to take place over a time span $\mathcal{T} \subseteq \mathbb{T}$ called the *lifetime* of the system. The temporal domain $\mathbb{T}$ is generally assumed to be $\mathbb{N}$ for discrete-time systems or $\mathbb{R}$ for continuous-time systems. We denote by time-varying graph the structure $\mathcal{G} = (V, E, \mathcal{T}, \rho, \zeta)$, where $\rho : E \times \mathcal{T} \rightarrow \{0, 1\}$, called *presence function*, indicates whether a given edge is present at a given time, and $\zeta : E \times \mathcal{T} \rightarrow \mathbb{T}$, called *latency function*, indicates the time it takes to cross a given edge if starting at a given date. Since the scope of this paper is social network analysis, we will deliberately omit the latency function, which makes more sense in a telecommunication network, and consider TVGs described as $\mathcal{G} = (V, E, \mathcal{T}, \rho)$.

Several levels of dynamics may take place over a network, and we separate them into *fine-grain* dynamics (how nodes precisely interact at small time-scales) and *coarse-grain* dynamics (how the network evolves over longer periods of time). Although we are mostly concerned with coarse-grain evolution in this paper, the next paragraph reviews some very central fine-grained concepts that may complement the present work in a near future. See [26] for a discussion about specific methods to study fine-grained or coarse-grained indicators in network analysis.

### B. Fine-grained Dynamics

A central concept in dynamic graphs is that of *journey* which is the temporal extension of the notion of path in static graphs and consequently forms a basis for many other temporal concepts. A sequence of couples $\mathcal{J} = \{(e_1, t_1), (e_2, t_2) \ldots, (e_k, t_k)\}$, such that $\{e_1, e_2, ..., e_k\}$ is a walk in $G$, is a *journey* in $\mathcal{G}$ if and only if $\forall i, 1 \leq i < k$, $\rho(e_i, t_i) = 1$ and $t_{i+1} \geq t_i$. We denote by $departure(\mathcal{J})$, and $arrival(\mathcal{J})$, the starting date $t_1$ and the last date $t_k$ of a journey $\mathcal{J}$, respectively. Journeys can be thought of as *paths over time* from a source to a destination and therefore have both a *topological* and a *temporal* length. The *topological length* of $\mathcal{J}$ is the number $|\mathcal{J}| = k$ of couples in $\mathcal{J}$ (i.e., the number of *hops*); its *temporal length* is its end-to-end duration: $||\mathcal{J}|| = arrival(\mathcal{J}) - departure(\mathcal{J})$.

The concept of distance in a dynamic setting can also be defined in terms of hops or time. In particular we can distinguish between at least three types of distances: the *shortest* one (minimum number of hops between two nodes), *foremost* one (minimizing $arrival(\mathcal{J})$ w.r.t. a given date) and the fastest one (minimizing $arrival(\mathcal{J}) - departure(\mathcal{J})$).

These two notions – of journeys and (temporal) distance – are central in analyses concerned with fine-grained interaction. Whether in the contexts of social or telecommunication networks, they have served as a basis to define higher temporal concepts including those of *connectivity over time* and *(time)-connected components* [3], *temporal eccentricity* and *temporal diameter* [5], or *temporal betweenness* and *closeness* [27], among others.

### C. Coarse-grained Dynamics

*1) TVGs as a sequence of footprints:* Given a TVG $\mathcal{G} = (V, E, \mathcal{T}, \rho)$, one can define the *footprint* of this graph from $t_1$ to $t_2$ as the static graph $G^{[t_1,t_2)} = (V, E^{[t_1,t_2)})$ such that $\forall e \in E, e \in E^{[t_1,t_2)} \iff \exists t \in [t_1, t_2), \rho(e, t) = 1$. Let the lifetime $\mathcal{T}$ of the time-varying graph be partitioned in consecutive sub-intervals $\tau = [t_0, t_1), [t_1, t_2) \ldots [t_i, t_{i+1}), \ldots$; where each $[t_k, t_{k+1})$ can be noted $\tau_k$. We call *sequence of footprints* of $\mathcal{G}$ according to $\tau$ the sequence $SF(\tau) = G^{\tau_0}, G^{\tau_1}, \ldots$. Since all the graphs in $SF$ are static graphs, any classical network parameters (degree, neighborhood, density, diameter, modularity, etc.) can be directly measured on them. In particular, we will denote by $N^{\tau_i}(x) = \{y \in V : (x, y) \in E^{\tau_i}\}$, and $deg^{\tau_i}(x) = |N^{\tau_i}(x)|$, the *neighborhood* and *degree*, respectively, of a given node $x$ in the footprint $G^{\tau_i} \in SF$. Note that, when observing the evolution of a parameter over SF, one can achieve different levels of granularity by varying the size of the footprint intervals. At one extreme, each interval could correspond to the smallest time unit (in discrete-time systems), or to the time between any two consecutive events (appearance/disappearance) and every footprint can be qualified as a *snapshot*. At the other side of the spectrum, i.e. taking $\tau = \mathcal{T}$, the sequence would consist of a single footprint that aggregates all interactions over the network lifetime. Looking at the network evolution through a sequence of static graphs corresponds to the approach of evolving graphs [9]. Note that this approach is sufficient as long as the studied parameters are *a*temporal (which is the case in the present paper). If they were instead temporal (e.g., looking at the *evolution* of the *temporal* distance over longer time spans), then a *sequence* of several *TVGs* would be required.

*2) Metrics Considered in this Study:* We consider the evolution of the following indicators over the SF sequence.

*a) Density:* The density measures how close the network is to a complete graph. Hence, the evolution of density provides a complete vision of the network's topology formation during time. The *density* $D_i$ at a given time interval $\tau_i$ is defined as: $D_i = \frac{|E^{\tau_i}|}{n_i * (n_i - 1)}$ where $G^{\tau_i} = (V, E^{\tau_i})$ is the footprint of $\mathcal{G}$ in the interval $\tau_i$, and $n_i = |V|$.

| Network Indicators | $G_a$ | $G_c$ |
|---|---|---|
| Network Diameter | 26 | 37 |
| Network Modularity | 0,706 | 0.617 |
| Network Average Clustering Coefficient | 0.5006 | 0.156 |

TABLE I
CO-AUTHORSHIPS AND CITATIONS GRAPHS STATIC MEASURES

*b) Clustering Coefficient:* The *clustering coefficient* is used in social network analysis to characterize the network architecture. More formally, by applying to footprints the definition of [29], the *clustering coefficient* $C^{\tau_i}(x)$ of a node $x$ in footprint $G^{\tau_i}$ indicates how close to a clique the neighborhood of $x$ is; in fact, it is the proportion of edges among its neighborhood divided by the maximum number of edges that could potentially exist between them.

*c) Modularity:* The *modularity*, introduced in [4], measures how the structure of a given network is modular, i.e. how it can be decomposed into subparts. Moreover, it quantifies the quality of a division of a network into modules or communities. Networks with high values of modularity are characterized by dense internal connections between nodes within groups (modules) but only sparse connections between different groups. The *modularity* of a pair of nodes $u$ and $v$ on footprint $G^{\tau_i}$ is defined as $M^{\tau_i}(u,v) = \frac{deg^{\tau_i}(u)*deg^{\tau_i}(v)}{2|E^{\tau_i}|}$.

### D. The Dataset

The scientific community analyzed in this work has been extracted from the hep-th (High Energy Physics Theory) portion of the arXiv website, an on-line repository available at http://arxiv.org/. In particular, the dataset is composed by a collection of papers and therefore their related citations from January 1992 to May 2003. For each paper the set of authors, the dates of the on-line publications on arXiv.org, and the references are provided.

## IV. The Networks Static Description

In this section we start the analysis by showing some indicators about the arXiv dataset without accounting for its temporal dimension. In fact, from the dataset, we can easily derive two graphs the first, namely the *co-authorships graph* which has authors as nodes and its undirected links stand for the relation of co-authoring a paper and the second, the *citations graph*, where nodes are the papers and the links (directed) are the references within papers. To have a more formal framework for the static analysis, the derived graphs can be defined as:

- the **co-authorship graph** as $G_a : (V_a, E)$ where nodes in $V_a$ are the authors and links $e \in E$ connect nodes co-authoring a paper.
- the **citations graph** as $G_c : (V_c, E)$ where the nodes in $V_c$ are the papers and each edge $e \in E$ corresponds to a reference to another paper.

In Table I we show some metrics about the citations and collaborations graphs. The diameters - e.g., the longest shortest path between to pairs of nodes (respectively authors and papers) - of both graphs have high values, meaning that nodes in the network are distant. The modularity, measuring how a network can be partitioned into modules or subparts, has high values on both graphs. Whereas the average clustering coefficient, of the collaborations graph, counting the number of triangles within nodes, is higher than in the citations graph.

Both graphs are composed by several connected islands with few interconnections within modules, and the co-authorships graph is more clustered than the citations graph but less dense.

## V. Temporalizing the Dataset

In this section we make explicit the temporal aspects, (i.e. the structural evolution) of the *citations* and the *co-authorships* graphs. In particular, we derive two time-varying graphs (TVG): the *co-authorships TVG*, with undirected edges and authors as nodes where a link stands for the relations of co-authoring a paper; and the *citations TVG* having papers as nodes and the links (directed) representing the citations within papers. The temporal dimension of both networks is derived by the paper's submission date.

More formally, we can define:

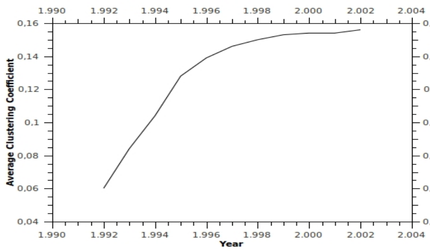
- the **co-authorships TVG** as a quadruplet $G_a^t : (V, E, \mathcal{T}, \rho)$ where the nodes in $v \in V$ are the authors and links $e \in E$ connect a couple of scientists co-authoring a paper. The temporal domain $\mathcal{T} = [t_a, t_b)$ of the function $\rho$, is the *lifetime* of each node $v$ that in this context is assumed as $t_a$ to be the submission date of the paper and $t_b = \infty$;
- the **citations TVG** as a quadruplet $G_c^t : (V, E, \mathcal{T}, \rho)$ where the nodes in the set $V$ are the papers and each edge $e \in E$ corresponds to a citation to another paper. As for the co-authorships TVG, the temporal dimension $\mathcal{T} = [t_a, t_b)$ of the presence function $\rho$ of $G_c^t$ is defined within the submission date of papers and $\infty$.

### A. Citations Network Evolution

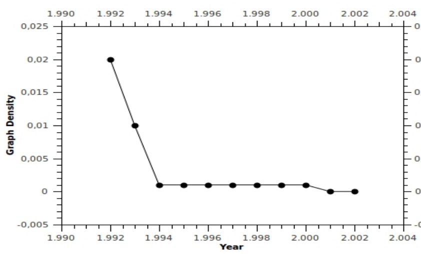
Here we show the evolution of the citations TVG $G_c^t$ by using the sequence of footprints. The values are computed by aggregating the interactions occurring at each sub-interval $SF(\tau)$ having $\tau$ fixed to one year. Figure 1(a) shows the evolution of the clustering coefficient, the curve is characterized by a low and stable trend. The density evolution, which is shown in Figure 1(b), presents the same low and decreasing behavior, meaning that both distances and interconnections among nodes (citations within papers) are stable. Finally, the modularity, shown in Figure 1(c), shows a decreasing but stable trend meaning that the interconnections among modules increase - e.g. the citation network evolves from a sparse configuration toward a denser and more homogeneous one.

### B. Co-authorships Network Evolution

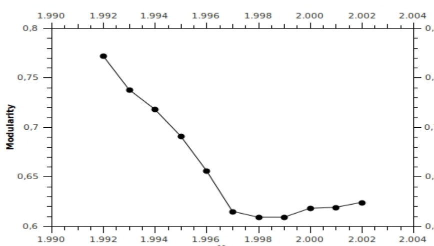
The co-authorships TVG presents a different structural evolution with respect to the temporal graph of citations analyzed in the previous section. The average clustering coefficient evolution in the time interval observed, shown in Figure 2(a), has an oscillating trend with higher values with respect to the




(a) Average Clustering Coefficient

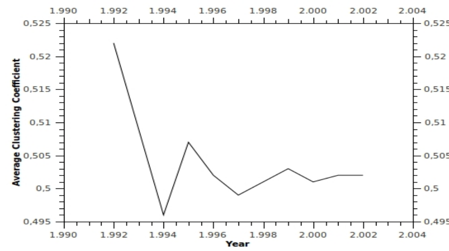



(b) Density

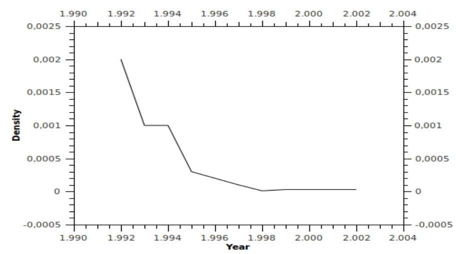



(c) Modularity

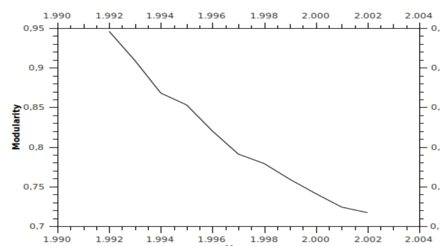
Fig. 1. Citations Graph Evolution




(a) Average Clustering Coefficient




(b) Density




(c) Modularity

Fig. 2. Co-authorships Graph Evolution

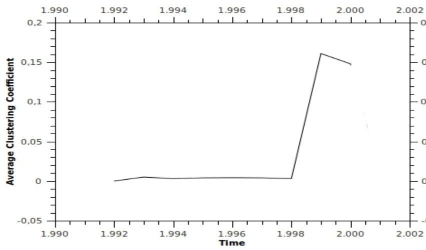
values reached by the temporal citations graph. In addition, $G_a^t$ has a more modular and denser structure, as shown in 2(c). Moreover, the modularity of the co-authorship network until 1997 has a similar behavior as observed in the citation network (but with higher values). After 1997 the modularity of the citations network is stable around an equilibrium point (0.6), while the number of modules in the co-authorship network has a constant decreasing rate at each year. The density (Figure 2(b)) decreases and after 1998 is stable. $G_a^t$ evolves toward a homogeneous configuration at the level of modules (modularity) but not among nodes (low clustering coefficient) the new incoming nodes join modules. Only few nodes act as bridges between group of authors.

## VI. Exploiting Interactions

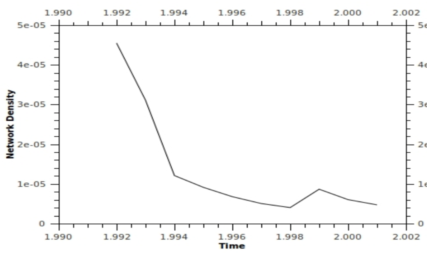
In this section we provide an additional data transformation in order to capture more details about the evolution of our scientific network. In particular we consider that the dynamics in scientific communities are based upon competitions and collaborations among authors and groups of scientists. Hence, in the analysis we want to capture a) the resulting emerging effects caused by these two opposite motivations and b) how they are expressed in terms of collaborations and citations patterns. To put it more explicitly, our dataset presents two interactions: the papers' co-authorships and the citations between papers. How their co-existence affects the scientific production and the scientific communities structural evolution? The dataset is transformed in an undirected graph, that we call the *cited co-authorships*, having as nodes the authors, weighted links representing the co-authorship on a paper, and when a paper is cited by another work, the links' weights, connecting the authors of the referenced paper, are then incremented. More formally, the graph of the *cited co-authorships* is defined as quadruplet $G_cc : (V, E, \mathcal{T}, \rho)$ on a discrete time. The nodes $v \in V$ are the authors, the set of edges $E$ represents a collaboration. The nodes appear on the graph the first time a paper they wrote has been published, and the interaction $L$ is weighted with a variable $w_i$, namely the *strength value* of a collaboration, that is incremented at each citation received by a paper produced by a given couple of nodes $(u, v)$. As the main aim of this work is to provide an illustrative (and interesting) application of TVGs, in the analysis we consider only the most proficient authors [17] - e.g, authors having links' strength values $w_i \geq 150$.

### A. Evolution of the Cited Co-authorships Network

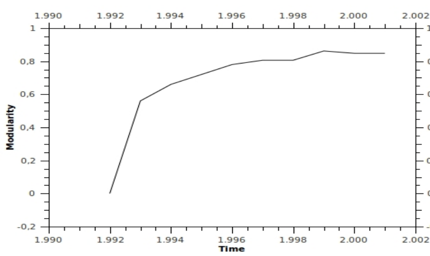
Figure 3(b) shows the density values for each element of the temporal sequence of footprints $SF(\tau)$ ($\tau = 1year$) of the interactions network of the most proficient scientists $G_i$. The density trend starts on very low values and then the graphs become denser with a very low counter-trend in 1999-2000 interval.




(a) Average Clustering Coefficient




(b) Density




(c) Modularity

Fig. 3. Cited co-authorships graph evolution

The growing rate of the modularity (3(c)) is characterized by an increasing rate until 1993, then it reaches its highest values during 1999-2000, but through a smoothed rate. The interconnections among separated groups starts in 1993, then it continues to grow, but with a more stable rate. Looking at the curve of the *average clustering coefficient* shown in (Figure 3(a)), we can see that the time interval between 1999 and 2000 separates a monotone trend from a decreasing one. We can interpret the *modularity* evolution as showing that nodes during the first phase are divided in several and separated groups, then the connections among these groups start to become denser that produces a network structure with a smaller number of larger communities (modules) - e.g. the network tends toward a structural homogeneity. Finally, in Table VI-A we show the evolution of the average degree, the average path length and of the degree power law. As for the previous indicators these values are computed on the sequence of footprints $SF(\tau)$ with $\tau$ fixed to one year of $G_i$.

The average path length, indicating the average distances among nodes, the power law degree, measuring how closely the degree distribution of a network follows a power-law scale and the evolution of average degree, counting the average number of connections at each node, show a significant

| Year | Average Degree | Average Path Length | Power Law |
|---|---|---|---|
| 1992 | 0,0095 | 1 | 0 |
| 1993 | 0,0176 | 1 | -1,386 |
| 1994 | 0,012 | 1 | -1,79 |
| 1995 | 0,0135 | 1,16 | -2,16 |
| 1996 | 0,132 | 1,13 | -2,27 |
| 1997 | 0,0118 | 1,12 | -2,5 |
| 1998 | 0,106 | 1,12 | -2,5 |
| **1999** | **0,066** | **3,92** | **-5,08** |
| **2000** | **0,64** | **3,79** | **-5,27** |
| 2001 | 0,6 | 3,82 | -5,25 |

TABLE II
CITED CO-AUTHORSHIPS NETWORK'S MEASUREMENTS

increase after 1999 and 2000 time interval.

## VII. Visualizing the Network Evolution

In this section we show how the TVG modeling approach is compliant with one of the widely diffused platforms ([2]) for network analysis and how it is possible to show the punctual evolution of networked datasets. Let starts by introducing Figure 4 showing the number of citations received at each semester by the most cited paper of the arXiv dataset.

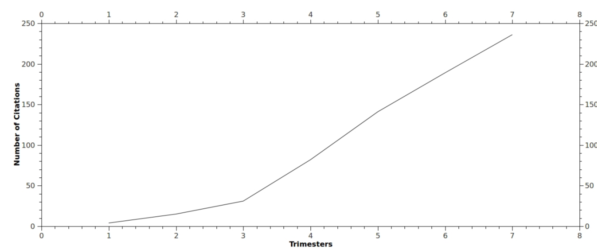


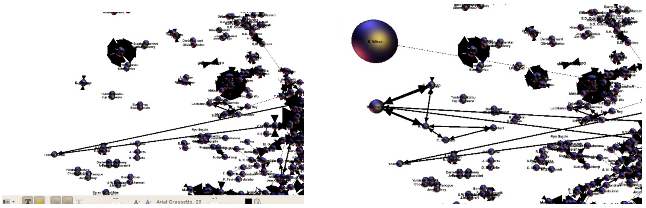

Fig. 4. the citations trend of the most cited paper for each semester

The citations rate has a strong increase after two semesters. The third semester coincides with the interval (1999-2000) captured in the previous section. Hence, in order to understand the effect of this paper, we show a sequence of snapshots on the topology in the neighborhood most cited paper authors. At the beginning there are only separated components as shown in Figure 5(a). Then a large node appears (Figure 5(b)), after that a node with a smaller diameter but with a higher number of links appears closer to the previous one. The biggest node is one of the authors of the most cited paper and, as we can see, the node has a very low number of connections (collaborations) in that time interval.

In Figure 6(a) the big node (a Nobel prize) and the hub node are connected, they publish a paper together with another node with a large diameter. Several islands start to link their clique and the process of diffusion continues by means of new hubs (Figure 6(b)).

## VIII. Conclusions

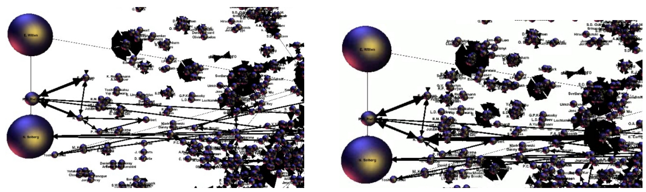
The temporal analysis as well as the effects of the interactions in the field social network provide several interesting insights about its evolution. In this paper we provide a first



(a) Before

(b) one of the authors (the biggest node) of the most cited paper appears

Fig. 5. The appearence of one of the most cited authors



(a) All the authors of the most cited papers appear.

(b) The portion of the graph becomes denser

Fig. 6. Densification

example on how the social networks' evolution can be qualitatively captured through TVG. In particular, we approach the definition of new methodologies for the visualization and the exploration of the dynamics in real dynamic social networks. The analysis addresses the co-existence of co-authorships and citations behaviors of scientists by focusing on the most proficient and cited authors interactions patterns and, in turn, on how they are affected by the selection process of citations. The analysis starts with a static vision on the dataset by showing the structure of the citations and co-authorships graphs derived by the dataset. Then, by adding the temporal dimension on both networks we characterize the structural changes of the co-authorships and citations graphs. The network evolves toward a denser structure, a significant increase occurs in 1999-2000 time interval causing the homogenization of communities around the authors of the most cited paper. Finally, through the cited co-authorship network we show how the citation process plays a significant role in determining the structural evolution of the network. It reveals the importance of a work in a specific scientific domain. Hence the more the citations a paper receives, the more authors move toward its arguments by joining group of authors working on a specific topic that, in turn, has been selected by the community and viceversa.

## IX. Acknowledgements

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