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UNA MIRADA HACIA COMUNIDADES DE APRENDIZAJE CON LENTES APROPIADAS: SUGERENCIAS E IDEAS DESDE CIENCIA DE REDES

Resumen: El nivel de *network thinking* en la educación - definido como la capacidad de considerar a los sistemas de aprendizaje centrándose en las relaciones entre los actores involucrados (principalmente profesores y alumnos) y no sólo en las características de los mismos – esta sin duda creciendo, con intensidades diferentes en función de el sector educativo, pero no al ritmo necesario. En el artículo argumentamos como la investigación y las prácticas educativas deben aumentar su capacidad de mirar a las comunidades de aprendizaje a través de "lentes" capaces de ver a las redes, apoyadas por métodos apropiados como la Social Network Analysis. La aplicación de la Social Network Analysis a la educación, especialmente en el caso de la educación a distancia, puede facilitar la comprensión de los patrones de interacción de los alumnos entre sí y con los profesores, y puede facilitar la consolidación de los nuevos enfoques para comprender los mecanismos de aprendizaje colaborativo. El artículo presenta y discute - desde un punto de vista educacional - un breve resumen de las principales aportaciones teóricas y prácticas de la Social Network Analysis - como las teorías de los "random networks", de los "small-world networks " o los "weak ties" - junto con algunas propiedades generales de las redes, pensando que el dominio de estas dinámicas es muy importante para los investigadores y profesionales de la educación, para entender y apoyar el aprendizaje colaborativo de manera significativa.

Palabras clave: Aprendizaje colaborativo; Análisis de Redes Sociales; Redes de aprendizaje; Intercambio de conocimiento; Conocimiento tácito.

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LOOKING AT LEARNING COMMUNITIES WITH THE APPROPRIATE GLASSES: HINTS AND IDEAS FROM NETWORK SCIENCES

Abstract: The level of *network thinking* within education – intended as the capacity to look at learning systems and communities by focussing on the relations among the involved actors (primarily teachers and learners) and not only on the actors characteristics – is growing, with different speeds depending on the educational sector, but not at the pace needed to keep up with the increasingly network nature of our societies. We claim that educational research and practices should increase their capacity to look at learning communities through appropriate "networking-sensitive" glasses, and get equipped with tools and methods – such as Social network Analysis - to properly understand and support these networks. The application of Social Network Analysis to education, especially in the case of distance learning, can allow understanding the patterns of interactions between teachers and learners, and can facilitate the consolidation of new approaches to understand collaboration mechanisms. The paper presents and discusses - from a learning viewpoint - a brief overview of the main theoretical and practical contributions coming from Social Network Analysis – such as the "random graphs", the "small-worlds" or the "weak-ties" theories – together with some general properties and dynamics of networks, believing that mastering these dynamics is extremely important for educational researchers and practitioners, when it comes to understanding and supporting meaningful collaborative learning.

Key words: collaborative learning; Social Network Analysis; learning networks; knowledge sharing; tacit knowledge.

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LOOKING AT LEARNING COMMUNITIES WITH THE APPROPRIATE GLASSES: HINTS AND IDEAS FROM NETWORK SCIENCES[1]

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1.- INSTILLING MORE "NETWORK THINKING" WITHIN EDUCATION.

"Network" is the buzzword of our times. Concepts such as information and knowledge society are increasingly used by sociology, economics and other disciplines as a way to describe and understand our world and its dynamics built on connections, nodes, and communication fluxes. In particular, the term *network society* describes a social endeavour where the internet is becoming a critical technical and social infrastructure of everyday life, crucially enabling individuals to communicate in new ways that reconfigure and enhance their interaction capacity (Castells 1996). Of course, networks are not a new phenomenon: human, social and institutional networks have always been there, "what is different is the density, extension and complexity of contemporary global networks and their propensity to channel increasingly diverse flows" (Bebbington and Kothari, 2005; 863).

The rise of the concept of network is having an impact on the way we think of ourselves and of our societies, facilitating the emergence of a diffused *network thinking*, through which we look at our world by focussing on the relations among the elements of the systems and not only on their characteristics. "Network thinking is poised to invade all domains of human activity and most field of human inquiry" (Barabási, 2002; 222). Even if it is probably early to say if we are witnessing the beginning of a knowledge revolution that will urge us to radically change our social and behavioural paradigms, it is clear that, to properly understand an increasingly network-based society, we need to get equipped with tools and approaches able to professionally look into the networks we are increasingly immersed in and to make sense of the information we collect. In other words, if we want to take advantage of the benefits that networks can bring to many areas of

[1] This paper is partly based on the work presented at the EDEN Research Workshop in Leuven in October 2012.

society, including education, we need to get equipped with tools that can allow us to grasp the increasingly networked nature of virtually any human and social phenomena.

The level of *network thinking* within education varies considerably depending on the educational sector we look at. As noted by the Learnovation Report (Dondi *et al*. 2009), professionals from corporate education and informal learners are more used to work and learn in collaborative fashions, by adopting peer learning practices and by constantly adapting their teaching and learning methods to the growing availability of (social) networking tools. On the other hand, embracing networking and collaborative tools and methods in formal learning setting such as school education is made more difficult, even in the few cases when the need is expressed by learners and accepted by teachers, by the slow adaptation dynamics of these systems to innovation processes.

In addition, when networking practices are adopted to facilitate teaching and learning, for example by using social media such as Facebook or Twitter or by applying peer learning and peer assessment practices, this is done starting from the often incontestable belief that working in collaboration (most of the time with the support of ICT) will have a positive impact on the motivation of students and will increase their attainments. In the case of teachers' collaboration, "the underlying assumption is that teachers' networks, like other learning networks, can offer participants informal ways to support competence building and personal and professional development" (Vuorikari and Scimeca, 2012). Nevertheless, most of the time this reasoning is not grounded on a sound understanding of the dynamics that govern cooperation among the components of a given network – the pupils of a class or the members of a learning team - and it only rarely takes into account the available research findings on networks behaviour coming from network sciences. In other words, most of the times educators and educational researchers are looking at learning networks without the appropriate "networking lenses"[2]. We believe that increasing the level of *network thinking* within education practices would be fundamental if we want to understand the motivation factors which lay behind the different cooperation attitudes of teachers and learners, and ultimately if we want to take the maximum benefit from any collaborative learning experience.

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[2] An exception is the work of European SchoolNet in the frame of the Tellnet project (Vuorikari *et al*. 2012), which we will describe later in the paper.

2.- SOCIAL NETWORK ANALYSIS

Network-based approaches can be used to analyse and understand many phenomena, from the human cell to the internet, from transport system to epidemic diseases. When network methodologies refer to relations among individuals and organisations we speak of "Social Network Analysis", often shortened to SNA. Breiger defines Social Network Analysis as "the disciplined inquiry into the patterning of relations among social actors, as well as the patterning of relationships among actors at different levels of analysis, such as persons and groups" (Breiger, 2004; 1). SNA is a multidisciplinary approach that encompasses sociologists, psychologists and anthropologists as well as mathematicians and physicists, and that makes quantitative investigations of behavioural patterns, focusing on relational aspects of groups, with less attention on individuals' attributes (Scott, 1992; Wasserman and Faust, 1994). In other words, social network analysis is focused on uncovering the patterning of social actors' interaction (Freeman, 2004).

As stated before, we believe that in order to be able to properly understand the dynamics behind learning communities and the increasing collaborative teaching and learning processes, educators and educational researchers must increase their capacity to *network think*. We will hereby propose a very short and incomplete panorama of the main scientific developments of Social Network Analysis, in order to stimulate the possible connections between these findings and the problems of education and educational research[3].

A first milestone contribution came from Paul Erdős who, in cooperation with his fellow Renyi, tried to answer to a fundamental question about networks: how do networks form? His theory, of which we will omit the mathematical demonstration, is that networks, despite of the complexity that they might reach, are formed in the simplest possible way, that is randomly. The *random network theory*, introduced in 1959, dominated scientific thinking for a couple of decades: if a network is too complex to be captured in simple terms, the only way to possibly describe it as random. Moreover, Erdős noted something important on the dynamic of random networks: if we start adding connections within a large network where just a few nodes are connected to each other, we will reach a *phase*

[3] A complete collection of some of the most influential papers on networks is available in the 2006 volume "The structure and dynamic of networks", by Newman, Barabási and Watts.

transition towards a situation where most of the nodes are linked into a connected network, or *giant component*. Phase transitions are fundamental moments in the development of any network, and are common also in learning communities. Typically, a moment comes when a group transforms from a mass of sometimes bilaterally connected individuals into a meaningful community, with its own shared learning objectives, working methods and collaboration rules: this "magical" moment in the life of every network, where order seems to prevail over chaos, can be utilised by the network animator to shape the future of the learning community coherently with its learning objectives.

Experience shows that the way social networks form and grow is far from being purely random, therefore some criticisms to the random network theory started to emerge already in the fifties. An important contribution came from Anatol Rapoport, who, building on the concept of homophily, that is the human tendency to associate with similar peers, demonstrated that social networks tend to evolve in such a way that groups of connected nodes will tend to *close the circle* among themselves (Rapoport, 1957). This model, called *random-biased network*, showed that networks do grow by following some predictable properties. Watts notes (2003) that

> the more context people share, the closer they are, and the more likely to be connected. Social beings, in other words, never actually start out on a tabula rasa […] because they possess social identities. By belonging to certain groups and playing certain roles, individuals acquire characteristics that make them more or less likely to interact with one another. Identity, in other words, drives the creation of social networks (p. 116).

Another fundamental contribution was provided in 1967 by Stanley Milgram, the father of the well-known theory of the six degrees of separation. Milgram affirmed that most of existing networks are *small world networks*, where nodes are separated from each other just by a few links. This theory, which was grounded on a famous experiment which was aimed to find the *distance* between any two people in the United States and which re-took the idea of the *cliques* developed in the 1950s by the Harvard school (Scott, 1992), was proved true by a number of empirical experiments in different contexts[4]. Amazingly

[4] "By studying billions of electronic messages, scientists worked out that any two strangers are, on average, distanced by precisely 6.6 degrees of separation. In other words, putting fractions to one side, you are linked by a string of seven or fewer acquaintances to Madonna, the Dalai Lama and the Queen. […] Researchers at Microsoft studied records of 30 billion electronic conversations among 180 million people in various

enough, virtually every network seems to obey to the *small world rule*: molecules in the cell are separated by an average distance of three chemical reactions, university professors in different fields are separated by four to six paper co-authorship links, etc. The small world theory is as interesting as highly misleading, since it suggests that nodes that are relatively close are easy to find; this is not the case if you do not know which is the path to follow in order to reach the desired node. A further important input came from Mark Granovetter, who demonstrated, in its 1977 paper "The strength of weak ties", that in many situations, such as news spreading or job search, acquaintances or "weak links" are more important that or closest friends or strong links[5]. By proposing this theory, Granovetter designed a completely different networking model with respect to the random network proposed by Erdős: he envisaged a society made of clusters weakly connected among each other, where nodes are therefore not connected randomly. These findings are very important for learning networks, since they give an indication of how networks tend to be structured and on how information and knowledge tend to flow across networks' links. Identifying the weak ties within a collaborative learning network in a context of professional development could for example tell us something about the potential of the network in terms of problem solving and on the possibility of a given learner within the network to solve challenging tasks by relying on peers through these weak ties.

It took almost thirty years for the random networks theory and the weak ties theories to be reconciled by Duncan Watts who, starting from the problem of crickets chirping synchronisation was able to propose a way to measure the level of clustering of a network (Watts and Steven, 1998). Also in this case a number of empirical experiments, supported by the improved computational capacity with respect to Erdős times, showed that clustering seems to be a common property across social networks. This theory adds to the

countries, according to the Washington Post. This was 'the first time a planetary-scale social network has been available,' they observed. The database covered the entire Microsoft Messenger instant-messaging network in June 2006, equivalent to roughly half the world's instant-messaging traffic at that time. Eric Horvitz and fellow researcher Jure Leskovec considered two people to be acquaintances if they had sent one another a message. They looked at the minimum chain lengths it would take to connect 180 billion different pairs of users in the database. They found that the average length was 6.6 hops, and that 78 per cent of the pairs could be connected in seven steps or fewer. But some were separated by as many as 29 steps" (Smith, 2008).

[5] The principle below this theory is that our friends are often friends with each other as well, and therefore tend to create clusters, while weaker ties are able to create connections beyond existing clusters.

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small world model the existence of some few mathematically calculated long links, which somehow connect clusters of nodes and are therefore able to radically cut the distance between every node in the network. Watts proved (2003) that adding just five long-distance links could reduce the average nodes distance of one-half, regardless of the dimension of the network. This model, combining the random logic of Erdős with the realistic existence of few weakly connected clusters, was soon enriched through the concept of *network hubs*: by analysing the existing connections among a number of webpages with massive use of computer calculation, Albert-Laszlo Barabási demonstrated (2002) that most of the analysed webpages were referenced by an average of other ten pages, while a very small number of them (three out of 203 millions) were referenced by almost a million other pages. These pages, such as Google or Amazon, represent the hubs of the network. This presence of hubs was proved in many different kinds of networks[6] as "ubiquitous, a generic building block of our complex, interconnected world" (Barabási, 2002; 63). Networks characterized by the presence of hubs are defined *scale-free networks*, and seem to obey to different laws with respect to random networks. In learning settings, being able to identify and to empower network hubs is fundamental to support the growth and flourishing of a network, since the collaborative behaviour of these hubs can strengthen the motivation of other learners within the group through a *collaborative cascade effect*, which increases the level of trust and of willingness to work together within the network.

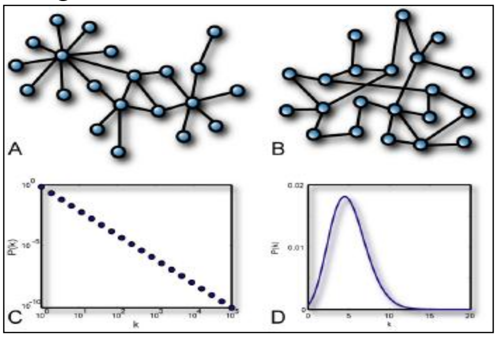

Figure 1 – Random networks (A and C) vs. scale-free networks (B and D).

(Source: https://nwb.slis.indiana.edu/community).

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[6] Such as the network of Hollywood actors through the famous Kevin Bacon game that tried to show that Kevin Bacon was at the centre of the Hollywood universe, see http://oracleofbacon.org.

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As shown in Figure 1, the degree distribution of random networks follows a bell curve, where most of the nodes have the same number of links and no node has a large number of links, while scale-free networks follow a power-law distribution, where most of the nodes have a few links and a few hubs have many. “Connectors […] are fundamental property of most networks. This discovery has turned everything we thought we knew about networks on its head. [...] Accounting for these highly connected nodes requires abandoning once and for all the random worldview” (Barabási, 2002; 56).

The two distributions in Figure 1 can be considered not only as representing different kinds of networks, but also different moments in the life of the same network. This intuition, which won to Kenneth Wilson the Nobel Prize in 1982, reveals something important about the behaviour of networks. Wilson demonstrated, though his theory of normalisation, that when a network is forced to undergo a phase transition, for example with the creation of some hubs, inevitably its distribution turns from a bell curve into a power law curve (Wilson, 1979). If we consider that virtually all systems in nature and in society tend to obey to bell curves[7], this theory suggests a way through which networks move from chaos to order by organising themselves. An example is again the World Wide Web, which started as a network of servers randomly connected to move, with the creation of a number of highly connected hubs, into a system that responds to a power law. As we have seen in the case of the emergence of networks giant components, all networks can be brought to a critical point at which they start to self-organise, abandoning random behaviour and starting to follow power-laws (Strogatz, 2003). This is the moment when a learning communities starts to take collaborative decisions on its objectives, targets and working methods as a group, and again identifying this moment is important to accompany the transition, always keeping in mind that – despite this property seems to be rather generalised - every learning community is composed of a given set of individuals and has therefore its own history and peculiarities.

A last important contribution comes from Nowak (2001) who, looking at networks from a biology evolution perspective, pointed out a few properties that define how networks evolve in relation to their structure. He went as far as defining a single coefficient that specifies the relative rate at which like-minded players tend to meet within a network, and therefore the probability that cooperation can flourish or that competition can appear.

[7] To make an example around 99% of the earth adult population is between 150 and 200 cm tall, with very few exceptions outside these limits.

These discoveries in terms of cooperation mechanism tell us what is behind the decision by a member of a network on weather to adopt a cooperative or a non-cooperative behaviour, and put these decisions in relation to the network structure and properties, opening the way for further research in the field of "evolutionary graph theory". This research line focuses on developing empirical models that, "using observations from a single network, at a single point in time, in combination with information on the characteristics of the participants, can be used for predicting features of the network that would arise in a population of agents with different characteristics or different constraints" (Christakis and Fowler, 2009; 1), and opens important research possibilities through Strategic Network Evolution Models (Toivonen et al. 2009) and Actor Based Models (Snijders, 2005). These models tend to look at networks as groups of actors defined by a fixed set of characteristics, whose development is driven by a combination of chance, through randomly arising opportunities for the formation of links, and choice, in the form of optimal decisions by the actors whether to establish the potential links. In the last years, evolutionary graph theory has demonstrated, among other things, that links within networks are associated with correlations in outcomes, showing for example that changes in weight of an individual is a predictor of weight changes among her/his friends, or that certain network configurations are correlated with improved group performance (Christakis and Fowler; 2009).

Concluding this brief overview, we can say that Social Network Analysis, after a period of self-definition where its boundaries, philosophy and working language of the area have been worked out[8], is taking its place in the realm of applied sciences and is, at the same time, getting attention by non-specialists and by policy makers, due to its capacity to describe our world in a new way and to somehow foresight the future through the analysis of possible developments of the many networks that constitute our society. In particular, SNA and networks mapping methods are applied in a number of non-academic fields, from business to policy consultancy (Berkowitz, 1982; Buchanan, 2002; Otte and Rousseau, 2002; Durland and Fredericks, 2007). In all these fields, SNA is appreciated for its capacity to capture the relationships among actors and to define what lies behind them, describing networks within their contexts. "SNA is more about telling the story of a network with quantitative tools than it is about summarising, organising, and determining influences" (Durland and Fredericks, 2007; 33). As noted by Newman,

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[8] Including some critical views, such as the one provided by Monge and Contractor, 2003.

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Barabási and Watts (2006), the science of networks is today increasingly focusing on real-world cases rather than on abstract networks models, and at the same time it is concentrating on the developments of networks over time and not only on their shape and properties, looking at networks as dynamic systems where each component influences and is influenced by the network structure.

3.- NETWORKS PROPERTIES

Although each network has its own peculiarities and characteristics, empirical studies show that some generalised rules on social network dynamics exist (Newman, Barabási and Watts, 2006). We will present here some of these general properties together with some concepts often used by SNA researchers, since these can be very important for education researchers and for teachers and tutors who deal with the need of fostering collaborative learning within different education and training settings.

A first important common property is that, *unless some restrictive conditions exist, networks tend to grow*. Even if during its lifecycle a network may lose some nodes, the general assumption, which has been proved by empirical analysis, is that networks tend to add nodes to their constituency. Networks have a tendency to expand by adding nodes following some general properties, the main being preferential attachment. In statistical terms, a new node will have more probabilities to be linked with highly connected nodes, following a "rich gets richer" pattern, also known as the Matthew law[9]. Of course, in real life this rule must deal with the finite nature of all networks and with the cost, in terms of money, time, or commitment, of connecting to a specific node, and must therefore be considered on a case-by-case basis. Further, new nodes tend to connect with nodes that share some similarities in terms of context, in a sort of affiliation pattern. In social network sciences, it is broadly accepted that each member of a network belongs to many different contexts that constitute her/his social identity. In a learning community, for example, by belonging to different groups such as an online discussion, a peer evaluation group or a project development cluster, individuals are set with characteristics that guide

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[9] This rule seems to be true since the Bible times, when evangelist Matthew wrote: "For everyone who has will be given more and he will have abundance. Whoever does not have, even what he has will be taken from him" (Matthew 25:29, quoted in Watts, 2003; 108).

the way they connect with other individuals or groups. These observations enable to somehow predict the way a specific network will grow and can be used to guide the network development. Another property, which is valid mostly for networks among individuals, has to do with the *dimension of networks*. Although in real life social networks go from extremely small to very large constituencies, especially in the case of Web 2.0 networks, some evidence suggests that the typical size of a social network tends to stabilize at around 150 members. This discovery, proposed by Dunbar (that is why in this context 150 is called Dunbar number) started from sociological and anthropological research around the maximum size of a village, and is confirmed by evolutionary psychology, which suggests that the number of 150 may represent some kind of limit of the average human ability to recognize members and track emotional facts about all members of a group. In the era when online groups composed of thousands of members flourish, this property can look out-dated, but in fact a number of studies confirm that even in these very large networks the meaningful collaborative groups are typically much smaller that the whole network[10]. A final important common trait among networks deals with the importance of the so-called *weak ties*. Granovetter (1983) noted that, even if an actor may only be able to establish a few strong ties due to possible constraints of human communication channels, more numerous weak ties can be important in seeking information across a network. Groups of strongly connected nodes have a tendency to share homogeneous opinions as well as common traits: however, being similar, each member of a group would also know more or less what the other members know. To find new information or insights, it will be important to look beyond the group through weakly connected nodes.

This property is very important for networks within learning settings, and can be conceptualised through the *long tail of networking*. The long tail refers to those - typically weak, but not for this less important as we have seen - connections among teachers and learners who are working and learning along different paths. The collaboration within a collaborative learning network can be in fact distinguished in two parts. A first collaboration area, of normally high intensity of collaboration and of high thematic concentration, is the one where teachers and learners collaborate with peers on the same learning path (a course, a pilot activity, a project-based experience) and that by actively participating in a network are able to learn more efficiently, more effectively and with

[10] See for example Breuer *et al*. 2009.

less effort what they would normally learn alone. A second collaboration area, which corresponds to the long tail of networking and which is indicated by the dark part in Figure 2, is the one where teachers and learners collaborate across learning paths, learning with and from peers with different backgrounds and sets of competencies.

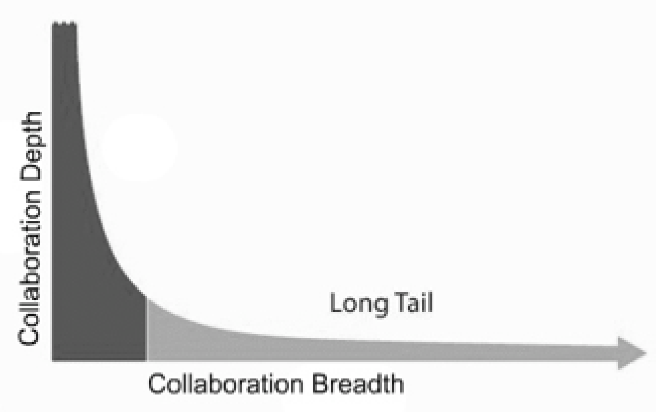

Figure 2 – The long tail of networking

By participating in a collaborative learning network, teachers and learners are in fact exposed to a number of stimulations which come from outside – or better from around – her/his area of specific interest, getting access to new ideas and activities that are being developed within the network around her/his specific areas of interest. This is the light part in the picture: here the cooperation intensity is lower, but the potential reach of the cooperation is much broader. Think for example of an health professional working in the field of cancer treatment who joins an online collaborative professional community: she/he will collaborate intensively with peers working in the same thematic field and possibly in the same geographic region, but will also get in contact with peers working on other sectors and will be exposed to a number of practices, such as for example how common problems are solved in other contexts or how a health programme be managed. These "knowledge externalities" are normally not among the main objectives of a teacher or a learner entering a network, but represent a very important set of knowledge. The importance of the weak connections which flourish along the long tail has been proved in the field of ICT-enabled collaborative learning at the school level, where research shows that weak ties can bring in new ideas and can connect participants so that information can flow through a network (Haythornthwaite, 2001, quoted in Schlager, 2009).

Valorising these knowledge externalities is very important for networked-learning and is connected to the important issue of tacit knowledge. When working in networks, pedagogical approaches must adapt to the specificities of collaborative learning, taking into account the importance, within networks, of tacit and implicit knowledge and the difficulty of quantify, codify and document it (Gillwald, 2004). Along with the predominant approach towards tacit or implicit knowledge, which is is to try to convert it to a form that can be handled using traditional knowledge management approaches, a number of new approaches are starting to appear, especially among communities of practice (Wenger, 1998; Duguid, 2005), which focus on supporting learners to develop knowledge through interaction with others in an environment where knowledge is created, nurtured and sustained. The ability to bring to the surface implicit assumptions, and the role that this can play in developing a shared understanding around specific issues, is perhaps one of the best means of building an appreciation of what is tacit without going through the effort of making it explicit. The knowledge and capacities of all the involved individuals (being teachers, facilitators or learners) should be identified as precisely as possible in order to combine existing distinctive competencies it to a desired result; missing parts have to be developed internally or generated from outside the network. Nonaka (1995) claims that explicit knowledge is easily expressed, captured, stored and reused; it can be transmitted as data and is found in databases, books, manuals and messages. In contrast, tacit knowledge is “highly personal, hard to formalize and therefore difficult to communicate to others, deeply rooted in action and in an individual’s commitment to a specific context, it consists partly of technical skills [and partly] of mental models, beliefs and perspectives so ingrained that we take them for granted and cannot easily articulate them” (p. 98). Tacit and explicit knowledge are mutually complementary entities, which interact with each other in the creative activities of human beings, that is, finally, a learning and knowledge exchange process. This process consists of four stages: socialization, when knowledge is transferred through observation, imitation and practice; externalization, triggered by dialogue and relying on the capacity to translate tacit knowledge into documents and procedures; combination, which is about reconfiguring explicit knowledge-bases by combining and categorising processes, and finally internalisation within the network (Nonaka, 1995). Further, tacit knowledge is very important to build a background context for explicit knowledge to acquire a specific value (Duguid, 2005).

4.- CONCLUSIONS AND WAYS FORWARD

The success of any networking venture depends on the capacity of the involved parties to successfully negotiate the aspects of their cooperation, and on how much the parties are able to work towards a common objective, openly sharing concerns and problems and working out solutions in a collaborative way. This is a fundamental condition to be met, we believe, also by collaborative learning communities, within formal and informal learning settings. Learning Networks approaches, as proposed by Sloep and Berlanga (2011) can in fact provide a solution to the increasing need of building the capacities required by the knowledge society in initial and professional education. The fact that all networking activities depend on negotiation and consensus building among human beings increases the creativity potential of networks but also their unpredictability, and therefore a sound understanding of the mechanisms and of the conditions which lay behind a successful collaboration experience must guide any collaboration support activity.

The scientific community is paying increasing attention to the study of networks (Newman *et al*., 2006). “Very few people realize, however, that the rapidly unfolding science of networks is uncovering phenomena that are far more exciting and revealing than the casual use of the word network could ever convey” (Barabási, 2002; 7). Network-based approaches, and especially Social Network Analysis (SNA), can be used to understand networks for what they are, since they “inquiry into the patterning of relations among social actors, as well as the patterning of relationships among actors at different levels of analysis, such as persons and groups” (Breiger, 2004; 1): in the education field, network science can help uncovering the patterning of teachers and learners interactions. Specifically, Learning Analytics can be useful in addressing the work of individual learners, whereas Social Learning Analytics can uncover dynamics of groups collaboration in knowledge co-creation (Vuorikari and Scimeca, 2012).

In order to balance the pure quantitative nature of SNA, qualitative complementary methods are advisable. “When used in conjunction with qualitative or ethnographic accounts, SNA techniques help show where information is and is not flowing and suggest where interventions might improve information flow” (Schlager *et al*. 2009, p. 5). In particular, the application of SNA to education, especially in the case of distance learning, can allow understanding the patterns of interactions between learners systematically (De Laat *et al*. 2007). For example, in their study on collaborative interactions in an online classroom, Russo and Koesten conclude that SNA offers an opportunity to understand how communication among members in an online learning environment influences specific learning outcomes (Russo and Koesten, 2007). In addition, SNA and network sciences can offer to education studies new approaches to understand learners' collaboration, as demonstrated by the work of Reffay and Chanier (2003) who adopted from SNA a measurable definition of group cohesion that did not exist in education science. Finally, it is important to notice that applying SNA to education networks is challenging in both methodological terms and in terms of resources which are needed to run such an analysis, both when relational data is collected through interviews and when it is automatically generated from large sets of heterogeneous data on the social interactions of teachers and students (Schlager *et al*. 2009)

In their study on the eTwinning community, Vuorikari and Scimeca demonstrate that the application of SNA to a teachers' community and the resulting analytics are able to highlight new insights into teachers' activities in relation to their professional development: a proper application of SNA has allowed "new hypothesis being created for further investigation on how teachers' co-operation takes place within a large-scale socio-technical network" (Vuorikari and Scimeca, 2012).

We believe that understanding the general properties and dynamics of networks that we have briefly presented in this paper is extremely important for educational researchers and practitioners when it comes to supporting meaningful collaborative learning. These issues would deserve further exploration and adaptation to real life cases within education. Specifically, it would be important to substantially apply Social Network Analysis techniques to learning networks, as suggested by Breuer (2009), hence looking at collaborative learning with the appropriate level of network thinking. These researches would contribute also to instil – as hinted at the beginning of the paper – more *network thinking* among education specialists, also helping educational researchers to "overcome conceptual and methodological obstacles that limit exploration of the frontiers of learning in cyber-enabled social networks" (Schlager *et al*. 2009; 16).

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