

THE COEVOLUTION OF KNOWLEDGE NETWORKS AND KNOWLEDGE CREATION

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Previous research has modeled the evolution of either knowledge creation or knowledge networks, but not their co-evolution. This work presents an agent-based model to cover this gap and challenge the intuition that both phenomena are mutually re-enforcing. The model consists on the rules of partner selection and the rules of knowledge creation by the agents. Agents in the knowledge network choose their partners depending on their previous collaboration history and on their attractiveness. Similarly, the amount of knowledge created by each agent depends on his number of partners and the knowledge he has created earlier. The simulations of the model show a wide variety of scenarios with different policy strategies suitable for each.

1. Introduction

The process of knowledge creation has received an increasing interest in the latest times. On the one hand, in the policy arena it is recognized that we are moving towards a true “knowledge economy” (Powell and Snellman, 2004). In such a case, the key economic performance would be the capability to create and diffuse new knowledge, should that be at the individual, organizational or regional level (Graf, 2006).

On the other hand, knowledge creation and diffusion have received an increasing attention from scholars from a broad range of disciplines (De Solla Price, 1965; Merton, 1968; Newman, 2001). The social sciences address knowledge as a social phenomenon. Knowledge is not created by isolated actions, but embedded in a social structure. New knowledge is created as a recombination of already existing knowledge (Schumpeter, 1934). Thus, knowledge will be created through the interactions of the agents involved (Powell et al., 1996). Those interactions provide the opportunity to share and combine their different skills, resources and knowledge (Guimera, 2005).

Therefore, one cannot address the question of how knowledge is created without considering the social network of the agents involved in this creation. A social network

is a set of people or groups, each of whom has some kind of relation with some of the others (Newman, 2001). The relation between the structure of the network and the innovative performance of the individuals or organizations involved has been thoroughly analyzed (for a broad review, see Ozman, 2009 and Phelps et al., 2012). Most studies focus on effect of the ego network structure (the structure of the network around one single agent) on the individual performance (Fleming et al., 2007; Granovetter, 1973). That is, how the number or the strength of the ties connecting an agent to the others affects his/her performance. The results, nonetheless, are not consistent throughout the studies. In some cases, the number of collaborations of an organization has been found to have a positive impact on its innovative performance, as it provides access to more sources of existing knowledge (Ahuja, 2000). In others, though, this impact can be negative, as those collaborations may be difficult to manage (Littler et al., 1998; Wynstra et al., 2001). Furthermore, some studies suggest that the effect might have, in fact, an inverted-U shape (McFadyen et al., 2009): a too sparse network does not allow for ideas to flow, but in a too dense network the ideas become redundant .

Given the wide range of possible effects, one might think that the process of knowledge creation is different for different sectors, or even that it might not be as network-related as theory suggests. The main aim of this paper is to analyze all this apparently different processes of knowledge creation in a network as a single process. We will create an agent-based model where agents interact and create knowledge. The model has two main components. The first one is the rule of partner selection, that it to say, the probability that an agent chooses another agent as a collaborator, and the other one is the rule of knowledge creation by an agent. Simulations of the model are presented to provide a first validation of the model (Fagiolo et al., 2007). We will see that changes in the parameters of the model can provide a wide range of theoretical scenarios, including the cases above mentioned.

The structure of the paper is as follows. Section 2 presents a literature review and grounds the structure of the model, presented in Section 3. Section 4 shows different simulations of the model for some representative sets of parameters. Finally, Section 5 discusses the different results.

2. Literature review

Knowledge networks

Knowledge creation is increasingly an interactive process. In some cases, as medical research, cooperation is reported to consistently increase the odds of fruitful research (Grebel, 2012). Even in cases where agents could try to conceal their new knowledge from potential competitors, the evidence is that agents interact and collaborate in order to create new knowledge (Fleming and Frenken, 2007). The most extreme case is interfirm collaboration. In the case of firms, new knowledge is sought as a source of competitive advantage (Henard and McFadyen, 2008), so the firms would prefer not to share it (Ahuja, 2000). Nonetheless, the fact is that firms collaborate actively, not only with suppliers and clients (Araujo and Mendes, 2009), but also with actual competitors (Alcacer and Zhao, 2011; Mudambi, 2008), in order to

create new knowledge. These collaborations allow firms to access needed assets, learn new skills, and develop or absorb new technologies (Guimera, 2005).

The structure of the network does not only affect an agent's performance but also his future behavior (Ahuja, 2000; Baum et al., 2010). As Barabási et al., (2002) point out, collaboration networks are a "prototype of evolving networks". Thus, the network cannot be considered as fixed and exogenous: links between agents are dynamic, they break and form, modifying the characteristics of the agents (Cowan et al., 2007). This collaborations are not chosen at random, but usually satisfy specific reasons (Wagner and Leydesdorff, 2005).

The formation of linkages between firms generally depends on their previous history (Baum et al., 2010). Usually, firms are more likely to collaborate with previous partners because these interactions increase trust and willingness of both parties to engage in a risky activity as knowledge creation (Cowan et al., 2006).

Moreover, a firm's decision to start new collaborations depends on the attractiveness of the potential partner and also on the firm's own attractiveness for those potential partners (Wagner and Leydesdorff, 2005). Firms with more experience are more likely to find partners (Balland et al., 2012; Powell et al., 1996).

Knowledge creation

Knowledge creation is an incremental process (Jaffe et al., 2000): no agent can create novel knowledge if he has not some background knowledge. Nonetheless, the innovative output of individuals, teams and organizations is deeply influenced by the structure of the network they are embedded in (Guler and Nerkar, 2012). Nonetheless, this relationship is not linear, but shows highly complex micro dynamics (Ahrweiler et al., 2011). Degree centrality, or the number of collaborations, can be found to enhance firm performance (Bell, 2005). Thus, policies that support networking can improve business performance as well as knowledge creation and exploitation (Cooke and Wills, 1999), and also improve the performance of a region (Fleming et al., 2007).

Nonetheless, the effect of the number of collaborations can have many moderations. Collaboration with agents of different classes, such as consumers (Araujo and Mendes, 2009) or universities (Azagra-Caro et al., 2012), can deliver better results than collaboration with likes. Repeated collaboration as a means to increase knowledge creation is more effective if the network is sparse than dense (McFadyen et al., 2009). Moreover, even though indirect ties (the collaborators of one's collaborators) have a positive effect on performance and knowledge creation, this effect is thinner as the number of direct ties or collaborators increases (Ahuja, 2000). Nonetheless, we will only consider direct ties because of their more forthright effect on knowledge creation, and to avoid to tangle the model unnecessary.

However, networking is a costly activity (Ozman, 2009). Having many partners increases the risk of opportunistic behavior and requires specific capabilities to lead to outcomes (Powell, 1998). And, as McFadyen and Cannella (2004) find, "the greater the number of different relationships that an individual must maintain, the less the effort the individual can put into creation activities". The effect of direct ties, thus, can be found to have an inverted-U shaped effect on the creation of knowledge (Molina-Morales and Martínez-Fernández, 2009).

3. The model

Let us consider a model where a set of $S = \{1, \dots, n\}$ agents interact over T periods of time. In each step, they will form a network and create a certain amount of knowledge. The network will be represented by its adjacency matrix Ω_t , where $\Omega_t(i, j)$ takes the value 1 if i and j collaborate in step t , and 0 otherwise. The network in each step will be created depending on the network and the knowledge created in previous steps. Likewise, the amount of knowledge created in each step will depend on the amount of knowledge created in previous steps and the structure of the network.

Knowledge creation

The amount of knowledge created by agent i at the time t , $\kappa(i, t)$, depends on the structure of his ego network and on the stock of knowledge he possesses (Equation $\kappa(i, t) = \theta \cdot gr(j, t) - \gamma \cdot gr(i, t)^2 + \alpha \cdot \frac{1}{\tau} \sum_{s=1}^{\tau} \kappa(j, t-s)$ (1)). On the one hand, the more collaborations he has, the more knowledge he produces, which is captured by parameter θ . Thus, θ can be interpreted as the amount of knowledge created in each collaboration. On the other hand, collaborations can be costly, and thus a very high number of collaborations can hamper the creation of knowledge. This is captured by parameter γ and the square of the number of collaborations, so small numbers of collaborations will have a positive effect, but high numbers will decrease the knowledge created.

Finally, some amount of the knowledge created in previous step will continue to create new knowledge. Parameter α measures how much new knowledge is created from the stock of knowledge of agent i . The length of the time window is τ , the number of periods before the knowledge becomes obsolete.

$$\kappa(i, t) = \theta \cdot gr(j, t) - \gamma \cdot gr(i, t)^2 + \alpha \cdot \frac{1}{\tau} \sum_{s=1}^{\tau} \kappa(j, t-s) \quad (1)$$

Knowledge network

The probability that agent i wants to collaborate with agent j is a linear combination of their previous history and the attractiveness of agent j (Equation $P(i \rightarrow j, t) = \lambda \Omega(i, j, t - \tau) + (1 - \lambda) \left(\mu \frac{\sum_{s=1}^{\tau} \kappa(j, t-s)/\tau}{\max_k \kappa(k, t-\tau)} + (1 - \mu) \frac{\sum_{s=1}^{\tau} gr(j, t-s)/\tau}{\max_k gr(k, t-\tau)} \right)$ (2)). Parameter λ measures the weight of the previous history, and must be constrained to $[0, 1]$. In turn, there are two sources of attractiveness: the knowledge stock and the history of collaborations. Parameter μ is the weight of the knowledge stock in the attractiveness. This function is inspired by the preferential attachment algorithm (Albert and Barabási, 2002; Barabási and Albert, 1999).

Finally, the probability that agents i and j collaborate is that either of them wants to collaborate with the other (Equation $P(i \leftrightarrow j) = P(i \rightarrow j \cup j \rightarrow i)$ (3)). In taking probabilities we account for the fact that they can be willing to collaborate but may not be able to do so for some reason.

$$P(i \rightarrow j, t) = \lambda \Omega(i, j, t - \tau) + (1 - \lambda) \left(\mu \frac{\sum_{s=1}^{\tau} \kappa(j, t-s)/\tau}{\max_k \kappa(k, t-\tau)} + (1 - \mu) \frac{\sum_{s=1}^{\tau} gr(j, t-s)/\tau}{\max_k gr(k, t-\tau)} \right) \quad (2)$$

$$P(i \leftrightarrow j) = P(i \rightarrow j \cup j \rightarrow i) \quad (3)$$

To follow the structure of the network during the simulations, the main indicator will be the average degree, or average number of collaborations per agent. The average degree D is a measure of density: the higher the average degree, the higher the density of the network. Other network indicators yield to similar conclusions, e.g. the average path length or the clustering coefficient (simulations available upon request).

4. Results

The model has been simulated for $n = 50$ agents and $T = 100$ time steps. In order to provide a visualization of the simulations, the average knowledge created and the average degree are drawn for some sets of parameters. The simulations show a variety of behavior, grouped as three scenarios depending on the overall slope of the charts. If the slopes have the same sign, the coevolution will be said to be parallel, if they have not, the coevolution will be opposite. Regardless of the sign, if one of the slopes is flat and the other is not, the coevolution will be independent.

The parallel coevolution: knowledge creation as a collaborative process

If knowledge is created through collaborations, the knowledge curve and the network curve evolve hand in hand (Figure 1). This kind of scenario is reproduced by the model for high values of θ . That is, when the creation of knowledge depends highly on the number of collaborations, the more an agent collaborates, the more knowledge he produces, no matter what the rest of the parameters are. This is, thus, the most common scenario of the model.

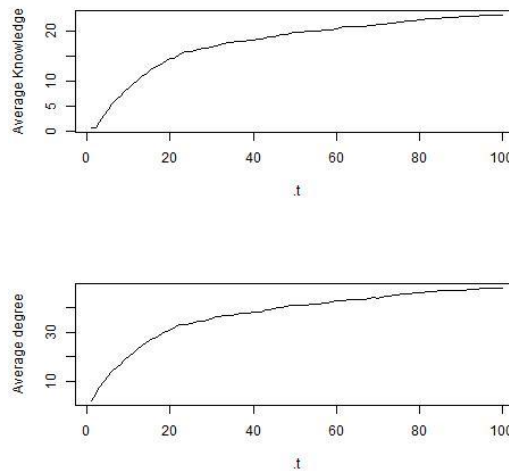


FIGURE 1: Parallel coevolution, collaboration based.
Parameter values: $\tau=1$, $\theta=0.9$, $\alpha=0.1$, $\gamma=0.1$, $\lambda=0.9$, $\mu=0.1$

The case depicted in Figure 1 is not the only kind of parallel coevolution that can be found. When knowledge creation is easy (high of α and low γ) and agents choose their partners depending on their attractiveness (low λ), a complete network emerges soon, where every agent collaborates with every other agent (Figure 2). In this case, once the agents have started collaborating, and thus creating knowledge, the process enters a circle until the network is completely dense and all agents create the maximum amount of knowledge they can create.

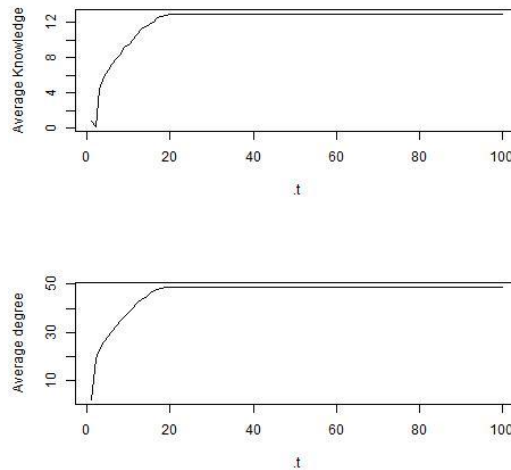


FIGURE 2: Parallel coevolution, complete network.
Parameter values: $\tau=1, \theta=0.5, \alpha=0.1, \gamma=0.1, \lambda=0.1, \mu=0.1$

When having many collaborators is costly (high γ) and the collaborations are done with previous partners (high λ), periods of decay can appear (Figure 3). When the density of the network starts to go down, the amount of knowledge created will drop and the process will be trapped in decay. This can happen after a period of growth thus leading to an inverted-U shape (Figure 4). This is most likely to happen if collaborations provide with high amounts of new knowledge (higher θ) and the attractiveness depends on the number of collaborators (low μ) rather than on the amount of knowledge.

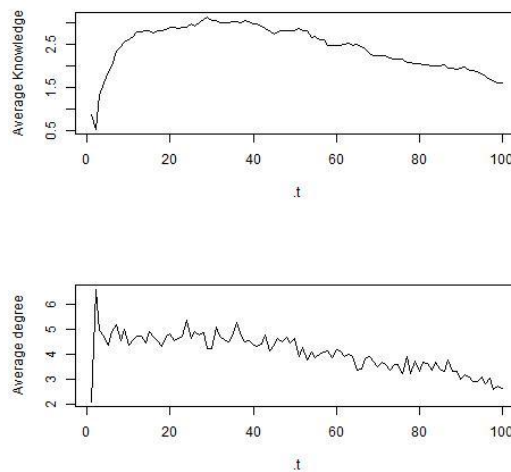


FIGURE 3: Parallel coevolution, decay.
Parameter values: $\tau=5, \theta=0.5, \alpha=0.5, \gamma=0.5, \lambda=0.9, \mu=0.9$

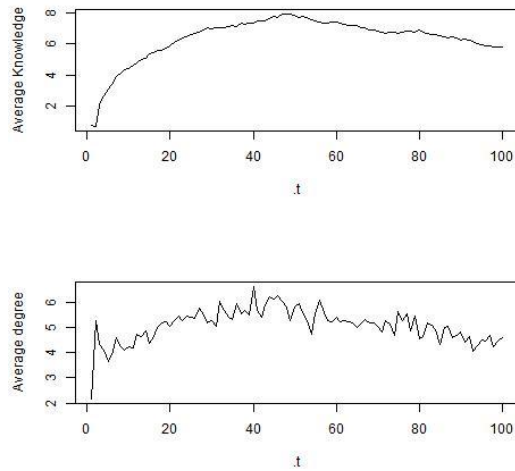


FIGURE 4: Parallel coevolution, inverted-u shape.
Parameter values: $\tau=5$, $\theta=0.9$, $\alpha=0.5$, $\gamma=0.5$, $\lambda=0.9$, $\mu=0.1$

Finally, when few knowledge can be produced from the stock (low α) and collaborators are chosen for their attractiveness (low λ), the network and the knowledge creation can experience a moment of rapid increase during the first training steps, followed by a stabilization around a certain structure (Figure 5).

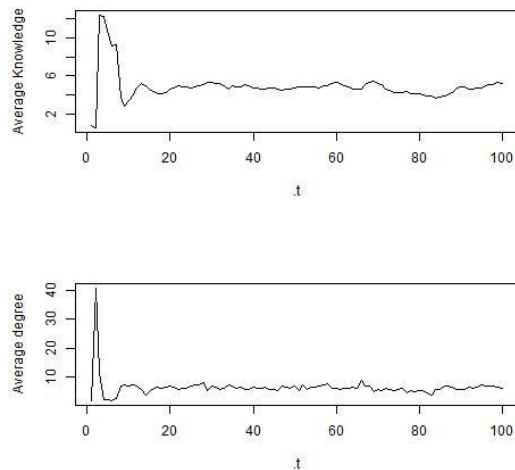


FIGURE 5: Parallel coevolution, flat slope.
Parameter values: $\tau=5$, $\theta=0.9$, $\alpha=0.1$, $\gamma=0.1$, $\lambda=0.1$, $\mu=0.9$

The independent coevolution: knowledge creation as an individual activity

When agents choose their partners depending on their attractiveness (low λ) and knowledge is created from the already existing knowledge (high α), the knowledge

creation and the network coevolve independently (Figure 6). The network stabilizes, and the knowledge created increases at each step.

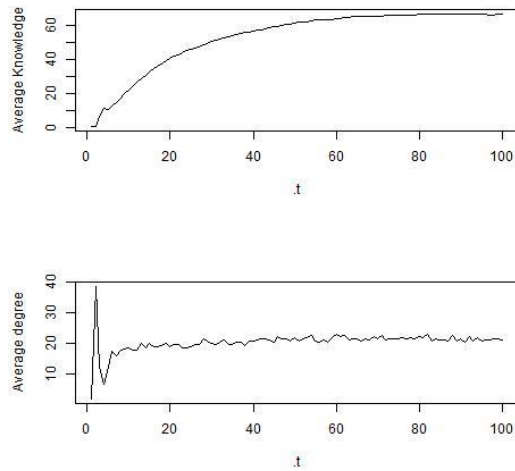


FIGURE 6: Independent coevolution.
Parameter values: $\tau=2$, $\theta=0.5$, $\alpha=0.9$, $\gamma=0.1$, $\lambda=0.1$, $\mu=0.9$

There is also another kind of independent coevolution (Figure 7Figure 9Figure 1). If the amount of knowledge created from the stock is higher than the stock ($\alpha > 1$), then the knowledge curve will grow exponentially. If collaborations are based on attractiveness (low λ), the number of collaborators is steady over time, leading to an independent coevolution.

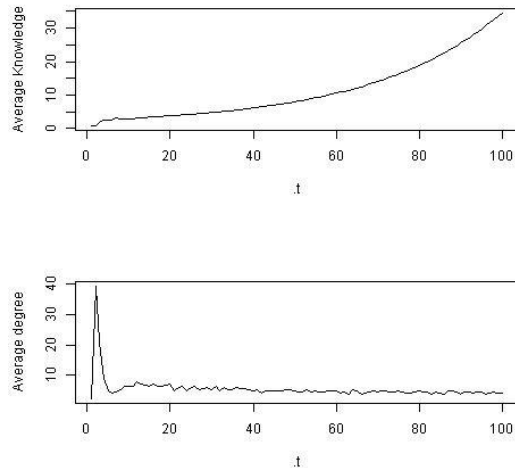


FIGURE 7: Independent coevolution, exponential growth.
Parameter values: $\tau=5$, $\theta=0.1$, $\alpha=1.1$, $\gamma=0.1$, $\lambda=0.1$, $\mu=0.9$

The opposite coevolution: costly collaboration depending on previous history

When knowledge is mainly created from already existing knowledge (high α and low θ), having many collaborators is costly (high γ), and agents continue collaborating with their previous partners (high λ), the knowledge creation and the network coevolve in opposite directions.

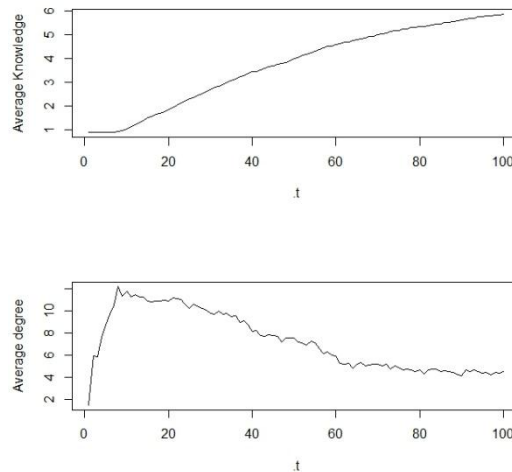


FIGURE 8: Opposite coevolution.
Parameter values: $\tau=2$, $\theta=0.1$, $\alpha=1$, $\gamma=0.9$, $\lambda=0.9$, $\mu=0.9$

As before, there is also another kind of opposite coevolution (Figure 9) where the knowledge curve will grow exponentially. This is associated with scenarios where the amount of knowledge created from the stock is higher than the stock of knowledge itself ($\alpha > 1$). If collaborations are based on previous collaboration (high λ), this effect will be combined with a decrease in the density of the network, leading to an opposite coevolution.

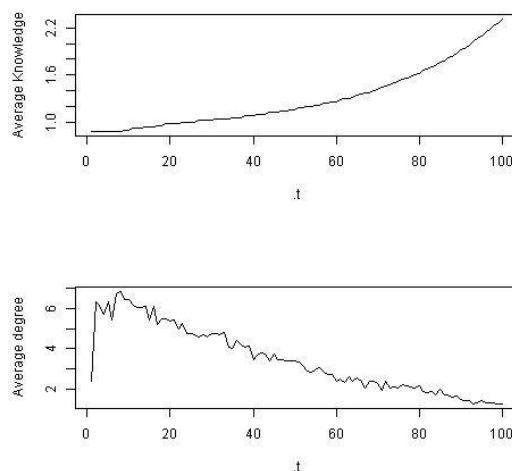


FIGURE 9: Opposite coevolution, exponential growth.
Parameter values: $\tau=5$, $\theta=0.1$, $\alpha=1.1$, $\gamma=0.5$, $\lambda=0.9$, $\mu=0.9$

5. Discussion and conclusion

This paper presents a simulation model of the coevolution of knowledge networks and knowledge creation. As knowledge creation is increasingly an interacting process, this kind of models is important to increase our understanding of the process. This paper suggests that different scenarios of knowledge creation in networks can arise. Depending on the importance of collaborations for the creation of knowledge, on the cost of these collaborations, and on how the collaborators are chosen, the overall behavior of the process can change.

The most intuitive scenario, a positive coevolution of knowledge creation and networks, is not the only possible one: in theory, increased knowledge creation can be independent of enlarged knowledge networks, or they can be even mutually excluding.

This has implications for policymaking. When the objective is to enhance the creation of knowledge, it is important to make sure which is the scenario we are facing. For instance, policies aimed at reducing the cost of collaborations can be fruitful in an environment where knowledge is created through collaborations, but they will not in cases where new knowledge is mainly created not from collaboration but from the individual stock of knowledge. In those cases, a better strategy might be to invest in individual equipment. Furthermore, when knowledge is created mainly from collaboration, periods of decay in the creation of knowledge can appear if the weight of previous collaboration is much higher than the weight of attractiveness new potential partners to determine current collaboration. If such was the case, policies should aim at reducing the importance on previous collaboration in the selection of partners. A legal framework that would increase the willingness to interact with unknown partners, or incentives to collaborate with outstanding partners, would help changing the framework to a preferable one.

This paper has several limitations, the first one being that the simulation model suggests different lines of action for different cases. Without identifying which case is the one faced, it is not possible to choose between those actions. In order to address this issue, the model will be empirically validated in future research. This empirical validation will help to identify the most likely parameters of a real knowledge creation process and it can lead to a comparison of different knowledge creation processes.

Furthermore, in a next stage of research it would be desirable to implement policy actions. The model would have to be able to incorporate parameter changes through time. Then, the possible actions suggested for the different scenarios could be tested as simulations, in a secure and costless way.

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