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Are bridging ties really advantageous? An experimental test of their advantage in a competitive social learning context

Eva Vriens*, Rense Corten

Department of Sociology/ICS, Utrecht University, The Netherlands

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ABSTRACT

Despite the widespread acceptance of the claim that bridging ties help to obtain profitable outcomes, its underlying mechanisms remain understudied. Starting from a multi-armed bandit problem, we tested the bridging tie hypothesis experimentally by studying the outcomes of social learning for different network positions (in terms of local clustering and closeness centrality) with and without competition. We found a positive effect of bridging ties, but only within one's direct network (i.e., when local clustering is lower), in competitive contexts, and for choices characterized by higher uncertainty. This stresses the importance of outlining more clearly the scope in which the bridging tie hypothesis applies.

Introduction

Social networks form an important source of information on which individuals base their opinions and actions. They have, for instance, been argued to convey news about new products and technologies (Conley and Udry, 2010; Duflo and Saez, 2003; Kremer and Miguel, 2007) and about job openings (Granovetter, 1995; Lin, 2001). In particular, lots of scholarly attention has been devoted to the hypothesis of Granovetter (1973) and Burt (1992) that actors with ties to otherwise distant social cliques obtain better individual outcomes (e.g., higher paid jobs).

This hypothesis, known as the bridging tie hypothesis, is widely accepted due to its intuitive appeal. Whether its underlying mechanisms apply, however, has up until recently rarely been questioned. The available support is largely based on observational studies that merely established correlations between network characteristics and individual outcomes (de Graaf and Flap, 1988; Lin, 2001). Only recently did scholars start making efforts to expose the underlying causal mechanisms and the evidence is mixed: while some studies (e.g., Conley and Udry, 2010; Mason and Watts, 2012) indeed find support for network effects, others, both observational (e.g., Mouw, 2003) and experimental (Choi et al., 2004; Hofstra et al., 2015; Rutten, 2014), could not relate bridging ties to better individual outcomes.

These results signify the importance of more thoroughly investigating the relationship between bridging ties and opportunities for receiving novel information by studying the exact underlying mechanisms as explicitly as possible, as well as the conditions under which these mechanisms are likely to operate. In this article, we do so by incorporating the impact of competition. In most situations described by seminal studies such as Granovetter (1973) and Burt (1992), the advantage of receiving novel information from one's network is discussed relative to the position of others. That is, the advantage is obtained only if the actor obtains it before others do. This interdependency in actors' behavior is likely to influence their learning strategies (Denrell and March, 2001): Rather than aiming to learn the *best* outcome as soon as possible, actors first and foremost have to obtain a *better* one.

To illustrate, for a scholar to benefit from his network in his pursuit to add to theory development, he should act quickly when he hears a colleague present about a promising new approach on a conference. If he immediately incorporates and improves this approach, he might be able to gain a competitive advantage over other scholars. If he waits too long, the first colleague will have published the results and the knowledge will have become more widespread. More scholars start working on this project, and it is more difficult to still gain a competitive advantage (Burt, 2004). We investigate how this competitive aspect of learning better alternatives before others do affects the relation between network positions and the likelihood of obtaining beneficial outcomes.

Altogether, we more rigorously test the mechanisms underlying the relationship between network positions and individual outcomes. We aim to answer the following questions: To what extent do bridging ties facilitate the actor's goal to obtain the best possi-

* Corresponding author at: Department of Sociology/ICS, Utrecht University, Padualaan 14, 3584 CH Utrecht, The Netherlands.
E-mail address: e.vriens@uu.nl (E. Vriens).

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ble outcome? And does the competitiveness of the learning context matter? We investigated these questions in a laboratory experiment, as that enables studying mechanisms of social learning in isolation (Falk and Heckman, 2009) and thereby to identify causal effects of social network positions.

We presented 200 subjects with a variant of the Iowa Gambling Task (Bechara et al., 1994), a decision task in which subjects have to learn the most profitable action among alternatives of uncertain profitability. They made multiple decisions over time and could infer new information (i.e., learn) from the outcomes of their own earlier actions and those of their neighbors. By varying network positions and whether or not the task is competitive, we exposed the conditions that facilitate or hinder the chance of making a profitable choice.

Theory

To understand to what extent information from one's network is used to make decisions we use the model of a multi-armed bandit problem (Robbins, 1952), named after the dilemma a gambler faces when deciding which of K slot machines (one-armed bandits) to play. This model reflects a decision task with uncertainty. Uncertainty, in this case, means that the actor is confronted with a range of possible actions (e.g., slot machines to play) and has to pick one without knowing in advance which generates the highest payoff (Bubeck and Cesa-Bianchi, 2012).

Multi-armed bandit problems are characterized by the stochastic nature of the actions' outcomes. Similar to slot machines, a suboptimal action might return multiple winnings purely by chance and an optimal action might return several failures. Therefore, actors are assumed to learn through reinforcement (Camerer, 2003, chap. 6), as multiple trials are needed to learn which action is more profitable (Auer et al., 1995).

Formally, we consider a range of K different actions $a \in A$ and an unknown state of the world θ, a random, exogenous variable that determines which action is most profitable (denoted as a^*) in terms of payoff maximization (Bala and Goyal, 1998). Although the actor is not informed about the exact value of θ, he does hold certain private beliefs x_i about it, composed of θ and a margin of error ε_i—the latter normally distributed with a mean of 0 and a standard deviation of 1 (DeMarzo et al., 2003). Based on these private beliefs x_i the actor chooses the action that supposedly yields the highest possible profit. When the decision task is repeated over multiple time periods, indexed in discrete steps by $t \in \{1, 2, \ldots\}$, the actor can integrate information from earlier experiences to update prior beliefs x_i, which decreases the difference between x_i and θ and therefore increases his chances of learning a^* (Goyal, 2012).

Learning strategies

To solve a multi-armed bandit problem, a payoff-maximizing actor aims to strike a proper balance between two learning strategies: exploration and exploitation (Auer et al., 1995; Mason and Watts, 2012). Exploration involves experimenting with new actions to gather new information to develop alternative solutions (Baum et al., 2000; March, 1991). To illustrate, a clinical researcher applying this strategy would try different treatments to see which provides the best results in terms of curing a disease.

The strategy is rewarding for it creates a large variety of information, which increases the chances of gaining insight into θ and therefore to learn about a^* (Fang et al., 2010). Nonetheless, it is often considered costly, because its outcomes are uncertain beforehand (Denrell and March, 2001). Each new action could both result in better and worse payoffs, meaning that the trial of new actions for future gain could go to the expense of current profit.

To avoid this actors often opt for exploitation instead; a learning strategy that reuses and refines existing knowledge and known solutions (Gupta et al., 2006). Exploiting actors stick to the action that previously generated the highest payoff. The clinical researcher, for instance, cannot endlessly experiment with new treatments on patients at random, hoping to one-day find the perfect cure. Instead, he might opt for the treatment that yielded the best results in earlier years.

It is easy to see that as long as the best solution has not been found, exploitation ultimately is not as profitable as exploration (March, 1991). However, embeddedness in a social network, with others facing the same or similar choice alternatives, shifts this balance to some extent (Mason and Watts, 2012). Within networks, another means of exploitation is to reuse and refine existing information arising from the experiences of others (Lazer and Friedman, 2007). In this respect, exploiting actors use opportunities for social learning, where they improve their decision by inferring information about θ from how others behave and/or from the payoff they receive (Gale and Kariv, 2003; Goyal, 2012). In our example, the clinical researcher might learn that a colleague experimented with a treatment that provided promising results and could opt to use the same treatment on his own patients.

By enabling social learning, exploitation also offers the actor more information than he otherwise would have had (Gupta et al., 2006). However, not only profitable actions spread through the network; information about suboptimal actions might spread as well, certainly when no one has learned a^*. So even though social learning might provide the actor with new information there is no guarantee that the integration of all currently available information helps him to ultimately grasp θ. To sustain learning about a^*, actors facing a multi-armed bandit problem should therefore find a proper balance between exploration and exploitation (Vermorel and Mohri, 2005).

In finding that balance, we follow Bala and Goyal (1998) and assume actors to be boundedly rational decision makers. They integrate information from their own experiences and those of others to increase knowledge about θ, but do not use this information to infer what these actors must have learned from their connections. Furthermore, they use this information to determine their own best course of action, but do not consider how their own actions could influence the behavior of others. Deviating from full rationality, these assumptions simplify the model in terms of tractability and enable translation to real-world settings (DeMarzo et al., 2003; Mobius et al., 2015).

In behavioral terms, it means that we expect the boundedly rational actor to favor social learning over independent exploration (Baum et al., 2000). He follows a neighbor in situations wherein this neighbor repeatedly received a higher payoff and only explores new alternatives when neither he nor his neighbors obtained profitable outcomes. When a single action repeatedly generates profitable payoffs, he sticks to exploiting this action (Lazer and Friedman, 2007).

Learning outcomes in different network positions

To predict the outcome of using social exploitation as a learning strategy, we have to take the network structure into account. That is, the probability that social exploitation enables an actor to learn a^* depends largely on how well connected he is—with connectedness determined by his position within the network (Mason and Watts, 2012). All actions taken by neighbors provide the actor with information, but some neighbors provide more valuable information than others.

To see how, consider a single component network g, composed of $N \geq 3$ actors connected in such a way that $e_{ij} \in g$ means an undirected tie exists between actors i and j (Mobius and Rosenblat,