Designing a CTSA-Based Social Network Intervention to Foster Cross-Disciplinary Team Science

Raffaele Vacca, Ph.D.[1,2], Christopher McCarty, Ph.D.[3], Michael Conlon, Ph.D.[2], and David R. Nelson, M.D.[2]

Abstract

This paper explores the application of network intervention strategies to the problem of assembling cross-disciplinary scientific teams in academic institutions. In a project supported by the University of Florida (UF) Clinical and Translational Science Institute, we used VIVO, a semantic-web research networking system, to extract the social network of scientific collaborations on publications and awarded grants across all UF colleges and departments. Drawing on the notion of network interventions, we designed an alteration program to add specific edges to the collaboration network, that is, to create specific collaborations between previously unconnected investigators. The missing collaborative links were identified by a number of network criteria to enhance desirable structural properties of individual positions or the network as a whole. We subsequently implemented an online survey ($N = 103$) that introduced the potential collaborators to each other through their VIVO profiles, and investigated their attitudes toward starting a project together. We discuss the design of the intervention program, the network criteria adopted, and preliminary survey results. The results provide insight into the feasibility of intervention programs on scientific collaboration networks, as well as suggestions on the implementation of such programs to assemble cross-disciplinary scientific teams in CTSA institutions. Clin Trans Sci 2015; Volume 8: 281–289

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Introduction

In the past several years, a wide consensus has developed on the notion that science is made in collaborative teams. A growing body of evidence shows that the highest impact work and the most groundbreaking inventions in contemporary science originate in larger and more cross-disciplinary teams.[1–4] Academic institutions, government agencies, research centers in the public and private sector alike, increasingly recognize that most of the problems we face today are complex and need to be addressed by teams that span different disciplines and organizations.[5–7] This realization has generated a new widespread emphasis on "team science," that is, the science that is made by teams; and on the "science of team science" (SciTS), that is, the study of the factors that facilitate or hinder effective collaboration in teams.

Clinical and Translational Science is considered team science *par excellence*. The breadth and complexity of the T1–T4 translational spectrum involve a combination of research methods and substantive focuses from biomedical sciences, clinical research, social sciences, computer science, economics, and business administration.[5] Therefore, understanding how to assemble and sustain cross-disciplinary teams is a top priority in Clinical and Translational Science institutions.[5,8,9] Most recently, in the September 2014 funding opportunity announcement for the CTSA program, National Center for Advancing Translational Sciences (NCATS) urged applicants to "describe their vision for creating a shared environment within their own CTSA hub, and within the CTSA network, [including] strategic goals to increase incentives for teamwork, to facilitate the assembly of multidisciplinary translational teams, to promote collaborations, and to increase knowledge and awareness of what works best in team science."[10]

While much research in SciTS has been concerned with team effectiveness, that is, how scientific collaborations can effectively function;[11–13] a different line of research in the field has dealt with the logical premise to team effectiveness, namely team assembly. Most of this work has investigated the processes by which cross-disciplinary teams self-assemble, formulating and testing hypotheses about different underlying behavioral, psychological, and social mechanisms.[14–16]

In this paper, we propose a different approach to the problem of team assembly, by drawing on the notion of social network interventions and exploring its application to team science. We report on a network intervention program designed at the University of Florida (UF) Clinical and Translational Science Institute (CTSI) in 2013 using VIVO, a semantic-web research networking system implemented at the university level.[17] The program mapped the UF scientific collaboration network to identify and connect researchers in specific locations of it. In other words, the program intervened on the UF collaboration network by adding specific missing links to it.

Querying VIVO, we constructed the network of all the scientific collaborations that resulted in a publication or an awarded grant at the university in 2012. We then applied a number of structural criteria to identify dyads and triads of unconnected researchers, whose collaboration would have enhanced certain structural properties of individuals or the whole network. Finally, we implemented an online survey that introduced the unconnected potential collaborators to each other via their VIVO profiles. Of course, team science requires not just connecting people in teams, but also understanding when and how these teams work. Both environmental and individual factors may facilitate or hinder team effectiveness,[18–21] and the personal decision on whether to join or not a scientific team varies depending on different facilitators and barriers.[22] To explore this problem, our survey investigated the potential collaborators' attitudes and views toward working with each other, and potential barriers and incentives to starting a collaboration. We discuss here the design of the intervention program and the survey results.

[1]College of Nursing, University of Florida, Gainesville, Florida, USA; [2]Clinical and Translational Science Institute, University of Florida, Gainesville, Florida, USA; [3]Bureau of Economic and Business Research, University of Florida, Gainesville, Florida, USA.

Correspondence: Raffaele Vacca (r.vacca@ufl.edu)

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Network Interventions

A well-established finding in the field of social network analysis[23,24] is that positions that span "structural holes" in network structure, bridging areas of a social network that are otherwise unconnected, are associated to creative ideas and innovation.[25] One of the mechanisms that explain this result is that individuals who are in a network position that spans structural holes tend to have access to diversity, that is, to be connected to different social circles with different backgrounds, expertise, views, and opinions.[25,26] This is consistent with the fundamental team science argument that team diversity is associated to creativity and innovation.[27–30] The basic intuition underlying the intervention program presented here is that, if certain structural positions or configurations of a social network are associated with creativity, innovation, or scientific success, we should try to intervene on the network to *create* those positions and configurations. This kind of network intervention has been called *alteration* in the social network literature.[31]

In general, a network intervention is a program that leverages social networks to promote behavioral change in a population or enhance individual or collective performance in an organization.[31,32] The notion has been applied for years in the health sciences, management, and marketing, and an insightful typology of network interventions has been recently proposed, which distinguishes four types of interventions:[31] the programs based on the identification of specific *individuals*; the ones based on the *segmentation* of the network into groups or communities; *induction* programs that stimulate interaction among connected people and accelerate the diffusion of specific information or behaviors in an existing social network; and *alteration* programs that effectively change the underlying social network, for example, by adding or removing nodes or edges.

Alteration is fundamentally different from the first three intervention strategies: while other strategies analyze and use the existing social network, alteration changes the network itself. In this sense, alteration is a more invasive form of network intervention, and a more difficult one to implement. Alteration programs may add or remove network nodes: for example, hiring a new employee who becomes part of a company's network, or quarantining a patient who is therefore removed from a contact network that spreads a disease. Alteration may also target network edges, adding new edges or removing existing edges between certain nodes. Edge alteration is not a typical network intervention, however, because there are normally strong reasons why people establish certain relations and avoid others. Intervening from the outside on the "natural" evolution of connectivity in a network, as shaped by specific behavioral, spatial, or organizational factors, can be particularly challenging.[31]

The project described in this paper is a program of network alteration that targeted edges in the scientific collaboration network of the UF. The program aimed to add new edges between investigators in specific locations of the university network. This is an innovative project for at least two reasons. First, this intervention targets a scientific collaboration network. In the past, network interventions have been implemented mostly on networks of social relations or interactions related to health outcomes, and on organizational networks within companies, rather than on scientific or scholarly networks.[31,32] Second, this intervention is an example of network alteration. This project did not limit itself to using a collaboration network as it existed; it was designed to change the network, by adding specific new links to it.

Induction versus Alteration on Scientific Collaboration Networks

A scientific collaboration network can be compared to a human brain in many ways. It constantly produces new knowledge, and it does so through connections—collaborations between scientists. Like connections in the brain, collaborations are not randomly placed in the network, rather they are patterned in a clustered structure, with clusters being determined by institutional, spatial, or disciplinary proximity. Just like in the human brain, between the clusters are areas that are *not* connected, holes in the network structure. In the human brain, *learning* develops as new associations between previously disconnected neurons are created.[33] Similarly, a scientific network produces innovations when new connections arise between previously disconnected areas, institutions, or disciplines.[5,25]

A scientific network may respond in different ways when new conditions arise, for example, a new funding opportunity. Existing connections may be activated—scientists who are already collaborating or have collaborated in the past start a new project. Or *new* connections may arise—a new project is started by scientists who have never worked together before. In fact, the former is the usual outcome as individuals are typically more likely to pick collaborators with whom they are more familiar, possibly because of prior collaborations.[19,34,35] As a consequence, the traditional way of funding academic research may have limitations, especially when it comes to stimulating cross-disciplinary research. In fact, in the framework of network interventions, the traditional way of funding research is a form of induction. It mostly uses the existing network as it is, and increases the volume of professional interactions along already established links. In the typical research funding process, agencies solicit applications for projects on specific topics from any investigator or team of investigators. Although there may be requirements about the team members, for example, collaborators may be required to have different college affiliations, funding is not targeted to specific areas of a scientific network—in fact, funding agencies have normally no exact knowledge of the scientific collaboration network that their announce is addressing.

With this kind of funding process, investigators need to be aware that an interdisciplinary offer exists, which is not necessarily the case. Furthermore, investigators may not realize that they have close indirect connections to potentially useful collaborators in other disciplines. As shown by abundant research on cognitive social structures, individuals' perceptions of the social network in which they are embedded are often inaccurate.[36] The knowledge that an investigator *A* has of the surrounding professional network may be limited to *A*'s collaborators, and perhaps *A*'s collaborators' collaborators. Thus, scientists typically respond to funding opportunity announcements by finding close and familiar professional partners, replicating existing collaborative relationships, or establishing new collaborations still within their professional comfort zone. When link formation is left to the natural evolution of the network, with no strategic intervention to add specific collaborative links at specific locations, new connections, if generated at all, tend to close gaps within already well-established collaborative clusters.

The idea of *alteration* on a scientific collaboration network is different from the traditional way of stimulating research by induction. A program of alteration starts from a map of the whole collaboration network it addresses. Such a network may be constructed from data on publication or grant collaborations

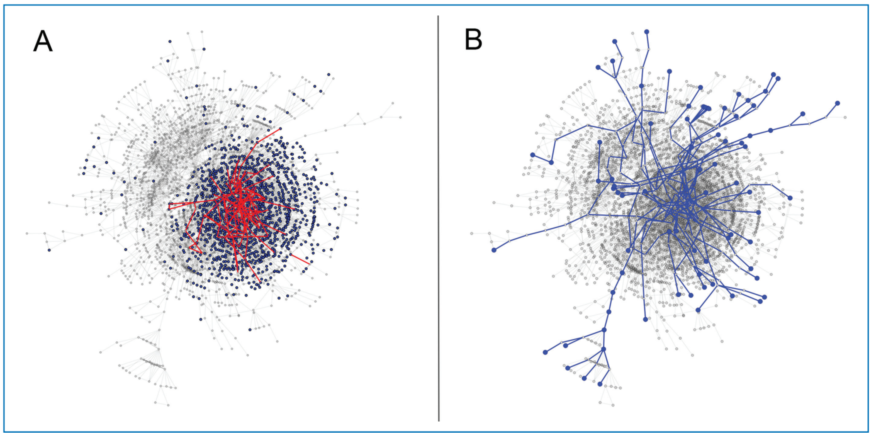

Figure 1. Induction versus alteration in the 2012 scientific collaboration network of the University of Florida. (A) shows collaborations activated by induction: Red paths are the shortest network paths between investigators whose collaboration resulted from the UF CTSI Pilot Project Awards. (B) shows collaborations targeted by alteration: The blue paths are the shortest network paths between investigators reached by the UF CTSI alteration program. Unlike induction, alteration activates collaborations that cut across institutional boundaries and disciplinary divides, spanning long distances in the university network.

at a given institution. Alteration identifies specific individuals whose collaboration is more likely to be successful and to improve the performance of the whole organization, by enhancing certain structural properties of single actors or the whole network. These researchers are approached, introduced to each other, and pilot projects are offered them to work on a proposal together. Thus, specific links are added to the network between specific collaborators and teams, on the basis of their position in the structure of the network.

Figure 1 illustrates the difference between traditional induction and the alteration approach on the scientific collaboration network of the UF. Panel A shows the links created by a traditional inductive funding program, the UF CTSI Pilot Project Awards. Virtually all the links that this program created were within the institutional boundaries of the university's Health Sciences Center: scientists mostly applied with partners within their institutional or disciplinary boundaries. The UF CTSI Pilot Project Awards data provide further evidence that investigators tend to naturally pick collaborators within their scientific comfort zone, ones with whom they are more familiar or have already collaborated in the past. On the other hand, Panel B shows the teams of collaborators that were connected by the alteration program introduced in this paper. The alteration program generated links that typically cut across disciplinary divides and structural holes in the network, to a much greater extent than the naturally occurring links of Panel A created by induction. Panel B's new collaborative links are very unlikely to be spontaneously established by individual researchers searching for new collaborators. The intervention of an external agent with a bird's-eye view of the network is the only way these specific collaborations may ever occur in the university.

Methods: Network Alteration Using VIVO

The data

Scientists can collaborate in many different ways, and different products may result from their collaboration.[37] While co-authorship is traditionally used as the only proxy of collaboration,[3,38] we enhanced this typical data source by combining collaborations on both publications and research grants. We used VIVO records on publications and grants at UF in 2012 to extract two networks: a publication network, where two individuals *A* and *B* are connected if they were coauthors on one or multiple academic articles in 2012; and a grant network, where *A* and *B* are connected if they participated to one or multiple grants together in 2012. We analyzed these two networks separately, but we also merged them into a "union" network, where *A* and *B* appear as collaborators if they either coauthored a publication in 2012, or participated to the same grant in 2012. We believe the union network to be the most comprehensive map available in our data of the actual scientific collaboration network at the UF.

The structural criteria to identify missing links

The alteration program was intended to create specific links in the university collaboration network on the basis of three general principles: (*i*) A link should be created if it is likely to result in a successful scientific collaboration. (*ii*) A link should be created if it enhances desirable structural properties of individual positions in the network. (*iii*) A link should be created if it enhances desirable structural properties of the whole collaboration network.

In light of these principles, a number of structural intervention criteria were defined, which identified specific missing links to be added. We use the expression "intervention criterion" to signify a *rule* which (*i*) is based on specific network measures, and (*ii*) when applied to a given network, identifies a specific dyad or triad of unconnected nodes. The one link in the dyad, or the three links in the triad, are the missing links that we are trying to add to the collaboration network. In the following, we discuss the five classes of intervention criteria used in the program.

Improving network cohesion

Improving network cohesion means increasing mutual awareness, communication, and interaction between areas of the scientific network that were previously separate, distant, and unaware of each other. By improving the overall cohesion of a network, we specifically mean two things: (*i*) Connecting separate and distant areas of the network. (*ii*) Reducing the overall sum of distances among nodes in the network. The word "distance" refers here to the geodesic distance, the number of links in the shortest path that separates two nodes in the network. Higher cohesion enhances the overview and the understanding that single investigators have of the whole network available to them. In a more cohesive network, scientists are more aware of each other and each other's work; they are more knowledgeable of the skills, resources, and potential collaborators available in their institution, and they are more capable of locating the expertise they need.

While improving network cohesion, our intervention program was also designed to foster *cross-disciplinary* interactions. Thus, we tried to increase cohesion by connecting scientists who were especially far apart in the university network, therefore likely to work in different disciplinary areas. This also means that these scientists are particularly unlikely to naturally hear about each other, be introduced by common colleagues, meet in the workplace, and ultimately start a collaboration. In this sense, the alteration strategy changes the natural course of network evolution to add links of particular interest, which would not spontaneously occur in the network. Three specific rules were used to identify missing links to enhance network cohesion.

Nodes separated by the longest geodesic distance within a given boundary

We picked dyads of researchers with the longest geodesic distance to each other. We constrained the search within certain institutional boundaries to increase the likelihood that the two scientists find common grounds for a collaboration. For example, we connected the two most distant researchers within the university's Health Sciences Center.

The most between-central, distant nodes

A between-central node is a researcher who falls on the shortest paths between many other researchers, and bridges unconnected areas of the network.[39] Linking to a bridge means indirectly linking to at least the two sides that are connected by that bridge. Therefore, connecting to a very between-central actor *A* means indirectly connecting to at least two separate areas of the collaboration network, the two areas *A* is bridging. Based on this argument, connecting *two* between-central nodes *A* and *B* to each other creates an indirect link between the multiple areas of the network that *A* and *B* are bridging. On the other hand, *A* and *B* may be both very between-central while bridging *the same* two areas in the network.[40] However, if *A* and *B* bridge the same areas of the network, the geodesic distance between them is normally short. Thus, among the top between-central scientists in the network, we connected the dyads that were farthest apart. This biased the selection toward between-central nodes that are bridging *different* regions of the network. A link between two bridges who connect multiple, separate sites of the network creates a further indirect bridge among these sites, which highly decreases overall distances between network nodes.

Nodes in distant communities

This strategy identifies and connects separate cohesive research communities in the network. The communities were identified using the Girvan–Newman algorithm.[41] In each community we picked the most peripheral nodes, those with the lowest degree centrality (number of existing collaborations), to be brokers with the other community. We connected peripheral nodes on the assumption that, as a consequence of their weaker commitment with their own community, they would be the most open to collaborating with outsiders.

Creating interdisciplinary teams

This strategy aims to explore factors that facilitate or hinder the formation of cross-disciplinary research teams. The basic idea is to detect separate groups of actors who work in different disciplines or research areas, and to establish links between them. We used department affiliation as a proxy of discipline or research area, and we operationalized a group as the set of a central researcher *A* and all of *A*'s collaborators (in graph-theoretic terms, *A*'s first-order neighborhood). We identified completely homogeneous groups in which all collaborators belonged to the same department, and we connected the central researchers from two such groups with different department affiliation. The goal was to create disciplinary diversity within collaboration groups, encouraging mix and cross-fertilization of ideas, interests, and research methods.

Spanning structural holes

This strategy consists in spanning holes in network structure[26] by putting certain actors in a brokering position between unconnected research communities. Brokering positions that span structural holes have been associated with innovation and "good ideas" in many settings:[25] criterion (3) tries to create such positions. We identified research communities using the Girvan–Newman algorithm,[41] and analyzed department affiliation in each community. We selected the most homogenous communities, those where all or most researchers belonged to a single department. We finally picked peripheral actors from two communities with different department affiliation, and created a connection between them. We targeted peripheral actors as brokers for the same reasons discussed for criterion (1.c).

This strategy can be seen as a mix of strategies (1.c) and (2). In (1.c) we also connect separate research communities, however we select communities on the basis of their higher distance in the network, rather than their different and internally homogeneous department affiliation. On the other hand, in strategy (3) we are picking two communities that are internally highly homogeneous with respect to department affiliation. Strategy (3) uses an actor attribute (department affiliation), whereas in (1.c) only the pattern of connectivity among actors is taken into account: (3) is more appropriate if the focus is on creating cross-disciplinary teams, whereas (1.c) should be favored if the priority is improving general cohesion in the network.

Strategy (2) also uses department affiliation to generate cross-disciplinary collaborations between groups with different affiliations. However, the difference from strategy (3) consists in the operationalization of the notion of group. In (2), groups are smaller network neighborhoods formed by a focal individual and all of his or her collaborators; in (3) groups are larger communities detected by the Girvan–Newman algorithm. A strategy like (2) is more appropriate if the ultimate goal is to create a single cross-disciplinary research team, which brings together two small groups formed by two focal individuals with their own collaborators. By contrast, in a strategy like (3), there is no expectation that the two connected groups will establish extensive collaborations and form a single team. Rather, strategy (3) is concerned with the individual brokering position of the two actors that we are linking, and whose connection creates a bridge between the two communities originally identified. The goal, in this case, is to create a position in which a scientist can benefit from spanning a structural hole and being exposed to information, expertise, and resources from two separate and different regions of the network.

Counterbalancing preferential attachment

Preferential attachment is the process of network growth in which new nodes join the network and are more likely to do so by attaching to nodes with higher centrality than to peripheral nodes.[42] In a network that grows by preferential attachment, popular, well-connected actors attract new collaborations more than peripheral ones. In scientific collaboration networks, preferential attachment implies that new, peripheral researchers tend to join the network by starting a collaboration with very central, well-established academic "stars" or "hubs";[3] more rarely are they aware of other peripheral researchers and inclined to work with them. This entails a process of cumulative advantage in science, whereby stars tend to attract more and more collaborators as they become more central, in a "rich-get-richer" dynamic that biases the distribution of collaborations, publications, and scientific rewards toward small scientific elites.[43,44]

Preferential attachment essentially means that the way the collaboration network is structured, and the way it channels information and resources, biases the manner in which scientists become aware of new potential collaborators. Investigators are disproportionally more exposed to information about already popular scientific stars, and much less exposed to the work of more peripheral, younger colleagues. However, the most popular network actors are not necessarily the best collaborators for a given project. A particular marginal actor could be a better fit for a given collaboration, and would probably have more time and effort than a network star to spend on a new project. Yet in the natural evolution of scientific collaboration networks, junior investigators are disadvantaged in establishing new collaborations, and unlikely to find each other's expertise. This is especially true for cross-disciplinary collaborations: unlike people in the same field, researchers in different disciplines lack opportunities to hear about each other (common professional meetings, scientific journals, list servers, etc.), therefore a search for collaborators in a different discipline is probably even more biased toward the most popular network stars.

These arguments suggest that preferential attachment may be an inefficient process for the formation of new collaborations. Strategy (4) explores the consequences of counterbalancing preferential attachment, by connecting two peripheral researchers who are unlikely to naturally link to each other.

Maintaining teams

All the alteration strategies described so far tend to add links between actors who are far apart in the network, belong to separate communities, and work within different disciplines. This creates connections that span structural holes in the network. While there is compelling evidence and a wide consensus on the value of bridging network positions and cross-disciplinary collaborations for creativity and innovation, we should not overlook the relevance of *intra*-disciplinary research.[45] Supporting research and collaboration within well-established disciplines and fields is important for at least two reasons. First, for there to be structural holes to span, there must exist separate cohesive communities in the first place. There can be no cross-disciplinary bridge if there are not multiple solid, well-established, and constantly maintained disciplines to be bridged. Second, cohesion within disciplines is also a value in itself. Cohesive within-discipline research groups facilitate incremental innovation, the improvement, and refinement of existing theories and models within a consolidated scientific paradigm. At the same time, while structural holes foster individual creativity by increasing autonomy and access to diversity, well-established and close-knit teams benefit creativity and learning by supporting safer relationships, shared languages, and good personal relationships.[46] If bridging across structural holes is good for radical innovation and creativity, density within cohesive subgroups is crucial to maintaining and updating "core" science, avoiding fragmentation and lack of agreed-upon directions in a discipline.

Strategy (5) develops this idea creating collaborative links within already existing cohesive teams as they emerge from network structure. This strategy selects small, dense Girvan–Newman subgroups detected in the network, and adds within-group missing links that preserve the cohesion of these teams.

The Online Survey

The network criteria (1)–(5) identified 123 dyads and 25 triads of previously unconnected investigators in the university's scientific collaboration network. An alteration program would ideally connect these dyads and triads, for example, by offering them targeted pilot grants. The goal of our project was to study the potential for such alteration program to be indeed implemented at the university level. We, therefore, launched an online survey in which each researcher in an identified dyad or triad was introduced to his or her potential collaborators through their VIVO online profile. The survey investigated the respondents' attitudes toward actually starting a collaboration with the proposed partners. Overall 254 respondents were identified: 195 of them were part of a selected dyad, and were introduced to a single collaborator; 59 of them were part of a triad, and were presented with two potential collaborators. The survey had a high response rate for online surveys: 41% of all emails that were sent received a complete response ($N = 103$). This does not account for emails that might have been sent to wrong addresses, or might have never been received. In fact, of the respondents who actually clicked on the survey link and saw the questionnaire, 78% completed it.

Results

Figure 2 shows the number of potential collaborations identified by each network criterion, and the geodesic distances spanned by these collaborations in the existing network. As expected, our criteria tend to select pairs of investigators that span long distances in the university network, with most selected collaborations involving distances of more than five steps. This confirms the substantial difference between alteration and an induction-based research funding program, which tends to stimulate collaborations between investigators who are much closer in the university network (see *Figure 1*).

The alteration program connected people who were mostly unaware of each other within the university network. The vast majority of them (74%) had never heard of the colleagues presented by the survey (*Table 1*). Only 5% had already collaborated with them in the past—although not necessarily in 2012, the year to which the data referred. This confirms the accuracy of the network data that can be extracted from VIVO. Individuals who are unconnected and distant in the constructed networks, have actually never collaborated: in other words, the publication, grant, and union networks are a good representation of the actual collaboration network in the university.

The identified potential collaborators mainly worked on different substantive topics and with different research methods. Their topics and methods did not match "at all" in about half of the cases (49% and 56%, respectively, *Table 2*). Just around 18% of respondents said that their research matched "moderately" or "quite a bit." This is the result we expected from the network criteria that were chosen, since most of the criteria were biased toward promoting cross-disciplinarity and connecting distant network regions. Doing cross-disciplinary research means precisely to bring together different research methods, expand one's interests to different substantive topics, or find the application of others' methods to one's current topics: a *mismatch* between substantive topics and research methods between two collaborators is indeed a precondition for cross-disciplinary research.

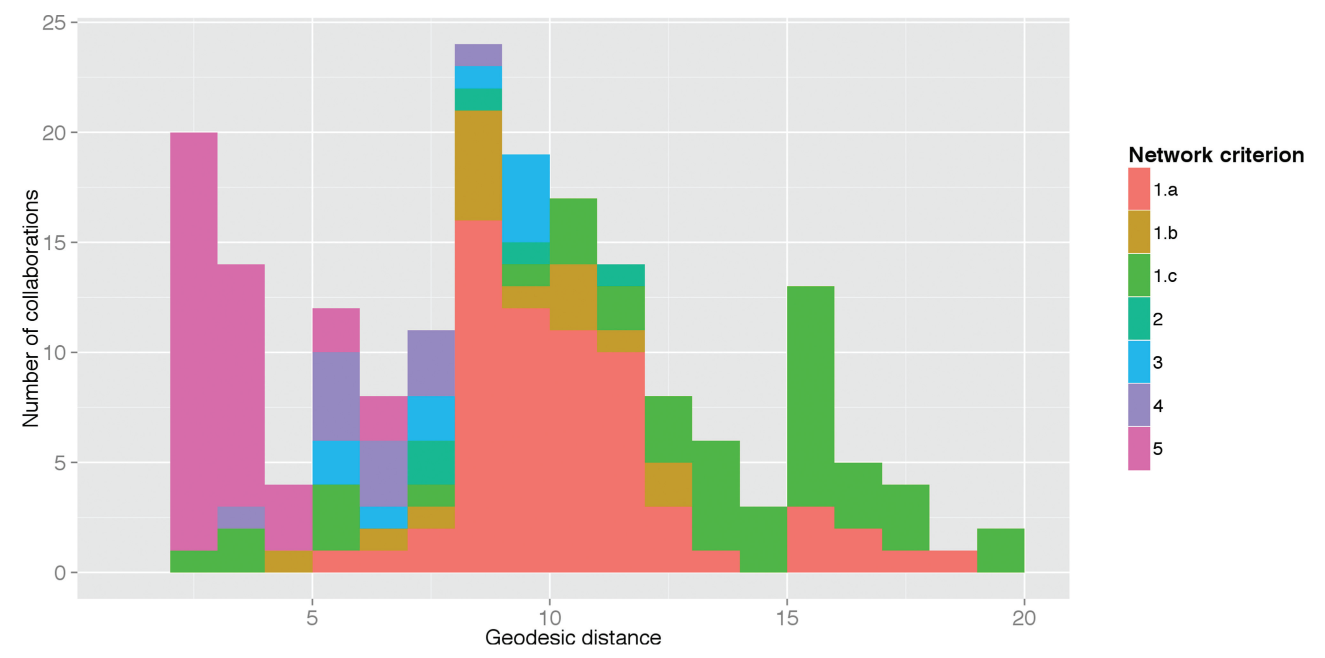

Figure 2. Distribution of the geodesic distances in new collaborations identified by the alteration program. Colors represent the different network criteria used to identify the missing collaborations. Network criteria are labeled as in the text.

	Do you know person X?
I never heard of X	74
I heard of X but we had no contact	9
I had contacts with X but we never collaborated	12
I already collaborated with X	5
Total	100

All figures are percentages.

Table 1. Responses to the question: "Do you know person X?"

	Do your and X's research match?	
	On substantive topics	On research methods
Not at all	49	56
A little	33	25
Moderately	13	10
Quite a bit	5	9
Extremely	0	0
Total	100	100

All figures are percentages.

Table 2. Responses to the question: "Do your and X's research match?"

Such a mismatch is arguably the main reason why the investigators reached by alteration are not likely to naturally pick each other as collaborators. Forty-eight percent of them believe that their collaboration would "unlikely" or "very unlikely" be successful (*Table 3*). On the other hand, approximately 30% of the respondents are undecided or feel that they need more information to respond, considering the proposed collaboration "neither unlikely nor likely" to be successful. Finally, slightly more than 20% say that the suggested collaboration is "likely" or "very likely" to succeed. When evaluating the likelihood of a successful collaboration, respondents are more pessimistic about patents and grants, considering their collaboration unlikely or very unlikely to result in any patent or grant in the 71% and the 55% of the cases, respectively, compared to 46% for publications (*Table 4*). Symmetrically, only 3% and 13% of the respondents think that the suggested collaboration is likely or very likely to produce a patent or grant, versus 27% for publications.

	How likely is your collaboration with X to be successful?
Very unlikely	27
Unlikely	21
Neither unlikely nor likely	31
Likely	18
Very likely	3
Total	100

All figures are percentages.

Table 3. Responses to the question: "How likely is your collaboration with X to be successful?"

The perceived likelihood of a successful collaboration is not constant across all the interviewed pairs of investigators—it is clearly affected by the geodesic distance between them. The more distant people are in the collaboration network, the less they see the potential for a collaboration with each other. Respondents who

	How likely is your collaboration with X to result in…		
	A publication?	A grant?	A patent?
Very unlikely	32	35	50
Unlikely	14	20	21
Neither unlikely nor likely	27	32	26
Likely	20	11	2
Very likely	7	2	1
Total	100	100	100

All figures are percentages.

Table 4. Responses to the question: "How likely is your collaboration with X to result in a publication/grant/patent?"

are within just 2–5 links are more optimistic, with around 75% of them believing that their collaboration is very likely, likely, or "neither unlikely nor likely" to succeed (*Figure 3*). This percentage shrinks for longer distances, dropping to around 50% for pairs 6–10 steps apart, 33% for pairs 11–15 steps apart, and 25% for pairs 16–20 steps apart.

The perceived likelihood of a successful collaboration is probably affected by the mismatch that respondents see with each other's research, which is predicted quite closely by geodesic distance as well (*Figure 4*). Even if they are not directly connected and have not collaborated in the last year, people who are closer in terms of network links tend to be more familiar with each other's work. On the other hand, the further apart researchers are in the network, the more they tend not to see a match between each other's work, either in substantive topics or in methods.

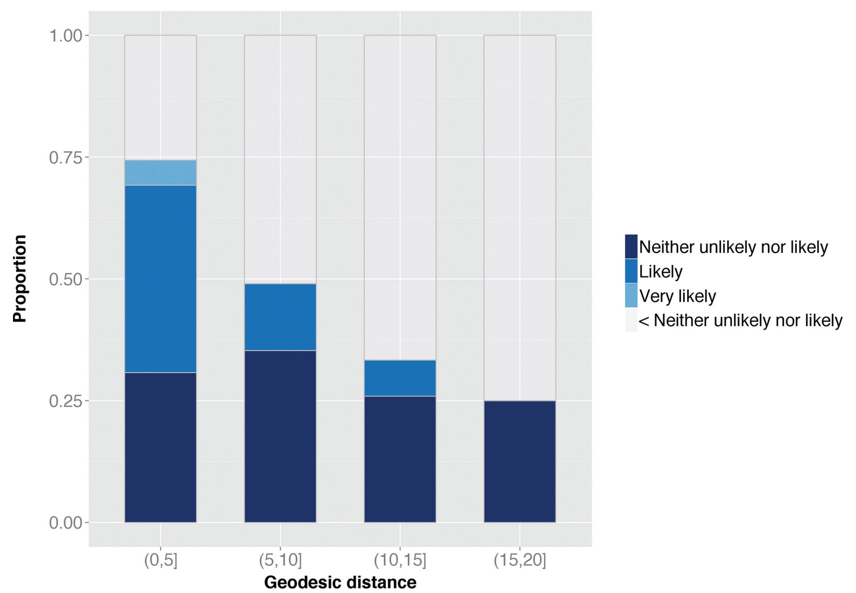

Figure 3. Proportions of responses to the question: "What is the likelihood that a collaboration between you and person X would be successful?" by range of geodesic distances spanned by the suggested collaboration. Possible answers: "Very likely," "Likely," "Neither unlikely nor likely," "Unlikely," "Very unlikely."

Discussion

We described the design of a program of systematic and theoretically grounded alteration of a scientific collaboration network at a university. We then presented preliminary results from a survey that explored investigators' reactions to this program, in particular their views on the potential success of the collaborative links that the program suggested.

The first strong result from the survey concerns the value of collaboration network data as they can be obtained from Web research networking tools such as VIVO. The publication and grant networks that we generated from the VIVO database provide an accurate map of the actual collaboration network at the UF. Individuals who appear as disconnected in the VIVO networks have actually never collaborated in the past. Furthermore, distances in the network predict actual dissimilarity in people's work, and their lack of familiarity with each other's research. Note that almost none of our survey respondents had actually met and collaborated in the past, therefore in principle they could have been all equally unaware of each other's work. Instead, the survey results show that being disconnected and three steps apart is very different than being disconnected and six steps apart in the collaboration network: investigators who are more distant see less match between each other's work.

This effect holds at higher distances, with researchers who are 12 or 18 steps apart being less and less acquainted with each other's work: in other words, investigators' familiarity with each other's research constantly decreases as a function of the geodesic distance that separates investigators. This means that the network data provided by research networking systems like VIVO can be used to construct a meaningful science map of a university's research activities, with network distances approximating actual distances in the contents of individuals' research; and cohesive communities in the networks approximating actual clusters of close research activities, similar for methods and substantive topics. The resulting semantic map of the research activities at a large university is potentially very useful for any program of intervention, coordination, and strategic planning of research.

Network alteration is a special kind of research intervention and planning program. Unlike the traditional way of funding research, alteration targets specific pairs or teams of investigators, and creates specific collaborative links that may otherwise never occur, were the scientific network left to its natural evolution. Therefore, alteration has the potential to create innovative connections and new ways of thinking in a university's "scientific brain," as well as to support existing research communities as they emerge from the network. The preliminary survey results presented here offer some suggestions for the actual implementation of an alteration program on a scientific collaboration network.

In the first place, the distance between scientists in the network should be taken into account, since it increases researchers' skepticism toward a possible collaboration. This means, for example, that the incentives offered to start a collaboration should be

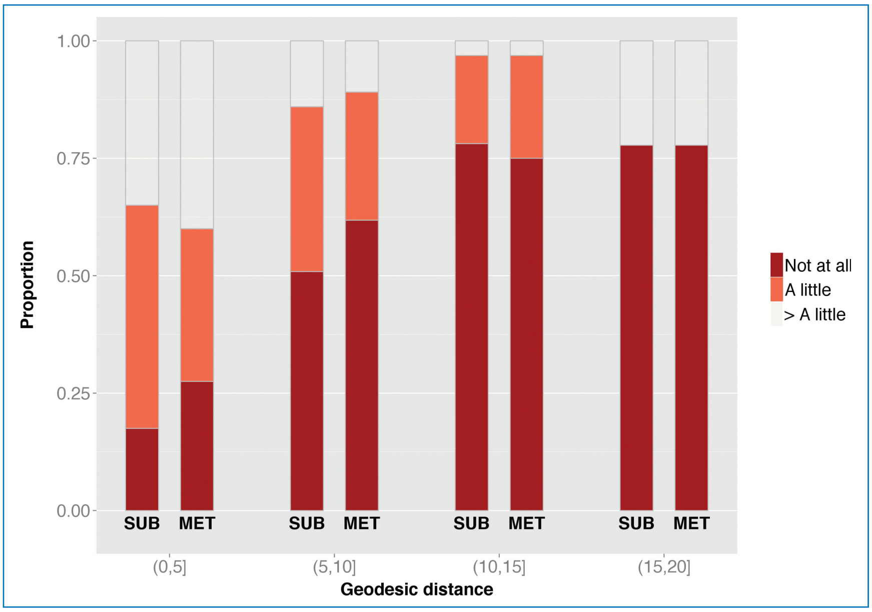

Figure 4. Proportions of responses to the questions: "How much do your substantive research interests match those of person X?" (SUB) and "How much do your research methods match those of person X?" (MET) by range of geodesic distances spanned by the suggested collaboration. Possible answers: "Not at all," "A little," "Moderately," "Quite a bit," "Extremely."

higher as the targeted individuals are more distant in the network. Ten links is probably a critical distance threshold, since for longer distances the percentage of researchers who are optimistic about the success of their collaboration falls well below 50%. On the other hand, collaborations are easier to create between individuals who are five steps or closer in the network.

In the second place, the survey results give some indications on the *kind* of collaborations that could be proposed by an alteration program. Researchers are clearly more reluctant to start a collaboration on a grant or a patent with someone with whom they have never worked. This probably points to a trust issue involved with patents and grants as opposed to publications. A consistent body of research has pointed to the relevance of interpersonal trust among team members for team effectiveness and creativity.[47–49] Patents and grants entail an economic aspect that requires more mutual trust between collaborators, therefore people who do not know each other may be less inclined to work together on a patent or a grant. On the other hand, investigators who do not know each other are definitely more optimistic about starting a new collaboration by working on a publication.

Conclusions and Future Directions

The project presented here did not actually implement the alteration program by creating the identified missing collaborations. We argue that CTSA institutes and hubs would be ideal frameworks for the effective implementation of this kind of programs. As suggested by Calhoun et al.,[8] an academic CTSI can take on the function of forming and coordinating multidisciplinary translational teams, including ones that are identified by an alteration strategy. During the implementation of an alteration program, CTSI "key resources" or cores can provide guidance and support in different stages of team maturity and for different aspects of team functioning.

As a concluding remark, it should be noted that the intervention approach presented here could be applied at larger scales than a university. The same network criteria that enhance cohesion or create bridging positions in a university network can easily be applied to a consortium of universities, or to a national network of CTSA hubs such as the one promoted by NCATS.[10] The development of semantic-web research networking tools like VIVO opens up new avenues to achieve this goal. VIVO and other compatible semantic-web applications are adopted at several universities across the country. Therefore, VIVO does not only provide reliable public data on single universities; it also creates a common platform that standardizes and ensures interoperability between data from different institutions. The first tools to link research networking systems across universities are already being explored and evaluated in CTSA organizations.[50] In the next few years, cross-university network interventions may conceivably be designed and implemented to facilitate the construction and efficient integration of a nationwide consortium of CTSA hubs.

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