Co-evolution of two networks representing different social relations in NetSense

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Abstract We examine the dynamics of co-evolution of two coupled social networks. The first is a cognitive network defined by nominations based on perceived prominence collected from repeated surveys of students during their first four semesters of college while the second is built from the behavioral network representing actual interactions between these individuals based on records of their mobile calls and text messages. We address three interrelated questions. First, we ask whether the formation or dissolution of a link in one of the networks precedes or succeeds formation or dissolution of the corresponding link in the other network (temporal dependencies). Second, we explore the causes of observed temporal dependencies between the two networks. For those temporal dependencies that are confirmed, we measure the predictive capacity of such dependencies. Finally, we examine whether there are systematic differences in the dissolution rates of symmetric (undirected) versus asymmetric (directed) edges in both networks. We find strong patterns of reciprocal temporal dependencies between the two networks. In particular, the creation of an edge in the *behavioral* network generally precedes the formation of a corresponding edge in the *cognitive* network. Conversely, the decay of a link in the cognitive network generally precedes a decline in the intensity of communication in the behavioral network. Finally, asymmetric edges in the cognitive network have lower overall communication volume and more asymmetric communication flows in the behavioral network.

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1 Introduction

In this paper we investigate how two different social networks, one a *cognitive* network composed of subjective nominations and another a *behavioral* network composed of objectively recorded communications, relate to one another. We aim to understand in detail the relationship between these two networks, as the link between cognition and behavior is a long-standing, but understudied, problem in social network analysis [6, 7]. A key question in this literature is whether behavior precedes cognition, such that contacts with which we frequently interact become more cognitively salient, or whether cognition precedes behavior, such that we increase the amount of interaction with those contacts that we consider subjectively salient [2].

To make headway on these questions, we use a data source that contains dynamic information on both the cognitive salience of contacts and actual behavioral traces of communication behavior between individuals. We examine whether two social networks built from these different kinds of connections are temporally coupled. Our main hypothesis is that there exist reciprocal linkages between cognitive salience and behavioral communication with increasing communication leading to greater cognitive salience and with declining cognitive salience leading to the dissolution of behavioral edges [3].

To evaluate this hypothesis, we investigate whether increases in communication lead to increases in cognitive salience and whether cognitive salience is associated with increased communication behavior. We also examine whether declining cognitive salience leads to a gradual decrease in actual communication. Finally, we ask whether non-reciprocity in cognitive salience is associated with non-reciprocity in actual communicative interaction [6], and whether persons who are exposed to sustained asymmetries in communication are motivated to cycle through more persons in their cognitive salience network in search of reciprocal interactions [8].

2 NetSense Data and the Networks

In this section, we introduce the NetSense data [10] and the networks derived from it. The data was collected at the University of Notre-Dame. At the start the Fall semester in 2011, 200 of the incoming freshmen were enrolled in the NetSense study. Over 150 participated until their graduation in the Spring of 2015. Students participating in the study received free smartphones with unlimited voice and text plans as an incentive for participation. We obtained time-stamped logs of communication records for all study participants. These data contain information on the the date, time and duration (for calls) and character length (for text messages). Data for the first four semesters (lasting from the Fall of 2011 to the Spring of 2013) of the project was available for this study.

Students participating in the NetSense study list up to twenty contacts at the beginning of each semester. Students were asked to list the names of those people with whom they thought they the most time communicating or interacting with. Below, we refer to these contacts as friends. These friends could be inside or outside the NetSense study. Because students were asked to also provide the primary phone number of each friend we can link each friend mentioned in the survey to the time-stamped smartphone data. Accordingly, We propose a model for analyzing co-evolution of multiple networks representing different kinds of social relations between nodes. The *behavioral* network consists of the behavioral edges based on communication records of both telephone calls and text messages between individuals. Weights on the edges in the behavioral network change everyday, depending on the volume of communication. The *cognitive* network includes cognitive edges that are based on (possibly asymmetric) nominations collected through the surveys. Edges in the cognitive network appear and disappear once per semester.

3 Related Work

A model to generate two social networks synthetically, with both the networks co-evolving, capturing the properties of both networks is introduced in [12]. A rapidly evolving network based on games is studied in [9]. Nodes in this network have varying incentives to build links. We observe similar behavior in the NetSense data, where certain edges have incentive to develop into an edge in one of the networks, while others do not. The co-evolution of edges in relation to individual behavior in school dormitories is investigated in [5]. The co-evolution of employee networks in organizations in relation to individual attitudes is studied in [7]. In contrast to these studies, we explore how two social networks co-evolve in time.

4 Analysis of Co-Evolution of NetSense Networks

We conduct several experiments on the NetSense data to study how the two networks co-evolve. We divide these experiments into two broad categories: analyzing precedence of dissolution and formation of edges in both the networks and analysis of asymmetric edges in each of the networks.

First, we deal with the question of whether the formation and dissolution of edges each of the networks studied (cognitive and behavioral) are systematically related to each other. To do so, we examine whether forming or increasing the strength of an edge in one network (e.g. behavioral) precedes a corresponding edge creation in the other (e.g. cognitive) network. We also study whether edge dissolution in one network is informative of a corresponding dissolution event in the other. For example, we can ask how often the emergence or strengthening of behavioral edges leads to the formation of cognitive edges in a subsequent semester. We look at factors that may cause edges to form or dissolve and then infer if there are any causal relationship between the two networks. For example, we observe that high levels of communication between edges in behavioral network is often associated with the formation of future cognitive edges. So we can infer that high communication volume in the behavioral network often leads to the appearance of subjectively meaningful ties in the cognitive network.

4.1 Does higher communication in behavioral network predict the appearance of edges in the cognitive network?

We start by investigating whether we can observe increases in communication between two people *before* an edge between them appears in the cognitive network. To this end, we measure the communication between students in the semester before one of them nominates the other as a friend in the survey, and ascertain whether there is a difference in previous communication volume between nodes that are subsequently connected in the cognitive network and those which are not. Table 1 lists these results. Figures 1a and 1b illustrate how number of calls and messages are distributed among to-be-formed and not-to-be-formed edges in the cognitive network.

Table 1: Difference in communication volume between nodes to-be-nominated and not-to-be-nominated as friends, and future friendship nominations based on volume of communication between the corresponding nodes.

Semester No.	to-be-nominated		not-to-be-nominated		Calls		Messages	
	No. Calls	No. Messages	No. Calls	No. Messages	Precision	Recall	Precision	Recall
Semester 1	40	407	5	58	70	82	78	88
Semester 2	52	782	6.5	105	72	74	72	70
Semester 3	18	248	4	41	73	75	78	80

We find that, indeed, edge weight in the behavioral network is a good predictor of whether an edge subsequently appears in the cognitive network. In the first semester, edges in which one of the participants subsequently nominates the other as a significant contact differ by a factor of 8 (in terms of calls) and by a factor of about 7 (in terms of text messages) from those in which no edge emerges. Similar differences can be observed for semesters 2 and 3.

We further examine whether edge weight in the behavioral network can be used to predict the appearance of future links in the cognitive network. Table 1 lists the results of these analyses. We find that we are able to predict a significant proportion of edges in the cognitive network using information from the behavioral network, about 70-80 %, with a reasonable recall [1]. The threshold that gives us the best balance between precision and recall can be found plotting ROC curves [2]. We infer that nomination as a friend is often preceded by high levels of communication between the corresponding nodes. Hence, there is strong reason to conclude that the dependence of the cognitive network on the behavioral network is causal.

4.2 Do edges in the cognitive network have stronger links in the behavioral network?

Next, we investigate whether we can observe significant differences in communication volume between two people once an edge appears in the cognitive network. To do so, we compare the communication volume (the weight of the edge in the behavioral network) between nodes connected by the edges that appear in the cognitive network and those which do not.

Table 2: Difference between connected and disconnected edges in the cognitive network in terms of weight in the behavioral network and prediction of future friendship nominations based in the cognitive network on the volume of communication in the behavioral network.

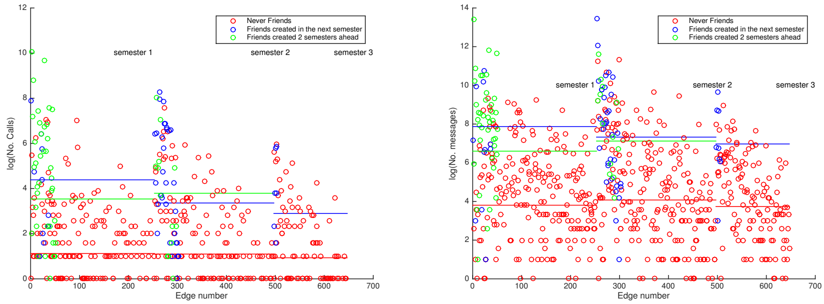
Semester No.	Friends		Non-friends		Calls		Messages	
	No. Calls	No. Messages	No. Calls	No. Messages	Precision	Recall	Precision	Recall
Semester 1	70	667	7	72	71	76	61	84
Semester 2	41	915	12	190	70	70	61	78
Semester 3	74	1063	5	51	66	74	64	90
Semester 4	34	729	4	37	68	72	62	86

Table 2 shows the results. We observe a large difference in communication volumes between these two edge classes, with edges in which one person nominates the other as a friend displaying high levels of behavioral interaction. For instance, in the first semester, nodes connected by edges that were connected in the cognitive network differed from those that were not by a factor of 7(for calls) and a factor of about 9 (for texts), with differences of similar magnitude holding for subsequent semesters.

We verify whether the volume of communication in the behavioral network can allow us to predict forming of an edge in the cognitive network. Table 2 shows that we can indeed predict a significant number of friendship nominations purely from communication volume in the behavioral network, about 70-90 %, with reasonable precision.

4.3 Do newly formed edges in the cognitive network differ from older edges in terms of communication levels between their nodes?

Next, we study how nodes connected by the newly formed and older links in the cognitive network differ in terms of their edge weight in the behavioral network. To this end, we measure the amount of communication between nodes joined by older (more than one semester) and newly formed (one semester) cognitive edges. We observe that cognitive edges joining nodes with higher communication levels nodes connected by than newer links in the friendship network. Table 3 lists these differences. Figures 2a and 2b illustrate how number of calls and messages are



(a) Number of Calls (b) Number of Messages

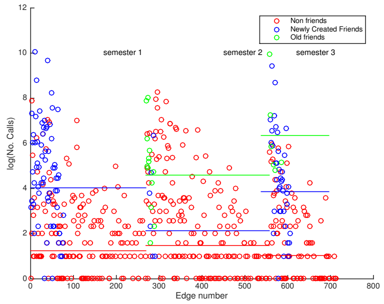
Fig. 1: Call and message volumes between to-be-friends in one semester (blue circles), to-be-friends in two semesters (green circles) and not-to-be-friends (red circles). Generally, to-be-friends have higher call and message volume than not-to-be-friends. The continuous lines show the average value for the circles of each color. The separation is large between red and green lines, red and blue lines, but small between blue and green lines. Most of the to-be-friends edges appear in the first and second semester, since very few new friendships are formed in the fourth semester.

distributed among pairs of nodes connected by to-be-formed and not-to-be-formed edges in the cognitive network.

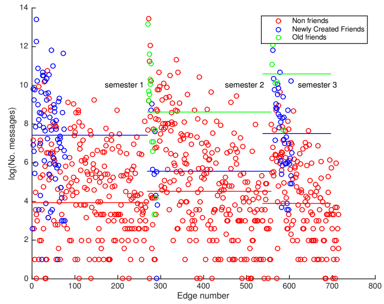
Table 3: Difference behavioral communication volume between old and new edges in the cognitive network.

Semester No.	Newly observed nominations		Nominations older than one semester	
	No. Calls	No. Messages	No. Calls	No. Messages
Semester 2	6	57	61	1340
Semester 3	63	1026	172	2447
Semester 4	7	256	53	1067

We also observe that as these newly formed cognitive edges age, the nodes connected by them come to have communication volumes similar to, or perhaps slightly higher, than cognitive edges that have existed for a longer time. To shed further light on this issue, we examine communication volumes of cognitive edges in the 3rd and the 4th semesters, and we divide them into edges which were created in the 2nd and the 3rd semesters respectively, and edges which existed since the 1st semester. We call the former moderately old edges and the latter very old edges. We observe that moderately old edges carry on an average of 49 calls and 903 calls, while



(a) Number of Calls



(b) Number of Messages

Fig. 2: Communication volumes nodes connected by old edges in the cognitive network (green circles), newly created edges in the same network (blue circles), and disconnected nodes (red circles). The continuous lines show the average value for the circles of the corresponding color in each semester. The separation is significant between all three lines. Generally, nodes connected by cognitive edges in which one person nominates the other as a friend have a higher communication volume. A significant number of persons that do not nominate each other, however, have high message volumes as well, but less so with the call volume.

very old edges exchange 29 calls and 795 messages. We infer that communication between nodes that are also connected in the cognitive network increases gradually, but then finally stabilizes over a period of time.

4.4 How likely does communication dissolve after the corresponding edge disappears in the cognitive network?

The next question we study is how likely are the communication links to dissolve after their corresponding cognitive edges dissolve. To assess that, we measure the rate at which dyads that dissolve their cognitive edges also dissolve the corresponding edges in the behavioral network, and compare that with the rate at which behavioral network links dissolve at random. We find that behavioral network dyads that first experience a dissolution event in the cognitive network are more likely to dissolve their behavioral edge than a random dyad does.

Let BDCN denote the average link dissolution rate in the behavioral network for persons who are not connected in the cognitive network, and BDCY denote the average link dissolution rate in the behavioral network for dyads that are connected in the cognitive network. In the third and fourth semesters, BDCN is significantly greater than BDCY, while the reverse in observed in the second. We observe values of 64%, 55% and 50% for BDCN for the three semesters, and 42%, 74% and 62% for for BDCY. We also measure the rate at which the nodes connected by the cognitive edges that persist into the following semester dissolve their behavioral edges, and denote it as BDCP. We find that BDCP is always 0, meaning that if there is link persistence in the cognitive network then there is always link persistence in the behavioral network.

4.5 Patterns of communication decay following link dissolution in the cognitive network

Finally, we examine whether edge weights in the behavioral network decrease after links in the cognitive network dissolve. We measure this effect using the "recency" score [4], where recent communication has higher weight than older communication. If there is a decrease in communication, the recency weighted score will be lower than communication score without weights.

- **Recency Score (RS):** Each semester lasts 5 months; odd numbered lasts from August to December, while even numbered lasts from January to May. We assign weights to communication during each month in the following manner: -0.3 for the 1st month, -0.1 for the 2nd month, 0.1 for the 3rd month, 0.3 for the 4th month and 0.5 for the 5th month.

- **Non-Recency Score (NRS):** We assign equal weights of 0.1 to communication in any of the months. We compare how much nodes connected by dissolving and persistent edges differ on both of these scores.

In Table 4, we list RS and NRS scores (computed from the behavioral network) for nodes connected by dissolving and persistent edges in the cognitive network. We then take the average numbers of calls and messages for these categories and compute the ratio of numbers of calls/messages between nodes connected by persistent cognitive edges to numbers of calls/messages between nodes joined by dissolving cognitive edges. We observe that the ratio increases when RS is used. This means, there is a bigger difference when RS is used, which indicates that nodes connected by dissolving edges in the cognitive network have more communication in the behavioral network during earlier months than in the later months. However, we do not observe this trend in the first semester, since the friendships are still developing, and communication is most likely to be increasing for all friendships.

We could draw the inference that students who dissolve cognitive links are much more likely not to communicate with each other at all, leading to a complete dissolution of the communication edge.

Table 4: Difference between to-be-friends and non-to-be-friends.

Semester 1							
NRS	Dissolved	Persistent	Ratio	RS	Dissolved	Persistent	Ratio
No. Calls	5	13	2.6	No. Calls	6	10	1.8
No. Texts	51	137	2.7	No. Texts	90	121	1.4
Semester 2							
NRS	Dissolved	Persistent	Ratio	RS	Dissolved	Persistent	Ratio
No. Calls	1	10	10.0	No. Calls	0.4	8.3	20.8
No. Texts	18	109	6.1	No. Texts	3.1	195	62.9
Semester 3							
NRS	Dissolved	Persistent	Ratio	RS	Dissolved	Persistent	Ratio
No. Calls	7	8	1.1	No. Calls	2.2	5.3	2.4
No. Texts	56	151	2.7	No.Texts	47	185	3.9

4.6 Analysis of asymmetric friendship cognitive edges

The NetSense data consists of periodic surveys where students nominate up to twenty friends at the beginning of every semester. We examine cognitive edges that are asymmetric, where only one of the respondents marked the other as a friend. We observe whether the nodes connected by these asymmetric edges in the cognitive network exhibit different patterns of communication and survival probabilities of the edges in the behavioral network. We find that asymmetric cognitive edges differ significantly from symmetric edges in both of these respects. The following sections illustrate the differences between asymmetric and symmetric cognitive edges.

4.6.1 Do nodes joined by asymmetric behavioral edges become dissolve their behavioral edges faster?

First, we examine if nodes connected by asymmetric edges in the cognitive network are more likely to dissolve their edges in the behavioral network than nodes connected by symmetric (mutual) cognitive edges. We measure the survival probabilities of behavioral edges between nodes connected by asymmetric and symmetric edges across all semesters. We observed that nodes connected by asymmetric cognitive edges are significantly more likely to dissolve their communication edges then symmetric cognitive edges.

The dissolution probabilities of of communication edges between nodes connected by the asymmetric cognitive edges are higher than communication edges between nodes with mutual cognitive edges in all three semesters. We observe that nodes joined by asymmetric edges have a dissolution probability of their communication edges of 90%, 87.5% and 50% in each of the three semesters, while such probabilities for symmetric edges have a dissolution probability of are 72%, 66% and 16% in each of the three semesters. We also observe an overall downward trend in the dissolution probability. Initially, these are very high for the first semester, but they decline steadily over time. However, even in the third semester nodes connected by asymmetric edges in the cognitive network are more than three times more likely to dissolve their communication edges in the behavioral network than nodes joined by symmetric cognitive edges.

4.6.2 Differences in Communication volumes between asymmetric and symmetric edges

Next, we examine if nodes connected by asymmetric and symmetric cognitive edges differ in communication volume in the behavioral network. As shown in Table 5, we observe that, apart from the first semester, there is a significant difference between asymmetric and symmetric edges, with symmetric edges communicating more. In the first semester, the same difference exist, but it is much smaller and visible only if the sum of calls and messages is taken into account.

4.6.3 Asymmetric cognitive edges and asymmetric communication edges

Next, we examine whether nodes connected by asymmetric edges in the cognitive network are also more likely to have asymmetric communication patterns in behavioral network as well. We define "asymmetric" edge in the the behavioral network whenever we observe one node initiating communications with the other node more often than the reverse. We compare communication imbalance between nodes connected by asymmetric cognitive edges and nodes joined by symmetric edges of this type. We find that symmetric edges always have less asymmetrical communication patterns in the behavioral network than asymmetric cognitive edges. To measure asymmetry in communication, we first compute the ratio of the volume of communication in which the source node is the initiator to the volume of communication in which the destination node is the initiator: we call this quantity OSC. We multiply the number of calls by 10, since messages are about 10 times more frequent than calls and add the product to the number of messages. We define a given edge as "asymmetric" in the behavioral network when the source node is an initiator of communication at least 20% more often than the destination node. Finally, we measure the percentage of asymmetric communication for nodes connected by both asymmetric and symmetric cognitive edges.

Table 5 shows the results of this analysis. We observe that nodes connected by symmetric cognitive edges have close to equal bi-directional communication in the behavioral network. In the first semester only 3% of the symmetric cognitive edges have corresponding behavioral edges asymmetric according to criterion define above. In comparison, asymmetric cognitive edges are much more likely to be asymmetric: In the first semester, asymmetric cognitive edges were about ten times more likely (31%) to feature imbalanced communication than the nodes connected by symmetric cognitive edges. .

Table 5: Difference in communication volume between nodes connected by asymmetric and symmetric cognitive edges.

Semester No.	Asymmetric edges			Symmetric edges		
	No. Calls	No. Messages	% of OSC	No. Calls	No. Messages	% of OSC
Semester 1	69	472	31	58	842	3
Semester 2	25	638	30	39	636	1
Semester 3	40	351	39	112	2038	10
Semester 4	10	256	31	70	1406	6

4.6.4 Communication behavior profile: the "asymmetric sender" profile

We classify nodes that are more likely to be involved in asymmetric communication as *asymmetric senders*. We then examine the communication behavior profile of these nodes to see if the asymmetric sender profile differs from symmetric sender profile. The goal is to verify if nodes with different communication profiles have different characteristics of their cognitive edges. We call students who initiate many asymmetric communications asymmetric senders as we expect them to be more likely to change their friends, given the well known psychological aversion to lack of reciprocity that has been demonstrated in the literature [11]. We find support for the hypothesis in the observation that asymmetric senders retain 7%, 16% and 38% of their friends, while balanced senders retain 25%, 50% and 88% of their friends in the succeeding semesters.

5 Conclusion

In this paper, we study the co-evolution in time of two networks defined by the NetSense data and observe that both networks influence each other temporally. We observe that formation of an edge in the behavioral network is associated with successive formation of a corresponding edge in the cognitive network. We also observe that dissolution of a cognitive edge is often associated with dissolution of its corresponding behavioral edge in the successive semester. So we conclude that both networks affect each other. We also investigate asymmetric cognitive edges, and conclude that the nodes they connect lower communication volume exchange, and lower survival probability than symmetric friendship edges. Moreover, asymmetric cognitive edges are more likely to have corresponding behavioral edges also asymmetric.

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