Professional Association Networks Based on Semantic Similarity of Papers Presented in Divisions versus Formal Membership Networks

James A. Danowski
Department of Communication.
University of Illinois at Chicago
Chicago, IL 60607 USA
jdanowski@gmail.com

ABSTRACT

We investigated possible causal relationships between a professional association's division network structure based on co-memberships, and the division network structure based on the semantic similarity of papers presented at annual meetings. Data from the International Communication Association (ICA), a basic-research focused organization of academic social scientists with 21 divisions, provide for an analysis at two points in time, 2007 and 2011. QAP correlations among the four networks entered into a quasi-experimental cross-lagged correlation design suggested evidence for possible causality. Compared to the no cause baseline, the time 1 co-membership network structure was a significant predictor of the time 2 semantic division network structure. The reverse relationship was not significant. As well, there is considerable reduction of the size of the synchronous correlation of the semantic and co-membership division networks from time 1 to time 2. Noteworthy was also the pattern of diachronic association of the same kind of network. The semantic division network at time 1 explained only 31% of the same network at time 2. Likewise, the co-membership network at time 1 explained only 25% of that network at time 2. This would be consistent with the basic research focus of the association. Such a focus privileges novelty. The paper uses theory to form the research questions and interpretations. Because of the limitations of the statistical model, and the case study design, these results should be taken as exploratory and suggestive. Future research may reduce these limitations.

General Terms

Algorithms, Experimentation, Theory, Measurement

Keywords

Semantic networks, social networks, organizational communication, professional associations

WebSci 2012, June 22–24, 2012, Evanston, Illinois, USA.

1. INTRODUCTION

Academic researchers project their epistemological and methodological orientations and the problems they chose to research through the content of papers they write [1]. Conference papers, having a considerably shorter time lag between writing and dissemination than journal publications or books, probably present a more reliable picture of scholars' current research orientations [2]. Professional associations are the primary collective social environment in which one best observes current trends in research and the manner in which it is communicated. Large associations, typically the main ones for a discipline, are differentiated into subunits such as divisions and interest groups as a way of managing the complexity of communication across the association [3]. Individuals typically belong to more than one division. This produces a system-level network of associations between divisions when aggregated across all members.

Barnett & Danowski [2] found that the networks based on co-memberships in divisions and interest groups (from now on just referred to as 'divisions.') of the International Communication Association (ICA) corresponded to the major subdivisions in the discipline based on content and methods reflected more broadly in journals and among department specializations at different universities. Seven years later Doerfel and Barnett [4] studied the links among the association's division network by analyzing only the similarity of the paper titles presented in pairs of divisions. They found a division network structure similar to Barnett and Danowski's.

Nevertheless, Barnett and Danowski constructed their network analysis on formal division co-memberships to make qualitative interpretations of the disciplinary significance of the quantitative patterns. On the other hand, Doerfel and Barnett compared their semantic division network structure to Barnett and Danowski's and concluded that they found a similar substantive and methodological basis for the division network structure, even though seven years had passed. Unfortunately, Doerfel and Barnett did not quantitatively compare the semantic-based division network with the formal co-membership division network. The absence of this direct comparison and the time lag between the studies motivates our research. The first question was:

RQ1: What is the degree of correspondence between networks among divisions based on semantic similarity versus on formal division co-membership similarity?

The current study is more precise than the previous two because it measured both kinds of networks and statistically compared them. A second question we addressed concerns the possible over- time relationships that may exist between these two forms of networks:

RQ2: What are the associations of the semantic-based and membership-based division networks over time?

Accordingly, we studied the networks at two points in time and used statistical procedures for comparing their similarities. We computed the over-time correlations as well as the synchronous correlations between the two kinds of networks. With data at two points in time it was possible to address another question:

RQ3: What are the possible causal or mutually causal relationships between the networks?

The paper next discusses related work. Following this we describe the methods used. Then we present results, and discuss their implications. We end with a discussion of limitations and directions for future research.

1. RELATED WORK

Giddens' theory of the "duality" of structure [5] explains the interplay of structure--the rules and resources in a social environment—and structuration, which is a result of the behaviors of individual agents in social systems to reproduce structure. They reflexively monitor structure and unintentionally engage in structuration behaviors that reproduce structure. Structure is both the medium for and the outcome of the conduct of agents who recursively organize it. This is considered the "duality" of structure.

Regarding the nature of this duality, Giddens argues that the structural properties of social systems do not exist outside of action but are chronically implicated in its production and reproduction. He emphasizes reflexive, not reflective, structuration agents. They operate on reflex rather than on fully conscious action.

Nevertheless, later Giddens [6] introduces a third element, individual intentionality. Because of personal intentions individuals may consciously conform to basic structuration processes or deviate from them. Although he does not refer to this in this way, we consider this as forming the 'triality of structure.' We see this third element as embedding in the system a possible destructive activity, destructuration resulting from reflective individual agent behaviors. Destruction can also be collectively intended. Individuals may collude to destroy structure and/or to restructure the system through anti-structuration behaviors.

2.1 Networks and Structuration Theory

In explicating his theories, Giddens avoids the "network" concept, apparently because of his disagreements with the structural sociologists, particularly Blau [7]. Giddens extensively criticized Blau for failing to put the locus of structural explanation at the individual agent level rather than considering that macro structures had some independent and strong effects on individual behavior. Blau explicitly focused on the importance of the communication network. Contractor, Whitbred, Fonti, Hyatt, O'Keefe, & Jones [8] point out that other scholars [9][10][11] have argued for network analysis to empirically assessing structuration theory. Network researchers have analyzed organizational behavior based on formal organizational structures as well as on informal structures such as emergent communication networks [12]. Monge and Eisenberg [13] examined semantic similarity of individuals' meanings for the organizational mission and network analyzed the individuals based on how similar their statements about the mission were.

Extending from this body of earlier network research, it would be appropriate and perhaps fruitful to consider semantic elements as fundamental to relations among social units with respect to macro-level structure, structuration, and destructuration processes resulting from behaviors of individual agents acting in concert with consciously formed collectivities, whether the individual is intentionally or unintentionally communicating in similar ways to others.

2.2 Communication Environment Considerations

Higher levels of analysis in the external environment of the association merit consideration regarding detructuration. Social media may make this process easier than in earlier times when more costly direct and face-to-face interpersonal communication was required for planned structural change. Now, it is possible for cascading herd behaviors to move virally through social systems and fuel larger social movements more rapidly [14]. This third aspect of structure would appear to make the duality of structure more tenuous. In terms of professional scientific associations, this third element may account for an increase or decrease over time in explained variation between the semantic-based division network and the formal membership-based division network. Given the reasoning about the increased use of social media, decreases would be more often expected than increases.

1.1 The Basic Disagreement

Meanwhile, although Giddens places the locus of structural explanation at the individual level, Blau [7] places it at higher levels in network. This provides for contradictory expectations regarding possible causal influence. Do individual level structurations have more force, or do the more macro structures, or is it a highly reciprocal relationship? Are changes in one more likely to precede changes in the other, or are changes virtually synchronous? Our research empirically explores these various cross-level possibilities to see which the evidence favors. At two points in time we analyze the content of papers presented to divisions to construct division networks representation structuration and destructuration. Co-membership in divisions records from the association enable creation of the division network more at the level of structure. We therefore can assess the triality of structure in the association.

2. METHODS

3.1 Data sources

3.1.1 Semantic data

One source of our data was the ICA conference program files. For the analysis of the 2007 conference content, a text file was extracted that included paper title and paper keywords. A period was inserted at the end of each paper's text. For the 2011 program the paper titles, keywords, and additionally, abstracts were available. To have comparable text for the two years, the abstracts were removed. Nevertheless, to see what effect using abstracts had we also created a file for 2011 that included them. We used a word-pair extraction of pairs appearing 3 words on either side of each word in the text. The narrative format of the abstract content was suited to a proximity-based word-pair approach. Each file was analyzed with WordLink in WORDij 3.0 [15][16][17][18]. AutoMap [19] and Catpac [20] have adopted this proximity approach and could be used in this kind of analysis.

Although WordLink is mainly a proximity-based word pair extraction program, it also produces a list of individual words and their frequencies in a text file. This was more suitable for the content format of titles only, because the frequencies of unique word pairs would be lower than in a narrative style of text in which the volume of such text is higher. The standard natural language processing procedure of dropping word pairs that occurred only once or twice would have left insufficient pairs for a robust similarity measure between pairs of divisions' titles. Word frequencies were therefore used for the main analysis, except for the comparison of the 2011 titles-only versus titles plus abstracts corpora. In each run, a standard "stop list" or drop list of common grammatical function words such as articles, prepositions, and conjunctions was used. No stemming was performed. The complete set of parameters for the titles-only WordLink runs are shown in the log file in Table 1. Because we used word not word pair frequencies the proximity window was irrelevant to this analysis.

Table 1. Wordlink Log File

```
Text file name: C:\Users\jad\Downloads\ICA2011prog2.txt

Configuration:
Drop list file name:
C:\Users\jad\Downloads\WORDij\WORDij\Documentation\drop
list.txt
Include list file name: none
Character filter file name:
C:\Users\jad\Downloads\WORDij\WORDij\character_filter_UTF
_10082011.txt
Select list file name: C:\Users\jad\Downloads\ICA2011select.txt
Drop words less frequent than: 3
Drop word pairs less frequent than: 3
Preserve wordpair order: yes
Include numbers as words: no
Link until sentence end: yes
Link steps: 3
Linkage Strength Method: CONSTANT
Remove punctuation inside words: yes
Compound words: combine
Using Porter stemming algorithm: no
Using Chinese filter: no
Replace English contracted forms: no
Replace 's ending by is word: no

The program processed the file in 0.355553 minutes.
```

For the main analysis we ran a separate WordLink extraction for each of the 21 divisions for each year. This was done in the same run by using the program's "select list" function to read headers inserted in the file marking the beginning of each division's papers. We also produced two aggregate analyses for all paper titles across all divisions for 2007 and 2011. This enabled creating a matrix for each year that had the master list of words from the aggregate file as rows and each division's word frequencies as columns. We created a program, Matrixer [21] to properly align each division's column of words with the master list from the aggregate file. It inserted zeros for the words that did not appear in a particular division.

For 2007 there were 772 unique words as rows, while for 2011 there were 1013 unique word rows. We input the 2-mode matrices into UCINET [22] and used its 'affiliation' transformation to a 1-mode column-based network. The similarities across the rows among pairs of columns became the network link strengths. For the 2011 comparison of the abstracts plus titles corpus compared to the titles only corpus, the former was based on the similarity in strengths of word pairs from the aggregate of all division content.

Because word pair extraction generates a large number of rows, here 25,508 for the 2-mode matrix for 2011 titles plus abstracts, UCINET was not able to do the affiliation conversion to a 1-mode network. So, we input the matrix into SPSS v20 and computed the proximities for each pair of divisions across the 25,508 word pairs. For valued data the proximity index is the Pearson correlation coefficient. We exported the 1-mode matrix output as an Excel file and input this into UCINET for further analysis.

3.1.2 Membership Records Data

Our other source of data was the ICA membership records provided by the association in an Excel spreadsheet having columns representing division and interest group units (n = 21) and one row for each member. Cell entries are 1 for membership and otherwise blank for non-membership in a division. In 2007 there were 4,265 individuals in the membership file. The 2011 membership file contained 3,925 individuals. The average member belonged to 2.6 divisions. For each year we converted these data using UCINET's 'affiliation' conversion from a 2-mode to a 1-mode network based on columns representing divisions.

We split each matrix at the median value, otherwise each division is nearly equally linked to every other division when the values of links are not used to differentiate them. Without a median split there would be virtually no variance in the structure of the networks for which to account. Nevertheless, we did not assign zeros and 1s after the split. We retained the valued link data for the pairs above the median.

3.1.3. Similarity Coefficients among Different Whole Networks

Using UCINET's (QAP) [23][24][25] we computed the Pearson correlations for each pair of entire division networks to index their overall degree of similarity. The networks' commonality of structure was compared to 5,000 random permutations of the network structures to see the proportion of the time that randomness produced the same commonality of network structure as the observed networks.

3.1.4 Cross-lagged Correlations to Assess Possible Causality

We explored possible causality between networks of divisions based on semantic similarity and those based on co-membership similarity. The Cross-Lagged Correlations Panel design statistical procedures of Rozelle and Campbell [26] were used. These were further discussed and interpreted by Kenny [27]. Rogosa [28] critiqued these methods, then Locasico [29] argued they were useful for exploratory analysis of causal relationships. The method is used to the present day.

Atkin, Galloway, and Nayman [30] provided a clear description:

> "'Conceptually, each cross-lagged correlation is compared to an average static correlation adjusted for unreliability due to temporal instability. It is inappropriate to compare a lagged correlation to a static correlation because the behavior measured changes over time, reducing the magnitude of the association. This genuine variability can be taken into account by multiplying the average static correlation by the stability coefficient that results from dividing the time-lagged correlation by the internal consistency component of the reliability coefficient." (p. 233)

To show evidence for cause, the cross-lagged correlation must significantly exceed this 'no cause' expected attenuation coefficient [26]. Because we do not have scales used on samples, but census values, and single networks for each observation, we used 1.0 for our reliability coefficients.

4. RESULTS

First of all, we wondered how much information we lost by dropping the abstracts from the 2011 program text and using only the paper titles, to make the 2007 and 2011 semantic data most comparable. The titles only semantic-based division networks from time 1 and time 2 were correlated at r=. 54 while using titles at time 1 and titles plus abstracts at time 2 resulted in an overtime correlation of r=.72 for the semantic-based division network structures. The removal of abstracts, therefore, resulted in a net loss of 3% of the variance.

4.1 Synchronous, Diachronic, and Diagonal Correlations for Networks

Figure 1 contains all of the correlations plus the no cause baseline coefficient, computed to be .24. Membership-based networks are correlated over time at r=.47. Synchronous correlation between the semantic and membership networks among divisions are correlated at r=.64 at time 1 while at r=.33 at time 2. That means 41% of the variance was accounted for at time 1 between the semantic and formal membership division networks while the time 2 synchronous relationship accounted for 11% of the variance. At time 2, therefore, semantic-based division networks are becoming more decoupled from the formal membership-based networks. This suggests increasing independence and flexibility in the semantic domain. It may be resulting from the third element of structuration theory, individual deviation from the formal structure, in other words, destructuration.

Both time 1 semantic-based division networks and time 2 membership-based division networks and Time 1 membership-based division networks to time 2 semantic-based division networks are above the no cause baseline. The time 1 semantic-based division network was correlated with the time 2 formal membership-based division network at r=.61, which exceeded the baseline by more than twice the required level. The r to z transformation and statistical significance test between this value and the no cause baseline resulted in a significant value (z=23.20, p < .0000, 1-tailed). On the other hand, the time 1 formal membership-based division network was correlated with the time 2 semantic-based division network at r=.26, only .02 above the no cause baseline which was not significant (z=1.07, p < .14, 1-tailed). There was no evidence for the time 1 semantic-based division networks causing changes in the time 2 co-membership-based network.

Time 1 membership-based network to time 2 semantic-based division network explains 37% percent of the variance. This suggests that the network of divisions based on formal membership leads to increased similarity of the network of divisions defined by paper title content. The membership network appears to promote the writing of papers that result in semantic-based division networks based to some extent on the earlier membership-based networks. Figures 2 through 5 show the networks as rendered by NetDraw [31].

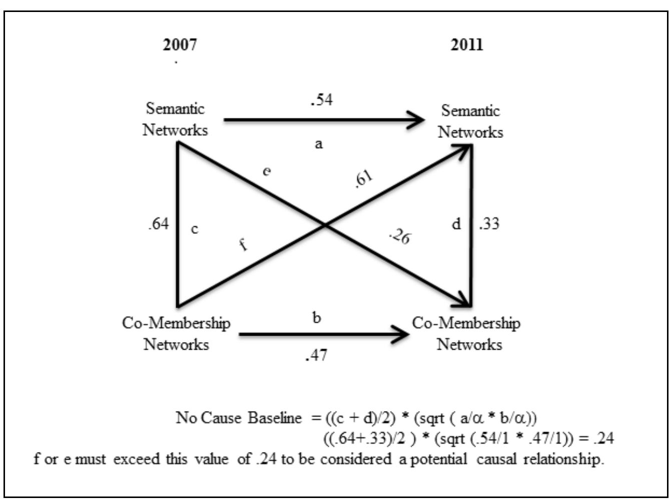

Figure 1. Cross-Lagged Correlations

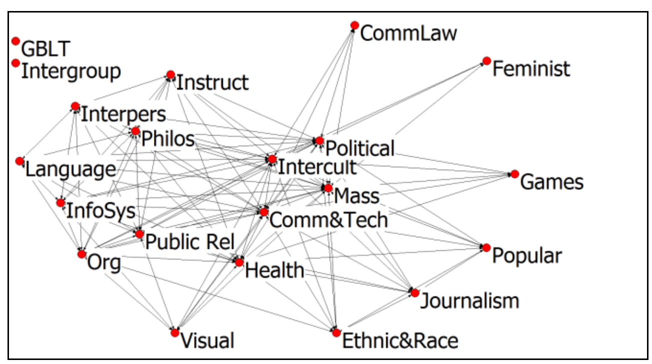

Figure 2. Network of Divisions Based on Semantic Similarity: 2007

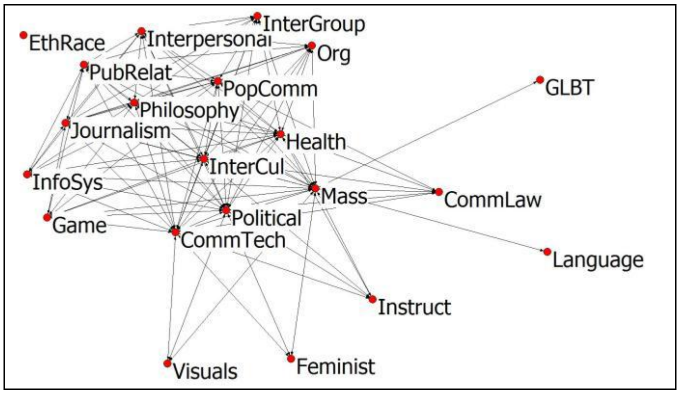

Figure 3. Network of Divisions Based on Semantic Similarity: 2011

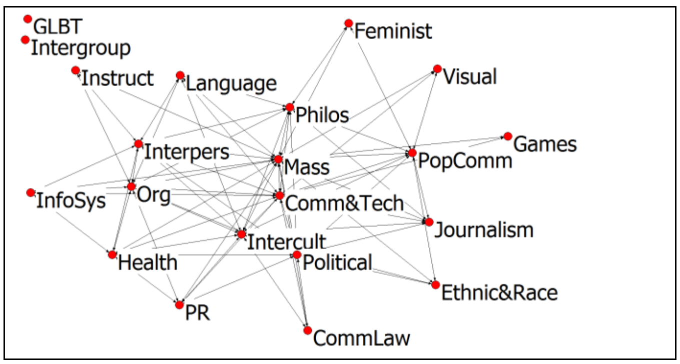

Figure 4. Network of Divisions Based on Co-Membership: 2007

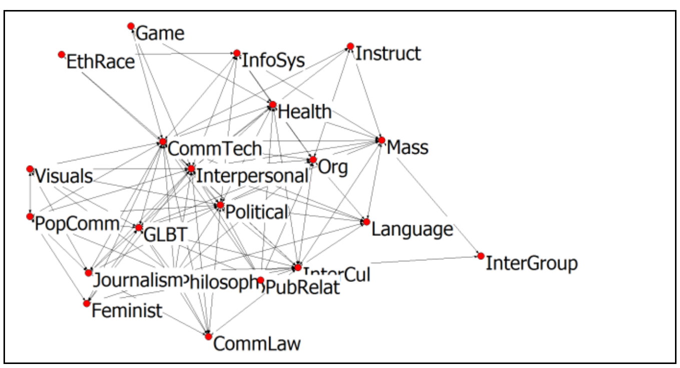

Figure 5. Network Divisions Based on Co-Membership: 2011

5. DISCUSSION

5.1 Interpretations

This study found several noteworthy patterns addressing the research questions posed: a) a possible causal relationship from the formal membership-based division network at time 1 to the semantic-based division network at time 2, b) the time 1 semantic division network was not significantly related to the time 2 co-membership division network, c) substantial decoupling of the semantic division network in 2011 from the membership division network in the same year, d) considerable change in the semantic division structure from time 1 to time 2, as well as, e) change in the co-membership division network from time 1 to time 2.

The formal membership-based division network at time 1 accounts for 37% of the variance in the semantic-based division network at time 2, a statistically significant relationship above the no cause baseline. This suggests that formal membership network may to some extent produce later semantic changes. The evidence for a time-ordered positive association contains two of the three elements typically considered for establishing causality. The third element is ruling out rival explanations. As an exploratory quantitative case study this research has established a basis for future research to attempt to replicate this finding and begin to rule out alternative explanations for the association over time.

Regarding Giddens' theory we only found that the earlier formal membership division network (structure) predicted the semantic division network (structuration) four years later. This supports just the first half of Giddens' thesis, structure provides the basis for individual structuration behaviors. But for the second half, that structuration reproduces structure, we found no evidence. The earlier semantic-based division network had no significant relationship with the formal membership division network four years later. The correlation was not significantly different from the no cause baseline. Giddens' theorized reciprocity of structure and structuration is called into question.

The diachronic and synchronic residual variation between 63% and 70% suggests that members produce semantic networks in papers delivered at the professional association annual meetings that reflect a lot of flexibility in content choices. Factors other than formal co-membership division networks appear to have more to do with paper topics. This may be evidence in support of Giddens' third element of the structure process, intentional individual deviation from the formal structure. This destructuration appears to have increased between 2007 and 2011. In quantitative terms this third element of the triality of structure accounts for nearly twice as much variance as the first part of the duality.

Moreover, we found that across the four-year lag there was only 22% shared variance between the two formal division co-membership networks. That suggests considerable change in these networks. Some members appear to be changing their divisional affiliations over the four-year period, or perhaps new members are choosing different subsets of divisions than existing members. Both processes may be operating. This indicates little support for the notion that the structure is stable, which would have been consistent with Giddens' assertion that there is a strong reciprocal relation that is mutually reinforcing. Perhaps, however, formal membership networks may not be deep enough structure to consider. Perhaps the formal co-membership network is an intermediate structure, or even possibly more akin to structuration. It may be that deeper structures are more consistent with Giddens' theories. These may be structure embodied in elements such as the association's mission statements, by-laws, board structure, decision processes, committees, journals, its divisions, business meetings and committees, and elections of officers.

Regarding semantic-based division networks, the network in 2011 had 63% of its variance unaccounted for. This may also support the third element of the structure theory, the individual intension effect. In this case it may suggest deviation from the normal structuration, rather than intended conformity. It is instead perhaps more consistent with destructuration. Nevertheless, we need future time points to see to what extent the 2011 semantic division network may predict the next period's membership division network.

Moving beyond Giddens' notions, perhaps choice of paper content, which was only 37% predicted by the earlier membership network, may be influenced by many other possible factors. There may be an influence from the job market based on what content areas may be sought by schools hiring over the past year. There may also be influence of secular trends or scholarly trends in the short-term popularity of particular content areas.

Another of our findings, on the synchronous correlations at the two points in time, suggest that in 2011 there appeared to be 30% less variance accounted for between semantic-based and formal-membership-based division networks than there was in 2007. There was a sizeable drop from 41% shared variance in 2007 to 11% in 2011. This decoupling may perhaps also be due in part to increased cascade or "herd" effects of social media.

We found support for this possibility in another study that increased use of communication technology in which individuals could see who was advocating what content and could determine their status was associated with more herd effects (widely forwarded emails). It appeared to explain the R-curve diffusion patterns we found rather than S-curve ones [14]. S-shaped curves are associated with greater influence of unmediated face-to-face communication networks, while R-curves are associated with more mediated communication of a less interpersonal nature, and more based on observing others communication and behaviors rather than interacting with them.

Anecdotal observation of the members of the association reveal that between 2007 and 2011 there appears to have been a rapidly growing participation in social networks such as Facebook and others, as well as additional internet-based media which do not involve as much interpersonal interaction as offline communication does. In fact, last year ICA institutionalized a form of social media. It created a virtual conference mainly for non-attendees of the on-site conference. It has social media characteristics. Over 700 people logged in to it this year.

Increased social media use may account for increased herd effects among researchers that may result in some decoupling of the formal divisions memberships from the paper topics individuals choose. Researchers may select their research topics based more on herd factors than on topics traditional tied to the formal division structure and communication within it.

Because the semantic-based division networks have considerable independence from the formal structure, if these findings are replicated, this suggests that studying organizational subunits' semantic similarity provide more revealing knowledge about organizational dynamics than the networks based on formal membership. Nevertheless, studying both gives a more complete picture of the organizational dynamics and one can predict a significant amount of changes in the semantic-based division network based from the prior network constituting one of the aspects of formal organizational structure.

The findings also suggest that studying semantic-based division structure to infer formal co-membership structure, as Doerfel and Barnett did, is not advisable. There are considerable residual variations that should not be overlooked. Our study had a four-year time lag. Doerfel and Barnett did their semantic division network study seven years after Barnett and Danowski's co-membership division network and interpreted the two networks to have similar structures. This longer lag would appear to perhaps further reduce the ability to predict formal structure from semantic structure, and the moderate correlations we found left a large amount of unexplained variance between semantic and membership-based division networks.

5.2 Limitations

This research studied an association at only two points in time, although it used a quasi-experimental design. We used a statistical technique for assessing possible causality that should be used with caution and mainly in exploratory investigations. Another limitation is the case study nature of the design. The data we used came only from a single professional association. Its activities may not be representative of other social science research associations. Such a suggestion requires studies of representative samples of a large number of such associations.

We found that using only paper titles is not a limitation. Adding abstracts added only 3% to variance explained. This may suggest that going further and using the full text of papers would perhaps not add much more explanatory power. But further empirical assessment is needed on this matter.

5.3 Future Research Directions

It would informative to conduct depth interviews with a representative sample of association members probing their reasons for selecting the paper topic(s) they submitted to ICA. Those who changed divisions to which they submitted papers from one year to the next would be separated out from those did not change and the semantic networks from the interviews would be analyzed for differences. Their participation in social media, and their scientific information source usage as well as their usage of other kinds of content would enable testing of the related propositions posed in this paper.

Studying more associations from other disciplines would be valuable for assessing the potential generalizability of possible findings and also for creating or ruling out alternative explanations for possible causal relations replicated.

6. ACKNOWLEDGMENTS

The author thanks Michael Haley and staff of the International Communication Association for providing data.

7. REFERENCES

[1] Carter-Thomas, S., & Rowley-Jolivet, E. 2003. Analysing the scientific conference presentation (CP): A methodological overview of a multimodal genre. *la revue du GERAS*, 39, 59-72.

[2] Barnett, G. A., & Danowski, J. A. 1992. The structure of Communication: A network analysis of the International Communication Association. *Human Communication Research*, 19, 2, 264-285.

[3] Hall, R. H. 1968. Professionalization and bureaucratization. *American Sociological Review*, 33,1, 92-104.

[4] Doerfel, M. L., & Barnett, G. A. 1999. A semantic network analysis of the International Communication Association. *Human Communication Research*, 25(4): 589-603.

[5] Giddens, A. 1984. *The constitution of society: outline of the theory of structuration.* Berkeley: University of California Press.

[6] Giddens, A. 1991. *Modernity and self-identity: Self and society in the late modern age*. Palo Alto: Stanford University Press.

[7] Blau, P. M. 1960. Structural effects. *American Sociological Review,* 25, 2, 178-193.

[8] Contractor, N., Whitbred, R., Fonti, F., Hyatt, A., O'Keefe, B., & Jones, P. 2000. Structuration theory and self-organizing networks. Unpublished Manuscript. Champaign-Urbana: University of Illinois.

[9] Barley, S. R. 1990. The alignment of technology and structure through roles and networks. *Administrative Science Quarterly*, 35, 61-103.

[10] Haines, V. A. 1988. Social network analysis, structuration theory and the holism-individualism debate. *Social Networks*, 10, 157-182.

[11] Poole, M. S., & McPhee, R. 1983. A structurational example of organizational climate. In L. Putnam & M. Pacanowsky (Eds.), *Organizational communication.* Beverly Hills: Sage.

[12] Monge, P.R. & Contractor, N. S. 2003. *Theories of communication networks.* Oxford, UK: Oxford University Press.

[13] Monge, P. R., & Eisenberg, E. M. 1987. Emergent communication networks. In F. M. Jablin, L.L. Putnam, K. H. Roberts, & L. W. Porter (Eds.), *Handbook of organizational communication* (pp. 304-342). Newbury Park, CA: Sage.

[14] Danowski, J. A., Riopelle, K., & Gluesing, J. 2011. The revolution in diffusion models caused by new media: The shift from s-shaped to convex curves. In G.A. Barnett & A. Vishwanath (Eds.) *The diffusion of innovations: A communication science perspective*, (pp. 123-144). New York: Peter Lang Publishing.

[15] Danowski, J. A. 1993a. WORDij: A word pair approach to information retrieval. *In Proceedings of the DARPA/NIST TREC Conference* (pp. 131-136). Washington, DC: National Institute of Standards and Technology.

[16] Danowski, J. A. 1993b. Network analysis of message content. G. Barnett, & W. Richards (Eds). *Progress in communication sciences XII* (pp. 197-222). Norwood, NJ: Ablex.

[17] Danowski, J. A. 2010a. WORDij 3. 0 Software for Semantic Network Analysis [computer program.] Chicago: University of Illinois.

[18] Danowski, J. A. 2010b. Inferences from word networks in messages. In K. Krippendorff & M. Bock (Eds.) *The content analysis reader* (pp. 421-430). Sage Publications.

[19] Diesner, J. & Carley, K. M. 2004. AutoMap1.2 – extract, analyze, represent, and compare mental models from texts. CASOS Technical Report, CMU-ISRI-04-100, Pittsburg, PA: Carnegie Mellon University.

[20] Chen, H., Evans, C., Battleson, B., Zubrow, E., & Woelfel, J. 2011. Procedures for the precise analysis of massive textual datasets. *Communication & Science Journal*, 2011Oct10.

[21] Danowski, J. A. 2012. Matrixer: software for creating 2-mode matrices of words or word pairs by separate files of text. Naperville, IL: Communication Research Network.

[22] Borgatti, S. P., Everett, M. G., & Freeman, L. C. 2002. UCINET for Windows: Software for Social Network Analysis. [computer program.] Harvard, MA: Analytic Technologies.

[23] Mantel N. 1967. The detection of disease clustering and a generalized regression approach. *Cancer Research*, 27(2), 209–22.

[24] Hubert L. J. 1987. *Assignment methods in combinatorial data analysis.* New York: Dekker.

[25] Krackhardt D. 1987. QAP partialling as a test of spuriousness. *Social Networks*, 9,171–186.

[26] Rozelle, R. M., & Campbell, D. T. 1969. More plausible rival hypotheses in the cross-lagged panel correlation technique. *Psychological Bulletin*, 71(1), 74-80.

[27] Kenny, D. A. 1975. Cross-lagged panel correlation: A test for spuriousness. *Psychological Bulletin,* 82(6), 887-903.

[28] Rogosa, D. 1980. A critique of cross-lagged correlation. *Psychological Bulletin*, 88(2), 245-258.

[29] Locascio, J. J. 1982. The cross-lagged correlation technique: reconsideration in terms of exploratory utility, assumption specification and robustness. *Educational and Psychological Measurement*, 42, 1023-1034.

[30] Atkin, C. K., Galloway, J., & Nayman, O. B. 1976. News media exposure, political knowledge and campaign interest. *Journalism Quarterly,* 53, 231 -237.

[31] Borgatti, S. P. 2002. NetDraw [computer program.] Harvard, MA: Analytic Technologies.