Cognitive Structures and Collaboration Patterns in Academia

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Abstract
This paper develops a coherent research framework which relates cognitive structure and the collaboration patterns into an integrated socio-knowledge analysis of a given scientific community. The framework extends co-word analysis combining it with social network analysis by introducing a novel model. The new model maps actors from co-authorship networks into a strategic diagram of scientists. The mapping is based on cohesiveness and pervasiveness of issues each author has published in the field. The paper adopts a longitudinal approach to trace knowledge diffusion within peculiarity of a national level socio-knowledge system identifying interplay in between scientists socio-knowledge structures and their research strategies, and their evolutions over time. The case covers Turkish management academia spanning the years from 1922 until 2008. It is seen that, within local community, diffusion of management knowledge is lead by academicians with certain socio-knowledge properties: they have more social ties and more diversified knowledge compared to the rest; knowledge they have is distinct compared to their peers in the network; they hold certain part of their knowledge exclusively, thus knowledge-wise they don't resemble the rest; but they keep a level of common knowledge with the rest of the community. However, academicians publishing at international arena do not show any significantly differing socio-cognitive properties from each other, instead, they are merely embedded in strongly connected groups.

Introduction

Motivation

Literature as a whole suggests that "studying the communication network of science as a whole is difficult because it is so vast, rapidly changing, and complicated that neither the participants nor the observers can attend to more than an isolated few of the communicative events at any given time. Moreover, the communicative practices overlie the cognitive processes, and these not only vary by field, but also are open to a wide variety of interpretations" (Morris and Martens, 2009: p. 218). For that reason, a set of different theoretical and methodological approaches have been developed or employed to examine various aspects of practices in scientific communities and institutions. Each of these approaches reveals a different view of practices in science and only "when combined, they can produce a multi- faceted map of the social structure, base knowledge, research topics" (p. 277). In that regard, this paper aims to advance a methodological framework which does examine knowledge diffusion and social structure interrelatedly. The proposed framework is demonstrated by an exemplary case, where management academia in Turkey from 1922 to 2008 is covered. This framework primes mutuality of knowledge and social structure theory borrowed from sociology of knowledge literature, where knowledge is perceived as an essentially social and societal category. This abstraction mutually interrelates social structure and knowledge (Merton, 1968; Mannheim, 1968; Scheler, 1980).

In that mutuality, from the social side, scientists as knowledge carriers or knowledge producers 'do not orient themselves exclusively toward their data nor toward the total society but to special segments of that society with their special demands, criteria of validity, of significant knowledge of pertinent problems.' (Merton, 1968: p. 536). On the other side, knowledge is both a medium of social action such as co-authorship and the result of scientists' actions either be individual or collective. In that respect, as a medium, knowledge enhances the capacity for collaboration, as well as, impacts the shape of resulting collaborative structure.

Research Question

The paper mainly aims to understand to what extent authors in Turkish management academia are distinguishable in terms of their individual level socio-cognitive patterns. The quest is tailored by addressing following detailed questions: (i) To what extent patterns at individual level socio-knowledge centralities are distinguish- able as of scientists' preferences on the strategic type of issue they pick to disseminate? (ii) To what extent structurally embeddedness of individual scientists are distinguishable as of their preferences on the strategic type of issue they pick to disseminate? (iii) To what extent relative cognitive structure of individual scientists are distinguishable as of their preferences on the strategic type of issue they pick to disseminate? The study does not primarily address the question why scientists do collaborate (Acedo et.al., 2006).

Relevant Studies

There are a few studies in the literature which examines social network structure and cognitive structure of scientists simultaneously. Peter Mika in a series of studies (Mika, 2005) attempts to combine social network structure and social cognitive structure of Semantic Web research field. He mines Web data to form the social network structure of the research community. Various clustering algorithms are used to detect research sub-groups. The author additionally forms a bi-partite graph of the community, where each author is linked to one or more topics represented by 24 key terms. These key terms are determined qualitatively examining the studies in the field. Noyon and Calero-Medina (2009) conduct a case study based on scientific activities of 21 selected faculty members in three Dutch universities of technology. They collect major publications of each faculty to form a publication portfolio of each one. They adopt natural language processing methods to extract keywords or noun phrases from the titles of the publications. They use this set of keywords to represent cognitive profile of each faculty. The cognitive profiles of individuals are then used as input to a similarity analysis in order to define the amount of research 'overlap' in between them. The overlaps are used to form cognitive similarity network of selected faculty members. They use this similarity network as a potential collaboration network. Theoretical and methodological foundations of this case study is based on Calero et.al. (2006).

A study by Mutschke and Haase (2001) explicates in detail how existence of relationship between researchers' position in social structure of scientific networks and the innovativeness of themes they examine can be related. Another but rather early work by Doerfel and Barnett (1999) investigates semantic network, namely overall cognitive structure of, International Communication Association (ICA) in 1991. The authors examine to what extent cognitive map of the association in 1991 resembles affiliation network of the community? They extract cognitive map of the association conducting content analysis on the titles of the papers presented at the annual meeting in 1991. Then, they relate a network based on scientists common institutional affiliation and one based on their cognitive similarity. Another relatively recent study by Calero-Medina and Noyons (2008) apply an hybrid approach by combining co-word analysis with citation analysis. The study further exemplifies potential of meta-network analysis at the study of knowledge diffusion. The authors attempt to trace development of a specific concept in management studies and its diffusion pattern over the years from its first occurrence in management literature.

Method

Meta-network Analysis

In this study bibliographic data is used to extract network relations. The three primary relations extracted from the set of bibliographic entities is represented by their corresponding

network models. They are, namely, co-authorship network (AxA), knowledge network (KxK), and knowledge dissemination network (AxK). Previous studies on scientific communities or on knowledge diffusion in large have either focused on co-authorship relations or semantic relations. There are a few number of studies which have integrated both set of relations. In this research, I integrate observed cognitive relations made by scientists by capturing it via knowledge dissemination network (AxK). Authorship information is one of the standard component of bibliographic entities. Establishing KxK and AxK relations, however, necessitates further data pre-processing in order to tokenize keywords of each title or paper. Once keywords of each bibliographic entry is tokenized, while co-occurrence of keywords is used to form KxK relations, co-occurrence of a keyword on an author's paper is used to form AxK relations. One of methodological contributions of this study is adoption of Meta-Network perspective, which principally allows to observe and analyse cascaded influences across different yet interrelated networks of relations. Meta-Networks have been introduced by a research team lead by network scientist Kathleen Carley (Carley et.al. 2009; Carley, 2002). Following list of metrics are either adopted or developed for this study while conducting meta-network analysis.

Knowledge Degree Centrality (KDD): This metric is measured and interpreted according to an author's activity at disseminating knowledge. The metric is adopted from out degree centrality of Wasserman and Faust (1994). Let assume that an AK matrix holds frequencies of themes (keywords, or knowledge) disseminated by each scientist. Rows denote authors (A) in the community and columns denote keywords observed within titles of publications by the authors in the community. Then Knowledge Degree Centrality (KDD) of an author is computed as $KDD_a = 1/n \sum^{n}_{k=1}(a,k)$, where n is number of unique keywords observed. It should be noted that AK matrix is a rectangular and asymmetric matrix, rep- resenting a bi-modal relation between scientists and pieces of knowledge they have disseminated via observed publications.

Triad Count: A triad is a relationship amongst three scientists. In mathematical terms, it is the count of co-authoring triples. Existing and prevalence of triads deemed to be relevant to network architecture which in term shapes the channels of knowledge diffusion (Scott, 2000; Geisler, 2007).

Clique Count: The measure computes the number of distinct cliques to which each author belongs. A clique is defined as a group of three or more actors that have many connections to each other and relatively fewer connections to those in other groups. The measure reflects sub-structures in the collaboration network that contribute to a cohesive whole (Wasserman and Faust, 1994).

Clustering Coefficient (CC): The clustering coefficient of an author is the density of his/her ego network which is the sub-graph induced by its immediate neighbours. Individual clustering coefficient estimates the intensity of one's ties with the others in the network. It estimates cohesiveness of ties between ego's immediate neighbours including the ego (Carley et.al., 2009).

Collaborator Exclusivity Index (CEI): Collaborator Exclusivity Index is used to detect authors who have connections that are unique in the community. In other words, it is used to detect authors who collaborate with someone with whom no one else has collaborated so far. The metric is developed for this work. A person with a high number of pendants would have a high collaborator exclusivity value. A pendant in network terms is a node who is connected to the community through a single person. The Collaborator Exclusivity Index (CEI), for an author a in the set of all authors A in the community, and where AA is the corresponding adjacency matrix, is defined as $CEI_a=1/n\sum^{|A|}_{j=1}AA(a,j)e^{(1-sum(AA(:,j)))}$

As a by product, this metric may be critical at assessing impact of a scientists who have 'external' ties. For instance, within a local community a scientist who have access to some other non-local scientist(s), with whom nobody else from other locals has a tie, may be critical at diffusing knowledge acquired during that very collaboration. However, it should be noted that in order to detect such an impact such unique collaborations should be visible within research data.

Socio-Knowledge Power (SKP): The measure indicates strength of a scientist both in terms of one's access to other peer scientists and one's expertise in the field. In other words, it combines one's social capital and one's knowledge portfolio. The social capital in that sense is measured by co-authorship information. Diversity and frequency of concepts that appears on one's articles is used to form his/her knowledge portfolio. Let AA' represent normalized co-authorship matrix and AK' represent normalized knowledge dissemination network. Then SKP of an author a can be computed as $SKP_a=1/m\sum^{m}_{k=1}M(a,k)$ with $M=[AA'|AK']$ and $m=|A|+|K|$. Note that M is formed by concatenating normalized AA and AK relations.

Cognitive Distinctiveness (CD): Cognitive Distinctiveness estimates the degree to which each pair of scientists has disseminated complementary knowledge, expressed as the percent of total knowledge disseminated within the community. In other words, it measures how distinct are two scientists based on the number of knowledge bits they hold oppositely (Carley, 2002).

Cognitive Similarity (CS): Cognitive Similarity estimates the degree to which each pair of scientists have disseminated overlapping knowledge. In other words, it measures the degree of similarity between authors based on the number of knowledge bits they both have (Carley, 2002).

Cognitive Resemblance (CR): Resemblance estimates the degree of resemblance between scientists based on the number of keywords they both have or both have not disseminated. In a way, it measures the degree to which each pair of author has the exact same knowledge (Carley, 2002).

Knowledge Exclusivity Index (KEI): Detects scientists who have singular knowledge. KEI measures the extent that an author has disseminated on a field that is unique to the community. Having published on a subject nobody else have published, may point that the scientist acts as a solo novice knowledge source for the rest of the community he/she is in (Carley, 2002).

Co-word Analysis

Relations established and observed by Knowledge Network (KxK) considers keywords as the atomic unit of analysis. However, it does not present or visualize rather abstracted semantic relations in between groups of keywords. Co-word analysis provides such higher level abstractions. Co-word analysis is a content analysis technique developed to study relationship in between ideas within the subject areas presented in publication documents (He, 1999). "Co-word analysis is based on the theory that research fields can be characterized and analysed based on patterns of keyword usage in publications" (Neff and Corley, 2009). The analysis based on co-occurrence frequency of pairs of words or phrases. Either a single word or a set of words forming a phrase may denote a key subject, a main theme or a basic concept. Then co-word analysis is employed to discover linkages among subjects or concepts in a field. Overall structure of linkages is used, for instance, to trace development of a field overtime. This technique has proved to be a powerful knowledge discovery tool to derive map of a sciences from bibliographic databases (Neff and Corley, 2009; Lee, 2008; Cahlik and Jirina, 2006; Borner et.al., 2003; Cahlik, 2000; He, 1999; Bhattacharya and Basu, 1998; Vanraan and Tijssen, 1993; Leydesdorff, 1992; Law and Whittaker, 1992; Whittaker, 1989).

Co-word analyses progressed by a sequence of steps such as data selection, data pruning and information coding processes followed by statistical and algorithmic analyses of retrieved information. Briefly, the first stage is extracting keywords from each document in data set. Then a co-occurrence matrix of keywords is generated. Various features of resulting co-occurrence matrix is analysed statistically or algorithmically based on research question at hand. The keywords can be extracted from titles, abstracts, listed keywords of papers or from other parts of a publication. Keywords which appear together on the same publication are used while forming a cluster. A cluster, which is formed by one or more words, then is treated as representing a concept, a specific research theme, an issue, a method or a theoretical framework. In other words, a cluster of keywords is understood as a short description of a research theme, where structure of mutually connected clusters is considered to present a research field (Cahlik, 2000). In the literature, network scientists have used different techniques to create clusters. Hierarchical clustering, agglomerative clustering, principal component analysis and factor analysis are amongst the most widely employed techniques (Rip and Courtial, 1984; Callon et.al., 1986; Tijssen and Vanraan, 1989; Turner and Rojouan, 1991; Qin, 1994; He, 1999; Neff and Corley, 2009).

Almost all of recent studies which employ co-word analysis do generate a strategic diagram to see overall structure of the specific domain or a scientific field under examination. In order to derive a strategic diagram, centrality and density value of each cluster is determined. The centrality of a cluster implies how strong each keyword or phrase within the cluster is linked to other keywords or phrases in the other clusters, and the density of a cluster implies how strongly each keyword within the cluster is linked to each other. Then, each cluster is mapped on a strategic diagram based on its normalized centrality and density value. Resulting strategic diagram is a two dimensional Cartesian map, where usually horizontal axis denotes centrality and vertical axis denotes density of the specific field under examination. The origin of the axis is the intersection of median or mean of centrality and density values.

Thus, if a cluster has relatively high centrality and density, it is assumed to be central and developed area, subject, or topic within the field. If a cluster however has both a very low density and and a very low centrality, it is assumed to be peripheral and undeveloped. On the other hand, a cluster with high centrality but low density implies that although the subject is central to the field it is not developed enough, while a cluster with low centrality but high density implies that although the subject is very much developed, it has not been central or has not become mainstream so has a marginal importance to the field under examination. Co-word analysis produces strategic diagram of a field, in other terms, the strategic map of a scientific field. More precisely, given a set of bibliographic entries which is able to cover or represent knowledge produced in a specific field at a specific time, co-word analysis attempts to position cluster of themes within the field regarding each cluster's internal cohesiveness and its field level pervasiveness.

Mapping Scientists onto Strategic Diagram of their Respective Research Fields

Previous conceptual and methodological studies in the literature, as we have discussed above, lead me to develop a composite framework. The framework enables to examine the structure and dynamics of a research field. It derives upon map of collaborations by researchers in the field in parallel to a map of base knowledge supporting the research in the same field. In other words, the approaches we have outlined earlier allows us to sketch out a map of subtopics and how they are related and to sketch out a second separate map of research teams doing research in the specialty.

The literature is not elaborating on how they appear to be linked. There are only a few attempts which relate cognitive structure of a field and collaboration in between scientists in the field (Morris and Martens, 2009). A sketch of methodological perspective of co-

authorship studies (e.g., Mutshcke, 2003) would be (i) consider the authors, (ii) apply social network methods, and (iii) speculate over the network positions of the authors regarding their role at diffusing the knowledge. This outline considers neither cognitive structure of individuals nor the community as a whole. That is, it lacks to reflect fundamentals of a theoretical framework where mutuality of social structure and production or diffusion of knowledge in the community is primed.

On co-word analysis side primacy is on strategic position of themes. It conceptualizes keywords or themes in a research field as actors, per se, developing upon the very idea of actor-network-theory or ANT (Callon, 1986; Law and Hassard, 1999), nevertheless, it fails to integrate direct or indirect impact of keywords as interactive non-human actors in a network of relations in between heterogeneous actors, where heterogeneity exists due to co-interaction of scientists and knowledge actants.

Some other scholars point the role of documents, instead of knowledge, themselves as actants and suggest to consider them in sociological studies on knowledge diffusion within scientific fields (e.g., Prior, 2008). Indeed, co-citation or citation analysis within the realm of scientometrics or informetrics have developed upon that conceptualization. In this study, when we attempt to relate cognitive structure and collaboration, documents act merely the role of a container for scientific knowledge and a collaboration space for the scientists.

Conventional strategic diagram is deficient in the sense that it isolates knowledge from its carriers. It does not constellate the knowledge generators regarding their contribution to different theme clusters. In other words, it does not hint what percent of a scientist's effort is towards main stream issues, or towards rather peripheral issues within that very field.

We propose a new method to overcome aforementioned deficiency. The proposed novel method combines meta-network analysis and conceptual clusters of conventional co-word analysis. The method is simply re-generation of strategic map of the field as of authors in the field. Putting it differently, it develops a metric in order to find each author's Centrality and Density. In that sense, it parallels conventional strategic diagrams.

Table 1. Centrality and density of each author observed within a bibliographic set.

Centrality	*Density*
$ASC_{author} = \sum_{\forall p \in P_a} \frac{1}{a_p} \left(\frac{\sum_{i=1,j=1}^{E_{ij}} (E_{iw}/C_{iw})}{n(N-n)} \right)$ where, ASC_{author} = Centrality of the author P = Set of papers by the author E = Equivalence index of word pair link C_{ij} = co-occurrence frequency of $i \wedge j$ appearing on the same paper. N = Total number of unique words used in titles within the period p = current paper in the set a_p = Number of collaborators of current paper in the set i = First word in the pairing, internal to the cluster w = Word in dataset, but not in the cluster n = Number of unique words in the cluster	$ASD_{author} = \sum_{\forall p \in P_a} \frac{1}{a_p} \left(\frac{\sum_{i=1,j=1}^{E_{ij}} (E_{ij}/C_{ij})}{(n(n-1))/2} \right)$ for $n > 1$ $= \sum_{\forall p \in P_a} \left(\frac{1}{a_p} \sum_{i=1,j=1}^{E_{ij}} E_{ij}/C_{ij} \right)$ for $n = 1$ where, ASD_{author} = Density of the author P = Set of papers by the author E = Equivalence index of word pair link C_{ij} = co-occurrence frequency of $i \wedge j$ appearing on the same paper. p = current paper in the set a_p = Number of collaborators of current paper in the set i = First word in the pairing j = Second word in the pairing n = Number of unique words in the cluster

Equations in Table 1 are used to identify centrality and density of each author observed within a bibliographic set. In words, equations sums of contributions of each paper of an author to each issue in the field. It examines each paper of an author and checks distribution of keywords of that very across the clusters in the field. Using this cluster identification information each author collects back his or her own contribution to a cluster as of the very paper he or she has published. The metric further takes into consideration the number of authors on the same paper. On the other way around, the metric can be interpreted as distributing back the portion of each author's contribution to theme clusters, where the share is represented by a tuple, the centrality of the issue and density of the issue. Based on this new pair of metrics, the model finds position of the authors on the strategic map. The axis of

author strategic maps are recomputed based on the average centrality of authors (ASC) and average density of authors (ASD). It should be noted that strategic map of scientists and the strategic map of the knowledge in the field are not necessarily the same two dimensional space. They are rather parallel and dual maps. Figure 1 demonstrates distribution of authors to the quadrants on the strategic diagram based on their computed ASC and ASD coordinates. The model is exploited to combine and examine the interplay between individual level positions on the strategic diagram and cognitive state of individuals as of their dissemination activities in a field of science.

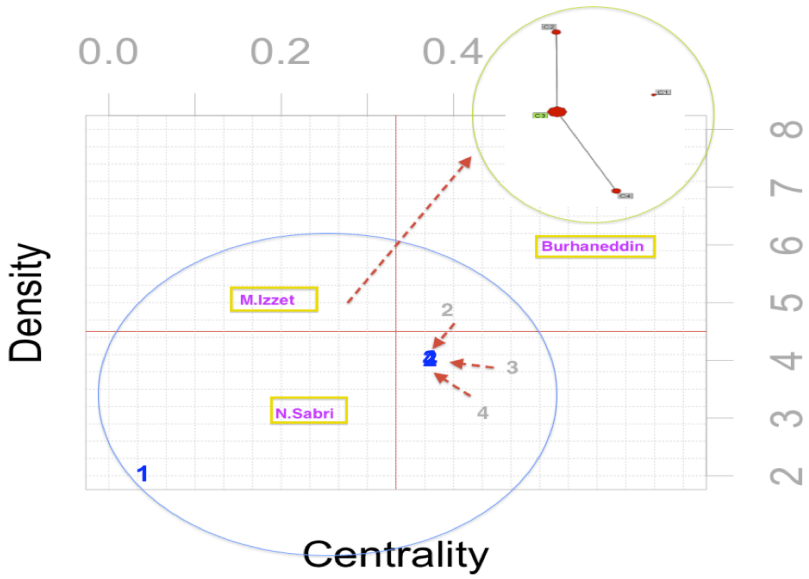

Figure 1. Distribution of authors on the strategic diagram based on their computed ASCs and ASDs.

Data

The source of primary data comprises of public records on scientific articles published in Turkey from 1922 to 2008, or from Turkey published in WoS spanning years from 1980 to 2008. The records on local publications have two separate sets as a consequence of institutional public policy changes. The first set is recorded and kept by Turkish National Library (MK), the second set is held by Turkish Academic Network and Information Center (ULAKBIM). A total of 13,264 journal articles in the field of management found to be valid for further analysis. In addition to national publications international publications were extracted from Web of Science[5]. Articles address information was used to extract papers with at least one author affiliated with an organization in Turkey. Only journal and proceeding papers are used. List of journals and proceedings in the data set is used to identify journals which publishes management or management related papers. Articles from those journals extracted out for further analysis. Eventually, 281 items covering the years from 1980 to 2008 is found valid.

Analysis and Results

Type of an issue is defined by its location on strategic diagram of a given field, which is determined by prevalence and cohesiveness of the issue in the field. Individual scientists' social or knowledge centralities, embeddedness, and their relative cognitive states are computed within meta-network analysis framework.

[5] See http://www.isiknowledge.com/

The relevant set of metrics which are given in the method section are used. In order to classify individuals' preferences on the type of issue they study and disseminate the model given by equations in Table 1. The equations enable to classify scientists's preferences on the diagram by their partial contribution to pervasiveness and cohesiveness of issues they have engaged in. Statistical tests are conducted for each individual property to determine if its distribution significantly differs on the quadrants of strategic diagram. Instead of regular parametric tests, Kruskal-Wallis test which is a nonparametric test is opted. It does not assume an underlying distribution for the test variables. Because, distribution of values of socio-cognitive properties of scientists does not necessarily follow a normal distribution. Besides, Kruskal-Wallis test allows to compare three or more groups of sample data (Hollander and Wolfe, 1973).

Socio-knowledge Centralities vs Strategic Quadrants

In order to probe distinguishing social centralities, degree, betweenness and closeness centrality values of individuals in their respective collaboration networks (AxA) are inspected. Socio-Knowledge Power (SKP), Knowledge Dissemination Degree (KDD) derived from Knowledge Dissemination Networks (AxK) are used to probe knowledge centrality of individuals.

Table 2 tabulates test results. Only statistically significant correlations are given. For instance, it is seen that distribution of closeness does not differ significantly on different quadrants. The quadrants which are populated with high values and low values are given.

Table 2. Socio-knowledge activity vs dissemination preferences.

	22-45	40-60	55-75	70-85	80-90	89-00	02-08	WoS(1980-2008)
High Quadrants ($p \ll 0.001$)								
Degree	-	-	-	-	-	-	-	Q1
Betweenness	-	-	-	-	Q1	-	-	Q1, Q3
SKP	Q1, Q2	Q1, Q4	Q1	Q1	Q1	Q1, Q4	Q1, Q4	-
KDD	Q1	-	Q1	Q1	Q1, Q4	Q1	Q1	-
Low Quadrants ($p \ll 0.001$)								
SKP	Q3	Q3	Q3	Q3	Q3	Q3, Q2	Q3, Q2	-
KDD	Q3	-	Q3	Q3, Q4	Q3	-	Q3, Q2	-

Of collaboration network centralities, it is seen that closeness of individuals to other members of the academia does not provide any implication or correlation on their decisions or choices of knowledge production process. However, it is seen that at international level publications centrality in the network is correlated on the preferences. High degree central and high betweenness central authors in WoS seen to populate the first quadrant. Besides, the ones with high betweenness are also observed to populate peripheral issues.

Of periods in local publication, it is seen that the ones with high betweenness centrality populate the first quadrant issues. The tabulated test results further explain that at international level publications, one's diversity in terms of knowledge items he/she have published is not correlated with his/her strategic choice of scientific endeavour. On the other hand, at national level publications it is other way around. The ones' with high socio-knowledge power (SKP) or knowledge dissemination degree (KDD) populates or may have manipulated mainstream issues. The ones with low SKP and KDD remains peripheral.

The results hint an important dichotomy in between socio-knowledge behaviour at publishing internally and externally. In WoS high social central authors publish or do collectively set the mainstream issues. Internally, it is the influence of individuals' socially enhanced knowledge diversity (SKP) and individual's dissemination activity (KDD) which is correlated with issues populating the map of the field. It should be noted that, the direction of causality is not clear with identified correlations.

Embeddedness vs Strategic Quadrants

In order to probe whether there is any significant correlation in between one's cliquishness in the collaboration network and one's preferences regarding the strategic type of issues one publishes, a set of embeddedness relevant metrics are estimated. They are individuals Clique Count, number of Triads they partake, density of their ego-networks estimated by their Clustering Coefficient (CC) and their Collaborator Exclusivity Index (CEI). All of the metrics are estimated from individuals' respective AxA networks. Table 3 tabulates test results.

It is seen that in international arena ones with highest clique counts are disseminating mainstream issues, while the ones with the lowest clique counts are disseminating relatively peripheral issues. A similar correlation is observed only in last decade at internal publications. Besides, significant correlation with ones CEI hints that isolated authors, when they form new ties, they preferentially attach with authors who publish mainstream issues. Analysis of social structure in earlier section supports the fact that authors with dense ego-networks, estimated via their CC values, are playing important role at diffusing or shaping mainstream issues.

Table 3. Embeddedness vs dissemination preferences.

	22-45	40-60	55-75	70-85	80-90	89-00	02-08	WoS(1980-2008)
High Quadrants ($p \ll 0.001$)								
Cliques	-	-	-	-	-	-	Q1	Q1, Q2, Q3
CC	-	-	-	-	Q1	Q1	Q1	-
CEI	-	-	-	-	-	-	Q1	-
Triads	-	-	-	-	-	-	Q1	-
Low Quadrants ($p \ll 0.001$)								
Cliques	-	-	-	-	-	-	-	Q4
CC	-	-	-	-	Q3	Q3	-	-

Relative Cognitive Structure vs Strategic Quadrants

Authors AxK relations based Knowledge Exclusivity Index(KEI), Cognitive Distinctiveness, Cognitive Similarity and Cognitive Resemblance metrics are estimated. The results are given in Table 4. Test results hint that individuals' cognitive state relative to other individuals in the network does not imply any correlations while publishing internationally. On the other side, relative cognitive state of individuals and their preferences at the choice of issues they pick to study and disseminate is very strongly correlated while publishing nationally.

Table 4. Relative cognitive structures vs dissemination preferences.

	22-45	40-60	55-75	70-85	80-90	89-00	02-08	WoS(1980-2008)
High Quadrants ($p \ll 0.001$)								
Distinctiveness	Q1, Q2	Q1, Q4, Q2	Q1	Q1	Q1	Q1	Q1	-
KEI	Q1, Q2	Q2	Q1	Q1	-	-	Q2	-
Similarity	Q3	Q4, Q3	Q1, Q4	Q1, Q4	Q4, Q1	Q4	Q3, Q4	-
Resemblance	-	Q3, Q2	Q3, Q2	Q3	Q3	-	-	-
Low Quadrants ($p \ll 0.001$)								
Distinctiveness	Q3	Q3	Q3	Q3	Q3	Q3	Q3	-
Similarity	Q1, Q2	Q2	Q2, Q3	Q2, Q3	Q3, Q2	Q2, Q3	Q2	-
Resemblance	-	Q1, Q4	Q1	Q1	Q1	-	-	-

While individuals with high cognitive distinctiveness dominate the first quadrant, the ones with low cognitive distinctiveness invariably populate the third quadrant. The ones in the third quadrant resemble to each other, but the ones in the first quadrant don't. Yet the ones in the first quadrant have high similarity as well. Presumably having common or overlapping issues with the rest but as well as owning unique knowledge keep individuals or makes individuals be at the first quadrant.

Figure 2 demonstrates a typical relation in between cognitive state of individuals with respect to the rest of the academia and their preferences at picking issues to publish. It is seen that in the period which spans from 1970 to 1985, the ones who publish mostly on mainstream or on

hot topics have distinct knowledge compared to their peers in the network, they hold certain knowledge exclusively, they don't resemble the rest, but keep a level of similarity with the academia.

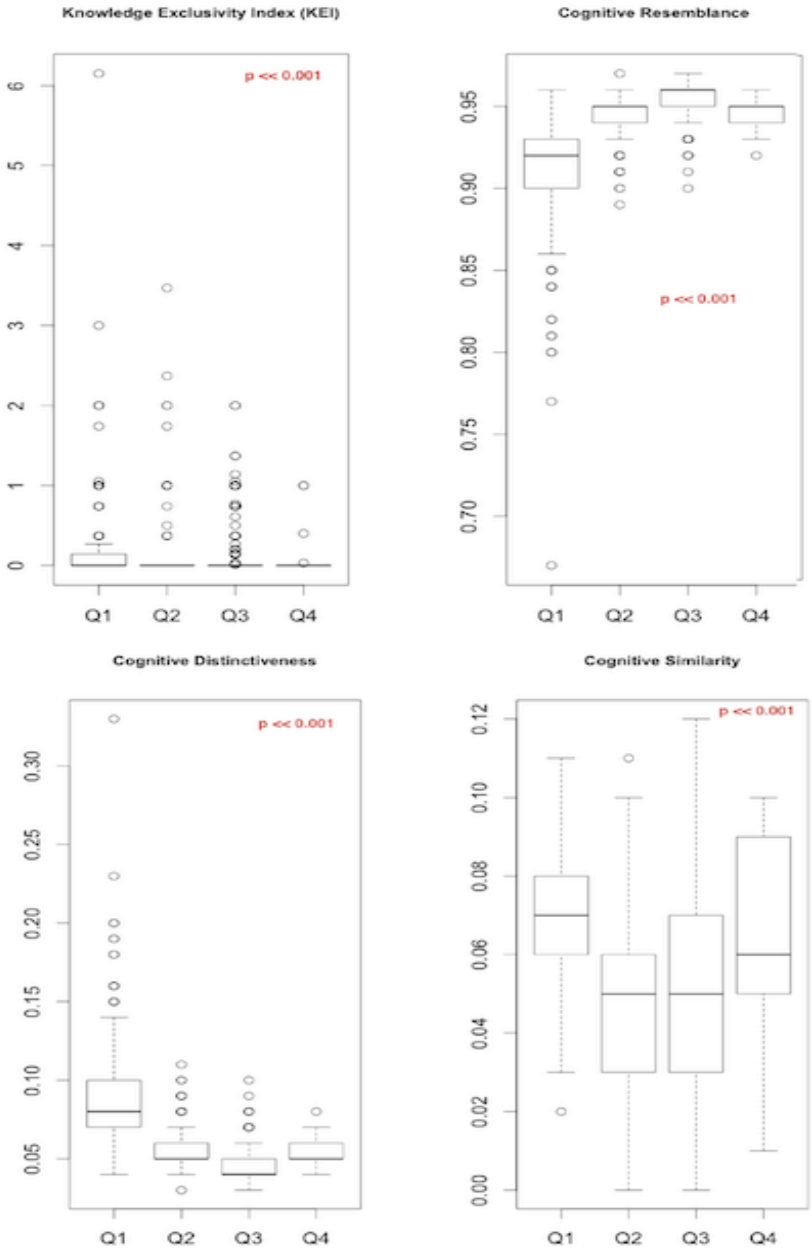

Figure 2. Relative cognitive structures vs distribution on quadrants, 1970-1985.

Conclusions

Proposed novel model which enables to reveal 'strategic' preferences of scientists at picking issues to publish is promising. It may provide new perspectives at the study of individual level knowledge dissemination practices. The model has enabled to observe that certain type of academicians within Turkey has lead diffusion of knowledge. For instance, presumably mainstream topics in the academia is set by them. They exhibit a common knowledge structure relative to the rest of the academia. They have more social ties and pieces of knowledge compared to the rest. Knowledge they have is distinct compared to their peers in the network, they hold certain part of their knowledge exclusively, thus knowledge-wise they don't resemble the rest, but they keep a level of similarity with the rest of the academia. On

the contrary, it is observed that authors who publish internationally are embedded in cliques or cohesive groups. Moreover, rate of collaboration at international publications are observed to be significantly higher than local publications. Besides, contrary to local publication practices, mainstream issues are not correlated with star authors who hold strong socio-knowledge capital but correlated with authors who are embedded in cohesive collaborating groups.

In general terms, the work emphasizes the interplay between knowledge and social structure. It has proposed and has elaborated a framework which relates knowledge structure and the collaboration patterns. The framework can be employed to examine socio-knowledge analysis of any scientific community.

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