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Examining the literature on "Networks in Space and in Time." An introduction

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Abstract

The special issue of "Networks in space and in time: methods and applications" contributes to the debate on contextual analysis in network science. It includes seven research papers that shed light on the analysis of network phenomena studied within geographic space and across temporal dimensions. In these papers, methodological issues as well as specific applications are described from different fields. We take the seven papers, study their citations and texts, and relate them to the broader literature. By exploiting the bibliographic information and the textual data of these seven documents, citation analysis and lexical correspondence analysis allow us to evaluate the connections among the papers included in this issue.

1 Introduction

In 2002, Katherine Faust and John Skvoretz wrote a highly influential paper titled *Comparing networks across space and time, size and species*. In the current issue of *Network Science*, we also focus on space and time as two fundamental elements of modern network analysis, leaving the role of size in the background. Moreover, we consider just a single species of network actors: scholars, and their intellectual efforts in the polymorphic discipline referred to as *network science*.

Even though the vast majority of network studies still examines a single network at one point in time, the goal of this introduction is to consider the articles published herein as connected units of a social and scientific space. We do this via a bibliographic data analysis and an in-depth document textual data analysis, showing how the concepts "space" and "time" characterize each paper and the entire reference literature as a set.

The analysis of the role of spatial proximity in influencing social relations, as well as how the past conditions the present realization of social structures, quoting Batagelj et al. (2014, p. 2), "... requires a concern with substance." All the papers in this issue share this concern and, to a certain extent, are linked by consideration of a spatial and/or a time dimension in the social space they investigate, or in the methodology they propose.

The papers come from a strict selection from those presented at the international workshop "*Networks in space and time: Models, data collection, and applications*" (*ARS'13*), held at the University of Roma Tre, Italy, in June 2013, and those collected afterwards by the call that followed the workshop. *ARS*—the acronym for *Analisi delle Reti Sociali*, "Social Network Analysis" in Italian—is a multidisciplinary association of scholars that promotes research on social networks through a biennial conference hosted by an Italian University (see http://www.ars15.unisa.it for more details). The fourth edition of the *ARS* workshop, held in 2013, was an occasion to present recent results on methodological developments, data collection issues, and applications of network analysis, with "space" and "time" as the two main catalytic elements to discuss. Here, with this special issue, we make a modest attempt to give credit to all those people who contributed to the organization of the workshop in Rome and to those involved in the selection process of the papers to be included in this special issue, especially the reviewers.

This is not, by any means, the first attempt to "cast in paper" the rapid evolution of the variety of ways to combine social network with spatial and longitudinal analyses. Recommended predecessors include Adams et al. (2012), where space is the contextual dimension used by the authors of a special issue of *Social Networks*. That issue provides a survey of the potential scenarios for the integration of network and spatial analytic strategies. From a different perspective, Snijders & Doreian (2010) and (2012) focus on model-based approaches to the study of network changes within the domain of longitudinal network analysis, using primarily stochastic actor-oriented models for network dynamics.

The original aim of our special issue was to collect papers considering time and space jointly. As will be seen, our intent was not to propose a fully specified paradigm for the analysis of dynamic spatial networks. On the contrary, we wish to give the reader of *Network Science* the possibility of tracking the different paths of the literature tackling this difficult task, all in one go.

The papers, introduced below, differ in their approach (theory vs. application), in their subject area (geography, economics, political science, and so forth), and in the proportion of attention devoted to time and to space. In this introduction, because of the diversity of the papers in this issue, we give the reader some guidance, using the instruments of our tradition. We first summarize the papers briefly, to examine the papers' content and the common factors, through: (1) citation network analysis, on references and on references of references, and (2) textual data analysis. We find that heterogeneity prevails, clustering occurs according to subject areas similarities, that methodologies and software availability act as bridges, and that a prevalent methodological corpus is present.

Since this literature on networks in space and time is still young, we encourage fellow scholars to critically explore the directions indicated by the present papers. New frontiers of research are moving toward the study of temporal and spatial networks. The availability of online data tracking relations, geolocation, and time-stamped data will undoubtedly foster future inquiries, both methodological and empirical. We are just at the beginning.

2 This issue—Our sample

The special issue starts with two papers illustrating different methodological procedures for analyzing networks that vary over time. The first, written by Ragozini, De Stefano, and D'Esposito, illustrates how dimension reduction methods can be used to visualize time-varying two-mode networks. Specifically, the authors propose a procedure based on multiple factor analysis and multiple correspondence analysis that allows static displays to be created for exploring network evolution and for analyzing the degree of similarity of actor/event network profiles over time, while preserving the different status of the two modes. By using McFarland's data on high school students' participation in extracurricular activities, the authors show various aspects of the method and possible interpretations of the results. We refer to this paper as RDSDE.

The second paper by Wit and Abbruzzo (WA) describes a method for estimating sparse networks from dynamic network data collected through time using a LASSO penalty function. A flexible class of sparse dynamic Gaussian graphical models can be used as a powerful analysis tool in network science. The models can be adjusted easily to accommodate flexible dynamics, that can deal with a wide variety of temporal network data. Here, the authors present two examples of dynamic networks in which the edge properties vary over time: a gene expression data and a time-varying network of behavior factors in an education setting.

The remaining five papers present some interesting methodological advancements for the analysis of social networks in time and in space with applications in different scientific fields.

The paper by Koskinen, Caimo, and Lomi (KCL) extends longitudinal exponential random graph model, as described in the recent ERGM literature, by essentially using a different estimation method based on a hierarchical model definition. It addresses the creation and deletion of ties due to both endogenous network dependencies and spatial embedding, tackling the problem of initial conditions and relaxing the assumption of time-homogeneity in order to capture changes in network dynamics. The proposed approach is illustrated by the analysis of foreign direct investments in the international electricity industry.

Box-Steffensmeier and Christenson (BSC) address the research question of factors supporting the formation of coalitions in the political process. It aims to assess differences in network structure among membership interest groups by using data on cosigner status for United States Supreme Court amicus curiae briefs, capturing all groups active in the first 10 years of the millennium. Using a two-stage approach of estimating ERGMs followed by distance-based multidimensional scaling of the ERGM parameters, the paper identifies the apparently distinct pattern of coalition building found among religious interest groups and self-identified political interest groups.

The paper by Cohen-Cole, Patacchini, and Zenou (CCPZ) develops a model of network interactions in the interbank market where the systemic risk is considered as the propagation of incentives or strategic behavior rather than the propagation of losses after default. The model has two main characteristics. First, it considers the link between propagation of financial risk and agent incentives on a network.

Second, the description of bank behavior within a network is used to illustrate how an understanding of this behavior can be formalized into a measure of systemic risk.

The key contribution of the paper by Sullivan, Lungeanu, DeChurch, and Contractor (SLDC) is to use an agent-based computational model which aims to study how space affects the emergence over time of divergent and convergent shared leadership networks inside a complex multi-team system. Specifically, it analyses the effect of "organizational" and "geographic" space on five structural features of leadership networks, including leadership capacity, leadership concentration, followership concentration, brokerage concentration, and between-team leadership. The model is used to carry out several experiments and build potentially testable hypotheses, whose validation comes from the analysis of the empirical data collected on 33 multi-team systems engaged in innovative tasks over a two-month period.

Lastly, the paper by Lagesse, Bordin, and Douady (LBD) focuses on the geometrical and spatial-geographical aspects of the road network skeleton. It explicitly takes into account the geographical characteristics of road networks, in particular their geometry at intersections. It proposes a new concept—"the way"—and illustrates its capacity to reveal hidden underlying structures in spatial networks. Starting from a new distance measure, the authors construct the measure "structurality", which counts how many turns it takes on average to go from a given road to the rest of the city. The reconstructed geographical element, the way, has not only a geographical and social meaning but also a historical one, associated to city expansions.

Given the strong heterogeneity of the papers, the rest of this introduction offers an attempt to put them in context. As mentioned earlier

- we define the citation network of the cited references from the seven papers, and
- construct the citation network of the cited references (Section 3);
- we study the emergence of a common vocabulary for dealing with networks in space and time, and lastly
- we use textual data analysis (Section 4), to describe the similarity and/or dissimilarity in bibliographic data and in the shared vocabulary of the papers.

3 An overview of the papers' contents: References

Citation analysis has a long tradition (Garfield et al., 1964) in comparing the impact and evolution of science in different fields (Lucio-Arias & Leydesdorff, 2008; Kejzar et al., 2010; Leydesdorff et al., 2011; Brughmans, 2013; Bodlaj & Batagelj, 2014). By counting the number of times a work has been cited by other works, it is able to map the seminal contributions that influenced the research tradition in a specific area, favoring scientific knowledge flow over time.

In this perspective, a citation network could be considered a network in which social ties (direct connections) and cultural ties (indirect connections beyond the boundary of personal acquaintanceship) could appear (White, 2011).

More formally, a citation network **C** is represented by a direct graph (acyclic network) defined by a collection of D documents (articles, working papers, books), or authors, where an arc going from the document d_i to document d_j is present if d_i

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Table 1. *Cited references by the seven citing papers.*

Paper		**1**	**2**	**3**	Final ref.	WoS ref.
Box-Steffensmeier, Christenson	**BSC**	1	27	63	90	40
Cohen-Cole, Patacchini, Zenou	**CCPZ**	0	6	42	48	22
Koskinen, Caimo, Lomi	**KCL**	3	16	29	45	26
Lagesse, Bordin, Douady	**LBD**	0	7	27	34	19
Ragozini, De Stefano, D'Esposito	**RDSDE**	0	14	30	44	18
Sullivan, Lungeanu, DeChurch, Contractor	**SLDC**	9	20	40	60	36
Wit, Abbruzzo	**WA**	2	3	20	23	16
Total		**15**	**93**	**251**	**344**	**177**

Note. (1) cited references before the review process; (2) cited references after the review process; (3) cited references stable throughout the whole process; (Final ref.) #. of cited references surviving the review process disregarding (1); (WoS ref.) #. of cited references found in WoS database.

"cites" d_j, or viceversa if d_j "is cited by" d_i (by considering the transposed citation network $\mathbf{C}^T$).[1]

Network analysis tools allow the extraction of the main cohesive subgroups and the main paths linking the most important contributions embedding in a specific scientific field (Batagelj et al., 2014, chapters 3–4), besides obtaining bibliographic coupling or co-citation networks[2] to analyze the relationship between documents. This makes it possible to identify major contributions in a specific research area or subfield, and group them into cohesive specialties.

3.1 Citation network analysis

Using the seven papers summarized in Section 2 as our sample, the citation network is derived in two steps. First, the bibliography of each paper is considered by extracting all cited references. Second, through the bibliography of the cited references, we define the work-by-work citation network between the cited works extracted in step one and the cited works identified in step two.

The numbers related to this first step of the procedure are reported in Table 1. The first two columns include the name of the authors and the acronym of the paper. Column (1) reports the number of references present before the review process and deleted afterwards; column (2) reports the number of references added after the review process; and column (3) reports the number of references stable throughout the whole process. The last two columns include the total number of references

[1] Either relations "cites" and "cited by" (or both) could be considered in citation analysis (Hummon & Doreian, 1989, p. 46). When the focus is on citing direction described in **C**, from the present to the past, a retention process is assumed in which the published papers are positioned in codified knowledge already established; whereas by considering $\mathbf{C}^T$ the analysis is conducted in terms of cited relations that reflect the diffusion of ideas from cited documents to citing ones by following the arrow of time in the forward direction (Lucio-Arias & Leydesdorff, 2008).

[2] As reported in Egghe & Rousseau (2002, p. 2): "A coupling unit between two documents is an item of reference used by these two documents. If such an item exists, the two documents are said to be bibliographically coupled. Similarly, two documents are said to be co-cited when they both appear in the reference list of a third document".

surviving the review process (Final ref.), and the number of cited papers appearing in the Web of Science—WoS—database (WoS ref.).

A total of 359 references was cited by the seven papers, with 15 references deleted after the review process and 93 new references added after the reviewers comments. Our interest in this first analysis of the cited references was to underpin the added value of the review process in suggesting the introduction of new works to be cited by the authors in order to improve and enrich the literature framework introduced in their contributions. We noticed that all papers have included new references after the review process, but for the papers by BSC, KCL, RDSDE, and SLDC the added references accounted for around 30% of the whole bibliography. Only the paper by SLDC deleted a considerable number of references included before the review process.

A network visualization of the seven citing papers (dark gray diamonds, labeled with the acronym of the paper) and the cited references by each of them is reported in Figure 1, in which the *node size* of cited references is related to the number of citations in the WoS core collection database,[3] including only the high-impact journals; the *node color* represents how many times a cited paper appears in the same citing paper (white=0, gray=1, black>1); and the *node shape* shows the papers cited only before (circle), after the review process (square) and those stable during the process (triangle).

The main cited references (more than one thousand citations) are related to the Albert and Barabasi (2002) work on complex networks, as well as statistical methodological works (Wasserman and Faust, 1994; Hunter and Handcock, 2006; Snijders et al., 2006; Handcock et al., 2008; Opshal, 2013), and to the Mcpherson et al. (2001) work on homophily. Following, with more than 100 citations, we found the seminal works devoted to the models and methods for static and dynamic network analysis. The references cited more than once (the "black" ones) make up 16.17% of the total references, with three citations on average. Only six references appear jointly in two or more papers. These well-known contributions in the network literature play a "bridging role" between paper BSC and KCL, SLDC and RDSDE, and between CCPZ and LBD, with WA being an isolate, in terms of its references.

3.2 Work-by-work citation network analysis

The bibliography and the details of the 344 cited references (those surviving the review process) are obtained by collecting archival data through the WoS system on 13th December 2014. As shown in Table 1, the WoS search resulted in a total of 172 papers (counting only once time the five works cited twice), which constitute the subsample of papers that we scrutinized. The 172 hits, i.e. papers with their descriptions (i.e. authors, title, abstract, keywords, publication properties, and our main interest, cited references), were exported as text files and converted into a collection of bibliographic networks.[4]

[3] For details visit the website http://www.isiknowledge.com.
[4] Various tools are available. We used the software Pajek and the tools provided by the Wos2Pajek procedure. For details visit the website http://pajek.imfm.si/doku.php?id=wos2pajek.

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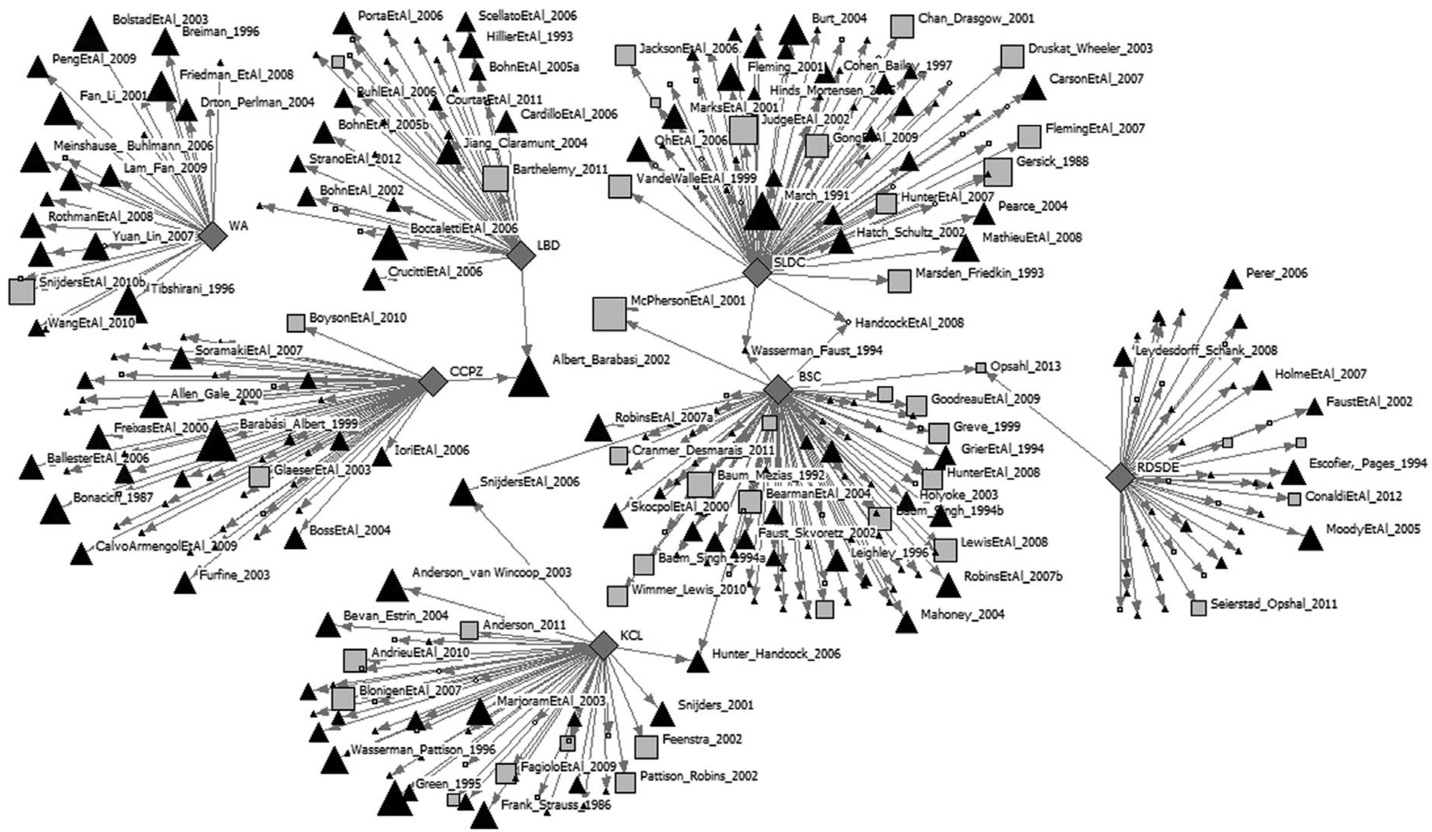

Fig. 1. Network visualization of the seven citing papers and all the 359 cited papers.

Note. Citing papers: dark gray diamonds. Cited references: *Node size* = logarithm of the number of WoS citations for only the high-impact journals included in this bibliographic archive; *node color* = number of times a cited reference appears in the citing paper (white = 0, gray = 1, black>1); *node shape*: papers cited only before (circle), after the review process (square), and those stable throughout the whole process (triangle).

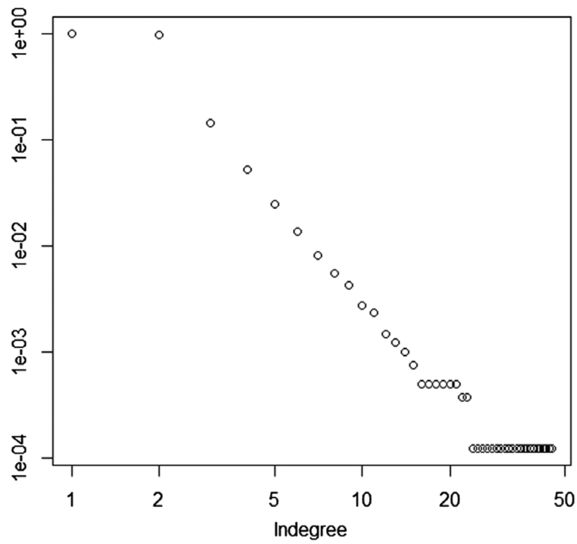

Fig. 2. Distribution of indegree work citations (step two).

Note. The indegree distribution of the publications in the citation network is plotted using a log log scale.

The second step of the procedure gives rise to a total of 8,032 articles or volumes in the citation network, generated by the collection of the bibliographic entries obtained. Figure 2 shows the number of citations received, i.e. the indegree, by each publication in the network. The distribution of the indegree citations seems to follow a power-law distribution describing scale-free networks. Most of the publications (84.57%) are cited once. Few works (Table 2) are cited more than 10 times with a maximum of 44 citations. Amongst others, the papers highly cited are the seminal contributions in the literature of space and time models for analyzing network data.

To derive the most important publications in the second step citation network, we use the search path count (SPC) algorithm,[5] obtaining arc citation weights (i.e. traversal weights). In the following, we consider the citation network **C** where the links are "cites" relations. By using the citing direction, we obtained a visualization that represents a knowledge codification mechanism as a reflexive process taking place in the present and reconstructing the past, i.e."one looks against the arrow of time" (Lucio-Arias & Leydesdorff, 2008, p. 17).[6] The algorithm assigns the normalized number of all paths from the "initial" node (with 0 indegree) to the "terminal" node (with 0 outdegree). From the weighted citation network, we obtain the main path network, starting from the source arc with the largest weight and appending step-by-step subsequent arcs with the highest weights, until a terminal node is reached.

[5] The SPC algorithm was proposed by Hummon & Doreian (1989) and it is implemented in Pajek (Batagelj, 2003).

[6] We performed also the citation analysis in terms of "cited-by" relations that reflect the diffusion of ideas from one paper into later ones by following the arrow of time in the forward direction (Lucio-Arias & Leydesdorff, 2008). This latter analysis yielded results that differ from the study of the "cites" relations. The results are available from the authors upon request.

Table 2. *Most cited publications.*

Most cited publications	Indegree
Wasserman, Faust, 1994	44
Wasserman, Pattison, 1996	22
Frank, Strauss, 1986	22
Watts, Strogatz, 1998	20
Holland, Leinhardt, 1981	14
Strauss, Ikeda, 1990	14
Snijders et al., 2006	13
Barabasi, Albert, 1999	13
Freeman. 1979	12
Feld, 1981	12
Albert, Barabasi, 2002	11
Granovetter, 1973	11
Hunter, Handcock, 2006	10
Geyer, 1992	10
Pattison, Wasserman, 1999	10
Handcock, 2003	10
Hillier, Hanson, 1984	10
Newman, 2003	10
Besag, 1974	10

Note. The numbers indicate received citations.

The 32 papers included in the main citations path (Figure 3) are characterized by an unique temporal trajectory, that goes from the early papers of Frank and Strauss (1986), Wasserman and Pattison (1996) on Markov graphs and p^* models, to the methodological developments in ERGMs introduced by Robins and Pattison (2001), Pattison and Robins (2002), and Robins et al. (2007) works, toward the latest contributions in studying dynamics networks in one-mode as well as affiliation data setting by Koskinen and Edling (2012) and Snijders et al. (2013). This seems to be the main trajectory from the past to the future of the literature on networks in space and time.

In addition, to identify some important components inside the overall citation network, the main cohesive sub-networks are extracted by setting a threshold of 0.03 for the arc weight in the new citation network derived from the SPC algorithm, and then by cutting all arcs with a weight lower than 0.03.[7]

The derived sub-network contains three weak components shown in Figure 4[8]: one main component with 21 works, and two small components with two or three references all cited by the LBD paper (cluster 4). From the analysis of the largest component, the literature of reference seems to be split into two interrelated blocks. On the one hand, the cited references of the BSC paper (cluster 1), together with

[7] We inspected the distribution of arc weights in the new citation network with line values derived from the SPC algorithm. We obtained 0.00 as lowest line value and 0.13 as the highest line value. By following the procedure described in de Nooy et al. (2011, p. 284–288), we first removed the lines with weights lower than 0.03, and then computed the weak components with minimum size of two in the new network.

[8] Node colors and number included in the label of Figure 4 are related to the seven citing papers in the special issue.

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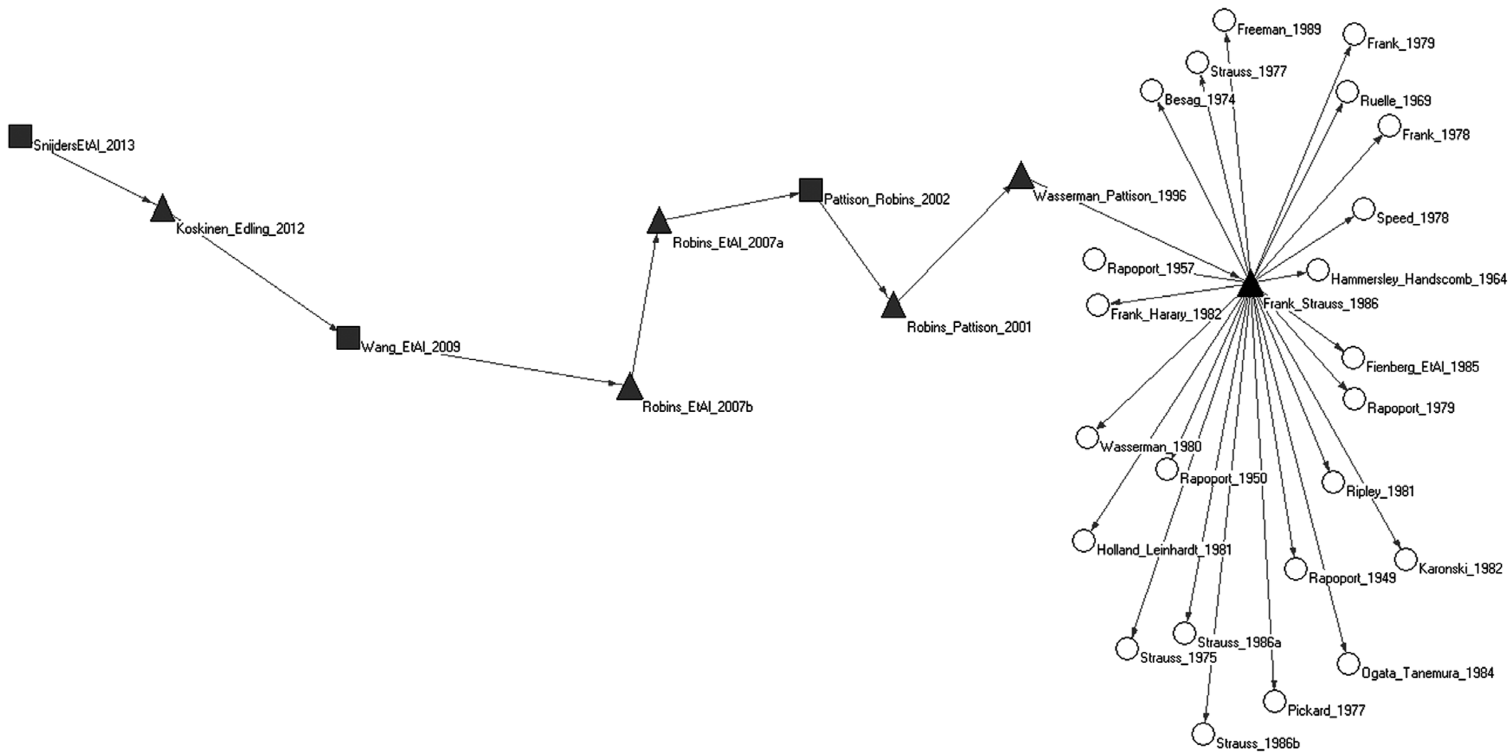

Fig. 3. Main citation path in the space and the time network literature.

Note. The citation path is derived from the citation network **C** by means of the SPC algorithm. The arrows indicate time dependence in reverse order by considering “cites” relations (from the present to the past). Node shape shows the papers cited only after the review process (gray squares), those stable along with the all process (gray triangles), and the references of the cited papers (white circles).

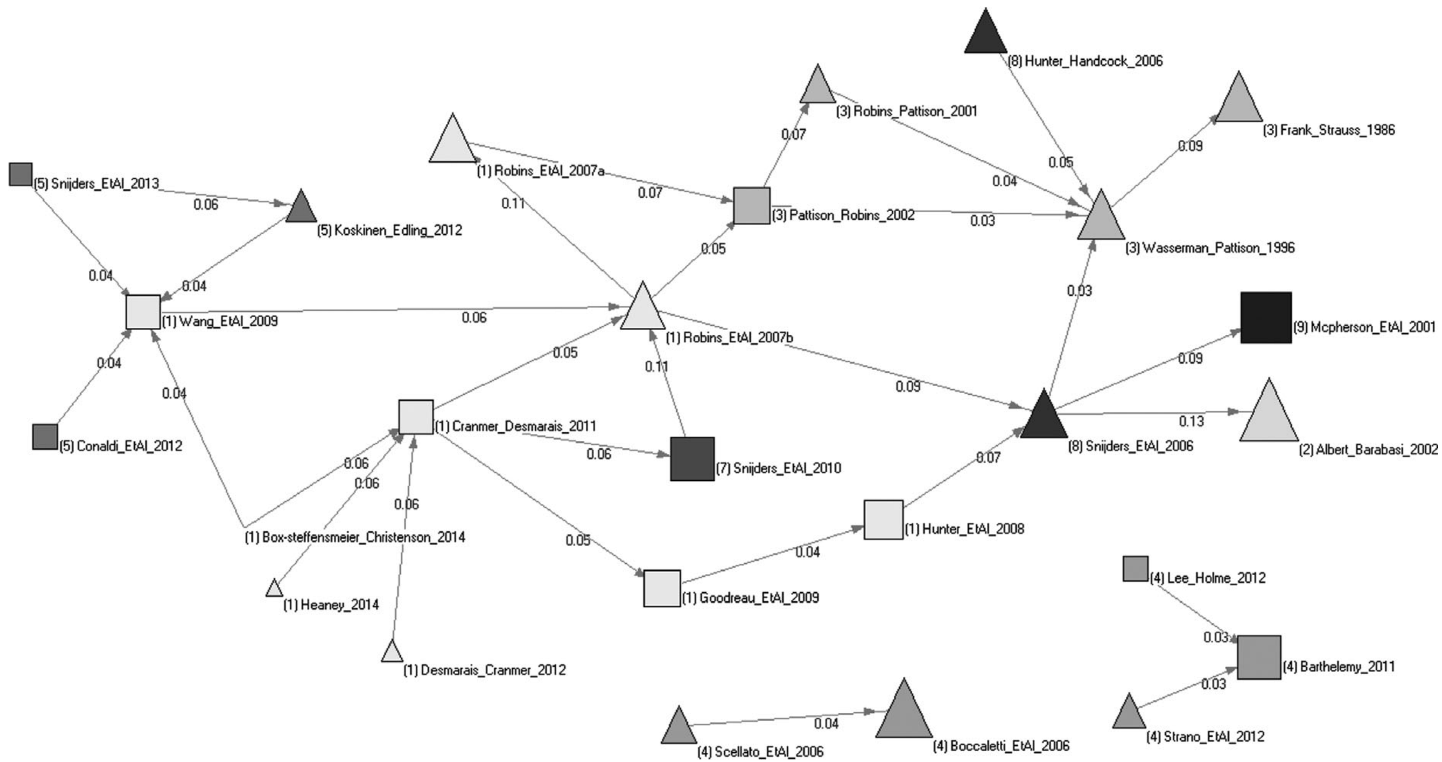

Fig. 4. All weak components of the citation sub-network obtained by removing lines with a value below 0.03.

Note. All weak component of minimum size two of the citation sub-network extracted by setting a threshold of 0.03 for arc weight citation. The arrows indicate time dependence in reverse order by considering "cites" relations in **C** (from the present to the past). Node size is related to the number of citations in the WoS archive; node shape shows the papers cited only after the review process (square), and those stable throughout the whole process (triangle); the gray-scale of node color represents the references of the seven papers highlighted by a progressive cluster number (1 = BSC; 2 = CCPZ, 3 = KCL, 4 = LBD, 5 = RDSDE, 6 = SLDC, 7 = WA, 8 = BSC + KCL, 9 = BSC + SLDC). The line's value is related to arc citation weights derived from the SPC algorithm. Some of the papers contribute to several clusters, while some clusters are made of references derived from two citing papers.

those of CCPZ (cluster 2), generate the main bulk of stepping-stones in this literature, WA (cluster 7) and BSC+KCL (cluster 8) contribute marginally, while BSC+SLDC (cluster 9) and RDSDE (cluster 5) operate at the periphery of the same block. On the other hand, KCL (cluster 3), alone and together with BSC (cluster 8), generates a separate extension of the main block. Apparently, LBD and SLDC do not contribute indirectly, through their references, to this main component, unlike all the other papers, in different weights.

The result of this second citation network analysis, partially reduces the impression received from the first, visualized in Figure 1. The evidence of a literature made of separated entities, thinly linked by methodological contributions, coexists with that of a strong cohesive component of theoretical, methodological and applied works, upon which the literature is, with some exceptions, solidly rooted.

4 An overview of the papers' contents: texts

A complementary way to examine the degree of similarity of the seven papers in this special issue is to consider the peculiarity of the vocabulary used by the authors of the papers. Textual data analysis, by means of well-known factorial methods (Lebart & Salem, 1988), could be a useful tool to discover latent patterns in a corpus and to associate documents with respect to some common semantic characteristics. Specifically, lexical correspondence analysis (Lebart et al., 1998) is able to identify the principal components of the association structure in a lexical table—$\mathbf{T}(p, n)$—with p words and n documents.

In our case, the textual data was extracted from the papers' introduction and conclusion. The document, made by assembling the original text from the seven papers, was firstly normalized and cleaned of stop words and neglectable characters (punctuation, blank spaces, etc.).[9] Then, the derived corpus was grammatically tagged to select the lexical part of the papers' contents. Following this procedure, a lexical matrix $\mathbf{T}$ of 66 words and 7 documents was obtained by setting, as a threshold value, the document frequency equal to 10. Finally, a correspondence analysis was performed on $\mathbf{T}$.[10]

A selection of the most relevant terms extracted from the seven papers is reported in Table 2, where the Gini concentration index reveals the words peculiar to specific documents (when the index value is near or equal to 1) and the terms shared by all documents (when the index value is near or equal to 0).

It seems that, on the one hand, the typical words used to describe space (*spatial*, *geography*,...) and time (*change*, *process*, *dynamic*,...) dimensions characterize all contributions with different weights. Space is more related to papers BSC and LBD, whereas the time dimension appears in a prominent position in papers KCL, RDSDE, and SLDC. On the other hand, specific words highlight in turn the main contribution of each paper: (1) in assessing differences in the structure of membership interest group networks through exponential random graph models and multidimensional scaling (*group*, *membership*, *industry*) [**BSC**]; (2) in introducing a model of network interactions in the interbank market (*bank*, *financial*, *market*, *risk*,

[9] The text pre-processing procedure was performed by using the Textual Mining R library.
[10] The software SPAD was adopted to obtain correspondence analysis of the lexical table $\mathbf{T}$.

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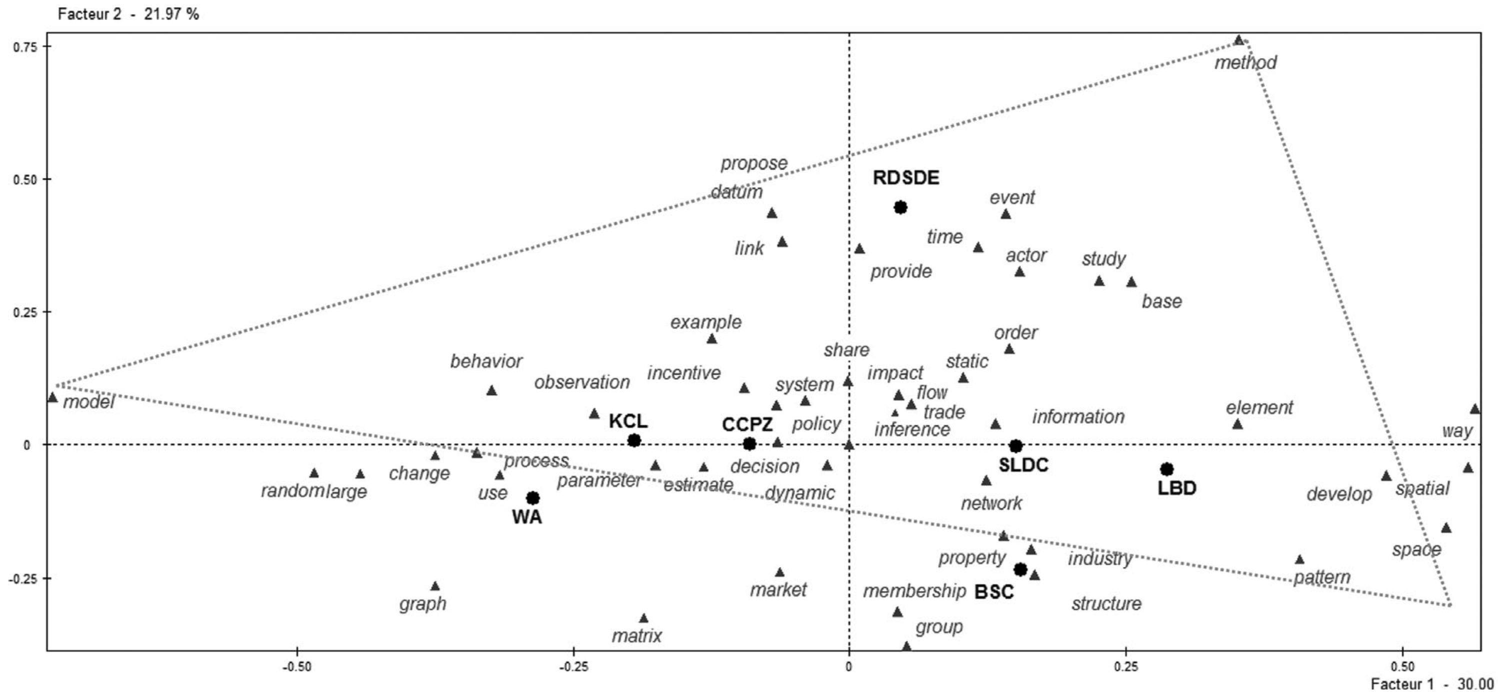

Fig. 5. Lexical correspondence analysis results: first factorial plane representing selected words and the seven papers.

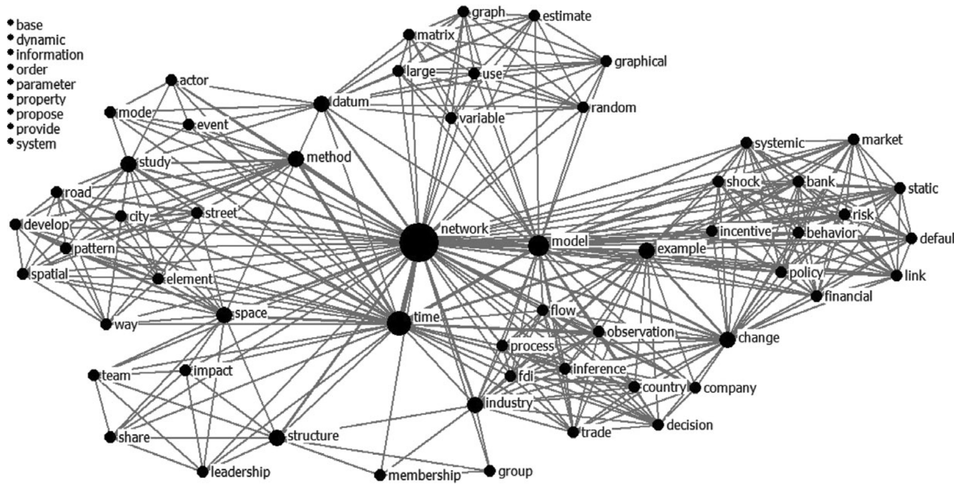

Fig. 6. Network of words: word-by-word adjacency matrix obtained from the cross-product of $\mathbf{T} \times \mathbf{T}^t$, where $\mathbf{T}$ is a dichotomized version of the lexical table words-by-documents by setting all frequencies greater than five equal to 1 and 0 otherwise. Node size is proportional to the total number of documents containing a term.

shock) [**CCPZ**]; (3) in developing a longitudinal exponential random graph model in the context of data on foreign direct investment relations (*company*, *country*, *fdi*) [**KCL**]; (4) in focusing on the spatial-geographical and geometrical aspects of the road network skeleton (*city*, *road*, *street*, *way*) [**LBD**]; (5) in presenting a factorial procedure based on multiple factor analysis and multiple correspondence analysis methods to deal with time-varying actor-by-event two-mode networks (*actor*, *event*, *method*, *mode*) [**RDSDE**]; (6) in using an agent-based model that draws upon research on leadership, networks, and innovation to specify generative mechanisms in space and time (*leadership*, *structure*, *team*) [**SLDC**]; (7) in proposing a flexible collection of ANOVA-like factorial graphical dynamic network models by selecting specific time dynamics (*graph*, *graphical*, *matrix*, *variable*) [**WA**]).

The results of the performed correspondence analysis on the lexical table **T** allow us to explore the vocabulary used in the different papers, identifying common and peculiar lemmas. Even if our sample is quite small, factorial analysis is instrumental in isolating the most relevant terms that describe the contents of this special issue.

Summarizing, the first factorial plane (Figure 5), derived from lexical correspondence analysis, displays the characteristic patterns resulting from the use and occurrence of the words selected from the analyzed corpus. In particular, the factorial map highlights the contrast between the key elements that characterize a method-driven micro-oriented approach (*method*, *time*, *actor*, *event*), located in the upper right side of the map, versus an application-driven macro-oriented approach (*group*, *membership*, *pattern*, *spatial*, *industry*, *market*), located in the bottom right side, opposite a parametric model-driven framework (*estimate*, *process*, *model*) on the left side. The position of each paper is superimposed on the lexical structure, clearly showing how each paper is placed in absolute and relative terms.

Reinforcing evidence comes from the combination of lexical correspondence analysis and network analysis (de Nooy, 2003; Balbi & Stawinoga, 2013). Indeed, a simple network visualization of the word-by-word adjacency matrix obtained by

Table 3. *The Lexical table* ***T*** *showing the frequency of some selected relevant words (on the rows) from the seven papers (on the columns) obtained by the text mining pre-processing phase of the seven documents. Last column reports the Gini concentration index.*

	BSC	CCPZ	KCL	LBD	RDSDE	SLDC	WA	Total	Gini index
Actor	0	0	1	0	9	0	0	10	0.97
Bank	0	30	0	0	0	0	0	30	1.00
Behavior	2	12	0	1	0	4	0	19	0.81
Change	2	10	9	2	2	0	0	25	0.64
City	0	0	0	11	0	0	0	11	1.00
Company	0	0	10	0	0	0	0	10	1.00
Country	0	0	20	0	0	0	0	20	1.00
Default	0	11	0	0	0	0	0	11	1.00
Dynamic	0	4	1	0	2	2	4	13	0.54
Event	0	2	3	0	8	0	0	13	0.82
Fdi	0	0	21	0	0	0	0	21	1.00
Financial	0	16	0	0	0	0	0	16	1.00
Flow	0	0	9	0	0	0	1	10	0.97
Graph	1	1	2	4	1	0	10	19	0.65
Graphical	0	0	0	0	0	0	15	15	1.00
Group	34	0	0	0	2	0	0	36	0.98
Incentive	1	9	0	0	0	0	0	10	0.97
Industry	10	1	7	0	0	0	0	18	0.83
Inference	0	0	8	0	0	0	2	10	0.93
Leadership	0	0	0	0	0	29	0	29	1.00
Market	0	19	0	0	1	0	0	20	0.98
Matrix	0	0	1	0	1	0	12	14	0.93
Membership	13	0	0	0	2	0	0	15	0.96
Method	1	5	1	6	9	0	1	23	0.59
Mode	0	0	0	0	10	0	0	10	1.00
Model	2	24	35	2	0	5	34	102	0.62
Network	29	40	16	35	19	7	20	166	0.30
Policy	2	9	0	0	0	0	0	11	0.94
Process	1	0	6	2	1	1	2	13	0.54
Risk	0	18	0	0	0	0	0	18	1.00
Road	0	0	0	31	0	0	0	31	1.00
Shock	0	14	0	0	0	0	0	14	1.00
Space	3	0	1	10	1	12	2	29	0.64
Spatial	2	2	1	6	0	0	1	12	0.64
Static	0	7	0	0	4	0	2	13	0.79
Street	0	0	0	11	0	0	0	11	1.00
Structure	7	3	0	0	2	9	0	21	0.70
Systemic	0	13	0	0	0	0	0	13	1.00
Team	0	0	0	0	0	14	0	14	1.00
Time	3	5	11	7	10	11	3	50	0.30
Trade	0	0	8	0	0	0	2	10	0.93
Variable	0	0	0	0	0	0	10	10	1.00
Way	2	3	0	20	0	0	2	27	0.84

the lexical table **T** words-by-documents[11] is shown in Figure 6. On the one hand, common terms (such as *network*, *method*, *model*, *space*, and *time*) are not surprisingly, given the specific context, highly interconnected and play a central role in linking specific groups of lemmas which characterize each of the seven papers. On the other hand, particular words are peculiar to few documents, highlighting the specialties of each paper in dealing with the topics of this special issue.

5 In conclusion

We do not wish to end this introduction with a strong conclusion. It is now time to read the papers. We hope that our brief introduction has reinforced your interest in this research area of network science.

References

Adams, J., Faust, K., & Lovasi, G. S. (Eds.) (2012). Capturing context: Integrating spatial and social network analyses. *Social Networks*, **34**(1), 1–5.

Balbi, S., & Stawinoga, A. (2013). Mining the ambiguity: correspondence and network analysis for discovering word sense. SIS Conference 2013 "Advances in Latent Variables. Methods, models and applications". 19–21 June 2013, Brescia (Italy).

Batagelj, V. (2003). Efficient algorithms for citation network analysis. ArXiv Preprint cs/0309023, 1–27.

Batagelj, V., Doreian, P., Ferligoj, A., & Kejzar, N. (Eds) (2014). *Understanding large temporal networks and spatial networks: Exploration, pattern searching, visualization and network evolution*. Chichester, UK: John Wiley & Sons Ltd.

Bodlaj, J., & Batagelj, V. (2014). Network analysis of publications on topological indices from the web of science. *Molecular Informatics*, **33**(8), 514–535.

Brughmans, T. (2013). Networks of networks: A citation network analysis of the adoption, use, and adaptation of formal network techniques in archaeology. *Literary and Linguistic Computing, The Journal of Digital Scholarship in the Humanities*, **28**(4), 538–562.

de Nooy, W. (2003). Fields and networks: Corresponding analysis and social network analysis in the framework of field theory. *Poetics*, **31**(5), 305–327.

de Nooy, W., Mrvar, A., & Batagelj, V. (2011). *Exploratory social network analysis with Pajek*. Cambridge: Cambridge University Press.

Egghe, L., & Rousseau, R. (2002). Co-citation, bibliographic coupling and a characterization of lattice citation networks. *Scientometrics*, **55**(3), 349–361.

Faust, K., & Skvoretz, J. (2002). Comparing networks across space and time, size and species. *Sociological Methodology*, **32**(1), 267–299.

Garfield, E., Sher, I. H., & Torpie, R. J. (1964). *The use of citation data in writing the history of science*. Philadelphia: The Institute for Scientific Information Inc.

Hummon, N. P., & Doreian, P. (1989). Connectivity in a citation network: The development of DNA theory. *Social Networks*, **11**(1), 39–63.

Kejzar, N., Cerne, S. K., & Batagelj, V. (2010). Network analysis of works on clustering and classification from web of science. In H. Locarek-Junge, & C. Weihs (Eds.), *Classification as a tool for research* (pp. 525–536). Berlin Heidelberg: Springer-Verlag.

Lebart, L., & Salem, A. (1988). *Statistique textuelle*. Paris: Dunod.

[11] We derived this adjacency matrix from the cross-product of $\mathbf{T} \times \mathbf{T}^t$, where **T** is a dichotomized version of the lexical table words-by-documents by setting all frequencies greater than five equal to 1 and 0 otherwise.

Lebart, L., Salem, A., & Berry L. (1998). *Exploring textual data*. The Netherlands: Kluwer Academic Publishers.

Leydesdorff, L., Hammarfelt, B., & Salah, A. (2011). The structure of the Arts & humanities citation index: A mapping on the basis of aggregated citations among 1,157 journals. *Journal of the American Society for Information Science and Technology*, **62**(12), 2414–2426.

Lucio-Arias, D., & Leydesdorff, L. (2008). Main-path analysis and path-dependent transitions in HistCite-based historiograms. *Journal of the American Society for Information Science and Technology*, **59**(12), 1948–1962.

Snijders, T. A., & Doreian, P. (Eds) (2010). Introduction to the special issue on network dynamics. *Social Networks*, **32**(1), 1–3.

Snijders, T. A., & Doreian, P. (Eds) (2012). Introduction to the special issue on network dynamics (Part 2). *Social Networks*, **34**(3), 289–290.

White, H. D. (2011). Scientific and scholarly networks. In J. Scott & P. J. Carrington (Eds.), *The SAGE handbook of social network analysis* (pp. 271–285). London: SAGE Publications Ltd.