Community Structure and Topical Differentiation in European RTD Collaborations

Michael J. Barber\textsuperscript{1}, Margarida Faria\textsuperscript{2}, Ludwig Streit\textsuperscript{2}, and Oleg Strogan\textsuperscript{2}

\textsuperscript{1}Austrian Research Centers GmbH—ARC, Bereich systems research, Vienna, Austria
\textsuperscript{2}Centro de Ciências Matemáticas, Universidade da Madeira, Funchal, Portugal

October 10, 2008

Abstract

We investigate research and development collaborations under the EU Framework Programs (FPs) for Research and Technological Development. The collaborations in the FPs give rise to bipartite networks, with edges existing between projects and the organizations taking part in them. A version of the modularity measure, adapted to bipartite networks, is presented. Communities are found so as to maximize the bipartite modularity. Projects in the resulting communities are shown to be topically differentiated.

1 Introduction

The EU Framework Programs (FPs) for Research and Technological Development were implemented to follow two main strategic objectives: First, strengthening the scientific and technological bases of European industry to foster international competitiveness and, second, the promotion of research activities in support of other EU policies. In spite of their different scopes, the fundamental rationale of the FPs has remained unchanged. All FPs share a few common structural key elements. First, only projects of limited duration that mobilize private and public funds at the national level are funded. Second, the focus of funding is on multinational and multi-actor collaborations that add value by operating at the European level. Third, project proposals are to be submitted by self-organized consortia and the selection for funding is based on specific scientific excellence and socio-economic relevance criteria (Roediger-Schluga and Barber 2006). By considering the constituents of these consortia, we can represent and analyze the FPs as networks of projects and organizations. The resulting networks are of substantial size, including over 50 thousand projects and over 30 thousand organizations.
We have general interest in studying a real-world network of large size and high complexity from a methodological point of view. Furthermore, socio-economic research emphasizes the central importance of collaborative activities in R&D for economic competitiveness (see, for instance, Fagerberg et al., 2005, among many others). Mainly for reasons of data availability, attempts to evaluate quantitatively the structure and function of the large social networks generated in the EU FPs have begun only in the last few years, using social network analysis and complex networks methodologies Almendral et al. (2007); Barber et al. (2006, 2008); Breschi and Cusmano (2004); Roediger-Schluga and Barber (2008). Studies to date point to the presence of a dense and hierarchical network. A highly connected core of frequent participants, taking leading roles within consortia, is linked to a large number of peripheral actors, forming a giant component that exhibits the characteristics of a small world.

Networks have attracted a burst of attention in the last decade (for useful reviews, see Albert and Barabási, 2002; Christensen and Albert, 2007; Dorogovtsev and Mendes, 2004; Newman, 2003), with applications to natural, social, and technological networks. Of great current interest is the identification of community structure within networks. Stated informally, a community is a portion of the network whose members are more tightly linked to one another than to other members of the network. A variety of approaches (Angelini et al., 2007; Clauset et al., 2004; Girvan and Newman, 2002; Gol'dshtein and Koganov, 2006; Hastings, 2006; Newman and Girvan, 2004; Newman and Leicht, 2007; Palla et al., 2005; Reichardt and Bornholdt, 2006) have been taken to explore this concept; Danon et al. (2005) and Newman (2004b) provide useful reviews. Detecting the community structure allows quantitative investigation of relevant heterogeneous substructures formed in the network.

We investigate networks of research and development collaborations under the FPs. The collaborations in the FPs give rise to bipartite networks, with edges existing between projects and the organizations taking part in them. With this construction, participating organizations are linked only through joint projects. The resulting networks are quite large compared to typical social networks, containing tens of thousands of vertices and edges. At this scale, visualization of the networks is quite difficult, so we instead take an algorithmic approach to community identification. A version of the modularity measure (Newman and Girvan, 2004), adapted to bipartite networks (Barber, 2007), is used to assess the quality of a division of the vertices into communities. Communities are found by maximizing the bipartite modularity. We consider topical differentiation of the communities found.

The rest of the paper is structured as follows. In section 2 we discuss the data used on the FPs, continuing with definition of networks from the data in section 3. We present in section 4 a summary of methods for identifying network communities, and apply the methods to the FP networks in section 5. Finally, we discuss the consequences of our findings in section 6.

2 Data Preparation

We draw on the latest version of the sysres EUPRO database. This database includes all information publicly available through the CORDIS projects database.  

1http://cordis.europa.eu
and is maintained by ARC systems research (ARC sys). The sysres EUPRO database presently comprises data on funded research projects of the EU FPs (complete for FP1–FP5, and about 70% complete for FP6) and all participating organizations. It contains systematic information on project objectives and achievements, project costs, project funding and contract type, as well as information on the participating organizations including the full name, the full address and the type of the organization.

For purposes of network analyses, the main challenge is the inconsistency of the raw data. Apart from incoherent spelling in up to four languages per country, organizations are labelled inhomogeneously. Entries may range from large corporate groupings, such as EADS, Siemens and Philips, or large public research organizations, like CNR, CNRS and CSIC, to individual departments and labs.

Due to these shortcomings, the raw data is of limited use for meaningful network analyses. Further, any fully automated standardization procedure is infeasible. Instead, a labor-intensive, manual data-cleaning process is used in building the database. Roediger-Schluga and Barber (2008) describe the data-cleaning process in detail; here, we restrict discussion to the steps of the process relevant to the present work. These are:

1. Identification of unique organization name. Organizational boundaries are defined by legal control. Entries are assigned to appropriate organizations using the more recently available organization name. Most records are easily identified, but, especially for firms, organization names may have changed frequently due to mergers, acquisitions, and divestitures.

2. Creation of subentities. This is the key step for mitigating the bias that arises from the different scales at which participants appear in the data set. Ideally, we use the actual group or organizational unit that participates in each project, but this information is only available for a subset of records, particularly in the case of firms. Instead, subentities that operate in fairly coherent activity areas are pragmatically defined. Wherever possible, subentities are identified at the second lowest hierarchical tier, with each subentity comprising one further hierarchical sub-layer. Thus, universities are broken down into faculties/schools, consisting of departments; research organizations are broken down into institutes, activity areas, etc., consisting of departments, groups or laboratories; and conglomerate firms are broken down into divisions, subsidiaries, etc. Subentities can frequently be identified from the contact information even in the absence of information on the actual participating organizational unit. Note that subentities may still vary considerably in scale.

3. Regionalization. The data set has been regionalized according to the European Nomenclature of Territorial Units for Statistics (NUTS) classification system where possible to the NUTS3 level. Mostly, this has been done via information on postal codes.

Due to resource limitations, only organizations appearing more than thirty times in the standardization table for FP1–FP5 have thus far been processed. This

\[^2\text{NUTS is a hierarchical system of regions used by the statistical office of the European Community for the production of regional statistics. At the top of the hierarchy are NUTS-0 regions (countries) below which are NUTS-1 regions and then NUTS-2 regions, etc.}\]
could bias the results; however, the networks have a structure such that the size of the bias is quite low (Roediger-Schluga and Barber 2008).

3 Network Definition

Using the sysres EUPRO database, for each FP we construct a network containing the collaborative projects and all organizational subentities\textsuperscript{3} that are participants in those projects. An organization is linked to a project if and only if the organization is a member of the project. Since an edge never exists between two organizations or two projects, the network is bipartite. The network edges are unweighted; in principle, the edges could be assigned weights to reflect the strength of the participation, but the data needed to assign the network weights is not available.

Previous investigations of the FPs often have made use of one-mode projection networks (Almendral et al. 2007; Barber et al. 2006; Breschi and Cusmano 2004; Roediger-Schluga and Barber 2008), especially for the organizations. While the projection networks can be useful, the construction of the projections intrinsically loses information available in the bipartite networks, which can lead to incorrect community structures (Guimerà et al. 2007). In the present work, we thus focus exclusively on representations of the Framework Programs as bipartite networks.

4 Community Structure

Of great current interest is the identification of community groups, or modules, within networks. Stated informally, a community group is a portion of the network whose members are more tightly linked to one another than to other members of the network. A variety of approaches (Angelini et al. 2007; Clauset et al. 2004; Girvan and Newman 2002; Gol'dshtein and Koganov 2006; Hastings 2006; Newman and Girvan 2004; Newman and Leicht 2007; Palla et al. 2005; Reichardt and Bornholdt 2006) have been taken to explore this concept; Danon et al. (2005) and Newman (2004b) provide useful reviews. Detecting community groups allows quantitative investigation of relevant subnetworks. Properties of the subnetworks may differ from the aggregate properties of the network as a whole, e.g., modules in the World Wide Web are sets of topically related web pages. Thus, identification of community groups within a network is a first step towards understanding the heterogeneous substructures of the network.

Methods for identifying community groups can be specialized to distinct classes of networks, such as bipartite networks (Barber 2007; Guimerà et al. 2007). This is immediately relevant for our study of the FP networks, allowing us to examine the community structure in the bipartite networks. Communities are expected to be formed of groups of organizations engaged in R&amp;D into similar topics, and the projects in which those organizations take part.

\textsuperscript{3}We work exclusively at the subentity level, and will interchangeably refer to organizations and subentities.
4.1 Modularity

To identify communities, we take as our starting point the modularity, introduced by Newman and Girvan (2004). Modularity makes intuitive notions of community groups precise by comparing network edges to those of a null model. The modularity $Q$ is proportional to the difference between the number of edges within communities $c$ and those for a null model:

$$Q \equiv \frac{1}{2M} \sum_c \sum_{i,j \in c} (A_{ij} - P_{ij}) .$$

(1)

Along with eq. (1), it is necessary to provide a null model, defining $P_{ij}$.

The standard choice for the null model constrains the degree distribution for the vertices to match the degree distribution in the actual network. Random graph models of this sort are obtained (Chung and Lu, 2002) by putting an edge between vertices $i$ and $j$ at random, with the constraint that on average the degree of any vertex $i$ is $d_i$. This constrains the expected adjacency matrix such that

$$d_i = E \left( \sum_j A_{ij} \right) .$$

(2)

Denote $E (A_{ij})$ by $P_{ij}$ and assume further that $P_{ij}$ factorizes into

$$P_{ij} = p_i p_j ,$$

(3)

leading to

$$P_{ij} \equiv \frac{d_i d_j}{2M} .$$

(4)

A consequence of the null model choice is that $Q = 0$ when all vertices are in the same community.

The goal now is to find a division of the vertices into communities such that the modularity $Q$ is maximal. An exhaustive search for a decomposition is out of the question: even for moderately large graphs there are far too many ways to decompose them into communities. Fast approximate algorithms do exist (see, for example Newman, 2004a; Pujol et al., 2006).

4.2 Finding Communities in Bipartite Networks

Specific classes of networks have additional constraints that can be reflected in the null model. For bipartite graphs, the null model should be modified to reproduce the characteristic form of bipartite adjacency matrices:

$$A = \begin{bmatrix} O & M \\ M^T & O \end{bmatrix} .$$

(5)

Recently, specialized modularity measures and search algorithms have been proposed for finding communities in bipartite networks (Barber, 2007; Guimerà et al., 2007). These measures and methods have not been studied as extensively as the versions with the standard null model shown above, but many of the algorithms can be adapted to the bipartite versions without difficulty. Limitations of modularity-based methods (e.g., the resolution limit described by Fortunato and Barthélemy, 2007) are expected to hold as well.
Community identification is then a search for high modularity partitions of the vertices into disjoint sets. An exhaustive search for the globally optimal solution is only feasible for the smallest networks, as the number of possible partitions of the vertices grows far too rapidly with network size. Several heuristics exist to find high-quality, if suboptimal, solutions in a reasonable length of time. For the FP networks, we use a two-stage search procedure:

1. Agglomerative hierarchical clustering, where small communities are successively joined into larger ones such that the modularity increases. This stage is based on the so-called fast modularity (FM) algorithm (Clauset et al., 2004).

2. Greedy search, where vertices are moved amongst existing communities to ensure the resulting partition is at a local optimum of modularity. This stage uses the bipartite, recursively induced modules (BRIM) algorithm (Barber, 2007).

The coarse structure is found with FM, with incremental improvements provided by BRIM.

In principle, the above approach should be continued until a maximum in the modularity is found. In practice, an excessively large number of communities for visualization purposes can result, obscuring the core community structure. To deal with this difficulty, communities are further merged, so long as the modularity stays near the maximum (within \(\approx 90\%\)) and the general structure of the communities is maintained (as determined with information theoretic methods, see Danon et al., 2005).

5 Communities in the Framework Program Networks

In fig. 1, we show a community structure for FP5, found as described above, with a modularity of \(Q = 0.644\) for 25 community groups. The communities are shown as vertices in a network, with the vertex positions determined using spectral methods (Seary and Richards, 2003). The area of each vertex is proportional to the number of edges from the original network within the corresponding community. The width of each edge in the community network is proportional to the number of edges in the original network connecting community members from the two linked groups. The vertices and edges are shaded to provide additional information about their topical structure, as described in the next section. Each vertex is numbered, with numbers assigned starting from 1 based on the size of the communities, with the largest communities having the smallest numbers.

The networks from all of the FPs show definite community structure. In each case, the modularity exceeds 0.6 (see table 1).

5.1 Topical Profiles of Communities

Projects are assigned one or more standardized subject indices. There are 49 subject indices in total, ranging from Aerospace to Waste Management. We
Figure 1: Community groups in the bipartite network of projects and organizations for FP5.

| FP | Number of Communities | Modularity |
|----|-----------------------|------------|
| 2  | 16                    | 0.641      |
| 3  | 14                    | 0.627      |
| 4  | 25                    | 0.662      |
| 5  | 25                    | 0.644      |
| 6  | 25                    | 0.632      |

Table 1: Communities in the FP networks. In each network, definite community structure is observed.
denote by
\[ f(t) > 0 \] (6)
the frequency of occurrence of the subject index \( t \) in the network, with
\[ \sum_t f(t) = 1 \] . (7)

Similarly we consider the projects within one community \( c \) and the frequency
\[ f_c(t) \geq 0 \] (8)
of any subject index \( t \) appearing in the projects only of that community. We call
\( f_c \) the topical profile of community \( c \) to be compared with that of the network as a whole.

Topical differentiation of communities can be measured by comparing their profiles, among each other or with respect to the overall network. This can be done in a variety of ways (Gibbs and Su, 2002), such as by the Kullback "distance"
\[ D_c = \sum_t f_c(t) \ln \frac{f_c(t)}{f(t)} \] . (9)
A true metric is given by
\[ d_c = \sum_t |f_c(t) - f(t)| \] , (10)
ranging from zero to two.

Topical differentiation is illustrated in figs. 2(a) and 2(b). In the figure, example profiles are shown, taken from the network in fig. 1. The community-specific profiles correspond to the communities 1 and 2 in fig. 1. Both communities are topically differentiated from the network as a whole, and with similar extent \((d_1 = 0.69, d_1 = 0.66)\). However, the actual topics are quite different, with community 1 dominated by subject indices relating to biotechnology and the life sciences, while community 2 is dominated by subject indices relating to manufacturing and transport.

6 Discussion

We have presented an investigation of networks derived from the European Union’s Framework Programs for Research and Technological Development. The networks are of substantial size, complexity, and economic importance. We have attempted to provide a coherent picture of the complete process, beginning with data preparation and network definition, then continuing with analysis of the network community structure.

We first considered the challenges involved in dealing with a large amount of imperfect data, detailing the tradeoffs made to clean the raw data into a usable form under finite resource constraints. The processed data was used to define bipartite networks with vertices consisting of all the projects and organizational subentities involved in each FP.

Next we analyzed the community structure of the Framework Programs. Using a modularity measure and search algorithm adapted to bipartite networks,
Figure 2: Community 1 shows strong topical differentiation ($d_1 = 0.69$) from the network as a whole, being dominated by topics in biotechnology and the life sciences. Community 2 also shows strong topical differentiation ($d_2 = 0.66$) from the network as a whole. Further, it is quite distinct from community 1, being dominated by manufacturing- and transport-related topics.
we identified communities from the networks. We found that the communities are topically differentiated based on the standardized subject indices for Framework Program projects.

The communities identified will serve as basis for further studies of the Framework Programs. A natural extension of the present work is to examine other properties by which the communities are differentiated. Properties of organizations making up the communities can be explored, much as the subject indices for the projects were examined in this work. Immediate candidates for consideration include the types of the organizations (e.g., universities or firms) and geographical location of the organizations (e.g., as countries or using NUTS classifications). Further, the communities will be used as a basis for modeling determinants of partner choice, such as with spatial interaction models (Scherngell and Barber, 2008a,b) or binary choice models (Paier and Scherngell, 2008), providing insight into the formation rules at work in heterogeneous subsets of the Framework Programs.

Acknowledgments

The authors gratefully acknowledge financial support from the European FP6-NEST-Adventure Programme, under contract number 028875, and from the Portuguese FCT, under projects POCTI/MAT/58321/2004/FSE-FEDER and FCT/POCTI-219/FEDER.

References

Reka Albert and Albert-Laszlo Barabási. Statistical mechanics of complex networks. Reviews of Modern Physics, 74(1):47, 2002. URL [http://link.aps.org/abstract/RMP/v74/p47](http://link.aps.org/abstract/RMP/v74/p47).

Juan A. Almendral, J. G. Oliveira, L. López, Miguel A. F. Sanjuán, and J. F. F. Mendes. The interplay of universities and industry through the FP5 network. New Journal of Physics, 9(6):183–98, 2007. doi: 10.1088/1367-2630/9/6/183. URL [http://www.iop.org/EJ/abstract/1367-2630/9/6/183/](http://www.iop.org/EJ/abstract/1367-2630/9/6/183/).

Leonardo Angelini, Stefano Boccaletti, Daniele Marinazzo, Mario Pellicoro, and Sebastiano Stramaglia. Identification of network modules by optimization of ratio association. Chaos: An Interdisciplinary Journal of Nonlinear Science, 17(2):023114, 2007. doi: 10.1063/1.2732162. URL [http://arxiv.org/abs/cond-mat/0610182](http://arxiv.org/abs/cond-mat/0610182).

Michael J. Barber. Modularity and community detection in bipartite networks. Physical Review E (Statistical, Nonlinear, and Soft Matter Physics), 76(6):066102, 2007. doi: 10.1103/PhysRevE.76.066102.

Michael J. Barber, Andreas Krueger, Tyll Krueger, and Thomas Roediger-Schluga. Network of European Union-funded collaborative research and development projects. Physical Review E (Statistical, Nonlinear, and Soft Matter Physics), 73(3):036132, 2006. doi: 10.1103/PhysRevE.73.036132. URL [http://link.aps.org/abstract/PRE/v73/e036132](http://link.aps.org/abstract/PRE/v73/e036132).
Michael J. Barber, Margarida Faria, Ludwig Streit, and Oleg Strogan. Searching for communities in bipartite networks. In Christopher C. Bernido and M. Victoria Carpio-Bernido, editors, Proceedings of the 5th Jagna International Workshop: Stochastic and Quantum Dynamics of Biomolecular Systems, New York, NY, 2008. Springer.

S. Breschi and L. Cusmano. Unveiling the texture of a European Research Area: Emergence of oligarchic networks under EU Framework Programmes. International Journal of Technology Management, 27(8):747–72, 2004.

Claire Christensen and Reka Albert. Using graph concepts to understand the organization of complex systems. International Journal of Bifurcation and Chaos, 17(7):2201–2214, 2007. URL http://arxiv.org/abs/q-bio.OT/0609036 Special Issue “Complex Networks’ Structure and Dynamics”.

Fan Chung and Linyuan Lu. Connected components in random graphs with given expected degree sequences. Annals of Combinatorics, 6(2):125–145, 2002.

Aaron Clauset, M. E. J. Newman, and Cristopher Moore. Finding community structure in very large networks. Physical Review E (Statistical, Nonlinear, and Soft Matter Physics), 70(6):066111, 2004. URL http://link.aps.org/abstract/PRE/v70/e066111.

Leon Danon, Albert Díaz-Guilera, Jordi Duch, and Alex Arenas. Comparing community structure identification. J. Stat. Mech., page P09008, 2005. doi: 10.1088/1742-5468/2005/09/P09008. URL http://www.iop.org/EJ/article/1742-5468/2005/09/P09008/jstat5_09_p09008.html.

S. N. Dorogovtsev and J. F. F. Mendes. The shortest path to complex networks. In N. Johnson, J. Efstathiou, and F. Reed-Tsochas, editors, Complex Systems and Inter-disciplinary Science. World Scientific, 2004. URL http://arxiv.org/abs/cond-mat/0404593.

J. Fagerberg, D.C. Mowery, and R.R. Nelson. The Oxford Handbook of Innovation. Oxford University Press, 2005.

Santo Fortunato and Marc Barthelemy. Resolution limit in community detection. PNAS, 104(1):36–41, 2007. doi: 10.1073/pnas.0605965104. URL http://www.pnas.org/cgi/reprint/104/1/36.pdf.

M. Girvan and M. E. J. Newman. Community structure in social and biological networks. PNAS, 99(12):7821–7826, 2002. URL http://www.pnas.org/cgi/content/abstract/99/12/7821.

V. Gol’dshein and G. A. Koganov. An indicator for community structure. Preprint, July 2006. URL http://arxiv.org/abs/physics/0607159.

Roger Guimerà, Marta Sales-Pardo, and Luís A. Nunes Amaral. Module identification in bipartite and directed networks. Physical Review E (Statistical, Nonlinear, and Soft Matter Physics), 76(3):036102, 2007. doi: 10.1103/PhysRevE.76.036102. URL http://link.aps.org/abstract/PRE/v76/e036102.
Matthew B. Hastings. Community detection as an inference problem. *Physical Review E (Statistical, Nonlinear, and Soft Matter Physics)*, 74(3):035102, 2006. doi: 10.1103/PhysRevE.74.035102. URL http://arxiv.org/abs/cond-mat/0604429.

M. E. J. Newman. Fast algorithm for detecting community structure in networks. *Physical Review E (Statistical, Nonlinear, and Soft Matter Physics)*, 69(6):066133, 2004a. URL http://link.aps.org/abstract/PRE/v69/e066133.

M. E. J. Newman. Detecting community structure in networks. *Eur. Phys. J. B*, 38:321–330, 2004b. URL http://www-personal.umich.edu/~mejn/papers/epjb.pdf.

M. E. J. Newman and M. Girvan. Finding and evaluating community structure in networks. *Physical Review E (Statistical, Nonlinear, and Soft Matter Physics)*, 69(2):026113, 2004. URL http://link.aps.org/abstract/PRE/v69/e026113.

M. E. J. Newman and E. A. Leicht. Mixture models and exploratory data analysis in networks. *PNAS*, 104(23):9564–9569, 2007. doi: 10.1073/pnas.0610537104. URL http://www.pnas.org/cgi/content/abstract/104/23/9564.

Mark E. J. Newman. The structure and function of complex networks. *SIAM Review*, 45:167–256, 2003. URL http://arxiv.org/abs/cond-mat/0303516.

Manfred Paier and Thomas Scherngell. Determinants of collaboration in European R&D networks: Empirical evidence from a binary choice model perspective. SSRN Working Paper Series No. 1120081, Rochester, NY, July 2008. URL http://ssrn.com/abstract=1120081.

Gergely Palla, Imre Derenyi, Illes Farkas, and Tamas Vicsek. Uncovering the overlapping community structure of complex networks in nature and society. *Nature*, 435:814–818, June 2005. doi: 10.1038/nature03607. URL http://arxiv.org/abs/physics/0506133.

Josep M. Pujol, Javier Bejar, and Jordi Delgado. Clustering algorithm for determining community structure in large networks. *Physical Review E (Statistical, Nonlinear, and Soft Matter Physics)*, 74(1):016107, 2006. URL http://link.aps.org/abstract/PRE/v74/e016107.

Joerg Reichardt and Stefan Bornholdt. Statistical mechanics of community detection. *Physical Review E (Statistical, Nonlinear, and Soft Matter Physics)*, 74(1):016110, 2006. URL http://link.aps.org/abstract/PRE/v74/e016110.

Thomas Roediger-Schluga and Michael J. Barber. The structure of R&D collaboration networks in the European Framework Programmes. Working Paper 2006-036, UNU-MERIT, 2006. URL http://www.merit.unu.edu/publications/wppdf/2006/wp2006-036.pdf.
Thomas Roediger-Schluga and Michael J. Barber. R&D collaboration networks in the European Framework Programmes: Data processing, network construction and selected results. *IJFIP*, 4(3/4):321–347, 2008. Special Issue on “Innovation Networks”.

Thomas Scherngell and Michael J. Barber. Spatial interaction modelling of cross-region R&D collaborations—empirical evidence from the EU Framework Programmes. In *Proceedings of the 1st ICC International Conference on Network Modelling and Economic Systems*, 2008a.

Thomas Scherngell and Michael J. Barber. The geography of cross-region R&D collaborations in Europe: Evidence from the EU Framework Programmes. In *Proceedings of the 48th Congress of the European Regional Science Association*, 2008b.

Andrew J. Seary and William D. Richards. Spectral methods for analyzing and visualizing networks: an introduction. In Ronald Breiger, Kathleen Carley, and Philippa Pattison, editors, *Dynamic Social Network Modeling and Analysis: Workshop Summary and Papers*, pages 209–228, Washington, D.C., 2003. The National Academies Press. URL [http://www.sfu.ca/~richards/Pages/NAS.AJS-WDR.pdf](http://www.sfu.ca/~richards/Pages/NAS.AJS-WDR.pdf).