Proposing Bipartite Network Analysis for the Evaluation of Regional Innovation Systems-/-Regions, Actors, and Content

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Abstract The paper proposes the application of bipartite network analysis based on graph theory on territorial innovation systems. Innovation systems theory (IS) points towards learning processes and interactions, but does not implement a networking infrastructure to facilitate those interactions intra- and inter-regionally. The combination of IS with notions of knowledge networks theory, e. g. cognitive proximity, form a powerful composition to employ bipartite network analysis. We present a simple (unipartite) network which is transformed into a bipartite representation. This enables us to analyze not only actors and regions, but also the exchanges and interactions in the typical innovation process at the same time. However, the data needs to be collected in a special format. This paper concludes by suggesting that a combination of bipartite and unipartite network analysis has distinct advantages over pure unipartite analyses as well as standard statistical methods alone.
Key words innovation systems, knowledge networks, methods of analysis, graph theory, bipartite network model

1 Introduction

During the last decade, many studies were concerned with the quantification of networks and collaboration in innovation processes from different angles (e. g. firm-/actor-based, with focus of regional questions, or a process analytical perspective). The state-of-the art method of analysis has been (and still is) a count of linkages from an innovating high-tech firm to other actors in the innovation system (e. g. [24], [39], [41], [42], [55], [37], [56]). This subject-oriented approach usually takes into consideration many actors in different regions during diverse stages of the innovation process. However, simple counting methods neither take into account the systemic nature of spatial innovation systems nor do they capture the systemic nature of the innovation process itself as proposed by Kline and Rosenberg [33]. As they usually analyze the innovation system through the perspective of only one type of actor, e. g. companies, they result in one-dimensional measures of linkage frequencies and connections with no idea of what is beyond these direct connections. However, an innovation system, simply defined, is a complex system of actors and, even more important, of collaboration and interaction between all entities. The modeling of complex interactions in multi-scalar innovation systems is assumed to be a great challenge for regional science [54].

Unipartite network analytical methods especially in the fields of social collaboration, technical networks or in biological networks are a powerful tool to explore the topology of innovation networks [59]. However, they have their own limits when it comes to the parallel analysis of processes and actors.

Given these shortcomings, it seems worth to start applying the mostly undiscovered tools of bipartite network analysis to regional innovation systems research. Bipartite network analysis can complement or even substitute for the established and simple linkage models as well as unipartite and 'flat' graphs with measures of systemic complexity. This implies a rather radical shift from uniform and subject-oriented counting towards bipartite network models based on graph theory. Those models are then capable of considering the systemic nature of innovation processes as well as different sorts of actors, regions and process states at the same time. Bipartite networks analysis reveals the potential for cooperation (accessibility) as well as actual connections. However, the data needs to be collected in a certain form. Suggestions for the data collection will be given in section 5.2 of this paper.

For pragmatic reasons and for reasons of understanding, we apply our findings to a fictitious data set, supported by simple visualization.

The rest of the paper is structured as follows: Section 2 recalls some relevant insights from the conceptual debate on territorial innovation systems and innovative networks, and introduces a fictive and simple network. Section 3 briefly introduces graph theory and relates it to the simple network. The outline of a simple bipartite model is introduced in section 4. Key challenges and situational factors that are necessary when using bipartite network analysis in this context as well as the prospects of this type of analysis are discussed in section 5. Section 6 concludes and sketches research prospects and challenges.

2 Understanding and Analyzing Knowledge Networks and Regional Innovation Systems

Innovation is the driving force of competition in a globalized knowledge economy. Striving for new knowledge, new technologies, and eventually new products, processes, and services requires a combination of knowledge stemming from different sources. The interplay of the main actors and the outcome of cooperation is the object of diverse theoretical concepts, e. g. knowledge networks or innovation networks, technological spillovers, innovative clusters, learning regions, innovation systems, etc. A number of reviews of the core ideas relating to these concepts as well as critical comments have been published recently, e. g. [46], [45], [14], [7], [26], [16], [43]. Most of the theories take into account spatial proximity as a crucial factor of success in R&D. Thus, territorially defined boundaries of knowledge networks seem to exist. Some authors challenge this view as being over-territorial [31]. For them, instead, other forms of proximity or distance – e. g. cognitive, social, or institutional – would exert influence on knowledge flows in networks as well (cp. [13], [20]).

The legal, institutional, and organizational context of knowledge networks is at the core of the concepts of territorial innovation systems (IS). National Innovation Systems as proposed by Nelson [47], Lundvall [40], or Freeman [25] define the broad ingredients of innovation systems (e. g. learning processes, main actors, institutional frames). Following the territorial perspective we find different scales of spaces to be at the center of analysis. In the last decade, national, regional and sub-regional/local systems were especially discussed. The influencing work of Cooke, Heidenreich, and Braczyk [19] further considered dynamic elements which represent the possibility of evolvement from one proposed type of IS into another. Etzkowitz and Leydesdoff [23] pick this notion up and theoretically consider an evolutionary model of innovation systems. Besides territorially-based concepts we find sector-based cluster concepts (e. g. [53]) or technological systems research that is well connected with the work of Lall for developing countries ([34], [35]).

All of these ideas are strong on theory, but, so far, lack of an analytical method that is aware of the systemic aspects and eventually delivers definite empirical evidence. Bunnell and Coe state that "focusing attention on just one spatial scale will rarely be adequate for a full understanding of innovation processes. […] the way forward is not merely to posit a need for multi-scalar approaches, but rather to explore interconnections and interrelations between and across scales." They instead propose a qualitative shift from the sole analysis of location spaces towards an analysis of connections between the relevant actors [16]. The IS theory alone is not delivering an explanation for the crucial role of external linkages, although they are very important for complementing and transforming internal linkages [2].

Consequently, if we consider the implications of this proposal and take into further consideration the fact that innovation processes are seldom a merely technical activity [51], then we would pay better attention to the exchange process as such. This can be done through systemic and empirical network analysis.

To serve as a basis for a bipartite network analysis, the ideas of innovation systems and networks have to be defined more strictly. In a simplified view, a global IS is constituted of many institutionally framing and non-overlapping NIS with a particular political, economical and social background, each of these, in turn, are constituted by non-overlapping RIS. A RIS is assumed to be the locus of a variety of actors which are concerned with innovation activities. So far, we only speak of unconnected territorialized 'containers' of individually learning agents. However, we go beyond the claim of Bunnell and Coe [16] who assume that the "scale as 'container' effectively means the relative neglect of broader networks that support innovation in particular locales." In Figure 1, the implicitly assumed cross-connection between the learning agents in the IS theory is represented by a layer of internal and, even more important, external interactions through a non-territorially confined knowledge network. This connects IS theory and knowledge networks theory. Furthermore, those interactions can not only represent knowledge exchanges but also other types of business processes which are relevant for innovation activities (e. g. financial support, venture capital provision).

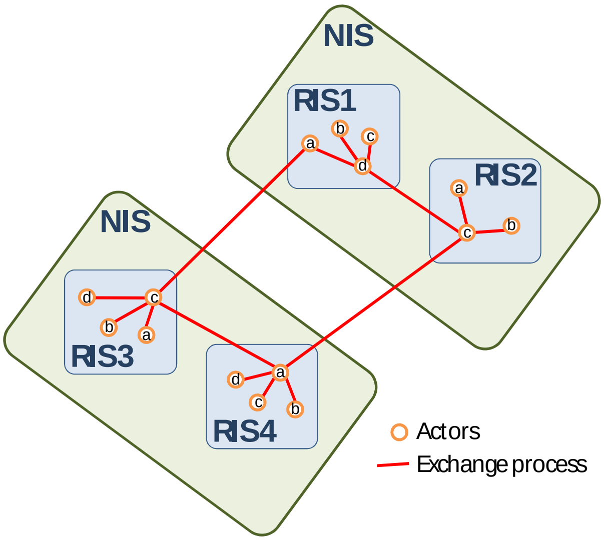

Figure 1 Definition, Discrimination and Connectivity between IS-Concepts and Concepts of Knowledge Networks

Source: own sketch

To analyze a simple network like the one depicted in Fig. 1, we can use social network analytical methods for unipartite graphs. However, as we will show, the analysis of quantitative data is not trivial when we have to cope with multifaceted phenomena like collaboration in innovation processes between different actors, originating from different locations in space, working together in different phases of the innovation process, and involving several sub-processes of business activities that are related to their particular innovation process. In such a case, bipartite network analysis offers more insights.

3 Graph Theory and Network Analysis

Graph theory is the mathematical source for ground-breaking algorithms that analyze the topologies and the properties of real-world networks. Beginning with Erdõs and Rényi [22], who studied random graphs in the late 1950s, the modeling of graphs got more and more pronounced and realistic with the following decades. Physicists are especially interested in developing the graph theory in order to analyze real networks. Recently, they were combining notions from statistical physics, complex systems theory, and graph theory to derive better models of real-world social, biological, or technical systems. A natural law seems to exist for most of the large systems, be it a biological food-web, a technical network like the internet, or the social community network of acquaintances. The degree distribution of all systems follows a power-law which is the expression of a natural tendency to self-optimize in terms of efficiency in reach and stability (cp. [62], [3]). The combination of efficiency and stability reflects the notion of optimal redundancy, which is inherent and important in socio-economic networks rather than efficient network structures alone [29].

A power-law of that sort always forms when a complex system has highly dense areas and clustering, as well as a short average distance from one entity to another at the same time. This phenomenon is known as a small world [64] and was popularly referred to as six degrees of separation, i.e. each person on this planet is separated by a maximum of 6 other people. Small world networks with power-law properties in the degree distribution are labeled scale-free, a term that originated from statistical physics [9]. For the analysis of those ‘flat’ and unipartite networks or 1-mode graphs there have been proposed numerous algorithms for diverse purposes in recent years (for an overview cp. [49], [48], [1], [21], [61]).

If there are limits to those promising methods, one can consider the uniformity of the nodes as a non-realistic representation for most of the activities that are going on in interacting systems. In graph theory however, there are not only unipartite networks but also bi- and multipartite networks. Bipartite networks consist of 2 different node types (=sets) with distinguishable functions. For example, a node can not only represent an actor, but also form a state or a process. This scheme is applied in the analysis of metabolic cell processes (e. g. protein interaction) in the field of bio-chemistry, for example [15]. For the purpose of innovation systems analysis both uni- and bipartite network models seem to complement each other in terms of insights and analytical capabilities.

Usually, bipartite networks have some sort of hierarchical dependency. A famous example of a bipartite network is the movie-actor network where actors constitute the set of bottom nodes and movies represent the set of top nodes [8]. A feature of a bipartite representation is that there are no edges between nodes of the same set, but only between the different sets. A movie cannot be linked to another movie, but the actor who plays in two movies connects both. Another telling example of bipartite representations of network structures is given by Robins and Alexander [57], as well as Conyon and Muldoon [18], who analyze boards of directors of companies, where members of the boards constitute one set and the boards represent the other set. Unfortunately, there is no way of using the same network measures and algorithms for bipartite networks as are use for unipartite networks. The methodological research on bipartite networks is just beginning. However, some promising algorithms have been proposed to analyze the clustering, density, centrality, and other properties ([28], [38], [44], [52], [12], [27], [57], [36]). The most common way of analyzing a bipartite network today is to project it into two unipartite networks (one for the top nodes and one for the bottom nodes) and analyze both projected networks in the familiar way (for a technical explanation of projections see e. g. [36]). A crucial obstacle to this method of projection is that important information about the connection is lost with the projection [27]. A misleading side-effect is the natural density of the resulting unipartite networks with high clustering, as all bottom nodes that are connected to a certain top node are fully connected to one another through this node by definition. This makes bipartite networks appear as networks of accessibility.

4 A Simple Bipartite Innovation Network Model

As denoted earlier, one important piece of information and a constituting element of innovation activities are the collaboration contents as a variety of processes (e. g. different phases of the innovation process according to Kline and Rosenberg, or distinct other non-technical business-activities necessary and related to innovation). Imagine a slightly modified innovation network from Fig 1. The interactions and ‘cross-scalar’ [6] connections are not uniform actions but rather different activities like generating ideas in a brain-storming process, developing a prototype, or defining a marketing concept for the introduction of the new product. This modification results in a network representation as shown in Fig. 2. The actors are connected by distinguishable edges in regard of content. Two actors can also form more than one like between each other according to the different collaboration and process activities between both actors.

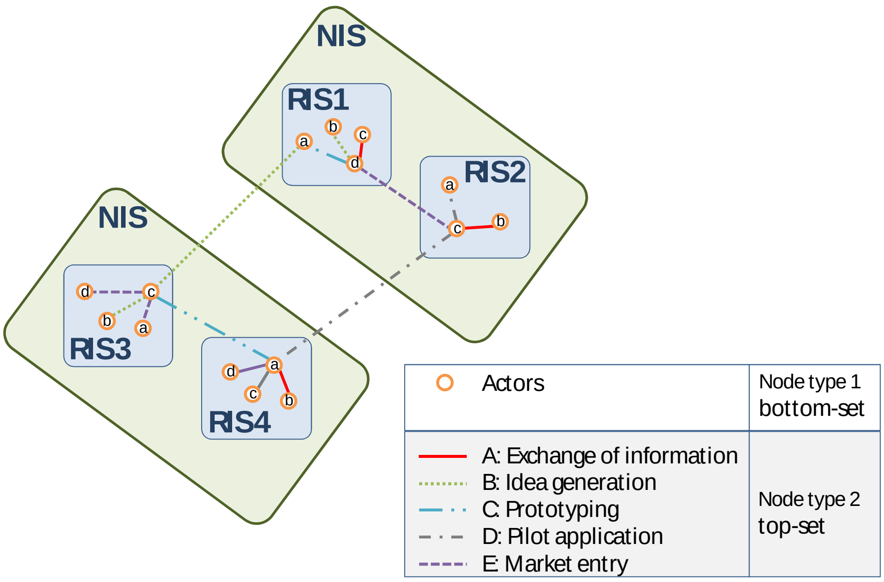

Figure 2 Representation of the Distinguishable Interactions/Connecting Processes as Edges in a Unipartite Network

Source: own sketch

If we distinguish the edges in Fig 2 according to the different types of process activities they represent, e. g. ‘Prototyping’, we generate a different meaning of a network, consisting of different edge-qualities which cannot be analyzed with common network analytical methods at all. But by taking the modified unipartite network from Fig 2 as a starting point, we are able to transform the different edge-qualities into a second type of node. From this simplified example in Fig 2 we can learn that we will get more information if we do an analysis which allows for the region, the type of actor and the type of connection between every two of those actors.

The important change in perspective seems straightforward if we take the following intermediate step: Consider nodes b (e. g. a university), d (e. g. an innovating company) and a (e. g. a supplier of d) in region 1. From the perspective of a unipartite network, the nodes a and b are connected indirectly through d. The innovating firm cooperates with the supplier for prototyping the new product and with a local university for idea generation. Since a is a diversified actor, it can not only be involved in prototyping, but also in idea generation, shown by its link to c in RIS 3. Hence, both a and b are capable of generating new ideas. Thus, they are potentially closer to each other than they appear in the unipartite analysis: a and b in RIS 1 are not directly connected; however, their capacity to be active in "idea generation" reflects a common sphere of activity, their "cognitive proximity" in the sense of Boschma's definition ([13]). To transform this cognitive proximity into a connection, we simply connect a and b from region 1 via a new node B (see fig. 3) in a bipartite network. Thus, the bipartite structure displays not only existing connection but also accessibility (for the difference between both terms cf. e. g. [32]).

One may ask which sort of advantages we get in doing this transformation? Simply put, we can answer different questions as with conventional analyses. The process of innovation itself moves into the spotlight. We might say how central a certain stage is compared to other stages and how 'far' different stages are away from each other. This percolation might be of interest in that respect. Further, we can figure out which actors from which territories are important for the innovation phases and how those patterns differ from region to region (cp. section 5.2).

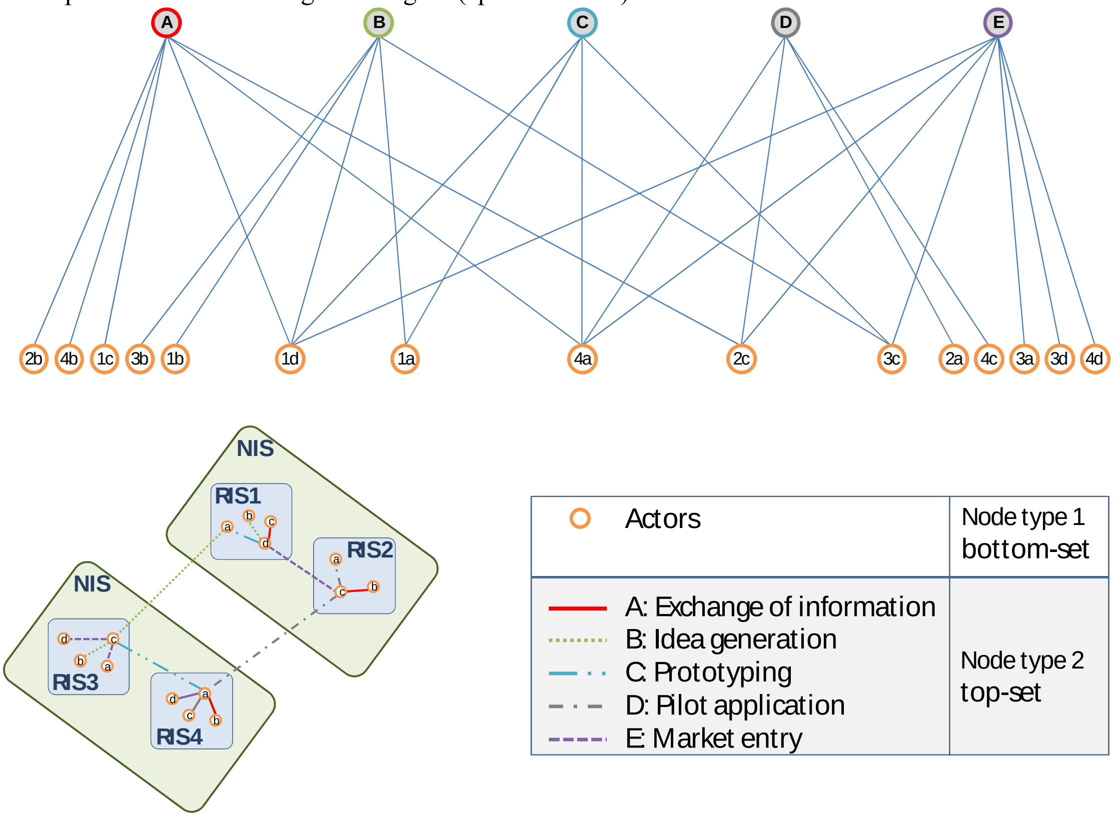

Figure 3 Transforming the Unipartite Network into a Bipartite Representation of an Innovation System
Source: own sketch

5 Applying the Bipartite Network Model to Real-World Networks: Key Challenges

In this section we focus on three key challenges of this method, the definition of nodes, implications for the data needed for empirical analyses, and the type of measures that can be generated.

Further, we briefly evaluate the discriminating advantages of this method compared to other well established ones. Many studies which are concerned with innovation systems are made up of questions that distinguish between functional actors and/or regions. We allow for this survey concept in the following application to build on common ground. Unfortunately, the data that has been generated through these surveys do not fit perfectly to the application of network analysis (cp. 5.2).

5.1 What Do the Network Nodes Tell Us?

The bottom nodes in Fig 3 are made up of different potential collaborators (e. g. suppliers, customers, universities, public research organizations, business service providers, or technical service providers) in distinguished local spaces. The top-nodes are formed by 5 different phases of a typical innovation process for the firm. These are information exchange, idea generation, prototyping, development of pilot applications and entering the market. This way of defining nodes in Fig 3 deserves some explanation. First, we focus on the bottom nodes, actors (companies, universities, etc.) and regions.

In the literature on cooperation in innovation systems and knowledge networks mentioned in sections 1 and 2, it is common to view collaborating organizations as interlinked subjects. The notion of an interlinked subject is equivalent to the notion of a node in a network. In a similar manner, regions have been viewed as nodes in many studies based on the notion of 'nodes in global networks' [5]. The latter view is based on the understanding that regions incorporate certain sets of actors and activities. Both concepts have been used in the traditional way of counting linkages between actors, and connecting these linkages with scales and distance (e. g. [24], [55], [37], [11]). Thus, our definition of bottom nodes mirrors the established methodological path.

However, the rationale behind this approach is at least debatable [58]: Why do these studies count linkages between actors and regions, but do not look at connections within collaborating organizations or regions? And, is it not contacts between individual people that matter in the end? Apart from the necessary aim to simplify the problem in empirical investigations, some justification can be derived from knowledge theory: Many studies implicitly or explicitly assume that knowledge is easily transferred between individuals (and actors) that have the chance to meet personally. This is clearly the case for individuals affiliated with the same organization or located in a confined regional setting. Such conditions allow for the transfer of explicit and implicit (tacit) knowledge. Thus, it makes sense to focus mainly on linkages to other actors or regions, as knowledge transfer over distance requires more effort and makes distant pools of knowledge accessible. Using frequently cited terminology, looking at 'global pipelines' may be more interesting than the 'local buzz' that is just around the corner ([10], [60], [17], [6]).

The idea that nodes should represent places of proximity facilitating 'buzz,' helps to understand the concept of top nodes in our network setup: The top nodes are defined as the five stages of the innovation process. Hence, they are neither places nor organizations. Instead they represent spheres of common interest, activities, and capabilities. For example, actors who are doing prototype development share some common capability and interest in that particular stage of the innovation process. These features allow them to share knowledge easily, even if they may have to bridge considerable spatial distance. Their proximity is not to be understood in spatial terms, but based on practice and knowledge background. Thus, the understanding of top nodes is very close to ideas of cognitive proximity respecting distance ([13], [50]) or communities of practice ([65], [4], [11]). If it is accepted to assume that knowledge can easily flow within confined regions, it should also be accepted that knowledge can easily flow in the context of special activities and knowledge flows may thus overcome organizational, i.e. the own firm/institution and territorial boundaries (for an overview of firm-centered intra-/inter-organizational knowledge flows see e. g. [63]).

Thus, we assume knowledge-exchange via 'buzz' to exist within nodes, and knowledge exchange via 'pipelines' to be facilitated by edges, i.e. by the linkages between nodes.

5.2 What Kind of Empirical Data Do We Need?

This network structure implies that the ability to be active in a certain phase of the innovation process in a sufficient precondition for cooperation, and collaboration only works through predefined types of cooperation, i.e. the top nodes. This point is critical. On the one hand, one can argue that this assumption reflects the reality much better than unipartite networks do: Many real-world networks are characterized by an underlying bipartite structure [27]: Collaboration in social networks always has content. This fact is reflected in the way many empirical surveys have been set up. They usually ask for both, information on the types and regions of partners, and on the phases of collaboration. Their main shortcoming in the light of network analysis is the fact that questions were usually posed in a way not well-suited for integration into network analysis [30]. On the other hand, the following example shows that one should be careful with the data we have. Who believes that a ship building company doing prototyping can easily and meaningfully cooperate with a biotech firm doing prototyping? The fact that both companies are prototyping is obviously not sufficient to assume they have the ability to cooperate with one another. In order to make the assumption useful, the data should contain information about the branches or the products involved. When the content of the top nodes, i.e. the content of cooperation, is defined in a precise way, the analysis of bipartite networks delivers meaningful results (see below).

However, if the top nodes do not display distinguishable content, the unlimited potential for collaboration generally assumed is as unrealistic as it is for the bottom nodes: We have accepted that many studies implicitly deal with the assumption of unlimited buzz within regions; so one could accept a similar inconsistency for the top nodes as well. We label this the "content inconsistency error." However, the central position of the top nodes in bipartite networks will encourage us to make sure we minimize the content inconsistency error in future investigations. We need fine-grained data.

5.3 What Can Be Found out using this Method

Advantage of numerical network analysis over visual description of netorks

With the representation in a simple model in this paper, we might have misleadingly shifted the attention towards a visual analysis possibility of networks. One can easily capture the properties of our most simple IS representation. However, real networks are far from being small and clearly arranged. We will find thousands or even millions of nodes connected by even more edges, which represent more than one distinct purpose of collaboration. Therefore, the network structure is invisible for the researcher and we have to focus on measures on the network properties. Newman [48] recalls: „How can I tell what this network looks like, when I can't actually look at it?" But we do have algorithms for the analysis of large data sets right now.

Advantage of network analytical methods over analytical statistics

The quantification of network characteristics, i. e. the topology of the network as well as important properties can go well beyond multivariate regression models. At least, they follow different purposes. To assess the complexity, we need to look beyond the first step of an exchange, and go further into the reciprocal dependencies. We are then able to evaluate the local and the global importance of actors for the whole picture. Moreover, we can identify disconnects in the network or cliques, i. e. intensively linked parts of the network. Centrality measures (e. g. degree, eigenvector degree, closeness, betweenness) can be derived through mathematical operations that are rather simple, but tricky to compute when the network becomes large. This is related to the interdependence of all nodes through the connecting edges. The identification of clustering, i.e. densely connected sub-components of the network, can lead to new insights on collaboration circles which might be completely independent from territorial affiliation.

Advantage of bipartite methods over unipartite methods

Usually, it is impossible to have network measures for processes and links, although some experimental edge property algorithms do exist within e. g. the NetworkX python package and might be available in other packages as well, – at least prospectively. The bipartite model enhances the analysis of these process properties if we construct the network accordingly. We then can derive the importance of certain processes for the whole innovation activity in a specific region. Further, we are able to name the most relevant actors, groups of actors, and differentiate the overall structural properties that might form region-specific patterns. For example, can close distance measures from one node-set to another be an indication of heterogeneity of a group of actors or regions? Overall, we can interpret most of the results as potential collaboration networks, rather than actual networks (which are derived directly from the unipartite network). The heterogeneity of a region, or a group of actors, might be a good indication of the maturity of the sub-system in the sense of a u-shape evolution as proposed by Hagedoorn and Duysters [29].

Advantages of a combination of unipartite and bipartite methods

The association of comparable measures from both methods can deliver interesting views and further accentuate results. The potential collaboration for each node/actor/region can be put into relation with the actual corresponding centrality measure of the same node. This might be an indication for optimality of network use of a specific node. A potential benefit of this information can be a strategic one. A firm would then know to whom they could connect the most effectively. This means strategic partnering could be assessed beforehand.

6 Conclusion and Implications for Future Research

This paper proposed a new form of analysis of innovation systems by bipartite data representation. The conceptual base comes from innovation systems theory and ideas from knowledge networks theory. This combination offers an explanation for methodological innovation, i.e. it analyzes the actors and their territorial origin at the same time as it analyzes the interacting processes.

With this bipartite representation we are able to shed light on the question of how interwoven the innovation process is and which type of potential collaborator is most influential in that process. However, bipartite networks answer different questions than unipartite networks or conventional analytical statistics. A comprehensive approach should allow for all of them to uncover the secrets of the influence of a region in the innovation processes.

Future research should consider new ways of data gathering, shifting away from a subject orientation (actor-centered) towards a project and process orientation. In our opinion it is worth trying to implement surveys that ask for detailed information meeting the requirements. We also think that this can be done in a conventional, standardized way. The more complete the survey is, the more we would be able to look behind the reasons that innovation processes drive to a successful end. To propose a new method of analysis always means that it has to be tested and evaluated against the current standard instruments of analysis. This is a crucial step and needs to be investigated most urgently.

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