Migration Networks: Applications of Network Analysis to Large-Scale Human Mobility

Valentin Danchev*, Stanford University, USA
Mason A. Porter, University of California, Los Angeles, USA

Abstract
An emerging area of research is the study of large-scale migration interactions as a network of nodes that represent places (e.g., countries, cities, and rural areas) and edges that encode migration interactions that connect those places. In this chapter, we review interdisciplinary applications of social and spatial network approaches for the analysis of migration networks. We focus in particular on global migration networks. We describe properties of global migration networks and outline network diagnostics and methods that are relevant to the study of such networks. We then present key findings and propose areas of future research to overcome current challenges. Research on migration networks is multidisciplinary; it connects migration studies to diverse research areas that include sociology, geography, regional science, network science, applied mathematics, computer science, and other areas. Consequently, a major objective of the present chapter is to highlight and foster interdisciplinary conversations.

Keywords
migration networks, social networks, spatial networks, network analysis, international migration, global migration

1 In this chapter, we draw on Danchev (2015) and Danchev and Porter (2018).
*vdanchev@stanford.edu
**Introduction**

Theories of migration (Hägerstrand, 1957, Salt, 2013 [1986], Kritz et al., 1992, Portes and Böröcz, 1989) have advanced the perspective that international migration is not an automatic response to origin and destination forces, but instead often takes place in networks or groups of origin and destinations that are already exchanging migration and other spatial flows. Building on this idea, one can study migration as a network of nodes (which represent geographically disperse places, such as rural areas, cities, provinces, or countries) and edges (which encode movements of diverse populations, such as displaced individuals, low-skilled workers, or skilled professionals) between places. Understanding bilateral movements in the context of broader patterns of interactions in such “migration networks” can inform public debate and migration governance. Of particular importance for the understanding of international movements of people are migration networks at the global scale. This is the primary focus of the present chapter. As we will discuss at length, social and spatial network analyses offer powerful tools to examine patterns of migration connectivity across space.

Network analysis concerns relationships between entities (e.g., individuals or countries), rather than solely the entities themselves; one uses it to study the patterns, antecedents, and implications of such relationships (Wasserman and Faust, 1994, Borgatti et al., 2009). Scholars from different fields—including sociology (Wasserman and Faust, 1994), economics (Jackson, 2008), political science (Maoz, 2011), applied mathematics (Porter, 2019), statistics (Kolaczyk, 2009), physics (Newman, 2018), social neuroscience (Baek et al., 2019), and others—have employed network analysis to study complex systems of interconnected entities. Taking into account system specificity, one can first carefully abstract a set of entities and a set of relationships and encode them as network nodes and edges, respectively. One can then analyze the patterns of relationships (in the form of network structure) that emerge from the interacting entities. By providing sources of opportunities and constraints, network architecture can impact not only the functioning of a system but also the performance of particular nodes, edges, and other structures (Wasserman and Faust, 1994: 3, Borgatti et al., 2009: 894, Newman, 2018). Network analysis provides powerful theoretical and computational tools for visualization,
analysis, and modeling of network structure and dynamics (Wasserman and Faust, 1994, Kolaczyk and Csárdi, 2014, Newman, 2018, Borgatti et al., 2018).

In addition to their social properties, migration networks are spatial (Danchev and Porter, 2018, Salt, 2013 [1986]). Spatial networks (Barthelemy, 2018) include both spatially-embedded networks, whose nodes and the edges are embedded in space in a literal sense (e.g., road networks), and spatially-influenced networks, in which space effects the probability of edge formation and/or the strengths of the edges. Migration networks fall into the second category. Like most social networks, migration networks are influenced by space, but they are not embedded into a low-dimensional space. Because of spatial constraints, and in line with longstanding theories of migration (Ravenstein, 1885, Zipf, 1946), longer-distance migration edges are less likely than shorter-distance edges to form and develop into strong edges.

It is convenient to categorize applications of network analysis of migration into two strands. The first strand focuses on migrant networks, which one constructs based on interpersonal relationships (e.g., kinship, friendship, or acquaintance) that link migrants and non-migrants (Massey et al., 1998: 42, Boyd, 1989). Migrant networks can spread information about destination opportunities and provide initial employment, accommodation, and overall assistance, thereby reducing movement costs and risks (MacDonald and MacDonald, 1964, Gurak and Caces, 1992, Massey et al., 1998, Boyd, 1989, Palloni et al., 2001, Liu, 2013). See Liu (2013), Comola and Mendola (2015), and Blumenstock et al. (2019) for recent research on these issues. Migrant networks also affect processes of integration, assimilation, and transnationalism. See Lubbers et al. (2010), Vacca et al. (2018), Verdery et al. (2018), Bilecen et al. (2018), Lubbers et al. (2018), and Martén et al. (2019) for recent work on these issues. The second strand, which focuses on migration networks, encompasses a multidisciplinary body of literature that leverages network methodology to study large-scale migration as a “mechanism that connects ‘places’” (Maier and Vyborny, 2008, Lemercier, 2010). Among other phenomena, researchers have examined networks of internal (intra-country) movements that connect rural areas in Northern France (Lemercier and Rosental, 2010) or states in the United States (Maier and Vyborny, 2008,

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2 Some networks of human mobility experience greater spatial constraints than migration networks. For example, daily commuting (Montis et al., 2013) depends on spatially embedded-networks (e.g., transportation).
Charyyev and Gunes, 2019), as well as global networks of international movements that connect different countries (Fagiolo and Mastrorillo, 2013, Davis et al., 2013, Tranos et al., 2015, Danchev and Porter, 2018, Windzio, 2018). In the present chapter, we focus on migration networks and especially on global migration networks.

Until recently, networks were used in migration theory and research (Kritz and Zlotnik, 1992, Salt, 1989) primarily as a metaphor without applying explicit network-based methodology. Since the 2010s, however, various studies have employed concepts and methods from network analysis to study migration. A recent special issue in the journal Social Networks (Bilecen et al., 2018) included research at the intersection of social networks and migration. Apart from the dyadic assumptions that underlie many migration theories (Massey et al., 1998), a major barrier to network analysis of international migration has been the lack of compatible migration data between world countries (Fagiolo and Mastrorillo, 2013, Özden et al., 2011).

Researchers now have access to publicly available global and regional longitudinal migration data, including global bilateral migrant stock (Özden et al., 2011, UN DESA, 2019) and estimates of global bilateral migration flows (Abel and Sander, 2014, Abel, 2018). Recent migration data sets stratify migration by different characteristics, including age and sex (UN DESA, 2019, Abel, 2018). Additionally, computational and geospatial techniques have been used to infer migration trajectories from individual geolocated data from online platforms, such as Twitter (Zagheni et al., 2014) and Facebook (Spyratos et al., 2019). The proliferation of available data sources, although not without limitations (Global Migration Group, 2017), paves the way for increasingly realistic network analyses of migration movements.

**Migration Networks: Directed, Weighted, Spatial, and Temporal Properties**

Danchev and Porter (2018) studied world migration in the form of directed, weighted, temporal, and spatial networks. We discuss those aspects in turn. As Ravenstein observed long ago (1885), when thinking about migration, one needs to consider the direction of movements, as movement from place A to place B is distinct from movement in the opposite direction. To encode migration direction, one constructs a directed migration network, in which each edge has an associated direction that corresponds to either out-migration or in-migration. Migration movements also
vary in terms of volume of migrant stock or flows. One can represent migration volumes by constructing a weighted network (Newman, 2018) in which each edge has an associated weight that encodes the flow or volume of migrant stock from place A to place B. Migration networks are also longitudinal, as reflected in global bilateral migration databases, which typically report migrant stock and flows at five-year or ten-year intervals. Rather than considering those time-windows as separate snapshots, recent network methods (Holme and Saramäki, 2012, Holme and Saramäki, 2019) and statistical models (Krivitsky and Handcock, 2014) enable increasingly realistic investigations of network dynamics. Finally, as we noted earlier, the spatial property of migration networks arises primarily from the geographical constraints on edges, which introduce costs (Barthelemy, 2018). Accordingly, we take a “migration network” to be a set of nodes that represent places and a set of edges that represent migration edges of some length (and an associated cost). For an illustration of a global migration network, see Figure 1.

![An example of a global migration network between countries. The positions of the nodes indicate the geographical locations of the countries. The edges encode bilateral migrant stock (Özden et al., 2011). We represent population size on the map by varying the gray scale (where darker tones indicate larger populations). [We create the network visualization using code from Traud et al. (2009) and Jeub et al. (2015) in MATLAB and the world map in the background using the package ‘rworldmap’ in R (South, 2011).] A similar figure appears in Danchev (2015) and in Danchev and Porter (2018).](image-url)
How Migration Networks Form

What migration-specific mechanisms generated a mixture of regional and global connectivity in spatial global migration networks over the last few decades (Danchev and Porter, 2018)?

Key factors that concentrate migration in geographical (and social) space include geographical proximity (Ravenstein, 1885, Zipf, 1946); social proximity, including former colonial links (as a proxy for institutional and cultural proximity) and common language (Fawcett, 1989, Portes and Böröcz, 1989); forced displacement of people; and global inequalities that trap migrants in peripheral geographical areas (Sassen, 2007, Held et al., 1999). These factors promote network fragmentation.

Another set of factors are associated with long-distance migration edges, which were once concentrated in few countries but are now spread among a larger pool of countries across the globe (Castles and Miller, 2009, Vertovec, 2010). Key factors include shrinking geographical and cultural distances as a consequence of transportation and communication advancements (Harvey, 1989), densified international capital flows (Sassen, 2007), global networks of financial markets, and multinational companies that facilitate movements of highly skilled professionals (Held et al., 1999: 304). These factors promote network integration.

Methods for Analyzing Migration Networks

We now discuss some network diagnostics, techniques, and models that are useful for characterizing the structure of migration networks.

Network Diagnostics

A simple diagnostic for examining the position of a country in a migration network is degree. A node’s degree measures how well connected it is by counting the number of edges that are attached to it. In directed migration networks, one distinguishes a country’s out-degree (i.e., the number of outgoing edges that originate at a node) from its in-degree (i.e., the number of incoming edges that terminate at a node) (Wasserman and Faust, 1994: 126). Out-degree and in-degree correspond to out-migration and in-migration, respectively. In weighted networks, it is also useful to consider node strength, which is usually measured as the total weight of the edges
that are attached to a node (Barrat et al., 2004: 2). Node degree and node strength are basic measures of “centrality” in networks. Central measures are ways to quantify the importance of nodes or edges in a network. In network analysis, out-degree can be an indication of expansiveness, whereas in-degree is often a notion of popularity (Wasserman and Faust, 1994, Opsahl et al., 2010). From this perspective, one expects that potential migrants from a country with a large out-degree have more opportunities (in the form of potential destinations). Nodes that have disproportionately more connections than the other nodes in a network are sometimes called “hubs” (Newman, 2018). In migration networks, hub countries are involved in the circulation of migrants to and from multiple countries. For discussions of other centrality measures (e.g., betweenness, closeness, and eigenvector centrality), see Borgatti et al. (2018) and (Newman, 2018). One can evaluate the heterogeneity of centrality scores across nodes in a network by calculating network centralization (Freeman, 1978, Borgatti et al., 2018).

An old idea in migration studies is that “every migratory current has a counter-current” (Grigg, 1977: 112, Ravenstein, 1885: 199). To capture this intuition, consider the network notion of “reciprocity”. Reciprocity measures if an edge from node A to node B is matched by an edge in the opposite direction. One way to define reciprocity is as the number of pairs of mutually connected nodes (i.e., reciprocal relationships) divided by the total number of node pairs with any edge between them (Butts, 2008: 27, Borgatti et al., 2018, Hanneman and Riddle, 2011). One way to generalize reciprocity to weighted networks is to consider two weighted edges as reciprocated if the ratio between them is at least a certain threshold.

A characteristic property of social and spatial networks is a tendency towards triadic closure (Davis, 1967, Wasserman and Faust, 1994, Barthelemy, 2018). In colloquial words, triadic closure refers to the tendency our friends to themselves be friends. More formally, it refers to the probability that two nodes with a connection to a common third node are themselves connected (Newman, 2018). Both geographical proximity and social proximity (e.g., common language) facilitate triadic closure. Measures of the tendency of triadic closure in binary networks include clustering coefficients (Newman, 2018) and transitivity (Wasserman and Faust, 1994). There are generalizations of clustering coefficients to directed (Fagiolo, 2007), weighted (Onnela et al., 2005, Saramäki et al., 2007), and multiplex (Cozzo et al., 2015) networks.
Reciprocity, clustering coefficients, and related measures characterize node neighborhoods but provide limited information about the connectivity in an entire network. One can use the mean shortest-path length, a measure of network distance between two nodes, as one indicator of global connectivity in a network. A path in a network is a sequence of adjacent nodes, so one can ‘travel’ from one node to another along these edges. The length of a path in an unweighted (i.e., binary) network is equal to the number of edges that are traversed. A shortest path is then a path that connects two nodes using the fewest possible number of edges (Newman, 2018: 132). In a directed network, one considers paths between origin nodes and destination nodes, and one then calculates path lengths in the same way. In a migration network, the directed shortest-path length between two countries is the minimum possible number of edges from an origin to a destination (see Kaluza et al., 2010). In weighted networks, one can also transform from edge weights to edge costs to examine other notions of path lengths.

One can obtain a broad view of global connectivity of a migration network by computing network densities. Edge density is the ratio of the actual edges in a network to the maximum possible number of edges in the network (Wasserman and Faust, 1994: 129, Borgatti et al., 2018). It takes values between 0 (if no edge is present) and 1 (if all edges are present).

**Spatial Network Diagnostics**

To examine spatial properties of migration networks, one can calculate diagnostics that combine network and geographical information. For example, a simple way of incorporating spatial information is to compute the probability of a migration edge in a given distance range, taking into account both actual and possible migration edges for the distance range. For a similar approach in the context of the “geography” of online social networks, see Backstrom et al. (2010). See Barthelemy (2018) for a review of spatial networks.

**Community Detection**

The systems approach to international migration defines a “migration system” as a set of countries with close historical, cultural, and economic linkages that exchange large numbers of migrants (Kritz et al., 1992, Fawcett, 1989, Salt, 1989). A major methodological difficulty is the
demarcation of the boundaries of migration systems (Zlotnik, 1992). Techniques of community detection offer a family of algorithmic methods to delineate migration systems and other “functional regions” (Ratti et al., 2010, Farmer and Fotheringham, 2011) on the basis of empirical connectivity. A “community” is a tightly-knit subnetwork of densely connected nodes that are loosely connected to the rest of a network (Porter et al., 2009, Fortunato and Hric, 2016). In Danchev and Porter (2018), we defined an international migration community as “a tightly-knit group of countries with dense internal migration connections [...] but sparse connections to and from other countries in a network”.

There has been an enormous proliferation of methods for algorithmic community detection in networks (Porter et al., 2009, Fortunato and Hric, 2016). One popular community-detection method, which has been employed in many network studies of global migration (e.g., Fagiolo and Mastrorillo, 2013, Davis et al., 2013, Tranos et al., 2015), is to maximize an objective function called “modularity” (Newman and Girvan, 2004, Newman, 2018). From a modularity perspective, an optimal division of a network into communities is one with the largest possible number (or total weights, in a weighted network) of intra-community edges compared to the expected number of such edges in a specified null model (Newman, 2006b, Bassett et al., 2013: 2). The purpose of a null model is to take into account ‘statistically surprising’ connectivity (Newman, 2006b: 8578).

The standard null model for modularity maximization (Newman, 2006a) works for (either unweighted or weighted) undirected networks. For migration networks, one can consider extensions of modularity that accommodate edge directionality and node attributes. For example, Leicht and Newman (2008) developed a null model for directed networks. Expert et al. (2011) and Sarzynska et al. (2016) developed null models for spatial networks (with known node locations), and Mucha et al. (2010) extended modularity maximization to time-dependent and multiplex networks. The choice of community-detection method depends on the properties of available migration data and research questions. When performing community detection, it is important to consider the parameter space, assumptions, and features of a method. For a recent review of community detection (including discussions of increasingly popular methods based on statistical inference), see Fortunato and Hric (2016).
**Statistical Network Models**

For testing network hypotheses, one can employ statistical models for social networks. The quadratic assignment procedure (QAP) of regression is appropriate for testing dyadic hypotheses (Dekker et al., 2007). A popular family of models called exponential random graph models (ERGMs) allows both cross-sectional and longitudinal examination of higher-order network dependencies, while accounting for covariates encoded in node attributes. For a review of ERGMs, see Lusher et al. (2013). For a discussion of various statistical models for network data, see Kolaczyk (2009).

**Prior Research and Key Findings on Migration Networks**

Probably one of the earliest works to integrate network analysis and migration studies is a paper by Vincent and Macleod (1974), who made analogies with physical networks (such as stream networks) to advance the argument that networks can influence migration patterns and therefore can inform the forecasting of migration rates. Vincent and Macleod (1974) examined patterns of internal migration by drawing on theories in regional science and on network methods in geography (Haggett and Chorley, 1969). In a pioneering work, Nogle (1994) used the systems approach to international migration, proposed by Fawcett and Arnold (1987) and Kritz and Zlotnik (1992), as a framework for studying migration flows within the European Union in the 1980s. By calculating centrality measures and applying techniques for detecting fully connected subgraphs (so-called “cliques”), Nogle (1994) identified a tendency towards a ‘Single Europe’, where more countries become interconnected via migration over time. In another proof-of-concept work, Maier and Vyborny (2008) applied network analysis in an exploratory study of internal migration between states in the United States. An important contribution of theirs was to define migration as a “mechanism that connects ‘places’”. Slater (2008) also examined a network of internal migration in the United States, with a focus on the role of “hubs” and “functional regions”. Inspired by the approach of Hägerstrand (1957) on migration fields, Lemercier and Rosental (2010) designed an innovative study of migration patterns between rural areas in 19th century Northern France using an actor-oriented model for network dynamics (Snijders et al., 2010).
More recently, with the availability of origin–destination (OD) matrices of bilateral migrant stock (Özden et al., 2011, UN DESA, 2019) and migration flows (Abel and Sander, 2014), many studies have employed network approaches to study global migration (Tranos et al., 2015, Davis et al., 2013, Fagiolo and Mastrorillo, 2013, Danchev, 2015, Novotný and Hasman, 2016, Abel et al., 2016, Peres et al., 2016, Danchev and Porter, 2018, Windzio, 2018, Cerqueti et al., 2019).

By calculating various network diagnostics and employing community detection, early research (e.g., Tranos et al., 2012, Davis et al., 2013, Fagiolo and Mastrorillo, 2013) highlighted several stylized observations about the network of international migration in the latter half of twentieth century. For example, Davis et al. (2013) and Fagiolo and Mastrorillo (2013) concluded that interconnectivity and globalization of migration have increased over time based on increasing “connectivity” (as reflected by the increase in value of various network diagnostics, such the number of migration connections and migration weights between countries, countries’ degrees and strengths, and clustering coefficients) and “reachability” (as reflected by decreasing mean shortest-path length). Davis et al. (2013) and Fagiolo and Mastrorillo (2013) also reported that these migration networks have a characteristic right-skewed edge-weight distribution, indicating that there are many edges that have a small to moderate number of migrants and a small number of edges that are responsible for many migrants. Third, Fagiolo and Mastrorillo (2013: 4) reported that “[t]he number of communities decreases across time” and concluded on this basis that “globalization has made the architecture of the IMN [International Migration Network] less fragmented and modules more strongly interconnected between them”. Similarly, Davis et al. (2013: 6) argued their case of “increasing globalization” by noting that “the ratio between the internal and total fluxes slowly decreases in time: 0.8 in 1960; 0.8 in 1970; 0.76 in 1980; 0.75 in 1990 and 2000.” A major conclusion of these studies is that world migration has become more interconnected, in line with broader globalization tendencies.

Informed by the international-migration systems approach (Salt, 1989, Kritz et al., 1992), some research (DeWaard et al., 2012, Abel et al., 2016) has employed community detection and other techniques to discover and characterize boundaries of migration systems. Abel et al. (2016) suggested that global migration in the second half of the 20th century is divided into
“geographically concentrated” systems that bound neighboring countries in geographical regions. This line of research, which lies at the intersection of migration studies and geography, has emphasized localizing spatial tendencies in international migration.

Many of the above results rely on the structure and boundaries of migration communities from maximizing the original modularity function (Newman and Girvan, 2004) or other algorithms for community detection (Fortunato and Hric, 2016) that were designed for non-spatial networks. In a recent paper (Danchev and Porter, 2018), we employed a spatial modularity function (Expert et al., 2011, Sarzynska et al., 2016) that incorporates the probability that a dyad of countries are assigned to the same community as a function both of migration connectivity between the two countries and as a function of the distance between them. In Danchev and Porter (2018), we detected international migration communities using a generalized modularity function for spatial, temporal, directed, and weighted networks. We also leveraged properties of the detected communities to adjudicate among conflicting theoretical accounts, concluding that over the second half of the 20th century “world migration is neither regionally concentrated nor globally interconnected, but instead exhibits a heterogeneous connectivity pattern that channels unequal migration opportunities across the world.” Given appropriate data availability and quality, tailored community-detection techniques have the potential to help uncover the impact of recent events—including the enlargement of the European Union, the global financial crisis, and the withdrawal of the United Kingdom from the European Union (“Brexit”)—on patterns of connectivity in global migration.

Windzio (2018) employed cross-sectional and longitudinal ERGMs to examine the impact of various factors—including geographical, demographic, economic, and linguistic ones—on migration between 202 countries during the period 1990–2013. They reported results that are consistent with migration theories, with (1) geographical distance tending to reduce the probability of migration edges between countries and (2) economic differences, shared geographical region, and similar religion and language tending to increase the probability of migration edges. Although they fit models using primarily binary data, the ERGM analysis of Windzio (2018) provides a good foundation for sophisticated modeling of network dependencies and countries’ attributes in global migration.
Future Research Directions

Rich, Geolocated, and ‘Big’ Migration Data

For a long time, research on international migration has relied exclusively on secondary administrative data collected via national census or population registers. Although such data are useful in many respects (e.g., their wide geographical coverage and public availability), in some contexts, country-level aggregation may prove too coarse for insightful network analysis. A more realistic representation of international migration requires location-specific data about mobility between actual settlements, as country-level aggregate data may obscure migration patterns. Consider, for example, that over 95% of the Bangladeshis in Britain (estimated at 200,000 people in the mid-1980s) originated from specific villages in the urban area of Sylhet, which is located in the northeastern part of Bangladesh (Gardner, 1995: 2, Skeldon, 2006: 22).

The ubiquity of public online information provides a valuable opportunity to collect place-specific, geolocated data about social interactions (Lazer et al., 2009) and human mobility (Gonzalez et al., 2008). Some recent research on international migration has collected and analyzed geolocated traces of human mobility from online platforms, such as LinkedIn (State et al., 2014), Facebook (Spyratos et al., 2019), and Twitter (Zagheni et al., 2014). Although such digital data are rarely representative of the studied populations and are restricted in their geographical and temporal coverage (IOM GMDAC, 2017), geolocated digital data about human mobility is a promising resource for studying migration networks. One can also combine geolocated digital data with census data. For example, Eagle et al. (2010) linked communication networks with national census data to study associations between network structure and socio-economic opportunities. The advancement of data integration and the construction of fine-grained migration networks requires interdisciplinary efforts across migration studies, geography, spatial and social network science, computational social science, “Big Data” approaches, machine learning, and other topics.

Multilayer Networks of Migration and Other Flows between Places

Thus far, we have restricted our discussion to ordinary (“monolayer”) networks, which include a single type of edge (e.g., with one value to encode the international migration flow between two
places). However, since the late 1980s, international migration has been viewed in the context of other spatial interactions, including economic ones (e.g., international trade), historical ones (e.g., previous colonial ties), cultural ones (e.g., language), and political ones (e.g., bilateral agreements) (Malmberg, 1997: 40, Kritz and Zlotnik, 1992, Portes and Böröcz, 1989, Fawcett, 1989). Additionally, research using large data from online networks indicates that there is a strong association between international social relationships and international migration (Takhteyev et al., 2012, Hale, 2014, Chi et al., 2020). To encode those various relationships between places, one can construct a multiplex network (Wasserman and Faust, 1994, Kivelä et al., 2014, Aleta and Moreno, 2019), in which nodes can be connected to each other via more than one type of relationship. In the example above, a multiplex network has multiple “layers”, each of which encodes a specific economic, historical, cultural, political, or communication relationships between countries. There has been little empirical examination of the relationships between multiple layers of international relationships, apart from Belyi et al. (2017) and network research on migration and trade (Sgrignoli et al., 2015, Fagiolo and Mastrorillo, 2014).

Multiplex networks can also facilitate examination of multiple types of international migration. In this case, different layers in a multiplex network encode different types of migration. Recent data sets provide bilateral migrant stock and migration flow estimates that are stratified by migrants’ attributes, including age (UN DESA, 2019, Brücker et al., 2013), gender (Özden et al., 2011, Abel, 2018), and educational attainment (Brücker et al., 2013, Docquier et al., 2009).

With advancements in migration data and network methodology, a multilayer network approach can provide both a theoretical framework and methodology for rigorously studying multiple socio-economic relationships and/or multiple types of migration between world countries.
Research Challenges

We outline several major research challenges for network analysis of migration networks. This emerging research area is in its early stages, and most studies have been concerned with the general applicability of network techniques to migration networks.

Most prior research on migration networks has employed standard techniques and diagnostics from network analysis. However, migration networks are neither purely spatial nor purely social, and it is important to develop new techniques and diagnostics that explicitly consider the interplay between spatial and social connectivity that underlies migration networks. Examples of research that advance methodologies at the intersection of spatial and social networks, and which may thus help advance research on migration networks, include Backstrom et al. (2010), Expert et al. (2011), Sarzynska et al. (2016), and Feng and Porter (2019).

Research on migration networks has also tended to be either atheoretical or to test propositions from prior migration theories, thereby missing an opportunity to develop new theoretical propositions about the roles of migration networks in perpetuating, generating, or alleviating global inequalities in mobility. For example, research on interpersonal networks has explored the conditions under which ethnic migrant networks have beneficial or adverse effects for economic integration of migrants (Portes, 1998, Martén et al., 2019).

Finally, to establish policy relevance and impact, network-based research on international migration should target research questions of societal importance. One example of policy-relevant work is (Bansak et al., 2018), which employed data-driven matching algorithms to assign refugees to jobs, thereby improving refugee integration.

Conclusions

For many decades, migration theories (Hägerstrand, 1957, Kritz and Zlotnik, 1992, Zlotnik, 1992, Mabogunje, 1970, Salt, 1989, Fawcett, 1989) developed the intuition that movements do not occur between independent origin–destination pairs as an automatic response to economic or other bilateral factors, but instead take place between a “network” of specific places that are already involved in a system of close relationships. However, such research lacked the formal language and techniques to systematically encode migration connections between places in a
network and study them as such. Over the last decade, the formalism and techniques from network analysis have been applied to international migration, yielding several insightful contributions. For example, the long-lasting problem of defining boundaries of international migration systems has been examined using algorithmic approaches for community detection. Additionally, the network structure and dynamics of world migration connections have been articulated in detail, revealing heterogeneities in migration opportunities.

Theory-driven and problem-driven investigations that foster public debate and inform evidence-based policy should help guide future research. It will be useful for network and migration research to leverage multiplex social and spatial networks, statistical network models, and rich disaggregated data sources to deliver an insightful understanding of real-world mobility. Achieving those targets requires interdisciplinary collaborations across many topics, including migration studies, spatial and social network science, computational social science, digital technologies, machine learning, and mathematics.

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