CHAPTER 12

NETWORK-BASED APPROACHES FOR STUDYING MIGRATIONS

António Fonseca
Information Sciences, Technologies and Architecture Research Center, Iscte

Jorge Louçã
Information Sciences, Technologies and Architecture Research Center, Iscte

Abstract

Recently the United Nations released an updated version of its Global Migration Dataset (UNHCR, 2017). We applied network science methods in order to uncover structural patterns within global migration flows observed in these data. Results revealed strong patterns in global migration, resulting from geographical and cultural constraints. Specifically, the Louvain community detection algorithm aggregated countries according with their linguistic, political, and economic affinities. Additionally, the Infomap community detection algorithm explored the distance and geography factors influencing migration flows. Both results weighted flow dynamics over a migration dataset related to the period from 1995 to 2017.

Keywords: refugees, global flows, algorithms network science

Introduction

Network science represents relations between objects within graphs, including a diversity of object properties and attributes, and allowing depicting the topology of these relations. The study of networks has emerged in a diversity of disciplines, as a way of analysing complex relational data, predominantly in Social Sciences. In network science, community structures emerge and reveal groups of nodes strongly interconnected such that we admit the existence of a set of similar characteristics between members of the group, interaction within the group, and some kind of collective sense of unit. The general definition of community, supporting community detection algorithms, is based on the principle that pairs of nodes are more likely to be connected if they belong to the same group/community, and less likely to be connected if they don't. Communities can also be revealed by selecting groups of nodes sharing common paths when assuming random hopping movement between nodes in the network (Fortunato, 2010).

Network science can be particularly useful for studying social dynamics, such as migration phenomena. Until recently, network science has not been used for characterising migration (Bilecen et al., 2018). This chapter contributes to overcome this drawback by presenting a quantitative study applying network science to migration data. The study is based on the Global Migration Dataset provided by United Nations (2917) and aims at characterising the structure of migration flows at global level.

Data

On December 2017 the Department of Economic and Social Affairs of the United Nations Secretariat (UNHCR) released a global migration dataset named *Trends in International Migrant Stock* (UNHCR, 2017). This dataset, as many others on migration, is based on estimates. Mostly international migration flow data are poor. Therefore, is reasonable to assume that little is known about the annual flow of people between the circa 250 countries of the world (Dennett, A., 2016). Except for some developed countries, most of the countries do not provide reliable data about movements of populations. However, it's remarkable that the UNHCR dataset includes at least one data source for 92% of 232 countries, covering 93% of the world estimated migrant population. The dataset doesn't quantify the flows of migrants between countries. Instead, it gives snapshots of migrant population (foreign born, foreign citizens, refugees) at midterm year of a five-year interval, between 1995 and 2015, plus 2017, by destination and country of origin.

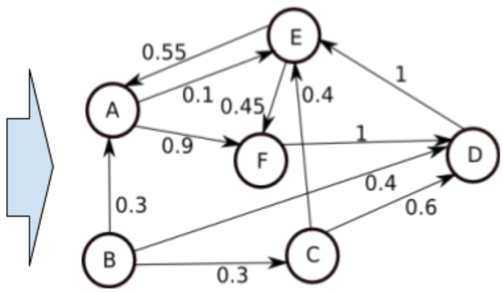
Even if the dataset isn't providing the actual flow of people between countries and regions of the world, it does however realistically depict the result of complex flows of people within the planet. People from distinct origins, as they settle in each country, determine the diversity of migrant populations.

Methods

Based on UNHCR's *Trends in International Migrant Stock* dataset, in which we have the total estimated population from each country living in another country, we defined a graph representing the probability for someone living in a given country to have moved from a different country:

Figure 1 – Example of a matrix of estimated population from each country living in another country, converted into a probability directed graph

0	Finland	France	French Guiana	French Polynesia	Gabon	Gambia	Georgia	Germany
Finland	0	2917	0	1	13	765	79	8246
France	3829	0	0	0	19780	1907	7584	233627
French Guiana	0	20934	0	0	0	0	0	0
French Polynesia	0	20918	0	0	0	0	0	360
Gabon	0	10403	0	0	0	0	0	57
Gambia	0	0	0	0	0	0	0	0
Georgia	0	0	0	0	0	0	0	1515
Germany	16290	145806	0	0	522	4419	22884	0
Ghana	0	216	0	0	0	36	0	0
Gibraltar	0	0	0	0	0	0	0	0
Greece	771	6695	0	10	8	50	83388	114343
Greenland	13	14	0	0	0	0	0	58
Grenada	0	0	0	0	0	0	0	0
Guadeloupe	0	55739	1191	0	0	0	0	314
Guam	0	0	0	0	0	0	0	0
Guatemala	0	258	20	0	0	0	0	640
Guinea	0	6459	0	0	0	3186	0	3335
Guinea-Bissau	0	110	0	0	0	1495	0	0
Guyana	0	0	0	0	0	0	0	0



Being M_{ij} the matrix of citizens from country i living in country j in the middle year of 5 years intervals, the probability that some citizen of country i will emigrate to country j in this 5-year interval is given by:

$$P(\text{emigrate}_{ij}) = M_{ij} / \sum_i M_{ij} \quad (1)$$

According with Dennett (2016), the measurement of the net flow of migrants should consider the number of migrants that already lived abroad in the destination countries by the beginning of the interval, the number that returned, the number of deceased, the number that transited, the number that were naturalised, and so on. However, for the general purpose of measuring interaction at global level, we claim that the value delivered by equation (1) is a good metric, since it provides the probability of interaction between two given countries within some time interval.

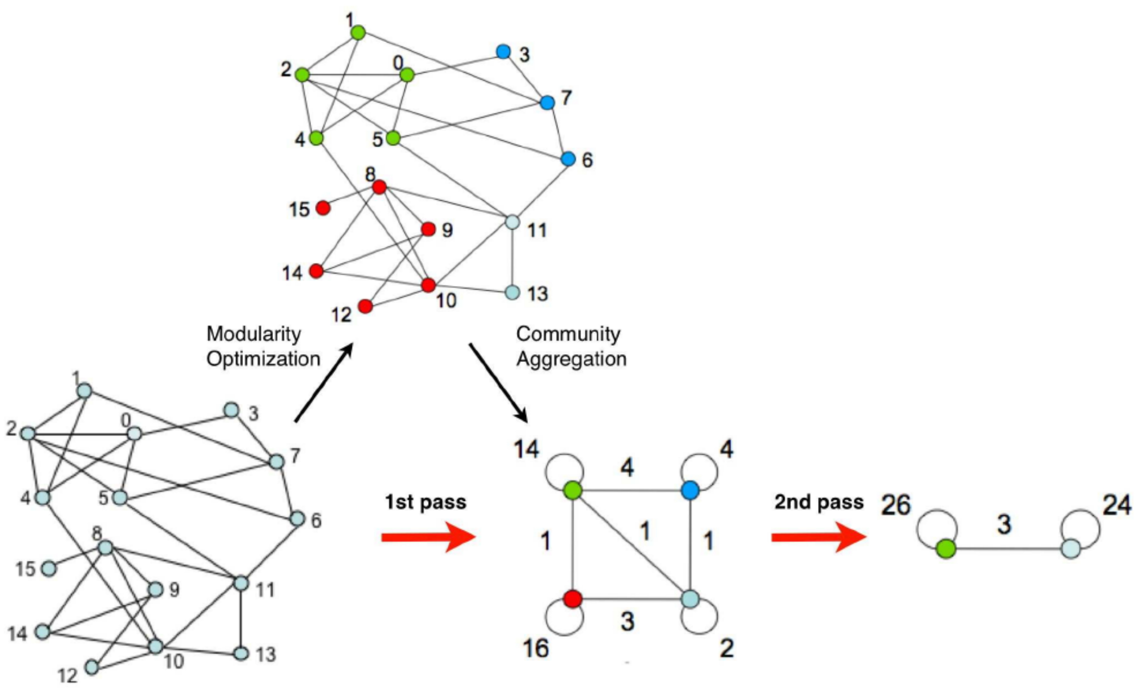
Having represented the migration interaction network as a graph, as depicted in Fig.1, we applied two distinct community detection algorithms in order to detect migration communities at global scale. Firstly, the Louvain algorithm (Blondel et al, 2008) provides community detection supported on the maximisation of a measure of modularity of the network. The interaction network is partitioned into a set C = {c_1, c_2… c_n} of communities, in which each node i is attributed to one, and only one, community $c_i \in C$ of countries. The modularity measure of the network is defined as:

$$Q\ (C) = \sum_{ij} [\ M_{ij} / M - (d_i\ d_j) / M^2\ ]\ \delta(c_i,c_j) \qquad (2)$$

were $M = \sum_{ij} M_{ij}$ is the sum of all migrants globally, $d_i = \sum_j M_{ij}$ and $d_j = \sum_i M_{ij}$ represent the number of emigrants and immigrants of each country, and δ is the Kronecker delta function. The Q measure quantifies the quality of the partition of the network, since the sum of inter-node weights is greater in communities with lesser outside connecting nodes, i.e. with lesser outside weighted degree.

The Louvain algorithm ingeniously aggregates nodes in the network, according to a iterative process depicted in Fig.2, in order to generate a partition C of the network maximising Q. Each pass is made of two phases: one where modularity is optimised by allowing only local changes of communities; another one where the communities are aggregated in order to build a new network. The passes are repeated iteratively until no increase of modularity is possible (Blondel et al, 2008). Modularity Q is thus a way of quantifying the interdependence between communities of countries when exchanging migrants.

Figure 2 – Visualisation of the steps the Louvain algorithm.



The second community detection algorithm used for detecting migration communities at global scale is the Infomap algorithm proposed by Rosvall and Bergstrom (2008). This algorithm processes data compression for community identification, by optimising a quality function specified for weighted and directed networks, called the Map Equation. This function depends on the probability that a random walker, in our case a person that randomly migrates between countries with the probabilities computed using equation (1), either stays within a community, or jumps between communities. The Infomap algorithm is implemented with a growing binary string that maps the trajectory of the walker (in our case, the migrant), concatenating code-blocks representing each country or community as they are visited. The function to be optimised, the Map Equation, indicates the length of the average string representing a walking on the partition C of the network:

$$L(C) = q\,H(Q) + \sum_i p_i\,H(P_i) \qquad (3)$$

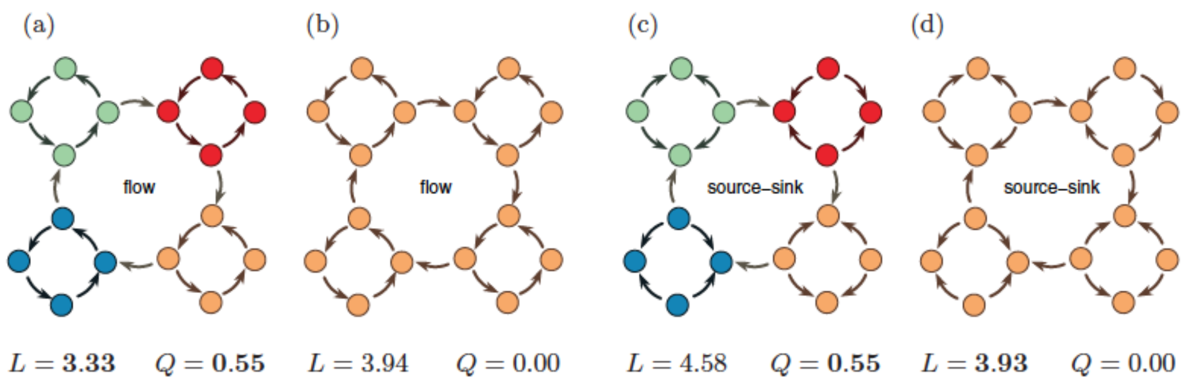
where H(Q) is the minimum code-length describing an average walk between communities, $H(P_i)$ is the minimum code-length depicting an average walk inside a community c_i, q is the probability of jumping between communities, and p_i is the probability of jumping inside a community c_i.

The core of the Infomap algorithm follows closely the Louvain method: neighbouring nodes are joined into modules, which are subsequently joined into super-modules, and so on. Firstly, each node is assigned to its own module. Then, in random sequential order, each node is moved to the neighbouring module resulting in the largest decrease of the map equation. If no move results in a decrease of the map equation, the node is kept in its original module. The procedure is repeated, each time in a new random sequential order, until no move generates a decrease of the map equation. This way, the network is rebuilt, where modules in previous level compose nodes in the actual level. This hierarchical rebuilding of the network is repeated until the map equation cannot be reduced further.

Both Louvain and Infomap algorithms return a partition of the network representing its community structure. However, we are looking forward to map migration flows, which is different from just assign individuals to some static communities. Let's consider the example in Fig.3, comparing two directed networks when the direction of flow is changed between some nodes. In each case both L(C) and Q(C) are calculated.

Following Rosvall et al. (2009), we seek to minimize L(C) and maximize Q(C) in each algorithm, so that partition (a) is chosen by both algorithms in the case of the 'flow' network, and partitions (c) and (d) are chosen in the case of the 'source-sink' network, as follows:

Figure 3 – Comparison between two directed networks when the direction of flow is changed between some nodes



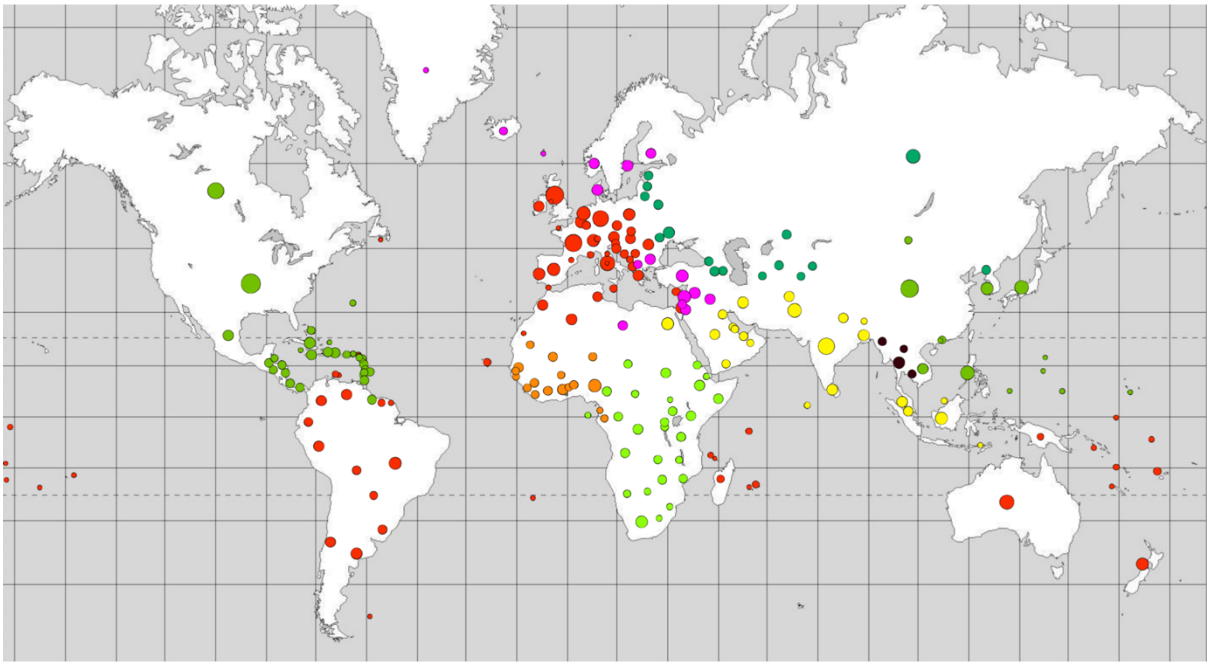
According to Rosvall et al. (2009), Infomap focus on system behaviour once the network has been formed, whereas the Louvain method is more focused on the network topology and its formation process. Both algorithms partition the network into four modules. In the (c) and (d) cases of source-sink network, as any random walker will not walk much more than a single step between nodes, the whole network is considered by the Infomap algorithm as a single module. Otherwise, from a flow-based perspective, (cases (a) and (b)), the two networks are diverse.

Results

Using the Louvain algorithm

The result of applying both algorithms to the UN dataset is the partition of the set including 232 countries into different communities (see details in Annex A). Fig.4 illustrates an example of partitions for 2017, using the Louvain algorithm.

Figure 4 – Countries grouped in the 8 communities represented by different colours and detected with the Louvain algorithm for the year 2017. The size of the circles is proportional to the migrant population.



Eight stable communities emerged from applying the Louvain algorithm, identifying different types of global migrations in data from 1990 to 2017:

Table 1 – Communities uncovered by the Louvain algorithm

Id	Community
1	Europe, North Africa, South America, Indic Ocean and Oceania
2	North and Central America, Caribbean and East Asia
3	Central, Eastern and Southern Africa
4	Southern Asia and the Arabian Peninsula
5	West Africa
6	Soviet Bloc
7	Scandinavia and Middle East
8	Thailand, Cambodia, Laos and Myanmar

Each community mentioned in Table 1 can be enlightened using the main arguments found on literature for explaining migration flows, as follows.

Community 1 is geographically related to the European sixteenth century expansion, with the exceptions of Sub-Saharan Africa and North and Central America. Before 2010 some countries belonging to the British Commonwealth appear grouped in a different independent block (see Annex A). However, after that year all countries involved in European expansion, except for Sub-Saharan Africa and Northern and Central America which constitute groups by their own, emerge as a single group of countries were the exchange of population is more intense.

Community 2 includes Northern America, Central America and the Caribbean and its migratory exchange with East Asia. There are US migrants in Australia, and European migrants in the US. These were the first immigrants in the New World, but more recently a large share of population exchange flowing into the US and Canada, comes from Mexico, Central America, and the Caribbean, with an extension to the other side of the Pacific were the Philippines have North America as its primary migratory destination. China is a vast country with major internal migration, but has also major migratory flows to North America, as well as to Hong Kong and Taiwan. This community is in line with the Castles (2013) explanation of US military presence in Korea, Vietnam and other Asian countries forging transnational links. Vietnam but also South Korea experienced long-term emigration to the USA after the Korean war. Japan has experienced considerable labour immigration since the mid 1980s and many migrants are *Nikkeijin*: descendants of past Japanese emigrants now admitted as labour migrants.

Community 3 represents Central, Eastern and Southern part of the Africa continent. From 1995 until 2010 the algorithm divides this large community into two distinct sub-communities grouping apart the Southernmost countries. Post-apartheid South Africa is the economic powerhouse of sub-Saharan Africa, drawing migrants from all over the continent, although primarily from the Southern Africa region. The bulk of African migrants move within the continent. Also, according to the UNHCR data, 'people in refugee-like situations' are here 14% of international migrants. Although this is a higher proportion than in other world regions, this means that still about 86 percent of international migration are not primarily refugees. Declining levels of conflict from 1990 led to a decrease in refugee migration in some parts of Africa. The number of refugees recorded by the UNHCR has declined from 6.8 million in 1995 to 2.4 million in 2010 (Castles 2013).

Community 4 concerns migration within Southern Asia, the Arabian Peninsula and Egypt, Malaysia and Indonesia.

All countries in the region experience both significant immigration and emigration, three of the top ten migration corridors include Asian countries: Bangladesh-India (3.5 million in 2005), India-United Arab Emirates (2.2 million) and Afghanistan-Iran (1.6 million). The huge construction projects in the Gulf oil countries caused mass recruitment of contract workers first from India and Pakistan, then from Indonesia and later from Bangladesh and Sri Lanka.

Community 5 is related to migration within West Africa. Data represented in Annex A shows that this migration community has been remarkably consistent and stable. Despite the relatively high incidence of conflict-related migration, economic migration predominates in Africa. Intra-regional mobility in West Africa has been dominated by a movement from the landlocked countries of the Sahel West Africa to the relatively more prosperous plantations, mines and cities of the Coastal West Africa. There has also been considerable transversal international migration within the coastal zone of mostly seasonal workers to the relatively wealthy economies of Côte d'Ivoire and Nigeria.

In what concerns Community 6, there is a very stable group of countries that exchanged populations along the three past decades. These countries are former Soviet Republics, with the notable exception of North Korea. After the II World War legal migration was restricted in the Eastern Bloc, it was in most cases only possible to reunite families or to allow members of minority ethnic groups to return to their homelands. With the fall of the Berlin Wall in 1989, a wave of liberalisation revolutions, sometimes called "Autumn of Nations" swept across the Bloc. Millions of people moved within and between the successor states of the former Soviet Union and Russia thus became a major country of immigration, with around 2 million ethnic Russians leaving or being displaced from the Baltic States, Ukraine, and other parts of the former Soviet Union. Although there were also migrant flows into Europe, and particularly to Israel, and to the rest of the globe, Russia's political and cultural influence maintained the former bloc united. There were also refugees from various conflicts and some 700.000 ecological displaced people, mainly from areas affected by the 1986 Chernobyl nuclear disaster.

Community 7, similarly to community 3, was composed before 2010 by two separate groups. One represents the Scandinavian Countries, Greenland, Bulgaria, and Turkey that before 2015 were included in the European community 1 referred above. The other represents the Arab countries of the middle East and Libya.

After 2015, the opening of Scandinavian countries like Sweden and Finland to refugees from the war conflicts involving nations with Islamic majorities, linked these two communities. In Middle East, current refugee issues remain centred on Palestinians and Syrians. Turkey and Egypt have evolved into central crossroads for refugee flows.

Community 8 is constituted by countries united by migrant flows to Thailand, mainly from Myanmar (80 percent in 2009). Thailand was before 1990 a typical emigration country. Fast economic growth in the 1990s lead to a transition. Developments in construction, as well as agricultural and manufacturing jobs, attract workers from Myanmar, Cambodia and Laos. According to Harkin et al. (2017), an estimated 3.25 million migrants were employed in Thailand in 2017, i.e., roughly 8.5 percent of the country's labour force. Historically, migrants crossed into Thailand through irregular channels, either on their own or through informal brokers. Many of the Burmese are also fleeing violence in their homeland and it is hard to distinguish clearly between economic migrants and refugees (Bylander, 2019).

Using the Infomap algorithm

The second phase for identifying communities concerned applying the Infomap algorithm to the UNHCR data. A different and more detailed set of communities was obtained through this method. In fact, twenty different communities emerged from the global migration dataset, representing a diversity of migration flows along the 1990–2017 time interval (see annex A). These communities are represented in the following table and its identification is straightforward:

Table 2 – Communities uncovered by the Infomap algorithm

Id	Community	Size
1	Developed Countries	118
2	Soviet Bloc	15
3	Middle East Arabian Countries	12
4	South Asia and Indian Subcontinent	9
5	Southern Africa	9

6	Central Africa	9
7	Sub Saharan Central and East Africa	8
8	Western West Africa	9
9	Eastern West Africa	8
10	Algeria and Western Sahara	2
11	Thailand, Cambodia, Laos and Myanmar	4
12	Malaysia and Singapore	2
13	Indonesia and Timor Leste	2
14	French Caribbean	4
15	British and US Caribbean	5
16	Comoros, Mayotte and Reunion	3
17	Micronesia Archipelago, Guam and Palau	4
18	French Polynesia, Vanuatu, New Caledonia, Wallis and Futuna	4
19	American Samoa and Samoa	2
20	Tuvalu, Kiribati and Nauru	3

Our interpretation of the partitions above is that two main factors determine global migrations. The first one has to do with cultural aspects. This is remarkable in the first half of the Infomap community list and mostly evident in the Louvain community list. On the one hand there is a large group, including most of the world population, mostly with Western influence. On the other, there are a diversity of groups with Soviet, Arab, Indian, or Pakistan and Bangladesh influence.

The second factor of segmentation relates to geography. Although the first community in the Infomap list is dispersed over the globe (i.e., "Developed Countries"), all the other communities are quite geographically localised.

In the second half of the list this proximity factor is apparent - i.e., different small island nations grouped not only by their cultural affinity but primarily by its geographic proximity.

Discussion and conclusion

The network analysis of global migration here performed, applying community detection, suggests alternative factors beyond the usual economic motives that primarily explain migratory flow magnitude. The communities detected showed both geographic proximity and socio-cultural affinity shaping migratory trajectories. Our methodology uncovered borders beyond normal borders, which constitute additional walls disconnecting world societies.

The Louvain algorithm presented a specific topology of the migration flow network, aggregating countries according with their cultural, linguistic, political, and most of all, economic affinities. Moreover, the Infomap algorithm allowed to explore the actual influence of distance and geography in determining population movements. Both results weighting flow dynamics over the migratory stock network of 1990-2017 confirm previous discussions on migration. One of the most pervasive empirical regularities in regional science is that any form of spatial interaction (migration, commuting, trade, information exchange, etc.) has the property of flows being positively related to stocks, whichever way measured, and inversely related to distance (Poot, 2016). Models like these are called ‘Gravity Models’ because they resemble Newton’s 1687 law of gravity. Gravity-like properties of internal migration flows had been admitted long time ago by Ravenstein (1885) and can now be supported by analysing the recently available datasets.

The consistency between the communities found by both methods and the explanation for migration flows generally found in literature, validate the use of these approaches for future research on migration phenomena. A planned extension of our research using Social Network Analysis methodologies may, in the future, reveal interesting properties associated with migration. Social network measures, such as centralities or spectral measures, might be correlated with further data as linguistic distance, immigration policy, geographic distance, colonial relationships, gross domestic product per capita, average years of schooling, destination wages, relative population size, social welfare spending, shared land border, young population share, existing migration stocks, total commercial trade, cultural similarity, illiteracy rates, political stability, inequality ratio, source poverty rate, common currency or common legislation.

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Annex A

Louvain Communities

Country	1990	1995	2000	2005	2010	2015	2017
Albania	1	1	1	1	1	1	1
Algeria	1	1	1	1	1	1	1
American Samoa	2	3	3	3	3	1	1
Andorra	1	1	1	1	1	1	1
Argentina	1	1	1	1	1	1	1
Aruba	2	2	2	1	1	1	1
Australia	2	3	3	3	3	1	1
Austria	1	1	1	1	1	1	1
Belgium	1	1	1	1	1	1	1
Bolivia (Plurinational State of)	1	1	1	1	1	1	1
Bosnia and Herzegovina	1	1	1	1	1	1	1
Brazil	1	1	1	1	1	1	1
Cabo Verde	1	1	1	1	1	1	1
Caribbean Netherlands	2	2	2	2	1	1	1
Channel Islands	2	3	3	3	3	1	1
Chile	1	1	1	1	1	1	1
Colombia	1	2	2	1	1	1	1
Comoros	1	1	1	1	1	1	1
Cook Islands	2	3	3	3	3	1	1
Croatia	1	1	1	1	1	1	1
Curaçao	1	1	1	1	1	1	1
Cyprus	2	3	3	3	3	1	1

Czechia	1	1	1	1	1	1	1
Ecuador	2	2	2	1	1	1	1
Falkland Islands (Malvinas)	2	3	3	3	3	1	1
Fiji	2	3	3	3	3	1	1
France	1	1	1	1	1	1	1
French Guiana	1	1	1	1	1	1	1
French Polynesia	1	1	1	1	1	1	1
Germany	1	1	1	1	1	1	1
Gibraltar	2	3	3	3	3	1	1
Greece	1	1	1	1	1	1	1
Guadeloupe	1	1	1	1	1	1	1
Holy See	1	1	1	1	1	1	1
Hungary	1	1	1	1	1	1	1
Ireland	2	3	3	3	3	1	1
Isle of Man	2	3	3	3	3	1	1
Israel	6	1	6	1	1	1	1
Italy	1	1	1	1	1	1	1
Kiribati	2	3	3	3	3	1	1
Liechtenstein	1	1	1	1	1	1	1
Luxembourg	1	1	1	1	1	1	1
Madagascar	1	1	1	1	1	1	1
Malta	2	3	3	3	3	1	1
Martinique	1	1	1	1	1	1	1
Mauritius	1	1	1	3	3	1	1
Mayotte	1	1	1	1	1	1	1
Monaco	1	1	1	1	1	1	1
Montenegro	1	1	1	1	1	1	1

Morocco	1	1	1	1	1	1	1
Nauru	2	3	3	3	3	1	1
Netherlands	1	1	1	1	1	1	1
New Caledonia	1	1	1	1	1	1	1
New Zealand	2	3	3	3	3	1	1
Niue	2	3	3	3	3	1	1
Papua New Guinea	2	3	3	3	3	1	1
Paraguay	1	1	1	1	1	1	1
Peru	2	2	2	1	1	1	1
Poland	6	1	1	1	1	1	1
Portugal	1	1	1	1	1	1	1
Réunion	1	1	1	1	1	1	1
Romania	1	1	1	1	1	1	1
Saint Helena	2	3	3	3	3	1	1
Saint Pierre and Miquelon	1	1	1	1	1	1	1
Samoa	2	3	3	3	3	1	1
San Marino	1	1	1	1	1	1	1
Serbia	1	1	1	1	1	1	1
Seychelles	2	2	3	3	1	1	1
Sint Maarten (Dutch part)	1	1	1	1	1	1	1
Slovakia	1	1	1	1	1	1	1
Slovenia	1	1	1	1	1	1	1
Solomon Islands	2	3	3	3	3	1	1
Spain	1	1	1	1	1	1	1
Suriname	1	1	1	1	1	1	1
Switzerland	1	1	1	1	1	1	1
Tokelau	2	3	3	3	3	1	1

Tonga	2	3	3	3	3	1	1
Tunisia	1	1	1	1	1	1	1
Tuvalu	2	3	3	3	3	1	1
United Kingdom	2	3	3	3	3	1	1
Uruguay	1	1	1	1	1	1	1
Vanuatu	1	1	1	1	1	1	1
Venezuela (Bolivarian Republic of)	1	2	2	1	1	1	1
Wallis and Futuna Islands	1	1	1	1	1	1	1
Western Sahara	1	1	1	1	1	1	1
Anguilla	2	2	2	2	2	2	2
Antigua and Barbuda	2	2	2	2	2	2	2
Bahamas	2	2	2	2	2	2	2
Barbados	2	2	2	2	2	2	2
Belize	2	2	2	2	2	2	2
Bermuda	2	3	2	2	2	2	2
British Virgin Islands	2	2	2	2	2	2	2
Canada	2	2	2	2	2	2	2
Cayman Islands	2	2	2	2	2	2	2
China	2	2	2	2	2	2	2
China Hong Kong SAR	2	2	2	2	2	2	2
China Macao SAR	2	2	2	2	2	2	2
Costa Rica	2	2	2	2	2	2	2
Cuba	2	2	2	2	2	2	2
Dominica	2	2	2	2	2	2	2
Dominican Republic	2	2	2	2	2	2	2
El Salvador	2	2	2	2	2	2	2
Grenada	2	2	2	2	2	2	2

Guam	2	2	2	2	2	2	2
Guatemala	2	2	2	2	2	2	2
Guyana	2	2	2	2	2	2	2
Haiti	2	2	2	2	2	2	2
Honduras	2	2	2	2	2	2	2
Jamaica	2	2	2	2	2	2	2
Japan	2	2	2	2	2	2	2
Marshall Islands	2	2	2	2	2	2	2
Mexico	2	2	2	2	2	2	2
Micronesia (Fed. States of)	2	2	2	2	2	2	2
Mongolia	6	6	6	6	6	2	2
Montserrat	2	2	3	3	2	2	2
Nicaragua	2	2	2	2	2	2	2
Northern Mariana Islands	2	2	2	2	2	2	2
Palau	2	2	2	2	2	2	2
Panama	2	2	2	2	2	2	2
Philippines	2	2	2	2	2	2	2
Puerto Rico	2	2	2	2	2	2	2
Republic of Korea	2	2	2	2	2	2	2
Saint Kitts and Nevis	2	2	2	2	2	2	2
Saint Lucia	2	2	2	2	2	2	2
Saint Vincent and the Grenadines	2	2	2	2	2	2	2
Trinidad and Tobago	2	2	2	2	2	2	2
Turks and Caicos Islands	2	2	2	2	2	2	2
United States of America	2	2	2	2	2	2	2
United States Virgin Islands	2	2	2	2	2	2	2
Viet Nam	2	2	2	2	2	2	2

Angola	3	7	7	7	7	3	3
Botswana	3	3	3	3	3	3	3
Burundi	3	7	7	7	7	3	3
Cameroon	5	5	5	5	7	3	3
Central African Republic	3	7	7	7	7	3	3
Chad	3	7	5	7	7	3	3
Congo	3	7	7	7	7	3	3
Democratic Republic of the Congo	3	7	7	7	7	3	3
Djibouti	3	7	7	7	7	3	3
Eritrea	3	7	7	7	7	3	3
Ethiopia	3	7	7	7	7	3	3
Kenya	3	7	7	7	7	3	3
Lesotho	3	3	3	3	3	3	3
Malawi	3	3	3	3	3	3	3
Mozambique	3	3	3	3	3	3	3
Namibia	3	3	7	3	3	3	3
Rwanda	3	7	7	7	7	3	3
Sao Tome and Principe	1	1	1	1	1	3	3
Somalia	3	7	7	7	7	3	3
South Africa	3	3	3	3	3	3	3
South Sudan	3	7	7	7	7	3	3
Sudan	3	7	7	7	7	3	3
Swaziland	3	3	3	3	3	3	3
Uganda	3	7	7	7	7	3	3
United Republic of Tanzania	3	7	7	7	7	3	3
Zambia	3	7	7	7	3	3	3
Zimbabwe	3	3	3	3	3	3	3

Afghanistan	4	4	4	4	4	4	4
Bahrain	4	4	4	4	4	4	4
Bangladesh	4	4	4	4	4	4	4
Bhutan	4	4	4	4	4	4	4
Brunei Darussalam	2	4	4	4	4	4	4
Egypt	4	4	4	4	4	4	4
India	4	4	4	4	4	4	4
Indonesia	4	4	4	4	4	4	4
Iran (Islamic Republic of)	4	4	4	4	4	4	4
Kuwait	4	4	4	4	4	4	4
Malaysia	2	4	4	4	4	4	4
Maldives	4	4	4	4	4	4	4
Nepal	4	4	4	4	4	4	4
Oman	4	4	4	4	4	4	4
Pakistan	4	4	4	4	4	4	4
Qatar	4	4	4	4	4	4	4
Saudi Arabia	4	4	4	4	4	4	4
Singapore	2	4	4	4	4	4	4
Sri Lanka	4	4	4	4	4	4	4
Timor-Leste	2	4	4	4	4	4	4
United Arab Emirates	4	4	4	4	4	4	4
Yemen	4	4	4	4	4	4	4
Benin	5	5	5	5	5	5	5
Burkina Faso	5	5	5	5	5	5	5
Côte d'Ivoire	5	5	5	5	5	5	5
Equatorial Guinea	5	5	5	5	5	5	5
Gabon	5	5	5	5	5	5	5

Gambia	5	5	5	5	5	5	5
Ghana	5	5	5	5	5	5	5
Guinea	5	5	5	5	5	5	5
Guinea-Bissau	5	5	5	5	5	5	5
Liberia	5	5	5	5	5	5	5
Mali	5	5	5	5	5	5	5
Mauritania	5	5	5	5	5	5	5
Niger	5	5	5	5	5	5	5
Nigeria	5	5	5	5	5	5	5
Senegal	5	5	5	5	5	5	5
Sierra Leone	5	5	5	5	5	5	5
Togo	5	5	5	5	5	5	5
Armenia	6	6	6	6	6	6	6
Azerbaijan	6	6	6	6	6	6	6
Belarus	6	6	6	6	6	6	6
Dem. People's Republic of Korea	2	6	6	6	6	6	6
Estonia	6	6	6	6	6	6	6
Georgia	6	6	6	6	6	6	6
Kazakhstan	6	6	6	6	6	6	6
Kyrgyzstan	6	6	6	6	6	6	6
Latvia	6	6	6	6	6	6	6
Lithuania	6	6	6	6	6	6	6
Republic of Moldova	6	6	6	6	6	6	6
Russian Federation	6	6	6	6	6	6	6
Tajikistan	6	6	6	6	6	6	6
Turkmenistan	6	6	6	6	6	6	6
Ukraine	6	6	6	6	6	6	6

Uzbekistan	6	6	6	6	6	6	6
Bulgaria	1	1	1	1	1	7	7
Denmark	1	1	1	1	1	1	7
Faeroe Islands	1	1	1	1	1	1	7
Finland	1	1	1	1	1	1	7
Greenland	1	1	1	1	1	1	7
Iceland	1	1	1	1	1	1	7
Iraq	4	4	4	9	9	7	7
Jordan	7	4	4	9	9	7	7
Lebanon	7	4	4	9	9	7	7
Libya	7	4	4	9	9	7	7
Norway	1	1	1	1	1	1	7
State of Palestine	7	4	4	9	9	7	7
Sweden	1	1	1	1	1	1	7
Syrian Arab Republic	7	4	4	9	9	7	7
TFYR Macedonia	1	1	1	1	1	7	7
Turkey	1	1	1	1	1	7	7
Cambodia	2	2	8	8	8	8	8
Lao People's Democratic Republic	2	4	8	8	8	8	8
Myanmar	4	4	8	8	8	8	8
Thailand	2	4	8	8	8	8	8

Infomap Communities

Country	1990	1995	2000	2005	2010	2015	2017
Afghanistan	15	15	15	15	1	15	1
Albania	1	1	1	1	1	1	1
Andorra	1	1	1	1	1	1	1
Argentina	1	1	1	1	1	1	1
Australia	1	1	1	1	1	1	1
Austria	1	1	1	1	1	1	1
Bahamas	1	1	1	1	1	1	1
Barbados	1	1	1	1	1	1	1
Belgium	1	1	1	1	1	1	1
Belize	1	1	1	1	1	1	1
Bermuda	1	1	1	1	1	1	1
Bolivia (Plurinational State of)	1	1	1	1	1	1	1
Bosnia and Herzegovina	1	1	1	1	1	1	1
Botswana	7	7	7	7	7	7	1
Brazil	1	1	1	1	1	1	1
Bulgaria	1	1	1	1	1	1	1
Cabo Verde	1	1	1	1	1	1	1
Canada	1	1	1	1	1	1	1
Cayman Islands	1	1	1	1	1	1	1
Channel Islands	1	1	1	1	1	1	1
Chile	1	1	1	1	1	1	1
China	1	1	1	1	1	1	1
China Hong Kong SAR	1	1	1	1	1	1	1
China Macao SAR	1	1	1	1	1	1	1

Colombia	1	1	1	1	1	1	1
Cook Islands	1	1	1	1	1	1	1
Costa Rica	1	1	1	1	1	1	1
Croatia	1	1	1	1	1	1	1
Cuba	1	1	1	1	1	1	1
Cyprus	1	1	1	1	1	1	1
Czechia	1	1	1	1	1	1	1
Denmark	1	1	1	1	1	1	1
Djibouti	12	1	4	12	1	1	1
Dominica	1	1	1	1	1	1	1
Dominican Republic	1	1	1	1	1	1	1
Ecuador	1	1	1	1	1	1	1
El Salvador	1	1	1	1	1	1	1
Faeroe Islands	1	1	1	1	1	1	1
Falkland Islands (Malvinas)	1	1	1	1	1	1	1
Fiji	1	1	1	1	1	1	1
Finland	1	1	1	1	1	1	1
France	1	1	1	1	1	1	1
Germany	1	1	1	1	1	1	1
Gibraltar	1	1	1	1	1	1	1
Greece	1	1	1	1	1	1	1
Greenland	1	1	1	1	1	1	1
Guatemala	1	1	1	1	1	1	1
Guyana	1	1	1	1	1	1	1
Haiti	1	1	1	1	1	1	1
Holy See	1	1	1	1	1	1	1
Honduras	1	1	1	1	1	1	1

Hungary	1	1	1	1	1	1	1
Iceland	1	1	1	1	1	1	1
Iran (Islamic Republic of)	15	15	15	15	1	15	1
Ireland	1	1	1	1	1	1	1
Isle of Man	1	1	1	1	1	1	1
Israel	1	1	1	1	1	1	1
Italy	1	1	1	1	1	1	1
Jamaica	1	1	1	1	1	1	1
Japan	1	1	1	1	1	1	1
Lesotho	7	7	7	7	7	7	1
Liechtenstein	1	1	1	1	1	1	1
Lithuania	2	2	2	2	1	1	1
Luxembourg	1	1	1	1	1	1	1
Madagascar	13	13	13	1	1	1	1
Malawi	7	7	7	7	7	7	1
Malta	1	1	1	1	1	1	1
Marshall Islands	1	1	1	1	1	1	1
Mauritius	1	1	1	1	1	1	1
Mexico	1	1	1	1	1	1	1
Monaco	1	1	1	1	1	1	1
Mongolia	2	2	2	1	1	1	1
Montenegro	1	1	1	1	1	1	1
Montserrat	1	1	1	1	1	1	1
Morocco	1	1	1	1	1	1	1
Mozambique	7	7	7	7	7	7	1
Namibia	7	7	7	7	7	7	1
Netherlands	1	1	1	1	1	1	1

New Zealand	1	1	1	1	1	1	1
Nicaragua	1	1	1	1	1	1	1
Niue	1	1	1	1	1	1	1
Norway	1	1	1	1	1	1	1
Panama	1	1	1	1	1	1	1
Papua New Guinea	1	1	1	1	1	1	1
Paraguay	1	1	1	1	1	1	1
Peru	1	1	1	1	1	1	1
Poland	1	1	1	1	1	1	1
Portugal	1	1	1	1	1	1	1
Puerto Rico	1	1	1	1	1	1	1
Republic of Korea	1	1	1	1	1	1	1
Romania	1	1	1	1	1	1	1
Saint Helena	1	1	1	1	1	1	1
Saint Lucia	6	1	1	1	6	1	1
Saint Pierre and Miquelon	1	1	1	1	1	1	1
Saint Vincent and the Grenadines	1	1	1	1	1	1	1
San Marino	1	1	1	1	1	1	1
Serbia	1	1	1	1	1	1	1
Seychelles	1	1	1	1	1	1	1
Slovakia	1	1	1	1	1	1	1
Slovenia	1	1	1	1	1	1	1
Solomon Islands	1	1	1	1	1	1	1
South Africa	7	7	7	7	7	7	1
Spain	1	1	1	1	1	1	1
Suriname	1	1	1	1	1	1	1
Swaziland	7	7	7	7	7	7	1

Sweden	1	1	1	1	1	1	1
Switzerland	1	1	1	1	1	1	1
TFYR Macedonia	1	1	1	1	1	1	1
Tokelau	1	1	1	1	1	1	1
Tonga	1	1	1	1	1	1	1
Trinidad and Tobago	1	1	1	1	1	1	1
Tunisia	1	1	1	1	1	1	1
Turkey	1	1	1	1	1	1	1
Turks and Caicos Islands	1	1	1	1	1	1	1
Tuvalu	18	1	1	1	1	1	1
United Kingdom	1	1	1	1	1	1	1
United States of America	1	1	1	1	1	1	1
Uruguay	1	1	1	1	1	1	1
Venezuela (Bolivarian Republic of)	1	1	1	1	1	1	1
Viet Nam	1	1	1	1	1	1	1
Zambia	7	7	7	7	7	7	1
Zimbabwe	7	7	7	7	7	7	1
Armenia	2	2	2	2	2	2	2
Azerbaijan	2	2	2	2	2	2	2
Belarus	2	2	2	2	2	2	2
Dem. People's Republic of Korea	2	2	2	2	2	2	2
Estonia	2	2	2	2	2	2	2
Georgia	2	2	2	2	2	2	2
Kazakhstan	2	2	2	2	2	2	2
Kyrgyzstan	2	2	2	2	2	2	2
Latvia	2	2	2	2	2	2	2
Republic of Moldova	2	2	2	2	2	2	2

Russian Federation	2	2	2	2	2	2	2
Tajikistan	2	2	2	2	2	2	2
Turkmenistan	2	2	2	2	2	2	2
Ukraine	2	2	2	2	2	2	2
Uzbekistan	2	2	2	2	2	2	2
Bahrain	3	14	14	3	3	3	3
Bangladesh	14	14	14	3	3	3	3
Bhutan	14	14	14	3	3	3	3
Brunei Darussalam	14	14	14	3	3	3	3
Egypt	3	3	3	3	3	3	3
India	14	14	14	3	3	3	3
Iraq	15	15	15	3	3	3	3
Jordan	3	3	3	3	3	3	3
Kuwait	3	3	3	3	3	3	3
Lebanon	3	3	3	3	3	3	3
Libya	3	3	3	3	3	3	3
Maldives	14	14	14	3	3	3	3
Nepal	14	14	14	3	3	3	3
Oman	3	3	3	3	3	3	3
Pakistan	14	14	14	3	3	3	3
Qatar	3	3	3	3	3	3	3
Saudi Arabia	3	3	3	3	3	3	3
Sri Lanka	14	14	14	3	3	3	3
State of Palestine	3	3	3	3	3	3	3
Syrian Arab Republic	3	3	3	3	3	3	3
United Arab Emirates	3	3	3	3	3	3	3
Yemen	3	3	3	3	3	3	3

Angola	4	4	4	4	4	4	4
Burundi	4	4	4	4	4	4	4
Cameroon	12	4	12	12	12	4	4
Central African Republic	12	4	4	12	12	4	4
Chad	12	4	12	12	12	4	4
Congo	4	4	4	4	4	4	4
Democratic Republic of the Congo	4	4	4	4	4	4	4
Eritrea	12	4	4	12	12	4	4
Ethiopia	12	4	4	12	12	4	4
Kenya	4	4	4	4	4	4	4
Rwanda	4	4	4	4	4	4	4
Sao Tome and Principe	1	1	1	1	1	4	4
Somalia	12	4	4	12	12	4	4
South Sudan	12	4	4	12	12	4	4
Sudan	12	4	4	12	12	4	4
Uganda	4	4	4	4	4	4	4
United Republic of Tanzania	4	4	4	4	4	4	4
Benin	5	5	5	5	5	5	5
Burkina Faso	5	5	5	5	5	5	5
Côte d'Ivoire	5	5	5	5	5	5	5
Equatorial Guinea	12	12	12	5	5	5	5
Gabon	12	12	12	5	5	5	5
Ghana	5	5	5	5	5	5	5
Liberia	12	12	12	12	5	5	5
Mali	5	5	5	5	5	5	5
Niger	5	5	5	5	5	5	5
Nigeria	5	5	5	5	5	5	5

Togo	5	5	5	5	5	5	5
French Guiana	6	6	6	6	6	6	6
Guadeloupe	6	6	6	6	6	6	6
Martinique	6	6	6	6	6	6	6
Sint Maarten (Dutch part)	1	1	1	1	6	6	6
Indonesia	3	3	8	8	8	8	8
Malaysia	17	8	8	8	8	8	8
Singapore	17	8	8	8	8	8	8
Timor-Leste	1	3	8	8	8	8	8
Guam	9	9	9	9	9	9	9
Micronesia (Fed. States of)	9	9	9	9	9	9	9
Northern Mariana Islands	9	9	9	9	9	9	9
Palau	9	9	9	9	9	9	9
Philippines	1	1	1	1	1	1	9
Anguilla	8	1	1	1	10	10	10
Antigua and Barbuda	8	1	1	1	10	10	10
British Virgin Islands	8	1	1	1	10	10	10
Grenada	1	1	1	1	10	10	10
Saint Kitts and Nevis	8	1	1	1	10	10	10
United States Virgin Islands	8	1	1	1	10	10	10
French Polynesia	11	11	11	11	11	11	11
New Caledonia	11	11	11	11	11	11	11
Vanuatu	11	11	11	11	11	11	11
Wallis and Futuna Islands	11	11	11	11	11	11	11
Gambia	12	12	12	12	12	12	12
Guinea	12	12	12	12	5	12	12
Guinea-Bissau	12	12	12	12	12	12	12

Mauritania	12	12	12	12	12	12	12
Senegal	12	12	12	12	12	12	12
Sierra Leone	12	12	12	12	5	12	12
Comoros	13	13	13	13	13	13	13
Mayotte	13	13	13	13	13	13	13
Réunion	13	13	13	13	13	13	13
Aruba	1	1	1	1	1	1	14
Cambodia	1	1	1	14	14	14	14
Caribbean Netherlands	1	1	1	1	1	1	14
Curaçao	1	1	1	1	1	1	14
Lao People's Democratic Republic	1	1	1	14	14	14	14
Myanmar	14	14	1	14	14	14	14
Thailand	1	1	1	14	14	14	14
American Samoa	16	16	16	16	16	16	16
Samoa	16	16	16	16	16	16	16
Algeria	1	1	17	17	17	17	17
Western Sahara	1	1	17	17	17	17	17
Kiribati	18	18	18	18	18	18	18
Nauru	18	18	18	18	18	18	18