# Rumours lead to self-organized migration routes

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#### Abstract

Migrants attempting to reach a safe destination often have to make navigation decisions based on very limited information that is to a large degree sourced from other migrants that have made the journey before. Communication between migrants could therefore be a key factor in determining the dynamics of migration. We study the effect of information transfer on the variability and optimality of migration routes using an agent-based model with explicit representation of geography, resources and the agents' knowledge thereof. We find that unless agents very quickly acquire objective information from the environment, a higher degree of social information exchange leads to less predictable and less optimal migration routes. This indicates that if a high proportion of information is socially received, routes are the result of selforganization rather than optimization. We suggest that similar effects should occur in all situations where individuals have to make complex decisions under limited information but in a social context.

#### Introduction

Next to birth and death, migration is one of the three fundamental processes of demography (Courgeau et al., 2017). Traditionally, theory on migration was largely embedded in the economical tradition and primarily concerned with economically motivated, voluntary migration, employing a topdown, population-level view (Radu, 2008). This appears to be a reasonable approach if certain conditions are met: If migrants are indeed largely looking for material benefits and are in a situation where they can make well-informed, rational decisions and if further transit from the country of origin to the destination provides no major complications, then the actions of individual migrants can be usefully aggregated into population-level flows.

These assumptions do, however, not always hold. First, in many cases considerations beyond economical benefits affect migration decisions. We know, for example, that existing social networks in, as well as knowledge about the target country can play an important role (De Haas, 2010). Second, the migration journey itself can be a challenging and unpredictable factor (Kingsley, 2016), in particular given recent developments in attitude towards migration in Western countries (Ekman, 2018). Migrants often have to travel large distances under severe resource constraints, while having to avoid police and border guards. However, when transiting through a third country, they usually have only limited information about the local conditions (Borkert et al., 2018). Finding a good travel route can therefore be difficult. Consequently in many cases migrants rely heavily on information provided by others that have made the journey before them (Dekker et al., 2018; Borkert et al., 2018). This could lead to a situation where migration depends as much on the dynamics of information transfer and social contacts as it does on material conditions and where interactions between individuals are a crucial part of the system dynamics.

We investigate if and to which degree social interactions and in particular information transfer can affect the establishment of migration routes and the efficiency of individual journeys. We do this with the help of a spatially explicit agent-based model. Agent-based models of migration are nothing new (e.g. Klabunde et al., 2015; Simon et al., 2016). Contrary to previous studies, however, we explicitly distinguish between the objective state of the world and the individuals' knowledge of that state and model in detail how this knowledge is exchanged between agents.

It is important to note that we do not attempt to make quantitative predictions about the real world or even model a specific real-world system. Instead our model is intended as a "proof of causality" that demonstrates how certain micro-processes can result in specific macroscopic patterns (Grimm et al., 2005).

## **MODEL DESCRIPTION**

We model a population of agents migrating through a network of cities and transport links towards a number of targets. Agents start out with no or very little knowledge about the world but can acquire knowledge either from their local environment or by communicating with other agents. Based on the information they have collected, they attempt to find the best path to one of the targets.

While our model is not intended as an accurate representation of a specific real-world scenario we very

parameter	explanation
$p_{kc}$	Prob. of staying in contact with other agents.
$p_{is}$	Prob. of communicating while staying.
$p_{ic}$	Prob. of communicating with contacts.
$  p_t$	Prob. of transferring an item of information.
$p_{fl}$	Prob. of discovering local links when staying.
$p_{fd}$	Prob. of learning about connected locations.
$x_s$	Exploration speed while staying.
$x_m$	Exploration speed while moving.
$e_i$	Communication error.
$c_i$	Convince; change doubt into trust.
$c_u$	Confuse; change trust into doubt.
$c_e$	Convert; change trust into trust.

Table 1: Most important model parameters.

loosely based model structure and parameter values on the situation of Syrian refugees on their way to Europe at the onset of the "refugee crisis" in 2015 (see https://www.southampton.ac.uk/baps/ inventory/data-sources.page).

The source code for the model in Julia (Bezanson et al., 2014) is publicly available at https://github.com/mhinsch/RRGraphs (tag ALife2019).

In the following we will explain each component of the model in more detail (see appendix for the algorithm in pseudo code).

### Environment

The simulated world consists of a random geometric graph (Gilbert, 1961) of 600 cities connected by transport links (see Figure 1). Cities have an inherent quality  $q \sim unif(0, 1)$  that represents how easy it is for migrants to stay in that city. This could include for example frequency of police controls, general safety, or availability of cheap accommodation. In addition, each city has an abstract resource availability (representing how easy it is to acquire food, money, clothes, etc.)  $r \sim unif(0, 1)$ . Transport links have a specific friction  $f \sim unif(0, 1)$  that determines how many resources are required to use them.

In addition to the regular cities there are 6 entry and exit locations, respectively, at the very edges of the simulated world, that represent border crossings. Entries and exits are connected by transport links to the nearest cities. As areas close to borders are usually strongly controlled we assume that these links have a substantially higher friction (unif(0, 10)).

#### Agents

Active agents at all times are either located in a city or transiting between cities. A mean number of 20 agents enter the world in every time step (using a Poisson process) by



Figure 1: Screenshot of the model. Top left: cities (blue) and transport links (green: fast, red: slow). Top right: Transport links, brighter color indicates more traffic. Bottom left: One agent's knowledge (planned path in red). Bottom right: The same agent's social network (green - direct links).

appearing at a randomly selected entry point. They are removed from the world, becoming inactive, as soon as they arrive at an exit point.

Agents have and collect information about the world. For each city and transport link they have either no information or estimates of the corresponding entity's properties (quality, resource availability, friction) together with trust values that indicate the assumed quality of each estimate.

Agents keep in contact with a number of other agents, enabling them to exchange information. An agent's contacts can be active or inactive and can be located anywhere (i.e. not necessarily at the same location as the agent). Agents lose contacts at a rate of 10% per time step.

In each time step agents that have a planned route move to the next city, while those that do not stay at their current location to gather information. Staying agents explore their surroundings, meet agents at the same location, exchanging information with them as well as potentially adding them to their list of contacts (with probability  $p_{kc}$ ), and potentially gain resources. Furthermore, all agents communicate with their contacts (see below) once per time step.

**Information exchange** Agents communicate with each of their contacts with a probability  $p_{ic}$  and - if they are not moving - with locally present agents with probability  $p_{is}$  per time step. When agents communicate, each item of information

is exchanged with a probability  $p_t$ . Information on locations or links that only one of two interacting agent is aware of is transferred directly. If both agents have information on a given feature they adapt their knowledge based on their respective beliefs and confidence.

We used a simple mass action approach (Horn and Jackson, 1972) to model knowledge exchange. An item of information is represented by a value estimate v and a level of trust  $t \in (0, 1)$  with its inverse doubt d = 1 - t. We assume that during an episode of communication the doubt and the trust portion of the agents interact independently and in proportion to their ratio (see below). Doubt interacting with doubt produces doubt. The part of an agent that doubts can be *convinced* (parameter  $c_i$ ) by an other agent's trust. Trust interacting with trust can either *confuse*  $(c_u)$  an agent, leading to doubt depending on the agents' difference in estimate  $\delta_v$ , or *convert*  $(c_e)$  it to the other's opinion. The new opinion  $(d'_A, v'_A)$  of agent A receiving agent B's opinion  $(d_B, v_B)$  is then calculated as:

$$\delta_{v} = \frac{|v_{A} - v_{B}|}{v_{A} + v_{B}}$$

$$d'_{A} = d_{A}d_{B} + (1 - c_{i})d_{A}t_{B} + c_{u}\delta_{v}t_{A}t_{B} \qquad (1)$$

$$v'_{A} = [t_{A}d_{B}v_{1} + c_{i}d_{A}t_{B}v_{B} + t_{A}t_{B}(1 - c_{u}\delta_{v})((1 - c_{e})v_{A} + c_{e}v_{B})]/(1 - d'_{A})$$

In some scenarios we assumed communication to be noisy (with error  $e_i$ ). In these cases agents receiving information perceive the other agent's trust/doubt and value wrongly and  $t_B$ ,  $d_B$  and  $v_B$  in equation 1 are replaced with their perceived counterparts:  $t_{B,p} = t_B + unif(-e_i, e_i)$ ,  $v_{B,p} = v_B + unif(-e_i, e_i)$ ,  $d_{B,p} = 1 - t_{B,p}$ .

**Exploration** While staying in a city or traveling along a transport link, agents improve their knowledge about the respective location or link by increasing the accuracy of their estimates of its properties as well as the corresponding trust values and by "discovering" geographically connected locations and links.

**Routes** Agents move through the world according to planned routes. These routes can either be complete paths to one of the exits or a single step to one of the neighboring cities. Any planning always happens solely based on the subjective information available to the agents.

Agents choose their routes based on the links' friction and the cities' suitability, attempting to minimize friction but discounting by the suitability of cities. The suitability s of a city c is a function of its specific quality q, resource availability r and proximity to the target x, where the former two are discounted by the agent's trust in the information:

$$s(c) = q_c^v q_c^t + \frac{r_c^v r_c^t}{10} + \frac{x_c}{2}$$
(2)

The movement costs m associated with a link l to city c are then calculated based on the links friction f as:

$$m_l = f_l^v \frac{4}{1+s(c)} \tag{3}$$

If an agent knows about any exit locations and can connect it to its current location, it plans an optimal path to that location minimizing the sum of movement costs m. If it does not know any exits or is not able to find a path to any of them it optimizes locally by picking from all links connected to its current location with probability proportional to 1/m.

**Resources** While staying in a city agents can increase their level of resources dependent on a city's resource availability. Traveling on a transport link on the other hand uses resources according to the link's friction. In the current version of the model resources are only used as a means to evaluate the agents' success and have no effect on their behaviour.

scenario	value	parameters			
		$p_{kc}$	$p_{is}$	$p_{ic}$	$p_t$
social	low	0.1	0.1	0.1	0.1
	medium	0.3	0.3	0.3	0.3
	high	0.6	0.6	0.6	0.6
		$p_{fl}$	$p_{fd}$	$x_s$	$x_m$
explore	low	0.1	0.1	0.3	0.3
	medium	0.5	0.3	0.5	0.5
	high	1.0	1.0	1.0	1.0

Results

Table 2: Parameter values for main scenarios (see Table 1 for more information).

We tested how different sources of information affect the optimality and predictability of migration routes. For that we defined three levels of social information exchange and three levels of exploration, each composed of several parameters (see Table 2). We changed the level of social information exchange by changing at the same time the probability to keep in contact with encountered agents, the probability to communicate and the probability to transfer information while communicating. The level of exploration consists of the probabilities to find links and destinations, respectively, as well as the speed with which agents adjust their estimates and trust values to external information. For each combination of these scenarios we also investigated the effects of imperfect communication ( $e_i = 0.1$ ).

For each parameter combination we ran ten replicates for two different random geographies each. As preliminary simulations showed that equilibrium is usually reached after 200-300 time steps, we ran each simulation for 500 time steps.



Figure 2: Mean capital for different levels of social activity and exploration in a scenario without (top) and with (bottom) communication error.

We find that the quality of migration routes as measured by the amount of capital individuals retain increases as expected with the efficacy of exploration. It decreases, however, with the amount of social activity (Figure 2), at least for medium and high exploration. At the same time we see that the variation (measured as relative standard deviation) in traffic per link within runs increases with social activity as well as (slightly) with level of exploration (Figure 3). An increase in communication as well as exploration therefore leads to traffic concentrating more strongly on a few migration routes. These are, however, worse (as measured in capital used) if communication is higher.

Noisy communication further reduces the quality of traveled routes (Figure 2), but boosts the effect of exploration on the concentration of routes.

To determine if individuals end up using similar migra-



Figure 3: Relative standard deviation of number of visitors over all links for different levels of social activity and exploration. Scenarios without (top) and with (bottom) communication error are shown.

tion routes for a given geography we calculated for each exit city the standard deviation over all replicate runs of the proportion of migrants it received over the course of the model run. The mean value of that measure over all cities is an indication of the "repeatability" (or rather its inverse) of migration routes across replicate runs. We find that higher exploration makes routes more deterministic, while more communication, in particular if it is error-free strongly increases the variation between replicate runs (Figure 4).

Summing up the results, if communication or exploration are high, most individuals follow similar routes (high variation in traffic within runs). For high communication, however these routes tend to be sub-optimal (low capital) and different for different replicate runs (high variation in traffic between runs).



Figure 4: Mean (over exit cities) of the standard deviation of proportion of visitors at the same city across replicate runs. Scenarios without (top) and with (bottom) communication error are shown.

In conclusion this indicates that if the proportion of information that individuals receive through communication with others as opposed to exploration is high, migration routes are the result of a process of social coordination rather than individual optimization. In this case the routes are therefore an emergent property of the interactions between individuals.

#### Discussion

We have shown that in an agent population navigating unfamiliar terrain the agents' reliance on social information can lead to the emergence of unpredictable, sub-optimal navigation routes.

This has direct consequences for migration research. While the integration of network effects lead to the insight that social effects are at least as important in determining migration decisions as economic factors (Radu, 2008) our results demonstrate that additional internal feedback mechanisms can make at least migration routes effectively unpredictable. In particular, in a situation with forced migration, however, or generally when preferences for specific target countries are weak, the route itself can strongly affect the choice of destination. Self-organized routes might therefore substantially reduce the predictability of the entire migration process.

These results have practical implications as well. Any third-party reaction to migration - be it political, in attempting to prevent or canalize it, or humanitarian, in trying to improve the migrants' often dire situation - has to rely to some degree on being able to predict where migrants are to be found at a given time (Frontex, 2018). This is made harder the less deterministic the routes are. On the other hand our results also show that providing migrants with comprehensive, reliable information might improve the situation for all parties. A practical recommendation to be deduced from these findings would therefore be that migrants should be provided with good, reliable travel information and that efforts should be made to increase the recipients' trust in that information.

Going beyond migration, what we found suggests that similar effects could occur in any situation where individuals make sequences of decisions based on limited information and have to choose between relying on (possibly incomplete) first-hand information or (possibly unreliable) group knowledge.

As it stands our model serves primarily as a conceptual proof of principle that demonstrates how certain effects will occur if a number of assumptions are met. In the next step it will be necessary to determine how applicable these results are to real-life situations.

To do this we are currently in the process of performing a systematic analysis of the response of various outputs, such as those shown in Figures 2, 3 and 4, to the changes in selected input parameters. In particular, in order to assess the uncertainty of the output and sensitivity to parameter changes, statistical emulators (meta-models) are being used, following the Gaussian process-based approach advocated for example by Oakley and O'Hagan (2004).

Furthermore we intend to develop a version of the model that more closely represents a specific real-world scenario. This includes basing as many parameter values as possible on empirical data, transitioning to continuous and realistic temporal and spatial scales and calibrating the model results to some real-life characteristics of the properties of existing migrant route networks.

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## Algorithm in pseudocode

create random world

```
for 500 time steps:
   n ~ Poisson(20) times:
        insert agent at random entry city
    for all agents:
        if previously moving or no plan:
            explore location
            exchange info locally
            gain contacts
            find optimal path or
                best next step
            update plan
        else:
            decide next step following plan
            explore transport link
            start move to target
        exchange info with contacts
        drop contacts
        if at exit:
```

remove