Collective navigation of complex networks: Participatory greedy routing

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Many networks are used to transfer information or goods, in other words, they are navigated. The larger the network, the more difficult it is to navigate efficiently. Indeed, information routing in the Internet faces serious scalability problems due to its rapid growth, recently accelerated by the rise of the Internet of Things. Large networks like the Internet can be navigated efficiently if nodes, or agents, actively forward information based on hidden maps underlying these systems. However, in reality most agents will deny to forward messages, which has a cost, and navigation is impossible. Can we design appropriate incentives that lead to participation and global navigability? Here, we present an evolutionary game where agents share the value generated by successful delivery of information or goods. We show that global navigability can emerge, but its complete breakdown is also possible. Furthermore, we show that the system tends to self-organize into local clusters of agents who participate in the navigation. This organizational principle can be exploited to favor the emergence of global navigability in the system.

The rapid growth of the Internet of Things is expected to lead to more than 50 billion connected devices by 2020, which implies challenges for the scalability of the digital infrastructure. Decentralized systems provide the required scalability in addition to the advantage of high transparency and a low risk of abuse by single, powerful entities. These architectures, however, face particular problems concerning their functionality. A key challenge is how to route information relying only on local knowledge. To accomplish this task, the alignment of incentives of the involved individuals or institutions in the routing process to achieve global navigability is of crucial importance.

Routing information is among the most important functions real complex networks must perform. Examples include biological networks like the human brain, social networks, and the Internet. Many real complex networks have shown to be navigable, where nodes efficiently route messages using the connectivity of the network without relying on knowledge about the global topology. This can be achieved by performing greedy routing in underlying geometric spaces. Greedy routing builds on nodes forwarding incoming messages to their neighbor that has the smallest distance to the destination measured in the underlying geometric space.

In reality, there is a cost associated to sending messages, which can be a physical cost or invested time or energy. This cost implies that individuals are unlikely to be willing to participate without incentives. Furthermore, if even a single node in a given message forwarding chain decides not to participate (defect), the entire delivery fails. This vulnerability of the navigation process raises serious concerns about the feasibility of navigation in realistic environments. Here, we introduce an incentive to participate in the navigation process and show that it can promote the emergence of global navigability. In reality, networks have a utility, and hence the successful delivery of information or goods generates value. We assume that this value is distributed equally among the individuals that took part in the forwarding process, which could be realized in digital environments by an appropriately designed cryptocurrency. In the following we study an evolutionary game that we call participatory greedy routing. We show that in the real IPv6 Internet topology as well as in synthetic networks, the mentioned incentive allows for the emergence of global cooperation and navigability in the system despite its vulnerability to defection. On the other hand, complete defection and the total breakdown of navigability is also possible. We shed light onto the conditions under which the system approaches the navigable state. In addition, we reveal that global cooperation emerges as the system self-organizes into local clusters of cooperators, which tend to spread...
and merge. Finally, building on this knowledge, we show how the initial minimal density of cooperators needed to drive the system to the navigable state can be reduced significantly by adopting an “act local” strategy.

Results

Navigation of complex networks via hidden metric spaces. It has been shown that real complex networks can be embedded into hidden hyperbolic metric spaces\(^\text{12, 13}\). In these mappings, each node \(i\) is mapped into the hyperbolic disc where it is represented by the polar coordinates \(r_i, \theta_i\). These coordinates, or hidden variables, abstract the popularity and similarity of nodes\(^\text{13}\). The radial coordinate \(r_i\) is related to the expected degree of node \(i\) and therefore abstracts its popularity. More popular nodes are placed towards the center of the disc and hence obtain a lower radial coordinate, which are distributed according to \(\rho(r) \propto e^{kr^2}\)\(^\text{14}\). The angular distance between nodes \(i\) and \(j\) given by \(\Delta \theta_{ij} = \pi - |\pi - \theta_i - \theta_j|\) is a measure of the similarity of \(i\) and \(j\). A lower distance means a higher similarity. In simple terms, in a social network nodes close to you in this space would be your peers rather than your geographic neighbors. In the following, we always refer to this measure of proximity. The hyperbolic distance\(^\text{15}\)

\[
x_{ij} = \cosh^{-1}(\cosh r_i \cosh r_j - \sinh r_i \sinh r_j \cos \Delta \theta_{ij}),
\]

comprises information about both the similarity and popularity of nodes \(i\) and \(j\). The connection probability for a given pair of nodes depends only on their hyperbolic distance. Given a real network, the coordinates of nodes can be inferred, using Maximum Likelihood Estimation techniques\(^\text{11-13}\). In the inferred hyperbolic maps, one can identify soft communities, which are clusters of nodes close to each other in the angular similarity space\(^\text{11, 15, 18, 20}\), predict missing links\(^\text{12, 13, 28}\), and perform efficient greedy routing reaching targets with high success rates and following approximately topologically shortest paths\(^\text{11-13, 18}\). Importantly, the synthetic networks generated in this work are small-world networks\(^\text{30, 31}\).

In greedy routing, each node forwards messages to her neighbor that is closest to the target in the underlying metric space. This means that node \(i\) forwards the message to its neighbor \(j\) located at the smallest hyperbolic distance to the target node \(t\), i.e. \(x_{ij} = \min_{l \in NB(i)} x_{lt}\), where \(l\) runs over all neighbors of \(i\) and \(x\) is the hyperbolic distance from Eq. 1. This process is illustrated in Fig. 1a. Only local knowledge about the coordinates of neighbors and those of the target is needed to perform routing. If a message is given back to a node it has already visited, the delivery fails (see ref. 19 for details).

However, greedy routing assumes that all nodes, or agents, participate in the process, which is not the case in reality. In the following, we consider a cost associated with sending messages and present incentives that can lead to global-scale cooperation and a high performance of the system.

Participatory greedy routing. Participating in the forwarding of messages implies a commitment of the involved agents in terms of time and resources, in other words, sending messages has a cost. Individual agents will only be willing to pay this cost if they obtain a benefit from using the network. Hence, it is essential to create an incentive that can enable the emergence of global cooperation among the agents in the system. Real networks perform certain functions, and hence successfully delivering information or goods generates value. In decentralized systems, this value is generated in a bottom-up way by the agents who perform the routing. Consequently, we assume that the value generated, which we call \(b\), is distributed equally among the agents that participate in the successful delivery. In addition, each agent that sends a message has to pay a cost, which we set to 1. This cost is paid even if the message is not delivered. Note that a single defector along the chain (except for the final destination) will lead to a failure of delivery (see Fig. 1b). Each forwarding chain is similar to a coordination game in
offers a natural representation of such clusters. In Fig. 3 we present an explicit realization of the system for synthetic networks (see Supplementary Video 1) and one for the IPv6 Internet network (see Supplementary Video 2), of nodes in a small angular interval of the underlying space (see Fig. 3b and c). Importantly, these clusters are located at the border of a cooperating cluster have a high probability of switching to cooperation, which results in a higher payoff than their defecting neighbors. This implies that defectors are more likely to switch to cooperation if they are surrounded by cooperators. Over time, the fraction of cooperators increases, as obtaining the reward for successfully delivering a message becomes less likely. Hence, defection decreases, which further decreases the system performance, which further decreases defection, and so on, leading eventually to a complete breakdown of cooperation and navigability. On the other hand, more cooperation means a better system performance, making cooperation a better strategy choice, which can lead to nearly full cooperation and navigability.

The final fate of the system is determined by the initial rate of cooperators \( C_0 \) and the payoff parameter \( b \). We find that in a large region of the phasespace either the functional state (blue region in Fig. 2a) or the non-functional state (white region) is approached with high probability. These regions are separated by a smaller region in which both states are approached with intermediate probabilities (red region).

Finally, note that, for full cooperation, participatory greedy routing degenerates towards greedy routing. In this optimal case, we find for the synthetic networks \( \gamma = 2.5 \) a success rate of \( (87.2 \pm 3.1)\% \) for greedy routing with an average of \( (4.1 \pm 0.3) \) hops. For the Internet IPv6 network, we find that \( (91.6 \pm 0.3) \) percent of the messages are delivered successfully with an average of \( (3.61 \pm 0.03) \) hops on average. In the functional state, participatory greedy routing yields a performance close to these optimal values (see Supplementary Materials).

**Self-organized local clusters drive global cooperation.** We observe that the spontaneous emergence of cooperating local clusters precedes the global emergence of cooperation\(^{16} \), and the underlying metric space offers a natural representation of such clusters. In Fig. 3 we present an explicit realization of the system for synthetic networks (see Supplementary Video 1) and one for the IPv6 Internet network (see Supplementary Video 2), where we start with a small fraction of cooperators that are chosen at random. Initially, the fraction of cooperators decreases (see Fig. 3a), but at the same time localized clusters of high cooperation emerge. Such clusters are sets of nodes in a small angular interval of the underlying space (see Fig. 3b and c). Importantly, these clusters are successful because message paths follow shortest distances, and hence nodes within such a cluster can communicate despite the initially very low cooperation and poor performance of the system globally. If enough value \( b \) is generated, these clusters can create a higher payoff than their defecting neighbors. This implies that defectors located at the border of a cooperating cluster have a high probability of switching to cooperation, which results in their assimilation of the cluster. Hence, the localized clusters of high cooperation grow and eventually merge until they cover a large fraction of the network. To sum up, in simple terms, global cooperation emerges from the spread of local clusters of cooperators.

**Clustering of cooperators reduces the initial “critical mass”.** We have seen that an initial “critical mass”, i.e. a certain minimal density of initial cooperators is needed to drive the system to the functional state. We find that less initial cooperators are needed if the networks are more heterogeneous (see Fig. 2c). The navigability
of the system—even for full cooperation—decreases quickly for $\gamma > 2.9$, which implies that it becomes very difficult to drive the system to the state of high cooperation (see Supplementary Materials). Note that most real complex networks have power-law exponents between 2 and 3 and are navigable\(^{11}\).

As discussed in the previous section, the system dynamically self-organizes into localized clusters of high cooperation, which then expand and merge, eventually giving rise to global cooperation\(^{36}\). We can exploit the understanding of this process to lower the minimal initial density of cooperators. In particular, instead of distributing them randomly, we can assign them to a certain region of the angular space (see Supplementary Fig. 1f) by assigning to node $i$ the strategy

$$S_i(0) = \begin{cases} 1 & \text{if } \theta_i \in [0, 2\pi C_0), \\ 0 & \text{else}, \end{cases}$$

(3)

where $\theta_i$ denotes the angular coordinate of node $i$. This leads on average to an initial density $C_0$ of cooperators due to the uniform distribution of angular coordinates in the model for the generation of synthetic networks (see Appendix). This strategy significantly reduces the minimal initial density of cooperators required to reach the desired functional state. We define a threshold of initial cooperators above which the functional state is approached with more than 50% probability. We find that starting with clustered initial cooperators can reduce this threshold by up to 50% for the synthetic networks considered ($\gamma = 2.7$), and by up to 24% for the IPv6 Internet topology (see Fig. 2c and f). To conclude, starting with local clusters of cooperators strongly favors the emergence of global cooperation and navigability.
The role of hubs. Hubs, i.e. nodes with very high degree, play an important role in the navigation process. In particular, the navigation process follows a “zoom in - zoom out” pattern, where hubs—forming large-range connections in the metric space—facilitate the transmission of messages across the network. Therefore, one...
would expect that a lower number of initial cooperators is needed to drive the system to the functional state if those cooperators are the hubs of the system.

To study the effect of selecting hubs as initial cooperators, we select \( NC_0 \) cooperators as before, but now instead of either selecting them uniformly at random or locating them in the angular space, we select nodes proportional to their degree \( k^{\alpha} \). The parameter \( \alpha \) then represents the strength of the preference of hubs to be among the initial cooperators, and for \( \alpha = 0 \) one recovers the random case. Results for different values of \( \alpha \) are shown in Fig. 4. Indeed, one observes a strong mitigation effect for higher values of \( \alpha \). We conclude that, if possible, targeting the hubs of the system constitutes an efficient strategy to favor the emergence of cooperation in the system.

Community structure of the real Internet network. As mentioned above, the real Internet IPv6 topology leads to similar results as for the case of synthetic networks. Especially, we again find a bistable behavior (see Fig. 2d and e), meaning that the system can be either in a state of high cooperation and navigability or nearly total defection and complete breakdown of navigability. We also find that clustering of the initial cooperators (note that the non-uniform distribution of angular coordinates requires a slightly different way to assign localized initial conditions, which we explain in Appendix) decreases the minimal density required to drive the system to the desired state (see Fig. 2f). In accordance with our findings concerning synthetic networks, the higher heterogeneity present in the Internet IPv6 topology (\( \gamma \approx 2.1 \)) favors the emergence of global cooperation and reduces the relative effect of clustered initial cooperators compared to distributing them randomly (compare Fig. 2c and f).

The existence of angular bins with significantly higher than average number of nodes is an indicator of a community structure that is present in real networks, in contrast to the synthetic networks considered here. In the real Internet IPv6 topology, the emerging clusters of high cooperation coincide—to some extent—with the community structure of the network (see Fig. 3e,f, and Supplementary Video 2).

Discussion
Real complex networks have shown to be navigable efficiently and relying only on local knowledge by performing greedy routing in underlying hidden metric spaces. However, greedy routing assumes that all nodes, or agents, participate in the process, which is often not the case in reality. Forwarding information has a cost for the agents, which can be a physical cost or invested time or energy. This cost is especially important because it causes a temptation for individual agents to defect (not participate in the navigation). The navigation process is vulnerable to defection because even a single defector leads to the failure of an entire forwarding chain. However, successfully delivering information in real networks generates value, which in decentralized systems is generated in a bottom-up way.

We assume that this value is shared among the agents that participate in the successful delivery. Agents can cooperate or defect, i.e. participate or not. We call this process participatory greedy routing. We show in the real IPv6 Internet network as well as in synthetic networks that, in participatory greedy routing, global cooperation can emerge from local interactions. We show that the system is effectively bistable, and can either be functional, in which case nearly the entire population cooperates and the network is highly navigable, or non-functional, which corresponds to the complete breakdown of navigability and nearly total defection. Interestingly, the emergence of global cooperation is preceded by the self-organization of the system into clusters of high cooperation. This organizational principle can be exploited to lower the critical initial density of cooperators needed to drive the system—with a high probability—to the desired functional state. We show that, if the initial cooperators are concentrated in a local cluster, the required minimal number of initial cooperators is reduced significantly. A similar effect can be obtained by selecting hubs as the initial cooperators.
The inclusion of a reputation system\textsuperscript{37}, competition between several networks\textsuperscript{18,38–40}, and adapting the network topology\textsuperscript{16} constitute interesting tasks for future work. Participatory navigation procedures like the one described in this manuscript are likely to play an important role in decentralized future digital environments and could sustain information routing in the Internet. Our results confirm that the emergence of global cooperation and navigability is possible with the correct incentives and that the adoption of participatory bottom-up navigation is favored by starting with local clusters of participating agents. This is particularly important for the implementation in real systems.

\section*{Methods}

\subsection*{Synthetic networks.} We construct synthetic networks using the $\Sigma^1$ model described in ref. \textsuperscript{14}, which we then map to its approximatively equivalent counterpart in the hyperbolic disc, the $\mathbb{H}^2$\textsuperscript{10} model.

$\Sigma^1$ model. In the $\Sigma^1$ model each node $i$ has a set of hidden variables $\kappa_i, \theta_i$. $\kappa_i$ denotes the expected degree of node $i$, and the angular coordinate $\theta_i \in [0, 2\pi)$ abstracts a similarity space. The model parameters are size $N$, the exponent for the power law degree distribution, $\gamma > 2$, average degree $k$, and temperature $T \in [0, 1]$. The network generation procedure then works as follows:

1. Assign hidden variables: For each of the $N$ nodes, we draw $\theta_i$ from the uniform distribution in $[0, 2\pi)$ and $\kappa_i$ from the probability density function

$$
\rho(\kappa) = (\gamma - 1)\kappa^{-\gamma},
$$

where $\kappa_{\text{min}}$ controls the expected mean degree $k$.

2. Now, we connect each pair of nodes $i, j$ with the probability

$$
\rho(\kappa_i, \theta_i; \kappa_j, \theta_j) = \frac{1}{1 + \left[ d(\theta_i, \theta_j) / \mu \right]^{\frac{1}{T}}},
$$

$$
d(\theta_i, \theta_j) = \frac{N}{2\pi} \Delta \theta_i, \Delta \theta_j = |\pi - |\theta_i - \theta_j||, 
$$

$$
\mu = \frac{\sin T \pi}{2k T \pi},
$$

where $d(\theta_i, \theta_j)$ denotes the angular distance between $i$ and $j$.

\textbf{Transformation to $\mathbb{H}^2$.} We transform the $\Sigma^1$ model to the $\mathbb{H}^2$ model in the hyperbolic disc by mapping the hidden variables $\kappa_i$ to radial coordinates $r_i$ according to

$$
r_i = R - 2 \ln \frac{\kappa_i}{\kappa_{\text{min}}},
$$

where $R$ denotes the disc radius given by

$$
R = 2 \ln \frac{N}{c},
$$

$$
c = k \sinh T \pi \left( \frac{\gamma - 2}{2 T} \right) \left( \frac{\gamma - 1}{2 T} \right) .
$$

Finally, note that in the $\mathbb{H}^2$ model the connection probability from Eq. (5) translates to the Fermi-Dirac distribution

$$
p(x_{ij}) = \frac{1}{1 + e^{x_{ij} - x_{ij}^{\text{min}}}},
$$

and depends only on the hyperbolic distance

$$
x_{ij} = \cosh^{-1}(\cosh r_i \cosh r_j - \sinh r_i \sinh r_j \cos \Delta \theta_i)
$$

between the nodes\textsuperscript{10}. 


The IPv6 Internet topology. In the IPv6 Internet topology each node represents an Autonomous System. The data was collected and developed by the Archipelago active measurement infrastructure (ARK) and CAIDA\(^1\). Autonomous Systems are constituents of the Internet infrastructure that are managed by a single entity and exchange traffic between them. Connections in the topology represent relationships between different Autonomous Systems to facilitate the exchange of traffic. The dataset\(^2\) consists of Autonomous Systems that route information using the IPv6 protocol. The topology used in\(^3\) was obtained by joining the connections during the first 15 days of January 2015 taken from\(^4\). The network has \(N = 5163\) nodes, a power law degree distribution with exponent \(\gamma = 2.1\), and average degree of \(<k> = 5.21\), and an average mean local clustering coefficient of \(c = 0.55\). The processed network data and its hyperbolic mapping were taken from publication\(^5\). The hyperbolic mapping was obtained using the HyperMap method\(^6,7\). An implementation of this method is publicly available at\(^8\).

Localized initial conditions in the IPv6 topology. To assign localized initial conditions in the real Internet, due to the non-uniform distribution of angular coordinates, we cannot proceed like in the case of synthetic networks described by Eq. (3). This procedure would lead to significantly different numbers of initial cooperators depending on which section of the angular space one selects. Instead, we perform as follows. First, we order all nodes according to their angular coordinate. Then, we randomly select a node, \(i\), and simply assign the nodes in the interval \([i, i + NC_i]\) to cooperators. The ordering then ensures that they all lie within an angular sector. We choose node \(i\) randomly so that the set of initial cooperators differs between different realizations.

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**Author Contributions**
K.-K.K. designed the research, performed the simulations, and prepared all figures. Both authors discussed the research and wrote the paper.

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