Impact of Social Mobility on Routing Protocols for Opportunistic Networks

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Abstract

Opportunistic networks are wireless mobile networks in which a continuous end-to-end path between a source and a destination is not necessary. Messages are stored at intermediate nodes, and opportunistically forwarded when a more suitable next hop towards the destination becomes available. A very interesting aspect is understanding how users' mobility patterns impact on the performance of routing protocols. Starting from this motivation, in this paper we take into consideration group mobility models, whose movement patterns have shown to be remarkably similar to real-world user movements. We consider routing protocols representative of a broad range of schemes, and highlight the impact of users social relationships and movement patterns on the protocols' performance.

1. Introduction

Opportunistic networks are emerging as one of the most interesting evolutions of the legacy MANET paradigm. In MANETs a continuous end-to-end path has to be established prior to exchange messages between a sender and a receiver. This means that all nodes wishing to communicate have to stay simultaneously connected to a common internetwork. This assumption may be rarely met in pervasive networking environment. Mobile devices (phones, PDAs, etc.) carried by users may be just sporadically connected to a common network, e.g. because users turn them off, or they get out of reach of other nodes, or due to the intrinsic variability and instability of wireless links. Furthermore, despite the increasing penetration of 3G and WiFi networks, assuming that the core infrastructure will be so extended to seamlessly cover any mobile device users may carry on is not very realistic. Legacy MANET solutions fail to provide end-to-end connectivity in such a scenario. Instead, opportunistic networks are designed to enable users communications even when the endpoints are *never* connected through a common inter-network at the same time.

Not surprisingly, routing & forwarding is currently one of the hottest topic in this research domain. Forwarding is generally multi-hop and based on the *store-carry-and-forward* paradigm. Nodes store messages they have to forward and carry them until they encounter another node deemed more suitable to bring the message (closer) to the eventual destination. A range of routing schemes have been proposed for opportunistic networks (see [6] for a detailed survey). It is possible to categorise them based on the amount of information they leverage to autonomically learn the features of the network they are immersed in. On the one end of the spectrum, in pure dissemination schemes, nodes are oblivious to any available information. They just rely on aggressively spreading the messages in the network, seeking to reach the destination. On the opposite end of the spectrum, context-aware schemes leverage context information available in the network to selectively identify good next hops towards the destination. We use HiBOp as representative of the latter class, and we briefly describe it in Section 2 (the complete description of HiBOp, along with other example of context-aware routing protocols, can be found in [1]). The most popular example of the former class is Epidemic forwarding [8], that we also take as the reference point for this work. Epidemic adopts limited-scope, TTL-based flooding. When two nodes (say, A and B) get in touch, they exchange summary vectors that summarise the set of messages each one is carrying in its buffer. Then, node A (node B) receives from node B (node A) those messages that it is not yet carrying and are available in node's B (node's A) buffer. For each *received* message the associated TTL counter is decreased. When the counter reaches 0, the associated message can be only delivered directly to the destination. Note that nodes do not discard forwarded messages and keep disseminating them upon encountering other nodes.

Routing in opportunistic networks intrinsically exploits nodes movements to overcome temporary network partitions. Therefore, users' mobility patterns actually play a key role in determining routing protocols performance. In this paper, we look at how characteristic features of human mobility affect routing in opportunistic networks. By comparing the performance of protocols at the opposite ends of the spectrum, we provide indication for a wide range of routing approaches.

Understanding the dependence between routing and mobility patterns is not widely addressed in the literature. The papers most closely related to our work are [3] and [5]. The work in [3] starts by modelling the distributions of contact times and inter-contact times between nodes observed in real traces. Authors find a good fit with power-law (heavy tailed) distributions, and analyse the impact of the parameter determining the tail heaviness on Epidemic-like protocols. Furthermore, they also show that popular mobility models such as Random Waypoint and Random Walk are not able to model those heavy tails, and are thus not the best choice to precisely study realistic opportunistic networks. Authors of [5] take the footsteps of [3] and propose the Community-based Mobility Model (CMM) based on social networks theories (see Section 3.1). They show that CMM is able to capture the heavy-tail characteristics of contact and inter-contact times. They also show that legacy-MANET routing protocols performance are completely different when CMM is used instead of Random Waypoint. In this paper we adopt a slightly modified version of CMM (as described in section 3.2), that however maintains the modelling accuracy of CMM.

The original contribution of this paper is twofold. On the one hand, we provide a sensitiveness analysis of relevant examples (Epidemic and HiBOp) of routing protocols for opportunistic networks, with respect to key parameters that determine users movement patterns. On the other hand, we compare the performance achieved by Epidemic and HiBOp both in terms of users' QoS and resource consumption. By highlighting the sensitiveness to users' movement patterns of two routing schemes at the opposite ends of the spectrum, we thus provide valuable indications for a broad range of routing schemes.

2. History Based Opportunistic Routing

HiBOp is a context-based forwarding protocol for opportunistic networks (completely described in [1]). The context is a collection of information that describes the community in which the user lives and the history of social relationships among users. At each node, basic data used to build the context can be personal information about the user (e.g. name), about her residence (e.g. address), about her work (e.g. institution), etc. In HiBOp nodes share their own data during contacts, and thus learn the context they are immersed in. Messages are forwarded through nodes that share more and more context data with the message destination. In the following we will assume that users are willing to share their personal data with all other nodes, not taking in consideration privacy and security problems (for further information see [1]).

More in detail, we assume that each node locally stores an Identity Table (IT), that contains personal information on the user that owns the device (an example is reported in Table 1). Nodes exchange ITs when getting in touch. At each node, its own IT and the set of current neighbours ITs represent the *Current Context*, which provides a snapshot of the context the node is currently in.

Table 1. Identity Table

Personal Information		*Residence*	
Name	John Doe	**City**	Pisa
Email	j.doe@iit.cnr.it	**Street**	Via Garibaldi, 2
...		...	

Current context is useful in order to evaluate the *instantaneous* fitness of a node to be a forwarder. But even if a node is not a good forwarder because of its current location/neighbors, it could be a valid carrier because of its habits and past experiences. Under the assumption that humans are most of the time "predictable", it is important to collect information about the context data seen by each node in the past, and the recurrence of these data in the node's Current Context. To this end, each data seen in the Current Context (i.e., each row in neighbours ITs) is recorded in a History Table (HT), together with a Continuity Probability index, that represents the probability of encountering that data in the future (actually more indices are used, as described in [1]).

The main idea of HiBOp forwarding is looking for nodes that show increasing *match* with personal data of the destination. High match means high similarity between node's and destination's contexts and, therefore, high probability for those nodes to encounter each other. Therefore, a node wishing to send a message through HiBOp specifies (any subset of) the destination's Identity Table in the message header. Any node in the path between the sender and the destination asks encountered nodes for their match with the destination, and hands over the message if an encountered node shows a greater match than its own. The detailed algorithms to evaluate matches are described in [1]. It is worth recalling here that matches are evaluated as delivery probabilities, and distinct probabilities are computed based on the Current Context (P_{CC}) only and on the History (P_H) only. The final probability is evaluated via standard smoothed average, as $P = \alpha \cdot P_H + (1-\alpha) \cdot P_{CC}, 0 \leq \alpha \leq 1$. The α parameters allows HiBOp to tune the relative importance of the Current Context and History.

In HiBOp just the source node is allowed to replicate the message, in order to tightly control the trade-off between reliability and message spread. Specifically, the source node replicates the message until the joint loss probability of nodes used for replication is below a system-defined threshold (p_l^{max}). HiBOp forwards a distinct *single* copy of the message along the k distinct paths, where $k = \min\left\{ j | \prod_{i=0}^{j} (1 - p_{(i)}) \leq p_l^{max} \right\}$, being $p_{(i)}$ is the delivery probability of the i-th node used for replication.

3. Group-based Mobility Models

Group-based mobility models are increasingly popular in the opportunistic networks research, because they are able to precisely represent human mobility. Besides traditional group-based mobility models (see [7]) new models have been proposed inspired by social network theories. Specifically, we focus on the Community Based Mobility Model (CMM) proposed in [5], which is based on small-world theories [4]. CMM has shown to accurately reproduce distinctive statistical properties of real-world users mobility patterns.

3.1. Original CMM

In CMM every node belongs to a social community (group). Nodes that are in the same social community are called *friends*, while nodes in different communities are called *non-friends*. Relationships between nodes are modelled through social links (each link has an associated weight). At the system start-up, all friends have a link to each other. Also two nodes that are not friends can have a link, according the the *rewiring probability* (p_r) parameter. Specifically, for each node, each link towards a friend is rewired to a non-friend with p_r probability.

Social links are then used to drive node movements. Nodes move in a grid, and each community is initially randomly placed in a square of the grid. Nodes' movement is made up of two component: first, a node has to select the cell towards which to move. Node selects the target cell according to the social attraction exerted by each cell on the node. Attraction is measured as the sum of the links' weights between the node and the nodes currently moving in or towards the cell. The target cell is finally selected based on the probabilities defined by cells' attraction (i.e., if a_j is the attraction of cell j, then the probability of selecting that cell is $a_j / \sum_j a_j$). After selecting the target cell, the "goal" within that cell (the precise point towards which the node will be heading) is selected according to a uniform distribution. Finally, speed is also selected accordingly to a uniform distribution within a user-specified range. CMM also allows for collective group movements. Specifically, once every *reconfiguration period* nodes of each group select a (different) cell and move to that cell. Reconfigurations are synchronous across groups, i.e., all groups start moving to the new cell at the same time. Therefore, during reconfigurations nodes of different groups may get in touch.

In a nutshell, CMM models the fact that humans are social (belong to groups), move towards other people they have relationships with (most likely within their group, but also outside their group), and occasionally move collectively with their group.

3.2. Home-Cell CMM

Despite its nice properties, by running simulations we have identified a side effect of CMM which may not be desirable. When nodes move outside their group (due to rewired links), they become a sort of *leaders* in their community, and other nodes follow them. Such a behavior can be also demonstrated analytically [2]. Intuitively, a node is seen as member of a cell *as soon as* it selects that cell for the next movement (not *when* the node reaches the cell). Therefore, for the whole duration of that node's movement, the *target* cell exerts a possibly strong attraction on the that node's friends. As the movement can last for several seconds, the probability of at least another node in the group to follow that node tends to be high. Ultimately, nodes movements outside the group starting cell generate an avalanche effect that brings all other nodes outside the cell. Groups tends therefore to mix a lot, and the physical association between a group and the "home" cell in which nodes were initially placed disappears.

This behavior fails in modelling scenarios in which there is a strong link between nodes of a group and a physical place (a cell in the grid). For example, in working places, when someone goes out of an office, the other colleagues usually do not follow him in all his movements (or however they should not!). To take this into account, we slightly modified the definition of groups social attraction. In the resulting Home-cell Community based Mobility Model (HCMM), each node is attracted by its *home cell* (i.e. the cell to which its community was assigned after a reconfiguration), based on the social attraction exerted on that node by all other nodes that are part of its group, *irrespective* of the current physical location of those nodes. In a sense, the social links between nodes of the same group are translated in a global attraction exerted by the group home cell. Social attraction towards nodes of different groups is evaluated as in CMM. When a node is in its home cell, the cell for the next movement is selected as in CMM. However, after a node reaches a cell which is not its home, it stays in the "foreign" cell with a given probability (p_e) for the next movement, and goes back home with probability $1 - p_e$. Therefore, it roams in the foreign cell for an average number of rounds equal to $p_e/1 - p_e$.

HCMM allows us to model a different kind of scenario, in which nodes are attracted towards a place (e.g., their office building) in which usually people of their group roam. Nodes are also attracted outside that place because of social relationships between groups, and spend some time in the foreign groups before heading back home. We have checked that HCMM still generates heavy-tail distributions for contact and inter-contact times, which is required to model realistic humans movements [2].

4. Routing and Social Mobility Patterns

The goal of this work is understanding how different humans mobility patterns impact on routing performance in opportunistic networks. We focus on Epidemic and HiBOp, to show how representative protocols belonging to opposite classes of routing schemes are sensitive to human movements' parameters.

We identify three main scenarios for our study. In the first one (Section 4.1), we analyse the reactivity of routing protocols to sudden contacts among groups. Specifically, we focus on closed groups (i.e., $p_r = 0$), and then we force groups to collectively move with varying frequency. Messages addressed to nodes outside the group can be delivered only during contacts between different group members during collective movements[1]. This analysis allows us to understand if routing protocols are able to exploit even those few chances to find good routes. We analysed this aspect by varying the reconfiguration interval parameter.

In the second scenario, (Section 4.2), we analyse the effect of social relationships between users. We want to understand how routing protocols react to different levels of users' sociality, measured as the probability of users having relationships outside their reference group. We clearly achieve this by varying the rewiring parameter (p_r). The higher p_r, the more nodes are "social", the lesser groups are closed communities.

In the third scenario, we look at how protocols work in completely closed groups. In this case no rewiring nor reconfigurations are allowed, and we place a different group in each cell of the grid. Therefore, the only chance of delivering messages between groups is by exploiting contacts between nodes at the borders of the cells. We study the routing protocols performance as a function of the nodes' transmission range. Basically, this scenario allows us to understand how protocols can exploit contacts that are not related to social relationships, but just happen because of physical co-location (e.g., contacts between people working for different companies in the same floor of a building).

We tested routing performance in terms of QoS perceived by users and resource consumption. The users QoS is evaluated in terms of messages delay and packet loss. Message delay is evaluated based on the first replica reaching the destination, while we counted a packet loss if all replicas get lost. Resource consumption is evaluated in terms of buffer occupation and bandwidth overhead. Specifically, the bandwidth overhead is computed as the ratio between the number of bytes generated in the whole network during a simulation run and the number of bytes generated by the senders. Note that we count in all overheads related to routing and forwarding, such as exchange of Identity Tables, requests for delivery probabilities, etc.

To highlight the effect of mobility only, we assume i) infinite buffers, ii) an ideal MAC level that completely avoids congestion impairments[2], iii) an ideal physical channel where nodes experience 0% packet loss within a circular transmission range and 100% packet loss outside; and iv) "infinite" bandwidth (in the sense that messages can be always exchanged when nodes get in touch). As throughly discussed in [1], this setup tends to favour dissemination-based schemes such as Epidemic. Finally, unless otherwise stated, our setup consists of 30 nodes evenly divided in three groups. We assume a square of size 1250mx1250m, divided in a 5x5 grid. The default transmission range is 125m. Unless otherwise stated 2 nodes for group generate messages, with an interspacing time exponentially distributed (with average 300s). Each message is destined to a friend or to a non-friend with 50% probability. Messages are timed-out after 18000s. Each simulation runs at least for 90000s (of simulated time). For particular setups we increased the run lengths so as to achieve a minimum amount of characteristic events in each run (e.g. reconfiguration runs with reconfiguration interval equal to 36000s last for 397000s). During the last 18000s senders do not generate any new message . Furthermore, statistics are collected by eliminating the initial transitory regime. Each setup was replicated 50 times: statistics presented hereafter are averaged over the 50 replicas, with confidence interval at 95% confidence level.

[1]The probability of contacts due to groups choosing adjacent cells is typically low due to the high number of cells with respect to the number of groups.

[2]We are extending simulations in order to take into account congestion.

Table 2. Users QoS (reconf)

	reconf (s)	HiBOp	Epidemic
ploss (%)	2250	0 ± 0	0 ± 0
	9000	7.61 ± 1.49	5.56 ± 1.37
	36000	26.7 ± 1.07	25.49 ± 1.07
delay (s)	2250	1158.32 ± 74.52	894.84 ± 61.02
	9000	3525.40 ± 255.09	3172.04 ± 230.72
	36000	5732.36 ± 185.65	5562.04 ± 190.41

4.1. Impact of Groups' Movements

It is worth recalling that in this scenario the rewiring probability is 0, and thus, except for reconfigurations, nodes do not have chances to meet. The reconfiguration interval varies between 2250s, 9000s, and 36000s. Table 2 shows the QoS performance as a function of the reconfiguration interval. As expected, both packet loss and delay increase with this parameter, because messages addressed outside the group of the sender are forced to wait for a reconfiguration. Note that, even though HiBOp provides higher packet loss and delay, the difference with Epidemic is quite thin. Note that, as buffers and bandwidth are not limited, Epidemic gives a reference upper bound on the performance achievable by any routing protocol. These results clearly shows that HiBOp is able to identify very good paths even during sporadic, sudden contacts during reconfigurations among nodes belonging to different groups.

The good performance in terms of users QoS shown by HiBOp comes along with a drastic reduction in resource usage. Figure 1 shows the buffer occupation over time as a percentage of the duration of a simulation run (points are average values over the replicas). HiBOp is much less greedy in spreading messages, and therefore the buffer occupation is drastically reduced. This is a general difference between

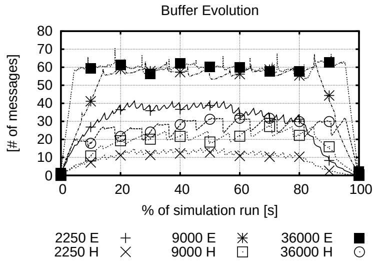

Figure 1. Buffer occupation

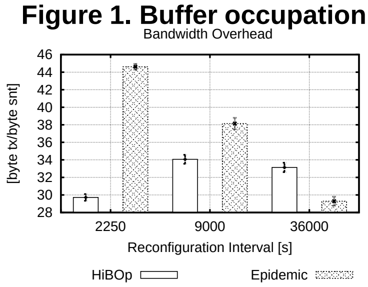

Figure 2. Bandwidth overhead (reconf)

Epidemic and HiBOp, which is confirmed in all scenarios we have tested. The extent of this reduction depends on the scenario, and can be as high as an order of magnitude. Finally, Figure 2 shows the bandwidth overhead of the two protocols. It allows us to highlight a main difference between HiBOp and Epidemic, related to how they react to movement patterns. Reducing the reconfiguration interval (from 36000s down to 2250s) means increasing the forwarding opportunities, because nodes get in touch with more peers more frequently. Epidemic does not use these additional "connectivity resources" wisely, as it is based on flooding. Therefore, the bandwidth overhead steadily increases. HiBOp behaves radically different. When groups do not mix (reconfiguration interval equal to 36000s) paths for messages going outside the sender's group are seldom available. In this case Epidemic uses less resources because it just floods the group. HiBOp instead periodically looks for new forwarding opportunities that are clearly unavailable. We are improving HiBOp to reduce overhead in this case. When groups mix a lot, (reconfiguration interval at 2250), nodes meet frequently and context information is thus able to spread between groups. HiBOp immediately finds very good paths towards destinations and does not need to replicate the messages broadly, thus resulting again in low overhead. At a reconfiguration interval of 9000s, there is an intermediate regime in which context information about nodes outside groups is available but is not very precise, and HiBOp needs to spread messages slightly more aggressively to reach the destinations.

4.2. Impact of Users' Sociality

To understand the impact of users sociality on routing performance we vary the rewiring parameter (p_r). A major difference occurs when the original CMM or the Home-cell CMM is adopted. As discussed in Section 3.1 CMM exhibits a "leader-follower" behavior: nodes follow their leaders and move with them all around the grid. Thus, nodes belonging to different communities are continuously mixed together, and varying p_r does not highlight any different behavior, because the effect of social relationships is masked by the chaotic and mixed movement of nodes. Just to give a representative example, Figure 3 shows the bandwidth overhead for different p_r values. Besides this, the comparison between HiBOp and Epidemic basically highlights the same features presented in Section 4.1: HiBOp delivers almost the same QoS to users, while drastically reducing the resource usage. Thanks to the very mixed environment, average delays are very small (few seconds) in both cases, and the packet loss is 0%.

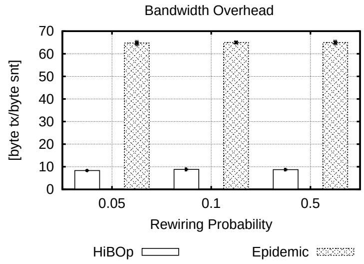

Figure 3. Bandwidth overhead (CMM)

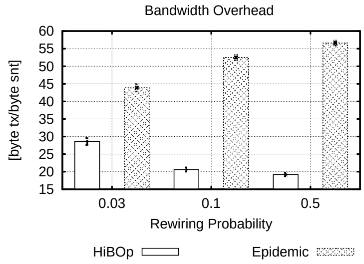

Figure 4. Bandwidth overhead (HCMM)

With HCMM things are quite different. When a node goes to a cell different from its home it shows to nodes in the "foreign" cell context information related to its home cell, thus becoming a good next hop for messages destined to its friends. On the other hand, it roams in the foreign cell for a number of rounds and collects context data about nodes in that cell. When it then comes back to the home cell, this knowledge can effectively be used for sending messages to that particular foreign cell. Indeed, that node is likely to go back to the *same* foreign cell after a while, because the social links towards nodes in that cell are still active. Clearly, when HCMM is used, the routing performance are sensitive to the users sociality, because users having social relationships with other groups are the only possible way of getting messages out of the originating group. This sensitiveness impacts differently on the resource usage of HiBOp and Epidemic, as shown by Figure 4. Similar remarks drawn with respect to reconfiguration intervals apply also here. The higher the users sociality (high p_r), the higher the mix between nodes and the forwarding opportunities. While Epidemic naively uses all these resources spreading messages, HiBOp leverages nodes' mixing (and the result-

Table 3. Average delay (HCMM)

	p_r	HiBOp	Epidemic
delay (s)	0.03	206.66 ± 51.81	135.86 ± 18.14
	0.1	134.58 ± 11.72	83.66 ± 7.54
	0.5	107.99 ± 7.99	75.45 ± 6.87

ing spread of context information) to identify good paths more and more accurately.

As far as the QoS performance figures (Table 3), again the packet loss is negligible, while – as expected – the average delay decreases as users become more social. However, the performance of HiBOp are still not far from the bound represented by Epidemic. It is also interesting to note that the delay of messages towards friends node tends to slightly *increase* as users become more social, because they spend (on average) more time outside their home group. However, as shown by Table 3, the advantage of connecting more efficiently users between groups as users become more social overwhelms the slight performance reduction experienced by friends.

4.3. Breaking Closed Groups

In this set of simulations we use a 3x3 grid with 9 groups of 5 nodes each. Just one node, located in the upper left cell sends messages, destined to a node in the lower right cell. Recall that the only way a message can reach its final destination is through edge contacts with nodes between which no social relation exists. By varying nodes' transmission range we can analyse how this edge effect impacts on forwarding. We use three values for the transmission range, i.e. 62.5m, 125m and 250m. Therefore, nodes cover – on average – less than half a cell, slightly less than a cell, and one and a half cell.

The bottomline of the results is that HiBOp is not suitable for networks with no sociality. At very small transmission ranges (62.5m) HiBOp is not able to deliver acceptable QoS (Table 4). HiBOp needs a minimum number of contacts between users to spread context information around. Indeed, at 125m HiBOp restores acceptable QoS at least in terms of packet loss, and is fully effective at 250m. Also in this case Epidemic and HiBOp behave differently with respect to the bandwidth overhead (Figure 5). At 62.5m HiBOp seldom forwards messages. As context data is not circulating, nodes in the sender's group are almost all equally fit to carry the messages closer to the destination. At high transmission range the context data is circulating effectively, and therefore good paths can be identified soon. Again, note that Epidemic is not able to exploit rich connectivity scenarios without flooding the network.

5. Conclusions

In this paper we have analysed the sensitiveness of a broad range of routing schemes for opportunistic networks to real-world users mobility patterns. Our main findings can be summarised as follows. Context-based routing actually provides an effective congestion control mechanism,

Table 4. Users QoS (closed groups)

	range (m)	HiBOp	Epidemic
ploss (%)	62.5	65.79 ± 9.29	0 ± 0
	125	0 ± 0	0 ± 0
	250	0 ± 0	0 ± 0
delay (s)	62.5	15579.56 ± 734.45	531.79 ± 19.14
	125	568.08 ± 157.71	103.00 ± 2.59
	250	1.51 ± 0.64	23.35 ± 0.52

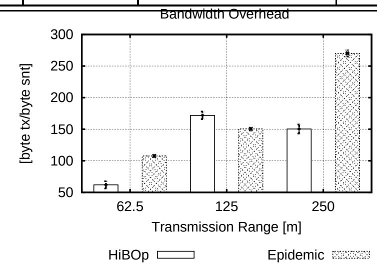

Figure 5. Bandwidth overhead (HCMM)

and, with respect to dissemination-based routing, provides acceptable QoS with drastically lower overhead, unless in very adverse scenarios. Indeed, HiBOp is able to automatically learn the connectivity opportunities determined by users movement patterns, and exploit them efficiently. This autonomic, self-learning feature is completely absent in dissemination-based routing schemes.

Our results also suggest a hybrid scheme for networks with varying levels of users' sociality. When groups are very isolated, context data cannot circulate, and cannot be used for taking effective forwarding decisions. In such cases, dissemination-based schemes seems the only way to enable communication between groups. As soon as users become more social, context information spreads in the network, and context-based routing becomes a preferable solution. An interesting follow-up of this work is how to exploit context information to distinguish these different scenarios and select the appropriate routing scheme.

From a complementary standpoint, our results show that in opportunistic networks *users sociality helps routing*: users' relationships outside their "home" community allow context information to spread in the network, and make forwarding more and more efficient.

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