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Design and performance evaluation of ContentPlace, a social-aware data dissemination system for opportunistic networks

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Abstract

In this paper we present and evaluate ContentPlace, a data dissemination system for opportunistic networks, i.e., mobile networks in which stable simultaneous multi-hop paths between communication endpoints cannot be provided. We consider a scenario in which users both produce and consume data objects. ContentPlace takes care of moving and replicate data objects in the network such that interested users receive them despite possible long disconnections, partitions etc. Thanks to ContentPlace, data producers and consumers are completely decoupled, and might be never connected to the network at the same point in time. The key feature of ContentPlace is learning and exploiting information about the social behaviour of the users to drive the data dissemination process. This allows ContentPlace to be more efficient both in terms of data delivery and in terms of resource usage with respect to reference alternative solutions. The performance of ContentPlace is deeply investigated both through simulation and analytical models.

Key words: opportunistic networks, data dissemination, social-aware networking, data-centric networks, performance evaluation

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1. Introduction

This paper is focused on the problem of data dissemination in opportunistic networks. Opportunistic networks [35] are a recent mobile networking paradigm stemming from the research on conventional Mobile Ad Hoc NETworks (MANET). In this paradigm nodes are assumed to be mobile, and forwarding of messages occurs based on the store-carry-and forward concept [16]. Specifically, no simultaneous end-to-end multi-hop path is required to enable communication between any two nodes, unlike conventional MANET. Instead, each node carrying a message for an intended destination evaluates the suitability of any other node it makes contact with as the next hop. Messages are thus opportunistically forwarded by exploiting nodes encounters, until they reach the intended destination. This paradigm enables end-to-end communication despite possible long disconnections of the communication endpoints and severe network partitions, which is usually cumbersome in traditional MANET architectures.

A significant share of research on opportunistic networks has focused on routing issues (see [35] for a survey). Instead, in this paper, we consider the problem of data dissemination. This is a key research problem, particularly in opportunistic networks. In this environment, according to the User-Generated Content wave, users are expected to generate large amounts of content by exploiting capability-rich mobile devices (such as PDAs, smartphones, etc), and to share them with people around them or people they have social relationships with. In the following, we refer to any piece of content (e.g., a picture or an mp3 file) as *data object*. The problem of efficiently disseminating data objects in opportunistic networks is thus very relevant, and not widely explored in the literature yet, as discussed in Section 2.

Data dissemination in opportunistic networks is a difficult problem. As the topology is very unstable, and users appear in and disappear from the network dynamically, content providers and content consumers might be completely unaware of each other, and never connected at the same time to the same part of the network. Therefore, data objects should be moved and replicated in the network in order to carry them to interested users despite disconnections and partitions. On the other hand, data dissemination systems should take care of both network and device resource constraints. For example, a trivial solution would be to flood the whole network with any generated data object, but this would clearly saturate both network resources (in terms of available bandwidth) and device resources (e.g., in terms of energy, storage, etc).

In this paper, we propose and evaluate ContentPlace, which is a data dissemination system for opportunistic networks that exploits social information about users behaviour in order to drive the dissemination process. Exploiting social information is a very promising research direction for opportunistic networks. In this environment the nodes are mobile devices users carry with them all the time. Therefore, the users social behaviour, being a key driver for their movement patterns, is also a key piece of context information to predict nodes' co-location and future encounters. ContentPlace assumes that users belong to social communities, and autonomically learns the time spent by them in each community, which types of data objects users of each communities are interested into, and how spread in the communities the data objects are. This information is used to evaluate the *utility* of each encountered data object. Specifically, each node, upon making contact with another peer, evaluates the utility of the data objects the peer is carrying with. Assuming that the buffer space devoted to the dissemination process is limited, the node selects which data objects to fetch from the peer, in order to maximise the total utility of the data objects in its own buffer. Therefore, the data dissemination process is driven by the interests and social behaviour of the users, and just requires local interactions between nodes that happen to come in contact.

We assume that users' mobility is driven by the social relationships among users, i.e., that users spend their time with their friends. This assumption may not be always satisfied. This is the case, e.g., of friends living in different part of the world or of virtual friends (e.g., Facebook or chatroom friends). However, also these relationships can be exploited to disseminate messages. For example, in the case of long distance friendship, the distance can be overcome by going through the traditional infrastructure and then switching again to ad hoc mode when this distance has been covered. The inclusion of such hybrid communications into our data dissemination system is currently under study.

After presenting ContentPlace in details in Sections 3 and 4, we provide a detailed simulation analysis in Section 5. Specifically, we compare different data dissemination policies that could be plugged in the general ContentPlace design, either considering or not considering social information. We show that social-aware policies outperform naive ones in which social information is not taken into account. Among the social-aware policies, we identify the one performing best (named Future), and highlight the reasons why it is the most efficient one. Finally, in Section 6 we provide an analytical model describing the behaviour of the Future policy, which shed additional light on its performance.

2. Related Work

Content dissemination systems have been widely investigated with respect to the conventional wired Internet. Extremely popular P2P systems (such as Napster, BitTorrent, Kazaa, Gnutella), are used for this purpose. Typically, the main idea of this vast body of work is to exploit overlay networks to build logical structures onto which data dissemination strategies are implemented. For example, Squirrel [25] is a P2P web-caching service built on top of Pastry [37], one of the most popular implementations of a structured overlay (in the form of a Distributed Hash Table, DHT). The solutions described in [9, 27] exploit unstructured and structured overlay networks, respectively, to approximate optimal replication of a given set of data objects. These papers also derive the optimal replica allocation through standard optimisation techniques. Approximations are then proposed as the optimal solutions require global knowledge which is not available in realistic settings. These policies allow each node to identify the set of peers in the overlay on which to replicate data. This body of work is related to ContentPlace as it studies replication and replacement policies in distributed systems. However, the proposed approaches rely on overlay networks that can hardly be built on opportunistic networks, especially if they are structured. Internet overlay networks are built on the assumptions of large bandwidth and small delays in peer-to-peer communications. Even overlay networks optimised for MANETs (e.g., CrossROAD [13] and XL-Gnutella [10]) assume that nodes of the network are quite well connected, such that MANET routing protocols can be used on them. As this is exactly the opposite of what happens in opportunistic networks, these solutions are not suitable to be used in such a networking environment.

Gossiping is another area of traditional distributed systems quite close to opportunistic networking in general, and to ContentPlace in particular. It is a general mechanism to disseminate messages in a network without assuming any global knowledge: Each node receiving a message replicates it to a subset of its peers. This general mechanism has been applied to a vast number of problems, both in wired and in wireless networks (see [17] for a brief survey). Just to mention a few examples, gossiping has been used as the underlying mechanism to build unstructured P2P networks [43], to implement multicast and routing in MANETs [19, 31], and for data dissemination in wired [15] and wireless networks [14]. Broadly speaking, most of the proposals for forwarding algorithms in opportunistic networks can be seen as instances of the gossiping scheme. In opportunistic networks each node carrying a message evaluates the opportunity of replicating the message on its current physical neighbours, based on information about the neighbours themselves and the destination. The choice of neighbours on which to replicate the message distinguishes the protocols, ranging from choosing all neighbours (as in Epidemic Routing [42]), to choosing the destination only [41], to choosing just those neighbour having higher probability of bringing the message closer to the destination (as in HiBOp [7]). Indeed, also ContenPlace can be seen as an instance of gossiping systems, as in ContentPlace nodes decide which data to exchange and replicate upon each contact. The main novelty of ContentPlace with respect to the traditional gossiping systems looking at data dissemination (such as [15, 14]) is that ContentPlace uses context information describing users' social relationships to choose the set of nodes where to replicate data objects, instead of simple probabilistic policies.

Another area related to ContentPlace is cooperative caching for MANETs. A first body work in this area is described in [45, 30]. These proposals require stable end-to-end paths between nodes to correctly operate. For example, in the algorithms proposed in [45], a data object is stored at intermediate nodes in the path between a node requesting the object, and the node issuing the object. Instead of caching the data object, nodes can cache the path towards the node issuing the object, if this is more convenient from a network traffic standpoint. Those nodes are then able to serve requests for the same object directly. Clearly such heuristics can work well in static MANETs, while are not suitable for opportunistic networks. PReCinCt [39] exploits a geographical DHT to identify regions responsible for a set of data objects (corresponding to a set of keys). Objects are replicated by requesting nodes only if they are outside the region of responsibility. The concept of identifying groups of users whose caches are managed as a unique collective cache is also used in [8, 20, 21]. Similarly to ContentPlace, these systems define groups as sets of users with similar behaviour (usually, similar movement or data access patterns). Indeed, unlike ContentPlace, the main focus of [21] is on algorithms to identify such groups, rather than on data management policies exploiting such a classification. In general, being tailored to MANETs, these systems assume that paths be rather stable at least within groups, and generate a significant amount of traffic to maintain knowledge of other nodes' caches. Therefore, they too are not suitable for opportunistic networks.

ContentPlace is also related to the vast literature on utility-based caching. This has been commonly adopted for web caching in the wired Internet (see [1] for a survey). In mobile networks, utility-based replacement schemes have been used both for MANETs (e.g., [39]) and for WLANs (e.g., [46, 40]). Routing for opportunistic networks exploiting a utility-based framework has also been proposed in [2]. ContentPlace inherits the general framework of this body of work, as the ContentPlace utility function is an instance of the general form used by all the other works in the literature. While [2] is focused on unicast routing, ContentPlace deals with content dissemination. Moreover, the main novelty of ContentPlace is the fact that its utility function is defined based on the social behaviour and relationships of the users.

The idea behind ContentPlace is to exploit social information on the environment the nodes operate in in order to enable the communication. In the framework of opportunistic networks, this idea has already been successfully applied to message forwarding (e.g., [7] [23] [34]). There the idea is to move messages closer and closer to their destinations following a path based on the social interactions between nodes (as in the famous "six degrees of separation" experiment [33]). In the case of forwarding protocols, however, messages have a specific destination node, while in ContentPlace, following the User Generated Content approach, content generators might be unaware of the nodes interested in their data, and so might be the content consumers about the nodes that generate the content they are interested in. In addition, even if pursuing a similar goal, ContentPlace does not rely on any underlying forwarding protocols and autonomously takes care of the data delivery process.

In principle, ContentPlace shares similarities with pub/sub systems proposed for mobile networks (e.g., [3],[12],[32], [48], [11], [47]). Among them, just the pub/sub system designed within the Haggle project [47] explicitly considers the social behaviour of users in the system's design. Furthermore, in pub/sub systems, support for intermittent connectivity is seldom provided. The work in [47] identifies social communities, and "hubs" within communities (i.e., nodes with the highest number of social links inside the community). An overlay network is then built between hubs, that act as the brokers of a standard pub/sub topic-based system. ContentPlace assumes the same community-detection mechanisms of [47]. However, ContentPlace does not provide any standard pub/sub system, and does not need any overlay infrastructure, which might be costly to maintain and rather unstable in opportunistic networks. With respect to SocialCast [11], ContentPlace uses a more complete utility function to drive the dissemination process. Specifically, ContentPlace takes into account the estimated utility for all social communities any given user is in touch with, and within each community, considers the interest for, and availability of, the data objects. Furthermore, the SocialCast dissemination mechanism is more oriented towards traditional forwarding than to actual dissemination with respect to ContentPlace. A fallback of this is that SocialCast works well when all members of each community are interested in the same type of content, but it is not clear how it works in the more general settings considered in this paper.

As is clear from this section, ContentPlace touches upon several areas relevant to the data dissemination problem. However, to the best of our knowledge, the only other works looking at content dissemination for opportunistic networks are the PodNet project [29], and the social-aware pub/sub system designed in [47]. As described in details in Section 5 we use an application and evaluation scenario similar to that defined for PodNet. In PodNet, users subscribe to channels they are interested into. Upon pairwise contacts, users exchange their interests and select which data objects to exchange. Different policies have been compared in [2]. With respect to PodNet, ContentPlace takes into consideration social relationships between users to select the data object to exchange, and provide a more general utility-based framework to design content dissemination policies. We actually compare ContentPlace with the best heuristics identified in [29], showing the advantage of the social-aware dimension.

This work is an extended version of our previous paper [5]. This work provides an extensive analytical model that deals with the average behavior of the best dissemination policy, the Future policy. Furthermore, we perform an analysis of the impact of inaccurate social information on the performance of the social-aware policy. This work is also related to [6], where a preliminary design and evaluation of ContentPlace have been presented.

3. ContentPlace general design

This section provides necessary background information required to present the main contribution of this paper by recalling the target application scenario and the main design features of the ContentPlace system.

3.1. Application scenario

The application scenario we target is similar to the one used in PodNet [29], named "podcasting for ad hoc networks". As in the typical opportunistic networking paradigm, we consider a number of mobile users whose devices cannot be encompassed by a conventional MANET. Instead, communication is achieved by opportunistically exploiting pair-wise contacts between users to exchange data objects, and bringing them towards eventual destinations. Sporadic contacts of users with point of access to the Internet (e.g., WiFi hotspots) are possible although not necessary. In podcasting applications, data objects (e.g., MP3 files, advertisements, software updates, ...) are organised in different *channels* to which users can subscribe. We assume that the channel(s) of a data object is decided by the source of the object at the generation time. Data objects might be generated from within the Internet, and "enter" the opportunistic network upon sporadic contacts of users with Internet Access Points. Or, data objects may be generated dynamically by the users of the opportunistic network according to the Web 2.0 model (e.g., users may wish to share pictures taken with their mobile phones). ContentPlace is responsible for the two main tasks of content dissemination, i.e., i) managing subscriptions to channels, and ii) bringing data objects to subscribed users (content distribution).

3.2. ContentPlace framework

At the high level, the rationale of ContentPlace is as follows. Since stable network structures cannot be assumed, ContentPlace only exploits direct interactions between nodes (contacts) to gather information about the users' subscriptions and current data objects availability. Each node uses this knowledge to decide which data objects "seen" on other nodes should be locally replicated, according to a *replication* policy. The main challenge of ContentPlace is defining a *local* replication policy (i.e., a policy that does not require precise information about the global state of the network) that achieves a *global* performance target (such as, for example, maximising the hit rate, the per-user fairness, the network efficiency).

More in detail, ContentPlace subscription management works as follows. Nodes just advertise the set of channels the local user is subscribed to upon encountering another node. As will be clear in the following, no per-node state is necessary, and thus unsubscription data objects are not required. As far as content distribution is concerned, the core of ContentPlace is the definition of the replication policy, which can be summarised as follows. ContentPlace defines a utility function by means of which each node can associate a utility value to any data object. When a node encounters a peer, it computes the utility values of all the data objects stored in the local and in the peer's cache[1]. Then, it selects the set of data objects that maximises the *local* utility of its cache, without violating the considered resource constraints (e.g., max cache size, available bandwidth, available energy, ...). The node fetches the selected objects that are in the peer's cache, and discards the locally stored objects that are not in the selected set anymore. Finally, a user receives a data object it is subscribed to when it is found in an encountered node's cache. As discussed in more detail in [6], the set of objects to store in the local cache upon each contact can be found by solving the following multi-constrained 0-1 knapsack problem:

$$\left\{\begin{array}{lll} \max & \sum_k U_k x_k & \\ \text{s.t.} & \sum_k c_{jk} x_k \leq 1 & j = 1, \ldots, m \\ & x_k \in \{0,1\} & \forall k \end{array}\right. , \quad (1)$$

where k denotes the k-th object that the node can select, U_k its utility, c_{jk} the percentage consumption of resource j related to fetching and storing object k, m the number of considered resources, and x_k the problem's variables. When the number of managed resource (m) is not big (which is quite reasonable), solving such problems is very fast from a computational standpoint [28]. Such a solution is therefore suitable to be implemented in resource constrained mobile devices.

It is clear that the core of the content distribution mechanism is the definition of the utility function. In the following sections, we discuss how information about the social behaviour of users can be leveraged to this end.

3.2.1. Utility function

To have a suitable representation of the users' social behaviour, we take inspiration from the caveman model proposed by Watts [44], which is a reference point in the field of social behaviour modelling. We assume that users can be grouped in communities. Users belonging to the same community have strong social relationships with each other. In general, users can belong to more than one community (a working community, a family community,

[1]Hereafter, we use the term cache to denote a memory buffer that a node contributes to the ContentPlace system.

etc.), each of which is a “home” community for that user. Users can also have relationships outside their home communities (“acquainted” communities). We assume that people movements are governed by their social relationships, and by the fact that communities are also bound to particular places (i.e., the community of office colleagues is bound to the office location). Therefore, users will spend their time in the places their home communities are bound to, and will also visit places of acquainted communities.

Different communities will have, in general, different interests. Therefore, the utility of the same data object will be different for different communities. Based on this remark, the utility of a data object computed by a node is made up of one *component* for each community its user has relationships with, be it either a home or an acquainted community. Formally, the utility function is defined as follows[2]:

$$U = \omega_l u_l + \sum_{i \neq l} \omega_i u_i = \sum_i \omega_i u_i \ , \tag{2}$$

where u_i is the i-th component and ω_i measures the social strength of the relationship between the user and the i-th community. Finally, in Equation 2 we stretch a bit the concept of community, and represent the *local* user just as another community the user is in touch with (i.e., the utility for the local user is represented by u_l). Note that the definition of the weights ω_i defines the social-oriented behaviour of ContentPlace. As the main focus of this paper is on this aspect, we now briefly describe the definition of the utility components, and discuss in detail the definition of weights in Section 4.

3.2.2. Utility components

ContentPlace uses the same definition for all utility components. In this paper we consider a simplified version of the general function defined by ContentPlace, and we also assume that i) the cache space is the only considered resource, and ii) data objects never expire. See [6] and the associated report for the discussion of more general cases. Inspired by the Web-caching literature [1], the utility of a data object for a community is the product of the object’s access probability from the community members (p_{ac}) by its cost c, divided by the object’s size. The cost is measured as a monotonically decreasing function of the object’s availability in the community (denoted

[2]For easy of reading, with respect to Equation 1 we drop here the k index, as this does not impact the clarity of the discussion.

as p_{av}), as the more the object is spread, the less it is costly to find it, the less the utility of further replicating it. Dividing by the object's size is also common in the Web-caching literature, as it also allows very simple approximations of the multi-constrained knapsack problem defined by Equation 1. Specifically, we use the following definition:

$$u = \frac{p_{ac} \cdot f_c(p_{av})}{s} = \frac{p_{ac} \cdot e^{-\lambda p_{av}}}{s} \ , \tag{3}$$

In Equation 3 we use an exponential function as cost function, which achieves a fairer behaviour with respect to a (more intuitive) linear decay, as shown in [6].

3.3. Architecture overview

In this Section we give an overview of the communication architecture of ContentPlace. Following the opportunistic networking paradigm, ContentPlace does not assume any specific technology (e.g., 802.11, Bluetooth) implementing the single hop wireless communication on which it is based. It only relies on the existence of an underlying abstraction level that manages the available interfaces and provides the correct mapping between them[38]. ContentPlace does not rely any routing protocols either, as it autonomously uses application layer information (in this case, information on the sociality of nodes) to disseminate objects across the network.

The dissemination of messages in ContentPlace exploits pair-wise contacts between nodes, during which an association is established (Figure 1). At the beginning of a contact, a new association is established if the two nodes are both free, i.e., not already engaged in an ongoing association. Otherwise, the association request is queued until the busy node becomes free again. During an association, each node acts as both the content uploader and the content downloader, for itself or on behalf of the other nodes of its communities. An association is completed when both peers have finished downloading data objects deemed useful (for themselves or for the nodes of their communities, according to Equation 2). An association can terminate unexpectedly before the downloading is completed, e.g., because the two nodes have moved out of range or because one of them has run out of battery. In this case, the association is closed, data objects that were successfully transferred are stored in the buffer, the others are discarded.

When a new association is established, the two nodes exchange the state of their respective buffers, i.e., they tell each other what data objects they

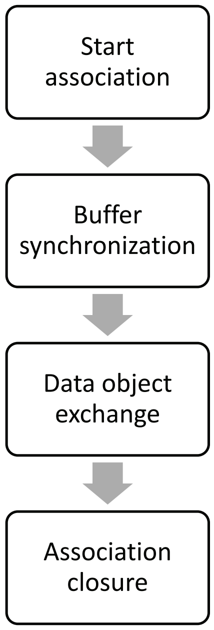


Figure 1: ContentPlace algorithm - Setting up an association

are currently storing. The algorithm described in Equation 1 is then run on the joint set of the locally stored objects and the objects advertised by the peer, and, if some of the peer's object are selected to be retrieved, a request is issued to the peer. When the peer has provided the requested objects, the requesting node stores the new objects in its buffer and closes the handshake on its side. The communication exchange is sketched in Figure 2.

Besides the data object exchange process, in ContentPlace nodes have also to keep up-to-date the estimates of the utility component's parameters (Equation 3). To this aim, nodes periodically broadcast a summary message containing the necessary information to compute these estimates. More details will be given in Section 4.2.

4. ContentPlace social design

The use of the social weights in Equation 2 permits full flexibility in the ContentPlace design. Specifically, it allows us to define and compare different social-oriented policies, as well as, in the limiting case, *non*-social policies such as a greedy behaviour. Although clearly not exhaustive, the set of social-oriented policies we compare covers a fairly large spectrum of

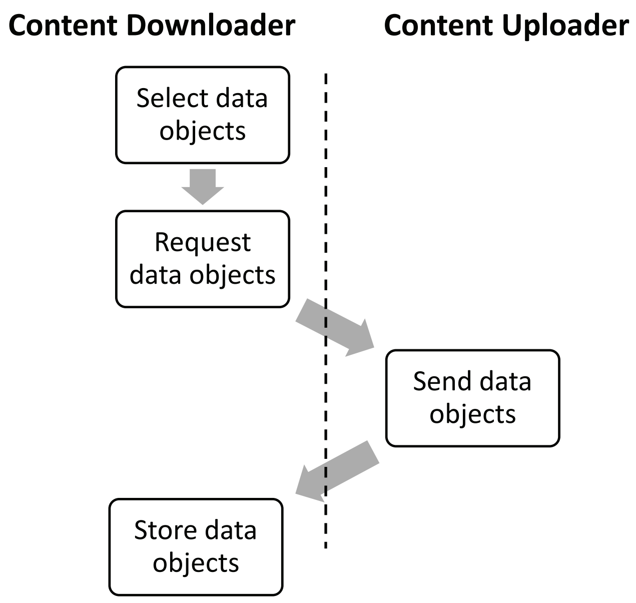


Figure 2: ContentPlace algorithm - Data object exchange

possible (reasonable) definitions. Overall, the global goal we wish to achieve is to optimise the hit rate for *all* users in *all* communities. Different policies clearly give different importance to the utility components. The comparison we carry out shows which are the components that provide the best behaviour with respect to the desired global target.

4.1. Policies definition

We consider the following policies:

Most Frequently Visited (MFV) Each community is given a weight proportional to the time spent by the user in that community. Specifically, if t_i is the time spent by the user in the i-th community since the system start-up, then w_i is equal to $t_i / \sum_i t_i$. With this policy, dissemination decisions of a user favour the communities the user is more likely to get in touch with.

Most Likely Next (MLN) The weight of the i-th community is equal to the probability of visiting the i-th community, conditioned to the fact that the user is in the current community. Hereafter, this probability is referred to as $P(c_i|CC)$, where C denotes the current community. The weight of the current community is set to 0. With this strategy, users favour the communities they will be visiting next, but do not contribute to data dissemination within their current community.

Future (F) As in MLN, the weight of the current community is set to 0. However, the weight of all other communities is set as in MFV, i.e., is proportional to the average time spent by the node in that community. With respect to MLN, with F we consider not only the most likely community for the next visit, but all the communities the user is in touch with.

Present (P) The weight of the current community is set to 1, and the weights of all other communities are set to 0. With this strategy, users always behave as members of the community they are currently in, and do not favour any other community.

Uniform Social (US) All the communities the user gets in touch with are given equal weight. Therefore, w_i is equal to 1 for the home and the acquainted communities.

Clearly, it would be possible to consider a number of additional strategies, by modifying the definition of the weights. The strategies we have selected are representative of several *reference* behaviours. In the US policy all communities a user is in touch with are given the same importance. In MFV the importance of a community is proportional to the time spent by the user in the community. P and MLN can be seen as opposite extreme customisations of MFV. In P only the current community is given importance. This is a MFV customisation which looks exclusively at the current "role" of the user, as a member of the current community, without any "look-ahead" behaviour. In MLN the current community is not given any importance, and only future communities are considered. MLN is thus a customisation of MFV with an extreme "look-akead" behaviour. Finally, F is an intermediate policy between MFV and MLN. It keeps the "look-ahead" behaviour of MLN, because it does not consider the current community. However, as in MLN, it considers *all* the other communities the user is in touch with, and not only the most likely one for the next visit.

Finally, for comparison purposes, we consider two non-social policies as well, and specifically a Greedy and a Uniform policy. In the Greedy policy all weights but the one of the local user are set to 0. In the Uniform policy all the weights are equal. As a minor, but important, remark, note that in this case a lot of data objects ends up having the same utility. In this case, a node breaks ties by choosing data objects according to a uniform distribution.

4.2. Social parameter estimation

The ContentPlace social-oriented policies require online, dynamic estimation of the utility components' parameters, as well as an estimation of the parameters required to compute the components' weights. In this section we describe how this can be achieved by avoiding any form of (controlled) flooding, such as that implemented by Epidemic Routing [42], which easily saturate networking resources [26]. Clearly, this choice calls for a trade-off between estimation accuracy and network overhead.

A necessary pre-requisite to estimate the parameters is to detect the communities in the network, and to enable nodes to understand in which community they are currently roaming. Fortunately, there are promising results about autonomic community detection in opportunistic networks ContentPlace can rely on, such as [22, 24]. These mechanisms allow nodes of an opportunistic network to i) be aware of the communities they belong to and have acquaintance with, and ii) be aware of the community in which they are currently in at any given point in time. We assume that one of these mechanisms is in operation.

4.2.1. Estimation of the social weights

The communities' weights defined in Section 4 can be easily computed thanks to the community detection features and, in some cases, by measuring the time spent by nodes in the different communities, and monitoring transitions between communities. Specifically, the strategies P, US and MLN just require community detection. This trivially holds true for P and US. MLN requires an estimate of the conditional probability of moving to future communities, starting from a given current community, i.e., $P(c_i|CC)$ where CC is the current community. This is equivalent to estimating the transition probabilities of a Markov process whose states are the different communities the user can visit. These probabilities can be estimated on line, by monitoring the transitions between communities during the user's movements. Finally, MFV and F can be implemented by measuring the time spent by the user in each community. In MFV, the weight ω_i is equal to $t_i/\sum_i t_i$, where t_i is the time spent by the user in community i. In F, the weights are defined as in MFV, unless for the weight of the current community, which is set to 0.

4.2.2. Estimation of the utility parameters

Gathering context information to compute utility components requires some more steps. According to Equations 2 and 3 to compute utility components for a given data object a node requires the size of the object (s), and estimates of the access probability (p_{ac}) and the availability of that object (p_{av}) in all the individual communities. Theoretically, to achieve the maximum precision of parameter estimation, nodes should advertise all information for all data objects they become aware of, and for all communities they happen to visit. Clearly, this would result in a very detailed computation of utility values, but in a huge networking overhead. Instead, we chose to exploit nodes' movements to save on network overhead, which is one of the basic principles of opportunistic networks. Basically, when two nodes meet they exchange a summary of data objects in their caches. From these snapshots, each node is able to compute, for each object, a fresh sample of the local availability $\hat{p}_{av,l}$, as the fraction of time during which the object has been seen on neighbours caches. This newly computed value is then used to update $p_{av,l}$ according to a standard smoothed average $p_{av,l} \leftarrow \alpha p_{av,l} + (1-\alpha)\hat{p}_{av,l}$. For what concerns $p_{ac,l}$, we assume that $p_{ac,l}$ is equal to 1 for those objects the user is interested into, and equal to 0 for the others.[3].

The estimation of the utility parameters for a generic community i, different from the local one, steams from the fact that,in ContentPlace, together with the summary vector describing its cache, each node also advertises the set of data objects *its local user* is interested into, and an estimate of the availability of the object for *its* local user, i.e., $p_{av,l}$. Then, every time period T, each node compute a fresh sample for $p_{ac,i}$ and $p_{av,i}$ as the arithmetic mean of the values advertised by the neighbours during T. Then these values are used to update $p_{ac,i}$ and $p_{av,i}$, using the standard smoothed average as seen above. For a more detailed explanation see [6].

Finally, note that the size s of a data object (for which a utility value is required) is easily derived from the summary vectors advertised by the neighbours.

[3]A more precise estimation of the access probability of the local user to a data object would require a refined model of the user behaviour as far as data access is concerned. However, this is an orthogonal problem with respect to the ContentPlace algorithms, and therefore we choose this simplified representation of users' access pattern.

5. Performance evaluation

In this section, we evaluate the performance of the social-oriented policies described in Section 4. To this aim, we developed a custom simulator that is extended from the one in [7] and uses the same assumptions for lower communication layers. As we discuss in the following, the simulation scenario we consider has been chosen as it is able to highlight *general* features of the social-oriented policies. Note that in [6] we have already presented results showing the impact of system parameters such as the cache size and the number of nodes, which are not evaluated here. The main focus of this analysis is to understand the impact of the different social-oriented policies. We also include in the comparison the two non-social policies, i.e., the Greedy and the Uniform policies. Uniform has been identified as the best heuristic (from a number of standpoints) in [29]. Furthermore, Greedy and Uniform have shown to achieve boundary performance result in [6]. Specifically, Uniform is the best possible policy in terms of fairness, while Greedy the best in terms of hit rate, *in a scenario with a single homogeneous community.*

We hereafter describe the default scenario for our simulations. The default scenario is composed of 45 nodes, divided into 3 communities, moving according to the HCMM model [4] in a 4x4 grid (1000m wide). HCMM is a mobility model inspired by the Watt's caveman model, that has shown to reproduce statistical figures of real user movement patterns, such as inter-contact times and contact duration [4]. In HCMM, each group represents a social community, and nodes within the same group have social relationships among themselves. Also nodes belonging to different communities can have social relations: according to the rewiring probability (p_r), each link towards a friend is rewired to a node belonging to a different community. Social links in HCMM are used to drive movements: each node moves towards a given community with a probability proportional to the number of links he has towards the community. Thus, the rewiring parameter allows us to control the degree of interactions between nodes of different communities. In our simulations, each group is initially assigned to a cell (its home-cell) avoiding that two groups are physically adjacent (no edge contacts between groups) or in the same cell. This allows to eliminate physical shortcuts between groups, which would bias the evaluation of the ability of policies to bring data objects from one community to the others. Therefore, nodes can exchange data only due to social mobility of nodes and not due to random colocation. The rest of HCMM parameters are as in Table 1. We consider as many channels as

Node Speed	uniform in [1,1.86] m/s
Transmission Range	20m
Sampling period	5s
Cost function parameter (λ)	15
Smoothed average parameter (α)	0.9

Table 1: Configuration Parameters

the number of groups (n_{gr}). Each group is the source for $1/n_{gr}$ of the objects belonging to each channel, i.e., $1/n_{gr}$-th of the objects of each channel are generated (at the beginning of the simulation) in each group. Note that a data object is *always* available from the node that generated it. To not interfere with the data dissemination performance figures, nodes generating data objects make them available through a separate buffer with respect to the cache. Therefore, for any node, the only way to obtain objects not generated in the local group is to get in touch directly (i.e., the node itself moves in a different group) or indirectly (i.e., one of the nodes of the local community goes out and then comes back, with the desired data object in its cache) with an external community. To have an integer number of objects generated in each group, we consider 99 data objects per channel. Each node can subscribe just to one channel. When not otherwise stated, nodes' interests are distributed according to a Zipf's law (with parameter 1) within each group. Unless otherwise stated, we consider 3 channels. The popularity of channels is rotated in each group, such that each channel is the most popular in one group, the second-most popular in another group, and the least popular in the last group. Cache space on a node can accommodate exactly all data objects belonging to an individual channel. An analysis with varying cache sizes has been presented in [6]. The cache size we choose is a good trade off between seeing the impact of dissemination policies, and avoiding data object disappearance due to low utility on too many caches.

Nodes' requests for data objects follow a Poisson process with parameter $\lambda = 200$ (on average 3 requests every 10 minutes for each node). Nodes can request data only for the channel they subscribe. Within the channel, the data object they request is select according to a uniform distribution. Requests are valid until the simulation ends. As we show in the following, the delay distribution highlights that our simulation length is long enough to reasonably approximate an infinite requests validity timeout. As requests are buffered at issuing node only, and do not occupy cache space, having infinite validity does not impact on the system's performance. Instead, it allows us to derive a complete analysis of the system's performance for increasing validity timeouts.

All policies are evaluated in terms of the quality of service (QoS) perceived by the users and the resource consumption. The QoS is measured in terms of hit rate, latency, system utility and fairness level. The hit rate is given by the number of successful requests divided by the number of overall requests. Note that, unless otherwise stated, we show hit rate related to infinite timeout values. As not all policies reach 100% hit rate even in this case, this index allows us to show the fraction of requests that *cannot* be served by the policies. We then separately investigate the hit rate index as a function of the validity timeout. The latency in satisfying the requests has been computed as the difference between the time at which the request is satisfied and and the time at which the request was generated. The system utility is computed as the sum of the channel hit rate weighted with the access probability of each channel, i.e., $SU = \sum_i p_{ac,i} hr_i$. The fairness of each policy has been computed according to the traditional Jain's fairness index (using the hit rate as a measure of the service level obtained by each channel). Resource consumption has been measured in terms of the traffic generated in the network, i.e., the average number of data transmitted by all nodes during the simulations. This includes data exchanged for context creation, buffer state data objects, request data objects and data objects themselves. Simulations run for 50000s. Exchanges of data objects upon nodes' contacts start after an initial transitory required by parameter estimators to reach the steady state. Results shown in the following section have a 95% confidence interval, obtained through standard independent replication techniques.

5.1. Analysis with uniform rewiring

Our first experiment is based on a configuration in which the rewiring probability is the same for all nodes, and equal to 5%. This means that the average number of social links across communities is the same for all the three communities. Although the probability of rewiring is not particularly high, it is already sufficient to mix communities enough to let data objects circulate across all communities, independently on the data dissemination policy. Indeed results in Figure 3 show that all policies achieve 100% hit rate. Furthermore, results do not change depending on the channel to which the travellers are subscribed (Figure 4).

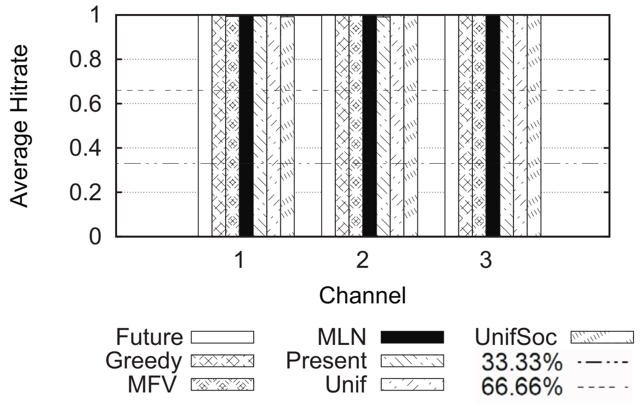


Figure 3: Hitrate with rewiring 0.05 - Travellers subscribed to ch.1

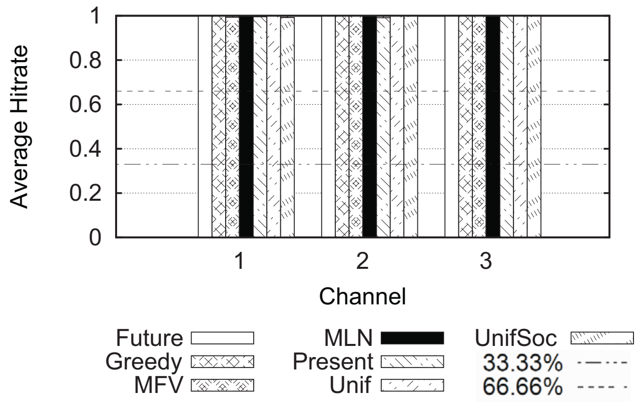
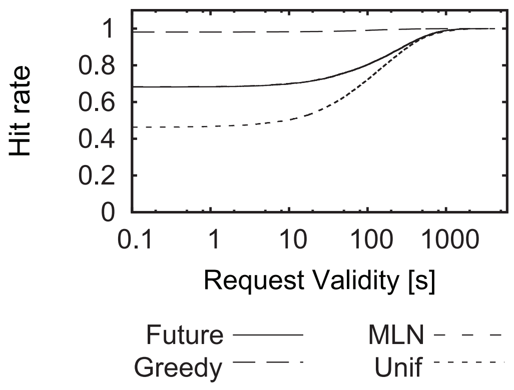
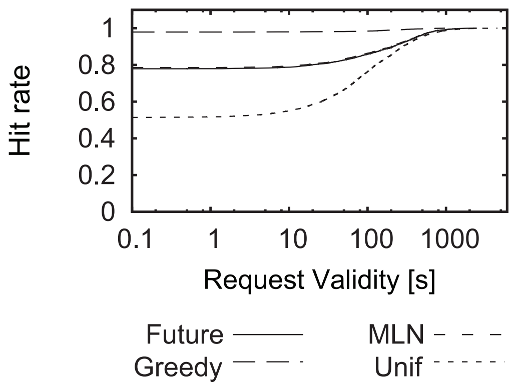


Figure 4: Hitrate with rewiring 0.05 - Travellers subscribed to ch.3

If we reduce the timeout of the request, we realize that the QoS provided by different policies may vary with the specific configuration. In fact, Figures 5(a) and 5(b) show that data objects are delivered faster by the Greedy policy, and more slowly by the Uniform policy. Thus, when reducing their timeout, many requests will not be fulfilled under the Uniform policy, resulting in an decrease in the hit rate. Again, the performance of the social-aware policies is halfway between the Greedy and the Uniform policy.



(a) Requests on ch. 1



(b) Requests on ch. 3

Figure 5: Hit rate with varying timeouts - Rewiring 0.05 - Travellers subscribed to ch. 1

Table 2 shows that policies are not equivalent, even when they provide the same hit rate. In fact, with respect to the bandwidth overhead, the Uniform policy uses triple the bandwidth that MFV, Present and Uniform Social need, and around 20 times more than Future and MLN. The most significant difference is between Greedy and Uniform, where the increase in the data transmitted is around 3500%. In the next Section we will see in more details the reason for this behaviour. Here we only highlight the fact that when not exploiting context information, the bandwidth consumption may become huge. Another implication of Table 2 is that a selfish policy (Greedy) can pay when the contacts between nodes are numerous and uniformly distributed. In fact, when nodes can freely move from one community to another and meet many other nodes, the likelihood of finding another node with the same interests is high, and therefore the data objects can easily be found by their interested nodes.

Bandwidth Overhead [MB]			
Greedy	175.45 ± 1.77	*MFV*	21583.80 ± 1112.72
Future	2589.45 ± 533.18	*UnifSoc*	21124.10 ± 1106.01
MLN	3412.71 ± 352.65	*Unif*	62306.43 ± 3828.69
Present	22796.61 ± 1447.52		

Table 2: Resource Consumption - Rewiring 0.05 - Travellers subscribed to ch. 1

Summarizing, when nodes are highly mixed, data objects spread naturally across the network, regardless of the policy used. However, policies differ in their resource consumption and in the speed of the resulting dissemination process. In a setting with high node mobility, the Greedy policy guarantees the lowest bandwidth overhead and the quickest delivery.

5.2. Analysis in the default scenario

Based on the results in Section 5.1, here we consider a less mixed mobility pattern, as follows. Each pair of communities is connected through just one node. Specifically Community 1 (C1) has two nodes (“travellers”) with relationships outside C1, one with Community 2 (C2), the other with Community 3 (C3). Hereafter, we show the performance figures related to nodes in C1. The same remarks can be done for nodes in the other communities, as well. Note that, from Equation 2, it is clear that the channel the traveller nodes are subscribed to (which affects the u_l component) impacts on the data dissemination process. For this reason, we replicate the experiments by varying the channel travellers are subscribed to.

Figure 6 shows the hit rate for C1, when travellers are subscribed to channel 1. Specifically, the group of boxes related to channel i show the hit rate achieved by nodes whose home community is C1 and are subscribed to channel i. Experiments with travellers subscribed to the other channels provide similar results for all policies but the Greedy, that achieves 100% hit rate only for the channel the travellers are subscribed to. Recall that these plots are related to an infinite validity timeout. When shorter timeouts are used, the misbehaviours of Present, MFV and Uniform Social we discuss hereafter become more serious. Also, the performance difference between MLN and Future (which already in this case appear as the best policies) and the other policies increase. We will analyse these aspects in detail in Section 5.3. As a preliminary remark note that, since data objects are always available at generating nodes, a hit rate of 33.33% is always guaranteed. We can identify four different behaviours. With the Greedy policy, travellers store only data objects to which they are directly interested. This results in a 100% hit rate on the subscribed channel and a 33.33% hit rate on the other channels (there is hit only on the 1/3 of data generated locally). As expected, the Greedy policy is able to improve the hit rate of the nodes interested in the same objects the travellers are interested, and is not able to disseminate other objects. With the Uniform policy, the hit rate of all channels improves and reaches about 80%. The set of social policies MFV, Present and Uniform Social all show a similar behaviour: they tend to be slightly unfavourable towards the most popular channel. This is due to the fact that nodes within the same group tend to synchronise their behaviour: when nodes realise that certain objects are poorly available, they all fetch them as soon as they become available. This results in the objects becoming highly available, and being dropped simultaneously by all nodes. A detailed analysis of the logs confirms this behaviour. Finally, MLN and Future policies have a very good hit rate in all cases. The key of these policies is that nodes do not consider the community in which they currently roam, but just future communities. It is easy to see that this results in *static* nodes (i.e. nodes without social relationships outside their home community) behaving greedily, and in travellers working to help communities they will visit in the future. This clearly avoids the problems related to the synchronisation effect of the other policies. Results related to the other communities (not shown here) highlight that these policies guarantee the same hit rates shown in Figure 6. This is quite important. For example it shows that nodes subscribed to channel 3 in C2 are able to get not only the locally generated objects, and not only the objects carried generated in C1 (directly carried by the traveller of C1 visiting C2), but even those objects generated in C3 that are firstly brought in C1 by the traveller of C1 visiting C3. The identification of these "social" paths is something that is peculiar of the ContentPlace MLN and Future policies. We can anticipate that this type of "collective" social behaviour, in which just travellers adopt a social-oriented strategy turns out to be the best solution. The above remarks are confirmed when considering

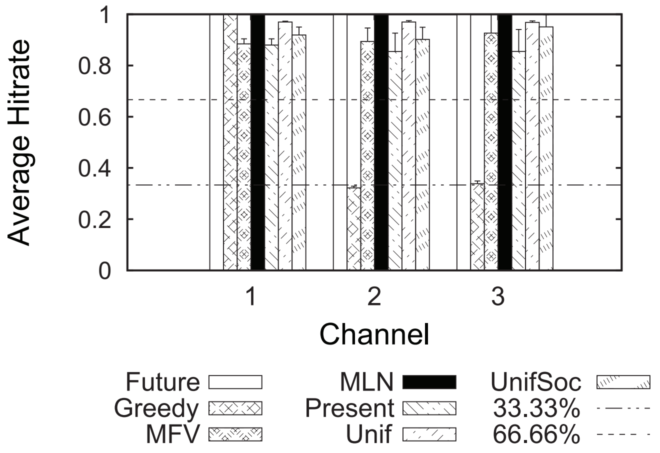


Figure 6: Hit Rate - Travellers subscribed to ch. 1

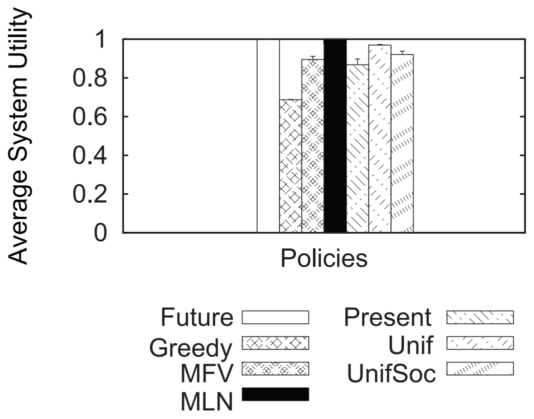


Figure 7: System Utility - Travellers subscribed to ch. 1

the system utility and fairness indices, as well (Figures 7 and 8): Future and MLN are the best policies, although Uniform closely approximate their performance. Note that the Greedy policy is the only one achieving low fairness. Figures 7 and 8 are related to the case when the travellers are

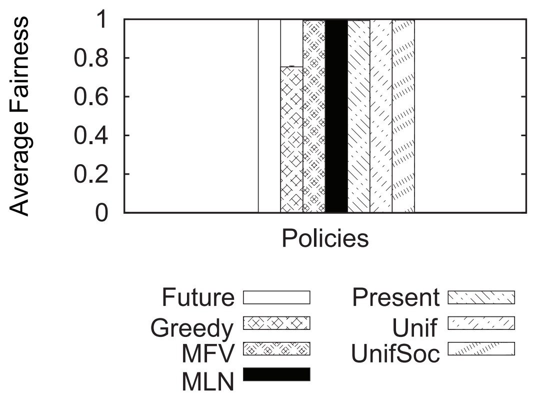


Figure 8: Fairness - Travellers subscribed to ch. 1

Bandwidth Overhead [MB]			
Greedy	68.89 ± 0.28	*MFV*	16497.79 ± 660.57
Future	508.32 ± 21.84	*UnifSoc*	16749.46 ± 430.16
MLN	509.05 ± 21.61	*Unif*	71974.40 ± 1316.68
Present	15500.51 ± 881.80		

Table 3: Resource Consumption - Travellers subscribed to ch. 1

subscribed to channel 1. Similar results are obtained in the other cases, as well.

Table 3 shows the bandwidth overhead for each protocol. The Uniform policy, although closely approximates MLN and Future in terms of hit rate and fairness, significantly overuses network resources. This is because nodes continuously exchange data objects as a consequence of the tie breaking policy (see Section 4.1). It is easy to show that this is the only way for Uniform to make objects circulate. Furthermore, MFV, Present and Uniform Social pay for their synchronisation problem also with regard to the bandwidth overhead. Instead, MLN and Future have a very good performance also with respect to network overhead, while the performance of the Greedy policy is paid in term of hit rate.

Finally, Figure 9 shows the CCDF of the delay for *satisfied* requests on channel 1, when the travellers are subscribed to channel 1. For the sake of readability, we only show the Greedy, Uniform, Future and MFV policies. The Present and Uniform Social policies are basically equivalent to MFV, while Future and MLN are overlapped. We show this plot only, as plots for the other cases are qualitatively similar. Clearly, Greedy achieves the best performance in this case. The other social-oriented policies other than MLN and Future suffer quite high delay. This is a side effect of the unwanted synchronisation issue that we have discussed above. Requests for data objects that have disappeared need long time to be satisfied. MFV and Future clearly outperform Uniform also from this standpoint. Note that the maximum delay is in the order of 20000s. This confirms that simulation runs of 50000s are reasonably long to consider the request timeouts as infinite.

In this section we have presented the policies behaviours with respect to all performance figures. In the following, we concentrate on the hit rate index only to highlight the policies different behaviour in different scenarios. The comparison with respect to the other performance figures is qualitatively similar to the one presented in this section.

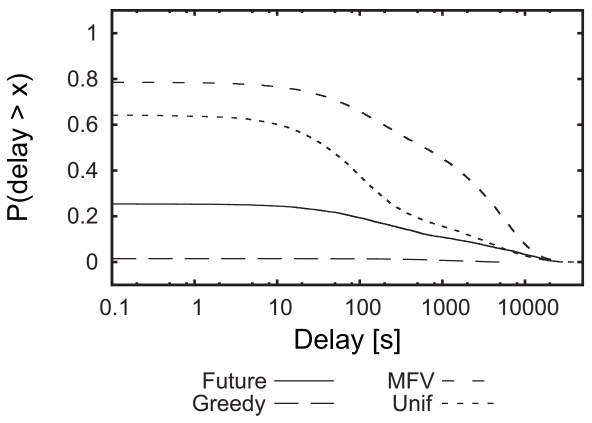
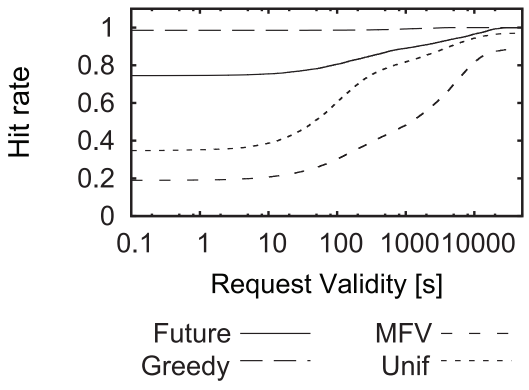


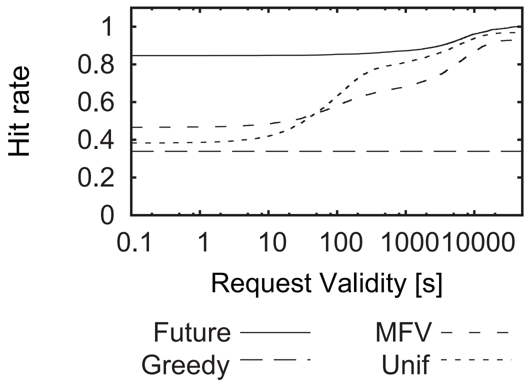
Figure 9: Delay CCDF for requests on channel 1 - Travellers subscribed to ch. 1

5.3. Reduced requests' validity timeouts

In this section we analyse the hit rate index as a function of the requests' timeout. Figures 10(a) and 10(b) show the hit rate for increasing requests' timeout. Again, we only present results related to the Greedy, MFV, Uniform and Future policies. Both plots are related to the case when travellers are subscribed to channel 1. Figure 10(a) shows the hit rate for requests on channel 1, while Figure 10(b) shows the hit rate for requests on channel 3. Thus, we consider requests on the most and least popular channels, respectively. Note that the hit rate in the Greedy policy do not change with the validity timeout. Recall that requests start after an initial transient in which the policies reach stability. Thus, the Greedy policy has already moved all the data objects it is able to move across communities. Uniform and the social policies increase the hit rate when the validity timeout increases. The dynamic is slower with respect to the Greedy policy, but they are definitely able to provide higher performance to channels that travellers are not subscribed to (see Figure 10(b)). In that case, as expected, the Greedy policy is not able to bring any new data objects in addition to those already generated in the community. Finally, again the MLN and Future policies confirm to be the best policies among the one investigated, for all the validity timeouts.



(a) Requests on ch. 1



(b) Requests on ch. 3

Figure 10: Hit rate with varying timeouts - Travellers subscribed to ch. 1

5.4. Uniform Zipf subscriptions

In this section we modify the default scenario by considering a different distribution for subscriptions to channels. Specifically, we continue to use a

Zipf distribution with parameter 1, but we do *not* rotate the most popular channels among communities. Channel 1 is always the most popular, channel 2 the second most-popular, channel 3 the least popular. Results have been derived in this case with a limited validity timeout equal to the expected time for a traveller to return in C1, which is about 250s. Figures 11 and 12 show the average hit rate and the system utility when the travellers are subscribed to channel 1 and 3, respectively, i.e. to the most and least popular channels. The main results we have found in this scenario is that the most popular channel receives the *worst* service for social-oriented policies other than MFN and Future. The channel travellers are subscribed to does not have a significant impact, as is clear by comparing the plots. This is a side effect of the synchronisation effect suffered by these policies. Since data objects of channel 1 are the most requested in *all* communities, they spread aggressively once available, and get easily dropped short afterwards, thus resulting in a high probability of being available just for limited amount of time (unless, of course for data objects generated within each community).

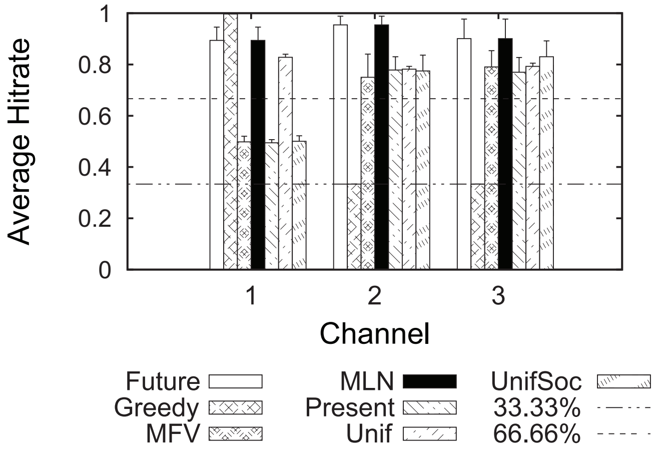


Figure 11: Hit rate with uniform subscriptions - Travellers subscribed to ch.1

5.5. Large number of travellers

In Section 5.2 we have suggested that policies, like Future and MLN, in which static users are greedy and travellers take care of moving data objects between communities result in the best social-oriented solutions. To further explore this claim, in this section we increase the number of travellers in C1 to 7. All of them are subscribed to channel 1, such that the set of static nodes

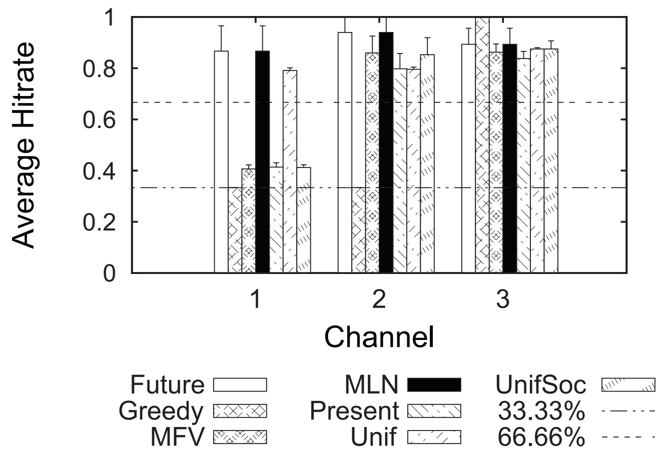


Figure 12: Hit rate with uniform subscriptions - Travellers subscribed to ch.3

subscribed to channel 1 in C1 is reduced to one node only. Figure 13 shows the hit rate related to C1. Also in this case, the validity timeout was set to the average time for the travellers to get back in C1. The main result in this scenario is that the hit rate of social-oriented policies other than MFN and Future tends to increase with respect to the case with less travellers. This is not surprising, as more travellers result in a more mixed scenario which (as highlighted at the beginning of Section 5.2), results in higher hit rates, in general. Also note that Future and MLN do not suffer from an increased number of travellers, because in C1 there is anyway enough overall cache space to let data objects of all nodes survive on static nodes.

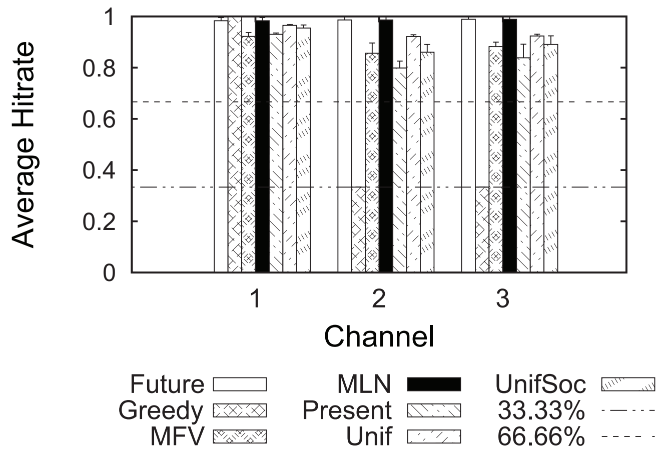


Figure 13: Hit rate - 7 travellers subscribed to ch. 1

5.6. Increased number of nodes

In Section 5.5 we have shown that an increased number of travellers improves the dissemination of data objects because it results in a more mixed scenario. In this section we want to evaluate the impact of an increased number of nodes that are not travellers. While the travellers have an active role by making possible the spreading of objects from one community to another, the nodes that always roam within the same community are just content generators/consumers and their contribution to the dissemination process is very limited. In this section we double the number of nodes in each community, going from 15 nodes to 30 nodes per community, and again we assign nodes' interests according to a Zipf's law with parameter $\alpha = 1$.

In terms of the hit rate, Figure 14 shows that the behaviour of the Greedy, Uniform, Future and MLN policy is approximately the same as in the case of 45 nodes (Figure 3). With many nodes, however, the performance of the social policies that suffer from synchronization problems worsens. The reason is that, with more nodes per community, the synchronization effect is stronger than before, and this results in a decrease in the hit rate. If we vary the request timeout, we find that the hit rate (Figure 15) shows the same trend as in Figure 10. Also, the delay CCDF (Figure 16) has the same pattern as in Figure 9. Therefore, from the QoS standpoint, increasing the number of nodes that are not travellers has only the effect of boosting the synchronization problems of the MFV, Present and Uniform Social policies.

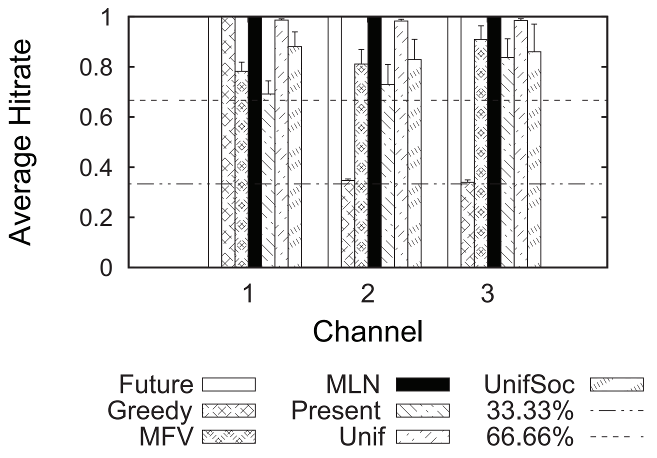
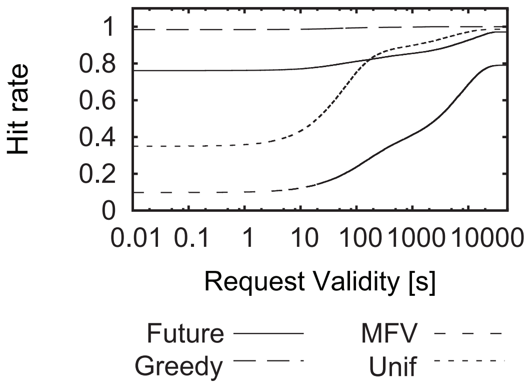
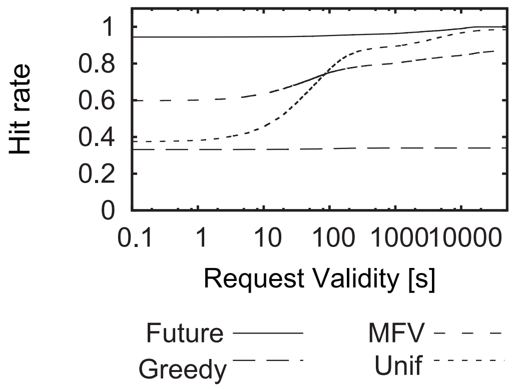


Figure 14: Hit rate with 90 nodes - travellers subscribed to ch.1



(a) Requests on ch. 1



(b) Requests on ch. 3

Figure 15: Hit rate with 90 nodes and varying timeouts - Travellers subscribed to ch. 1

In order to complete the analysis, in Table 4 we also give the results for the resource consumption. The most interesting finding here is that under the Uniform policy the bandwidth overhead with 90 nodes is about four times the overhead in the case of 45 nodes (Table 3). This means that the Uniform policy does not scale well with the number of nodes in the network, and this can be a problem in all cases in which resource usage is a concern. Instead, for all other policies there is a roughly linear dependence between the increase in the number of nodes and the resource consumption,thus implying a more judicious use of the network resources.

Considering both the QoS and the resource consumption, also in the case of an increased number of nodes per community, the best trade-off is provided by the Future and MLN social policies.

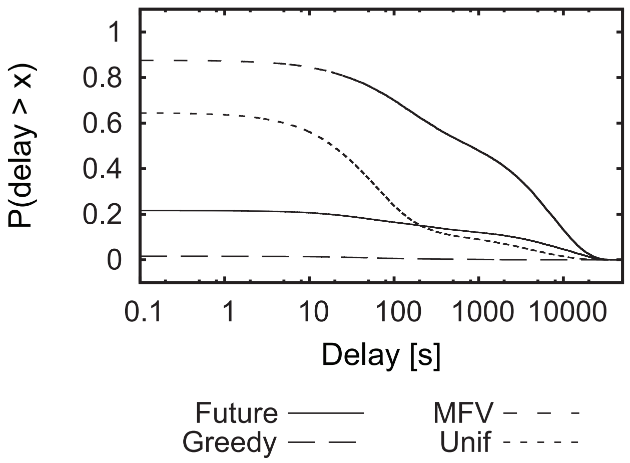


Figure 16: Delay CCDF for requests on channel 1 - Travellers subscribed to ch. 1

Bandwidth Overhead [MB]			
Greedy	181.86 ± 0.88	*MFV*	36758.21 ± 2937.98
Future	1114.23 ± 46.15	*UnifSoc*	36574.81 ± 3322.24
MLN	1132.90 ± 65.11	*Unif*	321973.33 ± 4324.55
Present	31836.81 ± 2457.00		

Table 4: Resource Consumption with 90 nodes - Travellers subscribed to ch. 1

5.7. Multi-hop social paths

The results presented so far show that in the considered scenarios MLN and Future are the best policies, and perform almost the same. However, there are cases in which they behave differently. Specifically, both MLN and Future fetch data objects by estimating social paths of travellers. Within any community, MLN just takes into consideration the *next* hop only, i.e., the next community it will visit. Future takes into consideration *all* the communities it is likely to visit in the near future, weighted by the probability of visiting each. Therefore, MLN might miss to exploit "multi-hop" social paths across multiple communities. To investigate this effect, we consider a scenario with one traveller only, belonging to C1, subscribed to channel 1. It can visit either C2 or C3 with equal probability when in C1, while always gets back to C1 after having been in C2 or C3. Furthermore, all nodes of C1 (C2, C3) are subscribed to channel 1 (2, 3). In this case, it is expected that MLN is not able to completely serve communities C2 and C3. While in C2 or C3, it will consider only the interests of users in C1, and thus it will only bring back data objects of channel 1. It will bring to C2 (C3) only data objects originated in C1 for channel 2 (3). On the other hand, Future is expected to provide 100% hit rate to all communities. This behaviour is totally confirmed by the simulation results in Figures 17 and 18, that show the hit rate as a function of the requests' validity timeout. As expected, both policies are fast in achieving the maximum hit rate. However, MLN can only serve 66.66% of the requests for users in C3, as it can only move the data objects of channel 3 generated in C1. Results similar to those in Figure 18 hold for community C2, as well.

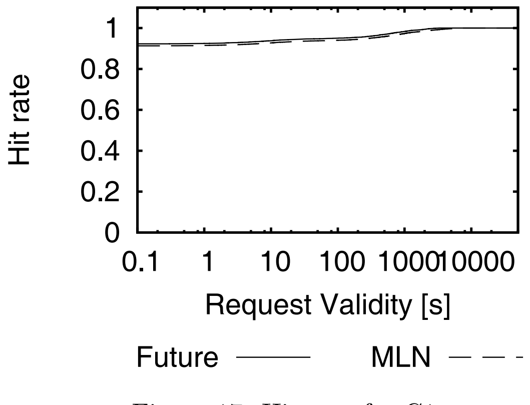


Figure 17: Hit rate for C1

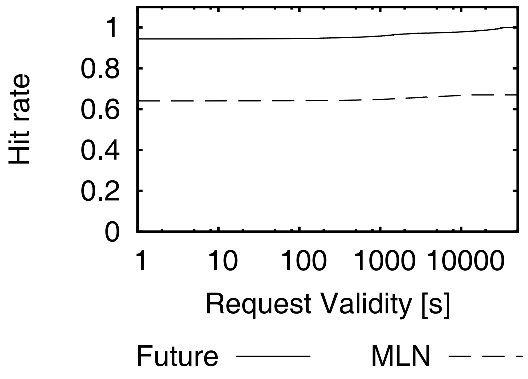


Figure 18: Hit rate for C3

6. Average Analysis of the Future policy

In this Section we perform an average analysis of the dissemination behavior of the Future policy, that we have shown to be the best in Section 5. The scenario we consider is that of two communities A and B, having N nodes each that roam locally in the community, with a traveler node commuting between A and B. We consider the following situation: i) an initial set of data has been already spread among the nodes of the two communities and its dissemination process has ended, leaving the system in a stationary state ii) at time $t = 0$ a new data object is generated for a generic channel ch_{new} within community B (given the symmetry of the topology, the choice of the generating community doesn't affect the analysis). The focus of our investigation is the time it takes for the traveler to deliver this new object to the interested nodes in community A (the underlying assumption is that there is at least one node in community A interested in the new data). We have chosen to restrict the analysis to the case of two communities, because this configuration represents the building block of every more complex scenario. In fact, the traveler's movements between multiple communities are nothing but a composition of its movement patterns between pairs of communities.

In this analysis, we assume that nodes' interest in the available channels follows a Zipf's distribution and that the ranking of the popularity of channels is the same in all communities. Then the probability that a generic node is interested in channel j (ranked j-th according to its popularity) is given by:

$$Pop\,(j) = \frac{1/j^{\alpha}}{\sum_{i=1}^{C} 1/i^{\alpha}}, \tag{4}$$

where α is the parameter of Zipf's distribution and C is the number of available channels. In this paper we consider $\alpha = 1$. Thus, Equation 4 becomes $Pop\,(j) = \frac{1}{jH_C}$, where H_C is C-th harmonic number. In addition, each node can be interested in just one channel and this interest implies that the node wants to receive a copy of each new data object of that channel as soon as possible, without the user issuing a specific request. For this reason, the terms "interested nodes" and "destinations" will hereafter be used interchangeably. In order to avoid the superposition of different effects, we assume that the traveler has not direct interest in any available data. We also assume that data objects never disappear. Given that, according to the Future policy, all nodes except for the traveler are greedy,it is reasonable to consider this condition verified when the nodes' buffers are not too small with respect to the number of data objects for their interested channel. We assume that the dissemination process stops when a given percentage of interested nodes in the same community has been reached by the data object. This percentage is referred to as replication factor. For data objects belonging to channel c, the replication factor $f(c)$ might range from $1/N_c$ and 1. In our analysis we consider $f(c) = \frac{1}{N_c}$, which is the worst case for the delay experienced by data objects. In our analysis we consider $f(c) = \frac{1}{N_c}$, i.e., each object is stored by one node only. This is the worst case for the time required by traveler to get in touch with a copy of the data object.

Throughout this Section we consider a simplified version of the utility function defined in Section 3.2.2. Instead of including in the availability the notion of redundancy (e.g., the availability for a data object with two copies in a community is higher than that for a data object with one copy), the availability used hereafter only reflects the presence or not of a data object. Therefore the availability is equal to 1 for data objects seen by the node, 0 otherwise.

For what concerns the mobility of nodes, we assume that inter-contact times between nodes roaming in the same community are exponentially distributed with rate λ. This assumption in backed up by the fact that, in HCMM, nodes, when roaming within a community, move according to the Random Waypoint mobility model, whose inter-contact times have been shown to follow an Exponential distribution [18]. This consideration holds true also for the traveler because it roams in either community A or B.

The dissemination process for our social-aware policies is heavily influenced by the accuracy of the statistics (access probability and availability) used by the travelers to make retrieval decisions. For example, in Section 5 the dissemination of data objects starts after a transitory during which the traveler has constructed the statistics for the access probability and availability. This is the best case for our social-aware policies, which are as good as the statistics that the traveler nodes are able to collect. Therefore, our analysis is split into two cases. We first consider the case in which the statistics used by the travelers are congruent with the state of the system. The second part of our analysis focuses on the functioning of the system when the social information is not yet available or is not precise. We refer to the latter part as *transient analysis*, because we target the transitory phase of collecting statistics, while the former is denoted as *stationary analysis*.

6.1. Stationary regime of context information

At time $t = 0$, when the available data objects have already been disseminated to the interested nodes and the context information on the traveler is up-to-date, the system is in a situation where each data object has utility equal to zero. In fact, being the data objects available in both communities, their availability (as seen by the traveler) is at the maximum level. If at time $t = 0$ a new data object is generated, this data object will be the only one with utility different from 0. This means that when the traveler gets in touch with the data object, it will get for sure a copy of it, being this data object the one with the highest utility. Therefore, when the context information on the traveler is correct, the delay for the new data object to reach its destinations depends only on the physical time for the traveler to get in touch with the data object and to get back to community B: i.e., the delay is only a function of the mobility characteristics of the system.

We define $E[D]$ as the expected delay from the generation of the new data object in community B to its delivery to its destinations in community A. $E[D]$ can be separated in its different components as follows:

$$E[D] = E[D_{fetch}] + E[D_{local}] \tag{5}$$

$E[D_{fetch}]$ is the average time required for the data object to enter the community A for the first time. $E[D_{local}]$ is the expected time for the interested nodes in community A to be reached by a copy of the data object. As we have assumed that a data object is not further disseminated when its replication level is reached, with $f(c) = \frac{1}{N_c}$ the spreading in the local community stops after the first interested node is reached. Therefore, in this case, $E[D_{local}]$

is equal to the expected time for the traveler to deliver a copy of the data object to the first interested node in community A.

When the new data object appears in community B at time $t = 0$, the travel can be in community A or in community B, and its location impacts on $E[D_{fetch}]$. Applying the law of total probability we can write $E[D_{fetch}]$ as

$$\begin{aligned} E[D_{fetch}] &= E[D_{fetch}|S_T = C_A] \cdot P(S_T = C_A) + \\ &\quad + E[D_{fetch}|S_T = C_B] \cdot P(S_T = C_B), \end{aligned} \tag{6}$$

where S_T is the community in which the traveler T is roaming when the data object is generated. The probability of finding the traveler in either community depends on the mobility model in use and is equal to the stationary distribution (if any) of the location of nodes. For the HCMM mobility model used in Section 5, these probabilities can easily be found [4]. Intuitively, the fact that the traveler commutes between the two communities suggests that the overall expected delay is a composition of multiples of the expected roaming time in these communities and it depends on how many round trips are required on average to retrieve and deliver the data object. The fact that the traveler can be in either community when the new data object is generated impacts on the delay for the first round trip. We define the duration of a normal round trip T_{cycle} as the time it takes for a traveler to come back to community A, given that it has just entered that community. T_{cycle} is the sum of the expected roaming time in two communities plus the expected time to travel from one community to the other.

$$T_{cycle} = E[T_A] + 2E[T_{tr}] + E[T_B] \tag{7}$$

When the data object is generated, the traveler can have been in either A or B for an unspecified amount of time and not having just entered that community. Therefore, for the first round trip we have to take into consideration the expected *remaining* roaming time in the community in which the traveler is roaming at $t = 0$, instead of the expected roaming time itself. However, if we assume that the roaming periods follow an Exponential distribution, then the expected remaining roaming times are equal to the expected roaming periods, according to the PASTA principle [36]. Thus, we have that $E[T_A|S_T = A] = E[T_A]$ and $E[T_B|S_T = B] = E[T_B]$. The only difference between the traveler starting from community A or community B is that, when the traveler starts from community B, it has a chance of getting in touch with the new data object immediately, without having to wait for the next round trip. This implies that in this case the contribution to the expected delay is shorter than when the traveler is roaming in A at $t = 0$. Finally, in both cases, once the traveler enters community A with the data object, the expected delay to reach the first destination is given by $E[D_{local}]$. After putting all these considerations together, we obtain:

$$T'_{cycle} = E[T_A] + 2E[T_{tr}] + E[T_B] \tag{8}$$

$$T'_{cycle-short} = E[T_{tr}] + E[T_B] \tag{9}$$

T_{cycle}, $T_{cycle-short}$ and $T'_{cycle-short}$ only depend on the the mobility of the traveler. Again applying the law of total expectation to Equation 6, we have:

$$E[D_{fetch}|S_T = C_A] = T'_{cycle} + \sum_{i=1}^{\infty} T_{cycle}(i-1) \cdot P(Y = i) \tag{10}$$

$$E[D_{fetch}|S_T = C_B] = T'_{cycle-short} + \sum_{i=1}^{\infty} T_{cycle}(i-1) \cdot P(Y = i), \tag{11}$$

where Y is a random variable representing the probability that the traveler fetches the data object at the i-th round (i.e., that the travel meets one of the nodes currently having a copy of the data object in community B).

If the number of nodes currently having a copy of the data object in community B is j, then the distribution of the delay until the first one is reached is the minimum over a set of j exponentially distributed random variables, all having the same rate λ. The minimum of these variables follows an Exponential distribution with rate equal to $j\lambda$ [36].

$$U_j = \min\{E_1, \cdots, E_j\} = \min\{\text{Exp}(\lambda), \cdots, \text{Exp}(\lambda)\} \sim \text{Exp}(j\lambda) \tag{12}$$

Then, the probability that the traveler sees the data object during a generic round i is equal to the probability of meeting one of the nodes currently having a copy of the data object before moving back to community A, i.e., within the roaming period T_B. As in our analysis there is just one node in B having a copy of the new data object, the probability that the traveler gets in touch with that node within a roaming period with distribution T_B is $P(U_1 < T_B)$. While we know from Equation 12 that U_1 follows an Exponential distribution with rate λ, the distribution of T_B depends on the mobility model in use. If, for the sake of tractability, we assume that T_B follows an

Exponential distribution with rate $\frac{1}{E[T_B]}$, using standard probability theory we obtain that $P(U_1 < T_B) = \frac{\lambda E[T_B]}{\lambda E[T_B]+1}$. Each roaming period in community B can be seen as a Bernoulli trial with success probability $p_B = P(U_1 < T_B)$. Thus, the probability that the traveller gets the data object at exactly the i-th roaming period follows a Geometric distribution:

$$P(Y = i) = (1 - p_B)^{i-1} p_B = \left(\frac{1}{\lambda E[T_B] + 1}\right)^{i-1} \frac{\lambda E[T_B]}{\lambda E[T_B] + 1}. \tag{13}$$

If we rewrite Equation 10 using Equation 13, we obtain:

$$E[D_{fetch}|S_T = C_A] = T'_{cycle} + \sum_{i=1}^{\infty} T_{cycle}(i-1)(1-p_B)^{i-1} p_B \tag{14}$$

After routine manipulation, Equation 14 becomes:

$$E[D_{fetch}|S_T = C_A] = T'_{cycle} + T_{cycle}\frac{1-p_B}{p_B} = T_{cycle}\frac{1}{p_B}, \tag{15}$$

where the last equality follows from the exponential assumption for the roaming times. For $E[D_{fetch}|S_T = C_B]$, the computation is the same, and so we have:

$$E[D_{fetch}|S_T = C_B] = T'_{cycle-short} + T_{cycle}\frac{1-p_B}{p_B} \tag{16}$$

Once the traveler has fetched the data object, the delay of the delivery to the first destination met depends on how long the traveler roams in community A. If during this roaming interval no destination is met, then we have to wait for an entire cycle for the traveler to be back in that community again, and so on. If the data object is delivered at the i-th round, then $E[D_{local}]$ is given by the delay up to the $i-1$-th round, plus the time required to reach the destination during the i-th round. Therefore, the expression for $E[D_{local}]$ is the following:

$$E[D_{local}] = E[U_{N_{ch_{new}}}] + \sum_{i=1}^{\infty} (i-1)\, T_{cycle} \cdot (1-p_A)^{i-1} p_A, \tag{17}$$

where p_A is the probability of meeting one of the interested nodes during the roaming period. As the number of nodes of community A interested in channel ch_{new} is $N_{ch_{new}}$, $p_A = P(U_{N_{ch_{new}}} < T_A)$. From Equation 12 we know that $U_{N_{ch_{new}}} \sim Exp(N_{ch_{new}}\lambda)$. Thus, $E[U_{N_{ch_{new}}}]$ is equal to $\frac{1}{N_{ch_{new}}\lambda}$ and $p_A = P(U_{N_{ch_{new}}} < T_A)$ is equal to $\frac{N_{ch_{new}}\lambda E[T_A]}{N_{ch_{new}}\lambda E[T_A]+1}$. Assuming independent and identically distributed node encounters and $Pop(j)$ as in Equation 4, the average number of nodes interested in channel ch_{new} is given by $N_j^n = Pop(j) * N^n$. After some manipulation we get:

$$\begin{aligned} E[D_{local}] &= \frac{1}{N_{ch_{new}}\lambda} + T_{cycle}\frac{1-p_A}{p_A} = \\ &= \frac{T_{cycle} + E[T_A]}{E[T_A]NPop(ch_{new})}. \end{aligned} \tag{18}$$

Now that we have the expressions for $E[D_{fetch}]$ and $E[D_{local}]$, the formula for $E[D]$ follows from simple substitutions in Equation 5.

In the remaining of this Section, we give a brief overview of the dependency of the delay on the characteristics of the mobility and the popularity of the channel. Figure 19 shows $E[D]$ against the popularity of the channel to which the new data object belongs. The channel for the new data object is selected among 100 channels. Small, medium and large values of λ correspond, respectively, to 0.0001, 0.001 and 0.01. These setting will be used throughout Section 6. In Figure 19 the delay experienced by the new data object decreases linearly with increasing popularity. The intuitive reason behind this behavior is that the lesser popular is a data object, the more difficult is for the traveler to find an interested node to which deliver the object. The second result from Figure 19 is that this trend worsens when the frequency of contacts is smaller. Figures 20 and 21 show the separated contributions to the overall delay with an intermediate value of λ and varying average roaming periods. In Figure 20, $E[T_A]$ is ten times smaller than $E[T_B]$ and $E[T_{tr}]$, while the opposite is true for Figure 21. When the roaming time in community B is long, it is very easy for the traveler to get the data object, and the overall delay is strictly dependent on $E[D_{local}]$. This effect is mitigated in Figure 21.

6.2. Transient regime of context information

The case in which at the time the new data object is generated, the traveler has not yet statistics on the popularity and availability of the data is the worst case for our social-aware dissemination policies. In fact, during the transitory period when the traveler builds these statistics from scratch, the precision of the collected social information might be unreliable and this may

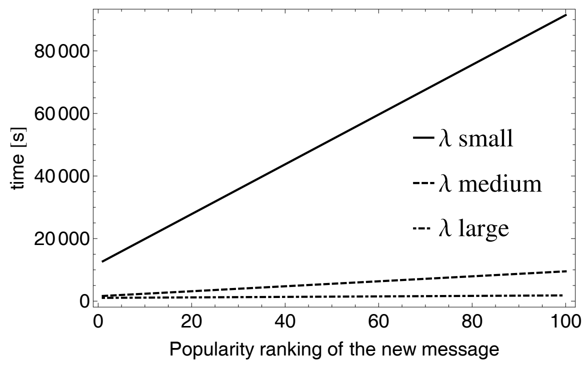


Figure 19: Expected delay

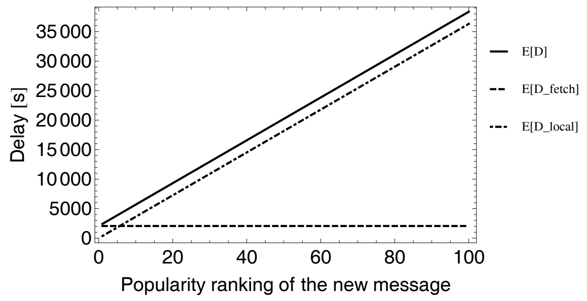


Figure 20: Expected delay with $E[T_B] = E[T_{tr}] = 1/10E[T_A]$

lead to wrong retrieval decisions on the traveler. To characterize the transient phase during which the traveler collects the information, it is worth focusing on two aspects: i) how the traveler gets in touch with the other nodes and ii) how the traveler gets in touch with the data objects.

6.2.1. Meetings between the traveler and the other nodes

The statistics on the interests and on the distribution of data objects for the nodes of a community are collected by traveler while it roams in that community. If the expected roaming time in a community A is $E[T_A]$ and the inter-contact time between the traveler and each other node is exponentially distributed with rate λ, the expected number of nodes met after the first roaming period (N^1) is equal to $N(1 - e^{-\lambda E[T_A]})$, being $(1 - e^{-\lambda E[T_A]})$ the probability of seeing a node during the roaming period. After the n-th round, the number of nodes met is $N^n = N(1 - e^{-\lambda n E[T_A]})$. In general, the traveler does not meet all nodes in the first roaming period, but multiple rounds

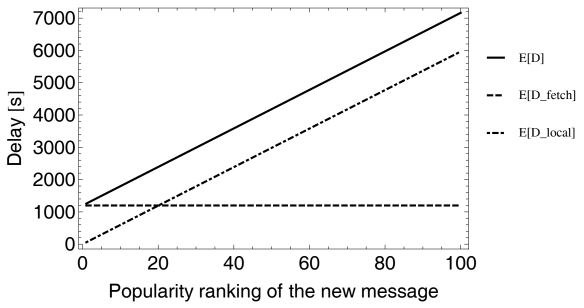


Figure 21: Expected delay with $E[T_B] = E[T_{tr}] = 10E[T_A]$

are required. Figure 22 shows the time required to meet all nodes [4] under different mobility conditions. When the nodes get in touch rarely (small λ), it takes some time for the traveler to meet all the nodes of a community, while, when the frequency of meetings is higher, the time required is much lower. It is also interesting to note that this time does not depend significantly on the number of nodes of the community.

Among the N^n nodes met after the n-th round, the average number of nodes interested in channel j is $N_j^n = Pop(j) * N^n$, given that we assume independent and identically distributed node encounters and $Pop(j)$ is as in Equation 4 . As the access probability p_{ac} to channel j for a generic community is equal to the proportion of nodes of that community interested in channel j, the access probability for channel j as seen by the traveler after round n is $p_{ac_j}^n = N_j^n / N^n = Pop(j)$. Thus, on average, the statistics on the access probability give a precise estimate of the interests of the nodes. This is because, being all nodes equally likely to be met, the distribution of the interests on the subset of nodes met is equal to the distribution of interests itself, as highlighted in Figure 23. As explained in Section 6, we consider a simplified version of the availability of a data object. This availability can be either 0, if the data object has been seen by the traveler, or 1 otherwise. In our scenario, all data objects are available in both communities A and B, except for the new data object. Therefore, the availability of these data objects should be 1. However, during each roaming period the traveler meets only a subset of the nodes of the community. This implies that the statistics

[4]Given that the exponential function has an asymptote towards infinity, we consider the process completed when $N - \epsilon$ nodes are reached, with ϵ very small.

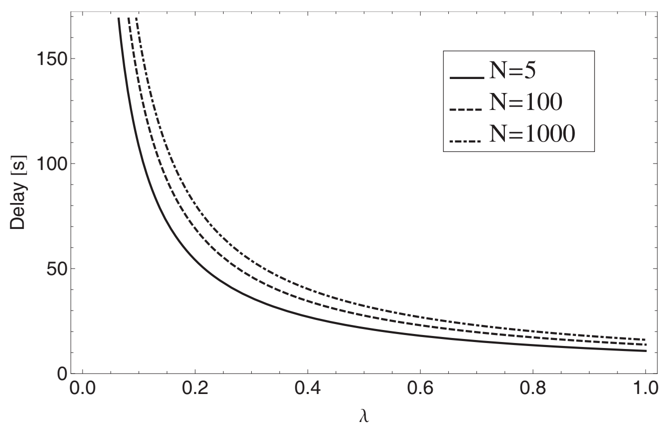


Figure 22: Time required to meet all nodes

that the traveler collect are not exact until all nodes have been met. We want to compute the error on the estimation of the availability of the data objects available in the system before $t = 0$. Given a replication factor $f(j) = \frac{1}{N_j}$ for channel j, when the traveler meets N_j^n nodes having data objects for channel j, the probability that a given data object is seen is equal to $f(j)N_j^n$. The complementary of this quantity gives the probability of not having seen an object yet, i.e., of having a wrong statistic for that data object. After trivial substitutions, we find the following expression for the error on the availability after round n-th:

$$e_{av_j}^n = e^{-\lambda n E[T_A]}, \tag{19}$$

Here the independence from the particular channel considered results from the fact that each data object is replicated on just one node (and therefore all data objects have the same probability of being found on a node). In Figure 24, the availability statistic is plotted as a function of time (discretized in rounds) for different mobility configurations. When the frequency of meetings between nodes is high, the statistic converges fast. The opposite holds true for small values of λ, when it takes some rounds for the availability to become up-to-date.

6.2.2. Data object discovery on the traveler

Now that we have an estimation on the statistics for the access probability and availability of data objects in a given community, we can focus on how this community is served when the traveler is outside. In particular, we need to find how data objects are seen by the traveler. When traveler roams in

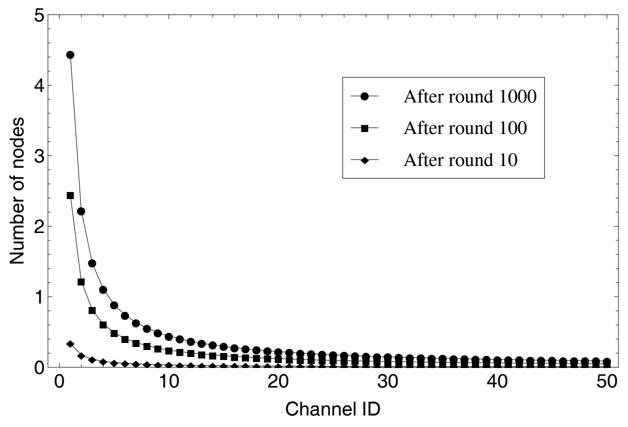


Figure 23: Interest distribution of nodes met

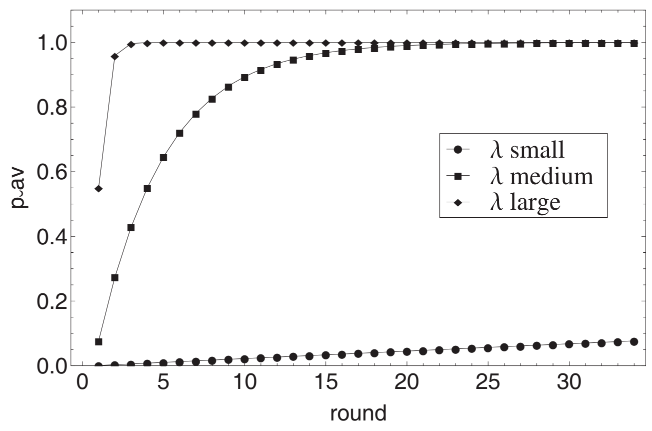


Figure 24: Availability statistics as a function of the time

community B, it sees all the data objects carried by the nodes that it meets. As we are interested in the average behavior of the traveler, we simplify the dissemination process in community B assuming that the traveler selects the data objects to be put in its buffer only once per roaming period and this selection is performed among all the data objects seen on average during that roaming period. If the average roaming period lasts for $E[T_B]$, during this time the traveler meets on average $E[Z_1]$ nodes having data objects of channel 1, $E[Z_2]$ for channel 2, and so on. By denoting with Q the number of data objects carried by each local nodes, as all these objects belong to the channel in which the node is interested, the average number of data objects seen during a roaming period for each channel j is

$$M_j = QE[Z_j] = QPop(j)(1 - e^{-\lambda E[T_B]}) = \frac{QN(1 - e^{-\lambda E[T_B]})}{jH_C}. \qquad (20)$$

Out of these M_j data objects, on average $W_j^n = e^n_{av_j} M_j$ are the data objects for which the traveler has wrong statistics. As the traveler has not seen these data objects yet, their availability is zero, although they are actually spread in the community. These data objects with wrong statistics are the ones that can slow down the retrieval of the new data object, because the traveler can erroneously think that some of these data objects are more important than the new one. This is actually the case when the old data objects with wrong statistics belong to channels that are more popular than the channel to which the new data object belongs. In fact, in the average case, the new data object is fetched by the traveler as soon as the number of data objects with wrong statistics seen during a round and being more popular than the new data object is less than the total size K of the traveler's buffer. The number of rounds for the traveler to fetch the new data object in the average case is thus:

$$n^{ch'_{new}}_{first} = \min_n \left\{ \sum_{i=1}^{ch_{new}-1} e^n_{av_i} M_i < K \right\} \qquad (21)$$

$$n^{ch''_{new}}_{first} = \min_n \left\{ \sum_{i=1}^{ch_{new}} e^n_{av_i} M_i < K \right\} \qquad (22)$$

$$n^{ch_{new}}_{first} = \frac{n^{ch'}_{first} + n^{ch''}_{first}}{2}. \qquad (23)$$

Note that we consider two values $n^{ch'_{new}}_{first}$ and $n^{ch'_{new}}_{first}$, corresponding to the cases where the new data object is considered, respectively, more or less important than the already existing data objects for the same channel. Also note that the inequality in Equations 21 and 22 has always a solution. In fact, $e^n_{av_j}$ is always decreasing with n, as it is the probability of not seeing each particular data object and M_j does not vary with n. Therefore $\sum_{i=1}^{ch_{new}-1} e^n_{av_i} M_i$ is decreasing, and it goes to 0 for $n \to \infty$. This implies that we can find n by solving equation $\sum_{i=1}^{ch_{new}-1} e^n_{av_i} M_i = K$ for n. The solution is as follows:

$$n^{ch'_{new}}_{first} = \frac{\ln(\frac{e^{E[T_B]\lambda}(e^{E[T_B]\lambda}-1)N(B)H_{ch_{new}-1}}{H_C})}{E[T_A]\lambda} \qquad (24)$$

$$n_{first}^{ch'_{new}} = \frac{\ln(\frac{e^{E[T_B]\lambda}(e^{E[T_B]\lambda}-1)N(B)H_{ch_{new}}}{H_C})}{E[T_A]\lambda} \quad (25)$$

For the computation of the time up to round $n_{first}^{ch_{new}}$, we have to consider both the case of the traveler starting from community A and that of the traveler starting from community B. Following the same line of reasoning of Section 6.1, we obtain:

$$\begin{aligned} E[D_{fetch}] &= E[D_{fetch}|S_T = C_A] \cdot P(S_T = C_A) + \\ &\quad + E[D_{fetch}|S_T = C_B] \cdot P(S_T = C_B) \quad (26) \\ E[D_{fetch}|S_T = C_A] &= T'_{cycle} + (n_{first}^{ch_{new}} - 1)T_{cycle} \quad (27) \\ E[D_{fetch}|S_T = C_B] &= T'_{cycle-short} + n_{first}^{ch_{new}} T_{cycle} \quad (28) \end{aligned}$$

Once the traveler has a copy of the data object, it will not drop it until the destination in community A has received the data object.

As the expression for $E[D_{local}]$ is equal to the one given in previous Section, we finally obtain $E[D]$ as:

$$E[D] = E[D_{fetch}] + E[D_{local}]$$

As in the previous Section, we conclude our analysis discussing a plot for the delay experienced on average by the new data object. Figure 25 shows $E[D]$ varying the popularity of the channel to which the new data object belongs. When the channel is very popular the delay is small because the data object is retrieved in the first few rounds or even in the first one (when λ is big). On the other end, when the data object belongs to an unpopular channel, the expected delay increases. The notable thing is, however, that the number of rounds required to get the new data object is *finite* for all channels. This is the main advantage of the Future policy with respect to the Greedy. In fact, the Greedy policy can result in lower delays for certain channel but in infinite delays for others, as shown in Section 5.2. With the Future policy the service is guaranteed to all channels, but the quality of that service in term of, in this case, the expected delay depends on the popularity of the channel. Note also the difference in the delays shown in Figure 25 and Figure 19: the inaccuracy of context information worsen the performance the Future policy.

7. Conclusions

In this paper we have focused on data dissemination issues for opportunistic networks. Specifically, we have presented and evaluated ContentPlace,

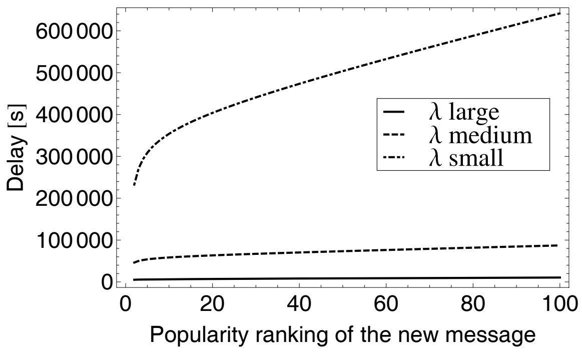


Figure 25: Average delay for a new data object to be retrieved by the traveler

which is a data dissemination system exploiting information about the social behaviour of the users in order to drive the dissemination process. We have provided extensive simulation results showing the advantage of social-aware policies over naive policies that do not take social information into account. In general, social-aware policies turn out to provide higher hit rate, to be more fair, and to be quicker to disseminate data objects with respect to the other policies. Among the social-aware policies, we have identified Future as the best one. Broadly speaking, Future takes into consideration the set of users (communities) each particular user will be in touch with in the near future, and carries data objects of interest to them. This simple behaviour allows Future to serve all users in an efficient and fair way. The behaviour of Future has been investigated both through simulation and analytical models.

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