A Personalized Recommender System for Pervasive Social Networks

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Abstract

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The current availability of interconnected portable devices, and the advent of the Web 2.0, raise the problem of supporting anywhere and anytime access to a huge amount of content, generated and shared by mobile users. On the one hand, acquaintances, through so-called Mobile Social Networks, further improving their social interactions with friends and acquaintances, through so-called Mobile Social Networks, further improving their social interactions with thrends and the pervasiveness of communication infrastructures spreading data (cellular networks, direct device-to-device contacts, interactions with ambient devices as in the Internet-of-Things) makes compulsory the deployment of solutions able to experience, and (*ii*) resource saving of both devices and network. In this work, we propose a novel framework for pervasive social networks, called *Pervasive PLIERS (p-PLIERS)*, able to discover and select, in a highly personalized way, contents of interest for single mobile users. p-PLIERS exploits the recently proposed PLIERS tag-based recommender system [2] as context a reasoning tool able to adapt recommendations to harcetorize the improvement, and it relies only on the exchange of single nodes' knowledge during proximity contacts and through device-to-device communications. We evaluated p-PLIERS by simulating its behavior in three different scenarios: a big event (Expo 2015), a conference venue (ACM KDDT)5), and a working day in the city of Helsinki. For each scenario, we used real or synthetic mobility traces and we extracted real datasets from Twitter interactions to characterize the generation and sharing of user contents. *Keywords*: pervasive content sharing, mobile social networks, opportunistic networks, personalized recommender systems for containing the order of online social networks (7]. However, most of the classical mechanisms for containfer OSNs and by video-on-demand services like works [7]. However, most of the classical mechanisms for containfer OSNs and by video-on-demand services like works

world will create and share information over the network. The availability of this data represents an important resource that is revolutionizing our society, but it is also posing some serious technological challenges in terms of maintenance, management, indexing and identification of contents. This affects especially mobile communications, where users want to be always connected and able to share contents anywhere and anytime. To alleviate the burden of data traffic on cellular networks, several solutions based

inclusion through experience sharing based on opportunistic communications, and to this aim they need efficient and personalized mechanisms for useful content selection and distribution.

The basic approaches to identify useful contents in opportunistic networks are based on publish/subscribe mechanisms. Users have to explicitly define their interests by subscribing to a fixed set of thematic channels and, when they encounter other mobile users, they can ask them for contents related to the channels they are subscribed to (see for example the PodNet project [19]). Other solutions exploit context information (e.g., the history of physical contacts between nodes, social information about the users or the presence of communities) to improve forward-

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ing and content dissemination to potentially interested users (ContentPlace [4], ProfileCast [15], SocialCast [8] and ICast [26]). They are generally defined as contextaware forwarding or content dissemination protocols, and context information generally includes information characterizing the user's behavior, her interests, generated and shared contents and the surrounding environment.

Recently researchers have investigated the possibility of using recommender systems [16] to identify useful contents also in the opportunistic environment (mainly based on content filtering and tag expansion) [9, 28, 29, 22]. Recommender systems perform better than publish/subscribe mechanisms by mainly relying on information about users' past actions (e.g., past purchases in e-commerce [17, 20] or past visualizations of multimedia content in video-ondemand services [3, 1]). At the same time, they can be included in the more general definition of context-aware systems, in which context information is mainly focused on content characterization and it is directly defined by users. In fact, through the use of Social Tagging Systems (STS), mobile users can directly define tags (i.e., labels) that describe contents from a semantic point of view. The ensemble of tags generated by users in a certain online system is known in the literature as folksonomy [22, 25]. An important aspect of folksonomies is that, differently from ontologies, no relationship between the terms is required a priori (hierarchical or not). On the contrary, these relationships are automatically built thanks to the tags created by the users and assigned to contents. Folksonomies have the ability to quickly adapt to changes in the user's vocabulary and to represent highly personalized information about the users' interests. These aspects fit well mobile users' behavior, especially when they define, generate, and share contents on-the-fly, while participating in an event or living a particular experience.

The richness of information contained in folksonomies can be used to improve the identification of interesting contents for each single user, and also to determine relationships and affinity between different users, depending on the content they generate and share. To this aim, it is essential to define an algorithm able to efficiently detect interesting content starting from the local user preferences and a limited knowledge of what is available on the network. This represents a context reasoning problem in a distributed and mobile environment, where each mobile device has a *local* representation of context information in the network (e.g., folksonomy in case of recommender systems). This local knowledge is a view of the global knowledge of the information available from the whole network. Nodes can enrich their local knowledge by sharing it with other nodes they physically encounter, through opportunistic communications. They can take decisions about which contents to download or forward to other nodes using their local knowledge. In this way, mobile users can identify interesting content locally, without accessing a centralized service. However, since folksonomies are based on user-defined tags, they also have some drawbacks. Synonyms,

homonyms, polysemies, and different users' tagging behavior make the reasoning process difficult to perform in some cases, and undermine the use of simple tag matching [14]. To overcome these limitations, a novel family of recommender systems, called Tag-based Recommender Systems [33], have been recently proposed for centralized infrastructures, where global knowledge is available. To understand whether a content is interesting for a user, tag-based recommender systems do not only consider tags that are directly associated with contents, but also the relations existing between tags, trying to extract a semantic meaning from the contents. To the best of our knowledge, currently there is no solution in the literature proposing the use of tag-based recommender systems in opportunistic networks. We think that this could substantially change the way mobile users and services can access contents, especially in Mobile Social Network scenarios.

We recently proposed a novel tag-based recommender system, called PLIERS [2], which outperforms the state-ofthe-art tag-based recommender systems defined for online social networks and centralized solutions. In this paper, we present a novel framework that exploits PLIERS principles in a completely decentralized environment, relying only on the exchange of single nodes' knowledge during proximity contacts and through D2D communications. We called it *Pervasive PLIERS (p-PLIERS)*. It represents a general framework for identifying useful and interesting contents in the mobile environment, on top of which several services can be built - from context-aware forwarding protocols, to content dissemination services (e.g., targeted advertising), to content sharing services, etc. We extensively evaluated the proposed solution through simulations considering three different application scenarios: (i) users attending Expo2015 during the World Food Day (one of the most crowded day of the entire event); (ii) users attending a scientific conference (ACM KDD 2015); (iii) users moving around the city of Helsinki during a working day. For each scenario, we selected appropriate mobility traces, synthetic or real (when available) and we extracted real datasets from geo-localized Twitter interactions. The datasets would reflect the behavior of mobile users, generating and sharing contents related to a specific event or, more in general, to their life in a European city.

The rest of the paper is organized as follows. In Section 2, we present a summary of the use of recommender systems in opportunistic networks for the identification of interesting contents. In Section 3, we describe PLIERS and we compare it with existing tag-based recommender systems. Then, in Section 4, we present p-PLIERS framework in detail. In Section 5, we provide a general description of the experimental scenarios that we considered for the evaluation of the proposed solution. Specifically, in Section 6, we present a comparison among existing recommender systems used in pervasive social networks, showing the advantages of PLIERS. In Section 7, we present p-PLIERS performance evaluation through simulations in the three different scenarios. Finally, we discuss examples of ser-

vices that can benefit from the framework in Section 8, and we conclude the paper in Section 9.

2. Related Work

In the last few years, many researchers have used Recommender Systems for disseminating content in a mobile and pervasive setting. Most of the approaches in the literature are based on popular Web Recommender Systems, conveniently modified for mobile environments – e.g., by reducing the computational complexity of the algorithms and limiting the amount of necessary memory.

The most popular and widely implemented system is represented by the *Collaborative Filtering* (CF) [13] approach. The simplest implementation of CF makes recommendations to a user based on items that other users with similar interests liked in the past. The similarity in interests between two users is calculated by a similarity metric (e.g., cosine similarity or Pearson correlation) between their respective histories (i.e., the sets of items they liked in the past). This kind of CF is also known as "user-based CF", in contrast to the "item-based CF" which models the preference of a user for an item based on ratings of similar items by the same user.

Typically, CF-based systems operate on second-order tensors (or matrices) that represent the relationships between users and items (or an item-item matrix for the item-based CF). For this reason, CF systems could suffer from scalability problems depending on the size of the data structures to be kept in memory and on the sparseness degree of the matrix. Since the number of items in STS is typically high and far beyond users' ability to evaluate even a small fraction of them, the data representation in a CF matrix is often highly sparse. Recent research work (e.g., [9, 28, 29]) focused on the reduction of the complexity of CF in order to identify useful content for mobile users in opportunistic networks and then optimize content dissemination. For example, differs [9] tries to classify users in two separate classes: mass-like minded and atypical users. The former set is composed by users whose preferences are similar to the interests of other users encountered in the past (i.e., the community). For this kind of users, the recommendation is simply based on the average of the community's preferences. For atypical users (i.e., users whose preferences differ from those of the community), instead, a user-based CF approach is applied, computed only among those other atypical users who similarly deviate from the community. Thereby, nodes exchange only the contents that CF identifies as attractive to the local users. MobHinter [28], instead, limits the CF computation to the most similar users according to a certain similarity measure, which takes into account different parameters (e.g., resources in common, similar behaviors, and so on). Moreover, it proposes different strategies to limit the amount of information exchanged by nodes every time they meet. However, even though there has been a complexity reduction to allow CF to run on mobile devices with limited

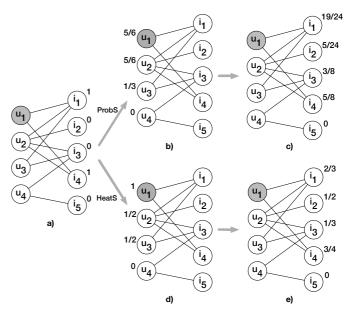


Figure 1: Application of ProbS and HeatS with a bipartite graph.[34]

computational resources, these approaches take into account just the relations existing between users and their preferences, while they neglect the nature of the items shared in the network and do not exploit all the available information from STS (i.e., the complete folksonomy).

Tag-expansion [22] is the only solution proposed in the literature to perform folksonomy-based reasoning for content dissemination in an opportunistic environment. Using this approach, each node builds a tag co-occurrence matrix to identify the tags that are most frequently used in conjunction with other tags (i.e., expanded tags), and it downloads an item if it is tagged with one of these tags. One of the main drawbacks is that a node could receive more items than those really interesting for it because the user may not be interested in the topics represented by the expanded tags. In addition, this approach can suffer from scalability problems depending on the dimension of the data structures to be kept in memory and on the sparseness of the matrix. Since the distribution of the popularity of tags in STS generally follows a long tail distribution [18], the data representation in a tag co-occurrence matrix could be often highly sparse.

2.1. Tag-based Recommender Systems

To overcome the limitations of tag-expansion in opportunistic networks, we propose to use a new family of recommender systems based on folksonomies: Tag-based Recommender Systems [33]. In the literature, many approaches for Tag-based Recommender Systems have been proposed, but – to the best of our knowledge – none of them has been so far employed in opportunistic networks. Among different possible tag-based solutions, diffusion-based [33] algorithms are the most promising ones for our reference scenario. These algorithms try to overcome the complexity and scalability issues by using graphs as a natural way

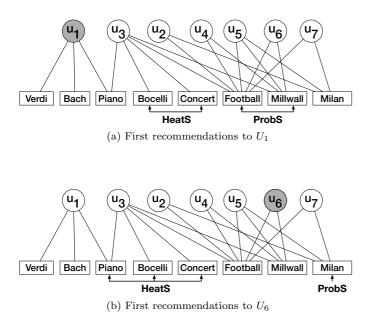


Figure 2: ProbS and HeatS suggestions.

to represent folksonomies. In these cases, nodes of these graphs represent users, items and/or tags, while their links represent relationships among nodes. Since nodes are divided into three separate classes, folksonomies are usually represented as tripartite graphs, or by separate bipartite graphs for user-item or user-tag relationships in order to further reduce the computational complexity. These approaches rely on the diffusion of fictitious resources within the folksonomy graph, starting from a node representing a target user (i.e., the target of the recommendation) and diffusing the resources by following links between nodes. This permits to identify relevant items (or tags) as those nodes that are indirectly connected to the target user via other users with whom she shares one or more connections. The higher the number of links connecting an item i to the items of the target user, the higher the score that i will receive for the recommendation. In this way, the recommender system exploits the structure of the graph to identify content relevant for the user. In addition, this approach gives the opportunity to exploit additional hidden information derived from graph-based analysis (e.g., community detection [12]), which could be used to further customize recommendations.

The oldest and most famous diffusion-based solutions are represented by two algorithms: *ProbS* (also known as *Mass Diffusion*) [35, 31] and *HeatS* [32]. By applying ProbS to user-item bipartite graphs, a generic resource is assigned to each item i_s directly linked to the target user u_t of the recommendation such that its value is 1 if an edge is present between u_t and i_s , and 0 otherwise. These items represent the content that the user has created or downloaded in the past. The resource is then split (*first diffusion step*) among the users directly connected to the item and each user receives the same portion of the resource. Subsequently, each user splits the portion of the received

resource among the items connected to her (second diffusion step) and each item then receives the same portion of the resource. The final score of each item i_i is given by the sum of the portions of resources that are assigned to it after the two diffusion steps. The set of all the scores obtained in this way is called *resource vector* and it can be used to rank the items not directly linked to the target user. The higher the score obtained by an item, the greater could be the interest in it for the target user. The mechanism of HeatS is similar to ProbS, but it is based on opposite rules: each time a resource (or a portion of it) is redistributed, it is divided by the number of edges connected to the node towards which it is heading to. Figure 1 depicts the diffusion steps of the two algorithms, highlighting the differences in the two recommendations. Although they may seem a good way to make recommendations, actually both of them are biased by the presence of extremely popular or non-popular items or tags, and they do not take into account the characteristics of the user's interests. For this reason, they present strong limitations if applied to STS. Specifically, ProbS tends to recommend most popular contents, while HeatS tends to highlight those with minimal popularity (i.e., with the smallest possible number of users connected to them). Figure 2 depicts an example of the described behavior. If we consider a target user interested in tags with low popularity $(u_1 \text{ in Figure 2a})$, HeatS will suggests tags with low popularity (that, however, may be of limited interest for the target user from a semantic point of view). On the other hand, ProbS tends to recommend tags with high popularity, possibly semantically unrelated with the user's interests. By contrast, if we consider a user with popular interests (u_6 in Figure 2b), ProbS highlights the correct tags and, instead, HeatS still (wrongly) recommends the less popular tags.

To overcome these limitations, a ProbS+HeatS hybrid approach (hereafter just *Hybrid*) [34] has been recently proposed in the literature. This algorithm calculates a linear combination of the results of ProbS and HeatS with a parameter λ governing the relative importance of one of the two original algorithms. However, the problem of Hybrid (and other recently proposed solutions [23, 21, 30, 24]), precisely lies in the use of parameters which can vary greatly depending on the nature of the dataset, and that are difficult to estimate in real situations.

PLIERS [2] solves the dilemma of the choice between popular or non-popular items in the network in a more natural way than the other diffusion-based algorithms, without requiring any parameters to tune, and ensuring that the popularity of recommended items is always comparable with the popularity of items already adopted by the users. PLIERS assumes that if the user is interested in general categories of items, with a high number of connected users (i.e., popular items), the recommendations will be general as well. On the other hand, if the user is interested in less popular items, the recommendations will prefer items with less connected users.

In addition, PLIERS assumes that a very popular item/tag

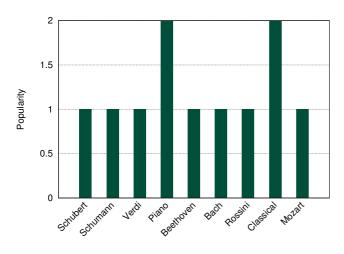


Figure 3: Tags popularity for User 1.

can semantically relate to a more "generic" topic compared to a less popular item/tag that, instead, describes a more "specific" topic. For example, any content related to the football club Millwall can be tagged with both tags "Millwall" and "Football" but the opposite is not always true: all content concerning football will not always be tagged with "Millwall". According to this assumption, we can therefore say that the tag "Football" refers to a more generic topic than that referred by the tag "Millwall". Users interested in the Millwall football club, but not connected to items tagged with "Football", are clearly not interested in all the items tagged with the latter tag, as these could contain information about other football clubs. PLIERS leverages this assumption to improve the recommendations and to provide more personalized items to the users. We demonstrated that PLIERS outperforms all the other diffusion-based approaches applied to Online Social Networks, both in terms of recommendation accuracy and personalization [2]. In this paper we present p-PLIERS, a framework able to merge the knowledge about users, interests and contents on single mobile devices and to evaluate the relevance of the available contents for each single user through PLIERS recommendations. To make the reader able to completely understand this new solution, we provide, in the next sections, an extended description of PLI-ERS notation and algorithm with respect to [2]. Then, in Section 4, we present p-PLIERS.

3. PLIERS: PopuLarity based ItEm Recommender System

In this section, we present PLIERS working principles on a simple bipartite graph, and its comparison with ProbS, HeatS and Hybrid. Then, we describe in detail how PLI-ERS can be applied to a tripartite graph, which is used by p-PLIERS to represent knowledge in opportunistic scenarios.

Table 1: Ranking for User 1 for PLIERS (PL), ProbS (Pr), HeatS (He) and Hybrid (Hy).

Tag	\mathbf{PL}	\mathbf{Pr}	He	Hy
orchestra (1)	1	12	1	1
debussy (1)	2	13	2	2
the pianoguys (1)	3	16	3	3
pavarotti (1)	4	19	4	4
nabucco (1)	5	20	5	5
millwall (22)	13	5	14	13
music (24)	15	4	15	14
sherlock (27)	16	3	16	15
sport (41)	19	2	19	18
startrek (44)	22	1	22	19

3.1. Notation

Formally, a folksonomy can be represented with three node sets: users $U = \{u_1, \ldots, u_n\}$, items $I = \{i_1, \ldots, i_m\}$ and tags $T = \{t_1, \ldots, t_k\}$. Consequently, each binary relation between them can be described using adjacency matrices, A^{UI} , A^{IT} , A^{UT} respectively for user-item, item-tag and user-tag relations. If the user u_l has collected the item i_s , we set $a_{l,s}^{UI} = 1$, otherwise $a_{l,s}^{UI} = 0$. Similarly, we set $a_{s,q}^{IT} = 1$ if i_s has been tagged with t_q and $a_{s,q}^{IT} = 0$ otherwise. Furthermore, connections between users and tags can be represented by an adjacency matrix A^{UT} , where $a_{l,q}^{UT} = 1$ if u_l owns items tagged with t_q , and $a_{l,q}^{UT} = 0$ otherwise. In the next subsection, we consider user-item bipartite graphs described by the A^{UI} adjacency matrix.

3.2. The algorithm

PLIERS is inspired by ProbS and shares with it the same two diffusion steps. In addition, PLIERS normalizes the value obtained by ProbS when comparing an item i_j with one of the items i_s of the target user u_t . This normalization is performed by multiplying the recommendation score by the cardinality of the intersection between the set of users connected to i_j and the set of users connected to i_s , divided by $k(i_j)$, which is the popularity of i_j . In this way, items with popularity similar to the popularity of the items of the target user, and that possibly share the same set of users, are preferred.

The final value of the item i_j for the target user u_t , in a graph with n users and m items, is then calculated by PLIERS with the following formula.

$$f_j^{pl} = \sum_{l=1}^n \sum_{s=1}^m \frac{a_{l,j} \cdot a_{l,s} \cdot a_{t,s}}{k(u_l) \cdot k(i_s)} \frac{|U_s \cap U_j|}{k(i_j)} \quad j = 1, \dots, m, \quad (1)$$

Here, U_j is the set of users connected to the item i_j , $k(i_j)$ is the popularity degree of the item i_j (i.e., the number of connected users), and $a_{x,y}$ is an element of the A^{UI} matrix. The higher the value of f_j^{pl} , the more item i_j is similar to the items already owned by u_t .

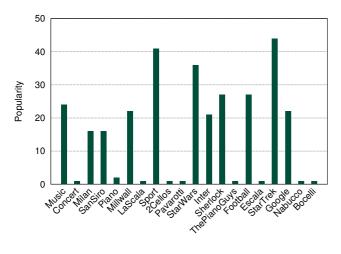


Figure 4: Tags popularity for User 3.

3.3. Working principles of PLIERS on a simple graph

To describe in detail the mechanism of PLIERS, and to prove its effectiveness, we manually built a synthetic usertag bipartite graph consisting of 64 users, 62 tags and a total of 612 edges. The graph represents the relation between a set of users and several tags, which are characterized by a variable degree of popularity. A link between a user and a tag indicates that the user owns that tag (i.e., she has already downloaded a content labeled with that tag).

Figure 5 shows the structure of a synthetic bipartite graph, highlighting the characteristics of two opposite cases: the first user (User 1), connected just to non-popular tags (more specific), and the second one (User 3), connected to tags with, on average, higher popularity. To clarify the difference between popular and non-popular tags: the tag "TV-Series" is far more popular than "SherlockHolmes" and, since the majority of users connected to the tag "SherlockHolmes" are also connected to "TV-Series" (but the opposite is not always true), semantically speaking, we can refer to "TV-Series" as a "superclass" of "Sherlock-Holmes".

In the following, we compare the differences in the recommendations lists (i.e., the resource vectors) generated by PLIERS, ProbS, HeatS and Hybrid for the two considered users.

User 1 is interested in topics related to classical music ("Schubert", "Verdi", "Rossini", etc.) that, in our graph, have a low popularity with mean equal to 1.22. Figure 3 depicts the popularity of each tag connected to User 1 in terms of number of users connected to that tag.

Table 1 contains the results obtained from the execution of the four algorithms, considering User 1 as the target. We reported the top 10 tags common to the rankings of all the algorithms, together with their position in each ranking, so as to better compare the differences among the approaches. Next to each tag, its popularity is reported. PLIERS, HeatS and Hybrid (with $\lambda = 0.5$ – the value generally used when there is no a priori knowledge on the

Table 2: Ranking for User 3 for PLIERS (PL), ProbS (Pr), HeatS (He) and Hybrid (Hy).

Tag	\mathbf{PL}	\mathbf{Pr}	\mathbf{He}	$\mathbf{H}\mathbf{y}$
3g (1)	26	26	5	18
bag(1)	24	24	4	17
carling (1)	23	23	3	16
cpu (1)	22	22	2	15
cricket (1)	25	25	1	14
seriea (19)	1	1	6	1
android (21)	4	8	21	6
googleglass (21)	3	7	20	5
mobile (21)	2	6	19	4
crime (23)	12	4	23	7
pop(23)	8	5	24	8
tv-series (34)	9	3	25	3
sci-fi (37)	5	2	22	2

data) recommend similar tags for the first 12 positions, highlighting tags with a popularity degree similar to those already connected to the user, and more semantically related with them (e.g., "Debussy", "Orchestra"). On the contrary, ProbS presents wrong recommendations in the first positions, by assigning a higher score to uncorrelated tags (from a semantic point of view), which are characterized with a popularity degree that deviates too much from that of the tags held by the user (e.g., "StarTrek", "Sport").

By contrast, **User 3** is interested in both non-popular tags (such as "Pavarotti", "2Cellos", and "Nabucco") and particularly popular ("StarTrek", "Star Wars", "Millwall") or generic tags ("Sport", "Music"), which increase the average popularity of her topics to the value of 15.3 (Figure 4). In this case, PLIERS adapts its recommendations to the "generic" nature of the target's interests, deviating from HeatS and agreeing with the suggestions made by ProbS and Hybrid (see Table 2).

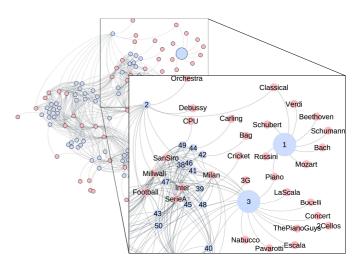


Figure 5: Structure of the synthetic user-tag bipartite graph.

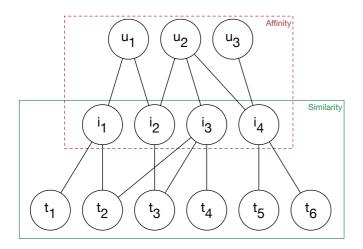


Figure 6: Affinity and similarity indices in a tripartite folksonomy graph.

3.4. Extension to tripartite graphs

The three adjacency matrices introduced in Section 3.1 can be represented as a tripartite graph G = (U, I, T, E, F)where U is the set of users in the folksonomy, I is the set of items, T is the set of tags, E is the set of links between users and items, and F is the set of links between items and tags. If an edge $e_{l,s}$ between the user-node u_l and the item-node i_s exists, we say that the user u_l was interested in the item i_s (i.e., she created or downloaded it in the past) and, in a completely analogous way, if the item-node i_s is connected to the tag-nodes t_i, \ldots, t_k , we mean that the item i_s was tagged with t_i, \ldots, t_k .

Recommender systems based on tripartite rather than bipartite graphs exploit all the information available from social tagging systems, and this can lead to better results in terms of recommendation accuracy and precision, as we show in Section 6.

As depicted in Figure 6, in a tripartite graph we can define two characteristic values:

- Affinity index: is the score obtained by PLIERS when applied on user-item links. This indicates the degree to which an item is close to the user's interests and preferences.
- **Similarity index:** is the score obtained by PLIERS when applied on tag-item links. This indicates the degree to which two items are similar in terms of the tags with which they are labeled.

More formally, we define the *affinity* index of an item i_j for a target user u_t with the following formula:

$$f_j^a = \sum_{l=1}^n \sum_{s=1}^m \frac{a_{l,j} \cdot a_{l,s} \cdot a_{t,s}}{k_i(u_l) \cdot k_u(i_s)} \cdot \frac{|U_s \cap U_j|}{k_u(i_j)},$$
(2)

where U_j is the set of users connected to the item i_j , $k_u(i_j)$ is the popularity degree of the item i_j (i.e., the number of connected users), $k_i(u_l)$ is the number of items connected to the user u_l , and $a_{x,y}$ is an element of the matrix A^{UI} .

Symmetrically, we define the *similarity* index of an item i_j with respect to the items already linked to the target user u_t , as

$$f_j^s = \sum_{z=1}^k \sum_{s=1}^m \frac{a_{z,j} \cdot a_{z,s} \cdot a_{t,s}}{k_i(t_z) \cdot k_t(i_s)} \cdot \frac{|T_s \cap T_j|}{k_t(i_j)},$$
(3)

where T_j is the set of tags connected to the item i_j , $k_t(i_j)$ is the number of tags with which the item i_j was marked, $k_i(t_z)$ is the number of items connected to the tag t_z , and $a_{x,y}$ is an element of the matrix A^{IT} .

We define the final score of an item i_j as the linear combination of the two indices (2) and (3) as follows.

$$f_j = \lambda \cdot f_j^a + (1 - \lambda) \cdot f_j^s, \tag{4}$$

where $\lambda \in [0, 1]$ is a tunable parameter of the algorithm with which we can weigh the links between users and items and those between items and tags.

4. Pervasive PLIERS

p-PLIERS implements a framework for the representation and exchange of context information describing contents and users among nodes of an opportunistic network. It exploits PLIERS for the evaluation of the collected knowledge and to provide personalized recommendations to the users about available interesting contents.

To this aim, p-PLIERS supports the maintenance of a local representation of the knowledge about the users, items and tags in the network and their relations (i.e., a local knowledge graph - LKG) on each node of the network. This knowledge is built by merging the information about contents created or downloaded by each local user, with the local knowledge of other nodes gathered during physical contacts. The nodes use this partial knowledge to evaluate the relevance of items (content) carried by other nodes in proximity, with respect to the interests of their local user. The evaluation is performed locally, without requiring centralized control and without the need of having a global knowledge of the network (i.e., global knowledge graph - GKG). We represent the LKG of each node as a tripartite graph as described in the previous section. When a node creates a new item, it updates its LKG by inserting the relation between the user entity that represents it in

Algorithm 1 p-PLIERS: Content discovery and evaluation in opportunistic networks

1: procedure ENCOUNTER(node n)
2: Send my LKG to n
3: $n_{LKG} \leftarrow \text{Receive } n \text{'s } LKG$
4: Update my LKG with n_{LKG}
5: $I \leftarrow \text{new discovered items}$
6: for each item $i \in I$ do
7: $score(i) \leftarrow evaluate i with PLIERS$
8: end for
9: end procedure

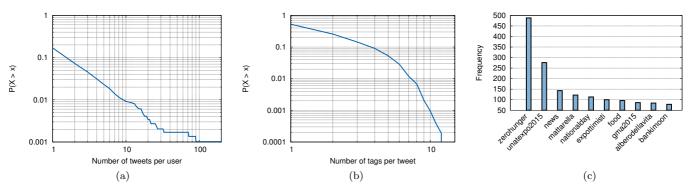


Figure 7: Descriptive statistics of the Twitter dataset used for the WFD@Expo2015 scenario. (a) CCDF of the number of tweets per user, (b) CCDF of the number of tags per tweet, and (c) Frequency of use of the most used tags.

the graph and the created item, and the relations between the item and its tags. When a node encounters another node in the network, the two nodes exchange their LKGs, and locally integrate them with the received information. The basic operations of our solution are summarized in Algorithm 1.

Our solution relies on the fact that, as we will demonstrate with simulations, using the local knowledge of each node is sufficient to correctly evaluate the relevance of contents, and leads to recommendations that are compatible with the results that one would obtain with a *global* knowledge about all the information available in the whole network at the time of the evaluation. This supports the decentralization of recommendations, and allows us to efficiently apply recommender systems, and PLIERS in particular, to dynamic mobile environments.

5. Experimental Evaluation: General Description

As a first set of experiments, we evaluated the accuracy of PLIERS recommendations with respect to other recommender systems typically used for content dissemination in opportunistic networks. To do so, we considered a *static* user-item-tag graph obtained from Twitter to evaluate the accuracy of the recommendations given by PLIERS. Then, we thoroughly evaluated p-PLIERS in three different *dynamic* opportunistic scenarios. In both cases (static and dynamic), we used graphs derived from real online tagged contents obtained from Twitter, and we set the parameter λ in equation 4 to 0.5.

Table 3: Statistics of the Twitter dataset used for the simulations.

Statistic	Value
N. of tweets	5,260
N. of users	2,946
N. of unique hashtags	3,292
Average n. of hashtags per tweet	2.12
Max n. of hashtags per tweet	13
Min n. of hashtags per tweet	1

The static scenario allowed us to evaluate the accuracy of PLIERS using a standard evaluation method (i.e. *link prediction*, as detailed in the following). For this scenario, we downloaded the tweets generated during World Food Day at Expo 2015 (WFD@Expo2015) in the urban area of Milan, and we built a tripartite graph composed by users, tweets, and their hashtags. This represents a realistic folksonomy graph of online tagged contents related to a popular event.

For the dynamic scenarios, we considered different situations in which pervasive communication systems may be used. Specifically, the scenarios are characterized by variable number of people moving with different mobility patterns generated by human mobility models or derived from real contact traces. Each scenario represents a specific application use case: (i) a big event (WFD@Expo2015), (ii) a conference (ACM KDD'15), and (iii) an urban area (Helsinki city center). We performed a set of simulations based on these scenarios, where each person is expected to use a mobile device able to communicate through D2D communications with other devices in proximity. In addition, each device allows the users to generate and tag contents over time, and uses p-PLIERS to identify potentially interesting contents created by others. We think that the scenarios cover a significant set of cases where pervasive and mobile systems may be applied, and represent thus the basis for realistic experimental evaluations.

6. PLIERS Experimental Evaluation in a Static Scenario

We compared the performances of PLIERS with respect to the other recommender systems proposed in the literature for opportunistic networks, namely user-based *Collaborative Filtering* and *Tag Expansion*. To assess the accuracy of the recommendations, we performed a *link prediction task* on a tripartite graph. This is a standard way to evaluate and compare recommender systems [16]. In essence, the technique consists in randomly removing a small portion of links from a folksonomy graph, then verifying whether the recommendations generated on the

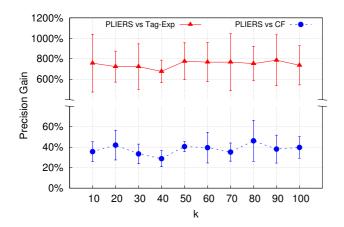


Figure 8: Precision gain obtained by PLIERS in a complete knowledge scenario.

pruned graph coincide with the removed links. Intuitively, a good recommender system should be able to identify the items that were originally connected to the removed links.

6.1. Dataset Description

We downloaded a dataset of 5,260 tweets generated during World Food Day at Expo 2015 through Twitter Streaming API. To do so, we applied a filter to Twitter API by indicating a set of hashtags (e.g., #Expo2015, #ExpoMilan2015, and other possible combinations) and we queried only tweets generated in the area of Milan. We decided to validate PLIERS using tweets generated in a limited area during a thematic event such as the WFD@Expo2015 since we think that the semantic relationships between the relative folksonomy entities is significant, and we expect to obtain meaningful and realistic recommendations.

The number of different users that generated the downloaded tweets is 2,946. We removed the hashtags that we used to filter the data (e.g., #Expo2015, #ExpoMilan) as they are contained in all the tweets, and they are thus not useful to describe the contents. In Table 3, we report the statistics of the dataset. Figure 7b and Figure 7a depict the CCDF of the number of tags per tweet and the number of tweets per user. It is worth noting that both CCDFs show a long-tailed distribution, a typical result for social networks. In addition, in Figure 7c, we depict the frequency of use of the 10 most used tags in the dataset.

6.2. Link Prediction Task

We removed 1 link from each user connected to at least 5 items with popularity greater than 1, and then we ran PLIERS and the other systems on the updated graph to generate the recommendation list for each user. Then, we calculated the percentage of removed links that are included in the recommendations of each algorithm (i.e., the "recovered links"). We selected the links to be removed in this particular way in order to avoid the complete isolation of the items connected to just a single user. In fact, in those cases, all the recommender systems would

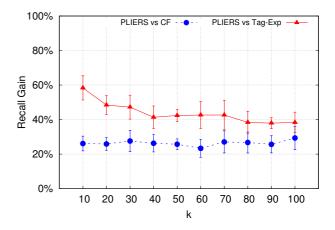


Figure 9: Recall gain obtained by PLIERS in a complete knowledge scenario.

not be able to recover the removed links, reducing the significance of the experimental results. The percentage of links between users and items we deleted from the original graph is equal to 1.4%. We computed the performances of each method using the measures of Precision (P) and Recall (R) [16], defined as follows:

$$P = \frac{1}{|U|} \sum_{u \in U} \frac{1}{|T(u)|} \sum_{t \in T(u)} \frac{1}{pos(t)},$$
(5)

$$R = \frac{1}{|U|} \sum_{u \in U} \frac{|L(u) \cap T(u)|}{|T(u)|},\tag{6}$$

where U is the set of users for whom we have removed links, L(u) is the recommendation list for the user u, T(u)is the set of links removed from the user u, and pos(t) is the position in which the removed item t appears in the list of recommended items L(u).

6.3. Results

Figures 8 and 9 depict respectively the Precision gain and the Recall gain of PLIERS with respect to both CF and Tag Expansion. The gains are expressed in percentage and identify the improvement obtained by PLIERS in terms of precision and recall with respect to the other algorithms. The parameter k in the figures represents, for CF, the number of users similar to the target user to be considered in the calculation, and for Tag Expansion the k tags more correlated with the tags of the target user to be considered. Higher values of k should therefore lead to better recommendations. It is worth noting that PLIERS outperforms the two reference algorithms for both measures, receiving a precision score up to eight times higher than that obtained by Tag Expansion and a score 40% higher than CF, even in case of very high values of k. With regard to the Recall measure, PLIERS obtains a score around 50% higher than that received by Tag Expansion and around 30% higher than that of CF.

These results indicate that PLIERS, being able to exploit all the information contained in the folksonomy graph (i.e., user-item-tag relationships), obtains better results than the state-of-the-art solutions used in opportunistic networks, which consider only partial user-item or item-tag relationships.

7. p-PLIERS Experimental Evaluation in Dynamic Scenarios

In [11], ElSherief et al. established theoretical limits on the performance of knowledge sharing in opportunistic social networks. They calculated how many contacts are needed to ensure that nodes are able to well approximate the global knowledge (i.e., all the available information in the network) for different sharing policies in a scenario where the global knowledge is static and defined a priori. We performed an empirical evaluation similar to that carried out in [11], but using more complex and realistic reference scenarios, where the information is dynamically generated over time by the nodes. Specifically, in our reference scenarios, the users are characterized by different mobility and content generation patterns.

7.1. p-PLIERS Pervasive Simulator

To simulate the dynamic scenarios, we implemented a high-level simulator that emulates the execution of p-PLIERS on a set of mobile nodes that generate contents over time. The simulator requires in input (i) a set of traces defining the physical contacts between nodes over time and (ii) a list of contents generated by the nodes and marked with a timestamp. Then, it calculates statistics to evaluate p-PLIERS both in terms of its ability to approximate the global knowledge from a local perspective, and the accuracy of the given recommendations. The simulation process proceeds in discrete steps, each of which represents 1 minute of simulated time. For each contact in the simulation steps, indicated by the timestamps in the contact traces, the involved nodes establish a D2D communication between each other and they perform the operations of Algorithm 1.

Note that the simulator is at a higher abstraction level than other existing network simulators (e.g., generic network simulators such as $ns-3^1$ or OMNeT++², and simulators specific for opportunistic networks such as TheONE³). Thus, at this level, we do not consider network-related issues, but we assume that, when two nodes are in contact, the communication channel between them was successfully established.

To represent the knowledge about the available content in the simulated mobile network, each node u maintains a *local* tripartite graph LKG_u that represents its (partial) knowledge about the associations between the contents in the network and the nodes which created them, and the associations between the contents and the tags associated with them.

The LKG of each node is initially empty. Every time a new item (tweet) *i* is created by node *u*, *u*, *i*, and each tag *t* associated with *i* are added to LKG_u (if not present), as well as the link connecting *u* and *i* (e_{ui}) and all the links connecting *i* and each of its tags *t* (f_{it}).

We also maintain GKG, the global tripartite graph that represents the complete knowledge of all the users, items, and tags in the network at a certain time.

7.2. Measures

At each time step of the simulation (i.e., every minute), the simulator calculates the following measures:

- a. Average similarity between the LKG of each node and the GKG.
- b. Average similarity between the vector of recommendations generated by PLIERS on the local and global graphs.

To calculate the similarity between tripartite graphs, we first flattened the graphs, obtaining two adjacency lists L_1 and L_2 , and then calculated the Jaccard index J on these lists:

$$J(L_1, L_2) = \frac{|L_1 \cap L_2|}{|L_1 \cup L_2|} \tag{7}$$

In the same way, the similarity of two ranked recommendation vectors R_1 and R_2 is calculated as $J(R_1, R_2)$.

Although the Jaccard index is a standard and widely used measure of similarity, it does not consider possible differences in terms of position in the rankings given by the recommendation vectors, but rather considers only the presence or absence of recommended items in the two vectors. To account for possible differences in terms of position of the same elements in the rankings produced either using local or global knowledge graphs, we also calculated a similarity measure based on Spearman's Footrule [6] defined as follows:

$$S(R_1, R_2) = 1 - \frac{\sum_{x \in R_1 \cap R_2} d(x, R_1, L_2)}{max(|R_1|, |R_2|)}, \qquad (8)$$

where

$$d(x, R_1, R_2) = \begin{cases} |R_1(x) - R_2(x)| & \text{if } x \in R_1 \cap R_2 \\ max(|R_1|, |R_2|) & \text{otherwise,} \end{cases}$$
(9)

where R(x) is the position of object x in the ordered set R. S is similar to the Jaccard index, but, in addition, it penalizes possible differences in terms of rankings of the elements in the resource vectors.

In addition, for each simulation step, we calculated:

¹https://www.nsnam.org/

²https://omnetpp.org/

³https://akeranen.github.io/the-one

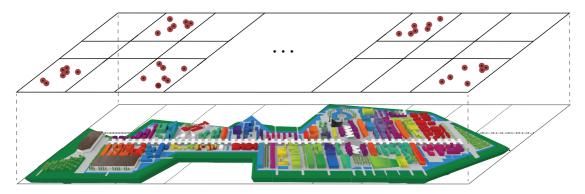


Figure 10: Map of Expo 2015 area with the position of five of the simulated communities. Note that the grid in the figure is only an example to show how we divided the area for the simulations, but it does not represent the real grid used.

- c. Number of contents generated by the nodes over time.
- d. Average number of contacts between nodes over time.

These measures are used to characterize the contact traces and the contents used in the different scenarios. We anticipate that the synthetic and the real traces that we used show similar properties (e.g., the contact traces used for the WFD@Expo2015 scenario show values compatible with those used in the conference scenario), thus supporting the significance of the synthetic trace.

We also calculated all the measures by considering that the interests of nodes may be limited in time. To do so, we calculated the measures using only the most recent contents generated in the network and considering only the information about these contents in the folksonomy graphs. In the simulations, we considered different "expiry date" for the contents, i.e., 1, 2 or 3 hours.

7.3. Scenario 1 - Big Event: World Food Day @Expo2015

As a first dynamic scenario for the evaluation of p-PLIERS, we considered a big event attended by a large number of people in a relatively large area. In this scenario, accessing the Internet from mobile devices may be problematic and thus obtaining useful content from D2D communications would provide an important source of information for the users. We considered the World Food Day at Expo 2015, organized on October 16, 2015. We assumed that people attending the event were able to create tagged contents from their mobile devices, and that other attendees might have been interested in obtaining these contents through D2D communications.

7.3.1. Mobility Traces

We simulated a set of nodes moving within an area of 300 x 2,000 meters, which coincides with the Expo area in Milan. Each node represents a person equipped with a mobile device. The mobility of nodes is simulated through the HCMM human mobility model [5]. The model generates contacts between nodes according to a Pareto distribution, as observed in real traces, and considers the

presence of "communities", i.e., each node has a higher probability to meet nodes within its own community than nodes belonging to different communities. This fits well with WFD@Expo2015 scenario, as the area was divided into several pavilions. We can reasonably assume that the mobility of people inside each pavilion was lower than the mobility of people moving between pavilions, and that, consequently, the density of intra-community contacts was higher than that of inter-community ones. We generated mobility traces through HCMM for 60 communities, approximately the number of pavilions at Expo (see Figure 10 for a graphical representation of a map of the area of Expo and the communities used in HCMM). We set a probability of inter-community contacts of 0.1 (this parameter is called "rewiring" probability in HCMM)⁴. The speed of nodes ranges between 0.01 m/s (almost steady nodes) and 1.86 m/s (nodes representing people walking relatively fast).

Using HCMM, we simulated the contacts between nodes for 13 hours, to cover the timespan of the WFD@Expo2015, from 10am (opening time) till 11pm (closing time). We considered that each node has a transmission range of 20 meters (the maximum distance to avoid that nodes in adjacent pavilions are constantly in contact with each other). When two nodes are in the transmission range of each other, HCMM generates a contact between them. We think that HCMM mobility model with these settings can well approximate the real mobility of people during WFD@Expo2015.

7.3.2. Content Generation

To have a realistic representation of multimedia contents generated during the WFD@Expo2015, we downloaded the tweets generated during the event, using the Twitter Streaming API. To be sure to obtain only information

 $^{^{4}}$ We performed the same simulations described in the following also with rewiring probabilities 0.2 and 0.3 (thus considering more dynamicity in the movements) and this resulted in a general, although slight, improvement due to a higher inter-community mobility of the nodes. Since the contact traces generated by setting a rewiring probability of 0.1 represent the worst case scenario, we present only the results for this parameter.

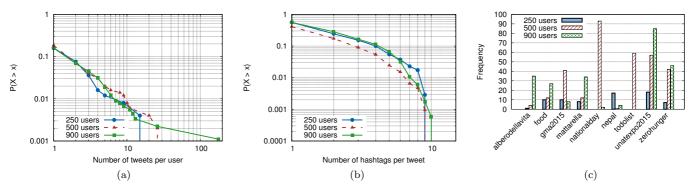


Figure 11: Descriptive statistics of the Twitter datasets used for the WFD@Expo2015 dynamic scenarios. (a) CCDF of the number of tweets per user, (b) CCDF of the number of tags per tweet, and (c) Frequency of use of the most used tags.

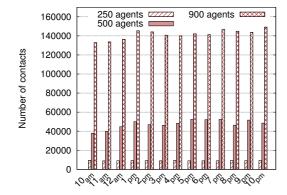


Figure 12: Overall number of contacts between nodes during the simulation for the Expo 2015 scenario.

related to Expo, we filtered our requests in the same way as done for the dataset collected for the evaluation in the static scenario presented in Section 6. With respect to the dataset used for the static scenario, we downloaded only tweets generated from 10am till 11pm, to cover the same span of time of the simulated contact traces. The obtained dataset contains 4,817 tweets generated by 2,660 users, and contains 3,008 unique hashtags.

We associated each node of the simulated contact traces with a Twitter user. In this way, the tweets of the Twitter user associated with each node represent contents that the node generated during the simulation.

7.3.3. Simulation Settings

We considered different settings for our simulations in order to analyze the possible impact of different parameters on the results. Specifically, we varied the number of nodes, simulating 250, 500, and 900 nodes in the considered area. As the number of users that tweeted during WFD@Expo2015 was higher than the number of simulated nodes (900 is the maximum number of nodes supported by HCMM), we sampled, for each setting, the Twitter users with a uniform random sampling.

In order to give an idea of the dynamics of content generation, Figures 11a and Figure 11b depict the CCDF of the

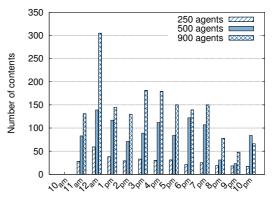


Figure 13: Number of contents generated by nodes during the simulation for the Expo 2015 scenario.

number of tweets generated by users and the number of hashtags per tweet respectively, for the samples extracted for the three settings (250, 500, and 900 nodes). The distribution of hashtags per tweet are approximately the same for the three samples: the majority of tweets have just one or two hashtags associated with them, whereas just few tweets are linked to more hashtags. Similarly, the number of users who generated a high number of tweets is low, when the majority of them has generated just one or two tweets.

Figure 11c depicts the frequency of use for the 5 most used tags for each sample. As expected, the most used tags are related to topics about the Expo2015 exhibition, the WFD and some special guests (e.g., "mattarella" refers to Sergio Mattarella, who is the actual President of Italy and was already in charge during the Expo in 2015, and he was invited as a special speaker for the WFD event). Figure 12 depicts the total number of contacts between nodes for each hour of simulation. It is worth noting that, for each setting, the number of contacts between nodes is roughly constant for the entire simulation time, but it greatly differs from one setting to another, providing thus significantly different cases in terms of opportunities of contact between nodes in the simulations.

Similarly, Figure 13 depicts the number of contents

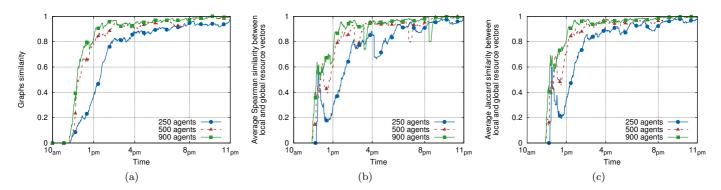


Figure 14: Results for the WFD@Expo2015 scenario. (a) Average Jaccard similarity between local graphs of the agents and the global graph, for different number of agents. (b) Average Spearman and (c) Jaccard similarity between the PLIERS resource vectors obtained on the local graphs of the agents and those obtained from the global graph, for different number of agents.

(tweets) generated by nodes for each hour of simulation. The distribution is similar for the three settings: during the lunch break (from 12am till 1pm) there is an increment in the generation of content, then it remain stable until the evening hours and decreases closer to the exposition closing time. It is worth noting that no tweets containing the selected hashtags have been generated between 10am and 11am, probably due to the low number of visitors in the very first part of the event.

7.3.4. Results

Figure 14a depicts the average Jaccard index between the local graphs of the agents and the global graph, for the different numbers of simulated agents. From the figure, we can note that, after a certain time, the similarity between the local graphs and the global graph, on average, reaches a very high level for all the different settings considered. After approximately two hours of simulated time, the similarity reaches $\sim 80\%$ for the cases with 900 and 500 agents, with slight variations, whereas ~ 4 hours are needed to reach the same level of similarity for the case with 250 agents. After that, the similarity remains quite stable until the end of the simulation for all the settings. This means that even with a small number of nodes (250)that generate items in a relatively large area (the whole area of Expo), the opportunities of contact are enough to have a good approximation of the knowledge about items and tags generated in the network, even after few hours. Interestingly enough, the differences between 250 and 900 agents does not have a substantial impact on the curve. The similarity between the results obtained by PLIERS on local and global graphs are depicted in Figure 14b and 14c. Specifically, the former figure depicts the average similarity S (derived from Spearman's Footrule) for the recommendation vectors of the two cases, while the latter figure depicts the average Jaccard index on the same recommendation vectors. From the figures, it is worth noting that, on average, the differences between the results obtained from local and global graphs are quite small. In addition, the figures clearly indicate that the results obtained on local

graphs converge to those on the global graph. The presence of negative peaks in Figure 14b that are not visible in Figure 14c highlights the higher sensitivity of the similarity measure S compared to the Jaccard index. These negative peaks indicate a slight decrease in the performances of PLIERS, which are nonetheless in the order of ~15% maximum, and the curve remains always above 0.6 for all the settings, at least after 4 hours of simulated time.

Figure 25a depicts the average similarity between the local graphs of the agents and the global graph, where only information generated not more than 1, 2 and 3 hours (of simulated time) before the calculations is respectively considered. Note that the figure is related to the simulation with 900 agents. The differences in terms of average similarity of the curves related to the simulations for 3 and 2 hours are similar to the results obtained without temporal limitations. This tells us that, nodes can make accurate recommendations even if they maintain limited information about past history and purge the older information from their memory. The case where only information generated in the last hour is considered, the similarity is slightly lower, but it is still around 75%, which could be enough for some applications.

7.4. Scenario 2 - Conference: KDD 2015

As a second dynamic scenario, we considered a school campus during a conference event, where people stay most of the time within rooms, but they regularly gather at breaks (e.g., coffee or lunch breaks). This is a typical scenario where pervasive and mobile communications could improve content delivery services and user experience in general. We assume that the contents generated during the conference can be shared by nodes through wireless communication, and we assess the potential impact of PLIERS in the accuracy of recommendations using only local information obtained by mobile nodes from direct interactions with other nodes, similarly to the previous scenario.

7.4.1. Mobility Traces

For this scenario, we used real contact traces representing the physical interactions of a group of students, professors,

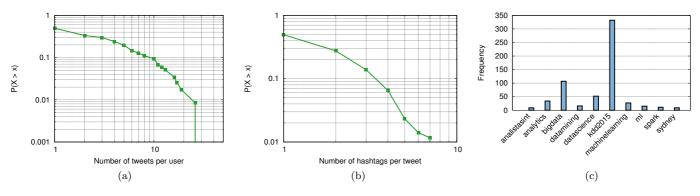


Figure 15: Descriptive statistics of the Twitter datasets used for the Conference scenario: (a) CCDF of the number of tweets per user, (b) CCDF of the number of tags per tweet, and (c) Frequency of use of the most used tags.

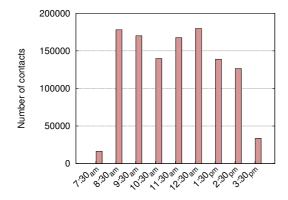


Figure 16: Overall number of contacts between nodes during the simulation for the conference scenario.

ans staff of an American high school during a typical school day [27]. These traces were obtained by distributing 789 wireless sensor network motes to all members of the school and asking them to carry these motes with them for the entire duration of a school day.

7.4.2. Content Generation

As we do not know the exact location of the American school where the contact traces have been collected, we tried to find an event from which to collect tagged online contents and where people were moving in a similar way to how students move within the area of a high school in the US. As American high schools are not organized into classes as in the EU, but rather around "study tracks" and students are free to decide which lectures to attend, we think that their movements can be assimilated to those of people attending a large conference. For this reason, we downloaded the tweets generated during a large computer science conference, namely the 21st ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD), organized in Sydney from 10 to 13 August 2015.

To download tweets generated during KDD by people who were physically attending the conference, we used Twitter REST API with a series of filters, as described in the following. We first downloaded all the tweets generated by

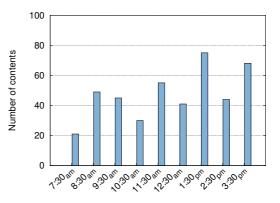


Figure 17: Number of contents generated by nodes during the simulation for the conference scenario.

@kdd_news, the official Twitter account of the conference. Then, we downloaded all tweets created by people "followed" by this account or "following" it and containing at least one of the set of hashtags generated (in total) by @kdd_news. Furthermore, we downloaded additional tweets by performing a second round of download considering the same set of users (followers and followees of @kdd_news) considering the set of hashtags of all the previously downloaded tweets. In this way, we are not limiting the download to tweets containing only the hashtags created by the official KDD account, but also those created by other users that co-occur with the former hashtags. This allowed us to collect also tweets that are semantically related with the conference. From the set of downloaded tweets, we kept only those generated during the days of the conference (10-13 August) and which are within the temporal span between 7.30am and 4.30pm Sydney time, coinciding with the intersection between the time window of the conference and that of the contact traces.

The total number of KDD tweets that we downloaded is 428 (distributed over the three conference days). These tweets have been created by 117 users, and contain a total 256 unique hashtags.

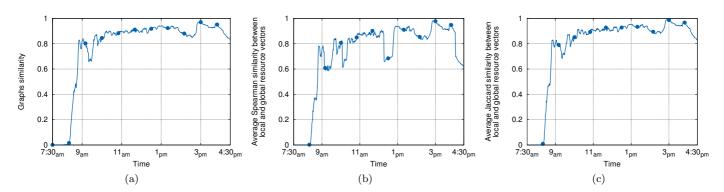


Figure 18: Results for the scenario of the KDD conference. (a) Average Jaccard similarity between local graphs of the agents and the global graph, for different number of agents. (b) Average Spearman and (c) Jaccard similarity between the PLIERS resource vectors obtained on the local graphs of the agents and those obtained from the global graph, for different number of agents.

7.4.3. Simulation Settings

Since the total number of Twitter users in our dataset is lower than the number of nodes in the contact traces, we decided to assign each Twitter user to a random node in the simulator. The nodes not associated with a Twitter user do not create any contents, but they are still part of the simulation and they can diffuse information within the mobile network. In addition, to maintain a sufficiently high number of generated contents, we considered that the tweets were generated on a single day, and we just considered the creation time of each tweet, and not its creation date.

Figure 15a and Figure 15b depict respectively the CCDF of the number of tweets generated per node and that of the number of tags per tweet considered in the simulation. The tags appearing with highest frequency during the simulation are depicted in Figure 15c. The number of contacts and the number of contents generated hourly during the simulation are depicted in Figure 16 and Figure 17 respectively. Figure 16. shows a number of contacts of the same order of magnitude as WFD@Expo15 for a comparable number of users.

7.4.4. Results

Figure 18a depicts the average similarity between local and global graphs for the simulation. The high value of similarity indicates that nodes are able, on average, to have a complete view of the contents around them even after a few hours of simulated time. In addition, also the similarity between the recommendations of PLIERS obtained by the nodes and the optimal recommendations they would have got using the global knowledge is very high both for the S measure (see Figure 18b) and for the Jaccard similarity index (Figure 18c).

The results obtained by limiting information lifetime at 1, 2, and 3 hours for this scenario are reported in Figure 25b. In this case, the results obtained for the most restrictive assumptions, considering only information generated 1 and 2 hours respectively before each step of the simulation, have a high variation and often go beyond a

similarity of 0.6. The similarity in these cases might be too low to obtain meaningful recommendations. Nevertheless, the results obtained for the threshold of 3 hours are very similar to those obtained without limiting the information lifetime. This indicates that, for this kind of scenario, a view of the contents generated within the last 3 hours could be enough to obtained accurate recommendations about freshly created information.

7.5. Scenario 3 - City: Helsinki

As a last scenario to test our solution, we chose the urban environment of the city center of Helsinki, a medium sized European city. Our choice was motivated by the need to test PLIERS on a larger scale than the previous scenarios. We extracted the contact traces of a typical working day in Helsinki using a realistic human mobility model highly customized on the considered area. Then, we downloaded the tweets generated within the same geographic area and we used them as content generated by nodes during the simulation.

7.5.1. Mobility Traces

In order to perform a realistic simulation, we extracted 24 hours of contacts between 800 nodes from the mobility traces generated by the working day mobility model for Helsinki [10] implemented in TheONE simulator. The mobility model uses several highly customized mobility submodels that define nodes behavior during different daily activities in the area of interest, such as staying at home, working, and evening activities with friends. The simulation area coincides with Helsinki city center, which was divided into four main districts, as depicted in Figure 19. In these districts, nodes live and work in the same geographic area forming thus four distinct groups. In addition, the model considers three other groups of nodes which live and work in different districts, as depicted in Figure 20. To simulate the movements between home and work, and between work and possible meeting points for evening activities, the model defines three additional mobility models: car travel mobility, public transportation

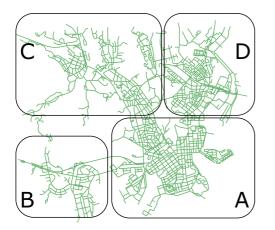


Figure 19: Graphical representation of the four groups of nodes in the mobility model of Helsinki which live and work in the same districts of the city.

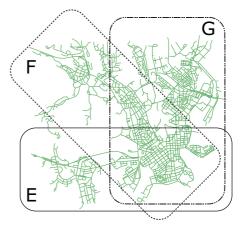


Figure 20: Graphical representation of the additional three groups of nodes in the mobility model of Helsinki which live and work in different districts of the city.

mobility, and walking mobility. For a complete description of each of the mobility sub-models included in the overall mobility model and to understand how they are combined together, we refer the reader to [10]. For the parameters of the models, we used the default values provided by TheONE simulator. Note that the values were directly derived for the city of Helsinki.

7.5.2. Content Generation

We downloaded the tweets generated in the area of Helsinki city center through Twitter Streaming API, by filtering the tweets for their location. We continuously downloaded tweets from May 27, 2016 to June 20, 2016, for a total of 24,732 tweets, which were generated by 4,477 users and 16,273 unique hashtags.

7.5.3. Simulation Settings

We performed three simulations using the same contact traces obtained by the Helsinki mobility model and varying the number of contents generated by each node. To do so, we selected, in the first case, only the tweets generated during a single working day randomly chosen among those in the collected dataset (May 2, 2016 - which was a typical working day in Helsinki). The number of Twitter users who generated contents on this day was 586. We randomly assigned these users to the 800 nodes of the contact traces. The remaining nodes do not generate contents, but they contribute to the forwarding of knowledge in the network. For the second simulation, we first selected all the users in the dataset who tweeted for at least two days (not necessarily consecutive days). Then, we randomly selected two days of tweeting activity for each user (filtering out additional tweets for the users who tweeted for more than two days). As the number of users was higher than 800, we simply randomly assigned each node in the contact traces to a randomly selected Twitter user. For the third simulation, we performed the same selection of the previous case, but for three days of tweeting activity.

Figure 21a and Figure 21b depict the CCDF of the number of tweets generated per node and the CCDF of the number of tags per tweet for this scenario, considering the three settings with contents generated over 1, 2, and 3 days. The tags with highest frequency for the three cases are depicted in Figure 21c. The number of contacts and the number of contents generated hourly during the simulation are depicted in Figure 22 and Figure 23 respectively.

7.5.4. Results

Figure 24a depicts the average similarity between local and global graphs during the three simulations. In the first half of the day the similarity is rather low (i.e., less than 20%). This is due to the fact that the agents are mostly found at home or work, and then they do not have many opportunities to meet new nodes from which they could get new information about contents generated in the network. When the agents stop working approximately at 5:30 p.m., the graphs similarity rapidly grows to over the 80%. This is because most of the agents go to the meeting points (e.g., shopping center, restaurants, pubs, etc...), which allow them to encounter nodes from different communities and then become aware of the content never seen before. Figures 24b and 24c depict respectively the average Spearman and Jaccard similarity between the recommendations of PLIERS obtained by the nodes and the optimal recommendations they would have got using the global knowledge. It is worth noting that the curves of the recommendations' similarity accurately reflect the similarity between the local and global graphs. This proves that the higher the accuracy of the vision of the local nodes and the greater will be the accuracy of the recommendations made by PLIERS.

The results obtained by limiting information lifetime at different hours for this scenario are reported in Figure 25c. In this case, the thresholds used in the other scenarios to limit the knowledge graphs are too restrictive, and the similarity between the local and global graphs remains be-

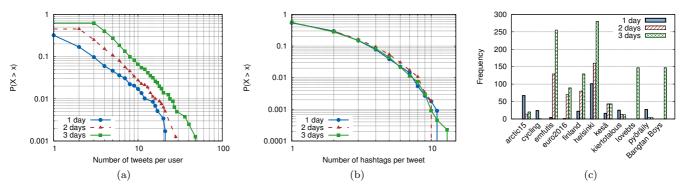


Figure 21: Descriptive statistics of the Twitter datasets used for the City scenario: (a) CCDF of the number of tweets per user, (b) CCDF of the number of tags per tweet, and (c) Frequency of use of the most used tags.

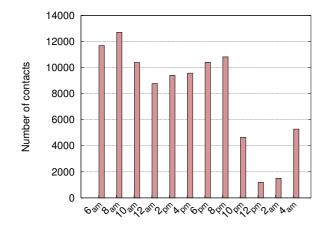


Figure 22: Number of contacts generated by nodes during the simulation.

neath of the 20%. For this reason, we used two higher threshold values: we considered only the information generated 5 and 10 hours before each step of the simulation. Considering the information generated during approximately half of the simulation time (i.e., 10 hours), the similarity between the local and global graphs considerably increases, and reaches 60%. This result suggests that, for a realistic urban scenario, at least a half day of knowledge about the contents generated by nodes is necessary to obtain sufficiently accurate results.

7.6. Discussion

The results for the three dynamic scenarios show that p-PLIERS is able to adapt to several types of realistic pervasive social networks and always provides accurate content recommendations.

We performed an additional analysis to verify that the results are not trivially related to the number of contacts between nodes and the number of contents generated over time. To do so, we calculated the correlation between the delta in terms of similarity at each step of the simulations with respect to the previous step and the number contacts and the number of contents at each step. The

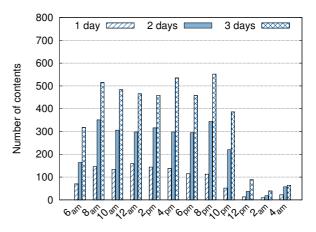


Figure 23: Number of contents between nodes during the simulation.

results of this correlation analysis are reported in Table 4 in the third and fourth columns. In particular, the two columns report the correlation values between the similarity delta (Y) and the number of generated contents (X1)and the number of contacts between agents (X2) respectively. The second column of the table reports the value for the coefficient of determination (R^2) of the linear regression analysis between the three measures, following the equation $Y = \beta_1 X_1 + \beta_2 X_2$. It is worth noting that, for all scenarios, the correlation and the R^2 values are rather low. This indicates that a simple analysis of the time series of the number of contacts and contents over time, alone, is not sufficient to describe the results of our simulations. From Table 4, we note that the impact of the number of contents generated is negatively correlated with the similarity of local and global graphs for the WFD@Expo2015 scenario. This is perhaps not too surprising, as a higher

number of contents requires more contacts to disseminate the generated knowledge. Interestingly enough, the effect is the opposite for KDD and Helsinki, where there is a positive correlation between the similarity delta and the number of contents. This might be a combined effect of the increasing number of contacts in the hours of the day when people have a higher activity on Twitter, as they probably

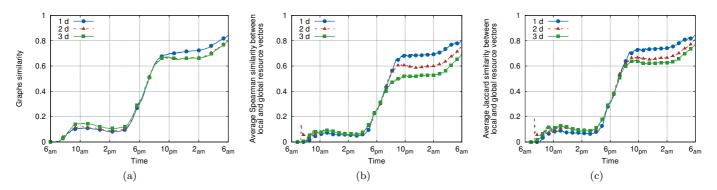


Figure 24: Results for the scenario of the city center of Helsinki. (a) Average Jaccard similarity between local graphs of the agents and the global graph, for different number of agents. (b) Average Spearman and (c) Jaccard similarity between the PLIERS resource vectors obtained on the local graphs of the agents and those obtained from the global graph, for different number of agents.

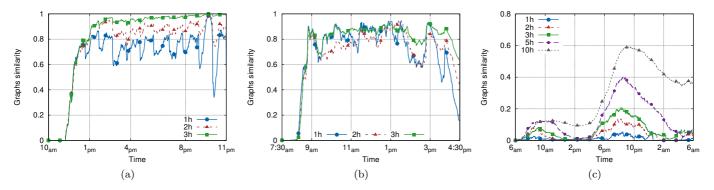


Figure 25: Average Jaccard similarity between local and global graphs, limiting the knowledge to different time windows in the past for the (a) Expo2015, (b) Conference, and (c) Helsinki scenarios.

coincide with the end of the working activity. Nevertheless, the linear regression based on the combination of the number of contact and contents is able to explain the variations in terms of similarity. This confirms once again that the dynamics of the considered scenarios cannot be simply described from aggregated measures, and the simulations were necessary for the complete evaluation of p-PLIERS. It is worth noting that p-PLIERS performs well even when knowledge is limited to a very short time window in the past, at least for scenarios where a relatively small geographic area is considered (WFD@Expo2015 and KDD scenarios). In fact, nodes do not need much time for understanding what is happening around them in these scenarios, and they can efficiently take decisions about currently available contents. This is particularly relevant for opportunistic networking scenarios, where nodes have very limited resources. For the urban scenario of Helsinki, in which the considered area is much larger than that of the other scenarios and the density of nodes is lower, the results indicate that a larger time window is required for a good approximation of the global knowledge about contents in the network. With a view to smart cities, a possible solution to improve the diffusion of knowledge and the accuracy of p-PLIERS in this type of scenario could be to exploit the public transportation system's nodes (e.g., buses, trams, or taxis) as additional information carriers.

8. Possible Applications

The algorithm proposed in this paper can represent a general framework for the development of opportunistic networking applications in several domains. From a high level perspective, we identified two separate cases where the algorithm could be useful for mobile applications in opportunistic settings. The former involves autonomous content dissemination by the nodes, whereas the latter requires the manual interaction of the user to explicitly download items in specific services.

8.1. Automatic Download for Content Dissemination and Routing

In this case, the algorithm could be used as part of an autonomous decision system for improving content dissemination services or routing algorithms in opportunistic network settings. Specifically, each node could use our algorithm to automatically decide which items are interesting for it or for other nodes in the network. Then, it can take decisions on the data to download or on the route that the messages must follow based on the calculated recommendations to improve opportunistic routing algorithms. Of course, these decisions could be improved by using information about physical contacts between nodes, as previously proposed by Lo Giusto et al. [22], and also

Table 4: Relation between graph similarity (Y) and (i) number of items generated at each simulation step (X_1) , (ii) number of contacts at each step (X_2) .

Scenario	$R^2 \text{ for fitting} Y = \beta_1 X_1 + \beta_2 X_2$	r_{YX_1}	r_{YX_2}
Expo - 250 agents	0.011	-0.017	0.117
Expo - 500 agents	0.075	-0.187	0.049
Expo - 900 agents	0.012	-0.074	0.057
KDD	0.011	0.057	-0.089
Helsinki - 1 day	0.032	0.175	$\begin{array}{c} 0.072 \\ 0.070 \\ 0.047 \end{array}$
Helsinki - 2 days	0.036	0.183	
Helsinki - 3 days	0.050	0.218	

additional context information not necessarily related to the folksonomies used in this work.

Note that the score calculated by recommender systems gives only a relative weight to each item, but does not provide an absolute importance to them, apart from excluding those items that receive a weight equal to 0. For this reason, in order to evaluate new items encountered in the network, it could be useful for the nodes to maintain a history of the scores received by other items seen in the past, or to compare the scores of new items with those of already downloaded items. An application based on this mechanism could evaluate the average importance of the items seen in the past, considering a fixed time window, and it can decide to download, for example, only the items that exceed this average. Other possible variations of this scheme may be considered, of course. For example, the node could download only the items exceeding a percentile of the distribution of the scores of the items seen in the past window. Alternatively, an application based on our algorithm may decide to download the items as soon as it finds them from its neighbors, without requiring to "scan" the network for a certain time before being able to decide which items are interesting and which ones are not. This could nonetheless require a buffer of items with limited size, which is possibly updated each time a new neighbor is encountered. The buffer is initially filled in with all the encountered items, but when the maximum size is reached, items are replaced by new items with higher recommendation scores.

8.2. Manual Download for File Sharing and Recommendation Services

Other possible application scenarios may require the users to directly interact with the algorithm to decide whether they want to download the recommended items or not. For example, the algorithm could be used by applications that search for multimedia files (e.g., songs or videos) from other peers, and use item recommendations to decide which of these files may be interesting for the users. The data download, in this case, could be performed by the user directly. The history of downloaded items may be used to update the interests of the users in the folksonomy graphs. More specifically, each time a user manually downloads an item, we are sure that the item is interesting for her, and we can thus add a link between the node representing the user in the folksonomy graph and the node representing the downloaded item, allowing more personalized recommendations in the future, based not only on the list of created items, but also on the history of downloaded items.

9. Conclusion

In this work, we presented p-PLIERS, a novel distributed algorithm implementing the PLIERS tag-based recommender system, which selects highly personalized contents of interest for mobile users in opportunistic networking scenarios. The algorithm is able to adapt to heterogeneous interest profiles of different users, and effectively operates also when limited knowledge about the system is maintained. It performs more accurate recommendations than other solutions proposed in literature in terms of personalization with respect to the interests of various users.

We validated the applicability of our proposal in real pervasive environments, by simulating the use of PLIERS for content dissemination in three realistic scenarios, a big event (WFD@Expo2015), a large conference (ACM KDD'15), and a working day in a city center (Helsinki). In these scenarios, contents are dynamically generated following the tweets created during the simulated time, and each node knows only part of the whole dataset, namely, the local information and the knowledge gathered from other nodes encountered while moving. Furthermore, nodes have limited memory from which old knowledge is purged. Also in this case, p-PLIERS proves to be able to provide effective recommendations, comparable to those achievable if global knowledge were accessible to nodes.

Future work consists in investigating other mechanisms to limit the knowledge held and exchanged by nodes – while preserving recommendations accuracy – such as the use of learning policies allowing nodes to discern and just maintain the most significant information to compute appropriate suggestions. In addition, we are currently working on the implementation of a prototypical application for content dissemination in opportunistic networks, which will allow us to evaluate the algorithm proposed in this paper in a real scenario.

10. Acknowledgement

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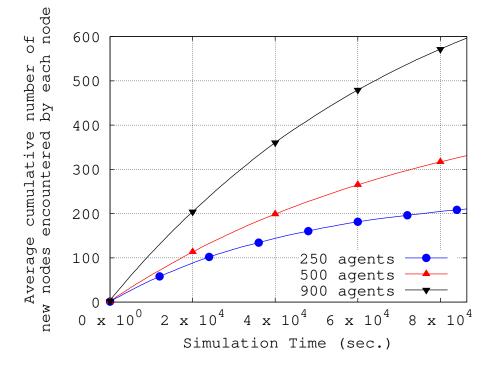
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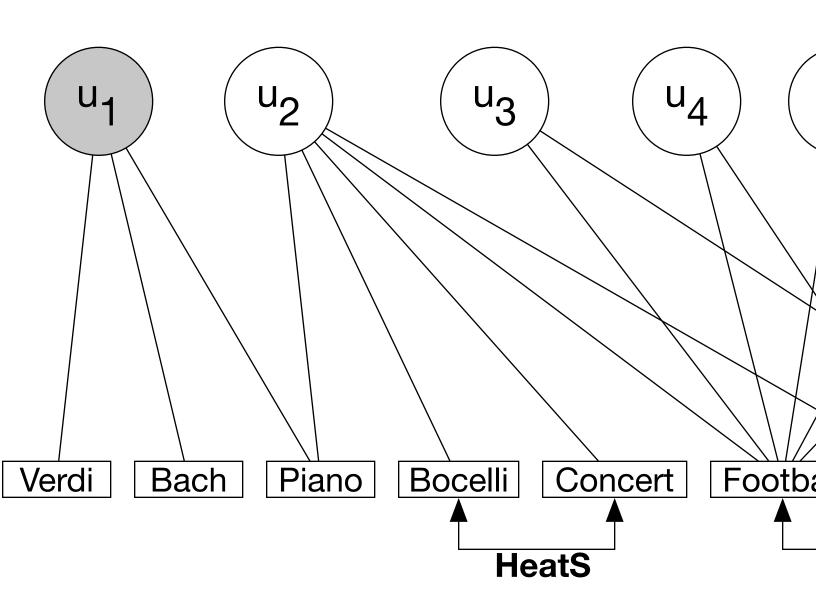
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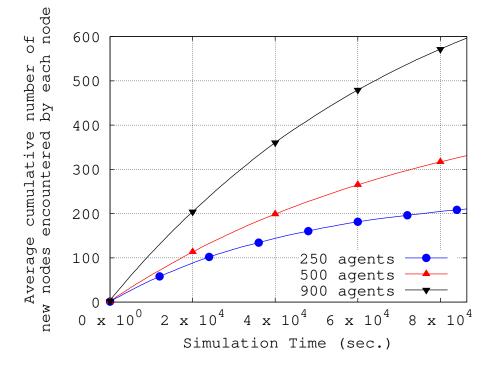
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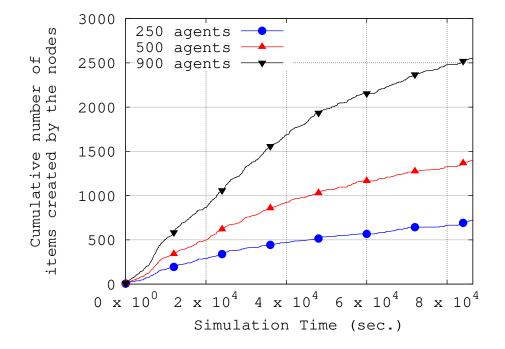
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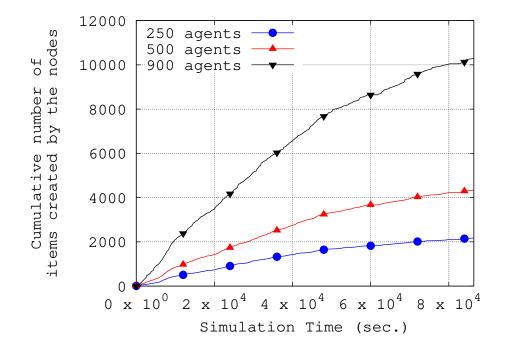
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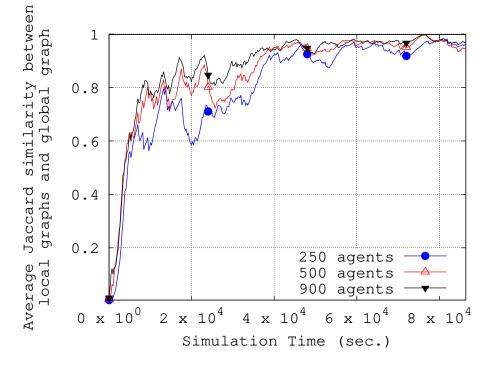


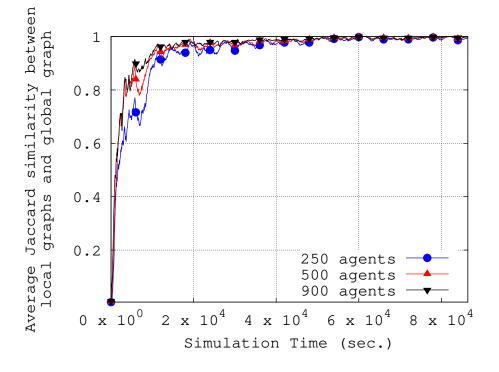




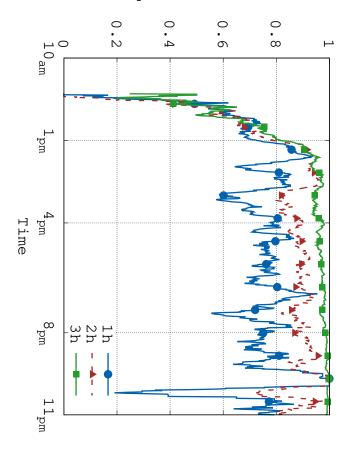




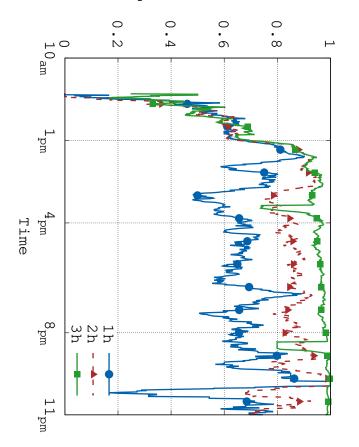




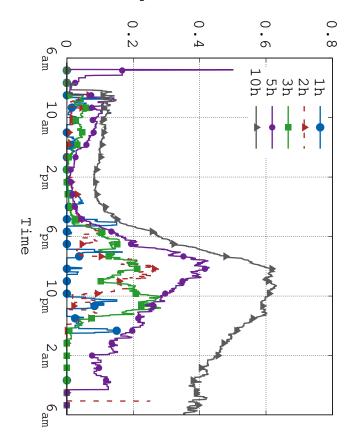
Average Jaccard similarity between local and global resource vectors



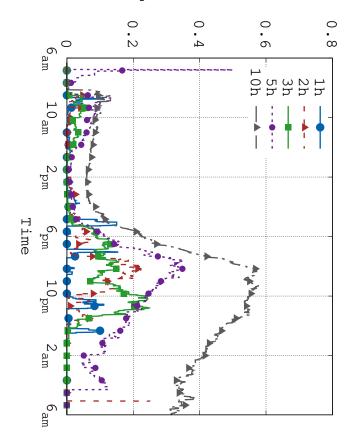
Average Spearman similarity between local and global resource vectors



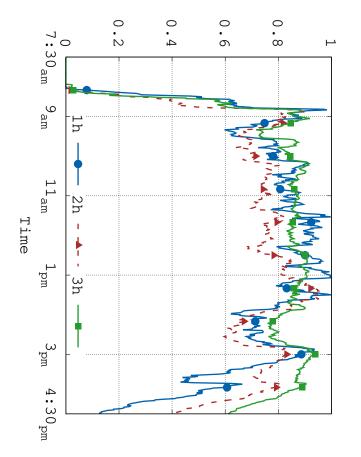
Average Jaccard similarity between local and global resource vectors

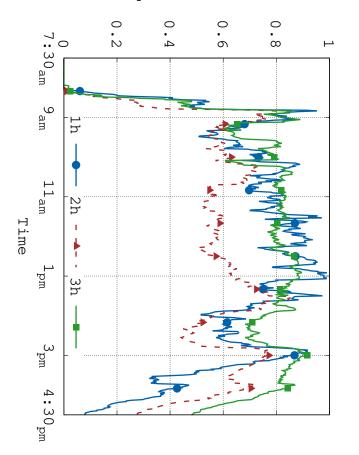


Average Spearman similarity between local and global resource vectors



Average Jaccard similarity between local and global resource vectors





Average Spearman similarity between local and global resource vectors

